TCD Project note III

Suprasanna Pradhan

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```
#Loading required packages
library(tidyverse)
## -- Attaching packages ----- tidyverse 1.2.1 --
## v ggplot2 3.2.1
                             0.3.2
                   v purrr
## v tibble 2.1.3 v dplyr 0.8.3
## v tidyr 0.8.3 v stringr 1.4.0
## v readr 1.3.1 v forcats 0.4.0
## -- Conflicts ------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
library(ggplot2)
library(caret)
## Loading required package: lattice
## Attaching package: 'caret'
## The following object is masked from 'package:purrr':
##
##
      lift
library(caretEnsemble)
##
## Attaching package: 'caretEnsemble'
## The following object is masked from 'package:ggplot2':
##
##
      autoplot
```

```
library(psych)
## Attaching package: 'psych'
## The following objects are masked from 'package:ggplot2':
##
##
      %+%, alpha
library(Amelia)
## Loading required package: Rcpp
## ##
## ## Amelia II: Multiple Imputation
## ## (Version 1.7.5, built: 2018-05-07)
## ## Copyright (C) 2005-2019 James Honaker, Gary King and Matthew Blackwell
## ## Refer to http://gking.harvard.edu/amelia/ for more information
## ##
library(mice)
## Attaching package: 'mice'
## The following object is masked from 'package:tidyr':
##
##
       complete
## The following objects are masked from 'package:base':
##
##
       cbind, rbind
library(GGally)
## Registered S3 method overwritten by 'GGally':
    method from
    +.gg ggplot2
```

```
##
## Attaching package: 'GGally'
## The following object is masked from 'package:dplyr':
##
##
       nasa
library(gutenbergr)
library(tidytext)
library(dplyr)
library(janeaustenr)
library(stringi)
library(tidyr)
library(rpart)
library(randomForest)
## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
## Attaching package: 'randomForest'
## The following object is masked from 'package:psych':
##
##
       outlier
## The following object is masked from 'package:dplyr':
##
##
       combine
## The following object is masked from 'package:ggplot2':
##
##
       margin
```

Importing Data set

```
library(readx1)
setwd("C:/Users/SuprasannaPradhan/Documents/My Files/Great Lakes Projects/Capstone Pro
ject TCD")
train_data1=read.csv("train_new.csv")
test_data1=read.csv("test_data.csv")
```

```
train_bank <- subset (train_data1, select= -c(1))
test_bank <- subset (test_data1, select= -c(1))
str(train_bank)</pre>
```

```
## 'data.frame': 9291 obs. of 14 variables:
## $ LIMIT BAL : num 20000 450000 100000 30000 20000 20000 270000 50000 120000
200000 ...
           : int 1112212111...
## $ SEX
## $ EDUCATION
                 : int 212222322...
## $ MARRIAGE : int 2 1 1 2 1 2 1 2 1 ...
## $ AGE
                  : int 33 45 30 22 24 31 26 53 28 32 ...
## $ DEFAULT : int 0 1 1 1 1 1 0 0 1 ...
## $ BILLED. AMT : num -0.391 -0.492 0.455 -0.208 -0.647 ...
## $ REPAY_STATUS. : num 0.1827 0.3363 0.0201 -0.2731 2.5181 ...
## $ PAID AMT
                : num -0.7188 1.278 -0.0873 -0.4301 -0.5607 ...
## $ TIMELY_PAID_AMT: num 0.543 0.523 0.431 -1.422 -1.695 ...
## $ RATIO PADI AMT1: num 0.419 -0.546 -0.411 -0.44 -0.027 ...
## $ RATIO_PADI_AMT2: num 0.37743 -2.66432 0.00851 -0.35402 -0.03372 ...
## $ RATIO PADI AMT3: num 0.3778 1.6226 -0.1 -0.0637 0.1059 ...
## $ RATIO_PADI_AMT4: num 0.62 0.416 0.325 0.922 0.141 ...
```

```
str(test_bank)
```

```
## 'data.frame': 9000 obs. of 14 variables:
## $ LIMIT_BAL : num 20000 120000 90000 50000 50000 20000 430000 180000 50000 5
00000 ...
   $ SEX
                   : int 2 2 2 2 1 1 2 2 1 1 ...
  $ EDUCATION
                  : int 2 2 2 2 2 3 2 1 2 1 ...
  $ MARRIAGE
                  : int 122112221...
  $ AGE
                   : int 24 26 34 37 57 35 41 29 33 58 ...
               : int 1100000010...
  $ DEFAULT
  $ BILLED._AMT : num -0.6551 -0.8545 -0.5227 -0.0487 -0.8533 ...
## $ REPAY STATUS. : num -1.56607 1.05357 0.09609 -0.00254 0.26657 ...
  $ PAID_AMT
                   : num -0.585 -0.416 -0.3 -0.435 1.929 ...
## $ TIMELY PAID AMT: num -2.74 0.164 0.487 0.527 -0.191 ...
## $ RATIO_PADI_AMT1: num -0.2887 -0.0338 -0.4383 -0.3948 -0.1997 ...
## $ RATIO PADI AMT2: num -0.334 0.465 0.44 0.403 -1.972 ...
  $ RATIO_PADI_AMT3: num   0.439 -0.132   0.264   0.548   0.866 ...
## $ RATIO PADI AMT4: num 0.152 1.461 0.74 0.567 1.09 ...
```

```
table(train_bank$DEFAULT)
```

```
##
## 0 1
## 4643 4648
```

Scale the data

```
#scale(train_bank)
```

Simple logit model on all variables

```
set.seed(1080)
bank_lg<- glm(DEFAULT ~ ., train_bank, family = "binomial"(link="logit"))
summary(bank_lg)</pre>
```

```
##
## Call:
## glm(formula = DEFAULT ~ ., family = binomial(link = "logit"),
       data = train bank)
##
## Deviance Residuals:
           1Q Median
      Min
                                  3Q
                                          Max
  -2.5842 -0.9796 0.2938 0.9860
                                     2.4416
## Coefficients:
                    Estimate Std. Error z value Pr(>|z|)
## (Intercept) 1.891e-01 1.828e-01 1.034 0.301045 
## LIMIT_BAL -8.208e-07 2.381e-07 -3.448 0.000566 ***
## SEX
                 -1.092e-01 4.743e-02 -2.303 0.021266 *
## EDUCATION
                  -3.273e-02 3.225e-02 -1.015 0.310172
## MARRIAGE -1.460e-01 4.868e-02 -2.999 0.002706 **
## AGE
                  5.595e-03 2.780e-03 2.013 0.044138 *
## BILLED. AMT -3.608e-02 2.500e-02 -1.443 0.148979
## REPAY STATUS. 4.129e-01 2.412e-02 17.122 < 2e-16 ***
## PAID AMT
                  -4.515e-01 3.196e-02 -14.126 < 2e-16 ***
## TIMELY_PAID_AMT -6.899e-01 2.354e-02 -29.306 < 2e-16 ***
## RATIO PADI AMT1 -9.910e-02 2.796e-02 -3.544 0.000394 ***
## RATIO PADI AMT2 -8.048e-02 2.608e-02 -3.086 0.002026 **
## RATIO_PADI_AMT3 8.423e-03 2.774e-02 0.304 0.761400
## RATIO PADI AMT4 -1.915e-01 2.616e-02 -7.322 2.44e-13 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
       Null deviance: 12880 on 9290 degrees of freedom
## Residual deviance: 10973 on 9277 degrees of freedom
## AIC: 11001
## Number of Fisher Scoring iterations: 4
```

Revised Logistic Regression Model

```
#View(test_bank)
logit_f1 <- subset(test_bank,select= -c(3,4,7,12,13))
#Logit_f1
bank_f1_lg<- glm(DEFAULT ~ ., logit_f1, family = "binomial"(link="logit"))
summary(bank_f1_lg)</pre>
```

```
##
## Call:
## glm(formula = DEFAULT ~ ., family = binomial(link = "logit"),
      data = logit_f1)
##
##
## Deviance Residuals:
      Min
                10 Median
                                 3Q
                                         Max
## -2.1535 -0.6108 -0.5145 -0.3320 2.8482
## Coefficients:
##
                   Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.346e+00 1.516e-01 -8.881 < 2e-16 ***
## LIMIT_BAL
                -1.199e-06 2.770e-07 -4.329 1.50e-05 ***
## SEX
                 -1.252e-01 5.754e-02 -2.176 0.02955 *
                  7.655e-03 3.023e-03 2.532 0.01134 *
## AGE
                 4.632e-01 2.707e-02 17.112 < 2e-16 ***
## REPAY_STATUS.
## PAID AMT
                  -3.757e-01 4.169e-02 -9.011 < 2e-16 ***
## TIMELY PAID AMT -7.051e-01 2.598e-02 -27.136 < 2e-16 ***
## RATIO PADI AMT1 -9.419e-02 3.626e-02 -2.598 0.00939 **
## RATIO_PADI_AMT4 -1.508e-01 3.003e-02 -5.021 5.13e-07 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '* 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
      Null deviance: 9504.6 on 8999 degrees of freedom
## Residual deviance: 7997.2 on 8991 degrees of freedom
## AIC: 8015.2
##
## Number of Fisher Scoring iterations: 5
```

library(car)

```
## Loading required package: carData
```

```
## Registered S3 methods overwritten by 'car':
## method from
## influence.merMod lme4
## cooks.distance.influence.merMod lme4
## dfbeta.influence.merMod lme4
## dfbetas.influence.merMod lme4
```

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:psych':
##
##
       logit
## The following object is masked from 'package:dplyr':
##
##
       recode
## The following object is masked from 'package:purrr':
##
##
       some
vif(bank_f1_lg)
                               SEX
##
         LIMIT_BAL
                                                AGE
                                                      REPAY_STATUS.
##
          1.256936
                          1.010270
                                           1.031040
                                                           1.111527
          PAID_AMT TIMELY_PAID_AMT RATIO_PADI_AMT1 RATIO_PADI_AMT4
##
          1.096350
                          1.018324
                                           1.038484
                                                           1.024806
```

Predcting

```
logit_pred_f1 = predict.glm(bank_f1_lg,newdata =test_bank,type = "response")
test_bank1<- cbind(test_bank,logit_pred_f1)</pre>
```

Checking Accuracy

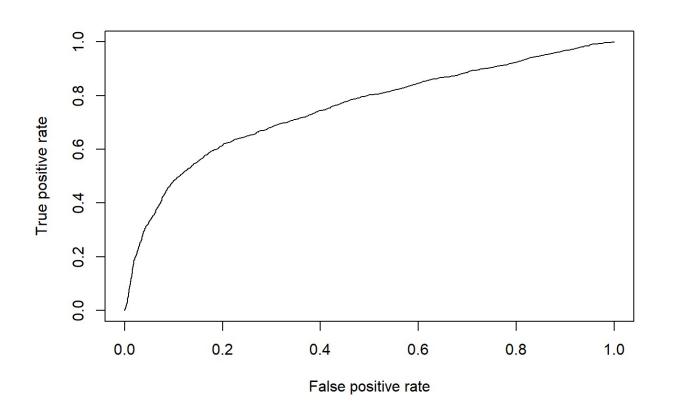
```
#View(test_bank1)
table(test_bank$DEFAULT,logit_pred_f1>0.5)
```

```
##
## FALSE TRUE
## 0 6672 340
## 1 1342 646
```

```
Accuracy = (6672+646)/(6672+340+1342)
Accuracy
```

```
## [1] 0.8759876
```

Validation on test data



```
auc_lg <- as.numeric(performance(DTpredROC1, "auc")@y.values)
auc_lg</pre>
```

```
## [1] 0.7520219
```

```
KS <- max(attr(perf1, 'y.values')[[1]]-attr(perf1, 'x.values')[[1]])
KS</pre>
```

```
## [1] 0.4184996
```

Gini

```
## Gini Coefficient
library(ineq)
gini = ineq(test_bank$DEFAULT, type="Gini")
gini
```

[1] 0.7791111

```
## n= 9291
##
  node), split, n, loss, yval, (yprob)
        * denotes terminal node
##
##
##
       1) root 9291 4643 1 (0.49973092 0.50026908)
##
         2) TIMELY PAID AMT>=-0.6144733 6272 2319 0 (0.63026148 0.36973852)
          4) REPAY STATUS. < 1.000148 5686 1940 0 (0.65881112 0.34118888)
##
            8) PAID_AMT>=0.7048767 1012 216 0 (0.78656126 0.21343874)
##
             16) PAID AMT>=2.234394 228
                                      17 0 (0.92543860 0.07456140) *
##
             17) PAID_AMT< 2.234394 784 199 0 (0.74617347 0.25382653)
##
##
               34) RATIO PADI AMT1>=-0.8005472 671 155 0 (0.76900149 0.23099851)
                 68) RATIO_PADI_AMT1< -0.3804398 186 27 0 (0.85483871 0.14516129)
##
*
                 69) RATIO_PADI_AMT1>=-0.3804398 485 128 0 (0.73608247 0.26391753)
##
##
                  138) RATIO PADI AMT1>=-0.3492855 471 118 0 (0.74946921 0.2505307
9)
##
                   276) TIMELY PAID AMT>=0.2063298 298 60 0 (0.79865772 0.2013422
8) *
##
                   277) TIMELY_PAID_AMT< 0.2063298 173 58 0 (0.66473988 0.3352601
2)
##
                     554) RATIO PADI AMT2>=-0.1305164 122 33 0 (0.72950820 0.2704
9180)
##
                      1108) RATIO_PADI_AMT4>=-0.4187486 112 27 0 (0.75892857 0.24
107143) *
##
                      1109) RATIO PADI AMT4< -0.4187486 10 4 1 (0.40000000 0.600
00000) *
##
                     555) RATIO PADI AMT2< -0.1305164 51 25 0 (0.50980392 0.49019
608) *
##
                  ##
                 70) AGE< 38.5 74 22 0 (0.70270270 0.29729730) *
##
                 71) AGE>=38.5 39
                                  17 1 (0.43589744 0.56410256) *
##
##
            9) PAID AMT< 0.7048767 4674 1724 0 (0.63115105 0.36884895)
             18) BILLED._AMT>=-0.4255529 2411 747 0 (0.69017005 0.30982995)
##
##
               36) LIMIT_BAL>=75000 1658 452 0 (0.72738239 0.27261761)
##
                 72) RATIO_PADI_AMT1< -0.1935291 998 226 0 (0.77354709 0.22645291)
                  144) RATIO_PADI_AMT3< 0.6952995 888 182 0 (0.79504505 0.20495495)
##
                   288) RATIO_PADI_AMT4>=0.210228 582 100 0 (0.82817869 0.1718213
##
1) *
##
                   289) RATIO PADI AMT4< 0.210228 306 82 0 (0.73202614 0.2679738
6)
##
                     578) LIMIT BAL>=145000 202 42 0 (0.79207921 0.20792079)
##
                      1156) REPAY_STATUS.>=-0.3865024 177 28 0 (0.84180791 0.1581
9209) *
##
                      000) *
```

```
##
                      579) LIMIT_BAL< 145000 104 40 0 (0.61538462 0.38461538)
##
                      1158) RATIO_PADI_AMT4< 0.1351998 81 25 0 (0.69135802 0.3086
4198) *
                       1159) RATIO PADI AMT4>=0.1351998 23 8 1 (0.34782609 0.6521
##
7391) *
##
                  145) RATIO PADI AMT3>=0.6952995 110 44 0 (0.60000000 0.40000000)
                    ##
6) *
##
                    291) RATIO PADI AMT1< -0.3811395 53 20 1 (0.37735849 0.6226415
1) *
                73) RATIO PADI AMT1>=-0.1935291 660 226 0 (0.65757576 0.34242424)
##
                  146) REPAY_STATUS.< -0.4930504 148 33 0 (0.77702703 0.22297297)
##
##
                    292) RATIO PADI AMT2>=-0.9765527 133 25 0 (0.81203008 0.187969
92) *
                   293) RATIO PADI AMT2< -0.9765527 15 7 1 (0.46666667 0.5333333
##
3) *
##
                 147) REPAY_STATUS.>=-0.4930504 512 193 0 (0.62304688 0.37695312)
                    294) RATIO PADI AMT4>=-0.7237819 469 168 0 (0.64179104 0.358208
##
96)
##
                      588) PAID AMT>=-1.279013 455 158 0 (0.65274725 0.34725275)
##
                      1176) RATIO_PADI_AMT2< -0.3540127 51 9 0 (0.82352941 0.176
47059) *
##
                     1177) RATIO_PADI_AMT2>=-0.3540127 404 149 0 (0.63118812 0.36
881188)
                        2354) RATIO PADI AMT2>=-0.2564896 384 135 0 (0.64843750 0.
35156250)
##
                          4708) REPAY_STATUS.>=-0.4200141 371 126 0 (0.66037736 0.
33962264)
##
                            9416) TIMELY PAID AMT< 0.7034911 331 105 0 (0.68277946
0.31722054)
##
                             000000) *
                             18833) PAID_AMT>=-0.6879101 311 104 0 (0.66559486 0.3
3440514)
                               37666) RATIO PADI AMT1< 2.907036 287 89 0 (0.68989
##
547 0.31010453)
                                 75332) REPAY STATUS.>=-0.0978989 52 6 0 (0.8846
1538 0.11538462) *
                                 75333) REPAY STATUS. < -0.0978989 235 83 0 (0.646
80851 0.35319149)
##
                                 150666) PAID AMT>=-0.3456294 189 59 0 (0.687830
69 0.31216931)
                                    301332) TIMELY PAID AMT>=0.5027466 15
                                                                          0 0
(1.00000000 0.00000000) *
                                    301333) TIMELY PAID AMT< 0.5027466 174 59 0
(0.66091954 0.33908046)
                                      602666) TIMELY PAID AMT< 0.4392857 148
                                                                            42 0
(0.71621622 0.28378378) *
                                      602667) TIMELY_PAID_AMT>=0.4392857 26
                                                                            9 1
```

```
(0.34615385 0.65384615) *
                                    150667) PAID_AMT< -0.3456294 46 22 1 (0.4782608
7 0.52173913) *
                                 37667) RATIO PADI AMT1>=2.907036 24 9 1 (0.375000
00 0.62500000) *
##
                             9417) TIMELY PAID AMT>=0.7034911 40 19 1 (0.47500000
0.52500000) *
                           4709) REPAY STATUS. < -0.4200141 13 4 1 (0.30769231 0.6
9230769) *
##
                          2355) RATIO_PADI_AMT2< -0.2564896 20     6 1 (0.30000000 0.7
0000000) *
##
                       589) PAID_AMT< -1.279013 14  4 1 (0.28571429 0.71428571) *
##
                     295) RATIO PADI AMT4< -0.7237819 43 18 1 (0.41860465 0.5813953
5) *
                37) LIMIT BAL< 75000 753 295 0 (0.60823373 0.39176627)
##
##
                  74) REPAY_STATUS.>=-0.02558607 577 210 0 (0.63604853 0.36395147)
##
                   148) RATIO PADI AMT4>=0.5302308 310 97 0 (0.68709677 0.31290323)
##
                     296) PAID AMT< -0.4174805 149 34 0 (0.77181208 0.22818792) *
##
                     297) PAID_AMT>=-0.4174805 161 63 0 (0.60869565 0.39130435)
##
                       594) BILLED. AMT>=-0.1486893 42 9 0 (0.78571429 0.21428571)
                       595) BILLED. AMT< -0.1486893 119 54 0 (0.54621849 0.4537815
##
1)
                        1190) BILLED. AMT< -0.3171202 54 17 0 (0.68518519 0.3148148
##
1) *
                        1191) BILLED. AMT>=-0.3171202 65 28 1 (0.43076923 0.5692307
##
7) *
                   149) RATIO PADI AMT4< 0.5302308 267 113 0 (0.57677903 0.42322097)
##
                     298) LIMIT BAL>=35000 191 71 0 (0.62827225 0.37172775)
##
                       596) BILLED._AMT< -0.244037 30 4 0 (0.86666667 0.133333333)
##
##
                       597) BILLED. AMT>=-0.244037 161 67 0 (0.58385093 0.41614907)
                        1194) REPAY_STATUS. < 0.0508605 90 28 0 (0.68888889 0.311111
##
11) *
##
                        1195) REPAY STATUS.>=0.0508605 71 32 1 (0.45070423 0.549295
77) *
##
                     299) LIMIT BAL< 35000 76 34 1 (0.44736842 0.55263158) *
##
                  75) REPAY_STATUS.< -0.02558607 176  85 0 (0.51704545 0.48295455)
##
                   150) AGE>=53.5 10
                                        1 0 (0.90000000 0.10000000) *
##
                   151) AGE< 53.5 166 82 1 (0.49397590 0.50602410)
##
                     302) REPAY STATUS. < -0.03234571 141 66 0 (0.53191489 0.4680851
1)
##
                       604) BILLED. AMT< 0.07650831 114 48 0 (0.57894737 0.4210526
3)
##
                       1208) RATIO PADI AMT3< -0.02379037 14 2 0 (0.85714286 0.14
285714) *
                        1209) RATIO PADI AMT3>=-0.02379037 100 46 0 (0.54000000 0.4
##
6000000)
                          2418) BILLED._AMT>=-0.3023209 67 26 0 (0.61194030 0.38805
##
```

```
970) *
##
                        2419) BILLED._AMT< -0.3023209 33 13 1 (0.39393939 0.60606
061) *
                     605) BILLED. AMT>=0.07650831 27 9 1 (0.33333333 0.66666667)
##
##
                   0) *
             19) BILLED. AMT< -0.4255529 2263 977 0 (0.56827221 0.43172779)
##
##
               38) PAID_AMT>=-1.078965 2087 867 0 (0.58457115 0.41542885)
                76) LIMIT_BAL>=145000 978 356 0 (0.63599182 0.36400818)
##
                 152) PAID AMT>=-0.4779268 581 180 0 (0.69018933 0.30981067)
##
##
                   304) BILLED._AMT>=-0.7307623 398 99 0 (0.75125628 0.24874372)
##
                     608) RATIO PADI AMT2>=0.05438328 183 33 0 (0.81967213 0.1803
2787) *
##
                     609) RATIO PADI AMT2< 0.05438328 215 66 0 (0.69302326 0.3069
7674)
##
                      1218) LIMIT_BAL< 470000 203 58 0 (0.71428571 0.28571429)
##
                        2436) BILLED. AMT< -0.4726066 191 51 0 (0.73298429 0.2670
1571) *
##
                        2437) BILLED. AMT>=-0.4726066 12 5 1 (0.41666667 0.58333
333) *
                      ##
##
                  305) BILLED._AMT< -0.7307623 183 81 0 (0.55737705 0.44262295)
##
                     610) AGE< 44.5 159 63 0 (0.60377358 0.39622642)
                      1220) REPAY_STATUS.< 0.07471067 100 30 0 (0.70000000 0.3000
##
0000) *
##
                     1221) REPAY_STATUS.>=0.07471067 59 26 1 (0.44067797 0.55932
203) *
                     611) AGE>=44.5 24     6 1 (0.25000000 0.75000000) *
##
                 153) PAID_AMT< -0.4779268 397 176 0 (0.55667506 0.44332494)
##
                   ##
*
##
                   307) REPAY STATUS.>=-1.065462 273 132 1 (0.48351648 0.51648352)
##
                     614) RATIO PADI AMT3< -0.5827417 35 10 0 (0.71428571 0.28571
429) *
##
                     615) RATIO PADI AMT3>=-0.5827417 238 107 1 (0.44957983 0.5504
2017)
##
                     1230) BILLED._AMT>=-0.6571899 209 100 1 (0.47846890 0.521531
10)
##
                        2460) BILLED. AMT< -0.6496236 12 2 0 (0.83333333 0.16666
667) *
                        2461) BILLED._AMT>=-0.6496236 197 90 1 (0.45685279 0.5431
##
4721)
##
                         4922) MARRIAGE>=1.5 84 38 0 (0.54761905 0.45238095) *
##
                         4923) MARRIAGE< 1.5 113 44 1 (0.38938053 0.61061947)
                           9846) RATIO PADI AMT1< -0.3895532 13 4 0 (0.69230769
##
0.30769231) *
                          9847) RATIO_PADI_AMT1>=-0.3895532 100 35 1 (0.3500000
0 0.65000000)
```

```
##
                              19694) RATIO PADI AMT2< -0.7615761 19 7 0 (0.631578
95 0.36842105) *
                              19695) RATIO PADI AMT2>=-0.7615761 81 23 1 (0.283950
##
62 0.71604938) *
                       1231) BILLED._AMT< -0.6571899 29 7 1 (0.24137931 0.7586206
9) *
                 77) LIMIT BAL< 145000 1109 511 0 (0.53922453 0.46077547)
##
##
                  154) RATIO PADI AMT4>=-1.089607 1009 444 0 (0.55996036 0.4400396
4)
##
                    308) RATIO_PADI_AMT4>=0.6008163 223 76 0 (0.65919283 0.3408071
7)
##
                       616) RATIO_PADI_AMT1>=-0.5215779 179 53 0 (0.70391061 0.2960
8939)
##
                       ##
                       1233) LIMIT BAL< 95000 152 51 0 (0.66447368 0.33552632)
##
                         2466) RATIO_PADI_AMT1< -0.4813234 34 5 0 (0.85294118 0.1
4705882) *
                         2467) RATIO PADI AMT1>=-0.4813234 118 46 0 (0.61016949 0.
38983051)
##
                           4934) BILLED. AMT>=-0.6187031 77 23 0 (0.70129870 0.298
70130) *
                           4935) BILLED. AMT< -0.6187031 41 18 1 (0.43902439 0.560
97561) *
                      617) RATIO PADI AMT1< -0.5215779 44 21 1 (0.47727273 0.52272
##
727) *
##
                   309) RATIO PADI AMT4< 0.6008163 786 368 0 (0.53180662 0.4681933
8)
##
                       618) AGE< 24.5 139 47 0 (0.66187050 0.33812950) *
##
                       619) AGE>=24.5 647 321 0 (0.50386399 0.49613601)
                       1238) TIMELY_PAID_AMT< 0.7801033 600 286 0 (0.52333333 0.476
66667)
##
                         2476) PAID AMT>=-0.7027773 473 209 0 (0.55813953 0.4418604
7)
##
                           4952) RATIO PADI AMT4< 0.5665761 400 164 0 (0.59000000
0.41000000)
                             9904) BILLED. AMT>=-0.7393585 336 126 0 (0.62500000 0.
37500000)
##
                              19808) TIMELY PAID AMT>=-0.04511526 312 111 0 (0.6442
3077 0.35576923)
                                39616) RATIO PADI AMT2>=0.5945616 53 9 0 (0.83018
868 0.16981132) *
                              39617) RATIO_PADI_AMT2< 0.5945616 259 102 0 (0.6061
7761 0.39382239)
                                  79234) TIMELY_PAID_AMT>=0.4893128 179 61 0 (0.65
921788 0.34078212) *
                                  79235) TIMELY_PAID_AMT< 0.4893128 80 39 1 (0.487
50000 0.51250000) *
                             19809) TIMELY PAID AMT< -0.04511526 24 9 1 (0.37500
000 0.62500000) *
```

```
##
                            9905) BILLED._AMT< -0.7393585 64 26 1 (0.40625000 0.5
9375000) *
##
                          4953) RATIO PADI AMT4>=0.5665761 73 28 1 (0.38356164 0.
61643836) *
##
                        2477) PAID AMT< -0.7027773 127 50 1 (0.39370079 0.6062992
1)
##
                          4954) TIMELY PAID AMT< -0.05351894 15
                                                              4 0 (0.73333333
0.26666667) *
                          4955) TIMELY PAID AMT>=-0.05351894 112 39 1 (0.34821429
##
0.65178571) *
                       8085) *
##
                  155) RATIO PADI AMT4< -1.089607 100 33 1 (0.33000000 0.67000000)
                    310) RATIO_PADI_AMT3< -0.5977489 11 2 0 (0.81818182 0.1818181
##
8) *
##
                    311) RATIO_PADI_AMT3>=-0.5977489 89 24 1 (0.26966292 0.7303370
8) *
##
               39) PAID AMT< -1.078965 176 66 1 (0.37500000 0.62500000)
##
                 78) LIMIT_BAL< 245000 111 54 0 (0.51351351 0.48648649)
##
                  157) AGE>=33.5 66 29 1 (0.43939394 0.56060606) *
##
                 79) LIMIT BAL>=245000 65
                                           9 1 (0.13846154 0.86153846) *
##
##
           5) REPAY_STATUS.>=1.000148 586 207 1 (0.35324232 0.64675768)
           10) REPAY STATUS. < 3.373648 520 200 1 (0.38461538 0.61538462)
##
             20) REPAY STATUS. < 1.778853 212 98 1 (0.46226415 0.53773585)
##
               40) REPAY STATUS.>=1.033171 176 87 0 (0.50568182 0.49431818)
##
##
                 80) RATIO_PADI_AMT4>=-1.170842 132 57 0 (0.56818182 0.43181818)
                  160) RATIO PADI AMT4< -0.6053733 17 2 0 (0.88235294 0.11764706)
##
*
                  161) RATIO PADI AMT4>=-0.6053733 115 55 0 (0.52173913 0.4782608
##
7)
##
                    322) RATIO PADI AMT2< 1.108128 90 36 0 (0.60000000 0.40000000)
##
                    323) RATIO PADI AMT2>=1.108128 25 6 1 (0.24000000 0.76000000)
##
                 81) RATIO PADI AMT4< -1.170842 44
                                                  14 1 (0.31818182 0.68181818) *
               41) REPAY STATUS. < 1.033171 36
                                            9 1 (0.25000000 0.75000000) *
##
             21) REPAY_STATUS.>=1.778853 308 102 1 (0.33116883 0.66883117)
##
               42) RATIO PADI AMT1>=-0.6084661 275 99 1 (0.36000000 0.64000000)
##
                 84) TIMELY_PAID_AMT>=0.9348192 199 83 1 (0.41708543 0.58291457)
##
##
                  168) RATIO PADI AMT4>=0.5695125 71 31 0 (0.56338028 0.43661972)
                  169) RATIO_PADI_AMT4< 0.5695125 128 43 1 (0.33593750 0.66406250)
##
                    338) RATIO_PADI_AMT1>=0.2565464 10
                                                      3 0 (0.70000000 0.3000000
##
0) *
                    339) RATIO PADI AMT1< 0.2565464 118 36 1 (0.30508475 0.6949152
##
5) *
##
                 43) RATIO_PADI_AMT1< -0.6084661 33
                                                  3 1 (0.09090909 0.90909091) *
##
```

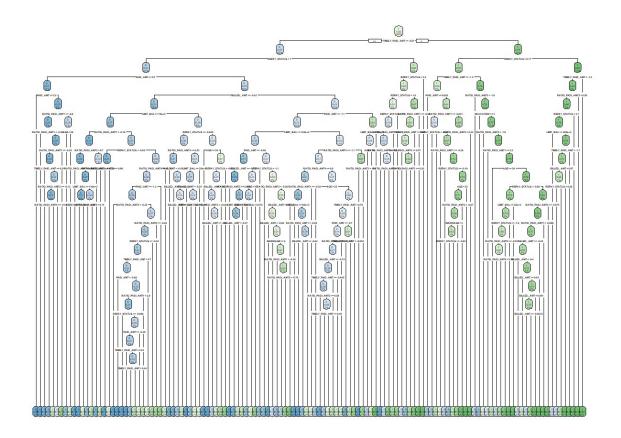
```
11) REPAY STATUS.>=3.373648 66 7 1 (0.10606061 0.89393939) *
##
##
         3) TIMELY_PAID_AMT< -0.6144733 3019 690 1 (0.22855250 0.77144750)
          6) REPAY STATUS. < 0.172774 1685 510 1 (0.30267062 0.69732938)
##
##
           12) TIMELY PAID AMT>=-1.367929 611 250 1 (0.40916530 0.59083470)
             24) PAID AMT>=0.02797305 95 32 0 (0.66315789 0.33684211) *
##
##
             25) PAID AMT< 0.02797305 516 187 1 (0.36240310 0.63759690)
               50) RATIO PADI AMT1>=-0.04064672 118 53 0 (0.55084746 0.44915254)
##
                100) REPAY_STATUS. < -0.561787 74  25 0 (0.66216216 0.33783784) *
##
                ##
               51) RATIO_PADI_AMT1< -0.04064672 398 122 1 (0.30653266 0.69346734)
##
                102) RATIO PADI AMT3< 0.3343695 369 120 1 (0.32520325 0.67479675)
##
                 204) RATIO_PADI_AMT1>=-0.3647836 96 43 1 (0.44791667 0.55208333)
##
                 205) RATIO_PADI_AMT1< -0.3647836 273 77 1 (0.28205128 0.7179487
##
2)
##
                   ##
                   411) REPAY STATUS.< -0.1900732 262 70 1 (0.26717557 0.7328244
3)
##
                     822) AGE< 52.5 239 69 1 (0.28870293 0.71129707)
##
                      1644) RATIO_PADI_AMT2< -0.6723654 224 69 1 (0.30803571 0.69
196429)
##
                       3288) MARRIAGE< 1.5 112 41 1 (0.36607143 0.63392857)
##
                         6576) REPAY STATUS.>=-0.8312857 10 3 0 (0.70000000 0.3
0000000) *
                         6577) REPAY STATUS. < -0.8312857 102 34 1 (0.33333333 0.
##
6666667) *
##
                        3289) MARRIAGE>=1.5 112 28 1 (0.25000000 0.750000000) *
##
                      1645) RATIO_PADI_AMT2>=-0.6723654 15
                                                          0 1 (0.0000000 1.000
00000) *
                     ##
##
                103) RATIO PADI AMT3>=0.3343695 29
                                                  2 1 (0.06896552 0.93103448) *
           13) TIMELY PAID AMT< -1.367929 1074 260 1 (0.24208566 0.75791434)
##
##
             26) RATIO PADI AMT2< -1.644013 18
                                            7 0 (0.61111111 0.38888889) *
             27) RATIO PADI AMT2>=-1.644013 1056 249 1 (0.23579545 0.76420455)
##
##
               54) EDUCATION>=3.5 10
                                     3 0 (0.70000000 0.30000000) *
               55) EDUCATION< 3.5 1046 242 1 (0.23135755 0.76864245)
##
##
                111) RATIO PADI AMT3>=-1.627155 1020 230 1 (0.22549020 0.77450980)
##
                 222) RATIO PADI AMT1>=2.167438 18 9 0 (0.50000000 0.50000000) *
##
##
                 223) RATIO PADI AMT1< 2.167438 1002 221 1 (0.22055888 0.77944112)
##
                   446) AGE>=53.5 59
                                    22 1 (0.37288136 0.62711864) *
                   447) AGE< 53.5 943 199 1 (0.21102863 0.78897137)
##
##
                     894) REPAY_STATUS.<-0.6823706 223 61 1 (0.27354260 0.726457
40)
##
                      1788) LIMIT_BAL>=25000 201 61 1 (0.30348259 0.69651741)
                        3576) REPAY_STATUS.>=-1.571277 169 58 1 (0.34319527 0.656
##
80473)
                         7152) RATIO_PADI_AMT4>=-0.5079225 137 52 1 (0.37956204
##
```

```
0.62043796)
                         0.43243243) *
                         14305) RATIO PADI AMT4>=0.1817267 100 31 1 (0.31000000
0.69000000) *
##
                        7153) RATIO PADI AMT4< -0.5079225 32 6 1 (0.18750000
0.81250000) *
                       3577) REPAY STATUS. < -1.571277 32 3 1 (0.09375000 0.9062
5000) *
##
                     1789) LIMIT_BAL< 25000 22     0 1 (0.00000000 1.00000000) *
                    895) REPAY STATUS.>=-0.6823706 720 138 1 (0.19166667 0.808333
##
33)
##
                     1790) RATIO PADI AMT2>=-0.07447176 471 105 1 (0.22292994 0.7
7707006)
                       3580) RATIO PADI AMT1< -0.09830139 375 93 1 (0.24800000
0.75200000)
                         7160) BILLED. AMT>=-0.4495703 228 68 1 (0.29824561 0.70
##
175439)
                         14320) BILLED._AMT< -0.4035051 14 6 0 (0.57142857 0.4
2857143) *
                         14321) BILLED._AMT>=-0.4035051 214 60 1 (0.28037383 0.
##
71962617)
                           28642) BILLED._AMT>=0.4529917 30 13 1 (0.43333333 0.
56666667) *
                           28643) BILLED. AMT< 0.4529917 184 47 1 (0.25543478
0.74456522)
##
                            57286) BILLED._AMT< 0.09121162 142 43 1 (0.3028169
0 0.69718310)
                              114572) BILLED. AMT>=-0.001614114 12 5 0 (0.5833
##
3333 0.41666667) *
                              114573) BILLED._AMT< -0.001614114 130 36 1 (0.276
92308 0.72307692) *
                             57287) BILLED._AMT>=0.09121162 42 4 1 (0.09523810
0.90476190) *
                      7161) BILLED. AMT< -0.4495703 147 25 1 (0.17006803 0.82
##
993197) *
                       87500000) *
                     1791) RATIO PADI AMT2< -0.07447176 249 33 1 (0.13253012 0.8
##
6746988) *
##
          7) REPAY STATUS.>=0.172774 1334 180 1 (0.13493253 0.86506747)
           14) TIMELY_PAID_AMT< -1.351992 760 133 1 (0.17500000 0.82500000)
##
             28) RATIO PADI AMT2< 0.5565909 506 101 1 (0.19960474 0.80039526)
##
##
              56) REPAY_STATUS. < 2.111825 304 72 1 (0.23684211 0.76315789)
##
               ##
               113) LIMIT_BAL< 355000 292 65 1 (0.22260274 0.77739726)
                 226) TIMELY_PAID_AMT< -1.674265 187 52 1 (0.27807487 0.72192513)
##
##
                   452) BILLED. AMT< 0.9709496 136 46 1 (0.33823529 0.66176471)
##
```

```
1) *
## 905) REPAY_STATUS.>=0.5836448 119 36 1 (0.30252101 0.6974789
9) *
## 453) BILLED._AMT>=0.9709496 51 6 1 (0.11764706 0.88235294) *
## 227) TIMELY_PAID_AMT>=-1.674265 105 13 1 (0.12380952 0.87619048)
*
## 57) REPAY_STATUS.>=2.111825 202 29 1 (0.14356436 0.85643564) *
## 29) RATIO_PADI_AMT>=-0.5565909 254 32 1 (0.12598425 0.87401575) *
## 15) TIMELY_PAID_AMT>=-1.351992 574 47 1 (0.08188153 0.91811847) *
```

```
rpart.plot(CT_model)
```

Warning: labs do not fit even at cex 0.15, there may be some overplotting



attributes(CT_model)

```
## $names
                                                    "call"
## [1] "frame"
                              "where"
## [4] "terms"
                              "cptable"
                                                    "method"
## [7] "parms"
                              "control"
                                                    "functions"
                              "splits"
                                                    "variable.importance"
## [10] "numresp"
## [13] "y"
                              "ordered"
##
## $xlevels
## named list()
##
## $ylevels
## [1] "0" "1"
##
## $class
## [1] "rpart"
```

```
CT_model$cptable
```

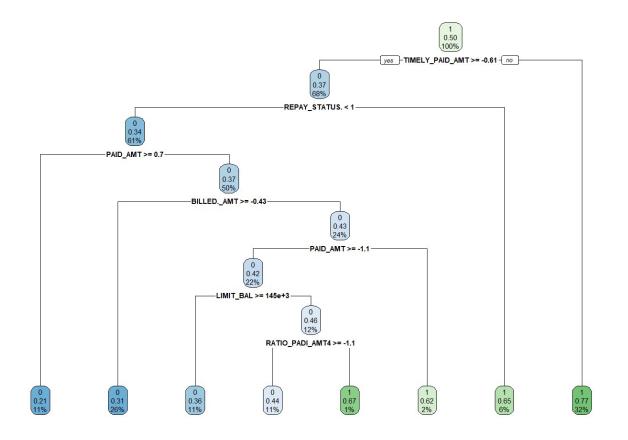
```
##
                CP nsplit rel error
                                        xerror
                                                      xstd
      0.3519276330
                        0 1.0000000 1.0230454 0.010377498
## 1
  2
      0.0370450140
                        1 0.6480724 0.6500108 0.009722263
      0.0031588772
                        2 0.6110274 0.6164118 0.009584658
##
  3
  4
      0.0026922249
                        7 0.5942279 0.6172733 0.009588369
      0.0025845359
                       12 0.5797975 0.6129658 0.009569715
## 5
  6
      0.0022255725
                       13 0.5772130 0.6142580 0.009575337
      0.0017230239
                       18 0.5653672 0.6149042 0.009578140
  7
      0.0015076459
                       21 0.5601981 0.6142580 0.009575337
## 8
## 9
      0.0012922679
                       23 0.5571829 0.6222270 0.009609520
  10 0.0011845789
                       27 0.5517984 0.6183502 0.009592995
  11 0.0011486826
                       29 0.5494292 0.6187810 0.009594840
## 12 0.0010768899
                       32 0.5459832 0.6194271 0.009597605
  13 0.0009692009
                       34 0.5438294 0.6213655 0.009605865
  14 0.0008884342
                       40 0.5371527 0.6248115 0.009620428
## 15 0.0008615120
                       48 0.5300452 0.6250269 0.009621333
## 16 0.0007538230
                       52 0.5265992 0.6284730 0.009635731
  17 0.0006461340
                       62 0.5179841 0.6332113 0.009655279
  18 0.0005743413
                       69 0.5132457 0.6347189 0.009661437
## 19 0.0005384450
                       72 0.5115227 0.6407495 0.009685781
  20 0.0005025486
                       76 0.5093689 0.6407495 0.009685781
  21 0.0004738316
                       80 0.5072152 0.6409649 0.009686642
## 22 0.0004307560
                       85 0.5048460 0.6450571 0.009702884
## 23 0.0003589633
                       89 0.5031230 0.6444109 0.009700334
## 24 0.0002153780
                       92 0.5020461 0.6472109 0.009711348
## 25 0.0001435853
                      102 0.4998923 0.6513030 0.009727267
## 26 0.0001346112
                      105 0.4994616 0.6541030 0.009738037
## 27 0.0001076890
                      113 0.4983847 0.6541030 0.009738037
## 28 0.0000000000
                      127 0.4964463 0.6571182 0.009749526
```

Pruning the tree

```
ptree = prune(CT_model, .0031, "CP")
ptree
```

```
## n= 9291
##
  node), split, n, loss, yval, (yprob)
##
         * denotes terminal node
##
##
     1) root 9291 4643 1 (0.4997309 0.5002691)
##
       2) TIMELY PAID AMT>=-0.6144733 6272 2319 0 (0.6302615 0.3697385)
##
         4) REPAY_STATUS. < 1.000148 5686 1940 0 (0.6588111 0.3411889)
##
           8) PAID_AMT>=0.7048767 1012 216 0 (0.7865613 0.2134387) *
           9) PAID AMT< 0.7048767 4674 1724 0 (0.6311510 0.3688490)
##
##
            18) BILLED._AMT>=-0.4255529 2411 747 0 (0.6901701 0.3098299) *
            19) BILLED._AMT< -0.4255529 2263 977 0 (0.5682722 0.4317278)
##
##
              38) PAID_AMT>=-1.078965 2087 867 0 (0.5845712 0.4154288)
##
                76) LIMIT BAL>=145000 978 356 0 (0.6359918 0.3640082) *
                77) LIMIT_BAL< 145000 1109 511 0 (0.5392245 0.4607755)
##
                 154) RATIO_PADI_AMT4>=-1.089607 1009 444 0 (0.5599604 0.4400396) *
##
##
                 155) RATIO_PADI_AMT4< -1.089607 100
                                                       33 1 (0.3300000 0.6700000) *
              39) PAID AMT< -1.078965 176
                                            66 1 (0.3750000 0.6250000) *
##
         5) REPAY STATUS.>=1.000148 586 207 1 (0.3532423 0.6467577) *
##
##
       3) TIMELY_PAID_AMT< -0.6144733 3019 690 1 (0.2285525 0.7714475) *
```

rpart.plot(ptree)



CT_model\$variable.importance

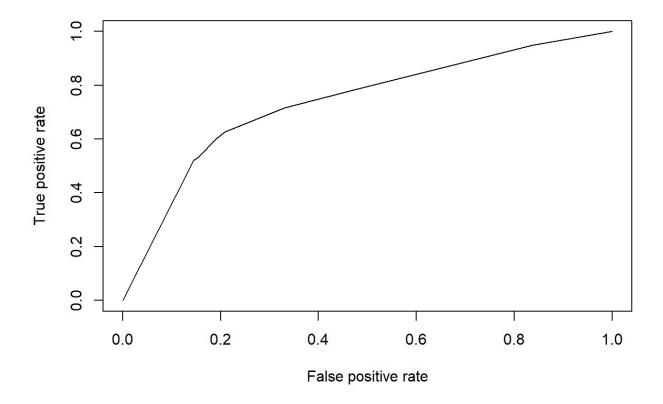
```
## TIMELY_PAID_AMT
                    REPAY_STATUS.
                                         PAID_AMT
                                                      BILLED._AMT
##
        806.215602
                       382.899461
                                       194.203815
                                                       164.608151
## RATIO_PADI_AMT4 RATIO_PADI_AMT2 RATIO_PADI_AMT1 RATIO_PADI_AMT3
##
       152.255511
                       125.071627
                                       109.634039
                                                        74.565264
##
        LIMIT_BAL
                              AGE
                                        EDUCATION
                                                         MARRIAGE
##
        68.850349
                        30.739832
                                         7.163986
                                                         5.436529
```

CART validation on test data

```
predTrain = predict(ptree, newdata = train_bank)
pred_class = predict(ptree, newdata = train_bank[,-6], type = "class")
predDT = predict(ptree, newdata = test_bank)
```

Validation on test data

```
library(ROCR)
DTpredROC_CT = prediction(predDT[,2],test_bank$DEFAULT)
perf2 =performance(DTpredROC_CT, "tpr", "fpr")
plot(perf2)
```



```
Auc <- as.numeric(performance(DTpredROC_CT, "auc")@y.values)
Auc</pre>
```

```
## [1] 0.7369729
```

KS

```
KS1 <- max(attr(perf2, 'y.values')[[1]]-attr(perf2, 'x.values')[[1]])
KS1</pre>
```

```
## [1] 0.4181934
```

Gini

```
## Gini Coefficient
library(ineq)
gini1 = ineq(test_bank$DEFAULT, type="Gini")
gini1
```

```
## [1] 0.7791111
```

```
#Check classification error using confusion matrix
#table(test_bank$DEFAULT,pred_class )
accuarcy <- (5715+1184)/(5715+1184+1297+804)
accuarcy</pre>
```

```
## [1] 0.7665556
```

Random Forest

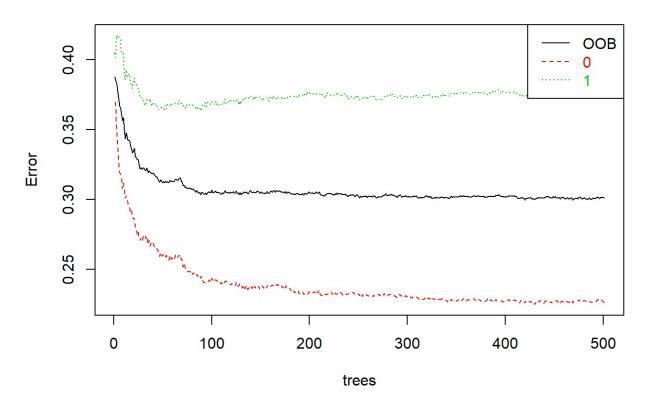
```
train_bank$DEFAULT=as.factor(train_bank$DEFAULT)
library(randomForest)
seed=101
set.seed(seed)
RF_model = randomForest(DEFAULT ~ ., data = train_bank, mtry = 3, nodesize =10, ntree
=501, importance = TRUE)
print(RF_model)
```

```
##
## Call:
0, ntree = 501, importance = TRUE)
##
             Type of random forest: classification
                  Number of trees: 501
##
## No. of variables tried at each split: 3
##
        OOB estimate of error rate: 30.09%
##
## Confusion matrix:
         1 class.error
      0
## 0 3591 1052 0.2265776
## 1 1744 2904 0.3752151
```

ploting RF moden

```
plot(RF_model, main="")
legend("topright", c("00B", "0", "1"), text.col=1:6, lty=1:3, col=1:3)
title(main="Error Rates Random Forest train_data")
```

Error Rates Random Forest train data



Checking OOB

```
rf_err_rate <- as.data.frame(RF_model$err.rate)
rf_err_rate$ID <- seq.int(nrow(rf_err_rate))
rf_err_rate[which(rf_err_rate$00B==min(rf_err_rate$00B)),]</pre>
```

```
## 420 0.2998601 0.2261469 0.373494 420
## 469 0.2998601 0.2261469 0.373494 469
```

```
min_tree<-min(rf_err_rate[which(rf_err_rate$00B==min(rf_err_rate$00B)),]$ID)</pre>
```

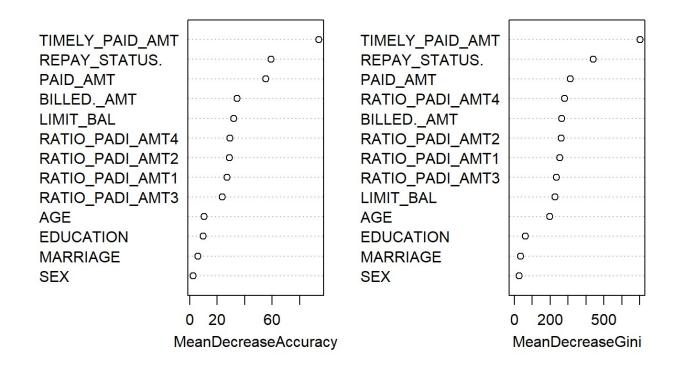
```
## List the importance of the variables.
impVar <- round(randomForest::importance(RF_model), 2)
impVar[order(impVar[,3],decreasing = TRUE),]</pre>
```

##		0	1	${\tt MeanDecreaseAccuracy}$	MeanDecreaseGini
##	TIMELY_PAID_AMT	76.59	41.05	93.85	700.48
##	REPAY_STATUS.	41.56	23.38	59.15	439.35
##	PAID_AMT	18.16	42.96	55.36	312.82
##	BILLEDAMT	16.83	20.24	34.56	265.57
##	LIMIT_BAL	15.94	23.68	32.12	226.66
##	RATIO_PADI_AMT4	16.31	15.72	29.22	280.35
##	RATIO_PADI_AMT2	10.11	20.30	28.91	263.15
##	RATIO_PADI_AMT1	2.46	29.72	27.23	254.00
##	RATIO_PADI_AMT3	7.73	17.35	23.93	235.53
##	AGE	13.06	0.56	10.64	198.71
##	EDUCATION	6.01	7.93	10.06	62.33
##	MARRIAGE	9.33	-2.24	5.91	35.17
##	SEX	1.98	1.38	2.47	27.94

Variable Importance: Graphical representation

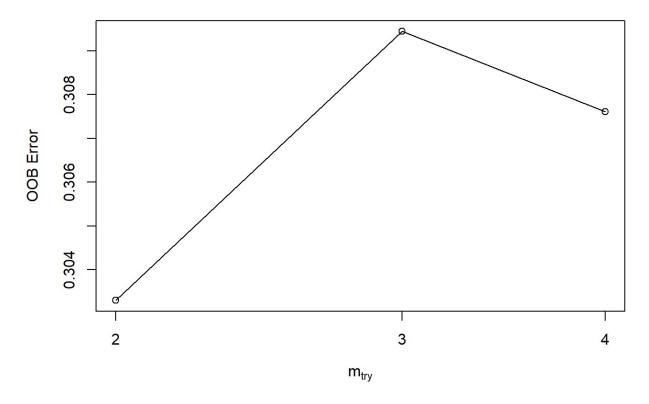
varImpPlot(RF_model)

RF_model



Optimal mtry value

```
## mtry = 3 00B error = 30.94%
## Searching left ...
## mtry = 2 00B error = 30.33%
## 0.01982609 1e-04
## Searching right ...
## mtry = 4 00B error = 30.76%
## -0.01419446 1e-04
```



#Validate RF model on test data

```
pred_RF =predict(tune_rf_model, newdata = test_bank[,-6], type="prob")
pred_RF_CL=predict(tune_rf_model, newdata = test_bank[,-6], type="class")
head(pred_RF)
```

```
## 0 1

## 1 0.294 0.706

## 2 0.408 0.592

## 3 0.884 0.116

## 4 0.826 0.174

## 5 0.704 0.296

## 6 0.672 0.328
```

```
class(pred_RF)
```

```
## [1] "matrix" "votes"
```

Deciling andrank order table

```
# deciling
decile <- function(x){</pre>
  deciles <- vector(length=10)</pre>
  for (i in seq(0.1,1,.1)){
    deciles[i*10] <- quantile(x, i, na.rm=T)</pre>
  return (
    ifelse(x<deciles[1], 1,
            ifelse(x<deciles[2], 2,
                    ifelse(x<deciles[3], 3,</pre>
                            ifelse(x<deciles[4], 4,
                                    ifelse(x<deciles[5], 5,
                                            ifelse(x<deciles[6], 6,
                                                    ifelse(x<deciles[7], 7,</pre>
                                                            ifelse(x<deciles[8], 8,
                                                                    ifelse(x<deciles[9], 9, 10</pre>
                                                                    ))))))))))
}
test_bank$deciles <- decile(pred_RF[,2])</pre>
```

Rank order

library(data.table)

```
library(tidyverse)
library(magrittr)

##
## Attaching package: 'magrittr'

## The following object is masked from 'package:purrr':
##
## set_names

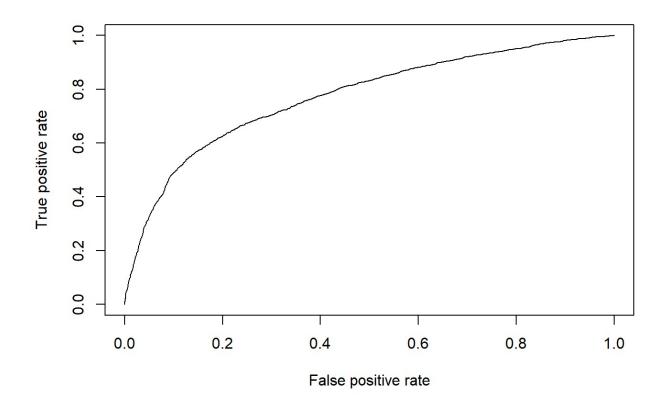
## The following object is masked from 'package:tidyr':
##
## extract
```

```
##
## Attaching package: 'data.table'
## The following objects are masked from 'package:dplyr':
##
       between, first, last
##
## The following object is masked from 'package:purrr':
##
##
       transpose
library(scales)
##
## Attaching package: 'scales'
## The following objects are masked from 'package:psych':
##
##
       alpha, rescale
## The following object is masked from 'package:purrr':
##
##
       discard
## The following object is masked from 'package:readr':
##
       col_factor
##
```

```
tmp_DT = data.table(test_bank)
rank <- tmp_DT[, list(</pre>
  cnt = length(DEFAULT),
  cnt_resp = sum(DEFAULT),
  cnt_non_resp = sum(DEFAULT ==0)) ,
  by=deciles][order(-deciles)]
rank$rrate <- round (rank$cnt_resp / rank$cnt,4);</pre>
rank$cum_resp <- cumsum(rank$cnt_resp)</pre>
rank$cum_non_resp <- cumsum(rank$cnt_non_resp)</pre>
rank$cum rel resp <- round(rank$cum resp / sum(rank$cnt resp),4);</pre>
rank$cum_rel_non_resp <- round(rank$cum_non_resp /sum(rank$cnt_non_resp),4);</pre>
rank$ks <- abs(rank$cum_rel_resp - rank$cum_rel_non_resp);</pre>
library(scales)
rank$rrate <- percent(rank$rrate)</pre>
rank$cum_rel_resp <- percent(rank$cum_rel_resp)</pre>
rank$cum_rel_non_resp <- percent(rank$cum_rel_non_resp)</pre>
View(rank)
```

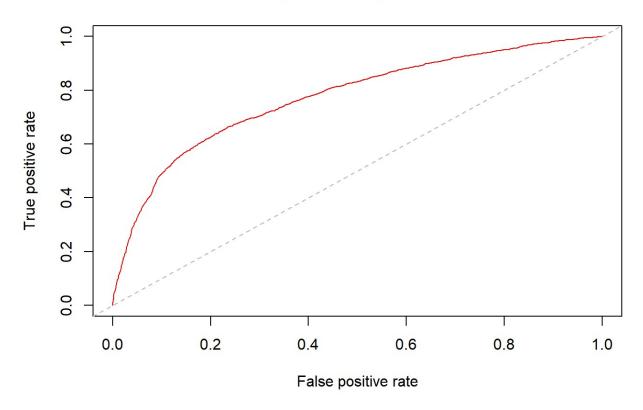
Validation with test data

```
library(ROCR)
RF_pred = ROCR::prediction(pred_RF[,2], test_bank$DEFAULT)
perfx = performance(RF_pred, "tpr", "fpr")
plot(perfx)
```



```
plot(perfx,col="red", main="parameters_ROC")
abline(0,1, lty = 8, col = "grey")
```

parameters_ROC



Performance Measures

Area Under Curve

```
Auc <- as.numeric(performance(RF_pred, "auc")@y.values)
Auc</pre>
```

```
## [1] 0.7739189
```

```
KS <- max(attr(perfx, 'y.values')[[1]]-attr(perfx, 'x.values')[[1]])
KS</pre>
```

```
## [1] 0.428749
```

```
## Gini Coefficient
library(ineq)
gini = ineq(pred_RF[,2], type="Gini")
gini
```

```
## [1] 0.3066809

## Classification Error
with(test_bank,table(DEFAULT,pred_RF_CL))

## pred_RF_CL
## DEFAULT 0 1
## 0 5500 1512
## 1 711 1277

accuracy <-(5509+1273)/(5509+1273+1503+715)
accuracy
## [1] 0.7535556
```

Machine learning approach with Ensemble Methods

```
#knn compare
library(class)
#View(train_bank)
#View(test_bank)
knn_fit<- knn(train = train_bank[,-6], test = test_bank[,-c(6,15)], cl=train_bank$DEFA
ULT,k =5,prob=TRUE)
knn_chk= table(test_bank$DEFAULT,knn_fit)
knn_chk</pre>
```

```
## knn_fit
## 0 1
## 0 4786 2226
## 1 805 1183
```

```
accuracy.knn = sum(diag(knn_chk))/sum(knn_chk)
accuracy.knn
```

```
## [1] 0.6632222
```

Naive Bayes

```
#naive bayes
library(e1071)
library(caret)
train_bank$DEFAULT = as.factor(train_bank$DEFAULT)
test_bank$DEFAULT = as.factor(test_bank$DEFAULT)
NB = naiveBayes(x =train_bank[-6], y =train_bank$DEFAULT)
pred.NB = predict(NB, newdata =test_bank[-6])
pred.NB
```

```
##
       ##
      ##
      [69] 0 0 1 0 0 0 0 1 0 1 1 1 1 1 1 0 0 1 0 0 0 0 0 0 1 1 0 0 0 1 0 0 1 1
      \begin{smallmatrix} 103 \end{smallmatrix} ] \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 1 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 0 \hspace{.1cm} 1 \hspace{.1cm} 0 \hspace{.
##
##
     [137] 0 0 0 0 0 0 1 0 0 0 0 1 0 1 1 0 0 1 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 0
     ##
##
     [205] 0 0 0 0 0 0 1 1 0 0 1 1 0 0 1 1 1 0 1 1 1 0 0 1 1 0 0 0 1 0 0 0 0 0
     [239] 1 0 1 0 0 0 0 1 1 0 0 0 0 0 0 1 1 0 0 1 0 0 0 0 1 1 0 0 0 0 0 1 0 0
##
     [273] 0 1 0 0 0 1 0 1 0 0 1 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0
##
     [307] 0 0 1 0 1 0 1 1 1 0 0 0 0 0 0 0 0 1 0 1 0 1 1 1 0 1 0 1 1 1 1 0 0 0 0
##
     [341] 1 1 0 1 0 1 1 1 1 1 0 0 0 1 1 1 1 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 1 1
##
##
     ##
##
     [443] 0 0 1 1 1 0 0 0 1 1 0 1 1 0 0 0 0 1 0 1 0 1 0 0 0 0 1 1 0 0 0 0 0 1
     ##
##
     [545] 1 1 0 0 0 1 1 0 0 0 0 1 1 0 1 0 0 0 1 1 1 0 1 0 1 0 1 1 1 1 1 0 0 1 0 0
##
     [579] 1 0 1 0 0 0 0 1 1 1 1 0 1 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 1 1
##
     ##
##
     [681] 0 0 0 0 1 1 1 0 0 1 0 1 1 1 1 0 1 0 0 1 1 0 1 0 0 1 1 1 0 1 0 0 0 1
     [715] 1 1 0 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 1
##
##
     ##
     ##
     [817] 1 0 0 0 0 1 1 0 0 0 1 0 1 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0
     ##
     ##
##
     [919] 1 0 0 1 0 1 1 0 1 1 0 0 1 0 1 1 0 0 1 0 1 1 1 0 0 0 0 0 0 1 0 0 1 1 1 0
##
     [953] 0 1 0 1 1 1 1 0 0 1 0 1 0 0 0 0 0 1 1 1 1 1 0 0 0 0 0 1 1 1 0 0 0 1
    [987] 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 1
## [1089] 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 1 1 0 0 0 0 1 0 0 0 1 0 1 1 0 0 0
## [1225] 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1
## [1327] 1 0 1 0 1 1 1 0 1 1 0 1 0 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 1 1 0
## [1463] 0 0 0 1 1 1 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 1 1
```

```
## [1667] 1 0 0 0 0 0 1 1 0 0 0 1 0 1 0 0 1 1 1 0 1 0 0 0 0 0 0 0 0 1 0
## [1735] 0 1 1 1 0 0 1 0 0 0 0 0 0 0 1 1 1 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1
## [1837] 0 0 0 1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 1 0 1 0 1 0 1 1 1 0 0 0 0 1 0
## [1973] 0 0 0 1 0 0 0 1 0 0 0 1 1 0 0 0 0 1 0 0 0 0 1 1 0 0 0 0 1 0 1 0 1 0 1
## [2007] 1 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 1 0 1 0 1 0 1 0 0 0 0 1
## [2041] 1 0 0 0 0 1 0 0 0 1 1 1 1 1 0 0 0 1 0 1 1 1 1 0 0 0 0 1 1 1 1 0 0 0 0 0 1
## [2075] 0 0 0 0 1 1 1 0 0 0 1 0 0 1 0 0 0 1 0 1 1 0 0 1 1 0 0 0 1 0 1 1
## [2177] 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 0 0 1 0
## [2211] 0 0 0 0 0 0 0 1 0 0 0 0 1 0 1 1 1 0 0 1 0 0 0 0 0 1 1 0 0 0 0 1 1 0
## [2381] 0 1 1 1 1 0 0 0 1 0 0 0 1 1 0 0 0 0 1 0 1 1 1 0 0 0 0 1 1 1 1 1 0 0 1 0
## [2483] 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0
## [2517] 0 0 1 0 0 0 1 1 0 0 0 1 1 1 0 0 0 1 0 1 0 1 0 1 0 1 0 1 0 0 0 0 1 0 0
## [2551] 0 1 1 0 0 0 1 0 0 1 0 0 0 0 0 1 1 0 1 1 0 0 1 0 0 0 0 0 0 1 1 0
## [2687] 1 0 0 0 1 1 0 1 1 1 0 1 0 0 0 1 0 0 0 1 1 0 1 0 0 0 1 0 0 0 1 0 0 1
## [2789] 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 1 0 0 1 1 0
## [2857] 0 1 1 0 0 0 0 1 1 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 1 1 0 0 1 0 0 0 1 0 0
## [2925] 0 1 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0
## [2959] 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 1 1 1 0 0 0 0 1 0 0 1
## [2993] 0 1 0 0 0 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0 0 1 1 0 1
## [3027] 0 1 0 0 1 0 0 0 1 1 1 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 1 0 0 0 1 0 1 0
## [3061] 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 1 1 1 1 0 1 1 1 0 0 0 0 0 0 0 0
## [3163] 1 0 0 1 0 1 0 0 0 0 0 1 0 0 0 0 1 1 1 0 0 0 0 1 1 0 1 0 1 0 1 0 1
## [3197] 0 0 1 1 0 1 1 0 0 0 1 1 0 1 1 0 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0
## [3231] 0 1 1 0 1 0 1 0 1 1 1 0 0 1 0 0 0 0 1 1 0 0 0 0 0 1 0 0 1 0 1 1 0 1
## [3265] 0 1 0 0 0 0 0 0 0 1 1 1 0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1
```

```
## [3401] 0 0 0 1 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 1 1
## [3503] 1 0 1 1 1 0 0 1 0 0 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 0 1 0 1 0 1 0 1
## [3537] 0 0 0 0 0 0 0 0 1 0 0 0 0 1 1 1 1 0 0 1 1 0 1 0 0 0 0 1 0
## [3605] 0 1 1 0 1 0 0 1 1 1 0 0 1 1 0 0 0 1 0 0 0 0 0 1 1 0 0 0 0 0 1 0 1 0
## [3673] 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 1 1 0 0 0 1 0 1 1 0 0 0
## [3775] 1 0 0 1 0 1 0 0 1 1 0 0 0 0 1 0 1 0 0 0 0 1 1 0 1 0 0 0 0 0 1 0
## [3809] 1 0 0 1 1 0 0 1 0 1 0 0 1 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 1 0 0 1 1 0 0
## [3945] 0 1 0 0 0 1 0 1 1 0 0 0 1 0 0 0 0 1 0 1 0 1 0 1 0 1 0 1 0 0 0 0 0 1 0
## [3979] 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0
## [4013] 0 1 0 1 0 0 0 0 0 1 1 1 0 0 1 1 1 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0
## [4047] 0 0 0 1 0 1 0 1 1 1 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 1 1 1 1 0
## [4081] 0 0 1 0 0 0 0 0 0 1 1 0 1 0 0 0 0 1 0 0 0 0 0 1 1 1 1 1 0 0 1 0 0 0 1
## [4115] 0 0 0 0 0 0 1 1 0 1 0 1 1 1 1 1 0 1 1 0 0 1 1 1 0 0 0 0 0 1 0 1 0 0
## [4285] 0 0 0 0 0 1 0 1 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 1 0 0 0 0 1 1 0 0
## [4353] 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 1 0 1 1 0 1 0 1 0 0 0
## [4421] 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 1 0 0 0 1 1 1 1 1 0 0
## [4455] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0
## [4489] 1 0 1 1 0 1 0 0 0 0 0 0 1 1 0 1 1 1 0 0 0 1 1 1 1 0 0 1 0 1 0 1 0 0 1
## [4659] 1 0 0 0 0 0 1 0 1 0 1 1 1 1 1 1 1 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1
## [4761] 0 1 1 0 1 1 0 0 1 1 0 0 1 1 1 0 1 1 0 0 0 1 1 1 0 1 1 0 0 1 1 1 0 0 1
## [4829] 0 0 0 0 0 0 1 0 1 0 1 0 1 1 1 0 0 1 1 1 0 0 0 0 1 1 1 0 0 1 0
## [4863] 1 0 1 0 0 0 0 1 0 0 1 0 0 0 1 0 0 1 1 1 0 1 1 1 0 1 1 1 0 0 1 1 0 1
## [4931] 0 0 0 0 0 1 0 0 1 1 0 1 0 0 1 0 0 1 1 0 1 0 0 0 1 1 0 1 0 0 0 0 0
```

```
## [5067] 1 1 1 1 0 0 0 1 1 0 1 0 1 0 1 0 0 0 1 1 0 0 0 0 1 1 0 1 0 0 0 0
## [5101] 0 0 1 0 0 0 0 0 1 0 0 0 0 1 1 0 0 1 1 0 0 1 1 0 0 1 1 0 0 1 1 0 0 1 0 1
## [5135] 1 0 0 1 1 0 0 0 0 0 1 0 0 0 0 1 1 0 1 1 0 0 0 1 1 0 0
## [5169] 1 0 0 0 1 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 1 1 0 0 0 0 1 0 0
## [5237] 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 1 1 1 1 1 1 1 1 1 0 1 0 1
## [5271] 1 1 1 0 0 0 0 0 0 1 1 0 0 1 0 1 0 0 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0
## [5305] 1 0 1 0 1 0 1 0 0 0 1 0 1 1 1 0 0 1 1 0 0 0 1 0 0 0 1 0 0 1 1 0 1 0 0
## [5373] 1 0 0 0 0 0 1 1 0 0 1 1 0 0 0 1 1 0 0 0 1 1 0 0 0 0 1 1 0 0 1 0 0 0 1 0
## [5407] 0 1 0 0 1 0 1 1 1 0 0 1 0 1 1 1 0 0 0 0 1 0 0 0 1 0 1 0 1 0 1 1 1 0 0
## [5441] 0 0 0 0 1 0 1 0 1 0 0 0 1 0 0 1 1 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0
## [5509] 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 1 0 0 1 1 1 0 1 0 1 1 0 0 0 1 0 0 1
## [5543] 1 0 0 0 0 0 0 0 1 1 0 1 1 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0
## [5611] 1 1 0 0 1 0 1 0 1 0 0 0 1 0 0 1 0 0 1 0 0 1 1 1 1 0 0 1 0 0 0
## [5645] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 1 0 0 1 0 0 0 1 0 0 0 0 1
## [5679] 0 1 1 0 1 0 0 1 1 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0
## [5747] 1 0 0 0 0 0 0 0 0 1 1 0 1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 1 0 1 0 1 0 0
## [5781] 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 1 0 1 0 0 0 0 0 1 1 0 0 1 0 0
## [5917] 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 1 0 1 0 0 1 1 1 0 0 0 1 0 0 0 0
## [5951] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 1 0 0 0 0 0 0
## [6019] 0 1 1 0 1 0 1 1 0 0 0 0 1 1 0 0 0 0 1 1 0 0 0 1 0 1 0 0 0 1 0 1 0 0 1 1 0
## [6053] 1 1 0 1 0 0 1 1 0 0 0 0 1 1 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
## [6121] 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 1 0 1 0 1 1 1 1 0 1 0 1 1 1 0 1
## [6257] 1 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0
## [6291] 0 1 0 0 1 0 1 1 0 0 0 0 1 0 0 0 0 1 0 0 1 0 1 1 0 1 1 1 0 0 0 0 0 0
## [6325] 1 0 1 1 0 0 1 0 0 0 1 0 0 0 1 0 1 1 1 0 1 0 0 0 0 0 0 1 1 1 1 0 0
## [6461] 0 0 0 1 0 0 1 0 0 0 1 0 1 0 0 1 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0
## [6597] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 1 0 0 0 0 0 0 1 1
```

```
## [6631] 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
## [6665] 0 1 0 0 0 0 0 0 1 0 0 0 0 1 1 1 0 0 0 1 1 0 0 0 0 1 0 1 0 1 0 0 1
## [6835] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0
## [6903] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0
## [6971] 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 1 1 0 0 0 1 1 0 0 0 1 0 0
## [7209] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0 0 1 1 0 1 0 1
## [7413] 1 1 0 0 0 0 0 1 0 0 1 0 1 0 0 1 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0
## [7447] 0 1 1 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 1 1 0 0 1 1 0 0 1 0 0 1 0 0 0 1 0 0 0
## [7481] 0 0 0 0 0 1 0 1 1 1 0 0 1 0 0 1 0 0 1 1 1 1 0 0 1 0 0 1 0 0 1 1 1 1 0 0 1 0 0 1 0 0 1
 \verb| ## [7549] 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 1 0 1 0 1 0 1 0 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 
## [7617] 0 0 1 0 0 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
## [7685] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0
## [7787] 0 0 1 0 1 1 0 0 1 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0
## [8059] 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 1 0 0 0 0 0 1 0 1 0 1 0 1 0 1
```

```
## [8331] 0 0 1 0 1 0 0 0 1 0 0 0 1 0 0 0 0 1 1 1 0 1 0 0 0 0 0 1 1 0 0 0 0
## [8433] 0 0 0 0 0 0 0 0 0 1 1 0 1 0 0 1 0 1 1 0 0 0 0 1 1 0 0 0 0
## [8603] 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 1 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 1
## [8671] 0 0 1 0 1 0 1 0 0 0 1 0 0 1 0 0 0 1 1 0 0 1 0 1 0 1 0 1 0 1 1 1
## [8705] 1 1 0 0 1 0 0 1 1 0 1 0 1 1 0 0 1 0 0 1 1 1 1 0 0 0 0 1 1 0 1 0 1 0 1 0
## [8739] 0 0 0 1 0 0 0 1 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 1 0 1 1 0 0 1 0 1 0 0
## [8773] 0 0 1 0 1 1 0 1 1 1 0 0 1 0 0 0 0 1 0 0 1 1 0 0 1 0 0 0 1 1 0 0 0
## [8807] 0 0 1 1 0 0 1 1 0 0 1 0 0 1 0 0 0 1 1 0 0 0 1 0 0 0 1 1 0 0 0 0 0 1
## [8875] 1 0 0 1 1 0 1 0 1 0 0 0 1 1 0 0 0 1 0 0 0 1 0 0 1 0 1 0 1 0 1 0 0 0
## [8909] 0 1 1 0 0 1 1 1 1 0 0 0 1 1 0 0 1 0 0 0 0 0 1 0 1 1 0 1 1 0 0 1 1 1
## [8943] 0 0 0 1 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 1 0 0 0 0 0 1 1 0 0 0 0 0
## Levels: 0 1
```

```
tab.NB =table(test_bank[,6], pred.NB)
tab.NB
```

```
## pred.NB
## 0 1
## 0 5370 1642
## 1 729 1259
```

```
accuracy.NB = sum(diag(tab.NB))/sum(tab.NB)
accuracy.NB
```

```
## [1] 0.7365556
```

```
confusionMatrix(pred.NB, test_bank$DEFAULT)
```

```
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction
                 0
            0 5370 729
##
            1 1642 1259
##
##
                  Accuracy : 0.7366
##
                    95% CI: (0.7273, 0.7456)
       No Information Rate: 0.7791
##
##
       P-Value [Acc > NIR] : 1
##
##
                     Kappa: 0.3427
##
##
    Mcnemar's Test P-Value : <2e-16
##
##
               Sensitivity: 0.7658
               Specificity: 0.6333
##
##
            Pos Pred Value: 0.8805
##
            Neg Pred Value: 0.4340
                Prevalence: 0.7791
##
##
            Detection Rate: 0.5967
##
      Detection Prevalence: 0.6777
##
         Balanced Accuracy: 0.6996
##
##
          'Positive' Class: 0
##
```

Naive Bayes classifier

##

impute

```
#names(train_bank)
#train_bank$DEFAULT = as.integer(train_bank$DEFAULT)
#test_bank$DEFAULT = as.integer(test_bank$DEFAULT)
#install.packages(mlr)
library(mlr)

## Loading required package: ParamHelpers

##
## Attaching package: 'mlr'

## The following object is masked from 'package:e1071':
```

```
## The following object is masked from 'package:ROCR':
##
##
       performance
## The following object is masked from 'package:caret':
##
##
       train
#Create a classification task for learning on bank Dataet and specify default feature
task = makeClassifTask(data = train_bank, target ="DEFAULT")
#Initialize the Naive Bayes classifier
selected_model = makeLearner("classif.naiveBayes")
#Train the model
NB_mlr= train(selected_model,task)
#Read the model learned
NB_mlr$learner.model
```

```
##
## Naive Bayes Classifier for Discrete Predictors
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
## A-priori probabilities:
##
        0
                    1
## 0.4997309 0.5002691
## Conditional probabilities:
##
     LIMIT_BAL
## Y
          [,1] [,2]
    0 174127.9 126738.5
##
    1 131340.4 114400.6
##
     SEX
##
## Y
          [,1] [,2]
##
    0 1.606935 0.4884836
    1 1.568417 0.4953504
##
##
##
     EDUCATION
## Y
          [,1] [,2]
    0 1.835236 0.7937926
##
##
    1 1.903614 0.7253323
##
##
     MARRIAGE
          [,1] [,2]
## Y
##
    0 1.563429 0.5205949
    1 1.521945 0.5256006
##
##
##
     AGE
## Y
          [,1] [,2]
    0 35.46866 9.093063
##
    1 35.80443 9.723742
##
##
##
     BILLED._AMT
             [,1] [,2]
## Y
    0 0.008420614 0.9801492
##
##
    1 -0.042941510 0.9762284
##
     REPAY_STATUS.
##
## Y
           [,1]
                   [,2]
##
    0 -0.08402265 0.7870855
    1 0.40146671 1.3678757
##
##
##
     PAID_AMT
```

```
## Y
              [,1]
                        [,2]
##
     0 0.07222019 0.9913057
##
     1 -0.22903501 0.6413568
##
##
      TIMELY_PAID_AMT
## Y
             [,1]
                       [,2]
     0 0.1593017 0.8065326
##
     1 -0.5536048 1.1702067
##
##
##
      RATIO_PADI_AMT1
## Y
              [,1]
                        [,2]
     0 0.02844571 0.9316682
##
     1 -0.07652734 0.7439935
##
##
##
      RATIO_PADI_AMT2
## Y
                         [,2]
               [,1]
##
     0 0.006558947 0.9229444
     1 -0.009970515 0.9391812
##
##
##
      RATIO_PADI_AMT3
## Y
               [,1]
                         [,2]
##
     0 -0.014470130 0.9407554
##
     1 0.005906947 0.7912172
##
##
      RATIO PADI AMT4
## Y
              [,1]
                        [,2]
##
     0 0.04260285 0.8371578
     1 -0.10099714 1.0038388
##
#Predict on the dataset without passing the target feature
predictions_mlr = as.data.frame(predict(NB_mlr, newdata = test_bank[,1:13]))
## Warning in predict.naiveBayes(.model$learner.model, newdata = .newdata, :
## Type mismatch between training and new data for variable 'RATIO_PADI_AMT4'.
## Did you use factors with numeric labels for training, and numeric values
## for new data?
table(test_bank$DEFAULT)
##
```

```
##Confusion matrix to check accuracy
table(predictions_mlr[,1],test_bank$DEFAULT)
```

##

0

7012 1988

1

```
##
## 0 7012 0
## 1 0 1988
```

```
predictions_mlr = as.data.frame(predict(NB_mlr, newdata = test_bank[,-6]))
table(predictions_mlr[,1],test_bank$DEFAULT)
```

```
##
## 0 1
## 0 5370 729
## 1 1642 1259
```

Bagging

```
#Bagging#
library(gbm)
```

```
## Loaded gbm 2.1.5
```

```
#install.packages('xgboost')
library(xgboost)
```

```
##
## Attaching package: 'xgboost'
```

```
## The following object is masked from 'package:dplyr':
##
## slice
```

```
## [1] 0.7672222
```

```
table(test_bank$DEFAULT,pred_class)
```

```
## pred_class
## 0 1
## 0 5724 1288
## 1 807 1181
```

XGBoost

```
# XGBoost
#install.packages('xgboost')
library(xgboost)
set.seed(123)
classifier = xgboost(data = as.matrix(train_bank[,-6]), label = train_bank$DEFAULT, nr
ounds = 10)
```

```
## [1] train-rmse:0.843655
## [2] train-rmse:0.666488
## [3] train-rmse:0.557688
## [4] train-rmse:0.492921
## [5] train-rmse:0.456142
## [6] train-rmse:0.436011
## [7] train-rmse:0.423342
## [8] train-rmse:0.415939
## [9] train-rmse:0.411865
## [10] train-rmse:0.408762
```

```
#Predicting the Test set results
y_pred <- predict(classifier, newdata = as.matrix(test_bank[-c(6,15)]))
y_pred = (y_pred >= 0.5)

# Making the Confusion Matrix
cm = table(test_bank$DEFAULT, y_pred)
cm
```

```
## y_pred
## TRUE
## 0 7012
## 1 1988
```

```
accuracy.bs = sum(diag(cm))/sum(cm)
accuracy.bs
```

```
## [1] 0.7791111
```

K-Fold Cross Validation

```
library(caret)
folds_bank = createFolds(train_bank$DEFAULT, k =10)
cv = lapply(folds_bank, function(x) {
    tr_fold = train_bank[-x, ]
    tt_fold = test_bank[x, ]
    classifier = xgboost(data = as.matrix(train_bank[-6]), label = train_bank$DEFAULT, nro
    unds = 10)
    y_pred = predict(classifier, newdata = as.matrix(tt_fold[-c(6,15)]))
    y_pred = (y_pred >= 0.5)
    cmx= table(tt_fold[,6], y_pred)
    accuracy = (cmx[1,1] + cmx[2,1]) / (cmx[1,1] + cmx[2,1] + cmx[1,1] + cmx[2,1])
    return(accuracy)
})
```

```
## [1]
       train-rmse:0.843655
## [2]
        train-rmse:0.666488
## [3]
        train-rmse:0.557688
        train-rmse:0.492921
## [4]
## [5]
        train-rmse:0.456142
        train-rmse:0.436011
## [6]
## [7]
        train-rmse:0.423342
## [8]
        train-rmse:0.415939
## [9]
        train-rmse:0.411865
## [10] train-rmse:0.408762
        train-rmse:0.843655
## [1]
## [2]
        train-rmse:0.666488
## [3]
        train-rmse:0.557688
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
## [6]
        train-rmse:0.436011
## [7]
        train-rmse:0.423342
## [8]
        train-rmse:0.415939
## [9]
        train-rmse:0.411865
## [10] train-rmse:0.408762
## [1]
        train-rmse:0.843655
## [2]
        train-rmse:0.666488
## [3]
        train-rmse:0.557688
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
        train-rmse:0.436011
## [6]
## [7]
        train-rmse:0.423342
## [8]
        train-rmse:0.415939
## [9]
        train-rmse:0.411865
## [10] train-rmse:0.408762
## [1]
        train-rmse:0.843655
## [2]
        train-rmse:0.666488
        train-rmse:0.557688
## [3]
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
## [6]
        train-rmse:0.436011
## [7]
        train-rmse:0.423342
        train-rmse:0.415939
## [8]
        train-rmse:0.411865
## [9]
## [10] train-rmse:0.408762
## [1]
        train-rmse:0.843655
## [2]
        train-rmse:0.666488
## [3]
        train-rmse:0.557688
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
##
  [6]
        train-rmse:0.436011
## [7]
        train-rmse:0.423342
## [8]
        train-rmse:0.415939
```

```
## [9] train-rmse:0.411865
## [10] train-rmse:0.408762
## [1]
        train-rmse:0.843655
## [2]
        train-rmse:0.666488
        train-rmse:0.557688
## [3]
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
## [6]
        train-rmse:0.436011
        train-rmse:0.423342
## [7]
## [8]
        train-rmse:0.415939
## [9]
        train-rmse:0.411865
## [10] train-rmse:0.408762
        train-rmse:0.843655
## [1]
## [2]
        train-rmse:0.666488
        train-rmse:0.557688
## [3]
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
## [6]
        train-rmse:0.436011
## [7]
        train-rmse:0.423342
## [8]
        train-rmse:0.415939
## [9]
        train-rmse:0.411865
## [10] train-rmse:0.408762
## [1]
       train-rmse:0.843655
## [2]
        train-rmse:0.666488
## [3]
        train-rmse:0.557688
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
## [6]
        train-rmse:0.436011
## [7]
        train-rmse:0.423342
## [8]
        train-rmse:0.415939
## [9]
        train-rmse:0.411865
## [10] train-rmse:0.408762
        train-rmse:0.843655
## [1]
## [2]
        train-rmse:0.666488
## [3]
        train-rmse:0.557688
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
        train-rmse:0.436011
## [6]
        train-rmse:0.423342
## [7]
## [8]
        train-rmse:0.415939
## [9]
        train-rmse:0.411865
## [10] train-rmse:0.408762
## [1]
        train-rmse:0.843655
## [2]
        train-rmse:0.666488
        train-rmse:0.557688
## [3]
## [4]
        train-rmse:0.492921
## [5]
        train-rmse:0.456142
## [6]
        train-rmse:0.436011
       train-rmse:0.423342
## [7]
```

```
## [8] train-rmse:0.415939
## [9] train-rmse:0.411865
## [10] train-rmse:0.408762
```

```
accuracy = mean(as.numeric(cv))
accuracy
```

```
## [1] 0.5
```