ml assignment

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

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

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

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

#importing dataset

```
getwd()
```

```
## [1] "C:/Users/Windows/OneDrive/Desktop"
```

```
setwd("C:/Users/Windows/OneDrive/Desktop")
data1 <- read.csv("UniversalBank.csv")
```

##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
```

```r
test.na <- is.na.data.frame("data1")
##Converting data types of attributes
data1$Education <- as.character(data1$Education)
is.character(data1$Education)
```

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

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

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

```r
##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
```

```r
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

```r
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 = 
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+
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.
```

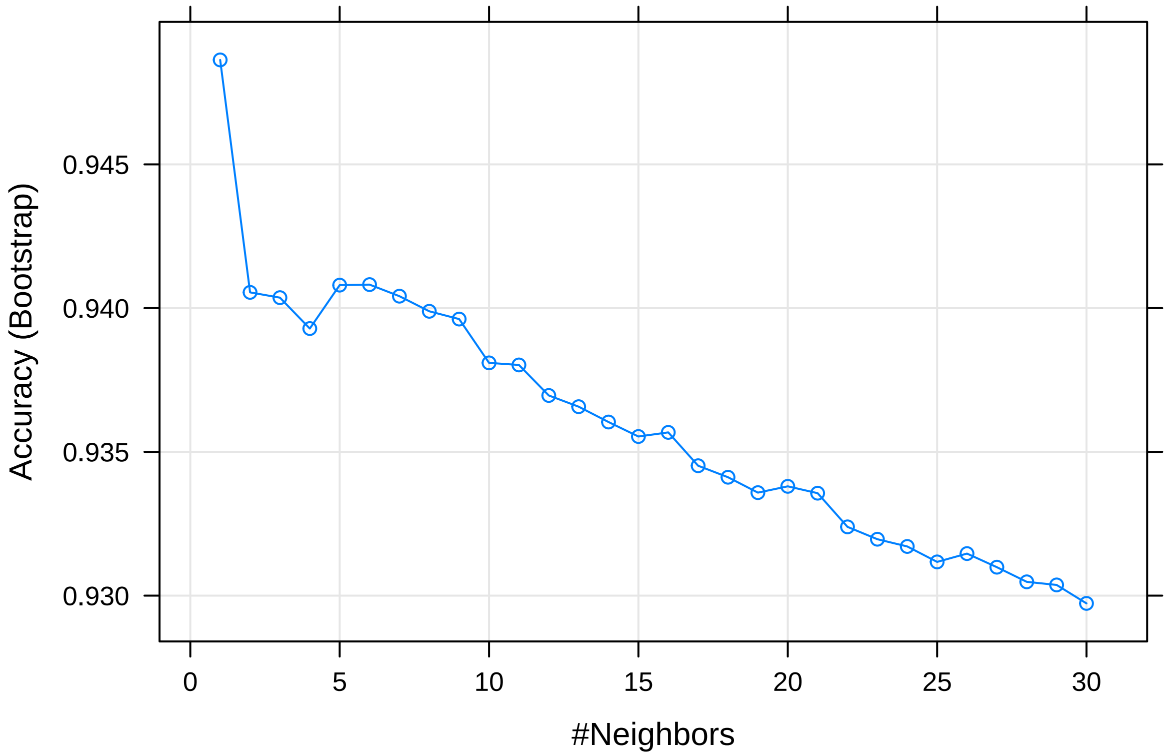
```r
best_k <- model$bestTune[[1]]
best_k
```

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

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

#Plotting the model

```r
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
```

```r
#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

```r
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).

```r
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