PREDICTIVE ANALYSIS USING STATISTICS

(UCS654)

Lab Assignment

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BE Third Year- COE

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March 2021

TELECOM CHURN ANALYSIS

Churn is a one of the biggest problems in the telecom industry. Research has shown that the average monthly churn rate among the top 4 wireless carriers in the US is 1.9% - 2%. So, for the analysis in this report I will be working with the telecom churn analysis from IBM dataset.

Initially we will need to pre-process our dataset for better testing results and the analysis, for pre-processing target will be to remove any null values if present in the dataset

PREPROCESSING AND ANALYSING DATA

churn <- read.csv("TelcoChurnData.csv")

glimpse(churn)

```
> glimpse(churn)
Rows: 7,043
Columns: 21
$ customerID       <chr> "7590-VHVEG", "5575-GNVDE", "3668-QPYBK", "7795-CFOCW", "9~
$ gender           <chr> "Female", "Male", "Male", "Male", "Female", "Female", "Mal~
$ SeniorCitizen    <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
$ Partner          <chr> "Yes", "No", "No", "No", "No", "No", "No", "No", "Yes", "N~
$ Dependents       <chr> "No", "No", "No", "No", "No", "No", "Yes", "No", "No", "Ye~
$ tenure           <int> 1, 34, 2, 45, 2, 8, 22, 10, 28, 62, 13, 16, 58, 49, 25, 69~
$ PhoneService     <chr> "No", "Yes", "Yes", "No", "Yes", "Yes", "Yes", "No", "Yes"~
$ MultipleLines    <chr> "No phone service", "No", "No", "No phone service", "No", ~
$ InternetService  <chr> "DSL", "DSL", "DSL", "DSL", "Fiber optic", "Fiber optic", ~
$ OnlineSecurity   <chr> "No", "Yes", "Yes", "Yes", "No", "No", "No", "Yes", "No", ~
$ OnlineBackup     <chr> "Yes", "No", "Yes", "No", "No", "No", "Yes", "No", "No", "~
$ DeviceProtection <chr> "No", "Yes", "No", "Yes", "No", "Yes", "No", "No", "Yes", ~
$ TechSupport      <chr> "No", "No", "No", "Yes", "No", "No", "No", "No", "Yes", "N~
$ StreamingTV      <chr> "No", "No", "No", "No", "No", "Yes", "Yes", "No", "Yes", "~
$ StreamingMovies  <chr> "No", "No", "No", "No", "No", "Yes", "No", "No", "Yes", "N~
$ Contract         <chr> "Month-to-month", "One year", "Month-to-month", "One year"~
$ PaperlessBilling <chr> "Yes", "No", "Yes", "No", "Yes", "Yes", "Yes", "No", "Yes"~
$ PaymentMethod    <chr> "Electronic check", "Mailed check", "Mailed check", "Bank ~
$ MonthlyCharges   <dbl> 29.85, 56.95, 53.85, 42.30, 70.70, 99.65, 89.10, 29.75, 10~
$ TotalCharges     <dbl> 29.85, 1889.50, 108.15, 1840.75, 151.65, 820.50, 1949.40, ~
$ Churn            <chr> "No", "No", "Yes", "No", "Yes", "Yes", "No", "No", "Yes", ~
```

- So, we obtained a summary of our dataset now our next target is to find out how many null values are in each of the columns

sapply(churn, function(x) sum(is.na(x)))

```
sapply(churn, function(x) sum(is.na(x)))
    customerID         gender  SeniorCitizen        Partner     Dependents 
             0              0              0              0              0 
        tenure   PhoneService  MultipleLines InternetService OnlineSecurity 
             0              0              0              0              0 
  OnlineBackup DeviceProtection   TechSupport    StreamingTV StreamingMovies 
             0              0              0              0              0 
      Contract PaperlessBilling  PaymentMethod MonthlyCharges   TotalCharges 
             0              0              0              0             11 
         Churn 
             0 
```

- So, we saw some of our data rows are having NULL values so next our aim would be to handle them. Firstly, we will see how much of the proportion of data is having this null values. We ran the following command in R.

sum(is.na(churn$TotalCharges))/nrow(churn)

```
> sum(is.na(churn$TotalCharges))/nrow(churn)
[1] 0.001561834
```

- So, as we can see it is small part of our dataset so we will remove them for them dataset for the further analysis on it

churn_clean <- churn[complete.cases(churn),]

- After having glimpse on the dataset, for making the analysis easier we will transform some of the value of the attributes in our dataset for further analysis. We will also drop the customer id column as we will not be using it in future

churn_clean$SeniorCitizen <- as.factor(mapvalues(churn_clean$SeniorCitizen,from=c("0","1"),to=c("No", "Yes")))

churn_clean$MultipleLines <- as.factor(mapvalues(churn_clean$MultipleLines, from=c("No phone service"), to=c("No")))

for(i in 10:15){

churn_clean[,i] <- as.factor(mapvalues(churn_clean[,i],from= c("No internet service"), to= c("No")))

}

churn_clean$customerID <- NULL

glimpse(churn_clean)

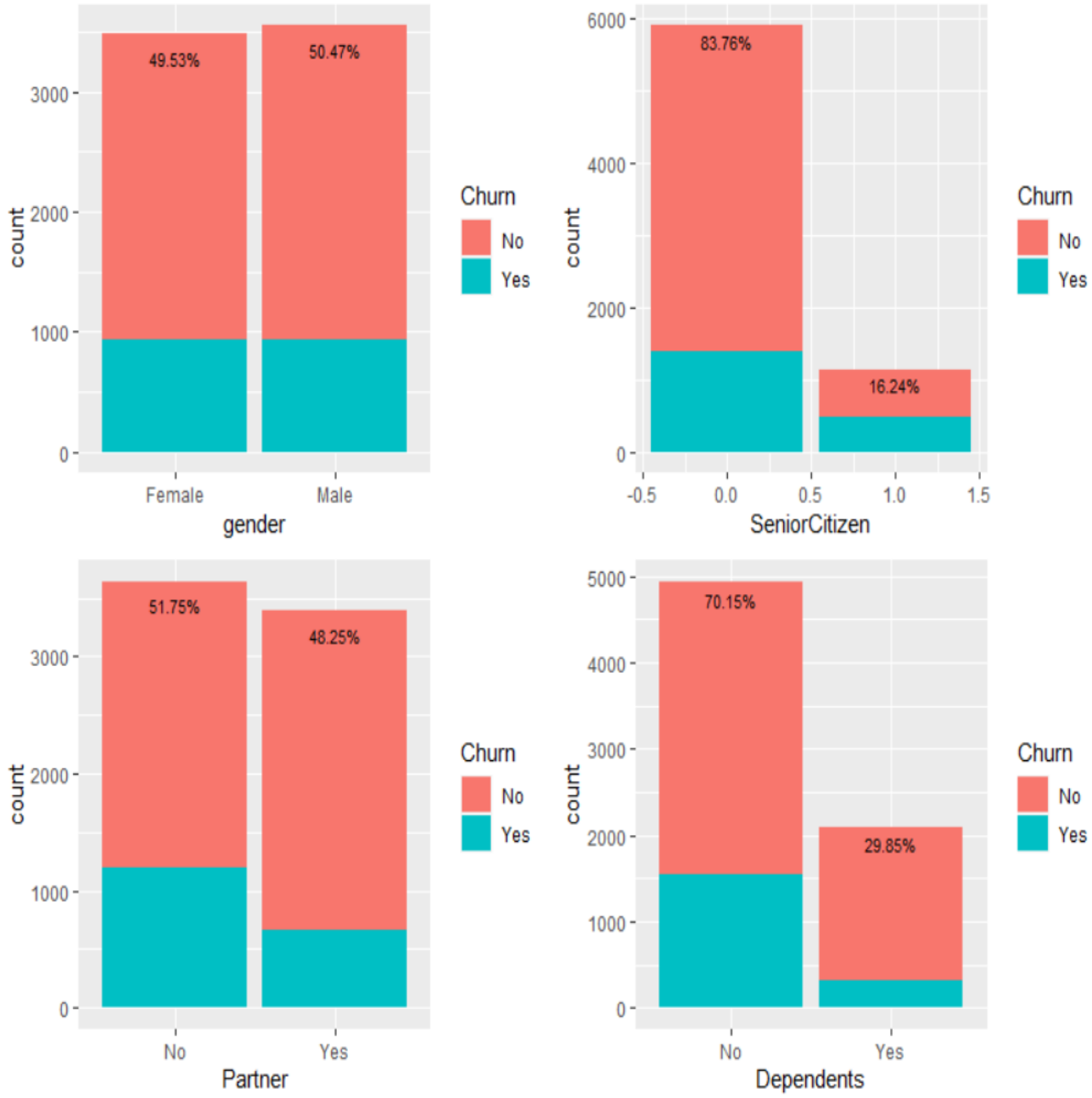
```
> glimpse(churn_clean)
Rows: 7,032
Columns: 20
$ gender           <chr> "Female", "Male", "Male", "Male", "Female", "Female", "~
$ SeniorCitizen    <fct> No, No, No, No, No, No, No, No, No, No, No, No, No, No,~
$ Partner          <chr> "Yes", "No", "No", "No", "No", "No", "No", "No", "Yes",~
$ Dependents       <chr> "No", "No", "No", "No", "No", "No", "Yes", "No", "No", ~
$ tenure           <int> 1, 34, 2, 45, 2, 8, 22, 10, 28, 62, 13, 16, 58, 49, 25,~
$ PhoneService     <chr> "No", "Yes", "Yes", "No", "Yes", "Yes", "Yes", "No", "Y~
$ MultipleLines    <fct> No, No, No, No, No, Yes, Yes, No, Yes, No, No, No, Yes,~
$ InternetService  <chr> "DSL", "DSL", "DSL", "DSL", "Fiber optic", "Fiber optic~
$ OnlineSecurity   <fct> No, Yes, Yes, Yes, No, No, No, Yes, No, Yes, Yes, No, N~
$ OnlineBackup     <fct> Yes, No, Yes, No, No, No, Yes, No, No, Yes, No, No, No,~
$ DeviceProtection <fct> No, Yes, No, Yes, No, Yes, No, No, Yes, No, No, No, Yes~
$ TechSupport      <fct> No, No, No, Yes, No, No, No, No, Yes, No, No, No, No, N~
$ StreamingTV      <fct> No, No, No, No, No, Yes, Yes, No, Yes, No, No, No, Yes,~
$ StreamingMovies  <fct> No, No, No, No, No, Yes, No, No, Yes, No, No, No, Yes, ~
$ Contract         <chr> "Month-to-month", "One year", "Month-to-month", "One ye~
$ PaperlessBilling <chr> "Yes", "No", "Yes", "No", "Yes", "Yes", "Yes", "No", "Y~
$ PaymentMethod    <chr> "Electronic check", "Mailed check", "Mailed check", "Ba~
$ MonthlyCharges   <dbl> 29.85, 56.95, 53.85, 42.30, 70.70, 99.65, 89.10, 29.75,~
$ TotalCharges     <dbl> 29.85, 1889.50, 108.15, 1840.75, 151.65, 820.50, 1949.4~
$ Churn            <chr> "No", "No", "Yes", "No", "Yes", "Yes", "No", "No", "Yes~
```

1. ANALYSING GENDER, SENIOR CITIZEN, PARTNER AND DEPENDENTS WITH CHURN

- So, finally we have cleaned our dataset now we will apply some of the statistical analysis techniques on the dataset to observe some of the patterns and draw some conclusions from it
- Firstly, we will look into some of bar charts for the gender, Senior Citizen, Partner and Dependents and see how our churn varies with these factors

```
#Gender plot
p1 <- ggplot(churn_clean, aes(x = gender)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)


#Senior citizen plot
p2 <- ggplot(churn_clean, aes(x = SeniorCitizen)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)


#Partner plot
p3 <- ggplot(churn_clean, aes(x = Partner)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count', position = position_dodge(.1), size = 3)
```

```
#Dependents plot
p4 <- ggplot(churn_clean, aes(x = Dependents)) +geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200, label = paste0(round(prop.table(..count..),4) * 100, '%')),
  stat = 'count',
   position = position_dodge(.1), size = 3)
#Plot demographic data within a grid
grid.arrange(p1, p2, p3, p4, ncol=2)
```



Now we will draw some conclusions from these bar plots of the following attributes in our dataset.

QUESTION 1

1. How many females are there who are Senior citizen?

```
> df2 <- filter(churn_clean,SeniorCitizen=="Yes" & gender=="Female")
> print(nrow(df2))
[1] 568
```

2. How many females are dependent and Senior Citizen?

```
> df2 <- filter(churn_clean,SeniorCitizen=="Yes" & gender=="Female" & Dependents=="Y
es")
> print(nrow(df2))
[1] 42
```

3. How many men are dependent and Senior Citizen?

```
> df2 <- filter(churn_clean,SeniorCitizen=="Yes" & gender=="Male" & Dependents=="Ye
s")
> print(nrow(df2))
[1] 49
```

4. How many are not Senior Citizen and Are dependents?

```
> df2 <- filter(churn_clean,SeniorCitizen=="No" & Dependents=="Yes")
> print(nrow(df2))
[1] 2008
```

5. How many of females have Partners?

```
> df2 <- filter(churn_clean,gender=="Female" & Partner=="Yes")
> print(nrow(df2))
[1] 1683
```

QUESTION 2

1. We now want to verify that whether the churn is dependent on the gender or not?

We will apply chi square test between the churn and gender attributes and if they are dependent then the p values at the X2 observed will be less than 0.05 which is our significance level.

Null hypothesis: Churn is independent of gender

Alternate Hypothesis: Churn is dependent on gender

```
> print(chisq.test(table(churn_clean$gender,churn_clean$Churn)))

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(churn_clean$gender, churn_clean$Churn)
X-squared = 0.47545, df = 1, p-value = 0.4905
```

We will accept our null hypothesis and hence Churn is independent of the gender.

2. We now want to verify that whether the Senior Citizen is a variable on which churn depends?

Null hypothesis: Churn is independent of Senior Citizen

Alternate Hypothesis: Churn is dependent on Senior Citizen

```
> print(chisq.test(table(churn_clean$SeniorCitizen,churn_clean$Churn)))

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(churn_clean$SeniorCitizen, churn_clean$Churn)
X-squared = 158.44, df = 1, p-value < 2.2e-16
```

As p is less than 0.05 so we will ACCEPT the ALTERNATE HYPOTHESIS and hence we can say that churn is dependent on the Senior Citizen attribute

3. Is chances of staying with the telecom company of people who are dependents greater than the chances of people who are not dependents.

Null Hypothesis: Chances of staying of not dependents = chances of staying of dependents

Alternate Hypothesis: Chances of staying of dependents > chances of staying of not dependents

```
d1 <- filter(churn_clean,Dependents=="Yes")

d2 <- filter(churn_clean,Dependents=="No")

d3 <- filter(d1,Churn=="No")

d4 <- filter(d2,Churn=="No")

prop.test(c(nrow(d3),nrow(d4)),c(nrow(d1),nrow(d2)),alternative=c("greater"))
```

```
        2-sample test for equality of proportions with continuity correction

data:  c(nrow(d3), nrow(d4)) out of c(nrow(d1), nrow(d2))
X-squared = 186.32, df = 1, p-value < 2.2e-16
alternative hypothesis: greater
95 percent confidence interval:
 0.1401989 1.0000000
sample estimates:
   prop 1    prop 2
0.8446879 0.6872086
```

ALTERNATE HYPOTHESIS is ACCEPTED. Hence, we can say that chances of staying of who are dependents is greater than chances of people who are not dependents staying with the telecom company as per the dataset analysis.

Summary of the above section

Most of the customers who are not senior citizens have a comparatively less chances of churn as compared to the ones who are senior citizen. People with a partner have a higher chance of not being churned by the telecom company service as per the bar chart.

2. ANALYSING COLUMNS OF SERVICES PROVIDED BY THE TELECOM COMPANY

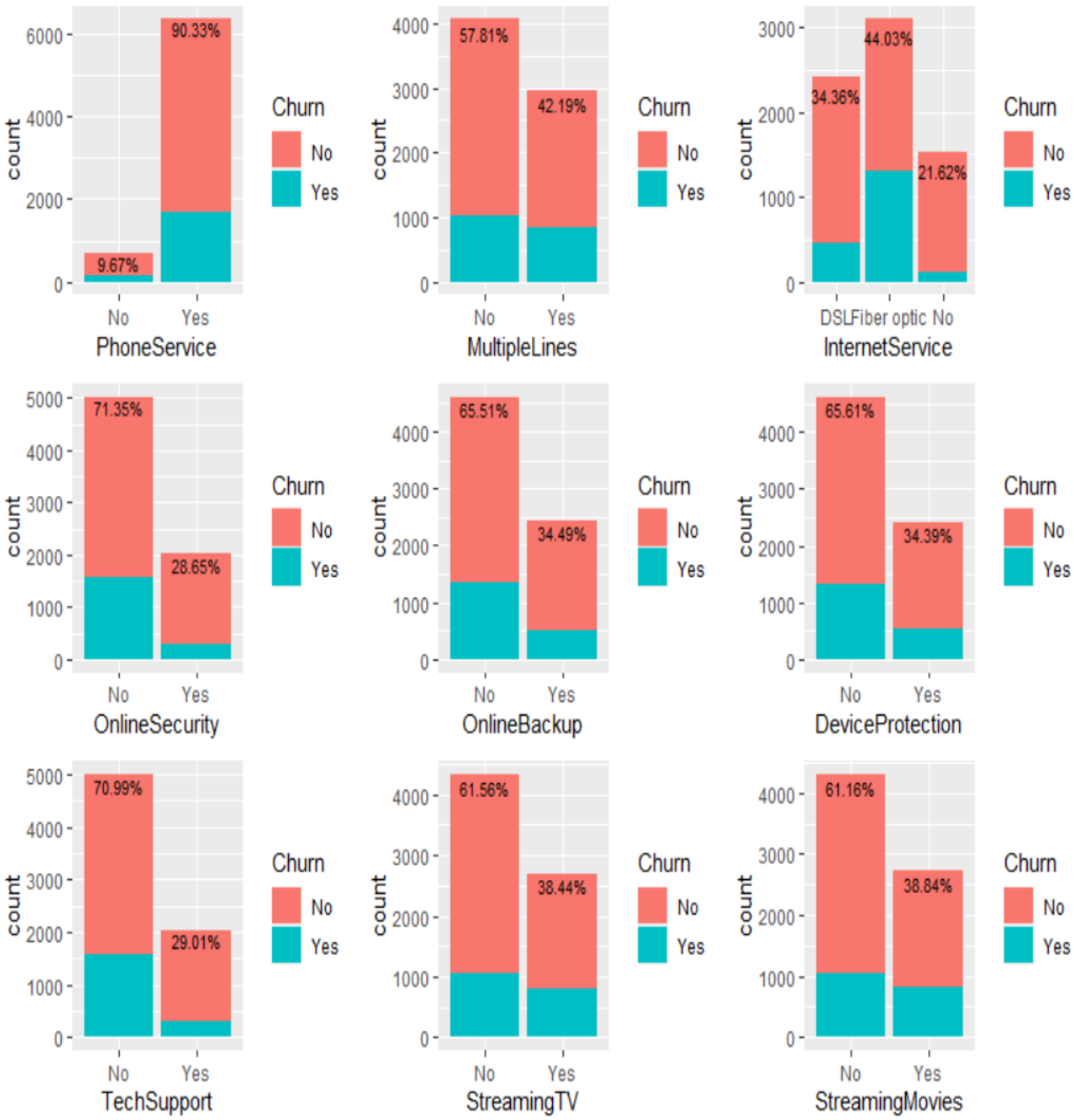
In this section will work on columns which include phone service, internet service, multiple Lines, Online security, Online backup, Device Protection, Tech support, Streaming Movies, Streaming TV.

Firstly, we will plot some charts in R to visualize these columns:

```
#Phone service plot
p5 <- ggplot(churn_clean, aes(x = PhoneService)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)

#Multiple phone lines plot
p6 <- ggplot(churn_clean, aes(x = MultipleLines)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)

#Internet service plot
p7 <- ggplot(churn_clean, aes(x = InternetService)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
```

```
        position = position_dodge(.1),
        size = 3)

#Online security service plot
p8 <- ggplot(churn_clean, aes(x = OnlineSecurity)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
            label = paste0(round(prop.table(..count..),4) * 100, '%')),
        stat = 'count',
        position = position_dodge(.1),
        size = 3)

#Online backup service plot
p9 <- ggplot(churn_clean, aes(x = OnlineBackup)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
            label = paste0(round(prop.table(..count..),4) * 100, '%')),
        stat = 'count',
        position = position_dodge(.1),
        size = 3)

#Device Protection service plot
p10 <- ggplot(churn_clean, aes(x = DeviceProtection)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
            label = paste0(round(prop.table(..count..),4) * 100, '%')),
        stat = 'count',
        position = position_dodge(.1),
        size = 3)
```

```
#Tech Support service plot
p11 <- ggplot(churn_clean, aes(x = TechSupport)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)

#Streaming TV service plot
p12 <- ggplot(churn_clean, aes(x = StreamingTV)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)

#Streaming Movies service plot
p13 <- ggplot(churn_clean, aes(x = StreamingMovies)) +geom_bar(aes(fill = Churn))
+ geom_text(aes(y = ..count.. -200, label = paste0(round(prop.table(..count..),4) * 100, '%')),
stat = 'count',
            position = position_dodge(.1),
            size = 3)
#Plot service data within a grid
grid.arrange(p5, p6, p7,p8, p9, p10,p11, p12, p13,ncol=3)
```



Question3:

1. How many of the customers opted for Phone Service as well as Internet Service?

```
> df<-filter(churn_clean,InternetService=="DSL" | InternetService=="Fiber optic" & PhoneService=="Yes")
> print(nrow(df))
[1] 5512
```

2. How many Customers opted for only Internet Service?

```
> df<-filter(churn_clean,InternetService=="DSL" | InternetService=="Fiber optic" & PhoneService=="No")
> print(nrow(df))
[1] 2416
```

3. How many customers opted for DSL as Internet Service?

```
> print(nrow(filter(churn_clean,InternetService=="DSL")))
[1] 2416
```

4. How many Customers opted for Fabric Optic as their Internet Service?

```
> print(nrow(filter(churn_clean,InternetService=="Fiber optic")))
[1] 3096
```

5. Is churn rate of customers who opted for DSL service less than churn rate of Fiber optic ones in our sample dataset?

```
cr1 <- (nrow(filter(churn_clean,InternetService=="Fiber optic" & Churn=="Yes")))/nrow(filter(churn_clean,InternetService=="Fiber optic"))

cr2 <- (nrow(filter(churn_clean,InternetService=="DSL" & Churn=="Yes")))/nrow(filter(churn_clean,InternetService=="DSL"))

print(cr2 < cr1)
```

```
> print(cr2 < cr1)
[1] TRUE
```

Question 4:

1. We will verify that whether the churn rate of people with multiple lines is less than churn rate of people with no multiple lines for the population?

As we know here success can be made similar to the churn rate being Yes. So, we will be applying test for comparing two proportions where we know total customers in that category and no of customers in that proportions who will be churned.

NULL HYPOTHESIS: Is churning rate of people with multiple Lines = Churning rate of people with no multiple lines

ALTERNATE HYPOTHESIS: Is churning rate of people with multiple Lines < Churning rate of people with no multiple lines

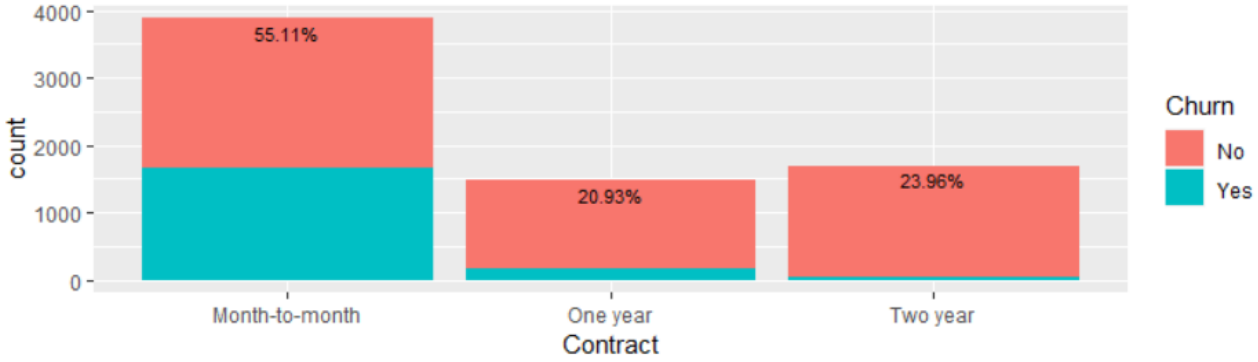
```
t1 <- table(churn_clean$Churn,churn_clean$MultipleLines)

tab_values <- as.numeric(t1)    # Extract values

N1 <- tab_values[2]+tab_values[1]

N2 <- tab_values[3]+tab_values[4]

prop.test(c(tab_values[4],tab_values[1]),c(N2,N1),alternative="less")
```

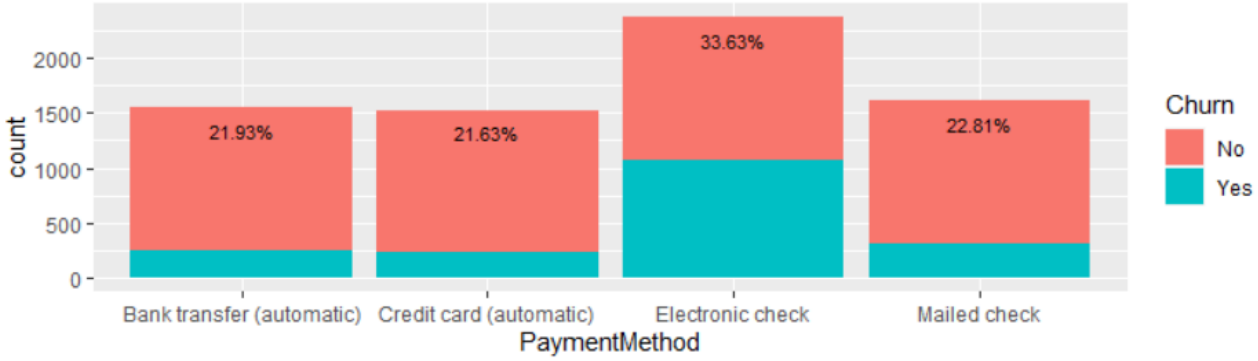
```
        2-sample test for equality of proportions with continuity correction

data:  c(tab_values[4], tab_values[1]) out of c(N2, N1)
X-squared = 1485.2, df = 1, p-value < 2.2e-16
alternative hypothesis: less
95 percent confidence interval:
 -1.0000000 -0.4449003
sample estimates:
   prop 1    prop 2
0.2864847 0.7493235
```

We can now safely conclude that the churn rate of the customers with multiple is less than the customers with no multiple lines as the values of p < 0.05 we will ACCEPT the ALTERNATE HYPTHESIS.

3. ANALYSING OTHER PAYMENT MODES, PAPER BILLNG AND CONTRACT

```
#Contract status plot
p14 <- ggplot(churn_clean, aes(x = Contract)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)
#Paperless billing plot
p15 <- ggplot(churn_clean, aes(x = PaperlessBilling)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)
#Payment method plot
p16 <- ggplot(churn_clean, aes(x = PaymentMethod)) +
  geom_bar(aes(fill = Churn)) +
  geom_text(aes(y = ..count.. -200,
                label = paste0(round(prop.table(..count..),4) * 100, '%')),
            stat = 'count',
            position = position_dodge(.1),
            size = 3)
#Plot contract data within a grid
grid.arrange(p14,p15,p16,ncol=1)
```





QUESTION 5

1. Is paperless billing dependent on Payment Method?

We do this test to check if according to our data paperless billing dependent on payment method which must be true in real scenario. So, we again perform a chi square test to test the two attributes are dependent or not

NULL HYPOTHESIS: Paperless Billing is independent of Payment Method

ALTERNATE HYPOTHESIS: Paperless Billing is dependent on Payment Method

print(chisq.test(table(churn_clean$PaymentMethod,churn_clean$PaperlessBilling)))

```
        Pearson's Chi-squared test

data:  table(churn_clean$PaymentMethod, churn_clean$PaperlessBilling)
X-squared = 431.3, df = 3, p-value < 2.2e-16
```

As the p value < 0.05 so the ALTERNATE HYPOTHESIS is ACCEPTED. Hence, we say that paper billing is dependent on the payment method.

2. Which Payment Method have maximum Churn Rate in the dataset?

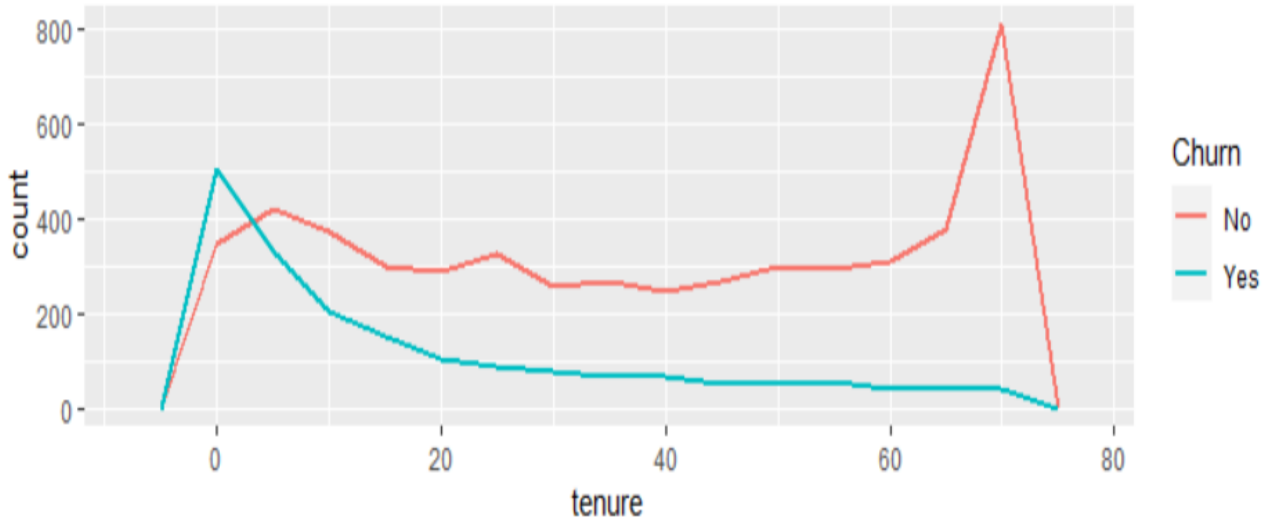
```
c1 <- nrow(filter(churn_clean,PaymentMethod == 'Credit card (automatic)' & Churn=="Yes"))/nrow(filter(churn_clean,PaymentMethod == 'Credit card (automatic)'))

c2 <- nrow(filter(churn_clean,PaymentMethod == 'Bank transfer (automatic)' & Churn=="Yes"))/nrow(filter(churn_clean,PaymentMethod == 'Bank transfer (automatic)'))

c3 <- nrow(filter(churn_clean,PaymentMethod == 'Electronic check' & Churn=="Yes"))/nrow(filter(churn_clean,PaymentMethod == 'Electronic check'))

c4 <- nrow(filter(churn_clean,PaymentMethod == 'Mailed check' & Churn=="Yes"))/nrow(filter(churn_clean,PaymentMethod == 'Mailed check'))

maxrate <- which.max(c(c1,c2,c3,c4))

print(maxrate)
```

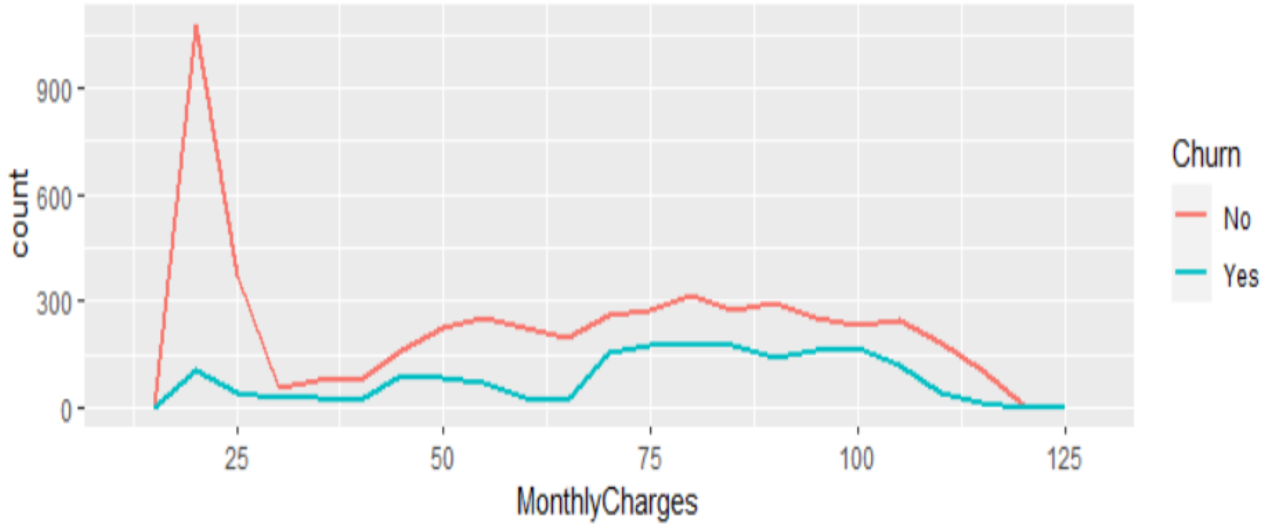
```
> maxrate <- which.max(c(c1,c2,c3,c4))
> print(maxrate)
[1] 3
```

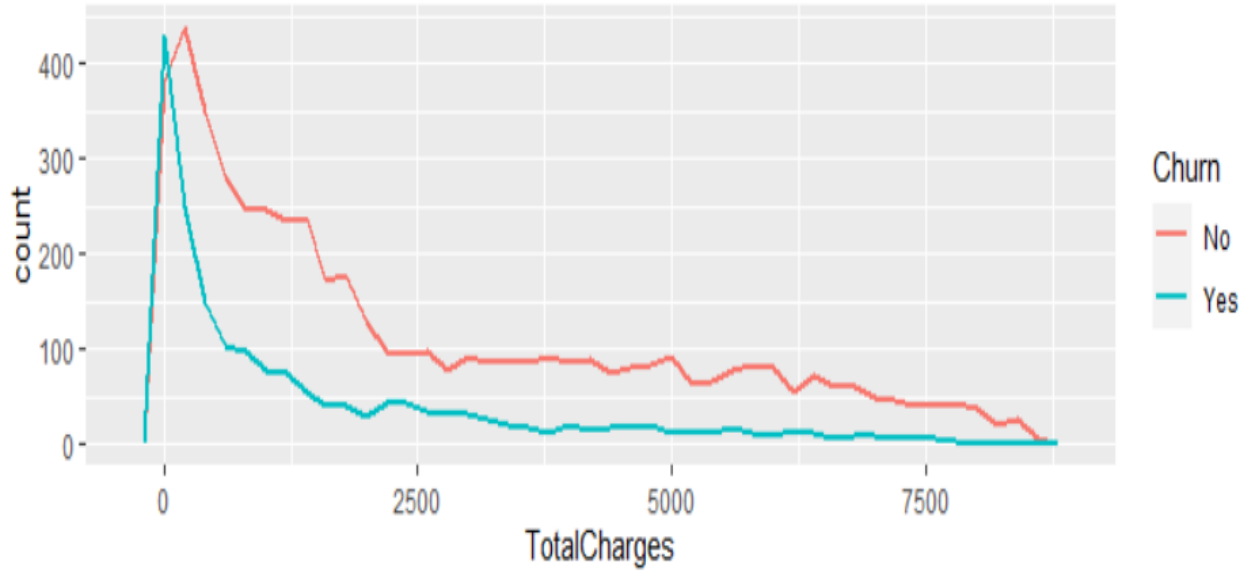
So, from the above output we conclude that customers who opt for electronic check have higher chances of being churned than other payment methods.

ANALYSING CONTINOUS ATTRIBUTES TENURE, TOTAL CHARGES AND MONTHLY CHARGES

```
#Tenure histogram

p17 <- ggplot(data = churn_clean, aes(tenure, color = Churn))+

  geom_freqpoly(binwidth = 5, size = 1)

#Monthly charges histogram

p18 <- ggplot(data = churn_clean, aes(MonthlyCharges, color = Churn))+

  geom_freqpoly(binwidth = 5, size = 1)

#Total charges histogram

p19 <- ggplot(data = churn_clean, aes(TotalCharges, color = Churn))+ geom_freqpoly(binwidth = 200, size = 1)

#Plot quantitative data within a grid

grid.arrange(p17,p18,p19,ncol=1)
```


800
600
400
200
0
count
0
20
40
60
80
tenure
Churn
No
Yes

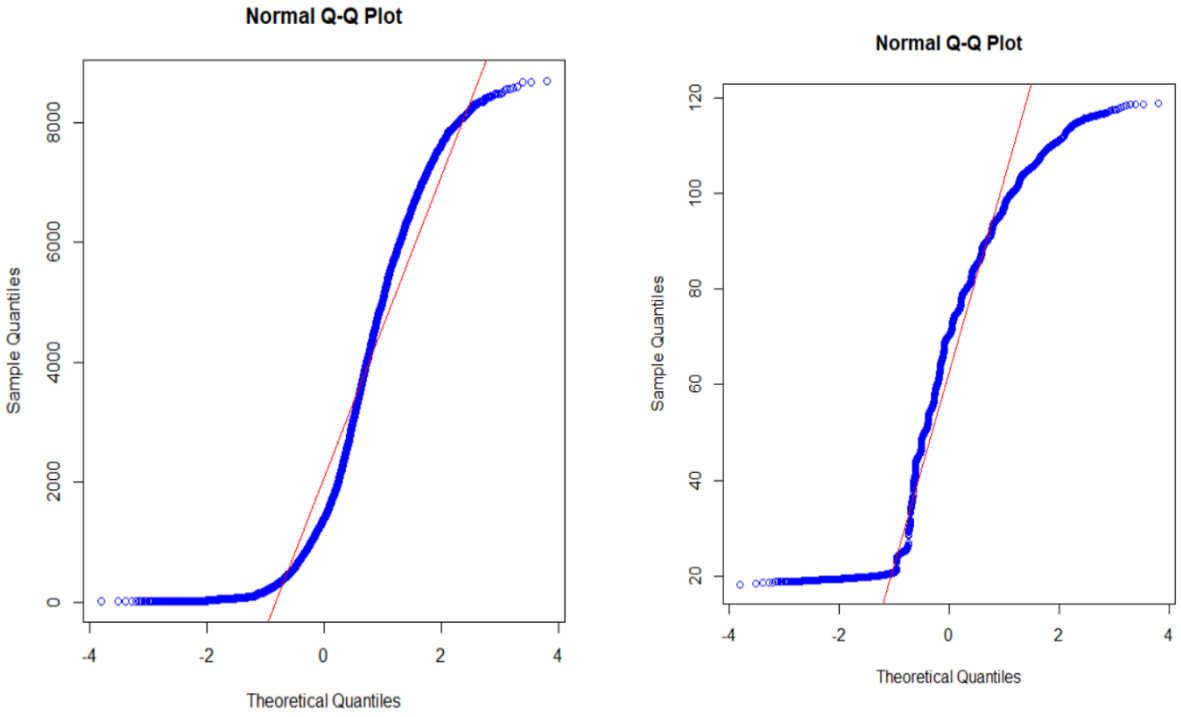

900
600
300
0
count
25
50
75
100
125
MonthlyCharges
Churn
No
Yes


400
300
200
100
0
count
0
2500
5000
7500
TotalCharges
Churn
No
Yes

The tenure variable is stacked at the tails, so a large proportion of customers have either been had the shortest (1 month) or longest (72 month) tenure. It appears as if the Monthly Charges variable is roughly normally distributed around $80 per month with a large stack near the lowest rates. The Total Charges variable is positively skewed with a large stack near the lower amounts.

We also check how total charges and Monthly Charges deviate from the Normal Distribution by using QQ plot

MONTHLY CHARGES **TOTAL CHARGES**



From the above two plots we can conclude that the 2 attributes monthly charges and total charges have negative kurtosis effect which is usually seen in the platykurtic distribution which is basically having thinner tails compared to normal distribution this may due to some of extreme negative or positive outcomes.

Question 6

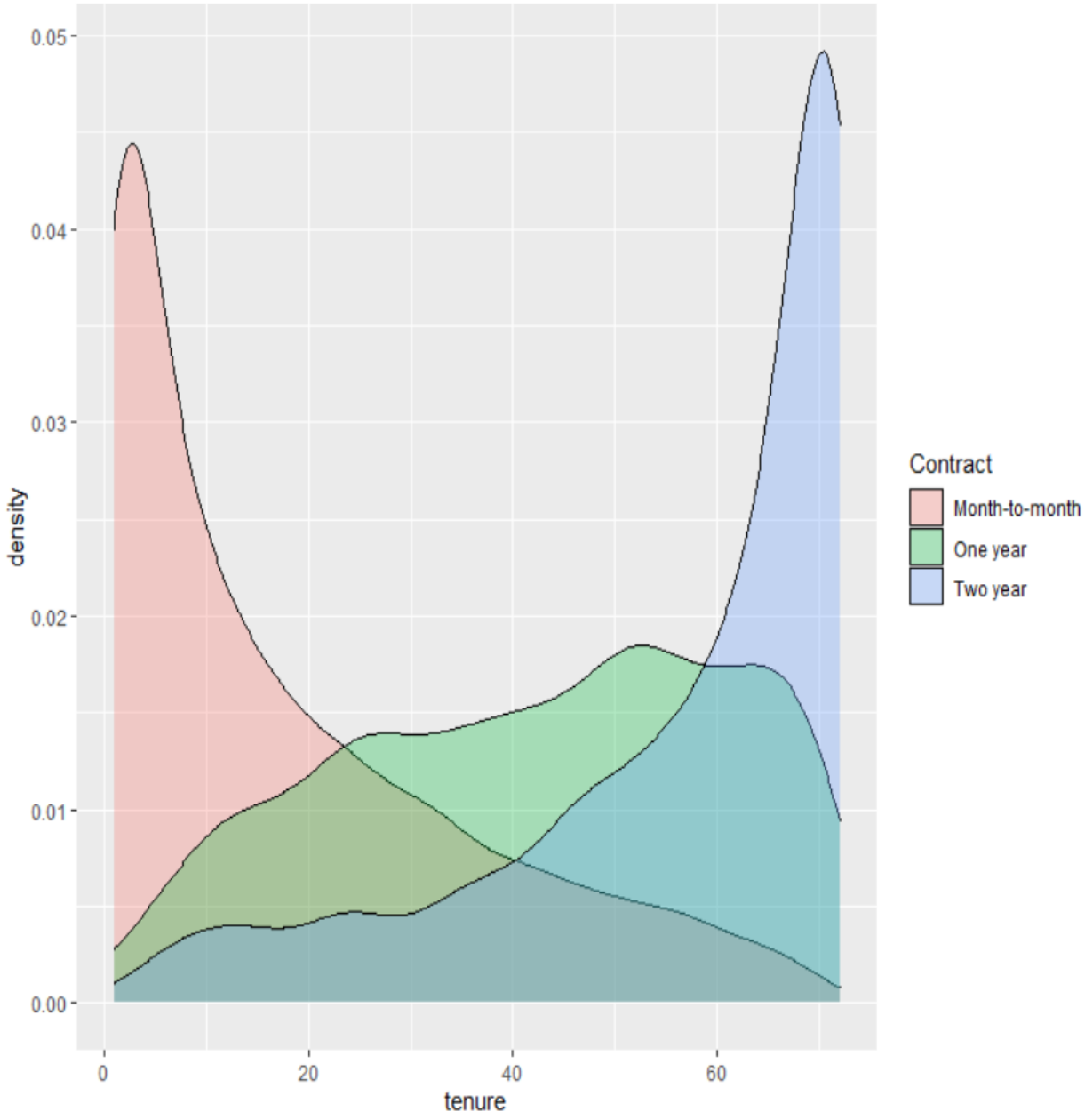
1. We will verify is tenure dependent on the Contract type opted by the customer

As we know that there are more than 2 categories in the contract and the tenure is continuous variable so we will opt for the anova test.

But before applying that we need two main conditions to be satisfied before hand by our sample is that all of them must be normally distributed and according to central limit theorem as n-> infinity we can assume normality in distribution.

We can also see through the plot below how the tenure is distributed in different contract types. This can be done by R commands as follows:

```
ptc<-ggplot(churn_clean, aes(x = tenure, fill = Contract)) +geom_density(alpha = .3)
ptc
```



After seeing the above plot, we can somewhat assume that for month-to-month contract our data is positively skewed normal distribution, and negatively skewed for the one year and the two-year contract types.

So, basically to compare population variances of different groups > 2 together we have a test in R named as Bartlett test in which the hypothesis is as follows,

NULL HYPOTHESIS - The population variances of all the groups are equal

ALTERNATE HYPOTHESIS – The population variances of all the groups are not equal.

```
> bartlett.test(tenure~Contract, data=churn_clean)

        Bartlett test of homogeneity of variances

data:  tenure by Contract
Bartlett's K-squared = 12.187, df = 2, p-value = 0.002258
```

After running the test on our dataset, we got the following output:

```
> bartlett.test(TotalCharges~PaymentMethod, data=churn_clean)

        Bartlett test of homogeneity of variances

data:  TotalCharges by PaymentMethod
Bartlett's K-squared = 465.3, df = 3, p-value < 2.2e-16
```

As, the p value is less than 0.05 we can say that we need to reject our null hypothesis and so the population variance are not equal in all these groups.

So, now we cannot apply simple one-way anova test. After a study, we can apply welch one way anova test in our case which is available in R by command oneway.test()

So, next step is to apply welchs one-way anova test on our two attributes:

NULL HYPOTHESIS: Means of all the groups are same

ALTERNATE HYPTHESIS: Means of all groups are not same

```
> oneway.test(tenure~Churn,data=churn_clean, var.equal = FALSE)

        One-way analysis of means (not assuming equal variances)

data:  tenure and Churn
F = 1223, num df = 1.0, denom df = 4045.5, p-value < 2.2e-16
```

As we can see that p value < 0.05, we reject null hypothesis so we can say means of all groups are not same.

We can also draw an interesting inference from f value that tenure is dependent on the monthly contract because the larger the F value, the more likely it is that the variation caused by the independent variable is real and not due to chance.

2. Is total Charges dependent on the Payment Method?

Again, we need to first check population variances are equal or not to decide whether to apply one way anova or welchs one way anova test with the total charges and the payment methods

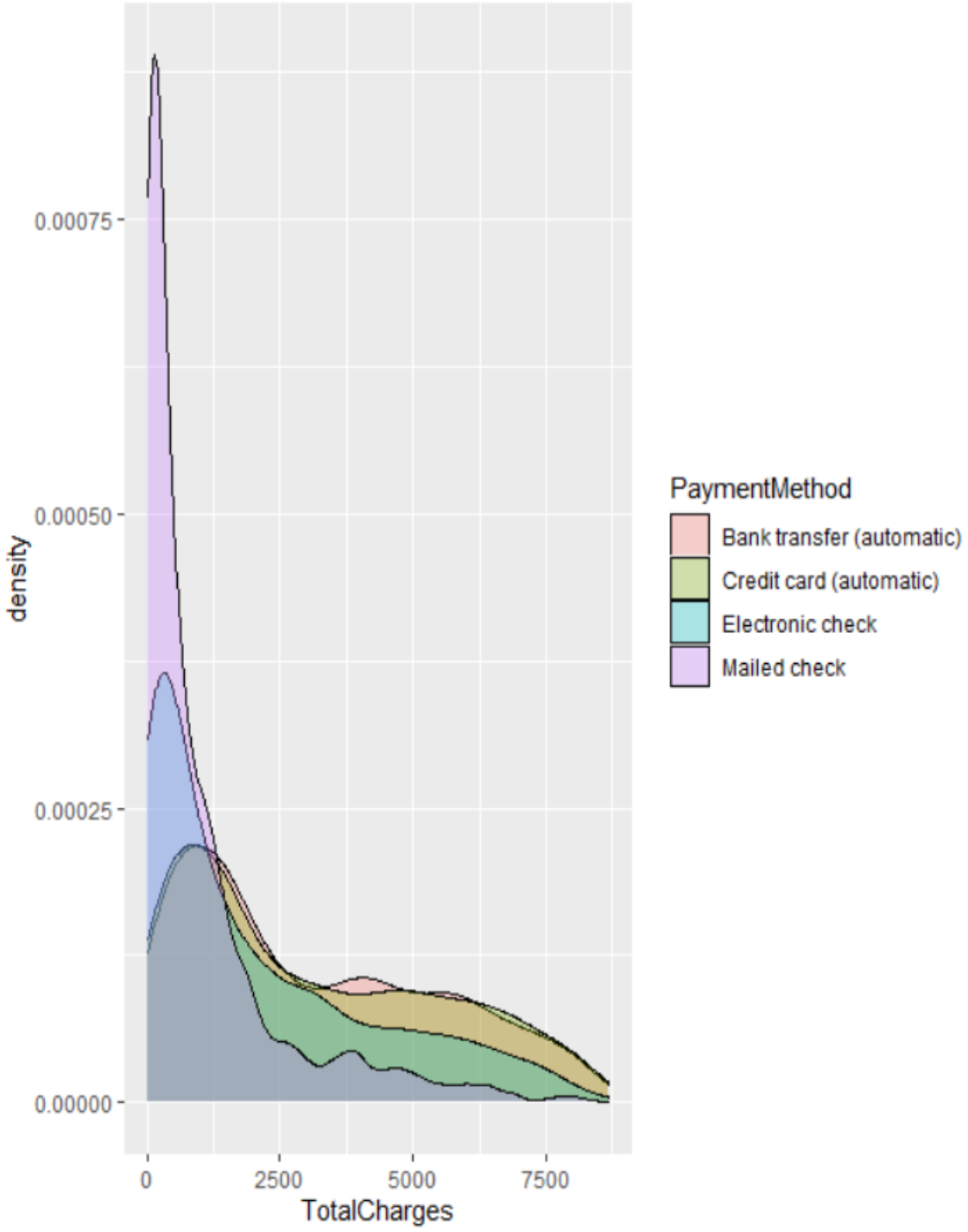
NULL HYPOTHESIS: Population Variances of all groups are equal

ALTERNATE HYPOTHESIS: Population Variances of all groups are not equal

So, we conclude that population variances are not equal and so we need to apply welchs one way anova test and we did it in R by running the command and output is as follows:

```
> oneway.test(TotalCharges~PaymentMethod,data=churn_clean, var.equal = FALSE)

        One-way analysis of means (not assuming equal variances)

data:  TotalCharges and PaymentMethod
F = 437.07, num df = 3.0, denom df = 3637.2, p-value < 2.2e-16
```

From the above test we can draw the conclusion that total Charges is dependent on the payment methods. Similarly, we can also visualize how total Charges are distributed according to different payment methods which we can see it with help of the distribution plot in R



3. Is churn dependent on the Monthly Charges?

As, we know that churn is having 2 categories and monthly charges is continuous variable so we will use t test.

But before applying we need to test whether the population variances of the two samples is equal or not to decide the type of t test.

```
> var.test(MonthlyCharges ~ Churn, churn_clean, alternative = "two.sided")

        F test to compare two variances

data:  MonthlyCharges by Churn
F = 1.5892, num df = 5162, denom df = 1868, p-value < 2.2e-16
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 1.473565 1.711558
sample estimates:
ratio of variances
          1.589167
```

From this we can conclude that the population variances of the two samples is not equal and so we will go for Welch's t test.

NULL HYPOTHESIS: Churn is independent of the Monthly Charges

ALTERNATE HYPOTHESIS: Churn is dependent on the Monthly Charges

result <- t.test(MonthlyCharges~Churn,data=churn_clean)

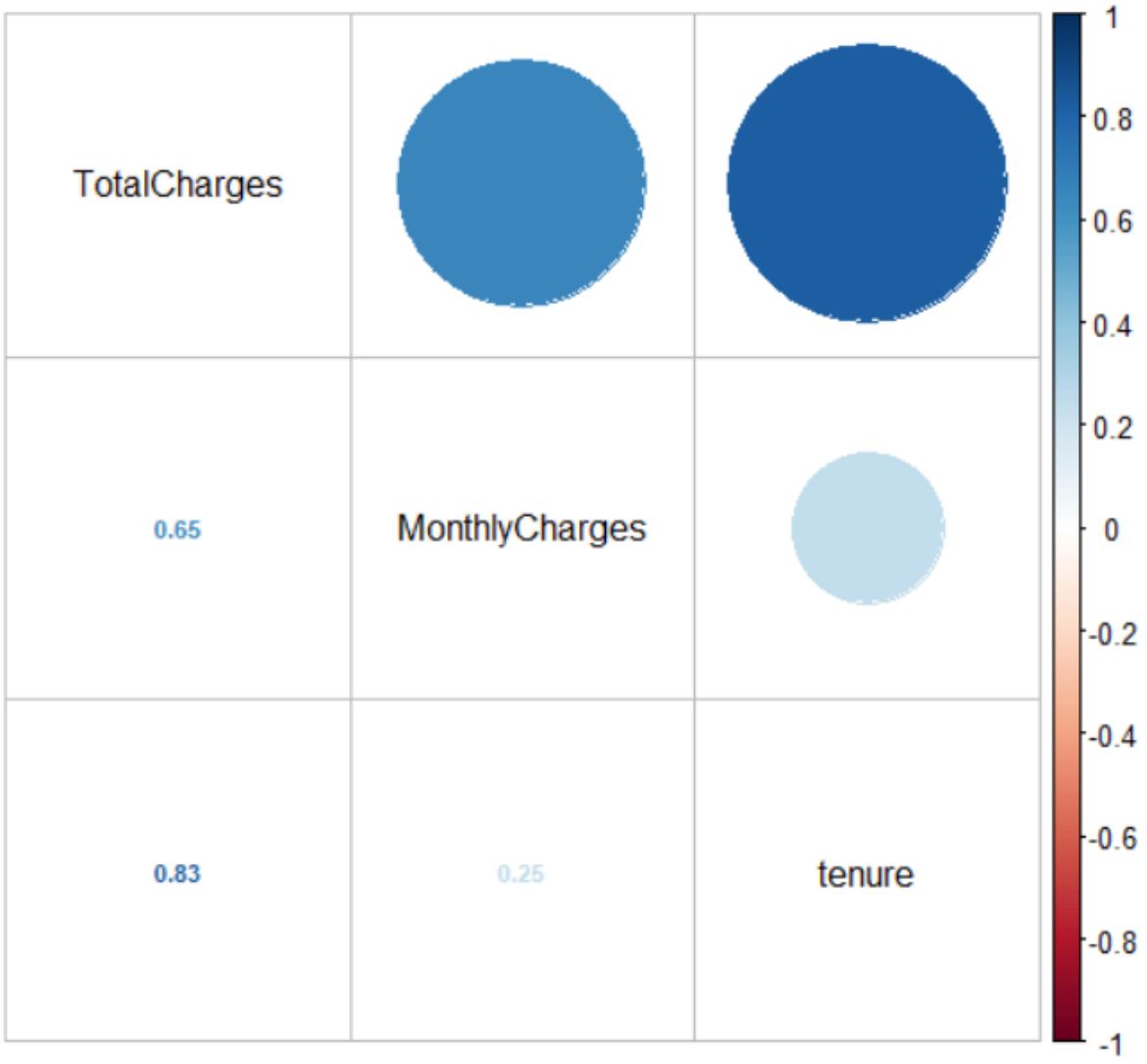
print(result)

```
        Welch Two Sample t-test

data:  MonthlyCharges by Churn
t = -18.341, df = 4139.7, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -14.53786 -11.72998
sample estimates:
 mean in group No mean in group Yes
         61.30741          74.44133
```

QUESTION 7: COMPARE THE CORRELATION AMONG THE CONTINUOUS VARIABLES THAT ARE TENURE, TOTAL CHARGES AND MONTHLY CHARGES

So, to accomplish above task we will make correlation plor in R

churn_clean %>% dplyr::select (TotalCharges, MonthlyCharges, tenure) %>%cor() %>%corrplot.mixed(upper = "circle", tl.col = "black", number.cex = 0.7)



The plot shows high correlations between Total charges & tenure and between Total Charges and Monthly Charges. Pay attention to these variables while training models later. Multicollinearity does not reduce the predictive power or reliability of the model as a whole, at least within the sample data set. But it affects calculations regarding individual predictors. Assume a number of linearly correlated covariates/features present in the data set and Random Forest as the method. Obviously, random selection per node may pick only (or mostly) collinear features which may/will result in a poor split, and this can happen repeatedly, thus negatively affecting the performance.

MODELS TRAINING AND PREDICTIONS

In order to assess the performance of our various modelling techniques, we can split the data into training and test subsets. We will model the training data and use these model parameters to make predictions with the test data. Let's call these data subsets dtrain and dtest.

We will randomly sample from the entire sample to create these subsets. The 'set.seed()' function argument can be changed in order to reset the random number generator used for sampling. The training subset will be roughly 70% of the original sample, with the remaining being the test subset.

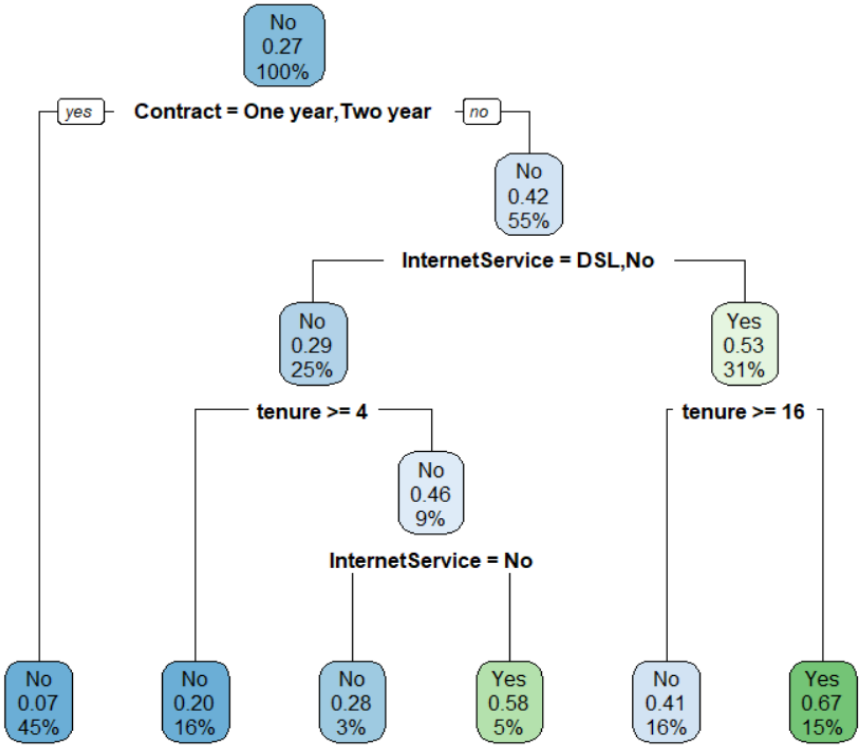
Splitting dataset into training and testing

```
set.seed(56)

split_train_test <- createDataPartition(churn_clean$Churn,p=0.7,list=FALSE)

dtrain<- churn_clean[split_train_test,]

dtest<-  churn_clean[-split_train_test,]

# Remove Total Charges from the training dataset

dtrain <- dtrain[,-19]

dtest <- dtest[,-19]
```

QUESTION 8

APPLY DECISION TREE AND FIND ITS ACCURACY ON THE DATASET?

```
tr_fit <- rpart(Churn ~., data = dtrain, method="class")

rpart.plot(tr_fit)


tr_prob1 <- predict(tr_fit, dtest)

tr_pred1 <- ifelse(tr_prob1[,2] > 0.5,"Yes","No")

table(Predicted = tr_pred1, Actual = dtest$Churn)


tr_prob2 <- predict(tr_fit, dtrain)

tr_pred2 <- ifelse(tr_prob2[,2] > 0.5,"Yes","No")

tr_tab1 <- table(Predicted = tr_pred2, Actual = dtrain$Churn)

tr_tab2 <- table(Predicted = tr_pred1, Actual = dtest$Churn)
```



The contract variable is the most important. Customers with month-to-month contracts are more likely to churn. Customers with DSL internet service are less likely to churn. Customers who have stayed longer than 15 months are less likely to churn. Now let's assess the prediction accuracy of the decision tree model by investigating how well it predicts churn in the test subset. We will begin with the confusion matrix, which is a useful display of classification accuracy. It displays the following information.

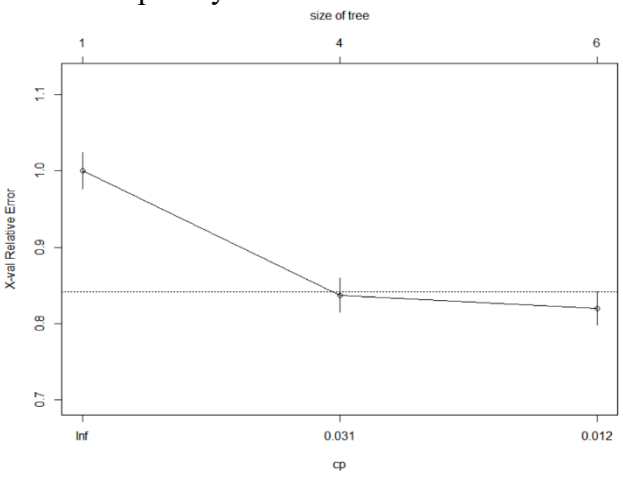
Sometimes, due to overfitting we may need to prune our tree and for this we have executed the command for our datasets:

printcp(tr_fit), plotcp(tr_fit)

So we for this we have the complexity parameter (cp) in rpart is the minimum improvement in the model needed at each node. It's based on the cost complexity of the model defined as:

$$\sum_{\text{Terminal Nodes}} Misclass_i + \lambda * (Splits)$$

- For the given tree, add up the misclassification at every terminal node.
- Then multiply the number of splits time a penalty term (lambda) and add it to the total misclassification.
- The lambda is determined through cross-validation and not reported in R.
- The cp we see using `printcp()` is the scaled version of lambda over the misclassifcation rate of the overall data.



Now we will make a confusion matrix on the testing data and find out the accuracy of the model

```
# Test

confusionMatrix(

  as.factor(tr_pred1),

  as.factor(dtest$Churn),

  positive = "Yes"

)

tr_acc <- sum(diag(tr_tab2))/sum(tr_tab2)

tr_acc
```

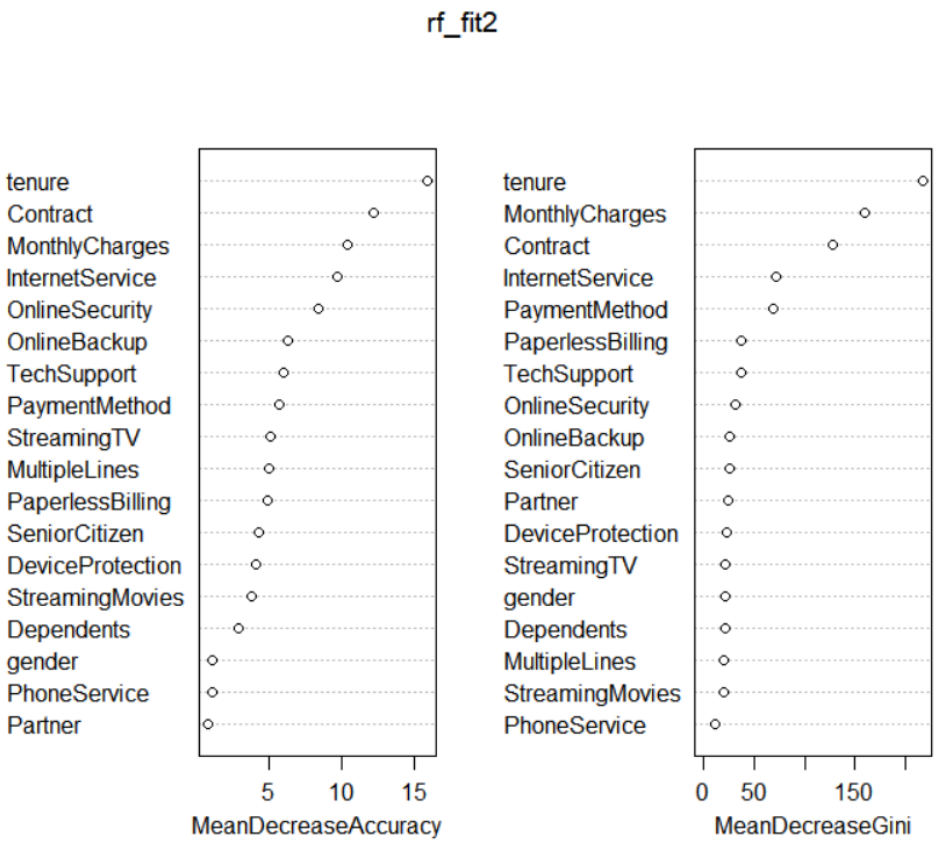
```
Confusion Matrix and Statistics

          Reference
Prediction   No  Yes
       No  1406  284
       Yes  142  276

               Accuracy : 0.7979
                 95% CI : (0.7801, 0.8149)
    No Information Rate : 0.7343
    P-Value [Acc > NIR] : 6.398e-12

                  Kappa : 0.4364

 Mcnemar's Test P-Value : 8.405e-12

            Sensitivity : 0.4929
            Specificity : 0.9083
         Pos Pred Value : 0.6603
         Neg Pred Value : 0.8320
             Prevalence : 0.2657
         Detection Rate : 0.1309
   Detection Prevalence : 0.1983
      Balanced Accuracy : 0.7006

       'Positive' Class : Yes

>
> tr_acc <- sum(diag(tr_tab2))/sum(tr_tab2)
> tr_acc
[1] 0.7979127
```

QUESTION 9: TRAIN A RANDOM FOREST ON YOUR DATASET AND FIND ITS ACCURACY ON THE TEST DATASET

rf_fit2 <- randomForest(as.factor(Churn) ~., data = dtrain, ntree = 75, mtry = 2, importance = TRUE, proximity = TRUE)

Display variable importance from random tree

varImpPlot(rf_fit2)



Similar to the decision tree, this random forest model has identified contract status and tenure length as important predictors for churn. Internet service status does not appear as important in this model.

Now, as we have trained our random forest on our training dataset, we will plot confusion matrix and find accuracy of it on test dataset

rf_pred1 <- predict(rf_fit2, dtest)

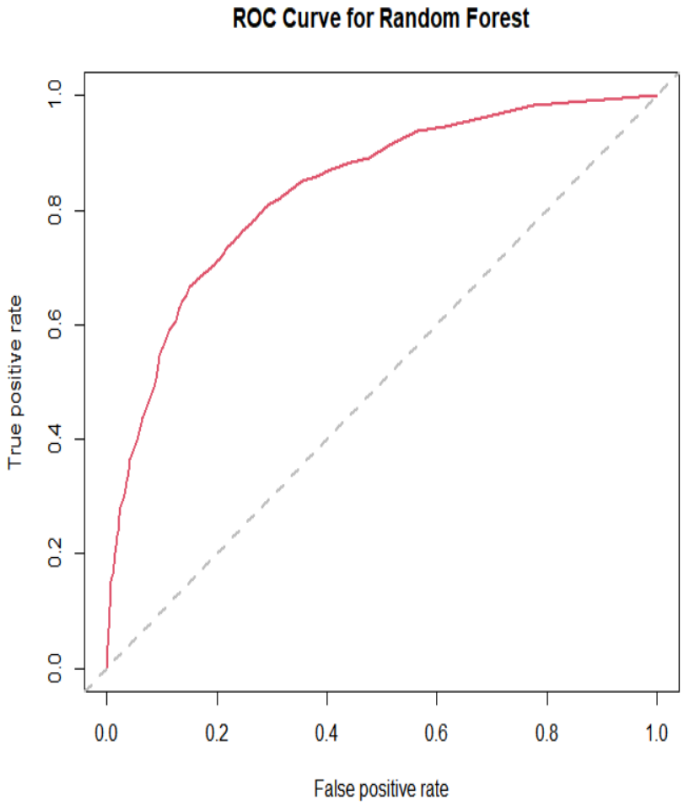
rf_tab2 <- table(Predicted = rf_pred1, Actual = dtest$Churn)

Test

confusionMatrix(

```
  as.factor(rf_pred1),
  as.factor(dtest$Churn),
  positive = "Yes"
)
rf_acc <- sum(diag(rf_tab2))/sum(rf_tab2)
rf_acc
pred1=predict(rf_fit2,dtest,type = "prob")
library(ROCR)
perf = prediction(pred1[,2], dtest$Churn)
auc = performance(perf, "auc")
pred3 = performance(perf, "tpr","fpr")
plot(pred3,main="ROC Curve for Random Forest",col=2,lwd=2)
abline(a=0,b=1,lwd=2,lty=2,col="gray")
```

```
Confusion Matrix and Statistics

          Reference
Prediction   No  Yes
       No  1424  293
       Yes  124  267

               Accuracy : 0.8022
                 95% CI : (0.7845, 0.819)
    No Information Rate : 0.7343
    P-Value [Acc > NIR] : 2.183e-13

                  Kappa : 0.439

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.4768
            Specificity : 0.9199
         Pos Pred Value : 0.6829
         Neg Pred Value : 0.8294
             Prevalence : 0.2657
         Detection Rate : 0.1267
   Detection Prevalence : 0.1855
      Balanced Accuracy : 0.6983

       'Positive' Class : Yes

>
> rf_acc <- sum(diag(rf_tab2))/sum(rf_tab2)
> rf_acc
[1] 0.8021822
```



QUESTION 10: TRAIN A LOGISTIC REGRESSION MODEL ON YOUR DATASET AND FIND ITS ACCURACY ON THE TEST DATASET

lr_fit <- glm(as.factor(Churn) ~., data = dtrain,family=binomial(link='logit'))

summary(lr_fit)

```
Call:
glm(formula = as.factor(Churn) ~ ., family = binomial(link = "logit"),
    data = dtrain)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9796  -0.6746  -0.2913   0.7076   3.1075

Coefficients:
                                    Estimate Std. Error z value Pr(>|z|)
(Intercept)                         0.441724   0.961202   0.460 0.645837
genderMale                         -0.007747   0.077510  -0.100 0.920383
SeniorCitizenYes                    0.235996   0.100570   2.347 0.018946 *
PartnerYes                         -0.071058   0.092374  -0.769 0.441748
DependentsYes                      -0.211223   0.106934  -1.975 0.048238 *
tenure                             -0.032358   0.002813 -11.505  < 2e-16 ***
PhoneServiceYes                    -0.165520   0.774096  -0.214 0.830685
MultipleLinesYes                    0.402807   0.210212   1.916 0.055341 .
InternetServiceFiber optic          1.265800   0.951204   1.331 0.183277
InternetServiceNo                  -1.445403   0.964685  -1.498 0.134051
OnlineSecurityYes                  -0.219603   0.211715  -1.037 0.299614
OnlineBackupYes                    -0.085143   0.208896  -0.408 0.683578
DeviceProtectionYes                 0.057192   0.209502   0.273 0.784860
TechSupportYes                     -0.296010   0.215162  -1.376 0.168898
StreamingTVYes                      0.427724   0.388682   1.100 0.271138
StreamingMoviesYes                  0.440124   0.389786   1.129 0.258837
ContractOne year                   -0.616267   0.127595  -4.830 1.37e-06 ***
ContractTwo year                   -1.331978   0.210434  -6.330 2.46e-10 ***
PaperlessBillingYes                 0.306490   0.088674   3.456 0.000548 ***
PaymentMethodCredit card (automatic) -0.202668   0.135368  -1.497 0.134350
PaymentMethodElectronic check       0.256878   0.112405   2.285 0.022296 *
PaymentMethodMailed check          -0.148949   0.136194  -1.094 0.274106
MonthlyCharges                     -0.017919   0.037834  -0.474 0.635769
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5702.8  on 4923  degrees of freedom
Residual deviance: 4104.9  on 4901  degrees of freedom
AIC: 4150.9

Number of Fisher Scoring iterations: 6
```

By examining the significance values, we see similar predictor variables of importance. Tenure length and contract status have the lowest p-values and can be identified as the best predictors of customer churn.

Now, we will again make confusion matrix and check accuracy of our logistic regression model on the dataset

lr_prob1 <- predict(lr_fit, dtest, type="response")

lr_pred1 <- ifelse(lr_prob1 > 0.5,"Yes","No")

table(Predicted = lr_pred1, Actual = dtest$Churn)

lr_tab2 <- table(Predicted = lr_pred1, Actual = dtest$Churn)

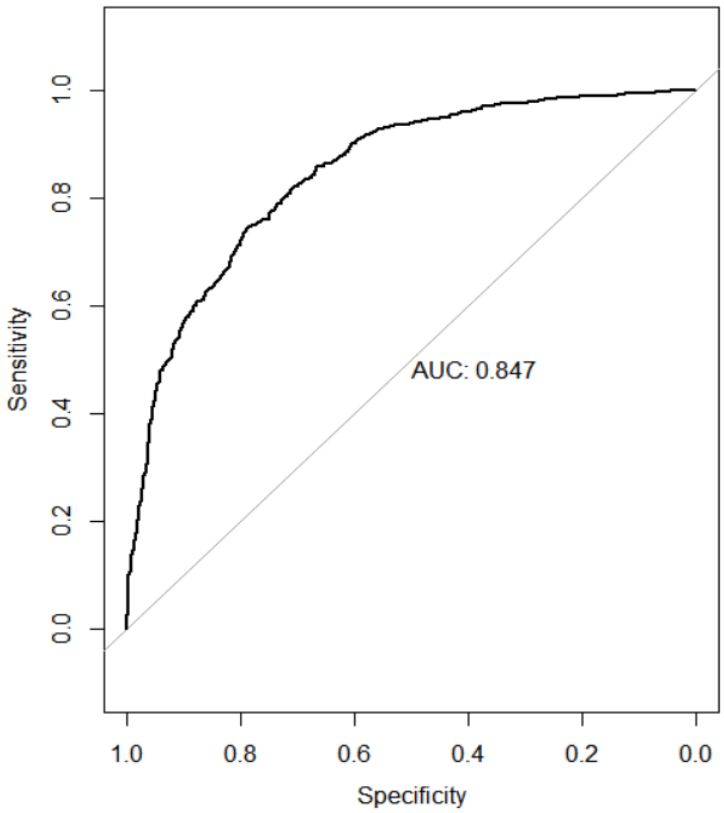
```
# Test
confusionMatrix(
  as.factor(lr_pred1),
  as.factor(dtest$Churn),
  positive = "Yes"
)
lr_acc <- sum(diag(lr_tab2))/sum(lr_tab2)
lr_acc
```

ROC Curve for the logistic regression is one of the other evaluations of the model we will do in our testing.

```
library(pROC)
res.roc <- roc(dtest$Churn, lr_prob1)
plot.roc(res.roc, print.auc = TRUE)
```

```
Confusion Matrix and Statistics

          Reference
Prediction   No  Yes
       No  1404  249
       Yes  144  311

               Accuracy : 0.8136
                 95% CI : (0.7963, 0.83)
    No Information Rate : 0.7343
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.4918

 Mcnemar's Test P-Value : 1.553e-07

            Sensitivity : 0.5554
            Specificity : 0.9070
         Pos Pred Value : 0.6835
         Neg Pred Value : 0.8494
             Prevalence : 0.2657
         Detection Rate : 0.1475
   Detection Prevalence : 0.2158
      Balanced Accuracy : 0.7312

       'Positive' Class : Yes

>
> lr_acc <- sum(diag(lr_tab2))/sum(lr_tab2)
> lr_acc
[1] 0.8135674
```

MODEL ACCURACY



LOGISTIC REGRESSION ROC CURVE

Lastly, we will compare some models together for classification on our dataset:

```
control <- trainControl(method="repeatedcv", number=10, repeats=3)
set.seed(7)
fit.cart <- train(Churn~., data=dtrain, method="rpart", trControl=control)
set.seed(7)
fit.lor <- train(Churn~., data=dtrain, method="glm", trControl=control)
#RF
set.seed(7)
fit.rf <- train(Churn~., data=dtrain, method="rf", trControl=control)
set.seed(7)
fit.knn <- train(Churn~., data=dtrain, method="knn", trControl=control)
results <- resamples(list(CART=fit.cart,RF=fit.rf, LOR=fit.lor, KNN=fit.knn))
scales <- list(x=list(relation="free"), y=list(relation="free"))
densityplot(results, scales=scales, pch = "|")
summary(results)
```