STATA MULTIVARIATE STATISTICS REFERENCE MANUAL
RELEASE 18

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Contents

Cross-referencing the documentation

When reading this manual, you will find references to other Stata manuals, for example, [U] **27 Overview of Stata estimation commands**; [R] **regress**; and [D] **reshape**. The first example is a reference to chapter 27, *Overview of Stata estimation commands*, in the *User's Guide*; the second is a reference to the `regress` entry in the *Base Reference Manual*; and the third is a reference to the `reshape` entry in the *Data Management Reference Manual*.

All the manuals in the Stata Documentation have a shorthand notation:

[GSM]	*Getting Started with Stata for Mac*
[GSU]	*Getting Started with Stata for Unix*
[GSW]	*Getting Started with Stata for Windows*
[U]	*Stata User's Guide*
[R]	*Stata Base Reference Manual*
[ADAPT]	*Stata Adaptive Designs: Group Sequential Trials Reference Manual*
[BAYES]	*Stata Bayesian Analysis Reference Manual*
[BMA]	*Stata Bayesian Model Averaging Reference Manual*
[CAUSAL]	*Stata Causal Inference and Treatment-Effects Estimation Reference Manual*
[CM]	*Stata Choice Models Reference Manual*
[D]	*Stata Data Management Reference Manual*
[DSGE]	*Stata Dynamic Stochastic General Equilibrium Models Reference Manual*
[ERM]	*Stata Extended Regression Models Reference Manual*
[FMM]	*Stata Finite Mixture Models Reference Manual*
[FN]	*Stata Functions Reference Manual*
[G]	*Stata Graphics Reference Manual*
[IRT]	*Stata Item Response Theory Reference Manual*
[LASSO]	*Stata Lasso Reference Manual*
[XT]	*Stata Longitudinal-Data/Panel-Data Reference Manual*
[META]	*Stata Meta-Analysis Reference Manual*
[ME]	*Stata Multilevel Mixed-Effects Reference Manual*
[MI]	*Stata Multiple-Imputation Reference Manual*
[MV]	*Stata Multivariate Statistics Reference Manual*
[PSS]	*Stata Power, Precision, and Sample-Size Reference Manual*
[P]	*Stata Programming Reference Manual*
[RPT]	*Stata Reporting Reference Manual*
[SP]	*Stata Spatial Autoregressive Models Reference Manual*
[SEM]	*Stata Structural Equation Modeling Reference Manual*
[SVY]	*Stata Survey Data Reference Manual*
[ST]	*Stata Survival Analysis Reference Manual*
[TABLES]	*Stata Customizable Tables and Collected Results Reference Manual*
[TS]	*Stata Time-Series Reference Manual*
[I]	*Stata Index*
[M]	*Mata Reference Manual*

Title

> **Intro —** Introduction to multivariate statistics manual

Description

This manual documents Stata's multivariate analysis features and is referred to as the [MV] manual in cross-references.

Following this entry, [MV] **Multivariate** provides an overview of the multivariate analysis features in Stata and Stata's multivariate analysis commands. The other parts of this manual are arranged alphabetically.

Stata is continually being updated, and Stata users are always writing new commands. To find out about the latest multivariate analysis features, type `search multivariate analysis` after installing the latest official updates; see [R] **update**.

Also see

[U] **1.3 What's new**

[R] **Intro** — Introduction to base reference manual

Title

> **Multivariate —** Introduction to multivariate commands

Description

The *Multivariate Reference Manual* organizes the commands alphabetically, which makes it easy to find individual command entries if you know the name of the command. This overview organizes and presents the commands conceptually, that is, according to the similarities in the functions that they perform. The table below lists the manual entries that you should see for additional information.

Cluster analysis.
These commands perform cluster analysis on variables or the similarity or dissimilarity values within a matrix. An introduction to cluster analysis and a description of the cluster and clustermat subcommands is provided in [MV] **cluster** and [MV] **clustermat**.

Discriminant analysis.
These commands provide both descriptive and predictive linear discriminant analysis (LDA), as well as predictive quadratic discriminant analysis (QDA), logistic discriminant analysis, and *k*th-nearest-neighbor (KNN) discriminant analysis. An introduction to discriminant analysis and the discrim command is provided in [MV] **discrim**.

Factor analysis and principal component analysis.
These commands provide reliability analysis using Cronbach's alpha, factor analysis of a correlation matrix, and principal component analysis (PCA) of a correlation or covariance matrix. The correlation or covariance matrix can be provided directly or computed from variables.

Rotation.
These commands provide methods for rotating a factor or PCA solution or for rotating a matrix. Also provided is Procrustean rotation analysis for rotating a set of variables to best match another set of variables.

Multivariate analysis of variance, multivariate regression, and related techniques.
These commands provide canonical correlation analysis, multivariate regression, multivariate analysis of variance (MANOVA), and comparison of multivariate means. Also provided are multivariate tests on means, covariances, and correlations, and tests for multivariate normality.

Structural equation modeling.
These commands provide multivariate linear models that can include observed and latent variables. These models include confirmatory factor analysis, multivariate regression, path analysis, mediator analysis, and more; see the *Stata Structural Equation Modeling Reference Manual*.

Multidimensional scaling and biplots.
These commands provide classic and modern (metric and nonmetric) MDS and two-dimensional biplots. MDS can be performed on the variables or on proximity data in a matrix or as proximity data in long format.

Correspondence analysis.
These commands provide simple correspondence analysis (CA) on the cross-tabulation of two categorical variables or on a matrix and multiple correspondence analysis (MCA) and joint correspondence analysis (JCA) on two or more categorical variables.

Bayesian analysis.

These commands provide Bayesian estimation of multivariate linear models, including multivariate normal regression; see the *Stata Bayesian Analysis Reference Manual*.

Item response theory.

These commands fit item response theory models to binary, ordinal, and nominal items, and their combinations. Postestimation features include graphical tools to plot characteristic curves and information functions; see the *Stata Item Response Theory Reference Manual*.

Multivariate time-series models.

These commands provide multivariate models for time-series data, including multivariate generalized autoregressive conditional heteroskedasticity (GARCH), vector autoregressive (VAR), vector error-correction (VEC), dynamic-factor, state-space, and dynamic stochastic general equilibrium (DSGE) models. Bayesian analysis of VAR and DSGE is also available.

Multivariate meta-regression.

These commands fit multivariate fixed-effects and random-effects meta-regression models. Various postestimation features, such as predicting random effects and assessing multivariate heterogeneity, are available; see *Stata Meta-Analysis Reference Manual*.

Cluster analysis

[MV] **cluster**	Introduction to cluster-analysis commands
[MV] **clustermat**	Introduction to clustermat commands
[MV] **matrix dissimilarity**	Compute similarity or dissimilarity measures; may be used by `clustermat`

Discriminant analysis

[MV] **discrim**	Introduction to discriminant-analysis commands
[MV] **discrim lda**	Linear discriminant analysis (LDA)
[MV] **discrim lda postestimation**	Postestimation tools for discrim lda
[MV] **candisc**	Canonical (descriptive) linear discriminant analysis
[MV] **discrim qda**	Quadratic discriminant analysis (QDA)
[MV] **discrim qda postestimation**	Postestimation tools for discrim qda
[MV] **discrim logistic**	Logistic discriminant analysis
[MV] **discrim logistic postestimation**	Postestimation tools for discrim logistic
[MV] **discrim knn**	kth-nearest-neighbor (KNN) discriminant analysis
[MV] **discrim knn postestimation**	Postestimation tools for discrim knn
[MV] **discrim estat**	Postestimation tools for discrim

Factor analysis and principal component analysis

[MV] **alpha**	Compute interitem correlations (covariances) and Cronbach's alpha
[MV] **factor**	Factor analysis
[MV] **factor postestimation**	Postestimation tools for factor and factormat
[MV] **pca**	Principal component analysis
[MV] **pca postestimation**	Postestimation tools for pca and pcamat
[MV] **rotate**	Orthogonal and oblique rotations after factor and pca
[MV] **screeplot**	Scree plot of eigenvalues
[MV] **scoreplot**	Score and loading plots

Rotation

[MV] **rotate**	Orthogonal and oblique rotations after factor and pca
[MV] **rotatemat**	Orthogonal and oblique rotation of a Stata matrix
[MV] **procrustes**	Procrustes transformation
[MV] **procrustes postestimation**	Postestimation tools for procrustes

Multivariate analysis of variance, multivariate regression, and related techniques

[MV] **canon**	Canonical correlations
[MV] **canon postestimation**	Postestimation tools for canon
[MV] **mvreg**	Multivariate regression
[MV] **mvreg postestimation**	Postestimation tools for mvreg
[MV] **manova**	Multivariate analysis of variance and covariance
[MV] **manova postestimation**	Postestimation tools for manova
[MV] **hotelling**	Hotelling's T^2 generalized means test
[MV] **mvtest**	Multivariate tests on means, covariances, correlations, and of normality
[R] **nlsur**	Estimation of nonlinear systems of equations
[R] **reg3**	Three-stage estimation for systems of simultaneous equations
[R] **sureg**	Zellner's seemingly unrelated regression

Structural equation modeling

[SEM] *Stata Structural Equation Modeling Reference Manual*

Multidimensional scaling and biplots

[MV] **mds**	Multidimensional scaling for two-way data
[MV] **mds postestimation**	Postestimation tools for mds, mdsmat, and mdslong
[MV] **mds postestimation plots**	Postestimation plots for mds, mdsmat, and mdslong
[MV] **mdslong**	Multidimensional scaling of proximity data in long format
[MV] **mdsmat**	Multidimensional scaling of proximity data in a matrix
[MV] **biplot**	Biplots

Correspondence analysis

[MV] **ca**	Simple correspondence analysis
[MV] **ca postestimation**	Postestimation tools for ca and camat
[MV] **ca postestimation plots**	Postestimation plots for ca and camat
[MV] **mca**	Multiple and joint correspondence analysis
[MV] **mca postestimation**	Postestimation tools for mca
[MV] **mca postestimation plots**	Postestimation plots for mca

Bayesian analysis

[BAYES] *Stata Bayesian Analysis Reference Manual*

Item response theory

[IRT] *Stata Item Response Theory Reference Manual*

Multivariate time-series models

[TS] *Stata Time-Series Reference Manual*

[DSGE] *Stata Dynamic Stochastic General Equilibrium Models Reference Manual*

Multivariate meta-regression

[META] *Stata Meta-Analysis Reference Manual*

Remarks and examples

Remarks are presented under the following headings:

> *Cluster analysis*
> *Discriminant analysis*
> *Factor analysis and principal component analysis*
> *Rotation*
> *Multivariate analysis of variance, multivariate regression, and related techniques*
> *Structural equation modeling*
> *Multidimensional scaling and biplots*
> *Correspondence analysis*
> *Bayesian analysis*
> *Item response theory*
> *Multivariate time-series models*
> *Multivariate meta-regression*

Cluster analysis

Cluster analysis is concerned with finding natural groupings, or clusters. Stata's cluster-analysis commands provide several hierarchical and partition clustering methods, postclustering summarization methods, and cluster-management tools. The hierarchical clustering methods may be applied to the data with the cluster command or to a user-supplied dissimilarity matrix with the clustermat command. See [MV] **cluster** for an introduction to cluster analysis and the cluster and clustermat suite of commands. For an alternative to cluster analysis, see [SEM] **Intro 5** for information on latent class analysis.

A wide variety of similarity and dissimilarity measures are available for comparing observations; see [MV] *measure_option*. Dissimilarity matrices, for use with clustermat, are easily obtained using the matrix dissimilarity command; see [MV] **matrix dissimilarity**. This provides the building blocks necessary for clustering variables instead of observations or for clustering using a dissimilarity not automatically provided by Stata; [MV] **clustermat** provides examples.

Discriminant analysis

Discriminant analysis may be used to describe differences between groups and to exploit those differences in allocating (classifying) observations to the groups. These two purposes of discriminant analysis are often called descriptive discriminant analysis and predictive discriminant analysis.

discrim has both descriptive and predictive LDA; see [MV] **discrim lda**. The candisc command computes the same thing as discrim lda, but with output tailored for the descriptive aspects of the discrimination; see [MV] **candisc**.

The remaining discrim subcommands provide alternatives to linear discriminant analysis for predictive discrimination. [MV] **discrim qda** provides quadratic discriminant analysis. [MV] **discrim logistic** provides logistic discriminant analysis. [MV] **discrim knn** provides *k*th-nearest-neighbor discriminant analysis.

Postestimation commands provide classification tables (confusion matrices), error-rate estimates, classification listings, and group summarizations. In addition, postestimation tools for LDA and QDA include display of Mahalanobis distances between groups, correlations, and covariances. LDA postestimation tools also include discriminant-function loading plots, discriminant-function score plots, scree plots, display of canonical correlations, eigenvalues, proportion of variance, likelihood-ratio tests for the number of nonzero eigenvalues, classification functions, loadings, structure matrix, standardized means, and ANOVA and MANOVA tables. See [MV] **discrim estat**, [MV] **discrim lda postestimation**, and [MV] **discrim qda postestimation**.

Factor analysis and principal component analysis

Cronbach's alpha is a measure of reliability often used as a preliminary step before factor analysis. Though not literally correct, alpha is sometimes conceptualized as the average correlation among all possible pairwise combinations of a group of variables. A value of alpha greater than 0.7 (sometimes 0.8) indicates high intracorrelation among a group of variables and is typically used as a criterion to determine that a subsequent factor analysis is appropriate. See [MV] **alpha** for details.

Factor analysis and principal component analysis (PCA) have dual uses. They may be used as a dimension-reduction technique, and they may be used in describing the underlying data.

In PCA, the leading eigenvectors from the eigen decomposition of the correlation or covariance matrix of the variables describe a series of uncorrelated linear combinations of the variables that contain most of the variance. For data reduction, a few of these leading components are retained. For describing the underlying structure of the data, the magnitudes and signs of the eigenvector elements are interpreted in relation to the original variables (rows of the eigenvector).

`pca` uses the correlation or covariance matrix computed from the dataset. `pcamat` allows the correlation or covariance matrix to be directly provided. The `vce(normal)` option provides standard errors for the eigenvalues and eigenvectors, which aids in their interpretation. See [MV] **pca** for details.

Factor analysis finds a few common factors that linearly reconstruct the original variables. Reconstruction is defined in terms of prediction of the correlation matrix of the original variables, unlike PCA, where reconstruction means minimum residual variance summed across all variables. Factor loadings are examined for interpretation of the structure of the data.

`factor` computes the correlation from the dataset, whereas `factormat` is supplied the matrix directly. They both display the eigenvalues of the correlation matrix, the factor loadings, and the "uniqueness" of the variables. See [MV] **factor** for details.

To perform factor analysis or PCA on binary data, compute the tetrachoric correlations and use these with `factormat` or `pcamat`. Tetrachoric correlations are available with the `tetrachoric` command; see [R] **tetrachoric**.

After factor analysis and PCA, a suite of commands are available that provide for rotation of the loadings; generation of score variables; graphing of scree plots, loading plots, and score plots; display of matrices and scalars of interest such as anti-image matrices, residual matrices, Kaiser–Meyer–Olkin measures of sampling adequacy, squared multiple correlations; and more. See [MV] **factor postestimation**, [MV] **pca postestimation**, [MV] **rotate**, [MV] **screeplot**, and [MV] **scoreplot** for details.

Rotation

Rotation provides a modified solution that is rotated from an original multivariate solution such that interpretation is enhanced. Rotation is provided through three commands: `rotate`, `rotatemat`, and `procrustes`.

`rotate` works directly after `pca`, `pcamat`, `factor`, and `factormat`. It knows where to obtain the component- or factor-loading matrix for rotation, and after rotating the loading matrix, it places the rotated results in `e()` so that all the postestimation tools available after `pca` and `factor` may be applied to the rotated results. See [MV] **rotate** for details.

Perhaps you have the component or factor loadings from a published source and want to investigate various rotations, or perhaps you wish to rotate a loading matrix from some other multivariate command. `rotatemat` provides rotations for a specified matrix. See [MV] **rotatemat** for details.

A large selection of orthogonal and oblique rotations are provided for `rotate` and `rotatemat`. These include varimax, quartimax, equamax, parsimax, minimum entropy, Comrey's tandem 1 and 2, promax power, biquartimax, biquartimin, covarimin, oblimin, factor parsimony, Crawford–Ferguson family, Bentler's invariant pattern simplicity, oblimax, quartimin, target, and weighted target rotations. Kaiser normalization is also available.

The `procrustes` command provides Procrustean analysis. The goal is to transform a set of source variables to be as close as possible to a set of target variables. The permitted transformations are any combination of dilation (uniform scaling), rotation and reflection (orthogonal and oblique transformations), and translation. Closeness is measured by the residual sum of squares. See [MV] **procrustes** for details.

A set of postestimation commands are available after `procrustes` for generating fitted values and residuals; for providing fit statistics for orthogonal, oblique, and unrestricted transformations; and for providing a Procrustes overlay graph. See [MV] **procrustes postestimation** for details.

Multivariate analysis of variance, multivariate regression, and related techniques

The first canonical correlation is the maximum correlation that can be obtained between a linear combination of one set of variables and a linear combination of another set of variables. The second canonical correlation is the maximum correlation that can be obtained between linear combinations of the two sets of variables subject to the constraint that these second linear combinations are orthogonal to the first linear combinations, and so on.

`canon` estimates these canonical correlations and provides the loadings that describe the linear combinations of the two sets of variables that produce the correlations. Standard errors of the loadings are provided, and tests of the significance of the canonical correlations are available. See [MV] **canon** for details.

Postestimation tools are available after `canon` for generating the variables corresponding to the linear combinations underlying the canonical correlations. Various matrices and correlations may also be displayed. See [MV] **canon postestimation** for details.

In canonical correlation, there is no real distinction between the two sets of original variables. In multivariate regression, however, the two sets of variables take on the roles of dependent and independent variables. Multivariate regression is an extension of regression that allows for multiple dependent variables. See [MV] **mvreg** for multivariate regression, and see [MV] **mvreg postestimation** for the postestimation tools available after multivariate regression.

Just as analysis of variance (ANOVA) can be formulated in terms of regression where the categorical independent variables are represented by indicator (sometimes called dummy) variables, multivariate

analysis of variance (MANOVA), a generalization of ANOVA that allows for multiple dependent variables, can be formulated in terms of multivariate regression where the categorical independent variables are represented by indicator variables. Multivariate analysis of covariance (MANCOVA) allows for both continuous and categorical independent variables.

The `manova` command fits MANOVA and MANCOVA models for balanced and unbalanced designs, including designs with missing cells, and for factorial, nested, or mixed designs, or designs involving repeated measures. Four multivariate test statistics—Wilks's lambda, Pillai's trace, the Lawley–Hotelling trace, and Roy's largest root—are computed for each term in the model. See [MV] **manova** for details.

Postestimation tools are available after `manova` that provide for univariate Wald tests of expressions involving the coefficients of the underlying regression model and that provide for multivariate tests involving terms or linear combinations of the underlying design matrix. Linear combinations of the dependent variables are also supported. Also available are marginal means, predictive margins, marginal effects, and average marginal effects. See [MV] **manova postestimation** for details.

Related to MANOVA is Hotelling's T^2 test of whether a set of means is zero or whether two sets of means are equal. It is a multivariate test that reduces to a standard t test if only one variable is involved. The `hotelling` command provides Hotelling's T^2 test; see [MV] **hotelling**, but also see [MV] **mvtest means** for more extensive multivariate means testing.

A suite of `mvtest` commands perform assorted multivariate tests. `mvtest means` performs one-sample and multiple-sample multivariate tests on means, assuming multivariate normality. `mvtest covariances` performs one-sample and multiple-sample multivariate tests on covariances, assuming multivariate normality. `mvtest correlations` performs one-sample and multiple-sample tests on correlations, assuming multivariate normality. `mvtest normality` performs tests for univariate, bivariate, and multivariate normality. See [MV] **mvtest**.

Related to multivariate regression, the `sureg`, `reg3`, `nlsur`, and `demandsys` commands fit models with more than one outcome variable. `sureg` fits a seemingly unrelated regression model, which is equivalent to the multivariate regression model fit by `mvreg` when the same set of covariates models each dependent variable. However, `sureg` extends this to allow for different covariates in each equation. The `reg3` command estimates a system of structural equations in which some equations include endogenous covariates. Both `sureg` and `reg3` fit linear models. The `nlsur` command fits a system of nonlinear equations. See [R] **sureg**, [R] **reg3**, [R] **nlsur**, and [R] **demandsys** for details.

Structural equation modeling

Structural equation modeling (SEM) is a flexible estimation method for fitting a variety of multivariate models, and it allows for latent (unobserved) variables. See [SEM] **Intro 5**.

Multidimensional scaling and biplots

Multidimensional scaling (MDS) is a dimension-reduction and visualization technique. Dissimilarities (for instance, Euclidean distances) between observations in a high-dimensional space are represented in a lower-dimensional space (typically two dimensions) so that the Euclidean distance in the lower-dimensional space approximates the dissimilarities in the higher-dimensional space.

The `mds` command provides classical and modern (metric and nonmetric) MDS for dissimilarities between observations with respect to the variables; see [MV] **mds**. A wide variety of similarity and dissimilarity measures are allowed (the same ones available for the `cluster` command); see [MV] *measure_option*.

mdslong and mdsmat provide MDS directly on the dissimilarities recorded either as data in long format (mdslong) or as a dissimilarity matrix (mdsmat); see [MV] **mdslong** and [MV] **mdsmat**.

Postestimation tools available after mds, mdslong, and mdsmat provide MDS configuration plots and Shepard diagrams; generation of the approximating configuration or the disparities, dissimilarities, distances, raw residuals and transformed residuals; and various matrices and scalars, such as Kruskal stress (loss), quantiles of the residuals per object, and correlations between disparities or dissimilarities and approximating distances. See [MV] **mds postestimation** and [MV] **mds postestimation plots**.

Biplots are two-dimensional representations of data. Both the observations and the variables are represented. The observations are represented by marker symbols, and the variables are represented by arrows from the origin. Observations are projected to two dimensions so that the distance between the observations is approximately preserved. The cosine of the angle between arrows approximates the correlation between the variables. A biplot aids in understanding the relationship between the variables, the observations, and the observations and variables jointly. The biplot command produces biplots; see [MV] **biplot**.

Correspondence analysis

Simple correspondence analysis (CA) is a technique for jointly exploring the relationship between rows and columns in a cross-tabulation. It is known by many names, including dual scaling, reciprocal averaging, and canonical correlation analysis of contingency tables.

ca performs CA on the cross-tabulation of two integer-valued variables or on two sets of crossed (stacked) integer-valued variables. camat performs CA on a matrix with nonnegative entries—perhaps from a published table. See [MV] **ca** for details.

A suite of commands are available following ca and camat. These include commands for producing CA biplots and dimensional projection plots; for generating fitted values, row coordinates, and column coordinates; and for displaying distances between row and column profiles, individual cell inertia contributions, χ^2 distances between row and column profiles, and the fitted correspondence table. See [MV] **ca postestimation** and [MV] **ca postestimation plots**.

mca performs multiple (MCA) or joint (JCA) correspondence analysis on two or more categorical variables and allows for crossing (stacking). See [MV] **mca**.

Postestimation tools available after mca provide graphing of category coordinate plots, dimensional projection plots, and plots of principal inertias; display of the category coordinates, optionally with column statistics; the matrix of inertias of the active variables after JCA; and generation of row scores. See [MV] **mca postestimation** and [MV] **mca postestimation plots**.

Bayesian analysis

Bayesian analysis provides a flexible framework for fitting a variety of Bayesian models, including multivariate models. See *Stata Bayesian Analysis Reference Manual*.

Item response theory

Item response theory (IRT) is used in the design, analysis, scoring, and comparison of tests and similar instruments whose purpose is to measure unobservable characteristics of the respondents; see *Stata Item Response Theory Reference Manual*.

Multivariate time-series models

For time-series data, a variety of multivariate models are available. These include multivariate GARCH models, vector autoregressive (VAR) models, vector error-correction (VEC) models, dynamic-factor models, and state-space models. See [TS] *Stata Time-Series Reference Manual*

Dynamic stochastic general equilibrium (DSGE) models are specialized multivariate time-series models that allow current values of variables to depend not only on past values but also on expectations of future values. See [DSGE] *Stata Dynamic Stochastic General Equilibrium Models Reference Manual.*

Bayesian VAR and Bayesian DSGE models are also available. See *Stata Bayesian Analysis Reference Manual.*

Multivariate meta-regression

Multivariate meta-regression models are used to investigate the relationship between study-level covariates, called moderators, and multiple dependent effect sizes reported by each study. Random-effects and fixed-effects models are available to fit the data using the `meta mvregress` command. For the random-effects models, several estimation methods are possible to estimate the covariance of the random effects. See [META] **meta mvregress** for details.

Postestimation tools include predicting the random effects and their variance–covariance matrix and other diagnostic tools for assessing the model assumptions. Multivariate heterogeneity may be quantified using the postestimation command `estat heterogeneity`. See [META] **meta mvregress postestimation**.

Also see

[R] **Intro** — Introduction to base reference manual

[MV] **Glossary**

Title

> **alpha —** Compute interitem correlations (covariances) and Cronbach's alpha

Description

alpha computes the interitem correlations or covariances for all pairs of variables in *varlist* and Cronbach's α statistic for the scale formed from them. At least two variables must be specified with alpha.

Quick start

Cronbach's alpha and the average interitem covariance of 6 variables

    alpha v1 v2 v3 v4 v5 v6

Same as above, but standardize the variables to give average interitem correlation

    alpha v1 v2 v3 v4 v5 v6, std

Same as above, and show table of item-test and item-rest correlations and the effect of removing each variable from the scale

    alpha v1 v2 v3 v4 v5 v6, std item

Same as above, and also list each interitem correlation

    alpha v1 v2 v3 v4 v5 v6, std item detail

Same as above, but force v2 and v5 to enter with reversed sign

    alpha v1 v2 v3 v4 v5 v6, std item detail reverse(v2 v5)

Same as above, and generate scalevar with the summative score (scale)

    alpha v1 v2 v3 v4 v5 v6, std item detail reverse(v2 v5) ///
        generate(scalevar)

Menu

Statistics > Multivariate analysis > Cronbach's alpha

Syntax

> alpha *varlist* [*if*] [*in*] [, *options*]

options	Description
Options	
<u>asis</u>	take sign of each item as is
<u>casewise</u>	delete cases with missing values
<u>detail</u>	list individual interitem correlations and covariances
<u>generate</u>(*newvar*)	save the generated scale in *newvar*
<u>item</u>	display item-test and item-rest correlations
<u>label</u>	include variable labels in output table
<u>min</u>(#)	must have at least *#* observations for inclusion
<u>reverse</u>(*varlist*)	reverse signs of these variables
<u>std</u>	standardize items in the scale to mean 0, variance 1

by and collect are allowed; see [U] **11.1.10 Prefix commands**.

Options

> ┌─────────┐
> │ Options │
> └─────────┘

asis specifies that the sense (sign) of each item be taken as presented in the data. The default is to determine the sense empirically and reverse the scorings for any that enter negatively.

casewise specifies that cases with missing values be deleted listwise. The default is pairwise computation of covariances and correlations.

detail lists the individual interitem correlations and covariances.

generate(*newvar*) specifies that the scale constructed from *varlist* be saved in *newvar*. Unless asis is specified, the sense of items entering negatively is automatically reversed. If std is also specified, the scale is constructed by using standardized (mean 0, variance 1) values of the individual items. Unlike most Stata commands, generate() does not use casewise deletion. A score is created for every observation for which there is a response to at least one item (one variable in *varlist* is not missing). The summative score is divided by the number of items over which the sum is calculated.

item specifies that item-test and item-rest correlations and the effects of removing an item from the scale be displayed. item is valid only when more than two variables are specified in *varlist*.

label requests that the detailed output table be displayed in a compact format that enables the inclusion of variable labels.

min(#) specifies that only cases with at least *#* observations be included in the computations. casewise is a shorthand for min(*k*), where *k* is the number of variables in *varlist*.

reverse(*varlist*) specifies that the signs (directions) of the variables (items) in *varlist* be reversed. Any variables specified in reverse() that are not also included in alpha's *varlist* are ignored.

std specifies that the items in the scale be standardized (mean 0, variance 1) before summing.

Remarks and examples

Cronbach's alpha (Cronbach 1951) assesses the reliability of a summative rating (Likert 1932) scale composed of the variables (called *items*) specified. The set of items is often called a *test* or *battery*. A scale is simply the sum of the individual item scores, reversing the scoring for statements that have negative correlations with the factor (for example, attitude) being measured. Scales can be formed by using the raw item scores or standardized item scores.

The reliability α is defined as the square of the correlation between the measured scale and the underlying factor. If you think of a test as being composed of a random sample of items from a hypothetical domain of items designed to measure the same thing, α represents the expected correlation of one test with an alternative form containing the same number of items. The square root of α is the estimated correlation of a test with errorless true scores (Nunnally and Bernstein 1994, 235).

In addition to reporting α, alpha generates the summative scale from the items (variables) specified and automatically reverses the sense of any when necessary. Stata's decision can be overridden by specifying the reverse(*varlist*) option.

Because it concerns reliability in measuring an unobserved factor, α is related to factor analysis. The test should be designed to measure one factor, and, because the scale will be composed of an unweighted sum, the factor loadings should all contribute roughly equal information to the score. Both of these assumptions can be verified with factor; see [MV] **factor**. Equality of factor loadings can also be assessed by using the item option.

▷ Example 1

To illustrate alpha, we apply it, first without and then with the item option, to the automobile dataset after randomly introducing missing values:

```
. use https://www.stata-press.com/data/r18/automiss
(1978 automobile data)

. alpha price headroom rep78 trunk weight length turn displ, std
Test scale = mean(standardized items)
Reversed item:  rep78
Average interitem correlation:      0.5251
Number of items in the scale:            8
Scale reliability coefficient:      0.8984
```

The scale derived from our somewhat arbitrarily chosen automobile items (variables) appears to be reasonable because the estimated correlation between it and the underlying factor it measures is $\sqrt{0.8984} \approx 0.9478$ and the estimated correlation between this battery of eight items and all other eight-item batteries from the same domain is 0.8984. Because the "items" are not on the same scale, it is important that std was specified so that the scale and its reliability were based on the sum of standardized variables. We could obtain the scale in a new variable called sc with the gen(sc) option.

Though the scale appears reasonable, we include the `item` option to determine if all the items fit the scale:

```
. alpha price headroom rep78 trunk weight length turn displ, std item
Test scale = mean(standardized items)
```

Item	Obs	Sign	Item-test correlation	Item-rest correlation	Average interitem correlation	alpha
price	70	+	0.5260	0.3719	0.5993	0.9128
headroom	66	+	0.6716	0.5497	0.5542	0.8969
rep78	61	−	0.4874	0.3398	0.6040	0.9143
trunk	69	+	0.7979	0.7144	0.5159	0.8818
weight	64	+	0.9404	0.9096	0.4747	0.8635
length	69	+	0.9382	0.9076	0.4725	0.8625
turn	66	+	0.8678	0.8071	0.4948	0.8727
displacement	63	+	0.8992	0.8496	0.4852	0.8684
Test scale					0.5251	0.8984

"Test" denotes the additive scale; here 0.5251 is the average interitem correlation, and 0.8984 is the alpha coefficient for a test scale based on all items.

"Obs" shows the number of nonmissing values of the items; "Sign" indicates the direction in which an item variable entered the scale; "−" denotes that the item was reversed. The remaining four columns in the table provide information on the effect of one item on the scale.

Column four gives the item-test correlations. Apart from the sign of the correlation for items that entered the scale in reversed order, these correlations are the same numbers as those computed by the commands

```
. alpha price headroom rep78 trunk weight length turn displ, std gen(sc)
. pwcorr sc price headroom rep78 trunk weight length turn displ
```

Typically, the item-test correlations should be roughly the same for all items. Item-test correlations may not be adequate to detect items that fit poorly because the poorly fitting items may distort the scale. Accordingly, it may be more useful to consider item-rest correlations (Nunnally and Bernstein 1994), that is, the correlation between an item and the scale that is formed by all other items. The average interitem correlations (covariances if `std` is omitted) of all items, excluding one, are shown in column six. Finally, column seven gives Cronbach's α for the test scale, which consists of all but the one item.

Here neither the `price` item nor the `rep78` item seems to fit well in the scale in all respects. The item-test and item-rest correlations of `price` and `rep78` are much lower than those of the other items. The average interitem correlation increases substantially by removing either `price` or `rep78`; apparently, they do not correlate strongly with the other items. Finally, we see that Cronbach's α coefficient will increase from 0.8984 to 0.9128 if the `price` item is dropped, and it will increase from 0.8984 to 0.9143 if `rep78` is dropped. For well-fitting items, we would of course expect that α decreases by shortening the test.

◁

▷ Example 2

The variable names for the automobile data are reasonably informative. This may not always be true; items in batteries commonly used to measure personality traits, attitudes, values, etc., are usually named with indexed names, for example, `item12a`, `item12b`, `item12c`. The `label` option forces `alpha` to produce the same statistical information in a more compact format that leaves room to include variable (item) labels. In this compact format, `alpha` excludes the number of nonmissing values of the items, displays the statistics using fewer digits, and uses somewhat cryptic headers:

```
. alpha price headroom rep78 trunk weight length turn displ, std item label detail
Test scale = mean(standardized items)
```

Items	S	it-cor	ir-cor	ii-cor	alpha	Label
price	+	0.526	0.372	0.599	0.913	Price
headroom	+	0.672	0.550	0.554	0.897	Headroom (in.)
rep78	−	0.487	0.340	0.604	0.914	Repair record 1978
trunk	+	0.798	0.714	0.516	0.882	Trunk space (cu. ft.)
weight	+	0.940	0.910	0.475	0.863	Weight (lbs.)
length	+	0.938	0.908	0.473	0.862	Length (in.)
turn	+	0.868	0.807	0.495	0.873	Turn circle (ft.)
displacement	+	0.899	0.850	0.485	0.868	Displacement (cu. in.)
Test scale				0.525	0.898	mean(standardized items)

```
Interitem correlations (reverse applied) (obs=pairwise, see below)
```

	price	headroom	rep78	trunk
price	1.0000			
headroom	0.1174	1.0000		
rep78	-0.0479	0.1955	1.0000	
trunk	0.2748	0.6841	0.2777	1.0000
weight	0.5093	0.5464	0.3624	0.6486
length	0.4511	0.5823	0.3162	0.7404
turn	0.3528	0.4067	0.4715	0.5900
displacement	0.5537	0.5166	0.3391	0.6471

	weight	length	turn	displacement
weight	1.0000			
length	0.9425	1.0000		
turn	0.8712	0.8589	1.0000	
displacement	0.8753	0.8422	0.7723	1.0000

```
Pairwise number of observations
```

	price	headroom	rep78	trunk
price	70			
headroom	62	66		
rep78	59	54	61	
trunk	65	61	59	69
weight	60	56	52	60
length	66	61	58	64
turn	62	58	56	62
displacement	59	58	51	58

	weight	length	turn	displacement
weight	64			
length	60	69		
turn	57	61	66	
displacement	54	58	56	63

Because the `detail` option was also specified, the interitem correlation matrix was printed, together with the number of observations used for each entry (because these varied across the matrix). Note the negative sign attached to `rep78` in the output, indicating the sense in which it entered the scale.

Better-looking output with less-cryptic headers is produced if the linesize is set to a value of at least 100:

```
. set linesize 100
. alpha price headroom rep78 trunk weight length turn displ, std item label
Test scale = mean(standardized items)
```

Item	Obs	Sign	Item-test corr.	Item-rest corr.	Interitem corr.	alpha	Label
price	70	+	0.5260	0.3719	0.5993	0.9128	Price
headroom	66	+	0.6716	0.5497	0.5542	0.8969	Headroom (in.)
rep78	61	-	0.4874	0.3398	0.6040	0.9143	Repair record 1978
trunk	69	+	0.7979	0.7144	0.5159	0.8818	Trunk space (cu. ft.)
weight	64	+	0.9404	0.9096	0.4747	0.8635	Weight (lbs.)
length	69	+	0.9382	0.9076	0.4725	0.8625	Length (in.)
turn	66	+	0.8678	0.8071	0.4948	0.8727	Turn circle (ft.)
displacement	63	+	0.8992	0.8496	0.4852	0.8684	Displacement (cu. in.)
Test scale					0.5251	0.8984	mean(standardized items)

◁

Users of `alpha` require some standard for judging values of α. We paraphrase Nunnally and Bernstein (1994, 265): In the early stages of research, modest reliability of 0.70 or higher will suffice; values in excess of 0.80 often waste time and funds. In contrast, where measurements on individuals are of interest, a reliability of 0.80 may not be nearly high enough. Even with a reliability of 0.90, the standard error of measurement is almost one-third as large as the standard deviation of test scores; a reliability of 0.90 is the minimum that should be tolerated, and a reliability of 0.95 should be considered the desirable standard.

Stored results

`alpha` stores the following in `r()`:

Scalars
r(alpha)	scale reliability coefficient
r(k)	number of items in the scale
r(cov)	average interitem covariance
r(rho)	average interitem correlation if `std` is specified

Matrices
r(Alpha)	scale reliability coefficient
r(ItemTestCorr)	item-test correlation
r(ItemRestCorr)	item-rest correlation
r(MeanInterItemCov)	average interitem covariance
r(MeanInterItemCorr)	average interitem correlation if `std` is specified

If the `item` option is specified, results are stored as row matrices for the k subscales when one variable is removed.

Methods and formulas

Let x_i, $i = 1, \ldots, k$, be the variables over which α is to be calculated. Let s_i be the sign with which x_i enters the scale. If `asis` is specified, $s_i = 1$ for all i. Otherwise, principal-factor analysis is performed on x_i, and the first factor's score is predicted; see [MV] **factor**. s_i is -1 if correlation of the x_i and the predicted score is negative and $+1$ otherwise.

Let r_{ij} be the correlation between x_i and x_j, c_{ij} be the covariance, and n_{ij} be the number of observations used in calculating the correlation or covariance. The average correlation is

$$\overline{r} = \frac{\sum\limits_{i=2}^{k} \sum\limits_{j=1}^{i-1} s_i s_j n_{ij} r_{ij}}{\sum\limits_{i=2}^{k} \sum\limits_{j=1}^{i-1} n_{ij}}$$

and the average covariance similarly is

$$\overline{c} = \frac{\sum\limits_{i=2}^{k} \sum\limits_{j=1}^{i-1} s_i s_j n_{ij} c_{ij}}{\sum\limits_{i=2}^{k} \sum\limits_{j=1}^{i-1} n_{ij}}$$

Let c_{ii} denote the variance of x_i, and define the average variance as

$$\overline{v} = \frac{\sum\limits_{i=1}^{k} n_{ii} c_{ii}}{\sum\limits_{i=1}^{k} n_{ii}}$$

If std is specified, the scale reliability α is calculated as defined by the general form of the Spearman–Brown Prophecy Formula (Nunnally and Bernstein 1994, 232; Allen and Yen 1979, 85–88):

$$\alpha = \frac{k\overline{r}}{1 + (k-1)\overline{r}}$$

This expression corresponds to α under the assumption that the summative rating is the sum of the standardized variables (Nunnally and Bernstein 1994, 234). If std is not specified, α is defined (Nunnally and Bernstein 1994, 232 and 234) as

$$\alpha = \frac{k\overline{c}}{\overline{v} + (k-1)\overline{c}}$$

Let x_{ij} reflect the value of item i in the jth observation. If std is specified, the jth value of the scale computed from the k x_{ij} items is

$$S_j = \frac{1}{k_j} \sum\limits_{i=1}^{k} s_i S(x_{ij})$$

where $S()$ is the function that returns the standardized (mean 0, variance 1) value if x_{ij} is not missing and returns zero if x_{ij} is missing. k_j is the number of nonmissing values in x_{ij}, $i = 1, \ldots, k$. If std is not specified, $S()$ is the function that returns x_{ij} or returns missing if x_{ij} is missing.

Lee Joseph Cronbach (1916–2001) was born in Fresno, California. He participated in a study of gifted children and completed high school at the age of 14. He obtained a doctoral degree in educational psychology from the University of Chicago, where he later served as an assistant professor. During World War II, he applied his expertise as a military psychologist for the U.S. Navy.

Cronbach is widely known for his paper on the alpha coefficient, which measures test reliability. While his work on the reliability coefficient was focused on psychological testing and education, Cronbach's alpha is used in several fields. He wrote an article with Paul Meehl on psychological test validity and later published a book with Goldine Gleser introducing generalizability theory.

Cronbach made a lasting impact on program evaluations through his collaborative research with faculty at Stanford, along with his book *Designing Evaluations of Educational and Social Programs*. He also played an active role in the American Psychological Association's work on test standards and later became president of the American Psychological Association. His many contributions are reflected in the honors he received from the American Education Research Association, the Educational Testing Service, and other associations.

Acknowledgment

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Also see

[MV] **factor** — Factor analysis

[R] **icc** — Intraclass correlation coefficients

Title

> **biplot —** Biplots

Description

biplot displays a two-dimensional biplot of a dataset. A biplot simultaneously displays the observations (rows) and the relative positions of the variables (columns). Marker symbols (points) are displayed for observations, and arrows are displayed for variables. Observations are projected to two dimensions such that the distance between the observations is approximately preserved. The cosine of the angle between arrows approximates the correlation between the variables.

Quick start

Biplot of v1, v2, v3, and v4
```
biplot v1 v2 v3 v4
```

Same as above, but use standardized instead of centered variables
```
biplot v1 v2 v3 v4, std
```

Same as above, but graph dimension 3 versus 1 instead of 2 versus 1
```
biplot v1 v2 v3 v4, std dim(3 1)
```

Biplot with separate row and column plots
```
biplot v1 v2 v3 v4, separate
```

Only graph the column plot
```
biplot v1 v2 v3 v4, norow
```

Biplot with different color row markers for each category of catvar
```
biplot v1 v2 v3 v4, rowover(catvar)
```

Label row observations using the values in variable mylabel
```
biplot v1 v2 v3 v4, rowlabel(mylabel)
```

Store biplot coordinates in new variables x and y
```
biplot v1 v2 v3 v4, generate(x y)
```

Menu

Statistics > Multivariate analysis > Biplot

Syntax

> biplot *varlist* [*if*] [*in*] [, *options*]

options	Description
[Main]	
rowover(*varlist*)	identify observations from different groups of *varlist*; may not be combined with separate or norow
dim(*# #*)	two dimensions to be displayed; default is dim(2 1)
std	use standardized instead of centered variables
alpha(*#*)	row weight = #; column weight = $1 - \#$; default is 0.5
stretch(*#*)	stretch the column (variable) arrows
mahalanobis	approximate Mahalanobis distance; implies alpha(0)
xnegate	negate the data relative to the x axis
ynegate	negate the data relative to the y axis
autoaspect	adjust aspect ratio on the basis of the data; default aspect ratio is 1
separate	produce separate plots for rows and columns; may not be combined with rowover()
nograph	suppress graph
table	display table showing biplot coordinates
[Rows]	
rowopts(*row_options*)	affect rendition of rows (observations)
row#opts(*row_options*)	affect rendition of rows (observations) in the #th group of *varlist* defined in rowover(); available only with rowover()
rowlabel(*varname*)	specify label variable for rows (observations)
norow	suppress row points; may not be combined with rowover()
generate(*newvar$_x$ newvar$_y$*)	store biplot coordinates for observations in variables *newvar$_x$* and *newvar$_y$*
[Columns]	
colopts(*col_options*)	affect rendition of columns (variables)
negcol	include negative column (variable) arrows
negcolopts(*col_options*)	affect rendition of negative columns (variables)
nocolumn	suppress column arrows
[Y axis, X axis, Titles, Legend, Overall]	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

collect is allowed; see [U] **11.1.10 Prefix commands**.

row_options	Description
marker_options	change look of markers (color, size, etc.)
marker_label_options	change look or position of marker labels
nolabel	remove the default row (variable) label from the graph
name(*name*)	override the default name given to rows (observations)

col_options	Description
pcarrow_options	affect the rendition of paired-coordinate arrows
nolabel	remove the default column (variable) label from the graph
name(*name*)	override the default name given to columns (variables)

Options

> [Main]

rowover(*varlist*) distinguishes groups among observations (rows) by highlighting observations on the plot for each group identified by equal values of the variables in *varlist*. By default, the graph contains a legend that consists of group names. rowover() may not be combined with separate or norow.

dim(*# #*) identifies the dimensions to be displayed. For instance, dim(3 2) plots the third dimension (vertically) versus the second dimension (horizontally). The dimension numbers cannot exceed the number of variables. The default is dim(2 1).

std produces a biplot of the standardized variables instead of the centered variables.

alpha(*#*) specifies that the variables be scaled by $\lambda^{\#}$ and the observations by $\lambda^{(1-\#)}$, where λ are the singular values. It is required that $0 \le \# \le 1$. The most common values are 0, 0.5, and 1. The default is alpha(0.5) and is known as the symmetrically scaled biplot or symmetric factorization biplot. The result with alpha(1) is the principal-component biplot, also called the row-preserving metric (RPM) biplot. The biplot with alpha(0) is referred to as the column-preserving metric (CPM) biplot.

stretch(*#*) causes the length of the arrows to be multiplied by *#*. For example, stretch(1) would leave the arrows the same length, stretch(2) would double their length, and stretch(0.5) would halve their length.

mahalanobis implies alpha(0) and scales the positioning of points (observations) by $\sqrt{n-1}$ and positioning of arrows (variables) by $1/\sqrt{n-1}$. This additional scaling causes the distances between observations to change from being approximately proportional to the Mahalanobis distance to instead being approximately equal to the Mahalanobis distance. Also, the inner products between variables approximate their covariance.

xnegate specifies that dimension-1 (x axis) values be negated (multiplied by -1).

ynegate specifies that dimension-2 (y axis) values be negated (multiplied by -1).

autoaspect specifies that the aspect ratio be automatically adjusted based on the range of the data to be plotted. This option can make some biplots more readable. By default, biplot uses an aspect ratio of one, producing a square plot. Some biplots will have little variation in the y-axis direction, and using the autoaspect option will better fill the available graph space while preserving the equivalence of distance in the x and y axes.

As an alternative to autoaspect, the *twoway_option* aspectratio() can be used to override the default aspect ratio. biplot accepts the aspectratio() option as a suggestion only and will override it when necessary to produce plots with balanced axes; that is, distance on the x axis equals distance on the y axis.

twoway_options, such as xlabel(), xscale(), ylabel(), and yscale(), should be used with caution. These *axis_options* are accepted but may have unintended side effects on the aspect ratio. See [G-3] *twoway_options*.

separate produces separate plots for the row and column categories. The default is to overlay the plots. separate may not be combined with rowover().

nograph suppresses displaying the graph.

table displays a table with the biplot coordinates.

┌─ Rows ───

rowopts(*row_options*) affects the rendition of the points plotting the rows (observations). This option may not be combined with rowover(). The following *row_options* are allowed:

   marker_options affect the rendition of markers drawn at the plotted points, including their shape, size, color, and outline; see [G-3] **marker_options**.

   marker_label_options specify the properties of marker labels; see [G-3] **marker_label_options**. mlabel() in rowopts() may not be combined with the rowlabel() option.

   nolabel removes the default row label from the graph.

   name(*name*) overrides the default name given to rows.

row#opts(*row_options*) affects rendition of the points plotting the rows (observations) in the #th group identified by equal values of the variables in *varlist* defined in rowover(). This option requires specifying rowover(). See rowopts() above for the allowed *row_options*, except mlabel() is not allowed with row#opts().

rowlabel(*varname*) specifies label variable for rows (observations).

norow suppresses plotting of row points. This option may not be combined with rowover().

generate(*newvar$_x$ newvar$_y$*) stores biplot coordinates for rows in variables *newvar$_x$* and *newvar$_y$*.

┌─ Columns ──

colopts(*col_options*) affects the rendition of the arrows and points plotting the columns (variables). The following *col_options* are allowed:

   pcarrow_options affect the rendition of paired-coordinate arrows; see [G-2] **graph twoway pcarrow**.

   nolabel removes the default column label from the graph.

   name(*name*) overrides the default name given to columns.

negcol includes negative column (variable) arrows on the plot.

negcolopts(*col_options*) affects the rendition of the arrows and points plotting the negative columns (variables). The *col_options* allowed are given above.

nocolumn suppresses plotting of column arrows.

┌─ Y axis, X axis, Titles, Legend, Overall ──────────────────────────────────────

twoway_options are any of the options documented in [G-3] **twoway_options**, excluding by(). These include options for titling the graph (see [G-3] **title_options**) and for saving the graph to disk (see [G-3] **saving_option**). See autoaspect above for a warning against using options such as xlabel(), xscale(), ylabel(), and yscale().

Remarks and examples

The biplot command produces what Cox and Cox (2001) refer to as the "classic biplot". Biplots were introduced by Gabriel (1971); also see Gabriel (1981). Gower and Hand (1996) discuss extensions and generalizations to biplots and place many of the well-known multivariate techniques into a generalized biplot framework extending beyond the classic biplot implemented by Stata's biplot command. Cox and Cox (2001), Jolliffe (2002), Gordon (1999), Jacoby (1998), Rencher and Christensen (2012), and Seber (1984) discuss the classic biplot. Kohler (2004) provides a Stata implementation of biplots.

Let $\mathbf{X}$ be the centered (or standardized if the std option is specified) data. A biplot splits the information in $\mathbf{X}$ into a portion related to the observations (rows of $\mathbf{X}$) and a portion related to the variables (columns of $\mathbf{X}$)

$$\mathbf{X} \approx (\mathbf{U}_2\,\mathbf{\Lambda}_2^{\alpha})(\mathbf{V}_2\,\mathbf{\Lambda}_2^{1-\alpha})'$$

where $0 \leq \alpha \leq 1$; see *Methods and formulas* for details. $\mathbf{U}_2\,\mathbf{\Lambda}_2^{\alpha}$ contains the plotting coordinates corresponding to observations (rows), and $\mathbf{V}_2\,\mathbf{\Lambda}_2^{1-\alpha}$ contains the plotting coordinates corresponding to variables (columns). In a biplot, the row coordinates are plotted as symbols, and the column coordinates are plotted as arrows from the origin.

The commonly used values for α are 0, 0.5, and 1. The default is 0.5. The alpha() option allows you to set α.

Biplots with an α of 1 are also called principal-component biplots because $\mathbf{U}_2\,\mathbf{\Lambda}_2$ contains the principal-component scores and $\mathbf{V}_2$ contains the principal-component coefficients. Euclidean distance between points in this kind of biplot approximates the Euclidean distance between points in the original higher-dimensional space.

Using an α of 0, Euclidean distances in the biplot are approximately proportional to Mahalanobis distances in the original higher-dimensional space. Also, the inner product of the arrows is approximately proportional to the covariances between the variables.

When you set α to 0 and specify the mahalanobis option, the Euclidean distances are not just approximately proportional but are approximately equal to Mahalanobis distances in the original space. Likewise, the inner products of the arrows are approximately equal (not just proportional) to the covariances between the variables. This means that the length of an arrow is approximately equal to the standard deviation of the variable it represents. Also, the cosine of the angle between two arrows is approximately equal to the correlation between the two variables.

A biplot with an α of 0.5 is called a symmetric factorization biplot or symmetrically scaled biplot. It often produces reasonable looking biplots where the points corresponding to observations and the arrows corresponding to variables are given equal weight. Using an α of 0 (or 1) causes the points (or the arrows) to be bunched tightly around the origin while the arrows (or the points) are predominant in the graph. Here many authors recommend picking a scaling factor for the arrows to bring them back into balance. The stretch() option allows you to do this.

Regardless of your choice of α, the position of a point in relation to an arrow indicates whether that observation is relatively large, medium, or small for that variable. Also, although the special conditions mentioned earlier may not strictly hold for all α, the biplot still aids in understanding the relationship between the variables, the observations, and the observations and variables jointly.

▷ Example 1

Gordon (1999, 176) provides a simple example of a biplot based on data having five rows and three columns.

```
. input v1 v2 v3

            v1          v2          v3
  1.    60    80 -240
  2.  -213    66  180
  3.   123 -186  180
  4.    -9    38  -60
  5.    39     2  -60
  6. end
. biplot v1 v2 v3
Biplot of 5 observations and 3 variables

    Explained variance by component 1 = 0.6283
    Explained variance by component 2 = 0.3717
            Total explained variance = 1.0000
```
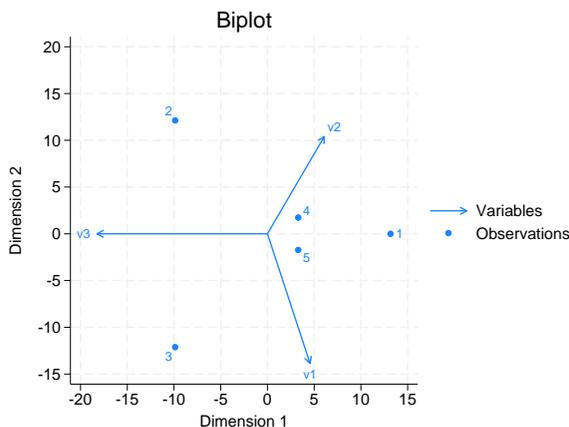

The first component accounts for 63% of the variance, and the second component accounts for the remaining 37%. All the variance is accounted for because, here, the 5-by-3 data matrix is only of rank 2.

Gordon actually used an α of 0 and performed the scaling to better match Mahalanobis distance. We do the same using the options `alpha(0)` and `mahalanobis`. (We could just use `mahalanobis` because it implies `alpha(0)`.) With an α of 0, Gordon decided to scale the arrows by a factor of 0.01. We accomplish this with the `stretch()` option and add options to provide a title and subtitle in place of the default title obtained previously.

```
. biplot v1 v2 v3, alpha(0) mahalanobis stretch(.01) title(Simple biplot)
> subtitle(See figure 6.10 of Gordon (1999))
Biplot of 5 observations and 3 variables

    Explained variance by component 1 = 0.6283
    Explained variance by component 2 = 0.3717
            Total explained variance = 1.0000
```

Simple biplot

See figure 6.10 of Gordon (1999)
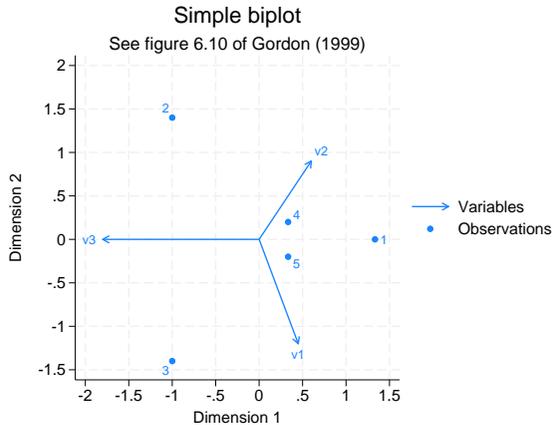
The outcome is little changed between the first and second biplot except for the additional titles and the scale of the x and y axes.

biplot allows you to highlight observations belonging to different groups by using option rowover(). Suppose our data come from two groups defined by variable group, group=1 and group=2.

```
. generate byte group = cond(_n<3, 1, 2)
. list
```

	v1	v2	v3	group
1.	60	80	-240	1
2.	-213	66	180	1
3.	123	-186	180	2
4.	-9	38	-60	2
5.	39	2	-60	2

Here is the previous biplot with group-specific markers:

```
. biplot v1 v2 v3, alpha(0) mahalanobis stretch(.01) title(Simple biplot)
> subtitle(Grouping variable group) rowover(group)
> row1opts(name("Group 1") msymbol(O) nolabel)
> row2opts(name("Group 2") msymbol(T) nolabel)
Biplot of 5 observations and 3 variables

    Explained variance by component 1 = 0.6283
    Explained variance by component 2 = 0.3717
             Total explained variance = 1.0000
```

Simple biplot
Grouping variable group
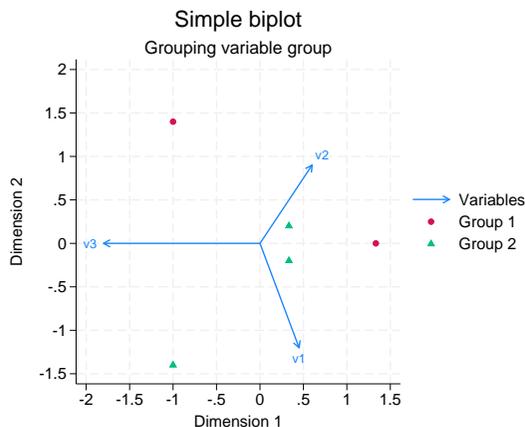
In the above example, groups are defined by a single variable `group` but you can specify multiple variables with `rowover()`. The rendition of group markers is controlled by options `row1opts()` and `row2opts()`. The marker labels are disabled by using the `nolabel` option.

◁

▷ Example 2

Table 7.1 of Cox and Cox (2001) provides the scores of 10 Renaissance painters on four attributes using a scale from 0 to 20, as judged by Roger de Piles in the 17th century.

```
. use https://www.stata-press.com/data/r18/renpainters, clear
(Scores by Roger de Piles for Renaissance painters)
. list, abbrev(12)
```

	painter	composition	drawing	colour	expression
1.	Del Sarto	12	16	9	8
2.	Del Piombo	8	13	16	7
3.	Da Udine	10	8	16	3
4.	Giulio Romano	15	16	4	14
5.	Da Vinci	15	16	4	14
6.	Michelangelo	8	17	4	8
7.	Fr. Penni	0	15	8	0
8.	Perino del Vaga	15	16	7	6
9.	Perugino	4	12	10	4
10.	Raphael	17	18	12	18

```
. biplot composition-expression, alpha(1) stretch(10) table
> rowopts(name(Painters)) rowlabel(painter) colopts(name(Attributes))
> title(Renaissance painters)
```

Biplot of 10 painters and 4 attributes

```
    Explained variance by component 1 = 0.6700
    Explained variance by component 2 = 0.2375
            Total explained variance = 0.9075
```

Biplot coordinates

Painters	dim1	dim2
Del Sarto	1.2120	0.0739
Del Piombo	-4.5003	5.7309
Da Udine	-7.2024	7.5745
Giulio Rom~o	8.4631	-2.5503
Da Vinci	8.4631	-2.5503
Michelangelo	0.1284	-5.9578
Fr Penni	-11.9449	-5.4510
Perino del~a	2.2564	-0.9193
Perugino	-7.8886	-0.8757
Raphael	11.0131	4.9251

Attributes	dim1	dim2
composition	6.4025	3.3319
drawing	2.4952	-3.3422
colour	-2.4557	8.7294
expression	6.8375	1.2348
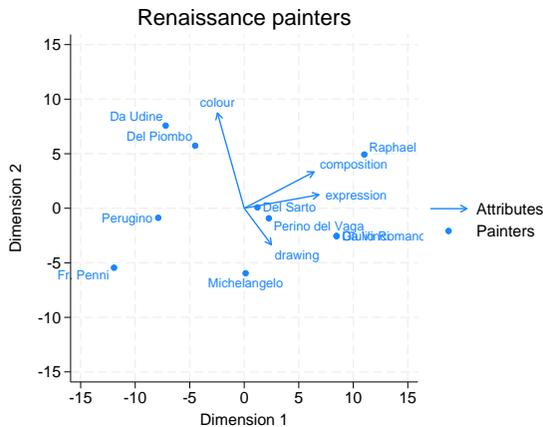
alpha(1) gave us an α of 1. stretch(10) made the arrows 10 times longer. table requested that the biplot coordinate table be displayed. rowopts() and colopts() affected the rendition of the rows (observations) and columns (variables). The name() suboption provided a name to use instead of the default names "Observations" and "Variables" in the graph legend and in the biplot coordinate table. The rowlabel(painter) option requested that the variable painter be used to label the row points (observations) in both the graph and table. The title() option was used to override the default title.

The default is to produce a square graphing region. Because the x axis containing the first component has more variability than the y axis containing the second component, there are often no observations or arrows appearing in the upper and lower regions of the graph. The autoaspect

option sets the aspect ratio and the x-axis and y-axis scales so that more of the graph region is used while maintaining the equivalent interpretation of distance for the x and y axes.

Here is the previous biplot with the omission of the `table` option and the addition of the `autoaspect` option. We also add the `ynegate` option to invert the orientation of the data in the y-axis direction to match the orientation shown in figure 7.1 of Cox and Cox (2001). We add the `negcol` option to include column (variable) arrows pointing in the negative directions, and the rendition of these negative columns (variables) is controlled by `negcolopts()`.

```
. biplot composition-expression, autoaspect alpha(1) stretch(10) ynegate
> rowopts(name(Painters)) rowlabel(painter) colopts(name(Attributes))
> title(Renaissance painters) negcol negcolopts(name(-Attributes))
Biplot of 10 painters and 4 attributes
     Explained variance by component 1 = 0.6700
     Explained variance by component 2 = 0.2375
             Total explained variance = 0.9075
```
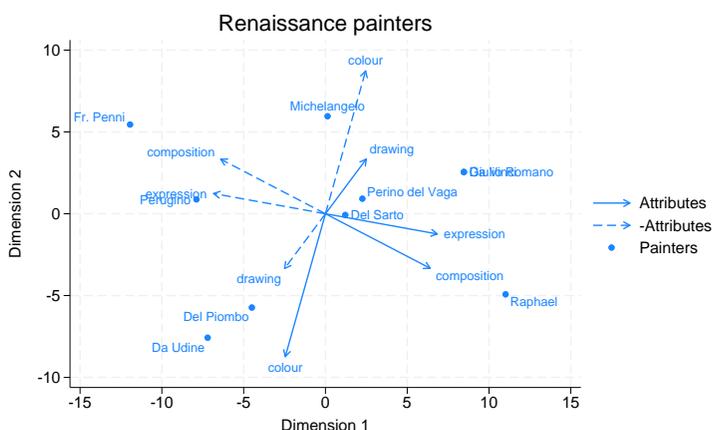

Stored results

`biplot` stores the following in `r()`:

Scalars
`r(rho1)`	explained variance by component 1
`r(rho2)`	explained variance by component 2
`r(rho)`	total explained variance
`r(alpha)`	value of `alpha()` option

Matrices
`r(U)`	biplot coordinates for the observations; stored only if the row dimension does not exceed Stata's maximum matrix size; as an alternative, use `generate()` to store biplot coordinates for the observations in variables
`r(V)`	biplot coordinates for the variables
`r(Vstretch)`	biplot coordinates for the variables times `stretch()` factor

Methods and formulas

Let $\mathbf{X}$ be the centered (standardized if `std` is specified) data with N rows (observations) and p columns (variables). A biplot splits the information in $\mathbf{X}$ into a portion related to the observations (rows of $\mathbf{X}$) and a portion related to the variables (columns of $\mathbf{X}$). This task is done using the singular value decomposition (SVD).

$$\mathbf{X} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{V}'$$

The biplot formula is derived from this SVD by first splitting $\boldsymbol{\Lambda}$, a diagonal matrix, into

$$\boldsymbol{\Lambda} = \boldsymbol{\Lambda}^{\alpha}\, \boldsymbol{\Lambda}^{1-\alpha}$$

and then retaining the first two columns of $\mathbf{U}$, the first two columns of $\mathbf{V}$, and the first two rows and columns of $\boldsymbol{\Lambda}$. Using the subscript 2 to denote this, the biplot formula is

$$\mathbf{X} \approx \mathbf{U}_2\, \boldsymbol{\Lambda}_2^{\alpha}\, \boldsymbol{\Lambda}_2^{1-\alpha}\, \mathbf{V}_2'$$

where $0 \leq \alpha \leq 1$. This is then written as

$$\mathbf{X} \approx (\mathbf{U}_2\, \boldsymbol{\Lambda}_2^{\alpha})(\mathbf{V}_2\, \boldsymbol{\Lambda}_2^{1-\alpha})'$$

$\mathbf{U}_2\, \boldsymbol{\Lambda}_2^{\alpha}$ contains the plotting coordinates corresponding to observations (rows) and $\mathbf{V}_2\, \boldsymbol{\Lambda}_2^{1-\alpha}$ contains the plotting coordinates corresponding to variables (columns). In a biplot, the row coordinates are plotted as symbols and the column coordinates are plotted as arrows from the origin.

Let λ_i be the ith diagonal of $\boldsymbol{\Lambda}$. The explained variance for component 1 is

$$\rho_1 = \left\{ \sum_{i=1}^{p} \lambda_i^2 \right\}^{-1} \lambda_1^2$$

and for component 2 is

$$\rho_2 = \left\{ \sum_{i=1}^{p} \lambda_i^2 \right\}^{-1} \lambda_2^2$$

The total explained variance is

$$\rho = \rho_1 + \rho_2$$

Acknowledgment

Kuno Ruben Gabriel (1929–2003) was born in Germany, raised in Israel, and studied at the London School of Economics and the Hebrew University of Jerusalem, earning a doctorate in demography in 1957. After several years on the faculty at the Hebrew University, he moved to the University of Rochester in 1975. His wide-ranging statistical interests spanned applications in meteorology, including weather-modification experiments, and medicine. Gabriel's best-known contribution is the biplot.

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Also see

[MV] **ca** — Simple correspondence analysis

[MV] **mds** — Multidimensional scaling for two-way data

[MV] **pca** — Principal component analysis

Title

> **ca** — Simple correspondence analysis

Description

ca performs a simple correspondence analysis (CA) and optionally creates a biplot of two categorical variables or multiple crossed variables. camat is similar to ca but is for use with a matrix containing cross-tabulations or other nonnegative values with strictly positive margins.

Quick start

Simple correspondence analysis of two categorical variables

Correspondence analysis of the cross-tabulation with rows catvar1 and columns catvar2

    ca catvar1 catvar2

Also produce the correspondence analysis biplot

    ca catvar1 catvar2, plot

Increase the number of dimensions from 2 to 3

    ca catvar1 catvar2, dimensions(3)

Use row and column principal coordinate normalization

    ca catvar1 catvar2, normalize(principal)

Simple correspondence analysis with crossed (stacked) variables

Correspondence analysis of the cross-tabulation of rows catvar1 and crossed columns mycol from the crossed variables catvar2 and catvar3

    ca catvar1 (mycol: catvar2 catvar3)

Same as above, but display compact tables and produce the correspondence analysis biplot

    ca catvar1 (mycol: catvar2 catvar3), compact plot

Simple correspondence analysis of a matrix

Correspondence analysis of the cross-tabulations contained in matrix M

    camat M

Also produce the correspondence analysis biplot

    camat M, plot

Menu

ca

Statistics > Multivariate analysis > Correspondence analysis > Two-way correspondence analysis (CA)

camat

Statistics > Multivariate analysis > Correspondence analysis > Two-way correspondence analysis of a matrix

Syntax

Simple correspondence analysis of two categorical variables

> ca *rowvar colvar* $\begin{bmatrix} if \end{bmatrix}$ $\begin{bmatrix} in \end{bmatrix}$ $\begin{bmatrix} weight \end{bmatrix}$ $\begin{bmatrix} , options \end{bmatrix}$

Simple correspondence analysis with crossed (stacked) variables

> ca *row_spec col_spec* $\begin{bmatrix} if \end{bmatrix}$ $\begin{bmatrix} in \end{bmatrix}$ $\begin{bmatrix} weight \end{bmatrix}$ $\begin{bmatrix} , options \end{bmatrix}$

Simple correspondence analysis of an $n_r \times n_c$ matrix

> camat *matname* $\begin{bmatrix} , options \end{bmatrix}$

where *spec* = *varname* | (*newvar* : *varlist*)

> and *matname* is an $n_r \times n_c$ matrix with n_r, $n_c \geq 2$.

options	Description
Model 2	
<u>dim</u>ensions(*#*)	number of dimensions (factors, axes); default is dim(2)
<u>norm</u>alize(*nopts*)	normalization of row and column coordinates
<u>rows</u>upp(*matname$_r$*)	matrix of supplementary rows
<u>col</u>supp(*matname$_c$*)	matrix of supplementary columns
<u>rown</u>ame(*string*)	label for rows
<u>coln</u>ame(*string*)	label for columns
missing	treat missing values as ordinary values (ca only)
Codes (ca only)	
<u>repo</u>rt(<u>variables</u>)	report coding of crossing variables
<u>repo</u>rt(<u>c</u>rossed)	report coding of crossed variables
<u>repo</u>rt(<u>a</u>ll)	report coding of crossing and crossed variables
<u>length</u>(<u>min</u>)	use minimal length unique codes of crossing variables
<u>length</u>(*#*)	use *#* as coding length of crossing variables
Reporting	
<u>ddim</u>ensions(*#*)	number of singular values to be displayed; default is ddim(.)
<u>noro</u>wpoints	suppress table with row category statistics
<u>noco</u>lpoints	suppress table with column category statistics
<u>compact</u>	display tables in a compact format
plot	plot the row and column coordinates
<u>maxl</u>ength(*#*)	maximum number of characters for labels; default is maxlength(12)

nopts	Description
<u>sym</u>metric	symmetric coordinates (<u>canonical</u>); the default
standard	row and column standard coordinates
<u>row</u>	row principal, column standard coordinates
<u>col</u>umn	column principal, row standard coordinates
<u>princ</u>ipal	row and column principal coordinates
#	power $0 \leq \# \leq 1$ for row coordinates; seldom used

bootstrap, by, collect, jackknife, rolling, and statsby are allowed with ca; see [U] **11.1.10 Prefix commands**.
  However, bootstrap and jackknife results should be interpreted with caution; identification of the ca parameters
  involves data-dependent restrictions, possibly leading to badly biased and overdispersed estimates (Milan and
  Whittaker 1995).

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

aweights are not allowed with the jackknife prefix; see [R] **jackknife**.

fweights, aweights, and iweights are allowed with ca; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> Model 2

dimensions(*#*) specifies the number of dimensions (= factors = axes) to be extracted. The default
is dimensions(2). If you specify dimensions(1), the row and column categories are placed on
one dimension. *#* should be strictly smaller than the number of rows and the number of columns,
counting only the active rows and columns, excluding supplementary rows and columns (see
options rowsupp() and colsupp()).

CA is a hierarchical method, so extracting more dimensions does not affect the coordinates and
decomposition of inertia of dimensions already included. The percentages of inertia accounting
for the dimensions are in decreasing order as indicated by singular values. The first dimension
accounts for the most inertia, followed by the second dimension, and then the third dimension,
etc.

normalize(*nopts*) specifies the normalization method, that is, how the row and column coordinates
are obtained from the singular vectors and singular values of the matrix of standardized residuals.
See *Normalization and interpretation of correspondence analysis* in *Remarks and examples* for a
discussion of these different normalization methods.

symmetric, the default, distributes the inertia equally over rows and columns, treating the
rows and columns symmetrically. The symmetric normalization is also known as the standard,
or canonical, normalization. This is the most common normalization when making a biplot.
normalize(symmetric) is equivalent to normalize(0.5). canonical is a synonym for
symmetric.

standard specifies that row and column coordinates should be in standard form (singular vec-
tors divided by the square root of mass). This normalization method is not equivalent to
normalize(*#*) for any *#*.

row specifies principal row coordinates and standard column coordinates. This option should be
chosen if you want to compare row categories. Similarity of column categories should not be
interpreted. The biplot interpretation of the relationship between row and column categories is
appropriate. normalize(row) is equivalent to normalize(1).

column specifies principal column coordinates and standard row coordinates. This option should
be chosen if you want to compare column categories. Similarity of row categories should not
be interpreted. The biplot interpretation of the relationship between row and column categories
is appropriate. normalize(column) is equivalent to normalize(0).

principal is the normalization to choose if you want to make comparisons among the row
categories and among the column categories. In this normalization, comparing row and column
points is not appropriate. Thus a biplot in this normalization is best avoided. In the principal
normalization, the row and column coordinates are obtained from the left and right singular
vectors, multiplied by the singular values. This normalization method is not equivalent to
normalize(*#*) for any *#*.

#, $0 \leq \# \leq 1$, is seldom used; it specifies that the row coordinates are obtained as the left singular
vectors multiplied by the singular values to the power *#*, whereas the column coordinates equal
the right singular vectors multiplied by the singular values to the power $1 - \#$.

rowsupp(*matname_r*) specifies a matrix of supplementary rows. *matname_r* should have n_c columns.
The row names of *matname_r* are used for labeling. Supplementary rows do not affect the computation
of the dimensions and the decomposition of inertia. They are, however, included in the plots and
in the table with statistics of the row points. Because supplementary points do not contribute to
the dimensions, their entries under the column labeled contrib are left blank.

colsupp(*matname_c*) specifies a matrix of supplementary columns. *matname_c* should have n_r rows. The column names of *matname_c* are used for labeling. Supplementary columns do not affect the computation of the dimensions and the decomposition of inertia. They are, however, included in the plots and in the table with statistics of the column points. Because supplementary points do not contribute to the dimensions, their entries under the column labeled contrib are left blank.

rowname(*string*) specifies a label to refer to the rows of the matrix. The default is rowname(rowvar) for ca and rowname(rows) for camat.

colname(*string*) specifies a label to refer to the columns of the matrix. The default is colname(colvar) for ca and colname(columns) for camat.

missing, allowed only with ca, treats missing values of *rowvar* and *colvar* as ordinary categories to be included in the analysis. Observations with missing values are omitted from the analysis by default.

Codes
---

report(*opt*) displays coding information for the crossing variables, crossed variables, or both. report() is ignored if you do not specify at least one crossed variable.

report(variables) displays the coding schemes of the crossing variables, that is, the variables used to define the crossed variables.

report(crossed) displays a table explaining the value labels of the crossed variables.

report(all) displays the codings of the crossing and crossed variables.

length(*opt*) specifies the coding length of crossing variables.

length(min) specifies that the minimal-length unique codes of crossing variables be used.

length(#) specifies that the coding length # of crossing variables be used, where # must be between 4 and 32.

Reporting
---

ddimensions(#) specifies the number of singular values to be displayed. The default is ddimensions(.), meaning all.

norowpoints suppresses the table with row point (category) statistics.

nocolpoints suppresses the table with column point (category) statistics.

compact specifies that the table with point statistics be displayed multiplied by 1,000 as proposed by Greenacre (2017), enabling the display of more columns without wrapping output. The compact tables can be displayed without wrapping for models with two dimensions at line size 79 and with three dimensions at line size 99.

plot displays a plot of the row and column coordinates in two dimensions. With row principal normalization, only the row points are plotted. With column principal normalization, only the column points are plotted. In the other normalizations, both row and column points are plotted. You can use cabiplot directly if you need another selection of points to be plotted or if you want to otherwise refine the plot; see [MV] **ca postestimation plots**.

maxlength(#) specifies the maximum number of characters for row and column labels in plots. The default is maxlength(12).

Note: The reporting options may be specified during estimation or replay.

Remarks and examples

Remarks are presented under the following headings:

Introduction

Correspondence analysis (CA) offers a geometric representation of the rows and columns of a two-way frequency table that is helpful in understanding the similarities between the categories of variables and the association between the variables. CA is formally equivalent to various other geometric approaches, including dual scaling, reciprocal averaging, and canonical correlation analysis of contingency tables (Greenacre 1984, chap. 4). For an informal introduction to CA and related metric approaches, see Weller and Romney (1990). Greenacre (2017) provides a much more thorough introduction with few mathematical prerequisites. More advanced treatments are given by Greenacre (1984) and Gower and Hand (1996).

In some respects, CA can be thought of as an analogue to principal components for nominal variables. It is also possible to interpret CA in reciprocal averaging (Greenacre 1984, 96–102; Cox and Cox 2001, 193–200), in optimal scaling (Greenacre 1984, 102–108), and in canonical correlations (Greenacre 1984, 108–116; Gower and Hand 1996, 183–185). Scaling refers to the assignment of scores to the categories of the row and column variables. Different criteria for the assignment of scores have been proposed, generally with different solutions. If the aim is to maximize the correlation between the scored row and column, the problem can be formulated in terms of CA. The optimal scores are the coordinates on the first dimension. The coordinates on the second and subsequent dimensions maximize the correlation between row and column scores subject to orthogonality constraints. See also [MV] **ca postestimation**.

A first example

▷ Example 1: A well-known correspondence analysis example

We illustrate CA with an example of smoking behavior by different ranks of personnel. This example is often used in the CA literature (for example, Greenacre 1984, 55; Greenacre 2017, 66), so you have probably encountered these (artificial) data before. By using these familiar data, we make it easier to relate the literature on CA to the output of the ca command.

```
. use https://www.stata-press.com/data/r18/ca_smoking
. tabulate rank smoking
```

Rank	None	Smoking intensity Light	Medium	Heavy	Total
Senior_mngr	4	2	3	2	11
Junior_mngr	4	3	7	4	18
Senior_empl	25	10	12	4	51
Junior_empl	18	24	33	13	88
Secretary	10	6	7	2	25
Total	61	45	62	25	193

ca displays the results of a CA on two categorical variables in a multipanel format.

```
. ca rank smoking
```

Correspondence analysis

Number of obs	=	193
Pearson chi2(12)	=	16.44
Prob > chi2	=	0.1718
Total inertia	=	0.0852
Number of dim.	=	2
Expl. inertia (%)	=	99.51

5 active rows
4 active columns

Dimension	Singular value	Principal inertia	chi2	Percent	Cumul. percent
Dim 1	.2734211	.0747591	14.43	87.76	87.76
Dim 2	.1000859	.0100172	1.93	11.76	99.51
Dim 3	.0203365	.0004136	0.08	0.49	100.00
Total		.0851899	16.44	100	

Statistics for row and column categories in symmetric normalization

Categories	Mass	Overall Quality	%inert	Dimension_1 Coord	Sqcorr	Contrib
rank						
Senior mngr	0.057	0.893	0.031	0.126	0.092	0.003
Junior mngr	0.093	0.991	0.139	-0.495	0.526	0.084
Senior empl	0.264	1.000	0.450	0.728	0.999	0.512
Junior empl	0.456	1.000	0.308	-0.446	0.942	0.331
Secretary	0.130	0.999	0.071	0.385	0.865	0.070
smoking						
None	0.316	1.000	0.577	0.752	0.994	0.654
Light	0.233	0.984	0.083	-0.190	0.327	0.031
Medium	0.321	0.983	0.148	-0.375	0.982	0.166
Heavy	0.130	0.995	0.192	-0.562	0.684	0.150

Categories	Dimension_2 Coord	Sqcorr	Contrib
rank			
Senior mngr	0.612	0.800	0.214
Junior mngr	0.769	0.465	0.551
Senior empl	0.034	0.001	0.003
Junior empl	-0.183	0.058	0.152
Secretary	-0.249	0.133	0.081
smoking			
None	0.096	0.006	0.029
Light	-0.446	0.657	0.463
Medium	-0.023	0.001	0.002
Heavy	0.625	0.310	0.506

The order in which we specify the variables is mostly immaterial. The first variable (`rank`) is also called the row variable, and the second (`smoking`) is the column variable. This ordering is important only as far as the interpretation of some options and some labeling of output are concerned. For instance, the option `norowpoints` suppresses the table with row points, that is, the categories of rank. `ca` requires two integer-valued variables. The rankings of the categories and the actual values used to code categories are not important. Thus, rank may be coded 1, 2, 3, 4, 5, or 0, 1, 4, 9, 16, or $-2, -1, 0, 1, 2$; it does not matter. We do suggest assigning value labels to the variables to improve the interpretability of tables and plots.

Correspondence analysis seeks to offer a low-dimensional representation describing how the row and column categories contribute to the inertia in a table. `ca` reports Pearson's test of independence, just like `tabulate` with the `chi2` option. Inertia is Pearson's χ^2 statistic divided by the sample size, $16.44/193 = 0.0852$. Pearson's χ^2 test has significance level $p = 0.1718$, casting doubt on any association between rows and columns. Still, given the prominence of this example in the CA literature, we will continue.

The first panel produced by `ca` displays the decomposition of total inertia in orthogonal dimensions—analogous to the decomposition of the total variance in principal component analysis (see [MV] **pca**). The first dimension accounts for 87.76% of the inertia; the second dimension accounts for 11.76% of the inertia. Because the dimensions are orthogonal, we may add the contributions of the two dimensions and say that the two leading dimensions account for $87.76\% + 11.76\% = 99.52\%$ of the total inertia. A two-dimensional representation seems in order. The remaining output is discussed later.

◁

How many dimensions?

▷ Example 2: Specifying the number of dimensions

In the first example with the smoking data, we displayed coordinates and statistics for a two-dimensional approximation of the rows and columns. This is the default. We can specify more or fewer dimensions with the option dimensions(). The maximum number is $\min(n_r - 1, n_c - 1)$. At this maximum, the χ^2 distances between the rows and columns are exactly represented by CA; 100% of the inertia is accounted for. This is called the saturated model; the fitted values of the CA model equal the observed correspondence table.

The minimum number of dimensions is one; the model with zero dimensions would be a model of independence of the rows and columns. With one dimension, the rows and columns of the table are identified by points on a line, with distance on the line approximating the χ^2 distance in the table, and a biplot is no longer feasible.

```
. ca rank smoking, dim(1)
Correspondence analysis                      Number of obs      =         193
                                             Pearson chi2(12)   =       16.44
                                             Prob > chi2        =      0.1718
                                             Total inertia      =      0.0852
        5 active rows                        Number of dim.     =           1
        4 active columns                     Expl. inertia (%)  =       87.76
```

| | Singular | Principal | | | Cumul. |
Dimension	value	inertia	chi2	Percent	percent
Dim 1	.2734211	.0747591	14.43	87.76	87.76
Dim 2	.1000859	.0100172	1.93	11.76	99.51
Dim 3	.0203365	.0004136	0.08	0.49	100.00
Total		.0851899	16.44	100	

Statistics for row and column categories in symmetric normalization

| | | Overall | | Dimension_1 | | |
Categories	Mass	Quality	%inert	Coord	Sqcorr	Contrib
rank						
Senior mngr	0.057	0.092	0.031	0.126	0.092	0.003
Junior mngr	0.093	0.526	0.139	-0.495	0.526	0.084
Senior empl	0.264	0.999	0.450	0.728	0.999	0.512
Junior empl	0.456	0.942	0.308	-0.446	0.942	0.331
Secretary	0.130	0.865	0.071	0.385	0.865	0.070
smoking						
None	0.316	0.994	0.577	0.752	0.994	0.654
Light	0.233	0.327	0.083	-0.190	0.327	0.031
Medium	0.321	0.982	0.148	-0.375	0.982	0.166
Heavy	0.130	0.684	0.192	-0.562	0.684	0.150

The first panel produced by ca does not depend on the number of dimensions extracted; thus, we will always see all singular values and the percentage of inertia explained by the associated dimensions. In the second panel, the only thing that depends on the number of dimensions is the overall quality of the approximation. The overall quality is the sum of the quality scores on the extracted dimensions and so increases with the number of extracted dimensions. The higher the quality, the better the χ^2 distances with other rows (columns) are represented by the extracted number of dimensions. In a saturated model, the overall quality is 1 for each row and column category.

So, how many dimensions should we retain? It is common for researchers to extract the minimum number of dimensions in a CA to explain at least 90% of the inertia, analogous to similar heuristic

rules on the number of components in principal component analysis. We could probably also search for a scree, the number of dimensions where the singular values flatten out (see [MV] **screeplot**). A `screeplot` of the singular values can be obtained by typing

```
. screeplot e(Sv)
  (output omitted)
```

where `e(Sv)` is the name where `ca` has stored the singular values.

◁

Statistics on the points

▷ Example 3: A more compact table of row and column statistics

We now turn our attention to the second panel. The overall section of the panel lists the following statistics:

- The mass of the category, that is, the proportion in the marginal distribution. The masses of all categories of a variable add up to 1.

- The quality of the approximation for a category, expressed as a number between 0 (very bad) and 1 (perfect). In a saturated model, quality is 1.

- The percentage of inertia contained in the category. Categories are divided through by the total inertia; the inertias of the categories of a variable add up to 100%.

For each of the dimensions, the panel lists the following:

- The coordinate of the category.

- The squared residuals between the profile and the categories. The sum of the squared residuals over the dimensions adds up to the quality of the approximation for the category.

- The contribution made by the categories to the dimensions. These add up to 1 over all categories of a variable.

The table with point statistics becomes pretty large, especially with more than two dimensions. `ca` can also list the second panel in a more compact form, saving space by multiplying all entries by 1,000; see Greenacre (2017).

```
. ca rank smoking, dim(2) compact
```

Correspondence analysis

		Number of obs	=	193
		Pearson chi2(12)	=	16.44
		Prob > chi2	=	0.1718
		Total inertia	=	0.0852
5 active rows		Number of dim.	=	2
4 active columns		Expl. inertia (%)	=	99.51

Dimension	Singular value	Principal inertia	chi2	Percent	Cumul. percent
Dim 1	.2734211	.0747591	14.43	87.76	87.76
Dim 2	.1000859	.0100172	1.93	11.76	99.51
Dim 3	.0203365	.0004136	0.08	0.49	100.00
Total		.0851899	16.44	100	

Statistics for row and column categories in symmetric norm. (x 1000)

Categories	Overall			Dimension 1			Dimension 2		
	Mass	Qualt	%inert	Coord	Sqcor	Contr	Coord	Sqcor	Contr
rank									
Senior mngr	57	893	31	126	92	3	612	800	214
Junior mngr	93	991	139	-495	526	84	769	465	551
Senior empl	264	1000	450	728	999	512	34	1	3
Junior empl	456	1000	308	-446	942	331	-183	58	152
Secretary	130	999	71	385	865	70	-249	133	81
smoking									
None	316	1000	577	752	994	654	96	6	29
Light	233	984	83	-190	327	31	-446	657	463
Medium	321	983	148	-375	982	166	-23	1	2
Heavy	130	995	192	-562	684	150	625	310	506

◁

Normalization and interpretation of correspondence analysis

The normalization method used in CA determines whether and how the similarity of the row categories, the similarity of the column categories, and the relationship (association) between the row and column variables can be interpreted in terms of the row and column coordinates and the origin of the plot.

How does one compare row points—provided that the normalization method allows such a comparison? Formally, the Euclidean distance between the row points approximates the χ^2 distances between the corresponding row profiles. Thus in the biplot, row categories mapped close together have similar row profiles; that is, the distributions on the column variable are similar. Row categories mapped widely apart have dissimilar row profiles. Moreover, the Euclidean distance between a row point and the origin approximates the χ^2 distance from the row profile and the row centroid, so it indicates how different a category is from the population.

An analogous interpretation applies to column points.

For the association between the row and column variables: in the CA biplot, you should not interpret the distance between a row point r and a column point c as the relationship of r and c. Instead, think in terms of the vectors origin to r (OR) and origin to c (OC). Remember that CA decomposes scaled deviations $d(r, c)$ from independence and $d(r, c)$ is approximated by the inner product of OR and OC. The larger the absolute value of $d(r, c)$, the stronger the association between r and c. In geometric terms, $d(r, c)$ can be written as the product of the length of OR, the length of OC, and the cosine of the angle between OR and OC.

What does this mean? First, consider the effects of the angle. The association in (r, c) is strongly positive if OR and OC point in roughly the same direction; the frequency of (r, c) is much higher than expected under independence, so r tends to flock together with c—if the points r and c are close together. Similarly, the association is strongly negative if OR and OC point in opposite directions. Here the frequency of (r, c) is much lower than expected under independence, so r and c are unlikely to occur simultaneously. Finally, if OR and OC are roughly orthogonal (angle = ± 90), the deviation from independence is small.

Second, the association of r and c increases with the lengths of OR and OC. Points far from the origin tend to have large associations. If a category is mapped close to the origin, all its associations with categories of the other variable are small: its distribution resembles the marginal distribution.

Here are the interpretations enabled by the main normalization methods as specified in the `normalize()` option.

Normalization method	Similarity row cat.	Similarity column cat.	Association row vs. column
`symmetric`	No	No	Yes
`principal`	Yes	Yes	No
`row`	Yes	No	Yes
`column`	No	Yes	Yes

If we say that a comparison between row categories or between column categories is not possible, we really mean that the χ^2 distance between row profiles or column profiles is actually approximated by a weighted Euclidean distance between the respective plots in which the weights depend on the inertia of the dimensions rather than on the standard Euclidean distance.

You may want to do a CA in principal normalization to study the relationship between the categories of a variable and do a CA in symmetric normalization to study the association of the row and column categories.

Plotting the points

▷ Example 4: A correspondence biplot

In our discussion of normalizations, we stated that CA offers simple geometric interpretations to the similarity of categories and the association of the variables. We may specify the option `plot` with `ca` during estimation or during replay.

```
. ca, norowpoints nocolpoints plot
```

Correspondence analysis

			Number of obs	=	193
			Pearson chi2(12)	=	16.44
			Prob > chi2	=	0.1718
			Total inertia	=	0.0852
5 active rows			Number of dim.	=	2
4 active columns			Expl. inertia (%)	=	99.51

Dimension	Singular value	Principal inertia	chi2	Percent	Cumul. percent
Dim 1	.2734211	.0747591	14.43	87.76	87.76
Dim 2	.1000859	.0100172	1.93	11.76	99.51
Dim 3	.0203365	.0004136	0.08	0.49	100.00
Total		.0851899	16.44	100	

Correspondence analysis biplot

Coordinates in symmetric normalization

The options `norowpoints` and `nocolpoints` suppress the large tables of statistics for the rows and columns. If we did not request the plot during estimation, we can still obtain it with the `cabiplot` postestimation command. Unlike requesting the plot at estimation time, `cabiplot` allows us to fine-tune the plot; see [MV] **ca postestimation plots**.

The horizontal dimension seems to distinguish smokers from nonsmokers, whereas the vertical dimensions can be interpreted as intensity of smoking. Because the orientations from the origin to `None` and from the origin to `Senior_empl` are so close, we conclude that senior employees tend not to smoke. Similarly, junior managers tend to be heavy smokers, and junior employees tend to be medium smokers.

◁

Supplementary points

A useful feature of CA is the ability to locate supplementary rows and columns in the space generated by the "active" rows and columns (see Greenacre [1984, 70–74]; Greenacre [2017, chap. 12], for an extensive discussion). Think of supplementary rows and columns as having mass 0; therefore, supplementary points do not influence the approximating space—their contribution values are zero.

▷ Example 5: Supplementary rows and columns

In our example, we want to include the national distribution of smoking intensity as a supplementary row.

ca requires that we define the supplementary row distributions as rows of a matrix. In this example, we have only one supplementary row, with the percentages of the smoking categories in a national sample. The matrix should have one row per supplementary row category and as many columns as there are active columns. We define the row name to obtain appropriately labeled output.

```
. matrix S_row = (42, 29, 20, 9)
. matrix rowname S_row = National
```

Before we show the CA analysis with the supplementary row, we also include two supplementary columns for the rank distribution of alcoholic beverage drinkers and nondrinkers. It will be interesting to see where smoking is located relative to drinking and nondrinking.

```
. matrix S_col = ( 0, 11 \
>                  1, 19 \
>                  5, 44 \
>                 10, 78 \
>                  7, 18)
. matrix colnames S_col = Nondrink Drink
```

We now invoke ca, specifying the names of the matrices with supplementary rows and columns with the options rowsupp() and colsupp().

```
. ca rank smoking, rowsupp(S_row) colsupp(S_col) plot
```

Correspondence analysis			Number of obs	=	193
			Pearson chi2(12)	=	16.44
			Prob > chi2	=	0.1718
			Total inertia	=	0.0852
5 active + 1 supplementary rows			Number of dim.	=	2
4 active + 2 supplementary columns			Expl. inertia (%)	=	99.51

Dimension	Singular value	Principal inertia	chi2	Percent	Cumul. percent
Dim 1	.2734211	.0747591	14.43	87.76	87.76
Dim 2	.1000859	.0100172	1.93	11.76	99.51
Dim 3	.0203365	.0004136	0.08	0.49	100.00
Total		.0851899	16.44	100	

Statistics for row and column categories in symmetric normalization

Categories	Mass	Overall Quality	%inert	Dimension_1 Coord	Sqcorr	Contrib
rank						
Senior mngr	0.057	0.893	0.031	0.126	0.092	0.003
Junior mngr	0.093	0.991	0.139	-0.495	0.526	0.084
Senior empl	0.264	1.000	0.450	0.728	0.999	0.512
Junior empl	0.456	1.000	0.308	-0.446	0.942	0.331
Secretary	0.130	0.999	0.071	0.385	0.865	0.070
suppl_rows						
National	0.518	0.761	0.644	0.494	0.631	
smoking						
None	0.316	1.000	0.577	0.752	0.994	0.654
Light	0.233	0.984	0.083	-0.190	0.327	0.031
Medium	0.321	0.983	0.148	-0.375	0.982	0.166
Heavy	0.130	0.995	0.192	-0.562	0.684	0.150
suppl_cols						
Nondrink	0.119	0.439	0.460	0.220	0.040	
Drink	0.881	0.838	0.095	-0.082	0.202	

Categories	Dimension_2 Coord	Sqcorr	Contrib
rank			
Senior mngr	0.612	0.800	0.214
Junior mngr	0.769	0.465	0.551
Senior empl	0.034	0.001	0.003
Junior empl	-0.183	0.058	0.152
Secretary	-0.249	0.133	0.081
suppl_rows			
National	-0.372	0.131	
smoking			
None	0.096	0.006	0.029
Light	-0.446	0.657	0.463
Medium	-0.023	0.001	0.002
Heavy	0.625	0.310	0.506
suppl_cols			
Nondrink	-1.144	0.398	
Drink	0.241	0.636	

Correspondence analysis biplot
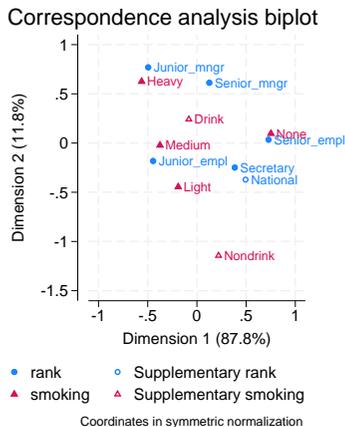
The first panel and the information about the five active rows and the four active columns have not changed—the approximating space is fully determined by the active rows and columns and is independent of the location of the supplementary rows and columns.

The table with statistics for the row and column categories now also contains entries for the supplementary rows and columns. The `contrib` entries for the supplementary points are blank. Supplementary points do not "contribute to" the location of the dimensions—their contribution is 0.000, but displaying blanks makes the point more clearly. All other columns for the supplementary points are informative. The inertia of supplementary points is the χ^2 distance to the respective centroid. The coordinates of supplementary points are obtained by applying the transition equations of the CA. Correlations of the supplementary profiles with the dimensions are also well defined. Finally, we may consider the quality of the two-dimensional approximation for the supplementary points. These are lower than for the active points, which will be the case in most applications—the active points exercise influence on the dimensions to improve their quality, whereas the supplementary points simply have to accept the dimensions as determined by the active points.

If we look at the biplot, the supplementary points are shown along with the active points. We may interpret the supplementary points just like the active points. Secretaries are close to the national sample in terms of smoking. Drinking alcohol is closer to the smoking categories than to nonsmoking, indicating that alcohol consumption and smoking are similar behaviors—but concluding that the *same* people smoke and drink is not possible because we do not have three-way data.

◁

Matrix input

▷ Example 6: Correspondence analysis of a frequency table

If we want to do a CA of a published two-way frequency table, we typically do not have immediate access to the data in the form of a dataset. We could enter the data with frequency weights.

```
. input rank smoking freq
  1.        1        1     4
  2.        1        2     2
  3.        1        3     3
 (output omitted )
 19.        5        3     7
 20.        5        4     2
 21.  end
. label define vl_rank  1  "Senior_mngr" ...
. label value rank vl_rank
. label define vl_smoke 1  "None" ...
. label value smoke vl_smoke
. ca rank smoking [fw=freq]
 (output omitted )
```

Or we may enter the data as a matrix and use `camat`. First, we enter the frequency matrix with proper column and row names and then list the matrix for verification.

```
. matrix F = (4,2,3,2 \ 4,3,7,4 \ 25,10,12,4 \ 18,24,33,13 \ 10,6,7,2)
. matrix colnames F = None Light Medium Heavy
. matrix rownames F = Senior_mngr Junior_mngr Senior_empl Junior_empl Secretary
. matlist F, border
```

	None	Light	Medium	Heavy
Senior_mngr	4	2	3	2
Junior_mngr	4	3	7	4
Senior_empl	25	10	12	4
Junior_empl	18	24	33	13
Secretary	10	6	7	2

We can use `camat` on `F` to obtain the same results as from the raw data. We use the `compact` option for a more compact table.

```
. camat F, compact
```

```
Correspondence analysis                          Number of obs      =         193
                                                 Pearson chi2(12)   =       16.44
                                                 Prob > chi2        =      0.1718
                                                 Total inertia      =      0.0852
       5 active rows                             Number of dim.     =           2
       4 active columns                          Expl. inertia (%)  =       99.51
```

| Dimension	Singular value	Principal inertia	chi2	Percent	Cumul. percent
Dim 1	.2734211	.0747591	14.43	87.76	87.76
Dim 2	.1000859	.0100172	1.93	11.76	99.51
Dim 3	.0203365	.0004136	0.08	0.49	100.00
Total		.0851899	16.44	100	

Statistics for row and column categories in symmetric norm. (x 1000)

Categories	Overall Mass	Overall Qualt	Overall %inert	Dimension 1 Coord	Dimension 1 Sqcor	Dimension 1 Contr	Dimension 2 Coord	Dimension 2 Sqcor	Dimension 2 Contr
rows									
Senior mngr	57	893	31	126	92	3	612	800	214
Junior mngr	93	991	139	-495	526	84	769	465	551
Senior empl	264	1000	450	728	999	512	34	1	3
Junior empl	456	1000	308	-446	942	331	-183	58	152
Secretary	130	999	71	385	865	70	-249	133	81
columns									
None	316	1000	577	752	994	654	96	6	29
Light	233	984	83	-190	327	31	-446	657	463
Medium	321	983	148	-375	982	166	-23	1	2
Heavy	130	995	192	-562	684	150	625	310	506

◁

▷ Example 7: Correspondence analysis of nonfrequency data

The command `camat` may also be used for a CA of nonfrequency data. The data should be nonnegative, with strictly positive margins. An example are the compositional data on the distribution of government R&D funds over 11 areas in five European countries in 1989; the data are listed in Greenacre (1993, 82). The expenditures are scaled to 1,000 within country, to focus the analysis on the intranational distribution policies. Moreover, with absolute expenditures, small countries, such as The Netherlands, would have been negligible in the analysis.

We enter the data as a Stata matrix. The command `matrix input` (see [P] **matrix define**) allows us to input row entries separated by blanks, rather than by commas; rows are separated by the backward slash (\).

```
. matrix input RandD = (
>    18   19   14   14    6 \
>    12   34    4   15   31 \
>    44   33   36   58   25 \
>    37   88   67  101   40 \
>    42   20   36   28   43 \
>    90  156  107  224  176 \
>    28   50   59   88   28 \
>   165  299  120  303  407 \
>    48  128  147   62  103 \
>   484  127  342   70   28 \
>    32   46   68   37  113)
```

```
. matrix colnames RandD = Britain West_Germany France Italy Netherlands
. matrix rownames RandD = Earth_exploration Pollution Human_health
>                         Energy Agriculture Industry Space University
>                         Nonoriented Defense Other
```

We perform a CA, suppressing the voluminous row- and column-point statistics. We want to show a biplot, and therefore we select symmetric normalization.

```
. camat RandD, dim(2) norm(symm) rowname(Source) colname(Country) norowpoints
> nocolpoints plot
```

Correspondence analysis   Number of obs   =   5,000
                                               Pearson chi2(40)   =   1321.55
                                               Prob > chi2   =   0.0000
                                               Total inertia   =   0.2643
         11 active rows   Number of dim.   =   2
         5 active columns   Expl. inertia (%) =   89.08

Dimension	Singular value	Principal inertia	chi2	Percent	Cumul. percent
Dim 1	.448735	.2013631	1006.82	76.18	76.18
Dim 2	.1846219	.0340852	170.43	12.90	89.08
Dim 3	.1448003	.0209671	104.84	7.93	97.01
Dim 4	.0888532	.0078949	39.47	2.99	100.00
Total		.2643103	1321.55	100	

Correspondence analysis biplot

Coordinates in symmetric normalization
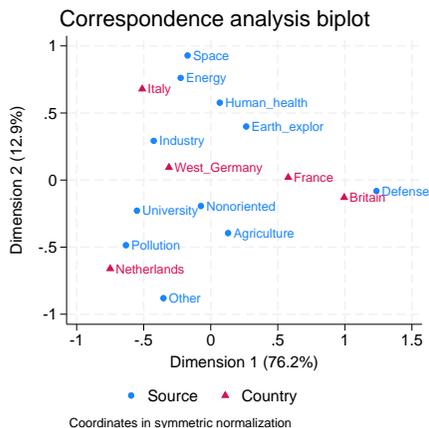
The two dimensions account for 89% of the inertia in this example, justifying an interpretation of the biplot. Let us focus on the position of The Netherlands. The orientation of The Netherlands from the origin is in the same direction as the orientation of pollution and university from the origin, indicating that The Netherlands spends more on academic research and on research to reduce environmental pollution than the average country. Earth exploration and human health are in the opposite direction, indicating investments much lower than average in these areas. Industry and agriculture are approximately orthogonal to the orientation of The Netherlands, indicating average investments by The Netherlands in these areas. Britain and France have big military investments, whereas Germany and Italy have more of an industrial orientation.

◁

❑ Technical note

The interpretation of the biplot is not fully in line with what we easily see in the row and column profiles—surprisingly, Greenacre does not seem to feel the need to comment on this. Why is this the case? The clue is in the statistics we did not show. Although the two dimensions account for 90% of the total inertia, this does not mean that all rows and columns are approximated to this extent. There are some row and column categories that are not well described in two dimensions. For instance, the quality of the Source categories Nonoriented, Agriculture, and Earth_exploration are only 0.063, 0.545, and 0.584, respectively, indicating that these rows are poorly represented in a two-dimensional space. The quality of West_Germany is also rather low at 0.577. Adding a third dimension improves the quality of the category Nonoriented but hardly affects the other two problematic categories. This effect can be seen only from the squared correlations between the third dimension and the profiles of the row and column categories—these correlations are small for all categories but Nonoriented. Thus, Nonoriented does not seem to really belong with the other categories and should probably be omitted from the analysis.

❑

Crossed variables

ca can include interactions between variables in the analysis; variables that contain interactions are called crossed or stacked variables, whereas the variables that make them up are the crossing or stacking variables.

▷ Example 8: Correspondence analysis with crossed variables

We illustrate crossed variables with ca by using the ISSP (1993) data from [MV] **mca**, which explores attitudes toward science and the environment. We are interested in whether responses to item A differ with education and gender. The item asks for a response to the statement "We believe too often in science, and not enough in feelings or faith," with a 1 indicating strong agreement and a 5 indicating strong disagreement. We are interested in how education and gender influence response. We cross the variables sex and edu into one demographic variable labeled Demo to explore this question.

```
. use https://www.stata-press.com/data/r18/issp93
(Selection from ISSP (1993))
. tabulate A edu
```

Too much science, not enough feelings & faith	Education (6 categories) Primary i	Primary c	Secondary	Secondary	Total
Agree strongly	7	59	29	11	119
Agree	15	155	84	27	322
Neither agree nor dis	7	84	65	18	204
Disagree	8	68	54	26	178
Disagree strongly	1	12	10	12	48
Total	38	378	242	94	871

Too much science, not enough feelings & faith	Education (6 categories) Tertiary	Tertiary	Total
Agree strongly	5	8	119
Agree	20	21	322
Neither agree nor dis	11	19	204
Disagree	8	14	178
Disagree strongly	5	8	48
Total	49	70	871

We notice immediately the long labels for variable `A` and on `edu`. We replace these labels with short labels that can be abbreviated, so that in our analysis we will easily be able to identify categories. We use the `length(2)` option to `ca` to ensure that labels from each of the crossing variables are restricted to two characters.

```
. label define response 1 "++" 2 "+" 3 "+/-" 4 "-" 5 "--"
. label values A response
. label define education 1 "-pri" 2 "pri" 3 "-sec" 4 "sec" 5 "-ter" 6 "ter"
. label values edu education
. ca A (Demo: sex edu), norowpoints nocolpoints length(2) plot norm(symmetric)
```

```
Correspondence analysis                    Number of obs     =        871
                                           Pearson chi2(44)  =      72.52
                                           Prob > chi2       =     0.0043
                                           Total inertia     =     0.0833
     5 active rows                         Number of dim.    =          2
    12 active columns                      Expl. inertia (%) =      80.17
```

| | Singular | Principal | | | Cumul. |
Dimension	value	inertia	chi2	Percent	percent
Dim 1	.2108455	.0444558	38.72	53.39	53.39
Dim 2	.14932	.0222965	19.42	26.78	80.17
Dim 3	.1009876	.0101985	8.88	12.25	92.42
Dim 4	.0794696	.0063154	5.50	7.58	100.00
Total		.0832662	72.52	100	

Correspondence analysis biplot

We see clearly that the responses of the males vary more widely than those of the females. Strong agreement with item A is most closely associated with females with little education, and strong disagreement is most closely associated with males with a secondary or tertiary education. Educated males are more closely associated with a negative response than educated females are, and females with little education are more closely associated with a positive response than males with little education are.

◁

Stored results

Let r be the number of rows, c be the number of columns, and f be the number of retained dimensions. `ca` and `camat` store the following in `e()`:

Scalars
e(N)	number of observations
e(f)	number of dimensions (factors, axes); maximum of $\min(r-1, c-1)$
e(inertia)	total inertia = e(X2)/e(N)
e(pinertia)	inertia explained by e(f) dimensions
e(X2)	χ^2 statistic
e(X2_df)	degrees of freedom $(r-1)(c-1)$
e(X2_p)	p-value for e(X2)

Macros
e(cmd)	ca (even for camat)
e(cmdline)	command as typed
e(Rcrossvars)	row crossing variable names (ca only)
e(Ccrossvars)	column crossing variable names (ca only)
e(varlist)	the row and column variable names (ca only)
e(wtype)	weight type (ca only)
e(wexp)	weight expression (ca only)
e(title)	title in estimation output
e(ca_data)	variables or crossed
e(Cname)	name for columns
e(Rname)	name for rows
e(norm)	normalization method
e(sv_unique)	1 if the singular values are unique, 0 otherwise
e(properties)	nob noV eigen
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(Ccoding)	column categories $(1{\times}c)$ (ca only)
e(Rcoding)	row categories $(1{\times}r)$ (ca only)
e(GSC)	column statistics $(c{\times}3(1{+}f))$
e(GSR)	row statistics $(r{\times}3(1{+}f))$
e(TC)	normalized column coordinates $(c{\times}f)$
e(TR)	normalized row coordinates $(r{\times}f)$
e(Sv)	singular values $(1{\times}f)$
e(C)	column coordinates $(c{\times}f)$
e(R)	row coordinates $(r{\times}f)$
e(c)	column mass (margin) $(c{\times}1)$
e(r)	row mass (margin) $(r{\times}1)$
e(P)	analyzed matrix $(r{\times}c)$
e(GSC_supp)	supplementary column statistics
e(GSR_supp)	supplementary row statistics
e(PC_supp)	principal coordinates supplementary column points
e(PR_supp)	principal coordinates supplementary row points
e(TC_supp)	normalized coordinates supplementary column points
e(TR_supp)	normalized coordinates supplementary row points

Functions
e(sample)	marks estimation sample (ca only)

Methods and formulas

Our presentation of simple CA follows that of Greenacre (1984, 83–125); see also Blasius and Greenacre (1994) and Rencher and Christensen (2012, 565–580). See Greenacre and Blasius (1994) for a concise presentation of CA from a computational perspective. Simple CA seeks a geometric representation of the rows and column of a (two mode) matrix with nonnegative entries in a common

low-dimensional space so that χ^2 distances between the rows and between the columns are well approximated by the Euclidean distances in the common space.

Let $\mathbf{N}$ be an $I \times J$ matrix with nonnegative entries and strictly positive margins. $\mathbf{N}$ may be frequencies of a two-way cross-tabulation, but this is not assumed in most of CA. Let $n = N_{++}$ be the overall sum of N_{ij} ("number of observations"). Define the *correspondence table* as the matrix $\mathbf{P}$ where $P_{ij} = N_{ij}/n$, so the overall sum of P_{ij} is $P_{++} = 1$. Let $\mathbf{r} = \mathbf{P}\,\mathbf{1}$ be the row margins, also known as the *row masses*, with elements $r_i > 0$. Similarly, $\mathbf{c} = \mathbf{P}'\mathbf{1}$ contains the column margins, or *column masses*, with elements $c_j > 0$.

CA is defined in terms of the generalized singular value decomposition (GSVD) of $\mathbf{P} - \mathbf{rc}'$ with respect to the inner products normed by $\mathbf{D}_r^{-1}$ and $\mathbf{D}_c^{-1}$, where $\mathbf{D}_r = \operatorname{diag}(\mathbf{r})$ and $\mathbf{D}_c = \operatorname{diag}(\mathbf{c})$. The GSVD can be expressed in terms of the orthonormal (or standard) SVD of the standardized residuals

$$\mathbf{Z} = \mathbf{D}_r^{-\frac{1}{2}}(\mathbf{P} - \mathbf{rc}')\mathbf{D}_c^{-\frac{1}{2}} \quad \text{with elements} \quad Z_{ij} = \frac{P_{ij} - r_i c_j}{\sqrt{r_i c_j}}$$

Denote by $\mathbf{Z} = \mathbf{R}\mathbf{\Lambda}\mathbf{C}'$ the SVD of $\mathbf{Z}$ with $\mathbf{R}'\mathbf{R} = \mathbf{C}'\mathbf{C} = \mathbf{I}$ and $\mathbf{\Lambda}$ a diagonal matrix with singular values in decreasing order. ca displays a warning message if $\mathbf{Z}$ has common singular values.

The *total principal inertia* of the correspondence table $\mathbf{P}$ is defined as $\chi^2/n = \sum_{i,j} Z_{ij}^2$, where χ^2 is Pearson's χ^2 statistic. We can express the inertia of $\mathbf{P}$ in terms of the singular values of $\mathbf{Z}$:

$$\text{inertia} = \frac{1}{n}\chi^2 = \sum_{k=1}^{\min(I-1, J-1)} \lambda_k^2$$

The inertia accounted for by d dimensions is $\sum_{k=1}^{d} \lambda_k^2$. The fraction of inertia accounted for (explained) by the d dimensions is defined as

$$\text{explained inertia} = \frac{\sum_{k=1}^{d} \lambda_k^2}{\sum_{k=1}^{\min(I-1, J-1)} \lambda_k^2}$$

Principal row ($\widetilde{R}_{ik}$) and principal column ($\widetilde{C}_{jk}$) coordinates are defined as

$$\widetilde{R}_{ik} = \frac{R_{ik}\lambda_k}{\sqrt{r_i}} = (\mathbf{D}_r^{-\frac{1}{2}}\mathbf{R}\mathbf{\Lambda})_{ik} \qquad \widetilde{C}_{jk} = \frac{C_{jk}\lambda_k}{\sqrt{c_j}} = (\mathbf{D}_c^{-\frac{1}{2}}\mathbf{C}\mathbf{\Lambda})_{jk}$$

The α-normalized row and column coordinates are defined as

$$R_{ik}^{(\alpha)} = \frac{R_{ik}\lambda_k^{\alpha}}{\sqrt{r_i}} \qquad C_{jk}^{(\alpha)} = \frac{C_{jk}\lambda_k^{1-\alpha}}{\sqrt{c_j}}$$

The row principal coordinates are obtained with $\alpha = 1$. The column principal coordinates are obtained with $\alpha = 0$. The symmetric coordinates are obtained with $\alpha = 1/2$.

Decomposition of inertia by rows ($\operatorname{In}^{(r)}$) and by columns ($\operatorname{In}^{(c)}$) is defined as

$$\operatorname{In}_i^{(r)} = \sum_{j=1}^{J} Z_{ij}^2 \qquad \operatorname{In}_j^{(c)} = \sum_{i=1}^{I} Z_{ij}^2$$

Quality of subspace approximations for the row and column categories are defined as

$$Q_i^{(r)} = \frac{r_i}{\text{In}_i^{(r)}} \sum_{k=1}^{d} \widetilde{R}_{ik}^2 \qquad Q_j^{(c)} = \frac{c_j}{\text{In}_j^{(c)}} \sum_{k=1}^{d} \widetilde{C}_{jk}^2$$

If $d = \min(I - 1, J - 1)$, the quality index satisfies $Q_i^{(r)} = Q_j^{(c)} = 1$.

CA provides several diagnostics for a more detailed analysis of inertia: what do the categories contribute to the inertia explained by the dimensions, and what do the dimensions contribute to the inertia explained for the categories?

The relative contributions of row i $(G_{ik}^{(r)})$ and of column j $(G_{jk}^{(c)})$ to the inertia of principal dimension k are defined as

$$G_{ik}^{(r)} = \frac{r_i \widetilde{R}_{ik}^2}{\lambda_k^2} \qquad G_{jk}^{(c)} = \frac{c_j \widetilde{C}_{jk}^2}{\lambda_k^2}$$

$G_{+k}^{(r)} = G_{+k}^{(c)} = 1$.

The correlations $H_{ik}^{(r)}$ of the ith row profile and kth principal row dimension and, analogously, $H_{jk}^{(c)}$ for columns are

$$H_{ik}^{(r)} = \frac{r_i}{\text{In}_i^{(r)}} \widetilde{R}_{ik}^2 \qquad H_{jk}^{(c)} = \frac{c_j}{\text{In}_j^{(c)}} \widetilde{C}_{jk}^2$$

We now define the quantities returned by the `estat` subcommands after `ca`. The row profiles are $\mathbf{U} = \mathbf{D}_r^{-1}\mathbf{P}$. The χ^2 distance between rows i_1 and i_2 of $\mathbf{P}$ is defined as the Mahalanobis distance between the respective row profiles $\mathbf{U}_{i_1}$ and $\mathbf{U}_{i_2}$ with respect to $\mathbf{D}_c$,

$$(\mathbf{U}_{i_1} - \mathbf{U}_{i_2})\mathbf{D}_c^{-1}(\mathbf{U}_{i_1} - \mathbf{U}_{i_2})'$$

The column profiles and the χ^2 distances between columns are defined analogously. The χ^2 distances for the approximated correspondence table are defined analogously in terms of $\widehat{\mathbf{P}}$.

The fitted or reconstructed values $\widehat{P}_{ij}$ are

$$\widehat{P}_{ij} = r_i c_j \left(1 + \lambda_k^{-1} \sum_{k=1}^{d} \widetilde{R}_{ik}\widetilde{C}_{jk} \right)$$

References

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Also see

[MV] **ca postestimation** — Postestimation tools for ca and camat

[MV] **ca postestimation plots** — Postestimation plots for ca and camat

[MV] **mca** — Multiple and joint correspondence analysis

[R] **tabulate twoway** — Two-way table of frequencies

[U] **20 Estimation and postestimation commands**

Title

> **ca postestimation —** Postestimation tools for ca and camat

Postestimation commands

The following postestimation commands are of special interest after `ca` and `camat`:

Command	Description
`cabiplot`	biplot of row and column points
`caprojection`	CA dimension projection plot
`estat coordinates`	display row and column coordinates
`estat distances`	display χ^2 distances between row and column profiles
`estat inertia`	display inertia contributions of the individual cells
`estat loadings`	display correlations of profiles and axes
`estat profiles`	display row and column profiles
* `estat summarize`	estimation sample summary
`estat table`	display fitted correspondence table
`screeplot`	plot singular values

*`estat summarize` is not available after `camat`.

The following standard postestimation commands are also available:

Command	Description
* `estimates`	cataloging estimation results
† `predict`	fitted values, row and column coordinates

*All `estimates` subcommands except `table` and `stats` are available.

†`predict` is not available after `camat`.

predict

Description for predict

predict creates a new variable containing predictions such as fitted values and row or column scores.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] *newvar* [*if*] [*in*] [, *statistic*]

statistic	Description
Main	
<u>fit</u>	fitted values; the default
<u>rows</u>core(*#*)	row score for dimension *#*
<u>cols</u>core(*#*)	column score for dimension *#*

predict is not available after camat.

Options for predict

> Main

fit specifies that fitted values for the correspondence analysis model be computed. fit displays the fitted values p_{ij} according to the correspondence analysis model. fit is the default.

rowscore(*#*) generates the row score for dimension *#*, that is, the appropriate elements from the normalized row coordinates.

colscore(*#*) generates the column score for dimension *#*, that is, the appropriate elements from the normalized column coordinates.

estat

Description for estat

estat coordinates displays the row and column coordinates.

estat distances displays the χ^2 distances between the row profiles and between the column profiles. Also, the χ^2 distances between the row and column profiles to the respective centers (marginal distributions) are displayed. Optionally, the fitted profiles rather than the observed profiles are used.

estat inertia displays the inertia (χ^2/N) contributions of the individual cells.

estat loadings displays the correlations of the row and column profiles and the axes, comparable to the loadings of principal component analysis.

estat profiles displays the row and column profiles; the row (column) profile is the conditional distribution of the row (column) given the column (row). This is equivalent to specifying the row and column options with the tabulate command; see [R] **tabulate twoway**.

estat summarize displays summary information about the row and column variables over the estimation sample.

estat table displays the fitted correspondence table. Optionally, the observed "correspondence table" and the expected table under independence are displayed.

Menu for estat

Statistics > Postestimation

Syntax for estat

Display row and column coordinates

> estat <u>co</u>ordinates [, norow <u>nocol</u>umn <u>for</u>mat(*%fmt*)]

Display χ^2 distances between row and column profiles

> estat <u>dist</u>ances [, norow <u>nocol</u>umn <u>ap</u>prox <u>for</u>mat(*%fmt*)]

Display inertia contributions of cells

> estat <u>in</u>ertia [, <u>to</u>tal <u>nos</u>cale <u>for</u>mat(*%fmt*)]

Display correlations of profiles and axes

> estat <u>lo</u>adings [, norow <u>nocol</u>umn <u>for</u>mat(*%fmt*)]

Display row and column profiles

> estat <u>pr</u>ofiles [, norow <u>nocol</u>umn <u>for</u>mat(*%fmt*)]

Display summary information

>   estat <u>summarize</u> [, <u>labels</u> <u>noheader</u> <u>noweights</u>]

Display fitted correspondence table

>   estat <u>table</u> [, fit obs <u>independence</u> <u>noscale</u> <u>format</u>(%*fmt*)]

options	Description
norow	suppress display of row results
nocolumn	suppress display of column results
<u>format</u>(%*fmt*)	display format; default is format(%9.4f)
approx	display distances between fitted (approximated) profiles
total	add row and column margins
<u>noscale</u>	display χ^2 contributions; default is inertias = χ^2/N (with estat inertia)
labels	display variable labels
<u>noheader</u>	suppress the header
<u>noweights</u>	ignore weights
fit	display fitted values from correspondence analysis model
obs	display correspondence table ("observed table")
<u>independence</u>	display expected values under independence
<u>noscale</u>	suppress scaling of entries to 1 (with estat table)

collect is allowed with all estat commands; see [U] **11.1.10 Prefix commands**.

Options for estat

norow, an option used with estat coordinates, estat distances, and estat profiles, suppresses the display of row results.

nocolumn, an option used with estat coordinates, estat distances, and estat profiles, suppresses the display of column results.

format(%*fmt*), an option used with many of the subcommands of estat, specifies the display format for the matrix, for example, format(%8.3f). The default is format(%9.4f).

approx, an option used with estat distances, computes distances between the fitted profiles. The default is to compute distances between the observed profiles.

total, an option used with estat inertia, adds row and column margins to the table of inertia or χ^2 (χ^2/N) contributions.

noscale, as an option used with estat inertia, displays χ^2 contributions rather than inertia ($= \chi^2/N$) contributions. (See below for the description of noscale with estat table.)

labels, an option used with estat summarize, displays variable labels.

noheader, an option used with estat summarize, suppresses the header.

noweights, an option used with estat summarize, ignores the weights, if any. The default when weights are present is to perform a weighted summarize on all variables except the weight variable itself. An unweighted summarize is performed on the weight variable.

fit, an option used with estat table, displays the fitted values for the correspondence analysis model. fit is implied if obs and independence are not specified.

obs, an option used with estat table, displays the observed table with nonnegative entries (the "correspondence table").

independence, an option used with estat table, displays the expected values p_{ij} assuming independence of the rows and columns, $p_{ij} = r_i c_j$, where r_i is the mass of row i and c_j is the mass of column j.

noscale, as an option used with estat table, normalizes the displayed tables to the sum of the original table entries. The default is to scale the tables to overall sum 1. (See above for the description of noscale with estat inertia.)

Remarks and examples

Remarks are presented under the following headings:

> Postestimation statistics
> Predicting new variables

Postestimation statistics

After you conduct a correspondence analysis, there are several additional tables to help you understand and interpret your results. Some of these tables resemble tables produced by other Stata commands but are provided as part of the ca postestimation suite of commands for a unified presentation style.

▷ Example 1: estat profiles, estat distances, estat table

We continue with the classic example of correspondence analysis, namely, the data on smoking in organizations. We extract only one dimension.

```
. use https://www.stata-press.com/data/r18/ca_smoking
. ca rank smoking, dim(1)
Correspondence analysis                  Number of obs      =         193
                                         Pearson chi2(12)   =       16.44
                                         Prob > chi2        =      0.1718
                                         Total inertia      =      0.0852
     5 active rows                       Number of dim.     =           1
     4 active columns                    Expl. inertia (%)  =       87.76
               Singular    Principal                              Cumul.
   Dimension      value      inertia        chi2     Percent     percent
      Dim 1    .2734211    .0747591         14.43       87.76       87.76
      Dim 2    .1000859    .0100172          1.93       11.76       99.51
      Dim 3    .0203365    .0004136          0.08        0.49      100.00
      Total                .0851899         16.44         100
```

Statistics for row and column categories in symmetric normalization

| | | Overall | | | Dimension_1 | |
Categories	Mass	Quality	%inert	Coord	Sqcorr	Contrib
rank						
Senior mngr	0.057	0.092	0.031	0.126	0.092	0.003
Junior mngr	0.093	0.526	0.139	-0.495	0.526	0.084
Senior empl	0.264	0.999	0.450	0.728	0.999	0.512
Junior empl	0.456	0.942	0.308	-0.446	0.942	0.331
Secretary	0.130	0.865	0.071	0.385	0.865	0.070
smoking						
None	0.316	0.994	0.577	0.752	0.994	0.654
Light	0.233	0.327	0.083	-0.190	0.327	0.031
Medium	0.321	0.982	0.148	-0.375	0.982	0.166
Heavy	0.130	0.684	0.192	-0.562	0.684	0.150

CA analyzes the similarity of row and of column categories by comparing the row profiles and the column profiles—some may prefer to talk about conditional distributions for a two-way frequency distribution, but CA is not restricted to this type of data.

```
. estat profiles
```

Row profiles (rows normalized to 1)

	None	Light	Medium	Heavy	Mass
Senior mngr	0.3636	0.1818	0.2727	0.1818	0.0570
Junior mngr	0.2222	0.1667	0.3889	0.2222	0.0933
Senior empl	0.4902	0.1961	0.2353	0.0784	0.2642
Junior empl	0.2045	0.2727	0.3750	0.1477	0.4560
Secretary	0.4000	0.2400	0.2800	0.0800	0.1295
Mass	0.3161	0.2332	0.3212	0.1295	

Column profiles (columns normalized to 1)

	None	Light	Medium	Heavy	Mass
Senior mngr	0.0656	0.0444	0.0484	0.0800	0.0570
Junior mngr	0.0656	0.0667	0.1129	0.1600	0.0933
Senior empl	0.4098	0.2222	0.1935	0.1600	0.2642
Junior empl	0.2951	0.5333	0.5323	0.5200	0.4560
Secretary	0.1639	0.1333	0.1129	0.0800	0.1295
Mass	0.3161	0.2332	0.3212	0.1295	

The tables also include the row and column masses—marginal probabilities. Two row categories are similar to the extent that their row profiles (that is, their distribution over the columns) are the same. Similar categories could be collapsed without distorting the information in the table. In CA, similarity or dissimilarity of the row categories is expressed in terms of the χ^2 distances between the rows. These are sums of squares, weighted with the inverse of the column masses. Thus a difference is counted "heavier" (inertia!) the smaller the respective column mass. In the table, we also add the χ^2 distances of the rows to the row centroid, that is, to the marginal distribution. This allows us to easily see which row categories are similar to each other as well as which row categories are similar to the population.

```
. estat distances, nocolumn
Chi2 distances between the row profiles
```

rank	Junior_~r	Senior_~l	Junior_~l	Secretary	center
Senior_mngr	0.3448	0.3721	0.3963	0.3145	0.2166
Junior_mngr		0.6812	0.3044	0.5622	0.3569
Senior_empl			0.6174	0.2006	0.3808
Junior_empl				0.4347	0.2400
Secretary					0.2162

We see that senior employees are especially dissimilar from junior managers in terms of their smoking behavior but are rather similar to secretaries. Also the senior employees are least similar to the average staff member among all staff categories.

One of the goals of CA is to come up with a low-dimensional representation of the rows and columns in a common space. One way to see the adequacy of this representation is to inspect the implied approximation for the χ^2 distances—are the similarities between the row categories and between the column categories adequately represented in lower dimensions?

```
. estat distances, nocolumn approx
Chi2 distances between the dim=1 approximations of the row profiles
```

rank	Junior_~r	Senior_~l	Junior_~l	Secretary	center
Senior_mngr	0.3247	0.3148	0.2987	0.1353	0.0658
Junior_mngr		0.6396	0.0260	0.4600	0.2590
Senior_empl			0.6135	0.1795	0.3806
Junior_empl				0.4340	0.2330
Secretary					0.2011

Some of the row distances are obviously poorly approximated, whereas the quality of other approximations is hardly affected. The dissimilarity in smoking behavior between junior managers and junior employees is particularly poorly represented in one dimension. From the CA with two dimensions, the second dimension is crucial to adequately represent the senior managers and the junior managers. By itself, this does not explain where the one-dimensional approximation fails; for this, we would have to take a closer look at the representation of the smoking categories as well.

A correspondence analysis can also be seen as equivalent to fitting the model

$$P_{ij} = r_i c_j (1 + R_{i1} C_{j1} + R_{i2} C_{j2} + \cdots)$$

to the correspondence table $\mathbf{P}$ by some sort of least squares, with parameters r_i, c_j, R_{ij}, and C_{jk}. We may compare the (observed) table $\mathbf{P}$ with the fitted table $\widehat{\mathbf{P}}$ to assess goodness of fit informally. Here we extract only one dimension, and so the fitted table is

$$\widehat{P}_{ij} = r_i c_j (1 + \widehat{R}_{i1} \widehat{C}_{j1})$$

with $\mathbf{R}$ and $\mathbf{C}$ the coordinates in symmetric (or row principal or column principal) normalization. We display the observed and fitted tables.

```
. estat table, fit obs
```

Correspondence table (normalized to overall sum = 1)

	None	Light	Medium	Heavy
Senior_mngr	0.0207	0.0104	0.0155	0.0104
Junior_mngr	0.0207	0.0155	0.0363	0.0207
Senior_empl	0.1295	0.0518	0.0622	0.0207
Junior_empl	0.0933	0.1244	0.1710	0.0674
Secretary	0.0518	0.0311	0.0363	0.0104

Approximation for dim = 1 (normalized to overall sum = 1)

	None	Light	Medium	Heavy
Senior_mngr	0.0197	0.0130	0.0174	0.0069
Junior_mngr	0.0185	0.0238	0.0355	0.0154
Senior_empl	0.1292	0.0531	0.0617	0.0202
Junior_empl	0.0958	0.1153	0.1710	0.0738
Secretary	0.0528	0.0280	0.0356	0.0132

Interestingly, some categories (for example, the junior employees, the nonsmokers, and the medium smokers) are very well represented in one dimension, whereas the quality of the fit of other categories is rather poor. This can, of course, also be inferred from the quality column in the ca output. We would consider the fit unsatisfactory and would refit the model with a second dimension.

◁

❑ Technical note

If the data are two-way cross-classified frequencies, as with ca, it may make sense to assume that the data are multinomial distributed, and the parameters can be estimated by maximum likelihood. The estimator has well-established properties in contrast to the estimation method commonly used in CA. One advantage is that sampling variability, for example, in terms of standard errors of the parameters, can be easily assessed. Also, the likelihood-ratio test against the saturated model may be used to select the number of dimensions to be extracted. See Van der Heijden and de Leeuw (1985).

❑

Predicting new variables

If you use ca to obtain the optimal scaling positions for the rows and columns, you may use predict to obtain the corresponding scores in the normalization used.

▷ Example 2: Predictions

First, we obtain scores for the first dimension.

```
. quietly ca rank smoking, normalize(symmetric) dim(2)
. predict r1, row(1)
. predict c1, col(1)
. describe r1 c1
```

Variable name	Storage type	Display format	Value label	Variable label
r1	float	%9.0g		rank score(1) in symmetric norm.
c1	float	%9.0g		smoking score(1) in symmetric norm.

```
. correlate r1 c1
(obs=193)
```

	r1	c1
r1	1.0000	
c1	0.2734	1.0000

The correlation of `r1` and `c1` is 0.2734, which equals the first singular value reported in the first panel by `ca`. In the same way, we may obtain scores for the second dimension.

```
. predict r2, row(2)
. predict c2, col(2)
. correlate r1 r2 c1 c2
(obs=193)
```

	r1	r2	c1	c2
r1	1.0000			
r2	-0.0000	1.0000		
c1	0.2734	0.0000	1.0000	
c2	0.0000	0.1001	0.0000	1.0000

The correlation between the row and column scores `r2` and `c2` for the second dimension is 0.1001, which is the same as the second singular value. Moreover, the row scores for dimensions 1 and 2 are not correlated, nor are the column scores.

◁

Obtaining the fitted values of the CA model is also possible,

$$\pi_{ij} = r_i c_j (1 + R_{i1} C_{i1} + R_{i2} C_{i2})$$

where $\mathbf{R}$ and $\mathbf{C}$ are the row and column scales in symmetric normalization. These may be used, say, to compute fit measures, for instance, from the Cressie–Read power family to analyze the fit of the CA model (Weesie 1997).

Stored results

`estat distances` stores the following in `r()`:

Matrices
    `r(Dcolumns)` χ^2 distances between the columns and between the columns and the column center
    `r(Drows)` χ^2 distances between the rows and between the rows and the row center

`estat inertia` stores the following in `r()`:

Matrices
    `r(Q)`   matrix of (squared) inertia (or χ^2) contributions

`estat loadings` stores the following in `r()`:

Matrices
    `r(LC)`   column loadings
    `r(LR)`   row loadings

`estat profiles` stores the following in `r()`:

Matrices
    `r(Pcolumns)`   column profiles (columns normalized to 1)
    `r(Prows)`   row profiles (rows normalized to 1)

`estat table` stores the following in `r()`:

Matrices
    `r(Fit)`   fitted (reconstructed) values
    `r(Fit0)`   fitted (reconstructed) values, assuming independence of row and column variables
    `r(Obs)`   correspondence table

Methods and formulas

See *Methods and formulas* in [MV] **ca** for information.

References

Van der Heijden, P. G. M., and J. de Leeuw. 1985. Correspondence analysis used complementary to loglinear analysis. *Psychometrika* 50: 429–447. https://doi.org/10.1007/BF02296262.

Weesie, J. 1997. sg68: Goodness-of-fit statistics for multinomial distributions. *Stata Technical Bulletin* 36: 26–28. Reprinted in *Stata Technical Bulletin Reprints*, vol. 6, pp. 183–186. College Station, TX: Stata Press.

Also see *References* in [MV] **ca**.

Also see

[MV] **ca** — Simple correspondence analysis

[MV] **ca postestimation plots** — Postestimation plots for ca and camat

[MV] **screeplot** — Scree plot of eigenvalues

[U] **20 Estimation and postestimation commands**

Title

> **ca postestimation plots —** Postestimation plots for ca and camat

Postestimation commands

The following postestimation commands are of special interest after `ca` and `camat`:

Command	Description
cabiplot	biplot of row and column points
caprojection	CA dimension projection plot

cabiplot

Description for cabiplot

cabiplot produces a plot of the row points or column points, or a biplot of the row and column points. In this plot, the (Euclidean) distances between row (column) points approximates the χ^2 distances between the associated row (column) profiles if the CA is properly normalized. Similarly, the association between a row and column point is approximated by the inner product of vectors from the origin to the respective points (see [MV] **ca**).

Menu for cabiplot

Statistics > Multivariate analysis > Correspondence analysis > Postestimation after CA > Biplot of row and column points

Syntax for cabiplot

cabiplot [, *options*]

options	Description
[Main]	
dim(*# #*)	the two dimensions to be displayed; default is dim(2 1)
norow	suppress row coordinates
nocolumn	suppress column coordinates
xnegate	negate the data relative to the x axis
ynegate	negate the data relative to the y axis
maxlength(*#*)	maximum number of characters for labels; default is maxlength(12)
origin	display the origin on the plot
originlopts(*line_options*)	affect rendition of origin axes
Rows	
rowopts(*row_opts*)	affect rendition of rows
Columns	
colopts(*col_opts*)	affect rendition of columns
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

row_opts and *col_opts*	Description
plot_options	change look of markers (color, size, etc.) and look or position of marker labels
suppopts(*plot_options*)	change look of supplementary markers and look or position of supplementary marker labels

plot_options	Description
marker_options	change look of markers (color, size, etc.)
marker_label_options	add marker labels; change look or position

Options for cabiplot

> **Main**

dim(*# #*) identifies the dimensions to be displayed. For instance, dim(3 2) plots the third dimension (vertically) versus the second dimension (horizontally). The dimension number cannot exceed the number of extracted dimensions. The default is dim(2 1).

norow suppresses plotting of row points.

nocolumn suppresses plotting of column points.

xnegate specifies that the x-axis values are to be negated (multiplied by -1).

ynegate specifies that the y-axis values are to be negated (multiplied by -1).

maxlength(*#*) specifies the maximum number of characters for row and column labels; the default is maxlength(12).

origin specifies that the origin be displayed on the plot. This is equivalent to adding the options xline(0, lcolor(black) lwidth(vthin)) yline(0, lcolor(black) lwidth(vthin)) to the cabiplot command.

originlopts(*line_options*) affects the rendition of the origin axes; see [G-3] *line_options*.

> **Rows**

rowopts(*row_opts*) affects the rendition of the rows. The following *row_opts* are allowed:

> *plot_options* affect the rendition of row markers, including their shape, size, color, and outline (see [G-3] *marker_options*) and specify if and how the row markers are to be labeled (see [G-3] *marker_label_options*).

> suppopts(*plot_options*) affects supplementary markers and supplementary marker labels; see above for description of *plot_options*.

> **Columns**

colopts(*col_opts*) affects the rendition of columns. The following *col_opts* are allowed:

> *plot_options* affect the rendition of column markers, including their shape, size, color, and outline (see [G-3] *marker_options*) and specify if and how the column markers are to be labeled (see [G-3] *marker_label_options*).

> suppopts(*plot_options*) affects supplementary markers and supplementary marker labels; see above for description of *plot_options*.

> **Y axis, X axis, Titles, Legend, Overall**

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding by(). These include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk (see [G-3] *saving_option*).

cabiplot automatically adjusts the aspect ratio on the basis of the range of the data and ensures that the axes are balanced. As an alternative, the *twoway_option* aspectratio() can be used to override the default aspect ratio. cabiplot accepts the aspectratio() option as a suggestion only and will override it when necessary to produce plots with balanced axes; that is, distance on the x axis equals distance on the y axis.

twoway_options, such as xlabel(), xscale(), ylabel(), and yscale() should be used with caution. These *axis_options* are accepted but may have unintended side effects on the aspect ratio. See [G-3] *twoway_options*.

caprojection

Description for caprojection

caprojection produces a line plot of the row and column coordinates. The goal of this graph is to show the ordering of row and column categories on each principal dimension of the analysis. Each principal dimension is represented by a vertical line; markers are plotted on the lines where the row and column categories project onto the dimensions.

Menu for caprojection

Statistics > Multivariate analysis > Correspondence analysis > Postestimation after CA > Dimension projection plot

Syntax for caprojection

> caprojection [, *options*]

options	Description
[Main]	
dim(*numlist*)	dimensions to be displayed; default is all
norow	suppress row coordinates
nocolumn	suppress column coordinates
alternate	alternate labels
maxlength(*#*)	number of characters displayed for labels; default is maxlength(12)
combine_options	affect the rendition of the combined column and row graphs
[Rows]	
rowopts(*row_opts*)	affect rendition of rows
[Columns]	
colopts(*col_opts*)	affect rendition of columns
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

row_opts and *col_opts*	Description
plot_options	change look of markers (color, size, etc.) and look or position of marker labels
suppopts(*plot_options*)	change look of supplementary markers and look or position of supplementary marker labels

plot_options	Description
marker_options	change look of markers (color, size, etc.)
marker_label_options	add marker labels; change look or position

Options for caprojection

Main
---

dim(*numlist*) identifies the dimensions to be displayed. By default, all dimensions are displayed.

norow suppresses plotting of rows.

nocolumn suppresses plotting of columns.

alternate causes adjacent labels to alternate sides.

maxlength(#) specifies the maximum number of characters for row and column labels; the default is maxlength(12).

combine_options affect the rendition of the combined plot; see [G-2] **graph combine**. *combine_options* may not be specified with either norow or nocolumn.

Rows
---

rowopts(*row_opts*) affects the rendition of rows. The following *row_opts* are allowed:

plot_options affect the rendition of row markers, including their shape, size, color, and outline (see [G-3] **marker_options**) and specify if and how the row markers are to be labeled (see [G-3] **marker_label_options**).

suppopts(*plot_options*) affects supplementary markers and supplementary marker labels; see above for description of *plot_options*.

Columns
---

colopts(*col_opts*) affects the rendition of columns. The following *col_opts* are allowed:

plot_options affect the rendition of column markers, including their shape, size, color, and outline (see [G-3] **marker_options**) and specify if and how the column markers are to be labeled (see [G-3] **marker_label_options**).

suppopts(*plot_options*) affects supplementary markers and supplementary marker labels; see above for description of *plot_options*.

Y axis, X axis, Titles, Legend, Overall
---

twoway_options are any of the options documented in [G-3] **twoway_options**, excluding by(). These include options for titling the graph (see [G-3] **title_options**) and for saving the graph to disk (see [G-3] **saving_option**).

Remarks and examples

In example 4 of [MV] **ca**, we showed that plots can be obtained simply by specifying the plot option during estimation (or replay). If the default plot is not exactly what you want, the cabiplot postestimation command provides control over the appearance of the plot.

▷ Example 1: cabiplot

For instance, if we constructed a CA in row principal normalization, we would want to look only at the (points for the) row categories, omitting the column categories. In this normalization, the Euclidean distances between the row points approximate the χ^2 distances between the corresponding row profiles, but the Euclidean distances between the column categories are a distortion of the χ^2 distances of the column profiles. We can use cabiplot with the nocolumn option to suppress the graphing of the column points.

```
. use https://www.stata-press.com/data/r18/ca_smoking
. quietly ca rank smoking, norm(principal)
. cabiplot, nocolumn legend(on label(1 rank))
```

Correspondence analysis biplot

Coordinates in principal normalization
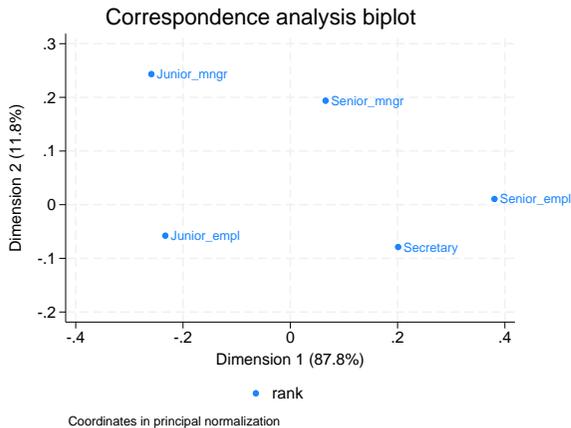
The default graph would not have provided a legend, so we included `legend(on label(1 rank))` to produce one. We see that secretaries have smoking behavior that is rather similar to that of senior employees but rather dissimilar to that of the junior managers, with the other two ranks taking intermediate positions. Because we actually specified the principal normalization, we may also interpret the distances between the smoking categories as approximations to χ^2 distances.

```
. cabiplot, norow legend(on label(1 smoking))
```

Correspondence analysis biplot

Coordinates in principal normalization
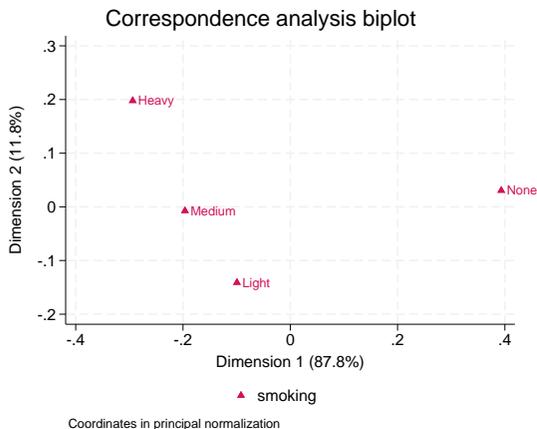
You may not like the orientation of the dimensions. For instance, in this plot, the smokers are on the left and the nonsmokers are on the right. It is more natural to locate the nonsmokers on the left and the smokers on the right so that smoking increases from left to right. This is accomplished with the `xnegate` option.

```
. cabiplot, xnegate norow legend(on label(1 smoking))
```

Correspondence analysis biplot

Coordinates in principal normalization

◁
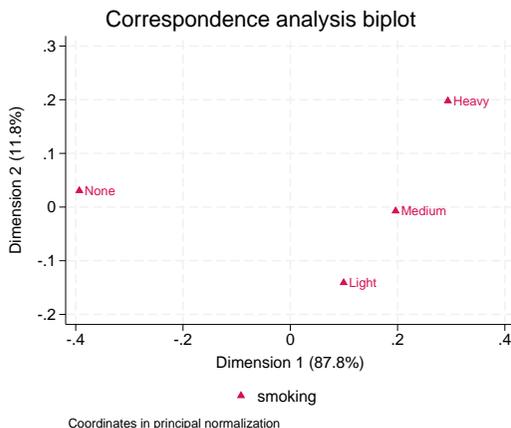
❑ Technical note

To see that negating is possible, think in terms of the fitted values

$$\widehat{P}_{ij} = r_i c_j (1 + \widehat{R}_{i1}\widehat{C}_{j1} + \widehat{R}_{i2}\widehat{C}_{j2} + \cdots)$$

If the sign of the first column of $\mathbf{R}$ and $\mathbf{C}$ is changed at the same time, the fitted values are not affected. This is true for all CA statistics, and it holds true for other columns of $\mathbf{R}$ and $\mathbf{C}$ as well.

❑

▷ Example 2: cabiplot with symmetric normalization

Using the symmetric normalization allows us to display a biplot where row categories may be compared with column categories. We execute ca again, with the `normalize(symmetric)` option, but suppress the output. This normalization somewhat distorts the interpretation of the distances between row points (or column points) as approximations to χ^2 distances. Thus the similarity of the staff categories (or smoking categories) cannot be adequately assessed. However, this plot allows us to study the association between smoking and rank.

```
. quietly ca rank smoking, normalize(symmetric) dim(2)
. cabiplot, origin
```

Correspondence analysis biplot

Coordinates in symmetric normalization
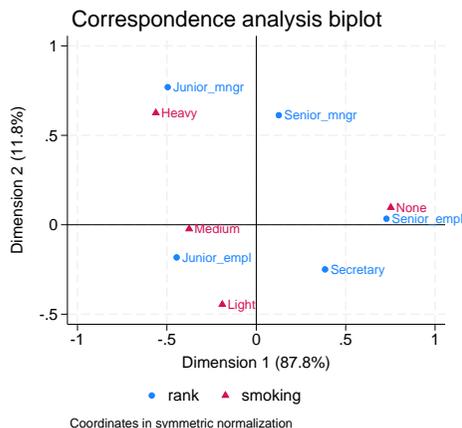
With this symmetric normalization, we do not interpret the distances between categories of `smoking` and `rank`. Rather, we have to think in terms of vectors from the origin. The inner product of vectors approximates the residuals from a model of independence of the rows and columns. The inner product depends on the lengths of the vectors and the (cosine of the) angle between the vectors. If the vectors point in the same direction, the residuals are positive—these row and column categories tend to occur together. In our example, we see that senior employees tend to be nonsmokers. If the vectors point in opposite directions, the residuals are negative—these row and column categories tend to be exclusive. In our example, senior managers tend not to be light smokers. Finally, if the vectors are orthogonal (± 90 degrees), the residuals tend to be small; that is, the observed frequencies correspond to what we expect under independence. For instance, junior managers have an average rate of light smoking.

Using various graph options, we can enhance the look of the plot.

```
. cabiplot, origin subtitle("Fictitious data, N = 193")
> legend(pos(2) ring(0) col(1) lab(1 Employee rank) lab(2 Smoking status))
```

Correspondence analysis biplot
Fictitious data, N = 193

Coordinates in symmetric normalization
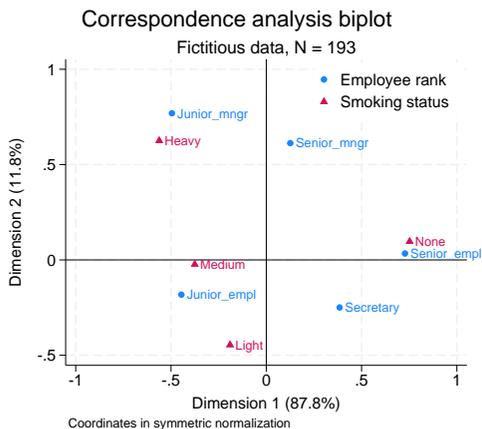
▷ Example 3: caprojection

`caprojection` produces a projection plot of the row and column coordinates after `ca` or `camat` and is especially useful if we think of CA as optimal scaling of the categories of the variables to maximize the correlations between the row and column variables. We continue where we left off with our previous example.

    . caprojection

CA dimension projection plot

Symmetric normalization
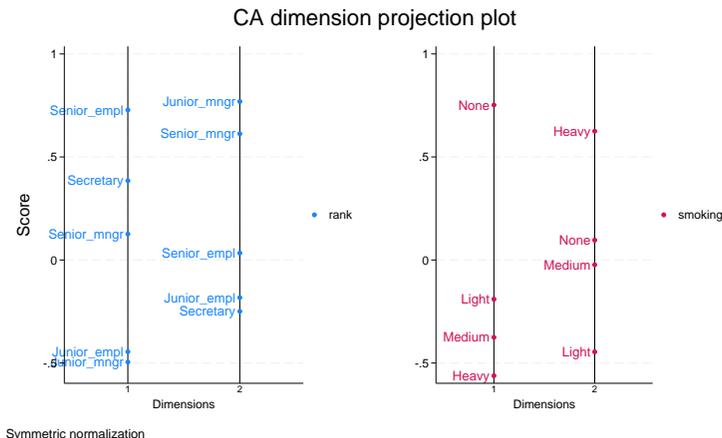
This example has relatively few categories, so we could visualize the orderings of the rows and columns from the previous biplots. However, CA is often used with larger problems, and in those cases, a projection plot is a useful presentation device.

◁

References

See *References* in [MV] **ca**.

Also see

[MV] **ca** — Simple correspondence analysis

[MV] **ca postestimation** — Postestimation tools for ca and camat

[MV] **screeplot** — Scree plot of eigenvalues

Title

---

candisc — Canonical linear discriminant analysis

Description

candisc performs canonical linear discriminant analysis (LDA). What is computed is the same as with [MV] **discrim lda**. The difference is in what is presented. See [MV] **discrim** for other discrimination commands.

Quick start

Canonical linear discriminant analysis of v1, v2, v3, and v4 for groups defined by catvar

```
candisc v1 v2 v3 v4, group(catvar)
```

Same as above, but use prior probabilities proportional to group size

```
candisc v1 v2 v3 v4, group(catvar) priors(proportional)
```

Present the leave-one-out classification table in addition to standard output

```
candisc v1 v2 v3 v4, group(catvar) lootable
```

Same as above, but suppress the resubstitution classification table

```
candisc v1 v2 v3 v4, group(catvar) lootable notable
```

Menu

Statistics > Multivariate analysis > Discriminant analysis > Canonical linear discriminant analysis

Syntax

> candisc *varlist* [*if*] [*in*] [*weight*], group(*groupvar*) [*options*]

options	Description
Model	
* group(*groupvar*)	variable specifying the groups
priors(*priors*)	group prior probabilities
ties(*ties*)	how ties in classification are to be handled
Reporting	
notable	suppress resubstitution classification table
lootable	display leave-one-out classification table
nostats	suppress display of canonical statistics
nocoef	suppress display of standardized canonical discriminant function coefficients
nostruct	suppress display of canonical structure matrix
nomeans	suppress display of group means on canonical variables

priors	Description
equal	equal prior probabilities; the default
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
missing	ties in group classification produce missing values; the default
random	ties in group classification are broken randomly
first	ties in group classification are set to the first tied group

* group() is required.

collect, statsby, and xi are allowed; see [U] 11.1.10 Prefix commands.

fweights are allowed; see [U] 11.1.6 weight.

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.

Options

> [Model]

group(*groupvar*) is required and specifies the name of the grouping variable. *groupvar* must be a numeric variable.

priors(*priors*) specifies the prior probabilities for group membership. The following *priors* are allowed:

> priors(equal) specifies equal prior probabilities. This is the default.

> priors(proportional) specifies group-size-proportional prior probabilities.

priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. The following *ties* are allowed:

ties(<u>missing</u>) specifies that ties in group classification produce missing values. This is the default.

ties(<u>random</u>) specifies that ties in group classification are broken randomly.

ties(<u>first</u>) specifies that ties in group classification are set to the first tied group.

> Reporting

notable suppresses the computation and display of the resubstitution classification table.

lootable displays the leave-one-out classification table.

nostats suppresses the display of the table of canonical statistics.

nocoef suppresses the display of the standardized canonical discriminant function coefficients.

nostruct suppresses the display of the canonical structure matrix.

nomeans suppresses the display of group means on canonical variables.

Remarks and examples

See [MV] **discrim** for background on discriminant analysis (classification) and see [MV] **discrim lda** for more information on linear discriminant analysis. What candisc displays by default with

```
. candisc x y z, group(group)
```

you can also obtain with the following sequence of discrim commands and estat postestimation commands.

```
. discrim x y z, group(group) notable
. estat canontest
. estat loadings
. estat structure
. estat grmeans, canonical
. estat classtable
```

The candisc command will appeal to those performing descriptive LDA.

▷ Example 1

Example 2 of [MV] **discrim knn** introduces a head-measurement dataset from Rencher and Christensen (2012, 291) that has six discriminating variables and three groups. The three groups are high school football players, college football players, and nonplayers. The data were collected as a preliminary step in determining the relationship between helmet design and neck injuries.

Descriptive discriminant analysis allows us to explore the relationship in this dataset between head measurements and the separability of the three groups.

```
. use https://www.stata-press.com/data/r18/head
(Table 8.3. Head measurements, Rencher and Christensen (2012))
. candisc wdim circum fbeye eyehd earhd jaw, group(group)
Canonical linear discriminant analysis
```

Fcn	Canon. Corr.	Eigen-value	Variance Prop.	Cumul.	Like-lihood Ratio	F	df1	df2	Prob>F
1	0.8107	1.91776	0.9430	0.9430	0.3071	10.994	12	164	0.0000 e
2	0.3223	.115931	0.0570	1.0000	0.8961	1.9245	5	83	0.0989 e

```
H0: This and smaller canon. corr. are zero;                      e = exact F
```

Standardized canonical discriminant function coefficients

	function1	function2
wdim	.6206412	.9205834
circum	-.0064715	-.0009114
fbeye	-.0047581	-.021145
eyehd	-.7188123	.5997882
earhd	-.3965116	-.3018196
jaw	-.5077218	-.9368745

Canonical structure

	function1	function2
wdim	.1482946	.3766581
circum	-.2714134	.1305383
fbeye	-.1405813	-.061071
eyehd	-.824502	.5363578
earhd	-.5177312	.1146999
jaw	-.2119042	-.3895934

Group means on canonical variables

group	function1	function2
High school	-1.910378	-.0592794
College	1.16399	-.3771343
Nonplayer	.7463888	.4364137

Resubstitution classification summary

```
┌─────────┐
│ Key     │
├─────────┤
│ Number  │
│ Percent │
└─────────┘
```

True group	Classified High school	College	Nonplayer	Total
High school	26	1	3	30
	86.67	3.33	10.00	100.00
College	1	20	9	30
	3.33	66.67	30.00	100.00
Nonplayer	2	8	20	30
	6.67	26.67	66.67	100.00
Total	29	29	32	90
	32.22	32.22	35.56	100.00
Priors	0.3333	0.3333	0.3333	

As seen in the canonical correlation table, the first linear discriminant function accounts for almost 95% of the variance. The standardized discriminant function coefficients (loadings) indicate that two of the variables, `circum` (head circumference) and `fbeye` (front-to-back measurement at eye level), have little discriminating ability for these three groups. The first discriminant function is contrasting `wdim` (head width at widest dimension) to a combination of `eyehd` (eye-to-top-of-head measurement), `earhd` (ear-to-top-of-head measurement), and `jaw` (jaw width).

The canonical structure coefficients, which measure the correlation between the discriminating variables and the discriminant function, are also shown. There is controversy on whether the standardized loadings or the structure coefficients should be used for interpretation; see Rencher and Christensen (2012, 301) and Huberty (1994, 262–264).

The group means on the canonical variables are shown, giving some indication of how the groups are separated. The means on the first function show the high school group separated farthest from the other two groups.

The resubstitution classification table, also known as a confusion matrix, indicates how many observations from each group are classified correctly or misclassified into the other groups. The college and nonplayer groups appear to have more misclassifications between them, indicating that these two groups are harder to separate.

All the postestimation tools of `discrim lda` are available after `candisc`; see [MV] **discrim lda postestimation**. For example, `estat grsummarize` can produce discriminating-variable summaries for each of our three groups.

```
. estat grsummarize
Estimation sample candisc
Summarized by group
```

Mean	group High school	College	Nonplayer	Total
wdim	15.2	15.42	15.58	15.4
circum	58.937	57.37967	57.77	58.02889
fbeye	20.10833	19.80333	19.81	19.90722
eyehd	13.08333	10.08	10.94667	11.37
earhd	14.73333	13.45333	13.69667	13.96111
jaw	12.26667	11.94333	11.80333	12.00444
N	30	30	30	90

A score plot graphs observation scores from the first two discriminant functions; see [MV] **scoreplot**. After `candisc`, `scoreplot` automatically labels the points with the value labels assigned to the groups. The value labels for our three groups are long—the resulting graph is too crowded.

To overcome this, we create a new label language (see [D] **label language**), define one letter labels for the groups, assign this label to our group variable, and then call `scoreplot`. We then reset the label language back to the default containing the longer, more descriptive value labels.

```
. label language short, new
(language short now current language)
. label define fball 1 "H" 2 "C" 3 "X"
. label values group fball
. scoreplot, msymbol(i) aspect(.625)
. label language default
```

Discriminant function scores
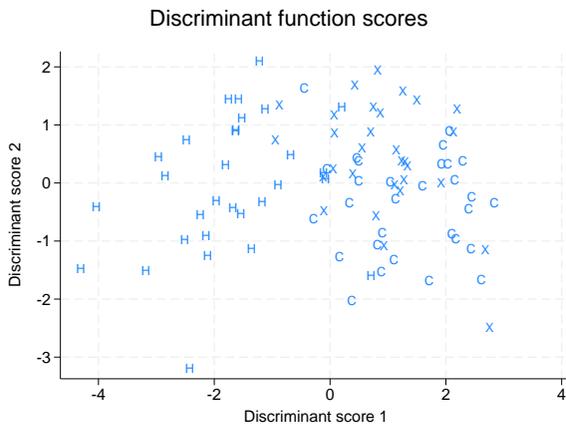
The score plot illustrates the separation due to the first and second canonical linear discriminant functions. As expected from our examination of the earlier descriptive output, the high school group (labeled H) is reasonably well separated from the college (labeled C) and nonplayer (labeled X) groups. There is some separation in the second dimension between the college and nonplayer groups, but with substantial overlap.

A loading plot provides a graphical way of looking at the standardized discriminant function coefficients (loadings) that we previously examined in tabular form.

. loadingplot

Standardized discriminant function loadings
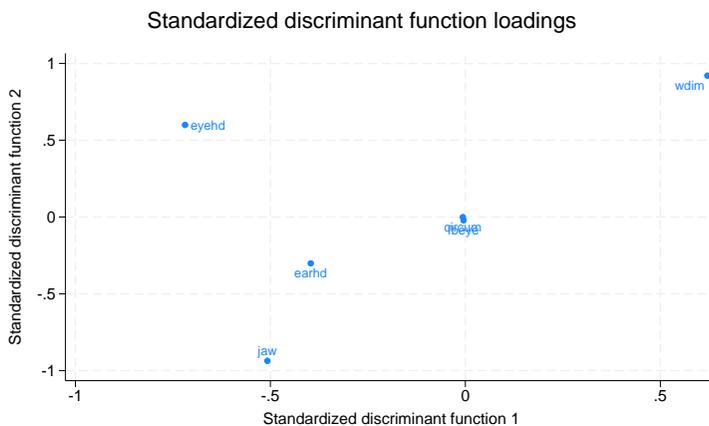
circum and fbeye are near the origin, indicating that they provide almost no discriminating ability in comparison to the other discriminating variables. The relative locations of the remaining variables indicate their contribution to the discriminant functions.

◁

Stored results

candisc stores the following in e():

Scalars
e(N)	number of observations
e(N_groups)	number of groups
e(k)	number of discriminating variables
e(f)	number of nonzero eigenvalues

Macros
e(cmd)	candisc
e(cmdline)	command as typed
e(groupvar)	name of group variable
e(grouplabels)	labels for the groups
e(varlist)	discriminating variables
e(wtype)	weight type
e(wexp)	weight expression
e(title)	title in estimation output
e(ties)	how ties are to be handled
e(properties)	nob noV eigen
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(groupcounts)	number of observations for each group
e(grouppriors)	prior probabilities for each group
e(groupvalues)	numeric value for each group
e(means)	group means on discriminating variables
e(SSCP_W)	pooled within-group SSCP matrix
e(SSCP_B)	between-groups SSCP matrix
e(SSCP_T)	total SSCP matrix
e(SSCP_W#)	within-group SSCP matrix for group #
e(W_eigvals)	eigenvalues of e(SSCP_W)
e(W_eigvecs)	eigenvectors of e(SSCP_W)
e(S)	pooled within-group covariance matrix
e(Sinv)	inverse of e(S)
e(sqrtSinv)	Cholesky (square root) of e(Sinv)
e(Ev)	eigenvalues of $\mathbf{W}^{-1}\mathbf{B}$
e(L_raw)	eigenvectors of $\mathbf{W}^{-1}\mathbf{B}$
e(L_unstd)	unstandardized canonical discriminant function coefficients
e(L_std)	within-group standardized canonical discriminant function coefficients
e(L_totalstd)	total-sample standardized canonical discriminant function coefficients
e(C)	classification coefficients
e(cmeans)	unstandardized canonical discriminant functions evaluated at group means
e(canstruct)	canonical structure matrix
e(candisc_stat)	canonical discriminant analysis statistics

Functions
e(sample)	marks estimation sample

Methods and formulas

See *Methods and formulas* in [MV] **discrim lda** for information.

References

Huberty, C. J. 1994. *Applied Discriminant Analysis*. New York: Wiley.

Rencher, A. C., and W. F. Christensen. 2012. *Methods of Multivariate Analysis*. 3rd ed. Hoboken, NJ: Wiley.

Also see

[MV] **discrim lda** — Linear discriminant analysis

[MV] **discrim lda postestimation** — Postestimation tools for discrim lda

[U] **20 Estimation and postestimation commands**

Title

> **canon —** Canonical correlations

Description

canon estimates canonical correlations and provides the coefficients for calculating the appropriate linear combinations corresponding to those correlations.

canon typed without arguments redisplays previous estimation results.

Quick start

Canonical correlations between 2 sets of variables

    canon (x1 x2 x3 x4) (y1 y2 y3 y4)

Same as above, but display y1–y4 first and then x1–x4

    canon (y1 y2 y3 y4) (x1 x2 x3 x4)

Same as above, and display linear combinations for only the first 2 canonical correlations

    canon (y1 y2 y3 y4) (x1 x2 x3 x4), first(2)

Same as above, and display the linear combinations for only the second canonical correlation

    canon (y1 y2 y3 y4) (x1 x2 x3 x4), lc(2)

With different numbers of variables in each set

    canon (y1 y2 y3) (x1 x2 x3 x4 x5)

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Canonical correlations

Syntax

> canon (*varlist₁*) (*varlist₂*) [*if*] [*in*] [*weight*] [, *options*]

options	Description
Model	
<u>lc</u>(*#*)	calculate the linear combinations for canonical correlation *#*
<u>first</u>(*#*)	calculate the linear combinations for the first *#* canonical correlations
<u>noc</u>onstant	do not subtract means when calculating correlations
Reporting	
<u>stdc</u>oef	output matrices of standardized coefficients
<u>stde</u>rr	display raw coefficients and conditionally estimated standard errors
<u>l</u>evel(*#*)	set confidence level; default is level(95)
<u>test</u>(*numlist*)	display significance tests for the specified canonical correlations
<u>notest</u>s	do not display tests
<u>f</u>ormat(%*fmt*)	numerical format for coefficient matrices; default is format(%8.4f)

by, collect, and statsby are allowed; see [U] **11.1.10 Prefix commands**.

aweights and fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> **[Model]**

<u>lc</u>(*#*) specifies that linear combinations for canonical correlation *#* be calculated. By default, all are calculated.

<u>first</u>(*#*) specifies that linear combinations for the first *#* canonical correlations be calculated. By default, all are calculated.

<u>noc</u>onstant specifies that means not be subtracted when calculating correlations.

> **[Reporting]**

<u>stdc</u>oef specifies that the first part of the output contain the standard coefficients of the canonical correlations in matrix form. The default is to present the raw coefficients of the canonical correlations in matrix form.

<u>stde</u>rr specifies that the first part of the output contains the raw coefficients of the canonical correlations, the conditionally estimated standard errors, and the conditionally estimated confidence intervals in the standard estimation table. The default is to present the raw coefficients of the canonical correlations in matrix form.

<u>l</u>evel(*#*) specifies the confidence level, as a percentage, for confidence intervals of the coefficients. The default is level(95) or as set by set level; see [U] **20.8 Specifying the width of confidence intervals**. These "confidence intervals" are the result of an approximate calculation; see the technical note later in this entry.

<u>test</u>(*numlist*) specifies that significance tests of the canonical correlations in the *numlist* be displayed. Because of the nature of significance testing, if there are three canonical correlations, test(1) will test the significance of all three correlations, test(2) will test the significance of canonical correlations 2 and 3, and test(3) will test the significance of the third canonical correlation alone.

notests specifies that significance tests of the canonical correlation not be displayed.

format(*%fmt*) specifies the display format for numbers in coefficient matrices; see [D] **format**. format(%8.4f) is the default. format() may not be specified with stderr.

Remarks and examples

Canonical correlations attempt to describe the relationships between two sets of variables. Given two sets of variables, $\mathbf{X} = (x_1, x_2, \ldots, x_K)$ and $\mathbf{Y} = (y_1, y_2, \ldots, y_L)$, the goal is to find linear combinations of $\mathbf{X}$ and $\mathbf{Y}$ so that the correlation between the linear combinations is as high as possible. That is, letting $\widehat{x}_1$ and $\widehat{y}_1$ be the linear combinations,

$$\widehat{x}_1 = \beta_{11}x_1 + \beta_{12}x_2 + \cdots + \beta_{1K}x_K$$
$$\widehat{y}_1 = \gamma_{11}y_1 + \gamma_{12}y_2 + \cdots + \gamma_{1L}y_L$$

you wish to find the maximum correlation between $\widehat{x}_1$ and $\widehat{y}_1$ as functions of the β's and the γ's. The second canonical correlation coefficient is defined as the ordinary correlation between

$$\widehat{x}_2 = \beta_{21}x_1 + \beta_{22}x_2 + \cdots + \beta_{2K}x_K \quad \text{and}$$
$$\widehat{y}_2 = \gamma_{21}y_1 + \gamma_{22}y_2 + \cdots + \gamma_{2L}y_L$$

This correlation is maximized subject to the constraints that $\widehat{x}_1$ and $\widehat{x}_2$, along with $\widehat{y}_1$ and $\widehat{y}_2$, are orthogonal and that $\widehat{x}_1$ and $\widehat{y}_2$, along with $\widehat{x}_2$ and $\widehat{y}_1$, are also orthogonal. The third and further correlations are defined similarly. There are $m = \min(K, L)$ such correlations.

Canonical correlation analysis originated with the work of Hotelling (1935, 1936). For an introduction, see Rencher and Christensen (2012, chap. 11), Johnson and Wichern (2007), or Afifi et al. (2020).

▷ Example 1

Consider two scientists trying to describe how "big" a car is. The first scientist takes physical measurements—the length, weight, headroom, and trunk space—whereas the second takes mechanical measurements—the engine displacement, mileage rating, gear ratio, and turning circle. Can they agree on a conceptual framework?

```
. use https://www.stata-press.com/data/r18/auto
(1978 automobile data)
. canon (length weight headroom trunk) (displ mpg gear_ratio turn)
Canonical correlation analysis                      Number of obs =        74
Raw coefficients for the first variable set
```

	1	2	3	4
length	0.0095	0.1441	0.0329	0.0212
weight	0.0010	-0.0037	-0.0010	0.0007
headroom	0.0351	-0.3701	1.5361	-0.0440
trunk	-0.0023	-0.0343	-0.2135	-0.3253

```
Raw coefficients for the second variable set
                         1         2         3         4
       displacement    0.0054   -0.0125    0.0191   -0.0005
                mpg   -0.0461   -0.0413    0.0683    0.2478
          gear_ratio   0.0330    1.0280    3.6596   -1.0311
                turn    0.0794    0.3113    0.0033    0.2240


Canonical correlations:
  0.9476   0.3400   0.0634   0.0447


Tests of significance of all canonical correlations
                         Statistic     df1       df2            F    Prob>F
         Wilks' lambda     .0897314      16   202.271      15.1900    0.0000 a
        Pillai's trace    1.01956        16       276       5.9009    0.0000 a
Lawley-Hotelling trace    8.93344        16       258      36.0129    0.0000 a
  Roy's largest root      8.79667         4        69     151.7426    0.0000 u
```

$$e = \text{exact}, \ a = \text{approximate}, \ u = \text{upper bound on } F$$

By default, `canon` presents the raw coefficients of the canonical correlations in matrix form, reports the canonical correlations, and finally reports the tests of significance of all canonical correlations. The two views on car size are closely related: the best linear combination of the physical measurements is correlated at almost 0.95 with the best linear combination of the mechanical measurements. All the tests are significant.

To see the standardized coefficients instead of the raw coefficients, we can use the `stdcoef` option on replay, which gives the standardized coefficients in matrix form. We specify the `notests` option to suppress the display of tests this time.

```
. canon, stdcoef notests

Canonical correlation analysis                      Number of obs =          74

Standardized coefficients for the first variable set
                         1         2         3         4
             length     0.2110    3.2095    0.7334    0.4714
             weight     0.7898   -2.8469   -0.7448    0.5308
           headroom     0.0297   -0.3131    1.2995   -0.0373
              trunk    -0.0098   -0.1466   -0.9134   -1.3914


Standardized coefficients for the second variable set
                         1         2         3         4
       displacement    0.4932   -1.1525    1.7568   -0.0493
                mpg   -0.2670   -0.2388    0.3954    1.4337
          gear_ratio    0.0150    0.4691    1.6698   -0.4705
                turn    0.3493    1.3694    0.0145    0.9857


Canonical correlations:
  0.9476   0.3400   0.0634   0.0447
```

❑ Technical note

canon, with the stderr option, reports standard errors for the coefficients in the linear combinations; most other software does not. You should view these standard errors as lower bounds for the true standard errors. It is based on the assumption that the coefficients for one set of measurements are correct for calculating the coefficients and standard errors of the other relationship on the basis of a linear regression.

After canon, if you predict a canonical variate and regress it on the other variable set, the variance you get from the regression will be the variance you get from canon multiplied by the square of the corresponding canonical correlation.

❑

Stored results

canon stores the following in e():

Scalars
e(N)	number of observations
e(df_r)	residual degrees of freedom
e(df)	degrees of freedom
e(df1)	numerator degrees of freedom for significance tests
e(df2)	denominator degrees of freedom for significance tests
e(n_lc)	the linear combination calculated
e(n_cc)	number of canonical correlations calculated
e(rank)	rank of e(V)

Macros
e(cmd)	canon
e(cmdline)	command as typed
e(wtype)	weight type
e(wexp)	weight expression
e(properties)	b V
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(b)	coefficient vector
e(stat_#)	statistics for canonical correlation #
e(stat_m)	statistics for overall model
e(canload11)	canonical loadings for $varlist_1$
e(canload22)	canonical loadings for $varlist_2$
e(canload12)	correlation between $varlist_1$ and the canonical variates from $varlist_2$
e(canload21)	correlation between $varlist_2$ and the canonical variates from $varlist_1$
e(rawcoef_var1)	raw coefficients for $varlist_1$
e(rawcoef_var2)	raw coefficients for $varlist_2$
e(stdcoef_var1)	standardized coefficients for $varlist_1$
e(stdcoef_var2)	standardized coefficients for $varlist_2$
e(ccorr)	canonical correlation coefficients
e(corr_var1)	correlation matrix for $varlist_1$
e(corr_var2)	correlation matrix for $varlist_2$
e(corr_mixed)	correlation matrix between $varlist_1$ and $varlist_2$
e(V)	variance–covariance matrix of the estimators

Functions
e(sample)	marks estimation sample

Methods and formulas

Let the covariance matrix between the two sets of variables be

$$\begin{pmatrix} \mathbf{S_{yy}} & \mathbf{S_{yx}} \\ \mathbf{S_{xy}} & \mathbf{S_{xx}} \end{pmatrix}$$

Here $\mathbf{y}$ indicates the first variable set and $\mathbf{x}$ indicates the second variable set.

The squared canonical correlations are the eigenvalues of $\mathbf{V} = \mathbf{S_{yy}^{-1}S_{yx}S_{xx}^{-1}S_{xy}}$ or $\mathbf{W} = \mathbf{S_{xx}^{-1}S_{xy}S_{yy}^{-1}S_{yx}}$ (either will work), which are both nonsymmetric matrices (Rencher 1998, 312–317; Rencher and Christensen 2012, 385–389). Let the eigenvalues of $\mathbf{V}$ (and $\mathbf{W}$) be called r_k, the eigenvectors of $\mathbf{V}$ be called $\mathbf{a}_k$, and the eigenvectors of $\mathbf{W}$ be called $\mathbf{b}_k$. These eigenvectors are the raw coefficients for calculating the canonical variates, which are the linear combinations for the two sets of variables with maximal correlation. The eigenvalue equation for $\mathbf{V}$ is

$$\mathbf{S_{yy}^{-1}S_{yx}S_{xx}^{-1}S_{xy}a}_k - r_k^2\mathbf{a}_k = 0$$

Premultiplying by $\mathbf{S_{xx}^{-1}S_{xy}}$, we see that

$$(\mathbf{S_{xx}^{-1}S_{xy}S_{yy}^{-1}S_{yx}})(\mathbf{S_{xx}^{-1}S_{xy}a}_k) - r_k^2\mathbf{S_{xx}^{-1}S_{xy}a}_k = 0$$

so the $\mathbf{b}_k$ are proportional to $\mathbf{S_{xx}^{-1}S_{xy}a}_k$. Eigenvectors are determined up to a scale factor, and we choose the eigenvectors to give canonical variates with variance one. The canonical variates with correlation r_k are given by

$$\mathbf{u}_k = \mathbf{a}_k\mathbf{x} \qquad \text{and} \qquad \mathbf{v}_k = \mathbf{b}_k\mathbf{y}$$

In fact

$$\mathbf{b}_k = \frac{1}{r_k}\mathbf{S_{xx}^{-1}S_{xy}a}_k$$

To calculate lower bounds for the standard errors in this form, assume that the eigenvectors $\mathbf{a}_k$ are fixed. The formula relating $\mathbf{a}_k$ and $\mathbf{b}_k$ is given above. The coefficients given by $\mathbf{b}_k$ have covariance matrix

$$\frac{1 - r_k^2}{r_k^2(n - k - 1)}\mathbf{S_{xx}^{-1}}$$

Here n is the number of observations and k is the number of variables in the set $\mathbf{x}$.

Likewise, we can let the correlation matrix between the two sets of variables be

$$\begin{pmatrix} \mathbf{R_{yy}} & \mathbf{R_{yx}} \\ \mathbf{R_{xy}} & \mathbf{R_{xx}} \end{pmatrix}$$

That is, $\mathbf{R_{yy}}$ is the correlation matrix of the first set of variables with themselves, $\mathbf{R_{xx}}$ is the correlation matrix of the second set of variables with themselves, and $\mathbf{R_{yx}}$ (and $\mathbf{R_{xy}}$) contains the cross-correlations.

Using correlation matrices, the squared canonical correlations are the eigenvalues of $\widetilde{\mathbf{V}} = \mathbf{R_{yy}^{-1}R_{yx}R_{xx}^{-1}R_{xy}}$ or $\widetilde{\mathbf{W}} = \mathbf{R_{xx}^{-1}R_{xy}R_{yy}^{-1}R_{yx}}$ (Rencher 1998, 318–319; Rencher and Christensen 2012, 389). The corresponding eigenvectors are the standardized coefficients for determining the canonical variates from the centered and standardized original variables (mean 0 and variance 1). Eigenvectors are determined only up to a scale factor; we choose the scale to give the canonical variates in standardized (variance 1) form.

If the eigenvalues are $r_1, r_2, \ldots, r_m$ where m is the number of canonical correlations, we test the hypothesis that there is no (linear) relationship between the two variable sets. This is equivalent to the statement that none of the correlations $r_1, r_2, \ldots, r_m$ is significant.

Wilks's (1932) lambda statistic is

$$\Lambda_1 = \prod_{i=1}^{m}(1 - r_i^2)$$

and is a likelihood-ratio statistic. This statistic is distributed as the Wilks Λ-distribution. Rejection of the null hypothesis is for small values of Λ_1.

Pillai's (1955) trace for canonical correlations is

$$V^{(m)} = \sum_{i=1}^{m} r_i^2$$

and the Lawley–Hotelling trace (Lawley 1938 and Hotelling 1951) is

$$U^{(m)} = \sum_{i=1}^{m} \frac{r_i^2}{1 - r_i^2}$$

Roy's (1939) largest root is given by

$$\theta = r_1^2$$

Rencher and Christensen (2012, 391–395) has tables providing critical values for these statistics and discussion on significance testing for canonical correlations.

Canonical loadings, the correlation between a variable set and its corresponding canonical variate set, are calculated by `canon` and used in [MV] **canon postestimation**.

For a note about Harold Hotelling, see [MV] **hotelling**.

Acknowledgment

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Also see

Title

> **canon postestimation** — Postestimation tools for canon

Postestimation commands

The following postestimation commands are of special interest after `canon`:

Command	Description
estat correlations	show correlation matrices
estat loadings	show loading matrices
estat rotate	rotate raw coefficients, standard coefficients, or loading matrices
estat rotatecompare	compare rotated and unrotated coefficients or loadings
screeplot	plot canonical correlations

The following standard postestimation commands are also available:

Command	Description
estat summarize	summary statistics for the estimation sample
estat vce	variance–covariance matrix of the estimators (VCE)
estimates	cataloging estimation results
etable	table of estimation results
lincom	point estimates, standard errors, testing, and inference for linear combinations of coefficients
nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients
predict	linear combinations and their SEs
predictnl	point estimates, standard errors, testing, and inference for generalized predictions
test	Wald tests of simple and composite linear hypotheses
testnl	Wald tests of nonlinear hypotheses

predict

Description for predict

predict creates a new variable containing predictions such as linear combinations and their standard errors.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] *newvar* [*if*] [*in*], *statistic** [<u>c</u>orrelation(*#*)]

*statistic**	Description
Main	
u	calculate linear combination of *varlist*$_1$
v	calculate linear combination of *varlist*$_2$
stdu	calculate standard error of the linear combination of *varlist*$_1$
stdv	calculate standard error of the linear combination of *varlist*$_2$

* There is no default statistic; you must specify one *statistic* from the list.

These statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample.

Options for predict

> Main

u and v calculate the linear combinations of *varlist*$_1$ and *varlist*$_2$, respectively. For the first canonical correlation, u and v are the linear combinations having maximal correlation. For the second canonical correlation, specified in predict with the correlation(2) option, u and v have maximal correlation subject to the constraints that u is orthogonal to the u from the first canonical correlation, and v is orthogonal to the v from the first canonical correlation. The third and higher correlations are defined similarly. Canonical correlations may be chosen either with the lc() option to canon or by specifying the correlation() option to predict.

stdu and stdv calculate the standard errors of the respective linear combinations.

correlation(*#*) specifies the canonical correlation for which the requested statistic is to be computed. The default is correlation(1). If the lc() option to canon was used to calculate a particular canonical correlation, then only this canonical correlation is in the estimation results. You can obtain estimates for it either by specifying correlation(1) or by omitting the correlation() option.

estat

Description for estat

estat correlations displays the correlation matrices calculated by canon for *varlist*$_1$ and *varlist*$_2$ and between the two lists.

estat loadings displays the canonical loadings computed by canon.

estat rotate performs orthogonal varimax rotation of the raw coefficients, standard coefficients, or canonical loadings. Rotation is calculated on the canonical loadings regardless of which coefficients or loadings are actually rotated.

estat rotatecompare displays the rotated and unrotated coefficients or loadings and the most recently rotated coefficients or loadings. This command may be used only if estat rotate has been performed first.

Menu for estat

Statistics > Postestimation

Syntax for estat

Display the correlation matrices

> estat <u>corr</u>elations [, <u>f</u>ormat(*% fmt*)]

Display the canonical loadings

> estat <u>loa</u>dings [, <u>f</u>ormat(*% fmt*)]

Perform orthogonal varimax rotation

> estat <u>rot</u>ate [, <u>raw</u>coefs <u>std</u>coefs <u>l</u>oadings <u>f</u>ormat(*% fmt*)]

Display the rotated and unrotated coefficients or loadings

> estat <u>rotate</u>compare [, <u>f</u>ormat(*% fmt*)]

collect is allowed with estat correlations, estat loadings, and estat rotate; see [U] **11.1.10 Prefix commands**.

Option for estat

format(*% fmt*) specifies the display format for numbers in matrices; see [D] **format**. format(%8.4f) is the default.

rawcoefs, an option for estat rotate, requests the rotation of raw coefficients. It is the default.

stdcoefs, an option for estat rotate, requests the rotation of standardized coefficients.

loadings, an option for estat rotate, requests the rotation of the canonical loadings.

Remarks and examples

In addition to the coefficients presented by `canon` in computing canonical correlations, several other matrices may be of interest.

▷ Example 1: Predictions

Recall from `canon` the example of two scientists trying to describe how "big" a car is. One took physical measurements—the length, weight, headroom, and trunk space—whereas the second took mechanical measurements—engine displacement, mileage rating, gear ratio, and turning radius. We discovered that these two views are closely related, with the best linear combination of the two types of measurements, the largest canonical correlation, at 0.9476. We can prove that the first canonical correlation is correct by calculating the two linear combinations and then calculating the ordinary correlation.

```
. use https://www.stata-press.com/data/r18/auto
(1978 automobile data)
. quietly canon (length weight headroom trunk) (displ mpg gear_ratio turn)
. predict physical, u corr(1)
. predict mechanical, v corr(1)
. correlate mechanical physical
(obs=74)
```

	mechan~l	physical
mechanical	1.0000	
physical	0.9476	1.0000

```
. drop mechanical physical
```

◁

▷ Example 2: Canonical loadings

Researchers are often interested in the canonical loadings, the correlations between the original variable lists and their canonical variates. The canonical loadings are used to interpret the canonical variates. However, as shown in the technical note later in this entry, Rencher (1988; 1992; 1998, sec. 8.6.3) and Rencher and Christensen (2012, 397) have shown that there is no information in these correlations about how one variable list contributes jointly to canonical correlation with the other. Loadings are still often discussed, and `estat loadings` reports these as well as the cross-loadings or correlations between *varlist*$_1$ and the canonical variates for *varlist*$_2$ and the correlations between *varlist*$_2$ and the canonical variates for *varlist*$_1$. The loadings and cross-loadings are all computed by `canon`.

```
. estat loadings
```

Canonical loadings for variable list 1

	1	2	3	4
length	0.9664	0.2481	0.0361	-0.0566
weight	0.9972	-0.0606	-0.0367	0.0235
headroom	0.5140	-0.1295	0.7134	-0.4583
trunk	0.6941	0.0644	-0.0209	-0.7167

Canonical loadings for variable list 2

	1	2	3	4
displacement	0.9404	-0.3091	0.1050	0.0947
mpg	-0.8569	-0.1213	0.1741	0.4697
gear_ratio	-0.7945	0.3511	0.4474	-0.2129
turn	0.9142	0.3286	-0.0345	0.2345

Correlation between variable list 1 and canonical variates from list 2

	1	2	3	4
length	0.9158	0.0844	0.0023	-0.0025
weight	0.9449	-0.0206	-0.0023	0.0011
headroom	0.4871	-0.0440	0.0452	-0.0205
trunk	0.6577	0.0219	-0.0013	-0.0320

Correlation between variable list 2 and canonical variates from list 1

	1	2	3	4
displacement	0.8912	-0.1051	0.0067	0.0042
mpg	-0.8120	-0.0413	0.0110	0.0210
gear_ratio	-0.7529	0.1194	0.0284	-0.0095
turn	0.8663	0.1117	-0.0022	0.0105

```
. matrix load2 = r(canload22)
```

◁

▷ Example 3: Predictions and correlation matrices

In example 2, we saved the loading matrix for *varlist₂*, containing the mechanical variables, and we wish to verify that it is correct. We predict the canonical variates for *varlist₂* and then find the canonical correlations between the canonical variates and the original mechanical variables as a means of getting the correlation matrices, which we then display using estat correlations. The mixed correlation matrix is the same as the loading matrix that we saved.

```
. predict mechanical1, v corr(1)
. predict mechanical2, v corr(2)
. predict mechanical3, v corr(3)
. predict mechanical4, v corr(4)
. quietly canon (mechanical1-mechanical4) (displ mpg gear_ratio turn)
. estat correlation
```
Correlations for variable list 1

	mechan~1	mechan~2	mechan~3	mechan~4
mechanical1	1.0000			
mechanical2	-0.0000	1.0000		
mechanical3	-0.0000	0.0000	1.0000	
mechanical4	-0.0000	-0.0000	-0.0000	1.0000

Correlations for variable list 2

	displa~t	mpg	gear_r~o	turn
displacement	1.0000			
mpg	-0.7056	1.0000		
gear_ratio	-0.8289	0.6162	1.0000	
turn	0.7768	-0.7192	-0.6763	1.0000

Correlations between variable lists 1 and 2

	mechan~1	mechan~2	mechan~3	mechan~4
displacement	0.9404	-0.3091	0.1050	0.0947
mpg	-0.8569	-0.1213	0.1741	0.4697
gear_ratio	-0.7945	0.3511	0.4474	-0.2129
turn	0.9142	0.3286	-0.0345	0.2345

```
. matlist load2, format(%8.4f) border(bottom)
```

	1	2	3	4
displacement	0.9404	-0.3091	0.1050	0.0947
mpg	-0.8569	-0.1213	0.1741	0.4697
gear_ratio	-0.7945	0.3511	0.4474	-0.2129
turn	0.9142	0.3286	-0.0345	0.2345

◁

▷ Example 4: Rotated canonical loadings

Here we observe the results of rotation of the canonical loadings, via the Kaiser varimax method outlined in Cliff and Krus (1976). This observation is often done for interpretation of the results; however, rotation destroys several fundamental properties of canonical correlation.

```
. quietly canon (length weight headroom trunk) (displ mpg gear_ratio turn)
. estat rotate, loadings
    Criterion          varimax
    Rotation class     orthogonal
    Normalization      none
```

Rotated canonical loadings

	1	2	3	4
length	0.3796	0.7603	0.4579	0.2613
weight	0.6540	0.5991	0.3764	0.2677
headroom	0.0390	0.1442	0.3225	0.9347
trunk	0.1787	0.2052	0.8918	0.3614
displacement	0.7638	0.4424	0.2049	0.4230
mpg	-0.3543	-0.4244	-0.8109	-0.1918
gear_ratio	-0.9156	-0.3060	-0.2292	0.1248
turn	0.3966	0.8846	0.2310	0.0832

Rotation matrix

	1	2	3	4
1	0.5960	0.6359	0.3948	0.2908
2	-0.6821	0.6593	0.1663	-0.2692
3	-0.3213	0.1113	-0.3400	0.8768
4	0.2761	0.3856	-0.8372	-0.2724

```
. estat rotatecompare
```

Rotated canonical loadings — orthogonal varimax

	1	2	3	4
length	0.3796	0.7603	0.4579	0.2613
weight	0.6540	0.5991	0.3764	0.2677
headroom	0.0390	0.1442	0.3225	0.9347
trunk	0.1787	0.2052	0.8918	0.3614
displacement	0.7638	0.4424	0.2049	0.4230
mpg	-0.3543	-0.4244	-0.8109	-0.1918
gear_ratio	-0.9156	-0.3060	-0.2292	0.1248
turn	0.3966	0.8846	0.2310	0.0832

Unrotated canonical loadings

	1	2	3	4
length	0.9664	0.2481	0.0361	-0.0566
weight	0.9972	-0.0606	-0.0367	0.0235
headroom	0.5140	-0.1295	0.7134	-0.4583
trunk	0.6941	0.0644	-0.0209	-0.7167
displacement	0.9404	-0.3091	0.1050	0.0947
mpg	-0.8569	-0.1213	0.1741	0.4697
gear_ratio	-0.7945	0.3511	0.4474	-0.2129
turn	0.9142	0.3286	-0.0345	0.2345

◁

❏ Technical note

estat loadings reports the canonical loadings or correlations between a *varlist* and its corresponding canonical variates. It is widely claimed that the loadings provide a more valid interpretation of the canonical variates. Rencher (1988; 1992; 1998, sec. 8.6.3) and Rencher and Christensen (2012, 397) has shown that a weighted sum of the correlations between an $x_j \in varlist_1$ and the canonical variates from $varlist_1$ is equal to the squared multiple correlation between x_j and the variables in $varlist_2$. The correlations do not give new information on the importance of a given variable in the context of the others. Rencher and Christensen (2012, 397) notes, "The researcher who uses these correlations for interpretation is unknowingly reducing the multivariate setting to a univariate one."

❏

Stored results

estat correlations stores the following in r():

Matrices
r(corr_var1)	correlations for *varlist₁*
r(corr_var2)	correlations for *varlist₂*
r(corr_mixed)	correlations between *varlist₁* and *varlist₂*

estat loadings stores the following in r():

Matrices
r(canload11)	canonical loadings for *varlist₁*
r(canload22)	canonical loadings for *varlist₂*
r(canload21)	correlations between *varlist₂* and the canonical variates for *varlist₁*
r(canload12)	correlations between *varlist₁* and the canonical variates for *varlist₂*

estat rotate stores the following in r():

Macros
r(coefficients)	coefficients rotated
r(class)	rotation classification
r(criterion)	rotation criterion

Matrices
r(AT)	rotated coefficient matrix
r(T)	rotation matrix

Methods and formulas

Cliff and Krus (1976) state that they use the Kaiser varimax method with normalization for rotation. The loading matrix, the correlation matrix between the original variables and their canonical variates, is already normalized. Consequently, normalization is not required, nor is it offered as an option.

Rotation after canonical correlation is a subject fraught with controversy. Although some researchers wish to rotate coefficients and loadings for greater interpretability, and Cliff and Krus (1976) have shown that some properties of canonical correlations are preserved by orthogonal rotation, rotation does destroy some of the fundamental properties of canonical correlation. Rencher (1992), Rencher and Christensen (2012), and Thompson (1984) contribute on the topic. Rencher speaks starkly against rotation. Thompson explains why rotation is desired as well as why it is at odds with the principles of canonical correlation analysis.

The researcher is encouraged to consider carefully his or her goals in canonical correlation analysis and these references when evaluating whether rotation is an appropriate tool to use.

Harris (2001) gives an amusing critique on the misuse of canonical loadings in the interpretation of canonical correlation analysis results. As mentioned, Rencher (1988; 1992; 1998, sec. 8.6.3) and Rencher and Christensen (2012, 397) critique the use of canonical loadings.

References

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Harris, R. J. 2001. *A Primer of Multivariate Statistics*. 3rd ed. Mahwah, NJ: Lawrence Erlbaum.

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Thompson, B. 1984. *Canonical Correlation Analysis: Uses and Interpretation*. Thousand Oaks, CA: Sage.

Also see

[MV] **canon** — Canonical correlations

[MV] **rotatemat** — Orthogonal and oblique rotations of a Stata matrix

[MV] **screeplot** — Scree plot of eigenvalues

[U] **20 Estimation and postestimation commands**

Title

cluster — Introduction to cluster-analysis commands

Description   Syntax   Remarks and examples   References   Also see

Description

Stata's cluster-analysis routines provide several hierarchical and partition clustering methods, postclustering summarization methods, and cluster-management tools. This entry presents an overview of cluster analysis, the cluster and clustermat commands (also see [MV] **clustermat**), as well as Stata's cluster-analysis management tools. The hierarchical clustering methods may be applied to the data by using the cluster command or to a user-supplied dissimilarity matrix by using the clustermat command.

The cluster command has the following *subcommand*s, which are detailed in their respective manual entries.

Partition-clustering methods for observations

kmeans	[MV] **cluster kmeans and kmedians**	Kmeans cluster analysis
kmedians	[MV] **cluster kmeans and kmedians**	Kmedians cluster analysis

Hierarchical clustering methods for observations

singlelinkage	[MV] **cluster linkage**	Single-linkage cluster analysis
averagelinkage	[MV] **cluster linkage**	Average-linkage cluster analysis
completelinkage	[MV] **cluster linkage**	Complete-linkage cluster analysis
waveragelinkage	[MV] **cluster linkage**	Weighted-average linkage cluster analysis
medianlinkage	[MV] **cluster linkage**	Median-linkage cluster analysis
centroidlinkage	[MV] **cluster linkage**	Centroid-linkage cluster analysis
wardslinkage	[MV] **cluster linkage**	Ward's linkage cluster analysis

Postclustering commands

stop	[MV] **cluster stop**	Cluster-analysis stopping rules
dendrogram	[MV] **cluster dendrogram**	Dendrograms for hierarchical cluster analysis
generate	[MV] **cluster generate**	Generate grouping variables from a cluster analysis

User utilities

notes	[MV] **cluster notes**	Cluster analysis notes
dir	[MV] **cluster utility**	Directory list of cluster analyses
list	[MV] **cluster utility**	List cluster analyses
drop	[MV] **cluster utility**	Drop cluster analyses
use	[MV] **cluster utility**	Mark cluster analysis as most recent one
rename	[MV] **cluster utility**	Rename cluster analyses
renamevar	[MV] **cluster utility**	Rename cluster-analysis variables

Programmer utilities

	[MV] **cluster programming subroutines**	Add cluster-analysis routines
query	[MV] **cluster programming utilities**	Obtain cluster-analysis attributes
set	[MV] **cluster programming utilities**	Set cluster-analysis attributes
delete	[MV] **cluster programming utilities**	Delete cluster-analysis attributes
parsedistance	[MV] **cluster programming utilities**	Parse (dis)similarity measure names
measures	[MV] **cluster programming utilities**	Compute (dis)similarity measures

The clustermat command has the following *subcommand*s, which are detailed along with the related cluster command manual entries. Also see [MV] **clustermat**.

Hierarchical clustering methods for matrices

singlelinkage	[MV] **cluster linkage**	Single-linkage cluster analysis
averagelinkage	[MV] **cluster linkage**	Average-linkage cluster analysis
completelinkage	[MV] **cluster linkage**	Complete-linkage cluster analysis
waveragelinkage	[MV] **cluster linkage**	Weighted-average linkage cluster analysis
medianlinkage	[MV] **cluster linkage**	Median-linkage cluster analysis
centroidlinkage	[MV] **cluster linkage**	Centroid-linkage cluster analysis
wardslinkage	[MV] **cluster linkage**	Ward's linkage cluster analysis

Also, the clustermat stop postclustering command has syntax similar to that of the cluster stop command; see [MV] **cluster stop**. For the remaining postclustering commands and user utilities, you may specify either cluster or clustermat—it does not matter which.

If you are new to Stata's cluster-analysis commands, we recommend that you first read this entry and then read the following:

[MV] *measure_option*	Option for similarity and dissimilarity measures
[MV] **clustermat**	Cluster analysis of a dissimilarity matrix
[MV] **cluster kmeans and kmedians**	Kmeans and kmedians cluster analysis
[MV] **cluster linkage**	Hierarchical cluster analysis
[MV] **cluster dendrogram**	Dendrograms for hierarchical cluster analysis
[MV] **cluster stop**	Cluster-analysis stopping rules
[MV] **cluster generate**	Generate grouping variables from a cluster analysis

Syntax

Cluster analysis of data

    cluster *subcommand* ...

Cluster analysis of a dissimilarity matrix

    clustermat *subcommand* ...

Remarks and examples

Remarks are presented under the following headings:

Introduction to cluster analysis

Cluster analysis attempts to determine the natural groupings (or clusters) of observations. Sometimes this process is called "classification", but this term is used by others to mean discriminant analysis, which is related but is not the same; see [MV] **discrim**. To avoid confusion, we will use "cluster analysis" or "clustering" when referring to finding groups in data. Defining cluster analysis is difficult (maybe impossible). Kaufman and Rousseeuw (1990) start their book by saying, "Cluster analysis is the art of finding groups in data." Everitt et al. (2011, 7) use the terms "cluster", "group", and "class" and say, concerning a formal definition for these terms, "In fact it turns out that such formal definition is not only difficult but may even be misplaced."

Everitt et al. (2011) and Gordon (1999) provide examples of the use of cluster analysis, such as in refining or redefining diagnostic categories in psychiatry, detecting similarities in artifacts by archaeologists to study the spatial distribution of artifact types, discovering hierarchical relationships in taxonomy, and identifying sets of similar cities so that one city from each class can be sampled in a market research task. Also, the activity now called "data mining" relies extensively on cluster-analysis methods.

We view cluster analysis as an exploratory data-analysis technique. According to Everitt, "Many cluster-analysis techniques have taken their place alongside other exploratory data-analysis techniques as tools of the applied statistician. The term exploratory is important here because it explains the largely absent 'p-value', ubiquitous in many other areas of statistics. ... Clustering methods are intended largely for generating rather than testing hypotheses" (1993, 10).

Although some have said that there are as many cluster-analysis methods as there are people performing cluster analysis. This is a gross understatement! There exist infinitely more ways to perform a cluster analysis than people who perform them.

There are several general types of cluster-analysis methods, each having many specific methods. Also, most cluster-analysis methods allow a variety of distance measures for determining the similarity or dissimilarity between observations. Some of the measures do not meet the requirements to be called a distance metric, so we use the more general term "dissimilarity measure" in place of distance. Similarity measures may be used in place of dissimilarity measures. There are an infinite number of similarity and dissimilarity measures. For instance, there are an infinite number of Minkowski distance metrics, with the familiar Euclidean, absolute-value, and maximum-value distances being special cases.

In addition to cluster method and dissimilarity measure choice, if you are performing a cluster analysis, you might decide to perform data transformations and/or variable selection before clustering. Then you might need to determine how many clusters there really are in the data, which you can do using stopping rules. There is a surprisingly large number of stopping rules mentioned in the literature. For example, Milligan and Cooper (1985) compare 30 different stopping rules.

Looking at all of these choices, you can see why there are more cluster-analysis methods than people performing cluster analysis.

Stata's cluster-analysis system

Stata's cluster and clustermat commands were designed to allow you to keep track of the various cluster analyses performed on your data. The main clustering subcommands—singlelinkage, averagelinkage, completelinkage, waveragelinkage, medianlinkage, centroidlinkage, wardslinkage (see [MV] **cluster linkage**), kmeans, and kmedians (see [MV] **cluster kmeans and kmedians**)—create named Stata cluster objects that keep track of the variables these methods create and hold other identifying information for the cluster analysis. These cluster objects become part of your dataset. They are saved with your data when your data are saved and are retrieved when you again use your dataset; see [D] **save** and [D] **use**.

Post–cluster-analysis subcommands are available with the cluster and clustermat commands so that you can examine the created clusters. Cluster-management tools are provided that allow you to add information to the cluster objects and to manipulate them as needed. The main clustering subcommands, postclustering subcommands, and cluster-management tools are discussed in the following sections.

Stata's clustering methods fall into two general types: partition and hierarchical. These two types are discussed below. There exist other types, such as fuzzy partition (where observations can belong to more than one group). Stata's cluster command is designed so that programmers can extend it by adding more methods; see [MV] **cluster programming subroutines** and [MV] **cluster programming utilities** for details.

❑ Technical note

If you are familiar with Stata's large array of estimation commands, be careful to distinguish between cluster analysis (the cluster command) and the vce(cluster *clustvar*) option (see [R] *vce_option*) allowed with many estimation commands. Cluster analysis finds groups in data. The vce(cluster *clustvar*) option allowed with various estimation commands indicates that the observations are independent across the groups defined by the option but are not necessarily independent within those groups. A grouping variable produced by the cluster command will seldom satisfy the assumption behind the use of the vce(cluster *clustvar*) option.

❑

Data transformations and variable selection

Stata's `cluster` command has no built-in data transformations, but because Stata has full data management and statistical capabilities, you can use other Stata commands to transform your data before calling the `cluster` command. Standardizing the variables is sometimes important to keep a variable with high variability from dominating the cluster analysis. In other cases, standardizing variables hides the true groupings present in the data. The decision to standardize or perform other data transformations depends on the type of data and the nature of the groups.

Data transformations (such as standardization of variables) and the variables selected for use in clustering can also greatly affect the groupings that are discovered. These and other cluster-analysis data issues are covered in Milligan and Cooper (1988) and Schaffer and Green (1996) and in many of the cluster-analysis texts, including Anderberg (1973); Gordon (1999); Everitt et al. (2011); and Späth (1980).

Similarity and dissimilarity measures

Several similarity and dissimilarity measures have been implemented for Stata's clustering commands for both continuous and binary variables. For information, see [MV] *measure_option*.

Partition cluster-analysis methods

Partition methods break the observations into a distinct number of nonoverlapping groups. Stata has implemented two partition methods, kmeans and kmedians.

One of the more commonly used partition clustering methods is called kmeans cluster analysis. In kmeans clustering, the user specifies the number of clusters, k, to create using an iterative process. Each observation is assigned to the group whose mean is closest, and then based on that categorization, new group means are determined. These steps continue until no observations change groups. The algorithm begins with k seed values, which act as the k group means. There are many ways to specify the beginning seed values.

A variation of kmeans clustering is kmedians clustering. The same process is followed in kmedians as in kmeans, except that medians, instead of means, are computed to represent the group centers at each step. See [MV] **cluster kmeans and kmedians** for the details of the `cluster kmeans` and `cluster kmedians` commands.

These partition-clustering methods will generally be quicker and will allow larger datasets than the hierarchical clustering methods outlined next. However, if you wish to examine clustering to various numbers of clusters, you will need to execute `cluster` many times with the partition methods. Clustering to various numbers of groups by using a partition method typically does not produce clusters that are hierarchically related. If this relationship is important for your application, consider using one of the hierarchical methods.

Hierarchical cluster-analysis methods

Hierarchical clustering creates hierarchically related sets of clusters. Hierarchical clustering methods are generally of two types: agglomerative or divisive.

Agglomerative hierarchical clustering methods begin with each observation's being considered as a separate group (N groups each of size 1). The closest two groups are combined ($N - 1$ groups, one of size 2 and the rest of size 1), and this process continues until all observations belong to the same group. This process creates a hierarchy of clusters.

In addition to choosing the similarity or dissimilarity measure to use in comparing 2 observations, you can choose what to compare between groups that contain more than 1 observation. The method used to compare groups is called a linkage method. Stata's `cluster` and `clustermat` commands provide several hierarchical agglomerative linkage methods, which are discussed in the next section.

Unlike hierarchical agglomerative clustering, divisive hierarchical clustering begins with all observations belonging to one group. This group is then split in some fashion to create two groups. One of these two groups is then split to create three groups; one of these three is then split to create four groups, and so on, until all observations are in their own separate group. Stata currently has no divisive hierarchical clustering commands. There are relatively few mentioned in the literature, and they tend to be particularly time consuming to compute.

To appreciate the underlying computational complexity of both agglomerative and divisive hierarchical clustering, consider the following information paraphrased from Kaufman and Rousseeuw (1990). The first step of an agglomerative algorithm considers $N(N - 1)/2$ possible fusions of observations to find the closest pair. This number grows quadratically with N. For divisive hierarchical clustering, the first step would be to find the best split into two nonempty subsets, and if all possibilities were considered, it would amount to $2^{(N-1)} - 1$ comparisons. This number grows exponentially with N.

Agglomerative methods

Stata's `cluster` and `clustermat` commands provide the following hierarchical agglomerative linkage methods: single, complete, average, Ward's method, centroid, median, and weighted average. There are others mentioned in the literature, but these are the best-known methods.

Single-linkage clustering computes the similarity or dissimilarity between two groups as the similarity or dissimilarity between the closest pair of observations between the two groups. Complete-linkage clustering, on the other hand, uses the farthest pair of observations between the two groups to determine the similarity or dissimilarity of the two groups. Average-linkage clustering uses the average similarity or dissimilarity of observations between the groups as the measure between the two groups. Ward's method joins the two groups that result in the minimum increase in the error sum of squares. The other linkage methods provide alternatives to these basic linkage methods.

The `cluster singlelinkage` and `clustermat singlelinkage` commands implement single-linkage hierarchical agglomerative clustering; see [MV] **cluster linkage** for details. Single-linkage clustering suffers (or benefits, depending on your point of view) from what is called chaining. Because the closest points between two groups determine the next merger, long, thin clusters can result. If this chaining feature is not what you desire, consider using one of the other methods, such as complete linkage or average linkage. Because of special properties that can be computationally exploited, single-linkage clustering is faster and uses less memory than the other linkage methods.

Complete-linkage hierarchical agglomerative clustering is implemented by the `cluster completelinkage` and `clustermat completelinkage` commands; see [MV] **cluster linkage** for details. Complete-linkage clustering is at the other extreme from single-linkage clustering. Complete linkage produces spatially compact clusters, so it is not the best method for recovering elongated cluster structures. Several sources, including Kaufman and Rousseeuw (1990), discuss the chaining of single linkage and the clumping of complete linkage.

Kaufman and Rousseeuw (1990) indicate that average linkage works well for many situations and is reasonably robust. The `cluster averagelinkage` and `clustermat averagelinkage` commands provide average-linkage clustering; see [MV] **cluster linkage**.

Ward (1963) presented a general hierarchical clustering approach where groups were joined to maximize an objective function. He used an error-sum-of-squares objective function to illustrate. Ward's method of clustering became synonymous with using the error-sum-of-squares criteria. Kaufman and Rousseeuw (1990) indicate that Ward's method does well with groups that are multivariate normal and spherical but does not do as well if the groups are of different sizes or have unequal numbers of observations. The `cluster wardslinkage` and `clustermat wardslinkage` commands provide Ward's linkage clustering; see [MV] **cluster linkage**.

At each step of the clustering, centroid linkage merges the groups whose means are closest. The centroid of a group is the componentwise mean and can be interpreted as the center of gravity for the group. Centroid linkage differs from average linkage in that centroid linkage is concerned with the distance between the means of the groups, whereas average linkage looks at the average distance between the points of the two groups. The `cluster centroidlinkage` and `clustermat centroidlinkage` commands provide centroid-linkage clustering; see [MV] **cluster linkage**.

Weighted-average linkage and median linkage are variations on average linkage and centroid linkage, respectively. In both cases, the difference is in how groups of unequal size are treated when merged. In average linkage and centroid linkage, the number of elements of each group is factored into the computation, giving correspondingly larger influence to the larger group. These two methods are called unweighted because each observation carries the same weight. In weighted-average linkage and median linkage, the two groups are given equal weighting in determining the combined group, regardless of the number of observations in each group. These two methods are said to be weighted because observations from groups with few observations carry more weight than observations from groups with many observations. The `cluster waveragelinkage` and `clustermat waveragelinkage` commands provide weighted-average linkage clustering. The `cluster medianlinkage` and `clustermat medianlinkage` commands provide median linkage clustering; see [MV] **cluster linkage**.

Lance and Williams's recurrence formula

Lance and Williams (1967) developed a recurrence formula that defines, as special cases, most of the well-known hierarchical clustering methods, including all the hierarchical clustering methods found in Stata. Anderberg (1973); Jain and Dubes (1988); Kaufman and Rousseeuw (1990); Gordon (1999); Everitt et al. (2011); and Rencher and Christensen (2012) discuss the Lance–Williams formula and how most popular hierarchical clustering methods are contained within it.

From the notation of Everitt et al. (2011, 78), the Lance–Williams recurrence formula is

$$d_{k(ij)} = \alpha_i d_{ki} + \alpha_j d_{kj} + \beta d_{ij} + \gamma |d_{ki} - d_{kj}|$$

where d_{ij} is the distance (or dissimilarity) between cluster i and cluster j; $d_{k(ij)}$ is the distance (or dissimilarity) between cluster k and the new cluster formed by joining clusters i and j; and α_i, α_j, β, and γ are parameters that are set based on the particular hierarchical cluster-analysis method.

The recurrence formula allows, at each new level of the hierarchical clustering, the dissimilarity between the newly formed group and the rest of the groups to be computed from the dissimilarities of the current grouping. This approach can result in a large computational savings compared with recomputing at each step in the hierarchy from the observation-level data. This feature of the recurrence formula allows `clustermat` to operate on a similarity or dissimilarity matrix instead of the data.

The following table shows the values of α_i, α_j, β, and γ for the hierarchical clustering methods implemented in Stata. n_i, n_j, and n_k are the number of observations in group i, j, and k, respectively.

Clustering linkage method	α_i	α_j	β	γ
Single	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$
Complete	$\frac{1}{2}$	$\frac{1}{2}$	0	$\frac{1}{2}$
Average	$\frac{n_i}{n_i + n_j}$	$\frac{n_j}{n_i + n_j}$	0	0
Weighted average	$\frac{1}{2}$	$\frac{1}{2}$	0	0
Centroid	$\frac{n_i}{n_i + n_j}$	$\frac{n_j}{n_i + n_j}$	$-\alpha_i\alpha_j$	0
Median	$\frac{1}{2}$	$\frac{1}{2}$	$-\frac{1}{4}$	0
Ward's	$\frac{n_i + n_k}{n_i + n_j + n_k}$	$\frac{n_j + n_k}{n_i + n_j + n_k}$	$\frac{-n_k}{n_i + n_j + n_k}$	0

For information on the use of various similarity and dissimilarity measures in hierarchical clustering, see the next two sections.

Dissimilarity transformations and the Lance and Williams formula

The Lance–Williams formula, which is used as the basis for computing hierarchical clustering in Stata, is designed for use with dissimilarity measures. Before performing hierarchical clustering, Stata transforms similarity measures, both continuous and binary, to dissimilarities. After cluster analysis, Stata transforms the fusion values (heights at which the various groups join in the hierarchy) back to similarities.

Stata's `cluster` command uses

$$\text{dissimilarity} = 1 - \text{similarity}$$

to transform from a similarity to a dissimilarity measure and back again; see Kaufman and Rousseeuw (1990, 21). Stata's similarity measures range from either 0 to 1 or -1 to 1. The resulting dissimilarities range from 1 down to 0 and from 2 down to 0, respectively.

For continuous data, Stata provides both the L2 and L2squared dissimilarity measures, as well as both the L(#) and Lpower(#) dissimilarity measures. Why have both an L2 and L2squared dissimilarity measure, and why have both an L(#) and Lpower(#) dissimilarity measure?

For single- and complete-linkage hierarchical clustering (and for kmeans and kmedians partition clustering), there is no need for the additional L2squared and Lpower(#) dissimilarities. The same cluster solution is obtained when using L2 and L2squared (or L(#) and Lpower(#)), except that the resulting heights in the dendrogram are raised to a power.

However, for the other hierarchical clustering methods, there is a difference. For some of these other hierarchical clustering methods, the natural default for dissimilarity measure is L2squared. For instance, the traditional Ward's (1963) method is obtained by using the L2squared dissimilarity option.

Warning concerning similarity or dissimilarity choice

With hierarchical centroid, median, Ward's, and weighted-average linkage clustering, Lance and Williams (1967); Anderberg (1973); Jain and Dubes (1988); Kaufman and Rousseeuw (1990); Everitt et al. (2011); and Gordon (1999) give various levels of warnings about using many of the similarity and dissimilarity measures ranging from saying that you should never use anything other than the default squared Euclidean distance (or Euclidean distance) to saying that the results may lack a useful interpretation.

Example 2 of [MV] cluster linkage illustrates part of the basis for this warning. The simple matching coefficient is used on binary data. The range of the fusion values for the resulting hierarchy is not between 1 and 0, as you would expect for the matching coefficient. The conclusions from the cluster analysis, however, agree well with the results obtained in other ways.

Stata does not restrict your choice of similarity or dissimilarity. If you are not familiar with these hierarchical clustering methods, use the default dissimilarity measure.

Synonyms

Cluster-analysis methods have been developed by researchers in many different disciplines. Because researchers did not always know what was happening in other fields, many synonyms for the different hierarchical cluster-analysis methods exist.

Blashfield and Aldenderfer (1978) provide a table of equivalent terms. Jain and Dubes (1988) and Day and Edelsbrunner (1984) also mention some of the synonyms and use various acronyms. Here is a list of synonyms:

Single linkage
  Nearest-neighbor method
  Minimum method
  Hierarchical analysis
  Space-contracting method
  Elementary linkage analysis
  Connectedness method

Complete linkage
  Furthest-neighbor method
  Maximum method
  Compact method
  Space-distorting method
  Space-dilating method
  Rank-order typal analysis
  Diameter analysis

Average linkage
  Arithmetic-average clustering
  Unweighted pair-group method using
    arithmetic averages
  UPGMA
  Unweighted clustering
  Group-average method
  Unweighted group mean
  Unweighted pair-group method

Weighted-average linkage
  Weighted pair-group method using
    arithmetic averages
  WPGMA
  Weighted group-average method

Centroid linkage
  Unweighted centroid method
  Unweighted pair-group centroid method
  UPGMC
  Nearest-centroid sorting

Median linkage
  Gower's method
  Weighted centroid method
  Weighted pair-group centroid method
  WPGMC
  Weighted pair method
  Weighted group method

Ward's method
  Minimum-variance method
  Error-sum-of-squares method
  Hierarchical grouping to minimize tr(W)
  HGROUP

Reversals

Unlike the other hierarchical methods implemented in Stata, centroid linkage and median linkage (see [MV] **cluster linkage**) can (and often do) produce reversals or crossovers; see Anderberg (1973), Jain and Dubes (1988), Gordon (1999), and Rencher and Christensen (2012). Normally, the dissimilarity or clustering criterion increases monotonically as the agglomerative hierarchical clustering progresses from many to few clusters. (For similarity measures, it monotonically decreases.) The dissimilarity value at which $k + 1$ clusters form will be larger than the value at which k clusters form. When the dissimilarity does not increase monotonically through the levels of the hierarchy, it is said to have reversals or crossovers.

The word *crossover*, in this context, comes from the appearance of the resulting dendrogram (see [MV] **cluster dendrogram**). In a hierarchical clustering without reversals, the dendrogram branches extend in one direction (increasing dissimilarity measure). With reversals, some of the branches reverse and go in the opposite direction, causing the resulting dendrogram to be drawn with crossing lines (crossovers).

When reversals happen, Stata still produces correct results. You can still generate grouping variables (see [MV] **cluster generate**) and compute stopping rules (see [MV] **cluster stop**). However, the cluster dendrogram command will not draw a dendrogram with reversals; see [MV] **cluster dendrogram**. In all but the simplest cases, dendrograms with reversals are almost impossible to interpret visually.

Hierarchical cluster analysis applied to a dissimilarity matrix

What if you want to perform a cluster analysis using a similarity or dissimilarity measure that Stata does not provide? What if you want to cluster variables instead of observations? The clustermat command gives you the flexibility to do either; see [MV] **clustermat**.

User-supplied dissimilarities

There are situations where the dissimilarity between objects is evaluated subjectively (perhaps on a scale from 1 to 10 by a rater). These dissimilarities may be entered in a matrix and passed to the clustermat command to perform hierarchical clustering. Likewise, if Stata does not offer the dissimilarity measure you desire, you may compute the dissimilarities yourself and place them in a matrix and then use clustermat to perform the cluster analysis. [MV] **clustermat** illustrates both of these situations.

Clustering variables instead of observations

Sometimes you want to cluster variables rather than observations, so you can use the cluster command. One approach to clustering variables in Stata is to use xpose (see [D] **xpose**) to transpose the variables and observations and then to use cluster. Another approach is to use the matrix dissimilarity command with the variables option (see [MV] **matrix dissimilarity**) to produce a dissimilarity matrix for the variables. This matrix is then passed to clustermat to obtain the hierarchical clustering. See [MV] **clustermat**.

Postclustering commands

Stata's cluster stop and clustermat stop commands are used to determine the number of clusters. Two stopping rules are provided, the Caliński and Harabasz (1974) pseudo-F index and the Duda, Hart, and Stork (2001, sec. 10.10) Je(2)/Je(1) index with associated pseudo-T^2. You can easily add stopping rules to the cluster stop command; see [MV] **cluster stop** for details.

The `cluster dendrogram` command presents the dendrogram (cluster tree) after a hierarchical cluster analysis; see [MV] **cluster dendrogram**. Options allow you to view the top portion of the tree or the portion of the tree associated with a group. These options are important with larger datasets because the full dendrogram cannot be presented.

The `cluster generate` command produces grouping variables after hierarchical clustering; see [MV] **cluster generate**. These variables can then be used in other Stata commands, such as those that tabulate, summarize, and provide graphs. For instance, you might use `cluster generate` to create a grouping variable. You then might use the `pca` command (see [MV] **pca**) to obtain the first two principal components of the data. You could follow that with a graph (see *Stata Graphics Reference Manual*) to plot the principal components, using the grouping variable from the `cluster generate` command to control the point labeling of the graph. This method would allow you to get one type of view into the clustering behavior of your data.

Cluster-management tools

You may add notes to your cluster analysis with the `cluster notes` command; see [MV] **cluster notes**. This command also allows you to view and delete notes attached to the cluster analysis.

The `cluster dir` and `cluster list` commands allow you to list the cluster objects and attributes currently defined for your dataset. `cluster drop` lets you remove a cluster object. See [MV] **cluster utility** for details.

Cluster objects are referred to by name. If no name is provided, many of the `cluster` commands will, by default, use the cluster object from the most recently performed cluster analysis. The `cluster use` command tells Stata which cluster object to use. You can change the name attached to a cluster object with the `cluster rename` command and the variables associated with a cluster analysis with the `cluster renamevar` command. See [MV] **cluster utility** for details.

You can exercise fine control over the attributes that are stored with a cluster object; see [MV] **cluster programming utilities**.

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Also see

[MV] **clustermat** — Introduction to clustermat commands

[MV] **cluster programming subroutines** — Add cluster-analysis routines

[MV] **cluster programming utilities** — Cluster-analysis programming utilities

[MV] **discrim** — Discriminant analysis

Title

clustermat — Introduction to clustermat commands

[Description](#)   [Syntax](#)   [Remarks and examples](#)   [References](#)   [Also see](#)

Description

clustermat performs hierarchical cluster analysis on the dissimilarity matrix *matname*. clustermat is part of the cluster suite of commands; see [MV] **cluster**. All Stata hierarchical clustering methods are allowed with clustermat. The partition-clustering methods (kmeans and kmedians) are not allowed because they require the data.

See [MV] **cluster** for a listing of all the cluster and clustermat commands. The cluster dendrogram command (see [MV] **cluster dendrogram**) will display the resulting dendrogram, the clustermat stop command (see [MV] **cluster stop**) will help in determining the number of groups, and the cluster generate command (see [MV] **cluster generate**) will produce grouping variables. Other useful cluster subcommands include notes, dir, list, drop, use, rename, and renamevar; see [MV] **cluster notes** and [MV] **cluster utility**.

Syntax

clustermat *linkage matname* ...

linkage	Description
<u>s</u>inglelinkage	single-linkage cluster analysis
<u>a</u>veragelinkage	average-linkage cluster analysis
<u>c</u>ompletelinkage	complete-linkage cluster analysis
<u>wav</u>eragelinkage	weighted-average linkage cluster analysis
<u>med</u>ianlinkage	median-linkage cluster analysis
<u>cent</u>roidlinkage	centroid-linkage cluster analysis
<u>wards</u>linkage	Ward's linkage cluster analysis

See [MV] **cluster linkage**.

clustermat stop has similar syntax to that of cluster stop; see [MV] **cluster stop**. For the remaining postclustering subcommands and user utilities, you may specify either cluster or clustermat—it does not matter which.

Remarks and examples

If you are clustering observations by using one of the similarity or dissimilarity measures provided by Stata, the cluster command is what you need. If, however, you already have a dissimilarity matrix or can produce one for a dissimilarity measure that Stata does not provide, or if you want to cluster variables instead of observations, the clustermat command is what you need.

▷ Example 1

Table 6 of Kaufman and Rousseeuw (1990) provides a subjective dissimilarity matrix among 11 sciences. Fourteen postgraduate economics students from different parts of the world gave subjective dissimilarities among these 11 sciences on a scale from 0 (identical) to 10 (very different). The final dissimilarity matrix was obtained by averaging the results from the students.

We begin by creating a label variable and a shorter version of the label variable corresponding to the 11 sciences. Then we create a row vector containing the lower triangle of the dissimilarity matrix.

```
. input str13 science

            science
 1. Astronomy
 2. Biology
 3. Chemistry
 4. Computer sci.
 5. Economics
 6. Geography
 7. History
 8. Mathematics
 9. Medicine
10. Physics
11. Psychology
12. end
. generate str4 shortsci = substr(science,1,4)

. matrix input D = (
> 0.00
> 7.86 0.00
> 6.50 2.93 0.00
> 5.00 6.86 6.50 0.00
> 8.00 8.14 8.21 4.79 0.00
> 4.29 7.00 7.64 7.71 5.93 0.00
> 8.07 8.14 8.71 8.57 5.86 3.86 0.00
> 3.64 7.14 4.43 1.43 3.57 7.07 9.07 0.00
> 8.21 2.50 2.93 6.36 8.43 7.86 8.43 6.29 0.00
> 2.71 5.21 4.57 4.21 8.36 7.29 8.64 2.21 5.07 0.00
> 9.36 5.57 7.29 7.21 6.86 8.29 7.64 8.71 3.79 8.64 0.00 )
```

There are several ways that we could have stored the dissimilarity information in a matrix. To avoid entering both the upper and lower triangle of the matrix, we entered the dissimilarities as a row vector containing the lower triangular entries of the dissimilarity matrix, including the diagonal of zeros (although there are options that would allow us to omit the diagonal of zeros). We typed `matrix input D = ...` instead of `matrix D = ...` so that we could omit the commas between entries; see [P] **matrix define**.

We now perform a complete-linkage cluster analysis on these dissimilarities. The `name()` option names the cluster analysis. We will name it `complink`. The `shape(lower)` option is what signals that the dissimilarity matrix is stored as a row vector containing the lower triangle of the dissimilarity matrix, including the diagonal of zeros. The `add` option indicates that the resulting cluster information should be added to the existing dataset. Here the existing dataset consists of the `science` label variable and the shortened version `shortsci`. See [MV] **cluster linkage** for details concerning these options. The short labels are passed to `cluster dendrogram` so that we can see which subjects were most closely related when viewing the dendrogram; see [MV] **cluster dendrogram**.

```
. clustermat completelinkage D, shape(lower) add name(complink)
. cluster dendrogram complink, labels(shortsci)
> title(Complete-linkage clustering)
> ytitle("Subjective dissimilarity" "0 = Same, 10 = Very different")
```
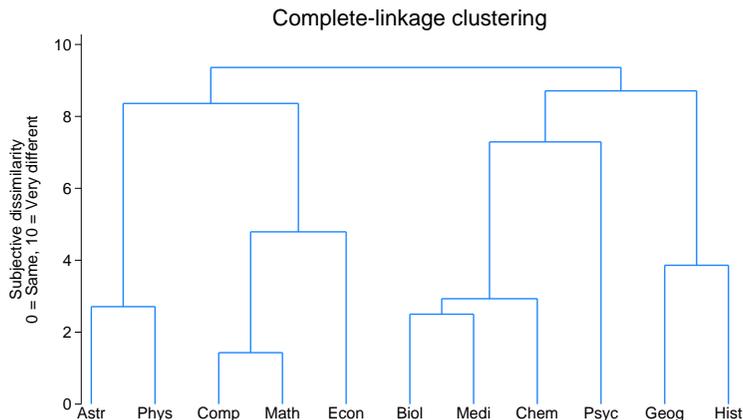

From the dendrogram, we see that mathematics and computer science were deemed most similar and that the economists most closely related their field of study to those two disciplines.

◁

▷ Example 2

Stata does not provide the Bray and Curtis (1957) dissimilarity measure first described by Odum (1950). Using the same notation as that found in [MV] *measure_option*, we find that the Bray–Curtis dissimilarity between observations i and j is

$$\frac{\sum_{a=1}^{p} |x_{ia} - x_{ja}|}{\sum_{a=1}^{p} (x_{ia} + x_{ja})}$$

Stata does not provide this measure because of the many cases where the measure is undefined (because of dividing by zero). However, when the data are positive the Bray–Curtis dissimilarity is well behaved.

Even though Stata does not automatically provide this measure, it is easy to obtain it and then use it with clustermat to perform hierarchical clustering. The numerator of the Bray–Curtis dissimilarity measure is the L1 (absolute value) distance. We use the matrix dissimilarity command (see [MV] **matrix dissimilarity**) to obtain the L1 dissimilarity matrix and then divide the elements of that matrix by the appropriate values to obtain the Bray–Curtis dissimilarity.

Fisher (1936) presented data, originally from Anderson (1935), on three species of iris. Measurements of the length and width of the sepal and petal were obtained for 50 samples of each of the three iris species. We obtained the data from Morrison (2005). Here we demonstrate average-linkage clustering of these 150 observations.

```
. use https://www.stata-press.com/data/r18/iris, clear
(Iris data)

. summarize seplen sepwid petlen petwid
```

Variable	Obs	Mean	Std. dev.	Min	Max
seplen	150	5.843333	.8280661	4.3	7.9
sepwid	150	3.057333	.4358663	2	4.4
petlen	150	3.758	1.765298	1	6.9
petwid	150	1.199333	.7622377	.1	2.5

```
. matrix dissimilarity irisD = seplen sepwid petlen petwid, L1

. egen rtot = rowtotal(seplen sepwid petlen petwid)

. forvalues a = 1/150 {
  2.        forvalues b = 1/150 {
  3.                mat irisD[`a',`b'] = irisD[`a',`b']/(rtot[`a']+rtot[`b'])
  4.        }
  5. }

. matlist irisD[1..5,1..5]
```

	obs1	obs2	obs3	obs4	obs5
obs1	0				
obs2	.035533	0			
obs3	.0408163	.026455	0		
obs4	.0510204	.026455	.0212766	0	
obs5	.0098039	.035533	.0408163	.0510204	0

The egen rowtotal() function provided the row totals used in the denominator of the Bray–Curtis dissimilarity measure; see [D] **egen**. We listed the dissimilarities between the first 5 observations.

We now compute the average-linkage cluster analysis on these 150 observations (see [MV] **cluster linkage**) and examine the Caliński–Harabasz pseudo-F index and the Duda–Hart Je(2)/Je(1) index (cluster stopping rules; see [MV] **cluster stop**) to try to determine the number of clusters.

```
. clustermat averagelink irisD, name(iris) add

. clustermat stop, variables(seplen sepwid petlen petwid)
```

Number of clusters	Calinski/ Harabasz pseudo-F
2	502.82
3	299.96
4	201.58
5	332.89
6	288.61
7	244.61
8	252.39
9	223.28
10	268.47
11	241.51
12	232.61
13	233.46
14	255.84
15	273.96

```
. clustermat stop, variables(seplen sepwid petlen petwid) rule(duda)
```

		Duda/Hart
Number of		pseudo
clusters	Je(2)/Je(1)	T-squared
1	0.2274	502.82
2	0.8509	17.18
3	0.8951	5.63
4	0.4472	116.22
5	0.6248	28.23
6	0.9579	2.55
7	0.5438	28.52
8	0.8843	5.10
9	0.5854	40.37
10	0.0000	.
11	0.8434	6.68
12	0.4981	37.28
13	0.5526	25.91
14	0.6342	16.15
15	0.6503	3.23

The stopping rules are not conclusive here. From the Duda–Hart pseudo-T^2 (small values) you might best conclude that there are three, six, or eight natural clusters. The Caliński and Harabasz pseudo-F (large values) indicates that there might be two, three, or five groups.

With the iris data, we know the three species. Let's compare the average-linkage hierarchical cluster solutions with the actual species. The cluster generate command (see [MV] **cluster generate**) will generate grouping variables for our hierarchical cluster analysis.

```
. cluster generate g = groups(2/6)
. tabulate g2 iris
```

		Iris species		
g2	Setosa	Versicolo	Virginica	Total
1	50	0	0	50
2	0	50	50	100
Total	50	50	50	150

```
. tabulate g3 iris
```

		Iris species		
g3	Setosa	Versicolo	Virginica	Total
1	50	0	0	50
2	0	46	50	96
3	0	4	0	4
Total	50	50	50	150

```
. tabulate g4 iris
```

		Iris species		
g4	Setosa	Versicolo	Virginica	Total
1	49	0	0	49
2	1	0	0	1
3	0	46	50	96
4	0	4	0	4
Total	50	50	50	150

```
. tabulate g5 iris
```

		Iris species		
g5	Setosa	Versicolo	Virginica	Total
1	49	0	0	49
2	1	0	0	1
3	0	45	15	60
4	0	1	35	36
5	0	4	0	4
Total	50	50	50	150

```
. tabulate g6 iris
```

		Iris species		
g6	Setosa	Versicolo	Virginica	Total
1	41	0	0	41
2	8	0	0	8
3	1	0	0	1
4	0	45	15	60
5	0	1	35	36
6	0	4	0	4
Total	50	50	50	150

The two-group cluster solution splits *Iris setosa* from *Iris versicolor* and *Iris virginica*. The three- and four-group cluster solutions appear to split off some outlying observations from the two main groups. The five-group solution finally splits most of *Iris virginica* from the *Iris versicolor* but leaves some overlap.

Though this is not shown here, cluster solutions that better match the known species can be found by using dissimilarity measures other than Bray–Curtis.

◁

▷ Example 3

The cluster command clusters observations. If you want to cluster variables, you have two choices. You can use xpose (see [D] **xpose**) to transpose the variables and observations, or you can use matrix dissimilarity with the variables option (see [MV] **matrix dissimilarity**) and then use clustermat.

In example 2 of [MV] **cluster kmeans and kmedians**, we introduce the women's club data. Thirty women were asked 35 yes–no questions. In [MV] **cluster kmeans and kmedians**, our interest was in clustering the 30 women for placement at luncheon tables. Here our interest is in understanding the relationship among the 35 variables. Which questions produced similar response patterns from the 30 women?

```
. use https://www.stata-press.com/data/r18/wclub, clear

. describe

Contains data from https://www.stata-press.com/data/r18/wclub.dta
 Observations:            30
    Variables:            35                    1 May 2022 16:56
```

Variable name	Storage type	Display format	Value label	Variable label
bike	byte	%8.0g		Enjoy bicycle riding Y/N
bowl	byte	%8.0g		Enjoy bowling Y/N
swim	byte	%8.0g		Enjoy swimming Y/N
jog	byte	%8.0g		Enjoy jogging Y/N
hock	byte	%8.0g		Enjoy watching hockey Y/N
foot	byte	%8.0g		Enjoy watching football Y/N
base	byte	%8.0g		Enjoy baseball Y/N
bask	byte	%8.0g		Enjoy basketball Y/N
arob	byte	%8.0g		Participate in aerobics Y/N
fshg	byte	%8.0g		Enjoy fishing Y/N
dart	byte	%8.0g		Enjoy playing darts Y/N
clas	byte	%8.0g		Enjoy classical music Y/N
cntr	byte	%8.0g		Enjoy country music Y/N
jazz	byte	%8.0g		Enjoy jazz music Y/N
rock	byte	%8.0g		Enjoy rock and roll music Y/N
west	byte	%8.0g		Enjoy reading western novels Y/N
romc	byte	%8.0g		Enjoy reading romance novels Y/N
scif	byte	%8.0g		Enjoy reading sci. fiction Y/N
biog	byte	%8.0g		Enjoy reading biographies Y/N
fict	byte	%8.0g		Enjoy reading fiction Y/N
hist	byte	%8.0g		Enjoy reading history Y/N
cook	byte	%8.0g		Enjoy cooking Y/N
shop	byte	%8.0g		Enjoy shopping Y/N
soap	byte	%8.0g		Enjoy watching soap operas Y/N
sew	byte	%8.0g		Enjoy sewing Y/N
crft	byte	%8.0g		Enjoy craft activities Y/N
auto	byte	%8.0g		Enjoy automobile mechanics Y/N
pokr	byte	%8.0g		Enjoy playing poker Y/N
brdg	byte	%8.0g		Enjoy playing bridge Y/N
kids	byte	%8.0g		Have children Y/N
hors	byte	%8.0g		Have a horse Y/N
cat	byte	%8.0g		Have a cat Y/N
dog	byte	%8.0g		Have a dog Y/N
bird	byte	%8.0g		Have a bird Y/N
fish	byte	%8.0g		Have a fish Y/N

```
Sorted by:
```

The `matrix dissimilarity` command allows us to compute the Jaccard similarity measure (the
`Jaccard` option), comparing variables (the `variables` option) instead of observations, saving one
minus the Jaccard measure (the `dissim(oneminus)` option) as a dissimilarity matrix.

```
. matrix dissimilarity clubD = , variables Jaccard dissim(oneminus)

. matlist clubD[1..5,1..5]
```

	bike	bowl	swim	jog	hock
bike	0				
bowl	.7333333	0			
swim	.5625	.625	0		
jog	.6	.8235294	.5882353	0	
hock	.8461538	.6	.8	.8571429	0

We pass the `clubD` matrix to `clustermat` and ask for a single-linkage cluster analysis. We need to specify the `clear` option to replace the 30 observations currently in memory with the 35 observations containing the cluster results. Using the `labelvar()` option, we also ask for a label variable, `question`, to be created from the `clubD` matrix row names. To see the resulting cluster analysis, we call `cluster dendrogram`; see [MV] **cluster dendrogram**.

```
. clustermat singlelink clubD, name(club) clear labelvar(question)
Number of observations (_N) was 0, now 35.

. describe

Contains data
 Observations:              35
    Variables:               4
─────────────────────────────────────────────────────────────────────────────
Variable        Storage    Display    Value
    name           type     format    label        Variable label
─────────────────────────────────────────────────────────────────────────────
club_id          byte      %8.0g
club_ord         byte      %8.0g
club_hgt         double    %10.0g
question         str4      %9s
─────────────────────────────────────────────────────────────────────────────
Sorted by:
      Note: Dataset has changed since last saved.

. cluster dendrogram club, labels(question)
>                xlabel(, angle(90) labsize(*.75))
>                title(Single-linkage clustering)
>                ytitle(1 - Jaccard similarity, suffix)
```
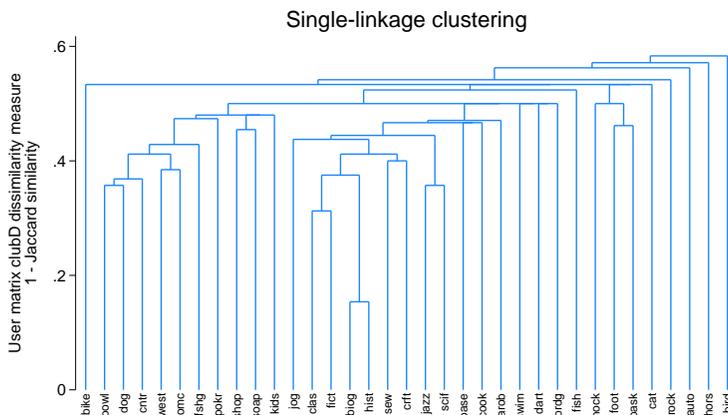

From these 30 women, we see that the `biog` (enjoy reading biographies) and `hist` (enjoy reading history) questions were most closely related. `auto` (enjoy automobile mechanics), `hors` (have a horse), and `bird` (have a bird) seem to be the least related to the other variables. These three variables, in turn, merge last into the supergroup containing the remaining variables.

◁

References

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Morrison, D. F. 2005. *Multivariate Statistical Methods.* 4th ed. Belmont, CA: Duxbury.

Odum, E. P. 1950. Bird populations of the Highlands (North Carolina) plateau in relation to plant succession and avian invasion. *Ecology* 31: 587–605. https://doi.org/10.2307/1931577.

Also see

[MV] **cluster programming subroutines** — Add cluster-analysis routines

[MV] **cluster programming utilities** — Cluster-analysis programming utilities

[MV] **cluster** — Introduction to cluster-analysis commands

Title

> **cluster dendrogram** — Dendrograms for hierarchical cluster analysis

Description

`cluster dendrogram` produces dendrograms (also called cluster trees) for a hierarchical clustering. See [MV] **cluster** for a discussion of cluster analysis, hierarchical clustering, and the available `cluster` commands.

Dendrograms graphically present the information concerning which observations are grouped together at various levels of (dis)similarity. At the bottom of the dendrogram, each observation is considered its own cluster. Vertical lines extend up for each observation, and at various (dis)similarity values, these lines are connected to the lines from other observations with a horizontal line. The observations continue to combine until, at the top of the dendrogram, all observations are grouped together.

The height of the vertical lines and the range of the (dis)similarity axis give visual clues about the strength of the clustering. Long vertical lines indicate more distinct separation between the groups. Long vertical lines at the top of the dendrogram indicate that the groups represented by those lines are well separated from one another. Shorter lines indicate groups that are not as distinct.

Quick start

Dendrogram of most recent cluster analysis
```
cluster dendrogram
```

Same as above
```
cluster tree
```

Same as above, but orient horizontally instead of vertically
```
cluster tree, horizontal
```

Dendrogram of cluster analysis named `myclus`
```
cluster tree myclus
```

Same as above, and apply leaf labels from variable `mylabels` instead of observation numbers
```
cluster tree myclus, labels(mylabels)
```

Same as above, but rotate leaf labels 90 degrees and reduce text size by half
```
cluster tree myclus, labels(mylabels)  ///
    xlabel(, angle(90) labsize(*.5))
```

Show top 20 branches and associated frequencies from most recent cluster analysis
```
cluster tree, cutnumber(20) showcount
```

Menu

Statistics > Multivariate analysis > Cluster analysis > Postclustering > Dendrograms

Syntax

> cluster <u>dendr</u>ogram [*clname*] [*if*] [*in*] [, *options*]

option	Description
[Main]	
quick	do not center parent branches
labels(*varname*)	name of variable containing leaf labels
cutnumber(*#*)	display top *#* branches only
cutvalue(*#*)	display branches above *#* (dis)similarity measure only
showcount	display number of observations for each branch
countprefix(*string*)	prefix the branch count with *string*; default is "n="
countsuffix(*string*)	suffix the branch count with *string*; default is empty string
countinline	put branch count in line with branch label
vertical	orient dendrogram vertically (default)
horizontal	orient dendrogram horizontally
Plot	
line_options	affect rendition of the plotted lines
Add plots	
addplot(*plot*)	add other plots to the dendrogram
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

Note: cluster <u>tree</u> is a synonym for cluster dendrogram.

In addition to the restrictions imposed by if and in, the observations are automatically restricted to those that were used in the cluster analysis.

Options

> [Main]

quick switches to a different style of dendrogram in which the vertical lines go straight up from the observations instead of the default action of being recentered after each merge of observations in the dendrogram hierarchy. Some people prefer this representation, and it is quicker to render.

labels(*varname*) specifies that *varname* be used in place of observation numbers for labeling the observations at the bottom of the dendrogram.

cutnumber(*#*) displays only the top *#* branches of the dendrogram. With large dendrograms, the lower levels of the tree can become too crowded. With cutnumber(), you can limit your view to the upper portion of the dendrogram. Also see the cutvalue() option.

cutvalue(*#*) displays only those branches of the dendrogram that are above the *#* (dis)similarity measure. With large dendrograms, the lower levels of the tree can become too crowded. With cutvalue(), you can limit your view to the upper portion of the dendrogram. Also see the cutnumber() option.

showcount requests that the number of observations associated with each branch be displayed below the branches. showcount is most useful with cutnumber() and cutvalue() because, otherwise, the number of observations for each branch is one. When this option is specified, a label for each branch is constructed by using a prefix string, the branch count, and a suffix string.

countprefix(*string*) specifies the prefix string for the branch count label. The default is countprefix(n=). This option implies the use of the showcount option.

countsuffix(*string*) specifies the suffix string for the branch count label. The default is an empty string. This option implies the use of the showcount option.

countinline requests that the branch count be put in line with the corresponding branch label. The branch count is placed below the branch label by default. This option implies the use of the showcount option.

vertical and horizontal specify whether the x and y coordinates are to be swapped before plotting—vertical (the default) does not swap the coordinates, whereas horizontal does.

⌐ Plot ⌐

line_options affect the rendition of the lines; see [G-3] *line_options*.

⌐ Add plots ⌐

addplot(*plot*) allows adding more graph twoway plots to the graph; see [G-3] *addplot_option*.

⌐ Y axis, X axis, Titles, Legend, Overall ⌐

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding by(). These include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk (see [G-3] *saving_option*).

Remarks and examples

Examples of the cluster dendrogram command can be found in [MV] **cluster linkage**, [MV] **cluster-mat**, [MV] **cluster stop**, and [MV] **cluster generate**. Here we illustrate some of the additional options available with cluster dendrogram.

▷ Example 1

Example 1 of [MV] **cluster linkage** introduces a dataset with 50 observations on four variables. Here we show the dendrogram for a complete-linkage analysis:

```
. use https://www.stata-press.com/data/r18/labtech
. cluster completelinkage x1 x2 x3 x4, name(L2clnk)
. cluster dendrogram L2clnk, labels(labtech) xlabel(, angle(90) labsize(*.75))
```
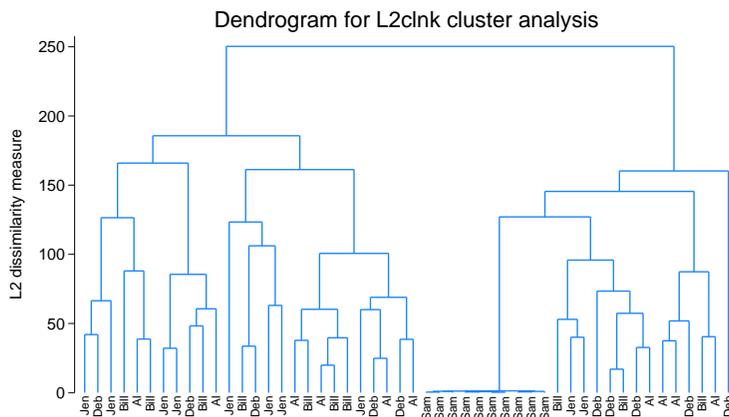

The same dendrogram can be rendered in a slightly different format by using the `quick` option:

```
. cluster dendrogram L2clnk, quick labels(labtech)
> xlabel(, angle(90) labsize(*.75))
```
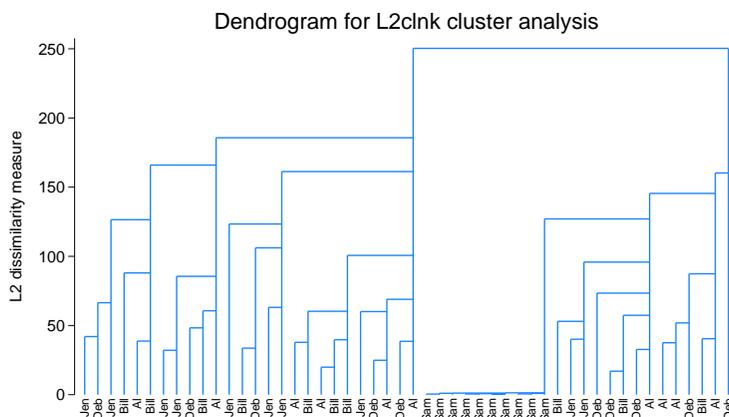

Some people prefer this style of dendrogram. As the name implies, this style of dendrogram is quicker to render.

You can use the `if` and `in` conditions to restrict the dendrogram to the observations for one subgroup. This task is usually accomplished with the `cluster generate` command, which creates a grouping variable; see [MV] **cluster generate**.

Here we show the third of three groups in the dendrogram by first generating the grouping variable for three groups and then using `if` in the command for `cluster dendrogram` to restrict it to the third of those three groups.

```
. cluster generate g3 = group(3)

. cluster tree if g3==3
```

Dendrogram for L2clnk cluster analysis
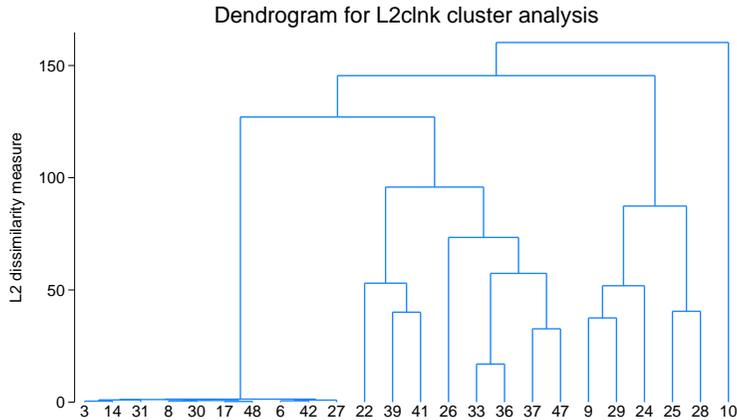
Because we find it easier to type, we used the synonym `tree` instead of `dendrogram`. We did not specify the cluster name, allowing it to default to the most recently performed cluster analysis. We also omitted the `labels()` and `xlabel()` options, which brings us back to the default action of showing, horizontally, the observation numbers.

This example has only 50 observations. When there are many observations, the dendrogram can become too crowded. You will need to limit which part of the dendrogram you display. One way to view only part of the dendrogram is to use `if` and `in` to limit to one particular group, as we did above.

The other way to limit your view of the dendrogram is to specify that you wish to view only the top portion of the tree. The `cutnumber()` and `cutvalue()` options allow you to do this:

```
. cluster tree, cutn(15) showcount
```
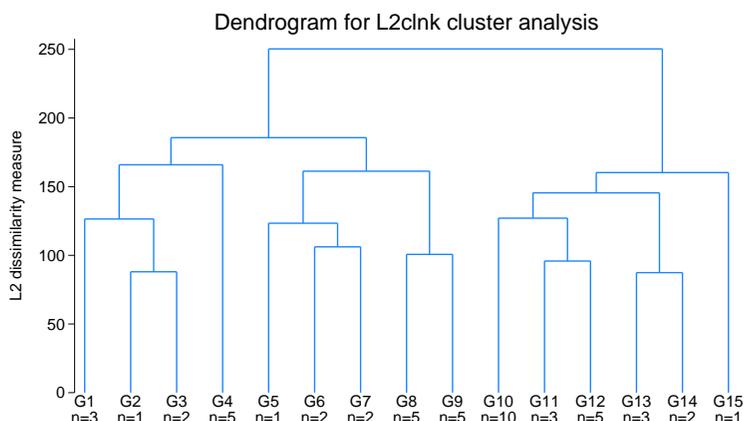

We limited our view to the top 15 branches of the dendrogram with `cutn(15)`. By default, the 15 branches were labeled G1–G15. The `showcount` option provided, below these branch labels, the number of observations in each of the 15 groups.

The `cutvalue()` option provides another way to limit the view to the top branches of the dendrogram. With this option, you specify the similarity or dissimilarity value at which to trim the tree.

```
. cluster tree, cutvalue(75.3)
> countprefix("(") countsuffix(" obs)") countinline
> ylabel(, angle(0)) horizontal
```
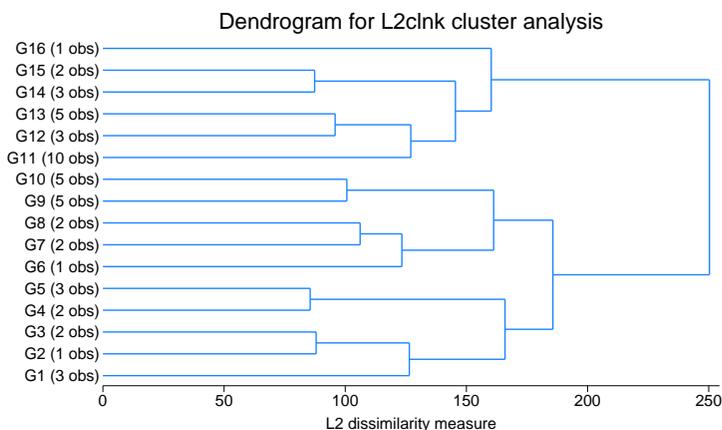

This time, we limited the dendrogram to those branches with dissimilarity greater than 75.3 by using the `cutvalue(75.3)` option. There were 16 branches (groups) that met that restriction. We used the `countprefix()` and `countsuffix()` options to display the number of observations in each branch as "(# obs)" instead of "n=#". The `countinline` option puts the branch counts in line with the branch labels. We specified the `horizontal` option and the `angle(0)` suboption of `ylabel()` to get a horizontal dendrogram with horizontal branch labels.

❑ Technical note

Programmers can control the graphical procedure executed when `cluster dendrogram` is called. This ability will be helpful to programmers adding new hierarchical clustering methods that require a different dendrogram algorithm. See [MV] **cluster programming subroutines** for details.

❑

In systematic zoology, Mayr, Linsley, and Usinger (1953, 312) introduced the term "dendrogram" for "A diagrammatic drawing in the form of a tree designed to indicate degrees of relationship as suggested by degrees of similarity." The first root, "dendron", means "tree": other linked words include "dendrite", "dendritic", and "rhododendron".

But thereby hangs a tale, or two, or three.

The term "dendrogram" was in due course copied from biological systematics and taxonomy into general scientific and statistical literature (for example, Sneath and Sokal [1962]; Hodson, Sneath, and Doran [1966]; Joyce and Channon [1966]). On the way, its meaning became more general, describing tree displays showing the structure of similarity and dissimilarity in nested classifications. The term became widely used in publications on what is now most often called cluster analysis: examples are the books of Sokal and Sneath (1963), Jardine and Sibson (1971), Sneath and Sokal (1973), Everitt (1993), Hartigan (1975), and Gordon (1981), and many others since.

Meanwhile, back in biology, Mayr emerged early as a leading critic of what some biologists, led by Sokal and Sneath, were calling "numerical taxonomy". His objections were evident in a polemic paper (Mayr 1965) and in his lengthy but lively and lucid history of much of biological thought (Mayr 1982). So there is some irony in his term being associated with projects he would not have approved (at least in biological systematics). Those imagining that classification is dull and dreary descriptive work will find ample documentation of scientists red in tooth and claw in Hull (1988), which despite its grand titles is focused on a detailed story of taxonomists' arguments with each other.

Inside biological taxonomy, the distinction is often now between "phenograms", meant to classify resemblance only, and "cladograms", meant to show also evolutionary pedigree.

Naturally, tree diagrams did not spring into existence with the term "dendrogram". Pietsch (2012) and Archibald (2014) give many well-reproduced diagrams from over several centuries showing supposed relationships between different organisms in biology. Lima (2011, 2014) sampled tree imagery even more broadly from many fields and from ancient and modern history to the present.

Ernst Walter Mayr (1904–2005) was a leading evolutionary biologist whose work ranged across systematics, taxonomy, exploration, ornithology, and history and philosophy of biology, especially on and around the concept of species. Mayr was born in Kempten in Germany. He completed his high school education in Dresden and went to university in Greifswald and Berlin. After fieldwork in New Guinea and the Solomon Islands, Mayr joined the American Museum of Natural History in 1931 and Harvard University in 1953, where he remained for the rest of his career. His many honors included membership of the National Academy of Sciences, foreign membership of the Royal Society, Balzan and Crafoord Prizes, and the U.S. National Medal of Science.

Mayr's coauthors, Earle Gorton Linsley (1910–2000) and Robert Leslie Usinger (1912–1968), were distinguished systematic entomologists based at the University of California at Berkeley.

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Also see

Title

cluster generate — Generate grouping variables from a cluster analysis

Description

cluster generate creates summary or grouping variables from a hierarchical cluster analysis; the result depends on the function. A single variable may be created containing a group number based on the requested number of groups or cutting the dendrogram at a specified (dis)similarity value. A set of new variables may be created if a range of group sizes is specified.

Users can add more cluster generate functions; see [MV] **cluster programming subroutines**.

Quick start

Generate grouping variable g5 with 5 groups from the most recent cluster analysis

    cluster generate g5 = groups(5)

Same as above, 4 grouping variables (g4, g5, g6, and g7) with 4, 5, 6, and 7 groups

    cluster generate g = groups(4/7)

Same as above, but use the cluster analysis named myclus

    cluster generate g = groups(4/7), name(myclus)

Generate grouping variable mygroups from the most recent cluster analysis by cutting the dendrogram at dissimilarity value 38

    cluster generate mygroups = cut(38)

Menu

Statistics > Multivariate analysis > Cluster analysis > Postclustering > Summary variables from cluster analysis

Syntax

Generate grouping variables for specified numbers of clusters

   cluster <u>gen</u>erate { *newvar* | *stub* } = <u>gr</u>oups(*numlist*) [, *options*]

Generate grouping variable by cutting the dendrogram

   cluster <u>gen</u>erate *newvar* = cut(*#*) [, <u>n</u>ame(*clname*)]

options	Description
<u>n</u>ame(*clname*)	name of cluster analysis to use in producing new variables
<u>ti</u>es(<u>er</u>ror)	produce error message for ties; default
<u>ti</u>es(<u>s</u>kip)	ignore requests that result in ties
<u>ti</u>es(<u>f</u>ewer)	produce results for largest number of groups smaller than your request
<u>ti</u>es(<u>m</u>ore)	produce results for smallest number of groups larger than your request

Options

name(*clname*) specifies the name of the cluster analysis to use in producing the new variables. The default is the name of the cluster analysis last performed, which can be reset by using the cluster use command; see [MV] **cluster utility**.

ties(error | skip | fewer | more) indicates what to do with the groups() function for ties. A hierarchical cluster analysis has ties when multiple groups are generated at a particular (dis)similarity value. For example, you might have the case where you can uniquely create two, three, and four groups, but the next possible grouping produces eight groups because of ties.

ties(error), the default, produces an error message and does not generate the requested variables.

ties(skip) specifies that the offending requests be ignored. No error message is produced, and only the requests that produce unique groupings will be honored. With multiple values specified in the groups() function, ties(skip) allows the processing of those that produce unique groupings and ignores the rest.

ties(fewer) produces the results for the largest number of groups less than or equal to your request. In the example above with groups(6) and using ties(fewer), you would get the same result that you would by using groups(4).

ties(more) produces the results for the smallest number of groups greater than or equal to your request. In the example above with groups(6) and using ties(more), you would get the same result that you would by using groups(8).

Remarks and examples

cluster generate provides two built-in functions: groups() and cut(). Examples of how to use the groups() function can be found in [MV] **cluster dendrogram**, [MV] **cluster linkage**, and [MV] **cluster stop**. More examples of the groups() and cut() functions of cluster generate are provided here.

The groups(*numlist*) function generates grouping variables, giving the grouping for the specified numbers of clusters from a hierarchical cluster analysis. If one number is given, *newvar* is produced with group numbers going from 1 to the number of clusters requested. If more than one number is specified, a new variable is generated for each number by using the provided *stub* name appended with the number.

The cut(*#*) function generates a grouping variable corresponding to cutting the dendrogram (see [MV] **cluster dendrogram**) of a hierarchical cluster analysis at the specified (dis)similarity value.

You may find it easier to understand these functions by looking at a dendrogram from a hierarchical cluster analysis. The cluster dendrogram command produces dendrograms (cluster trees) from a hierarchical cluster analysis; see [MV] **cluster dendrogram**.

▷ Example 1

Example 1 of [MV] **cluster linkage** examines a dataset with 50 observations with four variables. Here we use complete-linkage clustering and use the groups() function of cluster generate to produce a grouping variable, splitting the data into two groups.

```
. use https://www.stata-press.com/data/r18/labtech
. cluster completelinkage x1 x2 x3 x4, name(L2clnk)
. cluster dendrogram L2clnk, xlabel(, angle(90) labsize(*.75))
  (graph omitted)
. cluster generate g2 = group(2), name(L2clnk)
. codebook g2
```

g2		(unlabeled)

Type:	Numeric (byte)		
Range:	[1,2]	Units:	1
Unique values:	2	Missing .:	0/50
Tabulation:	Freq. Value		
	26 1		
	24 2		

```
. by g2, sort: summarize x*
```

```
-> g2 = 1
    Variable |        Obs        Mean   Std. dev.        Min        Max
```
Variable	Obs	Mean	Std. dev.	Min	Max
x1	26	91.5	37.29432	17.4	143
x2	26	74.58077	41.19319	4.8	142.1
x3	26	101.0077	36.95704	16.3	147.9
x4	26	71.77308	43.04107	6.6	146.1

```
-> g2 = 2
    Variable |        Obs        Mean   Std. dev.        Min        Max
```
Variable	Obs	Mean	Std. dev.	Min	Max
x1	24	18.8	23.21742	0	77
x2	24	30.05833	37.66979	0	143.6
x3	24	18.54583	21.68215	.2	69.7
x4	24	41.89167	43.62025	.1	130.9

The group() function of cluster generate created a grouping variable named g2, with ones indicating the 26 observations that belong to the left main branch of the dendrogram and twos indicating the 24 observations that belong to the right main branch of the dendrogram. The summary of the x variables used in the cluster analysis for each group shows that the second group is characterized by lower values.

We could have obtained the same grouping variable by using the cut() function of cluster generate.

```
. cluster generate g2cut = cut(200)
. table g2 g2cut, nototals
```

	g2cut	
	1	2
g2		
1	26	
2		24

We did not need to specify the name() option because this was the latest cluster analysis performed, which is the default. The table output shows that we obtained the same result with cut(200) as with group(2) for this example.

How many groups are produced if we cut the tree at the value 105.2?

```
. cluster generate z = cut(105.2)
. codebook z, tabulate(20)
```

───

z   (unlabeled)

───

```
                   Type: Numeric (byte)
                  Range: [1,11]                   Units: 1
          Unique values: 11                   Missing .: 0/50
              Tabulation: Freq.  Value
                             3   1
                             3   2
                             5   3
                             1   4
                             2   5
                             2   6
                            10   7
                            10   8
                             8   9
                             5   10
                             1   11
```

The codebook command (see [D] **codebook**) shows that the result of cutting the dendrogram at the value 105.2 produced 11 groups ranging in size from 1 to 10 observations.

The group() function of cluster generate may be used to create multiple grouping variables with one call. Here we create the grouping variables for groups of size 3–12:

```
. cluster generate gp = gr(3/12)
. summarize gp*
```

Variable	Obs	Mean	Std. dev.	Min	Max
gp3	50	2.26	.8033095	1	3
gp4	50	3.14	1.030356	1	4
gp5	50	3.82	1.438395	1	5
gp6	50	3.84	1.461897	1	6
gp7	50	3.96	1.603058	1	7
gp8	50	4.24	1.911939	1	8
gp9	50	5.18	2.027263	1	9
gp10	50	5.94	2.385415	1	10
gp11	50	6.66	2.781939	1	11
gp12	50	7.24	3.197959	1	12

Here we used abbreviations for generate and group(). The group() function takes a numlist; see [U] **11.1.8 numlist**. We specified 3/12, indicating the numbers 3–12. gp, the stub name we provide, is appended with the number as the variable name for each group variable produced.

◁

▷ Example 2

Example 2 of [MV] **cluster linkage** shows the following dendrogram from the single-linkage clustering of 30 observations on 60 variables. In that example, we used the group() function of cluster generate to produce a grouping variable for three groups. What happens when we try to obtain four groups from this clustering?

```
. use https://www.stata-press.com/data/r18/homework, clear
. cluster singlelinkage a1-a60, measure(matching)
cluster name: _clus_1
. cluster tree
```

Dendrogram for _clus_1 cluster analysis
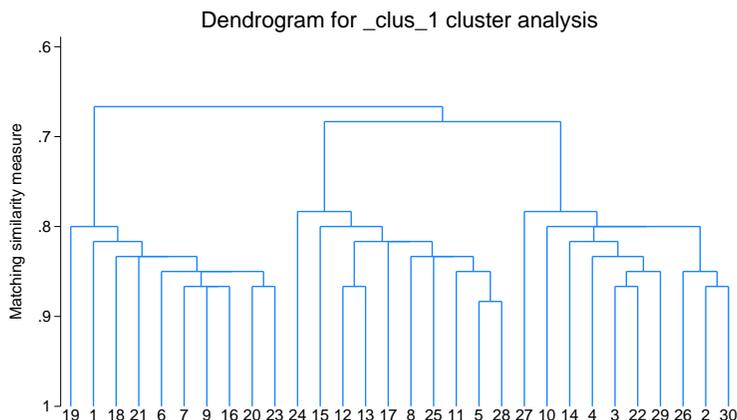

```
. cluster generate g4 = group(4)
cannot create 4 groups because of ties
r(198);
```

Stata complains that it cannot create four groups from this cluster analysis.

The ties() option gives us control over this situation. We just need to decide whether we want
more groups or fewer groups than we asked for when faced with ties. We demonstrate both ways.

```
. cluster generate more4 = gr(4), ties(more)
. cluster generate less4 = gr(4), ties(fewer)
. summarize more4 less4
```

Variable	Obs	Mean	Std. dev.	Min	Max
more4	30	2.933333	1.638614	1	5
less4	30	2	.8304548	1	3

For this cluster analysis, ties(more) with group(4) produces five groups, whereas ties(fewer)
with group(4) produces three groups.

The `ties(skip)` option is convenient when we want to produce a range of grouping variables.

```
. cluster generate group = gr(4/20), ties(skip)
. summarize group*
```

Variable	Obs	Mean	Std. dev.	Min	Max
group5	30	2.933333	1.638614	1	5
group9	30	4.866667	2.622625	1	9
group13	30	7.066667	3.92106	1	13
group18	30	9.933333	5.419844	1	18

With this cluster analysis, the only unique groupings available are 5, 9, 13, and 18 within the range 4–20.

◁

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **clustermat** — Introduction to clustermat commands

[D] **egen** — Extensions to generate

[D] **generate** — Create or change contents of variable

Title

> **cluster kmeans and kmedians** — Kmeans and kmedians cluster analysis

Description	Quick start	Menu	Syntax
Options	Remarks and examples	Methods and formulas	Reference
Also see			

Description

cluster kmeans and cluster kmedians perform kmeans and kmedians partition cluster analysis, respectively. See [MV] **cluster** for a general discussion of cluster analysis and a description of the other cluster commands.

Quick start

Kmeans cluster analysis using Euclidean distance of v1, v2, v3, and v4 to create 5 groups

    cluster kmeans v1 v2 v3 v4, k(5)

Same as above, and name the cluster analysis myclus

    cluster kmeans v1 v2 v3 v4, k(5) name(myclus)

Kmedians cluster analysis to create 7 groups using Canberra distance of v1, v2, and v3

    cluster kmedians v1 v2 v3, k(7) measure(Canberra)

Menu

cluster kmeans

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Kmeans

cluster kmedians

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Kmedians

Syntax

Kmeans cluster analysis

> cluster <u>k</u>means [*varlist*] [*if*] [*in*] , k(#) [*options*]

Kmedians cluster analysis

> cluster <u>kmed</u>ians [*varlist*] [*if*] [*in*] , k(#) [*options*]

options	Description
[Main]	
*k(#)	perform cluster analysis resulting in # groups
<u>measure</u>(*measure*)	similarity or dissimilarity measure; default is L2 (Euclidean)
<u>name</u>(*clname*)	name of resulting cluster analysis
[Options]	
start(*start_option*)	obtain *k* initial group centers by using *start_option*
keepcenters	append the *k* final group means or medians to the data
[Advanced]	
<u>g</u>enerate(*groupvar*)	name of grouping variable
<u>iterate</u>(#)	maximum number of iterations; default is iterate(10000)

*k(#) is required.

Options

[Main]

k(#) is required and indicates that # groups are to be formed by the cluster analysis.

measure(*measure*) specifies the similarity or dissimilarity measure. The default is measure(L2), Euclidean distance. This option is not case sensitive. See [MV] *measure_option* for detailed descriptions of the supported measures.

name(*clname*) specifies the name to attach to the resulting cluster analysis. If name() is not specified, Stata finds an available cluster name, displays it for your reference, and attaches the name to your cluster analysis.

[Options]

start(*start_option*) indicates how the *k* initial group centers are to be obtained. The available *start_option*s are

<u>k</u>random[(*seed#*)], the default, specifies that *k* unique observations be chosen at random, from among those to be clustered, as starting centers for the *k* groups. Optionally, a random-number seed may be specified to cause the command set seed *seed#* (see [R] **set seed**) to be applied before the *k* random observations are chosen.

<u>f</u>irstk[, <u>ex</u>clude] specifies that the first *k* observations from among those to be clustered be used as the starting centers for the *k* groups. With the exclude option, these first *k* observations are not included among the observations to be clustered.

<u>last</u>k[, <u>ex</u>clude] specifies that the last k observations from among those to be clustered be used
as the starting centers for the k groups. With the exclude option, these last k observations are
not included among the observations to be clustered.

<u>r</u>andom[(*seed#*)] specifies that k random initial group centers be generated. The values are
randomly chosen from a uniform distribution over the range of the data. Optionally, a random-
number seed may be specified to cause the command set seed *seed#* (see [R] **set seed**) to be
applied before the k group centers are generated.

<u>pr</u>andom[(*seed#*)] specifies that k partitions be formed randomly among the observations to be
clustered. The group means or medians from the k groups defined by this partitioning are to
be used as the starting group centers. Optionally, a random-number seed may be specified to
cause the command set seed *seed#* (see [R] **set seed**) to be applied before the k partitions
are chosen.

everykth specifies that k partitions be formed by assigning observations 1, $1 + k$, $1 + 2k$, ...
to the first group; assigning observations 2, $2 + k$, $2 + 2k$, ... to the second group; and so
on, to form k groups. The group means or medians from these k groups are to be used as the
starting group centers.

segments specifies that k nearly equal partitions be formed from the data. Approximately the first
N/k observations are assigned to the first group, the second N/k observations are assigned to
the second group, and so on. The group means or medians from these k groups are to be used
as the starting group centers.

group(*varname*) provides an initial grouping variable, *varname*, that defines k groups among the
observations to be clustered. The group means or medians from these k groups are to be used
as the starting group centers.

keepcenters specifies that the group means or medians from the k groups that are produced be
appended to the data. Alias variables are not allowed in *varlist* when this option is specified; see
[D] **frunalias** for advice on how to get around this restriction.

> Advanced

generate(*groupvar*) provides the name of the grouping variable to be created by cluster kmeans
or cluster kmedians. By default, this will be the name specified in name().

iterate(*#*) specifies the maximum number of iterations to allow in the kmeans or kmedians clustering
algorithm. The default is iterate(10000).

Remarks and examples

Two examples are presented, one using cluster kmeans with continuous data and the other using
cluster kmeans and cluster kmedians with binary data. Both commands work similarly with
the different types of data.

▷ Example 1

You have measured the flexibility, speed, and strength of the 80 students in your physical education
class. You want to split the class into four groups, based on their physical attributes, so that they can
receive the mix of flexibility, strength, and speed training that will best help them improve.

Here is a summary of the data and a matrix graph showing the data:

```
. use https://www.stata-press.com/data/r18/physed
. summarize flex speed strength
```

Variable	Obs	Mean	Std. dev.	Min	Max
flexibility	80	4.402625	2.788541	.03	9.97
speed	80	3.875875	3.121665	.03	9.79
strength	80	6.439875	2.449293	.05	9.57

```
. graph matrix flex speed strength
```
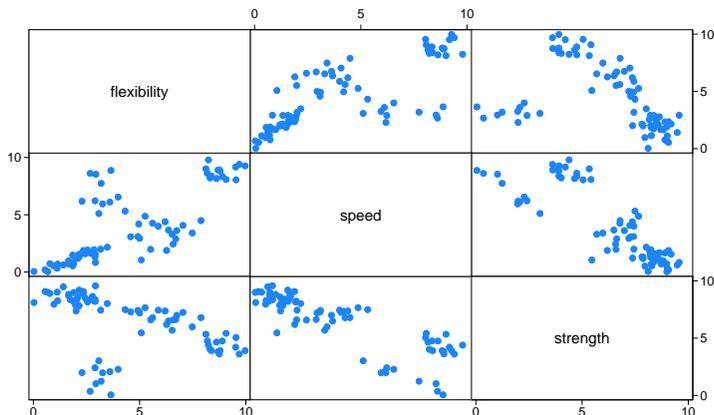

As you expected, based on what you saw the first day of class, the data indicate a wide range of levels of performance for the students. The graph seems to indicate that there are some distinct groups, which leads you to believe that your plan will work well.

You decide to perform a cluster analysis to create four groups, one for each of your class assistants. You have had good experience with kmeans clustering in the past and generally like the behavior of the absolute-value distance.

You do not really care what starting values are used in the cluster analysis, but you do want to be able to reproduce the same results if you ever decide to rerun your analysis. You decide to use the krandom() option to pick k of the observations at random as the initial group centers. You supply a random-number seed for reproducibility. You also add the keepcenters option so that the means of the four groups will be added to the bottom of your dataset.

```
. cluster k flex speed strength, k(4) name(g4abs) s(kr(385617)) mea(abs) keepcen
. cluster list g4abs
g4abs  (type: partition,  method: kmeans,  dissimilarity: L1)
     vars: g4abs (group variable)
    other: cmd: cluster kmeans flex speed strength, k(4) name(g4abs)
               s(kr(385617)) mea(abs) keepcen
          varlist: flexibility speed strength
          k: 4
          start: krandom(385617)
          range: 0 .
```

```
. table g4abs
```

	Frequency
Cluster ID	
1	15
2	20
3	10
4	35
Total	80

```
. list flex speed strength in 81/L, abbrev(12)
```

	flexibility	speed	strength
81.	8.852	8.743333	4.358
82.	5.9465	3.4485	6.8325
83.	3.157	6.988	1.641
84.	1.969429	1.144857	8.478857

```
. drop in 81/L
(4 observations deleted)
. tabstat flex speed strength, by(g4abs) stat(min mean max)

Summary statistics: Min, Mean, Max
Group variable: g4abs (Cluster ID)
```

g4abs	flexib~y	speed	strength
1	8.12	8.05	3.61
	8.852	8.743333	4.358
	9.97	9.79	5.42
2	4.32	1.05	5.46
	5.9465	3.4485	6.8325
	7.89	5.32	7.66
3	2.29	5.11	.05
	3.157	6.988	1.641
	3.99	8.87	3.02
4	.03	.03	7.38
	1.969429	1.144857	8.478857
	3.48	2.17	9.57
Total	.03	.03	.05
	4.402625	3.875875	6.439875
	9.97	9.79	9.57

After looking at the last 4 observations (which are the group means because you specified keep-
centers), you decide that what you really wanted to see was the minimum and maximum values
and the mean for the four groups. You remove the last 4 observations and then use the tabstat
command to view the desired statistics.

   Group 1, with 15 students, is already doing well in flexibility and speed but will need extra
strength training. Group 2, with 20 students, needs to emphasize speed training but could use some
improvement in the other categories as well. Group 3, the smallest, with 10 students, needs help
with flexibility and strength. Group 4, the largest, with 35 students, has serious problems with both
flexibility and speed, though they did well in the strength category.

Because you like looking at graphs, you decide to view the matrix graph again but with group numbers used as plotting symbols.

```
. graph matrix flex speed strength, m(i) mlabel(g4abs) mlabpos(0)
> mlabcolor(stblue)
```
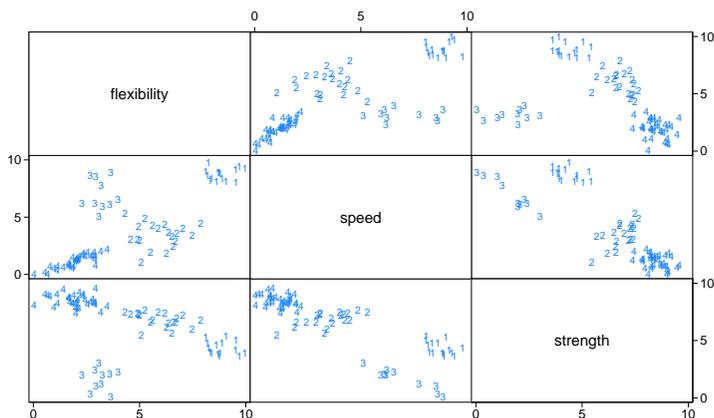

The groups, as shown in the graph, do appear reasonably distinct. However, you had hoped to have groups that were about the same size. You are curious what clustering to three or five groups would produce. For no good reason, you decide to use the first k observations as initial group centers for clustering to three groups and random numbers within the range of the data for clustering to five groups.

```
. cluster k flex speed strength, k(3) name(g3abs) start(firstk) measure(abs)
. cluster k flex speed strength, k(5) name(g5abs) start(random(33576))
> measure(abs)
. table g3abs g4abs, totals(g3abs)
```

		Cluster ID			
	1	2	3	4	Total
Cluster ID					
1			10		10
2		18		35	53
3	15	2			17

```
. table g5abs g4abs, totals(g5abs)
```

		Cluster ID			
	1	2	3	4	Total
Cluster ID					
1	15				15
2		9			9
3			10		10
4		11			11
5				35	35

With three groups, the unequal-group-size problem gets worse. With five groups, you still have one group with 35 observations, which is much larger than all other groups. Four groups seem like the

best option for this class. You will try to help the assistant assigned to group 4 in dealing with the larger group.

You might want to investigate the results of using different random seeds in the command used to generate the 4 groups earlier in this example. Because these data do not have clearly defined, well-separated clusters, there is a good chance that clusters based on different starting values will be different.

◁

▷ Example 2

You have just started a women's club. Thirty women from throughout the community have sent in their requests to join. You have them fill out a questionnaire with 35 yes–no questions relating to sports, music, reading, and hobbies. A description of the 35 variables is found in example 3 of [MV] **clustermat**.

In planning the first meeting of the club, you want to assign seats at the five lunch tables on the basis of shared interests among the women. You really want people placed together who share the same positive interests, not who share dislikes. From all the available binary similarity measures, you decide to use the Jaccard coefficient as the binary similarity measure because it does not include jointly zero comparisons in its formula; see [MV] *measure_option*. The Jaccard coefficient is also easy to understand.

You decide to examine the groupings produced by kmeans and kmedians clustering.

```
. use https://www.stata-press.com/data/r18/wclub, clear
. cluster kmeans bike-fish, k(5) measure(Jaccard) st(firstk) name(gr5)
. cluster kmed bike-fish, k(5) measure(Jaccard) st(firstk) name(kmedian5)
. cluster list kmedian5
kmedian5 (type: partition,  method: kmedians,  similarity: Jaccard)
      vars: kmedian5 (group variable)
     other: cmd: cluster kmedians bike-fish, k(5) measure(Jaccard) st(firstk)
                  name(kmedian5)
            varlist: bike bowl swim jog hock foot base bask arob fshg dart clas
                  cntr jazz rock west romc scif biog fict hist cook shop soap
                  sew crft auto pokr brdg kids hors cat dog bird fish
            k: 5
            start: firstk
            range: 1 0
```

You used the first *k* observations as starting centers for both kmeans and kmedians—the st(firstk) option.

What size groups did each method produce, and how closely did the results agree?

```
. table gr5 kmedian5
```

	Cluster ID					
	1	2	3	4	5	Total
Cluster ID						
1	7					7
2	1	6				7
3			5			5
4				5		5
5	1		1		4	6
Total	9	6	6	5	4	30

There is reasonably strong agreement between the results from `cluster kmeans` and `cluster kmedians`. Because the tables can seat only eight comfortably, the grouping produced by `cluster kmeans` will be used because the group sizes range from five to seven, whereas the groups from `cluster kmedians` range from four to nine.

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Methods and formulas

Kmeans cluster analysis and its variant, kmedians cluster analysis, are discussed in most cluster-analysis books; see *References* in [MV] **cluster**. [MV] **cluster** also provides a general discussion of cluster analysis, including kmeans and kmedians clustering, and discusses the available `cluster` subcommands.

Kmeans and kmedians clustering are iterative procedures that partition the data into k groups or clusters. The procedure begins with k initial group centers. Observations are assigned to the group with the closest center. The mean or median of the observations assigned to each of the groups is computed, and the process is repeated. These steps continue until all observations remain in the same group from the previous iteration.

To avoid endless loops, an observation will be reassigned to a different group only if it is closer to the other group center. For a tied distance between an observation and two or more group centers, the observation is assigned to its current group if that is one of the closest and to the lowest numbered group otherwise.

The `start()` option provides many ways to specify the beginning group centers. These include methods that specify the actual starting centers, as well as methods that specify initial partitions of the data from which the beginning centers are computed.

Some kmeans clustering algorithms recompute the group centers after each reassignment of an observation. Other algorithms, including Stata's `cluster kmeans` and `cluster kmedians` commands, recompute the group centers only after a complete pass through the data. A disadvantage of this method is that orphaned group centers—one that has no observations that are closest to it—can occur. The advantage of recomputing means only at the end of each pass through the data is that the sort order of the data does not potentially change your result.

Stata deals with orphaned centers by finding the observations that are farthest from the centers and using them as new group centers. The observations are then reassigned to the closest groups, including these new centers.

Continuous or binary data are allowed with `cluster kmeans` and `cluster kmedians`. The mean of a group of binary observations for a variable is the proportion of ones for that group of observations and variable. The median of a group of binary observations for a variable is almost always either zero or one. However, if there are an equal number of zeros and ones for a group, the median is 0.5. The binary similarity measures can accommodate the comparison of a binary observation to a proportion. See [MV] *measure_option* for details on this subject and for the formulas for all the available (dis)similarity measures.

Reference

Makles, A. 2012. Stata tip 110: How to get the optimal k-means cluster solution. *Stata Journal* 12: 347–351.

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **cluster notes** — Cluster analysis notes

[MV] **cluster stop** — Cluster-analysis stopping rules

[MV] **cluster utility** — List, rename, use, and drop cluster analyses

[MV] **clustermat** — Introduction to clustermat commands

Title

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cluster linkage — Hierarchical cluster analysis

Description

cluster and clustermat, with a specified linkage method, perform hierarchical agglomerative cluster analysis. The following common linkage methods are available: single, complete, average, Ward's method, centroid, median, and weighted average.

Quick start

Cluster analysis of data

Single-linkage cluster analysis using Euclidean distance of v1, v2, v3, and v4

    cluster singlelinkage v1 v2 v3 v4

Same as above

    cluster single v1 v2 v3 v4

Same as above, and name the cluster analysis singclus

    cluster single v1 v2 v3 v4, name(singclus)

Complete-linkage cluster analysis using absolute-value distance of v1, v2, and v3

    cluster completelinkage v1 v2 v3, measure(absolute)

Same as above

    cluster complete v1 v2 v3, measure(L1)

Cluster analysis of dissimilarity matrix

Replace current data with solution from single-linkage cluster analysis on matrix D

    clustermat single D, clear

Same as above, and name the cluster analysis Dclus

    clustermat single D, clear name(Dclus)

Add solution from average-linkage cluster analysis on matrix D to the existing data

    clustermat averagelinkage D, add

Menu

cluster singlelinkage

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Single linkage

cluster averagelinkage

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Average linkage

cluster completelinkage

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Complete linkage

cluster waveragelinkage

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Weighted-average linkage

cluster medianlinkage

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Median linkage

cluster centroidlinkage

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Centroid linkage

cluster wardslinkage

Statistics > Multivariate analysis > Cluster analysis > Cluster data > Ward's linkage

Syntax

Cluster analysis of data

> cluster *linkage* [*varlist*] [*if*] [*in*] [, *cluster_options*]

Cluster analysis of a dissimilarity matrix

> clustermat *linkage matname* [*if*] [*in*] [, *clustermat_options*]

linkage	Description
<u>single</u>linkage	single-linkage cluster analysis
<u>average</u>linkage	average-linkage cluster analysis
<u>complete</u>linkage	complete-linkage cluster analysis
<u>w</u>averagelinkage	weighted-average linkage cluster analysis
<u>median</u>linkage	median-linkage cluster analysis
<u>centroid</u>linkage	centroid-linkage cluster analysis
<u>wards</u>linkage	Ward's linkage cluster analysis

cluster_options	Description
Main	
<u>measure</u>(*measure*)	similarity or dissimilarity measure
<u>name</u>(*clname*)	name of resulting cluster analysis
Advanced	
<u>generate</u>(*stub*)	prefix for generated variables; default prefix is *clname*

clustermat_options	Description
Main	
<u>shape</u>(*shape*)	shape (storage method) of *matname*
add	add cluster information to data currently in memory
clear	replace data in memory with cluster information
<u>labelvar</u>(*varname*)	place dissimilarity matrix row names in *varname*
<u>name</u>(*clname*)	name of resulting cluster analysis
Advanced	
force	perform clustering after fixing *matname* problems
<u>generate</u>(*stub*)	prefix for generated variables; default prefix is *clname*

shape	*matname* is stored as a
<u>full</u>	square symmetric matrix; the default
<u>lower</u>	vector of rowwise lower triangle (with diagonal)
<u>llower</u>	vector of rowwise strict lower triangle (no diagonal)
<u>upper</u>	vector of rowwise upper triangle (with diagonal)
<u>uupper</u>	vector of rowwise strict upper triangle (no diagonal)

Options for cluster linkage commands

> ┌─ Main ───

measure(*measure*) specifies the similarity or dissimilarity measure. The default for averagelinkage, completelinkage, singlelinkage, and waveragelinkage is L2 (synonym <u>Euc</u>lidean). The default for centroidlinkage, medianlinkage, and wardslinkage is L2squared. This option is not case sensitive. See [MV] *measure_option* for a discussion of these measures.

Several authors advise using the L2squared *measure* exclusively with centroid, median, and Ward's linkage. See *Dissimilarity transformations and the Lance and Williams formula* and *Warning concerning similarity or dissimilarity choice* in [MV] **cluster** for details.

name(*clname*) specifies the name to attach to the resulting cluster analysis. If name() is not specified, Stata finds an available cluster name, displays it for your reference, and attaches the name to your cluster analysis.

> ┌─ Advanced ───

generate(*stub*) provides a prefix for the variable names created by cluster *linkage*. By default, the variable name prefix will be the name specified in name(). Three variables with the suffixes _id, _ord, and _hgt are created and attached to the cluster-analysis results. Users generally will not need to access these variables directly.

Centroid linkage and median linkage can produce reversals or crossovers; see [MV] **cluster** for details. When reversals happen, cluster centroidlinkage and cluster medianlinkage also create a fourth variable with the suffix _pht. This is a pseudoheight variable that is used by some postclustering commands to properly interpret the _hgt variable.

Options for clustermat linkage commands

> ┌─ Main ───

shape(*shape*) specifies the storage mode of *matname*, the matrix of dissimilarities. shape(full) is the default. The following shapes are allowed:

full specifies that *matname* is an $n \times n$ symmetric matrix.

lower specifies that *matname* is a row or column vector of length $n(n+1)/2$, with the rowwise lower triangle of the dissimilarity matrix including the diagonal of zeros.

$$\mathrm{D}_{11}\ \mathrm{D}_{21}\ \mathrm{D}_{22}\ \mathrm{D}_{31}\ \mathrm{D}_{32}\ \mathrm{D}_{33}\ \ldots\ \mathrm{D}_{n1}\ \mathrm{D}_{n2}\ \ldots\ \mathrm{D}_{nn}$$

llower specifies that *matname* is a row or column vector of length $n(n-1)/2$, with the rowwise lower triangle of the dissimilarity matrix excluding the diagonal.

$$\mathrm{D}_{21} \ \mathrm{D}_{31} \ \mathrm{D}_{32} \ \mathrm{D}_{41} \ \mathrm{D}_{42} \ \mathrm{D}_{43} \ \ldots \ \mathrm{D}_{n1} \ \mathrm{D}_{n2} \ \ldots \ \mathrm{D}_{n,n-1}$$

upper specifies that *matname* is a row or column vector of length $n(n+1)/2$, with the rowwise upper triangle of the dissimilarity matrix including the diagonal of zeros.

$$\mathrm{D}_{11} \ \mathrm{D}_{12} \ \ldots \ \mathrm{D}_{1n} \ \mathrm{D}_{22} \ \mathrm{D}_{23} \ \ldots \ \mathrm{D}_{2n} \ \mathrm{D}_{33} \ \mathrm{D}_{34} \ \ldots \ \mathrm{D}_{3n} \ \ldots \ \mathrm{D}_{nn}$$

uupper specifies that *matname* is a row or column vector of length $n(n-1)/2$, with the rowwise upper triangle of the dissimilarity matrix excluding the diagonal.

$$\mathrm{D}_{12} \ \mathrm{D}_{13} \ \ldots \ \mathrm{D}_{1n} \ \mathrm{D}_{23} \ \mathrm{D}_{24} \ \ldots \ \mathrm{D}_{2n} \ \mathrm{D}_{34} \ \mathrm{D}_{35} \ \ldots \ \mathrm{D}_{3n} \ \ldots \ \mathrm{D}_{n-1,n}$$

add specifies that clustermat's results be added to the dataset currently in memory. The number of observations (selected observations based on the if and in qualifiers) must equal the number of rows and columns of *matname*. Either clear or add is required if a dataset is currently in memory.

clear drops all the variables and cluster solutions in the current dataset in memory (even if that dataset has changed since the data were last saved) before generating clustermat's results. Either clear or add is required if a dataset is currently in memory.

labelvar(*varname*) specifies the name of a new variable to be created containing the row names of matrix *matname*.

name(*clname*) specifies the name to attach to the resulting cluster analysis. If name() is not specified, Stata finds an available cluster name, displays it for your reference, and attaches the name to your cluster analysis.

> Advanced

force allows computations to continue when *matname* is nonsymmetric or has nonzeros on the diagonal. By default, clustermat will complain and exit when it encounters these conditions. force specifies that clustermat operate on the symmetric matrix $(matname * matname')/2$, with any nonzero diagonal entries treated as if they were zero.

generate(*stub*) provides a prefix for the variable names created by clustermat. By default, the variable name prefix is the name specified in name(). Three variables are created and attached to the cluster-analysis results with the suffixes _id, _ord, and _hgt. Users generally will not need to access these variables directly.

Centroid linkage and median linkage can produce reversals or crossovers; see [MV] **cluster** for details. When reversals happen, clustermat centroidlinkage and clustermat medianlinkage also create a fourth variable with the suffix _pht. This is a pseudoheight variable that is used by some of the postclustering commands to properly interpret the _hgt variable.

Remarks and examples

cluster and clustermat, with a specified linkage method, perform hierarchical agglomerative cluster analysis. The following command linkage methods are available: single, complete, average, Ward's method, centroid, median, and weighted average. These methods are described in *Agglomerative methods* of [MV] **cluster**. Other methods are mentioned in the literature, but these are the best-known methods.

The clustermat *linkage* commands perform hierarchical agglomerative cluster analysis on the dissimilarity matrix *matname*. See [MV] **clustermat** for a general discussion of cluster analysis of dissimilarity matrices and a description of the other clustermat commands. A general discussion of agglomerative cluster analysis is provided in *Hierarchical cluster-analysis methods* of [MV] **cluster**.

After a cluster *linkage* or clustermat *linkage* command, the cluster dendrogram command (see [MV] **cluster dendrogram**) displays the resulting dendrogram, the cluster stop or clustermat stop command (see [MV] **cluster stop**) helps determine the number of groups, and the cluster generate command (see [MV] **cluster generate**) produces grouping variables.

▷ Example 1

As the senior data analyst for a small biotechnology firm, you are given a dataset with four chemical laboratory measurements on 50 different samples of a particular plant gathered from the rain forest. The head of the expedition that gathered the samples thinks, based on information from the natives, that an extract from the plant might reduce the negative side effects associated with your company's best-selling nutritional supplement.

While the company chemists and botanists continue exploring the possible uses of the plant and plan future experiments, the head of product development asks you to look at the preliminary data and to report anything that might be helpful to the researchers.

Although all 50 plants are supposed to be of the same type, you decide to perform a cluster analysis to see if there are subgroups or anomalies among them. You arbitrarily decide to use single-linkage clustering with the default Euclidean distance.

```
. use https://www.stata-press.com/data/r18/labtech
. cluster singlelinkage x1 x2 x3 x4, name(sngeuc)
. cluster list sngeuc
sngeuc  (type: hierarchical,  method: single,  dissimilarity: L2)
     vars: sngeuc_id (id variable)
           sngeuc_ord (order variable)
           sngeuc_hgt (height variable)
    other: cmd: cluster singlelinkage x1 x2 x3 x4, name(sngeuc)
           varlist: x1 x2 x3 x4
           range: 0 .
```

The cluster singlelinkage command generated some variables and created a cluster object with the name sngeuc, which you supplied as an argument. cluster list provides details about the cluster object; see [MV] **cluster utility**.

What you really want to see is the dendrogram for this cluster analysis; see [MV] **cluster dendrogram**.

```
. cluster dendrogram sngeuc, xlabel(, angle(90) labsize(*.75))
```


Dendrogram for sngeuc cluster analysis
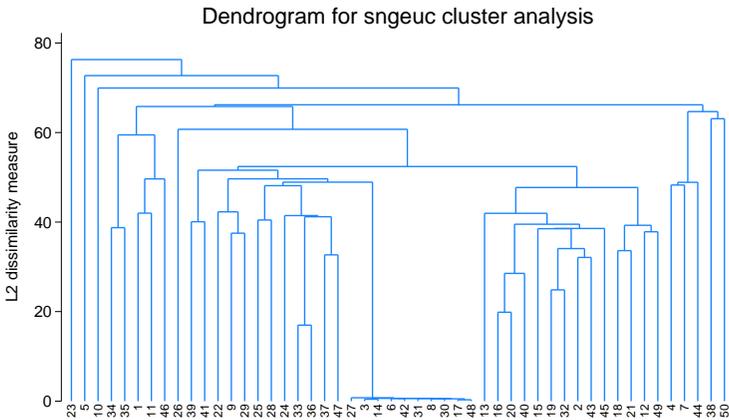
From your experience looking at dendrograms, two things jump out at you about this cluster analysis. The first is the observations showing up in the middle of the dendrogram that are all close to each other (short vertical bars) and are far from any other observations (the long vertical bar connecting them to the rest of the dendrogram). Next you notice that if you ignore those 10 observations, the rest of the dendrogram does not indicate strong clustering, as shown by the relatively short vertical bars in the upper portion of the dendrogram.

You start to look for clues why these 10 observations are so peculiar. Looking at scatterplots is usually helpful, so you examine the matrix of scatterplots.

```
. graph matrix x1 x2 x3 x4
```
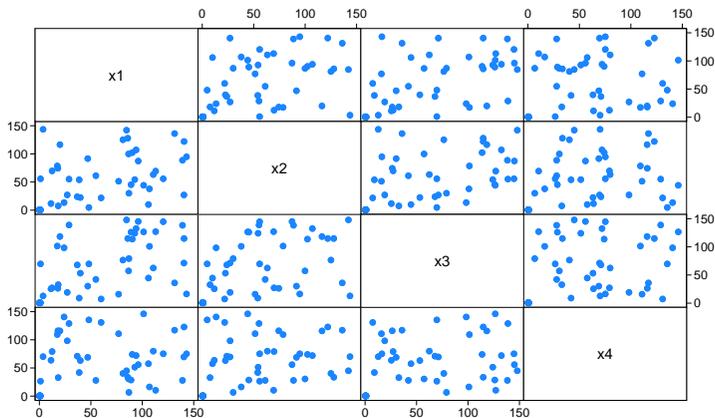

Unfortunately, these scatterplots do not indicate what might be going on.

Suddenly, from your past experience with the laboratory technicians, you have an idea of what to check next. Because of past data mishaps, the company started the policy of placing within each dataset a variable giving the name of the technician who produced the measurement. You decide to view the dendrogram, using the technician's name as the label instead of the default observation number.

```
. cluster dendrogram sngeuc, labels(labtech) xlabel(, angle(90) labsize(*.75))
```

Dendrogram for sngeuc cluster analysis
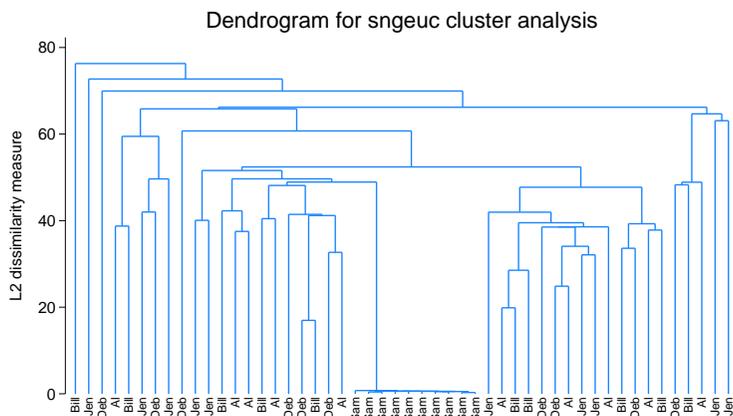
Your suspicions are confirmed. Sam, one of the laboratory technicians, has messed up again. You list the data and see that all his observations are between zero and one, whereas the other four technicians' data range up to about 150, as expected. It looks like Sam forgot, once again, to calibrate his sensor before analyzing his samples. You decide to save a note of your findings with this cluster analysis (see [MV] **cluster notes** for the details) and to send the data back to the laboratory to be fixed.

◁

▷ Example 2

The sociology professor of your graduate-level class gives, as homework, a dataset containing 30 observations on 60 binary variables, with the assignment to tell him something about the 30 subjects represented by the observations. You think that this assignment is too vague, but because your grade depends on it, you get to work trying to figure something out.

Among the analyses you try is the following cluster analysis. You decide to use single-linkage clustering with the simple matching binary coefficient because it is easy to understand. Just for fun, though it makes no difference to you, you specify the `generate()` option to force the generated variables to have `zstub` as a prefix. You let Stata pick a name for your cluster analysis by not specifying the `name()` option.

```
. use https://www.stata-press.com/data/r18/homework, clear

. cluster s a1-a60, measure(matching) gen(zstub)
cluster name: _clus_1

. cluster list
_clus_1  (type: hierarchical,  method: single,  similarity: matching)
      vars: zstub_id (id variable)
            zstub_ord (order variable)
            zstub_hgt (height variable)
     other: cmd: cluster singlelinkage a1-a60, measure(matching) gen(zstub)
            varlist: a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16 a17
                  a18 a19 a20 a21 a22 a23 a24 a25 a26 a27 a28 a29 a30 a31 a32
                  a33 a34 a35 a36 a37 a38 a39 a40 a41 a42 a43 a44 a45 a46 a47
                  a48 a49 a50 a51 a52 a53 a54 a55 a56 a57 a58 a59 a60
            range: 1 0
```

Stata selected `_clus_1` as the cluster name and created the variables `zstub_id`, `zstub_ord`, and `zstub_hgt`.

You display the dendrogram by using the `cluster tree` command, which is a synonym for `cluster dendrogram`. Because Stata uses the most recently performed cluster analysis by default, you do not need to type the name.

```
. cluster tree
```


Dendrogram for _clus_1 cluster analysis
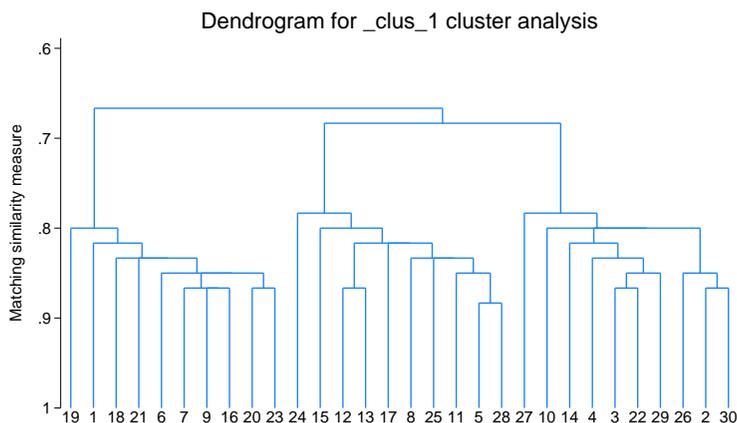
The dendrogram seems to indicate the presence of three groups among the 30 observations. You decide that this is probably the structure your teacher wanted you to find, and you begin to write up your report. You want to examine the three groups further, so you use the `cluster generate` command (see [MV] **cluster generate**) to create a grouping variable to make the task easier. You examine various summary statistics and tables for the three groups and finish your report.

After the assignment is turned in, your professor gives you the same dataset with the addition of one more variable, `truegrp`, which indicates the groupings he thinks are in the data. You do a cross-tabulation of the `truegrp` and `grp3`, your grouping variable, to see if you are going to get a good grade on the assignment.

```
. cluster generate grp3 = group(3)
. table grp3 truegrp, nototals
```

	truegrp		
	1	2	3
grp3			
1		10	
2			10
3	10		

Other than the numbers arbitrarily assigned to the three groups, both you and your professor agree. You rest easier that night knowing that you may survive one more semester.

In addition to examining single-linkage clustering of these data, you decide to see what median-linkage clustering shows. As with the single-linkage clustering, you pick the simple matching binary coefficient to measure the similarity between groups. The `name()` option is used to attach the name `medlink` to the cluster analysis. `cluster list` displays the details; see [MV] **cluster utility**.

```
. cluster median a1-a60, measure(match) name(medlink)

. cluster list medlink
medlink  (type: hierarchical,  method: median,  similarity: matching)
      vars: medlink_id (id variable)
            medlink_ord (order variable)
            medlink_hgt (real_height variable)
            medlink_pht (pseudo_height variable)
     other: cmd: cluster medianlinkage a1-a60, measure(match) name(medlink)
            varlist: a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16 a17
                a18 a19 a20 a21 a22 a23 a24 a25 a26 a27 a28 a29 a30 a31 a32
                a33 a34 a35 a36 a37 a38 a39 a40 a41 a42 a43 a44 a45 a46 a47
                a48 a49 a50 a51 a52 a53 a54 a55 a56 a57 a58 a59 a60
            range: 1 0
```

You attempt to use the `cluster dendrogram` command to display the dendrogram, but because this particular cluster analysis produced reversals, `cluster dendrogram` refuses to produce the dendrogram. You realize that with reversals, the resulting dendrogram would not be easy to interpret anyway.

You use the `cluster generate` command (see [MV] **cluster generate**) to create a three-group grouping variable, based on your median-linkage clustering, to compare with `truegrp`.

```
. cluster generate medgrp3 = group(3)

. table medgrp3 truegrp, nototals
```

	truegrp		
	1	2	3
medgrp3			
1		10	
2	10		
3			10

Because you were unable to view a dendrogram by using median-linkage clustering, you turn to Ward's linkage clustering method.

```
. cluster ward a1-a60, measure(match) name(wardlink)

. cluster list wardlink
wardlink  (type: hierarchical,  method: wards,  similarity: matching)
      vars: wardlink_id (id variable)
            wardlink_ord (order variable)
            wardlink_hgt (height variable)
     other: cmd: cluster wardslinkage a1-a60, measure(match) name(wardlink)
            varlist: a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16 a17
                a18 a19 a20 a21 a22 a23 a24 a25 a26 a27 a28 a29 a30 a31 a32
                a33 a34 a35 a36 a37 a38 a39 a40 a41 a42 a43 a44 a45 a46 a47
                a48 a49 a50 a51 a52 a53 a54 a55 a56 a57 a58 a59 a60
            range: 1 0
```

. cluster tree wardlink

Dendrogram for wardlink cluster analysis
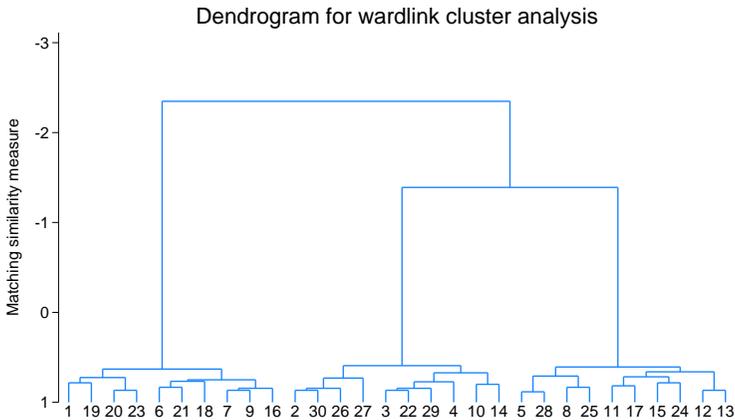
As with single-linkage clustering, the dendrogram from Ward's linkage clustering seems to indicate the presence of three groups among the 30 observations. However, notice the y-axis range for the resulting dendrogram. How can the matching similarity coefficient range from 1 to less than -2? By definition, the matching coefficient is bounded between 1 and 0. This is an artifact of the way Ward's linkage clustering is defined, and it underscores the warning mentioned in the discussion of the choice of *measure*. Also see *Dissimilarity transformations and the Lance and Williams formula* and *Warning concerning similarity or dissimilarity choice* in [MV] **cluster** for more details.

A cross-tabulation of `truegrp` and `wardgrp3`, a three-group grouping variable from this cluster analysis, is shown next.

. cluster generate wardgrp3 = group(3)

. table wardgrp3 truegrp, nototals

		truegrp	
	1	2	3
wardgrp3			
1		10	
2	10		
3			10

Other than the numbers arbitrarily assigned to the three groups, your teacher's conclusions and the results from the Ward's linkage clustering agree. So, despite the warning against using something other than squared Euclidean distance with Ward's linkage, you were still able to obtain a reasonable cluster-analysis solution with the matching similarity coefficient.

◁

▷ Example 3

The `wclub` dataset contains answers from 30 women to 35 yes–no questions. The variables are described in example 3 of [MV] **clustermat**. We are interested in seeing how weighted-average linkage clustering will cluster the 35 variables (instead of the observations).

We use the `matrix dissimilarity` command to produce a dissimilarity matrix equal to one minus the Jaccard similarity; see [MV] **matrix dissimilarity**.

```
. use https://www.stata-press.com/data/r18/wclub, clear

. matrix dissimilarity clubD = , variables Jaccard dissim(oneminus)

. clustermat waverage clubD, name(clubwav) clear labelvar(question)
Number of observations (_N) was 0, now 35.

. cluster dendrogram clubwav, labels(question)
> xlabel(, angle(90) labsize(*.75)) title(Weighted-average linkage clustering)
> ytitle(1 - Jaccard similarity, suffix)
```
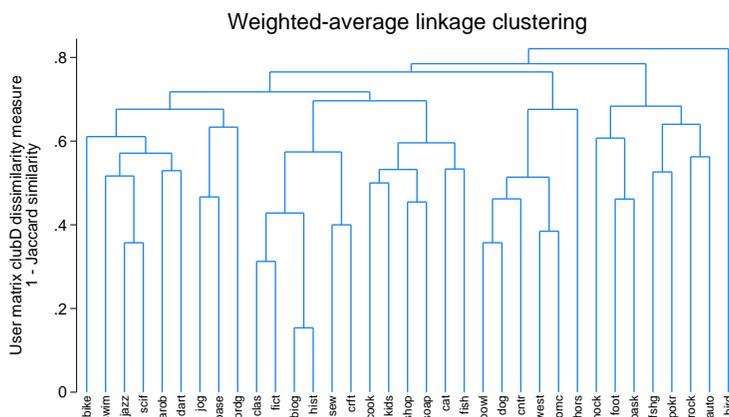

Weighted-average linkage clustering

From these 30 women, we see that the `biog` (enjoy reading biographies) and `hist` (enjoy reading history) questions were most closely related. `bird` (have a bird) seems to be the least related to the other variables. It merges last into the supergroup containing the remaining variables.

◁

❑ Technical note

cluster commands require a significant amount of memory and execution time. With many observations, the execution time may be significant.

❑

Methods and formulas

[MV] **cluster** discusses and compares the hierarchical clustering methods.

Conceptually, hierarchical agglomerative linkage clustering proceeds as follows. The N observations start out as N separate groups, each of size one. The two closest observations are merged into one group, producing $N - 1$ total groups. The closest two groups are then merged so that there are $N - 2$ total groups. This process continues until all the observations are merged into one large group, producing a hierarchy of groupings from one group to N groups. The difference between the various hierarchical-linkage methods depends on how they define "closest" when comparing groups.

For single-linkage clustering, the closest two groups are determined by the closest observations between the two groups.

In complete linkage, the closest two groups are determined by the farthest observations between the two groups.

For average-linkage clustering, the closest two groups are determined by the average (dis)similarity between the observations of the two groups.

The Lance–Williams formula provides the basis for extending the well-known Ward's method of clustering into the general hierarchical-linkage framework that allows a choice of (dis)similarity measures.

Centroid linkage merges the groups whose means are closest.

Weighted-average linkage clustering is similar to average-linkage clustering, except that it gives each group of observations equal weight. Average linkage gives each observation equal weight.

Median linkage is a variation on centroid linkage in that it treats groups of unequal size differently. Centroid linkage gives each observation equal weight. Median linkage, however, gives each group of observations equal weight, meaning that with unequal group sizes, the observations in the smaller group will have more weight than the observations in the larger group.

The linkage clustering algorithm produces two variables that together act as a pointer representation of a dendrogram. To this, Stata adds a third variable used to restore the sort order, as needed, so that the two variables of the pointer representation remain valid. The first variable of the pointer representation gives the order of the observations. The second variable has one less element and gives the height in the dendrogram at which the adjacent observations in the order variable join.

When reversals happen, a fourth variable, called a pseudoheight, is produced and is used by postclustering commands with the height variable to properly interpret the ordering of the hierarchy.

See [MV] *measure_option* for the details and formulas of the available *measure*s, which include (dis)similarity measures for continuous and binary data.

Joe H. Ward, Jr. (1926–2011) was born in Austin, Texas, and obtained degrees in mathematics and educational psychology from the University of Texas. He worked as a personnel research psychologist for the U.S. Air Force Human Resources Laboratory, applying educational psychology, statistics, and computers to a wide variety of procedures, most notably the widely used clustering method named for him. In retirement, he mentored and supported high school students in computers, statistics, science fairs, and basketball.

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **cluster dendrogram** — Dendrograms for hierarchical cluster analysis

[MV] **cluster generate** — Generate grouping variables from a cluster analysis

[MV] **cluster notes** — Cluster analysis notes

[MV] **cluster stop** — Cluster-analysis stopping rules

[MV] **cluster utility** — List, rename, use, and drop cluster analyses

[MV] **clustermat** — Introduction to clustermat commands

Title

---

cluster notes — Cluster analysis notes

Description

cluster notes is a set of commands to manage notes for a previously run cluster analysis. You can attach notes that become part of the data and are saved when the data are saved and retrieved when the data are used. cluster notes may also be used to list notes for all defined cluster analyses or for specific cluster analyses names.

cluster notes drop allows you to drop cluster notes.

Menu

Statistics > Multivariate analysis > Cluster analysis > Postclustering > Cluster analysis notes

Syntax

Add a note to a cluster analysis

  cluster <u>notes</u> *cluster* : *text*

List all cluster notes

  cluster <u>notes</u>

List cluster notes associated with specified cluster analyses

  cluster <u>notes</u> *clnamelist*

Drop cluster notes

  cluster <u>notes</u> drop *cluster* [in *numlist*]

Remarks and examples

The cluster-analysis system in Stata has many features that allow you to manage the various cluster analyses that you perform. See [MV] **cluster** for information on all the available cluster-analysis commands; see [MV] **cluster utility** for other `cluster` commands, including `cluster list`, that help you manage your analyses. The `cluster notes` command is modeled after Stata's `notes` command (see [D] **notes**), but they are different systems and do not interact.

▷ Example 1

We illustrate the `cluster notes` command starting with three cluster analyses that have already been performed. The `cluster dir` command shows us the names of all the existing cluster analyses; see [MV] **cluster utility**.

```
. cluster dir
sngeuc
sngabs
kmn3abs
. cluster note sngabs : I used single linkage with absolute value distance
. cluster note sngeuc : Euclidean distance and single linkage
. cluster note kmn3abs : This has the kmeans cluster results for 3 groups
. cluster notes
sngeuc
     notes:   1. Euclidean distance and single linkage
sngabs
     notes:   1. I used single linkage with absolute value distance
kmn3abs
     notes:   1. This has the kmeans cluster results for 3 groups
```

After adding a note to each of the three cluster analyses, we used the `cluster notes` command without arguments to list all the notes for all the cluster analyses.

The `*` and `?` characters may be used when referring to cluster names; see [U] **11.2 Abbreviation rules**.

```
. cluster note k* : Verify that observation 5 is correct.  I am suspicious that
> there was a typographical error or instrument failure in recording the
> information.
. cluster notes kmn3abs
kmn3abs
     notes:   1. This has the kmeans cluster results for 3 groups
              2. Verify that observation 5 is correct. I am suspicious that
                 there was a typographical error or instrument failure in
                 recording the information.
```

`cluster notes` expanded `k*` to `kmn3abs`, the only cluster name that begins with a `k`. Notes that extend to multiple lines are automatically wrapped when displayed. When entering long notes, you just continue to type until your note is finished. Pressing *Return* signals that you are done with that note.

After examining the dendrogram (see [MV] **cluster dendrogram**) for the `sngeuc` single-linkage cluster analysis and seeing one small group of data that split off from the main body of data at a very large distance, you investigate further and find data problems. You decide to add some notes to the `sngeuc` analysis.

```
. cluster note *euc : All of Sam's data looks wrong to me.

. cluster note *euc : I think Sam should be fired.

. cluster notes sng?*
sngeuc
     notes:   1. Euclidean distance and single linkage
              2. All of Sam's data looks wrong to me.
              3. I think Sam should be fired.

sngabs
     notes:   1. I used single linkage with absolute value distance
```

Sam, one of the lab technicians, who happens to be the owner's nephew and is paid more than you, really messed up. After adding these notes, you get second thoughts about keeping the notes attached to the cluster analysis (and the data). You decide you really want to delete those notes and to add a more politically correct note.

```
. cluster note sngeuc : Ask Jennifer to help Sam reevaluate his data.

. cluster note sngeuc
sngeuc
     notes:   1. Euclidean distance and single linkage
              2. All of Sam's data looks wrong to me.
              3. I think Sam should be fired.
              4. Ask Jennifer to help Sam reevaluate his data.

. cluster note drop sngeuc in 2/3

. cluster notes kmn3abs s*
kmn3abs
     notes:   1. This has the kmeans cluster results for 3 groups
              2. Verify that observation 5 is correct. I am suspicious that
                 there was a typographical error or instrument failure in
                 recording the information.

sngeuc
     notes:   1. Euclidean distance and single linkage
              2. Ask Jennifer to help Sam reevaluate his data.

sngabs
     notes:   1. I used single linkage with absolute value distance
```

Just for illustration purposes, the new note was added before deleting the two offending notes. `cluster notes drop` can take an `in` argument followed by a list of note numbers. The numbers correspond to those shown in the listing provided by the `cluster notes` command. After the deletions, the note numbers are reassigned to remove gaps. So `sngeuc` note 4 becomes note 2 after the deletion of notes 2 and 3 as shown above.

Without an `in` argument, the `cluster notes drop` command drops all notes associated with the named cluster.

◁

Remember that the cluster notes are stored with the data and, as with other updates you make to the data, the additions and deletions are not permanent until you save the data; see [D] **save**.

❑ Technical note

Programmers can access the notes (and all the other cluster attributes) by using the `cluster query` command; see [MV] **cluster programming utilities**.

❑

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **cluster programming utilities** — Cluster-analysis programming utilities

[MV] **cluster utility** — List, rename, use, and drop cluster analyses

[MV] **clustermat** — Introduction to clustermat commands

[D] **notes** — Place notes in data

[D] **save** — Save Stata dataset

Title

> **cluster programming subroutines —** Add cluster-analysis routines

  Description   Remarks and examples   Reference   Also see

Description

This entry describes how to extend Stata's `cluster` command; see [MV] **cluster**. Programmers can add subcommands to `cluster`, add functions to `cluster generate` (see [MV] **cluster generate**), add stopping rules to `cluster stop` (see [MV] **cluster stop**), and set up an alternative command to be executed when `cluster dendrogram` is called (see [MV] **cluster dendrogram**).

The `cluster` command also provides utilities for programmers; see [MV] **cluster programming utilities** to learn more.

Remarks and examples

Remarks are presented under the following headings:

> *Adding a cluster subroutine*
> *Adding a cluster generate function*
> *Adding a cluster stopping rule*
> *Applying an alternate cluster dendrogram routine*

Adding a cluster subroutine

You add a `cluster` subroutine by creating a Stata program with the name `cluster_subcmdname`. For example, to add the subcommand `xyz` to `cluster`, create `cluster_xyz.ado`. Users could then execute the `xyz` subcommand with

`cluster xyz ...`

Everything entered on the command line after `cluster xyz` is passed to the `cluster_xyz` command.

You can add new clustering methods, new cluster-management tools, and new postclustering programs. The `cluster` command has subcommands that can be helpful to cluster-analysis programmers; see [MV] **cluster programming utilities**.

▷ Example 1

We will add a `cluster` subroutine by writing a simple postcluster-analysis routine that provides a cross-tabulation of two cluster-analysis grouping variables. The syntax of the new command will be

> `cluster mycrosstab` *clname1 clname2* [, *tabulate_options*]

Here is the program:

```
program cluster_mycrosstab
        version 18.0            // (or version 18.5 for StataNow)
        gettoken clname1 0 : 0 , parse(" ,")
        gettoken clname2 rest : 0 , parse(" ,")
        cluster query `clname1'
        local groupvar1 `r(groupvar)'
        cluster query `clname2'
        local groupvar2 `r(groupvar)'
        tabulate `groupvar1' `groupvar2' `rest'
end
```

See [P] **gettoken** for information on the gettoken command, and see [R] **tabulate twoway** for information on the tabulate command. The cluster query command is one of the cluster programming utilities that is documented in [MV] **cluster programming utilities**.

We can demonstrate cluster mycrosstab in action. This example starts with two cluster analyses, cl1 and cl2. The dissimilarity measure and the variables included in the two cluster analyses differ. We want to see how closely the two cluster analyses match.

```
. use https://www.stata-press.com/data/r18/auto
(1978 automobile data)

. cluster kmeans gear head tr, L1 k(5) name(cl1) start(krandom(55234))
> gen(cl1gvar)

. cluster kmeans tr tu mpg, L(1.5) k(5) name(cl2) start(krandom(22132))
> gen(gvar2)

. cluster list, type method dissim var
cl2  (type: partition,  method: kmeans,  dissimilarity: L(1.5))
      vars: gvar2 (group variable)

cl1  (type: partition,  method: kmeans,  dissimilarity: L1)
      vars: cl1gvar (group variable)

. cluster mycrosstab cl1 cl2, chi2
```

			Cluster ID			
Cluster ID	1	2	3	4	5	Total
1	10	7	0	0	4	21
2	10	0	0	0	0	10
3	0	0	4	5	2	11
4	0	1	6	4	8	19
5	0	11	1	0	1	13
Total	20	19	11	9	15	74

```
           Pearson chi2(16) =  97.3723   Pr = 0.000
```

The chi2 option was included to demonstrate that we were able to exploit the existing options of tabulate with little programming effort. We just pass along to tabulate any of the extra arguments received by cluster_mycrosstab.

◁

Adding a cluster generate function

Programmers can add functions to the cluster generate command (see [MV] **cluster generate**) by creating a command called clusgen_*name*. For example, to add a function called abc() to cluster generate, you could create clusgen_abc.ado. Users could then execute

cluster generate *newvar* = abc(...) ...

Everything entered on the command line following cluster generate is passed to clusgen_abc.

▷ Example 2

Here is the beginning of a clusgen_abc program that expects an integer argument and has one option called name(*clname*), which gives the name of the cluster. If name() is not specified, the name defaults to that of the most recently performed cluster analysis. We will assume, for illustration purposes, that the cluster analysis must be hierarchical and will check for this in the clusgen_abc program.

```
program clusgen_abc
        version 18.0            // (or version 18.5 for StataNow)
        // we use gettoken to work our way through the parsing
        gettoken newvar 0 : 0 , parse(" =")
        gettoken temp 0 : 0 , parse(" =")
        if '"'temp'"' != "=" {
                error 198
        }
        gettoken temp 0 : 0 , parse(" (")
        if '"'temp'"' != "abc" {
                error 198
        }
        gettoken funcarg 0 : 0 , parse(" (") match(temp)
        if '"'temp'"' != "(" {
                error 198
        }
        // funcarg holds the integer argument to abc()
        confirm integer number 'funcarg'
        // we can now use syntax to parse the option
        syntax [, Name(str) ]
        // cluster query will give us the list of cluster names
        if '"'name'"' == "" {
                cluster query
                local clnames 'r(names)'
                if "'clnames'" == "" {
                        di as err "no cluster solutions defined"
                        exit 198
                }
                // first name in the list is the latest clustering
                local name : word 1 of 'clnames'
        }
        // cluster query followed by name will tell us the type
        cluster query 'name'
        if "'r(type)'" != "hierarchical" {
                di as err "only allowed with hierarchical clustering"
                exit 198
        }
        /*
           you would now pull more information from the call of
                         cluster query 'name'
           and do your computations and generate 'newvar'
        */
        ...
end
```

See [MV] **cluster programming utilities** for details on the cluster query command.

◁

Adding a cluster stopping rule

Programmers can add stopping rules to the rule() option of the cluster stop command (see [MV] **cluster stop**) by creating a Stata program with the name clstop_*name*. For example, to add a stopping rule named mystop so that cluster stop would now have a rule(mystop) option, you could create clstop_mystop.ado defining the clstop_mystop program. Users could then execute

    cluster stop [*clname*], rule(mystop) ...

The `clstop_mystop` program is passed the cluster name (*clname*) provided by the user (or the name of the current cluster result if no name is specified), followed by a comma and all the options entered by the user except for the `rule(mystop)` option.

▷ Example 3

We will add a `rule(stepsize)` option to `cluster stop`. This option implements the simple step-size stopping rule (see Milligan and Cooper 1985), which computes the difference in fusion values between levels in a hierarchical cluster analysis. (A fusion value is the similarity or dissimilarity measure at which clusters are fused or split in the hierarchical cluster structure.) Large values of the step-size stopping rule indicate groupings with more distinct cluster structure.

Examining cluster dendrograms (see [MV] **cluster dendrogram**) to visually determine the number of clusters is equivalent to using a visual approximation to the step-size stopping rule.

Here is the `clstop_stepsize` program:

```
program clstop_stepsize, sortpreserve rclass
        version 18.0            // (or version 18.5 for StataNow)
        syntax anything(name=clname) [, Depth(integer -1) ]
        cluster query 'clname'
        if "'r(type)'" != "hierarchical" {
                di as error ///
                    "rule(stepsize) only allowed with hierarchical clustering"
                exit 198
        }
        if "'r(pseudo_heightvar)'" != "" {
                di as error "dendrogram reversals encountered"
                exit 198
        }
        local hgtvar 'r(heightvar)'
        if '"'r(similarity)'"' != "" {
                sort 'hgtvar'
                local negsign "-"
        }
        else if '"'r(dissimilarity)'"' != "" {
                gsort -'hgtvar'
        }
        else {
                di as error "dissimilarity or similarity not set"
                exit 198
        }
        quietly count if !missing('hgtvar')
        local depth = cond('depth'<=1, r(N), min('depth',r(N)))
        tempvar diff
        qui gen double 'diff'='negsign'('hgtvar'-'hgtvar'[_n+1]) if _n<'depth'
        di
        di as txt "Depth" _col(10) "Stepsize"
        di as txt "{hline 17}"
        forvalues i = 1/'= 'depth'-1' {
                local j = 'i' + 1
                di as res 'j' _col(10) %8.0g 'diff'['i']
                return scalar stepsize_'j' = 'diff'['i']
        }
        return local rule "stepsize"
end
```

See [P] **syntax** for information about the syntax command, [P] **forvalues** for information about the forvalues looping command, and [P] **macro** for information about the '= ... ' macro function. The cluster query command is one of the cluster programming utilities that is documented in [MV] **cluster programming utilities**.

With this program, users can obtain the step-size stopping rule. We demonstrate this process by using an average-linkage hierarchical cluster analysis on the data found in the second example of [MV] **cluster linkage**. The dataset contains 30 observations on 60 binary variables. The simple matching coefficient is used as the similarity measure in the average-linkage clustering.

```
. use https://www.stata-press.com/data/r18/homework, clear
. cluster a a1-a60, measure(match) name(alink)
. cluster stop alink, rule(stepsize) depth(15)
```

Depth	Stepsize
2	.065167
3	.187333
4	.00625
5	.007639
6	.002778
7	.005952
8	.002381
9	.008333
10	.005556
11	.002778
12	0
13	0
14	.006667
15	.01

In the clstop_stepsize program, we included a depth() option. cluster stop, when called with the new rule(stepsize) option, can also have the depth() option. Here we specified that it stop at a depth of 15.

The largest step size, .187, happens at the three-group level of the hierarchy. This number, .187, represents the difference between the matching coefficient created when two groups are formed and that created when three groups are formed in this hierarchical cluster analysis.

The clstop_stepsize program could be enhanced by using a better output table format. An option could also be added that stores the results in a matrix.

◁

Applying an alternate cluster dendrogram routine

Programmers can change the behavior of the cluster dendrogram command (alias cluster tree); see [MV] **cluster dendrogram**. This task is accomplished by using the other() option of the cluster set command (see [MV] **cluster programming utilities**) with a *tag* of treeprogram and with *text* giving the name of the command to be used in place of the standard Stata program for cluster dendrogram. For example, if you had created a new hierarchical cluster-analysis method for Stata that needed a different algorithm for producing dendrograms, you would use the command

cluster set *clname*, other(treeprogram *progname*)

to set *progname* as the program to be executed when cluster dendrogram is called.

▷ Example 4

If we were creating a new hierarchical cluster-analysis method called `myclus`, we could create a program called `cluster_myclus` (see *Adding a cluster subroutine*). If `myclus` needed a different dendrogram routine from the standard one used within Stata, we could include the following line in `cluster_myclus.ado` at the point where we set the cluster attributes.

```
cluster set `clname', other(treeprogram myclustree)
```

We could then create a program called `myclustree` in a file called `myclustree.ado` that implements the particular dendrogram program needed by `myclus`.

◁

Reference

Milligan, G. W., and M. C. Cooper. 1985. An examination of procedures for determining the number of clusters in a dataset. *Psychometrika* 50: 159–179. https://doi.org/10.1007/BF02294245.

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **clustermat** — Introduction to clustermat commands

[MV] **cluster programming utilities** — Cluster-analysis programming utilities

Title

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cluster programming utilities — Cluster-analysis programming utilities

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Description

The `cluster query`, `cluster set`, `cluster delete`, `cluster parsedistance`, and `cluster measures` commands provide tools for programmers to add their own cluster-analysis subroutines to Stata's `cluster` command; see [MV] **cluster** and [MV] **cluster programming subroutines**. These commands make it possible for the new command to take advantage of Stata's cluster-management facilities.

`cluster query` provides a way to obtain the various attributes of a cluster analysis in Stata. If *clname* is omitted, `cluster query` returns in `r(names)` a list of the names of all currently defined cluster analyses. If *clname* is provided, the various attributes of the specified cluster analysis are returned in `r()`. These attributes include the type, method, (dis)similarity used, created variable names, notes, and any other information attached to the cluster analysis.

`cluster set` allows you to set the various attributes that define a cluster analysis in Stata, including naming your cluster results and adding the name to the master list of currently defined cluster results. With `cluster set`, you can provide information on the type, method, and (dis)similarity measure of your cluster-analysis results. You can associate variables and Stata characteristics (see [P] **char**) with your cluster analysis. `cluster set` also allows you to add notes and other specified fields to your cluster-analysis result. These items become part of the dataset and are saved with the data.

`cluster delete` allows you to delete attributes from a cluster analysis in Stata. This command is the inverse of `cluster set`.

`cluster parsedistance` takes the similarity or dissimilarity *measure* name and checks it against the list of those provided by Stata, taking account of allowed minimal abbreviations and aliases. Aliases are resolved (for instance, `Euclidean` is changed into the equivalent `L2`).

`cluster measures` computes the similarity or dissimilarity *measure* between the observations listed in the `compare()` option and the observations included based on the `if` and `in` conditions and places the results in the variables specified by the `generate()` option. See [MV] **matrix dissimilarity** for the `matrix dissimilarity` command that places (dis)similarities in a matrix.

Stata also provides a method for programmers to extend the `cluster` command by providing subcommands; see [MV] **cluster programming subroutines**.

Syntax

Obtain various attributes of a cluster analysis

    cluster query [*clname*]

Set various attributes of a cluster analysis

    cluster set [*clname*] [, *set_options*]

Delete attributes from a cluster analysis

    cluster <u>del</u>ete *clname* [, *delete_options*]

Check similarity and dissimilarity measure name

    cluster <u>parsedist</u>ance *measure*

Compute similarity and dissimilarity measure

    cluster measures *varlist* [*if*] [*in*] , <u>compare</u>(*numlist*) <u>gen</u>erate(*newvarlist*)

        [*measures_options*]

set_options	Description
<u>addn</u>ame	add *clname* to the master list of cluster analyses
<u>type</u>(*type*)	set the cluster type for *clname*
<u>method</u>(*method*)	set the name of the clustering method for the cluster analysis
<u>similarity</u>(*measure*)	set the name of the similarity measure used for the cluster analysis
<u>dissimilarity</u>(*measure*)	set the name of the dissimilarity measure used for the cluster analysis
<u>var</u>(*tag varname*)	set *tag* that points to *varname*
<u>char</u>(*tag charname*)	set *tag* that points to *charname*
<u>other</u>(*tag text*)	set *tag* with *text* attached to the tag marker
<u>note</u>(*text*)	add a note to the *clname*

delete_options	Description
<u>z</u>ap	delete all possible settings for *clname*
<u>del</u>name	remove *clname* from the master list of current cluster analyses
<u>t</u>ype	delete the cluster type entry from *clname*
<u>m</u>ethod	delete the cluster method entry from *clname*
<u>s</u>imilarity	delete the similarity entries from *clname*
<u>dis</u>similarity	delete the dissimilarity entries from *clname*
<u>note</u>s(*numlist*)	delete the specified numbered notes from *clname*
<u>alln</u>otes	remove all notes from *clname*
<u>v</u>ar(*tag*)	remove *tag* from *clname*
<u>allv</u>ars	remove all the entries pointing to variables for *clname*
<u>varz</u>ap(*tag*)	same as var(), but also delete the referenced variable
<u>allvarz</u>ap	same as allvars, but also delete the variables
<u>ch</u>ar(*tag*)	remove *tag* that points to a Stata characteristic from *clname*
<u>allch</u>ars	remove all entries pointing to Stata characteristics for *clname*
<u>charz</u>ap(*tag*)	same as char(), but also delete the characteristic
<u>allcharz</u>ap	same as allchars, but also delete the characteristics
<u>o</u>ther(*tag*)	delete *tag* and its associated text from *clname*
<u>allo</u>thers	delete all entries from *clname* that have been set using other()

measures_options	Description
* <u>compare</u>(*numlist*)	use *numlist* as the comparison observations
* <u>g</u>enerate(*newvarlist*)	create *newvarlist* variables
measure	(dis)similarity measure; see *Options for cluster measures* for available measures; default is L2
<u>propv</u>ars	interpret observations implied by if and in as proportions of binary observations
<u>propc</u>ompares	interpret comparison observations as proportions of binary observations

* compare(*numlist*) and generate(*newvarlist*) are required.

collect is allowed with cluster query; see [U] **11.1.10 Prefix commands**.

Options for cluster set

addname adds *clname* to the master list of currently defined cluster analyses. When *clname* is not specified, the addname option is mandatory, and here, cluster set automatically finds a cluster name that is not currently in use and uses this as the cluster name. cluster set returns the name of the cluster in r(name). If addname is not specified, the *clname* must have been added to the master list previously (for instance, through a previous call to cluster set).

type(*type*) sets the cluster type for *clname*. type(hierarchical) indicates that the cluster analysis is hierarchical-style clustering, and type(partition) indicates that it is a partition-style clustering. You are not restricted to these types. For instance, you might program some kind of fuzzy partition-clustering analysis, so you then use type(fuzzy).

method(*method*) sets the name of the clustering method for the cluster analysis. For instance, Stata uses method(kmeans) to indicate a kmeans cluster analysis and uses method(single) to indicate single-linkage cluster analysis. You are not restricted to the names currently used within Stata.

similarity(*measure*) and dissimilarity(*measure*) set the name of the similarity or dissimilarity measure used for the cluster analysis. For example, Stata uses dissimilarity(L2) to indicate the L2 or Euclidean distance. You are not restricted to the names currently used within Stata. See [MV] *measure_option* and [MV] **cluster** for a listing and discussion of (dis)similarity measures.

var(*tag varname*) sets a marker called *tag* in the cluster analysis that points to the variable *varname*. For instance, Stata uses var(group *varname*) to set a grouping variable from a kmeans cluster analysis. With single-linkage clustering, Stata uses var(id *idvarname*), var(order *ordervarname*), and var(height *hgtvarname*) to set the id, order, and height variables that define the cluster-analysis result. You are not restricted to the names currently used within Stata. Up to 10 var() options may be specified with a cluster set command.

char(*tag charname*) sets a marker called *tag* in the cluster analysis that points to the Stata characteristic named *charname*; see [P] **char**. This characteristic can be either an _dta[] dataset characteristic or a variable characteristic. Up to 10 char() options may be specified with a cluster set command.

other(*tag text*) sets a marker called *tag* in the cluster analysis with *text* attached to the *tag* marker. Stata uses other(k #) to indicate that k (the number of groups) was # in a kmeans cluster analysis. You are not restricted to the names currently used within Stata. Up to 10 other() options may be specified with a cluster set command.

note(*text*) adds a note to the *clname* cluster analysis. The cluster notes command (see [MV] **cluster notes**) is the command to add, delete, or view cluster notes. The cluster notes command uses the note() option of cluster set to add a note to a cluster analysis. Up to 10 note() options may be specified with a cluster set command.

Options for cluster delete

zap deletes all possible settings for cluster analysis *clname*. It is the same as specifying the delname, type, method, similarity, dissimilarity, allnotes, allcharzap, allothers, and allvarzap options.

delname removes *clname* from the master list of current cluster analyses. This option does not affect the various settings that make up the cluster analysis. To remove them, use the other options of cluster delete.

type deletes the cluster type entry from *clname*.

method deletes the cluster method entry from *clname*.

similarity and dissimilarity delete the similarity and dissimilarity entries, respectively, from *clname*.

notes(*numlist*) deletes the specified numbered notes from *clname*. The numbering corresponds to the returned results from the cluster query *clname* command. The cluster notes drop command (see [MV] **cluster notes**) drops a cluster note. It, in turn, calls cluster delete, using the notes() option to drop the notes.

allnotes removes all notes from the *clname* cluster analysis.

var(*tag*) removes from *clname* the entry labeled *tag* that points to a variable. This option does not delete the variable.

allvars removes all the entries pointing to variables for *clname*. This option does not delete the corresponding variables.

varzap(*tag*) is the same as var() and actually deletes the variable in question.

allvarzap is the same as allvars and actually deletes the variables.

char(*tag*) removes from *clname* the entry labeled *tag* that points to a Stata characteristic (see [P] **char**). This option does not delete the characteristic.

allchars removes all the entries pointing to Stata characteristics for *clname*. This option does not delete the characteristics.

charzap(*tag*) is the same as char() and actually deletes the characteristics.

allcharzap is the same as allchars and actually deletes the characteristics.

other(*tag*) deletes from *clname* the *tag* entry and its associated text, which were set by using the other() option of the cluster set command.

allothers deletes all entries from *clname* that have been set using the other() option of the cluster set command.

Options for cluster measures

compare(*numlist*) is required and specifies the observations to use as the comparison observations. Each of these observations will be compared with the observations implied by the if and in conditions, using the specified (dis)similarity *measure*. The results are stored in the corresponding new variable from the generate() option. There must be the same number of elements in *numlist* as there are variable names in the generate() option.

generate(*newvarlist*) is required and specifies the names of the variables to be created. There must be as many elements in *newvarlist* as there are numbers specified in the compare() option.

measure specifies the similarity or dissimilarity measure. The default is L2 (synonym Euclidean). This option is not case sensitive. See [MV] ***measure_option*** for detailed descriptions of the supported measures.

propvars is for use with binary measures and specifies that the observations implied by the if and in conditions be interpreted as proportions of binary observations. The default action with binary measures treats all nonzero values as one (excluding missing values). With propvars, the values are confirmed to be between zero and one, inclusive. See [MV] ***measure_option*** for a discussion of the use of proportions with binary measures.

propcompares is for use with binary measures. It indicates that the comparison observations (those specified in the compare() option) are to be interpreted as proportions of binary observations. The default action with binary measures treats all nonzero values as one (excluding missing values). With propcompares, the values are confirmed to be between zero and one, inclusive. See [MV] ***measure_option*** for a discussion of the use of proportions with binary measures.

Remarks and examples

▷ Example 1

Programmers can determine which cluster solutions currently exist by using the cluster query command without specifying a cluster name to return the names of all currently defined clusters.

```
. use https://www.stata-press.com/data/r18/auto
(1978 automobile data)
. cluster k gear turn trunk mpg displ, k(6) name(grpk6L2) measure(L2) gen(g6l2)
. cluster k gear turn trunk mpg displ, k(7) name(grpk7L2) measure(L2) gen(g7l2)
. cluster kmed gear turn trunk mpg displ, k(6) name(grpk6L1) measure(L1) gen(g6l1)
. cluster kmed gear turn trunk mpg displ, k(7) name(grpk7L1) measure(L1) gen(g7l1)
. cluster dir
grpk7L1
grpk6L1
grpk7L2
grpk6L2
. cluster query
. return list
macros:
              r(names) : "grpk7L1 grpk6L1 grpk7L2 grpk6L2"
```

Here there are four cluster solutions. A programmer can further process the `r(names)` returned macro.
For example, to determine which current cluster solutions used kmeans clustering, we would loop
through these four cluster solution names and, for each one, call `cluster query` to determine its
properties.

```
. local clusnames 'r(names)'
. foreach cname of local clusnames {
  2.         cluster query 'cname'
  3.         if "'r(method)'" == "kmeans" {
  4.                 local kmeancls 'kmeancls' 'cname'
  5.         }
  6. }
. di "{tab}Cluster analyses using kmeans: 'kmeancls'"
          Cluster analyses using kmeans: grpk7L2 grpk6L2
```

Here we examined `r(method)`, which records the name of the cluster-analysis method. Two of the
four cluster solutions used kmeans.

◁

▷ Example 2

We interactively demonstrate `cluster set`, `cluster delete`, and `cluster query`, though in
practice these would be used within a program.

First, we add the name `myclus` to the master list of cluster analyses and, at the same time, set
the type, method, and similarity.

```
. cluster set myclus, addname type(madeup) method(fake) similarity(who knows)
. cluster query
. return list
macros:
              r(names) : "myclus grpk7L1 grpk6L1 grpk7L2 grpk6L2"
. cluster query myclus
. return list
macros:
               r(name) : "myclus"
        r(similarity) : "who knows"
           r(method) : "fake"
             r(type) : "madeup"
```

cluster query shows that myclus was successfully added to the master list of cluster analyses and that the attributes that were cluster set can also be obtained.

Now we add a reference to a variable. We will use the word group as the *tag* for a variable mygrpvar. We also add another item called xyz and associate some text with the xyz item.

```
. cluster set myclus, var(group mygrpvar) other(xyz some important info)

. cluster query myclus

. return list

macros:
              r(name) : "myclus"
            r(o1_val) : "some important info"
            r(o1_tag) : "xyz"
          r(groupvar) : "mygrpvar"
          r(v1_name) : "mygrpvar"
            r(v1_tag) : "group"
        r(similarity) : "who knows"
            r(method) : "fake"
              r(type) : "madeup"
```

The cluster query command returned the mygrpvar information in two ways. The first way is with r(v#_tag) and r(v#_name). Here there is only one variable associated with myclus, so we have r(v1_tag) and r(v1_name). This information allows the programmer to loop over all the stored variable names without knowing beforehand what the *tag*s might be or how many there are. You could loop as follows:

```
                local i 1
                while "`r(v`i'_tag)'" != "" {
                        ...
                        local ++i
                }
```

The second way the variable information is returned is in an r() result with the *tag* name appended by var, r(*tag*var). In our example, this is r(groupvar). This second method is convenient when, as the programmer, you know exactly which *varname* information you are seeking.

The same logic applies to characteristic attributes that are cluster set.

Now we continue with our interactive example:

```
. cluster delete myclus, method var(group)

. cluster set myclus, note(a note) note(another note) note(a third note)

. cluster query myclus

. return list

macros:
              r(name) : "myclus"
             r(note3) : "a third note"
             r(note2) : "another note"
             r(note1) : "a note"
            r(o1_val) : "some important info"
            r(o1_tag) : "xyz"
        r(similarity) : "who knows"
              r(type) : "madeup"
```

We used cluster delete to remove the method and the group variable we had associated with myclus. Three notes were then added simultaneously by using the note() option of cluster set. In practice, users will use the cluster notes command (see [MV] **cluster notes**) to add and delete cluster notes. The cluster notes command is implemented with the cluster set and cluster delete programming commands.

We finish our interactive demonstration of these commands by deleting more attributes from `myclus` and then eliminating `myclus`. In practice, users would remove a cluster analysis with the `cluster drop` command (see [MV] **cluster utility**), which is implemented with the `zap` option of the `cluster delete` command.

```
. cluster delete myclus, allnotes similarity
. cluster query myclus
. return list
macros:
              r(name) : "myclus"
            r(o1_val) : "some important info"
            r(o1_tag) : "xyz"
              r(type) : "madeup"
. cluster delete myclus, zap
. cluster query
. return list
macros:
             r(names) : "grpk7L1 grpk6L1 grpk7L2 grpk6L2"
```

The cluster attributes that are `cluster set` become a part of the dataset. They are saved with the dataset when it is `saved` and are available again when the dataset is `used`; see [D] **save**.

◁

❑ Technical note

You may wonder how Stata's cluster-analysis data structures are implemented. Stata data characteristics (see [P] **char**) hold the information. The details of the implementation are not important, and in fact, we encourage you to use the `set`, `delete`, and `query` subcommands to access the cluster attributes. This way, if we ever decide to change the underlying implementation, you will be protected through Stata's version-control feature.

❑

▷ Example 3

The `cluster parsedistance` programming command takes as an argument the name of a similarity or dissimilarity measure. Stata then checks this name against those that are implemented within Stata (and available to you through the `cluster measures` command). Uppercase or lowercase letters are allowed, and minimal abbreviations are checked. Some of the measures have aliases, which are resolved so that a standard measure name is returned. We demonstrate the `cluster parsedistance` command interactively:

```
. cluster parsedistance max
. sreturn list
macros:
             s(drange) : "0 ."
              s(dtype) : "dissimilarity"
               s(unab) : "maximum"
               s(dist) : "Linfinity"
. cluster parsedistance Eucl
. sreturn list
macros:
             s(drange) : "0 ."
              s(dtype) : "dissimilarity"
               s(unab) : "Euclidean"
               s(dist) : "L2"
. cluster parsedistance correl
```

```
. sreturn list

macros:
              s(drange) : "1 -1"
               s(dtype) : "similarity"
                s(unab) : "correlation"
                s(dist) : "correlation"

. cluster parsedistance jacc

. sreturn list

macros:
              s(drange) : "1 0"
              s(binary) : "binary"
               s(dtype) : "similarity"
                s(unab) : "Jaccard"
                s(dist) : "Jaccard"
```

cluster parsedistance returns s(dtype) as either similarity or dissimilarity. It returns
s(dist) as the standard Stata name for the (dis)similarity and returns s(unab) as the unabbreviated
standard Stata name. s(drange) gives the range of the measure (most similar to most dissimilar).
If the measure is designed for binary variables, s(binary) is returned with the word binary, as
seen above.

See [MV] *measure_option* for a listing of the similarity and dissimilarity measures and their
properties.

◁

▷ Example 4

cluster measures computes the similarity or dissimilarity measure between each comparison
observation and the observations implied by the if and in conditions (or all the data if no if or in
conditions are specified).

We demonstrate with the auto dataset:

```
. use https://www.stata-press.com/data/r18/auto, clear
(1978 automobile data)

. cluster measures turn trunk gear in 1/10, compare(3 11) gen(z3 z11) L1

. format z* %8.2f

. list turn trunk gear z3 z11 in 1/11
```

	turn	trunk	gear_r~o	z3	z11
1.	40	11	3.58	6.50	14.30
2.	40	11	2.53	6.55	13.25
3.	35	12	3.08	0.00	17.80
4.	40	16	2.93	9.15	8.65
5.	43	20	2.41	16.67	1.13
6.	43	21	2.73	17.35	2.45
7.	34	10	2.87	3.21	20.59
8.	42	16	2.93	11.15	6.65
9.	43	17	2.93	13.15	4.65
10.	42	13	3.08	8.00	9.80
11.	44	20	2.28	.	.

Using the three variables turn, trunk, and gear_ratio, we computed the L1 (or absolute value)
distance between the third observation and the first 10 observations and placed the results in the
variable z3. The distance between the 11th observation and the first 10 was placed in variable z11.

   There are many measures designed for binary data. Below we illustrate `cluster measures` with the matching coefficient binary similarity measure. We have 8 observations on 10 binary variables, and we will compute the matching similarity measure between the last 3 observations and all 8 observations.

```
. use https://www.stata-press.com/data/r18/clprogxmpl1, clear
. cluster measures x1-x10, compare(6/8) gen(z6 z7 z8) matching
. format z* %4.2f
. list
```

	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	z6	z7	z8
1.	1	0	0	0	1	1	0	0	1	1	0.60	0.80	0.40
2.	1	1	1	0	0	1	0	1	1	0	0.70	0.30	0.70
3.	0	0	1	0	0	0	1	0	0	1	0.60	0.40	0.20
4.	1	1	1	1	0	0	0	1	1	1	0.40	0.40	0.60
5.	0	1	0	1	1	0	1	0	0	1	0.20	0.60	0.40
6.	1	0	1	0	0	1	0	0	0	0	1.00	0.40	0.60
7.	0	0	0	1	1	1	0	0	1	1	0.40	1.00	0.40
8.	1	1	0	1	0	1	0	1	0	0	0.60	0.40	1.00

   Stata treats all nonzero observations as one (except missing values, which are treated as missing values) when computing these binary measures.

   When the similarity measure between binary observations and the means of groups of binary observations is needed, the `propvars` and `propcompares` options of `cluster measures` provide the solution. The mean of binary observations is a proportion. The value 0.2 would indicate that 20% of the values were one and 80% were zero for the group. See [MV] *measure_option* for a discussion of binary measures. The `propvars` option indicates that the main body of observations should be interpreted as proportions. The `propcompares` option specifies that the comparison observations be treated as proportions.

   We compare 10 binary observations on five variables to 2 observations holding proportions by using the `propcompares` option:

```
. use https://www.stata-press.com/data/r18/clprogxmpl2, clear
. cluster measures a* in 1/10, compare(11 12) gen(c1 c2) matching propcompare
. list
```

	a1	a2	a3	a4	a5	c1	c2
1.	1	1	1	0	1	.6	.56
2.	0	0	1	1	1	.36	.8
3.	1	0	1	0	0	.76	.56
4.	1	1	0	1	1	.36	.44
5.	1	0	0	0	0	.68	.4
6.	0	0	1	1	1	.36	.8
7.	1	0	1	0	1	.64	.76
8.	1	0	0	0	1	.56	.6
9.	0	1	1	1	1	.32	.6
10.	1	1	1	1	1	.44	.6
11.	.8	.4	.7	.1	.2	.	.
12.	.5	0	.9	.6	1	.	.

Stored results

cluster query with no arguments stores the following in r():

Macros
    r(names)   cluster solution names

cluster query with an argument stores the following in r():

Macros
    r(name)   cluster name
    r(type)   type of cluster analysis
    r(method)   cluster-analysis method
    r(similarity)   similarity measure name
    r(dissimilarity)   dissimilarity measure name
    r(note#)   cluster note number #
    r(v#_tag)   variable tag number #
    r(v#_name)   varname associated with r(v#_tag)
    r(tagvar)   varname associated with tag
    r(c#_tag)   characteristic tag number #
    r(c#_name)   characteristic name associated with r(c#_tag)
    r(c#_val)   characteristic value associated with r(c#_tag)
    r(tagchar)   characteristic name associated with tag
    r(o#_tag)   other tag number #
    r(o#_val)   other value associated with r(o#_tag)

cluster set stores the following in r():

Macros
    r(name)   cluster name

cluster parsedistance stores the following in s():

Macros
    s(dist)   (dis)similarity measure name
    s(unab)   unabbreviated (dis)similarity measure name (before resolving alias)
    s(darg)   argument of (dis)similarities that take them, such as L(#)
    s(dtype)   similarity or dissimilarity
    s(drange)   range of measure (most similar to most dissimilar)
    s(binary)   binary if the measure is for binary observations

cluster measures stores the following in r():

Macros
    r(generate)   variable names from the generate() option
    r(compare)   observation numbers from the compare() option
    r(dtype)   similarity or dissimilarity
    r(distance)   the name of the (dis)similarity measure
    r(binary)   binary if the measure is for binary observations

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **clustermat** — Introduction to clustermat commands

[MV] **cluster programming subroutines** — Add cluster-analysis routines

Title

> **cluster stop —** Cluster-analysis stopping rules

Description

cluster stop and clustermat stop compute the stopping-rule value for each cluster solution. The commands currently provide two stopping rules, the Caliński and Harabasz pseudo-F index and the Duda–Hart Je(2)/Je(1) index. For both rules, larger values indicate more distinct clustering. Presented with the Duda–Hart Je(2)/Je(1) values are pseudo-T^2 values. Smaller pseudo-T^2 values indicate more distinct clustering.

Users can add more stop rules; see [MV] **cluster programming subroutines**.

Quick start

Cluster analysis of data

Caliński–Harabasz pseudo-F index stopping rule for the most recent cluster analysis
        cluster stop

Duda–Hart Je(2)/Je(1) index stopping rule
        cluster stop, rule(duda)

Same as above, but use results for the 5–20-group solutions instead of the default 1–15-group solutions
        cluster stop, rule(duda) groups(5/20)

Same as above, but for cluster analysis results named myclus
        cluster stop myclus, rule(duda) groups(5/20)

Same as above, but use variables v1 and v2 to compute the stopping rule instead of the variables used in myclus
        cluster stop myclus, rule(duda) groups(5/20) variables(v1 v2)

Cluster analysis of dissimilarity matrix

Caliński–Harabasz pseudo-F index stopping rule computed using v1, v2, and v3 from results named mymatclus
        clustermat stop mymatclus, variables(v1 v2 v3)

Menu

Statistics > Multivariate analysis > Cluster analysis > Postclustering > Cluster analysis stopping rules

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Syntax

Cluster analysis of data

> cluster stop [*clname*] [, *options*]

Cluster analysis of a dissimilarity matrix

> clustermat stop [*clname*] , <u>var</u>iables(*varlist*) [*options*]

where *clname* is the name of the cluster analysis. The default is the most recently performed cluster analysis, which can be reset using the cluster use command; see [MV] **cluster utility**.

options	Description
<u>rule</u>(calinski)	use Caliński–Harabasz pseudo-F index stopping rule; the default
<u>rule</u>(duda)	use Duda–Hart Je(2)/Je(1) index stopping rule
<u>rule</u>(*rule_name*)	use *rule_name* stopping rule; see *Options* for details
groups(*numlist*)	compute stopping rule for specified groups
<u>matrix</u>(*matname*)	save results in matrix *matname*
* <u>var</u>iables(*varlist*)	compute the stopping rule using *varlist*

* variables(*varlist*) is required with a clustermat solution and optional with a cluster solution.

collect is allowed; see [U] **11.1.10 Prefix commands**.

rule(*rule_name*) is not shown in the dialog box. See [MV] **cluster programming subroutines** for information on how to add stopping rules to the cluster stop command.

Options

rule(calinski | duda | *rule_name*) indicates the stopping rule. rule(calinski), the default, specifies the Caliński–Harabasz pseudo-F index. rule(duda) specifies the Duda–Hart Je(2)/Je(1) index.

rule(calinski) is allowed for both hierarchical and nonhierarchical cluster analyses. rule(duda) is allowed only for hierarchical cluster analyses.

You can add stopping rules to the cluster stop command (see [MV] **cluster programming subroutines**) by using the rule(*rule_name*) option. [MV] **cluster programming subroutines** illustrates how to add stopping rules by showing a program that adds a rule(stepsize) option, which implements the simple step-size stopping rule mentioned in Milligan and Cooper (1985).

groups(*numlist*) specifies the cluster groupings for which the stopping rule is to be computed. groups(3/20) specifies that the measure be computed for the three-group solution, the four-group solution, ..., and the 20-group solution.

With rule(duda), the default is groups(1/15). With rule(calinski) for a hierarchical cluster analysis, the default is groups(2/15). groups(1) is not allowed with rule(calinski) because the measure is not defined for the degenerate one-group cluster solution. The groups() option is unnecessary (and not allowed) for a nonhierarchical cluster analysis.

If there are ties in the hierarchical cluster-analysis structure, some (or possibly all) of the requested stopping-rule solutions may not be computable. cluster stop passes over, without comment, the groups() for which ties in the hierarchy cause the stopping rule to be undefined.

`matrix(`*matname*`)` saves the results in a matrix named *matname*.

With `rule(calinski)`, the matrix has two columns, the first giving the number of clusters and the second giving the corresponding Caliński–Harabasz pseudo-F stopping-rule index.

With `rule(duda)`, the matrix has three columns: the first column gives the number of clusters, the second column gives the corresponding Duda–Hart Je(2)/Je(1) stopping-rule index, and the third column provides the corresponding pseudo-T^2 values.

`variables(`*varlist*`)` specifies the variables to be used in the computation of the stopping rule. By default, the variables used for the cluster analysis are used. `variables()` is required for cluster solutions produced by `clustermat`.

Remarks and examples

Cluster-analysis stopping rules are used to determine the number of clusters. A stopping-rule value (also called an index) is computed for each cluster solution (for example, at each level of the hierarchy in a hierarchical cluster analysis). Larger values (or smaller, depending on the particular stopping rule) indicate more distinct clustering. See [MV] **cluster** for background information on cluster analysis and on the `cluster` and `clustermat` commands.

Everitt et al. (2011) and Gordon (1999) discuss the problem of determining the number of clusters and describe several stopping rules, including the Caliński–Harabasz (1974) pseudo-F index and the Duda–Hart (2001, sec. 10.10) Je(2)/Je(1) index. There are many cluster stopping rules. Milligan and Cooper (1985) evaluate 30 stopping rules, singling out the Caliński–Harabasz index and the Duda–Hart index as two of the best rules.

Large values of the Caliński–Harabasz pseudo-F index indicate distinct clustering. The Duda–Hart Je(2)/Je(1) index has an associated pseudo-T^2 value. A large Je(2)/Je(1) index value and a small pseudo-T^2 value indicate distinct clustering. See *Methods and formulas* at the end of this entry for details.

Example 2 of [MV] **clustermat** shows the use of the `clustermat stop` command.

Some stopping rules such as the Duda–Hart index work only with a hierarchical cluster analysis. The Caliński–Harabasz index, however, may be applied to both nonhierarchical and hierarchical cluster analyses.

▷ Example 1

Previously, you ran kmeans cluster analyses on data where you measured the flexibility, speed, and strength of the 80 students in your physical education class; see example 1 of [MV] **cluster kmeans and kmedians**. Your original goal was to split the class into four groups, though you also examined the three- and five-group kmeans cluster solutions as possible alternatives.

Now out of curiosity, you wonder what the Caliński–Harabasz stopping rule shows for the three-, four-, and five-group solutions from a kmedian clustering of this dataset.

```
. use https://www.stata-press.com/data/r18/physed
. cluster kmed flex speed strength, k(3) name(kmed3) measure(abs) start(lastk)
. cluster kmed flex speed strength, k(4) name(kmed4) measure(abs)
> start(kr(93947))
. cluster kmed flex speed strength, k(5) name(kmed5) measure(abs)
> start(prand(16872))
```

```
. cluster stop kmed3
```

Number of clusters	Calinski/ Harabasz pseudo-F
3	132.75

```
. cluster stop kmed4
```

Number of clusters	Calinski/ Harabasz pseudo-F
4	337.10

```
. cluster stop kmed5
```

Number of clusters	Calinski/ Harabasz pseudo-F
5	300.45

The four-group solution with a Caliński–Harabasz pseudo-F value of 337.10 is largest, indicating that the four-group solution is the most distinct compared with the three-group and five-group solutions.

The three-group solution has a much lower stopping-rule value of 132.75. The five-group solution, with a value of 300.45, is reasonably close to the four-group solution.

Though you do not think it will change your decision on how to split your class into groups, you are curious to see what a hierarchical cluster analysis might produce. You decide to try an average-linkage cluster analysis using the default Euclidean distance; see [MV] **cluster linkage**. You examine the resulting cluster analysis with the `cluster tree` command, which is an easier-to-type alias for the `cluster dendrogram` command; see [MV] **cluster dendrogram**.

```
. cluster averagelink flex speed strength, name(avglnk)
. cluster tree avglnk, xlabel(, angle(90) labsize(*.5))
```


Dendrogram for avglnk cluster analysis
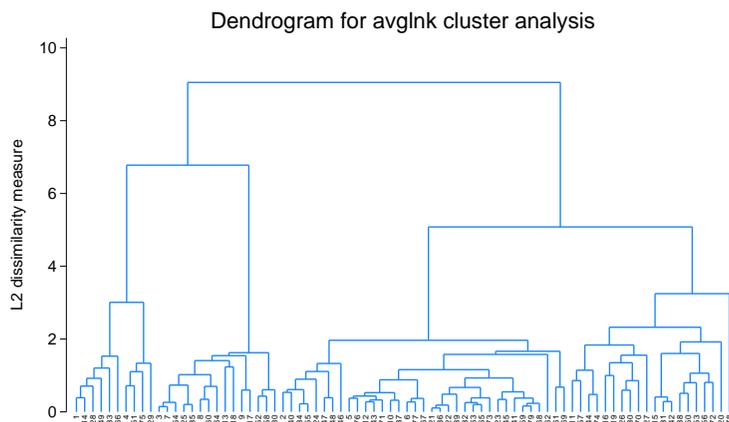
You are curious to see how the four- and five-group solutions from this hierarchical cluster analysis compare with the four- and five-group solutions from the kmedian clustering.

```
. cluster gen avgg = groups(4/5), name(avglnk)
. table kmed4 avgg4, nototals
```

	avgg4			
	1	2	3	4
Cluster ID				
1	10			
2			35	
3		15		
4				20

```
. table kmed5 avgg5, nototals
```

	avgg5				
	1	2	3	4	5
Cluster ID					
1			15		
2		15			
3				19	1
4			20		
5	10				

The four-group solutions are identical, except for the numbers used to label the groups. The five-group solutions are different. The kmedian clustering split the 35-member group into subgroups having 20 and 15 members. The average-linkage clustering instead split one member off from the 20-member group.

Now you examine the Caliński–Harabasz pseudo-F stopping-rule values associated with the kmedian hierarchical cluster analysis.

```
. cluster stop avglnk, rule(calinski)
```

Number of clusters	Calinski/ Harabasz pseudo-F
2	131.86
3	126.62
4	337.10
5	269.07
6	258.40
7	259.37
8	290.78
9	262.86
10	258.53
11	249.93
12	247.85
13	247.53
14	236.98
15	226.51

Because rule(calinski) is the default, you could have obtained this same table by typing

```
. cluster stop avglnk
```

or, because `avglnk` was the most recent cluster analysis performed, by typing

    . cluster stop

You did not specify the number of groups to examine from the hierarchical cluster analysis, so it defaulted to examining up to 15 groups. The highest Caliński–Harabasz pseudo-F value is 337.10 for the four-group solution.

What does the Duda–Hart stopping rule produce for this hierarchical cluster analysis?

    . cluster stop avglnk, rule(duda) groups(1/10)

Number of clusters	Je(2)/Je(1)	Duda/Hart pseudo T-squared
1	0.3717	131.86
2	0.1349	147.44
3	0.2283	179.19
4	0.8152	4.08
5	0.2232	27.85
6	0.5530	13.74
7	0.5287	29.42
8	0.6887	3.16
9	0.4888	8.37
10	0.7621	7.80

This time, we asked to see the results for one to 10 groups. The largest Duda–Hart Je(2)/Je(1) stopping-rule value is 0.8152, corresponding to four groups. The smallest pseudo-T^2 value is 3.16 for the eight-group solution, but the pseudo-T^2 value for the four-group solution is also low, with a value of 4.08.

Distinct clustering is characterized by large Caliński–Harabasz pseudo-F values, large Duda–Hart Je(2)/Je(1) values, and small Duda–Hart pseudo-T^2 values.

The conventional wisdom for deciding the number of groups based on the Duda–Hart stopping-rule table is to find one of the largest Je(2)/Je(1) values that corresponds to a low pseudo-T^2 value that has much larger T^2 values next to it. This strategy, combined with the results from the Caliński–Harabasz results, indicates that the four-group solution is the most distinct from this hierarchical cluster analysis.

◁

❑ Technical note

There is a good reason that the word "pseudo" appears in "pseudo-F" and "pseudo-T^2". Although these index values are based on well-known statistics, any p-values computed from these statistics would not be valid. Remember that cluster analysis searches for structure.

If you were to generate random observations, perform a cluster analysis, compute these stopping-rule statistics, and then follow that by computing what would normally be the p-values associated with the statistics, you would almost always end up with significant p-values.

Remember that you would expect, on average, five of every 100 groupings of your random data to show up as significant when you use .05 as your threshold for declaring significance. Cluster-analysis methods search for the best groupings, so there is no surprise that p-values show high significance, even when none exists.

Examining the stopping-rule index values relative to one another is useful, however, in finding relatively reasonable groupings that may exist in the data.

❑

❑ Technical note

As mentioned in *Methods and formulas*, ties in the hierarchical cluster structure cause some of the stopping-rule index values to be undefined. Discrete (as opposed to continuous) data tend to cause ties in a hierarchical clustering. The more discrete the data, the more likely it is that ties will occur (and the more of them you will encounter) within a hierarchy.

Even with so-called continuous data, ties in the hierarchical clustering can occur. We say "so-called" because most continuous data are truncated or rounded. For instance, miles per gallon, length, weight, etc., which may really be continuous, may be observed and recorded only to the tens, ones, tenths, or hundredths of a unit.

You can have data with no ties in the observations and still have many ties in the hierarchy. Ties in distances (or similarities) between observations and groups of observations cause the ties in the hierarchy.

Thus, do not be surprised when some (many) of the stopping-rule values that you request are not presented. Stata has decided not to break the ties arbitrarily, because the stopping-rule values may differ widely, depending on which split is made.

❑

❑ Technical note

The stopping rules also become less informative as the number of elements in the groups becomes small, that is, having many groups, each with few observations. We recommend that if you need to examine the stopping-rule values deep within your hierarchical cluster analysis, you do so skeptically.

❑

Stored results

cluster stop and clustermat stop with rule(calinski) stores the following in r():

Scalars
     r(calinski_#)   Caliński–Harabasz pseudo-F for # groups

Macros
     r(rule)   calinski
     r(label)   C-H pseudo-F
     r(longlabel)   Calinski & Harabasz pseudo-F

cluster stop and clustermat stop with rule(duda) stores the following in r():

Scalars
     r(duda_#)   Duda–Hart Je(2)/Je(1) value for # groups
     r(dudat2_#)   Duda–Hart pseudo-T^2 value for # groups

Macros
     r(rule)   duda
     r(label)   D-H Je(2)/Je(1)
     r(longlabel)   Duda & Hart Je(2)/Je(1)
     r(label2)   D-H pseudo-T-squared
     r(longlabel2)   Duda & Hart pseudo-T-squared

Methods and formulas

The Caliński–Harabasz pseudo-F stopping-rule index for g groups and N observations is

$$\frac{\text{trace}(\mathbf{B})/(g-1)}{\text{trace}(\mathbf{W})/(N-g)}$$

where $\mathbf{B}$ is the between-cluster sum of squares and cross-products matrix, and $\mathbf{W}$ is the within-cluster sum of squares and cross-products matrix.

Large values of the Caliński–Harabasz pseudo-F stopping-rule index indicate distinct cluster structure. Small values indicate less clearly defined cluster structure.

The Duda–Hart Je(2)/Je(1) stopping-rule index value is literally Je(2) divided by Je(1). Je(1) is the sum of squared errors within the group that is to be divided. Je(2) is the sum of squared errors in the two resulting subgroups.

Large values of the Duda–Hart pseudo-T^2 stopping-rule index indicate distinct cluster structure. Small values indicate less clearly defined cluster structure.

The Duda–Hart Je(2)/Je(1) index requires hierarchical clustering information. It needs to know at each level of the hierarchy which group is to be split and how. The Duda–Hart index is also local because the only information used comes from the group's being split. The information in the rest of the groups does not enter the computation.

In comparison, the Caliński–Harabasz rule does not require hierarchical information and is global because the information from each group is used in the computation.

A pseudo-T^2 value is also presented with the Duda and Hart Je(2)/Je(1) index. The relationship is

$$\frac{1}{\text{Je}(2)/\text{Je}(1)} = 1 + \frac{T^2}{N_1 + N_2 - 2}$$

where N_1 and N_2 are the numbers of observations in the two subgroups.

Je(2)/Je(1) will be zero when Je(2) is zero, that is, when the two subgroups each have no variability. An example of this is when the cluster being split has two distinct values that are being split into singleton subgroups. Je(1) will never be zero because we do not split groups that have no variability. When Je(2)/Je(1) is zero, the pseudo-T^2 value is undefined.

Ties in splitting a hierarchical cluster analysis create an ambiguity for the Je(2)/Je(1) measure. For example, to compute the measure for the case of going from five clusters to six, you need to identify the one cluster that will be split. With a tie in the hierarchy, you would instead go from five clusters directly to seven (just as an example). Stata refuses to produce an answer in this situation.

References

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Duda, R. O., P. E. Hart, and D. G. Stork. 2001. *Pattern Classification*. 2nd ed. New York: Wiley.

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Gordon, A. D. 1999. *Classification*. 2nd ed. Boca Raton, FL: Chapman and Hall/CRC.

Milligan, G. W., and M. C. Cooper. 1985. An examination of procedures for determining the number of clusters in a dataset. *Psychometrika* 50: 159–179. https://doi.org/10.1007/BF02294245.

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **clustermat** — Introduction to clustermat commands

Title

> **cluster utility** — List, rename, use, and drop cluster analyses

Description

These `cluster` utility commands allow you to view and manipulate the cluster objects that you have created. See [MV] **cluster** for an overview of cluster analysis and for the available `cluster` commands. If you want even more control over your cluster objects, or if you are programming new cluster subprograms, more `cluster` programmer utilities are available; see [MV] **cluster programming utilities** for details.

The `cluster dir` command provides a directory-style listing of all the currently defined clusters. `cluster list` provides a detailed listing of the specified clusters or of all current clusters if no cluster names are specified. The default action is to list all the information attached to the clusters. You may limit the type of information listed by specifying particular options.

The `cluster drop` command removes the named clusters. The keyword `_all` specifies that all current cluster analyses be dropped.

Stata cluster analyses are referred to by name. Many `cluster` commands default to using the most recently defined cluster analysis if no cluster name is provided. The `cluster use` command sets the specified cluster analysis as the most recently executed cluster analysis, so that, by default, this cluster analysis will be used if the cluster name is omitted from many of the `cluster` commands. You may use the * and ? name-matching characters to shorten the typing of cluster names; see [U] **11.2 Abbreviation rules**.

`cluster rename` allows you to rename a cluster analysis without changing any of the variable names attached to the cluster analysis. The `cluster renamevar` command, on the other hand, allows you to rename the variables attached to a cluster analysis and to update the cluster object with the new variable names. Do not use the `rename` command (see [D] **rename**) to rename variables attached to a cluster analysis because this would invalidate the cluster object. Use the `cluster renamevar` command instead.

Menu

cluster list

Statistics > Multivariate analysis > Cluster analysis > Postclustering > Detailed listing of clusters

cluster drop

Statistics > Multivariate analysis > Cluster analysis > Postclustering > Drop cluster analyses

cluster rename

Statistics > Multivariate analysis > Cluster analysis > Postclustering > Rename a cluster or cluster variables

Syntax

Directory-style listing of currently defined clusters

> cluster dir

Detailed listing of clusters

> cluster list [*clnamelist*] [, *list_options*]

Drop cluster analyses

> cluster drop { *clnamelist* | _all }

Mark a cluster analysis as the most recent one

> cluster use *clname*

Rename a cluster

> cluster rename *oldclname newclname*

Rename variables attached to a cluster

> cluster renamevar *oldvarname newvar* [, <u>name</u>(*clname*)]

> cluster renamevar *oldstub newstub* , <u>p</u>refix [<u>name</u>(*clname*)]

list_options	Description
Options	
<u>note</u>s	list cluster notes
<u>type</u>	list cluster analysis type
<u>method</u>	list cluster analysis method
<u>dissim</u>ilarity	list cluster analysis dissimilarity measure
<u>sim</u>ilarity	list cluster analysis similarity measure
<u>var</u>s	list variable names attached to the cluster analysis
<u>char</u>s	list any characteristics attached to the cluster analysis
<u>other</u>	list any "other" information
<u>all</u>	list all items and information attached to the cluster; the default

all does not appear in the dialog box.

Options for cluster list

> ┌─── Options ──

notes specifies that cluster notes be listed.

type specifies that the type of cluster analysis be listed.

method specifies that the cluster analysis method be listed.

dissimilarity specifies that the dissimilarity measure be listed.

similarity specifies that the similarity measure be listed.

vars specifies that the variables attached to the clusters be listed.

chars specifies that any Stata characteristics attached to the clusters be listed.

other specifies that information attached to the clusters under the heading "other" be listed.

The following option is available with cluster list but is not shown in the dialog box:

all, the default, specifies that all items and information attached to the cluster(s) be listed. You may instead pick among the notes, type, method, dissimilarity, similarity, vars, chars, and other options to limit what is presented.

Options for cluster renamevar

name(*clname*) indicates the cluster analysis within which the variable renaming is to take place. If name() is not specified, the most recently performed cluster analysis (or the one specified by cluster use) will be used.

prefix specifies that all variables attached to the cluster analysis that have *oldstub* as the beginning of their name be renamed, with *newstub* replacing *oldstub*.

Remarks and examples

▷ Example 1

We demonstrate these cluster utility commands by beginning with four already-defined cluster analyses. The dir and list subcommands provide listings of the cluster analyses.

```
. cluster dir
bcx3kmed
ayz5kmeans
abc_clink
xyz_slink
. cluster list xyz_slink
xyz_slink  (type: hierarchical,  method: single,  dissimilarity: L2)
     vars: xyz_slink_id (id variable)
           xyz_slink_ord (order variable)
           xyz_slink_hgt (height variable)
    other: cmd: cluster singlelinkage x y z, name(xyz_slink)
           varlist: x y z
           range: 0 .
```

```
. cluster list
bcx3kmed  (type: partition,  method: kmedians,  dissimilarity: L2)
      vars: bcx3kmed (group variable)
     other: cmd: cluster kmedians b c x, k(3) name(bcx3kmed)
            varlist: b c x
            k: 3
            start: krandom
            range: 0 .
ayz5kmeans  (type: partition,  method: kmeans,  dissimilarity: L2)
      vars: ayz5kmeans (group variable)
     other: cmd: cluster kmeans a y z, k(5) name(ayz5kmeans)
            varlist: a y z
            k: 5
            start: krandom
            range: 0 .
abc_clink  (type: hierarchical,  method: complete,  dissimilarity: L2)
      vars: abc_clink_id (id variable)
            abc_clink_ord (order variable)
            abc_clink_hgt (height variable)
     other: cmd: cluster completelinkage a b c, name(abc_clink)
            varlist: a b c
            range: 0 .
xyz_slink  (type: hierarchical,  method: single,  dissimilarity: L2)
      vars: xyz_slink_id (id variable)
            xyz_slink_ord (order variable)
            xyz_slink_hgt (height variable)
     other: cmd: cluster singlelinkage x y z, name(xyz_slink)
            varlist: x y z
            range: 0 .

. cluster list a*, vars
ayz5kmeans
      vars: ayz5kmeans (group variable)

abc_clink
      vars: abc_clink_id (id variable)
            abc_clink_ord (order variable)
            abc_clink_hgt (height variable)
```

`cluster dir` listed the names of the four currently defined cluster analyses. `cluster list` followed
by the name of one of the cluster analyses listed the information attached to that cluster analysis.
The `cluster list` command, without an argument, listed the information for all currently defined
cluster analyses. We demonstrated the `vars` option of `cluster list` to show that we can restrict
the information that is listed. Notice also the use of `a*` as the cluster name. The `*` here indicates that
any ending is allowed. For these four cluster analyses, Stata matches the names `ayz5kmeans` and
`abc_clink`.

   We now demonstrate the use of the `renamevar` subcommand.

```
. cluster renamevar ayz5kmeans g5km
variable ayz5kmeans not found in bcx3kmed
r(198);
. cluster renamevar ayz5kmeans g5km, name(ayz5kmeans)
. cluster list ayz5kmeans
ayz5kmeans  (type: partition,  method: kmeans,  dissimilarity: L2)
      vars: g5km (group variable)
     other: cmd: cluster kmeans a y z, k(5) name(ayz5kmeans)
            varlist: a y z
            k: 5
            start: krandom
            range: 0 .
```

The first use of `cluster renamevar` failed because we did not specify which cluster object to use (with the `name()` option), and the most recent cluster object, `bcx3kmed`, was not the appropriate one. After specifying the `name()` option with the appropriate cluster name, the `renamevar` subcommand changed the name as shown in the `cluster list` command that followed.

The `cluster use` command sets a particular cluster object as the default. We show this in conjunction with the `prefix` option of the `renamevar` subcommand.

```
. cluster use ayz5kmeans
. cluster renamevar g grp, prefix
. cluster renamevar xyz_slink_ wrk, prefix name(xyz*)
. cluster list ayz* xyz*
ayz5kmeans  (type: partition,  method: kmeans,  dissimilarity: L2)
      vars: grp5km (group variable)
     other: cmd: cluster kmeans a y z, k(5) name(ayz5kmeans)
            varlist: a y z
            k: 5
            start: krandom
            range: 0 .
xyz_slink  (type: hierarchical,  method: single,  dissimilarity: L2)
      vars: wrkid (id variable)
            wrkord (order variable)
            wrkhgt (height variable)
     other: cmd: cluster singlelinkage x y z, name(xyz_slink)
            varlist: x y z
            range: 0 .
```

The `cluster use` command placed `ayz5kmeans` as the current cluster object. The `cluster re-namevar` command that followed capitalized on this placement by leaving off the `name()` option. The `prefix` option allowed us to change the variable names, as demonstrated in the `cluster list` of the two changed cluster objects.

`cluster rename` changes the name of cluster objects. `cluster drop` allows us to drop some of or all the cluster objects.

```
. cluster rename xyz_slink bob
. cluster rename ayz* sam
. cluster list, type method vars
sam  (type: partition,  method: kmeans)
      vars: grp5km (group variable)
bob  (type: hierarchical,  method: single)
      vars: wrkid (id variable)
            wrkord (order variable)
            wrkhgt (height variable)
bcx3kmed  (type: partition,  method: kmedians)
      vars: bcx3kmed (group variable)
abc_clink  (type: hierarchical,  method: complete)
      vars: abc_clink_id (id variable)
            abc_clink_ord (order variable)
            abc_clink_hgt (height variable)
. cluster drop bcx3kmed abc_clink
. cluster dir
sam
bob
. cluster drop _all
. cluster dir
```

We used options with `cluster list` to limit what was presented. The `_all` keyword with `cluster drop` removed all currently defined cluster objects.

◁

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **cluster notes** — Cluster analysis notes

[MV] **cluster programming utilities** — Cluster-analysis programming utilities

[MV] **clustermat** — Introduction to clustermat commands

[D] **notes** — Place notes in data

[P] **char** — Characteristics

Title

discrim — Discriminant analysis

Description

discrim performs discriminant analysis, which is also known as classification. kth-nearest-neighbor (KNN) discriminant analysis, linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), and logistic discriminant analysis are available.

Syntax

discrim *subcommand* ... $\left[\, , \, ... \right]$

subcommand	Description
knn	kth-nearest-neighbor discriminant analysis
lda	linear discriminant analysis
logistic	logistic discriminant analysis
qda	quadratic discriminant analysis

Remarks and examples

Remarks are presented under the following headings:

> *Introduction*
> *A simple example*
> *Prior probabilities, costs, and ties*

Introduction

Discriminant analysis is used to describe the differences between groups and to exploit those differences in allocating (classifying) observations of unknown group membership to the groups. Discriminant analysis is also called classification in many references. However, several sources use the word classification to mean cluster analysis.

Some applications of discriminant analysis include medical diagnosis, market research, classification of specimens in anthropology, predicting company failure or success, placement of students (workers) based on comparing pretest results to those of past students (workers), discrimination of natural versus man-made seismic activity, fingerprint analysis, image pattern recognition, and signal pattern classification.

Most multivariate statistics texts have chapters on discriminant analysis, including Rencher (1998), Rencher and Christensen (2012), Johnson and Wichern (2007), Mardia, Kent, and Bibby (1979), Anderson (2003), Everitt and Dunn (2001), Tabachnick and Fidell (2019), and Albert and Harris (1987). Books dedicated to discriminant analysis include Lachenbruch (1975), Klecka (1980), Hand (1981), Huberty (1994), McLachlan (2004), and Afifi et al. (2020). Of these, McLachlan (2004) gives the most extensive coverage, including 60 pages of references.

If you lack observations with known group membership, use cluster analysis to discover the natural groupings in the data; see [MV] **cluster**. If you have data with known group membership, possibly with other data of unknown membership to be classified, use discriminant analysis to examine the differences between the groups, based on data where membership is known, and to assign group membership for cases where membership is unknown.

Some researchers are not interested in classifying unknown observations and are interested only in the descriptive aspects of discriminant analysis. For others, the classification of unknown observations is the primary consideration. Huberty (1994), Rencher (1998), Rencher and Christensen (2012), and others split their discussion of discrimination into two parts. Huberty labels the two parts descriptive discriminant analysis and predictive discriminant analysis. Rencher and Christensen reserve discriminant analysis for descriptive discriminant analysis and uses the label classification for predictive discriminant analysis.

There are many discrimination methods. discrim has both descriptive and predictive LDA; see [MV] **discrim lda**. If your interest is in descriptive LDA, candisc computes the same thing as discrim lda, but with output tailored for the descriptive aspects of the discrimination; see [MV] **candisc**.

The remaining discrim subcommands provide alternatives to LDA for predictive discrimination. [MV] **discrim qda** provides quadratic discriminant analysis (QDA). [MV] **discrim logistic** provides logistic discriminant analysis. [MV] **discrim knn** provides kth-nearest-neighbor (KNN) discrimination.

The discriminant analysis literature uses conflicting terminology for several features of discriminant analysis. For example, in descriptive LDA, what one source calls a classification function another source calls a discriminant function while calling something else a classification function. Check the *Methods and formulas* sections for the discrim subcommands for clarification.

A simple example

We demonstrate the predictive and descriptive aspects of discriminant analysis with a simple example.

▷ Example 1: Discriminant analysis for prediction

Johnson and Wichern (2007, 578) introduce the concepts of discriminant analysis with a two-group dataset. A sample of 12 riding-lawnmower owners and 12 nonowners is sampled from a city and the income in thousands of dollars and lot size in thousands of square feet are recorded. A riding-mower manufacturer wants to see if these two variables adequately separate owners from nonowners, and if so to then direct their marketing on the basis of the separation of owners from nonowners.

```
. use https://www.stata-press.com/data/r18/lawnmower2
(Johnson and Wichern (2007) table 11.1)
```

Riding-mower ownership
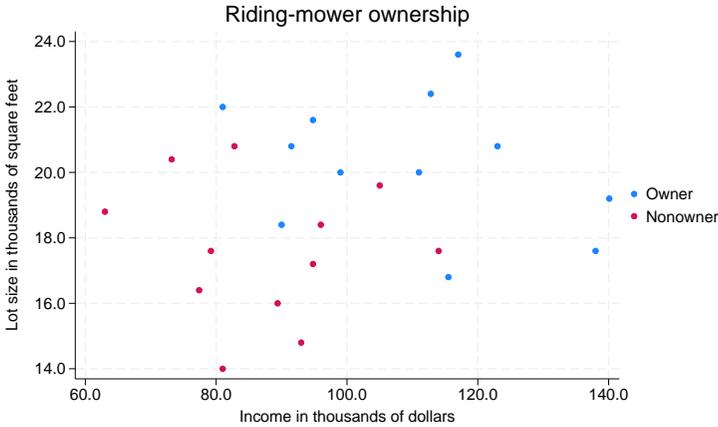
Do these two variables adequately separate riding-mower owners from nonowners so that the riding-mower manufacturer can base predictions of riding-mower ownership on income and lot size? The graph shows some separation of owners from nonowners, but with overlap. With predictive LDA we can quantify our ability to discriminate between riding-mower owners and nonowners.

```
. discrim lda lotsize income, group(owner)
Linear discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True owner	Classified Nonowner	Owner	Total
Nonowner	10	2	12
	83.33	16.67	100.00
Owner	1	11	12
	8.33	91.67	100.00
Total	11	13	24
	45.83	54.17	100.00
Priors	0.5000	0.5000	

The table presented by `discrim lda` (and the other `discrim` subcommands) is called a classification table or confusion matrix. It is labeled as a resubstitution classification table because the same observations used in estimating the discriminant model were classified using the model. The diagonal elements in the main body of the table show the number and percent correctly classified into each group. The off-diagonal elements show the misclassified number and percent. One owner and two nonowners were misclassified.

The resubstitution classification table provides an overly optimistic assessment of how well the linear discriminant function will predict the ownership status for observations that were not part of the training sample. A leave-one-out classification table provides a more realistic assessment for future prediction. The leave-one-out classification is produced by holding each observation out, one at a time; building an LDA model from the remaining training observations; and then classifying the held

out observation using this model. The leave-one-out classification table is available at estimation time, at playback, or through the `estat classtable` postestimation command.

```
. estat classtable, loo nopriors
```

Leave-one-out classification table

```
┌──────────┐
│   Key    │
├──────────┤
│  Number  │
│  Percent │
└──────────┘
```

	LOO Classified		
True owner	Nonowner	Owner	Total
Nonowner	9	3	12
	75.00	25.00	100.00
Owner	2	10	12
	16.67	83.33	100.00
Total	11	13	24
	45.83	54.17	100.00

With leave-one-out classification we see that 5, instead of only 3, of the 24 observations are misclassified.

The `predict` and `estat` commands provide other predictive discriminant analysis tools. `predict` generates variables containing the posterior probabilities of group membership or generates a group membership classification variable. `estat` displays classification tables, displays error-rate tables, and lists classifications and probabilities for the observations.

We now use `estat list` to show the resubstitution and leave-one-out classifications and posterior probabilities for those observations that were misclassified by our LDA model.

```
. estat list, class(loo) probabilities(loo) misclassified
```

	Classification			Probabilities		LOO Probabilities	
Obs	True	Class.	LOO Cl.	Nonowner	Owner	Nonowner	Owner
1	Owner	Nonown *	Nonown *	0.7820	0.2180	0.8460	0.1540
2	Owner	Owner	Nonown *	0.4945	0.5055	0.6177	0.3823
13	Nonown	Owner *	Owner *	0.2372	0.7628	0.1761	0.8239
14	Nonown	Nonown	Owner *	0.5287	0.4713	0.4313	0.5687
17	Nonown	Owner *	Owner *	0.3776	0.6224	0.2791	0.7209

`*` indicates misclassified observations

◁

We have used `discrim lda` to illustrate predictive discriminant analysis. The other `discrim` subcommands could also be used for predictive discrimination of these data.

Postestimation commands after `discrim lda` provide descriptive discriminant analysis; see [MV] **discrim lda postestimation** and [MV] **candisc**.

▷ Example 2: Discriminant analysis for description

The riding-mower manufacturer of the previous example wants to understand how income and lot size affect riding-mower ownership. Descriptive discriminant analysis provides tools for exploring

how the groups are separated. Fisher's (1936) linear discriminant functions provide the basis for descriptive LDA; see [MV] **discrim lda** and [MV] **discrim lda postestimation**. The postestimation command `estat loadings` allows us to view the discriminant function coefficients, which are also called loadings.

```
. estat loadings, standardized unstandardized
```

Canonical discriminant function coefficients

	function1
lotsize	.3795228
income	.0484468
_cons	-11.96094

Standardized canonical discriminant function coefficients

	function1
lotsize	.7845512
income	.8058419

We requested both the unstandardized and standardized coefficients. The unstandardized coefficients apply to unstandardized variables. The standardized coefficients apply to variables standardized using the pooled within-group covariance. Standardized coefficients are examined to assess the relative importance of the variables to the discriminant function.

The unstandardized coefficients determine the separating line between riding-mower owners and nonowners.

$$0 = 0.3795228\ \texttt{lotsize} + 0.0484468\ \texttt{income} - 11.96094$$

which can be reexpressed as

$$\texttt{lotsize} = -0.1276519\ \texttt{income} + 31.51574$$

We now display this line superimposed on the scatterplot of the data.
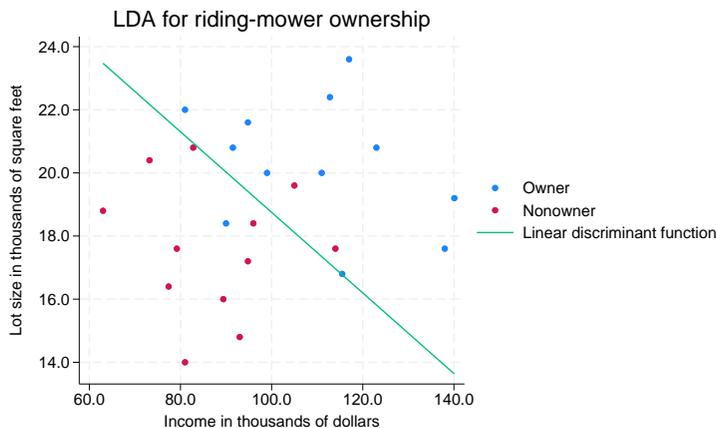
Other descriptive statistics and summaries are available; see [MV] **discrim lda postestimation**.

◁

Prior probabilities, costs, and ties

Classification is influenced by the selection of prior probabilities, assignment of costs to misclassification, and the method of handling ties in classification criteria.

Prior probabilities are the presumptive or a priori probabilities of group membership. Before you flip a balanced coin 10 times, you know the prior probability of getting heads is the same as getting tails—both are 0.5. Group prior probabilities, commonly called priors, must be taken into account in calculations of posterior probabilities; see *Methods and formulas* for details.

If the cost of misclassification is not equal over the groups, an optimal classification into groups must take misclassification cost into account. When there are two groups, members of the first group can be classified into the second, or members of the second group can be classified into the first. The relative undesirability of these two misclassifications may not be the same. Example 3 of [MV] **discrim knn** classifies poisonous and edible mushrooms. Misclassifying poisonous mushrooms as edible is a big deal at dinnertime.

The expected misclassification cost is the sum of the products of the cost for each misclassification multiplied by the probability of its occurrence. Let p_{ij} be the probability that an observation from group i is classified into group j, let c_{ij} be the cost of misclassifying an observation from group i into group j, and let q_i be the prior probability that the observation is from group i. The expected cost of misclassification is then

$$\text{cost} = \sum_{i,j\neq i}^{g} c_{ij}p_{ij}q_i$$

It is this expected cost that we wish to minimize. In the two-group case

$$\text{cost} = c_{12}p_{12}q_1 + c_{21}p_{21}q_2$$

and we can use cost-adjusted group prior probabilities, $\widehat{q}_i$, in the place of the prior probabilities to minimize the cost of misclassification.

$$\widehat{q}_1 = \frac{c_{12}q_1}{c_{12}q_1 + c_{21}q_2}$$

$$\widehat{q}_2 = \frac{c_{21}q_2}{c_{12}q_1 + c_{21}q_2}$$

With more than two groups, there is often not a simple rule to take costs into account. More discussion on this topic is provided by McLachlan (2004, 7–9), Huberty (1994, 68–69), Johnson and Wichern (2007, 606–609), and Anderson (2003, chap. 6).

See example 3 of [MV] **discrim knn** for an application of costs.

A tie in classification occurs when two or more group posterior probabilities are equal for an observation. Ties are most common with kth-nearest-neighbor discriminant analysis, though they can occur in other forms of discriminant analysis. There are several options for assigning tied observations. The default is to mark the observation as unclassified, that is, classified to a missing value. Ties can also be broken. For most forms of discriminant analysis ties can be broken in two ways—randomly or assigned to the first group that is tied. For kth-nearest-neighbor discriminant analysis, dissimilarities are calculated, and so ties may also be broken by choosing the group of the nearest of the tied observations. If this still results in a tie, the observation is unclassified.

Methods and formulas

See [MV] **discrim lda** for the methods and formulas for descriptive discriminant analysis.

For predictive discriminant analysis, let g be the number of groups, n_i the number of observations for group i, and q_i the prior probability for group i. Let $\mathbf{x}$ denote an observation measured on p discriminating variables. For consistency with the discriminant analysis literature, $\mathbf{x}$ will be a column vector, though it corresponds to a row in your dataset. Let $f_i(\mathbf{x})$ represent the density function for group i, and let $P(\mathbf{x}|G_i)$ denote the probability of observing $\mathbf{x}$ conditional on belonging to group i. Denote the posterior probability of group i given observation $\mathbf{x}$ as $P(G_i|\mathbf{x})$. With Bayes' theorem, we have

$$P(G_i|\mathbf{x}) = \frac{q_i f_i(\mathbf{x})}{\sum_{j=1}^{g} q_j f_j(\mathbf{x})}$$

Substituting $P(\mathbf{x}|G_i)$ for $f_i(\mathbf{x})$, we have

$$P(G_i|\mathbf{x}) = \frac{q_i P(\mathbf{x}|G_i)}{\sum_{j=1}^{g} q_j P(\mathbf{x}|G_j)}$$

An observation is classified as belonging to the group with the highest posterior probability.

The difference between the `discrim` subcommands is in the choice of $f_i(\mathbf{x})$. LDA, `discrim lda`, assumes that the groups are multivariate normal with equal covariance matrices; see [MV] **discrim lda**. QDA, `discrim qda`, assumes that the groups are multivariate normal, allowing the groups to have unequal covariance matrices; see [MV] **discrim qda**. Logistic discriminant analysis, `discrim logistic`, uses the multinomial logistic model to obtain the posterior probabilities; see [MV] **discrim logistic**. kth-nearest neighbor, `discrim knn`, uses a simple nonparametric estimate of $f_i(\mathbf{x})$, based on examination of the k closest observations; see [MV] **discrim knn**.

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Also see

[MV] **discrim estat** — Postestimation tools for discrim

[MV] **candisc** — Canonical linear discriminant analysis

[MV] **cluster** — Introduction to cluster-analysis commands

[U] **20 Estimation and postestimation commands**

Title

> **discrim estat —** Postestimation tools for discrim

Postestimation commands

The following postestimation commands are of special interest after `candisc`, `discrim knn`, `discrim lda`, `discrim logistic`, and `discrim qda`:

Command	Description
estat classtable	classification table
estat errorrate	classification error-rate estimation
estat grsummarize	group summaries
estat list	classification listing
estat summarize	estimation sample summary

There are more postestimation commands of special interest after `discrim lda` and `discrim qda`; see [MV] **discrim lda postestimation** and [MV] **discrim qda postestimation**.

Description for estat

`estat classtable` displays a cross-tabulation of the original groups with the classification groups. Classification percentages, average posterior probabilities, group prior probabilities, totals, and leave-one-out results are available.

`estat errorrate` displays error-rate estimates for the classification. Count-based estimates and both stratified and unstratified posterior-probability-based estimates of the error rate are available. These estimates can be resubstitution or leave-one-out estimates.

`estat grsummarize` presents estimation sample summary statistics for the discriminating variables for each group defined by the grouping variable. Means, medians, minimums, maximums, standard deviations, coefficients of variation, standard errors of the means, and group sizes may be displayed. Overall sample statistics are also available.

`estat list` lists group membership, classification, and probabilities for observations.

`estat summarize` summarizes the variables in the discriminant analysis over the estimation sample.

Quick start for estat

Classification table

Classification table computed using proportional prior probabilities

```
estat classtable, priors(proportional)
```

Leave-one-out classification table showing average posterior probability of classification into each group

```
estat classtable, looclass probabilities
```

Classification error-rate estimation

Error-rate table estimated from leave-one-out error count

```
estat errorrate, looclass
```

Error rates estimated from posterior probabilities using proportional prior probabilities

```
estat errorrate, pp priors(proportional)
```

Group summaries

Summary statistics by group

```
estat grsummarize
```

Mean, median, standard deviation, minimum, and maximum by group

```
estat grsummarize, mean median sd min max
```

Classification listing

Listing of group membership, classification, and probabilities including the leave-one-out results

```
estat list, classification(looclass) probabilities(loopr)
```

Same as above, but suppress the resubstitution classification

```
estat list, classification(looclass noclass)   ///
      probabilities(loopr nopr)
```

Estimation sample summary

Summary of variables from the most recent discriminant analysis and displaying variable labels

```
estat summarize, labels
```

Menu for estat

Statistics > Postestimation

Syntax for estat

Classification table

   estat <u>class</u>table $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$ *weight* $\big]$ $\big[$, *classtable_options* $\big]$

Classification error-rate estimation

   estat <u>err</u>orrate $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$ *weight* $\big]$ $\big[$, *errorrate_options* $\big]$

Group summaries

   estat <u>grsummarize</u> $\big[$, *grsummarize_options* $\big]$

Classification listing

   estat <u>list</u> $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$, *list_options* $\big]$

Estimation sample summary

   estat <u>summarize</u> $\big[$, <u>labels</u> <u>noheader</u> <u>noweights</u> $\big]$

classtable_options	Description
Main	
class	display the classification table; the default
looclass	display the leave-one-out classification table
Options	
priors(*priors*)	group prior probabilities; defaults to e(grouppriors)
nopriors	suppress display of prior probabilities
ties(*ties*)	how ties in classification are to be handled; defaults to e(ties)
title(*text*)	title for classification table
probabilities	display the average posterior probability of being classified into each group
nopercents	suppress display of percentages
nototals	suppress display of row and column totals
norowtotals	suppress display of row totals
nocoltotals	suppress display of column totals

priors	Description
equal	equal prior probabilities
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
<u>miss</u>ing	ties in group classification produce missing values
<u>r</u>andom	ties in group classification are broken randomly
<u>f</u>irst	ties in group classification are set to the first tied group
<u>n</u>earest	ties in group classification are assigned based on the closest observation, or missing if this still results in a tie; after discrim knn only

errorrate_options	Description
Main	
class	display the classification-based error-rate estimates table; the default
looclass	display the leave-one-out classification-based error-rate estimates table
count	use a count-based error-rate estimate
pp [(*ppopts*)]	use a posterior-probability-based error-rate estimate
Options	
<u>prior</u>s(*priors*)	group prior probabilities; defaults to e(grouppriors)
<u>nopri</u>ors	suppress display of prior probabilities
<u>ti</u>es(*ties*)	how ties in classification are to be handled; defaults to e(ties)
<u>tit</u>le(*text*)	title for error-rate estimate table
<u>noto</u>tal	suppress display of total column

ppopts	Description
<u>strat</u>ified	present stratified results
<u>uns</u>tratified	present unstratified results

grsummarize_options	Description
Main	
n [(*%fmt*)]	group sizes
<u>mea</u>n [(*%fmt*)]	means
<u>median</u> [(*%fmt*)]	medians
sd [(*%fmt*)]	standard deviations
cv [(*%fmt*)]	coefficients of variation
<u>seme</u>an [(*%fmt*)]	standard errors of the means
min [(*%fmt*)]	minimums
max [(*%fmt*)]	maximums
Options	
<u>noto</u>tal	suppress overall statistics
<u>transpose</u>	display groups by row instead of column

list_options	Description
Main	
<u>mis</u>classified	list only misclassified and unclassified observations
classification(*clopts*)	control display of classification
probabilities(*propts*)	control display of probabilities
<u>var</u>list[(*varopts*)]	display discriminating variables
[<u>no</u>]obs	display or suppress the observation number
<u>id</u>(*varname* [<u>for</u>mat(%*fmt*)])	display identification variable
Options	
<u>weight</u>[(*weightopts*)]	display frequency weights
<u>priors</u>(*priors*)	group prior probabilities; defaults to e(grouppriors)
<u>ties</u>(*ties*)	how ties in classification are to be handled; defaults to e(ties)
<u>sep</u>arator(#)	display a horizontal separator every # lines

clopts	Description
<u>noclass</u>	do not display the standard classification
<u>looclass</u>	display the leave-one-out classification
<u>notrue</u>	do not show the group variable
<u>nostar</u>	do not display stars indicating misclassified observations
<u>nolabel</u>	suppress display of value labels for the group and classification variables
<u>for</u>mat(%*fmt*)	format for group and classification variables; default is %5.0f for unlabeled numeric variables

propts	Description
<u>nopr</u>	suppress display of standard posterior probabilities
<u>loopr</u>	display leave-one-out posterior probabilities
<u>for</u>mat(%*fmt*)	format for probabilities; default is format(%7.4f)

varopts	Description
<u>none</u>	do not display discriminating variables; the default
<u>first</u>	display input variables before classifications and probabilities
<u>last</u>	display input variables after classifications and probabilities
<u>for</u>mat(%*fmt*)	format for input variables; default is the input variable format

weightopts	Description
<u>none</u>	do not display the weights
<u>for</u>mat(%*fmt*)	format for the weight; default is %3.0f for weights < 1,000, %5.0f for 1,000 < weights < 100,000, and %8.0g otherwise

collect is allowed with estat classtable, estat errorrate, estat grsummarize, and estat summarize; see [U] **11.1.10 Prefix commands**.

fweights are allowed; see [U] **11.1.6 weight**.

Options for estat

Options are presented under the following headings:

> Options for estat classtable
> Options for estat errorrate
> Options for estat grsummarize
> Options for estat list
> Options for estat summarize

Options for estat classtable

   ┌─────┐
   │ Main │

class, the default, displays the classification table. With in-sample observations, this is called the resubstitution classification table.

looclass displays a leave-one-out classification table, instead of the default classification table. Leave-one-out classification applies only to the estimation sample, and so, in addition to restricting the observations to those chosen with if and in qualifiers, the observations are further restricted to those included in e(sample).

   ┌────────┐
   │ Options │

priors(*priors*) specifies the prior probabilities for group membership. If priors() is not specified, e(grouppriors) is used. If nopriors is specified with priors(), prior probabilities are used for calculation of the classification variable but not displayed. The following *priors* are allowed:

priors(equal) specifies equal prior probabilities.

priors(proportional) specifies group-size-proportional prior probabilities.

priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

nopriors suppresses display of the prior probabilities. This option does not change the computations that rely on the prior probabilities specified in priors() or as found by default in e(grouppriors).

ties(*ties*) specifies how ties in group classification will be handled. If ties() is not specified, e(ties) determines how ties are handled. The following *ties* are allowed:

ties(missing) specifies that ties in group classification produce missing values.

ties(random) specifies that ties in group classification are broken randomly.

ties(first) specifies that ties in group classification are set to the first tied group.

ties(nearest) specifies that ties in group classification are assigned based on the closest observation, or missing if this still results in a tie. ties(nearest) is available after discrim knn only.

title(*text*) customizes the title for the classification table.

probabilities specifies that the classification table show the average posterior probability of being classified into each group. probabilities implies norowtotals and nopercents.

nopercents specifies that percentages are to be omitted from the classification table.

nototals specifies that row and column totals are to be omitted from the classification table.

norowtotals specifies that row totals are to be omitted from the classification table.

nocoltotals specifies that column totals are to be omitted from the classification table.

Options for estat errorrate

⌐ Main

class, the default, specifies that the classification-based error-rate estimates table be presented. The
    alternative to class is looclass.

looclass specifies that the leave-one-out classification error-rate estimates table be presented.

count, the default, specifies that the error-rate estimates be based on misclassification counts. The
    alternative to count is pp().

pp ⌈ (*ppopts*) ⌉ specifies that the error-rate estimates be based on posterior probabilities. pp is equivalent
    to pp(stratified unstratified). stratified indicates that stratified estimates be presented.
    unstratified indicates that unstratified estimates be presented. One or both may be specified.

⌐ Options

priors(*priors*) specifies the prior probabilities for group membership. If priors() is not specified,
    e(grouppriors) is used. If nopriors is specified with priors(), prior probabilities are used
    for calculation of the error-rate estimates but not displayed. The following *priors* are allowed:

  priors(equal) specifies equal prior probabilities.

  priors(proportional) specifies group-size-proportional prior probabilities.

  priors(*matname*) specifies a row or column vector containing the group prior probabilities.

  priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group
      prior probabilities.

nopriors suppresses display of the prior probabilities. This option does not change the computations
    that rely on the prior probabilities specified in priors() or as found by default in e(grouppriors).

ties(*ties*) specifies how ties in group classification will be handled. If ties() is not specified,
    e(ties) determines how ties are handled. The following *ties* are allowed:

  ties(missing) specifies that ties in group classification produce missing values.

  ties(random) specifies that ties in group classification are broken randomly.

  ties(first) specifies that ties in group classification are set to the first tied group.

  ties(nearest) specifies that ties in group classification are assigned based on the closest
      observation, or missing if this still results in a tie. ties(nearest) is available after discrim
      knn only.

title(*text*) customizes the title for the error-rate estimates table.

nototal suppresses the total column containing overall sample error-rate estimates.

Options for estat grsummarize

> [Main]

n [(%*fmt*)] specifies that group sizes be presented. The optional argument provides a display format. The default options are n and mean.

mean [(%*fmt*)] specifies that means be presented. The optional argument provides a display format. The default options are n and mean.

median [(%*fmt*)] specifies that medians be presented. The optional argument provides a display format.

sd [(%*fmt*)] specifies that standard deviations be presented. The optional argument provides a display format.

cv [(%*fmt*)] specifies that coefficients of variation be presented. The optional argument provides a display format.

semean [(%*fmt*)] specifies that standard errors of the means be presented. The optional argument provides a display format.

min [(%*fmt*)] specifies that minimums be presented. The optional argument provides a display format.

max [(%*fmt*)] specifies that maximums be presented. The optional argument provides a display format.

> [Options]

nototal suppresses display of the total column containing overall sample statistics.

transpose specifies that the groups are to be displayed by row. By default, groups are displayed by column. If you have more variables than groups, you might prefer the output produced by transpose.

Options for estat list

> [Main]

misclassified lists only misclassified and unclassified observations.

classification(*clopts*) controls display of the group variable and classification. By default, the standard classification is calculated and displayed along with the group variable in e(groupvar), using labels from the group variable if they exist. *clopts* may be one or more of the following:

noclass suppresses display of the standard classification. If the observations are those used in the estimation, classification is called resubstitution classification.

looclass specifies that the leave-one-out classification be calculated and displayed. The default is that the leave-one-out classification is not calculated. looclass is not allowed after discrim logistic.

notrue suppresses the display of the group variable. By default, e(groupvar) is displayed. notrue implies nostar.

nostar suppresses the display of stars indicating misclassified observations. A star is displayed by default when the classification is not in agreement with the group variable. nostar is the default when notrue is specified.

nolabel specifies that value labels for the group variable, if they exist, not be displayed for the group or classification or used as labels for the probability column names.

format(%*fmt*) specifies the format for the group and classification variables. If value labels are used, string formats are permitted.

probabilities(*propts*) controls the display of group posterior probabilities. *propts* may be one or more of the following:

  nopr suppresses display of the standard posterior probabilities. By default, the posterior probabilities are shown.

  loopr specifies that leave-one-out posterior probabilities be displayed. loopr is not allowed after discrim logistic.

  format(%*fmt*) specifies the format for displaying probabilities. The default is format(%7.4f).

varlist ⌈(*varopts*)⌉ specifies that the discriminating variables found in e(varlist) be displayed and specifies the display options for the variables.

  none specifies that discriminating variables are not to be displayed. This is the default.

  first specifies variables be displayed before classifications and probabilities.

  last specifies variables be displayed after classifications and probabilities.

  format(%*fmt*) specifies the format for the input variables. By default, the variable's format is used.

⌈no⌉obs indicates that observation numbers be or not be displayed. Observation numbers are displayed by default unless id() is specified.

id(*varname* ⌈format(%*fmt*)⌉) specifies the identification variable to display and, optionally, the format for that variable. By default, the format of *varname* is used.

┌─ Options ───

weight⌈(*weightopts*)⌉ specifies options for displaying weights. By default, if e(wexp) exists, weights are displayed.

  none specifies weights not be displayed. This is the default if weights were not used with discrim.

  format(%*fmt*) specifies a display format for the weights. If the weights are < 1,000, %3.0f is the default, %5.0f is the default if 1,000 < weights < 100,000, else %8.0g is used.

priors(*priors*) specifies the prior probabilities for group membership. If priors() is not specified, e(grouppriors) is used. The following *priors* are allowed:

  priors(equal) specifies equal prior probabilities.

  priors(proportional) specifies group-size-proportional prior probabilities.

  priors(*matname*) specifies a row or column vector containing the group prior probabilities.

  priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. If ties() is not specified, e(ties) determines how ties are handled. The following *ties* are allowed:

  ties(missing) specifies that ties in group classification produce missing values.

  ties(random) specifies that ties in group classification are broken randomly.

  ties(first) specifies that ties in group classification are set to the first tied group.

  ties(nearest) specifies that ties in group classification are assigned based on the closest observation, or missing if this still results in a tie. ties(nearest) is available after discrim knn only.

separator(#) specifies a horizontal separator line be drawn every # observations. The default is separator(5).

Options for estat summarize

`labels`, `noheader`, and `noweights` are the same as for the generic `estat summarize`; see [R] **estat summarize**.

Remarks and examples

Remarks are presented under the following headings:

There are several `estat` commands that apply after all the `discrim` subcommands. `estat summarize` and `estat grsummarize` summarize the discriminating variables over the estimation sample and by-group. `estat list` displays classifications, posterior probabilities, and more for selected observations. `estat classtable` and `estat errorrate` display the classification table, also known as a confusion matrix, and error-rate estimates based on the classification table.

Discriminating-variable summaries

`estat summarize` and `estat grsummarize` provide summaries of the variables involved in the preceding discriminant analysis model.

▷ Example 1

Example 3 of [MV] **discrim lda** introduces the famous iris data originally from Anderson (1935) and used by Fisher (1936) in the development of linear discriminant analysis. We continue our exploration of the linear discriminant analysis of the iris data and demonstrate the summary `estat` tools available after all `discrim` subcommands.

```
. use https://www.stata-press.com/data/r18/iris
(Iris data)
. discrim lda seplen sepwid petlen petwid, group(iris) notable
```

The `notable` option of `discrim` suppressed display of the classification table. We explore the use of `estat classtable` later.

What can we learn about the underlying discriminating variables? `estat summarize` gives a summary of the variables involved in the discriminant analysis, restricted to the estimation sample.

```
. estat summarize
  Estimation sample discrim                Number of obs =        150
```

Variable	Mean	Std. dev.	Min	Max
groupvar				
iris	2	.8192319	1	3
variables				
seplen	5.843333	.8280661	4.3	7.9
sepwid	3.057333	.4358663	2	4.4
petlen	3.758	1.765298	1	6.9
petwid	1.199333	.7622377	.1	2.5

`estat summarize` displays the mean, standard deviation, minimum, and maximum for the group variable, `iris`, and the four discriminating variables, `seplen`, `sepwid`, `petlen`, and `petwid`. Also shown is the number of observations. If we had fit our discriminant model on a subset of the data, `estat summarize` would have restricted its summary to those observations.

More interesting than an overall summary of the discriminating variables is a summary by our group variable, `iris`.

```
. estat grsummarize
Estimation sample discrim lda
Summarized by iris
```

	iris			
Mean	Setosa	Versicolor	Virginica	Total
seplen	5.006	5.936	6.588	5.843333
sepwid	3.428	2.77	2.974	3.057333
petlen	1.462	4.26	5.552	3.758
petwid	.246	1.326	2.026	1.199333
N	50	50	50	150

By default, `estat grsummarize` displays means of the discriminating variables for each group and overall (the total column), along with group sizes. The summary is restricted to the estimation sample.

The petal length and width of *Iris setosa* appear to be much smaller than those of the other two species. *Iris versicolor* has petal length and width between that of the other two species.

Other statistics may be requested. A look at the minimums and maximums might provide more insight into the separation of the three iris species.

```
. estat grsummarize, min max
Estimation sample discrim lda
Summarized by iris
```

		iris			
		Setosa	Versicolor	Virginica	Total
seplen					
	Min	4.3	4.9	4.9	4.3
	Max	5.8	7	7.9	7.9
sepwid					
	Min	2.3	2	2.2	2
	Max	4.4	3.4	3.8	4.4
petlen					
	Min	1	3	4.5	1
	Max	1.9	5.1	6.9	6.9
petwid					
	Min	.1	1	1.4	.1
	Max	.6	1.8	2.5	2.5

Although this table is helpful, an altered view of it might make comparisons easier. `estat grsummarize` allows a format to be specified with each requested statistic. We can request a shorter format for the minimum and maximum and specify a fixed format so that the decimal point lines up. `estat grsummarize` also has a `transpose` option that places the variables and requested statistics as columns and the groups as rows. If you have fewer discriminating variables than groups, this might be the most natural way to view the statistics. Here we have more variables, but with a narrow display format, the transposed view still works well.

```
. estat grsummarize, min(%4.1f) max(%4.1f) transpose
Estimation sample discrim lda
Summarized by iris
```

	seplen		sepwid		petlen		petwid	
iris	Min	Max	Min	Max	Min	Max	Min	Max
Setosa	4.3	5.8	2.3	4.4	1.0	1.9	0.1	0.6
Versicolor	4.9	7.0	2.0	3.4	3.0	5.1	1.0	1.8
Virginica	4.9	7.9	2.2	3.8	4.5	6.9	1.4	2.5
Total	4.3	7.9	2.0	4.4	1.0	6.9	0.1	2.5

The maximum petal length and width for *Iris setosa* are much smaller than the minimum petal length and width for the other two species. The petal length and width clearly separate *Iris setosa* from the other two species.

You are not limited to one or two statistics with `estat grsummarize`, and each statistic may have different requested display formats. The total column, or row if the table is transposed, can also be suppressed.

Using Stata's `graph box` command is another way of seeing the differences among the three iris species for the four discriminating variables.

```
. graph box seplen, over(iris) name(sl)
. graph box sepwid, over(iris) name(sw)
. graph box petlen, over(iris) name(pl)
. graph box petwid, over(iris) name(pw)
. graph combine sl sw pl pw, title(Characteristics of three iris species)
```


Characteristics of three iris species
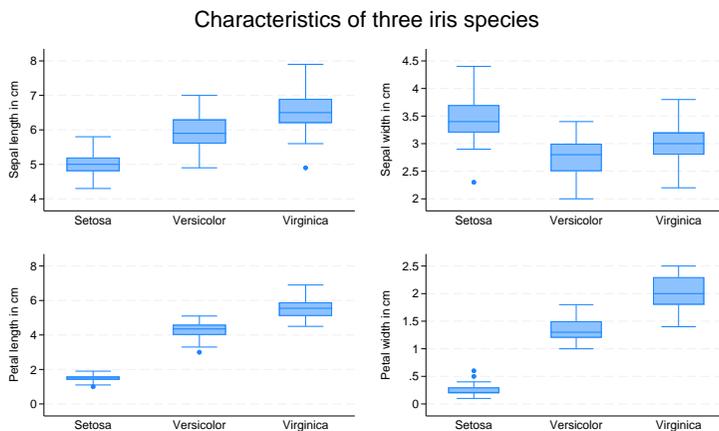
The box plots confirm the lack of overlap in the petal lengths and widths for *Iris setosa* compared with the other two iris species. Other differences between the species are also seen.

◁

More summary `estat` commands are available after `discrim lda`; see [MV] **discrim lda postestimation**.

Discrimination listings

Listing the true group, classified group, group posterior probabilities, and discriminating variables for observations of interest after discrim is easy with the estat list command.

▷ Example 2

Example 1 of [MV] discrim introduced the riding-mower data of Johnson and Wichern (2007) and presented a linear discriminant analysis that concluded with the use of estat list displaying the misclassified observations.

```
. use https://www.stata-press.com/data/r18/lawnmower2
(Johnson and Wichern (2007) table 11.1)
. discrim lda income lotsize, group(owner) notable
. estat list, class(loo) pr(loo) misclassified
```

	Classification			Probabilities		LOO Probabilities	
Obs	True	Class.	LOO Cl.	Nonowner	Owner	Nonowner	Owner
1	Owner	Nonown *	Nonown *	0.7820	0.2180	0.8460	0.1540
2	Owner	Owner	Nonown *	0.4945	0.5055	0.6177	0.3823
13	Nonown	Owner *	Owner *	0.2372	0.7628	0.1761	0.8239
14	Nonown	Nonown	Owner *	0.5287	0.4713	0.4313	0.5687
17	Nonown	Owner *	Owner *	0.3776	0.6224	0.2791	0.7209

* indicates misclassified observations

The misclassified option limited the listing to those observations that were misclassified by the linear discriminant model. class(loo) and pr(loo) added leave-one-out (LOO) classifications and probabilities to the resubstitution classifications and probabilities.

We demonstrate a few other options available with estat list. We can limit which observations are displayed with if and in qualifiers and can add the display of the discriminating variables with the varlist option. Here we limit the display to those observations that have income greater than $110,000.

```
. estat list if income > 110, varlist
```

	Data		Classification		Probabilities	
Obs	income	lotsize	True	Class.	Nonowner	Owner
2	115.5	16.8	Owner	Owner	0.4945	0.5055
5	117.0	23.6	Owner	Owner	0.0040	0.9960
6	140.1	19.2	Owner	Owner	0.0125	0.9875
7	138.0	17.6	Owner	Owner	0.0519	0.9481
8	112.8	22.4	Owner	Owner	0.0155	0.9845
10	123.0	20.8	Owner	Owner	0.0196	0.9804
12	111.0	20.0	Owner	Owner	0.1107	0.8893
17	114.0	17.6	Nonowner	Owner *	0.3776	0.6224

* indicates misclassified observations

Starting with the command above, we specify sep(0) to suppress the separator line that, by default, displays after every 5 observations. We eliminate the observation numbers with the noobs option. With the class() option: the looclass suboption adds the LOO classification; the noclass suboption suppress the resubstitution classification; and the nostar suboption eliminates the marking

of misclassified observations with asterisks. With `pr(loopr nopr)` we specify that LOO probabilities are to be displayed and resubstitution probabilities are to be suppressed.

```
. estat list if income > 110, sep(0) class(looclass noclass nostar)
> pr(loopr nopr) varlist noobs
```

Data		Classification		LOO Probabilities	
income	lotsize	True	LOO Cl	Nonowner	Owner
115.5	16.8	Owner	Nonowner	0.6177	0.3823
117.0	23.6	Owner	Owner	0.0029	0.9971
140.1	19.2	Owner	Owner	0.0124	0.9876
138.0	17.6	Owner	Owner	0.0737	0.9263
112.8	22.4	Owner	Owner	0.0168	0.9832
123.0	20.8	Owner	Owner	0.0217	0.9783
111.0	20.0	Owner	Owner	0.1206	0.8794
114.0	17.6	Nonowner	Owner	0.2791	0.7209

◁

Use the `if e(sample)` qualifier to restrict the listing from `estat list` to the estimation sample. Out-of-sample listings are obtained if your selected observations are not part of the estimation sample.

As an alternative to `estat list`, you can use `predict` after `discrim` to obtain the classifications, posterior probabilities, or whatever else is available for prediction from the `discrim` subcommand that you ran, and then use `list` to display your predictions; see [D] **list** and see example 2 of [MV] **discrim knn postestimation** for an example.

Classification tables and error rates

Classification tables (also known as confusion matrices) and error-rate estimate tables are available with the `estat classtable` and `estat errorrate` commands after `discrim`.

▷ Example 3

Example 2 of [MV] **discrim knn** introduces a head measurement dataset from Rencher and Christensen (2012, 291) with six discriminating variables and three groups. We perform a quadratic discriminant analysis (QDA) on the dataset to illustrate classification tables and error-rate estimation.

```
. use https://www.stata-press.com/data/r18/head
(Table 8.3. Head measurements, Rencher and Christensen (2012))

. discrim qda wdim circum fbeye eyehd earhd jaw, group(group)

Quadratic discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True group	Classified High school	College	Nonplayer	Total
High school	27	1	2	30
	90.00	3.33	6.67	100.00
College	2	21	7	30
	6.67	70.00	23.33	100.00
Nonplayer	1	4	25	30
	3.33	13.33	83.33	100.00
Total	30	26	34	90
	33.33	28.89	37.78	100.00
Priors	0.3333	0.3333	0.3333	

By default, `discrim` displayed the resubstitution classification table. A resubstitution classification table is obtained by classifying the observations used in building the discriminant model. The resubstitution classification table is overly optimistic as an indicator of how well you might classify other observations.

This resubstitution classification table shows that from the high school group 27 observations were correctly classified, 1 observation was classified as belonging to the college group, and 2 observations were classified as belonging to the nonplayer group. The corresponding percentages were also presented: 90%, 3.33%, and 6.67%. The college and nonplayer rows are read in a similar manner. For instance, there were 7 observations from the college group that were misclassified as nonplayers. Row and column totals are presented along with the group prior probabilities. See table 9.4 of Rencher and Christensen (2012, 321) for this same classification table.

There are various ways of estimating the error rate for a classification. `estat errorrate` presents the overall (total) error rate and the error rate for each group. By default, it uses a count-based estimate of the error rate.

```
. estat errorrate
```
Error rate estimated by error count

	group High school	College	Nonplayer	Total
Error rate	.1	.3	.166666667	.188888889
Priors	.333333333	.333333333	.333333333	

This is a resubstitution count-based error-rate estimate corresponding to the classification table previously presented. Three of the 30 high school observations were misclassified—a proportion of 0.1; 9 of the 30 college observations were misclassified—a proportion of 0.3; and 5 of the 30 nonplayers were misclassified—a proportion of 0.1667. The total error rate is computed as the sum of the group error rates times their prior probabilities—here 0.1889.

An error-rate estimate based on the posterior probabilities is also available with estat errorrate.

```
. estat errorrate, pp
```
Error rate estimated from posterior probabilities

Error rate	group High school	College	Nonplayer	Total
Stratified	.08308968	.337824355	.2030882	.208000745
Unstratified	.08308968	.337824355	.2030882	.208000745
Priors	.333333333	.333333333	.333333333	

Because we did not specify otherwise, we obtained resubstitution error-rate estimates. By default both the stratified and unstratified estimates are shown. The stratified estimates give less weight to probabilities where the group sample size is large compared with the group prior probabilities; see *Methods and formulas* for details. Here the stratified and unstratified estimates are the same. This happens when the prior probabilities are proportional to the sample sizes—here we have equal prior probabilities and equal group sizes.

For this example, the count-based and posterior-probability-based estimates are similar to one another.

Leave-one-out (LOO) estimation provides a more realistic assessment of your potential classification success with observations that were not used in building the discriminant analysis model. The loo option of estat classtable and estat errorrate specify a LOO estimation.

```
. estat classtable, loo nopercents nopriors nototals
```
Leave-one-out classification table

Key
Number

True group	LOO Classified High school	College	Nonplayer
High school	26	2	2
College	3	16	11
Nonplayer	4	9	17

   To demonstrate some of the available options, we specified the `nopercents` option to suppress the display of percentages; the `nopriors` option to suppress the display of the prior probabilities; and the `nototals` option to suppress row and column totals.

   If you compare this LOO classification table with the resubstitution classification table, you will see that fewer observations appear on the diagonal (were correctly classified) in the LOO table. The LOO estimates are less biased than the resubstitution estimates.

   We now examine the LOO error-rate estimates by using the `loo` option with the `estat error` command. We first produce the count-based estimates and then request the posterior-probability-based estimates. In the first case, we use the `nopriors` option to demonstrate that you can suppress the display of the prior probabilities. Suppressing the display does not remove their effect on the computations. In the second `estat errorrate` call, we specify that only the unstratified estimates be presented. (Because the prior probabilities and samples sizes match [are equal], the stratified results will be the same.)

```
. estat err, loo nopriors
Error rate estimated by leave-one-out error count
```

	group High school	College	Nonplayer	Total
Error rate	.133333333	.466666667	.433333333	.344444444

```
. estat err, loo pp(unstratified)
Error rate estimated from leave-one-out posterior probabilities
```

Error rate	group High school	College	Nonplayer	Total
Unstratified	.049034154	.354290969	.294376541	.232567222
Priors	.333333333	.333333333	.333333333	

   Instead of displaying percentages below the counts in the classification table, we can display average posterior probabilities. The `probabilities` option requests the display of average posterior probabilities. We add the `nopriors` option to demonstrate that the prior probabilities can be suppressed from the table. The classifications are still based on the prior probabilities; they are just not displayed.

```
. estat classtable, probabilities nopriors
Resubstitution average-posterior-probabilities classification table
```

Key
Number
Average posterior probability

True group	Classified High school	College	Nonplayer
High school	27 0.9517	1 0.6180	2 0.5921
College	2 0.6564	21 0.8108	7 0.5835
Nonplayer	1 0.4973	4 0.5549	25 0.7456
Total	30 0.9169	26 0.7640	34 0.7032

Both `estat classtable` and `estat errorrate` allow `if` and `in` qualifiers so that you can select the observations to be included in the computations and displayed. If you want to limit the table to the estimation sample, use `if e(sample)`. You can also do out-of-sample classification tables and error-rate estimation by selecting observations that were not part of the estimation sample.

◁

❑ Technical note

As noted by Huberty (1994, 92), the posterior-probability-based error-rate estimates for the individual groups may be negative. This may happen when there is a discrepancy between group prior probabilities and relative sample size.

Continuing with our last example, if we use prior probabilities of 0.2, 0.1, and 0.7 for the high school, college, and nonplayer groups, the nonplayer stratified error-rate estimate and the high school group unstratified error-rate estimate are negative.

```
. estat error, pp priors(.2, .1, .7)
Error rate estimated from posterior probabilities
```

Error rate	group High school	College	Nonplayer	Total
Stratified	.19121145	.737812235	−.001699715	.110833713
Unstratified	−.36619243	.126040785	.29616143	.146678593
Priors	.2	.1	.7	

❑

More examples of the use of `estat list`, `estat classtable`, and `estat errorrate` can be found in the other `discrim`-related manual entries.

Stored results

`estat classtable` stores the following in `r()`:

Matrices
    `r(counts)`   group counts
    `r(percents)`   percentages for each group (unless `nopercents` specified)
    `r(avgpostprob)`   average posterior probabilities classified into each group (`probabilities` only)

`estat errorrate` stores the following in `r()`:

Matrices
    `r(grouppriors)`   row vector of group prior probabilities used in the calculations
    `r(erate_count)`   matrix of error rates estimated from error counts (`count` only)
    `r(erate_strat)`   matrix of stratified error rates estimated from posterior probabilities (`pp` only)
    `r(erate_unstrat)`   matrix of unstratified error rates estimated from posterior probabilities (`pp` only)

`estat grsummarize` stores the following in `r()`:

Matrices
`r(count)`	group counts
`r(mean)`	means (`mean` only)
`r(median)`	medians (`median` only)
`r(sd)`	standard deviations (`sd` only)
`r(cv)`	coefficients of variation (`cv` only)
`r(semean)`	standard errors of the means (`semean` only)
`r(min)`	minimums (`min` only)
`r(max)`	maximums (`max` only)

Methods and formulas

Let $\mathbf{C}$ denote the classification table (also known as the confusion matrix), with rows corresponding to the true groups and columns corresponding to the assigned groups. Let C_{ij} denote the element from row i and column j of $\mathbf{C}$. C_{ij} represents the number of observations from group i assigned to group j. n_i is the number of observations from group i and $N = \sum_{i=1}^{g} n_i$ is the total sample size. $\mathcal{N}_i = \sum_{j=1}^{g} C_{ij}$ is the number of observations from group i that were classified into one of the g groups. If some observations from group i are unclassified (because of ties), $\mathcal{N}_i \neq n_i$ and $\mathcal{N} \neq N$ (where $\mathcal{N} = \sum \mathcal{N}_i$). Let q_i be the prior probability of group i.

`estat classtable` displays $\mathbf{C}$, with options controlling the display of cell percentages by row, average posterior probabilities, prior probabilities, row totals, and column totals.

McLachlan (2004, chap. 10) devotes a chapter to classification error-rate estimation. The `estat errorrate` command provides several popular error-rate estimates. Smith (1947) introduced the count-based apparent error-rate estimate. The count-based error-rate estimate for group i is

$$\widehat{E}_i^{(C)} = 1 - C_{ii}/\mathcal{N}_i$$

The overall (total) count-based error-rate estimate is

$$\widehat{E}^{(C)} = \sum_{i=1}^{g} q_i \widehat{E}_i^{(C)}$$

In general, $\widehat{E}^{(C)} \neq 1 - \sum_{i=1}^{g} C_{ii}/\mathcal{N}$, though some sources, Rencher and Christensen (2012, 319), appear to report this latter quantity.

If $\mathbf{C}$ is based on the same data used in the estimation of the discriminant analysis model, the error rates are called apparent error rates. Leave-one-out (LOO) error rates are obtained if $\mathbf{C}$ is based on a leave-one-out analysis where each observation to be classified is classified based on the discriminant model built excluding that observation; see Lachenbruch and Mickey (1968) and McLachlan (2004, 342).

Error rates can also be estimated from the posterior probabilities. Huberty (1994, 90–91) discusses hit rates (one minus the error rates) based on posterior probabilities and shows two versions of the posterior-probability based estimate—stratified and unstratified.

Let $\mathcal{P}_{ji}$ be the sum of the posterior probabilities for all observations from group j assigned to group i. The posterior-probability-based unstratified error-rate estimate for group i is

$$\widehat{E}_i^{(Pu)} = 1 - \frac{1}{\mathcal{N} q_i} \sum_{j=1}^{g} \mathcal{P}_{ji}$$

The overall (total) posterior-probability-based unstratified error-rate estimate is

$$\widehat{E}^{(Pu)} = \sum_{i=1}^{g} q_i \widehat{E}_i^{(Pu)}$$

The posterior-probability-based stratified error-rate estimate for group i is

$$\widehat{E}_i^{(Ps)} = 1 - \frac{1}{q_i} \sum_{j=1}^{g} \frac{q_j}{\mathcal{N}_j} \mathcal{P}_{ji}$$

The overall (total) posterior-probability-based stratified error-rate estimate is

$$\widehat{E}^{(Ps)} = \sum_{i=1}^{g} q_i \widehat{E}_i^{(Ps)}$$

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Also see

[MV] **discrim** — Discriminant analysis

[MV] **discrim knn postestimation** — Postestimation tools for discrim knn

[MV] **discrim lda postestimation** — Postestimation tools for discrim lda

[MV] **discrim logistic postestimation** — Postestimation tools for discrim logistic

[MV] **discrim qda postestimation** — Postestimation tools for discrim qda

[MV] **candisc** — Canonical linear discriminant analysis

[U] **20 Estimation and postestimation commands**

Title

Description	Quick start	Menu	Syntax
Options	Remarks and examples	Stored results	Methods and formulas
References	Also see		

Description

discrim knn performs kth-nearest-neighbor discriminant analysis. A wide selection of similarity and dissimilarity measures is available.

kth-nearest neighbor must retain the training data and search through the data for the k nearest observations each time a classification or prediction is performed. Consequently for large datasets, kth-nearest neighbor is slow and uses a lot of memory.

See [MV] **discrim** for other discrimination commands.

Quick start

kth-nearest-neighbor discriminant analysis of v1, v2, v3, and v4 for groups defined by catvar and $k = 5$

    discrim knn v1 v2 v3 v4, k(5) group(catvar)

Same as above, but use prior probabilities proportional to group size

    discrim knn v1 v2 v3 v4, k(5) group(catvar) priors(proportional)

Display only the leave-one-out classification table

    discrim knn v1 v2 v3 v4, k(5) group(catvar) lootable notable

Use absolute-value distance

    discrim knn v1 v2 v3 v4, k(5) group(catvar) measure(absolute)

Assume v1 and v2 are factor variables, and use the Dice similarity coefficient

    discrim knn ibn.v1 ibn.v2, k(5) group(catvar) measure(dice)

Menu

Statistics > Multivariate analysis > Discriminant analysis > Kth-nearest neighbor (KNN)

Syntax

> discrim knn *varlist* [*if*] [*in*] [*weight*], group(*groupvar*) k(#) [*options*]

options	Description
Model	
* group(*groupvar*)	variable specifying the groups
* k(#)	number of nearest neighbors
priors(*priors*)	group prior probabilities
ties(*ties*)	how ties in classification are to be handled
Measure	
measure(*measure*)	similarity or dissimilarity measure; default is measure(L2)
s2d(standard)	convert similarity to dissimilarity: $d(ij) = \sqrt{s(ii) + s(jj) - 2s(ij)}$, the default
s2d(oneminus)	convert similarity to dissimilarity: $d(ij) = 1 - s(ij)$
mahalanobis	Mahalanobis transform continuous data before computing dissimilarities
Reporting	
notable	suppress resubstitution classification table
lootable	display leave-one-out classification table

priors	Description
equal	equal prior probabilities; the default
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
missing	ties in group classification produce missing values; the default
random	ties in group classification are broken randomly
first	ties in group classification are set to the first tied group
nearest	ties in group classification are assigned based on the closest observation, or missing if this still results in a tie

* group() and k() are required.

varlist may contain factor variables; see [U] **11.4.3 Factor variables**.

collect and statsby are allowed; see [U] **11.1.10 Prefix commands**.

fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> **Model**

group(*groupvar*) is required and specifies the name of the grouping variable. *groupvar* must be a numeric variable.

k(*#*) is required and specifies the number of nearest neighbors on which to base computations. In the event of ties, the next largest value of k() is selected. Suppose that k(3) is selected. For a given observation, one must go out a distance d to find three nearest neighbors, but if, say, there are five data points all within distance d, then the computation will be based on all five nearest points.

priors(*priors*) specifies the prior probabilities for group membership. The following *priors* are allowed:

> priors(<u>e</u>qual) specifies equal prior probabilities. This is the default.

> priors(<u>p</u>roportional) specifies group-size-proportional prior probabilities.

> priors(*matname*) specifies a row or column vector containing the group prior probabilities.

> priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. The following *ties* are allowed:

> ties(<u>m</u>issing) specifies that ties in group classification produce missing values. This is the default.

> ties(<u>r</u>andom) specifies that ties in group classification are broken randomly.

> ties(<u>f</u>irst) specifies that ties in group classification are set to the first tied group.

> ties(<u>n</u>earest) specifies that ties in group classification are assigned based on the closest observation, or missing if this still results in a tie.

> **Measure**

measure(*measure*) specifies the similarity or dissimilarity measure. The default is measure(L2); all measures in [MV] *measure_option* are supported except for measure(Gower).

s2d(standard | oneminus) specifies how similarities are converted into dissimilarities.

> The available s2d() options, standard and oneminus, are defined as

$$
\begin{array}{ll}
\texttt{standard} & d(ij) = \sqrt{s(ii) + s(jj) - 2s(ij)} = \sqrt{2\{1 - s(ij)\}} \\
\texttt{oneminus} & d(ij) = 1 - s(ij)
\end{array}
$$

> s2d(standard) is the default.

mahalanobis specifies performing a Mahalanobis transformation on continuous data before computing dissimilarities. The data are transformed via the Cholesky decomposition of the within-group covariance matrix, and then the selected dissimilarity measure is performed on the transformed data. If the L2 (Euclidean) dissimilarity is chosen, this is the Mahalanobis distance. If the within-group covariance matrix does not have sufficient rank, an error is returned.

―――――――――― Reporting ――――――――――

notable suppresses the computation and display of the resubstitution classification table.

lootable displays the leave-one-out classification table.

Remarks and examples

Remarks are presented under the following headings:

Introduction

kth-nearest-neighbor (KNN) discriminant analysis dates at least as far back as Fix and Hodges (1951). An introductory treatment is available in Rencher and Christensen (2012). More advanced treatments are in Hastie, Tibshirani, and Friedman (2009) and McLachlan (2004).

KNN is a nonparametric discrimination method based on the k nearest neighbors of each observation. KNN can deal with binary data via one of the binary measures; see [MV] *measure_option*.

A first example

What distinguishes kth-nearest-neighbor analysis from other methods of discriminant analysis is its ability to distinguish irregular-shaped groups, including groups with multiple modes. We create a dataset with unusual boundaries that lends itself to KNN analysis and graphical interpretation.

▷ Example 1

We create a two-dimensional dataset on the plane with x and y values in $[-4, 4]$. In each quadrant we consider points within a circle with a square root of two radii, centered around the points $(2, 2)$, $(-2, 2)$, $(-2, -2)$, and $(2, -2)$. We set the group value to 1 to start and then replace it in the circles. In the first and third circles we set the group value to 2, and in the second and fourth circles we set the group value to 3. Outside the circles, the group value remains 1.

```
. set seed 98712321
. set obs 500
Number of observations (_N) was 0, now 500.
. generate x = 8*runiform() - 4
. generate y = 8*runiform() - 4
. generate group = 1
. replace group = 2 if (y+2)^2 + (x+2)^2 <= 2
(45 real changes made)
. replace group = 2 if (y-2)^2 + (x-2)^2 <= 2
(50 real changes made)
. replace group = 3 if (y+2)^2 + (x-2)^2 <= 2
(45 real changes made)
. replace group = 3 if (y-2)^2 + (x+2)^2 <= 2
(51 real changes made)
```

Next we define some local macros for function plots of the circles. This makes it easier to graph the boundary circles on top of the data. We set the graph option aspectratio(1) to force the aspect ratio to be 1; otherwise, the circles might appear to be ovals.

```
. local rp : di %12.10f 2+sqrt(2)

. local rm : di %12.10f 2-sqrt(2)

. local functionplot
> (function y =  sqrt(2-(x+2)^2) - 2, lpat(solid) range(-`rp' -`rm'))
> (function y = -sqrt(2-(x+2)^2) - 2, lpat(solid) range(-`rp' -`rm'))
> (function y =  sqrt(2-(x-2)^2) + 2, lpat(solid) range(-`rm'  `rp'))
> (function y = -sqrt(2-(x-2)^2) + 2, lpat(solid) range(-`rm'  `rp'))
> (function y =  sqrt(2-(x+2)^2) + 2, lpat(solid) range(-`rp' -`rm'))
> (function y = -sqrt(2-(x+2)^2) + 2, lpat(solid) range(-`rp' -`rm'))
> (function y =  sqrt(2-(x-2)^2) - 2, lpat(solid) range( `rm'  `rp'))
> (function y = -sqrt(2-(x-2)^2) - 2, lpat(solid) range( `rm'  `rp'))

. local graphopts
> aspectratio(1) legend(order(1 "Group 1" 2 "Group 2" 3 "Group 3"))

. twoway (scatter y x if group==1)
>        (scatter y x if group==2)
>        (scatter y x if group==3)
>        `functionplot' , `graphopts' name(original, replace)
>        title("Training data")
```


We perform three discriminant analyses on these data for comparison. We use linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and KNN. The results from logistic discriminant analysis are similar to those of LDA and are not included. With all three models, we use proportional probabilities, `priors(proportional)`. The probability of landing in a given group is proportional to the geometric area of that group; they are certainly not equal. Rather than doing geometric calculations for the prior probabilities, we use `priors(proportional)` to approximate this. We suppress the standard classification table with `notable`. Instead we look at the `lootable`, that is, leave-one-out (LOO) table, where the observation in question is omitted and its result is predicted from the rest of the data. Likewise, we predict the LOO classification (`looclass`). With KNN we get to choose a `measure()`; here we want the straight line distance between the points. This is the default, Euclidean distance, so we do not have to specify `measure()`.

We choose $k = 7$ for this run with 500 observations. See *Methods and formulas* for more information on choosing k.

```
. discrim lda x y, group(group) notable lootable priors(proportional)
```
Linear discriminant analysis
Leave-one-out classification summary

```
┌──────────┐
│ Key      │
├──────────┤
│ Number   │
│ Percent  │
└──────────┘
```

	Classified			
True group	1	2	3	Total
1	309	0	0	309
	100.00	0.00	0.00	100.00
2	95	0	0	95
	100.00	0.00	0.00	100.00
3	96	0	0	96
	100.00	0.00	0.00	100.00
Total	500	0	0	500
	100.00	0.00	0.00	100.00
Priors	0.6180	0.1900	0.1920	

LDA classifies all observations into group one, the group with the highest prior probability.

```
. discrim qda x y, group(group) notable lootable priors(proportional)
```
Quadratic discriminant analysis
Leave-one-out classification summary

```
┌──────────┐
│ Key      │
├──────────┤
│ Number   │
│ Percent  │
└──────────┘
```

	Classified			
True group	1	2	3	Total
1	258	31	20	309
	83.50	10.03	6.47	100.00
2	57	38	0	95
	60.00	40.00	0.00	100.00
3	77	0	19	96
	80.21	0.00	19.79	100.00
Total	392	69	39	500
	78.40	13.80	7.80	100.00
Priors	0.6180	0.1900	0.1920	

QDA has $185 \; (31 + 20 + 57 + 77)$ misclassified observations of 500, but it correctly classifies 38 of the 95 observations from group 2 and 19 of the 96 observations from group 3.

```
. discrim knn x y, group(group) k(7) notable lootable priors(proportional)
Kth-nearest-neighbor discriminant analysis
Leave-one-out classification summary
```

Key
Number
Percent

True group	Classified 1	2	3	Total
1	299	4	6	309
	96.76	1.29	1.94	100.00
2	13	82	0	95
	13.68	86.32	0.00	100.00
3	10	0	86	96
	10.42	0.00	89.58	100.00
Total	322	86	92	500
	64.40	17.20	18.40	100.00
Priors	0.6180	0.1900	0.1920	

In contrast to the other two models, KNN has only 33 $(4 + 6 + 13 + 10)$ misclassified observations. We can see how points are classified by KNN by looking at the following graph.

```
. predict cknn, looclass

. twoway (scatter y x if cknn==1 )
>         (scatter y x if cknn ==2)
>         (scatter y x if cknn ==3)
>         'functionplot', 'graphopts' name(knn, replace)
>         title("KNN LOO classification")
```
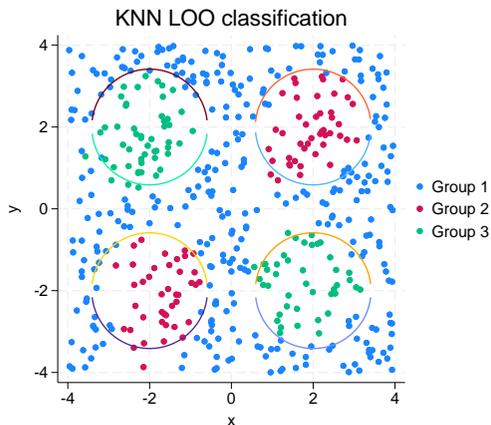

KNN has some resolution of the circles and correctly classifies most of the points. Its misclassified observations are near the boundaries of the circles, where nearest points fall on both sides of the boundary line.

Mahalanobis transformation

The Mahalanobis transformation eliminates the correlation between the variables and standardizes the variance of each variable, as demonstrated in example 2 of [MV] **discrim lda**. When the Mahalanobis transformation is used in conjunction with Euclidean distance, it is called Mahalanobis distance. The Mahalanobis transformation may be applied when any continuous measure is chosen, not just measure(Euclidean). See [MV] *measure_option* for a description of the available measures.

▷ Example 2

We will reproduce an example from Rencher and Christensen (2012, 290–292) that uses the Mahalanobis distance. Rencher and Christensen present data collected by G. R. Bryce and R. M. Barker of Brigham Young University as part of a preliminary study of a possible link between football helmet design and neck injuries. Six head dimensions were measured for each subject. Thirty subjects were sampled in each of three groups: high school football players (group 1), college football players (group 2), and nonfootball players (group 3). The six variables are wdim, head width at its widest dimension; circum, head circumference; fbeye, front-to-back measurement at eye level; eyehd, eye to top of head measurement; earhd, ear to top of head measurement; and jaw, jaw width.

These measurements will not have the same ranges. For example, the head circumference should be much larger than eye to top of head measurement. Mahalanobis distance is used to standardize the measurements.

```
. use https://www.stata-press.com/data/r18/head, clear
(Table 8.3. Head measurements, Rencher and Christensen (2012))

. discrim knn wdim-jaw, k(5) group(group) mahalanobis

Kth-nearest-neighbor discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True group	Classified High school	College	Nonplayer	Unclassified
High school	26 86.67	0 0.00	1 3.33	3 10.00
College	1 3.33	19 63.33	9 30.00	1 3.33
Nonplayer	1 3.33	4 13.33	22 73.33	3 10.00
Total	28 31.11	23 25.56	32 35.56	7 7.78
Priors	0.3333	0.3333	0.3333	

True group	Classified Total
High school	30 100.00
College	30 100.00
Nonplayer	30 100.00
Total	90 100.00
Priors	

A subset of this result is in Rencher and Christensen (2012, 331–332). Of the 90 original observations, 16 were misclassified and 7 observations were unclassified. Rencher and Christensen also state the error rate for this example is 0.193. We use estat errorrate to get the error rate.

```
. estat errorrate
Error rate estimated by error count
```

	group High school	College	Nonplayer	Total
Error rate	.037037037	.344827586	.185185185	.189016603
Priors	.333333333	.333333333	.333333333	

Note: 7 observations were not classified and are not included in the table.

Our error rate of 0.189 does not match that of Rencher and Christensen. Why is this? Rencher and Christensen calculates the error rate as the number of misclassified observations over the total

number of observations classified. This is $16/83 \approx 0.193$. We use the standard error-rate definition that takes into account the prior probabilities. From the high school group, there is one misclassified observation of 27 total observations classified from this group, so its error rate is $(1/27) \approx 0.037$, and its contribution to the total is $(1/27)(1/3)$. Likewise, the error rates for the college and nonplayer group are $(10/29) \approx 0.345$ and $(5/27) \approx 0.185$ respectively, with contributions of $(10/29)(1/3)$ and $(5/27)(1/3)$. Adding all contributions, we get the displayed error rate of 0.189. See *Methods and formulas* of [MV] **discrim estat** for details.

The unclassified observations are those that resulted in ties. We can force ties to be classified by changing the ties() option. The default is ties(missing), which says that ties are to be classified as missing values. Here we choose ties(nearest), which breaks the tie by classifying to the group of the nearest tied observation.

```
. discrim knn wdim-jaw, k(5) group(group) mahalanobis ties(nearest)
Kth-nearest-neighbor discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True group	Classified High school	College	Nonplayer	Total
High school	28	0	2	30
	93.33	0.00	6.67	100.00
College	1	20	9	30
	3.33	66.67	30.00	100.00
Nonplayer	1	4	25	30
	3.33	13.33	83.33	100.00
Total	30	24	36	90
	33.33	26.67	40.00	100.00
Priors	0.3333	0.3333	0.3333	

Compare this with example 1 in [MV] **candisc**, example 3 in [MV] **discrim estat**, and example 2 of [MV] **discrim logistic**.

◁

Binary data

In addition to the measures for continuous data, a variety of binary measures are available for KNN. Binary data can be created from any categorical dataset by using xi; see [R] **xi**.

▷ Example 3

You have invited some scientist friends over for dinner, including Mr. Mushroom (see vignette below), a real "fun guy". Mr. Mushroom is not only a researcher in mycology who enjoys studying mushrooms but also an enthusiastic mushroom gourmand who likes nothing better than to combine his interests in classification and cookery. His current research is identification of poisonous mushrooms from photographs. From the photographs, he can identify the shape of a mushroom's cap, the cap's

surface, the cap's color, the population of mushrooms, and, with some careful attention to detail in the surrounding area, the habitat.

William Alphonso Murrill (1867–1957) was a famous mycologist, taxonomist, and writer from the New York Botanical Gardens and was nicknamed "Mr. Mushroom". Although we borrowed his nickname, Mr. Mushroom and the events portrayed in this example are entirely fictitious. William Murrill's many scientific accomplishments include the 1916 book *Edible and Poisonous Mushrooms.*

Knowing your friend, you imagine that he will insist on bringing a mushroom dish to be unveiled and served at dinnertime—perhaps his experimental subjects. Although you know that he is a careful scientist and a gifted cook, you are stalked with worries about poisoning your other guests.

Late at night you cannot sleep for worrying about poisonous mushrooms, and you decide to do a little research into mushroom classification. You do a Google search online and find mushroom data at http://archive.ics.uci.edu/ml/datasets/Mushroom. For reference, these records are drawn from Lincoff (1981).

This is a large dataset of 8,124 observations on the *Agaricus* and *Lepiota*. Each species is identified as definitely edible, definitely poisonous, or of unknown edibility and not recommended. This last class was combined with the poisonous one. Lincoff (1981) clearly states that there is no simple rule for determining the edibility of a mushroom; no rule like "leaflets three, let it be" for Poison Oak and Ivy, a fact that does not seem comforting. Twenty-two attributes are collected, including those that Mr. Mushroom can identify from his photographs.

The mushroom data is a set of 23 variables that describe the cap of the mushroom, whether or not it has bruises, the gills, the veil, the stalk, the ring, the spores, the population, and the habitat. The variables that describe the cap, for example, are `capshape`, `capsurface`, and `capcolor`. The `capshape` variable, for example, has categories bell, conical, convex, flat, knobbed, and sunken. Other variables and categories are similar.

You read in this dataset by using `infile` and make some modifications, attaching notes to this dataset to describe what you did to the original mushroom data. Modifications include dropping categories of the variables of interest that completely determine whether a mushroom is poisonous. The full mushroom data are also available; `webuse mushroom_full` to obtain it.

```
. use https://www.stata-press.com/data/r18/mushroom
(Lincoff (1981) Audubon Guide; http://archive.ics.uci.edu/ml/datasets/Mushroom)

. tabulate habitat poison
```

habitat	poison edible	poisonous	Total
grasses	752	680	1,432
leaves	240	585	825
meadows	128	24	152
paths	136	1,008	1,144
urban	64	224	288
woods	1,848	1,268	3,116
Total	3,168	3,789	6,957

You can see by tabulating two of the variables, `habitat` and `poison`, that in each habitat you have some mushrooms that are poisonous as well as some that are edible. The other descriptive variables of interest produce similar results.

Each variable is a set of unordered categories. Thus, you can treat them as factor variables. Because your goal is to account for all categories, you will apply the factor-variable base operator ibn. to the categorical variables. For details, see [U] **11.4.3 Factor variables**.

With KNN you can choose a measure that is suited to these data. You expect data with many zeroes and few ones. A match of two ones is far more significant than two matching zeroes. Looking through the binary similarity measures in [MV] *measure_option*, you see that the Jaccard binary similarity coefficient reports the proportion of matches of ones when at least one of the observations contains a one, and the Dice binary similarity measure weighs matches of ones twice as heavily as the Jaccard measure. Either suits the situation, and you choose the Dice measure. The conversion from a similarity to a dissimilarity measure will be s2d(standard) by default.

The poisonous and edible mushrooms are split about half and half in the original dataset, and in the current subset of these data the ratio is still approximately half and half, so you do not specify priors, obtaining priors(equal), the default.

Because of the size of the dataset and the number of indicator variables created by the factor-variable base operator ibn., KNN analysis is slow. You decide to discriminate based on 2,000 points selected at random, approximately a third of the data.

```
. set seed 12345678

. generate u = runiform()

. sort u

. discrim knn ibn.population ibn.habitat ibn.bruises ibn.capshape
> ibn.capsurface ibn.capcolor in 1/2000, k(15) group(poison) measure(dice)
Kth-nearest-neighbor discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True poison	Classified edible	poisonous	Total
edible	848	65	913
	92.88	7.12	100.00
poisonous	29	1,058	1,087
	2.67	97.33	100.00
Total	877	1,123	2,000
	43.85	56.15	100.00
Priors	0.5000	0.5000	

In some settings, these results would be considered good. Of the original 2,000 mushrooms, you see that only 29 poisonous mushrooms have been misclassified as edible. However, even sporadic classification of a poisonous mushroom as edible is a much bigger problem than classifying an edible mushroom as poisonous. This does not take the cost of misclassification into account. You decide that calling a poisonous mushroom edible is at least 10 times worse than calling an edible mushroom poisonous. In the two-group case, you can easily use the priors() option to factor in this cost; see [MV] **discrim** or McLachlan (2004, 9). We set the prior probability of poisonous mushrooms 10 times higher than that of the edible mushrooms.

```
. estat classtable in 1/2000, priors(.09, .91)
```
Resubstitution classification table

```
┌──────────┐
│ Key      │
├──────────┤
│ Number   │
│ Percent  │
└──────────┘
```

True poison	Classified edible	poisonous	Total
edible	728	185	913
	79.74	20.26	100.00
poisonous	0	1,087	1,087
	0.00	100.00	100.00
Total	728	1,272	2,000
	36.40	63.60	100.00
Priors	0.0900	0.9100	

These results are reassuring. There are no misclassified poisonous mushrooms, although 185 edible mushrooms of the total 2,000 mushrooms in our model are misclassified.

You now check to see how this subsample of the data performs in predicting the poison status of the rest of the data. This takes a few minutes of computer time, but unlike using estat classtable above, the variable predicted will stay with your dataset until you drop it. tabulate can be used instead of estat classtable.

```
. predict cpoison, classification priors(.09, .91)
. label values cpoison poison
. tabulate poison cpoison
```

poison	classification edible	poisonous	Total
edible	2,450	718	3,168
poisonous	0	3,789	3,789
Total	2,450	4,507	6,957

This is altogether reassuring. Again, no poisonous mushrooms were misclassified. Perhaps there is no need to worry about dinnertime disasters, even with a fungus among us. You are so relieved that you plan on serving a Jello dessert to cap off the evening—your guests will enjoy a mold to behold. Under the circumstances, you think doing so might just be a "morel" imperative.

◁

Stored results

discrim knn stores the following in e():

Scalars
e(N)	number of observations
e(N_groups)	number of groups
e(k_nn)	number of nearest neighbors
e(k)	number of discriminating variables

Macros
e(cmd)	discrim
e(subcmd)	knn
e(cmdline)	command as typed
e(groupvar)	name of group variable
e(grouplabels)	labels for the groups
e(measure)	similarity or dissimilarity measure
e(measure_type)	dissimilarity or similarity
e(measure_binary)	binary, if binary measure specified
e(s2d)	standard or oneminus, if s2d() specified
e(varlist)	discriminating variables
e(wtype)	weight type
e(wexp)	weight expression
e(title)	title in estimation output
e(ties)	how ties are to be handled
e(mahalanobis)	mahalanobis, if Mahalanobis transform is performed
e(properties)	nob noV
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(groupcounts)	number of observations for each group
e(grouppriors)	prior probabilities for each group
e(groupvalues)	numeric value for each group
e(SSCP_W)	pooled within-group SSCP matrix
e(W_eigvals)	eigenvalues of e(SSCP_W)
e(W_eigvecs)	eigenvectors of e(SSCP_W)
e(S)	pooled within-group covariance matrix
e(Sinv)	inverse of e(S)
e(sqrtSinv)	Cholesky (square root) of e(Sinv)
e(community)	community of neighbors for prediction

Functions
e(sample)	marks estimation sample

Methods and formulas

Let g be the number of groups, n_i the number of observations for group i, and q_i the prior probability for group i. Let $\mathbf{x}$ denote an observation measured on p discriminating variables. For consistency with the discriminant analysis literature, $\mathbf{x}$ will be a column vector, though it corresponds to a row in your dataset. Let $f_i(\mathbf{x})$ represent the density function for group i, and let $P(\mathbf{x}|G_i)$ denote the probability of observing $\mathbf{x}$ conditional on belonging to group i. Denote the posterior probability of group i given observation $\mathbf{x}$ as $P(G_i|\mathbf{x})$. With Bayes's theorem, we have

$$P(G_i|\mathbf{x}) = \frac{q_i f_i(\mathbf{x})}{\sum_{j=1}^{g} q_j f_j(\mathbf{x})}$$

Substituting $P(\mathbf{x}|G_i)$ for $f_i(\mathbf{x})$, we have

$$P(G_i|\mathbf{x}) = \frac{q_i P(\mathbf{x}|G_i)}{\sum_{j=1}^{g} q_j P(\mathbf{x}|G_j)}$$

For KNN discrimination, we let k_i be the number of the k nearest neighbors from group i, and the posterior-probability formula becomes

$$P(G_i|\mathbf{x}) = \frac{\dfrac{q_i k_i}{n_i}}{\displaystyle\sum_{j=1}^{g} \dfrac{q_j k_j}{n_j}}$$

In the event that there are ties among the nearest neighbors, k is increased to accommodate the ties. If five points are all nearest and equidistant from a given $\mathbf{x}$, then an attempt to calculate the three nearest neighbors of $\mathbf{x}$ will actually obtain five nearest neighbors.

Determining the nearest neighbors depends on a dissimilarity or distance calculation. The available dissimilarity measures are described in [MV] *measure_option*. Continuous and binary measures are available. If a similarity measure is selected, it will be converted to a dissimilarity by either

standard $d(ij) = \sqrt{s(ii) + s(jj) - 2s(ij)} = \sqrt{2\{1 - s(ij)\}}$

oneminus $d(ij) = 1 - s(ij)$

With any of the continuous measures, a Mahalanobis transformation may be performed before computing the dissimilarities. For details on the Mahalanobis transformation, see *Methods and formulas* of [MV] **discrim lda**. The Mahalanobis transformation with Euclidean distance is called Mahalanobis distance.

Optimal choice of k for KNN is not an exact science. With two groups, k should be chosen as an odd integer to avoid ties. Rencher and Christensen (2012, 331) cites the research of Loftsgaarden and Quesenberry (1965), which suggests that an optimal k is $\sqrt{n_i}$, where n_i is a typical group size. Rencher and Christensen also suggest running with several different values of k and choosing the one that gives the best error rate. McLachlan (2004) cites Enas and Choi (1986), which suggests that when there are two groups of comparable size that k should be chosen approximately between $N^{3/8}$ or $N^{2/8}$, where N is the number of observations.

References

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Also see

Title

discrim knn postestimation — Postestimation tools for discrim knn

Postestimation commands

The following postestimation commands are of special interest after `discrim knn`:

Command	Description
estat classtable	classification table
estat errorrate	classification error-rate estimation
estat grsummarize	group summaries
estat list	classification listing
estat summarize	estimation sample summary

The following standard postestimation commands are also available:

Command	Description
*estimates	cataloging estimation results
predict	group membership, probabilities of group membership, etc.

*All `estimates` subcommands except `table` and `stats` are available; see [R] **estimates**.

predict

Description for predict

predict creates a new variable containing predictions such as group classifications, probabilities, leave-one-out group classifications, and leave-one-out probabilities.

Menu for predict

Statistics > Postestimation

Syntax for predict

predict [*type*] *newvar* [*if*] [*in*] [, *statistic options*]

predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*] [, *statistic options*]

statistic	Description
Main	
classification	group membership classification; the default when one variable is specified and group() is not specified
pr	probability of group membership; the default when group() is specified or when multiple variables are specified
* looclass	leave-one-out group membership classification; may be used only when one new variable is specified
* loopr	leave-one-out probability of group membership

options	Description
Main	
group(*group*)	the group for which the statistic is to be calculated
Options	
priors(*priors*)	group prior probabilities; defaults to e(grouppriors)
ties(*ties*)	how ties in classification are to be handled; defaults to e(ties)
noupdate	do not update the within-group covariance matrix with leave-one-out predictions

priors	Description
equal	equal prior probabilities
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
<u>missing</u>	ties in group classification produce missing values
<u>random</u>	ties in group classification are broken randomly
<u>first</u>	ties in group classification are set to the first tied group
<u>nearest</u>	ties in group classification are assigned based on the closest observation, or missing if this still results in a tie

You specify one new variable with classification or looclass and specify either one or e(N_groups) new variables with pr or loopr.

Unstarred statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample. Starred statistics are calculated only for the estimation sample, even when if e(sample) is not specified.

group() is not allowed with classification or looclass.

noupdate is an advanced option and does not appear in the dialog box.

Options for predict

> [Main]

classification, the default, calculates the group classification. Only one new variable may be specified.

pr calculates group membership posterior probabilities. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

looclass calculates the leave-one-out group classifications. Only one new variable may be specified. Leave-one-out calculations are restricted to e(sample) observations.

loopr calculates the leave-one-out group membership posterior probabilities. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables. Leave-one-out calculations are restricted to e(sample) observations.

group(*group*) specifies the group for which the statistic is to be calculated and can be specified using

> #1, #2, ..., where #1 means the first category of the e(groupvar) variable, #2 the second category, etc.;

> the values of the e(groupvar) variable; or

> the value labels of the e(groupvar) variable if they exist.

group() is not allowed with classification or looclass.

> [Options]

priors(*priors*) specifies the prior probabilities for group membership. If priors() is not specified, e(grouppriors) is used. The following *priors* are allowed:

priors(<u>equal</u>) specifies equal prior probabilities.

priors(<u>proportional</u>) specifies group-size-proportional prior probabilities.

priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. If ties() is not specified, e(ties) is used. The following *ties* are allowed:

ties(<u>m</u>issing) specifies that ties in group classification produce missing values.

ties(<u>r</u>andom) specifies that ties in group classification are broken randomly.

ties(<u>f</u>irst) specifies that ties in group classification are set to the first tied group.

ties(<u>n</u>earest) specifies that ties in group classification are assigned based on the closest observation, or missing if this still results in a tie.

The following option is available with predict after discrim knn but is not shown in the dialog box:

noupdate causes the within-group covariance matrix not to be updated with leave-one-out predictions. noupdate is an advanced, rarely used option that is valid only if a Mahalanobis transformation is specified.

Remarks and examples

*k*th-nearest-neighbor (KNN) discriminant analysis and postestimation can be time consuming for large datasets. The training data must be retained and then searched to find the nearest neighbors each time a classification or prediction is performed.

You can find more examples of postestimation with KNN in [MV] **discrim knn**, and more examples of the common estat subcommands in [MV] **discrim estat**.

▷ Example 1: Leave-one-out classification after KNN

Recall example 1 of [MV] **discrim knn**. We use a similar idea here, creating a two-dimensional dataset on the plane with x and y variables in $[-4, 4]$. Instead of random data, we choose data on a regular grid to make things easy to visualize, and once again, we assign groups on the basis of geometric calculations. To start, we assign all points a group value of one, then within four circles of radius 3, one in each quadrant, we change the group value to two in the circles in the first and third quadrants, and we change the group value to three in the circles in the second and fourth quadrants.

Instructions for creating this dataset and definitions for local macros associated with it are contained in its notes.

```
. use https://www.stata-press.com/data/r18/circlegrid
(Gridded circle data)
. local rp: di %12.10f 2+sqrt(3)
. local rm: di %12.10f 2-sqrt(3)
. local functionplot
> (function y =  sqrt(3-(x+2)^2) - 2, lpat(solid) range(-`rp' -`rm'))
> (function y = -sqrt(3-(x+2)^2) - 2, lpat(solid) range(-`rp' -`rm'))
> (function y =  sqrt(3-(x-2)^2) + 2, lpat(solid) range(-`rm'  `rp'))
> (function y = -sqrt(3-(x-2)^2) + 2, lpat(solid) range(-`rm'  `rp'))
> (function y =  sqrt(3-(x+2)^2) + 2, lpat(solid) range(-`rp' -`rm'))
> (function y = -sqrt(3-(x+2)^2) + 2, lpat(solid) range(-`rp' -`rm'))
> (function y =  sqrt(3-(x-2)^2) - 2, lpat(solid) range( `rm'  `rp'))
> (function y = -sqrt(3-(x-2)^2) - 2, lpat(solid) range( `rm'  `rp'))
. local graphopts
> aspectratio(1) legend(order(1 "Group 1" 2 "Group 2" 3 "Group 3"))
```

```
. twoway (scatter y x if group==1)
>        (scatter y x if group==2)
>        (scatter y x if group==3)
>        'functionplot' , 'graphopts' name(original, replace)
>        title("Training data")
```


We do a KNN discriminant analysis, choosing k(3). We elect to omit the standard classification table and instead take a look at the leave-one-out (LOO) classification table.

```
. discrim knn x y, group(group) k(3) priors(proportional) notable lootable
```

Kth-nearest-neighbor discriminant analysis
Leave-one-out classification summary

```
┌──────────┐
│   Key    │
├──────────┤
│  Number  │
│ Percent  │
└──────────┘
```

True group	Classified 1	2	3	Total
1	173	12	12	197
	87.82	6.09	6.09	100.00
2	8	114	0	122
	6.56	93.44	0.00	100.00
3	8	0	114	122
	6.56	0.00	93.44	100.00
Total	189	126	126	441
	42.86	28.57	28.57	100.00
Priors	0.4467	0.2766	0.2766	

We will predict the LOO classification, changing to `priors(equal)`, and look at the plot.

```
. predict cknn, looclass priors(equal)
warning: 8 ties encountered;
        ties are assigned to missing values.
(8 missing values generated)

. twoway (scatter y x if cknn==1)
>        (scatter y x if cknn==2)
>        (scatter y x if cknn==3)
>        `functionplot' , `graphopts' name(KNN, replace)
>        title("KNN classification")
```


KNN classification
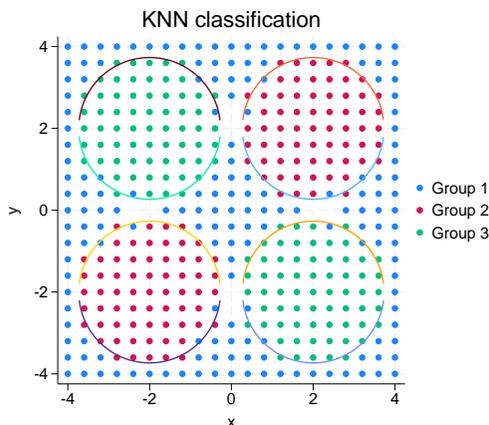
We see several empty spots on the grid. In our output, changing to `priors(equal)` created several ties that were assigned to missing values. Missing values are the blank places in our graph.

◁

▷ Example 2: Listing misclassified observations

Continuing where we left off, we use `estat list` to display LOO probabilities for the misclassified observations, but this produces a lot of output.

```
. estat list, misclass class(noclass looclass) pr(nopr loopr) priors(equal)
```

	Classification		LOO Probabilities		
Obs	True	LOO Cl.	1	2	3
24	1	2 *	0.3836	0.6164	0.0000
28	1	2 *	0.2374	0.7626	0.0000
34	1	3 *	0.2374	0.0000	0.7626
38	1	3 *	0.3836	0.0000	0.6164
50	2	1 *	0.5513	0.4487	0.0000
54	3	1 *	0.5513	0.0000	0.4487

(*output omitted*)

* indicates misclassified observations

Instead, we predict the LOO probabilities and list only those where the LOO classification is missing.

```
. predict pr*, loopr priors(equal)
. list group cknn pr* if missing(cknn)
```

	group	cknn	pr1	pr2	pr3
94.	1	.	.2373541	.381323	.381323
115.	1	.	.2373541	.381323	.381323
214.	1	.	.2373541	.381323	.381323
215.	1	.	.2373541	.381323	.381323
225.	1	.	.2373541	.381323	.381323
226.	1	.	.2373541	.381323	.381323
325.	1	.	.2373541	.381323	.381323
346.	1	.	.2373541	.381323	.381323

The missing LOO classifications represent ties for the largest probability.

◁

▷ Example 3: Out-of-sample KNN classification

LOO classification and LOO probabilities are available only in sample, but standard probabilities can be obtained out of sample. To demonstrate this, we continue where we left off, with the KNN model of example 2 still active. We drop our current data and generate some new data. We predict the standard classification with the new data and graph our results.

```
. clear
. set obs 500
Number of observations (_N) was 0, now 500.
. set seed 314159265
. generate x = 8*runiform() - 4
. generate y = 8*runiform() - 4
. predict cknn, class
```

```
. twoway (scatter y x if cknn==1)
>        (scatter y x if cknn==2)
>        (scatter y x if cknn==3)
>        'functionplot', 'graphopts' name(KNN2, replace)
>        title("Out-of-sample KNN classification", span)
```


◁
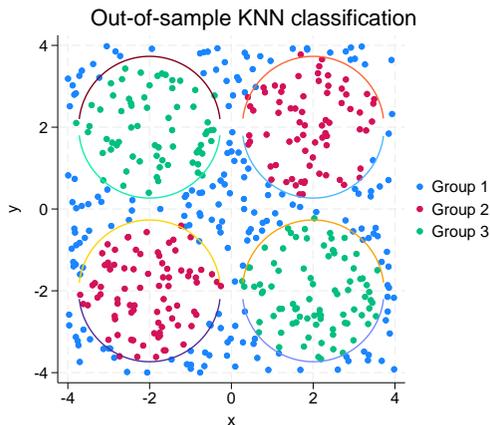
Methods and formulas

See [MV] **discrim knn** for methods and formulas.

Also see

[MV] **discrim knn** — kth-nearest-neighbor discriminant analysis

[MV] **discrim estat** — Postestimation tools for discrim

[MV] **discrim** — Discriminant analysis

[U] **20 Estimation and postestimation commands**

Title

---

discrim lda — Linear discriminant analysis

Description

discrim lda performs linear discriminant analysis. See [MV] **discrim** for other discrimination commands.

If you want canonical linear discriminant results displayed, see [MV] **candisc**.

Quick start

Linear discriminant analysis of v1, v2, v3, and v4 for groups defined by catvar
```
discrim lda v1 v2 v3 v4, group(catvar)
```

Same as above, but use prior probabilities proportional to group size
```
discrim lda v1 v2 v3 v4, group(catvar) priors(proportional)
```

Display the leave-one-out and the resubstitution classification tables
```
discrim lda v1 v2 v3 v4, group(catvar) lootable
```

Same as above, but suppress the resubstitution classification table
```
discrim lda v1 v2 v3 v4, group(catvar) lootable notable
```

Menu

Statistics > Multivariate analysis > Discriminant analysis > Linear (LDA)

Syntax

> discrim lda *varlist* $\lceil$*if*$\rceil$ $\lceil$*in*$\rceil$ $\lceil$*weight*$\rceil$, group(*groupvar*) $\lceil$*options*$\rceil$

options	Description
Model	
*group(*groupvar*)	variable specifying the groups
priors(*priors*)	group prior probabilities
ties(*ties*)	how ties in classification are to be handled
Reporting	
notable	suppress resubstitution classification table
lootable	display leave-one-out classification table

priors	Description
equal	equal prior probabilities; the default
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
missing	ties in group classification produce missing values; the default
random	ties in group classification are broken randomly
first	ties in group classification are set to the first tied group

*group() is required.

collect, statsby, and xi are allowed; see [U] **11.1.10 Prefix commands**.

fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

Model

group(*groupvar*) is required and specifies the name of the grouping variable. *groupvar* must be a numeric variable.

priors(*priors*) specifies the prior probabilities for group membership. The following *priors* are allowed:

    priors(equal) specifies equal prior probabilities. This is the default.

    priors(proportional) specifies group-size-proportional prior probabilities.

    priors(*matname*) specifies a row or column vector containing the group prior probabilities.

    priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. The following *ties* are allowed:

ties(<u>m</u>issing) specifies that ties in group classification produce missing values. This is the default.

ties(<u>r</u>andom) specifies that ties in group classification are broken randomly.

ties(<u>f</u>irst) specifies that ties in group classification are set to the first tied group.

   Reporting

notable suppresses the computation and display of the resubstitution classification table.

lootable displays the leave-one-out classification table.

Remarks and examples

discrim lda computes the same things as candisc, but candisc displays more information. The same information can be displayed after discrim lda by using the estat suite of commands; see [MV] **discrim lda postestimation**.

Remarks are presented under the following headings:

> *Introduction*
> *Descriptive LDA*
> *Predictive LDA*
> *A classic example*

Introduction

Linear discriminant analysis (LDA) was developed by different researchers, Fisher (1936) and Mahalanobis (1936), starting with different approaches to the problem of discriminating between groups. Kshirsagar and Arseven (1975), Green (1979), and Williams (1982) demonstrate the mathematical relationship between Fisher's linear discriminant functions and the classification functions from the Mahalanobis approach to LDA; see Rencher (1998, 239).

Fisher's approach to LDA forms the basis of descriptive LDA but can be used for predictive LDA. The Mahalanobis approach to LDA more naturally handles predictive LDA, allowing for prior probabilities and producing estimates of the posterior probabilities. The Mahalanobis approach to LDA also extends to quadratic discriminant analysis (QDA); see [MV] **discrim qda**.

Descriptive LDA

Fisher (1936) approached linear discriminant analysis by seeking the linear combination of the discriminating variables that provides maximal separation between the groups (originally two groups, but later extended to multiple groups). Maximal separation of groups is determined from an eigen analysis of $\mathbf{W}^{-1}\mathbf{B}$, where $\mathbf{B}$ is the between-group sum-of-squares and cross-products (SSCP) matrix, and $\mathbf{W}$ is the within-group SSCP matrix. The eigenvalues and eigenvectors of $\mathbf{W}^{-1}\mathbf{B}$ provide what are called Fisher's linear discriminant functions.

The first linear discriminant function is the eigenvector associated with the largest eigenvalue. This first discriminant function provides a linear transformation of the original discriminating variables into one dimension that has maximal separation between group means. The eigenvector associated with the second-largest eigenvalue is the second linear discriminant function and provides a dimension uncorrelated with (but usually not orthogonal to) the first discriminant function. The second discriminant function provides the maximal separation of groups in a second dimension. The third discriminant function provides the maximum separation of groups in a third dimension.

▷ Example 1

Two groups measured on two variables illustrate Fisher's approach to linear discriminant analysis.

```
. use https://www.stata-press.com/data/r18/twogroup
(Two groups)
```
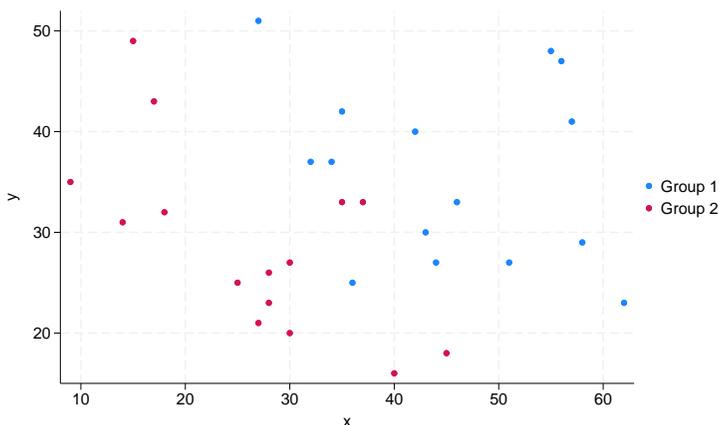

Splitting the two groups on the basis of y or x alone would leave a great deal of overlap between the groups. By eye it appears that a line with a slope of about −1 could be positioned between the two groups with only a few of the observations falling on the wrong side of the line.

Fisher's approach to LDA helps us find the best separating line.

```
. discrim lda y x, group(group) notable
```

`discrim lda` computes the information needed for both a predictive and descriptive linear discriminant analysis. We requested `notable`, which suppressed the display of the resubstitution classification table. We will examine this feature of `discrim lda` when we discuss predictive LDA. The descriptive features of LDA are available through postestimation commands.

```
. estat loadings, unstandardized
Canonical discriminant function coefficients
```

	function1
y	.0862145
x	.0994392
_cons	-6.35128

Fisher's linear discriminant functions provide the basis for what are called the canonical discriminant functions; see *Methods and formulas*. The canonical discriminant function coefficients are also called unstandardized loadings because they apply to the unstandardized discriminating variables (x and y). Because we have only two groups, there is only one discriminant function. From the coefficients or loadings of this discriminant function, we obtain a one-dimensional projection of the data that gives maximal separation between the two groups relative to the spread within the groups. The `estat loadings` postestimation command displayed these loadings; see [MV] **discrim lda postestimation**. After `estat loadings`, the unstandardized loadings are available in matrix `r(L_unstd)`. We take these values and determine the equation of the separating line between the groups and a line perpendicular to the separating line.

The unstandardized canonical discriminant function coefficients indicate that

$$0 = 0.0862145y + 0.0994392x - 6.35128$$

which in standard $y = mx + b$ form is

$$y = -1.1534x + 73.6684$$

which is the dividing line for classifying observations into the two groups for this LDA. A line perpendicular to this dividing line has slope $-1/-1.153 = 0.867$. The following graph shows the data with this dividing line and a perpendicular projection line.
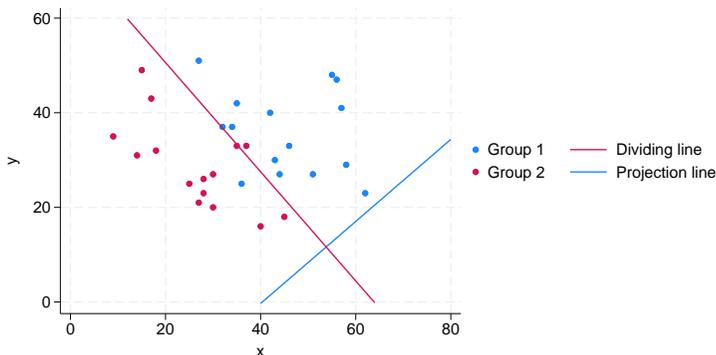
Another way of thinking about the discriminant function is that it projects the data from the original two dimensions down to one dimension—the line perpendicular to the dividing line. Classifications are based on which side of the separating line the observations fall.

Researchers often wish to know which of the discriminating variables is most important or helpful in discriminating between the groups. They want to examine the standardized loadings—the loadings that apply to standardized variables.

```
. estat loadings, standardized
Standardized canonical discriminant function coefficients
```

	function1
y	.7798206
x	1.057076

These coefficients or loadings apply to x and y that have been standardized using the pooled within-group covariance matrix. The loading for x is larger than that for y, indicating that it contributes more to the discrimination between the groups. Look back at the scatterplot to see that there is more separation between the groups in the x dimension than the y dimension. See [MV] **discrim lda postestimation** for more details of the estat loadings command.

Some researchers prefer to examine what are called structure coefficients.

```
. estat structure
Canonical structure
```

	function1
y	.3146309
x	.7138982

The `estat structure` command provides structure coefficients, which measure the correlation between each discriminating variable and the discriminant function; see [MV] **discrim lda postestimation**. Here the canonical structure coefficient for x is larger than that for y, leading to the same conclusion as with standardized loadings. There is disagreement in the literature concerning the use of canonical structure coefficients versus standardized loadings; see Rencher and Christensen (2012, 300–301) and Huberty (1994, 262–264).

◁

In addition to loading and structure coefficients, there are other descriptive LDA features available after `discrim lda`. These include canonical correlations and tests of the canonical correlations, classification functions, scree plots, loading plots, score plots, and various group summaries; see [MV] **discrim lda postestimation**.

If your main interest is in descriptive LDA, you may find the `candisc` command of interest; see [MV] **candisc**. `discrim lda` and `candisc` differ only in their default output. `discrim lda` shows classification tables. `candisc` shows canonical correlations, standardized coefficients (loadings), structure coefficients, and more. All the features found in [MV] **discrim lda postestimation** are available for both commands.

Predictive LDA

Another approach to linear discriminant analysis starts with the assumption that the observations from each group are multivariate normal with the groups having equal covariance matrices but different means. Mahalanobis (1936) distance plays an important role in this approach. An observation with unknown group membership is classified as belonging to the group with smallest Mahalanobis distance between the observation and group mean. Classification functions for classifying observations of unknown group membership can also be derived from this approach to LDA and formulas for the posterior probability of group membership are available.

As shown in *Methods and formulas*, Mahalanobis distance can be viewed as a transformation followed by Euclidean distance. Group membership is assigned based on the Euclidean distance in this transformed space.

▷ Example 2

We illustrate the Mahalanobis transformation and show some of the features of predictive discriminant analysis with a simple three-group example dataset named `threegroup.dta`.

Untransformed data
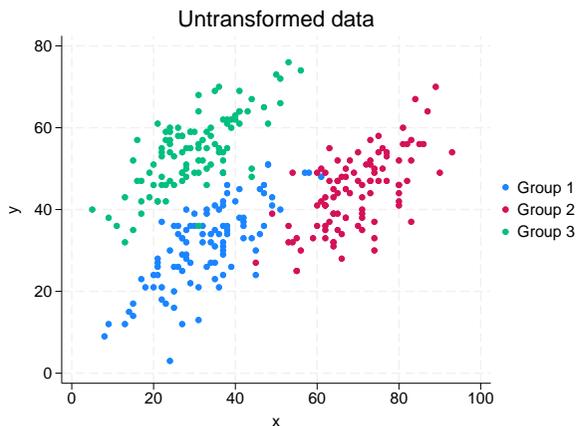
These three groups appear to have similar covariance structure—showing a positive correlation between x and y. There is some overlap of the three groups, but general identification of the groups does not appear difficult by human eye.

If we were to apply Euclidean distance for classifying this untransformed data, we would misclassify some observations that clearly should not be misclassified when judged by eye. For example, in the graph above, the observations from group 3 that have y values below 40 (found in the lower left of the group 3 cloud of points) are closer in Euclidean distance to the center of group 1.

The following graph shows the Mahalanobis-transformed data.

Mahalanobis transformed data
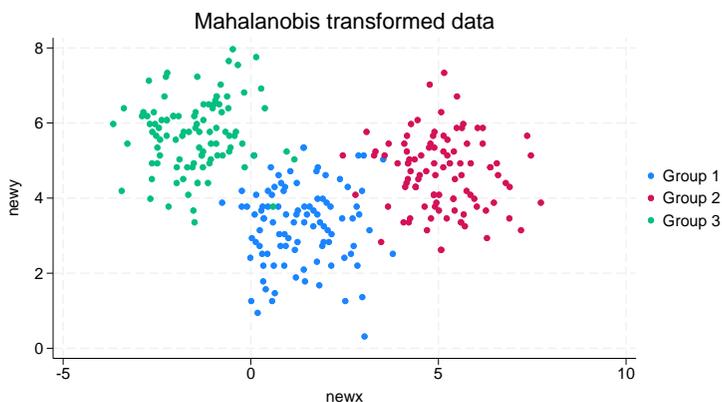
With the transformed data, using Euclidean distance between observations and group means works well.

Now let's see how well discrim lda can distinguish between the groups. By default, a resubstitution classification table is presented. The rows correspond to the known group and the columns to the grouping as assigned by the discrim model. The word resubstitution is used because the same observations that built the model are being classified by the model.

```
. discrim lda y x, group(group)
Linear discriminant analysis
Resubstitution classification summary
```

```
  ┌─────────┐
  │  Key    │
  ├─────────┤
  │ Number  │
  │ Percent │
  └─────────┘
```

	Classified			
True group	1	2	3	Total
1	93	4	3	100
	93.00	4.00	3.00	100.00
2	3	97	0	100
	3.00	97.00	0.00	100.00
3	3	0	97	100
	3.00	0.00	97.00	100.00
Total	99	101	100	300
	33.00	33.67	33.33	100.00
Priors	0.3333	0.3333	0.3333	

For these 300 observations, group 1 had 93 observations correctly classified, 4 observations misclassified into group 2, and 3 observations misclassified into group 3. Group 2 had 3 observations misclassified into group 1 and 97 observations correctly classified. Group 3 had 3 observations misclassified into group 1 and 97 observations correctly classified.

Generally, resubstitution classification tables give an overly optimistic view of how well you would classify an unknown observation. Leave-one-out (LOO) classification tables provide a more realistic assessment for classification success. With this 300-observation dataset, the LOO classification table gives the same results. We could see the LOO classification table by requesting it at estimation, by requesting it at replay, or by using the estat classtable command.

We now list the misclassified observations.

```
. estat list, varlist misclassified
```

| | Data | | Classification | | Probabilities | | |
Obs	y	x	True	Class.	1	2	3
19	49	37	1	3 *	0.2559	0.0000	0.7441
29	49	57	1	2 *	0.4245	0.5750	0.0005
47	49	37	1	3 *	0.2559	0.0000	0.7441
55	24	45	1	2 *	0.4428	0.5572	0.0000
70	48	61	1	2 *	0.0661	0.9339	0.0000
74	49	58	1	2 *	0.3041	0.6957	0.0003
92	37	22	1	3 *	0.3969	0.0000	0.6031
143	27	45	2	1 *	0.6262	0.3738	0.0000
161	39	49	2	1 *	0.8026	0.1973	0.0001
185	49	54	2	1 *	0.7782	0.2187	0.0030
238	48	44	3	1 *	0.8982	0.0017	0.1001
268	50	44	3	1 *	0.7523	0.0009	0.2469
278	36	31	3	1 *	0.9739	0.0000	0.0261

```
* indicates misclassified observations
```

The posterior probabilities for each displayed observation for each of the three groups is presented along with the true group and the classified group. The observation number is also shown. We added the discriminating variables x and y to the list with the varlist option. By default, estat list would list all the observations. The misclassified option restricts the list to those observations that were misclassified.

With predict we could generate classification variables, posterior probabilities, Mahalanobis squared distances from observations to group means, classification function scores (see *Methods and formulas*), and more. Fifteen estat commands provide more predictive and descriptive tools after discrim lda; see [MV] **discrim lda postestimation**.

◁

A classic example

We use the iris data from Fisher's (1936) pioneering LDA article to demonstrate the discrim lda command.

▷ Example 3

Fisher obtained the iris data from Anderson (1935). The data consist of four features measured on 50 samples from each of three iris species. The four features are the length and width of the sepal and petal. The three species are *Iris setosa*, *Iris versicolor*, and *Iris virginica*. Morrison (2005, app. B.2) is a modern source of the data.

```
. use https://www.stata-press.com/data/r18/iris
(Iris data)
```

Running `discrim lda` produces the resubstitution classification table.

```
. discrim lda seplen sepwid petlen petwid, group(iris)
Linear discriminant analysis
Resubstitution classification summary
```

```
  ┌─────────┐
  │   Key   │
  ├─────────┤
  │ Number  │
  │ Percent │
  └─────────┘
```

True iris	Classified Setosa	Versicolor	Virginica	Total
Setosa	50	0	0	50
	100.00	0.00	0.00	100.00
Versicolor	0	48	2	50
	0.00	96.00	4.00	100.00
Virginica	0	1	49	50
	0.00	2.00	98.00	100.00
Total	50	49	51	150
	33.33	32.67	34.00	100.00
Priors	0.3333	0.3333	0.3333	

One *Iris virginica* observation was misclassified as a *versicolor*, two *Iris versicolor* observations were misclassified as *virginica*, and no *Iris setosa* observations were misclassified in our resubstitution classification.

Which observations were misclassified?

```
. estat list, misclassified
```

	Classification		Probabilities		
Obs	True	Class.	Setosa	Versicolor	Virginica
71	Versicol	Virginic *	0.0000	0.2532	0.7468
84	Versicol	Virginic *	0.0000	0.1434	0.8566
134	Virginic	Versicol *	0.0000	0.7294	0.2706

```
* indicates misclassified observations
```

Postestimation command `estat list` shows that observations 71, 84, and 134 were misclassified and shows the estimated posterior probabilities for the three species for the misclassified observations.

We now examine the canonical discriminant functions for this LDA. The number of discriminant functions will be one fewer than the number of groups or will be the number of discriminating variables, whichever is less. With four discriminating variables and three species, we will have two discriminant functions. `estat loadings` displays the discriminant coefficients or loadings.

```
. estat loadings, unstandardized standardized
```

Canonical discriminant function coefficients

	function1	function2
seplen	-.8293776	-.0241021
sepwid	-1.534473	-2.164521
petlen	2.201212	.9319212
petwid	2.81046	-2.839188
_cons	-2.105106	6.661473

Standardized canonical discriminant function coefficients

	function1	function2
seplen	-.4269548	-.0124075
sepwid	-.5212417	-.7352613
petlen	.9472572	.4010378
petwid	.5751608	-.5810399

We requested the display of both unstandardized and standardized loadings. The two unstandardized discriminant functions provide linear combinations of the seplen, sepwid, petlen, and petwid discriminating variables—producing two new dimensions. The standardized canonical discriminant function coefficients indicate the relative importance and relationship between the discriminating variables and the discriminant functions. The first discriminant function compares seplen and sepwid, which have negative standardized coefficients, to petlen and petwid, which have positive standardized coefficients. The second discriminant function appears to be contrasting the two width variables from the two length variables, though this is not as distinct of a difference as found in the first discriminant function because the seplen variable in the second standardized discriminant function is close to zero.

Understanding the composition of the discriminant functions is aided by plotting the coefficients. loadingplot graphs the discriminant function coefficients (loadings); see [MV] **discrim lda postestimation** and [MV] **scoreplot**.

```
. loadingplot
```

Standardized discriminant function loadings
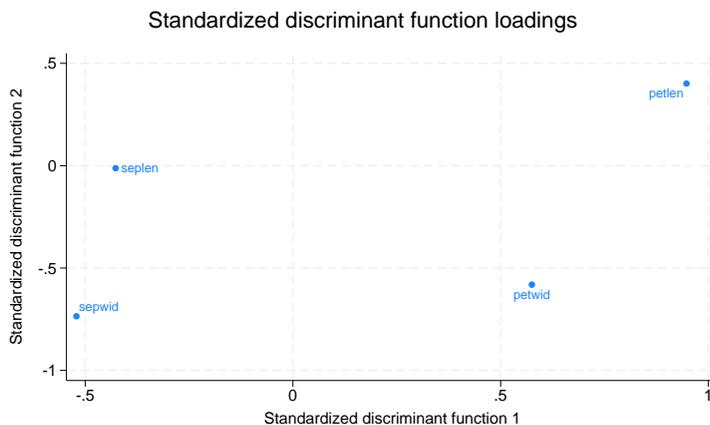
We now show a scatterplot of our three species projected onto the two dimensions of our discriminant solution. The scoreplot command takes care of most of the graphing details for us; see [MV] **discrim lda postestimation** and [MV] **scoreplot**. However, by default, scoreplot uses the full value labels for the three iris species and the resulting graph is busy. The iris dataset has two label languages predefined. The default label language has the full value labels. The other predefined label language

is called `oneletter`, and it uses a one-letter code as value labels for the three iris species. The `label language` command will switch between these two label languages; see [D] **label language**. We also use the `msymbol(i)` graph option so that the points will not be displayed—only the one-letter value labels will be displayed for each observation.

```
. label language oneletter
. scoreplot, msymbol(i)
>              note("S = Iris setosa, C = Iris versicolor, V = Iris virginica")
```


Discriminant function scores

S = Iris setosa, C = Iris versicolor, V = Iris virginica
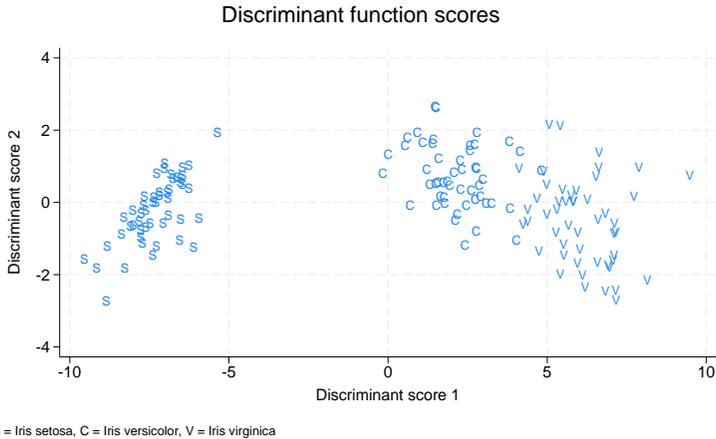
The *Iris setosa* are well separated from the other two species. *Iris versicolor* and *Iris virginica* show some overlap.

See example 1 of [MV] **discrim estat** and examples 6, 7, and 8, of [MV] **discrim lda postestimation** for more examples of what can be produced after `discrim lda` for this `iris` dataset.

◁

Stored results

discrim lda stores the following in e():

Scalars
    e(N)   number of observations
    e(N_groups)   number of groups
    e(k)   number of discriminating variables
    e(f)   number of nonzero eigenvalues

Macros
    e(cmd)   discrim
    e(subcmd)   lda
    e(cmdline)   command as typed
    e(groupvar)   name of group variable
    e(grouplabels)   labels for the groups
    e(varlist)   discriminating variables
    e(wtype)   weight type
    e(wexp)   weight expression
    e(title)   title in estimation output
    e(ties)   how ties are to be handled
    e(properties)   nob noV eigen
    e(estat_cmd)   program used to implement estat
    e(predict)   program used to implement predict
    e(marginsnotok) predictions disallowed by margins

Matrices
    e(groupcounts)   number of observations for each group
    e(grouppriors)   prior probabilities for each group
    e(groupvalues)   numeric value for each group
    e(means)   group means on discriminating variables
    e(SSCP_W)   pooled within-group SSCP matrix
    e(SSCP_B)   between-groups SSCP matrix
    e(SSCP_T)   total SSCP matrix
    e(SSCP_W#)   within-group SSCP matrix for group *#*
    e(W_eigvals)   eigenvalues of e(SSCP_W)
    e(W_eigvecs)   eigenvectors of e(SSCP_W)
    e(S)   pooled within-group covariance matrix
    e(Sinv)   inverse of e(S)
    e(sqrtSinv)   Cholesky (square root) of e(Sinv)
    e(Ev)   eigenvalues of $\mathbf{W}^{-1}\mathbf{B}$
    e(L_raw)   eigenvectors of $\mathbf{W}^{-1}\mathbf{B}$
    e(L_unstd)   unstandardized canonical discriminant function coefficients
    e(L_std)   within-group standardized canonical discriminant function coefficients
    e(L_totalstd)   total-sample standardized canonical discriminant function coefficients
    e(C)   classification coefficients
    e(cmeans)   unstandardized canonical discriminant functions evaluated at group means
    e(canstruct)   canonical structure matrix
    e(candisc_stat) canonical discriminant analysis statistics

Functions
    e(sample)   marks estimation sample

Methods and formulas

Methods and formulas are presented under the following headings:

> [Predictive LDA](#)
> [Descriptive LDA](#)

Predictive LDA

Let g be the number of groups, n_i the number of observations for group i, and q_i the prior probability for group i. Let $\mathbf{x}$ denote an observation measured on p discriminating variables. For consistency with the discriminant analysis literature, $\mathbf{x}$ will be a column vector, though it corresponds to a row in your dataset. Let $f_i(\mathbf{x})$ represent the density function for group i, and let $P(\mathbf{x}|G_i)$ denote the probability of observing $\mathbf{x}$ conditional on belonging to group i. Denote the posterior probability of group i given observation $\mathbf{x}$ as $P(G_i|\mathbf{x})$. With Bayes's theorem, we have

$$P(G_i|\mathbf{x}) = \frac{q_i f_i(\mathbf{x})}{\sum_{j=1}^{g} q_j f_j(\mathbf{x})}$$

Substituting $P(\mathbf{x}|G_i)$ for $f_i(\mathbf{x})$, we have

$$P(G_i|\mathbf{x}) = \frac{q_i P(\mathbf{x}|G_i)}{\sum_{j=1}^{g} q_j P(\mathbf{x}|G_j)}$$

LDA assumes that the groups are multivariate normal with equal covariance matrices. Let $\mathbf{S}$ denote the pooled within-group sample covariance matrix and $\overline{\mathbf{x}}_i$ denote the sample mean of group i. The $\overline{\mathbf{x}}_i$ are returned as the columns of the `e(means)` matrix. The squared Mahalanobis distance between observation $\mathbf{x}$ and $\overline{\mathbf{x}}_i$ is

$$D_i^2 = (\mathbf{x} - \overline{\mathbf{x}}_i)' \mathbf{S}^{-1} (\mathbf{x} - \overline{\mathbf{x}}_i)$$

Plugging these sample estimates into the multivariate normal density gives

$$P(\mathbf{x}|G_i) = (2\pi)^{-p/2} |\mathbf{S}|^{-1/2} e^{-D_i^2/2}$$

Substituting this into the formula for $P(G_i|\mathbf{x})$ and simplifying gives

$$P(G_i|\mathbf{x}) = \frac{q_i e^{-D_i^2/2}}{\sum_{j=1}^{g} q_j e^{-D_j^2/2}}$$

as the LDA posterior probability of observation $\mathbf{x}$ belonging to group i.

Computation of Mahalanobis distance can be broken down into two steps. Step one: transform the data by using the Mahalanobis transformation. Step two: compute the Euclidean distance of the transformed data.

Let $\mathbf{L}$ be the Cholesky factorization of $\mathbf{S}^{-1}$ such that $\mathbf{S}^{-1} = \mathbf{L}'\mathbf{L}$ and $\mathbf{L}$ is lower triangular. $\mathbf{L}$ is returned in matrix `e(sqrtSinv)`. Squared Mahalanobis distance can be expressed in terms of $\mathbf{L}$.

$$\begin{aligned} D_i^2 &= (\mathbf{x} - \overline{\mathbf{x}}_i)' \mathbf{S}^{-1} (\mathbf{x} - \overline{\mathbf{x}}_i) \\ &= (\mathbf{x} - \overline{\mathbf{x}}_i)' \mathbf{L}'\mathbf{L} (\mathbf{x} - \overline{\mathbf{x}}_i) \\ &= (\mathbf{L}\mathbf{x} - \mathbf{L}\overline{\mathbf{x}}_i)' (\mathbf{L}\mathbf{x} - \mathbf{L}\overline{\mathbf{x}}_i) \\ &= (\mathbf{z} - \overline{\mathbf{z}}_i)' (\mathbf{z} - \overline{\mathbf{z}}_i) \end{aligned}$$

which is the squared Euclidean distance between $\mathbf{z}$ and $\overline{\mathbf{z}}_i$. We call $\mathbf{z} = \mathbf{L}\mathbf{x}$ the Mahalanobis transformation.

The squared Mahalanobis distance between group means is produced by `estat grdistances`; see [MV] **discrim lda postestimation**.

Classification functions can be derived from the Mahalanobis formulation for LDA; see Rencher and Christensen (2012, 315–316) and Huberty (1994, 59). Let $L_i(\mathbf{x})$ denote the linear classification function for the ith group applied to observation $\mathbf{x}$. $L_i(\mathbf{x}) = \mathbf{c}_i'\mathbf{x} + c_{i0}$, where $\mathbf{c}_i = \overline{\mathbf{x}}_i'\mathbf{S}^{-1}$ and $c_{i0} = -(1/2)\overline{\mathbf{x}}_i'\mathbf{S}^{-1}\overline{\mathbf{x}}_i + \ln(q_i)$. The g linear classification functions are returned as the columns of matrix **e(C)** and through the `estat classfunction` command; see [MV] **discrim lda postestimation**. An observation can be classified based on largest posterior probability or based on largest classification function score.

Descriptive LDA

As with predictive LDA, let g be the number groups, n_i the number of training (sample) observations for group i, p the number of discriminating variables, and $N = \sum_{i=1}^{g} n_i$ the total number of observations. Also, let $\mathbf{W}$ be the within-group sums-of-squares and cross-products (SSCP) matrix and let $\mathbf{B}$ be the between-groups SSCP matrix. Fisher's (1936) linear discriminant functions are based on the eigenvalues and eigenvectors of $\mathbf{W}^{-1}\mathbf{B}$.

There are $s = \min(g - 1, p)$ nonzero eigenvalues of $\mathbf{W}^{-1}\mathbf{B}$. Let λ_1, λ_2, ..., λ_s denote the s eigenvalues in decreasing order. The eigenvalues are returned in e(Ev). Let $\mathbf{v}_1$, $\mathbf{v}_2$, ..., $\mathbf{v}_s$ denote the corresponding eigenvectors. Rencher and Christensen (2012, 289) outlines the approach for obtaining the eigenvalues and eigenvectors of the nonsymmetric $\mathbf{W}^{-1}\mathbf{B}$ matrix. Because $\mathbf{W}^{-1}\mathbf{B}$ is nonsymmetric, the resulting eigenvectors are not orthogonal but merely uncorrelated; see Rencher and Christensen (2012, 289). A matrix with the $\mathbf{v}_i$ as columns is returned in e(L_raw). The phrase raw coefficients is used by Klecka (1980, 22) to describe the $\mathbf{v}$ vectors.

Any constant multiple of the eigenvector $\mathbf{v}_i$ is still an eigenvector of $\mathbf{W}^{-1}\mathbf{B}$ associated with eigenvalue λ_i. Typically, $\mathbf{vu}_i = \mathbf{v}_i\sqrt{N - g}$ are used as the eigenvectors (discriminant functions) and are called unstandardized canonical discriminant functions because they correspond to the unstandardized discriminating variables. An extra element is added to the bottom of the $\mathbf{vu}$ vectors for the constant, so that if the $\mathbf{vu}$ vectors are applied as linear combinations of the discriminating variables, the resulting variables have mean zero; see Klecka (1980, 21–23). A matrix with the $\mathbf{vu}_i$ as columns is returned in e(L_unstd).

The means of the discriminating variables for each group are returned as the columns of the matrix e(means). These group means multiplied by the unstandardized discriminant-function coefficients, $\mathbf{vu}_i$, produce what are called group means on canonical variables and are returned in the matrix e(cmeans) and displayed with the command estat grmeans, canonical.

Standardized discriminant functions are obtained as $\mathbf{vs}_i = \mathbf{v}_i\sqrt{W_{ii}}$. The ith raw eigenvector is standardized by the square root of the ith diagonal element of the $\mathbf{W}$ matrix. These within-group standardized discriminant functions are used in assessing the importance and relationship of the original discriminating variables to the discriminant functions. A matrix with the $\mathbf{vs}_i$ as columns is returned in e(L_std).

Let $\mathbf{T}$ denote the total sample SSCP matrix. Total-sample standardized discriminant functions are computed as $\mathbf{vt}_i = \mathbf{v}_i\sqrt{T_{ii}(N - g)/(N - 1)}$. A matrix with the $\mathbf{vt}_i$ as columns is returned in e(L_totalstd). There is debate as to which of $\mathbf{vs}$ and $\mathbf{vt}$ should be used for interpretation; see Mueller and Cozad (1988), Nordlund and Nagel (1991), and Mueller and Cozad (1993).

The estat loadings command displays e(L_unstd), e(L_std), and e(L_totalstd); see [MV] discrim lda postestimation.

The canonical structure matrix measures the correlation between the discriminating variables and the discriminant function and is returned in matrix e(canstruct). The canonical structure matrix is equal to $\mathbf{WV}$ with the ith row divided by $\sqrt{W_{ii}}$, where $\mathbf{V}$ contains the $\mathbf{v}_i$ eigenvectors as columns. Rencher and Christensen (2012, 300) warns against the use of structure coefficients for interpretation, but Huberty (1994, 262–264) contends otherwise.

The returned matrix e(candisc_stat) contains columns for the information shown by estat canontest, including the eigenvalues, canonical correlations, proportion of variance, cumulative proportion of variance, likelihood-ratio test statistics, and the corresponding F tests, degrees of freedom, and p-values. See [MV] canon.

As noted in the *Introduction* section of *Remarks and examples*, Kshirsagar and Arseven (1975), Green (1979), and Williams (1982) demonstrate the mathematical relationship between Fisher's

linear discriminant functions (the basis for descriptive LDA) and the classification functions from the Mahalanobis approach to LDA (the basis for predictive LDA); see Rencher (1998, 239).

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Also see

Title

discrim lda postestimation — Postestimation tools for discrim lda

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Postestimation commands

The following postestimation commands are of special interest after `discrim lda`:

Command	Description
estat anova	ANOVA summaries table
estat canontest	tests of the canonical discriminant functions
estat classfunctions	classification functions
estat classtable	classification table
estat correlations	correlation matrices and p-values
estat covariance	covariance matrices
estat errorrate	classification error-rate estimation
estat grdistances	Mahalanobis and generalized squared distances between the group means
estat grmeans	group means and variously standardized or transformed means
estat grsummarize	group summaries
estat list	classification listing
estat loadings	canonical discriminant-function coefficients (loadings)
estat manova	MANOVA table
estat structure	canonical structure matrix
estat summarize	estimation sample summary
loadingplot	plot standardized discriminant-function loadings
scoreplot	plot discriminant-function scores
screeplot	plot eigenvalues

The following standard postestimation commands are also available:

Command	Description
*estimates	cataloging estimation results
predict	group membership, probabilities of group membership, etc.

*All `estimates` subcommands except `table` and `stats` are available; see [R] **estimates**.

predict

Description for predict

predict creates a new variable containing predictions such as group classifications, probabilities, Mahalanobis squared distances, discriminant function scores, leave-one-out probabilities, leave-one-out group classifications, and leave-one-out Mahalanobis squared distances.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] *newvar* [*if*] [*in*] [, *statistic options*]

> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*] [, *statistic options*]

statistic	Description
Main	
classification	group membership classification; the default when one variable is specified and group() is not specified
pr	probability of group membership; the default when group() is specified or when multiple variables are specified
mahalanobis	Mahalanobis squared distance between observations and groups
dscore	discriminant function score
clscore	group classification function score
* looclass	leave-one-out group membership classification; may be used only when one new variable is specified
* loopr	leave-one-out probability of group membership
* loomahal	leave-one-out Mahalanobis squared distance between observations and groups

options	Description
Main	
group(*group*)	the group for which the statistic is to be calculated
Options	
priors(*priors*)	group prior probabilities; defaults to e(grouppriors)
ties(*ties*)	how ties in classification are to be handled; defaults to e(ties)

priors	Description
<u>eq</u>ual	equal prior probabilities
<u>prop</u>ortional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
<u>miss</u>ing	ties in group classification produce missing values
<u>rand</u>om	ties in group classification are broken randomly
<u>fir</u>st	ties in group classification are set to the first tied group

You specify one new variable with classification or looclass; either one or e(N_groups) new variables with pr, loopr, mahalanobis, loomahal, or clscore; and one to e(f) new variables with dscore.

Unstarred statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample. Starred statistics are calculated only for the estimation sample, even when if e(sample) is not specified.

group() is not allowed with classification, dscore, or looclass.

Options for predict

> [Main]

classification, the default, calculates the group classification. Only one new variable may be specified.

pr calculates group membership posterior probabilities. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

mahalanobis calculates the squared Mahalanobis distance between the observations and group means. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

dscore produces the discriminant function score. Specify as many variables as leading discriminant functions that you wish to score. No more than e(f) variables may be specified.

clscore produces the group classification function score. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

looclass calculates the leave-one-out group classifications. Only one new variable may be specified. Leave-one-out calculations are restricted to e(sample) observations.

loopr calculates the leave-one-out group membership posterior probabilities. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables. Leave-one-out calculations are restricted to e(sample) observations.

loomahal calculates the leave-one-out squared Mahalanobis distance between the observations and group means. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables. Leave-one-out calculations are restricted to e(sample) observations.

group(*group*) specifies the group for which the statistic is to be calculated and can be specified using

> #1, #2, . . . , where #1 means the first category of the e(groupvar) variable, #2 the second category, etc.;

> the values of the e(groupvar) variable; or

> the value labels of the e(groupvar) variable if they exist.

group() is not allowed with classification, dscore, or looclass.

┌─── Options ───

priors(*priors*) specifies the prior probabilities for group membership. If priors() is not specified, e(grouppriors) is used. The following *priors* are allowed:

priors(<u>equal</u>) specifies equal prior probabilities.

priors(<u>proportional</u>) specifies group-size-proportional prior probabilities.

priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. If ties() is not specified, e(ties) is used. The following *ties* are allowed:

ties(<u>missing</u>) specifies that ties in group classification produce missing values.

ties(<u>random</u>) specifies that ties in group classification are broken randomly.

ties(<u>first</u>) specifies that ties in group classification are set to the first tied group.

estat

Description for estat

estat anova presents a table summarizing the one-way ANOVAs for each variable in the discriminant analysis.

estat canontest presents tests of the canonical discriminant functions. Presented are the canonical correlations, eigenvalues, proportion and cumulative proportion of variance, and likelihood-ratio tests for the number of nonzero eigenvalues.

estat classfunctions displays the classification functions.

estat correlations displays the pooled within-group correlation matrix, between-groups correlation matrix, total-sample correlation matrix, and/or the individual group correlation matrices. Two-tailed p-values for the correlations may also be requested.

estat covariance displays the pooled within-group covariance matrix, between-groups covariance matrix, total-sample covariance matrix, and/or the individual group covariance matrices.

estat grdistances provides Mahalanobis squared distances between the group means along with the associated F statistics and significance levels. Also available are generalized squared distances.

estat grmeans provides group means, total-sample standardized group means, pooled within-group standardized means, and canonical functions evaluated at the group means.

estat loadings present the canonical discriminant-function coefficients (loadings). Unstandardized, pooled within-class standardized, and total-sample standardized coefficients are available.

estat manova presents the MANOVA table associated with the discriminant analysis.

estat structure presents the canonical structure matrix.

Menu for estat

Statistics > Postestimation

Syntax for estat

ANOVA summaries table

    estat <u>an</u>ova

Tests of the canonical discriminant functions

    estat <u>canon</u>test

Classification functions

    estat <u>classf</u>unctions [, *classfunctions_options*]

Correlation matrices and p-values

    estat <u>cor</u>relations [, *correlations_options*]

Covariance matrices

    estat <u>cov</u>ariance [, *covariance_options*]

Mahalanobis and generalized squared distances between the group means

    estat <u>grd</u>istances [, *grdistances_options*]

Group means and variously standardized or transformed means

    estat <u>grm</u>eans [, *grmeans_options*]

Canonical discriminant-function coefficients (loadings)

    estat <u>lo</u>adings [, *loadings_options*]

MANOVA table

    estat <u>man</u>ova

Canonical structure matrix

    estat <u>str</u>ucture [, <u>format</u>(*%fmt*)]

classfunctions_options	Description
Main	
adjustequal	adjust the constant even when priors are equal
format(*%fmt*)	numeric display format; default is %9.0g
Options	
priors(*priors*)	group prior probabilities; defaults to e(grouppriors)
nopriors	suppress display of prior probabilities

correlations_options	Description
Main	
<u>with</u>in	display pooled within-group correlation matrix; the default
<u>betw</u>een	display between-groups correlation matrix
<u>tot</u>al	display total-sample correlation matrix
<u>gr</u>oups	display the correlation matrix for each group
all	display all the above
p	display two-sided p-values for requested correlations
<u>format</u>(*%fmt*)	numeric display format; default is %9.0g
<u>noh</u>alf	display full matrix even if symmetric

covariance_options	Description
Main	
<u>with</u>in	display pooled within-group covariance matrix; the default
<u>betw</u>een	display between-groups covariance matrix
<u>tot</u>al	display total-sample covariance matrix
<u>gr</u>oups	display the covariance matrix for each group
all	display all the above
<u>format</u>(*%fmt*)	numeric display format; default is %9.0g
<u>noh</u>alf	display full matrix even if symmetric

grdistances_options	Description
Main	
<u>mahal</u>anobis [(f p)]	display Mahalanobis squared distances between group means; the default
<u>gen</u>eralized	display generalized Mahalanobis squared distances between group means
all	equivalent to mahalanobis(f p) generalized
<u>format</u>(*%fmt*)	numeric display format; default is %9.0g
Options	
<u>pri</u>ors(*priors*)	group prior probabilities; defaults to e(grouppriors)

grmeans_options	Description
Main	
raw	display untransformed and unstandardized group means
<u>total</u>std	display total-sample standardized group means
<u>within</u>std	display pooled within-group standardized group means
<u>can</u>onical	display canonical functions evaluated at group means
all	display all the mean tables

loadings_options	Description
Main	
<u>stand</u>ardized	display pooled within-group standardized canonical discriminant function coefficients; the default
totalstandardized	display the total-sample standardized canonical discriminant function coefficients
<u>unstand</u>ardized	display unstandardized canonical discriminant function coefficients
all	display all the above
<u>f</u>ormat(*% fmt*)	numeric display format; default is %9.0g

collect is allowed with all estat commands; see [U] **11.1.10 Prefix commands**.

Options for estat

Options for estat are presented under the following headings:

> *Options for estat classfunctions*
> *Options for estat correlations*
> *Options for estat covariance*
> *Options for estat grdistances*
> *Options for estat grmeans*
> *Options for estat loadings*
> *Option for estat structure*

Options for estat classfunctions

　　　Main

adjustequal specifies that the constant term in the classification function be adjusted for prior probabilities even though the priors are equal. By default, equal prior probabilities are not used in adjusting the constant term. adjustequal has no effect with unequal prior probabilities.

format(*% fmt*) specifies the matrix display format. The default is format(%9.0g).

　　　Options

priors(*priors*) specifies the group prior probabilities. The prior probabilities affect the constant term in the classification function. By default, *priors* is determined from e(grouppriors). See *Options for predict* for the *priors* specification. By common convention, when there are equal prior probabilities the adjustment of the constant term is not performed. See adjustequal to override this convention.

nopriors specifies that the prior probabilities not be displayed. By default, the prior probabilities used in determining the constant in the classification functions are displayed as the last row in the classification functions table.

Options for estat correlations

　　　Main

within specifies that the pooled within-group correlation matrix be displayed. This is the default.

between specifies that the between-groups correlation matrix be displayed.

total specifies that the total-sample correlation matrix be displayed.

groups specifies that the correlation matrix for each group be displayed.

all is the same as specifying within, between, total, and groups.

p specifies that two-sided p-values be computed and displayed for the requested correlations.

format(% *fmt*) specifies the matrix display format. The default is format(%8.5f).

nohalf specifies that, even though the matrix is symmetric, the full matrix be printed. The default is to print only the lower triangle.

Options for estat covariance

> [Main]

within specifies that the pooled within-group covariance matrix be displayed. This is the default.

between specifies that the between-groups covariance matrix be displayed.

total specifies that the total-sample covariance matrix be displayed.

groups specifies that the covariance matrix for each group be displayed.

all is the same as specifying within, between, total, and groups.

format(% *fmt*) specifies the matrix display format. The default is format(%9.0g).

nohalf specifies that, even though the matrix is symmetric, the full matrix be printed. The default is to print only the lower triangle.

Options for estat grdistances

> [Main]

mahalanobis ⌈ (f p) ⌉ specifies that a table of Mahalanobis squared distances between group means be presented. mahalanobis(f) adds F tests for each displayed distance and mahalanobis(p) adds the associated p-values. mahalanobis(f p) adds both. The default is mahalanobis.

generalized specifies that a table of generalized Mahalanobis squared distances between group means be presented. generalized starts with what is produced by the mahalanobis option and adds a term accounting for prior probabilities. Prior probabilities are provided with the priors() option, or if priors() is not specified, by the values in e(grouppriors). By common convention, if prior probabilities are equal across the groups, the prior probability term is omitted and the results from generalized will equal those from mahalanobis.

all is equivalent to specifying mahalanobis(f p) and generalized.

format(% *fmt*) specifies the matrix display format. The default is format(%9.0g).

> [Options]

priors(*priors*) specifies the group prior probabilities and affects only the output of the generalized option. By default, *priors* is determined from e(grouppriors). See *Options for predict* for the *priors* specification.

Options for estat grmeans

> Main

raw, the default, displays a table of group means.

totalstd specifies that a table of total-sample standardized group means be presented.

withinstd specifies that a table of pooled within-group standardized group means be presented.

canonical specifies that a table of the unstandardized canonical discriminant functions evaluated at the group means be presented.

all is equivalent to specifying raw, totalstd, withinstd, and canonical.

Options for estat loadings

> Main

standardized specifies that the pooled within-group standardized canonical discriminant function coefficients be presented. This is the default.

totalstandardized specifies that the total-sample standardized canonical discriminant function coefficients be presented.

unstandardized specifies that the unstandardized canonical discriminant function coefficients be presented.

all is equivalent to specifying standardized, totalstandardized, and unstandardized.

format(*%fmt*) specifies the matrix display format. The default is format(%9.0g).

Option for estat structure

> Main

format(*%fmt*) specifies the matrix display format. The default is format(%9.0g).

Remarks and examples

Remarks are presented under the following headings:

> *Classification tables, error rates, and listings*
> *ANOVA, MANOVA, and canonical correlations*
> *Discriminant and classification functions*
> *Scree, loading, and score plots*
> *Means and distances*
> *Covariance and correlation matrices*
> *Predictions*

Classification tables, error rates, and listings

After discrim, including discrim lda, you can obtain classification tables, error-rate estimates, and listings; see [MV] **discrim estat**.

▷ Example 1: Predictive linear discriminant analysis

Example 1 of [MV] **manova** introduces the apple tree rootstock data from Andrews and Herzberg (1985, 357–360) and used in Rencher and Christensen (2012, 184). Descriptive linear discriminant analysis is often used after a multivariate analysis of variance (MANOVA) to explore the differences between groups found to be significantly different in the MANOVA.

We first examine the predictive aspects of the linear discriminant model on these data by examining classification tables, error-rate estimate tables, and classification listings.

To illustrate the ability of discrim lda and the postestimation commands of handling unequal prior probabilities, we perform our LDA using prior probabilities of 0.2 for the first four rootstock groups and 0.1 for the last two rootstock groups.

```
. use https://www.stata-press.com/data/r18/rootstock
(Table 6.2. Rootstock data, Rencher and Christensen (2012))
. discrim lda y1 y2 y3 y4, group(rootstock) priors(.2, .2, .2, .2, .1, .1)
Linear discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True rootstock	Classified 1	2	3	4	5	6	Total
1	7	0	0	1	0	0	8
	87.50	0.00	0.00	12.50	0.00	0.00	100.00
2	0	4	2	1	1	0	8
	0.00	50.00	25.00	12.50	12.50	0.00	100.00
3	0	1	6	1	0	0	8
	0.00	12.50	75.00	12.50	0.00	0.00	100.00
4	3	0	1	4	0	0	8
	37.50	0.00	12.50	50.00	0.00	0.00	100.00
5	0	3	2	0	2	1	8
	0.00	37.50	25.00	0.00	25.00	12.50	100.00
6	3	0	0	0	2	3	8
	37.50	0.00	0.00	0.00	25.00	37.50	100.00
Total	13	8	11	7	5	4	48
	27.08	16.67	22.92	14.58	10.42	8.33	100.00
Priors	0.2000	0.2000	0.2000	0.2000	0.1000	0.1000	

The prior probabilities are reported at the bottom of the table. The classification results are based, in part, on the selection of prior probabilities.

With only 8 observations per rootstock and six rootstock groups, we have small cell counts in our table, with many zero cell counts. Because resubstitution classification tables give an overly optimistic view of classification ability, we use the estat classtable command to request a leave-one-out (LOO) classification table and request the reporting of average posterior probabilities in place of percentages.

```
. estat classtable, probabilities loo
```
Leave-one-out average-posterior-probabilities classification table

Key
Number Average posterior probability

True rootstock	LOO Classified 1	2	3	4	5	6
1	5 0.6055	0 .	0 .	2 0.6251	0 .	1 0.3857
2	0 .	4 0.6095	2 0.7638	1 0.3509	1 0.6607	0 .
3	0 .	1 0.5520	6 0.7695	1 0.4241	0 .	0 .
4	4 0.5032	0 .	1 0.7821	3 0.5461	0 .	0 .
5	0 .	3 0.7723	2 0.5606	0 .	2 0.4897	1 0.6799
6	3 0.6725	0 .	0 .	0 .	2 0.4296	3 0.5763
Total	12 0.5881	8 0.6634	11 0.7316	7 0.5234	5 0.4999	5 0.5589
Priors	0.2000	0.2000	0.2000	0.2000	0.1000	0.1000

Zero cell counts report a missing value for the average posterior probability. We did not specify the priors() option with estat classtable, so the prior probabilities used in our LDA model were used.

estat errorrate estimates the error rates for each group. We use the pp option to obtain estimates based on the posterior probabilities instead of the counts.

```
. estat errorrate, pp
```
Error rate estimated from posterior probabilities

Error rate	rootstock 1	2	3	4	5
Stratified	.2022195	.431596	.0868444	.4899799	.627472
Unstratified	.2404022	.41446	.1889412	.5749832	.4953118
Priors	.2	.2	.2	.2	.1

Error rate	rootstock 6	Total
Stratified	.6416429	.3690394
Unstratified	.4027382	.3735623
Priors	.1	

We did not specify the priors() option, and estat errorrate defaulted to using the prior probabilities from the LDA model. Both stratified and unstratified estimates are shown for each rootstock group and for the overall total. See [MV] **discrim estat** for an explanation of the error-rate estimation.

We can list the classification results and posterior probabilities from our discriminant analysis model by using the estat list command. estat list allows us to specify which observations we wish to examine and what classification and probability results to report.

We request the LOO classification and LOO probabilities for all misclassified observations from the fourth rootstock group. We also suppress the resubstitution classification and probabilities from being displayed.

```
. estat list if rootstock==4, misclassified class(loo noclass) pr(loo nopr)
```

	Classification		LOO Probabilities					
Obs	True	LOO Cl.	1	2	3	4	5	6
25	4	1 *	0.5433	0.1279	0.0997	0.0258	0.0636	0.1397
26	4	3 *	0.0216	0.0199	0.7821	0.1458	0.0259	0.0048
27	4	1 *	0.3506	0.1860	0.0583	0.2342	0.0702	0.1008
29	4	1 *	0.6134	0.0001	0.0005	0.2655	0.0002	0.1202
32	4	1 *	0.5054	0.0011	0.0017	0.4856	0.0002	0.0059

* indicates misclassified observations

Four of the five misclassifications for rootstock group 4 were incorrectly classified as belonging to rootstock group 1.

◁

ANOVA, MANOVA, and canonical correlations

There is a mathematical relationship between Fisher's LDA and one-way MANOVA. They are both based on the eigenvalues and eigenvectors of the same matrix, $\mathbf{W}^{-1}\mathbf{B}$ (though in MANOVA the matrices are labeled $\mathbf{E}$ and $\mathbf{H}$ for error and hypothesis instead of $\mathbf{W}$ and $\mathbf{B}$ for within and between). See [MV] **manova** and [R] **anova** for more information on MANOVA and ANOVA. Researchers often wish to examine the MANOVA and univariate ANOVA results corresponding to their LDA model.

Canonical correlations are also mathematically related to Fisher's LDA. The canonical correlations between the discriminating variables and indicator variables constructed from the group variable are based on the same eigenvalues and eigenvectors as MANOVA and Fisher's LDA. The information from a canonical correlation analysis gives insight into the importance of each discriminant function in the discrimination. See [MV] **canon** for more information on canonical correlations.

The estat manova, estat anova, and estat canontest commands display MANOVA, ANOVA, and canonical correlation information after discrim lda.

▷ Example 2: MANOVA, ANOVA, and canonical correlation corresponding to LDA

Continuing with the apple tree rootstock example, we examine the MANOVA, ANOVA, and canonical correlation results corresponding to our LDA.

```
. estat manova
```

```
                              Number of obs =          48

                              W = Wilks' lambda     L = Lawley-Hotelling trace
                              P = Pillai's trace    R = Roy's largest root

            Source │ Statistic         df    F(df1,    df2) =    F   Prob>F

         rootstock │W    0.1540          5    20.0     130.3   4.94 0.0000 a
                   │P    1.3055               20.0     168.0   4.07 0.0000 a
                   │L    2.9214               20.0     150.0   5.48 0.0000 a
                   │R    1.8757                5.0      42.0  15.76 0.0000 u

          Residual │                     42

             Total │                     47
```

```
                  e = exact, a = approximate, u = upper bound on F
```

```
. estat anova
```

Univariate ANOVA summaries

```
                                                      Adj.
   Variable │  Model MS    Resid MS    Total MS    R-sq    R-sq     F      Pr > F

         y1 │ .07356042  .31998754   .29377189   0.1869  0.0901   1.931   0.1094
         y2 │ 4.1996621  12.14279    11.297777   0.2570  0.1685  2.9052   0.0243
         y3 │ 6.1139358  4.2908128    4.484762   0.5876  0.5385  11.969   0.0000
         y4 │ 2.4930912  1.7225248   1.8044999   0.5914  0.5428  12.158   0.0000
```

```
Number of obs = 48          Model df = 5          Residual df = 42
```

All four of the MANOVA tests reject the null hypothesis that the six rootstock groups have equal means. See example 1 of [MV] **manova** for an explanation of the MANOVA table.

estat anova presents a concise summary of univariate ANOVAs run on each of our four discriminating variables. Variables y3, trunk girth at 15 years, and y4, weight of tree above ground at 15 years, show the highest level of significance of the four variables.

estat canontest displays the canonical correlations and associated tests that correspond to our LDA model.

```
. estat canontest
```

Canonical linear discriminant analysis

```
           │                                   Like-
       Canon.     Eigen-      Variance         lihood
  Fcn  │ Corr.      value    Prop.   Cumul.    Ratio      F      df1    df2   Prob>F

    1  │ 0.8076   1.87567   0.6421   0.6421    0.1540   4.9369    20   130.3  0.0000 a
    2  │ 0.6645   .790694   0.2707   0.9127    0.4429   3.1879    12   106.1  0.0006 a
    3  │ 0.4317   .229049   0.0784   0.9911    0.7931   1.6799     6    82     0.1363 e
    4  │ 0.1591   .025954   0.0089   1.0000    0.9747   .54503     2    42     0.5839 e
```

```
  H0: This and smaller canon. corr. are zero;  e = exact F, a = approximate F
```

The number of nonzero eigenvalues in Fisher's LDA is $\min(g - 1, p)$ With $g = 6$ groups, and $p = 4$ discriminating variables, there are four nonzero eigenvalues. The four eigenvalues and the corresponding canonical correlations of $\mathbf{W}^{-1}\mathbf{B}$, ordered from largest to smallest, are reported along with the proportion and cumulative proportion of variance accounted for by each of the discriminant functions. Using one discriminant dimension is insufficient for capturing the variability of our four-dimensional data. With two dimensions we account for 91% of the variance. Using three of the four dimensions accounts for 99% of the variance. Little is gained from the fourth discriminant dimension.

Also presented are the likelihood-ratio tests of the null hypothesis that each canonical correlation and all smaller canonical correlations from this model are zero. The letter a is placed beside the p-values of the approximate F tests, and the letter e is placed beside the p-values of the exact F tests. The first two tests are highly significant, indicating that the first two canonical correlations are likely not zero. The third test has a p-value of 0.1363, so that we fail to reject that the third and fourth canonical correlation are zero.

◁

Discriminant and classification functions

See [MV] **discrim lda** for a discussion of linear discriminant functions and linear classification functions for LDA.

Discriminant functions are produced from Fisher's LDA. The discriminant functions provide a set of transformations from the original p-dimensional (the number of discriminating variables) space to the minimum of p and $g - 1$ (the number of groups minus 1) dimensional space. The discriminant functions are ordered in importance.

Classification functions are by-products of the Mahalanobis approach to LDA. There are always g classification functions—one for each group. They are not ordered by importance, and you cannot use a subset of them for classification.

A table showing the discriminant function coefficients is available with estat loadings (see example 3), and a table showing the classification function coefficients is available with estat classfunctions (see example 4).

▷ Example 3: Canonical discriminant functions and canonical structures

We continue with the apple tree rootstock example. The canonical discriminant function coefficients (loadings) are available through the estat loadings command. Unstandardized, pooled within-group standardized, and total-sample standardized coefficients are available. The all option requests all three, and the format() option provides control over the numeric display format used in the tables.

```
. estat loadings, all format(%6.2f)
Canonical discriminant function coefficients
```

	func~1	func~2	func~3	func~4
y1	-3.05	1.14	-1.00	23.42
y2	1.70	1.22	1.67	-3.08
y3	-4.23	-7.17	3.05	-2.01
y4	0.48	11.52	-5.51	3.10
_cons	15.45	12.20	-9.99	-12.47

Standardized canonical discriminant function coefficients

	func~1	func~2	func~3	func~4
y1	-0.27	0.10	-0.09	2.04
y2	0.92	0.65	0.90	-1.65
y3	-1.35	-2.29	0.97	-0.64
y4	0.10	2.33	-1.12	0.63

Total-sample standardized canonical discriminant function coefficients

	func~1	func~2	func~3	func~4
y1	-0.28	0.10	-0.09	2.14
y2	1.00	0.72	0.99	-1.81
y3	-1.99	-3.37	1.43	-0.95
y4	0.14	3.45	-1.65	0.93

The unstandardized canonical discriminant function coefficients shown in the first table are the function coefficients that apply to the unstandardized discriminating variables—y1 through y4 and a constant term. See example 5 for a graph, known as a score plot, that plots the observations transformed by these unstandardized canonical discriminant function coefficients.

The standardized canonical discriminant function coefficients are the coefficients that apply to the discriminating variables after they have been standardized by the pooled within-group covariance. These coefficients are appropriate for interpreting the importance and relationship of the discriminating variables within the discriminant functions. See example 5 for a graph, known as a loading plot, that plots these standardized coefficients.

The total-sample standardized canonical discriminant function coefficients are the coefficients that apply to the discriminating variables after they have been standardized by the total-sample covariance. See *Methods and formulas* of [MV] **discrim lda** for references discussing which of within-group and total-sample standardization is most appropriate.

For both styles of standardization, variable y1 has small (in absolute value) coefficients for the first three discriminant functions. This indicates that y1 does not play an important part in these discriminant functions. Because the fourth discriminant function accounts for such a small percentage of the variance, we ignore the coefficients from the fourth function when assessing the importance of the variables.

Some sources, see Huberty (1994), advocate the interpretation of structure coefficients, which measure the correlation between the discriminating variables and the discriminant functions, instead of standardized discriminant function coefficients; see the discussion in example 1 of [MV] **discrim lda** for references to this dispute. The estat structure command displays structure coefficients.

```
. estat structure, format(%9.6f)
```

Canonical structure

	function1	function2	function3	function4
y1	-0.089595	0.261416	0.820783	0.499949
y2	-0.086765	0.431180	0.898063	0.006158
y3	-0.836986	0.281362	0.457902	-0.103031
y4	-0.793621	0.572890	0.162901	-0.124206

Using structure coefficients for interpretation, we conclude that y1 is important for the second and third discriminant functions.

◁

▷ Example 4: LDA classification functions

Switching from Fisher's approach to LDA to Mahalanobis's approach to LDA, we examine what are called classification functions with the estat classfunctions command. Classification functions are applied to the unstandardized discriminating variables. The classification function that results in the largest value for an observation indicates the group to assign the observation.

Continuing with the rootstock LDA, we specify the format() option to control the display format of the classification coefficients.

```
. estat classfunctions, format(%8.3f)
```

Classification functions

	rootstock					
	1	2	3	4	5	6
y1	314.640	317.120	324.589	307.260	316.767	311.301
y2	-59.417	-63.981	-65.152	-59.373	-65.826	-63.060
y3	149.610	168.161	154.910	147.652	168.221	160.622
y4	-161.178	-172.644	-150.356	-153.387	-172.851	-175.477
_cons	-301.590	-354.769	-330.103	-293.427	-349.847	-318.099
Priors	0.200	0.200	0.200	0.200	0.100	0.100

The prior probabilities, used in constructing the coefficient for the constant term, are displayed as the last row in the table. We did not specify the `priors()` option, so the prior probabilities defaulted to those in our LDA model, which has rootstock group 5 and 6 with prior probabilities of 0.1, whereas the other groups have prior probabilities of 0.2.

See example 10 for applying the classification function to data by using the `predict` command.

◁

Scree, loading, and score plots

Examples of discriminant function loading plots and score plots (see [MV] **scoreplot**) can be found in example 3 of [MV] **discrim lda** and example 1 of [MV] **candisc**. Also available after `discrim lda` are scree plots; see [MV] **screeplot**.

▷ Example 5: Scree, loading, and score plots

Continuing with our rootstock example, the scree plot of the four nonzero eigenvalues we previously saw in the output of `estat canontest` in example 2 are graphed using the `screeplot` command.

```
. screeplot
```
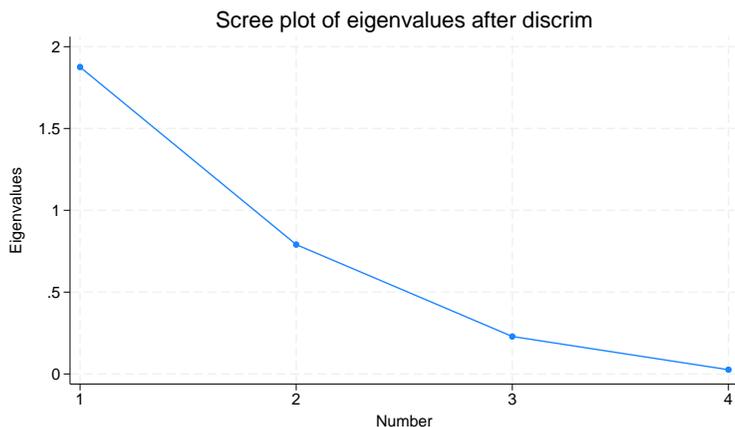

The *Remarks and examples* in [MV] **screeplot** concerning the use of scree plots for selecting the number of components in the context of `pca` apply also for selecting the number of discriminant functions after `discrim lda`. With these four eigenvalues, it is not obvious whether to choose the top

two or three eigenvalues. From the `estat canontest` output of example 2, the first two discriminant functions account for 91% of the variance, and three discriminant functions account for 99% of the variance.

The `loadingplot` command (see [MV] **scoreplot**) allows us to graph the pooled within-group standardized discriminant coefficients (loadings) that we saw in tabular form from the `estat loadings` command of example 3. By default only the loadings from the first two functions are graphed. We override this setting with the `components(3)` option, obtaining graphs of the first versus second, first versus third, and second versus third function loadings. The `combined` option switches from a matrix graph to a combined graph. The `msymbol(i)` option removes the plotting points, leaving the discriminating variable names in the graph, and the option `mlabpos(0)` places the discriminating variable names in the positions of the plotted points.

```
. loadingplot, components(3) combined msymbol(i) mlabpos(0)
```
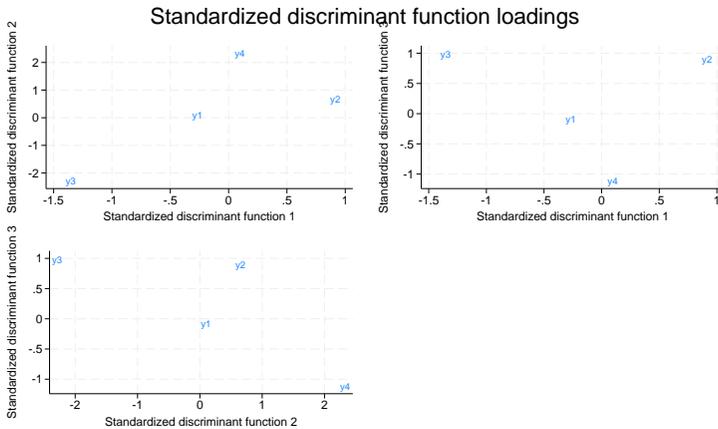

Variable `y1`, trunk girth at 4 years, is near the origin in all three graphs, indicating that it does not play a strong role in discriminating among our six rootstock groups. `y4`, weight of tree above ground at 15 years, does not play much of a role in the first discriminant function but does in the second and third discriminant functions.

The corresponding three score plots are easily produced with the `scoreplot` command; see [MV] **scoreplot**. Score plots graph the discriminant function–transformed observations (called scores).

```
. scoreplot, components(3) combined msymbol(i)
```

Discriminant function scores
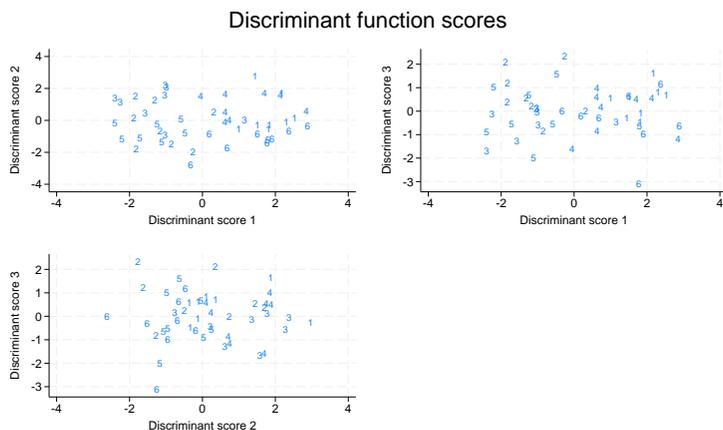
There is a lot of overlap, but some separation of the rootstock groups is apparent. One of the observations from group 6 seems to be sitting by itself in the bottom of the two graphs that have discriminant function 3 as the y axis. In example 11, we identify this point by using the `predict` command.

◁

Means and distances

The `estat grsummarize` command is available after all `discrim` commands and will display means, medians, minimums, maximums, standard deviations, group sizes, and more for the groups; see [MV] **discrim estat**. After `discrim lda`, the `estat grmeans` command will also display group means. It, however, has options for displaying the within-group standardized group means, the total-sample standardized group means, and the canonical discriminant functions evaluated at the group means.

▷ Example 6: Standardized group means and canonical discriminant functions at the means

We introduce the `estat grmeans` command with the iris data originally from Anderson (1935), introduced in example 3 of [MV] **discrim lda**.

```
. use https://www.stata-press.com/data/r18/iris
(Iris data)
. discrim lda seplen sepwid petlen petwid, group(iris) notable
```

The `notable` option of `discrim` suppressed the classification table.

By default, `estat grmeans` displays a table of the means of the discriminating variables for each group. You could obtain the same information along with other statistics with the `estat grsummarize` command; see [MV] **discrim estat**.

```
. estat grmeans
Group means
```

| | iris | | |
	Setosa	Versico~r	Virginica
seplen	5.006	5.936	6.588
sepwid	3.428	2.77	2.974
petlen	1.462	4.26	5.552
petwid	.246	1.326	2.026

Differences in the iris species can be seen within these means. For instance, the petal lengths and widths of the *Iris setosa* are smaller than those of the other two species. See color example 1 of [MV] **discrim estat** for further exploration of these differences.

The main purpose of `estat grmeans` is to present standardized or transformed means. The `totalstd` and `withinstd` options request the two available standardizations.

```
. estat grmeans, totalstd withinstd
Total-sample standardized group means
```

| | iris | | |
	Setosa	Versico~r	Virginica
seplen	-1.011191	.1119073	.8992841
sepwid	.8504137	-.6592236	-.1911901
petlen	-1.30063	.2843712	1.016259
petwid	-1.250704	.1661774	1.084526

```
Pooled within-group standardized group means
```

| | iris | | |
	Setosa	Versico~r	Virginica
seplen	-1.626555	.1800089	1.446546
sepwid	1.091198	-.8458749	-.2453234
petlen	-5.335385	1.166534	4.16885
petwid	-4.658359	.6189428	4.039416

The first table presents the total-sample standardized group means on the discriminating variables. These are the means for each group on the total-sample standardized discriminating variables.

The second table presents the pooled within-group standardized means on the discriminating variables. Instead of using the total-sample variance, the pooled within-group variance is used to standardize the variables. Of most interest in the context of an LDA is the within-group standardization.

The `canonical` option of `estat grmeans` displays the discriminant functions evaluated at the group means and gives insight into what the functions do to the groups.

```
. estat grmeans, canonical
Group means on canonical variables
```

iris	function1	function2
Setosa	-7.6076	-.215133
Versicolor	1.825049	.7278996
Virginica	5.78255	-.5127666

The first function places *Iris setosa* strongly negative and *Iris virginica* strongly positive with *Iris versicolor* in between. The second function places *Iris virginica* and *Iris setosa* negative and *Iris versicolor* positive.

◁

The Mahalanobis distance between the groups in an LDA helps in assessing which groups are similar and which are different.

▷ Example 7: Mahalanobis distance between groups

Continuing with the iris example, we use the `estat grdistances` command to view the squared Mahalanobis distances between the three iris species.

```
. estat grdistances
Mahalanobis squared distances between groups
                    iris
       iris              Setosa   Versicolor    Virginica

        Setosa              0
    Versicolor       89.864186            0
     Virginica       179.38471    17.201066            0
```

Iris setosa is farthest from *Iris virginica* with a squared Mahalanobis distance of 179. *Iris versicolor* and *Iris virginica* are closest with a squared Mahalanobis distance of 17.

Are these distances significant? Requesting F statistics and p-values associated with these Mahalanobis squared distances between means will help answer that question. The `mahalanobis()` option requests F tests, p-values, or both.

```
. estat grdistances, mahalanobis(f p)
Mahalanobis squared distances between groups

    ┌──────────────────────────────────┐
    │ Key                              │
    ├──────────────────────────────────┤
    │ Mahalanobis squared distance     │
    │ F with 4 and 144 df              │
    │ p-value                          │
    └──────────────────────────────────┘

                    iris
       iris              Setosa   Versicolor    Virginica

        Setosa              0
                            0
                            1

    Versicolor       89.864186            0
                     550.18889            0
                     3.902e-86            1

     Virginica       179.38471    17.201066            0
                     1098.2738    105.31265            0
                     9.20e-107    9.515e-42            1
```

All three of the means are statistically significantly different from one another.

The generalized squared distance between groups starts with the Mahalanobis squared distance between groups and adjusts for prior probabilities when they are not equal. With equal prior probabilities there will be no difference between the generalized squared distance and Mahalanobis squared distance. The `priors()` option specifies the prior probabilities for calculating the generalized squared distances.

To illustrate, we select prior probabilities of 0.2 for *I. setosa*, 0.3 for *I. versicolor*, and 0.5 for *I. virginica*.

```
. estat grdistances, generalized priors(.2, .3, .5)
```

Generalized squared distances between groups

	iris		
iris	Setosa	Versicolor	Virginica
Setosa	3.2188758	92.272131	180.77101
Versicolor	93.083061	2.4079456	18.587361
Virginica	182.60359	19.609012	1.3862944

This matrix is not symmetric and does not have zeros on the diagonal.

◁

Covariance and correlation matrices

Equal group covariance matrices is an important assumption underlying LDA. The estat covariance command displays the group covariance matrices, the pooled within-group covariance matrix, the between-groups covariance matrix, and the total-sample covariance matrix. The estat correlation command provides the corresponding correlation matrices, with an option to present p-values with the correlations.

▷ Example 8: Group covariances and correlations

Continuing our examination of LDA on the iris data, we request to see the pooled within-group covariance matrix and the covariance matrices for the three iris species.

```
. estat covariance, within groups
```

Pooled within-group covariance matrix

	seplen	sepwid	petlen	petwid
seplen	.2650082			
sepwid	.0927211	.1153878		
petlen	.1675143	.0552435	.1851878	
petwid	.0384014	.0327102	.0426653	.0418816

Group covariance matrices

iris: Setosa

	seplen	sepwid	petlen	petwid
seplen	.124249			
sepwid	.0992163	.1436898		
petlen	.0163551	.011698	.0301592	
petwid	.0103306	.009298	.0060694	.0111061

iris: Versicolor

	seplen	sepwid	petlen	petwid
seplen	.2664327			
sepwid	.0851837	.0984694		
petlen	.182898	.0826531	.2208163	
petwid	.0557796	.0412041	.073102	.0391061

iris: Virginica

	seplen	sepwid	petlen	petwid
seplen	.4043429			
sepwid	.0937633	.1040041		
petlen	.3032898	.0713796	.3045878	
petwid	.0490939	.0476286	.0488245	.0754327

All variables have positive covariance—not surprising for physical measurements (length and width).

We could have requested the between-groups covariance matrix and the total-sample covariance matrix. Options of `estat covariance` control how the covariance matrices are displayed.

Correlation matrices are also easily displayed. With `estat correlations` we show the pooled within-group correlation matrix, and add the p option to request display of p-values with the correlations. The p-values help us evaluate whether the correlations are statistically significant.

```
. estat corr, p
Pooled within-group correlation matrix
```

```
┌─────────────────┐
│ Key             │
├─────────────────┤
│ Correlation     │
│ Two-sided p-value│
└─────────────────┘
```

	seplen	sepwid	petlen	petwid
seplen	1.00000			
sepwid	0.53024	1.00000		
	0.00000			
petlen	0.75616	0.37792	1.00000	
	0.00000	0.00000		
petwid	0.36451	0.47053	0.48446	1.00000
	0.00001	0.00000	0.00000	

All correlations are statistically significant. The largest correlation is between the petal length and the sepal length.

◁

Predictions

The `predict` command after `discrim lda` has options for obtaining classifications, probabilities, Mahalanobis squared distances from observations to group means, and the leave-one-out (LOO) estimates of all of these. You can also obtain the discriminant scores and classification scores for observations. The predictions can be obtained in or out of sample.

▷ Example 9: Out-of-sample LDA classification and probabilities

We use the riding-mower data from Johnson and Wichern (2007) introduced in example 1 of [MV] **discrim** to illustrate out-of-sample prediction of classification and probabilities after an LDA.

```
. use https://www.stata-press.com/data/r18/lawnmower2
(Johnson and Wichern (2007) table 11.1)
. discrim lda lotsize income, group(owner) notable
```

Now we see how the LDA model classifies observations with income of $90,000, $110,000, and $130,000, each with a lot size of 20,000 square feet. We add 3 observations to the bottom of our dataset containing these values and then use `predict` to obtain the classifications and probabilities.

```
. input

         owner   income  lots~e
25. .   90 20
26. . 110 20
27. . 130 20
28. end
. predict grp in 25/L, class
(24 missing values generated)
. predict pr* in 25/L, pr
(24 missing values generated)
. list in 25/L
```

	owner	income	lotsize	grp	pr1	pr2
25.	.	90.0	20.0	0	.5053121	.4946879
26.	.	110.0	20.0	1	.1209615	.8790385
27.	.	130.0	20.0	1	.0182001	.9818

The observation with income of \$90,000 was classified as a nonowner, but it was a close decision with probabilities of 0.505 for nonowner and 0.495 for owner. The two other observations, with \$110,000 and \$130,000 income, were classified as owners, with higher probability of ownership for the higher income.

◁

The estat list, estat classtable, and estat errorrate commands (see [MV] **discrim estat**) obtain their information by calling predict. The LOO listings and tables from these commands are obtained by calling predict with the looclass and loopr options.

In addition to predictions and probabilities, we can obtain the classification scores for observations.

▷ Example 10: Classification scores

In example 4, we used the estat classfunctions command to view the classification functions for the LDA of the apple tree rootstock data. We can use predict to obtain the corresponding classification scores—the classification function applied to observations.

```
. use https://www.stata-press.com/data/r18/rootstock, clear
(Table 6.2. Rootstock data, Rencher and Christensen (2012))
. discrim lda y1 y2 y3 y4, group(rootstock) priors(.2,.2,.2,.2,.1,.1) notable
. predict clscr*, clscore
. format clscr* %6.1f
. list rootstock clscr* in 1/3, noobs
```

rootst~k	clscr1	clscr2	clscr3	clscr4	clscr5	clscr6
1	308.1	303.7	303.1	307.1	303.5	307.1
1	327.6	324.1	322.9	326.1	323.3	326.0
1	309.5	308.2	306.3	309.3	307.5	309.0

We did not specify the priors() option, so predict used the prior probabilities that were specified with our LDA model in determining the constant term in the classification function; see example 4 for a table of the classification functions. Observations may be classified to the group with

largest score. The first 3 observations belong to rootstock group 1 and are successfully classified as belonging to group 1 because the classification score in clscr1 is larger than the classification scores for the other groups.

◁

Scoring the discriminating variables by using Fisher's canonical discriminant functions is accomplished with the dscore option of predict.

▷ Example 11: Scoring the discriminant variables

Using the rootstock data in example 5, we noticed 1 observation, from group 6, near the bottom of the score plot where the third discriminant function was the y axis. The observation has a score for the third discriminant function that appears to be below -3. We will use the dscore option of predict to find the observation.

```
. predict ds*, dscore
. format ds* %5.0g
. list rootstock y* ds* if ds3 < -3
```

	rootst~k	y1	y2	y3	y4	ds1	ds2	ds3	ds4
42.	6	0.75	0.840	3.14	0.606	1.59	-1.44	-3.11	-1.93

Observation 42 is the one producing that third discriminant score.

◁

Stored results

estat anova stores the following in r():

Scalars
r(N)	number of observations
r(df_m)	model degrees of freedom
r(df_r)	residual degrees of freedom

Matrices
r(anova_stats)	ANOVA statistics for the model

estat canontest stores the following in r():

Scalars
r(N)	number of observations
r(N_groups)	number of groups
r(k)	number of variables
r(f)	number of canonical discriminant functions

Matrices
r(stat)	canonical discriminant statistics

estat classfunction stores the following in r():

Matrices
r(C)	classification function matrix
r(priors)	group prior probabilities

`estat correlations` stores the following in `r()`:

Matrices

r(Rho)	pooled within-group correlation matrix (within only)
r(P)	two-sided *p*-values for pooled within-group correlations (within and p only)
r(Rho_between)	between-groups correlation matrix (between only)
r(P_between)	two-sided *p*-values for between-groups correlations (between and p only)
r(Rho_total)	total-sample correlation matrix (total only)
r(P_total)	two-sided *p*-values for total-sample correlations (total and p only)
r(Rho_#)	group # correlation matrix (groups only)
r(P_#)	two-sided *p*-values for group # correlations (groups and p only)

`estat covariance` stores the following in `r()`:

Matrices

r(S)	pooled within-group covariance matrix (within only)
r(S_between)	between-groups covariance matrix (between only)
r(S_total)	total-sample covariance matrix (total only)
r(S_#)	group # covariance matrix (groups only)

`estat grdistances` stores the following in `r()`:

Scalars

r(df1)	numerator degrees of freedom (mahalanobis only)
r(df2)	denominator degrees of freedom (mahalanobis only)

Matrices

r(sqdist)	Mahalanobis squared distances between group means (mahalanobis only)
r(F_sqdist)	*F* statistics for tests that the Mahalanobis squared distances between group means are zero (mahalanobis only)
r(P_sqdist)	*p*-value for tests that the Mahalanobis squared distances between group means are zero (mahalanobis only)
r(gsqdist)	generalized squared distances between group means (generalized only)

`estat grmeans` stores the following in `r()`:

Matrices

r(means)	group means (raw only)
r(stdmeans)	total-sample standardized group means (totalstd only)
r(wstdmeans)	pooled within-group standardized group means (withinstd only)
r(cmeans)	group means on canonical variables (canonical only)

`estat loadings` stores the following in `r()`:

Matrices

r(L_std)	within-group standardized canonical discriminant function coefficients (standardized only)
r(L_totalstd)	total-sample standardized canonical discriminant function coefficients (totalstandardized only)
r(L_unstd)	unstandardized canonical discriminant function coefficients (unstandardized only)

`estat manova` stores the following in `r()`:

Scalars

r(N)	number of observations
r(df_m)	model degrees of freedom
r(df_r)	residual degrees of freedom

Matrices

r(stat_m)	multivariate statistics for the model

estat structure stores the following in r():

Matrices
    r(canstruct)   canonical structure matrix

Methods and formulas

See *Methods and formulas* of [MV] **discrim lda** for background on what is produced by predict, estat classfunctions, estat grdistances, estat grmeans, estat loadings, and estat structure. See [MV] **discrim estat** for more information on estat classtable, estat errorrate, estat grsummarize, and estat list. See [R] **anova** for background information on the ANOVAs summarized by estat anova; see [MV] **manova** for information on the MANOVA shown by estat manova; and see [MV] **canon** for background information on canonical correlations and related tests shown by estat canontest.

References

Anderson, E. 1935. The irises of the Gaspé Peninsula. *Bulletin of the American Iris Society* 59: 2–5.

Andrews, D. F., and A. M. Herzberg, ed. 1985. *Data: A Collection of Problems from Many Fields for the Student and Research Worker.* New York: Springer.

Huberty, C. J. 1994. *Applied Discriminant Analysis.* New York: Wiley.

Johnson, R. A., and D. W. Wichern. 2007. *Applied Multivariate Statistical Analysis.* 6th ed. Englewood Cliffs, NJ: Prentice Hall.

Rencher, A. C., and W. F. Christensen. 2012. *Methods of Multivariate Analysis.* 3rd ed. Hoboken, NJ: Wiley.

Also see

[MV] **discrim lda** — Linear discriminant analysis

[MV] **candisc** — Canonical linear discriminant analysis

[MV] **canon** — Canonical correlations

[MV] **discrim** — Discriminant analysis

[MV] **discrim estat** — Postestimation tools for discrim

[MV] **manova** — Multivariate analysis of variance and covariance

[MV] **scoreplot** — Score and loading plots

[MV] **screeplot** — Scree plot of eigenvalues

[U] **20 Estimation and postestimation commands**

Title

discrim logistic — Logistic discriminant analysis

Description

discrim logistic performs logistic discriminant analysis. See [MV] **discrim** for other discrimination commands.

Quick start

Logistic discriminant analysis of v1, v2, v3, and v4 for groups defined by catvar

    discrim logistic v1 v2 v3 v4, group(catvar)

Same as above, but use prior probabilities that are proportional to group size

    discrim logistic v1 v2 v3 v4, group(catvar) ///
        priors(proportional)

Same as above, but suppress iteration log

    discrim logistic v1 v2 v3 v4, group(catvar) ///
        priors(proportional) nolog

Assume v1 and v2 are factor variables, and use the Dice similarity coefficient

    discrim knn i.v1 i.v2, group(catvar) measure(dice)

Menu

Statistics > Multivariate analysis > Discriminant analysis > Logistic

Syntax

> discrim logistic *varlist* [*if*] [*in*] [*weight*], group(*groupvar*) [*options*]

options	Description
Model	
* group(*groupvar*)	variable specifying the groups
priors(*priors*)	group prior probabilities
<u>ties</u>(*ties*)	how ties in classification are to be handled
Reporting	
notable	suppress resubstitution classification table
[no]log	display or suppress the mlogit log-likelihood iteration log; default is to display

priors	Description
equal	equal prior probabilities; the default
<u>prop</u>ortional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
<u>miss</u>ing	ties in group classification produce missing values; the default
<u>ran</u>dom	ties in group classification are broken randomly
<u>fir</u>st	ties in group classification are set to the first tied group

* group() is required.

varlist may contain factor variables; see [U] **11.4.3 Factor variables**.

collect and statsby are allowed; see [U] **11.1.10 Prefix commands**.

fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

    ▁Model▁

group(*groupvar*) is required and specifies the name of the grouping variable. *groupvar* must be a numeric variable.

priors(*priors*) specifies the prior probabilities for group membership. The following *priors* are allowed:

  priors(<u>equal</u>) specifies equal prior probabilities. This is the default.

  priors(<u>prop</u>ortional) specifies group-size-proportional prior probabilities.

  priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. The following *ties* are allowed:

ties(<u>m</u>issing) specifies that ties in group classification produce missing values. This is the default.

ties(<u>r</u>andom) specifies that ties in group classification are broken randomly.

ties(<u>f</u>irst) specifies that ties in group classification are set to the first tied group.

_____ Reporting _____

notable suppresses the computation and display of the resubstitution classification table.

log and nolog specify whether to display the mlogit log-likelihood iteration log. The iteration log is displayed by default unless you used set iterlog off to suppress it; see set iterlog in [R] *set iter*.

Remarks and examples

Albert and Lesaffre (1986) explain that logistic discriminant analysis is a partially parametric method falling between parametric discrimination methods such as LDA and QDA (see [MV] **discrim lda** and [MV] **discrim qda**) and nonparametric discrimination methods such as kth-nearest-neighbor (KNN) discrimination (see [MV] **discrim knn**). Albert and Harris (1987) provide a good explanation of logistic discriminant analysis. Instead of making assumptions about the distribution of the data within each group, logistic discriminant analysis is based on the assumption that the likelihood ratios of the groups have an exponential form; see *Methods and formulas*. Multinomial logistic regression provides the basis for logistic discriminant analysis; see [R] **mlogit**. Multinomial logistic regression can handle binary and continuous regressors, and hence logistic discriminant analysis is also appropriate for binary and continuous discriminating variables.

▷ Example 1: A two-group logistic discriminant analysis

Morrison (2005, 443–445) provides data on 12 subjects with a senile-factor diagnosis and 37 subjects with a no-senile-factor diagnosis. The data consist of the Wechsler Adult Intelligence Scale (WAIS) subtest scores for information, similarities, arithmetic, and picture completion. Morrison (2005, 231) performs a logistic discriminant analysis on the two groups, using the similarities and picture completion scores as the discriminating variables.

```
. use https://www.stata-press.com/data/r18/senile
(Senility WAIS subtest scores)

. discrim logistic sim pc, group(sf) priors(proportional)

Iteration 0:   Log likelihood = -27.276352
Iteration 1:   Log likelihood = -19.531198
Iteration 2:   Log likelihood = -19.036702
Iteration 3:   Log likelihood = -19.018973
Iteration 4:   Log likelihood = -19.018928

Logistic discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

	Classified		
True sf	No-SF	SF	Total
No-SF	37	0	37
	100.00	0.00	100.00
SF	6	6	12
	50.00	50.00	100.00
Total	43	6	49
	87.76	12.24	100.00
Priors	0.7551	0.2449	

We specified the `priors(proportional)` option to obtain proportional prior probabilities for our logistic classification. These results match those of Morrison (2005, 231), though he does not state that his results are based on proportional prior probabilities. If you change to equal prior probabilities you obtain different classification results.

Which observations were misclassified? `estat list` with the `misclassified` option shows the six misclassified observations and the estimated probabilities.

```
. estat list, misclassified varlist
```

	Data		Classification		Probabilities	
Obs	sim	pc	True	Class.	No-SF	SF
38	5	8	SF	No-SF *	0.7353	0.2647
41	7	9	SF	No-SF *	0.8677	0.1323
44	9	8	SF	No-SF *	0.8763	0.1237
46	7	6	SF	No-SF *	0.6697	0.3303
48	10	3	SF	No-SF *	0.5584	0.4416
49	12	10	SF	No-SF *	0.9690	0.0310

* indicates misclassified observations

See example 1 of [MV] **discrim logistic postestimation** for more postestimation analysis with this logistic discriminant analysis.

◁

▷ Example 2: A three-group logistic discriminant analysis

Example 2 of [MV] discrim knn introduces a head measurement dataset with six discriminating variables and three groups; see Rencher and Christensen (2012, 290–292). We now apply discrim logistic to see how well the logistic model can discriminate between the groups.

```
. use https://www.stata-press.com/data/r18/head
(Table 8.3. Head measurements, Rencher and Christensen (2012))

. discrim logistic wdim circum fbeye eyehd earhd jaw, group(group)

Iteration 0:  Log likelihood = -98.875106
Iteration 1:  Log likelihood = -60.790737
Iteration 2:  Log likelihood = -53.746934
Iteration 3:  Log likelihood = -51.114631
Iteration 4:  Log likelihood = -50.249426
Iteration 5:  Log likelihood = -50.081199
Iteration 6:  Log likelihood = -50.072248
Iteration 7:  Log likelihood = -50.072216

Logistic discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True group	Classified High school	College	Nonplayer	Total
High school	27	2	1	30
	90.00	6.67	3.33	100.00
College	1	20	9	30
	3.33	66.67	30.00	100.00
Nonplayer	2	8	20	30
	6.67	26.67	66.67	100.00
Total	30	30	30	90
	33.33	33.33	33.33	100.00
Priors	0.3333	0.3333	0.3333	

The counts on the diagonal of the resubstitution classification table are similar to those obtained by discrim knn (see example 2 of [MV] discrim knn) and discrim lda (see example 1 of [MV] candisc), whereas discrim qda seems to have classified the nonplayer group more accurately (see example 3 of [MV] discrim estat).

◁

Stored results

discrim logistic stores the following in e():

Scalars
e(N)	number of observations
e(N_groups)	number of groups
e(k)	number of discriminating variables
e(ibaseout)	base outcome number

Macros
e(cmd)	discrim
e(subcmd)	logistic
e(cmdline)	command as typed
e(groupvar)	name of group variable
e(grouplabels)	labels for the groups
e(varlist)	discriminating variables
e(dropped)	variables dropped because of collinearity
e(wtype)	weight type
e(wexp)	weight expression
e(title)	title in estimation output
e(ties)	how ties are to be handled
e(properties)	b noV
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(b)	coefficient vector
e(groupcounts)	number of observations for each group
e(grouppriors)	prior probabilities for each group
e(groupvalues)	numeric value for each group

Functions
e(sample)	marks estimation sample

Methods and formulas

Let g be the number of groups, n_i the number of observations for group i, and q_i the prior probability for group i. Let $\mathbf{x}$ denote an observation measured on p discriminating variables. For consistency with the discriminant analysis literature, $\mathbf{x}$ will be a column vector, though it corresponds to a row in your dataset. Let $f_i(\mathbf{x})$ represent the density function for group i, and let $P(\mathbf{x}|G_i)$ denote the probability of observing $\mathbf{x}$ conditional on belonging to group i. Denote the posterior probability of group i given observation $\mathbf{x}$ as $P(G_i|\mathbf{x})$. With Bayes's theorem, we have

$$P(G_i|\mathbf{x}) = \frac{q_i f_i(\mathbf{x})}{\sum_{j=1}^{g} q_j f_j(\mathbf{x})}$$

Substituting $P(\mathbf{x}|G_i)$ for $f_i(\mathbf{x})$, we have

$$P(G_i|\mathbf{x}) = \frac{q_i P(\mathbf{x}|G_i)}{\sum_{j=1}^{g} q_j P(\mathbf{x}|G_j)}$$

Dividing both the numerator and denominator by $P(\mathbf{x}|G_g)$, we can express this as

$$P(G_i|\mathbf{x}) = \frac{q_i L_{ig}(\mathbf{x})}{\sum_{j=1}^{g} q_j L_{jg}(\mathbf{x})}$$

where $L_{ig}(\mathbf{x}) = P(\mathbf{x}|G_i)/P(\mathbf{x}|G_g)$ is the likelihood ratio of $\mathbf{x}$ for groups i and g.

This formulation of the posterior probability allows easy insertion of the Multinomial logistic model into the discriminant analysis framework. The multinomial logistic model expresses $L_{ig}(\mathbf{x})$ in a simple exponential form

$$L_{ig}(\mathbf{x}) = \exp(a_{0i} + \mathbf{a}_i' \mathbf{x})$$

see Albert and Harris (1987, 117). Logistic discriminant analysis uses `mlogit` to compute the likelihood ratios, $L_{ig}(\mathbf{x})$, and hence the posterior probabilities $P(G_i|\mathbf{x})$; see [R] **mlogit**. However, `mlogit` and `predict` after `mlogit` assume proportional prior probabilities. `discrim logistic` assumes equal prior probabilities unless you specify the `priors(proportional)` option.

References

Albert, A., and E. K. Harris. 1987. *Multivariate Interpretation of Clinical Laboratory Data.* New York: Dekker.

Albert, A., and E. Lesaffre. 1986. Multiple group logistic discrimination. *Computers and Mathematics with Applications* 12A(2): 209–224. https://doi.org/10.1016/B978-0-08-034000-5.50009-5.

Morrison, D. F. 2005. *Multivariate Statistical Methods.* 4th ed. Belmont, CA: Duxbury.

Rencher, A. C., and W. F. Christensen. 2012. *Methods of Multivariate Analysis.* 3rd ed. Hoboken, NJ: Wiley.

Also see

Title

> **discrim logistic postestimation —** Postestimation tools for discrim logistic

Postestimation commands

The following postestimation commands are of special interest after `discrim logistic`:

Command	Description
estat classtable	classification table
estat errorrate	classification error-rate estimation
estat grsummarize	group summaries
estat list	classification listing
estat summarize	estimation sample summary

The following standard postestimation commands are also available:

Command	Description
*estimates	cataloging estimation results
predict	group membership, probabilities of group membership, etc.

*All `estimates` subcommands except `table` and `stats` are available; see [R] **estimates**.

predict

Description for predict

predict creates a new variable containing predictions such as group classifications and probabilities.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] *newvar* [*if*] [*in*] [, *statistic options*]
>
> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*] [, *statistic options*]

statistic	Description
Main	
classification	group membership classification; the default when one variable is specified and group() is not specified
pr	probability of group membership; the default when group() is specified or when multiple variables are specified

options	Description
Main	
group(*group*)	the group for which the statistic is to be calculated
Options	
priors(*priors*)	group prior probabilities; defaults to e(grouppriors)
ties(*ties*)	how ties in classification are to be handled; defaults to e(ties)

priors	Description
equal	equal prior probabilities
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
missing	ties in group classification produce missing values
random	ties in group classification are broken randomly
first	ties in group classification are set to the first tied group

You specify one new variable with classification and specify either one or e(N_groups) new variables with pr. group() is not allowed with classification.

Options for predict

-------- Main --------

classification, the default, calculates the group classification. Only one new variable may be specified.

pr calculates group membership posterior probabilities. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

group(*group*) specifies the group for which the statistic is to be calculated and can be specified using

      #1, #2, ..., where #1 means the first category of the e(groupvar) variable, #2 the second category, etc.;

      the values of the e(groupvar) variable; or

      the value labels of the e(groupvar) variable if they exist.

group() is not allowed with classification.

-------- Options --------

priors(*priors*) specifies the prior probabilities for group membership. If priors() is not specified, e(grouppriors) is used. The following *priors* are allowed:

priors(<u>equal</u>) specifies equal prior probabilities.

priors(<u>proportional</u>) specifies group-size-proportional prior probabilities.

priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. If ties() is not specified, e(ties) is used. The following *ties* are allowed:

ties(<u>m</u>issing) specifies that ties in group classification produce missing values.

ties(<u>r</u>andom) specifies that ties in group classification are broken randomly.

ties(<u>f</u>irst) specifies that ties in group classification are set to the first tied group.

Remarks and examples

Classifications and probabilities after discrim logistic are obtained with the predict command. The common estat subcommands after discrim are also available for producing classification tables, error-rate tables, classification listings, and group summaries; see [MV] **discrim estat**.

▷ Example 1: Error rates and predictions for logistic discriminant analysis

Continuing with our logistic discriminant analysis of the senility dataset of Morrison (2005), introduced in example 1 of [MV] **discrim logistic**, we illustrate the use of the estat errorrate postestimation command.

```
. use https://www.stata-press.com/data/r18/senile
(Senility WAIS subtest scores)

. discrim logistic sim pc, group(sf) priors(proportional) notable nolog

. estat errorrate, pp
Error rate estimated from posterior probabilities
```

| | sf | | |
Error rate	No-SF	SF	Total
Stratified	.0305051	.5940575	.168518
Unstratified	.0305051	.5940575	.168518
Priors	.755102	.244898	

We specified the pp option to obtain the posterior probability–based error-rate estimates. The stratified and unstratified estimates are identical because proportional priors were used. The estimates were based on proportional priors because the logistic discriminant analysis model used proportional priors and we did not specify the priors() option in our call to estat errorrate.

The error-rate estimate for the senile-factor group is much higher than for the no-senile-factor group.

What error-rate estimates would we obtain with equal group priors?

```
. estat errorrate, pp priors(equal)
Error rate estimated from posterior probabilities
```

| | sf | | |
Error rate	No-SF	SF	Total
Stratified	.2508207	.2069481	.2288844
Unstratified	.06308	.4289397	.2460098
Priors	.5	.5	

Stratified and unstratified estimates are now different. This happens when group sizes have a different proportion from that of the prior probabilities.

Morrison (2005, 231) shows a classification of the subjects where, if the estimated probability of belonging to the senile-factor group is less than 0.35, he classifies the subject to the no-senile-factor group; if the probability is more than 0.66, he classifies the subject to the senile-factor group; and if the probability is between those extremes, he classifies the subject to an uncertain group.

We can use predict to implement this same strategy. The pr option requests probabilities. Because the model was estimated with proportional prior probabilities, the prediction, by default, will also be based on proportional prior probabilities.

```
. predict prob0 prob1, pr
. generate newgrp = 1
. replace newgrp = 0 if prob1 <= 0.35
(38 real changes made)
. replace newgrp = 2 if prob1 >= 0.66
(5 real changes made)
. label define newgrp 0 "No-SF" 1 "Uncertain" 2 "SF"
. label values newgrp newgrp
. tabulate sf newgrp
```

Senile-fac tor diagnosis	No-SF	newgrp Uncertain	SF	Total
No-SF	33	4	0	37
SF	5	2	5	12
Total	38	6	5	49

Six observations are placed in the uncertain group.

◁

Reference

Morrison, D. F. 2005. *Multivariate Statistical Methods*. 4th ed. Belmont, CA: Duxbury.

Also see

[MV] **discrim logistic** — Logistic discriminant analysis

[MV] **discrim** — Discriminant analysis

[MV] **discrim estat** — Postestimation tools for discrim

[U] **20 Estimation and postestimation commands**

Title

discrim qda — Quadratic discriminant analysis

Description

discrim qda performs quadratic discriminant analysis. See [MV] **discrim** for other discrimination commands.

Quick start

Quadratic discriminant analysis of v1, v2, v3, and v4 for groups defined by catvar
    discrim qda v1 v2 v3 v4, group(catvar)

Same as above, but use prior probabilities proportional to group size
    discrim qda v1 v2 v3 v4, group(catvar) priors(proportional)

Display the leave-one-out and the resubstitution classification tables
    discrim qda v1 v2 v3 v4, group(catvar) lootable

Same as above, but suppress the resubstitution classification table
    discrim qda v1 v2 v3 v4, group(catvar) lootable notable

Menu

Statistics > Multivariate analysis > Discriminant analysis > Quadratic (QDA)

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Syntax

> discrim qda *varlist* [*if*] [*in*] [*weight*], group(*groupvar*) [*options*]

options	Description
Model	
* group(*groupvar*)	variable specifying the groups
priors(*priors*)	group prior probabilities
ties(*ties*)	how ties in classification are to be handled
Reporting	
notable	suppress resubstitution classification table
lootable	display leave-one-out classification table

priors	Description
equal	equal prior probabilities; the default
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
missing	ties in group classification produce missing values; the default
random	ties in group classification are broken randomly
first	ties in group classification are set to the first tied group

* group() is required.

collect, statsby, and xi are allowed; see [U] **11.1.10 Prefix commands**.

fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

Model

group(*groupvar*) is required and specifies the name of the grouping variable. *groupvar* must be a numeric variable.

priors(*priors*) specifies the prior probabilities for group membership. The following *priors* are allowed:

priors(equal) specifies equal prior probabilities. This is the default.

priors(proportional) specifies group-size-proportional prior probabilities.

priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. The following *ties* are allowed:

ties(<u>m</u>issing) specifies that ties in group classification produce missing values. This is the default.

ties(<u>r</u>andom) specifies that ties in group classification are broken randomly.

ties(<u>f</u>irst) specifies that ties in group classification are set to the first tied group.

   Reporting

notable suppresses the computation and display of the resubstitution classification table.

lootable displays the leave-one-out classification table.

Remarks and examples

Quadratic discriminant analysis (QDA) was introduced by Smith (1947). It is a generalization of linear discriminant analysis (LDA). Both LDA and QDA assume that the observations come from a multivariate normal distribution. LDA assumes that the groups have equal covariance matrices. QDA removes this assumption, allowing the groups to have different covariance matrices.

One of the penalties associated with QDA's added flexibility is that if any groups have fewer observations, n_i, than discriminating variables, p, the covariance matrix for that group is singular and QDA cannot be performed. Even if there are enough observations to invert the covariance matrix, if the sample size is relatively small for a group, the estimation of the covariance matrix for that group may not do a good job of representing the group's population covariance, leading to inaccuracies in classification.

▷ Example 1: QDA classification tables and error rates

We illustrate QDA with a small dataset introduced in example 1 of [MV] **manova**. Andrews and Herzberg (1985, 357–360) present data on six apple tree rootstock groups with four measurements on eight trees from each group.

We request the display of the leave-one-out (LOO) classification table in addition to the standard resubstitution classification table produced by discrim qda.

```
. use https://www.stata-press.com/data/r18/rootstock
(Table 6.2. Rootstock data, Rencher and Christensen (2012))

. discrim qda y1 y2 y3 y4, group(rootstock) lootable
Quadratic discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True rootstock	Classified 1	2	3	4	5	6	Total
1	8	0	0	0	0	0	8
	100.00	0.00	0.00	0.00	0.00	0.00	100.00
2	0	7	0	1	0	0	8
	0.00	87.50	0.00	12.50	0.00	0.00	100.00
3	1	0	6	0	1	0	8
	12.50	0.00	75.00	0.00	12.50	0.00	100.00
4	0	0	1	7	0	0	8
	0.00	0.00	12.50	87.50	0.00	0.00	100.00
5	0	3	0	0	4	1	8
	0.00	37.50	0.00	0.00	50.00	12.50	100.00
6	2	0	0	0	1	5	8
	25.00	0.00	0.00	0.00	12.50	62.50	100.00
Total	11	10	7	8	6	6	48
	22.92	20.83	14.58	16.67	12.50	12.50	100.00
Priors	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	

Leave-one-out classification summary

```
┌─────────────┐
│     Key     │
├─────────────┤
│   Number    │
│   Percent   │
└─────────────┘
```

True rootstock	Classified 1	2	3	4	5	6	Total
1	2	0	0	3	1	2	8
	25.00	0.00	0.00	37.50	12.50	25.00	100.00
2	0	3	0	2	2	1	8
	0.00	37.50	0.00	25.00	25.00	12.50	100.00
3	1	2	4	0	1	0	8
	12.50	25.00	50.00	0.00	12.50	0.00	100.00
4	1	1	3	2	0	1	8
	12.50	12.50	37.50	25.00	0.00	12.50	100.00
5	0	4	1	0	2	1	8
	0.00	50.00	12.50	0.00	25.00	12.50	100.00
6	3	1	0	0	2	2	8
	37.50	12.50	0.00	0.00	25.00	25.00	100.00
Total	7	11	8	7	8	7	48
	14.58	22.92	16.67	14.58	16.67	14.58	100.00
Priors	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	

Compare the counts on the diagonal of the resubstitution classification table with those on the LOO table. The LOO table has fewer of the observations with correct classifications. The resubstitution classification table is overly optimistic.

The `estat errorrate` postestimation command provides estimates of the error rates for the groups. We request the count-based estimates, first for the resubstitution classification and then for the LOO classification. We also suppress display of the prior probabilities, which will default to equal across the groups because that is how we estimated our QDA model. See [MV] **discrim estat** for details of the `estat errorrate` command.

```
. estat errorrate, nopriors
```

Error rate estimated by error count

	rootstock 1	2	3	4	5
Error rate	0	.125	.25	.125	.5

	rootstock 6	Total
Error rate	.375	.2291667

```
. estat errorrate, nopriors looclass
```

Error rate estimated by leave-one-out error count

	rootstock				
	1	2	3	4	5
Error rate	.75	.625	.5	.75	.75

	rootstock	
	6	Total
Error rate	.75	.6875

The estimated group error rates are much higher in the LOO table.

See example 2 of [MV] **discrim qda postestimation** for an examination of the squared Mahalanobis distances between the rootstock groups. We could also list the misclassified observations, produce group summaries, examine covariances and correlations, and generate classification and probability variables and more; see [MV] **discrim qda postestimation**.

◁

See example 3 of [MV] **discrim estat** and example 1 of [MV] **discrim qda postestimation** for other examples of the use of discrim qda.

Stored results

discrim qda stores the following in e():

Scalars
    e(N)   number of observations
    e(N_groups)   number of groups
    e(k)   number of discriminating variables

Macros
    e(cmd)   discrim
    e(subcmd)   qda
    e(cmdline)   command as typed
    e(groupvar)   name of group variable
    e(grouplabels)   labels for the groups
    e(varlist)   discriminating variables
    e(wtype)   weight type
    e(wexp)   weight expression
    e(title)   title in estimation output
    e(ties)   how ties are to be handled
    e(properties)   nob noV
    e(estat_cmd)   program used to implement estat
    e(predict)   program used to implement predict
    e(marginsnotok)   predictions disallowed by margins

Matrices
    e(groupcounts)   number of observations for each group
    e(grouppriors)   prior probabilities for each group
    e(groupvalues)   numeric value for each group
    e(means)   group means on discriminating variables
    e(SSCP_W#)   within group SSCP matrix for group #
    e(W#_eigvals)   eigenvalues of e(SSCP_W#)
    e(W#_eigvecs)   eigenvectors of e(SSCP_W#)
    e(sqrtS#inv)   Cholesky (square root) of the inverse covariance matrix for group #

Functions
    e(sample)   marks estimation sample

Methods and formulas

Let g be the number of groups, n_i the number of observations for group i, and q_i the prior probability for group i. Let $\mathbf{x}$ denote an observation measured on p discriminating variables. For consistency with the discriminant analysis literature, $\mathbf{x}$ will be a column vector, though it corresponds to a row in your dataset. Let $f_i(\mathbf{x})$ represent the density function for group i, and let $P(\mathbf{x}|G_i)$ denote the probability of observing $\mathbf{x}$ conditional on belonging to group i. Denote the posterior probability of group i given observation $\mathbf{x}$ as $P(G_i|\mathbf{x})$. With Bayes's theorem, we have

$$P(G_i|\mathbf{x}) = \frac{q_i f_i(\mathbf{x})}{\sum_{j=1}^{g} q_j f_j(\mathbf{x})}$$

Substituting $P(\mathbf{x}|G_i)$ for $f_i(\mathbf{x})$, we have

$$P(G_i|\mathbf{x}) = \frac{q_i P(\mathbf{x}|G_i)}{\sum_{j=1}^{g} q_j P(\mathbf{x}|G_j)}$$

QDA assumes that the groups are multivariate normal. Let $\mathbf{S}_i$ denote the within-group sample covariance matrix for group i and $\overline{\mathbf{x}}_i$ denote the sample mean of group i. The squared Mahalanobis distance between observation $\mathbf{x}$ and $\overline{\mathbf{x}}_i$ is

$$D_i^2 = (\mathbf{x} - \overline{\mathbf{x}}_i)'\mathbf{S}_i^{-1}(\mathbf{x} - \overline{\mathbf{x}}_i)$$

Plugging these sample estimates into the multivariate normal density gives

$$P(\mathbf{x}|G_i) = (2\pi)^{-p/2}|\mathbf{S}_i|^{-1/2}e^{-D_i^2/2}$$

Substituting this into the formula for $P(G_i|\mathbf{x})$ and simplifying gives

$$P(G_i|\mathbf{x}) = \frac{q_i|\mathbf{S}_i|^{-1/2}e^{-D_i^2/2}}{\sum_{j=1}^{g} q_j|\mathbf{S}_j|^{-1/2}e^{-D_j^2/2}}$$

as the QDA posterior probability of observation $\mathbf{x}$ belonging to group i.

The squared Mahalanobis distance between group means is produced by `estat grdistances`; see [MV] **discrim qda postestimation**.

Classification functions can be derived from the Mahalanobis QDA; see Huberty (1994, 58). Let $Q_i(\mathbf{x})$ denote the quadratic classification function for the ith group applied to observation $\mathbf{x}$.

$$Q_i(\mathbf{x}) = -D_i^2/2 - \ln|\mathbf{S}_i|/2 + \ln(q_i)$$

An observation can be classified based on largest posterior probability or based on largest quadratic classification function score.

References

Andrews, D. F., and A. M. Herzberg, ed. 1985. *Data: A Collection of Problems from Many Fields for the Student and Research Worker*. New York: Springer.

Huberty, C. J. 1994. *Applied Discriminant Analysis*. New York: Wiley.

Rencher, A. C. 1998. *Multivariate Statistical Inference and Applications*. New York: Wiley.

Rencher, A. C., and W. F. Christensen. 2012. *Methods of Multivariate Analysis*. 3rd ed. Hoboken, NJ: Wiley.

Smith, C. A. B. 1947. Some examples of discrimination. *Annals of Eugenics* 13: 272–282. https://doi.org/10.1111/j.1469-1809.1946.tb02368.x.

Also see

[MV] **discrim qda postestimation** — Postestimation tools for discrim qda

[MV] **discrim** — Discriminant analysis

[U] **20 Estimation and postestimation commands**

Title

> **discrim qda postestimation —** Postestimation tools for discrim qda

Postestimation commands	predict	estat
Remarks and examples	Stored results	Methods and formulas
References	Also see	

Postestimation commands

The following postestimation commands are of special interest after `discrim qda`:

Command	Description
estat classtable	classification table
estat correlations	group correlation matrices and p-values
estat covariance	group covariance matrices
estat errorrate	classification error-rate estimation
estat grdistances	Mahalanobis and generalized squared distances between the group means
estat grsummarize	group summaries
estat list	classification listing
estat summarize	estimation sample summary

The following standard postestimation commands are also available:

Command	Description
*estimates	cataloging estimation results
predict	group membership, probabilities of group membership, etc.

*All `estimates` subcommands except `table` and `stats` are available; see [R] **estimates**.

predict

Description for predict

predict creates a new variable containing predictions such as group classifications, probabilities, Mahalanobis squared distances, leave-one-out group classifications, leave-one-out probabilities, and leave-one-out Mahalanobis squared distances.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] *newvar* [*if*] [*in*] [, *statistic options*]

> predict [*type*] { *stub** | *newvarlist* } [*if*] [*in*] [, *statistic options*]

statistic	Description
Main	
classification	group membership classification; the default when one variable is specified and group() is not specified
pr	probability of group membership; the default when group() is specified or when multiple variables are specified
mahalanobis	Mahalanobis squared distance between observations and groups
clscore	group classification function score
* looclass	leave-one-out group membership classification; may be used only when one new variable is specified
* loopr	leave-one-out probability of group membership
* loomahal	leave-one-out Mahalanobis squared distance between observations and groups

options	Description
Main	
group(*group*)	the group for which the statistic is to be calculated
Options	
priors(*priors*)	group prior probabilities; defaults to e(grouppriors)
ties(*ties*)	how ties in classification are to be handled; defaults to e(ties)

priors	Description
equal	equal prior probabilities
proportional	group-size-proportional prior probabilities
matname	row or column vector containing the group prior probabilities
matrix_exp	matrix expression providing a row or column vector of the group prior probabilities

ties	Description
missing	ties in group classification produce missing values
random	ties in group classification are broken randomly
<u>fir</u>st	ties in group classification are set to the first tied group

You specify one new variable with classification or looclass and specify either one or e(N_groups) new variables with pr, loopr, mahalanobis, loomahal, or clscore.

Unstarred statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample. Starred statistics are calculated only for the estimation sample, even when if e(sample) is not specified.

group() is not allowed with classification or looclass.

Options for predict

> [Main]

classification, the default, calculates the group classification. Only one new variable may be specified.

pr calculates group membership posterior probabilities. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

mahalanobis calculates the squared Mahalanobis distance between the observations and group means. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

clscore produces the group classification function score. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables.

looclass calculates the leave-one-out group classifications. Only one new variable may be specified. Leave-one-out calculations are restricted to e(sample) observations.

loopr calculates the leave-one-out group membership posterior probabilities. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables. Leave-one-out calculations are restricted to e(sample) observations.

loomahal calculates the leave-one-out squared Mahalanobis distance between the observations and group means. If you specify the group() option, specify one new variable. Otherwise, you must specify e(N_groups) new variables. Leave-one-out calculations are restricted to e(sample) observations.

group(*group*) specifies the group for which the statistic is to be calculated and can be specified using

> #1, #2, ..., where #1 means the first category of the e(groupvar) variable, #2 the second category, etc.;

> the values of the e(groupvar) variable; or

> the value labels of the e(groupvar) variable if they exist.

group() is not allowed with classification or looclass.

┌─── Options ───

priors(*priors*) specifies the prior probabilities for group membership. If priors() is not specified, e(grouppriors) is used. The following *priors* are allowed:

priors(equal) specifies equal prior probabilities.

priors(proportional) specifies group-size-proportional prior probabilities.

priors(*matname*) specifies a row or column vector containing the group prior probabilities.

priors(*matrix_exp*) specifies a matrix expression providing a row or column vector of the group prior probabilities.

ties(*ties*) specifies how ties in group classification will be handled. If ties() is not specified, e(ties) is used. The following *ties* are allowed:

ties(missing) specifies that ties in group classification produce missing values.

ties(random) specifies that ties in group classification are broken randomly.

ties(first) specifies that ties in group classification are set to the first tied group.

estat

Description for estat

estat correlations displays group correlation matrices. Two-tailed p-values for the correlations are also available.

estat covariance displays group covariance matrices.

estat grdistances provides Mahalanobis squared distances and generalized squared distances between the group means.

Menu for estat

Statistics > Postestimation

Syntax for estat

Group correlation matrices and p-values

  estat <u>corr</u>elations [, *correlations_options*]

Group covariance matrices

  estat <u>cov</u>ariance [, *covariance_options*]

Mahalanobis and generalized squared distances between the group means

  estat <u>gr</u>distances [, *grdistances_options*]

correlations_options	Description
Main	
p	display two-sided p-values
<u>fo</u>rmat(*%fmt*)	numeric display format; default is %9.0g
<u>noha</u>lf	display full matrix even if symmetric

covariance_options	Description
Main	
<u>fo</u>rmat(*%fmt*)	numeric display format; default is %9.0g
<u>noha</u>lf	display full matrix even if symmetric

grdistances_options	Description
Main	
<u>mahal</u>anobis	display Mahalanobis squared distances between group means; the default
<u>gen</u>eralized	display generalized Mahalanobis squared distances between group means
all	equivalent to mahalanobis generalized
<u>format</u>(*%fmt*)	numeric display format; default is %9.0g
Options	
<u>priors</u>(*priors*)	group prior probabilities; defaults to e(grouppriors)

collect is allowed with all estat commands; see [U] **11.1.10 Prefix commands**.

Options for estat

Options for estat are presented under the following headings:

> Options for estat correlations
> Options for estat covariance
> Options for estat grdistances

Options for estat correlations

> [Main]

p specifies that two-sided p-values be computed and displayed for the correlations.

format(*%fmt*) specifies the matrix display format. The default is format(%8.5f).

nohalf specifies that, even though the matrix is symmetric, the full matrix be printed. The default is to print only the lower triangle.

Options for estat covariance

> [Main]

format(*%fmt*) specifies the matrix display format. The default is format(%9.0g).

nohalf specifies that, even though the matrix is symmetric, the full matrix be printed. The default is to print only the lower triangle.

Options for estat grdistances

> [Main]

mahalanobis specifies that a table of Mahalanobis squared distances between group means be presented.

generalized specifies that a table of generalized Mahalanobis squared distances between group means be presented. generalized starts with what is produced by the mahalanobis option and adds a term for the possibly unequal covariances and a term accounting for prior probabilities. Prior probabilities are provided with the priors() option, or if priors() is not specified, by the values in e(grouppriors). By common convention, if prior probabilities are equal across the groups, the prior probability term is omitted.

all is equivalent to specifying mahalanobis and generalized.

format(%*fmt*) specifies the matrix display format. The default is format(%9.0g).

> Options

priors(*priors*) specifies the group prior probabilities and affects only the output of the generalized
option. By default, *priors* is determined from e(grouppriors). See *Options for predict* for the
priors specification.

Remarks and examples

The predict and estat commands after discrim qda help in exploring the QDA model. See
[MV] **discrim estat** for details of the estat subcommands common to all discrim subcommands.
Here we illustrate some of these common estat subcommands along with estat covariance,
estat correlations, and estat grdistances that are specific to discrim qda.

▷ Example 1: Group covariances and correlations and out-of-sample prediction

Everitt and Dunn (2001, 269) show data for male Egyptian skulls from the early and late predynastic
epochs. Ten observations from each epoch are provided. Four measurements were taken of each skull:
x1, maximum breadth; x2, basibregmatic height; x3, basialveolar length; and x4, nasal height. All
measurements were in millimeters. Everitt and Dunn obtained the data from Manly and Navarro
Alberto (2017).

We perform a quadratic discriminant analysis on this dataset and demonstrate the use of estat
and predict.

```
. use https://www.stata-press.com/data/r18/skulls
(Egyptian skulls)
. discrim qda x1 x2 x3 x4, group(predynastic)
Quadratic discriminant analysis
Resubstitution classification summary
```

Key
Number
Percent

True predynastic	Classified Early	Late	Total
Early	9	1	10
	90.00	10.00	100.00
Late	3	7	10
	30.00	70.00	100.00
Total	12	8	20
	60.00	40.00	100.00
Priors	0.5000	0.5000	

What kind of covariance structure do the two groups have? If they are similar to one another,
we might wish to switch to using LDA (see [MV] **discrim lda**) instead of QDA. estat covariance
displays the covariance matrices for our two groups.

```
. estat covariance
```

Group covariance matrices

  predynastic: Early

	x1	x2	x3	x4
x1	40.32222			
x2	7.188889	15.34444		
x3	13.18889	-7.322222	36.9	
x4	16.1	8.077778	-2.144444	11.43333

  predynastic: Late

	x1	x2	x3	x4
x1	43.12222			
x2	-4.966667	38.98889		
x3	9.388889	6.611111	10.27778	
x4	5.211111	12.74444	4.388889	9.122222

There appear to be differences, including differences in sign between some of the elements of the covariance matrices of the two groups. How substantial are these differences? The estat correlations command displays the correlation matrices for the groups. The p option requests that p-values be presented with the correlations.

```
. estat correlations, p
```

Group correlation matrices

  predynastic: Early

Key
Correlation
Two-sided p-value

	x1	x2	x3	x4
x1	1.00000			
x2	0.28901	1.00000		
	0.41800			
x3	0.34192	-0.30772	1.00000	
	0.33353	0.38707		
x4	0.74984	0.60986	-0.10440	1.00000
	0.01251	0.06119	0.77409	

```
    predynastic: Late
```

```
┌─────────────────────────┐
│ Key                     │
├─────────────────────────┤
│ Correlation             │
│ Two-sided p-value       │
└─────────────────────────┘
```

	x1	x2	x3	x4
x1	1.00000			
x2	-0.12113	1.00000		
	0.73889			
x3	0.44598	0.33026	1.00000	
	0.19640	0.35133		
x4	0.26274	0.67577	0.45327	1.00000
	0.46331	0.03196	0.18830	

Few of the correlations in the two matrices are statistically significant. We are less sure of the apparent differences between the covariance structures for these two groups.

Let's press forward anyway. Everitt and Dunn (2001, 269) ask for the prediction for an unknown skull. We input the unknown observation and then use `predict` to obtain the classification and probabilities of group membership for the observation.

```
. input

      predyna~c    x1    x2    x3    x4
 21. . 127 129 95 51
 22. end
. predict grp
(option classification assumed; group classification)

. predict pr1 pr2, pr

. label values grp epoch

. list x* grp pr1 pr2 in 21
```

	x1	x2	x3	x4	grp	pr1	pr2
21.	127	129	95	51	Late	.3654425	.6345575

This skull is classified by our QDA model as belonging to the late predynastic epoch with probability 0.63.

`estat list` could also be used to obtain this same information; see [MV] **discrim estat**.

```
. estat list in 21, varlist
```

	Data					Classification		Probabilities	
Obs	x1	x2	x3	x4		True	Class.	Early	Late
21	127	129	95	51			Late	0.3654	0.6346

We could use `predict` and `estat` to explore other aspects of this QDA model, including leave-one-out (LOO) classifications, probabilities, classification tables, and error-rate estimates.

◁

▷ Example 2: Mahalanobis and generalized distances between groups

Example 1 of [MV] **discrim qda** performs a QDA on the apple tree rootstock data found in Andrews and Herzberg (1985, 357–360). We now demonstrate the use of the estat grdistances command for examining the squared Mahalanobis distances and the squared generalized distances between the rootstock groups.

```
. use https://www.stata-press.com/data/r18/rootstock, clear
(Table 6.2. Rootstock data, Rencher and Christensen (2012))
. discrim qda y1 y2 y3 y4, group(rootstock) notable
. estat grdistances, all
```

Mahalanobis squared distances between groups

	rootstock				
rootstock	1	2	3	4	5
1	0	18.37241	7.89988	1.622808	14.78843
2	42.19008	0	5.489408	14.08784	1.502462
3	36.81811	1.908369	0	6.406024	15.48121
4	2.281963	14.77928	6.742393	0	25.72128
5	33.70858	1.855704	4.617755	16.34139	0
6	3.860684	17.32868	12.5828	11.24491	3.49512

	rootstock
rootstock	6
1	9.152132
2	30.45472
3	72.60112
4	29.01146
5	20.50925
6	0

Generalized squared distances between groups

	rootstock				
rootstock	1	2	3	4	5
1	-17.89946	2.47128	-9.577605	-14.60611	-1.796629
2	24.29063	-15.90113	-11.98808	-2.141072	-15.0826
3	18.91866	-13.99276	-17.47749	-9.822891	-1.103849
4	-15.61749	-1.121858	-10.73509	-16.22892	9.136221
5	15.80913	-14.04543	-12.85973	.1124762	-16.58506
6	-14.03877	1.427543	-4.894681	-4.984005	-13.08994

	rootstock
rootstock	6
1	-7.241371
2	14.06121
3	56.20761
4	12.61796
5	4.115752
6	-16.3935

Both tables are nonsymmetric. For QDA the Mahalanobis distance depends on the covariance of the reference group. The Mahalanobis distance for group i (the rows in the tables above) to group j (the columns in the tables above) will use the covariance matrix of group j in determining the distance. The generalized distance also factors in the prior probabilities for the groups, and so the diagonal elements are not zero and the entries can be negative. In either matrix, the smaller the number, the closer the groups.

◁

Stored results

estat correlations stores the following in r():

Matrices
   r(Rho_#)   group # correlation matrix
   r(P_#)   two-sided p-values for group # correlations

estat covariance stores the following in r():

Matrices
   r(S_#)   group # covariance matrix

estat grdistances stores the following in r():

Matrices
   r(sqdist)   Mahalanobis squared distances between group means (mahalanobis only)
   r(gsqdist)   generalized squared distances between group means (generalized only)

Methods and formulas

See *Methods and formulas* of [MV] **discrim qda** for background on what is produced by predict and estat grdistances. See [MV] **discrim estat** for more information on estat classtable, estat errorrate, estat grsummarize, and estat list.

References

Andrews, D. F., and A. M. Herzberg, ed. 1985. *Data: A Collection of Problems from Many Fields for the Student and Research Worker*. New York: Springer.

Everitt, B. S., and G. Dunn. 2001. *Applied Multivariate Data Analysis*. 2nd ed. London: Arnold.

Manly, B. F. J., and J. A. Navarro Alberto. 2017. *Multivariate Statistical Methods: A Primer*. 4th ed. Boca Raton, FL: CRC Press.

Rencher, A. C., and W. F. Christensen. 2012. *Methods of Multivariate Analysis*. 3rd ed. Hoboken, NJ: Wiley.

Also see

[MV] **discrim qda** — Quadratic discriminant analysis

[MV] **discrim** — Discriminant analysis

[MV] **discrim estat** — Postestimation tools for discrim

[U] **20 Estimation and postestimation commands**

Title

> **factor —** Factor analysis

Description

factor and factormat perform a factor analysis of a correlation matrix. The commands produce principal factor, iterated principal factor, principal-component factor, and maximum-likelihood factor analyses. factor and factormat display the eigenvalues of the correlation matrix, the factor loadings, and the uniqueness of the variables.

factor expects data in the form of variables, allows weights, and can be run for subgroups. factormat is for use with a correlation or covariance matrix.

Quick start

Principal-factor analysis using variables v1 to v5
```
factor v1 v2 v3 v4 v5
```

Same as above, but retain at most 3 factors
```
factor v1-v5, factors(3)
```

Principal-component factor analysis using variables v1 to v5
```
factor v1-v5, pcf
```

Maximum-likelihood factor analysis
```
factor v1-v5, ml
```

Same as above, but perform 50 maximizations with different starting values
```
factor v1-v5, ml protect(50)
```

Same as above, but set the seed for reproducibility
```
factor v1-v5, ml protect(50) seed(349285)
```

Principal-factor analysis based on a correlation matrix cmat with a sample size of 800
```
factormat cmat, n(800)
```

Same as above, retain only factors with eigenvalues greater than or equal to 1
```
factormat cmat, n(800) mineigen(1)
```

Menu

factor

Statistics > Multivariate analysis > Factor and principal component analysis > Factor analysis

factormat

Statistics > Multivariate analysis > Factor and principal component analysis > Factor analysis of a correlation matrix

Syntax

Factor analysis of data

<u>fac</u>tor *varlist* [*if*] [*in*] [*weight*] [, *method options*]

Factor analysis of a correlation matrix

factormat *matname*, n(#) [*method options factormat_options*]

matname is a square Stata matrix or a vector containing the rowwise upper or lower triangle of the correlation or covariance matrix. If a covariance matrix is provided, it is transformed into a correlation matrix for the factor analysis.

method	Description
Model 2	
pf	principal factor; the default
pcf	principal-component factor
ipf	iterated principal factor
ml	maximum likelihood factor

options	Description
Model 2	
<u>factors</u>(#)	maximum number of factors to be retained
<u>mineigen</u>(#)	minimum value of eigenvalues to be retained
<u>citerate</u>(#)	communality reestimation iterations (ipf only)
Reporting	
<u>blanks</u>(#)	display loadings as blank when |loadings| < #
<u>altdivisor</u>	use trace of correlation matrix as the divisor for reported proportions
Maximization	
<u>protect</u>(#)	perform # optimizations and report the best solution (ml only)
<u>random</u>	use random starting values (ml only); seldom used
<u>seed</u>(*seed*)	random-number seed (ml with protect() or random only)
maximize_options	control the maximization process; seldom used (ml only)
<u>noro</u>tated	display unrotated solution, even if rotated results are available (replay only)

norotated does not appear in the dialog box.

factormat_options	Description
Model	
shape(<u>full</u>)	*matname* is a square symmetric matrix; the default
shape(<u>lower</u>)	*matname* is a vector with the rowwise lower triangle (with diagonal)
shape(<u>upper</u>)	*matname* is a vector with the rowwise upper triangle (with diagonal)
<u>names</u>(*namelist*)	variable names; required if *matname* is triangular
forcepsd	modifies *matname* to be positive semidefinite
*n(#)	number of observations
sds(*matname₂*)	vector with standard deviations of variables
means(*matname₃*)	vector with means of variables

* n(#) is required for factormat.

bootstrap, by, collect, jackknife, rolling, and statsby are allowed with factor; see [U] **11.1.10 Prefix commands**. However, bootstrap and jackknife results should be interpreted with caution; identification of the factor parameters involves data-dependent restrictions, possibly leading to badly biased and overdispersed estimates (Milan and Whittaker 1995).

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

aweights are not allowed with the jackknife prefix; see [R] **jackknife**.

aweights and fweights are allowed with factor; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options for factor and factormat

> [Model 2]

pf, pcf, ipf, and ml indicate the type of estimation to be performed. The default is pf.

> pf specifies that the principal-factor method be used to analyze the correlation matrix. The factor loadings, sometimes called the factor patterns, are computed using the squared multiple correlations as estimates of the communality. pf is the default.

> pcf specifies that the principal-component factor method be used to analyze the correlation matrix. The communalities are assumed to be 1.

> ipf specifies that the iterated principal-factor method be used to analyze the correlation matrix. This reestimates the communalities iteratively.

> ml specifies the maximum-likelihood factor method, assuming multivariate normal observations. This estimation method is equivalent to Rao's canonical-factor method and maximizes the determinant of the partial correlation matrix. Hence, this solution is also meaningful as a descriptive method for nonnormal data. ml is not available for singular correlation matrices. At least three variables must be specified with method ml.

factors(#) and mineigen(#) specify the maximum number of factors to be retained. factors() specifies the number directly, and mineigen() specifies it indirectly, keeping all factors with eigenvalues greater than the indicated value. The options can be specified individually, together, or not at all.

> factors(#) sets the maximum number of factors to be retained for later use by the postestimation commands. factor always prints the full set of eigenvalues but prints the corresponding eigenvectors only for retained factors. Specifying a number larger than the number of variables in the *varlist* is equivalent to specifying the number of variables in the *varlist* and is the default.

mineigen(#) sets the minimum value of eigenvalues to be retained. The default for all methods except pcf is 5×10^{-6} (effectively zero), meaning that factors associated with negative eigenvalues will not be printed or retained. The default for pcf is 1. Many sources recommend mineigen(1), although the justification is complex and uncertain. If # is less than 5×10^{-6}, it is reset to 5×10^{-6}.

citerate(#) is used only with ipf and sets the number of iterations for reestimating the communalities. If citerate() is not specified, iterations continue until the change in the communalities is small. ipf with citerate(0) produces the same results that pf does.

> [Reporting]

blanks(#) specifies that factor loadings smaller than # (in absolute value) be displayed as blanks.

altdivisor specifies that reported proportions and cumulative proportions be computed using the trace of the correlation matrix, trace(e(C)), as the divisor. The default is to use the sum of all eigenvalues (even those that are negative) as the divisor.

> [Maximization]

protect(#) is used only with ml and requests that # optimizations with random starting values be performed along with squared multiple correlation coefficient starting values and that the best of the solutions be reported. The output also indicates whether all starting values converged to the same solution. When specified with a large number, such as protect(50), this provides reasonable assurance that the solution found is global and not just a local maximum. If trace is also specified (see [R] **Maximize**), the parameters and likelihoods of each maximization will be printed.

random is used only with ml and requests that random starting values be used. This option is rarely used and should be used only after protect() has shown the presence of multiple maximums.

seed(seed) is used only with ml when the random or protect() options are also specified. seed() specifies the random-number seed; see [R] **set seed**. If seed() is not specified, the random-number generator starts in whatever state it was last in.

maximize_options: iterate(#), [no]log, trace, tolerance(#), and ltolerance(#); see [R] **Maximize**. These options are seldom used.

The following option is available with factor but is not shown in the dialog box:

norotated specifies that the unrotated factor solution be displayed, even if a rotated factor solution is available. norotated is for use only with replaying results.

Options unique to factormat

> [Model]

shape(shape) specifies the shape (storage method) for the covariance or correlation matrix matname. The following shapes are supported:

full specifies that the correlation or covariance structure of k variables is a symmetric $k \times k$ matrix. This is the default.

lower specifies that the correlation or covariance structure of k variables is a vector with $k(k+1)/2$ elements in rowwise lower-triangular order,

$$C_{11} \ C_{21} \ C_{22} \ C_{31} \ C_{32} \ C_{33} \ \ldots \ C_{k1} \ C_{k2} \ \ldots \ C_{kk}$$

upper specifies that the correlation or covariance structure of k variables is a vector with $k(k+1)/2$ elements in rowwise upper-triangular order,

$$\text{C}_{11} \; \text{C}_{12} \; \text{C}_{13} \; \ldots \; \text{C}_{1k} \; \text{C}_{22} \; \text{C}_{23} \; \ldots \text{C}_{2k} \; \ldots \; \text{C}_{(k-1,k-1)} \; \text{C}_{(k-1,k)} \; \text{C}_{kk}$$

names(*namelist*) specifies a list of k different names to be used to document output and label estimation results and as variable names by predict. names() is required if the correlation or covariance matrix is in vectorized storage mode (that is, shape(lower) or shape(upper) is specified). By default, factormat verifies that the row and column names of *matname* and the column or row names of *matname*$_2$ and *matname*$_3$ from the sds() and means() options are in agreement. Using the names() option turns off this check.

forcepsd modifies the matrix *matname* to be positive semidefinite (psd) and so be a proper covariance matrix. If *matname* is not positive semidefinite, it will have negative eigenvalues. By setting negative eigenvalues to 0 and reconstructing, we obtain the least-squares positive-semidefinite approximation to *matname*. This approximation is a singular covariance matrix.

n(*#*), a required option, specifies the number of observations on which *matname* is based.

sds(*matname*$_2$) specifies a $k \times 1$ or $1 \times k$ matrix with the standard deviations of the variables. The row or column names should match the variable names, unless the names() option is specified. sds() may be specified only if *matname* is a correlation matrix. Specify sds() if you have variables in your dataset and want to use predict after factormat. sds() does not affect the computations of factormat but provides information so that predict does not assume that the standard deviations are one.

means(*matname*$_3$) specifies a $k \times 1$ or $1 \times k$ matrix with the means of the variables. The row or column names should match the variable names, unless the names() option is specified. Specify means() if you have variables in your dataset and want to use predict after factormat. means() does not affect the computations of factormat but provides information so that predict does not assume the means are zero.

Remarks and examples

Remarks are presented under the following headings:

> *Introduction*
> *Factor analysis*
> *Factor analysis from a correlation matrix*

Introduction

Factor analysis, in the sense of exploratory factor analysis, is a statistical technique for data reduction. It reduces the number of variables in an analysis by describing linear combinations of the variables that contain most of the information and that, we hope, admit meaningful interpretations.

Factor analysis originated with the work of Spearman (1904), and has since witnessed an explosive growth, especially in the social sciences and, interestingly, in chemometrics. For an introduction, we refer to Kim and Mueller (1978a, 1978b), van Belle, Fisher, Heagerty, and Lumley (2004, chap. 14), Hamilton (2013, chap. 11), and Afifi et al. (2020). Intermediate-level treatments include Gorsuch (1983) and Harman (1976). For mathematically more advanced discussions, see Mulaik (2010), Mardia, Kent, and Bibby (1979, chap. 9), and Fuller (1987).

Structural equation modeling provides a more general framework for performing factor analysis, including confirmatory factor analysis; see [SEM] **Intro 5**, [SEM] **Example 1**, and [SEM] **Example 3**.

Also see Kolenikov (2009) for another implementation of confirmatory factor analysis.

Factor analysis

Factor analysis finds a few common factors (say, q of them) that linearly reconstruct the p original variables

$$y_{ij} = z_{i1}b_{1j} + z_{i2}b_{2j} + \cdots + z_{iq}b_{qj} + e_{ij}$$

where y_{ij} is the value of the ith observation on the jth variable, z_{ik} is the ith observation on the kth common factor, b_{kj} is the set of linear coefficients called the factor loadings, and e_{ij} is similar to a residual but is known as the jth variable's unique factor. Everything except the left-hand-side variable is to be estimated, so the model has an infinite number of solutions. Various constraints are introduced to make the model determinate.

"Reconstruction" is typically defined in terms of prediction of the correlation matrix of the original variables, unlike principal components (see [MV] **pca**), where reconstruction means minimum residual variance summed across all equations (variables).

Once the factors and their loadings have been estimated, they are interpreted—an admittedly subjective process. Interpretation typically means examining the b_{kj}'s and assigning names to each factor. Because of the indeterminacy of the factor solution, we are not limited to examining solely the b_{kj}'s. The loadings could be rotated. Rotations come in two forms—orthogonal and oblique. If we restrict to orthogonal rotations, the rotated b_{kj}s, despite appearing different, are every bit as good as (and no better than) the original loadings. Oblique rotations are often desired but do not retain some important properties of the original solution; see example 3. Because there are an infinite number of potential rotations, different rotations could lead to different interpretations of the same data. These are not to be viewed as conflicting, but instead as two different ways of looking at the same thing. See [MV] **factor postestimation** and [MV] **rotate** for more information on rotation.

▷ Example 1: A simple factor analysis on six questions

We wish to analyze physicians' attitudes toward cost. Six questions about cost were asked of 568 physicians in the Medical Outcomes Study from Tarlov et al. (1989). We do not have the original data, so we used corr2data to create a dataset with the same correlation matrix. Factor analysis is often used to validate a combination of questions that looks meaningful at first glance. Here we wish to create a variable that summarizes the information on each physician's attitude toward cost.

Each response is coded on a five-point scale, where 1 means "agree" and 5 means "disagree":

```
. use https://www.stata-press.com/data/r18/bg2
(Physician-cost data)

. describe

Contains data from https://www.stata-press.com/data/r18/bg2.dta
 Observations:            568                  Physician-cost data
    Variables:              7                  11 Feb 2022 21:54
                                               (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
clinid	int	%9.0g		Physician identifier
bg2cost1	float	%9.0g		Best health care is expensive
bg2cost2	float	%9.0g		Cost is a major consideration
bg2cost3	float	%9.0g		Determine cost of tests first
bg2cost4	float	%9.0g		Monitor likely complications only
bg2cost5	float	%9.0g		Use all means regardless of cost
bg2cost6	float	%9.0g		Prefer unnecessary tests to missing tests

```
Sorted by: clinid
```

We perform the factorization on `bg2cost1`, `bg2cost2`, ..., `bg2cost6`.

```
. factor bg2cost1-bg2cost6
(obs=568)

Factor analysis/correlation                    Number of obs    =         568
    Method: principal factors                  Retained factors =           3
    Rotation: (unrotated)                       Number of params =          15
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.85389	0.31282	1.0310	1.0310
Factor2	0.54107	0.51786	0.6533	1.6844
Factor3	0.02321	0.17288	0.0280	1.7124
Factor4	-0.14967	0.03951	-0.1807	1.5317
Factor5	-0.18918	0.06197	-0.2284	1.3033
Factor6	-0.25115	.	-0.3033	1.0000

```
    LR test: independent vs. saturated:  chi2(15) =  269.07 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Factor3	Uniqueness
bg2cost1	0.2470	0.3670	-0.0446	0.8023
bg2cost2	-0.3374	0.3321	-0.0772	0.7699
bg2cost3	-0.3764	0.3756	0.0204	0.7169
bg2cost4	-0.3221	0.1942	0.1034	0.8479
bg2cost5	0.4550	0.2479	0.0641	0.7274
bg2cost6	0.4760	0.2364	-0.0068	0.7175

`factor` retained only the first three factors because the eigenvalues associated with the remaining factors are negative. According to the default `mineigen(0)` criterion, a factor must have an eigenvalue greater than zero to be retained. You can set this threshold higher by specifying `mineigen(#)`. Although `factor` elected to retain three factors, only the first two appear to be meaningful.

The first factor seems to describe the physician's average position on cost because it affects the responses to all the questions "positively", as shown by the signs in the first column of the factor-loading table. We say "positively" because, obviously, the signs on three of the loadings are negative. When we look back at the results of `describe`, however, we find that the direction of the responses on `bg2cost2`, `bg2cost3`, and `bg2cost4` are reversed. If the physician feels that cost should not be a major influence on medical treatment, he or she is likely to disagree with these three items and to agree with the other three.

The second factor loads positively (absolutely, not logically) on all six items and could be interpreted as describing the physician's tendency to agree with any good-sounding idea put forth. Psychologists refer to this as the "positive response set". On statistical grounds, we would probably keep this second factor, although on substantive grounds, we would be tempted to drop it.

We finally point to the column with the header "uniqueness". *Uniqueness* is the percentage of variance for the variable that is not explained by the common factors. The quantity "1 − *uniqueness*" is called *communality*. Uniqueness could be pure measurement error, or it could represent something that is measured reliably in that particular variable, but not by any of the others. The greater the uniqueness, the more likely that it is more than just measurement error. Values more than 0.6 are usually considered high; all the variables in this problem are even higher—more than 0.71. If the uniqueness is high, then the variable is not well explained by the factors.

◁

▷ Example 2: A different divisor for proportions

The cumulative proportions of the eigenvalues exceeded 1.0 in our factor analysis because of the negative eigenvalues. By default, the proportion and cumulative proportion columns are computed using the sum of all eigenvalues as the divisor. The `altdivisor` option allows you to display the proportions and cumulative proportions by using the trace of the correlation matrix as the divisor. This option is allowed at estimation time or when replaying results. We demonstrate by replaying the results with this option.

```
. factor, altdivisor
Factor analysis/correlation                     Number of obs     =        568
    Method: principal factors                   Retained factors =          3
    Rotation: (unrotated)                       Number of params =         15
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.85389	0.31282	0.1423	0.1423
Factor2	0.54107	0.51786	0.0902	0.2325
Factor3	0.02321	0.17288	0.0039	0.2364
Factor4	-0.14967	0.03951	-0.0249	0.2114
Factor5	-0.18918	0.06197	-0.0315	0.1799
Factor6	-0.25115	.	-0.0419	0.1380

```
    LR test: independent vs. saturated:  chi2(15) =  269.07 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Factor3	Uniqueness
bg2cost1	0.2470	0.3670	-0.0446	0.8023
bg2cost2	-0.3374	0.3321	-0.0772	0.7699
bg2cost3	-0.3764	0.3756	0.0204	0.7169
bg2cost4	-0.3221	0.1942	0.1034	0.8479
bg2cost5	0.4550	0.2479	0.0641	0.7274
bg2cost6	0.4760	0.2364	-0.0068	0.7175

Among the sources we examined, there was not a consensus on which divisor is most appropriate. Therefore, both are available.

◁

▷ Example 3: Principal-component factors instead of principal factors

`factor` provides several alternative estimation strategies for the factor model. We specified no options on the `factor` command when we fit our first model, so we obtained the principal-factor solution. The *communalities* (defined as $1 - uniqueness$) were estimated using the squared multiple correlation coefficients.

We could have instead obtained the estimates from "principal-component factors", treating the communalities as all 1—meaning that there are no unique factors—by specifying the pcf option:

```
. factor bg2cost1-bg2cost6, pcf
(obs=568)
Factor analysis/correlation                        Number of obs    =        568
    Method: principal-component factors            Retained factors =          2
    Rotation: (unrotated)                          Number of params =         11
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.70622	0.30334	0.2844	0.2844
Factor2	1.40288	0.49422	0.2338	0.5182
Factor3	0.90865	0.18567	0.1514	0.6696
Factor4	0.72298	0.05606	0.1205	0.7901
Factor5	0.66692	0.07456	0.1112	0.9013
Factor6	0.59236	.	0.0987	1.0000

```
    LR test: independent vs. saturated:  chi2(15) =  269.07 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Uniqueness
bg2cost1	0.3581	0.6279	0.4775
bg2cost2	-0.4850	0.5244	0.4898
bg2cost3	-0.5326	0.5725	0.3886
bg2cost4	-0.4919	0.3254	0.6521
bg2cost5	0.6238	0.3962	0.4539
bg2cost6	0.6543	0.3780	0.4290

Here we find that the principal-component factor model is inappropriate. It is based on the assumption that the uniquenesses are 0, but we find that there is considerable uniqueness—there is considerable variability left over after our two factors. We should use some other method.

◁

▷ Example 4: Iterated principal-factor analysis

We could have fit our model using iterated principal factors by specifying the ipf option. Here the initial estimates of the communalities would be the squared multiple correlation coefficients, but the solution would then be iterated to obtain different (better) estimates:

```
. factor bg2cost1-bg2cost6, ipf
(obs=568)
Factor analysis/correlation                        Number of obs    =        568
    Method: iterated principal factors             Retained factors =          5
    Rotation: (unrotated)                          Number of params =         15
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.08361	0.31752	0.5104	0.5104
Factor2	0.76609	0.53816	0.3608	0.8712
Factor3	0.22793	0.19469	0.1074	0.9786
Factor4	0.03324	0.02085	0.0157	0.9942
Factor5	0.01239	0.01256	0.0058	1.0001
Factor6	-0.00017	.	-0.0001	1.0000

```
    LR test: independent vs. saturated:  chi2(15) =  269.07 Prob>chi2 = 0.0000
```

```
Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
bg2cost1	0.2471	0.4059	-0.1349	-0.1303	0.0288	0.7381
bg2cost2	-0.4040	0.3959	-0.2636	0.0349	0.0040	0.6093
bg2cost3	-0.4479	0.4570	0.1290	0.0137	-0.0564	0.5705
bg2cost4	-0.3327	0.1943	0.2655	0.0091	0.0810	0.7744
bg2cost5	0.5294	0.3338	0.2161	-0.0134	-0.0331	0.5604
bg2cost6	0.5174	0.2943	-0.0801	0.1208	0.0265	0.6240

Here we retained too many factors. Unlike in principal factors or principal-component factors, we cannot simply ignore the unnecessary factors because the uniquenesses are reestimated from the data and therefore depend on the number of retained factors. We need to reestimate. We use the opportunity to demonstrate the option blanks(#) for displaying "small loadings" as blanks for easier reading:

```
. factor bg2cost1-bg2cost6, ipf factors(2) blanks(.30)
(obs=568)
Factor analysis/correlation                    Number of obs     =        568
    Method: iterated principal factors         Retained factors  =          2
    Rotation: (unrotated)                       Number of params  =         11
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.03954	0.30810	0.5870	0.5870
Factor2	0.73144	0.60785	0.4130	1.0000
Factor3	0.12359	0.11571	0.0698	1.0698
Factor4	0.00788	0.03656	0.0045	1.0743
Factor5	-0.02867	0.07418	-0.0162	1.0581
Factor6	-0.10285	.	-0.0581	1.0000

```
    LR test: independent vs. saturated:  chi2(15) =  269.07 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Uniqueness
bg2cost1		0.3941	0.7937
bg2cost2	-0.3590		0.7827
bg2cost3	-0.5189	0.4935	0.4872
bg2cost4	-0.3230		0.8699
bg2cost5	0.4667	0.3286	0.6742
bg2cost6	0.5179	0.3325	0.6212

```
(blanks represent abs(loading)<.3)
```

It is instructive to compare the reported uniquenesses for this model and the previous one, where five factors were retained. Also, compared with the results we obtained from principal factors, these results do not differ much.

◁

▷ Example 5: Maximum-likelihood factor analysis

Finally, we could have fit our model using the maximum likelihood method by specifying the ml option. The maximum likelihood method assumes that the data are multivariate normal distributed. If the factor model provides an adequate approximation to the data, maximum likelihood estimates have favorable properties compared with the other estimation methods. Rao (1955) has shown that his canonical factor method is equivalent to the maximum likelihood method. This method seeks to maximize canonical correlations between the manifest variables and the common factors. Thus ml may be used descriptively, even if we are unwilling to assume multivariate normality.

As with `ipf`, if we do not specify the number of factors, Stata retains more than two factors (it retained three), and, as with `ipf`, we will need to reestimate with the number of factors that we really want. To save paper, we will start by retaining two factors:

```
. factor bg2cost1-bg2cost6, ml factors(2)
(obs=568)
Iteration 0:   Log likelihood = -28.702162
Iteration 1:   Log likelihood = -7.0065234
Iteration 2:   Log likelihood = -6.8513798
Iteration 3:   Log likelihood = -6.8429502
Iteration 4:   Log likelihood = -6.8424747
Iteration 5:   Log likelihood = -6.8424491
Iteration 6:   Log likelihood = -6.8424477

Factor analysis/correlation                Number of obs    =        568
    Method: maximum likelihood             Retained factors =          2
    Rotation: (unrotated)                  Number of params =         11
                                           Schwarz's BIC    =    83.4482
    Log likelihood = -6.842448             (Akaike's) AIC   =    35.6849
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.02766	0.28115	0.5792	0.5792
Factor2	0.74651	.	0.4208	1.0000

```
LR test: independent vs. saturated:  chi2(15) =  269.07 Prob>chi2 = 0.0000
LR test:    2 factors vs. saturated:  chi2(4)  =   13.58 Prob>chi2 = 0.0087
```

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
bg2cost1	-0.1371	0.4235	0.8018
bg2cost2	0.4140	0.1994	0.7888
bg2cost3	0.6199	0.3692	0.4794
bg2cost4	0.3577	0.0909	0.8638
bg2cost5	-0.3752	0.4355	0.6695
bg2cost6	-0.4295	0.4395	0.6224

`factor` displays a likelihood-ratio test of independence against the saturated model with each estimation method. Because we are factor analyzing a correlation matrix, independence implies sphericity. Passing this test is necessary for a factor analysis to be meaningful.

In addition to the "standard" output, when you use the `ml` option, Stata reports a likelihood-ratio test of the number of factors in the model against the saturated model. This test is only approximately χ^2, and we have used the correction recommended by Bartlett (1951). There are many variations on this test in use by different statistical packages.

The following comments were made by the analyst looking at these results: "There is, in my opinion, weak evidence of more than two factors. The χ^2 test for more than two factors is really a test of how well you are fitting the correlation matrix. It is not surprising that the model does not fit it perfectly. The significance of 1%, however, suggests to me that there might be a third factor. As for the loadings, they yield a similar interpretation to other factor models we fit, although there are some noteworthy differences." When we challenged the analyst on this last statement, he added that he would want to rotate the resulting factors before committing himself further.

◁

❑ Technical note

Stata will sometimes comment, "Note: test formally not valid because a Heywood case was encountered". The approximations used in computing the χ^2 value and degrees of freedom are mathematically justified on the assumption that an *interior* solution to the factor maximum likelihood was found. This is the case in our example above, but that will not always be so.

Boundary solutions, called Heywood solutions, often produce uniquenesses of 0, and then at least at a formal level, the test cannot be justified. Nevertheless, we believe that the reported tests are useful, even in such circumstances, provided that they are interpreted cautiously. The maximum likelihood method seems to be particularly prone to producing Heywood solutions.

This message is also printed when, in principle, there are enough free parameters to completely fit the correlation matrix, another sort of boundary solution. We say "in principle" because the correlation matrix often cannot be fit perfectly, so you will see a positive χ^2 with zero degrees of freedom. This warning note is printed because the geometric assumptions underlying the likelihood-ratio test are violated.

❑

❑ Technical note

In a factor analysis with factors estimated with the maximum likelihood method, there may possibly be more than one local maximum, and you may want assurances that the maximum reported is the global maximum. Multiple maximums are especially likely when there is more than one group of variables, the groups are reasonably uncorrelated, and you attempt to fit a model with too few factors.

When you specify the protect(#) option, Stata performs # optimizations of the likelihood function, beginning each with random starting values, before continuing with the squared multiple correlations–initialized solution. Stata then selects the maximum of the maximums and reports it, along with a note informing you if other local maximums were found. protect(50) provides considerable assurance.

If you then wish to explore any of the nonglobal maximums, include the random option. This option, which is never specified with protect(), uses random starting values and reports the solution to which those random values converge. For multiple maximums, giving the command repeatedly will eventually report all local maximums. You are advised to set the random-number seed to ensure that your results are reproducible; see [R] **set seed**.

❑

Factor analysis from a correlation matrix

You may want to perform a factor analysis directly from a correlation matrix rather than from variables in a dataset. You may not have access to the dataset, or you may have used another method of estimating a correlation matrix—for example, as a matrix of tetrachoric correlations; see [R] **tetrachoric**. You can provide either a correlation or a covariance matrix—factormat will translate a covariance matrix into a correlation matrix.

▷ Example 6: Factor analysis of a correlation matrix

We illustrate with a small example with three variables on respondent's senses (visual, hearing, and taste), with a correlation matrix.

```
. matrix C = (1.000, 0.943,  0.771 \
>             0.943, 1.000,  0.605 \
>             0.771, 0.605,  1.000)
```

Elements within a row are separated by a comma, whereas rows are separated by a backslash, \.
We now use `factormat` to analyze C. There are two required options here. First, the option `n(979)`
specifies that the sample size is 979. Second, `factormat` has to have labels for the variables. It is
possible to define row and column names for C. We did not explicitly set the names of C, so Stata has
generated default row and columns names—`r1 r2 r3` for the rows, and `c1 c2 c3` for the columns.
This will confuse `factormat`: why does a symmetric correlation matrix have different names for the
rows and for the columns? `factormat` would complain about the problem and stop. We could set
the row and column names of C to be the same and invoke `factormat` again. We can also specify
the `names()` option with the variable names to be used.

```
. factormat C, n(979) names(visual hearing taste) fac(1) ipf
(obs=979)
```

Factor analysis/correlation   Number of obs   =   979
    Method: iterated principal factors   Retained factors =   1
    Rotation: (unrotated)   Number of params =   3

Warning: Solution is a Heywood case; that is, invalid or boundary values of
         uniqueness.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.43622	2.43609	1.0000	1.0000
Factor2	0.00013	0.00028	0.0001	1.0001
Factor3	-0.00015	.	-0.0001	1.0000

    LR test: independent vs. saturated: chi2(3) = 3425.87 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
visual	1.0961	-0.2014
hearing	0.8603	0.2599
taste	0.7034	0.5053

If we have the correlation matrix already in electronic form, this is a fine method. But if we have
to enter a correlation matrix by hand, we may rather want to exploit its symmetry to enter just the
upper triangle or lower triangle. This is not an issue with our small three-variable example, but what
about a correlation matrix of 25 variables? However, there is an advantage to entering the correlation
matrix in full symmetric form: redundancy offers some protection against making data entry errors;
`factormat` will complain if the matrix is not symmetric.

`factormat` allows us to enter just one of the triangles of the correlation matrix as a vector, that
is, a matrix with one row or column. We enter the upper triangle, including the diagonal,

```
. matrix Cup = (1.000, 0.943, 0.771,
>                      1.000, 0.605,
>                             1.000)
```

All elements are separated by a comma; indentation and the use of three lines are done for
readability. We could have typed, all the numbers "in a row".

```
. matrix Cup = (1.000, 0.943, 0.771, 1.000, 0.605, 1.000)
```

We have to specify the option `shape(upper)` to inform `factormat` that the elements in the vector
Cup are the upper triangle in rowwise order.

```
      . factormat Cup, n(979) shape(upper) fac(2) names(visual hearing taste)
        (output omitted )
```

If we had entered the lower triangle of C, a vector Clow, it would have been defined as

```
      . matrix Clow = (1.000, 0.943, 1.000, 0.771, 0.605, 1.000)
```

The features of factormat and factor are the same for estimation. Postestimation facilities are also the same—except that predict will not work after factormat, unless variables corresponding to the names() option exist in the dataset; see [MV] **factor postestimation**.

◁

Stored results

factor and factormat store the following in e():

Scalars
e(N)	number of observations
e(f)	number of retained factors
e(evsum)	sum of all eigenvalues
e(df_m)	model degrees of freedom
e(df_r)	residual degrees of freedom
e(chi2_i)	likelihood-ratio test of "independence vs. saturated"
e(df_i)	degrees of freedom of test of "independence vs. saturated"
e(p_i)	p-value of "independence vs. saturated"
e(ll_0)	log likelihood of null model (ml only)
e(ll)	log likelihood (ml only)
e(aic)	Akaike's AIC (ml only)
e(bic)	Schwarz's BIC (ml only)
e(chi2_1)	likelihood-ratio test of "# factors vs. saturated" (ml only)
e(df_1)	degrees of freedom of test of "# factors vs. saturated" (ml only)

Macros
e(cmd)	factor
e(cmdline)	command as typed
e(method)	pf, pcf, ipf, or ml
e(wtype)	weight type (factor only)
e(wexp)	weight expression (factor only)
e(title)	Factor analysis
e(mtitle)	description of method (for example, principal factors)
e(heywood)	Heywood case (when encountered)
e(matrixname)	input matrix (factormat only)
e(mineigen)	specified mineigen() option
e(factors)	specified factors() option
e(rngstate)	random-number state used (seed() option only)
e(properties)	nob noV eigen
e(rotate_cmd)	factor_rotate
e(estat_cmd)	factor_estat
e(predict)	factor_p
e(marginsnotok)	predictions disallowed by margins

Matrices
e(sds)	standard deviations of analyzed variables
e(means)	means of analyzed variables
e(C)	analyzed correlation matrix
e(Phi)	variance matrix common factors
e(L)	factor loadings
e(Psi)	uniqueness (variance of specific factors)
e(Ev)	eigenvalues

Functions
e(sample)	marks estimation sample (factor only)

`rotate` after `factor` and `factormat` stores items in `e()` along with the estimation command. See *Stored results* of [MV] **factor postestimation** and [MV] **rotate** for details.

Methods and formulas

This section describes the statistical factor model. Suppose that there are p variables and q factors. Let $\boldsymbol{\Psi}$ represent the $p \times p$ diagonal matrix of uniquenesses, and let $\boldsymbol{\Lambda}$ represent the $p \times q$ factor loading matrix. Let $\mathbf{f}$ be a $1 \times q$ matrix of factors. The standardized (mean 0, variance 1) vector of observed variables $\mathbf{x}$ $(1 \times p)$ is given by the system of regression equations

$$\mathbf{x} = \mathbf{f}\boldsymbol{\Lambda}' + \mathbf{e}$$

where $\mathbf{e}$ is a $1 \times p$ vector of errors with diagonal covariance equal to the uniqueness matrix $\boldsymbol{\Psi}$. The common factors $\mathbf{f}$ and the specific factors $\mathbf{e}$ are assumed to be uncorrelated.

Under the factor model, the correlation matrix of $\mathbf{x}$, called $\boldsymbol{\Sigma}$, is decomposed by factor analysis as

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}\boldsymbol{\Phi}\boldsymbol{\Lambda}' + \boldsymbol{\Psi}$$

There is an obvious freedom in reexpressing a given decomposition of $\boldsymbol{\Sigma}$. The default and unrotated form assumes uncorrelated common factors, $\boldsymbol{\Phi} = \mathbf{I}$. Stata performs this decomposition by an eigenvector calculation. First, an estimate is found for the uniqueness $\boldsymbol{\Psi}$, and then the columns of $\boldsymbol{\Lambda}$ are computed as the q leading eigenvectors, scaled by the square root of the appropriate eigenvalue.

See Harman (1976); Mardia, Kent, and Bibby (1979); Rencher (1998, chap. 10); and Rencher and Christensen (2012, chap. 13) for discussions of estimation methods in factor analysis. Basilevsky (1994) places factor analysis in a wider statistical context and details many interesting examples and links to other methods. For details about maximum likelihood estimation, see also Lawley and Maxwell (1971) and Clarke (1970).

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Also see

Title

> **factor postestimation** — Postestimation tools for factor and factormat

Postestimation commands

The following postestimation commands are of special interest after `factor` and `factormat`:

Command	Description
estat anti	anti-image correlation and covariance matrices
estat common	correlation matrix of the common factors
estat factors	AIC and BIC model-selection criteria for different numbers of factors
estat kmo	Kaiser–Meyer–Olkin measure of sampling adequacy
estat residuals	matrix of correlation residuals
estat rotatecompare	compare rotated and unrotated loadings
estat smc	squared multiple correlations between each variable and the rest
estat structure	correlations between variables and common factors
* estat summarize	estimation sample summary
loadingplot	plot factor loadings
rotate	rotate factor loadings
scoreplot	plot score variables
screeplot	plot eigenvalues

*`estat summarize` is not available after `factormat`.

The following standard postestimation commands are also available:

Command	Description
* estimates	cataloging estimation results; see [R] **estimates**
† predict	regression and Bartlett scores

*`estimates table` is not allowed, and `estimates stats` is allowed only with the `ml` factor method.

†`predict` after `factormat` works only if you have variables in memory that match the names specified in `factormat`. `predict` assumes mean zero and standard deviation one unless the `means()` and `sds()` options of `factormat` were provided.

predict

Description for predict

predict creates new variables containing predictions such as factors scored by the regression method or by the Bartlett method.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] {*stub*∗ | *newvarlist*} [*if*] [*in*] [, *statistic options*]

statistic	Description
Main	
<u>r</u>egression	regression scoring method; the default
<u>b</u>artlett	Bartlett scoring method

options	Description
Main	
<u>noro</u>tated	use unrotated results, even when rotated results are available
<u>not</u>able	suppress table of scoring coefficients
<u>for</u>mat(%*fmt*)	format for displaying the scoring coefficients

Options for predict

> **Main**

regression produces factors scored by the regression method. This is the default.

bartlett produces factors scored by the method suggested by Bartlett (1937, 1938). This method produces unbiased factors, but they may be less accurate than those produced by the default regression method suggested by Thomson (1951). Regression-scored factors have the smallest mean squared error from the true factors but may be biased.

norotated specifies that unrotated factors be scored even when you have previously issued a rotate command. The default is to use rotated factors if they are available and unrotated factors otherwise.

notable suppresses the table of scoring coefficients.

format(%*fmt*) specifies the display format for scoring coefficients.

estat

Description for estat

estat anti displays the anti-image correlation and anti-image covariance matrices. These are minus the partial covariance and minus the partial correlation matrices of all pairs of variables, holding all other variables constant.

estat common displays the correlation matrix of the common factors. For orthogonal factor loadings, the common factors are uncorrelated, and hence an identity matrix is shown. estat common is of more interest after oblique rotations.

estat factors displays model-selection criteria (AIC and BIC) for models with 1, 2, ..., # factors. Each model is estimated using maximum likelihood (that is, using the ml option of factor).

estat kmo specifies that the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy be displayed. KMO takes values between 0 and 1, with small values meaning that overall the variables have too little in common to warrant a factor analysis. Historically, the following labels are given to values of KMO (Kaiser 1974):

0.00 to 0.49	unacceptable
0.50 to 0.59	miserable
0.60 to 0.69	mediocre
0.70 to 0.79	middling
0.80 to 0.89	meritorious
0.90 to 1.00	marvelous

estat residuals displays the raw or standardized residuals of the observed correlations with respect to the fitted (reproduced) correlation matrix.

estat rotatecompare displays the unrotated factor loadings and the most recent rotated factor loadings.

estat smc displays the squared multiple correlations between each variable and all other variables. SMC is a theoretical lower bound for communality, so it is an upper bound for uniqueness. The pf factor method estimates the communalities by smc.

estat structure displays the factor structure, that is, the correlations between the variables and the common factors.

estat summarize displays summary statistics of the variables in the factor analysis over the estimation sample. This subcommand is, of course, not available after factormat.

Menu for estat

Statistics > Postestimation

Syntax for estat

Anti-image correlation/covariance matrices

> estat anti [, nocorr nocov <u>for</u>mat(%*fmt*)]

Correlation of common factors

> estat <u>com</u>mon [, <u>norot</u>ated <u>for</u>mat(%*fmt*)]

Model-selection criteria

> estat <u>factors</u> [, <u>factors</u>(#) <u>detail</u>]

Sample adequacy measures

> estat kmo [, <u>nov</u>ar <u>for</u>mat(%*fmt*)]

Residuals of correlation matrix

> estat <u>res</u>iduals [, <u>f</u>itted <u>obs</u> <u>s</u>residuals <u>for</u>mat(%*fmt*)]

Comparison of rotated and unrotated loadings

> estat <u>rot</u>atecompare [, <u>for</u>mat(%*fmt*)]

Squared multiple correlations

> estat smc [, <u>for</u>mat(%*fmt*)]

Correlations between variables and common factors

> estat <u>structure</u> [, <u>norot</u>ated <u>for</u>mat(%*fmt*)]

Summarize variables for estimation sample

> estat <u>summarize</u> [, <u>labels</u> <u>noheader</u> <u>noweights</u>]

collect is allowed with estat anti, estat common, estat factors, estat kmo, estat residuals, estat smc,
   estat structure, and estat summarize; see [U] 11.1.10 Prefix commands.

Options for estat

     Main

nocorr, an option used with estat anti, suppresses the display of the anti-image correlation matrix.

nocov, an option used with estat anti, suppresses the display of the anti-image covariance matrix.

format(%*fmt*) specifies the display format. The defaults differ between the subcommands.

norotated, an option used with estat common and estat structure, requests that the displayed
   and returned results be based on the unrotated original factor solution rather than on the last
   rotation (orthogonal or oblique).

factors(*#*), an option used with estat factors, specifies the maximum number of factors to include in the summary table.

detail, an option used with estat factors, presents the output from each run of factor (or factormat) used in the computations of the AIC and BIC values.

novar, an option used with estat kmo, suppresses the KMO measures of sampling adequacy for the variables in the factor analysis, displaying the overall KMO measure only.

fitted, an option used with estat residuals, displays the fitted (reconstructed) correlation matrix on the basis of the retained factors.

obs, an option used with estat residuals, displays the observed correlation matrix.

sresiduals, an option used with estat residuals, displays the matrix of standardized residuals of the correlations. Be careful when interpreting these residuals; see Jöreskog and Sörbom (1988).

labels, noheader, and noweights are the same as for the generic estat summarize command; see [R] **estat summarize**.

Remarks and examples

Remarks are presented under the following headings:

> Postestimation statistics
> Plots of eigenvalues, factor loadings, and scores
> Rotating the factor loadings
> Factor scores

Postestimation statistics

Many postestimation statistics are available after factor and factormat.

▷ Example 1: Squared multiple correlations

After factor and factormat there are several "classical" methods for assessing whether the variables have enough in common to have warranted the use of a factor model. One method is to examine the squared multiple correlations of each variable with all other variables—this is usually an upper bound to *communality* and thus a lower bound to $1 - uniqueness(= communality)$ of the variables.

```
. use https://www.stata-press.com/data/r18/bg2
(Physician-cost data)

. quietly factor bg2cost1-bg2cost6, factors(2) ml

. estat smc
Squared multiple correlations of variables with all other variables
```

Variable	smc
bg2cost1	0.1054
bg2cost2	0.1370
bg2cost3	0.1637
bg2cost4	0.0866
bg2cost5	0.1671
bg2cost6	0.1683

Other diagnostic tools, such as examining the anti-image correlation and anti-image covariance matrices (estat anti) and the Kaiser–Meyer–Olkin measure of sampling adequacy (estat kmo), are also available. See [MV] **pca postestimation** for an illustration of their use.

◁

▷ Example 2: Model-selection criteria

Another set of postestimation tools help in determining the number of factors that should be retained. Later we will show the use of screeplot for producing a scree plot—a plot of the explained variance by the common factors. This is often used as a visual guide for selecting the number of factors to retain.

Some authors advocate the standard model information criteria AIC and BIC for determining the number of factors (Schwarz 1978; Akaike 1987). This presupposes that the factors are extracted by maximum likelihood. estat factors provides these measures.

```
. estat factors
```
Factor analysis with different numbers of factors (maximum likelihood)

#factors	loglik	df_m	df_r	AIC	BIC
1	-60.53727	6	9	133.0745	159.1273
2	-6.842448	11	4	35.6849	83.44823
3	-3.34e-12	15	0	30	95.13182

no Heywood cases encountered

The table shows the AIC and BIC statistics for the models with 1, 2, and 3 factors. The three-factor model is saturated, with 0 degrees of freedom. In this trivial case, and excluding the saturated case, both criteria select the two-factor model.

◁

▷ Example 3: Structure matrix and observed correlations

Two estat subcommands display statistics that help in interpreting the model and the results—in particular after an oblique rotation. estat structure displays the *structure* matrix containing the correlations between the (manifest) variables and the common factors.

```
. estat structure
```
Structure matrix: correlations between variables and common factors

Variable	Factor1	Factor2
bg2cost1	-0.1371	0.4235
bg2cost2	0.4140	0.1994
bg2cost3	0.6199	0.3692
bg2cost4	0.3577	0.0909
bg2cost5	-0.3752	0.4355
bg2cost6	-0.4295	0.4395

This matrix of correlations coincides with the pattern matrix, that is, the matrix with factor loadings. This holds true for the unrotated factor solution as well as after an orthogonal rotation, such as a varimax rotation. It does not hold true after an oblique rotation. After an oblique rotation, the common factors are correlated. This correlation between the common factors also influences the correlation between the common factors and the manifest variables. The correlation matrix of the common factors is displayed by the common subcommand of estat. Because we have not yet rotated, we would see only an identity matrix. Later we show estat common output after an oblique rotation.

To assess the quality of a factor model, we may compare the observed correlation matrix $\mathbf{C}$ with the fitted ("reconstructed") matrix $\widehat{\boldsymbol{\Sigma}} = \widehat{\boldsymbol{\Lambda}}\widehat{\boldsymbol{\Phi}}\widehat{\boldsymbol{\Lambda}}' + \widehat{\boldsymbol{\Psi}}$ by examining the raw residuals $\mathbf{C} - \widehat{\boldsymbol{\Sigma}}$.

```
. estat residuals, obs fit
```

Observed correlations

Variable	bg2co~1	bg2co~2	bg2co~3	bg2co~4	bg2co~5	bg2co~6
bg2cost1	1.0000					
bg2cost2	0.0920	1.0000				
bg2cost3	0.0540	0.3282	1.0000			
bg2cost4	-0.0380	0.1420	0.2676	1.0000		
bg2cost5	0.2380	-0.1394	-0.0550	-0.0567	1.0000	
bg2cost6	0.2431	-0.0671	-0.1075	-0.1329	0.3524	1.0000

Fitted ("reconstructed") values for correlations

Variable	bg2co~1	bg2co~2	bg2co~3	bg2co~4	bg2co~5	bg2co~6
bg2cost1	1.0000					
bg2cost2	0.0277	1.0000				
bg2cost3	0.0714	0.3303	0.9999			
bg2cost4	-0.0106	0.1662	0.2553	1.0000		
bg2cost5	0.2359	-0.0685	-0.0718	-0.0946	1.0000	
bg2cost6	0.2450	-0.0902	-0.1040	-0.1137	0.3525	1.0000

Raw residuals of correlations (observed-fitted)

Variable	bg2co~1	bg2co~2	bg2co~3	bg2co~4	bg2co~5	bg2co~6
bg2cost1	-0.0000					
bg2cost2	0.0643	-0.0000				
bg2cost3	-0.0174	-0.0021	0.0001			
bg2cost4	-0.0274	-0.0242	0.0124	-0.0000		
bg2cost5	0.0021	-0.0709	0.0168	0.0379	0.0000	
bg2cost6	-0.0019	0.0231	-0.0035	-0.0193	-0.0002	-0.0000

To gauge the size of the residuals, `estat residuals` can also display the standardized residuals.

```
. estat residuals, sres
```

Standardized residuals of correlations

Variable	bg2co~1	bg2co~2	bg2co~3	bg2co~4	bg2co~5	bg2co~6
bg2cost1	-0.0001					
bg2cost2	1.5324	-0.0003				
bg2cost3	-0.4140	-0.0480	0.0011			
bg2cost4	-0.6538	-0.5693	0.2859	-0.0000		
bg2cost5	0.0484	-1.6848	0.3993	0.9003	0.0001	
bg2cost6	-0.0434	0.5480	-0.0836	-0.4560	-0.0037	-0.0000

Be careful when interpreting these standardized residuals, as they tend to be smaller than normalized residuals; that is, these residuals tend to have a smaller variance than 1 if the model is true (see Bollen [1989]).

◁

Plots of eigenvalues, factor loadings, and scores

Scree plots, factor loading plots, and score plots are easily obtained after `factor` and `factormat`.

▷ Example 4: The scree plot

The scree plot is a popular tool for determining the number of factors to be retained. A scree plot is a plot of the eigenvalues shown in decreasing order (Cattell 1966). We fit a factor model, extracting factors with the principal factor method.

```
. use https://www.stata-press.com/data/r18/sp2
. factor ghp31-ghp05, pcf
  (output omitted)
```

How many factors should we retain? We issue the `screeplot` command with the `mean` option, specifying that a horizontal line be plotted at the mean of the eigenvalues (a height of 1 because we are dealing with the eigenvalues of a correlation matrix).

```
. screeplot, mean
```
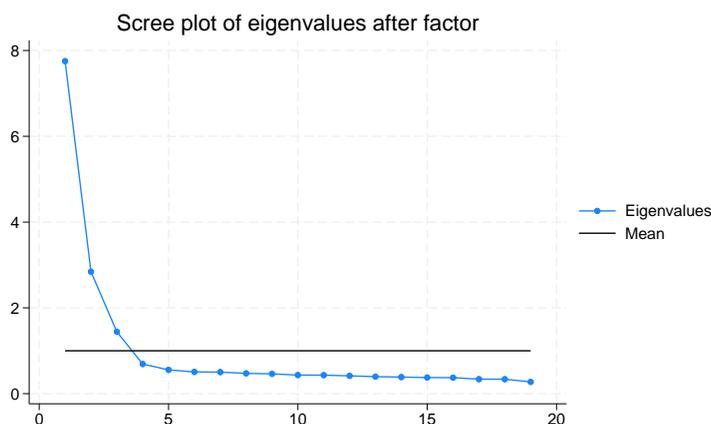

The plot suggests that we retain three factors, both because of the shape of the scree plot and because of Kaiser's well-known criterion suggesting that we retain factors with eigenvalue larger than 1. We may specify the option `mineigen(1)` during estimation to enforce this criterion. Here there is no need—`mineigen(1)` is the default with `pcf`.

◁

▷ Example 5: Factor loadings plot

A second plot that is sometimes useful is the factor loadings plot. We display the plot with the loadings of the leading two factors.

```
. loadingplot, xline(0) yline(0) aspect(1) note(Unrotated principal factors)
```


Factor loadings

Unrotated principal factors
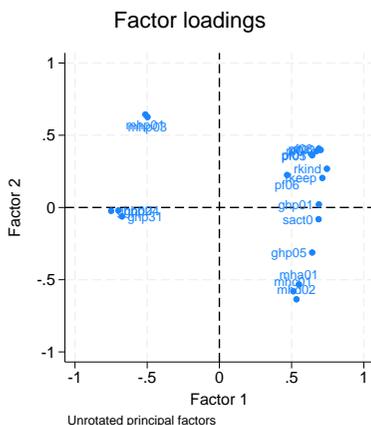
The plot makes it relatively easy to identify clusters of variables with similar loadings. With more than two factors, we can choose to see the multiple plots in a matrix style or a combined-graph style. The default is matrix style, but the combined style allows better control over various graph options—for instance, the addition of `xline(0)` and `yline(0)`. Here is a combined style graph.

```
. loadingplot, factors(3) combined xline(0) yline(0) aspect(1)
> xlabel(-0.8(0.4)0.8) ylabel(-0.8(0.4)0.8)
```


Factor loadings

◁
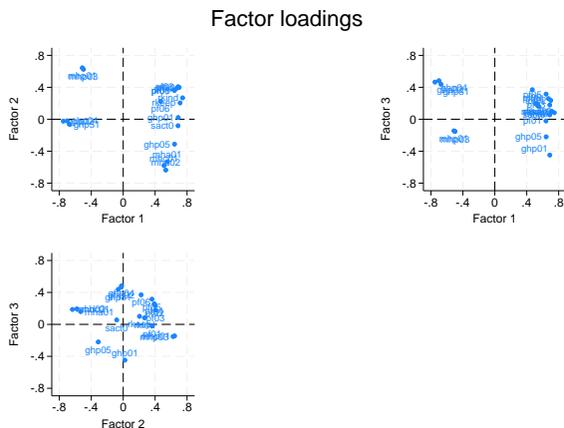
▷ Example 6: Score variables plot

Common factor scores can also be plotted for the observations by using the `scoreplot` command. (See the discussion of `predict` to see how you can produce score variables.)

```
. scoreplot, msymbol(smcircle) msize(tiny)
```


Score variables (factor)
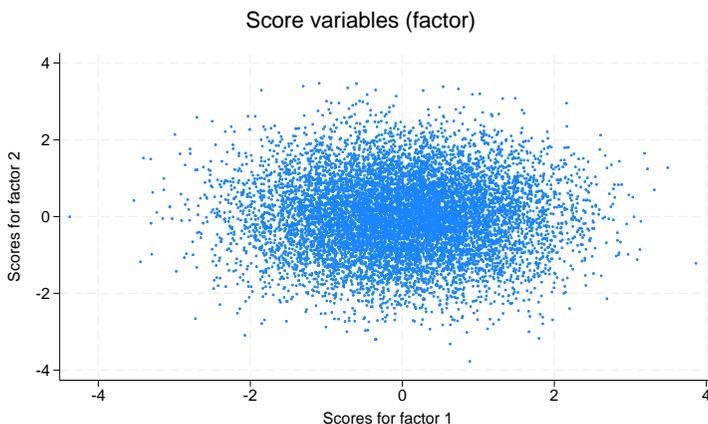
With so many observations, the plot's main purpose is to identify extreme cases. With smaller datasets with meaningful descriptions of the observations (for example, country names, brands), the score plot is good for visually clustering observations with similar loadings.

◁

See [MV] **scoreplot** for more examples of loadingplot and scoreplot.

❑ Technical note

The loading plots and score plots we have shown were for the original unrotated factor solution. After rotating (which we will discuss next), these plots display the most recent rotated solution. Specify option norotated to refer to the unrotated result. To display the plots of rotated and unrotated results at the same time, you may use either of the following two approaches. First, you may display them in different Graph windows.

```
. plotcmd, norotated name(name1)
. plotcmd, name(name2)
```

Alternatively, you may save the plots and create a combined graph

```
. plotcmd, norotated saving(name1)
. plotcmd, saving(name2)
. graph combine name1.gph name2.gph
```

See [G-2] **graph combine** for details.

❑

Rotating the factor loadings

Rotation is an attempt to describe the information in several factors by reexpressing them so that loadings on a few variables are as large as possible, and loadings on the rest of the variables are as small as possible. We have this freedom to reexpress because of the indeterminant nature of the factor model. For example, if you find that z_1 and z_2 are two factors, then $z_1 + z_2$ and $z_1 - z_2$ are equally valid solutions.

❑ Technical note

Said more technically: we are trying to find a set of f factor variables such that the observed variables can be best explained by regressing them on the f factor variables. Usually, f is a small number such as 1 or 2. If $f \geq 2$, there is an inherent indeterminacy in the construction of the factors because any linear combination of the calculated factors serves equally well as a set of regressors. Rotation capitalizes on this indeterminacy to create a set of variables that looks as much like the original variables as possible.

❑

The `rotate` command modifies the results of the last `factor` or `factormat` command to create a set of loadings that are more interpretable than those produced by `factor` or `factormat`. You may perform one factor analysis followed by several `rotate` commands, thus experimenting with different types of rotation. If you retain too few factors, the variables for several distinct concepts may be merged, as in our example below. If you retain too many factors, several factors may attempt to measure the same concept, causing the factors to get in each other's way, suggesting too many distinct concepts after rotation.

❑ Technical note

It is possible to restrict rotation to a number of leading factors. For instance, if you extracted three factors, you may specify the option `factors(2)` to `rotate` to exclude the third factor from being rotated. The new two leading factors are combinations of the initial two leading factors and are not affected by the fixed factor.

❑

▷ Example 7: Orthogonal varimax rotation

We return to our physician-cost example in [MV] **factor** and perform a factor analysis using the principal-component factor method, retaining two factors. We then tell `rotate` to apply the default orthogonal varimax rotation (Kaiser 1958).

```
. use https://www.stata-press.com/data/r18/bg2, clear
(Physician-cost data)
. quietly factor bg2cost1-bg2cost6, pcf factors(2)
. rotate
```

Factor analysis/correlation   Number of obs   =   568
    Method: principal-component factors   Retained factors =   2
    Rotation: orthogonal varimax (Kaiser off)   Number of params =   11

Factor	Variance	Difference	Proportion	Cumulative
Factor1	1.57170	0.03430	0.2619	0.2619
Factor2	1.53740	.	0.2562	0.5182

LR test: independent vs. saturated: chi2(15) = 269.07 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
bg2cost1	0.6853	0.2300	0.4775
bg2cost2	-0.0126	0.7142	0.4898
bg2cost3	-0.0161	0.7818	0.3886
bg2cost4	-0.1502	0.5703	0.6521
bg2cost5	0.7292	-0.1198	0.4539
bg2cost6	0.7398	-0.1537	0.4290

Factor rotation matrix

	Factor1	Factor2
Factor1	0.7460	-0.6659
Factor2	0.6659	0.7460

Here the factors are rotated so that the three "negative" items are grouped together and the three "positive" items are grouped.

Look at the uniqueness column. *Uniqueness* is the percentage of variance for the variable that is not explained by the common factors; we may also think of it as the variances of the specific factors for the variables. We stress that rotation involves the "common factors", so the *uniqueness* is not affected by the rotation. As we noted in [MV] **factor**, the uniqueness is relatively high in this example, placing doubt on the usefulness of the factor model here.

◁

▷ Example 8: More orthogonal varimax rotation

Here we examine 19 variables describing various aspects of health. These variables were collected from a random selection of 9,999 visitors to doctors' offices by Tarlov et al. (1989). Factor analysis yields three clear factors. We then examine several rotations of these three factors.

```
. use https://www.stata-press.com/data/r18/sp2

. describe
```

Contains data from https://www.stata-press.com/data/r18/sp2.dta
 Observations: 9,999
    Variables: 20   26 Jan 2022 09:26
                                                 (_dta has notes)

Variable name	Storage type	Display format	Value label	Variable label
patid	int	%9.0g		Case ID
ghp31	float	%9.0g		Health excellent, very good, good, fair, poor
pf01	float	%9.0g		How long limit vigorous activity
pf02	float	%9.0g		How long limit moderate activity
pf03	float	%9.0g		How long limit walk/climb
pf04	float	%9.0g		How long limit bend/stoop
pf05	float	%9.0g		How long limit walk 1 block
pf06	float	%9.0g		How long limit eat/dress/bath
rkeep	float	%9.0g		Does health keep work-job-hse
rkind	float	%9.0g		Can't do kind/amount of work
sact0	float	%9.0g		Last month limit activities
mha01	float	%9.0g		Last month very nervous
mhp03	float	%9.0g		Last month calm/peaceful
mhd02	float	%9.0g		Last month downhearted/blue
mhp01	float	%9.0g		Last month a happy person
mhc01	float	%9.0g		Last month down in the dumps
ghp01	float	%9.0g		Somewhat ill
ghp04	float	%9.0g		Healthy as anybody I know
ghp02	float	%9.0g		Health is excellent
ghp05	float	%9.0g		Feel bad lately

Sorted by: patid

We now perform our factorization, requesting that three factors be retained.

```
. factor ghp31-ghp05, factors(3)
(obs=9,999)
```

Factor analysis/correlation   Number of obs   =   9,999
    Method: principal factors   Retained factors =   3
    Rotation: (unrotated)   Number of params =   54

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.27086	4.90563	0.7534	0.7534
Factor2	2.36523	1.38826	0.2451	0.9985
Factor3	0.97697	1.00351	0.1012	1.0997
Factor4	-0.02654	0.00538	-0.0027	1.0970
Factor5	-0.03191	0.00378	-0.0033	1.0937
Factor6	-0.03569	0.00353	-0.0037	1.0900
Factor7	-0.03922	0.00271	-0.0041	1.0859
Factor8	-0.04193	0.00662	-0.0043	1.0815
Factor9	-0.04855	0.01015	-0.0050	1.0765
Factor10	-0.05870	0.00250	-0.0061	1.0704
Factor11	-0.06120	0.00224	-0.0063	1.0641
Factor12	-0.06344	0.00376	-0.0066	1.0575
Factor13	-0.06720	0.00345	-0.0070	1.0506
Factor14	-0.07065	0.00185	-0.0073	1.0432
Factor15	-0.07250	0.00033	-0.0075	1.0357
Factor16	-0.07283	0.00772	-0.0075	1.0282
Factor17	-0.08055	0.01190	-0.0083	1.0198
Factor18	-0.09245	0.00649	-0.0096	1.0103
Factor19	-0.09894	.	-0.0103	1.0000

LR test: independent vs. saturated: chi2(171) = 1.0e+05 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
ghp31	-0.6519	-0.0562	0.3440	0.4535
pf01	0.6150	0.3226	-0.0072	0.5177
pf02	0.6867	0.3737	0.2175	0.3415
pf03	0.6712	0.3774	0.1621	0.3807
pf04	0.6540	0.3588	0.2268	0.3921
pf05	0.6209	0.3258	0.2631	0.4392
pf06	0.4370	0.1803	0.2241	0.7263
rkeep	0.6868	0.1820	0.0870	0.4876
rkind	0.7244	0.2464	0.0780	0.4085
sact0	0.6556	-0.0719	0.0461	0.5628
mha01	0.5297	-0.4773	0.1268	0.4755
mhp03	-0.4810	0.5691	-0.1238	0.4294
mhd02	0.5208	-0.5949	0.1623	0.3485
mhp01	-0.4980	0.5955	-0.1225	0.3824
mhc01	0.4927	-0.5215	0.1531	0.4618
ghp01	0.6686	0.0194	-0.3621	0.4215
ghp04	-0.6833	-0.0195	0.4089	0.3656
ghp02	-0.7398	-0.0227	0.4212	0.2748
ghp05	0.6163	-0.2760	-0.1626	0.5175

The first factor is a general health factor. (To understand that claim, compare the factor loadings with the description of the variables as shown by `describe` above. Also, just as with the physician-cost data, the sense of some of the coded responses is reversed.) The second factor loads most highly on the five "mental health" items. The third factor loads most highly on "general health perception" items—those with names having the letters `ghp` in them. The other items describe "physical health".

These designations are based primarily on the wording of the questions, which is summarized in the variable labels.

```
. rotate, varimax
Factor analysis/correlation                    Number of obs    =      9,999
    Method: principal factors                  Retained factors =          3
    Rotation: orthogonal varimax (Kaiser off)  Number of params =         54
```

Factor	Variance	Difference	Proportion	Cumulative
Factor1	4.20556	0.83302	0.4358	0.4358
Factor2	3.37253	0.33756	0.3495	0.7852
Factor3	3.03497	.	0.3145	1.0997

```
    LR test: independent vs. saturated: chi2(171) = 1.0e+05 Prob>chi2 = 0.0000
Rotated factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Factor3	Uniqueness
ghp31	-0.2968	-0.1647	-0.6567	0.4535
pf01	0.5872	0.0263	0.3699	0.5177
pf02	0.7740	0.0848	0.2287	0.3415
pf03	0.7386	0.0580	0.2654	0.3807
pf04	0.7484	0.0842	0.2018	0.3921
pf05	0.7256	0.1063	0.1518	0.4392
pf06	0.5023	0.1268	0.0730	0.7263
rkeep	0.6023	0.2048	0.3282	0.4876
rkind	0.6590	0.1669	0.3597	0.4085
sact0	0.4187	0.3875	0.3342	0.5628
mha01	0.1467	0.6859	0.1803	0.4755
mhp03	-0.0613	-0.7375	-0.1514	0.4294
mhd02	0.0921	0.7893	0.1416	0.3485
mhp01	-0.0570	-0.7671	-0.1612	0.3824
mhc01	0.1102	0.7124	0.1359	0.4618
ghp01	0.2783	0.1977	0.6797	0.4215
ghp04	-0.2652	-0.1908	-0.7264	0.3656
ghp02	-0.2986	-0.2116	-0.7690	0.2748
ghp05	0.1755	0.4756	0.4748	0.5175

```
Factor rotation matrix
```

	Factor1	Factor2	Factor3
Factor1	0.6658	0.4796	0.5715
Factor2	0.5620	-0.8263	0.0387
Factor3	0.4908	0.2954	-0.8197

With rotation, the structure of the data becomes much clearer. The first rotated factor is physical health, the second is mental health, and the third is general health perception. The a priori designation of the items is confirmed.

After rotation, physical health is the first factor. `rotate` has ordered the factors by explained variance. Still, we warn that the importance of any factor must be gauged against the number of variables that purportedly measure it. Here we included nine variables that measured physical health, five that measured mental health, and five that measured general health perception. Had we started with only one mental health item, it would have had a high uniqueness, but we would not want to conclude that it was, therefore, largely noise.

◁

❑ Technical note

Some people prefer specifying the option `normalize` to apply a Kaiser normalization (Horst 1965), which places equal weight on all rows of the matrix to be rotated.

❑

▷ Example 9: Oblique oblimin rotation

The literature suggests that physical health and mental health are related. Also, general health perception may be largely a combination of the two. For these reasons, an oblique rotation of a two-factor solution is worth trying. We try the `oblique oblimin` rotation (Harman 1976).

```
. factor ghp31-ghp05, factors(2)
(obs=9,999)
```

Factor analysis/correlation	Number of obs =	9,999
Method: principal factors	Retained factors =	2
Rotation: (unrotated)	Number of params =	37

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.27086	4.90563	0.7534	0.7534
Factor2	2.36523	1.38826	0.2451	0.9985
Factor3	0.97697	1.00351	0.1012	1.0997
Factor4	-0.02654	0.00538	-0.0027	1.0970
Factor5	-0.03191	0.00378	-0.0033	1.0937
Factor6	-0.03569	0.00353	-0.0037	1.0900
Factor7	-0.03922	0.00271	-0.0041	1.0859
Factor8	-0.04193	0.00662	-0.0043	1.0815
Factor9	-0.04855	0.01015	-0.0050	1.0765
Factor10	-0.05870	0.00250	-0.0061	1.0704
Factor11	-0.06120	0.00224	-0.0063	1.0641
Factor12	-0.06344	0.00376	-0.0066	1.0575
Factor13	-0.06720	0.00345	-0.0070	1.0506
Factor14	-0.07065	0.00185	-0.0073	1.0432
Factor15	-0.07250	0.00033	-0.0075	1.0357
Factor16	-0.07283	0.00772	-0.0075	1.0282
Factor17	-0.08055	0.01190	-0.0083	1.0198
Factor18	-0.09245	0.00649	-0.0096	1.0103
Factor19	-0.09894	.	-0.0103	1.0000

LR test: independent vs. saturated: chi2(171) = 1.0e+05 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
ghp31	-0.6519	-0.0562	0.5718
pf01	0.6150	0.3226	0.5178
pf02	0.6867	0.3737	0.3888
pf03	0.6712	0.3774	0.4070
pf04	0.6540	0.3588	0.4435
pf05	0.6209	0.3258	0.5084
pf06	0.4370	0.1803	0.7765
rkeep	0.6868	0.1820	0.4952
rkind	0.7244	0.2464	0.4145
sact0	0.6556	-0.0719	0.5650
mha01	0.5297	-0.4773	0.4916
mhp03	-0.4810	0.5691	0.4448
mhd02	0.5208	-0.5949	0.3748
mhp01	-0.4980	0.5955	0.3974
mhc01	0.4927	-0.5215	0.4853
ghp01	0.6686	0.0194	0.5526
ghp04	-0.6833	-0.0195	0.5327
ghp02	-0.7398	-0.0227	0.4522
ghp05	0.6163	-0.2760	0.5439

. rotate, oblimin oblique

Factor analysis/correlation   Number of obs   =   9,999
    Method: principal factors   Retained factors =   2
    Rotation: oblique oblimin (Kaiser off)   Number of params =   37

Factor	Variance	Proportion	Rotated factors are correlated
Factor1	6.58719	0.6826	
Factor2	4.65444	0.4823	

    LR test: independent vs. saturated: chi2(171) = 1.0e+05 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
ghp31	-0.5517	-0.2051	0.5718
pf01	0.7179	-0.0747	0.5178
pf02	0.8115	-0.0968	0.3888
pf03	0.8022	-0.1068	0.4070
pf04	0.7750	-0.0951	0.4435
pf05	0.7249	-0.0756	0.5084
pf06	0.4743	-0.0044	0.7765
rkeep	0.6712	0.0939	0.4952
rkind	0.7478	0.0449	0.4145
sact0	0.4608	0.3340	0.5650
mha01	0.0652	0.6869	0.4916
mhp03	0.0401	-0.7587	0.4448
mhd02	-0.0280	0.8003	0.3748
mhp01	0.0462	-0.7918	0.3974
mhc01	0.0039	0.7160	0.4853
ghp01	0.5378	0.2484	0.5526
ghp04	-0.5494	-0.2541	0.5327
ghp02	-0.5960	-0.2736	0.4522
ghp05	0.2805	0.5213	0.5439

Factor rotation matrix

	Factor1	Factor2
Factor1	0.9277	0.6831
Factor2	0.3733	-0.7303

The first factor is defined predominantly by physical health and the second by mental health. General health perception loads on both, but more on physical health than mental health. To compare the rotated and unrotated solution, looking at both in parallel form is often useful.

. estat rotatecompare

Rotation matrix — oblique oblimin (Kaiser off)

Variable	Factor1	Factor2
Factor1	0.9277	0.6831
Factor2	0.3733	-0.7303

Factor loadings

| | Rotated | | Unrotated | |
Variable	Factor1	Factor2	Factor1	Factor2
ghp31	-0.5517	-0.2051	-0.6519	-0.0562
pf01	0.7179	-0.0747	0.6150	0.3226
pf02	0.8115	-0.0968	0.6867	0.3737
pf03	0.8022	-0.1068	0.6712	0.3774
pf04	0.7750	-0.0951	0.6540	0.3588
pf05	0.7249	-0.0756	0.6209	0.3258
pf06	0.4743	-0.0044	0.4370	0.1803
rkeep	0.6712	0.0939	0.6868	0.1820
rkind	0.7478	0.0449	0.7244	0.2464
sact0	0.4608	0.3340	0.6556	-0.0719
mha01	0.0652	0.6869	0.5297	-0.4773
mhp03	0.0401	-0.7587	-0.4810	0.5691
mhd02	-0.0280	0.8003	0.5208	-0.5949
mhp01	0.0462	-0.7918	-0.4980	0.5955
mhc01	0.0039	0.7160	0.4927	-0.5215
ghp01	0.5378	0.2484	0.6686	0.0194
ghp04	-0.5494	-0.2541	-0.6833	-0.0195
ghp02	-0.5960	-0.2736	-0.7398	-0.0227
ghp05	0.2805	0.5213	0.6163	-0.2760

Look again at the `factor` output. The variances of the first and second factor of the unrotated solution are 7.27 and 2.37, respectively. After an orthogonal rotation, the explained variance of $7.27 + 2.37$ is distributed differently over the two factors. For instance, if we typed `rotate, varimax` to obtain an orthogonal varimax rotation, we would see that the first factor has variance 5.75, and the second factor has 3.88—within rounding error $7.27 + 2.37 = 5.75 + 3.88$. The situation after an oblique rotation is different. The variances of the first and second factors are 6.59 and 4.65, which add up to more than in the orthogonal case. In the oblique case, the common factors are correlated and thus "partly explain the same variance". Therefore, the cumulative proportion of variance explained by the factors is not displayed here.

Most researchers would not be willing to accept a solution in which the common factors are highly correlated.

```
. estat common
```

Correlation matrix of the oblimin(0) rotated common factors

Factors	Factor1	Factor2
Factor1	1	
Factor2	.3611	1

The correlation of .36 seems acceptable, so we think that the oblique rotation was a success here.

◁

Factor scores

The `predict` command creates a set of new variables that are estimates of the first k common factors produced by `factor`, `factormat`, or `rotate`. Two types of scoring are available: regression or Thomson scoring and Bartlett scoring.

The number of variables may be less than the number of factors. If so, the first such factors will be used. If the number of variables is greater than the number of factors created or rotated, the unused factors will be filled with missing values.

▷ Example 10: Predicting scores

Using our automobile data, we wish to develop an index of roominess on the basis of a car's headroom, rear-seat leg room, and trunk space. We begin by extracting the factors of the three variables:

```
. use https://www.stata-press.com/data/r18/autofull
(Automobile models)

. factor headroom rear_seat trunk
(obs=74)
```

Factor analysis/correlation   Number of obs   =   74
    Method: principal factors   Retained factors =   1
    Rotation: (unrotated)   Number of params =   3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.71426	1.79327	1.1799	1.1799
Factor2	-0.07901	0.10329	-0.0544	1.1255
Factor3	-0.18231	.	-0.1255	1.0000

LR test: independent vs. saturated: chi2(3) =   82.93 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
headroom	0.7280	0.4700
rear_seat	0.7144	0.4897
trunk	0.8209	0.3261

All the factor loadings are positive, so we have indeed obtained a "roominess" factor. The `predict` command will now create the one retained factor, which we will call `f1`:

```
. predict f1
(option regression assumed; regression scoring)

Scoring coefficients (method = regression)
```

Variable	Factor1
headroom	0.28323
rear_seat	0.26820
trunk	0.45964

The table with scoring coefficients informs us that the factor is obtained as a weighted sum of standardized versions of `headroom`, `rear_seat`, and `trunk` with weights 0.28, 0.27, and 0.46.

If `factor` had retained more than one factor, typing `predict f1` would still have added only the first factor to our data. Typing `predict f1 f2`, however, would have added the first two factors to our data. `f1` is now our "roominess" index, so we might compare the roominess of domestic and foreign cars:

```
. table foreign, statistic(mean f1) statistic(sd f1)
```

	Mean	Standard deviation
Foreign		
Domestic	.2022442	.9031404
Foreign	-.4780318	.6106609
Total	4.51e-09	.8804116

We find that domestic cars are, on average, roomier than foreign cars, at least in our data.

◁

❑ Technical note

Are common factors not supposed to be normalized to have mean 0 and standard deviation 1? In our example above, the mean is 4.5×10^{-9} and the standard deviation is 0.88. Why is that?

For the mean, the deviation from zero is due to numerical roundoff, which would diminish dramatically if we had typed `predict double f1` instead. The explanation for the standard deviation of 0.88, on the other hand, is not numerical roundoff. At a theoretical level, the factor is supposed to have standard deviation 1, but the estimation method almost never yields that result unless an exact solution to the factor model is found. This happens for the same reason that, when you regress y on x, you do not get the same equation as if you regress x on y, unless x and y are perfectly collinear.

By the way, if you had two factors, you would expect the correlation between the two factors to be zero because that is how they are theoretically defined. The matrix algebra, however, does not usually work out that way. It is somewhat analogous to the fact that if you regress y on x and the regression assumption that the errors are uncorrelated with the dependent variable is satisfied, then it automatically cannot be satisfied if you regress x on y.

The covariance matrix of the estimated factors is

$$E(\widehat{\mathbf{f}}\widehat{\mathbf{f}}') = \mathbf{I} - (\mathbf{I} + \mathbf{\Gamma})^{-1}$$

where

$$\mathbf{\Gamma} = \mathbf{\Lambda}'\mathbf{\Psi}^{-1}\mathbf{\Lambda}$$

The columns of Λ are orthogonal to each other, but the inclusion of Ψ in the middle of the equation destroys that relationship unless all the elements of Ψ are equal.

❑

▷ Example 11: Rescaling the scores

Let's pretend that we work for the K. E. Watt Company, a fictional industry group that generates statistics on automobiles. Our "roominess" index has mean 0 and standard deviation 0.88, but indexes we present to the public generally have mean 100 and standard deviation 10. First, we wish to rescale our index:

```
. generate roomidx = (f1/.88041161)*10 + 100
. table foreign, statistic(mean roomidx) statistic(sd roomidx) statistic(freq)
> nformat(%9.2f)
```

	Mean	Standard deviation	Frequency
Foreign			
Domestic	102.30	10.26	52.00
Foreign	94.57	6.94	22.00
Total	100.00	10.00	74.00

Now when we release our results, we can write, "The K. E. Watt index of roominess shows that domestic cars are, on average, roomier, with an index of 102 versus only 95 for foreign cars."

Now let's find the "roomiest" car in our data:

```
. sort roomidx
. list fullname roomidx in l
```

	fullname	roomidx
74.	Merc. Marquis	116.7469

We can also write, "K. E. Watt finds that the Mercury Marquis is the roomiest automobile among those surveyed, with a roominess index of 117 versus an average of 100."

◁

❑ Technical note

`predict` provides two methods of scoring: the default regression scoring, which we have used above, and the optional Bartlett method. An artificial example will best illustrate the use and meaning of the methods. We begin by creating a known-to-be-correct factor model in which the true loadings are 0.4, 0.6, and 0.8. The variances of the unique factors are $1 - 0.4^2 = 0.84$, $1 - 0.6^2 = 0.64$, and $1 - 0.8^2 = 0.36$, respectively. We make the sample size large enough so that random fluctuations are not important.

```
. drop _all
. set seed 12345
. set obs 10000
Number of observations (_N) was 0, now 10,000.
. generate ftrue = rnormal()
. generate x1 = .4*ftrue + sqrt(.84)*rnormal()
```

```
. generate x2 = .6*ftrue + sqrt(.64)*rnormal()
. generate x3 = .8*ftrue + sqrt(.36)*rnormal()
. summarize x1 x2 x3
```

Variable	Obs	Mean	Std. dev.	Min	Max
x1	10,000	.0195519	1.011165	-3.778123	4.267452
x2	10,000	.0127835	1.001259	-3.828994	4.102375
x3	10,000	.0058335	1.002475	-3.595906	3.89754

Because we concocted our data, the iterated principal-factor method reproduces the true loadings most faithfully:

```
. factor x1 x2 x3, ipf factors(1)
(obs=10,000)
```

Factor analysis/correlation			Number of obs =	10,000
Method: iterated principal factors			Retained factors =	1
Rotation: (unrotated)			Number of params =	3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.16678	1.16662	1.0000	1.0000
Factor2	0.00016	0.00036	0.0001	1.0002
Factor3	-0.00020	.	-0.0002	1.0000

LR test: independent vs. saturated: chi2(3) = 3887.29 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
x1	0.4156	0.8273
x2	0.6046	0.6345
x3	0.7928	0.3715

Let us now compare regression and Bartlett scoring:

```
. predict freg
(option regression assumed; regression scoring)
Scoring coefficients (method = regression)
```

Variable	Factor1
x1	0.14449
x2	0.27410
x3	0.61377

```
. predict fbar, bartlett
Scoring coefficients (method = Bartlett)
```

Variable	Factor1
x1	0.20285
x2	0.38475
x3	0.86162

Comparing the two scoring vectors, we see that Bartlett scoring yields larger coefficients. The regression scoring method is biased insofar as $E(\text{freg}|\text{ftrue})$ is not ftrue, something we can reveal by regressing freg on ftrue:

```
. regress freg ftrue
```

Source	SS	df	MS		Number of obs	=	10,000
					F(1, 9998)	=	25339.34
Model	5107.57467	1	5107.57467		Prob > F	=	0.0000
Residual	2015.26671	9,998	.201566984		R-squared	=	0.7171
					Adj R-squared	=	0.7170
Total	7122.84138	9,999	.712355374		Root MSE	=	.44896

freg	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
ftrue	.7169557	.004504	159.18	0.000	.708127	.7257843
_cons	-.0088417	.00449	-1.97	0.049	-.0176429	-.0000404

Note the coefficient on `ftrue` of $0.717 < 1$. The Bartlett scoring method, on the other hand, is unbiased:

```
. regress fbar ftrue
```

Source	SS	df	MS		Number of obs	=	10,000
					F(1, 9998)	=	25339.33
Model	10065.1734	1	10065.1734		Prob > F	=	0.0000
Residual	3971.35998	9,998	.397215441		R-squared	=	0.7171
					Adj R-squared	=	0.7170
Total	14036.5334	9,999	1.40379372		Root MSE	=	.63025

fbar	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
ftrue	1.006458	.0063226	159.18	0.000	.9940642	1.018851
_cons	-.0124119	.006303	-1.97	0.049	-.024767	-.0000568

The zero bias of the Bartlett method comes at the costs of less accuracy, for example, in terms of the mean squared error.

```
. generate dbar = (fbar - ftrue)^2
. generate dreg = (freg - ftrue)^2
. summarize ftrue fbar freg dbar dreg
```

Variable	Obs	Mean	Std. dev.	Min	Max
ftrue	10,000	.0123322	.996866	-4.196032	3.815439
fbar	10,000	2.08e-10	1.184818	-3.78561	4.550449
freg	10,000	-6.44e-10	.8440115	-2.696714	3.241498
dbar	10,000	.3973295	.5654751	1.31e-09	7.656609
dreg	10,000	.2812835	.4053233	9.68e-10	4.814044

Neither estimator follows the assumption that the scaled factor has unit variance. The regression estimator has a variance less than 1, and the Bartlett estimator has a variance greater than 1.

The difference between the two scoring methods is not as important as it might seem because the bias in the regression method is only a matter of scaling and shifting.

```
. correlate freg fbar ftrue
(obs=10,000)
```

	freg	fbar	ftrue
freg	1.0000		
fbar	1.0000	1.0000	
ftrue	0.8468	0.8468	1.0000

Therefore, the choice of which scoring method we apply is largely immaterial.

❑

Stored results

Let p be the number of variables and f, the number of factors.

`predict`, in addition to generating variables, also stores the following in `r()`:

Macros
    `r(method)`   `regression` or `Bartlett`

Matrices
    `r(scoef)` $p \times f$ matrix of scoring coefficients

`estat anti` stores the following in `r()`:

Matrices
    `r(acov)` $p \times p$ anti-image covariance matrix
    `r(acorr)` $p \times p$ anti-image correlation matrix

`estat common` stores the following in `r()`:

Matrices
    `r(Phi)` $f \times f$ correlation matrix of common factors

`estat factors` stores the following in `r()`:

Matrices
    `r(stats)` $k \times 5$ matrix with log likelihood, degrees of freedom, AIC, and BIC
                                      for models with 1 to k factors estimated via maximum likelihood

`estat kmo` stores the following in `r()`:

Scalars
    `r(kmo)`   the Kaiser–Meyer–Olkin measure of sampling adequacy

Matrices
    `r(kmow)`   column vector of KMO measures for each variable

`estat residuals` stores the following in `r()`:

Matrices
    `r(fit)`   fitted matrix for the correlations, $\widehat{\mathbf{C}} = \widehat{\boldsymbol{\Lambda}}\widehat{\boldsymbol{\Phi}}\widehat{\boldsymbol{\Lambda}}' + \widehat{\boldsymbol{\Psi}}$
    `r(res)`   raw residual matrix $\mathbf{C} - \widehat{\mathbf{C}}$
    `r(SR)`   standardized residuals (`sresiduals` option only)

`estat smc` stores the following in `r()`:

Matrices
    `r(smc)`   vector of squared multiple correlations of variables with all other variables

`estat structure` stores the following in `r()`:

Matrices
    `r(st)` $p \times f$ matrix of correlations between variables and common factors

See [R] **estat summarize** for the stored results of `estat summarize`.

`rotate` after `factor` and `factormat` add to the existing `e()`:

Scalars
    `e(r_f)`   number of factors in rotated solution
    `e(r_fmin)`   rotation criterion value

Macros
    `e(r_class)`   orthogonal or oblique
    `e(r_criterion)`   rotation criterion
    `e(r_ctitle)`   title for rotation
    `e(r_normalization)` kaiser or none

Matrices
    `e(r_L)`   rotated loadings
    `e(r_T)`   rotation
    `e(r_Phi)`   correlations between common factors
    `e(r_Ev)`   explained variance by common factors

The factors in the rotated solution are in decreasing order of `e(r_Ev)`.

Methods and formulas

Methods and formulas are presented under the following headings:

> *estat*
> *rotate*
> *predict*

estat

See *Methods and formulas* of [MV] **pca postestimation** for the formulas for `estat anti`, `estat kmo`, and `estat smc`.

`estat residuals` computes the standardized residuals $\widetilde{r}_{ij}$ as

$$\widetilde{r}_{ij} = \frac{\sqrt{N}(r_{ij} - f_{ij})}{\sqrt{f_{ij}^2 + f_{ii}f_{jj}}}$$

suggested by Jöreskog and Sörbom (1986), where N is the number of observations, r_{ij} is the observed correlation of variables i and j, and f_{ij} is the fitted correlation of variables i and j. Also see Bollen (1989). Caution is warranted in interpretation of these residuals; see Jöreskog and Sörbom (1988).

`estat structure` computes the correlations of the variables and the common factors as $\boldsymbol{\Lambda\Phi}$.

rotate

See *Methods and formulas* of [MV] **rotatemat** for the details of rotation.

The correlation of common factors after rotation is $\mathbf{T}'\mathbf{T}$, where $\mathbf{T}$ is the factor rotation matrix, satisfying $\mathbf{L}_{\text{rotated}} = \mathbf{L}_{\text{unrotated}}(\mathbf{T}')^{-1}$

predict

The formula for regression scoring (Thomson 1951) in the orthogonal case is

$$\widehat{\mathbf{f}} = \mathbf{\Lambda}'\mathbf{\Sigma}^{-1}\mathbf{x}$$

where $\mathbf{\Lambda}$ is the unrotated or orthogonally rotated loading matrix. For oblique rotation, the regression scoring is defined as

$$\widehat{\mathbf{f}} = \mathbf{\Phi}\mathbf{\Lambda}'\mathbf{\Sigma}^{-1}\mathbf{x}$$

where $\mathbf{\Phi}$ is the correlation matrix of the common factors.

The formula for Bartlett scoring (Bartlett 1937, 1938) is

$$\mathbf{\Gamma}^{-1}\mathbf{\Lambda}'\mathbf{\Psi}^{-1}\mathbf{x}$$

where

$$\mathbf{\Gamma} = \mathbf{\Lambda}'\mathbf{\Psi}^{-1}\mathbf{\Lambda}$$

See Harman (1976) and Lawley and Maxwell (1971).

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Also see *References* in [MV] **factor**.

Also see

[MV] **factor** — Factor analysis

[MV] **rotate** — Orthogonal and oblique rotations after factor and pca

[MV] **scoreplot** — Score and loading plots

[MV] **screeplot** — Scree plot of eigenvalues

[U] **20 Estimation and postestimation commands**

Title

hotelling — Hotelling's T^2 generalized means test

Description

hotelling performs Hotelling's T^2 test of whether a set of means is zero or, alternatively, equal between two groups.

See [MV] **mvtest means** for generalizations of Hotelling's one-sample test with more general hypotheses, two-sample tests that do not assume that the covariance matrices are the same in the two groups, and tests with more than two groups.

Quick start

Hotelling's T^2 test that the means of v1, v2, and v3 are jointly zero
        hotelling v1 v2 v3

Same as above, but suppress the table of means
        hotelling v1 v2 v3, notable

Hotelling's T^2 test that the means of v1, v2, and v3 are the same in the two groups defined by catvar
        hotelling v1 v2 v3, by(catvar)

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Hotelling's generalized means test

Syntax

> hotelling *varlist* $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$ *weight* $\big]$ $\big[$, by(*varname*) <u>not</u>able $\big]$

collect is allowed; see [U] **11.1.10 Prefix commands**.

aweights and fweights are allowed; see [U] **11.1.6 weight**.

Note: hotel is a synonym for hotelling.

Options

>   Main

by(*varname*) specifies a variable identifying two groups; the test of equality of means between groups
     is performed. If by() is not specified, a test of means being jointly zero is performed.

notable suppresses printing a table of the means being compared.

Remarks and examples

hotelling performs Hotelling's T^2 test of whether a set of means is zero or two sets of means
are equal. It is a multivariate test that reduces to a standard t test if only one variable is specified.

▷ Example 1

You wish to test whether a new fuel additive improves gas mileage in both stop-and-go and
highway situations. Taking 12 cars, you fill them with gas and run them on a highway-style track,
recording their gas mileage. You then refill them and run them on a stop-and-go style track. Finally,
you repeat the two runs, but this time you use fuel with the additive. Your dataset is

```
. use https://www.stata-press.com/data/r18/gasexp

. describe

Contains data from https://www.stata-press.com/data/r18/gasexp.dta
 Observations:          12
    Variables:           5                          21 Nov 2022 12:56
───────────────────────────────────────────────────────────────────────
Variable      Storage   Display    Value
    name         type    format    label      Variable label
───────────────────────────────────────────────────────────────────────
id            byte      %9.0g                 Car ID
bmpg1         byte      %9.0g                 Track 1 before additive
ampg1         byte      %9.0g                 Track 1 after additive
bmpg2         byte      %9.0g                 Track 2 before additive
ampg2         float     %9.0g                 Track 2 after additive
───────────────────────────────────────────────────────────────────────

Sorted by:
```

To perform the statistical test, you jointly test whether the differences in before-and-after results are zero:

```
. generate diff1 = ampg1 - bmpg1
. generate diff2 = ampg2 - bmpg2
. hotelling diff1 diff2
     Variable │        Obs        Mean    Std. dev.        Min           Max
    ──────────┼───────────────────────────────────────────────────────────
        diff1 │         12        1.75     2.70101         -3             5
        diff2 │         12    2.083333    2.906367       -3.5           5.5

1-group Hotelling's T-squared = 9.6980676
F test statistic: ((12-2)/(12-1)(2)) x 9.6980676 = 4.4082126

H0: Vector of means is equal to a vector of zeros
            F(2,10) =    4.4082
     Prob > F(2,10) =    0.0424
```

The means are different at the 4.24% significance level.

◁

□ Technical note

We used Hotelling's T^2 test because we were testing two differences jointly. Had there been only one difference, we could have used a standard t test, which would have yielded the same results as Hotelling's test:

```
. ttest ampg1 = bmpg1
Paired t test
─────────────────────────────────────────────────────────────────────────────
Variable │     Obs        Mean    Std. err.    Std. dev.   [95% conf. interval]
─────────┼───────────────────────────────────────────────────────────────────
   ampg1 │      12       22.75    .9384465     3.250874    20.68449     24.81551
   bmpg1 │      12          21    .7881701     2.730301    19.26525     22.73475
─────────┼───────────────────────────────────────────────────────────────────
    diff │      12        1.75    .7797144      2.70101    .0338602      3.46614
─────────────────────────────────────────────────────────────────────────────
     mean(diff) = mean(ampg1 - bmpg1)                          t =    2.2444
 H0: mean(diff) = 0                               Degrees of freedom =        11

 Ha: mean(diff) < 0            Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.9768        Pr(|T| > |t|) = 0.0463        Pr(T > t) = 0.0232
. ttest diff1 = 0
One-sample t test
─────────────────────────────────────────────────────────────────────────────
Variable │     Obs        Mean    Std. err.    Std. dev.   [95% conf. interval]
─────────┼───────────────────────────────────────────────────────────────────
   diff1 │      12        1.75    .7797144      2.70101    .0338602      3.46614
─────────────────────────────────────────────────────────────────────────────
     mean = mean(diff1)                                        t =    2.2444
 H0: mean = 0                                     Degrees of freedom =        11

    Ha: mean < 0                 Ha: mean != 0                 Ha: mean > 0
 Pr(T < t) = 0.9768        Pr(|T| > |t|) = 0.0463        Pr(T > t) = 0.0232
```

```
. hotelling diff1
```

Variable	Obs	Mean	Std. dev.	Min	Max
diff1	12	1.75	2.70101	-3	5

```
1-group Hotelling's T-squared = 5.0373832
F test statistic: ((12-1)/(12-1)(1)) x 5.0373832 = 5.0373832

H0: Vector of means is equal to a vector of zeros
            F(1,11) =    5.0374
        Prob > F(1,11) =   0.0463
```

❑

▷ Example 2

Now consider a variation on the experiment: rather than using 12 cars and running each car with and without the fuel additive, you run 24 cars, 12 with the additive and 12 without. You have the following dataset:

```
. use https://www.stata-press.com/data/r18/gasexp2, clear
. describe
Contains data from https://www.stata-press.com/data/r18/gasexp2.dta
 Observations:            24
    Variables:             4                      21 Nov 2022 13:01
```

Variable name	Storage type	Display format	Value label	Variable label
id	byte	%9.0g		Car ID
mpg1	byte	%9.0g		Track 1
mpg2	float	%9.0g		Track 2
additive	byte	%9.0g	yesno	Additive?

```
Sorted by:
. tabulate additive
```

Additive?	Freq.	Percent	Cum.
No	12	50.00	50.00
Yes	12	50.00	100.00
Total	24	100.00	

This is an unpaired experiment because there is no natural pairing of the cars; you want to test that the means of mpg1 are equal for the two groups specified by additive, as are the means of mpg2:

```
. hotelling mpg1 mpg2, by(additive)
```

```
-> additive = No
```

Variable	Obs	Mean	Std. dev.	Min	Max
mpg1	12	21	2.730301	17	25
mpg2	12	19.91667	2.644319	16	24

```
-> additive = Yes
```

Variable	Obs	Mean	Std. dev.	Min	Max
mpg1	12	22.75	3.250874	17	28
mpg2	12	22	3.316625	16.5	27.5

```
2-group Hotelling's T-squared = 7.1347584
F test statistic: ((24-2-1)/(24-2)(2)) x 7.1347584 = 3.4052256

H0: Vectors of means are equal for the two groups
           F(2,21) =    3.4052
      Prob > F(2,21) =    0.0524
```

◁

❑ Technical note

As in the paired experiment, had there been only one test track, the t test would have yielded the same results as Hotelling's test:

```
. hotelling mpg1, by(additive)
```

```
-> additive = No
```

Variable	Obs	Mean	Std. dev.	Min	Max
mpg1	12	21	2.730301	17	25

```
-> additive = Yes
```

Variable	Obs	Mean	Std. dev.	Min	Max
mpg1	12	22.75	3.250874	17	28

```
2-group Hotelling's T-squared = 2.0390921
F test statistic: ((24-1-1)/(24-2)(1)) x 2.0390921 = 2.0390921

H0: Vectors of means are equal for the two groups
           F(1,22) =    2.0391
      Prob > F(1,22) =    0.1673
. ttest mpg1, by(additive)
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
No	12	21	.7881701	2.730301	19.26525	22.73475
Yes	12	22.75	.9384465	3.250874	20.68449	24.81551
Combined	24	21.875	.6264476	3.068954	20.57909	23.17091
diff		-1.75	1.225518		-4.291568	.7915684

```
    diff = mean(No) - mean(Yes)                              t =  -1.4280
H0: diff = 0                                Degrees of freedom =       22

   Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0837        Pr(|T| > |t|) = 0.1673          Pr(T > t) = 0.9163
```

With more than one pair of means, however, there is no t test equivalent to Hotelling's test, although there are other logically (but not practically) equivalent solutions. One is the discriminant function: if the means of mpg1 and mpg2 are different, the discriminant function should separate the groups along that dimension.

```
. regress additive mpg1 mpg2
```

Source	SS	df	MS		Number of obs	=	24
					F(2, 21)	=	3.41
Model	1.46932917	2	.734664585		Prob > F	=	0.0524
Residual	4.53067083	21	.21574623		R-squared	=	0.2449
					Adj R-squared	=	0.1730
Total	6	23	.260869565		Root MSE	=	.46448

additive	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
mpg1	-.4570407	.2416657	-1.89	0.072	-.959612	.0455306
mpg2	.5014605	.2376762	2.11	0.047	.0071859	.9957352
_cons	-.0120115	.7437049	-0.02	0.987	-1.55863	1.534607

This test would declare the means different at the 5.24% level. You could also have fit this model by using logistic regression:

```
. logit additive mpg1 mpg2
```

```
Iteration 0:   Log likelihood = -16.635532
Iteration 1:   Log likelihood = -13.395178
Iteration 2:   Log likelihood = -13.371201
Iteration 3:   Log likelihood = -13.371143
Iteration 4:   Log likelihood = -13.371143
```

Logistic regression					Number of obs =	24
					LR chi2(2) =	6.53
					Prob > chi2 =	0.0382
Log likelihood = -13.371143					Pseudo R2 =	0.1962

additive	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
mpg1	-2.306844	1.36139	-1.69	0.090	-4.975119	.3614307
mpg2	2.524477	1.367373	1.85	0.065	-.1555257	5.20448
_cons	-2.446527	3.689821	-0.66	0.507	-9.678443	4.78539

This test would have declared the means different at the 3.82% level.

Are the means different? Hotelling's T^2 and the discriminant function reject equality at the 5.24% level. The logistic regression rejects equality at the 3.82% level.

◻

Stored results

hotelling stores the following in r():

Scalars
r(N)	number of observations	r(T2)	Hotelling's T^2
r(k)	number of variables	r(df)	degrees of freedom

Methods and formulas

See Wilks (1962, 556–561) for a general discussion. The original formulation was by Hotelling (1931) and Mahalanobis (1930, 1936).

For the test that the means of k variables are 0, let $\overline{\mathbf{x}}$ be a $1 \times k$ matrix of the means and $\mathbf{S}$ be the estimated covariance matrix. Then $T^2 = \overline{\mathbf{x}}\mathbf{S}^{-1}\overline{\mathbf{x}}'$.

For two groups, the test of equality is $T^2 = (\overline{\mathbf{x}}_1 - \overline{\mathbf{x}}_2)\mathbf{S}^{-1}(\overline{\mathbf{x}}_1 - \overline{\mathbf{x}}_2)'$.

Harold Hotelling (1895–1973) was an American economist and statistician who made many important contributions to mathematical economics, multivariate analysis, and statistical inference. After obtaining degrees in journalism and mathematics, he taught and researched at Stanford, Columbia, and the University of North Carolina. His work generalizing Student's t ratio and on principal components, canonical correlation, multivariate analysis of variance, and correlation continues to be widely used.

Prasanta Chandra Mahalanobis (1893–1972) studied physics and mathematics at Calcutta and Cambridge. He became interested in statistics and on his return to India worked on applications in anthropology, meteorology, hydrology, and agriculture. Mahalanobis became the leader in Indian statistics, specializing in multivariate problems (including what is now called the Mahalanobis distance), the design of large-scale sample surveys, and the contribution of statistics to national planning.

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Also see

[MV] **manova** — Multivariate analysis of variance and covariance

[MV] **mvtest means** — Multivariate tests of means

[R] **regress** — Linear regression

[R] **ttest** — t tests (mean-comparison tests)

Title

> **manova —** Multivariate analysis of variance and covariance

Description

The `manova` command fits multivariate analysis-of-variance (MANOVA) and multivariate analysis-of-covariance (MANCOVA) models for balanced and unbalanced designs, including designs with missing cells, and for factorial, nested, or mixed designs, or designs involving repeated measures.

The `mvreg` command (see [MV] **mvreg**) will display the coefficients, standard errors, etc., of the multivariate regression model underlying the last run of `manova`.

See [R] **anova** for univariate ANOVA and ANCOVA models. See [MV] **mvtest covariances** for Box's test of MANOVA's assumption that the covariance matrices of the groups are the same, and see [MV] **mvtest means** for multivariate tests of means that do not make this assumption.

Quick start

One-way MANOVA model of y1 and y2 for factor a

    manova y1 y2 = a

Two-way full-factorial MANOVA model for factors a and b

    manova y1 y2 = a##b

Add continuous covariate x1 for a MANCOVA model

    manova y1 y2 = a##b c.x1

MANOVA model with factor b nested within a

    manova y1 y2 = a / b|a /

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > MANOVA

Syntax

> manova *depvarlist* = *termlist* [*if*] [*in*] [*weight*] [, *options*]

where *termlist* is a factor-variable list (see [U] **11.4.3 Factor variables**) with the following additional features:

- Variables are assumed to be categorical; use the c. factor-variable operator to override this.

- The | symbol (indicating nesting) may be used in place of the # symbol (indicating interaction).

- The / symbol is allowed after a *term* and indicates that the following *term* is the error term for the preceding *term*s.

options	Description
Model	
<u>noconstant</u>	suppress constant term
<u>dropemptycells</u>	drop empty cells from the design matrix

bootstrap, by, collect, jackknife, and statsby are allowed; see [U] **11.1.10 Prefix commands**.

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

aweights are not allowed with the jackknife prefix; see [R] **jackknife**.

aweights and fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> ⌐ Model ⌐

noconstant suppresses the constant term (intercept) from the model.

dropemptycells drops empty cells from the design matrix. If c(emptycells) is set to keep (see [R] **set emptycells**), this option temporarily resets it to drop before running the MANOVA model. If c(emptycells) is already set to drop, this option does nothing.

Remarks and examples

Remarks are presented under the following headings:

> *Introduction*
> *One-way MANOVA*
> *Reporting coefficients*
> *Two-way MANOVA*
> *N-way MANOVA*
> *MANCOVA*
> *MANOVA for Latin-square designs*
> *MANOVA for nested designs*
> *MANOVA for mixed designs*
> *MANOVA with repeated measures*

Introduction

MANOVA is a generalization of ANOVA allowing multiple dependent variables. Several books discuss MANOVA, including Anderson (2003); Mardia, Kent, and Bibby (1979); Morrison (2005); Rencher (1998); Rencher and Christensen (2012); Seber (1984); and Timm (1975). Introductory articles are provided by Pillai (1985) and Morrison (1998). Pioneering work is found in Wilks (1932), Pillai (1955), Lawley (1938), Hotelling (1951), and Roy (1939).

Four multivariate statistics are commonly computed in MANOVA: Wilks's lambda, Pillai's trace, Lawley–Hotelling trace, and Roy's largest root. See *Methods and formulas* for details.

Why four statistics? Arnold (1981), Rencher (1998), Rencher and Christensen (2012), Morrison (1998), Pillai (1985), and Seber (1984) provide guidance. All four tests are admissible, unbiased, and invariant. Asymptotically, Wilks's lambda, Pillai's trace, and the Lawley–Hotelling trace are the same, but their behavior under various violations of the null hypothesis and with small samples is different. Roy's largest root is different from the other three, even asymptotically.

None of the four multivariate criteria appears to be most powerful against all alternative hypotheses. For instance, Roy's largest root is most powerful when the null hypothesis of equal mean vectors is violated in such a way that the mean vectors tend to lie in one line within p-dimensional space. For most other situations, Roy's largest root performs worse than the other three statistics. Pillai's trace tends to be more robust to nonnormality and heteroskedasticity than the other three statistics.

The # symbol indicates interaction. The | symbol indicates nesting (a|b is read "a is nested within b"). A / between *term*s indicates that the *term* to the right of the slash is the error term for the *term*s to the left of the slash.

One-way MANOVA

A one-way MANOVA is obtained by specifying the dependent variables followed by an equal sign, followed by the categorical variable defining the groups.

▷ Example 1: One-way MANOVA with balanced data

Rencher and Christensen (2012, 183–186) presents an example of a balanced one-way MANOVA by using data from Andrews and Herzberg (1985, 357–360). The data from eight trees from each of six apple tree rootstocks are from table 6.2 of Rencher and Christensen (2012). Four dependent variables are recorded for each tree: trunk girth at 4 years (mm × 100), extension growth at 4 years (m), trunk girth at 15 years (mm × 100), and weight of tree above ground at 15 years (lb × 1000). The grouping variable is rootstock, and the four dependent variables are y1, y2, y3, and y4.

```
. use https://www.stata-press.com/data/r18/rootstock
(Table 6.2. Rootstock data, Rencher and Christensen (2012))

. describe

Contains data from https://www.stata-press.com/data/r18/rootstock.dta
 Observations:             48                  Table 6.2 Rootstock data,
                                                 Rencher and Christensen (2012)
    Variables:              5                  30 Aug 2022 14:00
                                               (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
rootstock	byte	%9.0g		
y1	float	%4.2f		Trunk girth at 4 years (mm x 100)
y2	float	%5.3f		Extension growth at 4 years (m)
y3	float	%4.2f		Trunk girth at 15 years (mm x 100)
y4	float	%5.3f		Weight of tree above ground at 15 years (lb x 1000)

```
Sorted by:

. list in 7/10
```

	rootst~k	y1	y2	y3	y4
7.	1	1.11	3.211	3.98	1.209
8.	1	1.16	3.037	3.62	0.750
9.	2	1.05	2.074	4.09	1.036
10.	2	1.17	2.885	4.06	1.094

There are six rootstocks and four dependent variables. We test to see if the four-dimensional mean vectors of the six rootstocks are different. The null hypothesis is that the mean vectors are the same for the six rootstocks. To obtain one-way MANOVA results, we type

```
. manova y1 y2 y3 y4 = rootstock
                       Number of obs =          48

                       W = Wilks' lambda     L = Lawley-Hotelling trace
                       P = Pillai's trace    R = Roy's largest root
```

Source		Statistic	df	F(df1,	df2) =	F	Prob>F	
rootstock	W	0.1540	5	20.0	130.3	4.94	0.0000	a
	P	1.3055		20.0	168.0	4.07	0.0000	a
	L	2.9214		20.0	150.0	5.48	0.0000	a
	R	1.8757		5.0	42.0	15.76	0.0000	u
Residual			42					
Total			47					

```
              e = exact, a = approximate, u = upper bound on F
```

All four multivariate tests reject the null hypothesis, indicating some kind of difference between the four-dimensional mean vectors of the six rootstocks.

Let's examine the output of `manova`. Above the table, it lists the number of observations used in the estimation. It also gives a key indicating that `W` stands for Wilks's lambda, `P` stands for Pillai's trace, `L` stands for Lawley–Hotelling trace, and `R` indicates Roy's largest root.

The first column of the table gives the source. Here we are testing the `rootstock` term (the only term in the model), and we are using residual error for the denominator of the test. Four lines of

output are presented for rootstock, one line for each of the four multivariate tests, as indicated by the W, P, L, and R in the second column of the table.

The next column gives the multivariate statistics. Here Wilks's lambda is 0.1540, Pillai's trace is 1.3055, the Lawley–Hotelling trace is 2.9214, and Roy's largest root is 1.8757. Some authors report λ_1 and others (including Rencher and Christensen) report $\theta = \lambda_1/(1 + \lambda_1)$ for Roy's largest root. Stata reports λ_1.

The column labeled "df" gives the hypothesis degrees of freedom, the residual degrees of freedom, and the total degrees of freedom. These are just as they would be for an ANOVA. Because there are six rootstocks, we have 5 degrees of freedom for the hypothesis. There are 42 residual degrees of freedom and 47 total degrees of freedom.

The next three columns are labeled "F(df1, df2) = F", and for each of the four multivariate tests, the degrees of freedom and F statistic are listed. The following column gives the associated p-values for the F statistics. Wilks's lambda has an F statistic of 4.94 with 20 and 130.3 degrees of freedom, which produces a p-value small enough that 0.0000 is reported. The F statistics and p-values for the other three multivariate tests follow on the three lines after Wilks's lambda.

The final column indicates whether the F statistic is exactly F distributed, is approximately F distributed, or is an upper bound. The letters e, a, and u indicate these three possibilities, as described in the footer at the bottom of the table. For this example, the F statistics (and corresponding p-values) for Wilks's lambda, Pillai's trace, and the Lawley–Hotelling trace are approximate. The F statistic for Roy's largest root is an upper bound, which means that the p-value is a lower bound.

Examining some of the underlying matrices and values used in the calculation of the four multivariate statistics is easy. For example, you can list the sum of squares and cross products (SSCP) matrices for error and the hypothesis that are found in the e(E) and e(H_m) returned matrices, the eigenvalues of $\mathbf{E}^{-1}\mathbf{H}$ obtained from the e(eigvals_m) returned matrix, and the three auxiliary values (s, m, and n) that are returned in the e(aux_m) matrix.

```
. mat list e(E)

symmetric e(E)[4,4]
            y1          y2          y3          y4
y1   .31998754
y2   1.6965639    12.14279
y3   .55408744   4.3636123   4.2908128
y4   .21713994   2.1102135   2.4816563   1.7225248

. mat list e(H_m)

symmetric e(H_m)[4,4]
            y1          y2          y3          y4
y1   .07356042
y2   .53738525   4.1996621
y3   .33226448   2.3553887   6.1139358
y4   .20846994   1.6371084   3.7810439   2.4930912

. mat list e(eigvals_m)

e(eigvals_m)[1,4]
            c1          c2          c3          c4
r1   1.8756709   .79069412   .22904906   .02595358

. mat list e(aux_m)

e(aux_m)[3,1]
       value
s          4
m          0
n       18.5
```

The values s, m, and n are helpful when you do not want to rely on the approximate F tests but instead want to look up critical values for the multivariate tests. Tables of critical values can be found in many multivariate texts, including Rencher (1998) and Rencher and Christensen (2012).

See example 1 in [MV] **manova postestimation** for an illustration of using test for Wald tests on expressions involving the underlying coefficients of the model and lincom for displaying linear combinations along with standard errors and confidence intervals from this MANOVA example.

See examples 1–5 in [MV] **discrim lda postestimation** for a descriptive linear discriminant analysis of the rootstock data. Many researchers use linear discriminant analysis as a method of exploring the differences between groups after a MANOVA model.

◁

▷ Example 2: One-way MANOVA with unbalanced data

Table 4.5 of Rencher (1998) presents data reported by Allison, Zappasodi, and Lurie (1962). The dependent variables y1, recording the number of bacilli inhaled per tubercle formed, and y2, recording tubercle size (in millimeters), were measured for four groups of rabbits. Group one (unvaccinated control) and group two (infected during metabolic depression) have seven observations each, whereas group three (infected during heightened metabolic activity) has 5 observations, and group four (infected during normal activity) has only 2 observations.

```
. use https://www.stata-press.com/data/r18/metabolic
(Table 4.5. Metabolic comparisons of rabbits, Rencher (1998))

. list
```

	group	y1	y2
1.	1	24	3.5
2.	1	13.3	3.5
3.	1	12.2	4
4.	1	14	4
5.	1	22.2	3.6
6.	1	16.1	4.3
7.	1	27.9	5.2
8.	2	7.4	3.5
9.	2	13.2	3
10.	2	8.5	3
11.	2	10.1	3
12.	2	9.3	2
13.	2	8.5	2.5
14.	2	4.3	1.5
15.	3	16.4	3.2
16.	3	24	2.5
17.	3	53	1.5
18.	3	32.7	2.6
19.	3	42.8	2
20.	4	25.1	2.7
21.	4	5.9	2.3

The one-way MANOVA for testing the null hypothesis that the two-dimensional mean vectors for the four groups of rabbits are equal is

```
. manova y1 y2 = group

                     Number of obs =          21
                     W = Wilks' lambda     L = Lawley-Hotelling trace
                     P = Pillai's trace    R = Roy's largest root
           Source │ Statistic        df    F(df1,    df2) =   F    Prob>F
          ─────────┼───────────────────────────────────────────────────────
            group │ W   0.1596        3     6.0      32.0     8.02 0.0000 e
                  │ P   1.2004              6.0      34.0     8.51 0.0000 a
                  │ L   3.0096              6.0      30.0     7.52 0.0001 a
                  │ R   1.5986              3.0      17.0     9.06 0.0008 u
          ─────────┼───────────────────────────────────────────────────────
         Residual │                  17
          ─────────┼───────────────────────────────────────────────────────
            Total │                  20
          ─────────┴───────────────────────────────────────────────────────
                     e = exact, a = approximate, u = upper bound on F
```

All four multivariate tests indicate rejection of the null hypothesis. This indicates that there are one or more differences among the two-dimensional mean vectors for the four groups. For this example, the F test for Wilks's lambda is exact because there are only two dependent variables in the model.

manovatest tests terms or linear combinations of the model's underlying design matrix. Example 2 of [MV] **manova postestimation** continues this example and illustrates manovatest.

◁

Reporting coefficients

The mvreg command (see [MV] **mvreg**) is used as a coefficient displayer after manova. Simply type mvreg to view the coefficients, standard errors, t statistics, p-values, and confidence intervals of the multivariate regression model underlying the previous manova.

▷ Example 3: Reporting coefficients by using mvreg

Continuing with example 2, we now use `mvreg` to display the coefficients underlying our MANOVA.

```
. mvreg
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P>F
y1	21	4	8.753754	0.5867	8.045716	0.0015
y2	21	4	.6314183	0.6108	8.891362	0.0009

	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
y1						
group						
2	-9.771429	4.679078	-2.09	0.052	-19.64342	.1005633
3	15.25143	5.125673	2.98	0.008	4.437203	26.06565
4	-3.028571	7.018617	-0.43	0.672	-17.83656	11.77942
_cons	18.52857	3.308608	5.60	0.000	11.54802	25.50912
y2						
group						
2	-1.371429	.3375073	-4.06	0.001	-2.083507	-.6593504
3	-1.654286	.3697207	-4.47	0.000	-2.434328	-.8742432
4	-1.514286	.5062609	-2.99	0.008	-2.582403	-.4461685
_cons	4.014286	.2386537	16.82	0.000	3.51077	4.517801

◁

`mvreg` options allowed on replay, such as `level()`, `vsquish`, and `base`, may also be specified to alter what is displayed.

Two-way MANOVA

You can include multiple explanatory variables with the `manova` command, and you can specify interactions by placing '`#`' between the variable names.

▷ Example 4: Two-way MANOVA with unbalanced data

Table 4.6 of Rencher (1998) presents unbalanced data from Woodard (1931) for a two-way MANOVA with three dependent variables (y1, y2, and y3) measured on patients with fractures of the jaw. y1 is age of patient, y2 is blood lymphocytes, and y3 is blood polymorphonuclears. The two design factors are `gender` (1 = male, 2 = female) and `fracture` (indicating the type of fracture: 1 = one compound fracture, 2 = two compound fractures, and 3 = one simple fracture). `gender` and `fracture` are numeric variables with value labels.

```
. use https://www.stata-press.com/data/r18/jaw
(Table 4.6. Two-way unbalanced data for fractures of the jaw, Rencher (1998))

. describe

Contains data from https://www.stata-press.com/data/r18/jaw.dta
 Observations:            27                  Table 4.6. Two-way unbalanced
                                                 data for fractures of the jaw --
                                                 Rencher (1998)
     Variables:             5                  20 Apr 2022 14:53
                                              (_dta has notes)
─────────────────────────────────────────────────────────────────────────────
Variable      Storage   Display    Value
    name         type    format    label     Variable label
─────────────────────────────────────────────────────────────────────────────
gender         byte     %9.0g      gender
fracture       byte     %22.0g     fractype
y1             byte     %9.0g                 Age
y2             byte     %9.0g                 Blood lymphocytes
y3             byte     %9.0g                 Blood polymorphonuclears
─────────────────────────────────────────────────────────────────────────────

Sorted by:

. list in 19/22
```

	gender	fracture	y1	y2	y3
19.	Male	One simple fracture	55	32	60
20.	Male	One simple fracture	30	34	62
21.	Female	One compound fracture	22	56	43
22.	Female	Two compound fractures	22	29	68

The two-way factorial MANOVA for these data is

```
. manova y1 y2 y3 = gender fracture gender#fracture
                  Number of obs =         27

                  W = Wilks' lambda      L = Lawley-Hotelling trace
                  P = Pillai's trace     R = Roy's largest root
        Source | Statistic       df    F(df1,    df2) =   F   Prob>F
```

Source		Statistic	df	F(df1,	df2) =	F	Prob>F	
Model	W	0.2419	5	15.0	52.9	2.37	0.0109	a
	P	1.1018		15.0	63.0	2.44	0.0072	a
	L	1.8853		15.0	53.0	2.22	0.0170	a
	R	0.9248		5.0	21.0	3.88	0.0119	u
Residual			21					
gender	W	0.7151	1	3.0	19.0	2.52	0.0885	e
	P	0.2849		3.0	19.0	2.52	0.0885	e
	L	0.3983		3.0	19.0	2.52	0.0885	e
	R	0.3983		3.0	19.0	2.52	0.0885	e
fracture	W	0.4492	2	6.0	38.0	3.12	0.0139	e
	P	0.6406		6.0	40.0	3.14	0.0128	a
	L	1.0260		6.0	36.0	3.08	0.0155	a
	R	0.7642		3.0	20.0	5.09	0.0088	u
gender#fracture	W	0.5126	2	6.0	38.0	2.51	0.0380	e
	P	0.5245		6.0	40.0	2.37	0.0472	a
	L	0.8784		6.0	36.0	2.64	0.0319	a
	R	0.7864		3.0	20.0	5.24	0.0078	u
Residual			21					
Total			26					

```
          e = exact, a = approximate, u = upper bound on F
```

For MANOVA models with more than one term, the output of `manova` shows test results for the overall model, followed by results for each term in the MANOVA.

The interaction term, `gender#fracture`, is significant at the 0.05 level. Wilks's lambda for the interaction has an exact F that produces a p-value of 0.0380.

Example 3 of [MV] **manova postestimation** illustrates how the `margins` postestimation command can be used to examine details of this significant interaction. It also illustrates how to obtain residuals by using `predict`.   ◁

N-way MANOVA

Higher-order MANOVA models are easily constructed using `#` to indicate the interaction terms.

▷ Example 5: MANOVA with interaction terms

Data on the wear of coated fabrics is provided by Box (1950) and is presented in table 6.20 of Rencher and Christensen (2012, 249). Variables `y1`, `y2`, and `y3` are the wear after successive 1,000 revolutions of an abrasive wheel. Three factors are also recorded. `treatment` is the surface treatment and has two levels. `filler` is the filler type, also with two levels. `proportion` is the proportion of filler and has three levels (25%, 50%, and 75%).

```
. use https://www.stata-press.com/data/r18/fabric
(Table 6.20. Wear of coated fabrics, Rencher and Christensen (2012))

. describe

Contains data from https://www.stata-press.com/data/r18/fabric.dta
 Observations:              24               Table 6.20 Wear of coated
                                               fabrics, Rencher and Christensen
                                               (2012)
     Variables:               6               30 Aug 2022 14:01
                                               (_dta has notes)
───────────────────────────────────────────────────────────────────────────────
Variable        Storage   Display    Value
    name           type    format    label      Variable label
───────────────────────────────────────────────────────────────────────────────
treatment        byte     %9.0g                 Surface treatment
filler           byte     %9.0g                 Filler type
proportion       byte     %9.0g      prop       Proportion of filler
y1               int      %9.0g                 First 1000 revolutions
y2               int      %9.0g                 Second 1000 revolutions
y3               int      %9.0g                 Third 1000 revolutions
───────────────────────────────────────────────────────────────────────────────

Sorted by:

. label list prop
prop:
           1 25%
           2 50%
           3 75%

. list
```

	treatm~t	filler	propor~n	y1	y2	y3
1.	0	1	25%	194	192	141
2.	0	1	50%	233	217	171
3.	0	1	75%	265	252	207
4.	0	1	25%	208	188	165
5.	0	1	50%	241	222	201
6.	0	1	75%	269	283	191
7.	0	2	25%	239	127	90
8.	0	2	50%	224	123	79
9.	0	2	75%	243	117	100
10.	0	2	25%	187	105	85
11.	0	2	50%	243	123	110
12.	0	2	75%	226	125	75
13.	1	1	25%	155	169	151
14.	1	1	50%	198	187	176
15.	1	1	75%	235	225	166
16.	1	1	25%	173	152	141
17.	1	1	50%	177	196	167
18.	1	1	75%	229	270	183
19.	1	2	25%	137	82	77
20.	1	2	50%	129	94	78
21.	1	2	75%	155	76	92
22.	1	2	25%	160	82	83
23.	1	2	50%	98	89	48
24.	1	2	75%	132	105	67

proportion is a numeric variable taking on values 1, 2, and 3, and is value-labeled with labels 25%, 50%, and 75%. treatment takes on values of 0 and 1, whereas filler is either 1 or 2.

First, we examine these data, ignoring the repeated-measures aspects of y1, y2, and y3. In example 12, we will take it into account.

```
. manova y1 y2 y3 = proportion##treatment##filler
```

	Number of obs =		24				
	W = Wilks' lambda		L = Lawley–Hotelling trace				
	P = Pillai's trace		R = Roy's largest root				
Source	Statistic	df	F(df1,	df2) =	F	Prob>F	
Model	W 0.0007	11	33.0	30.2	10.10	0.0000	a
	P 2.3030		33.0	36.0	3.60	0.0001	a
	L 74.4794		33.0	26.0	19.56	0.0000	a
	R 59.1959		11.0	12.0	64.58	0.0000	u
Residual		12					
proportion	W 0.1375	2	6.0	20.0	5.65	0.0014	e
	P 0.9766		6.0	22.0	3.50	0.0139	a
	L 5.4405		6.0	18.0	8.16	0.0002	a
	R 5.2834		3.0	11.0	19.37	0.0001	u
treatment	W 0.0800	1	3.0	10.0	38.34	0.0000	e
	P 0.9200		3.0	10.0	38.34	0.0000	e
	L 11.5032		3.0	10.0	38.34	0.0000	e
	R 11.5032		3.0	10.0	38.34	0.0000	e
proportion#	W 0.7115	2	6.0	20.0	0.62	0.7134	e
treatment	P 0.2951		6.0	22.0	0.63	0.7013	a
	L 0.3962		6.0	18.0	0.59	0.7310	a
	R 0.3712		3.0	11.0	1.36	0.3055	u
filler	W 0.0192	1	3.0	10.0	170.60	0.0000	e
	P 0.9808		3.0	10.0	170.60	0.0000	e
	L 51.1803		3.0	10.0	170.60	0.0000	e
	R 51.1803		3.0	10.0	170.60	0.0000	e
proportion#filler	W 0.1785	2	6.0	20.0	4.56	0.0046	e
	P 0.9583		6.0	22.0	3.37	0.0164	a
	L 3.8350		6.0	18.0	5.75	0.0017	a
	R 3.6235		3.0	11.0	13.29	0.0006	u
treatment#filler	W 0.3552	1	3.0	10.0	6.05	0.0128	e
	P 0.6448		3.0	10.0	6.05	0.0128	e
	L 1.8150		3.0	10.0	6.05	0.0128	e
	R 1.8150		3.0	10.0	6.05	0.0128	e
proportion#	W 0.7518	2	6.0	20.0	0.51	0.7928	e
treatment#filler	P 0.2640		6.0	22.0	0.56	0.7589	a
	L 0.3092		6.0	18.0	0.46	0.8260	a
	R 0.2080		3.0	11.0	0.76	0.5381	u
Residual		12					
Total		23					

e = exact, a = approximate, u = upper bound on F

The MANOVA table indicates that all the terms are significant, except for `proportion#treatment` and `proportion#treatment#filler`.

◁

❑ Technical note

MANOVA uses the same design matrix as ANOVA. `manova` saves the full variance–covariance matrix and coefficient vector. These need a dimension equal to the dimension of the design matrix times the number of variables in the *depvarlist*.

❑

MANCOVA

MANCOVA models are specified by including the covariates as *term*s in the `manova` preceded by the `c.` operator to indicate that they are to be treated as continuous instead of categorical variables.

▷ Example 6: MANCOVA

Table 4.9 of Rencher (1998) provides biochemical measurements on four weight groups. Rencher extracted the data from Brown and Beerstecher (1951) and Smith, Gnanadesikan, and Hughes (1962). Three dependent variables and two covariates are recorded for eight subjects within each of the four groups. The first two groups are underweight, and the last two groups are overweight. The dependent variables are modified creatinine coefficient (y1), pigment creatinine (y2), and phosphate in mg/mL (y3). The two covariates are volume in ml (x1) and specific gravity (x2).

```
. use https://www.stata-press.com/data/r18/biochemical
(Table 4.9. Biochemical measurements, Rencher (1998))

. describe

Contains data from https://www.stata-press.com/data/r18/biochemical.dta
 Observations:           32                   Table 4.9, Rencher (1998)
    Variables:            6                   22 Apr 2022 21:48
                                              (_dta has notes)

Variable      Storage   Display    Value
    name         type    format    label      Variable label

group          byte     %9.0g
y1             float    %9.0g                 Modified creatinine coefficient
y2             float    %9.0g                 pigment creatinine
y3             float    %9.0g                 Phosphate (mg/ml)
x1             int      %9.0g                 Volume (ml)
x2             byte     %9.0g                 Specific gravity

Sorted by:
```

Rencher performs three tests on these data. The first is a test of equality of group effects adjusted for the covariates. The second is a test that the coefficients for the covariates are jointly equal to zero. The third is a test that the coefficients for the covariates are equal across groups.

```
. manova y1 y2 y3 = group c.x1 c.x2
```

```
                Number of obs =         32

                W = Wilks' lambda     L = Lawley-Hotelling trace
                P = Pillai's trace    R = Roy's largest root
        Source | Statistic        df    F(df1,     df2) =    F    Prob>F
```

Source		Statistic	df	F(df1,	df2) =	F	Prob>F	
Model	W	0.0619	5	15.0	66.7	7.73	0.0000	a
	P	1.4836		15.0	78.0	5.09	0.0000	a
	L	6.7860		15.0	68.0	10.25	0.0000	a
	R	5.3042		5.0	26.0	27.58	0.0000	u
Residual			26					
group	W	0.1491	3	9.0	58.6	7.72	0.0000	a
	P	0.9041		9.0	78.0	3.74	0.0006	a
	L	5.3532		9.0	68.0	13.48	0.0000	a
	R	5.2872		3.0	26.0	45.82	0.0000	u
x1	W	0.6841	1	3.0	24.0	3.69	0.0257	e
	P	0.3159		3.0	24.0	3.69	0.0257	e
	L	0.4617		3.0	24.0	3.69	0.0257	e
	R	0.4617		3.0	24.0	3.69	0.0257	e
x2	W	0.9692	1	3.0	24.0	0.25	0.8576	e
	P	0.0308		3.0	24.0	0.25	0.8576	e
	L	0.0318		3.0	24.0	0.25	0.8576	e
	R	0.0318		3.0	24.0	0.25	0.8576	e
Residual			26					
Total			31					

```
            e = exact, a = approximate, u = upper bound on F
```

The test of equality of group effects adjusted for the covariates is shown in the MANCOVA table above. Rencher reports a Wilks's lambda value of 0.1491, which agrees with the value shown for the group term above. group is found to be significant.

The test that the coefficients for the covariates are jointly equal to zero is obtained using manovatest.

```
. manovatest c.x1 c.x2
```

```
                W = Wilks' lambda     L = Lawley-Hotelling trace
                P = Pillai's trace    R = Roy's largest root
        Source | Statistic        df    F(df1,     df2) =    F    Prob>F
```

Source		Statistic	df	F(df1,	df2) =	F	Prob>F	
x1 x2	W	0.4470	2	6.0	48.0	3.97	0.0027	e
	P	0.5621		6.0	50.0	3.26	0.0088	a
	L	1.2166		6.0	46.0	4.66	0.0009	a
	R	1.1995		3.0	25.0	10.00	0.0002	u
Residual			26					

```
            e = exact, a = approximate, u = upper bound on F
```

Wilks's lambda of 0.4470 agrees with the value reported by Rencher. With a p-value of 0.0027, we reject the null hypothesis that the coefficients for the covariates are jointly zero.

To test that the coefficients for the covariates are equal across groups, we perform a MANCOVA that includes our covariates (x1 and x2) interacted with group. We then use `manovatest` to obtain the combined test of equal coefficients for x1 and x2 across groups.

```
. manova y1 y2 y3 = group c.x1 c.x2 group#c.x1 group#c.x2
```

```
                    Number of obs =        32

                    W = Wilks' lambda      L = Lawley-Hotelling trace
                    P = Pillai's trace     R = Roy's largest root
```

Source	Statistic		df	F(df1,	df2) =	F	Prob>F	
Model	W	0.0205	11	33.0	53.7	4.47	0.0000	a
	P	1.9571		33.0	60.0	3.41	0.0000	a
	L	10.6273		33.0	50.0	5.37	0.0000	a
	R	7.0602		11.0	20.0	12.84	0.0000	u
Residual			20					
group	W	0.4930	3	9.0	44.0	1.65	0.1317	a
	P	0.5942		9.0	60.0	1.65	0.1226	a
	L	0.8554		9.0	50.0	1.58	0.1458	a
	R	0.5746		3.0	20.0	3.83	0.0256	u
x1	W	0.7752	1	3.0	18.0	1.74	0.1947	e
	P	0.2248		3.0	18.0	1.74	0.1947	e
	L	0.2900		3.0	18.0	1.74	0.1947	e
	R	0.2900		3.0	18.0	1.74	0.1947	e
x2	W	0.8841	1	3.0	18.0	0.79	0.5169	e
	P	0.1159		3.0	18.0	0.79	0.5169	e
	L	0.1311		3.0	18.0	0.79	0.5169	e
	R	0.1311		3.0	18.0	0.79	0.5169	e
group#x1	W	0.4590	3	9.0	44.0	1.84	0.0873	a
	P	0.6378		9.0	60.0	1.80	0.0869	a
	L	0.9702		9.0	50.0	1.80	0.0923	a
	R	0.6647		3.0	20.0	4.43	0.0152	u
group#x2	W	0.5275	3	9.0	44.0	1.47	0.1899	a
	P	0.5462		9.0	60.0	1.48	0.1747	a
	L	0.7567		9.0	50.0	1.40	0.2130	a
	R	0.4564		3.0	20.0	3.04	0.0527	u
Residual			20					
Total			31					

```
              e = exact, a = approximate, u = upper bound on F
```

```
. manovatest group#c.x1 group#c.x2
```

```
                    W = Wilks' lambda      L = Lawley-Hotelling trace
                    P = Pillai's trace     R = Roy's largest root
```

Source	Statistic		df	F(df1,	df2) =	F	Prob>F	
group#x1 group#x2	W	0.3310	6	18.0	51.4	1.37	0.1896	a
	P	0.8600		18.0	60.0	1.34	0.1973	a
	L	1.4629		18.0	50.0	1.35	0.1968	a
	R	0.8665		6.0	20.0	2.89	0.0341	u
Residual			20					

```
              e = exact, a = approximate, u = upper bound on F
```

Rencher reports 0.3310 for Wilks's lambda, which agrees with the results of `manovatest` above. Here we fail to reject the null hypothesis.

◁

MANOVA for Latin-square designs

▷ Example 7: MANOVA with Latin-square data

Exercise 5.11 from Timm (1975) presents data from a multivariate Latin-square design. Two dependent variables are measured in a 4×4 Latin square. W is the student's score on determining distances within the solar system. B is the student's score on determining distances beyond the solar system. The three variables comprising the square are `machine`, `ability`, and `treatment`, each at four levels.

```
. use https://www.stata-press.com/data/r18/solardistance
(Multivariate Latin square, Timm (1975), exercise 5.11 #1)
. describe
Contains data from https://www.stata-press.com/data/r18/solardistance.dta
 Observations:                16              Multivariate Latin square, Timm
                                                (1975), exercise 5.11 #1
      Variables:                5              23 Apr 2022 03:27
                                              (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
machine	byte	%9.0g		Teaching machine
ability	byte	%9.0g		Ability tracks
treatment	byte	%9.0g		Method of measuring astronomical distances
W	byte	%9.0g		Solar system distances (within)
B	byte	%9.0g		Solar system distances (beyond)

```
Sorted by:
. list
```

	machine	ability	treatm~t	W	B
1.	1	1	2	33	15
2.	1	2	1	40	4
3.	1	3	3	31	16
4.	1	4	4	37	10
5.	2	1	4	25	20
6.	2	2	3	30	18
7.	2	3	1	22	6
8.	2	4	2	25	18
9.	3	1	1	10	5
10.	3	2	4	20	16
11.	3	3	2	17	16
12.	3	4	3	12	4
13.	4	1	3	24	15
14.	4	2	2	20	13
15.	4	3	4	19	14
16.	4	4	1	29	20

```
. manova W B = machine ability treatment

                Number of obs =          16

                W = Wilks' lambda     L = Lawley-Hotelling trace
                P = Pillai's trace    R = Roy's largest root

      Source │ Statistic        df    F(df1,     df2) =    F   Prob>F

       Model │W    0.0378         9    18.0      10.0    2.30 0.0898 e
             │P    1.3658              18.0      12.0    1.44 0.2645 a
             │L   14.7756              18.0       8.0    3.28 0.0455 a
             │R   14.0137               9.0       6.0    9.34 0.0066 u

    Residual │                    6

     machine │W    0.0561         3     6.0      10.0    5.37 0.0101 e
             │P    1.1853               6.0      12.0    2.91 0.0545 a
             │L   12.5352               6.0       8.0    8.36 0.0043 a
             │R   12.1818               3.0       6.0   24.36 0.0009 u

     ability │W    0.4657         3     6.0      10.0    0.78 0.6070 e
             │P    0.5368               6.0      12.0    0.73 0.6322 a
             │L    1.1416               6.0       8.0    0.76 0.6199 a
             │R    1.1367               3.0       6.0    2.27 0.1802 u

   treatment │W    0.4697         3     6.0      10.0    0.77 0.6137 e
             │P    0.5444               6.0      12.0    0.75 0.6226 a
             │L    1.0988               6.0       8.0    0.73 0.6378 a
             │R    1.0706               3.0       6.0    2.14 0.1963 u

    Residual │                    6

       Total │                   15

        e = exact, a = approximate, u = upper bound on F
```

We find that `machine` is a significant factor in the model, whereas `ability` and `treatment` are not.

◁

MANOVA for nested designs

Nested terms are specified using a vertical bar. A|B is read as A nested within B. A|B|C is read as A nested within B, which is nested within C. A|B#C is read as A nested within the interaction of B and C. A#B|C is read as the interaction of A and B, which is nested within C.

Different error terms can be specified for different parts of the model. The forward slash is used to indicate that the next term in the model is the error term for what precedes it. For instance, `manova y1 y2 = A / B|A` indicates that the multivariate tests for A are to be tested using the SSCP matrix from B|A in the denominator. Error terms (terms following the slash) are generally not tested unless they are themselves followed by a slash. The residual-error SSCP matrix is the default error-term matrix.

For example, consider T_1 / T_2 / T_3, where T_1, T_2, and T_3 may be arbitrarily complex terms. `manova` will report T_1 tested by T_2 and T_2 tested by T_3. If we add one more slash on the end to form T_1 / T_2 / T_3 /, then `manova` will also report T_3 tested by the residual error.

When you have nested terms in your model, we recommend using the `dropemptycells` option of `manova` or setting `c(emptycells)` to `drop`; see [R] **set emptycells**. See the technical note at the end of the *Nested designs* section of [R] **anova** for details.

▷ Example 8: MANOVA with nested data

A chain of retail stores produced two training videos for sales associates. The videos teach how to increase sales of the store's primary product. The videos also teach how to follow up a primary sale with secondary sales of the accessories that consumers often use with the primary product. The company trainers are not sure which video will provide the best training. To decide which video to distribute to all their stores to train sales associates, they selected three stores to use one of the training videos and three other stores to use the other training video. From each store, two employees (sales associates) were selected to receive the training. The baseline weekly sales for each of these employees was recorded and then the increase in sales over their baseline was recorded for 3 or 4 different weeks. The videotrainer data are described below.

```
. use https://www.stata-press.com/data/r18/videotrainer
(Video training)

. describe

Contains data from https://www.stata-press.com/data/r18/videotrainer.dta
 Observations:            42                  Video training
    Variables:             5                  9 May 2022 12:50
─────────────────────────────────────────────────────────────────────────────
Variable      Storage   Display    Value
    name         type    format    label      Variable label
─────────────────────────────────────────────────────────────────────────────
video          byte     %9.0g                 Training video
store          byte     %9.0g                 Store (nested in video)
associate      byte     %9.0g                 Sales associate (nested in store)
primary        float    %9.0g                 Primary sales increase
extra          float    %9.0g                 Secondary sales increase
─────────────────────────────────────────────────────────────────────────────
Sorted by: video  store  associate
```

In this fully nested design, video is a fixed factor, whereas the remaining terms are random factors.

```
. manova primary extra = video / store|video / associate|store|video /,
> dropemptycells
```

```
                 Number of obs =              42

                 W = Wilks' lambda     L = Lawley-Hotelling trace
                 P = Pillai's trace    R = Roy's largest root
       Source | Statistic      df    F(df1,    df2) =    F   Prob>F
```
Model	W	0.2455	11	22.0	58.0	2.68	0.0014 e
	P	0.9320		22.0	60.0	2.38	0.0042 a
	L	2.3507		22.0	56.0	2.99	0.0005 a
	R	1.9867		11.0	30.0	5.42	0.0001 u
Residual			30				
video	W	0.1610	1	2.0	3.0	7.82	0.0646 e
	P	0.8390		2.0	3.0	7.82	0.0646 e
	L	5.2119		2.0	3.0	7.82	0.0646 e
	R	5.2119		2.0	3.0	7.82	0.0646 e
store|video			4				
store|video	W	0.3515	4	8.0	10.0	0.86	0.5775 e
	P	0.7853		8.0	12.0	0.97	0.5011 a
	L	1.4558		8.0	8.0	0.73	0.6680 a
	R	1.1029		4.0	6.0	1.65	0.2767 u
associate|store| video			6				
associate|store| video	W	0.5164	6	12.0	58.0	1.89	0.0543 e
	P	0.5316		12.0	60.0	1.81	0.0668 a
	L	0.8433		12.0	56.0	1.97	0.0451 a
	R	0.7129		6.0	30.0	3.56	0.0087 u
Residual			30				
Total			41				

```
              e = exact, a = approximate, u = upper bound on F
```

There appears to be a difference in the videos (with significance levels just a bit above the standard 5% level). There also appears to be a sales associate effect but not a store effect.

See example 4 of [MV] **manova postestimation** for a continuation of this example. It illustrates how to test pooled terms against nonresidual error terms by using the `manovatest` postestimation command. In that example, `store` is pooled with `associate` from the original fully specified MANOVA. Another way of pooling is to refit the model, discarding the higher-level terms. Be careful in doing this to ensure that the remaining lower-level terms have a numbering scheme that will not mistakenly consider different subjects as being the same. The `videotrainer` dataset has `associate` numbered uniquely, so we can simply type

```
. manova primary extra = video / associate|video /, dropemptycells

                  Number of obs =          42

                  W = Wilks' lambda      L = Lawley-Hotelling trace
                  P = Pillai's trace     R = Roy's largest root
         Source | Statistic        df    F(df1,    df2) =    F   Prob>F

          Model |W    0.2455        11     22.0     58.0    2.68 0.0014 e
                |P    0.9320               22.0     60.0    2.38 0.0042 a
                |L    2.3507               22.0     56.0    2.99 0.0005 a
                |R    1.9867               11.0     30.0    5.42 0.0001 u

       Residual |                   30

          video |W    0.4079         1      2.0      9.0    6.53 0.0177 e
                |P    0.5921                2.0      9.0    6.53 0.0177 e
                |L    1.4516                2.0      9.0    6.53 0.0177 e
                |R    1.4516                2.0      9.0    6.53 0.0177 e

 associate|video|                   10

 associate|video|W    0.3925        10     20.0     58.0    1.73 0.0546 e
                |P    0.7160               20.0     60.0    1.67 0.0647 a
                |L    1.2711               20.0     56.0    1.78 0.0469 a
                |R    0.9924               10.0     30.0    2.98 0.0100 u

       Residual |                   30

          Total |                   41

           e = exact, a = approximate, u = upper bound on F
```

and get the same results that we obtained using manovatest to get a pooled test after the full MANOVA; see example 4 of [MV] **manova postestimation**.

With store omitted from the model, video now has a significance level below 5%. The increase from 4 to 10 denominator degrees of freedom for the test of video provides a more powerful test.

The margins command provides a predictive marginal mean increase in sales based on the two videos. We could request the marginal means for primary sales increase or for extra sales increase, or we can use the expression() option to obtain the marginal means for combined primary and secondary sales increase. By default, the predicted means are constructed taking into account the number of observations in each cell.

```
. margins, within(video) expression(predict(eq(primary))+predict(eq(extra)))

Predictive margins                                     Number of obs = 42

Expression:   predict(eq(primary))+predict(eq(extra))
Within:       video
Empty cells: reweight

                      Delta-method
             Margin    std. err.     z     P>|z|    [95% conf. interval]

       video
           1 883.1395   30.01873   29.42   0.000    824.3039   941.9752
           2 698.0791   30.01873   23.25   0.000    639.2434   756.9147
```

Alternatively, we can examine the adjusted marginal mean increase in sales letting each cell have equal weight (regardless of its sample size) by using the asbalanced option of the margins command.

```
. margins, within(video) expression(predict(eq(primary))+predict(eq(extra)))
> asbalanced
Adjusted predictions                                      Number of obs = 42
Expression:  predict(eq(primary))+predict(eq(extra))
Within:      video
Empty cells: reweight
At: 1.video
          associate    (asbalanced)
    2.video
          associate    (asbalanced)
```

	Margin	Delta-method std. err.	z	P>|z|	[95% conf. interval]	
video						
1	876.8818	30.32981	28.91	0.000	817.4365	936.3271
2	695.315	30.32981	22.93	0.000	635.8697	754.7603

Though the values are different between the two tables, the conclusion is the same. Using training video 1 leads to increased primary and secondary sales.

◁

MANOVA for mixed designs

▷ Example 9: Split-plot MANOVA

reading2.dta has data from an experiment involving two reading programs and three skill-enhancement techniques. Ten classes of first-grade students were randomly assigned so that five classes were taught with one reading program and another five classes were taught with the other. The 30 students in each class were divided into six groups with 5 students each. Within each class, the six groups were divided randomly so that each of the three skill-enhancement techniques was taught to two of the groups within each class. At the end of the school year, a reading assessment test was administered to all the students. Two scores were recorded. The first was a reading score (score), and the second was a comprehension score (comprehension).

Example 13 of [R] anova uses reading.dta to illustrate mixed designs for ANOVA. reading2.dta is the same as reading.dta, except that the comprehension variable is added.

```
. use https://www.stata-press.com/data/r18/reading2
(Reading experiment data)
. describe
Contains data from https://www.stata-press.com/data/r18/reading2.dta
 Observations:          300                Reading experiment data
    Variables:            6                24 Apr 2022 08:31
                                           (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
score	byte	%9.0g		Reading score
comprehension	byte	%9.0g		Comprehension score
program	byte	%9.0g		Reading program
class	byte	%9.0g		Class nested in program
skill	byte	%9.0g		Skill enhancement technique
group	byte	%9.0g		Group nested in class and skill

```
Sorted by:
```

In this split-plot MANOVA, the whole-plot treatment is the two reading programs, and the split-plot treatment is the three skill-enhancement techniques.

For this split-plot MANOVA, the error term for `program` is `class` nested within `program`. The error term for `skill` and the `program` by `skill` interaction is the `class` by `skill` interaction nested within `program`. Other terms are also involved in the model and can be seen below.

```
. manova score comp = pr / cl|pr sk pr#sk / cl#sk|pr / gr|cl#sk|pr /,
> dropemptycells
```

		Number of obs =		300			
		W = Wilks' lambda		L = Lawley-Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source		Statistic	df	F(df1,	df2) =	F	Prob>F
Model	W	0.5234	59	118.0	478.0	1.55	0.0008 e
	P	0.5249		118.0	480.0	1.45	0.0039 a
	L	0.8181		118.0	476.0	1.65	0.0001 a
	R	0.6830		59.0	240.0	2.78	0.0000 u
Residual			240				
program	W	0.4543	1	2.0	7.0	4.20	0.0632 e
	P	0.5457		2.0	7.0	4.20	0.0632 e
	L	1.2010		2.0	7.0	4.20	0.0632 e
	R	1.2010		2.0	7.0	4.20	0.0632 e
class|program			8				
skill	W	0.6754	2	4.0	30.0	1.63	0.1935 e
	P	0.3317		4.0	32.0	1.59	0.2008 a
	L	0.4701		4.0	28.0	1.65	0.1908 a
	R	0.4466		2.0	16.0	3.57	0.0522 u
program#skill	W	0.3955	2	4.0	30.0	4.43	0.0063 e
	P	0.6117		4.0	32.0	3.53	0.0171 a
	L	1.5100		4.0	28.0	5.29	0.0027 a
	R	1.4978		2.0	16.0	11.98	0.0007 u
class#skill|program			16				
class#skill|program	W	0.4010	16	32.0	58.0	1.05	0.4265 e
	P	0.7324		32.0	60.0	1.08	0.3860 a
	L	1.1609		32.0	56.0	1.02	0.4688 a
	R	0.6453		16.0	30.0	1.21	0.3160 u
group|class#skill| program			30				
group|class#skill| program	W	0.7713	30	60.0	478.0	1.10	0.2844 e
	P	0.2363		60.0	480.0	1.07	0.3405 a
	L	0.2867		60.0	476.0	1.14	0.2344 a
	R	0.2469		30.0	240.0	1.98	0.0028 u
Residual			240				
Total			299				

e = exact, a = approximate, u = upper bound on F

The `program#skill` interaction is significant.

◁

MANOVA with repeated measures

One approach to analyzing repeated measures in an ANOVA setting is to use correction factors for terms in an ANOVA that involve the repeated measures. These correction factors attempt to correct for the violated assumption of independence of observations; see [R] **anova**. In this approach, the data are in long form; see [D] **reshape**.

Another approach to repeated measures is to use MANOVA with the repeated measures appearing as dependent variables, followed by tests involving linear combinations of these repeated measures. This approach involves fewer assumptions than the repeated-measures ANOVA approach.

The simplest possible repeated-measures design has no between-subject factors and only one within-subject factor (the repeated measures).

▷ Example 10: MANOVA with repeated-measures data

Here are data on five subjects, each of whom took three tests.

```
. use https://www.stata-press.com/data/r18/nobetween
. list
```

	subject	test1	test2	test3
1.	1	68	69	95
2.	2	50	74	69
3.	3	72	89	71
4.	4	61	64	61
5.	5	60	71	90

manova must be tricked into fitting a constant-only model. To do this, you generate a variable equal to one, use that variable as the single *term* in your manova, and then specify the noconstant option. From the resulting MANOVA, you then test the repeated measures with the ytransform() option of manovatest; see [MV] **manova postestimation** for syntax details.

```
. generate mycons = 1
. manova test1 test2 test3 = mycons, noconstant
```

```
                Number of obs =           5

                W = Wilks' lambda     L = Lawley-Hotelling trace
                P = Pillai's trace    R = Roy's largest root
```

Source	Statistic	df	F(df1,	df2) =	F	Prob>F
mycons	W 0.0076	1	3.0	2.0	86.91	0.0114 e
	P 0.9924		3.0	2.0	86.91	0.0114 e
	L 130.3722		3.0	2.0	86.91	0.0114 e
	R 130.3722		3.0	2.0	86.91	0.0114 e
Residual		4				
Total		5				

```
            e = exact, a = approximate, u = upper bound on F
```

```
. mat c = (1,0,-1\0,1,-1)
. manovatest mycons, ytransform(c)
 Transformations of the dependent variables
 (1)     test1 - test3
 (2)     test2 - test3
                      W = Wilks' lambda       L = Lawley-Hotelling trace
                      P = Pillai's trace      R = Roy's largest root
          Source | Statistic        df    F(df1,     df2) =    F    Prob>F

          mycons |W    0.2352        1        2.0     3.0      4.88 0.1141 e
                 |P    0.7648                 2.0     3.0      4.88 0.1141 e
                 |L    3.2509                 2.0     3.0      4.88 0.1141 e
                 |R    3.2509                 2.0     3.0      4.88 0.1141 e

        Residual |                    4

              e = exact, a = approximate, u = upper bound on F
```

The test produced directly with manova is not interesting. It is testing the hypothesis that the three test score means are zero. The test produced by manovatest is of interest. From the contrasts in the matrix c, you produce a test that there is a difference between the test1, test2, and test3 scores. Here the test produces a p-value of 0.1141, and you fail to reject the null hypothesis of equality between the test scores.

You can compare this finding with the results obtained from a repeated-measures ANOVA,

```
. reshape long test, i(subject) j(testnum)
. anova test subject testnum, repeated(testnum)
```

which produced an uncorrected p-value of 0.1160 and corrected p-values of 0.1181, 0.1435, and 0.1665 by using the Huynh–Feldt, Greenhouse–Geisser, and Box's conservative correction, respectively.

◁

▷ Example 11: Randomized block design with repeated measures

Milliken and Johnson (2009) demonstrate using manova to analyze repeated measures from a randomized block design used in studying the differences among varieties of sorghum. Table 27.1 of Milliken and Johnson (2009) provides the data. Four sorghum varieties were each planted in five blocks. A leaf-area index measurement was recorded for each of 5 weeks, starting 2 weeks after emergence.

The tests of interest include a test for equal variety marginal means, equal time marginal means, and a test for the interaction of variety and time. The MANOVA below does not directly provide these tests. manovatest after the manova gives the three tests of interest.

```
. use https://www.stata-press.com/data/r18/sorghum, clear
(Leaf area index on 4 sorghum varieties, Milliken & Johnson (2009))
. manova time1 time2 time3 time4 time5 = variety block
```

	Number of obs =		20				
	W = Wilks' lambda		L = Lawley-Hotelling trace				
	P = Pillai's trace		R = Roy's largest root				
Source	Statistic	df	F(df1,	df2) =	F	Prob>F	
Model	W 0.0001	7	35.0	36.1	9.50	0.0000	a
	P 3.3890		35.0	60.0	3.61	0.0000	a
	L 126.2712		35.0	32.0	23.09	0.0000	a
	R 109.7360		7.0	12.0	188.12	0.0000	u
Residual		12					
variety	W 0.0011	3	15.0	22.5	16.11	0.0000	a
	P 2.5031		15.0	30.0	10.08	0.0000	a
	L 48.3550		15.0	20.0	21.49	0.0000	a
	R 40.0068		5.0	10.0	80.01	0.0000	u
block	W 0.0047	4	20.0	27.5	5.55	0.0000	a
	P 1.7518		20.0	44.0	1.71	0.0681	a
	L 77.9162		20.0	26.0	25.32	0.0000	a
	R 76.4899		5.0	11.0	168.28	0.0000	u
Residual		12					
Total		19					

```
            e = exact, a = approximate, u = upper bound on F
```

Two matrices are needed for transformations of the time# variables. m1 is a row vector containing five ones. m2 provides contrasts for time#. The manovatest, showorder command lists the underlying ordering of columns for constructing two more matrices used to obtain linear combinations from the design matrix. Matrix c1 provides contrasts on variety. Matrix c2 is used to collapse to the overall margin of the design matrix to obtain time marginal means.

```
. matrix m1 = J(1,5,1)
. matrix m2 = (1,-1,0,0,0 \ 1,0,-1,0,0 \ 1,0,0,-1,0 \ 1,0,0,0,-1)
. manovatest, showorder
 Order of columns in the design matrix
        1: (variety==1)
        2: (variety==2)
        3: (variety==3)
        4: (variety==4)
        5: (block==1)
        6: (block==2)
        7: (block==3)
        8: (block==4)
        9: (block==5)
       10: _cons
. matrix c1 = (1,-1,0,0,0,0,0,0,0,0\1,0,-1,0,0,0,0,0,0,0\1,0,0,-1,0,0,0,0,0,0)
. matrix c2 = (.25,.25,.25,.25,.2,.2,.2,.2,.2,1)
```

The test for equal variety marginal means uses matrix m1 to obtain the sum of the time# variables and matrix c1 to provide the contrasts on variety. The second test uses m2 to provide contrasts on time# and matrix c2 to collapse to the appropriate margin for the test of time marginal means. The final test uses m2 for contrasts on time# and c1 for contrasts on variety to test the variety-by-time interaction.

```
. manovatest, test(c1) ytransform(m1)

 Transformation of the dependent variables
 (1)     time1 + time2 + time3 + time4 + time5

 Test constraints
 (1)     1.variety - 2.variety = 0
 (2)     1.variety - 3.variety = 0
 (3)     1.variety - 4.variety = 0
```

		W = Wilks' lambda		L = Lawley-Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source	Statistic		df	F(df1,	df2) =	F	Prob>F
manovatest	W	0.0435	3	3.0	12.0	88.05	0.0000 e
	P	0.9565		3.0	12.0	88.05	0.0000 e
	L	22.0133		3.0	12.0	88.05	0.0000 e
	R	22.0133		3.0	12.0	88.05	0.0000 e
Residual			12				

```
                  e = exact, a = approximate, u = upper bound on F

. manovatest, test(c2) ytransform(m2)

 Transformations of the dependent variables
 (1)     time1 - time2
 (2)     time1 - time3
 (3)     time1 - time4
 (4)     time1 - time5

 Test constraint
 (1)     .25*1.variety + .25*2.variety + .25*3.variety + .25*4.variety +
         .2*1.block + .2*2.block + .2*3.block + .2*4.block + .2*5.block + _cons
         = 0
```

		W = Wilks' lambda		L = Lawley-Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source	Statistic		df	F(df1,	df2) =	F	Prob>F
manovatest	W	0.0050	1	4.0	9.0	445.62	0.0000 e
	P	0.9950		4.0	9.0	445.62	0.0000 e
	L	198.0544		4.0	9.0	445.62	0.0000 e
	R	198.0544		4.0	9.0	445.62	0.0000 e
Residual			12				

```
                  e = exact, a = approximate, u = upper bound on F
```

```
. manovatest, test(c1) ytransform(m2)
```

Transformations of the dependent variables
```
(1)      time1 - time2
(2)      time1 - time3
(3)      time1 - time4
(4)      time1 - time5
```

Test constraints
```
(1)      1.variety - 2.variety = 0
(2)      1.variety - 3.variety = 0
(3)      1.variety - 4.variety = 0
```

		W = Wilks' lambda		L = Lawley–Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source	Statistic		df	F(df1,	df2) =	F	Prob>F
manovatest	W	0.0143	3	12.0	24.1	8.00 0.0000	a
	P	2.1463		12.0	33.0	6.91 0.0000	a
	L	12.1760		12.0	23.0	7.78 0.0000	a
	R	8.7953		4.0	11.0	24.19 0.0000	u
Residual			12				

```
                 e = exact, a = approximate, u = upper bound on F
```

   All three tests are significant, indicating differences in variety, in time, and in the variety-by-time interaction.

◁

▷ Example 12: MANOVA and dependent-variable effects

   Recall the fabric-data example from Rencher and Christensen (2012, 249) that we used in example 5 to illustrate a three-way MANOVA. Rencher and Christensen have an additional exercise to test the period effect (the y1, y2, and y3 repeated-measures variables) and the interaction of period with the other factors in the model. The ytransform() option of manovatest provides a method to do this; see [MV] **manova postestimation**. Here are the tests of the period effect interacted with each term in the model. We create the matrix c with rows corresponding to the linear and quadratic contrasts for the three dependent variables.

```
. quietly manova y1 y2 y3 = proportion##treatment##filler
. matrix c = (-1,0,1 \ -1,2,-1)
. manovatest proportion, ytransform(c)
```

Transformations of the dependent variables
```
(1)      - y1 + y3
(2)      - y1 + 2*y2 - y3
```

		W = Wilks' lambda		L = Lawley–Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source	Statistic		df	F(df1,	df2) =	F	Prob>F
proportion	W	0.4749	2	4.0	22.0	2.48 0.0736	e
	P	0.5454		4.0	24.0	2.25 0.0936	a
	L	1.0631		4.0	20.0	2.66 0.0630	a
	R	1.0213		2.0	12.0	6.13 0.0147	u
Residual			12				

```
                 e = exact, a = approximate, u = upper bound on F
```

```
. manovatest treatment, ytransform(c)
```

Transformations of the dependent variables
(1)   - y1 + y3
(2)   - y1 + 2*y2 - y3

| | W = Wilks' lambda | | L = Lawley-Hotelling trace | | | |
| | P = Pillai's trace | | R = Roy's largest root | | | |
Source	Statistic	df	F(df1,	df2) =	F	Prob>F
treatment	W 0.1419	1	2.0	11.0	33.27	0.0000 e
	P 0.8581		2.0	11.0	33.27	0.0000 e
	L 6.0487		2.0	11.0	33.27	0.0000 e
	R 6.0487		2.0	11.0	33.27	0.0000 e
Residual		12				

                   e = exact, a = approximate, u = upper bound on F

```
. manovatest proportion#treatment, ytransform(c)
```

Transformations of the dependent variables
(1)   - y1 + y3
(2)   - y1 + 2*y2 - y3

| | W = Wilks' lambda | | L = Lawley-Hotelling trace | | | |
| | P = Pillai's trace | | R = Roy's largest root | | | |
Source	Statistic	df	F(df1,	df2) =	F	Prob>F
proportion#treatment	W 0.7766	2	4.0	22.0	0.74	0.5740 e
	P 0.2276		4.0	24.0	0.77	0.5550 a
	L 0.2824		4.0	20.0	0.71	0.5972 a
	R 0.2620		2.0	12.0	1.57	0.2476 u
Residual		12				

                   e = exact, a = approximate, u = upper bound on F

```
. manovatest filler, ytransform(c)
```

Transformations of the dependent variables
(1)   - y1 + y3
(2)   - y1 + 2*y2 - y3

| | W = Wilks' lambda | | L = Lawley-Hotelling trace | | | |
| | P = Pillai's trace | | R = Roy's largest root | | | |
Source	Statistic	df	F(df1,	df2) =	F	Prob>F
filler	W 0.0954	1	2.0	11.0	52.17	0.0000 e
	P 0.9046		2.0	11.0	52.17	0.0000 e
	L 9.4863		2.0	11.0	52.17	0.0000 e
	R 9.4863		2.0	11.0	52.17	0.0000 e
Residual		12				

                   e = exact, a = approximate, u = upper bound on F

```
. manovatest proportion#filler, ytransform(c)

Transformations of the dependent variables
(1)    - y1 + y3
(2)    - y1 + 2*y2 - y3
```

		W = Wilks' lambda		L = Lawley-Hotelling trace		
		P = Pillai's trace		R = Roy's largest root		
Source	Statistic	df	F(df1,	df2) =	F	Prob>F
proportion#filler	W 0.6217	2	4.0	22.0	1.48	0.2436 e
	P 0.3870		4.0	24.0	1.44	0.2515 a
	L 0.5944		4.0	20.0	1.49	0.2439 a
	R 0.5698		2.0	12.0	3.42	0.0668 u
Residual		12				

e = exact, a = approximate, u = upper bound on F

```
. manovatest treatment#filler, ytransform(c)

Transformations of the dependent variables
(1)    - y1 + y3
(2)    - y1 + 2*y2 - y3
```

		W = Wilks' lambda		L = Lawley-Hotelling trace		
		P = Pillai's trace		R = Roy's largest root		
Source	Statistic	df	F(df1,	df2) =	F	Prob>F
treatment#filler	W 0.3867	1	2.0	11.0	8.72	0.0054 e
	P 0.6133		2.0	11.0	8.72	0.0054 e
	L 1.5857		2.0	11.0	8.72	0.0054 e
	R 1.5857		2.0	11.0	8.72	0.0054 e
Residual		12				

e = exact, a = approximate, u = upper bound on F

```
. manovatest proportion#treatment#filler, ytransform(c)

Transformations of the dependent variables
(1)    - y1 + y3
(2)    - y1 + 2*y2 - y3
```

		W = Wilks' lambda		L = Lawley-Hotelling trace		
		P = Pillai's trace		R = Roy's largest root		
Source	Statistic	df	F(df1,	df2) =	F	Prob>F
proportion# treatment#filler	W 0.7812	2	4.0	22.0	0.72	0.5857 e
	P 0.2290		4.0	24.0	0.78	0.5518 a
	L 0.2671		4.0	20.0	0.67	0.6219 a
	R 0.2028		2.0	12.0	1.22	0.3303 u
Residual		12				

e = exact, a = approximate, u = upper bound on F

The first test, `manovatest proportion, ytransform(c)`, provides the test of `proportion` interacted with the period effect. The F tests for Wilks's lambda, Pillai's trace, and the Lawley–Hotelling trace do not reject the null hypothesis with a significance level of 0.05 (p-values of 0.0736, 0.0936, and 0.0630). The F test for Roy's largest root is an upper bound, so the p-value of 0.0147 is a lower bound.

The tests of `treatment` interacted with the period effect, `filler` interacted with the period effect, and `treatment#filler` interacted with the period effect are significant. The remaining tests are not.

To test the period effect, we call `manovatest` with both the `ytransform()` and `test()` options. The `showorder` option guides us in constructing the matrix for the `test()` option.

```
. manovatest, showorder
 Order of columns in the design matrix
       1: (proportion==1)
       2: (proportion==2)
       3: (proportion==3)
       4: (treatment==0)
       5: (treatment==1)
       6: (proportion==1)*(treatment==0)
       7: (proportion==1)*(treatment==1)
       8: (proportion==2)*(treatment==0)
       9: (proportion==2)*(treatment==1)
      10: (proportion==3)*(treatment==0)
      11: (proportion==3)*(treatment==1)
      12: (filler==1)
      13: (filler==2)
      14: (proportion==1)*(filler==1)
      15: (proportion==1)*(filler==2)
      16: (proportion==2)*(filler==1)
      17: (proportion==2)*(filler==2)
      18: (proportion==3)*(filler==1)
      19: (proportion==3)*(filler==2)
      20: (treatment==0)*(filler==1)
      21: (treatment==0)*(filler==2)
      22: (treatment==1)*(filler==1)
      23: (treatment==1)*(filler==2)
      24: (proportion==1)*(treatment==0)*(filler==1)
      25: (proportion==1)*(treatment==0)*(filler==2)
      26: (proportion==1)*(treatment==1)*(filler==1)
      27: (proportion==1)*(treatment==1)*(filler==2)
      28: (proportion==2)*(treatment==0)*(filler==1)
      29: (proportion==2)*(treatment==0)*(filler==2)
      30: (proportion==2)*(treatment==1)*(filler==1)
      31: (proportion==2)*(treatment==1)*(filler==2)
      32: (proportion==3)*(treatment==0)*(filler==1)
      33: (proportion==3)*(treatment==0)*(filler==2)
      34: (proportion==3)*(treatment==1)*(filler==1)
      35: (proportion==3)*(treatment==1)*(filler==2)
      36: _cons
```

We create a row vector, m, starting with 1/3 for three columns (corresponding to `proportion`), followed by 1/2 for two columns (corresponding to `treatment`), followed by 1/6 for six columns (for `proportion#treatment`), followed by 1/2 for two columns (for `filler`), followed by 1/6 for six columns (for `proportion#filler`), followed by four columns of 1/4 (for `treatment#filler`), followed by 1/12 for 12 columns (corresponding to the `proportion#treatment#filler` term), and finally, a 1 for the last column (corresponding to the constant in the model). The test of period effect then uses this m matrix and the c matrix previously defined as the basis of the test for the period effect.

```
. matrix m = J(1,3,1/3), J(1,2,1/2), J(1,6,1/6), J(1,2,1/2), J(1,6,1/6),
> J(1,4,1/4), J(1,12,1/12), (1)

. manovatest, test(m) ytrans(c)

 Transformations of the dependent variables
 (1)     - y1 + y3
 (2)     - y1 + 2*y2 - y3

 Test constraint
 (1)     .3333333*1.proportion + .3333333*2.proportion + .3333333*3.proportion +
         .5*0.treatment + .5*1.treatment + .1666667*1.proportion#0.treatment +
         .1666667*1.proportion#1.treatment + .1666667*2.proportion#0.treatment +
         .1666667*2.proportion#1.treatment + .1666667*3.proportion#0.treatment +
         .1666667*3.proportion#1.treatment + .5*1.filler + .5*2.filler +
         .1666667*1.proportion#1.filler + .1666667*1.proportion#2.filler +
         .1666667*2.proportion#1.filler + .1666667*2.proportion#2.filler +
         .1666667*3.proportion#1.filler + .1666667*3.proportion#2.filler +
         .25*0.treatment#1.filler + .25*0.treatment#2.filler +
         .25*1.treatment#1.filler + .25*1.treatment#2.filler +
         .0833333*1.proportion#0.treatment#1.filler +
         .0833333*1.proportion#0.treatment#2.filler +
         .0833333*1.proportion#1.treatment#1.filler +
         .0833333*1.proportion#1.treatment#2.filler +
         .0833333*2.proportion#0.treatment#1.filler +
         .0833333*2.proportion#0.treatment#2.filler +
         .0833333*2.proportion#1.treatment#1.filler +
         .0833333*2.proportion#1.treatment#2.filler +
         .0833333*3.proportion#0.treatment#1.filler +
         .0833333*3.proportion#0.treatment#2.filler +
         .0833333*3.proportion#1.treatment#1.filler +
         .0833333*3.proportion#1.treatment#2.filler + _cons = 0
```

		W = Wilks' lambda		L = Lawley–Hotelling trace		
		P = Pillai's trace		R = Roy's largest root		
Source	Statistic		df	F(df1,	df2) =	F Prob>F
manovatest	W	0.0208	1	2.0	11.0	259.04 0.0000 e
	P	0.9792		2.0	11.0	259.04 0.0000 e
	L	47.0988		2.0	11.0	259.04 0.0000 e
	R	47.0988		2.0	11.0	259.04 0.0000 e
Residual			12			

```
                  e = exact, a = approximate, u = upper bound on F
```

This result agrees with the answers provided by Rencher and Christensen (2012).

◁

In the previous three examples, one factor has been encoded within the dependent variables. We have seen that the ytransform() option of manovatest provides the method for testing this factor and its interactions with the factors that appear on the right-hand side of the MANOVA.

More than one factor could be encoded within the dependent variables. Again the ytransform() option of manovatest allows us to perform multivariate tests of interest.

▷ Example 13: MANOVA and multiple dependent-variable effects

Table 6.14 of Rencher and Christensen (2012) provides an example with two within-subject factors represented in the dependent variables and one between-subject factor.

```
. use https://www.stata-press.com/data/r18/table614
(Table 6.14. Repeated measures experiment, Rencher and Christensen (2012))

. list in 9/12, noobs compress
```

c	sub~t	ab11	ab12	ab13	ab21	ab22	ab23	ab31	ab32	ab33
1	9	41	32	23	37	51	39	27	28	30
1	10	39	32	24	30	35	31	26	29	32
2	1	47	36	25	31	36	29	21	24	27
2	2	53	43	32	40	48	47	46	50	54

There are 20 observations. Factors a and b are encoded in the names of the nine dependent variables. Variable name ab23, for instance, indicates factor a at level 2 and factor b at level 3. Factor c is the between-subject factor.

We first compute a MANOVA by using the dependent variables and our one between-subject term.

```
. manova ab11 ab12 ab13 ab21 ab22 ab23 ab31 ab32 ab33 = c
```

```
                        Number of obs =          20

                        W = Wilks' lambda     L = Lawley-Hotelling trace
                        P = Pillai's trace    R = Roy's largest root

              Source | Statistic         df   F(df1,    df2) =    F    Prob>F
            ---------+---------------------------------------------------------
                   c | W    0.5330         1        9.0    10.0    0.97 0.5114 e
                     | P    0.4670                  9.0    10.0    0.97 0.5114 e
                     | L    0.8762                  9.0    10.0    0.97 0.5114 e
                     | R    0.8762                  9.0    10.0    0.97 0.5114 e
            ---------+---------------------------------------------------------
            Residual |                   18
            ---------+---------------------------------------------------------
               Total |                   19
            -----------------------------------------------------------------

                     e = exact, a = approximate, u = upper bound on F
```

This approach provides the basis for computing tests on all terms of interest. We use the `ytransform()` and `test()` options of `manovatest` with the following matrices to obtain the tests of interest.

```
. mat a = (2,2,2,-1,-1,-1,-1,-1,-1 \ 0,0,0,1,1,1,-1,-1,-1)
. mat b = (2,-1,-1,2,-1,-1,2,-1,-1 \ 0,1,-1,0,1,-1,0,1,-1)
. forvalues i = 1/2 {
  2.        forvalues j = 1/2 {
  3.                mat g = nullmat(g) \ vecdiag(a['i',1...]'*b['j',1...])
  4.        }
  5. }
. mat list g

g[4,9]
    c1  c2  c3  c4  c5  c6  c7  c8  c9
r1   4  -2  -2  -2   1   1  -2   1   1
r1   0   2  -2   0  -1   1   0  -1   1
r1   0   0   0   2  -1  -1  -2   1   1
r1   0   0   0   0   1  -1   0  -1   1
. mat j = J(1,9,1/9)
. mat xall = (.5,.5,1)
```

Matrices a and b correspond to factors a and b. Matrix g is the elementwise multiplication of each row of a with each row of b and corresponds to the a#b interaction. Matrix j is used to average the dependent variables, whereas matrix xall collapses over factor c.

Here are the tests for a, b, and a#b.

```
. manovatest, test(xall) ytrans(a)

Transformations of the dependent variables
(1)     2*ab11 + 2*ab12 + 2*ab13 - ab21 - ab22 - ab23 - ab31 - ab32 - ab33
(2)     ab21 + ab22 + ab23 - ab31 - ab32 - ab33

Test constraint
(1)     .5*1.c + .5*2.c + _cons = 0

                        W = Wilks' lambda      L = Lawley-Hotelling trace
                        P = Pillai's trace     R = Roy's largest root
            Source | Statistic        df    F(df1,    df2) =    F   Prob>F
        -----------+---------------------------------------------------------
        manovatest |W    0.6755         1      2.0     17.0    4.08 0.0356 e
                   |P    0.3245                2.0     17.0    4.08 0.0356 e
                   |L    0.4803                2.0     17.0    4.08 0.0356 e
                   |R    0.4803                2.0     17.0    4.08 0.0356 e
        -----------+---------------------------------------------------------
          Residual |                   18
        -----------+---------------------------------------------------------

                   e = exact, a = approximate, u = upper bound on F

. manovatest, test(xall) ytrans(b)

Transformations of the dependent variables
(1)     2*ab11 - ab12 - ab13 + 2*ab21 - ab22 - ab23 + 2*ab31 - ab32 - ab33
(2)     ab12 - ab13 + ab22 - ab23 + ab32 - ab33

Test constraint
(1)     .5*1.c + .5*2.c + _cons = 0

                        W = Wilks' lambda      L = Lawley-Hotelling trace
                        P = Pillai's trace     R = Roy's largest root
            Source | Statistic        df    F(df1,    df2) =    F   Prob>F
        -----------+---------------------------------------------------------
        manovatest |W    0.3247         1      2.0     17.0   17.68 0.0001 e
                   |P    0.6753                2.0     17.0   17.68 0.0001 e
                   |L    2.0799                2.0     17.0   17.68 0.0001 e
                   |R    2.0799                2.0     17.0   17.68 0.0001 e
        -----------+---------------------------------------------------------
          Residual |                   18
        -----------+---------------------------------------------------------

                   e = exact, a = approximate, u = upper bound on F

. manovatest, test(xall) ytrans(g)

Transformations of the dependent variables
(1)     4*ab11 - 2*ab12 - 2*ab13 - 2*ab21 + ab22 + ab23 - 2*ab31 + ab32 + ab33
(2)     2*ab12 - 2*ab13 - ab22 + ab23 - ab32 + ab33
(3)     2*ab21 - ab22 - ab23 - 2*ab31 + ab32 + ab33
(4)     ab22 - ab23 - ab32 + ab33

Test constraint
(1)     .5*1.c + .5*2.c + _cons = 0

                        W = Wilks' lambda      L = Lawley-Hotelling trace
                        P = Pillai's trace     R = Roy's largest root
            Source | Statistic        df    F(df1,    df2) =    F   Prob>F
        -----------+---------------------------------------------------------
        manovatest |W    0.2255         1      4.0     15.0   12.88 0.0001 e
                   |P    0.7745                4.0     15.0   12.88 0.0001 e
                   |L    3.4347                4.0     15.0   12.88 0.0001 e
                   |R    3.4347                4.0     15.0   12.88 0.0001 e
        -----------+---------------------------------------------------------
          Residual |                   18
        -----------+---------------------------------------------------------

                   e = exact, a = approximate, u = upper bound on F
```

Factors `a`, `b`, and `a#b` are significant with p-values of 0.0356, 0.0001, and 0.0001, respectively. The multivariate statistics are equivalent to the T^2 values Rencher and Christensen report using the relationship $T^2 = (n_1 + n_2 - 2) \times (1 - \Lambda)/\Lambda$ that applies in this situation. For instance, Wilks's lambda for factor `a` is reported as 0.6755 (and the actual value recorded in `r(stat)` is 0.67554286) so that $T^2 = (10 + 10 - 2) \times (1 - 0.67554286)/0.67554286 = 8.645$, as reported by Rencher and Christensen.

We now compute the tests for `c` and the interactions of `c` with the other terms in the model.

```
. manovatest c, ytrans(j)

Transformation of the dependent variables
(1)     .1111111*ab11 + .1111111*ab12 + .1111111*ab13 + .1111111*ab21 +
        .1111111*ab22 + .1111111*ab23 + .1111111*ab31 + .1111111*ab32 +
        .1111111*ab33
```

		W = Wilks' lambda		L = Lawley-Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source	Statistic		df	F(df1,	df2) =	F	Prob>F
c	W	0.6781	1	1.0	18.0	8.54	0.0091 e
	P	0.3219		1.0	18.0	8.54	0.0091 e
	L	0.4747		1.0	18.0	8.54	0.0091 e
	R	0.4747		1.0	18.0	8.54	0.0091 e
Residual			18				

```
                   e = exact, a = approximate, u = upper bound on F
. manovatest c, ytrans(a)

Transformations of the dependent variables
(1)     2*ab11 + 2*ab12 + 2*ab13 - ab21 - ab22 - ab23 - ab31 - ab32 - ab33
(2)     ab21 + ab22 + ab23 - ab31 - ab32 - ab33
```

		W = Wilks' lambda		L = Lawley-Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source	Statistic		df	F(df1,	df2) =	F	Prob>F
c	W	0.9889	1	2.0	17.0	0.10	0.9097 e
	P	0.0111		2.0	17.0	0.10	0.9097 e
	L	0.0112		2.0	17.0	0.10	0.9097 e
	R	0.0112		2.0	17.0	0.10	0.9097 e
Residual			18				

```
                   e = exact, a = approximate, u = upper bound on F
. manovatest c, ytrans(b)

Transformations of the dependent variables
(1)     2*ab11 - ab12 - ab13 + 2*ab21 - ab22 - ab23 + 2*ab31 - ab32 - ab33
(2)     ab12 - ab13 + ab22 - ab23 + ab32 - ab33
```

		W = Wilks' lambda		L = Lawley-Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source	Statistic		df	F(df1,	df2) =	F	Prob>F
c	W	0.9718	1	2.0	17.0	0.25	0.7845 e
	P	0.0282		2.0	17.0	0.25	0.7845 e
	L	0.0290		2.0	17.0	0.25	0.7845 e
	R	0.0290		2.0	17.0	0.25	0.7845 e
Residual			18				

```
                   e = exact, a = approximate, u = upper bound on F
```

```
. manovatest c, ytrans(g)

Transformations of the dependent variables
(1)      4*ab11 - 2*ab12 - 2*ab13 - 2*ab21 + ab22 + ab23 - 2*ab31 + ab32 + ab33
(2)      2*ab12 - 2*ab13 - ab22 + ab23 - ab32 + ab33
(3)      2*ab21 - ab22 - ab23 - 2*ab31 + ab32 + ab33
(4)      ab22 - ab23 - ab32 + ab33
```

		W = Wilks' lambda		L = Lawley-Hotelling trace			
		P = Pillai's trace		R = Roy's largest root			
Source		Statistic	df	F(df1,	df2) =	F	Prob>F
c	W	0.9029	1	4.0	15.0	0.40	0.8035 e
	P	0.0971		4.0	15.0	0.40	0.8035 e
	L	0.1075		4.0	15.0	0.40	0.8035 e
	R	0.1075		4.0	15.0	0.40	0.8035 e
Residual			18				

```
            e = exact, a = approximate, u = upper bound on F
```

The test of c is equivalent to an ANOVA using the sum or average of the dependent variables as the dependent variable. The test of c produces an F of 8.54 with a p-value of 0.0091, which agrees with the results of Rencher and Christensen (2012, 229–230).

The tests of a#c, b#c, and a#b#c produce p-values of 0.9097, 0.7845, and 0.8035, respectively.

In summary, the factors that are significant are a, b, a#b, and c.

◁

Stored results

manova stores the following in e():

Scalars
e(N)	number of observations
e(k)	number of parameters
e(k_eq)	number of equations in e(b)
e(df_m)	model degrees of freedom
e(df_r)	residual degrees of freedom
e(df_#)	degrees of freedom for term #
e(rank)	rank of e(V)

Macros
e(cmd)	manova
e(cmdline)	command as typed
e(depvar)	names of dependent variables
e(indepvars)	names of the right-hand-side variables
e(term_#)	term #
e(errorterm_#)	error term for term # (defined for terms using nonresidual error)
e(wtype)	weight type
e(wexp)	weight expression
e(r2)	R^2 for each equation
e(rmse)	RMSE for each equation
e(F)	F statistic for each equation
e(p_F)	p-value for F test for each equation
e(properties)	b V
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins
e(marginsdefault)	default predict() specification for margins
e(asbalanced)	factor variables fvset as asbalanced
e(asobserved)	factor variables fvset as asobserved

Matrices
e(b)	coefficient vector (a stacked version of e(B))
e(B)	coefficient matrix
e(E)	residual-error SSCP matrix
e(xpxinv)	generalized inverse of X'X
e(H_m)	hypothesis SSCP matrix for the overall model
e(stat_m)	multivariate statistics for the overall model
e(eigvals_m)	eigenvalues of $E^{-1}H$ for the overall model
e(aux_m)	s, m, and n values for the overall model
e(H_#)	hypothesis SSCP matrix for term #
e(stat_#)	multivariate statistics for term # (if computed)
e(eigvals_#)	eigenvalues of $E^{-1}H$ for term # (if computed)
e(aux_#)	s, m, and n values for term # (if computed)
e(V)	variance–covariance matrix of the estimators

Functions
e(sample)	marks estimation sample

Methods and formulas

Let Y denote the matrix of observations on the left-hand-side variables. Let X denote the design matrix based on the right-hand-side variables. The last column of X is equal to all ones (unless the noconstant option was specified). Categorical right-hand-side variables are placed in X as a set of indicator (sometimes called dummy) variables, whereas continuous variables enter as is. Columns of X corresponding to interactions are formed by multiplying the various combinations of columns for the variables involved in the interaction.

The multivariate model

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

leads to multivariate hypotheses of the form

$$\mathbf{C}\boldsymbol{\beta}\mathbf{A}' = \mathbf{0}$$

where $\boldsymbol{\beta}$ is a matrix of parameters, $\mathbf{C}$ specifies constraints on the design matrix $\mathbf{X}$ for a particular hypothesis, and $\mathbf{A}$ provides a transformation of $\mathbf{Y}$. $\mathbf{A}$ is often the identity matrix.

An estimate of $\boldsymbol{\beta}$ is provided by

$$\mathbf{B} = (\mathbf{X}'\mathbf{X})^{-}\mathbf{X}'\mathbf{Y}$$

The error sum of squares and cross products (SSCP) matrix is

$$\mathbf{E} = \mathbf{A}(\mathbf{Y}'\mathbf{Y} - \mathbf{B}'\mathbf{X}'\mathbf{X}\mathbf{B})\mathbf{A}'$$

and the SSCP matrix for the hypothesis is

$$\mathbf{H} = \mathbf{A}(\mathbf{C}\mathbf{B})'\{\mathbf{C}(\mathbf{X}'\mathbf{X})^{-}\mathbf{C}'\}^{-1}(\mathbf{C}\mathbf{B})\mathbf{A}'$$

The inclusion of weights, if specified, enters the formulas in a manner similar to that shown in *Methods and formulas* of [R] **regress**.

Let $\lambda_1 > \lambda_2 > \cdots > \lambda_s$ represent the nonzero eigenvalues of $\mathbf{E}^{-1}\mathbf{H}$. $s = \min(p, \nu_h)$, where p is the number of columns of $\mathbf{Y}\mathbf{A}'$ (that is, the number of y variables or number of resultant transformed left-hand-side variables), and ν_h is the hypothesis degrees of freedom.

Wilks's (1932) lambda statistic is

$$\Lambda = \prod_{i=1}^{s} \frac{1}{1 + \lambda_i} = \frac{|\mathbf{E}|}{|\mathbf{H} + \mathbf{E}|}$$

and is a likelihood-ratio test. This statistic is distributed as the Wilks's Λ distribution if $\mathbf{E}$ has the Wishart distribution, $\mathbf{H}$ has the Wishart distribution under the null hypothesis, and $\mathbf{E}$ and $\mathbf{H}$ are independent. The null hypothesis is rejected for small values of Λ.

Pillai's (1955) trace is

$$V = \sum_{i=1}^{s} \frac{\lambda_i}{1 + \lambda_i} = \text{trace}\left\{(\mathbf{E} + \mathbf{H})^{-1}\mathbf{H}\right\}$$

and the Lawley–Hotelling trace (Lawley 1938; Hotelling 1951) is

$$U = \sum_{i=1}^{s} \lambda_i = \text{trace}(\mathbf{E}^{-1}\mathbf{H})$$

and is also known as Hotelling's generalized T^2 statistic.

Roy's largest root is taken as λ_1, though some report $\theta = \lambda_1/(1+\lambda_1)$, which is bounded between zero and one. Roy's largest root provides a test based on the union-intersection approach to test construction introduced by Roy (1939).

Tables providing critical values for these four multivariate statistics are found in many of the books that discuss MANOVA, including Rencher (1998) and Rencher and Christensen (2012).

Let p be the number of columns of $\mathbf{YA}'$ (that is, the number of y variables or the number of resultant transformed y variables), ν_h be the hypothesis degrees of freedom, ν_e be the error degrees of freedom, $s = \min(\nu_h, p)$, $m = (|\nu_h - p| - 1)/2$, and $n = (\nu_e - p - 1)/2$. Transformations of these four multivariate statistics to F statistics are as follows.

For Wilks's lambda, an approximate F statistic (Rao 1951) with df_1 and df_2 degrees of freedom is

$$F = \frac{(1 - \Lambda^{1/t})\mathrm{df}_2}{(\Lambda^{1/t})\mathrm{df}_1}$$

where

$$\mathrm{df}_1 = p\nu_h \qquad \mathrm{df}_2 = wt + 1 - p\nu_h/2$$
$$w = \nu_e + \nu_h - (p + \nu_h + 1)/2$$
$$t = \left(\frac{p^2\nu_h^2 - 4}{p^2 + \nu_h^2 - 5}\right)^{1/2}$$

t is set to one if either the numerator or the denominator equals zero. This F statistic is exact when p equals 1 or 2 or when ν_h equals 1 or 2.

An approximate F statistic for Pillai's trace (Pillai 1954, 1956b) with $s(2m+s+1)$ and $s(2n+s+1)$ degrees of freedom is

$$F = \frac{(2n + s + 1)V}{(2m + s + 1)(s - V)}$$

An approximate F statistic for the Lawley–Hotelling trace (Pillai 1954, 1956a) with $s(2m+s+1)$ and $2sn + 2$ degrees of freedom is

$$F = \frac{2(sn + 1)U}{s^2(2m + s + 1)}$$

When p or ν_h are 1, an exact F statistic for Roy's largest root is

$$F = \lambda_1 \frac{\nu_e - p + 1}{p}$$

with $|\nu_h - p| + 1$ and $\nu_e - p + 1$ degrees of freedom. In other cases, an upper bound F statistic (providing a lower bound on the p-value) for Roy's largest root is

$$F = \lambda_1 \frac{\nu_e - d + \nu_h}{d}$$

with d and $\nu_e - d + \nu_h$ degrees of freedom, where $d = \max(p, \nu_h)$.

Samuel Stanley Wilks (1906–1964) was born in Texas. He gained degrees in architecture, mathematics, and statistics from North Texas Teachers' College and the universities of Texas and Iowa. After periods in Columbia and England, he moved to Princeton in 1933. Wilks published various widely used texts, was founding editor of the *Annals of Mathematical Statistics*, and made many key contributions to multivariate statistics. Wilks's lambda is named for him.

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Also see

Title

> **manova postestimation** — Postestimation tools for manova

Postestimation commands	predict	margins
manovatest	test	Remarks and examples
Stored results	Methods and formulas	Also see

Postestimation commands

The following postestimation commands are of special interest after `manova`:

Command	Description
manovatest	multivariate tests after `manova`
screeplot	plot eigenvalues

The following standard postestimation commands are also available:

Command	Description
contrast	contrasts and ANOVA-style joint tests of estimates
estat summarize	summary statistics for the estimation sample
estat vce	variance–covariance matrix of the estimators (VCE)
estimates	cataloging estimation results
etable	table of estimation results
lincom	point estimates, standard errors, testing, and inference for linear combinations of coefficients
margins	marginal means, predictive margins, marginal effects, and average marginal effects
marginsplot	graph the results from margins (profile plots, interaction plots, etc.)
nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients
predict	predictions and their SEs, residuals, etc.
predictnl	point estimates, standard errors, testing, and inference for generalized predictions
pwcompare	pairwise comparisons of estimates
test	Wald tests of simple and composite linear hypotheses
testnl	Wald tests of nonlinear hypotheses

predict

Description for predict

predict creates a new variable containing predictions such as fitted values, standard errors, residuals, and differences between the linear predictions.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] *newvar* [*if*] [*in*] [, <u>eq</u>uation(*eqno*[, *eqno*]) *statistic*]

statistic	Description
Main	
xb	$\mathbf{x}_j\mathbf{b}$, fitted values; the default
stdp	standard error of the fitted value
<u>res</u>iduals	residuals
<u>diff</u>erence	difference between the linear predictions of two equations
<u>stddp</u>	standard error of the fitted values for differences

These statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample.

Options for predict

> [Main]

equation(*eqno*[, *eqno*]) specifies the equation to which you are referring.

equation() is filled in with one *eqno* for the xb, stdp, and residuals options. equation(#1) would mean that the calculation is to be made for the first equation (that is, for the first dependent variable), equation(#2) would mean the second, and so on. You could also refer to the equations by their names. equation(income) would refer to the equation named income and equation(hours), to the equation named hours.

If you do not specify equation(), results are the same as if you had specified equation(#1).

difference and stddp refer to between-equations concepts. To use these options, you must specify two equations, for example, equation(#1,#2) or equation(income,hours). When two equations must be specified, equation() is required. With equation(#1,#2), difference computes the prediction of equation(#1) minus the prediction of equation(#2).

xb, the default, calculates the fitted values—the prediction of $\mathbf{x}_j\mathbf{b}$ for the specified equation.

stdp calculates the standard error of the prediction for the specified equation (the standard error of the estimated expected value or mean for the observation's covariate pattern). The standard error of the prediction is also referred to as the standard error of the fitted value.

residuals calculates the residuals.

difference calculates the difference between the linear predictions of two equations in the system.

stddp calculates the standard error of the difference in linear predictions $(\mathbf{x}_{1j}\mathbf{b} - \mathbf{x}_{2j}\mathbf{b})$ between equations 1 and 2.

For more information on using predict after multiple-equation estimation commands, see [R] **predict**.

margins

Description for margins

margins estimates margins of responses for linear predictions, fitted values, and differences between the linear predictions.

Menu for margins

Statistics > Postestimation

Syntax for margins

margins [*marginlist*] [, *options*]

margins [*marginlist*] , <u>predict</u>(*statistic* ...) [<u>predict</u>(*statistic* ...) ...] [*options*]

statistic	Description
default	linear predictions for each equation
xb	$\mathbf{x}_j\mathbf{b}$, fitted values
<u>diff</u>erence	difference between the linear predictions of two equations
<u>r</u>esiduals	not allowed with margins
stdp	not allowed with margins
<u>stddp</u>	not allowed with margins

xb defaults to the first equation.

Statistics not allowed with margins are functions of stochastic quantities other than e(b).

For the full syntax, see [R] **margins**.

manovatest

Description of manovatest

manovatest provides multivariate tests involving *term*s or linear combinations of the underlying design matrix from the most recently fit manova. The four multivariate test statistics are Wilks's lambda, Pillai's trace, Lawley–Hotelling trace, and Roy's largest root. The format of the output is similar to that shown by manova; see [MV] **manova**.

Menu for manovatest

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Multivariate tests after MANOVA

Syntax for manovatest

manovatest *term* $\begin{bmatrix} term \ \dots \end{bmatrix}$ $\begin{bmatrix} / \ term \ \begin{bmatrix} term \ \dots \end{bmatrix} \end{bmatrix}$ $\begin{bmatrix} , \ \underline{yt}ransform(matname) \end{bmatrix}$

manovatest , test(*matname*) $\begin{bmatrix} \underline{yt}ransform(matname) \end{bmatrix}$

manovatest , <u>showorder</u>

where *term* is a term from the *termlist* in the previously run manova.

collect is allowed with manovatest; see [U] **11.1.10 Prefix commands**.

Options for manovatest

ytransform(*matname*) specifies a matrix for transforming the y variables (the *depvarlist* from manova) as part of the test. The multivariate tests are based on $(\mathbf{AEA'})^{-1}(\mathbf{AHA'})$. By default, $\mathbf{A}$ is the identity matrix. ytransform() is how you specify an $\mathbf{A}$ matrix to be used in the multivariate tests. Specifying ytransform() provides the same results as first transforming the y variables with $\mathbf{YA'}$, where $\mathbf{Y}$ is the matrix formed by binding the y variables by column and $\mathbf{A}$ is the matrix stored in *matname*; then performing manova on the transformed y's; and finally running manovatest without ytransform().

The number of columns of *matname* must equal the number of variables in the *depvarlist* from manova. The number of rows must be less than or equal to the number of variables in the *depvarlist* from manova. *matname* should have columns in the same order as the *depvarlist* from manova. The column and row names of *matname* are ignored.

When ytransform() is specified, a listing of the transformations is presented before the table containing the multivariate tests. You should examine this table to verify that you have applied the transformation you desired.

test(*matname*) is required with the second syntax of manovatest. The rows of *matname* specify linear combinations of the underlying design matrix of the MANOVA that are to be jointly tested. The columns correspond to the underlying design matrix (including the constant if it has not been suppressed). The column and row names of *matname* are ignored.

A listing of the constraints imposed by the test() option is presented before the table containing the multivariate tests. You should examine this table to verify that you have applied the linear combinations you desired. Typing manovatest, showorder allows you to examine the ordering of the columns for the design matrix from the MANOVA.

showorder causes manovatest to list the definition of each column in the design matrix. showorder is not allowed with any other option or when *term*s are specified.

test

Description for test

In addition to the standard syntax of test (see [R] **test**), test after manova has two additionally allowed syntaxes; see below. test performs Wald tests of expressions involving the coefficients of the underlying regression model. Simple and composite linear hypotheses are possible.

Menu for test

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Wald test after MANOVA

Syntax for test

In addition to the standard syntax of test (see [R] **test**), test after manova also allows the following.

<u>test</u> , test(*matname*) [<u>m</u>test[(*opt*)] matvlc(*matname*)]   syntax A

<u>test</u> , <u>showorder</u>   syntax B

| syntax A | test expression involving the coefficients of the underlying multivariate regression model; you provide information as a matrix |
| syntax B | show underlying order of design matrix, which is useful when constructing the *matname* argument of the test() option |

Options for test

      Main

test(*matname*) is required with syntax A of test. The rows of *matname* specify linear combinations of the underlying design matrix of the MANOVA that are to be jointly tested. The columns correspond to the underlying design matrix (including the constant if it has not been suppressed). The column and row names of *matname* are ignored.

    A listing of the constraints imposed by the test() option is presented before the table containing the tests. You should examine this table to verify that you have applied the linear combinations you desired. Typing test, showorder allows you to examine the ordering of the columns for the design matrix from the MANOVA.

    matname should have as many columns as the number of dependent variables times the number of columns in the basic design matrix. The design matrix is repeated for each dependent variable.

showorder causes test to list the definition of each column in the design matrix. showorder is not allowed with any other option.

      Options

mtest[(*opt*)] specifies that tests be performed for each condition separately. *opt* specifies the method for adjusting *p*-values for multiple testing. Valid values for *opt* are

<u>b</u>onferroni	Bonferroni's method
<u>h</u>olm	Holm's method
<u>s</u>idak	Šidák's method
<u>noadjust</u>	no adjustment is to be made

Specifying mtest without an argument is equivalent to specifying mtest(noadjust).

The following option is available with `test` after `manova` but is not shown in the dialog box:

matvlc(*matname*), a programmer's option, saves the variance–covariance matrix of the linear combinations involved in the suite of tests. For the test of H_0: $\mathbf{Lb} = \mathbf{c}$, what is returned in *matname* is $\mathbf{LVL'}$, where $\mathbf{V}$ is the estimated variance–covariance matrix of $\mathbf{b}$.

Remarks and examples

Several postestimation tools are available after `manova`. We demonstrate these tools by extending examples 1, 2, 4, and 8 of [MV] **manova**.

▷ Example 1: test and lincom

Example 1 of [MV] **manova** presented a balanced one-way MANOVA on the rootstock data.

```
. use https://www.stata-press.com/data/r18/rootstock
(Table 6.2. Rootstock data, Rencher and Christensen (2012))
. manova y1 y2 y3 y4 = rootstock
(output omitted )
```

`test` provides Wald tests on expressions involving the underlying coefficients of the model, and `lincom` provides linear combinations along with standard errors and confidence intervals.

```
. test [y3]3.rootstock = ([y3]1.rootstock + [y3]2.rootstock)/2
 ( 1)  - .5*[y3]1b.rootstock - .5*[y3]2.rootstock + [y3]3.rootstock = 0
       F(  1,    42) =     5.62
            Prob > F =    0.0224
. lincom [y3]4.rootstock - [y1]4.rootstock
 ( 1)  - [y1]4.rootstock + [y3]4.rootstock = 0
```

	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
(1)	.2075001	.1443917	1.44	0.158	−.0838941	.4988943

If the equation portion of the expression is omitted, the first equation (first dependent variable) is assumed.

◁

The `manovatest` postestimation command provides multivariate tests of *term*s or linear combinations of the underlying design matrix from the most recent MANOVA model.

▷ Example 2: manovatest

In example 2 of [MV] **manova**, a one-way MANOVA on the metabolic dataset was shown.

```
. use https://www.stata-press.com/data/r18/metabolic
(Table 4.5. Metabolic comparisons of rabbits, Rencher (1998))
. manova y1 y2 = group
(output omitted )
```

`manovatest` can test *term*s from the preceding `manova`. Here we test the `group` term from our one-way MANOVA:

```
. manovatest group
                       W = Wilks' lambda       L = Lawley-Hotelling trace
                       P = Pillai's trace      R = Roy's largest root
          Source │ Statistic         df     F(df1,    df2) =    F    Prob>F

           group │ W    0.1596          3       6.0     32.0     8.02 0.0000 e
                 │ P    1.2004                  6.0     34.0     8.51 0.0000 a
                 │ L    3.0096                  6.0     30.0     7.52 0.0001 a
                 │ R    1.5986                  3.0     17.0     9.06 0.0008 u

        Residual │                     17

                 e = exact, a = approximate, u = upper bound on F
```

Using `manovatest` to test model *term*s is not interesting here. It merely repeats information already presented by `manova`. Later we will see useful applications of *term* testing via `manovatest`.

`manovatest` can also be used to test linear combinations of the underlying design matrix of the MANOVA model. Whereas the MANOVA indicates that there are differences in the groups, it does not indicate the nature of those differences. Rencher discusses three linear contrasts of interest for this example: group one (the control) versus the rest, group four versus groups two and three, and group two versus group three. The `test()` option of `manovatest` allows us to test these hypotheses.

Because we did not use the `noconstant` option with our `manova`, the underlying parameterization of the design matrix has the last column corresponding to the constant in the model, whereas the first four columns correspond to the four groups of rabbits. The `showorder` option of `manovatest` illustrates this point. The tests on the three contrasts of interest follow.

```
. manovatest, showorder
Order of columns in the design matrix
       1: (group==1)
       2: (group==2)
       3: (group==3)
       4: (group==4)
       5: _cons
. matrix c1 = (3,-1,-1,-1,0)
. manovatest, test(c1)
Test constraint
 (1)    3*1.group - 2.group - 3.group - 4.group = 0
                       W = Wilks' lambda       L = Lawley-Hotelling trace
                       P = Pillai's trace      R = Roy's largest root
          Source │ Statistic         df     F(df1,    df2) =    F    Prob>F

      manovatest │ W    0.4063          1       2.0     16.0    11.69 0.0007 e
                 │ P    0.5937                  2.0     16.0    11.69 0.0007 e
                 │ L    1.4615                  2.0     16.0    11.69 0.0007 e
                 │ R    1.4615                  2.0     16.0    11.69 0.0007 e

        Residual │                     17

                 e = exact, a = approximate, u = upper bound on F
. matrix c2 = (0,-1,-1,2,0)
```

```
. manovatest, test(c2)

Test constraint
 (1)    - 2.group - 3.group + 2*4.group = 0
```

	W = Wilks' lambda		L = Lawley-Hotelling trace		
	P = Pillai's trace		R = Roy's largest root		
Source	Statistic	df	F(df1, | df2) =	F	Prob>F

Source		Statistic	df	F(df1,	df2) =	F	Prob>F
manovatest	W	0.9567	1	2.0	16.0	0.36	0.7018 e
	P	0.0433		2.0	16.0	0.36	0.7018 e
	L	0.0453		2.0	16.0	0.36	0.7018 e
	R	0.0453		2.0	16.0	0.36	0.7018 e
Residual			17				

```
              e = exact, a = approximate, u = upper bound on F
. matrix c3 = (0,1,-1,0,0)

. manovatest, test(c3)

Test constraint
 (1)    2.group - 3.group = 0
```

	W = Wilks' lambda		L = Lawley-Hotelling trace		
	P = Pillai's trace		R = Roy's largest root		

Source		Statistic	df	F(df1,	df2) =	F	Prob>F
manovatest	W	0.4161	1	2.0	16.0	11.23	0.0009 e
	P	0.5839		2.0	16.0	11.23	0.0009 e
	L	1.4033		2.0	16.0	11.23	0.0009 e
	R	1.4033		2.0	16.0	11.23	0.0009 e
Residual			17				

```
              e = exact, a = approximate, u = upper bound on F
```

Because there is only 1 degree of freedom for each of the hypotheses, the F tests are exact (and identical for the four multivariate methods). The first test indicates that the mean vector for the control group is significantly different from the mean vectors for the other three groups. The second test, with a p-value of 0.7018, fails to reject the null hypothesis that group four equals groups two and three. The third test, with a p-value of 0.0009, indicates differences between the mean vectors of groups two and three.

Rencher also tests using weighted orthogonal contrasts. `manovatest` can do these tests as well.

```
. matrix c1w = (14,-7,-5,-2,0)

. manovatest, test(c1w)

Test constraint
 (1)    14*1.group - 7*2.group - 5*3.group - 2*4.group = 0
```

	W = Wilks' lambda		L = Lawley-Hotelling trace		
	P = Pillai's trace		R = Roy's largest root		

Source		Statistic	df	F(df1,	df2) =	F	Prob>F
manovatest	W	0.3866	1	2.0	16.0	12.70	0.0005 e
	P	0.6134		2.0	16.0	12.70	0.0005 e
	L	1.5869		2.0	16.0	12.70	0.0005 e
	R	1.5869		2.0	16.0	12.70	0.0005 e
Residual			17				

```
              e = exact, a = approximate, u = upper bound on F
. matrix c2w = (0,-7,-5,12,0)
```

```
. manovatest, test(c2w)

 Test constraint
 (1)    -7*2.group - 5*3.group + 12*4.group = 0
                          W = Wilks' lambda       L = Lawley-Hotelling trace
                          P = Pillai's trace      R = Roy's largest root
            Source │  Statistic          df    F(df1,     df2) =   F    Prob>F
        ───────────┼────────────────────────────────────────────────────────
        manovatest │W    0.9810            1      2.0       16.0    0.15 0.8580 e
                   │P    0.0190                   2.0       16.0    0.15 0.8580 e
                   │L    0.0193                   2.0       16.0    0.15 0.8580 e
                   │R    0.0193                   2.0       16.0    0.15 0.8580 e
        ───────────┼────────────────────────────────────────────────────────
          Residual │                      17
        ───────────┴────────────────────────────────────────────────────────
                     e = exact, a = approximate, u = upper bound on F
```

These two weighted contrasts do not lead to different conclusions compared with their unweighted counterparts.

◁

❑ Technical note

manovatest, test(*matname*) displays the linear combination (labeled "Test constraint") indicated by *matname*. You should examine this listing to make sure that the matrix you specify in test() provides the test you want.

❑

The margins postestimation command provides, among other things, tables of predicted means and confidence intervals that are based on the most recently fit model.

▷ Example 3: Margins, contrasts, and predictions

Example 4 of [MV] **manova** presented a two-way MANOVA model on the jaw data.

```
. use https://www.stata-press.com/data/r18/jaw
(Table 4.6. Two-way unbalanced data for fractures of the jaw, Rencher (1998))
. manova y1 y2 y3 = gender fracture gender#fracture
  (output omitted)
```

The interaction term, gender#fracture, was significant. margins may be used to examine the interaction; see [R] **margins**.

```
. margins gender#fracture, predict(equation(y1))
```

Adjusted predictions   Number of obs = 27

Expression: Linear prediction, predict(equation(y1))

	Margin	Delta-method std. err.	t	P>|t|	[95% conf. interval]	
gender# fracture						
Male # One compou..	39.5	4.171386	9.47	0.000	30.82513	48.17487
Male # Two compou..	26.875	3.612526	7.44	0.000	19.36234	34.38766
Male # One simple..	45.16667	4.171386	10.83	0.000	36.49179	53.84154
Female # One compou..	22	10.21777	2.15	0.043	.7509887	43.24901
Female # Two compou..	30.75	5.108884	6.02	0.000	20.12549	41.37451
Female # One simple..	36.5	7.225053	5.05	0.000	21.47468	51.52532

```
. margins gender#fracture, predict(equation(y2))
```

Adjusted predictions   Number of obs = 27

Expression: Linear prediction, predict(equation(y2))

	Margin	Delta-method std. err.	t	P>|t|	[95% conf. interval]	
gender# fracture						
Male # One compou..	35.5	2.150966	16.50	0.000	31.02682	39.97318
Male # Two compou..	32.375	1.862791	17.38	0.000	28.50111	36.24889
Male # One simple..	36.16667	2.150966	16.81	0.000	31.69349	40.63984
Female # One compou..	56	5.268768	10.63	0.000	45.043	66.957
Female # Two compou..	33.25	2.634384	12.62	0.000	27.7715	38.7285
Female # One simple..	33	3.725582	8.86	0.000	25.25223	40.74777

```
. margins gender#fracture, predict(equation(y3))
```
Adjusted predictions   Number of obs = 27
Expression: Linear prediction, predict(equation(y3))

	Margin	Delta-method std. err.	t	P>|t|	[95% conf. interval]	
gender# fracture						
Male # One compou..	61.16667	2.038648	30.00	0.000	56.92707	65.40627
Male # Two compou..	62.25	1.765521	35.26	0.000	58.5784	65.9216
Male # One simple..	58.16667	2.038648	28.53	0.000	53.92707	62.40627
Female # One compou..	43	4.993647	8.61	0.000	32.61514	53.38486
Female # Two compou..	64	2.496823	25.63	0.000	58.80757	69.19243
Female # One simple..	63.5	3.531041	17.98	0.000	56.1568	70.8432

The first `margins` table shows the predicted mean (marginal mean), standard error, z statistic, p-value, and confidence interval of y1 (age of patient) for each combination of `fracture` and `gender`. The second and third `margins` tables provide this information for y2 (blood lymphocytes) and y3 (blood polymorphonuclears). These three tables of predictions are the same as those you would obtain from `margins` after running `anova` for each of the three dependent variables separately.

The predicted y2 value is larger than the predicted y3 value for females with one compound fracture. For the other five combinations of `gender` and `fracture`, the relationship is reversed. There is only 1 observation for the combination of female and one compound fracture.

There are nine possible contrasts if we contrast women with men for every fracture type and every dependent variable. We will use `contrast` to estimate all nine contrasts and apply Scheffé's adjustment for multiple comparisons.

```
. contrast gender@fracture#_eqns, mcompare(scheffe)
```
Contrasts of marginal linear predictions

Margins: asbalanced

	df	F	P>F	Scheffe P>F
gender@fracture#_eqns				
One compound fracture 1	1	2.51	0.1278	0.9733
One compound fracture 2	1	12.98	0.0017	0.2333
One compound fracture 3	1	11.34	0.0029	0.3137
Two compound fractures 1	1	0.38	0.5424	1.0000
Two compound fractures 2	1	0.07	0.7889	1.0000
Two compound fractures 3	1	0.33	0.5732	1.0000
One simple fracture 1	1	1.08	0.3107	0.9987
One simple fracture 2	1	0.54	0.4698	0.9999
One simple fracture 3	1	1.71	0.2050	0.9929
Joint	9	2.57	0.0361	
Denominator	21			

Note: Scheffe-adjusted p-values are reported for tests on individual
      contrasts only.

	Number of comparisons
gender@fracture#_eqns	9

	Contrast	Std. err.	Scheffe [95% conf. interval]	
gender@fracture#_eqns				
(Female vs base)				
One compound fracture 1	-17.5	11.03645	-68.42869	33.42869
(Female vs base)				
One compound fracture 2	20.5	5.69092	-5.76126	46.76126
(Female vs base)				
One compound fracture 3	-18.16667	5.393755	-43.05663	6.723297
(Female vs base)				
Two compound fractures 1	3.875	6.257079	-24.99885	32.74885
(Female vs base)				
Two compound fractures 2	.875	3.226449	-14.01373	15.76373
(Female vs base)				
Two compound fractures 3	1.75	3.057972	-12.36128	15.86128
(Female vs base)				
One simple fracture 1	-8.666667	8.342772	-47.16513	29.8318
(Female vs base)				
One simple fracture 2	-3.166667	4.301931	-23.01831	16.68498
(Female vs base)				
One simple fracture 3	5.333333	4.077296	-13.48171	24.14838

Women do not differ significantly from men in any of the nine comparisons.

Let's examine the residuals with the `predict` command:

```
. predict y1res, residual equation(y1)
. predict y2res, residual equation(y2)
. predict y3res, residual equation(y3)
. list gender fracture y1res y2res y3res
```

	gender	fracture	y1res	y2res	y3res
1.	Male	One compound fracture	2.5	-.5	-.1666667
2.	Male	One compound fracture	2.5	7.5	-6.166667
3.	Male	One compound fracture	8.5	-.5	2.833333
4.	Male	One compound fracture	-4.5	-2.5	3.833333
5.	Male	One compound fracture	-14.5	-4.5	2.833333
6.	Male	One compound fracture	5.5	.5	-3.166667
7.	Male	Two compound fractures	-3.875	-5.375	1.75
8.	Male	Two compound fractures	-4.875	-.375	1.75
9.	Male	Two compound fractures	-1.875	-2.375	1.75
10.	Male	Two compound fractures	1.125	6.625	-6.25
11.	Male	Two compound fractures	-2.875	-1.375	6.75
12.	Male	Two compound fractures	25.125	-4.375	-2.25
13.	Male	Two compound fractures	-9.875	-2.375	1.75
14.	Male	Two compound fractures	-2.875	9.625	-5.25
15.	Male	One simple fracture	-13.16667	.8333333	-4.166667
16.	Male	One simple fracture	6.833333	-2.166667	3.833333
17.	Male	One simple fracture	7.833333	8.833333	-7.166667
18.	Male	One simple fracture	3.833333	-1.166667	1.833333
19.	Male	One simple fracture	9.833333	-4.166667	1.833333
20.	Male	One simple fracture	-15.16667	-2.166667	3.833333
21.	Female	One compound fracture	0	0	-2.84e-14
22.	Female	Two compound fractures	-8.75	-4.25	4
23.	Female	Two compound fractures	7.25	-8.25	9
24.	Female	Two compound fractures	-9.75	3.75	-5
25.	Female	Two compound fractures	11.25	8.75	-8
26.	Female	One simple fracture	6.5	-3	3.5
27.	Female	One simple fracture	-6.5	3	-3.5

The single observation for a female with one compound fracture has residuals that are within roundoff of zero. With only 1 observation for that cell of the design, this MANOVA model is forced to fit to that point. The largest residual (in absolute value) appears for observation 12, which has an age 25.125 higher than the model prediction for a male with two compound fractures.

◁

▷ Example 4: manovatest

Example 8 of [MV] **manova** presents a nested MANOVA on the `videotrainer` data.

```
. use https://www.stata-press.com/data/r18/videotrainer, clear
(Video training)
. manova primary extra = video / store|video / associate|store|video /,
> dropemptycells
  (output omitted )
```

The MANOVA indicated that `store` was not significant.

You decide to follow the rule of thumb that says to pool terms whose p-values are larger than 0.25. Wilks's lambda reports a p-value of 0.5775 for the test of `store|video` (see example 8 of [MV] **manova**). You decide to pool the `store` and `associate` terms in the MANOVA to gain power for the test of `video`. The forward-slash notation of `manova` is also allowed with `manovatest` to indicate nonresidual error terms. Here is the multivariate test of `video` using the pooled `store` and `associate` terms and then the multivariate test of the pooled term:

```
. manovatest video / store|video associate|store|video
                        W = Wilks' lambda      L = Lawley-Hotelling trace
                        P = Pillai's trace     R = Roy's largest root
            Source | Statistic        df    F(df1,    df2) =   F   Prob>F
            -------+-------------------------------------------------------
             video |W    0.4079         1     2.0       9.0    6.53 0.0177 e
                   |P    0.5921               2.0       9.0    6.53 0.0177 e
                   |L    1.4516               2.0       9.0    6.53 0.0177 e
                   |R    1.4516               2.0       9.0    6.53 0.0177 e
            -------+-------------------------------------------------------
       store|video |                    10
  associate|store| |
             video |
            -------+-------------------------------------------------------
              e = exact, a = approximate, u = upper bound on F
. manovatest store|video associate|store|video
                        W = Wilks' lambda      L = Lawley-Hotelling trace
                        P = Pillai's trace     R = Roy's largest root
            Source | Statistic        df    F(df1,    df2) =   F   Prob>F
            -------+-------------------------------------------------------
       store|video |W    0.3925        10    20.0      58.0    1.73 0.0546 e
  associate|store| |P    0.7160              20.0      60.0    1.67 0.0647 a
             video |L    1.2711              20.0      56.0    1.78 0.0469 a
                   |R    0.9924              10.0      30.0    2.98 0.0100 u
            -------+-------------------------------------------------------
          Residual |                    30
            -------+-------------------------------------------------------
              e = exact, a = approximate, u = upper bound on F
```

Pooling `store` with `associate` helps increase the power for the test of `video`.

You can show the univariate analysis for one of your dependent variables by using the `ytransform()` option of `manovatest`:

```
. mat primonly = (1,0)
. manovatest video / store|video associate|store|video, ytransform(primonly)
```

Transformation of the dependent variables
(1)   primary

```
                        W = Wilks' lambda        L = Lawley-Hotelling trace
                        P = Pillai's trace       R = Roy's largest root
            Source │ Statistic        df    F(df1,     df2) =    F   Prob>F
        ───────────┼──────────────────────────────────────────────────────
             video │W    0.8449         1     1.0      10.0     1.84 0.2053 e
                   │P    0.1551               1.0      10.0     1.84 0.2053 e
                   │L    0.1835               1.0      10.0     1.84 0.2053 e
                   │R    0.1835               1.0      10.0     1.84 0.2053 e
                   │
       store|video │                    10
  associate|store| │
             video │
        ───────────┴──────────────────────────────────────────────────────
```

            e = exact, a = approximate, u = upper bound on F

```
. manovatest store|video associate|store|video, ytransform(primonly)
```

Transformation of the dependent variables
(1)   primary

```
                        W = Wilks' lambda        L = Lawley-Hotelling trace
                        P = Pillai's trace       R = Roy's largest root
            Source │ Statistic        df    F(df1,     df2) =    F   Prob>F
        ───────────┼──────────────────────────────────────────────────────
       store|video │W    0.6119         10   10.0      30.0     1.90 0.0846 e
  associate|store| │P    0.3881              10.0      30.0     1.90 0.0846 e
             video │L    0.6344              10.0      30.0     1.90 0.0846 e
                   │R    0.6344              10.0      30.0     1.90 0.0846 e
                   │
          Residual │                    30
        ───────────┴──────────────────────────────────────────────────────
```

            e = exact, a = approximate, u = upper bound on F

See the second `manova` run from example 8 of [MV] **manova** for an alternate way of pooling the terms by refitting the MANOVA model.

◁

See examples 6, 10, 11, 12, and 13 of [MV] **manova** for more examples of `manovatest`, including examples involving both the `test()` and the `ytransform()` options.

Stored results

manovatest stores the following in r():

Scalars
    r(df)   hypothesis degrees of freedom
    r(df_r)   residual degrees of freedom

Matrices
    r(H)   hypothesis SSCP matrix
    r(E)   residual-error SSCP matrix
    r(stat)   multivariate statistics
    r(eigvals)   eigenvalues of $E^{-1}H$
    r(aux)   s, m, and n values

test after manova stores the following in r():

Scalars
    r(p)   two-sided p-value
    r(F) F statistic
    r(df)   hypothesis degrees of freedom
    r(df_r)   residual degrees of freedom
    r(drop)   0 if no constraints dropped, 1 otherwise
    r(dropped_#) index of #th constraint dropped

Macros
    r(mtmethod) method of adjustment for multiple testing

Matrices
    r(mtest)   multiple test results

Methods and formulas

See [MV] **manova** for methods and formulas for the multivariate tests performed by manovatest.

Also see

[MV] **manova** — Multivariate analysis of variance and covariance

[MV] **screeplot** — Scree plot of eigenvalues

[U] **20 Estimation and postestimation commands**

Title

> **matrix dissimilarity** — Compute similarity or dissimilarity measures

Description   Syntax   Options   Remarks and examples   References   Also see

Description

matrix dissimilarity computes a similarity, dissimilarity, or distance matrix.

Syntax

matrix dissimilarity *matname* = [*varlist*] [*if*] [*in*] [, *options*]

options	Description
measure	similarity or dissimilarity measure; default is L2 (Euclidean)
observations	compute similarities or dissimilarities between observations; the default
variables	compute similarities or dissimilarities between variables
names(*varname*)	row/column names for *matname* (allowed with observations)
allbinary	check that all values are 0, 1, or missing
proportions	interpret values as proportions of binary values
dissim(*method*)	change similarity measure to dissimilarity measure

where *method* transforms similarities to dissimilarities by using

$$
\begin{array}{ll}
\text{oneminus} & d_{ij} = 1 - s_{ij} \\
\underline{\text{st}}\text{andard} & d_{ij} = \sqrt{s_{ii} + s_{jj} - 2s_{ij}}
\end{array}
$$

Options

measure specifies one of the similarity or dissimilarity measures allowed by Stata. The default is L2, Euclidean distance. Many similarity and dissimilarity measures are provided for continuous data and for binary data; see [MV] *measure_option*.

observations and variables specify whether similarities or dissimilarities are computed between observations or variables. The default is observations.

names(*varname*) provides row and column names for *matname*. *varname* must be a string variable with a length of 32 or less in bytes. You will want to pick a *varname* that yields unique values for the row and column names. Uniqueness of values is not checked by matrix dissimilarity. names() is not allowed with the variables option. The default row and column names when the similarities or dissimilarities are computed between observations is obs#, where # is the observation number corresponding to that row or column.

allbinary checks that all values are 0, 1, or missing. Stata treats nonzero values as one (excluding missing values) when dealing with what are supposed to be binary data (including binary similarity *measure*s). allbinary causes matrix dissimilarity to exit with an error message if the values are not truly binary. allbinary is not allowed with proportions or the Gower *measure*.

proportions is for use with binary similarity *measure*s. It specifies that values be interpreted as proportions of binary values. The default action treats all nonzero values as one (excluding missing values). With proportions, the values are confirmed to be between zero and one, inclusive. See [MV] *measure_option* for a discussion of the use of proportions with binary *measure*s. proportions is not allowed with allbinary or the Gower *measure*.

dissim(*method*) specifies that similarity measures be transformed into dissimilarity measures. *method* may be oneminus or standard. oneminus transforms similarities to dissimilarities by using $d_{ij} = 1 - s_{ij}$ (Kaufman and Rousseeuw 1990, 21). standard uses $d_{ij} = \sqrt{s_{ii} + s_{jj} - 2s_{ij}}$ (Mardia, Kent, and Bibby 1979, 402). dissim() does nothing when the *measure* is already a dissimilarity or distance. See [MV] *measure_option* to see which *measure*s are similarities.

Remarks and examples

Commands such as cluster singlelinkage, cluster completelinkage, and mds (see [MV] **cluster** and [MV] **mds**) have options allowing the user to select the similarity or dissimilarity measure to use for its computation. If you are developing a command that requires a similarity or dissimilarity matrix, the matrix dissimilarity command provides a convenient way to obtain it.

The similarity or dissimilarity between each observation (or variable if the variables option is specified) and the others is placed in *matname*. The element in the ith row and jth column gives either the similarity or dissimilarity between the ith and jth observation (or variable). Whether you get a similarity or a dissimilarity depends upon the requested *measure*; see [MV] *measure_option*.

If the number of observations (or variables) is so large that storing the results in a matrix is not practical, you may wish to consider using the cluster measures command, which stores similarities or dissimilarities in variables; see [MV] **cluster programming utilities**.

When computing similarities or dissimilarities between observations, the default row and column names of *matname* are set to obs#, where # is the observation number. The names() option allows you to override this default. For similarities or dissimilarities between variables, the row and column names of *matname* are set to the appropriate variable names.

The order of the rows and columns corresponds with the order of your observations when you are computing similarities or dissimilarities between observations. Warning: If you reorder your data (for example, using sort or gsort) after running matrix dissimilarity, the row and column ordering will no longer match your data.

Another use of matrix dissimilarity is in performing a cluster analysis on variables instead of observations. The cluster command performs a cluster analysis of the observations; see [MV] **cluster**. If you instead wish to cluster variables, you can use the variables option of matrix dissimilarity to obtain a dissimilarity matrix that can then be used with clustermat; see [MV] **clustermat** and example 2 below.

▷ Example 1

Example 1 of [MV] **cluster linkage** introduces data with four chemical laboratory measurements on 50 different samples of a particular plant. Let's find the Canberra distance between the measurements performed by lab technician Bill found among the first 25 observations of the labtech dataset.

```
. use https://www.stata-press.com/data/r18/labtech
. matrix dissim D = x1 x2 x3 x4 if labtech=="Bill" in 1/25, canberra
. matrix list D
symmetric D[6,6]
             obs7        obs18       obs20       obs22       obs23       obs25
 obs7           0
obs18   1.3100445           0
obs20   1.1134916   .87626565           0
obs22    1.452748   1.0363077   1.0621064           0
obs23   1.0380665   1.4952796   .81602718   1.6888123           0
obs25   1.4668898   1.5139834   1.4492336   1.0668425   1.1252514           0
```

By default, the row and column names of the matrix indicate the observations involved. The Canberra distance between the 23rd observation and the 18th observation is 1.4952796. See [MV] *measure_option* for a description of the Canberra distance.

◁

▷ Example 2

Example 2 of [MV] **cluster linkage** presents a dataset with 30 observations of 60 binary variables, a1, a2, . . . , a30. In [MV] **cluster linkage**, the observations were clustered. Here we instead cluster the variables by computing the dissimilarity matrix by using matrix dissimilarity with the variables option followed by the clustermat command.

We use the matching option to obtain the simple matching similarity coefficient but then specify dissim(oneminus) to transform the similarities to dissimilarities by using the transformation $d_{ij} = 1 - s_{ij}$. The allbinary option checks that the variables really are binary (0/1) data.

```
. use https://www.stata-press.com/data/r18/homework
. matrix dissim Avars = a*, variables matching dissim(oneminus) allbinary
. matrix subA = Avars[1..5,1..5]
. matrix list subA
symmetric subA[5,5]
             a1          a2          a3          a4          a5
a1            0
a2           .4           0
a3           .4   .46666667           0
a4           .3          .3   .36666667           0
a5           .4          .4   .13333333          .3           0
```

We listed the first five rows and columns of the 60×60 matrix. The matrix row and column names correspond to the variable names.

To perform an average-linkage cluster analysis on the 60 variables, we supply the Avars matrix created by matrix dissimilarity to the clustermat averagelinkage command; see [MV] **cluster linkage**.

```
. clustermat averagelinkage Avars, clear
Number of observations (_N) was 0, now 60.
cluster name: _clus_1
. cluster generate g5 = groups(5)
. table g5
```

	Frequency
g5	
1	21
2	9
3	25
4	4
5	1
Total	60

We generated a variable, g5, indicating the five-group cluster solution and then tabulated to show how many variables were clustered into each of the five groups. Group five has only one member.

```
. list g5 if g5==5
```

	g5
13.	5

The member corresponds to the 13th observation in the current dataset, which in turn corresponds to variable a13 from the original dataset. It appears that a13 is not like the other variables.

◁

▷ Example 3

matrix dissimilarity drops observations containing missing values, except when the Gower measure is specified. The computation of the Gower dissimilarity between 2 observations is based on the variables where the 2 observations both have nonmissing values.

We illustrate using a dataset with 6 observations and 4 variables where only 2 of the observations have complete data.

```
. use https://www.stata-press.com/data/r18/gower, clear
. list
```

	b1	b2	x1	x2
1.	0	1	.76	.75
2.	.	.	.	.
3.	1	0	.72	.88
4.	.	1	.4	.
5.	0	.	.	.14
6.	0	0	.55	.

```
. matrix dissimilarity matL2 = b* x*, L2
. matlist matL2, format(%8.3f)
```

	obs1	obs3
obs1	0.000	
obs3	1.421	0.000

The resulting matrix is 2×2 and provides the dissimilarity between observations 1 and 3. All other observations contained at least one missing value.

However, with the `gower` measure we obtain a 6×6 matrix.

```
. matrix dissimilarity matgow = b1 b2 x1 x2, gower
. matlist matgow, format(%8.3f)
```

	obs1	obs2	obs3	obs4	obs5	obs6
obs1	0.000					
obs2	.	0.000				
obs3	0.572	.	0.000			
obs4	0.500	.	0.944	0.000		
obs5	0.412	.	1.000	.	0.000	
obs6	0.528	.	0.491	0.708	0.000	0.000

Because all the values for observation 2 are missing, the matrix contains missing values for the dissimilarity between observation 2 and the other observations. Notice the missing value in `matgow` for the dissimilarity between observations 4 and 5. There were no variables where observations 4 and 5 both had nonmissing values, and hence the Gower coefficient could not be computed.

◁

References

Kaufman, L., and P. J. Rousseeuw. 1990. *Finding Groups in Data: An Introduction to Cluster Analysis*. New York: Wiley.

Mardia, K. V., J. T. Kent, and J. M. Bibby. 1979. *Multivariate Analysis*. London: Academic Press.

Also see

[MV] **cluster** — Introduction to cluster-analysis commands

[MV] **cluster programming utilities** — Cluster-analysis programming utilities

[MV] **clustermat** — Introduction to clustermat commands

[MV] **mdsmat** — Multidimensional scaling of proximity data in a matrix

[MV] *measure_option* — Option for similarity and dissimilarity measures

[P] **matrix** — Introduction to matrix commands

Title

> **mca —** Multiple and joint correspondence analysis

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[References](#)	[Also see](#)		

Description

mca performs multiple correspondence analysis (MCA) or joint correspondence analysis (JCA) on a series of categorical variables. MCA and JCA are two generalizations of correspondence analysis (CA) of a cross-tabulation of two variables (see [MV] **ca**) to the cross-tabulation of multiple variables.

mca performs an analysis of two or more integer-valued variables. Crossing (also called stacking) of integer-valued variables is also allowed.

Quick start

Multiple and joint correspondence analysis

Correspondence analysis of the multiway cross-tabulation of catvar1, catvar2, and catvar3
    mca catvar1 catvar2 catvar3

Also produce the MCA coordinate plot
    mca catvar1 catvar2 catvar3, plot

Use 3 dimensions instead of 2, and display the tables compactly
    mca catvar1 catvar2 catvar3, dimensions(3) compact

Use principal normalization instead of the default standard normalization
    mca catvar1 catvar2 catvar3, normalize(principal)

Joint correspondence analysis of catvar1, catvar2, and catvar3
    mca catvar1 catvar2 catvar3, method(joint)

Multiple and joint correspondence analysis with crossed (stacked) variables

Multiple correspondence analysis of the multiway tabulation of catvar1, catvar2 and the crossed variables catvar3 and catvar4 with the crossed variables called z
    mca catvar1 catvar2 (z: catvar3 catvar4)

Same as above, but joint correspondence analysis
    mca catvar1 catvar2 (z: catvar3 catvar4), method(joint)

Menu

Statistics > Multivariate analysis > Correspondence analysis > Multiple correspondence analysis (MCA)

Syntax

Basic syntax for two or more categorical variables

> mca *varlist* [*if*] [*in*] [*weight*] [, *options*]

Full syntax for use with two or more categorical or crossed (stacked) categorical variables

> mca *speclist* [*if*] [*in*] [*weight*] [, *options*]

where

> *speclist* = *spec* [*spec* ...]
>
> *spec* = *varlist* | (*newvar* : *varlist*)

options	Description
[Model]	
<u>supp</u>lementary(*speclist*)	supplementary (passive) variables
<u>meth</u>od(<u>b</u>urt)	use the Burt matrix approach to MCA; the default
<u>meth</u>od(<u>i</u>ndicator)	use the indicator matrix approach to MCA
<u>meth</u>od(<u>j</u>oint)	perform a joint correspondence analysis (JCA)
<u>dim</u>ensions(*#*)	number of dimensions (factors, axes); default is dim(2)
<u>norm</u>alize(<u>s</u>tandard)	display standard coordinates; the default
<u>norm</u>alize(<u>p</u>rincipal)	display principal coordinates
<u>iter</u>ate(*#*)	maximum number of method(joint) iterations; default is iterate(250)
<u>tol</u>erance(*#*)	tolerance for method(joint) convergence criterion; default is tolerance(1e-5)
<u>miss</u>ing	treat missing values as ordinary values
<u>noadj</u>ust	suppress the adjustment of eigenvalues (method(burt) only)
[Codes]	
<u>report</u>(<u>var</u>iables)	report coding of crossing variables
<u>report</u>(<u>c</u>rossed)	report coding of crossed variables
<u>report</u>(<u>al</u>l)	report coding of crossing and crossed variables
<u>length</u>(<u>min</u>)	use minimal length unique codes of crossing variables
<u>length</u>(*#*)	use # as coding length of crossing variables
[Reporting]	
<u>ddim</u>ensions(*#*)	display # singular values; default is ddim(.) (all)
<u>points</u>(*varlist*)	display tables for listed variables; default is all variables
<u>compact</u>	display statistics table in a compact format
<u>log</u>	display the iteration log (method(joint) only)
<u>plot</u>	plot the coordinates (that is, mcaplot)
<u>maxl</u>ength(*#*)	maximum number of characters for labels in plot; default is maxlength(12)

bootstrap, by, collect, jackknife, rolling, and statsby are allowed with mca; see [U] **11.1.10 Prefix commands**. However, bootstrap and jackknife results should be interpreted with caution; identification of the mca parameters involves data-dependent restrictions, possibly leading to badly biased and overdispersed estimates (Milan and Whittaker 1995).

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> ◿ Model

supplementary(*speclist*) specifies that *speclist* are supplementary variables. Such variables do not affect the MCA solution, but their categories are mapped into the solution space. For method(indicator), this mapping uses the first method described by Greenacre (2006). For method(burt) and method(joint), the second and recommended method described by Greenacre (2006) is used, in which supplementary column principal coordinates are derived as a weighted average of the standard row coordinates, weighted by the supplementary profile. See the syntax diagram for the syntax of *speclist*.

method(*method*) specifies the method of MCA/JCA.

method(burt), the default, specifies MCA, a categorical variables analogue to principal component analysis (see [MV] **pca**). The Burt method performs a CA of the Burt matrix, a matrix of the two-way cross-tabulations of all pairs of variables.

method(indicator) specifies MCA via a CA on the indicator matrix formed from the variables.

method(joint) specifies JCA, a categorical variables analogue to factor analysis (see [MV] **factor**). This method analyzes a variant of the Burt matrix, in which the diagonal blocks are iteratively adjusted for the poor diagonal fit of MCA.

dimensions(#) specifies the number of dimensions (= factors = axes) to be extracted. The default is dimensions(2). If you specify dimensions(1), the categories are placed on one dimension. The number of dimensions is no larger than the number of categories in the active variables (regular and crossed) minus the number of active variables, and it can be less. This excludes supplementary variables. Specifying a larger number than the dimensions available results in extracting all dimensions.

MCA is a hierarchical method so that extracting more dimensions does not affect the coordinates and decomposition of inertia of dimensions already included. The percentages of inertia accounting for the dimensions are in decreasing order as indicated by the singular values. The first dimension accounts for the most inertia, followed by the second dimension, and then the third dimension, etc.

normalize(*normalization*) specifies the normalization method, that is, how the row and column coordinates are obtained from the singular vectors and singular values of the matrix of standardized residuals.

normalize(standard) specifies that coordinates are returned in standard normalization (singular values divided by the square root of the mass). This is the default.

normalize(principal) specifies that coordinates are returned in principal normalization. Principal coordinates are standard coordinates multiplied by the square root of the corresponding principal inertia.

iterate(#) is a technical and rarely used option specifying the maximum number of iterations. iterate() is permitted only with method(joint). The default is iterate(250).

tolerance(*#*) is a technical and rarely used option specifying the tolerance for subsequent modification of the diagonal blocks of the Burt matrix. tolerance() is permitted only with method(joint). The default is tolerance(1e-5).

missing treats missing values as ordinary values to be included in the analysis. Observations with missing values are omitted from the analysis by default.

noadjust suppresses principal inertia adjustment and is allowed with method(burt) only. By default, the principal inertias (eigenvalues of the Burt matrix) are adjusted. The unmodified principal inertias present a pessimistic measure of fit because MCA fits the diagonal of $\mathbf{P}$ poorly (see Greenacre [1984]).

⎡ Codes ⎤

report(*opt*) displays coding information for the crossing variables, crossed variables, or both. report() is ignored if you do not specify at least one crossed variable.

report(variables) displays the coding schemes of the crossing variables, that is, the variables used to define the crossed variables.

report(crossed) displays a table explaining the value labels of the crossed variables.

report(all) displays the codings of the crossing and crossed variables.

length(*opt*) specifies the coding length of crossing variables.

length(min) specifies that the minimal-length unique codes of crossing variables be used.

length(*#*) specifies that the coding length # of crossing variables be used, where # must be between 4 and 32.

⎡ Reporting ⎤

ddimensions(*#*) specifies the number of singular values to be displayed. If ddimensions() is greater than the number of singular values, all the singular values will be displayed. The default is ddimensions(.), meaning all singular values.

points(*varlist*) indicates the variables to be included in the tables. By default, tables are displayed for all variables. Regular categorical variables, crossed variables, and supplementary variables may be specified in points().

compact specifies that point statistics tables be displayed multiplied by 1,000, enabling the display of more columns without wrapping output. The compact tables can be displayed without wrapping for models with two dimensions at line size 79 and with three dimensions at line size 99.

log displays an iteration log. This option is permitted with method(joint) only.

plot displays a plot of the row and column coordinates in two dimensions. Use mcaplot directly to select different plotting points or for other graph refinements; see [MV] **mca postestimation plots**.

maxlength(*#*) specifies the maximum number of characters for labels in plots. The default is maxlength(12). # must be less than 32.

Note: The reporting options may be specified during estimation or replay.

Remarks and examples

Remarks are presented under the following headings:

Introduction

Multiple correspondence analysis (MCA) and joint correspondence analysis (JCA) are methods for analyzing observations on categorical variables. MCA is usually viewed as an extension of simple correspondence analysis (CA) to more than two variables. CA analyzes a two-way contingency table; MCA and JCA analyze a multiway table.

MCA can be viewed as a generalization of principal component analysis where the variables to be analyzed are categorical, not continuous. MCA performs a CA on a Burt or indicator matrix; it explores the relationships within a set of variables, whereas CA has more focus on exploring relationships between two sets of variables. JCA is an extension of MCA that attempts to remedy discrepancies between CA and MCA.

For an introduction to MCA via CA, see Rencher and Christensen (2012) or Everitt and Dunn (2001). For an advanced introduction to MCA without previous discussion of CA, see Gower and Hand (1996). Greenacre (2006) approaches MCA from CA, then JCA from MCA, and gives a more advanced treatment. [MV] **ca** also introduces MCA concepts. Gower (1990) explores MCA history.

Three methods are implemented here. We will start with the simplest and most intuitive representation of unordered categorical data: the indicator matrix, usually denoted $\mathbf{Z}$, a matrix of zeros and ones with columns for all categories of all variables and rows corresponding to observations. A value of one indicates that a category is observed; a zero indicates that it is not. MCA can be performed as a CA on the indicator matrix; an equivalent to this method is `method(indicator)` with mca.

Here is a manufactured indicator matrix $\mathbf{Z}$, with 10 observations on three categorical variables, $w, x,$ and y, each with two categories indicated by $w_1, w_2, x_1, x_2, y_1, y_2$:

$$
\mathbf{Z} = \begin{array}{c} \\ 1. \\ 2. \\ 3. \\ 4. \\ 5. \\ 6. \\ 7. \\ 8. \\ 9. \\ 10. \end{array}
\begin{array}{cccccc}
\text{obs} & w_1 & w_2 & x_1 & x_2 & y_1 & y_2 \\
\left(\begin{array}{cccccc}
1 & 0 & 1 & 0 & 1 & 0 \\
0 & 1 & 1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 & 1 & 0 \\
1 & 0 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 1 & 0 & 1 \\
1 & 0 & 1 & 0 & 0 & 1 \\
0 & 1 & 0 & 1 & 1 & 0 \\
1 & 0 & 0 & 1 & 1 & 0 \\
1 & 0 & 1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 & 1 & 0
\end{array}\right)
\end{array}
$$

For large datasets with many variables and observations, the indicator matrix is burdensome and can exceed memory limitations. The Burt matrix, usually denoted as $\mathbf{B}$, is a cross-tabulation of all categories of all variables. $\mathbf{B} = \mathbf{Z}'\mathbf{Z}$. The Burt matrix is smaller than the indicator matrix $\mathbf{Z}$. Performing CA on the Burt matrix and performing CA on the indicator matrix are related but not the same: they give equivalent standard coordinates, but the total principal inertias from the indicator

matrix approach and Burt matrix approach are different. Performing a CA of the Burt matrix without further calculation is method(burt) along with the noadjust option.

The Burt matrix, $\mathbf{B}$, corresponding to matrix $\mathbf{Z}$, above:

$$\mathbf{B} = \begin{array}{c} \\ w_1 \\ w_2 \\ x_1 \\ x_2 \\ y_1 \\ y_2 \end{array} \begin{array}{c} \begin{array}{cccccc} w_1 & w_2 & x_1 & x_2 & y_1 & y_2 \end{array} \\ \left(\begin{array}{cccccc} 7 & 0 & 4 & 3 & 3 & 4 \\ 0 & 3 & 1 & 2 & 3 & 0 \\ 4 & 1 & 5 & 0 & 3 & 2 \\ 3 & 2 & 0 & 5 & 3 & 2 \\ 3 & 3 & 3 & 3 & 6 & 0 \\ 4 & 0 & 2 & 2 & 0 & 4 \end{array} \right) \end{array}$$

Applying CA to the Burt matrix or indicator matrix artificially inflates the χ^2 distances between profiles and the total inertia; see Gower (2006). This can be partially remedied after CA of the Burt matrix by scale readjustments of the MCA solution. Performing adjustments after a CA of the Burt matrix is the default, that is, if no method is specified method(burt) is assumed; unadjusted estimates may be obtained by using the option noadjust.

The third method, JCA, generalizes CA more naturally to more than two categorical variables. JCA attempts to account for the variation in the off-diagonal submatrices of the Burt matrix. It corrects the inflation of the total inertia. The solution can no longer be obtained by one application of the singular value decomposition (as in CA). JCA is obtained by specifying the option method(joint) to mca.

Compare MCA on two variables and CA

We illustrate MCA with a dataset from the International Social Survey Program on environment (ISSP 1993). This example is used in the MCA literature; see Greenacre (2006). We will look at the questions on attitudes toward science. We use data from the West German sample only and remove all observations containing missing data; 871 observations remain. The survey questions are

How much do you agree or disagree with each of these statements?

    A. We believe too often in science, and not enough in feelings and faith.

    B. Overall, modern science does more harm than good.

    C. Any change humans cause in nature—no matter how scientific—is likely to make things worse.

    D. Modern science will solve our environmental problems with little change to our way of life.

Each question has five possible response categories:

    1. Agree strongly

    2. Agree

    3. Neither agree nor disagree

    4. Disagree

    5. Disagree strongly

Supplementary demographic information is also available as coded categorical variables:

    Sex: male, female

    Age: (six groups) 16–24, 25–34, 35–44, 45–54, 55–64, 65 and older

    Education: (six groups) primary incomplete, primary completed, secondary incomplete, secondary completed, tertiary incomplete, tertiary completed.

▷ Example 1

Here is a summary of these data.

```
. use https://www.stata-press.com/data/r18/issp93
(Selection from ISSP (1993))

. describe

Contains data from https://www.stata-press.com/data/r18/issp93.dta
 Observations:             871                  Selection from ISSP (1993)
    Variables:               8                  17 May 2022 09:36
                                                (_dta has notes)
─────────────────────────────────────────────────────────────────────────────
Variable      Storage   Display    Value
    name         type    format    label      Variable label
─────────────────────────────────────────────────────────────────────────────
id              int      %9.0g                 Respondent identifier
A               byte     %26.0g    agree5      Too much science, not enough
                                                 feelings & faith
B               byte     %26.0g    agree5      Science does more harm than good
C               byte     %26.0g    agree5      Any change makes nature worse
D               byte     %26.0g    agree5      Science will solve environmental
                                                 problems
sex             byte     %9.0g     sex         Sex
age             byte     %9.0g     age         Age (6 categories)
edu             byte     %20.0g    edu         Education (6 categories)
─────────────────────────────────────────────────────────────────────────────
Sorted by:
```

We begin by comparing MCA with two variables to CA with two variables. The default MCA analysis is a CA of the Burt matrix, performed with adjustment to the principal inertias. The unadjusted results from MCA will give different principal inertias from the CA, although the standard coordinates would

be the same. With adjustment, results are nearly identical. For a detailed discussion of the output of ca and mca, see [MV] ca.

```
. mca A B
Multiple/joint correspondence analysis        Number of obs   =        871
                                               Total inertia   =  .23775345
        Method: Burt/adjusted inertias         Number of axes  =          2
```

	Principal		Cumul.
Dimension	inertia	Percent	percent
Dim 1	.1686131	70.92	70.92
Dim 2	.0586785	24.68	95.60
Dim 3	.010444	4.39	99.99
Dim 4	.0000178	0.01	100.00
Total	.2377535	100.00	

Statistics for column categories in standard normalization

		Overall			Dimension_1	
Categories	Mass	Quality	%inert	Coord	Sqcorr	Contrib
A						
Agree stro~y	0.068	1.000	0.100	1.017	0.502	0.071
Agree	0.185	0.997	0.042	0.560	0.982	0.058
Neither ag~e	0.117	0.930	0.062	0.248	0.083	0.007
Disagree	0.102	0.922	0.123	-1.239	0.907	0.157
Disagree s~y	0.028	0.954	0.174	-2.741	0.845	0.207
B						
Agree stro~y	0.041	0.982	0.146	1.571	0.490	0.101
Agree	0.100	0.962	0.034	0.667	0.932	0.044
Neither ag~e	0.118	0.840	0.043	0.606	0.716	0.043
Disagree	0.161	0.769	0.043	-0.293	0.228	0.014
Disagree s~y	0.080	0.994	0.235	-1.926	0.900	0.298

	Dimension_2		
Categories	Coord	Sqcorr	Contrib
A			
Agree stro~y	1.718	0.498	0.202
Agree	0.116	0.015	0.002
Neither ag~e	-1.344	0.847	0.212
Disagree	-0.268	0.015	0.007
Disagree s~y	1.672	0.109	0.077
B			
Agree stro~y	2.671	0.493	0.291
Agree	-0.201	0.029	0.004
Neither ag~e	-0.427	0.124	0.022
Disagree	-0.764	0.541	0.094
Disagree s~y	1.055	0.094	0.089

With ca we use the norm(standard) option to obtain results in the same normalization as the preceding mca. [MV] ca discusses the normalize() option; mca has some of the normalize() options of ca.

The top table in the output for both ca and mca reports the principal inertias. The principal inertias reported by ca are simply the squares of the singular values. Two pieces of information reported by ca that are not reported by mca are the χ^2 value in the table and the explained inertia in the header. The χ^2 value is taken as a measure of dissimilarity between the row and column profiles

of the two-way table. χ^2 distance makes sense for a two-way table but has less justification when applied to the rows and columns of either the indicator matrix or the Burt matrix (Greenacre 2006). The explained inertia is the value from the cumulative percent column in the top table corresponding to the number of dimensions selected; it is simply not reported in the mca header.

The coordinates reported in the second table are the same. The mass, inertia, and contributions are half as large in mca as they are in ca; in ca the row and column each sum to the principal inertia, but in mca there are only columns, which sum to the principal inertia.

```
. ca A B, norm(standard)
Correspondence analysis                          Number of obs     =         871
                                                 Pearson chi2(16)  =      207.08
                                                 Prob > chi2       =      0.0000
                                                 Total inertia     =      0.2378
       5 active rows                             Number of dim.    =           2
       5 active columns                          Expl. inertia (%) =       95.60
```

Dimension	Singular value	Principal inertia	chi2	Percent	Cumul. percent
Dim 1	.4106252	.1686131	146.86	70.92	70.92
Dim 2	.2422364	.0586785	51.11	24.68	95.60
Dim 3	.1021961	.010444	9.10	4.39	99.99
Dim 4	.0042238	.0000178	0.02	0.01	100.00
Total		.2377535	207.08	100	

Statistics for row and column categories in standard normalization

| | | Overall | | Dimension_1 | | |
Categories	Mass	Quality	%inert	Coord	Sqcorr	Contrib
A						
Agree stro~y	0.137	1.000	0.200	1.017	0.502	0.141
Agree	0.370	0.997	0.084	0.560	0.982	0.116
Neither ag~e	0.234	0.930	0.123	0.248	0.083	0.014
Disagree	0.204	0.922	0.245	-1.239	0.907	0.314
Disagree s~y	0.055	0.954	0.348	-2.741	0.845	0.414
B						
Agree stro~y	0.082	0.982	0.291	1.571	0.490	0.201
Agree	0.200	0.962	0.068	0.667	0.932	0.089
Neither ag~e	0.235	0.840	0.086	0.606	0.716	0.087
Disagree	0.323	0.769	0.086	-0.293	0.228	0.028
Disagree s~y	0.161	0.994	0.470	-1.926	0.900	0.596

| | Dimension_2 | | |
Categories	Coord	Sqcorr	Contrib
A			
Agree stro~y	1.718	0.498	0.403
Agree	0.116	0.015	0.005
Neither ag~e	-1.344	0.847	0.423
Disagree	-0.268	0.015	0.015
Disagree s~y	1.672	0.109	0.154
B			
Agree stro~y	2.671	0.493	0.582
Agree	-0.201	0.029	0.008
Neither ag~e	-0.427	0.124	0.043
Disagree	-0.764	0.541	0.188
Disagree s~y	1.055	0.094	0.179

◁

MCA on four variables

Now we will take a look at MCA with more than two variables and at the different methods of performing MCA or JCA.

▷ Example 2

We continue to use the ISSP (1993) dataset, looking at all four questions on attitudes toward science. We use the default method of MCA, which is a CA of the Burt matrix for the data, followed by simple scale adjustments. We choose the principal normalization `normalize(principal)`, which scales the coordinates by the principal inertias. MCA with the Burt matrix and adjustments explains at least 79.1% of the total inertia in the first two dimensions.

```
. mca A-D, normalize(principal)
```

Multiple/joint correspondence analysis				Number of obs	=	871
				Total inertia	=	.17024552
Method: Burt/adjusted inertias				Number of axes	=	2

Dimension	Principal inertia	Percent	Cumul. percent
Dim 1	.0764553	44.91	44.91
Dim 2	.0582198	34.20	79.11
Dim 3	.009197	5.40	84.51
Dim 4	.0056697	3.33	87.84
Dim 5	.0011719	0.69	88.53
Dim 6	6.61e-06	0.00	88.53
Total	.1702455	100.00	

Statistics for column categories in principal normalization

| | | Overall | | | Dimension_1 | |
Categories	Mass	Quality	%inert	Coord	Sqcorr	Contrib
A						
Agree stro~y	0.034	0.963	0.060	0.508	0.860	0.115
Agree	0.092	0.659	0.023	0.151	0.546	0.028
Neither ag~e	0.059	0.929	0.037	-0.124	0.143	0.012
Disagree	0.051	0.798	0.051	-0.322	0.612	0.069
Disagree s~y	0.014	0.799	0.067	-0.552	0.369	0.055
B						
Agree stro~y	0.020	0.911	0.100	0.809	0.781	0.174
Agree	0.050	0.631	0.027	0.177	0.346	0.021
Neither ag~e	0.059	0.806	0.027	0.096	0.117	0.007
Disagree	0.081	0.620	0.033	-0.197	0.555	0.041
Disagree s~y	0.040	0.810	0.116	-0.374	0.285	0.074
C						
Agree stro~y	0.044	0.847	0.122	0.597	0.746	0.203
Agree	0.091	0.545	0.024	0.068	0.101	0.006
Neither ag~e	0.057	0.691	0.045	-0.171	0.218	0.022
Disagree	0.044	0.788	0.054	-0.373	0.674	0.080
Disagree s~y	0.015	0.852	0.071	-0.406	0.202	0.032
D						
Agree stro~y	0.017	0.782	0.039	0.333	0.285	0.025
Agree	0.067	0.126	0.012	-0.061	0.126	0.003
Neither ag~e	0.058	0.688	0.044	-0.106	0.087	0.009
Disagree	0.065	0.174	0.014	-0.061	0.103	0.003
Disagree s~y	0.043	0.869	0.034	0.196	0.288	0.022

| | Dimension_2 | | |
Categories	Coord	Sqcorr	Contrib
A			
Agree stro~y	0.176	0.103	0.018
Agree	−0.069	0.113	0.007
Neither ag~e	−0.289	0.786	0.084
Disagree	0.178	0.186	0.028
Disagree s~y	0.596	0.430	0.084
B			
Agree stro~y	0.331	0.131	0.038
Agree	−0.161	0.285	0.022
Neither ag~e	−0.233	0.690	0.055
Disagree	−0.068	0.065	0.006
Disagree s~y	0.509	0.526	0.179
C			
Agree stro~y	0.219	0.101	0.036
Agree	−0.143	0.444	0.032
Neither ag~e	−0.252	0.473	0.062
Disagree	0.153	0.114	0.018
Disagree s~y	0.728	0.650	0.136
D			
Agree stro~y	0.440	0.497	0.057
Agree	−0.002	0.000	0.000
Neither ag~e	−0.280	0.601	0.078
Disagree	−0.051	0.071	0.003
Disagree s~y	0.278	0.581	0.057

```
. mcaplot, overlay origin
```


MCA coordinate plot

Coordinates in principal normalization
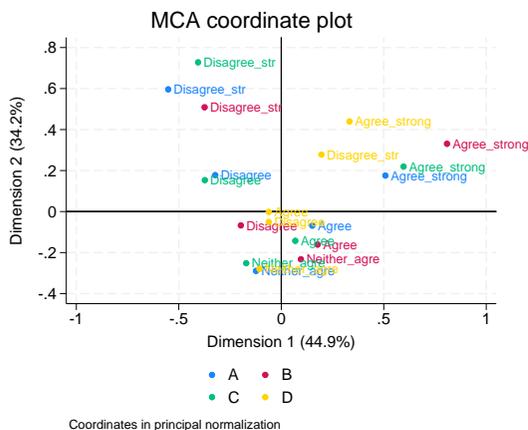
We displayed the origin axes in the plot with option `origin`. This plot makes it easier to see data associations. For more information on mcaplot, see [MV] **mca postestimation plots**.

A clear pattern is seen in the plot. Results from questions A, B, and C are clustered together, whereas question D forms a pattern of its own. Question D is formulated differently from A, B, and C, and the plot shows its incompatibility with the others.

Greenacre (2006, 70) produces this same plot. To obtain equivalent results, we reflect over the y axis with xnegate and adjust the scale of the graph with xlabel() and ylabel().

```
. mcaplot, overlay xnegate origin ylabel(-1(.5)1.5) xlabel(-1.5(.5)1)
```


◁
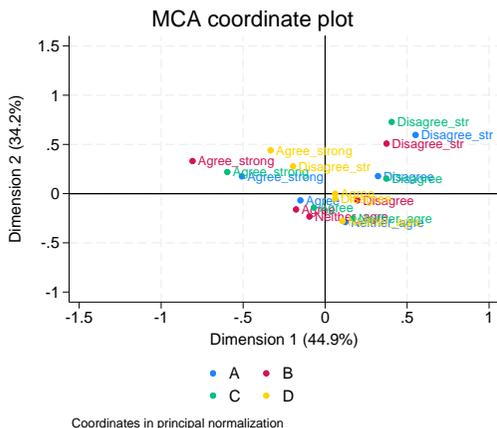
❑ Technical note

The percentage of inertia in the top table of the mca output does not add up to 100%, although all singular values are displayed. Why? The percentages are lower-bound estimates in the Burt method with adjustments.

❑

❑ Technical note

Readers who are familiar with the discussion of the normalize() option in [MV] ca might be wondering why we are doing analysis of coordinates in the principal normalization. Principal normalization in ca does not allow good associations between the row and column categories, and so the symmetric normalization is the default used for ca. Principal normalization does allow studying the row categories or column categories separately from each other in ca. In mca there are only column categories. Consequently, the principal normalization is often preferred.

❑

CA of the indicator matrix

▷ Example 3

We compare the previous result with that obtained using the method(indicator) option to perform an equivalent analysis to CA on the indicator matrix for these data. The first two dimensions explain only 22.2% of the total principal inertia.

```
. mca A-D, method(indicator)
```

Multiple/joint correspondence analysis

			Number of obs	=	871
			Total inertia	=	4
Method: Indicator matrix			Number of axes	=	2

Dimension	Principal inertia	Percent	Cumul. percent
Dim 1	.4573792	11.43	11.43
Dim 2	.4309658	10.77	22.21
Dim 3	.3219257	8.05	30.26
Dim 4	.3064732	7.66	37.92
Dim 5	.2756747	6.89	44.81
Dim 6	.251928	6.30	51.11
Dim 7	.2425591	6.06	57.17
Dim 8	.2349506	5.87	63.05
Dim 9	.225468	5.64	68.68
Dim 10	.2206291	5.52	74.20
Dim 11	.2098376	5.25	79.44
Dim 12	.1971485	4.93	84.37
Dim 13	.1778833	4.45	88.82
Dim 14	.1691119	4.23	93.05
Dim 15	.1528191	3.82	96.87
Dim 16	.1252462	3.13	100.00
Total	4	100.00	

Statistics for column categories in standard normalization

Categories	Mass	Overall Quality	%inert	Dimension_1 Coord	Sqcorr	Contrib
A						
Agree stro~y	0.034	0.280	0.054	1.837	0.244	0.078
Agree	0.092	0.100	0.039	0.546	0.080	0.019
Neither ag~e	0.059	0.218	0.048	-0.447	0.028	0.008
Disagree	0.051	0.220	0.050	-1.166	0.160	0.047
Disagree s~y	0.014	0.260	0.059	-1.995	0.106	0.037
B						
Agree stro~y	0.020	0.419	0.057	2.924	0.347	0.118
Agree	0.050	0.095	0.050	0.642	0.047	0.014
Neither ag~e	0.059	0.140	0.048	0.346	0.017	0.005
Disagree	0.081	0.127	0.042	-0.714	0.111	0.028
Disagree s~y	0.040	0.527	0.052	-1.354	0.161	0.050
C						
Agree stro~y	0.044	0.525	0.052	2.158	0.450	0.137
Agree	0.091	0.102	0.040	0.247	0.016	0.004
Neither ag~e	0.057	0.189	0.048	-0.619	0.051	0.015
Disagree	0.044	0.216	0.051	-1.349	0.179	0.054
Disagree s~y	0.015	0.312	0.059	-1.468	0.063	0.022
D						
Agree stro~y	0.017	0.155	0.058	1.204	0.049	0.017
Agree	0.067	0.008	0.046	-0.221	0.008	0.002
Neither ag~e	0.058	0.195	0.048	-0.385	0.020	0.006
Disagree	0.065	0.015	0.046	-0.222	0.008	0.002
Disagree s~y	0.043	0.168	0.052	0.708	0.048	0.015

```
                       Dimension_2
       Categories    Coord   Sqcorr   Contrib

  A
  Agree stro~y        0.727    0.036    0.012
        Agree        -0.284    0.020    0.005
  Neither ag~e       -1.199    0.190    0.055
     Disagree         0.737    0.060    0.018
  Disagree s~y        2.470    0.153    0.055

  B
  Agree stro~y        1.370    0.072    0.025
        Agree        -0.667    0.048    0.015
  Neither ag~e       -0.964    0.123    0.036
     Disagree        -0.280    0.016    0.004
  Disagree s~y        2.108    0.367    0.117

  C
  Agree stro~y        0.909    0.075    0.024
        Agree        -0.592    0.086    0.021
  Neither ag~e       -1.044    0.137    0.040
     Disagree         0.635    0.037    0.012
  Disagree s~y        3.017    0.249    0.089

  D
  Agree stro~y        1.822    0.106    0.038
        Agree        -0.007    0.000    0.000
  Neither ag~e       -1.159    0.175    0.051
     Disagree        -0.211    0.007    0.002
  Disagree s~y        1.152    0.120    0.038
```

```
. mcaplot, overlay origin
```
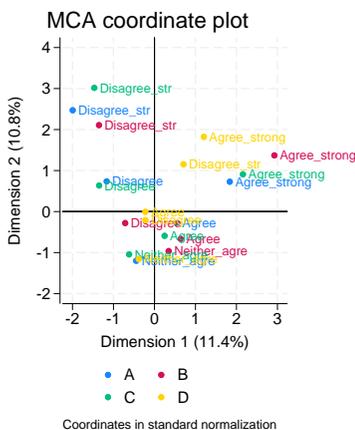

Even though the first two dimensions explain only 22.2% of the total inertia, and difficulties exist in justifying the full χ^2 geometry for the CA of the indicator matrix, the same clear pattern we saw in the previous plot is seen here. Variables A, B, and C are related, but variable D does not belong with the rest.

◁

CA of the Burt matrix

▷ Example 4

Now we will look at results with method(burt) and the noadjust option. This performs a CA on the Burt matrix without adjusting the principal inertias. This model does slightly better than the indicator matrix approach, explaining 35.0% of the principal inertia in the first two dimensions. We display column points only for variable A to reduce the output.

```
. mca A-D, method(burt) noadjust points(A)
Multiple/joint correspondence analysis         Number of obs     =        871
                                               Total inertia     =  1.1276841
      Method: Burt/unadjusted inertias         Number of axes    =          2
```

Dimension	Principal inertia	Percent	Cumul. percent
Dim 1	.2091957	18.55	18.55
Dim 2	.1857315	16.47	35.02
Dim 3	.1036362	9.19	44.21
Dim 4	.0939258	8.33	52.54
Dim 5	.0759966	6.74	59.28
Dim 6	.0634677	5.63	64.91
Dim 7	.0588349	5.22	70.12
Dim 8	.0552018	4.90	75.02
Dim 9	.0508358	4.51	79.53
Dim 10	.0486772	4.32	83.84
Dim 11	.0440318	3.90	87.75
Dim 12	.0388675	3.45	91.20
Dim 13	.0316425	2.81	94.00
Dim 14	.0285988	2.54	96.54
Dim 15	.0233537	2.07	98.61
Dim 16	.0156866	1.39	100.00
Total	1.127684	100.00	

Statistics for column categories in standard normalization

Categories		Overall			Dimension_1	
	Mass	Quality	%inert	Coord	Sqcorr	Contrib
A						
Agree stro~y	0.034	0.445	0.055	1.837	0.391	0.115
Agree	0.092	0.169	0.038	0.546	0.136	0.028
Neither ag~e	0.059	0.344	0.047	-0.447	0.047	0.012
Disagree	0.051	0.350	0.050	-1.166	0.258	0.069
Disagree s~y	0.014	0.401	0.060	-1.995	0.170	0.055

Categories		Dimension_2	
	Coord	Sqcorr	Contrib
A			
Agree stro~y	0.727	0.054	0.018
Agree	-0.284	0.033	0.007
Neither ag~e	-1.199	0.298	0.084
Disagree	0.737	0.092	0.028
Disagree s~y	2.470	0.231	0.084

We do not provide a plot for this mca example; it would be the same as the previous one. MCA via the indicator matrix or the Burt matrix produces the same standard coordinates, although they produce different principal inertias. If normalize(principal) is used, different coordinates will be produced. Principal normalization relies on the principal inertias for normalization.

For more information on normalization, see either *Methods and formulas* in mca or the discussion of normalization in [MV] **ca**.

◁

Joint correspondence analysis

▷ Example 5

JCA attempts to remedy inflation of the total inertia by the block diagonal submatrices of the Burt matrix and is implemented as method(joint). Results using JCA explain 90% of the principal inertia in the first two dimensions. With JCA, we must specify the dimensions we want in advance. The output contains principal inertias only for the first two dimensions (the default). For other methods, principal inertias for all dimensions are displayed. More dimensions can be requested with the dim() option. JCA is an iterative method, with repeated CAs and adjustments taking place until convergence is achieved.

We ask for coordinates in the principal normalization, norm(principal), and ask for coordinates of only variable A to be displayed.

```
. mca A-D, method(joint) norm(principal) points(A)
```

Multiple/joint correspondence analysis

				Number of obs	=	871
				Total inertia	=	.18242477
Method: Joint (JCA)				Number of axes	=	2

Dimension	Principal inertia	Percent	Cumul. percent
Dim 1	.099091	54.32	54.32
Dim 2	.0650329	35.65	89.97
Total	.1824248	100.00	

Statistics for column categories in principal normalization

		Overall			Dimension_1		
Categories	Mass	Quality	%inert		Coord	Sqcorr	Contrib
A							
Agree stro~y	0.034	0.964	0.052		-0.458	0.759	0.072
Agree	0.092	0.774	0.020		-0.169	0.733	0.027
Neither ag~e	0.059	0.884	0.030		0.048	0.025	0.001
Disagree	0.051	0.887	0.046		0.364	0.810	0.068
Disagree s~y	0.014	0.899	0.060		0.711	0.636	0.070

	Dimension_2		
Categories	Coord	Sqcorr	Contrib
A			
Agree stro~y	-0.238	0.205	0.030
Agree	0.040	0.042	0.002
Neither ag~e	0.281	0.859	0.071
Disagree	-0.112	0.077	0.010
Disagree s~y	-0.458	0.264	0.044

```
. mcaplot, overlay origin
```
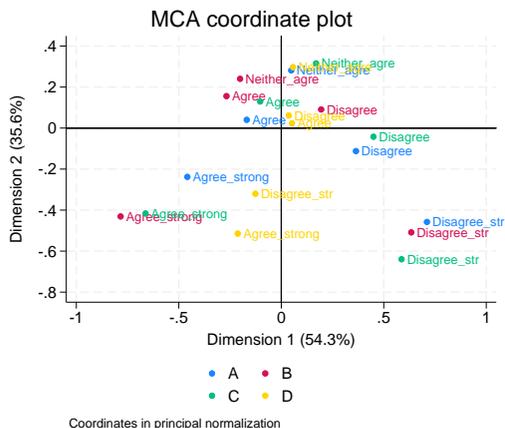

The plot shows the same relationships among the variables that we saw in the one after the indicator matrix approach to MCA. The main difference between the plots is the change in scale, partially because of the normalization and largely because of the change of method.

These same data are analyzed and plotted in Greenacre (2006, 66). To obtain an equivalent plot, we perform a reflection on the data with `ynegate`, add in the origin axes with `origin`, and use the same scale with options `xlabel()` and `ylabel()`,

```
. mcaplot, overlay ynegate origin ylabel(-1(.5)1.5) xlabel(-1.5(.5)1)
```
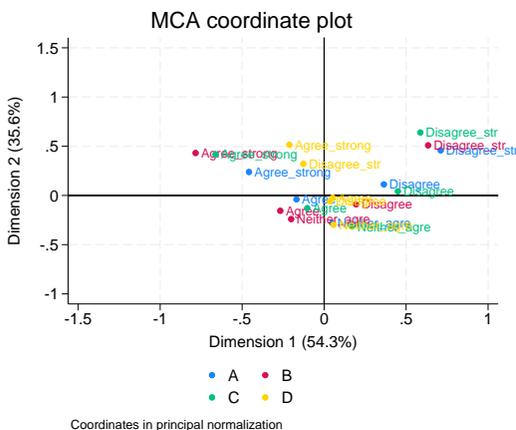

Note the similarities between this plot and the one obtained through the default approach to MCA via the Burt matrix and adjustments.

◁

Stored results

mca stores the following in e():

Scalars
  e(N)   number of observations
  e(f)   number of dimensions
  e(inertia)   total inertia
  e(ev_unique)   1 if all eigenvalues are distinct, 0 otherwise
  e(adjust)   1 if eigenvalues are adjusted, 0 otherwise (method(burt) only)
  e(converged)   1 if successful convergence, 0 otherwise (method(joint) only)
  e(iter)   number of iterations (method(joint) only)
  e(inertia_od)   proportion of off-diagonal inertia explained by extracted dimensions (method(joint) only)

Macros
  e(cmd)   mca
  e(cmdline)   command as typed
  e(names)   names of MCA variables (crossed or actual)
  e(supp)   names of supplementary variables
  e(defs)   per crossed variable: crossing variables separated by "\"
  e(missing)   missing, if specified
  e(crossed)   1 if there are crossed variables, 0 otherwise
  e(wtype)   weight type
  e(wexp)   weight expression
  e(title)   title in output
  e(method)   burt, indicator, or joint
  e(norm)   standard or principal
  e(properties)   nob noV eigen
  e(estat_cmd)   program used to implement estat
  e(predict)   program used to implement predict
  e(marginsnotok) predictions disallowed by margins

Matrices
  e(Coding#)   row vector with coding of variable #
  e(A)   standard coordinates for column categories
  e(F)   principal coordinates for column categories
  e(cMass)   column mass
  e(cDist)   distance column to centroid
  e(cInertia)   column inertia
  e(cGS)   general statistics of column categories
                  [.,1] column mass
                  [.,2] overall quality
                  [.,3] inertia/sum(inertia)
                  [.,3*f+1] dim f: coordinate in e(norm) normalization
                  [.,3*f+2] dim f: contribution of the profiles to principal axes
                  [.,3*f+3] dim f: contribution of principal axes to profiles
                            (= squared correlation of profile and axes)
  e(rSCW)   weight matrix for row standard coordinates
  e(Ev)   principal inertias/eigenvalues
  e(inertia_e)   explained inertia (percent)
  e(Bmod)   modified Burt matrix of active variables (method(joint) only)
  e(inertia_sub) variable-by-variable inertias (method(joint) only)

Functions
  e(sample)   marks estimation sample

Methods and formulas

Methods and formulas are presented under the following headings:

Notation

We use notation that is fairly standard in the literature on correspondence analysis (for example, Greenacre [2006]). Let $x_1, \ldots, x_q$ be categorical variables on N observations that are active in the analysis. To simplify notation, but without loss of generality, we assume that x_j is coded with consecutive integers $1, \ldots, n_j$. Let $\mathbf{Z}^{(j)}$ be the $N \times n_j$ binary indicator matrix associated with x_j, $\mathbf{Z}_{ih}^{(j)} = 1$ if and only if $x_{ij} = h$. Let

$$\mathbf{Z} = \left(\mathbf{Z}^{(1)}, \mathbf{Z}^{(2)}, \ldots, \mathbf{Z}^{(q)}\right)$$

be the $N \times J$ indicator matrix of the set of active x-variables, where $J = n_1 + \cdots + n_q$.

We will be consistent in letting i index observations $1, \ldots, N$, j index variables $1, \ldots, q$, and h index categories $1, \ldots, n_j$, or $1, \ldots, J$.

The $J \times J$ Burt matrix is defined as $\mathbf{B} = \mathbf{Z}'\mathbf{Z}$, or $\mathbf{B} = \mathbf{Z}'\mathbf{D}(w)\mathbf{Z}$, where w is the weight for the analysis and $\mathbf{D}(w)$ is a $J \times J$ square matrix with the weights on the diagonal and 0 off diagonal. The diagonal block of $\mathbf{B}$ associated with variable x_j is a diagonal matrix with the frequencies of x_j on the diagonal. The off-diagonal block of $\mathbf{B}$ associated with variables x_j and x_k is the two-way cross-tabulation of x_j and x_k.

In an analogous way, we define $\mathbf{B}^*$, the Burt matrix with more rows containing cross-tabulation from the supplementary variables. $\mathbf{B}^* = \mathbf{Z}^{*\prime}\mathbf{Z}$, where $\mathbf{Z}^*$ is the indicator matrix with more columns for the supplementary variables.

$\mathbf{D}(v)$, in general, represents a diagonal matrix with the elements of vector v on the diagonal and 0 off diagonal; $\mathbf{1}$ is a column vector of ones where length is defined by the context.

Using ca to compute MCA

The indicator approach to MCA involves an equivalent technique to performing a standard CA on the indicator matrix $\mathbf{Z}$; see Greenacre (2006). We refer to *Methods and formulas* in [MV] **ca** for details. The indicator approach could be handled by forming $\mathbf{Z}$ and invoking camat on $\mathbf{Z}$. If you had k categorical variables named v1, ..., vk, you could perform CA on the indicator matrix by taking the steps in the following code fragment:

```
tab v1, gen(V1_)
...
tab vk, gen(Vk_)
mkmat V1_* ... Vk_*, matrix(VALL)
camat VALL
```

CA of an indicator or Burt matrix

$\mathbf{Z}$ may be a rather large matrix: the number of rows is equal to the number of observations, and memory limitations would pose a limit for applications. Moreover, the interest in MCA is mostly on the column space, and so much computation would be wasted. Therefore, the implementation in mca exploits the close analogy between the indicator and Burt matrix approach for efficiency (see Greenacre [1984, chap. 5; 2006, app. A.3]). The consequence is that the CA results for the rows of $\mathbf{Z}$ are not computed. You may use the above scheme if you need row information.

Much literature (for example, Everitt and Dunn [2001]; Rencher and Christensen [2012]) identifies MCA with the application of CA on the Burt matrix $\mathbf{B} = \mathbf{Z}'\mathbf{Z}$.

This discussion is related to that of *Methods and formulas* in [MV] **ca**. We define

$$\mathbf{B}_{++} = \sum_{k=1}^{J} \sum_{h=1}^{J} \mathbf{B}_{kh}$$

$$\mathbf{P} = \mathbf{B}/\mathbf{B}_{++}$$

$$\mathbf{c} = \sum_{k=1}^{J} \mathbf{P}_{k*} = \mathbf{P}_{+*} = \mathbf{P}'\mathbf{1} \qquad \text{here } * \text{ represents all possible values}$$

$$\mathbf{S} = \mathbf{D}(\mathbf{c})^{-1/2}(\mathbf{P} - \mathbf{c}\mathbf{c}')\mathbf{D}(\mathbf{c})^{-1/2}$$

$\mathbf{c}$ is called the column mass. $\mathbf{D}(\mathbf{c})$ is the diagonal matrix with diagonal $\mathbf{c}$; $\mathbf{D}(\mathbf{c})^{-1/2}$ is therefore the diagonal matrix with elements $1/\sqrt{c_t}$, where c_t is an element of $\mathbf{c}$. $\mathbf{B}$ and $\mathbf{S}$ are symmetric. Thus the singular-value decomposition commonly associated with CA is equivalent to the spectral or eigen decomposition of $\mathbf{S}$.

$$\mathbf{S} = \mathbf{V}\mathbf{\Phi}\mathbf{V}', \qquad \phi_1 \geq \phi_2 \geq \ldots$$

For identification purposes and to facilitate resampling methods, the eigenvectors of $\mathbf{V}$ are directed so that for h, $\mathbf{V}_{kh} > 0$ for the first k for which $\mathbf{V}_{kh} \neq 0$. The standard column coordinates $\mathbf{A}$ are the same for the indicator and the Burt approach and are defined as

$$\mathbf{A} = \mathbf{D}(\mathbf{c})^{-1}\mathbf{V}$$

$\mathbf{D}(\mathbf{c})^{-1}$ is the diagonal matrix with elements $1/c_t$, where c_t is an element of $\mathbf{c}$.

In the indicator approach to MCA, the tth principal inertia is defined as $\lambda_t = \phi_t$, the total inertia as $\sum_t \lambda_t$. The inertia of column j or variable j, $\mathbf{In}^{(j)}$, is computed elementwise as

$$\mathrm{In}_h^{(j)} = \sum_{i=1}^{N} w_i \frac{(Z_{ih}^{(j)} - qc_h^{(j)})^2}{q^2 c_h^{(j)} w_+}$$

where $Z_{ih}^{(j)}$ is the i, hth element of the indicator matrix for variable j, w_i is the weight for observation i, q is the number of active variables, $c_h^{(j)}$ is the column mass of variable j for category h, and w_+ is the sum of the weights over the observations.

In the Burt approach to MCA, the unadjusted principal inertia is defined as $\lambda_t^{\mathrm{unadj}} = \phi_t^2$, the total unadjusted inertia as $\sum_t \lambda_t^{\mathrm{unadj}}$, and the unadjusted column inertias as $\mathbf{1}'\mathbf{S} \odot \mathbf{S}$, with $\odot$ the Hadamard or elementwise matrix product. The adjusted principal inertia, λ_t^{adj}, is defined as

$$\lambda_t^{\text{adj}} = \left(\frac{q}{q-1}\right)^2 \left(\phi_t^2 - \frac{1}{q}\right)^2 \quad \text{provided } q\phi_t > 1$$

The total inertia is defined as

$$\text{total inertia} = \left(\frac{q}{q-1}\right) \sum \phi_t^2 - \frac{(J-q)}{q^2}$$

The standard coordinates are independent of the principal inertia; with or without adjustment, these are defined as before

$$\mathbf{A} = \mathbf{D(c)}^{-1}\mathbf{V}$$

The principal coordinates $\mathbf{F}$ are defined as

$$\mathbf{F} = \mathbf{A}\mathbf{D(\Lambda)}^{1/2}$$

where $\mathbf{\Lambda}$ is a vector of adjusted or unadjusted principal inertias and $\mathbf{D(\Lambda)}^{1/2}$ is the diagonal matrix with elements $\lambda_t^{1/2}$ on the diagonals.

JCA

The implementation of JCA uses the alternating least-squares method proposed by Greenacre (1988, 2006). This algorithm forms a modification of the Burt matrix, changing the diagonal blocks associated with the variables, keeping the off-diagonal blocks unchanged. In the first iteration, $\mathbf{B}_0 = \mathbf{B}$. In iteration m, the blocks are replaced by the f-dimensional MCA approximation of the adjusted Burt matrix $\mathbf{B}_{m-1}$. Iteration continues until the change in the elements of $\mathbf{B}_m$ and $\mathbf{B}_{m-1}$ falls below a convergence tolerance. The JCA coordinates and inertias are computed from the converged solution, $\mathbf{B}_\infty$, analogous to the (adjusted) Burt method. The total inertia of the modified Burt matrix is defined as the sum of the inertias of the off-diagonal blocks.

To compute the f-dimensional MCA approximation of the adjusted Burt matrix $\mathbf{B}_{m-1}$, we perform MCA on $\mathbf{B}_{m-1}$ and then reconstruct the approximation of the data from the solution

$$\widehat{\mathbf{B}}_{hk} = \mathbf{B}_{++}c_h c_k \left(1 + \sum_{t=1}^{f} \phi_t^2 A_{ht} A_{kt}\right)$$

where A_{ht} is an element of the standard coordinate matrix $\mathbf{A}$, c_h and c_k are the column masses, and ϕ_t are the eigenvalues as in the computation of the CA of the Burt matrix. We then update the main diagonal submatrices of $\mathbf{B}_{m-1}$ with the corresponding entries of $\widehat{\mathbf{B}}$ to obtain $\mathbf{B}_m$.

Supplementary variables

The coordinates of supplementary variables are computed as weighted averages of the column coordinates by using the so-called CA transition formulas. As outlined by Greenacre (2006), standard coordinates may be used for averaging, with the profiles of the indicator representation of supplementary columns as weights. Supplementary principal column coordinates are computed as weighted averages of the standard active column coordinates, and then supplementary standard coordinates are computed by division by the principal inertias.

To compute, we add the supplementary variables to the Burt matrix as more rows; if $\mathbf{B}$ is the Burt matrix of the active variables then $\mathbf{B}^*$ is the Burt matrix with the additional cross-tabulation from the supplementary variables. Define $\mathbf{P}$ as above and $\mathbf{P}^*$ analogously with the supplementary variables added. MCA is performed on $\mathbf{B}$ as before, and information from this solution is then applied to $\mathbf{B}^*$. Let p^* represent the elements of $\mathbf{P}^*$. Let k index categories of supplementary variables, h index categories of active variables, and t index dimensions of the solution. Let $\mathbf{A}$ be the standard coordinates of the active variables, as computed previously. Then the principal coordinate for category k and dimension s is computed as:

$$g_{kt} = \sum_{h=1}^{J} \frac{p_{hk}^*}{p_{+k}^*} A_{ht}$$

Coordinates in standard coordinates are obtained by division by the square root of the corresponding principal inertia as described above.

predict

`predict` after `mca` produces variables with the MCA coordinates as displayed by `mca` for both active and supplementary variables. Formulas are shown above. `predict` can also compute row coordinates also known as row scores. Row coordinates computed are always based on the indicator method. The standard row coordinate for the tth dimension for the ith observation with indicator matrix elements Z_{ih} is computed as

$$R_{it} = \sum_{h=1}^{J} \frac{Z_{ih} A_{ht}}{q\sqrt{\phi_t}}$$

where $\mathbf{A}$ is the matrix of standard coordinates, q is the number of active variables in the analysis, and ϕ_t is an eigenvalue of the CA on the Burt matrix. To get the row coordinate in principal normalization, one multiplies by the square root of the corresponding principal inertia.

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Also see

Title

Postestimation commands

The following postestimation commands are of special interest after `mca`:

Command	Description
mcaplot	plot of category coordinates
mcaprojection	MCA dimension projection plot
estat coordinates	display of category coordinates
estat subinertia	matrix of inertias of the active variables (after JCA only)
estat summarize	estimation sample summary
screeplot	plot principal inertias (eigenvalues)

The following standard postestimation commands are also available:

Command	Description
*estimates	cataloging estimation results
predict	row scores (coordinates) and scores (coordinates) for an MCA variable

*All `estimates` subcommands except `table` and `stats` are available; [R] **estimates**.

predict

Description for predict

predict creates a new variable containing predictions such as row scores and scores (coordinates) for the MCA variable.

Menu for predict

Statistics > Postestimation

Syntax for predict

>   predict [*type*] *newvar* [*if*] [*in*] [, *statistic* <u>norm</u>alize(*norm*) <u>dim</u>ensions(*#*)]
>
>   predict [*type*] {*stub**|*newvarlist*} [*if*] [*in*] [, *statistic* <u>norm</u>alize(*norm*)
>
>   <u>dim</u>ensions(*numlist*)]

statistic	Description
Main	
<u>row</u>scores	row scores (coordinates); the default
score(*varname*)	scores (coordinates) for MCA variable *varname*

norm	Description
<u>st</u>andard	use standard normalization
principal	use principal normalization

Options for predict

> Main

rowscores specifies that row scores (row coordinates) be computed. The row scores returned are based on the indicator matrix approach to multiple correspondence analysis, even if another method was specified in the original mca estimation. The sample for which row scores are computed may exceed the estimation sample; for example, it may include supplementary rows (variables). score() and rowscores are mutually exclusive. rowscores is the default.

score(*varname*) specifies the name of a variable from the preceding MCA for which scores should be computed. The variable may be a regular categorical variable, a crossed variable, or a supplementary variable. score() and rowscores are mutually exclusive.

> Options

normalize(*norm*) specifies the normalization of the scores (coordinates). normalize(<u>st</u>andard) returns coordinates in standard normalization. normalize(principal) returns principal scores. The default is the normalization method specified with mca during estimation, or normalize(standard) if no method was specified.

dimensions(*#*) or dimensions(*numlist*) specifies the dimensions for which scores (coordinates) are computed. The number of dimensions specified should equal the number of variables in *newvarlist*. If dimensions() is not specified, scores for dimensions 1, ..., *k* are returned, where *k* is the number of variables in *newvarlist*. The number of variables in *newvarlist* should not exceed the number of dimensions extracted during estimation.

estat

Description for estat

estat coordinates displays the category coordinates, optionally with column statistics.

estat subinertia displays the matrix of inertias of the active variables (after JCA only).

estat summarize displays summary information of MCA variables over the estimation sample.

Menu for estat

Statistics > Postestimation

Syntax for estat

Display of category coordinates

estat <u>co</u>ordinates [*varlist*] [, *coordinates_options*]

Matrix of inertias of the active variables (after JCA only)

estat <u>subin</u>ertia

Estimation sample summary

estat <u>su</u>mmarize [, *summarize_options*]

Note: Variables in *varlist* must be from the preceding mca and may refer to either a regular categorical variable or a crossed variable. The variables in *varlist* may also be chosen from the supplementary variables.

coordinates_options	Description
<u>normal</u>ize(<u>s</u>tandard)	standard coordinates
<u>normal</u>ize(<u>p</u>rincipal)	principal coordinates
<u>stat</u>s	include mass, distance, and inertia
<u>form</u>at(*%fmt*)	display format; default is format(%9.4f)

summarize_options	Description
Main	
<u>cr</u>ossed	summarize crossed and uncrossed variables as used
<u>l</u>abels	display variable labels
<u>noh</u>eader	suppress the header
<u>now</u>eights	ignore weights

collect is allowed with all estat commands; see [U] **11.1.10 Prefix commands**.

Options for estat

Options for estat are presented under the following headings:

> *Options for estat coordinates*
> *Options for estat summarize*

Options for estat coordinates

normalize(*norm*) specifies the normalization of the scores (coordinates). normalize(standard) returns coordinates in standard normalization. normalize(principal) returns principal scores. The default is the normalization method specified with mca during estimation, or normalize(standard) if no method was specified.

stats includes the column mass, the distance of the columns to the centroid, and the column inertias in the table.

format(%*fmt*) specifies the display format for the matrix, for example, format(%8.3f). The default is format(%9.4f).

Options for estat summarize

Main

crossed specifies summarizing the crossed variables if crossed variables are used in the MCA, rather than the crossing variables from which they are formed. The default is to summarize the crossing variables and single categorical variables used in the MCA.

labels displays variable labels.

noheader suppresses the header.

noweights ignores the weights, if any. The default when weights are present is to perform a weighted summarize on all variables except the weight variable itself. An unweighted summarize is performed on the weight variable.

Remarks and examples

Remarks are presented under the following headings:

> *Postestimation statistics*
> *Predicting new variables*

Postestimation statistics

We continue to examine the ISSP (1993) dataset on the environment. We perform joint correspondence analysis.

▷ Example 1: Category coordinates and subinertias

```
. use https://www.stata-press.com/data/r18/issp93
(Selection from ISSP (1993))

. mca A-D, method(joint)
```

Multiple/joint correspondence analysis

	Number of obs	=	871
	Total inertia	=	.18242477
Method: Joint (JCA)	Number of axes	=	2

Dimension	Principal inertia	Percent	Cumul. percent
Dim 1	.099091	54.32	54.32
Dim 2	.0650329	35.65	89.97
Total	.1824248	100.00	

Statistics for column categories in standard normalization

Categories	Mass	Overall Quality	%inert	Dimension_1 Coord	Sqcorr	Contrib
A						
Agree stro~y	0.034	0.964	0.052	−1.456	0.759	0.072
Agree	0.092	0.774	0.020	−0.536	0.733	0.027
Neither ag~e	0.059	0.884	0.030	0.154	0.025	0.001
Disagree	0.051	0.887	0.046	1.157	0.810	0.068
Disagree s~y	0.014	0.899	0.060	2.258	0.636	0.070
B						
Agree stro~y	0.020	0.957	0.093	−2.490	0.735	0.126
Agree	0.050	0.851	0.031	−0.850	0.636	0.036
Neither ag~e	0.059	0.953	0.033	−0.639	0.393	0.024
Disagree	0.081	0.705	0.029	0.618	0.579	0.031
Disagree s~y	0.040	0.977	0.149	2.014	0.594	0.163
C						
Agree stro~y	0.044	0.983	0.149	−2.104	0.704	0.193
Agree	0.091	0.665	0.020	−0.327	0.257	0.010
Neither ag~e	0.057	0.839	0.047	0.539	0.188	0.016
Disagree	0.044	0.907	0.054	1.429	0.899	0.090
Disagree s~y	0.015	0.944	0.065	1.864	0.431	0.052
D						
Agree stro~y	0.017	0.850	0.034	−0.674	0.124	0.008
Agree	0.067	0.145	0.008	0.165	0.120	0.002
Neither ag~e	0.058	0.769	0.038	0.181	0.027	0.002
Disagree	0.065	0.178	0.010	0.116	0.047	0.001
Disagree s~y	0.043	0.929	0.030	−0.402	0.125	0.007

| | Dimension_2 | | |
Categories	Coord	Sqcorr	Contrib
A			
Agree stro~y	−0.934	0.205	0.030
Agree	0.158	0.042	0.002
Neither ag~e	1.103	0.859	0.071
Disagree	−0.440	0.077	0.010
Disagree s~y	−1.796	0.264	0.044
B			
Agree stro~y	−1.690	0.222	0.058
Agree	0.611	0.216	0.019
Neither ag~e	0.942	0.560	0.052
Disagree	0.356	0.126	0.010
Disagree s~y	−1.995	0.383	0.160
C			
Agree stro~y	−1.634	0.279	0.116
Agree	0.508	0.407	0.023
Neither ag~e	1.237	0.651	0.087
Disagree	−0.166	0.008	0.001
Disagree s~y	−2.509	0.513	0.094
D			
Agree stro~y	−2.018	0.727	0.070
Agree	0.092	0.024	0.001
Neither ag~e	1.166	0.741	0.079
Disagree	0.239	0.131	0.004
Disagree s~y	−1.256	0.804	0.068

If we wish to see the coordinates in the principal normalization, we do not need to rerun our analysis. We can use `estat coordinates` to display them.

```
. estat coordinates, norm(principal)
```

Column principal coordinates

Categories	dim1	dim2
A		
Agree_stro~y	-.4582629	-.2381115
Agree	-.1686314	.0402091
Neither_ag~e	.0484366	.2811716
Disagree	.3642677	-.1123168
Disagree_s~y	.7106647	-.4578886
B		
Agree_stro~y	-.783911	-.4310436
Agree	-.2674646	.1558017
Neither_ag~e	-.2010783	.2402487
Disagree	.1944504	.0906804
Disagree_s~y	.6341215	-.5088398
C		
Agree_stro~y	-.6623101	-.4166016
Agree	-.1029922	.1295649
Neither_ag~e	.169804	.3155628
Disagree	.4496893	-.0423339
Disagree_s~y	.5867913	-.6397215
D		
Agree_stro~y	-.2123187	-.5145647
Agree	.05208	.0233723
Neither_ag~e	.0569168	.297262
Disagree	.0365233	.0609881
Disagree_s~y	-.1264563	-.3203889

We may also be interested in the contributions of each submatrix of the Burt matrix to the total inertia. This can be obtained by estat subinertia. Compare with Greenacre (2006, table A.12).

```
. estat subinertia
```

Subinertias: decomposition of total inertia

Variable	A	B	C	D
A	.0074502			
B	.0148596	.022442		
C	.012149	.0185838	.0210336	
D	.0032898	.0053016	.0096583	.0038148

◁

Predicting new variables

Coordinates (scores) can be predicted after mca. You can predict either the column coordinates or the row coordinates.

▷ Example 2: Predictions

We will calculate row scores by hand and via `predict, rowscore`. Row scores are calculated off the indicator method approach. This calculation would not work with JCA, because the standard coordinates and the principal inertias are different for JCA. The principal inertias are also a problem with the Burt method, with and without adjustment. We use the `points(A)` option to restrict the output from mca. Four variables were used in the original mca. `predict` without the `dimensions()` option predicts the first dimension.

```
. mca A-D, method(indicator) points(A)
```

Multiple/joint correspondence analysis		Number of obs	=	871
		Total inertia	=	4
Method: Indicator matrix		Number of axes	=	2

Dimension	Principal inertia	Percent	Cumul. percent
Dim 1	.4573792	11.43	11.43
Dim 2	.4309658	10.77	22.21
Dim 3	.3219257	8.05	30.26
Dim 4	.3064732	7.66	37.92
Dim 5	.2756747	6.89	44.81
Dim 6	.251928	6.30	51.11
Dim 7	.2425591	6.06	57.17
Dim 8	.2349506	5.87	63.05
Dim 9	.225468	5.64	68.68
Dim 10	.2206291	5.52	74.20
Dim 11	.2098376	5.25	79.44
Dim 12	.1971485	4.93	84.37
Dim 13	.1778833	4.45	88.82
Dim 14	.1691119	4.23	93.05
Dim 15	.1528191	3.82	96.87
Dim 16	.1252462	3.13	100.00
Total	4	100.00	

Statistics for column categories in standard normalization

		Overall			Dimension_1		
Categories	Mass	Quality	%inert		Coord	Sqcorr	Contrib
A							
Agree stro~y	0.034	0.280	0.054		1.837	0.244	0.078
Agree	0.092	0.100	0.039		0.546	0.080	0.019
Neither ag~e	0.059	0.218	0.048		-0.447	0.028	0.008
Disagree	0.051	0.220	0.050		-1.166	0.160	0.047
Disagree s~y	0.014	0.260	0.059		-1.995	0.106	0.037

	Dimension_2		
Categories	Coord	Sqcorr	Contrib
A			
Agree stro~y	0.727	0.036	0.012
Agree	-0.284	0.020	0.005
Neither ag~e	-1.199	0.190	0.055
Disagree	0.737	0.060	0.018
Disagree s~y	2.470	0.153	0.055

```
. predict double a1, score(A)
. predict double b1, score(B)
. predict double c1, score(C)
```

```
. predict double d1, score(D)
. predict double r1, rowscore
. mat Ev = e(Ev)
. scalar phi1 = Ev[1,1]
. generate double rc = (a1+b1+c1+d1)/(4*sqrt(phi1))
. assert reldif(rc, r1) < 1e-14
```

In the indicator method approach, we can also find Cronbach's alpha either via the `alpha` command (see [MV] **alpha**) or by hand.

```
. alpha a1 b1 c1 d1
Test scale = mean(unstandardized items)
Average interitem covariance:      .2768234
Number of items in the scale:             4
Scale reliability coefficient:       0.6045
. scalar alpha = (4/(4-1))*(1-1/(4*phi1))
. display alpha
.60454338
```

◁

Stored results

`estat summarize` stores the following in `r()`:

Matrices
    r(stats) $k \times 4$ matrix of means, standard deviations, minimums, and maximums

`estat coordinates` stores the following in `r()`:

Macros
    r(norm)   normalization method of the coordinates
Matrices
    r(Coord)   column coordinates
    r(Stats)   column statistics: mass, distance, and inertia (option stats only)

`estat subinertia` stores the following in `r()`:

Matrices
    r(inertia_sub)   variable-by-variable inertias

Methods and formulas

See *Methods and formulas* in [MV] **mca**.

References

Greenacre, M. J. 2006. From simple to multiple correspondence analysis. In *Multiple Correspondence Analysis and Related Methods*, ed. M. J. Greenacre and J. Blasius. Boca Raton, FL: Chapman and Hall.

ISSP. 1993. International Social Survey Programme: Environment. http://www.issp.org.

Also see

Title

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mca postestimation plots — Postestimation plots for mca

[Postestimation commands](#)   [mcaplot](#)   [mcaprojection](#)   [Remarks and examples](#)
[Methods and formulas](#)   [References](#)   [Also see](#)

Postestimation commands

The following postestimation commands are of special interest after `mca`:

Command	Description
[mcaplot](#)	plot of category coordinates
[mcaprojection](#)	MCA dimension projection plot

mcaplot

Description for mcaplot

`mcaplot` produces a scatterplot of category points of the MCA variables in two dimensions.

Menu for mcaplot

Statistics > Multivariate analysis > Correspondence analysis > Postestimation after MCA or JCA > Plot of category
coordinates

Syntax for mcaplot

> `mcaplot` $\big[$ *speclist* $\big]$ $\big[$, *[options](#)* $\big]$

where

> $speclist = spec \ \big[\ spec \ \dots \ \big]$
>
> $spec = \textit{varlist} \, | \, (\textit{varname} \ \big[\, , \, \textit{plot\_options} \, \big])$

and variables in *varlist* or *varname* must be from the preceding `mca` and may refer to either a regular
categorical variable or a crossed variable. The variables may also be supplementary.

options	Description
Options	
combine_options	affect the rendition of the combined graphs
<u>o</u>verlay	overlay the plots of the variables; default is to produce separate plots
<u>dim</u>ensions($#_1$ $#_2$)	display dimensions $#_1$ and $#_2$; default is dimensions(2 1)
<u>norm</u>alize(<u>s</u>tandard)	display standard coordinates
<u>norm</u>alize(<u>p</u>rincipal)	display principal coordinates
<u>maxl</u>ength(#)	use # as maximum number of characters for labels; default is maxlength(12)
<u>xn</u>egate	negate the coordinates relative to the x axis
<u>yn</u>egate	negate the coordinates relative to the y axis
<u>o</u>rigin	mark the origin and draw origin axes
<u>originlo</u>pts(*line_options*)	affect the rendition of the origin axes
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

plot_options	Description
marker_options	change look of markers (color, size, etc.)
marker_label_options	add marker labels; change look or position
twoway_options	titles, legends, axes, added lines and text, regions, etc.

Options for mcaplot

    Plots

plot_options affect the rendition of markers, including their shape, size, color, and outline (see [G-3] *marker_options*) and specify if and how the markers are to be labeled (see [G-3] *marker_label_options*). These options may be specified for each variable. If the overlay option is not specified, then for each variable you may also specify many of the *twoway_options* excluding by(), name(), and aspectratio(); see [G-3] *twoway_options*. See *twoway_options* below for a warning against using options such as xlabel(), xscale(), ylabel(), and yscale().

    Options

combine_options affect the rendition of the combined plot; see [G-2] **graph combine**. *combine_options* may not be specified with overlay.

overlay overlays the biplot graphs for the variables. The default is to produce a combined graph of the biplot graphs.

dimensions($#_1$ $#_2$) identifies the dimensions to be displayed. For instance, dimensions(3 2) plots the third dimension (vertically) versus the second dimension (horizontally). The dimension number cannot exceed the number of extracted dimensions. The default is dimensions(2 1).

normalize(*norm*) specifies the normalization of the coordinates. normalize(standard) returns coordinates in standard normalization. normalize(principal) returns principal coordinates. The default is the normalization method specified with mca during estimation, or normalize(standard) if no method was specified.

maxlength(*#*) specifies the maximum number of characters for row and column labels; the default is maxlength(12).

xnegate specifies that the x-axis coordinates be negated (multiplied by -1).

ynegate specifies that the y-axis coordinates be negated (multiplied by -1).

origin marks the origin and draws the origin axes.

originlopts(*line_options*) affect the rendition of the origin axes. See [G-3] *line_options*.

<hr>

Y axis, X axis, Titles, Legend, Overall

twoway_options are any of the options documented in [G-3] *twoway_options* excluding by().

mcaplot automatically adjusts the aspect ratio on the basis of the range of the data and ensures that the axes are balanced. As an alternative, the *twoway_option* aspectratio() can be used to override the default aspect ratio. mcaplot accepts the aspectratio() option as a suggestion only and will override it when necessary to produce plots with balanced axes; that is, distance on the x axis equals distance on the y axis.

twoway_options such as xlabel(), xscale(), ylabel(), and yscale() should be used with caution. These options *axis_options* are accepted but may have unintended side effects on the aspect ratio. See [G-3] *twoway_options*.

mcaprojection

Description for mcaprojection

mcaprojection produces a projection plot of the coordinates of the categories of the MCA variables.

Menu for mcaprojection

Statistics > Multivariate analysis > Correspondence analysis > Postestimation after MCA or JCA > Dimension projection plot

Syntax for mcaprojection

> mcaprojection [*speclist*] [, *options*]

where

> *speclist* = *spec* [*spec* ...]
>
> *spec* = *varlist* | (*varname* [, *plot_options*])

and variables in *varlist* or *varname* must be from the preceding mca and may refer to either a regular categorical variable or a crossed variable. The variables may also be supplementary.

options	Description
Options	
<u>dim</u>ensions(*numlist*)	display *numlist* dimensions; default is all
<u>norm</u>alize(principal)	scores (coordinates) should be in principal normalization
<u>norm</u>alize(standard)	scores (coordinates) should be in standard normalization
<u>alt</u>ernate	alternate labels
<u>max</u>length(*#*)	use *#* as maximum number of characters for labels; default is maxlength(12)
combine_options	affect the rendition of the combined graphs
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

plot_options	Description
marker_options	change look of markers (color, size, etc.)
marker_label_options	add marker labels; change look or position
twoway_options	titles, legends, axes, added lines and text, regions, etc.

Options for mcaprojection

> Plots

plot_options affect the rendition of markers, including their shape, size, color, and outline (see [G-3] *marker_options*) and specify if and how the markers are to be labeled (see [G-3] *marker_label_options*). These options may be specified for each variable. If the over-lay option is not specified then for each variable you may also specify *twoway_options* excluding by() and name(); see [G-3] *twoway_options*.

> Options

dimensions(*numlist*) identifies the dimensions to be displayed. By default, all dimensions are displayed.

normalize(*norm*) specifies the normalization of the coordinates. normalize(standard) returns coordinates in standard normalization. normalize(principal) returns principal coordinates. The default is the normalization method specified with mca during estimation, or normalize(standard) if no method was specified.

alternate causes adjacent labels to alternate sides.

maxlength(*#*) specifies the maximum number of characters for row and column labels; the default is maxlength(12).

combine_options affect the rendition of the combined plot; see [G-2] **graph combine**. These options may not be used if only one variable is specified.

> Y axis, X axis, Titles, Legend, Overall

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding by().

Remarks and examples

Several examples of mcaplot were displayed in [MV] **mca**, so we will not give more examples here. The discussion in [MV] **ca postestimation** is also relevant.

We will focus on mcaprojection, which is the mca analogue of caprojection, just as mcaplot is the analogue of cabiplot.

▷ Example 1: MCA dimension projection plot

mcaprojection produces a projection plot of the column coordinates after mca. We continue with example 1 of [MV] **mca postestimation**. Say that we want to examine the projections in the principal normalization.

```
. use https://www.stata-press.com/data/r18/issp93
(Selection from ISSP (1993))

. mca A-D, method(joint)
 (output omitted )
```

```
. mcaprojection, norm(principal)
```

MCA dimension projection plot
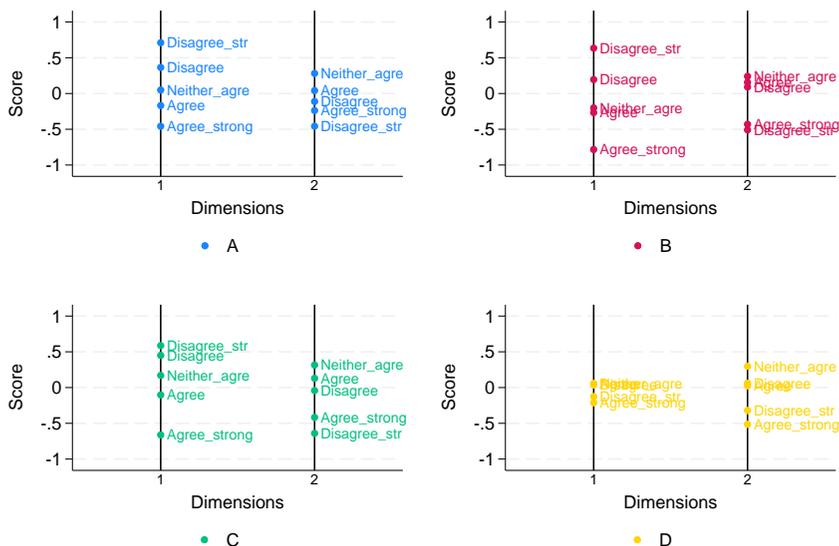
Principal normalization

We would see the same alignment of points in the standard normalization, but the scale would be changed. We have noted previously that item D does not behave like the other variables in the MCA. Each of the first three variables, A, B, and C, has its responses arrayed in order from strong disagreement to strong agreement on the first dimension. Here again, variable D is the only one of the four that shows a different ordering in its projection. We do not see a nice projection from strong disagreement to strong agreement on the second dimension, but an inspection indicates that the first three variables are all in the same order, with the last, D, opposed to the remainder.

◁

Methods and formulas

See *Methods and formulas* in [MV] **mca**.

References

See *References* in [MV] **mca**.

Also see

[MV] **mca** — Multiple and joint correspondence analysis

[MV] **mca postestimation** — Postestimation tools for mca

[MV] **ca** — Simple correspondence analysis,

[MV] **ca postestimation** — Postestimation tools for ca and camat

Title

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mds — Multidimensional scaling for two-way data

Description

mds performs multidimensional scaling (MDS) for dissimilarities between observations with respect to the specified variables. A wide selection of similarity and dissimilarity measures is available. mds performs classical metric MDS as well as modern metric and nonmetric MDS.

If your proximities are stored as variables in long format, see [MV] **mdslong**. For MDS with two-way proximity data in a matrix, see [MV] **mdsmat**.

Quick start

Classical metric multidimensional scaling of variables v1, v2, v3, and v4 with observations identified by idvar

    mds v1 v2 v3 v4, id(idvar)

Same as above, but use absolute-value distance and suppress the MDS configuration plot

    mds v1 v2 v3 v4, id(idvar) measure(absolute) noplot

Same as above, but increase dimensions from 2 to 3 for approximating configuration

    mds v1 v2 v3 v4, id(idvar) measure(absolute) noplot dimension(3)

Modern multidimensional scaling

    mds v1 v2 v3 v4, id(idvar) method(modern)

Same as above, but Procrustes rotate toward classical solution instead of the default principal orientation

    mds v1 v2 v3 v4, id(idvar) method(modern) normalize(classical)

Modern multidimensional scaling with Sammon mapping for the loss criterion

    mds v1 v2 v3 v4, id(idvar) loss(sammon)

Modern nonmetric multidimensional scaling

    mds v1 v2 v3 v4, id(idvar) method(nonmetric)

Menu

Statistics > Multivariate analysis > Multidimensional scaling (MDS) > MDS of data

Syntax

> mds *varlist* $\begin{bmatrix} if \end{bmatrix}$ $\begin{bmatrix} in \end{bmatrix}$, id(*varname*) $\begin{bmatrix} options \end{bmatrix}$

options	Description
[Model]	
* id(*varname*)	identify observations
<u>method</u>(*method*)	method for performing MDS
<u>loss</u>(*loss*)	loss function
<u>transform</u>(*tfunction*)	permitted transformations of dissimilarities
<u>normalize</u>(*norm*)	normalization method; default is normalize(principal)
<u>dimension</u>(*#*)	configuration dimensions; default is dimension(2)
addconstant	make distance matrix positive semidefinite
[Model 2]	
unit$\begin{bmatrix} (varlist_2) \end{bmatrix}$	scale variables to min $= 0$ and max $= 1$
std$\begin{bmatrix} (varlist_3) \end{bmatrix}$	scale variables to mean $= 0$ and sd $= 1$
<u>measure</u>(*measure*)	similarity or dissimilarity measure; default is L2 (Euclidean)
s2d(<u>standard</u>)	convert similarity to dissimilarity: $\text{dissim}_{ij} = \sqrt{\text{sim}_{ii} + \text{sim}_{jj} - 2\text{sim}_{ij}}$; the default
s2d(<u>oneminus</u>)	convert similarity to dissimilarity: $\text{dissim}_{ij} = 1 - \text{sim}_{ij}$
[Reporting]	
<u>neigen</u>(*#*)	maximum number of eigenvalues to display; default is neigen(10)
<u>config</u>	display table with configuration coordinates
noplot	suppress configuration plot
[Minimization]	
<u>initialize</u>(*initopt*)	start with configuration given in *initopt*
<u>tolerance</u>(*#*)	tolerance for configuration matrix; default is tolerance(1e-4)
<u>ltolerance</u>(*#*)	tolerance for loss criterion; default is ltolerance(1e-8)
<u>iterate</u>(*#*)	perform maximum *#* of iterations; default is iterate(1000)
<u>protect</u>(*#*)	perform *#* optimizations and report best solution; default is protect(1)
$\begin{bmatrix} no \end{bmatrix}$log	display or suppress the iteration log; default is to display
trace	display current configuration in iteration log
gradient	display current gradient matrix in iteration log
<u>sdprotect</u>(*#*)	advanced; see *Options* below

* id(*varname*) is required.

bootstrap, by, collect, jackknife, rolling, statsby, and xi are allowed; see [U] **11.1.10 Prefix commands**.
The maximum number of observations allowed in mds is the maximum matrix size; see [R] **Limits**.
sdprotect(*#*) does not appear in the dialog box.
See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

method	Description
<u>c</u>lassical	classical MDS; default if neither loss() nor transform() is specified
<u>mod</u>ern	modern MDS; default if loss() or transform() is specified; except when loss(stress) and transform(monotonic) are specified
<u>non</u>metric	nonmetric (modern) MDS; default when loss(stress) and transform(monotonic) are specified

loss	Description
<u>stress</u>	stress criterion, normalized by distances; the default
<u>n</u>stress	stress criterion, normalized by disparities
<u>ss</u>tress	squared stress criterion, normalized by distances
<u>nss</u>tress	squared stress criterion, normalized by disparities
<u>str</u>ain	strain criterion (with transform(identity) is equivalent to classical MDS)
<u>sam</u>mon	Sammon mapping

tfunction	Description
<u>i</u>dentity	no transformation; disparity = dissimilarity; the default
<u>po</u>wer	power α: disparity = dissimilarity$^{\alpha}$
<u>mono</u>tonic	weakly monotonic increasing functions (nonmetric scaling); only with loss(stress)

norm	Description
<u>pri</u>ncipal	principal orientation; location = 0; the default
<u>c</u>lassical	Procrustes rotation toward classical solution
<u>t</u>arget(*matname*) [, copy]	Procrustes rotation toward *matname*; ignore naming conflicts if copy is specified

initopt	Description
<u>c</u>lassical	start with classical solution; the default
<u>ran</u>dom [(#)]	start at random configuration, setting seed to #
<u>fr</u>om(*matname*) [, copy]	start from *matname*; ignore naming conflicts if copy is specified

Options

 Model

id(*varname*) is required and specifies a variable that identifies observations. A warning message is
 displayed if *varname* has duplicate values.

method(*method*) specifies the method for MDS.

 method(classical) specifies classical metric scaling, also known as "principal coordinates anal-
 ysis" when used with Euclidean proximities. Classical MDS obtains equivalent results to modern

MDS with `loss(strain)` and `transform(identity)` without weights. The calculations for classical MDS are fast; consequently, classical MDS is generally used to obtain starting values for modern MDS. If the options `loss()` and `transform()` are not specified, `mds` computes the classical solution, likewise if `method(classical)` is specified `loss()` and `transform()` are not allowed.

`method(modern)` specifies modern scaling. If `method(modern)` is specified but not `loss()` or `transform()`, then `loss(stress)` and `transform(identity)` are assumed. All values of `loss()` and `transform()` are valid with `method(modern)`.

`method(nonmetric)` specifies nonmetric scaling, which is a type of modern scaling. If `method(nonmetric)` is specified, `loss(stress)` and `transform(monotonic)` are assumed. Other values of `loss()` and `transform()` are not allowed.

`loss(`*loss*`)` specifies the loss criterion.

`loss(stress)` specifies that the stress loss function be used, normalized by the squared Euclidean distances. This criterion is often called Kruskal's stress-1. Optimal configurations for `loss(stress)` and for `loss(nstress)` are equivalent up to a scale factor, but the iteration paths may differ. `loss(stress)` is the default.

`loss(nstress)` specifies that the stress loss function be used, normalized by the squared disparities, that is, transformed dissimilarities. Optimal configurations for `loss(stress)` and for `loss(nstress)` are equivalent up to a scale factor, but the iteration paths may differ.

`loss(sstress)` specifies that the squared stress loss function be used, normalized by the fourth power of the Euclidean distances.

`loss(nsstress)` specifies that the squared stress criterion, normalized by the fourth power of the disparities (transformed dissimilarities) be used.

`loss(strain)` specifies the strain loss criterion. Classical scaling is equivalent to `loss(strain)` and `transform(identity)` but is computed by a faster noniterative algorithm. Specifying `loss(strain)` still allows transformations.

`loss(sammon)` specifies the Sammon (1969) loss criterion.

`transform(`*tfunction*`)` specifies the class of allowed transformations of the dissimilarities; transformed dissimilarities are called disparities.

`transform(identity)` specifies that the only allowed transformation is the identity; that is, disparities are equal to dissimilarities. `transform(identity)` is the default.

`transform(power)` specifies that disparities are related to the dissimilarities by a power function,

$$\text{disparity} = \text{dissimilarity}^{\alpha}, \qquad \alpha > 0$$

`transform(monotonic)` specifies that the disparities are a weakly monotonic function of the dissimilarities. This is also known as nonmetric MDS. Tied dissimilarities are handled by the primary method; that is, ties may be broken but are not necessarily broken. `transform(monotonic)` is valid only with `loss(stress)`.

`normalize(`*norm*`)` specifies a normalization method for the configuration. Recall that the location and orientation of an MDS configuration is not defined ("identified"); an isometric transformation (that is, translation, reflection, or orthonormal rotation) of a configuration preserves interpoint Euclidean distances.

`normalize(principal)` performs a principal normalization, in which the configuration columns have zero mean and correspond to the principal components, with positive coefficient for the observation with lowest value of `id()`. `normalize(principal)` is the default.

normalize(classical) normalizes by a distance-preserving Procrustean transformation of the configuration toward the classical configuration in principal normalization; see [MV] **procrustes**. normalize(classical) is not valid if method(classical) is specified.

normalize(target(*matname*) [, copy]) normalizes by a distance-preserving Procrustean transformation toward *matname*; see [MV] **procrustes**. *matname* should be an $n \times p$ matrix, where n is the number of observations and p is the number of dimensions, and the rows of *matname* should be ordered with respect to id(). The rownames of *matname* should be set correctly but will be ignored if copy is also specified.

Note on normalize(classical) and normalize(target()): the Procrustes transformation comprises any combination of translation, reflection, and orthonormal rotation—these transformations preserve distance. Dilation (uniform scaling) would stretch distances and is not applied. However, the output reports the dilation factor, and the reported Procrustes statistic is for the dilated configuration.

dimension(#) specifies the dimension of the approximating configuration. The default # is 2 and should not exceed the number of observations; typically, # would be much smaller. With method(classical), it should not exceed the number of positive eigenvalues of the centered distance matrix.

addconstant specifies that if the double-centered distance matrix is not positive semidefinite (psd), a constant should be added to the squared distances to make it psd and, hence, Euclidean. addconstant is allowed with classical MDS only.

Model 2

unit [(*varlist*₂)] specifies variables that are transformed to min $= 0$ and max $= 1$ before entering in the computation of similarities or dissimilarities. unit by itself, without an argument, is a shorthand for unit(_all). Variables in unit() should not be included in std().

std [(*varlist*₃)] specifies variables that are transformed to mean $= 0$ and sd $= 1$ before entering in the computation of similarities or dissimilarities. std by itself, without an argument, is a shorthand for std(_all). Variables in std() should not be included in unit().

measure(*measure*) specifies the similarity or dissimilarity measure. The default is measure(L2), Euclidean distance. This option is not case sensitive. See [MV] *measure_option* for detailed descriptions of the supported measures.

If a similarity measure is selected, the computed similarities will first be transformed into dissimilarities, before proceeding with the scaling; see the s2d() option below.

Classical metric MDS with Euclidean distance is equivalent to principal component analysis (see [MV] **pca**); the MDS configuration coordinates are the principal components.

s2d(standard | oneminus) specifies how similarities are converted into dissimilarities. By default, the command assumes dissimilarity data. Specifying s2d() indicates that your proximity data are similarities.

Dissimilarity data should have zeros on the diagonal (that is, an object is identical to itself) and nonnegative off-diagonal values. Dissimilarities need not satisfy the triangular inequality, $D(i,j)^2 \leq D(i,h)^2 + D(h,j)^2$. Similarity data should have ones on the diagonal (that is, an object is identical to itself) and have off-diagonal values between zero and one. In either case, proximities should be symmetric.

The available s2d() options, standard and oneminus, are defined as follows:

standard $\quad$ dissim$_{ij} = \sqrt{\text{sim}_{ii} + \text{sim}_{jj} - 2\text{sim}_{ij}} = \sqrt{2(1 - \text{sim}_{ij})}$

oneminus $\quad$ dissim$_{ij} = 1 - \text{sim}_{ij}$

s2d(standard) is the default.

s2d() should be specified only with measures in similarity form.

    Reporting

neigen(#) specifies the number of eigenvalues to be included in the table. The default is neigen(10). Specifying neigen(0) suppresses the table. This option is allowed with classical MDS only.

config displays the table with the coordinates of the approximating configuration. This table may also be displayed using the postestimation command estat config; see [MV] **mds postestimation**.

noplot suppresses the graph of the approximating configuration. The graph can still be produced later via mdsconfig, which also allows the standard graphics options for fine-tuning the plot; see [MV] **mds postestimation plots**.

    Minimization

These options are available only with method(modern) or method(nonmetric):

initialize(*initopt*) specifies the initial values of the criterion minimization process.

initialize(classical), the default, uses the solution from classical metric scaling as initial values. With protect(), all but the first run start from random perturbations from the classical solution. These random perturbations are independent and normally distributed with standard error equal to the product of sdprotect(#) and the standard deviation of the dissimilarities. initialize(classical) is the default.

initialize(random) starts an optimization process from a random starting configuration. These random configurations are generated from independent normal distributions with standard error equal to the product of sdprotect(#) and the standard deviation of the dissimilarities. The means of the configuration are irrelevant in MDS.

initialize(from(*matname*) [, copy]) sets the initial value to *matname*. *matname* should be an $n \times p$ matrix, where n is the number of observations and p is the number of dimensions, and the rows of *matname* should be ordered with respect to id(). The rownames of *matname* should be set correctly but will be ignored if copy is specified. With protect(), the second-to-last runs start from random perturbations from *matname*. These random perturbations are independent normal distributed with standard error equal to the product of sdprotect(#) and the standard deviation of the dissimilarities.

tolerance(#) specifies the tolerance for the configuration matrix. When the relative change in the configuration from one iteration to the next is less than or equal to tolerance(), the tolerance() convergence criterion is satisfied. The default is tolerance(1e-4).

ltolerance(#) specifies the tolerance for the fit criterion. When the relative change in the fit criterion from one iteration to the next is less than or equal to ltolerance(), the ltolerance() convergence is satisfied. The default is ltolerance(1e-8).

Both the tolerance() and ltolerance() criteria must be satisfied for convergence.

iterate(#) specifies the maximum number of iterations. The default is iterate(1000).

protect(#) requests that # optimizations be performed and that the best of the solutions be reported. The default is protect(1). See option initialize() on starting values of the runs. The output contains a table of the run, return code, iteration, and criterion value reached. Specifying a large number, such as protect(50), provides reasonable insight whether the solution found is a global minimum and not just a local minimum.

If any of the options log, trace, or gradient is also specified, iteration reports will be printed for each optimization run. Beware: this option will produce a lot of output.

log and nolog specify whether to display the iteration log. The iteration log is displayed by default unless you used set iterlog off to suppress it; see set iterlog in [R] *set iter*.

trace displays the configuration matrices in the iteration report. Beware: this option may produce a lot of output.

gradient displays the gradient matrices of the fit criterion in the iteration report. Beware: this option may produce a lot of output.

The following option is available with mds but is not shown in the dialog box:

sdprotect(#) sets a proportionality constant for the standard deviations of random configurations (init(random)) or random perturbations of given starting configurations (init(classical) or init(from())). The default is sdprotect(1).

Remarks and examples

Remarks are presented under the following headings:

> *Introduction*
> *Euclidean distances*
> *Non-Euclidean dissimilarity measures*
> *Introduction to modern MDS*
> *Protecting from local minimums*

Introduction

Multidimensional scaling (MDS) is a dimension-reduction and visualization technique. Dissimilarities (for instance, Euclidean distances) between observations in a high-dimensional space are represented in a lower-dimensional space (typically two dimensions) so that the Euclidean distance in the lower-dimensional space approximates the dissimilarities in the higher-dimensional space. See Kruskal and Wish (1978) for a brief nontechnical introduction to MDS. Young (1987) and Borg and Groenen (2005) offer more advanced textbook-sized treatments.

If you already have the similarities or dissimilarities of the n objects, you should continue by reading [MV] **mdsmat**.

In many applications of MDS, however, the similarity or dissimilarity of objects is not measured but rather *defined* by the researcher in terms of variables ("attributes") $x_1, \ldots, x_k$ that are measured on the objects. The pairwise dissimilarity of objects can be expressed using a variety of similarity or dissimilarity measures in the attributes (for example, Mardia, Kent, and Bibby [1979, sec. 13.4]; Cox and Cox [2001, sec. 1.3]). A common measure is the Euclidean distance L2 between the attributes of the objects i and j:

$$\text{L2}_{ij} = \left\{ (x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \cdots + (x_{ik} - x_{jk})^2 \right\}^{1/2}$$

A popular alternative is the L1 distance, also known as the `cityblock` or `Manhattan` distance. In comparison to L2, L1 gives less influence to larger differences in attributes:

$$\texttt{L1}_{ij} = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \cdots + |x_{ik} - x_{jk}|$$

In contrast, we may also define the extent of dissimilarity between 2 observations as the maximum absolute difference in the attributes and thus give a larger influence to larger differences:

$$\texttt{Linfinity}_{ij} = \max(|x_{i1} - x_{j1}|, |x_{i2} - x_{j2}|, \dots, |x_{ik} - x_{jk}|)$$

These three measures are special cases of the Minkowski distance $L(q)$, for $q = 2$ (L2), $q = 1$ (L1), and $q = \infty$ (`Linfinity`), respectively. Minkowski distances with other values of q may be used as well. Stata supports a wide variety of other similarity and dissimilarity measures, both for continuous variables and for binary variables. See [MV] *measure_option* for details.

Multidimensional scaling constructs approximations for dissimilarities, not for similarities. Thus, if a similarity measure is specified, `mds` first transforms the similarities into dissimilarities. Two methods to do this are available. The default `standard` method,

$$\text{dissim}_{ij} = \sqrt{\text{sim}_{ii} - 2\text{sim}_{ij} + \text{sim}_{jj}}$$

has a useful property: if the similarity matrix is positive semidefinite, a property satisfied by most similarity measures, the standard dissimilarities are Euclidean.

Usually, the number of observations exceeds the number of variables on which the observations are compared, but this is not a requirement for MDS. MDS creates an $n \times n$ dissimilarity matrix $\mathbf{D}$ from the n observations on k variables. It then constructs an approximation of $\mathbf{D}$ by the Euclidean distances in a matching configuration $\mathbf{Y}$ of n points in p-dimensional space:

$$\text{dissimilarity}(x_i, x_j) \approx \texttt{L2}(y_i, y_j) \quad \text{for all } i, j$$

Typically, of course, $p << k$, and most often $p = 1$, 2, or 3.

A wide variety of MDS methods have been proposed. `mds` performs classical and modern scaling. Classical scaling has its roots in Young and Householder (1938) and Torgerson (1952). MDS requires complete and symmetric dissimilarity interval-level data. To explore modern scaling, see Borg and Groenen (2005). Classical scaling results in an eigen decomposition, whereas modern scaling is accomplished by the minimization of a loss function. Consequently, eigenvalues are not available after modern MDS.

Computing the classical solution is straightforward, but with modern MDS the minimization of the loss criteria over configurations is a high-dimensional problem that is easily beset by convergence to local minimums. `mds` provides options to control the minimization process 1) by allowing the user to select the starting configuration and 2) by selecting the best solution among multiple minimization runs from random starting configurations.

Euclidean distances

▷ Example 1

The most popular dissimilarity measure is Euclidean distance. We illustrate with data from table 7.1 of Yang and Trewn (2004, 182). This dataset consists of eight variables with nutrition data on 25 breakfast cereals.

```
. use https://www.stata-press.com/data/r18/cerealnut
(Cereal nutrition)
. describe
Contains data from https://www.stata-press.com/data/r18/cerealnut.dta
 Observations:               25                  Cereal nutrition
    Variables:                9                  24 Feb 2022 17:19
                                                 (_dta has notes)
─────────────────────────────────────────────────────────────────────────
Variable      Storage   Display    Value
    name         type    format    label      Variable label
─────────────────────────────────────────────────────────────────────────
brand          str25    %25s                  Cereal Brand
calories       int      %9.0g                 Calories (Cal/oz)
protein        byte     %9.0g                 Protein (g)
fat            byte     %9.0g                 Fat (g)
Na             int      %9.0g                 Na (mg)
fiber          float    %9.0g                 Fiber (g)
carbs          float    %9.0g                 Carbs (g)
sugar          byte     %9.0g                 Sugar (g)
K              int      %9.0g                 K (mg)
─────────────────────────────────────────────────────────────────────────
Sorted by:
. summarize calories-K, sep(4)
    Variable │        Obs        Mean    Std. dev.        Min        Max
─────────────┼───────────────────────────────────────────────────────────
    calories │         25       109.6    21.30728         50        160
     protein │         25        2.68    1.314027          1          6
         fat │         25         .92    .7593857          0          2
          Na │         25       195.8    71.32204          0        320
─────────────┼───────────────────────────────────────────────────────────
       fiber │         25         1.7    2.056494          0          9
       carbs │         25        15.3    4.028544          7         22
       sugar │         25         7.4    4.609772          0         14
           K │         25        90.6     77.5043         15        320
. replace brand = subinstr(brand," ","_",.)
(20 real changes made)
```

We replaced spaces in the cereal brand names with underscores to avoid confusing which words in the brand names are associated with which points in the graphs we are about to produce. Removing spaces is not required.

The default dissimilarity measure used by mds is the Euclidean distance L2 computed on the raw data (unstandardized). The summary of the eight nutrition variables shows that K, Na, and calories—having much larger standard deviations—will largely determine the Euclidean distances.

```
. mds calories-K, id(brand)
Classical metric multidimensional scaling
Dissimilarity: L2, computed on 8 variables
                                      Number of obs        =          25
      Eigenvalues > 0     =        8    Mardia fit measure 1 =      0.9603
      Retained dimensions =        2    Mardia fit measure 2 =      0.9970
```

Dimension	Eigenvalue	abs(eigenvalue) Percent	Cumul.	(eigenvalue)^2 Percent	Cumul.
1	158437.92	56.95	56.95	67.78	67.78
2	108728.77	39.08	96.03	31.92	99.70
3	10562.645	3.80	99.83	0.30	100.00
4	382.67849	0.14	99.97	0.00	100.00
5	69.761715	0.03	99.99	0.00	100.00
6	12.520822	0.00	100.00	0.00	100.00
7	5.7559984	0.00	100.00	0.00	100.00
8	2.2243244	0.00	100.00	0.00	100.00
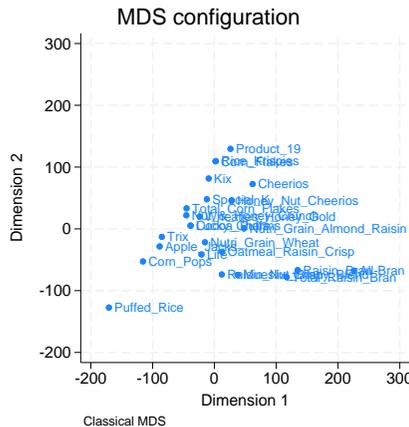
The default MDS configuration graph can be improved upon by using the mdsconfig postestimation command. We will demonstrate this in a moment. But first, we explain the output of mds.

mds has performed classical metric scaling and extracted two dimensions, which is the default action. To assess goodness of fit, the two statistics proposed by Mardia are reported (see Mardia, Kent, and Bibby [1979, sec. 14.4]). The statistics are defined in terms of the eigenvalues of the double-centered distance matrix. If the dissimilarities are truly Euclidean, all eigenvalues are nonnegative. Look at the eigenvalues. We may interpret these as the extent to which the dimensions account for dissimilarity between the cereals. Depending on whether you look at the eigenvalues or squared eigenvalues, it takes two or three dimensions to account for more than 99% of the dissimilarity.

We can produce a prettier configuration plot with the mdsconfig command; see [MV] **mds postestimation plots** for details. command; see [MV] **mds postestimation plots** for details.

```
. generate place = 3
. replace place = 9 if inlist(brand,"Rice_Krispies","Nut_&_Honey_Crunch",
> "Special_K","Raisin_Nut_Bran","Lucky_Charms")
(5 real changes made)
. replace place = 12 if inlist(brand,"Mueslix_Crispy_Blend")
(1 real change made)
. mdsconfig, autoaspect mlabvpos(place)
```
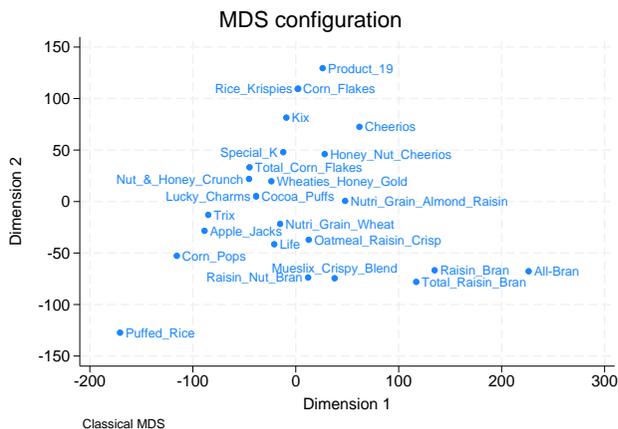

The *marker_label_option* `mlabvposition()` allowed fine control over the placement of the cereal brand names. We created a variable called `place` giving clock positions where the cereal names were to appear in relation to the plotted point. We set these to minimize overlap of the names. We also requested the `autoaspect` option to obtain better use of the graphing region while preserving the scale of the x and y axes.

MDS has placed the cereals so that all the brands fall within a triangle defined by Product 19, All-Bran, and Puffed Rice. You can examine the graph to see how close your favorite cereal is to the other cereals.

But, as we saw from the variable summary, three of the eight variables are controlling the distances. If we want to provide for a more equal footing for the eight variables, we can request that `mds` compute the Euclidean distances on standardized variables. Euclidean distance based on standardized variables is also known as the *Karl Pearson distance* (Pearson 1900). We obtain standardized measures with the option `std`.

```
. mds calories-K, id(brand) std noplot
```

Classical metric multidimensional scaling
Dissimilarity: L2, computed on 8 variables

			Number of obs	=	25
Eigenvalues > 0	=	8	Mardia fit measure 1 =		0.5987
Retained dimensions	=	2	Mardia fit measure 2 =		0.7697

Dimension	Eigenvalue	abs(eigenvalue) Percent	Cumul.	(eigenvalue)^2 Percent	Cumul.
1	65.645395	34.19	34.19	49.21	49.21
2	49.311416	25.68	59.87	27.77	76.97
3	38.826608	20.22	80.10	17.21	94.19
4	17.727805	9.23	89.33	3.59	97.78
5	11.230087	5.85	95.18	1.44	99.22
6	8.2386231	4.29	99.47	0.78	99.99
7	.77953426	0.41	99.87	0.01	100.00
8	.24053137	0.13	100.00	0.00	100.00

In this and the previous example, we did not specify a method() for mds and got classical metric scaling. Classical scaling is the default when method() is omitted and neither the loss() nor transform() option is specified.

Accounting for more than 99% of the underlying distances now takes more MDS-retained dimensions. For this example, we have still retained only two dimensions. We specified the noplot option because we wanted to exercise control over the configuration plot by using the mdsconfig command. We generate a variable named pos that will help minimize cereal brand name overlap.

```
. generate pos = 3
. replace pos = 5 if inlist(brand,"Honey_Nut_Cheerios","Raisin_Nut_Bran",
> "Nutri_Grain_Almond_Raisin")
(3 real changes made)
. replace pos = 8 if inlist(brand,"Oatmeal_Raisin_Crisp")
(1 real change made)
. replace pos = 9 if inlist(brand,"Corn_Pops","Trix","Nut_&_Honey_Crunch",
> "Rice_Krispies","Wheaties_Honey_Gold")
(5 real changes made)
. replace pos = 12 if inlist(brand,"Life")
(1 real change made)
```

```
. mdsconfig, autoaspect mlabvpos(pos)
```


MDS configuration

Classical MDS
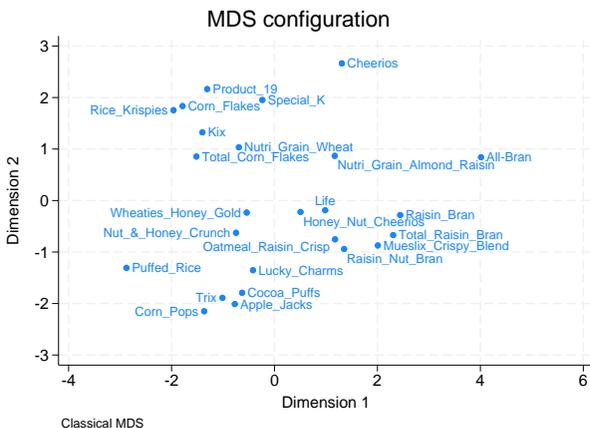
This configuration plot, based on the standardized variables, better incorporates all the nutrition data. If you are familiar with these cereal brands, spotting groups of similar cereals appearing near each other is easy. The bottom-left corner has several of the most sweetened cereals. The brands containing the word "Bran" all appear to the right of center. Rice Krispies and Puffed Rice are the farthest to the left.

Classical multidimensional scaling based on standardized Euclidean distances is actually equivalent to a principal component analysis of the correlation matrix of the variables. See Mardia, Kent, and Bibby (1979, sec. 14.3) for details.

We now demonstrate this property by doing a principal component analysis extracting the leading two principal components. See [MV] **pca** for details.

```
. pca calories-K, comp(2)
```

Principal components/correlation

			Number of obs	=	25
			Number of comp.	=	2
			Trace	=	8
Rotation: (unrotated = principal)			Rho	=	0.5987

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.73522	.680583	0.3419	0.3419
Comp2	2.05464	.436867	0.2568	0.5987
Comp3	1.61778	.879117	0.2022	0.8010
Comp4	.738659	.270738	0.0923	0.8933
Comp5	.46792	.124644	0.0585	0.9518
Comp6	.343276	.310795	0.0429	0.9947
Comp7	.0324806	.0224585	0.0041	0.9987
Comp8	.0100221	.	0.0013	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Unexplained
calories	0.1992	−0.0632	.8832
protein	0.3376	0.4203	.3253
fat	0.3811	−0.0667	.5936
Na	0.0962	0.5554	.3408
fiber	0.5146	0.0913	.2586
carbs	−0.2574	0.4492	.4043
sugar	0.2081	−0.5426	.2765
K	0.5635	0.0430	.1278

The proportion and cumulative proportion of the eigenvalues in the PCA match the percentages from MDS. We will ignore the interpretation of the principal components but move directly to the principal coordinates, also known as the scores of the PCA. We make a plot of the first and second scores, using the scoreplot command; see [MV] **scoreplot**. We specify the mlabel() option to label the cereals and the mlabvpos() option for fine control over placement of the brand names.

```
. replace pos = 11 if inlist(brand,"All-Bran")
(1 real change made)
. scoreplot, mlabel(brand) mlabvpos(pos)
```


Score variables (pca)
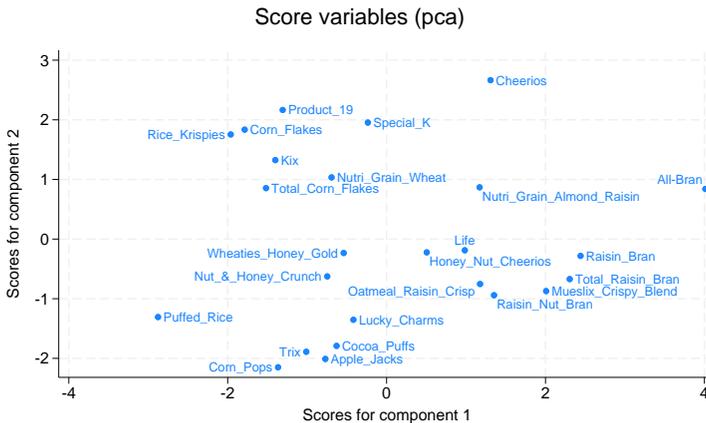
Compare this PCA score plot with the MDS configuration plot. Apart from some differences in how the graphs were rendered, they are the same.

◁

Non-Euclidean dissimilarity measures

With non-Euclidean dissimilarity measures, the parallel between PCA and MDS no longer holds.

▷ Example 2

To illustrate MDS with non-Euclidean distance measures, we will analyze books on multivariate statistics. Gifi (1990) reports on the number of pages devoted to seven topics in 20 textbooks on multivariate statistics. We added similar data on five more recent books.

```
. use https://www.stata-press.com/data/r18/mvstatsbooks, clear

. describe
```

Contains data from https://www.stata-press.com/data/r18/mvstatsbooks.dta
```
 Observations:           25
     Variables:            8                   15 Mar 2022 16:27
                                               (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
author	str17	%17s		
math	int	%9.0g		Math other than statistics (e.g., linear algebra)
corr	int	%9.0g		Correlation and regression, including linear structural and functional equations
fact	byte	%9.0g		Factor analysis and principal component analysis
cano	byte	%9.0g		Canonical correlation analysis
disc	int	%9.0g		Discriminant analysis, classification, and cluster analysis
stat	int	%9.0g		Statistics, incl. dist. theory, hypothesis testing & est.; categorical data
mano	int	%9.0g		Manova and the general linear model

Sorted by:

A brief description of the topics is given in the variable labels. For more details, we refer to Gifi (1990, 15). Here are the data:

```
. list, noobs
```

author	math	corr	fact	cano	disc	stat	mano
Roy57	31	0	0	0	0	164	11
Kendall57	0	16	54	18	27	13	14
Kendall75	0	40	32	10	42	60	0
Anderson58	19	0	35	19	28	163	52
CooleyLohnes62	14	7	35	22	17	0	56
(output omitted)							
GreenCaroll76	290	10	6	0	8	0	2
CailliezPages76	184	48	82	42	134	0	0
Giri77	29	0	0	0	41	211	32
Gnanadesikan77	0	19	56	0	39	75	0
Kshirsagar78	0	22	45	42	60	230	59
Thorndike78	30	128	90	28	48	0	0
MardiaKentBibby79	34	28	68	19	67	131	55
Seber84	16	0	59	13	116	129	101
Stevens96	23	87	67	21	30	43	249
EverittDunn01	0	54	65	0	56	20	30
Rencher02	38	0	71	19	105	135	131

For instance, the 1979 book by Mardia, Kent, and Bibby has 34 pages on mathematics (mostly linear algebra); 28 pages on correlation, regression, and related topics (in this particular case, simultaneous equations); etc. In most of these books, some pages are not classified. Anyway, the number of pages

and the amount of information per page vary widely among the books. A Euclidean distance measure is not appropriate here. Standardization does not help us here—the problem is not differences in the scales of the variables but those in the observations. One possibility is to transform the data into *compositional data* by dividing the variables by the total number of classified pages. See Mardia, Kent, and Bibby (1979, 377–380) for a discussion of specialized dissimilarity measures for compositional data. However, we can also use the correlation between observations (not between variables) as the similarity measure. The higher the correlation between the attention given to the various topics, the more similar two textbooks are. We do a classical MDS, suppressing the plot to first assess the quality of a two-dimensional representation.

```
. mds math-mano, id(author) measure(corr) noplot
Classical metric multidimensional scaling
    Similarity: correlation, computed on 7 variables
Dissimilarity: sqrt(2(1-similarity))

                                        Number of obs      =        25
    Eigenvalues > 0       =       6     Mardia fit measure 1 =    0.6680
    Retained dimensions   =       2     Mardia fit measure 2 =    0.8496
```

Dimension	Eigenvalue	abs(eigenvalue)		(eigenvalue)^2	
		Percent	Cumul.	Percent	Cumul.
1	8.469821	38.92	38.92	56.15	56.15
2	6.0665813	27.88	66.80	28.81	84.96
3	3.8157101	17.53	84.33	11.40	96.35
4	1.6926956	7.78	92.11	2.24	98.60
5	1.2576053	5.78	97.89	1.24	99.83
6	.45929376	2.11	100.00	0.17	100.00

Again the quality of a two-dimensional approximation is somewhat unsatisfactory, with 67% and 85% of the variation accounted for according to the two Mardia criteria. Still, let's look at the plot, using a title that refers to the self-referential aspect of the analysis (Smullyan 1986). We reposition some of the author labels to enhance readability by using the mlabvpos() option.

```
. generate spot = 3
. replace spot = 5 if inlist(author,"Seber84","Kshirsagar78","Kendall75")
(3 real changes made)
. replace spot = 2 if author=="MardiaKentBibby79"
(1 real change made)
. replace spot = 9 if inlist(author, "Dagnelie75","Rencher02",
> "GreenCaroll76","EverittDunn01","CooleyLohnes62","Morrison67")
(6 real changes made)
```

```
. mdsconfig, mlabvpos(spot) title(This plot needs no title)
```
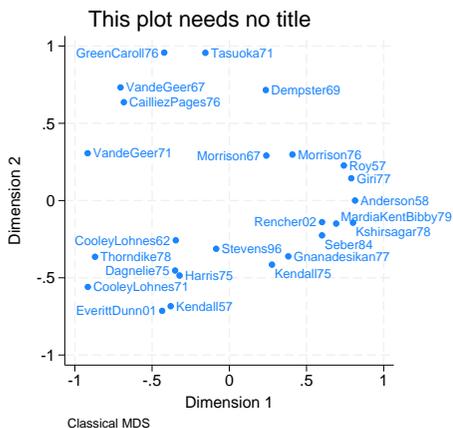

A striking characteristic of the plot is that the textbooks seem to be located on a circle. This is a phenomenon that is regularly encountered in multidimensional scaling and was labeled the "horseshoe effect" by Kendall (1971, 215–251). This phenomenon seems to occur especially in situations in which a one-dimensional representation of objects needs to be constructed, for example, in *seriation* applications, from data in which small dissimilarities were measured accurately but moderate and larger dissimilarities are "lumped together".

◁

❑ Technical note

These data could also be analyzed differently. A particularly interesting method is correspondence analysis (CA), which seeks a simultaneous geometric representation of the rows (textbooks) and columns (topics). We used `camat` to analyze these data. The results for the textbooks were not much different. Textbooks that were mapped as similar using MDS were also mapped this way by CA. The Green and Carroll book that appeared much different from the rest was also displayed away from the rest by CA. In the CA biplot, it was immediately clear that this book was so different because its pages were classified by Gifi (1990) as predominantly mathematical. But CA also located the topics in this space. The pattern was easy to interpret and was expected. The seven topics were mapped in three groups. `math` and `stat` appear as two groups by themselves, and the five applied topics were mapped close together. See [MV] **ca** for information on the `ca` command.

❑

Introduction to modern MDS

We return to the data on breakfast cereals explored above to introduce modern MDS. We repeat some steps taken previously and then perform estimation using options `loss(strain)` and `transform(identity)`, which we demonstrate are equivalent to classical MDS.

`mds` is an estimation or `eclass` command; see `program define` in [P] **program**. You can display its stored results using `ereturn list`. The configuration is stored as `e(Y)` and we will compare the configuration obtained from classical MDS with the equivalent one from modern MDS.

▷ Example 3

```
. use https://www.stata-press.com/data/r18/cerealnut, clear
(Cereal nutrition)
. replace brand = subinstr(brand," ","_",.)
(20 real changes made)
. quietly mds calories-K, id(brand) noplot
. mat Yclass = e(Y)
. mds calories-K, id(brand) meth(modern) loss(strain) trans(ident) noplot
Iteration 1:    strain =  594.12657
Iteration 2:    strain =  594.12657
Modern multidimensional scaling
Dissimilarity: L2, computed on 8 variables
    Loss criterion: strain = loss for classical MDS
    Transformation: identity (no transformation)
                                        Number of obs    =        25
                                        Dimensions       =         2
    Normalization: principal            Loss criterion   =  594.1266
. mat Ymod = e(Y)
. assert mreldif(Yclass, Ymod) < 1e-6
```

Note the output differences between modern and classical MDS. In modern MDS we have an iteration log from the minimization of the loss function. The method, measure, observations, dimensions, and number of variables are reported as before, but we do not have or display eigenvalues. The normalization is always reported in modern MDS and with `normalize(target())` for classical MDS. The loss criterion is simply the value of the loss function at the minimum.

◁

Protecting from local minimums

Modern MDS can sometimes converge to a local rather than a global minimum. To protect against this, multiple runs can be made, giving the best of the runs as the final answer. The option for performing this is `protect(#)`, where *#* is the number of runs to be performed. The `nolog` option is of particular use with `protect()`, because the iteration logs from the runs will create a lot of output. Repeating the minimization can take some time, depending on the number of runs selected and the number of iterations it takes to converge.

▷ Example 4

We choose `loss(stress)`, and `transform(identity)` is assumed with modern MDS. We omit the iteration logs to avoid a large amount of output. The number of iterations is available after estimation in `e(ic)`. We first do a run without the `protect()` option, and then we use `protect(50)` and compare our results.

```
. mds calories-K, id(brand) method(modern) loss(stress) nolog noplot
(transform(identity) assumed)

Modern multidimensional scaling
Dissimilarity: L2, computed on 8 variables

    Loss criterion: stress = raw_stress/norm(distances)
    Transformation: identity (no transformation)

                                          Number of obs    =         25
                                          Dimensions       =          2
    Normalization: principal              Loss criterion   =     0.0263
. di e(ic)
45

. mat Ystress = e(Y)

. set seed 123456789

. mds calories-K, id(brand) method(modern) loss(stress) nolog protect(50)
(transform(identity) assumed)

run  mrc  #iter     lossval
─────────────────────────────
  1    0     74    .02626681
  2    0    101    .02626681
  3    0     78    .02626681
  4    0     75    .02626681
  5    0     75    .02626681
  6    0     57    .02626681
  7    0     84    .02626681
  8    0     75    .02626681
  9    0     85    .02626681
 10    0     60    .02626681
 11    0     63    .02626681
 12    0     45    .02626681
 13    0     55    .02626681
 14    0     57    .02626682
 15    0     82    .02626682
 16    0     63    .02626682
 17    0     63    .02626682
 18    0     66    .02626682
 19    0     72    .02626682
 20    0     71    .02626682
 21    0     52    .02626682
 22    0     66    .02626683
 23    0     61    .02626683
 24    0     59    .02626683
 25    0     84    .02626684
 26    0    138     .026303
 27    0    100     .026303
 28    0     74     .026303
 29    0     55     .026303
 30    0     56     .026303
 31    0     67     .026303
 32    0     67     .026303
 33    0     75     .026303
 34    0     58     .026303
 35    0     60     .026303
 36    0     59     .026303
 37    0     53     .026303
 38    0     52     .026303
 39    0     87     .026303
 40    0     63    .02630301
 41    0     60    .02630301
 42    0     60    .02630301
 43    0     58    .02630301
```

```
44      0      66   .02630301
45      0      63   .02630301
46      0      56   .02630302
47      0      53   .02630302
48      0     131   .19899027
49      0     140   .23020403
50      0     170   .23794378
```

```
Modern multidimensional scaling
Dissimilarity: L2, computed on 8 variables

      Loss criterion: stress = raw_stress/norm(distances)
      Transformation: identity (no transformation)

                                             Number of obs    =         25
                                             Dimensions       =          2
      Normalization: principal              Loss criterion   =     0.0263

. mat YstressP = e(Y)

. assert mreldif(Ystress, YstressP) < 2e-3
```


MDS configuration

Modern MDS (loss = stress; transform = identity)

The output provided when `protect()` is specified includes a table with information on each run, sorted by the loss criterion value. The first column simply counts the runs. The second column gives the internal return code from modern MDS. This example only has values of 0, which indicate converged results. The column header `mrc` is clickable and opens a help file explaining the various MDS return codes. The number of iterations is in the third column. These runs converged in as few as 45 iterations to as many as 170. The loss criterion values are in the fourth column.

In this example, the results from our original run versus the protected run did not differ by much. However, looking at runs 48–50, we see loss criterion values that are much higher than the rest.

The graph from this protected modern MDS run may be compared with the first one produced. There are obvious similarities, though inspection indicates that the two are not the same.

◁

Stored results

mds stores the following in e():

Scalars
e(N)	number of observations
e(p)	number of dimensions in the approximating configuration
e(np)	number of strictly positive eigenvalues
e(addcons)	constant added to squared dissimilarities to force positive semidefiniteness
e(mardia1)	Mardia measure 1
e(mardia2)	Mardia measure 2
e(critval)	loss criterion value
e(alpha)	parameter of transform(power)
e(ic)	iteration count
e(rc)	return code
e(converged)	1 if converged, 0 otherwise

Macros
e(cmd)	mds
e(cmdline)	command as typed
e(method)	classical or modern MDS method
e(method2)	nonmetric, if method(nonmetric)
e(loss)	loss criterion
e(losstitle)	description loss criterion
e(tfunction)	identity, power, or monotonic, transformation function
e(transftitle)	description of transformation
e(id)	ID variable name (mds)
e(idtype)	int or str; type of id() variable
e(duplicates)	1 if duplicates in id(), 0 otherwise
e(labels)	labels for ID categories
e(strfmt)	format for category labels
e(varlist)	variables used in computing similarities or dissimilarities
e(dname)	similarity or dissimilarity measure name
e(dtype)	similarity or dissimilarity
e(s2d)	standard or oneminus (when e(dtype) is similarity)
e(unique)	1 if eigenvalues are distinct, 0 otherwise
e(init)	initialization method
e(irngstate)	initial random-number state used for init(random)
e(rngstate)	random-number state for solution
e(norm)	normalization method
e(targetmatrix)	name of target matrix for normalize(target)
e(properties)	nob noV for modern or nonmetric MDS; nob noV eigen for classical MDS
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(D)	dissimilarity matrix
e(Disparities)	disparity matrix for nonmetric MDS
e(Y)	approximating configuration coordinates
e(Ev)	eigenvalues
e(idcoding)	coding for integer identifier variable
e(coding)	variable standardization values; first column has value to subtract and second column has divisor
e(norm_stats)	normalization statistics
e(linearf)	two element vector defining the linear transformation; distance equals first element plus second element times dissimilarity

Functions
e(sample)	marks estimation sample

Methods and formulas

mds creates a dissimilarity matrix $\mathbf{D}$ according to the *measure* specified in option measure(). See [MV] *measure_option* for descriptions of these measures. Subsequently, mds uses the same subroutines as mdsmat to compute the MDS solution for $\mathbf{D}$. See *Methods and formulas* in [MV] **mdsmat** for information.

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Also see *References* in [MV] **mdsmat**.

Joseph Bernard Kruskal (1928–2010) was born in New York. His brothers were statistician William Henry Kruskal (1919–2005) and mathematician and physicist Martin David Kruskal (1925–2006). He earned degrees in mathematics from Chicago and Princeton and worked at Bell Labs until his retirement in 1993. In statistics, Kruskal made major contributions to multidimensional scaling. In computer science, he devised an algorithm for computing the minimal spanning tree of a weighted graph. His other interests include clustering and statistical linguistics.

Also see

[MV] **mds postestimation** — Postestimation tools for mds, mdsmat, and mdslong

[MV] **mds postestimation plots** — Postestimation plots for mds, mdsmat, and mdslong

[MV] **biplot** — Biplots

[MV] **ca** — Simple correspondence analysis

[MV] **factor** — Factor analysis

[MV] **mdslong** — Multidimensional scaling of proximity data in long format

[MV] **mdsmat** — Multidimensional scaling of proximity data in a matrix

[MV] **pca** — Principal component analysis

[U] **20 Estimation and postestimation commands**

Title

> **mds postestimation —** Postestimation tools for mds, mdsmat, and mdslong

Postestimation commands

The following postestimation commands are of special interest after mds, mdslong, and mdsmat:

Command	Description
estat config	coordinates of the approximating configuration
estat correlations	correlations between dissimilarities and approximating distances
estat pairwise	pairwise dissimilarities, approximating distances, and raw residuals
estat quantiles	quantiles of the residuals per object
estat stress	Kruskal stress (loss) measure (only after classical MDS)
* estat summarize	estimation sample summary
mdsconfig	plot of approximating configuration
mdsshepard	Shepard diagram
screeplot	plot eigenvalues (only after classical MDS)

*estat summarize is not available after mdsmat.

The following standard postestimation commands are also available:

Command	Description
* estimates	cataloging estimation results
predict	approximating configuration and pairwise statistics

*All estimates subcommands except table and stats are available.

predict

Description for predict

predict creates new variables containing predictions such as approximating configurations in Euclidean space and selected pairwise statistics.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] {*stub** | *newvarlist*} [*if*] [*in*] [, *statistic options*]

statistic	Description
[_Main_]	
<u>config</u>	approximating configuration; specify dimension() or fewer variables
<u>pair</u>wise(*pstats*)	selected pairwise statistics; specify same number of variables

pstats	Description
<u>dis</u>parities	disparities = transformed(dissimilarities)
<u>diss</u>imilarities	dissimilarities
<u>dist</u>ances	Euclidean distances between configuration points
<u>rr</u>esiduals	raw residual = dissimilarity − distance
<u>tr</u>esiduals	transformed residual = disparity − distance
<u>weig</u>hts	weights

options	Description
[_Main_]	
* <u>saving</u>(*filename*, replace)	save results to *filename*; use replace to overwrite existing *filename*
full	create predictions for all pairs of objects; pairwise() only

* saving() is required after mdsmat, after mds if pairwise() is selected, and after mdslong if config is selected.

Options for predict

> [_Main_]

config generates variables containing the approximating configuration in Euclidean space. Specify as many new variables as approximating dimensions (as determined by the dimension() option of mds, mdsmat, or mdslong), though you may specify fewer. estat config displays the same information but does not store the information in variables. After mdsmat and mdslong, you must also specify the saving() option.

pairwise(*pstats*) generates new variables containing pairwise statistics. The number of new variables should be the same as the number of specified statistics. The following statistics are allowed:

disparities generates the disparities, that is, the transformed dissimilarities. If no transformation is applied (modern MDS with transform(identity)), disparities are the same as dissimilarities.

dissimilarities generates the dissimilarities used in MDS. If mds, mdslong, or mdsmat was invoked on similarity data, the associated dissimilarities are returned.

distances generates the (unsquared) Euclidean distances between the fitted configuration points.

rresiduals generates the raw residuals: dissimilarities − distances.

tresiduals generates the transformed residuals: disparities − distances.

weights generates the weights. Missing proximities are represented by zero weights.

estat pairwise displays some of the same information but does not store the information in variables.

After mds and mdsmat, you must also specify the saving() option. With n objects, the pairwise dataset has $n(n-1)/2$ observations. In addition to the three requested variables, predict produces variables *id*1 and *id*2, which identify pairs of objects. With mds, *id* is the name of the identification variable (id() option), and with mdsmat, it is "Category".

saving(*filename* [, replace]) is required after mdsmat, after mds if pairwise() is selected, and after mdslong if config is selected. saving() indicates that the generated variables are to be created in a new Stata dataset and saved in the file named *filename*. Unless saving() is specified, the variables are generated in the current dataset.

replace indicates that *filename* specified in saving() may be overwritten.

full creates predictions for all pairs of objects (j_1, j_2). The default is to generate predictions only for pairs (j_1, j_2) where $j_1 > j_2$. full may be specified only with pairwise().

estat

Description for estat

estat config lists the coordinates of the approximating configuration.

estat correlations lists the Pearson and Spearman correlations between the disparities or dissimilarities and the Euclidean distances for each object.

estat pairwise lists the pairwise statistics: the disparities, the distances, and the residuals.

estat quantiles lists the quantiles of the residuals per object.

estat stress displays the Kruskal stress (loss) measure between the (transformed) dissimilarities and fitted distances per object (only after classical MDS).

estat summarize summarizes the variables in the MDS over the estimation sample. After mds, estat summarize also reports whether and how variables were transformed before computing similarities or dissimilarities.

Menu for estat

Statistics > Postestimation

Syntax for estat

List the coordinates of the approximating configuration

    estat <u>con</u>fig [, <u>maxl</u>ength(#) <u>form</u>at(% *fmt*)]

List the Pearson and Spearman correlations

    estat <u>cor</u>relations [, <u>maxl</u>ength(#) <u>form</u>at(% *fmt*) <u>notrans</u>form <u>noto</u>tal]

List the pairwise statistics: disparities, distances, and residuals

    estat <u>pair</u>wise [, <u>maxl</u>ength(#) <u>notrans</u>form <u>full</u> <u>separat</u>or]

List the quantiles of the residuals

    estat <u>qua</u>ntiles [, <u>maxl</u>ength(#) <u>form</u>at(% *fmt*) <u>noto</u>tal <u>notrans</u>form]

Display the Kruskal stress (loss) measure per point (only after classical MDS)

    estat <u>str</u>ess [, <u>maxl</u>ength(#) <u>form</u>at(% *fmt*) <u>noto</u>tal <u>notrans</u>form]

Summarize the variables in MDS

    estat <u>sum</u>marize [, <u>labe</u>ls]

options	Description
<u>maxl</u>ength(#)	maximum number of characters for displaying object names; default is 12
<u>form</u>at(% *fmt*)	display format
<u>noto</u>tal	suppress display of overall summary statistics
<u>notrans</u>form	use dissimilarities instead of disparities
<u>full</u>	display all pairs (j_1, j_2); default is $(j_1 > j_2)$ only
<u>separat</u>or	draw separating lines
<u>labe</u>ls	display variable labels

collect is allowed with estat correlations, estat quantiles, estat stress, and estat summarize; see
    [U] **11.1.10 Prefix commands**.

Options for estat

    maxlength(#), an option used with all but estat summarize, specifies the maximum number of
        characters of the object names to be displayed; the default is maxlength(12).

    format(% *fmt*), an option used with estat config, estat correlations, estat quantiles, and
        estat stress, specifies the display format; the default differs between the subcommands.

nototal, an option used with estat correlations, estat quantiles, and estat stress, suppresses the overall summary statistics.

notransform, an option used with estat correlations, estat pairwise, estat quantiles, and estat stress, specifies that the untransformed dissimilarities be used instead of the transformed dissimilarities (disparities).

full, an option used with estat pairwise, displays a row for all pairs (j_1, j_2). The default is to display rows only for pairs where $j_1 > j_2$.

separator, an option used with estat pairwise, draws separating lines between blocks of rows corresponding to changes in the first of the pair of objects.

labels, an option used with estat summarize, displays variable labels.

Remarks and examples

Remarks are presented under the following headings:

> Postestimation statistics
> Predictions

Postestimation statistics

After an MDS analysis, several facilities can help you better understand the analysis and, in particular, to assess the quality of the lower-dimensional Euclidean representation. We display results after classical MDS. All are available after modern MDS except for estat stress.

▷ Example 1: estat

We illustrate the MDS postestimation facilities with the Morse code digit-similarity dataset; see example 1 in [MV] **mdslong**.

```
. use https://www.stata-press.com/data/r18/morse_long
(Morse data (Rothkopf 1957))
. generate sim = freqsame/100
. mdslong sim, id(digit1 digit2) s2d(standard) noplot
  (output omitted )
```

MDS has produced a two-dimensional configuration with Euclidean distances approximating the dissimilarities between the Morse codes for digits. This configuration may be examined using the estat config command; see mdsconfig if you want to plot the configuration.

```
. estat config
```
Configuration in 2-dimensional Euclidean space (principal normalization)

digit1	dim1	dim2
0	0.5690	0.0162
1	0.4561	-0.3384
2	0.0372	-0.5854
3	-0.3878	-0.4516
4	-0.5800	-0.0770
5	-0.5458	-0.0196
6	-0.3960	0.4187
7	-0.0963	0.5901
8	0.3124	0.3862
9	0.6312	0.0608

This configuration is not unique. A translation, a reflection, and an orthonormal rotation of the configuration do not affect the interpoint Euclidean distances. All such transformations are equally reasonable MDS solutions. Thus you should not interpret aspects of these numbers (or of the configuration plot) that are not invariant to these transformations.

We now turn to the three `estat` subcommands that analyze the MDS residuals, that is, the differences between the disparities or dissimilarities and the matching Euclidean distances. There is a catch here. The raw residuals of MDS are not well behaved. For instance, the sum of the raw residuals is not zero—often it is not even close. The MDS solution does *not* minimize the sum of squares of the raw residuals Mardia, Kent, and Bibby (1979, 406–408). To create reasonable residuals with MDS, the dissimilarities can be transformed to disparities approximating the Euclidean distances. In classical MDS we use a linear transform f, fit by least squares. This is equivalent to Kruskal's Stress1 loss function. The modified residuals are defined as the differences between the linearly transformed dissimilarities and the matching Euclidean distances.

In modern MDS we have three types of transformations from dissimilarities to disparities to choose from: the identity (which does not transform the dissimilarities), a power transformation, and a monotonic transformation.

The three `estat` subcommands summarize the residuals in different ways. After classical MDS, `estat stress` displays the Kruskal loss or stress measures for each object and the overall total.

```
. estat stress
```

Stress between disparities and Euclidean distances

digit1	Kruskal
0	0.1339
1	0.1255
2	0.1972
3	0.2028
4	0.2040
5	0.2733
6	0.1926
7	0.1921
8	0.1715
9	0.1049
Total	0.1848

Second, after classical or modern MDS, the quantiles of the residuals are available, both overall and for the subgroup of object pairs in which an object is involved.

```
. estat quantiles
```

Quantiles of transformed residuals

digit1	N	min	p25	q50	q75	max
0	9	-.111732	-.088079	-.028917	.11202	.220399
1	9	-.170063	-.137246	-.041244	.000571	.11202
2	9	-.332717	-.159472	-.072359	.074999	.234867
3	9	-.136251	-.120398	-.072359	.105572	.365833
4	9	-.160797	-.014099	.03845	.208215	.355053
5	9	-.09971	-.035357	.176337	.325043	.365833
6	9	-.137246	-.113564	-.075008	.177448	.325043
7	9	-.332717	-.170063	-.124129	.03845	.176337
8	9	-.186452	-.134831	-.041244	.075766	.220399
9	9	-.160797	-.104403	-.088079	-.064316	-.030032
Total	90	-.332717	-.113564	-.041244	.105572	.365833

The dissimilarities for the Morse code of digit 5 are fit considerably worse than for all other Morse codes. Digit 5 has the largest Kruskal stress (0.273) and median residual (0.176).

Finally, after classical or modern MDS, `estat correlations` displays the Pearson and Spearman correlations between the (transformed or untransformed) dissimilarities and the Euclidean distances.

```
. estat correlations

Correlations of disparities and Euclidean distances
```

digit1	N	Pearson	Spearman
0	9	0.9510	0.9540
1	9	0.9397	0.7782
2	9	0.7674	0.4017
3	9	0.7922	0.7815
4	9	0.9899	0.9289
5	9	0.9412	0.9121
6	9	0.8226	0.8667
7	9	0.8444	0.4268
8	9	0.8505	0.7000
9	9	0.9954	0.9333
Total	90	0.8602	0.8301

◁

Predictions

It is possible to generate variables containing the results from the MDS analysis. MDS operates at two levels: first at the level of the objects and second at the level of relations between the objects or pairs of objects. You can generate variables at both of these levels.

The `config` option of `predict` after an MDS requests that the coordinates of the objects in the matching configuration be stored in variables. You may specify as many variables as there are retained dimensions. You may also specify fewer variables. The first variable will store the coordinates from the first dimension. The second variable, if any, will store the coordinates from the second dimension, and so on.

The `pairwise()` option specifies that a given selection of the pairwise statistics are stored in variables. The statistics available are the disparities, dissimilarities, fitted distances, raw residuals, transformed residuals, and weights. The raw residuals are the difference between dissimilarities and the fitted distances, and the transformed residuals are the difference between the disparities and the fitted distances.

There is a complicating issue. With n objects, there are $n(n-1)/2$ pairs of objects. So, to store properties of objects, you need n observations, but to store properties of pairs of objects, you need $n(n-1)/2$ observations. So, where do you store the variables? `predict` after MDS commands can save the predicted variables in a new dataset. Specify the option `saving(`*filename*`)`. Such a dataset will automatically have the appropriate object identification variable or variables.

Sometimes it is also possible to store the variables in the dataset you have in memory: object-level variables in an object-level dataset and pairwise-level variables in a pairwise-level dataset.

After `mds` you have a dataset in memory in which the observations are associated with the MDS objects. Here you can store object-level variables directly in the dataset in memory. To do so, you just omit the `saving()` option. Here it is not possible to store the pairwise statistics in the dataset in memory. The pairwise statistics have to be stored in a new dataset.

After mdslong, the dataset in memory is in a pairwise form, so the variables predicted with the option pairwise() can be stored in the dataset in memory. It is, of course, also possible to store the pairwise variables in a new dataset; the choice is yours. With pairwise data in memory, you cannot store the object-level predicted variables into the data in memory; you need to specify the name of a new dataset.

After mdsmat, you always need to save the predicted variables in a new dataset.

▷ Example 2: Predictions

Continuing with example 1; the dataset in memory is in long form. Thus we can store the pairwise statistics with the dataset in memory.

```
. predict tdissim eudist resid, pairwise
. list in 1/10
```

	digit1	digit2	freqsame	sim	tdissim	eudist	resid
1.	2	1	62	.62	.3227682	.4862905	−.1635224
2.	3	1	16	.16	.957076	.851504	.105572
3.	3	2	59	.59	.3732277	.4455871	−.0723594
4.	4	1	6	.06	1.069154	1.068583	.0005709
5.	4	2	23	.23	.8745967	.7995979	.0749988
6.	4	3	38	.38	.6841489	.4209922	.2631567
7.	5	1	12	.12	1.002667	1.051398	−.048731
8.	5	2	8	.08	1.047234	.8123672	.2348665
9.	5	3	27	.27	.8257753	.4599419	.3658335
10.	5	4	56	.56	.4218725	.0668193	.3550532

Because we used mdslong, the object-level statistics must be saved in a file.

```
. predict d1 d2, config saving(digitdata)
. describe digit* d1 d2 using digitdata
```

Variable name	Storage type	Display format	Value label	Variable label
digit1	byte	%9.0g		
d1	float	%9.0g		MDS dimension 1
d2	float	%9.0g		MDS dimension 2

The information in these variables was already shown with estat config. The dataset created has variables d1 and d2 with the coordinates of the Morse digits on the two retained dimensions and an identification variable digit1. Use merge to add these variables to the data in memory; see [D] merge.

◁

Stored results

`estat correlations` stores the following in `r()`:

Matrices
r(R)	statistics per object; columns with # of obs., Pearson corr., and Spearman corr.
r(T)	overall statistics; # of obs., Pearson corr., and Spearman corr.

`estat quantiles` stores the following in `r()`:

Macros
r(dtype)	adjusted or raw; dissimilarity transformation

Matrices
r(Q)	statistics per object; columns with # of obs., min., p25, p50, p75, and max.
r(T)	overall statistics; # of obs., min., p25, p50, p75, and max.

`estat stress` stores the following in `r()`:

Macros
r(dtype)	adjusted or raw; dissimilarity transformation

Matrices
r(S)	Kruskal's stress/loss measure per object
r(T)	1×1 matrix with the overall Kruskal stress/loss measure

Methods and formulas

See [MV] **mdsmat** for information on the methods and formulas for multidimensional scaling.

For classical MDS, let D_{ij} be the dissimilarity between objects i and j, $1 \le i, j \le n$. We assume $D_{ii} = 0$ and $D_{ij} = D_{ji}$. Let E_{ij} be the Euclidean distance between rows i and j of the matching configuration $\mathbf{Y}$. In classical MDS, $\mathbf{D} - \mathbf{E}$ is not a well-behaved residual matrix. We follow the approach used in metric and nonmetric MDS to transform D_{ij} to "optimally match" E_{ij}, with $\widehat{D}_{ij} = a + bD_{ij}$, where a and b are chosen to minimize the residual sum of squares. This is a simple regression problem and is equivalent to minimizing Kruskal's stress measure (Kruskal 1964; Cox and Cox 2001, 63)

$$\text{Kruskal}(\widehat{\mathbf{D}}, \mathbf{E}) = \left\{ \frac{\sum (E_{ij} - \widehat{D}_{ij})^2}{\sum E_{ij}^2} \right\}^{1/2}$$

with summation over all pairs (i, j). We call the $\widehat{D}_{ij}$ the adjusted or transformed dissimilarities. If the transformation step is skipped by specifying the option `notransform`, we set $\widehat{D}_{ij} = D_{ij}$.

In `estat stress`, the decomposition of Kruskal's stress measure over the objects is displayed. $\text{Kruskal}(\widehat{\mathbf{D}}, \mathbf{E})_i$ is defined analogously with summation over all $j \ne i$.

For modern MDS, the optimal transformation to disparities, $f(\mathbf{D}) \rightarrow \widehat{\mathbf{D}}$, is calculated during the estimation. See [MV] **mdsmat** for details. For `transform(power)`, the power is stored in `e(alpha)`. For `transform(monotonic)`, the disparities themselves are stored as `e(Disparities)`.

References

Borg, I., and P. J. F. Groenen. 2005. *Modern Multidimensional Scaling: Theory and Applications*. 2nd ed. New York: Springer.

Cox, T. F., and M. A. A. Cox. 2001. *Multidimensional Scaling*. 2nd ed. Boca Raton, FL: Chapman and Hall/CRC.

Kruskal, J. B. 1964. Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika* 29: 1–27. https://doi.org/10.1007/bf02289565.

Mardia, K. V., J. T. Kent, and J. M. Bibby. 1979. *Multivariate Analysis*. London: Academic Press.

Also see *References* in [MV] **mdsmat**.

Also see

[MV] **mds** — Multidimensional scaling for two-way data

[MV] **mdslong** — Multidimensional scaling of proximity data in long format

[MV] **mdsmat** — Multidimensional scaling of proximity data in a matrix

[MV] **mds postestimation plots** — Postestimation plots for mds, mdsmat, and mdslong

[MV] **screeplot** — Scree plot of eigenvalues

[U] **20 Estimation and postestimation commands**

Title

> **mds postestimation plots —** Postestimation plots for mds, mdsmat, and mdslong

[Postestimation commands](#)   [mdsconfig](#)   [mdsshepard](#)   [Remarks and examples](#)
[References](#)   [Also see](#)

Postestimation commands

The following postestimation commands are of special interest after mds, mdslong, and mdsmat:

Command	Description
[mdsconfig](#)	plot of approximating configuration
[mdsshepard](#)	Shepard diagram

For more information on these commands, see below. Also see [MV] **mds postestimation**.

mdsconfig

Description for mdsconfig

mdsconfig produces a plot of the approximating Euclidean configuration. By default, dimensions 1 and 2 are plotted.

Menu for mdsconfig

Statistics > Multivariate analysis > Multidimensional scaling (MDS) > Postestimation > Approximating configuration plot

Syntax for mdsconfig

> mdsconfig [, *options*]

options	Description
Main	
<u>dim</u>ensions(*# #*)	two dimensions to be displayed; default is dimensions(2 1)
xnegate	negate data relative to the x axis
ynegate	negate data relative to the y axis
autoaspect	adjust aspect ratio on the basis of the data; default aspect ratio is 1
<u>max</u>length(*#*)	maximum number of characters used in marker labels
cline_options	affect rendition of the lines connecting points
marker_options	change look of markers (color, size, etc.)
marker_label_options	change look or position of marker labels
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

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Options for mdsconfig

> [Main]

dimensions(*# #*) identifies the dimensions to be displayed. For instance, dimensions(3 2) plots
the third dimension (vertically) versus the second dimension (horizontally). The dimension number
cannot exceed the number of extracted dimensions. The default is dimensions(2 1).

xnegate specifies that the data be negated relative to the x axis.

ynegate specifies that the data be negated relative to the y axis.

autoaspect specifies that the aspect ratio be automatically adjusted based on the range of the data to
be plotted. This option can make some plots more readable. By default, mdsconfig uses an aspect
ratio of one, producing a square plot. Some plots will have little variation in the y-axis direction,
and use of the autoaspect option will better fill the available graph space while preserving the
equivalence of distance in the x and y axes.

As an alternative to autoaspect, the *twoway_option* aspectratio() can be used to override
the default aspect ratio. mdsconfig accepts the aspectratio() option as a suggestion only and
will override it when necessary to produce plots with balanced axes; that is, distance on the x
axis equals distance on the y axis.

twoway_options, such as xlabel(), xscale(), ylabel(), and yscale(), should be used with
caution. These *axis_options* are accepted but may have unintended side effects on the aspect ratio.

maxlength(*#*) specifies the maximum number of characters for object names used to mark the
points; the default is maxlength(12).

cline_options affect the rendition of the lines connecting the plotted points; see [G-3] *cline_options*.
If you are drawing connected lines, the appearance of the plot depends on the sort order of the
data.

marker_options affect the rendition of the markers drawn at the plotted points, including their shape,
size, color, and outline; see [G-3] *marker_options*.

marker_label_options specify if and how the markers are to be labeled; see [G-3] *marker_label_options*.

> [Y axis, X axis, Titles, Legend, Overall]

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding by(). These
include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk
(see [G-3] *saving_option*). See autoaspect above for a warning against using options such as
xlabel(), xscale(), ylabel(), and yscale().

mdsshepard

Description for mdsshepard

mdsshepard produces a Shepard diagram of the disparities against the Euclidean distances. Ideally, the points in the plot should be close to the $y = x$ line. Optionally, separate plots are generated for each "row" (value of id()).

Menu for mdsshepard

Statistics > Multivariate analysis > Multidimensional scaling (MDS) > Postestimation > Shepard diagram

Syntax for mdsshepard

mdsshepard [, *options*]

options	Description
Main	
notransform	use dissimilarities instead of disparities
autoaspect	adjust aspect ratio on the basis of the data; default aspect ratio is 1
separate	draw separate Shepard diagrams for each object
marker_options	change look of markers (color, size, etc.)
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*
byopts(*by_option*)	affect the rendition of combined graphs; separate only

Options for mdsshepard

> Main

notransform uses dissimilarities instead of disparities, that is, suppresses the transformation of the dissimilarities.

autoaspect specifies that the aspect ratio be automatically adjusted based on the range of the data to be plotted. By default, mdsshepard uses an aspect ratio of one, producing a square plot.

See the description of the autoaspect option of mdsconfig for more details.

separate displays separate plots of each value of the ID variable. This may be time consuming if the number of distinct ID values is not small.

marker_options affect the rendition of the markers drawn at the plotted points, including their shape, size, color, and outline; see [G-3] *marker_options*.

> Y axis, X axis, Titles, Legend, Overall

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding by(). These include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk (see [G-3] *saving_option*). See the autoaspect option of mdsconfig for a warning against using options such as xlabel(), xscale(), ylabel(), and yscale().

byopts(*by_option*) is documented in [G-3] **by_option**. This option affects the appearance of the combined graph and is allowed only with the `separate` option.

Remarks and examples

The matching configuration plot and Shepard diagram are easily obtained after an MDS analysis.

▷ Example 1: configuration plot

By default, `mds`, `mdsmat`, and `mdslong` display the MDS matching configuration plot. If you want to exercise control over the graph, you can specify the `noplot` option of `mds`, `mdsmat`, or `mdslong` and then use the `mdsconfig` postestimation graph command.

Continuing with example 1 of [MV] **mds postestimation**, we produce a configuration plot with an added title and subtitle.

```
. use https://www.stata-press.com/data/r18/morse_long
(Morse data (Rothkopf 1957))
. generate sim = freqsame/100
. mdslong sim, id(digit1 digit2) s2d(standard) noplot
(output omitted)
. mdsconfig, title(Morse code digit dissimilarity) subtitle(Data: Rothkopf 1957)
```
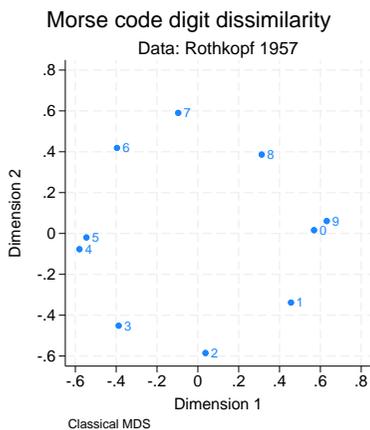

The plot has an aspect ratio of one so that 1 unit on the horizontal dimension equals 1 unit on the vertical dimension. Thus the "straight-line" distance in the plot is really (proportional to) the Euclidean distance between the points in the configuration and hence approximates the dissimilarities between the objects—here the Morse codes for digits.

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▷ Example 2: Shepard diagram

A second popular plot for MDS is the Shepard diagram. This is a plot of the Euclidean distances in the matching configuration against the "observed" dissimilarities. As we explained before, in classical MDS a linear transformation is applied to the dissimilarities to fit the Euclidean distances as close as possible (in the least-squares sense). In modern MDS the transformation may be the identity (no transformation), a power function, or a monotonic function. A Shepard diagram is a plot of the $n(n-1)/2$ transformed dissimilarities, called disparities, against the Euclidean distances.

```
. mdsshepard
```


Shepard diagram
Classical MDS
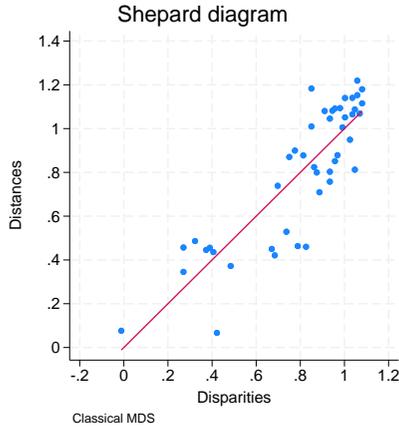
If the Euclidean configuration is close to the disparities between the objects, all points would be close to the $y = x$ line. Deviations indicate lack of fit. To simplify the diagnosis of whether there are specific objects that are poorly represented, Shepard diagrams can be produced for each object separately. Such plots consist of n small plots with $n - 1$ points each, namely, the disparities and Euclidean distances to all other objects.

```
. mdsshepard, separate
(mdsshepard is producing a separate plot for each obs; this may take a while)
```


Shepard diagrams
Classical MDS
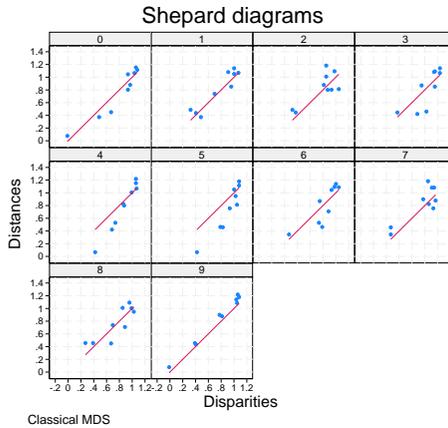
Other examples of mdsconfig are found in [MV] **mds**, [MV] **mdslong**, and [MV] **mdsmat**.

Roger Newland Shepard (1929–2022) was born in Palo Alto, California, earned degrees at Stanford and Yale, and worked at Bell Labs and Harvard before returning to Stanford in 1968. One of the world's leading psychologists and cognitive scientists, he has worked on perception, mental imagery, representation, learning, and generalization. Shepard is noted within statistical science primarily for his work on nonmetric multidimensional scaling. He is a member of the U.S. National Academy of Sciences and a recipient of the National Medal of Science.

References

See *References* in [MV] **mds**.

Also see

[MV] **mds** — Multidimensional scaling for two-way data

[MV] **mdslong** — Multidimensional scaling of proximity data in long format

[MV] **mdsmat** — Multidimensional scaling of proximity data in a matrix

[MV] **mds postestimation** — Postestimation tools for mds, mdsmat, and mdslong

[MV] **screeplot** — Scree plot of eigenvalues

Title

mdslong — Multidimensional scaling of proximity data in long format

Description

mdslong performs multidimensional scaling (MDS) for two-way proximity data in long format with an explicit measure of similarity or dissimilarity between objects. mdslong performs classical metric MDS as well as modern metric and nonmetric MDS.

For MDS with two-way proximity data in a matrix, see [MV] **mdsmat**. If you are looking for MDS on a dataset, based on dissimilarities between observations over variables, see [MV] **mds**.

Quick start

Classical multidimensional scaling based on dissimilarities in variable d between subjects identified by variables i and j

    mdslong d, id(i j)

Same as above, but suppress the MDS configuration plot and use 3 dimensions for the approximating configuration

    mdslong d, id(i j) noplot dimension(3)

Modern multidimensional scaling

    mdslong d, id(i j) method(modern)

Same as above, but with Sammon mapping loss criterion and Procrustes rotation toward the classical solution

    mdslong d, id(i j) loss(sammon) normalize(classical)

Nonmetric modern multidimensional scaling

    mdslong d, id(i j) method(nonmetric)

Menu

Statistics > Multivariate analysis > Multidimensional scaling (MDS) > MDS of proximity-pair data

Syntax

> mdslong *depvar* [*if*] [*in*] [*weight*], id(*var₁ var₂*) [*options*]

options	Description
Model	
* <u>id</u>(*var₁ var₂*)	identify comparison pairs (object₁, object₂)
<u>method</u>(*method*)	method for performing MDS
<u>loss</u>(*loss*)	loss function
<u>transform</u>(*tfunction*)	permitted transformations of dissimilarities
<u>normalize</u>(*norm*)	normalization method; default is normalize(principal)
s2d(<u>standard</u>)	convert similarity to dissimilarity: dissim$_{ij}$ = $\sqrt{\text{sim}_{ii} + \text{sim}_{jj} - 2\text{sim}_{ij}}$; the default
s2d(<u>oneminus</u>)	convert similarity to dissimilarity: dissim$_{ij}$ = $1 - \text{sim}_{ij}$
force	correct problems in proximity information
<u>dimension</u>(#)	configuration dimensions; default is dimension(2)
<u>addconstant</u>	make distance matrix positive semidefinite (classical MDS only)
Reporting	
<u>neigen</u>(#)	maximum number of eigenvalues to display; default is neigen(10) (classical MDS only)
<u>config</u>	display table with configuration coordinates
<u>noplot</u>	suppress configuration plot
Minimization	
<u>initialize</u>(*initopt*)	start with configuration given in *initopt*
<u>tolerance</u>(#)	tolerance for configuration matrix; default is tolerance(1e-4)
<u>ltolerance</u>(#)	tolerance for loss criterion; default is ltolerance(1e-8)
<u>iterate</u>(#)	perform maximum # of iterations; default is iterate(1000)
<u>protect</u>(#)	perform # optimizations and report best solution; default is protect(1)
[no]<u>log</u>	display or suppress the iteration log; default is to display
<u>trace</u>	display current configuration in iteration log
<u>gradient</u>	display current gradient matrix in iteration log
<u>sdprotect</u>(#)	advanced; see [description](#) below

* id(*var₁ var₂*) is required.

by, collect, and statsby are allowed; see [U] **11.1.10 Prefix commands**.

aweights and fweights are allowed for methods modern and nonmetric; see [U] **11.1.6 weight**.

The maximum number of compared objects allowed is the maximum matrix size; see [R] **Limits**.

sdprotect(#) does not appear in the dialog box.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

method	Description
<u>c</u>lassical	classical MDS; default if neither loss() nor transform() is specified
<u>mod</u>ern	modern MDS; default if loss() or transform() is specified; except when loss(stress) and transform(monotonic) are specified
<u>non</u>metric	nonmetric (modern) MDS; default when loss(stress) and transform(monotonic) are specified

loss	Description
<u>st</u>ress	stress criterion, normalized by distances; the default
<u>nst</u>ress	stress criterion, normalized by disparities
<u>sst</u>ress	squared stress criterion, normalized by distances
<u>nsst</u>ress	squared stress criterion, normalized by disparities
<u>stra</u>in	strain criterion (with transform(identity) is equivalent to classical MDS)
<u>sa</u>mmon	Sammon mapping

tfunction	Description
<u>i</u>dentity	no transformation; disparity = dissimilarity; the default
<u>p</u>ower	power α: disparity = dissimilarity$^{\alpha}$
<u>m</u>onotonic	weakly monotonic increasing functions (nonmetric scaling); only with loss(stress)

norm	Description
<u>p</u>rincipal	principal orientation; location = 0; the default
<u>c</u>lassical	Procrustes rotation toward classical solution
<u>t</u>arget(*matname*) [, copy]	Procrustes rotation toward *matname*; ignore naming conflicts if copy is specified

initopt	Description
<u>c</u>lassical	start with classical solution; the default
<u>random</u> [(#)]	start at random configuration, setting seed to #
<u>f</u>rom(*matname*) [, copy]	start from *matname*; ignore naming conflicts if copy is specified

Options

> #### Model

id(*var₁ var₂*) is required. The pair of variables *var₁* and *var₂* should uniquely identify comparisons. *var₁* and *var₂* are string or numeric variables that identify the objects to be compared. *var₁* and *var₂* should be of the same data type; if they are value labeled, they should be labeled with the same value label. Using value-labeled variables or string variables is generally helpful in identifying the points in plots and tables.

Example data layout for `mdslong proxim, id(i1 i2)`.

proxim	i1	i2
7	1	2
10	1	3
12	1	4
4	2	3
6	2	4
3	3	4

If you have multiple measurements per pair, we suggest that you specify the mean of the measures as the proximity and the inverse of the variance as the weight.

method(*method*) specifies the method for MDS.

method(classical) specifies classical metric scaling, also known as "principal coordinates analysis" when used with Euclidean proximities. Classical MDS obtains equivalent results to modern MDS with loss(strain) and transform(identity) without weights. The calculations for classical MDS are fast; consequently, classical MDS is generally used to obtain starting values for modern MDS. If the options loss() and transform() are not specified, mds computes the classical solution, likewise if method(classical) is specified loss() and transform() are not allowed.

method(modern) specifies modern scaling. If method(modern) is specified but not loss() or transform(), then loss(stress) and transform(identity) are assumed. All values of loss() and transform() are valid with method(modern).

method(nonmetric) specifies nonmetric scaling, which is a type of modern scaling. If method(nonmetric) is specified, loss(stress) and transform(monotonic) are assumed. Other values of loss() and transform() are not allowed.

loss(*loss*) specifies the loss criterion.

loss(stress) specifies that the stress loss function be used, normalized by the squared Euclidean distances. This criterion is often called Kruskal's stress-1. Optimal configurations for loss(stress) and for loss(nstress) are equivalent up to a scale factor, but the iteration paths may differ. loss(stress) is the default.

loss(nstress) specifies that the stress loss function be used, normalized by the squared disparities, that is, transformed dissimilarities. Optimal configurations for loss(stress) and for loss(nstress) are equivalent up to a scale factor, but the iteration paths may differ.

loss(sstress) specifies that the squared stress loss function be used, normalized by the fourth power of the Euclidean distances.

loss(nsstress) specifies that the squared stress criterion, normalized by the fourth power of the disparities (transformed dissimilarities) be used.

loss(strain) specifies the strain loss criterion. Classical scaling is equivalent to loss(strain) and transform(identity) but is computed by a faster noniterative algorithm. Specifying loss(strain) still allows transformations.

loss(sammon) specifies the Sammon (1969) loss criterion.

transform(*tfunction*) specifies the class of allowed transformations of the dissimilarities; transformed dissimilarities are called disparities.

transform(identity) specifies that the only allowed transformation is the identity; that is, disparities are equal to dissimilarities. transform(identity) is the default.

`transform(power)` specifies that disparities are related to the dissimilarities by a power function,

$$\text{disparity} = \text{dissimilarity}^{\alpha}, \qquad \alpha > 0$$

`transform(monotonic)` specifies that the disparities are a weakly monotonic function of the dissimilarities. This is also known as nonmetric MDS. Tied dissimilarities are handled by the primary method; that is, ties may be broken but are not necessarily broken. `transform(monotonic)` is valid only with `loss(stress)`.

`normalize(`*norm*`)` specifies a normalization method for the configuration. Recall that the location and orientation of an MDS configuration is not defined ("identified"); an isometric transformation (that is, translation, reflection, or orthonormal rotation) of a configuration preserves interpoint Euclidean distances.

`normalize(principal)` performs a principal normalization, in which the configuration columns have zero mean and correspond to the principal components, with positive coefficient for the observation with lowest value of `id()`. `normalize(principal)` is the default.

`normalize(classical)` normalizes by a distance-preserving Procrustean transformation of the configuration toward the classical configuration in principal normalization; see [MV] **procrustes**. `normalize(classical)` is not valid if `method(classical)` is specified.

`normalize(target(`*matname*`)` [`, copy`])` normalizes by a distance-preserving Procrustean transformation toward *matname*; see [MV] **procrustes**. *matname* should be an $n \times p$ matrix, where $n$ is the number of observations and $p$ is the number of dimensions, and the rows of *matname* should be ordered with respect to `id()`. The rownames of *matname* should be set correctly but will be ignored if `copy` is also specified.

Note on `normalize(classical)` and `normalize(target())`: the Procrustes transformation comprises any combination of translation, reflection, and orthonormal rotation—these transformations preserve distance. Dilation (uniform scaling) would stretch distances and is not applied. However, the output reports the dilation factor, and the reported Procrustes statistic is for the dilated configuration.

`s2d(standard | oneminus)` specifies how similarities are converted into dissimilarities. By default, the command assumes dissimilarity data. Specifying `s2d()` indicates that your proximity data are similarities.

Dissimilarity data should have zeros on the diagonal (that is, an object is identical to itself) and nonnegative off-diagonal values. Dissimilarities need not satisfy the triangular inequality, $D(i,j)^2 \leq D(i,h)^2 + D(h,j)^2$. Similarity data should have ones on the diagonal (that is, an object is identical to itself) and have off-diagonal values between zero and one. In either case, proximities should be symmetric. See option `force` if your data violate these assumptions.

The available `s2d()` options, `standard` and `oneminus`, are defined as follows:

`standard`	$\text{dissim}_{ij} = \sqrt{\text{sim}_{ii} + \text{sim}_{jj} - 2\text{sim}_{ij}} = \sqrt{2(1 - \text{sim}_{ij})}$
`oneminus`	$\text{dissim}_{ij} = 1 - \text{sim}_{ij}$

`s2d(standard)` is the default.

`s2d()` should be specified only with measures in similarity form.

`force` corrects problems with the supplied proximity information. In the long format used by `mdslong`, multiple measurements on (i, j) may be available. Including both (i, j) and (j, i) would be treated as multiple measurements. This is an error, even if the measures are identical. Option `force` uses

the mean of the measurements. `force` also resolves problems on the diagonal, that is, comparisons of objects with themselves; these should have zero dissimilarity or unit similarity. `force` does not resolve incomplete data, that is, pairs (i, j) for which no measurement is available. Out-of-range values are also not fixed.

`dimension(#)` specifies the dimension of the approximating configuration. The default is `dimension(2)`, and # should not exceed the number of positive eigenvalues of the centered distance matrix.

`addconstant` specifies that if the double-centered distance matrix is not positive semidefinite (psd), a constant should be added to the squared distances to make it psd and, hence, Euclidean. This option is allowed with classical MDS only.

Reporting

`neigen(#)` specifies the number of eigenvalues to be included in the table. The default is `neigen(10)`. Specifying `neigen(0)` suppresses the table. This option is allowed with classical MDS only.

`config` displays the table with the coordinates of the approximating configuration. This table may also be displayed using the postestimation command `estat config`; see [MV] **mds postestimation**.

`noplot` suppresses the graph of the approximating configuration. The graph can still be produced later via `mdsconfig`, which also allows the standard graphics options for fine-tuning the plot; see [MV] **mds postestimation plots**.

Minimization

These options are available only with `method(modern)` or `method(nonmetric)`:

`initialize(initopt)` specifies the initial values of the criterion minimization process.

`initialize(classical)`, the default, uses the solution from classical metric scaling as initial values. With `protect()`, all but the first run start from random perturbations from the classical solution. These random perturbations are independent and normally distributed with standard error equal to the product of `sdprotect(#)` and the standard deviation of the dissimilarities. `initialize(classical)` is the default.

`initialize(random)` starts an optimization process from a random starting configuration. These random configurations are generated from independent normal distributions with standard error equal to the product of `sdprotect(#)` and the standard deviation of the dissimilarities. The means of the configuration are irrelevant in MDS.

`initialize(from(matname) [ , copy ])` sets the initial value to *matname*. *matname* should be an $n \times p$ matrix, where n is the number of observations and p is the number of dimensions, and the rows of *matname* should be ordered with respect to `id()`. The rownames of *matname* should be set correctly but will be ignored if `copy` is specified. With `protect()`, the second-to-last runs start from random perturbations from *matname*. These random perturbations are independent normal distributed with standard error equal to the product of `sdprotect(#)` and the standard deviation of the dissimilarities.

`tolerance(#)` specifies the tolerance for the configuration matrix. When the relative change in the configuration from one iteration to the next is less than or equal to `tolerance()`, the `tolerance()` convergence criterion is satisfied. The default is `tolerance(1e-4)`.

`ltolerance(#)` specifies the tolerance for the fit criterion. When the relative change in the fit criterion from one iteration to the next is less than or equal to `ltolerance()`, the `ltolerance()` convergence is satisfied. The default is `ltolerance(1e-8)`.

Both the `tolerance()` and `ltolerance()` criteria must be satisfied for convergence.

iterate(*#*) specifies the maximum number of iterations. The default is iterate(1000).

protect(*#*) requests that *#* optimizations be performed and that the best of the solutions be reported. The default is protect(1). See option [initialize()](#) on starting values of the runs. The output contains a table of the return code, the criterion value reached, and the seed of the random number used to generate the starting value. Specifying a large number, such as protect(50), provides reasonable insight whether the solution found is a global minimum and not just a local minimum.

If any of the options log, trace, or gradient is also specified, iteration reports will be printed for each optimization run. Beware: this option will produce a lot of output.

log and nolog specify whether to display the iteration log. The iteration log is displayed by default unless you used set iterlog off to suppress it; see set iterlog in [R] *set iter*.

trace displays the configuration matrices in the iteration report. Beware: this option may produce a lot of output.

gradient displays the gradient matrices of the fit criterion in the iteration report. Beware: this option may produce a lot of output.

The following option is available with mdslong but is not shown in the dialog box:

sdprotect(*#*) sets a proportionality constant for the standard deviations of random configurations (init(random)) or random perturbations of given starting configurations (init(classical) or init(from())). The default is sdprotect(1).

Remarks and examples

Remarks are presented under the following headings:

> *Introduction*
> *Proximity data in long format*
> *Modern nonmetric MDS*

Introduction

Multidimensional scaling (MDS) is a dimension-reduction and visualization technique. Dissimilarities (for instance, Euclidean distances) between observations in a high-dimensional space are represented in a lower-dimensional space (typically two dimensions) so that the Euclidean distance in the lower-dimensional space approximates the dissimilarities in the higher-dimensional space. See Kruskal and Wish (1978) for a brief nontechnical introduction to MDS. Young (1987) and Borg and Groenen (2005) are more advanced textbook-sized treatments.

mdslong performs MDS on data in long format. *depvar* specifies proximity data in either dissimilarity or similarity form. The comparison pairs are identified by two variables specified in the required option id(). Exactly 1 observation with a nonmissing *depvar* should be included for each pair (i, j). Pairs are unordered; you do not include observations for both (i, j) and (j, i). Observations for comparisons of objects with themselves (i, i) are optional. See option force if your data violate these assumptions.

When you have multiple independent measurements of the dissimilarities, you may specify the mean of these dissimilarity measurements as the combined measurement and specify $1/(\text{\# of measurements})$ or $1/\text{variance(measurements)}$ as weights. For more discussion of weights in MDS, we refer to Borg and Groenen (2005, sec. 11.3). Weights should be irreducible; that is, it is not possible to split the objects into disjointed groups with all intergroup weights 0.

In some applications, the similarity or dissimilarity of objects is defined by the researcher in terms of variables (attributes) measured on the objects. If you need MDS of this form, you should continue by reading [MV] **mds**.

Often, however, proximities—that is, similarities or dissimilarities—are measured directly. For instance, psychologists studying the similarities or dissimilarities in a set of stimuli—smells, sounds, faces, concepts, etc.—may have subjects rate the dissimilarity of pairs of stimuli. Linguists have subjects rate the similarity or dissimilarity of pairs of dialects. Political scientists have subjects rate the similarity or dissimilarity of political parties or candidates for political office. In other fields, relational data are studied that may be interpreted as proximities in a more abstract sense. For instance, sociologists study interpersonal contact frequencies in groups ("social networks"); these measures are sometimes interpreted in terms of similarities.

A wide variety of MDS methods have been proposed. mdslong performs classical and modern scaling. Classical scaling has its roots in Young and Householder (1938) and Torgerson (1952). MDS requires complete and symmetric dissimilarity interval-level data. To explore modern scaling, see Borg and Groenen (2005). Classical scaling results in an eigen decomposition, whereas modern scaling is accomplished by the minimization of a loss function. Consequently, eigenvalues are not available after modern MDS.

Computing the classical solution is straightforward, but with modern MDS the minimization of the loss criteria over configurations is a high-dimensional problem that is easily beset by convergence to local minimums. mdslong provides options to control the minimization process 1) by allowing the user to select the starting configuration and 2) by selecting the best solution among multiple minimization runs from random starting configurations.

Proximity data in long format

One format for proximity data is called the "long format", with an observation recording the dissimilarity d_{ij} of the "objects" i and j. This requires three variables: one variable to record the dissimilarities and two variables to identify the comparison pair. The MDS command mdslong requires

- Complete data without duplicates: there is exactly 1 observation for each combination (i, j) or (j, i).

- Optional diagonal: you may, but need not, specify dissimilarities for the reflexive pairs (i, i). If you do, you need not supply values for all (i, i).

▷ Example 1

We illustrate the use of mdslong with a popular dataset from the MDS literature. Rothkopf (1957) had 598 subjects listen to pairs of Morse codes for the 10 digits and for the 26 letters, recording for each pair of codes the percentage of subjects who declared the codes to be the same. The data on the 10 digits are reproduced in Mardia, Kent, and Bibby (1979, 395).

```
. use https://www.stata-press.com/data/r18/morse_long
(Morse data (Rothkopf 1957))

. list in 1/10
```

	digit1	digit2	freqsame
1.	2	1	62
2.	3	1	16
3.	3	2	59
4.	4	1	6
5.	4	2	23
6.	4	3	38
7.	5	1	12
8.	5	2	8
9.	5	3	27
10.	5	4	56

Sixty-two percent of the subjects declare that the Morse codes for 1 and 2 are the same, 16%
declare that 1 and 3 are the same, 59% declare 2 and 3 to be the same, etc. We may think that these
percentages are similarity measures between the Morse codes: the more similar two Morse codes, the
higher the percentage is of subjects who do not distinguish them. The reported percentages suggest,
for example, that 1 and 2 are similar to approximately the same extent as 2 and 3, whereas 1 and
3 are much less similar. This is the kind of relationship you would expect with data that can be
adequately represented with MDS.

We transform our data to a zero-to-one scale.

```
. generate sim = freqsame/100
```

and invoke mdslong on sim, specifying that the proximity variable sim be interpreted as similarities,
and we use option s2d(standard) to convert to dissimilarities by using the standard conversion.

```
. mdslong sim, id(digit1 digit2) s2d(standard)
Classical metric multidimensional scaling
Similarity variable: sim in long format
Dissimilarity: sqrt(2(1-similarity))
                                        Number of obs       =         10
    Eigenvalues > 0        =         9   Mardia fit measure 1 =     0.5086
    Retained dimensions    =         2   Mardia fit measure 2 =     0.7227
```

		abs(eigenvalue)		(eigenvalue)^2	
Dimension	Eigenvalue	Percent	Cumul.	Percent	Cumul.
1	1.9800226	30.29	30.29	49.47	49.47
2	1.344165	20.57	50.86	22.80	72.27
3	1.063133	16.27	67.13	14.26	86.54
4	.66893922	10.23	77.36	5.65	92.18
5	.60159396	9.20	86.56	4.57	96.75
6	.42722301	6.54	93.10	2.30	99.06
7	.21220785	3.25	96.35	0.57	99.62
8	.1452025	2.22	98.57	0.27	99.89
9	.09351288	1.43	100.00	0.11	100.00

MDS configuration

Classical MDS

The two-dimensional representation provides a reasonable, but certainly not impressive, fit to the data. The plot itself is interesting, though, with the digits being roughly 45 degrees apart, except for the pairs (0,9) and (4,5), which are mapped almost at the same locations. Interpretation is certainly helped if you see the circular structure in the Morse codes.

digit	morse code
1	. - - - -
2	. . - - -
3	. . . - -
4	. . . . -
5	. . . . .
6	- . . . .
7	- - . . .
8	- - - . .
9	- - - - .
0	- - - - -

◁

▷ Example 2

You might have your data in wide instead of long format. The Morse code dataset in wide format has 10 observations, 10 data variables d1, ..., d9, d0, and one case identifier.

```
. use https://www.stata-press.com/data/r18/morse_wide, clear
(Morse data (Rothkopf 1957))
. describe

Contains data from https://www.stata-press.com/data/r18/morse_wide.dta
 Observations:           10                   Morse data (Rothkopf 1957)
    Variables:           11                   14 Feb 2022 20:28
                                              (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
digit	byte	%9.0g		
d1	byte	%9.0g		
d2	byte	%9.0g		
d3	byte	%9.0g		
d4	byte	%9.0g		
d5	byte	%9.0g		
d6	byte	%9.0g		
d7	byte	%9.0g		
d8	byte	%9.0g		
d9	byte	%9.0g		
d0	byte	%9.0g		

```
Sorted by:
. list
```

	digit	d1	d2	d3	d4	d5	d6	d7	d8	d9	d0
1.	1	84	62	16	6	12	12	20	37	57	52
2.	2	62	89	59	23	8	14	25	25	28	18
3.	3	16	59	86	38	27	33	17	16	9	9
4.	4	6	23	38	89	56	34	24	13	7	7
5.	5	12	8	27	56	90	30	18	10	5	5
6.	6	12	14	33	34	30	86	65	22	8	18
7.	7	20	25	17	24	18	65	85	65	31	15
8.	8	37	25	16	13	10	22	65	88	58	39
9.	9	57	28	9	7	5	8	31	58	91	79
10.	0	52	18	9	7	5	18	15	39	79	94

Stata does not provide an MDS command to deal directly with the wide format because it is easy to convert the wide format into the long format with the reshape command; see [D] **reshape**.

```
. reshape long d, i(digit) j(other)
(j = 0 1 2 3 4 5 6 7 8 9)
```

Data	Wide	->	Long
Number of observations	10	->	100
Number of variables	11	->	3
j variable (10 values)		->	other
xij variables:			
	d0 d1 ... d9	->	d

Now our data are in long format, and we can use mdslong to obtain a MDS analysis.

```
. generate sim = d/100
. mdslong sim, id(digit other) s2d(standard) noplot
objects should have unit similarity to themselves
r(198);
```

mdslong complains. The wide data—and hence also the long data that we now have—also contain the frequencies in which two identical Morse codes were recognized as the same. This is not 100%. Auditive memory is not perfect, posing a problem for the standard MDS model. We can solve this by ignoring the diagonal observations:

```
. mdslong ... if digit != other ...
```

We may also specify the force option. The force option will take care of a problem that has not yet surfaced, namely, that mdslong requires 1 observation for each pair (i, j). In the long data as now created, we have duplicates observations (i, j) and (j, i). force will symmetrize the proximity information, but it will not deal with multiple measurements in general; having 2 or more observations for (i, j) is an error. If you have multiple measurements, you may average the measurements and use weights.

```
. mdslong sim, id(digit other) s2d(standard) force noplot
Classical metric multidimensional scaling
Similarity variable: sim in long format
Dissimilarity: sqrt(2(1-similarity))
```

		Number of obs	=	10
Eigenvalues > 0	=	9	Mardia fit measure 1 =	0.5086
Retained dimensions	=	2	Mardia fit measure 2 =	0.7227

Dimension	Eigenvalue	abs(eigenvalue)		(eigenvalue)^2	
		Percent	Cumul.	Percent	Cumul.
1	1.9800226	30.29	30.29	49.47	49.47
2	1.344165	20.57	50.86	22.80	72.27
3	1.063133	16.27	67.13	14.26	86.54
4	.66893922	10.23	77.36	5.65	92.18
5	.60159396	9.20	86.56	4.57	96.75
6	.42722301	6.54	93.10	2.30	99.06
7	.21220785	3.25	96.35	0.57	99.62
8	.1452025	2.22	98.57	0.27	99.89
9	.09351288	1.43	100.00	0.11	100.00

The output produced by mdslong here is identical to what we saw earlier.

◁

Modern nonmetric MDS

Unlike classical MDS, modern MDS is calculated via the minimization of the loss function. Eigenvalues are no longer calculated. We look at nonmetric MDS, which is a type of modern MDS in which the transformation from distances to disparities is not an identifiable function as in modern metric MDS but is instead a general monotonic function.

▷ Example 3

We return to the Rothkopf (1957) Morse codes in long format. When we specify method(nonmetric), we assume loss(stress) and transform(monotonic).

```
. use https://www.stata-press.com/data/r18/morse_long, clear
(Morse data (Rothkopf 1957))

. generate sim = freqsame/100

. mdslong sim, id(digit1 digit2) s2d(standard) meth(nonmetric)
(loss(stress) assumed)
(transform(monotonic) assumed)

Iteration 1t:   stress =  .14719847
Iteration 1c:   stress =  .11378737
  (output omitted)
Iteration 89t:   stress =  .07228281
Iteration 89c:   stress =  .07228281

Modern multidimensional scaling
Similarity variable: sim in long format
Dissimilarity: sqrt(2(1-similarity))

    Loss criterion: stress = raw_stress/norm(distances)
    Transformation: monotonic (nonmetric)
                                           Number of obs    =          10
                                           Dimensions       =           2
        Normalization: principal           Loss criterion   =      0.0723
```


MDS configuration

Modern MDS (loss = stress; transform = monotonic)
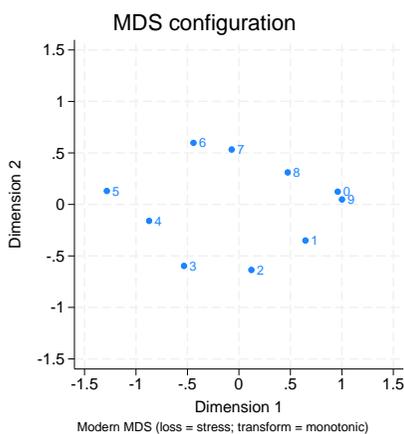
Each iteration has two steps associated with it. The two parts to each iteration consist of modifying the transformation (the T-step) and modifying the configuration (the C-step). If the transform(identity) option had been used, there would not be a T-step. In the iteration log, you see these as *Iteration 1t* and *Iteration 1c*. The rest of the output from modern MDS is explained in [MV] **mds**.

Although there is a resemblance between this graph and the first graph, the points are not as circular or as evenly spaced as they are in the first example, and a great deal more distance is seen between points 4 and 5. Nonmetric MDS depends only on the ordinal properties of the data and admits transformations that may radically change the appearance of the configuration.

◁

After mdslong, all MDS postestimation tools are available. For instance, you may analyze residuals with estat quantile, you may produce a Shepard diagram, etc.; see [MV] **mds postestimation** and [MV] **mds postestimation plots**.

Stored results

mdslong stores the following in e():

Scalars
e(N)	number of underlying observations
e(p)	number of dimensions in the approximating configuration
e(np)	number of strictly positive eigenvalues
e(addcons)	constant added to squared dissimilarities to force positive semidefiniteness
e(mardia1)	Mardia measure 1
e(mardia2)	Mardia measure 2
e(critval)	loss criterion value
e(npos)	number of pairs with positive weights
e(wsum)	sum of weights
e(alpha)	parameter of transform(power)
e(ic)	iteration count
e(rc)	return code
e(converged)	1 if converged, 0 otherwise

Macros
e(cmd)	mdslong
e(cmdline)	command as typed
e(method)	classical or modern MDS method
e(method2)	nonmetric, if method(nonmetric)
e(loss)	loss criterion
e(losstitle)	description loss criterion
e(tfunction)	identity, power, or monotonic, transformation function
e(transftitle)	description of transformation
e(id)	two ID variable names identifying compared object pairs
e(idtype)	int or str; type of id() variable
e(duplicates)	1 if duplicates in id(), 0 otherwise
e(labels)	labels for ID categories
e(mxlen)	maximum length of category labels
e(depvar)	dependent variable containing dissimilarities
e(dtype)	similarity or dissimilarity; type of proximity data
e(s2d)	standard or oneminus (when e(dtype) is similarity)
e(wtype)	weight type
e(wexp)	weight expression
e(unique)	1 if eigenvalues are distinct, 0 otherwise
e(init)	initialization method
e(irngstate)	initial random-number state used for init(random)
e(rngstate)	random-number state for solution
e(norm)	normalization method
e(targetmatrix)	name of target matrix for normalize(target)
e(properties)	nob noV for modern or nonmetric MDS; nob noV eigen for classical MDS
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
    e(D)   dissimilarity matrix
    e(Disparities) disparity matrix for nonmetric MDS
    e(Y)   approximating configuration coordinates
    e(Ev)   eigenvalues
    e(W)   weight matrix
    e(idcoding)   coding for integer identifier variable
    e(norm_stats)   normalization statistics
    e(linearf)   two element vector defining the linear transformation; distance
                      equals first element plus second element times dissimilarity

Functions
    e(sample)   marks estimation sample

Methods and formulas

See *Methods and formulas* in [MV] **mdsmat** for information.

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See [MV] **mdsmat** for more references.

Also see

[MV] **mds postestimation** — Postestimation tools for mds, mdsmat, and mdslong

[MV] **mds postestimation plots** — Postestimation plots for mds, mdsmat, and mdslong

[MV] **biplot** — Biplots

[MV] **ca** — Simple correspondence analysis

[MV] **factor** — Factor analysis

[MV] **mds** — Multidimensional scaling for two-way data

[MV] **mdsmat** — Multidimensional scaling of proximity data in a matrix

[MV] **pca** — Principal component analysis

[U] **20 Estimation and postestimation commands**

Title

> **mdsmat —** Multidimensional scaling of proximity data in a matrix

Description

mdsmat performs multidimensional scaling (MDS) for two-way proximity data with an explicit measure of similarity or dissimilarity between objects, where the proximities are found in a user-specified matrix. mdsmat performs classical metric MDS as well as modern metric and nonmetric MDS.

If your proximities are stored as variables in long format, see [MV] **mdslong**. If you are looking for MDS on a dataset on the basis of dissimilarities between observations over variables, see [MV] **mds**.

Quick start

Classical multidimensional scaling based on dissimilarities in matrix M

    mdsmat M

Same as above, but suppress the MDS configuration plot and use 3 dimensions for the approximating configuration

    mdsmat M, noplot dimension(3)

Modern multidimensional scaling based on dissimilarities in matrix M

    mdsmat M, method(modern)

Same as above, but with Sammon mapping loss criterion and Procrustes rotation toward the classical solution

    mdsmat M, loss(sammon) normalize(classical)

Nonmetric modern multidimensional scaling based on dissimilarities in matrix M

    mdsmat M, method(nonmetric)

Menu

Statistics > Multivariate analysis > Multidimensional scaling (MDS) > MDS of proximity matrix

Syntax

> mdsmat *matname* [, *options*]

options	Description
[Model]	
<u>meth</u>od(*method*)	method for performing MDS
loss(*loss*)	loss function
<u>trans</u>form(*tfunction*)	permitted transformations of dissimilarities
<u>norm</u>alize(*norm*)	normalization method; default is normalize(principal)
<u>names</u>(*namelist*)	variable names corresponding to row and column names of the matrix; required with all but shape(full)
shape(<u>f</u>ull)	*matname* is a square symmetric matrix; the default
shape(<u>lower</u>)	*matname* is a vector with the rowwise lower triangle (with diagonal)
shape(<u>llower</u>)	*matname* is a vector with the rowwise strictly lower triangle (no diagonal)
shape(<u>upper</u>)	*matname* is a vector with the rowwise upper triangle (with diagonal)
shape(<u>uupper</u>)	*matname* is a vector with the rowwise strictly upper triangle (no diagonal)
s2d(<u>standard</u>)	convert similarity to dissimilarity: $d_{ij} = \sqrt{s_{ii} + s_{jj} - 2s_{ij}}$
s2d(<u>oneminus</u>)	convert similarity to dissimilarity: $d_{ij} = 1 - s_{ij}$
[Model 2]	
<u>dim</u>ension(*#*)	configuration dimensions; default is dimension(2)
force	fix problems in proximity information
<u>addc</u>onstant	make distance matrix positive semidefinite (classical MDS only)
weight(*matname*)	specifies a weight matrix with the same shape as the proximity matrix
[Reporting]	
<u>neig</u>en(*#*)	maximum number of eigenvalues to display; default is neigen(10) (classical MDS only)
config	display table with configuration coordinates
noplot	suppress configuration plot
[Minimization]	
<u>init</u>ialize(*initopt*)	start with configuration given in *initopt*
<u>tol</u>erance(*#*)	tolerance for configuration matrix; default is tolerance(1e-4)
<u>ltol</u>erance(*#*)	tolerance for loss criterion; default is ltolerance(1e-8)
<u>iter</u>ate(*#*)	perform maximum *#* of iterations; default is iterate(1000)
<u>protect</u>(*#*)	perform *#* optimizations and report best solution; default is protect(1)
[no]log	display or suppress the iteration log; default is to display
trace	display current configuration in iteration log
gradient	display current gradient matrix in iteration log
<u>sdprotect</u>(*#*)	advanced; see *Options* below

collect is allowed; see [U] **11.1.10 Prefix commands**.

sdprotect(*#*) does not appear in the dialog box.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

method	Description
<u>c</u>lassical	classical MDS; default if neither loss() nor transform() is specified
<u>mod</u>ern	modern MDS; default if loss() or transform() is specified; except when loss(stress) and transform(monotonic) are specified
<u>non</u>metric	nonmetric (modern) MDS; default when loss(stress) and transform(monotonic) are specified

loss	Description
<u>stress</u>	stress criterion, normalized by distances; the default
<u>n</u>stress	stress criterion, normalized by disparities
<u>ss</u>stress	squared stress criterion, normalized by distances
<u>nss</u>stress	squared stress criterion, normalized by disparities
<u>stra</u>in	strain criterion (with transform(identity) is equivalent to classical MDS)
<u>sa</u>mmon	Sammon mapping

tfunction	Description
<u>ide</u>ntity	no transformation; disparity = dissimilarity; the default
<u>pow</u>er	power α: disparity = dissimilarity$^{\alpha}$
<u>mon</u>otonic	weakly monotonic increasing functions (nonmetric scaling); only with loss(stress)

norm	Description
<u>pri</u>ncipal	principal orientation; location = 0; the default
<u>cl</u>assical	Procrustes rotation toward classical solution
<u>t</u>arget(*matname*) [, copy]	Procrustes rotation toward *matname*; ignore naming conflicts if copy is specified

initopt	Description
<u>cl</u>assical	start with classical solution; the default
<u>ra</u>ndom [(#)]	start at random configuration, setting seed to #
<u>fr</u>om(*matname*) [, copy]	start from *matname*; ignore naming conflicts if copy is specified

Options

    Model

method(*method*) specifies the method for MDS.

    method(classical) specifies classical metric scaling, also known as "principal coordinates analysis" when used with Euclidean proximities. Classical MDS obtains equivalent results to modern MDS with loss(strain) and transform(identity) without weights. The calculations for classical MDS are fast; consequently, classical MDS is generally used to obtain starting values

for modern MDS. If the options `loss()` and `transform()` are not specified, `mds` computes the classical solution, likewise if `method(classical)` is specified `loss()` and `transform()` are not allowed.

`method(modern)` specifies modern scaling. If `method(modern)` is specified but not `loss()` or `transform()`, then `loss(stress)` and `transform(identity)` are assumed. All values of `loss()` and `transform()` are valid with `method(modern)`.

`method(nonmetric)` specifies nonmetric scaling, which is a type of modern scaling. If `method(nonmetric)` is specified, `loss(stress)` and `transform(monotonic)` are assumed. Other values of `loss()` and `transform()` are not allowed.

`loss(`*loss*`)` specifies the loss criterion.

`loss(stress)` specifies that the stress loss function be used, normalized by the squared Euclidean distances. This criterion is often called Kruskal's stress-1. Optimal configurations for `loss(stress)` and for `loss(nstress)` are equivalent up to a scale factor, but the iteration paths may differ. `loss(stress)` is the default.

`loss(nstress)` specifies that the stress loss function be used, normalized by the squared disparities, that is, transformed dissimilarities. Optimal configurations for `loss(stress)` and for `loss(nstress)` are equivalent up to a scale factor, but the iteration paths may differ.

`loss(sstress)` specifies that the squared stress loss function be used, normalized by the fourth power of the Euclidean distances.

`loss(nsstress)` specifies that the squared stress criterion, normalized by the fourth power of the disparities (transformed dissimilarities) be used.

`loss(strain)` specifies the strain loss criterion. Classical scaling is equivalent to `loss(strain)` and `transform(identity)` but is computed by a faster noniterative algorithm. Specifying `loss(strain)` still allows transformations.

`loss(sammon)` specifies the Sammon (1969) loss criterion.

`transform(`*tfunction*`)` specifies the class of allowed transformations of the dissimilarities; transformed dissimilarities are called disparities.

`transform(identity)` specifies that the only allowed transformation is the identity; that is, disparities are equal to dissimilarities. `transform(identity)` is the default.

`transform(power)` specifies that disparities are related to the dissimilarities by a power function,

$$\text{disparity} = \text{dissimilarity}^{\alpha}, \qquad \alpha > 0$$

`transform(monotonic)` specifies that the disparities are a weakly monotonic function of the dissimilarities. This is also known as nonmetric MDS. Tied dissimilarities are handled by the primary method; that is, ties may be broken but are not necessarily broken. `transform(monotonic)` is valid only with `loss(stress)`.

`normalize(`*norm*`)` specifies a normalization method for the configuration. Recall that the location and orientation of an MDS configuration is not defined ("identified"); an isometric transformation (that is, translation, reflection, or orthonormal rotation) of a configuration preserves interpoint Euclidean distances.

`normalize(principal)` performs a principal normalization, in which the configuration columns have zero mean and correspond to the principal components, with positive coefficient for the observation with lowest value of `id()`. `normalize(principal)` is the default.

normalize(classical) normalizes by a distance-preserving Procrustean transformation of the configuration toward the classical configuration in principal normalization; see [MV] **procrustes**. normalize(classical) is not valid if method(classical) is specified.

normalize(target(*matname*) [, copy]) normalizes by a distance-preserving Procrustean transformation toward *matname*; see [MV] **procrustes**. *matname* should be an $n \times p$ matrix, where n is the number of observations and p is the number of dimensions, and the rows of *matname* should be ordered with respect to id(). The rownames of *matname* should be set correctly but will be ignored if copy is also specified.

Note on normalize(classical) and normalize(target()): the Procrustes transformation comprises any combination of translation, reflection, and orthonormal rotation—these transformations preserve distance. Dilation (uniform scaling) would stretch distances and is not applied. However, the output reports the dilation factor, and the reported Procrustes statistic is for the dilated configuration.

names(*namelist*) is required with all but shape(full). The number of names should equal the number of rows (and columns) of the full similarity or dissimilarity matrix and should not contain duplicates.

shape(*shape*) specifies the storage mode of the existing similarity or dissimilarity matrix *matname*. The following storage modes are allowed:

full specifies that *matname* is a symmetric $n \times n$ matrix.

lower specifies that *matname* is a row or column vector of length $n(n+1)/2$, with the rowwise lower triangle of the similarity or dissimilarity matrix including the diagonal.

$$D_{11} \ D_{21} \ D_{22} \ D_{31} \ D_{32} \ D_{33} \ \ldots \ D_{n1} \ D_{n2} \ \ldots \ D_{nn}$$

llower specifies that *matname* is a row or column vector of length $n(n-1)/2$, with the rowwise lower triangle of the similarity or dissimilarity matrix excluding the diagonal.

$$D_{21} \ D_{31} \ D_{32} \ D_{41} \ D_{42} \ D_{43} \ \ldots \ D_{n1} \ D_{n2} \ \ldots \ D_{n,n-1}$$

upper specifies that *matname* is a row or column vector of length $n(n+1)/2$, with the rowwise upper triangle of the similarity or dissimilarity matrix including the diagonal.

$$D_{11} \ D_{12} \ \ldots \ D_{1n} \ D_{22} \ D_{23} \ \ldots \ D_{2n} \ D_{33} \ D_{34} \ \ldots \ D_{3n} \ \ldots \ D_{nn}$$

uupper specifies that *matname* is a row or column vector of length $n(n-1)/2$, with the rowwise upper triangle of the similarity or dissimilarity matrix excluding the diagonal.

$$D_{12} \ D_{13} \ \ldots \ D_{1n} \ D_{23} \ D_{24} \ \ldots \ D_{2n} \ D_{34} \ D_{35} \ \ldots \ D_{3n} \ \ldots \ D_{n-1,n}$$

s2d(standard | oneminus) specifies how similarities are converted into dissimilarities. By default, the command assumes dissimilarity data. Specifying s2d() indicates that your proximity data are similarities.

Dissimilarity data should have zeros on the diagonal (that is, an object is identical to itself) and nonnegative off-diagonal values. Dissimilarities need not satisfy the triangular inequality, $D(i,j)^2 \leq D(i,h)^2 + D(h,j)^2$. Similarity data should have ones on the diagonal (that is, an object is identical to itself) and have off-diagonal values between zero and one. In either case, proximities should be symmetric. See option force if your data violate these assumptions.

The available s2d() options, standard and oneminus, are defined as follows:

$$
\begin{array}{ll}
\text{standard} & \text{dissim}_{ij} = \sqrt{\text{sim}_{ii} + \text{sim}_{jj} - 2\text{sim}_{ij}} = \sqrt{2(1 - \text{sim}_{ij})} \\
\text{oneminus} & \text{dissim}_{ij} = 1 - \text{sim}_{ij}
\end{array}
$$

s2d(standard) is the default.

s2d() should be specified only with measures in similarity form.

> ◣ Model 2 ◢

dimension(#) specifies the dimension of the approximating configuration. The default is dimension(2), and # should not exceed the number of positive eigenvalues of the centered distance matrix.

force corrects problems with the supplied proximity information. force specifies that the dissimilarity matrix be symmetrized; the mean of D_{ij} and D_{ji} is used. Also, problems on the diagonal (similarities: $D_{ii} \neq 1$; dissimilarities: $D_{ii} \neq 0$) are fixed. force does not fix missing values or out-of-range values (that is, $D_{ij} < 0$ or similarities with $D_{ij} > 1$). Analogously, force symmetrizes the weight matrix.

addconstant specifies that if the double-centered distance matrix is not positive semidefinite (psd), a constant should be added to the squared distances to make it psd and, hence, Euclidean.

weight(*matname*) specifies a symmetric weight matrix with the same shape as the proximity matrix; that is, if shape(lower) is specified, the weight matrix must have this shape. Weights should be nonnegative. Missing weights are assumed to be 0. Weights must also be irreducible; that is, it is not possible to split the objects into disjointed groups with all intergroup weights 0. weight() is not allowed with method(classical), but see loss(strain).

> ◣ Reporting ◢

neigen(#) specifies the number of eigenvalues to be included in the table. The default is neigen(10). Specifying neigen(0) suppresses the table. This option is allowed with classical MDS only.

config displays the table with the coordinates of the approximating configuration. This table may also be displayed using the postestimation command estat config; see [MV] **mds postestimation**.

noplot suppresses the graph of the approximating configuration. The graph can still be produced later via mdsconfig, which also allows the standard graphics options for fine-tuning the plot; see [MV] **mds postestimation plots**.

> ◣ Minimization ◢

These options are available only with method(modern) or method(nonmetric):

initialize(*initopt*) specifies the initial values of the criterion minimization process.

initialize(classical), the default, uses the solution from classical metric scaling as initial values. With protect(), all but the first run start from random perturbations from the classical solution. These random perturbations are independent and normally distributed with standard error equal to the product of sdprotect(#) and the standard deviation of the dissimilarities. initialize(classical) is the default.

initialize(random) starts an optimization process from a random starting configuration. These random configurations are generated from independent normal distributions with standard error equal to the product of sdprotect(#) and the standard deviation of the dissimilarities. The means of the configuration are irrelevant in MDS.

initialize(from(*matname*) [, copy]) sets the initial value to *matname*. *matname* should be an $n \times p$ matrix, where n is the number of observations and p is the number of dimensions, and the rows of *matname* should be ordered with respect to id(). The rownames of *matname* should be set correctly but will be ignored if copy is specified. With protect(), the second-to-last runs start from random perturbations from *matname*. These random perturbations are independent normal distributed with standard error equal to the product of sdprotect(#) and the standard deviation of the dissimilarities.

tolerance(#) specifies the tolerance for the configuration matrix. When the relative change in the configuration from one iteration to the next is less than or equal to tolerance(), the tolerance() convergence criterion is satisfied. The default is tolerance(1e-4).

ltolerance(#) specifies the tolerance for the fit criterion. When the relative change in the fit criterion from one iteration to the next is less than or equal to ltolerance(), the ltolerance() convergence is satisfied. The default is ltolerance(1e-8).

Both the tolerance() and ltolerance() criteria must be satisfied for convergence.

iterate(#) specifies the maximum number of iterations. The default is iterate(1000).

protect(#) requests that # optimizations be performed and that the best of the solutions be reported. The default is protect(1). See option initialize() on starting values of the runs. The output contains a table of the return code, the criterion value reached, and the seed of the random number used to generate the starting value. Specifying a large number, such as protect(50), provides reasonable insight whether the solution found is a global minimum and not just a local minimum.

If any of the options log, trace, or gradient is also specified, iteration reports will be printed for each optimization run. Beware: this option will produce a lot of output.

log and nolog specify whether to display the iteration log. The iteration log is displayed by default unless you used set iterlog off to suppress it; see set iterlog in [R] *set iter*.

trace displays the configuration matrices in the iteration report. Beware: this option may produce a lot of output.

gradient displays the gradient matrices of the fit criterion in the iteration report. Beware: this option may produce a lot of output.

The following option is available with mdsmat but is not shown in the dialog box:

sdprotect(#) sets a proportionality constant for the standard deviations of random configurations (init(random)) or random perturbations of given starting configurations (init(classical) or init(from())). The default is sdprotect(1).

Remarks and examples

Remarks are presented under the following headings:

Introduction

Multidimensional scaling (MDS) is a dimension-reduction and visualization technique. Dissimilarities (for instance, Euclidean distances) between observations in a high-dimensional space are represented in a lower-dimensional space (typically two dimensions) so that the Euclidean distance in the lower-dimensional space approximates the dissimilarities in the higher-dimensional space. See

Kruskal and Wish (1978) for a brief nontechnical introduction to MDS. Young (1987) and Borg and Groenen (2005) are more advanced textbook-sized treatments.

mdsmat performs MDS on a similarity or dissimilarity matrix *matname*. You may enter the matrix as a symmetric square matrix or as a vector (matrix with one row or column) with only the upper or lower triangle; see option shape() for details. *matname* should not contain missing values. The diagonal elements should be 0 (dissimilarities) or 1 (similarities). If you provide a square matrix (that is, shape(full)), names of the objects are obtained from the matrix row and column names. The row names should all be distinct, and the column names should equal the row names. Equation names, if any, are ignored. In any of the vectorized shapes, names are specified with option names(), and the matrix row and column names are ignored.

See option force if your matrix violates these assumptions.

In some applications, the similarity or dissimilarity of objects is defined by the researcher in terms of variables (attributes) measured on the objects. If you need to do MDS of this form, you should continue by reading [MV] **mds**.

Often, however, proximities—that is, similarities or dissimilarities—are measured directly. For instance, psychologists studying the similarities or dissimilarities in a set of stimuli—smells, sounds, faces, concepts, etc.—may have subjects rate the dissimilarity of pairs of stimuli. Linguists have subjects rate the similarity or dissimilarity of pairs of dialects. Political scientists have subjects rate the similarity or dissimilarity of political parties or candidates for political office. In other fields, relational data are studied that may be interpreted as proximities in a more abstract sense. For instance, sociologists study interpersonal contact frequencies in groups ("social networks"); these measures are sometimes interpreted in terms of similarities.

A wide variety of MDS methods have been proposed. mdsmat performs classical and modern scaling. Classical scaling has its roots in Young and Householder (1938) and Torgerson (1952). MDS requires complete and symmetric dissimilarity interval-level data. To explore modern scaling, see Borg and Groenen (2005). Classical scaling results in an eigen decomposition, whereas modern scaling is accomplished by the minimization of a loss function. Consequently, eigenvalues are not available after modern MDS.

Computing the classical solution is straightforward, but with modern MDS the minimization of the loss criteria over configurations is a high-dimensional problem that is easily beset by convergence to local minimums. mdsmat provides options to control the minimization process 1) by allowing the user to select the starting configuration and 2) by selecting the best solution among multiple minimization runs from random starting configurations.

Proximity data in a Stata matrix

To perform MDS of relational data, you must enter the data in a suitable format. One convenient format is a Stata matrix. You may want to use this format for analyzing data that you obtain from a printed source.

▷ Example 1

Many texts on multidimensional scaling illustrate how locations can be inferred from a table of geographic distances. We will do this too, using an example of distances in miles between 14 locations in Texas, representing both manufactured and natural treasures:

```
          Big Bend │   0  523  551  243  322  412  263  596  181  313  553
     Corpus Christi │ 523    0  396  280  705  232  619  226  342  234   30
             Dallas │ 551  396    0  432  643  230  532  243  494  317  426
            Del Rio │ 243  280  432    0  427  209  339  353   62   70  310
            El Paso │ 322  705  643  427    0  528  110  763  365  525  735
     Enchanted Rock │ 412  232  230  209  528    0  398  260  271   69  262
      Guadalupe Mnt │ 263  619  532  339  110  398    0  674  277  280  646
            Houston │ 596  226  243  353  763  260  674    0  415  292  256
            Langtry │ 181  342  494   62  365  271  277  415    0  132  372
        Lost Maples │ 313  234  317   70  525   69  280  292  132    0  264
        Padre Island │ 553   30  426  310  735  262  646  256  372  264    0
    Pedernales Falls │ 434  216  235  231  550   40  420  202  293  115  246
         San Antonio │ 397  141  274  154  564   91  475  199  216   93  171
           StataCorp │ 426  205  151  287  606  148  512   83  318  202  316
```

```
          Big Bend │ 434  397  426
     Corpus Christi │ 216  141  205
             Dallas │ 235  274  151
            Del Rio │ 231  154  287
            El Paso │ 550  564  606
     Enchanted Rock │  40   91  148
      Guadalupe Mnt │ 420  475  512
            Houston │ 202  199   83
            Langtry │ 293  216  318
        Lost Maples │ 115   93  202
        Padre Island │ 246  171  316
    Pedernales Falls │   0   75  116
         San Antonio │  75    0  154
           StataCorp │ 116  154    0
```

Note the inclusion of StataCorp, which is located in the twin cities of Bryan/College Station (BCS). To get the data into Stata, we will enter only the strictly upper triangle as a Stata one-dimensional matrix and collect the names in a `global` macro for later use. We are using the strictly upper triangle (that is, omitting the diagonal) because the diagonal of a dissimilarity matrix contains all zeros—there is no need to enter them.

```
. matrix input D = (
>    523  551  243  322  412  263  596  181  313  553  434  397  426
>         396  280  705  232  619  226  342  234   30  216  141  205
>              432  643  230  532  243  494  317  426  235  274  151
>                   427  209  339  353   62   70  310  231  154  287
>                        528  110  763  365  525  735  550  564  606
>                             398  260  271   69  262   40   91  148
>                                  674  277  280  646  420  475  512
>                                       415  292  256  202  199   83
>                                            132  372  293  216  318
>                                                 264  115   93  202
>                                                      246  171  316
>                                                            75  116
>                                                               154 )

. global names
>    Big_Bend       Corpus_Christi  Dallas        Del_Rio
>    El_Paso        Enchanted_Rock  Guadalupe_Mnt  Houston
>    Langtry        Lost_Maples     Padre_Island   Pedernales_Falls
>    San_Antonio  StataCorp
```

The triangular data entry is just typographical and is useful for catching data entry errors. As far as Stata is concerned, we could have typed all the numbers in one long row. We use `matrix input`

D = rather than `matrix define D =` or just `matrix D =` so that we do not have to separate entries with commas.

With the data now in Stata, we may use `mdsmat` to infer the locations in Texas and produce a map:

```
. mdsmat D, names($names) shape(uupper)
Classical metric multidimensional scaling
Dissimilarity matrix: D
                                        Number of obs          =         14
    Eigenvalues > 0       =         8   Mardia fit measure 1 =     0.7828
    Retained dimensions   =         2   Mardia fit measure 2 =     0.9823
```

Dimension	Eigenvalue	abs(eigenvalue) Percent	Cumul.	(eigenvalue)^2 Percent	Cumul.
1	691969.62	62.63	62.63	92.45	92.45
2	172983.05	15.66	78.28	5.78	98.23
3	57771.995	5.23	83.51	0.64	98.87
4	38678.916	3.50	87.01	0.29	99.16
5	19262.579	1.74	88.76	0.07	99.23
6	9230.7695	0.84	89.59	0.02	99.25
7	839.70996	0.08	89.67	0.00	99.25
8	44.989372	0.00	89.67	0.00	99.25
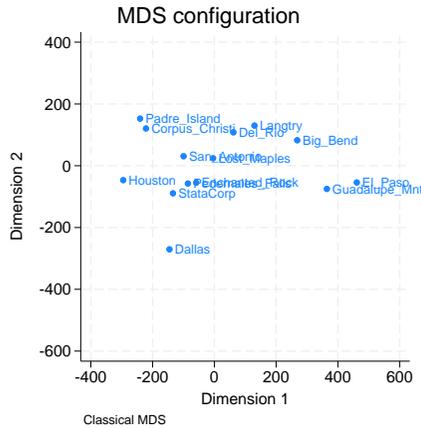
The representation of the distances in two dimensions provides a reasonable, but not great, fit; the percentage of eigenvalues accounted for is 78%.

By default, `mdsmat` produces a configuration plot. Enhancements to the configuration plot are possible using the `mdsconfig` postestimation graphics command; see [MV] **mds postestimation plots**. We present the configuration plot with the `autoaspect` option to obtain better use of the available space while preserving the equivalence of distance in the x and y axes. We negate the direction of the x axis with the `xnegate` option to flip the configuration horizontally and flip the direction of the y axis with the `ynegate` option. We also change the default title and control the placement of labels.

```
. set obs 14
Number of observations (_N) was 0, now 14.

. generate pos = 3

. replace pos = 4 in 6
(1 real change made)

. replace pos = 2 in 10
(1 real change made)

. mdsconfig, autoaspect xnegate ynegate mlabvpos(pos)
> title(MDS for 14 Texas locations)
```
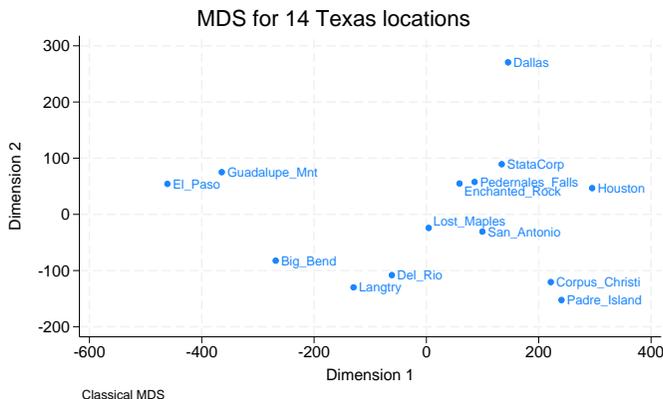

Look at the graph produced by `mdsconfig` after `mdsmat`. You will probably recognize a twisted (and slightly distorted) map of Texas. The vertical orientation of the map is not correctly north–south; you would probably want to turn the map some 20 degrees clockwise. Why didn't `mdsmat` get it right? It could not have concluded the correct rotation from the available distance information. Any orthogonal rotation of the map would produce the same distances. The orientation of the map is *not identified.* Finally, the "location" of the map cannot be inferred from the distances. Translating the coordinates does not change the distances. As far as `mdsmat` is concerned, Texas could be part of China.

◁

Modern MDS and local minimums

Modern MDS can converge to a local rather than a global minimum. We give an example where this happens and show how the `protect()` option can guard against this. `protect(#)` performs multiple minimizations and reports the best one. The output is explained in [MV] **mds**.

▷ Example 2

Continuing from where we left off, we perform modern MDS, using an initial random configuration with the `init(random(512308))` option. The number 512,308 sets the seed so that this run may be replicated.

```
. mdsmat D, names($names) shape(uupper) meth(modern) init(random(512308)) nolog
> noplot
(loss(stress) assumed)
(transform(identity) assumed)

Modern multidimensional scaling
Dissimilarity matrix: D
     Loss criterion: stress = raw_stress/norm(distances)
     Transformation: identity (no transformation)
                                              Number of obs   =         14
                                              Dimensions      =          2
     Normalization: principal                 Loss criterion  =     0.0858
. mdsconfig, autoaspect xnegate ynegate mlabvpos(pos)
> title(Padre Island heads north?)
```


Modern MDS (loss = stress; transform = identity)
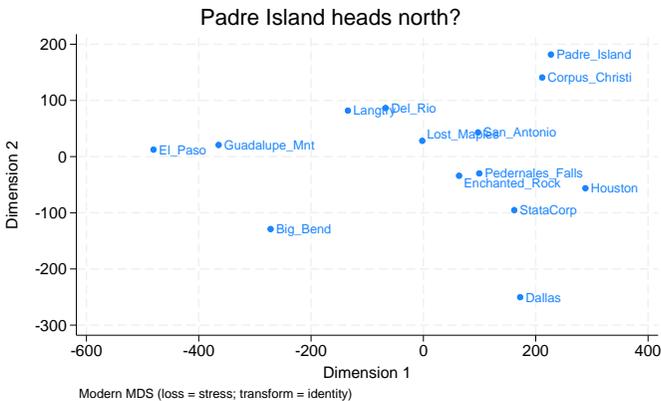
This graph has some resemblance to the one we saw before, but any Texan can assure you that Padre Island should not end up north of Dallas.

We check this result by rerunning with `protect(10)`. This will repeat the minimization and report the best result. Larger values of `protect()` give us more assurance that we have found the global minimum, but here `protect(10)` is sufficient to tell us that our original `mdsmat` found a local, not a global, minimum.

```
. mdsmat D, names($names) shape(uupper) meth(modern) init(random(512308)) nolog
> protect(10) noplot
(loss(stress) assumed)
(transform(identity) assumed)

run   mrc   #iter      lossval

  1    0     61      .06180059
  2    0     48       .0618006
  3    0     49       .0618006
  4    0     42       .0618006
  5    0     52       .0618006
  6    0     84      .08581202
  7    0     83      .08581202
  8    0     70      .08581202
  9    0     89      .12189371
 10    0     66      .12189371


Modern multidimensional scaling
Dissimilarity matrix: D

     Loss criterion: stress = raw_stress/norm(distances)
     Transformation: identity (no transformation)

                                            Number of obs    =          14
                                            Dimensions       =           2
     Normalization: principal               Loss criterion   =      0.0618

. mdsconfig, autoaspect xnegate ynegate mlabvpos(pos)
> title(Padre Island is back where it belongs)
```


Modern MDS (loss = stress; transform = identity)
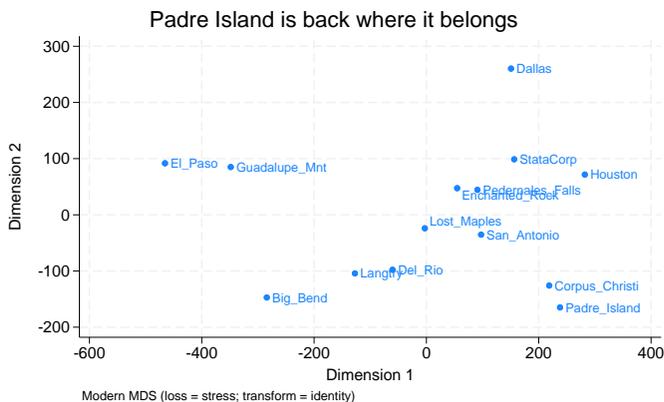
The original run had a loss criterion of 0.0858, but after using the `protect()` option the loss criterion was much lower—0.0618. We also see that Padre Island is back down south where it belongs. It is clear that the original run converged to a local minimum. You can see the original results appear as the final output line of the first table in the output after using `protect(10)`. The seed in the table is a hexadecimal representation of how the seed is stored internally. The number 512,308 in `init(random(512308))` is convenient shorthand for specifying the seed; the two are equivalent. If we wish, we could repeat the command with a larger value of `protect()` to assure ourselves that 0.0618 is indeed the global minimum.

◁

After `mdsmat`, all MDS postestimation tools are available. For instance, you may analyze residuals with `estat quantile`, you may produce a Shepard diagram, etc.; see [MV] **mds postestimation** and [MV] **mds postestimation plots**.

Stored results

`mdsmat` stores the following in `e()`:

Scalars
`e(N)`	number of rows or columns (i.e., number of observations)
`e(p)`	number of dimensions in the approximating configuration
`e(np)`	number of strictly positive eigenvalues
`e(addcons)`	constant added to squared dissimilarities to force positive semidefiniteness
`e(mardia1)`	Mardia measure 1
`e(mardia2)`	Mardia measure 2
`e(critval)`	loss criterion value
`e(wsum)`	sum of weights
`e(alpha)`	parameter of `transform(power)`
`e(ic)`	iteration count
`e(rc)`	return code
`e(converged)`	1 if converged, 0 otherwise

Macros
`e(cmd)`	`mdsmat`
`e(cmdline)`	command as typed
`e(method)`	`classical` or `modern` MDS method
`e(method2)`	`nonmetric`, if `method(nonmetric)`
`e(loss)`	loss criterion
`e(losstitle)`	description loss criterion
`e(dmatrix)`	name of analyzed matrix
`e(tfunction)`	`identity`, `power`, or `monotonic`, transformation function
`e(transftitle)`	description of transformation
`e(dtype)`	`similarity` or `dissimilarity`; type of proximity data
`e(s2d)`	`standard` or `oneminus` (when `e(dtype)` is `similarity`)
`e(unique)`	1 if eigenvalues are distinct, 0 otherwise
`e(init)`	initialization method
`e(irngstate)`	initial random-number state used for `init(random)`
`e(rngstate)`	random-number state for solution
`e(norm)`	normalization method
`e(targetmatrix)`	name of target matrix for `normalize(target)`
`e(properties)`	`nob noV` for modern or nonmetric MDS; `nob noV eigen` for classical MDS
`e(estat_cmd)`	program used to implement `estat`
`e(predict)`	program used to implement `predict`
`e(marginsnotok)`	predictions disallowed by `margins`

Matrices
`e(D)`	dissimilarity matrix
`e(Disparities)`	disparity matrix for nonmetric MDS
`e(Y)`	approximating configuration coordinates
`e(Ev)`	eigenvalues
`e(W)`	weight matrix
`e(norm_stats)`	normalization statistics
`e(linearf)`	two element vector defining the linear transformation; distance equals first element plus second element times dissimilarity

Methods and formulas

Methods and formulas are presented under the following headings:

> *Classical multidimensional scaling*
> *Modern multidimensional scaling*
> *Conversion of similarities to dissimilarities*

Classical multidimensional scaling

Let $\mathbf{D}$ be an $n \times n$ dissimilarity matrix. The matrix $\mathbf{D}$ is said to be *Euclidean* if there are coordinates $\mathbf{Y}$ so that

$$D_{ij}^2 = (\mathbf{Y}_i - \mathbf{Y}_j)(\mathbf{Y}_i - \mathbf{Y}_j)'$$

Here $\mathbf{Y}_i$ and $\mathbf{Y}_j$ are the ith and jth column vectors extracted from $\mathbf{Y}$. Let $\mathbf{A} = -(1/2)\mathbf{D} \odot \mathbf{D}$, with $\odot$ being the Hadamard or elementwise matrix product, and define $\mathbf{B}$ as the double-centered distance matrix

$$\mathbf{B} = \mathbf{HAH} \qquad \text{with} \qquad \mathbf{H} = \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}'$$

$\mathbf{D}$ is Euclidean if and only if $\mathbf{B}$ is positive semidefinite. Assume for now that $\mathbf{D}$ is indeed Euclidean. The spectral or eigen decomposition of $\mathbf{B}$ is written as $\mathbf{B} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}'$, with $\mathbf{U}$ the orthonormal matrix of eigenvectors normed to 1, and $\mathbf{\Lambda}$ a diagonal matrix with nonnegative values (the eigenvalues of $\mathbf{B}$) in decreasing order. The coordinates $\mathbf{Y}$ are defined in terms of the spectral decomposition $\mathbf{Y} = \mathbf{U}\mathbf{\Lambda}^{1/2}$. These coordinates are centered $\mathbf{Y}'\mathbf{1} = \mathbf{0}$.

The spectral decomposition can also be used to obtain a low-dimensional configuration $\widetilde{\mathbf{Y}}$, $n \times p$, so that the interrow distances of $\widetilde{\mathbf{Y}}$ approximate $\mathbf{D}$. Mardia, Kent, and Bibby (1979, sec. 14.4) discuss some characterizations under which the leading p columns of $\mathbf{Y}$ are an optimal choice of $\widetilde{\mathbf{Y}}$. These characterizations also apply to the case when $\mathbf{B}$ is not positive semidefinite, so some of the λ's are negative; we require that $\lambda_p > 0$.

Various other approaches have been proposed to deal with the case when the matrix $\mathbf{B}$ is not positive semidefinite, that is, when $\mathbf{B}$ has negative eigenvalues (see Cox and Cox 2001, 45–48). An easy solution is to add a constant to the off-diagonal elements of $\mathbf{D} \odot \mathbf{D}$ to make $\mathbf{B}$ positive semidefinite. The smallest such constant is $-2\lambda_n$, where λ_n is the smallest eigenvalue of $\mathbf{B}$ (Lingoes 1971). See Cailliez (1983) for a solution to the additive constant problem in terms of the dissimilarities instead of the squared dissimilarities.

Goodness-of-fit statistics for a configuration in p dimensions have been proposed by Mardia (1978) in characterizations of optimality properties of the classical solution

$$\text{Mardia}_1 = \frac{\sum_{i=1}^{p} |\lambda_i|}{\sum_{i=1}^{n} |\lambda_i|}$$

and

$$\text{Mardia}_2 = \frac{\sum_{i=1}^{p} \lambda_i^2}{\sum_{i=1}^{n} \lambda_i^2}$$

Modern multidimensional scaling

Let $\mathbf{D}$ be a symmetric $n \times n$ matrix of observed dissimilarities. We assume that proximity data in the form of similarities have already been transformed into dissimilarities. Let $\mathbf{W}$ be an $n \times n$ matrix of nonnegative weights. With unweighted MDS, we define $W_{ij} = 1$. For a configuration of n points in k-dimensional space represented by the $n \times k$ matrix $\mathbf{Y}$, let $\mathbf{B}(\mathbf{Y})$ be the $n \times n$ matrix of Euclidean distances between the rows of $\mathbf{Y}$. We consider $\mathcal{F}$ to be some class of permitted transformations from $n \times n$ real matrices to $n \times n$ real matrices.

Modern metric and nonmetric multidimensional scaling involves the minimization of a loss criterion

$$L\{f(\mathbf{D}), \mathbf{B}(\mathbf{Y}), \mathbf{W}\}$$

over the configurations $\mathbf{Y}$ and transformations $f \in \mathcal{F}$. Whether a scaling method is labeled metric or nonmetric depends on the class $\mathcal{F}$. In nonmetric scaling, $\mathcal{F}$ is taken to be the class of monotonic functions. If $\mathcal{F}$ is a regular parameterized set of functions, one commonly labels the scaling as metric.

$\mathbf{D}$ is the matrix of proximities or dissimilarities, $\mathbf{B}(\mathbf{Y})$ is the matrix of distances, and the result of $f(\mathbf{D}) = \widehat{\mathbf{D}}$ is the matrix of disparities.

The `mdsmat` command supports the following loss criteria:

1. **stress** specifies Kruskal's stress-1 criterion: the Euclidean norm of the difference between the distances and the disparities, normalized by the Euclidean norm of the distances.

$$\mathbf{stress}(\widehat{\mathbf{D}}, \mathbf{B}, \mathbf{W}) = \left\{ \frac{\sum_{ij} W_{ij}(B_{ij} - \widehat{D}_{ij})^2}{\sum_{ij} W_{ij} B_{ij}^2} \right\}^{1/2}$$

2. **nstress** specifies the square root of the normalized stress criterion: the Euclidean norm of the difference between the distances and the disparities, normalized by the Euclidean norm of the disparities.

$$\mathbf{nstress}(\widehat{\mathbf{D}}, \mathbf{B}, \mathbf{W}) = \left\{ \frac{\sum_{ij} W_{ij}(B_{ij} - \widehat{D}_{ij})^2}{\sum_{ij} W_{ij} \widehat{D}_{ij}^2} \right\}^{1/2}$$

   nstress normalizes with the disparities, **stress** with the distances.

3. **sammon** specifies the Sammon mapping criterion (Sammon 1969; Neimann and Weiss 1979): the sum of the scaled, squared differences between the distances and the disparities, normalized by the sum of the disparities.

$$\mathbf{sammon}(\widehat{\mathbf{D}}, \mathbf{B}, \mathbf{W}) = \frac{\sum_{ij} W_{ij}(B_{ij} - \widehat{D}_{ij})^2 / \widehat{D}_{ij}}{\sum_{ij} W_{ij} \widehat{D}_{ij}}$$

4. **sstress** specifies the squared stress criterion: the Euclidean norm of the difference between the squared distances and the squared disparities, normalized by the Euclidean norm of the squared distances.

$$\mathbf{sstress}(\widehat{\mathbf{D}}, \mathbf{B}, \mathbf{W}) = \left\{ \frac{\sum_{ij} W_{ij}(B_{ij}^2 - \widehat{D}_{ij}^2)^2}{\sum_{ij} W_{ij} B_{ij}^4} \right\}^{1/2}$$

5. **nsstress** specifies the normalized squared stress criterion: the Euclidean norm of the difference between the squared distances and the squared disparities, normalized by the Euclidean norm of the squared disparities.

$$\mathbf{nsstress}(\widehat{\mathbf{D}}, \mathbf{B}, \mathbf{W}) = \left\{ \frac{\sum_{ij} W_{ij}(B_{ij}^2 - \widehat{D}_{ij}^2)^2}{\sum_{ij} W_{ij} \widehat{D}_{ij}^4} \right\}^{1/2}$$

   nsstress normalizes with the disparities, **sstress** with the distances.

6. **strain** specifies the strain criterion,

$$\textbf{strain}(\widehat{\mathbf{D}}, \mathbf{B}, \mathbf{W}) = \frac{\sqrt{\text{trace}(\mathbf{X}'\mathbf{X})}}{\sum_{ij} W_{ij}}$$

where

$$\mathbf{X} = \mathbf{W} \odot \left\{ \widehat{\mathbf{D}} - \mathbf{B}(\widetilde{\mathbf{Y}}) \right\}$$

where $\widetilde{\mathbf{Y}}$ is the centered configuration of $\mathbf{Y}$. Without weights, $W_{ij} = 1$, and without transformation, that is, $\widehat{\mathbf{D}} = \mathbf{D}$, minimization of the strain criterion is equivalent to classical metric scaling.

The mdsmat command supports three classes of permitted transformations, $f \in \mathcal{F}$: 1) the class of all weakly monotonic transformations, 2) the power class of functions where f is defined elementwise on $\mathbf{D}$ as $f(D_{ij}, \alpha) = D_{ij}^{\alpha}$ (Critchley 1978; Cox and Cox 2001), and 3) the trivial identity case of $f(\mathbf{D}) = \mathbf{D}$.

Minimization of a loss criterion with respect to the configuration $\mathbf{Y}$ and the permitted transformation $f \in \mathcal{F}$ is performed with an alternating algorithm in which the configuration $\mathbf{Y}$ is modified (the C-step) and the transformation f is adjusted (the T-step) to reduce loss. Obviously, no T-step is made with the identity transformation. The classical solution is the default starting configuration. Iteration continues until the C-step and T-step reduce loss by less than the tolerance for convergence or the maximum number of iterations is performed. The C-step is taken by steepest descent using analytical gradients and an optimal stepsize computed using Brent's bounded minimization (Brent 1973). The implementation of the T-step varies with the specified class of transformations. In the nonmetric case of monotonic transformations, we use isotonic regression (Kruskal 1964a, 1964b; Cox and Cox 2001), using the primary approach to ties (Borg and Groenen 2005, 40). For power transformations, we again apply Brent's minimization method.

Given enough iterations, convergence is usually not a problem. However, the alternating algorithm may not converge to a global minimum. mdsmat provides some protection by repeated runs from different initial configurations. However, as Euclidean distances $\mathbf{B}(\mathbf{Y})$ are invariant with respect to isometric transformations (rotations, translations) of $\mathbf{Y}$, some caution is required to compare different runs and, similarly, to compare the configurations obtained from different scaling methods. mdsmat normalizes the optimal configuration by centering and via the orthogonal Procrustean rotation without dilation toward the classical or a user-specified solution; see [MV] **procrustes**.

Conversion of similarities to dissimilarities

If a similarity measure was selected, it is turned into a dissimilarity measure by using one of two methods. The *standard* conversion method is

$$\text{dissim}_{ij} = \sqrt{\text{sim}_{ii} + \text{sim}_{jj} - 2\text{sim}_{ij}}$$

With the similarity of an object to itself being 1, this is equivalent to

$$\text{dissim}_{ij} = \sqrt{2(1 - \text{sim}_{ij})}$$

This conversion method has the attractive property that it transforms a positive-semidefinite similarity matrix into a Euclidean distance matrix (see Mardia, Kent, and Bibby 1979, 402).

We also offer the *one-minus* method

$$\text{dissim}_{ij} = 1 - \text{sim}_{ij}$$

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Also see

Title

[Description](#)   [Syntax](#)   [Options](#)   [References](#)   [Also see](#)

Description

Several commands have options that allow you to specify a similarity or dissimilarity measure designated as *measure* in the syntax; see [MV] **cluster**, [MV] **mds**, [MV] **discrim knn**, and [MV] **matrix dissimilarity**. These options are documented here. Most analysis commands (for example, cluster and mds) transform similarity measures to dissimilarity measures as needed.

Syntax

> *command* ..., ... <u>measure</u>(*measure*) ...

or

> *command* ..., ... *measure* ...

measure	Description
cont_measure	similarity or dissimilarity measure for continuous data
binary_measure	similarity measure for binary data
mixed_measure	dissimilarity measure for a mix of binary and continuous data

cont_measure	Description
L2	Euclidean distance (Minkowski with argument 2)
<u>Euclidean</u>	alias for L2
L(2)	alias for L2
L2squared	squared Euclidean distance
Lpower(2)	alias for L2squared
L1	absolute-value distance (Minkowski with argument 1)
<u>abs</u>olute	alias for L1
cityblock	alias for L1
<u>manhat</u>tan	alias for L1
L(1)	alias for L1
Lpower(1)	alias for L1
<u>Linf</u>inity	maximum-value distance (Minkowski with infinite argument)
<u>max</u>imum	alias for Linfinity
L(#)	Minkowski distance with # arguments
<u>Lp</u>ower(#)	Minkowski distance with # arguments raised to # power
<u>Can</u>berra	Canberra distance
<u>corr</u>elation	correlation coefficient similarity measure
<u>ang</u>ular	angular separation similarity measure
angle	alias for angular

binary_measure	Description
matching	simple matching similarity coefficient
Jaccard	Jaccard binary similarity coefficient
Russell	Russell and Rao similarity coefficient
Hamann	Hamann similarity coefficient
Dice	Dice similarity coefficient
antiDice	anti-Dice similarity coefficient
Sneath	Sneath and Sokal similarity coefficient
Rogers	Rogers and Tanimoto similarity coefficient
Ochiai	Ochiai similarity coefficient
Yule	Yule similarity coefficient
Anderberg	Anderberg similarity coefficient
Kulczynski	Kulczyński similarity coefficient
Pearson	Pearson's ϕ similarity coefficient
Gower2	similarity coefficient with same denominator as Pearson

mixed_measure	Description
Gower	Gower's dissimilarity coefficient

Options

Measures are divided into those for continuous data and binary data. *measure* is not case sensitive. Full definitions are presented in *Similarity and dissimilarity measures for continuous data*, *Similarity measures for binary data*, and *Dissimilarity measures for mixed data*.

The similarity or dissimilarity measure is most often used to determine the similarity or dissimilarity between observations. However, sometimes the similarity or dissimilarity between variables is of interest.

Similarity and dissimilarity measures for continuous data

Here are the similarity and dissimilarity measures for continuous data available in Stata. In the following formulas, p represents the number of variables, N is the number of observations, and x_{iv} denotes the value of observation i for variable v.

The formulas are presented in two forms. The first is the formula used when computing the similarity or dissimilarity between observations. The second is the formula used when computing the similarity or dissimilarity between variables.

L2 (aliases Euclidean and L(2))
requests the Minkowski distance metric with argument 2. For comparing observations i and j, the formula is

$$\left\{ \sum_{a=1}^{p} (x_{ia} - x_{ja})^2 \right\}^{1/2}$$

and for comparing variables u and v the formula is

$$\left\{\sum_{k=1}^{N}(x_{ku}-x_{kv})^2\right\}^{1/2}$$

L2 is best known as Euclidean distance and is the default dissimilarity measure for discrim knn, mds, matrix dissimilarity, and all the cluster subcommands except for centroidlinkage, medianlinkage, and wardslinkage, which default to using L2squared; see [MV] **discrim knn**, [MV] **mds**, [MV] **matrix dissimilarity**, and [MV] **cluster**.

L2squared (alias Lpower(2))
    requests the square of the Minkowski distance metric with argument 2. For comparing observations i and j, the formula is

$$\sum_{a=1}^{p}(x_{ia}-x_{ja})^2$$

and for comparing variables u and v, the formula is

$$\sum_{k=1}^{N}(x_{ku}-x_{kv})^2$$

L2squared is best known as squared Euclidean distance and is the default dissimilarity measure for the centroidlinkage, medianlinkage, and wardslinkage subcommands of cluster; see [MV] **cluster**.

L1 (aliases absolute, cityblock, manhattan, L(1), and Lpower(1))
    requests the Minkowski distance metric with argument 1. For comparing observations i and j, the formula is

$$\sum_{a=1}^{p}|x_{ia}-x_{ja}|$$

and for comparing variables u and v, the formula is

$$\sum_{k=1}^{N}|x_{ku}-x_{kv}|$$

L1 is best known as absolute-value distance.

Linfinity (alias maximum)
    requests the Minkowski distance metric with infinite argument. For comparing observations i and j, the formula is

$$\max_{a=1,\ldots,p}|x_{ia}-x_{ja}|$$

and for comparing variables u and v, the formula is

$$\max_{k=1,\ldots,N} |x_{ku} - x_{kv}|$$

Linfinity is best known as maximum-value distance.

L(#)

requests the Minkowski distance metric with argument #. For comparing observations i and j, the formula is

$$\left(\sum_{a=1}^{p} |x_{ia} - x_{ja}|^{\#} \right)^{1/\#} \qquad\qquad \# \geq 1$$

and for comparing variables u and v, the formula is

$$\left(\sum_{k=1}^{N} |x_{ku} - x_{kv}|^{\#} \right)^{1/\#} \qquad\qquad \# \geq 1$$

We discourage using extremely large values for #. Because the absolute value of the difference is being raised to the value of #, depending on the nature of your data, you could experience numeric overflow or underflow. With a large value of #, the L() option will produce results similar to those of the Linfinity option. Use the numerically more stable Linfinity option instead of a large value for # in the L() option.

See Anderberg (1973) for a discussion of the Minkowski metric and its special cases.

Lpower(#)

requests the Minkowski distance metric with argument #, raised to the # power. For comparing observations i and j, the formula is

$$\sum_{a=1}^{p} |x_{ia} - x_{ja}|^{\#} \qquad\qquad \# \geq 1$$

and for comparing variables u and v, the formula is

$$\sum_{k=1}^{N} |x_{ku} - x_{kv}|^{\#} \qquad\qquad \# \geq 1$$

As with L(#), we discourage using extremely large values for #; see the discussion above.

Canberra

requests the following distance metric when comparing observations i and j

$$\sum_{a=1}^{p} \frac{|x_{ia} - x_{ja}|}{|x_{ia}| + |x_{ja}|}$$

and the following distance metric when comparing variables u and v

$$\sum_{k=1}^{N} \frac{|x_{ku} - x_{kv}|}{|x_{ku}| + |x_{kv}|}$$

When comparing observations, the Canberra metric takes values between 0 and p, the number of variables. When comparing variables, the Canberra metric takes values between 0 and N, the number of observations; see Gordon (1999) and Gower (1985). Gordon (1999) explains that the Canberra distance is sensitive to small changes near zero.

correlation

requests the correlation coefficient similarity measure. For comparing observations i and j, the formula is

$$\frac{\sum_{a=1}^{p}(x_{ia} - \overline{x}_{i.})(x_{ja} - \overline{x}_{j.})}{\left\{\sum_{a=1}^{p}(x_{ia} - \overline{x}_{i.})^2 \sum_{b=1}^{p}(x_{jb} - \overline{x}_{j.})^2\right\}^{1/2}}$$

and for comparing variables u and v, the formula is

$$\frac{\sum_{k=1}^{N}(x_{ku} - \overline{x}_{.u})(x_{kv} - \overline{x}_{.v})}{\left\{\sum_{k=1}^{N}(x_{ku} - \overline{x}_{.u})^2 \sum_{l=1}^{N}(x_{lv} - \overline{x}_{.v})^2\right\}^{1/2}}$$

where $\overline{x}_{i.} = (\sum_{a=1}^{p} x_{ia})/p$ and $\overline{x}_{.u} = (\sum_{k=1}^{N} x_{ku})/N$.

The correlation similarity measure takes values between -1 and 1. With this measure, the relative direction of the two vectors is important. The correlation similarity measure is related to the angular separation similarity measure (described next). The correlation similarity measure gives the cosine of the angle between the two vectors measured from the mean; see Gordon (1999).

angular (alias angle)

requests the angular separation similarity measure. For comparing observations i and j, the formula is

$$\frac{\sum_{a=1}^{p} x_{ia} x_{ja}}{\left(\sum_{a=1}^{p} x_{ia}^2 \sum_{b=1}^{p} x_{jb}^2\right)^{1/2}}$$

and for comparing variables u and v, the formula is

$$\frac{\sum_{k=1}^{N} x_{ku} x_{kv}}{\left(\sum_{k=1}^{N} x_{ku}^2 \sum_{l=1}^{N} x_{lv}^2\right)^{1/2}}$$

The angular separation similarity measure is the cosine of the angle between the two vectors measured from zero and takes values from -1 to 1; see Gordon (1999).

Similarity measures for binary data

Similarity measures for binary data are based on the four values from the cross-tabulation of observation i and j (when comparing observations) or variables u and v (when comparing variables).

For comparing observation i and j, the cross-tabulation is

		obs. j	
		1	0
obs.	1	a	b
i	0	c	d

a is the number of variables where observations i and j both had ones, and d is the number of variables where observations i and j both had zeros. The number of variables where observation i is one and observation j is zero is b, and the number of variables where observation i is zero and observation j is one is c.

For comparing variables u and v, the cross-tabulation is

		var. v	
		1	0
var.	1	a	b
u	0	c	d

a is the number of observations where variables u and v both had ones, and d is the number of observations where variables u and v both had zeros. The number of observations where variable u is one and variable v is zero is b, and the number of observations where variable u is zero and variable v is one is c.

Stata treats nonzero values as one when a binary value is expected. Specifying one of the binary similarity measures imposes this behavior unless some other option overrides it (for instance, the `allbinary` option of `matrix dissimilarity`; see [MV] **matrix dissimilarity**).

Hubálek (1982) gives an extensive list of binary similarity measures. Gower (1985) lists 15 binary similarity measures, 14 of which are implemented in Stata. (The excluded measure has many cases where the quantity is undefined, so it was not implemented.) Anderberg (1973) gives an interesting table where many of these measures are compared based on whether the zero–zero matches are included in the numerator, whether these matches are included in the denominator, and how the weighting of matches and mismatches is handled. Hilbe (1992b, 1992a) implemented an early Stata command for computing some of these (as well as other) binary similarity measures.

The formulas for some of these binary similarity measures are undefined when either one or both of the vectors (observations or variables depending on which are being compared) are all zeros (or, sometimes, all ones). Gower (1985) says concerning these cases, "These coefficients are then conventionally assigned some appropriate value, usually zero."

The following binary similarity coefficients are available. Unless stated otherwise, the similarity measures range from 0 to 1.

matching

    requests the simple matching (Zubin 1938, Sokal and Michener 1958) binary similarity coefficient

$$\frac{a+d}{a+b+c+d}$$

    which is the proportion of matches between the 2 observations or variables.

Jaccard

    requests the Jaccard (1901, 1908) binary similarity coefficient

$$\frac{a}{a+b+c}$$

    which is the proportion of matches when at least one of the vectors had a one. If both vectors are all zeros, this measure is undefined. Stata then declares the answer to be one, meaning perfect agreement. This is a reasonable choice for most applications and will cause an all-zero vector to have similarity of one only with another all-zero vector. In all other cases, an all-zero vector will have Jaccard similarity of zero to the other vector.

    The Jaccard coefficient was discovered earlier by Gilbert (1884).

Russell

    requests the Russell and Rao (1940) binary similarity coefficient

$$\frac{a}{a+b+c+d}$$

Hamann

    requests the Hamann (1961) binary similarity coefficient

$$\frac{(a+d)-(b+c)}{a+b+c+d}$$

    which is the number of agreements minus disagreements divided by the total. The Hamann coefficient ranges from -1, perfect disagreement, to 1, perfect agreement. The Hamann coefficient is equal to twice the simple matching coefficient minus 1.

Dice

    requests the Dice binary similarity coefficient

$$\frac{2a}{2a+b+c}$$

    suggested by Czekanowski (1932), Dice (1945), and Sørensen (1948). The Dice coefficient is similar to the Jaccard similarity coefficient but gives twice the weight to agreements. Like the Jaccard coefficient, the Dice coefficient is declared by Stata to be one if both vectors are all zero, thus avoiding the case where the formula is undefined.

`antiDice`

requests the binary similarity coefficient

$$\frac{a}{a + 2(b + c)}$$

which is credited to Anderberg (1973) but was shown earlier by Sokal and Sneath (1963, 129). We did not call this the Anderberg coefficient because there is another coefficient better known by that name; see the `Anderberg` option. The name `antiDice` is our creation. This coefficient takes the opposite view from the Dice coefficient and gives double weight to disagreements. As with the Jaccard and Dice coefficients, the anti-Dice coefficient is declared to be one if both vectors are all zeros.

`Sneath`

requests the Sneath and Sokal (1962) binary similarity coefficient

$$\frac{2(a + d)}{2(a + d) + (b + c)}$$

which is similar to the simple matching coefficient but gives double weight to matches. Also compare the Sneath and Sokal coefficient with the Dice coefficient, which differs only in whether it includes d.

`Rogers`

requests the Rogers and Tanimoto (1960) binary similarity coefficient

$$\frac{a + d}{(a + d) + 2(b + c)}$$

which takes the opposite approach from the Sneath and Sokal coefficient and gives double weight to disagreements. Also compare the Rogers and Tanimoto coefficient with the anti-Dice coefficient, which differs only in whether it includes d.

`Ochiai`

requests the Ochiai (1957) binary similarity coefficient

$$\frac{a}{\left\{(a + b)(a + c)\right\}^{1/2}}$$

The formula for the Ochiai coefficient is undefined when one or both of the vectors being compared are all zeros. If both are all zeros, Stata declares the measure to be one, and if only one of the two vectors is all zeros, the measure is declared to be zero.

The Ochiai coefficient was presented earlier by Driver and Kroeber (1932).

`Yule`

requests the Yule (see Yule [1900] and Yule and Kendall [1950]) binary similarity coefficient

$$\frac{ad - bc}{ad + bc}$$

which ranges from -1 to 1. The formula for the Yule coefficient is undefined when one or both of the vectors are either all zeros or all ones. Stata declares the measure to be 1 when $b+c=0$, meaning that there is complete agreement. Stata declares the measure to be -1 when $a+d=0$, meaning that there is complete disagreement. Otherwise, if $ad-bc=0$, Stata declares the measure to be 0. These rules, applied before using the Yule formula, avoid the cases where the formula would produce an undefined result.

Anderberg
requests the Anderberg binary similarity coefficient

$$\left(\frac{a}{a+b} + \frac{a}{a+c} + \frac{d}{c+d} + \frac{d}{b+d}\right)\Big/4$$

The Anderberg coefficient is undefined when one or both vectors are either all zeros or all ones. This difficulty is overcome by first applying the rule that if both vectors are all ones (or both vectors are all zeros), the similarity measure is declared to be one. Otherwise, if any of the marginal totals $(a+b, a+c, c+d, b+d)$ are zero, then the similarity measure is declared to be zero.

Though this similarity coefficient is best known as the Anderberg coefficient, it appeared earlier in Sokal and Sneath (1963, 130).

Kulczynski
requests the Kulczyński (1927) binary similarity coefficient

$$\left(\frac{a}{a+b} + \frac{a}{a+c}\right)\Big/2$$

The formula for this measure is undefined when one or both of the vectors are all zeros. If both vectors are all zeros, Stata declares the similarity measure to be one. If only one of the vectors is all zeros, the similarity measure is declared to be zero.

Pearson
requests Pearson's (1900) ϕ binary similarity coefficient

$$\frac{ad-bc}{\left\{(a+b)(a+c)(d+b)(d+c)\right\}^{1/2}}$$

which ranges from -1 to 1. The formula for this coefficient is undefined when one or both of the vectors are either all zeros or all ones. Stata declares the measure to be 1 when $b+c=0$, meaning that there is complete agreement. Stata declares the measure to be -1 when $a+d=0$, meaning that there is complete disagreement. Otherwise, if $ad-bc=0$, Stata declares the measure to be 0. These rules, applied before using Pearson's ϕ coefficient formula, avoid the cases where the formula would produce an undefined result.

Gower2
requests the binary similarity coefficient

$$\frac{ad}{\left\{(a+b)(a+c)(d+b)(d+c)\right\}^{1/2}}$$

which is presented by Gower (1985) but appeared earlier in Sokal and Sneath (1963, 130). Stata uses the name Gower2 to avoid confusion with the better-known Gower coefficient, which is used with a mix of binary and continuous data.

The formula for this similarity measure is undefined when one or both of the vectors are all zeros or all ones. This is overcome by first applying the rule that if both vectors are all ones (or both vectors are all zeros) then the similarity measure is declared to be one. Otherwise, if $ad = 0$, the similarity measure is declared to be zero.

Dissimilarity measures for mixed data

Here is one measure that works with a mix of binary and continuous data. Binary variables are those containing only zeros, ones, and missing values; all other variables are treated as continuous.

Gower
    requests the Gower (1971) dissimilarity coefficient for a mix of binary and continuous variables. For comparing observations i and j, the formula is

$$\frac{\sum_v \delta_{ijv} d_{ijv}}{\sum_v \delta_{ijv}}$$

where δ_{ijv} is a binary indicator equal to 1 whenever both observations i and j are nonmissing for variable v, and zero otherwise. Observations with missing values are not included when using cluster or mds, and so if an observation is included, $\delta_{ijv} = 1$ and $\sum_v \delta_{ijv}$ is the number of variables. However, using matrix dissimilarity with the Gower option does not exclude observations with missing values. See [MV] **cluster**, [MV] **mds**, and [MV] **matrix dissimilarity**.

For binary variables v,

$$d_{ijv} = \begin{cases} 0 & \text{if } x_{iv} = x_{jv} \\ 1 & \text{otherwise} \end{cases}$$

This is the same as the matching measure.

For continuous variables v,

$$d_{ijv} = \frac{|x_{iv} - x_{jv}|}{\left\{\max_k(x_{kv}) - \min_k(x_{kv})\right\}}$$

d_{ijv} is set to 0 if $\max_k(x_{kv}) - \min_k(x_{kv}) = 0$, that is, if the range of the variable is zero. This is the L1 measure divided by the range of the variable.

For comparing variables u and v, the formula is

$$\frac{\sum_i \delta_{iuv} d_{iuv}}{\sum_i \delta_{iuv}}$$

where δ_{iuv} is a binary indicator equal to 1 whenever both variables u and v are nonmissing for observation i, and zero otherwise. If there are no missing values, $\sum_i \delta_{iuv}$ is the number of observations; otherwise, it is the number of observations for which neither variable u nor v has a missing value.

If all the variables are binary,

$$d_{iuv} = \begin{cases} 0 & \text{if } x_{iu} = x_{iv} \\ 1 & \text{otherwise} \end{cases}$$

If at least one variable is continuous,

$$d_{iuv} = \frac{|x_{iu} - x_{iv}|}{\left\{ \max_v(x_{iv}) - \min_v(x_{iv}) \right\}}$$

d_{iuv} is set to 0 if $\max_v(x_{iv}) - \min_v(x_{iv}) = 0$, that is, if the range of the observation is zero.

The Gower measure interprets binary variables as those with only 0, 1, or missing values. All other variables are treated as continuous.

In [MV] **matrix dissimilarity**, missing observations are included only in the calculation of the Gower dissimilarity, but the formula for this dissimilarity measure is undefined when all the values of δ_{ijv} or δ_{iuv} are zero. The dissimilarity is then set to missing.

❑ Technical note: Matrix dissimilarity and the Gower measure

Normally the commands

```
. matrix dissimilarity gm = x1 x2 y1, Gower
. clustermat waverage gm, add
```

and

```
. cluster waverage x1 x2 y1, measure(Gower)
```

will yield the same results, and likewise with mdsmat and mds. However, if any of the variables contain missing observations, this will not be the case. cluster and mds exclude all observations that have missing values for any of the variables of interest, whereas matrix dissimilarity with the Gower option does not. See [MV] **cluster**, [MV] **mds**, and [MV] **matrix dissimilarity** for more information.

Note: matrix dissimilarity without the Gower option does exclude all observations that have missing values for any of the variables of interest.

❑

❑ Technical note: Binary similarity measures applied to averages

Some cluster-analysis methods (such as Stata's kmeans and kmedians clustering) need to compute the similarity or dissimilarity between observations and group averages or group medians; see [MV] **cluster**. With binary data, a group average is interpreted as a proportion.

A group median for binary data will be zero or one, except when there are an equal number of zeros and ones. Here Stata calls the median 0.5, which can also be interpreted as a proportion.

In Stata's cluster kmeans and cluster kmedians commands for comparing a binary observation to a group proportion (see *Partition cluster-analysis methods* in [MV] **cluster**), the values of a, b, c, and d are obtained by assigning the appropriate fraction of the count to these values. In our earlier table showing the relationship of a, b, c, and d in the cross-tabulation of observation i and observation j, we replace observation j by the group-proportions vector. Then when observation i is 1, we add the corresponding proportion to a and add one minus that proportion to b. When observation i is 0, we add the corresponding proportion to c and add one minus that proportion to d. After the values of a, b, c, and d are computed in this way, the binary similarity measures are computed using the formulas as already described.

❑

John Clifford Gower (1930–2019) was born in London. He studied mathematics and statistics at the Universities of Cambridge and Manchester. From 1955 until his retirement in 1990, he worked at Rothamsted Experimental Station in Hertfordshire (where R. A. Fisher, W. G. Cochran, F. Yates, J. A. Nelder, and R. W. M. Wedderburn also worked at various times). Gower's initial focus was on computing: the Elliott 401 computer then at Rothamsted (now visible in the Science Museum in London) was probably the first in the world to be devoted entirely to agricultural and biological research. From the mid 1960s, his main emphasis was applied multivariate analysis, especially classification problems and graphical methods. That led to first-authored books on biplots and Procrustes problems and to several highly cited papers. In retirement, Gower was long associated with the Open University. He traveled and collaborated widely and actively supported several learned societies.

Paul Jaccard (1868–1944) was a Swiss botanist who was born in Sainte-Croix (Vaud) and died in Zürich. He studied at Lausanne, Zürich, and Paris before being appointed to posts at Lausanne in 1894, where he specialized in plant geography, undertaking fieldwork in Egypt, Sweden, and Turkestan. In 1903, Jaccard returned to Zürich to a chair in general botany and plant physiology at ETH. His interests there centered on the microscopic analysis of wood, and anatomical and physiological studies of the growth of trees.

Robert Reuven Sokal (1926–2012) was born in Vienna to a Jewish family. He gained degrees from St. John's University in Shanghai and the University of Chicago. Sokal worked at the University of Kansas–Lawrence and (from 1969) the State University of New York–Stony Brook. He was one of the leaders in the development of numerical taxonomy (Sokal and Sneath 1963; Sneath and Sokal 1973) and was prominent in the application of statistical methods within biological systematics. With F. J. Rohlf, he authored one of the leading biometrics texts (Sokal and Rohlf 2011). In the latter stages of his career, his interests centered on genetic variation in human populations, European ethnohistory, and spatial statistics. Sokal was a member of the U.S. National Academy of Sciences.

Peter Henry Andrews Sneath (1923–2011) was born in Ceylon (now Sri Lanka) and studied medicine in Cambridge and London. After military service, he specialized in microbial systematics and the application of computers to biomedical science, working for the Medical Research Council in the UK and the University of Leicester. With Robert Sokal, Sneath wrote the two initial texts on numerical taxonomy. He is a Fellow of the Royal Society. A bacterial taxon, the genus *Sneathia*, was named after him in 2002.

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Also see

Title

mvreg — Multivariate regression

Description

mvreg fits a multivariate regression model for several dependent variables with the same independent variables.

Quick start

Multivariate regression of three y variables on two x variables

    mvreg y1 y2 y3 = x1 x2

Add [indicator variables](#) for each level of categorical variable catvar

    mvreg y1 y2 y3 = x1 x2 i.catvar

Model of three y variables on five x variables reporting the correlations between the residuals and the Breusch–Pagan test of independence

    mvreg y1 y2 y3 = x1 x2 x3 x4 x5, corr

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Multivariate regression

Syntax

> mvreg *depvars* = *indepvars* [*if*] [*in*] [*weight*] [, *options*]

options	Description
Model	
<u>noconst</u>ant	suppress constant term
Reporting	
<u>level</u>(*#*)	set confidence level; default is level(95)
corr	report correlation matrix
display_options	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
noheader	suppress header table from above coefficient table
<u>notab</u>le	suppress coefficient table
coeflegend	display legend instead of statistics

indepvars may contain factor variables; see [U] **11.4.3 Factor variables**.

depvars and *indepvars* may contain time-series operators; see [U] **11.4.4 Time-series varlists**.

bayes, bootstrap, by, collect, jackknife, mi estimate, rolling, and statsby are allowed; see [U] **11.1.10 Prefix commands**. For more details, see [BAYES] **bayes: mvreg**.

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

aweights are not allowed with the jackknife prefix; see [R] **jackknife**.

aweights and fweights are allowed; see [U] **11.1.6 weight**.

noheader, notable, and coeflegend do not appear in the dialog box.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> ┌─────────┐
> │ Model │
> └─────────┘

noconstant suppresses the constant term (intercept) in the model.

> ┌───────────┐
> │ Reporting │
> └───────────┘

level(*#*) specifies the confidence level, as a percentage, for confidence intervals. The default is level(95) or as set by set level; see [U] **20.8 Specifying the width of confidence intervals**.

corr displays the correlation matrix of the residuals between the equations.

display_options: noci, nopvalues, <u>noomitted</u>, vsquish, noemptycells, <u>base</u>levels, <u>allbase</u>levels, <u>nofvlabel</u>, fvwrap(*#*), fvwrapon(*style*), cformat(*%fmt*), pformat(*%fmt*), sformat(*%fmt*), and nolstretch; see [R] **Estimation options**.

The following options are available with mvreg but are not shown in the dialog box:

noheader suppresses display of the table reporting F statistics, R^2, and root mean squared error above the coefficient table.

notable suppresses display of the coefficient table.

coeflegend; see [R] **Estimation options**.

Remarks and examples

Multivariate regression differs from multiple regression in that *several* dependent variables are jointly regressed on the same independent variables. Multivariate regression is related to Zellner's seemingly unrelated regression (see [R] **sureg**), but because the same set of independent variables is used for each dependent variable, the syntax is simpler, and the calculations are faster.

The individual coefficients and standard errors produced by mvreg are identical to those that would be produced by regress estimating each equation separately. The difference is that mvreg, being a joint estimator, also estimates the between-equation covariances, so you can test coefficients across equations and, in fact, the test syntax makes such tests more convenient.

▷ Example 1

Using the automobile data, we fit a multivariate regression for space variables (headroom, trunk, and turn) in terms of a set of other variables, including three performance variables (displacement, gear_ratio, and mpg):

```
. use https://www.stata-press.com/data/r18/auto
(1978 automobile data)
. mvreg headroom trunk turn = price mpg displ gear_ratio length weight
```

Equation	Obs	Parms	RMSE	"R-sq"	F	P>F
headroom	74	7	.7390205	0.2996	4.777213	0.0004
trunk	74	7	3.052314	0.5326	12.7265	0.0000
turn	74	7	2.132377	0.7844	40.62042	0.0000

	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
headroom						
price	-.0000528	.000038	-1.39	0.168	-.0001286	.0000229
mpg	-.0093774	.0260463	-0.36	0.720	-.061366	.0426112
displacement	.0031025	.0024999	1.24	0.219	-.0018873	.0080922
gear_ratio	.2108071	.3539588	0.60	0.553	-.4956976	.9173119
length	.015886	.012944	1.23	0.224	-.0099504	.0417223
weight	-.0000868	.0004724	-0.18	0.855	-.0010296	.0008561
_cons	-.4525117	2.170073	-0.21	0.835	-4.783995	3.878972
trunk						
price	.0000445	.0001567	0.28	0.778	-.0002684	.0003573
mpg	-.0220919	.1075767	-0.21	0.838	-.2368159	.1926322
displacement	.0032118	.0103251	0.31	0.757	-.0173971	.0238207
gear_ratio	-.2271321	1.461926	-0.16	0.877	-3.145149	2.690885
length	.170811	.0534615	3.20	0.002	.0641014	.2775206
weight	-.0015944	.001951	-0.82	0.417	-.0054885	.0022997
_cons	-13.28253	8.962868	-1.48	0.143	-31.17249	4.607429
turn						
price	-.0002647	.0001095	-2.42	0.018	-.0004833	-.0000462
mpg	-.0492948	.0751542	-0.66	0.514	-.1993031	.1007136
displacement	.0036977	.0072132	0.51	0.610	-.0106999	.0180953
gear_ratio	-.1048432	1.021316	-0.10	0.919	-2.143399	1.933712
length	.072128	.0373487	1.93	0.058	-.0024204	.1466764
weight	.0027059	.001363	1.99	0.051	-.0000145	.0054264
_cons	20.19157	6.261549	3.22	0.002	7.693467	32.68968

We should have specified the `corr` option so that we would also see the correlations between the residuals of the equations. We can correct our omission because `mvreg`—like all estimation commands—typed without arguments redisplays results. The `noheader` and `notable` (read "no-table") options suppress redisplaying the output we have already seen:

```
. mvreg, notable noheader corr

Correlation matrix of residuals:

             headroom       trunk        turn
headroom       1.0000
   trunk       0.4986      1.0000
    turn      -0.1090     -0.0628      1.0000

Breusch-Pagan test of independence: chi2(3) =     19.566, Pr = 0.0002
```

The Breusch–Pagan test is significant, so the residuals of these three space variables are not independent of each other.

The three performance variables among our independent variables are `mpg`, `displacement`, and `gear_ratio`. We can jointly test the significance of these three variables in all the equations by typing

```
. test mpg displacement gear_ratio

 ( 1)  [headroom]mpg = 0
 ( 2)  [trunk]mpg = 0
 ( 3)  [turn]mpg = 0
 ( 4)  [headroom]displacement = 0
 ( 5)  [trunk]displacement = 0
 ( 6)  [turn]displacement = 0
 ( 7)  [headroom]gear_ratio = 0
 ( 8)  [trunk]gear_ratio = 0
 ( 9)  [turn]gear_ratio = 0

       F(  9,    67) =      0.33
            Prob > F =    0.9622
```

These three variables are not, as a group, significant. We might have suspected this from their individual significance in the individual regressions, but this multivariate test provides an overall assessment with one p-value.

We can also perform a test for the joint significance of all three equations:

```
. test [headroom]
(output omitted )
. test [trunk], accum
(output omitted )
. test [turn], accum
 ( 1)  [headroom]price = 0
 ( 2)  [headroom]mpg = 0
 ( 3)  [headroom]displacement = 0
 ( 4)  [headroom]gear_ratio = 0
 ( 5)  [headroom]length = 0
 ( 6)  [headroom]weight = 0
 ( 7)  [trunk]price = 0
 ( 8)  [trunk]mpg = 0
 ( 9)  [trunk]displacement = 0
 (10)  [trunk]gear_ratio = 0
 (11)  [trunk]length = 0
 (12)  [trunk]weight = 0
 (13)  [turn]price = 0
 (14)  [turn]mpg = 0
 (15)  [turn]displacement = 0
 (16)  [turn]gear_ratio = 0
 (17)  [turn]length = 0
 (18)  [turn]weight = 0
       F( 18,    67) =    19.34
            Prob > F =    0.0000
```

The set of variables as a whole is strongly significant. We might have suspected this, too, from the individual equations.

◁

❑ Technical note

The `mvreg` command provides a good way to deal with multiple comparisons. If we wanted to assess the effect of `length`, we might be dissuaded from interpreting any of its coefficients except that in the `trunk` equation. `[trunk]length`—the coefficient on `length` in the `trunk` equation—has a p-value of 0.002, but in the other two equations, it has p-values of only 0.224 and 0.058.

A conservative statistician might argue that there are 18 tests of significance in `mvreg`'s output (not counting those for the intercept), so p-values more than $0.05/18 = 0.0028$ should be declared insignificant at the 5% level. A more aggressive but, in our opinion, reasonable approach would be to first note that the three equations are jointly significant, so we are justified in making some interpretation. Then we would work through the individual variables using `test`, possibly using $0.05/6 = 0.0083$ (6 because there are six independent variables) for the 5% significance level. For instance, examining `length`:

```
. test length
 ( 1)  [headroom]length = 0
 ( 2)  [trunk]length = 0
 ( 3)  [turn]length = 0
       F( 3,    67) =     4.94
            Prob > F =    0.0037
```

The reported significance level of 0.0037 is less than 0.0083, so we will declare this variable significant. `[trunk]length` is certainly significant with its p-value of 0.002, but what about in the remaining two equations with p-values 0.224 and 0.058? We perform a joint test:

```
. test [headroom]length [turn]length

 ( 1)  [headroom]length = 0
 ( 2)  [turn]length = 0

       F(  2,    67) =     2.91
            Prob > F =    0.0613
```

At this point, reasonable statisticians could disagree. The 0.06 significance value suggests no interpretation, but these were the two least-significant values out of three, so we would expect the p-value to be a little high. Perhaps an equivocal statement is warranted: there seems to be an effect, but chance cannot be excluded.

❑

Stored results

mvreg stores the following in e():

Scalars
e(N)	number of observations
e(k)	number of parameters in each equation
e(k_eq)	number of equations in e(b)
e(df_r)	residual degrees of freedom
e(chi2)	Breusch–Pagan χ^2 (corr only)
e(df_chi2)	degrees of freedom for Breusch–Pagan χ^2 (corr only)
e(rank)	rank of e(V)

Macros
e(cmd)	mvreg
e(cmdline)	command as typed
e(depvar)	names of dependent variables
e(eqnames)	names of equations
e(wtype)	weight type
e(wexp)	weight expression
e(r2)	R^2 for each equation
e(rmse)	RMSE for each equation
e(F)	F statistic for each equation
e(p_F)	p-value for F test for each equation
e(properties)	b V
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsok)	predictions allowed by margins
e(marginsnotok)	predictions disallowed by margins
e(marginsdefault)	default predict() specification for margins
e(asbalanced)	factor variables fvset as asbalanced
e(asobserved)	factor variables fvset as asobserved

Matrices
e(b)	coefficient vector
e(Sigma)	$\widehat{\Sigma}$ matrix
e(V)	variance–covariance matrix of the estimators

Functions
e(sample)	marks estimation sample

In addition to the above, the following is stored in r():

Matrices
r(table)	matrix containing the coefficients with their standard errors, test statistics, p-values, and confidence intervals

Note that results stored in r() are updated when the command is replayed and will be replaced when any r-class command is run after the estimation command.

Methods and formulas

Given q equations and p independent variables (including the constant), the parameter estimates are given by the $p \times q$ matrix

$$\mathbf{B} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{Y}$$

where $\mathbf{Y}$ is an $n \times q$ matrix of dependent variables and $\mathbf{X}$ is a $n \times p$ matrix of independent variables. $\mathbf{W}$ is a weighting matrix equal to $\mathbf{I}$ if no weights are specified. If weights are specified, let $\mathbf{v}$: $1 \times n$ be the specified weights. If `fweight` frequency weights are specified, $\mathbf{W} = \text{diag}(\mathbf{v})$. If `aweight` analytic weights are specified, $\mathbf{W} = \text{diag}\{\mathbf{v}/(\mathbf{1}'\mathbf{v})(\mathbf{1}'\mathbf{1})\}$, meaning that the weights are normalized to sum to the number of observations.

The residual covariance matrix is

$$\mathbf{R} = \{\mathbf{Y}'\mathbf{W}\mathbf{Y} - \mathbf{B}'(\mathbf{X}'\mathbf{W}\mathbf{X})\mathbf{B}\}/(n-p)$$

The estimated covariance matrix of the estimates is $\mathbf{R} \otimes (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}$. These results are identical to those produced by `sureg` when the same list of independent variables is specified repeatedly; see [R] **sureg**.

The Breusch and Pagan (1980) χ^2 statistic—a Lagrange multiplier statistic—is given by

$$\lambda = n \sum_{i=1}^{q} \sum_{j=1}^{i-1} r_{ij}^2$$

where r_{ij} is the estimated correlation between the residuals of the equations and n is the number of observations. It is distributed as χ^2 with $q(q-1)/2$ degrees of freedom.

References

Breusch, T. S., and A. R. Pagan. 1980. The Lagrange multiplier test and its applications to model specification in econometrics. *Review of Economic Studies* 47: 239–253. https://doi.org/10.2307/2297111.

Oberfichtner, M., and H. Tauchmann. 2021. Stacked linear regression analysis to facilitate testing of hypotheses across OLS regressions. *Stata Journal* 21: 411–429.

Also see

[MV] **mvreg postestimation** — Postestimation tools for mvreg

[MV] **manova** — Multivariate analysis of variance and covariance

[BAYES] **bayes: mvreg** — Bayesian multivariate regression

[MI] **Estimation** — Estimation commands for use with mi estimate

[R] **nlsur** — Estimation of nonlinear systems of equations

[R] **reg3** — Three-stage estimation for systems of simultaneous equations

[R] **regress** — Linear regression

[R] **regress postestimation** — Postestimation tools for regress

[R] **sureg** — Zellner's seemingly unrelated regression

[SEM] **Intro 5** — Tour of models

[U] **20 Estimation and postestimation commands**

Title

> **mvreg postestimation** — Postestimation tools for mvreg

Postestimation commands

The following postestimation commands are available after `mvreg`:

Command	Description
[contrast](#)	contrasts and ANOVA-style joint tests of estimates
[estat summarize](#)	summary statistics for the estimation sample
[estat vce](#)	variance–covariance matrix of the estimators (VCE)
[estimates](#)	cataloging estimation results
[etable](#)	table of estimation results
*[forecast](#)	dynamic forecasts and simulations
[hausman](#)	Hausman's specification test
[lincom](#)	point estimates, standard errors, testing, and inference for linear combinations of coefficients
[margins](#)	marginal means, predictive margins, marginal effects, and average marginal effects
[marginsplot](#)	graph the results from margins (profile plots, interaction plots, etc.)
[nlcom](#)	point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients
[predict](#)	predictions and their SEs, residuals, etc.
[predictnl](#)	point estimates, standard errors, testing, and inference for generalized predictions
[pwcompare](#)	pairwise comparisons of estimates
[test](#)	Wald tests of simple and composite linear hypotheses
[testnl](#)	Wald tests of nonlinear hypotheses

*`forecast` is not appropriate with `mi` estimation results.

predict

Description for predict

predict creates a new variable containing predictions such as linear predictions, standard errors, residuals, and differences between the linear predictions.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] *newvar* [*if*] [*in*] [, equation(*eqno*[, *eqno*]) *statistic*]

statistic	Description
Main	
xb	linear prediction; the default
stdp	standard error of the linear prediction
residuals	residuals
difference	difference between the linear predictions of two equations
stddp	standard error of the difference in linear predictions

These statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample.

Options for predict

> Main

equation(*eqno*[, *eqno*]) specifies the equation to which you are referring.

equation() is filled in with one *eqno* for the xb, stdp, and residuals options. equation(#1) would mean the calculation is to be made for the first equation, equation(#2) would mean the second, and so on. You could also refer to the equations by their names. equation(income) would refer to the equation named income and equation(hours), to the equation named hours.

If you do not specify equation(), results are the same as if you specified equation(#1).

difference and stddp refer to between-equation concepts. To use these options, you must specify two equations, for example, equation(#1,#2) or equation(income,hours). When two equations must be specified, equation() is required. With equation(#1,#2), difference computes the prediction of equation(#1) minus the prediction of equation(#2).

xb, the default, calculates the fitted values—the prediction of $\mathbf{x}_j\mathbf{b}$ for the specified equation.

stdp calculates the standard error of the prediction for the specified equation (the standard error of the predicted expected value or mean for the observation's covariate pattern). The standard error of the prediction is also referred to as the standard error of the fitted value.

residuals calculates the residuals.

difference calculates the difference between the linear predictions of two equations in the system.

stddp is allowed only only after you have previously fit a multiple-equation model. The standard error of the difference in linear predictions $(\mathbf{x}_{1j}\mathbf{b} - \mathbf{x}_{2j}\mathbf{b})$ between equations 1 and 2 is calculated.

For more information on using predict after multiple-equation estimation commands, see [R] **predict**.

margins

Description for margins

margins estimates margins of responses for linear predictions, fitted values, and differences between the linear predictions.

Menu for margins

Statistics > Postestimation

Syntax for margins

> margins [*marginlist*] [, *options*]
>
> margins [*marginlist*] , <u>predict</u>(*statistic* ...) [<u>predict</u>(*statistic* ...) ...] [*options*]

statistic	Description
default	linear predictions for each equation
xb	$\mathbf{x}_j\mathbf{b}$, fitted values
<u>difference</u>	difference between the linear predictions of two equations
stdp	not allowed with margins
<u>residuals</u>	not allowed with margins
<u>stddp</u>	not allowed with margins

xb defaults to the first equation.

Statistics not allowed with margins are functions of stochastic quantities other than e(b).

For the full syntax, see [R] **margins**.

Also see

[MV] **mvreg** — Multivariate regression

[U] **20 Estimation and postestimation commands**

Title

---
mvtest — Multivariate tests

Description   Syntax   References   Also see

Description

mvtest performs multivariate tests on means, covariances, and correlations and tests of univariate, bivariate, and multivariate normality. The tests of means, covariances, and correlations assume multivariate normality (Mardia, Kent, and Bibby 1979). Both one-sample and multiple-sample tests are provided. All multiple-sample tests provided by mvtest assume independent samples.

Structural equation modeling provides a more general framework for estimating means, covariances, and correlations and testing for differences across groups; see [SEM] **Intro 5** and [SEM] **Example 16**.

Syntax

mvtest *subcommand* ... $\left[$, ... $\right]$

subcommand	Description	See
means	test means	[MV] **mvtest means**
covariances	test covariances	[MV] **mvtest covariances**
correlations	test correlations	[MV] **mvtest correlations**
normality	test multivariate normality	[MV] **mvtest normality**

References

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Also see

Title

> **mvtest correlations —** Multivariate tests of correlations

Description

mvtest correlations performs one-sample and multiple-sample tests on correlations. These tests assume multivariate normality.

See [MV] **mvtest** for more multivariate tests.

Quick start

Lawley's test that the correlations of variables v1, v2, v3, and v4 are equal

        mvtest correlations v1 v2 v3 v4

Jennrich's test that the correlation matrix equals hypothesized matrix mymat

        mvtest correlations v1 v2 v3 v4, equals(mymat)

Jennrich's test for equal correlations with samples defined by catvar

        mvtest correlations v1 v2 v3 v4 v5, by(catvar)

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Multivariate test of means, covariances, and normality

Syntax

Multiple-sample tests

>   mvtest <u>cor</u>relations *varlist* $\begin{bmatrix} if \end{bmatrix}$ $\begin{bmatrix} in \end{bmatrix}$ $\begin{bmatrix} weight \end{bmatrix}$, by(*groupvars*) $\begin{bmatrix} multisample\_options \end{bmatrix}$

One-sample tests

>   mvtest <u>cor</u>relations *varlist* $\begin{bmatrix} if \end{bmatrix}$ $\begin{bmatrix} in \end{bmatrix}$ $\begin{bmatrix} weight \end{bmatrix}$ $\begin{bmatrix} , one\text{-}sample\_options \end{bmatrix}$

multisample_options	Description
Model	
* by(*groupvars*)	compare subsamples with same values in *groupvars*
<u>missing</u>	treat missing values in *groupvars* as ordinary values

> * by(*groupvars*) is required.

one-sample_options	Description
Options	
<u>compound</u>	test that correlation matrix is compound symmetric (equal correlations); the default
<u>equals</u>(*C*)	test that correlation matrix equals matrix *C*

> bootstrap, by, jackknife, rolling, and statsby are allowed; see [U] **11.1.10 Prefix commands**.
> Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.
> aweights are not allowed with the jackknife prefix; see [R] **jackknife**.
> aweights and fweights are allowed; see [U] **11.1.6 weight**.

Options for multiple-sample tests

> Model

by(*groupvars*) is required with the multiple-sample version of the test. Observations with the same values in *groupvars* form each sample. Observations with missing values in *groupvars* are ignored, unless the missing option is specified. A Wald test due to Jennrich (1970) is displayed.

missing specifies that missing values in *groupvars* are treated like ordinary values.

Options for one-sample tests

> Options

compound, the default, tests the hypothesis that the correlation matrix of the variables is compound symmetric, that is, that the correlations of all variables in *varlist* are the same. Lawley's (1963) χ^2 test is displayed.

equals(*C*) tests the hypothesis that the correlation matrix of *varlist* is *C*. The matrix *C* should be $k \times k$, symmetric, and positive definite. *C* is converted to a correlation matrix if needed. The row and column names of *C* are immaterial. A Wald test due to Jennrich (1970) is displayed.

Remarks and examples

Remarks are presented under the following headings:

> *One-sample tests for correlation matrices*
> *A multiple-sample test for correlation matrices*

One-sample tests for correlation matrices

Both one-sample and multiple-sample tests of correlation matrices are provided with the mvtest correlations command. The one-sample tests include Lawley's (1963) test that the correlation matrix is compound symmetric (that is, all correlations are equal), and the Wald test proposed by Jennrich (1970) that the correlation matrix equals a given correlation matrix.

▷ Example 1

The gasoline-powered milk-truck dataset introduced in example 1 of [MV] **mvtest means** has price per mile for fuel, repair, and capital. We test if the correlations between these three variables are equal (that is, the correlation matrix is compound symmetric) using the compound option of mvtest correlations.

```
. use https://www.stata-press.com/data/r18/milktruck
(Milk transportation costs for 25 gasoline trucks (Johnson and Wichern 2007))

. mvtest correlations fuel repair capital, compound

Test that correlation matrix is compound symmetric (all correlations equal)
        Lawley chi2(2) =      7.75
            Prob > chi2 =    0.0208
```

We reject the null hypothesis and conclude that there are probably differences in the correlations of the three cost variables.

◁

▷ Example 2

Using the equals() option of mvtest correlations, we test the hypothesis that fuel and repair costs have a correlation of 0.75, while the correlation between capital and these two variables is zero.

```
. matrix C = (1, 0.75, 0 \ 0.75, 1, 0 \ 0, 0, 1)

. matrix list C

symmetric C[3,3]
      c1    c2    c3
r1     1
r2   .75     1
r3     0     0     1

. mvtest correlations fuel repair capital, equals(C)

Test that correlation matrix equals specified pattern C
       Jennrich chi2(3) =      4.55
            Prob > chi2 =    0.2077
```

We fail to reject this null hypothesis.

◁

A multiple-sample test for correlation matrices

A multiple-sample test of equality of correlation matrices is provided by the `mvtest correlations` command with the `by()` option defining the multiple samples (groups).

▷ Example 3

Psychological test score data are introduced in example 2 of [MV] **mvtest covariances**. We test whether the correlation matrices for the four test scores are the same for males and females.

```
. use https://www.stata-press.com/data/r18/genderpsych
(Four psychological test scores, Rencher and Christensen (2012))
. mvtest correlations y1 y2 y3 y4, by(gender)
Test of equality of correlation matrices across samples
        Jennrich chi2(6) =      5.01
             Prob > chi2 =    0.5422
```

We fail to reject the null hypothesis of equal correlation matrices for males and females.

◁

Stored results

`mvtest correlations` stores the following in `r()`:

Scalars
    `r(chi2)` χ^2 statistic
    `r(df)`   degrees of freedom for χ^2 test
    `r(p_chi2)` p-value for χ^2 test

Macros
    `r(chi2type)` type of model χ^2 test

Methods and formulas

Methods and formulas are presented under the following headings:

        One-sample tests for correlation matrices
        A multiple-sample test for correlation matrices

One-sample tests for correlation matrices

Let the sample consist of N i.i.d. observations from a k-variate multivariate normal distribution $\mathrm{MVN}_k(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, with sample correlation matrix $\mathbf{R}$.

To test that a correlation matrix equals a given matrix, $\mathbf{R}_0$, `mvtest correlations` computes a Wald test proposed by Jennrich (1970):

$$\chi^2_{\mathrm{ocf}} = \frac{1}{2}\mathrm{trace}(\mathbf{ZZ}) - \mathrm{diagonal}(\mathbf{Z})' \left(\mathbf{I} + \mathbf{R}_0 \bullet \mathbf{R}_0^{-1}\right)^{-1} \mathrm{diagonal}(\mathbf{Z})$$

where $\mathbf{Z} = \sqrt{N}\mathbf{R}_0^{-1}\left(\mathbf{R} - \mathbf{R}_0\right)$ and $\bullet$ denotes the Hadamard product. χ^2_{ocf} is asymptotically χ^2 distributed with $k(k-1)/2$ degrees of freedom.

To test that the correlation matrix is compound symmetric, that is, to test that all correlations are equal, the likelihood-ratio test is somewhat cumbersome. Lawley (1963) offers an asymptotically equivalent test that is computationally simple (Johnson and Wichern 2007, 457–458):

$$\chi^2_{\text{occ}} = \frac{N-1}{(1-\overline{R})^2} \left\{ \sum_{i=2}^{k} \sum_{j=1}^{i-1} (R_{ij} - \overline{R})^2 - u \sum_{h=1}^{k} (\overline{R}_h - \overline{R})^2 \right\}$$

where

$$\overline{R} = \frac{2}{k(k-1)} \sum_{i=2}^{k} \sum_{j=1}^{i-1} R_{ij}$$

$$\overline{R}_h = \frac{1}{k-1} \sum_{i=1; i \neq h}^{k} R_{ih}$$

$$u = \frac{(k-1)^2 \left\{ 1 - (1-\overline{R})^2 \right\}}{k - (k-2)(1-\overline{R})^2}$$

and R_{ij} denotes element (i,j) of the $k \times k$ correlation matrix $\mathbf{R}$. χ^2_{occ} is asymptotically χ^2 distributed with $(k-2)(k+1)/2$ degrees of freedom. Aitkin, Nelson, and Reinfurt (1968) study the quality of this χ^2 approximation for k up to six and various correlations, and conclude that the approximation is adequate for N as small as 25.

A multiple-sample test for correlation matrices

Let there be $m \geq 2$ independent samples with the jth sample containing N_j i.i.d. observations from a k-variate multivariate normal distribution, $\text{MVN}_k(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)$, with sample correlation matrix $\mathbf{R}_j$, $j = 1, \ldots, m$. Let $N = \sum_{j=1}^{m} N_j$.

To test for the equality of correlation matrices across m independent samples, mvtest correlations computes a Wald test proposed by Jennrich (1970):

$$\chi^2_{\text{mc}} = \sum_{j=1}^{m} \left\{ \frac{1}{2} \text{trace} \left(\mathbf{Z}_j^2 \right) - \text{diagonal} \left(\mathbf{Z}_j \right)' \left(\mathbf{I} + \overline{\mathbf{R}} \bullet \overline{\mathbf{R}}^{-1} \right)^{-1} \text{diagonal} \left(\mathbf{Z}_j \right) \right\}$$

where $\overline{\mathbf{R}} = 1/N \sum_{j=1}^{m} N_j \mathbf{R}_j$, $\mathbf{Z}_j = \sqrt{N_j} \, \overline{\mathbf{R}}^{-1} \left(\mathbf{R}_j - \overline{\mathbf{R}} \right)$, and $\bullet$ denotes the Hadamard product. χ^2_{mc} is asymptotically χ^2 distributed with $(m-1)k(k-1)/2$ degrees of freedom.

References

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Also see

[MV] **canon** — Canonical correlations

[R] **correlate** — Correlations of variables

Title

---

mvtest covariances — Multivariate tests of covariances

Description

mvtest covariances performs one-sample and multiple-sample multivariate tests on covariances. These tests assume multivariate normality.

See [MV] **mvtest** for other multivariate tests. See [R] **sdtest** for univariate tests of standard deviations.

Quick start

Test that the covariance matrix of v1, v2, v3, and v4 is diagonal

    mvtest covariances v1 v2 v3 v4

Test that the covariance matrix is spherical

    mvtest covariances v1 v2 v3 v4, spherical

Test that the covariance matrix is compound symmetric

    mvtest covariances v1 v2 v3 v4, compound

Test that the covariance matrix of the variables equals matrix mymat

    mvtest covariances v1 v2 v3 v4, equals(mymat)

Test that the covariance matrix is block diagonal with v1, v2, and v3 as block 1, v4 as block 2, and v5 and v6 as block 3

    mvtest cov v1 v2 v3 v4 v5 v6, block(v1 v2 v3 || v4 || v5 v6)

Box's M test that the covariance matrix of v1, v2, and v3 is the same across the groups defined by catvar

    mvtest cov v1 v2 v3, by(catvar)

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Multivariate test of means, covariances, and normality

Syntax

Multiple-sample tests

> mvtest <u>cov</u>ariances *varlist* $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$ *weight* $\big]$, by(*groupvars*) $\big[$ *multisample_options* $\big]$

One-sample tests

> mvtest <u>cov</u>ariances *varlist* $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$ *weight* $\big]$ $\big[$, *one-sample_options* $\big]$

multisample_options	Description
Model	
* by(*groupvars*)	compare subsamples with same values in *groupvars*
<u>miss</u>ing	treat missing values in *groupvars* as ordinary values

* by(*groupvars*) is required.

one-sample_options	Description
Options	
<u>diag</u>onal	test that covariance matrix is diagonal; the default
<u>spher</u>ical	test that covariance matrix is spherical
<u>compound</u>	test that covariance matrix is compound symmetric
<u>equals</u>(*C*)	test that covariance matrix equals matrix *C*
* <u>block</u>(*varlist*₁ $\big[$ || ... $\big]$)	test that covariance matrix is block diagonal with blocks corresponding to *varlist#*

* The full specification is <u>block</u>(*varlist*₁ $\big[$ || *varlist*₂ $\big[$ || ... $\big]$ $\big]$).

bootstrap, by, collect, jackknife, rolling, and statsby are allowed; see [U] **11.1.10 Prefix commands**.
Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.
aweights are not allowed with the jackknife prefix; see [R] **jackknife**.
aweights and fweights are allowed; see [U] **11.1.6 weight**.

Options for multiple-sample tests

> **Model**

by(*groupvars*) is required with the multiple-sample version of the test. Observations with the same values in *groupvars* form a sample. Observations with missing values in *groupvars* are ignored, unless the missing option is specified.

A modified likelihood-ratio statistic testing the equality of covariance matrices for the multiple independent samples defined by by() is presented along with an F and χ^2 approximation due to Box (1949). This test is also known as Box's M test.

missing specifies that missing values in *groupvars* are treated like ordinary values.

Options for one-sample tests

⌐ Options └───

diagonal, the default, tests the hypothesis that the covariance matrix is diagonal, that is, that the variables in *varlist* are independent. A likelihood-ratio test with first-order Bartlett correction is displayed.

spherical tests the hypothesis that the covariance matrix is diagonal with constant diagonal values, that is, that the variables in *varlist* are homoskedastic and independent. A likelihood-ratio test with first-order Bartlett correction is displayed.

compound tests the hypothesis that the covariance matrix is compound symmetric, that is, that the variables in *varlist* are homoskedastic and that every pair of two variables has the same covariance. A likelihood-ratio test with first-order Bartlett correction is displayed.

equals(*C*) specifies that the hypothesized covariance matrix for the k variables in *varlist* is *C*. The matrix *C* must be $k \times k$, symmetric, and positive definite. The row and column names of *C* are ignored. A likelihood-ratio test with first-order Bartlett correction is displayed.

block(*varlist*₁ [|| *varlist*₂ [|| ...]]) tests the hypothesis that the covariance matrix is block diagonal with blocks *varlist*₁, *varlist*₂, etc. Variables in *varlist* not included in *varlist*₁, *varlist*₂, etc., are treated as an additional block. With this pattern, variables in different blocks are independent, but no assumptions are made on the within-block covariance structure. A likelihood-ratio test with first-order Bartlett correction is displayed.

Remarks and examples

Remarks are presented under the following headings:

> One-sample tests for covariance matrices
> A multiple-sample test for covariance matrices

One-sample tests for covariance matrices

One-sample and multiple-sample tests for covariance matrices are provided by the mvtest covariances command. One-sample tests include the test that the covariance matrix of *varlist* is diagonal, spherical, compound symmetric, block diagonal, or equal to a given matrix.

▷ Example 1

The gasoline-powered milk-truck dataset introduced in example 1 of [MV] **mvtest means** has price per mile for fuel, repair, and capital. We test if the covariance matrix for these three variables has any special structure.

```
. use https://www.stata-press.com/data/r18/milktruck
(Milk transportation costs for 25 gasoline trucks (Johnson and Wichern 2007))
. mvtest covariances fuel repair capital, diagonal
Test that covariance matrix is diagonal
   Adjusted LR chi2(3) =     17.91
           Prob > chi2 =    0.0005
. mvtest covariances fuel repair capital, spherical
Test that covariance matrix is spherical
   Adjusted LR chi2(5) =     21.53
           Prob > chi2 =    0.0006
```

```
. mvtest covariances fuel repair capital, compound

Test that covariance matrix is compound symmetric
    Adjusted LR chi2(4) =      11.29
            Prob > chi2 =     0.0235
```

We reject the hypotheses that the covariance is diagonal, spherical, or compound symmetric.

We now test whether there is covariance between `fuel` and `repair`, with `capital` not covarying with these two variables. Thus we hypothesize a block diagonal structure of the form

$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_{11}^2 & \sigma_{12} & 0 \\ \sigma_{21} & \sigma_{22}^2 & 0 \\ 0 & 0 & \sigma_{33}^2 \end{pmatrix}$$

for the covariance matrix. The `block()` option of `mvtest covariances` provides the test:

```
. mvtest covariances fuel repair capital, block(fuel repair || capital)

Test that covariance matrix is block diagonal
    Adjusted LR chi2(2) =       3.52
            Prob > chi2 =     0.1722
```

We fail to reject the null hypothesis. The covariance matrix might have the block diagonal structure we hypothesized.

The same p-value could have been obtained from Stata's canonical correlation command:

```
. canon (fuel repair) (capital)
  (output omitted)
```

See [MV] **canon**.

Now, in addition to hypothesizing that the covariance is block diagonal, we specifically hypothesize that the variance for `capital` is 10, the variance of `fuel` is three times that of `capital`, the variance of `repair` is two times that of `capital`, and that there is no covariance between `capital` and the other two variables, while there is a covariance of 15 between `fuel` and `repair`. We test that hypothesis by using the `equals()` option.

```
. mat B = (30, 15, 0 \ 15, 20, 0 \ 0, 0, 10)

. matrix list B

symmetric B[3,3]
     c1  c2  c3
r1   30
r2   15  20
r3    0   0  10

. mvtest covariances fuel repair capital, equals(B)

Test that covariance matrix equals matrix B
    Adjusted LR chi2(6) =       5.48
            Prob > chi2 =     0.4837
```

We fail to reject the null hypothesis; the covariance might follow the structure hypothesized.

◁

❑ Technical note

If each block comprises a single variable, the test of independent subvectors reduces to a test that the covariance matrix is diagonal. Thus the following two commands are equivalent:

```
mvtest covariances x1 x2 x3 x4 x5, block(x1 || x2 || x3 || x4 || x5)
```

and

```
mvtest covariances x1 x2 x3 x4 x5, diagonal
```

❑

A multiple-sample test for covariance matrices

The by() option of mvtest covariances provides a modified likelihood-ratio statistic testing the equality of covariance matrices for the multiple independent samples defined by by(). This test is also known as Box's M test. There are both F and χ^2 approximations for the null distribution of the test.

▷ Example 2

We illustrate the multiple-sample test of equality of covariance matrices by using four psychological test scores on 32 men and 32 women (Rencher and Christensen 2012; Beall 1945).

```
. use https://www.stata-press.com/data/r18/genderpsych
(Four psychological test scores, Rencher and Christensen (2012))
. mvtest covariances y1 y2 y3 y4, by(gender)
Test of equality of covariance matrices across 2 samples
      Modified LR chi2 =    14.5606
       Box F(10,18377.7) =      1.35      Prob > F =  0.1950
           Box chi2(10) =     13.55   Prob > chi2 =  0.1945
```

Both the F and the χ^2 approximations indicate that we cannot reject the null hypothesis that the covariance matrices for males and females are equal (Rencher and Christensen 2012, 269).

◁

Equality of group covariance matrices is an assumption of multivariate analysis of variance (see [MV] **manova**) and linear discriminant analysis (see [MV] **discrim lda**). Box's M test, produced by mvtest covariances with the by() option, is often recommended for testing this assumption.

Stored results

mvtest covariances stores the following in r():

Scalars
r(chi2)	χ^2
r(df)	degrees of freedom for χ^2 test
r(p_chi2)	p-value for χ^2 test
r(F_Box)	F statistic for Box test (by() only)
r(df_m_Box)	model degrees of freedom for Box test (by() only)
r(df_r_Box)	residual degrees of freedom for Box test (by() only)
r(p_F_Box)	p-value for Box's F test (by() only)

Macros
r(chi2type)	type of model χ^2 test

Methods and formulas

When comparing the formulas in this section with those found in some multivariate texts, be aware of whether they define the sample covariance matrix with a divisor of N or $N - 1$. We use N. The formulas for several of the statistics are presented differently depending on your choice of divisor (but are still equivalent).

Methods and formulas are presented under the following headings:

> One-sample tests for covariance matrices
> A multiple-sample test for covariance matrices

One-sample tests for covariance matrices

Let the sample consist of N i.i.d. observations, $\mathbf{x}_i$, $i = 1, \ldots, N$, from a k-variate multivariate normal distribution, $\text{MVN}_k(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, with sample mean $\overline{\mathbf{x}} = 1/N \sum_{i=1}^{N} \mathbf{x}_i$, sample covariance matrix $\mathbf{S} = 1/N \sum_{i=1}^{N} (\mathbf{x}_i - \overline{\mathbf{x}})(\mathbf{x}_i - \overline{\mathbf{x}})'$, and sample correlation matrix $\mathbf{R}$.

To test that a covariance matrix equals a given matrix, $H_0 : \boldsymbol{\Sigma} = \boldsymbol{\Sigma}_0$, `mvtest covariances` computes a likelihood-ratio test with Bartlett correction (Rencher and Christensen 2012, 260–261):

$$\chi^2_{\text{ovf}} = (N - 1) \left\{ 1 - \frac{1}{6(N-1) - 1} \left(2k + 1 - \frac{2}{k+1} \right) \right\}$$
$$\times \left\{ \ln |\boldsymbol{\Sigma}_0| - \ln \left| \frac{N}{N-1} \mathbf{S} \right| + \text{trace}\left(\frac{N}{N-1} \mathbf{S} \boldsymbol{\Sigma}_0^{-1} \right) - k \right\}$$

which is approximately χ^2 distributed with $k(k+1)/2$ degrees of freedom.

To test for a spherical covariance matrix, $H_0 : \boldsymbol{\Sigma} = \sigma^2 \mathbf{I}$, `mvtest covariances` computes a likelihood-ratio test with Bartlett correction (Rencher and Christensen 2012, 261–262):

$$\chi^2_{\text{ovs}} = \left\{ (N - 1) - \frac{2k^2 + k + 2}{6k} \right\} \left[k \ln \left\{ \text{trace}\,(\mathbf{S}) \right\} - \ln |\mathbf{S}| - k \ln(k) \right]$$

which is approximately χ^2 distributed with $k(k+1)/2 - 1$ degrees of freedom.

To test for a diagonal covariance matrix, $H_0 : \boldsymbol{\Sigma}_{ij} = 0$ for $i \neq j$, `mvtest covariances` computes a likelihood-ratio test with first-order Bartlett correction (Rencher and Christensen 2012, 275):

$$\chi^2_{\text{ovd}} = -\left(N - 1 - \frac{2k+5}{6} \right) \ln |\mathbf{R}|$$

which is approximately χ^2 distributed with $k(k-1)/2$ degrees of freedom.

To test for a compound-symmetric covariance matrix, $H_0 : \boldsymbol{\Sigma} = \sigma^2 \{ (1 - \rho)\mathbf{I} + \rho \mathbf{1}\mathbf{1}' \}$, that is, a covariance matrix with common variance σ^2 and common correlation ρ, `mvtest covariances` computes a likelihood-ratio test with first-order Bartlett correction (Rencher and Christensen 2012, 263–264):

$$\chi^2_{\text{ovc}} = \left\{ N - 1 - \frac{k(k+1)^2(2k-3)}{6(k-1)(k^2 + k - 4)} \right\}$$
$$\times \left[k \ln \left(s^2 \right) + (k-1) \ln(1-r) + \ln\{1 + (k-1)r\} - \ln |\mathbf{S}| \right]$$

where

$$s^2 = \frac{1}{k} \sum_{j=1}^{k} s_{jj} \qquad \text{and} \qquad r = \frac{1}{k(k-1)s^2} \sum_{j=1}^{k} \sum_{h=1,h\neq j}^{k} s_{jh}$$

where s_{jh} is the (j,h) element of $\mathbf{S}$. χ^2_{ovc} is approximately χ^2 distributed with $k(k+1)/2 - 2$ degrees of freedom.

To test that a covariance matrix is block diagonal with b diagonal blocks and with k_j variables in block j, mvtest covariances computes a likelihood-ratio test with first-order Bartlett correction (Rencher and Christensen 2012, 271–272). Thus variables in different blocks are hypothesized to be independent.

$$\chi^2_{\text{ovb}} = \left(N - 1 - \frac{2a_3 + 3a_2}{6a_2}\right)\left(\sum_{j=1}^{b} \ln|\mathbf{S}_j| - \ln|\mathbf{S}|\right)$$

where $a_2 = k^2 - \sum_{j=1}^{b} k_j^2$, $a_3 = k^3 - \sum_{j=1}^{b} k_j^3$, and $\mathbf{S}_j$ is the covariance matrix for the jth block. χ^2_{ovb} is approximately χ^2 distributed with $a_2/2$ degrees of freedom.

A multiple-sample test for covariance matrices

Let there be $m \geq 2$ independent samples with the jth sample containing N_j i.i.d. observations, $\mathbf{x}_{ji}$, $i = 1, \ldots, N_j$, from a k-variate multivariate normal distribution $\text{MVN}_k(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)$. The observed jth sample mean is $\overline{\mathbf{x}}_j = 1/N_j \sum_{i=1}^{N_j} \mathbf{x}_{ji}$ and covariance is $\mathbf{S}_j = 1/N_j \sum_{i=1}^{N_j} (\mathbf{x}_{ji} - \overline{\mathbf{x}}_j)(\mathbf{x}_{ji} - \overline{\mathbf{x}}_j)'$. Let $N = \sum_{j=1}^{m} N_j$.

To test the equality of covariance matrices in m independent samples, $H_0 : \boldsymbol{\Sigma}_1 = \boldsymbol{\Sigma}_2 = \cdots = \boldsymbol{\Sigma}_m$, mvtest covariances computes a modified likelihood-ratio statistic, which is an unbiased variant of the likelihood-ratio statistic (Rencher and Christensen 2012, 266–268):

$$-2\ln(M) = (N - m)\ln\left|\mathbf{S}_{\text{pooled}}\right| - \sum_{j=1}^{m}\left\{(N_j - 1)\ln\left|\frac{N_j}{N_j - 1}\mathbf{S}_j\right|\right\}$$

where $\mathbf{S}_{\text{pooled}} = \sum_{j=1}^{m}(N_j\mathbf{S}_j)/(N - m)$. Asymptotically, $-2\ln(M)$ is χ^2 distributed. Box (1949, 1950) derived more accurate χ^2 and F approximations (Rencher and Christensen 2012, 267–268).

Box's χ^2 approximation is given by

$$\chi^2_{\text{mv}} = -2(1 - c_1)\ln(M)$$

which is approximately χ^2 distributed with $(m-1)k(k+1)/2$ degrees of freedom.

Box's F approximation is given by

$$F_{\text{mv}} = \begin{cases} -2b_1\ln(M) & \text{if } c_2 > c_1^2 \\[2ex] \dfrac{2a_2b_2\ln(M)}{a_1\{1 + 2b_2\ln(M)\}} & \text{otherwise} \end{cases}$$

which is approximately F distributed with a_1 and a_2 degrees of freedom.

In the χ^2 and F approximations, we have

$$c_1 = \left\{ \sum_{j=1}^{m} (N_j - 1)^{-1} - (N - m)^{-1} \right\} \frac{2k^2 + 3k - 1}{6(k+1)(m-1)}$$

$$c_2 = \left\{ \sum_{j=1}^{m} (N_j - 1)^{-2} - (N - m)^{-2} \right\} \frac{(k-1)(k+2)}{6(m-1)}$$

$a_1 = (m-1)k(k+1)/2$, $a_2 = (a_1 + 2)/|c_2 - c_1^2|$, $b_1 = (1 - c_1 - a_1/a_2)/a_1$, and $b_2 = (1 - c_1 + 2/a_2)/a_2$.

References

Beall, G. 1945. Approximate methods in calculating discriminant functions. *Psychometrika* 10: 205–217. https://doi.org/10.1007/BF02310469.

Box, G. E. P. 1949. A general distribution theory for a class of likelihood criteria. *Biometrika* 36: 317–346. https://doi.org/10.2307/2332671.

——. 1950. Problems in the analysis of growth and wear curves. *Biometrics* 6: 362–389. https://doi.org/10.2307/3001781.

Johnson, R. A., and D. W. Wichern. 2007. *Applied Multivariate Statistical Analysis*. 6th ed. Englewood Cliffs, NJ: Prentice Hall.

Rencher, A. C., and W. F. Christensen. 2012. *Methods of Multivariate Analysis*. 3rd ed. Hoboken, NJ: Wiley.

Also see

Title

---

mvtest means — Multivariate tests of means

Description

mvtest means performs one-sample and multiple-sample multivariate tests on means. These tests assume multivariate normality.

See [MV] **mvtest** for other multivariate tests.

Quick start

Test that the means of v1, v2, and v3 are equal

    mvtest means v1 v2 v3

Test that the means of v1, v2, and v3 are zero

    mvtest means v1 v2 v3, zero

Test that the means vector equals the hypothesized vector myvec

    mvtest means v1 v2 v3, equals(myvec)

Test that the means of v1, v2, and v3 are the same across groups defined by catvar assuming
  homogeneous covariance matrices

    mvtest means v1 v2 v3, by(catvar)

Same as above, but allow heterogeneous covariance matrices

    mvtest means v1 v2 v3, by(catvar) heterogeneous

Same as above, but use a likelihood-ratio test instead of a Wald test

    mvtest means v1 v2 v3, by(catvar) lr

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Multivariate test of means, covariances, and normality

Syntax

Multiple-sample tests

> mvtest <u>means</u> *varlist* [*if*] [*in*] [*weight*] , by(*groupvars*) [*multisample_options*]

One-sample tests

> mvtest <u>means</u> *varlist* [*if*] [*in*] [*weight*] [, *one-sample_options*]

multisample_options	Description
Model	
* by(*groupvars*)	compare subsamples with same values in *groupvars*
<u>missing</u>	treat missing values in *groupvars* as ordinary values
Options	
<u>homo</u>geneous	test for equal means with homogeneous covariance matrices across by-groups; the default
<u>heter</u>ogeneous	James's test for equal means, allowing heterogeneous covariance matrices across by-groups
lr	likelihood-ratio test for equal means, allowing heterogeneous covariance matrices across by-groups
<u>protect</u>(*spec*)	run protection as a safeguard against local minimum with the group means as initial values; use only with lr option

* by(*groupvars*) is required.

one-sample_options	Description
Options	
<u>equal</u>	test that variables in *varlist* have equal means; the default
<u>zero</u>	test that means of *varlist* are all equal to 0
<u>equals</u>(*M*)	test that mean vector equals vector *M*
<u>linear</u>(*V*)	test that mean vector of *varlist* satisfies linear hypothesis described by matrix *V*

bootstrap, by, collect, jackknife, rolling, and statsby are allowed; see [U] **11.1.10 Prefix commands**.

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

aweights are not allowed with the jackknife prefix; see [R] **jackknife**.

aweights and fweights are allowed; see [U] **11.1.6 weight**.

Options for multiple-sample tests

    Model

by(*groupvars*) is required with the multiple-sample version of the test. Observations with the same values in *groupvars* form a sample. Observations with missing values in *groupvars* are ignored, unless the missing option is specified.

missing specifies that missing values in *groupvars* are treated like ordinary values.

---

homogeneous, the default, specifies the hypothesis that the mean vectors are the same across the by-groups, assuming homogeneous covariance matrices across the by-groups. homogeneous produces the four standard tests of multivariate means (Wilks's lambda, Pillai's trace, Lawley–Hotelling trace, and Roy's largest root).

heterogeneous removes the assumption that the covariance matrices are the same across the by-groups. This is the multivariate Behrens–Fisher problem. With two groups, the MNV test, an affine-invariant modification by Krishnamoorthy and Yu (2004) of the Nel–Van der Merwe (1986) test, is displayed. With more than two groups, the Wald test, with p-values adjusted as proposed by James (1954), is displayed.

lr removes the assumption that the covariance matrices are the same across the by-groups and specifies that a likelihood-ratio test be presented. The associated estimation problem may have multiple local optima, though this seems rare with two groups.

protect(*spec*) is a technical option accompanying lr, specifying that the "common means" model is fit from different starting values to ascertain with some confidence whether a global optimum to the underlying estimation problem was reached. The Mardia–Kent–Bibby (1979) proposal for initialization of the common means is always used as well. If the different trials do not converge to the same solution, the "best" one is used to obtain the test, and a warning message is displayed.

protect(groups) specifies to fit the common means model using each of the group means as starting values for the common means.

protect(randobs, reps(#)) specifies to fit the common means model using # random observations as starting values for the common means.

protect(#) is a convenient shorthand for protect(randobs, reps(#)).

Options with one-sample tests

equal performs Hotelling's test of the hypothesis that the means of all variables in *varlist* are equal.

zero performs Hotelling's test of the hypothesis that the means of all variables in *varlist* are 0.

equals(*M*) performs Hotelling's test that the vector of means of the k variables in *varlist* equals *M*. The matrix *M* must be a $k \times 1$ or $1 \times k$ vector. The row and column names of *M* are ignored.

linear(*V*) performs Hotelling's test that the means satisfy a user-specified set of linear constraints, represented by *V*. *V* must be a matrix vector with k or $k + 1$ columns, where k is the number of variables in *varlist*. Let *A* be a matrix of the first k columns of *V*. Let *b* be the last column of *V* if *V* has $k + 1$ columns and a column of 0s otherwise. The linear hypothesis test is that *A* times a column vector of the means of *varlist* equals *b*. mvtest ignores matrix row and column names.

Remarks and examples

Remarks are presented under the following headings:

One-sample tests for mean vectors
Multiple-sample tests for mean vectors

One-sample tests for mean vectors

One-sample and multiple-sample tests of means are available with the `mvtest means` command. One-sample tests include tests that the means of *varlist* are equal, the means of *varlist* equal a given vector, the means of *varlist* are zero, and linear combinations of the means of *varlist* equal a given vector.

We first explore the use of `mvtest means` for testing the one-sample hypothesis that the means of *varlist* are equal.

▷ Example 1

The cost on a per-mile basis of 25 gasoline trucks used for transporting milk are provided in three categories: fuel, repair, and capital (Johnson and Wichern 2007, 269).

```
. use https://www.stata-press.com/data/r18/milktruck
(Milk transportation costs for 25 gasoline trucks (Johnson and Wichern 2007))

. summarize
```

Variable	Obs	Mean	Std. dev.	Min	Max
fuel	25	12.56	5.382	4.24	29.11
repair	25	8.1612	4.631723	1.35	17.44
capital	25	10.5444	3.687688	3.28	17.59

Are the means of the three costs equal? The `equal` option of `mvtest means` provides a way of testing this hypothesis.

```
. mvtest means fuel repair capital, equal

Test that all means are the same
        Hotelling T2 =     35.25
    Hotelling F(2,23) =     16.89
           Prob > F =    0.0000
```

We reject the null hypothesis of equal means for fuel, repair, and capital costs.

◁

Hotelling's T^2 statistic is a multivariate generalization of the univariate t statistic; see [R] **ttest**. A test of the bivariate hypothesis that the means of the repair and capital costs are equal could be obtained with

```
ttest repair == capital
```

or with

```
mvtest means repair capital, equal
```

The square of the t statistic from `ttest` equals the T^2 value from `mvtest means`. With `ttest`, you are limited to comparing the means of two variables; with `mvtest means`, you can simultaneously compare the means of two or more variables.

The `equals()` option of `mvtest means` provides Hotelling's T^2 statistic for the test that the mean vector for *varlist* equals a given vector. This provides a multivariate generalization of the univariate t statistic obtained using the `ttest` *varname* == *#* syntax of [R] **ttest**.

▷ Example 2

   We compare the measurements of the available and exchangeable soil calcium (y1 and y2) and turnip-green calcium (y3) at 10 locations in the South (Rencher and Christensen 2012, 66; Kramer and Jensen 1969) to the values 15.0, 6.0, and 2.85 respectively (Rencher and Christensen 2012, 133–134).

```
. use https://www.stata-press.com/data/r18/turnip
(Calcium in soil and turnip greens, Rencher and Christensen (2012))
. summarize y*
    Variable |        Obs        Mean    Std. dev.        Min         Max
-------------+--------------------------------------------------------------
          y1 |         10        28.1     11.85514          6          40
          y2 |         10        7.18     8.499908        1.6          30
          y3 |         10       3.089     .5001211        2.7        4.38
. matrix Mstd = (15.0, 6.0, 2.85)
. mvtest means y* , equals(Mstd)
Test that means equal vector Mstd
        Hotelling T2 =      24.56
     Hotelling F(3,7) =       6.37
            Prob > F =     0.0207
```

   The calcium measurements from these 10 locations in the South do not appear to match the hypothesized values.

◁

   The `zero` option of `mvtest means` tests the hypothesis that the means of *varlist* are zero. The same result could be obtained by creating a column or row vector of the appropriate length filled with zeros and supplying that to the `equals()` option.

```
mvtest means y1 y2 y3, zero
```

would give the same test as

```
matrix Zero = 0,0,0
mvtest means y1 y2 y3, equals(Zero)
```

This same test against a zero-mean vector can be obtained with the `hotelling` command; see [MV] **hotelling**. For example,

```
hotelling y1 y2 y3
```

   `mvtest means` also tests that linear combinations of the means of *varlist* equal a given vector.

▷ Example 3

   The `linear()` option of `mvtest means` can be used to obtain the same result as in example 1, testing that the fuel, repair, and capital costs are equal. We do this by constructing two appropriate linear combinations of our three variables and testing that the means of these two linear combinations are zero.

```
. use https://www.stata-press.com/data/r18/milktruck
(Milk transportation costs for 25 gasoline trucks (Johnson and Wichern 2007))
. matrix C = 1, -1, 0 \ 0, 1, -1
. matrix list C
C[2,3]
    c1  c2  c3
r1   1  -1   0
r2   0   1  -1
```

```
. mvtest means fuel repair capital, linear(C)

Test that mean vector satisfies linear hypothesis C
        Hotelling T2 =      35.25
    Hotelling F(2,23) =     16.89
           Prob > F =      0.0000
```

We formed a matrix C that contrasted fuel to repair (the first row of C) and repair to capital (the second row of C). Note that we need not set the matrix row and column names of C. By default, the linear contrast was tested equal to a vector of zeros.

We could explicitly append an extra column of zeros in our matrix and obtain the same result.

```
. matrix Czero = C, (0 \ 0)

. matrix list Czero

Czero[2,4]
    c1  c2  c3  c4
r1   1  -1   0   0
r2   0   1  -1   0

. mvtest means fuel repair capital, linear(Czero)

Test that mean vector satisfies linear hypothesis Czero
        Hotelling T2 =      35.25
    Hotelling F(2,23) =     16.89
           Prob > F =      0.0000
```

Values other than zeros could have been appended to C to test if the linear combinations equal those other values.

◁

Rencher and Christensen (2012, 152–154) discusses one-sample profile analysis. The linear() option of mvtest means allows you to do this and other one-sample comparisons of interest.

Multiple-sample tests for mean vectors

Multiple-sample tests of mean vectors are also supported by mvtest means. The groups defining the multiple samples are specified with the by() option. The test that is presented depends on whether homogeneity of variance is assumed and whether there are more than two groups. The homogeneity option, the default, provides four standard multivariate tests (Wilks's lambda, Pillai's trace, Lawley–Hotelling trace, and Roy's largest root) under the assumption that the group covariance matrices are equal. The remaining possibilities do not assume equal covariances for the groups. The heterogeneous option with two by-groups presents the affine-invariant modification by Krishnamoorthy and Yu (2004) of the test proposed by Nel and Van der Merwe (1986). The heterogeneous option with more than two by-groups presents a Wald test along with James's approximation to the p-value of the test. The lr option also removes the assumption of equal covariance matrices for the groups and produces a likelihood-ratio test for the equality of the group means.

▷ Example 4

In example 2 of [MV] **manova**, we introduce two variables measured on four groups of rabbits. The groups have differing sample sizes. mvtest means with the by() option can test the hypothesis that the means of the two variables are the same for the four groups of rabbits under the assumption that the groups have equal covariance matrices.

```
. use https://www.stata-press.com/data/r18/metabolic
(Table 4.5 Metabolic comparisons of rabbits -- Rencher (1998))

. mvtest means y1 y2, by(group)

Test for equality of 4 group means, assuming homogeneity
```

	Statistic	F(df1,	df2)	= F	Prob>F	
Wilks' lambda	0.1596	6.0	32.0	8.02	0.0000	e
Pillai's trace	1.2004	6.0	34.0	8.51	0.0000	a
Lawley-Hotelling trace	3.0096	6.0	30.0	7.52	0.0001	a
Roy's largest root	1.5986	3.0	17.0	9.06	0.0008	u

e = exact, a = approximate, u = upper bound on F

We reject the null hypothesis and conclude that the means are likely different between the four groups of rabbits.

The statistics reported above are the same as reported by manova y1 y2 = group in example 2 of [MV] **manova**. mvtest means y1 y2, by(group) homogeneous would also have produced the same results because homogeneous is the default when by() is specified.

◁

▷ Example 5

Continuing with the rabbit data, restricting ourselves to examining only the first two groups of rabbits and continuing to assume equal covariance matrices, we obtain the following:

```
. mvtest means y1 y2 if group < 3, by(group)

Test for equality of 2 group means, assuming homogeneity
```

	Statistic	F(df1,	df2)	= F	Prob>F	
Wilks' lambda	0.3536	2.0	11.0	10.05	0.0033	e
Pillai's trace	0.6464	2.0	11.0	10.05	0.0033	e
Lawley-Hotelling trace	1.8279	2.0	11.0	10.05	0.0033	e
Roy's largest root	1.8279	2.0	11.0	10.05	0.0033	e

e = exact, a = approximate, u = upper bound on F

We reject the null hypothesis of equal means for the two groups of rabbits.

With only two groups, the four multivariate tests above are equivalent. Because there were only two groups, we could have also produced this same F test with hotelling y1 y2 if group < 3, by(group); see [MV] **hotelling**.

◁

▷ Example 6

We now remove the assumption of equal covariance matrices for these two groups of rabbits and see if our conclusions change.

```
. mvtest means y1 y2 if group < 3, by(group) heterogeneous

Test for equality of 2 group means, allowing for heterogeneity
          MNV F(2,9.5) =      9.92
            Prob > F =    0.0047
```

Removing the assumption of equal covariance matrices still leads to rejection of the null hypothesis that the means for the two groups of rabbits are equal.

Because there were only two groups, an F statistic based on an affine-invariant modification by Krishnamoorthy and Yu (2004) of the test proposed by Nel and Van der Merwe (1986) was presented.

◁

▷ Example 7

If we attempt to test all four groups of rabbits while removing the assumption of equal covariance matrices,

```
. mvtest means y1 y2, by(group) heterogeneous
```

we receive an error message indicating that we have a singular covariance matrix. This is because there are only two observations for the fourth group of rabbits.

If we omit the fourth group, we obtain

```
. mvtest means y1 y2 if group < 4, by(group) heterogeneous
Test for equality of 3 group means, allowing for heterogeneity
            Wald chi2(4) =     34.08
              Prob > chi2 =    0.0000  (chi-squared approximation)
              Prob > chi2 =    0.0017  (James' approximation)
```

With more than two groups, a Wald χ^2 statistic is presented along with two p-values. The first p-value is the approximate one based on the χ^2 distribution with four degrees of freedom. The second, more accurate, p-value is based on James's (1954) approximation. Both p-values lead to rejection of the null hypothesis; the three groups of rabbits are unlikely to have equal means.

◁

▷ Example 8

We can request a likelihood-ratio test instead of a Wald test by specifying the `lr` option. Like `heterogeneous`, the `lr` option does not assume that the group covariance matrices are equal.

```
. mvtest means y1 y2 if group < 4, by(group) lr
Test for equality of 3 group means, allowing for heterogeneity
              LR chi2(4) =     21.32
             Prob > chi2 =    0.0003
```

The likelihood-ratio test also leads us to reject the null hypothesis of equal means for the three groups of rabbits.

◁

The computation of the likelihood-ratio test requires fitting the multivariate normal distribution with common means while allowing for different covariance matrices. The iterative fitting process may converge to local solutions rather than to the global solution, invalidating the reported test (Buot, Hoşten, and Richards 2007). As a precaution, you may use the `protect()` option to request fitting from different starting values so that the test results are based on the best solution found, and you can check whether the likelihood surface has multiple optima.

Stored results

mvtest means without the by() option (that is, a one-sample means test) stores the following in r():

Scalars
    r(T2)   Hotelling T^2
    r(F) F statistic
    r(df_m)   model degrees of freedom
    r(df_r)   residual degrees of freedom
    r(p_F) p-value for F test

Macros
    r(Ftype)   type of model F test

mvtest means with by() but without the lr or heterogeneous options (that is, a multiple-sample means test, assuming homogeneity) stores the following in r():

Scalars
    r(F) F statistic
    r(df_m)   model degrees of freedom
    r(df_r)   residual degrees of freedom
    r(p_F) p-value for F test

Macros
    r(Ftype)   type of model F test

Matrices
    r(stat_m)   MANOVA model tests

mvtest means with by() defining two groups and with the heterogeneous option (that is, a two-sample test of means, allowing for heterogeneity) stores the following in r():

Scalars
    r(F) F statistic
    r(df_m)   model degrees of freedom
    r(df_r)   residual degrees of freedom
    r(p_F) p-value for F test

Macros
    r(Ftype)   type of model F test

mvtest means with by() defining more than two groups and with the heterogeneous option (that is, a multiple-sample test of means, allowing for heterogeneity) stores the following in r():

Scalars
    r(chi2) χ^2 statistic
    r(df)   degrees of freedom for χ^2 test
    r(p_chi2) p-value for χ^2 test
    r(p_chi2_James) p-value for Wald test via James's approximation

Macros
    r(chi2type)   type of model χ^2 test

mvtest means with the by() and lr options (that is, a likelihood-ratio multiple-sample test of means, allowing for heterogeneity) stores the following in r():

Scalars
    r(chi2) χ^2 statistic
    r(df)   degrees of freedom for χ^2 test
    r(p_chi2) p-value for χ^2 test
    r(rc)   return code
    r(uniq)   1/0 if protection runs yielded/did not yield same solution (protect() only)
    r(nprotect)   number of protection runs (protect() only)
Macros
    r(chi2type)   type of model χ^2 test
Matrices
    r(M)   maximum likelihood estimate of means

Methods and formulas

When comparing the formulas in this section with those found in some multivariate texts, be aware of whether they define the sample covariance matrix with a divisor of N or $N - 1$. We use N. The formulas for several of the statistics are presented differently depending on your choice of divisor (but are still equivalent).

Methods and formulas are presented under the following headings:

One-sample tests for mean vectors

Let the sample consist of N i.i.d. observations, $\mathbf{x}_i$, $i = 1, \ldots, N$, from a k-variate multivariate normal distribution, $\mathrm{MVN}_k(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, with sample mean $\overline{\mathbf{x}} = 1/N \sum_{i=1}^{N} \mathbf{x}_i$ and sample covariance matrix $\mathbf{S} = 1/N \sum_{i=1}^{N} (\mathbf{x}_i - \overline{\mathbf{x}})(\mathbf{x}_i - \overline{\mathbf{x}})'$.

mvtest means with the equals() option tests that a mean vector equals a fixed vector, $H_0 : \boldsymbol{\mu} = \boldsymbol{\mu}_0$, and produces a Hotelling T^2 statistic, which is equivalent to the likelihood-ratio test (Mardia, Kent, and Bibby 1979, 125–126)

$$T^2_{\mathrm{omf}} = (N - 1)(\overline{\mathbf{x}} - \boldsymbol{\mu}_0)' \mathbf{S}^{-1} (\overline{\mathbf{x}} - \boldsymbol{\mu}_0)$$

Under the null hypothesis,

$$F_{\mathrm{omf}} = \frac{N - k}{(N - 1)k} T^2_{\mathrm{omf}}$$

is distributed $F(k, N - k)$.

mvtest means with the zero option tests that the mean vector equals $\mathbf{0}$ and is obtained from T^2_{omf} by setting $\boldsymbol{\mu}_0 = \mathbf{0}$. For this case, denote Hotelling's T^2 as T^2_{omz} and the corresponding F statistic as F_{omz}.

mvtest means with the linear() option tests that the mean vector $\boldsymbol{\mu}$ satisfies a linear hypothesis, $H_0 : \mathbf{C}\boldsymbol{\mu} = \mathbf{b}$, and produces a Hotelling T^2 test, which is equivalent to the likelihood-ratio test (Mardia, Kent, and Bibby 1979, 132–133)

$$T^2_{\mathrm{omc}} = (N - 1)(\mathbf{C}\overline{\mathbf{x}} - \mathbf{b})' (\mathbf{C}\mathbf{S}\mathbf{C}')^{-1} (\mathbf{C}\overline{\mathbf{x}} - \mathbf{b})$$

Under the null hypothesis,

$$F_{\text{omc}} = \frac{N - q}{(N - 1)q} T_{\text{omc}}^2$$

is distributed $F(q, N - q)$, where q is the rank of $\mathbf{CSC}'$, typically the number of rows of $\mathbf{C}$.

mvtest means with the equal option tests that all means are equal and is obtained from T_{omc}^2 by setting $\mathbf{C} = (\mathbf{I}, -\mathbf{1})$ and $\mathbf{b} = \mathbf{0}$. For this case, denote Hotelling's T^2 as T_{ome}^2 and the corresponding F statistic as F_{ome}.

Multiple-sample tests for mean vectors

Let there be $m \geq 2$ independent samples with the jth sample containing N_j i.i.d. observations, $\mathbf{x}_{ji}$, $i = 1, \ldots, N_j$, from a k-variate multivariate normal distribution, $\text{MVN}_k(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)$. The observed jth sample mean is $\overline{\mathbf{x}}_j = 1/N_j \sum_{i=1}^{N_j} \mathbf{x}_{ji}$ and covariance is $\mathbf{S}_j = 1/N_j \sum_{i=1}^{N_j} (\mathbf{x}_{ji} - \overline{\mathbf{x}}_j)(\mathbf{x}_{ji} - \overline{\mathbf{x}}_j)'$. Let $N = \sum_{j=1}^{m} N_j$.

The tests for the hypothesis that the mean vector is the same across m independent samples, obtained from mvtest means with the by() option, come in four different flavors, depending on whether the additional assumption is made that the covariance matrix $\mathbf{S}_j$ is the same over the m samples (the homogeneous and heterogeneous options) and on the number of samples (whether the by() option defines more than two groups). If equal covariance is not assumed, the problem is commonly referred to as the multivariate Behrens–Fisher problem.

When assuming equal covariance matrices for the by() groups (the homogeneous option, the default), mvtest means tests the equality of the group means by using manova to compute the classic quartet of test statistics: Wilks's lambda, Pillai's trace, Lawley–Hotelling trace, and Roy's largest root. See [MV] manova for details. For $m = 2$ samples, the four tests are equivalent.

mvtest means has the heterogeneous and lr options, which remove the assumption of equal covariance matrices for the by() groups. The statistic produced with the heterogeneous option depends on whether there are $m = 2$ groups or $m > 2$ groups.

With the heterogeneous option and $m = 2$ samples, the test for equal means is computed using the affine-invariant modification by Krishnamoorthy and Yu (2004) of the test proposed by Nel and Van der Merwe (1986):

$$T_{\text{mm2}}^2 = (\overline{\mathbf{x}}_1 - \overline{\mathbf{x}}_2)' \widetilde{\mathbf{S}}^{-1} (\overline{\mathbf{x}}_1 - \overline{\mathbf{x}}_2)$$

where

$$F_{\text{mm2}} = \frac{v - k + 1}{vk} T_{\text{mm2}}^2$$

is approximately $F(k, v - k + 1)$ distributed, and where $\widetilde{\mathbf{S}}_j = \mathbf{S}_j/(N_j - 1)$, $\widetilde{\mathbf{S}} = \widetilde{\mathbf{S}}_1 + \widetilde{\mathbf{S}}_2$, $v = k(k + 1)/(a_1 + a_2)$, and

$$a_j = \left[\text{trace}\left\{ \left(\widetilde{\mathbf{S}}_j \widetilde{\mathbf{S}}^{-1}\right)^2 \right\} + \text{trace}\left(\widetilde{\mathbf{S}}_j \widetilde{\mathbf{S}}^{-1}\right)^2 \right] / (N_j - 1)$$

With the `heterogeneous` option and $m > 2$ samples, `mvtest means` computes the Wald test for equal means (Seber 1984, 445–447)

$$T_{\text{mmw}} = \sum_{j=1}^{m} (\overline{\mathbf{x}}_j - \overline{\overline{\mathbf{x}}})' \mathbf{W}_j (\overline{\mathbf{x}}_j - \overline{\overline{\mathbf{x}}})$$

where $\mathbf{W}_j = \{\mathbf{S}_j/(N_j - 1)\}^{-1}$, $\mathbf{W} = \sum_{j=1}^{m} \mathbf{W}_j$, and $\overline{\overline{\mathbf{x}}} = \mathbf{W}^{-1} \sum_{j=1}^{m} \mathbf{W}_j \overline{\mathbf{x}}_j$.

James (1954) showed that the upper α quantile of T_{mmw} under the null hypothesis can, to order N_i^{-1}, be obtained as $\chi_{r,\alpha}^2 (a + b\chi_{r,\alpha}^2)$, where $\chi_{r,\alpha}^2$ is the upper α quantile of a χ^2 with $r = k(m-1)$ degrees of freedom, and

$$a = 1 + \frac{1}{2r} \sum_{j=1}^{m} \frac{\left\{\text{trace}\left(\mathbf{I} - \mathbf{W}^{-1}\mathbf{W}_j\right)\right\}^2}{N_j - 1}$$

$$b = \frac{1}{r(r+2)} \left[\sum_{j=1}^{m} \frac{\text{trace}\left\{\left(\mathbf{I} - \mathbf{W}^{-1}\mathbf{W}_j\right)^2\right\}}{N_j - 1} + \frac{\left\{\text{trace}\left(\mathbf{I} - \mathbf{W}^{-1}\mathbf{W}_j\right)\right\}^2}{2(N_j - 1)}\right]$$

`mvtest` computes the p-value associated with the observed T_{mmw} by inverting James's expansion with a scalar solver using Brent's (1973) algorithm.

With the `lr` option, `mvtest means` provides a likelihood-ratio test for constant means across $m \geq 2$ samples, without the assumption of constant covariances. To fit the null model with a common mean, $\boldsymbol{\mu}_c$, an iterative procedure proposed by Mardia, Kent, and Bibby (1979, 142–143) is used. Let h denote the iteration. Let $\widehat{\boldsymbol{\Sigma}}_j^{(0)} = \mathbf{S}_j$, and $\widehat{\boldsymbol{\mu}}_c^{(0)}$ be obtained using the second formula below, then iterate these two formulas starting with $h = 1$ until convergence is achieved.

$$\widehat{\boldsymbol{\Sigma}}_j^{(h)} = \mathbf{S}_j + \left(\overline{\mathbf{x}}_j - \widehat{\boldsymbol{\mu}}_c^{(h-1)}\right)\left(\overline{\mathbf{x}}_j - \widehat{\boldsymbol{\mu}}_c^{(h-1)}\right)'$$

$$\widehat{\boldsymbol{\mu}}_c^{(h)} = \left\{\sum_{j=1}^{m} N_j \left(\widehat{\boldsymbol{\Sigma}}_j^{(h)}\right)^{-1}\right\}^{-1} \left\{\sum_{j=1}^{m} N_j \left(\widehat{\boldsymbol{\Sigma}}_j^{(h)}\right)^{-1} \overline{\mathbf{x}}_j\right\}$$

The likelihood-ratio χ^2 statistic

$$\chi_{\text{mml}}^2 = \sum_{j=1}^{m} N_j \ln\left\{1 + \left(\overline{\mathbf{x}}_j - \widehat{\boldsymbol{\mu}}_c^{(h)}\right)'\left(\widehat{\boldsymbol{\Sigma}}_j^{(h)}\right)^{-1}\left(\overline{\mathbf{x}}_j - \widehat{\boldsymbol{\mu}}_c^{(h)}\right)\right\}$$

is approximately χ^2 distributed with $k(m-1)$ degrees of freedom.

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Also see

[MV] **hotelling** — Hotelling's T^2 generalized means test

[MV] **manova** — Multivariate analysis of variance and covariance

[R] **mean** — Estimate means

[R] **ttest** — t tests (mean-comparison tests)

Title

---

mvtest normality — Multivariate normality tests

Description

mvtest normality performs tests for univariate, bivariate, and multivariate normality.

See [MV] **mvtest** for more multivariate tests.

Quick start

Doornik–Hansen omnibus test for multivariate normality for v1, v2, v3, and v4

    mvtest normality v1 v2 v3 v4

Also show Henze–Zirkler's consistent test, Mardia's multivariate kurtosis test, and Mardia's multivariate skewness test

    mvtest normality v1 v2 v3 v4,   ///
        stats(dhansen hzirkler kurtosis skewness)

Same as above

    mvtest normality v1 v2 v3 v4, stats(all)

Also show Doornik–Hansen test for bivariate normality for each pair of variables

    mvtest normality v1 v2 v3 v4, stats(all) bivariate

Same as above, but show univariate normality tests from sktest instead of the bivariate tests

    mvtest normality v1 v2 v3 v4, stats(all) univariate

Show all multivariate, bivariate, and univariate tests of normality for v1, v2, v3, and v4

    mvtest normality v1 v2 v3 v4, stats(all) bivariate univariate

Menu

Statistics > Multivariate analysis > MANOVA, multivariate regression, and related > Multivariate test of means, covariances, and normality

Syntax

> mvtest normality *varlist* [*if*] [*in*] [*weight*] [, *options*]

options	Description
Options	
<u>univ</u>ariate	display tests for univariate normality (sktest)
<u>biv</u>ariate	display tests for bivariate normality (Doornik–Hansen)
<u>stat</u>s(*stats*)	statistics to be computed

stats	Description
<u>dh</u>ansen	Doornik–Hansen omnibus test; the default
<u>hz</u>irkler	Henze–Zirkler's consistent test
<u>kurt</u>osis	Mardia's multivariate kurtosis test
<u>skew</u>ness	Mardia's multivariate skewness test
all	all tests listed here

bootstrap, by, collect, jackknife, rolling, and statsby are allowed; see [U] **11.1.10 Prefix commands**.
Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.
aweights are not allowed with the jackknife prefix; see [R] **jackknife**.
fweights are allowed; see [U] **11.1.6 weight**.

Options

> ⌐Options⌐

univariate specifies that tests for univariate normality be displayed, as obtained from sktest; see
[R] **sktest**.

bivariate specifies that the Doornik–Hansen (2008) test for bivariate normality be displayed for
each pair of variables.

stats(*stats*) specifies one or more test statistics for multivariate normality. Multiple *stats* are separated
by white space. The following *stats* are available:

dhansen produces the Doornik–Hansen (2008) omnibus test.

hzirkler produces Henze–Zirkler's (1990) consistent test.

kurtosis produces the test based on Mardia's (1970) measure of multivariate kurtosis.

skewness produces the test based on Mardia's (1970) measure of multivariate skewness.

all is a convenient shorthand for stats(dhansen hzirkler kurtosis skewness).

Remarks and examples

Univariate and multivariate tests of normality are provided by the mvtest normality command.

▷ Example 1

The classic Fisher iris data from Anderson (1935) consists of four features measured on 50 samples from each of three iris species. The four features are the length and width of the sepal and petal. The three species are *Iris setosa*, *Iris versicolor*, and *Iris virginica*. We hypothesize that these features might be normally distributed within species, though they are likely not normally distributed across species. We will examine the *Iris setosa* data.

```
. use https://www.stata-press.com/data/r18/iris
(Iris data)
. kdensity petlen if iris==1, name(petlen, replace) title(Petal length)
. kdensity petwid if iris==1, name(petwid, replace) title(Petal width)
. kdensity sepwid if iris==1, name(sepwid, replace) title(Sepal width)
. kdensity seplen if iris==1, name(seplen, replace) title(Sepal length)
. graph combine petlen petwid seplen sepwid, title("Iris setosa data")
```


Iris setosa data
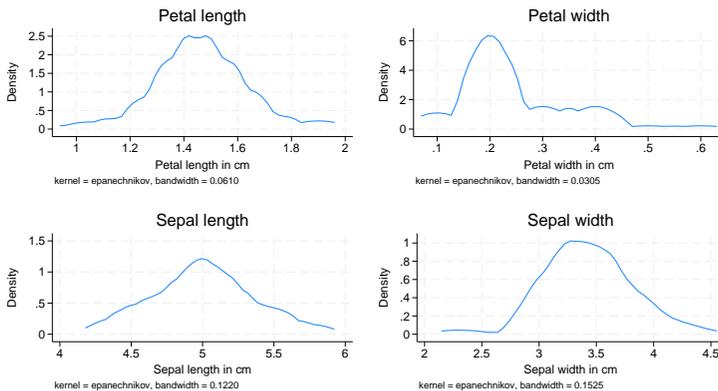
We perform all multivariate, univariate, and bivariate tests of normality.

```
. mvtest norm pet* sep* if iris==1, bivariate univariate stats(all)
```

Test for univariate normality

			joint	
Variable	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
petlen	0.7403	0.1447	2.36	0.3074
petwid	0.0010	0.0442	12.03	0.0024
seplen	0.7084	0.8157	0.19	0.9075
sepwid	0.8978	0.1627	2.07	0.3553

Doornik-Hansen test for bivariate normality

Pair of variables		chi2	df	Prob>chi2
petlen	petwid	17.47	4	0.0016
	seplen	5.76	4	0.2177
	sepwid	8.50	4	0.0748
petwid	seplen	14.97	4	0.0048
	sepwid	19.15	4	0.0007
seplen	sepwid	5.92	4	0.2049

Test for multivariate normality

Mardia mSkewness =	3.079721	chi2(20) =	27.860	Prob>chi2 =	0.1128
Mardia mKurtosis =	26.53766	chi2(1) =	1.677	Prob>chi2 =	0.1953
Henze-Zirkler =	.9488453	chi2(1) =	2.707	Prob>chi2 =	0.0999
Doornik-Hansen		chi2(8) =	24.414	Prob>chi2 =	0.0020

From the univariate tests of normality, `petwid` does not appear to be normally distributed: p-values of 0.0010 for skewness, 0.0442 for kurtosis, and 0.0024 for the joint univariate test. The univariate tests of the other three variables do not lead to a rejection of the null hypothesis of normality.

The bivariate tests of normality show a rejection (at the 5% level) of the null hypothesis of bivariate normality for all pairs of variables that include `petwid`. Other pairings fail to reject the null hypothesis of bivariate normality.

Of the four multivariate normality tests, only the Doornik–Hansen test rejects the null hypothesis of multivariate normality, p-value of 0.0020.

◁

The Doornik–Hansen (2008) test and Mardia's (1970) test for multivariate kurtosis take computing time roughly proportional to the number of observations. In contrast, the computing time of the test by Henze–Zirkler (1990) and Mardia's (1970) test for multivariate skewness are roughly proportional to the square of the number of observations.

Stored results

mvtest normality stores the following in r():

Scalars

r(p_dh)	p-value for Doornik–Hansen test (stats(dhansen))
r(df_dh)	degrees of freedom of chi2_dh (stats(dhansen))
r(chi2_dh)	Doornik–Hansen statistic (stats(dhansen))
r(rank_hz)	rank of covariance matrix (stats(hzirkler))
r(p_hz)	p-value for two-sided Henze–Zirkler's test (stats(hzirkler))
r(z_hz)	normal variate associated with hz (stats(hzirkler))
r(V_hz)	expected variance of log(hz) (stats(hzirkler))
r(E_hz)	expected value of log(hz) (stats(hzirkler))
r(hz)	Henze–Zirkler discrepancy statistic (stats(hzirkler))
r(rank_mkurt)	rank of covariance matrix (stats(kurtosis))
r(p_mkurt)	p-value for Mardia's multivariate kurtosis test (stats(kurtosis))
r(z_mkurt)	normal variate associated with Mardia mKurtosis (stats(kurtosis))
r(chi2_mkurt)	χ^2 of Mardia mKurtosis (stats(kurtosis))
r(mkurt)	Mardia mKurtosis test statistic (stats(kurtosis))
r(rank_mskew)	rank for Mardia mSkewness test (stats(skewness))
r(p_mskew)	p-value for Mardia's multivariate skewness test (stats(skewness))
r(df_mskew)	degrees of freedom of Mardia mSkewness test (stats(skewness))
r(chi2_mskew)	χ^2 of Mardia mSkewness test (stats(skewness))
r(mskew)	Mardia mSkewness test statistic (stats(skewness))

Matrices

r(U_dh)	matrix with the skewness and kurtosis of orthonormalized variables (used in the Doornik–Hansen test): b1, b2, z(b1), and z(b2) (stats(dhansen))
r(Btest)	bivariate test statistics (bivariate)
r(Utest)	univariate test statistics (univariate)

Methods and formulas

There are N independent k-variate observations, $\mathbf{x}_i$, $i = 1, \ldots, N$. Let $\mathbf{X}$ denote the $N \times k$ matrix of observations. We wish to test whether these observations are multivariate normal distributed, $\text{MVN}_k(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. The sample mean is $\overline{\mathbf{x}} = 1/N \sum_i \mathbf{x}_i$, and the sample covariance matrix is $\mathbf{S} = 1/N \sum (\mathbf{x}_i - \overline{\mathbf{x}})(\mathbf{x}_i - \overline{\mathbf{x}})'$.

Methods and formulas are presented under the following headings:

> *Mardia mSkewness and mKurtosis*
> *Henze–Zirkler*
> *Doornik–Hansen*

Mardia mSkewness and mKurtosis

Mardia (1970) defined multivariate skewness, $b_{1,k}$, and kurtosis, $b_{2,k}$, as

$$b_{1,k} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} g_{ij}^3 \qquad \text{and} \qquad b_{2,k} = \frac{1}{N} \sum_{i=1}^{N} g_{ii}^2$$

where $g_{ij} = (\mathbf{x}_i - \overline{\mathbf{x}})' \mathbf{S}^{-1} (\mathbf{x}_j - \overline{\mathbf{x}})$. The test statistic

$$z_1 = \frac{(k+1)(N+1)(N+3)}{6\{(N+1)(k+1) - 6\}} b_{1,k}$$

is approximately χ^2 distributed with $k(k+1)(k+2)/6$ degrees of freedom. The test statistic

$$z_2 = \frac{b_{2,k} - k(k+2)}{\sqrt{8k(k+2)/N}}$$

is approximately $N(0,1)$ distributed. Also see Rencher and Christensen (2012, 108); Mardia, Kent, and Bibby (1979, 20–22); and Seber (1984, 148–149).

Henze–Zirkler

The Henze–Zirkler (1990) test, under the assumption that $\mathbf{S}$ is nonsingular, is

$$T = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \exp\left\{ -\frac{\beta^2}{2}(\mathbf{x}_i - \mathbf{x}_j)'\mathbf{S}^{-1}(\mathbf{x}_i - \mathbf{x}_j) \right\}$$

$$- 2(1 + \beta^2)^{-k/2} \sum_{i=1}^{N} \exp\left\{ -\frac{\beta^2}{2(1+\beta^2)}(\mathbf{x}_i - \overline{\mathbf{x}})'\mathbf{S}^{-1}(\mathbf{x}_i - \overline{\mathbf{x}}) \right\}$$

$$+ N(1 + 2\beta^2)^{-k/2}$$

where

$$\beta = \frac{1}{\sqrt{2}} \left\{ \frac{N(2k+1)}{4} \right\}^{1/(k+4)}$$

As $N \to \infty$, the first two moments of T are given by

$$E(T) = 1 - (1 + 2\beta^2)^{-k/2} \left\{ 1 + \frac{k\beta^2}{1+2\beta^2} + \frac{k(k+2)\beta^4}{2(1+2\beta^2)^2} \right\}$$

$$\text{Var}(T) = 2(1 + 4\beta^2)^{-k/2} + 2(1+2\beta^2)^{-k} \left\{ 1 + \frac{2k\beta^4}{(1+2\beta^2)^2} + \frac{3k(k+2)\beta^8}{4(1+2\beta^2)^4} \right\}$$

$$- 4w^{-k/2} \left\{ 1 + \frac{3k\beta^4}{2w} + \frac{k(k+2)\beta^8}{2w^2} \right\}$$

where $w = (1 + \beta^2)(1 + 3\beta^2)$.

Henze–Zirkler suggest obtaining a p-value from the assumption, supported by a series of simulations, that T is approximately lognormal distributed. Thus let $VZ = \ln\left\{1 + \text{Var}(T)/E(T)^2\right\}$ and $EZ = \ln\left\{E(T)\right\} - VZ/2$. The transformation $Z = \left\{\ln(T) - EZ\right\}/\sqrt{VZ}$. The p-value of Z is computed as $p = 2\Phi(-|Z|)$, where $\Phi()$ is the cumulative normal distribution.

Doornik–Hansen

For the Doornik–Hansen (2008) test, the multivariate observations are transformed, then the univariate skewness and kurtosis for each transformed variable is computed, and then these are combined into an approximate χ^2 statistic.

Let $\mathbf{V}$ be a matrix with ith diagonal element equal to $S_{ii}^{-1/2}$, where S_{ii} is the ith diagonal element of $\mathbf{S}$. $\mathbf{C} = \mathbf{VSV}$ is then the correlation matrix. Let $\mathbf{H}$ be a matrix with columns equal to the eigenvectors of $\mathbf{C}$, and let $\mathbf{\Lambda}$ be a diagonal matrix with the corresponding eigenvalues. Let $\check{\mathbf{X}}$ be the centered version of $\mathbf{X}$, that is, $\overline{\mathbf{x}}$ subtracted from each row. The data are then transformed using $\dot{\mathbf{X}} = \check{\mathbf{X}}\mathbf{VH\Lambda}^{-1/2}\mathbf{H}'$.

The univariate skewness and kurtosis for each column of $\dot{\mathbf{X}}$ is then computed. The general formula for univariate skewness is $\sqrt{b_1} = m_3/m_2^{3/2}$ and kurtosis is $b_2 = m_4/m_2^2$, where $m_p = 1/N \sum_{i=1}^{N}(x_i - \overline{x})^p$. Let $\dot{x}_i$ denote the ith observation from the selected column of $\dot{\mathbf{X}}$. Because by construction the mean of $\dot{x}$ is zero and the variance m_2 is one, the formulas simplify to $\sqrt{b_1} = m_3$ and $b_2 = m_4$, where $m_p = 1/N \sum_{i=1}^{N} \dot{x}_i^p$.

The univariate skewness, $\sqrt{b_1}$, is transformed into an approximately normal variate, z_1, as in D'Agostino (1970):

$$z_1 = \delta \log\left(y + \sqrt{1 + y^2}\right)$$

where

$$y = \left\{ \frac{b_1(\omega^2 - 1)(N+1)(N+3)}{12(N-2)} \right\}^{1/2}$$

$$\delta = \left(\log\sqrt{\omega^2}\right)^{-1/2}$$

$$\omega^2 = -1 + \sqrt{2(\beta - 1)}$$

$$\beta = \frac{3(N^2 + 27N - 70)(N+1)(N+3)}{(N-2)(N+5)(N+7)(N+9)}$$

The univariate kurtosis, b_2, is transformed from a gamma variate into a χ^2-variate and then into a standard normal variable, z_2, using the Wilson–Hilferty (1931) transform:

$$z_2 = \sqrt{9\alpha}\left\{ \left(\frac{\chi}{2\alpha}\right)^{1/3} - 1 + \frac{1}{9\alpha} \right\}$$

where

$$\chi = 2f(b_2 - 1 - b_1)$$

$$\alpha = a + b_1 c$$

$$f = \frac{(N+5)(N+7)(N^3 + 37N^2 + 11N - 313)}{12\delta}$$

$$c = \frac{(N-7)(N+5)(N+7)(N^2 + 2N - 5)}{6\delta}$$

$$a = \frac{(N-2)(N+5)(N+7)(N^2 + 27N - 70)}{6\delta}$$

$$\delta = (N-3)(N+1)(N^2 + 15N - 4)$$

The z_1 and z_2 associated with the columns of $\dot{\mathbf{X}}$ are collected into vectors $\mathbf{Z}_1$ and $\mathbf{Z}_2$. The statistic $\mathbf{Z}_1'\mathbf{Z}_1 + \mathbf{Z}_2'\mathbf{Z}_2$ is approximately χ^2 distributed with $2k$ degrees of freedom.

Acknowledgment

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Also see

[R] **sktest** — Skewness and kurtosis tests for normality

[R] **swilk** — Shapiro–Wilk and Shapiro–Francia tests for normality

Title

pca — Principal component analysis

Description

pca and pcamat display the eigenvalues and eigenvectors from the principal component analysis (PCA) eigen decomposition. The eigenvectors are returned in orthonormal form, that is, uncorrelated and normalized.

pca can be used to reduce the number of variables or to learn about the underlying structure of the data. pcamat provides the correlation or covariance matrix directly. For pca, the correlation or covariance matrix is computed from the variables in *varlist*.

Quick start

Principal component analysis of data

Principal component analysis of v1, v2, v3, and v4
    pca v1 v2 v3 v4

Same as above, but retain only 2 components
    pca v1 v2 v3 v4, components(2)

Same as above, but retain only those components with eigenvalues greater than or equal to 0.5
    pca v1 v2 v3 v4, mineigen(.5)

Principal component analysis of covariance matrix instead of correlation matrix
    pca v1 v2 v3 v4, covariance

Principal component analysis of a correlation matrix

Principal component analysis of matrix C representing the correlations from 1,000 observations
    pcamat C, n(1000)

Same as above, but retain only 4 components
    pcamat C, n(1000) components(4)

Menu

pca

Statistics > Multivariate analysis > Factor and principal component analysis > Principal component analysis (PCA)

pcamat

Statistics > Multivariate analysis > Factor and principal component analysis > PCA of a correlation or covariance matrix

Syntax

Principal component analysis of data

> pca *varlist* [*if*] [*in*] [*weight*] [, *options*]

Principal component analysis of a correlation or covariance matrix

> pcamat *matname*, n(#) [*options pcamat_options*]

matname is a $k \times k$ symmetric matrix or a $k(k+1)/2$ long row or column vector containing the upper or lower triangle of the correlation or covariance matrix.

options	Description
Model 2	
components(#)	retain maximum of # principal components; factors() is a synonym
mineigen(#)	retain eigenvalues larger than #; default is 1e-5
correlation	perform PCA of the correlation matrix; the default
covariance	perform PCA of the covariance matrix
vce(none)	do not compute VCE of the eigenvalues and vectors; the default
vce(normal)	compute VCE of the eigenvalues and vectors assuming multivariate normality
Reporting	
level(#)	set confidence level; default is level(95)
blanks(#)	display loadings as blanks when |loadings| < #
novce	suppress display of SEs even though calculated
* means	display summary statistics of variables
Advanced	
tol(#)	advanced option; see *Options* for details
ignore	advanced option; see *Options* for details
norotated	display unrotated results, even if rotated results are available (replay only)

* means is not allowed with pcamat.

norotated is not shown in the dialog box.

pcamat_options	Description
Model	
shape(full)	*matname* is a square symmetric matrix; the default
shape(lower)	*matname* is a vector with the rowwise lower triangle (with diagonal)
shape(upper)	*matname* is a vector with the rowwise upper triangle (with diagonal)
names(*namelist*)	variable names; required if *matname* is triangular
forcepsd	modifies *matname* to be positive semidefinite
* n(#)	number of observations
sds(*matname₂*)	vector with standard deviations of variables
means(*matname₃*)	vector with means of variables

* n() is required for pcamat.

`bootstrap`, `by`, `collect`, `jackknife`, `rolling`, `statsby`, and `xi` are allowed with `pca`; see [U] **11.1.10 Prefix commands**. However, `bootstrap` and `jackknife` results should be interpreted with caution; identification of the `pca` parameters involves data-dependent restrictions, possibly leading to badly biased and overdispersed estimates (Milan and Whittaker 1995).

Weights are not allowed with the `bootstrap` prefix; see [R] **bootstrap**.

`aweights` are not allowed with the `jackknife` prefix; see [R] **jackknife**.

`aweights` and `fweights` are allowed with `pca`; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> ┌─ Model 2 ──

`components(#)` and `mineigen(#)` specify the maximum number of components (eigenvectors or factors) to be retained. `components()` specifies the number directly, and `mineigen()` specifies it indirectly, keeping all components with eigenvalues greater than the indicated value. The options can be specified individually, together, or not at all. `factors()` is a synonym for `components()`.

   `components(#)` sets the maximum number of components (factors) to be retained. `pca` and `pcamat` always display the full set of eigenvalues but display eigenvectors only for retained components. Specifying a number larger than the number of variables in *varlist* is equivalent to specifying the number of variables in *varlist* and is the default.

   `mineigen(#)` sets the minimum value of eigenvalues to be retained. The default is `1e-5` or the value of `tol()` if specified.

   Specifying `components()` and `mineigen()` affects only the number of components to be displayed and stored in `e()`; it does not enforce the assumption that the other eigenvalues are 0. In particular, the standard errors reported when `vce(normal)` is specified do not depend on the number of retained components.

`correlation` and `covariance` specify that principal components be calculated for the correlation matrix and covariance matrix, respectively. The default is `correlation`. Unlike factor analysis, PCA is not scale invariant; the eigenvalues and eigenvectors of a covariance matrix differ from those of the associated correlation matrix. Usually, a PCA of a covariance matrix is meaningful only if the variables are expressed in the same units.

   For `pcamat`, do not confuse the type of the matrix to be analyzed with the type of *matname*. Obviously, if *matname* is a correlation matrix and the option `sds()` is not specified, it is not possible to perform a PCA of the covariance matrix.

`vce(none | normal)` specifies whether standard errors are to be computed for the eigenvalues, the eigenvectors, and the (cumulative) percentage of explained variance (confirmatory PCA). These standard errors are obtained assuming multivariate normality of the data and are valid only for a PCA of a covariance matrix. Be cautious if applying these to correlation matrices.

> ┌─ Reporting ──

`level(#)` specifies the confidence level, as a percentage, for confidence intervals. The default is `level(95)` or as set by `set level`; see [U] **20.8 Specifying the width of confidence intervals**. `level()` is allowed only with `vce(normal)`.

`blanks(#)` shows blanks for loadings with absolute value smaller than #. This option is ignored when specified with `vce(normal)`.

`novce` suppresses the display of standard errors, even though they are computed, and displays the PCA results in a matrix/table style. You can specify `novce` during estimation in combination with `vce(normal)`. More likely, you will want to use `novce` during replay.

means displays summary statistics of the variables over the estimation sample. This option is not available with pcamat.

tol(#) is an advanced, rarely used option and is available only with vce(normal). An eigenvalue, ev_i, is classified as being close to zero if $ev_i <$ tol $\times$ max(ev). Two eigenvalues, ev_1 and ev_2, are "close" if abs($ev_1 - ev_2$) $<$ tol $\times$ max(ev). The default is tol(1e-5). See option ignore below and the technical note later in this entry.

ignore is an advanced, rarely used option and is available only with vce(normal). It continues the computation of standard errors and tests, even if some eigenvalues are suspiciously close to zero or suspiciously close to other eigenvalues, violating crucial assumptions of the asymptotic theory used to estimate standard errors and tests. See the technical note later in this entry.

The following option is available with pca and pcamat but is not shown in the dialog box:

norotated displays the unrotated principal components, even if rotated components are available. This option may be specified only when replaying results.

Options unique to pcamat

shape(*shape_arg*) specifies the shape (storage mode) for the covariance or correlation matrix *matname*. The following shapes are supported:

full specifies that the correlation or covariance structure of k variables is stored as a symmetric $k \times k$ matrix. Specifying shape(full) is optional in this case.

lower specifies that the correlation or covariance structure of k variables is stored as a vector with $k(k + 1)/2$ elements in rowwise lower-triangular order:

$$C_{11}\ C_{21}\ C_{22}\ C_{31}\ C_{32}\ C_{33}\ \ldots\ C_{k1}\ C_{k2}\ \ldots\ C_{kk}$$

upper specifies that the correlation or covariance structure of k variables is stored as a vector with $k(k + 1)/2$ elements in rowwise upper-triangular order:

$$C_{11}\ C_{12}\ C_{13}\ \ldots\ C_{1k}\ C_{22}\ C_{23}\ \ldots C_{2k}\ \ldots\ C_{(k-1k-1)}\ C_{(k-1k)}\ C_{kk}$$

names(*namelist*) specifies a list of k different names, which are used to document output and to label estimation results and are used as variable names by predict. By default, pcamat verifies that the row and column names of *matname* and the column or row names of *matname₂* and *matname₃* from the sds() and means() options are in agreement. Using the names() option turns off this check.

forcepsd modifies the matrix *matname* to be positive semidefinite (psd) and so to be a proper covariance matrix. If *matname* is not positive semidefinite, it will have negative eigenvalues. By setting negative eigenvalues to 0 and reconstructing, we obtain the least-squares positive-semidefinite approximation to *matname*. This approximation is a singular covariance matrix.

n(#) is required and specifies the number of observations.

sds(*matname₂*) specifies a $k \times 1$ or $1 \times k$ matrix with the standard deviations of the variables. The row or column names should match the variable names, unless the names() option is specified. sds() may be specified only if *matname* is a correlation matrix.

means(*matname*$_3$) specifies a $k{\times}1$ or $1{\times}k$ matrix with the means of the variables. The row or column names should match the variable names, unless the names() option is specified. Specify means() if you have variables in your dataset and want to use predict after pcamat.

Remarks and examples

Principal component analysis (PCA) is commonly thought of as a statistical technique for data reduction. It helps you reduce the number of variables in an analysis by describing a series of uncorrelated linear combinations of the variables that contain most of the variance. In addition to data reduction, the eigenvectors from a PCA are often inspected to learn more about the underlying structure of the data.

PCA originated with the work of Pearson (1901) and Hotelling (1933). For an introduction, see van Belle, Fisher, Heagerty, and Lumley (2004) or Afifi et al. (2020). More advanced treatments are Mardia, Kent, and Bibby (1979, chap. 8), and Rencher and Christensen (2012, chap. 12). For monograph-sized treatments, including extensive discussions of the relationship between PCA and related approaches, see Jackson (2003) and Jolliffe (2002).

The objective of PCA is to find unit-length ($\mathbf{L}'\mathbf{L} = \mathbf{I}$) linear combinations of the variables with the greatest variance. The first principal component has maximal overall variance. The second principal component has maximal variance among all unit-length linear combinations that are uncorrelated to the first principal component, etc. The last principal component has the smallest variance among all unit-length linear combinations of the variables. All principal components combined contain the same information as the original variables, but the important information is partitioned over the components in a particular way: the components are orthogonal, and earlier components contain more information than later components. PCA thus conceived is just a linear transformation of the data. It does not assume that the data satisfy a specific statistical model, though it does require that the data be interval-level data—otherwise taking linear combinations is meaningless.

PCA is scale dependent. The principal components of a covariance matrix and those of a correlation matrix are different. In applied research, PCA of a covariance matrix is useful only if the variables are expressed in commensurable units.

❑ Technical note

Principal components have several useful properties. Some of these are geometric. Both the principal components and the principal scores are uncorrelated (orthogonal) among each other. The f leading principal components have maximal generalized variance among all f unit-length linear combinations.

It is also possible to interpret PCA as a fixed-effects factor analysis with homoskedastic residuals

$$y_{ij} = \mathbf{a}'_i\mathbf{b}_j + e_{ij} \qquad i = 1, \ldots, n \qquad j = 1, \ldots, p$$

where y_{ij} are the elements of the matrix $\mathbf{Y}$, $\mathbf{a}_i$ (scores) and $\mathbf{b}_j$ (loadings) are f-vectors of parameters, and e_{ij} are independent homoskedastic residuals. (In factor analysis, the scores $\mathbf{a}_i$ are random rather than fixed, and the residuals are allowed to be heteroskedastic in j.) It follows that $E(\mathbf{Y})$ is a matrix of rank f, with f typically substantially less than n or p. Thus we may think of PCA as a regression model with a restricted number but unknown independent variables. We may also say that the expected values of the rows (or columns) of $\mathbf{Y}$ are in some unknown f-dimensional space.

For more information on these properties and for other characterizations of PCA, see Jackson (2003) and Jolliffe (2002).

❑

▷ Example 1: Principal component analysis of audiometric data

We consider a dataset of audiometric measurements on 100 males, age 39. The measurements are minimal discernible intensities at four different frequencies with the left and right ear (see Jackson 2003, 106). The variable lft1000 refers to the left ear at 1,000 Hz.

```
. use https://www.stata-press.com/data/r18/audiometric
(Audiometric measures)

. correlate lft* rght*
(obs=100)
```

	lft500	lft1000	lft2000	lft4000	rght500	rght1000	rght2000
lft500	1.0000						
lft1000	0.7775	1.0000					
lft2000	0.4012	0.5366	1.0000				
lft4000	0.2554	0.2749	0.4250	1.0000			
rght500	0.6963	0.5515	0.2391	0.1790	1.0000		
rght1000	0.6416	0.7070	0.4460	0.2632	0.6634	1.0000	
rght2000	0.2372	0.3597	0.7011	0.3165	0.1589	0.4142	1.0000
rght4000	0.2041	0.2169	0.3262	0.7097	0.1321	0.2201	0.3746

	rght4000
rght4000	1.0000

As you may have expected, measurements on the same ear are more highly correlated than measurements on different ears. Also, measurements on different ears at the same frequency are more highly correlated than at different frequencies. Because the variables are in commensurable units, it would make theoretical sense to analyze the covariance matrix of these variables. However, the variances of the measures differ widely:

```
. summarize lft* rght*, sep(4)
```

Variable	Obs	Mean	Std. dev.	Min	Max
lft500	100	-2.8	6.408643	-10	15
lft1000	100	-.5	7.571211	-10	20
lft2000	100	2	10.94061	-10	45
lft4000	100	21.35	19.61569	-10	70
rght500	100	-2.6	7.123726	-10	25
rght1000	100	-.7	6.396811	-10	20
rght2000	100	1.6	9.289942	-10	35
rght4000	100	21.35	19.33039	-10	75

In an analysis of the covariances, the higher frequency measures would dominate the results. There is no clinical reason for such an effect (see also Jackson [2003]). Therefore, we will analyze the correlation matrix.

```
. pca lft* rght*
```

Principal components/correlation

			Number of obs	=	100
			Number of comp.	=	8
			Trace	=	8
Rotation: (unrotated = principal)			Rho	=	1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.92901	2.31068	0.4911	0.4911
Comp2	1.61832	.642997	0.2023	0.6934
Comp3	.975325	.508543	0.1219	0.8153
Comp4	.466782	.126692	0.0583	0.8737
Comp5	.34009	.0241988	0.0425	0.9162
Comp6	.315891	.11578	0.0395	0.9557
Comp7	.200111	.0456375	0.0250	0.9807
Comp8	.154474	.	0.0193	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6
lft500	0.4011	-0.3170	0.1582	-0.3278	0.0231	0.4459
lft1000	0.4210	-0.2255	-0.0520	-0.4816	-0.3792	-0.0675
lft2000	0.3664	0.2386	-0.4703	-0.2824	0.4392	-0.0638
lft4000	0.2809	0.4742	0.4295	-0.1611	0.3503	-0.4169
rght500	0.3433	-0.3860	0.2593	0.4876	0.4975	0.1948
rght1000	0.4114	-0.2318	-0.0289	0.3723	-0.3513	-0.6136
rght2000	0.3115	0.3171	-0.5629	0.3914	-0.1108	0.2650
rght4000	0.2542	0.5135	0.4262	0.1591	-0.3960	0.3660

Variable	Comp7	Comp8	Unexplained
lft500	0.3293	-0.5463	0
lft1000	-0.0331	0.6227	0
lft2000	-0.5255	-0.1863	0
lft4000	0.4269	0.0839	0
rght500	-0.1594	0.3425	0
rght1000	-0.0837	-0.3614	0
rght2000	0.4778	0.1466	0
rght4000	-0.4139	-0.0508	0

pca shows two panels. The first panel lists the eigenvalues of the correlation matrix, ordered from largest to smallest. The corresponding eigenvectors are listed in the second panel. These are the principal components and have unit length; the columnwise sum of the squares of the loadings is 1 $(0.4011^2 + 0.4210^2 + \cdots + 0.2542^2 = 1)$.

Remark: Literature and software that treat principal components in combination with factor analysis tend to display principal components normed to the associated eigenvalues rather than to 1. This normalization is available in the postestimation command estat loadings; see [MV] **pca postestimation**.

The eigenvalues add up to the sum of the variances of the variables in the analysis—the "total variance" of the variables. Because we are analyzing a correlation matrix, the variables are standardized to have unit variance, so the total variance is 8. The eigenvalues are the variances of the principal components. The first principal component has variance 3.93, explaining 49% (3.93/8) of the total variance. The second principal component has variance 1.62 or 20% (1.62/8) of the total variance. Principal components are uncorrelated. You may want to verify that; for instance,

$$0.4011(-0.3170) + 0.4210(-0.2255) + \cdots + 0.2542(0.5135) = 0$$

As a consequence, we may also say that the first two principal components explain the sum of the variances of the individual components, or $49 + 20 = 69\%$ of the total variance. Had the components been correlated, they would have partly represented the same information, so the information contained in the combination would not have been equal to the sum of the information of the components. All eight principal components combined explain all variance in all variables; therefore, the unexplained variances listed in the second panel are all zero, and Rho $= 1.00$ as shown above the first panel.

More than 85% of the variance is contained in the first four principal components. We can list just these components with the option components(4).

```
. pca lft* rght*, components(4)
Principal components/correlation                Number of obs    =       100
                                                Number of comp.  =         4
                                                Trace            =         8
      Rotation: (unrotated = principal)         Rho              =    0.8737
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.92901	2.31068	0.4911	0.4911
Comp2	1.61832	.642997	0.2023	0.6934
Comp3	.975325	.508543	0.1219	0.8153
Comp4	.466782	.126692	0.0583	0.8737
Comp5	.34009	.0241988	0.0425	0.9162
Comp6	.315891	.11578	0.0395	0.9557
Comp7	.200111	.0456375	0.0250	0.9807
Comp8	.154474	.	0.0193	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
lft500	0.4011	-0.3170	0.1582	-0.3278	.1308
lft1000	0.4210	-0.2255	-0.0520	-0.4816	.1105
lft2000	0.3664	0.2386	-0.4703	-0.2824	.1275
lft4000	0.2809	0.4742	0.4295	-0.1611	.1342
rght500	0.3433	-0.3860	0.2593	0.4876	.1194
rght1000	0.4114	-0.2318	-0.0289	0.3723	.1825
rght2000	0.3115	0.3171	-0.5629	0.3914	.07537
rght4000	0.2542	0.5135	0.4262	0.1591	.1303

The first panel is not affected. The second panel now lists the first four principal components. These four components do not contain all information in the data, and therefore some of the variances in the variables are unaccounted for or unexplained. These equal the sums of squares of the loadings in the deleted components, weighted by the associated eigenvalues. The unexplained variances in all variables are of similar order. The average unexplained variance is equal to the overall unexplained variance of 13% $(1 - 0.87)$.

Look more closely at the principal components. The first component has positive loadings of roughly equal size on all variables. It can be interpreted as overall sensitivity of a person's ears. The second principal component has positive loadings on the higher frequencies with both ears and negative loadings for the lower frequencies. Thus the second principal component distinguishes sensitivity for higher frequencies versus lower frequencies. The third principal component similarly differentiates sensitivity at medium frequencies from sensitivity at other frequencies. Finally, the fourth principal component has negative loadings on the left ear and positive loadings on the right ear; it differentiates the left and right ear.

We stated earlier that the first principal component had similar loadings on all eight variables. This can be tested if we are willing to assume that the data are multivariate normal distributed. For this case, pca can estimate the standard errors and related statistics. To conserve paper, we request only the results of the first two principal components and specify the option vce(normal).

```
. pca l* r*, comp(2) vce(normal)
(with PCA/correlation, SEs and tests are approximate)
Principal components/correlation                Number of obs    =         100
                                                Number of comp.  =           2
                                                Trace            =           8
                                                Rho              =      0.6934
SEs assume multivariate normality               SE(Rho)          =      0.0273
```

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Eigenvalues						
Comp1	3.929005	.5556453	7.07	0.000	2.839961	5.01805
Comp2	1.618322	.2288653	7.07	0.000	1.169754	2.066889
Comp1						
lft500	.4010948	.0429963	9.33	0.000	.3168236	.485366
lft1000	.4209908	.0359372	11.71	0.000	.3505551	.4914264
lft2000	.3663748	.0463297	7.91	0.000	.2755702	.4571794
lft4000	.2808559	.0626577	4.48	0.000	.1580491	.4036628
rght500	.343251	.0528285	6.50	0.000	.2397091	.446793
rght1000	.4114209	.0374312	10.99	0.000	.3380571	.4847846
rght2000	.3115483	.0551475	5.65	0.000	.2034612	.4196354
rght4000	.2542212	.066068	3.85	0.000	.1247303	.3837121
Comp2						
lft500	-.3169638	.067871	-4.67	0.000	-.4499885	-.1839391
lft1000	-.225464	.0669887	-3.37	0.001	-.3567595	-.0941686
lft2000	.2385933	.1079073	2.21	0.027	.0270989	.4500877
lft4000	.4741545	.0967918	4.90	0.000	.284446	.6638629
rght500	-.3860197	.0803155	-4.81	0.000	-.5434352	-.2286042
rght1000	-.2317725	.0674639	-3.44	0.001	-.3639994	-.0995456
rght2000	.317059	.1215412	2.61	0.009	.0788427	.5552752
rght4000	.5135121	.0951842	5.39	0.000	.3269544	.7000697

```
LR test for independence:       chi2(28)  =      448.21   Prob > chi2 =   0.0000
LR test for    sphericity:       chi2(35)  =      451.11   Prob > chi2 =   0.0000
```

Explained variance by components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	3.929005	0.4911	0.0394	0.4911	0.0394	.056663
Comp2	1.618322	0.2023	0.0271	0.6934	0.0273	.015812
Comp3	.9753248	0.1219	0.0178	0.8153	0.0175	-.014322
Comp4	.4667822	0.0583	0.0090	0.8737	0.0127	.007304
Comp5	.34009	0.0425	0.0066	0.9162	0.0092	.026307
Comp6	.3158912	0.0395	0.0062	0.9557	0.0055	-.057717
Comp7	.2001111	0.0250	0.0040	0.9807	0.0031	-.013961
Comp8	.1544736	0.0193	0.0031	1.0000	0.0000	-.020087

Here pca acts like an estimation command. The output is organized in different equations. The first equation contains the eigenvalues. The second equation named, Comp1, is the first principal component, etc. pca reports, for instance, standard errors of the eigenvalues. Although testing the values of eigenvalues may, up to now, be rare in applied research, interpretation of results should take stability into consideration. It makes little sense to report the first eigenvalue as 3.929 if you see that the standard error is 0.56.

pca has also reported the standard errors of the principal components. It has also estimated the covariances.

```
. estat vce
  (output omitted)
```

Showing the large amount of information contained in the VCE matrix is not useful by itself. The fact that it has been estimated, however, enables us to test properties of the principal components. Does it make good sense to talk about the loadings of the first principal component being of the same size? We use `testparm` with two options; see [R] **test**. `eq(Comp1)` specifies that we are testing coefficients for equation `Comp1`, that is, the first principal component. `equal` specifies that instead of testing that the coefficients are zero, we want to test that the coefficients are equal to each other—a more sensible hypothesis because principal components are normalized to 1.

```
. testparm lft* rght*, equal eq(Comp1)
 ( 1)  - [Comp1]lft500 + [Comp1]lft1000 = 0
 ( 2)  - [Comp1]lft500 + [Comp1]lft2000 = 0
 ( 3)  - [Comp1]lft500 + [Comp1]lft4000 = 0
 ( 4)  - [Comp1]lft500 + [Comp1]rght500 = 0
 ( 5)  - [Comp1]lft500 + [Comp1]rght1000 = 0
 ( 6)  - [Comp1]lft500 + [Comp1]rght2000 = 0
 ( 7)  - [Comp1]lft500 + [Comp1]rght4000 = 0

        chi2(  7) =     7.56
      Prob > chi2 =    0.3729
```

We cannot reject the null hypothesis of equal loadings, so our interpretation of the first component does not seem to conflict with the data.

pca also displays standard errors of the proportions of variance explained by the leading principal components. Again this information is useful primarily to indicate the strength of formulations of results rather than to test hypotheses about these statistics. The information is also useful to compare studies: if in one study the leading two principal components explain 70% of variance, whereas in a replicating study they explain 80%, are these differences significant given the sampling variation?

Because pca is an estimation command just like `regress` or `xtlogit`, you may replay the output by typing just pca. If you have used pca with the `vce(normal)` option, you may use the option `novce` at estimation or during replay to display the standard PCA output.

```
. pca, novce
Principal components/correlation                 Number of obs    =        100
                                                 Number of comp.  =          2
                                                 Trace            =          8
        Rotation: (unrotated = principal)        Rho              =     0.6934
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.92901	2.31068	0.4911	0.4911
Comp2	1.61832	.642997	0.2023	0.6934
Comp3	.975325	.508543	0.1219	0.8153
Comp4	.466782	.126692	0.0583	0.8737
Comp5	.34009	.0241988	0.0425	0.9162
Comp6	.315891	.11578	0.0395	0.9557
Comp7	.200111	.0456375	0.0250	0.9807
Comp8	.154474	.	0.0193	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Unexplained
lft500	0.4011	-0.3170	.2053
lft1000	0.4210	-0.2255	.2214
lft2000	0.3664	0.2386	.3805
lft4000	0.2809	0.4742	.3262
rght500	0.3433	-0.3860	.2959
rght1000	0.4114	-0.2318	.248
rght2000	0.3115	0.3171	.456
rght4000	0.2542	0.5135	.3193

◁

❑ Technical note

Inference on the eigenvalues and eigenvectors of a covariance matrix is based on a series of assumptions:

(A1) The variables are multivariate normal distributed.

(A2) The variance–covariance matrix of the observations has all distinct and strictly positive eigenvalues.

Under assumptions A1 and A2, the eigenvalues and eigenvectors of the sample covariance matrix can be seen as maximum likelihood estimates for the population analogues that are asymptotically (multivariate) normally distributed (Anderson 1963; Jackson 2003). See Tyler (1981) for related results for elliptic distributions. Be cautious when interpreting because the asymptotic variances are rather sensitive to violations of assumption A1 (and A2). Wald tests of hypotheses that are in conflict with assumption A2 (for example, testing that the first and second eigenvalues are the same) produce incorrect p-values.

Because the statistical theory for a PCA of a correlation matrix is much more complicated, pca and pcamat compute standard errors and tests of a correlation matrix as if it were a covariance matrix. This practice is in line with the application of asymptotic theory in Jackson (2003). This will usually lead to some underestimation of standard errors, but we believe that this problem is smaller than the consequences of deviations from normality.

You may conduct tests for multivariate normality using the mvtest normality command (see [MV] **mvtest normality**):

```
. mvtest normality lft* rght*, stats(all)

Test for multivariate normality

    Mardia mSkewness =  14.52785    chi2(120) =  251.052   Prob>chi2 =  0.0000
    Mardia mKurtosis =  94.53331      chi2(1) =   33.003   Prob>chi2 =  0.0000
    Henze-Zirkler    =   1.272529     chi2(1) =  118.563   Prob>chi2 =  0.0000
    Doornik-Hansen                   chi2(16) =   95.318   Prob>chi2 =  0.0000
```

These tests cast serious doubt on the multivariate normality of the variables. We advise caution in interpreting the inference results. Time permitting, you may want to turn to bootstrap methods for inference on the principal components and eigenvalues, but you should be aware of some serious identification problems in using the bootstrap here (Milan and Whittaker 1995).

❑

▷ Example 2: Analyzing the covariance instead of the correlation

We remarked before that the principal components of a correlation matrix are generally different from the principal components of a covariance matrix. pca defaults to performing the PCA of the correlation matrix. To obtain a PCA of the covariance matrix, specify the `covariance` option.

```
. pca l* r*, comp(4) covariance
```

Principal components/covariance			Number of obs	=	100
			Number of comp.	=	4
			Trace	=	1154.5
Rotation: (unrotated = principal)			Rho	=	0.9396

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	706.795	527.076	0.6122	0.6122
Comp2	179.719	68.3524	0.1557	0.7679
Comp3	111.366	24.5162	0.0965	0.8643
Comp4	86.8501	57.4842	0.0752	0.9396
Comp5	29.366	9.53428	0.0254	0.9650
Comp6	19.8317	6.67383	0.0172	0.9822
Comp7	13.1578	5.74352	0.0114	0.9936
Comp8	7.41432	.	0.0064	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
lft500	0.0835	0.2936	-0.0105	0.3837	7.85
lft1000	0.1091	0.3982	0.0111	0.3162	11.71
lft2000	0.2223	0.5578	0.0558	-0.4474	11.13
lft4000	0.6782	-0.1163	-0.7116	-0.0728	.4024
rght500	0.0662	0.2779	-0.0226	0.4951	12.42
rght1000	0.0891	0.3119	0.0268	0.2758	11.14
rght2000	0.1707	0.3745	0.2721	-0.4496	14.71
rght4000	0.6560	-0.3403	0.6441	0.1550	.4087

As expected, the results are less clear. The total variance to be analyzed is 1,154.5; this is the sum of the variances of the eight variables, that is, the trace of the covariance matrix. The leading principal components now account for a larger fraction of the variance; this is often the case with covariance matrices where the variables have widely different variances. The principal components are somewhat harder to interpret; mainly the loadings are no longer of roughly comparable size.

◁

▷ Example 3: PCA directly from a correlation matrix

Sometimes you do not have the original data but have only the correlation or covariance matrix. pcamat performs a PCA for such a matrix. To simplify presentation, we use the data on the left ear.

```
. correlate lft*, cov
(obs=100)
```

	lft500	lft1000	lft2000	lft4000
lft500	41.0707			
lft1000	37.7273	57.3232		
lft2000	28.1313	44.4444	119.697	
lft4000	32.101	40.8333	91.2121	384.775

Suppose that we have the covariances of the variables but not the original data. `correlate` stores the covariances in `r(C)`, so we can use that matrix and invoke `pcamat` with the options `n(100)`, specifying the number of observations, and `names()`, providing the variable names.

```
. matrix Cfull = r(C)
. pcamat Cfull, comp(2) n(100) names(lft500 lft1000 lft2000 lft4000)
Principal components/correlation                    Number of obs    =        100
                                                    Number of comp.  =          2
                                                    Trace            =          4
       Rotation: (unrotated = principal)            Rho              =     0.8169
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.37181	1.47588	0.5930	0.5930
Comp2	.895925	.366238	0.2240	0.8169
Comp3	.529687	.327106	0.1324	0.9494
Comp4	.202581	.	0.0506	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Unexplained
lft500	0.5384	-0.4319	.1453
lft1000	0.5730	-0.3499	.1116
lft2000	0.4958	0.2955	.3387
lft4000	0.3687	0.7770	.1367

If we had to type in the covariance matrix, to avoid excess typing `pcamat` allows you to provide the covariance (or correlation) matrix with just the upper or lower triangular elements including the diagonal. (Thus, for correlations, you have to enter the 1s for the diagonal.) For example, we could enter the lower triangle of our covariance matrix row by row up to and including the diagonal as a one-row Stata matrix.

```
. matrix Clow = (41.0707, 37.7273, 57.3232, 28.1313, 44.4444,
>                119.697, 32.101,  40.8333, 91.2121, 384.775)
```

The matrix `Clow` has one row and 10 columns. To make seeing the structure easier, we prefer to enter these numbers in the following way:

```
. matrix Clow = (41.0707,
>                37.7273, 57.3232,
>                28.1313, 44.4444, 119.697,
>                32.101,  40.8333, 91.2121, 384.775)
```

When using the lower or upper triangle stored in a row or column vector, it is not possible to define the variable names as row or column names of the matrix; the option `names()` is required. Moreover, we have to specify the option `shape(lower)` to inform `pcamat` that the vector contains the lower triangle, not the upper triangle.

```
. pcamat Clow, comp(2) shape(lower) n(100) names(lft500 lft1000 lft2000 lft4000)
  (output omitted )
```

◁

Stored results

pca and pcamat without the vce(normal) option store the following in e():

Scalars
e(N)	number of observations
e(f)	number of retained components
e(rho)	fraction of explained variance
e(trace)	trace of e(C)
e(lndet)	ln of the determinant of e(C)
e(cond)	condition number of e(C)

Macros
e(cmd)	pca (even for pcamat)
e(cmdline)	command as typed
e(Ctype)	correlation or covariance
e(wtype)	weight type
e(wexp)	weight expression
e(title)	title in output
e(properties)	nob noV eigen
e(rotate_cmd)	program used to implement rotate
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(C)	$p \times p$ correlation or covariance matrix
e(means)	$1 \times p$ matrix of means
e(sds)	$1 \times p$ matrix of standard deviations
e(Ev)	$1 \times p$ matrix of eigenvalues (sorted)
e(L)	$p \times f$ matrix of eigenvectors = components
e(Psi)	$1 \times p$ matrix of unexplained variance

Functions
e(sample)	marks estimation sample

pca and pcamat with the vce(normal) option store the above, as well as the following:

Scalars
e(v_rho)	variance of e(rho)
e(chi2_i)	χ^2 statistic for test of independence
e(df_i)	degrees of freedom for test of independence
e(p_i)	p-value for test of independence
e(chi2_s)	χ^2 statistic for test of sphericity
e(df_s)	degrees of freedom for test of sphericity
e(p_s)	p-value for test of sphericity
e(rank)	rank of e(V)

Macros
e(vce)	multivariate normality
e(properties)	b V eigen

Matrices
e(b)	$1 \times p + fp$ coefficient vector (all eigenvalues and retained eigenvectors)
e(Ev_bias)	$1 \times p$ matrix: bias of eigenvalues
e(Ev_stats)	$p \times 5$ matrix with statistics on explained variance
e(V)	variance–covariance matrix of the estimates e(b)

Methods and formulas

Methods and formulas are presented under the following headings:

> Notation
> Inference on eigenvalues and eigenvectors
> More general tests for multivariate normal distributions

Notation

Let $\mathbf{C}$ be the $p \times p$ correlation or covariance matrix to be analyzed. The spectral or eigen decomposition of $\mathbf{C}$ is

$$\mathbf{C} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}' = \sum_{i=1}^{p} \lambda_i \mathbf{v}_i \mathbf{v}_i'$$

$$\mathbf{v}_i' \mathbf{v}_j = \delta_{ij} \qquad \text{(that is, orthonormality)}$$

$$\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$$

The eigenvectors $\mathbf{v}_i$ are also known as the principal components. The direction (sign) of principal components is not defined. pca returns principal components signed so that $\mathbf{1}'\mathbf{v}_i > 0$. In PCA, "total variance" equals $\text{trace}(\mathbf{C}) = \sum \lambda_j$.

Inference on eigenvalues and eigenvectors

The asymptotic distribution of the eigenvectors $\widehat{\mathbf{v}}_i$ and eigenvalues $\widehat{\lambda}_i$ of a covariance matrix $\mathbf{S}$ for a sample from a multivariate normal distribution $N(\mu, \mathbf{\Sigma})$ was derived by Girshick (1939); for more results, see also Anderson (1963) and Jackson (2003). Higher-order expansions are discussed in Lawley (1956). See Tyler (1981) for related results for elliptic distributions. The theory of the exact distribution is rather complicated (Muirhead 1982, chap. 9) and hard to implement. If we assume that eigenvalues of $\mathbf{\Sigma}$ are distinct and strictly positive, the eigenvalues and eigenvectors of $\mathbf{S}$ are jointly asymptotically multivariate normal distributed with the following moments (up to order n^{-3}):

$$E(\widehat{\lambda}_i) = \lambda_i \left\{ 1 + \frac{1}{n} \sum_{j \neq i}^{k} \left(\frac{\lambda_j}{\lambda_i - \lambda_j} \right) \right\} + O(n^{-3})$$

$$\text{Var}(\widehat{\lambda}_i) = \frac{2\lambda_i^2}{n} \left\{ 1 - \frac{1}{n} \sum_{j \neq i}^{k} \left(\frac{\lambda_j}{\lambda_i - \lambda_j} \right)^2 \right\} + O(n^{-3})$$

$$\text{Cov}(\widehat{\lambda}_i, \widehat{\lambda}_j) = \frac{2}{n^2} \left(\frac{\lambda_i \lambda_j}{\lambda_i - \lambda_j} \right)^2 + O(n^{-3})$$

$$\text{Var}(\widehat{\mathbf{v}}_i) = \frac{1}{n} \sum_{j \neq i}^{k} \frac{\lambda_i \lambda_j}{(\lambda_i - \lambda_j)^2} \mathbf{v}_j \mathbf{v}_j'$$

$$\text{Cov}(\widehat{\mathbf{v}}_i, \widehat{\mathbf{v}}_j) = -\frac{1}{n} \frac{\lambda_i \lambda_j}{(\lambda_i - \lambda_j)^2} \mathbf{v}_i \mathbf{v}_j'$$

For the asymptotic theory of the cumulative proportion of variance explained, see Kshirsagar (1972, 454).

More general tests for multivariate normal distributions

The likelihood-ratio χ^2 test of independence (Basilevsky 1994, 187) is

$$\chi^2 = -\left(n - \frac{2p+5}{6}\right) \ln\{\det(\mathbf{C})\}$$

with $p(p-1)/2$ degrees of freedom.

The likelihood-ratio χ^2 test of sphericity (Basilevsky 1994, 192) is

$$\chi^2 = -\left(n - \frac{2p^2+p+2}{6p}\right)\left[\ln\{\det(\widetilde{\mathbf{\Lambda}})\} - p\ln\left\{\frac{\text{trace}(\widetilde{\mathbf{\Lambda}})}{p}\right\}\right]$$

with $(p+2)(p-1)/2$ degrees of freedom and with $\widetilde{\mathbf{\Lambda}}$ the eigenvalues of the correlation matrix.

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Also see

[MV] **pca postestimation** — Postestimation tools for pca and pcamat

[MV] **alpha** — Compute interitem correlations (covariances) and Cronbach's alpha

[MV] **biplot** — Biplots

[MV] **canon** — Canonical correlations

[MV] **factor** — Factor analysis

[D] **corr2data** — Create dataset with specified correlation structure

[R] **tetrachoric** — Tetrachoric correlations for binary variables

[U] **20 Estimation and postestimation commands**

Title

Postestimation commands

The following postestimation commands are of special interest after pca and pcamat:

Command	Description
estat anti	anti-image correlation and covariance matrices
estat kmo	Kaiser–Meyer–Olkin measure of sampling adequacy
estat loadings	component-loading matrix in one of several normalizations
estat residuals	matrix of correlation or covariance residuals
estat rotatecompare	compare rotated and unrotated components
estat smc	squared multiple correlations between each variable and the rest
*estat summarize	display summary statistics over the estimation sample
loadingplot	plot component loadings
rotate	rotate component loadings
scoreplot	plot score variables
screeplot	plot eigenvalues

*estat summarize is not available after pcamat.

The following standard postestimation commands are also available:

Command	Description
†estat vce	variance–covariance matrix of the estimators (VCE)
estimates	cataloging estimation results
etable	table of estimation results
*lincom	point estimates, standard errors, testing, and inference for linear combinations of coefficients
*nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients
predict	score variables, fitted values, and residuals
*predictnl	point estimates, standard errors, testing, and inference for generalized predictions
*test	Wald tests of simple and composite linear hypotheses
*testnl	Wald tests of nonlinear hypotheses

†estat vce is available after pca and pcamat with the vce(normal) option.

*lincom, nlcom, predictnl, test, and testnl are available only after pca with the vce(normal) option.

predict

Description for predict

predict creates new variables containing predictions such as scores, fitted values, raw residuals, and residual sums of squares.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] {*stub**|*newvarlist*} [*if*] [*in*] [, *statistic options*]

statistic	# of vars.	Description (k = # of orig. vars.; f = # of components)
Main		
score	$1, \ldots, f$	scores based on the components; the default
fit	k	fitted values using the retained components
residual	k	raw residuals from the fit using the retained components
q	1	residual sums of squares

options	Description
Main	
norotated	use unrotated results, even when rotated results are available
center	base scores on centered variables
notable	suppress table of scoring coefficients
format(*%fmt*)	format for displaying the scoring coefficients

Options for predict

Note on pcamat: predict requires that variables with the correct names be available in memory. Apart from centered scores, means() should have been specified with pcamat. If you used pcamat because you have access only to the correlation or covariance matrix, you cannot use predict.

    Main

score calculates the scores for components $1, \ldots, \#$, where $\#$ is the number of variables in *newvarlist*.

fit calculates the fitted values, using the retained components, for each variable. The number of variables in *newvarlist* should equal the number of variables in the *varlist* of pca; see [MV] **pca**.

residual calculates for each variable the raw residuals (residual = observed − fitted), with the fitted values computed using the retained components.

q calculates the Rao statistics (that is, the sums of squares of the omitted components) weighted by the respective eigenvalues. This equals the residual sums of squares between the original variables and the fitted values.

norotated uses unrotated results, even when rotated results are available.

center bases scores on centered variables. This option is relevant only for a PCA of a covariance matrix, in which the scores are based on uncentered variables by default. Scores for a PCA of a correlation matrix are always based on the standardized variables.

notable suppresses the table of scoring coefficients.

format(% *fmt*) specifies the display format for scoring coefficients. The default is format(%8.4f).

estat

Description for estat

estat anti displays the anti-image correlation and anti-image covariance matrices. These are minus the partial covariance and minus the partial correlation of all pairs of variables, holding all other variables constant.

estat kmo displays the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy. KMO takes values between 0 and 1, with small values indicating that overall the variables have too little in common to warrant a PCA. Historically, the following labels are given to values of KMO (Kaiser 1974):

0.00 to 0.49	unacceptable
0.50 to 0.59	miserable
0.60 to 0.69	mediocre
0.70 to 0.79	middling
0.80 to 0.89	meritorious
0.90 to 1.00	marvelous

estat loadings displays the component-loading matrix in one of several normalizations of the columns (eigenvectors).

estat residuals displays the difference between the observed correlation or covariance matrix and the fitted (reproduced) matrix using the retained factors.

estat rotatecompare displays the unrotated (principal) components next to the most recent rotated components.

estat smc displays the squared multiple correlations between each variable and all other variables. SMC is a theoretical lower bound for communality and thus an upper bound for the unexplained variance.

estat summarize displays summary statistics of the variables in the principal component analysis over the estimation sample. This subcommand is not available after pcamat.

Menu for estat

Statistics > Postestimation

Syntax for estat

Display the anti-image correlation and covariance matrices

    estat anti [, nocorr nocov <u>for</u>mat(%*fmt*)]

Display the Kaiser–Meyer–Olkin measure of sampling adequacy

    estat kmo [, <u>nov</u>ar <u>for</u>mat(%*fmt*)]

Display the component-loading matrix

    estat <u>load</u>ings [, <u>c</u>norm(<u>unit</u> | <u>eigen</u> | <u>inv</u>eigen) <u>for</u>mat(%*fmt*)]

Display the differences in matrices

    estat <u>res</u>iduals [, <u>o</u>bs <u>f</u>itted <u>for</u>mat(%*fmt*)]

Display the unrotated and rotated components

    estat <u>rota</u>tecompare [, <u>for</u>mat(%*fmt*)]

Display the squared multiple correlations

    estat smc [, <u>for</u>mat(%*fmt*)]

Display the summary statistics

    estat <u>sum</u>marize [, <u>labels</u> <u>noheader</u> <u>noweights</u>]

collect is allowed with estat anti, estat kmo, estat loadings, estat residuals, estat smc, and estat
    summarize; see [U] **11.1.10 Prefix commands**.

Options for estat

nocorr, an option used with estat anti, suppresses the display of the anti-image correlation matrix,
that is, minus the partial correlation matrix of all pairs of variables, holding constant all other
variables.

nocov, an option used with estat anti, suppresses the display of the anti-image covariance matrix,
that is, minus the partial covariance matrix of all pairs of variables, holding constant all other
variables.

format(%*fmt*) specifies the display format. The defaults differ between the subcommands.

novar, an option used with estat kmo, suppresses the Kaiser–Meyer–Olkin measures of sampling
adequacy for the variables in the principal component analysis, displaying the overall KMO measure
only.

cnorm(unit | eigen | inveigen), an option used with estat loadings, selects the normaliza-
tion of the eigenvectors, the columns of the principal-component loading matrix. The following
normalizations are available

unit	ssq(column) = 1; the default
eigen	ssq(column) = eigenvalue
inveigen	ssq(column) = 1/eigenvalue

with ssq(column) being the sum of squares of the elements in a column and eigenvalue, the eigenvalue associated with the column (eigenvector).

obs, an option used with estat residuals, displays the observed correlation or covariance matrix for which the PCA was performed.

fitted, an option used with estat residuals, displays the fitted (reconstructed) correlation or covariance matrix based on the retained components.

labels, noheader, and noweights are the same as for the generic estat summarize command; see [R] **estat summarize**.

Remarks and examples

After computing the principal components and the associated eigenvalues, you have more issues to resolve. How many components do you want to retain? How well is the correlation or covariance matrix approximated by the retained components? How can you interpret the principal components? Is it possible to improve the interpretability by rotating the retained principal components? And, when these issues have been settled, the component scores are probably needed for later research.

The rest of this entry describes the specific tools available for these purposes.

Remarks are presented under the following headings:

> *Postestimation statistics*
> *Plots of eigenvalues, component loadings, and scores*
> *Rotating the components*
> *How rotate interacts with pca*
> *Predicting the component scores*

In addition to these specific postestimation tools, general tools are available as well. pca is an estimation command, so it is possible to manage a series of PCA analyses with the estimates command; see [R] **estimates**. If you have specified the vce(normal) option, pca has stored the coefficients e(b) and the associated variance–covariance matrix e(V), and you can use standard Stata commands to test hypotheses about the principal components and eigenvalues ("confirmatory principal component analysis"), for instance, with the test, lincom, and testnl commands. We caution you to test only hypotheses that do not violate the assumptions of the theory underlying the derivation of the covariance matrix. In particular, all eigenvalues are assumed to be different and strictly positive. Thus it makes no sense to use test to test the hypothesis that the smallest four eigenvalues are equal (let alone that they are equal to zero.)

Postestimation statistics

pca displays the principal components in unit normalization; the sum of squares of the principal loadings equals 1. This parallels the standard conventions in mathematics concerning eigenvectors. Some texts and some software use a different normalization. Some texts multiply the eigenvectors by the square root of the eigenvalues. In this normalization, the sum of the squared loadings equals the variance explained by that component. estat loadings can display the loadings in this normalization.

```
. use https://www.stata-press.com/data/r18/audiometric
(Audiometric measures)
. pca l* r*, comp(4)
  (output omitted)
```

```
. estat loadings, cnorm(eigen)
```

Principal component loadings (unrotated)
    component normalization: sum of squares(column) = eigenvalue

	Comp1	Comp2	Comp3	Comp4
lft500	.795	-.4032	.1562	-.2239
lft1000	.8345	-.2868	-.05132	-.3291
lft2000	.7262	.3035	-.4645	-.193
lft4000	.5567	.6032	.4242	-.1101
rght500	.6804	-.4911	.2561	.3331
rght1000	.8155	-.2948	-.0285	.2544
rght2000	.6175	.4033	-.5559	.2674
rght4000	.5039	.6533	.4209	.1087

How close the retained principal components approximate the correlation matrix can be seen from the fitted (reconstructed) correlation matrix and from the residuals, that is, the difference between the observed and fitted correlations.

```
. estat residual, fit format(%7.3f)
```

Fitted correlation matrix

Variable	lft500	lft1000	lft2000	lft4000	rght500
lft500	0.869				
lft1000	0.845	0.890			
lft2000	0.426	0.606	0.872		
lft4000	0.290	0.306	0.412	0.866	
rght500	0.704	0.586	0.162	0.155	0.881
rght1000	0.706	0.683	0.467	0.236	0.777
rght2000	0.182	0.340	0.778	0.322	0.169
rght4000	0.179	0.176	0.348	0.841	0.166

Variable	rg~1000	rg~2000	rg~4000
rght1000	0.818		
rght2000	0.469	0.925	
rght4000	0.234	0.370	0.870

```
Residual correlation matrix
```

Variable	lft500	lft1000	lft2000	lft4000	rght500
lft500	0.131				
lft1000	-0.067	0.110			
lft2000	-0.024	-0.070	0.128		
lft4000	-0.035	-0.031	0.013	0.134	
rght500	-0.008	-0.034	0.077	0.024	0.119
rght1000	-0.064	0.024	-0.021	0.027	-0.114
rght2000	0.056	0.020	-0.076	-0.005	-0.010
rght4000	0.025	0.041	-0.022	-0.131	-0.034

Variable	rg~1000	rg~2000	rg~4000
rght1000	0.182		
rght2000	-0.054	0.075	
rght4000	-0.014	0.005	0.130

All off diagonal residuals are small, except perhaps the two measurements at the highest frequency.

estat also provides some of the standard methods for studying correlation matrices to assess whether the variables have strong linear relations with each other. In a sense, these methods could be seen as preestimation rather than as postestimation methods. The first method is the inspection of the squared multiple correlation (the regression R^2) of each variable on all other variables.

```
. estat smc
Squared multiple correlations of variables with all other variables
```

Variable	smc
lft500	0.7113
lft1000	0.7167
lft2000	0.6229
lft4000	0.5597
rght500	0.5893
rght1000	0.6441
rght2000	0.5611
rght4000	0.5409

The SMC measures help identify variables that cannot be explained well from the other variables. For such variables, you should reevaluate whether they should be included in the analysis. In our examples, none of the SMCs are so small as to warrant exclusion. Two other statistics are offered. First, we can inspect the anti-image correlation and covariance matrices, that is, the negative of correlations (covariances) of the variables partialing out all other variables. If many of these correlations or covariances are "high", the relationships between some of the variables have little to do with the other variables, indicating that it will not be possible to obtain a low-dimensional reduction of the data.

```
. estat anti, nocov format(%7.3f)
Anti-image correlation coefficients ——— partialing out all other variables
```

Variable	lft500	lft1000	lft2000	lft4000	rght500	rg~1000
lft500	1.000					
lft1000	-0.561	1.000				
lft2000	-0.051	-0.267	1.000			
lft4000	-0.014	0.026	-0.285	1.000		
rght500	-0.466	0.131	0.064	-0.017	1.000	
rght1000	0.023	-0.389	0.043	-0.042	-0.441	1.000
rght2000	0.085	0.068	-0.617	0.161	0.067	-0.248
rght4000	-0.047	-0.002	0.150	-0.675	0.019	0.023

Variable	rg~2000	rg~4000
rght2000	1.000	
rght4000	-0.266	1.000

The Kaiser–Meyer–Olkin measure of sampling adequacy compares the correlations and the partial correlations between variables. If the partial correlations are relatively high compared to the correlations, the KMO measure is small, and a low-dimensional representation of the data is not possible.

```
. estat kmo
Kaiser-Meyer-Olkin measure of sampling adequacy
```

Variable	kmo
lft500	0.7701
lft1000	0.7767
lft2000	0.7242
lft4000	0.6449
rght500	0.7562
rght1000	0.8168
rght2000	0.6673
rght4000	0.6214
Overall	0.7328

Using the Kaiser (1974) characterization of KMO values,

|	
0.00 to 0.49	unacceptable
0.50 to 0.59	miserable
0.60 to 0.69	mediocre
0.70 to 0.79	middling
0.80 to 0.89	meritorious
0.90 to 1.00	marvelous

we declare our KMO value, 0.73, middling.

Plots of eigenvalues, component loadings, and scores

After computing the principal components, we probably wish to determine how many components to keep. In factor analysis the question of the "true" number of factors is a complicated one. With PCA, it is a little more straightforward. We may set a percentage of variance we wish to account for, say, 90%, and retain just enough components to account for at least that much of the variance. Usually you will want to weigh the costs associated with using more components in later analyses against the benefits of the extra variance they account for. The relative magnitudes of the eigenvalues indicate the amount of variance they account for. A useful tool for visualizing the eigenvalues relative to one another, so that you can decide the number of components to retain, is the scree plot proposed by Cattell (1966); see [MV] **screeplot**.

```
. screeplot, mean
```
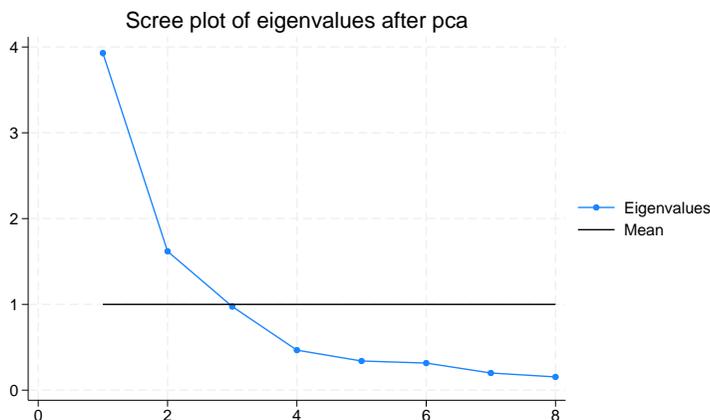

Because we are analyzing a correlation matrix, the mean eigenvalue is 1. We wish to retain the components associated with the high part of the scree plot and drop the components associated with the lower flat part of the scree plot. The boundary between high and low is not clear here, but we would choose two or three components, although the fourth component had the nice interpretation of the left versus the right ear; see [MV] **pca**.

A problem in interpreting the scree plot is that no guidance is given with respect to its stability under sampling. How different could the plot be with different samples? The approximate variance of an eigenvalue $\widehat{\lambda}$ of a covariance matrix for multivariate normal distributed data is $2\lambda^2/n$. From this we can derive confidence intervals for the eigenvalues. These scree plot confidence intervals aid in the selection of important components.

```
. screeplot, ci
(caution is advised in interpreting an asymptotic theory-based confidence
 interval of eigenvalues of a correlation matrix)
```


Scree plot of eigenvalues after pca
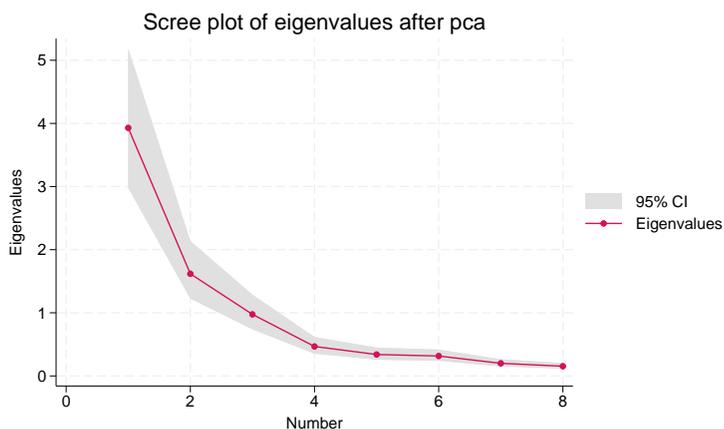
Despite our appreciation of the underlying interpretability of the fourth component, the evidence still points to retaining two or three principal components.

Plotting the components is sometimes useful in interpreting a PCA. We may look at the components from the perspective of the columns (variables) or the rows (observations). The associated plots are produced by the commands loadingplot (variables) and scoreplot (observations).

By default, the first two components are used to produce the loading plot.

```
. loadingplot
```


Component loadings
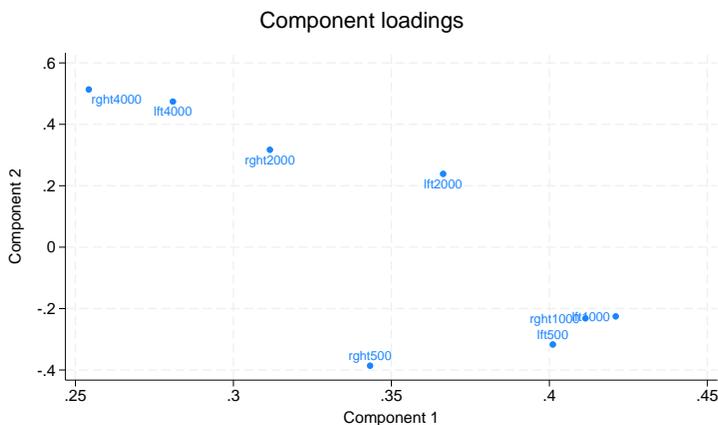
You may request more components, in which case each possible pair of requested components will be graphed. You can choose between a matrix or combined graph layout for the multiple graphs. Here we show the combined layout.

```
. loadingplot, comp(3) combined
```


Component loadings
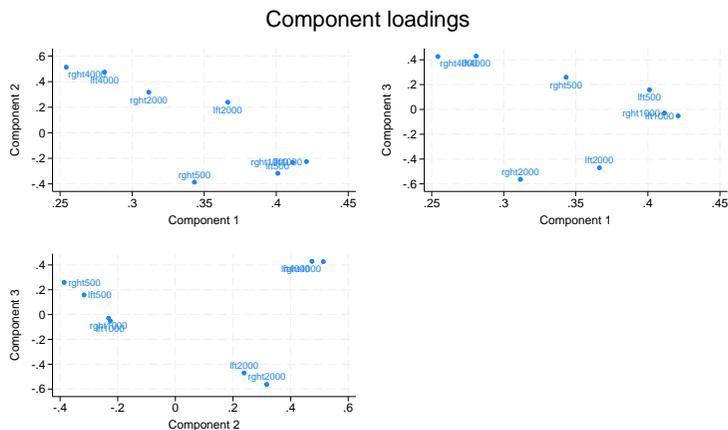
Score plots approach the display of principal components from the perspective of the observations. `scoreplot` and `loadingplot` have most of their options in common; see [MV] **scoreplot**. Unlike `loadingplot`, which automatically uses the variable names as marker labels, with `scoreplot` you use the `mlabel()` graph option to provide meaningful marker labels. Score plots are especially helpful if the observations are well-known objects, such as countries, firms, or brands. The score plot may help you visualize the principal components with your background knowledge of these objects. Score plots are sometimes useful for detecting outliers; see Jackson (2003).

❑ Technical note

In [MV] **pca**, we noted that PCA may also be interpreted as fixed-effects factor analysis; in that interpretation, the selection of the number of components to be retained is of comparable complexity as in factor analysis.

❑

Rotating the components

Rotating principal components is a disputed issue and one in which reasonable people may disagree. `pca` computes the principal components. Rotating the solution destroys some of the properties of principal components. In particular, the first rotated component no longer has maximal variance, the second rotated component no longer has maximal variance among those linear combinations uncorrelated to the first component, etc. If preserving the maximal variance property is very important to your interpretations, do not rotate.

On the other hand, when we rotate, say, the leading three principal components, the total variance explained by the three rotated components is equal to the variance explained by the three principal components. If you applied an orthogonal rotation, the rotated components are still uncorrelated. The only thing that has changed is that the explanation is distributed differently among the three rotated components. If the rotated components have a clearer interpretation, you may actually prefer to use them in your subsequent work.

After `pca`, a wide variety of rotations are available; see [MV] **rotate**. The default method of rotation is varimax, rotating the principal components to maximize the sum over the columns of the within-column variances.

```
. rotate
```

Principal components/correlation

```
Number of obs     =       100
Number of comp.   =         4
Trace             =         8
```
Rotation: orthogonal varimax (Kaiser off)   Rho   =   0.8737

Component	Variance	Difference	Proportion	Cumulative
Comp1	2.11361	.400444	0.2642	0.2642
Comp2	1.71316	.118053	0.2141	0.4783
Comp3	1.59511	.0275517	0.1994	0.6777
Comp4	1.56756	.	0.1959	0.8737

Rotated components

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
lft500	0.5756	0.0265	-0.1733	0.1781	.1308
lft1000	0.6789	-0.0289	-0.0227	-0.0223	.1105
lft2000	0.3933	0.0213	0.5119	-0.2737	.1275
lft4000	0.1231	0.6987	-0.0547	-0.0885	.1342
rght500	-0.0005	0.0158	-0.0380	0.7551	.1194
rght1000	0.0948	-0.0248	0.2289	0.5481	.1825
rght2000	-0.1173	-0.0021	0.8047	0.0795	.07537
rght4000	-0.1232	0.7134	0.0550	0.0899	.1303

Component rotation matrix

	Comp1	Comp2	Comp3	Comp4
Comp1	0.6663	0.3784	0.4390	0.4692
Comp2	-0.3055	0.6998	0.4012	-0.5059
Comp3	-0.0657	0.6059	-0.7365	0.2936
Comp4	-0.6770	-0.0022	0.3224	0.6616

rotate now labels one of the columns of the first table as "Variance" instead of "Eigenvalue"; the rotated components have been ordered in decreasing order of variance. The variance explained by the four rotated components equals 87.37%, which is identical to the explained variance by the four leading principal components. But whereas the principal components have rather dispersed eigenvalues, the four rotated components all explain about the same fraction of the variance.

You may also choose to rotate only a few of the retained principal components. In contrast to most methods of factor analysis, the principal components are not affected by the number of retained components. However, the first two rotated components are different if you are rotating all four components or only the leading two or three principal components.

```
. rotate, comp(3)
```

Principal components/correlation			Number of obs	=	100
			Number of comp.	=	4
			Trace	=	8
Rotation: orthogonal varimax (Kaiser off)			Rho	=	0.8737

Component	Variance	Difference	Proportion	Cumulative
Comp1	2.99422	1.16842	0.3743	0.3743
Comp2	1.8258	.123163	0.2282	0.6025
Comp3	1.70264	1.23585	0.2128	0.8153
Comp4	.466782	.	0.0583	0.8737

Rotated components

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
lft500	0.5326	-0.0457	0.0246	-0.3278	.1308
lft1000	0.4512	0.1618	-0.0320	-0.4816	.1105
lft2000	0.0484	0.6401	0.0174	-0.2824	.1275
lft4000	0.0247	0.0011	0.6983	-0.1611	.1342
rght500	0.5490	-0.1799	0.0163	0.4876	.1194
rght1000	0.4521	0.1368	-0.0259	0.3723	.1825
rght2000	-0.0596	0.7148	-0.0047	0.3914	.07537
rght4000	-0.0200	0.0059	0.7138	0.1591	.1303

Component rotation matrix

	Comp1	Comp2	Comp3	Comp4
Comp1	0.7790	0.5033	0.3738	0.0000
Comp2	-0.5932	0.3987	0.6994	0.0000
Comp3	0.2030	-0.7666	0.6092	-0.0000
Comp4	0.0000	-0.0000	-0.0000	1.0000

The three-component varimax-rotated solution differs from the leading three components from the four component varimax-rotated solution. The fourth component is not affected by a rotation among the leading three component—it is still the fourth principal component.

So, how interpretable are rotated components? We believe that for this example the original components had a much clearer interpretation than the rotated components. Notice how the clear symmetry in the treatment of left and right ears has been broken.

To add further to an already controversial method, we may use oblique rotation methods. An example is the oblique oblimin method.

```
. rotate, oblimin oblique
```

Principal components/correlation			Number of obs	=	100
			Number of comp.	=	4
			Trace	=	8
Rotation: oblique oblimin (Kaiser off)			Rho	=	0.8737

Component	Variance	Proportion	Rotated comp. are correlated
Comp1	2.21066	0.2763	
Comp2	1.71164	0.2140	
Comp3	1.69708	0.2121	
Comp4	1.62592	0.2032	

```
Rotated components
```

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
lft500	0.5834	0.0259	0.1994	-0.1649	.1308
lft1000	0.6797	-0.0292	0.0055	-0.0157	.1105
lft2000	0.3840	0.0216	-0.2489	0.5127	.1275
lft4000	0.1199	0.6988	-0.0857	-0.0545	.1342
rght500	0.0261	0.0146	0.7561	-0.0283	.1194
rght1000	0.1140	-0.0257	0.5575	0.2370	.1825
rght2000	-0.1158	-0.0022	0.0892	0.8048	.07537
rght4000	-0.1209	0.7134	0.0848	0.0549	.1303

```
Component rotation matrix
```

	Comp1	Comp2	Comp3	Comp4
Comp1	0.6836	0.3773	0.5053	0.4523
Comp2	-0.3250	0.7008	-0.5137	0.3916
Comp3	-0.0550	0.6054	0.2774	-0.7337
Comp4	-0.6557	-0.0029	0.6408	0.3238

The oblique rotation methods do not change the variance that is unexplained by the components. But this time, the rotated components are no longer uncorrelated. This makes measuring the importance of the rotated components more ambiguous, a problem that is similar to ambiguities in interpreting importance of correlated independent variables. In this oblique case, the sum of the variances of the rotated components equals 90.6% $(0.2763 + 0.2140 + 0.2121 + 0.2032)$ of the total variance. This is larger than the 87.37% of variance explained by the four principal components. The oblique rotated components partly explain the same variance, and this shared variance is entering multiple times into the total.

How rotate interacts with pca

rotate stores the rotated component loadings and associated statistics in e(), the estimation storage area, along with the regular pca estimation results. Replaying pca will display the rotated results again.

Other postestimation statistics also use the rotated results whenever this is meaningful. For instance, loadingplot would display the rotated loadings. These postestimation commands have an option norotated that specifies that the unrotated results, that is, the principal components, be used. Thus

```
. pca, norotated
(output omitted)
```

displays the standard pca output for the unrotated (principal) solution, and

```
. loadingplot, norotated
(output omitted)
```

produces the loading plot for the unrotated (principal) solution.

If you execute rotate again, the new rotate results are stored with the pca estimation, replacing the previous rotate results. Thus pca knows about at most one rotation.

To compare rotated and unrotated results, it is of course possible to replay the rotated results (pca) and unrotated results (pca, norotate) consecutively. You would especially seek to compare the loadings. Such a comparison is easier if the loadings are displayed in parallel. This feature is provided with the estat command rotatecompare.

```
. estat rotatecompare
```

Rotation matrix — oblique oblimin (Kaiser off)

Variable	Comp1	Comp2	Comp3	Comp4
Comp1	0.6836	0.3773	0.5053	0.4523
Comp2	-0.3250	0.7008	-0.5137	0.3916
Comp3	-0.0550	0.6054	0.2774	-0.7337
Comp4	-0.6557	-0.0029	0.6408	0.3238

Rotated component loadings

Variable	Comp1	Comp2	Comp3	Comp4
lft500	0.5834	0.0259	0.1994	-0.1649
lft1000	0.6797	-0.0292	0.0055	-0.0157
lft2000	0.3840	0.0216	-0.2489	0.5127
lft4000	0.1199	0.6988	-0.0857	-0.0545
rght500	0.0261	0.0146	0.7561	-0.0283
rght1000	0.1140	-0.0257	0.5575	0.2370
rght2000	-0.1158	-0.0022	0.0892	0.8048
rght4000	-0.1209	0.7134	0.0848	0.0549

Unrotated component loadings

Variable	Comp1	Comp2	Comp3	Comp4
lft500	0.4011	-0.3170	0.1582	-0.3278
lft1000	0.4210	-0.2255	-0.0520	-0.4816
lft2000	0.3664	0.2386	-0.4703	-0.2824
lft4000	0.2809	0.4742	0.4295	-0.1611
rght500	0.3433	-0.3860	0.2593	0.4876
rght1000	0.4114	-0.2318	-0.0289	0.3723
rght2000	0.3115	0.3171	-0.5629	0.3914
rght4000	0.2542	0.5135	0.4262	0.1591

Finally, sometimes you may want to remove rotation results permanently; for example, you decide to continue with the unrotated (principal) solution. Because all postestimation commands operate on the rotated solution by default, you would have to add the option `norotated` over and over again. Instead, you can remove the rotated solution with the command

```
. rotate, clear
```

❑ Technical note

pca results may be stored and restored with `estimates`, just like other estimation results. If you have stored PCA estimation results without rotated results, and later `rotate` the solution, the rotated results are not automatically stored as well. The pca would need to be stored again.

❑

Predicting the component scores

After deciding on the number of components and, possibly, the rotation of the components, you may want to estimate the component scores for all respondents. To estimate only the first component scores, which here is called pc1:

```
. predict pc1
(score assumed)
(3 components skipped)

Scoring coefficients
    sum of squares(column-loading) = 1
```

Variable	Comp1	Comp2	Comp3	Comp4
lft500	0.4011	-0.3170	0.1582	-0.3278
lft1000	0.4210	-0.2255	-0.0520	-0.4816
lft2000	0.3664	0.2386	-0.4703	-0.2824
lft4000	0.2809	0.4742	0.4295	-0.1611
rght500	0.3433	-0.3860	0.2593	0.4876
rght1000	0.4114	-0.2318	-0.0289	0.3723
rght2000	0.3115	0.3171	-0.5629	0.3914
rght4000	0.2542	0.5135	0.4262	0.1591

The table is informing you that pc1 could be obtained as a weighted sum of standardized variables,

```
. egen std_lft500   = std(lft500)
. egen std_lft1000  = std(lft1000)
. egen std_rght4000 = std(rght4000)
. gen pc1 = 0.4011*std_lft500 + 0.4210*std_lft1000 + ... + 0.2542*std_rght4000
```

(egen's std() function converts a variable to its standardized form (mean 0, variance 1); see [D] **egen**.) The principal-component scores are in standardized units after a PCA of a correlation matrix and in the original units after a PCA of a covariance matrix.

It is possible to predict other statistics as well. For instance, the fitted values of the eight variables by the first four principal components are obtained as

```
. predict f_1-f_8, fit
```

The predicted values are in the units of the original variables, with the means substituted back in. If we had retained all eight components, the fitted values would have been identical to the observations.

❑ Technical note

The fitted values are meaningful in the interpretation of PCA as rank-restricted multivariate regression. The component scores are the "x variables"; the component loadings are the regression coefficients. If the PCA was computed for a correlation matrix, you could think of the regression as being in standardized units. The fitted values are transformed from the standardized units back to the original units.
                                                                                                                            ❑

❑ Technical note

You may have observed that the scoring coefficients were equal to the component loadings. This holds true for the principal components in unit normalization and for the orthogonal rotations thereof; it does not hold for oblique rotations.
                                                                                                                            ❑

Stored results

Let p be the number of variables and f, the number of factors.

`predict`, in addition to generating variables, also stores the following in `r()`:

Matrices
    `r(scoef)` $p \times f$ matrix of scoring coefficients

`estat anti` stores the following in `r()`:

Matrices
    `r(acov)` $p \times p$ anti-image covariance matrix
    `r(acorr)` $p \times p$ anti-image correlation matrix

`estat kmo` stores the following in `r()`:

Scalars
    `r(kmo)`   the Kaiser–Meyer–Olkin measure of sampling adequacy

Matrices
    `r(kmow)`   column vector of KMO measures for each variable

`estat loadings` stores the following in `r()`:

Macros
    `r(cnorm)`   component normalization: `eigen`, `inveigen`, or `unit`

Matrices
    `r(A)` $p \times f$ matrix of normalized component loadings

`estat residuals` stores the following in `r()`:

Matrices
    `r(fit)` $p \times p$ matrix of fitted values
    `r(residual)` $p \times p$ matrix of residuals

`estat smc` stores the following in `r()`:

Matrices
    `r(smc)`   vector of squared multiple correlations of variables with all other variables

See the returned results of `estat summarize` in [R] **estat summarize** and of `estat vce` in [R] **estat vce** (available when `vce(normal)` is specified with `pca` or `pcamat`).

`rotate` after `pca` and `pcamat` add to the existing `e()`:

Scalars
    `e(r_f)`   number of components in rotated solution
    `e(r_fmin)`   rotation criterion value

Macros
    `e(r_class)`   `orthogonal` or `oblique`
    `e(r_criterion)`   rotation criterion
    `e(r_ctitle)`   title for rotation
    `e(r_normalization)` `kaiser` or `none`

Matrices
    `e(r_L)`   rotated loadings
    `e(r_T)`   rotation
    `e(r_Ev)`   explained variance by rotated components

The components in the rotated solution are in decreasing order of `e(r_Ev)`.

Methods and formulas

estat anti computes and displays the anti-image covariance matrix $\mathbf{C}$ and the anti-image correlation matrix $\mathbf{A}$

$$\mathbf{C} = \{\text{diag}(\mathbf{R})\}^{-1/2} \, \mathbf{R} \, \{\text{diag}(\mathbf{R})\}^{-1/2}$$

$$\mathbf{A} = \{\text{diag}(\mathbf{R})\}^{-1} \, \mathbf{R} \, \{\text{diag}(\mathbf{R})\}^{-1}$$

where $\mathbf{R}$ is the inverse of the correlation matrix.

estat kmo computes the "Kaiser–Meyer–Olkin measure of sampling adequacy" (KMO) and is defined as

$$\text{KMO} = \frac{\sum_{\mathcal{S}} r_{ij}^2}{\sum_{\mathcal{S}} (a_{ij}^2 + r_{ij}^2)}$$

where $\mathcal{S} = (i, j; i \neq j)$; r_{ij} is the correlation of variables i and j; and a_{ij} is the anti-image correlation. The variable-wise measure KMO_i is defined analogously as

$$\text{KMO}_i = \frac{\sum_{\mathcal{P}} r_{ij}^2}{\sum_{\mathcal{P}} (a_{ij}^2 + r_{ij}^2)}$$

where $\mathcal{P} = (j; i \neq j)$.

estat loadings displays the component loadings in different normalizations (see Jackson [2003, 16–18]; he labels them as $\mathbf{U}$, $\mathbf{V}$, and $\mathbf{W}$ vectors). Let $\mathbf{C} = \mathbf{L}\mathbf{\Lambda}\mathbf{L}'$ be the spectral or eigen decomposition of the analyzed correlation or covariance matrix $\mathbf{C}$, with $\mathbf{L}$ the orthonormal eigenvectors of $\mathbf{C}$, and $\mathbf{\Lambda}$ a diagonal matrix of eigenvalues. The principal components $\mathbf{A}$, that is, the eigenvectors $\mathbf{L}$, are displayed in one of the following normalizations:

cnorm(unit)	$\mathbf{A} = \mathbf{L}$	and so	$\mathbf{A}'\mathbf{A} = \mathbf{I}$
normal(eigen)	$\mathbf{A} = \mathbf{L}\mathbf{\Lambda}^{1/2}$	and so	$\mathbf{A}'\mathbf{A} = \mathbf{\Lambda}$
normal(inveigen)	$\mathbf{A} = \mathbf{L}\mathbf{\Lambda}^{-1/2}$	and so	$\mathbf{A}'\mathbf{A} = \mathbf{\Lambda}^{-1}$

Normalization of the component loadings affects the normalization of the component scores.

The standard errors of the components are available only in unit normalization, that is, as normalized eigenvectors.

estat residuals computes the fitted values $\mathbf{F}$ for the analyzed correlation or covariance matrix $\mathbf{C}$ as $\mathbf{F} = \mathbf{L}\mathbf{\Lambda}\mathbf{L}'$ over the retained components, with $\mathbf{L}$ being the retained components in unit normalization and $\mathbf{\Lambda}$ being the associated eigenvalues. The residuals are simply $\mathbf{C} - \mathbf{F}$.

estat smc displays the squared multiple correlation coefficients SMC_i of each variable on the other variables in the analysis. These are conveniently computed from the inverse $\mathbf{R}$ of the correlation matrix $\mathbf{C}$,

$$\text{SMC}_i = 1 - \mathbf{R}_{ii}^{-1}$$

See [MV] **rotate** and [MV] **rotatemat** for details concerning the rotation methods and algorithms used.

The variance of the rotated loadings $\mathbf{L}_{\text{r}}$ is computed as $\mathbf{L}_{\text{r}'}\mathbf{C}\mathbf{L}_{\text{r}}$.

To understand predict after pca and pcamat, think of PCA as a fixed-effects factor analysis with homoskedastic residuals

$$\mathbf{Z} = \mathbf{A}\mathbf{L}' + \mathbf{E}$$

L contains the loadings, and **A** contains the scores. **Z** is the centered variables for a PCA of a covariance matrix and standardized variables for a PCA of a correlation matrix. **A** is estimated by OLS regression of **Z** on **L**

$$\widehat{\mathbf{A}} = \mathbf{ZB} \qquad \mathbf{B} = \mathbf{L}(\mathbf{L'L})^{-}$$

The columns of **A** are called the scores. The matrix **B** contains the scoring coefficients. The PCA-fitted values for **Z** are defined as the fitted values from this regression, or in matrix terms,

$$\widehat{\mathbf{Z}} = \mathbf{ZP_L} = \mathbf{ZL}(\mathbf{L'L})^{-}\mathbf{L'}$$

with $\mathbf{P_L}$ the orthogonal projection on (the rowspace of) **L**.

This formulation allows orthogonal as well as oblique loadings **L** as well as loadings in different normalizations.

The above formulation is in transformed units. `predict` transforms the fitted values back to the original units. The component scores are left in transformed units, with one exception. After a PCA of covariances, means are substituted back in unless the option `centered` is specified. The residuals are returned in the original units. The residual sums of squares (over the variables) and the normalized versions are in transformed units.

References

Cattell, R. B. 1966. The scree test for the number of factors. *Multivariate Behavioral Research* 1: 245–276. https://doi.org/10.1207/s15327906mbr0102_10.

Jackson, J. E. 2003. *A User's Guide to Principal Components.* New York: Wiley.

Kaiser, H. F. 1974. An index of factor simplicity. *Psychometrika* 39: 31–36.

Also see *References* in [MV] **pca**.

Also see

[MV] **pca** — Principal component analysis

[MV] **rotate** — Orthogonal and oblique rotations after factor and pca

[MV] **scoreplot** — Score and loading plots

[MV] **screeplot** — Scree plot of eigenvalues

[U] **20 Estimation and postestimation commands**

Title

---
procrustes — Procrustes transformation

Description

procrustes performs the Procrustean analysis, a standard method of multidimensional scaling in which the goal is to transform the source varlist to be as close as possible to the target varlist. Closeness is measured by the residual sum of squares. The permitted transformations are any combination of dilation (uniform scaling), rotation and reflection (that is, orthogonal or oblique transformations), and translation. procrustes deals with complete cases only. procrustes assumes equal weights or scaling for the dimensions. Variables measured on different scales should be standardized before using procrustes.

Quick start

Procrustes transform source variables x1 and x2 to be close to target variables y1 and y2
        procrustes (y1 y2) (x1 x2)

Add a third source variable, x3, and target variable, y3
        procrustes (y1 y2 y3) (x1 x2 x3)

Same as above, but allow an oblique instead of an orthogonal rotation
        procrustes (y1 y2 y3) (x1 x2 x3), transform(oblique)

Same as above, but suppress dilation
        procrustes (y1 y2 y3) (x1 x2 x3), transform(oblique) norho

Menu

Statistics > Multivariate analysis > Procrustes transformations

Syntax

>   procrustes (*varlist$_y$*) (*varlist$_x$*) $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$ *weight* $\big]$ $\big[$, *options* $\big]$

options	Description
Model	
<u>transform(or</u>thogonal)	orthogonal rotation and reflection transformation; the default
<u>transform(ob</u>lique)	oblique rotation transformation
<u>transform(un</u>restricted)	unrestricted transformation
<u>noconst</u>ant	suppress the constant
<u>norho</u>	suppress the dilation factor ρ (set $\rho = 1$)
force	allow overlap and duplicates in *varlist$_y$* and *varlist$_x$* (advanced)
Reporting	
<u>nofit</u>	suppress table of fit statistics by target variable

bootstrap, by, collect, jackknife, and statsby are allowed; see [U] **11.1.10 Prefix commands**.

Weights are not allowed with the bootstrap prefix; see [R] **bootstrap**.

aweights are not allowed with the jackknife prefix; see [R] **jackknife**.

aweights and fweights are allowed; see [U] **11.1.6 weight**.

See [U] **20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

> Model

transform(*transform*) specifies the transformation method. The following transformation methods
are allowed:

>   orthogonal specifies that the linear transformation matrix **A** should be orthogonal, $\mathbf{A}'\mathbf{A} = \mathbf{A}\mathbf{A}' = \mathbf{I}$. This is the default.

>   oblique specifies that the linear transformation matrix **A** should be oblique, $\mathrm{diag}(\mathbf{A}\mathbf{A}') = \mathbf{1}$.

>   unrestricted applies no restrictions to **A**, making the procrustes transformation equivalent to
    multivariate regression with uncorrelated errors; see [MV] **mvreg**.

noconstant specifies that the translation component **c** is fixed at **0** (the 0 vector).

norho specifies that the dilation (scaling) constant ρ is fixed at 1. This option is not relevant with
    transform(unrestricted); here ρ is always fixed at 1.

force, an advanced option, allows overlap and duplicates in the target variables *varlist$_y$* and source
    variables *varlist$_x$*.

> Reporting

nofit suppresses the table of fit statistics per target variable. This option may be specified during
    estimation and upon replay.

Remarks and examples

Remarks are presented under the following headings:

Introduction to Procrustes methods

The name *Procrustes analysis* was applied to optimal matching of configurations by Hurley and Cattell (1962) and refers to Greek mythology. The following account follows Cox and Cox (2001, 123). Travelers from Eleusis to Athens were kindly invited by Damastes to spend the night at his place. Damastes, however, practiced a queer kind of hospitality. If guests would not fit the bed, Damastes would either stretch them to make them fit, or chop off extremities if they were too long. Therefore, he was given the nickname Procrustes—ancient Greek for "the stretcher". Theseus, a warrior, finally gave Procrustes some of his own medicine.

Procrustes methods have been applied in many areas. Gower and Dijksterhuis (2004) mention applications in psychometrics (for example, the matching of factor loading matrices), image analysis, market research, molecular biology, biometric identification, and shape analysis.

Formally, procrustes solves the minimization problem

$$\text{Minimize} \,|\, \mathbf{Y} - (\mathbf{1}\mathbf{c}' + \rho\,\mathbf{X}\,\mathbf{A})\,|$$

where $\mathbf{c}$ is a row vector representing the translation, ρ is the scalar "dilation factor", $\mathbf{A}$ is the rotation and reflection matrix (orthogonal, oblique, or unrestricted), and $|.|$ denotes the L2 norm. The goal is to transform the source $\mathbf{X}$ to be as close as possible to the target $\mathbf{Y}$. The permitted Closeness is measured by the residual sum of squares.

Some of the early work on Procrustes analysis was done by Mosier (1939), Green (1952), Hurley and Cattell (1962), and Browne (1967); see Gower and Dijksterhuis (2004).

Orthogonal Procrustes analysis

▷ Example 1

We illustrate `procrustes` with John Speed's historical 1610 map of the Worcestershire region in England, engraved and printed by Jodocus Hondius in Amsterdam in 1611–1612. Used with permission of Peen (2007).
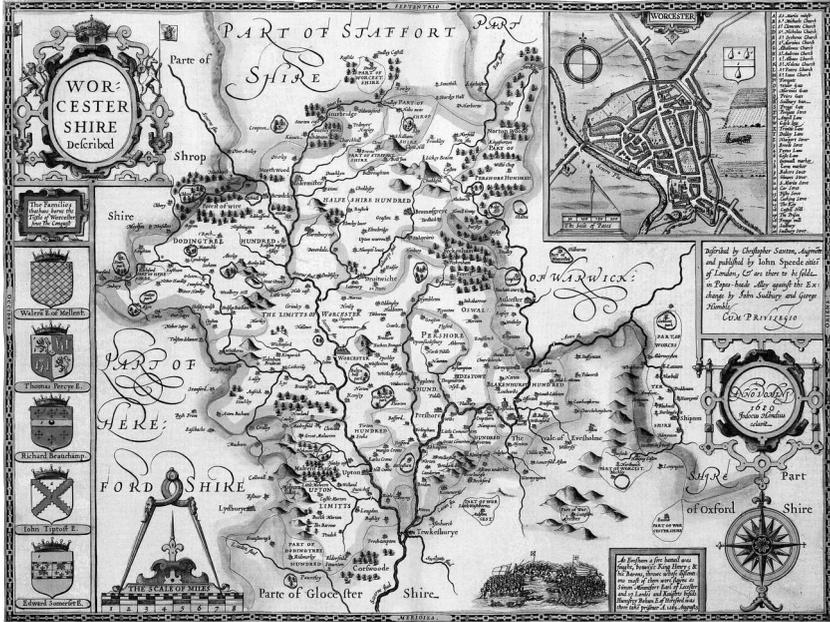
We analyze the accuracy of this map. Cox and Cox (2001) present data on the locations of 20 towns and villages on this old map, as well as the locations on a modern map from the Landranger Series of Ordnance Survey Maps. The locations were measured relative to the lower-left corner of the maps. We list this small dataset, specifying the `noobs` option to prevent wrapping and `sep(0)` to suppress internal horizontal lines.

```
. use https://www.stata-press.com/data/r18/speed_survey
(Data on Speed's Worcestershire map (1610))

. list name lname speed_x speed_y survey_x survey_y, sep(0) noobs
```

| name | lname | speed_x | speed_y | survey_x | survey_y |
|------|-------|---------|---------|----------|----------|
| Alve | Alvechurch | 192 | 211 | 1027 | 725 |
| Arro | Arrow | 217 | 155 | 1083 | 565 |
| Astl | Astley | 88 | 180 | 787 | 677 |
| Beck | Beckford | 193 | 66 | 976 | 358 |
| Beng | Bengeworth | 220 | 99 | 1045 | 435 |
| Crad | Cradley | 79 | 93 | 736 | 471 |
| Droi | Droitwich | 136 | 171 | 893 | 633 |
| Ecki | Eckington | 169 | 81 | 922 | 414 |
| Eves | Evesham | 211 | 105 | 1037 | 437 |
| Hall | Hallow | 113 | 142 | 828 | 579 |
| Hanb | Hanbury | 162 | 180 | 944 | 637 |
| Inkb | Inkberrow | 188 | 156 | 1016 | 573 |
| Kemp | Kempsey | 128 | 108 | 848 | 490 |
| Kidd | Kidderminster | 104 | 220 | 826 | 762 |
| Mart | Martley | 78 | 145 | 756 | 598 |
| Stud | Studley | 212 | 185 | 1074 | 632 |
| Tewk | Tewkesbury | 163 | 40 | 891 | 324 |
| UpSn | UpperSnodsbury | 163 | 138 | 943 | 544 |
| Upto | Upton | 138 | 71 | 852 | 403 |
| Worc | Worcester | 125 | 132 | 850 | 545 |

You will probably conclude immediately that the scales of the two maps differ and that the coordinates are expressed with respect to different reference points; the lower-left corners of the maps correspond to different physical locations. Another distinction will not be so obvious—at least not by looking at these numbers: the orientations of the maps may well differ. We display as scatterplots Speed's data (speed_x, speed_y) and the modern survey data (survey_x, survey_y).

```
. scatter speed_y speed_x, mlabel(name) ytitle("") xtitle("")
> yscale(off) xscale(off) ylabel(,nogrid) xlabel(,nogrid)
> title(Historic map of 20 towns and villages in Worcestershire)
> subtitle((Speed 1610)) graphregion(fcolor(gs14))
```


Historic map of 20 towns and villages in Worcestershire
(Speed 1610)
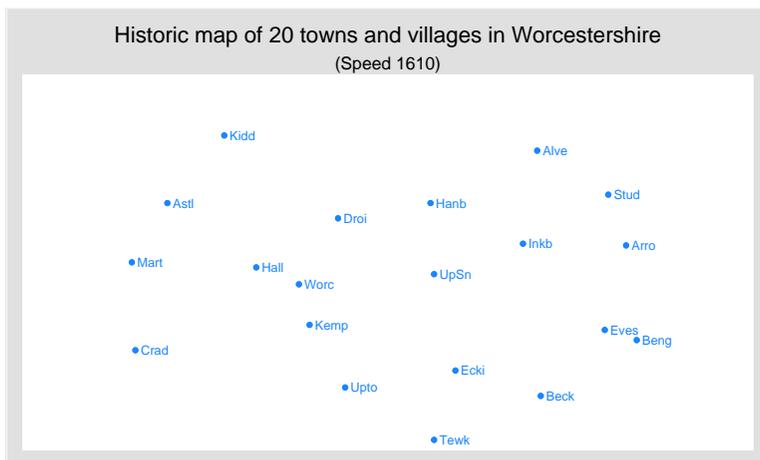
```
. scatter survey_y survey_x, mlabel(name) ytitle("") xtitle("")
> yscale(off) xscale(off) ylabel(,nogrid) xlabel(, nogrid)
> title(Modern map of 20 towns and villages in Worcestershire)
> subtitle((Landranger series of Ordnance Survey Maps))
> graphregion(fcolor(gs14))
```


Modern map of 20 towns and villages in Worcestershire
(Landranger series of Ordnance Survey Maps)
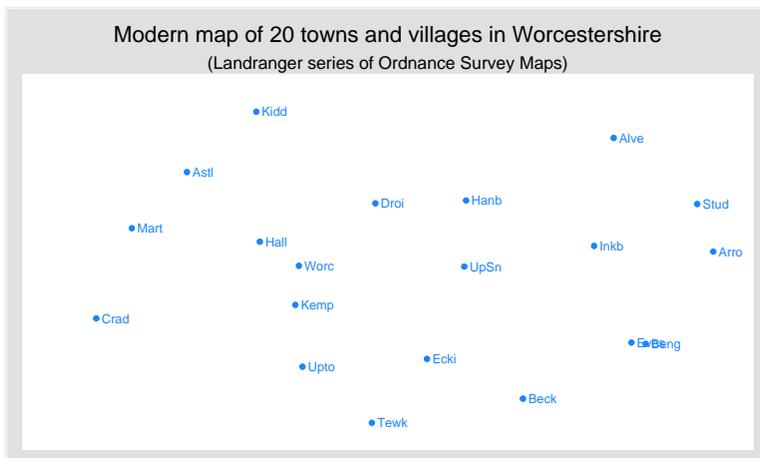
To gauge the accuracy of the historic map, we must account for differences in scale, location, and orientation. Because the area depicted on the map is relatively small, we think that it is justified to ignore the curvature of the earth and approximate distances along the globe with Euclidean distances, and apply a Procrustes analysis,

$$\text{survey\_map} = \text{transformation}(\text{speed\_map}) + \text{residual}$$

choosing the transformation (from among the allowed transformations) to minimize the residual in terms of the residual sum of squares. The transformation should allow for, in mathematical terms, translation, uniform scaling, and two-dimensional orthogonal rotation. The uniform scaling factor is often described as the dilation factor, a positive scalar. The transformation from source to target configuration can be written as

$$(\text{survey\_x} \quad \text{survey\_y}) = (c_x \quad c_y) + \rho (\text{speed\_x} \quad \text{speed\_y}) \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + (\text{res\_x} \quad \text{res\_y})$$

or simply as

$$\text{survey\_map} = \text{translation} + \text{dilation} \times \text{speed\_map} \times \text{rotation} + \text{residual}$$

The matrix

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$

should satisfy the constraint that it represents an orthogonal rotation—it should maintain the lengths of vectors and the angles between vectors. We estimate the translation $(c_x \quad c_y)$, dilation factor ρ, and the rotation matrix $\mathbf{A}$ with the procrustes command.

```
. procrustes (survey_x survey_y) (speed_x speed_y)
Procrustes analysis (orthogonal)              Number of observations =         20
                                              Model df (df_m)        =          4
                                              Residual df (df_r)     =         36
                                              SS(target)             =     495070
                                              RSS(target)            =   1973.384
                                              RMSE = root(RSS/df_r)   =   7.403797
                                              Procrustes = RSS/SS    =     0.0040
```

Translation c

	survey_x	survey_y
_cons	503.8667	293.9878

Rotation and reflection matrix A (orthogonal)

	survey_x	survey_y
speed_x	.9841521	-.1773266
speed_y	.1773266	.9841521

Dilation factor

```
        rho =    2.3556
```

Fit statistics by target variable

Statistics	survey_x	survey_y
SS	216310.2	278759.8
RSS	1081.36	892.0242
RMSE	7.750841	7.039666
Procrustes	.0049991	.0032
Corr_y_yhat	.9976669	.9985076

We can read the elements of the transformation from the output: the translation from the Speed map onto the survey map is (504, 294). The scale of the survey and Speed maps differ by a factor of 2.36. The orientations of the maps also differ somewhat; if the maps had been oriented the same, we would have expected the rotation to be an identity matrix. Note that $.984^2 + .177^2 = 1$, subject to rounding error—indeed the rotation is "norm preserving". A counterclockwise rotation in a plane over θ can be written as

$$\begin{pmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{pmatrix}$$

See appendix B in Gower and Dijksterhuis (2004). Here $\cos(\theta) = 0.984$, so $\theta = \cos^{-1}(0.984) = 0.179$ radians. For easier interpretation, we convert this into degrees. The difference in the orientation of the two maps is $360 \times 0.179/(2\pi) = 10.3$ degrees.

The other output produced by procrustes may be more familiar. procrustes estimated four parameters: the angle of rotation, two translation parameters, and the dilation factor ρ. SS(target) is the centered sum of squares of the survey data, and is meaningful mostly in relation to the residual sum of squares RSS(target). The Procrustes statistic, defined as RSS/SS, measures the size of the residuals relative to the variation in the target variables; it is equivalent to $1 - R^2$ in a regression analysis context. The smaller the Procrustes statistic, the closer the correspondence of Speed's map to the survey map. The number in this case, 0.004, is small indeed. Another way of looking at fit is via the square root of the mean squared residual error, RMSE, a measure for the average size of residuals.

The last output table describes how well the transformed Speed coordinates match the survey coordinates, separately for the horizontal (x) and the vertical (y) coordinates. In this case, we do not see disturbing differences between the coordinates. By definition, the overall Procrustes statistic and the overall RMSE are averages of the coordinate statistics. Because Procrustes analysis treats (weights) both coordinates the same and independently, analogous to the sphericity assumption in multivariate regression or MANOVA analysis, the comparable statistics for the different coordinates is reassuring.

This example is continued in [MV] **procrustes postestimation**, demonstrating how to generate fitted values and residual sum of squares with predict, how to produce a graph showing the target overlaid with the transformed source values with procoverlay, and how to produce various summaries and comparisons with estat.

◁

A Procrustes analysis fits the transformation subject to the constraint that $\mathbf{A}$ is orthogonal; for other constraints, see below. In two dimensions, there are actually two types of orthogonal matrices: rotations and reflections. Think of left and right hands. A rotation transforms a left hand into a left hand, never into a right hand; rotation preserves orientation. A reflection changes a left hand into a right hand; reflections invert orientation. In algebraic terms, an orthogonal matrix $\mathbf{A}$ satisfies $\det(\mathbf{A}) = \pm 1$. $\mathbf{A}$ is a rotation if $\det(\mathbf{A}) = 1$, and $\mathbf{A}$ is a reflection if $\det(\mathbf{A}) = -1$. In more than two dimensions, the classification of orthogonal transformations is more complicated.

▷ Example 2

In example 1, we treated the location, dilation, and orientation as estimable aspects of the transformation. It is possible to omit the location and dilation aspects—though, admittedly, from a casual inspection as well as the substantial understanding of the data, these aspects are crucial. For instance, we may omit the dilation factor—that is, assume $\rho = 1$—with the norho option.

```
. procrustes (survey_x survey_y) (speed_x speed_y), norho
```

Procrustes analysis (orthogonal)

```
                                        Number of observations =          20
                                        Model df (df_m)         =           3
                                        Residual df (df_r)      =          37
                                        SS(target)              =      495070
                                        RSS(target)             =    165278.1
                                        RMSE = root(RSS/df_r)   =    66.83544
                                        Procrustes = RSS/SS     =      0.3338
```

Translation c

	survey_x	survey_y
_cons	741.4458	435.6215

Rotation and reflection matrix A (orthogonal)

	survey_x	survey_y
speed_x	.9841521	-.1773266
speed_y	.1773266	.9841521

Dilation factor

```
            rho =    1.0000
```

Fit statistics by target variable

Statistics	survey_x	survey_y
SS	216310.2	278759.8
RSS	70385.78	94892.36
RMSE	61.68174	71.61925
Procrustes	.3253928	.340409
Corr_y_yhat	.9976669	.9985076

As expected, the optimal transformation without dilation implies a much weaker relation between the Speed and Survey maps; the Procrustes statistic has increased from 0.0040 to 0.3338. We conclude that we cannot adequately describe the correspondence between the maps if we ignore differences in scale.

◁

Is an orthogonal Procrustes analysis symmetric?

In examples 1 and 2, we transformed the Speed map to optimally match the modern Survey map. We could also have reversed the procedure, that is, transform the Survey map to match the Speed map.

▷ Example 3

Here we change the order of the Speed and Survey map in our call to `procrustes` from example 1.

```
. procrustes (speed_x speed_y) (survey_x survey_y)
```

Procrustes analysis (orthogonal)

Number of observations =	20
Model df (df_m) =	4
Residual df (df_r) =	36
SS(target) =	88862.75
RSS(target) =	354.2132
RMSE = root(RSS/df_r) =	3.136759
Procrustes = RSS/SS =	0.0040

Translation c

	speed_x	speed_y
_cons	-187.0142	-159.5801

Rotation and reflection matrix A (orthogonal)

	speed_x	speed_y
survey_x	.9841521	.1773266
survey_y	-.1773266	.9841521

Dilation factor

rho =   0.4228

Fit statistics by target variable

Statistics	speed_x	speed_y
SS	41544.95	47317.8
RSS	218.3815	135.8317
RMSE	3.483146	2.747036
Procrustes	.0052565	.0028706
Corr_y_yhat	.9975074	.9986641

The implied transformations are similar but not identical. For instance, the product of estimated scale factors is $2.3556 \times 0.4228 = 0.9959$, which is close to 1 but not identical to 1—this is not due to roundoff error. Why do the results differ? Think about the analogy with regression analysis. The regression of Y on X and the regression of X on Y generally imply different relationships between the variables. In geometric terms, one minimizes the sum of squares of the "vertical" distances between the data point and the regression line, whereas the other minimizes the "horizontal" distances. The implied regression lines are the same if the variance in X and Y are the same. Even if this does not hold, the proportion of explained variance R^2 in both regressions is the same. In Procrustes analysis, an analogous relationship holds between the analyses "Speed = transformed(Survey) + E" and "Survey = transformed(Speed) + E". Both analyses yield the same Procrustes statistic. The implied analyses are equivalent (that is, the implied transformation in one analysis is the mathematical inverse of the transformation in the other analysis) only if the Speed and Survey data are scaled so that the trace of the associated covariance matrices is the same.

◁

Other transformations

A Procrustes analysis can also be applied with other classes of transformations. Browne (1967) analyzed Procrustes analyses with oblique rotations. Cramer (1974) and ten Berge and Nevels (1977) identified and solved some problems in Browne's solution (but still ignore the problem that the derived oblique rotations are not necessarily orientation preserving). `procrustes` supports oblique transformations. `procrustes` also allows dilation; see *Methods and formulas*.

▷ Example 4

Even though the orthogonal Procrustes analysis of example 1 demonstrated a similarity between the two configurations assuming an orthogonal transformation, we now investigate what happens with an oblique transformation.

```
. procrustes (survey_x survey_y) (speed_x speed_y), trans(oblique)
```

Procrustes analysis (oblique)

Number of observations	= 20
Model df (df_m)	= 5
Residual df (df_r)	= 35
SS(target)	= 495070
RSS(target)	= 1967.854
RMSE = root(RSS/df_r)	= 7.498294
Procrustes = RSS/SS	= 0.0040

Translation c

	survey_x	survey_y
_cons	503.0093	292.4346

Rotation and reflection matrix A (oblique)

	survey_x	survey_y
speed_x	.9835969	-.1737553
speed_y	.1803803	.9847889

Dilation factor

            rho =   2.3562

Fit statistics by target variable

Statistics	survey_x	survey_y
SS	216310.2	278759.8
RSS	1080.677	887.1769
RMSE	7.858307	7.1201
Procrustes	.004996	.0031826
Corr_y_yhat	.9976685	.9985163

We see that the optimal oblique transformation is almost orthogonal; the columns of the oblique rotation and reflection matrix are almost perpendicular. The dilation factor and translation vector hardly differ from the orthogonal case shown in example 1. Finally, we see that the residual sum of squares decreased little, namely, from 1,973.4 to 1,967.9.

◁

Procrustes analysis can be interpreted as multivariate regression $\mathbf{Y} = \mathbf{c} + \mathbf{x}\mathbf{B} + \mathbf{e}$ in which some nonlinear restriction is applied to the coefficients $\mathbf{B}$. Procrustes analysis assumes $\mathbf{B} = \rho\mathbf{A}$ with $\mathbf{A}$

assumed to be orthogonal or **A** assumed to be oblique. The intercepts of the multivariate regression are, of course, the translation of the Procrustean transform. In contrast to multivariate regression, it is assumed that the distribution of the residuals **e** is spherical; that is, all that is assumed is that $\text{var}(\mathbf{e}) = \sigma^2 \mathbf{I}$. This assumption affects standard errors, not the estimated coefficients. Multivariate regression serves as a useful baseline to gauge the extent to which the Procrustean analysis is appropriate. `procrustes` supports the `transform(unrestricted)` option and displays the fitted model in a format comparable to Procrustes analysis.

▷ Example 5

We demonstrate with Speed's map data.

```
. procrustes (survey_x survey_y) (speed_x speed_y), trans(unrestricted)
Procrustes analysis (unrestricted)          Number of observations =           20
                                             Model df (df_m)         =            6
                                             Residual df (df_r)      =           34
                                             SS(target)              =       495070
                                             RSS(target)             =     1833.435
                                             RMSE = root(RSS/df_r)   =     7.343334
                                             Procrustes = RSS/SS     =       0.0037
Translation c
```

	survey_x	survey_y
_cons	510.8028	288.243

Rotation and reflection matrix A (unrestricted)

	survey_x	survey_y
speed_x	2.27584	-.4129564
speed_y	.4147244	2.355725

Fit statistics by target variable

Statistics	survey_x	survey_y
SS	216310.2	278759.8
RSS	1007.14	826.2953
RMSE	7.696981	6.971772
Procrustes	.004656	.0029642
Corr_y_yhat	.9976693	.9985168

Because we already saw that there is almost no room to improve on the orthogonal Procrustes transform with this particular dataset, dropping the restrictions on the coefficients hardly improves the fit. For instance, the residual sum of squares further decreases from 1,967.9 in the oblique case to 1,833.4 in the unrestricted case, with only a small reduction in the value of the Procrustes statistic.

◁

Stored results

procrustes stores the following in e():

Scalars
e(N)	number of observations
e(rho)	dilation factor
e(P)	Procrustes statistic
e(ss)	total sum of squares, summed over all y variables
e(rss)	residual sum of squares, summed over all y variables
e(rmse)	root mean squared error
e(urmse)	root mean squared error (unadjusted for # of estimated parameters)
e(df_m)	model degrees of freedom
e(df_r)	residual degrees of freedom
e(ny)	number of y variables (target variables)

Macros
e(cmd)	procrustes
e(cmdline)	command as typed
e(ylist)	y variables (target variables)
e(xlist)	x variables (source variables)
e(transform)	orthogonal, oblique, or unrestricted
e(uniqueA)	1 if rotation is unique, 0 otherwise
e(wtype)	weight type
e(wexp)	weight expression
e(properties)	nob noV
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(marginsnotok)	predictions disallowed by margins

Matrices
e(c)	translation vector
e(A)	orthogonal transformation matrix
e(ystats)	matrix containing fit statistics

Functions
e(sample)	marks estimation sample

Methods and formulas

Methods and formulas are presented under the following headings:

> Introduction
> Orthogonal transformations
> Oblique transformations
> Unrestricted transformations
> Reported statistics

Introduction

A Procrustes analysis is accomplished by solving a matrix minimization problem

$$\text{Minimize} \, | \, \mathbf{Y} - (\mathbf{1}\mathbf{c}' + \rho \, \mathbf{X} \, \mathbf{A}) \, |$$

with respect to $\mathbf{A}$, $\mathbf{c}$, and ρ. $\mathbf{A}$ is a matrix representing a linear transformation, $\rho > 0$ is a scalar called the "dilation factor", $\mathbf{c}$ is a translation (row-) vector, and $|.|$ is the Frobenius (or L2) norm. Three classes of transformations are available in procrustes: orthogonal, oblique, and unrestricted. The orthogonal class consists of all orthonormal matrices $\mathbf{A}$, that is, all square matrices that satisfy $\mathbf{A}'\mathbf{A} = \mathbf{I}$, representing orthogonal norm-preserving rotations and reflections. The oblique class comprises all normal matrices $\mathbf{A}$, characterized by $\text{diag}(\mathbf{A}'\mathbf{A}) = \mathbf{1}$. Oblique transformations preserve the length of vectors but not the angles between vectors—orthogonal vectors will generally not remain orthogonal under oblique transformations. Finally, the unrestricted class consists of all conformable regular matrices $\mathbf{A}$.

Define $\widetilde{\mathbf{Y}}$ and $\widetilde{\mathbf{X}}$ as the centered $\mathbf{Y}$ and $\mathbf{X}$, respectively, if a constant $\mathbf{c}$ is included in the analysis and as the uncentered $\mathbf{Y}$ and $\mathbf{X}$ otherwise.

The derivation of the optimal $\mathbf{A}$ obviously differs for the three classes of transformations.

Orthogonal transformations

The solution for the orthonormal case can be expressed in terms of the singular value decomposition of $\widetilde{\mathbf{Y}}'\widetilde{\mathbf{X}}$,

$$\widetilde{\mathbf{Y}}'\widetilde{\mathbf{X}} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{V}'$$

where $\mathbf{U}'\mathbf{U} = \mathbf{V}'\mathbf{V} = \mathbf{I}$. Then

$$\widehat{\mathbf{A}} = \mathbf{V}\mathbf{U}'$$

$\widehat{\mathbf{A}}$ is the same whether or not scaling is required, that is, whether ρ is a free parameter or a fixed parameter. When ρ is a free parameter, the optimal ρ is

$$\widehat{\rho} = \frac{\mathrm{trace}(\widehat{\mathbf{A}}\widetilde{\mathbf{Y}}'\widetilde{\mathbf{X}})}{\mathrm{trace}(\widetilde{\mathbf{X}}'\widetilde{\mathbf{X}})}$$

See ten Berge (1977) for a modern and elementary derivation; see Mardia, Kent, and Bibby (1979) for a derivation using matrix differential calculus.

Oblique transformations

Improving on earlier studies by Browne (1967) and Cramer (1974), ten Berge and Nevels (1977) provide a full algorithm to compute the optimal oblique rotation without dilation, that is, with uniform scaling $\rho = 1$. In contrast to the orthogonal case, the optimal oblique rotation $\widehat{\mathbf{A}}$ depends on ρ. To the best of our knowledge, this case has not been treated in the literature (J. M. F. ten Berge, 2004, pers. comm.). However, an "alternating least squares" extension of the ten Berge and Nevels (1977) algorithm deals with this case.

For each iteration, step (a) follows ten Berge and Nevels (1977) for calculating $\widetilde{\mathbf{Y}}$ and $\widehat{\rho}\widetilde{\mathbf{X}}$. In step (b) of an iteration, ρ is optimized, keeping $\widehat{\mathbf{A}}$ fixed, with solution

$$\widehat{\rho} = \frac{\mathrm{trace}(\widehat{\mathbf{A}}\widetilde{\mathbf{Y}}'\widetilde{\mathbf{X}})}{\mathrm{trace}(\widetilde{\mathbf{X}}'\widetilde{\mathbf{X}}\widehat{\mathbf{A}}\widehat{\mathbf{A}}')}$$

Iteration continues while the relative decrease in the residual sum of squares is large enough. This algorithm is ensured to yield a local optimum of the residual sum of squares as the RSS decreases both when updating the rotation $\mathbf{A}$ and when updating the dilation factor ρ. Beware that the algorithm is not guaranteed to find the global minimum.

Unrestricted transformations

In the unrestricted solution, the dilation factor ρ is fixed at 1. The computation of the Procrustes transformation is obviously equivalent to the least-squares solution of multivariate regression

$$\widehat{\mathbf{A}} = (\widetilde{\mathbf{X}}'\widetilde{\mathbf{X}})^{-1}\widetilde{\mathbf{X}}'\widetilde{\mathbf{Y}}$$

Given $\widehat{\mathbf{A}}$ and $\widehat{\rho}$, the optimal translation $\widehat{\mathbf{c}}$ can be written as

$$\widehat{\mathbf{c}} = \mathbf{Y}'\mathbf{1} - \widehat{\rho}\widehat{\mathbf{A}}\mathbf{X}$$

If the constant is suppressed, $\mathbf{c}$ is simply set to $\mathbf{0}$.

Reported statistics

procrustes computes and displays the following statistics for each target variable separately and globally by adding the appropriate sums of squares over all target variables. The predicted values $\widehat{\mathbf{Y}}$ for $\mathbf{Y}$ are defined as

$$\widehat{\mathbf{Y}} = \mathbf{1}\widehat{\mathbf{c}}' + \widehat{\rho}\mathbf{X}\widehat{\mathbf{A}}$$

The Procrustes statistic, P, is a scaled version of the squared distance of $\mathbf{Y}$:

$$P = \text{RSS}/\text{SS}$$

where

$$\text{RSS} = \text{trace}((\mathbf{Y} - \widehat{\mathbf{Y}})(\mathbf{Y} - \widehat{\mathbf{Y}})')$$

$$\text{SS} = \text{trace}(\widetilde{\mathbf{Y}}'\widetilde{\mathbf{Y}})$$

Note that $0 \leq P \leq 1$, and a small value of P means that $\mathbf{Y}$ is close to the transformed value of $\mathbf{X}$, that is, the $\mathbf{X}$ and $\mathbf{Y}$ configurations are similar. In the literature, this statistic is often denoted by R^2. It is easy to confuse this with the R^2 statistic in a regression context, which is actually $1 - P$.

A measure for the size of the residuals is the root mean squared error,

$$\text{RMSE} = \sqrt{\text{RSS}/\text{df}_\text{r}}$$

Here df_r are $Nn_y - \text{df}_\text{m}$, with $\text{df}_\text{m} = n_y n_x + n_y + 1 - k$, and with N the number of observations, n_y and n_x the number of target variables and source variables, respectively, and k, the number of restrictions, defined as

orthogonal: $k = n_x(n_x - 1)/2$
oblique: $k = n_y$
unrestricted: $k = 1$

procrustes computes $\text{RMSE}(j)$ for target variable y_j as

$$\text{RMSE}(j) = \sqrt{\text{RSS}(j)/(\text{df}_\text{r}/n_y)}$$

Finally, procrustes computes the Pearson correlation between y_j and $\widehat{y}_j$. For the unrestricted transformation, this is just the square root of the explained variance $1 - P(j)$, where $P(j) = \text{RSS}(j)/\text{SS}$. For the orthogonal and oblique transformation, this relationship does not hold.

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Also see

Title

> **procrustes postestimation —** Postestimation tools for procrustes

Postestimation commands

The following postestimation commands are of special interest after `procrustes`:

Command	Description
estat compare	fit statistics for orthogonal, oblique, and unrestricted transformations
estat mvreg	display multivariate regression resembling unrestricted transformation
estat summarize	display summary statistics over the estimation sample
procoverlay	produce a Procrustes overlay graph

The following standard postestimation commands are also available:

Command	Description
*estimates	cataloging estimation results
predict	predictions and residuals

*All `estimates` subcommands except `table` and `stats` are available; see [R] **estimates**.

predict

Description for predict

predict creates new variables containing predictions such as fitted values, unstandardized residuals, and residual sum of squares.

Menu for predict

Statistics > Postestimation

Syntax for predict

> predict [*type*] {*stub** | *newvarlist*} [*if*] [*in*], [*statistic*]

statistic	Description
Main	
<u>fit</u>ted	fitted values $\mathbf{1}\,\mathbf{c}' + \rho\,\mathbf{X}\,\mathbf{A}$; the default (specify $\#_y$ vars)
<u>res</u>iduals	unstandardized residuals (specify $\#_y$ vars)
q	residual sum of squares over the target variables (specify one var)

These statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample.

Options for predict

> **⌐ Main ⌐**

fitted, the default, computes fitted values, that is, the least-squares approximations of the target (*varlist*$_y$) variables. You must specify the same number of new variables as there are target variables.

residuals computes the raw (unstandardized) residuals for each target (*varlist*$_y$) variable. You must specify the same number of new variables as there are target variables.

q computes the residual sum of squares over all variables, that is, the squared Euclidean distance between the target and transformed source points. Specify one new variable.

estat

Description for estat

estat compare displays a table with fit statistics of the three transformations provided by procrustes: orthogonal, oblique, and unrestricted. The two additional procrustes analyses are performed on the same sample as the original procrustes analysis and with the same options. F tests comparing the models are provided.

estat mvreg produces the mvreg (see [MV] **mvreg**) output related to the unrestricted Procrustes analysis (the transform(unrestricted) option of procrustes).

estat summarize displays summary statistics over the estimation sample of the target and source variables (*varlist_y* and *varlist_x*).

Menu for estat

Statistics > Postestimation

Syntax for estat

Table of fit statistics

> estat <u>com</u>pare [, <u>det</u>ail]

Comparison of mvreg *and* procrustes *output*

> estat <u>mv</u>reg [, *mvreg_options*]

Display summary statistics

> estat <u>su</u>mmarize [, <u>labels</u> <u>nohea</u>der <u>noweights</u>]

collect is allowed with estat compare and estat summarize; see [U] **11.1.10 Prefix commands**.

Options for estat

detail, an option with estat compare, displays the standard procrustes output for the two additional transformations.

mvreg_options, allowed with estat mvreg, are any of the options allowed by mvreg; see [MV] **mvreg**. The constant is already suppressed if the Procrustes analysis suppressed it.

labels, noheader, and noweights are the same as for the generic estat summarize command; see [R] **estat summarize**.

procoverlay

Description for procoverlay

procoverlay displays a plot of the target variables overlaid with the fitted values derived from the source variables. If there are more than two target variables, multiple plots are shown in one graph.

Menu for procoverlay

Statistics > Multivariate analysis > Procrustes overlay graph

Syntax for procoverlay

procoverlay [*if*] [*in*] [, *procoverlay_options*]

procoverlay_options	Description
Main	
<u>autoa</u>spect	adjust aspect ratio on the basis of the data; default aspect ratio is 1
<u>targeto</u>pts(*target_opts*)	affect the rendition of the target
<u>sourceo</u>pts(*source_opts*)	affect the rendition of the source
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*
By	
<u>byo</u>pts(*by_option*)	affect the rendition of combined graphs

target_opts	Description
Main	
<u>nolab</u>el	removes the default observation label from the target
marker_options	change look of markers (color, size, etc.)
marker_label_options	change look or position of marker labels

source_opts	Description
Main	
<u>nolab</u>el	removes the default observation label from the source
marker_options	change look of markers (color, size, etc.)
marker_label_options	change look or position of marker labels

Options for procoverlay

autoaspect specifies that the aspect ratio be automatically adjusted based on the range of the data to be plotted. This option can make some procoverlay plots more readable. By default, procoverlay uses an aspect ratio of one, producing a square plot.

As an alternative to autoaspect, the *twoway_option* aspectratio() can be used to override the default aspect ratio. procoverlay accepts the aspectratio() option as a suggestion only and will override it when necessary to produce plots with balanced axes, that is, where distance on the x axis equals distance on the y axis.

twoway_options, such as xlabel(), xscale(), ylabel(), and yscale(), should be used with caution. These *axis_options* are accepted but may have unintended side effects on the aspect ratio. See [G-3] *twoway_options*.

targetopts(*target_opts*) affects the rendition of the target plot. The following *target_opts* are allowed:

nolabel removes the default target observation label from the graph.

marker_options affect the rendition of markers drawn at the plotted points, including their shape, size, color, and outline; see [G-3] *marker_options*.

marker_label_options specify if and how the markers are to be labeled; see [G-3] *marker_label_options*.

sourceopts(*source_opts*) affects the rendition of the source plot. The following *source_opts* are allowed:

nolabel removes the default source observation label from the graph.

marker_options affect the rendition of markers drawn at the plotted points, including their shape, size, color, and outline; see [G-3] *marker_options*.

marker_label_options specify if and how the markers are to be labeled; see [G-3] *marker_label_options*.

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding by(). These include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk (see [G-3] *saving_option*). See autoaspect above for a warning against using options such as xlabel(), xscale(), ylabel(), and yscale().

byopts(*by_option*) is documented in [G-3] *by_option*. This option affects the appearance of the combined graph and is ignored, unless there are more than two target variables specified in procrustes.

Remarks and examples

The examples in [MV] **procrustes** demonstrated a Procrustes transformation of a historical map, produced by John Speed in 1610, to a modern map. Here we demonstrate the use of procrustes postestimation tools in assessing the accuracy of Speed's map. Example 1 of [MV] **procrustes** performed the following analysis:

```
. use https://www.stata-press.com/data/r18/speed_survey
(Data on Speed's Worcestershire map (1610))

. procrustes (survey_x survey_y) (speed_x speed_y)
  (output omitted)
```

See example 1 of [MV] **procrustes**. The following examples are based on this procrustes analysis.

▷ Example 1: Predictions

Did John Speed get the coordinates of the towns right—up to the location, scale, and orientation of his map relative to the modern map? In example 1 of [MV] **procrustes**, we demonstrated how the optimal transformation from the historical coordinates to the modern (true) coordinates can be estimated by procrustes.

It is possible to "predict" the configuration of 20 cities on Speed's historical map, optimally transformed (rotated, dilated, and translated) to approximate the true configuration. predict with the fitted option expects the same number of variables as the number of target (dependent) variables (survey_x and survey_y).

```
. predict fitted_x fitted_y
(option fitted assumed; fitted values)
```

We omitted the fitted option because it is the default.

It is often useful to also compute the (squared) distance between the true location and the transformed location of the historical map. This can be seen as a quality measure—the larger the value, the more Speed erred in the location of the respective town.

```
. predict q, q
```

We now list the target data (survey_x and survey_y, the values from the modern map), the fitted values (fitted_x and fitted_y, produced by predict), and the squared distance between them (q, produced by predict with the q option).

```
. list name survey_x survey_y fitted_x fitted_y q, sep(0) noobs
```

name	survey_x	survey_y	fitted_x	fitted_y	q
Alve	1027	725	1037.117	702.9464	588.7149
Arro	1083	565	1071.682	562.6791	133.4802
Astl	787	677	783.0652	674.5216	21.62482
Beck	976	358	978.8665	366.3761	78.37637
Beng	1045	435	1055.245	431.6015	116.51
Crad	736	471	725.8594	476.5895	134.075
Droi	893	633	890.5839	633.6066	6.205747
Ecki	922	414	929.4932	411.1757	64.12465
Eves	1037	437	1036.887	449.2707	150.5827
Hall	828	579	825.1494	575.9836	17.22464
Hanb	944	637	954.6189	643.6107	156.4629
Inkb	1016	573	1004.869	577.1111	140.7917
Kemp	848	490	845.7215	490.8959	5.994327
Kidd	826	762	836.8665	760.5699	120.1264
Mart	756	598	745.2623	597.5585	115.4937
Stud	1074	632	1072.622	634.3164	7.264294
Tewk	891	324	898.4571	318.632	84.42448
UpSn	943	544	939.3932	545.8247	16.33858
Upto	852	403	853.449	400.9419	6.335171
Worc	850	545	848.7917	547.7881	9.233305

We see that Speed especially erred in the location of Alvechurch—it is off by no less than $\sqrt{588} = 24$ miles, whereas the average error is about 8 miles. In a serious analysis of this dataset, we would check the data on Alvechurch, and, if we found it to be in order, consider whether we should actually drop Alvechurch from the analysis. In this illustration, we ignore this potential problem.

◁

▷ Example 2: Procrustes overlay graph

Although the numerical information convinces us that Speed's map is generally accurate, a plot will convey this message more convincingly. `procoverlay` produces a plot that contains the target (survey) coordinates and the Procrustes-transformed historical coordinates. We could just type

    . procoverlay

However, we decide to set several options to produce a presentation-quality graph. The suboption `mlabel()` of `target()` (or of `source()`) adds labels, identifying the towns. Because the target and source points are so close, there can be no confusing how they are matched. Displaying the labels twice in the plot is not helpful for this dataset. Therefore, we choose to label the target points, but not the source points using the `nolabel` suboption of `source()`. We preserve the equivalence of the x and y scale while using as much of the graphing region as possible with the `autoaspect` option. The `span` suboption of `title()` allows the long title to extend beyond the graph region if needed. We override the default legend by using the `legend()` option.

    . procoverlay, target(mlabel(name)) source(nolabel) autoaspect
    > title(Historic map of 20 towns and villages in Worcestershire, span)
    > subtitle(Overlaid with actual positions)
    > legend(label(1 Historic map) label(2 Actual position))

◁
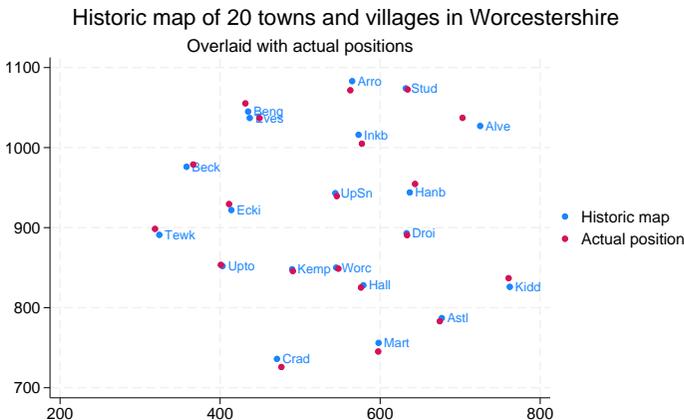
▷ Example 3: estat

`estat` offers three specific facilities after `procrustes`. These can all be seen as convenience tools that accomplish simple analyses, ensuring that the same variables and the same observations are used as in the Procrustes analysis.

The variables involved in the Procrustes analysis can be summarized over the estimation sample, for instance, to gauge differences in scales and location of the target and source variables.

```
. estat summarize
  Estimation sample procrustes                    Number of obs =          20
```

Variable	Mean	Std. dev.	Min	Max
target				
survey_x	916.7	106.6993	736	1083
survey_y	540.1	121.1262	324	762
source				
speed_x	153.95	46.76084	78	220
speed_y	133.9	49.90401	40	220

From the summarization, the two maps have different origins and scale.

As pointed out in [MV] **procrustes**, orthogonal and oblique Procrustes analyses can be thought of as special cases of multivariate regression (see [MV] **mvreg**), subject to nonlinear restrictions on the coefficient matrix. Comparing the Procrustes statistics and the transformations for each of the three classes of transformations is helpful in selecting a transformation. The `compare` subcommand of `estat` provides summary information for the optimal transformations in each of the three classes.

```
. estat compare
  Summary statistics for three transformations
```

	Procrustes	df_m	df_r	rmse
orthogonal	0.0040	4	36	7.403797
oblique	0.0040	5	35	7.498294
unrestricted	0.0037	6	34	7.343334

(F tests comparing the models suppressed)

The Procrustes statistic is ensured to decrease (not increase) from orthogonal to oblique to unrestricted because the associated classes of transformations are getting less restrictive. The model degrees of freedom (df_m) of the three transformation classes are the dimension of the classes, that is, the number of "free parameters". For instance, with orthogonal transformations between two source and two target variables, there is 1 degree of freedom for the rotation (representing the rotation angle), 2 degrees of freedom for the translation, and 1 degree of freedom for dilation (uniform scaling), that is, four in total. The residual degrees of freedom (df_r) are the number of observations (number of target variables times the number of observations) minus the model degrees of freedom. The root mean squared error RMSE, defined as

$$\text{RMSE} = \sqrt{\frac{\text{RSS}}{\text{df}_r}}$$

does not, unlike the Procrustes statistic, surely become smaller with the less restrictive models. In this example, in fact, the RMSE of the orthogonal transformation is smaller than that of the oblique transformation. This indicates that the additional degree of freedom allowing for skew rotations does not produce a closer fit. In this example, we see little reason to relax orthogonal transformations; very little is gained in terms of the Procrustes statistic (an illness-of-fit measure) or the RMSE. In this interpretation, we used our intuition to guide us whether a difference in fit is substantively and statistically meaningful—formal significance tests are not provided.

Finally, the unrestricted transformation can be estimated with `procrustes ..., trans- form(unrestricted)`. This analysis is related to a multivariate regression with the target variables as the dependent variables and the source variables as the independent variables. Although the unrestricted Procrustes analysis assumes spherical (uncorrelated homoskedastic) residuals, this

restrictive assumption is not made in multivariate regression as estimated by the `mvreg` command. The comparable multivariate regression over the same estimation sample can be viewed simply by typing

```
. estat mvreg
```
Multivariate regression, similar to "procrustes ..., transform(unrestricted)"

Equation	Obs	Parms	RMSE	"R-sq"	F	P>F
survey_x	20	3	7.696981	0.9953	1817.102	0.0000
survey_y	20	3	6.971772	0.9970	2859.068	0.0000

	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
survey_x						
speed_x	2.27584	.0379369	59.99	0.000	2.1958	2.35588
speed_y	.4147244	.0355475	11.67	0.000	.3397257	.489723
_cons	510.8028	8.065519	63.33	0.000	493.7861	527.8196
survey_y						
speed_x	-.4129564	.0343625	-12.02	0.000	-.485455	-.3404579
speed_y	2.355725	.0321982	73.16	0.000	2.287793	2.423658
_cons	288.243	7.305587	39.46	0.000	272.8296	303.6564

This analysis is seen as postestimation after a Procrustes analysis, so it does not change the "last estimation results". We may still replay `procrustes` and use other `procrustes` postestimation commands.

◁

Stored results

`estat compare` after `procrustes` stores the following in `r()`:

Matrices
  r(cstat)   Procrustes statistics, degrees of freedom, and RMSEs
  r(fstat) F statistics, degrees of freedom, and p-values

`estat mvreg` does not return results.

`estat summarize` after `procrustes` stores the following in `r()`:

Matrices
  r(stats)   means, standard deviations, minimums, and maximums

Methods and formulas

The predicted values for the jth variable are defined as

$$\widehat{y}_j = \widehat{c}_j + \widehat{\rho} \, \mathbf{X} \, \widehat{\mathbf{A}}[., j]$$

The residual for y_j is simply $y_j - \widehat{y}_j$. The "rowwise" quality q of the approximation is defined as the residual sum of squares:

$$q = \sum_j (y_j - \widehat{y}_j)^2$$

The entries of the summary table produced by estat compare are described in *Methods and formulas* of [MV] **procrustes**. The F tests produced by estat compare are similar to standard nested model tests in linear models.

References

See *References* in [MV] **procrustes**.

Also see

[MV] **procrustes** — Procrustes transformation

[MV] **mvreg** — Multivariate regression

[U] **20 Estimation and postestimation commands**

Title

> **rotate —** Orthogonal and oblique rotations after factor and pca

Description

rotate performs a rotation of the loading matrix after factor, factormat, pca, or pcamat; see
[MV] **factor** and [MV] **pca**. Many rotation criteria (such as varimax and oblimin) are available that
can be applied with respect to the orthogonal and oblique class of rotations.

rotate, clear removes the rotation results from the estimation results.

If you want to rotate a given matrix, see [MV] **rotatemat**.

If you want a Procrustes rotation, which rotates variables optimally toward other variables, see
[MV] **procrustes**.

Quick start

Orthogonal varimax rotation of loading matrix after pca or factor

    rotate

Same as above, but apply the minimum entropy rotation criterion

    rotate, entropy

Same as above, but apply oblique quartimin rotation criterion

    rotate, oblique quartimin

Same as above, but rotate the Kaiser normalized matrix

    rotate, oblique quartimin normalize

Menu

Statistics > Multivariate analysis > Factor and principal component analysis > Postestimation > Rotate loadings

Syntax

> <u>rot</u>ate [, *options*]

> <u>rot</u>ate, clear

options	Description
[Main]	
<u>orth</u>ogonal	restrict to orthogonal rotations; the default, except with promax()
<u>obl</u>ique	allow oblique rotations
rotation_methods	rotation criterion
<u>norm</u>alize	rotate Kaiser normalized matrix
<u>fac</u>tors(#)	rotate # factors or components; default is to rotate all
<u>comp</u>onents(#)	synonym for factors()
[Reporting]	
<u>bla</u>nks(#)	display loadings as blanks when |loading| < #; default is blanks(0)
<u>det</u>ail	show rotatemat output; seldom used
<u>for</u>mat(%*fmt*)	display format for matrices; default is format(%9.5f)
<u>nol</u>oading	suppress display of rotated loadings
<u>noro</u>tation	suppress display of rotation matrix
[Optimization]	
optimize_options	control the maximization process; seldom used

collect is allowed; see [U] 11.1.10 Prefix commands.

rotation_methods	Description
* <u>var</u>imax	varimax (orthogonal only); the default
vgpf	varimax via the GPF algorithm (orthogonal only)
<u>quartimax</u>	quartimax (orthogonal only)
<u>equamax</u>	equamax (orthogonal only)
<u>parsimax</u>	parsimax (orthogonal only)
<u>entropy</u>	minimum entropy (orthogonal only)
tandem1	Comrey's tandem 1 principle (orthogonal only)
tandem2	Comrey's tandem 2 principle (orthogonal only)
* <u>pro</u>max[(#)]	promax power # (implies oblique); default is promax(3)
<u>obli</u>min[(#)]	oblimin with $\gamma = $ #; default is oblimin(0)
cf(#)	Crawford–Ferguson family with $\kappa = $ #, $0 \leq$ # ≤ 1
<u>bent</u>ler	Bentler's invariant pattern simplicity
<u>oblimax</u>	oblimax
<u>quartimin</u>	quartimin
<u>tar</u>get(*Tg*)	rotate toward matrix *Tg*
<u>par</u>tial(*Tg W*)	rotate toward matrix *Tg*, weighted by matrix *W*

* varimax and promax ignore all *optimize_options*.

Options

> Main

orthogonal specifies that an orthogonal rotation be applied. This is the default.

> See *Rotation criteria* below for details on the *rotation_methods* available with orthogonal.

oblique specifies that an oblique rotation be applied. This often yields more interpretable factors
with a simpler structure than that obtained with an orthogonal rotation. In many applications (for
example, after factor and pca) the factors before rotation are orthogonal (uncorrelated), whereas
the oblique rotated factors are correlated.

> See *Rotation criteria* below for details on the *rotation_methods* available with oblique.

clear specifies that rotation results be cleared (removed) from the last estimation command. clear
may not be combined with any other option.

> rotate stores its results within the e() results of pca and factor, overwriting any previous
rotation results. Postestimation commands such as predict operate on the last rotated results, if
any, instead of the unrotated results, and allow you to specify norotated to use the unrotated
results. The clear option of rotate allows you to remove the rotation results from e(), thus
freeing you from having to specify norotated for the postestimation commands.

normalize requests that the rotation be applied to the Kaiser normalization (Horst 1965) of the
matrix $\mathbf{A}$, so that the rowwise sums of squares equal 1. Kaiser normalization applies to the rotated
columns only (see the factors() option below).

factors(#), and synonym components(#), specifies the number of factors or components (columns
of the loading matrix) to be rotated, counted "from the left", that is, with the lowest column index.
The other columns are left unrotated. All columns are rotated by default.

> Reporting

blanks(#) shows blanks for loadings with absolute values smaller than #.

detail displays the rotatemat output; seldom used.

format(% *fmt*) specifies the display format for matrices. The default is format(%9.5f).

noloading suppresses the display of the rotated loadings.

norotation suppresses the display of the optimal rotation matrix.

> Optimization

optimize_options are seldom used; see [MV] **rotatemat**.

Rotation criteria

In the descriptions below, the matrix to be rotated is denoted as $\mathbf{A}$, p denotes the number of rows
of $\mathbf{A}$, and f denotes the number of columns of $\mathbf{A}$ (factors or components). If $\mathbf{A}$ is a loading matrix
from factor or pca, p is the number of variables, and f is the number of factors or components.

Criteria suitable only for orthogonal rotations

varimax and vgpf apply the orthogonal varimax rotation (Kaiser 1958). varimax maximizes the
variance of the squared loadings within factors (columns of $\mathbf{A}$). It is equivalent to cf($1/p$) and to
oblimin(1). varimax, the most popular rotation, is implemented with a dedicated fast algorithm
and ignores all *optimize_options*. Specify vgpf to switch to the general GPF algorithm used for
the other criteria.

quartimax uses the quartimax criterion (Harman 1976). quartimax maximizes the variance of the squared loadings within the variables (rows of $\mathbf{A}$). For orthogonal rotations, quartimax is equivalent to cf(0) and to oblimax.

equamax specifies the orthogonal equamax rotation. equamax maximizes a weighted sum of the varimax and quartimax criteria, reflecting a concern for simple structure within variables (rows of $\mathbf{A}$) as well as within factors (columns of $\mathbf{A}$). equamax is equivalent to oblimin($p/2$) and cf(#), where $\# = f/(2p)$.

parsimax specifies the orthogonal parsimax rotation. parsimax is equivalent to cf(#), where $\# = (f - 1)/(p + f - 2)$.

entropy applies the minimum entropy rotation criterion (Jennrich 2004).

tandem1 specifies that the first principle of Comrey's tandem be applied. According to Comrey (1967), this principle should be used to judge which "small" factors should be dropped.

tandem2 specifies that the second principle of Comrey's tandem be applied. According to Comrey (1967), tandem2 should be used for "polishing".

Criteria suitable only for oblique rotations

promax$\big[(\#)\big]$ specifies the oblique promax rotation. The optional argument specifies the promax power. Not specifying the argument is equivalent to specifying promax(3). Values smaller than 4 are recommended, but the choice is yours. Larger promax powers simplify the loadings (generate numbers closer to zero and one) but at the cost of additional correlation between factors. Choosing a value is a matter of trial and error, but most sources find values in excess of 4 undesirable in practice. The power must be greater than 1 but is not restricted to integers.

Promax rotation is an oblique rotation method that was developed before the "analytical methods" (based on criterion optimization) became computationally feasible. Promax rotation comprises an oblique Procrustean rotation of the original loadings $\mathbf{A}$ toward the elementwise #-power of the orthogonal varimax rotation of $\mathbf{A}$.

Criteria suitable for orthogonal and oblique rotations

oblimin$\big[(\#)\big]$ specifies that the oblimin criterion with $\gamma = \#$ be used. When restricted to orthogonal transformations, the oblimin() family is equivalent to the orthomax criterion function. Special cases of oblimin() include

γ	Special case
0	quartimax / quartimin
1/2	biquartimax / biquartimin
1	varimax / covarimin
$p/2$	equamax

p = number of rows of $\mathbf{A}$.

γ defaults to zero. Jennrich (1979) recommends $\gamma \le 0$ for oblique rotations. For $\gamma > 0$, it is possible that optimal oblique rotations do not exist; the iterative procedure used to compute the solution will wander off to a degenerate solution.

cf(#) specifies that a criterion from the Crawford–Ferguson (1970) family be used with $\kappa = \#$. cf(κ) can be seen as $(1 - \kappa)\mathrm{cf}_1(\mathbf{A}) + (\kappa)\mathrm{cf}_2(\mathbf{A})$, where $\mathrm{cf}_1(\mathbf{A})$ is a measure of row parsimony and $\mathrm{cf}_2(\mathbf{A})$ is a measure of column parsimony. $\mathrm{cf}_1(\mathbf{A})$ attains its greatest lower bound when no row of $\mathbf{A}$ has more than one nonzero element, whereas $\mathrm{cf}_2(\mathbf{A})$ reaches zero if no column of $\mathbf{A}$ has more than one nonzero element.

For orthogonal rotations, the Crawford–Ferguson family is equivalent to the oblimin() family. For orthogonal rotations, special cases include the following:

κ	Special case
0	quartimax / quartimin
$1/p$	varimax / covarimin
$f/(2p)$	equamax
$(f-1)/(p+f-2)$	parsimax
1	factor parsimony

p = number of rows of **A**.
f = number of columns of **A**.

bentler specifies that the "invariant pattern simplicity" criterion (Bentler 1977) be used.

oblimax specifies the oblimax criterion. oblimax maximizes the number of high and low loadings. oblimax is equivalent to quartimax for orthogonal rotations.

quartimin specifies that the quartimin criterion be used. For orthogonal rotations, quartimin is equivalent to quartimax.

target(*Tg*) specifies that **A** be rotated as near as possible to the conformable matrix *Tg*. Nearness is expressed by the Frobenius matrix norm.

partial(*Tg W*) specifies that **A** be rotated as near as possible to the conformable matrix *Tg*. Nearness is expressed by a weighted (by *W*) Frobenius matrix norm. *W* should be nonnegative and usually is zero–one valued, with ones identifying the target values to be reproduced as closely as possible by the factor loadings, whereas zeros identify loadings to remain unrestricted.

Remarks and examples

Remarks are presented under the following headings:

>Orthogonal rotations
>Oblique rotations
>Other types of rotation

In this entry, we focus primarily on the rotation of factor loading matrices in factor analysis. rotate may also be used after pca, with the same syntax. We advise caution in the interpretation of rotated loadings in principal component analysis because some of the optimality properties of principal components are not preserved under rotation. See [MV] **pca postestimation** for more discussion of this point.

Orthogonal rotations

The interpretation of a factor analytical solution is not always easy—an understatement, many will agree. This is due partly to the standard way in which the inherent indeterminacy of factor analysis is resolved. Orthogonal transformations of the common factors and the associated factor loadings are possible without affecting the reconstructed (fitted) correlation matrix and preserving the property that common factors are uncorrelated. This gives considerable freedom in selecting an orthogonal rotation to facilitate the interpretation of the factor loadings. Thurstone (1935) offered criteria for a "simple structure" required for a psychologically meaningful factor solution. These informal criteria for interpretation were then formalized into formal rotation criteria, for example, Harman (1976) and Gorsuch (1983).

▷ Example 1: Orthogonal varimax rotation

We illustrate `rotate` by using a factor analysis of the correlation matrix of eight physical variables (height, arm span, length of forearm, length of lower leg, weight, bitrochanteric diameter, chest girth, and chest width) of 305 girls.

```
. matrix input R = (1000  846   805   859   473   398   301   382 \
>                    846 1000   881   826   376   326   277   415 \
>                    805  881  1000   801   380   319   237   345 \
>                    859  826   801  1000   436   329   327   365 \
>                    473  376   380   436  1000   762   730   629 \
>                    398  326   319   329   762  1000   583   577 \
>                    301  277   237   327   730   583  1000   539 \
>                    382  415   345   365   629   577   539  1000)
. matrix R = R/1000
. matrix colnames R = height  arm_span  fore_arm  lower_leg
>                     weight  bitrod    ch_girth  ch_width
. matrix rownames R = height  arm_span  fore_arm  lower_leg
>                     weight  bitrod    ch_girth  ch_width
. matlist R, border format(%7.3f)
```

	height	arm_s~n	fore_~m	lower~g	weight	bitrod	ch_gi~h	ch_wi~h
height	1.000							
arm_span	0.846	1.000						
fore_arm	0.805	0.881	1.000					
lower_leg	0.859	0.826	0.801	1.000				
weight	0.473	0.376	0.380	0.436	1.000			
bitrod	0.398	0.326	0.319	0.329	0.762	1.000		
ch_girth	0.301	0.277	0.237	0.327	0.730	0.583	1.000	
ch_width	0.382	0.415	0.345	0.365	0.629	0.577	0.539	1.000

We extract two common factors with the iterated principal-factor method. See the description of `factormat` in [MV] **factor** for details on running a factor analysis on a Stata matrix rather than on a dataset.

```
. factormat R, n(305) fac(2) ipf
(obs=305)
```

Factor analysis/correlation   Number of obs   =   305
    Method: iterated principal factors   Retained factors =   2
    Rotation: (unrotated)   Number of params =   15

| Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.44901	2.93878	0.7466	0.7466
Factor2	1.51023	1.40850	0.2534	1.0000
Factor3	0.10173	0.04705	0.0171	1.0171
Factor4	0.05468	0.03944	0.0092	1.0263
Factor5	0.01524	0.05228	0.0026	1.0288
Factor6	-0.03703	0.02321	-0.0062	1.0226
Factor7	-0.06025	0.01415	-0.0101	1.0125
Factor8	-0.07440	.	-0.0125	1.0000

LR test: independent vs. saturated: chi2(28) = 2092.68 Prob>chi2 = 0.0000

```
Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Uniqueness
height	0.8560	-0.3244	0.1620
arm_span	0.8482	-0.4115	0.1112
fore_arm	0.8082	-0.4090	0.1795
lower_leg	0.8309	-0.3424	0.1923
weight	0.7503	0.5712	0.1108
bitrod	0.6307	0.4922	0.3600
ch_girth	0.5687	0.5096	0.4169
ch_width	0.6074	0.3507	0.5081

The default factor solution is rather poor from the perspective of a "simple structure", namely, that variables should have high loadings on few (one) factors and factors should ideally have only low and high values. A plot of the loadings is illuminating.

```
. loadingplot, xlab(0(.2)1) ylab(-.4(.2).6) aspect(1) yline(0) xline(0)
```


Factor loadings
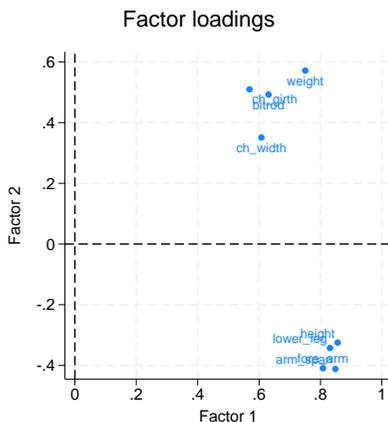
There are two groups of variables. We would like to see one group of variables close to one axis and the other group of variables close to the other axis. Turning the plot by about 45 degrees counterclockwise should make this possible and offer a much "simpler" structure. This is what the `rotate` command accomplishes.

```
. rotate
Factor analysis/correlation                      Number of obs     =        305
    Method: iterated principal factors          Retained factors  =          2
    Rotation: orthogonal varimax (Kaiser off)    Number of params  =         15
```

Factor	Variance	Difference	Proportion	Cumulative
Factor1	3.39957	0.83989	0.5705	0.5705
Factor2	2.55968	.	0.4295	1.0000

```
LR test: independent vs. saturated:  chi2(28) = 2092.68 Prob>chi2 = 0.0000
```

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
height	0.8802	0.2514	0.1620
arm_span	0.9260	0.1770	0.1112
fore_arm	0.8924	0.1550	0.1795
lower_leg	0.8708	0.2220	0.1923
weight	0.2603	0.9064	0.1108
bitrod	0.2116	0.7715	0.3600
ch_girth	0.1515	0.7484	0.4169
ch_width	0.2774	0.6442	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.8018	0.5976
Factor2	-0.5976	0.8018

See [MV] **factor** for the interpretation of the first panel. Here we will focus on the second and third panel. The rotated factor loadings satisfy

$$\text{Factor1}_{\text{rotated}} = 0.8018 \times \text{Factor1}_{\text{unrotated}} - 0.5976 \times \text{Factor2}_{\text{unrotated}}$$

$$\text{Factor2}_{\text{rotated}} = 0.5976 \times \text{Factor1}_{\text{unrotated}} + 0.8018 \times \text{Factor2}_{\text{unrotated}}$$

The uniqueness—the variance of the specific factors—is not affected, because we are changing only the coordinates in common factor space. The purpose of rotation is to make factor loadings easier to interpret. The first factor loads high on the first four variables and low on the last four variables; for the second factor, the roles are reversed. This is really a simple structure according to Thurstone's criteria. This is clear in the plot of the factor loadings.

. loadingplot, xlab(0(.2)1) ylab(0(.2)1) aspect(1) yline(0) xline(0)

Factor loadings
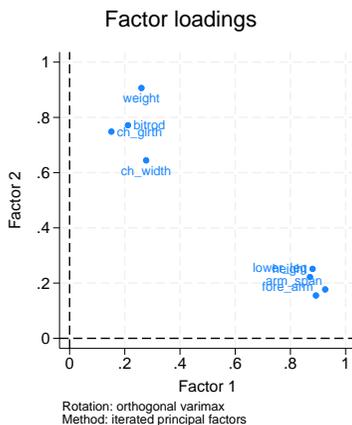
rotate provides several different rotations. You may make your intention clearer by typing the command as

. rotate, orthogonal varimax
  (output omitted)

rotate defaults to orthogonal (angle and length preserving) rotations of the axes; thus, orthogonal may be omitted. The default rotation method is varimax, probably the most popular method. We warn that the varimax rotation is not appropriate if you expect a general factor contributing to all variables (see also Gorsuch 1983, chap. 9). In such a case you could, for instance, consider a quartimax rotation.

◁

▷ Example 2: Orthogonal varimax rotation with normalization

rotate has performed what is known as "raw varimax", rotating the axes to maximize the sum of the variance of the squared loadings in the columns—the variance in a column is large if it comprises small and large (in the absolute sense) values. In rotating the axes, rows with large initial loadings—that is, with high communalities—have more influence than rows with only small values. Kaiser suggested that in the computation of the optimal rotation, all rows should have the same weight. This is usually known as the Kaiser normalization and sometimes known as the Horst normalization (Horst 1965). The option normalize applies this normalization method for rotation.

```
. rotate, normalize
Factor analysis/correlation                        Number of obs    =      305
    Method: iterated principal factors            Retained factors =        2
    Rotation: orthogonal varimax (Kaiser on)      Number of params =       15
```

Factor	Variance	Difference	Proportion	Cumulative
Factor1	3.31500	0.67075	0.5563	0.5563
Factor2	2.64425	.	0.4437	1.0000

```
    LR test: independent vs. saturated:  chi2(28) = 2092.68 Prob>chi2 = 0.0000
Rotated factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Uniqueness
height	0.8724	0.2775	0.1620
arm_span	0.9203	0.2045	0.1112
fore_arm	0.8874	0.1815	0.1795
lower_leg	0.8638	0.2478	0.1923
weight	0.2332	0.9137	0.1108
bitrod	0.1885	0.7775	0.3600
ch_girth	0.1292	0.7526	0.4169
ch_width	0.2581	0.6522	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.7837	0.6212
Factor2	-0.6212	0.7837

Here the raw and normalized varimax rotated loadings are not much different.

◁

In the first example, loadingplot after rotate showed the rotated loadings, not the unrotated loadings. How can this be? Remember that Stata estimation commands store their results in e(), which we can list using ereturn list.

```
. ereturn list
scalars:
                  e(f) =  2
                  e(N) =  305
               e(df_m) =  15
               e(df_r) =  13
              e(chi2_i) =  2092.68137837692
               e(df_i) =  28
                e(p_i) =  0
              e(evsum) =  5.95922412962743
                e(r_f) =  2
macros:
      e(r_normalization) : "kaiser"
             e(r_class) : "orthogonal"
         e(r_criterion) : "varimax"
            e(r_ctitle) : "varimax"
            e(cmdline) : "factormat R, n(305) fac(2) ipf"
                e(cmd) : "factor"
        e(marginsnotok) : "_ALL"
          e(properties) : "nob noV eigen"
              e(title) : "Factor analysis"
            e(predict) : "factor_p"
          e(estat_cmd) : "factor_estat"
         e(rotate_cmd) : "factor_rotate"
           e(rngstate) : "XAA1055b80bcee95e83ca9e2d41adfb0f0806ad6e5dec14687.."
            e(factors) : "factors(2)"
            e(mtitle) : "iterated principal factors"
            e(method) : "ipf"
         e(matrixname) : "R"
matrices:
               e(r_Ev) :  1 x 2
              e(r_Phi) :  2 x 2
                e(r_T) :  2 x 2
                e(r_L) :  8 x 2
                 e(C) :  8 x 8
               e(Phi) :  2 x 2
                 e(L) :  8 x 2
               e(Psi) :  1 x 8
                e(Ev) :  1 x 8
functions:
               e(sample)
```

When you replay an estimation command, it simply knows where to look, so that it can redisplay the output. rotate does something that few other postestimation commands are allowed to do: it adds information to the estimation results computed by factor or pca. But to avoid confusion, it writes in e() fields with the prefix r_. For instance, the matrix e(r_L) contains the rotated loadings.

If you replay factor after rotate, factor will display the rotated results. And this is what all factor and pca postestimation commands do. For instance, if you predict after rotate, predict will use the rotated results. Of course, it is still possible to operate on the unrotated results. factor, norotated replays the unrotated results. predict with the norotated option computes the factor scores for the unrotated results.

rotate stores information only about the most recent rotation, overwriting any information from the previous rotation. If you need the previous results again, run rotate with the respective options again; you do not need to run factor again. It is also possible to use estimates store to store estimation results for different rotations, which you may later restore and replay at will. See [R] **estimates store** for details.

If you no longer need the rotation results, you may type

```
. rotate, clear
```

to clean up the rotation result and return the `factor` results back to their pristine state (as if `rotate` had never been called).

▷ Example 3: Orthogonal quartimax and orthogonal oblimin rotations

`rotate` provides many more orthogonal rotations. Previously we stated that the varimax rotation can be thought of as the rotation that maximizes the varimax criterion, namely, the variance of the squared loadings summed over the columns. A column of loadings with a high variance tends to contain a series of large values and a series of low values, achieving the simplicity aim of factor analytic interpretation. The other types of rotation simply maximize other concepts of simplicity. For instance, the quartimax rotation aims at rowwise simplicity—preferably, the loadings within variables fall into a grouping of a few large ones and a few small ones, using again the variance in squared loadings as the criterion to be maximized.

```
. rotate, quartimax normalize
```

Factor analysis/correlation				Number of obs	=	305
Method: iterated principal factors				Retained factors	=	2
Rotation: orthogonal quartimax (Kaiser on)				Number of params	=	15

Factor	Variance	Difference	Proportion	Cumulative
Factor1	3.32371	0.68818	0.5577	0.5577
Factor2	2.63553	.	0.4423	1.0000

LR test: independent vs. saturated: chi2(28) = 2092.68 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
height	0.8732	0.2749	0.1620
arm_span	0.9210	0.2017	0.1112
fore_arm	0.8880	0.1788	0.1795
lower_leg	0.8646	0.2452	0.1923
weight	0.2360	0.9130	0.1108
bitrod	0.1909	0.7769	0.3600
ch_girth	0.1315	0.7522	0.4169
ch_width	0.2601	0.6514	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.7855	0.6188
Factor2	-0.6188	0.7855

Here the quartimax and the varimax rotated results are rather similar. This need not be the case—varimax focuses on simplicity within columns (factors) and quartimax within rows (variables). It is possible to compromise, rotating to strive for a weighted sum of row simplicity and column simplicity. This is known as the orthogonal oblimin criterion; in the orthogonal case, `oblimin()` is equivalent to the Crawford–Ferguson (option `cf()`) family and to the orthomax family. These are parameterized families of criteria with, for instance, the following special cases:

	oblimin(0)	quartimax rotation
	oblimin(0.5)	biquartimax rotation
	oblimin(1)	varimax rotation

```
. rotate, oblimin(0.5) normalize
Factor analysis/correlation                      Number of obs    =      305
    Method: iterated principal factors          Retained factors =        2
    Rotation: orthogonal oblimin (Kaiser on)    Number of params =       15
```

Factor	Variance	Difference	Proportion	Cumulative
Factor1	3.31854	0.67783	0.5569	0.5569
Factor2	2.64071	.	0.4431	1.0000

```
    LR test: independent vs. saturated:  chi2(28) = 2092.68 Prob>chi2 = 0.0000
```
Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
height	0.8727	0.2764	0.1620
arm_span	0.9206	0.2033	0.1112
fore_arm	0.8877	0.1804	0.1795
lower_leg	0.8642	0.2468	0.1923
weight	0.2343	0.9134	0.1108
bitrod	0.1895	0.7772	0.3600
ch_girth	0.1301	0.7525	0.4169
ch_width	0.2589	0.6518	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.7844	0.6202
Factor2	-0.6202	0.7844

Because the varimax and orthomax rotation are relatively close, the factor loadings resulting from an optimal rotation of a compromise criterion are close as well.

The orthogonal quartimax rotation may be obtained in different ways, namely, directly or by the appropriate member of the oblimin() or cf() families:

```
. rotate, quartimax
(output omitted)
. rotate, oblimin(0)
(output omitted)
. rotate, cf(0)
(output omitted)
```

◁

❑ Technical note

The orthogonal varimax rotation also belongs to the oblimin and Crawford–Ferguson families.

```
. rotate, varimax
(output omitted)
. rotate, oblimin(1)
(output omitted)
. rotate, cf(0.125)
(output omitted)
```

(The $0.125 = 1/8$ above is 1 divided by the number of variables.) All three produce the orthogonal varimax rotation. (There is actually a fourth way, namely rotate, vgpf.) There is, however, a subtle difference in algorithms used. The varimax rotation as specified by the varimax option (which is also the default) is computed by the classic algorithm of cycling through rotations of two factors at a time. The other ways use the general "gradient projection" algorithm proposed by Jennrich; see [MV] **rotatemat** for more information.

◻

Oblique rotations

In addition to orthogonal rotations, oblique rotations are also available.

▷ Example 4: Oblique oblimin rotation

The rotation methods that we have discussed so far are all orthogonal: the angles between the axes are unchanged, so the rotated factors are uncorrelated.

Returning to our original factor analysis,

```
. factormat R, n(305) fac(2) ipf
(output omitted)
```

we examine the correlation matrix of the common factors,

```
. estat common
Correlation matrix of the common factors
```

Factors	Factor1	Factor2
Factor1	1	
Factor2	0	1

and see that they are uncorrelated.

The indeterminacy in the factor analytic model, however, allows us to consider other transformations of the common factors, namely, oblique rotations. These are rotations of the axes that preserve the norms of the rows of the loadings but not the angles between the axes or the angles between the rows. There are advantages and disadvantages of oblique rotations. See, for instance, Gorsuch (1983, chap. 9). In many substantive theories, there seems little reason to impose the restriction that the common factors be uncorrelated. The additional freedom in choosing the axes generally leads to more easily interpretable factors, sometimes to a great extent. However, although most researchers are willing to accept mildly correlated factors, they would prefer to use fewer of such factors.

rotate provides an extensive menu of oblique rotations; with a few exceptions, criteria suitable for orthogonal rotations are also suitable for oblique rotation. Again oblique rotation can be conceived of as maximizing some "simplicity" criterion. We illustrate with the oblimin oblique rotation.

```
. rotate, oblimin oblique normalize
Factor analysis/correlation                    Number of obs     =        305
    Method: iterated principal factors         Retained factors  =          2
    Rotation: oblique oblimin (Kaiser on)      Number of params  =         15
```

Factor	Variance	Proportion	Rotated factors are correlated
Factor1	3.95010	0.6629	
Factor2	3.35832	0.5635	

```
    LR test: independent vs. saturated:  chi2(28) = 2092.68 Prob>chi2 = 0.0000
Rotated factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Uniqueness
height	0.8831	0.0648	0.1620
arm_span	0.9560	-0.0288	0.1112
fore_arm	0.9262	-0.0450	0.1795
lower_leg	0.8819	0.0344	0.1923
weight	0.0047	0.9408	0.1108
bitrod	-0.0069	0.8032	0.3600
ch_girth	-0.0653	0.7923	0.4169
ch_width	0.1042	0.6462	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.9112	0.7930
Factor2	-0.4120	0.6092

The oblique rotation yields a much "simpler" structure in the Thurstone (1935) sense than that of the orthogonal rotations. This time, the common factors are moderately correlated.

```
. estat common
Correlation matrix of the oblimin(0) rotated common factors
```

Factors	Factor1	Factor2
Factor1	1	
Factor2	.4716	1

◁

❑ Technical note

The numerical maximization of a simplicity criterion with respect to the class of orthogonal or oblique rotations proceeds in a stepwise method, making small improvements from an initial guess, until no more small improvements are possible. Such a procedure is not guaranteed to converge to the global optimum but to a local optimum instead. In practice, we experience few such problems. To some extent, this is because we have a reasonable starting value using the unrotated factors or loadings. As a safeguard, Stata starts the improvement from multiple initial positions chosen at random from the classes of orthonormal and normal rotation matrices. If the maximization procedure converges to the same criterion value at each trial, we may be reasonably certain that we have found the global optimum. Let us illustrate.

```
. set seed 123
. rotate, oblimin oblique normalize protect(10)
Trial   1 : min criterion   .0181657
Trial   2 : min criterion   .0181657
Trial   3 : min criterion   .0181657
Trial   4 : min criterion   .0181657
Trial   5 : min criterion   .0181657
Trial   6 : min criterion   .0181657
Trial   7 : min criterion   .0181657
Trial   8 : min criterion   .0181657
Trial   9 : min criterion   458260.7
Trial  10 : min criterion   .0181657
```

Factor analysis/correlation		Number of obs	=	305
Method: iterated principal factors		Retained factors	=	2
Rotation: oblique oblimin (Kaiser on)		Number of params	=	15

Factor	Variance	Proportion	Rotated factors are correlated
Factor1	3.95010	0.6629	
Factor2	3.35832	0.5635	

LR test: independent vs. saturated: chi2(28) = 2092.68 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
height	0.8831	0.0648	0.1620
arm_span	0.9560	-0.0288	0.1112
fore_arm	0.9262	-0.0450	0.1795
lower_leg	0.8819	0.0344	0.1923
weight	0.0047	0.9408	0.1108
bitrod	-0.0069	0.8032	0.3600
ch_girth	-0.0653	0.7923	0.4169
ch_width	0.1042	0.6462	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.9112	0.7930
Factor2	-0.4120	0.6092

Here three of the random trials converged to distinct rotations from the rest. Specifying options `log` and `trace` would demonstrate that in these cases, the initial configurations were so far off that no improvements could be found. In a real application, we would probably rerun `rotate` with more trials, say, `protect(50)`, for more reassurance.

❑

❑ Technical note

There is another but almost trivial source of nonuniqueness. All simplicity criteria supported by `rotate` and `rotatemat` are invariant with respect to permutations of the rows and of the columns. Also, the signs of rotated loadings are undefined. `rotatemat`, the computational engine of `rotate`, makes sure that all columns have a positive orientation, that is, have a positive sum. `rotate`, after `factor` and `pca`, also sorts the columns into decreasing order of explained variance.

❑

Other types of rotation

rotate supports a few rotation methods that do not fit into the scheme of "simplicity maximization". The first is known as the target rotation, which seeks to rotate the factor loading matrix to approximate as much as possible a target matrix of the same size as the factor loading matrix.

▷ Example 5: Rotation toward a target matrix

We continue with our same example. If we had expected a factor loading structure in which the first group of four variables would load especially high on the first factor and the second group of four variables on the second factor, we could have set up the following target matrix.

```
. matrix W = ( 1,0 \ 1,0 \ 1,0 \ 1,0 \ 0,1 \ 0,1 \ 0,1 \ 0,1 )

. matrix list W

W[8,2]
     c1   c2
r1    1    0
r2    1    0
r3    1    0
r4    1    0
r5    0    1
r6    0    1
r7    0    1
r8    0    1
```

It is also possible to request an orthogonal or oblique rotation toward the target **W**.

```
. rotate, target(W) normalize
```

Factor analysis/correlation	Number of obs =	305
Method: iterated principal factors	Retained factors =	2
Rotation: orthogonal target (Kaiser on)	Number of params =	15

Factor	Variance	Difference	Proportion	Cumulative
Factor1	3.30616	0.65307	0.5548	0.5548
Factor2	2.65309	.	0.4452	1.0000

LR test: independent vs. saturated: chi2(28) = 2092.68 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
height	0.8715	0.2802	0.1620
arm_span	0.9197	0.2073	0.1112
fore_arm	0.8869	0.1843	0.1795
lower_leg	0.8631	0.2505	0.1923
weight	0.2304	0.9144	0.1108
bitrod	0.1861	0.7780	0.3600
ch_girth	0.1268	0.7530	0.4169
ch_width	0.2561	0.6530	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.7817	0.6236
Factor2	-0.6236	0.7817

With this target matrix, the result is not far different from the varimax and other orthogonal rotations.

◁

▷ Example 6: Oblique promax rotation

For our last example, we return to the early days of factor analysis, the time before fast computing. Analytical methods for orthogonal rotation, such as varimax, were developed relatively early. Analogous methods for oblique rotations proved more complicated. Hendrickson and White (1964) proposed a computationally simple method to obtain an oblique rotation that comprises an oblique Procrustes rotation of the factor loadings toward a signed power of the varimax rotation of the factor loadings. The promax method has one parameter, the power to which the varimax loadings are raised. Larger promax powers simplify the factor loadings (that is, generate more zeros and ones) at the cost of more correlation between the common factors. Generally, we recommend that you keep the power in the range (1,4] and not restricted to integers. Specifying promax is equivalent to promax(3).

```
. rotate, promax normalize
```

Factor analysis/correlation   Number of obs   =   305
    Method: iterated principal factors   Retained factors =   2
    Rotation: oblique promax (Kaiser on)   Number of params =   15

Factor	Variance	Proportion	Rotated factors are correlated
Factor1	3.92727	0.6590	
Factor2	3.31295	0.5559	

LR test: independent vs. saturated: chi2(28) = 2092.68 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
height	0.8797	0.0744	0.1620
arm_span	0.9505	-0.0176	0.1112
fore_arm	0.9205	-0.0340	0.1795
lower_leg	0.8780	0.0443	0.1923
weight	0.0214	0.9332	0.1108
bitrod	0.0074	0.7966	0.3600
ch_girth	-0.0509	0.7851	0.4169
ch_width	0.1152	0.6422	0.5081

Factor rotation matrix

	Factor1	Factor2
Factor1	0.9069	0.7832
Factor2	-0.4214	0.6218

In this simple two-factor example, the promax solution is similar to the oblique oblimin solution.

◁

Stored results

rotate adds stored results named e(r*name*) to the stored results that were already defined by factor or pca.

rotate adds to the following results:

Scalars
e(r_f)	number of factors/components in rotated solution
e(r_fmin)	rotation criterion value

Macros
e(r_class)	orthogonal or oblique
e(r_criterion)	rotation criterion
e(r_ctitle)	title for rotation
e(r_normalization)	kaiser or none

Matrices
e(r_L)	rotated loadings
e(r_T)	rotation
e(r_Phi)	correlations between common factors (after factor only)
e(r_Ev)	explained variance by common factors (factor) or rotated components (pca)

The factors/components in the rotated solution are in decreasing order of e(r_Ev).

❑ Technical note

The rest of this section contains information of interest to programmers who want to provide rotate support to other estimation commands. Similar to other postestimation commands, such as estat and predict, rotate invokes a handler command. The name of this command is extracted from the field e(rotate_cmd). The estimation command *cmd* should set this field appropriately. For instance, pca sets the macro e(rotate_cmd) to pca_rotate. The command pca_rotate implements rotation after pca and pcamat, using rotatemat as the computational engine. pca_rotate does not display output itself; it relies on pca to do so.

For consistent behavior for end users and programmers alike, we recommend that the estimation command *cmd*, the driver commands, and other postestimation commands adhere to the following guidelines:

Driver command

- The rotate driver command for *cmd* should be named *cmd*_rotate.

- *cmd*_rotate should be an e-class command, that is, returning in e().

- Make sure that *cmd*_rotate is invoked after the correct estimation command (for example, if "'e(cmd)'" != "pca" ...).

- Allow at least the option <u>det</u>ail and any option available to rotatemat.

- Extract from e() the matrix you want to rotate; invoke rotatemat on the matrix; and run this command quietly (that is, suppress all output) unless the option detail was specified.

- Extract the r() objects returned by rotatemat; see *Methods and formulas* of [MV] **rotatemat** for details.

- Compute derived results needed for your estimator.

- Store in e() fields (macros, scalars, matrices) named r_*name*, adding to the existing e() fields.

  Store the macros returned by rotatemat under the same named prefixed with r_. In particular, the macro e(r_criterion) should be set to the name of the rotation criterion returned by rotatemat as r(criterion). Other commands can check this field to find out whether rotation results are available.

We suggest that only the most recent rotation results be stored, overwriting any existing `e(r_*)` results. The programmer command `_rotate_clear` clears any existing `r_*` fields from `e()`.

- Display the rotation results by replaying *cmd*.

Estimation command cmd

- In *cmd*, define `e(rotate_cmd)` to *cmd*`_rotate`.

- *cmd* should be able to display the rotated results and should default to do so if rotated results are available. Include an option `noROTated` to display the unrotated results.

- You may use the programmer command `_rotate_text` to obtain a standard descriptive text for the rotation method.

Other postestimation commands

- Other postestimation commands after *cmd* should operate on the rotated results whenever they are appropriate and available, unless the option `noROTated` specifies otherwise.

- Mention that you operate on the unrotated results only if rotated results are available, but the user or you as the programmer decided not to use them.

❑

Methods and formulas

See *Methods and formulas* of [MV] **rotatemat**.

Henry Felix Kaiser (1927–1992) was born in Morristown, New Jersey, and educated in California, where he earned degrees at Berkeley in between periods of naval service during and after World War II. A specialist in psychological and educational statistics and measurement, Kaiser worked at the Universities of Illinois and Wisconsin before returning to Berkeley in 1968. He made several contributions to factor analysis, including varimax rotation (the subject of his PhD) and a measure for assessing sampling adequacy. Kaiser is remembered as an eccentric who spray-painted his shoes in unusual colors and listed ES (Eagle Scout) as his highest degree.

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Also see *References* in [MV] **rotatemat**.

Also see

[MV] **factor** — Factor analysis

[MV] **factor postestimation** — Postestimation tools for factor and factormat

[MV] **pca** — Principal component analysis

[MV] **pca postestimation** — Postestimation tools for pca and pcamat

[MV] **procrustes** — Procrustes transformation

[MV] **rotatemat** — Orthogonal and oblique rotations of a Stata matrix

Title

> **rotatemat —** Orthogonal and oblique rotations of a Stata matrix

Description

rotatemat applies a linear transformation to the specified matrix so that the result minimizes a criterion function over all matrices in a class of feasible transformations. Two classes are supported: orthogonal (orthonormal) and oblique. A wide variety of criterion functions are available, representing different ways to measure the "simplicity" of a matrix. Most of these criteria can be applied with both orthogonal and oblique rotations.

This entry describes the computation engine for orthogonal and oblique transformations of Stata matrices. This command may be used directly on any Stata matrix.

If you are interested in rotation after factor, factormat, pca, or pcamat, see [MV] **factor postestimation**, [MV] **pca postestimation**, and the general description of rotate as a postestimation facility in [MV] **rotate**.

Menu

Statistics > Multivariate analysis > Orthogonal and oblique rotations of a matrix

Syntax

> rotatemat *matrix_L* [, *options*]

options	Description
Main	
<u>orth</u>ogonal	restrict to orthogonal rotations; the default, except with promax()
<u>obl</u>ique	allow oblique rotations
rotation_methods	rotation criterion
<u>norm</u>alize	rotate Kaiser normalized matrix
Reporting	
<u>f</u>ormat(*[% fmt](fmt)*)	display format for matrices; default is format(%9.5f)
<u>bl</u>anks(*#*)	display loadings as blanks when |loading| < *#*; default is blanks(0)
<u>nodi</u>splay	suppress all output except log and trace
<u>nol</u>oading	suppress display of rotated loadings
<u>noro</u>tation	suppress display of rotation matrix
<u>matn</u>ame(*string*)	descriptive label of the matrix to be rotated
<u>coln</u>ames(*string*)	descriptive name for columns of the matrix to be rotated
Optimization	
optimize_options	control the optimization process; seldom used

collect is allowed; see [U] **11.1.10 Prefix commands**.

rotation_methods	Description
* <u>var</u>imax	varimax (**orthogonal** only); the default
<u>vg</u>pf	varimax via the GPF algorithm (**orthogonal** only)
<u>q</u>uartimax	quartimax (**orthogonal** only)
<u>e</u>quamax	equamax (**orthogonal** only)
<u>par</u>simax	parsimax (**orthogonal** only)
<u>ent</u>ropy	minimum entropy (**orthogonal** only)
<u>tandem1</u>	Comrey's tandem 1 principle (**orthogonal** only)
<u>tandem2</u>	Comrey's tandem 2 principle (**orthogonal** only)
* <u>pro</u>max [(*#*)]	promax power *#* (implies **oblique**); default is promax(3)
<u>obli</u>min [(*#*)]	oblimin with $\gamma = \#$; default is oblimin(0)
<u>cf</u>(*#*)	Crawford–Ferguson family with $\kappa = \#$, $0 \leq \# \leq 1$
<u>ben</u>tler	Bentler's invariant pattern simplicity
<u>oblima</u>x	oblimax
<u>quartimi</u>n	quartimin
<u>t</u>arget(*Tg*)	rotate toward matrix *Tg*
<u>par</u>tial(*Tg W*)	rotate toward matrix *Tg*, weighted by matrix *W*

*varimax and promax ignore all *optimize_options*.

Options

    ⌐ Main ⌐

orthogonal specifies that an orthogonal rotation be applied. This is the default.

    See *Rotation criteria* below for details on the *rotation_methods* available with orthogonal.

oblique specifies that an oblique rotation be applied. This often yields more interpretable factors
    with a simpler structure than that obtained with an orthogonal rotation. In many applications (for
    example, after factor and pca), the factors before rotation are orthogonal (uncorrelated), whereas
    the oblique rotated factors are correlated.

    See *Rotation criteria* below for details on the *rotation_methods* available with oblique.

normalize requests that the rotation be applied to the Kaiser normalization (Horst 1965) of the
    matrix **A** so that the rowwise sums of squares equal 1.

    ⌐ Reporting ⌐

format(%*fmt*) specifies the display format for matrices. The default is format(%9.5f).

blanks(#) specifies that small values of the rotated matrix—that is, those elements of $\mathbf{A}(\mathbf{T}')^{-1}$
    that are less than # in absolute value—are displayed as spaces.

nodisplay suppresses all output except the log and trace.

noloading suppresses the display of the rotated loadings.

norotation suppresses the display of the optimal rotation matrix.

matname(*string*) is a rarely used output option; it specifies a descriptive label of the matrix to be
    rotated.

colnames(*string*) is a rarely used output option; it specifies a descriptive name to refer to the columns
    of the matrix to be rotated. For instance, colnames(components) specifies that the output label
    the columns as "components". The default is "factors".

    ⌐ Optimization ⌐

optimize_options control the iterative optimization process. These options are seldom used.

    iterate(#) is a rarely used option; it specifies the maximum number of iterations. The default
        is iterate(1000).

    log specifies that an iteration log be displayed.

    trace is a rarely used option; it specifies that the rotation be displayed at each iteration.

    tolerance(#) is one of three criteria for declaring convergence and is rarely used. The tol-
        erance() convergence criterion is satisfied when the relative change in the rotation matrix **T**
        from one iteration to the next is less than or equal to #. The default is tolerance(1e-6).

    gtolerance(#) is one of three criteria for declaring convergence and is rarely used. The gtol-
        erance() convergence criterion is satisfied when the Frobenius norm of the gradient of the
        criterion function $c(\ )$ projected on the manifold of orthogonal matrices or of normal matrices
        is less than or equal to #. The default is gtolerance(1e-6).

    ltolerance(#) is one of three criteria for declaring convergence and is rarely used. The ltoler-
        ance() convergence criterion is satisfied when the relative change in the minimization criterion
        $c(\ )$ from one iteration to the next is less than or equal to #. The default is ltolerance(1e-6).

protect(*#*) requests that *#* optimizations with random starting values be performed and that the best of the solutions be reported. The output also indicates whether all starting values converged to the same solution. When specified with a large number, such as protect(50), this provides reasonable assurance that the solution found is the global maximum and not just a local maximum. If trace is also specified, the rotation matrix and rotation criterion value of each optimization will be reported.

maxstep(*#*) is a rarely used option; it specifies the maximum number of step-size halvings. The default is maxstep(20).

init(*matname*) is a rarely used option; it specifies the initial rotation matrix. *matname* should be square and regular (nonsingular) and have the same number of columns as the matrix *matrix_L* to be rotated. It should be orthogonal ($\mathbf{T'T} = \mathbf{TT'} = \mathbf{I}$) or normal ($\text{diag}(\mathbf{T'T}) = \mathbf{1}$), depending on whether orthogonal or oblique rotations are performed. init() cannot be combined with random. If neither init() nor random is specified, the identity matrix is used as the initial rotation.

random is a rarely used option; it specifies that a random orthogonal or random normal matrix be used as the initial rotation matrix. random cannot be combined with init(). If neither init() nor random is specified, the identity matrix is used as the initial rotation.

Rotation criteria

In the descriptions below, the matrix to be rotated is denoted as $\mathbf{A}$, p denotes the number of rows of $\mathbf{A}$, and f denotes the number of columns of $\mathbf{A}$ (factors or components). If $\mathbf{A}$ is a loading matrix from factor or pca, p is the number of variables and f is the number of factors or components.

Criteria suitable only for orthogonal rotations

varimax and vgpf apply the orthogonal varimax rotation (Kaiser 1958). varimax maximizes the variance of the squared loadings within factors (columns of $\mathbf{A}$). It is equivalent to cf(*1/p*) and to oblimin(1). varimax, the most popular rotation, is implemented with a dedicated fast algorithm and ignores all *optimize_options*. Specify vgpf to switch to the general GPF algorithm used for the other criteria.

quartimax uses the quartimax criterion (Harman 1976). quartimax maximizes the variance of the squared loadings within the variables (rows of $\mathbf{A}$). For orthogonal rotations, quartimax is equivalent to cf(0) and to oblimax.

equamax specifies the orthogonal equamax rotation. equamax maximizes a weighted sum of the varimax and quartimax criteria, reflecting a concern for simple structure within variables (rows of $\mathbf{A}$) as well as within factors (columns of $\mathbf{A}$). equamax is equivalent to oblimin(*p/2*) and cf(*#*), where $\# = f/(2p)$.

parsimax specifies the orthogonal parsimax rotation. parsimax is equivalent to cf(*#*), where $\# = (f-1)/(p+f-2)$.

entropy applies the minimum entropy rotation criterion (Jennrich 2004).

tandem1 specifies that the first principle of Comrey's tandem be applied. According to Comrey (1967), this principle should be used to judge which "small" factors be dropped.

tandem2 specifies that the second principle of Comrey's tandem be applied. According to Comrey (1967), tandem2 should be used for "polishing".

Criteria suitable only for oblique rotations

promax$\big[$(#)$\big]$ specifies the oblique promax rotation. The optional argument specifies the promax power. Not specifying the argument is equivalent to specifying promax(3). Values less than 4 are recommended, but the choice is yours. Larger promax powers simplify the loadings (generate numbers closer to zero and one) but at the cost of additional correlation between factors. Choosing a value is a matter of trial and error, but most sources find values in excess of 4 undesirable in practice. The power must be greater than 1 but is not restricted to integers.

Promax rotation is an oblique rotation method that was developed before the "analytical methods" (based on criterion optimization) became computationally feasible. Promax rotation comprises an oblique Procrustean rotation of the original loadings $\mathbf{A}$ toward the elementwise #-power of the orthogonal varimax rotation of $\mathbf{A}$.

Criteria suitable for orthogonal and oblique rotations

oblimin$\big[$(#)$\big]$ specifies that the oblimin criterion with $\gamma = \#$ be used. When restricted to orthogonal transformations, the oblimin() family is equivalent to the orthomax criterion function. Special cases of oblimin() include

γ	Special case
0	quartimax / quartimin
1/2	biquartimax / biquartimin
1	varimax / covarimin
$p/2$	equamax

p = number of rows of $\mathbf{A}$.

γ defaults to zero. Jennrich (1979) recommends $\gamma \leq 0$ for oblique rotations. For $\gamma > 0$, it is possible that optimal oblique rotations do not exist; the iterative procedure used to compute the solution will wander off to a degenerate solution.

cf(#) specifies that a criterion from the Crawford–Ferguson (1970) family be used with $\kappa = \#$. cf(κ) can be seen as $(1 - \kappa)\text{cf}_1(\mathbf{A}) + (\kappa)\text{cf}_2(\mathbf{A})$, where $\text{cf}_1(\mathbf{A})$ is a measure of row parsimony and $\text{cf}_2(\mathbf{A})$ is a measure of column parsimony. $\text{cf}_1(\mathbf{A})$ attains its greatest lower bound when no row of $\mathbf{A}$ has more than one nonzero element, whereas $\text{cf}_2(\mathbf{A})$ reaches zero if no column of $\mathbf{A}$ has more than one nonzero element.

For orthogonal rotations, the Crawford–Ferguson family is equivalent to the oblimin() family. For orthogonal rotations, special cases include the following:

κ	Special case
0	quartimax / quartimin
$1/p$	varimax / covarimin
$f/(2p)$	equamax
$(f-1)/(p+f-2)$	parsimax
1	factor parsimony

p = number of rows of $\mathbf{A}$.
f = number of columns of $\mathbf{A}$.

bentler specifies that the "invariant pattern simplicity" criterion (Bentler 1977) be used.

oblimax specifies the oblimax criterion, which maximizes the number of high and low loadings. oblimax is equivalent to quartimax for orthogonal rotations.

quartimin specifies that the quartimin criterion be used. For orthogonal rotations, quartimin is
equivalent to quartimax.

target(*Tg*) specifies that $\mathbf{A}$ be rotated as near as possible to the conformable matrix *Tg*. Nearness
is expressed by the Frobenius matrix norm.

partial(*Tg W*) specifies that $\mathbf{A}$ be rotated as near as possible to the conformable matrix *Tg*.
Nearness is expressed by a weighted (by *W*) Frobenius matrix norm. *W* should be nonnegative
and usually is zero–one valued, with ones identifying the target values to be reproduced as closely
as possible by the factor loadings, whereas zeros identify loadings to remain unrestricted.

Remarks and examples

Remarks are presented under the following headings:

Introduction

For an introduction to rotation, see Harman (1976) and Gorsuch (1983).

rotatemat applies a linear transformation $\mathbf{T}$ to the specified matrix *matrix_L*, which we will call
$\mathbf{A}$, so that the result $c(\mathbf{A}(\mathbf{T}')^{-1})$ minimizes a criterion function $c(\ )$ over all matrices $\mathbf{T}$ in a class
of feasible transformations.

Two classes are supported: orthogonal (orthonormal) and oblique. Orthonormal rotations comprise
all orthonormal matrices $\mathbf{T}$, such that $\mathbf{T}'\mathbf{T} = \mathbf{T}\mathbf{T}' = \mathbf{I}$; here $\mathbf{A}(\mathbf{T}')^{-1}$ simplifies to $\mathbf{A}\mathbf{T}$. Oblique
rotations are characterized by $\mathrm{diag}(\mathbf{T}'\mathbf{T}) = \mathbf{1}$. All supported rotation criteria are invariant with respect
to permutations of the columns and change of signs of the columns. rotatemat returns the solution
with positive column sums and with columns sorted by the L2 norm; columns are ordered with respect
to the L1 norm if the columns have the same L2 norm.

A wide variety of criteria $c(\ )$ is available, representing different ways to measure the "simplicity"
of a matrix. Most of these criteria can be applied with both orthogonal and oblique rotations. A
discussion of the different criteria and of the rotations with which they may be combined is provided
in *Rotation criteria*.

A factor analysis of 24 psychological tests on 145 seventh- and eighth-grade school children with
four retained factors is used for illustration. Factors were extracted with maximum likelihood. The
loadings are reported by Harman (1976). We enter the factor loadings as a Stata matrix with 24 rows
and four columns. For more information, we add full descriptive labels as comments and short labels
as row names.

```
. matrix input L = (
>    601    019    388    221 \        Visual perception
>    372   -025    252    132 \        Cubes
>    413   -117    388    144 \        Paper form board
>    487   -100    254    192 \        Flags
>    691   -304   -279    035 \        General information
>    690   -409   -200   -076 \        Paragraph comprehension
>    677   -409   -292    084 \        Sentence completion
>    674   -189   -099    122 \        Word classification
>    697   -454   -212   -080 \        Word meaning
>    476    534   -486    092 \        Addition
>    558    332   -142   -090 \        Code
>    472    508   -139    256 \        Counting dots
>    602    244    028    295 \        Straight-curved capitals
>    423    058    015   -415 \        Word recognition
>    394    089    097   -362 \        Number recognition
>    510    095    347   -249 \        Figure recognition
>    466    197   -004   -381 \        Object-number
>    515    312    152   -147 \        Number-figure
>    443    089    109   -150 \        Figure-word
>    614   -118    126   -038 \        Deduction
>    589    227    057    123 \        Numerical puzzles
>    608   -107    127   -038 \        Problem reasoning
>    687   -044    138    098 \        Series completion
>    651    177   -212   -017 )        Arithmetic problems
. matrix colnames L = F1 F2 F3 F4
. matrix rownames L = visual    cubes      board
>                     flags     general    paragraph
>                     sentence  wordclas   wordmean
>                     add       code       dots
>                     capitals  wordrec    numbrec
>                     figrec    obj-num    num-fig
>                     fig-word  deduct     numpuzz
>                     reason    series     arith
. matrix L = L/1000
```

Thus using `rotatemat`, we can study various rotations of L without access to the full data or the correlation matrix.

Orthogonal rotations

We can rotate the matrix L according to an extensive list of criteria, including orthogonal rotations.

▷ Example 1: Orthogonal varimax rotation

The default rotation, orthogonal varimax, is probably the most popular method:

```
. rotatemat L, format(%6.3f)
Rotation of L[24,4]

    Criterion               varimax
    Rotation class          orthogonal
    Kaiser normalization    off
Rotated factors
```

	F1	F2	F3	F4
visual	0.247	0.151	0.679	0.128
cubes	0.171	0.060	0.425	0.078
board	0.206	-0.049	0.549	0.097
flags	0.295	0.068	0.504	0.050
general	0.765	0.214	0.117	0.067
paragraph	0.802	0.074	0.122	0.160
sentence	0.826	0.148	0.117	-0.008
wordclas	0.612	0.230	0.290	0.061
wordmean	0.840	0.049	0.112	0.152
add	0.166	0.846	-0.076	0.082
code	0.222	0.533	0.134	0.313
dots	0.048	0.705	0.257	0.025
capitals	0.240	0.500	0.450	0.020
wordrec	0.249	0.124	0.032	0.526
numbrec	0.178	0.109	0.106	0.499
figrec	0.158	0.076	0.401	0.510
obj-num	0.197	0.262	0.060	0.539
num-fig	0.096	0.352	0.311	0.422
fig-word	0.204	0.175	0.232	0.336
deduct	0.443	0.115	0.365	0.255
numpuzz	0.233	0.428	0.389	0.169
reason	0.432	0.120	0.363	0.256
series	0.440	0.228	0.472	0.184
arith	0.409	0.509	0.150	0.228

```
Orthogonal rotation
```

	F1	F2	F3	F4
F1	0.677	0.438	0.475	0.352
F2	-0.632	0.737	0.049	0.232
F3	-0.376	-0.458	0.760	0.268
F4	-0.011	0.234	0.441	-0.866

◁

The varimax rotation $\mathbf{T}$ of $\mathbf{A}$ maximizes the (raw) varimax criterion over all orthogonal $\mathbf{T}$, which for $p \times f$ matrices is defined as (Harman 1976)

$$c_{\text{varimax}}(\mathbf{A}) = \frac{1}{p} \sum_{j=1}^{f} \left\{ \left(\sum_{i=1}^{p} A_{ij}^4 \right) - \frac{1}{p} \left(\sum_{i=1}^{p} A_{ij}^2 \right)^2 \right\}$$

The criterion $c_{\text{varimax}}(\mathbf{A})$ can be interpreted as the sum over the columns of the variances of the squares of the loadings A_{ij}. A column with large variance will typically consist of many small values and a few large values. Achieving such "simple" columnwise distributions is often helpful for interpretation.

❑ Technical note

The raw varimax criterion as defined here has been criticized because it weights variables by the size of their loadings, that is, by their communalities. This is often not desirable. A common rotation strategy is to weight all rows equally by rescaling to the same rowwise sum of squared loadings. This is known as the Kaiser normalization. You may request this normalized solution with the `normalize` option. The default in `rotatemat` and in `rotate` (see [MV] **rotate**) is not to normalize.

❑

Many other criteria for the rotation of matrices have been proposed and studied in the literature. Most of these criteria can be stated in terms of a "simplicity function". For instance, quartimax rotation (Carroll 1953) seeks to achieve interpretation within rows—in a factor analytic setup, this means that variables should have a high loading on a few factors and a low loading on the other factors. The quartimax criterion is defined as (Harman 1976)

$$c_{\text{quartimax}}(\mathbf{A}) = \left(\frac{1}{pf} \sum_{i=1}^{p} \sum_{j=1}^{f} A_{ij}^4 \right) - \left(\frac{1}{pf} \sum_{i=1}^{p} \sum_{j=1}^{f} A_{ij}^2 \right)^2$$

▷ Example 2: Orthogonal quartimax rotation

We display the quartimax solution, use blanks to represent loadings with absolute values smaller than 0.3, and suppress the display of the rotation matrix.

```
. rotatemat L, quartimax format(%6.3f) norotation blanks(0.3)
```
Rotation of L[24,4]

```
    Criterion                quartimax
    Rotation class           orthogonal
    Kaiser normalization     off
    Criterion value          -1.032898
    Number of iterations     35
```
Rotated factors (blanks represent abs()<.3)

	F1	F2	F3	F4
visual	0.374		0.630	
cubes			0.393	
board			0.513	
flags	0.379		0.450	
general	0.791			
paragraph	0.827			
sentence	0.838			
wordclas	0.669			
wordmean	0.860			
add		0.829		
code	0.316	0.521		
dots		0.701		
capitals	0.348	0.482	0.393	
wordrec	0.316			0.492
numbrec				0.469
figrec			0.382	0.470
obj-num				0.503
num-fig		0.357		0.383
fig-word				
deduct	0.528			
numpuzz	0.342	0.414	0.340	
reason	0.517			
series	0.543		0.395	
arith	0.490	0.478		

◁

Some of the criteria supported by `rotatemat` are defined as one-parameter families. The oblimin(γ) criterion and the Crawford and Ferguson cf(κ) criterion families contain the varimax and quartimax criteria as special cases; that is, they can be obtained by certain values of γ and κ, respectively. Intermediate parameter values provide compromises between varimax's aim of column simplification and quartimax's aim of row simplification. Varimax and quartimax are equivalent to oblimin(1) and oblimin(0), respectively. A compromise, oblimin(0.5), is also known as biquartimax.

▷ Example 3: Orthogonal biquartimax rotation

Because the varimax and quartimax solutions are so close for our matrix L, the biquartimax compromise will also be rather close.

```
. rotatemat L, oblimin(0.5) format(%6.3f) norotation
  (output omitted )
```

◁

❏ Technical note

You may have noticed a difference between the output of `rotatemat` in the default case or equivalently when we type

        . rotatemat L, varimax

and in other cases. In the default case, no mention is made of the criterion value and the number of iterations. `rotatemat` uses a fast special algorithm for this most common case, whereas for other rotations it uses a general gradient projection algorithm (GPF) proposed by Jennrich (2001, 2002); see also Bernaards and Jennrich (2005). The general algorithm is used to obtain the varimax rotation if you specify the option `vgpf` rather than `varimax`.

❏

The rotations we have illustrated are orthogonal—the lengths of the rows and the angles between the rows are not affected by the rotations. We may verify—we do not show this in the manual to conserve paper—that after an orthogonal rotation of L

        . matlist L*L'

and

        . matlist r(AT)*r(AT)'

return the same 24 by 24 matrix, whereas

        . matlist r(T)*r(T)'

and

        . matlist r(T)'*r(T)

both return a 2×2 identity matrix. `rotatemat` returns in `r(AT)` the rotated matrix and in `r(T)` the rotation matrix.

Oblique rotations

`rotatemat` provides a second class of rotations: oblique rotations. These rotations maintain the norms of the rows of the matrix but not their inner products. In geometric terms, interpreting the rows of the matrix to be rotated as vectors, both the orthogonal and the oblique rotations maintain the lengths of the vectors. Under orthogonal transformations, the angles between the vectors are also left unchanged—these transformations comprise true reorientations in space and reflections. Oblique rotations do not conserve angles between vectors. If the vectors are orthogonal before rotations—as will be the case if we are rotating factor or component loading matrices—this will no longer be the case after the rotation. The "freedom" to select angles between the rows allows oblique rotations to generate simpler loading structures than the orthogonal rotations—sometimes much simpler. In a factor analytic setting, the disadvantage is, however, that the rotated factors are correlated.

`rotatemat` can obtain oblique rotations for most of the criteria that are available for orthogonal rotations; some of the criteria (such as the entropy criterion) are available only for the orthogonal case.

▷ Example 4: Oblique oblimin rotation

We illustrate with the psychological tests matrix L and apply the oblique oblimin criterion.

```
. rotatemat L, oblimin oblique format(%6.3f) blanks(0.3)
Rotation of L[24,4]
    Criterion               oblimin(0)
    Rotation class          oblique
    Kaiser normalization    off
    Criterion value         .1957363
    Number of iterations    78
Rotated factors (blanks represent abs()<.3)
```

	F1	F2	F3	F4
visual		0.686		
cubes		0.430		
board		0.564		
flags		0.507		
general	0.771			
paragraph	0.808			
sentence	0.865			
wordclas	0.560			
wordmean	0.857			
add			0.864	
code			0.460	0.305
dots			0.701	
capitals		0.437	0.442	
wordrec				0.571
numbrec				0.543
figrec		0.314		0.540
obj-num				0.584
num-fig				0.438
fig-word				0.341
deduct	0.325			
numpuzz		0.344	0.347	
reason	0.311			
series		0.417		
arith			0.428	

```
Oblique rotation
```

	F1	F2	F3	F4
F1	0.823	0.715	0.584	0.699
F2	-0.483	0.019	0.651	0.213
F3	-0.299	0.587	-0.435	0.207
F4	-0.006	0.379	0.213	-0.651

The option `oblique` requested an oblique rotation rather than the default `orthogonal`. You may verify that `r(AT)` equals `L * inv(r(T)')` within reasonable roundoff with

```
. matlist r(AT) - L * inv(r(T)')
  (output omitted)
```

The correlation between the rotated dimensions is easily obtained.

```
. matlist r(T)' * r(T)
```

	F1	F2	F3	F4
F1	1			
F2	.4026978	1		
F3	.294928	.2555824	1	
F4	.4146879	.3784689	.3183115	1

◁

Promax rotation

rotatemat also offers promax rotation.

▷ Example 5: Oblique promax rotation

We use the matrix L to illustrate promax rotation.

```
. rotatemat L, promax blanks(0.3) format(%6.3f)
Rotation of L[24,4]
```

Criterion	promax(3)
Rotation class	oblique
Kaiser normalization	off

Rotated factors (blanks represent abs()<.3)

	F1	F2	F3	F4
visual		0.775		
cubes		0.487		
board		0.647		
flags		0.572		
general	0.786			
paragraph	0.825			
sentence	0.888			
wordclas	0.543			
wordmean	0.878			
add			0.921	
code			0.466	
dots			0.728	
capitals		0.468	0.441	
wordrec				0.606
numbrec				0.570
figrec		0.364		0.539
obj-num				0.610
num-fig				0.425
fig-word				0.337
deduct		0.323		
numpuzz		0.369	0.336	
reason		0.322		
series		0.462		
arith			0.436	

```
Oblique rotation
```

	F1	F2	F3	F4
F1	0.841	0.829	0.663	0.743
F2	-0.462	0.020	0.614	0.215
F3	-0.282	0.478	-0.386	0.159
F4	-0.012	0.290	0.184	-0.614

The correlation between the rotated dimensions can be obtained as

```
. matlist r(T)' * r(T)
```

	F1	F2	F3	F4
F1	1			
F2	.5491588	1		
F3	.3807942	.4302401	1	
F4	.4877064	.5178414	.4505817	1

◁

Stored results

rotatemat stores the following in r():

Scalars
   r(f)   criterion value
   r(iter)   number of GPF iterations
   r(rc)   return code
   r(nnconv)   number of nonconvergent trials; protect() only

Macros
   r(cmd)   rotatemat
   r(ctitle)   descriptive label of rotation method
   r(ctitle12)   version of r(ctitle) at most 12 characters long
   r(criterion)   criterion name (e.g., oblimin)
   r(class)   orthogonal or oblique
   r(normalization)   kaiser or none
   r(carg)   criterion argument

Matrices
   r(T)   optimal transformation $\mathbf{T}$
   r(AT)   optimal $\mathbf{AT} = \mathbf{A}(\mathbf{T}')^{-1}$
   r(fmin)   minimums found; protect() only

Methods and formulas

rotatemat minimizes a scalar-valued criterion function $c(\mathbf{AT})$ with respect to the set of orthogonal matrices $\mathbf{T}'\mathbf{T} = \mathbf{I}$, or $c(\mathbf{A}(\mathbf{T}')^{-1})$ with respect to the normal matrix, $\text{diag}(\mathbf{T}'\mathbf{T}) = \mathbf{1}$. For orthonormal $\mathbf{T}$, $\mathbf{T} = (\mathbf{T}')^{-1}$.

The rotation criteria can be conveniently written in terms of scalar-valued functions; see Bernaards and Jennrich (2005). Define the inner product $\langle \mathbf{A}, \mathbf{B} \rangle = \text{trace}(\mathbf{A}'\mathbf{B})$. $|\mathbf{A}| = \sqrt{\langle \mathbf{A}, \mathbf{A} \rangle}$ is called the Frobenius norm of the matrix $\mathbf{A}$. Let $\mathbf{\Lambda}$ be a $p \times k$ matrix. Denote by $\mathbf{X}^2$ the direct product $\mathbf{X} \cdot \mathbf{X}$. See Harman (1976) for information on many of the rotation criteria and references to the authors originally proposing the criteria. Sometimes we list an alternative reference. Our notation is similar to that of Bernaards and Jennrich (2005).

   `rotatemat` uses the iterative "gradient projection algorithm" (Jennrich 2001, 2002) for the optimization of the criterion over the permissible transformations. Different versions are provided for optimal orthogonal and oblique rotations; see Bernaards and Jennrich (2005).

Varimax (orthogonal only)

   Varimax is equivalent to oblimin with $\gamma = 1$ or to the Crawford–Ferguson family with $\kappa = 1/p$; see below.

Quartimax (orthogonal only)

$$c(\mathbf{\Lambda}) = \sum_i \sum_r \lambda_{ir}^4 = -\frac{1}{4} \left\langle \mathbf{\Lambda}^2, \mathbf{\Lambda}^2 \right\rangle$$

Equamax (orthogonal only)

   Equamax is equivalent to oblimin with $\gamma = p/2$ or to the Crawford–Ferguson family with $\kappa = f/(2p)$; see below.

Parsimax (orthogonal only)

   Parsimax is equivalent to the Crawford–Ferguson family with $\kappa = (f-1)/(p+f-2)$; see below.

Entropy (orthogonal only); see Jennrich (2004)

$$c(\mathbf{\Lambda}) = -\frac{1}{2} \left\langle \mathbf{\Lambda}^2, \, \log\mathbf{\Lambda}^2 \right\rangle$$

Tandem principal 1 (orthogonal only); see Comrey (1967)

$$c(\mathbf{\Lambda}) = - \left\langle \mathbf{\Lambda}^2, (\mathbf{\Lambda}\mathbf{\Lambda}')^2 \mathbf{\Lambda}^2 \right\rangle$$

Tandem principal 2 (orthogonal only); see Comrey (1967)

$$c(\mathbf{\Lambda}) = \left\langle \mathbf{\Lambda}^2, \{\mathbf{1}\mathbf{1}' - (\mathbf{\Lambda}\mathbf{\Lambda}')^2\}\mathbf{\Lambda}^2 \right\rangle$$

Promax (oblique only)

Promax does not fit in the maximizing-of-a-simplicity-criterion framework that is at the core of `rotatemat`. The promax method (Hendrickson and White 1964) was proposed before computing power became widely available. The promax rotation comprises three steps:

1. Perform an orthogonal rotation on $\mathbf{A}$; `rotatemat` uses varimax.

2. Raise the elements of the rotated matrix to some power, preserving the signs of the elements. Typically, the power is taken from the range [2,4]. This operation is meant to distinguish more clearly between small and large values.

3. The matrix from step 2 is used as the target for an oblique Procrustean rotation from the original matrix $\mathbf{A}$. The method to compute this rotation in promax is different from the method in the `procrustes` command (see [MV] **procrustes**). The latter produces the real least-squares oblique rotation; promax uses an approximation.

Oblimin; see Jennrich (1979)

$$c(\mathbf{\Lambda}) = \frac{1}{4} \left\langle \mathbf{\Lambda}^2, \{\mathbf{I} - (\gamma/p)\mathbf{1}\mathbf{1}'\}\mathbf{\Lambda}^2(\mathbf{1}\mathbf{1}' - \mathbf{I}) \right\rangle$$

Orthomax and oblimin are equivalent when restricted to orthogonal rotations. Special cases of `oblimin()` include the following:

γ	Special case
0	quartimin
1/2	biquartimin
$p/2$	equamax
1	varimax

Crawford and Ferguson (1970) family

$$c(\mathbf{\Lambda}) = \frac{1-\kappa}{4} \left\langle \mathbf{\Lambda}^2, \mathbf{\Lambda}^2(\mathbf{1}\mathbf{1}' - \mathbf{I}) \right\rangle + \frac{\kappa}{4} \left\langle \mathbf{\Lambda}^2, (\mathbf{1}\mathbf{1}' - \mathbf{I})\mathbf{\Lambda}^2 \right\rangle$$

When restricted to orthogonal transformations, `cf()` and `oblimin()` are in fact equivalent. Special cases of `cf()` include the following:

κ	Special case
0	quartimax
$1/p$	varimax
$f/(2p)$	equamax
$(f-1)/(p+f-2)$	parsimax
1	factor parsimony

Bentler's invariant pattern simplicity; see Bentler (1977)

$$c(\mathbf{\Lambda}) = \log[\det\{(\mathbf{\Lambda}^2)'\mathbf{\Lambda}^2\}] - \log(\det[\text{diag}\{(\mathbf{\Lambda}^2)'\mathbf{\Lambda}^2\}])$$

Oblimax

$$c(\mathbf{\Lambda}) = -\log(\langle \mathbf{\Lambda}^2, \mathbf{\Lambda}^2 \rangle) + 2\log(\langle \mathbf{\Lambda}, \mathbf{\Lambda} \rangle)$$

For orthogonal transformations, oblimax is equivalent to quartimax; see above.

Quartimin

$$c(\mathbf{\Lambda}) = \sum_{r \neq s} \sum_i \lambda_{ir}^2 \lambda_{is}^2 = -\frac{1}{4} \left\langle \mathbf{\Lambda}^2, \mathbf{\Lambda}^2(\mathbf{1}\mathbf{1}' - \mathbf{I}) \right\rangle$$

Target

$$c(\mathbf{\Lambda}) = \frac{1}{2}|\mathbf{\Lambda} - \mathbf{H}|^2$$

for given target matrix $\mathbf{H}$.

Partially specified target

$$c(\mathbf{\Lambda}) = |\mathbf{W} \cdot (\mathbf{\Lambda} - \mathbf{H})|^2$$

for given target matrix $\mathbf{H}$, nonnegative weighting matrix $\mathbf{W}$ (usually zero–one valued) and with $\cdot$ denoting the direct product.

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Also see

[MV] **rotate** — Orthogonal and oblique rotations after factor and pca

[MV] **procrustes** — Procrustes transformation

Title

> **scoreplot** — Score and loading plots

Description

scoreplot produces scatterplots of the score variables after factor, factormat, pca, or pcamat, and scatterplots of the discriminant score variables after discrim lda or candisc.

loadingplot produces scatterplots of the loadings (factors or components) after factor, factormat, pca, or pcamat, and the standardized discriminant function loadings after discrim lda or candisc.

Quick start

Plot score variables

Plot score variables after a command such as pca or factor
    scoreplot

Same as above, but add labels found in variable mylabel
    scoreplot, mlabel(mylabel)

Same as above, but increase number of factors from 2 to 4
    scoreplot, mlabel(mylabel) factors(4)

Same as above, but use unrotated results and combine plots instead of displaying matrix plot
    scoreplot, mlabel(mylabel) factors(4) combined norotated

Plot loadings

Plot the loadings after a command such as pca or factor
    loadingplot

Same as above, but increase the number of factors from 2 to 4
    loadingplot, factors(4)

Same as above, but use unrotated results and combine plots instead of displaying matrix plot
    loadingplot, factors(4) combined norotated

Menu

scoreplot

Statistics > Multivariate analysis > Factor and principal component analysis > Postestimation > Score variables plot

loadingplot

Statistics > Multivariate analysis > Factor and principal component analysis > Postestimation > Loading plot

Syntax

Plot score variables

    scoreplot $\big[$ *if* $\big]$ $\big[$ *in* $\big]$ $\big[$, *scoreplot_options* $\big]$

Plot the loadings (factors, components, or discriminant functions)

    loadingplot $\big[$, *loadingplot_options* $\big]$

scoreplot_options	Description
[Main]	
<u>fac</u>tors(*#*)	number of factors/scores to be plotted; default is factors(2)
components(*#*)	synonym for factors()
norotated	use unrotated factors or scores, even if rotated results exist
matrix	graph as a matrix plot, available only when factors(2) is specified; default is a scatterplot
combined	graph as a combined plot, available when factors(*# > 2*); default is a matrix plot
half	graph lower half only; allowed only with matrix
graph_matrix_options	affect the rendition of the matrix graph
combine_options	affect the rendition of the combined graph
<u>score</u>opt(*predict_opts*)	options for predict generating score variables
marker_options	change look of markers (color, size, etc.)
marker_label_options	change look or position of marker labels
Y axis, X axis, Titles, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

loadingplot_options	Description
[Main]	
<u>fac</u>tors(*#*)	number of factors/scores to be plotted; default is factors(2)
components(*#*)	synonym for factors()
norotated	use unrotated factors or scores, even if rotated results exist
matrix	graph as a matrix plot, available only when factors(2) is specified; default is a scatterplot
combined	graph as a combined plot, available when factors(*# > 2*); default is a matrix plot
half	graph lower half only; allowed only with matrix
graph_matrix_options	affect the rendition of the matrix graph
combine_options	affect the rendition of the combined graph
maxlength(*#*)	abbreviate variable names to # characters; default is maxlength(12)
marker_options	change look of markers (color, size, etc.)
marker_label_options	change look or position of marker labels
Y axis, X axis, Titles, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

Options

▢ Main

factors(#) produces plots for all combinations of score variables up to #. # should not exceed the number of retained factors (components or discriminant functions) and defaults to 2. components() is a synonym. No plot is produced with factors(1).

norotated uses unrotated results, even when rotated results are available. The default is to use rotated results if they are available. norotated is ignored if rotated results are not available.

matrix specifies that plots be produced using graph matrix; see [G-2] **graph matrix**. This is the default when three or more factors are specified. This option may not be used with combined.

combined specifies that plots be produced using graph combine; see [G-2] **graph combine**. This option may not be used with matrix.

half specifies that only the lower half of the matrix be graphed. half can be specified only with the matrix option.

graph_matrix_options affect the rendition of the matrix plot; see [G-2] **graph matrix**.

combine_options affect the rendition of the combined plot; see [G-2] **graph combine**. *combine_options* may not be specified unless factors() is greater than 2.

scoreopt(*predict_opts*), an option used with scoreplot, specifies options for predict to generate the score variables. For example, after factor, scoreopt(bartlett) specifies that Bartlett scoring be applied.

maxlength(#), an option used with loadingplot, causes the variable names (used as point markers) to be abbreviated to # characters. The abbrev() function performs the abbreviation, and if # is less than 5, it is treated as 5; see [FN] **String functions**.

marker_options affect the rendition of markers drawn at the plotted points, including their shape, size, color, and outline; see [G-3] *marker_options*.

marker_label_options specify if and how the markers are to be labeled; see [G-3] *marker_label_options*.

▢ Y axis, X axis, Titles, Overall

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding by(). These include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk (see [G-3] *saving_option*).

Remarks and examples

One of the main results from a principal component analysis, factor analysis, or a linear discriminant analysis is a set of eigenvectors that are called components, factors, or linear discriminant functions. These are stored in what is called a loading matrix. pca, pcamat, factor, and factormat store the loading matrix in e(L). If there were p variables involved in the PCA or factor analysis, and f components or factors were retained, there will be p rows and f columns in the resulting loading matrix. discrim lda and candisc store the standardized canonical discriminant function coefficients or loadings in e(L_std).

The columns of the loading matrix are in order of importance. For instance, with PCA, the first column of the loading matrix is the component that accounts for the most variance, the second column accounts for the next most variance, and so on.

In a loading plot, the values from one column of the loading matrix are plotted against the values from another column of the loading matrix. Of most interest is the plot of the first and second columns (the first and second components, factors, or discriminant functions), and this is what `loadingplot` produces by default. The rows of the loading matrix provide the points to be graphed. Variable names are automatically used as the marker labels for these points.

▷ Example 1: Loading plot

We use the Renaissance painters' data introduced in example 2 of [MV] **biplot**. There are four attribute variables recorded for 10 painters. We examine the first two principal component loadings for this dataset.

```
. use https://www.stata-press.com/data/r18/renpainters
(Scores by Roger de Piles for Renaissance painters)

. pca composition drawing colour expression
(output omitted)

. loadingplot
```


Component loadings
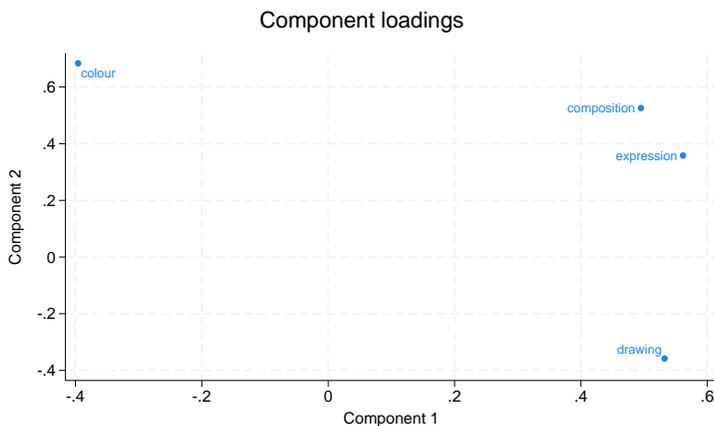
From the first component, we see that color (or colour, if you prefer) is separated from the other three attributes (variables): composition, expression, and drawing. From the second component, the difference in drawing stands out.

◁

Score plots approach the view of the loading matrix from the perspective of the observations. `predict` after `pca` and `factor` produces scores; see [MV] **pca postestimation** and [MV] **factor postestimation**. `predict` after `discrim lda` and `candisc` can request discriminant function scores; see [MV] **discrim lda postestimation**. A score for an observation from a particular column of the loading matrix is obtained as the linear combination of that observation's data by using the coefficients found in the loading. From the raw variables, the linear combinations described in the columns of the loading matrix are applied to generate new component or factor score variables. A score plot graphs one score variable against another. By default, `scoreplot` graphs the scores generated from the first and second columns of the loading matrix (the first two components or factors).

▷ Example 2: Score plot

We continue with the PCA of the Renaissance painters.

```
. scoreplot
```


Score variables (pca)
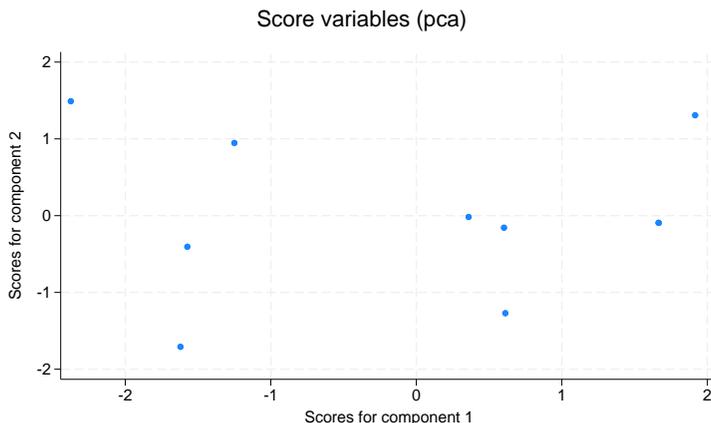
Unlike `loadingplot`, which can use the variable names as labels, `scoreplot` does not automatically know how to label the points after `factor` and `pca`. The graph above is not helpful. The *marker_label_option* `mlabel()` takes care of this.

```
. scoreplot, mlabel(painter) aspect(1) xlabel(-2(1)3) ylabel(-2(1)3)
> title(Renaissance painters)
```


Renaissance painters
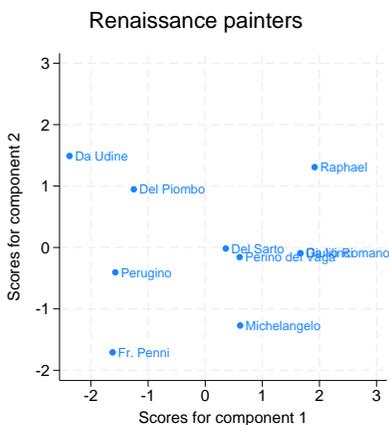
We added a few other options to improve the graph. We extended the axes to include the value 3 so that there would be room for the marker labels, imposed an aspect ratio of 1, and added a title.

The score plot gives us a feeling for the similarities and differences between the painters. Da Udine is in an opposite corner from Michelangelo. The other two corners have Fr. Penni and Raphael.

You could refer to the loading plot and compare it with this score plot to see that the corner with Da Udine is most associated with the `colour` variable, whereas the corner with Michelangelo is best associated with `drawing`. Raphael is in the corner where the variables `composition` and `expression` are predominant.

If you like to make these kinds of associations between the variables and the observations, you will enjoy using the `biplot` command. It provides a joint view of the variables and observations; see [MV] **biplot**.

◁

After a rotation, the rotated factor or component loading matrix is stored in `e(r_L)`. By default, both `loadingplot` and `scoreplot` work with the rotated loadings if they are available. The `norotated` option allows you to obtain the graphs for the unrotated loadings and scores.

You can also request a matrix or combined graph for all combinations of the first several components or factors with the `components()` option (or the alias `factors()`).

▷ Example 3: Score plots after a rotation

Even though the results from our initial look at the principal components of the Renaissance painters seem clear enough, we continue our demonstration by showing the score plots for the first three components after a rotation. See [MV] **rotate** for information on rotation in general, and see [MV] **pca postestimation** for specific guidance and warnings concerning rotation after a PCA.

```
. rotate
(output omitted )
. scoreplot, mlabel(painter) components(3) combined
> aspect(.8) xlabel(-2(1)3) ylabel(-2(1)2)
```
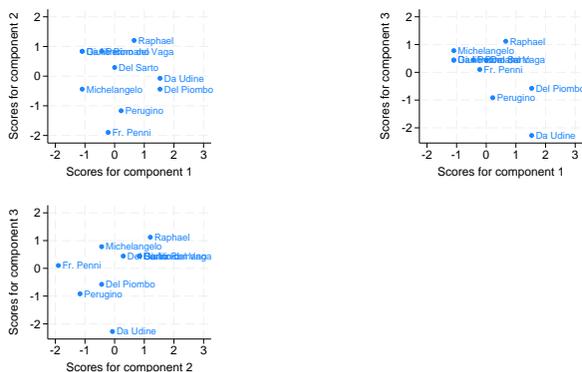

By default, the rotation information was included as a note in the graph. We specified `compo-nents(3)` to obtain all paired plots between the first three components. The `combined` option selected the combined view instead of the default matrix view of the graphs. The `aspect()`, `xlabel()`, and `ylabel()` options provide reasonable use of the graphing region while providing the same scale in the horizontal and vertical directions.

◁

As the number of `factors()` or `components()` increases, the graphing area for each plot gets smaller. Although the default matrix view (option `matrix`) may be the most natural, the combined view (option `combined`) displays half as many graphs. However, the combined view uses more space for the labeling of axes than the matrix view. Regardless of the choice, with many requested factors or components, the graphs become too small to be of any use. In `loadingplot`, the `maxlength()` option will trim the variable name marker labels that are automatically included. This may help reduce

overlap when multiple small graphs are shown. You can go further and remove these marker labels by using the mlabel("") option.

Other examples of loadingplot and scoreplot are found in [MV] **pca postestimation**, [MV] **factor postestimation**, [MV] **discrim lda**, and [MV] **discrim lda postestimation**.

Also see

[MV] **candisc** — Canonical linear discriminant analysis

[MV] **discrim lda** — Linear discriminant analysis

[MV] **discrim lda postestimation** — Postestimation tools for discrim lda

[MV] **factor** — Factor analysis

[MV] **factor postestimation** — Postestimation tools for factor and factormat

[MV] **pca** — Principal component analysis

[MV] **pca postestimation** — Postestimation tools for pca and pcamat

[MV] **screeplot** — Scree plot of eigenvalues

Title

> **screeplot —** Scree plot of eigenvalues

Description

screeplot produces a scree plot of the eigenvalues of a covariance or correlation matrix.

screeplot automatically obtains the eigenvalues after candisc, discrim lda, factor, factormat, pca, and pcamat. screeplot also works automatically to plot singular values after ca and camat, canonical correlations after canon, and eigenvalues after manova, mca, mds, mdsmat, and mdslong.

screeplot lets you obtain a scree plot in other cases by directly specifying *eigvals*, a vector containing the eigenvalues.

Quick start

Scree plot of the eigenvalues after a command such as pca or factor

    screeplot

Add a horizontal line at the mean of the eigenvalues

    screeplot, mean

Scree plot with confidence intervals after pca

    screeplot, ci

Menu

Statistics > Multivariate analysis > Factor and principal component analysis > Postestimation > Scree plot of eigenvalues

Syntax

> screeplot [*eigvals*] [, *options*]

scree is a synonym for screeplot.

options	Description
Main	
<u>neigen</u>(*#*)	graph only largest *#* eigenvalues; default is to plot all eigenvalues
Mean	
<u>mean</u>	graph horizontal line at the mean of the eigenvalues
<u>meanl</u>opts(*cline_options*)	affect rendition of the mean line
CI	
ci [(*ci_options*)]	graph confidence intervals (after pca only); ci is a synonym for ci(asymptotic)
Plot	
cline_options	affect rendition of the lines connecting points
marker_options	change look of markers (color, size, etc.)
Add plots	
<u>addplot</u>(*plot*)	add other plots to the generated graph
Y axis, X axis, Titles, Legend, Overall	
twoway_options	any options other than by() documented in [G-3] *twoway_options*

collect is allowed; see [U] **11.1.10 Prefix commands**.

ci_options	Description
<u>asym</u>ptotic	compute asymptotic confidence intervals; the default
<u>het</u>eroskedastic	compute heteroskedastic bootstrap confidence intervals
<u>hom</u>oskedastic	compute homoskedastic bootstrap confidence intervals
area_options	affect the rendition of the confidence bands
table	produce a table of confidence intervals
<u>level</u>(*#*)	set confidence level; default is level(95)
<u>reps</u>(*#*)	number of bootstrap simulations; default is reps(200)
seed(*str*)	random-number seed used for the bootstrap simulations

Options

⌐ **Main** ⌐

neigen(*#*) specifies the number of eigenvalues to plot. The default is to plot all eigenvalues.

⌐ **Mean** ⌐

mean displays a horizontal line at the mean of the eigenvalues.

`meanlopts(`*cline_options*`)` affects the rendition of the mean reference line added using the `mean` option; see [G-3] *cline_options*.

⌐ CI ̄

`ci` [(*ci_options*)] displays confidence intervals for the eigenvalues. The option `ci` is a synonym for `ci(asymptotic)`. The following methods for estimating confidence intervals are available:

`ci(asymptotic)` specifies the asymptotic distribution of the eigenvalues of a central Wishart distribution, the distribution of the covariance matrix of a sample from a multivariate normal distribution. The asymptotic theory applied to correlation matrices is not fully correct, probably giving confidence intervals that are somewhat too narrow.

`ci(heteroskedastic)` specifies a parametric bootstrap by using the percentile method and assuming that the eigenvalues are from a matrix that is multivariate normal with the same eigenvalues as observed.

`ci(homoskedastic)` specifies a parametric bootstrap by using the percentile method and assuming that the eigenvalues are from a matrix that is multivariate normal with all eigenvalues equal to the mean of the observed eigenvalues. For a PCA of a correlation matrix, this mean is 1.

`ci(`*area_options*`)` affects the rendition of the confidence bands; see [G-3] *area_options*.

`ci(table)` produces a table with the confidence intervals.

`ci(level(`*#*`))` specifies the confidence level, as a percentage, for confidence intervals. The default is `level(95)` or as set by `set level`; see [U] **20.8 Specifying the width of confidence intervals**.

`ci(reps(`*#*`))` specifies the number of simulations to be performed for estimating the confidence intervals. This option is valid only when `heteroskedastic` or `homoskedastic` is specified. The default is `reps(200)`.

`ci(seed(`*str*`))` sets the random-number seed used for the parametric bootstrap. Setting the seed makes sure that results are reproducible. See `set seed` in [R] **set seed**. This option is valid only when `heteroskedastic` or `homoskedastic` is specified.

The confidence intervals are not adjusted for "simultaneous inference".

⌐ Plot ̄

cline_options affect the rendition of the lines connecting the plotted points; see [G-3] *cline_options*.

marker_options affect the rendition of markers drawn at the plotted points, including their shape, size, color, and outline; see [G-3] *marker_options*.

⌐ Add plots ̄

`addplot(`*plot*`)` provides a way to add other plots to the generated graph; see [G-3] *addplot_option*.

⌐ Y axis, X axis, Titles, Legend, Overall ̄

twoway_options are any of the options documented in [G-3] *twoway_options*, excluding `by()`. These include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk (see [G-3] *saving_option*).

Remarks and examples

Cattell (1966) introduced scree plots, which are visual tools used to help determine the number of important components or factors in multivariate settings, such as principal component analysis and factor analysis; see [MV] **pca** and [MV] **factor**. The scree plot is examined for a natural break between the large eigenvalues and the remaining small eigenvalues. The word "scree" is used in reference to the appearance of the large eigenvalues as the hill and the small eigenvalues as the debris of loose rocks at the bottom of the hill. Examples of scree plots can be found in most books that discuss principal component analysis or factor analysis, including Hamilton (1992, 249–288), Rencher and Christensen (2012), and Hamilton (2013, chap. 11).

▷ Example 1: Scree plots after principal component analysis

Multivariate commands, such as pca and factor (see [MV] **pca** and [MV] **factor**), produce eigenvalues and eigenvectors. The screeplot command graphs the eigenvalues, so you can decide how many components or factors to retain.

We demonstrate scree plots after a principal component analysis. Say that we have been hired by the restaurant industry to study expenditures on eating and drinking. We have data on 898 U.S. cities:

```
. use https://www.stata-press.com/data/r18/emd
(1980 city data)
. pca ln_eat - hhsize
  (output omitted)
. screeplot
```


Scree plot of eigenvalues after pca
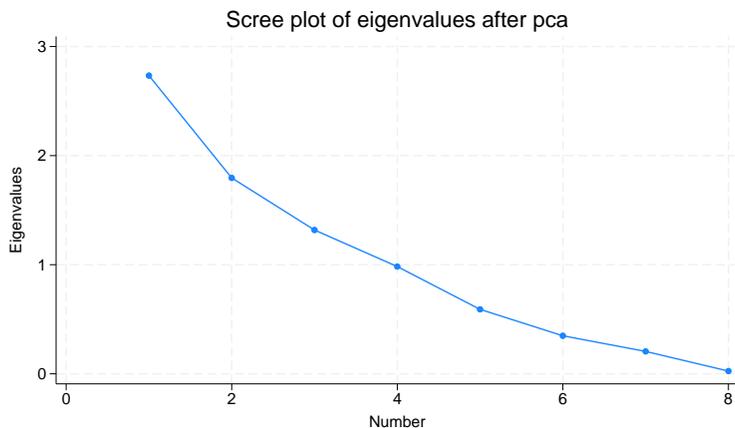
This scree plot does not suggest a natural break between high and low eigenvalues.

We render this same scree plot with the addition of confidence bands by using the ci() option. The asymptotic suboption selects confidence intervals that are based on the assumption of asymptotic normality. Because the asymptotic theory applied to correlation matrices is not fully correct, we also use the level() suboption to adjust the confidence interval. The table suboption displays a table of the eigenvalues and lower and upper confidence interval values.

```
. scree, ci(asympt level(90) table)
(caution is advised in interpreting an asymptotic theory-based confidence
 interval of eigenvalues of a correlation matrix)
```

	eigval	low	high
Comp1	2.733531	2.497578	2.991777
Comp2	1.795623	1.640628	1.965261
Comp3	1.318192	1.204408	1.442725
Comp4	.9829996	.8981487	1.075867
Comp5	.5907632	.5397695	.6465744
Comp6	.3486276	.3185346	.3815635
Comp7	.2052582	.1875407	.2246496
Comp8	.0250056	.0228472	.027368
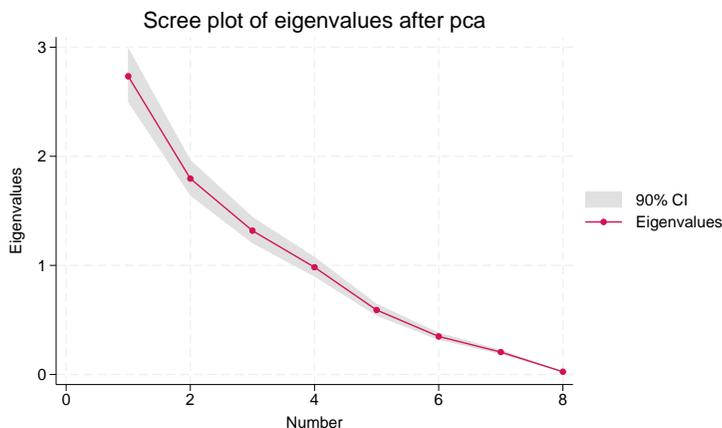
screeplot warned us about using asymptotic confidence intervals with eigenvalues based on a correlation matrix. screeplot knew that the eigenvalues were based on a correlation matrix instead of a covariance matrix by examining the information available in the e() results from the pca that we ran.

Instead of displaying an asymptotic confidence band, we now display a parametric bootstrap confidence interval. We select the heteroskedastic suboption of ci() that allows for unequal eigenvalues. The reps() and seed() suboptions control the execution of the bootstrap. The mean option provides a horizontal line at the mean of the eigenvalues, here at 1 because we are dealing with a principal component analysis performed on a correlation matrix.

```
. scree, ci(hetero reps(1000) seed(18228)) mean
```


Scree plot of eigenvalues after pca
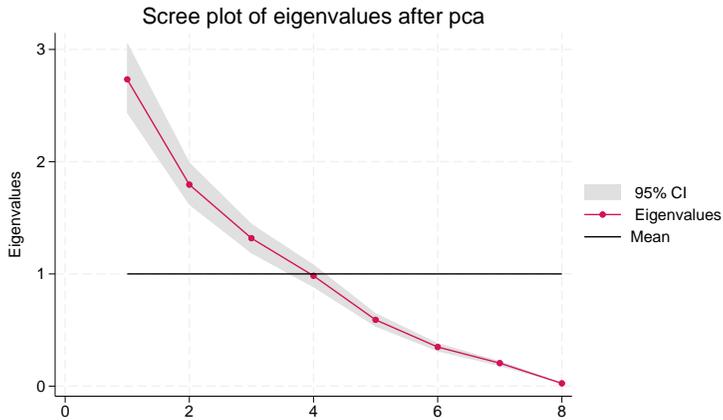
Our final scree plot switches to computing the bootstrap confidence intervals on the basis of the assumption that the eigenvalues are equal to the mean of the observed eigenvalues (using the homoskedastic suboption of ci()). We again set the seed by using the seed() suboption.

```
. scree, ci(homo seed(56227))
```


Scree plot of eigenvalues after pca
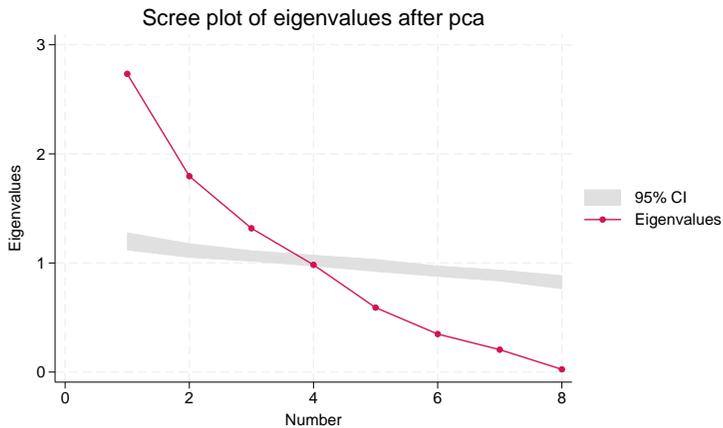
The graph indicates that our data do not support using the homoskedastic assumption.

◁

Stored results

screeplot stores the following in r():

Scalars
    r(level)   confidence level for confidence intervals

Macros
    r(Ctype)   correlation or covariance
    r(ci)   method for estimating confidence interval
    r(rngstate)   random-number state used for parametric bootstrap

Matrices
    r(ci)   confidence intervals
    r(eigvals)   eigenvalues

Scree is an English word with Old Norse origins. In geomorphology, scree denotes an accumulation of loose, coarse, usually angular debris at the foot of steep rock slopes (Luckman 2004). The accumulation must be sufficiently thick to be independent of the underlying slope; thus thin veneers of rock particles do not qualify. Screes are themselves quite steep; angles between $30°$ and $40°$ are common.

Outside geomorphology, and, notably, in some discussions of scree plots, the term is commonly misapplied to imply deposits on much gentler slopes, or those gentler slopes themselves, and by extension parts of curves thought similar to either.

However appropriate in general or in particular, the term *scree plot* is so widely used in multivariate statistics that it is echoed in the name of this Stata command.

References

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Rencher, A. C., and W. F. Christensen. 2012. *Methods of Multivariate Analysis.* 3rd ed. Hoboken, NJ: Wiley.

Also see

[MV] **factor** — Factor analysis

[MV] **mds** — Multidimensional scaling for two-way data

[MV] **pca** — Principal component analysis

Glossary

agglomerative hierarchical clustering methods. Agglomerative hierarchical clustering methods are bottom-up methods for hierarchical clustering. Each observation begins in a separate group. The closest pair of groups is agglomerated or merged in each iteration until all the data are in one cluster. This process creates a hierarchy of clusters. Contrast to *divisive hierarchical clustering methods*.

anti-image correlation matrix or **anti-image covariance matrix**. The image of a variable is defined as that part which is predictable by regressing each variable on all the other variables; hence, the anti-image is the part of the variable that cannot be predicted. The anti-image correlation matrix $\mathbf{A}$ is a matrix of the negatives of the partial correlations among variables. Partial correlations represent the degree to which the factors explain each other in the results. The diagonal of the anti-image correlation matrix is the Kaiser–Meyer–Olkin measure of sampling adequacy for the individual variables. Variables with small values should be eliminated from the analysis. The anti-image covariance matrix $\mathbf{C}$ contains the negatives of the partial covariances and has one minus the squared multiple correlations in the principal diagonal. Most of the off-diagonal elements should be small in both anti-image matrices in a good factor model. Both anti-image matrices can be calculated from the inverse of the correlation matrix $\mathbf{R}$ via

$$\mathbf{A} = \{\text{diag}(\mathbf{R})\}^{-1}\mathbf{R}\{\text{diag}(\mathbf{R})\}^{-1}$$
$$\mathbf{C} = \{\text{diag}(\mathbf{R})\}^{-1/2}\mathbf{R}\{\text{diag}(\mathbf{R})\}^{-1/2}$$

Also see *Kaiser–Meyer–Olkin measure of sampling adequacy*.

average-linkage clustering. Average-linkage clustering is a hierarchical clustering method that uses the average proximity of observations between groups as the proximity measure between the two groups.

Bayes's theorem. Bayes's theorem states that the probability of an event, A, conditional on another event, B, is generally different from the probability of B conditional on A, although the two are related. Bayes's theorem is that

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

where $P(A)$ is the marginal probability of A, and $P(A|B)$ is the conditional probability of A given B, and likewise for $P(B)$ and $P(B|A)$.

Bentler's invariant pattern simplicity rotation. Bentler's (1977) rotation maximizes the invariant pattern simplicity. It is an oblique rotation that minimizes the criterion function

$$c(\mathbf{\Lambda}) = -\log[|(\mathbf{\Lambda}^2)'\mathbf{\Lambda}^2|] + \log[|\text{diag}\{(\mathbf{\Lambda}^2)'\mathbf{\Lambda}^2\}|]$$

See *Crawford–Ferguson rotation* for a definition of $\mathbf{\Lambda}$. Also see *oblique rotation*.

between matrix and **within matrix**. The between and within matrices are SSCP matrices that measure the spread between groups and within groups, respectively. These matrices are used in multivariate analysis of variance and related hypothesis tests: Wilks's lambda, Roy's largest root, Lawley–Hotelling trace, and Pillai's trace.

Here we have k independent random samples of size n. The between matrix $\mathbf{H}$ is given by

$$\mathbf{H} = n \sum_{i=1}^{k} (\overline{\mathbf{y}}_{i\bullet} - \overline{\mathbf{y}}_{\bullet\bullet})(\overline{\mathbf{y}}_{i\bullet} - \overline{\mathbf{y}}_{\bullet\bullet})' = \sum_{i=1}^{k} \frac{1}{n} \mathbf{y}_{i\bullet} \mathbf{y}_{i\bullet}' - \frac{1}{kn} \mathbf{y}_{\bullet\bullet} \mathbf{y}_{\bullet\bullet}'$$

The within matrix $\mathbf{E}$ is defined as

$$\mathbf{E} = \sum_{i=1}^{k} \sum_{j=1}^{n} (\mathbf{y}_{ij} - \overline{\mathbf{y}}_{i\bullet})(\mathbf{y}_{ij} - \mathbf{y}_{i\bullet})' = \sum_{i=1}^{k} \sum_{j=1}^{n} \mathbf{y}_{ij} \mathbf{y}_{ij}' - \sum_{i=1}^{k} \frac{1}{n} \mathbf{y}_{i\bullet} \mathbf{y}_{i\bullet}'$$

Also see *SSCP matrix*.

biplot. A biplot is a scatterplot which represents both observations and variables simultaneously. There are many different biplots; variables in biplots are usually represented by arrows and observations are usually represented by points.

biquartimax rotation or **biquartimin rotation**. Biquartimax rotation and biquartimin rotation are synonyms. They put equal weight on the varimax and quartimax criteria, simplifying the columns and rows of the matrix. This is an oblique rotation equivalent to an oblimin rotation with $\gamma = 0.5$. Also see *varimax rotation*, *quartimax rotation*, and *oblimin rotation*.

boundary solution or **Heywood solution**. See *Heywood case*.

CA. See *correspondence analysis*.

canonical correlation analysis. Canonical correlation analysis attempts to describe the relationships between two sets of variables by finding linear combinations of each so that the correlation between the linear combinations is maximized.

canonical discriminant analysis. Canonical linear discriminant analysis is LDA where describing how groups are separated is of primary interest. Also see *linear discriminant analysis*.

canonical loadings. The canonical loadings are coefficients of canonical linear discriminant functions. Also see *canonical discriminant analysis* and *loading*.

canonical variate set. The canonical variate set is a linear combination or weighted sum of variables obtained from canonical correlation analysis. Two sets of variables are analyzed in canonical correlation analysis. The first canonical variate of the first variable set is the linear combination in standardized form that has maximal correlation with the first canonical variate from the second variable set. The subsequent canonical variates are uncorrelated to the previous and have maximal correlation under that constraint.

centered data. A centered dataset has zero mean. You can center data $\mathbf{x}$ by taking $\mathbf{x} - \overline{\mathbf{x}}$.

centroid-linkage clustering. Centroid-linkage clustering is a hierarchical clustering method that computes the proximity between two groups as the proximity between the group means.

classical scaling. Classical scaling is a method of performing MDS via an eigen decomposition. This is contrasted to modern MDS, which is achieved via the minimization of a loss function. Also see *multidimensional scaling* and *modern scaling*.

classification. Classification is the act of allocating or classifying observations to groups as part of discriminant analysis. In some sources, classification is synonymous with cluster analysis.

classification function. Classification functions can be obtained after LDA or QDA. They are functions based on Mahalanobis distance for classifying observations to the groups. See *discriminant function* for an alternative. Also see *linear discriminant analysis* and *quadratic discriminant analysis*.

classification table. A classification table, also known as a confusion matrix, gives the count of observations from each group that are classified into each of the groups as part of a discriminant analysis. The element at (i, j) gives the number of observations that belong to the ith group but were classified into the jth group. High counts are expected on the diagonal of the table where observations are correctly classified, and small values are expected off the diagonal. The columns of the matrix are categories of the predicted classification; the rows represent the actual group membership.

cluster analysis. Cluster analysis is a method for determining natural groupings or clusters of observations.

cluster tree. See *dendrogram*.

clustering. See *cluster analysis*.

common factors. Common factors are found by factor analysis. They linearly reconstruct the original variables. In factor analysis, reconstruction is defined in terms of prediction of the correlation matrix of the original variables.

communality. Communality is the proportion of a variable's variance explained by the common factors in factor analysis. It is also "$1 -$ uniqueness". Also see *uniqueness*.

complete-linkage clustering. Complete-linkage clustering is a hierarchical clustering method that uses the farthest pair of observations between two groups to determine the proximity of the two groups.

component scores. Component scores are calculated after PCA. Component scores are the coordinates of the original variables in the space of principal components.

Comrey's tandem 1 and 2 rotations. Comrey (1967) describes two rotations, the first (tandem 1) to judge which "small" factors should be dropped, the second (tandem 2) for "polishing".

Tandem principle 1 minimizes the criterion

$$c(\mathbf{\Lambda}) = \left\langle \mathbf{\Lambda}^2, (\mathbf{\Lambda}\mathbf{\Lambda}')^2 \mathbf{\Lambda}^2 \right\rangle$$

Tandem principle 2 minimizes the criterion

$$c(\mathbf{\Lambda}) = \left\langle \mathbf{\Lambda}^2, \{\mathbf{1}\mathbf{1}' - (\mathbf{\Lambda}\mathbf{\Lambda}')^2\}\mathbf{\Lambda}^2 \right\rangle$$

See *Crawford–Ferguson rotation* for a definition of $\mathbf{\Lambda}$.

configuration. The configuration in MDS is a representation in a low-dimensional (usually 2-dimensional) space with distances in the low-dimensional space approximating the dissimilarities or disparities in high-dimensional space. Also see *multidimensional scaling*, *dissimilarity*, and *disparity*.

configuration plot. A configuration plot after MDS is a (usually 2-dimensional) plot of labeled points showing the low-dimensional approximation to the dissimilarities or disparities in high-dimensional space. Also see *multidimensional scaling*, *dissimilarity*, and *disparity*.

confusion matrix. A confusion matrix is a synonym for a classification table after discriminant analysis. See *classification table*.

contrast or **contrasts**. In ANOVA, a contrast in k population means is defined as a linear combination

$$\delta = c_1\mu_1 + c_2\mu_2 + \cdots + c_k\mu_k$$

where the coefficients satisfy

$$\sum_{i=1}^{k} c_i = 0$$

In the multivariate setting (MANOVA), a contrast in k population mean vectors is defined as

$$\boldsymbol{\delta} = c_1 \boldsymbol{\mu}_1 + c_2 \boldsymbol{\mu}_2 + \cdots c_k \boldsymbol{\mu}_k$$

where the coefficients again satisfy

$$\sum_{i=1}^{k} c_i = 0$$

The univariate hypothesis $\delta = 0$ may be tested with `contrast` (or `test`) after ANOVA. The multivariate hypothesis $\boldsymbol{\delta} = 0$ may be tested with `manovatest` after MANOVA.

correspondence analysis. Correspondence analysis (CA) gives a geometric representation of the rows and columns of a two-way frequency table. The geometric representation is helpful in understanding the similarities between the categories of variables and associations between variables. CA is calculated by singular value decomposition. Also see *singular value decomposition*.

correspondence analysis projection. A correspondence analysis projection is a line plot of the row and column coordinates after CA. The goal of this graph is to show the ordering of row and column categories on each principal dimension of the analysis. Each principal dimension is represented by a vertical line; markers are plotted on the lines where the row and column categories project onto the dimensions. Also see *correspondence analysis*.

costs. Costs in discriminant analysis are the cost of misclassifying observations.

covarimin rotation. Covarimin rotation is an orthogonal rotation equivalent to varimax. Also see *varimax rotation*.

Crawford–Ferguson rotation. Crawford–Ferguson (1970) rotation is a general oblique rotation with several interesting special cases.

Special cases of the Crawford–Ferguson rotation include

κ	Special case
0	quartimax / quartimin
$1/p$	varimax / covarimin
$f/(2p)$	equamax
$(f-1)/(p+f-2)$	parsimax
1	factor parsimony

$p = $ number of rows of $\mathbf{A}$.
$f = $ number of columns of $\mathbf{A}$.

Where $\mathbf{A}$ is the matrix to be rotated, $\mathbf{T}$ is the rotation and $\boldsymbol{\Lambda} = \mathbf{AT}$. The Crawford–Ferguson rotation is achieved by minimizing the criterion

$$c(\boldsymbol{\Lambda}) = \frac{1-\kappa}{4} \left\langle \boldsymbol{\Lambda}^2, \boldsymbol{\Lambda}^2(\mathbf{11'} - \mathbf{I}) \right\rangle + \frac{\kappa}{4} \left\langle \boldsymbol{\Lambda}^2, (\mathbf{11'} - \mathbf{I})\boldsymbol{\Lambda}^2 \right\rangle$$

Also see *oblique rotation*.

crossed variables or **stacked variables**. In CA and MCA crossed categorical variables may be formed from the interactions of two or more existing categorical variables. Variables that contain these interactions are called crossed or stacked variables.

crossing variables or **stacking variables**. In CA and MCA, crossing or stacking variables are the existing categorical variables whose interactions make up a crossed or stacked variable.

curse of dimensionality. The curse of dimensionality is a term coined by Richard Bellman (1961) to describe the problem caused by the exponential increase in size associated with adding extra dimensions to a mathematical space. On the unit interval, 10 evenly spaced points suffice to sample with no more distance than 0.1 between them; however a unit square requires 100 points, and a unit cube requires 1000 points. Many multivariate statistical procedures suffer from the curse of dimensionality. Adding variables to an analysis without adding sufficient observations can lead to imprecision.

dendrogram or **cluster tree**. A dendrogram or cluster tree graphically presents information about how observations are grouped together at various levels of (dis)similarity in hierarchical cluster analysis. At the bottom of the dendrogram, each observation is considered its own cluster. Vertical lines extend up for each observation, and at various (dis)similarity values, these lines are connected to the lines from other observations with a horizontal line. The observations continue to combine until, at the top of the dendrogram, all observations are grouped together. Also see *hierarchical clustering*.

dilation. A dilation stretches or shrinks distances in Procrustes rotation.

dimension. A dimension is a parameter or measurement required to define a characteristic of an object or observation. Dimensions are the variables in the dataset. Weight, height, age, blood pressure, and drug dose are examples of dimensions in health data. Number of employees, gross income, net income, tax, and year are examples of dimensions in data about companies.

discriminant analysis. Discriminant analysis is used to describe the differences between groups and to exploit those differences when allocating (classifying) observations of unknown group membership. Discriminant analysis is also called classification in many references.

discriminant function. Discriminant functions are formed from the eigenvectors from Fisher's approach to LDA. See *linear discriminant analysis*. See *classification function* for an alternative.

discriminating variables. Discriminating variables in a discriminant analysis are analyzed to determine differences between groups where group membership is known. These differences between groups are then exploited when classifying observations to the groups.

disparity. Disparities are transformed dissimilarities, that is, dissimilarity values transformed by some function. The class of functions to transform dissimilarities to disparities may either be 1) a class of metric, or known functions such as linear functions or power functions that can be parameterized by real scalars or 2) a class of more general (nonmetric) functions, such as any monotonic function. Disparities are used in MDS. Also see *dissimilarity*, *multidimensional scaling*, *metric scaling*, and *nonmetric scaling*.

dissimilarity, **dissimilarity matrix**, and **dissimilarity measure**. Dissimilarity or a dissimilarity measure is a quantification of the difference between two things, such as observations or variables or groups of observations or a method for quantifying that difference. A dissimilarity matrix is a matrix containing dissimilarity measurements. Euclidean distance is one example of a dissimilarity measure. Contrast to *similarity*. Also see *proximity* and *Euclidean distance*.

divisive hierarchical clustering methods. Divisive hierarchical clustering methods are top-down methods for hierarchical clustering. All the data begin as a part of one large cluster; with each iteration, a cluster is broken into two to create two new clusters. At the first iteration there are two

clusters, then three, and so on. Divisive methods are very computationally expensive. Contrast to *agglomerative hierarchical clustering methods*.

eigenvalue. An eigenvalue is the scale factor by which an eigenvector is multiplied. For many multivariate techniques, the size of an eigenvalue indicates the importance of the corresponding eigenvector. Also see *eigenvector*.

eigenvector. An eigenvector of a linear transformation is a nonzero vector that is either left unaffected or simply multiplied by a scale factor after the transformation.

Here $\mathbf{x}$ is an eigenvector of linear transformation $\mathbf{A}$ with eigenvalue λ:

$$\mathbf{A}\mathbf{x} = \lambda\mathbf{x}$$

For many multivariate techniques, eigenvectors form the basis for analysis and interpretation. Also see *loading*.

equamax rotation. Equamax rotation is an orthogonal rotation whose criterion is a weighted sum of the varimax and quartimax criteria. Equamax reflects a concern for simple structure within the rows and columns of the matrix. It is equivalent to oblimin with $\gamma = p/2$, or to the Crawford–Ferguson family with $\kappa = f/2p$, where p is the number of rows of the matrix to be rotated, and f is the number of columns. Also see *orthogonal rotation*, *varimax rotation*, *quartimax rotation*, *oblimin rotation*, and *Crawford–Ferguson rotation*.

Euclidean distance. The Euclidean distance between two observations is the distance one would measure with a ruler. The distance between vector $\mathbf{P} = (P_1, P_2, \ldots, P_n)$ and $\mathbf{Q} = (Q_1, Q_2, \ldots, Q_n)$ is given by

$$D(\mathbf{P}, \mathbf{Q}) = \sqrt{(P_1 - Q_1)^2 + (P_2 - Q_2)^2 + \cdots + (P_n - Q_n)^2} = \sqrt{\sum_{i=1}^{n}(P_i - Q_i)^2}$$

factor. A factor is an unobserved random variable that is thought to explain variability among observed random variables.

factor analysis. Factor analysis is a statistical technique used to explain variability among observed random variables in terms of fewer unobserved random variables called factors. The observed variables are then linear combinations of the factors plus error terms.

If the correlation matrix of the observed variables is $\mathbf{R}$, then $\mathbf{R}$ is decomposed by factor analysis as

$$\mathbf{R} = \mathbf{\Lambda}\mathbf{\Phi}\mathbf{\Lambda}' + \mathbf{\Psi}$$

$\mathbf{\Lambda}$ is the loading matrix, and $\mathbf{\Psi}$ contains the specific variances, for example, the variance specific to the variable not explained by the factors. The default unrotated form assumes uncorrelated common factors, $\mathbf{\Phi} = \mathbf{I}$.

factor loading plot. A factor loading plot produces a scatter plot of the factor loadings after factor analysis.

factor loadings. Factor loadings are the regression coefficients which multiply the factors to produce the observed variables in the factor analysis.

factor parsimony. Factor parsimony is an oblique rotation, which maximizes the column simplicity of the matrix. It is equivalent to a Crawford–Ferguson rotation with $\kappa = 1$. Also see *oblique rotation* and *Crawford–Ferguson rotation*.

factor scores. Factor scores are computed after factor analysis. Factor scores are the coordinates of the original variables, $\mathbf{x}$, in the space of the factors. The two types of scoring are regression scoring (Thomson 1951) and Bartlett (1937, 1938) scoring.

Using the symbols defined in *factor analysis*, the formula for regression scoring is

$$\widehat{\mathbf{f}} = \mathbf{\Lambda}'\mathbf{R}^{-1}\mathbf{x}$$

In the case of oblique rotation the formula becomes

$$\widehat{\mathbf{f}} = \mathbf{\Phi}\mathbf{\Lambda}'\mathbf{R}^{-1}\mathbf{x}$$

The formula for Bartlett scoring is

$$\widehat{\mathbf{f}} = \mathbf{\Gamma}^{-1}\mathbf{\Lambda}'\mathbf{\Psi}^{-1}\mathbf{x}$$

where

$$\mathbf{\Gamma} = \mathbf{\Lambda}'\mathbf{\Psi}^{-1}\mathbf{\Lambda}$$

Also see *factor analysis*.

Heywood case or **Heywood solution**. A Heywood case can appear in factor analysis output; this indicates that a boundary solution, called a Heywood solution, was produced. The geometric assumptions underlying the likelihood-ratio test are violated, though the test may be useful if interpreted cautiously.

hierarchical clustering and **hierarchical clustering methods**. In hierarchical clustering, the data are placed into clusters via iterative steps. Contrast to *partition clustering*. Also see *agglomerative hierarchical clustering methods* and *divisive hierarchical clustering methods*.

Hotelling's T^2 generalized means test. Hotelling's T^2 generalized means test is a multivariate test that reduces to a standard t test if only one variable is specified. It tests whether one set of means is zero or if two sets of means are equal.

inertia. In CA, the inertia is related to the definition in applied mathematics of "moment of inertia", which is the integral of the mass times the squared distance to the centroid. Inertia is defined as the total Pearson χ^2 for the two-way table divided by the total number of observations, or the sum of the squared singular values found in the singular value decomposition.

$$\text{total inertia} = \frac{1}{n}\chi^2 = \sum_k \lambda_k^2$$

In MCA, the inertia is defined analogously. In the case of the indicator or Burt matrix approach, it is given by the formula

$$\text{total inertia} = \left(\frac{q}{q-1}\right)\sum \phi_t^2 - \frac{(J-q)}{q^2}$$

where q is the number of active variables, J is the number of categories and ϕ_t is the tth (unadjusted) eigenvalue of the eigen decomposition. In JCA the total inertia of the modified Burt matrix is defined as the sum of the inertias of the off-diagonal blocks. Also see *correspondence analysis* and *multiple correspondence analysis*.

iterated principal-factor method. The iterated principal-factor method is a method for performing factor analysis in which the communalities $\widehat{h}_i^2$ are estimated iteratively from the loadings in $\widehat{\mathbf{\Lambda}}$ using

$$\widehat{h}_i^2 = \sum_{j=1}^{m} \widehat{\lambda}_{ij}^2$$

Also see *factor analysis* and *communality*.

JCA. An acronym for joint correspondence analysis; see *multiple correspondence analysis*.

joint correspondence analysis. See *multiple correspondence analysis*.

Kaiser–Meyer–Olkin measure of sampling adequacy. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy takes values between 0 and 1, with small values meaning that the variables have too little in common to warrant a factor analysis or PCA. Historically, the following labels have been given to values of KMO (Kaiser 1974):

0.00 to 0.49	unacceptable
0.50 to 0.59	miserable
0.60 to 0.69	mediocre
0.70 to 0.79	middling
0.80 to 0.89	meritorious
0.90 to 1.00	marvelous

kmeans. Kmeans is a method for performing partition cluster analysis. The user specifies the number of clusters, k, to create using an iterative process. Each observation is assigned to the group whose mean is closest, and then based on that categorization, new group means are determined. These steps continue until no observations change groups. The algorithm begins with k seed values, which act as the k group means. There are many ways to specify the beginning seed values. Also see *partition clustering*.

kmedians. Kmedians is a variation of kmeans. The same process is performed, except that medians instead of means are computed to represent the group centers at each step. Also see *kmeans* and *partition clustering*.

KMO. See *Kaiser–Meyer–Olkin measure of sampling adequacy*.

KNN. See *kth nearest neighbor*.

Kruskal stress. The Kruskal stress measure (Kruskal 1964; Cox and Cox 2001, 63) used in MDS is given by

$$\text{Kruskal}(\widehat{\mathbf{D}}, \mathbf{E}) = \left\{ \frac{\sum (E_{ij} - \widehat{D}_{ij})^2}{\sum E_{ij}^2} \right\}^{1/2}$$

where D_{ij} is the dissimilarity between objects i and j, $1 \le i, j \le n$, and $\widehat{D}_{ij}$ is the disparity, that is, the transformed dissimilarity, and E_{ij} is the Euclidean distance between rows i and j of the matching configuration. Kruskal stress is an example of a loss function in modern MDS. After classical MDS, `estat stress` gives the Kruskal stress. Also see *classical scaling*, *multidimensional scaling*, and *stress*.

kth nearest neighbor. kth-nearest-neighbor (KNN) discriminant analysis is a nonparametric discrimination method based on the k nearest neighbors of each observation. Both continuous and binary data can be handled through the different similarity and dissimilarity measures. KNN analysis can distinguish irregular-shaped groups, including groups with multiple modes. Also see *discriminant analysis* and *nonparametric methods*.

Lawley–Hotelling trace. The Lawley–Hotelling trace is a test statistic for the hypothesis test H_0 : $\boldsymbol{\mu}_1 = \boldsymbol{\mu}_2 = \cdots = \boldsymbol{\mu}_k$ based on the eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_s$ of $\mathbf{E}^{-1}\mathbf{H}$. It is defined as

$$U^{(s)} = \mathrm{trace}(\mathbf{E}^{-1}\mathbf{H}) = \sum_{i=1}^{s} \lambda_i$$

where $\mathbf{H}$ is the between matrix and $\mathbf{E}$ is the within matrix, see *between matrix*.

LDA. See *linear discriminant analysis*.

leave one out. In discriminant analysis, classification of an observation while leaving it out of the estimation sample is done to check the robustness of the analysis; thus the phrase "leave one out" (LOO). Also see *discriminant analysis*.

linear discriminant analysis. Linear discriminant analysis (LDA) is a parametric form of discriminant analysis. In Fisher's (1936) approach to LDA, linear combinations of the discriminating variables provide maximal separation between the groups. The Mahalanobis (1936) formulation of LDA assumes that the observations come from multivariate normal distributions with equal covariance matrices. Also see *discriminant analysis* and *parametric methods*.

linkage. In cluster analysis, the linkage refers to the measure of proximity between groups or clusters.

loading. A loading is a coefficient or weight in a linear transformation. Loadings play an important role in many multivariate techniques, including factor analysis, PCA, MANOVA, LDA, and canonical correlations. In some settings, the loadings are of primary interest and are examined for interpretability. For many multivariate techniques, loadings are based on an eigenanalysis of a correlation or covariance matrix. Also see *eigenvector*.

loading plot. A loading plot is a scatter plot of the loadings after LDA, factor analysis or PCA.

logistic discriminant analysis. Logistic discriminant analysis is a form of discriminant analysis based on the assumption that the likelihood ratios of the groups have an exponential form. Multinomial logistic regression provides the basis for logistic discriminant analysis. Because multinomial logistic regression can handle binary and continuous regressors, logistic discriminant analysis is also appropriate for binary and continuous discriminating variables. Also see *discriminant analysis*.

LOO. See *leave one out*.

loss. Modern MDS is performed by minimizing a loss function, also called a loss criterion. The loss quantifies the difference between the disparities and the Euclidean distances.

Loss functions include Kruskal's stress and its square, both normalized with either disparities or distances, the strain criterion which is equivalent to classical metric scaling when the disparities equal the dissimilarities, and the Sammon (1969) mapping criterion which is the sum of the scaled, squared differences between the distances and the disparities, normalized by the sum of the disparities.

Also see *multidimensional scaling*, *Kruskal stress*, *classical scaling*, and *disparity*.

Mahalanobis distance. The Mahalanobis distance measure is a scale-invariant way of measuring distance. It takes into account the correlations of the dataset.

Mahalanobis transformation. The Mahalanobis transformation takes a Cholesky factorization of the inverse of the covariance matrix $\mathbf{S}^{-1}$ in the formula for Mahalanobis distance and uses it to transform the data. If we have the Cholesky factorization $\mathbf{S}^{-1} = \mathbf{L}'\mathbf{L}$, then the Mahalanobis transformation of $\mathbf{x}$ is $\mathbf{z} = \mathbf{L}\mathbf{x}$, and $\mathbf{z}'\mathbf{z} = D_M^2(\mathbf{x})$.

MANCOVA. MANCOVA is multivariate analysis of covariance. See *multivariate analysis of variance*.

MANOVA. *multivariate analysis of variance*.

mass. In CA and MCA, the mass is the marginal probability. The sum of the mass over the active row or column categories equals 1.

matching coefficient. The matching similarity coefficient is used to compare two binary variables. If a is the number of observations that both have value 1, and d is the number of observations that both have value 0, and b, c are the number of $(1, 0)$ and $(0, 1)$ observations, respectively, then the matching coefficient is given by

$$\frac{a + d}{a + b + c + d}$$

Also see *similarity measure*.

matching configuration. In MDS, the matching configuration is the low dimensional configuration whose distances approximate the high-dimensional dissimilarities or disparities. Also see *multidimensional scaling*, *dissimilarity*, and *disparity*.

matching configuration plot. After MDS, this is a scatter plot of the matching configuration.

maximum-likelihood factor method. The maximum-likelihood factor method is a method for performing factor analysis that assumes multivariate normal observations. It maximizes the determinant of the partial correlation matrix; thus, this solution is also meaningful as a descriptive method for nonnormal data. Also see *factor analysis*.

MCA. See *multiple correspondence analysis*.

MDS. See *multidimensional scaling*.

MDS configuration plot. See *configuration plot*.

measure. A measure is a quantity representing the proximity between objects or method for determining the proximity between objects. Also see *proximity*.

median-linkage clustering. Median-linkage clustering is a hierarchical clustering method that uses the distance between the medians of two groups to determine the similarity or dissimilarity of the two groups. Also see *cluster analysis* and *agglomerative hierarchical clustering methods*.

metric scaling. Metric scaling is a type of MDS, in which the dissimilarities are transformed to disparities via a class of known functions. This is contrasted to *nonmetric scaling*. Also see *multidimensional scaling*.

minimum entropy rotation. The minimum entropy rotation is an orthogonal rotation achieved by minimizing the deviation from uniformity (entropy). The minimum entropy criterion (Jennrich 2004) is

$$c(\mathbf{\Lambda}) = -\frac{1}{2} \left\langle \mathbf{\Lambda}^2, \log \mathbf{\Lambda}^2 \right\rangle$$

See *Crawford–Ferguson rotation* for a definition of $\mathbf{\Lambda}$. Also see *orthogonal rotation*.

misclassification rate. The misclassification rate calculated after discriminant analysis is, in its simplest form, the fraction of observations incorrectly classified. See *discriminant analysis*.

modern scaling. Modern scaling is a form of MDS that is achieved via the minimization of a loss function that compares the disparities (transformed dissimilarities) in the higher-dimensional space and the distances in the lower-dimensional space. Contrast to *classical scaling*. Also see *dissimilarity*, *disparity*, *multidimensional scaling*, and *loss*.

multidimensional scaling. Multidimensional scaling (MDS) is a dimension-reduction and visualization technique. Dissimilarities (for instance, Euclidean distances) between observations in a high-dimensional space are represented in a lower-dimensional space which is typically two dimensions

so that the Euclidean distance in the lower-dimensional space approximates in some sense the dissimilarities in the higher-dimensional space. Often the higher-dimensional dissimilarities are first transformed to disparities, and the disparities are then approximated by the distances in the lower-dimensional space. Also see *dissimilarity*, *disparity*, *classical scaling*, *loss*, *modern scaling*, *metric scaling*, and *nonmetric scaling*.

multiple correspondence analysis. Multiple correspondence analysis (MCA) and joint correspondence analysis (JCA) are methods for analyzing observations on categorical variables. MCA and JCA analyze a multiway table and are usually viewed as an extension of CA. Also see *correspondence analysis*.

multivariate analysis of covariance. See *multivariate analysis of variance*.

multivariate analysis of variance. Multivariate analysis of variance (MANOVA) is used to test hypotheses about means. Four multivariate statistics are commonly computed in MANOVA: Wilks's lambda, Pillai's trace, Lawley–Hotelling trace, and Roy's largest root. Also see *Wilks's lambda*, *Pillai's trace*, *Lawley–Hotelling trace*, and *Roy's largest root*.

multivariate regression. Multivariate regression is a method of estimating a linear (matrix) model

$$\mathbf{Y} = \mathbf{XB} + \mathbf{\Xi}$$

Multivariate regression is estimated by least-squares regression, and it can be used to test hypotheses, much like MANOVA.

nearest neighbor. See *kth nearest neighbor*.

nonmetric scaling. Nonmetric scaling is a type of modern MDS in which the dissimilarities may be transformed to disparities via any monotonic function as opposed to a class of known functions. Contrast to *metric scaling*. Also see *multidimensional scaling*, *dissimilarity*, *disparity*, and *modern scaling*.

nonparametric methods. Nonparametric statistical methods, such as KNN discriminant analysis, do not assume the population fits any parameterized distribution.

normalization. Normalization presents information in a standard form for interpretation. In CA the row and column coordinates can be normalized in different ways depending on how one wishes to interpret the data. Normalization is also used in rotation, MDS, and MCA.

oblimax rotation. Oblimax rotation is a method for oblique rotation which maximizes the number of high and low loadings. When restricted to orthogonal rotation, oblimax is equivalent to quartimax rotation. Oblimax minimizes the oblimax criterion

$$c(\mathbf{\Lambda}) = -\log(\langle \mathbf{\Lambda}^2, \mathbf{\Lambda}^2 \rangle) + 2\log(\langle \mathbf{\Lambda}, \mathbf{\Lambda} \rangle)$$

See *Crawford–Ferguson rotation* for a definition of $\mathbf{\Lambda}$. Also see *oblique rotation*, *orthogonal rotation*, and *quartimax rotation*.

oblimin rotation. Oblimin rotation is a general method for oblique rotation, achieved by minimizing the oblimin criterion

$$c(\mathbf{\Lambda}) = \frac{1}{4} \left\langle \mathbf{\Lambda}^2, \{\mathbf{I} - (\gamma/p)\mathbf{1}\mathbf{1}'\}\mathbf{\Lambda}^2(\mathbf{1}\mathbf{1}' - \mathbf{I}) \right\rangle$$

Oblimin has several interesting special cases:

γ	Special case
0	quartimax / quartimin
1/2	biquartimax / biquartimin
1	varimax / covarimin
$p/2$	equamax

p = number of rows of $\mathbf{A}$.

See *Crawford–Ferguson rotation* for a definition of $\mathbf{\Lambda}$ and $\mathbf{A}$. Also see *oblique rotation*.

oblique rotation or **oblique transformation**. An oblique rotation maintains the norms of the rows of the matrix but not their inner products. In geometric terms, this maintains the lengths of vectors, but not the angles between them. In contrast, in orthogonal rotation, both are preserved.

ordination. Ordination is the ordering of a set of data points with respect to one or more axes. MDS is a form of ordination.

orthogonal rotation or **orthogonal transformation**. Orthogonal rotation maintains both the norms of the rows of the matrix and also inner products of the rows of the matrix. In geometric terms, this maintains both the lengths of vectors and the angles between them. In contrast, oblique rotation maintains only the norms, that is, the lengths of vectors.

parametric methods. Parametric statistical methods, such as LDA and QDA, assume the population fits a parameterized distribution. For example, for LDA we assume the groups are multivariate normal with equal covariance matrices.

parsimax rotation. Parsimax rotation is an orthogonal rotation that balances complexity between the rows and the columns. It is equivalent to the Crawford–Ferguson family with $\kappa = (f-1)/(p+f-2)$, where p is the number of rows of the original matrix, and f is the number of columns. See *orthogonal rotation* and *Crawford–Ferguson rotation*.

partially specified target rotation. Partially specified target rotation minimizes the criterion

$$c(\mathbf{\Lambda}) = \|\mathbf{W} \otimes (\mathbf{\Lambda} - \mathbf{H})\|^2$$

for a given target matrix $\mathbf{H}$ and a nonnegative weighting matrix $\mathbf{W}$ (usually zero–one valued). See *Crawford–Ferguson rotation* for a definition of $\mathbf{\Lambda}$.

partition clustering and **partition cluster-analysis methods**. Partition clustering methods break the observations into a distinct number of nonoverlapping groups. This is accomplished in one step, unlike hierarchical cluster-analysis methods, in which an iterative procedure is used. Consequently, this method is quicker and will allow larger datasets than the hierarchical clustering methods. Contrast to *hierarchical clustering*. Also see *kmeans* and *kmedians*.

PCA. See *principal component analysis*.

Pillai's trace. Pillai's trace is a test statistic for the hypothesis test $H_0 : \boldsymbol{\mu}_1 = \boldsymbol{\mu}_2 = \cdots = \boldsymbol{\mu}_k$ based on the eigenvalues $\lambda_1, \ldots, \lambda_s$ of $\mathbf{E}^{-1}\mathbf{H}$. It is defined as

$$V^{(s)} = \text{trace}[(\mathbf{E} + \mathbf{H})^{-1}\mathbf{H}] = \sum_{i=1}^{s} \frac{\lambda_i}{1 + \lambda_i}$$

where $\mathbf{H}$ is the between matrix and $\mathbf{E}$ is the within matrix. See *between matrix*.

posterior probabilities. After discriminant analysis, the posterior probabilities are the probabilities of a given observation being assigned to each of the groups based on the prior probabilities, the training data, and the particular discriminant model. Contrast to *prior probabilities*.

principal component analysis. Principal component analysis (PCA) is a statistical technique used for data reduction. The leading eigenvectors from the eigen decomposition of the correlation or the covariance matrix of the variables describe a series of uncorrelated linear combinations of the variables that contain most of the variance. In addition to data reduction, the eigenvectors from a PCA are often inspected to learn more about the underlying structure of the data.

principal factor method. The principal factor method is a method for factor analysis in which the factor loadings, sometimes called factor patterns, are computed using the squared multiple correlations as estimates of the communality. Also see *factor analysis* and *communality*.

prior probabilities Prior probabilities in discriminant analysis are the probabilities of an observation belonging to a group before the discriminant analysis is performed. Prior probabilities are often based on the prevalence of the groups in the population as a whole. Contrast to *posterior probabilities*.

Procrustes rotation. A Procrustes rotation is an orthogonal or oblique transformation, that is, a restricted Procrustes transformation without translation or dilation (uniform scaling).

Procrustes transformation. The goal of Procrustes transformation is to transform the source matrix $\mathbf{X}$ to be as close as possible to the target $\mathbf{Y}$. The permitted transformations are any combination of dilation (uniform scaling), rotation and reflection (that is, orthogonal or oblique transformations), and translation. Closeness is measured by residual sum of squares. In some cases, unrestricted Procrustes transformation is desired; this allows the data to be transformed not just by orthogonal or oblique rotations, but by all conformable regular matrices $\mathbf{A}$. Unrestricted Procrustes transformation is equivalent to a multivariate regression.

The name comes from Procrustes of Greek mythology; Procrustes invited guests to try his iron bed. If the guest was too tall for the bed, Procrustes would amputate the guest's feet, and if the guest was too short, he would stretch the guest out on a rack.

Also see *orthogonal rotation*, *oblique rotation*, *dilation*, and *multivariate regression*.

promax power rotation. Promax power rotation is an oblique rotation. It does not fit in the minimizing-a-criterion framework that is at the core of most other rotations. The promax method (Hendrickson and White 1964) was proposed before computing power became widely available. The promax rotation consists of three steps:

1. Perform an orthogonal rotation.

2. Raise the elements of the rotated matrix to some power, preserving the sign of the elements. Typically the power is in the range $2 \leq \text{power} \leq 4$. This operation is meant to distinguish clearly between small and large values.

3. The matrix from step two is used as the target for an oblique Procrustean rotation from the original matrix.

proximity, **proximity matrix**, and **proximity measure**. Proximity or a proximity measure means the nearness or farness of two things, such as observations or variables or groups of observations or a method for quantifying the nearness or farness between two things. A proximity is measured by a similarity or dissimilarity. A proximity matrix is a matrix of proximities. Also see *similarity* and *dissimilarity*.

QDA. See *quadratic discriminant analysis*.

quadratic discriminant analysis. Quadratic discriminant analysis (QDA) is a parametric form of discriminant analysis and is a generalization of LDA. Like LDA, QDA assumes that the observations

come from a multivariate normal distribution, but unlike LDA, the groups are not assumed to have equal covariance matrices. Also see *discriminant analysis*, *linear discriminant analysis*, and *parametric methods*.

quartimax rotation. Quartimax rotation maximizes the variance of the squared loadings within the rows of the matrix. It is an orthogonal rotation that is equivalent to minimizing the criterion

$$
c(\mathbf{\Lambda}) = \sum_i \sum_r \lambda_{ir}^4 = -\frac{1}{4} \left\langle \mathbf{\Lambda}^2, \mathbf{\Lambda}^2 \right\rangle
$$

See *Crawford–Ferguson rotation* for a definition of $\mathbf{\Lambda}$.

quartimin rotation. Quartimin rotation is an oblique rotation that is equivalent to quartimax rotation when quartimin is restricted to orthogonal rotations. Quartimin is equivalent to oblimin rotation with $\gamma = 0$. Also see *quartimax rotation*, *oblique rotation*, *orthogonal rotation*, and *oblimin rotation*.

reflection. A reflection is an orientation reversing orthogonal transformation, that is, a transformation that involves negating coordinates in one or more dimensions. A reflection is a Procrustes transformation.

repeated measures. Repeated measures data have repeated measurements for the subjects over some dimension, such as time—for example test scores at the start, midway, and end of the class. The repeated observations are typically not independent. Repeated-measures ANOVA is one approach for analyzing repeated measures data, and MANOVA is another. Also see *sphericity*.

rotation. A rotation is an orientation preserving orthogonal transformation. A rotation is a Procrustes transformation.

Roy's largest root. Roy's largest root test is a test statistic for the hypothesis test $H_0 : \boldsymbol{\mu}_1 = \cdots = \boldsymbol{\mu}_k$ based on the largest eigenvalue of $\mathbf{E}^{-1}\mathbf{H}$. It is defined as

$$
\theta = \frac{\lambda_1}{1 + \lambda_1}
$$

Here $\mathbf{H}$ is the between matrix, and $\mathbf{E}$ is the within matrix. See *between matrix*.

Sammon mapping criterion. The Sammon (1969) mapping criterion is a loss criterion used with MDS; it is the sum of the scaled, squared differences between the distances and the disparities, normalized by the sum of the disparities. Also see *multidimensional scaling*, *modern scaling*, and *loss*.

score. A score for an observation after factor analysis, PCA, or LDA is derived from a column of the loading matrix and is obtained as the linear combination of that observation's data by using the coefficients found in the loading.

score plot. A score plot produces scatterplots of the score variables after factor analysis, PCA, or LDA.

scree plot. A scree plot is a plot of eigenvalues or singular values ordered from greatest to least after an eigen decomposition or singular value decomposition. Scree plots help determine the number of factors or components in an eigen analysis. Scree is the accumulation of loose stones or rocky debris lying on a slope or at the base of a hill or cliff; this plot is called a scree plot because it looks like a scree slope. The goal is to determine the point where the mountain gives way to the fallen rock.

Shepard diagram. A Shepard diagram after MDS is a 2-dimensional plot of high-dimensional dissimilarities or disparities versus the resulting low-dimensional distances. Also see *multidimensional scaling*.

similarity, **similarity matrix**, and **similarity measure**. A similarity or a similarity measure is a quantification of how alike two things are, such as observations or variables or groups of observations, or a method for quantifying that alikeness. A similarity matrix is a matrix containing similarity measurements. The matching coefficient is one example of a similarity measure. Contrast to *dissimilarity*. Also see *proximity* and *matching coefficient*.

single-linkage clustering. Single-linkage clustering is a hierarchical clustering method that computes the proximity between two groups as the proximity between the closest pair of observations between the two groups.

singular value decomposition. A singular value decomposition (SVD) is a factorization of a rectangular matrix. It says that if $\mathbf{M}$ is an $m \times n$ matrix, there exists a factorization of the form

$$\mathbf{M} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^*$$

where $\mathbf{U}$ is an $m \times m$ unitary matrix, $\boldsymbol{\Sigma}$ is an $m \times n$ matrix with nonnegative numbers on the diagonal and zeros off the diagonal, and $\mathbf{V}^*$ is the conjugate transpose of $\mathbf{V}$, an $n \times n$ unitary matrix. If $\mathbf{M}$ is a real matrix, then so is $\mathbf{V}$, and $\mathbf{V}^* = \mathbf{V}'$.

sphericity. Sphericity is the state or condition of being a sphere. In repeated measures ANOVA, sphericity concerns the equality of variance in the difference between successive levels of the repeated measure. The multivariate alternative to ANOVA, called MANOVA, does not require the assumption of sphericity. Also see *repeated measures*.

SSCP matrix. SSCP is an acronym for the sums of squares and cross products. Also see *between matrix*.

stacked variables. See *crossed variables*.

stacking variables. See *crossing variables*.

standardized data. A standardized dataset has a mean of zero and a standard deviation of one. You can standardize data $\mathbf{x}$ by taking $(\mathbf{x} - \bar{\mathbf{x}})/\sigma$, where σ is the standard deviation of the data.

stopping rules. Stopping rules for hierarchical cluster analysis are used to determine the number of clusters. A stopping-rule value (also called an index) is computed for each cluster solution, that is, at each level of the hierarchy in hierarchical cluster analysis. Also see *hierarchical clustering*.

stress. See *Kruskal stress* and *loss*.

structure. Structure, as in factor structure, is the correlations between the variables and the common factors after factor analysis. Structure matrices are available after factor analysis and LDA. Also see *factor analysis* and *linear discriminant analysis*.

supplementary rows or columns or **supplementary variables**. Supplementary rows or columns can be included in CA, and supplementary variables can be included in MCA. They do not affect the CA or MCA solution, but they are included in plots and tables with statistics of the corresponding row or column points. Also see *correspondence analysis* and *multiple correspondence analysis*.

SVD. See *singular value decomposition*.

target rotation. Target rotation minimizes the criterion

$$c(\boldsymbol{\Lambda}) = \frac{1}{2}\|\boldsymbol{\Lambda} - \mathbf{H}\|^2$$

for a given target matrix $\mathbf{H}$.

See *Crawford–Ferguson rotation* for a definition of $\boldsymbol{\Lambda}$.

taxonomy. Taxonomy is the study of the general principles of scientific classification. It also denotes classification, especially the classification of plants and animals according to their natural relationships. Cluster analysis is a tool used in creating a taxonomy and is synonymous with numerical taxonomy. Also see *cluster analysis*.

tetrachoric correlation. A tetrachoric correlation estimates the correlation coefficients of binary variables by assuming a latent bivariate normal distribution for each pair of variables, with a threshold model for manifest variables.

ties. After discriminant analysis, ties in classification occur when two or more posterior probabilities are equal for an observation. They are most common with KNN discriminant analysis.

total inertia or **total principal inertia**. The total (principal) inertia in CA and MCA is the sum of the principal inertias. In CA, total inertia is the Pearson χ^2/n. In CA, the principal inertias are the singular values; in MCA the principal inertias are the eigenvalues. Also see *correspondence analysis* and *multiple correspondence analysis*.

uniqueness. In factor analysis, the uniqueness is the percentage of a variable's variance that is not explained by the common factors. It is also "$1 -$ communality". Also see *communality*.

unrestricted transformation. An unrestricted transformation is a Procrustes transformation that allows the data to be transformed, not just by orthogonal and oblique rotations, but by all conformable regular matrices. This is equivalent to a multivariate regression. Also see *Procrustes transformation* and *multivariate regression*.

varimax rotation. Varimax rotation maximizes the variance of the squared loadings within the columns of the matrix. It is an orthogonal rotation equivalent to oblimin with $\gamma = 1$ or to the Crawford–Ferguson family with $\kappa = 1/p$, where p is the number of rows of the matrix to be rotated. Also see *orthogonal rotation*, *oblimin rotation*, and *Crawford–Ferguson rotation*.

Ward's linkage clustering. Ward's-linkage clustering is a hierarchical clustering method that joins the two groups resulting in the minimum increase in the error sum of squares.

weighted-average linkage clustering. Weighted-average linkage clustering is a hierarchical clustering method that uses the weighted average similarity or dissimilarity of the two groups as the measure between the two groups.

Wilks's lambda. Wilks's lambda is a test statistic for the hypothesis test $H_0 : \boldsymbol{\mu}_1 = \boldsymbol{\mu}_2 = \cdots = \boldsymbol{\mu}_k$ based on the eigenvalues $\lambda_1, \ldots, \lambda_s$ of $\mathbf{E}^{-1}\mathbf{H}$. It is defined as

$$\Lambda = \frac{|\mathbf{E}|}{|\mathbf{E} + \mathbf{H}|} = \prod_{i=1}^{s} \frac{1}{1 + \lambda_i}$$

where $\mathbf{H}$ is the between matrix and $\mathbf{E}$ is the within matrix. See *between matrix*.

Wishart distribution. The Wishart distribution is a family of probability distributions for nonnegative-definite matrix-valued random variables ("random matrices"). These distributions are of great importance in the estimation of covariance matrices in multivariate statistics.

within matrix. See *between matrix*.

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Subject and author index

See the combined subject index and the combined author index in the *Stata Index*.