Assignment 2 (FML)

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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.

Questions - Answers

1. How would this customer be classified? This new customer would be classified as 0, does not take the personal loan
2. The best K is 3

Data Import and Cleaning

First, load the required libraries

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

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

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

```
library(e1071)
```

Read the data

```
universal.df <- read.csv("C:/Users/manus/OneDrive/Desktop/FML ASSIGNMENTS/2/UniversalBank.csv")
dim(universal.df)
```

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

```
t(t(names(universal.df)))
```

```
##       [,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"
```

```
# The t function creates a transpose of the dataframe
```

Drop ID and ZIP

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

Split Data into 60% training and 40% validation. There are many ways to do this. We will look at 2 different ways. Before we split, let us transform categorical variables into dummy variables

```
# 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))
```

```
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"
```

```
# Second approach
library(caTools)
set.seed(1)
split <- sample.split(universal_m.df, SplitRatio = 0.6)
training_set <- subset(universal_m.df, split == TRUE)
validation_set <- subset(universal_m.df, split == FALSE)

# Print the sizes of the training and validation sets
print(paste("The size of the training set is:", nrow(training_set)))
```

```
## [1] "The size of the training set is: 2858"
```

```
print(paste("The size of the validation set is:", nrow(validation_set)))
```

```
## [1] "The size of the validation set is: 2142"
```

Now, let us 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])
```

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?

```r
# Let's 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)

# Now, let us predict using knn
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
```

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

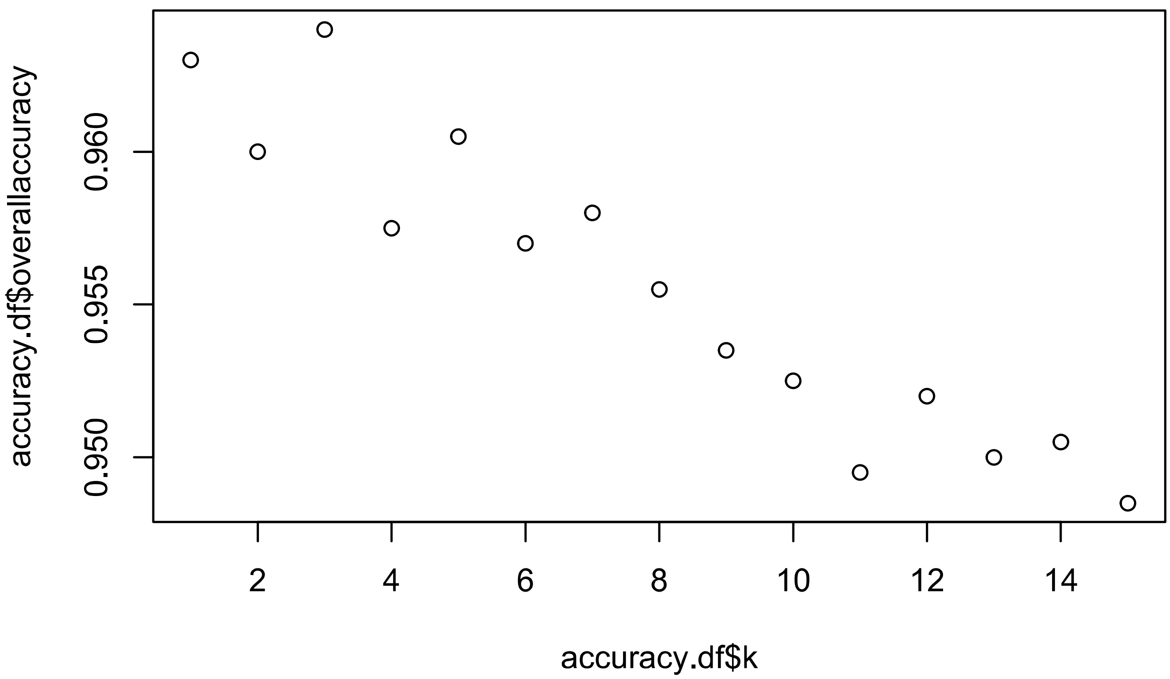
```r
# Calculate the accuracy for each value of k
# Set the range of k values to consider

accuracy.df <- data.frame(k = seq(1, 15, 1), overallaccuracy = rep(0, 15))
for(i in 1:15) {
  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
```

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



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

```r
# Finding the best k value
best_k <- which.max(accuracy.df$overallaccuracy)

# Use the best k value to make predictions on the validation data
best_k_pred <- class::knn(train = train.norm.df,
                         test = valid.norm.df,
                         cl = train.df$Personal.Loan, k = best_k)

# confusion matrix
confusion_matrix <- confusionMatrix(best_k_pred,
                                    as.factor(valid.df$Personal.Loan),
                                    positive = "1")
confusion_matrix
```

```
## 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 : 0.6927
##             Specificity : 0.9950
##          Pos Pred Value : 0.9404
##          Neg Pred Value : 0.9659
##              Prevalence : 0.1025
##          Detection Rate : 0.0710
##    Detection Prevalence : 0.0755
##       Balanced Accuracy : 0.8438
##
##        'Positive' Class : 1
##
```

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 Credit Card = 1. Classify the customer using the best k.

```r
# Assume the best k is 3
best_k <- 3

# Loading new customer's information
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's data
new_customer_norm <- predict(norm.values, new_customer)

# Use k = 3 to make predictions for the new customer
best_k_pred_new_customer <- class::knn(train = train.norm.df,
                                       test = new_customer_norm,
```

```r
                                            cl = train.df$Personal.Loan,
                                              k = best_k)

# Print the classification result
best_k_pred_new_customer
```

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

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 setwith that of the training and validation sets. Comment on the differences and their reason.

```r
# spliting the data to 50% training, 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])

# Now let us predict using K-NN

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),
```

```r
         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
##
```

```r
# Confusion Matrix for test set

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
##
```

```
# Confusion matrix for training set

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
##
```

Difference

##Test vs.Train:

Accuracy: Train has a higher accuracy compared to Test.

Reason: This because of differences in the datasets used for evaluation. Train may have a more balanced or easier-to-predict dataset.

Sensitivity (True Positive Rate): Train has higher sensitivity compared to Test.

Reason: This indicates that Train's model is better at correctly identifying positive cases (e.g., loan acceptances). It may have a lower false negative rate.

Specificity (True Negative Rate): Train has higher specificity compared to Test.

Reason: This suggests that Train's model is better at correctly identifying negative cases (e.g., loan rejections). It may have a lower false positive rate.

Positive Predictive Value (Precision): Train has a higher positive predictive value compared to Test.

Reason: Train's model is more precise in predicting positive cases, resulting in fewer false positive predictions.

Train vs.Vlidation:

Accuracy: Train still has a higher accuracy compared to Validation.

Reason: Similar to the comparison with Test, Train may have a more balanced or easier-to-predict dataset.

Sensitivity (True Positive Rate): Train has higher sensitivity compared to Validation.

Reason: Train's model is better at correctly identifying positive cases. This indicates that Validation's model may have a higher false negative rate.

Specificity (True Negative Rate): Train has higher specificity compared to Validation.

Reason: Train's model is better at correctly identifying negative cases. Validation's model may have a slightly higher false positive rate.

Positive Predictive Value (Precision): Train still has a higher positive predictive value compared to Validation.

Reason: Train's model is more precise in predicting positive cases, resulting in fewer false positive predictions.

Reasons for Differences:

Data set Differences: Variations in the composition and distribution of data between different sets can significantly impact model performance. For illustration, one data set may be more imbalanced, making it harder to prognosticate rare events.

Model Variability: Differences in model configurations or arbitrary initialization of model parameters can lead to variations in performance.

Hyperparameter Tuning: Different hyper parameter settings, similar as the choice of k in k- NN or other model-specific parameters, can affect model performance.

Sample Variability: In small data sets, variations in the specific samples included in the confirmation and test sets can impact performance criteria .

Randomness: Some models, similar as neural networks, involve randomness in their optimization process, leading to slight variations.