FML_Assignment_2

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#Summary

1) If the new client does not obtain a personal loan, it would be counted as zero.
2) K=3 provides the ideal balance between disregarding predictor information and overfitting.
3) The confusion matrix for the validation data, which used the best K and parameters like TP=142, TN=1786, FP=63, and FN=9 with accuracy of 0.964, can be found below.
4) The customer would be categorized as 0, declines the personal loan after using the best K.

Due to the distinct functions and properties of training, validation, and test sets, differences in confusion matrices should be anticipated. Disparities could be a sign of possible problems like over fitting or different data collection.

It's essential to keep an eye on these variations and make corrections to guarantee that the model generalizes effectively to new data.

Over fitting: A model may perform remarkably well on training data but poorly on fresh data if it fits the training data too closely.

Variability: There may be small differences in performance metrics between the validation and test sets due to randomness in the data and the model training process.

Data Representatives: Performance variations may occur if the test or validation sets are not representative of the total distribution of data.

##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

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###Data Import and Cleaning

First, loading the libraries

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

```
## Loading required package: ggplot2

## Loading required package: lattice
```

```
library(e1071)
```

#Read the data.

```
universal.df <- read.csv("C:/Users/user/OneDrive/Documents/UniversalBank (2).csv")
dim(universal.df)
```

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

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

```
##       [,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"
```

```
getwd()
```

```
## [1] "C:/Users/user/Downloads/Assignment_1_FML/Assignment_2"
```

#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

```r
# Education needs to be converted to factor
universal.df$Education <- as.factor(universal.df$Education)

# Now, Assigning 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"
```

#Now, let us normalize the data

```r
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])
```

###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?

```
# We have converted all categorical variables to dummy variables
# 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
```

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

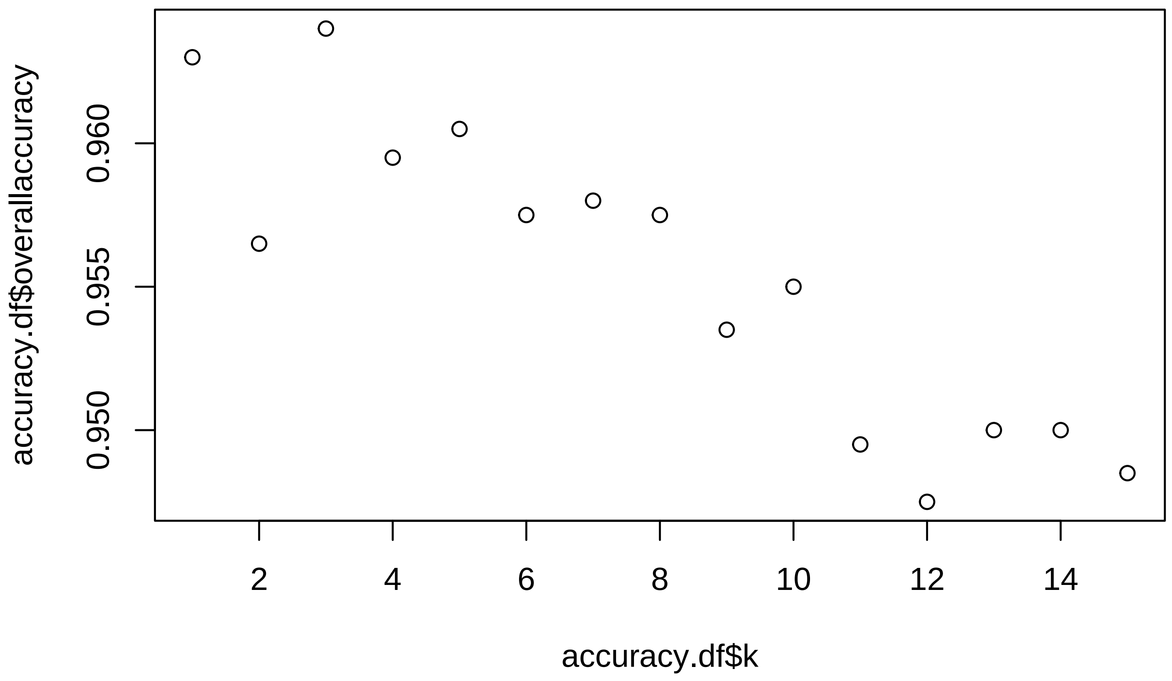
```
# Calculate the accuracy for each value of k
# Set the range of k values to consider

accuracy.df <- data.frame(k = seq(1, 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
```

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



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

```
# Based on validation accuracy, displaying the best k

best_k <- which(accuracy.df$overallaccuracy == max(accuracy.df$overallaccuracy))

# To classify the validation data, choose the best k

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

# Creating a confusion matrix
conf_matrix <- confusionMatrix(knn.pred_best,
                               as.factor(valid.df$Personal.Loan), positive = "1")

# Displaying it
conf_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
# Make a data frame with the same column names for the new customer
# Make a data frame with appropriate column names for the new client.
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,  # If a column name contains a space, use backticks.
  `CD Account` = 0,
  Online = 1,
  `Credit Card` = 1
)

# The same preprocessing should be used to normalize the new customer data.
```

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

# Predict whether customer accepts the loan using the best k
new_customer_classification <- class::knn(train = train.norm.df,
                                          test = new.cust.norm,
                                          cl = train.df$Personal.Loan, k = best_k)

# Displaying the classification result
new_customer_classification
```

```
## [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 set with that of the training and validation sets. Comment on the differences and their reason.

#Comment on the differences and their reason:

Due to the distinct functions and properties of training, validation, and test sets, differences in confusion matrices should be anticipated.

Disparities could be a sign of possible problems like overfitting or different data collection.

It's essential to keep an eye on these variations and make corrections to guarantee that the model generalizes effectively to new data.

```r
# Setting  the seed for reproducibility
set.seed(1)

# Divide the data into sets for training (50%) and validation (30%) and test (20%).

train.index <- sample(1:nrow(universal_m.df), 0.5 * nrow(universal_m.df))
valid.test.index <- setdiff(1:nrow(universal_m.df), train.index)
valid.index <- sample(valid.test.index, 0.3 * length(valid.test.index))
test.index <- setdiff(valid.test.index, valid.index)

train.df <- universal_m.df[train.index, ]
valid.df <- universal_m.df[valid.index, ]
test.df <- universal_m.df[test.index, ]

# Normalize the data for each set

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])
test.norm.df <- predict(norm.values, test.df[, -10])

# Using the best k classifying the data
knn.pred_train <- class::knn(train = train.norm.df,
                             test = train.norm.df,
                             cl = train.df$Personal.Loan, k = best_k)
```

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

knn.pred_test <- class::knn(train = train.norm.df,
                            test = test.norm.df,
                            cl = train.df$Personal.Loan, k = best_k)

# Creating confusion matrices for every set

conf_matrix_train <- confusionMatrix(knn.pred_train,
                                     as.factor(train.df$Personal.Loan), positive = "1")

conf_matrix_valid <- confusionMatrix(knn.pred_valid,
                                     as.factor(valid.df$Personal.Loan), positive = "1")

conf_matrix_test <- confusionMatrix(knn.pred_test,
                                    as.factor(test.df$Personal.Loan), positive = "1")

# Display the confusion matrices

conf_matrix_train
```

```
## 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
##
```

```
conf_matrix_valid
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 678  20
##          1   5  47
##
##                Accuracy : 0.9667
##                  95% CI : (0.9512, 0.9783)
##     No Information Rate : 0.9107
##     P-Value [Acc > NIR] : 1.009e-09
##
##                   Kappa : 0.7721
##
##  Mcnemar's Test P-Value : 0.00511
##
##             Sensitivity : 0.70149
##             Specificity : 0.99268
##          Pos Pred Value : 0.90385
##          Neg Pred Value : 0.97135
##              Prevalence : 0.08933
##          Detection Rate : 0.06267
##    Detection Prevalence : 0.06933
##       Balanced Accuracy : 0.84709
##
##        'Positive' Class : 1
##
```

```
conf_matrix_test
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1564   57
##          1    5  124
##
##                Accuracy : 0.9646
##                  95% CI : (0.9548, 0.9727)
##     No Information Rate : 0.8966
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7812
##
##  Mcnemar's Test P-Value : 9.356e-11
##
##             Sensitivity : 0.68508
##             Specificity : 0.99681
##          Pos Pred Value : 0.96124
##          Neg Pred Value : 0.96484
##              Prevalence : 0.10343
##          Detection Rate : 0.07086
##    Detection Prevalence : 0.07371
##       Balanced Accuracy : 0.84095
##
##        'Positive' Class : 1
##
```