# FML Assignment 3

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#### #IMPORTING THE DATASET

Df <- read.csv("C:/Users/Nikitha/Downloads/UniversalBank.csv")</pre>

#### **#CONVERTING THE PREDICTOR ATTRIBUTE TO FACTORS**

```
Df$Personal.Loan <- as.factor(Df$Personal.Loan)
Df$Online <- as.factor(Df$Online)
Df$CreditCard <- as.factor(Df$CreditCard)</pre>
```

#### **#CHECKING FOR NULL VALUES**

sum(is.na(Df))

## [1] 0

## **#LOADING THE LIBRARIES**

#### library(class)

## Warning: package 'class' was built under R version 4.1.3

## library(caret)

## Warning: package 'caret' was built under R version 4.1.3

## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 4.1.3

## Loading required package: lattice

library(e1071)
library(dplyr)

## Warning: package 'dplyr' was built under R version 4.1.3

```
##
## 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(ggplot2)
library(reshape)
## Warning: package 'reshape' was built under R version 4.1.3
##
## Attaching package: 'reshape'
## The following object is masked from 'package:dplyr':
##
##
       rename
## The following object is masked from 'package:class':
##
##
       condense
library(melt)
## Warning: package 'melt' was built under R version 4.1.3
library(ISLR)
## Warning: package 'ISLR' was built under R version 4.1.3
library(reshape2)
## Warning: package 'reshape2' was built under R version 4.1.3
## Attaching package: 'reshape2'
```

```
## The following objects are masked from 'package:reshape':
 ##
 ##
         colsplit, melt, recast
 library(readr)
 ## Warning: package 'readr' was built under R version 4.1.3
 library(naivebayes)
 ## Warning: package 'naivebayes' was built under R version 4.1.3
 ## naivebayes 0.9.7 loaded
 library(pROC)
 ## Warning: package 'pROC' was built under R version 4.1.3
 ## Type 'citation("pROC")' for a citation.
 ##
 ## Attaching package: 'pROC'
 ## The following objects are masked from 'package:stats':
 ##
 ##
         cov, smooth, var
#DATA PARTITION TO 60:40
 set.seed(123)
 datapart <- createDataPartition(Df$Personal.Loan,p=.6, list=F)</pre>
 Train <- Df[datapart,]</pre>
 Validate <- Df[-datapart,]</pre>
#DATA NORMALIZATION
 norm_model <- preProcess(Train[,-c(10,13:14)],</pre>
                  method=c("center","scale"))
 Train_norm <- predict(norm_model,Train)</pre>
 Validate_norm <- predict(norm_model,Validate)</pre>
```

#A. Create a pivot table for the training data with Online as a column variable, CC as a row variable, and Loan as a secondary row variable

```
tab1<- ftable(Train_norm[,c(14,10,13)])
tab1</pre>
```

```
Online
##
                                        0
                                             1
## CreditCard Personal.Loan
## 0
                                      791 1144
              0
##
              1
                                       79 125
## 1
              0
                                      310
                                           467
##
                                       33
                                            51
```

- #B. This is the probability of loan acceptance (Loan = 1) conditional on having a bank credit card (CC = 1) and being an active user of online banking services (Online = 1)] = 51/(51+467) = 0.0984.
- #C. Creating two separate pivot tables for the training data. One having Loan (rows) as a function of Online (columns) and the other having Loan (rows) as a function of CC

```
melt1 = melt(Train, id=c("CreditCard", "Personal.Loan"), variable = "Online")
```

```
## Warning: attributes are not identical across measure variables; they will be
## dropped
```

```
castbank = dcast(melt1, CreditCard+Personal.Loan~Online)
```

```
## Aggregation function missing: defaulting to length
```

```
castbank[,c(1:2,14)]
```

```
##
     CreditCard Personal.Loan Online
## 1
              0
                              0
                                  1935
## 2
               0
                              1
                                   204
## 3
               1
                                   777
                              0
## 4
               1
                              1
                                    84
```

#D.Compute the following quantities [P(A | B) i.e. the probability of A given B]

```
ftable(Train_norm[,c(10,13)])
```

```
## Online 0 1
## Personal.Loan
## 0 1101 1611
## 1 112 176
```

```
ftable(Train_norm[,c(10,14)])
```

```
## CreditCard 0 1
## Personal.Loan
## 0 1935 777
## 1 204 84
```

```
ftable(Train_norm[,10])
```

```
## 0 1
##
## 2712 288
```

```
#1. P(CC = 1 \mid Loan = 1) = (84/84+204) = 0.291 \#2. P(Online = 1 \mid Loan = 1) = (176/176+112) = 0.611 \#3. P(Loan = 1) = (288/288+2712) = 0.096 \#4. P(CC = 1 \mid Loan = 0) = (777/777+1935) = 0.286 \#5. P(Online = 1 \mid Loan = 0) = (1611/1611+1101) = 0.595 \#6. P(Loan = 0) = (2712/2712+288) = 0.904
```

#E. Use the quantities computed above to compute the naive Bayes probability P(Loan = 1 | CC = 1, Online = 1)

```
\#(0.291 \times 0.611 \times 0.096) / (0.271 \times 0.611 \times 0.096) + (0.286 \times 0.595 \times 0.904) = 0.1000
```

#F. We can see that the values attained in steps b, 0.0984, and a, 0.1000, are practically identical, although the probability with Naive Bayes is slightly higher.

#G. Run the Naive Bayes Model on the data

```
Naive <- naive_bayes(Personal.Loan~Online+CreditCard,data=Train_norm)
Naive
```

```
##
##
##
 Call:
## naive_bayes.formula(formula = Personal.Loan ~ Online + CreditCard,
   data = Train norm)
##
##
##
##
## Laplace smoothing: 0
##
##
 ______
##
##
 A priori probabilities:
##
##
## 0.904 0.096
##
##
##
##
 Tables:
##
## -----
 ::: Online (Bernoulli)
 ______
##
## Online 0
##
   0 0.4059735 0.3888889
##
   1 0.5940265 0.6111111
##
## -----
##
 ::: CreditCard (Bernoulli)
## -----
##
## CreditCard
##
     0 0.7134956 0.7083333
##
     1 0.2865044 0.2916667
##
## ------
```

#Naive Bayes Model results for the consumer taking the loan, using their credit card, and using online banking are 0.1000, which is equivalent to the result in E.

# #Examining the AUC value and ROC curve

```
Naive <- naiveBayes(Personal.Loan~Online+CreditCard,data=Train_norm)
Naive
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##
## 0.904 0.096
##
## Conditional probabilities:
##
      Online
## Y
                         1
    0 0.4059735 0.5940265
##
   1 0.3888889 0.6111111
##
##
##
     CreditCard
## Y
               0
                         1
   0 0.7134956 0.2865044
##
##
     1 0.7083333 0.2916667
predlab <- predict(Naive, Validate norm, type = "raw")</pre>
head(predlab)
##
## [1,] 0.9082737 0.09172629
## [2,] 0.9021538 0.09784623
## [3,] 0.9061594 0.09384060
## [4,] 0.9082737 0.09172629
## [5,] 0.9082737 0.09172629
## [6,] 0.8999139 0.10008606
roc(Validate norm$Online,predlab[,2])
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
##
## Call:
## roc.default(response = Validate_norm$Online, predictor = predlab[,
                                                                            2])
## Data: predlab[, 2] in 803 controls (Validate_norm$Online 0) < 1197 cases (Validate_norm$Onlin</pre>
e 1).
## Area under the curve: 1
```

```
plot.roc(Validate_norm$Online,predlab[,2])
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases</pre>
```

