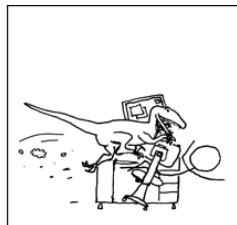
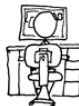
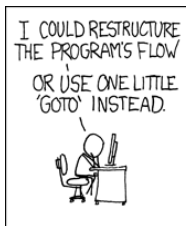


# STAT406- Methods of Statistical Learning Lecture 5

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<http://xkcd.com/292/>

# Comparing models

- AIC suggests a submodel
- Prediction-wise the full model is better
- AIC can be highly variable

# “Smoother” model selection

- Ridge regression
- Can be thought as a type of feature selection
- It is a member of a larger class called “shrinkage methods”
- However, its origins are rather different

# Without loss of generality...

- If covariates are centered,  $\sum_{i=1}^n \mathbf{x}_i = \mathbf{0}$

$$\arg \min_{\alpha, \beta} \sum_{i=1}^n (y_i - \alpha - \beta' \mathbf{x}_i)^2$$

satisfies

$$\hat{\alpha}_n = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y}_n,$$

and

$$\hat{\beta}_{LS} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{Y},$$

# Without loss of generality...

- We can always assume that

$$\sum_{i=1}^n \mathbf{x}_i = \mathbf{0}$$

and hence

$$\hat{\alpha}_n = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y}_n ,$$

- In what follows, there is no intercept

# Shrinkage methods

- When covariates are correlated, LS estimators can be highly variable

$$\hat{\beta}_{LS} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{Y}$$

$$\text{var}(\hat{\beta}_n) = \sigma^2 (\mathbf{X}'\mathbf{X})^{-1}$$

- When  $\mathbf{X}'\mathbf{X}$  is close to singular...

# Ridge Regression

- One way to “avoid” this problem is to add a “ridge” to  $\mathbf{X}'\mathbf{X}$ ...

$$\hat{\beta}_{RR} = (\mathbf{X}'\mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}'\mathbf{Y}$$

where  $\lambda > 0$  and

$$\mathbf{I}_p = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ 0 & \dots & \ddots & 0 \\ 0 & \dots & \dots & 1 \end{pmatrix}$$



# Ridge Regression

- This is equivalent to solving

$$\min_{\boldsymbol{\beta}} \sum_{i=1}^n (y_i - \boldsymbol{\beta}' \mathbf{x}_i)^2 + \lambda \|\boldsymbol{\beta}\|_2^2$$

# Ridge Regression

- And also equivalent to solving

$$\min_{\beta} \sum_{i=1}^n (y_i - \beta' \mathbf{x}_i)^2$$

subject to

$$\sum_{j=1}^p \beta_j^2 \leq C$$

for some  $C > 0$

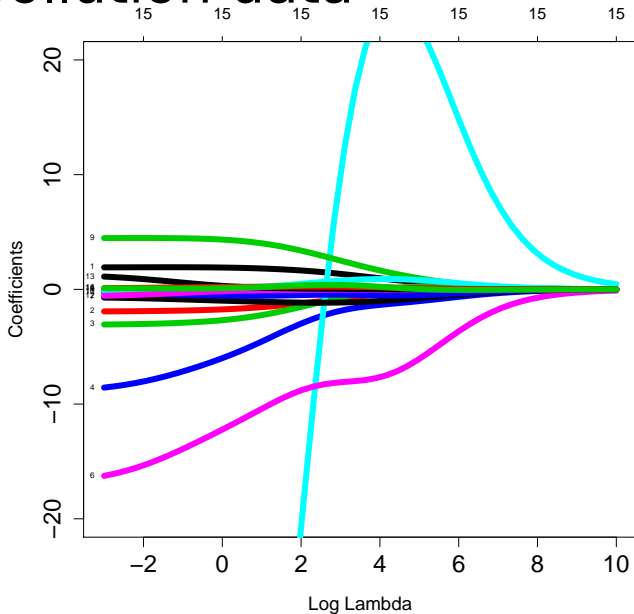
# Bias / variance trade-off

- Ridge regression was originally proposed as a “hack” to “push”  $\mathbf{X}'\mathbf{X}$  away from singularity
- It can also be thought as a way of reducing the variance of  $\hat{\beta}_n$
- This may increase the bias of the estimator, but if the variance is reduced even more, we might gain overall in expected squared error performance...

# Ridge regression

- We now have a sequence (“path”) of estimators (one for each  $\lambda > 0$ )
- $\mathbf{X}'\mathbf{X} + \lambda \mathbf{I}_p$  is always non-singular for  $\lambda > 0$  (why?)
- Why are they called “shrinkage methods”?

# Air pollution data



# Questions

- What does  $\lambda$  measure?
- How do I choose one among these infinitely many “solutions”?

# Effective degrees of freedom

- How many “effective” parameters are we using?
- In linear regression, we have  $p$  parameters
- A more general definition is as follows. For a fitting method producing  $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$ ,

$$\text{edf} = \frac{1}{\sigma^2} \sum_{i=1}^n \text{cov}(\hat{y}_i, y_i)$$

Efron, B. (1986). How biased is the apparent error rate of a prediction rule? Journal of the American Statistical Association, 81(394):461-470.

# Effective degrees of freedom

- It is easy to see that for least squares predictors, we have

$$\hat{\mathbf{y}} = \mathbf{H} \mathbf{y}$$

with

$$\mathbf{H} = \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'$$

and

$$\text{edf} = \frac{1}{\sigma^2} \sum_{i=1}^n \text{cov}(\hat{y}_i, y_i) = \text{trace}(\mathbf{H}) = p$$



# Effective degrees of freedom

- More in general, for any linear predictor

$$\hat{\mathbf{y}} = \mathbf{S} \mathbf{y}$$

we have

$$\text{edf} = \text{trace}(\mathbf{S}) = \sum_{i=1}^n \mathbf{s}_{i,i}$$

# Effective degrees of freedom

- The ridge regression fit satisfies

$$\hat{\mathbf{y}} = \mathbf{S}_\lambda \mathbf{y}$$

where

$$\mathbf{S}_\lambda = \mathbf{X} (\mathbf{X}'\mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}'$$

$$\text{trace}(\mathbf{S}) = ?$$

# Effective degrees of freedom

- Using the singular value decomposition (SVD) of  $\mathbf{X}$

$$\mathbf{X} = \mathbf{U} \mathbf{\Lambda} \mathbf{V}'$$

where  $\mathbf{U} \in \mathbb{R}^{n \times p}$ ,  $\mathbf{V} \in \mathbb{R}^{p \times p}$  with

$$\mathbf{U}'\mathbf{U} = \mathbf{I}_p = \mathbf{V}'\mathbf{V}$$

and

$$\mathbf{\Lambda} = \text{diag}(d_1, \dots, d_p),$$

we have

$$\text{trace}(\mathbf{S}) = \sum_{i=1}^p \left( \frac{d_i^2}{d_i^2 + \lambda} \right)$$

# Effective degrees of freedom

- For example, in the Air Pollution data example, if we use

$$\lambda = \exp(6)$$

we get

$$\text{edf} = 9.9$$

# How do we select $\lambda$ ?

How can we select  $\lambda$ ?

# How do we select $\lambda$ ?

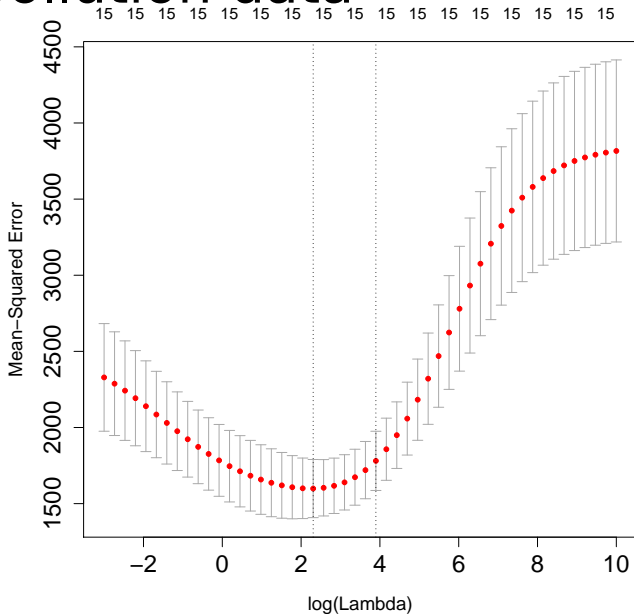
CV!

```
library(glmnet)
airp <- read.table('rutgers-lib-30861_CSV-1.csv'
                  header=TRUE, sep=',')

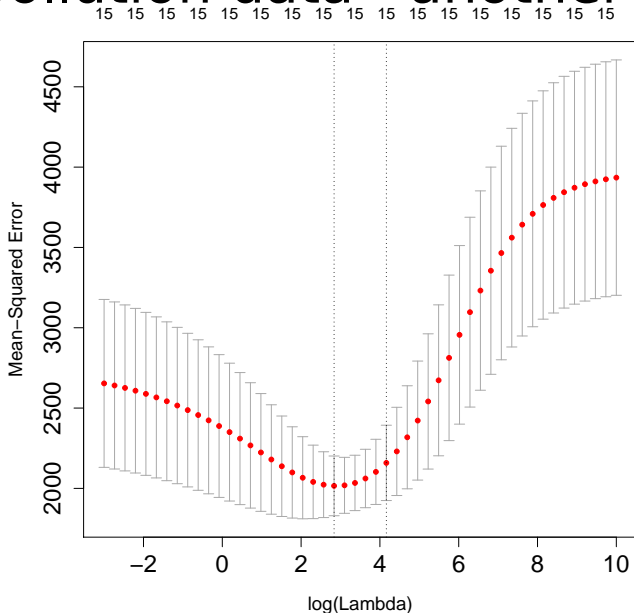
y <- as.vector(airp$MORT)
xm <- as.matrix(airp[, -16])
lambdas <- exp( seq(-3, 10, length=50))

set.seed(123)
tmp <- cv.glmnet(x=xm, y=y, lambda=lambdas,
                nfolds=5, alpha=0,
                family='gaussian')
```

# Air pollution data



# Air pollution data - another run





# Questions

- How are the standard errors estimated?
- Can we use AIC to compare these models?
- Why or why not?
  - If the answer is yes, how?
  - If the answer is no, why not?

# CV

## Cross validation selects

$$\lambda_{\text{op}} \approx \exp(3)$$

$$\text{edf} \approx 13$$

## Stepwise selects

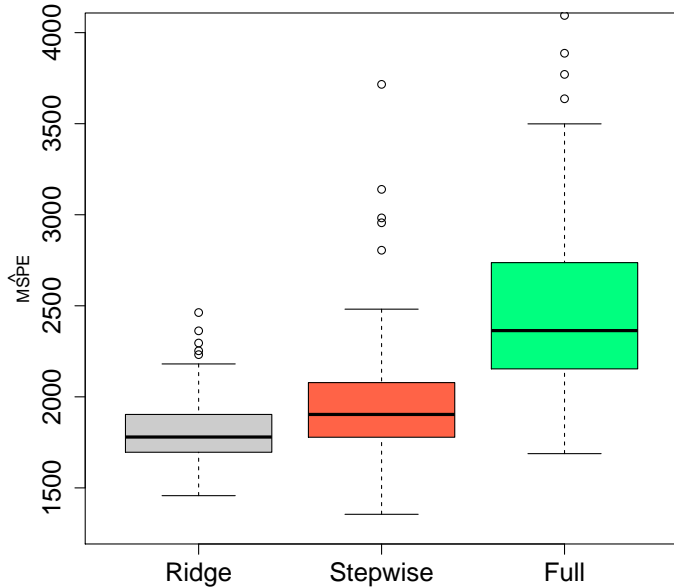
Call:

```
lm(formula = MORT ~ NONW + EDUC + JANT + SO.  
+ PREC + JULT + POPN, data = airp)
```

Coefficients:

(Intercept)	NONW	EDUC	JANT
1429.1866	5.2161	-16.9656	-1.8934
SO.	PREC	JULT	POPN
0.2253	1.6485	-2.3006	-62.0118

## Air pollution – 100 5-fold CV runs



# Sometimes...

- Selecting variables is not always necessary in terms of prediction accuracy.
- One such an example is discussed on Github (Lecture 4)...
- ...and revised in Lecture 5. Read it carefully.