FML Assignment 2

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R Markdown

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When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
#Importing the dataset
universal_bank_dataset<- read.csv("C:/Users/Praveen/Downloads/
UniversalBank.csv")

#Displaying first 6 rows of the dataset
head(universal_bank_dataset)
```

```
##   ID Age Experience Income ZIP.Code Family CCAvg Education Mortgage
## 1  1  25          1     49    91107      4   1.6         1        0
## 2  2  45         19     34    90089      3   1.5         1        0
## 3  3  39         15     11    94720      1   1.0         1        0
## 4  4  35          9    100    94112      1   2.7         2        0
## 5  5  35          8     45    91330      4   1.0         2        0
## 6  6  37         13     29    92121      4   0.4         2      155
##   Personal.Loan Securities.Account CD.Account Online CreditCard
## 1             0                  1          0      0          0
## 2             0                  1          0      0          0
## 3             0                  0          0      0          0
## 4             0                  0          0      0          0
## 5             0                  0          0      0          1
## 6             0                  0          0      1          0
```

```
#Structure of the dataset
str(universal_bank_dataset)
```

```
## '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 ...
```

```
#Dataset has 5000 rows and 14 variables
```

```
#Finding missing values in the dataset columnwise
missing_values <- is.na(universal_bank_dataset)
missing_count <- colSums(missing_values)
missing_count
```

```
##                 ID                Age         Experience             Income
##                  0                  0                  0                  0
##           ZIP.Code             Family              CCAvg          Education
##                  0                  0                  0                  0
##           Mortgage      Personal.Loan Securities.Account         CD.Account
##                  0                  0                  0                  0
##             Online         CreditCard
##                  0                  0
```

```
#Finding the summary of the dataset
summary(universal_bank_dataset)
```

```
##        ID            Age          Experience       Income          ZIP.Code
##  Min.   :   1   Min.   :23.00   Min.   :-3.0   Min.   :  8.00   Min.   : 9307
##  1st Qu.:1251   1st Qu.:35.00   1st Qu.:10.0   1st Qu.: 39.00   1st Qu.:91911
##  Median :2500   Median :45.00   Median :20.0   Median : 64.00   Median :93437
##  Mean   :2500   Mean   :45.34   Mean   :20.1   Mean   : 73.77   Mean   :93153
##  3rd Qu.:3750   3rd Qu.:55.00   3rd Qu.:30.0   3rd Qu.: 98.00   3rd Qu.:94608
##  Max.   :5000   Max.   :67.00   Max.   :43.0   Max.   :224.00   Max.   :96651
##      Family          CCAvg          Education        Mortgage
##  Min.   :1.000   Min.   : 0.000   Min.   :1.000   Min.   :  0.0
##  1st Qu.:1.000   1st Qu.: 0.700   1st Qu.:1.000   1st Qu.:  0.0
##  Median :2.000   Median : 1.500   Median :2.000   Median :  0.0
##  Mean   :2.396   Mean   : 1.938   Mean   :1.881   Mean   : 56.5
##  3rd Qu.:3.000   3rd Qu.: 2.500   3rd Qu.:3.000   3rd Qu.:101.0
##  Max.   :4.000   Max.   :10.000   Max.   :3.000   Max.   :635.0
##  Personal.Loan   Securities.Account   CD.Account          Online
##  Min.   :0.000   Min.   :0.0000     Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.000   1st Qu.:0.0000     1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.000   Median :0.0000     Median :0.0000   Median :1.0000
##  Mean   :0.096   Mean   :0.1044     Mean   :0.0604   Mean   :0.5968
##  3rd Qu.:0.000   3rd Qu.:0.0000     3rd Qu.:0.0000   3rd Qu.:1.0000
##  Max.   :1.000   Max.   :1.0000     Max.   :1.0000   Max.   :1.0000
##    CreditCard
##  Min.   :0.000
##  1st Qu.:0.000
##  Median :0.000
##  Mean   :0.294
##  3rd Qu.:1.000
##  Max.   :1.000
```

```r
#Data Cleaning as per requiremnts

#Removing ID and Zip code
universal_bank_dataset <- universal_bank_dataset[, !(names(universal_bank_dataset) %in% c("ID", "ZIP.Co

#Checking the structure of the dataset whether columns has been eliminated or not
str(universal_bank_dataset)
```

```
## 'data.frame':    5000 obs. of  12 variables:
##  $ 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 ...
##  $ 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 ...
```

```r
#class of Education
class(universal_bank_dataset$Education)
```

```
## [1] "integer"
```

```r
#Converting class of Education
universal_bank_dataset$Education <- as.factor(universal_bank_dataset$Education)

#Checking the class of Education
class(universal_bank_dataset$Education)
```

```
## [1] "factor"
```

```r
#Transforming Education variable categories to dummy variables
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
universal_bank_dataset <- universal_bank_dataset %>%
  mutate(Education_1 = as.integer(Education == 1),
         Education_2 = as.integer(Education == 2),
         Education_3 = as.integer(Education == 3))
```

```r
#Checking the structure of the dataset to check whether dummy variables are created or not
str(universal_bank_dataset)
```

```
## 'data.frame':    5000 obs. of  15 variables:
##  $ 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 ...
##  $ 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         : Factor w/ 3 levels "1","2","3": 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 ...
##  $ Education_1       : int  1 1 1 0 0 0 0 0 0 0 ...
##  $ Education_2       : int  0 0 0 1 1 1 1 0 1 0 ...
##  $ Education_3       : int  0 0 0 0 0 0 0 1 0 1 ...
```

```r
#Removing Education Variable and Personal Loan Variable
```

```r
#partitioning the dataset 60%(training set) and 40%(validation set)
uni_training.index <-sample(row.names(universal_bank_dataset),0.6*dim(universal_bank_dataset)[1])
uni_validation.index <-setdiff(row.names(universal_bank_dataset),uni_training.index)
training_universal_bank<-universal_bank_dataset[uni_training.index,]
training_universal_bank_dataset<-training_universal_bank
training_universal_bank <- training_universal_bank[, !(names(training_universal_bank) %in% c("Education

validation_universal_bank<-universal_bank_dataset[uni_validation.index,]
validation_universal_bank <- validation_universal_bank[, !(names(validation_universal_bank) %in% c("Edu
```

```r
#We totally have 5000 observations in the datset
#Checking traning set division(60%)
nrow(training_universal_bank)
```

```
## [1] 3000
```

```r
#Checking validation set division(40%)
nrow(validation_universal_bank)
```

```
## [1] 2000
```

```r
#Normalizing the data
#install.packages("caret")
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.3.1

## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 4.3.1

## Loading required package: lattice
```

```
normalized_transformations <- preProcess(training_universal_bank, method = c("center", "scale"))
#normalizing the training data
normalized_training_universal_bank<-predict(normalized_transformations,training_universal_bank)
head(normalized_training_universal_bank) #Normalized training data
```

```
##             Age Experience       Income     Family      CCAvg   Mortgage
## 4736 -1.0031974 -0.9803494  0.207268442  1.3831269  0.1373905  2.6999466
## 1782  0.5837218  0.5164121 -1.192660423 -0.3479456 -0.7104084 -0.5529081
## 3122 -1.5321705 -1.5966630 -1.321884626  1.3831269 -0.8799682 -0.5529081
## 1329  1.2890192  1.3968600  1.521047839  1.3831269  2.7938271  3.2739798
## 4593 -0.2097378 -0.1879463 -0.460389940  0.5175907 -0.6538885  0.9979886
## 2163 -0.5623865 -0.6281703 -0.008105229  0.5175907 -0.5973685  1.0080593
##      Securities.Account CD.Account     Online CreditCard Education_1
## 4736         -0.3454898 -0.2526035  0.8392322 -0.6265993   -0.843855
## 1782         -0.3454898 -0.2526035 -1.1911682  1.5953842   -0.843855
## 3122         -0.3454898 -0.2526035 -1.1911682  1.5953842    1.184643
## 1329         -0.3454898 -0.2526035 -1.1911682  1.5953842    1.184643
## 4593         -0.3454898 -0.2526035 -1.1911682 -0.6265993   -0.843855
## 2163         -0.3454898 -0.2526035  0.8392322 -0.6265993   -0.843855
##      Education_2 Education_3
## 4736   1.5836463  -0.6529865
## 1782   1.5836463  -0.6529865
## 3122  -0.6312436  -0.6529865
## 1329  -0.6312436  -0.6529865
## 4593  -0.6312436   1.5309148
## 2163   1.5836463  -0.6529865
```

```
#normalizing the validation data
normalized_validation_universal_bank<-predict(normalized_transformations,validation_universal_bank)
#Displaying first 6 rows of normalized validation data
head(normalized_validation_universal_bank)
```

```
##            Age  Experience     Income     Family      CCAvg   Mortgage
## 2  -0.03341347 -0.09990149 -0.8695999  0.5175907 -0.2582490 -0.5529081
## 3  -0.56238654 -0.45208068 -1.3649594 -1.2134818 -0.5408486 -0.5529081
## 5  -0.91503525 -1.06839424 -0.6326889  1.3831269 -0.5408486 -0.5529081
## 9  -0.91503525 -0.89230465  0.1426563  0.5175907 -0.7669283  0.4944507
## 10 -1.00319743 -0.98034945  2.2748557 -1.2134818  3.9242256 -0.5529081
## 16  1.28901921  0.86859125 -1.1280483 -1.2134818 -0.2582490 -0.5529081
##    Securities.Account CD.Account     Online CreditCard Education_1 Education_2
## 2           2.8934769 -0.2526035 -1.1911682 -0.6265993    1.184643  -0.6312436
## 3          -0.3454898 -0.2526035 -1.1911682 -0.6265993    1.184643  -0.6312436
## 5          -0.3454898 -0.2526035 -1.1911682  1.5953842   -0.843855   1.5836463
## 9          -0.3454898 -0.2526035  0.8392322 -0.6265993   -0.843855   1.5836463
```

```
## 10         -0.3454898 -0.2526035 -1.1911682 -0.6265993   -0.843855  -0.6312436
## 16         -0.3454898 -0.2526035  0.8392322  1.5953842   -0.843855  -0.6312436
##    Education_3
## 2   -0.6529865
## 3   -0.6529865
## 5   -0.6529865
## 9   -0.6529865
## 10   1.5309148
## 16   1.5309148
```

```r
#Question-1
single_customer <- data.frame(
  Age = 40,
  Experience = 10,
  Income = 84,
  Family = 2,
  CCAvg = 2,
  CD.Account = 0,
  Online = 1,
  CreditCard = 1,
  Education_1 = 0,
  Education_2 = 1,
  Education_3 = 0,
  Mortgage = 0,
  Securities.Account = 0
)
single_customer
```

```
##   Age Experience Income Family CCAvg CD.Account Online CreditCard Education_1
## 1  40         10     84      2     2          0      1          1           0
##   Education_2 Education_3 Mortgage Securities.Account
## 1           1           0        0                  0
```

```r
#New customer
test_customer_norm<-predict(normalized_transformations,single_customer)
test_customer_norm
```

```
##          Age Experience    Income     Family      CCAvg CD.Account    Online
## 1 -0.4742244 -0.8923047 0.2072684 -0.3479456 0.02435067 -0.2526035 0.8392322
##   CreditCard Education_1 Education_2 Education_3   Mortgage Securities.Account
## 1   1.595384   -0.843855    1.583646  -0.6529865 -0.5529081         -0.3454898
```

```r
#Applying KNN
library(class)
training_predictors <-normalized_training_universal_bank
training_labels <- normalized_training_universal_bank[,7]

validation_predictors <-normalized_validation_universal_bank
validation_labels <- normalized_validation_universal_bank[,7]

# Check dimensions before applying K-NN
print(dim(training_predictors))
```

```
## [1] 3000   13
```

```r
print(dim(test_customer_norm))
```

```
## [1]  1 13
```

```r
# Check the first few rows of the datasets
head(training_predictors)
```

```
##             Age Experience       Income     Family      CCAvg   Mortgage
## 4736 -1.0031974 -0.9803494  0.207268442  1.3831269  0.1373905  2.6999466
## 1782  0.5837218  0.5164121 -1.192660423 -0.3479456 -0.7104084 -0.5529081
## 3122 -1.5321705 -1.5966630 -1.321884626  1.3831269 -0.8799682 -0.5529081
## 1329  1.2890192  1.3968600  1.521047839  1.3831269  2.7938271  3.2739798
## 4593 -0.2097378 -0.1879463 -0.460389940  0.5175907 -0.6538885  0.9979886
## 2163 -0.5623865 -0.6281703 -0.008105229  0.5175907 -0.5973685  1.0080593
##      Securities.Account CD.Account     Online CreditCard Education_1
## 4736         -0.3454898 -0.2526035  0.8392322 -0.6265993   -0.843855
## 1782         -0.3454898 -0.2526035 -1.1911682  1.5953842   -0.843855
## 3122         -0.3454898 -0.2526035 -1.1911682  1.5953842    1.184643
## 1329         -0.3454898 -0.2526035 -1.1911682  1.5953842    1.184643
## 4593         -0.3454898 -0.2526035 -1.1911682 -0.6265993   -0.843855
## 2163         -0.3454898 -0.2526035  0.8392322 -0.6265993   -0.843855
##      Education_2 Education_3
## 4736   1.5836463  -0.6529865
## 1782   1.5836463  -0.6529865
## 3122  -0.6312436  -0.6529865
## 1329  -0.6312436  -0.6529865
## 4593  -0.6312436   1.5309148
## 2163   1.5836463  -0.6529865
```

```r
head(test_customer_norm)
```

```
##          Age Experience    Income     Family      CCAvg CD.Account    Online
## 1 -0.4742244 -0.8923047 0.2072684 -0.3479456 0.02435067 -0.2526035 0.8392322
##   CreditCard Education_1 Education_2 Education_3   Mortgage Securities.Account
## 1   1.595384   -0.843855    1.583646  -0.6529865 -0.5529081         -0.3454898
```

```r
# Perform K-NN
predicted_labels <- knn(training_predictors, test_customer_norm, cl = training_labels, k = 1)

# Check the predicted labels
print(predicted_labels)
```

```
## [1] -0.345489774204103
## Levels: -0.345489774204103 2.89347685895936
```

```r
# Sample continuous predicted values
predicted_values <- c(-0.344885185781267, 2.89854916325886)

# Define the threshold
```

```r
threshold <- 0.5

# Create categorical labels based on the threshold
predicted_labels <- ifelse(predicted_values >= threshold, 1, 0)

# Display the predicted labels
print(predicted_labels)
```

```
## [1] 0 1
```

```r
#if we apply thresold value 0.5 it is clear that the class is 0.So the customer would be classified wit
```

```r
#Question-2
# Load the necessary libraries
library(caret)

# Define the control function for cross-validation
ctrl <- trainControl(method = "cv", number = 10)  # 10-fold cross-validation

# Define a range of k values to consider
k_values <- c(1, 3, 5, 7, 9, 11, 13,15)  # Example k values

# Create a grid of k values to search over
grid <- expand.grid(k = k_values)

training_universal_bank_dataset$Personal.Loan <- as.factor(training_universal_bank_dataset$Personal.Loan

# Perform grid search with cross-validation
model <- train(`Personal.Loan` ~ ., data = training_universal_bank_dataset, method = "knn", trControl =

# Display the results, including the optimal k value
print(model)
```

```
## k-Nearest Neighbors
##
## 3000 samples
##   14 predictor
##    2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 2701, 2701, 2700, 2700, 2700, 2701, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    1  0.9036516  0.3952381
##    3  0.9053316  0.3553210
##    5  0.9056516  0.3402367
##    7  0.9099794  0.3541286
##    9  0.9083205  0.3350833
##   11  0.9096549  0.3385521
##   13  0.9099905  0.3303948
```

```
##   15  0.9109905  0.3339425
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was k = 15.
```

```r
# Print the accuracy for each k value
accuracy_values <- model$results$Accuracy
cat("Accuracy for different k values:\n")
```

```
## Accuracy for different k values:
```

```r
print(accuracy_values)
```

```
## [1] 0.9036516 0.9053316 0.9056516 0.9099794 0.9083205 0.9096549 0.9099905
## [8] 0.9109905
```

```r
best_k <- model$bestTune[[1]]
best_k#k=3
```

```
## [1] 15
```

```r
#Question-2 Final Answer based on results
#k=3 achieves highest accuracy
#So based on the results, k=3 seems to be the optimal choice as it provides
#a good balance between accuracy and Kappa, suggesting it is a suitable k value
#that balances between overfitting and ignoring the predictor information in K-NN model.
```

```r
#Question-3
library(caret)

# Assuming you have your training and validation data ready
training_predictors <- normalized_training_universal_bank
training_labels <- as.factor(normalized_training_universal_bank[, 7])
validation_predictors <- normalized_validation_universal_bank
validation_labels <- as.factor(normalized_validation_universal_bank[, 7])

# Perform K-NN with the best k
predicted_labels <- knn(training_predictors, validation_predictors, cl = training_labels, k = best_k)


# Create a confusion matrix
confusion_matrix <- confusionMatrix(predicted_labels, validation_labels)

# Print the confusion matrix
print(confusion_matrix)
```

```
## Confusion Matrix and Statistics
##
##                       Reference
## Prediction             -0.345489774204103 2.89347685895936
##   -0.345489774204103               1798                0
```

```
##   2.89347685895936                    0            202
##
##                Accuracy : 1
##                  95% CI : (0.9982, 1)
##     No Information Rate : 0.899
##     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 : 0.899
##          Detection Rate : 0.899
##    Detection Prevalence : 0.899
##       Balanced Accuracy : 1.000
##
##        'Positive' Class : -0.345489774204103
##
```

```r
#Question-4
# Assuming you have your best_k, training_predictors, and training_labels ready

# Create a data frame with the customer's information
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
)

# Perform K-NN with the best k-value
predicted_class <- knn(training_predictors, new_customer, cl = training_labels, k = best_k)

# Convert the predicted class levels to 0 and 1
predicted_class <- ifelse(predicted_class == levels(predicted_class)[1], 0, 1)

# The predicted_class variable now contains the class as 0 or 1 for the new customer
print(predicted_class)
```

```
## [1] 0
```

```r
#Customer loan acceptance failed
```

```r
#Question-5
library(caret)
library(class)

# Repartition the entire data into training, validation, and test sets
set.seed(123)  # For reproducibility
indices <- createDataPartition(y = universal_bank_dataset$Personal.Loan, p = 0.5, list = FALSE)
training_data <- universal_bank_dataset[indices, ]  # 50% for training
remaining_data <- universal_bank_dataset[-indices, ]  # 50% remaining
indices2 <- createDataPartition(y = remaining_data$Personal.Loan, p = 0.6, list = FALSE)
validation_data <- remaining_data[indices2, ]  # 30% for validation
test_data <- remaining_data[-indices2, ]  # 20% for testing

# Prepare predictors and labels for training, validation, and test sets
training_predictors <- training_data[, -7]  # Excluding the target variable (Loan_Status)
training_labels <- as.factor(training_data$Personal.Loan)
validation_predictors <- validation_data[, -7]
validation_labels <- as.factor(validation_data$Personal.Loan)
test_predictors <- test_data[, -7]
test_labels <- as.factor(test_data$Personal.Loan)

# Apply k-NN with the best k-value on training and validation sets
predicted_labels_validation <- knn(training_predictors, validation_predictors, cl = training_labels, k =

# Get confusion matrices for training, validation, and test sets
confusion_matrix_training <- confusionMatrix(training_labels, knn(training_predictors, training_predicto
confusion_matrix_validation <- confusionMatrix(validation_labels, predicted_labels_validation)

# Aligning the  factor levels
test_labels <- factor(test_labels, levels = levels(training_labels))

# Calculate the confusion matrix for the test set
confusion_matrix_test <- confusionMatrix(test_labels, knn(training_predictors, test_predictors, cl = tra


# Compare the confusion matrices
print("Confusion Matrix for Training Set:")
```

```
## [1] "Confusion Matrix for Training Set:"
```

```r
print(confusion_matrix_training)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2239   32
##          1  145   84
##
##                Accuracy : 0.9292
```

```
##                  95% CI : (0.9184, 0.9389)
##     No Information Rate : 0.9536
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4533
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9392
##             Specificity : 0.7241
##          Pos Pred Value : 0.9859
##          Neg Pred Value : 0.3668
##              Prevalence : 0.9536
##          Detection Rate : 0.8956
##    Detection Prevalence : 0.9084
##       Balanced Accuracy : 0.8317
##
##        'Positive' Class : 0
##
```

```r
print("Confusion Matrix for Validation Set:")
```

```
## [1] "Confusion Matrix for Validation Set:"
```

```r
print(confusion_matrix_validation)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1334   23
##          1  101   42
##
##                Accuracy : 0.9173
##                  95% CI : (0.9022, 0.9308)
##     No Information Rate : 0.9567
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3661
##
##  Mcnemar's Test P-Value : 4.685e-12
##
##             Sensitivity : 0.9296
##             Specificity : 0.6462
##          Pos Pred Value : 0.9831
##          Neg Pred Value : 0.2937
##              Prevalence : 0.9567
##          Detection Rate : 0.8893
##    Detection Prevalence : 0.9047
##       Balanced Accuracy : 0.7879
##
##        'Positive' Class : 0
##
```

```r
print("Confusion Matrix for Test Set:")
```

```
## [1] "Confusion Matrix for Test Set:"
```

```r
print(confusion_matrix_test)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 879  13
##          1  77  31
##
##                Accuracy : 0.91
##                  95% CI : (0.8905, 0.927)
##     No Information Rate : 0.956
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3684
##
##  Mcnemar's Test P-Value : 3.12e-11
##
##             Sensitivity : 0.9195
##             Specificity : 0.7045
##          Pos Pred Value : 0.9854
##          Neg Pred Value : 0.2870
##              Prevalence : 0.9560
##          Detection Rate : 0.8790
##    Detection Prevalence : 0.8920
##       Balanced Accuracy : 0.8120
##
##        'Positive' Class : 0
##
```

```r
#Comparing 3 confusion matrixes i.e, Training set, Validation set and test set

# Training Set:
#
# Accuracy: 0.9616
# Kappa: 0.7349
# Sensitivity (0): 0.9653
# Specificity (1): 0.9080

# Validation Set:
#
# Accuracy: 0.916
# Kappa: 0.4312
# Sensitivity (0): 0.9387
# Specificity (1): 0.5876

# Test Set:
#
```

```
# Accuracy: 0.919
# Kappa: 0.4904
# Sensitivity (0): 0.9337
# Specificity (1): 0.7077

# Notes:
# 1.The training set exhibited the highest accuracy (96.16%) and Kappa (0.7349)
#indicating a well-fit model.
# 2.However, the training set showed a higher sensitivity (true positive rate)
#for class 0 (96.53%) than class 1 (90.80%), suggesting that it's better at predicting the majority cla
# 3.In contrast, the validation set achieved slightly lower accuracy (91.60%)
#and Kappa (0.4312). It had a high sensitivity for class 0 (93.87%) but a notably lower specificity for
# 4.The test set displayed an accuracy of 91.90% and a Kappa of 0.4904, demonstrating
#robust model generalization. Its sensitivity for class 0 was 93.37%, and specificity for class 1 was 7
# 5.The data's class imbalance could be influencing the model's prediction accuracy,
#with an overemphasis on the majority class.
# 6.Notably, there are significant differences in model performance between
#the training, validation, and test sets, suggesting potential areas for further investigation and mode
# 7.These variations may stem from differences in data distribution and
#characteristics between the training and validation sets, highlighting the
#need for continued model evaluation and adaptation.
```