Analysis on Approval or Denial of Loan

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1. Introduction

A small-scale business or large-scale business may require a loan at any point of time, starting from creating the initial investment or in order to pay the debts or for growing the business. Loans can be savior for any business. But in order to get this loan the business has to go through a rigorous process which is done by the bank who gives the loan. As the loan is lending the money to a party, a various analysis is done on which the acceptance of the loan and even the amount of the loan can be predicted and further approved. So, in this project we would do the analysis on the data set of the companies from 1947 to 2014, who had applied for the for loans.

The data set consists of the factors on which the approval or denial of the loan depends.

2. Data

The Data set is collected from U.S. Small Business Administrator.

Number of Rows: 899164

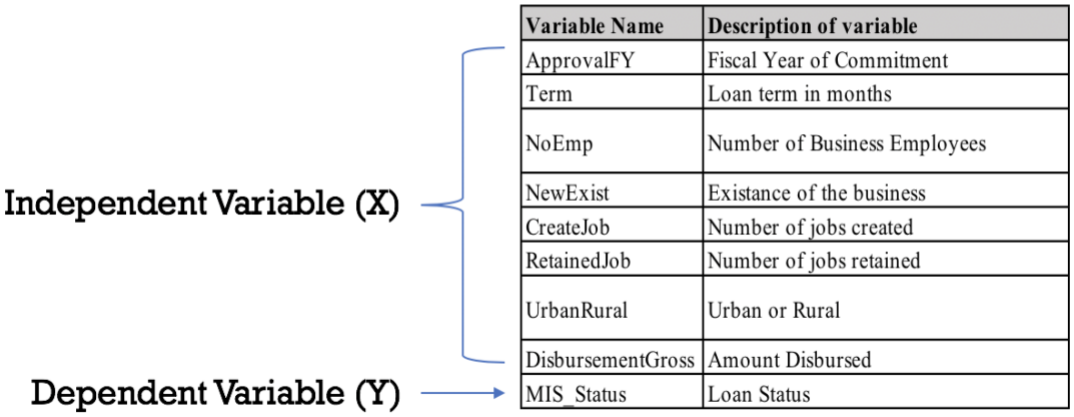
Number of Columns: 27

The columns defines the various factors on which our final outcome would depend. With all this factor we would do creation of the best fitted model which would help us to reach the final outcome.

Variable Name	Data type	Description of variable
LoanNr_ChkDgt	Text	Identifier – Primary Key
Name	Text	Borrower Name
City	Text	Borrower City
State	Text	Borrower State
Zip	Text	Borrower Zip Code
Bank	Text	Bank Name
BankState	Text	Bank State
NAICS	Text	North American Industry Classification System code
ApprovalDate	Date/Time	Date SBA Commitment Issued
ApprovalFY	Text	Fiscal Year of Commitment
Term	Number	Loan term in months
NoEmp	Number	Number of Business Employees
NewExist	Text	1 = Existing Business, 2 = New Business
CreateJob	Number	Number of jobs created
RetainedJob	Number	Number of jobs retained
FranchiseCode	Text	Franchise Code 00000 or 00001 = No Franchise
UrbanRural	Text	1= Urban, 2= Rural, 0 = Undefined
RevLineCr	Text	Revolving Line of Credit : Y = Yes
LowDoc	Text	LowDoc Loan Program: Y = Yes, N = No

ChgOffDate	Date/Time	The date when a loan is declared to be in default
DisbursementDate	Date/Time	Disbursement Date
DisbursementGross	Currency	Amount Disbursed
BalanceGross	Currency	Gross amount outstanding
MIS_Status	Text	Loan Status
ChgOffPrinGr	Currency	Charged-off Amount
GrAppv	Currency	Gross Amount of Loan Approved by Bank
SBA_Appv	Currency	SBA's Guaranteed Amount of Approved Loan

But after some brain storming is found the below column the most informative and factors that may be most impactful for approval or denial of the loan



Variable Name	Description of variable
ApprovalFY	Fiscal Year of Commitment
Term	Loan term in months
NoEmp	Number of Business Employees
NewExist	Existance of the business
CreateJob	Number of jobs created
RetainedJob	Number of jobs retained
UrbanRural	Urban or Rural
DisbursementGross	Amount Disbursed
MIS_Status	Loan Status

3. Problems to be Solved

1. Identify which explanatory variables may be good "predictors" or risk indicators of the level of risk associated with approval of the loan;
2. Work through the stages in model building and validation;

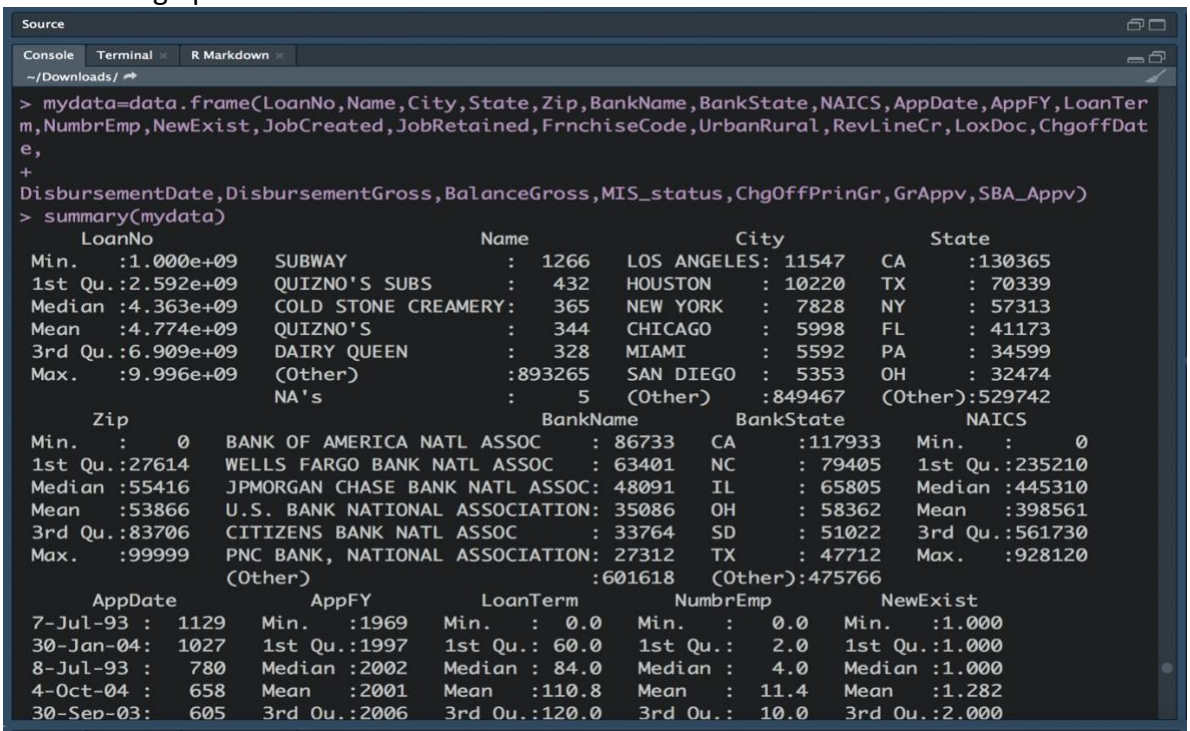
4. Solutions

In this project I would the one sampled and two sampled hypothesis testing along with that I would built the various classification models like the K-Nearest Neighbor, Naïve Bayes, Logistic Regression and Decision Tree. From all this model I would able to get the best factors in order to get the loan approved.

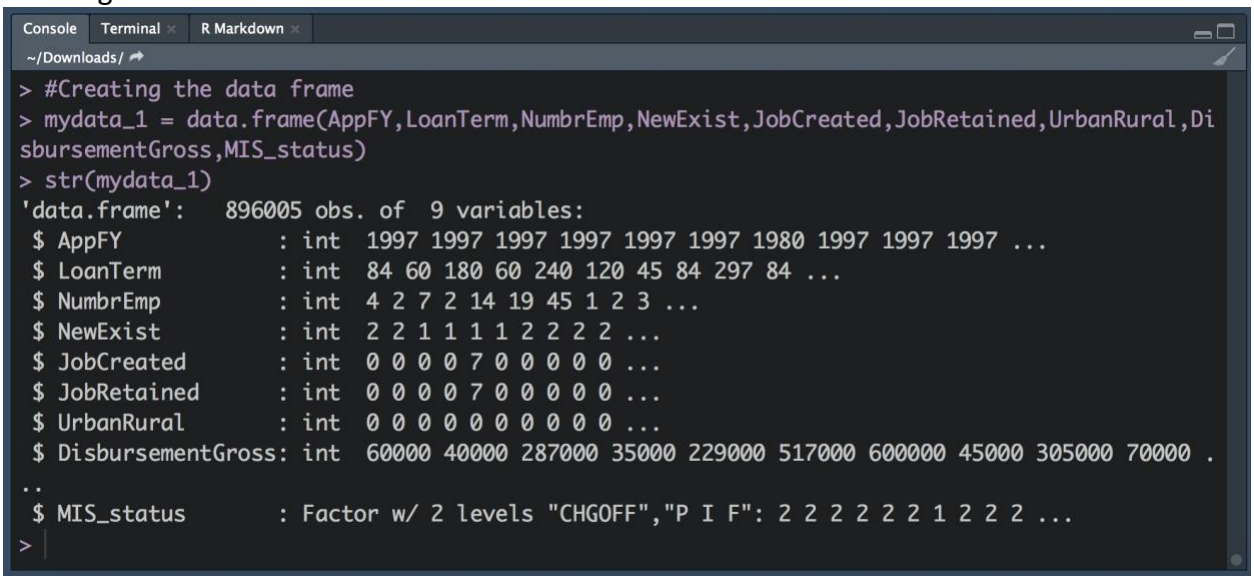
5. Experiments and Results

5.1. Methods and Process

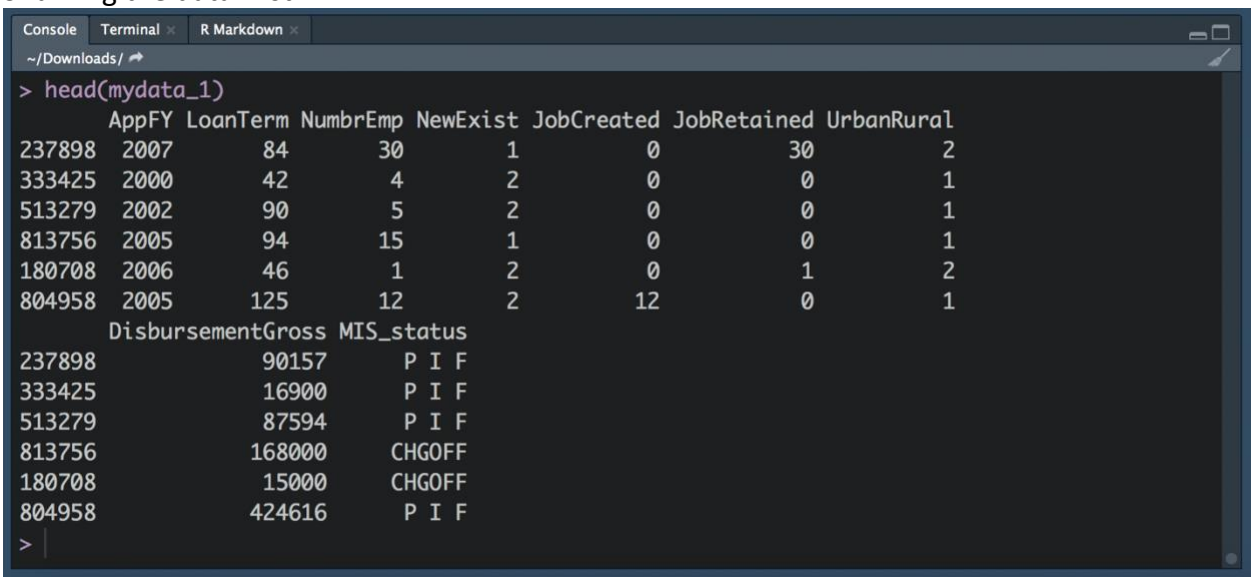
First Loading up the data into the R



Creating the data frame



Shuffling the data first

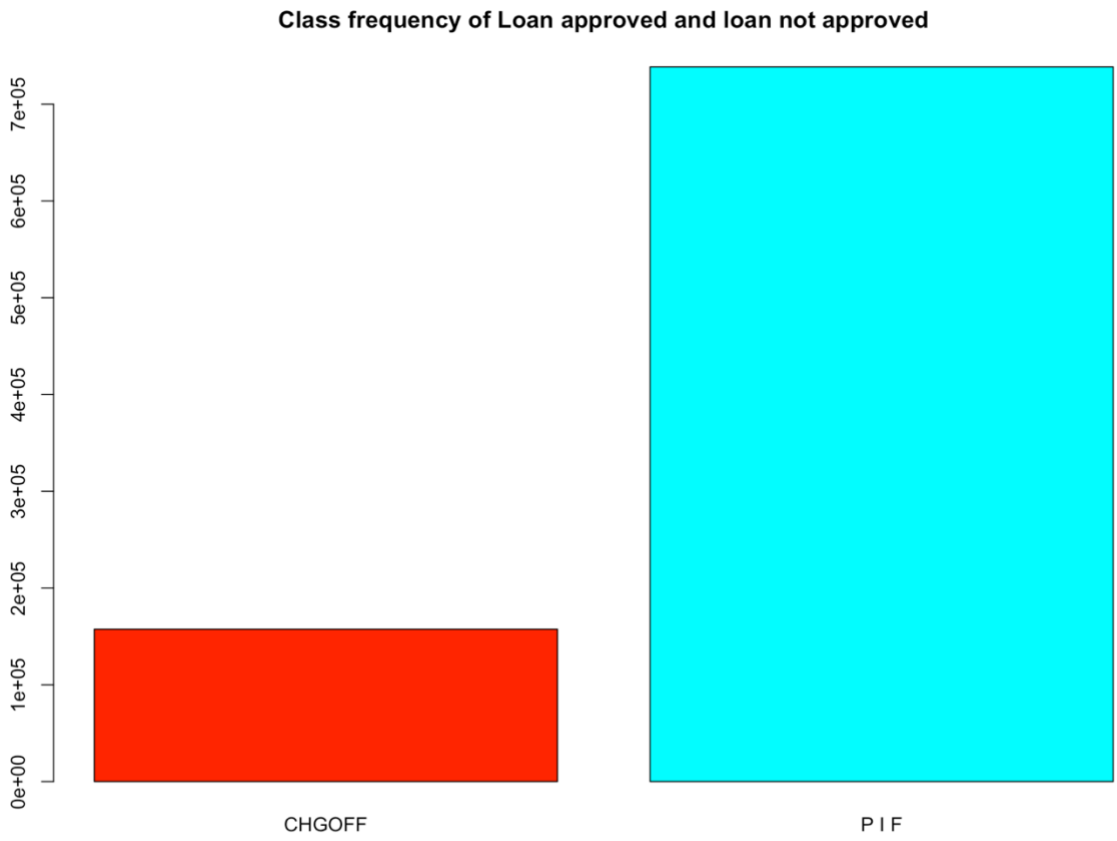


5.2. Descriptive Statistics

5.2.1 Bar Graph

Here, the bar graph is drawn between the frequency of the CHGOFF values and PIF values present in the data. This gives overall percentage of loan approved since 1947 to 2014.

```
Console  Terminal  R Markdown
~/Downloads/
> library(plyr)
> opt=count(MIS_status)
> cf=opt$freq
> labels=opt$x
> opt
       x   freq
1 CHGOFF 157481
2  P I F 738524
> barplot(cf,main="Class frequency of Loan approved and loan not approved",names.arg=labels,c
ol = rainbow(length(cf)))
>
```



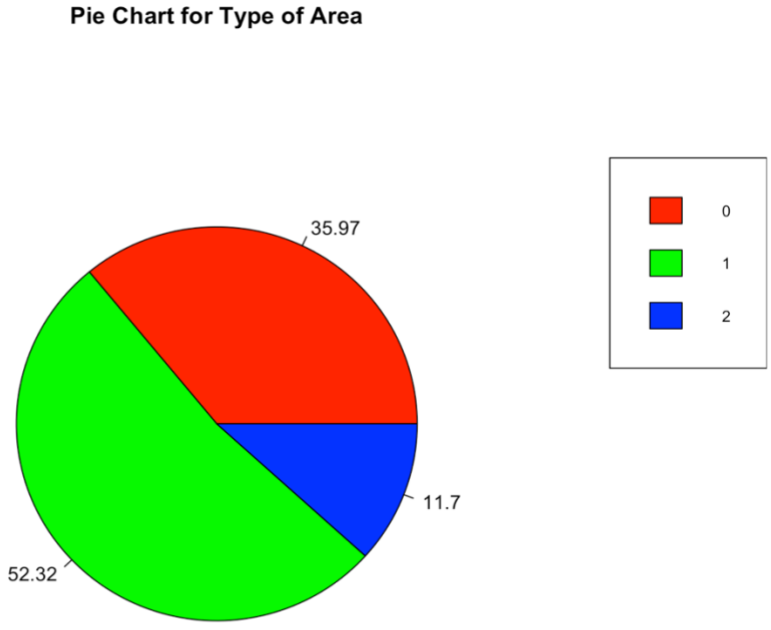
5.2.3. Pie Chart

The pie chart describes the percentage division of the companies present in data in undefined, urban and rural areas.

```
Console   Terminal   R Markdown
~/Downloads/
> #pie chart
> opt1=count(UrbanRural)
> cf1=opt1$freq
> labels1=opt1$x
> crf=table(my_data$UrbanRural)/nrow(my_data)
> piepercent=round(100*crf/sum(crf),2)
> crf

        0         1         2
0.3597279 0.5232236 0.1170485
> pie(crf,label=piepercent,main="Pie Chart for Type of Area", col = rainbow(length(crf)))
> legend("topright", c("0","1","2"),cex=0.8,fill=rainbow(length(crf)))
> piepercent

    0     1     2
35.97 52.32 11.70
>
```

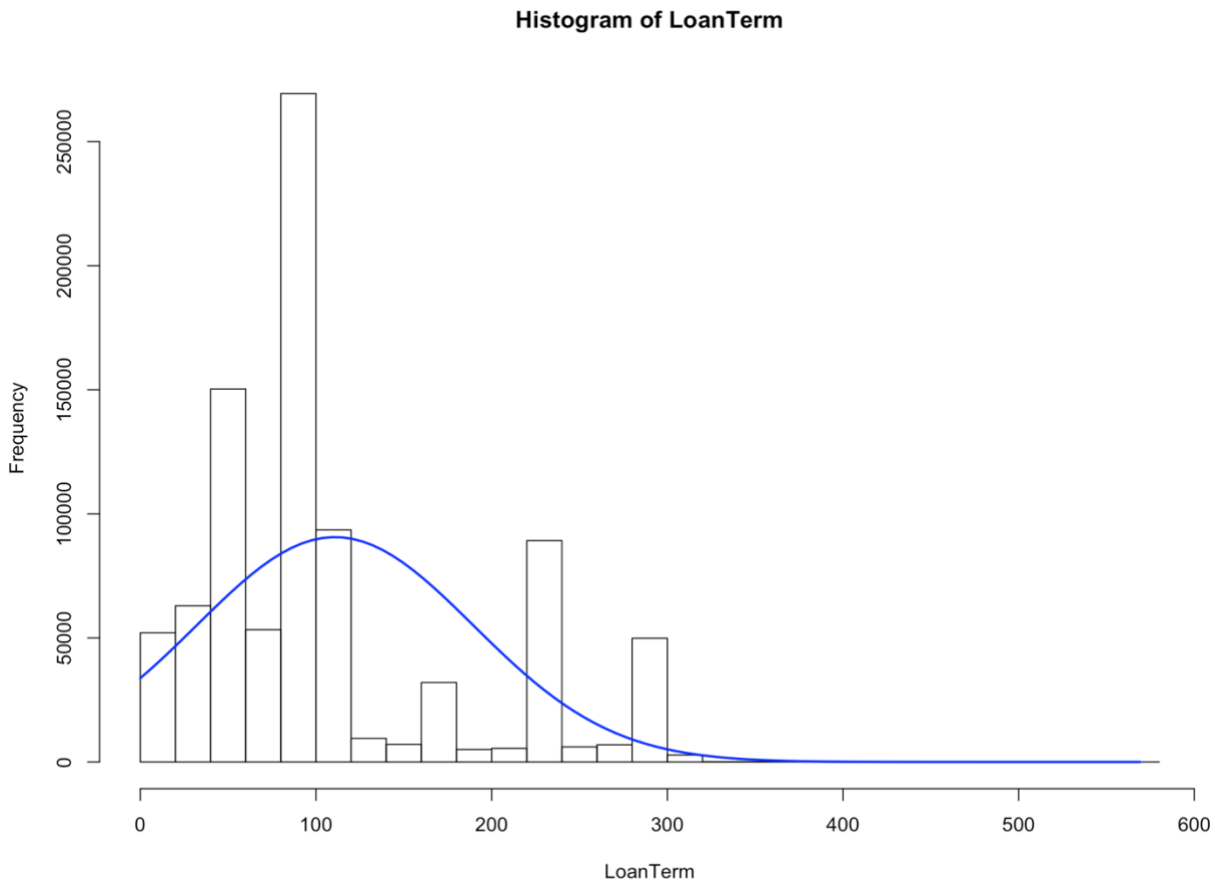


0-Undefined, 1-Urban, 2-Rural

5.2.4 Histogram

The histogram here tells different terms in month for which the loan was required by the companies.

```
> #histogram
> h=hist(LoanTerm)
> xfit<-seq(min(LoanTerm),max(LoanTerm),length=100)
> yfit<-dnorm(xfit,mean=mean(LoanTerm),sd=sd(LoanTerm))
> yfit <- yfit*diff(h$mids[1:2])*length(LoanTerm)
> lines(xfit, yfit, col="blue", lwd=2)
>
```



5.3. Hypothesis Testing 1

This is a one sampled hypothesis where

H_0 : The sample disbursement mean is equal to 216153
H_1: The sample disbursement mean is greater than 216153
Confidence interval: 95%

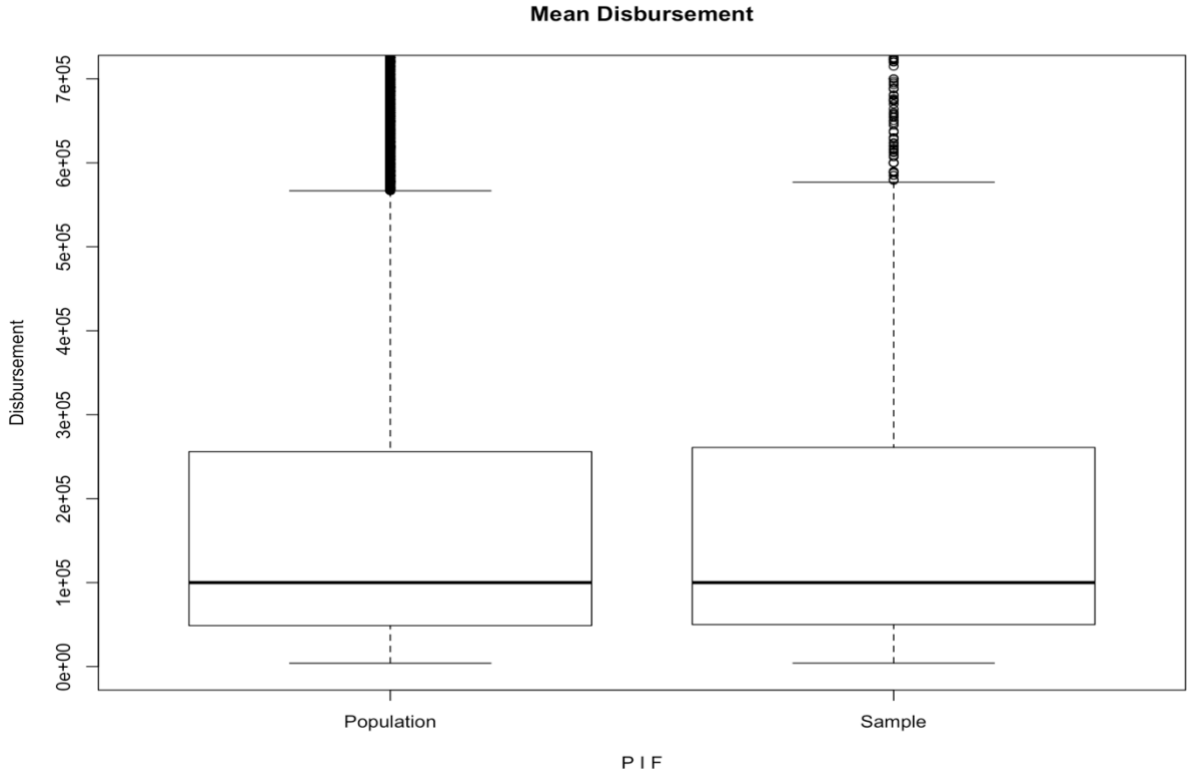
```
> z.test(ne_sample$DisbursementGross,NULL,alternative = "greater",mu=216153,sigma.x=sd(ne_sam
ple$DisbursementGross),conf.level = 0.95)

        One-sample z-Test

data:  ne_sample$DisbursementGross
z = 1.0018, p-value = 0.1582
alternative hypothesis: true mean is greater than 216153
95 percent confidence interval:
 212162     NA
sample estimates:
mean of x
 222371.1

>
```

Since the p-value is greater than 0.05, we accept the null hypothesis that the sample distribution mean is equal to 216153 at 95% confidence level interval

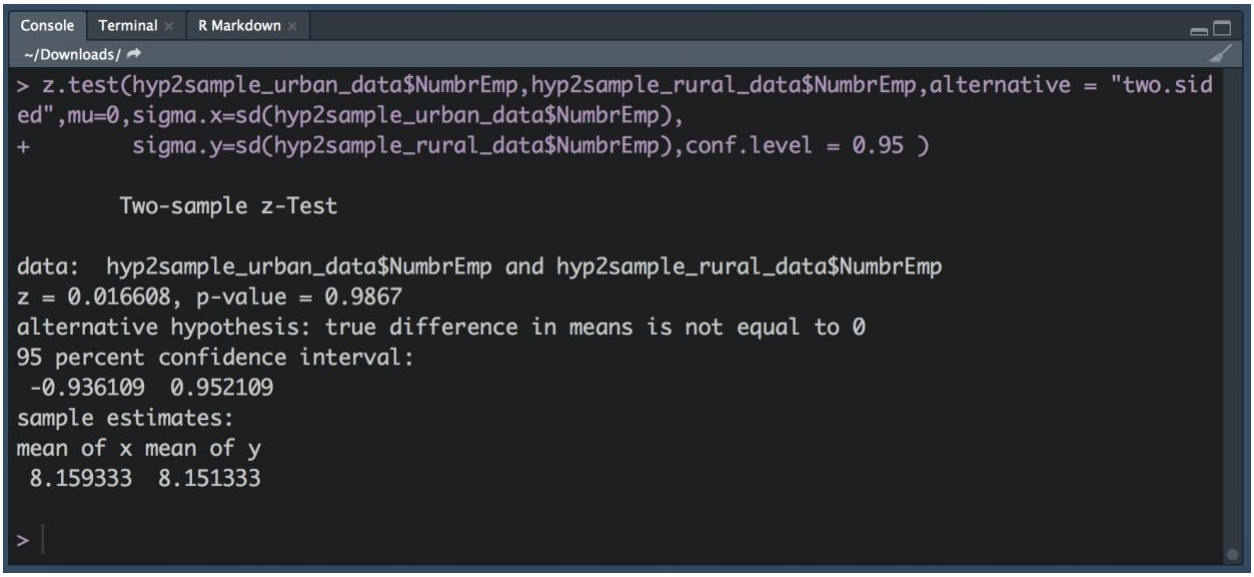


With the help of the box plot, we can visualize the null hypothesis being accepted.

5.4. Hypothesis Test 2

This is a Two sampled hypothesis testing in which one of the samples is the number of employees in urban area and the second is the number of employees in rural area. Here,

H_0 : The difference between the mean of number of employees in urban and and in rural is 0
H_1: The difference between the mean of number of employees in urban and and in rural is not 0
Confidence interval: 95%



Since, the p-vlaue is greater is 0.05, we accept the null hypothesis that is difference between the mean number of employees in urban and in rural is 0 at a confidence interval of 95%.

5.5. Classification Models

5.5.1. K- Nearest Neighbor

Predicting the model using the K-Nearest Neighbor

--> First the data is pre-processed

-> The X variables are converted to numeric

-> The Y variable is kept as categorical or factored variable

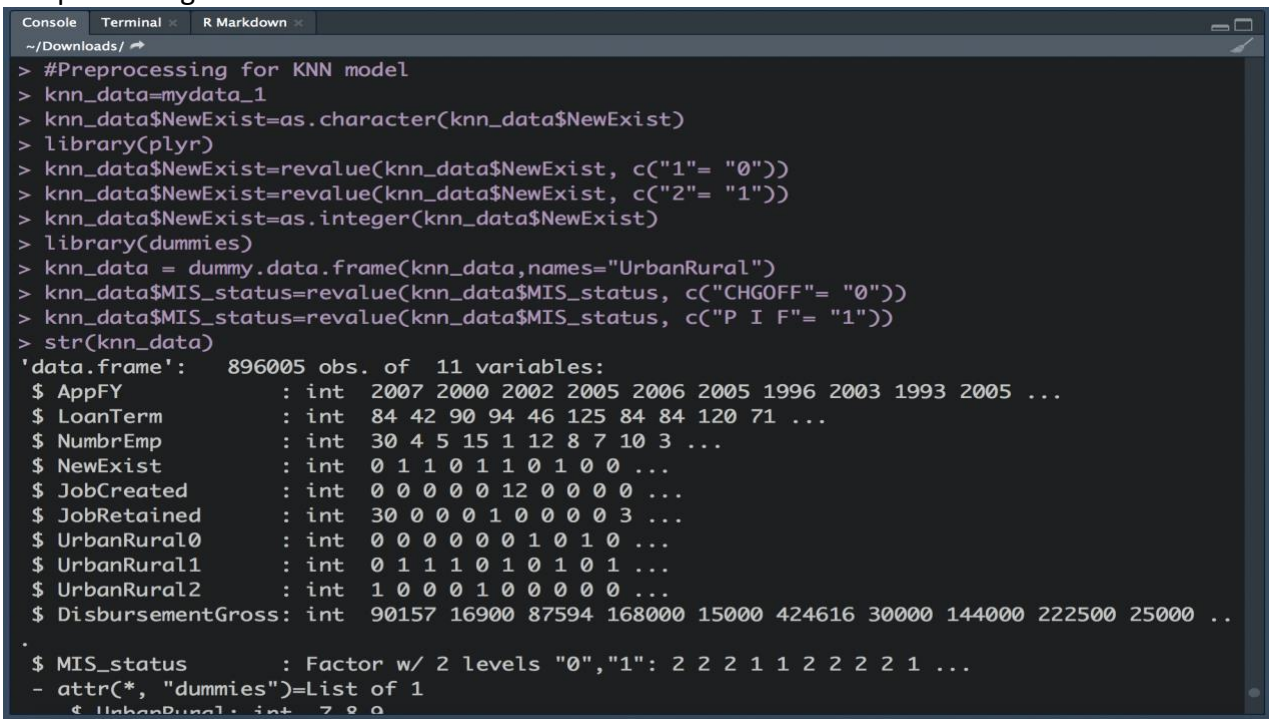
-> The whole data is brought into same scale

--> The data is then divided into testing and training

--> The Model is built with different K values (here: 200,300,499) on training data

--> Accuracy is found for all the models on the testing data

Pre-processing the data



Scaling the data

```
Console  Terminal  R Markdown
~/Downloads/
> #Scalling the preprocessed knn data
> #extracting numerical data
> num.vars.knn <- sapply(knn_data, is.numeric)
> #normalizing the knn data
> knn_data[num.vars.knn] = lapply(knn_data[num.vars.knn],scale)
> head(knn_data)
            AppFY   LoanTerm     NumbrEmp   NewExist  JobCreated JobRetained UrbanRural0
237898  0.9910201 -0.3399390  0.252576382 -0.6265058 -0.03559242  0.08106884  -0.7495568
333425 -0.1930129 -0.8723731 -0.100506890  1.5961525 -0.03559242 -0.04551841  -0.7495568
513279  0.1452822 -0.2638770 -0.086926764  1.5961525 -0.03559242 -0.04551841  -0.7495568
813756  0.6527249 -0.2131690  0.048874494 -0.6265058 -0.03559242 -0.04551841  -0.7495568
180708  0.8218725 -0.8216651 -0.141247268  1.5961525 -0.03559242 -0.04129883  -0.7495568
804958  0.6527249  0.1798180  0.008134117  1.5961525  0.01514011 -0.04551841  -0.7495568
       UrbanRural1 UrbanRural2 DisbursementGross MIS_status
237898  -1.0475773   2.7465364        -0.3869226          1
333425   0.9545824  -0.3640945        -0.6416164          1
513279   0.9545824  -0.3640945        -0.3958335          1
813756   0.9545824  -0.3640945        -0.1162846          0
180708  -1.0475773   2.7465364        -0.6482222          0
804958   0.9545824  -0.3640945         0.7758963          1
>
```

Dividing the pre-processed data into training and testing by setting index

```
Console  Terminal  R Markdown
~/Downloads/
> #dividing the pre-processed data into training and testing
> set.seed(1)
> train=1:716804
> knn.train.data <- knn_data[train,]          #train data
> knn.tst.data = knn_data[-train,]            #test data
> str(knn.train.data)
'data.frame':   716804 obs. of  11 variables:
 $ AppFY           : num [1:716804, 1] 0.991 -0.193 0.145 0.653 0.822 ...
 $ LoanTerm        : num [1:716804, 1] -0.34 -0.872 -0.264 -0.213 -0.822 ...
 $ NumbrEmp        : num [1:716804, 1] 0.2526 -0.1005 -0.0869 0.0489 -0.1412 ...
 $ NewExist        : num [1:716804, 1] -0.627 1.596 1.596 -0.627 1.596 ...
 $ JobCreated      : num [1:716804, 1] -0.0356 -0.0356 -0.0356 -0.0356 -0.0356 ...
 $ JobRetained     : num [1:716804, 1] 0.0811 -0.0455 -0.0455 -0.0455 -0.0413 ...
 $ UrbanRural0     : num [1:716804, 1] -0.75 -0.75 -0.75 -0.75 -0.75 ...
 $ UrbanRural1     : num [1:716804, 1] -1.048 0.955 0.955 0.955 -1.048 ...
 $ UrbanRural2     : num [1:716804, 1] 2.747 -0.364 -0.364 -0.364 2.747 ...
 $ DisbursementGross: num [1:716804, 1] -0.387 -0.642 -0.396 -0.116 -0.648 ...
 $ MIS_status      : Factor w/ 2 levels "0","1": 2 2 2 1 1 2 2 2 2 1 ...
 - attr(*, "dummies")=List of 1
  ..$ UrbanRural: int  7 8 9
> str(knn.tst.data)
'data.frame':   179201 obs. of  11 variables:
 $ AppFY           : num [1:179201, 1] 0.484 1.16 0.653 -1.884 -1.208 ...
 $ LoanTerm        : num [1:179201, 1] -0.34 -0.758 0.75 1.638 1.448 ...
 $ NumbrEmp        : num [1:179201, 1] -0.141 -0.128 -0.114 -0.114 -0.128 ...
 $ NewExist        : num [1:179201, 1] -0.627 1.596 1.596 -0.627 1.596 ...
 $ JobCreated      : num [1:179201, 1] -0.0356 -0.0187 -0.0356 -0.0356 -0.0356 ...
 $ JobRetained     : num [1:179201, 1] -0.0413 -0.0371 -0.0455 -0.0455 -0.0455 ...
```

For building the models with different Ks

```
> knn.200 = knn(knn.train.data,knn.tst.data,knn.train.MIS,k=200)
> #finding the accuracy of the models built on testing data
> accuracy(knn.tst.MIS, knn.200)
[1] 0.8252856
> knn.300 = knn(knn.train.data,knn.tst.data,knn.train.MIS,k=300)
> accuracy(knn.tst.MIS, knn.300)
[1] 0.8252856
> accuracy(knn.tst.MIS, knn.499)
Error in mean(actual != predicted) : object 'knn.499' not found
> knn.499 = knn(knn.train.data,knn.tst.data,knn.train.MIS,k=499)
> accuracy(knn.tst.MIS, knn.499)
[1] 0.8252856
```

The Accuracy at K= 200: 82.52%
The Accuracy at K= 300: 82.52%
The Accuracy at K= 499: 82.52%

5.5.2. Naïve Bayes

Predicting the model using the Naïve Bayes Classifier

→ First the data is pre-processed

-> The X variables are converted to categorical

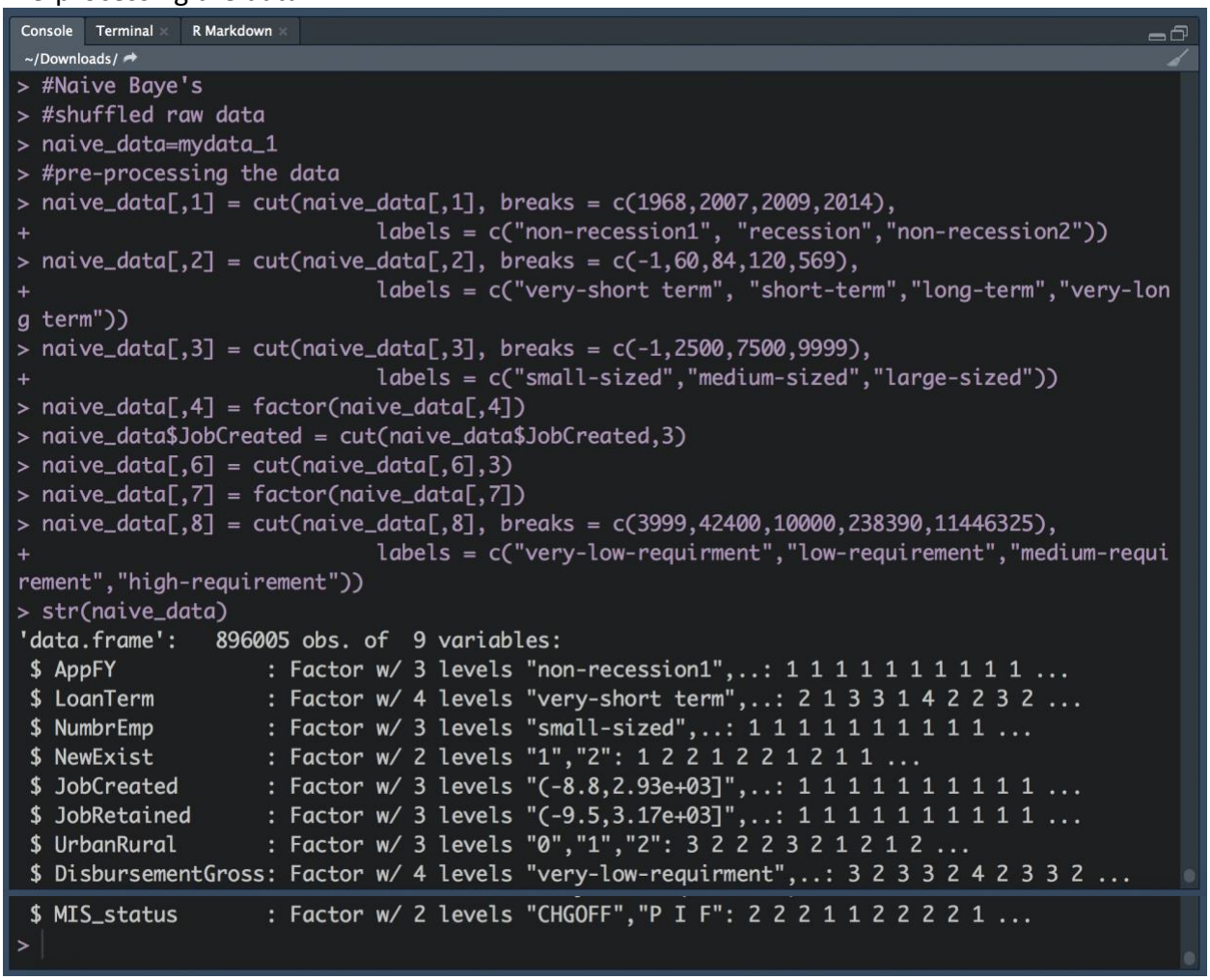
-> The Y variable is kept as categorical or factored variable

→ The data is then divided into testing and training

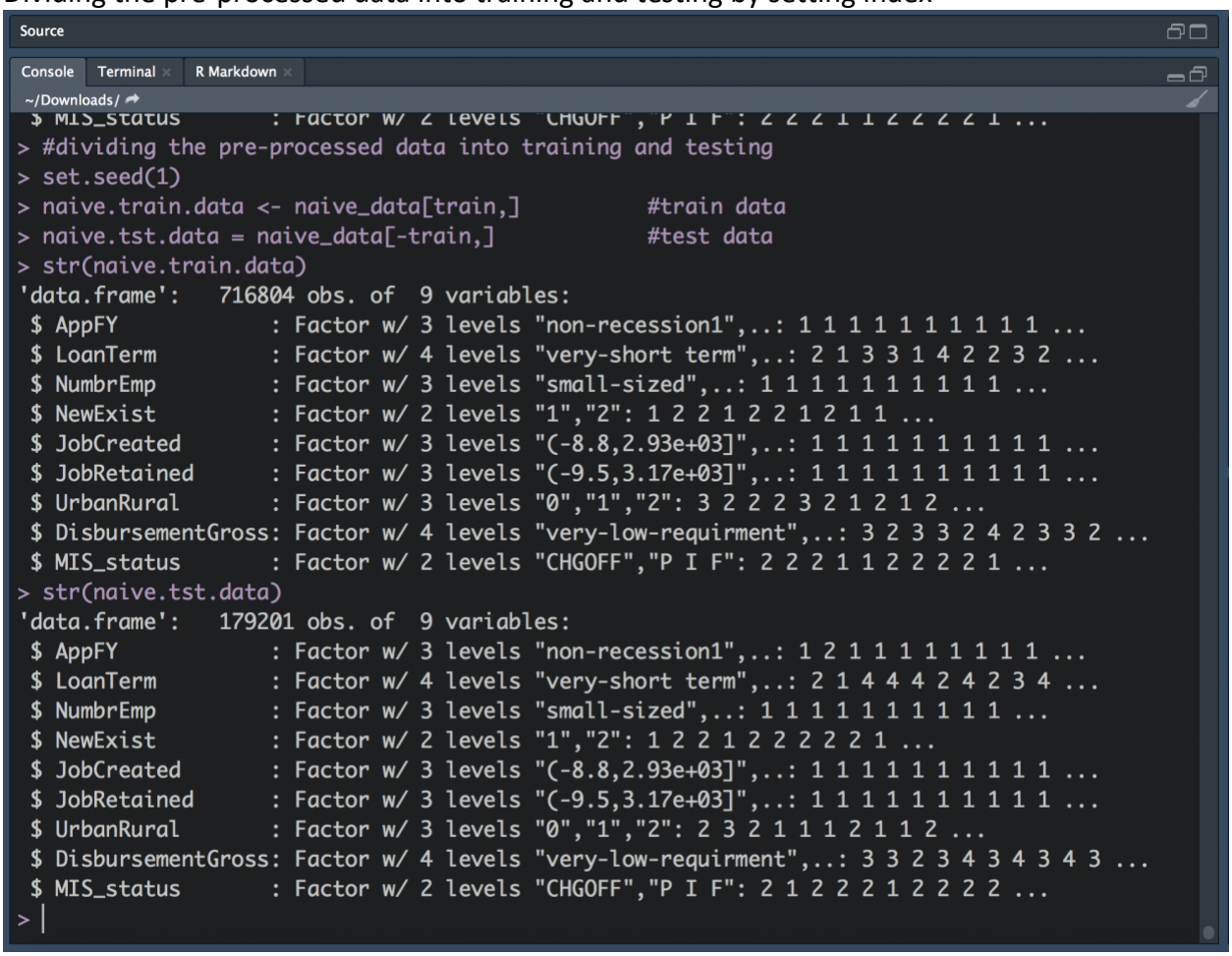
→ The Model is built with on training data

→ Accuracy is found for all the models on the testing data

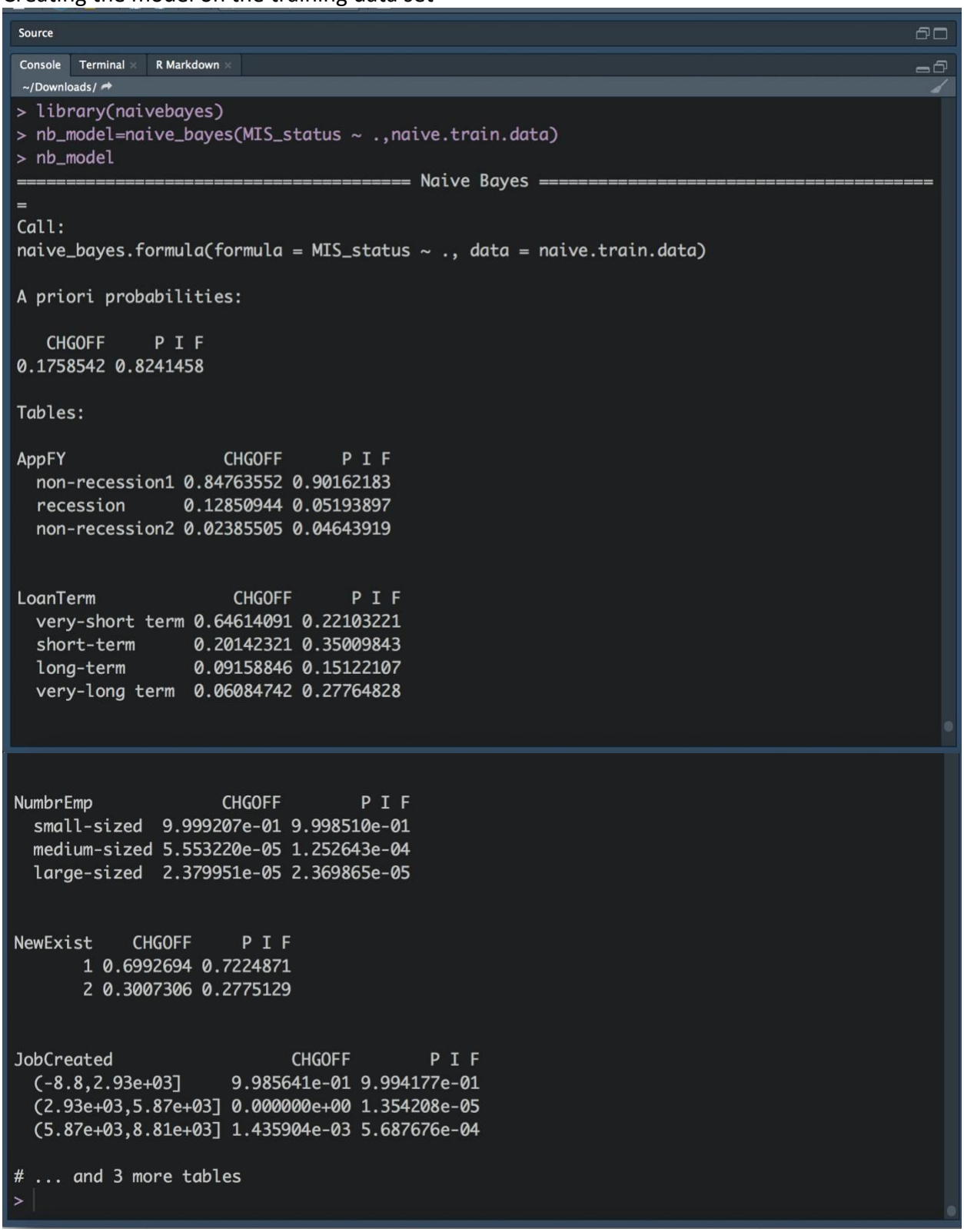
Pre-processing the data



Dividing the pre-processed data into training and testing by setting index



Creating the model on the training data set



Evaluating the accuracy on testing data

```
> head(predict(nb_model, naive.tst.data, type = "prob"))
          CHGOFF     P I F
[1,] 0.147893373 0.8521066
[2,] 0.651007390 0.3489926
[3,] 0.092508537 0.9074915
[4,] 0.015353258 0.9846467
[5,] 0.008609267 0.9913907
[6,] 0.043823834 0.9561762
> library(Metrics)
> accuracy(naive.tst.data[,9], pred)
[1] 0.8237063
>
```

5.5.3 Logistic Regression

Predicting the model using the Logistic Classifier

→ First the data is pre-processed

-> The X variables are converted to numerical

-> The Y variable is kept as categorical or factored variable

→ The data is then divided into testing and training

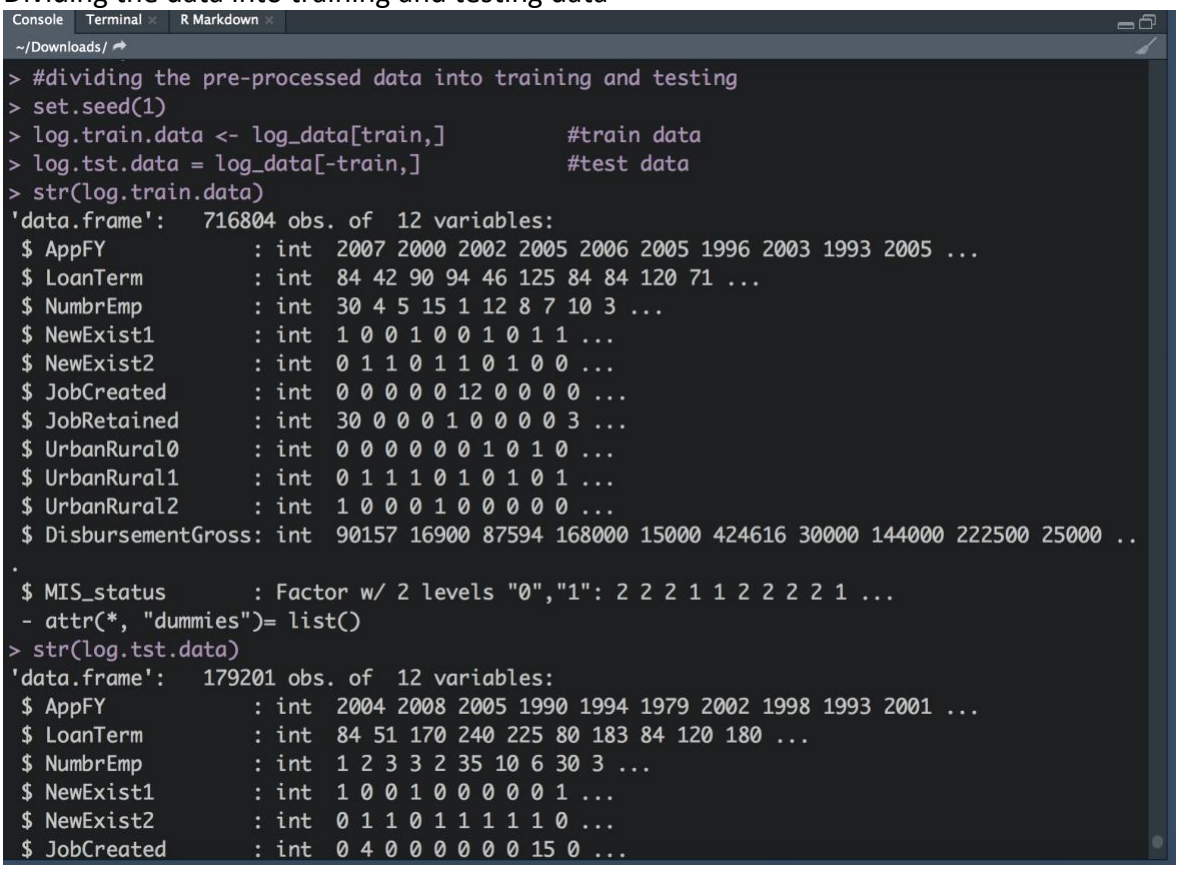
→ The Model is built with on training data

→ Accuracy is found for all the models on the testing data

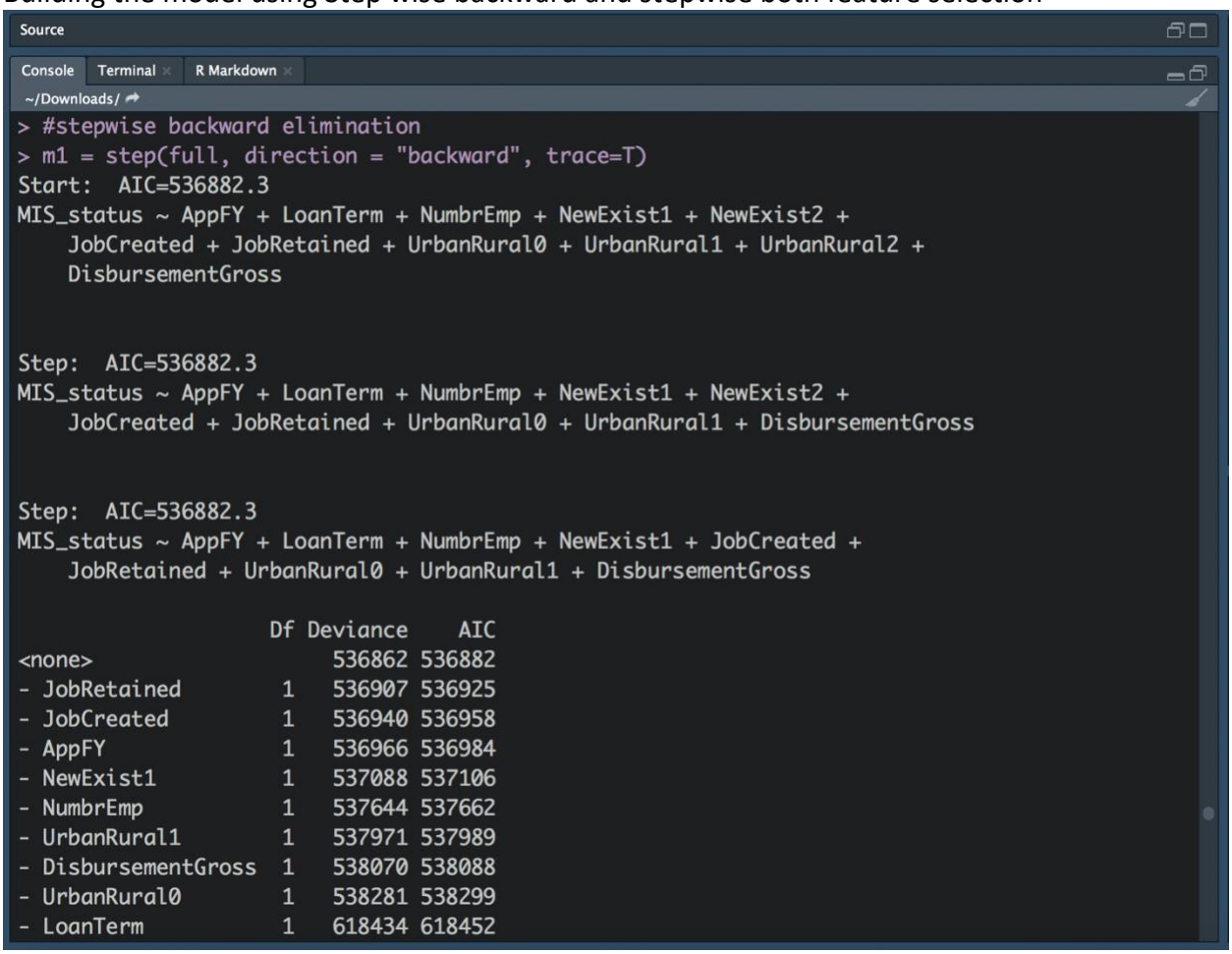
Pre-processing the data

```
> #logistic regression
> log_data=mydata_1
> #pre-processing the data
> log_data=dummy.data.frame(log_data, names = c("NewExist","UrbanRural"))
> log_data=dummy.data.frame(log_data, names = c("NewExist","UrbanRural"))
> log_data$MIS_status=revalue(log_data$MIS_status, c("CHGOFF"= "0"))
> log_data$MIS_status=revalue(log_data$MIS_status, c("P I F"= "1"))
> str(log_data)
'data.frame':   896005 obs. of  12 variables:
 $ AppFY            : int  2007 2000 2002 2005 2006 2005 1996 2003 1993 2005 ...
 $ LoanTerm         : int  84 42 90 94 46 125 84 84 120 71 ...
 $ NumbrEmp         : int  30 4 5 15 1 12 8 7 10 3 ...
 $ NewExist1        : int  1 0 0 1 0 0 1 0 1 1 ...
 $ NewExist2        : int  0 1 1 0 1 1 0 1 0 0 ...
 $ JobCreated       : int  0 0 0 0 0 12 0 0 0 0 ...
 $ JobRetained      : int  30 0 0 0 1 0 0 0 0 3 ...
 $ UrbanRural0      : int  0 0 0 0 0 0 1 0 1 0 ...
 $ UrbanRural1      : int  0 1 1 1 0 1 0 1 0 1 ...
 $ UrbanRural2      : int  1 0 0 0 1 0 0 0 0 0 ...
 $ DisbursementGross: int  90157 16900 87594 168000 15000 424616 30000 144000 222500 25000 ..
.
 $ MIS_status       : Factor w/ 2 levels "0","1": 2 2 2 1 1 2 2 2 2 1 ...
 - attr(*, "dummies")= list()
>
```

Dividing the data into training and testing data



Building the model using Step wise backward and stepwise both feature selection



```
Console  Terminal  R Markdown
~/Downloads/
> #stepwise both
> m2 = step(base,scope=list(upper=full, lower=~1), direction="both",trace=T)
Start:  AIC=654825.7
MIS_status ~ DisbursementGross

                   Df Deviance    AIC
+ LoanTerm          1   556606 556612
+ UrbanRural0       1   623062 623068
+ AppFY             1   624629 624635
+ UrbanRural1       1   629867 629873
+ NumbrEmp          1   652819 652825
+ JobRetained       1   654708 654714
+ JobCreated        1   654719 654725
+ UrbanRural2       1   654746 654752
+ NewExist1         1   654760 654766
+ NewExist2         1   654760 654766
<none>                 654822 654826
- DisbursementGross  1   666697 666699

Step:  AIC=556611.7
MIS_status ~ DisbursementGross + LoanTerm

                   Df Deviance    AIC
+ UrbanRural0       1   540250 540258
+ UrbanRural1       1   543140 543148
+ AppFY             1   544721 544729
+ NumbrEmp          1   553697 553705
+ JobCreated        1   556134 556142
```

Evaluating the accuracy from the built model, on testing data

```
Console  Terminal  R Markdown
~/Downloads/
> #accuracy of the model built stepwise backward elimination
> predict(m1, type="response", newdata = log.tst.data)
   728681    301447    842177    363666    612327    885021    574713    104787    577671
0.7896916 0.6851742 0.9653859 0.9980562 0.9961322 0.9313318 0.9730202 0.9060290 0.9542696
   417193    738408    188886    772372    355083    798644    773313    329283    593215
0.9748247 0.6363417 0.9107818 0.9247818 0.8828600 0.9265232 0.5034838 0.9096678 0.9350523
   804895      6071    327121    593583    861817    376248    682371    600925     71378
0.7199917 0.8070550 0.9961934 0.9979384 0.9981911 0.7679044 0.9992800 0.9663982 0.9241337
   480336    369347    293003    616685    511848    330204     83353    367738    843005
0.5835051 0.9982130 0.7942671 0.9979225 0.9983760 0.9708874 0.3557181 0.7073985 0.9992636
   169520    460851    807116    589480    410142    749127    715791    493195    163201
0.8704741 0.9920700 0.8979081 0.9730017 0.9402468 0.9163382 0.6654706 0.9159298 0.8040284
    81077    146733    317157    629261    886471    349024    599672     39717    568717
0.9730954 0.7786693 0.5233934 0.7890969 0.8599462 0.9265038 0.8919144 0.8975737 0.6602562
   693781    274204    575639    127267    811106    224229    549005    336254    471505
0.7793836 0.5640858 0.9193494 0.8028245 0.9980577 0.6119973 0.9965617 0.7899614 0.9737902
   383859    189619    289890    814449    442498    356073    839278    236500    663521
0.9976358 0.7988605 0.7824101 0.8871543 0.9909096 0.9266328 0.8732773 0.1159151 0.9609691
   227877    774393    859035    852602    412011    716195    233112    155661    670352
0.7806704 0.8876991 0.9546603 0.9652563 0.8101046 0.9344260 0.7278260 0.7998073 0.8178499
   227108    686903    667811    241552    796932    607242     90979    571311    640899
0.7764496 0.8016275 0.8237563 0.7780392 0.9976275 0.6098806 0.9651068 0.8907215 0.9895693
    97134    686884    695873    427698    730652    195545     13634    658787    396524
0.7769539 0.5839777 0.7293566 0.9994142 0.7968936 0.9981035 0.6737933 0.9891459 0.8601824
   722650    807515     31890    287987    575193    436293     99355    165412    687537
```

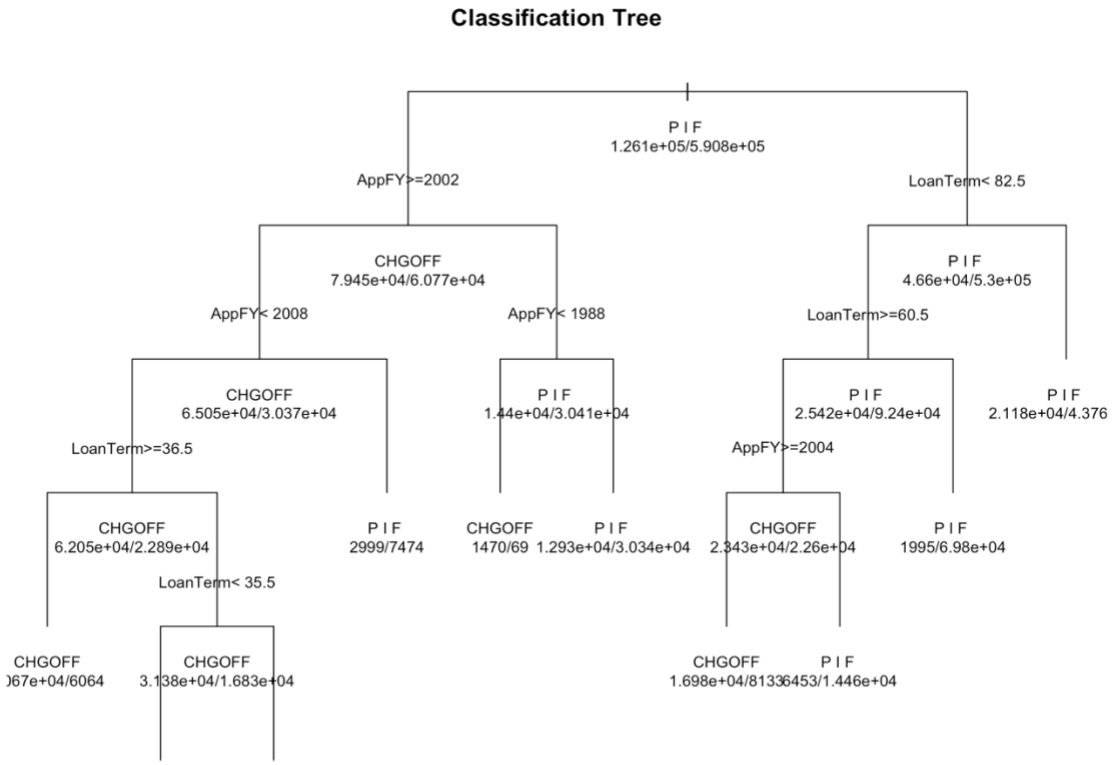
```
Console  Terminal  R Markdown
~/Downloads/
Error in mean(actual != predicted) : object 'log.test.MIS' not found
> accuracy(log.tst.MIS,prob1)      #accuracy of model 1
Error in mean(actual != predicted) : object 'log.tst.MIS' not found
> #dividing the label into testing and training
> log.train.MIS=log.train.data$MIS_status
> log.tst.MIS=log.tst.data$MIS_status
> accuracy(log.tst.MIS,prob1)      #accuracy of model 1
[1] 0.8374563
```

5.5.4. Decision Tree

→ No need to perform the pre-processing
→ Split the data into testing and training
→ Built the decision tree on training data set
→ Evaluate the accuracy with the model built on testing data

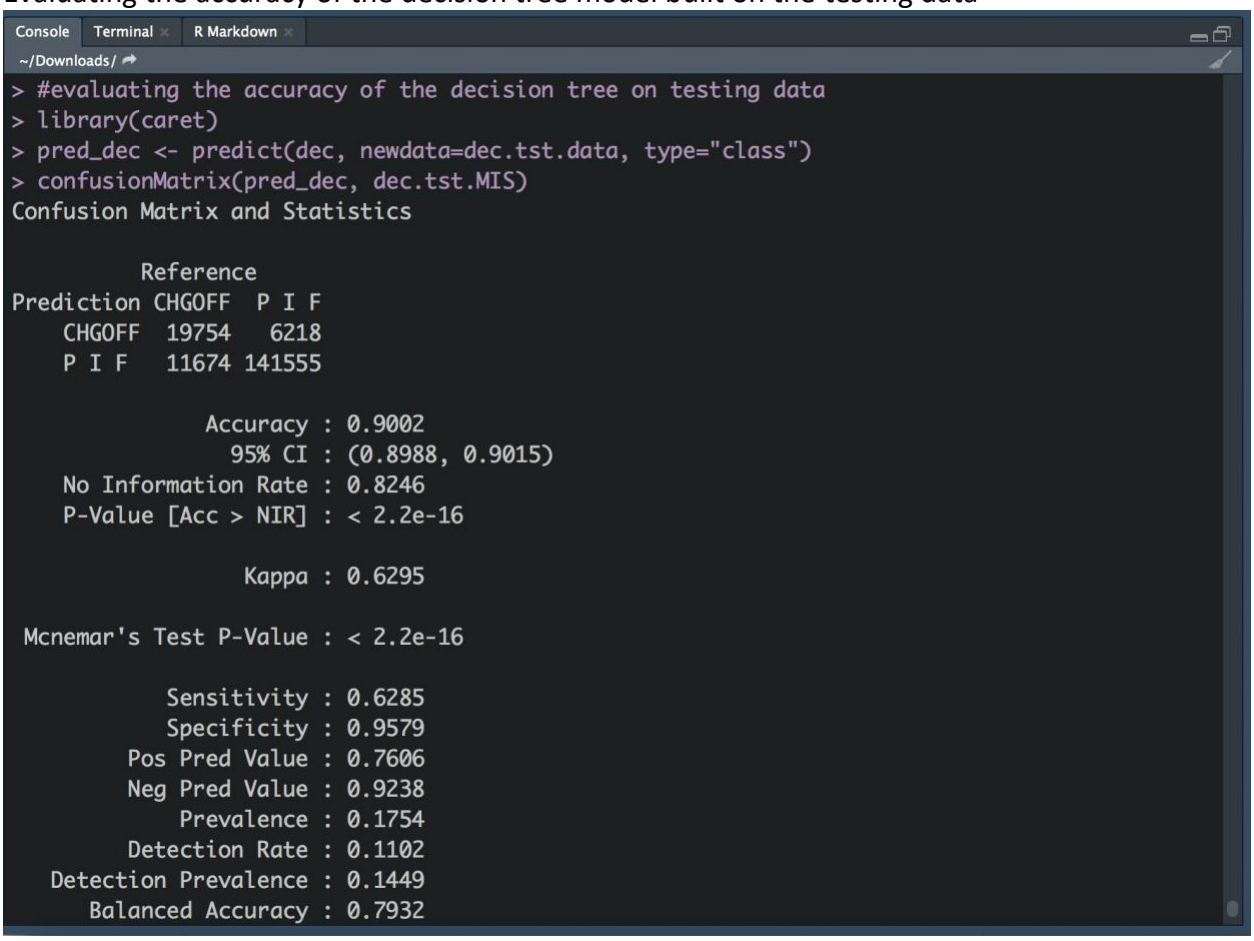
```
Console  Terminal  R Markdown
~/Downloads/
> #decision tree
> dec_data=mydata_1
> #dividing the pre-processed data into training and testing
> set.seed(1)
> dec.train.data <- dec_data[train,]          #train data
> dec.tst.data = dec_data[-train,]            #test data
> str(dec.train.data)
'data.frame':   716804 obs. of  9 variables:
 $ AppFY            : int  2007 2000 2002 2005 2006 2005 1996 2003 1993 2005 ...
 $ LoanTerm         : int  84 42 90 94 46 125 84 84 120 71 ...
 $ NumbrEmp         : int  30 4 5 15 1 12 8 7 10 3 ...
 $ NewExist         : int  1 2 2 1 2 2 1 2 1 1 ...
 $ JobCreated       : int  0 0 0 0 0 12 0 0 0 0 ...
 $ JobRetained      : int  30 0 0 0 1 0 0 0 0 3 ...
 $ UrbanRural       : int  2 1 1 1 2 1 0 1 0 1 ...
 $ DisbursementGross: int  90157 16900 87594 168000 15000 424616 30000 144000 222500 25000 ..
.
 $ MIS_status       : Factor w/ 2 levels "CHGOFF","P I F": 2 2 2 1 1 2 2 2 2 1 ...
> str(dec.tst.data)
'data.frame':   179201 obs. of  9 variables:
 $ AppFY            : int  2004 2008 2005 1990 1994 1979 2002 1998 1993 2001 ...
 $ LoanTerm         : int  84 51 170 240 225 80 183 84 120 180 ...
 $ NumbrEmp         : int  1 2 3 3 2 35 10 6 30 3 ...
 $ NewExist         : int  1 2 2 1 2 2 2 2 2 1 ...
 $ JobCreated       : int  0 4 0 0 0 0 0 0 15 0 ...
 $ JobRetained      : int  1 2 0 0 0 0 0 0 15 3 ...
 $ UrbanRural       : int  1 2 1 0 0 0 1 0 0 1 ...
 $ DisbursementGross: int  180916 55500 37000 115000 395000 200000 275000 230000 750000 18900
```

```
> #dividing the label in training and testing
> dec.train.MIS=dec.train.data$MIS_status
> dec.tst.MIS=dec.tst.data$MIS_status
> #building the decision tree model
> dec = rpart(MIS_status~.,method="class", data=dec.train.data)
> #plotting the decision tree
> plot(dec, uniform=TRUE, main="Classification Tree")
> text(dec, use.n=TRUE, all=TRUE, cex=.8)
>
```



Decision Tree

Evaluating the accuracy of the decision tree model built on the testing data



5.6. Evaluations and Results

Classification Model	Accuracy
K-nearest neighbor	82.52%
Naïve Bayes	82.37%
Logistic Regression	83.74%
Decision Tree	90.02%

5.7. Findings

On comparing all the above classification models Decision Tree gives the best accuracy of 90.02%.

6. Conclusions and Future Work

6.1. Conclusions

From the above analysis I can conclude that with the help Decision Tree you can predict the best fitted model in order to predict best factors that are most responsible for the approval of the loan.

From this prediction the analysis team will get to know which factors can lead to approval of the loan thus making their task easy in order to predict the approval or denial of the loan for any future application.

6.2. Limitations

The limitation which I found performing the analysis was while the K-Nearest classification. R Studio supports only a maximum of 499 K values. So, since the data selected here is too large, I could have used more K values in order to get some better accuracy.

6.3. Potential Improvements or Future Work

As for the future work I would test for the overfitting issue in the decision tree, and if found I would do the pruning to solve that issue.

Also, I would perform the random forest on this to know some of the more accuracies.

Also, I would perform linear regression on the approved amount by the bank to the company, in order to predict the dependency of approved amount on various independent factors.

Variable Name	Data type	Description of variable
LoanNr_ChkDgt	Text	Identifier – Primary Key
Name	Text	Borrower Name
City	Text	Borrower City
State	Text	Borrower State
Zip	Text	Borrower Zip Code
Bank	Text	Bank Name
BankState	Text	Bank State
NAICS	Text	North American Industry Classification System code
ApprovalDate	Date/Time	Date SBA Commitment Issued
ApprovalFY	Text	Fiscal Year of Commitment
Term	Number	Loan term in months
NoEmp	Number	Number of Business Employees
NewExist	Text	1 = Existing Business, 2 = New Business
CreateJob	Number	Number of jobs created
RetainedJob	Number	Number of jobs retained
FranchiseCode	Text	Franchise Code 00000 or 00001 = No Franchise
UrbanRural	Text	1= Urban, 2= Rural, 0 = Undefined
RevLineCr	Text	Revolving Line of Credit : Y = Yes
LowDoc	Text	LowDoc Loan Program: Y = Yes, N = No
ChgOffDate	Date/Time	The date when a loan is declared to be in default
DisbursementDate	Date/Time	Disbursement Date
DisbursementGross	Currency	Amount Disbursed
BalanceGross	Currency	Gross amount outstanding
MIS_Status	Text	Loan Status
ChgOffPrinGr	Currency	Charged-off Amount
GrAppv	Currency	Gross Amount of Loan Approved by Bank
SBA_Appv	Currency	SBA’s Guaranteed Amount of Approved Loan