FML Assignment 2

2024-02-25

Loading the data using read.csv. There are 14 columns and 5000 observations.

```
dataset <- read.csv("./UniversalBank.csv")
dim(dataset)
## [1] 5000 14</pre>
```

Removing the columns ID and Zip code from the dataset.

```
dataset <- dataset[,-c(1,5)]</pre>
```

Data splitting.

Transformation of categorical variables with numerical values into factors is performed. The dummyVars() function is used to create dummy variables for the values in the Education column. This is then applied to the dataset using predict() function. The set.seed() function helps maintain uniformity in values even if the code is executed multiple times. The Dataset is split into train_dataset as 60% of the observations while the rest 40% are set as valid_dataset as mentioned in the question. Education contains three categories which on substituting with dummy variables is converted to binary output variables of 0 and 1.

```
dataset$Education <- as.factor(dataset$Education)

categories <- dummyVars(~., data = dataset) ## Converting education to dummy categories
dataset <- as.data.frame(predict(categories,dataset))

set.seed(1)
training_indices <- sample(row.names(dataset), 0.6*dim(dataset)[1])
validation_indices <- setdiff(row.names(dataset), training_indices)
train_dataset <- dataset[training_indices,]
valid_dataset <- dataset[validation_indices,]
t(t(names(train_dataset)))</pre>
```

```
## [,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"
```

Normalization of data is done using the z-score normalization method by passing the "center", "scale" into method() function. The function preProcess() performs normalization which is then applied to both training and validation dataset using the predict() function. The column with personal laon shouldn't be used for normalization and hence excluded.

```
normalized.train <- train_dataset[,-10]
normalized.valid <- valid_dataset[,-10]

normalized.values <- preProcess(train_dataset[, -10], method=c("center", "scale"))
normalized.train <- predict(normalized.values, train_dataset[, -10])
normalized.valid <- predict(normalized.values, valid_dataset[, -10])</pre>
```

The following are the details provided about the first 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.

The details of the first customer are loaded as a dataframe into customer1. This is then normalised using the normalized.values model and applied using the predict() function to store the normalised values of the first customer in normalized_customer1.

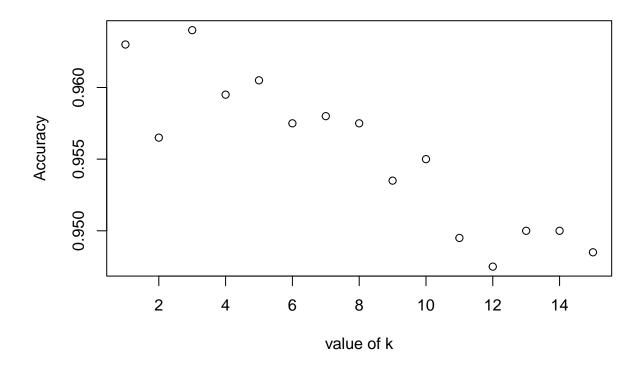
```
customer1 <- data.frame(</pre>
  Age = 40,
  Experience = 10,
  Income = 84.
  Family = 2,
  CCAvg = 2,
  Education.1 = 0,
  Education.2 = 1,
  Education.3 = 0,
  Mortgage = 0,
  Securities.Account = 0,
  CD.Account = 0,
  Online = 1,
  CreditCard = 1
)
normalized_customer1 <- customer1</pre>
normalized_customer1 <- predict(normalized.values, normalized_customer1)</pre>
```

k-NN classification is performed and printed as knn_predictor using the knn() function in the class library. The k value is set to 1 as mentioned in the question.

The classification of the customer is "0". This means the customer would not accept the personal loan as printed by knn_predictor.

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

#Choice of k. The accuracy with respect to validation set is calculated using k-NN for each value of k from 1 to 15. The plot() function is used to strike a value for k such that it balances between overfitting and underfitting without the inclusion of noise in the data. The k value was found to be 3. Accuracy is plotted on the y-axis across the different values of k along the x-axis.



#Confusion matrix for validation data The given value of k for confusion matrix is 3. The same is performed using the confusionMatrix() function and is printed as selectedk_matrix. Here Personal Loan column is converted as factor.

```
knn_predictor <- class::knn(train = normalized.train,</pre>
                          test = normalized.valid,
                          cl = train_dataset$Personal.Loan, k = 3)
selectedk_matrix <- confusionMatrix(knn_predictor,</pre>
                                         as.factor(valid_dataset$Personal.Loan),positive = "1")
selectedk_matrix
## Confusion Matrix and Statistics
##
##
             Reference
##
  Prediction
                  0
                       1
##
            0 1786
                      63
                     142
##
            1
                  9
##
##
                   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
##
##
```

The following details about the customer was provided: 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 CreditCard = 1. This was stored as a data frame in customer2. This was then normalized using the normalized.values which has the preProcess() function and applied using the predict() function. This was set to normalized_customer2.

```
customer2 <- data.frame(</pre>
  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
)
normalized_customer2 <- customer2</pre>
normalized_customer2 <- predict(normalized.values,normalized_customer2)</pre>
```

k-NN is performed on the normalized_customer2 using the previously identified k value of 3. The customer is classified as "0", that means no personal loan.

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

#Re-partitioning data The dataset was re-partitioned into training, validation and test sets with 50%, 30% and 20% of the observations respectively and printed as new_training_set, new_valid_set, new_test_set.

```
#Re partitioning the data.
new_training_index <- sample(row.names(dataset), 0.5*dim(dataset)[1])
new_valid_index <- sample(setdiff(row.names(dataset), new_training_index), 0.3*dim(dataset)[1])
new_test_index <- setdiff(setdiff(row.names(dataset), new_training_index), new_valid_index)
new_training_set <- dataset[new_training_index,]
new_valid_set <- dataset[new_valid_index,]
new_test_set <- dataset[new_test_index,]</pre>
```

Normalization of the data is performed using the preProcess() and predict() functions on all of the new training, validation and test datasets.

```
new_train_norm <- new_training_set[,-10] # Note that Personal Income is the 10th variable
new_valid_norm <- new_valid_set[-10]
new_test_norm <- new_test_set[-10]

new_norm <- preProcess(new_training_set[, -10], method=c("center", "scale"))
new_train_norm <- predict(new_norm, new_training_set[, -10])
new_valid_norm <- predict(new_norm, new_valid_set[, -10])
new_test_norm<- predict(new_norm, new_test_set[-10])</pre>
```

Using the knn() funtion and the confusionMatrix() functions led to the identification that model performs well on training data.

```
## Confusion Matrix and Statistics
##
            Reference
## Prediction 0
                     1
           0 2254
##
                    50
                6 190
##
##
##
                 Accuracy : 0.9776
##
                   95% CI: (0.971, 0.983)
##
      No Information Rate: 0.904
      P-Value [Acc > NIR] : < 2.2e-16
##
##
##
                    Kappa: 0.8594
##
##
   Mcnemar's Test P-Value: 9.132e-09
##
              Sensitivity: 0.7917
##
##
              Specificity: 0.9973
           Pos Pred Value: 0.9694
##
           Neg Pred Value: 0.9783
##
##
               Prevalence: 0.0960
##
           Detection Rate: 0.0760
```

```
## Detection Prevalence : 0.0784
## Balanced Accuracy : 0.8945
##
## 'Positive' Class : 1
##
```

Using the knn()funtion and the confusionMatrix() functions on validation data.

```
knn_valid_predictor <- class::knn(train = new_train_norm,</pre>
                         test = new_valid_norm,
                         cl = new_training_set$Personal.Loan, k = 3)
validation_matrix <- confusionMatrix(knn_valid_predictor,as.factor(new_valid_set$Personal.Loan),positiv
validation_matrix
## Confusion Matrix and Statistics
##
##
             Reference
                 0
## Prediction
##
            0 1343
                     46
                     94
##
            1
                17
##
##
                  Accuracy: 0.958
                    95% CI: (0.9466, 0.9676)
##
##
       No Information Rate: 0.9067
##
       P-Value [Acc > NIR] : 2.658e-14
##
##
                     Kappa: 0.7264
##
    Mcnemar's Test P-Value: 0.0004192
##
##
##
               Sensitivity: 0.67143
##
               Specificity: 0.98750
##
            Pos Pred Value: 0.84685
            Neg Pred Value: 0.96688
##
##
                Prevalence: 0.09333
##
            Detection Rate: 0.06267
      Detection Prevalence: 0.07400
##
##
         Balanced Accuracy: 0.82946
##
          'Positive' Class : 1
##
##
```

Using the knn() and the confusionMatrix() functions on test data.

The accuracy of training set is greater than validation and testing data. Accuracy of test set is higher than validation set. This is described as overfitting. The inability of the model to generalise when new test set is provided leads to overfitting of the model.

```
## Confusion Matrix and Statistics
##
##
            Reference
## Prediction 0 1
           0 896 34
##
              4 66
##
            1
##
##
                 Accuracy: 0.962
                   95% CI : (0.9482, 0.973)
##
##
       No Information Rate : 0.9
       P-Value [Acc > NIR] : 1.383e-13
##
##
##
                     Kappa : 0.7564
##
##
   Mcnemar's Test P-Value : 2.546e-06
##
##
              Sensitivity: 0.6600
##
              Specificity: 0.9956
##
           Pos Pred Value : 0.9429
##
            Neg Pred Value: 0.9634
##
               Prevalence : 0.1000
##
           Detection Rate: 0.0660
##
      Detection Prevalence : 0.0700
##
         Balanced Accuracy: 0.8278
##
##
          'Positive' Class : 1
##
```