Machine Learning Assignment-3 sai rohan paritala

```
library("dplyr")
library("tidyr")
library("ggplot2")
library("ROCR")
library("caret")
library("tidyverse")
library("tm")
library("SnowballC")
library("softImpute")
library("Hmisc")
library('tinytex')
library('gplots')
library('FNN')
library("dplyr")
library("tidyr")
library("caTools")
library("reshape2")
library("e1071")
```

```
rm(list=ls())
bank = read.csv("UniversalBank.csv")
bank$Personal.Loan = as.factor(bank$Personal.Loan)
bank$Online = as.factor(bank$Online)
bank$CreditCard = as.factor(bank$CreditCard)
set.seed(1)
train.index <- sample(row.names(bank), 0.6*dim(bank)[1])
test.index <- setdiff(row.names(bank), train.index)
train.df <- bank[train.index, ]
test.df <- bank[test.index, ]
train <- bank[train.index, ]
test = bank[train.index,]
```

#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. The values inside the table should convey the count. In R use functions melt() and cast(), or function table().

```
melted.bank = melt(train,id=c("CreditCard","Personal.Loan"),variable= "Online")
recast.bank=dcast(melted.bank,CreditCard+Personal.Loan~Online)
recast.bank[,c(1:2,14)]
```

CreditCard <fct>	Personal.Loan <fct>	Online <int>
0	0	1924
0	1	198
1	0	801
1	1	77

4 rows

#b. Consider the task of classifying a customer who owns a bank credit card and is actively using online banking services. Looking at the pivot table, what is the probability that this customer will accept the loan offer? [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)].

```
melted.bankc1 = melt(train,id=c("Personal.Loan"),variable = "Online")
```

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

```
melted.bankc2 = melt(train,id=c("CreditCard"),variable = "Online")
```

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

```
recast.bankc1=dcast(melted.bankc1,Personal.Loan~Online)
recast.bankc2=dcast(melted.bankc2,CreditCard~Online)
```

#c.Create two separate pivot tables for the training data. One will have Loan (rows) as a function of Online (columns) and the other will have Loan (rows) as a function of CC

```
Loanline=recast.bankc1[,c(1,13)]
LoanCC = recast.bankc2[,c(1,14)]
Loanline
```

Personal.Loan	Online

<fct>	<int>
0	2725
1	275

2 rows

```
LoanCC
```

CreditCard	**Online**
<fct>	<int>
0	2122
1	878

2 rows

#d. Compute the following quantities [P (A | B) means “the probability of A given B”]: i. P (CC = 1 | Loan = 1) (the proportion of credit card holders among the loan acceptors) ii. P(Online=1|Loan=1) iii. P (Loan = 1) (the proportion of loan acceptors) iv. P(CC=1|Loan=0) v. P(Online=1|Loan=0) vi. P(Loan=0)

```
table(train[,c(14,10)])
```

```
##             Personal.Loan
## CreditCard     0    1
##          0 1924  198
##          1  801   77
```

```
table(train[,c(13,10)])
```

```
##       Personal.Loan
## Online    0    1
##      0 1137  109
##      1 1588  166
```

```
table(train[,c(10)])
```

```
## 
##    0    1 
## 2725  275
```

```
probability1<-77/(77+198)
probability1
```

```
## [1] 0.28
```

```
probability2<-166/(166+109)
probability2
```

```
## [1] 0.6036364
```

```
probability3<-275/(275+2725)
probability3
```

```
## [1] 0.09166667
```

```
probability4<-801/(801+1924)
probability4
```

```
## [1] 0.293945
```

```
probability5<-1588/(1588+1137)
probability5
```

```
## [1] 0.5827523
```

```
probability6<-2725/(2725+275)
probability6
```

```
## [1] 0.9083333
```

#e. Use the quantities computed above to compute the naive Ba1 probability P(Loan = 1 | CC = 1, Online = 1)

```
(probability1*probability2*probability3)/((probability1*probability2*probability3)+(p
robability4*probability5*probability6))
```

```
## [1] 0.09055758
```

#f. Compare this value with the one obtained from the pivot table in (b). Which is a more accurate estimate?

9.05% are very similar to the 9.7% the difference between the exact method and the naive-baise method is the exact method would need the the exact same independent variable classifications to predict, where the naive bayes method does not.

#g. Which of the entries in this table are needed for computing P (Loan = 1 | CC = 1, Online = 1)? In R, run naive Bayes on the data. Examine the model output on training data, and find the entry that corresponds to P (Loan = 1 | CC = 1, Online = 1). Compare this to the number you obtained in (e).

```
naive.train = train.df[,c(10,13:14)]
naive.test = test.df[,c(10,13:14)]
naivebayes = naiveBayes(Personal.Loan~.,data=naive.train)
naivebayes
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##          0          1
## 0.90833333 0.09166667
##
## Conditional probabilities:
##    Online
## Y           0         1
##   0 0.4172477 0.5827523
##   1 0.3963636 0.6036364
##
##    CreditCard
## Y          0        1
##   0 0.706055 0.293945
##   1 0.720000 0.280000
```

the naive bayes is the exact same output we recieved in the previous methods. (.280)*(.603)* (.09)/(.280.*603*.09+.29.*58*.908) = .09 which is the same response provided as above.