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library(class)  
library(caret)

## Loading required package: ggplot2

## Loading required package: lattice

## Loading required package : ggplot2

## Loading required package : lattice

library(e1071)

Universal\_Bank <- read.csv("C:\\Users\\archa\\Downloads\\UniversalBank.csv")  
dim(Universal\_Bank)

## [1] 5000 14

###The command above loads the file into an R DataFrame. ####The ‘Dim’ function shows the total number of rows and columns.

summary(Universal\_Bank)

## 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

###The data provided above serves as a summary of the given dataset.

Universal\_Bank$ID <- NULL  
Universal\_Bank$ZIP.Code <- NULL

###The command mentioned above removed the ‘ID’ and ‘ZIP.Code’ columns.

summary(Universal\_Bank)

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

###Above is the updated summary of the dataset after removing the ‘ID’ and ‘ZIP.Code’ columns.

Universal\_Bank$Education <- as.factor(Universal\_Bank$Education)  
Dummy\_Var <- dummyVars(~., data = Universal\_Bank)  
Universal\_updated <- as.data.frame(predict(Dummy\_Var,Universal\_Bank))

###In the command mentioned earlier, ‘Education’ is transformed into a factor, and subsequently, dummy variables are created for Education.

set.seed(1)  
train\_data <- sample(row.names(Universal\_updated), 0.6\*dim(Universal\_updated)[1])  
valid\_data <- setdiff(row.names(Universal\_updated), train\_data)  
train\_df <- Universal\_updated[train\_data,]  
valid\_df <- Universal\_updated[valid\_data,]  
summary(train\_df)

## Age Experience Income Family   
## Min. :23.00 Min. :-3.00 Min. : 8.00 Min. :1.000   
## 1st Qu.:36.00 1st Qu.:10.00 1st Qu.: 39.00 1st Qu.:1.000   
## Median :45.00 Median :20.00 Median : 63.00 Median :2.000   
## Mean :45.43 Mean :20.19 Mean : 73.08 Mean :2.388   
## 3rd Qu.:55.00 3rd Qu.:30.00 3rd Qu.: 98.00 3rd Qu.:3.000   
## Max. :67.00 Max. :43.00 Max. :224.00 Max. :4.000   
## CCAvg Education.1 Education.2 Education.3   
## Min. : 0.000 Min. :0.0000 Min. :0.000 Min. :0.0000   
## 1st Qu.: 0.700 1st Qu.:0.0000 1st Qu.:0.000 1st Qu.:0.0000   
## Median : 1.500 Median :0.0000 Median :0.000 Median :0.0000   
## Mean : 1.915 Mean :0.4173 Mean :0.285 Mean :0.2977   
## 3rd Qu.: 2.500 3rd Qu.:1.0000 3rd Qu.:1.000 3rd Qu.:1.0000   
## Max. :10.000 Max. :1.0000 Max. :1.000 Max. :1.0000   
## Mortgage Personal.Loan Securities.Account CD.Account   
## Min. : 0.00 Min. :0.00000 Min. :0.0000 Min. :0.00000   
## 1st Qu.: 0.00 1st Qu.:0.00000 1st Qu.:0.0000 1st Qu.:0.00000   
## Median : 0.00 Median :0.00000 Median :0.0000 Median :0.00000   
## Mean : 57.34 Mean :0.09167 Mean :0.1003 Mean :0.05367   
## 3rd Qu.:102.00 3rd Qu.:0.00000 3rd Qu.:0.0000 3rd Qu.:0.00000   
## Max. :635.00 Max. :1.00000 Max. :1.0000 Max. :1.00000   
## Online CreditCard   
## Min. :0.0000 Min. :0.0000   
## 1st Qu.:0.0000 1st Qu.:0.0000   
## Median :1.0000 Median :0.0000   
## Mean :0.5847 Mean :0.2927   
## 3rd Qu.:1.0000 3rd Qu.:1.0000   
## Max. :1.0000 Max. :1.0000

###In the given command, the data has been split into 60% training set and a 40% validation set.

train\_norm\_df <- train\_df[,-10]  
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])

###In this command, note that ‘Personal Income’ is the 10th Variable that has been normalized.

#1 > Age = 40, Experience = 10,Income = 84,Family = 2,CCAvg = 2, Education\_1 = 0, Education\_2 = 1, Education\_3 = 0, Securities Account = 0, CD Account = 0, Online = 1, and Credit card = 1. Perform a k-NN classification with all predictors except ID and ZIP codeusing k = 1.Remember to transform categorical predictors with more than two catergories into dummy variables first. Specify the success class as 1 (loan acceptance), and use the default cutoff value of 0.5. How would this customer be classified?

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)  
New\_Customer\_norm <- New\_Customer  
New\_Customer\_norm <- predict(norm\_values, New\_Customer\_norm)

###The command above involves assigning all data elements to a fresh variable named ‘New\_Customer’ and subsequently normalizing the data stored within ‘New\_Customer’.

knn.predictional <- class::knn(train\_norm\_df, test = New\_Customer\_norm, cl = train\_df$Personal.Loan)  
knn.predictional

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

###The command mentioned earlier utilized ‘knn’ (k-nearest neighbors) to generate ‘Prediction 1’.

#2> What is a choice of k that between overfitting and ignoring the predictor information?

accuracy.df <- data.frame(k = seq(1, 15, 1), overallaccuracy = rep(0,15))  
for(i in 1:15)  
{  
 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")$overall[1]  
}  
which(accuracy.df[,2] == max(accuracy.df[,2]))

## [1] 3

###In the previously mentioned command, calculate the accuracy for each value of ‘k’ within a defined range of the variable ‘k’.

#3 > Show the confusion matrix foe the validation data that results from using the best k.

knn.prediction2 <- class::knn(train = train\_norm\_df,  
 test = valid\_norm\_df,  
 cl= train\_df$Personal.Loan, k=3)  
knn.prediction2

## [1] 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 0 0  
## [38] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [75] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [112] 0 0 1 0 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0  
## [149] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0  
## [186] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [223] 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [260] 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 1 0 1 0 0 0 0 0 1  
## [297] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0  
## [334] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [371] 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0  
## [408] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [445] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0  
## [482] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0  
## [519] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0  
## [556] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [593] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0  
## [630] 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [667] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [704] 0 0 0 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [741] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [778] 0 0 1 0 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0  
## [815] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1  
## [852] 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0  
## [889] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 1 0 0 0  
## [926] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0  
## [963] 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0  
## [1000] 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1037] 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0  
## [1074] 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0  
## [1111] 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0  
## [1148] 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0  
## [1185] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 1 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1222] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1259] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1296] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0  
## [1333] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1370] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0  
## [1407] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1444] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1481] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1518] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1555] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1592] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0  
## [1629] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0  
## [1666] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1703] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 1 0 0 0 0  
## [1740] 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0  
## [1777] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1814] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [1851] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1888] 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1925] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0  
## [1962] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1999] 0 0  
## Levels: 0 1

Confusion.matrix <- confusionMatrix(knn.prediction2, as.factor(valid\_df$Personal.Loan), positive = "1")  
Confusion.matrix

## 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 : 0.6927   
## Specificity : 0.9950   
## Pos Pred Value : 0.9404   
## Neg Pred Value : 0.9659   
## Prevalence : 0.1025   
## Detection Rate : 0.0710   
## Detection Prevalence : 0.0755   
## Balanced Accuracy : 0.8438   
##   
## 'Positive' Class : 1   
##

###The confusion matrix given represents the validation data produced using the best ‘k’ value.

#4 > Consider the following customer: 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 and Credit Card = 1. Classify the customer using the best k.

New\_Customer1 <- 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  
 )  
New\_Cust\_norm1 <- New\_Customer1  
New\_Cust\_norm1 <- predict(norm\_values, New\_Cust\_norm1)  
knn.prediction3 <- class::knn(train = train\_norm\_df,  
 test = New\_Cust\_norm1,  
 cl= train\_df$Personal.Loan,k=3)  
knn.prediction3

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

###The confusion matrix presented is derived from the validation dataset, utilizing the best ‘k’ value.

#5 > Repartition the data, this time into training, validation, and tests sets(50% : 30% : 20%). Apply the k-NN method with the k chosen above. Compare the confusion matrix of the test set with that of the training and validation sets. Comment on the differences and their reason.

set.seed(1)  
  
train\_index1 <- sample(row.names(Universal\_updated),0.5\*dim(Universal\_updated)[1])  
train\_df1 <- Universal\_updated[train\_index1,]  
  
valid\_index1 <- setdiff(row.names(Universal\_updated), train\_index1)  
valid\_df1 <-Universal\_updated[valid\_index1, ]  
  
valid\_index2 <- sample(row.names(valid\_df1), 0.6\*dim(valid\_df1)[1])  
valid\_df2 <- valid\_df1[valid\_index2, ]  
  
test\_index1 <- setdiff(row.names(valid\_df1),valid\_index2)  
test\_df1 <- valid\_df1[test\_index1, ]

###The command above involves dividing the data into training, validation, and testing sets, with proportions of 50%, 30%, and 20% respectively.

train\_norm\_df1 <- train\_df1[,-10]  
valid\_norm\_df2 <- valid\_df2[,-10]  
test\_norm\_df1 <-test\_df1[,-10]  
  
norm\_values1 <- preProcess(train\_df1[,-10], method = c("center","scale"))  
  
train\_norm\_df1 <- predict(norm\_values1, train\_df1[,-10])  
valid\_norm\_df2 <- predict(norm\_values1, valid\_df2[,-10])  
test\_norm\_df1 <- predict(norm\_values1, test\_df1[,-10])

### Normalized the data above.

knn\_prediction4 <- class::knn(train = train\_norm\_df1,  
 test = train\_norm\_df1,  
 cl= train\_df1$Personal.Loan, k= 3)  
knn\_prediction4

## [1] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [38] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0  
## [75] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [112] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [149] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 1 0 0 0 0 0 0 0  
## [186] 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [223] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0  
## [260] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [297] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [334] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0  
## [371] 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0  
## [408] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [445] 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [482] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [519] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 1 0 0 0 0 0 1 1 0  
## [556] 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [593] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [630] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [667] 0 0 1 1 0 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0  
## [704] 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0  
## [741] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [778] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [815] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0  
## [852] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [889] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [926] 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0  
## [963] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0  
## [1000] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1037] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1074] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0  
## [1111] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0  
## [1148] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0  
## [1185] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1  
## [1222] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1259] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0  
## [1296] 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1333] 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0  
## [1370] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0  
## [1407] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1444] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1  
## [1481] 1 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0  
## [1518] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 1 0 0 0 0 0 0 0 0 0  
## [1555] 1 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [1592] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1629] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1666] 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1  
## [1703] 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1740] 0 0 1 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1777] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1814] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0  
## [1851] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1888] 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0  
## [1925] 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1962] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1999] 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0  
## [2036] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1  
## [2073] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [2110] 1 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0  
## [2147] 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [2184] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1  
## [2221] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0  
## [2258] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1  
## [2295] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1  
## [2332] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [2369] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [2406] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 1 0 1  
## [2443] 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [2480] 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## Levels: 0 1

###The above is knn-prediction of 50% Training data.

confusionMatrix1 <- confusionMatrix(knn\_prediction4, as.factor(train\_df1$Personal.Loan))  
confusionMatrix1

## 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 : 0.9978   
## Specificity : 0.7672   
## Pos Pred Value : 0.9767   
## Neg Pred Value : 0.9727   
## Prevalence : 0.9072   
## Detection Rate : 0.9052   
## Detection Prevalence : 0.9268   
## Balanced Accuracy : 0.8825   
##   
## 'Positive' Class : 0   
##

knn\_prediction5 <- class::knn(train = train\_norm\_df1,  
 test = valid\_norm\_df2,  
 cl= train\_df1$Personal.Loan, k=3)  
knn\_prediction5

## [1] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0  
## [38] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [75] 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [112] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [149] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [186] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [223] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0  
## [260] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [297] 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1  
## [334] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0  
## [371] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [408] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [445] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [482] 0 0 1 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [519] 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 0 1 0 0  
## [556] 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0  
## [593] 0 0 1 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [630] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0  
## [667] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [704] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [741] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [778] 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [815] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [852] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [889] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [926] 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0  
## [963] 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1000] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1037] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0  
## [1074] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1111] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0  
## [1148] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0  
## [1185] 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1222] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0  
## [1259] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1296] 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0  
## [1333] 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1370] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0  
## [1407] 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1444] 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1481] 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0  
## Levels: 0 1

###The above is knn\_prediction of 30% Validation data.

confusion.matrix2 <- confusionMatrix(knn\_prediction5, as.factor(valid\_df2$Personal.Loan))  
confusion.matrix2

## 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 : 0.9956   
## Specificity : 0.6912   
## Pos Pred Value : 0.9700   
## Neg Pred Value : 0.9400   
## Prevalence : 0.9093   
## Detection Rate : 0.9053   
## Detection Prevalence : 0.9333   
## Balanced Accuracy : 0.8434   
##   
## 'Positive' Class : 0   
##

knn\_prediction6 <- class::knn(train = train\_norm\_df1,  
 test = test\_norm\_df1,  
 cl= train\_df1$Personal.Loan, k= 3)  
knn\_prediction6

## [1] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [38] 0 0 0 0 1 0 0 1 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [75] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [112] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 1 0 0 0 0 0 0 0 0 0  
## [149] 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0  
## [186] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1  
## [223] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0  
## [260] 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [297] 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [334] 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [371] 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [408] 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0  
## [445] 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0  
## [482] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0  
## [519] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0  
## [556] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1  
## [593] 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0  
## [630] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [667] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0  
## [704] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [741] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0  
## [778] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0  
## [815] 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0  
## [852] 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0  
## [889] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1  
## [926] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0  
## [963] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0  
## [1000] 0  
## Levels: 0 1

###The above is knn-prediction of 20% Testing data.

confusion\_matrix3 <- confusionMatrix(knn\_prediction6, as.factor(test\_df1$Personal.Loan))  
confusion\_matrix3

## 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 : 0.9955   
## Specificity : 0.6875   
## Pos Pred Value : 0.9619   
## Neg Pred Value : 0.9506   
## Prevalence : 0.8880   
## Detection Rate : 0.8840   
## Detection Prevalence : 0.9190   
## Balanced Accuracy : 0.8415   
##   
## 'Positive' Class : 0   
##

#Based on the data presented above, it’s evident that the training accuracy slightly surpasses that of the test and validation sets. This suggests that the algorithm is functioning efficiently and according to expectations.

The confusion matrix for the testing set differs from that of the training and validation sets.

\*Predictions are less precise as the accuracy of the test model is inferior to that of the training and validation sets.

\*Additionally, the Kappa statistic for the test case is low. Sensitivity and specificity for the test case are also low compared to them, suggesting a limited ability to identify positive and negative cases, respectively.

Overall, the confusion matrix for the test case is inferior to theirs, with potential variations attributed to factors such as data set selection, parameter configuration, and approach strategy.