k_NN Classification - Universal Bank

##Loading Data and packages

```
getwd()
```

```
## [1] "/Users/sampathnikhilkumar/Desktop"
```

```
data1 <- data.frame(read.csv("UniversalBank.csv"))
str(data1)
```

```
## 'data.frame':    5000 obs. of  14 variables:
##  $ ID                : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ Age               : int  25 45 39 35 35 37 53 50 35 34 ...
##  $ Experience        : int  1 19 15 9 8 13 27 24 10 9 ...
##  $ Income            : int  49 34 11 100 45 29 72 22 81 180 ...
##  $ ZIP.Code          : int  91107 90089 94720 94112 91330 92121 91711 93943 90089 93023 ...
##  $ Family            : int  4 3 1 1 4 4 2 1 3 1 ...
##  $ CCAvg             : num  1.6 1.5 1 2.7 1 0.4 1.5 0.3 0.6 8.9 ...
##  $ Education         : int  1 1 1 2 2 2 2 3 2 3 ...
##  $ Mortgage          : int  0 0 0 0 0 155 0 0 104 0 ...
##  $ Personal.Loan     : int  0 0 0 0 0 0 0 0 0 1 ...
##  $ Securities.Account: int  1 1 0 0 0 0 0 0 0 0 ...
##  $ CD.Account        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Online            : int  0 0 0 0 0 1 1 0 1 0 ...
##  $ CreditCard        : int  0 0 0 0 1 0 0 1 0 0 ...
```

```
library("ISLR")
library("caret")
```

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

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

```
library("class")
library("ggplot2")
library("gmodels")
```

##Data Cleaning

```
data1 <- data1[,c(-1,-5)]
head(data1, n=5)
```

```
##   Age Experience Income Family CCAvg Education Mortgage Personal.Loan
## 1  25          1     49      4   1.6         1        0             0
## 2  45         19     34      3   1.5         1        0             0
## 3  39         15     11      1   1.0         1        0             0
## 4  35          9    100      1   2.7         2        0             0
## 5  35          8     45      4   1.0         2        0             0
##   Securities.Account CD.Account Online CreditCard
## 1                  1          0      0          0
## 2                  1          0      0          0
## 3                  0          0      0          0
## 4                  0          0      0          0
## 5                  0          0      0          1
```

```
test.na <- is.na.data.frame("data1")

##Converting data types of attributes
data1$Education <- as.character(data1$Education)
is.character(data1$Education)
```

```
## [1] TRUE
```

```
data1$Personal.Loan <- as.factor(data1$Personal.Loan)
is.factor(data1$Personal.Loan)
```

```
## [1] TRUE
```

```
##Dummying Variables
DummyVariables <- dummyVars(~Education, data1)
head(predict(DummyVariables, data1))
```

```
##   Education1 Education2 Education3
## 1          1          0          0
## 2          1          0          0
## 3          1          0          0
## 4          0          1          0
## 5          0          1          0
## 6          0          1          0
```

```
data2 <- predict(DummyVariables,data1)

##Combining Data
data3 <- data1[,-6]
data4 <- cbind(data3,data2)
colnames(data4)
```

```
##  [1] "Age"                "Experience"         "Income"
##  [4] "Family"             "CCAvg"              "Mortgage"
##  [7] "Personal.Loan"      "Securities.Account" "CD.Account"
## [10] "Online"             "CreditCard"         "Education1"
## [13] "Education2"         "Education3"
```

##Data Partition and Normalization

```
set.seed(123)
Data_Part_Train <- createDataPartition(data4$Personal.Loan, p=0.6, list=F)
Train_Data <- data4[Data_Part_Train,]
Validation_Data <- data4[-Data_Part_Train,]

#Normalizing the training dataset
Model_Z_Normalized <- preProcess(Train_Data[,-c(7,12:14)], method=c("center","scale"))

Normalized_Data_Train <- predict(Model_Z_Normalized, Train_Data)

Normalized_Data_Validation <- predict(Model_Z_Normalized, Validation_Data)

#summary(Normalized_Data_Train)
#summary(Normalized_Data_Validation)
```

##Inserting a test set and normalizing it

```
test_data <- cbind.data.frame(Age = 40,Experience = 10, Income = 84, Family = 2, CCAvg = 2, Mortgage = 0

Test_Normalized <- predict(Model_Z_Normalized, test_data)
```

#1. Running the knn model on the test dataset with k=1

```
Train_Predictors <- Normalized_Data_Train[,-7]
Validation_Predictors <- Normalized_Data_Validation[,-7]

Train_Labels <- Normalized_Data_Train[,7]
Validate_Lables <- Normalized_Data_Validation[,7]

Predicted_K <- knn(Train_Predictors, Test_Normalized, cl=Train_Labels, k=1)

head(Predicted_K)
```

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

When k=1 the customer is classified as 0 which indicates that the loan is not accepted. Since factor 1 is classified as loan acceptance and 0 is not accepted.

#2. Choice of k that balances between overfitting and ignoring the predictor information

```
set.seed(455)
search_grid <- expand.grid(k=c(1:30))
#trtcontrol <- trainControl(method="repeatedcv")
model <- train(Personal.Loan~Age+Experience+Income+Family+CCAvg+Mortgage+Securities.Account+CD.Account+C
model
```

```
## k-Nearest Neighbors
##
## 3000 samples
```

```
##   13 predictor
##    2 classes: '0', '1'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 3000, 3000, 3000, 3000, 3000, 3000, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    1  0.9486329  0.6739443
##    2  0.9405480  0.6118584
##    3  0.9403636  0.5980966
##    4  0.9392894  0.5855648
##    5  0.9407990  0.5836956
##    6  0.9408178  0.5747129
##    7  0.9404153  0.5630616
##    8  0.9398896  0.5554862
##    9  0.9396189  0.5509399
##   10  0.9380957  0.5331053
##   11  0.9380233  0.5288976
##   12  0.9369616  0.5198382
##   13  0.9365720  0.5134500
##   14  0.9360384  0.5068074
##   15  0.9355341  0.4985038
##   16  0.9356776  0.4971309
##   17  0.9345174  0.4854181
##   18  0.9341181  0.4822415
##   19  0.9335817  0.4755456
##   20  0.9338016  0.4741894
##   21  0.9335631  0.4724520
##   22  0.9323913  0.4612421
##   23  0.9319614  0.4563577
##   24  0.9317099  0.4537991
##   25  0.9311729  0.4471843
##   26  0.9314622  0.4503100
##   27  0.9309886  0.4446960
##   28  0.9304798  0.4385601
##   29  0.9303716  0.4362160
##   30  0.9297296  0.4283101
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was k = 1.
```

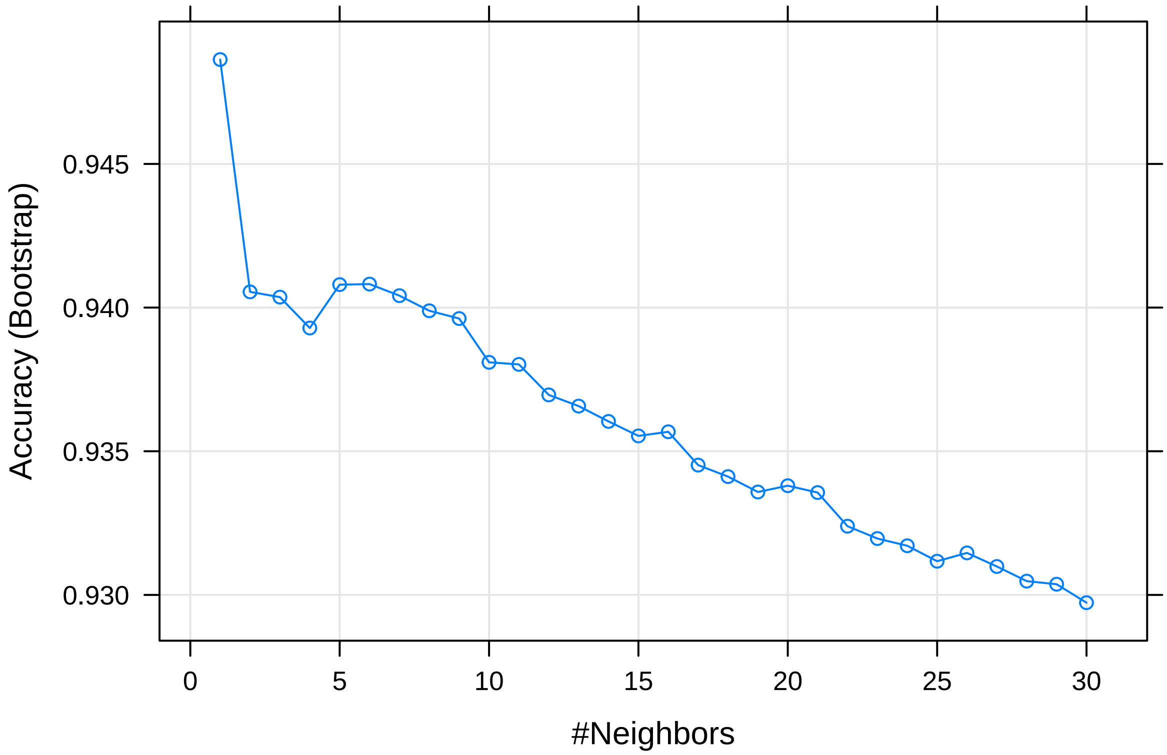
```r
best_k <- model$bestTune[[1]]
best_k
```

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

The k value which balances between over fitting and ignoring the predictor information is k = 1.

#Plotting the model

```
plot(model)
```



#3. Confusion matrix being deployed over the validation data

```
pred_training <- predict(model,Normalized_Data_Validation[,-7])
confusionMatrix(pred_training, Validate_Lables)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1789   54
##          1   19  138
##
##                Accuracy : 0.9635
##                  95% CI : (0.9543, 0.9713)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7711
##
##  Mcnemar's Test P-Value : 6.909e-05
##
##             Sensitivity : 0.9895
##             Specificity : 0.7188
```

```
##          Pos Pred Value : 0.9707
##          Neg Pred Value : 0.8790
##              Prevalence : 0.9040
##          Detection Rate : 0.8945
##    Detection Prevalence : 0.9215
##       Balanced Accuracy : 0.8541
##
##        'Positive' Class : 0
##
```

Miscalculations = 73, Accuracy = 0.9635, Sensitivity = 0.9895

#4. Running the test data with best k choosen above

```
test_best_k <- knn(Train_Predictors, Test_Normalized, cl=Train_Labels, k=best_k)
head(test_best_k)
```

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

With the best k being choosen, the customer is classified as 0 which indicates that the loan is not accepted.

#5. Repartitioning the data into training(50%), validation(30%) and test(20%) and running the entire model with best k

```
set.seed(422)
data_part <- createDataPartition(data4$Personal.Loan, p=0.5, list = F)
n_train_data <- data4[data_part,]
nd_test_data <- data4[-data_part,]

data_part_v <- createDataPartition(nd_test_data$Personal.Loan,p=0.6, list =F)
n_validate_data <- nd_test_data[data_part_v,]
n_test_data <- nd_test_data[-data_part_v,]

#Normalization
norm_m <- preProcess(n_train_data[,-c(7,12:14)],method=c("center","scale"))

train_z <- predict(norm_m, n_train_data)
validate_z <- predict(norm_m, n_validate_data)
test_z <- predict(norm_m, n_test_data)

#Defining the predictors and labels
n_train_predictor <- train_z[,-7]
n_validate_predictor <- validate_z[,-7]
n_test_predictor <- test_z[,-7]

n_train_labels <- train_z[,7]
n_validate_labels <- validate_z[,7]
n_test_labels <- test_z[,7]

#running the knn model over train dataset
n_model <- knn(n_train_predictor,n_train_predictor,cl=n_train_labels,k=best_k)
head(n_model)
```

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

```
#running the knn model over validation dataset
n_model1 <- knn(n_train_predictor,n_validate_predictor,cl=n_train_labels,k=best_k)
head(n_model1)
```

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

```
#running the knn model over test dataset
n_model2 <- knn(n_train_predictor,n_test_predictor,cl=n_train_labels,k=best_k)
head(n_model2)
```

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

#Using CrossTable to compare the Test vs Training and Validation

```
confusionMatrix(n_model,n_train_labels)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2260    0
##          1    0  240
##
##                Accuracy : 1
##                  95% CI : (0.9985, 1)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 1
##
##  Mcnemar's Test P-Value : NA
##
##             Sensitivity : 1.000
##             Specificity : 1.000
##          Pos Pred Value : 1.000
##          Neg Pred Value : 1.000
##              Prevalence : 0.904
##          Detection Rate : 0.904
##    Detection Prevalence : 0.904
##       Balanced Accuracy : 1.000
##
##        'Positive' Class : 0
##
```

#Train_Data - Miscalculations = 0 Accuracy = 1 Sensitivity = 1 #(This is because both the train and test datasets are same, model has already seen the data and hence it cannot predict anything wrong, which results in 100% Accuracy and 0 Miscalulations).

```
confusionMatrix(n_model1,n_validate_labels)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1334   55
##          1   22   89
##
##                Accuracy : 0.9487
##                  95% CI : (0.9363, 0.9593)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : 1.261e-10
##
##                   Kappa : 0.6705
##
##  Mcnemar's Test P-Value : 0.0002656
##
##             Sensitivity : 0.9838
##             Specificity : 0.6181
##          Pos Pred Value : 0.9604
##          Neg Pred Value : 0.8018
##              Prevalence : 0.9040
##          Detection Rate : 0.8893
##    Detection Prevalence : 0.9260
##       Balanced Accuracy : 0.8009
##
##        'Positive' Class : 0
##
```

#Validation Data - Miscalculations = 22 + 55 = 77 Accuracy = 0.9487 Sensitivity = 0.9838

```
confusionMatrix(n_model2,n_test_labels)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 891  26
##          1  13  70
##
##                Accuracy : 0.961
##                  95% CI : (0.9471, 0.9721)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : 5.695e-12
##
##                   Kappa : 0.7608
##
##  Mcnemar's Test P-Value : 0.05466
##
##             Sensitivity : 0.9856
##             Specificity : 0.7292
```

```
##          Pos Pred Value : 0.9716
##          Neg Pred Value : 0.8434
##              Prevalence : 0.9040
##          Detection Rate : 0.8910
##    Detection Prevalence : 0.9170
##       Balanced Accuracy : 0.8574
##
##        'Positive' Class : 0
##
```

#Test_Data - Miscalculations = 39 Accuracy = 0.961 Sensitivity = 0.9856

#Interpretation: When comparing the test with that of training and validation, we shall exclude train from this consideration because a model will mostly result in 100% accuracy when it has the seen data.

Miscalculations: Validation - 77, Test - 39

Accuracy: Validation - 0.9487, Test - 0.961

Sensitivty: Validation - 0.9838, Test - 0.9856

We see that the Test data has fewer misalculations, greater accuracy and sensitivity when compared to that of the validation data, by this we can say that the model works well on the unseen data.