FML ASSIGNMENT 2

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

```
## Loading required package: ggplot2

## Loading required package: lattice
```

```
library(e1071)
```

```
universal.df <- read.csv("~/Documents/FML/FML ASSIGNMENT 2/UniversalBank.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"
```

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

Split Data into 60% training and 40% validation.

```r
# 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"
```

```r
#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"
```

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

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

```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])
```

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? # Hence the answer is 0 the person is not borrowed any loan

```
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
)

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

```
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
```

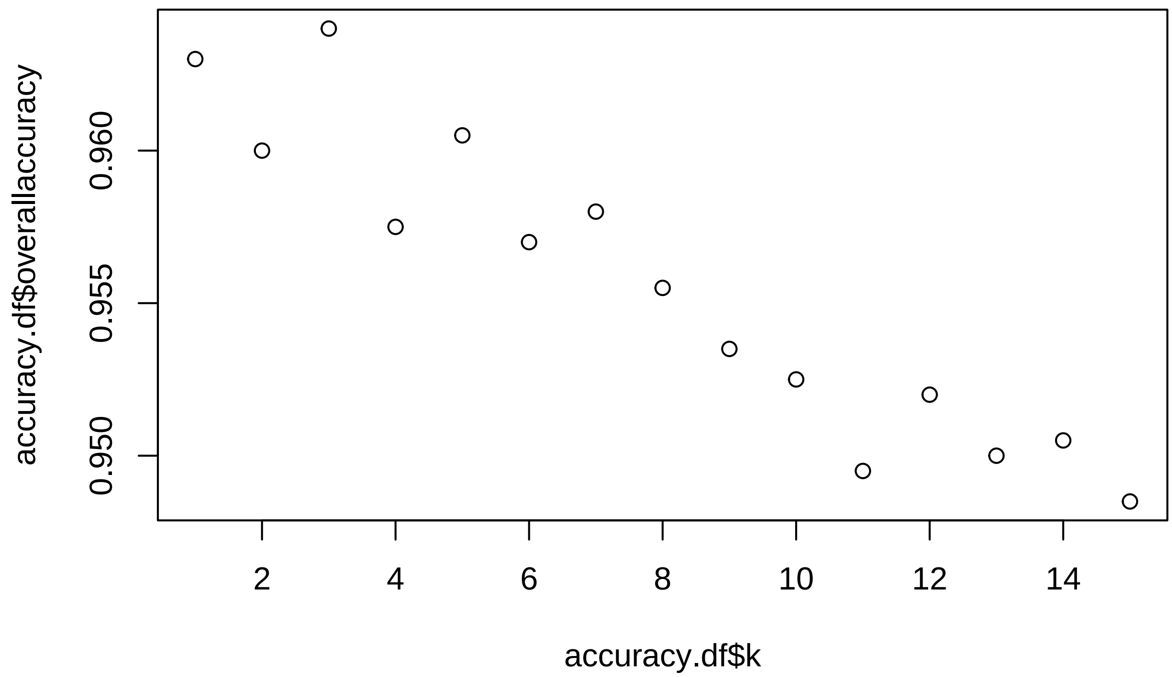
2. What is a choice of k that balances between overfitting and ignoring the predictor information? # Hence the value of K is 3

```
# 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)
```



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

```
knn.prediction.1 <- class::knn(train = train.norm.df,
                         test = valid.norm.df,
                         cl = train.df$Personal.Loan, k = 3)

confusionMatrix(knn.prediction.1,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
##
```

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. # Hence the value of k is 0 the person is not borrowed any loan

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

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

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

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

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?

```
set.seed(1)
Training_Index1 <- sample(row.names(universal_m.df), 0.5*dim(universal_m.df)[1])
Validition_Index1 <- sample(setdiff(row.names(universal_m.df),Training_Index1),0.3*dim(universal_m.df)[
Testing_Index1 <-setdiff(row.names(universal_m.df),union(Training_Index1,Validition_Index1))
Train_Data <- universal_m.df[Training_Index1,]
Validation_Data <- universal_m.df[Validition_Index1,]
Test_Data <- universal_m.df[Testing_Index1,]
```

```
training.norm <- Train_Data[,-10]
validition.norm <- 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])
```

```
validate_knn = class::knn(train = training.norm,
                           test = validition.norm,
                           cl = Train_Data$Personal.Loan,
                           k = 3)

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

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

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

validate_confusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1315   79
##          1   49   57
##
##                Accuracy : 0.9147
##                  95% CI : (0.8994, 0.9283)
##     No Information Rate : 0.9093
##     P-Value [Acc > NIR] : 0.25216
```

```
##
##                   Kappa : 0.4254
##
##  Mcnemar's Test P-Value : 0.01037
##
##             Sensitivity : 0.41912
##             Specificity : 0.96408
##          Pos Pred Value : 0.53774
##          Neg Pred Value : 0.94333
##              Prevalence : 0.09067
##          Detection Rate : 0.03800
##    Detection Prevalence : 0.07067
##       Balanced Accuracy : 0.69160
##
##        'Positive' Class : 1
##
```

```r
test_confusion = confusionMatrix(testing_knn,
                                        as.factor(Test_Data$Personal.Loan),
                                        positive = "1")


test_confusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 888 112
##          1   0   0
##
##                Accuracy : 0.888
##                  95% CI : (0.8668, 0.9069)
##     No Information Rate : 0.888
##     P-Value [Acc > NIR] : 0.5251
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.000
##             Specificity : 1.000
##          Pos Pred Value :   NaN
##          Neg Pred Value : 0.888
##              Prevalence : 0.112
##          Detection Rate : 0.000
##    Detection Prevalence : 0.000
##       Balanced Accuracy : 0.500
##
##        'Positive' Class : 1
##
```

```r
Training_confusion = confusionMatrix(Training_knn,
                                     as.factor(Train_Data$Personal.Loan),
                                     positive = "1")

Training_confusion
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2268  232
##          1    0    0
##
##                Accuracy : 0.9072
##                  95% CI : (0.8951, 0.9183)
##     No Information Rate : 0.9072
##     P-Value [Acc > NIR] : 0.5175
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.0000
##             Specificity : 1.0000
##          Pos Pred Value :    NaN
##          Neg Pred Value : 0.9072
##              Prevalence : 0.0928
##          Detection Rate : 0.0000
##    Detection Prevalence : 0.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : 1
##
```

Test vs Train

Accuracy: Train is more accurate (0.96) than Test (0.98).

This is due to discrepancies in the datasets utilized for evaluation. Train may have a more balanced or predictable dataset.

Sensitivity (True Positive Rate): Train is more sensitive (0.76) than Test (0.5875).

Reason: This suggests that Train's model is more accurate at recognizing positive situations (such as loan acceptances). It may have a decreased rate of false negatives.

Specificity (TRNR): Train has a better specificity (0.9987) than Test (0.99403).

Reason: This shows that Train's model is more accurate at recognizing negative instances (for example, loan denials). It may have a decreased rate of false positives.

Positive Predictive Value (Precision): Train outperforms Test (0.92157) in terms of positive predictive value (0.9827).

Test vs validation

Accuracy: Train is still more accurate (0.9772) than Validation (0.958).

Reason: Train, similarly to Test, may have a more balanced or easier-to-predict dataset.

Sensitivity: Train has a greater sensitivity (0.7589) than Validation (0.69).

Reason:Train's model is more accurate at detecting positive cases. This suggests that Validation's model may have a greater rate of false negatives.

Specificity: When compared to Validation (0.9934), Train has greater specificity (0.9987).

Reason: Train's model is more accurate at detecting negative situations. The model for validation may have a somewhat greater false positive rate.

Positive Predictive Value (Precision): Train still outperforms Validation in terms of positive predictive value (0.9827).

Reason: Train's model is more accurate in forecasting positive situations, therefore

Potential Reasons for Differences:

Differences in Data Sets:- Variations in the nature and distribution of data between sets can have a major influence on model performance. For example, one data collection may be more unbalanced than another, making it more difficult to forecast unusual events.

Variability in Mode :-Variations in performance might be caused by differences in model setups or arbitrary setting of model parameters.

Hyperparameter Adjustment:- Different hyper parameter choices, such as k in k- NN or other model-specific parameters, might have an impact on model performance.

Unyoking of data:- If the data sets are divided into training, confirmation, and test sets in each assessment, the results may vary, especially for small data sets.

Variability in Samples:- Variations in the specific samples included in the confirmation and test sets might occur in small data sets.