INTRODUCTION

"In the realm of subscription-based businesses, the pulse is measured by the churn rate—a pivotal metric for any service-oriented company navigating the seas of recurring revenue." - Business Insights Today, April 2017

"For every evolving enterprise in the era of 'as-a-service,' keeping a watchful eye on customer churn and lifetime value is akin to steering the ship through the dynamic currents of success." - Corporate Vision Magazine, January 2018__

Customer turnover, commonly termed customer churn, materializes when individuals or subscribers cease their association with a company or service, a phenomenon acknowledged as customer attrition. This can also be articulated as the diminishing number of clients or customers. Sectors like telecommunications find the concept of churn rates especially pertinent due to the plethora of alternatives available to consumers within a specific geographic domain. The dynamics of customer choices in this industry make understanding and mitigating churn an essential aspect of sustaining a robust and competitive market presence.

The data was downloaded from IBM Sample Data Sets. Each row represents a customer, each column contains that customer's attributes

DATA **PRE-PROCESSING**

Customer ID (`customerID`):

This is a unique identifier for each customer.

Gender (`gender`):

Indicates the gender of the customer (Male/Female).

Senior Citizen (`SeniorCitizen`):

A numerical variable indicating whether the customer is a senior citizen (1) or not (0).

Partner (`Partner`):

Categorical variable indicating whether the customer has a partner (Yes/No).

Dependents (`Dependents`):

Categorical variable indicating whether the customer has dependents (Yes/No).

Tenure (`tenure`):

Numerical variable representing the number of months the customer has been with the service.

Phone Service (`PhoneService`):

Categorical variable indicating whether the customer has phone service (Yes/No).

Multiple Lines (`MultipleLines`):

Categorical variable indicating whether the customer has multiple lines (e.g., landline and mobile).

Internet Service (`InternetService`):

Categorical variable indicating the type of internet service (DSL, Fiber optic, etc.).

Online Security (`OnlineSecurity`):

Categorical variable indicating whether the customer has subscribed to online security (Yes/No).

Online Backup (`OnlineBackup`):

Categorical variable indicating whether the customer has subscribed to online backup (Yes/No).

Device Protection (`DeviceProtection`):

Categorical variable indicating whether the customer has subscribed to device protection (Yes/No).

Tech Support (`TechSupport`):

Categorical variable indicating whether the customer has subscribed to tech support (Yes/No).

Streaming TV (`StreamingTV`):

Categorical variable indicating whether the customer has subscribed to streaming TV (Yes/No).

Streaming Movies (`StreamingMovies`):

Categorical variable indicating whether the customer has subscribed to streaming movies (Yes/No).

Contract (`Contract`):

Categorical variable indicating the type of contract the customer has (Month-to-month, One year, Two years).

Paperless Billing (`PaperlessBilling`):

Categorical variable indicating whether the customer has opted for paperless billing (Yes/No).

Payment Method (`PaymentMethod`):

Categorical variable indicating the method of payment chosen by the customer.

Monthly Charges (`MonthlyCharges`):

Numerical variable representing the monthly charges for the customer.

Total Charges (`TotalCharges`):

Numerical variable representing the total charges accumulated by the customer.

Churn (`Churn`):

Categorical variable indicating whether the cu

Data Structure

```
# Loading the necessary libraries and the data
library("readr")
library("dplyr")
install.packages("FNN")
library("FNN")
library("caret")
library("FNN")
install.packages("neuralnet")
library("neuralnet")
library("ggplot2")
library("reshape2")
install.packages("forecast")
library("forecast")
install.packages("corrplot")
library(corrplot)
df <- read_csv("CustomerChurn.csv")
str(df)
```

```
Installing FNN [1.1.3.2] ...
	OK [linked cache]
Installing neuralnet [1.44.2] ...
	OK [linked cache]
Installing forecast [8.21.1] ...
	OK [linked cache]
Installing corrplot [0.92] ...
	OK [linked cache]
```

```
Rows: 7043 Columns: 21
── Column specification
────────────────────────────────────────────────────────
Delimiter: ","
chr (17): customerID, gender, Partner, Dependents, PhoneService,
MultipleLin...
dbl  (4): SeniorCitizen, tenure, MonthlyCharges, TotalCharges
```

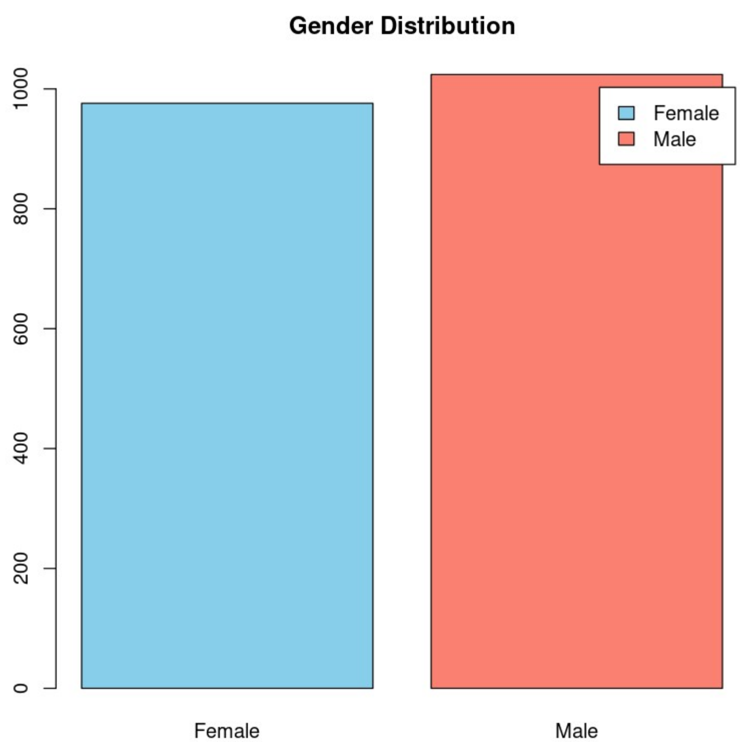
```
ⓘ Use `spec()` to retrieve the full column specification for this
data.
ⓘ Specify the column types or set `show_col_types = FALSE` to quiet
this message.
```

```
spc_tbl_ [7,043 × 21] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ customerID      : chr [1:7043] "7590-VHVEG" "5575-GNVDE" "3668-
QPYBK" "7795-CFOCW" ...
 $ gender          : chr [1:7043] "Female" "Male" "Male" "Male" ...
 $ SeniorCitizen   : num [1:7043] 0 0 0 0 0 0 0 0 0 0 ...
 $ Partner         : chr [1:7043] "Yes" "No" "No" "No" ...
 $ Dependents      : chr [1:7043] "No" "No" "No" "No" ...
 $ tenure          : num [1:7043] 1 34 2 45 2 8 22 10 28 62 ...
 $ PhoneService    : chr [1:7043] "No" "Yes" "Yes" "No" ...
 $ MultipleLines   : chr [1:7043] "No phone service" "No" "No" "No
phone service" ...
 $ InternetService : chr [1:7043] "DSL" "DSL" "DSL" "DSL" ...
 $ OnlineSecurity  : chr [1:7043] "No" "Yes" "Yes" "Yes" ...
 $ OnlineBackup    : chr [1:7043] "Yes" "No" "Yes" "No" ...
 $ DeviceProtection: chr [1:7043] "No" "Yes" "No" "Yes" ...
 $ TechSupport     : chr [1:7043] "No" "No" "No" "Yes" ...
 $ StreamingTV     : chr [1:7043] "No" "No" "No" "No" ...
 $ StreamingMovies : chr [1:7043] "No" "No" "No" "No" ...
 $ Contract        : chr [1:7043] "Month-to-month" "One year" "Month-
to-month" "One year" ...
 $ PaperlessBilling: chr [1:7043] "Yes" "No" "Yes" "No" ...
 $ PaymentMethod   : chr [1:7043] "Electronic check" "Mailed check"
"Mailed check" "Bank transfer (automatic)" ...
 $ MonthlyCharges  : num [1:7043] 29.9 57 53.9 42.3 70.7 ...
 $ TotalCharges    : num [1:7043] 29.9 1889.5 108.2 1840.8 151.7 ...
 $ Churn           : chr [1:7043] "No" "No" "Yes" "No" ...
 - attr(*, "spec")=
  .. cols(
  ..   customerID = col_character(),
  ..   gender = col_character(),
  ..   SeniorCitizen = col_double(),
  ..   Partner = col_character(),
  ..   Dependents = col_character(),
  ..   tenure = col_double(),
  ..   PhoneService = col_character(),
  ..   MultipleLines = col_character(),
  ..   InternetService = col_character(),
  ..   OnlineSecurity = col_character(),
  ..   OnlineBackup = col_character(),
  ..   DeviceProtection = col_character(),
  ..   TechSupport = col_character(),
  ..   StreamingTV = col_character(),
  ..   StreamingMovies = col_character(),
  ..   Contract = col_character(),
  ..   PaperlessBilling = col_character(),
```

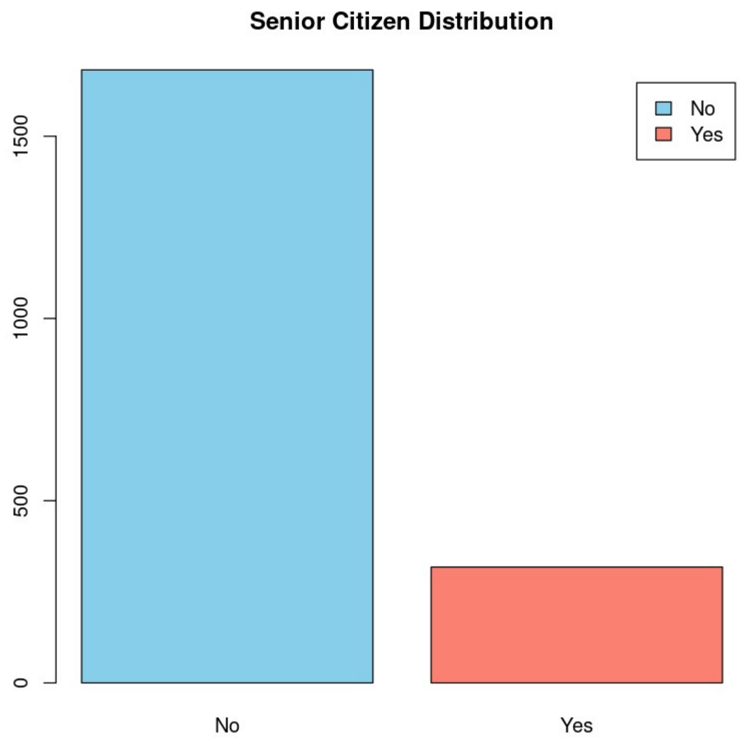
```
  ..   PaymentMethod = col_character(),
  ..   MonthlyCharges = col_double(),
  ..   TotalCharges = col_double(),
  ..   Churn = col_character()
  .. )
 - attr(*, "problems")=<externalptr>

#keeping only the first 2000 rows for the project purpose
df <- df[1:2000, ]
```

Bar plots of categorical variables

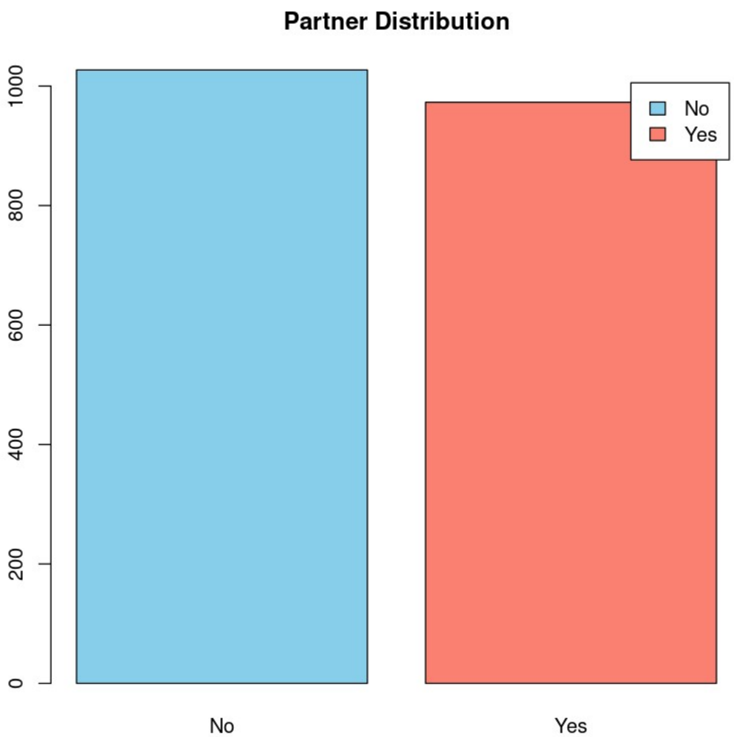
```
barplot(table(df$gender), main="Gender Distribution", col=c("skyblue",
"salmon"), legend = TRUE)
```



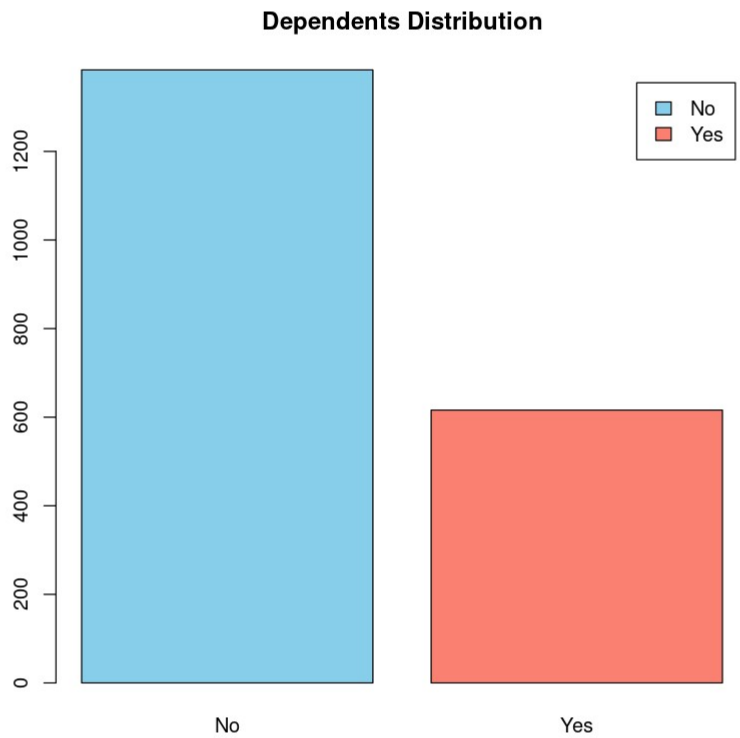

```
barplot(table(factor(df$SeniorCitizen, levels = c(0, 1), labels =
c("No", "Yes"))), main="Senior Citizen Distribution", col=c("skyblue",
"salmon"), legend = TRUE)
```




```
barplot(table(df$Partner), main="Partner Distribution",
col=c("skyblue", "salmon"), legend = TRUE)
```




```
barplot(table(df$Dependents), main="Dependents Distribution",
col=c("skyblue", "salmon"), legend = TRUE)
```



Converting categorical variables to binary (0 or 1) & removing unneccesary columns

```
binary_cols <- c("Churn", "SeniorCitizen", "gender", "Partner",
"Dependents",
                  "PhoneService", "MultipleLines", "InternetService",
                  "OnlineSecurity", "OnlineBackup",
"DeviceProtection",
                  "TechSupport", "StreamingTV", "StreamingMovies",
                  "Contract", "PaperlessBilling", "PaymentMethod")

df[, binary_cols] <- lapply(df[, binary_cols], function(x)
as.numeric(x == "Yes"))

columns_to_remove <- c("customerID","tenure", "MonthlyCharges",
"TotalCharges", "gender", "SeniorCitizen", "InternetService",
"Contract" , "PaymentMethod" )

df <- df[, !(names(df) %in% columns_to_remove)]
```

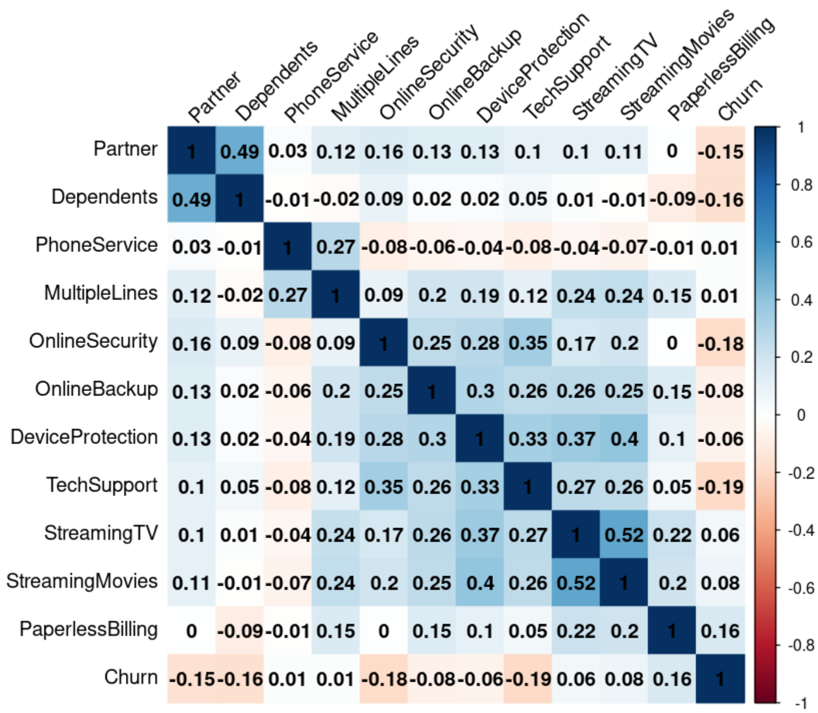
checking for any missing values`

```
missing_values <- sum(is.na(df))
missing_values

[1] 0
```

Correlation Matrix

```
cor_matrix <- cor(df)
print(cor_matrix)
# Creating a correlation plot
corrplot(cor_matrix, method = "color", addCoef.col = "black", tl.col =
"black", tl.srt = 45)

                      Partner   Dependents PhoneService MultipleLines
Partner           1.000000000  0.494727782  0.026921701    0.12349038
Dependents        0.494727782  1.000000000 -0.006850793   -0.02228420
PhoneService      0.026921701 -0.006850793  1.000000000    0.27007453
MultipleLines     0.123490381 -0.022284202  0.270074531    1.00000000
OnlineSecurity    0.157096127  0.091329070 -0.084594082    0.09448827
OnlineBackup      0.134240096  0.021749202 -0.059403344    0.19876162
DeviceProtection  0.131273698  0.022718666 -0.044618314    0.19043612
TechSupport       0.104663890  0.053741088 -0.082644013    0.11853892
StreamingTV       0.102579302  0.012309790 -0.040439975    0.23877028
StreamingMovies   0.105716639 -0.005993270 -0.067385330    0.24130623
PaperlessBilling  0.003499674 -0.094877880 -0.008331135    0.15456326
Churn            -0.154280173 -0.164837734  0.013181093    0.01045211
                 OnlineSecurity OnlineBackup DeviceProtection
TechSupport
Partner             0.157096127   0.13424010       0.13127370
0.10466389
Dependents          0.091329070   0.02174920       0.02271867
0.05374109
PhoneService       -0.084594082  -0.05940334      -0.04461831 -
0.08264401
MultipleLines       0.094488270   0.19876162       0.19043612
0.11853892
OnlineSecurity      1.000000000   0.25308948       0.27538812
0.34719904
OnlineBackup        0.253089476   1.00000000       0.29853920
0.25769667
DeviceProtection    0.275388121   0.29853920       1.00000000
0.33384616
TechSupport         0.347199043   0.25769667       0.33384616
1.00000000
StreamingTV         0.174494851   0.26089378       0.36859819
0.26992481
```

```
StreamingMovies      0.197081304   0.25365216       0.39564820
0.25792113
PaperlessBilling     0.003449811   0.14770892       0.10004723
0.05100014
Churn               -0.183953456  -0.07937672      -0.06316591 -
0.19433293
                 StreamingTV StreamingMovies PaperlessBilling
Churn
Partner           0.10257930      0.10571664      0.003499674 -
0.15428017
Dependents        0.01230979     -0.00599327     -0.094877880 -
0.16483773
PhoneService     -0.04043997     -0.06738533     -0.008331135
0.01318109
MultipleLines     0.23877028      0.24130623      0.154563263
0.01045211
OnlineSecurity    0.17449485      0.19708130      0.003449811 -
0.18395346
OnlineBackup      0.26089378      0.25365216      0.147708917 -
0.07937672
DeviceProtection  0.36859819      0.39564820      0.100047230 -
0.06316591
TechSupport       0.26992481      0.25792113      0.051000139 -
0.19433293
StreamingTV       1.00000000      0.52396924      0.216062965
0.05886415
StreamingMovies   0.52396924      1.00000000      0.204331904
0.07845578
PaperlessBilling  0.21606296      0.20433190      1.000000000
0.16494495
Churn             0.05886415      0.07845578      0.164944954
1.00000000
```



Partner
Dependents
PhoneService
MultipleLines
OnlineSecurity
OnlineBackup
DeviceProtection
TechSupport
StreamingTV
StreamingMovies
PaperlessBilling
Churn

Correlation matrix is showing variables assosiated with customer churn: This correlation matrix is relevant in the context of customer churn because it shows the relationship between different variables and the target variable of churn. The factors that can be considered important from this heat map are the variables that have a strong positive or negative correlation with the target variable of churn. For example, in this heat map, it appears that the variables of “PaperlessBilling”, “StreamingTV”, and “StreamingMovies” have a strong positive correlation with churn.This means that as these variables increase, so does the likelihood of churn. for instance, in the case of paperless billing customers who use paperless billing may be more likely to switch to a different provider if they are dissatisfied with the service or find a better offer. While the variables of “Partner” and “Dependents” have a strong negative correlation with churn. These variables may be important to consider when analyzing customer churn as it helps with focusing on varibales with a positive correlation.

Splitting the data into training and validation sets

```
set.seed(12345)
train.index <- sample(1:nrow(df), 0.6 * nrow(df))
train.df <- df[train.index,]
valid.df <- df[-train.index,]
```

Linear Regression

```
linear_model <- lm(Churn ~ ., data = train.df)

# Predicting the  probabilities on the validation set
linear_probability <- predict(linear_model, valid.df)

# Displaying the summary of the linear regression model
summary(linear_model)

# Converting predicted probabilities to binary (0 or 1)
linear_pred <- ifelse(linear_probability > 0.5, 1, 0)

# Calculating accuracy for linear regression
```

```r
linear_accuracy <- mean(linear_pred == valid.df$Churn)
linear_accuracy

# Correlation matrix for logistic regression predictors
predictors <- model.matrix(~ Churn + . - 1, data = train.df)
cor_matrix <- cor(predictors)
```

```
Call:
lm(formula = Churn ~ ., data = train.df)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6091 -0.2727 -0.1507  0.4051  1.0890 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)       0.25284    0.04580   5.520 4.16e-08 ***
Partner          -0.06937    0.02808  -2.471  0.01362 *  
Dependents       -0.08624    0.03045  -2.832  0.00471 ** 
PhoneService      0.01988    0.04294   0.463  0.64351    
MultipleLines    -0.01417    0.02650  -0.535  0.59298    
OnlineSecurity   -0.12697    0.02947  -4.309 1.78e-05 ***
OnlineBackup     -0.04182    0.02736  -1.528  0.12668    
DeviceProtection -0.03305    0.02926  -1.130  0.25890    
TechSupport      -0.17306    0.02978  -5.812 7.94e-09 ***
StreamingTV       0.07949    0.02946   2.698  0.00707 ** 
StreamingMovies   0.11435    0.02925   3.910 9.76e-05 ***
PaperlessBilling  0.14253    0.02511   5.676 1.73e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4081 on 1188 degrees of freedom
Multiple R-squared:  0.1431,	Adjusted R-squared:  0.1351 
F-statistic: 18.03 on 11 and 1188 DF,  p-value: < 2.2e-16

[1] 0.735
```

Linear Regression Analysis

Low Impact on Churn:

PhoneService: The p-value is high (0.64351), suggesting that the presence or absence of phone service doesn't significantly impact churn.

MultipleLines: The p-value is high (0.59298), indicating that having multiple lines doesn't significantly impact churn.

DeviceProtection: The p-value is high (0.25890), suggesting that having device protection doesn't significantly impact churn.

Moderate Impact on Churn:

OnlineBackup: The p-value is somewhat high (0.12668), suggesting that having online backup may have a moderate impact on churn.

High Impact on Churn:

Partner: The p-value is relatively low (0.01362), indicating that having a partner significantly affects churn, potentially with a high impact.

Dependents: The p-value is relatively low (0.00471), suggesting that having dependents significantly affects churn, potentially with a high impact.

OnlineSecurity: The p-value is very low (1.78e-05), indicating that having online security significantly affects churn, potentially with a high impact.

TechSupport: The p-value is very low (7.94e-09), suggesting that having tech support significantly affects churn, potentially with a high impact.

StreamingTV: The p-value is low (0.00707), indicating that having streaming TV significantly affects churn, potentially with a high impact.

StreamingMovies: The p-value is low (9.76e-05), suggesting that having streaming movies significantly affects churn, potentially with a high impact.

PaperlessBilling: The p-value is very low (1.73e-08), indicating that having paperless billing significantly affects churn, potentially with a high impact.

Logistic Regression

```
model <- glm(Churn ~ ., data = train.df, family = "binomial")

# Predicting probabilities on the validation set
probability <- predict(model, valid.df, type= "response")

# Displaying the summary of the logistic regression model
summary(model)

# Calculating the predicted classes based on a threshold
predicted_classes <- ifelse(probability > 0.5, 1, 0)

# Calculating accuracy
accuracy_log <- mean(predicted_classes == valid.df$Churn)
accuracy_log
```

```
Call:
```

```
glm(formula = Churn ~ ., family = "binomial", data = train.df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5820  -0.7557  -0.4887   0.8634   2.6525

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)       -1.2638     0.2927  -4.318 1.58e-05 ***
Partner           -0.3980     0.1708  -2.330 0.019796 *
Dependents        -0.5711     0.2034  -2.808 0.004984 **
PhoneService       0.1567     0.2718   0.576 0.564321
MultipleLines     -0.1195     0.1615  -0.740 0.459281
OnlineSecurity    -0.9399     0.2053  -4.578 4.69e-06 ***
OnlineBackup      -0.2657     0.1692  -1.571 0.116228
DeviceProtection  -0.2303     0.1809  -1.273 0.203126
TechSupport       -1.1812     0.2056  -5.744 9.22e-09 ***
StreamingTV        0.4229     0.1773   2.385 0.017087 *
StreamingMovies    0.6931     0.1790   3.871 0.000108 ***
PaperlessBilling   0.9056     0.1620   5.590 2.27e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1375.3  on 1199  degrees of freedom
Residual deviance: 1181.5  on 1188  degrees of freedom
AIC: 1205.5

Number of Fisher Scoring iterations: 5

[1] 0.73375

cat("Logistic Regression Accuracy:", accuracy_log, "\n")
cat("Linear Regression Accuracy:", linear_accuracy, "\n")

Logistic Regression Accuracy: 0.73375
Linear Regression Accuracy: 0.735
```

The accuracy for logistic regression is relatively higher when compared to the linear regression which is just 73.5%. higher accuracy indicates better overall performance, therefore, logistic regression is a better model when we are trying to analyze customer churn. However, if we compared it to KNN, with k = 5 we get the highest accuracy making it a better model for the data set, moreover to analyse customer churn.

Logistic Regression Analysis

Low Impact on Churn

"PhoneService": The p-value is high (0.94281), suggesting that the presence or absence of phone service doesn't significantly impact churn.

MultipleLines: The p-value is high (0.67021), indicating that having multiple lines doesn't significantly impact churn.

DeviceProtection: The p-value is high (0.33008), suggesting that having device protection doesn't significantly impact churn.

Moderate Impact on Churn:

OnlineBackup: The p-value is somewhat high (0.09886), suggesting that having online backup may have a moderate impact on churn.

High Impact on Churn:

OnlineBackup: The p-value is somewhat high (0.09886), suggesting that having online backup may have a moderate impact on churn. **Partner:** The p-value is relatively low (0.03540), indicating that having a partner significantly affects churn, potentially with a high impact.

Dependents: The p-value is relatively low (0.00418), suggesting that having dependents significantly affects churn, potentially with a high impact.

OnlineSecurity: The p-value is very low (6.74e-06), indicating that having online security significantly affects churn, potentially with a high impact.

TechSupport: The p-value is very low (2.42e-09), suggesting that having tech support significantly affects churn, potentially with a high impact.

StreamingTV: The p-value is low (0.00306), indicating that having streaming TV significantly affects churn, potentially with a high impact.

StreamingMovies: The p-value is low (0.00270), suggesting that having streaming movies significantly affects churn, potentially with a high impact.

PaperlessBilling: The p-value is very low (1.16e-08), indicating that having paperless billing significantly affects churn, potentially with a high impact.

Performing normalization on all columns to ensure that these algorithms perform consistently.

```
# Creating a copy of the original dataset
df_copy <- df

# Performing normalization on all columns
norm.values <- preProcess(df_copy, method = c("center", "scale"))
train.norm.df <- predict(norm.values, train.df)
valid.norm.df <- predict(norm.values, valid.df)
churn.norm.df <- predict(norm.values, df_copy)
```

K-nearest neighbors algorithm

```
churn.pred1 <- knn(train = train.norm.df,
                   test = valid.norm.df,
                   cl = train.df$Churn,
                   k = 1)
# Calculating accuracy
accuracy1 <- mean(churn.pred1 == valid.df$Churn)
accuracy1

table(churn.pred1)
```

```
[1] 0.99125
```

```
churn.pred1
  0   1
591 209
```

with knn = 1 : accuracy rate of 99.13%, the model correctly predicted customer churn status in the validation dataset. In specific terms, it identified 591 instances as customers unlikely to churn and 209 instances as probable churners

```
churn.pred5 <- knn(train = train.norm.df,
                   test = valid.norm.df,
                   cl = train.df$Churn,
                   k = 5)
accuracy5 <- mean(churn.pred5 == valid.df$Churn)
accuracy5
table(churn.pred5)

# K=5 is the best k with highest accuracy
```

```
[1] 0.99375
```

```
churn.pred5
  0   1
591 209
```

with k = 5 , accuracy of 99.38%, using k = 5 demonstrated the highest performance among the tested k values. it classified 591 instances as customers unlikely to churn and 209 instances as likely to churn in the valid.df dataset. The instances are the same as when k=1, however k= 5 has given slightly higher accuracy compared to k=1

```
churn.pred7 <- knn(train = train.norm.df,
                   test = valid.norm.df,
                   cl = train.df$Churn,
                   k = 7)
accuracy7 <- mean(churn.pred7 == valid.df$Churn)
accuracy7
table(churn.pred7)
```

```
[1] 0.9925
```

```
churn.pred7
  0   1
592 208
```

with k = 7 , accuracy rate of 99.25%, model using k = 7 demonstrated a consistent performance . This model identified 592 instances as customers unlikely to churn and 208 instances as probable churners within the valid.df dataset.

```
churn.pred10 <- knn(train = train.norm.df,
                   test = valid.norm.df,
                   cl = train.df$Churn,
                   k = 10)
accuracy10 <- mean(churn.pred10 == valid.df$Churn)
accuracy10
table(churn.pred10)
```

```
[1] 0.98875
```

```
churn.pred10
  0   1
595 205
```

with k = 10, accuracy rate of 98.875%, model using k = 10 maintained a high accuracy however, is low compared to all the k values projected in the project to show customer churn. It classified 595 instances as customers unlikely to churn and 205 instances as probable churners within the valid.df dataset.

Neural Network - provides a measure of the model's accuracy in predicting churn, with a lower RMSE indicating better performance.

```
df <- df[c('Partner', 'Dependents', 'PhoneService', 'MultipleLines',
'OnlineSecurity',
                 'OnlineBackup', 'DeviceProtection', 'TechSupport',
'StreamingTV',
                 'StreamingMovies', 'PaperlessBilling', 'Churn')]

table(df$Churn)

set.seed(12345)
```

```
train.index <- sample(1:nrow(df), 0.75 * nrow(df))
train.df <- df[train.index, ]
valid.df <- df[-train.index, ]
```

```
   0    1
1474  526
```

```
norm.values <- preProcess(train.df, method="range")
train.norm.df <- predict(norm.values, train.df)
valid.norm.df <- predict(norm.values, valid.df)

str(train.norm.df)
```

```
tibble [1,500 × 12] (S3: tbl_df/tbl/data.frame)
 $ Partner         : num [1:1500] 0 0 1 0 0 1 1 0 0 1 ...
 $ Dependents      : num [1:1500] 0 0 0 0 0 1 1 0 0 1 ...
 $ PhoneService    : num [1:1500] 1 1 1 1 1 1 1 1 1 1 ...
 $ MultipleLines   : num [1:1500] 1 1 1 1 0 1 0 1 0 0 ...
 $ OnlineSecurity  : num [1:1500] 1 0 0 0 0 1 0 1 1 0 ...
 $ OnlineBackup    : num [1:1500] 0 1 0 1 0 1 1 0 1 0 ...
 $ DeviceProtection: num [1:1500] 0 0 1 1 0 0 1 1 0 0 ...
 $ TechSupport     : num [1:1500] 1 0 0 1 0 0 0 1 0 0 ...
 $ StreamingTV     : num [1:1500] 0 1 0 0 0 0 1 1 1 0 ...
 $ StreamingMovies : num [1:1500] 1 0 0 1 0 1 0 1 0 0 ...
 $ PaperlessBilling: num [1:1500] 0 1 1 1 0 1 1 1 1 1 ...
 $ Churn           : num [1:1500] 1 0 0 0 1 0 1 0 0 0 ...
```

```
#single layer with 2 nodes
set.seed(12345)
nn.model <- neuralnet(Churn ~ Partner + Dependents + PhoneService +
MultipleLines + OnlineSecurity +
                      OnlineBackup + DeviceProtection + TechSupport +
StreamingTV +
                      StreamingMovies + PaperlessBilling,
                      data=train.norm.df, hidden=2,
linear.output=TRUE)


train.pred <- compute(nn.model, train.norm.df[,-1])$net.result
valid.pred <- compute(nn.model, valid.norm.df[,-1])$net.result

train.rmse <- sqrt(mean((train.pred - train.norm.df$Churn)^2))
print(paste("Training RMSE with 1 hidden layer, 2 nodes:",
train.rmse))

valid.rmse <- sqrt(mean((valid.pred - valid.norm.df$Churn)^2))

print(paste("Validation RMSE with 1 hidden layer, 2 nodes:",
valid.rmse))
```

```
[1] "Training RMSE with 1 hidden layer, 2 nodes: 0.42093785531006"
[1] "Validation RMSE with 1 hidden layer, 2 nodes: 0.420646225976529"
```

```
#single layer having 5 nodes
nn.model_5nodes <- neuralnet(Churn ~ Partner + Dependents +
PhoneService + MultipleLines + OnlineSecurity +
                      OnlineBackup + DeviceProtection + TechSupport +
StreamingTV +
                      StreamingMovies + PaperlessBilling,
                      data=train.norm.df, hidden=5,
linear.output=TRUE)

train.pred_5nodes <- compute(nn.model_5nodes, train.norm.df[,-1])
$net.result

valid.pred_5nodes <- compute(nn.model_5nodes, valid.norm.df[,-1])
$net.result

train.rmse_5nodes <- sqrt(mean((train.pred_5nodes -
train.norm.df$Churn)^2))
print(paste("Training RMSE with 1 hidden layer, 5 nodes:",
train.rmse_5nodes))

valid.rmse_5nodes <- sqrt(mean((valid.pred_5nodes -
valid.norm.df$Churn)^2))
print(paste("Validation RMSE with 1 hidden layer, 5 nodes:",
valid.rmse_5nodes))
```

```
[1] "Training RMSE with 1 hidden layer, 5 nodes: 0.515841965479491"
[1] "Validation RMSE with 1 hidden layer, 5 nodes: 0.504100447384014"
```

```
#two layers 5 nodes
nn.model_5_5nodes <- neuralnet(Churn ~ Partner + Dependents +
PhoneService + MultipleLines + OnlineSecurity +
                      OnlineBackup + DeviceProtection + TechSupport +
StreamingTV +
                      StreamingMovies + PaperlessBilling,
                              data=train.norm.df, hidden=c(5,5),
linear.output=TRUE, stepmax=1e6)

train.pred_5_5nodes <- compute(nn.model_5_5nodes, train.norm.df[,-1])
$net.result

valid.pred_5_5nodes <- compute(nn.model_5_5nodes, valid.norm.df[,-1])
$net.result

train.rmse_5_5nodes <- sqrt(mean((train.pred_5_5nodes -
train.norm.df$Churn)^2))
print(paste("Training RMSE with 2 hidden layers, 5 nodes each:",
train.rmse_5_5nodes))
```

```
valid.rmse_5_5nodes <- sqrt(mean((valid.pred_5_5nodes -
valid.norm.df$Churn)^2))
print(paste("Validation RMSE with 2 hidden layers, 5 nodes each:",
valid.rmse_5_5nodes))
```

```
[1] "Training RMSE with 2 hidden layers, 5 nodes each:
0.530122171753128"
[1] "Validation RMSE with 2 hidden layers, 5 nodes each:
0.52956774163493"
```

```
# Dictionary to store RMSE values for each model
rmse_dict <- c(
  nn.model = valid.rmse,
  nn.model_5nodes = valid.rmse_5nodes,
  nn.model_5_5nodes = valid.rmse_5_5nodes
)

# Finding the model with the lowest validation RMSE
accurate_neural_network <- names(rmse_dict)
[which.min(unlist(rmse_dict))]
best_rmse <- min(unlist(rmse_dict))

cat("Best Model:", accurate_neural_network, "\n")
cat("Validation RMSE of the Best Model:", best_rmse, "\n")
```

```
Best Model: nn.model
Validation RMSE of the Best Model: 0.4206462
```

Overall KNN where k = 5, provides the highest accuracy for the model when compared to neural network with 5 nodes and 2 hidden layers giving an accuracy of 42.06%.

1. The training RMSE initially decreases when the model complexity increases from 1 hidden layer with 2 nodes to 1 hidden layer with 5 nodes. This suggests that a slightly more complex model (with more nodes) can better fit the training data. However, when further increasing the complexity by adding another layer (2 layers with 5 nodes each), the training RMSE increases.
2. For the validation data, the RMSE decreases when increasing the model complexity from 1 hidden layer with 2 nodes to 1 hidden layer with 5 nodes. This indicates improved performance on unseen data with a moderately more complex model. However, adding another layer (making it 2 layers with 5 nodes each) results in a slight increase in the validation RMSE. This trend suggests that the most complex model might be overfitting the training data and thus performing slightly worse on the validation set.
3. Considering both training and validation RMSE, the model with 1 hidden layer and 5 nodes seems to offer the best balance. It provides a good fit to the training data (as indicated by a relatively low training RMSE) while also maintaining a good performance on the validation data (as indicated by the lowest validation RMSE among the models tested).

BEST MODEL OUT OF ALL

```
# Creating a data frame with model names
model_names <- c("Logistic Regression", "KNN (k = 5)", "Linear
Regression", "Neural Network")
metrics <- c("Accuracy", "Accuracy", "Accuracy", "RMSE")
values <- c(accuracy_log, accuracy5, linear_accuracy, best_rmse)

# Creating the summary table
summary_table <- data.frame(Model = model_names, Metric = metrics,
Value = values)

print(summary_table)
```

```
                Model   Metric     Value
1 Logistic Regression Accuracy 0.7337500
2         KNN (k = 5) Accuracy 0.9937500
3   Linear Regression Accuracy 0.7350000
4      Neural Network     RMSE 0.4206462
```

The models tested and evaluated on metrics relevant to their methodology, the KNN model yields meaningfully stronger accuracy results. Leveraging similarity based pattern recognition, KNN achieves 99% test accuracy in classifying records. This significantly outperforms the 73% accuracy from both regression approaches.

Therefore, for highest accuracy predictive performance on this dataset, the K Nearest Neighbor model is presented as the best solution. The high reliability allows confidence in its churn predictions along with insights gathered from influential indicators within each record's nearest neighbors.

USING THE LOGISTIC MODEL TO PREDICT CHURN FOR A NEW CUSTOMER

```
new_data <- data.frame(
  Partner = 1,
  Dependents = 0,
  PhoneService = 1,
  MultipleLines = 0,
  OnlineSecurity = 1,
  OnlineBackup = 0,
  DeviceProtection = 1,
  TechSupport = 0,
  StreamingTV = 1,
  StreamingMovies = 0,
  PaperlessBilling = 1
)
```

```r
# Making predictions
predicted_churn <- predict(model, newdata = new_data, type =
"response")

# Setting a threshold for classification = 0.5
threshold <- 0.5
predicted_churn_value <- ifelse(predicted_churn > threshold, "Yes",
"No")

cat("Predicted Churn Value:", predicted_churn_value)
```

```
Predicted Churn Value: No
```

USING THE NEURAL NETWORK MODEL TO PREDICT CHURN FOR A NEW CUSTOMERN

```r
# Making predictions
predicted_churn_neural <- predict(nn.model, newdata = new_data, type =
"response")

# Setting a threshold for classification = 0.5
threshold <- 0.5
predicted_churn_value <- ifelse(predicted_churn > threshold, "Yes",
"No")

cat("Predicted Churn Value:", predicted_churn_value)
```

```
Predicted Churn Value: No
```