Assignment 2

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summary

The assignment’s objective is to predict, using KNN(k-Nearest Neighbors)Classification, if the loan offer will be accepted by consumers of Universal Bank. The dataset contains demographic information about the clients as well as other confidential information. The required libraries are installed, the dataset is first read, and then unnecessary The data is eventually normalized after columns are removed and category categories are changed into dummy variables. The dataset was then divided into two sets, training and validation, with respective weights of 60% and 40%. data. A new customer was categorized as either accepting or rejecting a loan offer using k-NN with k=1. By measuring the balance between overfitting and underfitting, the ideal k value was found. accuracy on the test set, where k=3 is the best.

Problem Statement Universal bank is a young bank growing rapidly in terms of overall customer acquisition. The majority of these customers are liability customers (depositors) with varying sizes of relationship with the bank. The customer base of asset customers (borrowers) is quite small, and the bank is interested in expanding this baserapidly in more loan business. In particular, it wants to explore ways of converting its liability customers topersonal loan customers.

A campaign that the bank ran last year for liability customers showed a healthy conversion rate of over 9% success. This has encouraged the retail marketing department to devise smarter campaigns with better target marketing. The goal is to use k-NN to predict whether a new customer will accept a loan offer. This will serve as the basis for the design of a new campaign. The file UniversalBank.csv contains data on 5000 customers. The data include customer demographic information (age, income, etc.), the customer’s relationship with the bank (mortgage, securities account,etc.), and the customer response to the last personal loan campaign (Personal Loan). Among these 5000 customers, only 480 (= 9.6%) accepted the personal loan that was offered to them in the earlier campaign.

Partition the data into training (60%) and validation (40%) sets

install “class”,“caret”,“e1071” call the libraries “class”,“caret”,“e1071”

```
library(class)

library(caret)

## Loading required package: ggplot2

## Loading required package: lattice
```

```r
library(e1071)
```

Read the bank csv file

```r
c <- read.csv("C://Users//LENOVO//Desktop//universal banks//UniversalBank
(1).csv")
dim(c)
```

```
## [1] 5000   14
```

```r
head(c)
```

```
##   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
```

```r
t(t(names(c))) #transpose of the datafram
```

```
##       [,1]
##  [1,] "ID"
##  [2,] "Age"
##  [3,] "Experience"
##  [4,] "Income"
##  [5,] "ZIP.Code"
##  [6,] "Family"
##  [7,] "CCAvg"
##  [8,] "Education"
##  [9,] "Mortgage"
## [10,] "Personal.Loan"
## [11,] "Securities.Account"
## [12,] "CD.Account"
## [13,] "Online"
## [14,] "CreditCard"
```

Dropping “id” and “zip” attributes for the dataset

```r
new_data <-c[,-c(1,5)]
dim(new_data)
```

```
## [1] 5000   12
```

converting the education attribute from int to char

```r
new_data$Education <- as.factor(new_data$Education)
```

creating the dummy variables for the "education" attribute

```r
dummy <- dummyVars(~.,data=new_data)
the_data <- as.data.frame(predict(dummy,new_data))

set.seed(1)
train.data <- sample(row.names(the_data), 0.6*dim(the_data)[1])
valid.data <- setdiff(row.names(the_data),train.data)
train <- the_data[train.data,]
valid <- the_data[valid.data,]
t(t(names(train)))

##       [,1]
##  [1,] "Age"
##  [2,] "Experience"
##  [3,] "Income"
##  [4,] "Family"
##  [5,] "CCAvg"
##  [6,] "Education.1"
##  [7,] "Education.2"
##  [8,] "Education.3"
##  [9,] "Mortgage"
## [10,] "Personal.Loan"
## [11,] "Securities.Account"
## [12,] "CD.Account"
## [13,] "Online"
## [14,] "CreditCard"

summary(train)

##       Age          Experience        Income            Family     
##  Min.   :23.00   Min.   :-3.00   Min.   :  8.00   Min.   :1.000  
##  1st Qu.:36.00   1st Qu.:10.00   1st Qu.: 39.00   1st Qu.:1.000  
##  Median :45.00   Median :20.00   Median : 63.00   Median :2.000  
##  Mean   :45.43   Mean   :20.19   Mean   : 73.08   Mean   :2.388  
##  3rd Qu.:55.00   3rd Qu.:30.00   3rd Qu.: 98.00   3rd Qu.:3.000  
##  Max.   :67.00   Max.   :43.00   Max.   :224.00   Max.   :4.000  
##      CCAvg          Education.1      Education.2     Education.3    
##  Min.   : 0.000   Min.   :0.0000   Min.   :0.000   Min.   :0.0000  
##  1st Qu.: 0.700   1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000  
##  Median : 1.500   Median :0.0000   Median :0.000   Median :0.0000  
##  Mean   : 1.915   Mean   :0.4173   Mean   :0.285   Mean   :0.2977  
##  3rd Qu.: 2.500   3rd Qu.:1.0000   3rd Qu.:1.000   3rd Qu.:1.0000  
##  Max.   :10.000   Max.   :1.0000   Max.   :1.000   Max.   :1.0000  
##     Mortgage       Personal.Loan     Securities.Account   CD.Account     
##  Min.   :  0.00   Min.   :0.00000   Min.   :0.0000     Min.   :0.00000  
##  1st Qu.:  0.00   1st Qu.:0.00000   1st Qu.:0.0000     1st Qu.:0.00000  
```

```
##  Median :  0.00   Median :0.00000   Median :0.0000     Median :0.00000
##  Mean   : 57.34   Mean   :0.09167   Mean   :0.1003     Mean   :0.05367
##  3rd Qu.:102.00   3rd Qu.:0.00000   3rd Qu.:0.0000     3rd Qu.:0.00000
##  Max.   :635.00   Max.   :1.00000   Max.   :1.0000     Max.   :1.00000
##      Online          CreditCard
##  Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000
##  Median :1.0000   Median :0.0000
##  Mean   :0.5847   Mean   :0.2927
##  3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.0000
```

```
cat("The size of the training dataset is:",nrow(train))
```

```
## The size of the training dataset is: 3000
```

```
summary(valid)
```

```
##       Age          Experience        Income           Family
##  Min.   :23.0   Min.   :-3.00   Min.   :  8.00   Min.   :1.000
##  1st Qu.:35.0   1st Qu.:10.00   1st Qu.: 39.00   1st Qu.:1.000
##  Median :45.0   Median :20.00   Median : 64.00   Median :2.000
##  Mean   :45.2   Mean   :19.97   Mean   : 74.81   Mean   :2.409
##  3rd Qu.:55.0   3rd Qu.:30.00   3rd Qu.: 99.00   3rd Qu.:3.000
##  Max.   :67.0   Max.   :43.00   Max.   :218.00   Max.   :4.000
##      CCAvg          Education.1     Education.2     Education.3
##  Min.   : 0.000   Min.   :0.000   Min.   :0.000   Min.   :0.000
##  1st Qu.: 0.700   1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.000
##  Median : 1.600   Median :0.000   Median :0.000   Median :0.000
##  Mean   : 1.973   Mean   :0.422   Mean   :0.274   Mean   :0.304
##  3rd Qu.: 2.600   3rd Qu.:1.000   3rd Qu.:1.000   3rd Qu.:1.000
##  Max.   :10.000   Max.   :1.000   Max.   :1.000   Max.   :1.000
##     Mortgage       Personal.Loan    Securities.Account   CD.Account
##  Min.   :  0.00   Min.   :0.0000   Min.   :0.0000     Min.   :0.0000
##  1st Qu.:  0.00   1st Qu.:0.0000   1st Qu.:0.0000     1st Qu.:0.0000
##  Median :  0.00   Median :0.0000   Median :0.0000     Median :0.0000
##  Mean   : 55.24   Mean   :0.1025   Mean   :0.1105     Mean   :0.0705
##  3rd Qu.: 97.25   3rd Qu.:0.0000   3rd Qu.:0.0000     3rd Qu.:0.0000
##  Max.   :617.00   Max.   :1.0000   Max.   :1.0000     Max.   :1.0000
##      Online         CreditCard
##  Min.   :0.000   Min.   :0.000
##  1st Qu.:0.000   1st Qu.:0.000
##  Median :1.000   Median :0.000
##  Mean   :0.615   Mean   :0.296
##  3rd Qu.:1.000   3rd Qu.:1.000
##  Max.   :1.000   Max.   :1.000
```

```
cat("The size of the validation dataset is:",nrow(valid))
```

```
## The size of the validation dataset is: 2000
```

Normalizing the dataset

```
train.norm <- train[,-10]
valid.norm <- valid[,-10]
norm <- preProcess(train[,-10],method=c("center","scale"))
train.norm <- predict(norm,train[,-10])
valid.norm <- predict(norm,valid[,-10])
```

QUESTIONS Consider the following customer: 1. Age = 40, Experience = 10, Income = 84, Family = 2, CCAvg = 2, Education_1 = 0, Education_2 = 1, Education_3 = 0, Mortgage = 0, Securities Account = 0, CD Account = 0, Online = 1, and Credit Card = 1. Perform a k-NN classification with all predictors except ID and ZIP code using k = 1. Remember to transform categorical predictors with more than two categories into dummy variables first. Specify the success class as 1 (loan acceptance), and use the default cutoff value of 0.5. How would this customer be classified

Creating new customer data

```
new.cust <- data.frame(
Age = 40,
Experience = 10,
Income = 84,
Family = 2,
CCAvg = 2,
Education.1 = 0,
Education.2 = 1,
Education.3 = 0,
Mortgage = 0,
Securities.Account = 0,
CD.Account = 0,
Online = 1,
CreditCard = 1)
# Normalize the new customer dataset
cust.norm <- predict(norm, new.cust)
```

Performing the kNN classification

```
prediction <- class::knn(train = train.norm,
test = cust.norm,
cl = train$Personal.Loan, k = 1)
prediction

## [1] 0
## Levels: 0 1
```

2.What is a choice of k that balances between over fitting and ignoring the predictor information?

```
# Calculate the accuracy for each value of k
# Set the range of k values to consider
accuracy <- data.frame(k = seq(1, 15, 1), overallaccuracy = rep(0, 15))
```

```r
for(i in 1:15) {
kn <- class::knn(train = train.norm,
test = valid.norm,
cl = train$Personal.Loan, k = i)
accuracy[i, 2] <- confusionMatrix(kn,
as.factor(valid$Personal.Loan),positive = "1")$overall[1]
}
which(accuracy[,2] == max(accuracy[,2]))
```

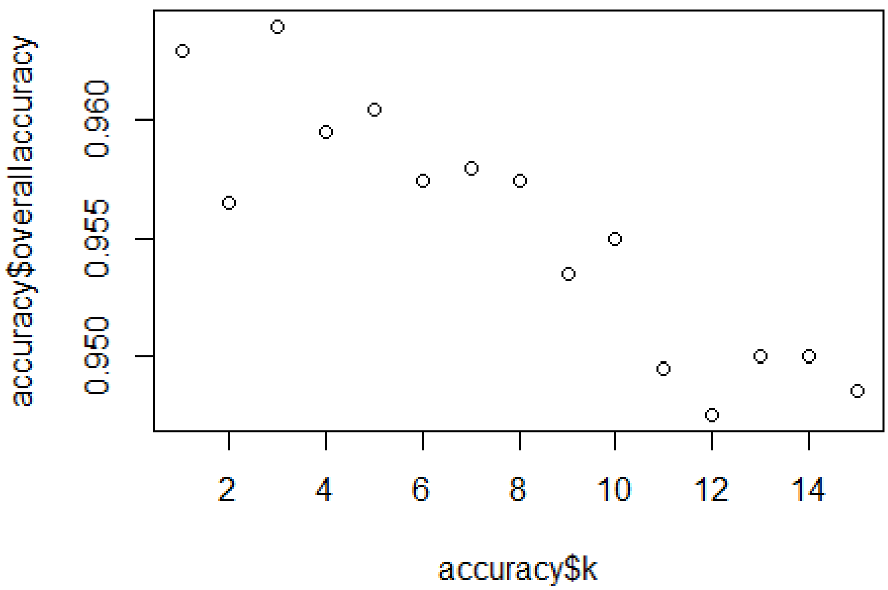
```
## [1] 3
```

```r
accuracy
```

```
##     k overallaccuracy
## 1   1          0.9630
## 2   2          0.9565
## 3   3          0.9640
## 4   4          0.9595
## 5   5          0.9605
## 6   6          0.9575
## 7   7          0.9580
## 8   8          0.9575
## 9   9          0.9535
## 10 10          0.9550
## 11 11          0.9495
## 12 12          0.9475
## 13 13          0.9500
## 14 14          0.9500
## 15 15          0.9485
```

The best performing k in the range of 1 to 15 is 3.This k balances overfitting and ignoring predictions, and it is the most accurate for 3

```r
plot(accuracy$k,accuracy$overallaccuracy)
```



3. Show the confusion matrix for the validation data that results from using the best k.
confusion matrix

```
pred <- class::knn(train = train.norm,
test = valid.norm,
cl = train$Personal.Loan, k=3)
confusionMatrix(pred,as.factor(valid$Personal.Loan))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1786   63
##          1    9  142
##
##                Accuracy : 0.964
##                  95% CI : (0.9549, 0.9717)
##     No Information Rate : 0.8975
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7785
##
##  Mcnemar's Test P-Value : 4.208e-10
##
##             Sensitivity : 0.9950
##             Specificity : 0.6927
##          Pos Pred Value : 0.9659
```

```
##          Neg Pred Value : 0.9404
##              Prevalence : 0.8975
##          Detection Rate : 0.8930
##    Detection Prevalence : 0.9245
##       Balanced Accuracy : 0.8438
##
##        'Positive' Class : 0
##
```

4. Consider the following customer: Age = 40, Experience = 10, Income = 84,Family = 2, CCAvg = 2, Education_1 = 0, Education_2 = 1, Education_3 = 0,Mortgage = 0, Securities Account = 0, CD Account = 0, Online = 1 and CreditCard = 1. Classify the customer using the best k.

Now creating the second new customer dataset

```
customer2.df <- data.frame(
Age = 40,
Experience = 10,
Income = 84,
Family = 2,
CCAvg = 2,
Education.1 = 0,
Education.2 = 1,
Education.3 = 0,
Mortgage = 0,
Securities.Account = 0,
CD.Account = 0,
Online = 1,
CreditCard = 1)
#Normalizing the 2nd customer dataset
cust_norm2 <- predict(norm , customer2.df)
```

Question-5: Repeating the process by partitioning the data into three parts -50%, 30%, 20%,Apply the k-NN method with the k chosen above. Compare the confusion matrix of the test set with that of the training and validation sets. Comment on the differences and their reason.

```
set.seed(600)
Train_Index <- sample(row.names(the_data), .5*dim(the_data)[1])#create train
index

#create validation index
Val_Index <-
sample(setdiff(row.names(the_data),Train_Index),.3*dim(the_data)[1])
Test_Index =setdiff(row.names(the_data),union(Train_Index,Val_Index))#create
test index
train.df <- the_data[Train_Index,]
cat("The size of the new training dataset is:", nrow(train.df))

## The size of the new training dataset is: 2500
```

```r
valid.df <- the_data[Val_Index, ]
cat("The size of the new validation dataset is:", nrow(valid.df))

## The size of the new validation dataset is: 1500

test.df <- the_data[Test_Index, ]
cat("The size of the new test dataset is:", nrow(test.df))

## The size of the new test dataset is: 1000
```

Data Normalizing

```r
norm.values <- preProcess(train.df[, -10], method=c("center", "scale"))
train.df.norm <- predict(norm.values, train.df[, -10])
valid.df.norm <- predict(norm.values, valid.df[, -10])
test.df.norm <- predict(norm.values, test.df[,-10])
```

Performing kNN and creating the confusion matrix on training, testing, validation data

```r
pred3 <- class::knn(train = train.df.norm,
test = test.df.norm,
cl = train.df$Personal.Loan, k=3)
confusionMatrix(pred3,as.factor(test.df$Personal.Loan))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 900  33
##          1   6  61
##
##                Accuracy : 0.961
##                  95% CI : (0.9471, 0.9721)
##     No Information Rate : 0.906
##     P-Value [Acc > NIR] : 2.125e-11
##
##                   Kappa : 0.7372
##
##  Mcnemar's Test P-Value : 3.136e-05
##
##             Sensitivity : 0.9934
##             Specificity : 0.6489
##          Pos Pred Value : 0.9646
##          Neg Pred Value : 0.9104
##              Prevalence : 0.9060
##          Detection Rate : 0.9000
##    Detection Prevalence : 0.9330
##       Balanced Accuracy : 0.8212
##
##        'Positive' Class : 0
##
```

```r
pred4 <- class::knn(train = train.df.norm,
test = valid.df.norm,
cl = train.df$Personal.Loan, k=3)
confusionMatrix(pred4,as.factor(valid.df$Personal.Loan))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1339   57
##          1    6   98
##
##                Accuracy : 0.958
##                  95% CI : (0.9466, 0.9676)
##     No Information Rate : 0.8967
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7347
##
##  Mcnemar's Test P-Value : 2.988e-10
##
##             Sensitivity : 0.9955
##             Specificity : 0.6323
##          Pos Pred Value : 0.9592
##          Neg Pred Value : 0.9423
##              Prevalence : 0.8967
##          Detection Rate : 0.8927
##    Detection Prevalence : 0.9307
##       Balanced Accuracy : 0.8139
##
##        'Positive' Class : 0
##
```

```r
pred4 <- class::knn(train = train.df.norm,
test = valid.df.norm,
cl = train.df$Personal.Loan, k=3)
confusionMatrix(pred4,as.factor(valid.df$Personal.Loan))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1339   57
##          1    6   98
##
##                Accuracy : 0.958
##                  95% CI : (0.9466, 0.9676)
##     No Information Rate : 0.8967
##     P-Value [Acc > NIR] : < 2.2e-16
##
```

```
##                    Kappa : 0.7347
##
##  Mcnemar's Test P-Value : 2.988e-10
##
##             Sensitivity : 0.9955
##             Specificity : 0.6323
##          Pos Pred Value : 0.9592
##          Neg Pred Value : 0.9423
##              Prevalence : 0.8967
##          Detection Rate : 0.8927
##    Detection Prevalence : 0.9307
##       Balanced Accuracy : 0.8139
##
##        'Positive' Class : 0
##
```