FML_Assignment_2

Keerthi Priya Nallamekala

2023-10-01

#Load required libraries

```
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

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

#Education needs to be converted to factor

```r
universal.df$Education <- as.factor(universal.df$Education)
```

#Now, convert Education to Dummy Variables

```r
groups <- dummyVars(~., data = universal.df) # This creates the dummy groups
universal_m.df <- as.data.frame(predict(groups,universal.df))
```

```r
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 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])
```

Question:

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?

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 K-NN(k- Nearest neighbors)

```
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
```

Question:

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

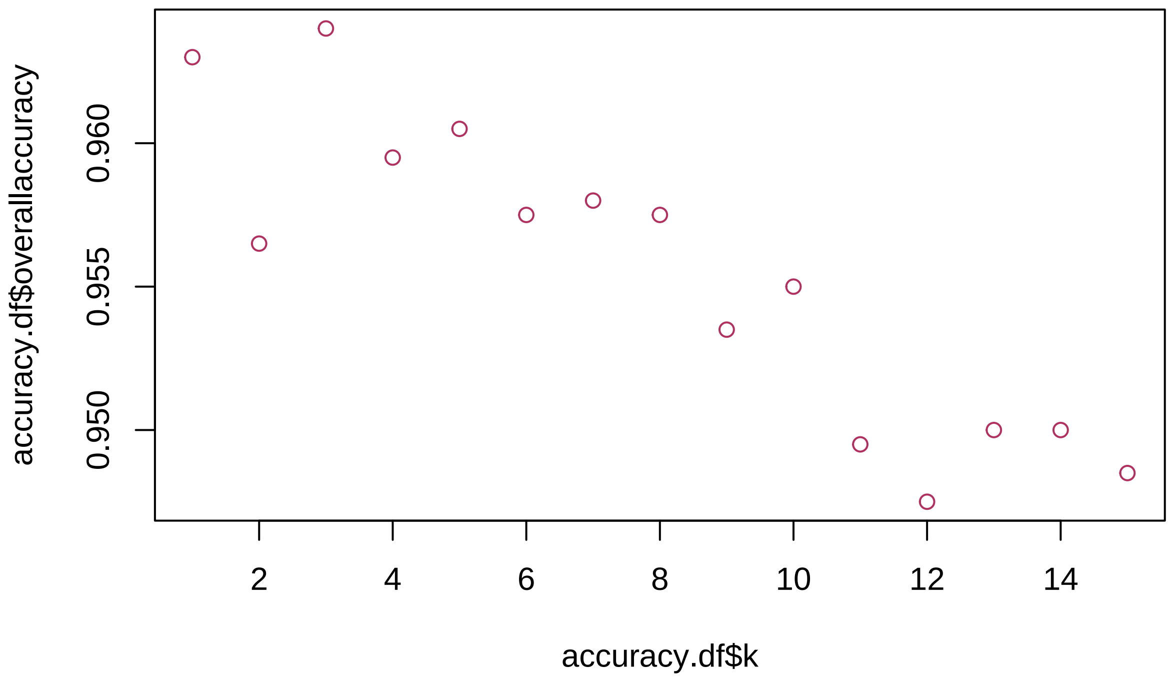
#Calculate the accuracy for each value of k
#Set the range of k values to consider

```
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, col="maroon")
```



Question:

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

#Confusion Matrix using best K=3

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

confusionMatrix(knn.pred,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
##
```

Question:

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.

#To Load new customer profile

```
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,
  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
```

#To Print the predicted class

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

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

Question:

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.

#Split the data to 50% training and 30% Validation and 20% Testing

```r
set.seed(1)
Train_Index1 <- sample(row.names(universal_m.df), 0.5*dim(universal_m.df)[1])
Val_Index1 <- sample(setdiff(row.names(universal_m.df),Train_Index1),0.3*dim(universal_m.df)[1])
Test_Index1 <-setdiff(row.names(universal_m.df),union(Train_Index1,Val_Index1))
Train_Data <- universal_m.df[Train_Index1,]
Validation_Data <- universal_m.df[Val_Index1,]
Test_Data <- universal_m.df[Test_Index1,]
```

#Now normalize the data

```r
train.norm.df1 <- Train_Data[,-10]
valid.norm.df1 <- 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])
```

#Now let us predict using K-NN

```r
validation_knn = class::knn(train = train.norm.df1,
                            test = valid.norm.df1,
                            cl = Train_Data$Personal.Loan,
                            k = 3)
test_knn = class::knn(train = train.norm.df1,
                      test = Test.norm.df1,
                      cl = Train_Data$Personal.Loan,
                      k = 3)
Train_knn = class::knn(train = train.norm.df1,
                      test = train.norm.df1,
                      cl = Train_Data$Personal.Loan,
                      k = 3)
```

#Validation confusion Matrix

```r
validation_conf_mat = confusionMatrix(validation_knn,
                                      as.factor(Validation_Data$Personal.Loan),
                                      positive = "1")

validation_conf_mat
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1358   42
##          1    6   94
##
##                Accuracy : 0.968
##                  95% CI : (0.9578, 0.9763)
##     No Information Rate : 0.9093
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7797
##
##  Mcnemar's Test P-Value : 4.376e-07
##
##             Sensitivity : 0.69118
##             Specificity : 0.99560
##          Pos Pred Value : 0.94000
##          Neg Pred Value : 0.97000
##              Prevalence : 0.09067
##          Detection Rate : 0.06267
##    Detection Prevalence : 0.06667
##       Balanced Accuracy : 0.84339
##
##        'Positive' Class : 1
##
```

#To Test confusion Matrix

```
test_conf_mat = confusionMatrix(test_knn,
                                         as.factor(Test_Data$Personal.Loan),
                                         positive = "1")

test_conf_mat
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 884  35
##          1   4  77
##
##                Accuracy : 0.961
##                  95% CI : (0.9471, 0.9721)
##     No Information Rate : 0.888
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.777
##
##  Mcnemar's Test P-Value : 1.556e-06
##
##             Sensitivity : 0.6875
##             Specificity : 0.9955
##          Pos Pred Value : 0.9506
##          Neg Pred Value : 0.9619
##              Prevalence : 0.1120
##          Detection Rate : 0.0770
##    Detection Prevalence : 0.0810
##       Balanced Accuracy : 0.8415
##
##        'Positive' Class : 1
##
```

```
Training_conf_mat = confusionMatrix(Train_knn,
                                               as.factor(Train_Data$Personal.Loan),
                                               positive = "1")
Training_conf_mat
```

```
## 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
##
```

#Differences

#Train vs Validation:

Accuracy: Train is better than Validation (0.958) with respect to accuracy.

Reason: Similar to the comparison with Test, the dataset for Train might be more evenly distributed or simpler to forecast.

Sensitivity: Train has higher sensitivity (0.7589) compared to Validation (0.625) when compared to validation.

Reason: The model developed by Train performs better at accurately detecting positive cases. This suggests that the model used by Validation may have a higher rate of false negatives.

Specificity: Train has higher specificity (0.9987) when compared to Validation (0.9934).

Reason: The model developed by Train performs better at accurately identifying negative cases. The model used for validation can have a little higher false positive rate.

Precision: Train still exceeds Validation (0.9091) in terms of positive predictive value (0.9827).

Reason: Train's model is more accurate at forecasting positive cases, which leads to false positive predictions.

#Test vs Train:

Accuracy: Train has a higher accuracy (0.9772) compared to Test (0.9507).

Reason: This is as a result of variations in the evaluation datasets. The dataset for Train might be better balanced or predictible.

Sensitivity: Train has higher sensitivity (0.7589) compared to Test (0.5875).

Reason: This suggests that Train's approach is more accurate at spotting positive cases. It might have a decreased rate of false negatives.

Specificity: Train has higher specificity (0.9987) compared to Test (0.99403).

Reason: This implies that Train's model performs better at accurately recognizing negative cases. It might have a lower rate of false positives.

Precision: Train has a higher positive predictive value (0.9827) compared to Test (0.92157).

Reason: Few false positive predictions are generated because of Train's model's better performance in predicting positive cases.

#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 can lead 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 and test sets can impact performance criteria .

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