

Assignment 3

Swathi Suragowni Ravindranath

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```
BankData <- read.csv("C:/Users/ravin/Downloads/UniversalBank.csv")
summary(BankData)
```

```
##           ID           Age           Experience           Income           ZIP.Code
## Min.      : 1      Min.      :23.00      Min.      : -3.0      Min.      : 8.00      Min.      : 9307
## 1st Qu.:1251      1st Qu.:35.00      1st Qu.:10.0      1st Qu.: 39.00      1st Qu.:91911
## Median :2500      Median :45.00      Median :20.0      Median : 64.00      Median :93437
## Mean     :2500      Mean     :45.34      Mean     :20.1      Mean     : 73.77      Mean     :93153
## 3rd Qu.:3750      3rd Qu.:55.00      3rd Qu.:30.0      3rd Qu.: 98.00      3rd Qu.:94608
## Max.      :5000      Max.      :67.00      Max.      :43.0      Max.      :224.00      Max.      :96651
##           Family           CCAvg           Education           Mortgage
## Min.      :1.000      Min.      : 0.000      Min.      :1.000      Min.      : 0.0
## 1st Qu.:1.000      1st Qu.: 0.700      1st Qu.:1.000      1st Qu.: 0.0
## Median :2.000      Median : 1.500      Median :2.000      Median : 0.0
## Mean     :2.396      Mean     : 1.938      Mean     :1.881      Mean     : 56.5
## 3rd Qu.:3.000      3rd Qu.: 2.500      3rd Qu.:3.000      3rd Qu.:101.0
## Max.      :4.000      Max.      :10.000      Max.      :3.000      Max.      :635.0
## Personal.Loan      Securities.Account      CD.Account      Online
## Min.      :0.000      Min.      :0.0000      Min.      :0.0000      Min.      :0.0000
## 1st Qu.:0.000      1st Qu.:0.0000      1st Qu.:0.0000      1st Qu.:0.0000
## Median :0.000      Median :0.0000      Median :0.0000      Median :1.0000
## Mean     :0.096      Mean     :0.1044      Mean     :0.0604      Mean     :0.5968
## 3rd Qu.:0.000      3rd Qu.:0.0000      3rd Qu.:0.0000      3rd Qu.:1.0000
## Max.      :1.000      Max.      :1.0000      Max.      :1.0000      Max.      :1.0000
##           CreditCard
## Min.      :0.000
## 1st Qu.:0.000
## Median :0.000
## Mean     :0.294
## 3rd Qu.:1.000
## Max.      :1.000
```

```
library(caret)
```

```
## Loading required package: ggplot2
```

```
## Loading required package: lattice
```

```
library(ISLR)
library(e1071)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
library(class)
library(reshape2)
library(ggplot2)
library(gmodels)
library(lattice)
```

#converting variables

```
BankData$Personal.Loan <- factor(BankData$Personal.Loan)
BankData$Online <- factor(BankData$Online)
BankData$CreditCard <- factor(BankData$CreditCard)
df= BankData
```

#TASK1

```
set.seed(64060)
Train_index <- createDataPartition(df$Personal.Loan, p = 0.6, list = FALSE)
train.df = df[Train_index,]
validation.df = df[~Train_index,]

mytable <- xtabs(~ CreditCard + Online + Personal.Loan , data = train.df)
ftable(mytable)
```

```
##               Personal.Loan    0    1
## CreditCard Online
## 0           0           772   75
##           1          1152  120
## 1           0           309   34
##           1           479   59
```

#TASK2

```
probability = 59/(59+479)
probability
```

```
## [1] 0.1096654
```

#Q3

```
table(Personal.Loan = train.df$Personal.Loan, Online = train.df$Online)
```

```
##           Online
## Personal.Loan    0    1
##           0 1081 1631
##           1  109  179
```

```
table(Personal.Loan = train.df$Personal.Loan, CreditCard = train.df$CreditCard)
```

```
##           CreditCard
## Personal.Loan    0    1
##           0 1924  788
##           1  195   93
```

```
table(Personal.Loan = train.df$Personal.Loan)
```

```
## Personal.Loan
##      0      1
## 2712  288
```

#TASK4

#i. $P(CC = 1 \mid Loan = 1)$ (the proportion of credit card holders among the loan acceptors)

```
Probablity1 <- 93/(93+195)
Probablity1
```

```
## [1] 0.3229167
```

#ii. $P(Online = 1 \mid Loan = 1)$

```
Probablity2 <- 179/(179+109)
Probablity2
```

```
## [1] 0.6215278
```

#iii. $P(Loan = 1)$ (the proportion of loan acceptors)

```
Probablity3 <- 288/(288+2712)
Probablity3
```

```
## [1] 0.096
```

#iv. $P(CC = 1 \mid Loan = 0)$

```
Probablity4 <- 788/(788+1924)
Probablity4
```

```
## [1] 0.2905605
```

```
#v.  $P(\text{Online} = 1 \mid \text{Loan} = 0)$ 
Probablity5 <- 1631/(1631+1081)
Probablity5
```

```
## [1] 0.6014012
```

```
#vi.  $P(\text{Loan} = 0)$ 
Probablity6 <- 2712/(2712+288)
Probablity6
```

```
## [1] 0.904
```

```
#Q5
```

```
Task5Probablity <- (Probablity1*Probablity2*Probablity3)/
((Probablity1*Probablity2*Probablity3) +(Probablity4*Probablity5*Probablity6))

Task5Probablity
```

```
## [1] 0.1087106
```

```
#TASK6
```

```
##Value we got from question 2 and in the question 5 are nearly same
#Difference #between exact method and naive bayes method is the exact method
#We need the similar independent variable and classification to pridict, whereas the naive bayes
#method doesn't. We can justify that value we got from the question 2 i.e 0.1096654 more precise.
#because we have taken the same values from the pivot table.
```

```
#Task7
```

```
#Run naive Bayes on the data. Examine the model output on training data, and find the entry
#that corresponds to  $P(\text{Loan} = 1 \mid \text{CC} = 1, \text{Online} = 1)$ . Compare this to the number you
#obtained in (E).
```

```
nb.model <- naiveBayes(Personal.Loan~ Online + CreditCard, data = train.df)
To_Predict=data.frame(Online=1, CreditCard= 1)
predict(nb.model, To_Predict,type = 'raw')
```

```
## Warning in predict.naiveBayes(nb.model, To_Predict, type = "raw"): Type mismatch
## between training and new data for variable 'Online'. Did you use factors with
## numeric labels for training, and numeric values for new data?
```

```
## Warning in predict.naiveBayes(nb.model, To_Predict, type = "raw"): Type mismatch
## between training and new data for variable 'CreditCard'. Did you use factors
## with numeric labels for training, and numeric values for new data?
```

```
##           0           1
## [1,] 0.9153656 0.08463445
```

```
#The value we got from question 7 is 0.08463445 and value derived from the task 5 is 0.1087106.
# the result is almost same that we got from Task5.
# There is min difference because of the rounding off.
#The difference will not effect the rank .
```