FML Assignment-2

Rashed Syed

2023-10-22

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

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

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

```
library(e1071)
```

Read the data.

```
universal.df <- read.csv("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"
```

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
# 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"
```

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?

```r
# 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

```r
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?

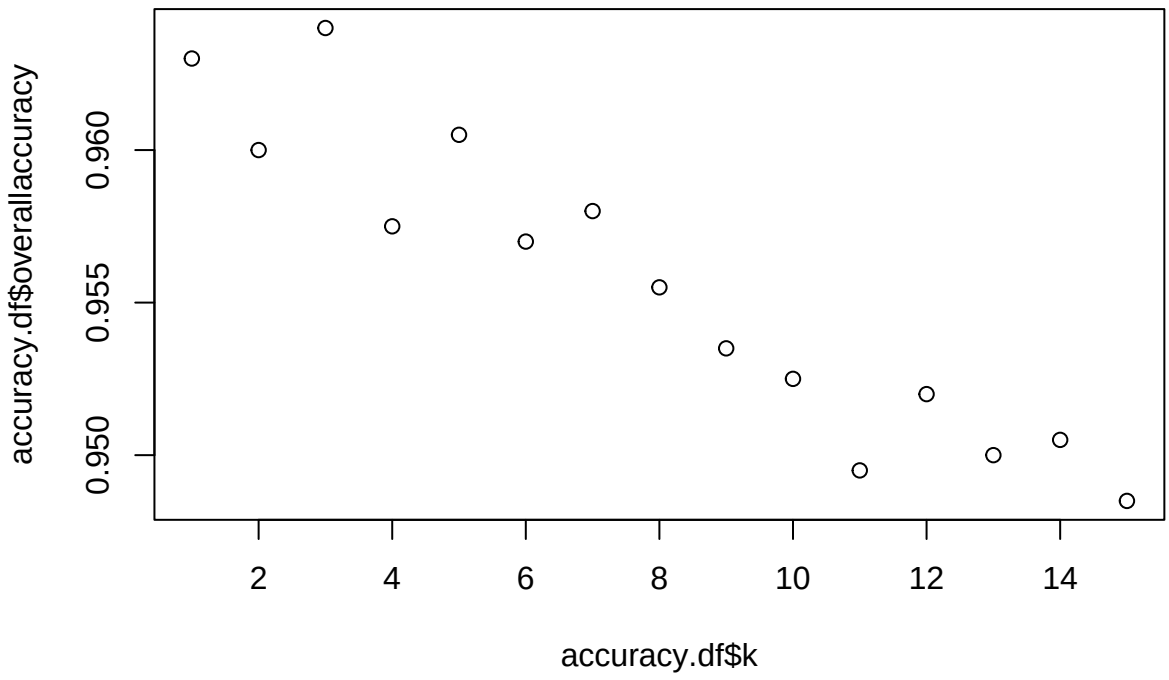
```
# Calculate the accuracy for each value of k
# Set the range of k values to consider

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.

*confusion matrix for the validation data from using the best k=3

```
k<-3
knn.pred <- class::knn(train = train.norm.df,
                       test = valid.norm.df,
                       cl = train.df$Personal.Loan, k = 3)
Conf_matrix <- confusionMatrix(knn.pred,
               as.factor(valid.df$Personal.Loan),positive="1")
print(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
##
```

Our accuracy is .9527(which means we have an error of 4.7%).false-negative is also very low.Precision(TP/(TP+FP) is low at near 64% - this would be the worst metric as we want to target the most responsive customers,the model's precision and false-positive rate(Type I error) are troublesome.

---

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.

we are now using the model to assess it.

```
customertest = data.frame(Age = as.integer(40),
                          Experience = as.integer(10),
                          Income = as.integer(84),
                          Family = as.integer(2),
```

```
                          CCAvg = as.integer(2),
                          Education1 = as.integer(0),
                          Education2 = as.integer(1),
                          Education3 = as.integer(0),
                          Mortgage = as.integer(0),
                          Securities.Account = as.integer(0),
                          CD.Account = as.integer(0),
                          Online = as.integer(1),
                          CreditCard = as.integer(1))
#load the data into a customertest dataframe.

#Normalize the new customer
new.cust.norm <- new_customer
new.cust.norm <- predict(norm.values,new.cust.norm)

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

```
## [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.*

Repartitioning for a test set

```
set.seed(2)
train.index <- sample(row.names(universal_m.df),0.5*dim(universal_m.df)[1])
valid.index <- sample(setdiff(row.names(universal_m.df),train.index),
                      0.3*dim(universal_m.df)[1])
test.index <- setdiff(row.names(universal_m.df),c(train.index,valid.index))
train.df   <- universal_m.df[train.index,]
valid.df   <- universal_m.df[valid.index,]
test.df    <- universal_m.df[test.index,]
```

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

RUN KNN FOR VALIDATION,TRAIN AND TEST

Confusion Matrix for validation set

```
k<-3

knn.pred <- class::knn(train = train.norm.df,
                       test = valid.norm.df,
                       cl = train.df$Personal.Loan, k = 3)
Conf_matrix <- confusionMatrix(knn.pred,
               as.factor(valid.df$Personal.Loan),positive="1")
print(Conf_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1336   64
##          1    7   93
##
##                Accuracy : 0.9527
##                  95% CI : (0.9407, 0.9629)
##     No Information Rate : 0.8953
##     P-Value [Acc > NIR] : 7.433e-16
##
##                   Kappa : 0.6992
##
##  Mcnemar's Test P-Value : 3.012e-11
##
##             Sensitivity : 0.59236
##             Specificity : 0.99479
##          Pos Pred Value : 0.93000
##          Neg Pred Value : 0.95429
##              Prevalence : 0.10467
##          Detection Rate : 0.06200
##    Detection Prevalence : 0.06667
##       Balanced Accuracy : 0.79357
##
##        'Positive' Class : 1
##
```

#confusion matrix for test set

```
k<-3

knn.pred <- class::knn(train = train.norm.df,
                       test = test.norm.df,
                       cl = train.df$Personal.Loan, k = 3)
Conf_matrix <- confusionMatrix(knn.pred,
               as.factor(test.df$Personal.Loan),positive="1")
print(Conf_matrix)
```

```
## Confusion Matrix and Statistics
```

```
##
##           Reference
## Prediction   0   1
##          0 922  28
##          1   4  46
##
##                Accuracy : 0.968
##                  95% CI : (0.9551, 0.978)
##     No Information Rate : 0.926
##     P-Value [Acc > NIR] : 1.208e-08
##
##                   Kappa : 0.7256
##
##  Mcnemar's Test P-Value : 4.785e-05
##
##             Sensitivity : 0.6216
##             Specificity : 0.9957
##          Pos Pred Value : 0.9200
##          Neg Pred Value : 0.9705
##              Prevalence : 0.0740
##          Detection Rate : 0.0460
##    Detection Prevalence : 0.0500
##       Balanced Accuracy : 0.8087
##
##        'Positive' Class : 1
##
```

#Confusion Matrix for train set

```
k<-3

knn.pred <- class::knn(train = train.norm.df,
                       test = train.norm.df,
                       cl = train.df$Personal.Loan, k = 3)
Conf_matrix <- confusionMatrix(knn.pred,
               as.factor(train.df$Personal.Loan),positive="1")
print(Conf_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2246   61
##          1    5  188
##
##                Accuracy : 0.9736
##                  95% CI : (0.9665, 0.9795)
##     No Information Rate : 0.9004
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8365
##
##  Mcnemar's Test P-Value : 1.288e-11
```

```
##
##             Sensitivity : 0.7550
##             Specificity : 0.9978
##          Pos Pred Value : 0.9741
##          Neg Pred Value : 0.9736
##              Prevalence : 0.0996
##          Detection Rate : 0.0752
##    Detection Prevalence : 0.0772
##       Balanced Accuracy : 0.8764
##
##        'Positive' Class : 1
##
```

###Difference

##Test vs.Train:

Accuracy: Train has a higher accuracy (0.9736) compared to Test (0.968). 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 (0.7550) compared to Test (0.6216).

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 (0.9978) compared to Test (0.9957).

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 (0.9741) compared to Test (0.9200).

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

##Train vs.Validation:

Accuracy: Train still has a higher accuracy (0.9736) compared to Validation (0.958).

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 (0.7589) compared to Validation (0.625).

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

Specificity (True Negative Rate): Train has higher specificity (0.9987) compared to Validation (0.9934).

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 (0.9827) compared to Validation (0.9091).

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

#Potential 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 canlead 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.

Data unyoking If the data sets are resolve else into training, confirmation, and test sets in each evaluation,this can lead to variations in results, especially for small data sets.

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

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