Hamed_HW2

Load the cpus dataset from the MASS package

```
library(MASS)
library(leaps)
data(cpus)
attach(cpus)
library(caret)

## Loading required package: lattice

## Loading required package: ggplot2
```

Use syct, mmin , mmax , cach , chmin, chmax as the predictors (independent variables) to predict performance (perf)

Perform best subset selection in order to choose the best predictors from the above predictors

```
regfit.full <- regsubsets(perf ~ syct + mmin + mmax + cach + chmin +
chmax,data=cpus,nvmax = 6)
summary(regfit.full)

## Subset selection object
## Call: regsubsets.formula(perf ~ syct + mmin + mmax + cach + chmin +
##     chmax, data = cpus, nvmax = 6)
## 6 Variables  (and intercept)
##       Forced in Forced out
## syct      FALSE      FALSE
## mmin      FALSE      FALSE
## mmax      FALSE      FALSE
## cach      FALSE      FALSE
## chmin     FALSE      FALSE
## chmax     FALSE      FALSE
## 1 subsets of each size up to 6
## Selection Algorithm: exhaustive
##          syct mmin mmax cach chmin chmax
## 1  ( 1 ) " "  " "  "*"  " "  " "   " "  
## 2  ( 1 ) " "  " "  "*"  "*"  " "   " "  
## 3  ( 1 ) " "  "*"  "*"  " "  " "   "*"  
## 4  ( 1 ) " "  "*"  "*"  "*"  " "   "*"  
## 5  ( 1 ) "*"  "*"  "*"  "*"  " "   "*"  
## 6  ( 1 ) "*"  "*"  "*"  "*"  "*"   "*"  
```

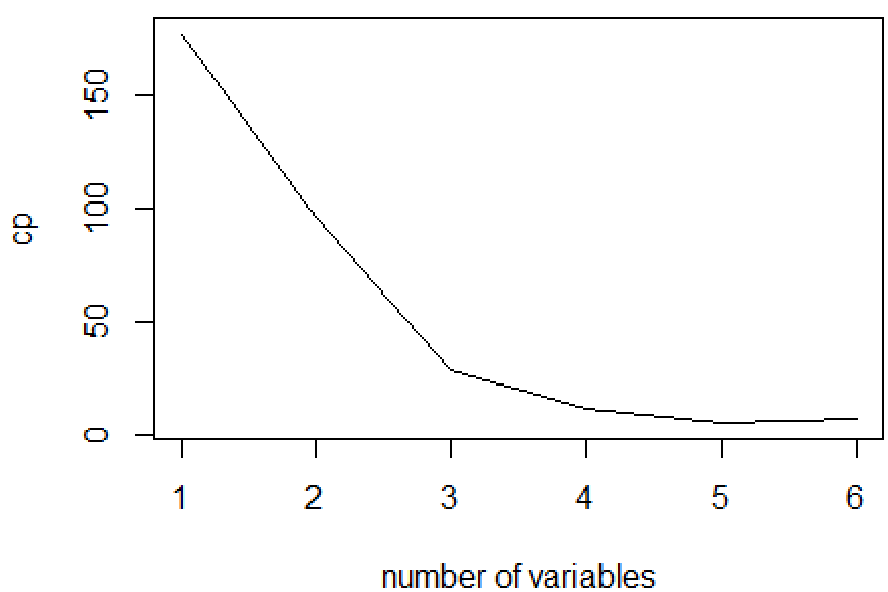
What is the best model obtained according to Cp, BIC, and adjusted R2?

```
reg.summary_sub <- summary(regfit.full)
reg.summary_sub$cp

## [1] 176.563616  95.808585  28.225948  10.977588   5.099604   7.000000

reg.summary_sub$bic

## [1] -274.7146 -320.4675 -370.5300 -383.5185 -386.1684 -380.9290

reg.summary_sub$adjr2

## [1] 0.7435259 0.7981760 0.8444189 0.8567846 0.8614788 0.8608616
```

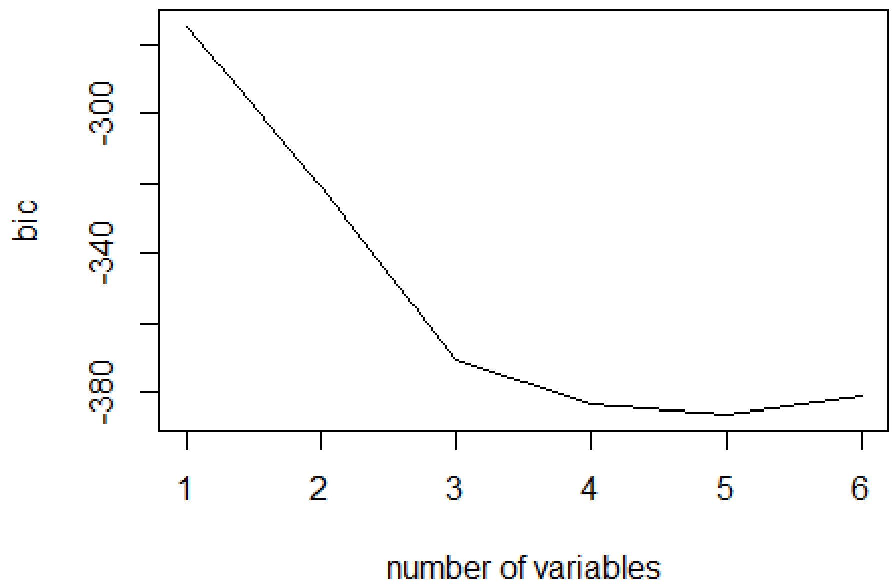
Show some plots to provide evidence for your answer,

and report the coefficients of the best model obtained for each criteria.

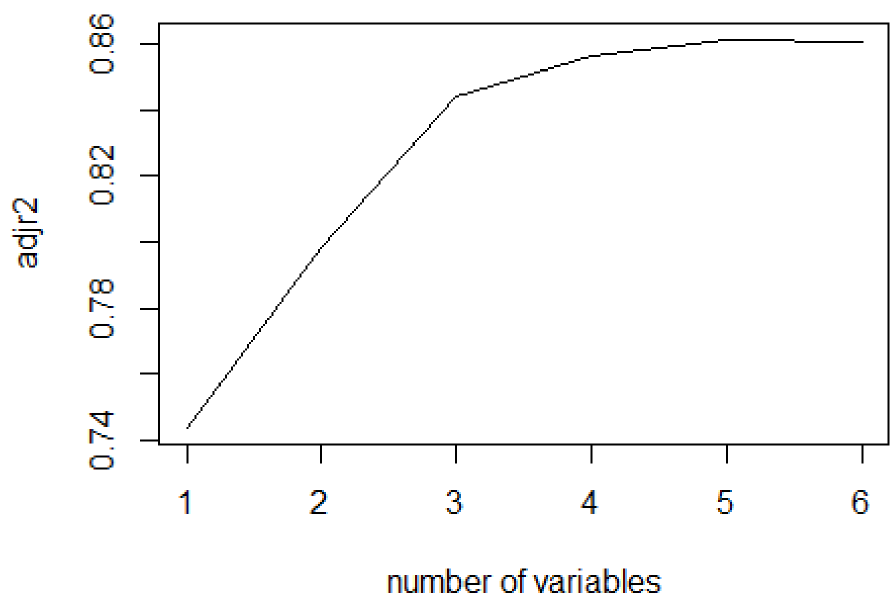
```
plot(reg.summary_sub$cp,xlab="number of variables" ,ylab="cp" ,type="l")
```




```
plot(reg.summary_sub$bic,xlab="number of variables" ,ylab="bic" ,type="l")
```



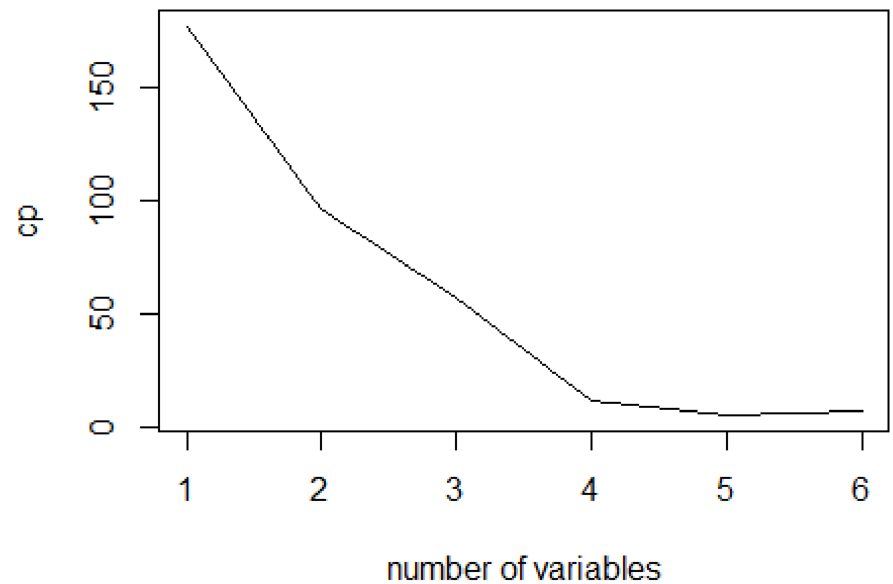

```
plot(reg.summary_sub$adjr2,xlab="number of variables" ,ylab="adjr2"
,type="l")
```



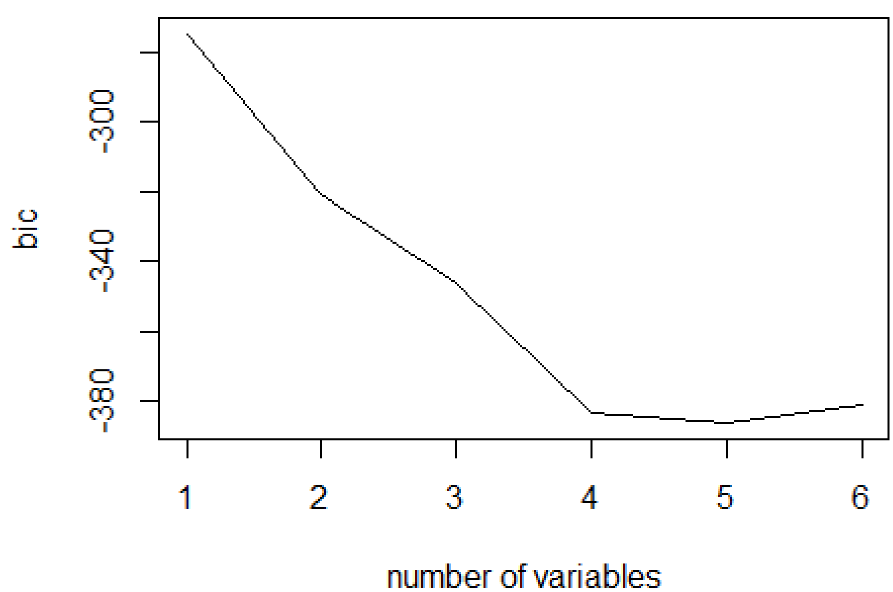
Repeat using forward stepwise selection and also using backwards stepwise selection.

How does your answer compare to the best subset results?

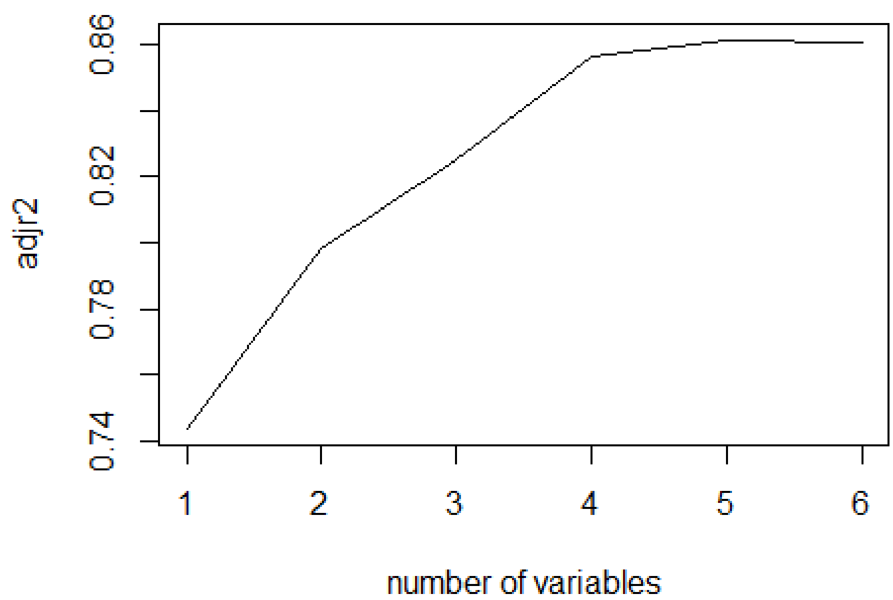
```
# Forward Stepwise Selection
regfit.fwd <- regsubsets(perf ~ syct + mmin + mmax + cach + chmin +
chmax,data=cpus,nvmax = 6, method = "forward")
summary(regfit.fwd)

## Subset selection object
## Call: regsubsets.formula(perf ~ syct + mmin + mmax + cach + chmin +
##     chmax, data = cpus, nvmax = 6, method = "forward")
## 6 Variables  (and intercept)
##       Forced in Forced out
## syct      FALSE      FALSE
## mmin      FALSE      FALSE
## mmax      FALSE      FALSE
## cach      FALSE      FALSE
## chmin     FALSE      FALSE
## chmax     FALSE      FALSE
## 1 subsets of each size up to 6
## Selection Algorithm: forward
##          syct mmin mmax cach chmin chmax
## 1  ( 1 ) " "  " "  "*"  " "  " "   " "
## 2  ( 1 ) " "  " "  "*"  "*"  " "   " "
## 3  ( 1 ) " "  "*"  "*"  "*"  " "   " "
## 4  ( 1 ) " "  "*"  "*"  "*"  " "   "*"
## 5  ( 1 ) "*"  "*"  "*"  "*"  " "   "*"
## 6  ( 1 ) "*"  "*"  "*"  "*"  "*"   "*"

reg.summary_fwd <- summary(regfit.fwd)
reg.summary_fwd$cp

## [1] 176.563616  95.808585  56.684812  10.977588   5.099604   7.000000

reg.summary_fwd$bic

## [1] -274.7146 -320.4675 -346.0709 -383.5185 -386.1684 -380.9290

reg.summary_fwd$adjr2

## [1] 0.7435259 0.7981760 0.8251032 0.8567846 0.8614788 0.8608616

plot(reg.summary_fwd$cp,xlab="number of variables" ,ylab="cp" ,type="l")
```




```r
plot(reg.summary_fwd$bic,xlab="number of variables" ,ylab="bic" ,type="l")
```

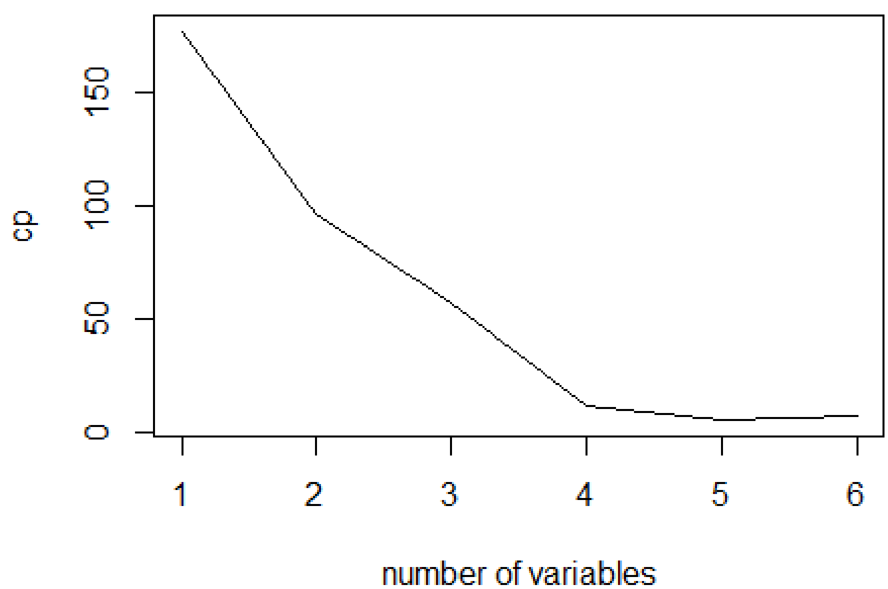


```
plot(reg.summary_fwd$adjr2,xlab="number of variables" ,ylab="adjr2"
,type="l")
```

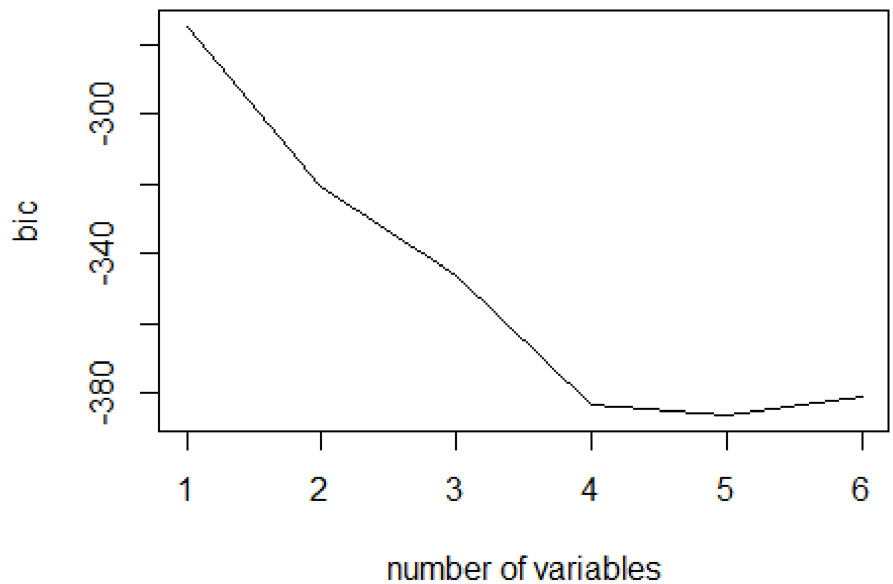



```
# Backward Stepwise Selection
regfit.bwd <- regsubsets(perf ~ syct + mmin + mmax + cach + chmin +
chmax,data=cpus,nvmax = 6, method = "backward")
summary(regfit.bwd)

## Subset selection object
## Call: regsubsets.formula(perf ~ syct + mmin + mmax + cach + chmin +
##     chmax, data = cpus, nvmax = 6, method = "backward")
## 6 Variables  (and intercept)
##       Forced in Forced out
## syct      FALSE      FALSE
## mmin      FALSE      FALSE
## mmax      FALSE      FALSE
## cach      FALSE      FALSE
## chmin     FALSE      FALSE
## chmax     FALSE      FALSE
## 1 subsets of each size up to 6
## Selection Algorithm: backward
##          syct mmin mmax cach chmin chmax
## 1  ( 1 ) " "  "*"  " "  " "  " "   " "
## 2  ( 1 ) " "  "*"  " "  " "  " "   "*"
## 3  ( 1 ) " "  "*"  "*"  " "  " "   "*"
## 4  ( 1 ) " "  "*"  "*"  "*"  " "   "*"
```

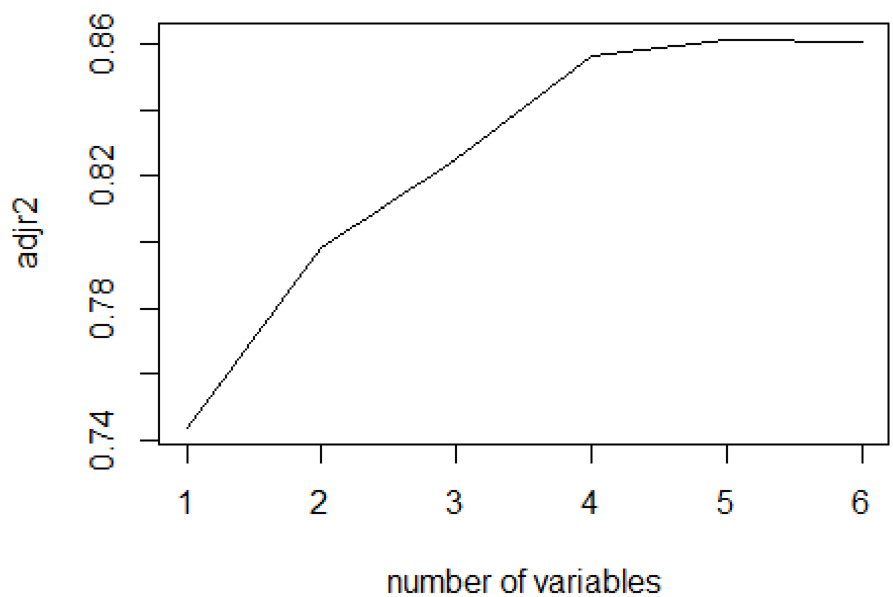
```
## 5  ( 1 ) "*"  "*"  "*"  "*"  " "   "*"
## 6  ( 1 ) "*"  "*"  "*"  "*"  "*"   "*"

reg.summary_bwd <- summary(regfit.fwd)
reg.summary_bwd$cp

## [1] 176.563616  95.808585  56.684812  10.977588   5.099604   7.000000

reg.summary_bwd$bic

## [1] -274.7146 -320.4675 -346.0709 -383.5185 -386.1684 -380.9290

reg.summary_bwd$adjr2

## [1] 0.7435259 0.7981760 0.8251032 0.8567846 0.8614788 0.8608616

plot(reg.summary_bwd$cp,xlab="number of variables" ,ylab="cp" ,type="l")
```




```
plot(reg.summary_bwd$bic,xlab="number of variables" ,ylab="bic" ,type="l")
```




```
plot(reg.summary_bwd$adjr2,xlab="number of variables" ,ylab="adjr2"
,type="l")
```



```
library(ISLR)
data(College)
attach(College)
head(College)

##                              Private Apps Accept Enroll Top10perc
Top25perc
## Abilene Christian University     Yes 1660   1232    721        23
52
## Adelphi University               Yes 2186   1924    512        16
29
## Adrian College                   Yes 1428   1097    336        22
50
## Agnes Scott College              Yes  417    349    137        60
89
## Alaska Pacific University        Yes  193    146     55        16
44
## Albertson College                Yes  587    479    158        38
62
##                              F.Undergrad P.Undergrad Outstate Room.Board
Books
## Abilene Christian University        2885         537     7440       3300
450
## Adelphi University                  2683        1227    12280       6450
750
## Adrian College                      1036          99    11250       3750
400
## Agnes Scott College                  510          63    12960       5450
450
## Alaska Pacific University            249         869     7560       4120
800
## Albertson College                    678          41    13500       3335
500
##                              Personal PhD Terminal S.F.Ratio perc.alumni
Expend
## Abilene Christian University     2200  70       78      18.1          12
7041
## Adelphi University               1500  29       30      12.2          16
10527
## Adrian College                   1165  53       66      12.9          30
8735
## Agnes Scott College               875  92       97       7.7          37
19016
## Alaska Pacific University        1500  76       72      11.9           2
10922
## Albertson College                 675  67       73       9.4          11
9727
##                              Grad.Rate
## Abilene Christian University        60
## Adelphi University                  56
```

```
## Adrian College                              54
## Agnes Scott College                         59
## Alaska Pacific University                   15
## Albertson College                           55

library(caret)
```

Predict the number of applications received using the other variables in the College data set in library ISLR

```
colnames(College)

##  [1] "Private"     "Apps"        "Accept"      "Enroll"      "Top10perc"
##  [6] "Top25perc"   "F.Undergrad" "P.Undergrad" "Outstate"    "Room.Board"
## [11] "Books"       "Personal"    "PhD"         "Terminal"    "S.F.Ratio"
## [16] "perc.alumni" "Expend"      "Grad.Rate"
```

(a) Split the data set into a training set and a test set using caret library and

fit each of the following models using caret and ten fold cross validation.

```
intrain <- createDataPartition(College$Apps,p=0.75,list = FALSE)
train1 <- College[intrain,]
test1 <- College[-intrain,]

trctrl <- trainControl(method= "cv", number=10)

nrow(train1)

## [1] 585

nrow(test1)

## [1] 192
```

(b) Fit a linear model using ordinary least squares on the training set,

and report the test mean squared error obtained.

```
ols <- train(Apps ~., data = train1,
             trControl=trctrl,
             preProcess=c('scale','center'))
ols
```

```
## Random Forest
##
## 585 samples
##  17 predictor
##
## Pre-processing: scaled (17), centered (17)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 528, 527, 525, 526, 527, 527, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##    2    1498.896  0.8799545  716.3014
##    9    1268.750  0.9032436  522.0455
##   17    1268.218  0.8974584  517.7527
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 17.
```

```r
# Report  test mean squared
ols$results
```

```
##   mtry     RMSE  Rsquared      MAE   RMSESD RsquaredSD    MAESD
## 1    2 1498.896 0.8799545 716.3014 1116.489 0.08867297 183.5196
## 2    9 1268.750 0.9032436 522.0455 1141.621 0.10361832 162.3887
## 3   17 1268.218 0.8974584 517.7527 1145.685 0.11315247 176.5862
```

```r
ols$results$RMSE^2
```

```
## [1] 2246690 1609727 1608376
```

```r
cat("test mean squared error")
```

```
## test mean squared error
```

```r
# Predict for the test dataset
ln_pred <-predictions <- predict(ols, newdata= test1)
# Mean squared error in the test dataset
ln_mse <- mean(( predictions - test1$Apps)^2)
ln_mse
```

```
## [1] 1195690
```

(c) Fit a ridge regression model on the training set, with λ chosen by cross-validation.

Report the test mean squared error obtained. Report the value of λ used in the mode

```
ridge_fit <- train(Apps ~., data = train1,
                   method="ridge",
                   trControl=trctrl,
                   preProcess=c('scale','center'))
ridge_fit

## Ridge Regression
##
## 585 samples
##  17 predictor
##
## Pre-processing: scaled (17), centered (17)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 527, 527, 526, 526, 526, 527, ...
## Resampling results across tuning parameters:
##
##   lambda  RMSE      Rsquared   MAE
##   0e+00   1036.263  0.9248218  606.4225
##   1e-04   1036.334  0.9248477  606.3501
##   1e-01   1197.058  0.9188929  700.9011
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was lambda = 0.

ridgeGrid <- data.frame(lambda = seq(0, .2, length = 15))
ridge_fit <- train(Apps~.,data=train1,
                 method="ridge",
                 tuneGrid=ridgeGrid,
                 trControl=trctrl,
                 preProcess=c('scale','center'))
ridge_fit

## Ridge Regression
##
## 585 samples
##  17 predictor
##
## Pre-processing: scaled (17), centered (17)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 529, 527, 527, 525, 526, 527, ...
## Resampling results across tuning parameters:
##
##   lambda      RMSE      Rsquared   MAE
```

```
##   0.00000000  1067.551  0.9281832  618.2244
##   0.01428571  1065.748  0.9311674  614.8620
##   0.02857143  1076.910  0.9315776  620.8149
##   0.04285714  1093.498  0.9309338  633.0227
##   0.05714286  1112.704  0.9297919  649.3933
##   0.07142857  1133.205  0.9284120  666.8707
##   0.08571429  1154.331  0.9269287  685.0552
##   0.10000000  1175.742  0.9254146  703.2052
##   0.11428571  1197.265  0.9239095  721.0767
##   0.12857143  1218.820  0.9224348  739.2864
##   0.14285714  1240.375  0.9210017  757.5451
##   0.15714286  1261.919  0.9196151  775.3353
##   0.17142857  1283.457  0.9182766  793.0985
##   0.18571429  1304.996  0.9169857  810.6974
##   0.20000000  1326.546  0.9157409  828.3609
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was lambda = 0.01428571.
```

```
# Generate predictions with test dataset
ridge_pred <- predict(ridge_fit, newdata = test1)
head(ridge_pred)
```

```
##                 Adrian College              Albertson College
##                      1264.7578                       689.1371
##      Alderson-Broaddus College                    Alma College
##                       638.8626                      1795.4662
## American International College                 Amherst College
##                      1144.8377                      3424.4456
```

```
# Calculate Mean Square Error (MSE) ridge_mse
ridge_mse <- mean((ridge_pred - test1$Apps)^2)
ridge_mse
```

```
## [1] 1469828
```

```
# Predicting the ridge_fit
predict(ridge_fit$finalModel, type='coef', mode='norm')$coefficients
```

```
##    PrivateYes   Accept    Enroll Top10perc  Top25perc F.Undergrad
P.Undergrad
## 0     0.00000    0.000    0.0000    0.0000    0.00000     0.00000
0.00000
## 1     0.00000 3107.494    0.0000    0.0000    0.00000     0.00000
0.00000
## 2     0.00000 3406.305    0.0000  298.8110    0.00000     0.00000
0.00000
## 3     0.00000 3516.470    0.0000  355.4996    0.00000     0.00000
0.00000
## 4   -85.10238 3532.268    0.0000  393.1734    0.00000     0.00000
0.00000
```

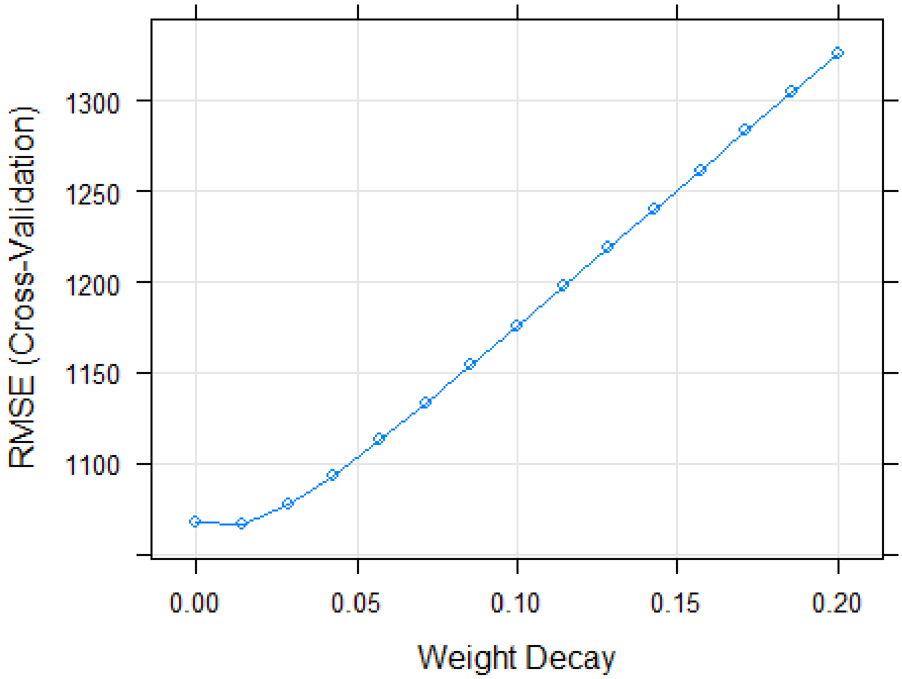
```
## 5  -123.23259 3533.393    0.0000  405.9061    0.00000     0.00000
0.00000
## 6  -132.88931 3532.487    0.0000  415.1257    0.00000     0.00000
0.00000
## 7  -134.14308 3532.690    0.0000  416.3824    0.00000     0.00000
0.00000
## 8  -142.35585 3536.760    0.0000  438.9648    0.00000     0.00000
0.00000
## 9  -145.07089 3537.104    0.0000  442.9592    0.00000     0.00000
0.00000
## 10 -159.86816 3534.901    0.0000  469.7317    0.00000     0.00000
14.08922
## 11 -166.94460 3534.157    0.0000  481.2025    0.00000     0.00000
20.28294
## 12 -186.33993 3613.729 -104.3296  508.8359    0.00000     0.00000
40.47082
## 13 -201.04461 3675.025 -180.6745  571.8337  -50.46454     0.00000
54.97060
## 14 -214.09929 3730.100 -250.4806  627.3609  -94.90267     0.00000
66.62224
## 15 -221.36345 3760.528 -289.0791  657.8563 -119.50862     0.00000
73.03312
## 16 -223.09537 3772.408 -326.0164  670.9452 -131.10416    25.06694
74.22332
## 17 -226.55307 3803.837 -424.9786  706.0117 -161.82271    91.40697
77.57179
##      Outstate Room.Board    Books  Personal         PhD   Terminal
S.F.Ratio
## 0     0.00000    0.00000 0.000000  0.000000    0.000000   0.000000
0.000000
## 1     0.00000    0.00000 0.000000  0.000000    0.000000   0.000000
0.000000
## 2     0.00000    0.00000 0.000000  0.000000    0.000000   0.000000
0.000000
## 3     0.00000    0.00000 0.000000  0.000000    0.000000   0.000000
0.000000
## 4     0.00000    0.00000 0.000000  0.000000    0.000000   0.000000
0.000000
## 5     0.00000   26.59073 0.000000  0.000000    0.000000   0.000000
0.000000
## 6     0.00000   36.28786 0.000000  0.000000    0.000000   0.000000
0.000000
## 7     0.00000   37.25613 0.000000  0.000000   -2.073079   0.000000
0.000000
## 8   -34.84148   63.45019 0.000000  0.000000  -30.770448   0.000000
0.000000
## 9   -44.72034   69.28797 0.000000  0.000000  -37.773772   0.000000
0.000000
## 10 -105.78909  105.18079 0.000000  0.000000  -83.405011   0.000000
0.000000
```

```
## 11 -131.38425  121.11433 0.000000  0.000000  -96.816664  -8.138322
0.000000
## 12 -174.83996  134.30637 0.000000  0.000000 -114.322952 -17.710458
0.000000
## 13 -206.03288  144.10892 0.000000  0.000000 -126.019576 -18.751976
0.000000
## 14 -232.94781  153.21363 0.000000  7.027112 -136.107651 -19.685471
0.000000
## 15 -247.70460  158.01594 1.275852 10.647493 -141.450186 -20.425112
0.000000
## 16 -252.83583  159.82638 1.832312 11.633432 -143.868318 -21.301852
0.000000
## 17 -266.30652  164.98313 3.093920 14.757475 -150.815095 -23.655286
6.612105
##    perc.alumni   Expend  Grad.Rate
## 0      0.00000   0.0000   0.000000
## 1      0.00000   0.0000   0.000000
## 2      0.00000   0.0000   0.000000
## 3      0.00000  81.9782   0.000000
## 4      0.00000 148.0035   0.000000
## 5      0.00000 160.2378   0.000000
## 6    -14.68213 167.1304   0.000000
## 7    -15.29255 167.9205   0.000000
## 8    -19.41647 189.2174   0.000000
## 9    -21.44036 195.3512   5.159169
## 10   -33.98853 233.3089  40.423469
## 11   -38.90375 249.7533  55.454746
## 12   -41.64644 271.4519  73.750186
## 13   -42.08003 280.5936  88.472860
## 14   -41.60042 288.2754 102.198266
## 15   -41.24444 292.4828 109.825551
## 16   -40.77802 294.7074 113.448015
## 17   -39.04298 303.8768 123.081749
```

```r
# See what lambda was used in the ridge
ridge_fit$bestTune$lambda
```

```
## [1] 0.01428571
```

```r
# Plot the lambdas to see how the lambda was chosen (minimum RMSE)
plot(ridge_fit)
```



(d) Fit a lasso model on the training set, with fraction chosen by cross validation.

Report the test mean squared error obtained, along with the number of non-zero coefficient estimates and the fraction.

```
lasso <- train(Apps ~., data = train1,
               method= 'lasso',
               preProc=c('scale','center'),
               trControl=trctrl)
lasso

## The lasso
##
## 585 samples
##  17 predictor
##
## Pre-processing: scaled (17), centered (17)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 526, 528, 525, 527, 525, 526, ...
## Resampling results across tuning parameters:
##
##   fraction  RMSE      Rsquared   MAE
##   0.1       3099.302  0.9140627  2076.3624
```

```
##   0.5       1082.136  0.9314001   576.6874
##   0.9       1026.635  0.9365021   602.9177
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was fraction = 0.9.
```

```
lassoGrid <- data.frame(fraction = seq(0.05, .8, length = 15))
lasso <- train(Apps ~., data = train1,
               method='lasso',
               preProc=c('scale','center'),
               tuneGrid = lassoGrid,
               trControl=trctrl)
# Generate predictions with test dataset
lasso_pred <- predict(lasso, newdata = test1)

# Calculate Mean Square Error (MSE)
lasso_mse <- mean(lasso_pred - test1$Apps)^2
lasso_mse
```

```
## [1] 5.282411
```

```
# See the coefficients of the regression (the last row is the final
coeffcients)
predict(lasso$finalModel, type='coefficients', mode='norm')$coefficients
```

```
##    PrivateYes   Accept     Enroll Top10perc  Top25perc F.Undergrad
P.Undergrad
## 0     0.00000    0.000    0.00000    0.0000    0.00000      0.0000
0.00000
## 1     0.00000 3118.519    0.00000    0.0000    0.00000      0.0000
0.00000
## 2     0.00000 3412.191    0.00000  293.6716    0.00000      0.0000
0.00000
## 3     0.00000 3543.425    0.00000  360.0307    0.00000      0.0000
0.00000
## 4   -64.34795 3554.396    0.00000  387.8549    0.00000      0.0000
0.00000
## 5   -87.18885 3554.697    0.00000  395.3741    0.00000      0.0000
0.00000
## 6   -89.18293 3554.464    0.00000  397.2842    0.00000      0.0000
0.00000
## 7   -96.90407 3555.585    0.00000  404.9843    0.00000      0.0000
0.00000
## 8  -108.77504 3561.492    0.00000  439.3036    0.00000      0.0000
0.00000
## 9  -116.84280 3600.314  -45.62726  451.9002    0.00000      0.0000
0.00000
## 10 -130.87969 3659.902 -117.03541  469.0630    0.00000      0.0000
0.00000
## 11 -143.87277 3723.532 -198.92921  489.3963    0.00000      0.0000
14.66885
```

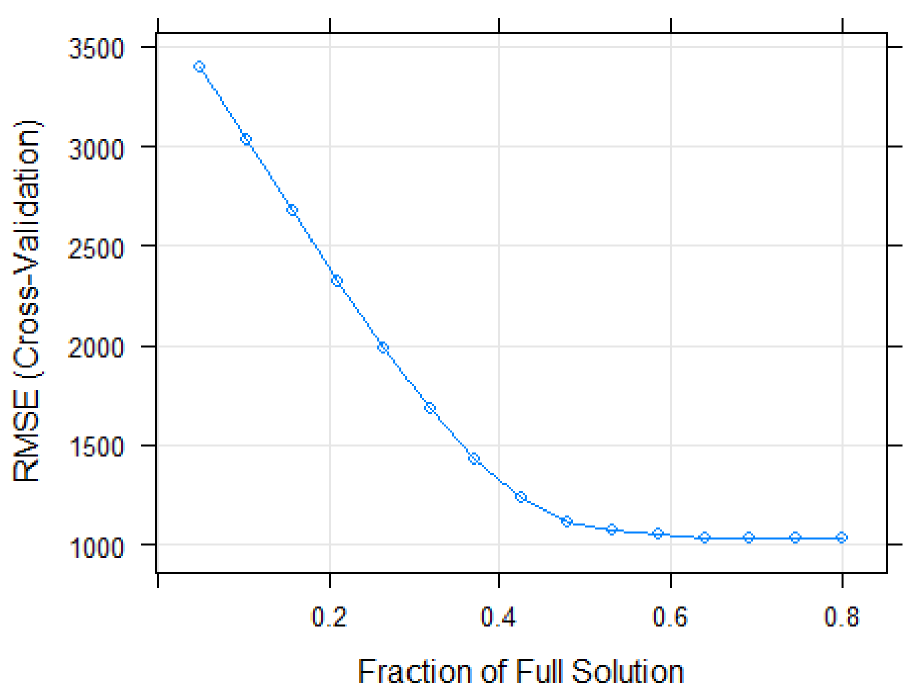
```
## 12 -163.70017 3816.901 -318.84036  519.1336    0.00000      0.0000
36.32149
## 13 -176.62501 3878.790 -394.52176  581.4808  -49.81138      0.0000
49.74382
## 14 -210.30132 4041.844 -597.11480  742.3108 -178.14841      0.0000
81.37388
## 15 -216.10470 4112.781 -835.29127  812.1246 -239.96087    171.7969
85.18803
## 16 -217.03504 4123.959 -872.83523  823.0672 -249.71417    198.8725
85.78119
## 17 -217.11401 4124.669 -875.19759  823.7565 -250.33417    200.5906
85.81556
##      Outstate Room.Board     Books Personal        PhD   Terminal
S.F.Ratio
## 0     0.00000    0.00000 0.0000000  0.00000    0.00000   0.000000
0.0000000
## 1     0.00000    0.00000 0.0000000  0.00000    0.00000   0.000000
0.0000000
## 2     0.00000    0.00000 0.0000000  0.00000    0.00000   0.000000
0.0000000
## 3     0.00000    0.00000 0.0000000  0.00000    0.00000   0.000000
0.0000000
## 4     0.00000    0.00000 0.0000000  0.00000    0.00000   0.000000
0.0000000
## 5     0.00000   15.89804 0.0000000  0.00000    0.00000   0.000000
0.0000000
## 6     0.00000   17.89628 0.0000000  0.00000    0.00000   0.000000
0.0000000
## 7     0.00000   23.79990 0.0000000  0.00000  -12.67536   0.000000
0.0000000
## 8   -54.47427   64.11197 0.0000000  0.00000  -55.99901   0.000000
0.0000000
## 9   -72.85521   70.46131 0.0000000  0.00000  -65.49958   0.000000
0.0000000
## 10 -104.76370   79.75910 0.0000000  0.00000  -80.74236   0.000000
0.0000000
## 11 -137.29498   87.83562 0.0000000  0.00000  -97.90737   0.000000
0.0000000
## 12 -184.37387  100.31231 0.0000000  0.00000 -116.06260  -9.082052
0.0000000
## 13 -213.21537  108.31070 0.0000000  0.00000 -126.87369  -8.555821
0.0000000
## 14 -286.05657  130.11651 0.0000000 18.63705 -154.12468  -7.272111
0.0000000
## 15 -309.32808  136.44430 0.0000000 23.44908 -166.25414 -10.463126
0.0000000
## 16 -312.95887  137.37273 0.3717955 24.12972 -168.09089 -11.038567
0.0000000
## 17 -313.19058  137.42593 0.3991982 24.16412 -168.19789 -11.074925 -
0.1120441
```

```
##     perc.alumni    Expend   Grad.Rate
## 0     0.000000    0.0000    0.000000
## 1     0.000000    0.0000    0.000000
## 2     0.000000    0.0000    0.000000
## 3     0.000000   97.7062    0.000000
## 4     0.000000  147.6031    0.000000
## 5     0.000000  154.7367    0.000000
## 6    -3.029819  156.1379    0.000000
## 7    -6.633261  160.8712    0.000000
## 8   -12.169565  193.3602    0.000000
## 9   -12.077931  201.7602    0.000000
## 10  -13.868335  217.0680    9.492627
## 11  -15.232503  232.1583   21.884916
## 12  -16.730465  254.4692   39.965940
## 13  -16.194739  260.9267   52.254455
## 14  -12.440556  276.5087   85.898496
## 15   -8.154701  285.7632  102.264835
## 16   -7.452478  287.2115  104.856871
## 17   -7.416487  287.2462  105.020853
```

```
# See what fraction was used in the lasso regression
lasso$bestTune$fraction
```

```
## [1] 0.8
```

```
# Plot the fractions to see how the fraction was chosen (minimum RMSE)
plot(lasso)
```



(e) Fit a PCR model on the training set, with no. of principal components M chosen by cross-validation.

Report the test mean squared error obtained, along with the value of M selected by cross-validation.

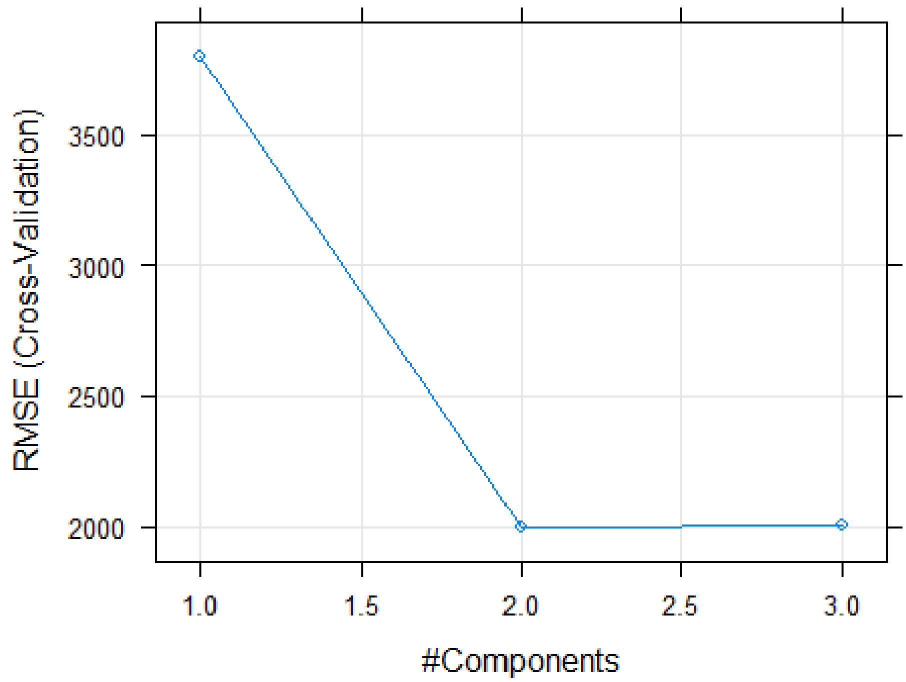
```
pcr_fit <- train(Apps ~., data=train1,
                 preProc = c('center', 'scale'),
                 method='pcr',
                 trControl=trctrl)
pcr_fit

## Principal Component Analysis
##
## 585 samples
##  17 predictor
##
## Pre-processing: centered (17), scaled (17)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 525, 526, 528, 525, 525, 526, ...
## Resampling results across tuning parameters:
##
##   ncomp  RMSE      Rsquared    MAE
##   1      3805.440  0.01645192  2585.426
##   2      1992.716  0.75646996  1297.173
##   3      2000.603  0.75407555  1312.703
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was ncomp = 2.

# Generate predictions with test dataset
pcr_pred <- predict(pcr_fit, test1)

# Calculate Mean Square Error (MSE)
pcr_mse <- mean(pcr_pred - test1$Apps)^2
pcr_mse

## [1] 35092.46

# See the coefficients of the regression
pcr_fit$finalModel$coefficients

## , , 1 comps
##
##                .outcome
## PrivateYes   29.495042
## Accept       -1.143878
## Enroll       -7.574264
## Top10perc    46.421089
```

```
## Top25perc    42.358269
## F.Undergrad -11.009675
## P.Undergrad -18.015828
## Outstate     51.955779
## Room.Board   39.793887
## Books         4.213103
## Personal    -22.830621
## PhD          34.234778
## Terminal     33.988896
## S.F.Ratio   -37.327140
## perc.alumni  40.258632
## Expend       46.885412
## Grad.Rate    40.424021
##
## , , 2 comps
##
##                .outcome
## PrivateYes  -460.68162
## Accept       652.47172
## Enroll       683.66489
## Top10perc    297.06783
## Top25perc    346.76339
## F.Undergrad  683.94502
## P.Undergrad  417.65542
## Outstate     -40.58215
## Room.Board    57.14744
## Books        175.76323
## Personal     265.54569
## PhD          454.86023
## Terminal     440.62044
## S.F.Ratio    139.05725
## perc.alumni  -96.85047
## Expend       171.49869
## Grad.Rate     26.33576
```

```
# See the number of principal components used in the regression
pcr_fit$bestTune$ncomp
```

```
## [1] 2
```

```
# Plot principal components vs RMSE to see how the no of components was
chosen
plot(pcr_fit)
```



(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 <- train(Apps ~., data=train1,
                 preProc = c('center', 'scale'),
                 method='kernelpls',
                 trControl=trctrl)
pls_fit

## Partial Least Squares
##
## 585 samples
##  17 predictor
##
## Pre-processing: centered (17), scaled (17)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 525, 528, 526, 526, 526, 527, ...
## Resampling results across tuning parameters:
##
##   ncomp  RMSE      Rsquared   MAE
##   1      1800.981  0.8093431  1165.4165
```

```
##   2      1415.929  0.8874875   801.8750
##   3      1347.589  0.8969791   801.1473
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was ncomp = 3.
```

```r
pls.pred <- predict(pls_fit, test1)

# Calculate Mean Square Error (MSE)
pls_fit_mse <-mean(pcr_pred - test1$Apps)^2
pls_fit_mse
```

```
## [1] 35092.46
```

```r
# Plot principal components vs RMSE to see how the no of components was
chosen
pls_fit$finalModel$coefficients
```

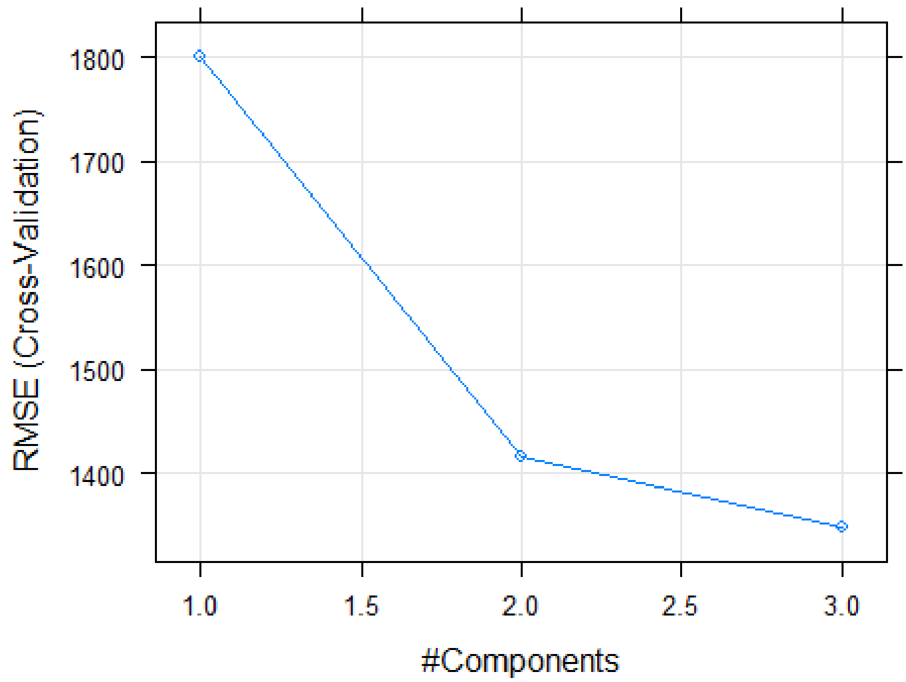
```
## , , 1 comps
##
##                 .outcome
## PrivateYes  -410.350479
## Accept       883.505125
## Enroll       774.103805
## Top10perc    298.515791
## Top25perc    323.306950
## F.Undergrad  743.040277
## P.Undergrad  353.787168
## Outstate       3.524867
## Room.Board   129.390197
## Books        135.726697
## Personal     196.589653
## PhD          349.585400
## Terminal     333.685650
## S.F.Ratio    113.301372
## perc.alumni -105.320445
## Expend       206.700110
## Grad.Rate    110.737131
##
## , , 2 comps
##
##                .outcome
## PrivateYes  -235.78288
## Accept      1712.81438
## Enroll      1006.09523
## Top10perc    167.91993
## Top25perc     91.62511
## F.Undergrad  861.49776
## P.Undergrad   85.48709
## Outstate      46.34354
## Room.Board   294.53788
```

```
## Books        -33.72818
## Personal     -41.53068
## PhD         -166.65869
## Terminal    -183.18808
## S.F.Ratio     76.51053
## perc.alumni -219.25455
## Expend       222.43450
## Grad.Rate    306.05485
##
## , , 3 comps
##
##                .outcome
## PrivateYes  -165.027643
## Accept      1879.814879
## Enroll       984.395684
## Top10perc    219.852877
## Top25perc    109.962439
## F.Undergrad  813.214636
## P.Undergrad   -2.954522
## Outstate     119.359042
## Room.Board   369.151457
## Books        -45.066065
## Personal    -112.849103
## PhD         -189.220502
## Terminal    -202.784951
## S.F.Ratio      7.853934
## perc.alumni -178.371574
## Expend       302.654354
## Grad.Rate    370.889345
```

```r
# See the number of principal components used in the regression
pls_fit$bestTune$ncomp
```

```
## [1] 3
```

```r
plot(pls_fit)
```

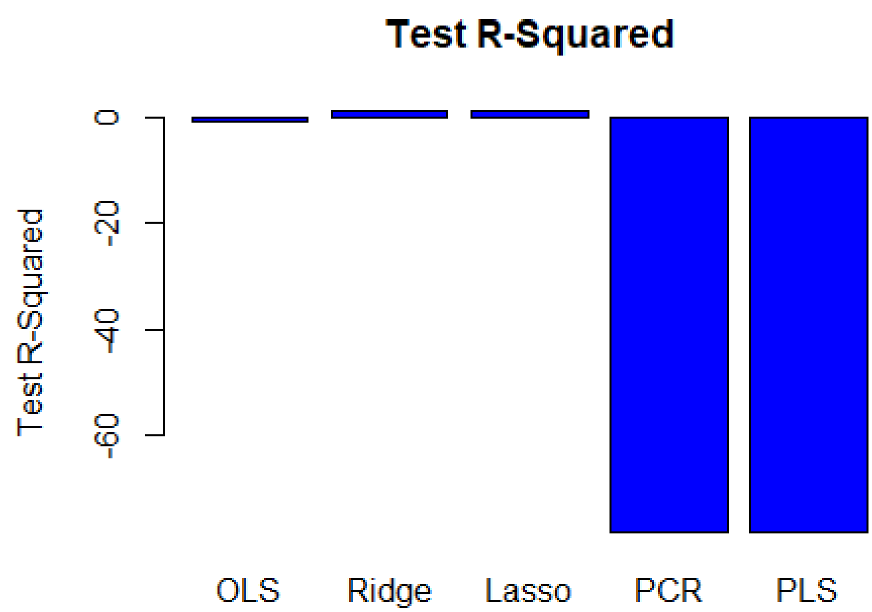


(g) Comment on the results obtained.

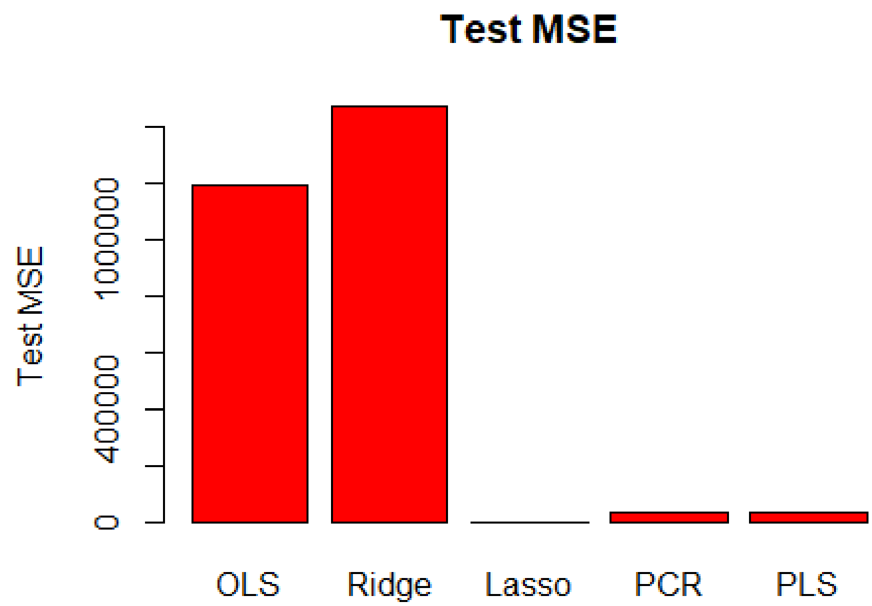
Is there much difference among the test errors resulting from these five approaches?

```
avg_test <- mean(test1[,"Apps"])

linear_r2 <- -1-mean((test1[,"Apps"]-ln_pred)^2)/mean((test1[,"Apps"]-
avg_test)^2)

ridge_r2 <- 1 - mean((test1[, "Apps"] -ridge_pred)^2) /mean((test1[, "Apps"]
- avg_test)^2)
lasso_r2 <- 1 - mean((test1[, "Apps"] -lasso_pred)^2) /mean((test1[, "Apps"]
- avg_test)^2)

pcr_r2 <- 1 - mean((test1[, "Apps"] -(pcr_mse))^2) /mean((test1[, "Apps"] -
avg_test)^2)

pls_r2 <- 1 - mean((test1[, "Apps"] -(pls_fit_mse))^2) /mean((test1[, "Apps"]
-avg_test)^2)

par(mfrow <- c(1,2))

## NULL
```

```r
barplot(c(linear_r2,ridge_r2,lasso_r2,pcr_r2,pls_r2),col="blue",
        names.arg = c("OLS","Ridge","Lasso","PCR","PLS"),main="Test R-Squared", ylab="Test R-Squared")
```




```r
barplot(c(ln_mse,ridge_mse, lasso_mse, pcr_mse, pls_fit_mse), col="red",

names.arg=c("OLS","Ridge", "Lasso", "PCR", "PLS"), main = "Test MSE", ylab = "Test MSE")
```



1.Load the Cars93 dataset in the MASS package in R

```
library(MASS)
data(Cars93)
attach(Cars93)
head(Cars93)

##   Manufacturer   Model    Type Min.Price Price Max.Price MPG.city
MPG.highway
## 1        Acura Integra   Small      12.9  15.9      18.8       25
31
## 2        Acura  Legend Midsize      29.2  33.9      38.7       18
25
## 3         Audi      90 Compact      25.9  29.1      32.3       20
26
## 4         Audi     100 Midsize      30.8  37.7      44.6       19
26
## 5          BMW    535i Midsize      23.7  30.0      36.2       22
30
## 6        Buick Century Midsize      14.2  15.7      17.3       22
31
##              AirBags DriveTrain Cylinders EngineSize Horsepower  RPM
## 1               None      Front         4        1.8        140 6300
## 2 Driver & Passenger      Front         6        3.2        200 5500
## 3        Driver only      Front         6        2.8        172 5500
## 4 Driver & Passenger      Front         6        2.8        172 5500
```

```
## 5        Driver only       Rear          4         3.5         208 5700
## 6        Driver only      Front          4         2.2         110 5200
##   Rev.per.mile Man.trans.avail Fuel.tank.capacity Passengers Length
Wheelbase
## 1         2890             Yes                13.2          5    177
102
## 2         2335             Yes                18.0          5    195
115
## 3         2280             Yes                16.9          5    180
102
## 4         2535             Yes                21.1          6    193
106
## 5         2545             Yes                21.1          4    186
109
## 6         2565              No                16.4          6    189
105
##   Width Turn.circle Rear.seat.room Luggage.room Weight  Origin
Make
## 1    68          37           26.5           11   2705 non-USA Acura
Integra
## 2    71          38           30.0           15   3560 non-USA  Acura
Legend
## 3    67          37           28.0           14   3375 non-USA       Audi
90
## 4    70          37           31.0           17   3405 non-USA      Audi
100
## 5    69          39           27.0           13   3640 non-USA      BMW
535i
## 6    69          41           28.0           16   2880     USA Buick
Century

cars_data <- na.omit(Cars93)
```

2.Run a principal component analysis on columns 4 through 8 in the dataset

```
cars_pca <- prcomp(cars_data[4:8], scale=TRUE)
summary(cars_pca)

## Importance of components:
##                           PC1    PC2     PC3     PC4      PC5
## Standard deviation     2.0045 0.9198 0.28510 0.23339 0.002231
## Proportion of Variance 0.8036 0.1692 0.01626 0.01089 0.000000
## Cumulative Proportion  0.8036 0.9728 0.98910 1.00000 1.000000

cars_pca$center

##   Min.Price       Price   Max.Price    MPG.city MPG.highway
##    16.82683    19.17073    21.51585    23.08537    29.97561
```

```r
# The scaling factor that was used to scale the variables
cars_pca$scale
```

```
##   Min.Price       Price   Max.Price    MPG.city MPG.highway 
##    8.921953    9.959318   11.446337    5.593650    5.011039
```

```r
# To see the eigen vectors (loadings for each variable for each PC)
cars_pca$rotation
```

```
##                    PC1        PC2          PC3         PC4           PC5
## Min.Price    0.4721737 -0.2602795 -0.756860888  0.07049906 -0.3626265737
## Price        0.4721263 -0.3510487  0.027649698 -0.00453180  0.8081314972
## Max.Price    0.4534056 -0.4075026  0.639508057 -0.06300006 -0.4641394246
## MPG.city    -0.4167658 -0.5698611  0.002012706  0.70820942 -0.0001597383
## MPG.highway -0.4181846 -0.5641094 -0.131994257 -0.69962830 -0.0001421337
```

```r
# To see the square root of the eigen values
cars_pca$sdev
```

```
## [1] 2.004548487 0.919797562 0.285098882 0.233391212 0.002231334
```

```r
# To see the rotated data (i.e the centered/scaled data multiplied by the
rotation matrix)
cars_pca$x
```

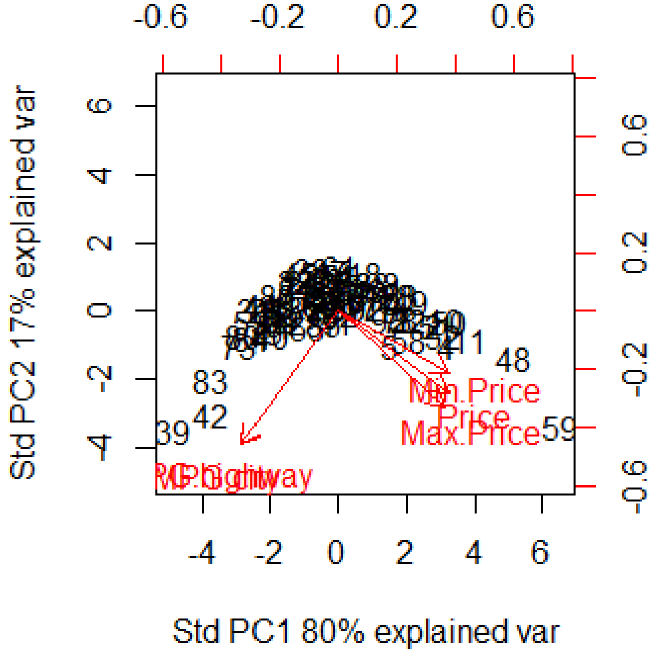
```
##            PC1         PC2         PC3           PC4           PC5
## 1  -0.69858943  0.01615709  0.14600836  0.0847955922  4.247297e-03
## 2   2.82788093 -0.41371802  0.08057144  0.0473127678 -4.234604e-03
## 3   1.93971012 -0.23673460 -0.03600106  0.1722480637 -1.668366e-04
## 4   3.16844579 -1.01883459  0.25904390  0.0127452685 -2.181258e-04
## 5   1.53760504 -0.99716825  0.26637670 -0.1722613299  3.967243e-03
## 6  -0.47516733  0.34431293 -0.04971220 -0.2764138097 -3.909529e-03
## 7   0.71642906  0.48496538 -0.19532057 -0.2188882064  2.967178e-06
## 8   1.59743162  0.83340417 -0.15958695 -0.1774620528 -4.007785e-03
## 9   1.58152961  0.05320129 -0.43962827 -0.0565204087 -3.304811e-04
## 10  3.12085802 -0.26357817 -0.37437438 -0.1630341927  3.606756e-03
## 11  3.86851278 -0.81304426 -0.38355474 -0.1651587508 -6.337031e-04
## 12 -1.48703209 -0.31242749  0.35268689 -0.6441696675  3.568628e-04
## 13 -1.53478066  0.14426208 -0.23169874 -0.3031324315  4.784595e-05
## 14 -0.09187560  1.04995010  0.06649467 -0.2406865680  3.653089e-04
## 15 -0.22303952  0.64846347  0.13248679 -0.1362552586  3.157684e-04
## 18  0.75380027  1.11455240 -0.10505909 -0.1954174133  2.077278e-04
## 20  0.31804725  0.62892793 -0.25874818 -0.0848761905  9.304125e-06
## 21 -0.28662115  0.57500004 -0.00667607  0.2724738004  1.778741e-04
## 22  2.03828202 -0.25617326 -0.49671953  0.2159234186 -4.913652e-04
## 23 -2.07056635  0.05746204  0.04218692  0.3206712304 -3.858780e-03
## 24 -1.02110001  0.90224205  0.30993768  0.1026647834  5.277031e-04
## 25 -0.47984162  1.03886281  0.09883728  0.2792841838  3.698491e-04
## 27 -0.07548687  0.91454480 -0.04616873  0.1651864436  2.258265e-04
## 28  1.73925252  0.49588297  0.67924674  0.1368893053  5.027852e-04
## 29 -1.69464255 -0.25832947  0.38014933  0.2868328355  3.309032e-04
```

```
## 30  0.42399373  0.52377695 -0.02346508 -0.1078083542 -3.919558e-03
## 31 -2.46478362  0.04245206 -0.02810870  0.5816682710  1.533007e-04
## 32 -1.25254553  0.91384925  0.15176422 -0.0237475159 -3.609484e-03
## 33 -0.75306516  1.24212158  0.08085644  0.2821014909  4.227120e-04
## 34 -0.33215577  0.52987370  0.49867026 -0.0445005467  5.345706e-04
## 35 -0.77859359  0.42865995 -0.02593491  0.1176920775  1.734638e-04
## 37  0.26729435  0.09229487  0.28902383 -0.2956707335  2.712657e-04
## 38  0.97316645  0.80262907 -0.15968763 -0.0647280554  7.371709e-05
## 39 -4.88107845 -3.50361720 -0.33343352  0.0937215038  3.361621e-03
## 40 -1.93359847 -0.70671952 -0.17068306  0.0394117594 -1.117671e-04
## 41 -0.06773357 -0.27788816  0.02656105 -0.0326567835 -4.048849e-03
## 42 -3.75412489 -3.03231728 -0.03940443  0.1255794949 -4.611339e-04
## 43 -0.40553590 -0.05006207  0.20783065 -0.0486398958  2.071891e-04
## 44 -2.24112387  0.18169177  0.05395169  0.3202308692  2.468820e-04
## 45 -1.10322311  1.14636111  0.07628560 -0.0009995234  4.407784e-04
## 46 -1.81322203  0.17307141 -0.06246174 -0.1918583021 -3.879701e-03
## 47 -0.25215625  1.18551956  0.09088981  0.0264405981  4.461264e-03
## 48  5.13722378 -1.35673203 -0.52248544  0.3967972381 -9.783664e-04
## 49  2.13367512  0.32310578 -0.34071669  0.2328725715  3.800287e-03
## 50  3.22469282 -0.28448166 -0.50290750  0.3864779498  3.467096e-03
## 51  2.92020159 -0.43707937 -0.48278526 -0.1679855885 -5.515926e-04
## 52  3.08826801 -0.72349574 -0.43106734 -0.0472630535 -6.039417e-04
## 53 -2.53292048 -0.29311970 -0.10706401 -0.2330838747  4.144736e-03
## 54 -1.90653683 -0.41101810 -0.19004668 -0.2115340985 -3.800002e-05
## 55 -0.92488051 -0.48187030 -0.05533899 -0.1961073019 -2.750871e-05
## 58  2.08913743 -0.85614879 -0.22496438 -0.2376931200 -4.475992e-03
## 59  6.48935020 -3.39879761  1.22756499  0.0492339085 -3.394412e-04
## 60 -0.34699631  0.96983867  0.02575602  0.5545583847 -3.782516e-03
## 61  0.06967101  1.30602920 -0.11477934  0.0609494113  2.703455e-04
## 62 -1.93789860 -0.05735908  0.19070831  0.3059312620  2.645786e-04
## 63  1.83311612  0.48545771  0.17045320  0.1851822688 -3.909694e-03
## 64 -1.73464486 -0.21060668  0.22178162  0.3021425690  2.368237e-04
## 65 -0.56462434  0.25253978  0.13501580  0.1014366318  4.285720e-03
## 67  0.83760275  0.43891485 -0.21652955  0.3202879289 -7.062521e-05
## 68 -0.92269817  0.37059752 -0.13767412 -0.0135127374  1.036109e-04
## 69 -0.47765843  0.18212629  0.01377049 -0.1561316359  1.437843e-04
## 71  0.69844172  0.49303915 -0.15049166 -0.2231041942  3.653023e-05
## 72 -0.67207110  0.47895667  0.21649383 -0.0322706140  3.531832e-04
## 73 -2.90853398 -1.02365896 -0.23293274 -0.5367347614 -4.180333e-03
## 74 -1.20001976  0.70481369  0.09365158 -0.1608717692  3.668522e-04
## 75  0.24534478  0.77703562  0.27981665 -0.2624467648  4.250237e-04
## 76  0.44873589  0.81344802  0.20078856 -0.1132317058  3.561321e-04
## 77  1.16563535  0.09852933  0.28728944 -0.2668576052  2.122562e-04
## 78  1.81451566 -0.23015236  0.70612022  0.1017613050  3.479684e-04
## 79 -2.16334665 -0.59030735 -0.06638094 -0.5072767723  4.099462e-03
## 80 -2.81565541 -0.71547341 -0.07451594  0.2703170145 -1.040308e-05
## 81 -1.27626423  0.64199531 -0.05696292  0.2490035828  2.244657e-04
## 82  0.03895853 -0.03244286  0.11109096 -0.0250436175  1.161092e-04
## 83 -3.73412636 -2.02702223 -0.20191090  0.1894267330 -4.397862e-03
## 84 -2.55721319 -0.75941363  0.01509660  0.1343622267  3.347597e-05
```

```
## 85 -0.44420554 -0.35774604  0.22863403 -0.0666021354  1.526426e-04
## 86  0.01765895  0.31332158  0.14297196 -0.0118801972  2.192836e-04
## 88 -1.77851353  0.48431549 -0.08885214 -0.1733456675  2.297622e-04
## 90  0.26859123  0.12644140 -0.01528227 -0.2665667437  7.200484e-05
## 91  1.39779865  0.67772010 -0.25247133  0.0849142983 -5.649245e-05
## 92  0.82933924  0.09473021 -0.24993932  0.0385725289  3.905359e-03
## 93  1.45029326 -0.20991090 -0.21433746 -0.0936716221  3.828190e-03
```

3.Plot the biplot

```
biplot(cars_pca,xlab="Std PC1 80% explained var",ylab="Std PC2 17% explained
var", scale=0)
```

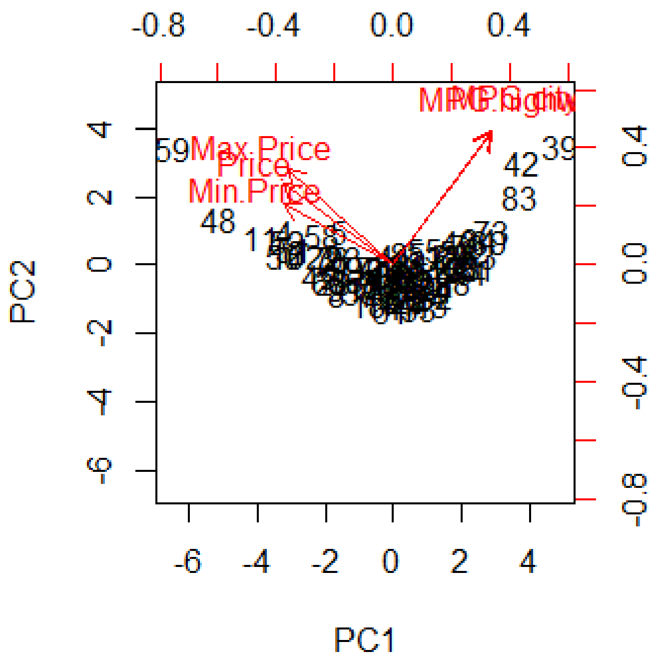


4.Calculate the percent of variance explained

```
cars_pca$sdev

## [1] 2.004548487 0.919797562 0.285098882 0.233391212 0.002231334

cars_var <- cars_pca$sdev^2
cars_var

## [1] 4.018215e+00 8.460276e-01 8.128137e-02 5.447146e-02 4.978852e-06

cars_ve <- cars_var/sum(cars_var)
cars_ve
```

```
## [1] 8.036429e-01 1.692055e-01 1.625627e-02 1.089429e-02 9.957703e-07
```

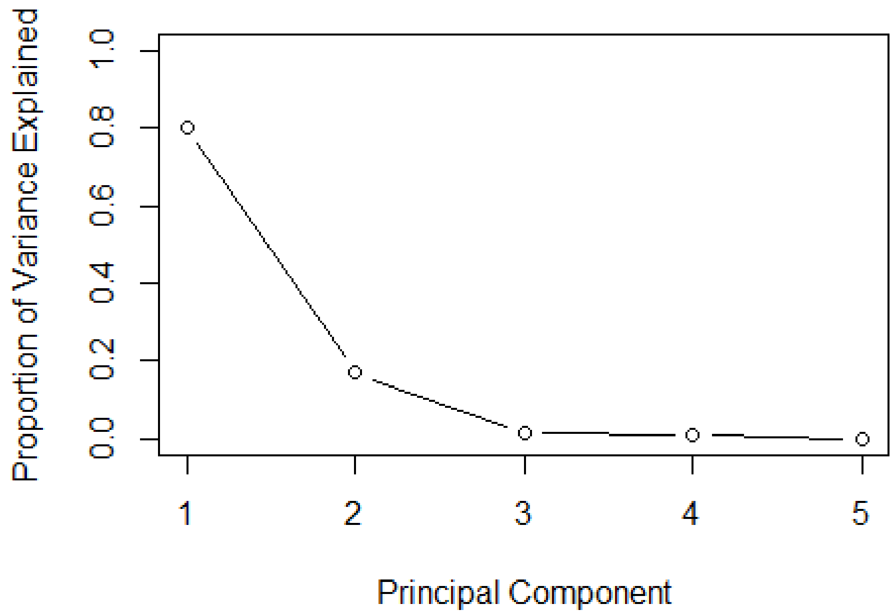
```r
# Change the direction of the plot.  Does not alter the values.
cars_pca$rotation=-cars_pca$rotation
cars_pca$x=-cars_pca$x
biplot(cars_pca, scale=0)
```



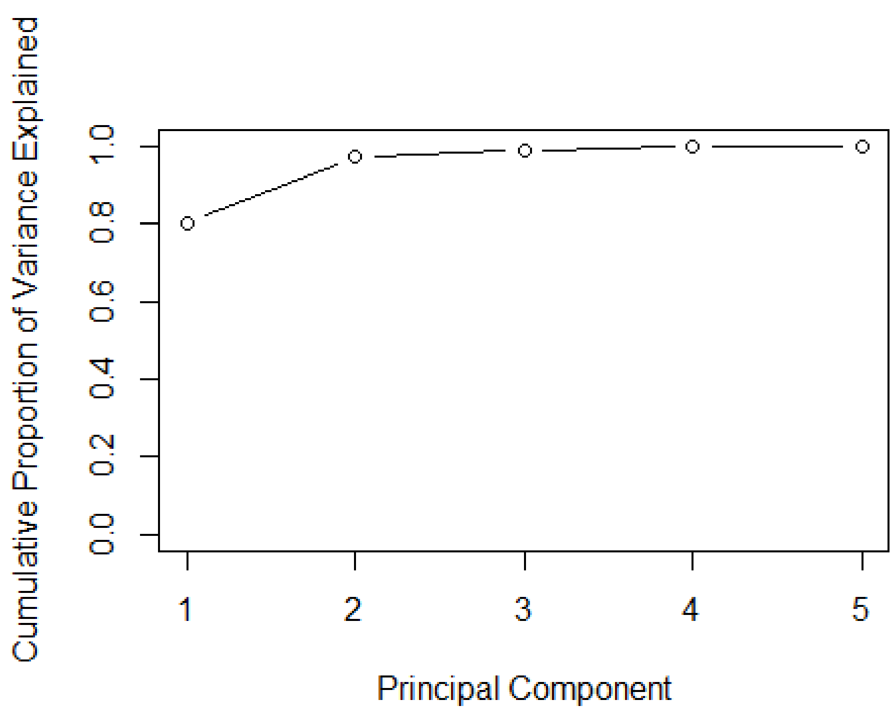
5.Plot the percent of variance explained

Compute percentage variance explained

```r
plot(cars_ve, xlab="Principal Component", ylab="Proportion of Variance
Explained", ylim=c(0,1),type='b')
```




```r
# Compute percentage variance explained
plot(cumsum(cars_ve), xlab="Principal Component", ylab="Cumulative Proportion
of Variance Explained", ylim=c(0,1),type='b')
```



6.How much of the variance does the first two principal components explain?

```
summary(cars_pca)

## Importance of components:
##                           PC1    PC2     PC3     PC4      PC5
## Standard deviation     2.0045 0.9198 0.28510 0.23339 0.002231
## Proportion of Variance 0.8036 0.1692 0.01626 0.01089 0.000000
## Cumulative Proportion  0.8036 0.9728 0.98910 1.00000 1.000000
```