THERA BANK PROJECT

DATA MINING

PROJECT OBJECTIVE:

This case study is prepared for "Thera Bank – Loan Purchase Modelling" for their personal loan campaign so that they Can target right customers who have a higher probability of purchasing the loan. The objective is to build the best model using Data Mining techniques which can classify right customers.

We will be performing below steps and will analyse the data using Data Mining techniques to identify such customers.

- Understanding about the given data and doing EDA with appropriate graphs.
- Applying appropriate clustering on the data.
- Build appropriate models on both the test and train data using CART & Random Forest method.
- Check the performance of all the models that you have built (test and train).
- Use all the model performance measures to evaluate the model which is built.
- Share your remarks on which model performs the best.

PROJECT APPROACH

- EDA - Basic data summary, Univariate, Bivariate analysis, graphs
- Applying CART <plot the tree>
- Interpret the CART model output <pruning, remarks on pruning, plot the pruned tree>
- Applying Random Forests<plot the tree>
- Interpret the RF model output <with remarks, making it meaningful for everybody
- Confusion matrix interpretation
- Interpretation of other Model Performance Measures < AUC, ROC>
- Remarks on Model validation exercise <Which model performed the best>

ASSUMPTIONS

- Age (in Years)
- Experience (in Years)
- Income
- Family Members
- CC Avg (Credit Card Average)
- Education
- Mortgage
- Personal Loan
- Securities Account
- CD Account
- Online
- Credit Card

Environment Set up and Data Import

Install necessary Packages and Invoke Libraries

Use this section to install necessary packages and invoke associated libraries. Having all the packages at the same places increases code readability.
Below are the Packages used in this project:

library(readr)

library(dplyr)

library(ggplot2)

library (grid Extra)

library(lattice)

library (Data Explorer)

library(grDevices)

library(factoextra)

library(caret)

library(rpart)

library (rpart. plot)

library (random Forest)

library(ranger)

library (Metrics)

library (ROCit)

library (Kable Extra)

library(fpc)

library (NbClust)

library(e1071)

Set up working Directory

Setting a working directory on starting of the R session makes importing and exporting data files and code files easier. Basically, working directory is the location/ folder on the PC where you have the data, codes etc. related to the project.

Read & Import Dataset

The given dataset is in .csv format. Hence, the command ‘read.csv’ is used for importing the file.

Analysis of dataset

Dataset has 5000 rows of observations and 14 variables

Family Members have 18 observations missing

Since 18 obs rows having “NA” as family members are also having vital other predictors we might as well replace NA with “zeros” to factor them instead of discarding them.

Basic data summary, Univariate, Bivariate analysis, graphs

Structure

```
str(bank)
'data.frame':	5000 obs. of  14 variables:
 $ ID                     : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Age..in.years.         : int  25 45 39 35 35 37 53 50 35 34 ...
 $ Experience..in.years.: int  1 19 15 9 8 13 27 24 10 9 ...
 $ Income..in.K.year.    : int  49 34 11 100 45 29 72 22 81 180 ...
 $ ZIP.Code              : int  91107 90089 94720 94112 91330 92121 91711 9
3943 90089 93023 ...
 $ Family.members        : int  4 3 1 1 4 4 2 1 3 1 ...
 $ CCAvg                 : num  1.6 1.5 1 2.7 1 0.4 1.5 0.3 0.6 8.9 ...
 $ Education             : int  1 1 1 2 2 2 2 3 2 3 ...
 $ Mortgage              : int  0 0 0 0 0 155 0 0 104 0 ...
 $ Personal.Loan         : int  0 0 0 0 0 0 0 0 0 1 ...
 $ Securities.Account    : int  1 1 0 0 0 0 0 0 0 0 ...
 $ CD.Account            : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Online                : int  0 0 0 0 0 1 1 0 1 0 ...
 $ CreditCard            : int  0 0 0 0 1 0 0 1 0 0 ...
```

Summary

```
summary(bank)
       ID        Age..in.years.  Experience..in.years. Income..in.K.year.
ZIP.Code      Family.members
 Min.   :   1   Min.   :23.00   Min.   :-3.0          Min.   :  8.00     M
in.   : 9307   Min.   :1.000
 1st Qu.:1251   1st Qu.:35.00   1st Qu.:10.0          1st Qu.: 39.00     1
st Qu.:91911   1st Qu.:1.000
 Median :2500   Median :45.00   Median :20.0          Median : 64.00     M
edian :93437   Median :2.000
 Mean   :2500   Mean   :45.34   Mean   :20.1          Mean   : 73.77     M
ean   :93153   Mean   :2.397
 3rd Qu.:3750   3rd Qu.:55.00   3rd Qu.:30.0          3rd Qu.: 98.00     3
rd Qu.:94608   3rd Qu.:3.000
 Max.   :5000   Max.   :67.00   Max.   :43.0          Max.   :224.00     M
ax.   :96651   Max.   :4.000

NA's   :18
     CCAvg          Education        Mortgage      Personal.Loan   Securiti
es.Account   CD.Account
 Min.   : 0.000   Min.   :1.000   Min.   :  0.0   Min.   :0.000   Min.   :
0.0000      Min.   :0.0000
 1st Qu.: 0.700   1st Qu.:1.000   1st Qu.:  0.0   1st Qu.:0.000   1st Qu.:
0.0000      1st Qu.:0.0000
 Median : 1.500   Median :2.000   Median :  0.0   Median :0.000   Median :
0.0000      Median :0.0000
 Mean   : 1.938   Mean   :1.881   Mean   : 56.5   Mean   :0.096   Mean   :
0.1044      Mean   :0.0604
 3rd Qu.: 2.500   3rd Qu.:3.000   3rd Qu.:101.0   3rd Qu.:0.000   3rd Qu.:
0.0000      3rd Qu.:0.0000
 Max.   :10.000   Max.   :3.000   Max.   :635.0   Max.   :1.000   Max.   :
1.0000      Max.   :1.0000

     Online         CreditCard
 Min.   :0.0000   Min.   :0.000
 1st Qu.:0.0000   1st Qu.:0.000
 Median :1.0000   Median :0.000
 Mean   :0.5968   Mean   :0.294
 3rd Qu.:1.0000   3rd Qu.:1.000
 Max.   :1.0000   Max.   :1.000
```

Dimension

```
> dim(bank)
[1] 5000   14
```

Checking for Missing Valves

```
any(is.na(bank))
[1] TRUE
```

Columns Which have Missing Valves

```
sapply(bank,function(x)sum(is.na(x)))
                    ID          Age..in.years.  Experience..in.years.     Incom
e..in.K.year.
                     0                     0                     0
0
              ZIP.Code          Family.members                 CCAvg
Education
                     0                    18                     0
0
              Mortgage           Personal.Loan    Securities.Account
CD.Account
                     0                     0                     0
0
                Online              CreditCard
                     0                     0
```

After replacing with Zero

```
bank[is.na(bank)]=0
> any(is.na(bank))
[1] FALSE
```

```
dim(bank)
[1] 5000   14
```

Looking at the dataset we realize the following aspects (raw check)

- ID and Zip code columns will not help much in analysis since they are basically addon - para information
- Experience has got negative values. We will fix them with corresponding positive values making more sense
- Columns like Personal Loan, CD Account, Online et.al are factor values with levels “0” and “1” . Save Education which is ordered factor with 3 levels 1 < 2 < 3

```
str(bank)
'data.frame':	5000 obs. of  14 variables:
 $ ID                    : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Age..in.years.        : int  25 45 39 35 35 37 53 50 35 34 ...
 $ Experience..in.years.: int  1 19 15 9 8 13 27 24 10 9 ...
 $ Income..in.K.year.    : int  49 34 11 100 45 29 72 22 81 180 ...
 $ ZIP.Code              : int  91107 90089 94720 94112 91330 92121 91711 9
3943 90089 93023 ...
 $ Family.members        : num  4 3 1 1 4 4 2 1 3 1 ...
 $ CCAvg                 : num  1.6 1.5 1 2.7 1 0.4 1.5 0.3 0.6 8.9 ...
 $ Education             : int  1 1 1 2 2 2 2 3 2 3 ...
 $ Mortgage              : int  0 0 0 0 0 155 0 0 104 0 ...
 $ Personal.Loan         : int  0 0 0 0 0 0 0 0 0 1 ...
 $ Securities.Account    : int  1 1 0 0 0 0 0 0 0 0 ...
 $ CD.Account            : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Online                : int  0 0 0 0 0 1 1 0 1 0 ...
 $ CreditCard            : int  0 0 0 0 1 0 0 1 0 0 ...
```

```
summary(bank)
       ID        Age..in.years.  Experience..in.years. Income..in.K.year.  
ZIP.Code     Family.members 
 Min.   :   1   Min.   :23.00   Min.   :-3.0          Min.   :  8.00     M
in.   : 9307   Min.   :0.000  
 1st Qu.:1251   1st Qu.:35.00   1st Qu.:10.0          1st Qu.: 39.00     1
st Qu.:91911   1st Qu.:1.000  
 Median :2500   Median :45.00   Median :20.0          Median : 64.00     M
edian :93437   Median :2.000  
 Mean   :2500   Mean   :45.34   Mean   :20.1          Mean   : 73.77     M
ean   :93153   Mean   :2.389  
 3rd Qu.:3750   3rd Qu.:55.00   3rd Qu.:30.0          3rd Qu.: 98.00     3
rd Qu.:94608   3rd Qu.:3.000  
 Max.   :5000   Max.   :67.00   Max.   :43.0          Max.   :224.00     M
ax.   :96651   Max.   :4.000  
     CCAvg            Education        Mortgage      Personal.Loan   Securiti
es.Account   CD.Account   
 Min.   : 0.000   Min.   :1.000   Min.   :  0.0   Min.   :0.000   Min.   :
0.0000      Min.   :0.0000  
 1st Qu.: 0.700   1st Qu.:1.000   1st Qu.:  0.0   1st Qu.:0.000   1st Qu.:
0.0000      1st Qu.:0.0000  
 Median : 1.500   Median :2.000   Median :  0.0   Median :0.000   Median :
0.0000      Median :0.0000  
 Mean   : 1.938   Mean   :1.881   Mean   : 56.5   Mean   :0.096   Mean   :
0.1044      Mean   :0.0604  
 3rd Qu.: 2.500   3rd Qu.:3.000   3rd Qu.:101.0   3rd Qu.:0.000   3rd Qu.:
0.0000      3rd Qu.:0.0000  
 Max.   :10.000   Max.   :3.000   Max.   :635.0   Max.   :1.000   Max.   :
1.0000      Max.   :1.0000  
     Online             CreditCard   
 Min.   :0.0000   Min.   :0.000  
 1st Qu.:0.0000   1st Qu.:0.000  
 Median :1.0000   Median :0.000  
 Mean   :0.5968   Mean   :0.294  
 3rd Qu.:1.0000   3rd Qu.:1.000  
 Max.   :1.0000   Max.   :1.000  
```

```
removing ID and Zipcode column from dataset
bank=bank[,-c(1,5)]
```

```
Converting multiple coloumns into Factor columns
col=c("Education","Personal.Loan","Securities.Account","CD.Account","Onlin
e","CreditCard")
> bank[col]=lapply(bank[col],factor)
```

```
converting Education into ordered factors .ordinal variable
bank$Education=factor(bank$Education,levels= c("1","2","3"),order=TRUE)
```

```
Changing the name of few variables for ease of use
bank = bank%>% rename(Age = "Age..in.years.", Experience ="Experience..in.
years.",
+                         Income = "Income..in.K.year.")
```

Checking for Rows having negative valves as Experience

```
head(bank[bank$Experience<0,])
    Age Experience Income Family.members CCAvg Education Mortgage Personal
.Loan Securities.Account
90   25         -1    113              4  2.30         3        0
0                  0
227  24         -1     39              2  1.70         2        0
0                  0
316  24         -2     51              3  0.30         3        0
0                  0
452  28         -2     48              2  1.75         3       89
0                  0
525  24         -1     75              4  0.20         1        0
0                  0
537  25         -1     43              3  2.40         2      176
0                  0
    CD.Account Online CreditCard
90           0      0          1
227          0      0          0
316          0      1          0
452          0      1          0
525          0      1          0
537          0      1          0
```

After Fixing them up below is the dimension we can see

```
bank$Experience= abs(bank$Experience)
> dim(bank)
[1] 5000   12
```

Summary

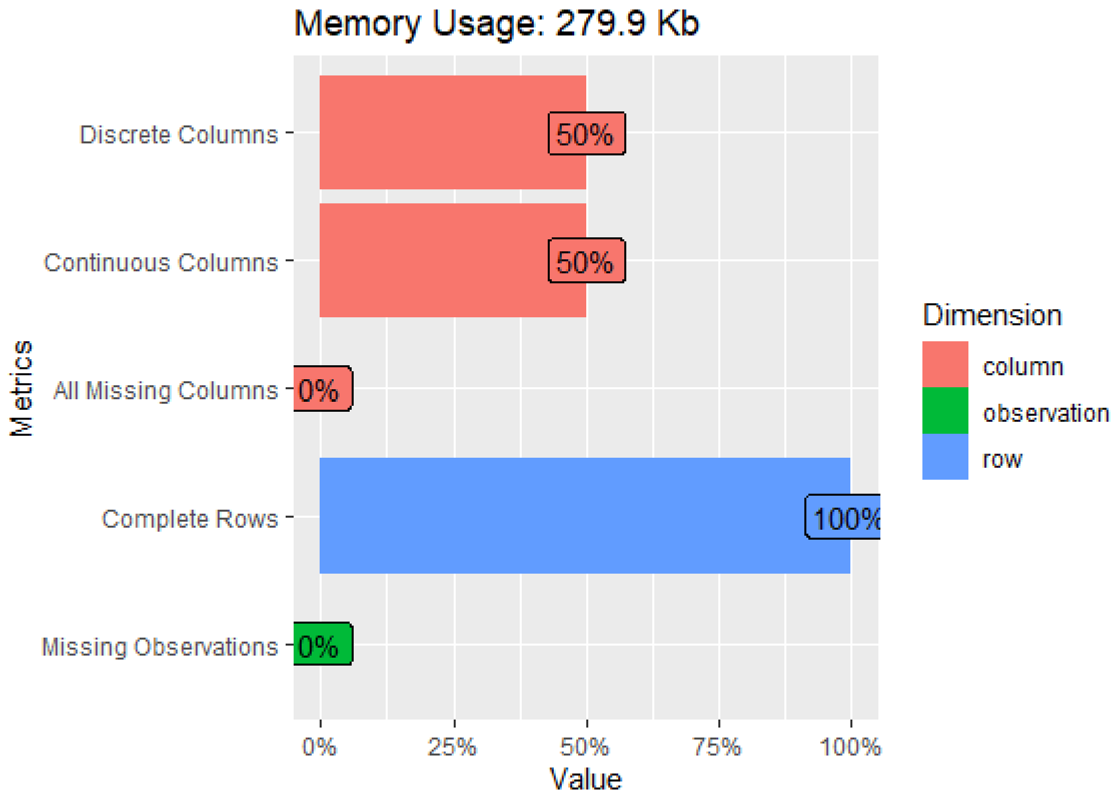
```
summary(bank)
      Age          Experience        Income        Family.members      CCAv
g         Education
 Min.   :23.00   Min.   : 0.00   Min.   :  8.00   Min.   :0.000   Min.   :
0.000   1:2096
 1st Qu.:35.00   1st Qu.:10.00   1st Qu.: 39.00   1st Qu.:1.000   1st Qu.:
0.700   2:1403
 Median :45.00   Median :20.00   Median : 64.00   Median :2.000   Median :
1.500   3:1501
 Mean   :45.34   Mean   :20.13   Mean   : 73.77   Mean   :2.389   Mean   :
1.938
 3rd Qu.:55.00   3rd Qu.:30.00   3rd Qu.: 98.00   3rd Qu.:3.000   3rd Qu.:
2.500
 Max.   :67.00   Max.   :43.00   Max.   :224.00   Max.   :4.000   Max.   :
10.000
    Mortgage      Personal.Loan Securities.Account CD.Account Online   Cred
itCard
 Min.   :  0.0   0:4520        0:4478             0:4698      0:2016   0:35
30
 1st Qu.:  0.0   1: 480        1: 522             1: 302      1:2984   1:14
70
 Median :  0.0
 Mean   : 56.5
```

```
3rd Qu.:101.0
Max.   :635.0
```

Here comes the Plotting Version of all Datasets

- **Introduction Plot**

```
plot_intro(bank)
```



In this plot we can see the dimensions in Column , Observation and Row are different .

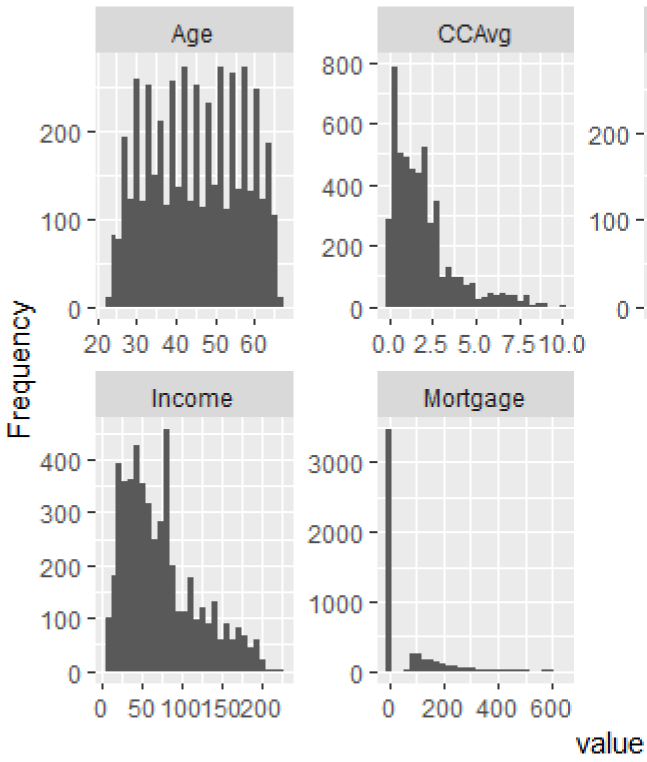
Columns are showing 50%

Missing Observations 0%

Row 100%

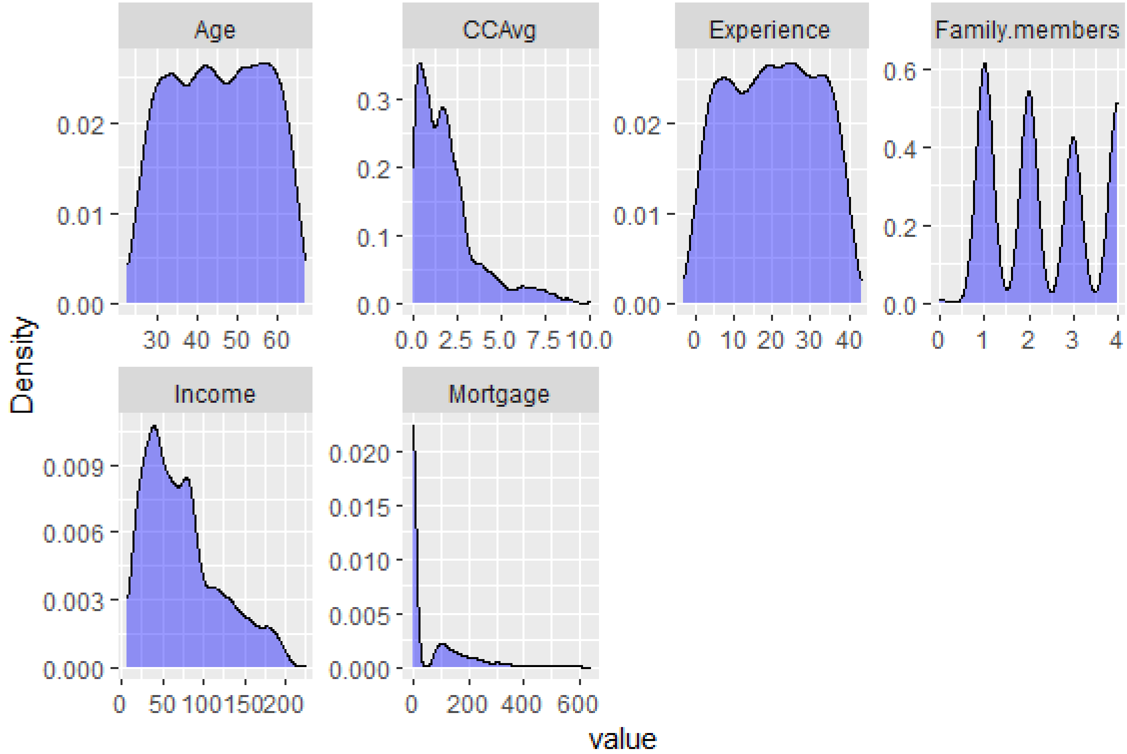
Histogram Distributions of Dataset

```
plot_histogram(bank)
```



Density Plot for all Numerical Variables

```
plot_density(bank,geom_density_args = list(fill="blue",alpha=0.4))
```



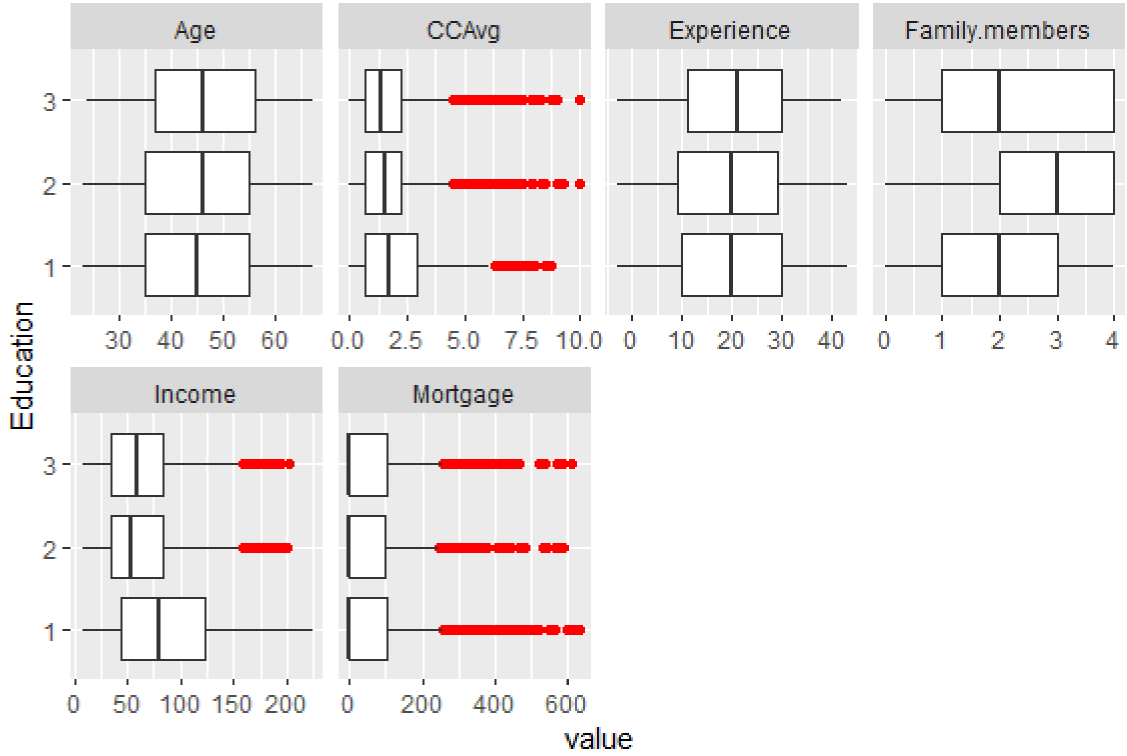
Box plots by Education Classes

Insight

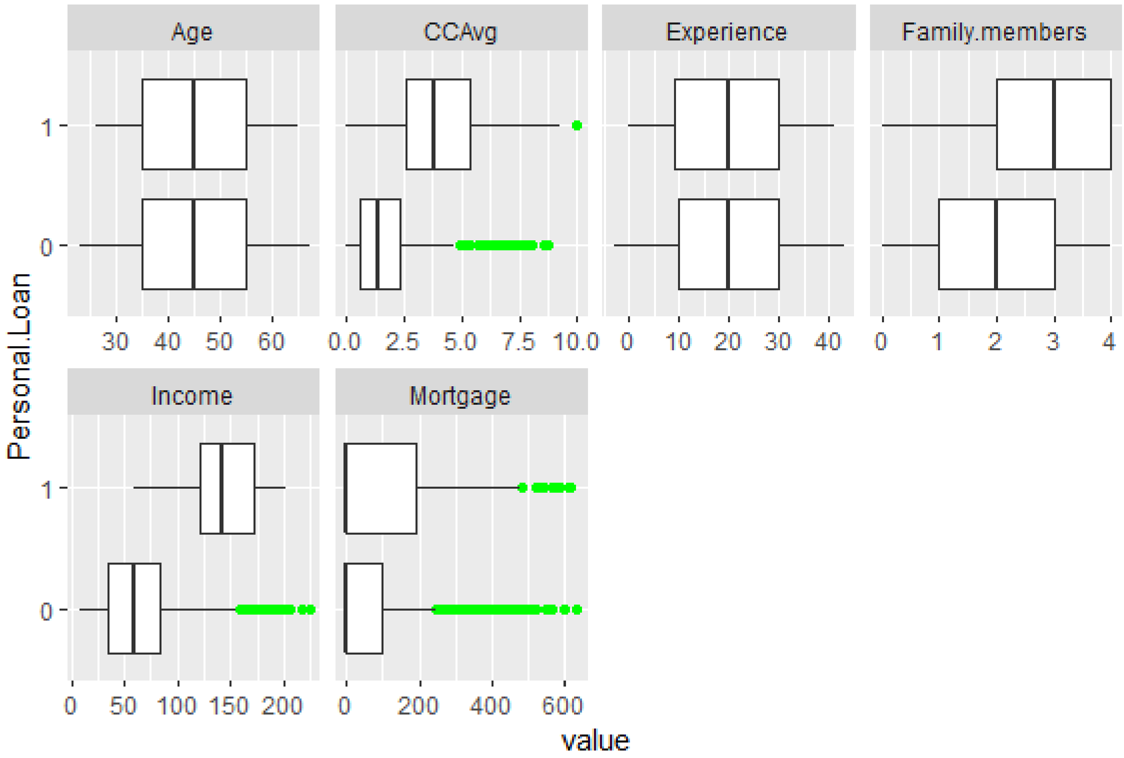
- Credit Card and Mortagage predictors have lots of outliers accross all three levels of Education
- Income has lots of outliers in Grad and Advanced professionals

```
➢ Plotting boxplot by factor of Education for all the numerical variab
  les##
➢ > plot_boxplot(bank, by="Education",
➢ +                geom_boxplot_args = list("outlier.color"="red"))
```

`



```
Plotting boxplot for Personal Loan (Response variable) for all numerical v
ariables##
> plot_boxplot(bank, by="Personal.Loan",geom_boxplot_args = list("outlier.
color"="green"))
```



Following plots give us a good insight about how two categories of Personal Loan predictor are stacked across various other predictors like

- Income vs Mortgage (scatter)
- Income (density)
- Mortgage (density)
- Age (density)
- Experience (density)
- Income vs Education (histogram)

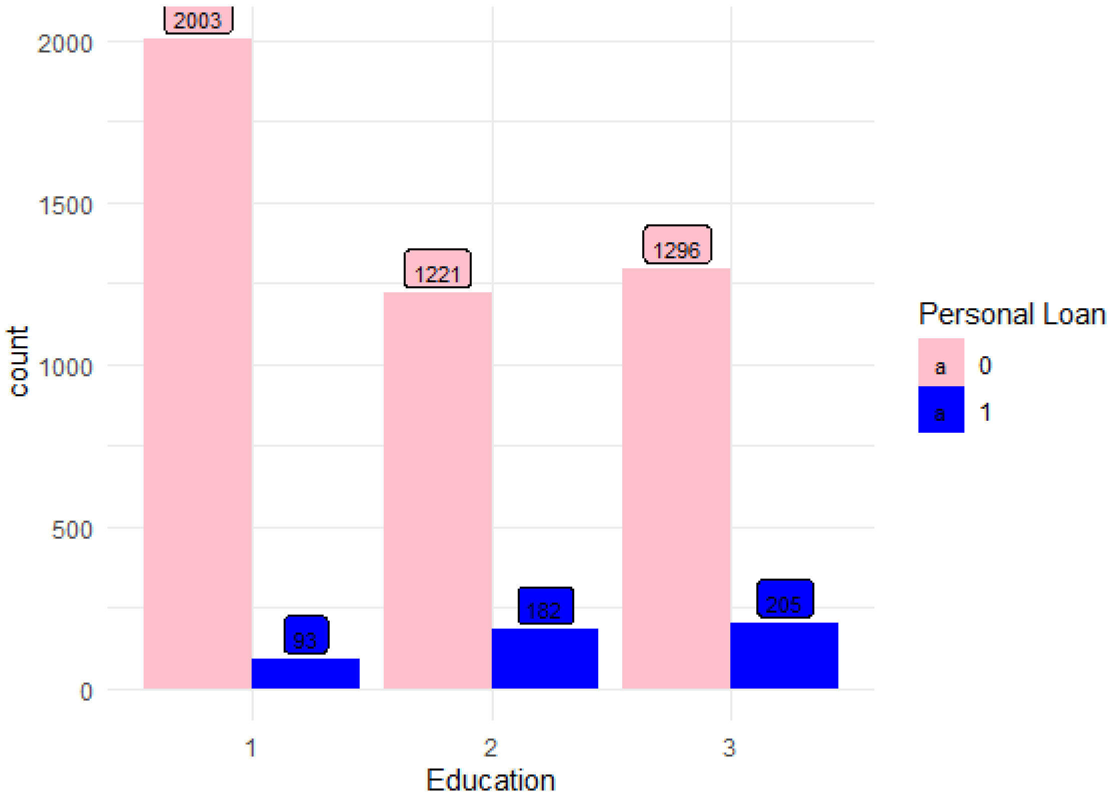
```
Plotting GGPlot for all variables##
> p1 = ggplot(bank, aes(Income, fill= Personal.Loan)) + geom_density(alpha
=0.4)
> p2 = ggplot(bank, aes(Mortgage, fill= Personal.Loan)) + geom_density(alp
ha=0.4)
> p3 = ggplot(bank, aes(Age, fill= Personal.Loan)) + geom_density(alpha=0.
4)
```

```
> p4 = ggplot(bank, aes(Experience, fill= Personal.Loan)) + geom_density(a
lpha=0.4)
> p5 = ggplot(bank, aes(Income, fill= Education)) + geom_histogram(alpha=0
.4, bins = 70)
> p6 = ggplot(bank, aes(Income, Mortgage, color = Personal.Loan)) +
+   geom_point(alpha = 0.7)
> grid.arrange(p1, p2, p3, p4, p5, p6, ncol = 2, nrow = 3)
```

Education

- ➢ Proportion of no-loan takers is very high across all three categories of Education - Undergrad, Grad, and Advanced Profn
- ➢ Data is almost skewed towards No-Personal Loans which makes good suspects and prospects depending on target category of bank
- ➢ There is good jump from 93(undergrads) to 205 (Advanced Profs)

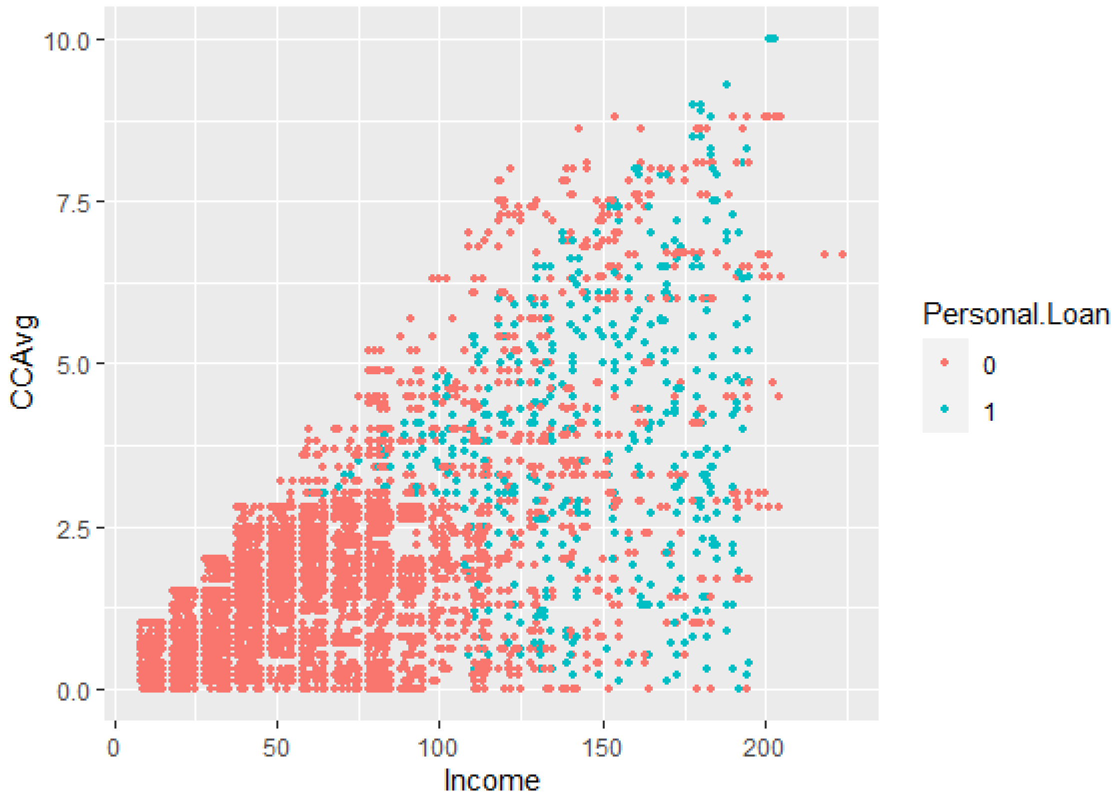
```
➢  GGplot Education##
➢  > ggplot(bank, aes(Education,fill= Personal.Loan)) +
➢  +   geom_bar(stat = "count", position = "dodge") +
➢  +   geom_label(stat = "count", aes(label= ..count..),
➢  +              size = 3, position = position_dodge(width = 0.9), vju
   st=-0.15)+
➢  +   scale_fill_manual("Personal Loan", values = c("0" = "pink", "1"
   = "blue"))+
➢  +   theme_minimal()
```



Credit Card is very good indicator of who we can target bothways

- Prospects who spend more may need to pay off their debt by taking Personal Loan
- Other category is who have good income but hesitate to spend can be offered loans on good conditions for their lifestyle and personal needs
- Virtually People having income in 1st quartile i.e. between 38 K to 90K have no Personal loans and moderate Credit Card spending (under 3000)
- People earning between 40K to 100K and having CC spend less than $ 2500 can become good prime targets keeping other predictors constant and we see a good chunk of them in graph

```
➢  GGPlot for Creditcard##
➢  > ggplot(bank, aes(Income,y = CCAvg, color = Personal.Loan)) +
➢  +   geom_point(size = 1)
```



Mortgage is another good indicator of who can be targeted.

- By offering good terms to people having zero Mortgage
- Others under considerate Mortgage like lets say 150K to settle their loans of high interest with low interest Personal Loans

```
GGplot for Mortgage##
> ggplot(bank, aes(Income,y = Mortgage, color = Personal.Loan)) +
+   geom_point(size = 1)
```

Clustering

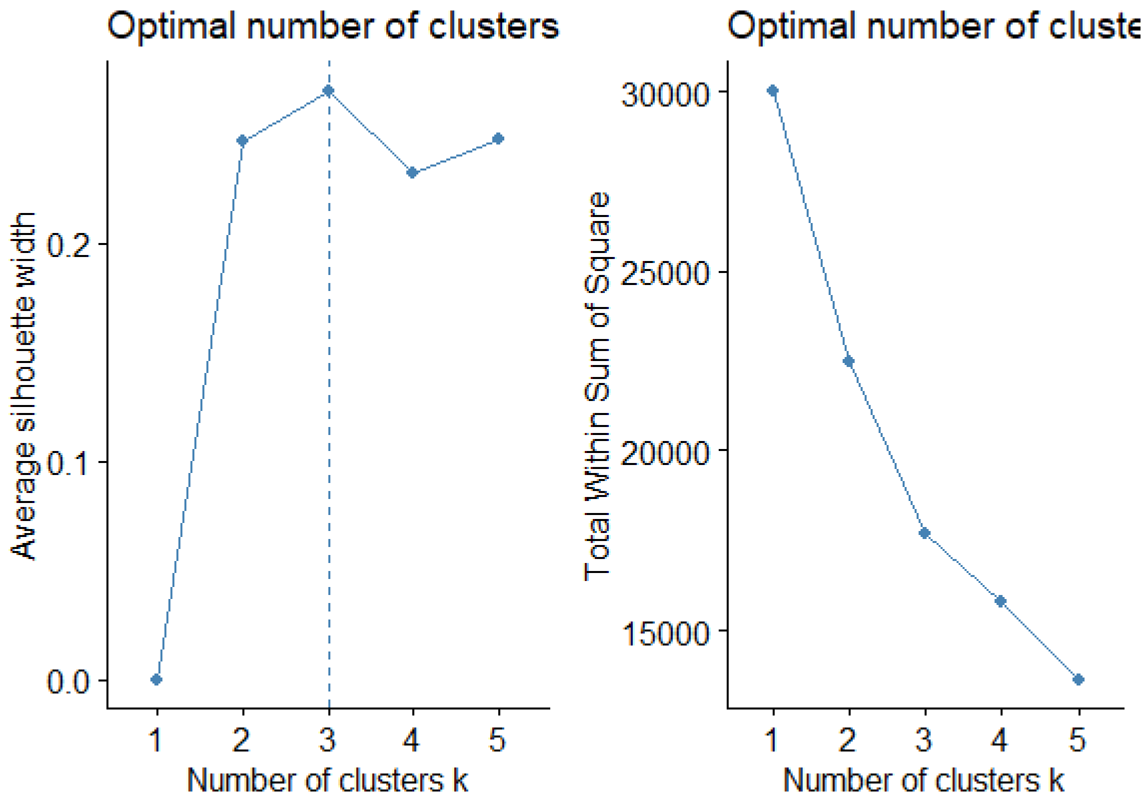
Primarily hierarchial and kmeans clustering are two best suited methods for unsupervised learning.

Since we have a very large dataset (5000 obs) we cannot use hierarchial method.Kmeans suits this type of data categorization

```
bank.clus = bank %>% select_if(is.numeric)
> bank.scaled = scale(bank.clus, center = TRUE)
> bank.dist = dist(bank.scaled, method = "euclidean")
```

Checking Optimal Number of clusters to categorize dataset

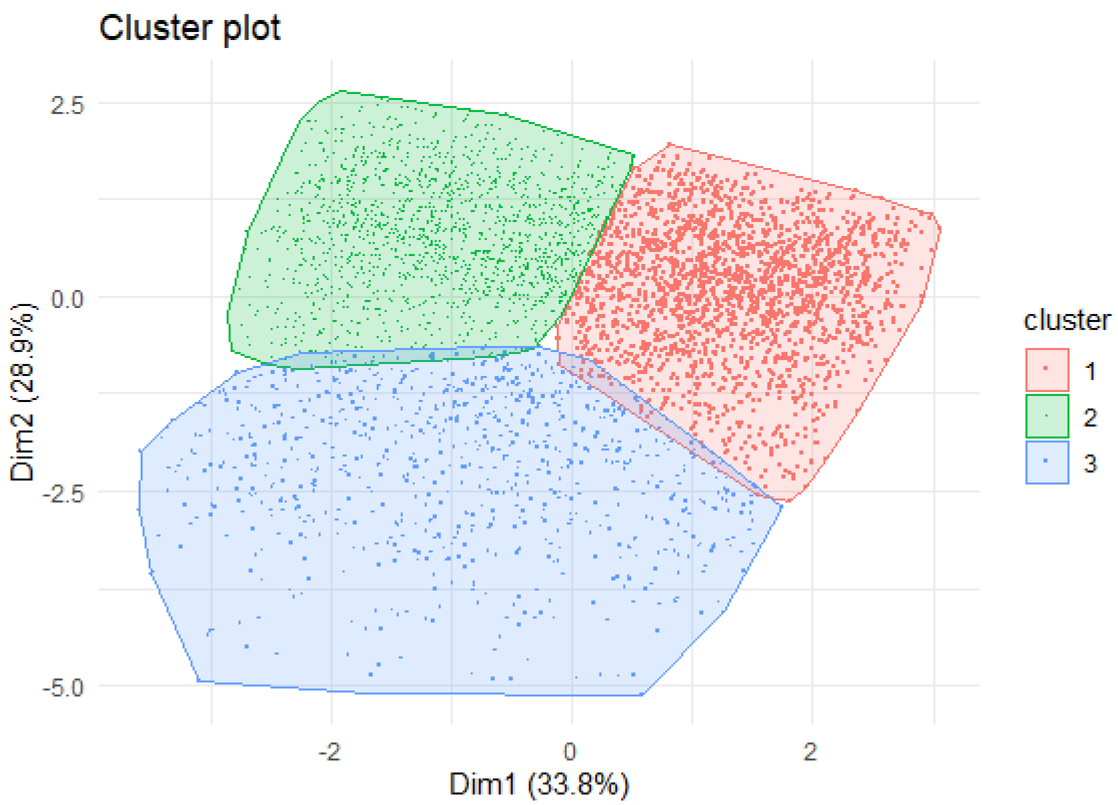
```
p12 = fviz_nbclust(bank.scaled, kmeans, method = "silhouette", k.max = 5)
> p21 = fviz_nbclust(bank.scaled, kmeans, method = "wss", k.max = 5)
> grid.arrange(p12, p21, ncol=2)
```



Running Kmeans with 3 centres and iterating it with nstart 10 times

```
set.seed(8787)
> bank.clusters = kmeans(bank.scaled, 3, nstart = 10)
```

```
fviz_cluster(bank.clusters, bank.scaled, geom = "point",
+              ellipse = TRUE, pointsize = 0.2, ) + theme_minimal()
```



Insights

- Silhouette and withing clusters sum of squares (wss) method, indicate we can divide our dataset into 3 clusters
- This intuitively conincides with Education levels (3) as a wild guess. It makes sense that banks prefer Educated people who have good earning potential or may have in future increasing financial needs to support their lifestyle and needs
- Kmeans divides the dataset into 3 clusters of size 2149, 2012, and 839

Splitting of Dataset into Train - Test set

```
set.seed(1233)
> bank.index=sample(1:nrow(bank),nrow(bank)*0.70)
> bank.train=bank[bank.index,]
> bank.test=bank[-bank.index,]
```

```
> dim(bank.test)
[1] 1500   12
```

```
dim(bank.train)
[1] 3500   12
```

Checking the Ration of Personal Loans in Each Partition

```
table(bank.train$Personal.Loan)

   0    1 
3151  349 
> table(bank.test$Personal.Loan)

   0    1 
1369  131 
```

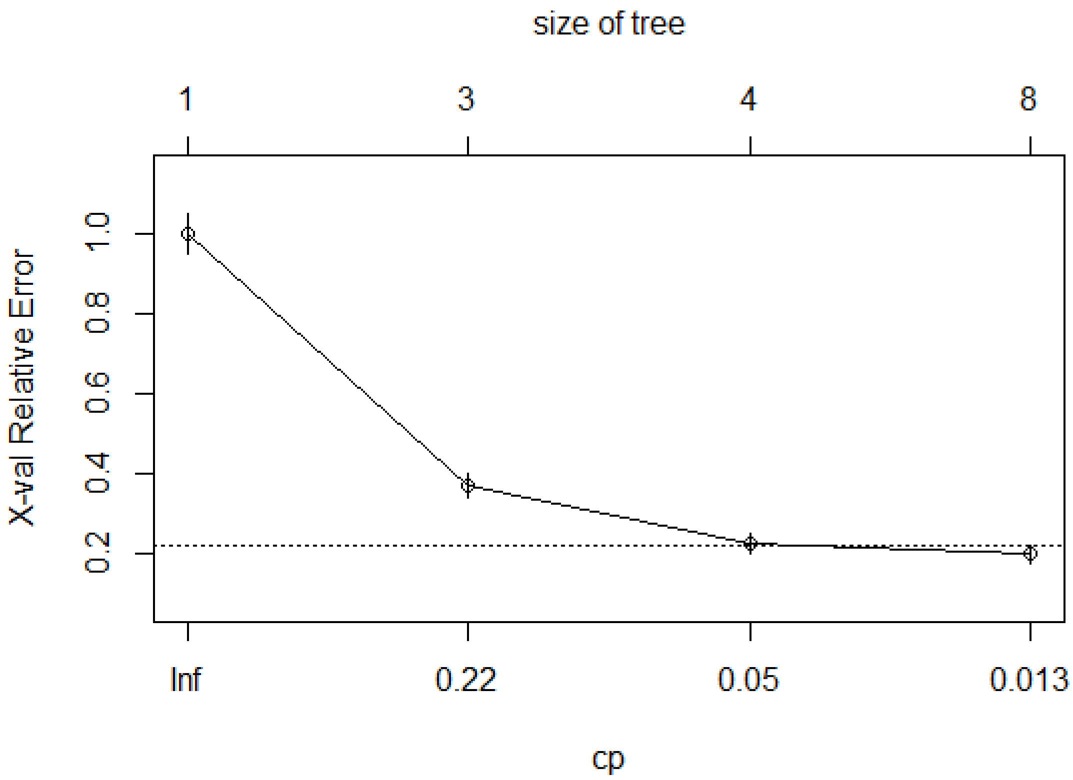
Split	Class 0 (no loan)	Class 1 (Loan)
bank train	3151	359
bank test	1369	131

<u>Cart Model</u>

Classification trees use recursive partitioning algorithms to learn and grow on data

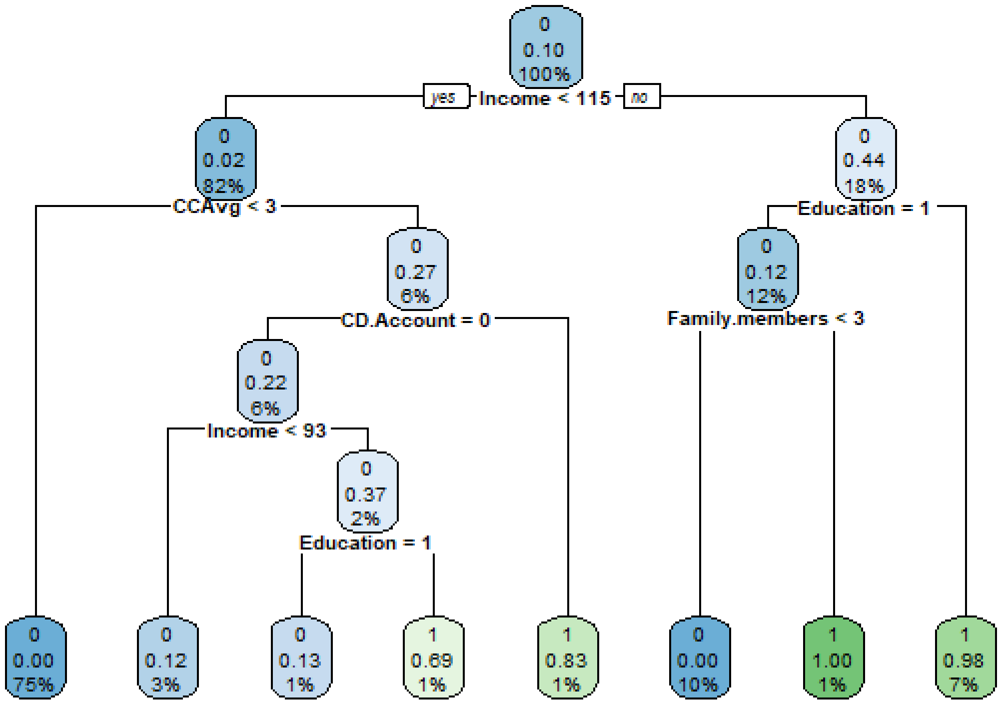
```
set.seed(233)
> cart.model.gini= rpart(Personal.Loan~., data=bank.train,method = "class"
,
+                          parms = list(split="gini"))
```

```
plotcp(cart.model.gini)
```



Plotting the Classification Tree

```
rpart.plot(cart.model.gini,cex = 0.6)
```



checking the cptable to gauge the best cross validated error and corresponding

complexity parameter

```
cart.model.gini$cptable
          CP nsplit rel error    xerror       xstd
1 0.32521490      0 1.0000000 1.0000000 0.05078991
2 0.14326648      2 0.3495702 0.3696275 0.03193852
3 0.01719198      3 0.2063037 0.2263610 0.02517855
4 0.01000000      7 0.1346705 0.1977077 0.02356543
```

Checking for the Variable importance for Splitting of Tree

```
cart.model.gini$variable.importance
     Education         Income Family.members          CCAvg      CD.Account
Mortgage      Experience
    232.137107     188.541598     142.501489     106.606257       56.904176
27.306276        3.445512
           Age         Online
      3.437672       1.751040
```

Insight

- Education, Income, Family Member, CC Avg and CD Account are important predictors on which data is split by tree algo
- Is clearly reflected in the built cart tree by the algorithm too
- First split happens on whether Income is less than or greater than $ 115K
- Complexity parameter almost lowers to 0.05 (graph) with relative 0.2 as cross validated error

Pruned Cart Tree

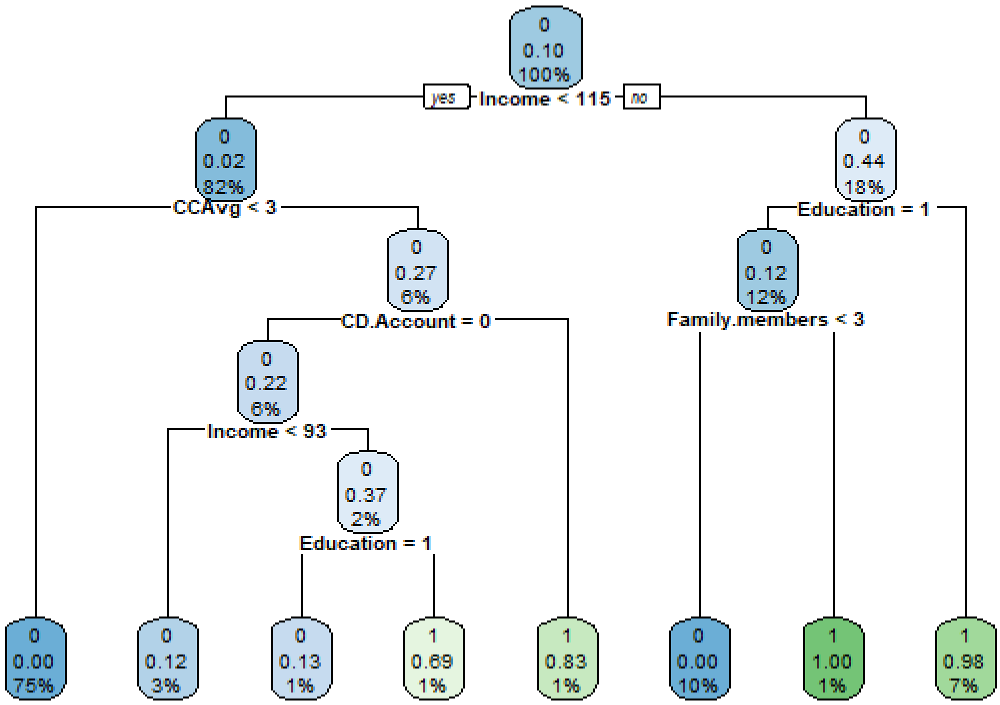
Tree can be pruned using the complexity parameter for controlling the overfitting

prunning the tree using the best complexity parameter

```
pruned.model=prune(cart.model.gini,cp=0.015)
```

Plotting the prunned Tree

```
rpart.plot(pruned.model,cex=0.65)
```



Cart Prediction

```
cart.pred=predict(pruned.model,bank.test,type="prob")
> cart.pred.prob.1=cart.pred[,1]
> head(cart.pred.prob.1,10)
         3          4          7          8         10         13 
17         18         19 
0.99734244 0.99734244 0.99734244 0.99734244 0.02109705 0.31428571 0.021097
05 0.99734244 0.02109705 
        22 
0.99734244
```

Since this is a loan prediction and we want to be more careful to weed out possible defaulters rather then deny the disbursal to dserving prospects We will set the threshold for probability as high as 0.70

All the predicted probabilities >=0.7 will be considered as class "1" and rest class "0"

Using the Confusion Matrix to gauge the performance of Models

Setting the threshold for probabilities to be considered as 1

```
threshold = 0.70
> bank.test$Loanprediction = ifelse(cart.pred.prob.1 >= threshold, 1, 0)
> bank.test$Loanprediction = as.factor(bank.test$Loanprediction)
> Cart.Confusion.Matrix =confusionMatrix(bank.test$Loanprediction,
+                                         reference = bank.test$Personal.Lo
an, positive = "1")
> Cart.Confusion.Matrix
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0    8  121
         1 1361   10
                                          
               Accuracy : 0.012           
                 95% CI : (0.0071, 0.0189)
    No Information Rate : 0.9127          
    P-Value [Acc > NIR] : 1               
                                          
                  Kappa : -0.1738         
                                          
 Mcnemar's Test P-Value : <2e-16          
                                          
            Sensitivity : 0.076336        
            Specificity : 0.005844        
         Pos Pred Value : 0.007294        
         Neg Pred Value : 0.062016        
             Prevalence : 0.087333        
         Detection Rate : 0.006667        
   Detection Prevalence : 0.914000        
      Balanced Accuracy : 0.041090        
                                          
       'Positive' Class : 1
```

We can see that even Pruned CART tree has very low accuracy of just 1.67 % even after tuning its complexity parameter

Random Forest Model

Random forest is an ensemble method used by combining weak and strong learners to give a better accuracy or output. Its a combination of multiple trees each chosen randomly to grow on dataset Uses averaging in the sense that weak and strong learners combined produce better results rather than a single CART tree.

Two packages have been used to model the training dataset:

- Random Forest
- Ranger (better than random forest)

Modelling using Random Forest package

```
set.seed(1233)
> RandomForest.model = randomForest(Personal.Loan~., data = bank.train)
> print(RandomForest.model)

Call:
 randomForest(formula = Personal.Loan ~ ., data = bank.train)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 3

        OOB estimate of  error rate: 1.31%
Confusion matrix:
     0   1 class.error
0 3147   4 0.001269438
1   42 307 0.120343840
```

Print the Error Rate

```
err=RandomForest.model$err.rate
> head(err)
            OOB          0         1
[1,] 0.04441041 0.02815700 0.1865672
[2,] 0.03998119 0.02405858 0.1822430
[3,] 0.03709369 0.01994907 0.1930502
[4,] 0.03410641 0.01472810 0.2147887
[5,] 0.03294946 0.01560837 0.1921824
[6,] 0.02968176 0.01190476 0.1890244
```

Out of Bag Error

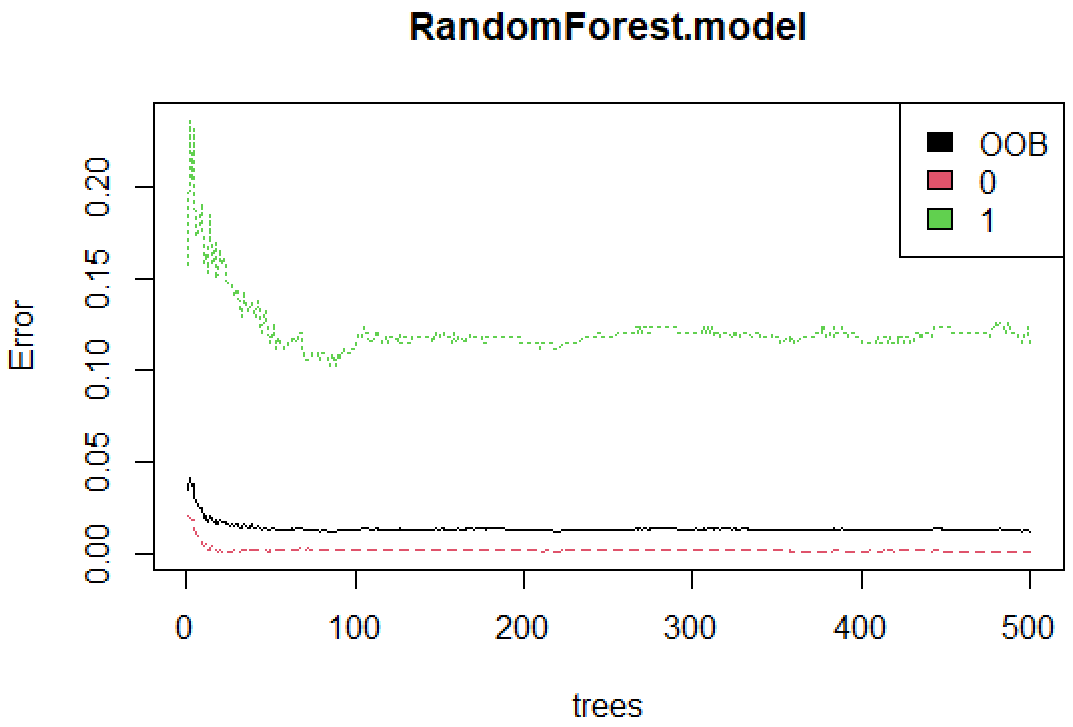
```
oob_err=err[nrow(err),"OOB"]
> print(oob_err)
       OOB
0.01314286
```

Following plot depicts the Out of Bag error for Class 0 and Class 1 and Overall OOB error. Also suggests the optimal trees we can use to tune Random forest model.

Somewhere 250 - 350 trees should suffice as it saves time to train less trees and achieve same or even better results depending on cases.

Plot the OBB Error

```
plot(RandomForest.model)
> legend(x="topright",legend = colnames(err),fill=1:ncol(err))
```



Prediction for Random Forest Package

```
ranfost.pred = predict(RandomForest.model, bank.test, type = "prob")[,1]
> bank.test$RFpred = ifelse(ranfost.pred>=0.8,"1","0")
> bank.test$RFpred = as.factor(bank.test$RFpred)
> levels(bank.test$RFpred)
[1] "0" "1"
```

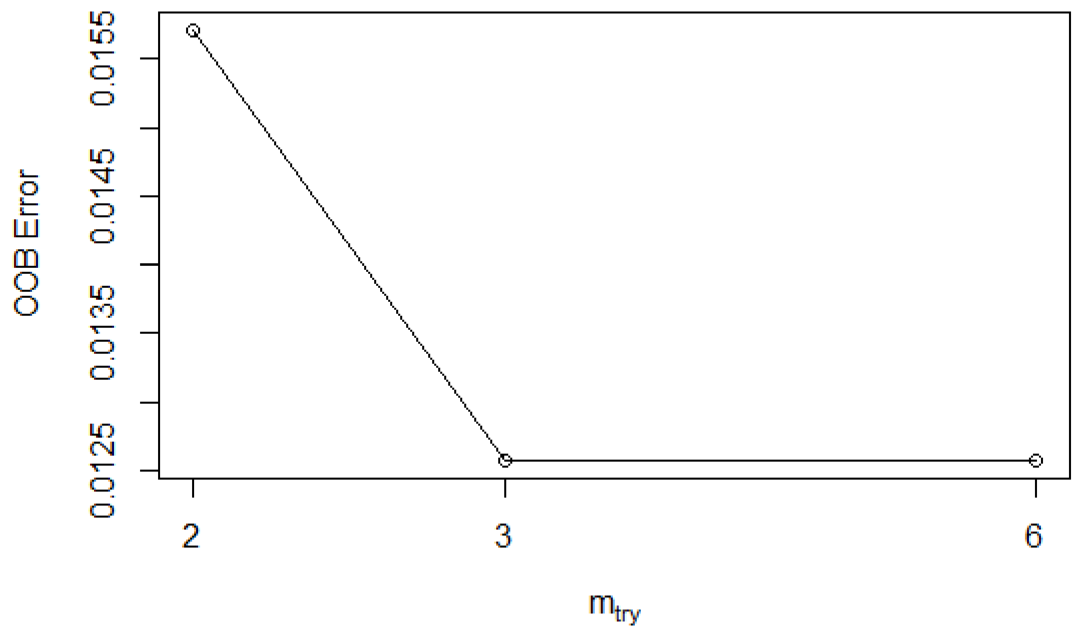
```
RFConf.Matx = confusionMatrix(bank.test$RFpred, bank.test$Personal.Loan, p
ositive = "1")
> RFConf.Matx
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0   21  125
         1 1348    6

               Accuracy : 0.018
                 95% CI : (0.0119, 0.0261)
    No Information Rate : 0.9127
    P-Value [Acc > NIR] : 1

                  Kappa : -0.1798

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.045802
            Specificity : 0.015340
         Pos Pred Value : 0.004431
         Neg Pred Value : 0.143836
             Prevalence : 0.087333
         Detection Rate : 0.004000
   Detection Prevalence : 0.902667
      Balanced Accuracy : 0.030571

       'Positive' Class : 1
```

```
table(bank.test$Personal.Loan)

   0    1
1369  131
```

Tuning the Random Forest algo

Using the tuneRF function to random forest algorithm to get some idea about improving the performance

```
set.seed(333)
> tuned.RandFors = tuneRF(x = subset(bank.train, select = -Personal.Loan),
+                           y= bank.train$Personal.Loan,
+                           ntreeTry = 501, doBest = T)
mtry = 3  OOB error = 1.31%
Searching left ...
mtry = 2        OOB error = 1.54%
-0.173913 0.05
Searching right ...
mtry = 6        OOB error = 1.09%
0.173913 0.05
mtry = 11       OOB error = 1.4%
-0.2894737 0.05
```




```
print(tuned.RandFors)

Call:
 randomForest(x = x, y = y, mtry = res[which.min(res[, 2]), 1])
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 6

        OOB estimate of  error rate: 1.17%
Confusion matrix:
     0   1 class.error
0 3143   8 0.002538877
1   33 316 0.094555874
```

Modelling using ranger package

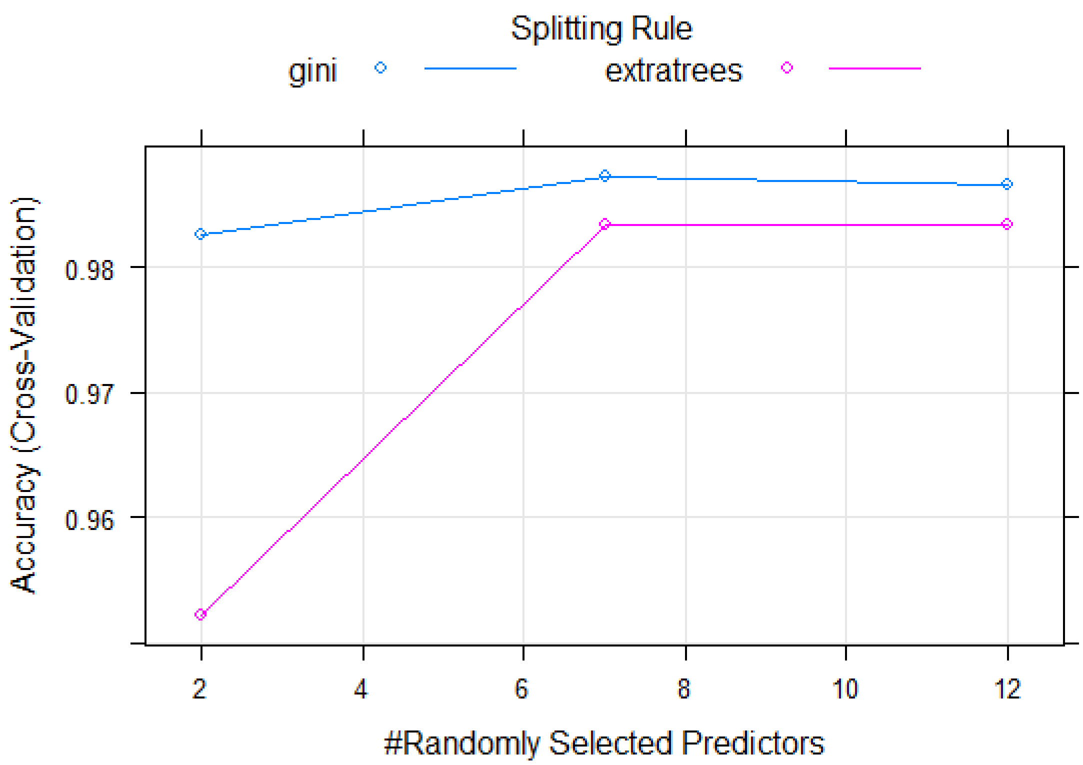
Ranger package has been built atop randomforest package and has got better performance then rf models as it has less parameters to tune on.

Mostly we need to bother about mtry only which is the number of variables we will use to build various trees. This takes care of other parameters like minimum number of splits , nodes etc.

Since this is classification problem it automatically chooses best method to for split rules and uses minimum node size as 1.

```
set.seed(999)
> RG.model = train(Personal.Loan~., data = bank.train, tuneLength = 3,
+                  method = "ranger",
+                  trControl= trainControl(method = 'cv',
+                                          number = 5,
+                                          verboseIter = FALSE))
> RG.model
Random Forest

3500 samples
  11 predictor
   2 classes: '0', '1'

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 2800, 2799, 2801, 2800, 2800
Resampling results across tuning parameters:

  mtry  splitrule   Accuracy   Kappa
   2    gini        0.9825698  0.8951556
   2    extratrees  0.9522865  0.6607763
   7    gini        0.9871428  0.9261065
   7    extratrees  0.9834277  0.9031313
  12    gini        0.9865702  0.9227363
  12    extratrees  0.9834261  0.9035594

Tuning parameter 'min.node.size' was held constant at a value of 1
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were mtry = 7, splitrule = gini and mi
n.node.size = 1.
```

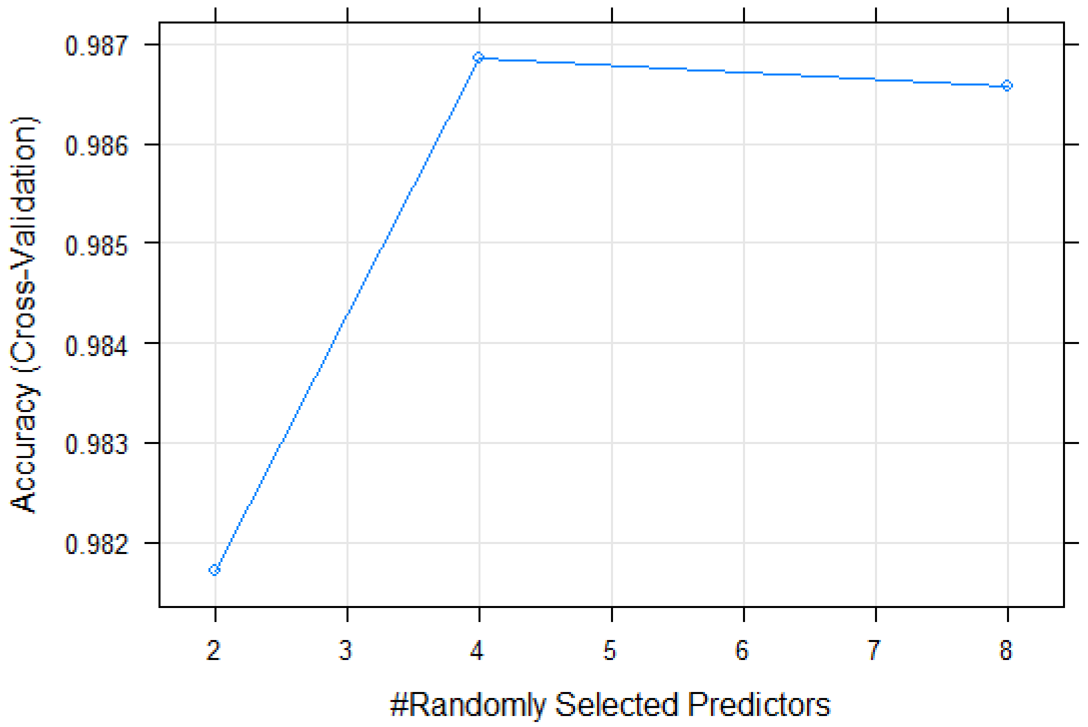
```
plot(RG.model)
```



Tuning Ranger Grid

```
tuneGrid = data.frame(.mtry = c(2,4,8), .splitrule = "gini", .min.node.siz
e=1)
> set.seed(22222)
> RFgrid.model = train(Personal.Loan~., data = bank.train, tuneGrid = tune
Grid,
+                       method = "ranger",
+                       trControl= trainControl(method = 'cv',
+                                               number = 5, verboseIter = F
ALSE))
> RFgrid.model
Random Forest

3500 samples
  11 predictor
   2 classes: '0', '1'

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 2800, 2800, 2799, 2801, 2800
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
  2     0.9817139  0.8899808
  4     0.9868563  0.9239223
  8     0.9865718  0.9220990

Tuning parameter 'splitrule' was held constant at a value of gini
Tuning parameter 'min.node.size' was
 held constant at a value of 1
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were mtry = 4, splitrule = gini and mi
n.node.size = 1.
```

```
plot(RFgrid.model)
```



Refined ranger Model

After the grid tunining we settle the number of trees to 511 and mtry = 4

```
set.seed(101)
> Range.model = ranger(Personal.Loan~., data = bank.train, num.trees = 511
,
+                       mtry = 4, min.node.size = 1, verbose = FALSE)
> Range.model
Ranger result

Call:
 ranger(Personal.Loan ~ ., data = bank.train, num.trees = 511,      mtry = 
4, min.node.size = 1, verbose = FALSE)

Type:                             Classification
Number of trees:                  511
Sample size:                      3500
Number of independent variables:  11
Mtry:                             4
Target node size:                 1
Variable importance mode:         none
Splitrule:                        gini
OOB prediction error:             1.31 %
```

Prediction of RangeR package

Using ranger package and its grid model approach of cross validation we observe that its able to predict 120 cases of class 1 (Loan) correctly out of available 131 cases.

This quantum jump from all previous models

```
range.pred = predict(Range.model, bank.test)
> table(bank.test$Personal.Loan, range.pred$predictions)

       0    1
  0 1363    6
  1   11  120
```

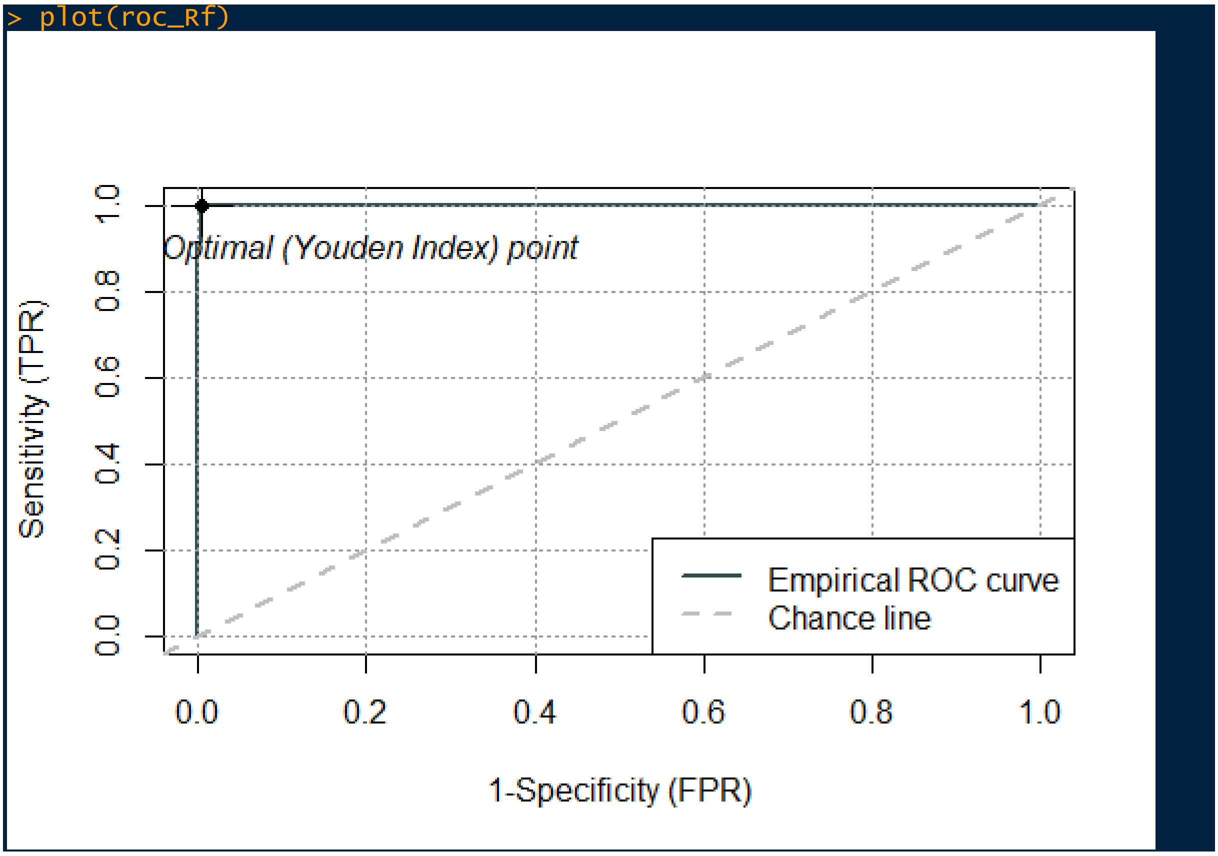
Confusion Matrix of RangeR Package

```
Range.ConMatx = confusionMatrix(range.pred$predictions,
+                                  bank.test$Personal.Loan, positive = "1")
> Range.ConMatx
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 1363   11
         1    6  120

               Accuracy : 0.9887
                 95% CI : (0.9819, 0.9934)
    No Information Rate : 0.9127
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.9277

 Mcnemar's Test P-Value : 0.332

            Sensitivity : 0.91603
            Specificity : 0.99562
         Pos Pred Value : 0.95238
         Neg Pred Value : 0.99199
             Prevalence : 0.08733
         Detection Rate : 0.08000
   Detection Prevalence : 0.08400
      Balanced Accuracy : 0.95582

       'Positive' Class : 1
```

Plotting of ROC Curve

Plotting of ROC curve is another way of checking the Classification Model's performance. It is curve between Sensitivity (True Positive Rate) and 1 - Specifivity (False Positive Rate)

```
Prediction.Labels = as.numeric(range.pred$predictions)
> Actual.Labels = as.numeric(bank.test$Personal.Loan)
> roc_Rf = rocit(score = Prediction.Labels, class = Actual.Labels)
```



Conclusion

Various types of models were attempted Some raw, some refined and tuned to display their dissimilarity in approaching the same dataset under mostly similar conditions.

If given a choice between low OOB (out of bag) error and Accuracy. I will go with accuracy as this case demands so.

As financial institution we want to be more than 100% sure that there should be no tolerance for defaults and we are able to earn from interest income

Model Name	OOB errors %	Accuracy %
CART	0.21	1.67
Random Forest	1.2	1.8
Tuned Random Forest	1.17	90.3
Ranger Random Forest	1.31	98.8

So by this we can conclude that under any Circumstances ranger (Random Forest) performs the best on dataset with accuracy of 98%.

THANK YOU