



Courage
Inspiration
Trust
Youth
Uniqueness

SDSC3006 Lab

6-Shrinkage method

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Ridge Regression

Introduction

- Least squares: Minimize RSS

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

- Ridge Regression: Minimize RSS+Penalty(l2)

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

- Reason of shrinkage penalty: consider not only model fitting, but also shrinking the estimates of coefficients.(Trade-off)
- Tuning parameter λ : control the relative impact of two terms.

Initialize Data

- Hitters data set: predict a baseball player's Salary based on various statistics associated with performance in the previous year.

```
library(ISLR)
names(Hitters)
dim(Hitters)
sum(is.na(Hitters$Salary))
Hitters=na.omit(Hitters)
dim(Hitters)
sum(is.na(Hitters))
```

Fitting using Ridge

##the function glmnet() in the glmnet package

```
install.packages("glmnet")
```

```
library(glmnet)
```

#create dataset for fitting

```
x=model.matrix(Salary~.,Hitters)[-1]    #x: 19 predictors
```

```
y=Hitters$Salary
```

#why remove the 1st column?

##consider a vector of lambda values ranging from 10^{10} to 10^{-2}

```
grid=10^seq(10,-2,length=100)  #length: points of grid
```

```
ridge.mod=glmnet(x,y,alpha=0,lambda=grid)
```

```
#alpha=0:Ridge    alpha=1: LASSO
```

```
dim(coef(ridge.mod))    #20*100
```

Results

##the 50th value of lambda

```
ridge.mod$lambda[50]
```

```
coef(ridge.mod)[,50]
```

##Norm of the estimates

```
sqrt(sum(coef(ridge.mod)[-1,50]^2))
```

##the 60th value of lambda

```
ridge.mod$lambda[60]
```

```
coef(ridge.mod)[,60]
```

```
sqrt(sum(coef(ridge.mod)[-1,60]^2))
```

##For new value of lambda

##for example, lambda=25

```
predict(ridge.mod,s=25,type="coefficients")[1:20,]
```

Cross validation for Ridge

```
##split the data into a training and a test set
```

```
set.seed(1)
```

```
train=sample(1:nrow(x), nrow(x)/2)
```

```
test=(-train)
```

```
y.test=y[test]
```

```
##fit ridge regression on training data
```

```
grid=10^seq(10,-2,length=100)
```

```
ridge.mod=glmnet(x[train,],y[train],alpha=0,lambda=grid)
```

```
##predict on test set using lamda=4, 1e10, 0
```

```
ridge.pred1=predict(ridge.mod,s=4,newx=x[test,])
```

```
mean((ridge.pred1-y.test)^2)    #test MSE
```

```
ridge.pred2=predict(ridge.mod,s=1e10,newx=x[test,])
```

```
mean((ridge.pred2-y.test)^2)
```

```
ridge.pred3=predict(ridge.mod,s=0,newx=x[test,])
```

```
mean((ridge.pred3-y.test)^2)
```


Select Tuning Parameter

##cross validation to get the best lambda

```
set.seed(1)
```

```
cv.out=cv.glmnet(x[train,],y[train],alpha=0)    #default is 10-folds CV
```

```
plot(cv.out)
```

```
bestlam=cv.out$lambda.min
```

```
bestlam
```

##now predict with the best lambda

```
ridge.pred=predict(ridge.mod,s=bestlam,newx=x[test,])
```

```
mean((ridge.pred-y.test)^2)
```

##refit ridge regression on the full dataset

```
out=glmnet(x,y,alpha=0)
```

```
predict(out,type="coefficients",s=bestlam)[1:20,]
```

LASSO Regression

Introduction

- Least squares: Minimize RSS

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

- LASSO Regression: Minimize RSS+Penalty(l1)

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

- Advantage: can perform feature(variable) selection.
- Difference: Ridge reduces the coefficients by same proportion, while LASSO shrinks the coefficients by similar amount(some coefficients go to 0 if very small).

LASSO implementation

##for LASSO we use alpha=1

```
lasso.mod=glmnet(x[train,],y[train],alpha=1,lambda=grid)  
plot(lasso.mod)
```

##use CV to find the optimal lambda

```
set.seed(1)  
cv.out=cv.glmnet(x[train,],y[train],alpha=1)  
plot(cv.out)  
bestlam=cv.out$lambda.min
```

LASSO implementation

##use best lambda for prediction

```
lasso.pred=predict(lasso.mod,s=bestlam,newx=x[test,])  
mean((lasso.pred-y.test)^2)  
out=glmnet(x,y,alpha=1,lambda=grid)  
lasso.coef=predict(out,type="coefficients",s=bestlam)[1:20,]
```

##check the estimated coefficients and the '0' coefficients

```
lasso.coef  
lasso.coef[lasso.coef!=0]
```