Untitled

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```
#question-1
UniversalBank<-read.csv("./UniversalBank.csv")
head(UniversalBank) #Viewing imported dataset UniversalBank
```

```
##   ID Age Experience Income ZIPCode Family CCAvg Education Mortgage PersonalLoan
## 1  1  25          1     49   91107      4   1.6         1        0            0
## 2  2  45         19     34   90089      3   1.5         1        0            0
## 3  3  39         15     11   94720      1   1.0         1        0            0
## 4  4  35          9    100   94112      1   2.7         2        0            0
## 5  5  35          8     45   91330      4   1.0         2        0            0
## 6  6  37         13     29   92121      4   0.4         2      155            0
##   SecuritiesAccount CDAccount 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
## 6                 0         0      1          0
```

```
#Converting PersonalLoan to factor datatype
UniversalBank$PersonalLoan = as.factor(UniversalBank$PersonalLoan)

#Removing variables which are not used
remove_data<-subset(UniversalBank,select=-c(ID,ZIPCode))
head(remove_data)
```

```
##   Age Experience Income Family CCAvg Education Mortgage PersonalLoan
## 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
## 6  37         13     29      4   0.4         2      155            0
##   SecuritiesAccount CDAccount 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
## 6                 0         0      1          0
```

```
UniversalBank<-remove_data

#checking for null values
null_values <- is.na(UniversalBank)
```

```
#Creating dummy variables for categorical variable Education
Education_1<-ifelse(UniversalBank$Education == '1',1,0)
Education_2<-ifelse(UniversalBank$Education == '2',1,0)
Education_3<-ifelse(UniversalBank$Education == '3',1,0)
```

```
UniBank<-data.frame(Age=UniversalBank$Age,Experience=UniversalBank$Experience,Income=UniversalBank$Inco
```

```
#Splitting data into 60% and 40%
set.seed(123)
library(caret)
```

```
## Loading required package: ggplot2

## Loading required package: lattice
```

```
Split_data <- createDataPartition(UniBank$PersonalLoan,p=.6,list=FALSE,times=1)
Training <- UniBank[Split_data,]
Validation <- UniBank[-Split_data,]
```

```
#Normalization

Normalization <- preProcess(Training[,-(6:9)],method = c("center","scale"))
Training_norm = predict(Normalization,Training)

Validation_norm = predict(Normalization,Validation)
```

```
#Creating TEST Dataset with given values
library(class)
Test_predictor<-data.frame(Age=40,Experience=10,Income=84,Family=2,CCAvg=2,Education_1=0,Education_2=1,

Normalization_test = predict(Normalization,Test_predictor)

Train_predictor = Training_norm[,-9]
Validate_predictor = Validation_norm[,-9]

Train_label<-Training_norm[,9]

Validate_label<-Validation_norm[,9]

Prediction <-knn(Train_predictor,
                 Normalization_test,
                 cl=Train_label,
                 k=1)
Prediction
```

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

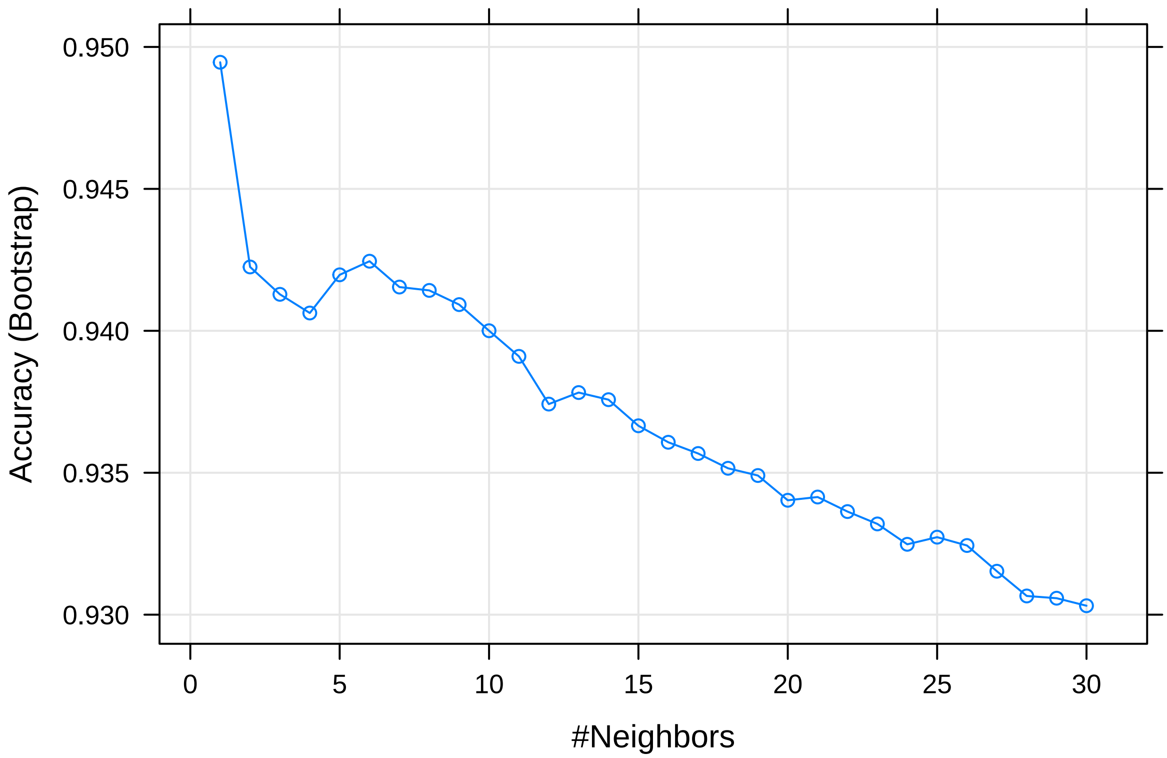
```r
#question-2
#BestValueK
set.seed(321)
SearchGrid <- expand.grid(k=seq(1:30))
model <- train(PersonalLoan~.,data=Training_norm,method="knn",tuneGrid=SearchGrid)
model
```

```
## 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  0.9494606  0.6790540
##    2  0.9422495  0.6280947
##    3  0.9412847  0.6134538
##    4  0.9406270  0.6016192
##    5  0.9419724  0.6002352
##    6  0.9424516  0.5964779
##    7  0.9415414  0.5813768
##    8  0.9414230  0.5739398
##    9  0.9409234  0.5622319
##   10  0.9400033  0.5504214
##   11  0.9390992  0.5405417
##   12  0.9374193  0.5250147
##   13  0.9378248  0.5264158
##   14  0.9375736  0.5209409
##   15  0.9366545  0.5095868
##   16  0.9360740  0.5031104
##   17  0.9356776  0.4995591
##   18  0.9351571  0.4930217
##   19  0.9349029  0.4902960
##   20  0.9340303  0.4808043
##   21  0.9341448  0.4819498
##   22  0.9336325  0.4767749
##   23  0.9331972  0.4711490
##   24  0.9324792  0.4637587
##   25  0.9327311  0.4626125
##   26  0.9324367  0.4611510
##   27  0.9315305  0.4514573
##   28  0.9306597  0.4421025
##   29  0.9305808  0.4389133
##   30  0.9303154  0.4362343
##
## 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
```

```r
plot(model)
```




```r
#Conclusion: K=1 is the choice that balances between overfitting and ignoring the predictor information
```

```r
#question-3
#Confusion Matrix

Prediction_new <- predict(model,Validate_predictor)

confusionMatrix(Prediction_new,Validate_label)
```

```
## 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
##
```

```
#question-4

testing_best_k <- knn(Train_predictor,Normalization_test , cl=Train_label, k=best_k)
head(testing_best_k)
```

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

```
#Conclusion: Based on the K value- we can conclude that the customer won't accept a personal loan.
```

```
#question-5
#Splitting data into 50%,30%,20%
set.seed(456)
Split_data_train <- createDataPartition(UniBank$PersonalLoan,p=.5,list=FALSE,times=1)
Train.df <- UniBank[Split_data_train,]


Split_data_validate <- createDataPartition(UniBank$PersonalLoan,p=.3,list=FALSE,times=1)
Validate.df <- UniBank[Split_data_validate,]

Split_data_test <- createDataPartition(UniBank$PersonalLoan,p=.2,list=FALSE,times=1)
Test.df <- UniBank[Split_data_test,]

#Normalizing the data
Normalize <- preProcess(Train.df[,-(6:9)],method = c("center","scale"))
Train_norm.df = predict(Normalize,Train.df)
Validate_norm.df = predict(Normalize,Validate.df)
Test_norm.df = predict(Normalize,Test.df)

#Finding knn value
Train_predict = Train_norm.df[,-9]
Valid_predict = Validate_norm.df[,-9]
Test_predict = Test_norm.df[,-9]
```

```r
Train_label_new = Train_norm.df[,9]
Valid_label_new = Validate_norm.df[,9]
Test_label_new = Test_norm.df[,9]

Prediction_train <- knn(Train_predict,Train_predict,cl=Train_label_new,k=best_k)

Prediction_valid <- knn(Train_predict,Valid_predict,cl=Train_label_new,k=best_k)

Prediction_test <- knn(Train_predict,Test_predict,cl=Train_label_new,k=best_k)

#Training_data:
confusionMatrix(Prediction_train,Train_label_new)
```

```
## 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
##
```

```r
#Accuracy: 1; Sensitivity:1

#Validation_data
confusionMatrix(Prediction_valid,Valid_label_new)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1344   21
##          1   12  123
```

```
##
##                Accuracy : 0.978
##                  95% CI : (0.9692, 0.9848)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.8696
##
##  Mcnemar's Test P-Value : 0.1637
##
##             Sensitivity : 0.9912
##             Specificity : 0.8542
##          Pos Pred Value : 0.9846
##          Neg Pred Value : 0.9111
##              Prevalence : 0.9040
##          Detection Rate : 0.8960
##    Detection Prevalence : 0.9100
##       Balanced Accuracy : 0.9227
##
##        'Positive' Class : 0
##
```

```
#Accuracy:0.978;Sensitivity:0.991

#Test_data
confusionMatrix(Prediction_test,Test_label_new)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 900   8
##          1   4  88
##
##                Accuracy : 0.988
##                  95% CI : (0.9791, 0.9938)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.9296
##
##  Mcnemar's Test P-Value : 0.3865
##
##             Sensitivity : 0.9956
##             Specificity : 0.9167
##          Pos Pred Value : 0.9912
##          Neg Pred Value : 0.9565
##              Prevalence : 0.9040
##          Detection Rate : 0.9000
##    Detection Prevalence : 0.9080
##       Balanced Accuracy : 0.9561
##
##        'Positive' Class : 0
##
```

```
#Accuracy:0.988;Sensitivity:0.9956

#Conclusion:Based on the values of Accuracy and Sensitivity observed through confusionMatrix, we can co
```