Naive Bayes with RFE

For this Naive Bayes model, I used RFE as variables reduction method, which selected only four variables out of 24 variables. The AUC is 73.6. From the ROC plot we can conclude that the max Balanced Accuracy is 70.8 with sensitivity of 87.18318 and specificity of 54.43669.

```
library(caret)
library(tidyr)
library(MASS)
library(e1071)
library(pROC)
```

Reading the data

```
data1 <- read.table(file = "C://Users/cs_mo/Downloads/ISYE7406/ProjectCreditCard/creditcards.csv", head
names(data1)[25] <- 'default'
head(data1)
```

```
##   ID LIMIT_BAL SEX EDUCATION MARRIAGE AGE PAY_0 PAY_2 PAY_3 PAY_4 PAY_5 PAY_6
## 1  1     20000   2         2        1  24     2     2    -1    -1    -2    -2
## 2  2    120000   2         2        2  26    -1     2     0     0     0     2
## 3  3     90000   2         2        2  34     0     0     0     0     0     0
## 4  4     50000   2         2        1  37     0     0     0     0     0     0
## 5  5     50000   1         2        1  57    -1     0    -1     0     0     0
## 6  6     50000   1         1        2  37     0     0     0     0     0     0
##   BILL_AMT1 BILL_AMT2 BILL_AMT3 BILL_AMT4 BILL_AMT5 BILL_AMT6 PAY_AMT1 PAY_AMT2
## 1      3913      3102       689         0         0         0        0      689
## 2      2682      1725      2682      3272      3455      3261        0     1000
## 3     29239     14027     13559     14331     14948     15549     1518     1500
## 4     46990     48233     49291     28314     28959     29547     2000     2019
## 5      8617      5670     35835     20940     19146     19131     2000    36681
## 6     64400     57069     57608     19394     19619     20024     2500     1815
##   PAY_AMT3 PAY_AMT4 PAY_AMT5 PAY_AMT6 default
## 1        0        0        0        0       1
## 2     1000     1000        0     2000       1
## 3     1000     1000     1000     5000       0
## 4     1200     1100     1069     1000       0
## 5    10000     9000      689      679       0
## 6      657     1000     1000      800       0
```

Removing 167 outliers as identified in the data exploration part

```r
out <- boxplot.stats(data1$LIMIT_BAL)$out
out_ind <- which(data1$LIMIT_BAL %in% c(out))
mydata1 <- data1[-out_ind,]
dim(mydata1)
```

```
## [1] 29833    25
```

Cleaning up Marriage and Education feature

```r
mydata1$MARRIAGE[mydata1$MARRIAGE == "0"] <- "3"
mydata1$EDUCATION[mydata1$EDUCATION== "6"]<-"4"
mydata1$EDUCATION[mydata1$EDUCATION== "5"]<-"4"
mydata1$EDUCATION[mydata1$EDUCATION== "0"]<-"4"
```

```r
mydata1$default[mydata1$default=="0"] <- "ND"
mydata1$default[mydata1$default=="1"] <- "DEF"
```

Removing the ID column…

```r
mydata <- mydata1[,2:25]
head(mydata)
```

```
##   LIMIT_BAL SEX EDUCATION MARRIAGE AGE PAY_0 PAY_2 PAY_3 PAY_4 PAY_5 PAY_6
## 1     20000   2         2        1  24     2     2    -1    -1    -2    -2
## 2    120000   2         2        2  26    -1     2     0     0     0     2
## 3     90000   2         2        2  34     0     0     0     0     0     0
## 4     50000   2         2        1  37     0     0     0     0     0     0
## 5     50000   1         2        1  57    -1     0    -1     0     0     0
## 6     50000   1         1        2  37     0     0     0     0     0     0
##   BILL_AMT1 BILL_AMT2 BILL_AMT3 BILL_AMT4 BILL_AMT5 BILL_AMT6 PAY_AMT1 PAY_AMT2
## 1      3913      3102       689         0         0         0        0      689
## 2      2682      1725      2682      3272      3455      3261        0     1000
## 3     29239     14027     13559     14331     14948     15549     1518     1500
## 4     46990     48233     49291     28314     28959     29547     2000     2019
## 5      8617      5670     35835     20940     19146     19131     2000    36681
## 6     64400     57069     57608     19394     19619     20024     2500     1815
##   PAY_AMT3 PAY_AMT4 PAY_AMT5 PAY_AMT6 default
## 1        0        0        0        0     DEF
## 2     1000     1000        0     2000     DEF
## 3     1000     1000     1000     5000      ND
## 4     1200     1100     1069     1000      ND
## 5    10000     9000      689      679      ND
## 6      657     1000     1000      800      ND
```

```r
dim(mydata)
```

```
## [1] 29833    24
```

Splitting the data....

```
set.seed(7406)
flag<- sort(sample(1:29833,4475))
data_train  <- mydata[-flag,]
data_test <- mydata[flag,]
dim(data_train)
```

```
## [1] 25358    24
```

```
dim(data_test)
```

```
## [1] 4475   24
```

```
head(data_train)
```

```
##   LIMIT_BAL SEX EDUCATION MARRIAGE AGE PAY_0 PAY_2 PAY_3 PAY_4 PAY_5 PAY_6
## 1     20000   2         2        1  24     2     2    -1    -1    -2    -2
## 2    120000   2         2        2  26    -1     2     0     0     0     2
## 3     90000   2         2        2  34     0     0     0     0     0     0
## 4     50000   2         2        1  37     0     0     0     0     0     0
## 5     50000   1         2        1  57    -1     0    -1     0     0     0
## 7    500000   1         1        2  29     0     0     0     0     0     0
##   BILL_AMT1 BILL_AMT2 BILL_AMT3 BILL_AMT4 BILL_AMT5 BILL_AMT6 PAY_AMT1 PAY_AMT2
## 1      3913      3102       689         0         0         0        0      689
## 2      2682      1725      2682      3272      3455      3261        0     1000
## 3     29239     14027     13559     14331     14948     15549     1518     1500
## 4     46990     48233     49291     28314     28959     29547     2000     2019
## 5      8617      5670     35835     20940     19146     19131     2000    36681
## 7    367965    412023    445007    542653    483003    473944    55000    40000
##   PAY_AMT3 PAY_AMT4 PAY_AMT5 PAY_AMT6 default
## 1        0        0        0        0     DEF
## 2     1000     1000        0     2000     DEF
## 3     1000     1000     1000     5000      ND
## 4     1200     1100     1069     1000      ND
## 5    10000     9000      689      679      ND
## 7    38000    20239    13750    13770      ND
```

```
data_train[,3] <- as.numeric(data_train[,3])
data_train[,4] <- as.numeric(data_train[,4])


x_train <- (data_train[,1:23])
y_train <- data_train[,24]

data_test[,3] <- as.numeric(data_test[,3])
data_test[,4] <- as.numeric(data_test[,4])
x_test <- data_test[,1:23]
y_test <- data_test[,24]
```

RFE for variable selection. The results shows the top 4 variables that gives the higest accuracy.We can use these variables and built Naive Bayes model.

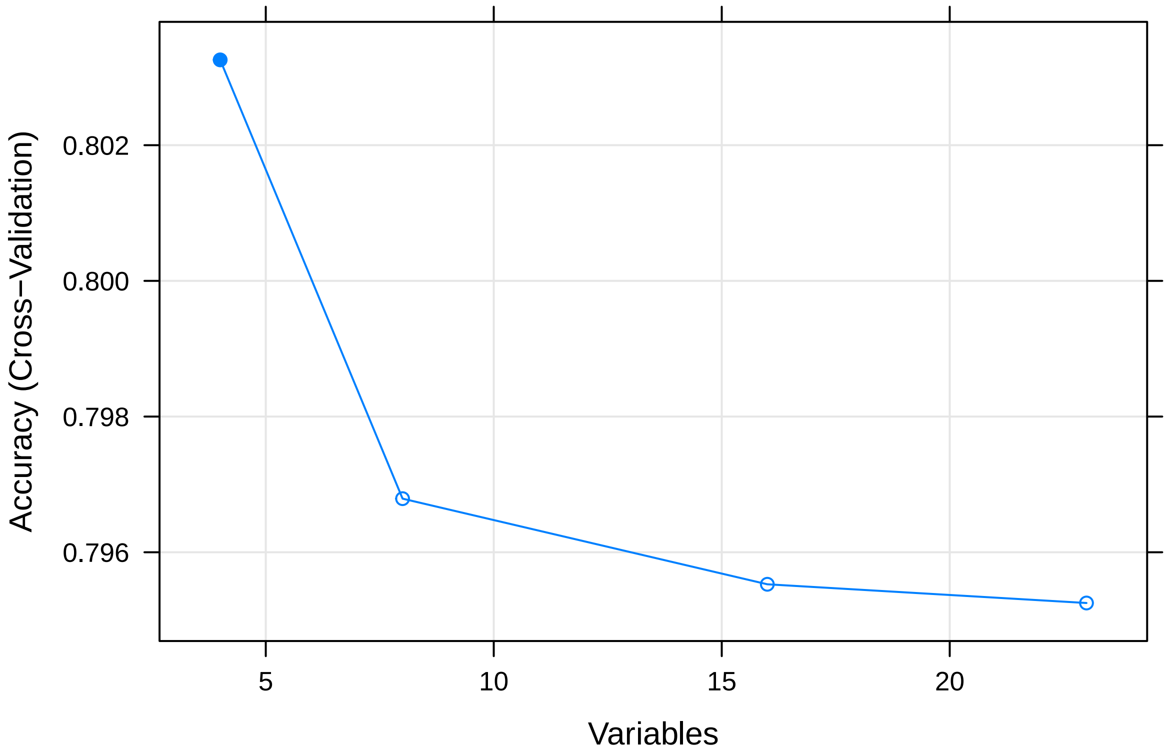
```
set.seed(7406)

control <- rfeControl(functions = nbFuncs,
                      method = "cv",

                      number =5)
```

```
rfemodel <- rfe(x_train,
                as.factor(y_train),
                szes = c(1:23),
                rfeControl=control)
```

```
print(rfemodel)
```

```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (5 fold)
##
## Resampling performance over subset size:
##
##  Variables Accuracy  Kappa AccuracySD KappaSD Selected
##          4   0.8033 0.2326   0.003256 0.02121        *
##          8   0.7968 0.1928   0.004061 0.02901
##         16   0.7955 0.1873   0.004839 0.03993
##         23   0.7953 0.1872   0.005872 0.04211
##
## The top 4 variables (out of 4):
##    PAY_0, PAY_2, PAY_3, LIMIT_BAL
```

```
plot(rfemodel, type=c("g", "o"))
```




```
red_df <- x_train[,6:8]
red_df$LIMIT_BAL <- x_train[,1]
head(red_df)
```

```
##   PAY_0 PAY_2 PAY_3 LIMIT_BAL
## 1     2     2    -1     20000
## 2    -1     2     0    120000
## 3     0     0     0     90000
## 4     0     0     0     50000
## 5    -1     0    -1     50000
## 7     0     0     0    500000
```

```
red_model <- naiveBayes(red_df,as.factor(y_train),laplace =1)
red_pred <- predict(red_model, x_test)
red_cf <-confusionMatrix(red_pred,as.factor(y_test))
red_cf
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  DEF   ND
##        DEF  446  273
##        ND   557 3199
##
##                Accuracy : 0.8145
```

```
##                  95% CI : (0.8028, 0.8258)
##     No Information Rate : 0.7759
##     P-Value [Acc > NIR] : 1.324e-10
##
##                   Kappa : 0.407
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.44467
##             Specificity : 0.92137
##          Pos Pred Value : 0.62031
##          Neg Pred Value : 0.85170
##              Prevalence : 0.22413
##          Detection Rate : 0.09966
##    Detection Prevalence : 0.16067
##       Balanced Accuracy : 0.68302
##
##        'Positive' Class : DEF
##
```

```
red_pred1 <- predict(red_model,x_test, type= "raw",index =2 )
head(red_pred1)
```

```
##             DEF         ND
## [1,] 0.11101405 0.88898595
## [2,] 0.92469628 0.07530372
## [3,] 0.08036284 0.91963716
## [4,] 0.10392840 0.89607160
## [5,] 0.11101405 0.88898595
## [6,] 0.55672161 0.44327839
```

CF with threshold value of 0.90 As we can see that this improves the model's sensitivity and balanced accuracy. However, it reduces the overall accuracy of the model.

```
tr_0.90 <- ifelse(red_pred1[,1]>0.90,"DEF","ND")
table(tr_0.90)
```

```
## tr_0.90
##  DEF   ND
##  441 4034
```

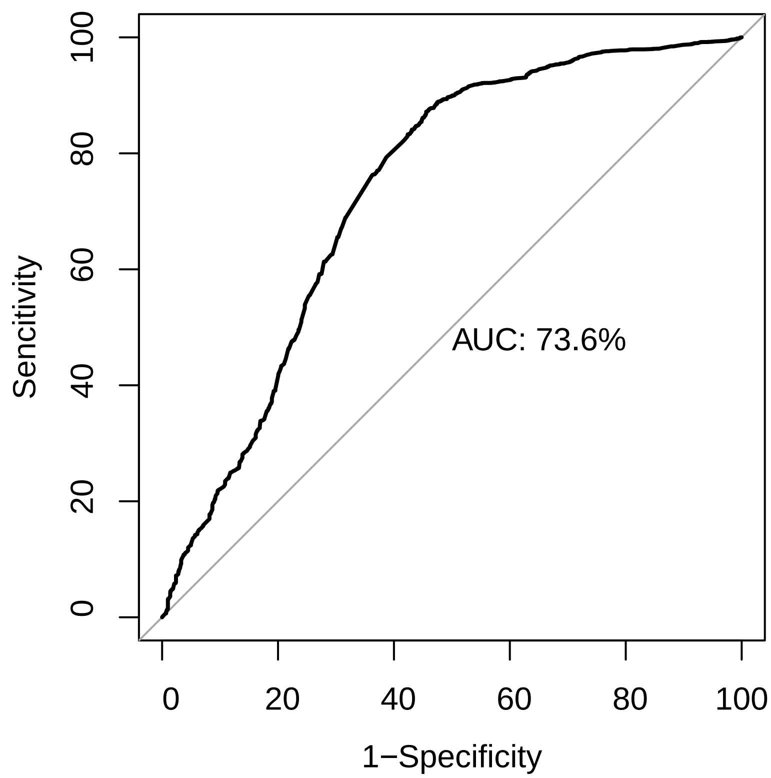
```
cf1 <- confusionMatrix(as.factor(y_test),as.factor(tr_0.90))
cf1
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  DEF   ND
##        DEF  296  707
##        ND   145 3327
```

```
##
##                Accuracy : 0.8096
##                  95% CI : (0.7978, 0.821)
##     No Information Rate : 0.9015
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3164
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.67120
##             Specificity : 0.82474
##          Pos Pred Value : 0.29511
##          Neg Pred Value : 0.95824
##              Prevalence : 0.09855
##          Detection Rate : 0.06615
##    Detection Prevalence : 0.22413
##       Balanced Accuracy : 0.74797
##
##        'Positive' Class : DEF
##
```

We can also build the ROC plot and compare the sensitivity and specificity for different threshold values.

```
par(pty ="s")
roc(y_test, red_pred1[,1], plot = TRUE, legacy.axes = T, percent = TRUE,
    print.auc =TRUE,

    #auc.polygon = TRUE,
    xlab= "1-Specificity",
    ylab= "Sencitivity"
    #xlab ="False Positive Percentage",
    #ylab =" True positive Percentage"
    )
```




```
##
## Call:
## roc.default(response = y_test, predictor = red_pred1[, 1], percent = TRUE,     plot = TRUE, legacy.a
##
## Data: red_pred1[, 1] in 1003 controls (y_test DEF) > 3472 cases (y_test ND).
## Area under the curve: 73.55%
```

```
roc.info1 <- roc(y_test, red_pred1[,1], plot = FALSE, legacy.axes = TRUE)
auc(roc.info1)
```

```
## Area under the curve: 0.7355
```

```
roc.df1 <- data.frame(sensitivity = roc.info1$sensitivities*100,
                      specificity =(roc.info1$specificities)*100,
                      thresholds = roc.info1$thresholds)
```

```
#(roc.df1)
```

```
roc.df1$Balance <- ((roc.df1$sensitivity + roc.df1$specificity)/2)
head(roc.df1)
```

```
##   sensitivity specificity thresholds  Balance
## 1   100.00000   0.0000000        Inf 50.00000
## 2    99.97120   0.0997009          1 50.03545
```

```
## 3    99.97120   0.1994018          1 50.08530
## 4    99.94240   0.1994018          1 50.07090
## 5    99.94240   0.2991027          1 50.12075
## 6    99.91359   0.2991027          1 50.10635
```

Printing the top 10 records with the highest Balance accuracy.

```r
df1 <- roc.df1[with(roc.df1,order(-Balance)),]
head(df1)
```

```
##     sensitivity specificity thresholds  Balance
## 366    87.18318    54.43669  0.2040761 70.80993
## 367    87.15438    54.43669  0.2023805 70.79553
## 365    87.21198    54.33699  0.2058032 70.77449
## 359    87.50000    54.03789  0.2239782 70.76894
## 358    87.67281    53.83848  0.2258698 70.75565
## 360    87.47120    54.03789  0.2224196 70.75454
```