

Customer Churn

Abhay Kulkarni

7/20/2019

Contents

1	Introduction	3
1.1	What is Customer Churn	3
1.2	Why Predict Customer Churn	3
2	Libraries/ Packages	4
3	Project Objective	6
3.1	EDA	6
3.2	Build Models and compare them to get to the best one	6
3.3	Actionable Insights	6
4	Step by Step Approach	7
4.1	EDA	7
4.1.1	Set Working Directory	7
4.1.2	Import Data	7
4.1.3	Check Dataset	7
4.1.4	Creating Backup of the original dataset	9
4.1.5	AccountWeeks, DataUsage, DataUsage, CustServCalls, DayMins, DayCalls, Monthly-Charge, OverageFee, RoamMins are incorrectly imported as factors. Convert factors to numeric data types.	9
4.1.6	Checking sturcture of data	10
4.1.7	Dataset details	10
4.1.8	Visualize dataset	10
4.1.9	Checking for Missing Values	11
4.1.10	Check if there are Outliers	13
4.1.11	Outlier Treatment. Winsorizing.	14
4.1.12	Outliers Treated.	15
4.1.13	Checking Churn data split	15
4.1.14	Visualize Dependent Variable(Churn) proportion split	15
4.1.15	Dependent Variables VS Independent Variables	16
5	Build Models	26
5.1	Pre Process(Train and Test Split)	26
5.1.1	Before Balance VS After Balance	26
5.2	Logistic Regression	26
5.2.1	Full Model for stepwise variable selection and elimination	27
5.2.2	Empty Model for stepwise variable selection and elimination	28
5.2.3	Backward Selection of significant variables	28
5.2.4	Forward Slection	29
5.2.5	Modelling Logistic Regression with Cross Validation	31
5.2.6	Logistic Regression Model	31
5.2.7	Checking for Multicollinearity	32
5.2.8	Predicting for Train Data	32
5.2.9	Probabilities	32
5.2.10	Covertng Probabilites to 0 and 1	46

5.2.11	ConfusionMatrix and Training Model Evaluation	51
5.2.12	Accuracy of Train, Precision , Recall, Sensitivity and F score	51
5.2.13	Model Evaluation Table	52
5.2.14	ROC Curve Plot	52
5.2.15	Predicting Test Data	53
5.2.16	Covertng Probabilites to 0 and 1	53
5.2.17	ConfusionMatrix and Test Data Model Evaluation	56
5.2.18	Accuracy of Train, Precision , Recall, Sensitivity and F score	56
5.2.19	Model Evaluation Table	56
5.2.20	ROC Curve Plot	57
5.3	KNN	58
5.3.1	What is KNN	58
5.3.2	Fitting KNN to the Training set and Predicting the Test set results	58
5.3.3	Confusion Matrix	59
5.3.4	Trying Different K value	59
5.3.5	Try k 9	60
5.3.6	Try K 15	60
5.3.7	Try K 25	60
5.3.8	Try K 35	61
5.3.9	Model Evaluation Table	62
5.4	Naive Bayes	63
5.4.1	What is Naive Bayes	63
5.4.2	Naive Bayes. Is it applicable here?	63
5.4.3	Fitting Naive Bayes to training set	63
5.4.4	Prediciting Naive Bayes Test Dataset	63
5.4.5	ConfusionMatrix	64
5.4.6	Model Evaluation Table	66
5.5	Model Comparison using Model Performance metrics	67
5.5.1	Interpretation	67
5.5.2	Conclusion:	67
5.5.3	Recommendation:	67

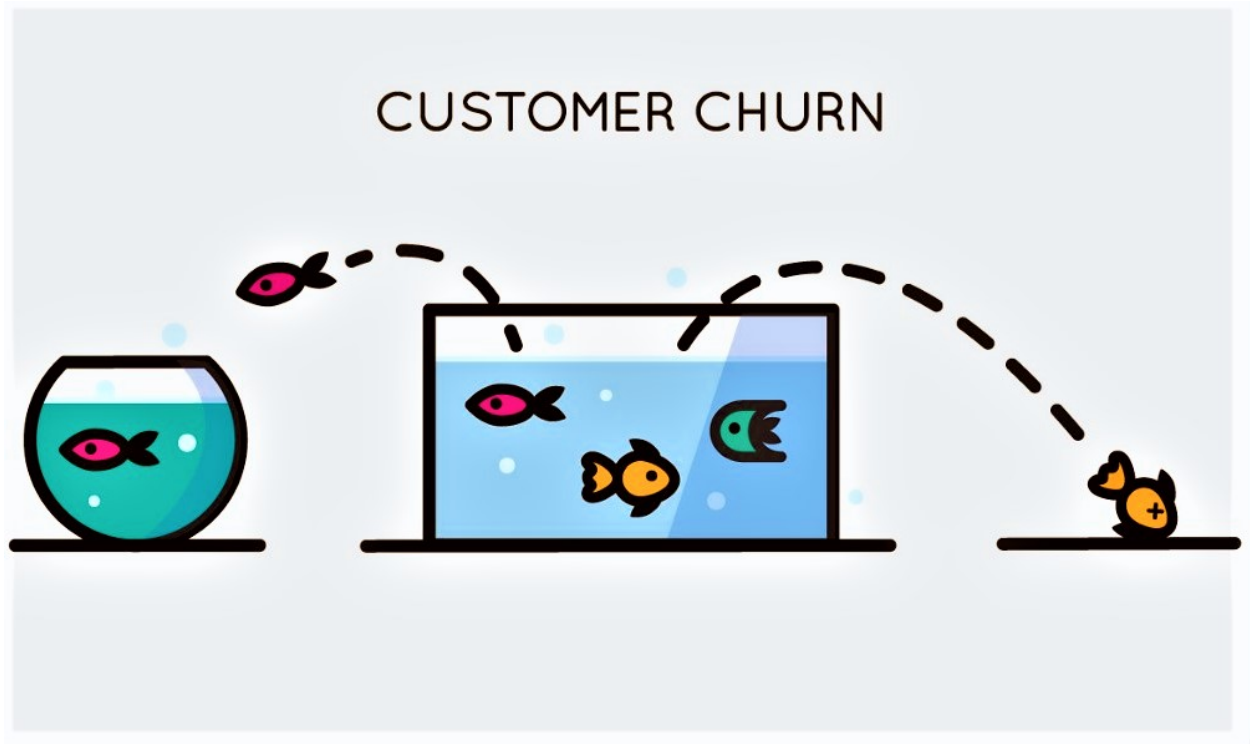


Figure 1: Customer Churn

Customer Churn in Telecom Industry

1 Introduction

1.1 What is Customer Churn

Customer attrition, also known as customer churn, customer turnover, or customer defection, is the loss of clients or customers.

1.2 Why Predict Customer Churn

Current organizations face a huge challenge: to be able to anticipate to customers' abandon in order to retain them on time, reducing this way costs and risks and gaining efficiency and competitiveness.

2 Libraries/ Packages

```
library(DataExplorer)

## Warning: package 'DataExplorer' was built under R version 3.5.3
library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.5.3
library(caTools)

## Warning: package 'caTools' was built under R version 3.5.3
library(xlsx)

## Warning: package 'xlsx' was built under R version 3.5.2
library(skimr)

## Warning: package 'skimr' was built under R version 3.5.3
##
## Attaching package: 'skimr'
## The following object is masked from 'package:stats':
##
##     filter
library(caret)

## Warning: package 'caret' was built under R version 3.5.3
## Loading required package: lattice
## Warning: package 'lattice' was built under R version 3.5.2
library(cowplot)

## Warning: package 'cowplot' was built under R version 3.5.3
##
## *****
## Note: As of version 1.0.0, cowplot does not change the
## default ggplot2 theme anymore. To recover the previous
## behavior, execute:
## theme_set(theme_cowplot())
## *****
library(caTools)
library(ROSE)

## Warning: package 'ROSE' was built under R version 3.5.3
## Loaded ROSE 0.0-3
library(ROCR)

## Warning: package 'ROCR' was built under R version 3.5.3
## Loading required package: gplots
```

```

## Warning: package 'gplots' was built under R version 3.5.2
##
## Attaching package: 'gplots'
## The following object is masked from 'package:stats':
##
##      lowess
library(MLmetrics)

## Warning: package 'MLmetrics' was built under R version 3.5.3
##
## Attaching package: 'MLmetrics'
## The following objects are masked from 'package:caret':
##
##      MAE, RMSE
## The following object is masked from 'package:base':
##
##      Recall
library(MASS)

## Warning: package 'MASS' was built under R version 3.5.3
library(class)

## Warning: package 'class' was built under R version 3.5.2
library(e1071)

## Warning: package 'e1071' was built under R version 3.5.3
library(car)

## Warning: package 'car' was built under R version 3.5.3
## Loading required package: carData
## Warning: package 'carData' was built under R version 3.5.2

```

3 Project Objective

Customer Churn is a burning problem for Telecom companies. In this project, we simulate one such case of customer churn where we work on a data of postpaid customers with a contract. The data has information about the customer usage behaviour, contract details and the payment details. The data also indicates which were the customers who cancelled their service. Based on this past data, we need to build a model which can predict whether a customer will cancel their service in the future or not.

You are expected to do the following :

3.1 EDA

- How does the data look like, Univariate and bivariate analysis. Plots and charts which illustrate the relationships between variables
- Look out for outliers and missing value
- Check and treat for multicollinearity
- Summarize the insights you get from EDA

3.2 Build Models and compare them to get to the best one

- Logistic Regression
- KNN
- Naive Bayes
- Model Comparison using Model Performance metrics & Interpretation

3.3 Actionable Insights

- Interpretation & Recommendations from the best model

4 Step by Step Approach

4.1 EDA

4.1.1 Set Working Directory

```
setwd("Z:\\Projects\\Predictive\\Customer Churn")
getwd()
```

```
## [1] "Z:/Projects/Predictive/Customer Churn"
```

4.1.2 Import Data

```
mydata<-read.xlsx2("Cellphone.xlsx", sheetIndex = 2, header = TRUE)
```

Imported the xlsx datasheet with index 2 as the data is in the 2nd sheet.

4.1.3 Check Dataset

```
skim(mydata)
```

```
## Skim summary statistics
##   n obs: 3333
##   n variables: 11
##
## -- Variable type:factor -----
##      variable missing complete    n n_unique
##   AccountWeeks      0    3333 3333      212
##      Churn          0    3333 3333        2
##   ContractRenewal    0    3333 3333        2
##   CustServCalls      0    3333 3333       10
##      DataPlan        0    3333 3333        2
##      DataUsage       0    3333 3333      174
##      DayCalls        0    3333 3333      119
##      DayMins         0    3333 3333     1667
##   MonthlyCharge      0    3333 3333      656
##   OverageFee         0    3333 3333     1024
##      RoamMins        0    3333 3333      162
##
##                                     top_counts ordered
##   105: 43, 87: 42, 101: 40, 93: 40      FALSE
##           0: 2850, 1: 483, NA: 0      FALSE
##           1: 3010, 0: 323, NA: 0      FALSE
##   1: 1181, 2: 759, 0: 697, 3: 429      FALSE
##           0: 2411, 1: 922, NA: 0      FALSE
##           0: 1813, 0.3: 41, 0      FALSE
##   102: 78, 105: 75, 107: 69, 95: 69      FALSE
##           154: 8, 159: 8, 174: 8, 162: 7      FALSE
##           50: 84, 46: 75, 45: 74, 49: 73      FALSE
##           8.5: 13, 10      FALSE
##           10: 62, 11.: 59, 10      FALSE
```

Findings

*There are 3333 observations and 11 variables.

```
str(mydata)
```

```
## 'data.frame': 3333 obs. of 11 variables:
## $ Churn : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ AccountWeeks : Factor w/ 212 levels "1","10","100",...: 33 10 43 196 186 22 26 53 21 47 ...
## $ ContractRenewal: Factor w/ 2 levels "0","1": 2 2 2 1 1 1 2 1 2 1 ...
## $ DataPlan : Factor w/ 2 levels "0","1": 2 2 1 1 1 1 2 1 1 2 ...
## $ DataUsage : Factor w/ 174 levels "0","0.11","0.12",...: 104 141 1 1 1 1 79 1 10 116 ...
## $ CustServCalls : Factor w/ 10 levels "0","1","2","3",...: 2 2 1 3 4 1 4 1 2 1 ...
## $ DayMins : Factor w/ 1667 levels "0","100","100.1",...: 1306 477 1176 1442 521 1022 976 435 ...
## $ DayCalls : Factor w/ 119 levels "0","100","101",...: 12 25 16 91 15 118 108 99 117 104 ...
## $ MonthlyCharge : Factor w/ 656 levels "100","100.3000000000000001",...: 593 530 224 272 125 272 580 ...
## $ OverageFee : Factor w/ 1024 levels "0","1.56","10",...: 1012 1003 652 532 768 105 514 597 517 ...
## $ RoamMins : Factor w/ 162 levels "0","1.1","1.3",...: 4 41 26 129 5 126 138 134 150 16 ...
```

Findings

* AccountWeeks, DataUsage, DataUsage, CustServCalls, DayMins, DayCalls, MonthlyCharge, OverageFee, RoamMins are incorrectly imported as factors. Convert factors to numeric data types.

* Churn , ContractRenewal and DataPlan are factor variables.

4.1.4 Creating Backup of the original dataset

```
cleandata <- data.frame(mydata)
```

4.1.5 AccountWeeks, DataUsage, DataUsage, CustServCalls, DayMins, DayCalls, Monthly-Charge, OverageFee, RoamMins are incorrectly imported as factors. Convert factors to numeric data types.

```
cleandata$AccountWeeks<-as.numeric(as.character(cleandata$AccountWeeks))
```

```
cleandata$DataUsage<-as.numeric(as.character(cleandata$DataUsage))
```

```
cleandata$CustServCalls<-as.numeric(as.character(cleandata$CustServCalls))
```

```
cleandata$DayMins<-as.numeric(as.character(cleandata$DayMins))
```

```
cleandata$DayCalls<-as.numeric(as.character(cleandata$DayCalls))
```

```
cleandata$DayCalls<-as.numeric(as.character(cleandata$DayCalls))
```

```
cleandata$MonthlyCharge<-as.numeric(as.character(cleandata$MonthlyCharge))
```

```
cleandata$OverageFee<-as.numeric(as.character(cleandata$OverageFee))
```

```
cleandata$RoamMins<-as.numeric(as.character(cleandata$RoamMins))
```

4.1.6 Checking sturcture of data

```
str(cleandata)
```

```
## 'data.frame':  3333 obs. of  11 variables:
## $ Churn          : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ AccountWeeks   : num  128 107 137 84 75 118 121 147 117 141 ...
## $ ContractRenewal: Factor w/ 2 levels "0","1": 2 2 2 1 1 1 2 1 2 1 ...
## $ DataPlan       : Factor w/ 2 levels "0","1": 2 2 1 1 1 1 2 1 1 2 ...
## $ DataUsage      : num   2.7 3.7 0 0 0 0 2.03 0 0.19 3.02 ...
## $ CustServCalls  : num   1 1 0 2 3 0 3 0 1 0 ...
## $ DayMins        : num  265 162 243 299 167 ...
## $ DayCalls       : num  110 123 114 71 113 98 88 79 97 84 ...
## $ MonthlyCharge  : num   89 82 52 57 41 57 87.3 36 63.9 93.2 ...
## $ OverageFee     : num   9.87 9.78 6.06 3.1 7.42 ...
## $ RoamMins       : num   10 13.7 12.2 6.6 10.1 6.3 7.5 7.1 8.7 11.2 ...
```

4.1.7 Dataset details

```
introduce(cleandata)
```

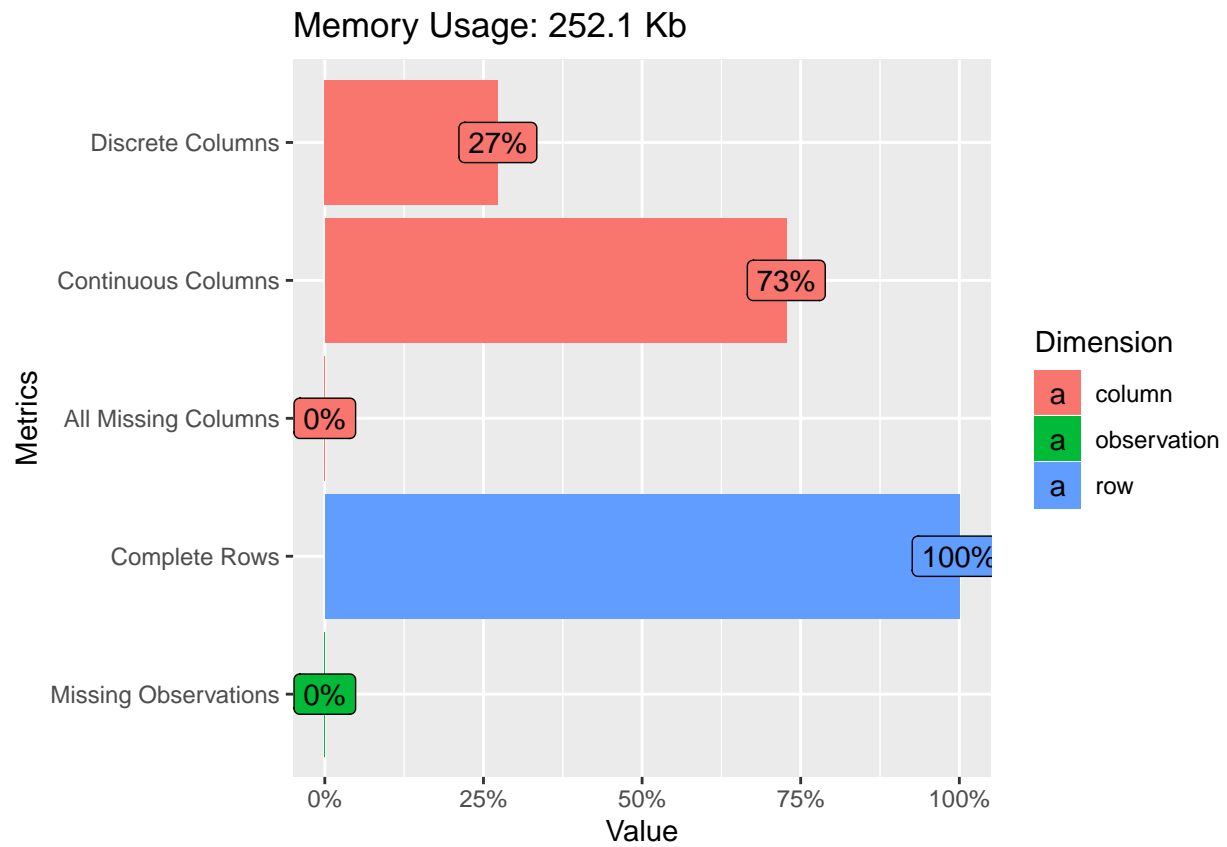
```
##  rows columns discrete_columns continuous_columns all_missing_columns
## 1 3333      11              3              8              0
##  total_missing_values complete_rows total_observations memory_usage
## 1                   0          3333          36663          258112
```

Findings

- There are **3333 Rows** and **11 Columns**
- 3 discrete colums and 8 continuous columns

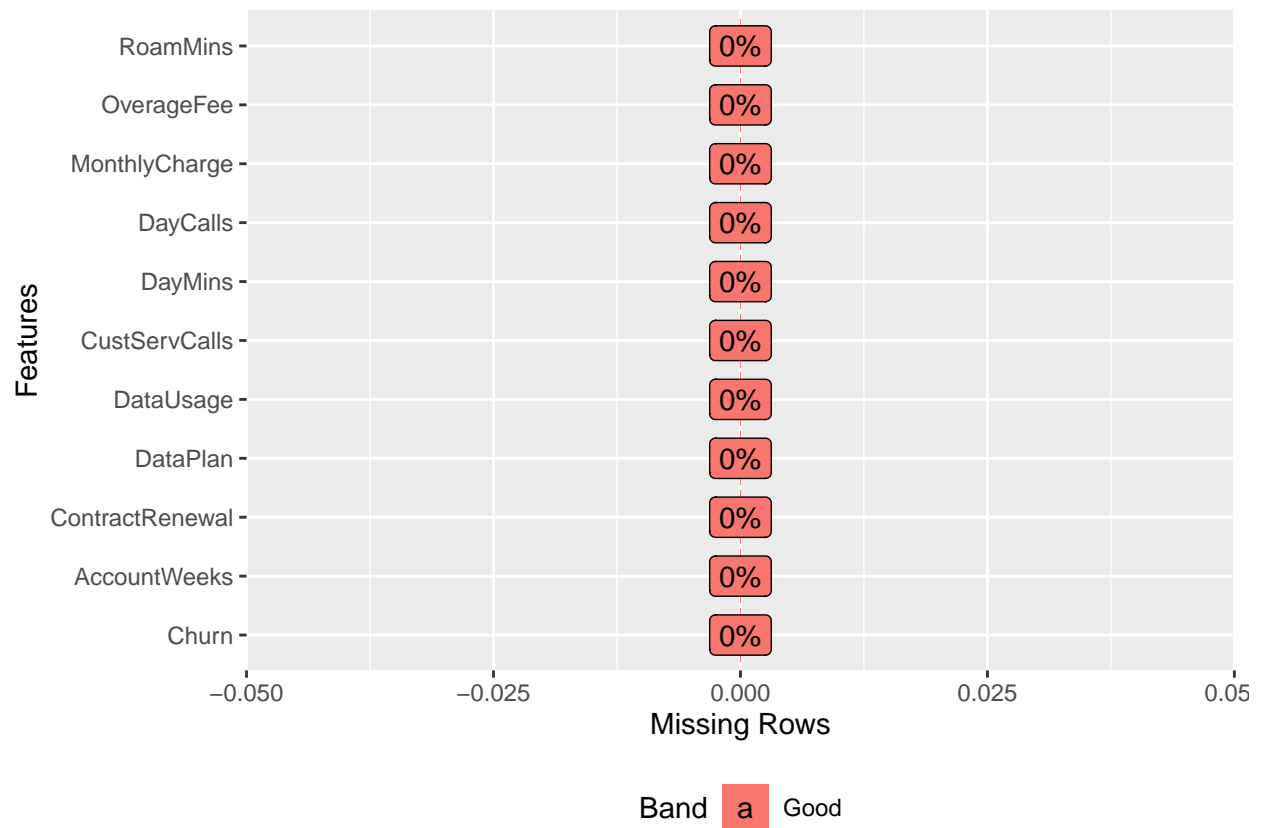
4.1.8 Visualize dataset

```
plot_intro(cleandata)
```



4.1.9 Checking for Missing Values

```
plot_missing(cleandata)
```



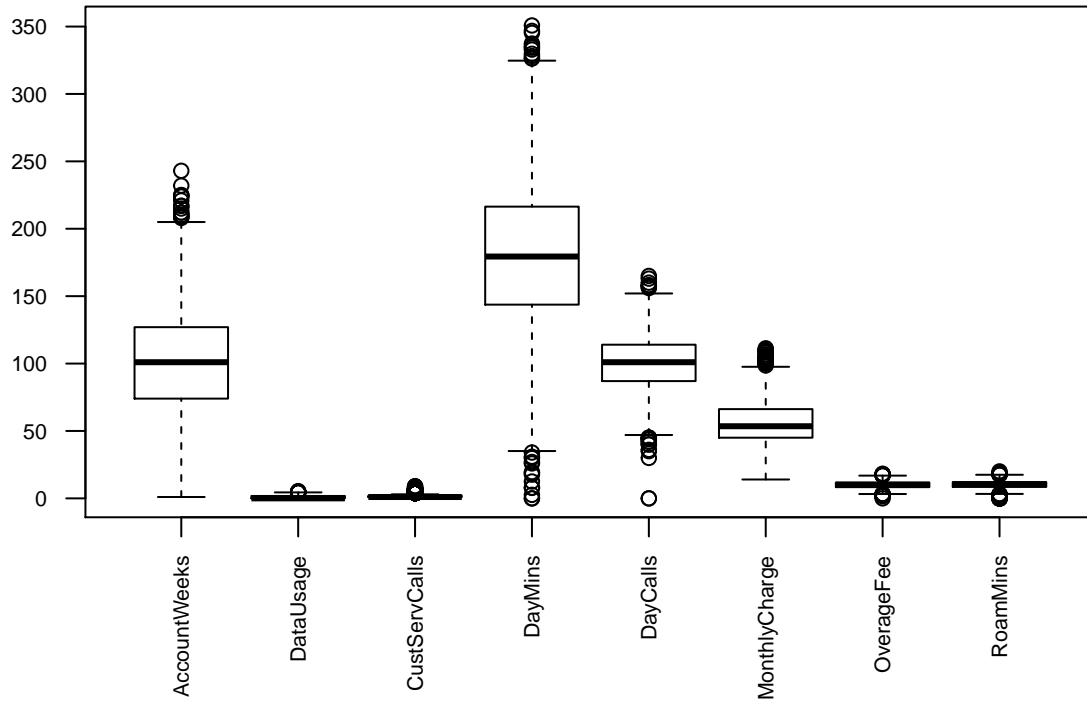
Findings

- There are no missing values in the dataset.

```
scaledata <- data.frame(cleandata)
```

4.1.10 Check if there are Outliers

```
boxplot(scaledata[,c(2,5,6,7,8,9,10,11)],las=2,cex.axis=0.7)
```



Findings

- There are outliers in the dataset.
-

4.1.11 Outlier Treatment. Winsorizing.

```
summary(scaledata$AccountWeeks)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       1.0   74.0   101.0   101.1   127.0   243.0
```

```
benchAccountWeeks <- 127.0 + 1.5* IQR(scaledata$AccountWeeks)
```

```
scaledata$AccountWeeks[scaledata$AccountWeeks>benchAccountWeeks] <- benchAccountWeeks
```

```
summary(scaledata$DataUsage)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.0000  0.0000  0.0000  0.8165  1.7800  5.4000
```

```
benchDataUsage <- 1.78 + 1.5* IQR(scaledata$DataUsage)
```

```
scaledata$DataUsage[scaledata$DataUsage>benchDataUsage] <- benchDataUsage
```

```
summary(scaledata$DayMins)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0.0   143.7   179.4   179.8   216.4   350.8
```

```
benchDayMins <- 216.4 + 1.5* IQR(scaledata$DayMins)
```

```
scaledata$DayMins[scaledata$DayMins>benchDayMins] <- benchDayMins
```

```
summary(scaledata$DayCalls)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0.0   87.0   101.0   100.4   114.0   165.0
```

```
benchDayCalls <- 114.0 + 1.5* IQR(scaledata$DayCalls)
```

```
scaledata$DayCalls[scaledata$DayCalls>benchDayCalls] <- benchDayCalls
```

```
summary(scaledata$MonthlyCharge)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    14.00   45.00   53.50   56.31   66.20   111.30
```

```
benchMonthlyCharge <- 66.20 + 1.5* IQR(scaledata$MonthlyCharge)
```

```
scaledata$MonthlyCharge[scaledata$MonthlyCharge>benchMonthlyCharge] <- benchMonthlyCharge
```

```
summary(scaledata$OverageFee)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0.00    8.33   10.07   10.05   11.77   18.19
```

```
benchOverageFee <- 11.77 + 1.5* IQR(scaledata$OverageFee)
```

```
scaledata$OverageFee[scaledata$OverageFee>benchOverageFee] <- benchOverageFee
```

```
summary(scaledata$RoamMins)
```

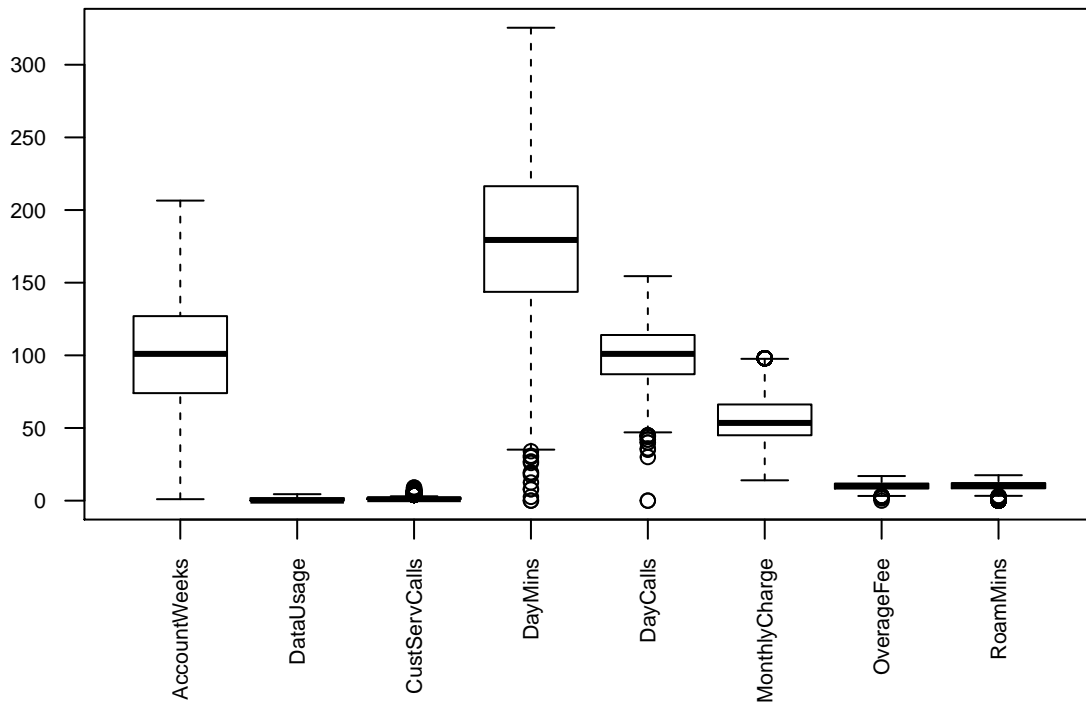
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0.00    8.50   10.30   10.24   12.10   20.00
```

```
benchRoamMins <- 12.10 + 1.5* IQR(scaledata$RoamMins)
```

```
scaledata$RoamMins[scaledata$RoamMins>benchRoamMins] <- benchRoamMins
```

4.1.12 Outliers Treated.

```
boxplot(scaledata[,c(2,5,6,7,8,9,10,11)],las=2,cex.axis=0.7)
```



4.1.13 Checking Churn data split

```
table(scaledata$Churn)
```

```
##  
##      0      1  
## 2850  483  
483/(2850+483)*100
```

```
## [1] 14.49145
```

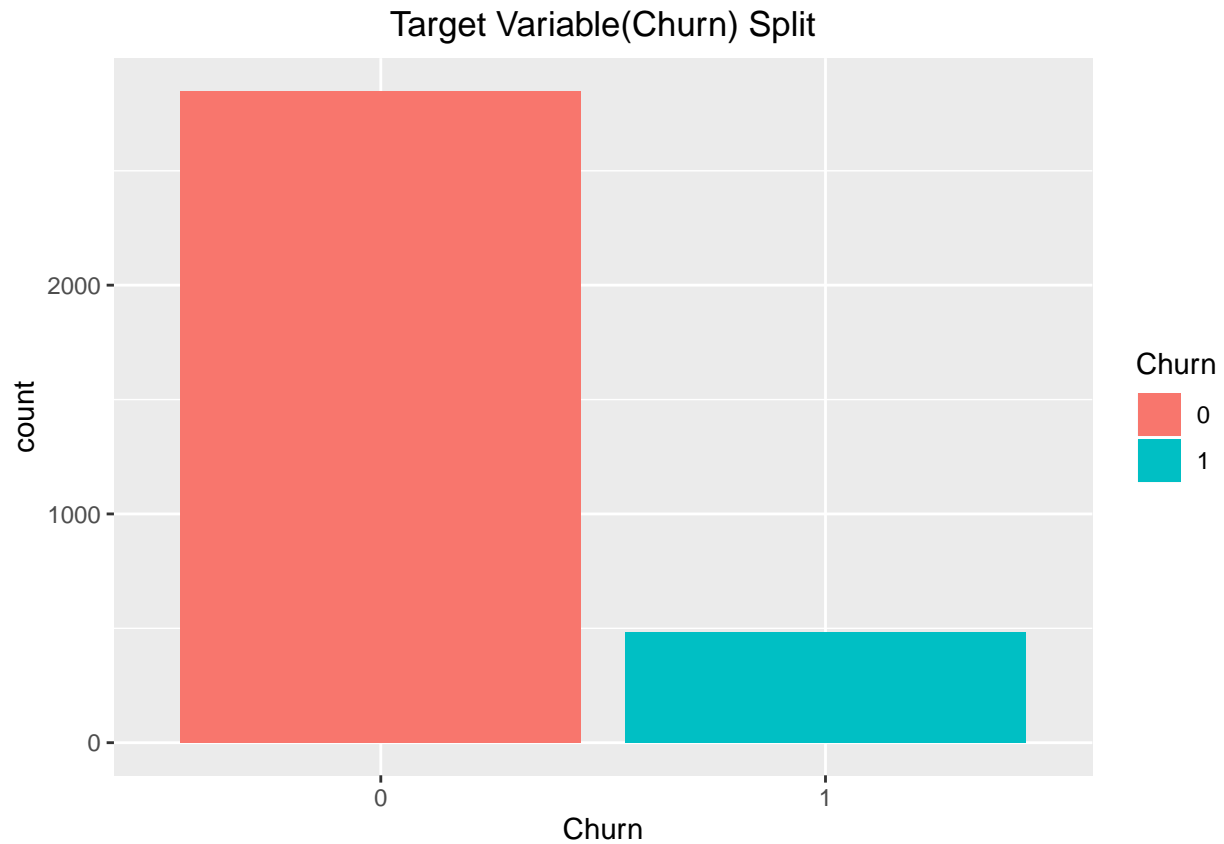
Findings

- Minority Class (1) is only 14.49 percent of the total Churn class. It is less than 15%.
- Data will be balanced.

4.1.14 Visualize Dependent Variable(Churn) proportion split

```
ggplot(scaledata) +  
  aes(x = Churn, fill = Churn) +  
  geom_bar() +
```

```
scale_fill_hue() +
labs(title = "Target Variable(Churn) Split") + theme(plot.title = element_text(hjust = 0.5))
```

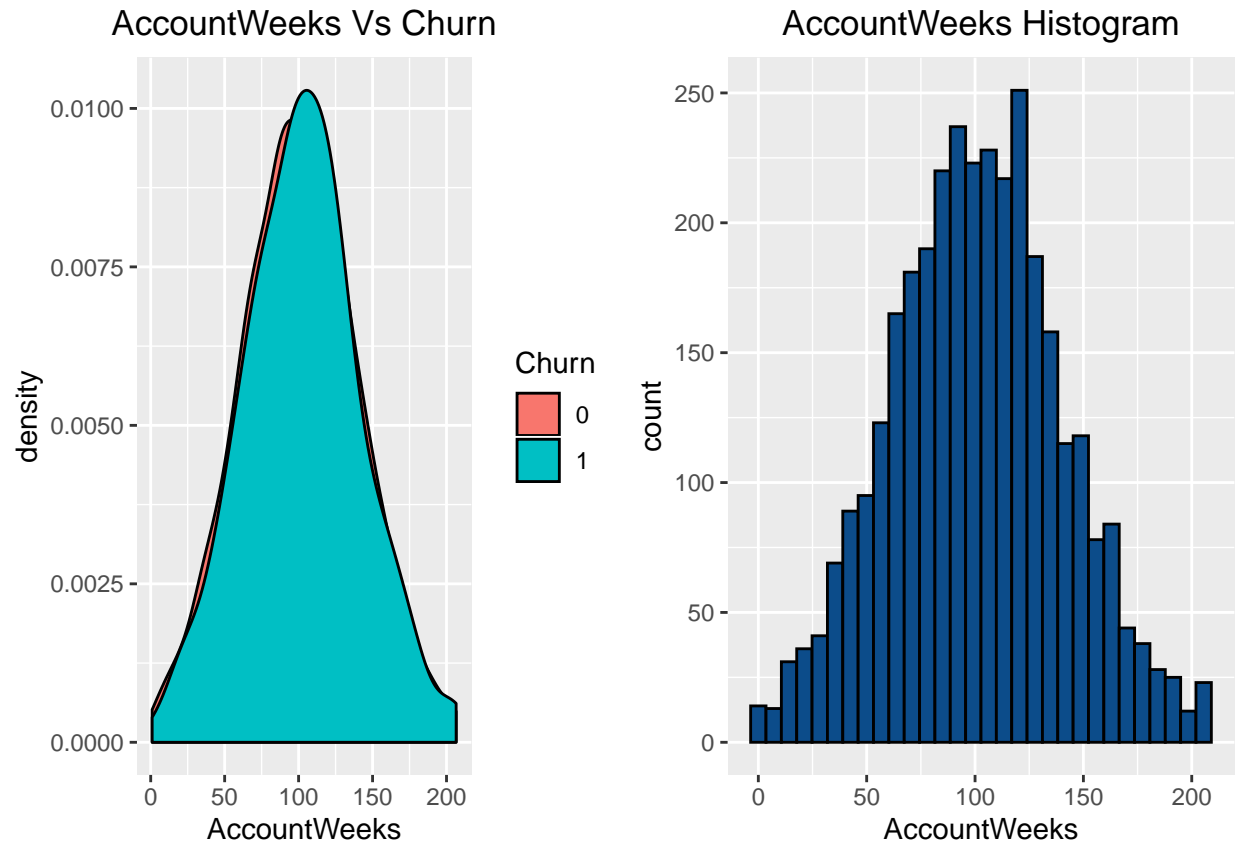


4.1.15 Dependent Variables VS Independent Variables

```
d1 <- ggplot(scaledata) +
  aes(x = AccountWeeks, fill = Churn) +
  geom_density(adjust = 1L) +
  scale_fill_hue() +
  labs(title = "AccountWeeks Vs Churn") +
  theme(plot.title = element_text(hjust = 0.5))

h1 <- ggplot(scaledata) +
  aes(x = AccountWeeks) +
  geom_histogram(bins = 30L, fill = "#0c4c8a", colour="black") +
  labs(title = "AccountWeeks Histogram") +
  theme(plot.title = element_text(hjust = 0.5))

plot_grid(d1,h1)
```

Findings

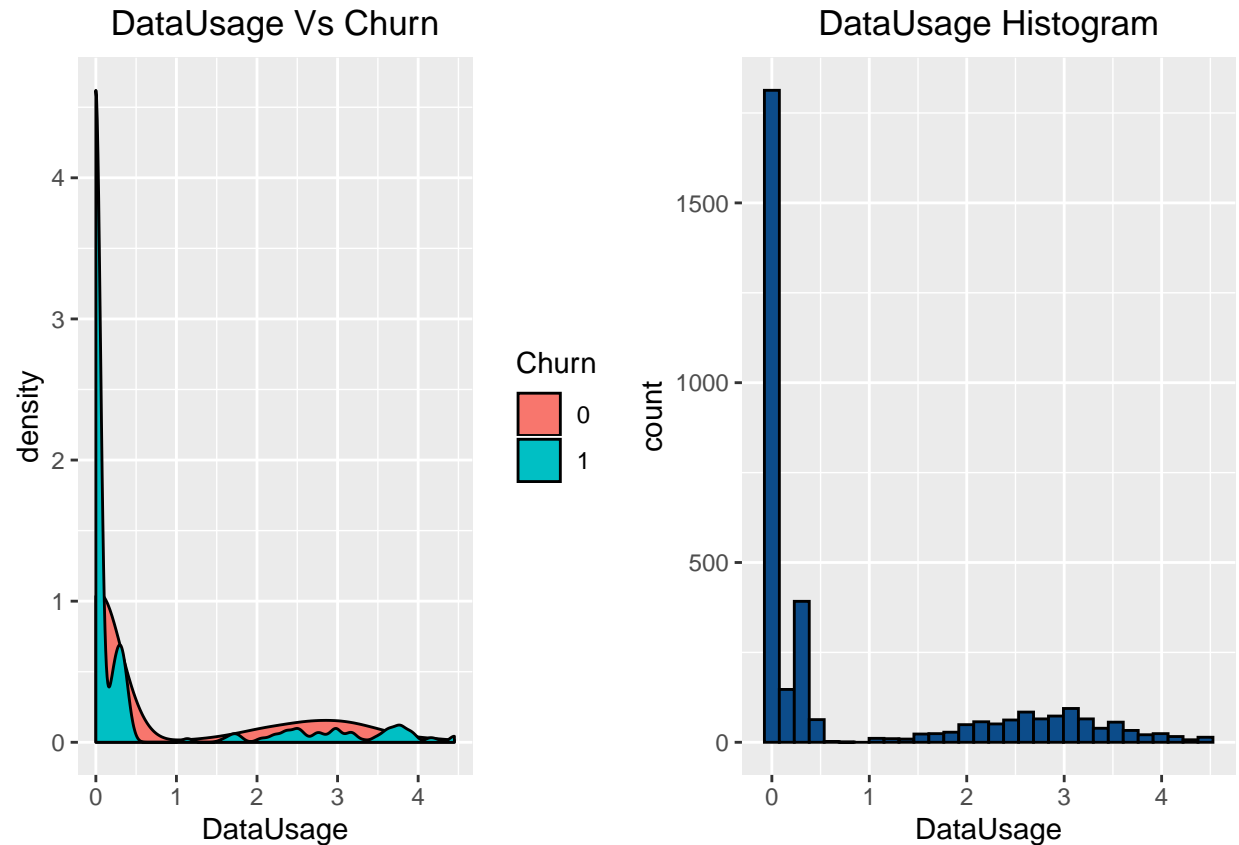
Density plot: AccountWeeks around 100 has more Churn Count.

Histogram: We can say that the frequency distribution for AccountWeeks are normally distributed.

```
d2 <- ggplot(scaledata) +
  aes(x = DataUsage, fill = Churn) +
  geom_density(adjust = 1L) +
  scale_fill_hue() +
  labs(title = "DataUsage Vs Churn") +
  theme(plot.title = element_text(hjust = 0.5))

h2 <- ggplot(scaledata) +
  aes(x = DataUsage) +
  geom_histogram(bins = 30L, fill = "#0c4c8a", colour="black") +
  labs(title = "DataUsage Histogram") +
  theme(plot.title = element_text(hjust = 0.5))

plot_grid(d2,h2)
```



Findings

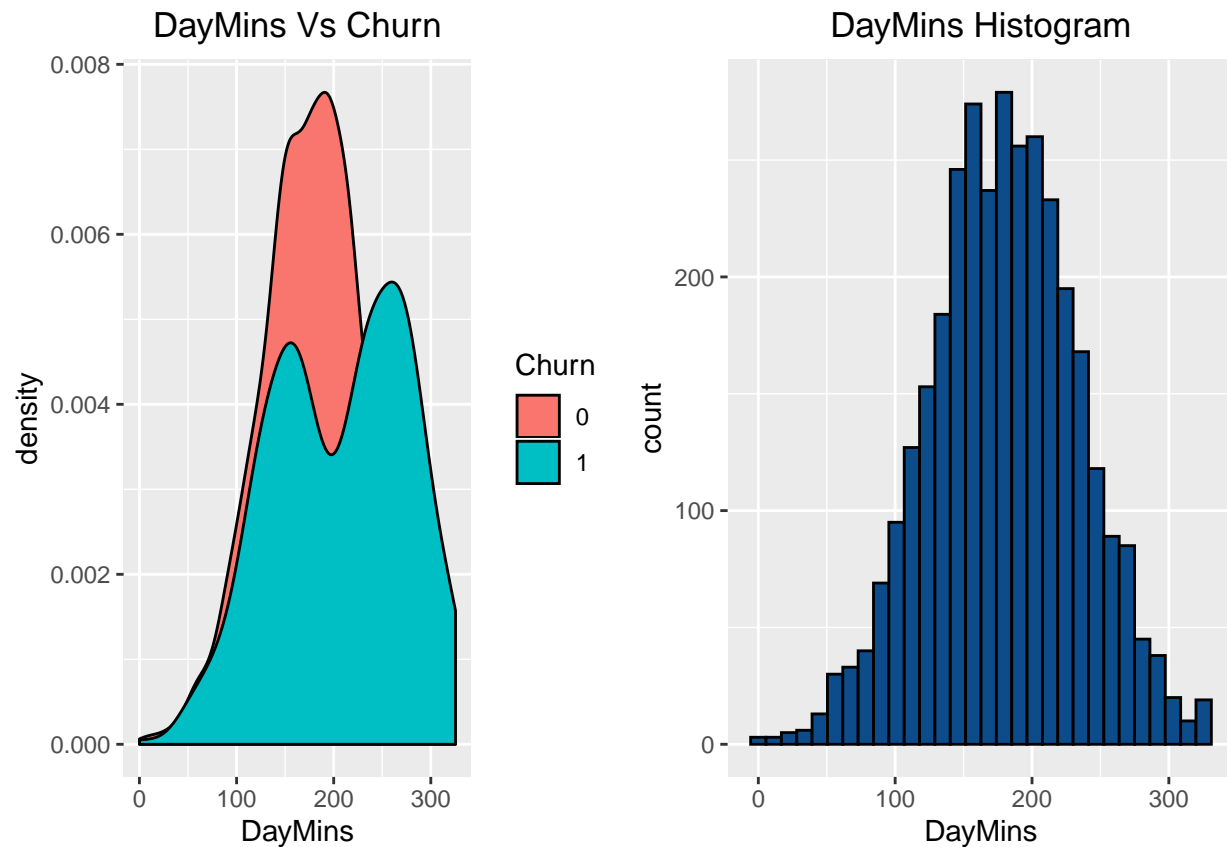
Density plot: There are more 0 DataUsage in the dataset.

Histogram: There are more 0 DataUsage in the dataset.

```
d3 <- ggplot(scaledata) +
  aes(x = DayMins, fill = Churn) +
  geom_density(adjust = 1L) +
  scale_fill_hue() +
  labs(title = "DayMins Vs Churn") +
  theme(plot.title = element_text(hjust = 0.5))

h3 <- ggplot(scaledata) +
  aes(x = DayMins) +
  geom_histogram(bins = 30L, fill = "#0c4c8a", colour="black") +
  labs(title = "DayMins Histogram") +
  theme(plot.title = element_text(hjust = 0.5))

plot_grid(d3,h3)
```



Findings

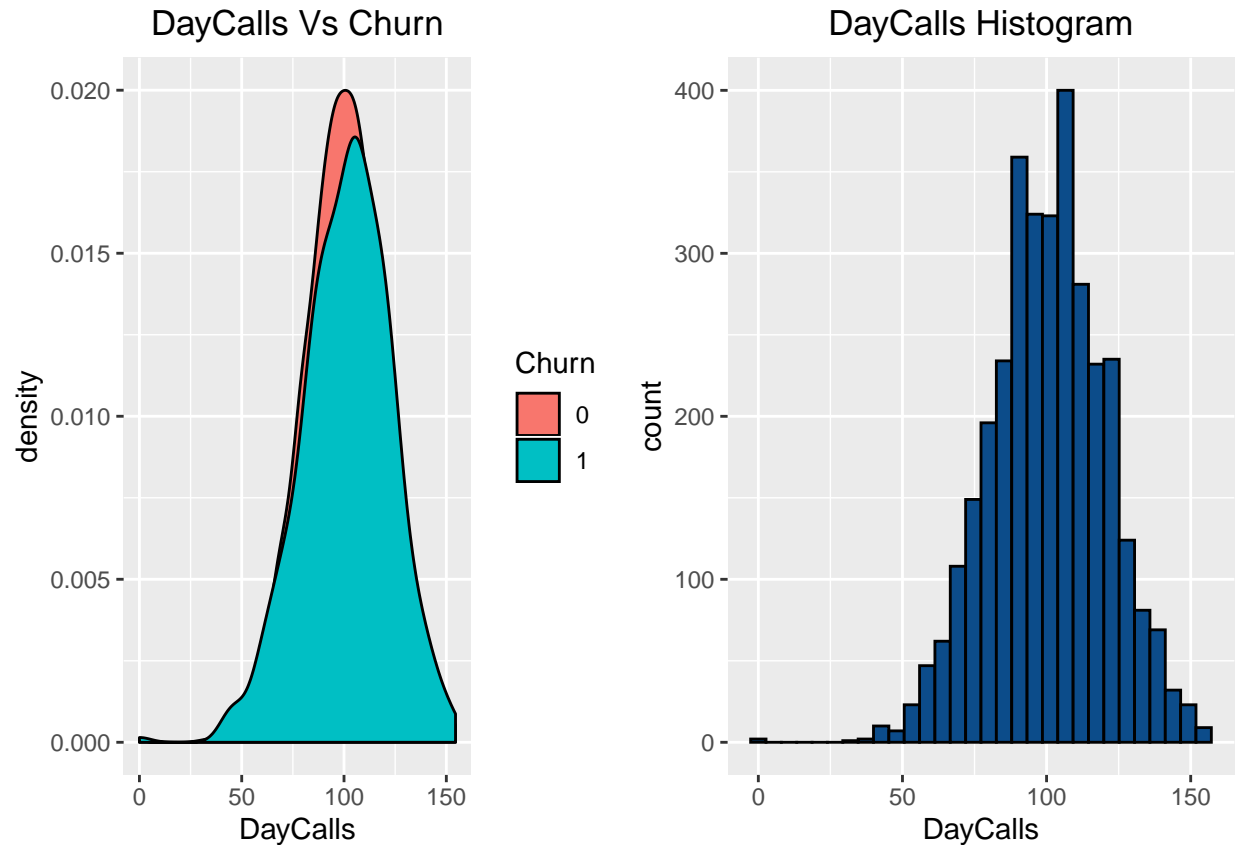
Density plot: Customers have Churned more for DayMins between 150 and 280 .

Histogram: DaysMins is normally Distributed

```
d4 <- ggplot(scaledata) +
  aes(x = DayCalls, fill = Churn) +
  geom_density(adjust = 1L) +
  scale_fill_hue() +
  labs(title = "DayCalls Vs Churn") +
  theme(plot.title = element_text(hjust = 0.5))

h4 <- ggplot(scaledata) +
  aes(x = DayCalls) +
  geom_histogram(bins = 30L, fill = "#0c4c8a", colour="black") +
  labs(title = "DayCalls Histogram") +
  theme(plot.title = element_text(hjust = 0.5))

plot_grid(d4,h4)
```



Findings

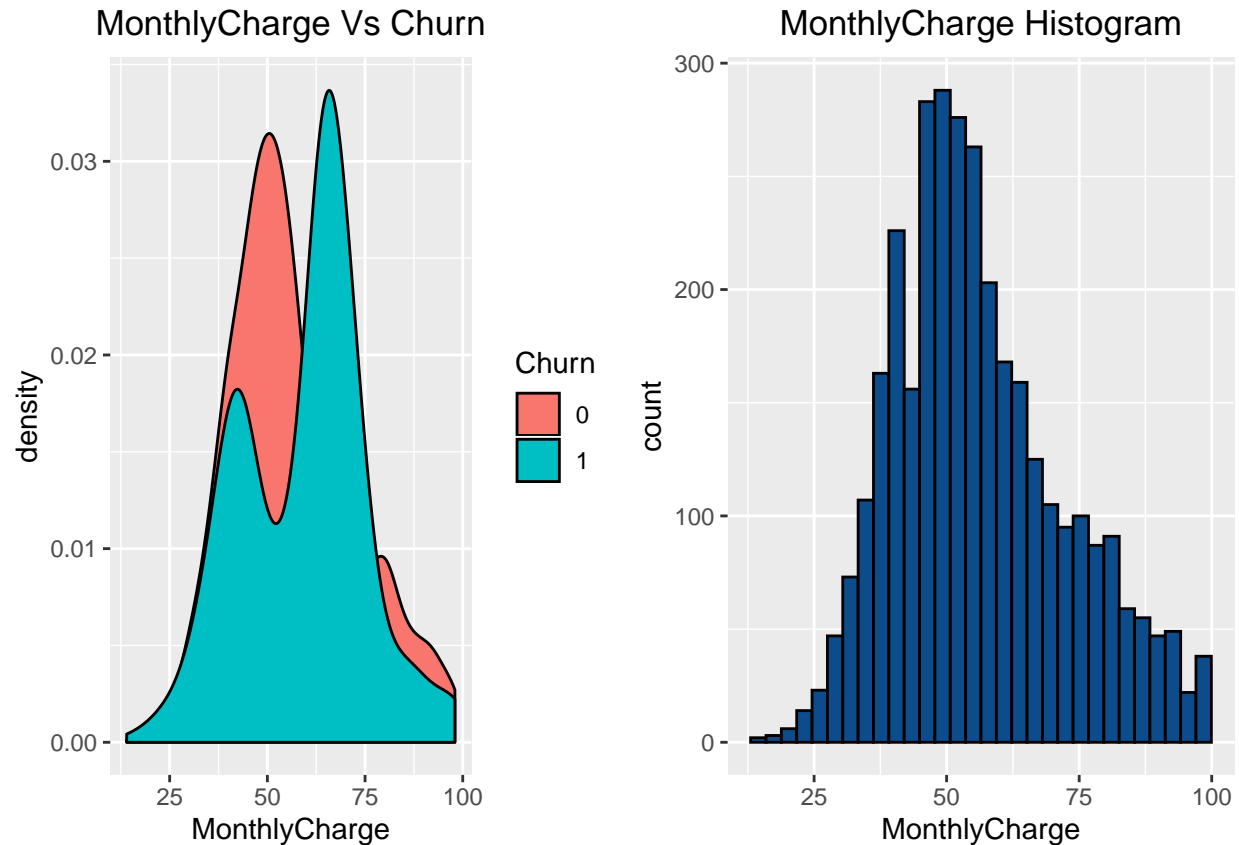
Density plot: DayCalls are almost evenly distributed for Churn and Not Churn .

Histogram: DayCalls is normally Distributed

```
d5 <- ggplot(scaledata) +
  aes(x = MonthlyCharge, fill = Churn) +
  geom_density(adjust = 1L) +
  scale_fill_hue() +
  labs(title = "MonthlyCharge Vs Churn") +
  theme(plot.title = element_text(hjust = 0.5))

h5 <- ggplot(scaledata) +
  aes(x = MonthlyCharge) +
  geom_histogram(bins = 30L, fill = "#0c4c8a", colour="black") +
  labs(title = "MonthlyCharge Histogram") +
  theme(plot.title = element_text(hjust = 0.5))

plot_grid(d5,h5)
```



Findings

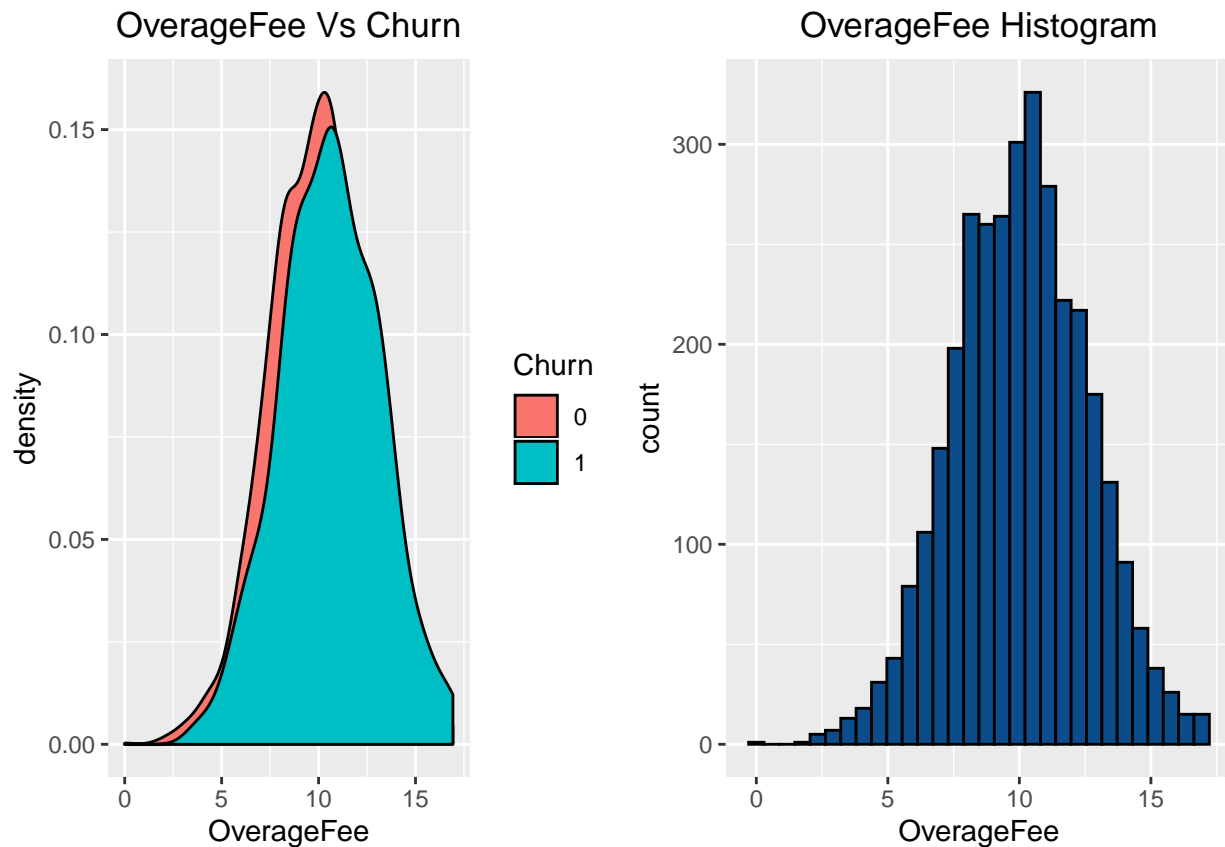
Density plot: Customer with average monthly bill between **50 and 75** is more likely to Churn.

Histogram: MonthlyCharge is normally Distributed

```
d6 <- ggplot(scaledata) +
  aes(x = OverageFee, fill = Churn) +
  geom_density(adjust = 1L) +
  scale_fill_hue() +
  labs(title = "OverageFee Vs Churn") +
  theme(plot.title = element_text(hjust = 0.5))

h6 <- ggplot(scaledata) +
  aes(x = OverageFee) +
  geom_histogram(bins = 30L, fill = "#0c4c8a", colour="black") +
  labs(title = "OverageFee Histogram") +
  theme(plot.title = element_text(hjust = 0.5))

plot_grid(d6,h6)
```



Findings

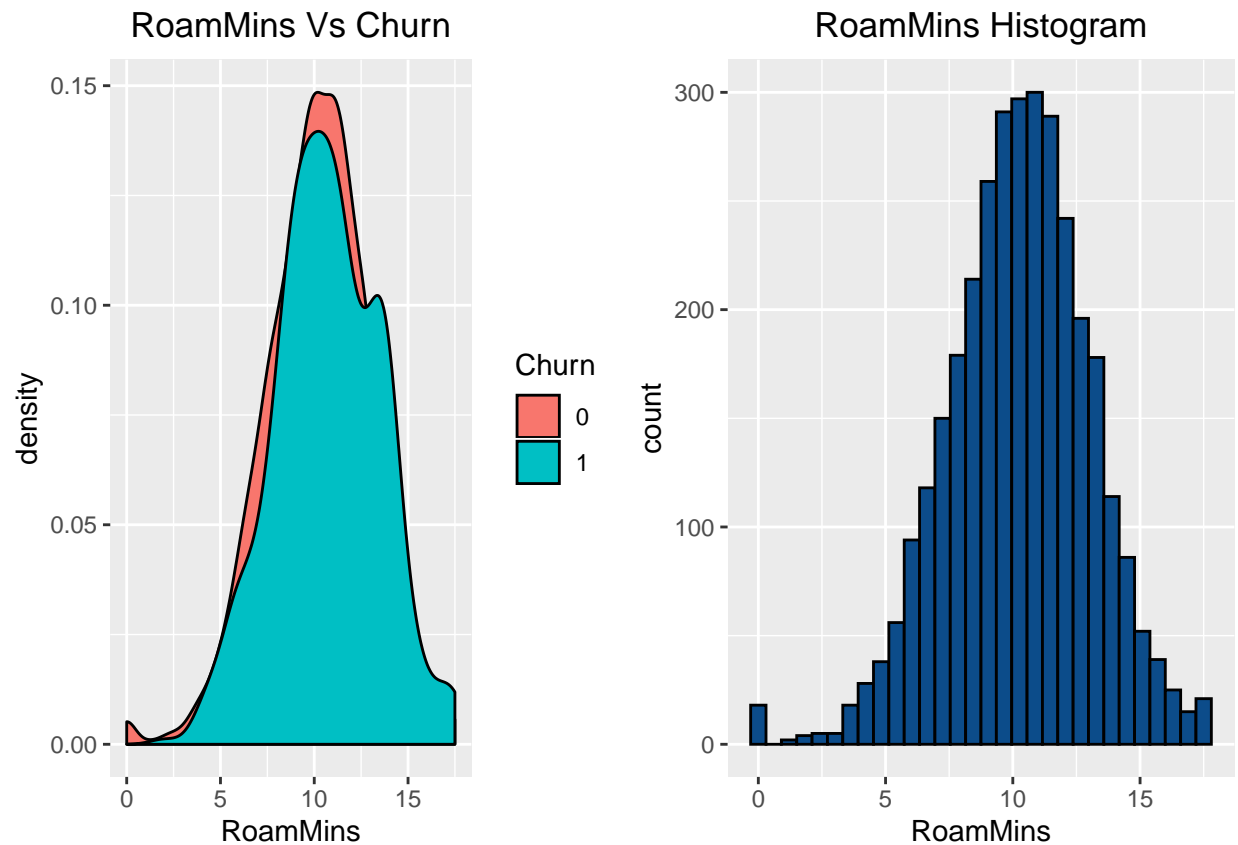
Density plot: Customer with Overcharge fee between **5 and 15** are more likely to cancel the service.

Histogram: Overcharge is normally Distributed

```
d7 <- ggplot(scaledata) +
  aes(x = RoamMins, fill = Churn) +
  geom_density(adjust = 1L) +
  scale_fill_hue() +
  labs(title = "RoamMins Vs Churn") +
  theme(plot.title = element_text(hjust = 0.5))

h7 <- ggplot(scaledata) +
  aes(x = RoamMins) +
  geom_histogram(bins = 30L, fill = "#0c4c8a", colour="black") +
  labs(title = "RoamMins Histogram") +
  theme(plot.title = element_text(hjust = 0.5))

plot_grid(d7,h7)
```



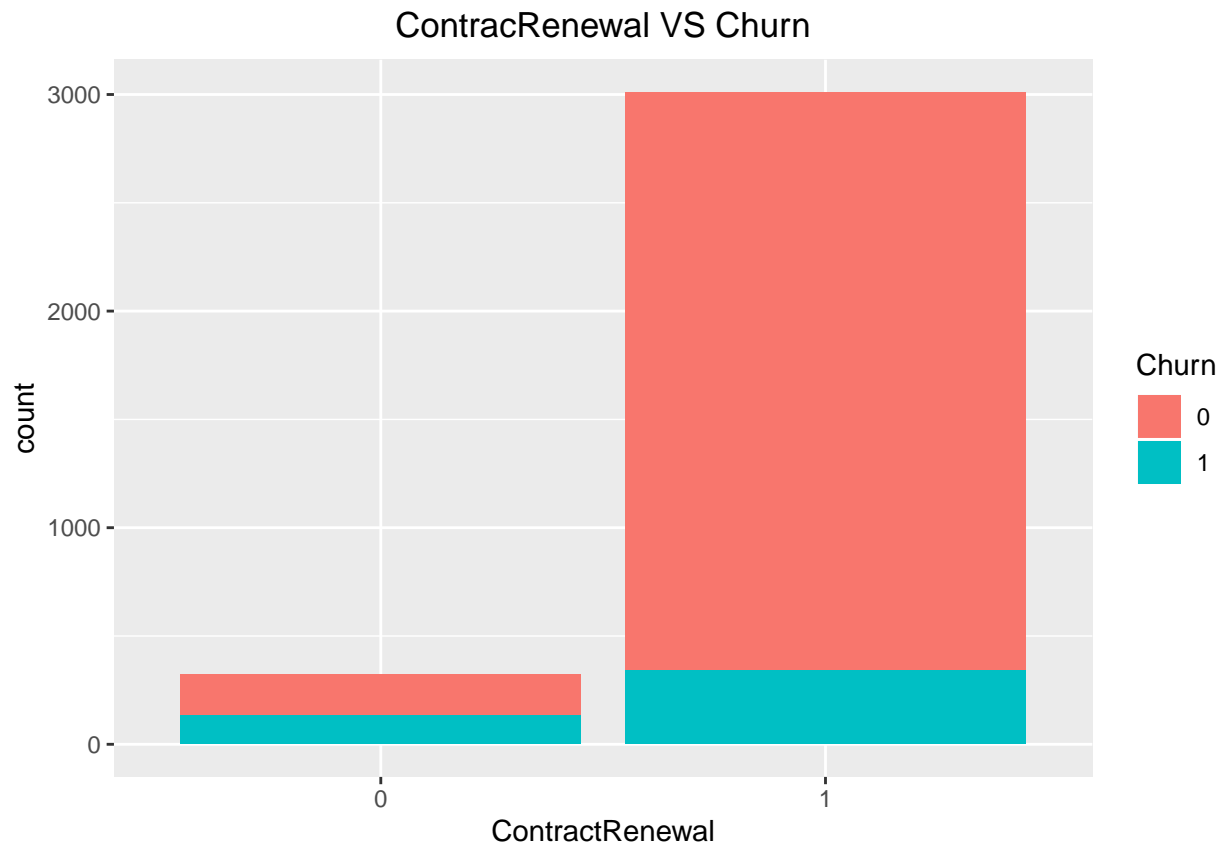
Findings

Density plot: Out of Customers who have cancelled the service for RoamMins are most around 10 minutes

Histogram: RoamMins is normally Distributed

```
h8<- ggplot(scaledata) +
  aes(x = ContractRenewal, fill = Churn) +
  geom_bar() +
  scale_fill_hue() +
  labs(title = "ContractRenewal VS Churn") +
  theme(plot.title = element_text(hjust = 0.5))
```

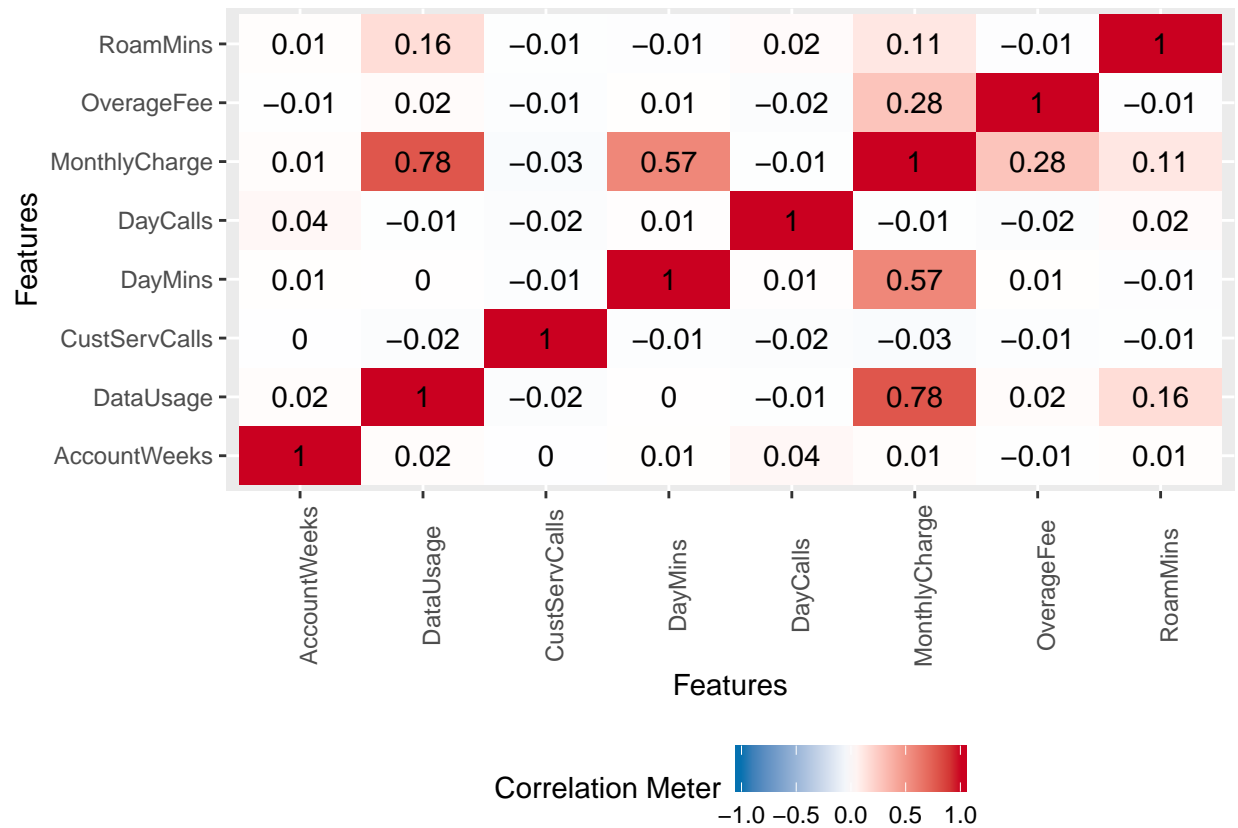
h8



Findings

Bar Chart: Customers who have renewed the plan are more likely to stay with the company

```
plot_correlation(scaledata, type = c("continuous"))
```

Findings

- DataUsage and MonthlyCharge are Highly Correlated.
- MonthlyCharge and DayMins are Highly Correlated.

5 Build Models

5.1 Pre Process(Train and Test Split)

```
seed <- 101
set.seed(seed)
sample <- sample.split(scaledata,SplitRatio = 0.7)
churn.train <- subset(scaledata,sample == TRUE)
churn.test <- subset(scaledata,sample == FALSE)
nrow(churn.train)

## [1] 2121
nrow(churn.test)

## [1] 1212
### Balance Dataset with ROSE package
BalancedData=ROSE(Churn~.,data=churn.train,seed=seed)$data
```

5.1.1 Before Balance VS After Balance

```
table(churn.train$Churn)

##
##    0    1
## 1830  291
table(BalancedData$Churn)

##
##    0    1
## 1062 1059
```

Findings

- Dataset is now BALANCED

5.2 Logistic Regression

Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable, although many more complex extensions exist. In regression analysis, logistic regression (or logit regression) is estimating the parameters of a logistic model (a form of binary regression).

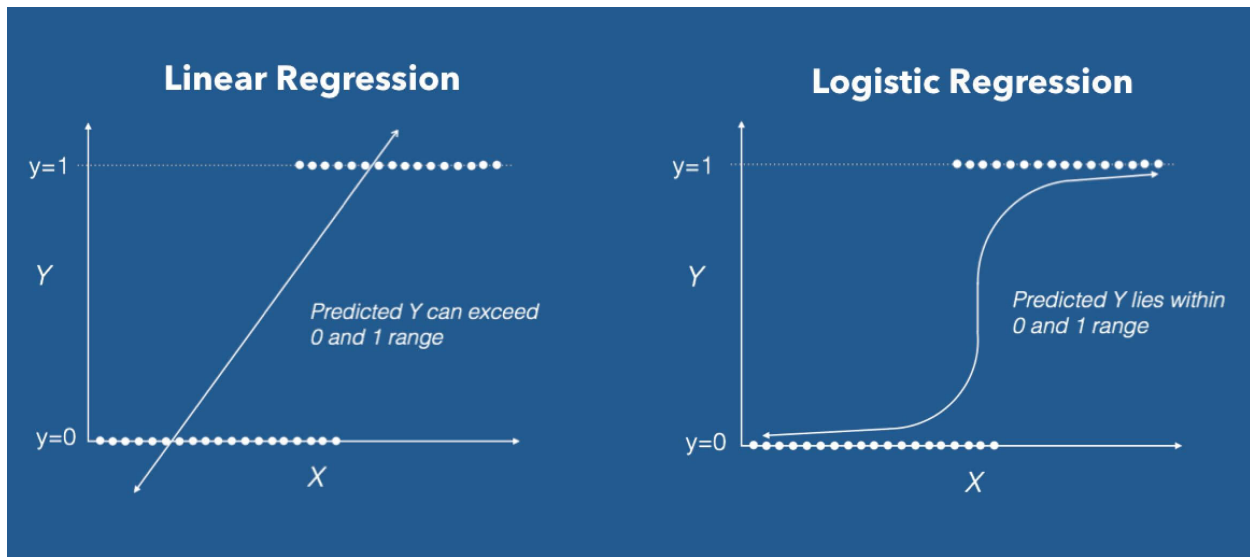


Figure 2: Logistic VS Linear

5.2.1 Full Model for stepwise variable selection and elimination

```
fullmod <- glm(Churn ~ ., family=binomial, data = BalancedData)

summary(fullmod)

##
## Call:
## glm(formula = Churn ~ ., family = binomial, data = BalancedData)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6895  -0.8910  -0.2079   0.9166   2.7396
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -2.280535   0.4230727  -5.389 7.07e-08 ***
## AccountWeeks -0.0016946  0.0011316  -1.498 0.134263
## ContractRenewal1 -2.4252907  0.1698024 -14.283 < 2e-16 ***
## DataPlan1      -1.2451647  0.2480346  -5.020 5.16e-07 ***
## DataUsage      -0.0460423  0.0692316  -0.665 0.506021
## CustServCalls   0.4355874  0.0318817  13.663 < 2e-16 ***
## DayMins         0.0060290  0.0009854   6.119 9.45e-10 ***
## DayCalls        0.0038169  0.0022627   1.687 0.091635 .
## MonthlyCharge   0.0171697  0.0046837   3.666 0.000247 ***
## OverageFee      0.0899965  0.0196366   4.583 4.58e-06 ***
## RoamMins        0.0567465  0.0167447   3.389 0.000702 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2940.3  on 2120  degrees of freedom
```

```
## Residual deviance: 2315.4 on 2110 degrees of freedom
## AIC: 2337.4
##
## Number of Fisher Scoring iterations: 4
```

5.2.2 Empty Model for stepwise variable selection and elimination

```
emptyModel<- glm(Churn ~ 1,family=binomial,data = BalancedData)
summary(emptyModel)
```

```
##
## Call:
## glm(formula = Churn ~ 1, family = binomial, data = BalancedData)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.176  -1.176  -1.176   1.179   1.179
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.002829   0.043427  -0.065   0.948
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2940.3 on 2120 degrees of freedom
## Residual deviance: 2940.3 on 2120 degrees of freedom
## AIC: 2942.3
##
## Number of Fisher Scoring iterations: 3
```

5.2.3 Backward Selection of significant variables

```
backwards = step(fullmod)

## Start:  AIC=2337.4
## Churn ~ AccountWeeks + ContractRenewal + DataPlan + DataUsage +
##      CustServCalls + DayMins + DayCalls + MonthlyCharge + OverageFee +
##      RoamMins
##
##              Df Deviance    AIC
## - DataUsage    1  2315.8 2335.8
## <none>          2315.4 2337.4
## - AccountWeeks 1  2317.6 2337.6
## - DayCalls      1  2318.2 2338.2
## - RoamMins      1  2327.0 2347.0
## - MonthlyCharge 1  2329.0 2349.0
## - OverageFee    1  2336.7 2356.7
## - DataPlan      1  2341.2 2361.2
## - DayMins       1  2354.0 2374.0
## - CustServCalls 1  2534.1 2554.1
## - ContractRenewal 1  2587.1 2607.1
##
## Step:  AIC=2335.84
```

```
## Churn ~ AccountWeeks + ContractRenewal + DataPlan + CustServCalls +
##      DayMins + DayCalls + MonthlyCharge + OverageFee + RoamMins
##
##           Df Deviance    AIC
## <none>           2315.8 2335.8
## - AccountWeeks    1   2318.2 2336.2
## - DayCalls        1   2318.7 2336.7
## - RoamMins        1   2327.0 2345.0
## - MonthlyCharge   1   2329.0 2347.0
## - OverageFee      1   2337.5 2355.5
## - DayMins         1   2355.7 2373.7
## - DataPlan        1   2378.2 2396.2
## - CustServCalls   1   2535.0 2553.0
## - ContractRenewal 1   2587.3 2605.3
```

5.2.4 Forward Slection

```
forwards = step(emptyModel,scope=list(lower=formula(emptyModel),upper=formula(fullmod)), direction="forw
```

```
## Start:  AIC=2942.33
## Churn ~ 1
##
##           Df Deviance    AIC
## + ContractRenewal  1   2736.0 2740.0
## + CustServCalls    1   2839.6 2843.6
## + DayMins          1   2854.5 2858.5
## + DataPlan         1   2880.7 2884.7
## + DataUsage        1   2902.3 2906.3
## + OverageFee       1   2907.8 2911.8
## + RoamMins         1   2920.0 2924.0
## + MonthlyCharge    1   2929.9 2933.9
## + DayCalls         1   2937.6 2941.6
## <none>             2940.3 2942.3
## + AccountWeeks     1   2940.3 2944.3
##
## Step:  AIC=2739.97
## Churn ~ ContractRenewal
##
##           Df Deviance    AIC
## + CustServCalls    1   2594.0 2600.0
## + DayMins          1   2630.6 2636.6
## + DataPlan         1   2675.4 2681.4
## + DataUsage        1   2692.8 2698.8
## + OverageFee       1   2697.7 2703.7
## + MonthlyCharge    1   2723.6 2729.6
## + RoamMins         1   2729.0 2735.0
## + DayCalls         1   2731.9 2737.9
## <none>             2736.0 2740.0
## + AccountWeeks     1   2735.3 2741.3
##
## Step:  AIC=2599.99
## Churn ~ ContractRenewal + CustServCalls
##
##           Df Deviance    AIC
```

```

## + DayMins      1  2444.4 2452.4
## + DataPlan     1  2523.0 2531.0
## + OverageFee   1  2543.3 2551.3
## + DataUsage    1  2545.4 2553.4
## + MonthlyCharge 1  2570.2 2578.2
## + RoamMins     1  2585.5 2593.5
## + DayCalls     1  2589.4 2597.4
## <none>         2594.0 2600.0
## + AccountWeeks 1  2592.9 2600.9
##
## Step:  AIC=2452.39
## Churn ~ ContractRenewal + CustServCalls + DayMins
##
##           Df Deviance    AIC
## + DataPlan      1  2386.2 2396.2
## + DataUsage     1  2406.6 2416.6
## + OverageFee    1  2407.8 2417.8
## + RoamMins      1  2430.8 2440.8
## + DayCalls      1  2441.4 2451.4
## <none>          2444.4 2452.4
## + AccountWeeks  1  2442.8 2452.8
## + MonthlyCharge 1  2443.4 2453.4
##
## Step:  AIC=2396.2
## Churn ~ ContractRenewal + CustServCalls + DayMins + DataPlan
##
##           Df Deviance    AIC
## + OverageFee    1  2349.2 2361.2
## + MonthlyCharge 1  2350.8 2362.8
## + RoamMins      1  2371.8 2383.8
## <none>          2386.2 2396.2
## + DayCalls      1  2384.2 2396.2
## + AccountWeeks  1  2384.7 2396.7
## + DataUsage     1  2386.0 2398.0
##
## Step:  AIC=2361.25
## Churn ~ ContractRenewal + CustServCalls + DayMins + DataPlan +
##           OverageFee
##
##           Df Deviance    AIC
## + MonthlyCharge 1  2331.7 2345.7
## + RoamMins      1  2333.4 2347.4
## + DayCalls      1  2347.0 2361.0
## <none>          2349.2 2361.2
## + AccountWeeks  1  2347.8 2361.8
## + DataUsage     1  2349.1 2363.1
##
## Step:  AIC=2345.65
## Churn ~ ContractRenewal + CustServCalls + DayMins + DataPlan +
##           OverageFee + MonthlyCharge
##
##           Df Deviance    AIC
## + RoamMins      1  2320.7 2336.7
## + DayCalls      1  2329.3 2345.3

```

```
## + AccountWeeks 1 2329.6 2345.6
## <none> 2331.7 2345.7
## + DataUsage 1 2331.6 2347.6
##
## Step: AIC=2336.74
## Churn ~ ContractRenewal + CustServCalls + DayMins + DataPlan +
## OverageFee + MonthlyCharge + RoamMins
##
## Df Deviance AIC
## + DayCalls 1 2318.2 2336.2
## + AccountWeeks 1 2318.7 2336.7
## <none> 2320.7 2336.7
## + DataUsage 1 2320.2 2338.2
##
## Step: AIC=2336.16
## Churn ~ ContractRenewal + CustServCalls + DayMins + DataPlan +
## OverageFee + MonthlyCharge + RoamMins + DayCalls
##
## Df Deviance AIC
## + AccountWeeks 1 2315.8 2335.8
## <none> 2318.2 2336.2
## + DataUsage 1 2317.6 2337.6
##
## Step: AIC=2335.84
## Churn ~ ContractRenewal + CustServCalls + DayMins + DataPlan +
## OverageFee + MonthlyCharge + RoamMins + DayCalls + AccountWeeks
##
## Df Deviance AIC
## <none> 2315.8 2335.8
## + DataUsage 1 2315.4 2337.4
```

Findings

- From both Forward Selection and Backward Elimination, we see that DataUsage is insignificant feature.
- Build model without DataUsage

5.2.5 Modelling Logistic Regression with Cross Validation

```
fitControl <- trainControl(
  method = "repeatedcv",
  number = 10,

  savePredictions = TRUE
)
```

5.2.6 Logistic Regression Model

```
lregmodel<- glm(Churn ~ ContractRenewal + CustServCalls + DayMins + DataPlan +
                OverageFee + MonthlyCharge + RoamMins + DayCalls + AccountWeeks,data=BalancedData,fam
summary(lregmodel)

##
## Call:
```

```
## glm(formula = Churn ~ ContractRenewal + CustServCalls + DayMins +
##      DataPlan + OverageFee + MonthlyCharge + RoamMins + DayCalls +
##      AccountWeeks, family = "binomial", data = BalancedData)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.6848  -0.8882  -0.2024   0.9141   2.7517
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -2.2659985   0.4226733  -5.361 8.27e-08 ***
## ContractRenewal1 -2.4223623   0.1695870 -14.284 < 2e-16 ***
## CustServCalls    0.4360201   0.0318788  13.677 < 2e-16 ***
## DayMins         0.0060928   0.0009805   6.214 5.17e-10 ***
## DataPlan1      -1.3612594   0.1767530  -7.701 1.35e-14 ***
## OverageFee      0.0905252   0.0196241   4.613 3.97e-06 ***
## MonthlyCharge    0.0167706   0.0046417   3.613 0.000303 ***
## RoamMins        0.0549779   0.0165200   3.328 0.000875 ***
## DayCalls        0.0038420   0.0022621   1.698 0.089431 .
## AccountWeeks    -0.0017205   0.0011306  -1.522 0.128091
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2940.3  on 2120  degrees of freedom
## Residual deviance: 2315.8  on 2111  degrees of freedom
## AIC: 2335.8
##
## Number of Fisher Scoring iterations: 4
```

5.2.7 Checking for Multicollinearity

```
vif(lregmodel)
```

```
## ContractRenewal    CustServCalls      DayMins      DataPlan
##      1.105116      1.155222      1.777375      2.125319
##      OverageFee    MonthlyCharge      RoamMins      DayCalls
##      1.146748      2.959555      1.050082      1.008879
##      AccountWeeks
##      1.012100
```

Findings

- Values below 4 indicates that there is no Multicollinearity

5.2.8 Predicting for Train Data

```
logpred<- predict(lregmodel,BalancedData[-1],type = "response")
```

5.2.9 Probabilities

```
logpred
```

```
##      1      2      3      4      5      6
```


##	0.34584066	0.19929893	0.05871543	0.24279324	0.42689615	0.08637136
##	7	8	9	10	11	12
##	0.36184384	0.46336282	0.35992386	0.17423454	0.15590466	0.16936702
##	13	14	15	16	17	18
##	0.19613675	0.27503938	0.37828311	0.21942511	0.45267783	0.53286568
##	19	20	21	22	23	24
##	0.29498312	0.10203806	0.45848804	0.44216439	0.25036871	0.45866522
##	25	26	27	28	29	30
##	0.20152063	0.36478359	0.40224855	0.47804593	0.79313361	0.49090121
##	31	32	33	34	35	36
##	0.62100035	0.50584914	0.43813658	0.59947232	0.34346128	0.07400533
##	37	38	39	40	41	42
##	0.53125875	0.41332439	0.34348894	0.17318168	0.24580521	0.17620273
##	43	44	45	46	47	48
##	0.24198814	0.24424332	0.39056003	0.30875867	0.16719006	0.28579054
##	49	50	51	52	53	54
##	0.31124749	0.20923260	0.33965235	0.21683885	0.08490931	0.14589154
##	55	56	57	58	59	60
##	0.36440439	0.05009680	0.49542592	0.61039104	0.46311643	0.37831005
##	61	62	63	64	65	66
##	0.68890712	0.12844203	0.44795196	0.10221381	0.73580517	0.23183734
##	67	68	69	70	71	72
##	0.24827720	0.27487511	0.41421734	0.28658899	0.10968131	0.16900834
##	73	74	75	76	77	78
##	0.45467369	0.69312689	0.28030920	0.14508598	0.73434064	0.13838513
##	79	80	81	82	83	84
##	0.95373736	0.18942396	0.80110242	0.09165667	0.14669483	0.31974373
##	85	86	87	88	89	90
##	0.43142902	0.43068704	0.28602604	0.08876965	0.31474910	0.08338423
##	91	92	93	94	95	96
##	0.43466008	0.27082715	0.39563372	0.29699269	0.25099837	0.07679091
##	97	98	99	100	101	102
##	0.19452422	0.14048134	0.27058691	0.27042154	0.78590801	0.43965101
##	103	104	105	106	107	108
##	0.53761269	0.67635019	0.21628967	0.29400412	0.56659343	0.19677108
##	109	110	111	112	113	114
##	0.42501870	0.111144975	0.19336020	0.20223066	0.68140269	0.73593466
##	115	116	117	118	119	120
##	0.09239227	0.25132783	0.52597808	0.25795550	0.65821154	0.22459178
##	121	122	123	124	125	126
##	0.11465833	0.32199726	0.56818205	0.21646461	0.37960551	0.15445344
##	127	128	129	130	131	132
##	0.13349176	0.29185540	0.35614012	0.24209241	0.04826275	0.27135591
##	133	134	135	136	137	138
##	0.82087548	0.62110556	0.30355658	0.26128304	0.26756064	0.21972234
##	139	140	141	142	143	144
##	0.25011436	0.18164232	0.75014766	0.91856604	0.77774201	0.22153308
##	145	146	147	148	149	150
##	0.76654872	0.22417625	0.36808600	0.16144712	0.21087695	0.20759384
##	151	152	153	154	155	156
##	0.14002723	0.45804053	0.65869359	0.15221613	0.70083266	0.22300062
##	157	158	159	160	161	162
##	0.38289645	0.24794880	0.37257335	0.77978453	0.26708720	0.35264122
##	163	164	165	166	167	168

##	0.19501623	0.03147396	0.29860365	0.09145077	0.71434888	0.54102295
##	169	170	171	172	173	174
##	0.12749066	0.29008874	0.18126563	0.60314345	0.34385226	0.19427470
##	175	176	177	178	179	180
##	0.25763646	0.11367157	0.55589352	0.16876090	0.68932729	0.33185082
##	181	182	183	184	185	186
##	0.57590680	0.05178085	0.20199528	0.54890352	0.55218308	0.19555649
##	187	188	189	190	191	192
##	0.27912561	0.82178781	0.14010903	0.38008997	0.54439352	0.77130672
##	193	194	195	196	197	198
##	0.43902509	0.05026143	0.21827082	0.32870849	0.06167798	0.24562087
##	199	200	201	202	203	204
##	0.39094137	0.97278854	0.34364146	0.31084758	0.45518121	0.11245972
##	205	206	207	208	209	210
##	0.61829524	0.30216885	0.79333448	0.29540366	0.09418310	0.34917558
##	211	212	213	214	215	216
##	0.17384114	0.25908142	0.21002256	0.14755671	0.32296766	0.27979556
##	217	218	219	220	221	222
##	0.48500107	0.22393729	0.61590590	0.19395490	0.82193697	0.55199579
##	223	224	225	226	227	228
##	0.39544801	0.93404579	0.53784371	0.11703283	0.46825815	0.21675191
##	229	230	231	232	233	234
##	0.16175047	0.28408279	0.42703993	0.23387361	0.54205006	0.07143750
##	235	236	237	238	239	240
##	0.48296990	0.24594903	0.17426007	0.56420054	0.26539557	0.27249303
##	241	242	243	244	245	246
##	0.15433818	0.18666783	0.46292860	0.21858907	0.15337231	0.23834509
##	247	248	249	250	251	252
##	0.52709350	0.62147197	0.38833533	0.20344177	0.50154886	0.16178468
##	253	254	255	256	257	258
##	0.43856408	0.39210181	0.24220892	0.08890848	0.25598232	0.46056019
##	259	260	261	262	263	264
##	0.36653701	0.87720488	0.33609825	0.30049054	0.23878720	0.45920898
##	265	266	267	268	269	270
##	0.64201649	0.28525184	0.11513109	0.24413295	0.71487122	0.17592230
##	271	272	273	274	275	276
##	0.37087567	0.33040866	0.23266609	0.77513729	0.22047105	0.55083937
##	277	278	279	280	281	282
##	0.84298048	0.29612890	0.29198178	0.42743991	0.40329909	0.51070958
##	283	284	285	286	287	288
##	0.35713927	0.42030841	0.46202703	0.43249581	0.30465611	0.24511915
##	289	290	291	292	293	294
##	0.19336120	0.21728838	0.32000437	0.28003467	0.57141524	0.39766359
##	295	296	297	298	299	300
##	0.58015373	0.81787996	0.49247617	0.50070975	0.45433231	0.21963799
##	301	302	303	304	305	306
##	0.27846523	0.30445713	0.22901870	0.29744626	0.62965529	0.29664393
##	307	308	309	310	311	312
##	0.34356581	0.51919137	0.12733202	0.53734599	0.27148086	0.24856984
##	313	314	315	316	317	318
##	0.28855603	0.34709918	0.21869549	0.19241859	0.48100463	0.53807754
##	319	320	321	322	323	324
##	0.53844002	0.37662228	0.44958085	0.77096935	0.23787540	0.42561294
##	325	326	327	328	329	330

##	0.46513891	0.34623008	0.26661116	0.39898448	0.51031721	0.59334057
##	331	332	333	334	335	336
##	0.50874982	0.47368609	0.33034824	0.41630234	0.39028293	0.20044680
##	337	338	339	340	341	342
##	0.04903479	0.32234887	0.29838277	0.31961006	0.50193921	0.17193159
##	343	344	345	346	347	348
##	0.11906910	0.04763083	0.37542391	0.18415340	0.90183737	0.31939341
##	349	350	351	352	353	354
##	0.44652706	0.52734867	0.44980190	0.19084769	0.27980858	0.19845090
##	355	356	357	358	359	360
##	0.88014145	0.16839264	0.52118378	0.33771813	0.73949250	0.16776376
##	361	362	363	364	365	366
##	0.24929271	0.07221404	0.28242691	0.11353183	0.31143616	0.54478081
##	367	368	369	370	371	372
##	0.66601684	0.45855883	0.77781981	0.42495911	0.34754233	0.37469605
##	373	374	375	376	377	378
##	0.15242819	0.66531872	0.32837905	0.22743591	0.30025211	0.45766673
##	379	380	381	382	383	384
##	0.26329224	0.47456593	0.10074962	0.56100155	0.61357211	0.10770252
##	385	386	387	388	389	390
##	0.09388195	0.72925358	0.18902388	0.34505316	0.29503798	0.23109144
##	391	392	393	394	395	396
##	0.29239949	0.64002643	0.30291066	0.20669054	0.37541306	0.28871878
##	397	398	399	400	401	402
##	0.11326691	0.49916891	0.17031941	0.57070504	0.36861106	0.36126549
##	403	404	405	406	407	408
##	0.28032371	0.35177895	0.19431272	0.20779514	0.45190662	0.17613644
##	409	410	411	412	413	414
##	0.42632983	0.59927880	0.08391001	0.07416958	0.07562769	0.58095842
##	415	416	417	418	419	420
##	0.41290591	0.37094630	0.69377142	0.93213240	0.16649906	0.28668888
##	421	422	423	424	425	426
##	0.50173349	0.25178102	0.28660802	0.73275841	0.59182592	0.30299504
##	427	428	429	430	431	432
##	0.86122808	0.28750907	0.48334806	0.27815951	0.57033667	0.48679372
##	433	434	435	436	437	438
##	0.83983236	0.47324645	0.20752720	0.22474201	0.90428302	0.29878166
##	439	440	441	442	443	444
##	0.33841118	0.35464431	0.89555574	0.22657489	0.39450973	0.32220958
##	445	446	447	448	449	450
##	0.40249692	0.54019412	0.52172723	0.24900996	0.09817625	0.16513447
##	451	452	453	454	455	456
##	0.14722543	0.05872109	0.19345062	0.16525182	0.21552530	0.54925918
##	457	458	459	460	461	462
##	0.36109115	0.17811739	0.47287236	0.67600070	0.20634962	0.26638782
##	463	464	465	466	467	468
##	0.03246218	0.34166304	0.15430194	0.20663788	0.22483713	0.22699018
##	469	470	471	472	473	474
##	0.27809411	0.52291721	0.50444561	0.64961752	0.44403886	0.58802731
##	475	476	477	478	479	480
##	0.41759616	0.46005742	0.19835607	0.89848734	0.33276889	0.29058748
##	481	482	483	484	485	486
##	0.19081635	0.30009312	0.37006322	0.47898758	0.09201452	0.15538646
##	487	488	489	490	491	492

##	0.76463941	0.38392079	0.44406820	0.72275291	0.02026988	0.08239856
##	493	494	495	496	497	498
##	0.30985483	0.28307009	0.30123773	0.40047276	0.24765509	0.15334375
##	499	500	501	502	503	504
##	0.51029249	0.46050077	0.53050675	0.05775646	0.03219159	0.19570145
##	505	506	507	508	509	510
##	0.19999592	0.63785306	0.47281005	0.13878101	0.30998782	0.50164659
##	511	512	513	514	515	516
##	0.46210351	0.27169764	0.59823779	0.35303308	0.09850590	0.70692385
##	517	518	519	520	521	522
##	0.28359646	0.73033577	0.17008262	0.67269306	0.40299119	0.12711346
##	523	524	525	526	527	528
##	0.30457054	0.47962926	0.66192454	0.24326909	0.36343948	0.55795142
##	529	530	531	532	533	534
##	0.20377843	0.21726763	0.53407019	0.18736736	0.64884936	0.29308046
##	535	536	537	538	539	540
##	0.59391772	0.18075011	0.58092772	0.64688714	0.33433188	0.85954970
##	541	542	543	544	545	546
##	0.09363944	0.34722609	0.11205964	0.28929334	0.15648819	0.23798434
##	547	548	549	550	551	552
##	0.45404159	0.47137325	0.04675290	0.23293045	0.18477613	0.44716726
##	553	554	555	556	557	558
##	0.14829158	0.66690677	0.24201741	0.43687714	0.29849888	0.64631130
##	559	560	561	562	563	564
##	0.33297198	0.19864932	0.61665025	0.56616694	0.28923472	0.09732860
##	565	566	567	568	569	570
##	0.43538017	0.03310017	0.26102351	0.37915440	0.35212464	0.38289613
##	571	572	573	574	575	576
##	0.23023056	0.51617223	0.36249228	0.19257462	0.18336268	0.36961801
##	577	578	579	580	581	582
##	0.49765432	0.33341275	0.38356051	0.16415971	0.52696695	0.13663246
##	583	584	585	586	587	588
##	0.31073386	0.13119512	0.18314563	0.24940659	0.20763917	0.21299109
##	589	590	591	592	593	594
##	0.18488536	0.35166247	0.71576117	0.14683666	0.19636194	0.10018767
##	595	596	597	598	599	600
##	0.57609009	0.36487332	0.43255623	0.21467366	0.41629196	0.43243588
##	601	602	603	604	605	606
##	0.36779214	0.38062198	0.42857574	0.65194633	0.30297210	0.20670544
##	607	608	609	610	611	612
##	0.63641679	0.74226567	0.29172648	0.37267508	0.36238544	0.74472364
##	613	614	615	616	617	618
##	0.34975846	0.73474516	0.42481437	0.17212956	0.24564069	0.44090206
##	619	620	621	622	623	624
##	0.19511743	0.05652070	0.46496559	0.09716544	0.25268440	0.30521113
##	625	626	627	628	629	630
##	0.41302473	0.40782873	0.48318669	0.41832596	0.08867477	0.31636769
##	631	632	633	634	635	636
##	0.48357600	0.51040824	0.28583947	0.32308992	0.47970452	0.30484741
##	637	638	639	640	641	642
##	0.47283463	0.22372289	0.45411606	0.41799770	0.61816447	0.31890875
##	643	644	645	646	647	648
##	0.35600987	0.57271632	0.51283474	0.49187259	0.25541094	0.16686045
##	649	650	651	652	653	654

##	0.21819859	0.39347422	0.17932623	0.70611044	0.45834087	0.51195018
##	655	656	657	658	659	660
##	0.25921349	0.74841169	0.32725088	0.39231546	0.21626637	0.23133315
##	661	662	663	664	665	666
##	0.37737166	0.30501503	0.71554825	0.88740905	0.92536428	0.31608937
##	667	668	669	670	671	672
##	0.80626259	0.35551452	0.23271174	0.21341428	0.33922134	0.32595899
##	673	674	675	676	677	678
##	0.22222714	0.36281871	0.24817699	0.22142976	0.25675467	0.16200025
##	679	680	681	682	683	684
##	0.11758738	0.66779841	0.74064743	0.32241571	0.16574790	0.90041778
##	685	686	687	688	689	690
##	0.10374611	0.51641342	0.59901133	0.15542955	0.07096092	0.50946621
##	691	692	693	694	695	696
##	0.60843479	0.13444025	0.69084234	0.17104351	0.08507809	0.96396333
##	697	698	699	700	701	702
##	0.24459756	0.25254638	0.74763922	0.72137828	0.58155095	0.33028515
##	703	704	705	706	707	708
##	0.54924923	0.14687552	0.19056997	0.13526343	0.28755461	0.24425528
##	709	710	711	712	713	714
##	0.08661234	0.14786192	0.39471318	0.46768524	0.08682624	0.14870271
##	715	716	717	718	719	720
##	0.52866743	0.22304274	0.31270565	0.19436564	0.49833026	0.44719156
##	721	722	723	724	725	726
##	0.63021733	0.28129826	0.18481710	0.18772378	0.11209265	0.37576525
##	727	728	729	730	731	732
##	0.10105833	0.14831683	0.20325049	0.09580351	0.37529356	0.52156964
##	733	734	735	736	737	738
##	0.64565424	0.89286458	0.15347268	0.14081545	0.29538871	0.49247319
##	739	740	741	742	743	744
##	0.17939799	0.16787541	0.79468335	0.42959274	0.41627859	0.41511599
##	745	746	747	748	749	750
##	0.43734411	0.23542468	0.64733400	0.11611937	0.64496403	0.08511272
##	751	752	753	754	755	756
##	0.18802329	0.80036739	0.27949334	0.92767460	0.11548658	0.80725988
##	757	758	759	760	761	762
##	0.13111764	0.16747376	0.81862468	0.02994937	0.54086961	0.36966345
##	763	764	765	766	767	768
##	0.84628633	0.64655148	0.23355683	0.14324576	0.73741535	0.40590763
##	769	770	771	772	773	774
##	0.30057084	0.28350602	0.72295326	0.24458696	0.36548180	0.54630220
##	775	776	777	778	779	780
##	0.55794923	0.20868348	0.50790268	0.33301151	0.45828201	0.34237745
##	781	782	783	784	785	786
##	0.34564874	0.48099018	0.43486372	0.24716317	0.35079866	0.66076193
##	787	788	789	790	791	792
##	0.64619822	0.38211143	0.37863392	0.25785833	0.15557398	0.57323716
##	793	794	795	796	797	798
##	0.10851721	0.48198048	0.24011059	0.21842380	0.70916102	0.56802617
##	799	800	801	802	803	804
##	0.55414684	0.18693136	0.10837618	0.26948894	0.21196136	0.08559393
##	805	806	807	808	809	810
##	0.45710847	0.43646910	0.43504994	0.82500443	0.51676872	0.19309128
##	811	812	813	814	815	816

##	0.70123042	0.22829114	0.40666017	0.43107283	0.03324461	0.42477650
##	817	818	819	820	821	822
##	0.64610867	0.30428141	0.35278039	0.64806478	0.15064084	0.46927853
##	823	824	825	826	827	828
##	0.38654814	0.65887098	0.53001098	0.36672765	0.43519643	0.20397842
##	829	830	831	832	833	834
##	0.24673109	0.23082469	0.24906334	0.15866812	0.14995572	0.39864153
##	835	836	837	838	839	840
##	0.24772971	0.28173802	0.51489079	0.15838075	0.76594256	0.61087126
##	841	842	843	844	845	846
##	0.51771233	0.64586016	0.23216593	0.26694887	0.25130233	0.23792526
##	847	848	849	850	851	852
##	0.15377402	0.55831076	0.31173075	0.49651709	0.20362833	0.14617181
##	853	854	855	856	857	858
##	0.47628801	0.55343374	0.25268063	0.26623438	0.31734122	0.22511433
##	859	860	861	862	863	864
##	0.19123506	0.51282027	0.23344840	0.44556463	0.81996417	0.21676970
##	865	866	867	868	869	870
##	0.64323095	0.24040931	0.28628228	0.24287836	0.12951499	0.21779395
##	871	872	873	874	875	876
##	0.47730675	0.22808247	0.44339328	0.22319852	0.19410882	0.13910206
##	877	878	879	880	881	882
##	0.40232460	0.62306030	0.14966064	0.19786854	0.12105646	0.29764383
##	883	884	885	886	887	888
##	0.83424507	0.45973688	0.11605839	0.38464252	0.85109607	0.35297011
##	889	890	891	892	893	894
##	0.22239150	0.30762833	0.62324023	0.30333231	0.30109212	0.71886696
##	895	896	897	898	899	900
##	0.44414671	0.64268105	0.13379542	0.20093578	0.13724980	0.17567349
##	901	902	903	904	905	906
##	0.15517203	0.21744572	0.07878583	0.48496276	0.56440180	0.50169923
##	907	908	909	910	911	912
##	0.60161104	0.37229756	0.46218221	0.61757294	0.58798349	0.14600850
##	913	914	915	916	917	918
##	0.07166507	0.35719339	0.33794099	0.66712857	0.30912291	0.68347791
##	919	920	921	922	923	924
##	0.52371756	0.20693528	0.54270369	0.37020135	0.17242531	0.25596527
##	925	926	927	928	929	930
##	0.24625703	0.21185517	0.32676163	0.33967504	0.46206496	0.56660184
##	931	932	933	934	935	936
##	0.06947378	0.68466169	0.87645291	0.14247808	0.78995078	0.34734518
##	937	938	939	940	941	942
##	0.45900697	0.22765783	0.55629819	0.18965458	0.15274212	0.10350301
##	943	944	945	946	947	948
##	0.20324211	0.19312209	0.08940659	0.57287665	0.21721223	0.44401974
##	949	950	951	952	953	954
##	0.18711594	0.32214731	0.16462878	0.32790447	0.17518204	0.46365233
##	955	956	957	958	959	960
##	0.85197882	0.15992148	0.13139995	0.41659513	0.29491620	0.37002359
##	961	962	963	964	965	966
##	0.11548803	0.95142149	0.01481569	0.34325058	0.39328799	0.11171120
##	967	968	969	970	971	972
##	0.82994416	0.28974455	0.43078694	0.42865121	0.15454166	0.64518032
##	973	974	975	976	977	978

##	0.55694236	0.13382257	0.40668883	0.20316663	0.82831771	0.42083174
##	979	980	981	982	983	984
##	0.47576716	0.12556231	0.14866109	0.11125076	0.56653879	0.12535385
##	985	986	987	988	989	990
##	0.11352374	0.11724897	0.35181953	0.13436548	0.32498148	0.67795321
##	991	992	993	994	995	996
##	0.70953910	0.33924216	0.39134132	0.13652903	0.30821240	0.56384299
##	997	998	999	1000	1001	1002
##	0.43447362	0.55395433	0.17992096	0.94603000	0.25506712	0.43920888
##	1003	1004	1005	1006	1007	1008
##	0.52007317	0.43434769	0.44799938	0.51755514	0.43458523	0.19870775
##	1009	1010	1011	1012	1013	1014
##	0.59037209	0.39445498	0.16614249	0.18796127	0.64418936	0.07947131
##	1015	1016	1017	1018	1019	1020
##	0.21207680	0.54313061	0.49235524	0.09484359	0.22856256	0.95019288
##	1021	1022	1023	1024	1025	1026
##	0.17523237	0.51890287	0.36984288	0.17230941	0.34051191	0.28272115
##	1027	1028	1029	1030	1031	1032
##	0.19572939	0.09451496	0.09684715	0.42545217	0.14718406	0.52959191
##	1033	1034	1035	1036	1037	1038
##	0.17923403	0.23254593	0.23531173	0.82110792	0.07872139	0.34464525
##	1039	1040	1041	1042	1043	1044
##	0.49384185	0.61640245	0.10635898	0.44082935	0.05044867	0.83772805
##	1045	1046	1047	1048	1049	1050
##	0.85598867	0.65692415	0.79155826	0.81930649	0.13707331	0.87346514
##	1051	1052	1053	1054	1055	1056
##	0.32285172	0.24840973	0.17789422	0.44868590	0.85629681	0.55404493
##	1057	1058	1059	1060	1061	1062
##	0.26638500	0.11801231	0.05986661	0.44322460	0.09740258	0.08776564
##	1063	1064	1065	1066	1067	1068
##	0.24372879	0.79879020	0.90735761	0.78101838	0.67548273	0.19469561
##	1069	1070	1071	1072	1073	1074
##	0.63605039	0.52008232	0.19198692	0.44096944	0.59566613	0.18278445
##	1075	1076	1077	1078	1079	1080
##	0.85363838	0.31747618	0.87810250	0.77453296	0.82787623	0.89335049
##	1081	1082	1083	1084	1085	1086
##	0.68253276	0.48770570	0.91156668	0.92862392	0.80861149	0.93282363
##	1087	1088	1089	1090	1091	1092
##	0.74063207	0.58465648	0.14671688	0.75110168	0.51673207	0.51073354
##	1093	1094	1095	1096	1097	1098
##	0.93770233	0.21674230	0.64356455	0.56614689	0.97108034	0.86635407
##	1099	1100	1101	1102	1103	1104
##	0.94292510	0.59176061	0.63206749	0.50807293	0.78328588	0.89866981
##	1105	1106	1107	1108	1109	1110
##	0.40459465	0.88441469	0.95268297	0.58840360	0.12435205	0.95495338
##	1111	1112	1113	1114	1115	1116
##	0.46555046	0.58881523	0.37452312	0.15153556	0.88451949	0.53715038
##	1117	1118	1119	1120	1121	1122
##	0.30612616	0.71341989	0.62735620	0.83315124	0.61547116	0.48506901
##	1123	1124	1125	1126	1127	1128
##	0.64673007	0.29085738	0.29799973	0.50031374	0.76358978	0.95483468
##	1129	1130	1131	1132	1133	1134
##	0.08319340	0.58229499	0.53655067	0.36472949	0.12577039	0.45504620
##	1135	1136	1137	1138	1139	1140

##	0.97195274	0.75042123	0.14751586	0.30676941	0.94506701	0.47136196
##	1141	1142	1143	1144	1145	1146
##	0.74318848	0.23949375	0.95466258	0.73483359	0.90379685	0.81306477
##	1147	1148	1149	1150	1151	1152
##	0.74590490	0.93499789	0.43505138	0.59984600	0.63959152	0.58642762
##	1153	1154	1155	1156	1157	1158
##	0.65108950	0.37939685	0.91698002	0.90749731	0.86011258	0.25379104
##	1159	1160	1161	1162	1163	1164
##	0.91265740	0.68982809	0.66021266	0.71552734	0.62820312	0.82905940
##	1165	1166	1167	1168	1169	1170
##	0.91770576	0.87742287	0.90649914	0.95310319	0.47014682	0.18540461
##	1171	1172	1173	1174	1175	1176
##	0.76449041	0.18995383	0.78283825	0.33453956	0.59283584	0.66433189
##	1177	1178	1179	1180	1181	1182
##	0.38421203	0.40031823	0.20072351	0.89918022	0.66106939	0.56184633
##	1183	1184	1185	1186	1187	1188
##	0.79259889	0.14511403	0.57510226	0.63718605	0.79566735	0.54234771
##	1189	1190	1191	1192	1193	1194
##	0.29364310	0.84421497	0.83673895	0.69506896	0.80842096	0.25487434
##	1195	1196	1197	1198	1199	1200
##	0.23341102	0.89359519	0.68962544	0.57910930	0.77976157	0.52881039
##	1201	1202	1203	1204	1205	1206
##	0.66723667	0.55084724	0.93116529	0.96997013	0.58143330	0.88271263
##	1207	1208	1209	1210	1211	1212
##	0.65630082	0.70431054	0.41257057	0.70629683	0.50024186	0.57979616
##	1213	1214	1215	1216	1217	1218
##	0.62538692	0.58212796	0.37002718	0.17160565	0.70416216	0.41434901
##	1219	1220	1221	1222	1223	1224
##	0.24420089	0.70718595	0.50368782	0.71831515	0.29208989	0.55387296
##	1225	1226	1227	1228	1229	1230
##	0.60587061	0.71439248	0.50780061	0.77506108	0.80577614	0.73794657
##	1231	1232	1233	1234	1235	1236
##	0.13526719	0.64308006	0.51865927	0.32968406	0.96829110	0.59350277
##	1237	1238	1239	1240	1241	1242
##	0.69442665	0.69536562	0.46649746	0.45148255	0.64118507	0.37323189
##	1243	1244	1245	1246	1247	1248
##	0.91897976	0.41309186	0.49698362	0.98034992	0.92505155	0.72096407
##	1249	1250	1251	1252	1253	1254
##	0.37060251	0.70580203	0.74071943	0.72694866	0.65889187	0.56544540
##	1255	1256	1257	1258	1259	1260
##	0.97475735	0.26690673	0.08491678	0.96854773	0.35681838	0.88225140
##	1261	1262	1263	1264	1265	1266
##	0.80401035	0.48046661	0.83958126	0.96754299	0.98215853	0.33120125
##	1267	1268	1269	1270	1271	1272
##	0.93532352	0.71655975	0.38569160	0.90109830	0.60888096	0.86243277
##	1273	1274	1275	1276	1277	1278
##	0.17981125	0.71918593	0.87219978	0.93842223	0.86307409	0.87288033
##	1279	1280	1281	1282	1283	1284
##	0.64979440	0.37983811	0.63824412	0.47122518	0.38284314	0.69985511
##	1285	1286	1287	1288	1289	1290
##	0.37093253	0.51735771	0.80321926	0.63085120	0.67041328	0.30498062
##	1291	1292	1293	1294	1295	1296
##	0.94584161	0.95135043	0.52307853	0.91104599	0.11562801	0.83324367
##	1297	1298	1299	1300	1301	1302

##	0.95426728	0.79502536	0.35302761	0.54716510	0.76195846	0.66398728
##	1303	1304	1305	1306	1307	1308
##	0.69867268	0.79913608	0.93843561	0.43019609	0.87199932	0.78723675
##	1309	1310	1311	1312	1313	1314
##	0.69380334	0.84837942	0.85502255	0.73857626	0.18159730	0.62265522
##	1315	1316	1317	1318	1319	1320
##	0.29135044	0.92612827	0.90988100	0.48180938	0.76807328	0.50048274
##	1321	1322	1323	1324	1325	1326
##	0.19903403	0.24520456	0.66779331	0.41610156	0.49132434	0.78930632
##	1327	1328	1329	1330	1331	1332
##	0.88380083	0.71510646	0.62294672	0.71436685	0.66017061	0.72030056
##	1333	1334	1335	1336	1337	1338
##	0.84242614	0.56616066	0.12118702	0.81148975	0.54912355	0.80475713
##	1339	1340	1341	1342	1343	1344
##	0.64434498	0.39280941	0.86774903	0.75724899	0.68041035	0.74495874
##	1345	1346	1347	1348	1349	1350
##	0.93727507	0.44641987	0.98296295	0.74590399	0.71285144	0.46888857
##	1351	1352	1353	1354	1355	1356
##	0.30917189	0.66780708	0.72996658	0.96074752	0.89492399	0.67564944
##	1357	1358	1359	1360	1361	1362
##	0.84689881	0.66762752	0.62217779	0.31938606	0.20618554	0.22874538
##	1363	1364	1365	1366	1367	1368
##	0.54609591	0.58932498	0.74025399	0.70484739	0.72723723	0.93119491
##	1369	1370	1371	1372	1373	1374
##	0.45277516	0.72529052	0.19139688	0.80723378	0.70340589	0.78518951
##	1375	1376	1377	1378	1379	1380
##	0.86505212	0.86384249	0.37548672	0.81804507	0.15231979	0.84120731
##	1381	1382	1383	1384	1385	1386
##	0.27521364	0.63965013	0.92641178	0.40003911	0.75696398	0.89376078
##	1387	1388	1389	1390	1391	1392
##	0.58287361	0.89514236	0.98352479	0.38855111	0.45931147	0.07200530
##	1393	1394	1395	1396	1397	1398
##	0.57609194	0.95064715	0.61512040	0.54799176	0.58232065	0.89667274
##	1399	1400	1401	1402	1403	1404
##	0.73364785	0.68182909	0.14182653	0.52183615	0.91718960	0.43468897
##	1405	1406	1407	1408	1409	1410
##	0.95775753	0.77229422	0.65599517	0.97117969	0.93687298	0.77671408
##	1411	1412	1413	1414	1415	1416
##	0.83501142	0.79465000	0.97504354	0.31710556	0.17362954	0.62389253
##	1417	1418	1419	1420	1421	1422
##	0.56778791	0.69115271	0.88119231	0.75543314	0.22271307	0.15632449
##	1423	1424	1425	1426	1427	1428
##	0.58621011	0.94577983	0.49259359	0.27648848	0.43927273	0.77059143
##	1429	1430	1431	1432	1433	1434
##	0.49435061	0.31073930	0.53183167	0.78989101	0.71897335	0.62384341
##	1435	1436	1437	1438	1439	1440
##	0.83680106	0.05575673	0.36285551	0.24095523	0.75290195	0.85474865
##	1441	1442	1443	1444	1445	1446
##	0.64206863	0.71331712	0.46385444	0.45561028	0.15020224	0.77485224
##	1447	1448	1449	1450	1451	1452
##	0.39105353	0.71638384	0.76895603	0.65894342	0.22780451	0.51897576
##	1453	1454	1455	1456	1457	1458
##	0.52068806	0.46985252	0.86606992	0.64591211	0.85461119	0.53192345
##	1459	1460	1461	1462	1463	1464

##	0.49912787	0.95288133	0.19483351	0.47282409	0.36930556	0.72520014
##	1465	1466	1467	1468	1469	1470
##	0.32370692	0.46767935	0.38599762	0.41864472	0.60400854	0.90262023
##	1471	1472	1473	1474	1475	1476
##	0.62956693	0.16987253	0.82372777	0.53374969	0.55858701	0.97834177
##	1477	1478	1479	1480	1481	1482
##	0.84528761	0.51071100	0.95864280	0.85587117	0.53284949	0.64012280
##	1483	1484	1485	1486	1487	1488
##	0.86181466	0.90909095	0.96352880	0.71405262	0.78409247	0.53116658
##	1489	1490	1491	1492	1493	1494
##	0.34472363	0.81042694	0.67653248	0.87876608	0.47849871	0.47164732
##	1495	1496	1497	1498	1499	1500
##	0.37074609	0.88428650	0.56008987	0.45381378	0.44797671	0.46750473
##	1501	1502	1503	1504	1505	1506
##	0.79840581	0.52530256	0.96612178	0.63560011	0.52431765	0.48690417
##	1507	1508	1509	1510	1511	1512
##	0.38144830	0.60363754	0.89516794	0.69600756	0.90815345	0.57618675
##	1513	1514	1515	1516	1517	1518
##	0.65585022	0.86551570	0.40525927	0.70549746	0.63009728	0.89920234
##	1519	1520	1521	1522	1523	1524
##	0.50017607	0.53696175	0.45922806	0.40146602	0.78823796	0.74391168
##	1525	1526	1527	1528	1529	1530
##	0.70540414	0.88124758	0.65169214	0.94684552	0.85825820	0.54127261
##	1531	1532	1533	1534	1535	1536
##	0.59368259	0.30646940	0.45181892	0.77119987	0.63516217	0.37611743
##	1537	1538	1539	1540	1541	1542
##	0.74265600	0.88170380	0.55728467	0.42119401	0.24569365	0.74102018
##	1543	1544	1545	1546	1547	1548
##	0.55787187	0.31411250	0.93852108	0.69333568	0.97009120	0.60249602
##	1549	1550	1551	1552	1553	1554
##	0.67072835	0.96729970	0.57386011	0.71688717	0.49024591	0.49929989
##	1555	1556	1557	1558	1559	1560
##	0.54490874	0.61642608	0.64700272	0.96101978	0.34144232	0.67180790
##	1561	1562	1563	1564	1565	1566
##	0.75628111	0.74796697	0.25187668	0.65323862	0.65869126	0.35670623
##	1567	1568	1569	1570	1571	1572
##	0.62732793	0.41749793	0.96305880	0.76175352	0.19511882	0.83327964
##	1573	1574	1575	1576	1577	1578
##	0.71908408	0.81732686	0.63428671	0.86966801	0.91326473	0.52989831
##	1579	1580	1581	1582	1583	1584
##	0.84915022	0.92983725	0.38039968	0.42333959	0.55549579	0.87312220
##	1585	1586	1587	1588	1589	1590
##	0.79494367	0.36312098	0.48149148	0.89143405	0.24525395	0.52222168
##	1591	1592	1593	1594	1595	1596
##	0.31923026	0.73168362	0.44806304	0.46975862	0.75139586	0.67176286
##	1597	1598	1599	1600	1601	1602
##	0.45973570	0.78537667	0.99702231	0.65292379	0.43193361	0.83447784
##	1603	1604	1605	1606	1607	1608
##	0.70126536	0.55725462	0.59609737	0.76857328	0.27243802	0.78956604
##	1609	1610	1611	1612	1613	1614
##	0.39811949	0.43072404	0.58265605	0.92386269	0.83990436	0.92000510
##	1615	1616	1617	1618	1619	1620
##	0.50228284	0.56002258	0.95315074	0.73812852	0.23804117	0.36872849
##	1621	1622	1623	1624	1625	1626

##	0.84568590	0.90967828	0.26877077	0.85434688	0.95174171	0.55393616
##	1627	1628	1629	1630	1631	1632
##	0.74744680	0.79185113	0.77919529	0.12002065	0.91140386	0.94065482
##	1633	1634	1635	1636	1637	1638
##	0.59147742	0.85160369	0.25974475	0.56336658	0.83806545	0.65858277
##	1639	1640	1641	1642	1643	1644
##	0.78013615	0.92598058	0.46921505	0.60028526	0.23406159	0.96522693
##	1645	1646	1647	1648	1649	1650
##	0.50087034	0.87012298	0.95333780	0.33190392	0.89785332	0.41821397
##	1651	1652	1653	1654	1655	1656
##	0.32170738	0.48814494	0.83320235	0.89299438	0.88080642	0.41695220
##	1657	1658	1659	1660	1661	1662
##	0.34380927	0.71210971	0.69903514	0.88853119	0.11448264	0.81112082
##	1663	1664	1665	1666	1667	1668
##	0.92314353	0.86836096	0.13989286	0.32197170	0.44822694	0.75174280
##	1669	1670	1671	1672	1673	1674
##	0.74137169	0.81709128	0.83715617	0.86340458	0.43012772	0.41512524
##	1675	1676	1677	1678	1679	1680
##	0.46560906	0.46974971	0.96722427	0.73642964	0.32995288	0.45757360
##	1681	1682	1683	1684	1685	1686
##	0.36888447	0.64512696	0.50026412	0.45789435	0.69572629	0.82316277
##	1687	1688	1689	1690	1691	1692
##	0.96350853	0.92439693	0.96396354	0.95584645	0.45452283	0.45912747
##	1693	1694	1695	1696	1697	1698
##	0.38299252	0.92173062	0.47580056	0.48959417	0.71742576	0.80675410
##	1699	1700	1701	1702	1703	1704
##	0.78730238	0.38775341	0.26056734	0.83515482	0.92829263	0.80148639
##	1705	1706	1707	1708	1709	1710
##	0.63844507	0.82453884	0.45019640	0.76426720	0.42944984	0.74521603
##	1711	1712	1713	1714	1715	1716
##	0.90898348	0.82149583	0.63894735	0.62104130	0.84986457	0.61902631
##	1717	1718	1719	1720	1721	1722
##	0.41991411	0.94704688	0.87839532	0.49981607	0.96816742	0.64362167
##	1723	1724	1725	1726	1727	1728
##	0.77332250	0.71838914	0.72265882	0.98678087	0.79196987	0.65234506
##	1729	1730	1731	1732	1733	1734
##	0.49689952	0.96161890	0.55548794	0.63885431	0.41010106	0.64402014
##	1735	1736	1737	1738	1739	1740
##	0.54149412	0.15024621	0.29791585	0.70620054	0.95697127	0.84381266
##	1741	1742	1743	1744	1745	1746
##	0.25383323	0.95622999	0.91278259	0.36640686	0.92835347	0.49132010
##	1747	1748	1749	1750	1751	1752
##	0.18688687	0.23808434	0.62112168	0.32746559	0.51727099	0.20307795
##	1753	1754	1755	1756	1757	1758
##	0.75952096	0.02269038	0.65067704	0.88934408	0.30274743	0.79789817
##	1759	1760	1761	1762	1763	1764
##	0.17779883	0.49978137	0.42032306	0.70016505	0.92030987	0.40972840
##	1765	1766	1767	1768	1769	1770
##	0.72048307	0.91574418	0.90146115	0.38730674	0.92949411	0.81087360
##	1771	1772	1773	1774	1775	1776
##	0.34011497	0.70881937	0.40973246	0.86292765	0.90777122	0.15797114
##	1777	1778	1779	1780	1781	1782
##	0.49521420	0.35604199	0.96778872	0.60106928	0.59904456	0.60010276
##	1783	1784	1785	1786	1787	1788

##	0.64997923	0.65849773	0.91375795	0.91080665	0.27842510	0.65557266
##	1789	1790	1791	1792	1793	1794
##	0.98818589	0.45662678	0.33005043	0.70419632	0.86705000	0.66122259
##	1795	1796	1797	1798	1799	1800
##	0.76903000	0.89579269	0.21573015	0.56344912	0.75022968	0.58468860
##	1801	1802	1803	1804	1805	1806
##	0.81683955	0.63568914	0.61222886	0.63572082	0.69262353	0.36284751
##	1807	1808	1809	1810	1811	1812
##	0.88919333	0.48703279	0.74485644	0.46038921	0.82625663	0.23835382
##	1813	1814	1815	1816	1817	1818
##	0.65995267	0.73009807	0.23295473	0.68225797	0.79502116	0.88637929
##	1819	1820	1821	1822	1823	1824
##	0.37592848	0.90645652	0.85516410	0.82580341	0.76547007	0.64243580
##	1825	1826	1827	1828	1829	1830
##	0.81387047	0.74416539	0.32022166	0.66324973	0.49133186	0.39254702
##	1831	1832	1833	1834	1835	1836
##	0.81917644	0.84447159	0.26432238	0.33647017	0.20077637	0.92004376
##	1837	1838	1839	1840	1841	1842
##	0.30719240	0.92986253	0.55248020	0.73760586	0.51267320	0.48537756
##	1843	1844	1845	1846	1847	1848
##	0.26322753	0.55092222	0.73964723	0.44661647	0.39796337	0.47514531
##	1849	1850	1851	1852	1853	1854
##	0.57580388	0.43312879	0.61482642	0.61497297	0.68922498	0.31534168
##	1855	1856	1857	1858	1859	1860
##	0.54121482	0.62598013	0.87842697	0.63391190	0.78615461	0.43093844
##	1861	1862	1863	1864	1865	1866
##	0.80103002	0.87922879	0.95344683	0.40174039	0.80472382	0.76554963
##	1867	1868	1869	1870	1871	1872
##	0.57259880	0.92577807	0.88117509	0.55050163	0.61890595	0.71293413
##	1873	1874	1875	1876	1877	1878
##	0.58383993	0.71687555	0.58001956	0.97216018	0.31249998	0.31828995
##	1879	1880	1881	1882	1883	1884
##	0.67174542	0.85151487	0.50073433	0.15408353	0.84604691	0.57503356
##	1885	1886	1887	1888	1889	1890
##	0.24872791	0.55433032	0.58129965	0.73563906	0.12507083	0.14990262
##	1891	1892	1893	1894	1895	1896
##	0.64471236	0.95429118	0.91560112	0.93023751	0.55023207	0.96905885
##	1897	1898	1899	1900	1901	1902
##	0.16720913	0.76510433	0.53827771	0.66206225	0.67196398	0.95394465
##	1903	1904	1905	1906	1907	1908
##	0.31019183	0.84643488	0.59143510	0.90408222	0.68778430	0.30173429
##	1909	1910	1911	1912	1913	1914
##	0.79376506	0.89695766	0.88843801	0.63071432	0.69281982	0.46714573
##	1915	1916	1917	1918	1919	1920
##	0.88451946	0.69503540	0.41562079	0.48106657	0.94082871	0.73067786
##	1921	1922	1923	1924	1925	1926
##	0.49164672	0.49349435	0.95136180	0.38028195	0.63765683	0.66625482
##	1927	1928	1929	1930	1931	1932
##	0.26020089	0.51408286	0.33989021	0.48563324	0.51963881	0.79700060
##	1933	1934	1935	1936	1937	1938
##	0.73214186	0.73712219	0.33931787	0.61735371	0.91834356	0.12228080
##	1939	1940	1941	1942	1943	1944
##	0.63905528	0.33878116	0.70111076	0.77027679	0.78979717	0.41618678
##	1945	1946	1947	1948	1949	1950

##	0.70958417	0.67476352	0.26789067	0.13150066	0.93900807	0.67084171
##	1951	1952	1953	1954	1955	1956
##	0.13867575	0.94447746	0.70734067	0.72474156	0.79494707	0.53435233
##	1957	1958	1959	1960	1961	1962
##	0.81016558	0.86622307	0.61919754	0.83240303	0.64699876	0.65005600
##	1963	1964	1965	1966	1967	1968
##	0.69251430	0.63652141	0.73188653	0.95589402	0.71049798	0.85435745
##	1969	1970	1971	1972	1973	1974
##	0.49007349	0.37337773	0.57008338	0.75101483	0.54211171	0.52744529
##	1975	1976	1977	1978	1979	1980
##	0.48847258	0.63177177	0.92914921	0.75257020	0.15528047	0.92351130
##	1981	1982	1983	1984	1985	1986
##	0.50611309	0.92434862	0.53698427	0.66577616	0.67856590	0.95959105
##	1987	1988	1989	1990	1991	1992
##	0.87226501	0.82350504	0.44713441	0.56545646	0.35114337	0.37990932
##	1993	1994	1995	1996	1997	1998
##	0.86676482	0.82309855	0.70294987	0.76460778	0.76743242	0.41478120
##	1999	2000	2001	2002	2003	2004
##	0.82306551	0.86769920	0.87569438	0.95948271	0.77609196	0.96804465
##	2005	2006	2007	2008	2009	2010
##	0.45872076	0.29223317	0.78530329	0.71090012	0.40747672	0.59688588
##	2011	2012	2013	2014	2015	2016
##	0.98511271	0.65308326	0.70341210	0.48133928	0.25926080	0.95474281
##	2017	2018	2019	2020	2021	2022
##	0.67370066	0.70487006	0.57590747	0.79489137	0.44801441	0.71695130
##	2023	2024	2025	2026	2027	2028
##	0.61257832	0.78596642	0.40268541	0.78086040	0.80137865	0.65955207
##	2029	2030	2031	2032	2033	2034
##	0.85292417	0.69810640	0.64650226	0.61899777	0.61446798	0.92967833
##	2035	2036	2037	2038	2039	2040
##	0.37406193	0.38375491	0.57445351	0.85577267	0.93813827	0.66942534
##	2041	2042	2043	2044	2045	2046
##	0.75288707	0.78369968	0.16995037	0.81135600	0.75604272	0.62001925
##	2047	2048	2049	2050	2051	2052
##	0.96962551	0.34461341	0.44802556	0.85643521	0.56836365	0.27147031
##	2053	2054	2055	2056	2057	2058
##	0.58887776	0.98765678	0.37219134	0.65790322	0.55036261	0.65769635
##	2059	2060	2061	2062	2063	2064
##	0.86733201	0.53286135	0.60352762	0.36957402	0.91938430	0.45896666
##	2065	2066	2067	2068	2069	2070
##	0.95074899	0.80826542	0.40247190	0.29650393	0.47331786	0.66165167
##	2071	2072	2073	2074	2075	2076
##	0.90585834	0.80010879	0.70089487	0.96227804	0.63658203	0.83106654
##	2077	2078	2079	2080	2081	2082
##	0.56362285	0.53964653	0.54896697	0.47339930	0.95384206	0.54860025
##	2083	2084	2085	2086	2087	2088
##	0.15844043	0.23418441	0.70741735	0.94918450	0.92585945	0.60191378
##	2089	2090	2091	2092	2093	2094
##	0.69678318	0.76763533	0.97752328	0.92157889	0.10865254	0.96430500
##	2095	2096	2097	2098	2099	2100
##	0.70172001	0.32111389	0.39665399	0.97814822	0.91221833	0.97077856
##	2101	2102	2103	2104	2105	2106
##	0.13465015	0.31019297	0.74903665	0.72671279	0.57967003	0.73403772
##	2107	2108	2109	2110	2111	2112

```
## 0.58582887 0.71015643 0.36319724 0.50856624 0.39177683 0.65871816
##      2113      2114      2115      2116      2117      2118
## 0.78893024 0.54472068 0.76340527 0.89195661 0.53278499 0.66537012
##      2119      2120      2121
## 0.82538750 0.59534387 0.23004189
```

5.2.10 Covertng Probabilites to 0 and 1

```
ypredlog <- ifelse(logpred > 0.5,1,0)
ypredlog
```

```
##      1      2      3      4      5      6      7      8      9     10     11     12     13     14     15
##      0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
##     16     17     18     19     20     21     22     23     24     25     26     27     28     29     30
##      0      0      1      0      0      0      0      0      0      0      0      0      0      1      0
##     31     32     33     34     35     36     37     38     39     40     41     42     43     44     45
##      1      1      0      1      0      0      1      0      0      0      0      0      0      0      0
##     46     47     48     49     50     51     52     53     54     55     56     57     58     59     60
##      0      0      0      0      0      0      0      0      0      0      0      0      1      0      0
##     61     62     63     64     65     66     67     68     69     70     71     72     73     74     75
##      1      0      0      0      1      0      0      0      0      0      0      0      0      1      0
##     76     77     78     79     80     81     82     83     84     85     86     87     88     89     90
##      0      1      0      1      0      1      0      0      0      0      0      0      0      0      0
##     91     92     93     94     95     96     97     98     99    100    101    102    103    104    105
##      0      0      0      0      0      0      0      0      0      0      1      0      1      1      0
##    106    107    108    109    110    111    112    113    114    115    116    117    118    119    120
##      0      1      0      0      0      0      0      1      1      0      0      1      0      1      0
##    121    122    123    124    125    126    127    128    129    130    131    132    133    134    135
##      0      0      1      0      0      0      0      0      0      0      0      0      1      1      0
##    136    137    138    139    140    141    142    143    144    145    146    147    148    149    150
##      0      0      0      0      0      1      1      1      0      1      0      0      0      0      0
##    151    152    153    154    155    156    157    158    159    160    161    162    163    164    165
##      0      0      1      0      1      0      0      0      0      1      0      0      0      0      0
##    166    167    168    169    170    171    172    173    174    175    176    177    178    179    180
##      0      1      1      0      0      0      1      0      0      0      0      1      0      1      0
##    181    182    183    184    185    186    187    188    189    190    191    192    193    194    195
##      1      0      0      1      1      0      0      1      0      0      1      1      0      0      0
##    196    197    198    199    200    201    202    203    204    205    206    207    208    209    210
##      0      0      0      0      1      0      0      0      0      1      0      1      0      0      0
##    211    212    213    214    215    216    217    218    219    220    221    222    223    224    225
##      0      0      0      0      0      0      0      0      1      0      1      1      0      1      1
##    226    227    228    229    230    231    232    233    234    235    236    237    238    239    240
##      0      0      0      0      0      0      0      1      0      0      0      0      1      0      0
##    241    242    243    244    245    246    247    248    249    250    251    252    253    254    255
##      0      0      0      0      0      0      1      1      0      0      1      0      0      0      0
##    256    257    258    259    260    261    262    263    264    265    266    267    268    269    270
##      0      0      0      0      1      0      0      0      0      1      0      0      0      1      0
##    271    272    273    274    275    276    277    278    279    280    281    282    283    284    285
##      0      0      0      1      0      1      1      0      0      0      0      1      0      0      0
##    286    287    288    289    290    291    292    293    294    295    296    297    298    299    300
##      0      0      0      0      0      0      0      1      0      1      1      0      1      0      0
##    301    302    303    304    305    306    307    308    309    310    311    312    313    314    315
##      0      0      0      0      1      0      0      1      0      1      0      0      0      0      0
##    316    317    318    319    320    321    322    323    324    325    326    327    328    329    330
```

##	0	0	1	1	0	0	1	0	0	0	0	0	0	1	1
##	331	332	333	334	335	336	337	338	339	340	341	342	343	344	345
##	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
##	346	347	348	349	350	351	352	353	354	355	356	357	358	359	360
##	0	1	0	0	1	0	0	0	0	1	0	1	0	1	0
##	361	362	363	364	365	366	367	368	369	370	371	372	373	374	375
##	0	0	0	0	0	1	1	0	1	0	0	0	0	1	0
##	376	377	378	379	380	381	382	383	384	385	386	387	388	389	390
##	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0
##	391	392	393	394	395	396	397	398	399	400	401	402	403	404	405
##	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
##	406	407	408	409	410	411	412	413	414	415	416	417	418	419	420
##	0	0	0	0	1	0	0	0	1	0	0	1	1	0	0
##	421	422	423	424	425	426	427	428	429	430	431	432	433	434	435
##	1	0	0	1	1	0	1	0	0	0	1	0	1	0	0
##	436	437	438	439	440	441	442	443	444	445	446	447	448	449	450
##	0	1	0	0	0	1	0	0	0	0	1	1	0	0	0
##	451	452	453	454	455	456	457	458	459	460	461	462	463	464	465
##	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
##	466	467	468	469	470	471	472	473	474	475	476	477	478	479	480
##	0	0	0	0	1	1	1	0	1	0	0	0	1	0	0
##	481	482	483	484	485	486	487	488	489	490	491	492	493	494	495
##	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
##	496	497	498	499	500	501	502	503	504	505	506	507	508	509	510
##	0	0	0	1	0	1	0	0	0	0	1	0	0	0	1
##	511	512	513	514	515	516	517	518	519	520	521	522	523	524	525
##	0	0	1	0	0	1	0	1	0	1	0	0	0	0	1
##	526	527	528	529	530	531	532	533	534	535	536	537	538	539	540
##	0	0	1	0	0	1	0	1	0	1	0	1	1	0	1
##	541	542	543	544	545	546	547	548	549	550	551	552	553	554	555
##	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
##	556	557	558	559	560	561	562	563	564	565	566	567	568	569	570
##	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0
##	571	572	573	574	575	576	577	578	579	580	581	582	583	584	585
##	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
##	586	587	588	589	590	591	592	593	594	595	596	597	598	599	600
##	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
##	601	602	603	604	605	606	607	608	609	610	611	612	613	614	615
##	0	0	0	1	0	0	1	1	0	0	0	1	0	1	0
##	616	617	618	619	620	621	622	623	624	625	626	627	628	629	630
##	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
##	631	632	633	634	635	636	637	638	639	640	641	642	643	644	645
##	0	1	0	0	0	0	0	0	0	0	1	0	0	1	1
##	646	647	648	649	650	651	652	653	654	655	656	657	658	659	660
##	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0
##	661	662	663	664	665	666	667	668	669	670	671	672	673	674	675
##	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0
##	676	677	678	679	680	681	682	683	684	685	686	687	688	689	690
##	0	0	0	0	1	1	0	0	1	0	1	1	0	0	1
##	691	692	693	694	695	696	697	698	699	700	701	702	703	704	705
##	1	0	1	0	0	1	0	0	1	1	1	0	1	0	0
##	706	707	708	709	710	711	712	713	714	715	716	717	718	719	720
##	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
##	721	722	723	724	725	726	727	728	729	730	731	732	733	734	735

##	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0
##	736	737	738	739	740	741	742	743	744	745	746	747	748	749	750
##	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0
##	751	752	753	754	755	756	757	758	759	760	761	762	763	764	765
##	0	1	0	1	0	1	0	0	1	0	1	0	1	1	0
##	766	767	768	769	770	771	772	773	774	775	776	777	778	779	780
##	0	1	0	0	0	1	0	0	1	1	0	1	0	0	0
##	781	782	783	784	785	786	787	788	789	790	791	792	793	794	795
##	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0
##	796	797	798	799	800	801	802	803	804	805	806	807	808	809	810
##	0	1	1	1	0	0	0	0	0	0	0	0	1	1	0
##	811	812	813	814	815	816	817	818	819	820	821	822	823	824	825
##	1	0	0	0	0	0	1	0	0	1	0	0	0	1	1
##	826	827	828	829	830	831	832	833	834	835	836	837	838	839	840
##	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
##	841	842	843	844	845	846	847	848	849	850	851	852	853	854	855
##	1	1	0	0	0	0	0	1	0	0	0	0	0	1	0
##	856	857	858	859	860	861	862	863	864	865	866	867	868	869	870
##	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0
##	871	872	873	874	875	876	877	878	879	880	881	882	883	884	885
##	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0
##	886	887	888	889	890	891	892	893	894	895	896	897	898	899	900
##	0	1	0	0	0	1	0	0	1	0	1	0	0	0	0
##	901	902	903	904	905	906	907	908	909	910	911	912	913	914	915
##	0	0	0	0	1	1	1	0	0	1	1	0	0	0	0
##	916	917	918	919	920	921	922	923	924	925	926	927	928	929	930
##	1	0	1	1	0	1	0	0	0	0	0	0	0	0	1
##	931	932	933	934	935	936	937	938	939	940	941	942	943	944	945
##	0	1	1	0	1	0	0	0	1	0	0	0	0	0	0
##	946	947	948	949	950	951	952	953	954	955	956	957	958	959	960
##	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
##	961	962	963	964	965	966	967	968	969	970	971	972	973	974	975
##	0	1	0	0	0	0	1	0	0	0	0	1	1	0	0
##	976	977	978	979	980	981	982	983	984	985	986	987	988	989	990
##	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1
##	991	992	993	994	995	996	997	998	999	1000	1001	1002	1003	1004	1005
##	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0
##	1006	1007	1008	1009	1010	1011	1012	1013	1014	1015	1016	1017	1018	1019	1020
##	1	0	0	1	0	0	0	1	0	0	1	0	0	0	1
##	1021	1022	1023	1024	1025	1026	1027	1028	1029	1030	1031	1032	1033	1034	1035
##	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
##	1036	1037	1038	1039	1040	1041	1042	1043	1044	1045	1046	1047	1048	1049	1050
##	1	0	0	0	1	0	0	0	1	1	1	1	1	0	1
##	1051	1052	1053	1054	1055	1056	1057	1058	1059	1060	1061	1062	1063	1064	1065
##	0	0	0	0	1	1	0	0	0	0	0	0	0	1	1
##	1066	1067	1068	1069	1070	1071	1072	1073	1074	1075	1076	1077	1078	1079	1080
##	1	1	0	1	1	0	0	1	0	1	0	1	1	1	1
##	1081	1082	1083	1084	1085	1086	1087	1088	1089	1090	1091	1092	1093	1094	1095
##	1	0	1	1	1	1	1	1	0	1	1	1	1	0	1
##	1096	1097	1098	1099	1100	1101	1102	1103	1104	1105	1106	1107	1108	1109	1110
##	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1
##	1111	1112	1113	1114	1115	1116	1117	1118	1119	1120	1121	1122	1123	1124	1125
##	0	1	0	0	1	1	0	1	1	1	1	0	1	0	0
##	1126	1127	1128	1129	1130	1131	1132	1133	1134	1135	1136	1137	1138	1139	1140

##	1	1	1	0	1	1	0	0	0	1	1	0	0	1	0
##	1141	1142	1143	1144	1145	1146	1147	1148	1149	1150	1151	1152	1153	1154	1155
##	1	0	1	1	1	1	1	1	0	1	1	1	1	0	1
##	1156	1157	1158	1159	1160	1161	1162	1163	1164	1165	1166	1167	1168	1169	1170
##	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0
##	1171	1172	1173	1174	1175	1176	1177	1178	1179	1180	1181	1182	1183	1184	1185
##	1	0	1	0	1	1	0	0	0	1	1	1	1	0	1
##	1186	1187	1188	1189	1190	1191	1192	1193	1194	1195	1196	1197	1198	1199	1200
##	1	1	1	0	1	1	1	1	0	0	1	1	1	1	1
##	1201	1202	1203	1204	1205	1206	1207	1208	1209	1210	1211	1212	1213	1214	1215
##	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0
##	1216	1217	1218	1219	1220	1221	1222	1223	1224	1225	1226	1227	1228	1229	1230
##	0	1	0	0	1	1	1	0	1	1	1	1	1	1	1
##	1231	1232	1233	1234	1235	1236	1237	1238	1239	1240	1241	1242	1243	1244	1245
##	0	1	1	0	1	1	1	1	0	0	1	0	1	0	0
##	1246	1247	1248	1249	1250	1251	1252	1253	1254	1255	1256	1257	1258	1259	1260
##	1	1	1	0	1	1	1	1	1	1	0	0	1	0	1
##	1261	1262	1263	1264	1265	1266	1267	1268	1269	1270	1271	1272	1273	1274	1275
##	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1
##	1276	1277	1278	1279	1280	1281	1282	1283	1284	1285	1286	1287	1288	1289	1290
##	1	1	1	1	0	1	0	0	1	0	1	1	1	1	0
##	1291	1292	1293	1294	1295	1296	1297	1298	1299	1300	1301	1302	1303	1304	1305
##	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1
##	1306	1307	1308	1309	1310	1311	1312	1313	1314	1315	1316	1317	1318	1319	1320
##	0	1	1	1	1	1	1	0	1	0	1	1	0	1	1
##	1321	1322	1323	1324	1325	1326	1327	1328	1329	1330	1331	1332	1333	1334	1335
##	0	0	1	0	0	1	1	1	1	1	1	1	1	1	0
##	1336	1337	1338	1339	1340	1341	1342	1343	1344	1345	1346	1347	1348	1349	1350
##	1	1	1	1	0	1	1	1	1	1	0	1	1	1	0
##	1351	1352	1353	1354	1355	1356	1357	1358	1359	1360	1361	1362	1363	1364	1365
##	0	1	1	1	1	1	1	1	1	0	0	0	1	1	1
##	1366	1367	1368	1369	1370	1371	1372	1373	1374	1375	1376	1377	1378	1379	1380
##	1	1	1	0	1	0	1	1	1	1	1	0	1	0	1
##	1381	1382	1383	1384	1385	1386	1387	1388	1389	1390	1391	1392	1393	1394	1395
##	0	1	1	0	1	1	1	1	1	0	0	0	1	1	1
##	1396	1397	1398	1399	1400	1401	1402	1403	1404	1405	1406	1407	1408	1409	1410
##	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1
##	1411	1412	1413	1414	1415	1416	1417	1418	1419	1420	1421	1422	1423	1424	1425
##	1	1	1	0	0	1	1	1	1	1	0	0	1	1	0
##	1426	1427	1428	1429	1430	1431	1432	1433	1434	1435	1436	1437	1438	1439	1440
##	0	0	1	0	0	1	1	1	1	1	0	0	0	1	1
##	1441	1442	1443	1444	1445	1446	1447	1448	1449	1450	1451	1452	1453	1454	1455
##	1	1	0	0	0	1	0	1	1	1	0	1	1	0	1
##	1456	1457	1458	1459	1460	1461	1462	1463	1464	1465	1466	1467	1468	1469	1470
##	1	1	1	0	1	0	0	0	1	0	0	0	0	1	1
##	1471	1472	1473	1474	1475	1476	1477	1478	1479	1480	1481	1482	1483	1484	1485
##	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
##	1486	1487	1488	1489	1490	1491	1492	1493	1494	1495	1496	1497	1498	1499	1500
##	1	1	1	0	1	1	1	0	0	0	1	1	0	0	0
##	1501	1502	1503	1504	1505	1506	1507	1508	1509	1510	1511	1512	1513	1514	1515
##	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0
##	1516	1517	1518	1519	1520	1521	1522	1523	1524	1525	1526	1527	1528	1529	1530
##	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1
##	1531	1532	1533	1534	1535	1536	1537	1538	1539	1540	1541	1542	1543	1544	1545

##	1	0	0	1	1	0	1	1	1	0	0	1	1	0	1
##	1546	1547	1548	1549	1550	1551	1552	1553	1554	1555	1556	1557	1558	1559	1560
##	1	1	1	1	1	1	1	0	0	1	1	1	1	0	1
##	1561	1562	1563	1564	1565	1566	1567	1568	1569	1570	1571	1572	1573	1574	1575
##	1	1	0	1	1	0	1	0	1	1	0	1	1	1	1
##	1576	1577	1578	1579	1580	1581	1582	1583	1584	1585	1586	1587	1588	1589	1590
##	1	1	1	1	1	0	0	1	1	1	0	0	1	0	1
##	1591	1592	1593	1594	1595	1596	1597	1598	1599	1600	1601	1602	1603	1604	1605
##	0	1	0	0	1	1	0	1	1	1	0	1	1	1	1
##	1606	1607	1608	1609	1610	1611	1612	1613	1614	1615	1616	1617	1618	1619	1620
##	1	0	1	0	0	1	1	1	1	1	1	1	1	0	0
##	1621	1622	1623	1624	1625	1626	1627	1628	1629	1630	1631	1632	1633	1634	1635
##	1	1	0	1	1	1	1	1	1	0	1	1	1	1	0
##	1636	1637	1638	1639	1640	1641	1642	1643	1644	1645	1646	1647	1648	1649	1650
##	1	1	1	1	1	0	1	0	1	1	1	1	0	1	0
##	1651	1652	1653	1654	1655	1656	1657	1658	1659	1660	1661	1662	1663	1664	1665
##	0	0	1	1	1	0	0	1	1	1	0	1	1	1	0
##	1666	1667	1668	1669	1670	1671	1672	1673	1674	1675	1676	1677	1678	1679	1680
##	0	0	1	1	1	1	1	0	0	0	0	1	1	0	0
##	1681	1682	1683	1684	1685	1686	1687	1688	1689	1690	1691	1692	1693	1694	1695
##	0	1	1	0	1	1	1	1	1	1	0	0	0	1	0
##	1696	1697	1698	1699	1700	1701	1702	1703	1704	1705	1706	1707	1708	1709	1710
##	0	1	1	1	0	0	1	1	1	1	1	0	1	0	1
##	1711	1712	1713	1714	1715	1716	1717	1718	1719	1720	1721	1722	1723	1724	1725
##	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1
##	1726	1727	1728	1729	1730	1731	1732	1733	1734	1735	1736	1737	1738	1739	1740
##	1	1	1	0	1	1	1	0	1	1	0	0	1	1	1
##	1741	1742	1743	1744	1745	1746	1747	1748	1749	1750	1751	1752	1753	1754	1755
##	0	1	1	0	1	0	0	0	1	0	1	0	1	0	1
##	1756	1757	1758	1759	1760	1761	1762	1763	1764	1765	1766	1767	1768	1769	1770
##	1	0	1	0	0	0	1	1	0	1	1	1	0	1	1
##	1771	1772	1773	1774	1775	1776	1777	1778	1779	1780	1781	1782	1783	1784	1785
##	0	1	0	1	1	0	0	0	1	1	1	1	1	1	1
##	1786	1787	1788	1789	1790	1791	1792	1793	1794	1795	1796	1797	1798	1799	1800
##	1	0	1	1	0	0	1	1	1	1	1	0	1	1	1
##	1801	1802	1803	1804	1805	1806	1807	1808	1809	1810	1811	1812	1813	1814	1815
##	1	1	1	1	1	0	1	0	1	0	1	0	1	1	0
##	1816	1817	1818	1819	1820	1821	1822	1823	1824	1825	1826	1827	1828	1829	1830
##	1	1	1	0	1	1	1	1	1	1	1	0	1	0	0
##	1831	1832	1833	1834	1835	1836	1837	1838	1839	1840	1841	1842	1843	1844	1845
##	1	1	0	0	0	1	0	1	1	1	1	0	0	1	1
##	1846	1847	1848	1849	1850	1851	1852	1853	1854	1855	1856	1857	1858	1859	1860
##	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0
##	1861	1862	1863	1864	1865	1866	1867	1868	1869	1870	1871	1872	1873	1874	1875
##	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
##	1876	1877	1878	1879	1880	1881	1882	1883	1884	1885	1886	1887	1888	1889	1890
##	1	0	0	1	1	1	0	1	1	0	1	1	1	0	0
##	1891	1892	1893	1894	1895	1896	1897	1898	1899	1900	1901	1902	1903	1904	1905
##	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1
##	1906	1907	1908	1909	1910	1911	1912	1913	1914	1915	1916	1917	1918	1919	1920
##	1	1	0	1	1	1	1	1	0	1	1	0	0	1	1
##	1921	1922	1923	1924	1925	1926	1927	1928	1929	1930	1931	1932	1933	1934	1935
##	0	0	1	0	1	1	0	1	0	0	1	1	1	1	0
##	1936	1937	1938	1939	1940	1941	1942	1943	1944	1945	1946	1947	1948	1949	1950

```
##      1      1      0      1      0      1      1      1      0      1      1      0      0      1      1
## 1951 1952 1953 1954 1955 1956 1957 1958 1959 1960 1961 1962 1963 1964 1965
##      0      1      1      1      1      1      1      1      1      1      1      1      1      1      1
## 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980
##      1      1      1      0      0      1      1      1      1      0      1      1      1      0      1
## 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995
##      1      1      1      1      1      1      1      1      0      1      0      0      1      1      1
## 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010
##      1      1      0      1      1      1      1      1      1      0      0      1      1      0      1
## 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024 2025
##      1      1      1      0      0      1      1      1      1      1      0      1      1      1      0
## 2026 2027 2028 2029 2030 2031 2032 2033 2034 2035 2036 2037 2038 2039 2040
##      1      1      1      1      1      1      1      1      1      0      0      1      1      1      1
## 2041 2042 2043 2044 2045 2046 2047 2048 2049 2050 2051 2052 2053 2054 2055
##      1      1      0      1      1      1      1      0      0      1      1      0      1      1      0
## 2056 2057 2058 2059 2060 2061 2062 2063 2064 2065 2066 2067 2068 2069 2070
##      1      1      1      1      1      1      0      1      0      1      1      0      0      0      1
## 2071 2072 2073 2074 2075 2076 2077 2078 2079 2080 2081 2082 2083 2084 2085
##      1      1      1      1      1      1      1      1      1      0      1      1      0      0      1
## 2086 2087 2088 2089 2090 2091 2092 2093 2094 2095 2096 2097 2098 2099 2100
##      1      1      1      1      1      1      1      0      1      1      0      0      1      1      1
## 2101 2102 2103 2104 2105 2106 2107 2108 2109 2110 2111 2112 2113 2114 2115
##      0      0      1      1      1      1      1      1      0      1      0      1      1      1      1
## 2116 2117 2118 2119 2120 2121
##      1      1      1      1      1      0
```

5.2.11 ConfusionMatrix and Training Model Evaluation

```
ConfusionMatrix(ypredlog, BalancedData$Churn)
```

```
##      y_pred
## y_true  0   1
##      0 802 260
##      1 308 751
```

5.2.12 Accuracy of Train, Precision , Recall, Sensitivity and F score

```
accuracy.meas(ypredlog,BalancedData$Churn)
```

```
##
## Call:
## accuracy.meas(response = ypredlog, predicted = BalancedData$Churn)
##
## Examples are labelled as positive when predicted is greater than 0.5
##
## precision: 0.477
## recall: 1.000
## F: 0.323
```

```
Accuracy(ypredlog,BalancedData$Churn)
```

```
## [1] 0.7322018
```

```
Sensitivity(BalancedData$Churn, ypredlog)
```

```
## [1] 0.7551789
```

```
Specificity(BalancedData$Churn,ypredlog)
```

```
## [1] 0.7091596
```

```
AUC(y_pred = ypredlog,y_true = BalancedData$Churn)
```

```
## [1] 0.7321692
```

5.2.13 Model Evaluation Table

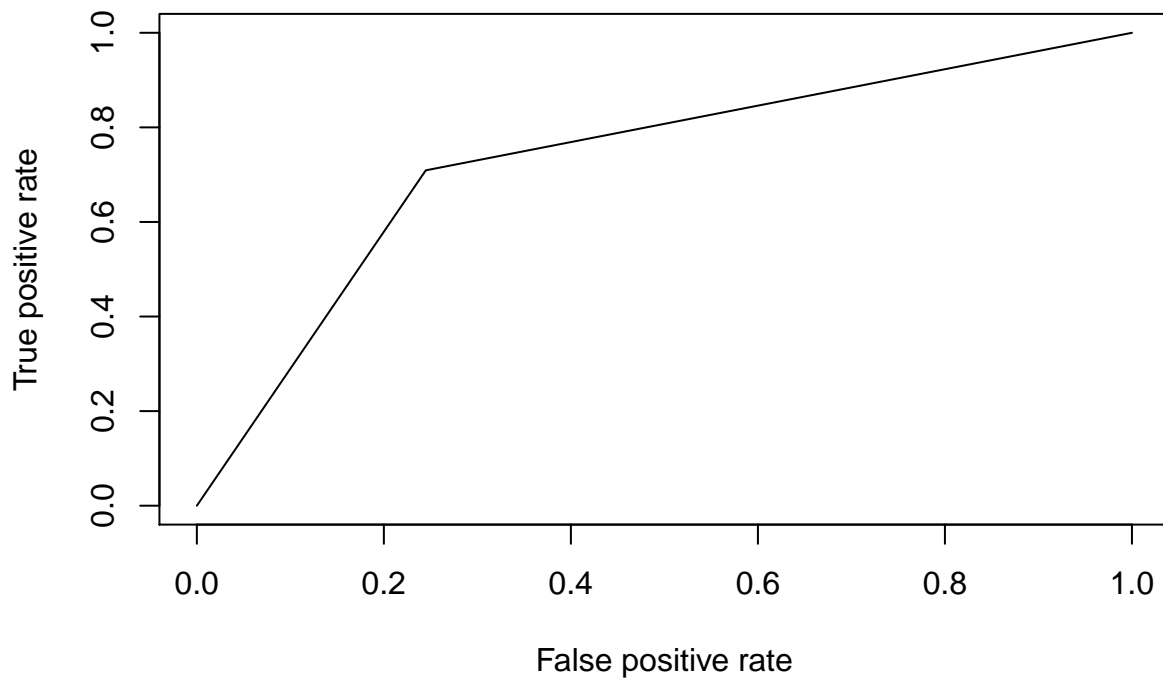
Accuracy	0.7322018
Sensitivity	0.7551789
Specificity	0.7091596
F Score	0.323
AUC	0.7321692

5.2.14 ROC Curve Plot

```
rocrpred2=prediction(ypredlog,BalancedData$Churn)  
as.numeric(performance(rocrpred2,"auc")@y.values)
```

```
## [1] 0.7321692
```

```
pref2=performance(rocrpred2,"tpr","fpr")  
plot(pref2)
```



5.2.15 Predicting Test Data

```
logpredtest <- predict(lregmodel, churn.test[-1], type = "response")
```

5.2.16 Covertng Probabilites to 0 and 1

```
logpredtestprob <- ifelse(logpredtest > 0.5, 1, 0)
logpredtestprob
```

```
##      3      4      9     11     14     15     20     22     25     26     31     33     36     37     42
##      0      1      1      1      1      1      0      0      0      1      0      0      1      0      1
##     44     47     48     53     55     58     59     64     66     69     70     75     77     80     81
##      0      1      0      1      1      0      1      0      0      0      1      0      1      0      1
##     86     88     91     92     97     99    102    103    108    110    113    114    119    121    124
##      0      0      0      0      0      0      0      0      0      1      1      0      0      1      0
##    125    130    132    135    136    141    143    146    147    152    154    157    158    163    165
##      0      0      0      0      1      0      0      1      0      0      0      1      0      0      0
##    168    169    174    176    179    180    185    187    190    191    196    198    201    202    207
##      0      0      0      1      1      1      1      0      0      0      0      1      0      1      0
##    209    212    213    218    220    223    224    229    231    234    235    240    242    245    246
##      1      1      0      0      0      0      0      1      1      0      1      0      1      0      0
##    251    253    256    257    262    264    267    268    273    275    278    279    284    286    289
##      0      1      1      0      0      0      0      0      0      0      0      0      0      0      0
##    290    295    297    300    301    306    308    311    312    317    319    322    323    328    330
##      1      0      0      0      0      1      1      1      0      0      0      0      0      0      0
##    333    334    339    341    344    345    350    352    355    356    361    363    366    367    372
##      1      0      1      0      0      0      0      1      1      0      1      0      1      1      1
##    374    377    378    383    385    388    389    394    396    399    400    405    407    410    411
##      1      0      0      1      0      0      0      1      0      0      0      1      0      0      0
##    416    418    421    422    427    429    432    433    438    440    443    444    449    451    454
##      1      0      0      1      0      1      0      0      0      0      0      1      0      0      0
##    455    460    462    465    466    471    473    476    477    482    484    487    488    493    495
##      1      0      1      0      1      0      0      0      1      0      0      1      0      1      0
##    498    499    504    506    509    510    515    517    520    521    526    528    531    532    537
##      1      1      1      0      0      1      1      0      1      0      0      0      0      0      0
##    539    542    543    548    550    553    554    559    561    564    565    570    572    575    576
##      0      0      1      1      1      1      1      0      0      0      0      1      0      1      0
##    581    583    586    587    592    594    597    598    603    605    608    609    614    616    619
##      1      0      0      1      0      0      0      0      0      0      0      0      1      0      0
##    620    625    627    630    631    636    638    641    642    647    649    652    653    658    660
##      1      0      1      1      0      0      0      0      0      0      0      0      0      0      0
##    663    664    669    671    674    675    680    682    685    686    691    693    696    697    702
##      0      0      0      0      1      0      1      0      0      0      1      1      0      0      0
##    704    707    708    713    715    718    719    724    726    729    730    735    737    740    741
##      0      0      0      0      0      0      0      1      0      1      0      1      1      0      0
##    746    748    751    752    757    759    762    763    768    770    773    774    779    781    784
##      0      0      0      0      1      0      1      1      0      0      0      1      1      1      1
##    785    790    792    795    796    801    803    806    807    812    814    817    818    823    825
##      0      0      1      1      0      0      0      0      0      0      0      0      0      0      0
##    828    829    834    836    839    840    845    847    850    851    856    858    861    862    867
##      0      0      0      0      0      0      0      0      1      0      1      0      0      0      0
##    869    872    873    878    880    883    884    889    891    894    895    900    902    905    906
##      0      1      0      1      1      0      0      0      0      1      1      0      1      1      1
##    911    913    916    917    922    924    927    928    933    935    938    939    944    946    949
```

##	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
##	950	955	957	960	961	966	968	971	972	977	979	982	983	988	990
##	1	0	0	0	1	0	0	0	1	0	1	0	0	1	1
##	993	994	999	1001	1004	1005	1010	1012	1015	1016	1021	1023	1026	1027	1032
##	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0
##	1034	1037	1038	1043	1045	1048	1049	1054	1056	1059	1060	1065	1067	1070	1071
##	1	0	1	0	1	0	0	0	0	0	0	1	0	0	0
##	1076	1078	1081	1082	1087	1089	1092	1093	1098	1100	1103	1104	1109	1111	1114
##	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1
##	1115	1120	1122	1125	1126	1131	1133	1136	1137	1142	1144	1147	1148	1153	1155
##	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0
##	1158	1159	1164	1166	1169	1170	1175	1177	1180	1181	1186	1188	1191	1192	1197
##	0	1	0	1	0	1	0	1	0	0	1	0	0	1	0
##	1199	1202	1203	1208	1210	1213	1214	1219	1221	1224	1225	1230	1232	1235	1236
##	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
##	1241	1243	1246	1247	1252	1254	1257	1258	1263	1265	1268	1269	1274	1276	1279
##	0	1	0	1	0	1	0	0	1	0	0	0	1	0	0
##	1280	1285	1287	1290	1291	1296	1298	1301	1302	1307	1309	1312	1313	1318	1320
##	0	1	0	0	0	0	0	1	0	1	0	0	0	0	1
##	1323	1324	1329	1331	1334	1335	1340	1342	1345	1346	1351	1353	1356	1357	1362
##	1	0	0	0	0	1	1	0	0	0	1	0	1	0	0
##	1364	1367	1368	1373	1375	1378	1379	1384	1386	1389	1390	1395	1397	1400	1401
##	0	0	1	0	0	0	1	0	0	1	0	1	1	1	0
##	1406	1408	1411	1412	1417	1419	1422	1423	1428	1430	1433	1434	1439	1441	1444
##	0	1	0	0	1	1	0	0	1	0	0	0	1	0	1
##	1445	1450	1452	1455	1456	1461	1463	1466	1467	1472	1474	1477	1478	1483	1485
##	1	1	0	0	0	1	1	0	0	0	1	0	0	1	1
##	1488	1489	1494	1496	1499	1500	1505	1507	1510	1511	1516	1518	1521	1522	1527
##	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0
##	1529	1532	1533	1538	1540	1543	1544	1549	1551	1554	1555	1560	1562	1565	1566
##	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0
##	1571	1573	1576	1577	1582	1584	1587	1588	1593	1595	1598	1599	1604	1606	1609
##	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
##	1610	1615	1617	1620	1621	1626	1628	1631	1632	1637	1639	1642	1643	1648	1650
##	0	1	0	0	0	0	0	1	0	0	1	1	0	0	0
##	1653	1654	1659	1661	1664	1665	1670	1672	1675	1676	1681	1683	1686	1687	1692
##	0	1	0	1	0	0	0	1	1	0	0	0	0	0	1
##	1694	1697	1698	1703	1705	1708	1709	1714	1716	1719	1720	1725	1727	1730	1731
##	0	0	0	1	1	1	1	1	0	1	1	0	0	0	0
##	1736	1738	1741	1742	1747	1749	1752	1753	1758	1760	1763	1764	1769	1771	1774
##	0	0	0	1	0	0	0	1	1	0	0	0	1	0	1
##	1775	1780	1782	1785	1786	1791	1793	1796	1797	1802	1804	1807	1808	1813	1815
##	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0
##	1818	1819	1824	1826	1829	1830	1835	1837	1840	1841	1846	1848	1851	1852	1857
##	0	1	0	1	0	0	0	0	0	0	1	0	0	1	0
##	1859	1862	1863	1868	1870	1873	1874	1879	1881	1884	1885	1890	1892	1895	1896
##	0	0	1	1	1	1	0	1	1	0	1	0	0	0	0
##	1901	1903	1906	1907	1912	1914	1917	1918	1923	1925	1928	1929	1934	1936	1939
##	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0
##	1940	1945	1947	1950	1951	1956	1958	1961	1962	1967	1969	1972	1973	1978	1980
##	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
##	1983	1984	1989	1991	1994	1995	2000	2002	2005	2006	2011	2013	2016	2017	2022
##	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0
##	2024	2027	2028	2033	2035	2038	2039	2044	2046	2049	2050	2055	2057	2060	2061

##	0	0	1	0	0	0	1	0	1	0	0	0	1	1	0
##	2066	2068	2071	2072	2077	2079	2082	2083	2088	2090	2093	2094	2099	2101	2104
##	0	1	0	1	1	0	0	0	1	0	0	0	0	0	1
##	2105	2110	2112	2115	2116	2121	2123	2126	2127	2132	2134	2137	2138	2143	2145
##	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0
##	2148	2149	2154	2156	2159	2160	2165	2167	2170	2171	2176	2178	2181	2182	2187
##	1	0	0	1	1	0	1	1	0	0	0	0	0	0	1
##	2189	2192	2193	2198	2200	2203	2204	2209	2211	2214	2215	2220	2222	2225	2226
##	0	0	0	0	1	1	1	0	0	1	1	0	0	0	0
##	2231	2233	2236	2237	2242	2244	2247	2248	2253	2255	2258	2259	2264	2266	2269
##	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0
##	2270	2275	2277	2280	2281	2286	2288	2291	2292	2297	2299	2302	2303	2308	2310
##	0	1	0	0	0	0	1	1	0	0	0	0	0	1	1
##	2313	2314	2319	2321	2324	2325	2330	2332	2335	2336	2341	2343	2346	2347	2352
##	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0
##	2354	2357	2358	2363	2365	2368	2369	2374	2376	2379	2380	2385	2387	2390	2391
##	1	1	0	1	0	1	0	0	0	1	0	1	1	0	0
##	2396	2398	2401	2402	2407	2409	2412	2413	2418	2420	2423	2424	2429	2431	2434
##	1	1	1	1	0	0	0	1	0	1	0	0	1	0	1
##	2435	2440	2442	2445	2446	2451	2453	2456	2457	2462	2464	2467	2468	2473	2475
##	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0
##	2478	2479	2484	2486	2489	2490	2495	2497	2500	2501	2506	2508	2511	2512	2517
##	0	0	0	0	0	1	0	0	1	0	1	0	1	0	0
##	2519	2522	2523	2528	2530	2533	2534	2539	2541	2544	2545	2550	2552	2555	2556
##	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0
##	2561	2563	2566	2567	2572	2574	2577	2578	2583	2585	2588	2589	2594	2596	2599
##	0	0	0	0	0	1	0	0	0	1	1	0	0	1	0
##	2600	2605	2607	2610	2611	2616	2618	2621	2622	2627	2629	2632	2633	2638	2640
##	0	1	1	0	0	0	0	0	0	0	1	0	0	1	0
##	2643	2644	2649	2651	2654	2655	2660	2662	2665	2666	2671	2673	2676	2677	2682
##	1	0	0	0	0	0	0	0	1	1	0	1	0	0	0
##	2684	2687	2688	2693	2695	2698	2699	2704	2706	2709	2710	2715	2717	2720	2721
##	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0
##	2726	2728	2731	2732	2737	2739	2742	2743	2748	2750	2753	2754	2759	2761	2764
##	0	1	0	0	0	0	1	0	0	1	0	0	0	1	0
##	2765	2770	2772	2775	2776	2781	2783	2786	2787	2792	2794	2797	2798	2803	2805
##	1	0	0	1	0	1	1	1	1	0	1	0	0	0	0
##	2808	2809	2814	2816	2819	2820	2825	2827	2830	2831	2836	2838	2841	2842	2847
##	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0
##	2849	2852	2853	2858	2860	2863	2864	2869	2871	2874	2875	2880	2882	2885	2886
##	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0
##	2891	2893	2896	2897	2902	2904	2907	2908	2913	2915	2918	2919	2924	2926	2929
##	0	0	1	1	0	1	0	0	0	1	0	1	0	0	0
##	2930	2935	2937	2940	2941	2946	2948	2951	2952	2957	2959	2962	2963	2968	2970
##	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0
##	2973	2974	2979	2981	2984	2985	2990	2992	2995	2996	3001	3003	3006	3007	3012
##	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0
##	3014	3017	3018	3023	3025	3028	3029	3034	3036	3039	3040	3045	3047	3050	3051
##	0	0	1	0	0	1	0	0	1	0	0	0	0	0	1
##	3056	3058	3061	3062	3067	3069	3072	3073	3078	3080	3083	3084	3089	3091	3094
##	0	0	1	1	1	0	0	0	0	1	1	0	0	0	1
##	3095	3100	3102	3105	3106	3111	3113	3116	3117	3122	3124	3127	3128	3133	3135
##	0	0	0	0	0	0	1	1	0	0	0	0	1	1	0
##	3138	3139	3144	3146	3149	3150	3155	3157	3160	3161	3166	3168	3171	3172	3177

```
##      0      0      0      1      1      0      0      0      0      0      0      0      0      0      0
## 3179 3182 3183 3188 3190 3193 3194 3199 3201 3204 3205 3210 3212 3215 3216
##      0      1      1      0      1      0      0      0      1      0      1      1      0      1      0
## 3221 3223 3226 3227 3232 3234 3237 3238 3243 3245 3248 3249 3254 3256 3259
##      0      1      1      1      0      0      0      1      0      0      0      0      0      1      1
## 3260 3265 3267 3270 3271 3276 3278 3281 3282 3287 3289 3292 3293 3298 3300
##      0      0      0      1      0      0      0      1      0      0      0      1      0      0      0
## 3303 3304 3309 3311 3314 3315 3320 3322 3325 3326 3331 3333
##      1      0      0      0      0      0      1      0      0      0      1      0
```

5.2.17 ConfusionMatrix and Test Data Model Evaluation

```
ConfusionMatrix(logpredtestprob, churn.test$Churn)
```

```
##      y_pred
## y_true   0   1
##      0 801 219
##      1  51 141
```

5.2.18 Accuracy of Train, Precision , Recall, Sensitivity and F score

```
accuracy.meas(logpredtestprob, churn.test$Churn)
```

```
##
## Call:
## accuracy.meas(response = logpredtestprob, predicted = churn.test$Churn)
##
## Examples are labelled as positive when predicted is greater than 0.5
##
## precision: 0.297
## recall: 1.000
## F: 0.229
```

```
Accuracy(logpredtestprob, churn.test$Churn)
```

```
## [1] 0.7772277
```

```
Sensitivity(churn.test$Churn, logpredtestprob)
```

```
## [1] 0.7852941
```

```
Specificity(churn.test$Churn, logpredtestprob)
```

```
## [1] 0.734375
```

```
AUC(y_pred = logpredtestprob, y_true = churn.test$Churn)
```

```
## [1] 0.7598346
```

5.2.19 Model Evaluation Table

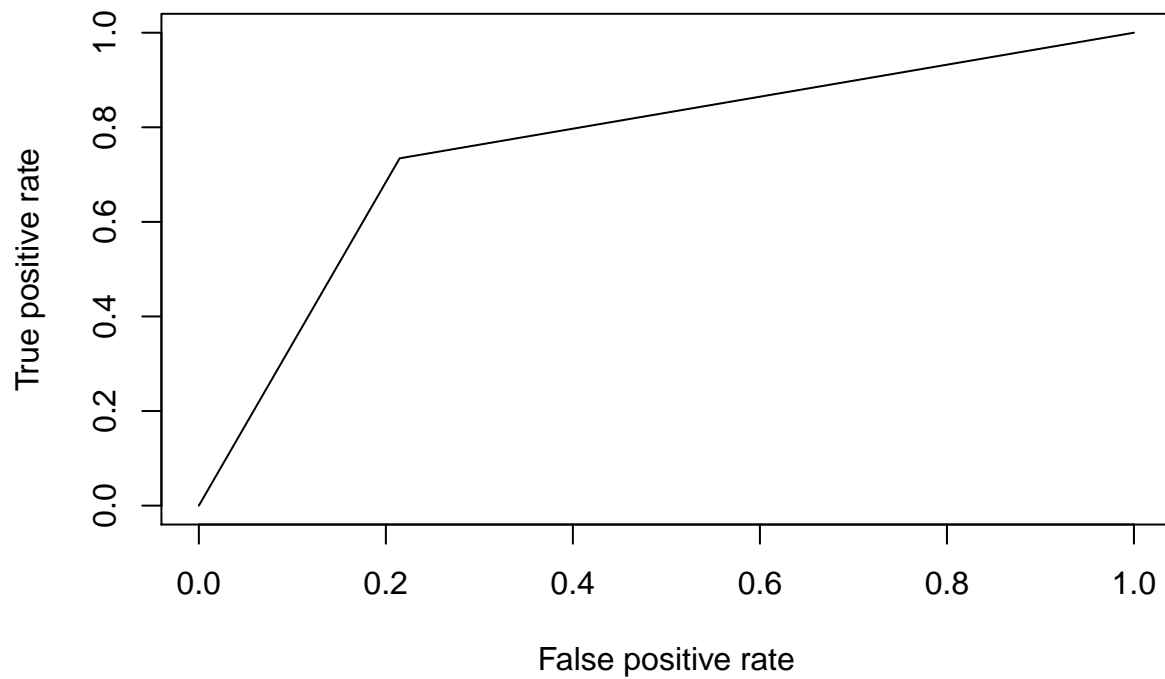
Accuracy	0.7772277
Sensitivity	0.7852941
Specificity	0.734375
F Score	0.229
AUC	0.7598346

5.2.20 ROC Curve Plot

```
rocrpred=prediction(logpredtestprob,churn.test$Churn)
as.numeric(performance(rocrpred,"auc")@y.values)
```

```
## [1] 0.7598346
```

```
pref=performance(rocrpred,"tpr","fpr")
plot(pref)
```



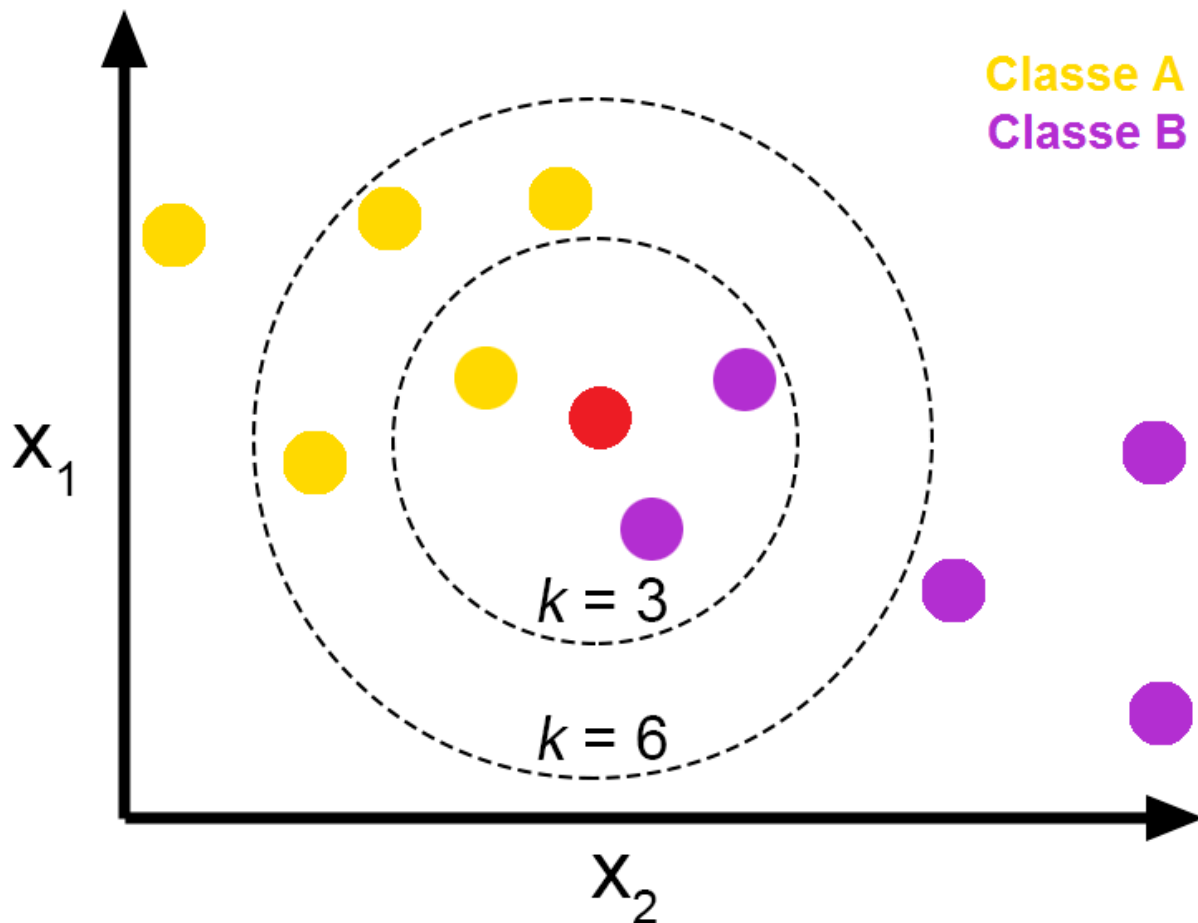


Figure 3: KNN

5.3 KNN

5.3.1 What is KNN

KNN (K — Nearest Neighbors) is one of many (supervised learning) algorithms used in data mining and machine learning, it's a classifier algorithm where the learning is based “how similar” is a data (a vector) from other .

5.3.2 Fitting KNN to the Training set and Predicting the Test set results

```
ypredKNN <- knn(train = BalancedData[,-1],
               test = churn.test[,-1],
               cl= BalancedData[,1],
               k=5
              )
```

ypredKNN

```
##      [1] 1 1 0 0 0 0 0 1 1 0 0 0 1 1 0 0 1 0 0 1 1 0 0 0 1 1 0 0 0 1 1 0 1 0 1 0
##     [35] 1 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 1 1 0 1 0 0 1 0 1 0 0 0 0
##     [69] 1 1 0 1 1 1 1 1 0 0 1 0 1 0 1 1 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0
##    [103] 0 1 0 0 0 0 0 1 1 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 1 0
```

```

## [137] 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 1 0 0 1 1 0 1 1 0 1 0 1 0 0 1 0
## [171] 1 1 1 1 0 0 0 0 0 1 0 1 1 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 1 1 0 0
## [205] 0 1 1 0 0 1 1 0 1 0 0 1 1 0 0 0 1 0 0 1 0 1 0 0 1 0 0 1 0 0 0 0 1 0
## [239] 0 1 0 0 1 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 1 1 0 1 0 0
## [273] 0 0 0 0 0 0 1 0 0 0 0 1 1 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0
## [307] 1 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 1 1 1 0 0 0 1 1 1 0 0 0 0 1
## [341] 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 1 0
## [375] 0 0 0 0 1 0 0 1 0 0 1 0 0 1 0 1 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 0 1
## [409] 1 0 1 0 0 0 0 1 0 1 0 1 0 1 0 1 0 1 0 0 1 0 1 0 1 0 1 1 0 0 0 0 0 0
## [443] 0 0 0 0 0 1 0 1 1 1 1 0 0 1 0 0 0 0 0 0 1 1 0 0 1 0 0 1 1 1 0 0 0 0
## [477] 1 1 0 0 0 0 0 0 1 1 0 0 1 1 1 0 1 0 0 0 1 0 0 0 0 0 1 1 0 1 1 0 0 0
## [511] 1 0 0 0 0 0 1 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1
## [545] 0 0 0 1 0 1 0 0 1 0 0 0 1 1 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0
## [579] 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 1 1 0 1 0 1 1 1 0 0 1
## [613] 0 0 1 0 0 0 0 1 0 1 0 1 0 0 1 0 1 1 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0
## [647] 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 1 1 1 0 0 0 1 0 0 0 1 0 1 0 1
## [681] 0 1 1 0 1 1 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 1 0 1 0 0 0
## [715] 0 1 0 0 1 0 1 0 0 0 0 0 1 1 0 0 0 0 1 0 1 1 0 1 1 0 1 1 0 0 0 0 1 0
## [749] 1 1 0 0 1 0 0 0 0 1 0 0 0 1 0 1 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 1 0
## [783] 0 1 1 0 0 0 1 0 1 0 0 0 1 1 1 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 1
## [817] 0 0 1 0 1 1 1 1 1 0 1 1 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 1 1 0 0 0
## [851] 0 1 1 0 0 1 1 0 0 1 1 1 0 1 0 0 0 0 0 0 1 1 1 1 0 0 1 1 0 1 0 1 0 0
## [885] 1 1 1 1 0 0 1 0 1 0 0 0 0 0 1 1 1 1 1 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0
## [919] 1 1 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 1 1 0 1 0 1 0 0
## [953] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 1 0 0 0 1 0 0 0 0 1 0 0 1 0 0 1 1 1 0
## [987] 0 1 0 0 1 0 0 1 1 0 1 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1 0 1 1 0 1 1
## [1021] 0 0 0 0 0 1 1 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 1 0 0 1
## [1055] 0 1 0 0 0 1 0 1 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0
## [1089] 1 1 0 1 0 0 0 1 0 1 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 1 0 1 0 1
## [1123] 1 1 0 1 0 1 0 1 1 0 0 0 0 1 1 1 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
## [1157] 1 0 1 0 0 1 1 1 0 0 1 1 0 0 0 0 1 1 0 0 1 0 0 0 0 0 0 0 1 1 0 0 0 0
## [1191] 0 1 0 0 0 0 0 0 1 1 1 0 0 0 1 0 1 1 0 0 0 0
## Levels: 0 1

```

5.3.3 Confusion Matrix

```
ConfusionMatrix(ypredKNN, churn.test$Churn)
```

```

##      y_pred
## y_true  0   1
##      0 712 308
##      1 100  92

```

```
Accuracy(ypredKNN, churn.test$Churn)
```

```
## [1] 0.6633663
```

5.3.4 Trying Different K value

```

ypredKNN2 <- knn(train = BalancedData[, -1],
                 test = churn.test[, -1],
                 cl= BalancedData[, 1],
                 k=3
                )

```

```
ConfusionMatrix(ypredKNN2, churn.test$Churn)
```

```
##      y_pred
## y_true  0   1
##      0 677 343
##      1 100  92
```

```
Accuracy(ypredKNN2, churn.test$Churn)
```

```
## [1] 0.6344884
```

5.3.5 Try k 9

```
ypredKNN3 <- knn(train = BalancedData[,-1],
                 test = churn.test[,-1],
                 cl= BalancedData[,1],
                 k=9
                )
```

```
ConfusionMatrix(ypredKNN3, churn.test$Churn)
```

```
##      y_pred
## y_true  0   1
##      0 754 266
##      1 103  89
```

```
Accuracy(ypredKNN3, churn.test$Churn)
```

```
## [1] 0.6955446
```

5.3.6 Try K 15

```
ypredKNN4 <- knn(train = BalancedData[,-1],
                 test = churn.test[,-1],
                 cl= BalancedData[,1],
                 k=15
                )
```

```
ConfusionMatrix(ypredKNN4, churn.test$Churn)
```

```
##      y_pred
## y_true  0   1
##      0 789 231
##      1 110  82
```

```
Accuracy(ypredKNN4, churn.test$Churn)
```

```
## [1] 0.7186469
```

5.3.7 Try K 25

```
ypredKNN5 <- knn(train = BalancedData[,-1],
                 test = churn.test[,-1],
                 cl= BalancedData[,1],
                 k=25
                )
```

```
ConfusionMatrix(ypredKNN5, churn.test$Churn)
```

```
##          y_pred
## y_true    0    1
##          0 815 205
##          1 110  82
```

```
Accuracy(ypredKNN5, churn.test$Churn)
```

```
## [1] 0.740099
```

5.3.8 Try K 35

```
ypredKNN6 <- knn(train = BalancedData[,-1],
                 test = churn.test[,-1],
                 cl= BalancedData[,1],
                 k=35
                )
```

```
ConfusionMatrix(ypredKNN6, churn.test$Churn)
```

```
##          y_pred
## y_true    0    1
##          0 827 193
##          1 109  83
```

```
Accuracy(ypredKNN6, churn.test$Churn)
```

```
## [1] 0.7508251
```

```
Sensitivity(churn.test$Churn, ypredKNN6)
```

```
## [1] 0.8107843
```

```
Specificity(churn.test$Churn, ypredKNN6)
```

```
## [1] 0.4322917
```

```
accuracy.meas(ypredKNN6, churn.test$Churn)
```

```
##
## Call:
## accuracy.meas(response = ypredKNN6, predicted = churn.test$Churn)
##
## Examples are labelled as positive when predicted is greater than 0.5
##
## precision: 0.228
## recall: 1.000
## F: 0.185
```

```
KNNAUC<- AUC(ypredKNN6, churn.test$Churn)
```

```
KNNAUC
```

```
## [1] 0.621538
```

5.3.9 Model Evaluation Table

Accuracy	0.7508251
Sensitivity	0.8107843
Specificity	0.4322917
F Score	0.185
AUC	0.621538

Naive Bayes



In machine learning, naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naive) independence assumptions between the features.

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

using Bayesian probability terminology, the above equation can be written as

$$\text{Posterior} = \frac{\text{prior} \times \text{likelihood}}{\text{evidence}}$$

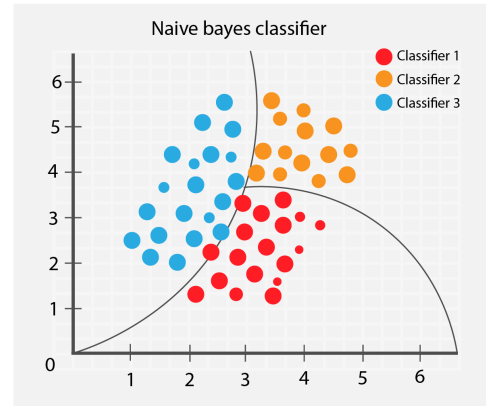


Figure 4: Naive Bayes

5.4 Naive Bayes

5.4.1 What is Naive Bayes

In machine learning, naive Bayes classifiers are a family of simple “probabilistic classifiers” based on applying Bayes’ theorem with strong (naive) independence assumptions between the features.

5.4.2 Naive Bayes. Is it applicable here?

YES it is applicable. Naive Bayes is a **probabilistic classifiers**. Here we’ll use it to predict probability if Customer Cancelled(Churn) or Not Cancelled the service.

5.4.3 Fitting Naive Bayes to training set

```
classnaive <- naiveBayes(x=BalancedData[-1],
                        y=BalancedData$Churn)
```

5.4.4 Predicting Naive Bayes Test Dataset

```
ypredNB<- predict(classnaive,newdata = churn.test[-1])
ypredNB
```

```
##      [1] 0 1 0 1 0 1 0 1 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0
##      [35] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 1 1 0
##      [69] 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##     [103] 0 0 0 1 0 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 1 0 1 0 1 1 0 0
##     [137] 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 1
##     [171] 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 1 0 0
##     [205] 0 0 1 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 1 0 1 0 0 0 0 0 0
##     [239] 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 1 0 0 0 0
##     [273] 0 0 0 0 0 1 0 0 0 1 1 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
##     [307] 0 0 0 0 1 0 0 0 0 0 1 0 1 1 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0
```

```
## [341] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0
## [375] 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 1 1
## [409] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 1 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0
## [443] 0 0 0 0 0 1 0 1 0 1 0 1 0 1 0 0 1 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0
## [477] 0 0 0 1 1 0 0 0 0 0 1 1 0 1 1 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 1 1 0
## [511] 0 1 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0
## [545] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [579] 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 1 1 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0
## [613] 0 0 1 0 0 0 1 1 1 0 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 0
## [647] 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 1 0 0 1 0 1 0 1
## [681] 1 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
## [715] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0
## [749] 1 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0
## [783] 0 1 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 1 0 0 0 0 0 0 1 0 0 1 0 0
## [817] 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0 0 1
## [851] 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0 0 1 1 0 0 1 1 1 1 0 0 0 1 0 1 0 0 1 0
## [885] 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 1 0 0 1 0 0 0 0 0 0 0 0
## [919] 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 0 0 0 0
## [953] 0 0 0 1 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 1 1 0 0 0 0
## [987] 0 0 0 0 0 1 0 1 1 0 0 0 0 1 0 0 1 0 1 0 0 0 0 0 1 0 0 0 0 1 1 0 0 1 0 0 0
## [1021] 0 0 0 0 1 0 1 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 1 0 0
## [1055] 0 1 0 0 0 0 0 0 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 0 0 1 0 0 1 1
## [1089] 1 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 1 0 1 0 0
## [1123] 0 0 0 0 0 0 0 0 0 0 1 1 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
## [1157] 1 0 0 1 0 0 0 1 0 0 1 0 1 0 0 0 1 0 1 0 0 0 0 1 0 0 0 1 0 0 1 1 0 0 0 1 0
## [1191] 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 1 0
## Levels: 0 1
```

5.4.5 ConfusionMatrix

```
ConfusionMatrix(ypredNB, churn.test$Churn)
```

```
##      y_pred
## y_true  0   1
##      0 886 134
##      1  44 148
```

```
Accuracy(ypredNB, churn.test$Churn)
```

```
## [1] 0.8531353
```

```
Sensitivity(churn.test$Churn, ypredNB)
```

```
## [1] 0.8686275
```

```
Specificity(churn.test$Churn, ypredNB)
```

```
## [1] 0.7708333
```

```
accuracy.meas(ypredNB, churn.test$Churn)
```

```
##
## Call:
## accuracy.meas(response = ypredNB, predicted = churn.test$Churn)
##
## Examples are labelled as positive when predicted is greater than 0.5
##
```



```
## precision: 0.233  
## recall: 1.000  
## F: 0.189
```

```
NBAUC<- AUC(ypredNB, churn.test$Churn)
```

```
NBAUC
```

```
## [1] 0.8197304
```

5.4.6 Model Evaluation Table

Accuracy	0.8531353
Sensitivity	0.8686275
Specificity	0.7708333
F Score	0.189
AUC	0.8197304

5.5 Model Comparison using Model Performance metrics

	Logistic Regression	KNN	Naive Bayes
Accuracy	0.7772277	0.7508251	0.8531353
Sensitivity	0.7852941	0.8107843	0.8686275
Specificity	0.734375	0.4322917	0.7708333
F Score	0.229	0.185	0.189
AUC	0.7598346	0.621538	0.8197304

5.5.1 Interpretation

- From the above model Comparison we can see that **Naive Bayes** is performing the best.

5.5.2 Conclusion:

- We can see that all the models are performing similarly. However, Naive Bayes is performing the best. Naive Bayes is able to predict Customers who are going to cancel the service.
- ContractRenewal + CustServCalls + DayMins are the main factors which makes customer continue or cancel the service.

5.5.3 Recommendation:

- CustServCalls greatly contribute influence customer's decision to continue or cancel the service. It look like Customer Service has to be improved. There are many customers calling customer service 10 times. Company must invest in training resources and improve their customer service quality and reduce the number of customer service calls.