Title

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lroc — Compute area under ROC curve and graph the curve

Description

`lroc` graphs the ROC curve and calculates the area under the curve.

`lroc` requires that the current estimation results be from `logistic`, `logit`, `probit`, or `ivprobit`; see [R] **logistic**, [R] **logit**, [R] **probit**, or [R] **ivprobit**.

Quick start

Graph and compute area under ROC curve for current estimation results

```
lroc
```

Add "My Title" as title of graph

```
lroc, title(My Title)
```

Suppress graph

```
lroc, nograph
```

Menu

Statistics > Binary outcomes > Postestimation > ROC curve after logistic/logit/probit/ivprobit

Syntax

```
lroc [depvar] [if] [in] [weight] [, options]
```

options	Description
Main	
`all`	compute area under ROC curve and graph curve for all observations
`nograph`	suppress graph
Advanced	
`beta(`*matname*`)`	row vector containing model coefficients
Plot	
cline_options	change look of the line
marker_options	change look of markers (color, size, etc.)
marker_label_options	add marker labels; change look or position
Reference line	
`rlopts(`*cline_options*`)`	affect rendition of the reference line
Add plots	
`addplot(`*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***

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

`lroc` is not appropriate after the `svy` prefix.

Options

Main

`all` requests that the statistic be computed for all observations in the data, ignoring any `if` or `in` restrictions specified by the estimation command.

`nograph` suppresses graphical output.

Advanced

`beta(`*matname*`)` specifies a row vector containing model coefficients. The columns of the row vector must be labeled with the corresponding names of the independent variables in the data. The dependent variable *depvar* must be specified immediately after the command name. See *Models other than the last fitted model* later in this entry.

Plot

cline_options, *marker_options*, and *marker_label_options* affect the rendition of the ROC curve—the plotted points connected by lines. These options affect the size and color of markers, whether and how the markers are labeled, and whether and how the points are connected; see [G-3] ***cline_options***, [G-3] ***marker_options***, and [G-3] ***marker_label_options***.

Reference line

`rlopts(`*cline_options*`)` affects the rendition of the reference line; see [G-3] ***cline_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

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Remarks are presented under the following headings:

Introduction

Stata also has a suite of commands for performing both parametric and nonparametric receiver operating characteristic (ROC) analysis. See [R] **roc** for an overview of these commands.

`lroc` graphs the ROC curve—a graph of sensitivity versus one minus specificity as the cutoff c is varied—and calculates the area under it. Sensitivity is the fraction of observed positive-outcome cases that are correctly classified; specificity is the fraction of observed negative-outcome cases that are correctly classified. When the purpose of the analysis is classification, you must choose a cutoff.

The curve starts at $(0, 0)$, corresponding to $c = 1$, and continues to $(1, 1)$, corresponding to $c = 0$. A model with no predictive power would be a 45° line. The greater the predictive power, the more bowed the curve, and hence the area beneath the curve is often used as a measure of the predictive power. A model with no predictive power has area 0.5; a perfect model has area 1.

The ROC curve was first discussed in signal detection theory (Peterson, Birdsall, and Fox 1954) and then was quickly introduced into psychology (Tanner and Swets 1954). It has since been applied in other fields, particularly medicine (for instance, Metz [1978]). For a classic text on ROC techniques, see Green and Swets (1966).

`lsens` also plots sensitivity and specificity; see [R] **lsens**.

▷ Example 1

Hardin and Hilbe (2018) examine data from the National Canadian Registry of Cardiovascular Disease (FASTRAK), sponsored by Hoffman-La Roche Canada. They model death within 48 hours based on whether a patient suffers an anterior infarct (heart attack) rather than an inferior infarct using a logistic regression and evaluate the model using an ROC curve. We replicate their analysis here.

Both anterior and inferior refer to sites on the heart where damage occurs. The model is also adjusted for `hcabg`, whether the subject has had a cardiac bypass surgery (CABG); `age`, a four-category age-group indicator; and `killip`, a four-level risk indicator.

We load the data and then estimate the parameters of the logistic regression with `logistic`. Factor-variable notation is used for each predictor, because they are categorical; see [U] **11.4.3 Factor variables**.

```
. use https://www.stata-press.com/data/r16/heart
(Heart attacks)
. logistic death i.site i.hcabg i.killip i.age
Logistic regression                             Number of obs     =      4,483
                                                LR chi2(8)        =     211.37
                                                Prob > chi2       =     0.0000
Log likelihood = -636.62553                     Pseudo R2         =     0.1424
```

death	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
site						
Anterior	1.901333	.3185757	3.83	0.000	1.369103	2.640464
1.hcabg	2.105275	.7430694	2.11	0.035	1.054076	4.204801
killip						
2	2.251732	.4064423	4.50	0.000	1.580786	3.207453
3	2.172105	.584427	2.88	0.004	1.281907	3.680487
4	14.29137	5.087654	7.47	0.000	7.112964	28.71423
age						
60-69	1.63726	.5078582	1.59	0.112	.8914261	3.007115
70-79	4.532029	1.206534	5.68	0.000	2.689568	7.636647
>=80	8.893222	2.41752	8.04	0.000	5.219991	15.15125
_cons	.0063961	.0016541	-19.54	0.000	.0038529	.010618

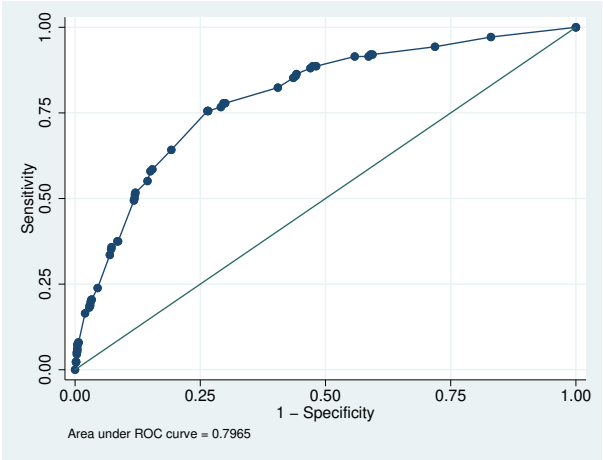
```
Note: _cons estimates baseline odds.
```

The odds ratios for a unit change in each covariate are reported by `logistic`. At fixed values of the other covariates, patients who enter Canadian hospitals with an anterior infarct have nearly twice the odds of death within 48 hours than those with an inferior infarct. Those who have had a previous CABG have approximately twice the risk of death of those who have not. Those with higher Killip risks and those who are older are also at greater risk of death.

We use `lroc` to draw the ROC curve for the model. The area under the curve of approximately 0.8 indicates acceptable discrimination for the model.

```
. lroc
Logistic model for death

number of observations =      4483
area under ROC curve   =    0.7965
```



Samples other than the estimation sample

`lroc` can be used with samples other than the estimation sample. By default, `lroc` remembers the estimation sample used with the last `logistic`, `logit`, `probit`, or `ivprobit` command. To override this, simply use an `if` or `in` restriction to select another set of observations, or specify the `all` option to force the command to use all the observations in the dataset.

See example 3 in [R] **estat gof** for an example of using `lroc` with a sample other than the estimation sample.

Models other than the last fitted model

By default, `lroc` uses the last model fit by `logistic`, `logit`, `probit`, or `ivprobit`. You may also directly specify the model to `lroc` by inputting a vector of coefficients with the `beta()` option and passing the name of the dependent variable *depvar* to `lroc`.

▷ Example 2

Suppose that someone publishes the following logistic model of low birthweight:

$$\Pr(\texttt{low}=1) = F(-0.02\,\texttt{age} - 0.01\,\texttt{lwt} + 1.3\,\texttt{black} + 1.1\,\texttt{smoke} + 0.5\,\texttt{ptl} + 1.8\,\texttt{ht} + 0.8\,\texttt{ui} + 0.5)$$

where F is the cumulative logistic distribution. These coefficients are not odds ratios; they are the equivalent of what `logit` produces.

We can see whether this model fits our data. First, we enter the coefficients as a row vector and label its columns with the names of the independent variables plus `_cons` for the constant (see [P] **matrix define** and [P] **matrix rownames**).

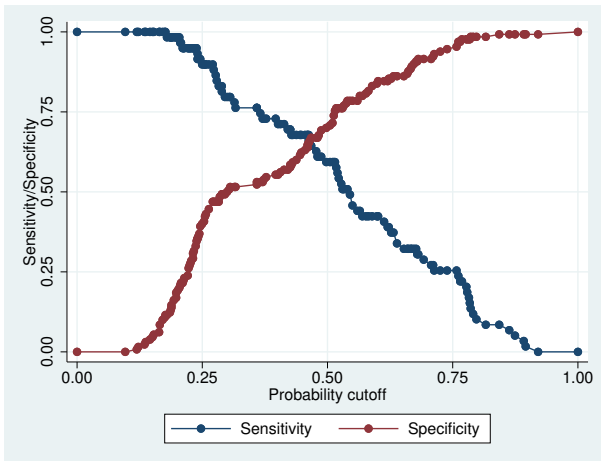
```
. use https://www.stata-press.com/data/r16/lbw3, clear
(Hosmer & Lemeshow data)
. matrix input b = (-.02, -.01, 1.3, 1.1, .5, 1.8, .8, .5)
. matrix colnames b = age lwt black smoke ptl ht ui _cons
```

Here we use `lroc` to examine the predictive ability of the model:

```
. lroc low, beta(b) nograph
Logistic model for low
number of observations =       189
area under ROC curve   =    0.7275
```

The area under the curve indicates that this model does have some predictive power. We can obtain a graph of sensitivity and specificity as a function of the cutoff probability by typing

```
. lsens low, beta(b)
```



See [R] **lsens**.

Stored results

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

Scalars

`r(N)`	number of observations
`r(area)`	area under the ROC curve

Methods and formulas

The ROC curve is a graph of *sensitivity* against (1 − *specificity*). This is guaranteed to be a monotone nondecreasing function because the number of correctly predicted successes increases and the number of correctly predicted failures decreases as the classification cutoff c decreases.

The area under the ROC curve is the area on the bottom of this graph and is determined by integrating the curve. The vertices of the curve are determined by sorting the data according to the predicted index, and the integral is computed using the trapezoidal rule.

References

Green, D. M., and J. A. Swets. 1966. *Signal Detection Theory and Psychophysics*. New York: Wiley.

Hardin, J. W., and J. M. Hilbe. 2018. *Generalized Linear Models and Extensions*. 4th ed. College Station, TX: Stata Press.

Hosmer, D. W., Jr., S. A. Lemeshow, and R. X. Sturdivant. 2013. *Applied Logistic Regression*. 3rd ed. Hoboken, NJ: Wiley.

Metz, C. E. 1978. Basic principles of ROC analysis. *Seminars in Nuclear Medicine* 8: 283–298.

Peterson, W. W., T. G. Birdsall, and W. C. Fox. 1954. The theory of signal detectability. *Transactions IRE Professional Group on Information Theory* PGIT-4: 171–212.

Tanner, W. P., Jr., and J. A. Swets. 1954. A decision-making theory of visual detection. *Psychological Review* 61: 401–409.

Also see

[R] **logistic** — Logistic regression, reporting odds ratios

[R] **logit** — Logistic regression, reporting coefficients

[R] **probit** — Probit regression

[R] **ivprobit** — Probit model with continuous endogenous covariates

[R] **lsens** — Graph sensitivity and specificity versus probability cutoff

[R] **estat classification** — Classification statistics and table

[R] **estat gof** — Pearson or Hosmer–Lemeshow goodness-of-fit test

[R] **roc** — Receiver operating characteristic (ROC) analysis

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