

## Class 6 - Classification Analysis

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr   1.5.1
## v ggplot2    3.5.1      v tibble    3.2.1
## v lubridate  1.9.4      v tidyr     1.3.1
## v purrr      1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(mice)
```

```
##
## Attaching package: 'mice'
##
## The following object is masked from 'package:stats':
##
##   filter
##
## The following objects are masked from 'package:base':
##
##   cbind, rbind
```

```
data = read.csv("G:/My Drive/Master-Data-Science/Semester_1/Business_Analytics/Data/index.csv", header=
str(data)
```

```
## 'data.frame':   1000 obs. of  21 variables:
## $ Creditability      : int  1 1 1 1 1 1 1 1 1 1 ...
## $ Account.Balance    : int  1 1 2 1 1 1 1 1 4 2 ...
## $ Duration.of.Credit..month. : int  18 9 12 12 12 10 8 6 18 24 ...
## $ Payment.Status.of.Previous.Credit: int  4 4 2 4 4 4 4 4 2 ...
## $ Purpose            : int  2 0 9 0 0 0 0 0 3 3 ...
## $ Credit.Amount      : int  1049 2799 841 2122 2171 2241 3398 1361 1098 3758 ...
## $ Value.Savings.Stocks : int  1 1 2 1 1 1 1 1 1 3 ...
## $ Length.of.current.employment : int  2 3 4 3 3 2 4 2 1 1 ...
## $ Instalment.per.cent : int  4 2 2 3 4 1 1 2 4 1 ...
## $ Sex...Marital.Status : int  2 3 2 3 3 3 3 3 2 2 ...
## $ Guarantors          : int  1 1 1 1 1 1 1 1 1 1 ...
## $ Duration.in.Current.address : int  4 2 4 2 4 3 4 4 4 4 ...
## $ Most.valuable.available.asset : int  2 1 1 1 2 1 1 1 3 4 ...
## $ Age..years.         : int  21 36 23 39 38 48 39 40 65 23 ...
```

```
## $ Concurrent.Credits          : int  3 3 3 3 1 3 3 3 3 3 ...
## $ Type.of.apartment          : int  1 1 1 1 2 1 2 2 2 1 ...
## $ No.of.Credits.at.this.Bank : int  1 2 1 2 2 2 2 1 2 1 ...
## $ Occupation                 : int  3 3 2 2 2 2 2 2 1 1 ...
## $ No.of.dependents           : int  1 2 1 2 1 2 1 2 1 1 ...
## $ Telephone                  : int  1 1 1 1 1 1 1 1 1 1 ...
## $ Foreign.Worker             : int  1 1 1 2 2 2 2 2 1 1 ...
```

```
unique(data$No.of.Credits.at.this.Bank)
```

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

```
table(data$Purpose)/1000*100
```

```
##
##      0      1      2      3      4      5      6      8      9     10
## 23.4 10.3 18.1 28.0  1.2  2.2  5.0  0.9  9.7  1.2
```

```
data$Creditability = as.factor(data$Creditability)
data$Account.Balance <- replace(data$Account.Balance, data$Account.Balance==4, 3)
data$Account.Balance = factor(data$Account.Balance, levels = seq(1,3), labels = c('No Account', 'No bal

data$Payment.Status.of.Previous.Credit[data$Payment.Status.of.Previous.Credit <=1] = 1
data$Payment.Status.of.Previous.Credit[data$Payment.Status.of.Previous.Credit ==2] = 2
data$Payment.Status.of.Previous.Credit[data$Payment.Status.of.Previous.Credit >=3] = 3
data$Payment.Status.of.Previous.Credit = factor(data$Payment.Status.of.Previous.Credit, levels = seq(1,3), labels = c('None', 'Bel

data$Value.Savings.Stocks[data$Value.Savings.Stocks == 4] = 3
data$Value.Savings.Stocks[data$Value.Savings.Stocks == 5] = 4
data$Value.Savings.Stocks = factor(data$Value.Savings.Stocks, levels = seq(1,4), labels = c('None', 'Bel

data$Length.of.current.employment[data$Length.of.current.employment == 2] = 1
data$Length.of.current.employment[data$Length.of.current.employment == 3] = 2
data$Length.of.current.employment[data$Length.of.current.employment == 4] = 3
data$Length.of.current.employment[data$Length.of.current.employment == 5] = 4
data$Length.of.current.employment = factor(data$Length.of.current.employment, levels = seq(1,4), labels = c('None', 'Bel

data$Sex...Marital.Status[data$Sex...Marital.Status <=2] = 1
data$Sex...Marital.Status[data$Sex...Marital.Status ==3] = 2
data$Sex...Marital.Status[data$Sex...Marital.Status ==4] = 3
data$Sex...Marital.Status = factor(data$Sex...Marital.Status, levels = seq(1,3), labels = c('Male Divor

data$No.of.Credits.at.this.Bank[data$No.of.Credits.at.this.Bank >= 3] = 2
data$No.of.Credits.at.this.Bank = factor(data$No.of.Credits.at.this.Bank, levels = seq(1,2), labels = c('None', 'Bel

data$Guarantors[data$Guarantors >= 2] = 2
data$Guarantors = factor(data$Guarantors, levels = seq(1,2), labels = c('None', 'Yes'))

data$Concurrent.Credits[data$Concurrent.Credits <=2] = 1
data$Concurrent.Credits[data$Concurrent.Credits ==3] = 2
data$Concurrent.Credits = factor(data$Concurrent.Credits, levels = seq(1,2), labels = c('Other Banks or
```

```
data = data[-21]

data$Purpose[data$Purpose ==1] = 1
data$Purpose[data$Purpose ==2] = 2
data$Purpose[data$Purpose %in% c(3,4,5,6)] = 3
data$Purpose[data$Purpose %in% c(8,9,10,0)] = 4
data$Purpose = factor(data$Purpose, levels = seq(1,4), labels = c('New Car','Used Car','Home Related','Other'))
```

```
md.pattern(data)
```

```
##  /\      /\
## { '---' }
## { 0  0 }
## ==> V <== No need for mice. This data set is completely observed.
##  \  \ /  /
##   '-----'
```



```
##      Credibility Account.Balance Duration.of.Credit..month.
## 1000             1             1             1
##             0             0             0
##      Payment.Status.of.Previous.Credit Purpose Credit.Amount
## 1000                               1       1             1
##                               0       0             0
##      Value.Savings.Stocks Length.of.current.employment Instalment.per.cent
```

```
## 1000          1          1          1
##             0          0          0
## Sex...Marital.Status Guarantors Duration.in.Current.address
## 1000          1          1          1
##             0          0          0
## Most.valuable.available.asset Age..years. Concurrent.Credits
## 1000          1          1          1
##             0          0          0
## Type.of.apartment No.of.Credits.at.this.Bank Occupation No.of.dependents
## 1000          1          1          1          1
##             0          0          0          0
## Telephone
## 1000          1 0
##             0 0
```

```
str(data)
```

```
## 'data.frame': 1000 obs. of 20 variables:
## $ Creditability : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 ...
## $ Account.Balance : Factor w/ 3 levels "No Account","No balance",...: 1 1 2 1 1 1 1 1 ...
## $ Duration.of.Credit..month. : int 18 9 12 12 12 10 8 6 18 24 ...
## $ Payment.Status.of.Previous.Credit: Factor w/ 3 levels "Some Problems",...: 3 3 2 3 3 3 3 3 2 ...
## $ Purpose : Factor w/ 4 levels "New Car","Used Car",...: 2 4 4 4 4 4 4 4 3 ...
## $ Credit.Amount : int 1049 2799 841 2122 2171 2241 3398 1361 1098 3758 ...
## $ Value.Savings.Stocks : Factor w/ 4 levels "None","Below 100 DM",...: 1 1 2 1 1 1 1 1 1 ...
## $ Length.of.current.employment : Factor w/ 4 levels "Below 1 year (including unemployed)",...: 1 ...
## $ Instalment.per.cent : int 4 2 2 3 4 1 1 2 4 1 ...
## $ Sex...Marital.Status : Factor w/ 3 levels "Male Divorces/Single",...: 1 2 1 2 2 2 2 2 ...
## $ Guarantors : Factor w/ 2 levels "None","Yes": 1 1 1 1 1 1 1 1 1 ...
## $ Duration.in.Current.address : int 4 2 4 2 4 3 4 4 4 4 ...
## $ Most.valuable.available.asset : int 2 1 1 1 2 1 1 1 3 4 ...
## $ Age..years. : int 21 36 23 39 38 48 39 40 65 23 ...
## $ Concurrent.Credits : Factor w/ 2 levels "Other Banks or Dept Stores",...: 2 2 2 2 1 ...
## $ Type.of.apartment : int 1 1 1 1 2 1 2 2 2 1 ...
## $ No.of.Credits.at.this.Bank : Factor w/ 2 levels "1","More than 1": 1 2 1 2 2 2 2 1 2 1 ...
## $ Occupation : int 3 3 2 2 2 2 2 2 1 1 ...
## $ No.of.dependents : int 1 2 1 2 1 2 1 2 1 1 ...
## $ Telephone : int 1 1 1 1 1 1 1 1 1 1 ...
```

## Statistical Testing

Chi-square for

```
Categorical.Table = data.frame(
  'Variable' = character(),
  'p-value' = numeric()
)

for (i in colnames(data[, -c(1,3,6,14)])){
  test = chisq.test(table(data$Creditability, data[, i]))
  test2 = data.frame(i, test$p.value)
  Categorical.Table = rbind(Categorical.Table, test2)
}
```

```
}
Categorical.Table
```

```
##                                i test.p.value
## 1                Account.Balance 5.742621e-27
## 2 Payment.Status.of.Previous.Credit 1.557328e-12
## 3                        Purpose 2.760708e-04
## 4                Value.Savings.Stocks 8.335937e-08
## 5      Length.of.current.employment 4.220685e-04
## 6                Instalment.per.cent 1.400333e-01
## 7                Sex...Marital.Status 1.043498e-02
## 8                        Guarantors 1.000000e+00
## 9      Duration.in.Current.address 8.615521e-01
## 10 Most.valuable.available.asset 2.858442e-05
## 11                Concurrent.Credits 4.763431e-04
## 12                Type.of.apartment 8.810311e-05
## 13      No.of.Credits.at.this.Bank 1.693042e-01
## 14                        Occupation 5.965816e-01
## 15                No.of.dependents 1.000000e+00
## 16                        Telephone 2.788762e-01
```

## Train test split

```
indexes = sample(1:1000, size = 500)
Train = data[indexes,]
Test = data[-indexes,]
```

## Logistic Regression

generalized linear model = glm()

- when y is discrete/binary

$$H_0 : B_j = 0 H_1 : B_j \neq 0$$

## Create initial model

```
logisticmodel50 = glm(Creditability~Account.Balance+Payment.Status.of.Previous.Credit+Purpose+Value.Sav
summary(logisticmodel50)
```

```
##
## Call:
## glm(formula = Creditability ~ Account.Balance + Payment.Status.of.Previous.Credit +
##      Purpose + Value.Savings.Stocks + Length.of.current.employment +
```

```

## Sex...Marital.Status + Most.valuable.available.asset + Type.of.apartment +
## Concurrent.Credits + Duration.in.Current.address + Credit.Amount +
## Age..years., family = "binomial", data = Train)
##
## Coefficients:
##
## Estimate
## (Intercept) 1.006e-01
## Account.BalanceNo balance 3.098e-01
## Account.BalanceSome balance 1.615e+00
## Payment.Status.of.Previous.CreditPaid Up 7.344e-01
## Payment.Status.of.Previous.CreditNo Problems(in this bank) 1.253e+00
## PurposeUsed Car -1.556e-01
## PurposeHome Related -4.363e-01
## PurposeOther -9.007e-01
## Value.Savings.StocksBelow 100 DM 1.149e-01
## Value.Savings.Stocks[100, 1000) 8.636e-01
## Value.Savings.StocksAbove 1000 DM 1.336e+00
## Length.of.current.employment[1,4) -4.843e-01
## Length.of.current.employment[4,7) 1.024e+00
## Length.of.current.employmentAbove 7 2.128e-01
## Sex...Marital.StatusMale Married/Widowed 5.081e-01
## Sex...Marital.StatusFemale 3.474e-01
## Most.valuable.available.asset -2.706e-01
## Type.of.apartment -2.999e-02
## Concurrent.CreditsNone 1.839e-01
## Duration.in.Current.address -1.644e-01
## Credit.Amount -8.544e-05
## Age..years. 1.613e-02
##
## Std. Error z value
## (Intercept) 8.890e-01 0.113
## Account.BalanceNo balance 2.914e-01 1.063
## Account.BalanceSome balance 2.963e-01 5.453
## Payment.Status.of.Previous.CreditPaid Up 3.754e-01 1.956
## Payment.Status.of.Previous.CreditNo Problems(in this bank) 3.889e-01 3.221
## PurposeUsed Car 5.251e-01 -0.296
## PurposeHome Related 4.972e-01 -0.877
## PurposeOther 4.841e-01 -1.861
## Value.Savings.StocksBelow 100 DM 3.578e-01 0.321
## Value.Savings.Stocks[100, 1000) 4.459e-01 1.937
## Value.Savings.StocksAbove 1000 DM 4.030e-01 3.315
## Length.of.current.employment[1,4) 3.016e-01 -1.606
## Length.of.current.employment[4,7) 4.035e-01 2.537
## Length.of.current.employmentAbove 7 3.613e-01 0.589
## Sex...Marital.StatusMale Married/Widowed 2.561e-01 1.984
## Sex...Marital.StatusFemale 4.416e-01 0.787
## Most.valuable.available.asset 1.270e-01 -2.131
## Type.of.apartment 2.299e-01 -0.130
## Concurrent.CreditsNone 2.922e-01 0.629
## Duration.in.Current.address 1.143e-01 -1.439
## Credit.Amount 4.542e-05 -1.881
## Age..years. 1.212e-02 1.331
##
## Pr(>|z|)
## (Intercept) 0.909897
## Account.BalanceNo balance 0.287789

```

```

## Account.BalanceSome balance 4.97e-08 ***
## Payment.Status.of.Previous.CreditPaid Up 0.050442 .
## Payment.Status.of.Previous.CreditNo Problems(in this bank) 0.001278 **
## PurposeUsed Car 0.766946
## PurposeHome Related 0.380218
## PurposeOther 0.062814 .
## Value.Savings.StocksBelow 100 DM 0.748123
## Value.Savings.Stocks[100, 1000) 0.052771 .
## Value.Savings.StocksAbove 1000 DM 0.000917 ***
## Length.of.current.employment[1,4) 0.108293
## Length.of.current.employment[4,7) 0.011183 *
## Length.of.current.employmentAbove 7 0.555811
## Sex...Marital.StatusMale Married/Widowed 0.047300 *
## Sex...Marital.StatusFemale 0.431437
## Most.valuable.available.asset 0.033086 *
## Type.of.apartment 0.896195
## Concurrent.CreditsNone 0.529045
## Duration.in.Current.address 0.150292
## Credit.Amount 0.059933 .
## Age..years. 0.183337
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 609.16 on 499 degrees of freedom
## Residual deviance: 470.72 on 478 degrees of freedom
## AIC: 514.72
##
## Number of Fisher Scoring iterations: 5

```

## Optimize model

```

logisticmodel50final = glm(Creditability~Account.Balance + Payment.Status.of.Previous.Credit + Purpose +
summary(logisticmodel50final)

```

```

##
## Call:
## glm(formula = Creditability ~ Account.Balance + Payment.Status.of.Previous.Credit +
## Purpose + Length.of.current.employment + Sex...Marital.Status,
## family = "binomial", data = Train)
##
## Coefficients:
## Estimate Std. Error
## (Intercept) -0.87234 0.54749
## Account.BalanceNo balance 0.35787 0.26145
## Account.BalanceSome balance 1.83244 0.27878
## Payment.Status.of.Previous.CreditPaid Up 0.95727 0.34069
## Payment.Status.of.Previous.CreditNo Problems(in this bank) 1.38639 0.36325
## PurposeUsed Car -0.08772 0.47511
## PurposeHome Related -0.25652 0.44019
## PurposeOther -0.64564 0.43185

```

```
## Length.of.current.employment[1,4) -0.35418 0.28674
## Length.of.current.employment[4,7) 0.92450 0.38003
## Length.of.current.employmentAbove 7 0.26054 0.32096
## Sex...Marital.StatusMale Married/Widowed 0.42585 0.23592
## Sex...Marital.StatusFemale 0.57170 0.42675
## z value Pr(>|z|)
## (Intercept) -1.593 0.111081
## Account.BalanceNo balance 1.369 0.171060
## Account.BalanceSome balance 6.573 4.93e-11 ***
## Payment.Status.of.Previous.CreditPaid Up 2.810 0.004957 **
## Payment.Status.of.Previous.CreditNo Problems(in this bank) 3.817 0.000135 ***
## PurposeUsed Car -0.185 0.853526
## PurposeHome Related -0.583 0.560057
## PurposeOther -1.495 0.134904
## Length.of.current.employment[1,4) -1.235 0.216757
## Length.of.current.employment[4,7) 2.433 0.014987 *
## Length.of.current.employmentAbove 7 0.812 0.416934
## Sex...Marital.StatusMale Married/Widowed 1.805 0.071072 .
## Sex...Marital.StatusFemale 1.340 0.180355
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 609.16 on 499 degrees of freedom
## Residual deviance: 503.43 on 487 degrees of freedom
## AIC: 529.43
##
## Number of Fisher Scoring iterations: 4
```

## Obtain fitted values

```
fit50 = fitted.values(logisticmodel50final)
head(fit50)
```

```
##      542      873      156      587      818      656
## 0.8229738 0.8403520 0.8967508 0.6352489 0.6877547 0.7135468
```

## Change binary response

```
thres = rep(0,500)
for (i in 1:500) {
  if(fit50[i]>0.5) {
    thres[i] = 1
  }
  else {
    thres[i] = 0
  }
}
str(thres)
```



```
## num [1:500] 1 1 1 1 1 1 1 1 1 1 ...
```

```
str(Train$Creditability)
```

```
## Factor w/ 2 levels "0","1": 2 1 2 2 1 2 2 2 2 2 ...
```

## Create cross table

```
conf.mat = table(Train$Creditability, thres)
conf.mat
```

```
##      thres
##        0   1
##    0  55  94
##    1  40 311
```

## Compute accuracy

```
LR_train_acc = sum(diag(conf.mat))/500*100
```

## Perform on testing data

```
print(sum(diag(ct)))
```

```
library(gmodels)
# Perform modeling on testing data
pr = predict(logisticmodel50final, data=Test, type='response')

# Set threshold
thres_pred = rep(0, 500)
for (i in 1:500) {
  if(pr[i] > 0.5) {
    thres_pred[i] = 1
  }
  else {
    thres_pred[i] = 0
  }
}
str(thres_pred)
```

```
## num [1:500] 1 1 1 1 1 1 1 1 1 1 ...
```

```
ct = CrossTable(Test$Creditability, thres_pred, digits=1, prop.r=F, prop.t=F, prop.chisq = F, chisq = F)
```

```
##
##
```

```
##      Cell Contents
## |-----|
## |                N |
## |      N / Col Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##          | thres_pred
## Test$Creditability |      0 |      1 | Row Total |
## -----|-----|-----|-----|
##          0 |      31 |     120 |      151 |
##          |      0.3 |      0.3 |          |
## -----|-----|-----|-----|
##          1 |      64 |     285 |      349 |
##          |      0.7 |      0.7 |          |
## -----|-----|-----|-----|
##      Column Total |      95 |     405 |      500 |
##          |      0.2 |      0.8 |          |
## -----|-----|-----|-----|
##
##
```

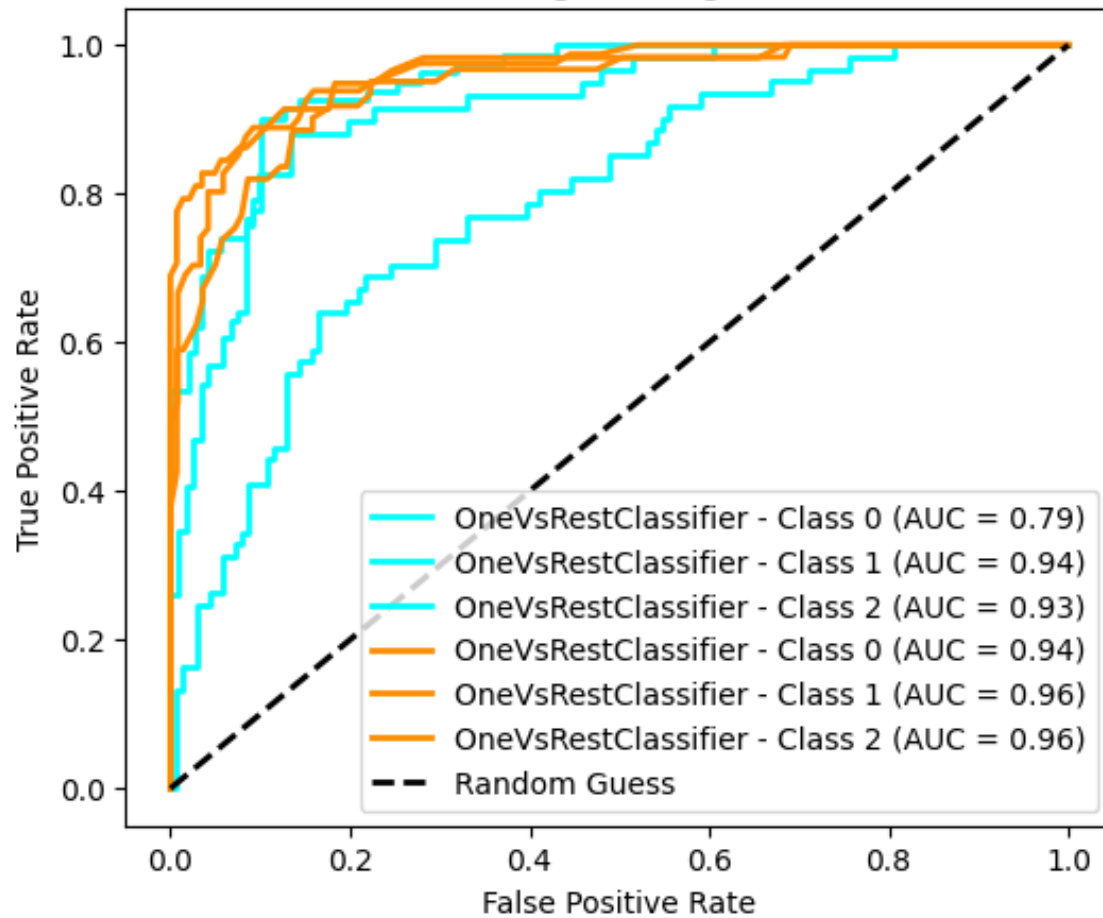
```
print(ct)
```

```
## $t
##      y
## x      0      1
## 0  31 120
## 1  64 285
##
## $prop.row
##      y
## x      0      1
## 0 0.2052980 0.7947020
## 1 0.1833811 0.8166189
##
## $prop.col
##      y
## x      0      1
## 0 0.3263158 0.2962963
## 1 0.6736842 0.7037037
##
## $prop.tbl
##      y
## x      0      1
## 0 0.062 0.240
## 1 0.128 0.570
```

```
conf.mat2 = table(Test$Creditability, thres_pred)
LR_test_acc = sum(diag(conf.mat2))/500*100
```

## Plot ROC AUC Curve

Multiclass ROC Curve with Logistic Regression and Random Forest

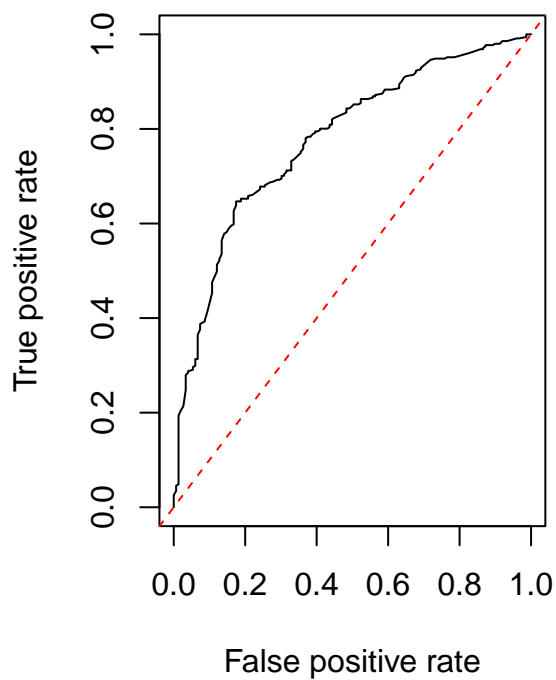


```
library(ROCR)

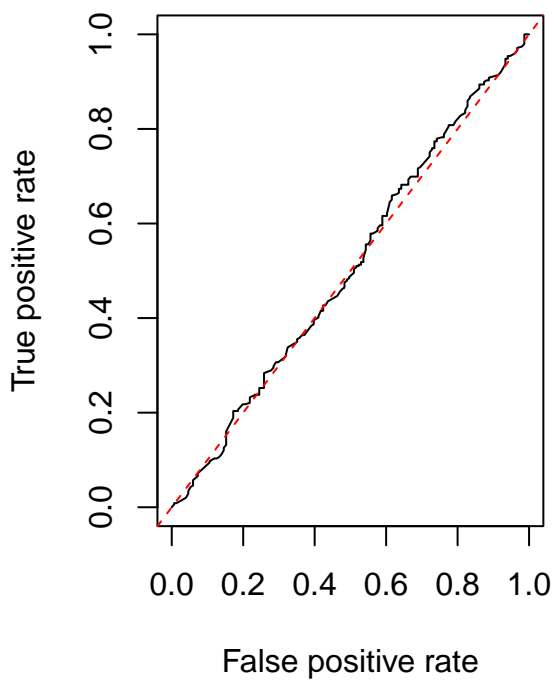
par(mfrow=c(1,2))
#Training Data
prod_pred = prediction(fit50, Train$Creditability)
perf = performance(prod_pred,'tpr','fpr')
plot(perf, main='ROC-AUC Curve Training Data');abline(a = 0, b = 1, col = "red", lty = 2)

#Testing Data
prod_pred = prediction(prr, Test$Creditability)
perf = performance(prod_pred,'tpr','fpr')
plot(perf, main='ROC-AUC Curve Testing Data');abline(a = 0, b = 1, col = "red", lty = 2)
```

**ROC-AUC Curve Training Data**



**ROC-AUC Curve Testing Data**



## Tree Based Index

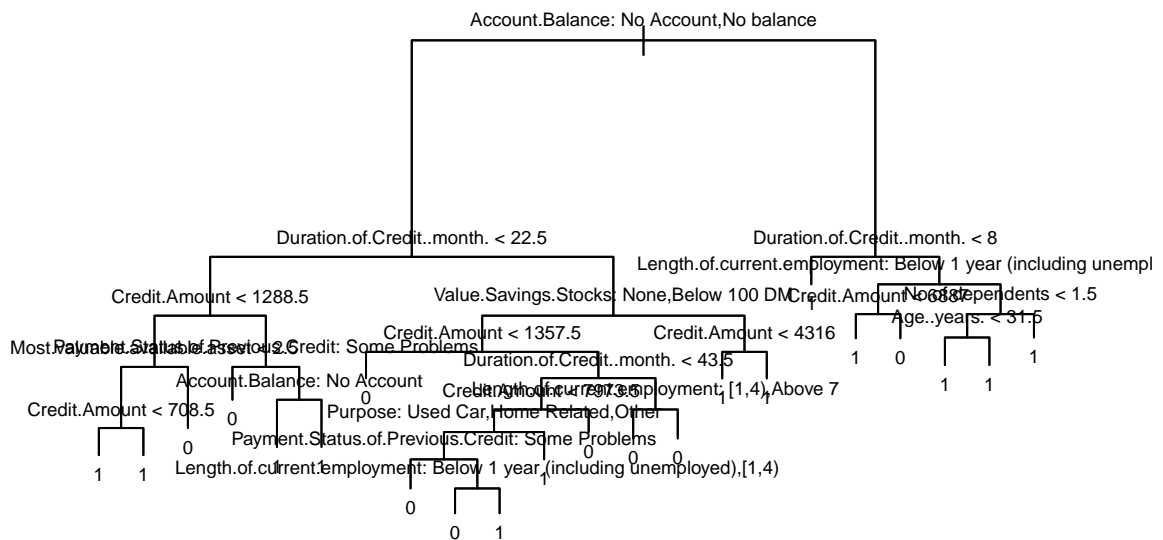
Gini Index - recursive partition

## Model Building

```
library(tree)
```

```
tree_model = tree(Creditability ~ Account.Balance+Duration.of.Credit..month.+Payment.Status.of.Previous  
Guarantors+Duration.in.Current.address+Most.valuable.available.asset+Age..years.+Concurrent.Credits+Type
```

```
plot(tree_model);text(tree_model, pretty=0, cex=0.6)
```



## Evaluate Train Set

```
train_pred = predict(tree_model, Train, type='class')
ct1 = table(Train$Creditability, train_pred)
T_Train_acc = sum(diag(ct1))/500*100
```

## Evaluate Test Set

```
test_pred = predict(tree_model, Test, type='class')
ct2 = table(Train$Creditability, test_pred)
T_Test_acc = sum(diag(ct2))/500*100
```

## ROC AUC Curve

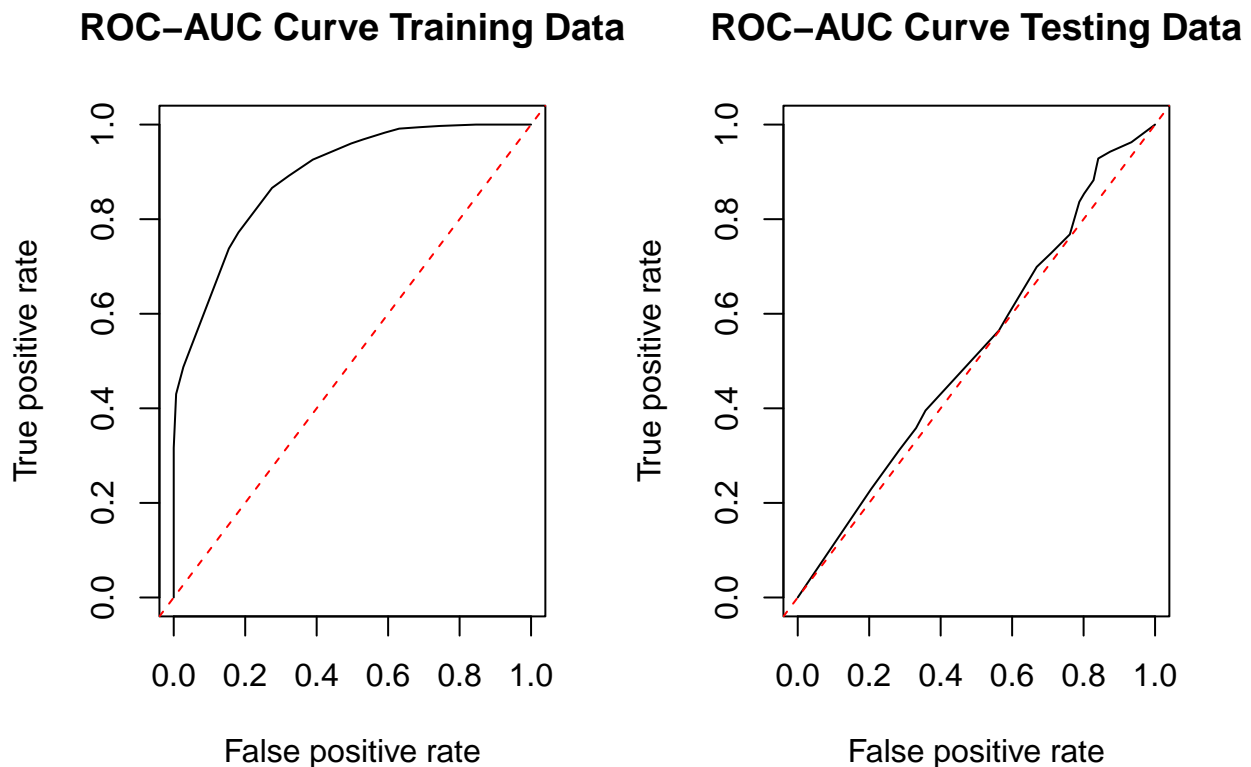
```
# Training Data
fit_tree_train = predict(tree_model, data=Train)

prod_pred = prediction(fit_tree_train[,2], Train$Creditability)
perf1 = performance(prod_pred, 'tpr', 'fpr')
```

```
# Testing Data
fit_tree_test = predict(tree_model, data=Test)

prod_pred = prediction(fit_tree_test[,2], Test$Creditability)
perf2 = performance(prod_pred, 'tpr', 'fpr')

par(mfrow=c(1,2))
plot(perf1, main='ROC-AUC Curve Training Data');abline(a = 0, b = 1, col = "red", lty = 2)
plot(perf2, main='ROC-AUC Curve Testing Data');abline(a = 0, b = 1, col = "red", lty = 2)
```



## Pruning

```
tree_model_prune = prune.misclass(tree_model, best=8)
```

## Evaluate Train Set

```
train_prune_pred = predict(tree_model_prune, Train, type='class')
ct3 = table(Train$Creditability, train_prune_pred)
TP_Train_acc = sum(diag(ct3))/500*100
```

## Evaluate Test Set

```
test_prune_pred = predict(tree_model_prune, Test, type='class')
ct4 = table(Train$Creditability, test_prune_pred)
TP_Test_acc = sum(diag(ct4))/500*100
```

## ROC AUC Curve

```
# Train Dataset

fit_tree_prune_train = predict(tree_model_prune, data=Train)

prod_pred = prediction(fit_tree_prune_train[,2], Train$Creditability)
perf1 = performance(prod_pred, 'tpr', 'fpr')

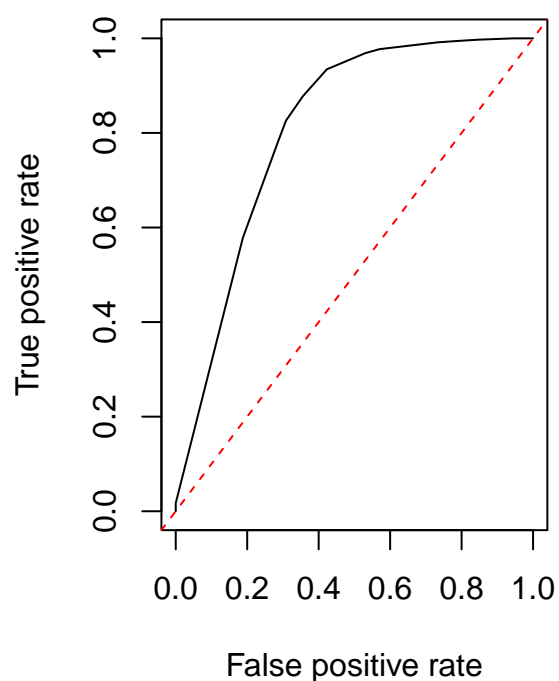
# Test Dataset

fit_tree_prune_test = predict(tree_model_prune, data=Test)

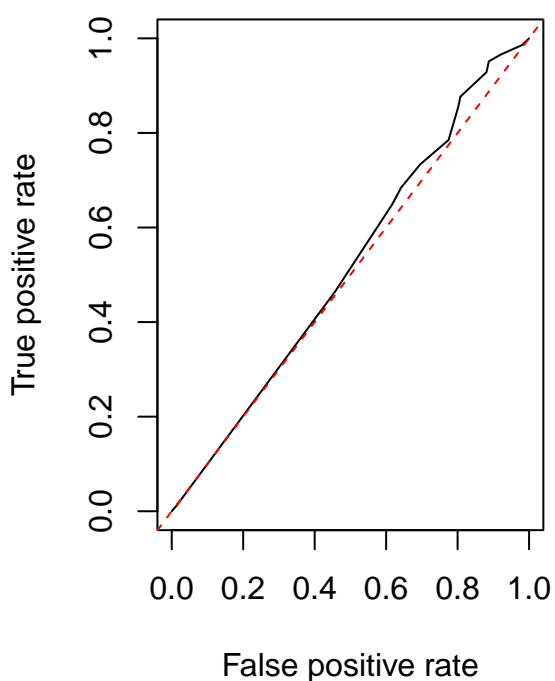
prod_pred = prediction(fit_tree_prune_test[,2], Test$Creditability)
perf2 = performance(prod_pred, 'tpr', 'fpr')

par(mfrow=c(1,2))
plot(perf1, main='ROC-AUC Curve Training Data');abline(a = 0, b = 1, col = "red", lty = 2)
plot(perf2, main='ROC-AUC Curve Testing Data');abline(a = 0, b = 1, col = "red", lty = 2)
```

ROC-AUC Curve Training Data



ROC-AUC Curve Testing Data



## Combine accuracy

```
data.frame(
  Models = c('Logistic Regression', 'Tree', 'Tree Pruned'),
  Train = c(LR_train_acc, T_Train_acc, TP_Train_acc),
  Test = c(LR_test_acc, T_Test_acc, TP_Test_acc)
)
```

```
##           Models Train Test
## 1 Logistic Regression  73.2 63.2
## 2                Tree  83.2 62.8
## 3          Tree Pruned  82.8 64.2
```