Assignment_2

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Summary This problem explains the structure of customer data and relationship between customer and bank. In R I used the k-NN to predict whether a new customer will accept a personal loan for Universal bank. This predictive model serves the basis of designing a campaign to target the potential loan customers more effectively. The choice of K should be based on the characteristics of data and the problem we are trying to solve. If the value is small the model become sensitive to noise and out liners in data and it can be too complex and closely to the data. If it is an intermediate value the over fitting and ignoring information balanced.

Confusion matrix for the validation data needs the actual class labels and predicted class labels based on k-NN models.

So I would like to add some info about this problems

- Train has a higher accuracy of 0.9772 when it compared to Test 0.9507
- Train has higher sensitivity of 0.7589 when it compared to Test 0.5875 (TPR)
- This indicates that Train's model is correct and identifying positive cases. It may have lower false negative rate
- The higher specificity is 0.9987 when compared to Test 0.99403

These above information were collected from the result of implementation and execution in R

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 base rapidly in more loan business. In particular, it wants to explore ways of converting its liability customers to personal 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.

Load required libraries

```
library(class)
library(caret)
```

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

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

```
library(e1071)
library(knitr)
```

```
universal.df <- read.csv("D:/FUNDAMENTAL OF MACHINE LEARNING/Assignment_2/UniversalBank.csv")
dim(universal.df)
```

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

```
t(t(names(universal.df))) # The t function creates a transpose of the data frame
```

```
##       [,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"
```

```
universal.df <- universal.df[,-c(1,5)]

# Only Education needs to be converted to factor

universal.df$Education <- as.factor(universal.df$Education)

# Now, convert Education to Dummy Variables

groups <- dummyVars(~., data = universal.df) # This creates the dummy groups

universal_m.df <- as.data.frame(predict(groups,universal.df))
```

Split the data into 60% on training and 40 % on Validation

```
set.seed(1)  # Important to ensure that we get the same sample if we rerun the code
train.index <- sample(row.names(universal_m.df), 0.6*dim(universal_m.df)[1])
valid.index <- setdiff(row.names(universal_m.df), train.index)
train.df <- universal_m.df[train.index,]
valid.df <- universal_m.df[valid.index,]
t(t(names(train.df)))
```

```
##       [,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"
```

Normalize the data

```
train.norm.df <- train.df[,-10] # Note that Personal Income is the 10th variable
valid.norm.df <- valid.df[,-10]

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

Question (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?

We have converted all categorical variables to dummy variables

Now create a new sample

```
new_customer <- 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

```
new.cust.norm <- new_customer
new.cust.norm <- predict(norm.values, new.cust.norm)
```

Predict using K-NN(k- Nearest neighbors)

```
knn.pred1 <- class::knn(train = train.norm.df,
                       test = new.cust.norm,
                       cl = train.df$Personal.Loan, k = 1)
knn.pred1
```

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

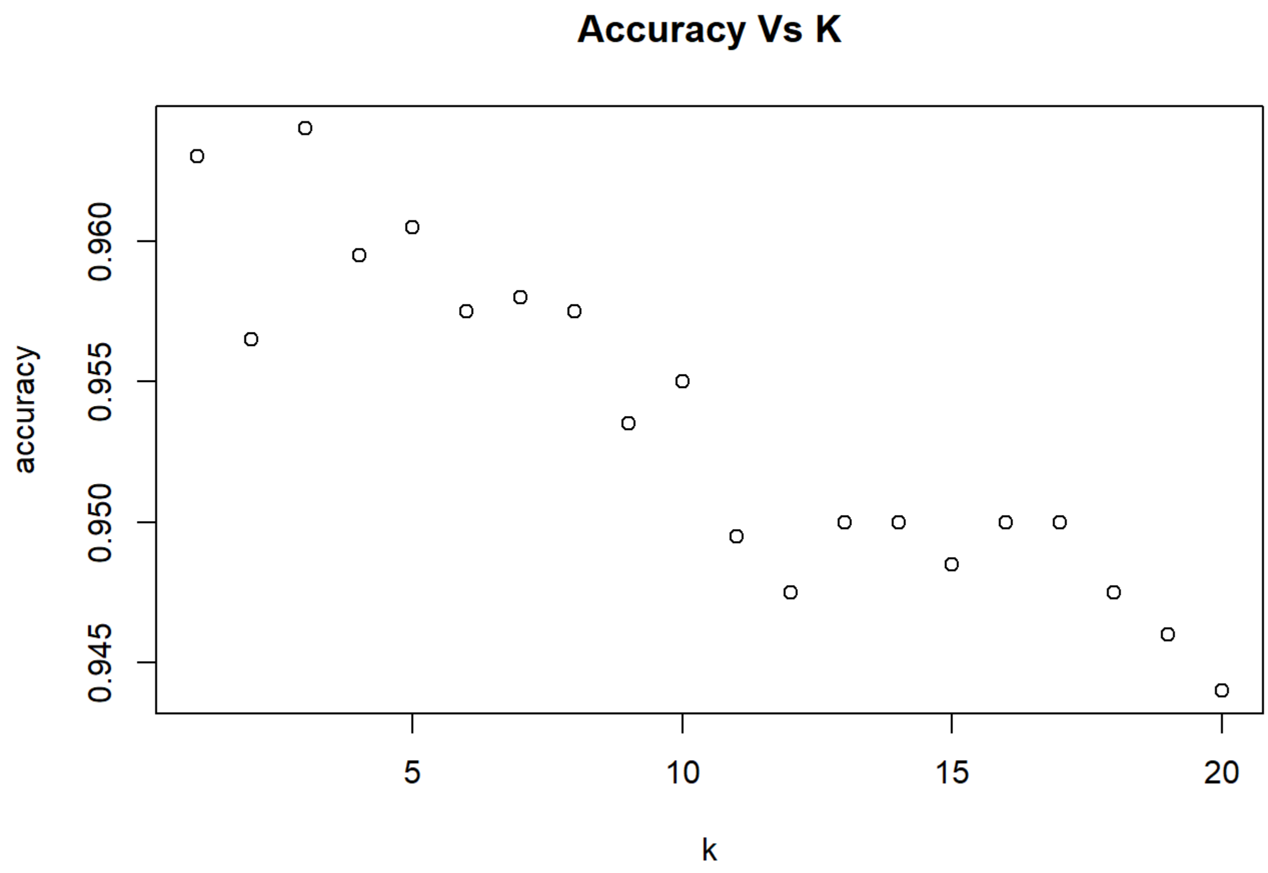
Question (2)

What is a choice of k that balances between overfitting and ignoring the predictor information? # Calculate the accuracy for each value of k
Set the range of k values to consider

```
accuracy.df <- data.frame(k = seq(1, 20, 1), overallaccuracy = rep(0, 20))
for(i in 1:20)
  {knn.pred <- class::knn(train = train.norm.df,
                         test = valid.norm.df,
                         cl = train.df$Personal.Loan, k = i)
  accuracy.df[i, 2] <- confusionMatrix(knn.pred,as.factor(valid.df$Personal.Loan),positive =
"1")$overall[1]
}
which(accuracy.df[,2] == max(accuracy.df[,2]))
```

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

```
plot(accuracy.df$k,accuracy.df$overallaccuracy, main = "Accuracy Vs K", xlab = "k", ylab = "a
ccuracy")
```



Question (3)

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

Confusion Matrix using best K=3

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

confusionMatrix(knn.pred,as.factor(valid.df$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
##
```

Question (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, C
D Account = 0, Online = 1 and Credit Card = 1. Classify the customer using the best k.
```

Load new customer profile

```
new_customer2<-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,
  CDAccount = 0,
  Online = 1,
  CreditCard = 1)
```

```
knn.pred1 <- class::knn(train = train.norm.df,
                        test = new.cust.norm,
                        cl = train.df$Personal.Loan, k = 3)
knn.pred1
```

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

Print the predicted class (1 for loan acceptance, 0 for loan rejection)

```
print("This customer is classified as: Loan Rejected")
```

```
## [1] "This customer is classified as: Loan Rejected"
```

Question (5)

```
 Repartition the data, this time into training, validation, and test sets (50% : 30% : 20%).
Apply the k-NN method with the k chosen above. Compare the confusion matrix of the test set w
ith that of the training and validation sets. Comment on the differences and their reason.
```

Split the data into 50% training and 30% Validation and 20% Testing

```
set.seed(1)
Train_Index1 <- sample(row.names(universal_m.df), 0.5*dim(universal_m.df)[1])
Val_Index1 <- sample(setdiff(row.names(universal_m.df),Train_Index1),0.3*dim(universal_m.df)
[1])
Test_Index1 <-setdiff(row.names(universal_m.df),union(Train_Index1,Val_Index1))
Train_Data <- universal_m.df[Train_Index1,]
Validation_Data <- universal_m.df[Val_Index1,]
Test_Data <- universal_m.df[Test_Index1,]
```

normalize the data

```
train.norm.df1 <- Train_Data[,-10]
valid.norm.df1 <- Validation_Data[,-10]
Test.norm.df1  <-Test_Data[,-10]

norm.values1 <- preProcess(Train_Data[, -10], method=c("center", "scale"))
train.norm.df1 <- predict(norm.values1, Train_Data[,-10])
valid.norm.df1 <- predict(norm.values1, Validation_Data[,-10])
Test.norm.df1 <-predict(norm.values1,Test_Data[,-10])
```

Predict using K-NN(k- Nearest neighbors)

```
validation_knn = class::knn(train = train.norm.df1,
                           test = valid.norm.df1,
                           cl = Train_Data$Personal.Loan,
                           k = 3)

test_knn = class::knn(train = train.norm.df1,
                     test = Test.norm.df1,
                     cl = Train_Data$Personal.Loan,
                     k = 3)

Train_knn = class::knn(train = train.norm.df1,
                     test = train.norm.df1,
                     cl = Train_Data$Personal.Loan,
                     k = 3)
```

Validation confusion Matrix

```
validation_confusion_matrix = confusionMatrix(validation_knn,
                                               as.factor(Validation_Data$Personal.Loan),
                                               positive = "1")

validation_confusion_matrix
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1358   42
##          1    6   94
##
##                Accuracy : 0.968
##                  95% CI : (0.9578, 0.9763)
##     No Information Rate : 0.9093
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7797
##
##  Mcnemar's Test P-Value : 4.376e-07
##
##             Sensitivity : 0.69118
##             Specificity : 0.99560
##          Pos Pred Value : 0.94000
##          Neg Pred Value : 0.97000
##              Prevalence : 0.09067
##          Detection Rate : 0.06267
##    Detection Prevalence : 0.06667
##       Balanced Accuracy : 0.84339
##
##        'Positive' Class : 1
##
```

Test confusion Matrix

```
test_confusion_matrix = confusionMatrix(test_knn,
                                         as.factor(Test_Data$Personal.Loan),
                                         positive = "1")


test_confusion_matrix
```

```
## Confusion Matrix and Statistics
## 
##           Reference
## Prediction   0   1
##          0 884  35
##          1   4  77
##                                          
##                Accuracy : 0.961          
##                  95% CI : (0.9471, 0.9721)
##     No Information Rate : 0.888          
##     P-Value [Acc > NIR] : < 2.2e-16      
##                                          
##                   Kappa : 0.777          
##                                          
##  Mcnemar's Test P-Value : 1.556e-06      
##                                          
##             Sensitivity : 0.6875         
##             Specificity : 0.9955         
##          Pos Pred Value : 0.9506         
##          Neg Pred Value : 0.9619         
##              Prevalence : 0.1120         
##          Detection Rate : 0.0770         
##    Detection Prevalence : 0.0810         
##       Balanced Accuracy : 0.8415         
##                                          
##        'Positive' Class : 1              
## 
```

```
Training_confusion_matrix = confusionMatrix(Train_knn,
                                               as.factor(Train_Data$Personal.Loan),
                                               positive = "1")

Training_confusion_matrix
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2263   54
##          1    5  178
##
##                Accuracy : 0.9764
##                  95% CI : (0.9697, 0.982)
##     No Information Rate : 0.9072
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8452
##
##  Mcnemar's Test P-Value : 4.129e-10
##
##             Sensitivity : 0.7672
##             Specificity : 0.9978
##          Pos Pred Value : 0.9727
##          Neg Pred Value : 0.9767
##              Prevalence : 0.0928
##          Detection Rate : 0.0712
##    Detection Prevalence : 0.0732
##       Balanced Accuracy : 0.8825
##
##        'Positive' Class : 1
##
```