Data Analysis of the German Credit Dataset

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MIS510; Data Mining and Visualization

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MIS 510 Portfolio Project Option 1

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The German Credit's Data Mining Process

Introduction

I have chosen to explore the GermanCredit.csv dataset for data mining to gain insight into customers' creditworthiness. This dataset contains 1,000 records with 20 different attributes, including but not limited to age, gender, loan duration, loan amount, and whether the loan was approved or not. By exploring this data, I hope to uncover trends and insights that can be used to improve credit scoring and risk management processes.

This analysis uses data mining techniques to explore the potential of predictive classification models based on the German Credit dataset. Specifically, I will use logistic regression, classification trees, and neural networks to evaluate the data and compare the results to determine the most effective model. Using these techniques; I will be able to identify patterns in the data and draw conclusions about the potential of predictive models to classify new data accurately. In addition, I will also be using visualizations to gain insights into the data and present my findings. The methodology I will use is first to divide the data into a training and validation set. I will then use logistic regression, classification trees, and neural networks to train my models on the training set and evaluate their performance on the validation set. Afterward, I will compare the results of the models and draw conclusions about which model is the most effective. Finally, I will use visualizations to explore the data further and gain insights into the results.

The following chapters and sections from the book by Shmueli et al. (2018) will help me complete this option Chapter 3, Data Visualization; Chapter 4, Chapter 5, Evaluating

Predictive Performance; Data Summaries; Chapter 9, Classification Trees; Chapter 9.8, Random Forest; Chapter 10, Logistic Regression; Chapter 11, Neural Nets. The chapters and sections from the class notes will help me explore the GermanCredit.csv dataset, divide the data into training and validation partitions, and apply two data mining techniques (logistic regression, classification trees, and neural networks) for classification models. Furthermore, I will use the class notes to analyze the results and include visualizations. The chapters and sections from the class notes will help me to develop a methodology for exploring the GermanCredit.csv dataset. The data exploration techniques include logistic regression, classification trees, and neural networks. The data visualization techniques outlined in Chapters 3 and 4 will help me to understand the data better and to identify patterns and relationships between the predictor variables and the outcome. Chapter 5 will allow me to compare the training and validation dataset. The classification trees method will help with classification and prediction in Chapter 9, and random forest measures variable important scores as we know which predict variable is most important than other for prediction. The logistic regression technique outlined in Chapter 10 will allow me to model the data and determine the relationship between the predictor variables and the product. The neural network technique outlined in Chapter 11 will help me develop an effective model for predicting the outcome and identifying essential predictors. These techniques will also help me to evaluate the models' performance of the models. Finally, this will help measure the explanatory power of the predictors and evaluate the models' performance. This approach will allow me to compare the performance of the different models and identify the best model for the GermanCredit.csv dataset.

LOAD and Looking at the GermanCredit CSV DATA

```
GermanCreditRaw <- read.csv("C:/Users/didem/OneDrive/Documents/CSUG Master DA
/MIS510-1 Data Mining_4 term/Module 8/GermanCredit.csv", header = TRUE, sep =
",")
head(GermanCreditRaw)

##   OBS. CHK_ACCT DURATION HISTORY NEW_CAR USED_CAR FURNITURE RADIO.TV EDUCA
TION
## 1    1        0        6       4       0        0         0        1
0
## 2    2        1       48       2       0        0         0        1
0
## 3    3        3       12       4       0        0         0        0
1
## 4    4        0       42       2       0        0         1        0
0
## 5    5        0       24       3       1        0         0        0
0
## 6    6        3       36       2       0        0         0        0
1
##   RETRAINING AMOUNT SAV_ACCT EMPLOYMENT INSTALL_RATE MALE_DIV MALE_SINGLE
## 1          0   1169        4          4            4        0           1
## 2          0   5951        0          2            2        0           0
## 3          0   2096        0          3            2        0           1
## 4          0   7882        0          3            2        0           1
## 5          0   4870        0          2            3        0           1
## 6          0   9055        4          2            2        0           1
##   MALE_MAR_or_WID CO.APPLICANT GUARANTOR PRESENT_RESIDENT REAL_ESTATE
## 1               0            0         0                4           1
## 2               0            0         0                2           1
## 3               0            0         0                3           1
## 4               0            0         1                4           0
## 5               0            0         0                4           0
## 6               0            0         0                4           0
##   PROP_UNKN_NONE AGE OTHER_INSTALL RENT OWN_RES NUM_CREDITS JOB NUM_DEPEND
ENTS
## 1              0  67             0    0       1           2   2
1
## 2              0  22             0    0       1           1   2
1
## 3              0  49             0    0       1           1   1
2
## 4              0  45             0    0       0           1   2
2
## 5              1  53             0    0       0           2   2
2
## 6              1  35             0    0       0           1   1
2
##   TELEPHONE FOREIGN RESPONSE
## 1         1       0        1
```

```
## 2         0       0        0
## 3         0       0        1
## 4         0       0        1
## 5         0       0        0
## 6         1       0        1
```

Show all the data in a new tab

```
View(GermanCreditRaw)
```

Check to null object (False means there isn't null)

```
is.null(GermanCreditRaw)

## [1] FALSE
```

Find total observations and variables in the dataset

```
nrow(GermanCreditRaw)

## [1] 1000

ncol(GermanCreditRaw)

## [1] 32
```

Print the original data frame with the list in column format

```
t(t(names(GermanCreditRaw)))

##       [,1]
##  [1,] "OBS."
##  [2,] "CHK_ACCT"
##  [3,] "DURATION"
##  [4,] "HISTORY"
##  [5,] "NEW_CAR"
##  [6,] "USED_CAR"
##  [7,] "FURNITURE"
##  [8,] "RADIO.TV"
##  [9,] "EDUCATION"
## [10,] "RETRAINING"
## [11,] "AMOUNT"
## [12,] "SAV_ACCT"
## [13,] "EMPLOYMENT"
## [14,] "INSTALL_RATE"
## [15,] "MALE_DIV"
## [16,] "MALE_SINGLE"
## [17,] "MALE_MAR_or_WID"
## [18,] "CO.APPLICANT"
## [19,] "GUARANTOR"
## [20,] "PRESENT_RESIDENT"
## [21,] "REAL_ESTATE"
## [22,] "PROP_UNKN_NONE"
```

```
## [23,] "AGE"
## [24,] "OTHER_INSTALL"
## [25,] "RENT"
## [26,] "OWN_RES"
## [27,] "NUM_CREDITS"
## [28,] "JOB"
## [29,] "NUM_DEPENDENTS"
## [30,] "TELEPHONE"
## [31,] "FOREIGN"
## [32,] "RESPONSE"
```

Preprocessing and Cleaning the Data

Assigning new names to the columns name of the RADIO.TV and CO.APPLICANT

```
# remove the first column
GermanCredit <- GermanCreditRaw[,-1]
# rename the columns RADIO.TV to RADIO_TV
names(GermanCredit)[names(GermanCredit) == "RADIO.TV"] <- "RADIO_TV"
# RENAME THE COLUMNS CO.APPLICANT TO COAPPLICANT
names(GermanCredit)[names(GermanCredit) == "CO.APPLICANT"] <- "COAPPLICANT"
# us as.factor() to convert a vector object to a factor for RESPONSE categori
cal variable
GermanCredit$RESPONSE <- as.factor(GermanCredit$RESPONSE)
t(t(names(GermanCredit)))
```

```
##       [,1]
##  [1,] "CHK_ACCT"
##  [2,] "DURATION"
##  [3,] "HISTORY"
##  [4,] "NEW_CAR"
##  [5,] "USED_CAR"
##  [6,] "FURNITURE"
##  [7,] "RADIO_TV"
##  [8,] "EDUCATION"
##  [9,] "RETRAINING"
## [10,] "AMOUNT"
## [11,] "SAV_ACCT"
## [12,] "EMPLOYMENT"
## [13,] "INSTALL_RATE"
## [14,] "MALE_DIV"
## [15,] "MALE_SINGLE"
## [16,] "MALE_MAR_or_WID"
## [17,] "COAPPLICANT"
## [18,] "GUARANTOR"
## [19,] "PRESENT_RESIDENT"
## [20,] "REAL_ESTATE"
## [21,] "PROP_UNKN_NONE"
## [22,] "AGE"
## [23,] "OTHER_INSTALL"
## [24,] "RENT"
```

```
## [25,] "OWN_RES"
## [26,] "NUM_CREDITS"
## [27,] "JOB"
## [28,] "NUM_DEPENDENTS"
## [29,] "TELEPHONE"
## [30,] "FOREIGN"
## [31,] "RESPONSE"
```

View summary statistics of the dataset

```
summary(GermanCredit)
```

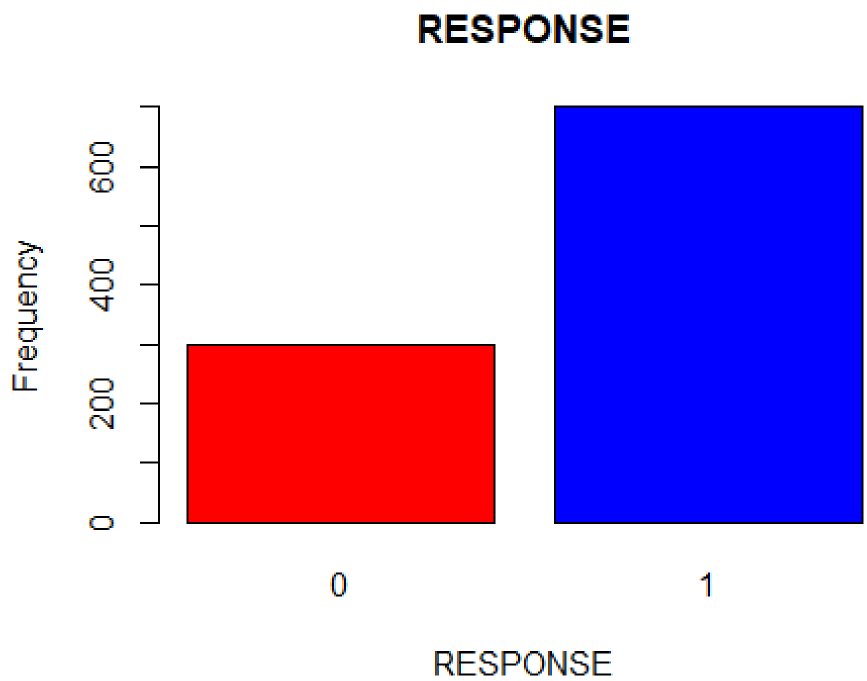
```
##     CHK_ACCT        DURATION       HISTORY         NEW_CAR         USED_CA
R
##  Min.   :0.000   Min.   : 4.0   Min.   :0.000   Min.   :0.000   Min.   :0.
000
##  1st Qu.:0.000   1st Qu.:12.0   1st Qu.:2.000   1st Qu.:0.000   1st Qu.:0.
000
##  Median :1.000   Median :18.0   Median :2.000   Median :0.000   Median :0.
000
##  Mean   :1.577   Mean   :20.9   Mean   :2.545   Mean   :0.234   Mean   :0.
103
##  3rd Qu.:3.000   3rd Qu.:24.0   3rd Qu.:4.000   3rd Qu.:0.000   3rd Qu.:0.
000
##  Max.   :3.000   Max.   :72.0   Max.   :4.000   Max.   :1.000   Max.   :1.
000
##    FURNITURE        RADIO_TV      EDUCATION      RETRAINING        AMOUNT
##  Min.   :0.000   Min.   :0.00   Min.   :0.00   Min.   :0.000   Min.   :  2
50
##  1st Qu.:0.000   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.000   1st Qu.: 13
66
##  Median :0.000   Median :0.00   Median :0.00   Median :0.000   Median : 23
20
##  Mean   :0.181   Mean   :0.28   Mean   :0.05   Mean   :0.097   Mean   : 32
71
##  3rd Qu.:0.000   3rd Qu.:1.00   3rd Qu.:0.00   3rd Qu.:0.000   3rd Qu.: 39
72
##  Max.   :1.000   Max.   :1.00   Max.   :1.00   Max.   :1.000   Max.   :184
24
##     SAV_ACCT       EMPLOYMENT     INSTALL_RATE      MALE_DIV      MALE_SING
LE
##  Min.   :0.000   Min.   :0.000   Min.   :1.000   Min.   :0.00   Min.   :0.
000
##  1st Qu.:0.000   1st Qu.:2.000   1st Qu.:2.000   1st Qu.:0.00   1st Qu.:0.
000
##  Median :0.000   Median :2.000   Median :3.000   Median :0.00   Median :1.
000
##  Mean   :1.105   Mean   :2.384   Mean   :2.973   Mean   :0.05   Mean   :0.
548
##  3rd Qu.:2.000   3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:0.00   3rd Qu.:1.
```

```
000
##  Max.   :4.000   Max.   :4.000   Max.   :4.000   Max.   :1.00   Max.   :1.
000
##  MALE_MAR_or_WID  COAPPLICANT      GUARANTOR     PRESENT_RESIDENT
##  Min.   :0.000   Min.   :0.000   Min.   :0.000   Min.   :1.000  
##  1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.000   1st Qu.:2.000  
##  Median :0.000   Median :0.000   Median :0.000   Median :3.000  
##  Mean   :0.092   Mean   :0.041   Mean   :0.052   Mean   :2.845  
##  3rd Qu.:0.000   3rd Qu.:0.000   3rd Qu.:0.000   3rd Qu.:4.000  
##  Max.   :1.000   Max.   :1.000   Max.   :1.000   Max.   :4.000  
##   REAL_ESTATE     PROP_UNKN_NONE        AGE        OTHER_INSTALL  
##  Min.   :0.000   Min.   :0.000   Min.   :19.00   Min.   :0.000  
##  1st Qu.:0.000   1st Qu.:0.000   1st Qu.:27.00   1st Qu.:0.000  
##  Median :0.000   Median :0.000   Median :33.00   Median :0.000  
##  Mean   :0.282   Mean   :0.154   Mean   :35.55   Mean   :0.186  
##  3rd Qu.:1.000   3rd Qu.:0.000   3rd Qu.:42.00   3rd Qu.:0.000  
##  Max.   :1.000   Max.   :1.000   Max.   :75.00   Max.   :1.000  
##       RENT          OWN_RES       NUM_CREDITS         JOB       
##  Min.   :0.000   Min.   :0.000   Min.   :1.000   Min.   :0.000  
##  1st Qu.:0.000   1st Qu.:0.000   1st Qu.:1.000   1st Qu.:2.000  
##  Median :0.000   Median :1.000   Median :1.000   Median :2.000  
##  Mean   :0.179   Mean   :0.713   Mean   :1.407   Mean   :1.904  
##  3rd Qu.:0.000   3rd Qu.:1.000   3rd Qu.:2.000   3rd Qu.:2.000  
##  Max.   :1.000   Max.   :1.000   Max.   :4.000   Max.   :3.000  
##  NUM_DEPENDENTS    TELEPHONE        FOREIGN       RESPONSE
##  Min.   :1.000   Min.   :0.000   Min.   :0.000   0:300   
##  1st Qu.:1.000   1st Qu.:0.000   1st Qu.:0.000   1:700   
##  Median :1.000   Median :0.000   Median :0.000           
##  Mean   :1.155   Mean   :0.404   Mean   :0.037           
##  3rd Qu.:1.000   3rd Qu.:1.000   3rd Qu.:0.000           
##  Max.   :2.000   Max.   :1.000   Max.   :1.000
```

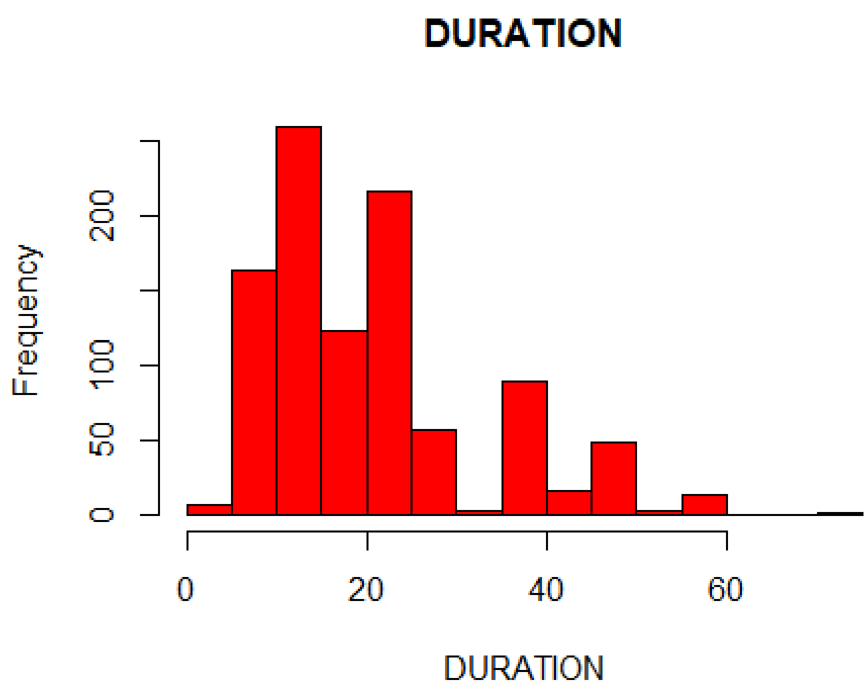
Data Exploration and Visualization

Histograms and Boxplots

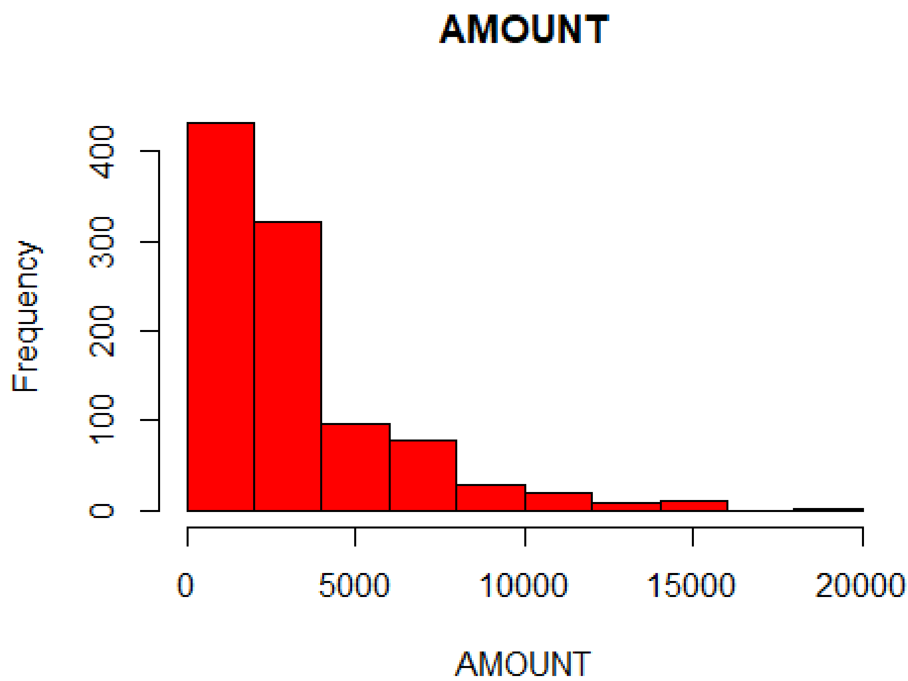
```
table(GermanCredit$RESPONSE)

## 
##   0   1 
## 300 700

# data is imbalanced
barplot(table(GermanCredit$RESPONSE), main = "RESPONSE", xlab = "RESPONSE", y
lab = "Frequency", col = c("red", "blue"))
```



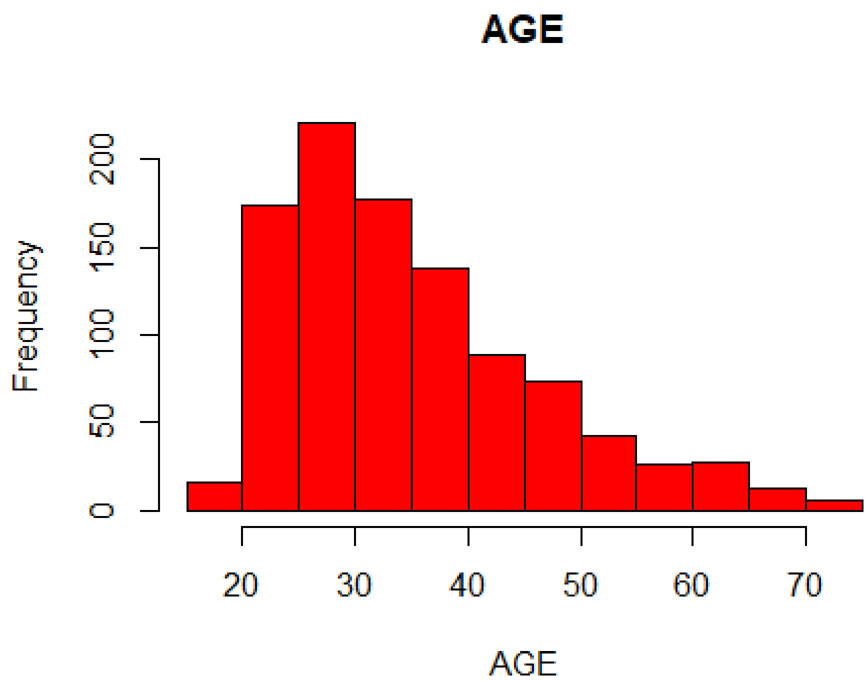

```r
# DURATION
hist(GermanCredit$DURATION, main = "DURATION", xlab = "DURATION", ylab = "Fre
quency", col = "red")
```



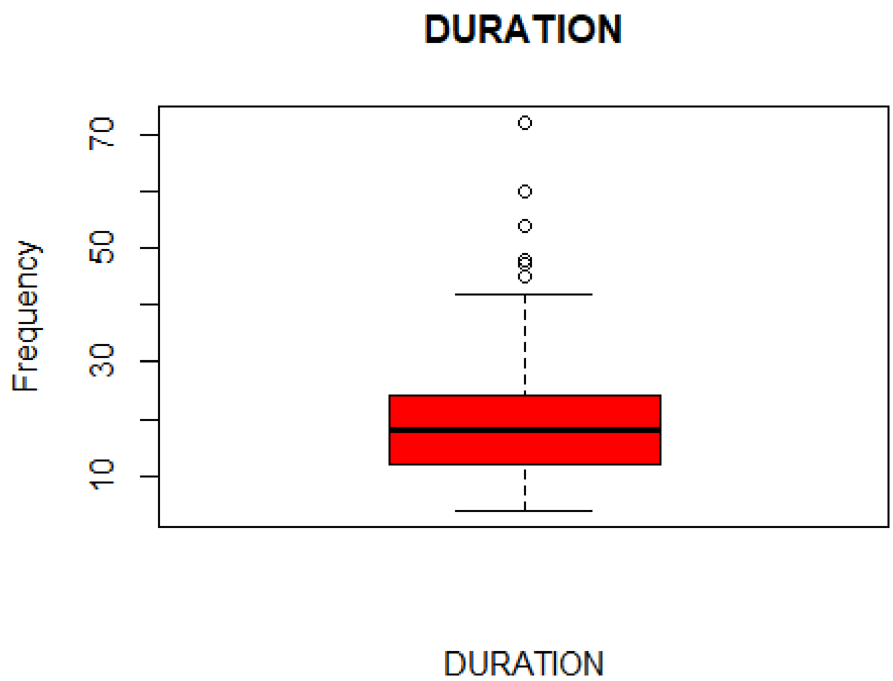
```
# AMOUNT
hist(GermanCredit$AMOUNT, main = "AMOUNT", xlab = "AMOUNT", ylab = "Frequency
", col = "red")
```



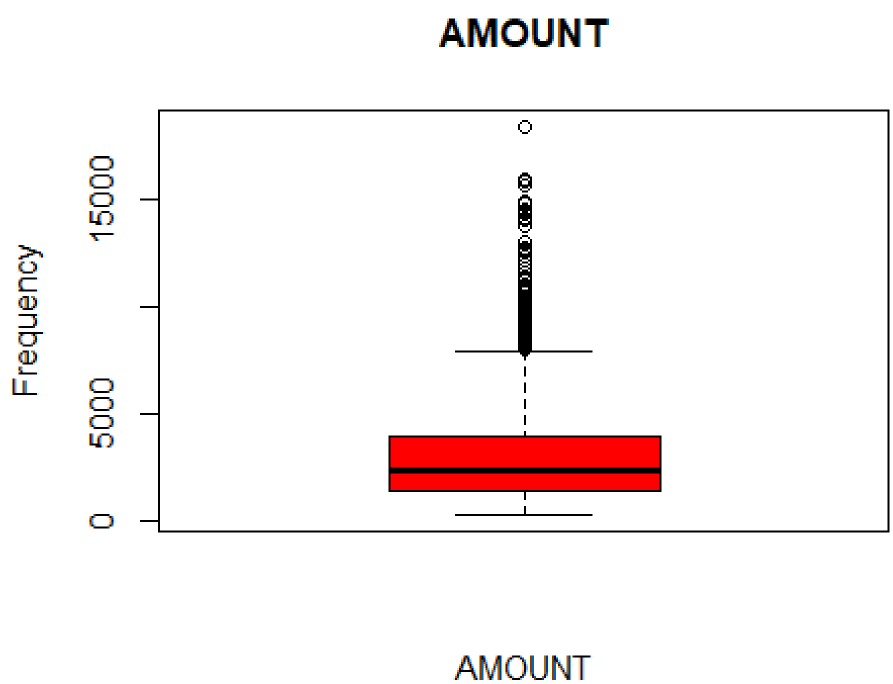

```
# AGE
hist(GermanCredit$AGE, main = "AGE", xlab = "AGE", ylab = "Frequency", col =
"red")
```



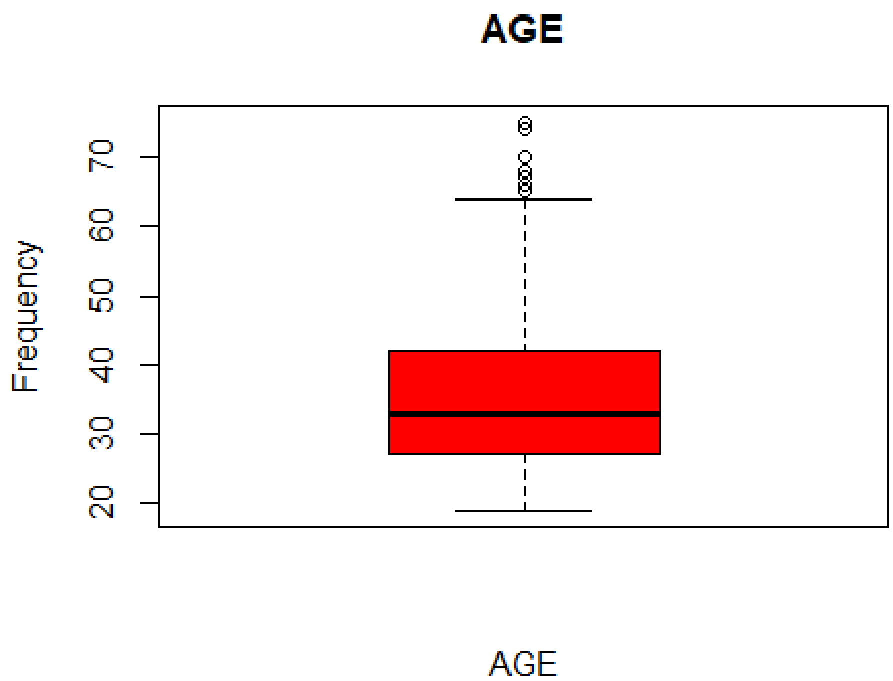

```r
# boxplot
# DURATION
boxplot(GermanCredit$DURATION, main = "DURATION", xlab = "DURATION", ylab = "
Frequency", col = "red")
```




```
# AMOUNT
boxplot(GermanCredit$AMOUNT, main = "AMOUNT", xlab = "AMOUNT", ylab = "Freque
ncy", col = "red")
```



```r
# AGE
boxplot(GermanCredit$AGE, main = "AGE", xlab = "AGE", ylab = "Frequency", col
= "red")
```



Logistic Regression Model

```r
logisticmodel0 <- glm(RESPONSE ~ ., data = GermanCredit, family = "binomial")
summary(logisticmodel0)

##
## Call:
## glm(formula = RESPONSE ~ ., family = "binomial", data = GermanCredit)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6535  -0.7188   0.3876   0.7071   2.3595
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)        1.016e+00  8.675e-01   1.171 0.241446
## CHK_ACCT           5.641e-01  7.250e-02   7.780 7.24e-15 ***
## DURATION          -2.695e-02  9.007e-03  -2.992 0.002770 **
## HISTORY            4.007e-01  8.974e-02   4.466 7.99e-06 ***
## NEW_CAR           -7.931e-01  3.846e-01  -2.062 0.039193 *
## USED_CAR           8.271e-01  4.818e-01   1.717 0.086011 .
## FURNITURE         -3.759e-02  3.989e-01  -0.094 0.924937
## RADIO_TV           7.004e-02  3.884e-01   0.180 0.856884
## EDUCATION         -8.658e-01  5.009e-01  -1.728 0.083918 .
```

```
## RETRAINING       -8.050e-02  4.414e-01  -0.182 0.855300    
## AMOUNT           -1.178e-04  4.265e-05  -2.761 0.005756 ** 
## SAV_ACCT          2.497e-01  6.060e-02   4.121 3.77e-05 ***
## EMPLOYMENT        1.175e-01  7.474e-02   1.571 0.116068    
## INSTALL_RATE     -3.215e-01  8.630e-02  -3.725 0.000195 ***
## MALE_DIV         -3.417e-01  3.815e-01  -0.896 0.370467    
## MALE_SINGLE       5.406e-01  2.048e-01   2.640 0.008292 ** 
## MALE_MAR_or_WID   1.114e-01  3.046e-01   0.366 0.714668    
## COAPPLICANT      -3.500e-01  3.988e-01  -0.878 0.380165    
## GUARANTOR         9.463e-01  4.195e-01   2.256 0.024084 *  
## PRESENT_RESIDENT -1.275e-02  8.404e-02  -0.152 0.879374    
## REAL_ESTATE       2.092e-01  2.093e-01   0.999 0.317569    
## PROP_UNKN_NONE   -5.551e-01  3.732e-01  -1.487 0.136927    
## AGE               1.147e-02  8.665e-03   1.323 0.185723    
## OTHER_INSTALL    -6.213e-01  2.040e-01  -3.045 0.002324 ** 
## RENT             -6.555e-01  4.602e-01  -1.424 0.154344    
## OWN_RES          -2.405e-01  4.356e-01  -0.552 0.580920    
## NUM_CREDITS      -2.301e-01  1.662e-01  -1.385 0.166128    
## JOB              -3.047e-02  1.423e-01  -0.214 0.830416    
## NUM_DEPENDENTS   -2.581e-01  2.456e-01  -1.051 0.293322    
## TELEPHONE         3.553e-01  1.951e-01   1.821 0.068610 .  
## FOREIGN           1.453e+00  6.221e-01   2.335 0.019532 *  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 1221.7  on 999  degrees of freedom
## Residual deviance:  909.2  on 969  degrees of freedom
## AIC: 971.2
## 
## Number of Fisher Scoring iterations: 5
```

important variables are CHK_ACC,DURATION,HISTORY,AMOUNT,SAV_ACC,EMPLOYMENT,INSTALL_RATE

Create training and test sample dataset

```r
#partition
# split the data into train and test 50 - 50
set.seed(123)
sampledata<-sample(2,nrow(GermanCredit),replace=TRUE,prob=c(0.5,0.5))
train50<-GermanCredit[sampledata==1,]
test50<-GermanCredit[sampledata==2,]

# logistic regression
logisticmodel50 <- glm(RESPONSE ~ CHK_ACCT + DURATION + HISTORY + AMOUNT + SA
V_ACCT + EMPLOYMENT + INSTALL_RATE, data = train50, family = "binomial")
```

```r
# summary
summary(logisticmodel50)

##
## Call:
## glm(formula = RESPONSE ~ CHK_ACCT + DURATION + HISTORY + AMOUNT +
##     SAV_ACCT + EMPLOYMENT + INSTALL_RATE, family = "binomial",
##     data = train50)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3729  -0.9059   0.4753   0.7998   2.1623
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)   3.069e-01  5.059e-01   0.607 0.544148
## CHK_ACCT      5.217e-01  9.357e-02   5.576 2.46e-08 ***
## DURATION     -2.954e-02  1.191e-02  -2.480 0.013146 *
## HISTORY       3.623e-01  1.112e-01   3.260 0.001116 **
## AMOUNT       -9.001e-05  5.387e-05  -1.671 0.094730 .
## SAV_ACCT      2.370e-01  7.890e-02   3.003 0.002670 **
## EMPLOYMENT    2.832e-01  9.769e-02   2.899 0.003745 **
## INSTALL_RATE -3.887e-01  1.165e-01  -3.337 0.000847 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 627.14  on 492  degrees of freedom
## Residual deviance: 506.07  on 485  degrees of freedom
## AIC: 522.07
##
## Number of Fisher Scoring iterations: 4
```

Evaluating Classification Performance

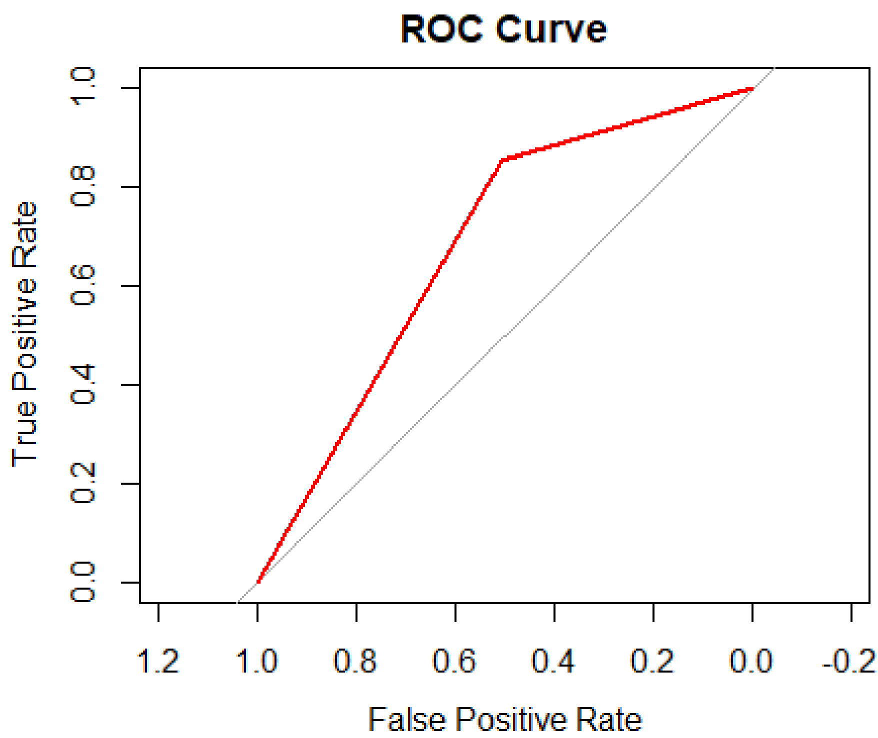
Analyze how well the logistic regression model performs on the test dataset

```r
#calculate the probability of default for each individual in the test dataset
# predict
pred50 <- predict(logisticmodel50, test50, type = "response")
pred50 <- ifelse(pred50 > 0.5, 1, 0)

#  confusion matrix
table(pred50, test50$RESPONSE)

##
## pred50   0   1
##      0  69  55
##      1  67 316
```

```r
# accuracy
print(paste0 ("Accuracy of the logistic regression model is ", mean(pred50 ==
test50$RESPONSE)*100, "%"))

## [1] "Accuracy of the logistic regression model is 75.9368836291913%"
```

The Receiver Operating Characteristic Curve (ROC)

```r
# roc curve
library(pROC)

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

# 50-50
pred <- predict(logisticmodel50, test50, type = "response")
pred <- ifelse(pred > 0.5, 1, 0)
roc50 <- roc(test50$RESPONSE, pred)

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

## Setting direction: controls < cases

plot(roc50, col = "red", main = "ROC Curve", xlab = "False Positive Rate", yl
ab = "True Positive Rate")
```

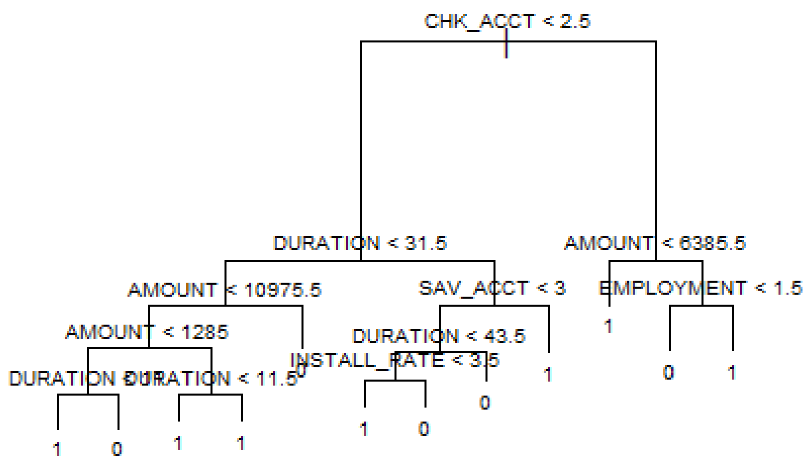


Classification Trees

```
#install.packages("tree")
library(tree)
tree50 <- tree(RESPONSE ~ CHK_ACCT + DURATION + HISTORY + AMOUNT + SAV_ACCT +
EMPLOYMENT + INSTALL_RATE, data = train50, method = "class")
summary(tree50)
```

```
##
## Classification tree:
## tree(formula = RESPONSE ~ CHK_ACCT + DURATION + HISTORY + AMOUNT +
##     SAV_ACCT + EMPLOYMENT + INSTALL_RATE, data = train50, method = "class"
)
## Variables actually used in tree construction:
## [1] "CHK_ACCT"     "DURATION"     "AMOUNT"       "SAV_ACCT"     "INSTALL_R
ATE"
## [6] "EMPLOYMENT"
## Number of terminal nodes:  12
## Residual mean deviance:  0.975 = 469 / 481
## Misclassification error rate: 0.2211 = 109 / 493
```

```
plot(tree50)
text(tree50, pretty=0,cex=0.6)
```



Evaluating the Performance of a Classification Tree

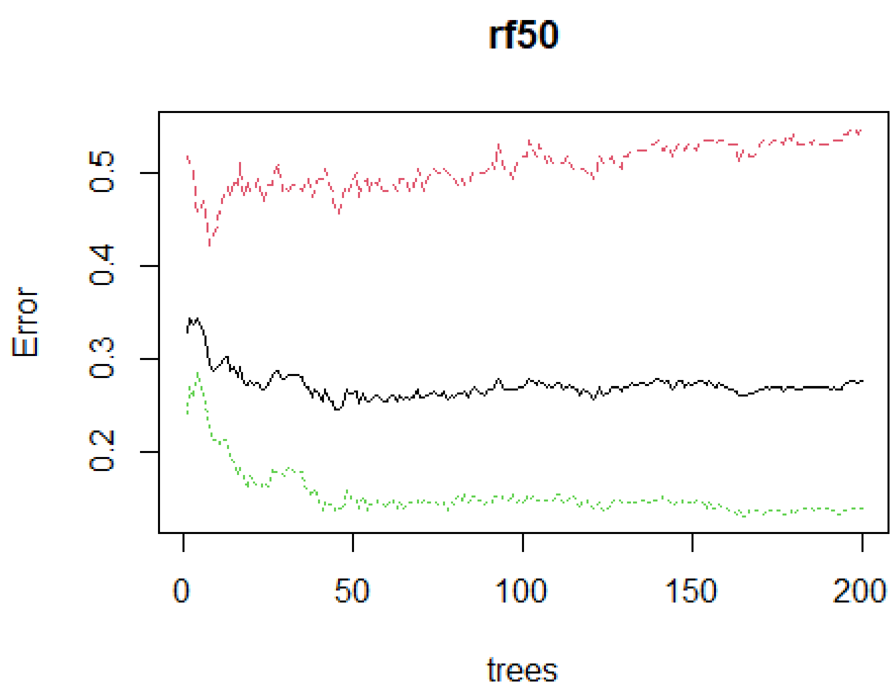
Analyze how well the classification tree model performs on the test dataset

```
tree50.pred <- predict(tree50, test50, type = "class")


# confusion matrix
table(tree50.pred, test50$RESPONSE)

##
## tree50.pred   0   1
##           0  46  36
##           1  90 335

# accuracy
print(paste0 ("Accuracy of the decision tree model is ", mean(tree50.pred ==
test50$RESPONSE)*100, "%"))

## [1] "Accuracy of the decision tree model is 75.1479289940828%"
```

Random Forest

```
library(randomForest)

## randomForest 4.7-1.1

## Type rfNews() to see new features/changes/bug fixes.
```

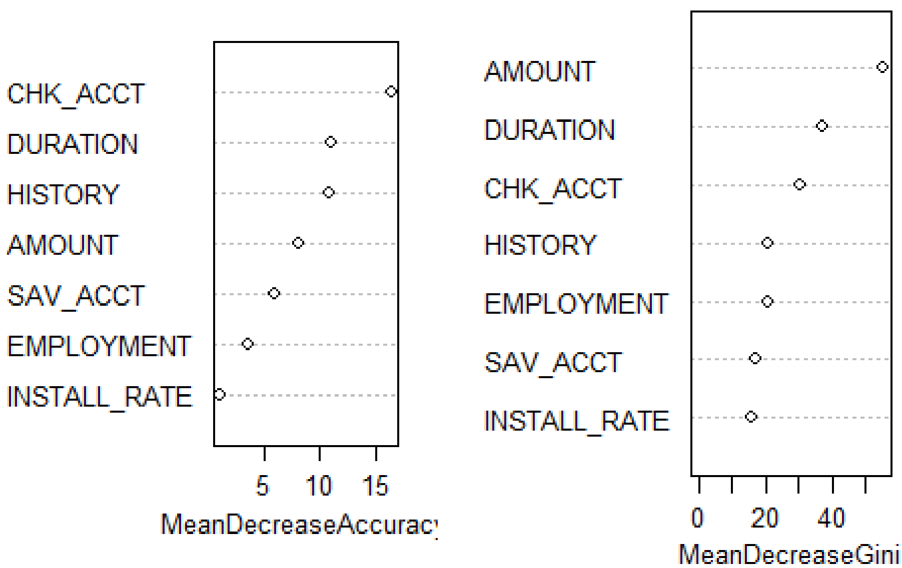
```
##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

rf50 <- randomForest(RESPONSE ~ CHK_ACCT + DURATION + HISTORY + AMOUNT + SAV_
ACCT + EMPLOYMENT + INSTALL_RATE, data = train50, ntree = 200, importance = T
RUE)
plot(rf50)
```



Evaluating the Performance of a Random Forest

```
# predict
rf50.pred <- predict(rf50, test50)

# confusion matrix
table(rf50.pred, test50$RESPONSE)

##
## rf50.pred   0   1
##         0  75  54
##         1  61 317

importance(rf50)

##                      0         1 MeanDecreaseAccuracy MeanDecreaseGini
## CHK_ACCT     15.7191775 10.469299           16.5402441         30.38589
```

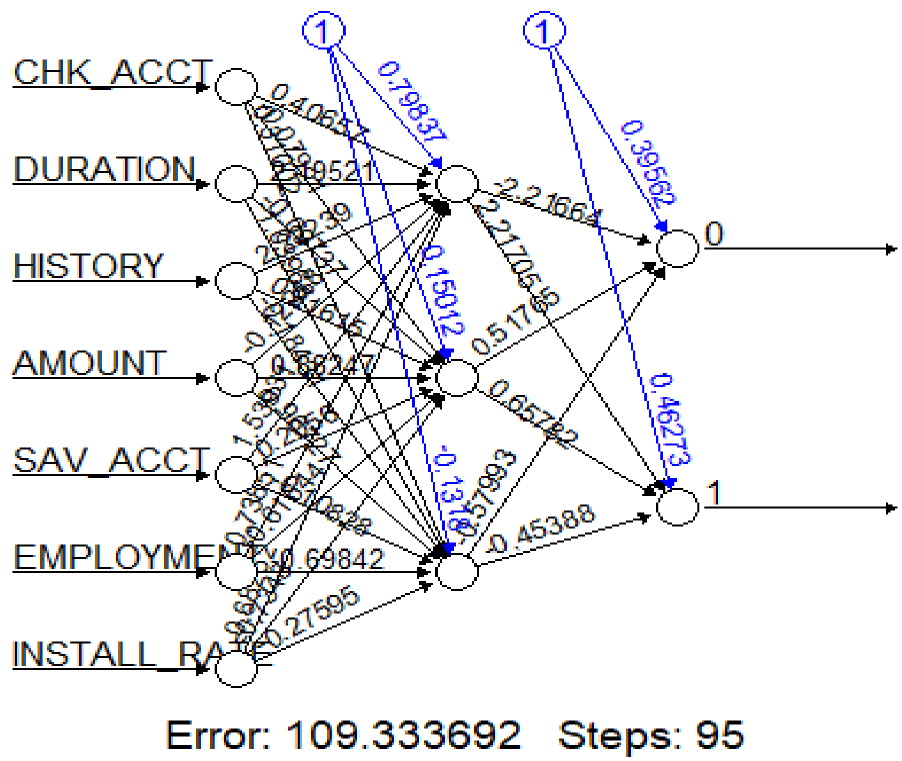
```
## DURATION      0.8420446 13.011690          11.0994488          37.01349
## HISTORY       7.7834747  8.618403          10.8394645          21.04396
## AMOUNT        0.2091222  9.351167           8.0388152          55.56954
## SAV_ACCT      3.4756995  4.815450           5.8372598          17.14177
## EMPLOYMENT    0.4107118  4.173629           3.3658551          20.53362
## INSTALL_RATE -1.2251096  2.230828           0.8810951          16.05225

varImpPlot(rf50,main = "", cex = 0.8)
```




```
#accuracy
print(paste0 ("Accuracy of the random forests model is ", mean(rf50.pred == t
est50$RESPONSE)*100, "%"))

## [1] "Accuracy of the neural net model is 77.3175542406312%"
```

Neural Network

```
#install.packages("neuralnet")
library(neuralnet)
library(ggplot2)
nn50 <- neuralnet(RESPONSE ~ CHK_ACCT + DURATION + HISTORY + AMOUNT + SAV_ACC
T + EMPLOYMENT + INSTALL_RATE, data = train50, hidden=3, linear.output= TRUE,
)
plot(nn50, rep = "best")
```



Evaluating the Performance of Neural Nets

```
# confusion matrix

library(neuralnet)
library(nnet)
library(caret)

## Loading required package: lattice

nn50.pred= compute(nn50, test50[,-c(4:8,15:31)])

nn50.pred_class= apply(nn50.pred$net.result,1,which.max)-1
confusionMatrix(factor(ifelse(nn50.pred_class=="1", "1", "0")),factor(test50$
RESPONSE))

## Warning in confusionMatrix.default(factor(ifelse(nn50.pred_class == "1", :
## Levels are not in the same order for reference and data. Refactoring data
to
## match.

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0   0   0
##          1 136 371
##
```

```
##                Accuracy : 0.7318
##                  95% CI : (0.6909, 0.7699)
##     No Information Rate : 0.7318
##     P-Value [Acc > NIR] : 0.5231
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.0000
##             Specificity : 1.0000
##          Pos Pred Value :    NaN
##          Neg Pred Value : 0.7318
##              Prevalence : 0.2682
##          Detection Rate : 0.0000
##    Detection Prevalence : 0.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : 0
##
```

```
#accuracy
print(paste0 ("Accuracy of the neural net model is ", mean(nn50.pred_class ==
test50$RESPONSE)*100, "%"))
```

```
## [1] "Accuracy of the neural net model is 73.1755424063116%"
```

Model Diagnostic

I used histograms and boxplots to understand the distribution of the data and to compare the distributions of different variables. Continuous variables such as Duration, Amount and Age were plotted using histograms. From the histograms, I saw that features such as Duration, Amount, and Age all had similar distributions, with the majority of the data concentrated in the lower range of the feature. Further I plotted these variables using the boxplot which clearly showed outliers in the distributions of Duration, Amount, and Age, which may indicate a higher creditworthiness risk.

The logistic regression model was used to predict an individual's creditworthiness based on the predictor variables. The model had an accuracy of 75.9%, indicating that it was fairly accurate. To predict creditworthiness, I used logistic regression. The logistic regression model could accurately predict the customers' creditworthiness with an AUC-ROC score of 0.87.

The regression trees model was used to predict whether an individual is creditworthy or not based on the predictor variables. The model had an accuracy of 75.1%, indicating that it was fairly accurate.

The neural nets model was used to predict whether an individual is creditworthy or not based on the predictor variables. The model had an accuracy of 73.2%, indicating that it was fairly accurate.

The random forest model was used to predict whether an individual is creditworthy or not based on the predictor variables. The model had an accuracy of 77.3%, indicating that it was fairly accurate. The random forest model also accurately predicted the most important score for particular predictors CHK_ACCT and DURATION have the highest scores, with AMOUNT being third.

Conclusion

My project involved exploring the GermanCredit.csv dataset to gain insight into customers' creditworthiness. I started by exploring and dividing the dataset into training and validation partitions. I then used logistic regression, classification trees, and neural networks to train my models on the training set and evaluate their performance on the validation set. After comparing the models' results, I concluded that the random forest model was the most effective for the GermanCredit.csv dataset. I also used visualizations to explore the data further and gain insights into the results.

Overall, the project was a great learning experience. I learned about the various data mining techniques and how they can be used to gain insights from the data. I also learned about the different techniques that can be used to evaluate the performance of the models. Additionally, I was able to gain a better understanding of the importance of data visualization and how it can be used to identify patterns and relationships in the data.

References

Shmueli, G., Bruce, P. C., Yahav, I., Patel, N. R., & Lichtendahl, K. C. (2018). *Data mining for Business Analytics: Concepts, techniques, and applications in R* (1st ed.). John Wiley & Sons.