Homework 4

```r
library("GGally")

library("DAAG")

library(tree)
library(randomForest)

library(pROC)

set.seed(1234)
```

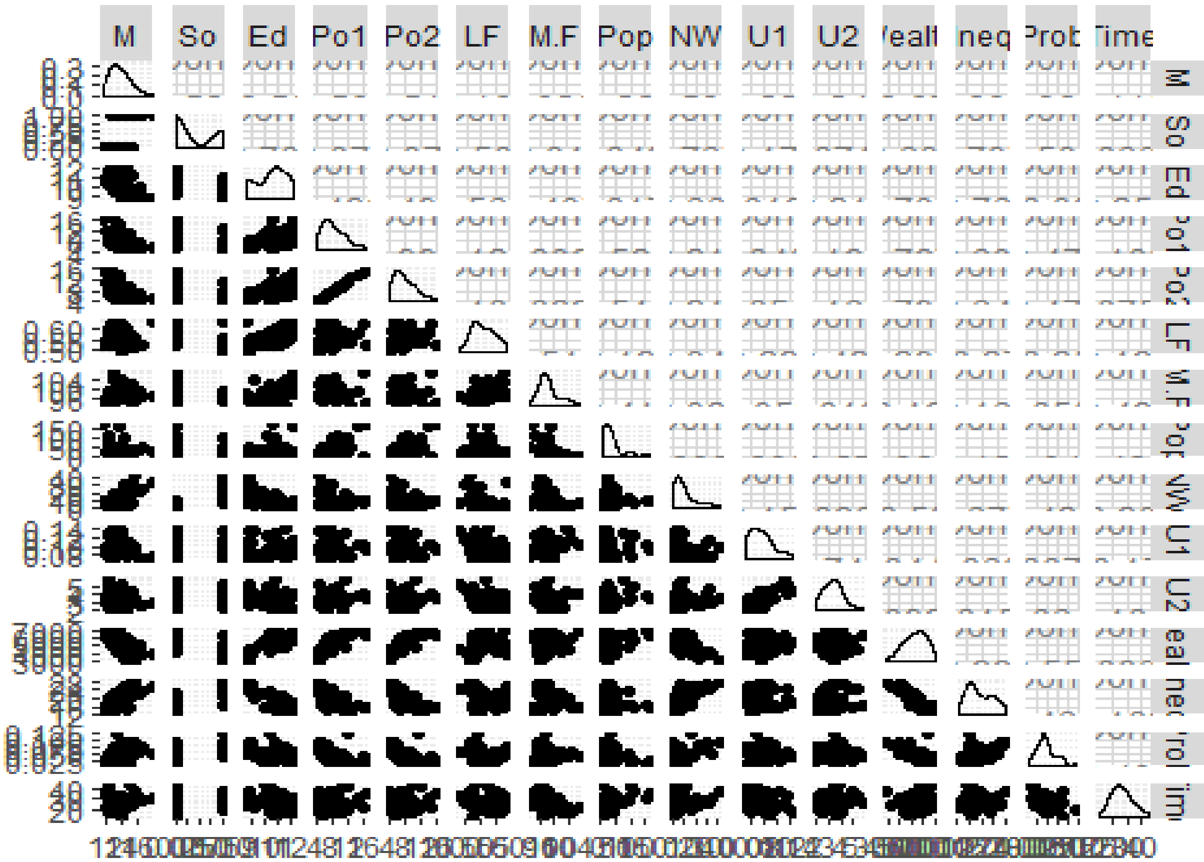
Question 9.1

Using the same crime data set uscrime.txt as in Question 8.2, apply Principal Component Analysis and then create a regression model using the first few principal components. Specify your new model in terms of the original variables (not the principal components), and compare its quality to that of your solution to Question 8.2. You can use the R function prcomp for PCA.

```r
crime<-
read.table("http://www.statsci.org/data/general/uscrime.txt",header=TRUE)
head(crime)

##      M So   Ed  Po1  Po2    LF   M.F Pop   NW    U1  U2 Wealth Ineq
## 1 15.1  1  9.1  5.8  5.6 0.510  95.0  33 30.1 0.108 4.1   3940 26.1
## 2 14.3  0 11.3 10.3  9.5 0.583 101.2  13 10.2 0.096 3.6   5570 19.4
## 3 14.2  1  8.9  4.5  4.4 0.533  96.9  18 21.9 0.094 3.3   3180 25.0
## 4 13.6  0 12.1 14.9 14.1 0.577  99.4 157  8.0 0.102 3.9   6730 16.7
## 5 14.1  0 12.1 10.9 10.1 0.591  98.5  18  3.0 0.091 2.0   5780 17.4
## 6 12.1  0 11.0 11.8 11.5 0.547  96.4  25  4.4 0.084 2.9   6890 12.6
##       Prob    Time Crime
## 1 0.084602 26.2011   791
## 2 0.029599 25.2999  1635
## 3 0.083401 24.3006   578
## 4 0.015801 29.9012  1969
## 5 0.041399 21.2998  1234
## 6 0.034201 20.9995   682
```

Check out if there are correlations between the predictors

```r
names(crime)

##  [1] "M"      "So"     "Ed"     "Po1"    "Po2"    "LF"     "M.F"
##  [8] "Pop"    "NW"     "U1"     "U2"     "Wealth" "Ineq"   "Prob"
## [15] "Time"   "Crime"

ggpairs(crime,columns=c("M","So","Ed","Po1","Po2","LF","M.F","Pop","NW","U1",
"U2","Wealth","Ineq","Prob","Time"))
```



There are correlations between Po1 vs Po2, Wealth vs Ed/Po1/Po2/Ineq . So PCA is a good choose.

Remove the response variable (it's in the 16th column)

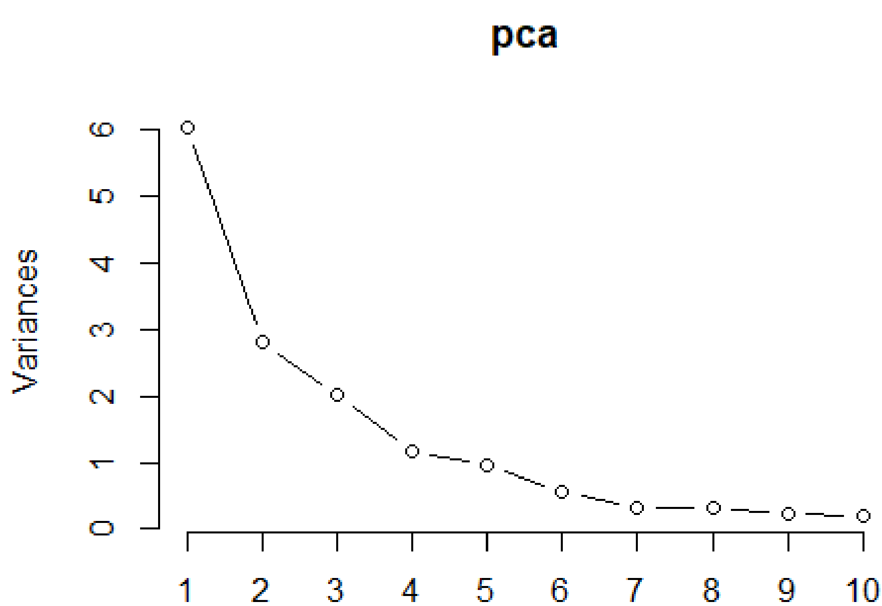
```
vars<-crime[-16]
pca<-prcomp(vars, scale = TRUE)
summary(pca)

## Importance of components:
##                           PC1    PC2    PC3     PC4     PC5     PC6
## Standard deviation     2.4534 1.6739 1.4160 1.07806 0.97893 0.74377
## Proportion of Variance 0.4013 0.1868 0.1337 0.07748 0.06389 0.03688
## Cumulative Proportion  0.4013 0.5880 0.7217 0.79920 0.86308 0.89996
##                            PC7     PC8     PC9    PC10    PC11    PC12
## Standard deviation     0.56729 0.55444 0.48493 0.44708 0.41915 0.35804
## Proportion of Variance 0.02145 0.02049 0.01568 0.01333 0.01171 0.00855
## Cumulative Proportion  0.92142 0.94191 0.95759 0.97091 0.98263 0.99117
##                           PC13   PC14    PC15
## Standard deviation     0.26333 0.2418 0.06793
## Proportion of Variance 0.00462 0.0039 0.00031
## Cumulative Proportion  0.99579 0.9997 1.00000
```

Get the eigenvector of the matrix

```
eigen<-pca$rotation
```

Use the screeplot to plot the variance of each princpal component

```
screeplot(pca,type="line",col="black")
```



Get the first 4 pc

pc<-pca$x[,1:4]

Fit a linear regression model with the these 4 pc

```
crimepc<-as.data.frame(cbind(pc1,crime$Crime))
```

```
modelpca<-lm(V5~.,crimepc)
```

```
summary(modelpca)
```

```
Call:
lm(formula = V5 ~ ., data = crimepc)

Residuals:
```

```
    Min      1Q  Median      3Q     Max 
-557.76 -210.91  -29.08  197.26  810.35 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   905.09      49.07  18.443  < 2e-16 ***
PC1            65.22      20.22   3.225  0.00244 ** 
PC2           -70.08      29.63  -2.365  0.02273 *  
PC3            25.19      35.03   0.719  0.47602    
PC4            69.45      46.01   1.509  0.13872    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 336.4 on 42 degrees of freedom
Multiple R-squared:  0.3091,	Adjusted R-squared:  0.2433 
F-statistic: 4.698 on 4 and 42 DF,  p-value: 0.003178
```

Get the parameters for the original model, scaled

beta0<-modelpca$coefficients[1]

betas<-modelpca$coefficients[2:5]

Coefficents equals beta times eigenvector matrix

alpha<-eigen[,1:4] %*% betas

alpha

```
             [,1]
M      -21.277963
So      10.223091
Ed      14.352610
Po1     63.456426
Po2     64.557974
LF     -14.005349
M.F    -24.437572
Pop     39.830667
NW      15.434545
U1     -27.222281
U2       1.425902
Wealth  38.607855
Ineq   -27.536348
Prob     3.295707
Time    -6.612616
```

```
mean <- sapply(vars, mean)
sd <- sapply(vars, sd)
```

Get the un-scaled coefficents for each input

```
alpha_org<- alpha/sd
```

Get the un-scaled intercept

```
beta_org <-beta0-sum(alpha* mean/sd)
point<-data.frame(
 M = 14.0,
 So = 0,
 Ed = 10.0,
 Po1 = 12.0,
 Po2 = 15.5,
 LF = 0.640,
 M.F = 94.0,
 Pop = 150,
 NW = 1.1,
 U1 = 0.120,
 U2 = 3.6,
 Wealth = 3200,
 Ineq = 20.1,
 Prob = 0.04,
 Time = 39.0
)

predict<-beta_org+sum(alpha_org*point)
```

Cross validate the model

rate<-crime[,16]

PClist <- as.data.frame(pca$x[, 1:4])

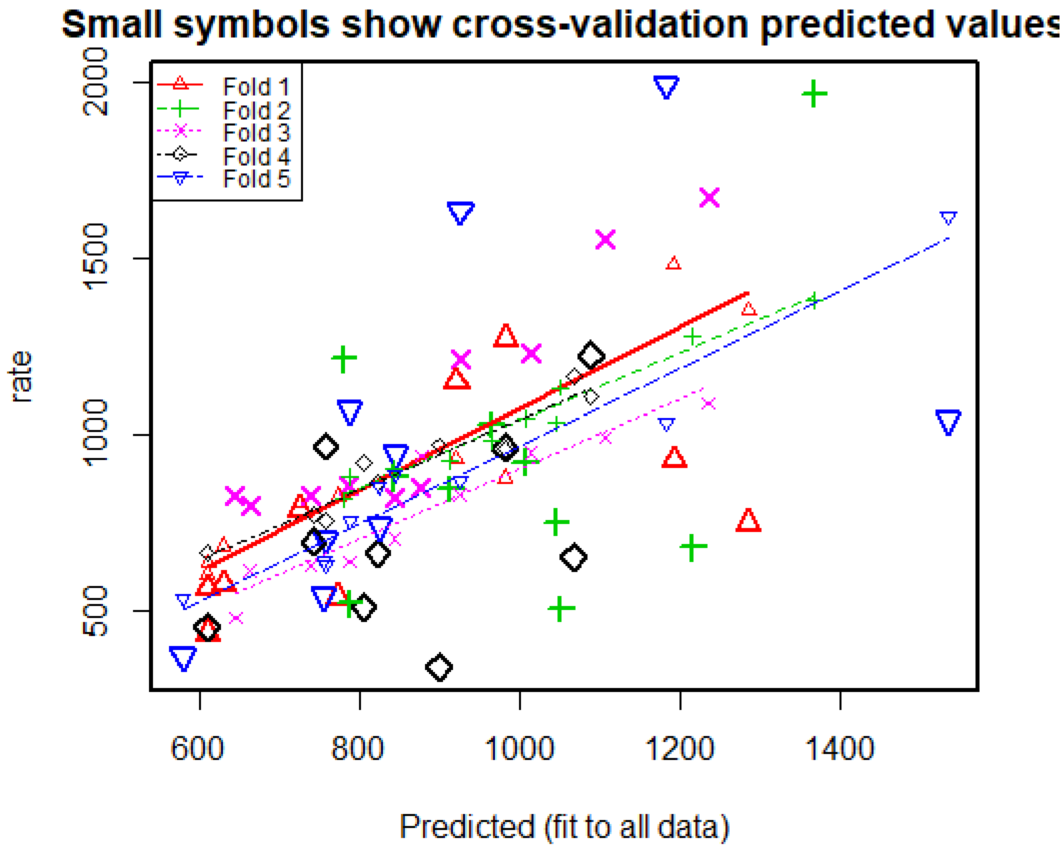
PC<-cbind(rate, PClist)

model2 <- lm(rate ~ ., PC)

cv <-cv.lm(PC, model2, m = 5)

```
Analysis of Variance Table

Response: rate
          Df  Sum Sq Mean Sq F value Pr(>F)
PC1        1 1177568 1177568   10.40 0.0024 **
PC2        1  633037  633037    5.59 0.0227 *
PC3        1   58541   58541    0.52 0.4760
PC4        1  257832  257832    2.28 0.1387
Residuals 42 4753950  113189
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1



fold 1
Observations in test set: 9
                1    3   17   18   19   22   36    38   40
Predicted   726.3  630  774 1192 1286  612  982 610.7  922
cvpred      806.4  687  828 1483 1355  638  879 606.3  935
rate        791.0  578  539  929  750  439 1272 566.0 1151
CV residual -15.4 -109 -289 -554 -605 -199  393 -40.3  216

Sum of squares = 1010591    Mean square = 112288    n = 9

fold 2
Observations in test set: 10
               4    6    12   25   28   32   34    41     44   46
Predicted   1368 1216 913.8  788  781 1046 1007 843.8  965.3 1051
cvpred      1381 1282 929.4  881  817 1033 1046 906.3  982.7 1134
rate        1969  682 849.0  523 1216  754  923 880.0 1030.0  508
CV residual  588 -600 -80.4 -358  399 -279 -123 -26.3   47.3 -626

Sum of squares = 1487411    Mean square = 148741    n = 10

fold 3
Observations in test set: 10
               5    8   9   11  15   23  37  39  43    47
Predicted   1014 1107 788 1236 664  926 646 739 845 878.1
cvpred       950  992 642 1090 615  831 481 629 707 942.3
```

```
rate        1234 1555 856 1674 798 1216 831 826 823 849.0
CV residual  284  563 214  584 183  385 350 197 116 -93.3

Sum of squares = 1149649    Mean square = 114965    n = 10

fold 4
Observations in test set: 9
                  7   13   14   20  24   27    30   35   45
Predicted   982.362  806  824 1089 758  900 743.3 1067  610
cvpred      963.673  923  865 1110 757  971 774.4 1167  665
rate        963.000  511  664 1225 968  342 696.0  653  455
CV residual  -0.673 -412 -201  115 211 -629 -78.4 -514 -210

Sum of squares = 977599    Mean square = 108622    n = 9

fold 5
Observations in test set: 9
               2    10    16   21   26   29   31   33   42
Predicted    927 758.2 845.0  825 1183 1535  580  790  757
cvpred       873 634.6 889.8  852 1036 1620  535  758  643
rate        1635 705.0 946.0  742 1993 1043  373 1072  542
CV residual  762  70.4  56.2 -110  957 -577 -162  314 -101

Sum of squares = 1986093    Mean square = 220677    n = 9

Overall (Sum over all 9 folds)
    ms
140667
Warning message:
In cv.lm(PC, model2, m = 5) :

 As there is >1 explanatory variable, cross-validation
 predicted values for a fold are not a linear function
 of corresponding overall predicted values.  Lines that
 are shown for the different folds are approximate
```



mn<- mean(rate)

R2 <- 1 - attr(cv, "ms") * nrow(crime) / sum((rate - mn) ^ 2)

R2

```
[1] 0.0392
```

In conclusion, the model generated by the PCA method is:

Crime=1666.485-16.9307630*M+21.3436771*So+12.8297238*Ed +21.3521593*Po1+23.0883154*Po2

-346.5657125*LF-8.2930969*M.F+1.0462155*Pop+1.5009941*NW-1509.9345216*U1+1.6883674*U2

+0.0400119*Wealth-6.9020218*Ineq+144.9492678*Prob-0.9330765*Time

The adjusted R-square of this model is 0.2433, cross-validated R-square is 0.0392,which is pretty low. The crime rate for the city with given data is 1112.678

Compared to my model for question 8.2, with predictors, Ed, Po1, M.F, U1,U2,Ineq,Prob, and R-square: 0.7444, and crime rate: 1038.296,

My conclusion is, adding more principle components to the model may be helpful (currently we used first 4 components). Although PCA method addressed for the correlations between the predictors and ranked the coordinates by importance, it didn't address for the over fitting, which is a big issue in our data.

Question 10.1

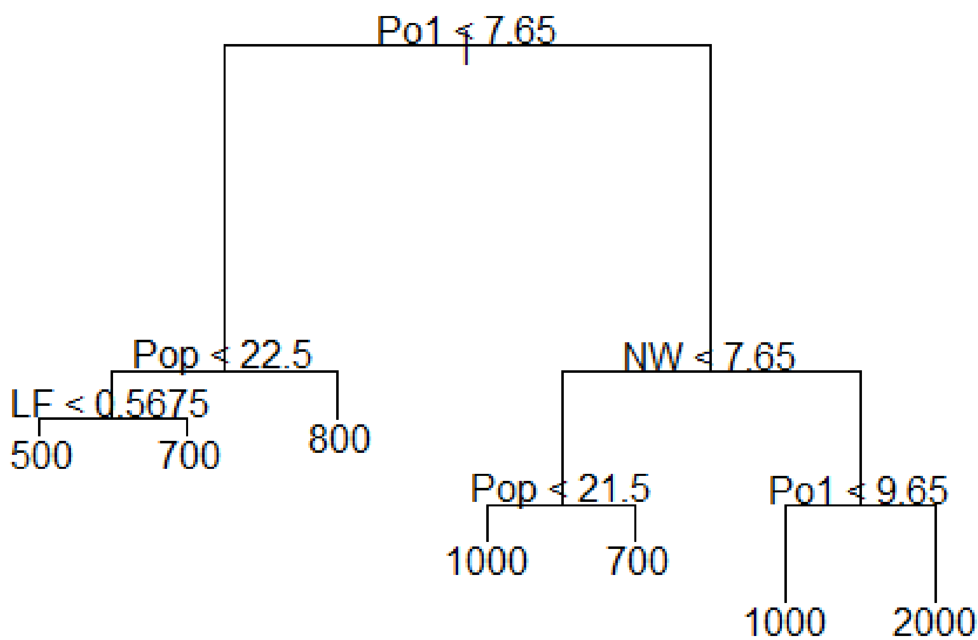
Using the same crime data set uscrime.txt as in Questions 8.2 and 9.1, find the best model you can using

(a) a regression tree model, and

(b) a random forest model.

(a) a regression tree model

```
fita<-tree(Crime~.,data=crime)

plot(fita)

text(fita)
```



summary(fita)

```
Regression tree:
tree(formula = Crime ~ ., data = crime)
Variables actually used in tree construction:
[1] "Po1" "Pop" "LF"  "NW"
Number of terminal nodes:  7
Residual mean deviance:  47400 = 1900000 / 40
Distribution of residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   -574     -98      -2       0     111     490
```

Since we only have 47 data points for the crime data. I used the whole dataset to fit the tree model, instead of half of them.

From the summary, I found that only "Po1" "Pop" "LF" "NW" are used in the construction of the tree. There are 7 terminal nodes.

Check out how the tree was split

fita$frame

```
      var  n     dev yval splits.cutleft splits.cutright
1      Po1 47 6880928  905          <7.65           >7.65
2      Pop 23  779243  670          <22.5           >22.5
4       LF 12  243811  550        <0.5675         >0.5675
8   <leaf>  7   48519  467
9   <leaf>  5   77757  668
5   <leaf> 11  179471  800
3       NW 24 3604163 1131          <7.65           >7.65
6      Pop 10  557575  887          <21.5           >21.5
12 <leaf>  5  146391 1049
13 <leaf>  5  147771  725
7      Po1 14 2027225 1305          <9.65           >9.65
14 <leaf>  6  170828 1041
15 <leaf>  8 1124985 1503
```

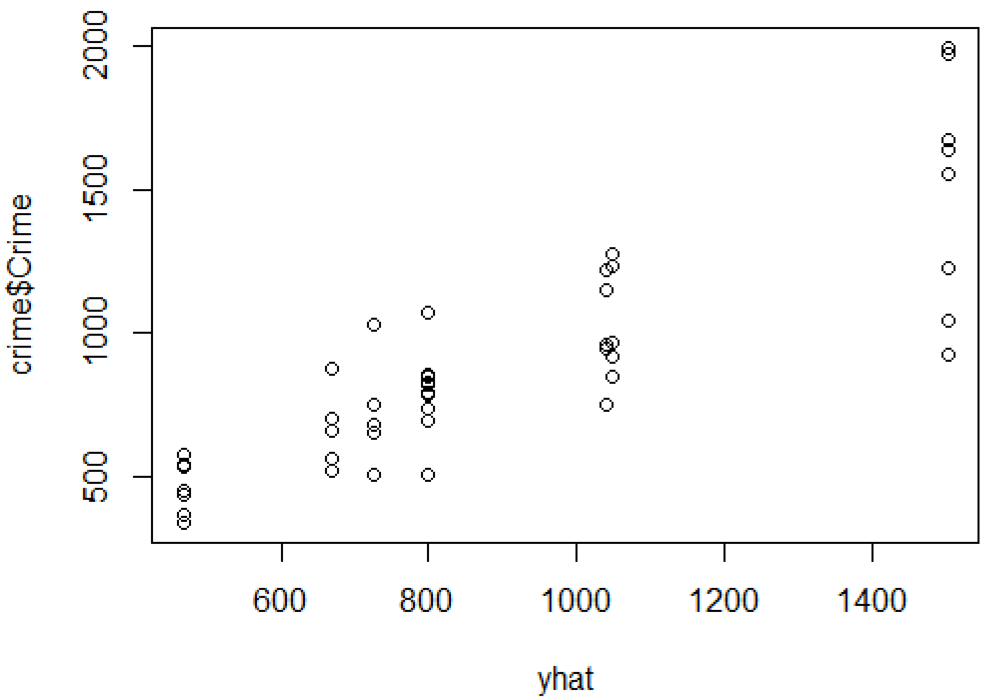
fita$where

```
1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27
6 13  4 13  9 10 12 13  6  5 13  6  6  5  6 12  4 13 10 13  6  4 12  9  5 13  4
28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
12 13  6  4 12  6  9 10  9  6  5  6 12  5  4  6 10  4 10  9
```

Manually calculate R square to see how it fits

yhat<-predict(fita)

plot(yhat,crime$Crime)



sse<-sum((yhat - crime$Crime) ^ 2)

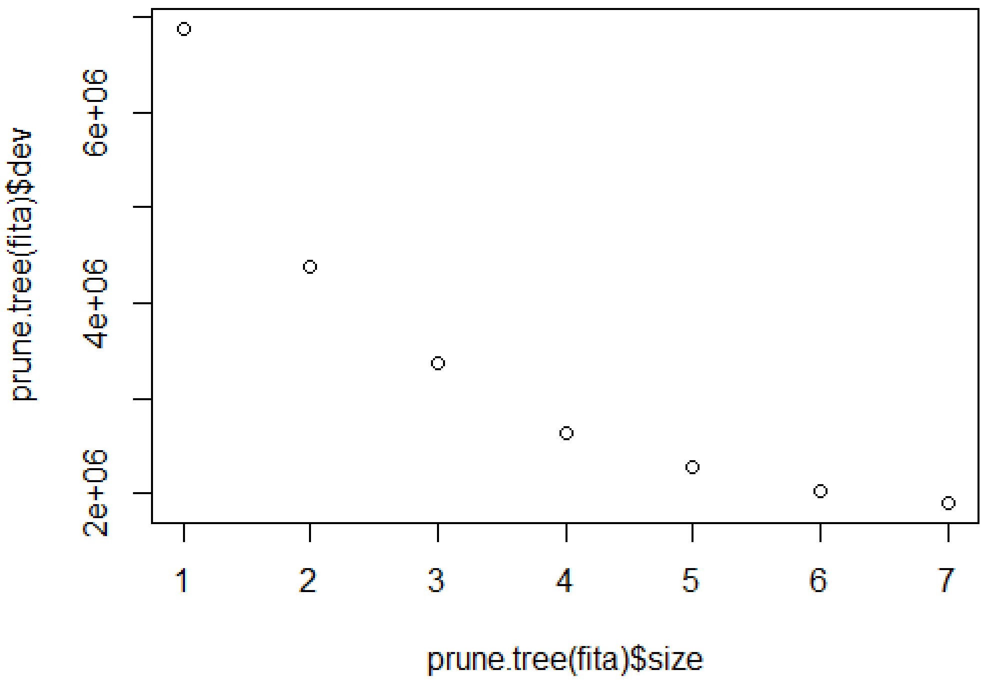
sst<-sum((crime$Crime - mean(crime$Crime)) ^ 2) #total sum of squares

1 - sse / sst

```
[1] 0.724
```

Prune tree

plot(prune.tree(fita)$size,prune.tree(fita)$dev)

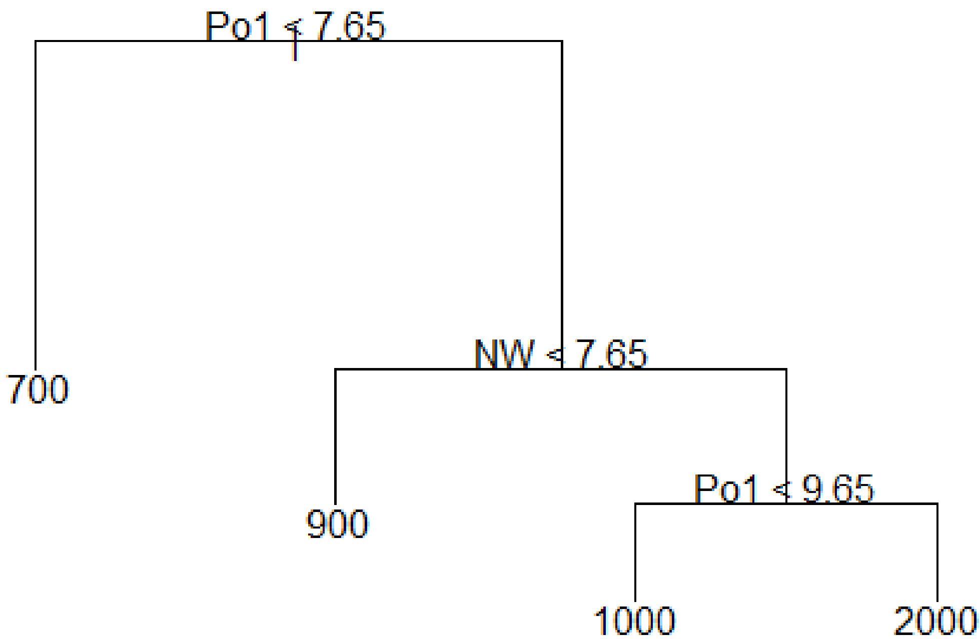


Prune tree to 4 leaves is desired

fit4<-prune.tree(fita,best=4)

plot(fit4)

text(fit4)



summary(fit4)

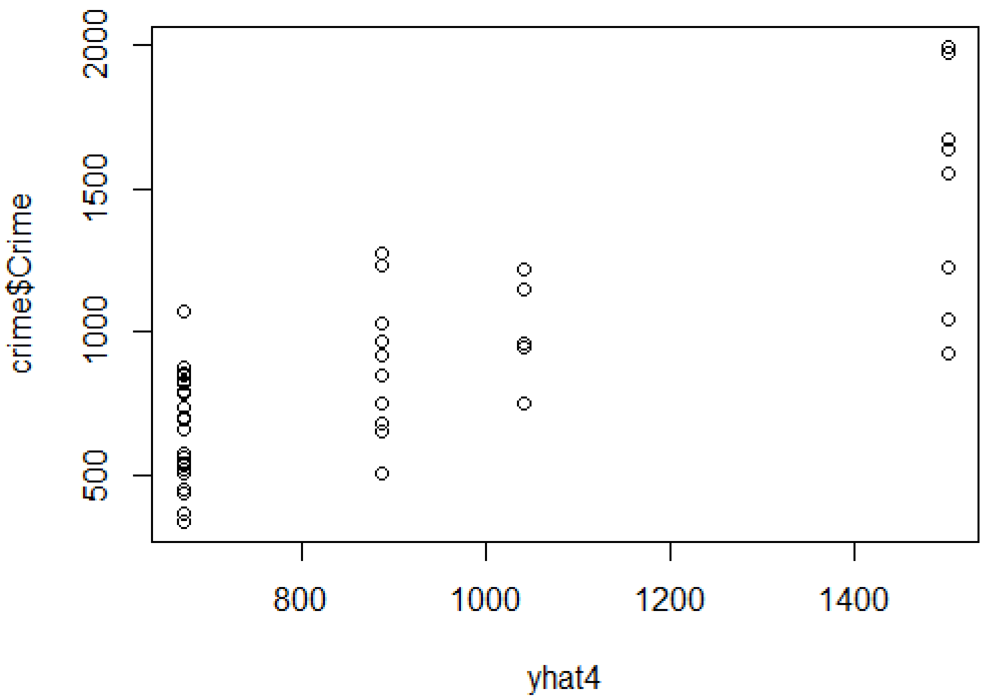
```
Regression tree:
snip.tree(tree = fita, nodes = c(6L, 2L))
Variables actually used in tree construction:
[1] "Po1" "NW"
Number of terminal nodes:  4
Residual mean deviance:  61200 = 2630000 / 43
Distribution of residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   -574    -153      35       0     159     490
```

Now Only po1 and NW was included, the residual mean deviance is 61220.

Calculate R square

yhat4<-predict(fit4)

plot(yhat4,crime$Crime)



sse4<-sum((yhat4 - crime$Crime) ^ 2)

sst4<-sum((crime$Crime - mean(crime$Crime)) ^ 2) #total sum of squares

1 - sse4 / sst4

```
[1] 0.617
```

The R square dropped from 0.7244962 to 0.6174017, which was expected, because we have fewer predictors left in the model.

Now do a cross validate on the pruned tree

cv<-cv.tree(fit4)

cv$dev

```
[1] 6247077 7117073 6105515 8367604
```

cv$size

```
[1] 4 3 2 1
```

The deviance becomes 7608563, even larger, indicating our model is not a good fit.

(b) Random forest model

Set the number of predictors at each split of the tree to be 4 (mtry=4),which is calculated based 1+log(n)=1+log(16)=4

rf <- randomForest(Crime ~ ., data=crime, mtry=4,importance=TRUE, na.action=na.omit)

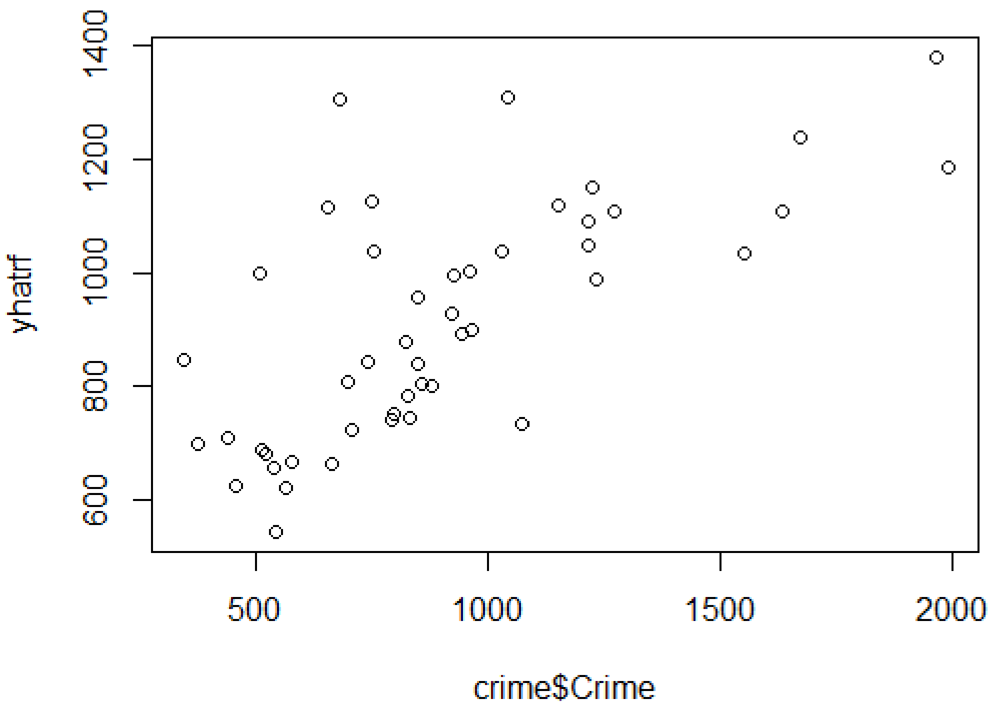
rf

```
Call:
 randomForest(formula = Crime ~ ., data = crime, mtry = 4, importance = TRUE, 
na.action = na.omit)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 4

          Mean of squared residuals: 79589
                    % Var explained: 45.6
```

Plot of actual vs. predicted crime values

yhatrf <- predict(rf)

plot(crime$Crime, yhatrf)



Calculate sum of square error-resdiduals

SSres <- sum((yhatrf-crime$Crime)^2)

Calculate sum of square error-total and R-squared

SStot <- sum((crime$Crime - mean(crime$Crime))^2)

rs <- 1 - SSres/SStot

rs

```
[1] 0.456
```

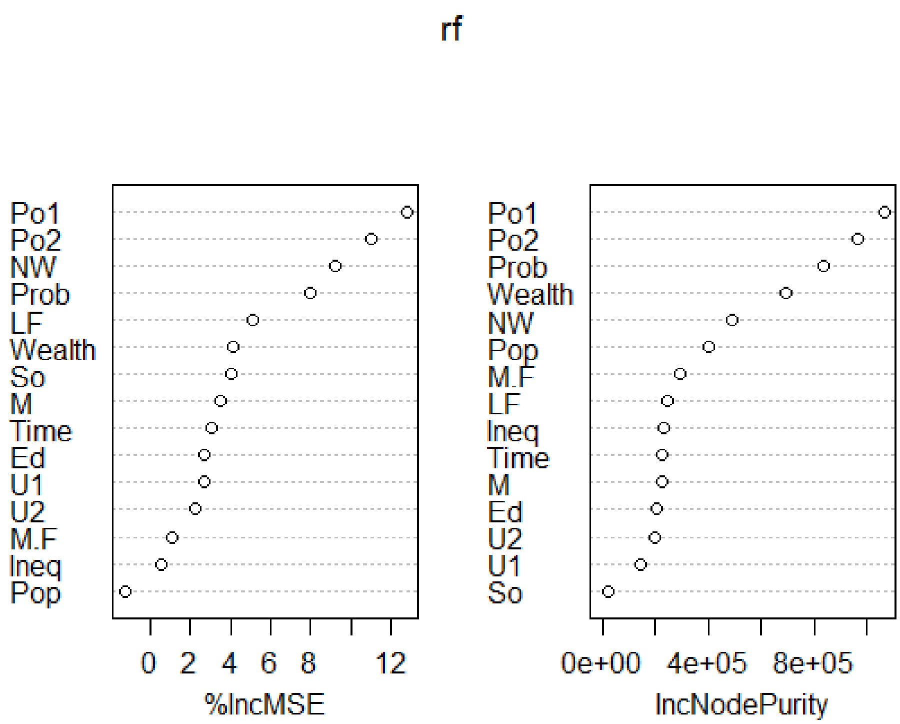
This model is slightly better than the previous model.But it is not a real model. Iit is the average of all the different trees, which is better than just one tree.

variable importance

```
round(importance(rf), 2)
```

```
       %IncMSE IncNodePurity
M         3.47        223237
So        4.01         24806
Ed        2.66        203437
Po1      12.80       1066501
Po2      10.99        964128
LF        5.14        245356
M.F       1.10        295984
Pop      -1.30        403125
NW        9.21        491851
U1        2.64        143057
U2        2.23        197509
Wealth    4.11        690687
Ineq      0.52        234308
Prob      7.97        837428
Time      3.01        226674
```

varImpPlot(rf)



We can see that Po1 is the most important variable among all the predictors. It also suggest the overfitting if we use all the predictors in the model.

Question 10.2

Describe a situation or problem from your job, everyday life, current events, etc., for which a logistic

regression model would be appropriate. List some (up to 5) predictors that you might use.

The likelihood of the applicant be admitted to the graduate school Predictors:

1. **GRE score,**
2. **GPA from the undergraduate,**
3. **have related research experience or not,**
4. **whether or not the undergraduate major is related to the program applying for**

Question 10.3

1. Using the GermanCredit data set germancredit.txt, use logistic regression to find a good predictive model for whether credit applicants are good credit risks or not. Show your model (factors used and their coefficients), the software output, and the quality of fit.

```
credit<- read.table("german.data")
head(credit)
```

```
##    V1 V2  V3  V4   V5  V6  V7 V8  V9  V10 V11  V12 V13  V14  V15 V16  V17
## 1 A11  6 A34 A43 1169 A65 A75  4 A93 A101   4 A121  67 A143 A152   2 A173
## 2 A12 48 A32 A43 5951 A61 A73  2 A92 A101   2 A121  22 A143 A152   1 A173
## 3 A14 12 A34 A46 2096 A61 A74  2 A93 A101   3 A121  49 A143 A152   1 A172
## 4 A11 42 A32 A42 7882 A61 A74  2 A93 A103   4 A122  45 A143 A153   1 A173
## 5 A11 24 A33 A40 4870 A61 A73  3 A93 A101   4 A124  53 A143 A153   2 A173
## 6 A14 36 A32 A46 9055 A65 A73  2 A93 A101   4 A124  35 A143 A153   1 A172
##   V18  V19  V20 V21
## 1   1 A192 A201   1
## 2   1 A191 A201   2
## 3   2 A191 A201   1
## 4   2 A191 A201   1
## 5   2 A191 A201   2
## 6   2 A192 A201   1
```

```
str(credit)
```

```
## 'data.frame':    1000 obs. of  21 variables:
##  $ V1 : Factor w/ 4 levels "A11","A12","A13",..: 1 2 4 1 1 4 4 2 4 2 ...
##  $ V2 : int  6 48 12 42 24 36 24 36 12 30 ...
##  $ V3 : Factor w/ 5 levels "A30","A31","A32",..: 5 3 5 3 4 3 3 3 3 5 ...
```

```
##  $ V4 : Factor w/ 10 levels "A40","A41","A410",..: 5 5 8 4 1 8 4 2 5 1 ...
##  $ V5 : int  1169 5951 2096 7882 4870 9055 2835 6948 3059 5234 ...
##  $ V6 : Factor w/ 5 levels "A61","A62","A63",..: 5 1 1 1 1 5 3 1 4 1 ...
##  $ V7 : Factor w/ 5 levels "A71","A72","A73",..: 5 3 4 4 3 3 5 3 4 1 ...
##  $ V8 : int  4 2 2 2 3 2 3 2 2 4 ...
##  $ V9 : Factor w/ 4 levels "A91","A92","A93",..: 3 2 3 3 3 3 3 3 1 4 ...
##  $ V10: Factor w/ 3 levels "A101","A102",..: 1 1 1 3 1 1 1 1 1 1 ...
##  $ V11: int  4 2 3 4 4 4 4 2 4 2 ...
##  $ V12: Factor w/ 4 levels "A121","A122",..: 1 1 1 2 4 4 2 3 1 3 ...
##  $ V13: int  67 22 49 45 53 35 53 35 61 28 ...
##  $ V14: Factor w/ 3 levels "A141","A142",..: 3 3 3 3 3 3 3 3 3 3 ...
##  $ V15: Factor w/ 3 levels "A151","A152",..: 2 2 2 3 3 3 2 1 2 2 ...
##  $ V16: int  2 1 1 1 2 1 1 1 1 2 ...
##  $ V17: Factor w/ 4 levels "A171","A172",..: 3 3 2 3 3 2 3 4 2 4 ...
##  $ V18: int  1 1 2 2 2 2 1 1 1 1 ...
##  $ V19: Factor w/ 2 levels "A191","A192": 2 1 1 1 1 2 1 2 1 1 ...
##  $ V20: Factor w/ 2 levels "A201","A202": 1 1 1 1 1 1 1 1 1 1 ...
##  $ V21: int  1 2 1 1 2 1 1 1 1 2 ...
```

Accordingly to the description, we found that V21 is the response. 1 means good, 2 means bad. Recode the V21 to be a 0/1 variable, instead of 1/2

```
credit$V21[credit$V21==1]<-0
credit$V21[credit$V21==2]<-1
```

Divide the data into training and test datasets.

```
trainno <- sample(1:nrow(credit), size = round(nrow(credit)*0.7), replace =
FALSE)
train <- credit[trainno,]
test<- credit[-trainno,]
```

Fit the logistic model

```
log<-glm(V21~.,data=train,family=binomial(link="logit"))
summary(log)

##
## Call:
## glm(formula = V21 ~ ., family = binomial(link = "logit"), data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9894  -0.6316  -0.2844   0.5607   2.7712
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  4.145e-01  1.412e+00   0.293 0.769176
## V1A12       -5.691e-01  2.826e-01  -2.014 0.043993 *
## V1A13       -9.997e-01  4.345e-01  -2.301 0.021396 *
## V1A14       -1.981e+00  3.044e-01  -6.509 7.57e-11 ***
```

```
## V2           2.384e-02  1.146e-02   2.081 0.037438 *
## V3A31        1.183e+00  7.156e-01   1.653 0.098312 .
## V3A32       -8.881e-02  5.584e-01  -0.159 0.873638
## V3A33       -5.834e-01  6.099e-01  -0.957 0.338774
## V3A34       -1.323e+00  5.695e-01  -2.322 0.020207 *
## V4A41       -1.779e+00  4.929e-01  -3.610 0.000307 ***
## V4A410       6.396e-02  9.810e-01   0.065 0.948015
## V4A42       -6.925e-01  3.418e-01  -2.026 0.042774 *
## V4A43       -9.077e-01  3.209e-01  -2.829 0.004669 **
## V4A44       -6.715e-01  9.159e-01  -0.733 0.463487
## V4A45       -1.905e-01  6.888e-01  -0.277 0.782109
## V4A46       -2.280e-01  5.014e-01  -0.455 0.649233
## V4A48       -1.157e+00  1.351e+00  -0.857 0.391482
## V4A49       -8.954e-02  3.941e-01  -0.227 0.820265
## V5           1.789e-04  5.568e-05   3.213 0.001313 **
## V6A62       -1.459e-01  3.608e-01  -0.405 0.685816
## V6A63       -5.666e-02  4.604e-01  -0.123 0.902048
## V6A64       -7.304e-01  5.976e-01  -1.222 0.221658
## V6A65       -1.294e+00  3.428e-01  -3.773 0.000161 ***
## V7A72       -5.221e-01  5.568e-01  -0.938 0.348351
## V7A73       -6.229e-01  5.344e-01  -1.166 0.243777
## V7A74       -1.373e+00  5.814e-01  -2.361 0.018235 *
## V7A75       -7.513e-01  5.330e-01  -1.409 0.158691
## V8           3.515e-01  1.146e-01   3.068 0.002153 **
## V9A92       -1.056e+00  4.911e-01  -2.150 0.031521 *
## V9A93       -1.287e+00  4.808e-01  -2.677 0.007431 **
## V9A94       -9.030e-01  5.949e-01  -1.518 0.129011
## V10A102      5.670e-01  4.892e-01   1.159 0.246489
## V10A103     -1.771e+00  6.244e-01  -2.837 0.004557 **
## V11          3.038e-02  1.111e-01   0.273 0.784591
## V12A122      5.665e-01  3.361e-01   1.686 0.091891 .
## V12A123      3.049e-01  3.107e-01   0.981 0.326462
## V12A124      1.126e+00  5.160e-01   2.182 0.029089 *
## V13         -1.561e-02  1.175e-02  -1.329 0.183844
## V14A142     -6.678e-01  5.323e-01  -1.255 0.209627
## V14A143     -6.982e-01  2.960e-01  -2.359 0.018342 *
## V15A152     -7.042e-01  2.928e-01  -2.405 0.016165 *
## V15A153     -8.727e-01  5.865e-01  -1.488 0.136744
## V16          4.489e-01  2.321e-01   1.934 0.053112 .
## V17A172      1.107e+00  8.815e-01   1.256 0.209218
## V17A173      1.198e+00  8.462e-01   1.416 0.156874
## V17A174      1.201e+00  8.478e-01   1.417 0.156550
## V18          6.828e-02  3.218e-01   0.212 0.831962
## V19A192     -6.701e-01  2.641e-01  -2.538 0.011160 *
## V20A202     -1.520e+00  8.447e-01  -1.799 0.071946 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 853.51  on 699  degrees of freedom
## Residual deviance: 571.94  on 651  degrees of freedom
## AIC: 669.94
##
## Number of Fisher Scoring iterations: 6
```

Keep the significant preditors under p-value=0.1,for the categorical predictors, keep them if any of the categories are significant. Then re-fit the model

```
log2<-
glm(V21~V1+V2+V3+V4+V5+V6+V7+V8+V9+V10+V12+V14+V16+V19+V20,data=train,family=
binomial(link="logit"))
summary(log2)
```

```
##
## Call:
## glm(formula = V21 ~ V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 + V9 +
##     V10 + V12 + V14 + V16 + V19 + V20, family = binomial(link = "logit"),
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1214  -0.6483  -0.2913   0.5920   2.7799
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  2.851e-01  1.040e+00   0.274 0.784106
## V1A12       -6.247e-01  2.768e-01  -2.257 0.024021 *
## V1A13       -1.148e+00  4.261e-01  -2.694 0.007055 **
## V1A14       -2.013e+00  2.981e-01  -6.753 1.45e-11 ***
## V2           2.335e-02  1.112e-02   2.100 0.035753 *
## V3A31        9.932e-01  6.935e-01   1.432 0.152091
## V3A32       -1.948e-01  5.429e-01  -0.359 0.719776
## V3A33       -6.234e-01  5.984e-01  -1.042 0.297499
## V3A34       -1.456e+00  5.545e-01  -2.626 0.008634 **
## V4A41       -1.647e+00  4.714e-01  -3.493 0.000479 ***
## V4A410      -1.807e-01  9.518e-01  -0.190 0.849462
## V4A42       -5.854e-01  3.360e-01  -1.742 0.081439 .
## V4A43       -8.615e-01  3.126e-01  -2.756 0.005845 **
## V4A44       -8.063e-01  9.435e-01  -0.855 0.392761
## V4A45       -4.838e-01  6.711e-01  -0.721 0.470968
## V4A46       -1.709e-01  4.955e-01  -0.345 0.730189
## V4A48       -1.028e+00  1.286e+00  -0.799 0.424009
## V4A49       -1.522e-01  3.865e-01  -0.394 0.693758
## V5           1.751e-04  5.289e-05   3.310 0.000932 ***
## V6A62        2.042e-02  3.463e-01   0.059 0.952985
## V6A63       -7.969e-02  4.498e-01  -0.177 0.859365
## V6A64       -7.470e-01  5.898e-01  -1.266 0.205378
## V6A65       -1.246e+00  3.349e-01  -3.720 0.000199 ***
## V7A72       -5.074e-02  4.710e-01  -0.108 0.914201
```

```
## V7A73       -1.768e-01  4.423e-01  -0.400 0.689397
## V7A74       -8.837e-01  4.950e-01  -1.785 0.074243 .
## V7A75       -4.078e-01  4.537e-01  -0.899 0.368781
## V8           3.368e-01  1.103e-01   3.054 0.002257 **
## V9A92       -8.548e-01  4.785e-01  -1.786 0.074028 .
## V9A93       -1.233e+00  4.701e-01  -2.624 0.008700 **
## V9A94       -6.741e-01  5.798e-01  -1.163 0.244924
## V10A102      6.601e-01  4.876e-01   1.354 0.175818
## V10A103     -1.715e+00  5.998e-01  -2.859 0.004253 **
## V12A122      5.097e-01  3.257e-01   1.565 0.117623
## V12A123      3.091e-01  2.987e-01   1.035 0.300678
## V12A124      8.195e-01  3.813e-01   2.149 0.031622 *
## V14A142     -7.085e-01  5.220e-01  -1.357 0.174661
## V14A143     -6.281e-01  2.891e-01  -2.173 0.029792 *
## V16          4.308e-01  2.229e-01   1.933 0.053242 .
## V19A192     -6.423e-01  2.416e-01  -2.658 0.007859 **
## V20A202     -1.539e+00  8.367e-01  -1.839 0.065913 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 853.51  on 699  degrees of freedom
## Residual deviance: 584.77  on 659  degrees of freedom
## AIC: 666.77
##
## Number of Fisher Scoring iterations: 5
```

For the categorical variables, not all the levels are significant. So create a binary (0/1) variable for each of them: 0 for not significant, 1 for significant

```r
train$V1A12[train$V1=="A12"]<-1
train$V1A12[train$V1!="A12"]<-0

train$V1A13[train$V1=="A13"]<-1
train$V1A13[train$V1!="A13"]<-0

train$V1A14[train$V1=="A14"]<-1
train$V1A14[train$V1!="A14"]<-0

train$V3A34[train$V1=="A34"]<-1
train$V3A34[train$V1!="A34"]<-0

train$V4A41[train$V1=="A41"]<-1
train$V4A41[train$V1!="A41"]<-0

train$V4A42[train$V1=="A42"]<-1
train$V4A42[train$V1!="A42"]<-0

train$V4A43[train$V1=="A43"]<-1
```

```
train$V4A43[train$V1!="A43"]<-0

train$V6A65[train$V1=="A65"]<-1
train$V6A65[train$V1!="A65"]<-0

train$V7A74[train$V1=="A74"]<-1
train$V7A74[train$V1!="A74"]<-0

train$V9A92[train$V1=="A92"]<-1
train$V9A92[train$V1!="A92"]<-0

train$V9A93[train$V1=="A93"]<-1
train$V9A93[train$V1!="A93"]<-0

train$V10A103[train$V1=="A103"]<-1
train$V10A103[train$V1!="A103"]<-0

train$V12A124[train$V1=="A124"]<-1
train$V12A124[train$V1!="A124"]<-0

train$V14A143[train$V1=="A143"]<-1
train$V14A143[train$V1!="A143"]<-0

train$V19A192[train$V1=="A192"]<-1
train$V19A192[train$V1!="A192"]<-0

train$V20A202[train$V1=="A202"]<-1
train$V20A202[train$V1!="A202"]<-0
```

Re-fit the model with these significant variables

```
log3<-
glm(V21~V1A12+V1A13+V1A14+V2+V3A34+V4A41+V4A42+V4A43+V5+V6A65+V7A74+V8+V9A92+
V9A93+V10A103+V12A124+V14A143+V16+V19A192+V20A202,data=train,family=binomial(
link="logit"))
summary(log3)

##
## Call:
## glm(formula = V21 ~ V1A12 + V1A13 + V1A14 + V2 + V3A34 + V4A41 +
##     V4A42 + V4A43 + V5 + V6A65 + V7A74 + V8 + V9A92 + V9A93 +
##     V10A103 + V12A124 + V14A143 + V16 + V19A192 + V20A202, family =
binomial(link = "logit"),
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9255  -0.8605  -0.4281   0.9381   2.4280
##
## Coefficients: (13 not defined because of singularities)
```

```
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.173e+00  4.258e-01  -2.755  0.00586 **
## V1A12       -5.140e-01  2.220e-01  -2.316  0.02058 *
## V1A13       -1.166e+00  3.830e-01  -3.045  0.00233 **
## V1A14       -2.313e+00  2.540e-01  -9.107  < 2e-16 ***
## V2           2.538e-02  9.340e-03   2.718  0.00657 **
## V3A34               NA         NA      NA       NA
## V4A41               NA         NA      NA       NA
## V4A42               NA         NA      NA       NA
## V4A43               NA         NA      NA       NA
## V5           9.641e-05  4.164e-05   2.316  0.02058 *
## V6A65               NA         NA      NA       NA
## V7A74               NA         NA      NA       NA
## V8           1.633e-01  9.208e-02   1.773  0.07620 .
## V9A92               NA         NA      NA       NA
## V9A93               NA         NA      NA       NA
## V10A103             NA         NA      NA       NA
## V12A124             NA         NA      NA       NA
## V14A143             NA         NA      NA       NA
## V16         -7.674e-02  1.574e-01  -0.488  0.62581
## V19A192             NA         NA      NA       NA
## V20A202             NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 853.51  on 699  degrees of freedom
## Residual deviance: 702.82  on 692  degrees of freedom
## AIC: 718.82
##
## Number of Fisher Scoring iterations: 5
```

Only keep the significant terms

```
log4<-
glm(V21~V1A12+V1A13+V1A14+V2+V5+V8,data=train,family=binomial(link="logit"))
summary(log4)
```

```
##
## Call:
## glm(formula = V21 ~ V1A12 + V1A13 + V1A14 + V2 + V5 + V8, family =
binomial(link = "logit"),
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9446  -0.8595  -0.4272   0.9275   2.4128
##
```

```
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)    
## (Intercept) -1.285e+00  3.596e-01  -3.574 0.000352 ***
## V1A12       -5.099e-01  2.218e-01  -2.299 0.021477 *  
## V1A13       -1.155e+00  3.820e-01  -3.023 0.002503 ** 
## V1A14       -2.316e+00  2.539e-01  -9.123  < 2e-16 ***
## V2           2.545e-02  9.339e-03   2.725 0.006436 ** 
## V5           9.637e-05  4.162e-05   2.316 0.020582 *  
## V8           1.633e-01  9.207e-02   1.774 0.076030 .  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 853.51  on 699  degrees of freedom
## Residual deviance: 703.06  on 693  degrees of freedom
## AIC: 717.06
## 
## Number of Fisher Scoring iterations: 5
```

Now every term are significant, this is the final model

Add the remained binary variables to the test dataset

```
test$V1A12[test$V1=="A12"]<-1
test$V1A12[test$V1!="A12"]<-0

test$V1A13[test$V1=="A13"]<-1
test$V1A13[test$V1!="A13"]<-0

test$V1A14[test$V1=="A14"]<-1
test$V1A14[test$V1!="A14"]<-0
```

Validate the model using the test dataset

```
yhatlog<-predict(log4,test,type = "response")
head(yhatlog)
```

```
##         5         8         9        16        18        20 
## 0.5707649 0.5292916 0.0644921 0.5256126 0.6417318 0.1024695
```

Round the yhatlog to be 0/1 variabls

```
y<- as.integer(yhatlog > 0.5)
head(y)
```

```
## [1] 1 1 0 1 1 0
```

```
t <- table(y,test$V21)
t
```

```
##
## y      0   1
##    0 182  58
##    1  27  33
```

```
correct<-(182+33)/300
correct
```

```
## [1] 0.7166667
```

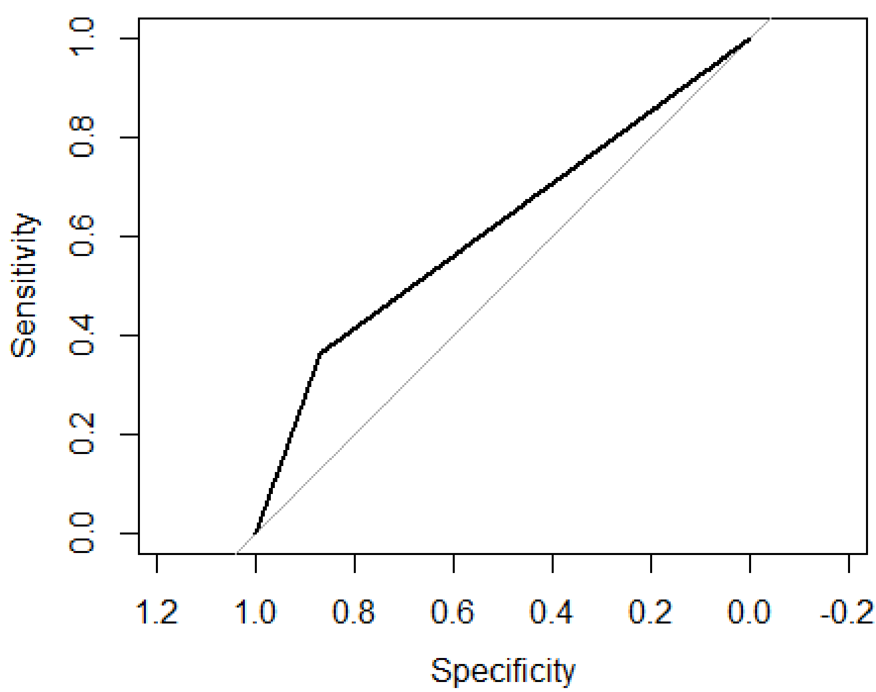
```
roc<-roc(test$V21,y)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

Plot the ROC curve

```
plot(roc)
```




```
roc
```

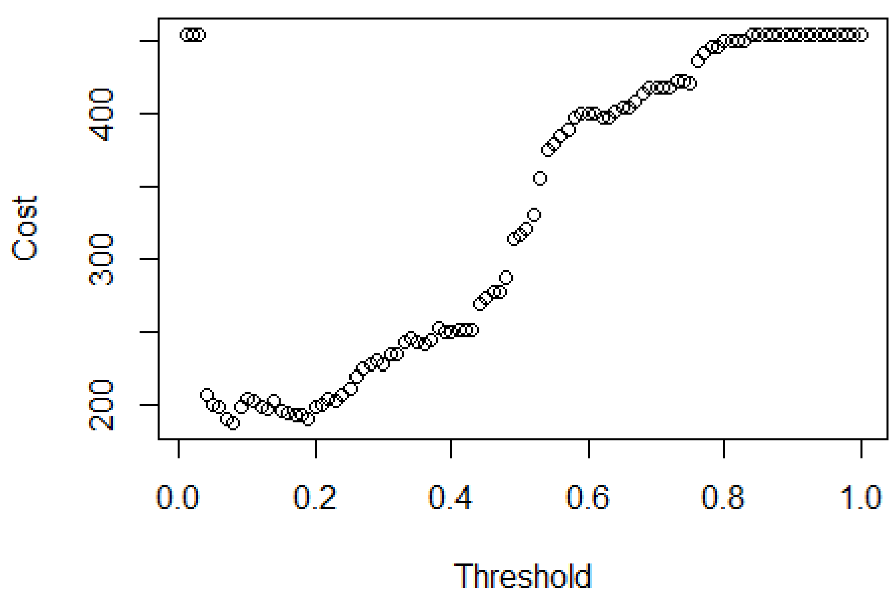
```
##
## Call:
## roc.default(response = test$V21, predictor = y)
##
## Data: y in 209 controls (test$V21 0) < 91 cases (test$V21 1).
## Area under the curve: 0.6167
```

The model I developed is: log(p/(1-p))=-1.285e+00-5.099e-01*V1A12-1.155e+00*V1A13-2.316e+00*V1A14+2.545e-02*V2+9.637e-05*V5+1.633e-01*V8 The accuracy rate is 71.67%, AIC is 717.06,and AUC is 61.67%,which means the model will correctly classify the samples 61.67% of the times.

2. Because the model gives a result between 0 and 1, it requires setting a threshold probability to separate between good and bad answers. In this data set, they estimate that incorrectly identifying a bad customer as good, is 5 times worse than incorrectly classifying a good customer as bad. Determine a good threshold probability based on your model.

Calculating loss for the cost for thresholds ranging from 0.01 to 1.

```
cost <- c()
for(i in 1:100){
        y.hat<- as.integer(yhatlog > (i/100)) #0.01-100

        table<-as.matrix(table(y.hat,test$V21))

        if(nrow(table)>1) { cst1 <- table[2,1] } else { cst1 <- 0 }
        if(ncol(table)>1) { cst2 <- table[1,2] } else { cst2 <- 0 }
        cost <- c(cost, cst1+cst2*5)
}

plot(c(1:100)/100,cost,xlab = "Threshold",ylab = "Cost")
```



```r
which.min(cost)
```

```
## [1] 8
```

```r
cost
```

```
##   [1] 455 455 455 207 200 198 190 187 198 204 202 198 197 202 195 194 192
##  [18] 192 189 198 200 204 202 207 211 219 224 227 230 227 234 235 242 245
##  [35] 242 241 244 252 249 249 251 251 251 269 274 277 278 287 314 317 321
##  [52] 330 356 375 379 385 389 397 401 401 400 398 397 402 405 405 409 414
##  [69] 419 419 419 418 423 423 422 437 442 446 446 451 451 450 450 455 455
##  [86] 455 455 455 455 455 455 455 455 455 455 455 455 455 455 455
```

When threshold=0.08, we have minimum cost 187.