FML Assignment 3

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#Importing dataset

```
nb <- read.csv("~/Desktop/kent /BUSINESS ANALYTICS /ASSIGNMENT 
1/UniversalBank.csv")
summary("nb.csv")

##    Length     Class      Mode 
##         1 character character
```

#CONVERTING THE ATTRIBUTE OF THE PREDICTOR TO FACTORS

```
head(nb)

##   ID Age Experience Income ZIP.Code Family CCAvg Education Mortgage
## 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   1.0         1        0
## 4  4  35          9    100    94112      1   2.7         2        0
## 5  5  35          8     45    91330      4   1.0         2        0
## 6  6  37         13     29    92121      4   0.4         2      155
##   Personal.Loan Securities.Account CD.Account Online CreditCard
## 1             0                  1          0      0          0
## 2             0                  1          0      0          0
## 3             0                  0          0      0          0
## 4             0                  0          0      0          0
## 5             0                  0          0      0          1
## 6             0                  0          0      1          0

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

#CHECKING VALUES FOR NULL

```
sum(is.na(nb))

## [1] 0
```

#LOADING THE LIBRARIES

```
library(class)
 library(caret)

## Loading required package: ggplot2
```

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

```
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(ggplot2)
library(reshape)
```

```
##
## Attaching package: 'reshape'

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

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

```
library(melt)
library(ISLR)
library(reshape2)
```

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

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

```
library(readr)
library(naivebayes)
```

```
## naivebayes 0.9.7 loaded
```

```
library(pROC)
```

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

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

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

#DATA COMPONENT TO 60:40

```
set.seed(123)
 datapart <- createDataPartition(nb$Personal.Loan,p=.6, list=F)
 Train <- nb[datapart,]
 Validate <- nb[-datapart,]
```

#DATA NORMALIZATION

```
normalization.model <- preProcess(Train[,-c(10,13:14)],
                 method=c("center","scale"))
 Train.normalization <- predict(normalization.model,Train)
 Validate.normalization<- predict(normalization.model,Validate)
```

#A: In a pivot table, make Online a column variable, CC a row variable, and Loan a secondary row variable for the training data.

```
pivot<- ftable(Train.normalization[,c(14,10,13)])
pivot

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

#B. This is the probability that you will be approved for a loan (Loan = 1) if you have a bank credit card (CC = 1) and use online banking services frequently (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             0    777
## 4          1             1     84
```

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

```
ftable(Train.normalization[,c(10,13)])

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

ftable(Train.normalization[,c(10,14)])

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

ftable(Train.normalization[,10])

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

#1. P(CC = 1 | Loan = 1) = (84/84+204) = 0.291 #2. P(Online = 1 | Loan = 1) = (176/176+112) = 0.611 #3. P(Loan = 1) = (288/288+2712) = 0.096 #4. P(CC = 1 | Loan = 0) = (777/777+1935) = 0.286 #5. P(Online = 1 | 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 x 0.611 x 0.096) / (0.271 x 0.611 x 0.096) + (0.286 x 0.595 x 0.904)
= 0.1000
```

#F. Although the probability using Naive Bayes is slightly higher, we can see that the values obtained in steps b, which are 0.0984 and a, which are 0.1000, are practically the same.

#G. Run the Naive Bayes Model on the data

```
Naiv <- naive_bayes(Personal.Loan~Online+CreditCard,data=Train.normalization)
Naiv

##
## ================================== Naive Bayes
==================================
##
##  Call:
## naive_bayes.formula(formula = Personal.Loan ~ Online + CreditCard,
##     data = Train.normalization)
##
```

```
## -----------------------------------------------------------------------------
-------
## 
## Laplace smoothing: 0
## 
## -----------------------------------------------------------------------------
-------
## 
##  A priori probabilities: 
## 
##     0     1 
## 0.904 0.096 
## 
## -----------------------------------------------------------------------------
-------
## 
##  Tables: 
## 
## -----------------------------------------------------------------------------
-------
##  ::: Online (Bernoulli) 
## -----------------------------------------------------------------------------
-------
## 
## Online         0         1
##      0 0.4059735 0.3888889
##      1 0.5940265 0.6111111
## 
## -----------------------------------------------------------------------------
-------
##  ::: CreditCard (Bernoulli) 
## -----------------------------------------------------------------------------
-------
## 
## CreditCard         0         1
##          0 0.7134956 0.7083333
##          1 0.2865044 0.2916667
## 
## -----------------------------------------------------------------------------
-------

#The results of the Naive Bayes Model for the borrower's use of their credit
card, online banking, and loan are 0.1000, which is the same as the result in
E.

#Looking at the ROC curve and AUC value
Naiv <- naiveBayes(Personal.Loan~Online+CreditCard,data=Train.normalization)
 Naiv
```

```
##
## 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 0.4059735 0.5940265
##   1 0.3888889 0.6111111
##
##    CreditCard
## Y           0         1
##   0 0.7134956 0.2865044
##   1 0.7083333 0.2916667
```

```
predlab <- predict(Naiv,Validate.normalization,type = "raw")
head(predlab)
```

```
##              0          1
## [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.normalization$Online,predlab[,2])
```

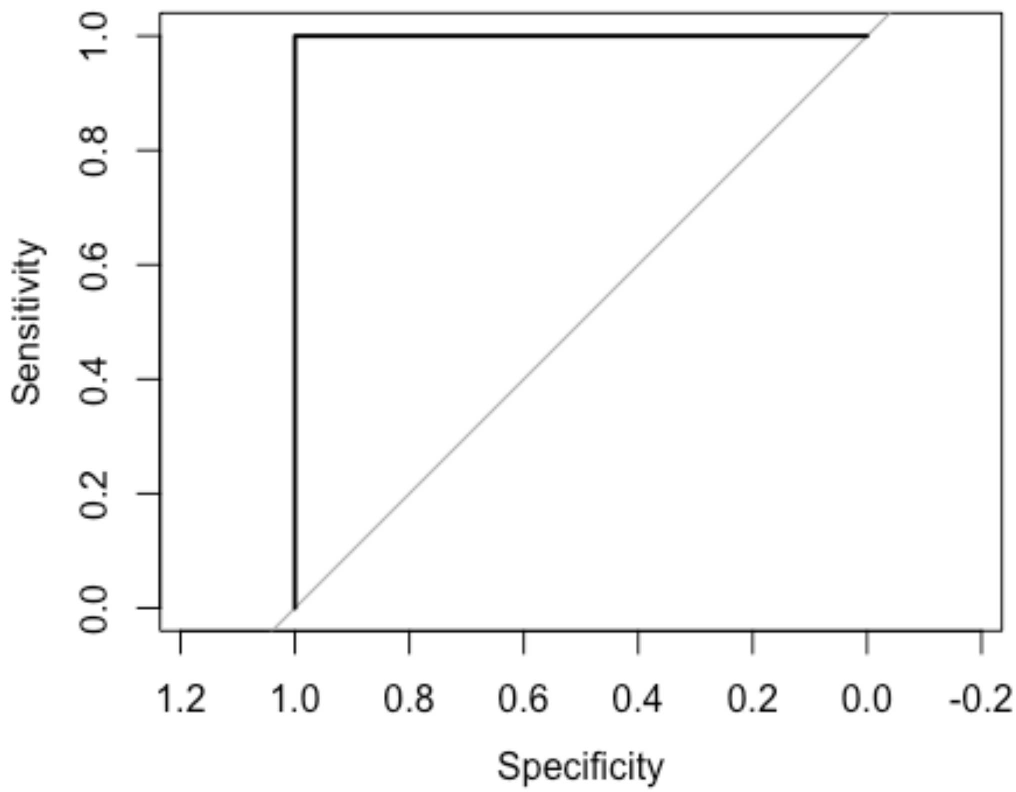
```
## Setting levels: control = 0, case = 1
```

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

```
##
## Call:
## roc.default(response = Validate.normalization$Online, predictor =
predlab[,     2])
##
## Data: predlab[, 2] in 803 controls (Validate.normalization$Online 0) <
1197 cases (Validate.normalization$Online 1).
## Area under the curve: 1
```

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

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



Sensitivity
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
Specificity