FML ASSIGNMENT 2

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2023-10-05

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.

# 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"

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

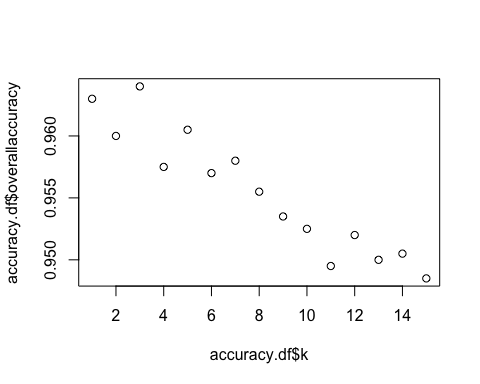
## [1] 0  
## Levels: 0 1

1. 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)



1. 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   
##

1. 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)[1])  
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   
##

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   
##

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.