Assignment_2

Manasa Akkinapally

10-01-2023

Assignment Problem Statement

Universal bank is a young bank growing rapidly in terms of overall customer acquisition. The majority of these customers are liability customers (depositors) with varying sizes of relationship with the bank. The customer base of asset customers (borrowers) is quite small, and the bank is interested in expanding this base rapidly in more loan business. In particular, it wants to explore ways of converting its liability customers to personal loan customers.

A campaign that the bank ran last year for liability customers showed a healthy conversion rate of over 9% success. This has encouraged the retail marketing department to devise smarter campaigns with better target marketing. The goal is to use k-NN to predict whether a new customer will accept a loan offer. This will serve as the basis for the design of a new campaign.

The file UniversalBank.csv contains data on 5000 customers. The data include customer demographic information (age, income, etc.), the customer's relationship with the bank (mortgage, securities account, etc.), and the customer response to the last personal loan campaign (Personal Loan). Among these 5000 customers, only 480 (= 9.6%) accepted the personal loan that was offered to them in the earlier campaign.

Partition the data into training (60%) and validation (40%) sets.

Load required libraries

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

```
## Loading required package: ggplot2

## Loading required package: lattice
```

```r
library(e1071)
library(knitr)
```

Read the UniversalBank data

```r
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 data frame
```

```
##       [,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)]
```

Transform categorical variables into dummy variables

```
# 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))
```

Split the data to 60% training and 40 % Validation

```
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

```
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

```
1. Age = 40, Experience = 10, Income = 84, Family = 2, CCAvg = 2, Education_1 = 0, Education_2 = 1, Edu
```

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 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
```

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

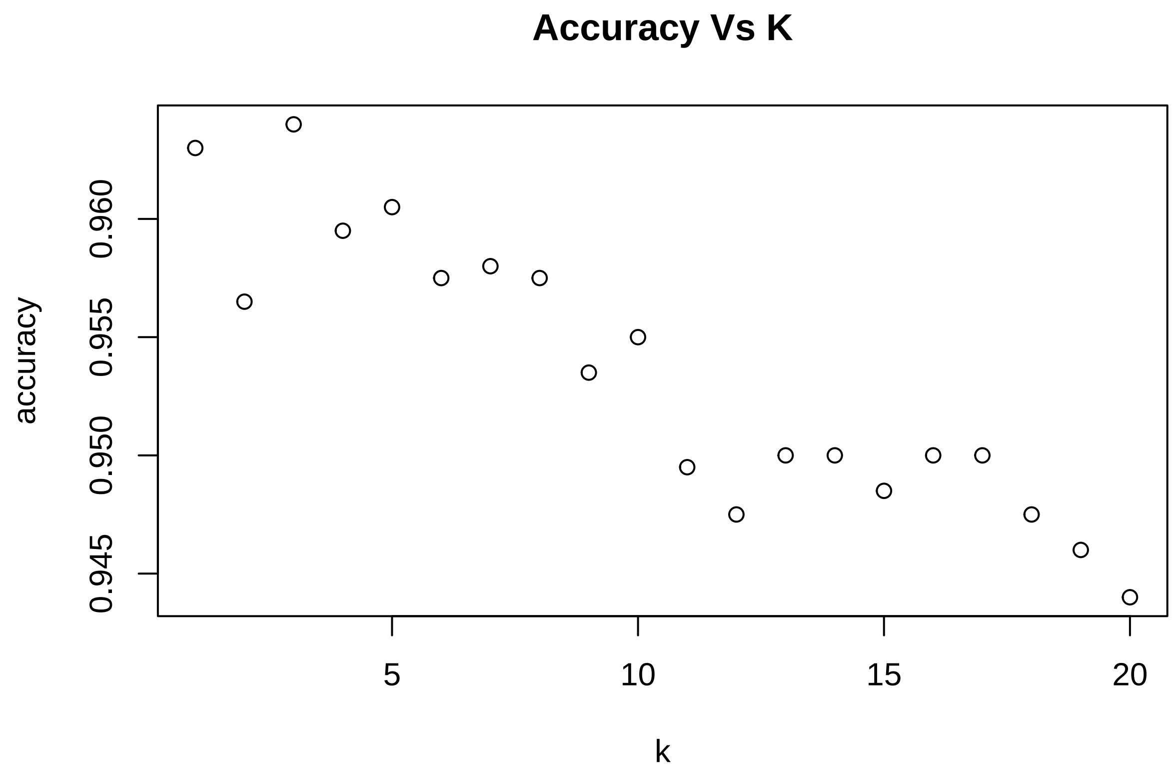
Calculate the accuracy for each value of k

Set the range of k values to consider

```
accuracy.df <- data.frame(k = seq(1, 20, 1), overallaccuracy = rep(0, 20))
for(i in 1:20)
  {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")$overal
}
which(accuracy.df[,2] == max(accuracy.df[,2]))
```

```
## [1] 3
```

```
plot(accuracy.df$k,accuracy.df$overallaccuracy, main = "Accuracy Vs K", xlab = "k", ylab = "accuracy")
```



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
##
```

```
4.Consider the following customer: Age = 40, Experience = 10, Income = 84, Family = 2, CCAvg = 2, Educa
```

Load new customer profile

```
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.pred1 <- class::knn(train = train.norm.df,
                       test = new.cust.norm,
                       cl = train.df$Personal.Loan, k = 3)
knn.pred1
```

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

Print the predicted class (1 for loan acceptance, 0 for loan rejection)

```
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 th
```

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

```
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

```
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(k- Nearest neighbors)

```
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

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

validation_confusion_matrix
```

```
## 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
##
```

Test confusion Matrix

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


test_confusion_matrix
```

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

Training_confusion_matrix
```

```
## 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
##
```

Difference

Potential Reasons for Differences:

Differences in data sets can have a significant impact on the performance of models. For example, one data set may have a higher imbalance, making it more difficult to predict rare event

Variations in performance can occur due to differences in model configurations or the arbitrary initialization of model parameters

Different hyperparameter configurations, such as the selection of k in k-NN or other model-specific parameters, can impact the performance of the model

When the data sets are divided into training, validation, and test sets during each evaluation, there can be variations in results, particularly for small data sets

In smaller datasets, the inclusion of different samples in the confirmation and test sets can have an impact on performance criteria, leading to sample variability

Certain models, such as neural networks, incorporate randomness into their optimization process, resulting in minor deviations