Stopping stepwise: Why stepwise and similar selection methods are bad, and what you should use

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Summary and further reading
The problem

- Too many IVs in regression
- Not sure which are good
- Need some help in speeding the selection process
- Problem exists in many types of regression
Extent of this talk

- Brief theory on stepwise
- Various example data sets
- No bootstrapping, etc.
- PROC GLMSELECT, lasso and lars
- Only OLS regression
- ‘Stepwise’ used for forward, backward, stepwise etc.
Some theory on why stepwise is bad

- The basic problem - one test vs. many
- The result:
  - Standard errors are biased toward 0
  - p-values also biased toward 0
  - Parameter estimates biased away from 0
  - Models too complex
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Summary and further reading
In some fields you never do a regression with all noise.

However, we sometimes do have variables that are garbage, or are unrelated to the DV.

If you do, you hope that the output doesn’t call the garbage a pearl.
100 cases, 50 variables

- For the first test, we ran a regression with 100 subjects and 50 independent variables — all white noise
- The defaults in stepwise are SLE = .15, SLS = .15
- The final model included 15 IVs, 5 sig at \( p < .05 \)
- Forward: default SLE = .50, 29 IVs, 5 sig at \( p < .05 \)
- Backward: default SLS = .10, 10 IVs, 8 sig at \( p < .05 \)
That’s a lot of IVs per subject, but with N = 1000
The final stepwise model had 10 IVs, again, 5 sig. at \( p < .05 \)
Forward: 28 IVs, 5 sig. at \( p < .05 \)
Backward: 8 IVs, 5 sig. at \( p < .05 \)
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Summary and further reading
More often, some of your IVs are real and some are noise
Here, you want to sort the pearls from the garbage
100 cases, 50 + 1 variables

- If we add one IV that is linearly related to the DV, $r = .32$
- Stepwise with the default settings has 14 IVs, but NOT the real one
- Backward: Real one plus 1
- Forward: Real one plus 23
1000 cases, 50 + 1 variables

- With 1000 cases, 51 IVs, one real, same r
- Stepwise: Real variable is included, but so are 9 others
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Summary and further reading
A single outlier in a perfect world

- Sometimes, you violate assumptions
- Outliers and leverage points happen
- $N = 100$, 50 noise IVs, 1 real IV, 1 outliers
- Only real variable included, but param est now .72 (not 1)
Multiple outliers in that perfect world

- N = 100, 50 noise IVs, 1 real, 2 outliers
- Only real variable included, but param est now .44 (not 1)
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Summary and further reading
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- If you can, the best solution is expert knowledge
- If the key is not the particular IVs and explanation: PLS, multimodel averaging
- If there are a small number of sensible models: AIC or BIC
- Otherwise….LASSO or LAR
Partial least squares

- One standard data reduction method is PCA
- This leads to principal components regression
- But the PCs may not relate to the DV
- PLS finds linear combinations of the IVs that are related to the DV
Multimodel averaging

- I am not expert in this (see Burnham and Anderson)
- Key idea is to combine models
- Various methods have been proposed
AIC and BIC

- Akaike Information Criterion and Bayes’ Information criterion are ways to penalize models for complexity
- B and A suggest comparing various ‘sensible’ models based on AIC
Experimental PROC in v9
Download from SAS website
Implements a variety of model selection schemes
Has a variety of cross-validation methods
Not intended to replace PROC GLM or REG, too few options
PROC GLMSELECT <options>;
CLASS variable;
MODEL variable = <effects></options>;
SCORE <DATA = dataset> <OUT = dataset>;
PROC GLMSELECT statement — key options

- DATA =
- TESTDATA =
- VALDATA =
- PLOTS =
MODEL statement - selection options

- Forward
- Backward
- Stepwise
- Lasso
- LAR
The CHOOSE = criterion option chooses from a list of models based on a criterion.

Available criteria are: adjrsq, aic, aicc, bic, cp, cv, press, sbc, validate.

CV is residual sum squares based on k-fold CV.

VALIDATE is avg. sq. error for validation data.
The STOP = criterion option stops the selection process.

Available criteria are: adjrsq, aic aicc, bic, cp cv, press, sbc, sl, validate
MODEL statement - some other options

- HIERARCHY =
- CVDETAILS= AND CVMETHOD=
- STATS =
- STB
Uses of GLMSELECT

- You can combine the options in lots of ways. e.g.

  ```r
  selection = forward(stop = AIC sle = .2)
  selection = forward(stop = 20 choose = AICC)
  ```
Brief theory of LASSO

- Least Absolute Shrinkage Selection Operator — Developed by Tibshirani (1994)
- Shrinkage method
- Constrains the sum of the absolute regression coefficients
- Center and scale all variables then minimize

\[ ||y - X\beta||^2 \text{ subject to } \sum_{j=1}^{m} |\beta_j| \leq t \]
LASSO with defaults applied to the above problems

- \( N = 100, 50 \) IVs, all noise . . . none selected
- \( N = 1000, 50 \) IVs, all noise . . . none selected
- \( N = 100, 50 \) noise variables, 1 real . . . none selected
- \( N = 1000, 50 \) noise variables, 1 real . . . only real selected
- \( N = 100, 50 \) noise variables, 1 real, 1 outlier . . . . param est now .99
- \( N = 100, 50 \) noise variables, 1 real, 2 outliers . . . . . . . . . . no variables included
Brief theory of LAR

- All variables are centered, covariates are scaled
- Starts with all parameters = 0
- Adds parameters based on correlations with current residual
- Results on above problems essentially identical with LASSO
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Summary and further reading
In any statistical problem, the key is substantive knowledge.

If that is not available, then methods such as LASSO and LAR are better than old-fashioned methods.
Further reading

► On the general problem:
  1. Harrell: Regression modeling strategies
  2. Burnham and Anderson: Model selection and multimodel averaging

► On LASSO and LARS
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