# Telecom Churn Case Study

With 21 predictor variables we need to predict whether a particular customer will switch to another telecom provider or not. In telecom terminology, this is referred to as churning and not churning, respectively.

## Step 1: Importing and Merging Data

```
# Suppressing Warnings
import warnings
warnings.filterwarnings('ignore')

# Importing Pandas and NumPy
import pandas as pd, numpy as np

data_details = pd.read_csv("Datasets/Dictionary.csv",encoding='latin-
1')
data_details
```

```
    S.No.     Variable Name   \
0       1        CustomerID
1       2            Gender
2       3     SeniorCitizen
3       4           Partner
4       5        Dependents
5       6            Tenure
6       7      PhoneService
7       8     MultipleLines
8       9   InternetService
9      10    OnlineSecurity
10     11      OnlineBackup
11     12  DeviceProtection
12     13       TechSupport
13     14       StreamingTV
14     15   StreamingMovies
15     16          Contract
16     17  PaperlessBilling
17     18     PaymentMethod
18     19    MonthlyCharges
19     20      TotalCharges
20     21             Churn

                                              Meaning
0                       The unique ID of each customer
1                               The gender of a person
2   Whether a customer can be classified as a seni...
3   If a customer is married/ in a live-in relatio...
4   If a customer has dependents (children/ retire...
5   The time for which a customer has been using t...
6   Whether a customer has a landline phone servic...
```

```
7   Whether a customer has multiple lines of inter...
8   The type of internet services chosen by the cu...
9        Specifies if a customer has online security.
10         Specifies if a customer has online backup.
11  Specifies if a customer has opted for device p...
12  Whether a customer has opted for tech support ...
13  Whether a customer has an option of TV streaming.
14  Whether a customer has an option of Movie stre...
15        The type of contract a customer has chosen.
16  Whether a customer has opted for paperless bil...
17      Specifies the method by which bills are paid.
18  Specifies the money paid by a customer each mo...
19  The total money paid by the customer to the co...
20  This is the target variable which specifies if...
```

```python
# Importing all datasets
churn_data = pd.read_csv("Datasets/churn_data.csv")
churn_data.head()
```

```
   customerID  tenure PhoneService        Contract PaperlessBilling  \
0  7590-VHVEG       1           No  Month-to-month              Yes
1  5575-GNVDE      34          Yes        One year               No
2  3668-QPYBK       2          Yes  Month-to-month              Yes
3  7795-CFOCW      45           No        One year               No
4  9237-HQITU       2          Yes  Month-to-month              Yes

               PaymentMethod  MonthlyCharges TotalCharges Churn
0           Electronic check           29.85        29.85    No
1               Mailed check           56.95       1889.5    No
2               Mailed check           53.85       108.15   Yes
3  Bank transfer (automatic)           42.30      1840.75    No
4           Electronic check           70.70       151.65   Yes
```

```python
customer_data = pd.read_csv("Datasets/customer_data.csv")
customer_data.head()
```

```
   customerID  gender  SeniorCitizen Partner Dependents
0  7590-VHVEG  Female              0     Yes         No
1  5575-GNVDE    Male              0      No         No
2  3668-QPYBK    Male              0      No         No
3  7795-CFOCW    Male              0      No         No
4  9237-HQITU  Female              0      No         No
```

```python
internet_data = pd.read_csv("Datasets/internet_data.csv")
internet_data.head()
```

```
   customerID     MultipleLines InternetService OnlineSecurity
OnlineBackup  \
0  7590-VHVEG  No phone service             DSL             No
Yes
1  5575-GNVDE                No             DSL            Yes
```

```
No
2  3668-QPYBK                No           DSL            Yes
Yes
3  7795-CFOCW  No phone service           DSL            Yes
No
4  9237-HQITU                No   Fiber optic             No
No

  DeviceProtection TechSupport StreamingTV StreamingMovies
0               No          No          No              No
1              Yes          No          No              No
2               No          No          No              No
3              Yes         Yes          No              No
4               No          No          No              No
```

Combining all data files into one consolidated dataframe

```
# Merging on 'customerID'
df_1 = pd.merge(churn_data, customer_data, how='inner',
on='customerID')

# Final dataframe with all predictor variables
telecom = pd.merge(df_1, internet_data, how='inner', on='customerID')
```

## Step 2: Inspecting the Dataframe

```
# Let's see the head of our master dataset
telecom.head()

   customerID  tenure PhoneService        Contract PaperlessBilling  \
0  7590-VHVEG       1           No  Month-to-month              Yes
1  5575-GNVDE      34          Yes        One year               No
2  3668-QPYBK       2          Yes  Month-to-month              Yes
3  7795-CFOCW      45           No        One year               No
4  9237-HQITU       2          Yes  Month-to-month              Yes

               PaymentMethod  MonthlyCharges TotalCharges Churn
gender  ...  \
0           Electronic check           29.85        29.85    No
Female  ...
1               Mailed check           56.95       1889.5    No
Male  ...
2               Mailed check           53.85       108.15   Yes
Male  ...
3  Bank transfer (automatic)           42.30      1840.75    No
Male  ...
4           Electronic check           70.70       151.65   Yes
Female  ...

   Partner Dependents     MultipleLines InternetService OnlineSecurity
```

```
\
0      Yes         No  No phone service             DSL              No

1       No         No                No             DSL             Yes

2       No         No                No             DSL             Yes

3       No         No  No phone service             DSL             Yes

4       No         No                No     Fiber optic              No


  OnlineBackup DeviceProtection TechSupport StreamingTV
StreamingMovies
0          Yes               No          No          No
No
1           No              Yes          No          No
No
2          Yes               No          No          No
No
3           No              Yes         Yes          No
No
4           No               No          No          No
No

[5 rows x 21 columns]
```

```
# Let's check the dimensions of the dataframe
telecom.shape
```

```
(7043, 21)
```

```
# let's look at the statistical aspects of the dataframe
telecom.describe()
```

```
            tenure  MonthlyCharges  SeniorCitizen
count  7043.000000     7043.000000    7043.000000
mean     32.371149       64.761692       0.162147
std      24.559481       30.090047       0.368612
min       0.000000       18.250000       0.000000
25%       9.000000       35.500000       0.000000
50%      29.000000       70.350000       0.000000
75%      55.000000       89.850000       0.000000
max      72.000000      118.750000       1.000000
```

```
# Let's see the type of each column
telecom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
```

```
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   tenure            7043 non-null   int64  
 2   PhoneService      7043 non-null   object 
 3   Contract          7043 non-null   object 
 4   PaperlessBilling  7043 non-null   object 
 5   PaymentMethod     7043 non-null   object 
 6   MonthlyCharges    7043 non-null   float64
 7   TotalCharges      7043 non-null   object 
 8   Churn             7043 non-null   object 
 9   gender            7043 non-null   object 
 10  SeniorCitizen     7043 non-null   int64  
 11  Partner           7043 non-null   object 
 12  Dependents        7043 non-null   object 
 13  MultipleLines     7043 non-null   object 
 14  InternetService   7043 non-null   object 
 15  OnlineSecurity    7043 non-null   object 
 16  OnlineBackup      7043 non-null   object 
 17  DeviceProtection  7043 non-null   object 
 18  TechSupport       7043 non-null   object 
 19  StreamingTV       7043 non-null   object 
 20  StreamingMovies   7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

## Step 3: Data Preparation

Converting some binary variables (Yes/No) to 0/1

```
# List of variables to map

varlist =  ['PhoneService', 'PaperlessBilling', 'Churn', 'Partner', 
'Dependents']

# Defining the map function
def binary_map(x):
    return x.map({'Yes': 1, "No": 0})

# Applying the function to the housing list
telecom[varlist] = telecom[varlist].apply(binary_map)

telecom.head()
```

```
   customerID  tenure  PhoneService        Contract  PaperlessBilling  
\
0  7590-VHVEG       1             0  Month-to-month                 1   

1  5575-GNVDE      34             1        One year                 0   
```

```
2  3668-QPYBK       2             1  Month-to-month                1

3  7795-CFOCW      45             0        One year                0

4  9237-HQITU       2             1  Month-to-month                1


               PaymentMethod  MonthlyCharges TotalCharges  Churn
gender  ...  \
0           Electronic check           29.85        29.85      0
Female  ...
1               Mailed check           56.95       1889.5      0
Male  ...
2               Mailed check           53.85       108.15      1
Male  ...
3  Bank transfer (automatic)           42.30      1840.75      0
Male  ...
4           Electronic check           70.70       151.65      1
Female  ...

   Partner  Dependents     MultipleLines InternetService
OnlineSecurity  \
0        1           0  No phone service             DSL
No
1        0           0                No             DSL
Yes
2        0           0                No             DSL
Yes
3        0           0  No phone service             DSL
Yes
4        0           0                No     Fiber optic
No

  OnlineBackup DeviceProtection TechSupport StreamingTV
StreamingMovies
0          Yes               No          No          No
No
1           No              Yes          No          No
No
2          Yes               No          No          No
No
3           No              Yes         Yes          No
No
4           No               No          No          No
No

[5 rows x 21 columns]
```

For categorical variables with multiple levels, create dummy features (one-hot encoded)

```
# Creating a dummy variable for some of the categorical variables and dropping the first one.
dummy1 = pd.get_dummies(telecom[['Contract', 'PaymentMethod', 'gender', 'InternetService']], drop_first=True)

# Adding the results to the master dataframe
telecom = pd.concat([telecom, dummy1], axis=1)

telecom.head()
```

```
   customerID  tenure  PhoneService        Contract  PaperlessBilling  \
0  7590-VHVEG       1             0  Month-to-month                 1

1  5575-GNVDE      34             1        One year                 0

2  3668-QPYBK       2             1  Month-to-month                 1

3  7795-CFOCW      45             0        One year                 0

4  9237-HQITU       2             1  Month-to-month                 1


              PaymentMethod  MonthlyCharges TotalCharges  Churn  gender  ...  \
0          Electronic check           29.85        29.85      0  Female  ...
1              Mailed check           56.95       1889.5      0    Male  ...
2              Mailed check           53.85       108.15      1    Male  ...
3  Bank transfer (automatic)           42.30      1840.75      0    Male  ...
4          Electronic check           70.70       151.65      1  Female  ...

   StreamingTV  StreamingMovies  Contract_One year Contract_Two year  \
0           No               No              False             False

1           No               No               True             False

2           No               No              False             False

3           No               No               True             False

4           No               No              False             False
```

```
  PaymentMethod_Credit card (automatic) PaymentMethod_Electronic check 
\
0                                  False                           True   

1                                  False                          False   

2                                  False                          False   

3                                  False                          False   

4                                  False                           True   


  PaymentMethod_Mailed check gender_Male InternetService_Fiber 
optic  \
0                      False       False                         False   

1                       True        True                         False   

2                       True        True                         False   

3                      False        True                         False   

4                      False       False                          True   


  InternetService_No  
0              False  
1              False  
2              False  
3              False  
4              False  

[5 rows x 29 columns]

# Creating dummy variables for the remaining categorical variables and 
dropping the level with big names.

# Creating dummy variables for the variable 'MultipleLines'
ml = pd.get_dummies(telecom['MultipleLines'], prefix='MultipleLines')
# Dropping MultipleLines_No phone service column
ml1 = ml.drop(['MultipleLines_No phone service'], axis=1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,ml1], axis=1)


# Creating dummy variables for the variable 'OnlineSecurity'.
os = pd.get_dummies(telecom['OnlineSecurity'], 
prefix='OnlineSecurity')
os1 = os.drop(['OnlineSecurity_No internet service'], axis=1)
```

```
# Adding the results to the master dataframe
telecom = pd.concat([telecom,os1], axis=1)


# Creating dummy variables for the variable 'OnlineBackup'.
ob = pd.get_dummies(telecom['OnlineBackup'], prefix='OnlineBackup')
ob1 = ob.drop(['OnlineBackup_No internet service'], axis=1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,ob1], axis=1)


# Creating dummy variables for the variable 'DeviceProtection'.
dp = pd.get_dummies(telecom['DeviceProtection'],
prefix='DeviceProtection')
dp1 = dp.drop(['DeviceProtection_No internet service'], axis=1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,dp1], axis=1)


# Creating dummy variables for the variable 'TechSupport'.
ts = pd.get_dummies(telecom['TechSupport'], prefix='TechSupport')
ts1 = ts.drop(['TechSupport_No internet service'], axis=1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,ts1], axis=1)


# Creating dummy variables for the variable 'StreamingTV'.
st =pd.get_dummies(telecom['StreamingTV'], prefix='StreamingTV')
st1 = st.drop(['StreamingTV_No internet service'], axis=1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,st1], axis=1)


# Creating dummy variables for the variable 'StreamingMovies'.
sm = pd.get_dummies(telecom['StreamingMovies'],
prefix='StreamingMovies')
sm1 = sm.drop(['StreamingMovies_No internet service'], axis=1)
# Adding the results to the master dataframe
telecom = pd.concat([telecom,sm1], axis=1)

telecom.head()
```

| | customerID | tenure | PhoneService | Contract | PaperlessBilling \ |
|---|---|---|---|---|---|
| 0 | 7590-VHVEG | 1 | 0 | Month-to-month | 1 |
| 1 | 5575-GNVDE | 34 | 1 | One year | 0 |
| 2 | 3668-QPYBK | 2 | 1 | Month-to-month | 1 |
| 3 | 7795-CFOCW | 45 | 0 | One year | 0 |

```
4  9237-HQITU       2            1  Month-to-month                1


                 PaymentMethod  MonthlyCharges TotalCharges  Churn
gender  ...  \
0           Electronic check           29.85        29.85      0
Female  ...
1               Mailed check           56.95       1889.5      0
Male  ...
2               Mailed check           53.85       108.15      1
Male  ...
3  Bank transfer (automatic)           42.30      1840.75      0
Male  ...
4           Electronic check           70.70       151.65      1
Female  ...

   OnlineBackup_No  OnlineBackup_Yes  DeviceProtection_No  \
0            False              True                 True
1             True             False                False
2            False              True                 True
3             True             False                False
4             True             False                 True

  DeviceProtection_Yes TechSupport_No TechSupport_Yes
StreamingTV_No  \
0                False           True           False           True

1                 True           True           False           True

2                False           True           False           True

3                 True          False            True           True

4                False           True           False           True


  StreamingTV_Yes StreamingMovies_No StreamingMovies_Yes
0           False               True               False
1           False               True               False
2           False               True               False
3           False               True               False
4           False               True               False

[5 rows x 43 columns]
```

## Dropping the repeated variables

```
# We have created dummies for the below variables, so we can drop them
telecom =
telecom.drop(['Contract','PaymentMethod','gender','MultipleLines','Int
```

```
ernetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies'], axis=1)

# Assuming 'TotalCharges' column contains strings that represent
numeric values
telecom['TotalCharges'] = pd.to_numeric(telecom['TotalCharges'],
errors='coerce')

# 'coerce' option will replace any parsing errors with NaN values

telecom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 32 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   customerID                             7043 non-null   object
 1   tenure                                 7043 non-null   int64
 2   PhoneService                           7043 non-null   int64
 3   PaperlessBilling                       7043 non-null   int64
 4   MonthlyCharges                         7043 non-null   float64
 5   TotalCharges                           7032 non-null   float64
 6   Churn                                  7043 non-null   int64
 7   SeniorCitizen                          7043 non-null   int64
 8   Partner                                7043 non-null   int64
 9   Dependents                             7043 non-null   int64
 10  Contract_One year                      7043 non-null   bool
 11  Contract_Two year                      7043 non-null   bool
 12  PaymentMethod_Credit card (automatic)  7043 non-null   bool
 13  PaymentMethod_Electronic check         7043 non-null   bool
 14  PaymentMethod_Mailed check             7043 non-null   bool
 15  gender_Male                            7043 non-null   bool
 16  InternetService_Fiber optic            7043 non-null   bool
 17  InternetService_No                     7043 non-null   bool
 18  MultipleLines_No                       7043 non-null   bool
 19  MultipleLines_Yes                      7043 non-null   bool
 20  OnlineSecurity_No                      7043 non-null   bool
 21  OnlineSecurity_Yes                     7043 non-null   bool
 22  OnlineBackup_No                        7043 non-null   bool
 23  OnlineBackup_Yes                       7043 non-null   bool
 24  DeviceProtection_No                    7043 non-null   bool
 25  DeviceProtection_Yes                   7043 non-null   bool
 26  TechSupport_No                         7043 non-null   bool
 27  TechSupport_Yes                        7043 non-null   bool
 28  StreamingTV_No                         7043 non-null   bool
 29  StreamingTV_Yes                        7043 non-null   bool
 30  StreamingMovies_No                     7043 non-null   bool
 31  StreamingMovies_Yes                    7043 non-null   bool
```

```
dtypes: bool(22), float64(2), int64(7), object(1)
memory usage: 701.7+ KB
```

Now you can see that you have all variables as numeric.

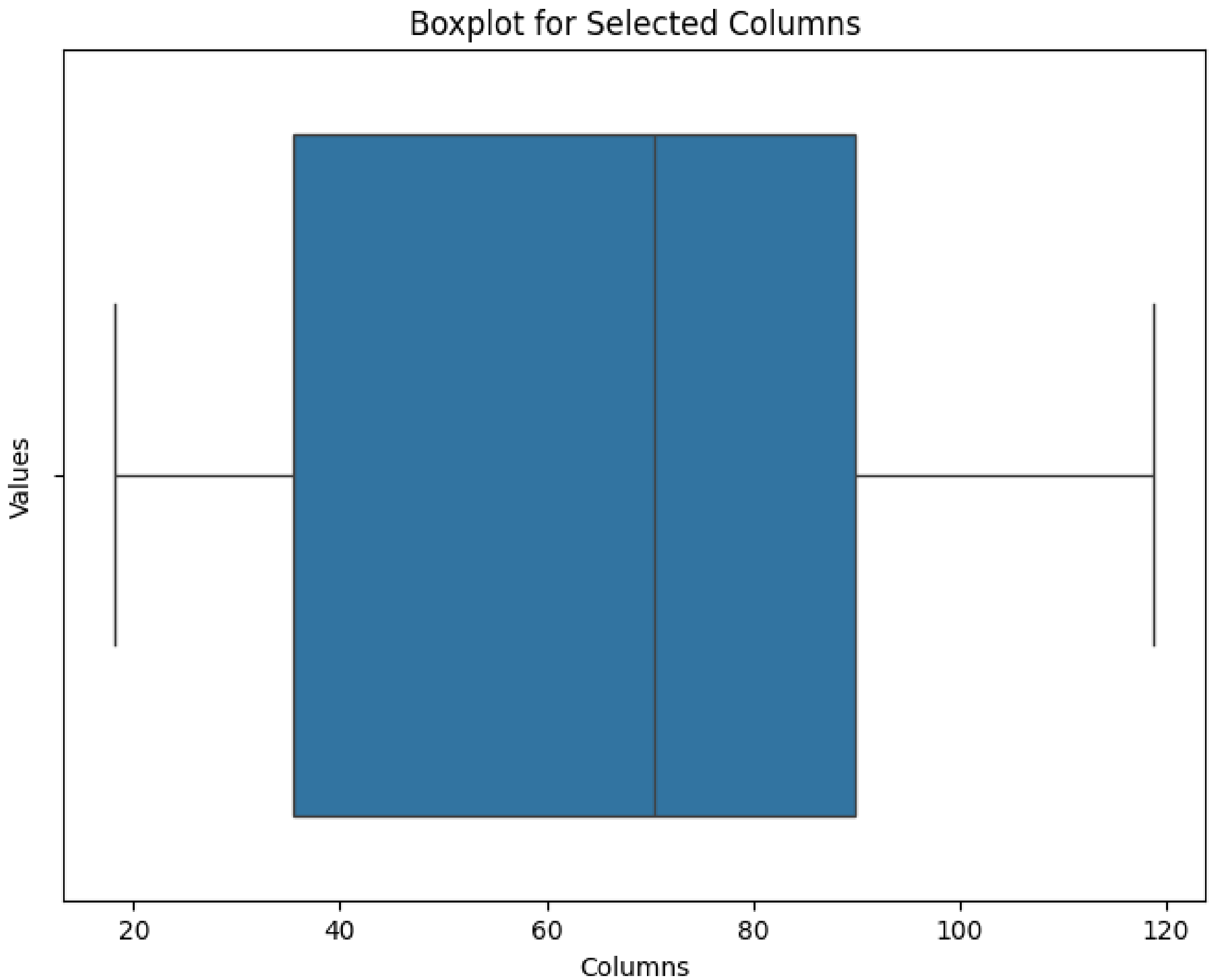
# Checking for Outliers

```
# Checking for outliers in the continuous variables
num_telecom =
telecom[['tenure','MonthlyCharges','SeniorCitizen','TotalCharges']]

num_telecom.head()

   tenure  MonthlyCharges  SeniorCitizen  TotalCharges
0       1           29.85              0         29.85
1      34           56.95              0       1889.50
2       2           53.85              0        108.15
3      45           42.30              0       1840.75
4       2           70.70              0        151.65

num_telecom.describe()

            tenure  MonthlyCharges  SeniorCitizen  TotalCharges
count  7043.000000     7043.000000    7043.000000   7032.000000
mean     32.371149       64.761692       0.162147   2283.300441
std      24.559481       30.090047       0.368612   2266.771362
min       0.000000       18.250000       0.000000     18.800000
25%       9.000000       35.500000       0.000000    401.450000
50%      29.000000       70.350000       0.000000   1397.475000
75%      55.000000       89.850000       0.000000   3794.737500
max      72.000000      118.750000       1.000000   8684.800000
```

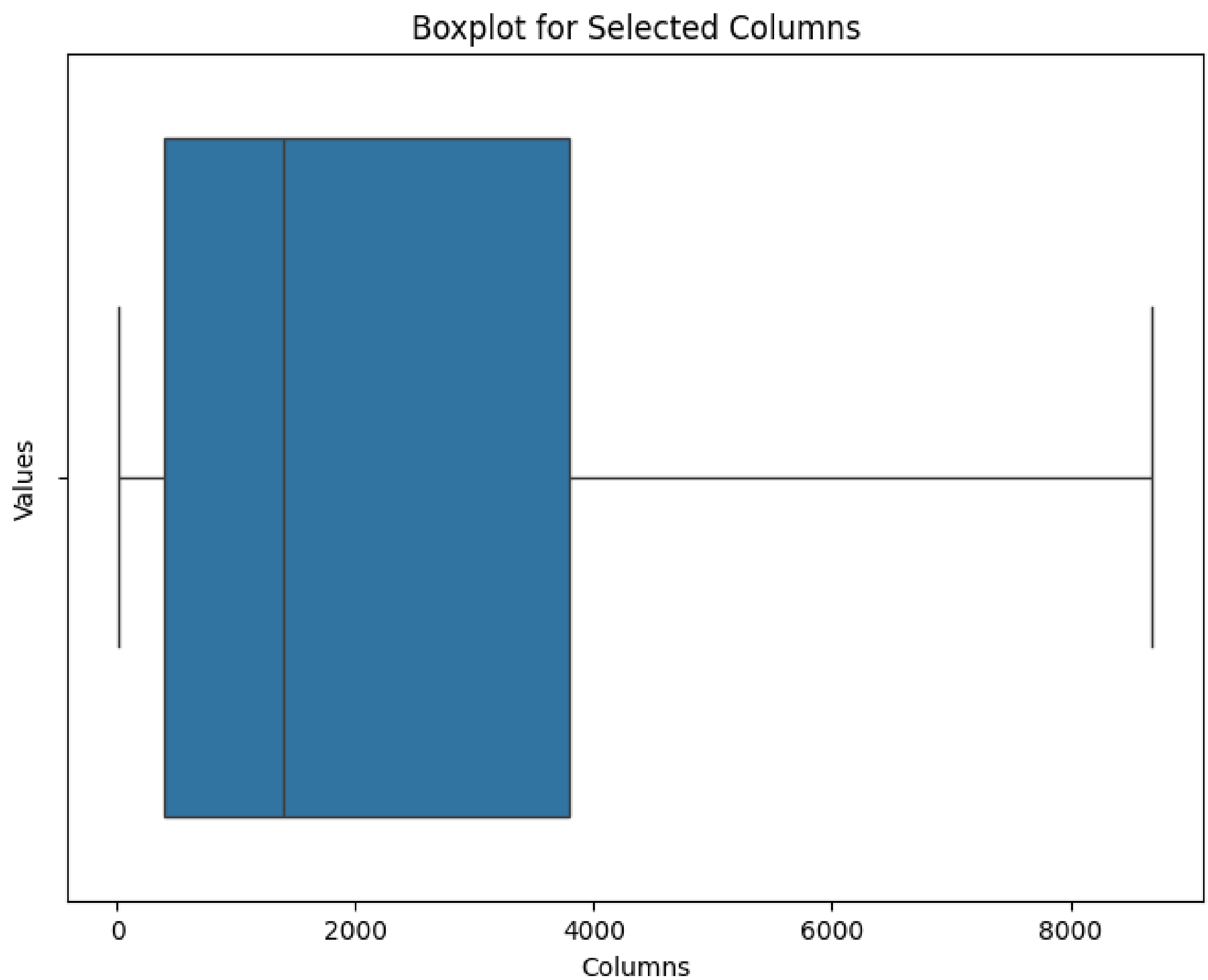
## ***Plotting boxplots for the variable***

- **MonthlyCharges**
- **TotalChagres**

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.boxplot(data=telecom,x=telecom['MonthlyCharges'])
plt.title('Boxplot for Selected Columns')
plt.ylabel('Values')
plt.xlabel('Columns')
plt.show()
```




```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.boxplot(data=telecom,x=telecom['TotalCharges'])
plt.title('Boxplot for Selected Columns')
plt.ylabel('Values')
plt.xlabel('Columns')
plt.show()
```




```
# Checking outliers at 25%, 50%, 75%, 90%, 95% and 99%
num_telecom.describe(percentiles=[.25, .5, .75, .90, .95, .99])
```

| | tenure | MonthlyCharges | SeniorCitizen | TotalCharges |
|---|---|---|---|---|
| count | 7043.000000 | 7043.000000 | 7043.000000 | 7032.000000 |
| mean | 32.371149 | 64.761692 | 0.162147 | 2283.300441 |
| std | 24.559481 | 30.090047 | 0.368612 | 2266.771362 |
| min | 0.000000 | 18.250000 | 0.000000 | 18.800000 |
| 25% | 9.000000 | 35.500000 | 0.000000 | 401.450000 |
| 50% | 29.000000 | 70.350000 | 0.000000 | 1397.475000 |
| 75% | 55.000000 | 89.850000 | 0.000000 | 3794.737500 |
| 90% | 69.000000 | 102.600000 | 1.000000 | 5976.640000 |
| 95% | 72.000000 | 107.400000 | 1.000000 | 6923.590000 |
| 99% | 72.000000 | 114.729000 | 1.000000 | 8039.883000 |
| max | 72.000000 | 118.750000 | 1.000000 | 8684.800000 |

From the distribution shown above, you can see that there no outliers in your data. The numbers are gradually increasing.

## Checking for Missing Values and Imputing Them

```
# Adding up the missing values (column-wise)
telecom.isnull().sum()
```

```
customerID                                0
tenure                                    0
PhoneService                              0
PaperlessBilling                          0
MonthlyCharges                            0
TotalCharges                             11
Churn                                     0
SeniorCitizen                             0
Partner                                   0
Dependents                                0
Contract_One year                         0
Contract_Two year                         0
PaymentMethod_Credit card (automatic)     0
PaymentMethod_Electronic check            0
PaymentMethod_Mailed check                0
gender_Male                               0
InternetService_Fiber optic               0
InternetService_No                        0
MultipleLines_No                          0
MultipleLines_Yes                         0
OnlineSecurity_No                         0
OnlineSecurity_Yes                        0
OnlineBackup_No                           0
OnlineBackup_Yes                          0
DeviceProtection_No                       0
DeviceProtection_Yes                      0
TechSupport_No                            0
TechSupport_Yes                           0
StreamingTV_No                            0
StreamingTV_Yes                           0
StreamingMovies_No                        0
StreamingMovies_Yes                       0
dtype: int64
```

It means that 11/7043 = 0.001561834 i.e 0.1%, best is to remove these observations from the analysis

```
# Checking the percentage of missing values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

```
customerID                               0.00
tenure                                   0.00
PhoneService                             0.00
PaperlessBilling                         0.00
MonthlyCharges                           0.00
```

```
TotalCharges                                 0.16
Churn                                        0.00
SeniorCitizen                                0.00
Partner                                      0.00
Dependents                                   0.00
Contract_One year                            0.00
Contract_Two year                            0.00
PaymentMethod_Credit card (automatic)        0.00
PaymentMethod_Electronic check               0.00
PaymentMethod_Mailed check                   0.00
gender_Male                                  0.00
InternetService_Fiber optic                  0.00
InternetService_No                           0.00
MultipleLines_No                             0.00
MultipleLines_Yes                            0.00
OnlineSecurity_No                            0.00
OnlineSecurity_Yes                           0.00
OnlineBackup_No                              0.00
OnlineBackup_Yes                             0.00
DeviceProtection_No                          0.00
DeviceProtection_Yes                         0.00
TechSupport_No                               0.00
TechSupport_Yes                              0.00
StreamingTV_No                               0.00
StreamingTV_Yes                              0.00
StreamingMovies_No                           0.00
StreamingMovies_Yes                          0.00
dtype: float64
```

```
# Removing NaN TotalCharges rows
telecom = telecom[~np.isnan(telecom['TotalCharges'])]

# Checking percentage of missing values after removing the missing
values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

```
customerID                                   0.0
tenure                                       0.0
PhoneService                                 0.0
PaperlessBilling                             0.0
MonthlyCharges                               0.0
TotalCharges                                 0.0
Churn                                        0.0
SeniorCitizen                                0.0
Partner                                      0.0
Dependents                                   0.0
Contract_One year                            0.0
Contract_Two year                            0.0
PaymentMethod_Credit card (automatic)        0.0
PaymentMethod_Electronic check               0.0
```

```
PaymentMethod_Mailed check              0.0
gender_Male                             0.0
InternetService_Fiber optic             0.0
InternetService_No                      0.0
MultipleLines_No                        0.0
MultipleLines_Yes                       0.0
OnlineSecurity_No                       0.0
OnlineSecurity_Yes                      0.0
OnlineBackup_No                         0.0
OnlineBackup_Yes                        0.0
DeviceProtection_No                     0.0
DeviceProtection_Yes                    0.0
TechSupport_No                          0.0
TechSupport_Yes                         0.0
StreamingTV_No                          0.0
StreamingTV_Yes                         0.0
StreamingMovies_No                      0.0
StreamingMovies_Yes                     0.0
dtype: float64
```

Now we don't have any missing values

## Step 4: Test-Train Split

```
from sklearn.model_selection import train_test_split

# Putting feature variable to X
X = telecom.drop(['Churn','customerID'], axis=1)

X.head()

   tenure  PhoneService  PaperlessBilling  MonthlyCharges
TotalCharges  \
0       1             0                 1           29.85
29.85
1      34             1                 0           56.95
1889.50
2       2             1                 1           53.85
108.15
3      45             0                 0           42.30
1840.75
4       2             1                 1           70.70
151.65

   SeniorCitizen  Partner  Dependents  Contract_One year  Contract_Two
year  \
0              0        1           0              False
False
1              0        0           0               True
False
```

```
2                0        0            0               False
False
3                0        0            0                True
False
4                0        0            0               False
False

   ...  OnlineBackup_No  OnlineBackup_Yes  DeviceProtection_No  \
0  ...            False              True                 True
1  ...             True             False                False
2  ...            False              True                 True
3  ...             True             False                False
4  ...             True             False                 True

   DeviceProtection_Yes  TechSupport_No  TechSupport_Yes
StreamingTV_No  \
0                 False            True            False
True
1                  True            True            False
True
2                 False            True            False
True
3                  True           False             True
True
4                 False            True            False
True

   StreamingTV_Yes  StreamingMovies_No  StreamingMovies_Yes
0            False                True                False
1            False                True                False
2            False                True                False
3            False                True                False
4            False                True                False

[5 rows x 30 columns]
```

```python
# Putting response variable to y
y = telecom['Churn']

y.head()
```

```
0    0
1    0
2    1
3    0
4    1
Name: Churn, dtype: int64
```

```python
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, 
train_size=0.7, test_size=0.3, random_state=100)
```

## Step 5: Feature Scaling

```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train[['tenure','MonthlyCharges','TotalCharges']] = 
scaler.fit_transform(X_train[['tenure','MonthlyCharges','TotalCharges'
]])

X_train.head()
```

```
        tenure  PhoneService  PaperlessBilling  MonthlyCharges  
TotalCharges  \
879   0.019693             1                 1       -0.338074     -
0.276449   
5790  0.305384             0                 1       -0.464443     -
0.112702   
6498 -1.286319             1                 1        0.581425     -
0.974430   
880  -0.919003             1                 1        1.505913     -
0.550676   
2784 -1.163880             1                 1        1.106854     -
0.835971   

      SeniorCitizen  Partner  Dependents  Contract_One year  \
879               0        0           0              False   
5790              0        1           1              False   
6498              0        0           0              False   
880               0        0           0              False   
2784              0        0           1              False   

      Contract_Two year  ...  OnlineBackup_No  OnlineBackup_Yes  \
879               False  ...            False              True   
5790              False  ...            False              True   
6498              False  ...            False              True   
880               False  ...            False              True   
2784              False  ...             True             False   

      DeviceProtection_No  DeviceProtection_Yes  TechSupport_No  \
879                  True                 False            True   
5790                 True                 False            True   
6498                False                  True            True   
880                 False                  True           False   
2784                False                  True           False   
```

```
      TechSupport_Yes  StreamingTV_No  StreamingTV_Yes
StreamingMovies_No  \
879             False            True            False
True
5790            False           False             True
False
6498            False            True            False
True
880              True           False             True
False
2784             True           False             True
False

      StreamingMovies_Yes
879                 False
5790                 True
6498                False
880                  True
2784                 True

[5 rows x 30 columns]

### Checking the Churn Rate
churn = (sum(telecom['Churn'])/len(telecom['Churn'].index))*100
churn

26.578498293515356
```

We have almost 27% churn rate

## Step 6: Looking at Correlations

```
# Importing matplotlib and seaborn
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

telecom.info()

<class 'pandas.core.frame.DataFrame'>
Index: 7032 entries, 0 to 7042
Data columns (total 32 columns):
 #   Column                                 Non-Null Count  Dtype  
---  ------                                 --------------  -----  
 0   customerID                             7032 non-null   object 
 1   tenure                                 7032 non-null   int64  
 2   PhoneService                           7032 non-null   int64  
 3   PaperlessBilling                       7032 non-null   int64  
 4   MonthlyCharges                         7032 non-null   float64
 5   TotalCharges                           7032 non-null   float64
```

```
 6   Churn                                   7032 non-null   int64
 7   SeniorCitizen                           7032 non-null   int64
 8   Partner                                 7032 non-null   int64
 9   Dependents                              7032 non-null   int64
 10  Contract_One year                       7032 non-null   bool
 11  Contract_Two year                       7032 non-null   bool
 12  PaymentMethod_Credit card (automatic)  7032 non-null   bool
 13  PaymentMethod_Electronic check          7032 non-null   bool
 14  PaymentMethod_Mailed check              7032 non-null   bool
 15  gender_Male                             7032 non-null   bool
 16  InternetService_Fiber optic             7032 non-null   bool
 17  InternetService_No                      7032 non-null   bool
 18  MultipleLines_No                        7032 non-null   bool
 19  MultipleLines_Yes                       7032 non-null   bool
 20  OnlineSecurity_No                       7032 non-null   bool
 21  OnlineSecurity_Yes                      7032 non-null   bool
 22  OnlineBackup_No                         7032 non-null   bool
 23  OnlineBackup_Yes                        7032 non-null   bool
 24  DeviceProtection_No                     7032 non-null   bool
 25  DeviceProtection_Yes                    7032 non-null   bool
 26  TechSupport_No                          7032 non-null   bool
 27  TechSupport_Yes                         7032 non-null   bool
 28  StreamingTV_No                          7032 non-null   bool
 29  StreamingTV_Yes                         7032 non-null   bool
 30  StreamingMovies_No                      7032 non-null   bool
 31  StreamingMovies_Yes                     7032 non-null   bool
dtypes: bool(22), float64(2), int64(7), object(1)
memory usage: 755.4+ KB
```

```
telecom.columns
```

```
Index(['customerID', 'tenure', 'PhoneService', 'PaperlessBilling',
       'MonthlyCharges', 'TotalCharges', 'Churn', 'SeniorCitizen',
'Partner',
       'Dependents', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check',
       'gender_Male', 'InternetService_Fiber optic',
'InternetService_No',
       'MultipleLines_No', 'MultipleLines_Yes', 'OnlineSecurity_No',
       'OnlineSecurity_Yes', 'OnlineBackup_No', 'OnlineBackup_Yes',
       'DeviceProtection_No', 'DeviceProtection_Yes',
'TechSupport_No',
       'TechSupport_Yes', 'StreamingTV_No', 'StreamingTV_Yes',
       'StreamingMovies_No', 'StreamingMovies_Yes'],
      dtype='object')
```

```
telecom['customerID']
```

```
0       7590-VHVEG
1       5575-GNVDE
2       3668-QPYBK
3       7795-CFOCW
4       9237-HQITU
           ...
7038    6840-RESVB
7039    2234-XADUH
7040    4801-JZAZL
7041    8361-LTMKD
7042    3186-AJIEK
Name: customerID, Length: 7032, dtype: object
```

- **Dropping the** *customerID*** column from the telecom dataset.**

- **and creating the** *tele_corr*** variableand creating the correlation table**

```
tele_corr = telecom.drop('customerID',axis=1,inplace=True)

tele_corr

telecom_corr = telecom.corr()
telecom_corr
```

```
                                         tenure  PhoneService  \
tenure                                 1.000000      0.007877
PhoneService                           0.007877      1.000000
PaperlessBilling                       0.004823      0.016696
MonthlyCharges                         0.246862      0.248033
TotalCharges                           0.825880      0.113008
Churn                                 -0.354049      0.011691
SeniorCitizen                          0.015683      0.008392
Partner                                0.381912      0.018397
Dependents                             0.163386     -0.001078
Contract_One year                      0.202338     -0.003142
Contract_Two year                      0.563801      0.004442
PaymentMethod_Credit card (automatic)  0.232800     -0.006916
PaymentMethod_Electronic check        -0.210197      0.002747
PaymentMethod_Mailed check            -0.232181     -0.004463
gender_Male                            0.005285     -0.007515
InternetService_Fiber optic            0.017930      0.290183
InternetService_No                    -0.037529      0.171817
MultipleLines_No                      -0.323891      0.315218
MultipleLines_Yes                      0.332399      0.279530
OnlineSecurity_No                     -0.265987     -0.058546
OnlineSecurity_Yes                     0.328297     -0.091676
```

```
OnlineBackup_No                             -0.314769     -0.092579
OnlineBackup_Yes                             0.361138     -0.052133
DeviceProtection_No                         -0.314820     -0.075421
DeviceProtection_Yes                         0.361520     -0.070076
TechSupport_No                              -0.264363     -0.055102
TechSupport_Yes                              0.325288     -0.095138
StreamingTV_No                              -0.246814     -0.123159
StreamingTV_Yes                              0.280264     -0.021383
StreamingMovies_No                          -0.252890     -0.111273
StreamingMovies_Yes                          0.285402     -0.033477

                                       PaperlessBilling
MonthlyCharges  \
tenure                                         0.004823
0.246862
PhoneService                                   0.016696
0.248033
PaperlessBilling                               1.000000
0.351930
MonthlyCharges                                 0.351930
1.000000
TotalCharges                                   0.157830
0.651065
Churn                                          0.191454
0.192858
SeniorCitizen                                  0.156258
0.219874
Partner                                       -0.013957
0.097825
Dependents                                    -0.110131        -
0.112343
Contract_One year                             -0.052278
0.004810
Contract_Two year                             -0.146281        -
0.073256
PaymentMethod_Credit card (automatic)         -0.013726
0.030055
PaymentMethod_Electronic check                 0.208427
0.271117
PaymentMethod_Mailed check                    -0.203981        -
0.376568
gender_Male                                   -0.011902        -
0.013779
InternetService_Fiber optic                    0.326470
0.787195
InternetService_No                            -0.320592        -
0.763191
MultipleLines_No                              -0.151974        -
0.338514
```

```
MultipleLines_Yes                                             0.163746
0.490912
OnlineSecurity_No                                             0.267592
0.360220
OnlineSecurity_Yes                                           -0.004051
0.296447
OnlineBackup_No                                               0.144218
0.210126
OnlineBackup_Yes                                              0.127056
0.441529
DeviceProtection_No                                           0.166253
0.171057
DeviceProtection_Yes                                          0.104079
0.482607
TechSupport_No                                                0.229875
0.321267
TechSupport_Yes                                               0.037536
0.338301
StreamingTV_No                                                0.046715
0.016015
StreamingTV_Yes                                               0.224241
0.629668
StreamingMovies_No                                            0.058987
0.017271
StreamingMovies_Yes                                           0.211583
0.627235

                                       TotalCharges     Churn
SeniorCitizen  \
tenure                                     0.825880 -0.354049
0.015683
PhoneService                               0.113008  0.011691
0.008392
PaperlessBilling                           0.157830  0.191454
0.156258
MonthlyCharges                             0.651065  0.192858
0.219874
TotalCharges                               1.000000 -0.199484
0.102411
Churn                                     -0.199484  1.000000
0.150541
SeniorCitizen                              0.102411  0.150541
1.000000
Partner                                    0.319072 -0.149982
0.016957
Dependents                                 0.064653 -0.163128       -
0.210550
Contract_One year                          0.170569 -0.178225       -
0.046491
```

```
Contract_Two year                          0.358036 -0.301552      -
0.116205
PaymentMethod_Credit card (automatic)      0.182663 -0.134687      -
0.024359
PaymentMethod_Electronic check            -0.060436  0.301455
0.171322
PaymentMethod_Mailed check                -0.294708 -0.090773      -
0.152987
gender_Male                                0.000048 -0.008545      -
0.001819
InternetService_Fiber optic                0.360769  0.307463
0.254923
InternetService_No                        -0.374878 -0.227578      -
0.182519
MultipleLines_No                          -0.396765 -0.032654      -
0.136377
MultipleLines_Yes                          0.469042  0.040033
0.142996
OnlineSecurity_No                         -0.064515  0.342235
0.185145
OnlineSecurity_Yes                         0.412619 -0.171270      -
0.038576
OnlineBackup_No                           -0.177633  0.267595
0.087539
OnlineBackup_Yes                           0.510100 -0.082307
0.066663
DeviceProtection_No                       -0.189485  0.252056
0.094403
DeviceProtection_Yes                       0.522881 -0.066193
0.059514
TechSupport_No                            -0.084270  0.336877
0.205254
TechSupport_Yes                            0.432868 -0.164716      -
0.060577
StreamingTV_No                            -0.197144  0.128435
0.048664
StreamingTV_Yes                            0.515709  0.063254
0.105445
StreamingMovies_No                        -0.202605  0.130920
0.034196
StreamingMovies_Yes                        0.519867  0.060860
0.119842

                                        Partner  Dependents  \
tenure                                 0.381912    0.163386
PhoneService                           0.018397   -0.001078
PaperlessBilling                      -0.013957   -0.110131
MonthlyCharges                         0.097825   -0.112343
TotalCharges                           0.319072    0.064653
```

```
Churn                                  -0.149982   -0.163128
SeniorCitizen                           0.016957   -0.210550
Partner                                 1.000000    0.452269
Dependents                              0.452269    1.000000
Contract_One year                       0.083067    0.069222
Contract_Two year                       0.247334    0.201699
PaymentMethod_Credit card (automatic)  0.082327    0.061134
PaymentMethod_Electronic check         -0.083207   -0.149274
PaymentMethod_Mailed check             -0.096948    0.056448
gender_Male                            -0.001379    0.010349
InternetService_Fiber optic             0.001235   -0.164101
InternetService_No                     -0.000286    0.138383
MultipleLines_No                       -0.130028    0.023388
MultipleLines_Yes                       0.142561   -0.024307
OnlineSecurity_No                      -0.129394   -0.186979
OnlineSecurity_Yes                      0.143346    0.080786
OnlineBackup_No                        -0.135626   -0.137421
OnlineBackup_Yes                        0.141849    0.023639
DeviceProtection_No                    -0.146702   -0.128053
DeviceProtection_Yes                    0.153556    0.013900
TechSupport_No                         -0.108875   -0.171164
TechSupport_Yes                         0.120206    0.063053
StreamingTV_No                         -0.123394   -0.099912
StreamingTV_Yes                         0.124483   -0.016499
StreamingMovies_No                     -0.117488   -0.078245
StreamingMovies_Yes                     0.118108   -0.038375

                                        Contract_One year  ...  \
tenure                                           0.202338  ...
PhoneService                                    -0.003142  ...
PaperlessBilling                                -0.052278  ...
MonthlyCharges                                   0.004810  ...
TotalCharges                                     0.170569  ...
Churn                                           -0.178225  ...
SeniorCitizen                                   -0.046491  ...
Partner                                          0.083067  ...
Dependents                                       0.069222  ...
Contract_One year                                1.000000  ...
Contract_Two year                               -0.288843  ...
PaymentMethod_Credit card (automatic)            0.067590  ...
PaymentMethod_Electronic check                  -0.109546  ...
PaymentMethod_Mailed check                       0.000197  ...
gender_Male                                      0.007755  ...
InternetService_Fiber optic                     -0.076809  ...
InternetService_No                               0.038061  ...
MultipleLines_No                                 0.001694  ...
MultipleLines_Yes                               -0.003594  ...
OnlineSecurity_No                               -0.122360  ...
OnlineSecurity_Yes                               0.100658  ...
```

```
OnlineBackup_No                                    -0.112133  ...
OnlineBackup_Yes                                    0.084113  ...
DeviceProtection_No                                -0.130038  ...
DeviceProtection_Yes                                0.102911  ...
TechSupport_No                                     -0.118709  ...
TechSupport_Yes                                     0.096258  ...
StreamingTV_No                                     -0.093495  ...
StreamingTV_Yes                                     0.061930  ...
StreamingMovies_No                                 -0.096613  ...
StreamingMovies_Yes                                 0.064780  ...

                                       OnlineBackup_No
OnlineBackup_Yes  \
tenure                                       -0.314769
0.361138
PhoneService                                 -0.092579          -
0.052133
PaperlessBilling                              0.144218
0.127056
MonthlyCharges                                0.210126
0.441529
TotalCharges                                 -0.177633
0.510100
Churn                                         0.267595          -
0.082307
SeniorCitizen                                 0.087539
0.066663
Partner                                      -0.135626
0.141849
Dependents                                   -0.137421
0.023639
Contract_One year                            -0.112133
0.084113
Contract_Two year                            -0.287128
0.111391
PaymentMethod_Credit card (automatic)        -0.088189
0.090455
PaymentMethod_Electronic check                0.236414          -
0.000364
PaymentMethod_Mailed check                   -0.098438          -
0.174075
gender_Male                                   0.008605          -
0.013093
InternetService_Fiber optic                   0.227363
0.165940
InternetService_No                           -0.464528          -
0.380990
MultipleLines_No                             -0.036126          -
0.230724
```

```
MultipleLines_Yes                                   -0.018853
0.202228
OnlineSecurity_No                                    0.378167
0.057475
OnlineSecurity_Yes                                   0.004708
0.283285
OnlineBackup_No                                      1.000000          -
0.641788
OnlineBackup_Yes                                    -0.641788
1.000000
DeviceProtection_No                                  0.361238
0.025934
DeviceProtection_Yes                                 0.025045
0.303058
TechSupport_No                                       0.385055
0.047079
TechSupport_Yes                                     -0.002871
0.293705
StreamingTV_No                                       0.316440
0.040505
StreamingTV_Yes                                      0.074460
0.281601
StreamingMovies_No                                   0.307188
0.047094
StreamingMovies_Yes                                  0.084142
0.274523

                                       DeviceProtection_No  \
tenure                                           -0.314820
PhoneService                                     -0.075421
PaperlessBilling                                  0.166253
MonthlyCharges                                    0.171057
TotalCharges                                     -0.189485
Churn                                             0.252056
SeniorCitizen                                     0.094403
Partner                                          -0.146702
Dependents                                       -0.128053
Contract_One year                                -0.130038
Contract_Two year                                -0.338520
PaymentMethod_Credit card (automatic)            -0.108008
PaymentMethod_Electronic check                    0.239173
PaymentMethod_Mailed check                       -0.085850
gender_Male                                      -0.003163
InternetService_Fiber optic                       0.217449
InternetService_No                               -0.465468
MultipleLines_No                                 -0.026582
MultipleLines_Yes                                -0.018242
OnlineSecurity_No                                 0.371496
OnlineSecurity_Yes                                0.012940
```

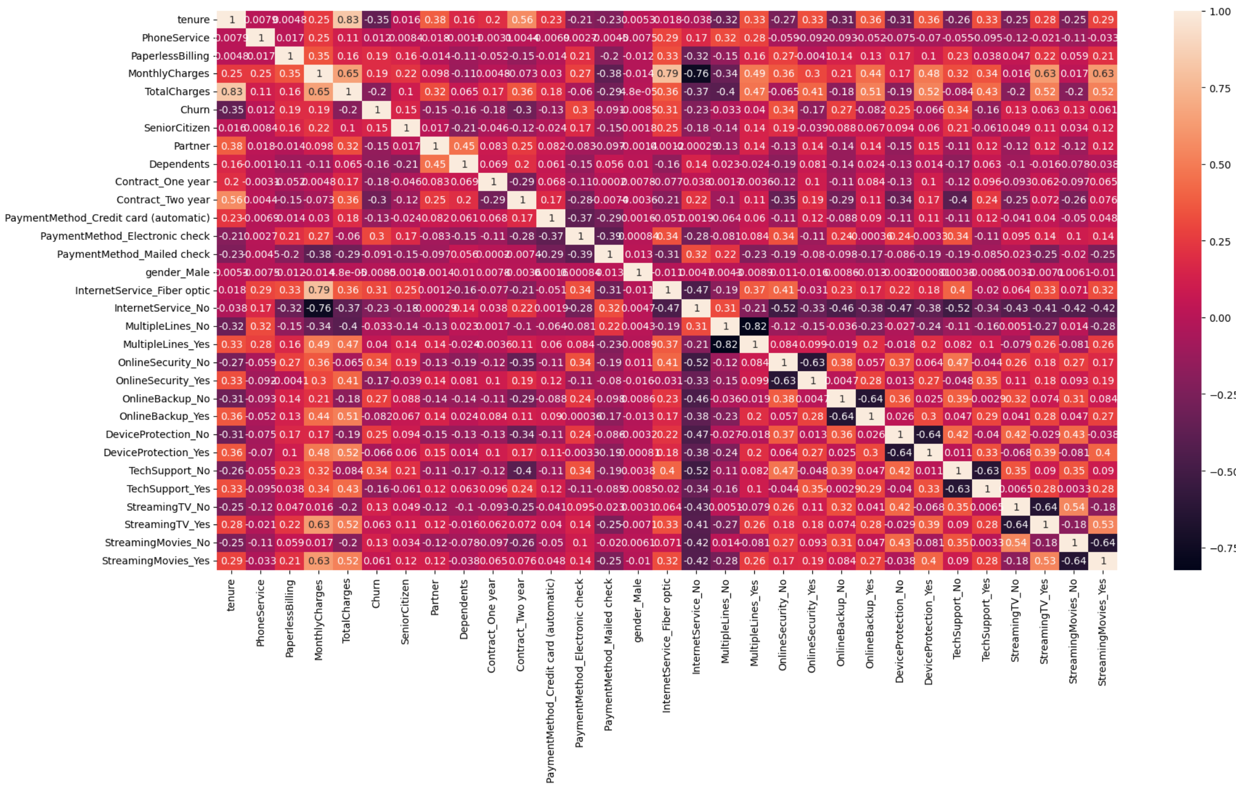
```
OnlineBackup_No                                     0.361238
OnlineBackup_Yes                                    0.025934
DeviceProtection_No                                 1.000000
DeviceProtection_Yes                               -0.641670
TechSupport_No                                      0.419653
TechSupport_Yes                                    -0.040135
StreamingTV_No                                      0.420013
StreamingTV_Yes                                    -0.029028
StreamingMovies_No                                  0.429705
StreamingMovies_Yes                                -0.037978

                                       DeviceProtection_Yes
TechSupport_No  \
tenure                                             0.361520       -
0.264363
PhoneService                                      -0.070076       -
0.055102
PaperlessBilling                                   0.104079
0.229875
MonthlyCharges                                     0.482607
0.321267
TotalCharges                                       0.522881       -
0.084270
Churn                                             -0.066193
0.336877
SeniorCitizen                                      0.059514
0.205254
Partner                                            0.153556       -
0.108875
Dependents                                         0.013900       -
0.171164
Contract_One year                                  0.102911       -
0.118709
Contract_Two year                                  0.165248       -
0.397788
PaymentMethod_Credit card (automatic)              0.111252       -
0.107761
PaymentMethod_Electronic check                    -0.003308
0.338529
PaymentMethod_Mailed check                        -0.187325       -
0.186388
gender_Male                                       -0.000807
0.003815
InternetService_Fiber optic                        0.176356
0.401869
InternetService_No                                -0.380151       -
0.518599
MultipleLines_No                                  -0.240847       -
0.114036
```

```
MultipleLines_Yes                                           0.201733
0.082396
OnlineSecurity_No                                           0.064389
0.470113
OnlineSecurity_Yes                                          0.274875        -
0.047742
OnlineBackup_No                                             0.025045
0.385055
OnlineBackup_Yes                                            0.303058
0.047079
DeviceProtection_No                                        -0.641670
0.419653
DeviceProtection_Yes                                        1.000000
0.010856
TechSupport_No                                              0.010856
1.000000
TechSupport_Yes                                             0.332850        -
0.631310
StreamingTV_No                                             -0.067785
0.346743
StreamingTV_Yes                                             0.389924
0.089703
StreamingMovies_No                                         -0.080986
0.346651
StreamingMovies_Yes                                         0.402309
0.090218

                                       TechSupport_Yes  StreamingTV_No
\
tenure                                        0.325288       -0.246814

PhoneService                                 -0.095138       -0.123159

PaperlessBilling                              0.037536        0.046715

MonthlyCharges                                0.338301        0.016015

TotalCharges                                  0.432868       -0.197144

Churn                                        -0.164716        0.128435

SeniorCitizen                                -0.060577        0.048664

Partner                                       0.120206       -0.123394

Dependents                                    0.063053       -0.099912

Contract_One year                             0.096258       -0.093495

Contract_Two year                             0.240924       -0.254456
```

```
PaymentMethod_Credit card (automatic)          0.117024       -0.041309
PaymentMethod_Electronic check                -0.114807        0.095426
PaymentMethod_Mailed check                    -0.084631       -0.022650
gender_Male                                   -0.008507        0.003088
InternetService_Fiber optic                   -0.020299        0.063911
InternetService_No                            -0.335695       -0.428285
MultipleLines_No                              -0.155534        0.005131
MultipleLines_Yes                              0.100421       -0.078894
OnlineSecurity_No                             -0.044177        0.257301
OnlineSecurity_Yes                             0.354458        0.105369
OnlineBackup_No                               -0.002871        0.316440
OnlineBackup_Yes                               0.293705        0.040505
DeviceProtection_No                           -0.040135        0.420013
DeviceProtection_Yes                           0.332850       -0.067785
TechSupport_No                                -0.631310        0.346743
TechSupport_Yes                                1.000000        0.006463
StreamingTV_No                                 0.006463        1.000000
StreamingTV_Yes                                0.277549       -0.644458
StreamingMovies_No                             0.003349        0.538052
StreamingMovies_Yes                            0.280155       -0.178077

                                          StreamingTV_Yes
StreamingMovies_No  \
tenure                                         0.280264            -
0.252890
PhoneService                                  -0.021383            -
0.111273
PaperlessBilling                               0.224241
0.058987
MonthlyCharges                                 0.629668
```

```
0.017271
TotalCharges                                    0.515709           -
0.202605
Churn                                           0.063254
0.130920
SeniorCitizen                                   0.105445
0.034196
Partner                                         0.124483           -
0.117488
Dependents                                     -0.016499           -
0.078245
Contract_One year                               0.061930           -
0.096613
Contract_Two year                               0.072124           -
0.258495
PaymentMethod_Credit card (automatic)           0.040010           -
0.049817
PaymentMethod_Electronic check                  0.144747
0.102617
PaymentMethod_Mailed check                     -0.247712           -
0.019648
gender_Male                                    -0.007124
0.006078
InternetService_Fiber optic                     0.329744
0.070657
InternetService_No                             -0.414951           -
0.424739
MultipleLines_No                               -0.267466
0.014149
MultipleLines_Yes                               0.257804           -
0.080905
OnlineSecurity_No                               0.182890
0.265258
OnlineSecurity_Yes                              0.175514
0.093342
OnlineBackup_No                                 0.074460
0.307188
OnlineBackup_Yes                                0.281601
0.047094
DeviceProtection_No                            -0.029028
0.429705
DeviceProtection_Yes                            0.389924           -
0.080986
TechSupport_No                                  0.089703
0.346651
TechSupport_Yes                                 0.277549
0.003349
StreamingTV_No                                 -0.644458
0.538052
StreamingTV_Yes                                 1.000000           -
```

```
0.182340
StreamingMovies_No                                     -0.182340
1.000000
StreamingMovies_Yes                                     0.533380            -
0.644512

                                                StreamingMovies_Yes
tenure                                                     0.285402
PhoneService                                              -0.033477
PaperlessBilling                                           0.211583
MonthlyCharges                                             0.627235
TotalCharges                                               0.519867
Churn                                                      0.060860
SeniorCitizen                                              0.119842
Partner                                                    0.118108
Dependents                                                -0.038375
Contract_One year                                          0.064780
Contract_Two year                                          0.075603
PaymentMethod_Credit card (automatic)                      0.048398
PaymentMethod_Electronic check                             0.137420
PaymentMethod_Mailed check                                -0.250290
gender_Male                                               -0.010105
InternetService_Fiber optic                                0.322457
InternetService_No                                        -0.418450
MultipleLines_No                                          -0.275995
MultipleLines_Yes                                          0.259194
OnlineSecurity_No                                          0.174999
OnlineSecurity_Yes                                         0.187426
OnlineBackup_No                                            0.084142
OnlineBackup_Yes                                           0.274523
DeviceProtection_No                                       -0.037978
DeviceProtection_Yes                                       0.402309
TechSupport_No                                             0.090218
TechSupport_Yes                                            0.280155
StreamingTV_No                                            -0.178077
StreamingTV_Yes                                            0.533380
StreamingMovies_No                                        -0.644512
StreamingMovies_Yes                                        1.000000

[31 rows x 31 columns]

# Let's see the correlation matrix
plt.figure(figsize = (20,10))        # Size of the figure
sns.heatmap(telecom_corr,annot = True)
plt.show()
```



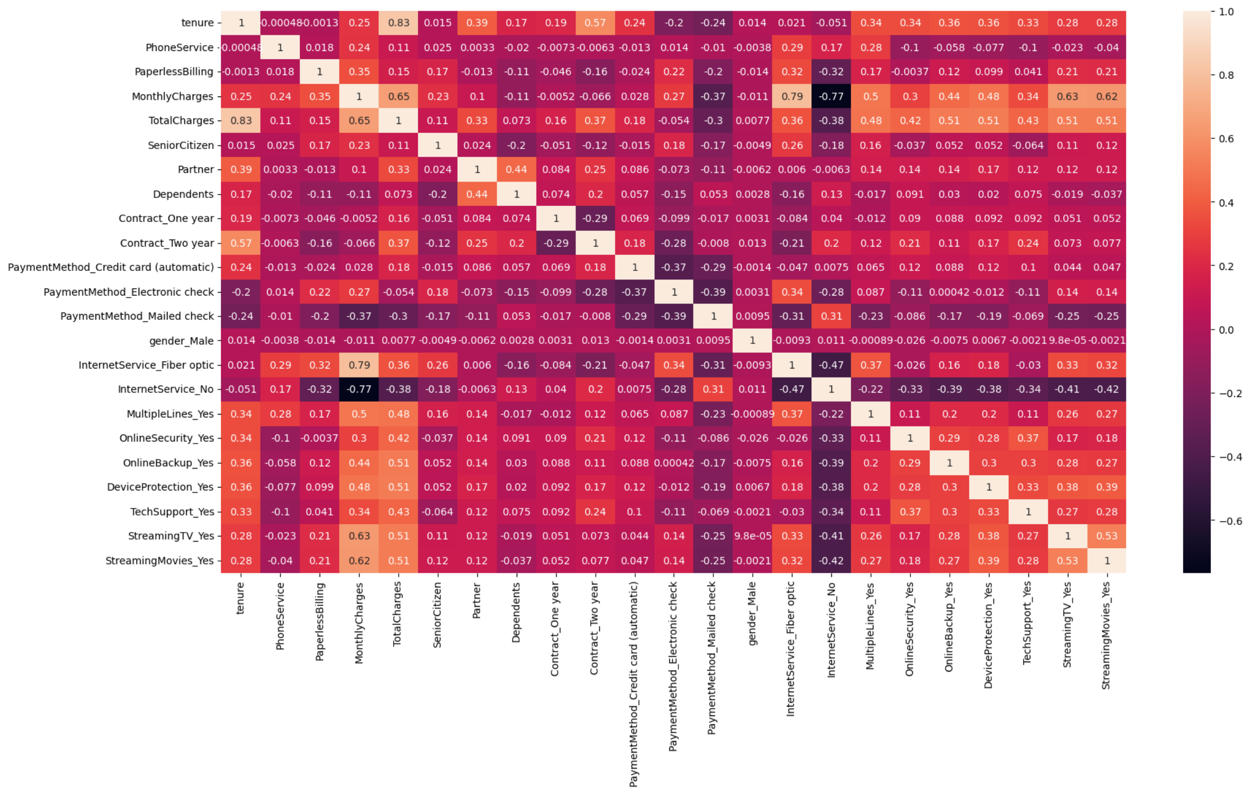
## Dropping highly correlated dummy variables

```
X_test =
X_test.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No',
'DeviceProtection_No','TechSupport_No',
                       'StreamingTV_No','StreamingMovies_No'], axis=1)
X_train =
X_train.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No'
,'DeviceProtection_No','TechSupport_No',
                        'StreamingTV_No','StreamingMovies_No'],
axis=1)
```

### Checking the Correlation Matrix

After dropping highly correlated variables now let's check the correlation matrix again.

```
plt.figure(figsize = (20,10))
sns.heatmap(X_train.corr(),annot = True)
plt.show()
```




# Step 7: Model Building

Let's start by splitting our data into a training set and a test set.

## Running Your First Training Model

```
import statsmodels.api as sm

y_train.info()

<class 'pandas.core.series.Series'>
Index: 4922 entries, 879 to 5649
Series name: Churn
Non-Null Count  Dtype
--------------  -----
4922 non-null   int64
dtypes: int64(1)
memory usage: 76.9 KB
```

**Here i have passed the** *X_train.astype(int)*** as I was getting the error assocaited with the**

***Panda data cast to numpy dtypoe of onject***

```
# Logistic regression model
logm1 = sm.GLM(y_train,(sm.add_constant(X_train.astype(int))), family
= sm.families.Binomial())
logm1.fit().summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:                  Churn   No. Observations:
4922
Model:                            GLM   Df Residuals:
4898
Model Family:                Binomial   Df Model:
23
Link Function:                  Logit   Scale:
1.0000
Method:                          IRLS   Log-Likelihood:
-2018.7
Date:            Wed, 14 Feb 2024   Deviance:
4037.4
Time:                        00:03:32   Pearson chi2:
5.19e+03
No. Iterations:                     7   Pseudo R-squ. (CS):
0.2803
Covariance Type:            nonrobust

======================================================================
===================================
                                            coef    std err          z
P>|z|      [0.025      0.975]
----------------------------------------------------------------------
-----------------------------------
const                                    -0.9649      0.216     -4.468
0.000      -1.388      -0.542
tenure                                   -1.0401      0.091    -11.438
0.000      -1.218      -0.862
PhoneService                             -0.4162      0.167     -2.495
0.013      -0.743      -0.089
PaperlessBilling                          0.3119      0.090      3.473
0.001       0.136       0.488
MonthlyCharges                            0.2035      0.141      1.445
```

```
0.148      -0.073       0.480
TotalCharges                                  -0.0445       0.115      -0.387
0.699      -0.270       0.181
SeniorCitizen                                  0.3415       0.101       3.392
0.001       0.144       0.539
Partner                                       -0.0227       0.092      -0.246
0.806      -0.204       0.158
Dependents                                    -0.1274       0.107      -1.194
0.233      -0.337       0.082
Contract_One year                             -0.8627       0.126      -6.833
0.000      -1.110      -0.615
Contract_Two year                             -1.4803       0.211      -7.031
0.000      -1.893      -1.068
PaymentMethod_Credit card (automatic)    -0.2265       0.136      -1.669
0.095      -0.492       0.040
PaymentMethod_Electronic check                 0.2225       0.112       1.993
0.046       0.004       0.441
PaymentMethod_Mailed check                    -0.1708       0.137      -1.251
0.211      -0.438       0.097
gender_Male                                   -0.0375       0.078      -0.479
0.632      -0.191       0.116
InternetService_Fiber optic                    0.8007       0.113       7.055
0.000       0.578       1.023
InternetService_No                            -0.8865       0.195      -4.549
0.000      -1.268      -0.505
MultipleLines_Yes                              0.1820       0.095       1.922
0.055      -0.004       0.368
OnlineSecurity_Yes                            -0.4024       0.102      -3.944
0.000      -0.602      -0.202
OnlineBackup_Yes                              -0.2295       0.091      -2.513
0.012      -0.409      -0.051
DeviceProtection_Yes                          -0.0468       0.095      -0.492
0.623      -0.233       0.140
TechSupport_Yes                               -0.3725       0.102      -3.649
0.000      -0.573      -0.172
StreamingTV_Yes                                0.2253       0.102       2.201
0.028       0.025       0.426
StreamingMovies_Yes                            0.1555       0.101       1.533
0.125      -0.043       0.354
======================================================================
===================================
"""
```

## Step 8: Feature Selection Using RFE

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
```

```python
from sklearn.feature_selection import RFE

# Assuming you have already initialized your logistic regression model (logreg),
# and X_train, y_train are your training data and labels respectively.

# Create RFE object without specifying the number of features initially
rfe = RFE(estimator=logreg, n_features_to_select=13)  # Choose 13 features OR Running RFE with 13 variables as output

# Fit RFE to your training data
rfe.fit(X_train, y_train)
```

```
RFE(estimator=LogisticRegression(), n_features_to_select=13)
```

```python
rfe.support_
```

```
array([ True, False, False,  True,  True,  True, False, False,  True,
        True,  True, False,  True, False,  True,  True,  True, False,
       False, False, False,  True,  True])
```

```python
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

```
[('tenure', True, 1),
 ('PhoneService', False, 5),
 ('PaperlessBilling', False, 2),
 ('MonthlyCharges', True, 1),
 ('TotalCharges', True, 1),
 ('SeniorCitizen', True, 1),
 ('Partner', False, 9),
 ('Dependents', False, 8),
 ('Contract_One year', True, 1),
 ('Contract_Two year', True, 1),
 ('PaymentMethod_Credit card (automatic)', True, 1),
 ('PaymentMethod_Electronic check', False, 6),
 ('PaymentMethod_Mailed check', True, 1),
 ('gender_Male', False, 10),
 ('InternetService_Fiber optic', True, 1),
 ('InternetService_No', True, 1),
 ('MultipleLines_Yes', True, 1),
 ('OnlineSecurity_Yes', False, 4),
 ('OnlineBackup_Yes', False, 7),
 ('DeviceProtection_Yes', False, 11),
 ('TechSupport_Yes', False, 3),
 ('StreamingTV_Yes', True, 1),
 ('StreamingMovies_Yes', True, 1)]
```

```python
col = X_train.columns[rfe.support_]

X_train.columns[~rfe.support_]
```

```
Index(['PhoneService', 'PaperlessBilling', 'Partner', 'Dependents',
       'PaymentMethod_Electronic check', 'gender_Male',
'OnlineSecurity_Yes',
       'OnlineBackup_Yes', 'DeviceProtection_Yes', 'TechSupport_Yes'],
      dtype='object')
```

## Assessing the model with StatsModels

```
X_train_sm = sm.add_constant(X_train[col].astype(int))
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results
======================================================================
========
Dep. Variable:                   Churn   No. Observations:
4922
Model:                             GLM   Df Residuals:
4908
Model Family:                 Binomial   Df Model:
13
Link Function:                   Logit   Scale:
1.0000
Method:                           IRLS   Log-Likelihood:
-2052.5
Date:                 Wed, 14 Feb 2024   Deviance:
4104.9
Time:                         00:03:33   Pearson chi2:
5.13e+03
No. Iterations:                      7   Pseudo R-squ. (CS):
0.2704
Covariance Type:             nonrobust
======================================================================
===================================
                                            coef    std err          z
P>|z|      [0.025      0.975]
----------------------------------------------------------------------
-----------------------------------
const                                    -1.4141      0.112    -12.582
0.000      -1.634      -1.194
tenure                                   -1.1486      0.087    -13.247
0.000      -1.318      -0.979
MonthlyCharges                           -0.1255      0.124     -1.010
0.312      -0.369       0.118
TotalCharges                             -0.0626      0.113     -0.554
```

```
0.579      -0.284      0.159
SeniorCitizen                                    0.4440      0.097      4.563
0.000       0.253      0.635
Contract_One year                               -1.0366      0.123     -8.444
0.000      -1.277     -0.796
Contract_Two year                               -1.8063      0.206     -8.776
0.000      -2.210     -1.403
PaymentMethod_Credit card (automatic)           -0.4057      0.111     -3.654
0.000      -0.623     -0.188
PaymentMethod_Mailed check                      -0.3741      0.110     -3.406
0.001      -0.589     -0.159
InternetService_Fiber optic                      0.9290      0.102      9.101
0.000       0.729      1.129
InternetService_No                              -0.9911      0.175     -5.675
0.000      -1.333     -0.649
MultipleLines_Yes                                0.1778      0.092      1.933
0.053      -0.003      0.358
StreamingTV_Yes                                  0.3242      0.099      3.285
0.001       0.131      0.518
StreamingMovies_Yes                              0.2718      0.098      2.787
0.005       0.081      0.463
======================================================================
===================================
"""

# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

```
879     0.225072
5790    0.306164
6498    0.660029
880     0.496342
2784    0.756564
3874    0.195583
5387    0.465042
6623    0.783330
4465    0.135317
5364    0.391447
dtype: float64
```

```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

```
array([0.22507155, 0.30616397, 0.66002883, 0.49634191, 0.75656385,
       0.19558296, 0.46504224, 0.78333005, 0.13531664, 0.39144748])
```

Creating a dataframe with the actual churn flag and the predicted probabilities

```
y_train_pred_final = pd.DataFrame({'Churn':y_train.values,
'Churn_Prob':y_train_pred})
y_train_pred_final['CustID'] = y_train.index
y_train_pred_final.head()
```

| | Churn | Churn_Prob | CustID |
|---|---|---|---|
| 0 | 0 | 0.225072 | 879 |
| 1 | 0 | 0.306164 | 5790 |
| 2 | 1 | 0.660029 | 6498 |
| 3 | 1 | 0.496342 | 880 |
| 4 | 1 | 0.756564 | 2784 |

Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0

```
y_train_pred_final['predicted'] =
y_train_pred_final.Churn_Prob.map(lambda x: 1 if x > 0.5 else 0)

# Let's see the head
y_train_pred_final.head()
```

| | Churn | Churn_Prob | CustID | predicted |
|---|---|---|---|---|
| 0 | 0 | 0.225072 | 879 | 0 |
| 1 | 0 | 0.306164 | 5790 | 0 |
| 2 | 1 | 0.660029 | 6498 | 1 |
| 3 | 1 | 0.496342 | 880 | 0 |
| 4 | 1 | 0.756564 | 2784 | 1 |

```
from sklearn import metrics

# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Churn,
y_train_pred_final.predicted )
print(confusion)
```

```
[[3288  347]
 [ 644  643]]
```

```
# Predicted     not_churn    churn
# Actual
# not_churn        3270      365
# churn            579       708

# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn,
y_train_pred_final.predicted))
```

```
0.7986590816741163
```

Checking VIFs

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import
variance_inflation_factor
```

## Here I have done the same type conversion

```
X_train[col] = X_train[col].astype(int)

# Create a dataframe that will contain the names of all the feature
variables and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i
in range(X_train[col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

| | Features | VIF |
|---|---|---|
| 1 | MonthlyCharges | 4.63 |
| 9 | InternetService_No | 3.46 |
| 8 | InternetService_Fiber optic | 2.78 |
| 2 | TotalCharges | 2.72 |
| 11 | StreamingTV_Yes | 2.58 |
| 12 | StreamingMovies_Yes | 2.57 |
| 5 | Contract_Two year | 2.56 |
| 10 | MultipleLines_Yes | 2.21 |
| 0 | tenure | 2.03 |
| 4 | Contract_One year | 1.60 |
| 7 | PaymentMethod_Mailed check | 1.54 |
| 6 | PaymentMethod_Credit card (automatic) | 1.40 |
| 3 | SeniorCitizen | 1.29 |

There are a few variables with high VIF. It's best to drop these variables as they aren't helping much with prediction and unnecessarily making the model complex. The variable 'PhoneService' has the highest VIF. So let's start by dropping that.

```
# col = col.drop('PhoneService', 1)
col

Index(['tenure', 'MonthlyCharges', 'TotalCharges', 'SeniorCitizen',
       'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Credit card (automatic)', 'PaymentMethod_Mailed
check',
       'InternetService_Fiber optic', 'InternetService_No',
       'MultipleLines_Yes', 'StreamingTV_Yes', 'StreamingMovies_Yes'],
      dtype='object')
```

```python
# Let's re-run the model using the selected variables
X_train_sm = sm.add_constant(X_train[col])
logm3 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:                  Churn   No. Observations:
4922
Model:                            GLM   Df Residuals:
4908
Model Family:                Binomial   Df Model:
13
Link Function:                  Logit   Scale:
1.0000
Method:                          IRLS   Log-Likelihood:
-2052.5
Date:                Wed, 14 Feb 2024   Deviance:
4104.9
Time:                        00:03:33   Pearson chi2:
5.13e+03
No. Iterations:                     7   Pseudo R-squ. (CS):
0.2704
Covariance Type:            nonrobust

======================================================================
===================================
                                            coef    std err          z
P>|z|      [0.025      0.975]
----------------------------------------------------------------------
-----------------------------------
const                                    -1.4141      0.112    -12.582
0.000      -1.634      -1.194
tenure                                   -1.1486      0.087    -13.247
0.000      -1.318      -0.979
MonthlyCharges                           -0.1255      0.124     -1.010
0.312      -0.369       0.118
TotalCharges                             -0.0626      0.113     -0.554
0.579      -0.284       0.159
SeniorCitizen                             0.4440      0.097      4.563
0.000       0.253       0.635
Contract_One year                        -1.0366      0.123     -8.444
0.000      -1.277      -0.796
Contract_Two year                        -1.8063      0.206     -8.776
0.000      -2.210      -1.403
```

```
PaymentMethod_Credit card (automatic)     -0.4057      0.111     -3.654
0.000      -0.623      -0.188
PaymentMethod_Mailed check                -0.3741      0.110     -3.406
0.001      -0.589      -0.159
InternetService_Fiber optic                0.9290      0.102      9.101
0.000       0.729       1.129
InternetService_No                        -0.9911      0.175     -5.675
0.000      -1.333      -0.649
MultipleLines_Yes                          0.1778      0.092      1.933
0.053      -0.003       0.358
StreamingTV_Yes                            0.3242      0.099      3.285
0.001       0.131       0.518
StreamingMovies_Yes                        0.2718      0.098      2.787
0.005       0.081       0.463
======================================================================
===================================
"""

y_train_pred = res.predict(X_train_sm).values.reshape(-1)

y_train_pred[:10]

array([0.22507155, 0.30616397, 0.66002883, 0.49634191, 0.75656385,
       0.19558296, 0.46504224, 0.78333005, 0.13531664, 0.39144748])

y_train_pred_final['Churn_Prob'] = y_train_pred

# Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0
y_train_pred_final['predicted'] =
y_train_pred_final.Churn_Prob.map(lambda x: 1 if x > 0.5 else 0)
y_train_pred_final.head()

   Churn  Churn_Prob  CustID  predicted
0      0    0.225072     879          0
1      0    0.306164    5790          0
2      1    0.660029    6498          1
3      1    0.496342     880          0
4      1    0.756564    2784          1

# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn,
y_train_pred_final.predicted))

0.7986590816741163
```

So overall the accuracy hasn't dropped much.

## Let's check the VIFs again

```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
```

```python
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i
in range(X_train[col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

```
                                   Features   VIF
1                            MonthlyCharges  4.63
9                        InternetService_No  3.46
8               InternetService_Fiber optic  2.78
2                              TotalCharges  2.72
11                          StreamingTV_Yes  2.58
12                      StreamingMovies_Yes  2.57
5                         Contract_Two year  2.56
10                        MultipleLines_Yes  2.21
0                                    tenure  2.03
4                         Contract_One year  1.60
7                PaymentMethod_Mailed check  1.54
6   PaymentMethod_Credit card (automatic)  1.40
3                             SeniorCitizen  1.29
```

```python
# Let's drop TotalCharges since it has a high VIF
col = col.drop('TotalCharges')
col
```

```
Index(['tenure', 'MonthlyCharges', 'SeniorCitizen', 'Contract_One
year',
       'Contract_Two year', 'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Mailed check', 'InternetService_Fiber optic',
       'InternetService_No', 'MultipleLines_Yes', 'StreamingTV_Yes',
       'StreamingMovies_Yes'],
      dtype='object')
```

```python
# Let's re-run the model using the selected variables
X_train_sm = sm.add_constant(X_train[col])
logm4 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm4.fit()
res.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results

======================================================================
========
Dep. Variable:                  Churn   No. Observations:
4922
Model:                            GLM   Df Residuals:
4909
Model Family:                Binomial   Df Model:
```

```
12
Link Function:                     Logit   Scale:
1.0000
Method:                             IRLS   Log-Likelihood:
-2052.6
Date:                   Wed, 14 Feb 2024   Deviance:
4105.2
Time:                           00:03:34   Pearson chi2:
5.14e+03
No. Iterations:                        7   Pseudo R-squ. (CS):
0.2703
Covariance Type:               nonrobust

======================================================================
===================================
                                                  coef    std err          z
P>|z|      [0.025      0.975]
----------------------------------------------------------------------
-----------------------------------
const                                          -1.4184      0.112    -12.640
0.000      -1.638      -1.198
tenure                                         -1.1638      0.082    -14.156
0.000      -1.325      -1.003
MonthlyCharges                                 -0.1400      0.121     -1.154
0.249      -0.378       0.098
SeniorCitizen                                   0.4421      0.097      4.550
0.000       0.252       0.632
Contract_One year                              -1.0488      0.121     -8.678
0.000      -1.286      -0.812
Contract_Two year                              -1.8391      0.197     -9.314
0.000      -2.226      -1.452
PaymentMethod_Credit card (automatic)    -0.4063      0.111     -3.660
0.000      -0.624      -0.189
PaymentMethod_Mailed check                     -0.3759      0.110     -3.422
0.001      -0.591      -0.161
InternetService_Fiber optic                     0.9259      0.102      9.075
0.000       0.726       1.126
InternetService_No                             -0.9875      0.174     -5.660
0.000      -1.329      -0.645
MultipleLines_Yes                               0.1746      0.092      1.901
0.057      -0.005       0.355
StreamingTV_Yes                                 0.3238      0.099      3.278
0.001       0.130       0.517
StreamingMovies_Yes                             0.2719      0.098      2.785
0.005       0.081       0.463
======================================================================
===================================
"""

y_train_pred = res.predict(X_train_sm).values.reshape(-1)
```

```
y_train_pred[:10]
```

```
array([0.22377733, 0.30519026, 0.66178811, 0.49079395, 0.75527772,
       0.19490745, 0.47138094, 0.7838037 , 0.13336463, 0.38883453])
```

```
y_train_pred_final['Churn_Prob'] = y_train_pred

# Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0
y_train_pred_final['predicted'] =
y_train_pred_final.Churn_Prob.map(lambda x: 1 if x > 0.5 else 0)
y_train_pred_final.head()
```

| | Churn | Churn_Prob | CustID | predicted |
|---|---|---|---|---|
| 0 | 0 | 0.223777 | 879 | 0 |
| 1 | 0 | 0.305190 | 5790 | 0 |
| 2 | 1 | 0.661788 | 6498 | 1 |
| 3 | 1 | 0.490794 | 880 | 0 |
| 4 | 1 | 0.755278 | 2784 | 1 |

```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn,
y_train_pred_final.predicted))
```

```
0.7978464039008533
```

The accuracy is still practically the same.

## Let's now check the VIFs again

```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i
in range(X_train[col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

| | Features | VIF |
|---|---|---|
| 1 | MonthlyCharges | 4.27 |
| 8 | InternetService_No | 3.46 |
| 7 | InternetService_Fiber optic | 2.71 |
| 10 | StreamingTV_Yes | 2.58 |
| 11 | StreamingMovies_Yes | 2.56 |
| 4 | Contract_Two year | 2.40 |
| 9 | MultipleLines_Yes | 2.19 |
| 0 | tenure | 1.78 |
| 3 | Contract_One year | 1.57 |
| 6 | PaymentMethod_Mailed check | 1.54 |
| 5 | PaymentMethod_Credit card (automatic) | 1.40 |
| 2 | SeniorCitizen | 1.29 |

All variables have a good value of VIF. So we need not drop any more variables and we can proceed with making predictions using this model only

```
# Let's take a look at the confusion matrix again
confusion = metrics.confusion_matrix(y_train_pred_final.Churn,
y_train_pred_final.predicted )
confusion
```

```
array([[3289,  346],
       [ 649,  638]], dtype=int64)
```

```
# Actual/Predicted     not_churn    churn
        # not_churn        3269      366
        # churn            595       692

# Let's check the overall accuracy.
metrics.accuracy_score(y_train_pred_final.Churn,
y_train_pred_final.predicted)
```

```
0.7978464039008533
```

## Metrics beyond simply accuracy

```
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives

# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

```
0.49572649572649574
```

```
# Let us calculate specificity
TN / float(TN+FP)
```

```
0.9048143053645117
```

```
# Calculate false postive rate - predicting churn when customer does
not have churned
print(FP/ float(TN+FP))
```

```
0.0951856946354883
```

```
# positive predictive value
print (TP / float(TP+FP))
```

```
0.6483739837398373
```

```
# Negative predictive value
print (TN / float(TN+ FN))
```

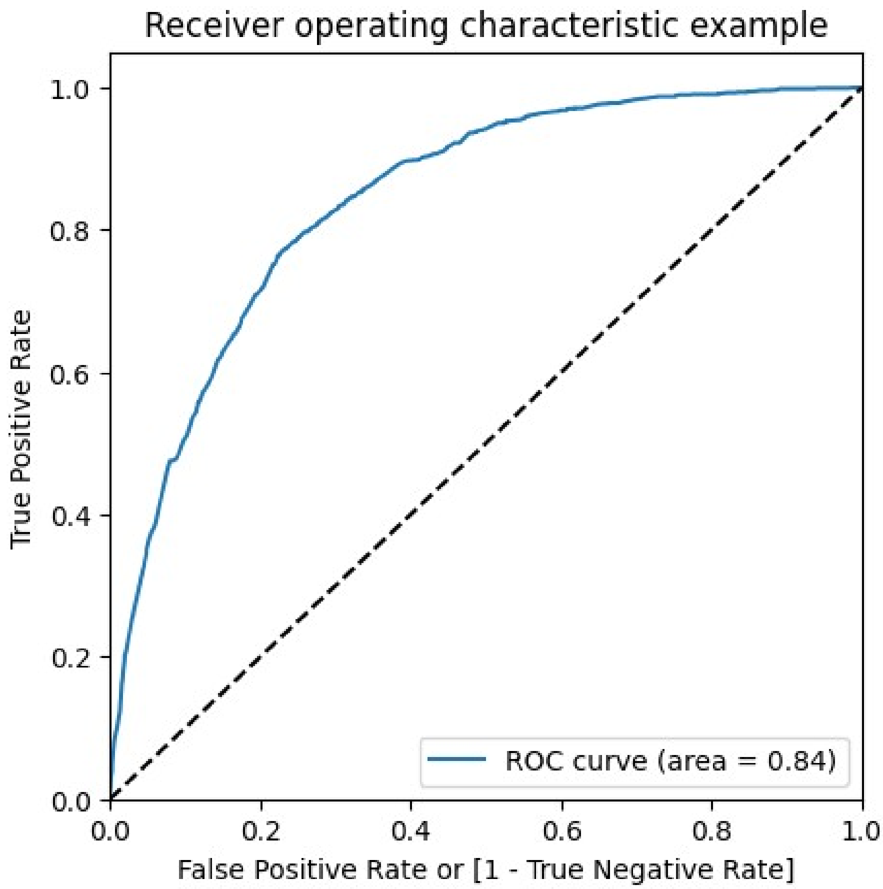
```
0.835195530726257
```

## Step 9: Plotting the ROC Curve

An ROC curve demonstrates several things:

- It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate =
False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None

fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Churn,
y_train_pred_final.Churn_Prob, drop_intermediate = False )

draw_roc(y_train_pred_final.Churn, y_train_pred_final.Churn_Prob)
```




## Step 10: Finding Optimal Cutoff Point

Optimal cutoff probability is that prob where we get balanced sensitivity and specificity

```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_pred_final[i]= y_train_pred_final.Churn_Prob.map(lambda x:
1 if x > i else 0)
y_train_pred_final.head()
```

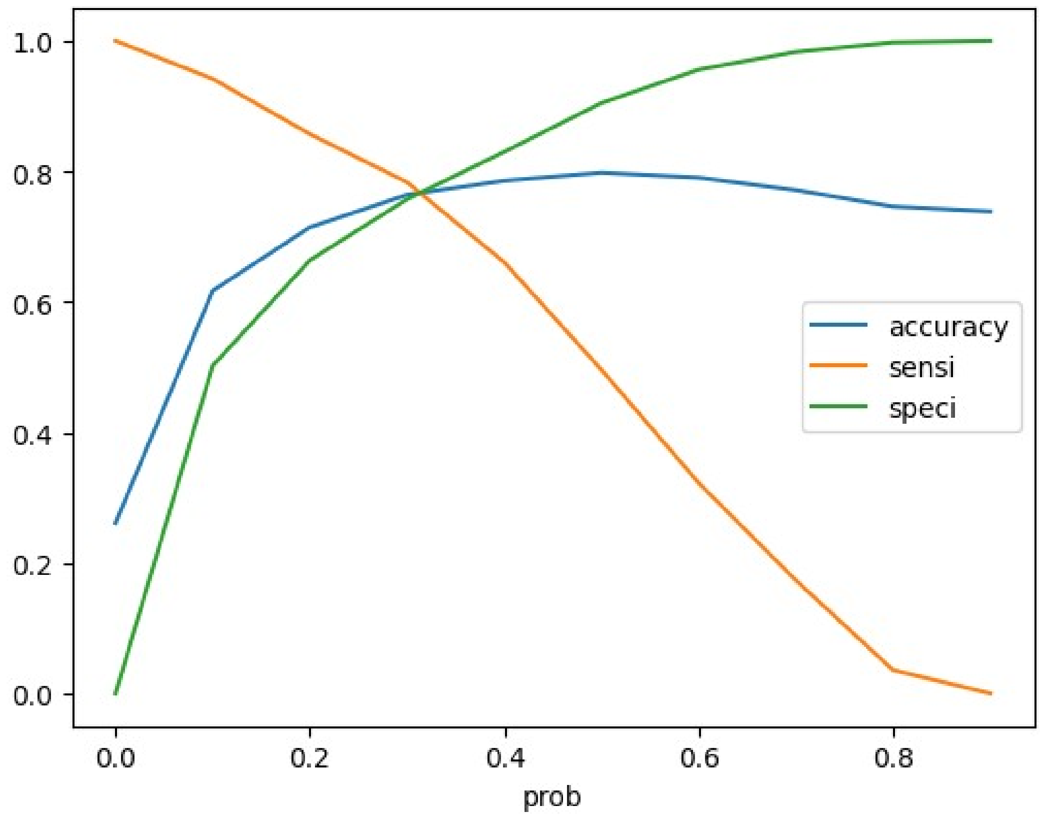
```
   Churn  Churn_Prob  CustID  predicted  0.0  0.1  0.2  0.3  0.4  0.5
0.6  \
0      0    0.223777     879          0    1    1    1    0    0    0
0
1      0    0.305190    5790          0    1    1    1    1    0    0
0
2      1    0.661788    6498          1    1    1    1    1    1    1
1
3      1    0.490794     880          0    1    1    1    1    1    0
0
4      1    0.755278    2784          1    1    1    1    1    1    1
```

```
1

   0.7  0.8  0.9
0    0    0    0
1    0    0    0
2    0    0    0
3    0    0    0
4    1    0    0
```

```
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

# TP = confusion[1,1] # true positive
# TN = confusion[0,0] # true negatives
# FP = confusion[0,1] # false positives
# FN = confusion[1,0] # false negatives

num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in num:
    cm1 = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
print(cutoff_df)
```

```
     prob  accuracy     sensi     speci
0.0   0.0  0.261479  1.000000  0.000000
0.1   0.1  0.617229  0.941725  0.502338
0.2   0.2  0.714344  0.857032  0.663824
0.3   0.3  0.764120  0.783217  0.757359
0.4   0.4  0.785656  0.660451  0.829986
0.5   0.5  0.797846  0.495726  0.904814
0.6   0.6  0.790329  0.322455  0.955983
0.7   0.7  0.771231  0.173271  0.982944
0.8   0.8  0.746038  0.035742  0.997524
0.9   0.9  0.738521  0.000000  1.000000
```

```
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
plt.show()
```




From the curve above, 0.3 is the optimum point to take it as a cutoff probability.

```
y_train_pred_final['final_predicted'] =
y_train_pred_final.Churn_Prob.map( lambda x: 1 if x > 0.3 else 0)

y_train_pred_final.head()
```

```
   Churn  Churn_Prob  CustID  predicted  0.0  0.1  0.2  0.3  0.4  0.5
0.6  \
0      0    0.223777     879          0    1    1    1    0    0    0
0
1      0    0.305190    5790          0    1    1    1    1    0    0
0
2      1    0.661788    6498          1    1    1    1    1    1    1
1
3      1    0.490794     880          0    1    1    1    1    1    0
0
4      1    0.755278    2784          1    1    1    1    1    1    1
1

   0.7  0.8  0.9  final_predicted
0    0    0    0                0
1    0    0    0                1
2    0    0    0                1
```

```
3    0    0    0                1
4    1    0    0                1
```

```
# Let's check the overall accuracy.
metrics.accuracy_score(y_train_pred_final.Churn,
y_train_pred_final.final_predicted)
```

```
0.7641202763104429
```

```
confusion2 = metrics.confusion_matrix(y_train_pred_final.Churn,
y_train_pred_final.final_predicted )
confusion2
```

```
array([[2753,  882],
       [ 279, 1008]], dtype=int64)
```

```
TP = confusion2[1,1] # true positive
TN = confusion2[0,0] # true negatives
FP = confusion2[0,1] # false positives
FN = confusion2[1,0] # false negatives
```

```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

```
0.7832167832167832
```

```
# Let us calculate specificity
TN / float(TN+FP)
```

```
0.7573590096286107
```

```
# Calculate false postive rate - predicting churn when customer does
not have churned
print(FP/ float(TN+FP))
```

```
0.24264099037138928
```

```
# Positive predictive value
print (TP / float(TP+FP))
```

```
0.5333333333333333
```

```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.9079815303430079
```

## Precision and Recall

```
#Looking at the confusion matrix again
```

```
confusion = metrics.confusion_matrix(y_train_pred_final.Churn,
y_train_pred_final.predicted )
confusion
```

```
array([[3289,  346],
       [ 649,  638]], dtype=int64)
```

Precision

TP / TP + FP

```
confusion[1,1]/(confusion[0,1]+confusion[1,1])
```

```
0.6483739837398373
```

Recall

TP / TP + FN

```
confusion[1,1]/(confusion[1,0]+confusion[1,1])
```

```
0.49572649572649574
```

Using sklearn utilities for the same

```
from sklearn.metrics import precision_score, recall_score

# ?precision_score

precision_score(y_train_pred_final.Churn,
y_train_pred_final.predicted)
```

```
0.6483739837398373
```

```
recall_score(y_train_pred_final.Churn, y_train_pred_final.predicted)
```

```
0.49572649572649574
```

## Precision and recall tradeoff

```
from sklearn.metrics import precision_recall_curve

y_train_pred_final['Churn']
```

```
0       0
1       0
2       1
3       1
4       1
       ..
4917    0
```

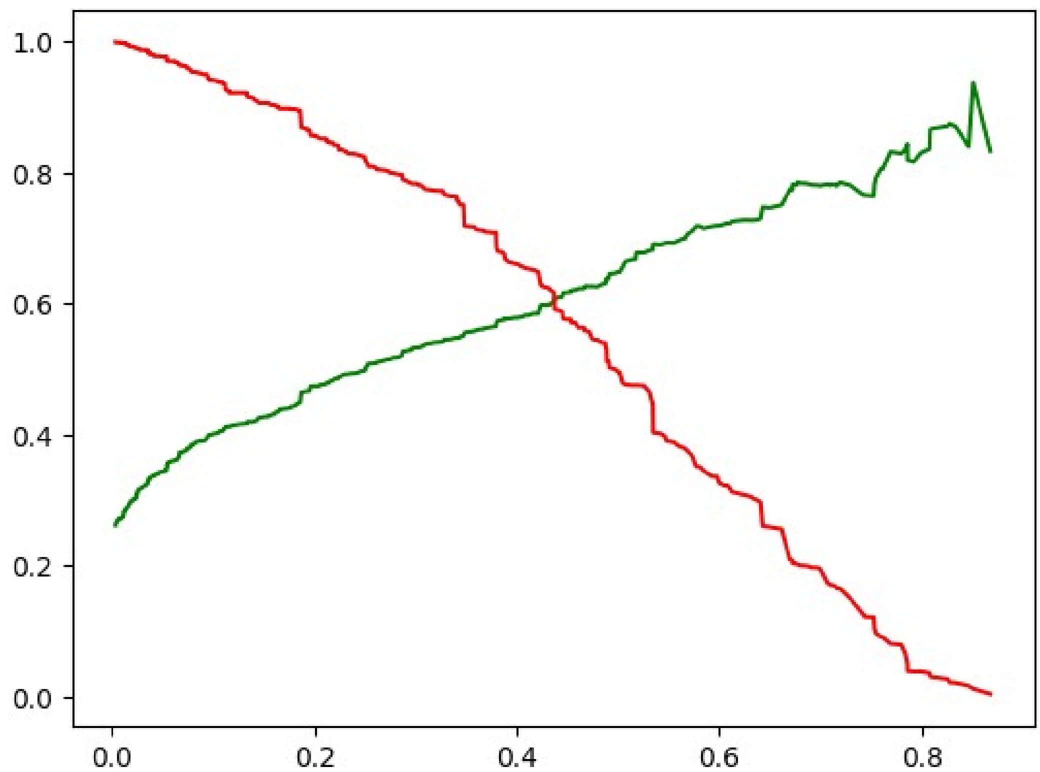
```
4918    0
4919    0
4920    0
4921    0
Name: Churn, Length: 4922, dtype: int64
```

```
y_train_pred_final['predicted']
```

```
0       0
1       0
2       1
3       0
4       1
       ..
4917    0
4918    0
4919    0
4920    0
4921    0
Name: predicted, Length: 4922, dtype: int64
```

```
p, r, thresholds = precision_recall_curve(y_train_pred_final.Churn,
y_train_pred_final.Churn_Prob)
```

```
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.show()
```




## Step 11: Making predictions on the test set

```
X_test[['tenure','MonthlyCharges','TotalCharges']] =
scaler.transform(X_test[['tenure','MonthlyCharges','TotalCharges']])

X_test = X_test[col]
X_test.head()

        tenure  MonthlyCharges  SeniorCitizen  Contract_One year  \
942  -0.347623        0.499951              0              False
3730  0.999203        1.319685              0              False
1761  1.040015       -1.342374              0              False
2283 -1.286319        0.223935              0              False
1872  0.346196       -1.500335              0              False

      Contract_Two year  PaymentMethod_Credit card (automatic)  \
942               False                                   True
3730              False                                   True
1761               True                                   True
2283              False                                  False
1872               True                                  False

      PaymentMethod_Mailed check  InternetService_Fiber optic  \
942                        False                         True
3730                       False                         True
1761                       False                        False
```

```
2283                            True                             True
1872                           False                            False

      InternetService_No  MultipleLines_Yes  StreamingTV_Yes  \
942                False              False            False
3730               False               True             True
1761                True               True            False
2283               False              False            False
1872                True              False            False

      StreamingMovies_Yes
942                  True
3730                 True
1761                False
2283                False
1872                False

X_test_sm = sm.add_constant(X_test)
```

Making predictions on the test set

```
X_test_sm.info()

<class 'pandas.core.frame.DataFrame'>
Index: 2110 entries, 942 to 4987
Data columns (total 13 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   const                                  2110 non-null   float64
 1   tenure                                 2110 non-null   float64
 2   MonthlyCharges                         2110 non-null   float64
 3   SeniorCitizen                          2110 non-null   int64
 4   Contract_One year                      2110 non-null   bool
 5   Contract_Two year                      2110 non-null   bool
 6   PaymentMethod_Credit card (automatic)  2110 non-null   bool
 7   PaymentMethod_Mailed check             2110 non-null   bool
 8   InternetService_Fiber optic            2110 non-null   bool
 9   InternetService_No                     2110 non-null   bool
 10  MultipleLines_Yes                      2110 non-null   bool
 11  StreamingTV_Yes                        2110 non-null   bool
 12  StreamingMovies_Yes                    2110 non-null   bool
dtypes: bool(9), float64(3), int64(1)
memory usage: 101.0 KB
```

## **Here I have created the** ***float_columns***** having the float type**

```
float_columns = X_test_sm.select_dtypes(include=['float64'])
```

```
float_columns.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2110 entries, 942 to 4987
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   const           2110 non-null   float64
 1   tenure          2110 non-null   float64
 2   MonthlyCharges  2110 non-null   float64
dtypes: float64(3)
memory usage: 65.9 KB
```

```
# X_test_sm[float_columns] = X_test_sm[float_columns].astype(int)
# running this code will throw an error
```

## Here is the error I encountered while runnign this code

X_test_sm Error.png

## Running the code for a sample_df and predicting the *y_test_pred*** usng the ***res*** model**

```
# sample_df = X_test_sm.astype(int)

# sample_df.info()

# sample_df_pred = res.predict(sample_df)
```

## Converting the X_test_sm type into *integer*****

```
X_test_sm = X_test_sm.astype(int)

X_test_sm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2110 entries, 942 to 4987
Data columns (total 13 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   const                                  2110 non-null   int32
 1   tenure                                 2110 non-null   int32
 2   MonthlyCharges                         2110 non-null   int32
 3   SeniorCitizen                          2110 non-null   int32
 4   Contract_One year                      2110 non-null   int32
 5   Contract_Two year                      2110 non-null   int32
 6   PaymentMethod_Credit card (automatic)  2110 non-null   int32
 7   PaymentMethod_Mailed check             2110 non-null   int32
 8   InternetService_Fiber optic            2110 non-null   int32
```

```
 9   InternetService_No                        2110 non-null   int32
 10  MultipleLines_Yes                         2110 non-null   int32
 11  StreamingTV_Yes                           2110 non-null   int32
 12  StreamingMovies_Yes                       2110 non-null   int32
dtypes: int32(13)
memory usage: 123.6 KB
```

```
y_test_pred = res.predict(X_test_sm)
```

```
y_test_pred[:10]
```

```
942     0.348223
3730    0.433291
1761    0.004069
2283    0.573301
1872    0.016223
1970    0.730093
2532    0.344433
1616    0.011196
2485    0.421194
5914    0.194907
dtype: float64
```

```
# Converting y_pred to a dataframe which is an array
y_pred_1 = pd.DataFrame(y_test_pred)
```

```
# Let's see the head
y_pred_1.head()
```

| | 0 |
|---|---|
| 942 | 0.348223 |
| 3730 | 0.433291 |
| 1761 | 0.004069 |
| 2283 | 0.573301 |
| 1872 | 0.016223 |

```
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
```

```
# Putting CustID to index
y_test_df['CustID'] = y_test_df.index
```

```
# Removing index for both dataframes to append them side by side
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
```

```
# Appending y_test_df and y_pred_1
y_pred_final = pd.concat([y_test_df, y_pred_1],axis=1)
```

```
y_pred_final.head()
```

```
   Churn  CustID         0
0      0     942  0.348223
1      1    3730  0.433291
2      0    1761  0.004069
3      1    2283  0.573301
4      0    1872  0.016223
```

```
# Renaming the column
y_pred_final= y_pred_final.rename(columns={ 0 : 'Churn_Prob'})
```

## **Here changing the** *Reindex_axis*** method to ***reindex*** as the previous got outdated**

```
# Rearranging the columns
y_pred_final = y_pred_final.reindex(['CustID','Churn','Churn_Prob'],
axis=1)

# Let's see the head of y_pred_final
y_pred_final.head()
```

```
   CustID  Churn  Churn_Prob
0     942      0    0.348223
1    3730      1    0.433291
2    1761      0    0.004069
3    2283      1    0.573301
4    1872      0    0.016223
```

```
y_pred_final['final_predicted'] = y_pred_final.Churn_Prob.map(lambda
x: 1 if x > 0.42 else 0)

y_pred_final.head()
```

```
   CustID  Churn  Churn_Prob  final_predicted
0     942      0    0.348223                0
1    3730      1    0.433291                1
2    1761      0    0.004069                0
3    2283      1    0.573301                1
4    1872      0    0.016223                0
```

```
# Let's check the overall accuracy.
metrics.accuracy_score(y_pred_final.Churn,
y_pred_final.final_predicted)
```

```
0.7729857819905214
```

```
confusion2 = metrics.confusion_matrix(y_pred_final.Churn,
y_pred_final.final_predicted )
confusion2
```

```
array([[1259,  269],
       [ 210,  372]], dtype=int64)
```

```python
TP = confusion2[1,1] # true positive
TN = confusion2[0,0] # true negatives
FP = confusion2[0,1] # false positives
FN = confusion2[1,0] # false negatives

# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

```
0.6391752577319587
```

```python
# Let us calculate specificity
TN / float(TN+FP)
```

```
0.8239528795811518
```