irt 1pl — One-parameter logistic model

Description

irt 1pl fits one-parameter logistic (1PL) models to binary items. In the 1PL model, items vary in their difficulty but share the same discrimination parameter.

Quick start

1PL model for binary items b1 to b10

    irt 1pl b1-b10

Group estimates by parameter type and sort items by difficulty

    estat report, byparm sort(b)

Plot ICCs for all items

    irtgraph icc

Menu

Statistics > IRT (item response theory)

Syntax

> irt 1pl *varlist* [*if*] [*in*] [*weight*] [, *options*]

options	Description
group(*varname*)	fit model for different groups
Model	
cns(*spec*)	apply specified parameter constraints
listwise	drop observations with any missing items
SE/Robust	
vce(*vcetype*)	*vcetype* may be oim, robust, cluster *clustvar*, bootstrap, or jackknife
Reporting	
level(*#*)	set confidence level; default is level(95)
notable	suppress coefficient table
noheader	suppress output header
display_options	control columns and column formats
Integration	
intmethod(*intmethod*)	integration method
intpoints(*#*)	set the number of integration points; default is intpoints(7)
Maximization	
maximize_options	control the maximization process; seldom used
startvalues(*svmethod*)	method for obtaining starting values
noestimate	do not fit the model; show starting values instead
estmetric	show parameter estimates in the estimation metric
dnumerical	use numerical derivative techniques
coeflegend	display legend instead of statistics

intmethod	Description
mvaghermite	mean–variance adaptive Gauss–Hermite quadrature; the default
mcaghermite	mode-curvature adaptive Gauss–Hermite quadrature
ghermite	nonadaptive Gauss–Hermite quadrature

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

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

vce() and weights are not allowed with the svy prefix; see [SVY] **svy**.

fweights, iweights, and pweights are allowed; see [U] **11.1.6 weight**.

startvalues(), noestimate, estmetric, dnumerical, and coeflegend do not appear in the dialog box.

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

Options

group(*varname*) specifies that the model be fit separately for the different values of *varname*; see [IRT] **irt, group( )** for details.

___Model___

cns(*spec*) constrains item parameters to a fixed value or constrains two or more parameters to be equal; see [IRT] **irt constraints** for details.

listwise handles missing values through listwise deletion, which means that the entire observation is omitted from the estimation sample if any of the items are missing for that observation. By default, all nonmissing items in an observation are included in the likelihood calculation; only missing items are excluded.

___SE/Robust___

vce(*vcetype*) specifies the type of standard error reported, which includes types that are derived from asymptotic theory (oim), that are robust to some kinds of misspecification (robust), that allow for intragroup correlation (cluster *clustvar*), and that use bootstrap or jackknife methods (bootstrap, jackknife); see [R] *vce_option*.

___Reporting___

level(*#*); see [R] **Estimation options**.

notable suppresses the estimation table, either at estimation or upon replay.

noheader suppresses the output header, either at estimation or upon replay.

display_options: noci, nopvalues, cformat(*%fmt*), pformat(*%fmt*), sformat(*%fmt*), and nolstretch; see [R] **Estimation options**.

___Integration___

intmethod(*intmethod*) specifies the integration method to be used for computing the log likelihood. mvaghermite performs mean and variance adaptive Gauss–Hermite quadrature; mcaghermite performs mode and curvature adaptive Gauss–Hermite quadrature; and ghermite performs nonadaptive Gauss–Hermite quadrature.

The default integration method is mvaghermite.

intpoints(*#*) sets the number of integration points for quadrature. The default is intpoints(7), which means that seven quadrature points are used to compute the log likelihood.

The more integration points, the more accurate the approximation to the log likelihood. However, computation time increases with the number of integration points.

___Maximization___

maximize_options: difficult, technique(*algorithm_spec*), iterate(*#*), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(*#*), ltolerance(*#*), nrtolerance(*#*), nonrtolerance, and from(*init_specs*); see [R] **Maximize**. Those that require special mention for irt are listed below.

from() accepts a properly labeled vector of initial values or a list of coefficient names with values. A list of values is not allowed.

The following options are available with `irt` but are not shown in the dialog box:

`startvalues()` specifies how starting values are to be computed. Starting values specified in `from()` override the computed starting values.

`startvalues(zero)` specifies that all starting values be set to 0. This option is typically useful only when specified with the `from()` option.

`startvalues(constantonly)` builds on `startvalues(zero)` by fitting a constant-only model for each response to obtain estimates of intercept and cutpoint parameters.

`startvalues(fixedonly)` builds on `startvalues(constantonly)` by fitting a full fixed-effects model for each response variable to obtain estimates of coefficients along with intercept and cutpoint parameters. You can also add suboption `iterate(#)` to limit the number of iterations `irt` allows for fitting the fixed-effects model.

`startvalues(ivloadings)` builds on `startvalues(fixedonly)` by using instrumental-variable methods with the generalized residuals from the fixed-effects models to compute starting values for latent-variable loadings. This is the default behavior.

`noestimate` specifies that the model is not to be fit. Instead, starting values are to be shown (as modified by the above options if modifications were made), and they are to be shown using the `coeflegend` style of output. An important use of this option is before you have modified starting values at all; you can type the following:

```
. irt ..., ... noestimate
. matrix b = e(b)
. ... (modify elements of b) ...
. irt ..., ... from(b)
```

`estmetric` displays parameter estimates in the slope-intercept metric that is used for estimation.

`dnumerical` specifies that during optimization, the gradient vector and Hessian matrix be computed using numerical techniques instead of analytical formulas. By default, `irt` uses analytical formulas for computing the gradient and Hessian for all integration methods.

`coeflegend`; see [R] **Estimation options**.

Remarks and examples

Remarks are presented under the following headings:

>*Overview*
>*Video example*

Overview

The following discussion is about how to use `irt` to fit 1PL models to binary items. If you are new to the IRT features in Stata, we encourage you to read [IRT] **irt** first.

In the 1PL model, item responses are typically of the form yes or no, correct or incorrect, agree or disagree, etc. Items are assumed to be equally discriminating and vary in their difficulty only. The probability of person j providing a positive answer to item i is given by

$$\Pr(Y_{ij} = 1|\theta_j) = \frac{\exp\{a(\theta_j - b_i)\}}{1 + \exp\{a(\theta_j - b_i)\}} \qquad \theta_j \sim N(0, 1) \tag{1}$$

where a represents the discrimination common to all items, b_i represents the difficulty of item i, and θ_j is the latent trait of person j.

A related model attributable to Rasch (1960) uses a different parameterization of (1) with $a = 1$ and $\theta_j \sim N(0, \sigma^2)$. Although philosophically different from the 1PL model, the Rasch model produces equivalent predictions of the latent trait; see [SEM] **Example 28g** for a model fit using the Rasch parameterization. See *Item response theory* in [BAYES] **bayesmh** and Balov (2016) for examples demonstrating Bayesian estimation of this model.

▷ Example 1: Fitting a 1PL model

To illustrate the 1PL model, we use an abridged version of the mathematics and science data from De Boeck and Wilson (2004). Student responses to test items are coded 1 for correct and 0 for incorrect. Here we list the first five observations.

```
. use https://www.stata-press.com/data/r19/masc1
(Data from De Boeck & Wilson (2004))

. list in 1/5
```

	q1	q2	q3	q4	q5	q6	q7	q8	q9
1.	1	1	1	0	0	0	0	1	0
2.	0	0	1	0	0	0	0	1	1
3.	0	0	0	1	0	0	1	0	0
4.	0	0	1	0	0	0	0	0	1
5.	0	1	1	0	0	0	0	1	0

Looking across the rows, we see that the first student correctly answered items q1, q2, q3, and q8, the second student correctly answered items q3, q8, and q9, and so on.

We fit a 1PL model to binary items q1–q9 as follows:

```
. irt 1pl q1-q9
Fitting fixed-effects model:
Iteration 0:  Log likelihood = -4275.6606
Iteration 1:  Log likelihood = -4269.7861
Iteration 2:  Log likelihood = -4269.7825
Iteration 3:  Log likelihood = -4269.7825
Fitting full model:
Iteration 0:  Log likelihood = -4153.3609
Iteration 1:  Log likelihood =  -4142.374
Iteration 2:  Log likelihood = -4142.3516
Iteration 3:  Log likelihood = -4142.3516
```

One-parameter logistic model   Number of obs = 800
Log likelihood = -4142.3516

		Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
	Discrim	.852123	.0458445	18.59	0.000	.7622695	.9419765
q1							
	Diff	-.7071339	.1034574	-6.84	0.000	-.9099066	-.5043612
q2							
	Diff	-.1222008	.0963349	-1.27	0.205	-.3110138	.0666122
q3							
	Diff	-1.817693	.1399523	-12.99	0.000	-2.091994	-1.543391
q4							
	Diff	.3209596	.0976599	3.29	0.001	.1295498	.5123695
q5							
	Diff	1.652719	.1329494	12.43	0.000	1.392144	1.913295
q6							
	Diff	.6930617	.1031842	6.72	0.000	.4908243	.8952991
q7							
	Diff	1.325001	.1205805	10.99	0.000	1.088668	1.561335
q8							
	Diff	-2.413443	.1691832	-14.27	0.000	-2.745036	-2.08185
q9							
	Diff	-1.193206	.1162054	-10.27	0.000	-1.420965	-.965448

Because the discrimination parameter is the same for all items, it is listed only once. The estimate of 0.85 suggests poor discrimination; that is, in the vicinity of a given difficulty estimate, any two students with distinct abilities would have similar predicted probabilities of success giving a correct answer to an item. If the items were highly discriminating, the calculated probabilities would be farther away from each other.

The estimates of the difficulty parameter correspond to the point on the ability scale at which $\Pr(Y = 1|\theta) = 0.5$. Because we assume a zero mean for θ, an item is said to be relatively easy if its difficulty estimate is negative and relatively hard if its difficulty estimate is positive.

In the following, we use `estat report` to replay the table of estimated IRT parameters and control how the output is reported. We include the `byparm` option, which arranges the output by parameter rather than by item, and the `sort(b)` option, which displays the items in an ascending order of difficulty. This makes it easy to see that item q8 is least difficult and item q5 is most difficult.

```
. estat report, byparm sort(b)
```

One-parameter logistic model   Number of obs = 800
Log likelihood = -4142.3516

|	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Discrim	.852123	.0458445	18.59	0.000	.7622695	.9419765
Diff						
q8	-2.413443	.1691832	-14.27	0.000	-2.745036	-2.08185
q3	-1.817693	.1399523	-12.99	0.000	-2.091994	-1.543391
q9	-1.193206	.1162054	-10.27	0.000	-1.420965	-.965448
q1	-.7071339	.1034574	-6.84	0.000	-.9099066	-.5043612
q2	-.1222008	.0963349	-1.27	0.205	-.3110138	.0666122
q4	.3209596	.0976599	3.29	0.001	.1295498	.5123695
q6	.6930617	.1031842	6.72	0.000	.4908243	.8952991
q7	1.325001	.1205805	10.99	0.000	1.088668	1.561335
q5	1.652719	.1329494	12.43	0.000	1.392144	1.913295

For the 1PL model, the ICC plots the probability of a successful response as a function of θ, using the estimated 1PL parameters. In the following, we use `irtgraph icc` to plot the ICCs. The `blocation` option adds a vertical line at the estimated difficulties; see [IRT] **irtgraph icc**. The `xlabel()` option creates more legible axis labels (see [G-3] *axis_label_options*).

```
. irtgraph icc, blocation xlabel(, alt)
```


Item characteristic curves
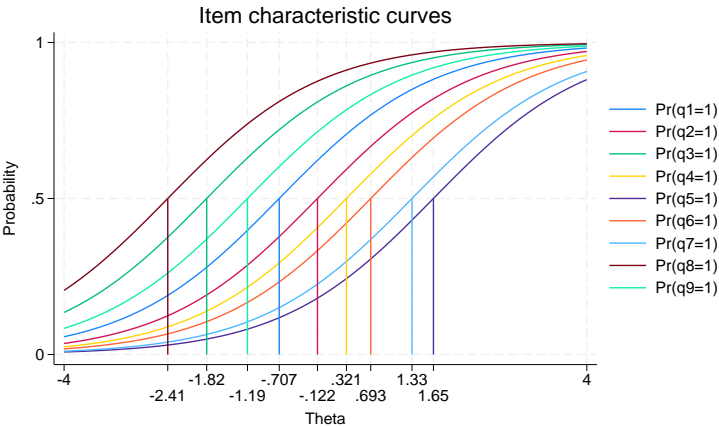
The TCC plots the expected score as a function of θ, using the estimated 1PL parameters. We use `irtgraph tcc` to plot the TCC. For 9 binary items, it is clear that the total score ranges from 0 to 9. The `thetalines()` option plots the expected scores at the specified values of θ.

```
. irtgraph tcc, thetalines(-1.96 0 1.96)
```

Test characteristic curve
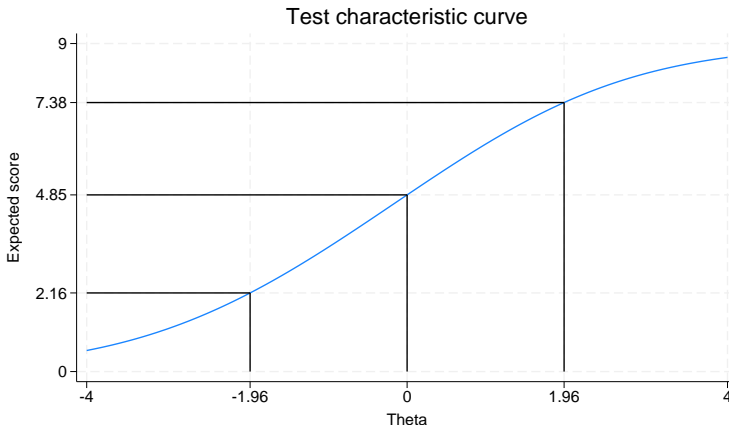
This plot tells us what kind of scores to expect from individuals with different levels of the latent trait. For example, we can expect above-average individuals to score 4.85 or above. Actually, no one is expected to score 4.85 on a 9-item test, so a more realistic statement is that we expect above-average individuals to score above 4.

Using the 95% critical values from the standard normal distribution (-1.96 and 1.96), this plot also tells us that we can expect 95% of randomly selected people to score between 2.16 and 7.38. Again, a more realistic statement is that we expect about 95% of randomly selected people to score between 2 and 7.

◁

Video example

Item response theory using Stata: One-parameter logistic (1PL) models

Stored results

irt 1pl 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(k_dv)	number of dependent variables
e(k_rc)	number of covariances
e(k_rs)	number of variances
e(irt_k_eq)	number of IRT equations
e(k_items1)	number of items in first IRT equation
e(ll)	log likelihood
e(N_clust)	number of clusters
e(N_groups)	number of groups
e(n_quad)	number of integration points

e(rank)	rank of e(V)
e(ic)	number of iterations
e(rc)	return code
e(converged)	1 if target model converged, 0 otherwise

Macros
e(cmd)	gsem
e(cmd2)	irt
e(cmdline)	command as typed
e(model1)	1pl
e(items1)	names of items in first IRT equation
e(depvar)	names of all item variables
e(wtype)	weight type
e(wexp)	weight expression
e(title)	title in estimation output
e(clustvar)	name of cluster variable
e(groupvar)	name of group variable
e(family#)	family for the #th *item*
e(link#)	link for the #th *item*
e(intmethod)	integration method
e(vce)	*vcetype* specified in vce()
e(vcetype)	title used to label Std. err.
e(opt)	type of optimization
e(which)	max or min; whether optimizer is to perform maximization or minimization
e(method)	estimation method: ml
e(ml_method)	type of ml method
e(user)	name of likelihood-evaluator program
e(technique)	maximization technique
e(datasignature)	the checksum
e(datasignaturevars)	variables used in calculation of checksum
e(properties)	b V
e(estat_cmd)	program used to implement estat
e(predict)	program used to implement predict
e(covariates)	list of covariates
e(footnote)	program used to implement the footnote display

Matrices
e(_N)	sample size for each item
e(b)	coefficient vector, slope-intercept parameterization
e(b_pclass)	parameter class
e(Cns)	constraints matrix
e(ilog)	iteration log (up to 20 iterations)
e(gradient)	gradient vector
e(V)	variance–covariance matrix of the estimators
e(V_modelbased)	model-based variance
e(groupvalue)	vector of group values in e(groupvar)
e(nobs)	vector with number of observations per group

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

Let Y_{ij} represent the (yet to be observed) outcome for item i from person j, and let y_{ij} be the observed value of Y_{ij}. Without loss of generality, we will use the terms "correct" and "incorrect" in reference to the outcomes of Y_{ij}. Furthermore, we will refer to $y_{ij} = 1$ as correct and $y_{ij} = 0$ as incorrect.

Using the IRT parameterization, we see that the probability of person j with latent trait level θ_j providing a correct response to item i is given by

$$\Pr(Y_{ij} = 1 | a, b_i, \theta_j) = \frac{\exp\{a(\theta_j - b_i)\}}{1 + \exp\{a(\theta_j - b_i)\}}$$

where a represents discrimination, and b_i represents the difficulty of item i. `irt 1pl` fits the model using the slope-intercept form, so the probability for providing a correct answer is parameterized as

$$\Pr(Y_{ij} = 1 | \alpha, \beta_i, \theta_j) = \frac{\exp(\alpha\theta_j + \beta_i)}{1 + \exp(\alpha\theta_j + \beta_i)}$$

The transformation between these two parameterizations is

$$a = \alpha \qquad b_i = -\frac{\beta_i}{\alpha}$$

Let $p_{ij} = \Pr(Y_{ij} = 1 | \alpha, \beta_i, \theta_j)$ and $q_{ij} = 1 - p_{ij}$. Conditional on θ_j, the item responses are assumed to be independent, so the conditional density for person j is given by

$$f(\mathbf{y}_j | \boldsymbol{B}, \theta_j) = \prod_{i=1}^{I} p_{ij}^{y_{ij}} q_{ij}^{1-y_{ij}}$$

where $\mathbf{y}_j = (y_{1j}, \ldots, y_{Ij})$, $\boldsymbol{B} = (\alpha, \beta_1, \ldots, \beta_I)$, and I is the number of items.

Missing items are skipped over in the above product by default. When the `listwise` option is specified, persons with any missing items are dropped from the estimation sample.

The likelihood for person j is computed by integrating out the latent variable from the joint density

$$L_j(\boldsymbol{B}) = \int_{-\infty}^{\infty} f(\mathbf{y}_j | \boldsymbol{B}, \theta_j)\, \phi(\theta_j)\, d\theta_j$$

where $\phi(\cdot)$ is the density function for the standard normal distribution. The log likelihood for the estimation sample is simply the sum of the log likelihoods from the N persons in the estimation sample.

$$\log L(\boldsymbol{B}) = \sum_{j=1}^{N} \log L_j(\boldsymbol{B})$$

The integral in the formula for $L_j(\boldsymbol{B})$ is generally not tractable, so we must use numerical methods.

Models for multiple groups, Gauss–Hermite quadrature, and adaptive quadrature are documented in *Methods and formulas* of [IRT] **irt hybrid**.

References

Balov, N. 2016. Bayesian binary item response theory models using bayesmh. *The Stata Blog: Not Elsewhere Classified.* https://blog.stata.com/2016/01/18/bayesian-binary-item-response-theory-models-using-bayesmh/.

De Boeck, P., and M. Wilson, eds. 2004. *Explanatory Item Response Models: A Generalized Linear and Nonlinear Approach.* New York: Springer. https://doi.org/10.1007/978-1-4757-3990-9.

Rasch, G. 1960. *Probabilistic Models for Some Intelligence and Attainment Tests.* Copenhagen: Danish Institute of Educational Research.

Also see

[IRT] **irt 1pl postestimation** — Postestimation tools for irt 1pl

[IRT] **irt** — Introduction to IRT models

[IRT] **irt 2pl** — Two-parameter logistic model

[IRT] **irt 3pl** — Three-parameter logistic model

[IRT] **irt constraints** — Specifying constraints

[SEM] **Example 28g** — One-parameter logistic IRT (Rasch) model

[SEM] **gsem** — Generalized structural equation model estimation command

[SVY] **svy estimation** — Estimation commands for survey data

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