New in Stata 16

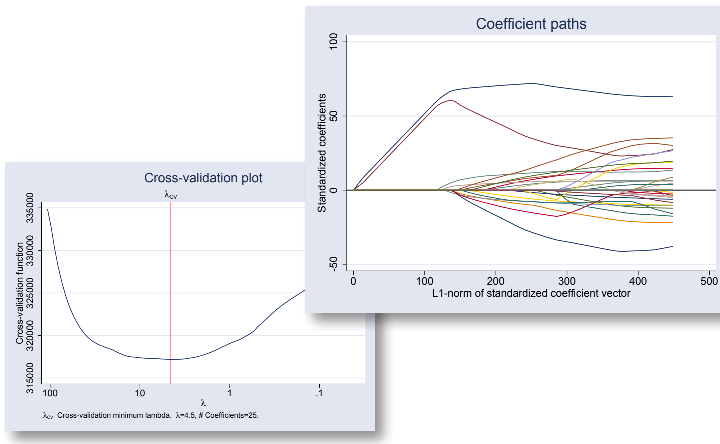
Lasso—variable selection, prediction, inference

All the tools you expect for lasso machine learning

- Lasso, square-root lasso, and elastic net
- Cross-validation
- Adaptive lasso
- Knot analysis
- Coefficient paths

Alongside cutting-edge inferential methods

- Robust to mistakes in variable selection
- Proper inference for coefficients of interest
- Double selection
- Partialing out
- Cross-fit partialing out
- Double machine learning



Select predictors for continuous, binary, and count outcomes

Lasso with selection via cross-validation

```
. lasso linear  y x1-x1000
. lasso logit   y x1-x1000
. lasso probit  y x1-x1000
. lasso poisson y x1-x1000
```

Adaptive lasso

```
. lasso linear y x1-x1000, selection(adaptive)
```

Selection via plugin method

```
. lasso linear y x1-x1000, selection(plugin)
```

Elastic net with selection via cross-validation

```
. elasticnet linear  y x1-x1000
. elasticnet logit   y x1-x1000
. elasticnet probit  y x1-x1000
. elasticnet poisson y x1-x1000
```

Square-root lasso

```
. sqrtlasso y x1-x1000
```

Examine the results

View selected variables

```
. lassoknots
. lassoinfo
. lassocoef
```

Plot cross-validation function

```
. cvplot
```

Plot coefficient path

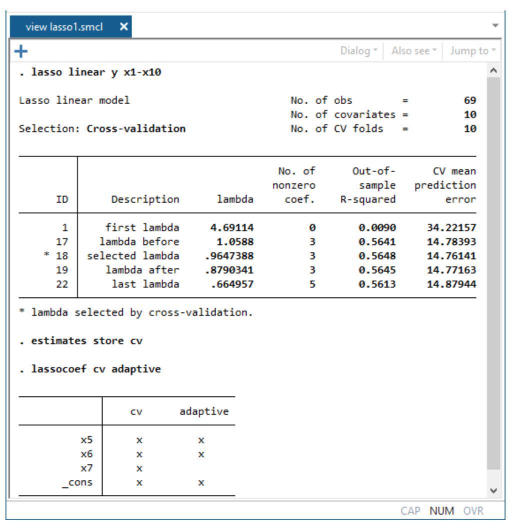
```
. coefpath
```

Obtain predictions

```
. use newdata
. predict yhat
```

Evaluate fit

```
. lassogof
```




```
. lasso linear y x1-x10

Lasso linear model                         No. of obs         =        69
                                           No. of covariates  =        10
Selection: Cross-validation                No. of CV folds    =        10

--------------------------------------------------------------------------
         |                                No. of      Out-of-      CV mean
         |                               nonzero       sample   prediction
      ID |     Description      lambda     coef.    R-squared        error
---------+----------------------------------------------------------------
       1 |    first lambda     4.69114         0       0.0090     34.22157
      17 |   lambda before      1.0588         3       0.5641     14.78393
    * 18 | selected lambda    .9647388         3       0.5648     14.76141
      19 |    lambda after    .8790341         3       0.5645     14.77163
      22 |     last lambda     .664957         5       0.5613     14.87944
--------------------------------------------------------------------------
* lambda selected by cross-validation.

. estimates store cv

. lassocoef cv adaptive

------------------------------------
             |      cv      adaptive
-------------+----------------------
          x5 |      x          x
          x6 |      x          x
          x7 |      x
       _cons |      x          x
------------------------------------
```

Lasso for inference

With lasso inferential methods, you can estimate coefficients, standard errors, test statistics, and confidence intervals for variables of interest while using lassos to select from a potentially large number of control variables.

Double-selection method; estimate coefficients for x1 and categorical x2; selection of controls via plugin

```
. dsregress y x1 i.x2, controls(c1-c1000)
```

Logit model for binary outcome; estimate odds ratios for x1 and x2

```
. dslogit y x1 i.x2, controls(c1-c1000)
```

Poisson model for count outcome; estimate incidence-rate ratios for x1 and x2

```
. dspoisson y x1 i.x2, controls(c1-c1000)
```

Selection of controls via cross-validation

```
. dsregress y x1 i.x2, controls(c1-c1000)
  selection(cv)
```

Partialing-out method

```
. poregress y x1 i.x2, controls(c1-c1000)
```

Cross-fit partialing-out method (double machine learning)

```
. xporegress poregress y x1 i.x2, controls(c1-c1000)
```

view lasso2.smcl

```
. dsregress y x1 i.x2, controls(c1-c8)

Double-selection linear model         Number of obs               =         69
                                      Number of controls          =          8
                                      Number of selected controls =          6
                                      Wald chi2(5)                =       6.24
                                      Prob > chi2                 =     0.2835

------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .1272712    .256027     0.50   0.619    -.3745326     .629075
             |
          x2 |
           2 |   .2792513   1.270518     0.22   0.826    -2.210918     2.76942
           3 |  -.2613078   1.358118    -0.19   0.847     -2.92317    2.400554
           4 |   .7492284   1.427334     0.52   0.600    -2.048295    3.546752
           5 |   4.082883   1.905783     2.14   0.032     .3476163     7.81815
------------------------------------------------------------------------------
```

Evaluate results using Stata's standard tools

Perform tests on coefficients

```
. test x1=1
```

Estimate contrasts such as differences across levels

```
. contrast ar.x2
```

view "lasso3.smcl"

```
. test x1=1

 ( 1)  x1 = 1

           chi2(  1) =   11.62
         Prob > chi2 =    0.0007

. contrast ar.x2, nowald

Contrasts of marginal linear predictions

Margins      : asbalanced

--------------------------------------------------------------
             |   Contrast   Std. Err.     [95% Conf. Interval]
-------------+------------------------------------------------
          x2 |
   (2 vs 1)  |   .2792513   1.270518     -2.210918     2.76942
   (3 vs 2)  |  -.5405591   .8160264     -2.139941    1.058823
   (4 vs 3)  |   1.010536   .8213126     -.5992068    2.620279
   (5 vs 4)  |   3.333655   2.073229     -.7297991    7.397108
--------------------------------------------------------------
```

Explore underlying lassos

View selected controls in the lasso for y

```
. lassocoef (., for(y))
```

Plot coefficient path in the lasso for y

```
. coefpath, for(y)
```