

Ch 6.2: Shrinkage - The Lasso

Lecture 18 - CMSE 381

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Announcements

Last time:

- Ridge Regression

This time:

- The Lasso

Announcements:

- HW4 due Sunday
- HW5 released
- Think about the project, choose partner in crime

CMSE381_F2025_Schedule : Schedule

	M	9/22	Project Day & Review		
	W	9/24	Midterm #1		
12	F	9/26	Leave one out CV	5.1.1, 5.1.2	
13	M	9/29	k-fold CV	5.1.3	
14	W	10/1	More k-fold CV	5.1.4-5	
15	F	10/3	k-fold CV for classification	5.1.5	
16	M	10/6	Subset selection	6.1	
17	W	10/8	Shrinkage: Ridge	6.2.1	
18	F	10/10	Shrinkage: Lasso	6.2.2	HW #4 Due Sun 10/12
19	M	10/13	PCA	6.3	
20	W	10/15	PCR	6.3	
	F	10/17	Review		
	M	10/20	Fall Break		
	W	10/22	Midterm #2		
21	F	10/24	Polynomial & Step Functions	7.1-7.2	HW #5 Due Sun 10/28
22	M	10/27	Step Functions; Basis functions; Start Splines	7.2-7.4	
23	W	10/29	Regression Splines	7.4	

Section 1

Last time

Goal

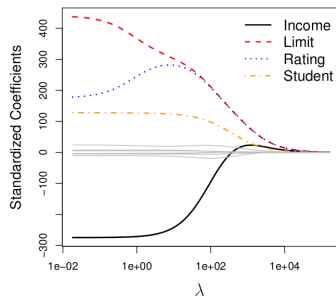
- Fit model using all p predictors
- Aim to constrain (regularize) coefficient estimates
- Shrink the coefficient estimates towards 0

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

Ridge regression

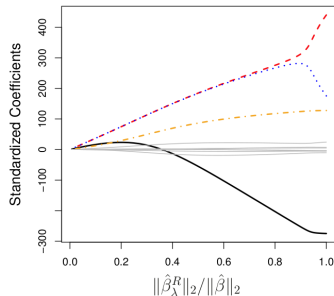
Before:

$$RSS = \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2$$



After:

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2 = RSS + \lambda \sum_{j=1}^p \beta_j^2$$



Scale equivariance (or lack thereof)

Scale equivariant: Multiplying a variable by c (cX_i) just returns a coefficient multiplied by $1/c$ ($1/c\beta_i$)

Solution: standardize predictors

$$\tilde{x}_{ij} = \frac{x_{ij}}{\sqrt{\frac{1}{n} \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2}}$$

- Least squares is scale equivariant
- Ridge regression is not

Section 2

The Lasso

Same goal as before

- Fit model using all p predictors
- Aim to constrain (regularize) coefficient estimates
- Shrink the coefficient estimates towards 0

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

The lasso

Least Squares:

$$RSS = \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2$$

Ridge:

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2 = RSS + \lambda \sum_{j=1}^p \beta_j^2$$

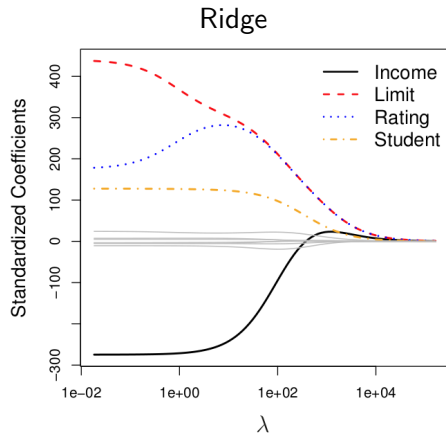
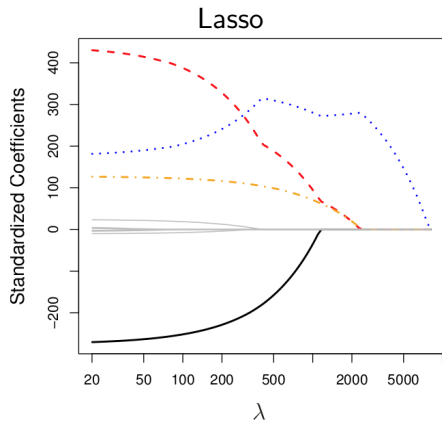
The Lasso:

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p |\beta_j| = RSS + \lambda \sum_{j=1}^p |\beta_j|$$

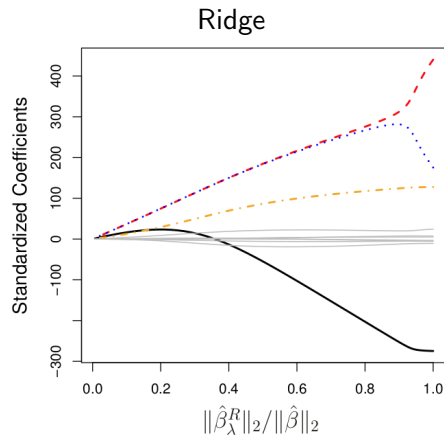
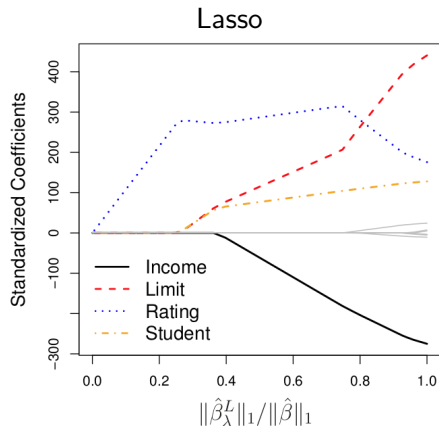
Subsets with lasso

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p |\beta_j| = RSS + \lambda \sum_{j=1}^p |\beta_j|$$

An example on Credit data set



More example on Credit data set

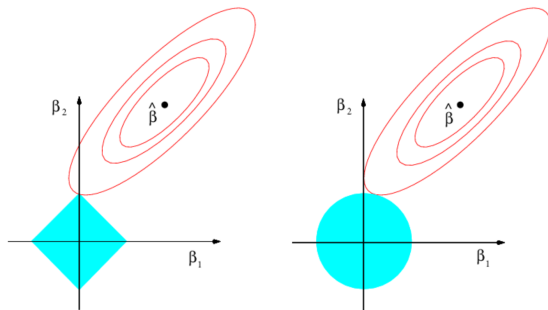


Why the hell lasso can select variable (while ridge cannot)?

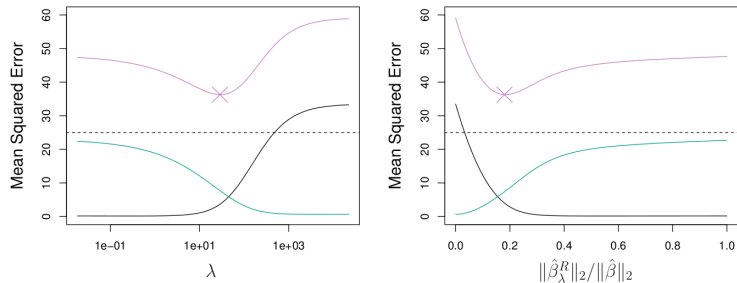
Alternative formulation of lasso & ridge regression ([play more with \$\ell_p\$](#))

$$\min_{\beta} \sum (y_i - \hat{y}_i)^2 \text{ where } \sum |\beta_j| \leq s$$

$$\min_{\beta} \sum (y_i - \hat{y}_i)^2 \text{ where } \sum |\beta_j|^2 \leq s$$



Bias-Variance tradeoff

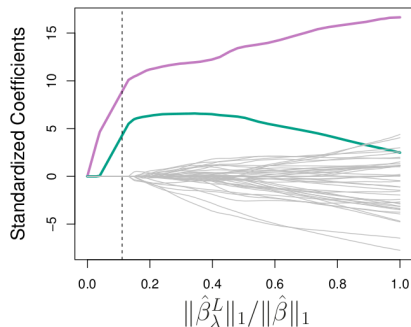
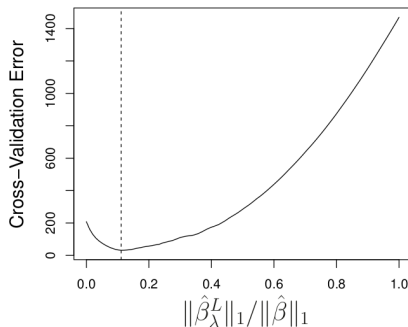


Squared bias (black), variance (green), and test mean squared error (purple) for simulated data.

Using Cross-Validation to find λ

- Choose a grid of λ values
- Compute the (k -fold) cross-validation error for each value of λ
- Select the tuning parameter value λ for which the CV error is smallest.
- The model is re-fit using all of the available observations and the selected value of the tuning parameter.

10-fold CV choice of λ for lasso and simulated data



Coding example

Ridge vs Lasso

Ridge Regression:

Lasso:

Least Squares:

$$RSS = \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2$$

Ridge:

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2 = RSS + \lambda \sum_{j=1}^p \beta_j^2$$

The Lasso:

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p |\beta_j| = RSS + \lambda \sum_{j=1}^p |\beta_j|$$

Next time

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