MINI PROJECT
- Bank Personal Loan

Model Report

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Project Overview

Machine learning is the scientific study of algorithms and statistical models that computer systems use in order to perform a specific task effectively without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. Machine learning algorithms are used in a wide variety of applications, such as email filtering, and computer vision, where it is infeasible to develop an algorithm of specific instructions for performing the task. Machine learning is closely related to computational statistics, which focuses on making predictions using computers. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a field of study within machine learning, and focuses on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

The analysis is carried out in the R environment for statistical computing and visualisation, which is an open-source dialect of the S statistical computing language. It is free, runs on most computing platforms, and contains contributions

The objective of the Project is to target the market of Personal Loans for the Bank by the given data.

Project Approach

- **Data Exploration**
- **Understanding the Attribute**
- **Data Visualisation**
- **Data Partition**
- **Cart – Model building**
- **Cart – training data Model Performance**
- **Cart – Holdout**

- **Data Exploration**

  - Set working directory

  - #setwd("F:/r data machine learning")

#getwd()

>"F:/r data machine learning"

  - Read Input File

➢ mydata=read.csv("Bank Personal Loan Dataset.csv", header = T)

  - Names of the columns

>names(mydata)

```
"ID"                "Age..in.years."
 "Experience..in.years." "Income..in.K.month."
 "ZIP.Code"             "Family.members"
 "CCAvg"                "Education"
  "Mortgage"             "Personal.Loan"
 "Securities.Account"    "CD.Account"
 "Online"               "CreditCard"
```

*Hence, the column name 'ID' is just the column number, and do not have any use and explanatory power . So, we can drop it .

#mydata=mydata[,2:13]

```
          "Age..in.years."       "Experience..in.years."
      "Income..in.K.month."   "ZIP.Code"
       "Family.members"       "CCAvg"
         "Education"           "Mortgage"
       "Personal.Loan"        "Securities.Account"
         "CD.Account"           "Online"
          "CreditCard"
```

#Head(mydata)

>

Age in years.	Experience in years.	Income..in.K.month.	ZIP.Code
25	1	49	91107
45	19	34	90089
39	15	11	94720
35	9	100	94112
35	8	45	91330
37	13	29	92121

Family members	CCAvg	Education	Mortgage	Personal.Loan
4	1.6	1	0	0
3	1.5	1	0	0
1	1.0	1	0	0
1	2.7	2	0	0
4	1.0	2	0	0
4	0.4	2	155	0

Securities	Account	CD Account	Online	CreditCard
1	1	0	0	0
2	1	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	1
6	0	0	1	0

- Dimension of data

```
# dim(mydata)
   5000   13
```

- Structure of data

str(mydata)

```
'data.frame':5000 obs. of  13 variables:
 $ 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.month.  : int  49 34 11 100 45 29 72 22 81 180 ...
 $ ZIP.Code             : int  91107 90089 94720 94112 91330 92121 91711 93943 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 of data

#Summary(mydata)

Age in years	Experience in years	Income in K.month.
Min. :23.00	Min. :-3.0	Min. : 8.00
1st Qu.:35.00	1st Qu.:10.0	1st Qu.: 39.00
Median :45.00	Median :20.0	Median : 64.00
Mean :45.34	Mean :20.1	Mean : 73.77
3rd Qu.:55.00	3rd Qu.:30.0	3rd Qu.: 98.00
Max. :67.00	Max. :43.0	Max. :224.00

ZIP.Code	Family.members	CCAvg	Education
Min. : 9307	Min. :1.000	Min. : 0.000	Min. :1.000
1st Qu.:91911	1st Qu.:1.000	1st Qu.: 0.700	1st Qu.:1.000
Median :93437	Median :2.000	Median : 1.500	Median :2.000
Mean :93153	Mean :2.397	Mean : 1.938	Mean :1.881
3rd Qu.:94608	3rd Qu.:3.000	3rd Qu.: 2.500	3rd Qu.:3.000
Max. :96651	Max. :4.000	Max. :10.000	Max. :3.000

Mortgage	Personal.Loan	Securities.Account	CD.Account
Min. : 0.0	Min. :0.000	Min. :0.0000	Min. :0.0000
1st Qu.: 0.0	1st Qu.:0.000	1st Qu.:0.0000	1st Qu.:0.0000
Median : 0.0	Median :0.000	Median :0.0000	Median :0.0000
Mean : 56.5	Mean :0.096	Mean :0.1044	Mean :0.0604
3rd Qu.:101.0	3rd Qu.:0.000	3rd Qu.:0.0000	3rd Qu.:0.0000

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

- Understanding the Attribute

The binary category have five variables as below:

- Personal Loan - Did this customer accept the personal loan offered in the last campaign? **This is our target variable**
- Securities Account - Does the customer have a securities account with the bank?
- CD Account - Does the customer have a certificate of deposit (CD) account with the bank?
- Online - Does the customer use internet banking facilities?
- Credit Card - Does the customer use a credit card issued by UniversalBank?

Interval variables are as below:

- Age - Age of the customer
- Experience - Years of experience
- Income - Annual income in dollars
- CCAvg - Average credit card spending
- Mortage - Value of House Mortgage

Ordinal Categorical Variables are:

- Family - Family size of the customer
- Education - education level of the customer

The nominal variable is :

- ID
- Zip Code

- **Target variable : Personal Loan**

- Table(Personal.loan)

Personal loan

```
0    1
4520  480
```

Prop.table(table(Personal.loan))

```
    0     1
0.904 0.096
```

Key observations:

Number of Rows and Columns:

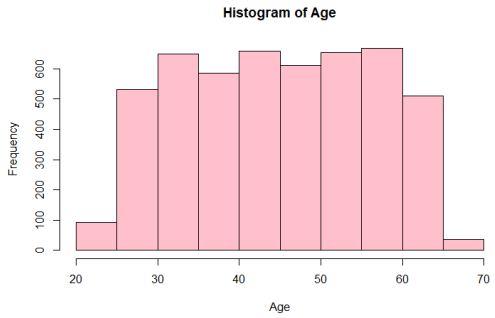
> The number of rows in the dataset is 5,000
> The number of columns (Features) in the dataset is 14

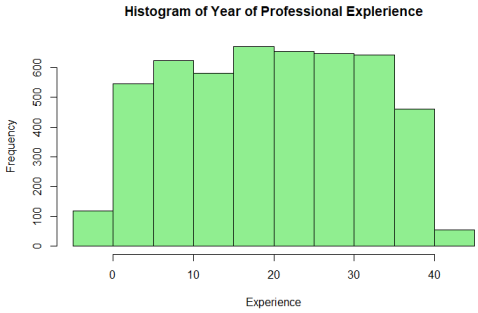
Proportion of Responders Vs Non Responders:

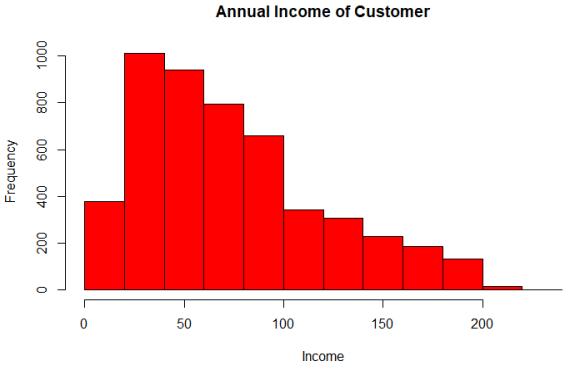
> Customers with Personal Loans: 480 (9.6%)
> Total Non-Responder Records: 4520 (90.4%)

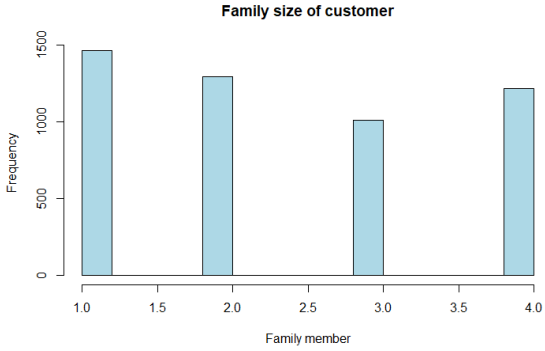
- **Data Visulaisation**

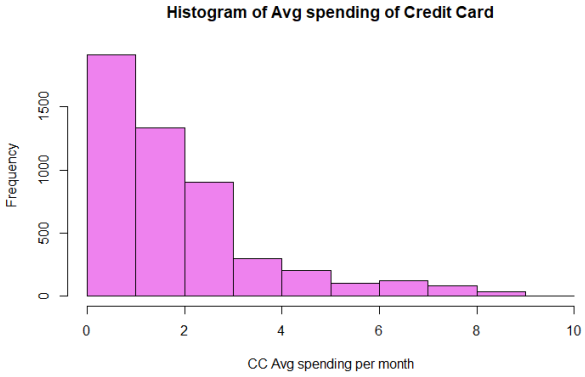
- **Histogram of All Variable**

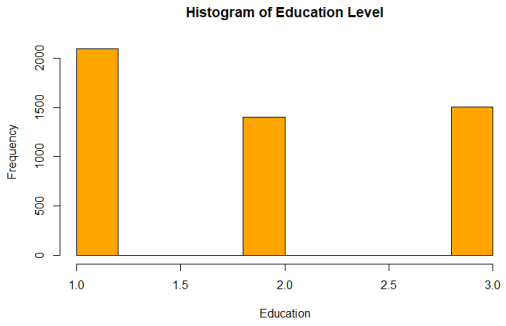

Histogram of Age
Frequency
0
100
200
300
400
500
600
20
30
40
50
60
70
Age

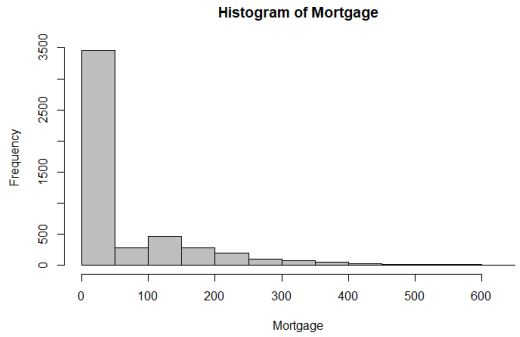

Histogram of Year of Professional Experience
Frequency
0
100
200
300
400
500
600
0
10
20
30
40
Experience

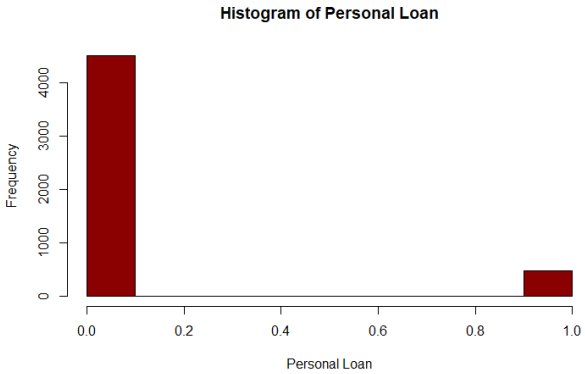

Annual Income of Customer
Frequency
0
200
400
600
800
1000
0
50
100
150
200
Income

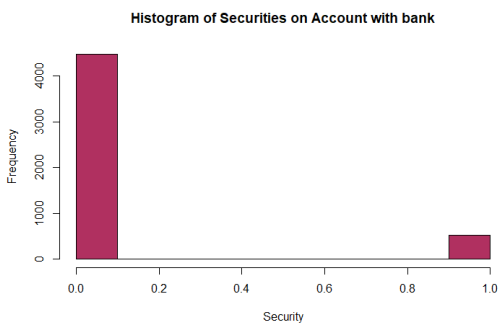

Family size of customer
Frequency
0
500
1000
1500
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Family member

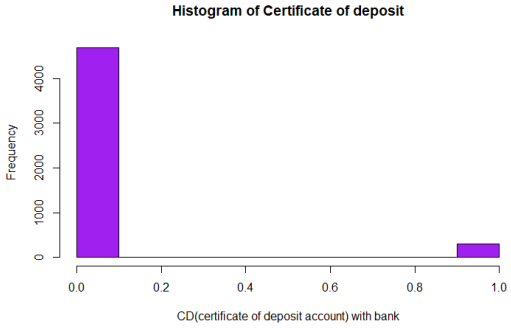

Histogram of Avg spending of Credit Card
Frequency
0
500
1000
1500
0
2
4
6
8
10
CC Avg spending per month

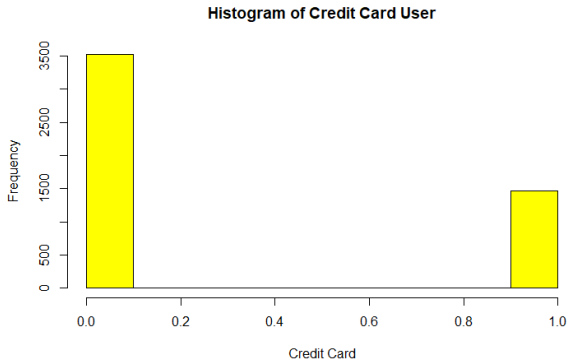

Histogram of Education Level
Frequency
0
500
1000
1500
2000
1.0
1.5
2.0
2.5
3.0
Education


Histogram of Mortgage
Frequency
0
500
1500
2500
3500
0
100
200
300
400
500
600
Mortgage

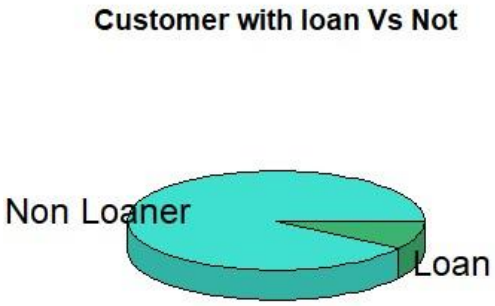

Histogram of Personal Loan
Frequency
0
1000
2000
3000
4000
0.0
0.2
0.4
0.6
0.8
1.0
Personal Loan

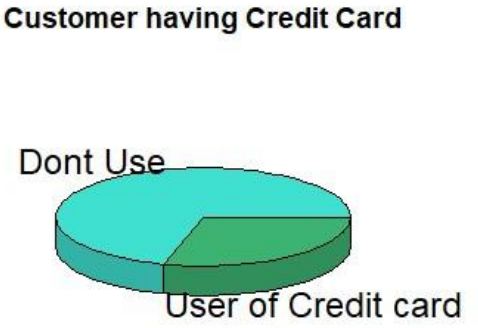

Histogram of Securities on Account with bank
Frequency
0
1000
2000
3000
4000
0.0
0.2
0.4
0.6
0.8
1.0
Security

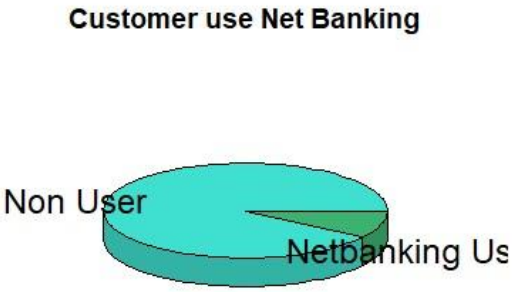

Histogram of Certificate of deposit
Frequency
0
1000
2000
3000
4000
0.0
0.2
0.4
0.6
0.8
1.0
CD(certificate of deposit account) with bank

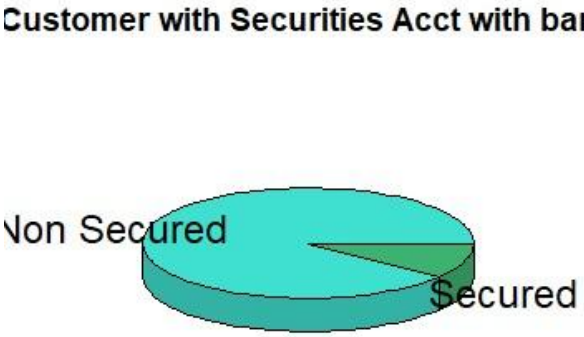

Histogram of Credit Card User
Frequency
0
500
1500
2500
3500
0.0
0.2
0.4
0.6
0.8
1.0
Credit Card

- Pie chart of binary Attributes









- Data Partition

 # Splitting data in Train and Test dataset

```
indexes=sample(1:nrow(mydata), size = 0.3*nrow(mydata))
mytest= mydata[indexes,]
dim(test)
mytrain=mydata[-indexes,]
dim(mydata)
```

Hence, After Splitting the data

- Dim(mytest)

```
1500  14
```

- Dim(mytrain)

```
3500  14
```

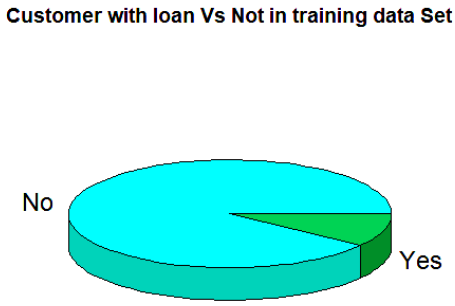
#Check if the partition is correct

```
-table(mytrain$Personal.Loan)

   0    1
3146  354

- table(mytest$Personal.Loan)

   0    1
1374  126

-prop.table((table(mytrain$Personal.Loan)))

        0         1
0.8988571 0.1011429

-prop.table((table(mytest$Personal.Loan)))

0     1
0.916 0.084
```

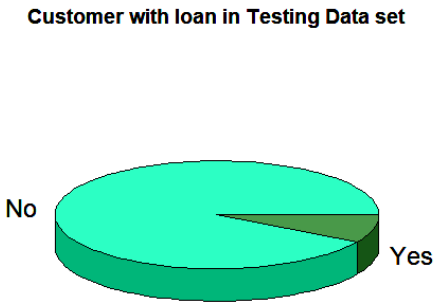
Pie chart after Data Partition

- Comparison on Customers having Personal Loan or Not

Training data set



Testing data set



Model Building - Cart

The CART algorithm is structured as a sequence of questions, the answers to which determine what the next question, if any should be. The result of these questions is a tree like structure where the ends are terminal nodes at which point there are no more questions.

 # Setting the control parameter

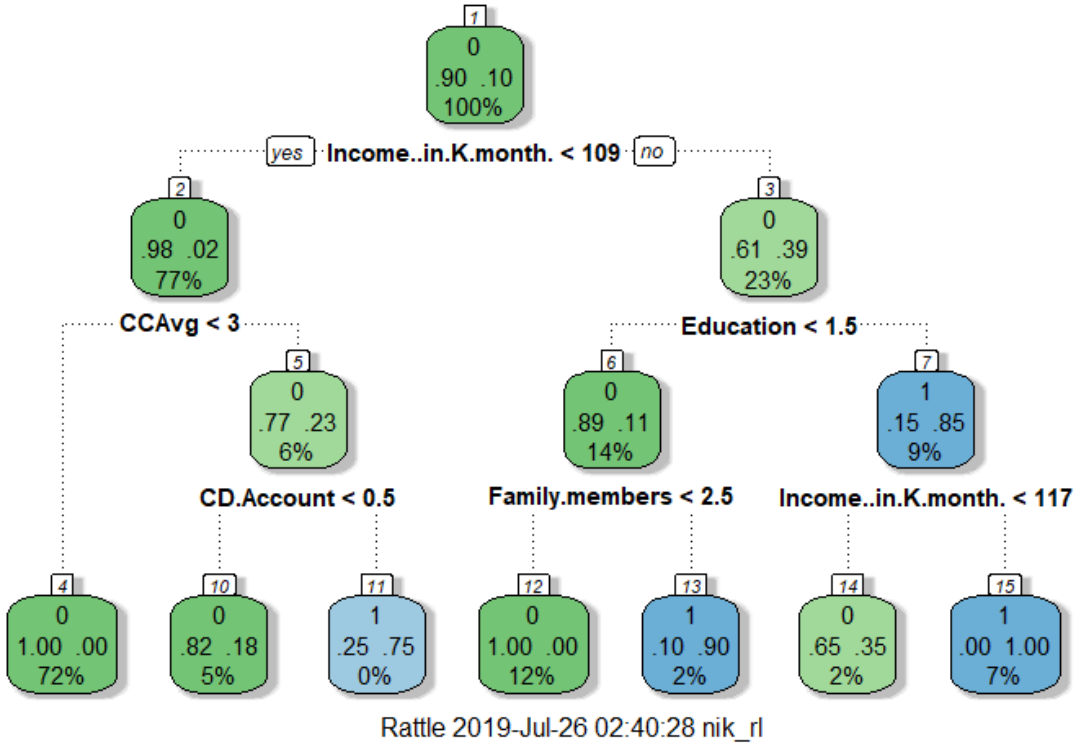
```
r.ctrl = rpart.control(minsplit=100, minbucket = 10, cp = 0, xval = 10)
```

#Creating the Rpart and model1

-M1

```
n= 3500

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 3500 354 0 (0.89885714 0.10114286)
   2) Income..in.K.month.< 108.5 2705  45 0 (0.98336414 0.01663586)
     4) CCAvg< 2.95 2509   0 0 (1.00000000 0.00000000) *
     5) CCAvg>=2.95 196  45 0 (0.77040816 0.22959184)
      10) CD.Account< 0.5 180  33 0 (0.81666667 0.18333333) *
      11) CD.Account>=0.5 16   4 1 (0.25000000 0.75000000) *
   3) Income..in.K.month.>=108.5 795 309 0 (0.61132075 0.38867925)
     6) Education< 1.5 496  54 0 (0.89112903 0.10887097)
      12) Family.members< 2.5 436   0 0 (1.00000000 0.00000000) *
      13) Family.members>=2.5 60   6 1 (0.10000000 0.90000000) *
     7) Education>=1.5 299  44 1 (0.14715719 0.85284281)
      14) Income..in.K.month.< 116.5 68  24 0 (0.64705882 0.35294118) *
      15) Income..in.K.month.>=116.5 231   0 1 (0.00000000 1.00000000)
```

➢ Fancy Rpartplot



➢ Printcp

Classification tree:
rpart(formula = Personal.Loan ~ ., data = mytrain[, -1], method = "class",
control = r.ctrl)

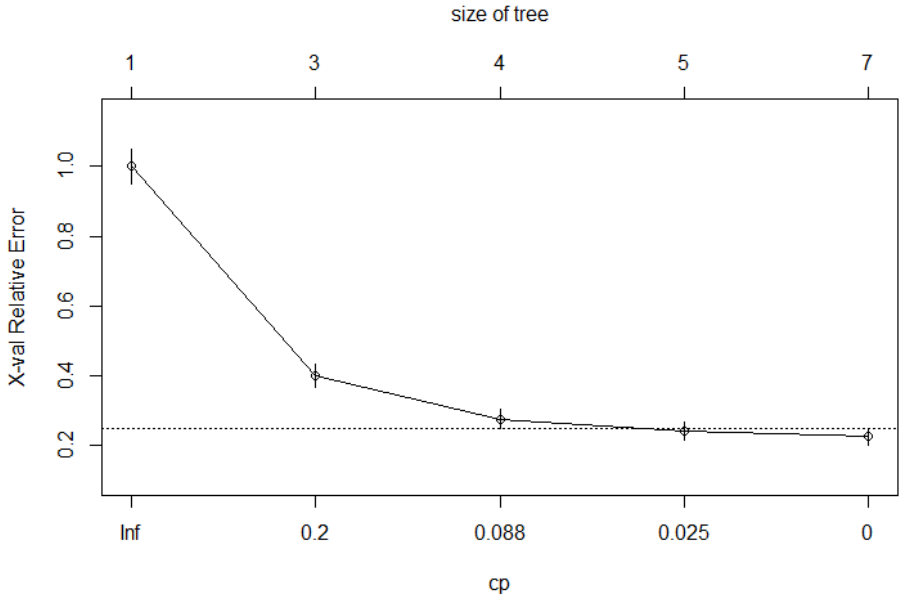
Variables actually used in tree construction:
[1] CCAvg CD.Account Education
[4] Family.members Income..in.K.month.

Root node error: 354/3500 = 0.10114

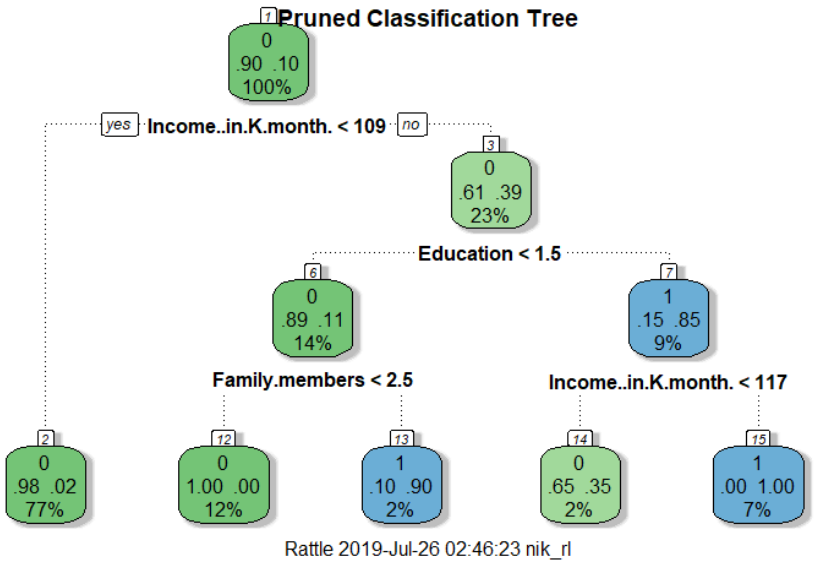
n= 3500

	CP	nsplit	rel error	xerror	xstd
1	0.298023	0	1.00000	1.00000	0.050390
2	0.135593	2	0.40395	0.40113	0.032972
3	0.056497	3	0.26836	0.27684	0.027570
4	0.011299	4	0.21186	0.24294	0.025873
5	0.000000	6	0.18927	0.22599	0.024976

➢ Tree Performance Graph



➢ Final Cart Model tree



➢ Prediction Score

ID	Age..in.years.	Experience..in.years.	Income..in.K.month.
1	25	1	49
2	45	19	34
3	39	15	11
4	35	9	100
5	35	8	45
6	37	13	29

ZIP.Code	Family.members	CCAvg	Education	Mortgage	Personal.Loan
91107	4	1.6	1	0	0
90089	3	1.5	1	0	0
94720	1	1.0	1	0	0
94112	1	2.7	2	0	0
91330	4	1.0	2	0	0
92121	4	0.4	2	155	0

Securities.Account	CD.Account	Online	CreditCard	predict.class
1	0	0	0	0
1	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	1	0
0	0	1	0	0

predict.score.0	predict.score.1	deciles
0.98336414	0.01663586	9
0.98336414	0.01663586	9
0.98336414	0.01663586	9
0.98336414	0.01663586	9
0.98336414	0.01663586	9
0.98336414	0.01663586	9

➢ Performance on Training data set

The following model performance measures will be calculated on the training set to gauge the goodness of the model:

-Rank ordering
-Ks
-Area
-Gini

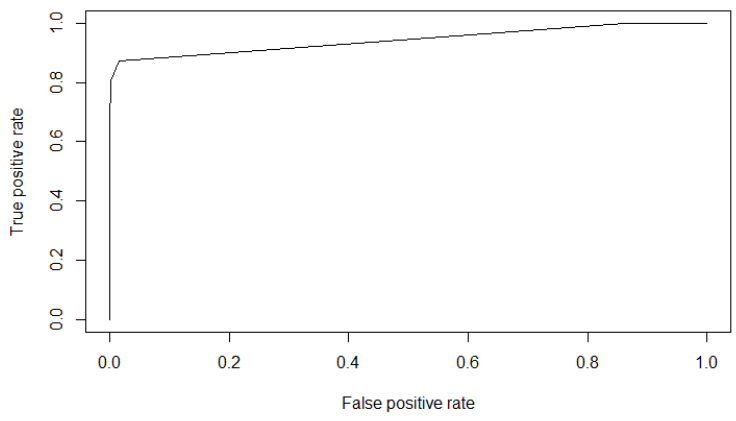
-Rank ordering

Column1	Column2	Column3	Column4	Column5	Column6	Column7	Column8	Column9	Column10	Column11
	deciles	cnt	cnt_resp	cnt_non_resp	rrate	cum_resp	cum_non_resp	cum_rel_resp	cum_rel_non_resp	ks
1	10	359	309	50	86.10%	309	50	87.30%	1.60%	85.7
2	9	2705	45	2660	1.70%	354	2710	100.00%	86.10%	13.86
3	2	436	0	436	0.00%	354	3146	100.00%	100.00%	0

-KS and Area Curve

		predict.class	
Personal.Loan		0	1
	0	3140	6
	1	69	285

-Plot



- KS

0.8569882

- Auc

0.9434903

- Gini

0.7972688

Cart Model Performance

KS – 85.69%
AUC- 94.34&
Gini- 79.72%

With ks – 85%, Auc-94%, & Gini coeffeicient ass 79% indicates to be an effective and good model.

Hold Out Sample

- Model building with Oversampled data

  - Syntax for the node path

```
node number: 2
   root
   Income..in.K.month.< 108.5

 node number: 14
   root
   Income..in.K.month.>=108.5
   Education>=1.5
   Income..in.K.month.< 116.5
```

  - Scoring Holdout Sample

➢ Head (mytest)

ID	Age..in.years.	Experience..in.years.	Income..in.K.month.
3501	51	26	90
3502	65	39	105
3503	32	8	58
3504	29	3	53
3505	46	20	15
3506	64	39	103

ZIP.Code	Family.members	CCAvg	Education	Mortgage	Personal.Loan
94110	1	2.8	2	0	0
91380	4	1.7	3	0	0
95616	3	2.0	1	90	0
95814	4	2.1	3	0	0
95370	4	0.6	3	0	0
90304	1	0.8	3	0	0

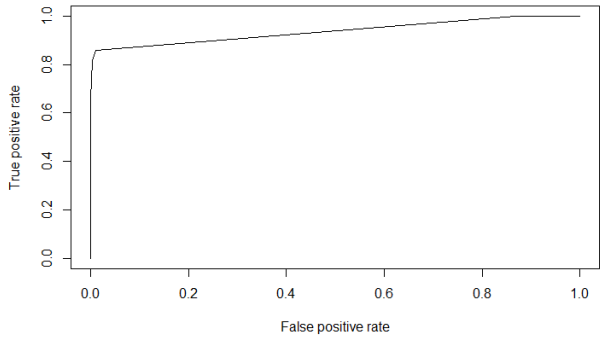
Securities.Account	CD.Account	Online	CreditCard	predict.class
0	0	1	1	0
1	0	1	0	0
0	0	1	0	0
0	0	1	0	0
1	0	1	0	0
0	0	1	1	0

predict.score.0	predict.score.1	deciles
0.98336414	0.01663586	10
0.98336414	0.01663586	10
0.98336414	0.01663586	10
0.98336414	0.01663586	10
0.98336414	0.01663586	10
0.98336414	0.01663586	10

Holdout Ranking

	deciles	cnt	cnt_resp	cnt_non_resp	rrate	cum_resp	cum_non_resp	cum_rel_resp	cum_rel_non_resp	ks
1	10	1319	126	1193	9.55%	126	1193	100%	86.80%	13.17
2	2	181	0	181	0.00%	126	1374	100%	100.00%	0

Holdout test



Personal.Loan	predict.class 0	1
0	1370	4
1	23	103

- **AUC**

0.9367621

- **KS**

0.8469536

- **Gini**

0.7899441

Summary – Cart Model Performance (holdout Sample)

1. **Ks : 84%**
2. **Auc: 93%**
3. **Gini: 78%**

Hence, Ks with 84%, Auc with 93%, and Gini with 78%; indicated to be a helpful and good model in performance.

Cart Conclusion

Measures	Train	Test	Deviation
KS	**85.69%**	**84%**	**1.69%**
AUC	**94.34%**	**93%**	**1.34%**
GINI	**79.72%**	**78%**	**1.72%**

Conclusion

- If we compare with the train data set, there is just minor difference between the resulting tests.
- It can be observed that most of the Model Performance values for Training & Testing sets are around 1%
- Hence, the model is performing well.
- The percentage deviation between Training and Testing Dataset also is reasonably under control, suggesting a robust model.

Thank You

Source Code

```
#Library(“plotrix”)
#Library(“ggplot2”)
#Library(“crplot”)
#library(caret”)
#library(rpart)
#library(rpart.plot)
#library(corrplot)
#library(rattle)
#library(RColorBrewer)
#library(data.table)
#library(scales)
#library(ROCR)
#library(ineq)
-----------------------------------------------------------------------
setwd("F:/r data machine learning")
getwd()
fulldata=read.csv("bankdata.csv", header = T)
mytrain=read.csv("Bank Personal Loan Dataset.csv", header = T)
mytest=read.csv("bankholdout.csv", header = T)
mytrain
mytest
head(mytrain)
head(mytest)
summary(mytrain)
variable.names("ID", "Age","Experience","Income","ZIP Code","Family
members","CCAvg","Education","Mortgage","Personal Loan","Securities
Account","CD Account","Online","CreditCard")
dim(mytest)
dim(mytrain)
names(mytrain)
names(mytest)
head(mytrain)
attach(mytrain)
attach(mytest)

table(mytrain$Personal.Loan)
table(mytest$Personal.Loan)
```

```
prop.table(table(mytrain$Personal.Loan))
prop.table(table(mytest$Personal.Loan))



colSums(is.na(fulldata))

table(fulldata$Personal.Loan)
prop.table(table(fulldata$Personal.Loan))


prop.table(table(fulldata$Personal.Loan))

table(mytrain$Personal.Loan)
table(mytest$Personal.Loan)
prop.table((table(mytrain$Personal.Loan)))
prop.table((table(mytest$Personal.Loan)))
```

Data Visualisation

```
#Graph
hist(mydata$Age..in.years., col = 'pink', main = 'Histogram of Age', xlab =
'Age')
hist(mydata$Experience..in.years., col = 'light green', main = 'Histogram of
Explerience',xlab = 'Experience')
hist(mydata$Income..in.K.month., col = 'red', main = 'Histogram of
Income',xlab = 'Income')
hist(mydata$Family.members, col = 'light blue', main = 'Histogram of Family
member',xlab = 'Family member')
hist(mydata$CCAvg, col = 'violet', main = 'Histogram of Avg spending of
Credit Card',xlab = 'CC Avg spending per month')
hist(mydata$Education, col = 'orange', main = 'Histogram of Education
Level',xlab = 'Education')
hist(mydata$Mortgage, col = 'grey', main = 'Histogram of Mortgage',xlab =
'Mortgage')
hist(mydata$Personal.Loan, col = 'Dark Red', main = 'Histogram of Personal
Loan', xlab = 'Personal Loan')
hist(mydata$Securities.Account, col = 'maroon', main = 'Histogram of
Securities on Account with bank', xlab = 'Security')
hist(mydata$CD.Account, col = 'purple', main = 'Histogram of Certificate of
deposit', xlab = 'CD(certificate of deposit account) with bank')
```

```
hist(mydata$Online, col = 'dark green', main = 'Histogram of Online Bankers',
xlab='online Banking')
hist(mydata$CreditCard, col = 'yellow', main = 'Histogram of Credit Card User',
xlab='Credit Card')

#Pie Chart

library("plotrix")
pie3D(prop.table((table(fulldata$Personal.Loan))),
      main='Customer with loan Vs Not',
      #explode=0.1,
      labels=c("Non Loaner", "Loan"),
      col = c("Turquoise", "Medium Sea Green")
)


pie3D(prop.table((table(fulldata$Securities.Account))),
      main='Customer with Securities Acct with bank',
      #explode=0.1,
      labels=c("Non Secured", "Secured"),
      col = c("Turquoise", "Medium Sea Green")
)

pie3D(prop.table((table(fulldata$CD.Account))),
      main='Customer with Certificate of deposit',
      #explode=0.1,
      labels=c("Non Certified", "Certified"),
      col = c("Turquoise", "Medium Sea Green")
)

pie3D(prop.table((table(fulldata$Personal.Loan))),
      main='Customer use Net Banking',
      #explode=0.1,
      labels=c("Non User", "Netbanking User"),
      col = c("Turquoise", "Medium Sea Green")
)

pie3D(prop.table((table(fulldata$CreditCard))),
      main='Customer having Credit Card',
      #explode=0.1,
      labels=c("Dont Use", "User of Credit card"),
      col = c("Turquoise", "Medium Sea Green")
)
```

```
#Data Partition
indexes=sample(1:nrow(mydata), size = 0.3*nrow(mydata))
test= mydata[indexes,]
dim(test)
train=mydata[-indexes,]
dim(mydata)
#piechart after data partition

par(mfrow=c(1,1))

pie3D(prop.table((table(mytrain$Personal.Loan))),
      main='Customer with loan Vs Not in training data Set',
      #explode=0.1,
      labels=c("No", "Yes"),
      col = c("Turquoise", "Medium Sea Green")
)

pie3D(prop.table((table(mytest$Personal.Loan))),
      main='Customer with loan in Testing Data set',
      #explode=0.1,
      labels=c("No", "Yes"),
      col = c("Aquamarine", "Dark Sea Green")
)
```

Cart

```
## loading the library
library(rpart)
library(rpart.plot)

table(mytrain$Personal.Loan)

## Target Rate
sum(mytrain$Personal.Loan)/5000


## setting the control paramter inputs for rpart
r.ctrl = rpart.control(minsplit=100, minbucket = 10, cp = 0, xval = 10)


## calling the rpart function to build the tree
```

```
##m1 <- rpart(formula = Ta ~ ., data =
CTDF.dev[which(CTDF.dev$Holding_Period>10),-1], method = "class",
control = r.ctrl)
m1 <- rpart(formula = Personal.Loan ~ .,
           data = mytrain[,-1], method = "class",
           control = r.ctrl)
m1


install.packages("rattle")
install.packages("RcolorBrewer")
library(rattle)
##install.packages
library(RColorBrewer)
fancyRpartPlot(m1)


## to find how the tree performs
printcp(m1)
plotcp(m1)

##rattle()
## Pruning Code
ptree<- prune(m1, cp= 0.025 ,"CP")
printcp(ptree)
fancyRpartPlot(ptree, uniform=TRUE,  main="Pruned Classification Tree",
               )


## Let's use rattle to see various model evaluation measures
##rattle()

View(mytrain)
## Scoring syntax
?predict
mytrain$predict.class <- predict(ptree, mytrain, type="class")
mytrain$predict.score <- predict(ptree, mytrain, type="prob")


View(mytrain)
head(mytrain)
```

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

class(mytrain$predict.score)
## deciling
mytrain$deciles <- decile(mytrain$predict.score[,2])
View(mytrain)
head(mytrain)
## Ranking code

install.packages("data.table")
install.packages("scales")
library(data.table)
library(scales)
tmp_DT = data.table(mytrain)
rank <- tmp_DT[, list(
  cnt = length(Personal.Loan),
  cnt_resp = sum(Personal.Loan),
  cnt_non_resp = sum(Personal.Loan == 0)) ,
  by=deciles][order(-deciles)]
rank$rrate <- round(rank$cnt_resp / rank$cnt,4);
rank$cum_resp <- cumsum(rank$cnt_resp)
rank$cum_non_resp <- cumsum(rank$cnt_non_resp)
rank$cum_rel_resp <- round(rank$cum_resp / sum(rank$cnt_resp),4);
rank$cum_rel_non_resp <- round(rank$cum_non_resp /
sum(rank$cnt_non_resp),4);
rank$ks <- abs(rank$cum_rel_resp - rank$cum_rel_non_resp) * 100;
```

```
rank$rrate <- percent(rank$rrate)
rank$cum_rel_resp <- percent(rank$cum_rel_resp)
rank$cum_rel_non_resp <- percent(rank$cum_rel_non_resp)

View(rank)



install.packages("ROCR")
install.packages("ineq")
library(ROCR)
library(ineq)
pred <- prediction(mytrain$predict.score[,2], mytrain$Personal.Loan)
perf <- performance(pred, "tpr", "fpr")
plot(perf)
KS <- max(attr(perf, 'y.values')[[1]]-attr(perf, 'x.values')[[1]])
auc <- performance(pred,"auc");
auc <- as.numeric(auc@y.values)

gini = ineq(mytrain$predict.score[,2], type="Gini")

with(mytrain, table(Personal.Loan, predict.class))
auc
KS
gini

View(rank)

#oversampled dataset


## Syntax to get the node path

tree.path <- path.rpart(ptree, node = c(2, 14))
nrow(mytest)

## Scoring Holdout sample
mytest$predict.class <- predict(ptree, mytest, type="class")
mytest$predict.score <- predict(ptree, mytest, type="prob")


mytest$deciles <- decile(mytest$predict.score[,2])
View(mytest)
```

```
head(mytest)
## Ranking code
tmp_DT = data.table(mytest)
h_rank = tmp_DT[, list(
  cnt = length(Personal.Loan),
  cnt_resp = sum(Personal.Loan),
  cnt_non_resp = sum(Personal.Loan == 0)) ,
  by=deciles][order(-deciles)]
h_rank$rrate <- round(h_rank$cnt_resp / h_rank$cnt,4);
h_rank$cum_resp <- cumsum(h_rank$cnt_resp)
h_rank$cum_non_resp <- cumsum(h_rank$cnt_non_resp)
h_rank$cum_rel_resp <- round(h_rank$cum_resp / sum(h_rank$cnt_resp),4);
h_rank$cum_rel_non_resp <- round(h_rank$cum_non_resp /
sum(h_rank$cnt_non_resp),4);
h_rank$ks <- abs(h_rank$cum_rel_resp - h_rank$cum_rel_non_resp)*100;
h_rank$rrate <- percent(h_rank$rrate)
h_rank$cum_rel_resp <- percent(h_rank$cum_rel_resp)
h_rank$cum_rel_non_resp <- percent(h_rank$cum_rel_non_resp)

View(h_rank)
head(h_rank)
pred <- prediction(mytest$predict.score[,2], mytest$Personal.Loan)
perf <- performance(pred, "tpr", "fpr")
KS <- max(attr(perf, 'y.values')[[1]]-attr(perf, 'x.values')[[1]])
auc <- performance(pred,"auc");
auc <- as.numeric(auc@y.values)

gini = ineq(mytest$predict.score[,2], type="Gini")

with(mytest, table(Personal.Loan, predict.class))
auc
KS
gini

# Thank You
```

The END
