Computational Statistics II

Lab 6 Homework

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1. (Question 9, Page 263) In this exercise, we will predict the number of applications received using the other variables in the College data set.
   a. Split the data set into a training set and a test set.

   ```
   library(ISLR)

   set.seed(2)
   train = sample(c(TRUE, FALSE), nrow(College), rep=TRUE)
   test = (!train)
   ```

   b. Fit a linear model using least squares on the training set and report the test error obtained.

   ```
   library(leaps)
   regfit.best = regsubsets(Apps~., data=College[train,], nvmax = 18)
   test.mat = model.matrix(Apps~., data = College[test,])

   # Vector to store errors for different models
   val.errors = rep(NA, 18)

   for(i in 1:17){
     coefi = coef(regfit.best, id = i)
     pred = test.mat[, names(coefi)]%*%coefi
     val.errors[i] = mean((College$Apps[test]-pred)^2)
   }

   # Determining the minimum value for errors in vector
   min_error = which.min(val.errors)
   cat("Error using linear regression is ", val.errors[min_error])
   ```

   ```
   > cat("Error using linear regression is ", val.errors[min_error])
   Error using linear regression is  1556804
   ```

   c. Fit a ridge regression model on the training set, with λ chosen by cross-validation. Report the test error obtained.

   ```
   library(glmnet)
   x = model.matrix(Apps~., College)[,-1]
   y = College$Apps

   # Getting the best lambda using cross validation
   ```

```r
cv.out = cv.glmnet(x[train,], y[train], alpha = 0)
best_lambda = cv.out$lambda.min

grid=10^seq(10,-2, length =50)
ridge.mod = glmnet(x[train,], y[train], alpha = 0, lambda = best_lambda)
ridge.pred = predict(ridge.mod, s= best_lambda, newx = x[test,])
error = mean((ridge.pred - y[test])^2)
cat("Error using ridge regression is", error)
```

```
> cat("Error using ridge regression is", error)
Error using ridge regression is 2455040
```

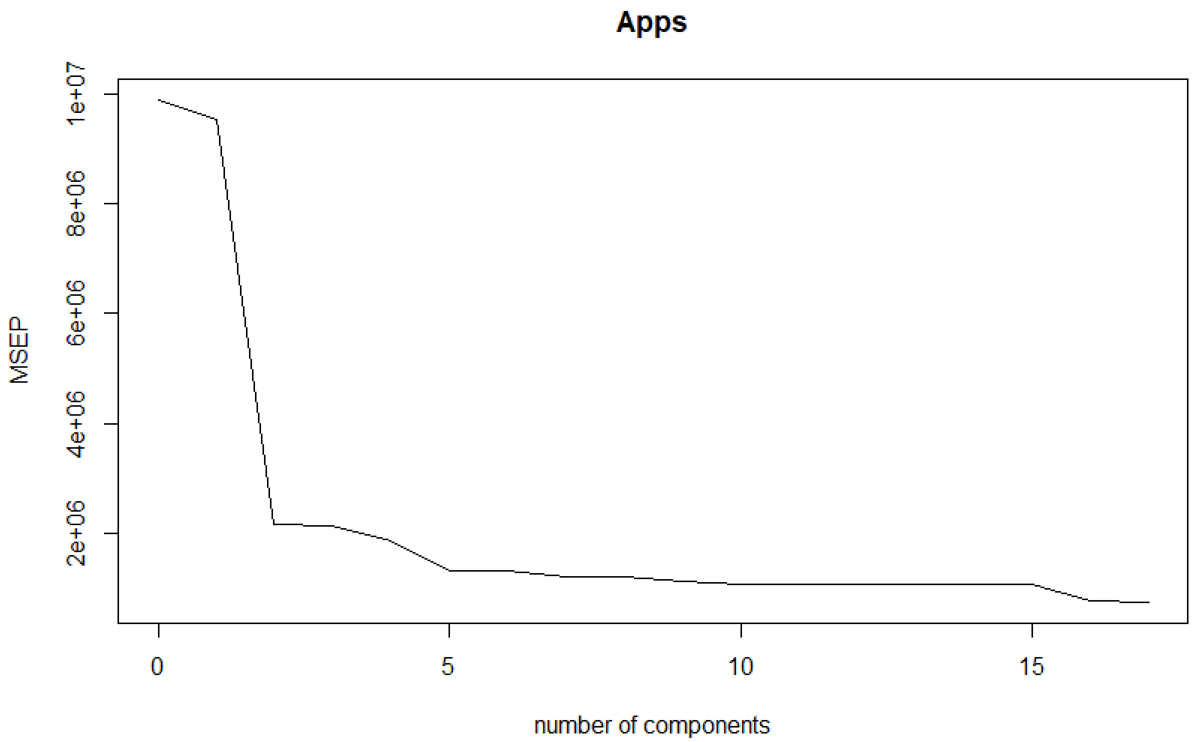
d. Fit a lasso model on the training set, with λ chosen by cross validation. Report the test error obtained, along with the number of non-zero coefficient estimates.

```r
cv.out = cv.glmnet(x[train,], y[train], alpha = 1)
best_lambda = cv.out$lambda.min
lasso.mod = glmnet(x[train,], y[train], alpha = 1, lambda = best_lambda)
out = glmnet(x, y, alpha = 1, lambda = best_lambda)
lasso.coef = predict(out, type="coefficients", s= best_lambda)[1:18,]
num_of_non_zero_coefficients = length(lasso.coef[lasso.coef != 0])
lasso.pred = predict(lasso.mod, s=best_lambda, newx=x[test,])
error = mean((lasso.pred-y[test])^2)
cat("Number of non-zero coefficients is ", num_of_non_zero_coefficients)
cat("Error using lasso regression is", error)
```

```
> cat("Number of non-zero coefficients is ", num_of_no
Number of non-zero coefficients is  16
> cat("Error using lasso regression is", error)
Error using lasso regression is 1619724
>
```

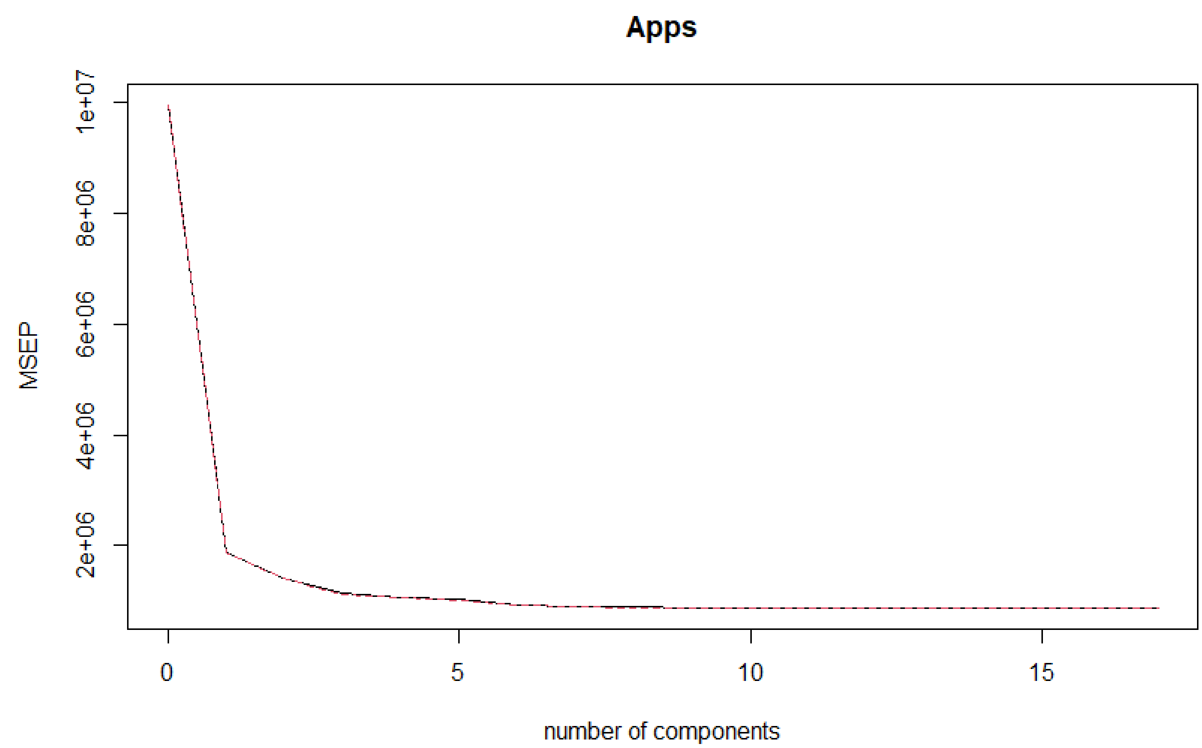
e. Fit a PCR model on the training set, with M chosen by cross validation. Report the test error obtained, along with the value of M selected by cross-validation.

```r
library(pls)
pcr.fit = pcr(Apps~., data=College, subset = train, scale=TRUE, valication="CV")
validationplot(pcr.fit, val.type="MSEP")
# We see that the lowest cross validation error occurs when M = 17
pcr.pred = predict(pcr.fit, x[test,], ncomp = 17)
error = mean ((pcr.pred-y[test])^2)
cat("Error using pcr is", error)
```




```
> cat("Error using pcr is", error)
Error using pcr is 1556804
> 
```

f. Fit a PLS model on the training set, with M chosen by cross validation. Report the test error obtained, along with the value of M selected by cross-validation.
pls.fit = plsr(Apps~., data = College, subset = train, scale = TRUE, validation="CV")
validationplot(pls.fit, val.type="MSEP")
 # We see that the lowest cross validation error occurs when M = 17
pls.pred = predict(pls.fit, x[test,], ncomp = 17)
error = mean((pls.pred-y[test])^2)
cat("Error using pcr is", error)




```
> cat("Error using pls is", error)
Error using pls is 1556804
```

g. Comment on the results obtained. How accurately can we predict the number of college applications received? Is there much difference among the test errors resulting from these five approaches?

Regression Method	**Mean Squared Error**
Linear Regression	1556804
Ridge Regression	2455040
Lasso Regression	1619724
PCR	1556804
PLS	1556804

We can see that the Linear regression, PCR and PLS have the same accuracy, giving the test result of 1556804. Ridge regression appears to be the last on the list giving the highest amount of test error.