150B/355B
Introduction to Machine Learning for Social Science
TA Section 4

Haemin Jee and Tongtong Zhang

February 2, 2018

Road Map

1. Overfitting

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2. Lasso Regression

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   - Cross Validation

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   - Bias-Variance Tradeoff

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1. Overfitting
2. Lasso Regression
   - Cross Validation
   - Bias-Variance Tradeoff
3. R code in lectures this week

Document-Term Matrices

$$\boldsymbol{X} = \begin{array}{llllll} & \text{Word1} & \text{Word2} & \text{Word3} & \dots & \text{WordP} \\ \text{Doc1} & 1 & 0 & 0 & \dots & 3 \\ \text{Doc2} & 0 & 2 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \\ \text{DocN} & 0 & 0 & 0 & \dots & 5 \end{array}$$

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Let $p = (\Pr(\text{Desk}_i = 1))$

$$\text{logit}(p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_P X_P$$

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When overfitting happens, small perturbation in the training data can lead to substantial change in your model coefficients and thereby, lead to substantial change in your the predictions on the test set.

Overfitting

Reasons for overfitting:

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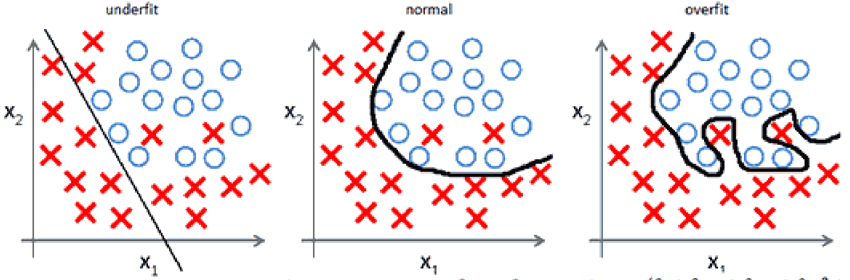

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Suppose we have two highly correlated predictors, X_1 and X_2.

```
base<-1:100
set.seed(12345)
X1<-base+rnorm(100,0,0.01)
#both x1 and x2 have the same base with a little noise
X2<-base+rnorm(100,0,0.01)
cor(X1,X2)

## [1] 0.9999999
```

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```
set.seed(1234)
Y<-X1+X2+rnorm(100,0,1) #1st random sample
lm(Y~X1+X2)$coefficients

## (Intercept)          X1          X2
##  -0.6004386   4.0852277  -2.0765643

set.seed(123456) # at a different seed, error term is different
Y<-X1+X2+rnorm(100,0,1) #2nd random sample with small changes in Y
lm(Y~X1+X2)$coefficients

## (Intercept)          X1          X2
##   0.2576408 -14.6233034  16.6191533
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With only small perturbation in the error term (Y), we got very different coefficients!

LASSO Regression

Overcoming Overfitting $\rightsquigarrow$ LASSO Regression

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Linear Regression: Choose $\beta's$ to minimize sum of squared residuals

$$\beta_{\text{OLS}} = \text{argmin}_{\beta} \sum_{i=1}^{N} (Y_i - \beta \cdot \boldsymbol{x}_i)^2$$

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subject to a constraint on coefficients:

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Re-write in the Lagrangian form:

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Re-write in the Lagrangian form:

$$\beta_{\text{LASSO}} = \text{argmin}_{\beta} \sum_{i=1}^{N} (Y_i - \boldsymbol{\beta} \cdot \boldsymbol{x}_i)^2 + \lambda \sum_{p=1}^{P} |\beta_p|$$

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\text{MSE} &= \frac{\sum_{i=1}^{N} (Y_i - \widehat{p}_{i,\lambda})^2}{N}
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In practice, we use cross-validation to complete these procedures

LASSO Regression in Practice

K-fold Cross Validation

Iteration	Training	Validation ("Test")
1	Group2, Group3, Group 4, ..., Group K	Group 1
2	Group 1, Group3, Group 4, ..., Group K	Group 2
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Common K's: 5-fold, 10-fold, N (LOOCV)

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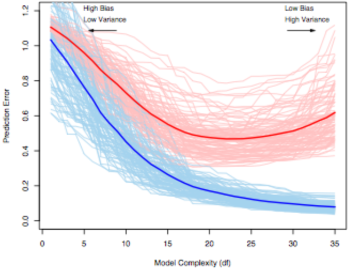

FIGURE 7.1. *Behavior of test sample and training sample error as the model complexity is varied. The light blue curves show the training error* $\overline{\text{err}}$*, while the light red curves show the conditional test error* $\text{Err}_{\mathcal{T}}$ *for 100 training sets of size 50 each, as the model complexity is increased. The solid curves show the expected test error* Err *and the expected training error* $\text{E}[\overline{\text{err}}]$.

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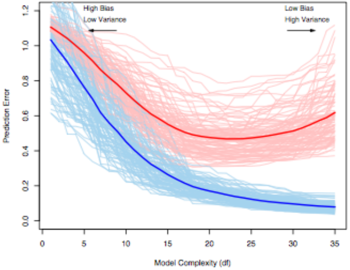

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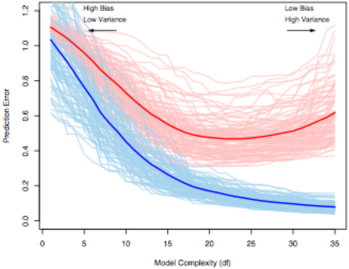

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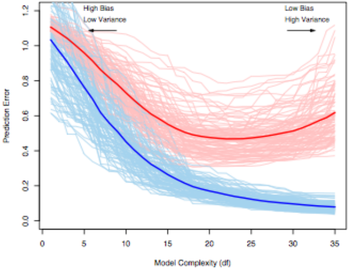

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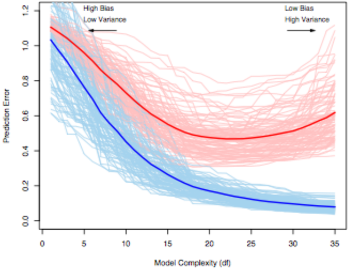

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  - Reduce variance by minimizing MSE on out-of-sample data.

R code!

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- Solution: LASSO regression

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- While choosing features, we want to avoid overfitting (too many features, too little generalizability)
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  3. We have our model!