

Assignment_3

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Importing required packages including `naivebayes` package

```
#install.packages("reshape")  
#install.packages("reshape2")  
#install.packages("melt")  
#install.packages("naivebayes")  
#install.packages("pROC")
```

loading the necessary libraries

```
library(readr)  
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(caret)
```

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

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

```
library(class)  
library(melt)  
library(reshape)
```

```
##  
## Attaching package: 'reshape'  
  
## The following object is masked from 'package:class':  
##  
##   condense
```

```
## The following object is masked from 'package:dplyr':
##
##   rename
```

```
library(reshape2)
```

```
##
## Attaching package: 'reshape2'
```

```
## The following objects are masked from 'package:reshape':
##
##   colsplit, melt, recast
```

```
library(ggplot2)
library(ISLR)
library(naivebayes)
```

```
## naivebayes 0.9.7 loaded
```

```
library(e1071)
library(pROC)
```

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

```
##
## Attaching package: 'pROC'
```

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

Importing the dataset and assigning it to the variable `bank`. Using the `head` function to display first six rows of the dataset `bank`.

```
bank <- read_csv("~/Downloads/UniversalBank.csv")
```

```
## Rows: 5000 Columns: 14
## -- Column specification -----
## Delimiter: ","
## dbl (14): ID, Age, Experience, Income, ZIP Code, Family, CCAvg, Education, M...
##
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
```

```
head(bank)
```

```
## # A tibble: 6 x 14
##   ID   Age Experience Income 'ZIP Code' Family CCAvg Education Mortgage
##   <dbl> <dbl>      <dbl>  <dbl>      <dbl>  <dbl> <dbl>      <dbl>      <dbl>
```

```
## 1      1      25          1      49      91107      4      1.6          1          0
## 2      2      45          19      34      90089      3      1.5          1          0
## 3      3      39          15      11      94720      1      1            1          0
## 4      4      35           9     100      94112      1      2.7          2          0
## 5      5      35           8      45      91330      4      1            2          0
## 6      6      37          13      29      92121      4      0.4          2         155
## # i 5 more variables: 'Personal Loan' <dbl>, 'Securities Account' <dbl>,
## #   'CD Account' <dbl>, Online <dbl>, CreditCard <dbl>
```

The `is.na()` function is used to check if there are any missing values in the dataset and is assigned to `bank_na` variable.

```
bank_na <- is.na.data.frame("universalbank")
```

The column Online, Credit card and personal loan have categorical variables which are converted to factors using the `as.factor()` function.

```
bank$Online<- as.factor(bank$Online)
bank$CreditCard<- as.factor(bank$CreditCard)
bank$`Personal Loan`<- as.factor(bank$`Personal Loan`)
```

#Data Partition and Normalization The process of Data partition is performed to create the training data that is assigned to `Train_data` containing 60% of the dataset `bank` and the Validation data assigned to `Valid_data` containing the remaining 40% of the dataset `bank`.

```
set.seed(333)
Train_Index<- createDataPartition(bank$`Personal Loan`, p=0.6, list=FALSE)
Train_data <-bank[Train_Index,]
Valid_data <-bank[-Train_Index,]
```

Both Training and validation data is normalised using the functions `preProcess()` and `predict()` and assigned to `Train_normalised` and `Valid_normalised` respectively.

```
Model_normalised <- preProcess(Train_data[, -c(10,13:14)],method = c("center", "scale"))
Train_normalised <- predict(Model_normalised,Train_data)
Valid_normalised<- predict(Model_normalised,Valid_data)
```

The following code chunk creates a pivot table for training data using the `table()` function.

```
Table.OCP <- table(Train_normalised$`Personal Loan`, Train_normalised$Online, Train_normalised$CreditCard)
Table.OCP
```

```
## , , Credit Card = 0
##
##           Online
## Personal Loan    0    1
##           0  786 1120
##           1   73  135
##
## , , Credit Card = 1
##
##           Online
```

```
## Personal Loan    0    1
##                0 305 501
##                1  31  49
```

Part B: Computing $P(\text{Loan} = 1 \mid \text{Online} = 1 \text{ \& } \text{CC} = 1)$ As we look that the pivot table created in part A out of the total 550 records where of active online banking users with credit cards, 49 had accepted a personal loan, so

$$P(\text{Loan} = 1 \mid \text{CC} = 1 \text{ and } \text{Online} = 1) = \frac{49}{550} = 0.089$$

Computing $P(\text{loan} = 1 \mid \text{Online} = 1 \text{ \& } \text{CC} = 1)$

```
Table.OCP[2,2,2] / (Table.OCP[2,2,2] + Table.OCP[1,2,2])
```

```
## [1] 0.08909091
```

Part C: Creating two separate pivot tables for Training data. One will have Loan as rows which is as a function of Online i.e columns and the other will have Loan (rows) as a function of CC. The 'table()' function is used.

```
online_table <- table(Train_normalised$`Personal Loan`, Train_normalised$Online, dnn=c("Personal Loan", "Online"))
online_table
```

```
##           Online
## Personal Loan    0    1
##           0 1091 1621
##           1  104  184
```

```
credit_table <- table(Train_normalised$`Personal Loan`, Train_data$CreditCard, dnn=c("Personal Loan", "Credit Card"))
credit_table
```

```
##           Credit Card
## Personal Loan    0    1
##           0 1906  806
##           1  208   80
```

Part D : Computing the following quantities: i) $P(\text{CC} = 1 \mid \text{Loan} = 1)$ (the proportion of credit card holders among the loan acceptors) i)

$$P(\text{CC} = 1 \mid \text{Loan} = 1) = 80 / 80 + 208$$

```
probability_ccl <- credit_table[2,2] / (credit_table[2,2] + credit_table[2,1])
probability_ccl
```

```
## [1] 0.2777778
```

ii) $P(\text{Online} = 1 \mid \text{Loan} = 1)$ ii)

$$P(\text{Online} = 1 \mid \text{Loan} = 1) = 184 / 184 + 104$$

```
probability_ol <- online_table[2,2] / (online_table[2,2] + online_table[2,1])
probability_ol
```

```
## [1] 0.6388889
```

iii) $P(\text{Loan} = 1)$ (the proportion of loan acceptors) iii)

$$P(\text{Loan} = 1) = 288 / (288 + 2712)$$

```
probability_loan <- sum(Train_normalised$`Personal Loan`==1) / length(Train_normalised$`Personal Loan`)
probability_loan
```

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

iv) $P(\text{CC} = 1 \mid \text{Loan} = 0)$

v)

$$P(\text{CC} = 1 \mid \text{Loan} = 0) = 806 / (806 + 1906)$$

```
probability_ccnl <- credit_table[1,2] / (credit_table[1,2] + credit_table[1,1])
probability_ccnl
```

```
## [1] 0.2971976
```

v) $P(\text{Online} = 1 \mid \text{Loan} = 0)$ v)

$$P(\text{Online} = 1 \mid \text{Loan} = 0) = 1621 / (1621 + 1091)$$

```
probability_onl <- online_table[1,2] / (online_table[1,2] + online_table[1,1])
probability_onl
```

```
## [1] 0.5977139
```

vi) $P(\text{Loan} = 0)$ vi)

$$P(\text{Loan} = 0) = 2712 / (2712 + 288)$$

```
probability_nl <- sum(Train_normalised$`Personal Loan`==0) / length(Train_normalised$`Personal Loan`)
probability_nl
```

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

Part E : The computed quantities from above were used for the Naive Bayes probability $P(\text{Loan} = 1 \mid \text{CC} = 1, \text{Online} = 1)$.

$$P(\text{Loan} = 1 \mid \text{CC} = 1, \text{Online} = 1) = (0.6388 \times 0.2777 \times 0.096) / (0.6388 \times 0.2777 \times 0.096 + 0.5977 \times 0.2972 \times 0.904) = 0.09591693$$

```
(probability_ol * probability_cc1 * probability_loan) / (probability_ol * probability_cc1 * probability_onl + probability_cc0 * probability_loan)
```

```
## [1] 0.09591693
```

Part F: The pivot table values from (B) is compared with Naive bayes probability.

From the Naive Bayes classifier, a higher value for $P(\text{Loan} = 1 \mid \text{CC} = 1, \text{Online} = 1)$ is obtained than with the direct computation obtained in part B. Interestingly, in part D we got the value of $P(\text{Loan} = 1)$ as 0.096 same as value obtained in Naive Bayes classifier. So the concerned person being an online user with a bank-issued credit card is independent of the probability of the person accepting loan as suggested by Naive Bayes approach.

Part G: Performing Naive Bayes on the data using the `naiveBayes()` function and assigning to the variable `naive_data`. The value that is obtained for the probability of loan acceptance ($\text{Loan} = 1$) conditional on having a bank credit card ($\text{CC} = 1$) and being an active user of online banking services ($\text{Online} = 1$) from Naive bayes as seen is 0.09591693, which is equal to the value derived in part E.

```
naive_data <- naiveBayes(`Personal Loan`~Online+CreditCard,data=Train_normalised)
naive_data
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##      0      1
## 0.904 0.096
##
## Conditional probabilities:
##      Online
## Y      0      1
## 0 0.4022861 0.5977139
## 1 0.3611111 0.6388889
##
##      CreditCard
## Y      0      1
## 0 0.7028024 0.2971976
## 1 0.7222222 0.2777778
```

AUC Value and ROC Curve

Plotting AUC (Area under curve) and ROC (Receiver Operating Characteristic) curve below using the `predict()` function by passing `naive_data` followed by using the `roc()` function and the `plot.roc()` (removing the second column).

```
label_predicted <- predict(naive_data, Valid_normalised, type = "raw")
head(label_predicted)
```

```
##      0      1
## [1,] 0.9107805 0.08921953
## [2,] 0.9107805 0.08921953
## [3,] 0.8955384 0.10446160
## [4,] 0.8955384 0.10446160
```

```
## [5,] 0.9181923 0.08180773
## [6,] 0.9107805 0.08921953
```

```
roc(Valid_normalised$Online, label_predicted[,2])
```

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

```
## Setting direction: controls < cases
```

```
##
```

```
## Call:
```

```
## roc.default(response = Valid_normalised$Online, predictor = label_predicted[, 2])
```

```
##
```

```
## Data: label_predicted[, 2] in 821 controls (Valid_normalised$Online 0) < 1179 cases (Valid_normalised$Online 1)
```

```
## Area under the curve: 1
```

```
plot.roc(Valid_normalised$Online, label_predicted[,2])
```

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

```
## Setting direction: controls < cases
```

