Customer Churn Analysis and Prediction

Project Overview

- Customer churn refers to the phenomenon where customers stop doing business with a company or stop using its services. In simple terms, it's when customers leave or "churn away" from a business, often switching to a competitor or just stopping their use of the service altogether. It's an important metric for companies because retaining existing customers is typically more cost-effective than acquiring new ones, so high churn rates can negatively impact a company's revenue and growth.

- The data used in this project is a dataset obtained from Kaggle(a telco dataset).
  The aim of this project seeeks to analyse the churn rate of customers of this organisation based on certain features. Amongst such features include; Whether or not the customer is a senior citizen. Whether the customer has a partner, dependents. The tenure of use of the customer etc.

In [1]:
```
# Importing the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
# Reading the data
data = pd.read_csv('CustomerChurn.csv')
data
```

Out[2]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service
1	5575-GNVDE	Male	0	No	No	34	Yes	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service
4	9237-HQITU	Female	0	No	No	2	Yes	No
...	...	...	...	...	...	...	...	...
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes
7042	3186-AJIEK	Male	0	No	No	66	Yes	No

7043 rows × 21 columns

In [3]:
```
# Checking the shape(dimension) of the data
data.shape
```

Out[3]:
```
(7043, 21)
```

In [4]:

```
# The columns in the data set are listed below;
for column in data.columns:
    print (column)
```

```
customerID
gender
SeniorCitizen
Partner
Dependents
tenure
PhoneService
MultipleLines
InternetService
OnlineSecurity
OnlineBackup
DeviceProtection
TechSupport
StreamingTV
StreamingMovies
Contract
PaperlessBilling
PaymentMethod
MonthlyCharges
TotalCharges
Churn
```

In [5]:
```
# Getting basic information about the data
data.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   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [6]:
```
data.head(2)
pd.options.display.max_columns
```

Out[6]:
```
20
```

In [7]:
```
# checking the data types of all columns
data.dtypes
```

Out[7]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

- Senior Citizen is not considered numerical because it is more orr less of a categorical(boolean) feature
- 75% of the customers have tenure less than 55 months

In [8]:
```
# checking for customers who churned
data['Churn'].value_counts()
```

Out[8]:
```
No     5174
Yes    1869
Name: Churn, dtype: int64
```

In [9]:
```
(data['Churn'].value_counts()/ len(data))*100
```

Out[9]:
```
No     73.463013
Yes    26.536987
Name: Churn, dtype: float64
```

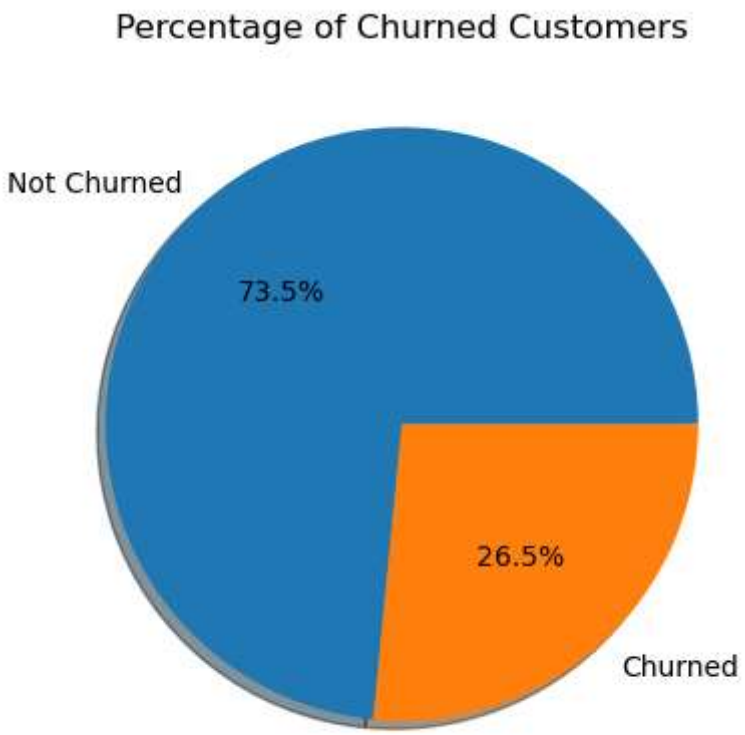
- Customer churn rate is 26.54% which is slightly above a quarter

In [10]:

```
# Visualising number of customers who have churned
plt.title('Percentage of Churned Customers')
plt.pie(x= data['Churn'].value_counts(),
        autopct= '%1.1f%%', labels=['Not Churned', 'Churned'], shadow= True)
```

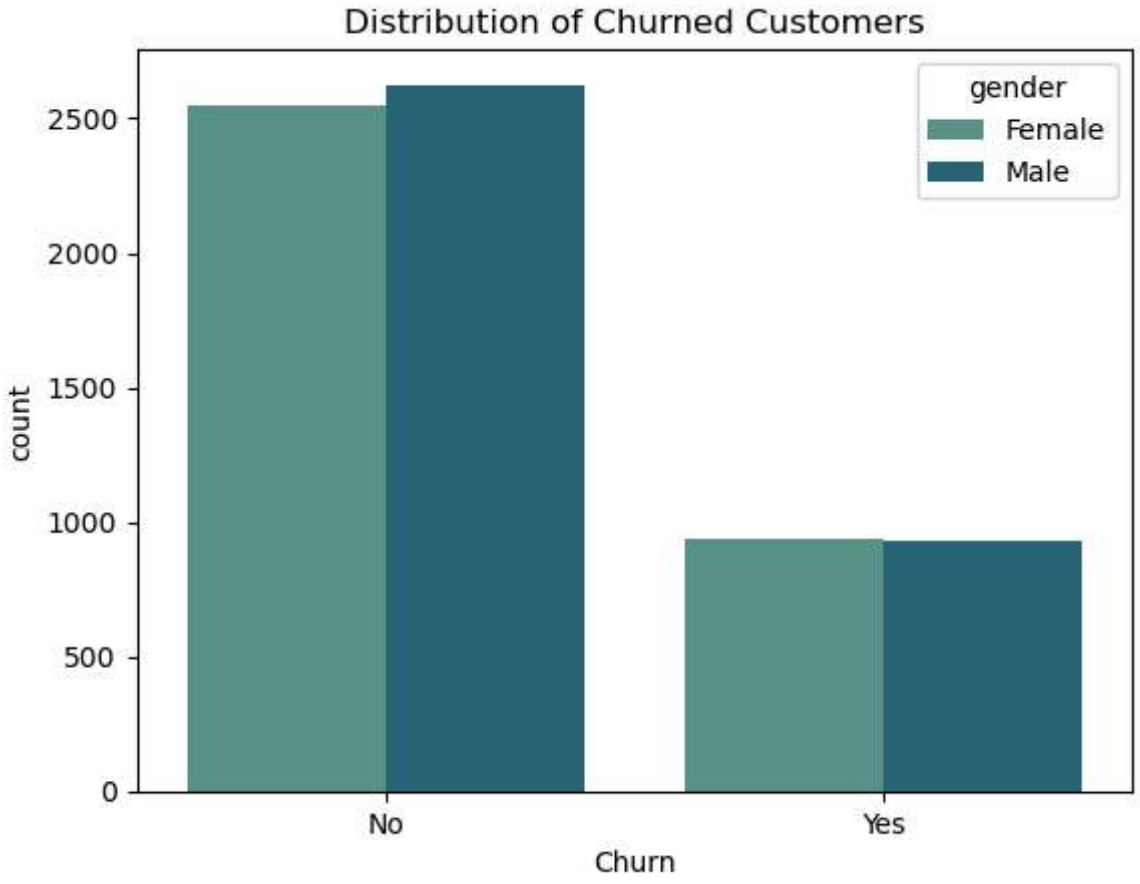
Out[10]:

```
([<matplotlib.patches.Wedge at 0x21e52f2be20>,
  <matplotlib.patches.Wedge at 0x21e535dea30>],
 [Text(-0.7393678277834757, 0.8144539368428056, 'Not Churned'),
  Text(0.7393677515287918, -0.8144540060674139, 'Churned')],
 [Text(-0.4032915424273503, 0.44424760191425755, '73.5%'),
  Text(0.4032915008338864, -0.4442476396731348, '26.5%')])
```



In [11]:
```
1 plt.title('Distribution of Churned Customers')
2 sns.countplot(x= data['Churn'], hue= data['gender'], palette='crest')
```

Out[11]:
```
<AxesSubplot:title={'center':'Distribution of Churned Customers'}, xlabel='Churn', ylabel='count'>
```



- There is no significant difference between males and females who have churned

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

Data Cleaning

In [13]:
```
df = data.copy()
df
```

Out[13]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service
1	5575-GNVDE	Male	0	No	No	34	Yes	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service
4	9237-HQITU	Female	0	No	No	2	Yes	No
...	...	...	...	...	...	...	...	...
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes
7042	3186-AJIEK	Male	0	No	No	66	Yes	No

7043 rows × 21 columns

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

In [15]:
```
1 df['TotalCharges'].value_counts()
```

Out[15]:
```
           11
20.2       11
19.75       9
20.05       8
19.9        8
           ..
6849.4      1
692.35      1
130.15      1
3211.9      1
6844.5      1
Name: TotalCharges, Length: 6531, dtype: int64
```

In [16]:

```
# Converting the 'Total Charges' column into an appropriate data type
df['TotalCharges'] = df['TotalCharges'].astype('int', errors='ignore')
df.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   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [17]:

```
# Missing Value treatment
df.dropna(how = 'any', inplace=True)
```

In [18]:
```
1 df.isnull().sum()
```

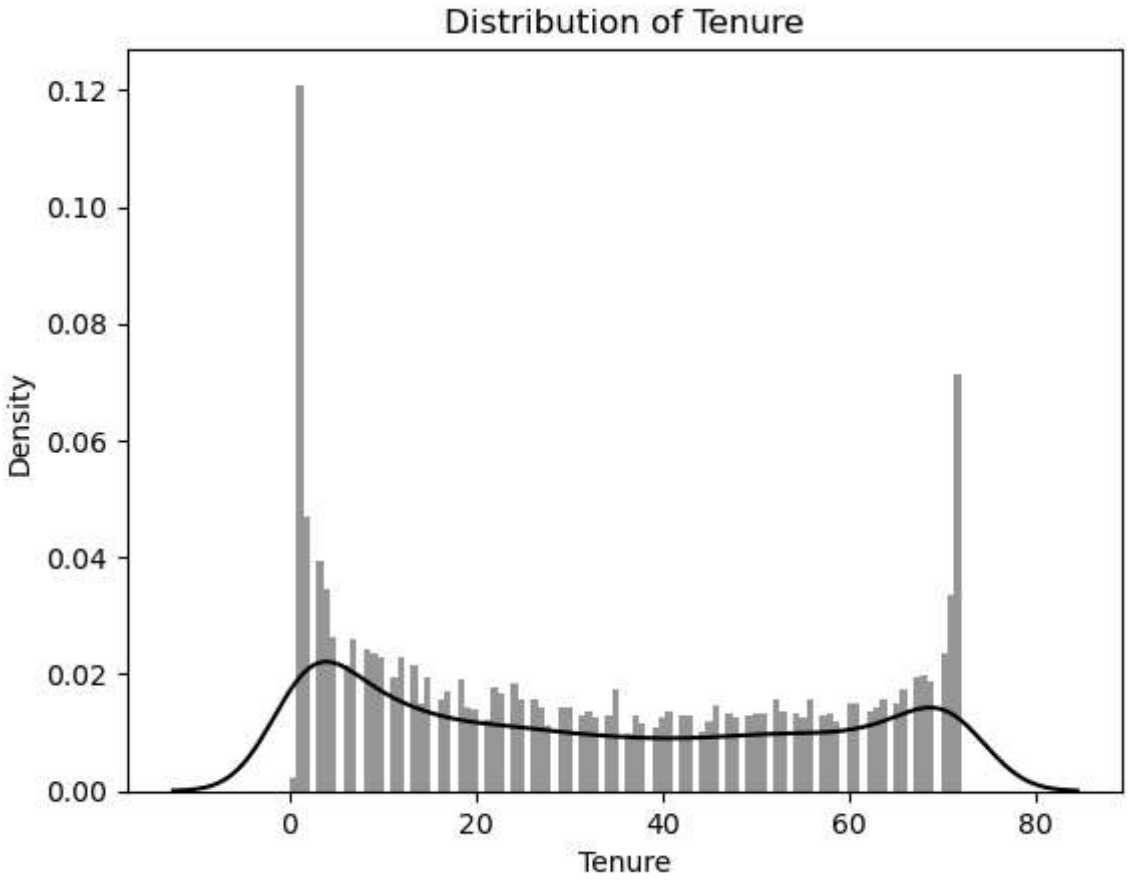
Out[18]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [19]:

```
# Visualising the distribution of tenure
import warnings
warnings.filterwarnings(action= 'ignore')
plt.title('Distribution of Tenure')
plt.xlabel('Tenure')
sns.distplot(x= df['tenure'], color= 'black', bins= 100)
```

Out[19]:

```
<AxesSubplot:title={'center':'Distribution of Tenure'}, xlabel='Tenure', ylabel
='Density'>
```



Data Analysis

In [20]:
```
1 df.head()
```

Out[20]:

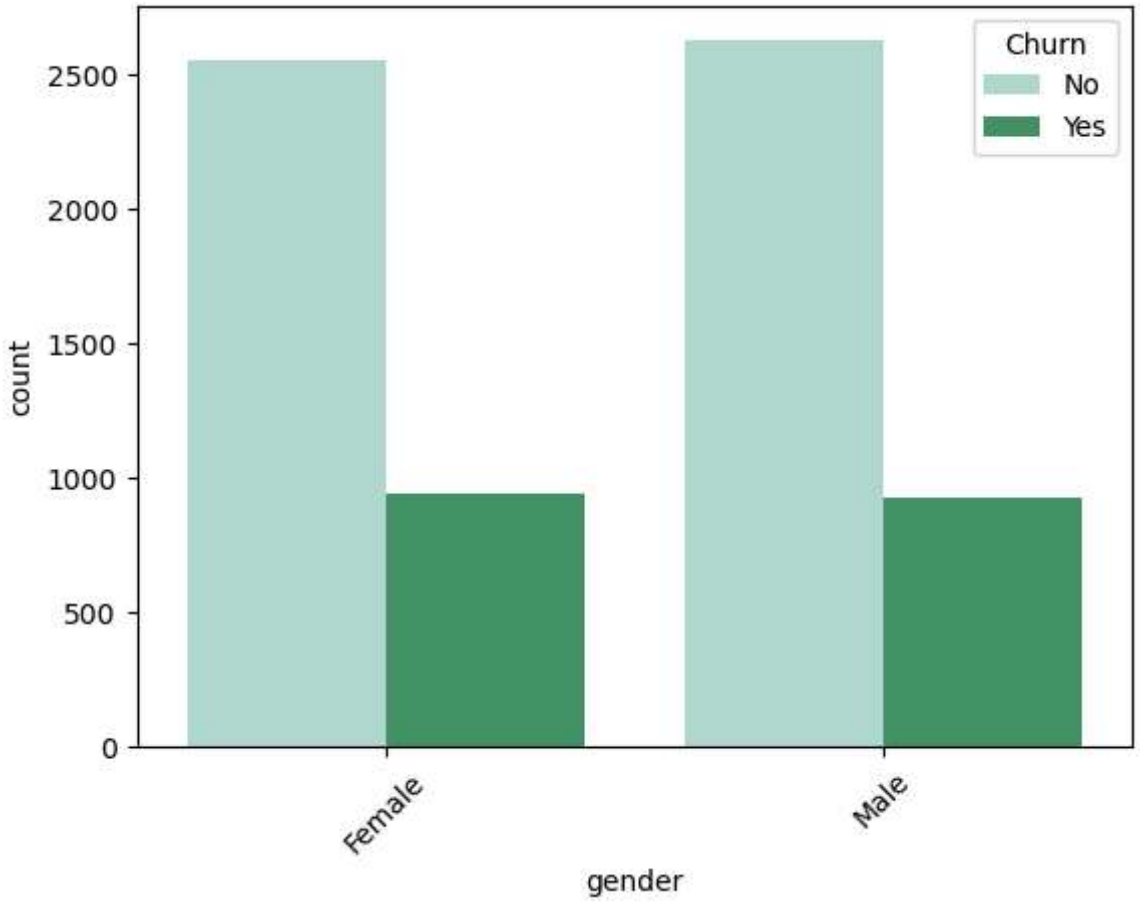
	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

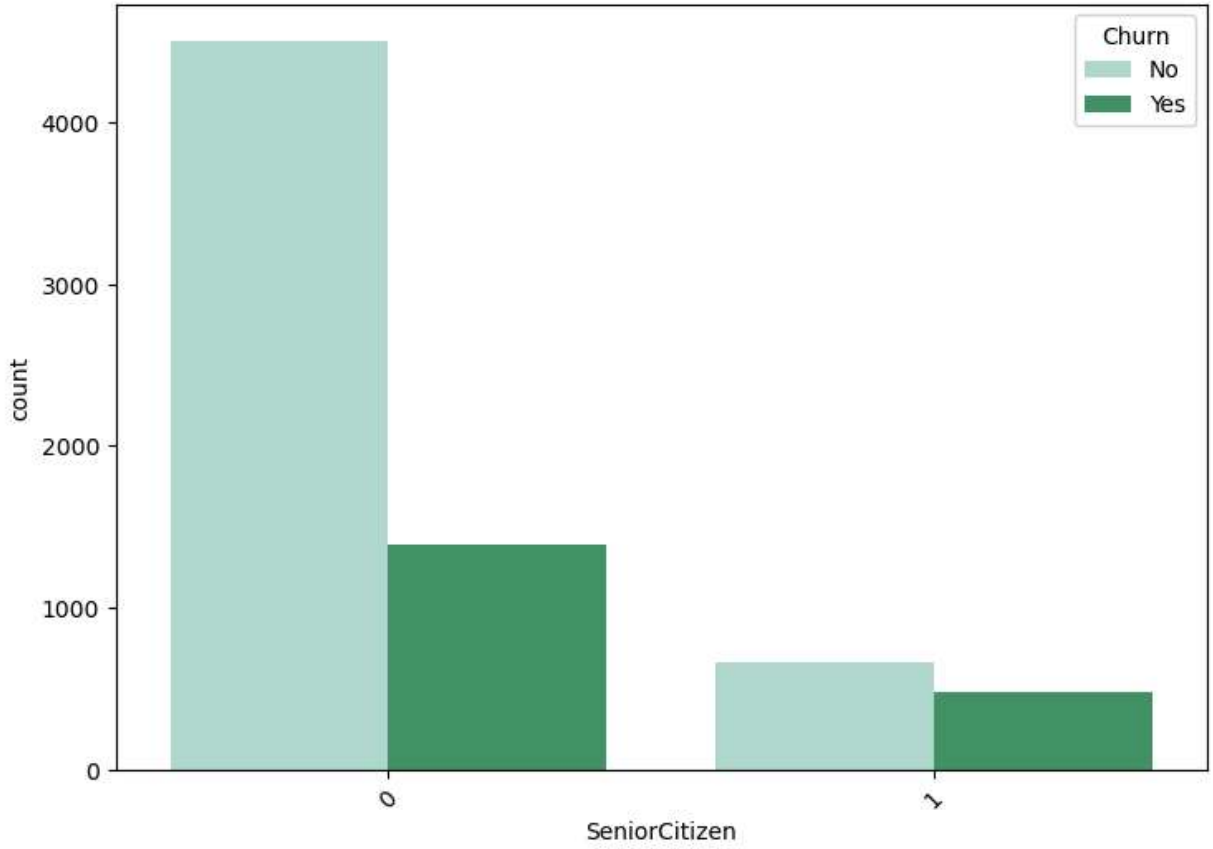
5 rows × 21 columns

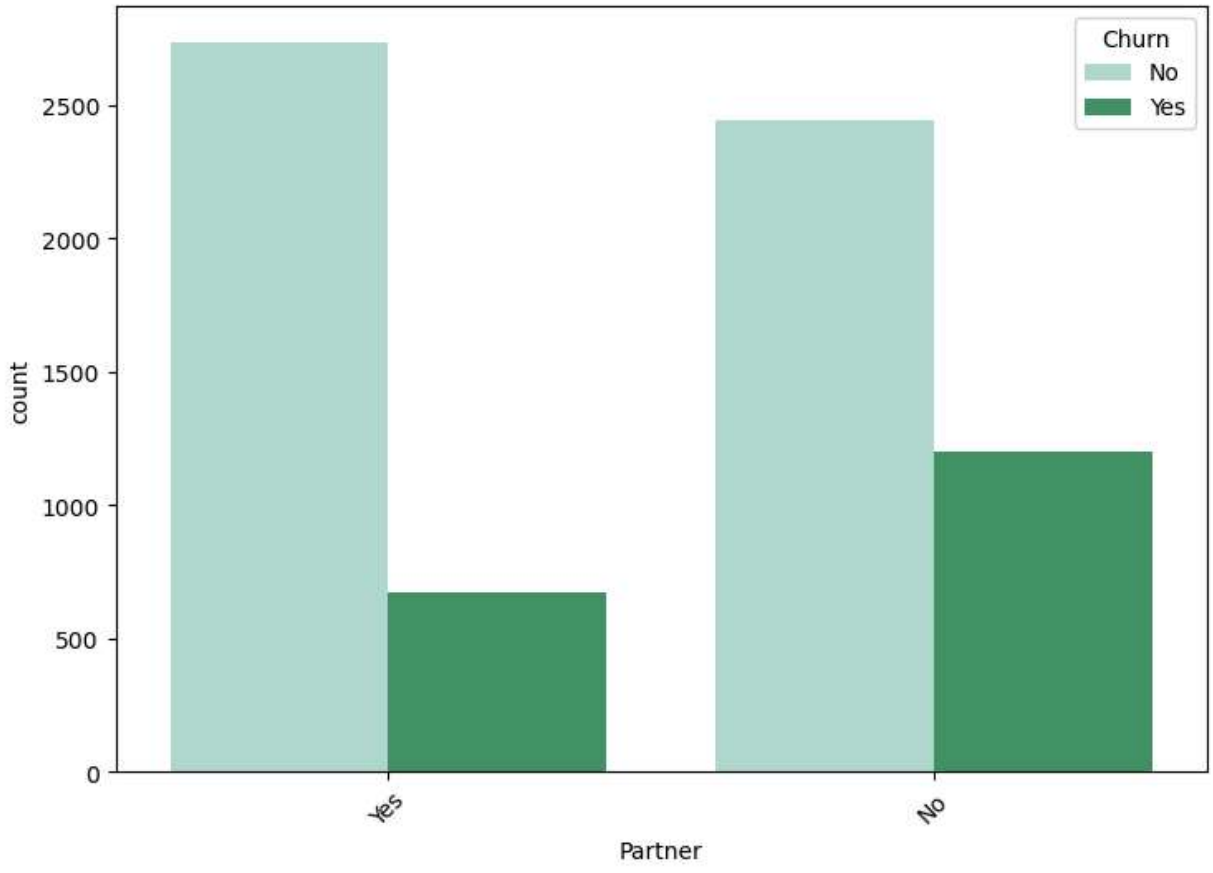
Univariate Analysis

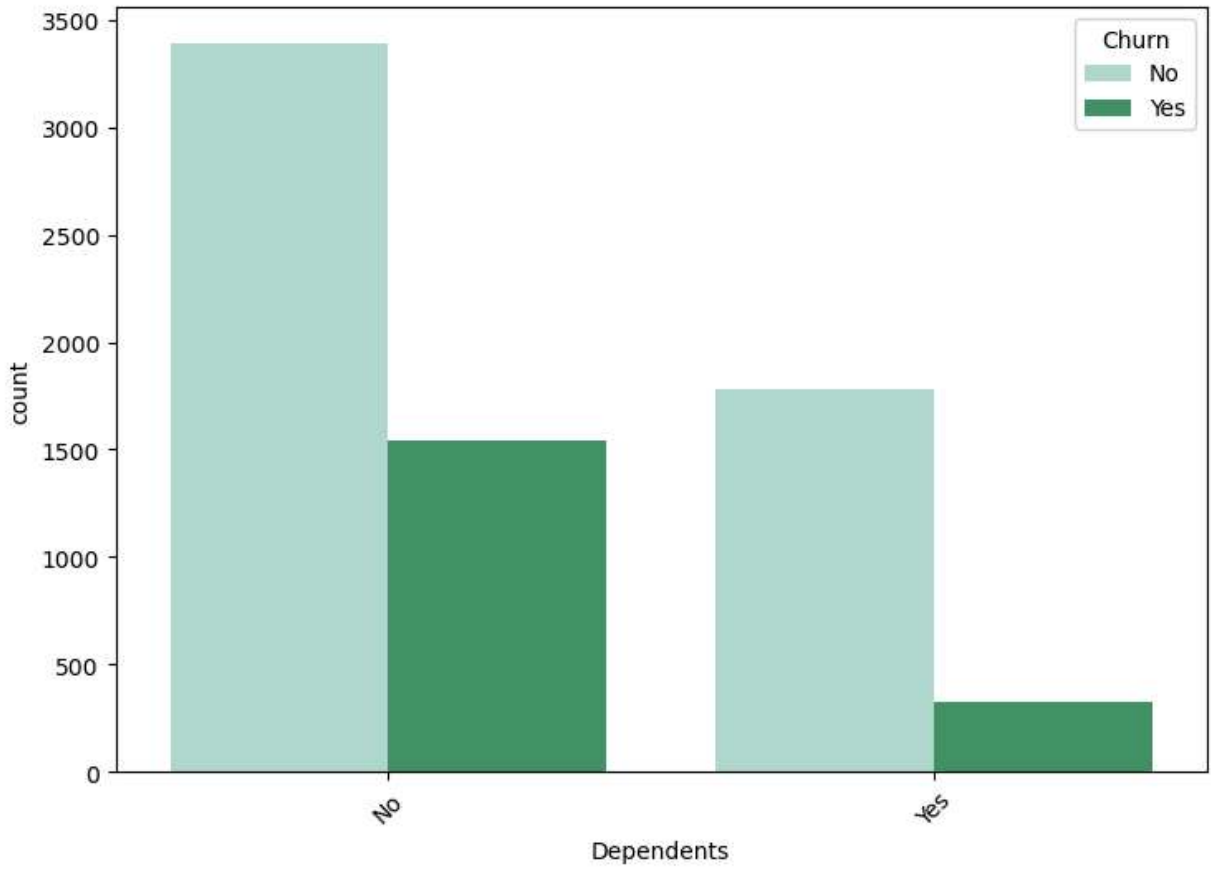
In [21]:

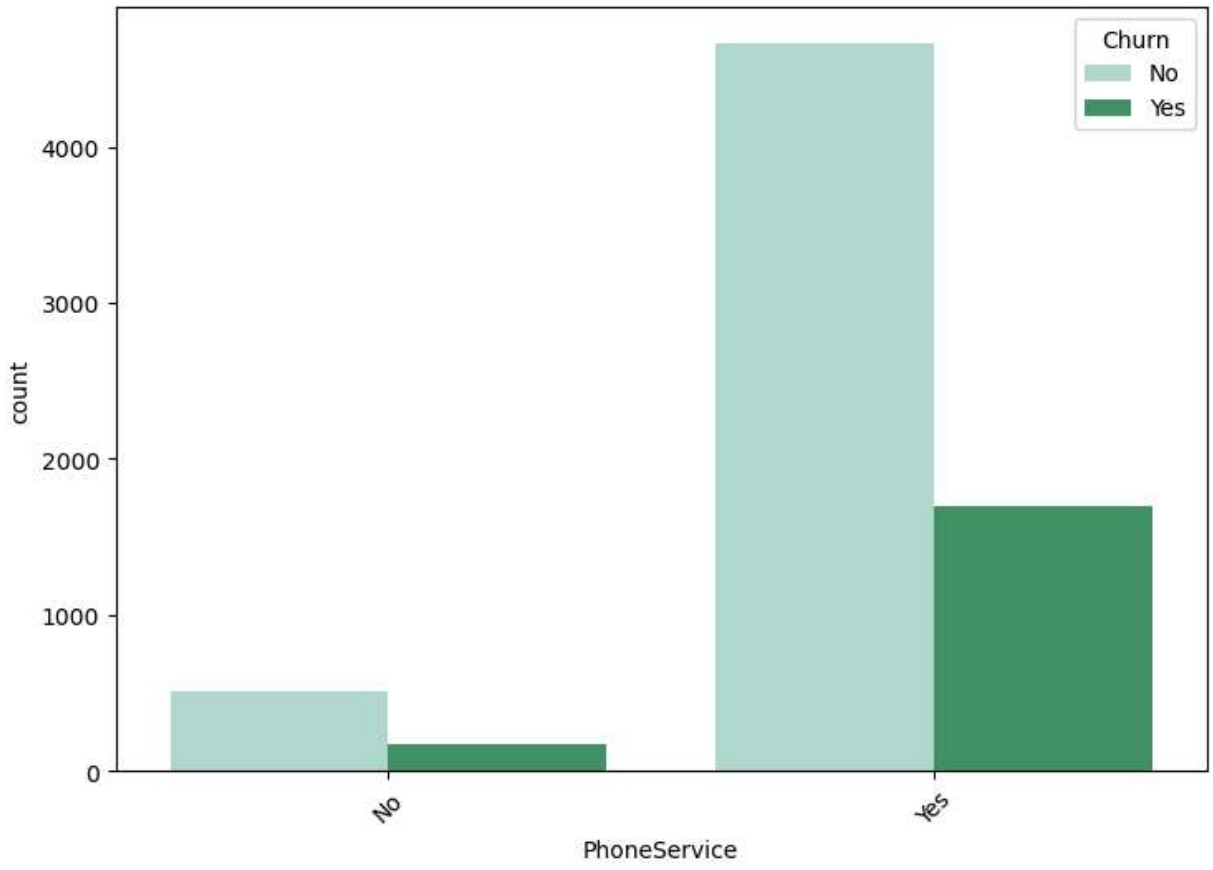
```
# Performing Univariate analysis on various featuers of the data in relation
for i, predictor in enumerate(df.drop(columns= ['MonthlyCharges', 'TotalChar
    plt.figure(figsize=(8.5, 6))
    plt.figure(i)
    plt.xticks(rotation= 45)
    sns.countplot(x= predictor, data= df, hue= 'Churn', palette='BuGn')
```

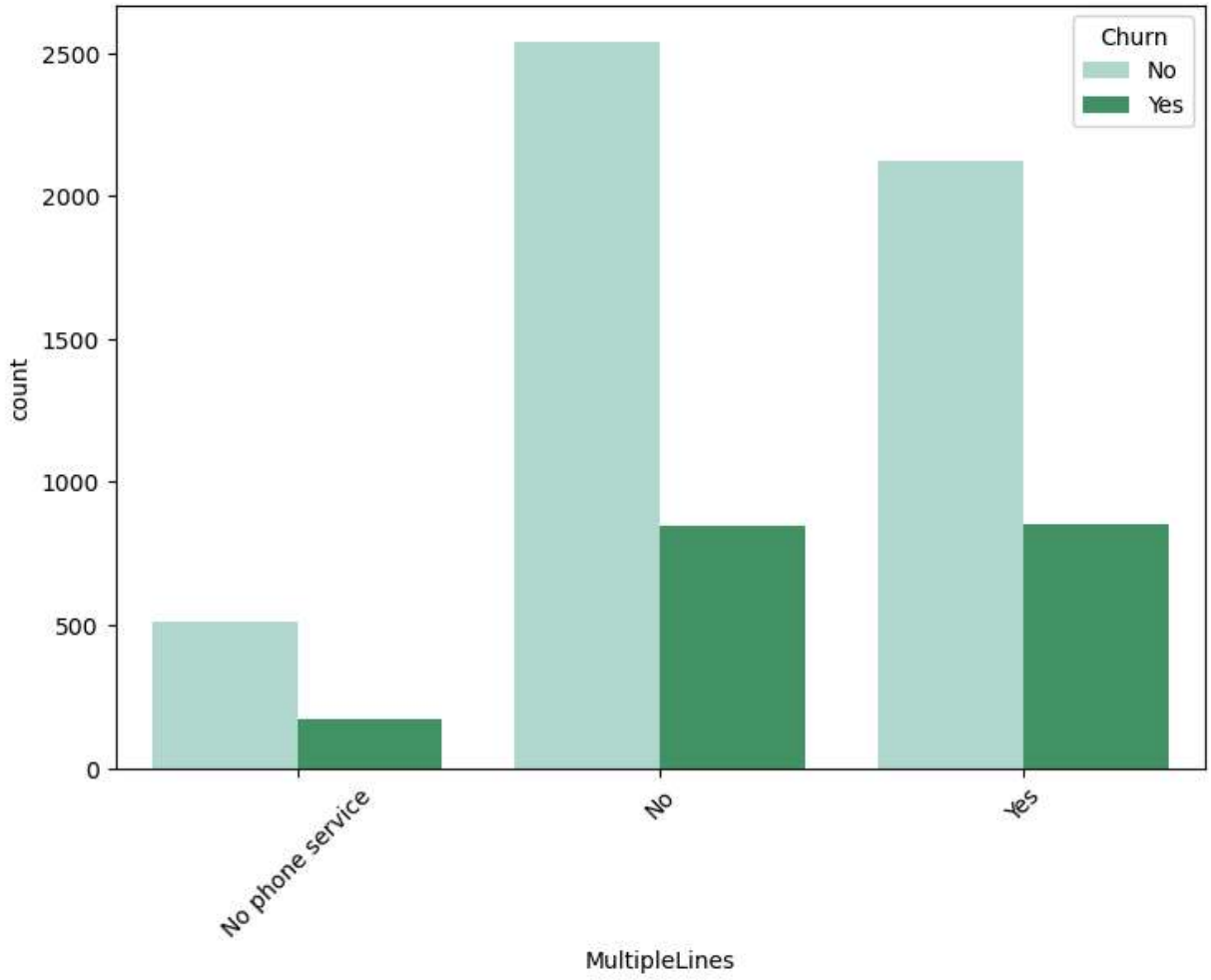


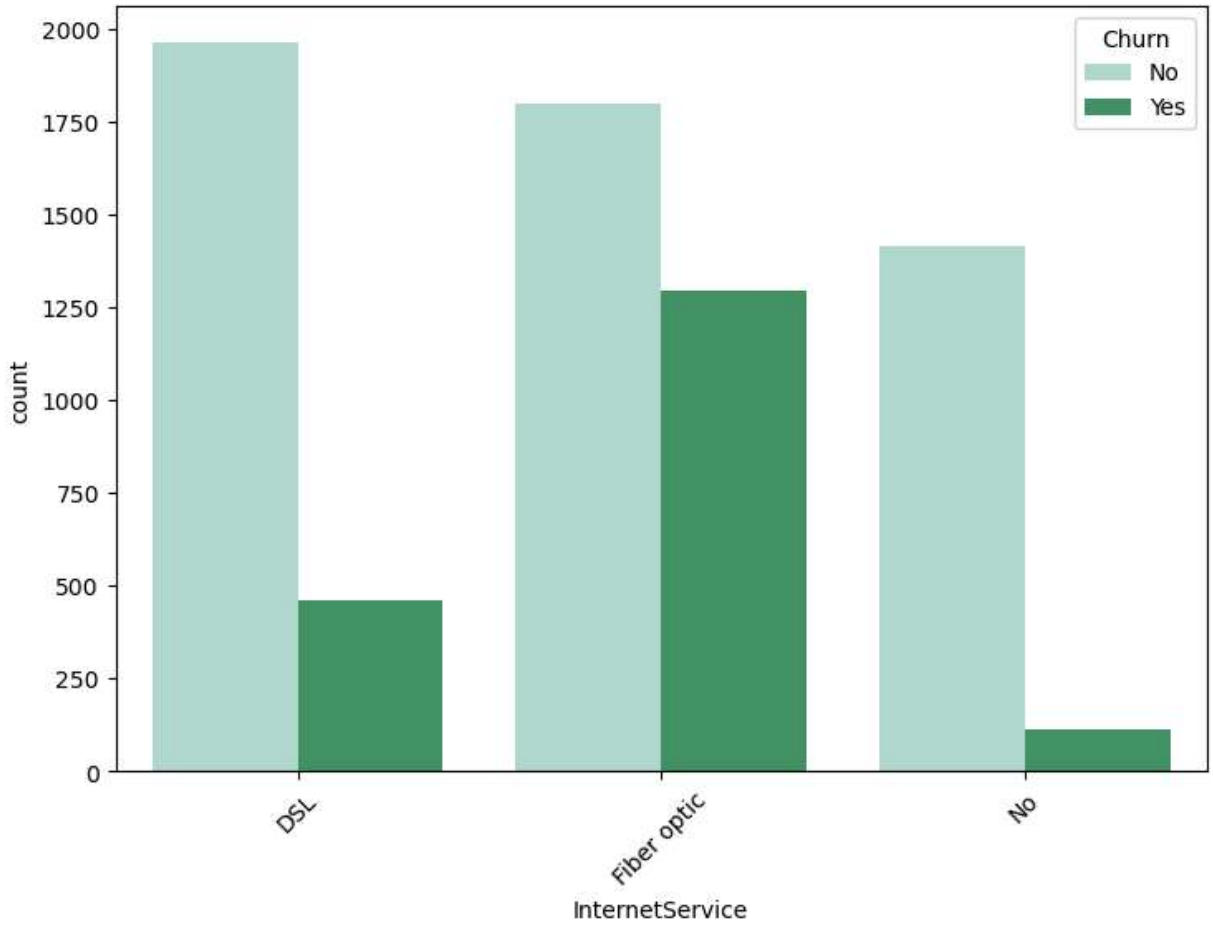

Churn
No
Yes
4000
3000
2000
1000
0
count
0
1
SeniorCitizen

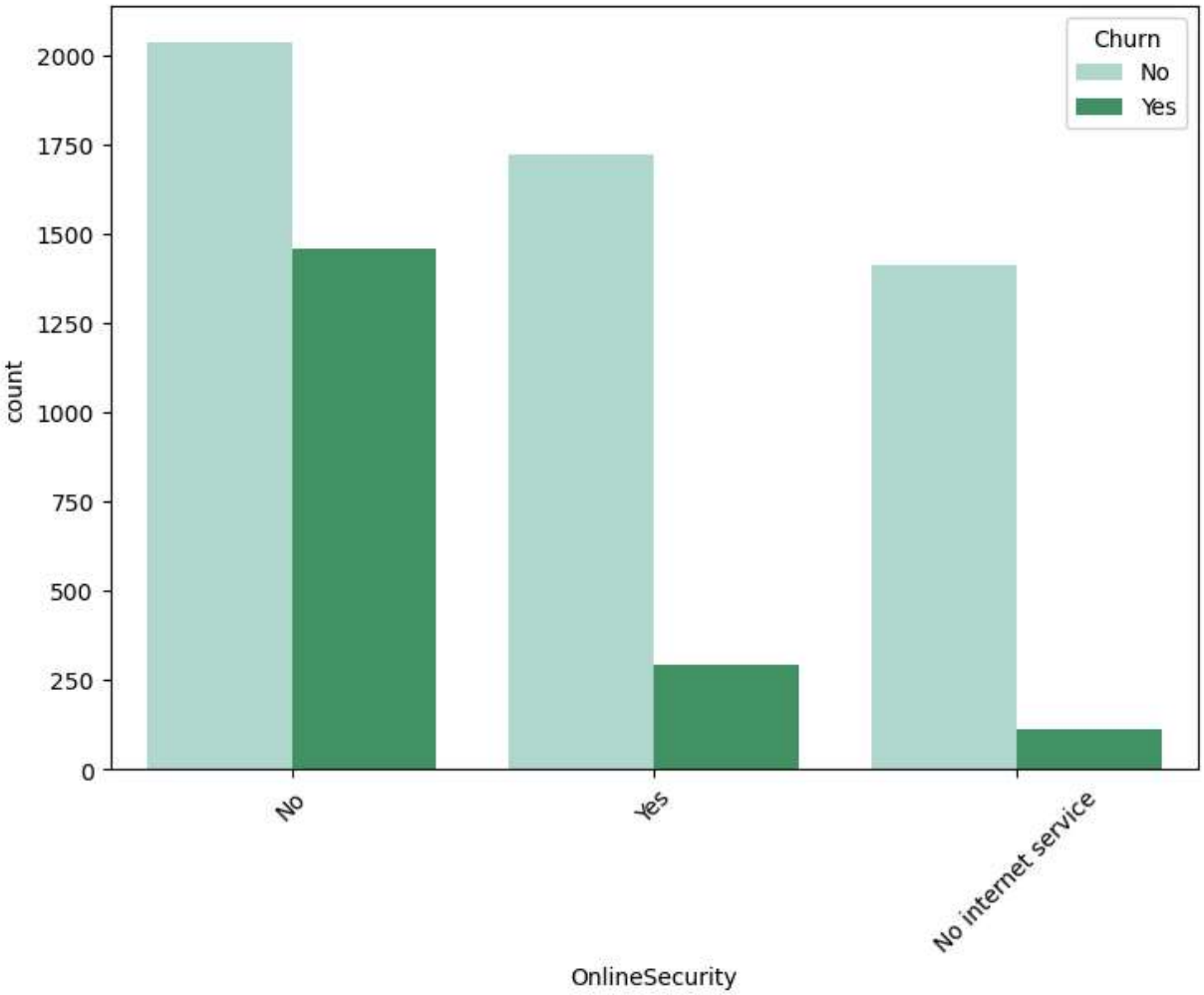

Churn
No
Yes
2500
2000
1500
1000
500
0
count
Yes
No
Partner

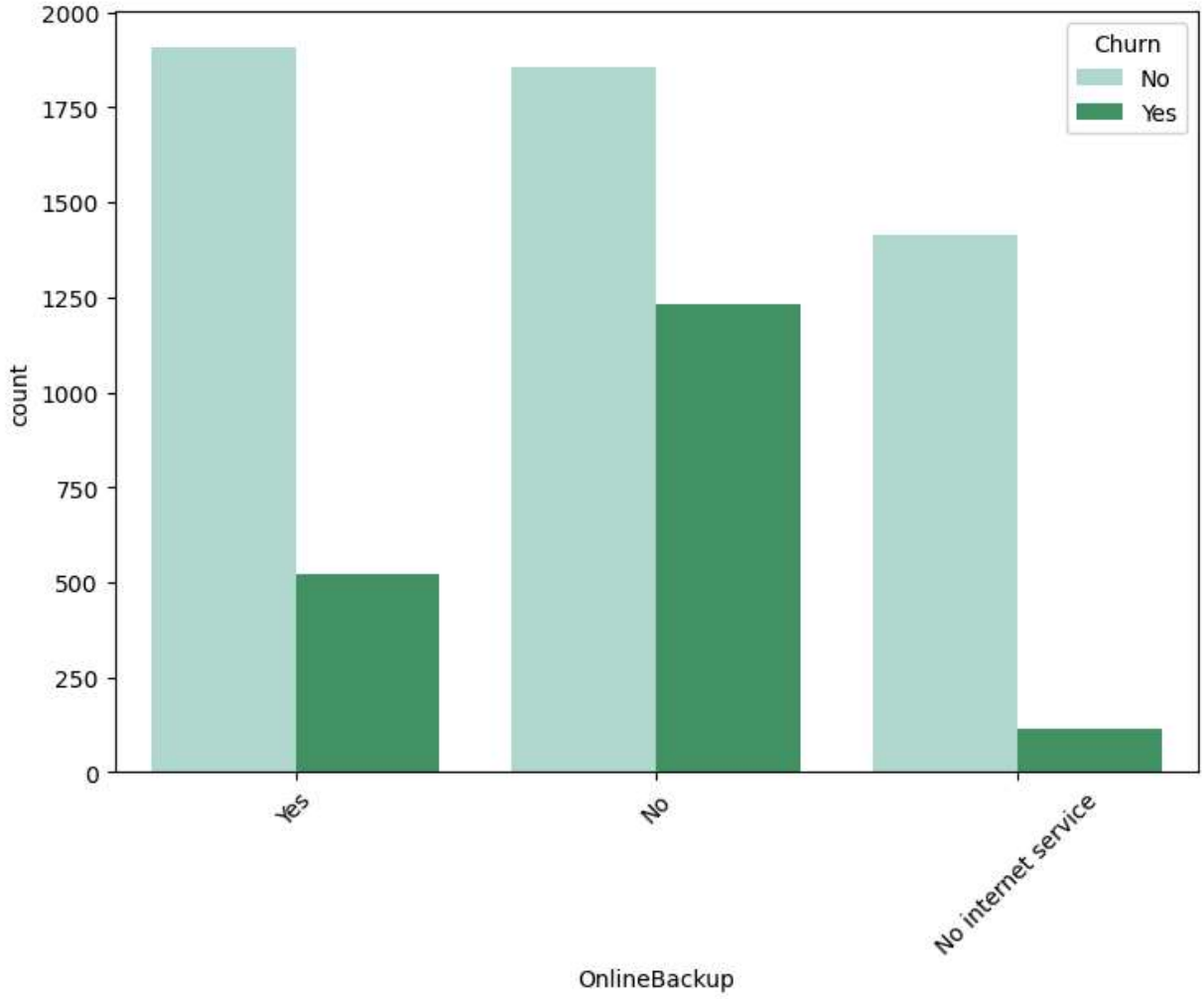

Churn
No
Yes
3500
3000
2500
2000
1500
1000
500
0
count
No
Yes
Dependents

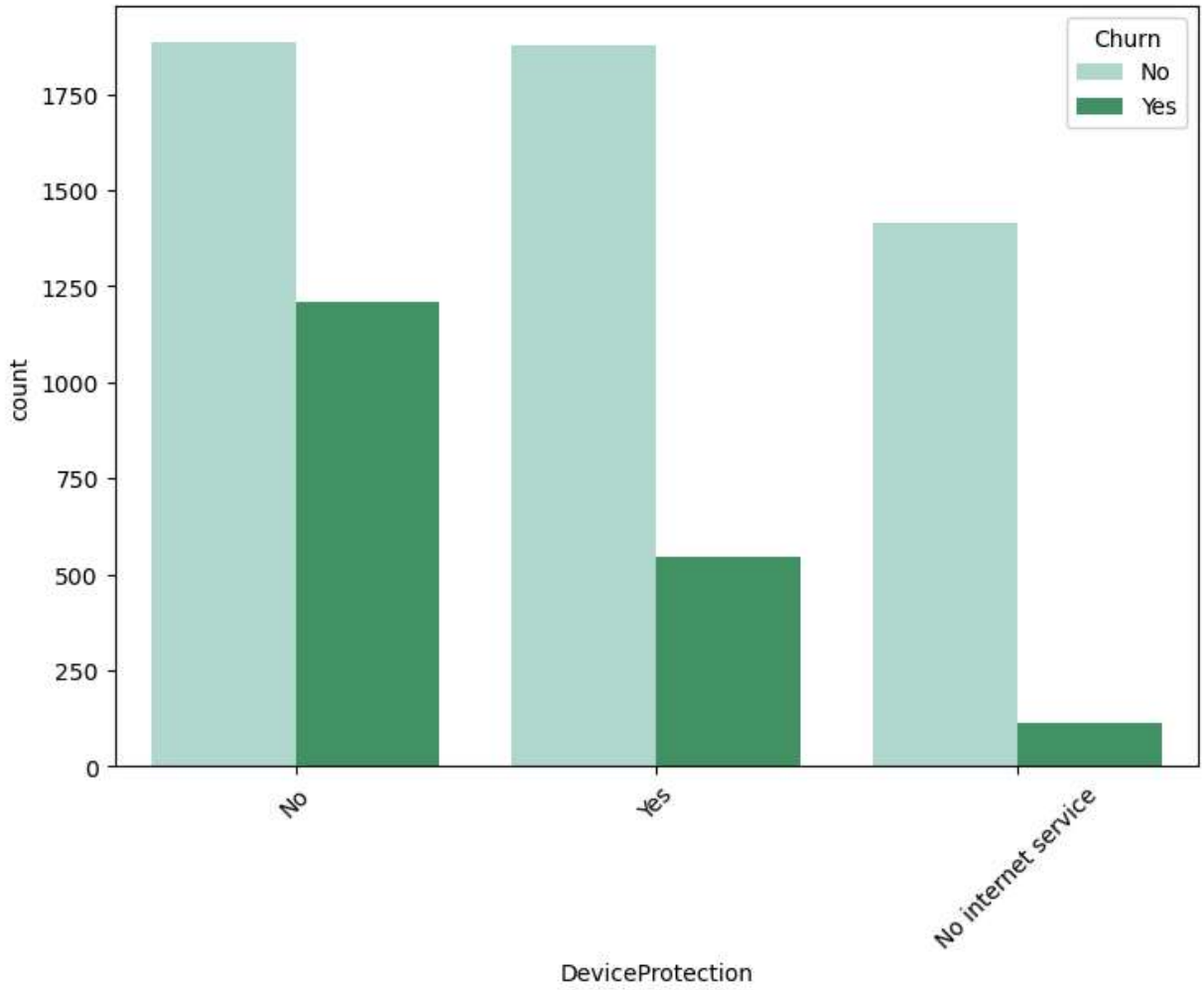

Churn
No
Yes
4000
3000
2000
1000
0
count
No
Yes
PhoneService

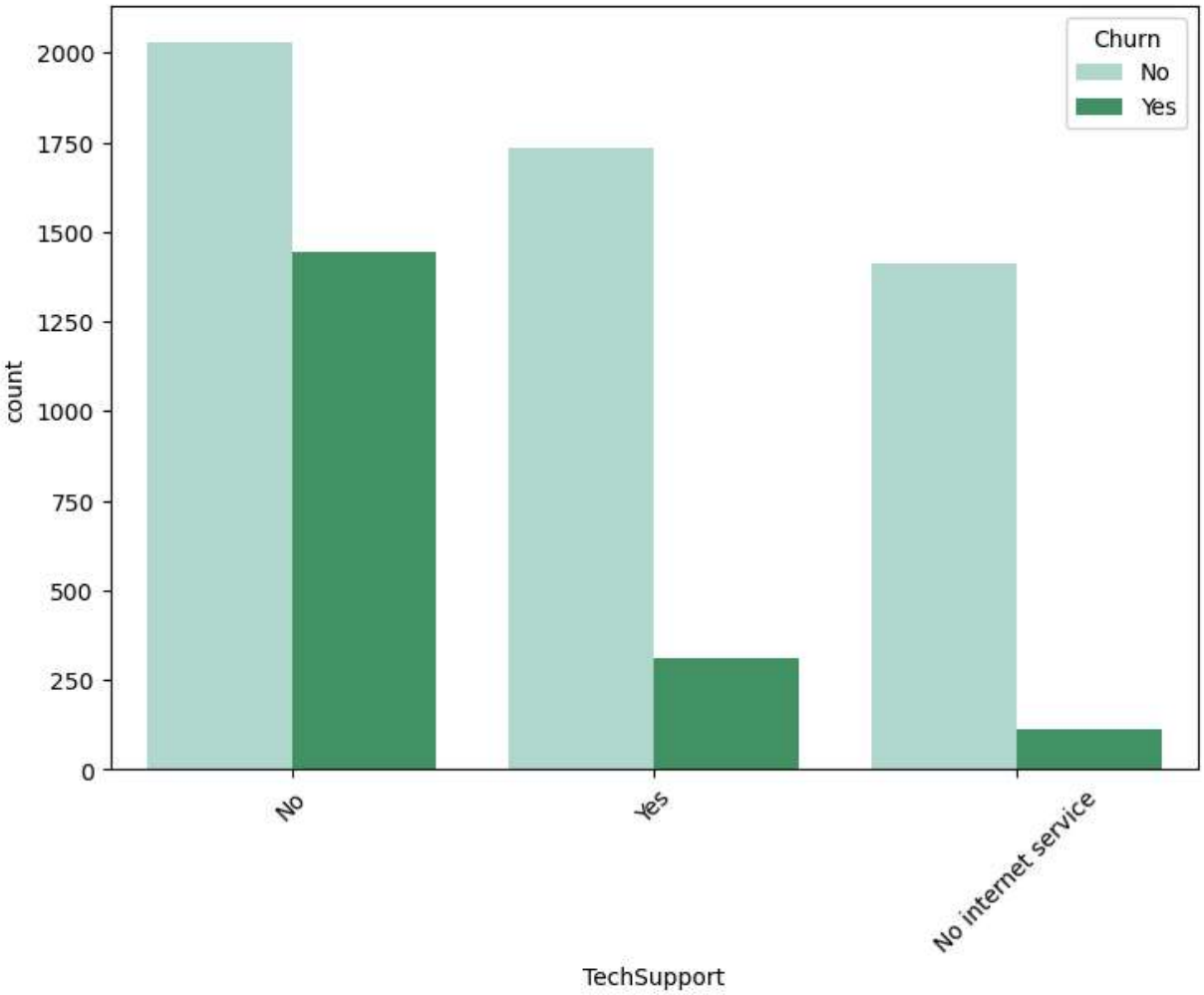

Churn
No
Yes
2500
2000
1500
1000
500
0
count
No phone service
No
Yes
MultipleLines

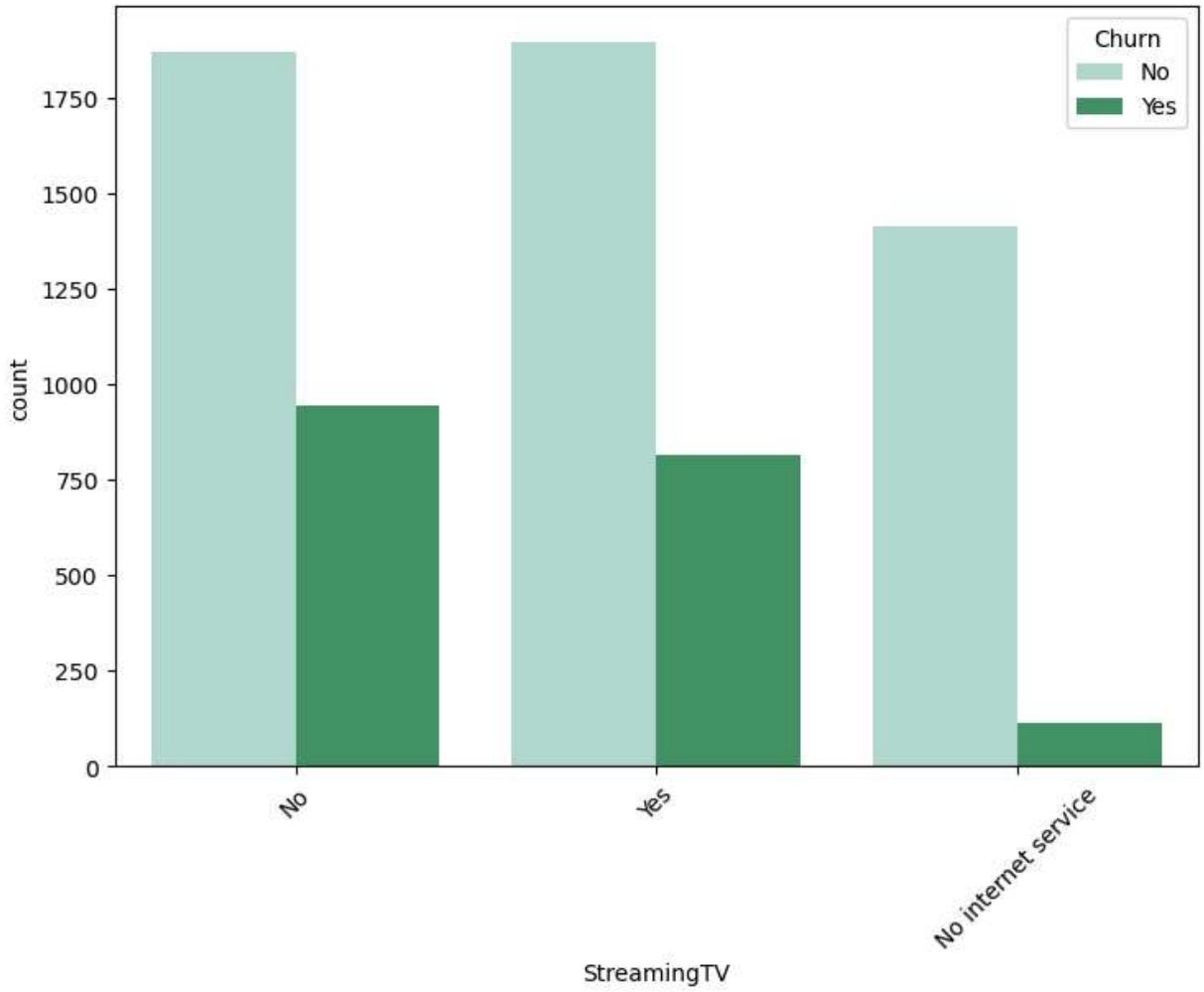

Churn
No
Yes
2000
1750
1500
1250
1000
750
500
250
0
count
DSL
Fiber optic
No
InternetService

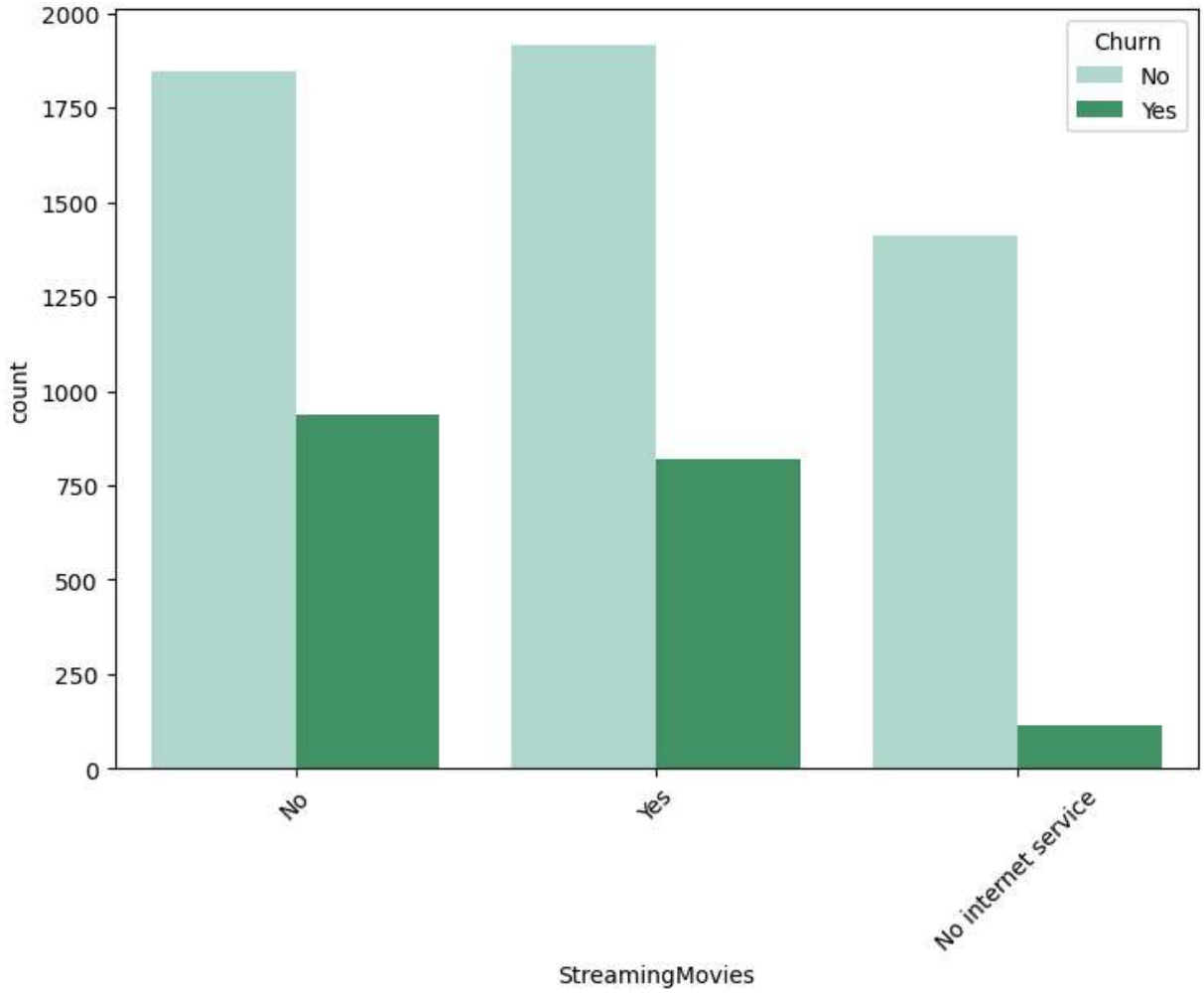

Churn
No
Yes
2000
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
OnlineSecurity

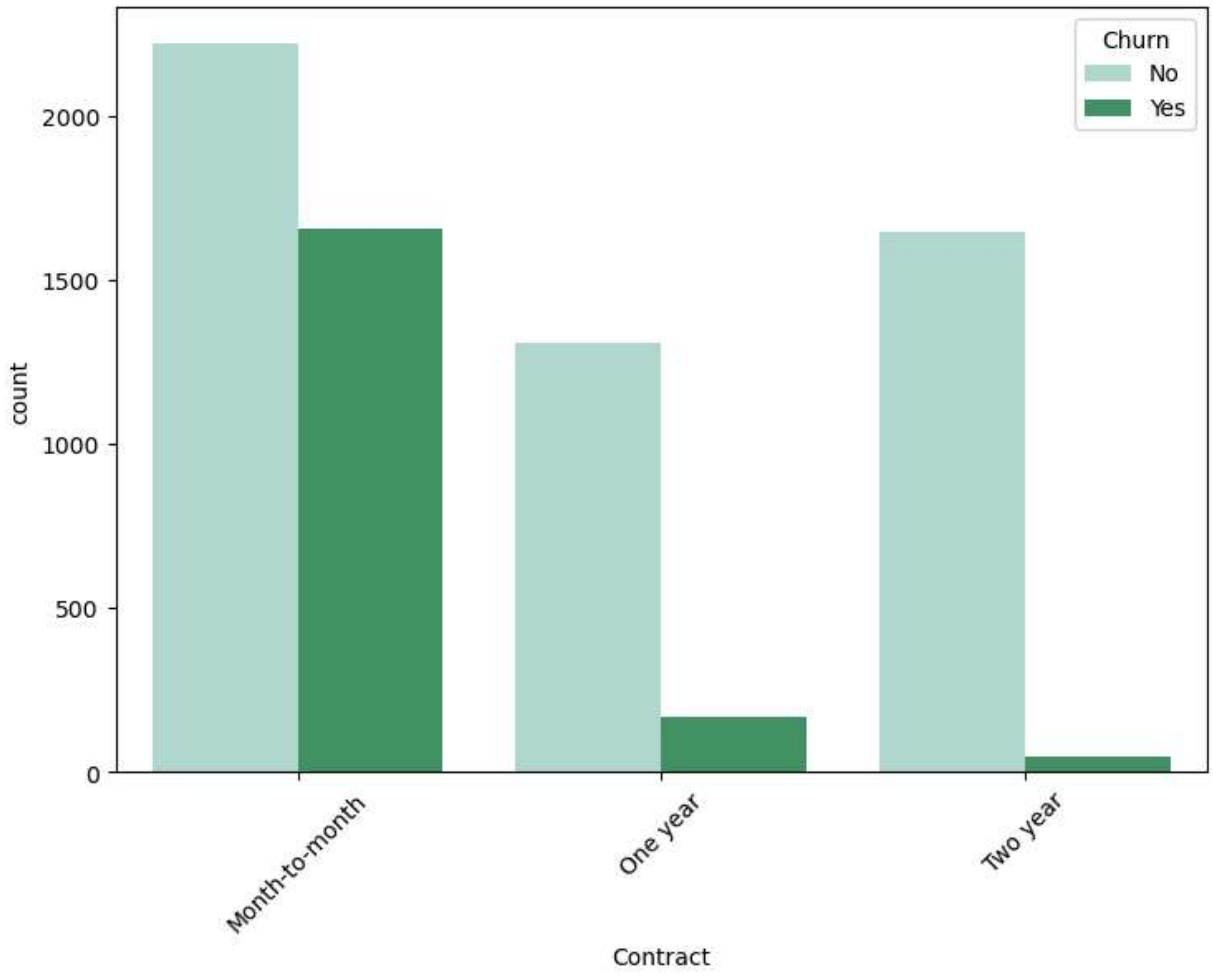

Churn
No
Yes
2000
1750
1500
1250
1000
750
500
250
0
count
Yes
No
No internet service
OnlineBackup

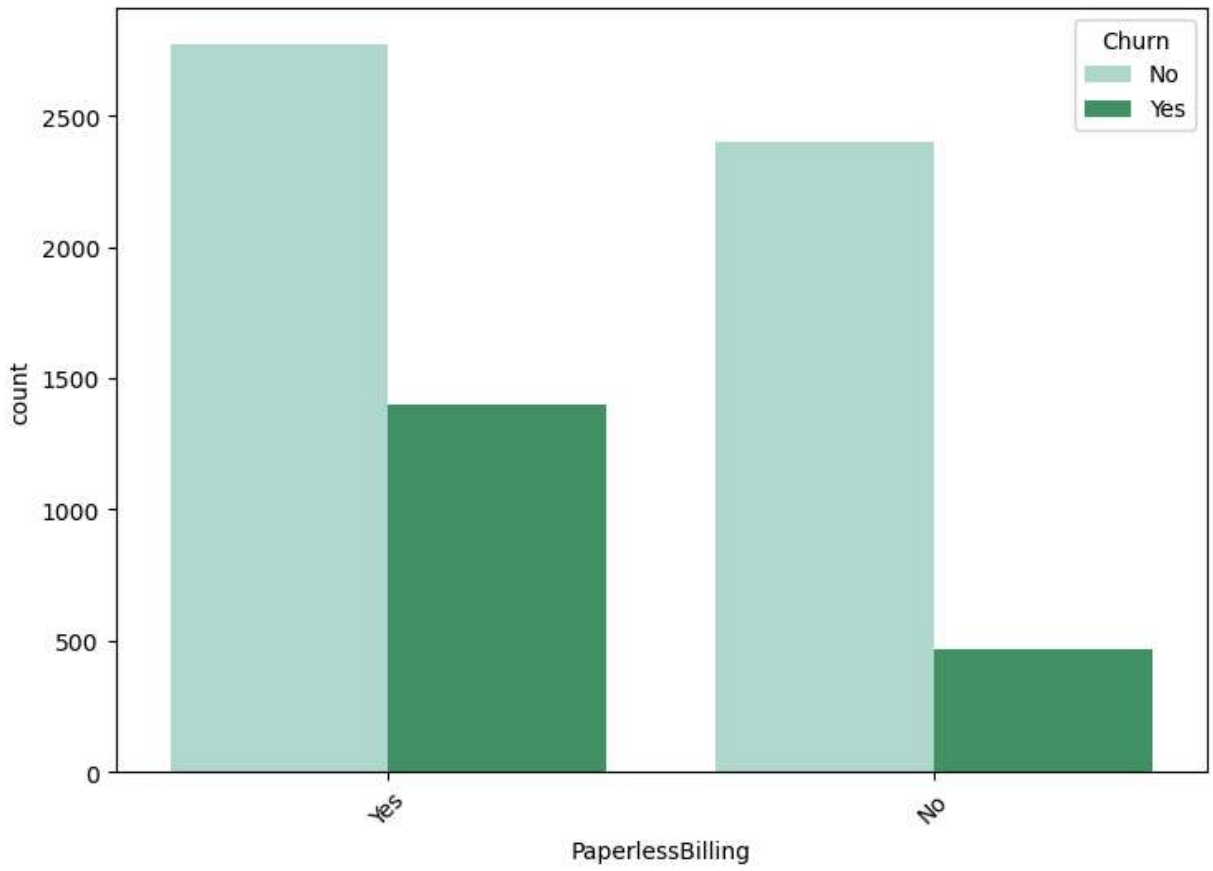

Churn
No
Yes
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
DeviceProtection

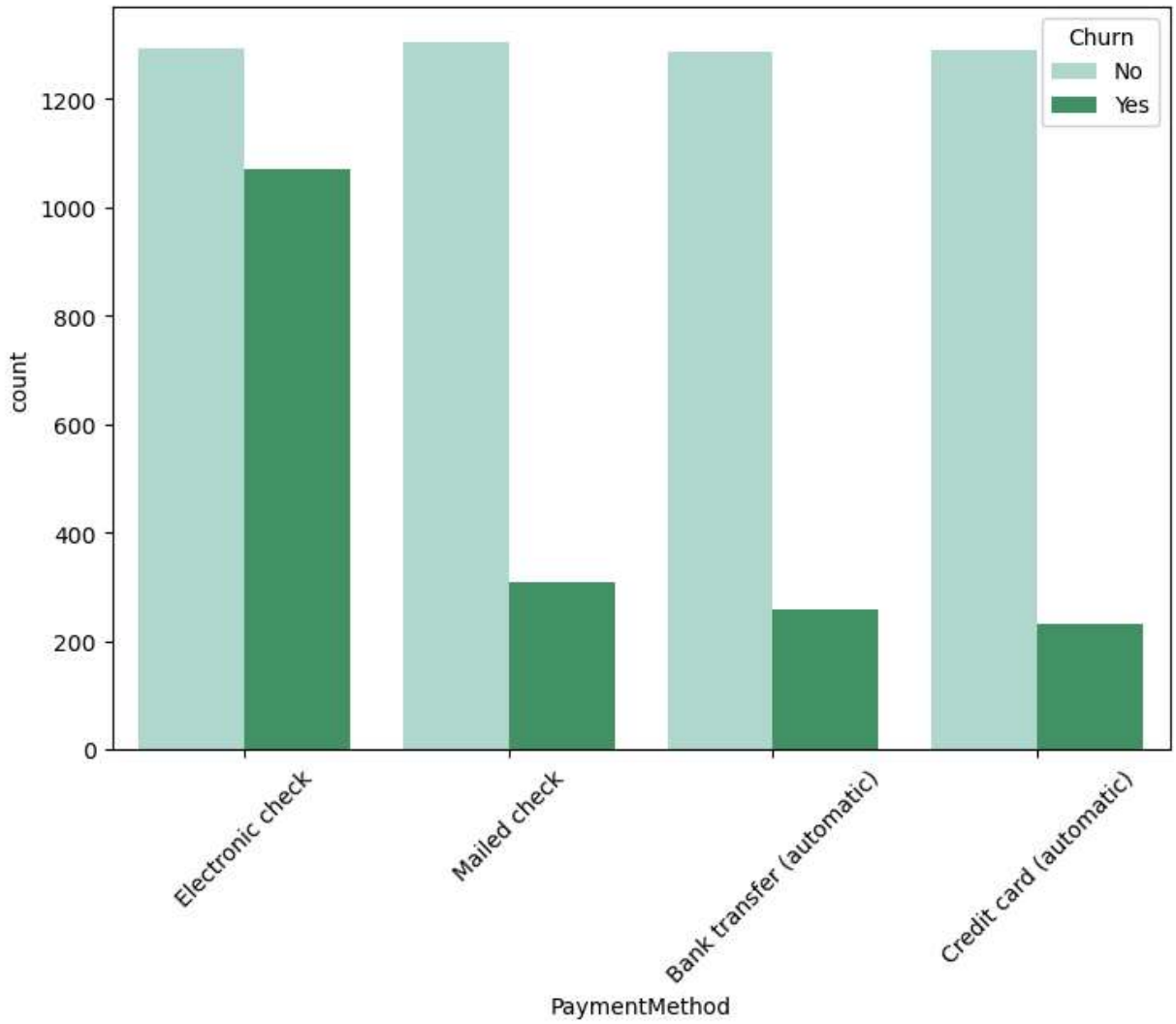

Churn
No
Yes
2000
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
TechSupport


Churn
No
Yes
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
StreamingTV

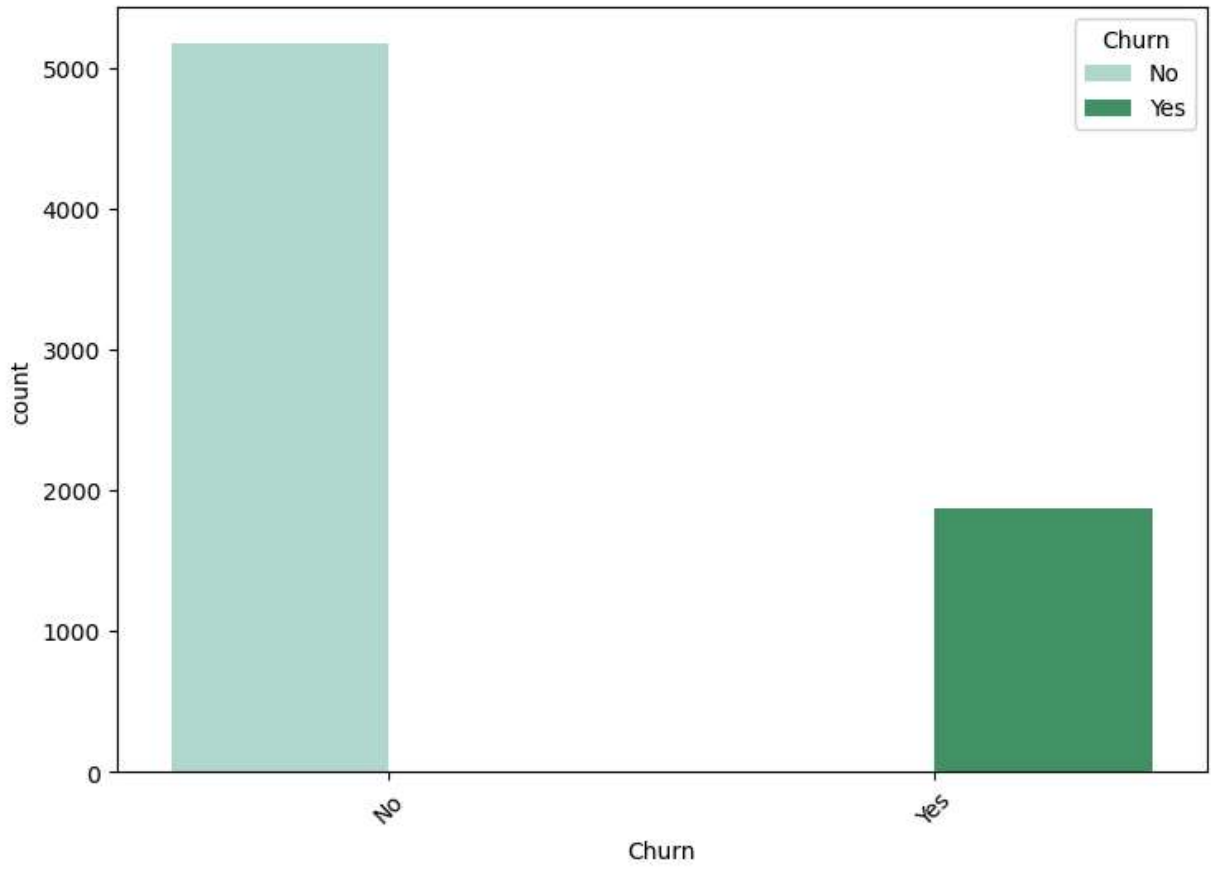

Churn
No
Yes
2000
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
StreamingMovies


Churn
No
Yes
2000
1500
1000
500
0
count
Month-to-month
One year
Two year
Contract


Churn
No
Yes
2500
2000
1500
1000
500
0
count
Yes
No
PaperlessBilling



<Figure size 850x600 with 0 Axes>



In [22]:
```
1 df.columns
```

Out[22]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [23]:
```
1 df['PaymentMethod'].value_counts()
```

Out[23]:
```
Electronic check             2365
Mailed check                 1612
Bank transfer (automatic)    1544
Credit card (automatic)      1522
Name: PaymentMethod, dtype: int64
```

In [24]:
```
1 pd.crosstab(df['PaymentMethod'], df['Churn'])
```

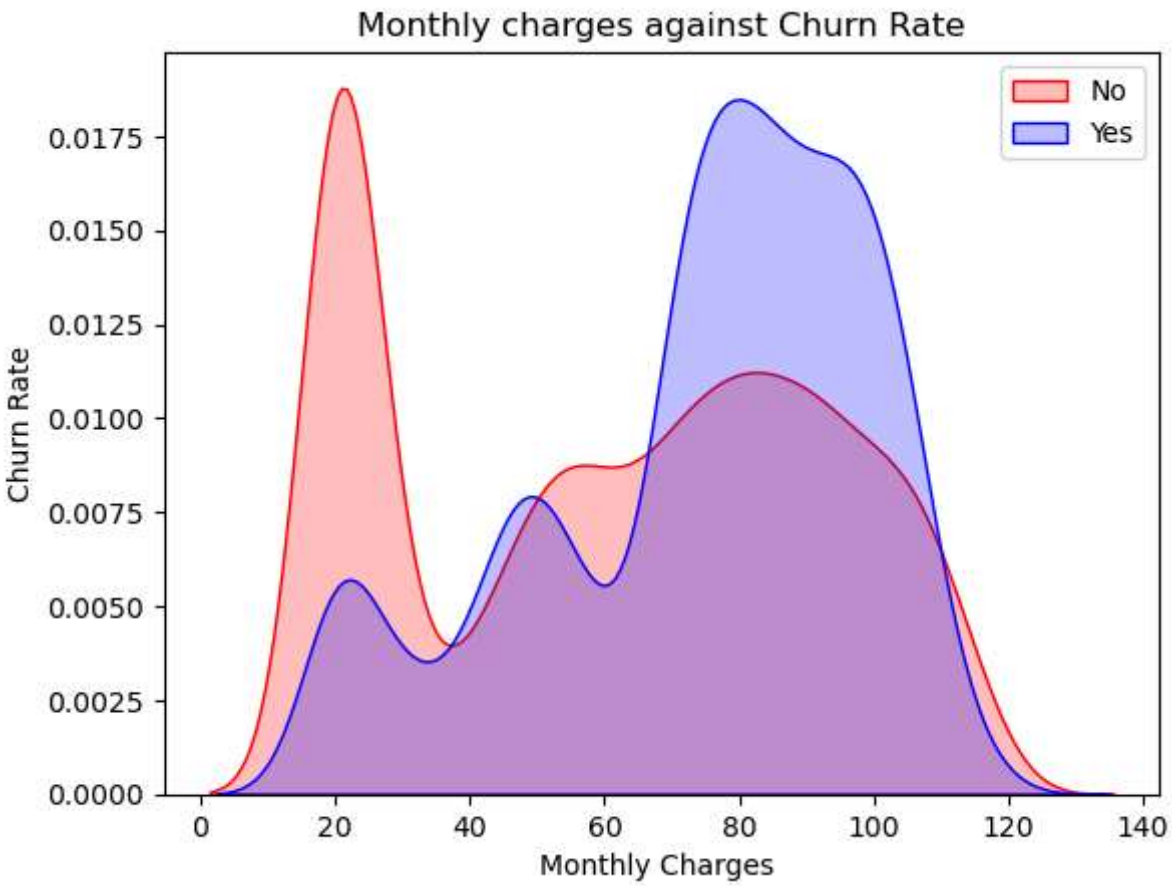
Out[24]:

Churn	No	Yes
PaymentMethod		
Bank transfer (automatic)	1286	258
Credit card (automatic)	1290	232
Electronic check	1294	1071
Mailed check	1304	308

In [25]:
```
# Encoding all categorical values
# df_dummies = pd.get_dummies(df.drop(columns=['TotalCharges', 'MonthlyCharg
# df_dummies
```

In [27]:
```
# checking relationship between Monthly charges and Churn rate
plt.title('Monthly charges against Churn Rate')
plt.ylabel('Churn Rate')
plt.xlabel('Monthly Charges ')
Churn = sns.kdeplot(df.MonthlyCharges[(df['Churn'] == 'No')], color='Red', s
Churn = sns.kdeplot(df.MonthlyCharges[(df['Churn'] == 'Yes')],
                                    ax= Churn, color='blue', shade= True)
plt.legend(['No', 'Yes'])
```

Out[27]: <matplotlib.legend.Legend at 0x21e56ed5f40>



- Customers tend to churn at higher monthly charges compared to lower monthly charges

In [28]:
```
# Converting data into their appropriate datatypes
df['TotalCharges'] = df['TotalCharges'].astype('int', errors='ignore')
```

In [29]:
```
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors= 'coerce')
```

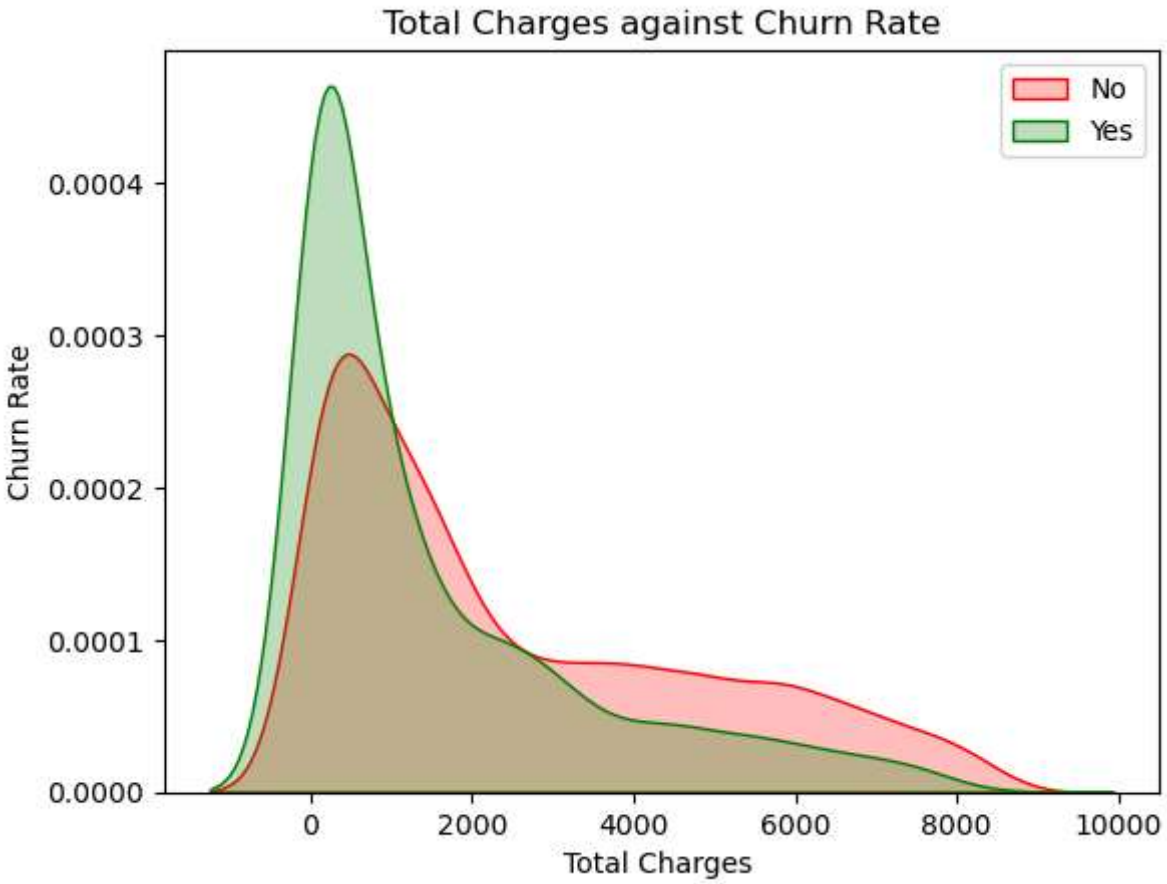
In [30]:
```
1 df.dtypes
```

Out[30]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges        float64
Churn                object
dtype: object
```

In [31]:

```
# Checking total charges against churn rate
plt.title('Total Charges against Churn Rate')
plt.ylabel('Churn Rate')
plt.xlabel('Total Charges ')
Churn = sns.kdeplot(df.TotalCharges[(df['Churn'] == 'No')], color='Red', sha
Churn = sns.kdeplot(df.TotalCharges[(df['Churn'] == 'Yes')],
                                    ax= Churn, color='green', shade= True)
plt.legend(['No', 'Yes'])
```

Out[31]: <matplotlib.legend.Legend at 0x21e56f5ba30>



In [35]:
```
1 df.head()
```

Out[35]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 21 columns

In [36]:
```
1 from sklearn.preprocessing import LabelEncoder
2 encoder = LabelEncoder()
```

In [37]:
```
1 df['Churn_encoded'] = encoder.fit_transform(df['Churn'])
```

In [38]:
```
1 df.head()
```

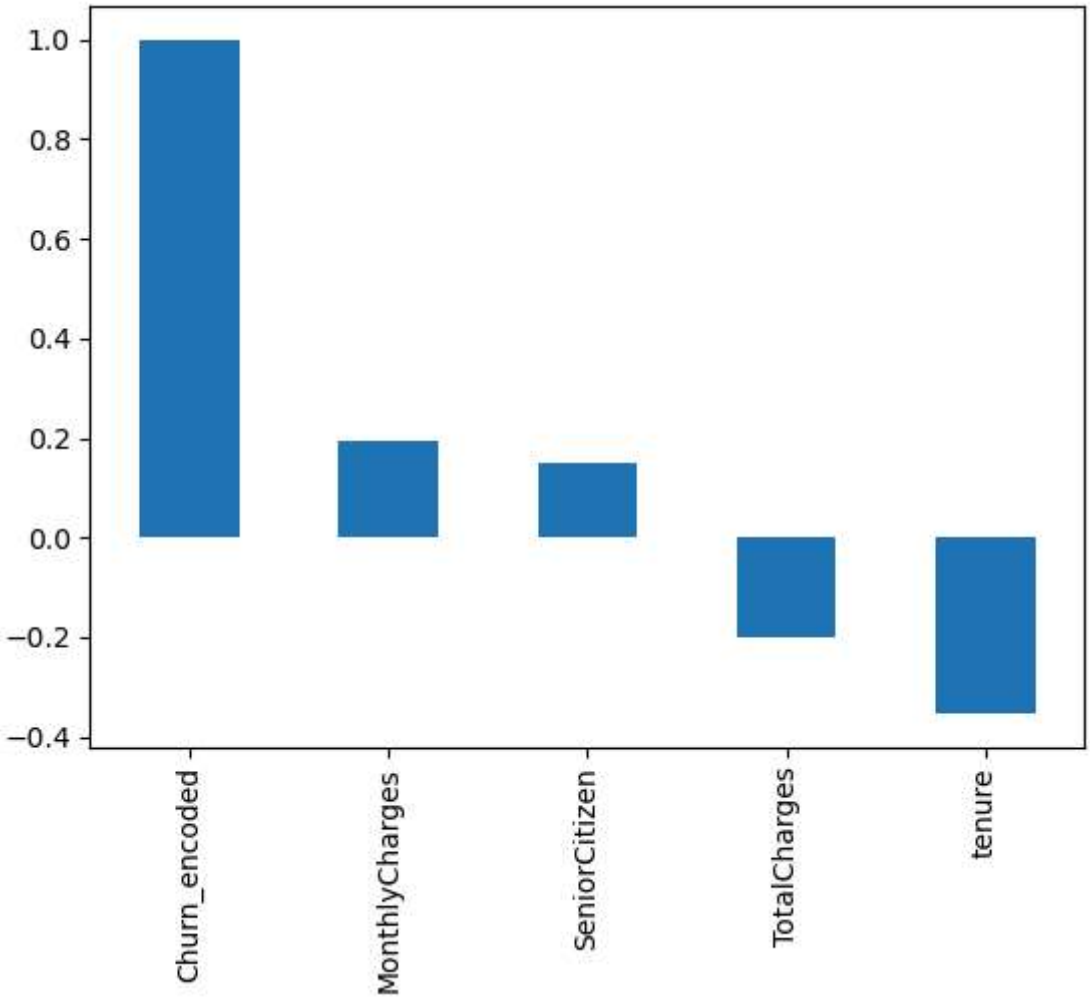
Out[38]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 22 columns

In [39]:
```
# Checking the correlation of predictors with churn
df.corr()['Churn_encoded'].sort_values(ascending= False).plot(kind= 'bar')
```

Out[39]: <AxesSubplot:>



In [42]:
```
df_dummies = pd.get_dummies(df.drop(columns= ['customerID','tenure', 'Monthl
                                              'TotalCharges', 'Churn_encoded
df_dummies.head()
```

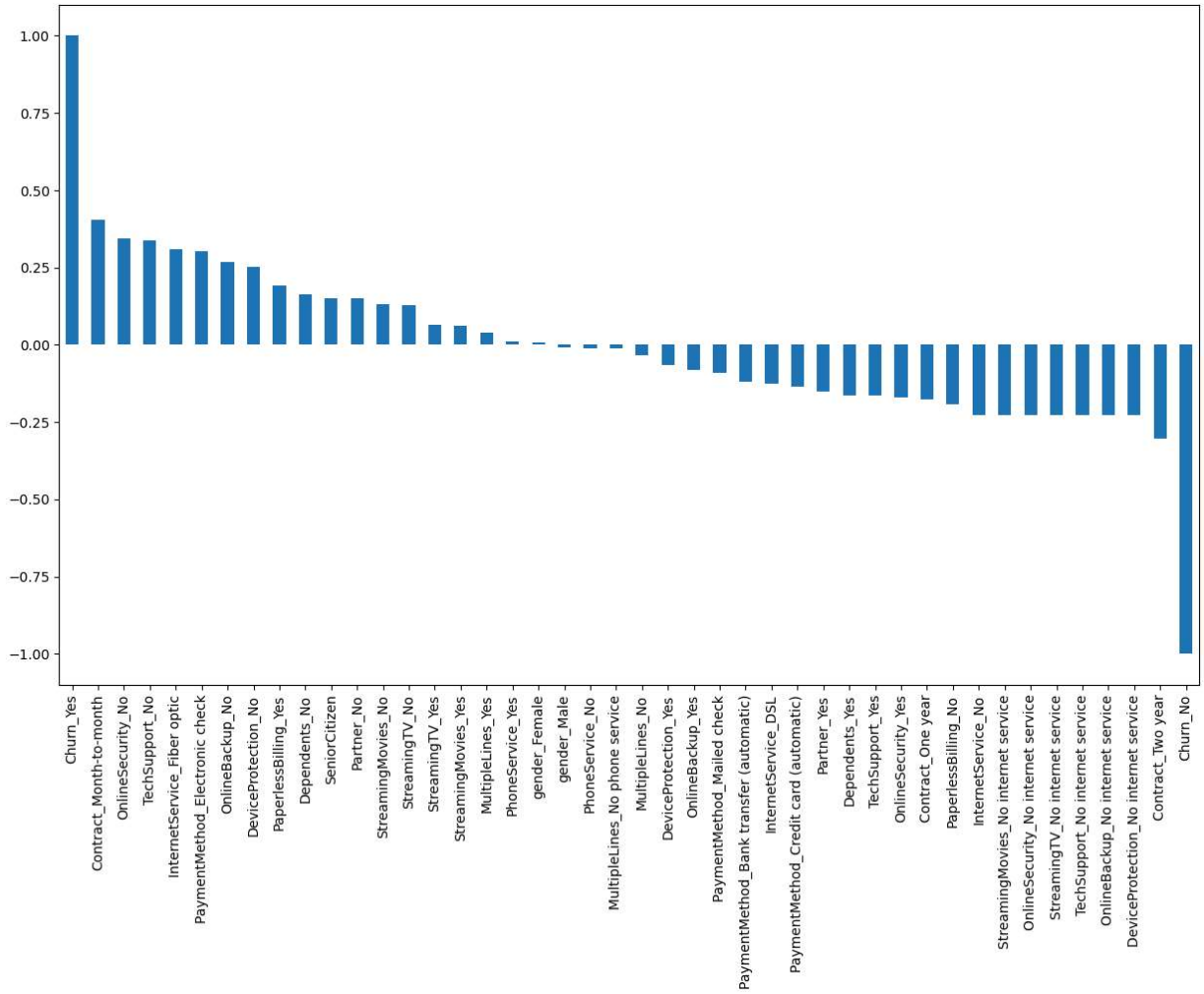
Out[42]:

	SeniorCitizen	gender_Female	gender_Male	Partner_No	Partner_Yes	Dependents_No	Dependent
0	0	1	0	0	1	1	
1	0	0	1	1	0	1	
2	0	0	1	1	0	1	
3	0	0	1	1	0	1	
4	0	1	0	1	0	1	

5 rows × 44 columns

In [43]:
```
# Checking the correlation of predictors with churn
plt.figure(figsize=(15, 9))
df_dummies.corr()['Churn_Yes' ].sort_values(ascending= False).plot(kind= 'ba
```

Out[43]: <AxesSubplot:>



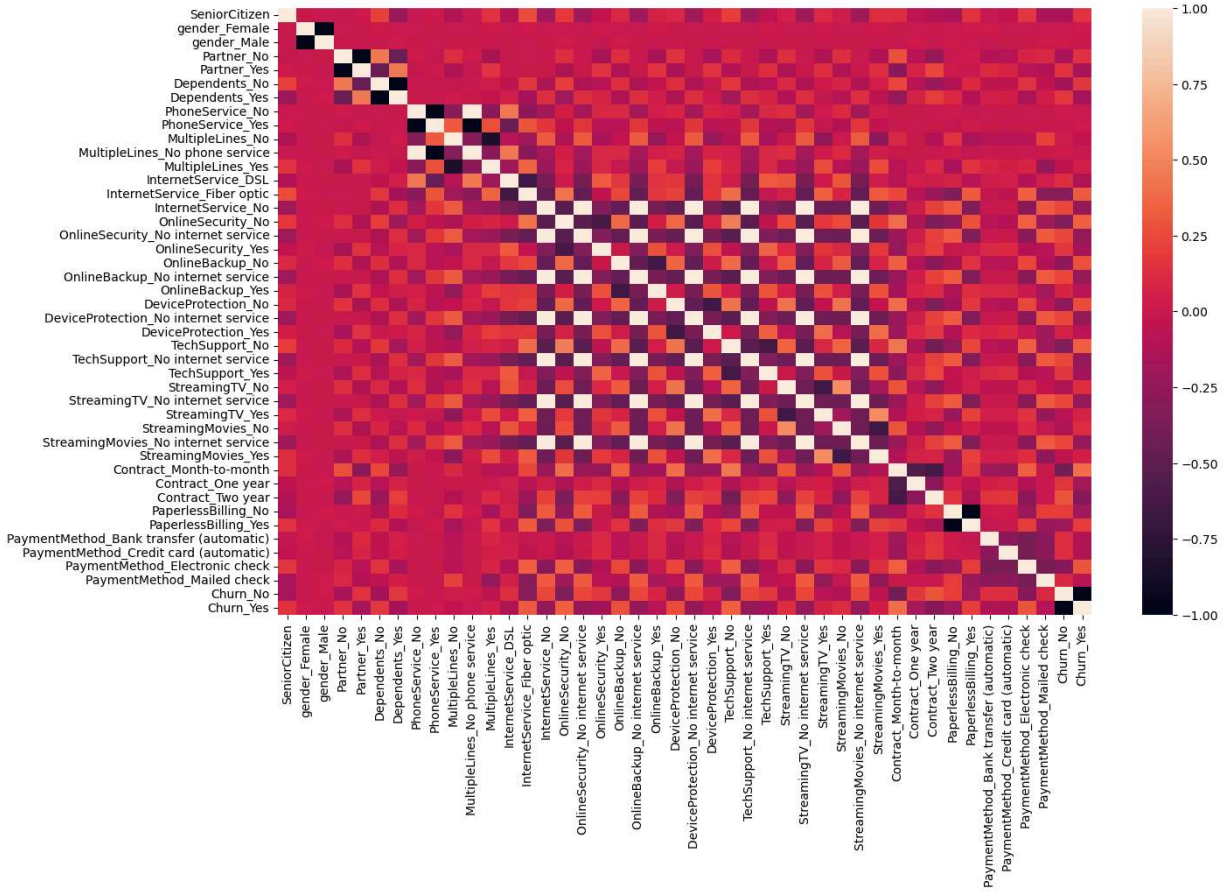
- In instances of month-to-month Contract, No Online Security, No tech Support and others, Customers tend to churn.

- In instances of long term Contract, Device protection, Tech Support and others, Customers tend not to churn.

- Factors like gender, Multi-lines, and Phone service have little or no impact on customer churning

In [44]:
```
# Visualising correlation between various variables
plt.figure(figsize=(15,9))
sns.heatmap(df_dummies.corr())
```

Out[44]: <AxesSubplot:>



Univariate Analysis

In [45]:
```
df_target0 = df.loc[df['Churn_encoded']==0]
df_target1 = df.loc[df['Churn_encoded']==1]
```

In [46]:
```
len(df_target0), len(df_target1)
```

Out[46]: (5174, 1869)

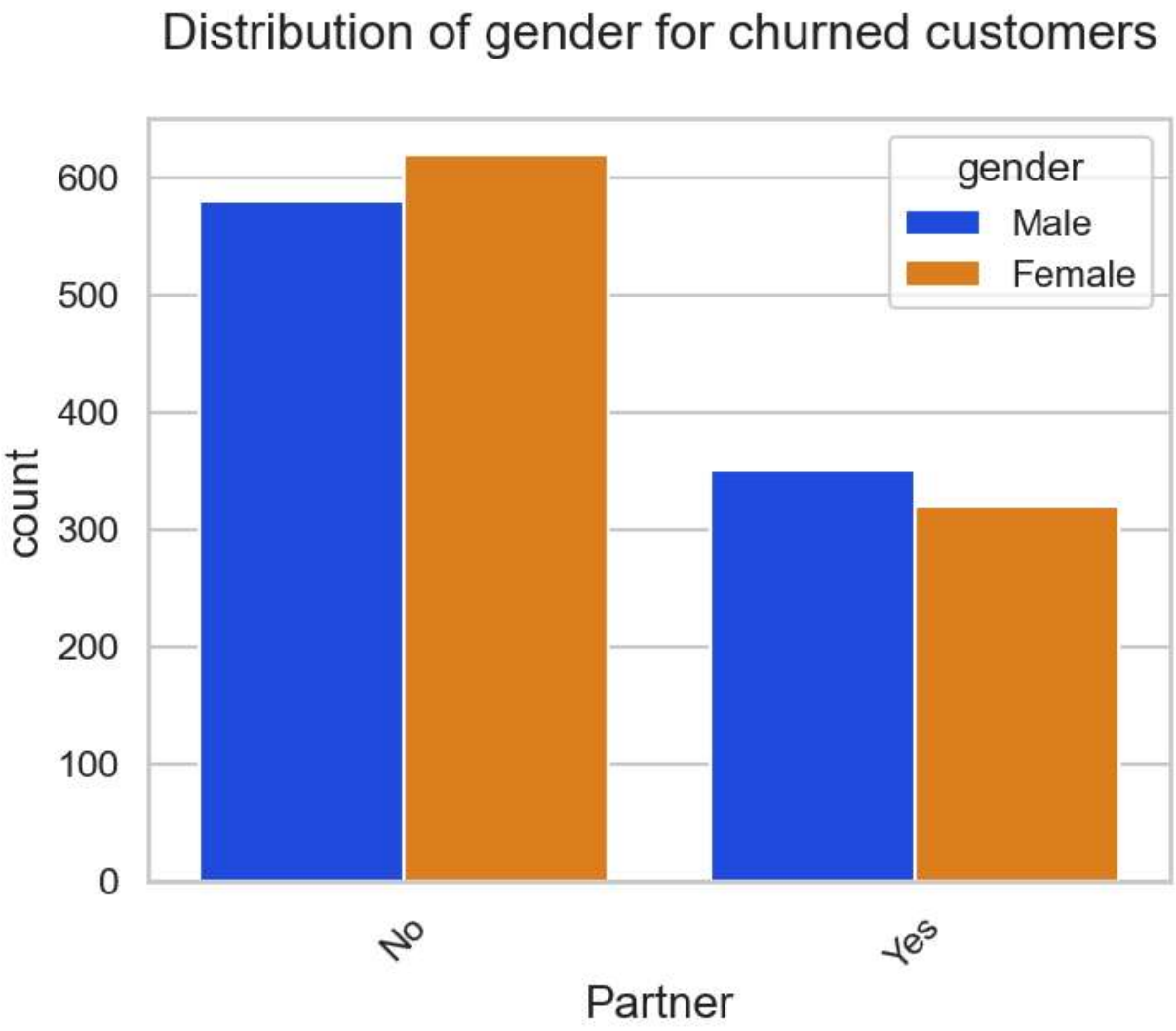
In [47]:
```
# Creating a function to plot the relationships between various categorical
def uniplot(df, col, title, hue= None ):
    sns.set_style('whitegrid')
    sns.set_context('talk')
    plt.rcParams['axes.labelsize'] = 20
    plt.rcParams['axes.titlesize'] = 22
    plt.rcParams['axes.titlepad'] = 30

    temp = pd.Series(data =hue)
    fig, ax = plt.subplots()
    width = len(df[col].unique()) + 2 + 4*len(temp.unique())
    fig.set_size_inches(width, 6)
    plt.xticks(rotation= 45)
    plt.yscale('linear')
    plt.title(title)
    ax = sns.countplot(data= df, x= col, order= df[col].value_counts().index

    plt.show()
```

In [48]:
```
df.nunique()
```

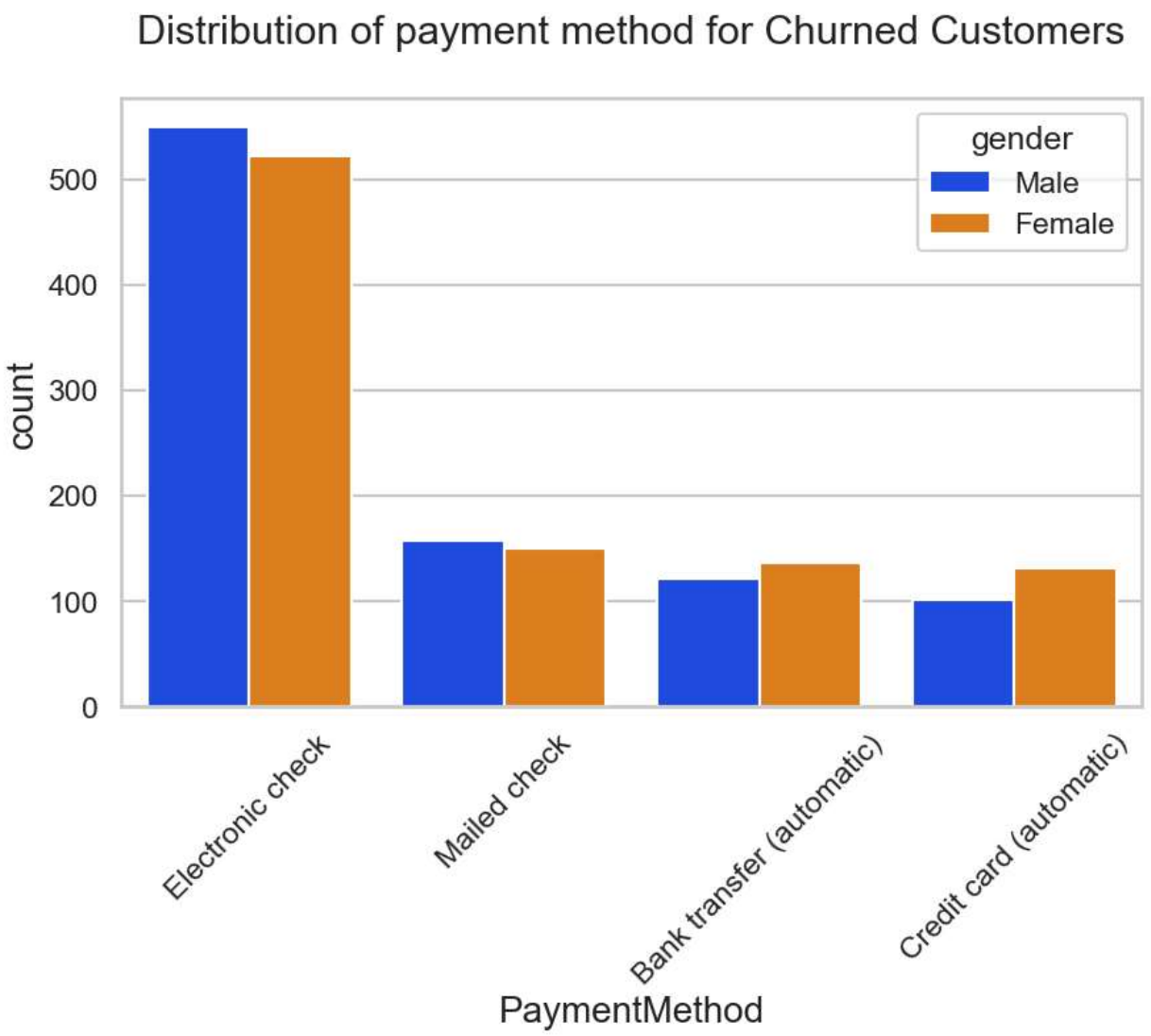
Out[48]:
```
customerID          7043
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                73
PhoneService           2
MultipleLines          3
InternetService        3
OnlineSecurity         3
OnlineBackup           3
DeviceProtection       3
TechSupport            3
StreamingTV            3
StreamingMovies        3
Contract               3
PaperlessBilling       2
PaymentMethod          4
MonthlyCharges      1585
TotalCharges        6530
Churn                  2
Churn_encoded          2
dtype: int64
```

In [49]:

```
# Distribution of gender for Churned customers
uniplot(df_target1, col= 'Partner', title= 'Distribution of gender for churn
```



In [50]:
```
# Distribution of payment method for Churned customers
uniplot(df_target1, col= 'PaymentMethod', title= 'Distribution of payment me
```



- Customers who use Electronic check form the highest churners however, the difference in terms of gender is not much
- Credit card users are the least churners with females forming the highest portion

In [69]:

```
for i, column in enumerate(df.columns):
    print(df[column].value_counts())
```

```
7590-VHVEG    1
3791-LGQCY    1
6008-NAIXK    1
5956-YHHRX    1
5365-LLFYV    1
             ..
9796-MVYXX    1
2637-FKFSY    1
1552-AAGRX    1
4304-TSPVK    1
3186-AJIEK    1
Name: customerID, Length: 7043, dtype: int64
Male      3555
Female    3488
Name: gender, dtype: int64
0    5901
1    1142
Name: SeniorCitizen, dtype: int64
No     3641
Yes    3402
Name: Partner, dtype: int64
No     4933
Yes    2110
Name: Dependents, dtype: int64
1     613
72    362
2     238
3     200
4     176
     ...
28     57
39     56
44     51
36     50
0      11
Name: tenure, Length: 73, dtype: int64
Yes    6361
No      682
Name: PhoneService, dtype: int64
No     4072
Yes    2971
Name: MultipleLines, dtype: int64
Fiber optic    3096
DSL            2421
No             1526
Name: InternetService, dtype: int64
No                     3498
Yes                    2019
No internet service    1526
Name: OnlineSecurity, dtype: int64
No                     3088
Yes                    2429
No internet service    1526
Name: OnlineBackup, dtype: int64
No                     3095
Yes                    2422
No internet service    1526
```

```
Name: DeviceProtection, dtype: int64
No                     3473
Yes                    2044
No internet service    1526
Name: TechSupport, dtype: int64
No                     2810
Yes                    2707
No internet service    1526
Name: StreamingTV, dtype: int64
No                     2785
Yes                    2732
No internet service    1526
Name: StreamingMovies, dtype: int64
Month-to-month    3875
Two year          1695
One year          1473
Name: Contract, dtype: int64
Yes    4171
No     2872
Name: PaperlessBilling, dtype: int64
Electronic check             2365
Mailed check                 1612
Bank transfer (automatic)    1544
Credit card (automatic)      1522
Name: PaymentMethod, dtype: int64
20.05     61
19.85     45
19.95     44
19.90     44
20.00     43
          ..
23.65      1
114.70     1
43.65      1
87.80      1
78.70      1
Name: MonthlyCharges, Length: 1585, dtype: int64
20.20      11
19.75       9
20.05       8
19.90       8
19.65       8
           ..
6849.40     1
692.35      1
130.15      1
3211.90     1
6844.50     1
Name: TotalCharges, Length: 6530, dtype: int64
No     5174
Yes    1869
Name: Churn, dtype: int64
0    5174
1    1869
Name: Churn_encoded, dtype: int64
```

In [67]:
```
df['MultipleLines'].replace({'No phone service': 'No'}, inplace=True)
```

In [68]:
```
df['MultipleLines'].value_counts()
```

Out[68]:
```
No     4072
Yes    2971
Name: MultipleLines, dtype: int64
```

Prediction of Customer Churn

In [73]:
```
df_1 = df.drop('Churn_encoded', axis= 1)
df_1.head()
```

Out[73]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 21 columns

In [74]:
```
df_1.head()
```

Out[74]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 21 columns

In [75]:
```
1 df.columns
```

Out[75]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn',
       'Churn_encoded'],
      dtype='object')
```

In [77]:
```
1 # Separating dataframe into two dataframes to enable proper encoding
2 df_pred_1 = df_1[['customerID', 'tenure', 'MonthlyCharges', 'TotalCharges']]
3 df_pred_1.head()
```

Out[77]:

	customerID	tenure	MonthlyCharges	TotalCharges
0	7590-VHVEG	1	29.85	29.85
1	5575-GNVDE	34	56.95	1889.50
2	3668-QPYBK	2	53.85	108.15
3	7795-CFOCW	45	42.30	1840.75
4	9237-HQITU	2	70.70	151.65

In [78]:
```
1 df_pred_3 = df_1.drop(columns= ['customerID', 'tenure', 'MonthlyCharges', 'T
2 df_pred_3.head()
```

Out[78]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineS
0	Female	0	Yes	No	No	No	DSL	
1	Male	0	No	No	Yes	No	DSL	
2	Male	0	No	No	Yes	No	DSL	
3	Male	0	No	No	No	No	DSL	
4	Female	0	No	No	Yes	No	Fiber optic	

In [79]:

```
# # Encoding Categorical variables
df_pred_2 = pd.get_dummies(df_pred_3, drop_first= True)
df_pred_2
```

Out[79]:

	SeniorCitizen	gender_Male	Partner_Yes	Dependents_Yes	PhoneService_Yes	MultipleLines_Y
0	0	0	1	0	0	
1	0	1	0	0	1	
2	0	1	0	0	1	
3	0	1	0	0	0	
4	0	0	0	0	1	
...	...	...	...	...	...	
7038	0	1	1	1	1	
7039	0	0	1	1	1	
7040	0	0	1	1	0	
7041	1	1	1	0	1	
7042	0	1	0	0	1	

7043 rows × 27 columns

In [83]:
```
# Merging the cumerical features and the encoded categorical features
df_pred = pd.concat([df_pred_1, df_pred_2], axis= 'columns')
df_pred
```

Out[83]:

	customerID	tenure	MonthlyCharges	TotalCharges	SeniorCitizen	gender_Male	Partner_Yes
0	7590-VHVEG	1	29.85	29.85	0	0	1
1	5575-GNVDE	34	56.95	1889.50	0	1	0
2	3668-QPYBK	2	53.85	108.15	0	1	0
3	7795-CFOCW	45	42.30	1840.75	0	1	0
4	9237-HQITU	2	70.70	151.65	0	0	0
...	...	...	...	...	...	...	...
7038	6840-RESVB	24	84.80	1990.50	0	1	1
7039	2234-XADUH	72	103.20	7362.90	0	0	1
7040	4801-JZAZL	11	29.60	346.45	0	0	1
7041	8361-LTMKD	4	74.40	306.60	1	1	1
7042	3186-AJIEK	66	105.65	6844.50	0	1	0

7043 rows × 31 columns

In [106]:
```
# Model training
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
```

In [95]:
```
x = df_pred.drop(['Churn_Yes','customerID'], axis= 1)
```

In [96]:

```
1 print(x)
```

```
      tenure  MonthlyCharges  TotalCharges  SeniorCitizen  gender_Male  \
0          1           29.85         29.85              0            0
1         34           56.95       1889.50              0            1
2          2           53.85        108.15              0            1
3         45           42.30       1840.75              0            1
4          2           70.70        151.65              0            0
...      ...             ...           ...            ...          ...
7038      24           84.80       1990.50              0            1
7039      72          103.20       7362.90              0            0
7040      11           29.60        346.45              0            0
7041       4           74.40        306.60              1            1
7042      66          105.65       6844.50              0            1

      Partner_Yes  Dependents_Yes  PhoneService_Yes  MultipleLines_Yes  \
0               1               0                 0                  0
1               0               0                 1                  0
2               0               0                 1                  0
3               0               0                 0                  0
4               0               0                 1                  0
...           ...             ...               ...                ...
7038            1               1                 1                  1
7039            1               1                 1                  1
7040            1               1                 0                  0
7041            1               0                 1                  1
7042            0               0                 1                  0

      InternetService_Fiber optic  ...  StreamingTV_No internet service  \
0                               0  ...                                0
1                               0  ...                                0
2                               0  ...                                0
3                               0  ...                                0
4                               1  ...                                0
...                           ...  ...                              ...
7038                            0  ...                                0
7039                            1  ...                                0
7040                            0  ...                                0
7041                            1  ...                                0
7042                            1  ...                                0

      StreamingTV_Yes  StreamingMovies_No internet service  \
0                   0                                   0
1                   0                                   0
2                   0                                   0
3                   0                                   0
4                   0                                   0
...               ...                                 ...
7038                1                                   0
7039                1                                   0
7040                0                                   0
7041                0                                   0
7042                1                                   0

      StreamingMovies_Yes  Contract_One year  Contract_Two year  \
0                       0                  0                  0
1                       0                  1                  0
2                       0                  0                  0
3                       0                  1                  0
```

```
4                      0                  0                  0
...                  ...                ...                ...
7038                   1                  1                  0
7039                   1                  1                  0
7040                   0                  0                  0
7041                   0                  0                  0
7042                   1                  0                  1

      PaperlessBilling_Yes  PaymentMethod_Credit card (automatic)  \
0                        1                                      0
1                        0                                      0
2                        1                                      0
3                        0                                      0
4                        1                                      0
...                    ...                                    ...
7038                     1                                      0
7039                     1                                      1
7040                     1                                      0
7041                     1                                      0
7042                     1                                      0

      PaymentMethod_Electronic check  PaymentMethod_Mailed check
0                                  1                           0
1                                  0                           1
2                                  0                           1
3                                  0                           0
4                                  1                           0
...                              ...                         ...
7038                               0                           1
7039                               0                           0
7040                               1                           0
7041                               0                           1
7042                               0                           0

[7043 rows x 29 columns]
```

In [97]:
```
y = df_pred['Churn_Yes']
```

In [98]:
```
# Splitting data into training data and testing data
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size= 0.2, ran
```

In [111]:
```
# Hyperparameter tuning
model = XGBClassifier()
parameters = {'n_estimators':[100,200, 300],
    'max_depth':[10,50, 75],
    'learning_rate': [0.005, 0.05, 0.1]

}
```

In [112]:
```
tune = GridSearchCV(model, parameters)
```

In [113]:
```
1 tune.get_params
```

Out[113]:
```
<bound method BaseEstimator.get_params of GridSearchCV(estimator=XGBClassifier
(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None, device=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=Non
e,
                                     feature_types=None, gamma=None,
                                     grow_policy=None, importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None, max_b...
                                     max_cat_threshold=None,
                                     max_cat_to_onehot=None,
                                     max_delta_step=None, max_depth=None,
                                     max_leaves=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     multi_strategy=None, n_estimators=None,
                                     n_jobs=None, num_parallel_tree=None,
                                     random_state=None, ...),
                   param_grid={'learning_rate': [0.005, 0.05, 0.1],
                               'max_depth': [10, 50, 75],
                               'n_estimators': [100, 200, 300]})>
```

In [114]:
```
1 tune.fit(x_train, y_train)
```

Out[114]:
```
GridSearchCV(estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None, device=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=Non
e,
                                     feature_types=None, gamma=None,
                                     grow_policy=None, importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None, max_b...
                                     max_cat_threshold=None,
                                     max_cat_to_onehot=None,
                                     max_delta_step=None, max_depth=None,
                                     max_leaves=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     multi_strategy=None, n_estimators=None,
                                     n_jobs=None, num_parallel_tree=None,
                                     random_state=None, ...),
                   param_grid={'learning_rate': [0.005, 0.05, 0.1],
                               'max_depth': [10, 50, 75],
                               'n_estimators': [100, 200, 300]})
```

In [115]:
```
1 tune.best_params_
```

Out[115]:
```
{'learning_rate': 0.005, 'max_depth': 10, 'n_estimators': 300}
```

In [116]:
```
tune.best_score_
```

Out[116]:
```
0.7909130166855529
```

In [128]:
```
test_pred = tune.predict(x_test)
Accuracy = accuracy_score(y_test, test_pred)
print('Testing data Accuracy is: ', round(Accuracy*100, 2),'%')
```

```
Testing data Accuracy is:  79.06 %
```

- The model is 79% percent accurate in predicting customer churnung rate

In [129]:
```
train_pred = tune.predict(x_train)
accuracy = accuracy_score(y_train, train_pred)
print('Training data Accuracy is: ', round(accuracy*100, 2),'%')
```

```
Training data Accuracy is:  86.88 %
```

Conclusion

- Key factors that affect churn rate are;
  - Customer care quality
  - Cost of Service
  - Network quality

- It is advised that:
  - Electronic payment method is improved/reviewed since it forms the highest churners.
  - Technical support system should be enhanced.
  - Attractive packages should be offered to short-term subscription customers to convert them to long-term. This will maintain them and reduce their churning.
  - Service packages should be offered to customers at highly competitive prices as possible.