### elasticnet — Elastic net for prediction and model selection

<table>
<thead>
<tr>
<th>Description</th>
<th>Quick start</th>
<th>Menu</th>
<th>Syntax</th>
</tr>
</thead>
<tbody>
<tr>
<td>Options</td>
<td>Remarks and examples</td>
<td>Stored results</td>
<td>Methods and formulas</td>
</tr>
<tr>
<td>References</td>
<td>Also see</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Description

elasticnet selects covariates and fits linear, logistic, probit, Poisson, and Cox proportional hazards models using elastic net. Results from elasticnet can be used for prediction and model selection.

elasticnet saves but does not display estimated coefficients. The postestimation commands listed in [LASSO] lasso postestimation can be used to generate predictions, report coefficients, and display measures of fit.

For an introduction to lasso, see [LASSO] Lasso intro.

#### Quick start

Fit a linear model for $y_1$, and select covariates from $x_1$ to $x_{100}$ using cross-validation (CV)

```
elasticnet linear y1 x1-x100
```

Same as above, but specify the grid $\alpha = 0.1, 0.2, \ldots, 1$ using a numlist

```
elasticnet linear y1 x1-x100, alpha(0.1(0.1)1)
```

Same as above, but force $x_1$ and $x_2$ to be in the model while elasticnet selects $x_3$ to $x_{100}$

```
elasticnet linear y1 (x1 x2) x3-x100, alpha(0.1(0.1)1)
```

Fit a logistic model for binary outcome $y_2$ with grid $\alpha = 0.7, 0.8, 0.9, 1$

```
elasticnet logit y2 x1-x100, alpha(0.7 0.8 0.9 1)
```

Same as above, and set a random-number seed for reproducibility

```
elasticnet logit y2 x1-x100, alpha(0.7 0.8 0.9 1) rseed(1234)
```

Fit a Poisson model for count outcome $y_3$ with exposure time

```
elasticnet poisson y3 x1-x100, alpha(0.1(0.1)1) exposure(time)
```

Calculate the CV function beyond the CV minimum to get the full coefficient paths, knots, etc.

```
elasticnet linear y1 x1-x100, alpha(0.1(0.1)1) selection(cv, alllambdas)
```

Turn off the early stopping rule, and iterate over $\lambda$’s until a minimum is found or until the end of the $\lambda$ grid is reached

```
elasticnet linear y1 x1-x100, alpha(0.1(0.1)1) stop(0)
```

Fit a Cox proportional hazards model for $t$ with failure indicator $\text{fail}$, and select covariates from $x_1$ to $x_{100}$ using CV

```
stset t, failure(fail)
elasticnet cox x1-x100
```

Same as above, but select covariates by minimizing the BIC

```
elasticnet cox x1-x100, selection(bic)
```
Syntax

For linear, logit, probit, and Poisson models

```
elasticnet model depvar [(alwaysvars)] othervars [if] [in] [weight] [, options]
```

For Cox models

```
elasticnet cox [(alwaysvars)] othervars [if] [in] [, options]
```

`model` is one of linear, logit, probit, or poisson.

`alwaysvars` are variables that are always included in the model.

`othervars` are variables that `elasticnet` will choose to include in or exclude from the model.

```
Model          Description

*noconstant    suppress constant term
selection(cv [ , cv_opts]) select mixing parameter \( \alpha^* \) and lasso penalty
                     parameter \( \lambda^* \) using CV
selection(bic [ , bic_opts]) select mixing parameter \( \alpha^* \) and lasso penalty
                      parameter \( \lambda^* \) using BIC
selection(none) do not select \( \alpha^* \) or \( \lambda^* \)
offset(varname_o) include `varname_o` in model with coefficient constrained to 1
exposure(varname_e) include `ln(varname_e)` in model with coefficient constrained
                    to 1 (poisson model only)
*cluster(clustvar) specify cluster variable `clustvar`

Optimization

[no]log          display or suppress an iteration log
rseed(#)         set random-number seed
alphas(numlist | matname) specify the \( \alpha \) grid with `numlist` or a matrix
grid(#_g [, ratio(#_g) min(#_g)]) specify the set of possible \( \lambda \)’s using a logarithmic grid with
                     \( #_g \) grid points

crossgrid(augmented) augment the \( \lambda \) grids for each \( \alpha \) as necessary to produce a
                     single \( \lambda \) grid; the default
crossgrid(union) use the union of the \( \lambda \) grids for each \( \alpha \) to produce a single
                     \( \lambda \) grid
crossgrid(different) use different \( \lambda \) grids for each \( \alpha \)
stop(#)          tolerance for stopping the iteration over the \( \lambda \) grid early
cvtolerance(#)  tolerance for identification of the CV function minimum
bictolerance(#) tolerance for identification of the BIC function minimum
tolerance(#)     convergence tolerance for coefficients based on their values
dtolerance(#)    convergence tolerance for coefficients based on deviance
### penaltywt(matname)

Programmer’s option for specifying a vector of weights for the coefficients in the penalty term

### cv_opts

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>folds(#)</strong></td>
</tr>
<tr>
<td><strong>alllambdas</strong></td>
</tr>
<tr>
<td><strong>serule</strong></td>
</tr>
<tr>
<td><strong>stopok</strong></td>
</tr>
<tr>
<td><strong>strict</strong></td>
</tr>
<tr>
<td><strong>gridminok</strong></td>
</tr>
</tbody>
</table>

### bic_opts

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>alllambdas</strong></td>
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<tr>
<td><strong>stopok</strong></td>
</tr>
<tr>
<td><strong>strict</strong></td>
</tr>
<tr>
<td><strong>gridminok</strong></td>
</tr>
<tr>
<td><strong>postselection</strong></td>
</tr>
</tbody>
</table>

*noconstant and `cluster()` are not allowed with `elasticnet cox`.

You must `stset` your data before using `elasticnet cox`; see [ST] `stset`.

`alwaysvars` and `othervars` may contain factor variables; see [U] 11.4.3 Factor variables.

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

Default weights are not allowed. `iweights` are allowed with all `sel_method` options. `fweights` are allowed when `selection(plugin), selection(bic), or selection(none)` is specified. See [U] 11.1.6 weight. For `elasticnet cox`, weights must be specified when you `stset` your data.

`penaltywt(matname)` does not appear in the dialog box.

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

See [LASSO lasso fitting] for an overview of the lasso estimation procedure and a detailed description of how to set options to control it.

**Model**

- noconstant omits the constant term. Note, however, when there are factor variables among the othervars, elasticnet can potentially create the equivalent of the constant term by including all levels of a factor variable. This option is likely best used only when all the othervars are continuous variables and there is a conceptual reason why there should be no constant term. This option is not allowed with cox.

- selection(cv), selection(bic), and selection(none) specify the selection method used to select $\lambda^*$. 
  
  selection(cv [, cv_opts]) is the default. It selects the ($\alpha^*, \lambda^*$) that give the minimum of the CV function.

  - folds(#) specifies that CV with # folds be done. The default is folds(10).

  - alllambdas specifies that, for each $\alpha$, models be fit for all $\lambda$’s in the grid or until the stop(#) tolerance is reached. By default, models are calculated sequentially from largest to smallest $\lambda$, and the CV function is calculated after each model is fit. If a minimum of the CV function is found, the computation ends at that point without evaluating additional smaller $\lambda$’s.

  - alllambdas computes models for these additional smaller $\lambda$’s. Because computation time is greater for smaller $\lambda$, specifying alllambdas may increase computation time manyfold. Specifying alllambdas is typically done only when a full plot of the CV function is wanted for assurance that a true minimum has been found. Regardless of whether alllambdas is specified, the selected ($\alpha^*, \lambda^*$) will be the same.

  - serule selects $\lambda^*$ based on the “one-standard-error rule” recommended by Hastie, Tibshirani, and Wainwright (2015, 13–14) instead of the $\lambda$ that minimizes the CV function. The one-standard-error rule selects, for each $\alpha$, the largest $\lambda$ for which the CV function is within a standard error of the minimum of the CV function. Then, from among these ($\alpha, \lambda$) pairs, the one with the smallest value of the CV function is selected.

  - stopok, strict, and gridminok specify what to do when, for a value of $\alpha$, the CV function does not have an identified minimum at any value of $\lambda$ in the grid. A minimum is identified at $\lambda_{cvmin}$ when the CV function at both larger and smaller adjacent $\lambda$’s is greater than it is at $\lambda_{cvmin}$. When the CV function for a value of $\alpha$ has an identified minimum, these options all do the same thing: ($\alpha, \lambda_{cvmin}$) becomes one of the ($\alpha, \lambda$) pairs that potentially can be selected as the smallest value of the CV function. In some cases, however, the CV function declines monotonically as $\lambda$ gets smaller and never rises to identify a minimum. When the CV function does not have an identified minimum, stopok and gridminok make alternative picks for $\lambda$ in the ($\alpha, \lambda$) pairs that will be assessed for the smallest value of the CV function. The option strict makes no alternative pick for $\lambda$. You may specify only one of stopok, strict, or gridminok; stopok is the default if you do not specify one. With each of these options, estimation results are always left in place, and alternative ($\alpha, \lambda$) pairs can be selected and evaluated.

  - stopok specifies that, for a value of $\alpha$, when the CV function does not have an identified minimum and the stop(#) stopping tolerance for $\lambda$ was reached at $\lambda_{stop}$, the pair ($\alpha, \lambda_{stop}$) is picked as one of the pairs that potentially can be selected as the smallest value of the CV function. $\lambda_{stop}$ is the smallest $\lambda$ for which coefficients are estimated, and it is assumed that $\lambda_{stop}$ has a CV function value close to the true minimum for that
value of $\alpha$. When no minimum is identified for a value of $\alpha$ and the stop(#) criterion is not met, an error is issued.

**strict** requires the CV function to have an identified minimum for each value of $\alpha$, and if not, an error is issued.

**gridminok** is a rarely used option that specifies that, for a value of $\alpha$, when the CV function has no identified minimum and the stop(#) stopping criterion was not met, $\lambda_{gmin}$, the minimum of the $\lambda$ grid, is picked as part of a pair $(\alpha, \lambda_{gmin})$ that potentially can be selected as the smallest value of the CV function.

The **gridminok** criterion is looser than the default **stopok**, which is looser than **strict**. With **strict**, the selected $(\alpha^*, \lambda^*)$ pair is the minimum of the CV function chosen from the $(\alpha, \lambda_{cvm\text{in}})$ pairs, where all $\lambda$’s under consideration are identified minimums. With **stopok**, the set of $(\alpha, \lambda)$ pairs under consideration for the minimum of the CV function include identified minimums, $\lambda_{cvm\text{in}}$, or values, $\lambda_{\text{stop}}$, that met the stopping criterion. With **gridminok**, the set of $(\alpha, \lambda)$ pairs under consideration for the minimum of the CV function potentially include $\lambda_{cvm\text{in}}$, $\lambda_{\text{stop}}$, or $\lambda_{gmin}$.

**selection(bic [, bic_opts])** selects $(\alpha^*, \lambda^*)$ by using the Bayesian information criterion (BIC) function. It selects the $(\alpha^*, \lambda^*)$ with the minimum BIC function value.

**bic_opts** are **alllambdas**, **stopok**, **strict**, **gridminok**, and **postselection**.

**alllambdas** specifies that, for each $\alpha$, models be fit for all $\lambda$’s in the grid or until the stop(#) tolerance is reached. By default, models are calculated sequentially from largest to smallest $\lambda$, and the BIC function is calculated after each model is fit. If a minimum of the BIC function is found, the computation ends at that point without evaluating additional smaller $\lambda$’s.

**alllambdas** computes models for these additional smaller $\lambda$’s. Because computation time is greater for smaller $\lambda$, specifying **alllambdas** may increase computation time manyfold. Specifying **alllambdas** is typically done only when a full plot of the BIC function is wanted for assurance that a true minimum has been found. Regardless of whether **alllambdas** is specified, the selected $(\alpha^*, \lambda^*)$ will be the same.

**stopok**, **strict**, and **gridminok** specify what to do when, for a value of $\alpha$, the BIC function does not have an identified minimum at any value of $\lambda$ in the grid. A minimum is identified at $\lambda_{\text{bicmin}}$ when the BIC function at both larger and smaller adjacent $\lambda$’s is greater than it is at $\lambda_{\text{bicmin}}$. When the BIC function for a value of $\alpha$ has an identified minimum, these options all do the same thing: $(\alpha, \lambda_{\text{bicmin}})$ becomes one of the $(\alpha, \lambda)$ pairs that potentially can be selected as the smallest value of the BIC function. In some cases, however, the BIC function declines monotonically as $\lambda$ gets smaller and never rises to identify a minimum. When the BIC function does not have an identified minimum, **stopok** and **gridminok** make alternative picks for $\lambda$ in the $(\alpha, \lambda)$ pairs that will be assessed for the smallest value of the BIC function. The option **strict** makes no alternative pick for $\lambda$. You may specify only one of **stopok**, **strict**, or **gridminok**; **stopok** is the default if you do not specify one. With each of these options, estimation results are always left in place, and alternative $(\alpha, \lambda)$ pairs can be selected and evaluated.

**stopok** specifies that, for a value of $\alpha$, when the BIC function does not have an identified minimum and the stop(#) stopping tolerance for $\lambda$ was reached at $\lambda_{\text{stop}}$, the pair $(\alpha, \lambda_{\text{stop}})$ is picked as one of the pairs that potentially can be selected as the smallest value of the BIC function. $\lambda_{\text{stop}}$ is the smallest $\lambda$ for which coefficients are estimated, and it is assumed that $\lambda_{\text{stop}}$ has a BIC function value close to the true minimum for that value of $\alpha$. When no minimum is identified for a value of $\alpha$ and the stop(#) criterion is not met, an error is issued.
strict requires the BIC function to have an identified minimum for each value of \( \alpha \), and if not, an error is issued.

gridminok is a rarely used option that specifies that, for a value of \( \alpha \), when the BIC function has no identified minimum and the \texttt{stop(#)} stopping criterion was not met, \( \lambda_{gmin} \), the minimum of the \( \lambda \) grid, is picked as part of a pair \( (\alpha, \lambda_{gmin}) \) that potentially can be selected as the smallest value of the BIC function.

The gridminok criterion is looser than the default stopok, which is looser than strict. With strict, the selected \( (\alpha^*, \lambda^*) \) pair is the minimum of the BIC function chosen from the \( (\alpha, \lambda_{bicmin}) \) pairs, where all \( \lambda \)'s under consideration are identified minimums. With stopok, the set of \( (\alpha, \lambda) \) pairs under consideration for the minimum of the BIC function include identified minimums, \( \lambda_{bicmin} \), or values, \( \lambda_{stop} \), that met the stopping criterion. With gridminok, the set of \( (\alpha, \lambda) \) pairs under consideration for the minimum of the BIC function potentially include \( \lambda_{bicmin} \), \( \lambda_{stop} \), or \( \lambda_{gmin} \).

\texttt{postselection} specifies to use the postselection coefficients to compute the BIC function.

By default, the penalized coefficients are used. \texttt{selection(none)} does not select an \( (\alpha^*, \lambda^*) \) pair. In this case, the elastic net is estimated for a grid of values for \( \lambda \) for each \( \alpha \), but no attempt is made to determine which \( (\alpha, \lambda) \) pair is best. The postestimation command \texttt{lassoknots} can be run to view a table of \( \lambda \)'s that define the knots (that is, the distinct sets of nonzero coefficients) for each \( \alpha \). The \texttt{lassoselect} command can then be used to select an \( (\alpha^*, \lambda^*) \) pair, and \texttt{lassogof} can be run to evaluate the prediction performance of the selected pair.

When \texttt{selection(none)} is specified, neither the CV function nor the BIC function is computed. If you want to view the knot table with values of the CV function shown and then select \( (\alpha^*, \lambda^*) \), you must specify \texttt{selection(cv)}. Similarly, if you want to view the knot table with values of the BIC function shown, you must specify \texttt{selection(bic)}. There are no suboptions for \texttt{selection(none)}.

\texttt{offset(varname}) \texttt{o} specifies that \texttt{varname} \texttt{o} be included in the model with its coefficient constrained to be 1.

\texttt{exposure(varname}} \texttt{e} can be specified only for the \texttt{poisson} model. It specifies that \texttt{ln(varname} \texttt{e}) be included in the model with its coefficient constrained to be 1.

\texttt{cluster(clustvar)} specifies the cluster variable \texttt{clustvar}. Specifying a cluster variable will affect how the log-likelihood function is computed and the sample split in cross-validation. The log-likelihood function is computed as the sum of the log likelihood at the cluster levels. If option \texttt{selection(cv)} is specified, the cross-validation sample is split by the clusters defined by \texttt{clustvar}. That is, the subsample in each fold is drawn on the cluster level. Therefore, all observations in a cluster are kept together in the same subsample. This option is not allowed with \texttt{elasticnet cox}.

\texttt{[no]}\texttt{log} displays or suppresses a log showing the progress of the estimation.

\texttt{rseed(#)} sets the random-number seed. This option can be used to reproduce results for \texttt{selection(cv)}. (\texttt{selection(bic)} and \texttt{selection(none)} do not use random numbers.) \texttt{rseed(#)} is equivalent to typing \texttt{set seed #} prior to running \texttt{elasticnet}. See \texttt{[R] set seed}.

\texttt{alphas(numlist | matname)} specifies either a numlist or a matrix containing the grid of values for \( \alpha \). The default is \texttt{alphas(0.5 0.75 1)}. Specifying a small, nonzero value of \( \alpha \) for one of the values of \texttt{alphas()} will result in lengthy computation time because the optimization algorithm for a penalty that is mostly ridge regression with a little lasso mixed in is inherently inefficient. Pure ridge regression (\( \alpha = 0 \)), however, is computationally efficient.
grid($g$, [ratio($g$) min($g$)]) specifies the set of possible $\lambda$'s using a logarithmic grid with $g$ grid points.

$g$ is the number of grid points for $\lambda$. The default is $g = 100$. The grid is logarithmic with the $i$th grid point ($i = 1, \ldots, n = g$) given by $\ln \lambda_i = [(i-1)/(n-1)] r + \ln \lambda_{g_{\max}}$, where $\lambda_{g_{\max}} = \lambda_1$ is the maximum, $\lambda_{g_{\min}} = \lambda_n = \text{min}(g)$ is the minimum, and $r = \lambda_{g_{\min}}/\lambda_{g_{\max}} = \text{ratio}(g)$ is the ratio of the minimum to the maximum.

declarationR{grid(augmented), grid(union), and grid(different) specify the type of two-dimensional grid used for ($\alpha, \lambda$). grid(augmented) and grid(union) produce a grid that is the product of two one-dimensional grids. That is, the $\lambda$ grid is the same for every value of $\alpha$. grid(different) uses different $\lambda$ grids for different values of $\alpha$.

declarationR{crossgrid(augmented), the default grid, is formed by an augmentation algorithm. First, a suitable $\lambda$ grid for each $\alpha$ is computed. Then, nonoverlapping segments of these grids are formed and combined into a single $\lambda$ grid.

declarationR{crossgrid(union) specifies that the union of $\lambda$ grids across each value of $\alpha$ be used. That is, a $\lambda$ grid for each $\alpha$ is computed, and then they are combined by simply putting all the $\lambda$ values into one grid that is used for each $\alpha$. This produces a fine grid that can cause the computation to take a long time without significant gain in most cases.

declarationR{crossgrid(different) specifies that different $\lambda$ grids be used for each value of $\alpha$. This option is rarely used. Using different $\lambda$ grids for different values of $\alpha$ complicates the interpretation of the CV selection method. When the $\lambda$ grid is not the same for every value of $\alpha$, comparisons are based on parameter intervals that are not on the same scale.

$\text{stop}(g)$ specifies a tolerance that is the stopping criterion for the $\lambda$ iterations. The default is $1e-5$. Estimation starts with the maximum grid value, $\lambda_{g_{\max}}$, and iterates toward the minimum grid value, $\lambda_{g_{\min}}$. When the relative difference in the deviance produced by two adjacent $\lambda$ grid values is less than $\text{stop}(g)$, the iteration stops and no smaller $\lambda$'s are evaluated. The value of $\lambda$ that meets this tolerance is denoted by $\lambda_{\text{stop}}$. Typically, this stopping criterion is met before the iteration reaches $\lambda_{g_{\min}}$.

Setting $\text{stop}(g)$ to a larger value means that iterations are stopped earlier at a larger $\lambda_{\text{stop}}$. To produce coefficient estimates for all values of the $\lambda$ grid, you can specify $\text{stop}(0)$. Note, however, that computations for small $\lambda$'s can be extremely time consuming. In terms of time, when you use selection(cv) or selection(bic), the optimal value of $\text{stop}(g)$ is the largest value that allows estimates for just enough $\lambda$'s to be computed to identify the minimum of the CV or BIC function. When setting $\text{stop}(g)$ to larger values, be aware of the consequences of the default $\lambda^*$ selection procedure given by the default stopok. You may want to override the stopok behavior by using strict.

declarationR{cvtolerance($g$) is a rarely used option that changes the tolerance for identifying the minimum CV function. For linear models, a minimum is identified when the CV function rises above a nominal minimum for at least three smaller $\lambda$'s with a relative difference in the CV function greater than $g$. For nonlinear models, at least five smaller $\lambda$'s are required. The default is $1e-3$. Setting $g$ to a bigger value makes a stricter criterion for identifying a minimum and brings more assurance
that a declared minimum is a true minimum, but it also means that models may need to be fit for additional smaller $\lambda$, which can be time consuming. See *Methods and formulas* for [LASSO lasso] for more information about this tolerance and the other tolerances.

**bictolerance(#)** is a rarely used option that changes the tolerance for identifying the minimum BIC function. A minimum is identified when the BIC function rises above a nominal minimum for at least two smaller $\lambda$'s with a relative difference in the BIC function greater than #. The default is 1e−2. Setting # to a bigger value makes a stricter criterion for identifying a minimum and brings more assurance that a declared minimum is a true minimum, but it also means that models may need to be fit for additional smaller $\lambda$, which can be time consuming. See *Methods and formulas* in [LASSO lasso] for more information about this tolerance and the other tolerances.

**tolerance(#)** is a rarely used option that specifies the convergence tolerance for the coefficients. Convergence is achieved when the relative change in each coefficient is less than this tolerance. The default is tolerance(1e-7).

**dtolerance(#)** is a rarely used option that changes the convergence criterion for the coefficients. When dtolerance(#) is specified, the convergence criterion is based on the change in deviance instead of the change in the values of coefficient estimates. Convergence is declared when the relative change in the deviance is less than #. More-accurate coefficient estimates are typically achieved by not specifying this option and instead using the default tolerance(1e-7) criterion or specifying a smaller value for tolerance(#).

The following option is available with elasticnet but is not shown in the dialog box:

**penaltywt(matname)** is a programmer’s option for specifying a vector of weights for the coefficients in the penalty term. The contribution of each coefficient to the lasso penalty term is multiplied by its corresponding weight. Weights must be nonnegative. By default, each coefficient’s penalty weight is 1.

### Remarks and examples

Elastic net, originally proposed by Zou and Hastie (2005), extends lasso to have a penalty term that is a mixture of the absolute-value penalty used by lasso and the squared penalty used by ridge regression. Coefficient estimates from elastic net are more robust to the presence of highly correlated covariates than are lasso solutions.

For the linear model, the penalized objective function for elastic net is

$$Q = \frac{1}{2N} \sum_{i=1}^{N} \left( y_i - \beta_0 - x_i \beta' \right)^2 + \lambda \sum_{j=1}^{p} \left( \frac{1-\alpha}{2} \beta_j^2 + \alpha |\beta_j| \right)$$

where $\beta$ is the $p$-dimensional vector of coefficients on covariates $x$. The estimated $\beta$ are those that minimize $Q$ for given values of $\alpha$ and $\lambda$.

As with lasso, $p$ can be greater than the sample size $N$. When $\alpha = 1$, elastic net reduces to lasso. When $\alpha = 0$, elastic net reduces to ridge regression.

When $\alpha > 0$, elastic net, like lasso, produces sparse solutions in which many of the coefficient estimates are exactly zero. When $\alpha = 0$, that is, ridge regression, all coefficients are nonzero, although typically many are small.

Ridge regression has long been used as a method to keep highly collinear variables in a regression model used for prediction. The ordinary least-squares (OLS) estimator becomes increasingly unstable as the correlation among the covariates grows. OLS produces wild coefficient estimates on highly correlated covariates that cancel each other out in terms of fit. The ridge regression penalty removes this instability and produces point estimates that can be used for prediction in this case.
None of the ridge regression estimates are exactly zero because the squared penalty induces a
smooth tradeoff around 0 instead of the kinked-corner tradeoff induced by lasso. By mixing the two
penalties, elastic net retains the sparse-solution property of lasso, but it is less variable than the lasso
in the presence of highly collinear variables. The coefficient paths of elastic-net solutions are also
smoother over \( \lambda \) than are lasso solutions because of the added ridge-regression component.

To fit a model with elasticnet, you specify a set of candidate \( \alpha \)'s and a grid of \( \lambda \) values. CV
is performed on the combined set of \((\alpha, \lambda)\) values, and the \((\alpha^*, \lambda^*)\) pair that minimizes the value
of the CV function is selected.

This procedure follows the convention of Hastie, Tibshirani, and Wainwright (2015), which is to
specify a few values for \( \alpha \) and a finer grid for \( \lambda \). The idea is that only a few points in the space
between ridge regression and lasso are worth reviewing, but a finer grid over \( \lambda \) is needed to trace
out the paths of which coefficients are not zero.

The default candidate values of \( \alpha \) are 0.5, 0.75, and 1. Typically, you would use the default first
and then set \( \alpha \) using the \texttt{alpha(numlist)} option to get lower and upper bounds on \( \alpha^* \). Models for
small, nonzero values of \( \alpha \) take more time to estimate than \( \alpha = 0 \) and larger values of \( \alpha \). This is
because the algorithm for fitting a model that is mostly ridge regression with a little lasso mixed in
is inherently inefficient. Pure ridge or mostly lasso models are faster.

The \( \lambda \) grid is set automatically, and the default settings are typically sufficient to determine \( \lambda^* \).
The default grid can be changed using the \texttt{grid()} option. See \texttt{LASSO lasso fitting} for a detailed
description of the CV selection process and how to set options to control it.

Example 1: Elastic net and data that are not highly correlated

We will fit an elastic-net model using the example dataset from \texttt{LASSO lasso examples}. It has
stored variable lists created by \texttt{vl}. See \texttt{D vl} for a complete description of the \texttt{vl} system and how
to use it to manage large variable lists.

After we load the dataset, we type \texttt{vl rebuild} to make the saved variable lists active again.

```
. use https://www.stata-press.com/data/r18/fakesurvey_vl
(Fictitious survey data with \texttt{vl})
. vl rebuild
Rebuilding \texttt{vl} macros ...
```

<table>
<thead>
<tr>
<th>Macro</th>
<th># Vars</th>
<th>Description</th>
</tr>
</thead>
<tbody>
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<td>factor-variable list</td>
</tr>
<tr>
<td>$ifactors</td>
<td></td>
<td>factor-variable list</td>
</tr>
</tbody>
</table>

We have four user-defined variable lists, \texttt{demographics}, \texttt{factors}, \texttt{idemographics}, and \texttt{ifactors}. The variable lists \texttt{idemographics} and \texttt{ifactors} contain factor-variable versions of the
categorical variables in \texttt{demographics} and \texttt{factors}. That is, a variable \texttt{q3} in \texttt{demographics} is
\texttt{i.q3} in \texttt{idemographics}. See \texttt{LASSO lasso examples} to see how we created these variable lists.
We are going to use `idemographics` and `ifactors` along with the system-defined variable list `vlcontinuous` as arguments to `elasticnet`. Together they contain the potential variables we want to specify. Variable lists are actually global macros, and when we use them as arguments in commands, we put a `$` in front of them.

We also set the random-number seed using the `rseed()` option so we can reproduce our results.

```
. elasticnet linear q104 $idemographics $ifactors $vlcontinuous, rseed(1234)
```

10-fold cross-validation with 109 lambdas ...

| Grid value 1: | lambda = 1.818102 | no. of nonzero coef. = 0 |
| Grid value 37: | lambda = .0737359 | no. of nonzero coef. = 80 |

10-fold cross-validation complete ... minimum found

alpha 2 of 3: alpha = 0.75

10-fold cross-validation with 109 lambdas ...

| Grid value 34: | lambda = .0974746 | no. of nonzero coef. = 126 |
| Grid value 37: | lambda = .0737359 | no. of nonzero coef. = 80 |

10-fold cross-validation complete ... minimum found

alpha 3 of 3: alpha = 0.5

10-fold cross-validation with 109 lambdas ...

| Grid value 31: | lambda = .1288556 | no. of nonzero coef. = 139 |

Elastic net linear model

| Selection: Cross-validation |
| No. of obs = 914 |
| No. of covariates = 277 |
| No. of CV folds = 10 |

<table>
<thead>
<tr>
<th>alpha</th>
<th>ID</th>
<th>Description</th>
<th>lambda</th>
<th>no. of nonzero coef.</th>
<th>R-squared</th>
<th>Out-of-sample prediction error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.000</td>
<td>1</td>
<td>first lambda</td>
<td>1.818102</td>
<td>0</td>
<td>-0.0016</td>
<td>18.34476</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>lambda before</td>
<td>.1174085</td>
<td>58</td>
<td>0.3543</td>
<td>11.82553</td>
</tr>
<tr>
<td></td>
<td>* 33</td>
<td>selected lambda</td>
<td>.1069782</td>
<td>64</td>
<td>0.3547</td>
<td>11.81814</td>
</tr>
<tr>
<td></td>
<td>34</td>
<td>lambda after</td>
<td>.0974746</td>
<td>66</td>
<td>0.3545</td>
<td>11.8222</td>
</tr>
<tr>
<td></td>
<td>37</td>
<td>last lambda</td>
<td>.0737359</td>
<td>80</td>
<td>0.3487</td>
<td>11.92887</td>
</tr>
<tr>
<td>0.750</td>
<td>38</td>
<td>first lambda</td>
<td>1.818102</td>
<td>0</td>
<td>-0.0016</td>
<td>18.34476</td>
</tr>
<tr>
<td></td>
<td>71</td>
<td>last lambda</td>
<td>.0974746</td>
<td>126</td>
<td>0.3473</td>
<td>11.95437</td>
</tr>
<tr>
<td>0.500</td>
<td>72</td>
<td>first lambda</td>
<td>1.818102</td>
<td>0</td>
<td>-0.0012</td>
<td>18.33643</td>
</tr>
<tr>
<td></td>
<td>102</td>
<td>last lambda</td>
<td>.1288556</td>
<td>139</td>
<td>0.3418</td>
<td>12.0549</td>
</tr>
</tbody>
</table>

* alpha and lambda selected by cross-validation.

CV selected $\alpha^* = 1$, that is, the results from an ordinary lasso.
All models we fit using elastic net on these data selected $\alpha^* = 1$. The data are not correlated enough to need elastic net.

Example 2: Elastic net and data that are highly correlated

The dataset in example 1, fakesurvey_vl, contained data we created in a simulation. We did our simulation again setting the correlation parameters to much higher values, up to $\rho = 0.95$, and we created two groups of highly correlated variables, with correlations between variables from different groups much lower. We saved these data in a new dataset named fakesurvey2_vl. Elastic net was proposed not just for highly correlated variables but especially for groups of highly correlated variables.

We load the new dataset and run vl rebuild.

```
. use https://www.stata-press.com/data/r18/fakesurvey2_vl, clear
(Fictitious survey data with vl)
vl rebuild
Rebuilding vl macros ...
(output omitted)
```

In anticipation of elastic net showing interesting results this time, we randomly split our data into two samples of equal sizes. One we will fit models on, and the other we will use to test their predictions. We use splitsample to generate a variable indicating the samples.

```
. set seed 1234
. splitsample, generate(sample) nsplit(2)
. label define svalues 1 "Training" 2 "Testing"
. label values sample svalues
```

We fit an elastic-net model using the default $\alpha$'s.

```
. elasticnet linear q104 $idemographics $ifactors $vlcontinuous
   > if sample == 1, rseed(1234)
alpha 1 of 3: alpha = 1
(output omitted)
10-fold cross-validation with 109 lambdas ...
Grid value 1: lambda = 6.323778 no. of nonzero coef. = 0
Folds: 1...5....10 CVF = 26.82324
(output omitted)
Grid value 42: lambda = .161071 no. of nonzero coef. = 29
Folds: 1...5....10 CVF = 15.12964
... cross-validation complete ... minimum found
alpha 2 of 3: alpha = 0.75
(output omitted)
10-fold cross-validation with 109 lambdas ...
Grid value 1: lambda = 6.323778 no. of nonzero coef. = 0
Folds: 1...5....10 CVF = 26.82324
(output omitted)
Grid value 40: lambda = .1940106 no. of nonzero coef. = 52
Folds: 1...5....10 CVF = 15.07523
... cross-validation complete ... minimum found
alpha 3 of 3: alpha = 0.5
(output omitted)
```
10-fold cross-validation with 109 lambdas ...
Grid value 1: lambda = 6.323778 no. of nonzero coef. = 0
Folds: 1...5....10 CVF = 26.78722
(output omitted)
Grid value 46: lambda = .11102 no. of nonzero coef. = 115
Folds: 1...5....10 CVF = 14.90808
... cross-validation complete ... minimum found
Elastic net linear model
No. of obs = 449
No. of covariates = 275
Selection: Cross-validation
No. of CV folds = 10

<table>
<thead>
<tr>
<th>alpha ID</th>
<th>Description</th>
<th>lambda</th>
<th>no. of nonzero coef.</th>
<th>R-squared</th>
<th>prediction error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.000</td>
<td>first lambda</td>
<td>6.323778</td>
<td>0</td>
<td>-0.0036</td>
<td>26.82324</td>
</tr>
<tr>
<td>42</td>
<td>last lambda</td>
<td>.161071</td>
<td>29</td>
<td>0.4339</td>
<td>15.12964</td>
</tr>
<tr>
<td>0.750</td>
<td>first lambda</td>
<td>6.323778</td>
<td>0</td>
<td>-0.0036</td>
<td>26.82324</td>
</tr>
<tr>
<td>82</td>
<td>last lambda</td>
<td>.1940106</td>
<td>52</td>
<td>0.4360</td>
<td>15.07523</td>
</tr>
<tr>
<td>0.500</td>
<td>first lambda</td>
<td>6.323778</td>
<td>0</td>
<td>-0.0022</td>
<td>26.78722</td>
</tr>
<tr>
<td>83</td>
<td>lambda before</td>
<td>.161071</td>
<td>87</td>
<td>0.4473</td>
<td>14.77189</td>
</tr>
<tr>
<td>124</td>
<td>selected lambda</td>
<td>.1467619</td>
<td>92</td>
<td>0.4476</td>
<td>14.76569</td>
</tr>
<tr>
<td>125</td>
<td>selected lambda</td>
<td>.133724</td>
<td>96</td>
<td>0.4468</td>
<td>14.78648</td>
</tr>
<tr>
<td>126</td>
<td>lambda after</td>
<td>.11102</td>
<td>115</td>
<td>0.4422</td>
<td>14.90808</td>
</tr>
</tbody>
</table>

* alpha and lambda selected by cross-validation.
. estimates store elasticnet

Wonderful! It selected $\alpha^* = 0.5$. We should not stop here, however. There may be smaller values of $\alpha$ that give lower minimums of the CV function. If the number of observations and number of potential variables are not too large, you could specify the option alpha(0(0.1)1) the first time you run elasticnet. However, if we did this, the command would take much longer to run than the default. It will be especially slow for $\alpha = 0.1$ as we mentioned earlier.

. elasticnet linear q104 $idemographics $ifactors $v1continuous
> if sample == 1, rseed(1234) alpha(0.1 0.2 0.3)
a 1 of 3: alpha = .3
(output omitted)
10-fold cross-validation with 113 lambdas ...
Grid value 1: lambda = 31.61889 no. of nonzero coef. = 0
Folds: 1...5....10 CVF = 26.82324
(output omitted)
Grid value 59: lambda = .160193 no. of nonzero coef. = 122
Folds: 1...5....10 CVF = 14.84229
... cross-validation complete ... minimum found
alpha 2 of 3: alpha = .2
(output omitted)
10-fold cross-validation with 113 lambdas ...
Grid value 1: lambda = 31.61889 no. of nonzero coef. = 0
Folds: 1...5....10 CVF = 26.82324
(output omitted)
Grid value 56: lambda = .2117657 no. of nonzero coef. = 137
Folds: 1...5....10 CVF = 14.81594
... cross-validation complete ... minimum found

alpha 3 of 3: alpha = .1
(output omitted)

10-fold cross-validation with 113 lambdas ...
Grid value 1: lambda = 31.61889 no. of nonzero coef. = 0
Folds: 1...5....10 CVF = 26.81813
(output omitted)

Grid value 51: lambda = .3371909 no. of nonzero coef. = 162
Folds: 1...5....10 CVF = 14.81783
... cross-validation complete ... minimum found

Elastic net linear model
No. of obs = 449
No. of covariates = 275
Selection: Cross-validation
No. of CV folds = 10

<table>
<thead>
<tr>
<th>alpha</th>
<th>Description</th>
<th>lambda</th>
<th>coef.</th>
<th>R-squared</th>
<th>error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.300</td>
<td>first lambda</td>
<td>31.61889</td>
<td>0</td>
<td>-0.0036</td>
<td>26.82324</td>
</tr>
<tr>
<td></td>
<td>last lambda</td>
<td>.160193</td>
<td>122</td>
<td>0.4447</td>
<td>14.84229</td>
</tr>
<tr>
<td>0.200</td>
<td>first lambda</td>
<td>31.61889</td>
<td>0</td>
<td>-0.0036</td>
<td>26.82324</td>
</tr>
<tr>
<td></td>
<td>lambda before</td>
<td>.3371909</td>
<td>108</td>
<td>0.4512</td>
<td>14.66875</td>
</tr>
<tr>
<td></td>
<td>selected lambda</td>
<td>.3072358</td>
<td>118</td>
<td>0.4514</td>
<td>14.66358</td>
</tr>
<tr>
<td></td>
<td>lambda after</td>
<td>.2799418</td>
<td>125</td>
<td>0.4509</td>
<td>14.67566</td>
</tr>
<tr>
<td></td>
<td>last lambda</td>
<td>.2117657</td>
<td>137</td>
<td>0.4457</td>
<td>14.81594</td>
</tr>
<tr>
<td>0.100</td>
<td>first lambda</td>
<td>31.61889</td>
<td>0</td>
<td>-0.0034</td>
<td>26.81813</td>
</tr>
<tr>
<td></td>
<td>last lambda</td>
<td>.3371909</td>
<td>162</td>
<td>0.4456</td>
<td>14.81783</td>
</tr>
</tbody>
</table>

* alpha and lambda selected by cross-validation.

The selected $\alpha^*$ is 0.2. This value is better, according to CV, than $\alpha = 0.1$ or $\alpha = 0.3$. 

Estimates store elasticnet
We can plot the CV function for the selected $\alpha^* = 0.2$.

```
  cvplot
```

![Cross-validation plot]

The CV function looks quite flat around the selected $\lambda^*$. We could assess alternative $\lambda$ (and alternative $\alpha$) using `lassoknots`. We run `lassoknots` with options requesting the number of nonzero coefficients be shown (nonzero), along with the CV function (cvmpe) and estimates of the out-of-sample $R^2$ (osr2).

```
  . lassoknots, display(nonzero cvmpe osr2)
```

<table>
<thead>
<tr>
<th>alpha</th>
<th>ID</th>
<th>lambda</th>
<th>nonzero coef.</th>
<th>CV mean pred. error</th>
<th>Out-of-sample R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.300</td>
<td>15</td>
<td>9.603319</td>
<td>4</td>
<td>26.42296</td>
<td>0.0114</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>54</td>
<td>.2550726</td>
<td>92</td>
<td>14.67746</td>
<td>0.4509</td>
</tr>
<tr>
<td></td>
<td>55</td>
<td>.2324126</td>
<td>98</td>
<td>14.66803</td>
<td>0.4512</td>
</tr>
<tr>
<td></td>
<td>56</td>
<td>.2117657</td>
<td>105</td>
<td>14.67652</td>
<td>0.4509</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>59</td>
<td>.160193</td>
<td>122</td>
<td>14.84229</td>
<td>0.4447</td>
</tr>
<tr>
<td>0.200</td>
<td>69</td>
<td>14.40498</td>
<td>4</td>
<td>26.54791</td>
<td>0.0067</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>110</td>
<td>.3371909</td>
<td>108</td>
<td>14.66875</td>
<td>0.4512</td>
</tr>
<tr>
<td></td>
<td>111</td>
<td>.3072358</td>
<td>118</td>
<td>14.66358</td>
<td>0.4514</td>
</tr>
<tr>
<td></td>
<td>112</td>
<td>.2799418</td>
<td>125</td>
<td>14.67566</td>
<td>0.4509</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>115</td>
<td>.2117657</td>
<td>137</td>
<td>14.81594</td>
<td>0.4457</td>
</tr>
<tr>
<td>0.100</td>
<td>117</td>
<td>28.80996</td>
<td>4</td>
<td>26.67947</td>
<td>0.0018</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(output omitted)
When we examine the output from `lassoknots`, we see that the CV function appears rather flat along $\lambda$ from the minimum and also across $\alpha$.

#### Example 3: Ridge regression

Let’s continue with the previous example and fit a ridge regression. We do this by specifying $\alpha(0)$.

```stata
. elasticnet linear q104 $idemographics $ifactors $vlcontinuous > if sample == 1, rseed(1234) alpha(0)
```

Evaluating up to 100 lambdas in grid...

Grid value 1: $\lambda = 3.16e+08$ no. of nonzero coef. = 275

Grid value 2: $\lambda = 2880.996$ no. of nonzero coef. = 275

Grid value 99: $\lambda = .3470169$ no. of nonzero coef. = 275

Grid value 100: $\lambda = .3161889$ no. of nonzero coef. = 275

10-fold cross-validation with 100 lambdas...

Fold 1 of 10: 10....20....30....40....50....60....70....80....90....100

Fold 10 of 10: 10....20....30....40....50....60....70....80....90....100

... cross-validation complete

Elastic net linear model

<table>
<thead>
<tr>
<th>No. of obs =</th>
<th>449</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of covariates =</td>
<td>275</td>
</tr>
</tbody>
</table>

Selection: Cross-validation

| No. of CV folds = | 10 |

<table>
<thead>
<tr>
<th>alpha</th>
<th>ID</th>
<th>Description</th>
<th>lambda</th>
<th>coef.</th>
<th>R-squared</th>
<th>Out-of-sample prediction error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>1</td>
<td>first lambda</td>
<td>3161.889</td>
<td>275</td>
<td>-0.0036</td>
<td>26.82323</td>
</tr>
<tr>
<td></td>
<td>88</td>
<td>lambda before</td>
<td>.9655953</td>
<td>275</td>
<td>0.4387</td>
<td>15.00168</td>
</tr>
<tr>
<td>* 89</td>
<td></td>
<td>selected lambda</td>
<td>.8798144</td>
<td>275</td>
<td>0.4388</td>
<td>14.99956</td>
</tr>
<tr>
<td></td>
<td>90</td>
<td>lambda after</td>
<td>.8016542</td>
<td>275</td>
<td>0.4386</td>
<td>15.00425</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>last lambda</td>
<td>.3161889</td>
<td>275</td>
<td>0.4198</td>
<td>15.50644</td>
</tr>
</tbody>
</table>

* alpha and lambda selected by cross-validation.

. estimates store ridge
In this implementation, ridge regression selects $\lambda^*$ using CV. We can plot the CV function.

```
.cvplot
```

![Cross-validation plot](image)

$\lambda_{CV} = 0$ is the cross-validation minimum $\alpha$.
$\lambda_{CV} = .88$ is the cross-validation minimum $\lambda$; # coefficients = 275.

**Example 4: Comparing elastic net, ridge regression, and lasso**

We fit elastic net and ridge on half of the sample in the previous examples so we could evaluate the prediction on the other half of the sample.

Let’s continue with the data from example 2 and example 3 and fit a lasso.

```
. lasso linear q104 $idemographics $ifactors $vlcontinuous
> if sample == 1, rseed(1234)
note: 1.q14 omitted because of collinearity with another variable.
note: 1.q136 omitted because of collinearity with another variable.
10-fold cross-validation with 100 lambdas...
Grid value 1:  lambda = 3.161889  no. of nonzero coef. = 0
(output omitted)
Grid value 33:  lambda = .161071  no. of nonzero coef. = 29
Folds: 1...5...10  CVF = 15.12964
... cross-validation complete ... minimum found
Lasso linear model  No. of obs = 449
       No. of covariates = 275
Selection: Cross-validation
       No. of CV folds = 10

<table>
<thead>
<tr>
<th>ID</th>
<th>Description</th>
<th>lambda</th>
<th>No. of nonzero coef.</th>
<th>Out-of-sample R-squared</th>
<th>CV mean prediction error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>first lambda</td>
<td>3.161889</td>
<td>0</td>
<td>0.0020</td>
<td>26.67513</td>
</tr>
<tr>
<td>28</td>
<td>lambda before</td>
<td>.2564706</td>
<td>18</td>
<td>0.4348</td>
<td>15.10566</td>
</tr>
<tr>
<td>* 29</td>
<td>selected lambda</td>
<td>.2336864</td>
<td>21</td>
<td>0.4358</td>
<td>15.07917</td>
</tr>
<tr>
<td>30</td>
<td>lambda after</td>
<td>.2129264</td>
<td>21</td>
<td>0.4355</td>
<td>15.08812</td>
</tr>
<tr>
<td>33</td>
<td>last lambda</td>
<td>.161071</td>
<td>29</td>
<td>0.4339</td>
<td>15.12964</td>
</tr>
</tbody>
</table>

* lambda selected by cross-validation.
```

```
. estimates store lasso
```
We stored the results of the earlier elastic net and ridge in memory using `estimates store`. We did the same for the lasso results. Now we can compare out-of-sample prediction using `lassogof`.

```stata
. lassogof elasticnet ridge lasso, over(sample)
Penalized coefficients
```

<table>
<thead>
<tr>
<th>Name</th>
<th>sample</th>
<th>MSE</th>
<th>R-squared</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>elasticnet</td>
<td>Training</td>
<td>11.70471</td>
<td>0.5520</td>
<td>480</td>
</tr>
<tr>
<td></td>
<td>Testing</td>
<td>14.60949</td>
<td>0.4967</td>
<td>501</td>
</tr>
<tr>
<td>ridge</td>
<td>Training</td>
<td>11.82482</td>
<td>0.5576</td>
<td>449</td>
</tr>
<tr>
<td></td>
<td>Testing</td>
<td>14.88123</td>
<td>0.4809</td>
<td>476</td>
</tr>
<tr>
<td>lasso</td>
<td>Training</td>
<td>13.41709</td>
<td>0.4823</td>
<td>506</td>
</tr>
<tr>
<td></td>
<td>Testing</td>
<td>14.91674</td>
<td>0.4867</td>
<td>513</td>
</tr>
</tbody>
</table>

Elastic net did better out of sample based on the mean squared error and $R^2$ than ridge and lasso.

Note that the numbers of observations for both the training and testing samples were slightly different for each of the models. `splitsample` split the sample exactly in half with 529 observations in each half sample. The sample sizes across the models differ because the different models contain different sets of selected variables; hence, the pattern of missing values is different. If you want to make the half samples exactly equal after missing values are dropped, an optional varlist containing the dependent variable and all the potential variables can be used with `splitsample` to omit any missing values in these variables. See `[D] splitsample`.

Before we conclude that elastic net won out over ridge and lasso, we must point out that we were not fair to lasso. Theory states that for the lasso linear model, postselection coefficients provide slightly better predictions. See `predict` in `[LASSO] lasso postestimation`.

We run `lassogof` again for the lasso results, this time specifying that postselection coefficients be used.

```stata
. lassogof lasso, over(sample) postselection
Postselection coefficients
```

<table>
<thead>
<tr>
<th>Name</th>
<th>sample</th>
<th>MSE</th>
<th>R-squared</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>lasso</td>
<td>Training</td>
<td>13.14487</td>
<td>0.4928</td>
<td>506</td>
</tr>
<tr>
<td></td>
<td>Testing</td>
<td>14.62903</td>
<td>0.4966</td>
<td>513</td>
</tr>
</tbody>
</table>

We declare a tie with elastic net!

Postselection coefficients should not be used with `elasticnet` and, in particular, with ridge regression. Ridge works by shrinking the coefficient estimates, and these are the estimates that should be used for prediction. Because postselection coefficients are OLS regression coefficients for the selected coefficients and because ridge always selects all variables, postselection coefficients after ridge are OLS regression coefficients for all potential variables, which clearly we do not want to use for prediction.
elasticnet — Elastic net for prediction and model selection

Stored results

elasticnet stores the following in e():

Scalars

- **e(N)**: number of observations
- **e(N_clust)**: number of clusters
- **e(k_allvars)**: number of potential variables
- **e(k_nonzero_sel)**: number of nonzero coefficients for selected model
- **e(k_nonzero_cv)**: number of nonzero coefficients at CV mean function minimum
- **e(k_nonzero_serule)**: number of nonzero coefficients for one-standard-error rule
- **e(k_nonzero_min)**: minimum number of nonzero coefficients among estimated λ’s
- **e(k_nonzero_max)**: maximum number of nonzero coefficients among estimated λ’s
- **e(k_nonzero_bic)**: number of nonzero coefficients at BIC function minimum
- **e(alpha_sel)**: value of selected α∗
- **e(alpha_cv)**: value of α at CV mean function minimum
- **e(lambda_sel)**: value of selected λ∗
- **e(lambda_gmin)**: value of λ at grid minimum
- **e(lambda_gmax)**: value of λ at grid maximum
- **e(lambda_last)**: value of last λ computed
- **e(lambda_cv)**: value of λ at CV mean function minimum
- **e(lambda_serule)**: value of λ for one-standard-error rule
- **e(lambda_bic)**: value of λ at BIC function minimum
- **e(ID_sel)**: ID of selected λ∗
- **e(ID_cv)**: ID of λ at CV mean function minimum
- **e(ID_serule)**: ID of λ for one-standard-error rule
- **e(ID_bic)**: ID of λ at BIC function minimum
- **e(cvm_min)**: minimum CV mean function value
- **e(cvm_serule)**: CV mean function value at one-standard-error rule
- **e(devratio_min)**: minimum deviance ratio
- **e(devratio_max)**: maximum deviance ratio
- **e(L1_min)**: minimum value of ℓ1-norm of penalized unstandardized coefficients
- **e(L1_max)**: maximum value of ℓ1-norm of penalized unstandardized coefficients
- **e(L2_min)**: minimum value of ℓ2-norm of penalized unstandardized coefficients
- **e(L2_max)**: maximum value of ℓ2-norm of penalized unstandardized coefficients
- **e(ll_sel)**: log-likelihood value of selected model
- **e(n_lambda)**: number of λ’s
- **e(n_fold)**: number of CV folds
- **e(stop)**: stopping rule tolerance

Macros

- **e(cmd)**: elasticnet
- **e(cmdline)**: command as typed
- **e(depvar)**: name of dependent variable
- **e(allvars)**: names of all potential variables
- **e(allvars_sel)**: names of all selected variables
- **e(alwaysvars)**: names of always-included variables
- **e(othervars_sel)**: names of other selected variables
- **e(post_sel_vars)**: all variables needed for postelastic net
- **e(clustvar)**: name of cluster variable
- **e(lasso_selection)**: selection method
- **e(sel_criterion)**: criterion used to select λ∗
- **e(crossgrid)**: type of two-dimensional grid
- **e(model)**: linear, logit, probit, poisson, or cox
- **e(title)**: title in estimation output
- **e(rngstate)**: random-number state used
- **e(properties)**: b
- **e(predict)**: program used to implement predict
- **e(marginsnotok)**: predictions disallowed by margins

Matrices

- **e(b)**: penalized unstandardized coefficient vector
- **e(b_standardized)**: penalized standardized coefficient vector
- **e(b_postselection)**: postselection coefficient vector
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

The methods and formulas for elastic net are given in Methods and formulas in [LASSO] lasso. Here we provide the methods and formulas for ridge regression, which is a special case of elastic net.

Unlike lasso and elastic net, ridge regression has a differentiable objective function, and there is a closed-form solution to the problem of minimizing the objective function. The solutions for ridge regression with nonlinear models are obtained by iteratively reweighted least squares.

The estimates of a generalized linear model (GLM) ridge regression model are obtained by minimizing

\[ Q_L = \sum_{i=1}^{N} \tilde{w}_i f(y_i, \beta_0 + x_i \beta') + \frac{\lambda}{2} \sum_{j=1}^{p} \kappa_j \beta_j^2 \]

where \( N \) is the number of observations; \( \tilde{w}_i \) is the normalized observation-level weight; \( f(\cdot) \) is the likelihood contribution for the regress, logit, probit, or poisson model; \( \beta_0 \) is the intercept; \( x_i \) is the \( 1 \times p \) vector of covariates; \( \beta \) is the \( 1 \times p \) vector of coefficients; \( \lambda \) is the ridge penalty parameter, which must be greater than or equal to 0; and \( \kappa_j \) are coefficient-level weights (which by default are all 1).

The normalized weights \( \tilde{w}_i \) sum to 1. That is,

\[ \tilde{w}_i = \frac{w_i}{\sum_{i=1}^{N} w_i} \]

where \( w_i \) is the original observation-level weight. If weights are not specified with elasticnet, \( w_i = 1 \) and \( \tilde{w}_i = 1/N \).

The penalized objective function of the ridge regression for the cox model is

\[ Q_L = -\sum_{j=1}^{N_f} \sum_{i \in D_j} \tilde{w}_i \left[ x_i \beta' - \log \left\{ \sum_{\ell \in R_j} \tilde{w}_\ell \exp(x_\ell \beta') \right\} \right] + \frac{\lambda}{2} \sum_{j=1}^{p} \kappa_j \beta_j^2 \]

where \( j \) indexes the ordered failure times \( t(j), j = 1, \ldots, N_f; D_j \) is the set of observations that fail at \( t(j) \); and \( R_j \) is the set of observations \( k \) that are at risk at time \( t(j) \) (that is, all \( k \) such that \( t_{0k} < t(j) \leq t_k \), and \( t_{0k} \) is the entry time for the \( k \)th observation).

When the model is linear,

\[ f(y_i, \beta_0 + x_i \beta') = \frac{1}{2} (y_i - \beta_0 - x_i \beta')^2 \]
When the model is logit,

\[ f(y_i, \beta_0 + x_i\beta') = -y_i(\beta_0 + x_i\beta') + \ln\{1 + \exp(\beta_0 + x_i\beta')\} \]

When the model is probit,

\[ f(y_i, \beta_0 + x_i\beta') = -y_i \ln\{\Phi(\beta_0 + x_i\beta')\} - (1 - y_i) \ln\{1 - \Phi(\beta_0 + x_i\beta')\} \]

When the model is poisson,

\[ f(y_i, \beta_0 + x_i\beta') = -y_i(\beta_0 + x_i\beta') + \exp(\beta_0 + x_i\beta') \]

For the linear model, the point estimates are given by

\[ (\widehat{\beta}_0, \widehat{\beta})' = \left( \frac{1}{N} \sum_{i=1}^{N} \tilde{w}_i \tilde{x}_i' \tilde{x}_i + \lambda \tilde{I} \right)^{-1} \sum_{i=1}^{N} \tilde{w}_i y_i \tilde{x}_i' \]

where \( \tilde{x}_i = (1, x_i) \) and \( \tilde{I} \) is a diagonal matrix with the coefficient-level weights 0, \( \kappa_1, \ldots, \kappa_p \) on the diagonal.

For the nonlinear models, the optimization problem is solved using iteratively reweighted least squares. See Segerstedt (1992) and Nyquist (1991) for details of the iteratively reweighted least-squares algorithm for the GLM ridge-regression estimator.

References


Also see

[LASSO] lasso postestimation — Postestimation tools for lasso for prediction

[LASSO] lasso — Lasso for prediction and model selection

[LASSO] Lasso intro — Introduction to lasso

[LASSO] sqrtlasso — Square-root lasso for prediction and model selection

[R] logit — Logistic regression, reporting coefficients

[R] poisson — Poisson regression

[R] probit — Probit regression

[R] regress — Linear regression

[ST] stset — Declare data to be survival-time data

[U] 20 Estimation and postestimation commands