Project Title :Customer Churn Analytics:

Problem Statement:

The objective of this project is to analyze customer churn in a telecom company. Customer churn refers to the phenomenon where customers switch from one service provider to another or cancel their subscription altogether. By analyzing customer chum patterns, we aim to identify the factors that contribute to churn and develop strategies to mitigate it.

Project Description:

In this project, we will work with a dataset from a telecom company that includes information about their customers, such as demographics, customer Accounting information, Service information. The dataset will also include a churn indicator that specifies nether a customer has churned or not.

Desired problen come(Objective or goal)The main objective is to find out the reasons for call drops and voice connectivity Built a classification predictive model to predict call drop

DesiredOutcome:

our main goal is to bulid a computer program that can predict when a customer might leave the company

Algorithms:

LogisticRegression,DecisionTreeClassifier,RandomForestClassifer,AddaboostClassifier,GradientBoostClassifer

About Data

Data is divided into 3 Types

Demographic information:

• gender: Whether the customer is a male or a female.

• SeniorCitizen: Whether the customer is a senior citizen or not (1, 0).

• Partner: Whether the customer has a partner or not (Yes, No)

• Dependents : Whether the customer has dependents or not (Yes, No)

Customer Acconting Information:

• Contract: The contract term of the customer (Month-to-month, One year, Two year)

• PaperlessBilling : Whether the customer has paperless billing or not (Yes, No)

• MonthlyCharges: The amount charged to the customer monthly

• TotalCharges: The total amount charged to the customer

• tenure: Number of months the customer has stayed with the company

• PaymentMethod: The customer's payment method (Electronic check, Mailed check, Bank transfer (au card (automatic))

• customeriD: Customer ID

Service information

PhoneService: Whether the customer has a phone service or not (yes, No)

• MultipleLines: Whether the customer has multiple lines or not (yes, No, No phone service)

• InternetService: Customer's internet service provider (DSL, Fiber optic, No)

• OnlineSecurity: Whether the customer has online security or not (yes, No, No internet service)

• OnlineBackup: Whether the customer has online backup or not (Yes, No, No internet service)

• DeviceProtection: Whether the customer has device protection or not (yes, No, No internet service)

• TechSupport: Whether the customer has tech support or not (yes, No, No internet service)

• Streaming TV: Whether the customer has streaming TV or not (Yes, No, No internet service)

•StreamingMovies: Whether the customer has streaming movies or not (Yes, No, No internet service)

Traget variable

• Churn: Whether the customer churn or not (yes or No)*

1. Data Preparation - (EDA & Feature Engineering -Data Analytics)

In [1]:

```
#EDA
import numpy as np
import pandas as pd

#data visualations
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
import os
os.getcwd()
#os.chdir(r"C:\Users\RAGHAVENDER GOUD\dataminds project")
```

Out[2]: 'C:\\Users\\sumit\\Data Science\\Live Project\\Projects end to end\\Customer'

In [3]:
```
telco_base_data = pd.read_csv('Telco-Customer-Churn.csv')
```

In [4]:
```
telco_base_data.head()
```

Out[4]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtecti
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	'
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	'
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	

5 rows × 21 columns

In [5]:
```
telco_base_data['InternetService'].unique()
```

Out[5]: array(['DSL', 'Fiber optic', 'No'], dtype=object)

In [6]:
```
telco_base_data.shape
```

Out[6]: (7043, 21)

In [7]:
```
telco_base_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
```

Knowling the unique values

In [8]:
```
for col in telco_base_data.columns:
    print("column: {} - Unique Values: {}\n".format(col,telco_base_data[col].unique()))
```

```
column: customerID - Unique Values: ['7590-VHVEG' '5575-GNVDE' '3668-QPYBK' ... '4801-JZAZL' '8361-LTMKD'
 '3186-AJIEK']

column: gender - Unique Values: ['Female' 'Male']

column: SeniorCitizen - Unique Values: [0 1]

column: Partner - Unique Values: ['Yes' 'No']

column: Dependents - Unique Values: ['No' 'Yes']

column: tenure - Unique Values: [ 1 34  2 45  8 22 10 28 62 13 16 58 49 25 69 52 71 21 12 30 47 72 17 27
  5 46 11 70 63 43 15 60 18 66  9  3 31 50 64 56  7 42 35 48 29 65 38 68
 32 55 37 36 41  6  4 33 67 23 57 61 14 20 53 40 59 24 44 19 54 51 26  0
 39]

column: PhoneService - Unique Values: ['No' 'Yes']

column: MultipleLines - Unique Values: ['No phone service' 'No' 'Yes']

column: InternetService - Unique Values: ['DSL' 'Fiber optic' 'No']

column: OnlineSecurity - Unique Values: ['No' 'Yes' 'No internet service']

column: OnlineBackup - Unique Values: ['Yes' 'No' 'No internet service']

column: DeviceProtection - Unique Values: ['No' 'Yes' 'No internet service']

column: TechSupport - Unique Values: ['No' 'Yes' 'No internet service']

column: StreamingTV - Unique Values: ['No' 'Yes' 'No internet service']

column: StreamingMovies - Unique Values: ['No' 'Yes' 'No internet service']

column: Contract - Unique Values: ['Month-to-month' 'One year' 'Two year']

column: PaperlessBilling - Unique Values: ['Yes' 'No']

column: PaymentMethod - Unique Values: ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
```

```
column: MonthlyCharges - Unique Values: [29.85 56.95 53.85 ... 63.1  44.2  78.7 ]

column: TotalCharges - Unique Values: ['29.85' '1889.5' '108.15' ... '346.45' '306.6' '6844.5']

column: Churn - Unique Values: ['No' 'Yes']
```

In [9]:

```
telco_base_data.columns.values
```

Out[9]:

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

In [10]:

```
telco_base_data.TotalCharges = pd.to_numeric(telco_base_data.TotalCharges, errors='coerce')
```

In [11]:
```
telco_base_data.dtypes
```

Out[11]:
```
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 [12]:
```
telco_base_data.describe()
```

Out[12]:

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

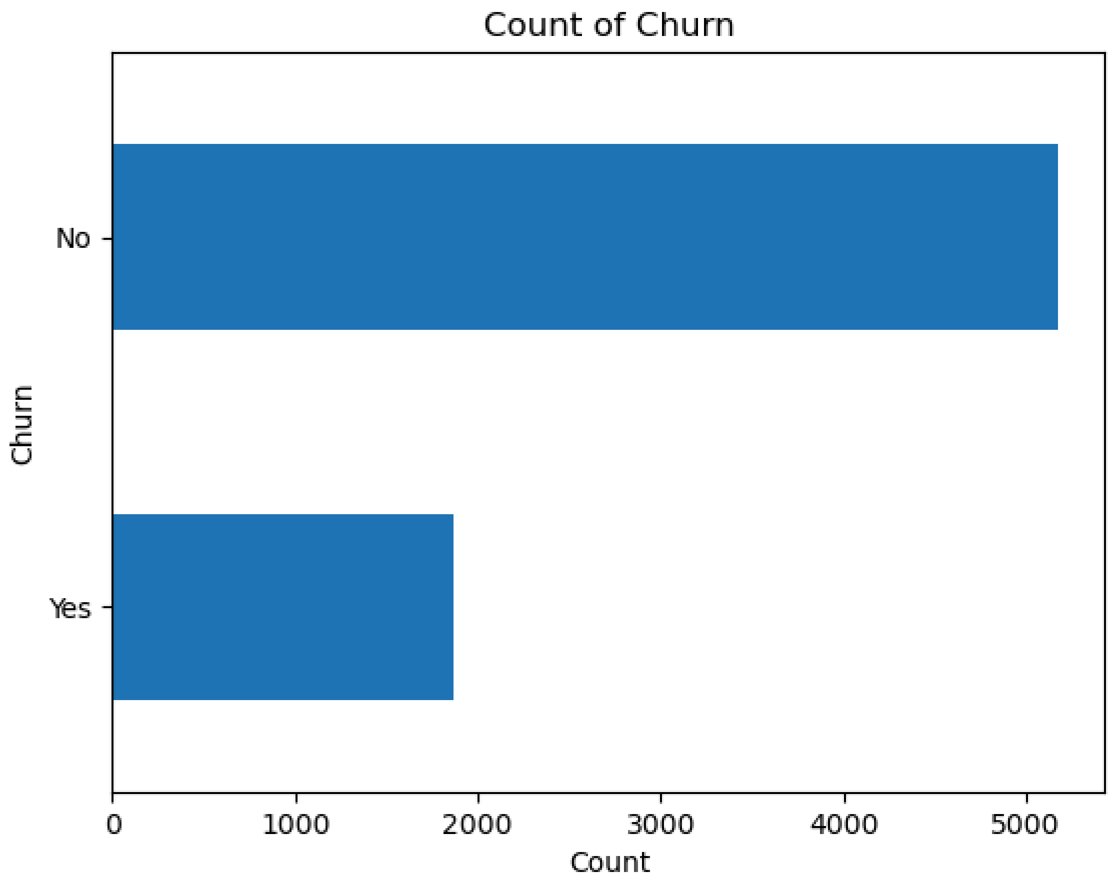
SeniorCitizen is actually a categorical hence the 25%-50%-75% distribution is not propoer

75% customers have tenure less than 55 months

Average Monthly charges are USD 64.76 whereas 25% customers pay more than USD 89.85 per month

In [13]:

```
telco_base_data['Churn'].value_counts().plot(kind='barh')
plt.xlabel("Count")
plt.ylabel("Churn")
plt.title("Count of Churn")
plt.gca().invert_yaxis()  # Invert y-axis to have 'No Churn' on top
plt.show()

```



In [14]:
```
telco_base_data['Churn'].value_counts()/len(telco_base_data)
```

Out[14]:
```
Churn
No     0.73463
Yes    0.26537
Name: count, dtype: float64
```

In [15]:
```
telco_base_data['Churn'].value_counts()
```

Out[15]:
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

In [16]:
```
telco_base_data.info(verbose=True)
```

```
<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      7032 non-null   float64
 20  Churn             7043 non-null   object 
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

In [17]:
```
telco_data=telco_base_data.copy()
```

In [18]:
```
telco_data.isna().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        11
Churn                0
dtype: int64
```

In [19]:

```
telco_data.loc[telco_data['TotalCharges'].isna()==True]
```

Out[19]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProt
488	4472-LVYGI	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	...	
753	3115-CZMZD	Male	0	No	Yes	0	Yes	No	No	No internet service	...	No i
936	5709-LVOEQ	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	...	
1082	4367-NUYAO	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	...	No i
1340	1371-DWPAZ	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	...	
3331	7644-OMVMY	Male	0	Yes	Yes	0	Yes	No	No	No internet service	...	No i
3826	3213-VVOLG	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	...	No i
4380	2520-SGTTA	Female	0	Yes	Yes	0	Yes	No	No	No internet service	...	No i
5218	2923-ARZLG	Male	0	Yes	Yes	0	Yes	No	No	No internet service	...	No i
6670	4075-WKNIU	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	...	
6754	2775-SEFEE	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	...	

11 rows × 21 columns

In [20]:
```
telco_data.dtypes
```

Out[20]:
```
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 [21]:
```
telco_data.isna().sum()/len(telco_data)
```

Out[21]:
```
customerID          0.000000
gender              0.000000
SeniorCitizen       0.000000
Partner             0.000000
Dependents          0.000000
tenure              0.000000
PhoneService        0.000000
MultipleLines       0.000000
InternetService     0.000000
OnlineSecurity      0.000000
OnlineBackup        0.000000
DeviceProtection    0.000000
TechSupport         0.000000
StreamingTV         0.000000
StreamingMovies     0.000000
Contract            0.000000
PaperlessBilling    0.000000
PaymentMethod       0.000000
MonthlyCharges      0.000000
TotalCharges        0.001562
Churn               0.000000
dtype: float64
```

4. Missing Value Treatement

Since the % of these records compared to total dataset is very low ie 0.0015%, it is safe to ignore them from further processing.

In [22]:
```
#Removing missing values
telco_data.dropna(how = 'any', inplace = True)
```

5. Divide customers into bins based on tenure e.g. for tenure < 12 months: assign a tenure group if 1-12, for tenure between 1 to 2 Yrs, tenure group of 13-24; so on...

In [23]:

```
# Get the max tenure
print(telco_data['tenure'].max()) #72
```

```
72
```

In [24]:

```

# Define the bins and labels
bins = [0, 12, 24, 36, 48, 60, 72]
labels = ['1 - 12', '13 - 24', '25 - 36', '37 - 48', '49 - 60', '61 - 72']

# Create the tenure_group column
telco_data['tenure_group'] = pd.cut(telco_data['tenure'], bins=bins, labels=labels, right=False)

```

In [25]:

```
 telco_data['tenure_group'].value_counts()


```

Out[25]:

```
tenure_group
1 - 12     2058
61 - 72    1121
13 - 24    1047
25 - 36     876
49 - 60     820
37 - 48     748
Name: count, dtype: int64
```

In [26]:
```
telco_data['tenure_group'].value_counts()/len(telco_data)
```

Out[26]:
```
tenure_group
1 - 12     0.292662
61 - 72    0.159414
13 - 24    0.148891
25 - 36    0.124573
49 - 60    0.116610
37 - 48    0.106371
Name: count, dtype: float64
```

6. Remove columns not required for processing

In [27]:
```
#drop column customerID and tenure
telco_data.drop(columns= ['customerID','tenure'], axis=1, inplace=True)
telco_data.head()
```

Out[27]:

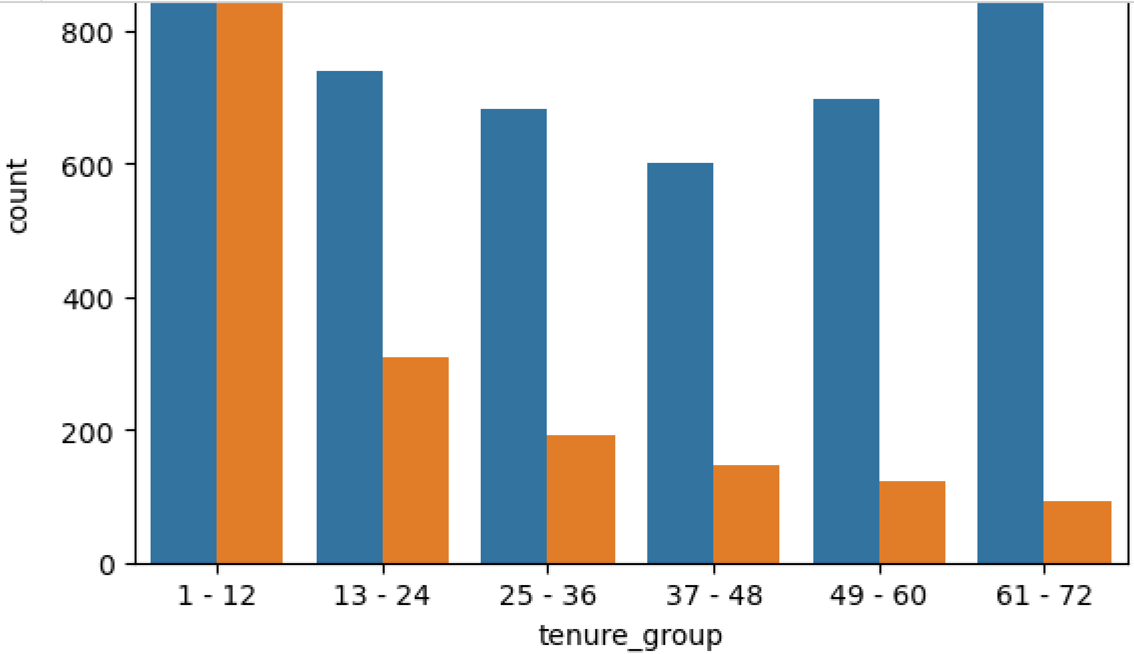
	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	Tech
0	Female	0	Yes	No	No	No phone service	DSL	No	Yes	No	
1	Male	0	No	No	Yes	No	DSL	Yes	No	Yes	
2	Male	0	No	No	Yes	No	DSL	Yes	Yes	No	
3	Male	0	No	No	No	No phone service	DSL	Yes	No	Yes	
4	Female	0	No	No	Yes	No	Fiber optic	No	No	No	

Data Exploration

1. * Plot distibution of individual predictors by churn

Univariate Analysis

In [28]:
```
for i, predictor in enumerate(telco_data.drop(columns=['Churn', 'TotalCharges', 'MonthlyCharges'])):
    plt.figure(i)
    sns.countplot(data=telco_data, x=predictor, hue='Churn')
```



2. Convert the target variable 'Churn' in a binary numeric variable i.e. Yes=1 ; No = 0

In [29]:
```
telco_data['Churn'] = np.where(telco_data.Churn == 'Yes',1,0)
```

In [30]:
```
telco_data.sample(3)
```

Out[30]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	T
4590	Female	1	No	No	Yes	Yes	Fiber optic	Yes	No	Yes	
1595	Male	1	No	No	Yes	No	Fiber optic	No	Yes	No	
2335	Male	0	No	No	Yes	No	DSL	Yes	No	Yes	

In [31]:
```
telco_data.dtypes
```

Out[31]:
```
gender                object
SeniorCitizen          int64
Partner               object
Dependents            object
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                  int32
tenure_group        category
dtype: object
```

3. Convert all the categorical variables into dummy variables

In [32]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
le
```

Out[32]:
```
▾ LabelEncoder
LabelEncoder()
```

In [33]:
```
categ=['gender','SeniorCitizen', 'tenure_group' ,'Partner', 'Dependents', 'PhoneService',
       'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
       'Contract', 'PaperlessBilling', 'PaymentMethod',  'Churn',]

telco_data[categ] = telco_data[categ].apply(le.fit_transform)
```

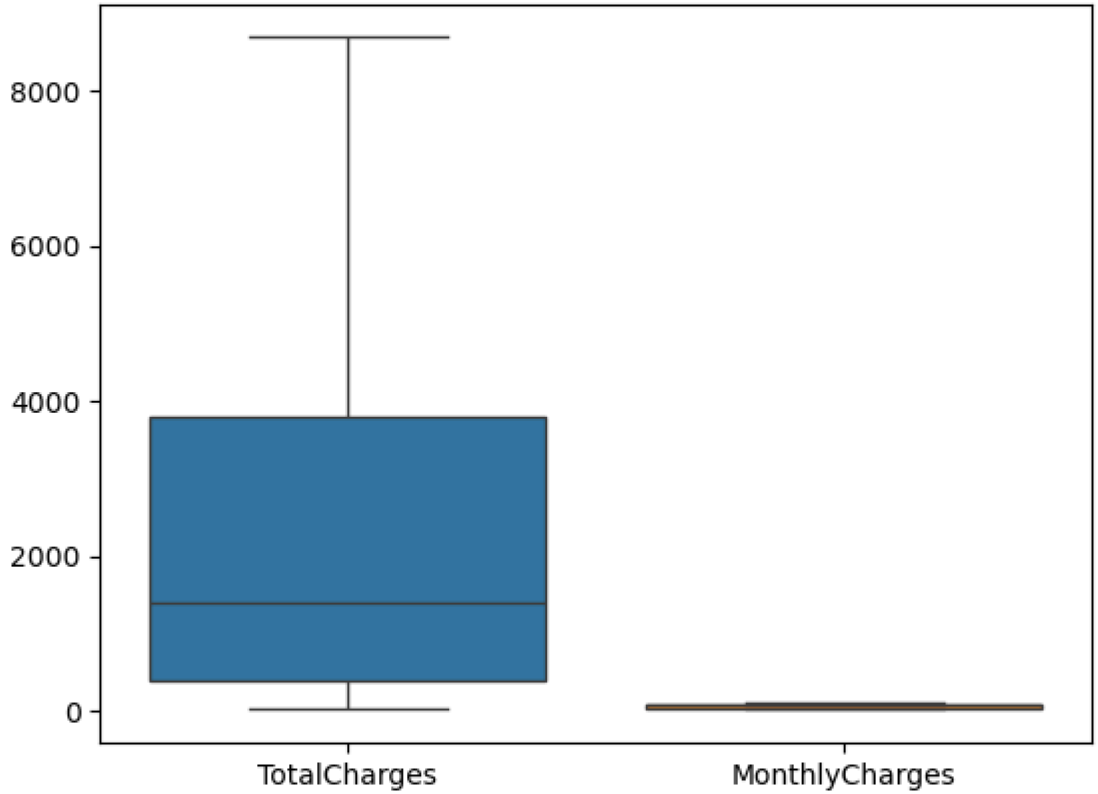
In [34]:
```
telco_data.sample(3)
```

Out[34]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	T
3185	0	1	0	0	0	1	0	0	0	0	
6178	0	1	1	0	1	0	2	1	1	1	
2810	0	1	1	1	1	2	1	0	0	2	

In [35]:
```
sns.boxplot(data = telco_data[['TotalCharges', 'MonthlyCharges']])
```

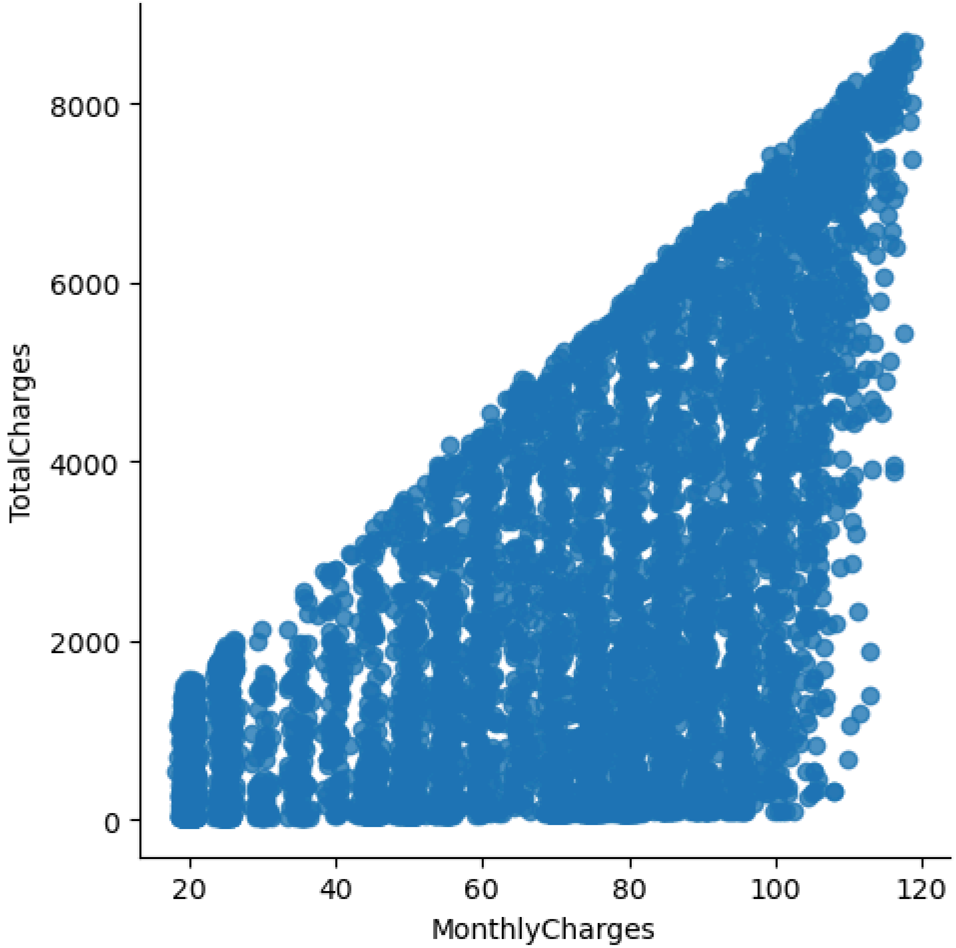
Out[35]: <Axes: >



4. * Relationship between Monthly Charges and Total Charges

In [36]:
```
sns.lmplot(data=telco_data, x='MonthlyCharges', y='TotalCharges', fit_reg=False)
```

Out[36]: <seaborn.axisgrid.FacetGrid at 0x24c68ae7910>

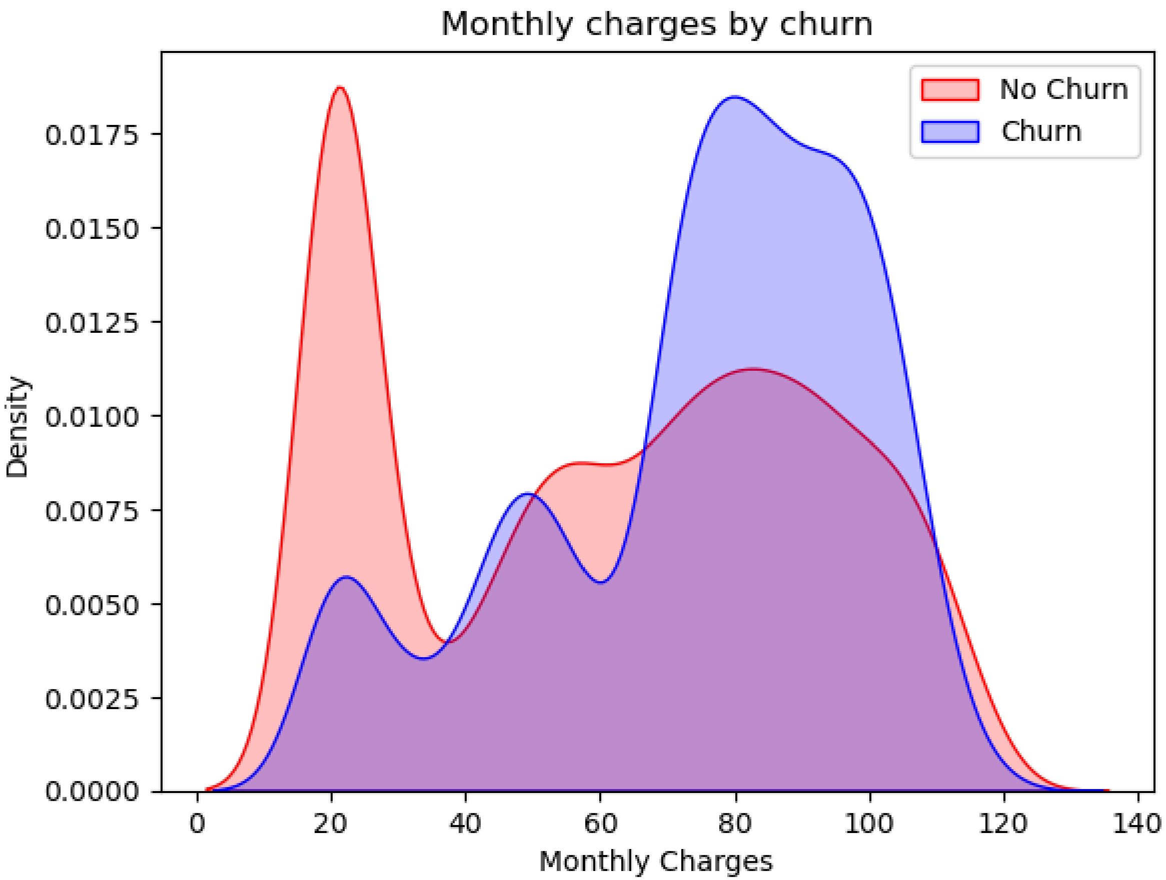


5. * Churn by Monthly Charges and Total Charges

In [37]:
```
# kernel density estimate (KDE) plot.
Mth = sns.kdeplot(telco_data.MonthlyCharges[(telco_data["Churn"] == 0) ],
                color="Red", shade = True)
Mth = sns.kdeplot(telco_data.MonthlyCharges[(telco_data["Churn"] == 1) ],
                ax =Mth, color="Blue", shade= True)
Mth.legend(["No Churn","Churn"],loc='upper right')
Mth.set_ylabel('Density')
Mth.set_xlabel('Monthly Charges')
Mth.set_title('Monthly charges by churn')
```

```
C:\Users\sumit\AppData\Local\Temp\ipykernel_6084\1021104028.py:2: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  Mth = sns.kdeplot(telco_data.MonthlyCharges[(telco_data["Churn"] == 0) ],
C:\Users\sumit\AppData\Local\Temp\ipykernel_6084\1021104028.py:4: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  Mth = sns.kdeplot(telco_data.MonthlyCharges[(telco_data["Churn"] == 1) ],
```

Out[37]:
```
Text(0.5, 1.0, 'Monthly charges by churn')
```

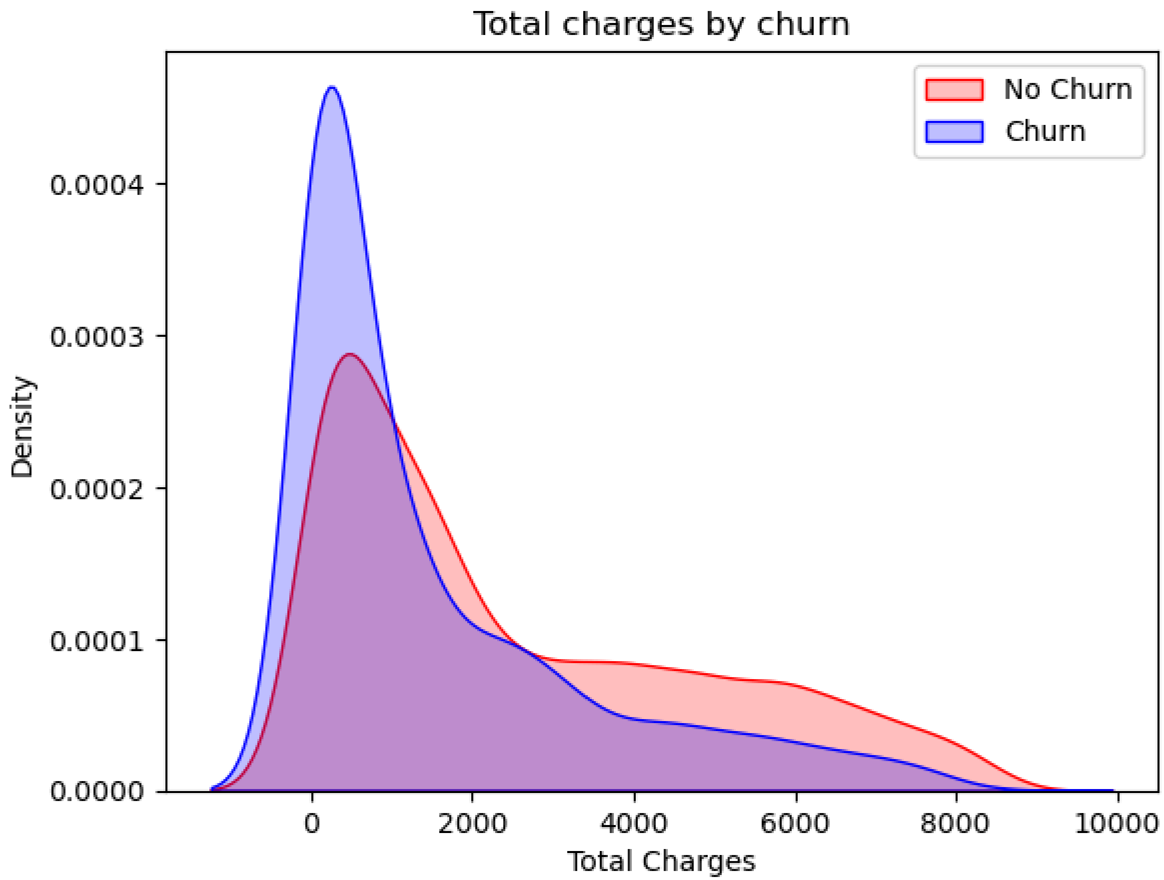


Insight: Churn is high when Monthly Charges are high

In [38]:
```
Tot = sns.kdeplot(telco_data.TotalCharges[(telco_data["Churn"] == 0) ],
                color="Red", shade = True)
Tot = sns.kdeplot(telco_data.TotalCharges[(telco_data["Churn"] == 1) ],
                ax =Tot, color="Blue", shade= True)
Tot.legend(["No Churn","Churn"],loc='upper right')
Tot.set_ylabel('Density')
Tot.set_xlabel('Total Charges')
Tot.set_title('Total charges by churn')
```

```
C:\Users\sumit\AppData\Local\Temp\ipykernel_6084\2039743036.py:1: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  Tot = sns.kdeplot(telco_data.TotalCharges[(telco_data["Churn"] == 0) ],
C:\Users\sumit\AppData\Local\Temp\ipykernel_6084\2039743036.py:3: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  Tot = sns.kdeplot(telco_data.TotalCharges[(telco_data["Churn"] == 1) ],
```

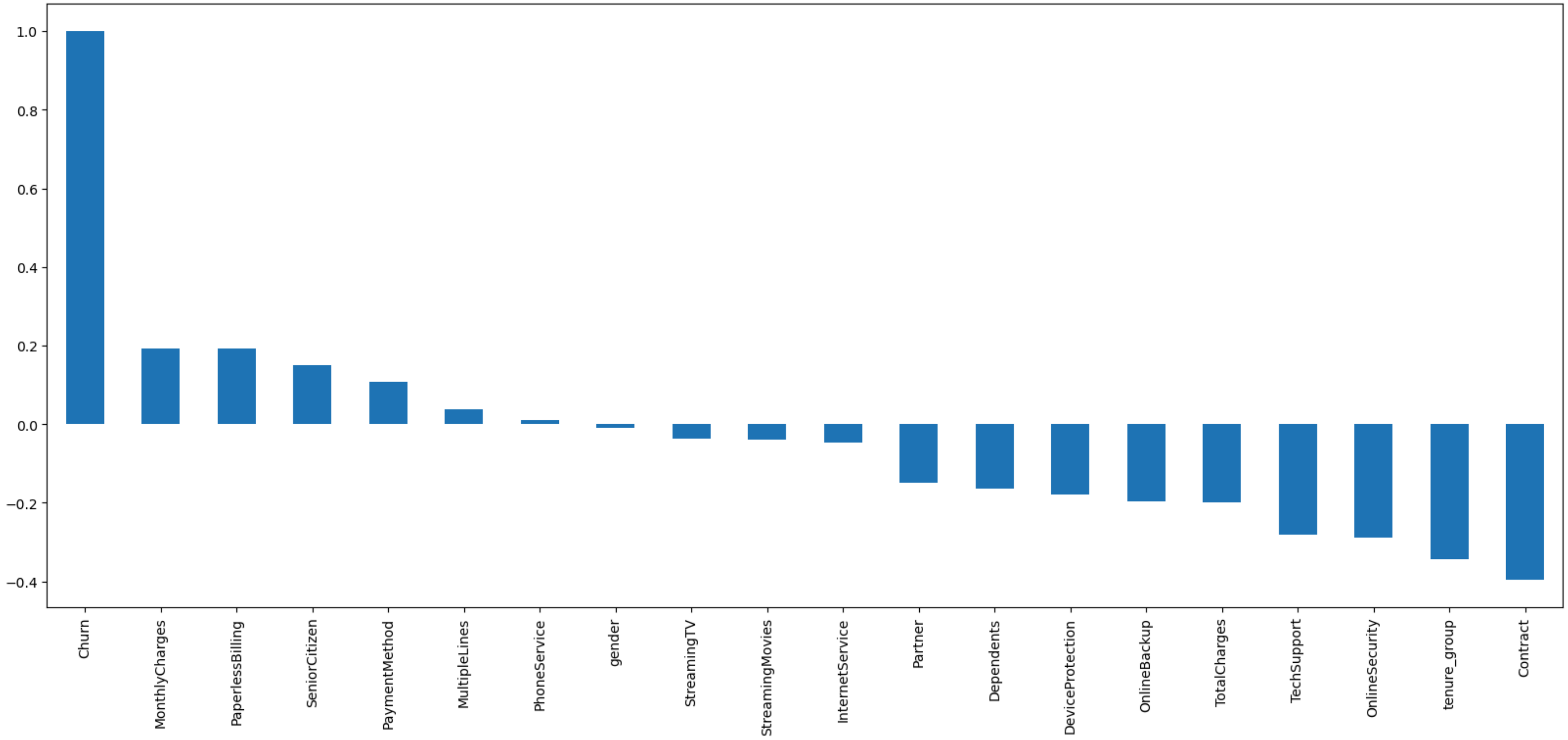
Out[38]:
```
Text(0.5, 1.0, 'Total charges by churn')
```



***6. Build a corelation of all predictors with 'Churn' ***

In [39]:
```
plt.figure(figsize=(20,8))
telco_data.corr()['Churn'].sort_values(ascending = False).plot(kind='bar')
```

Out[39]: <Axes: >



***Derived Insight: ***

HIGH Churn seen in case of Month to month contracts, No online security, No Tech support, First year of subscription and Fibre Optics Internet

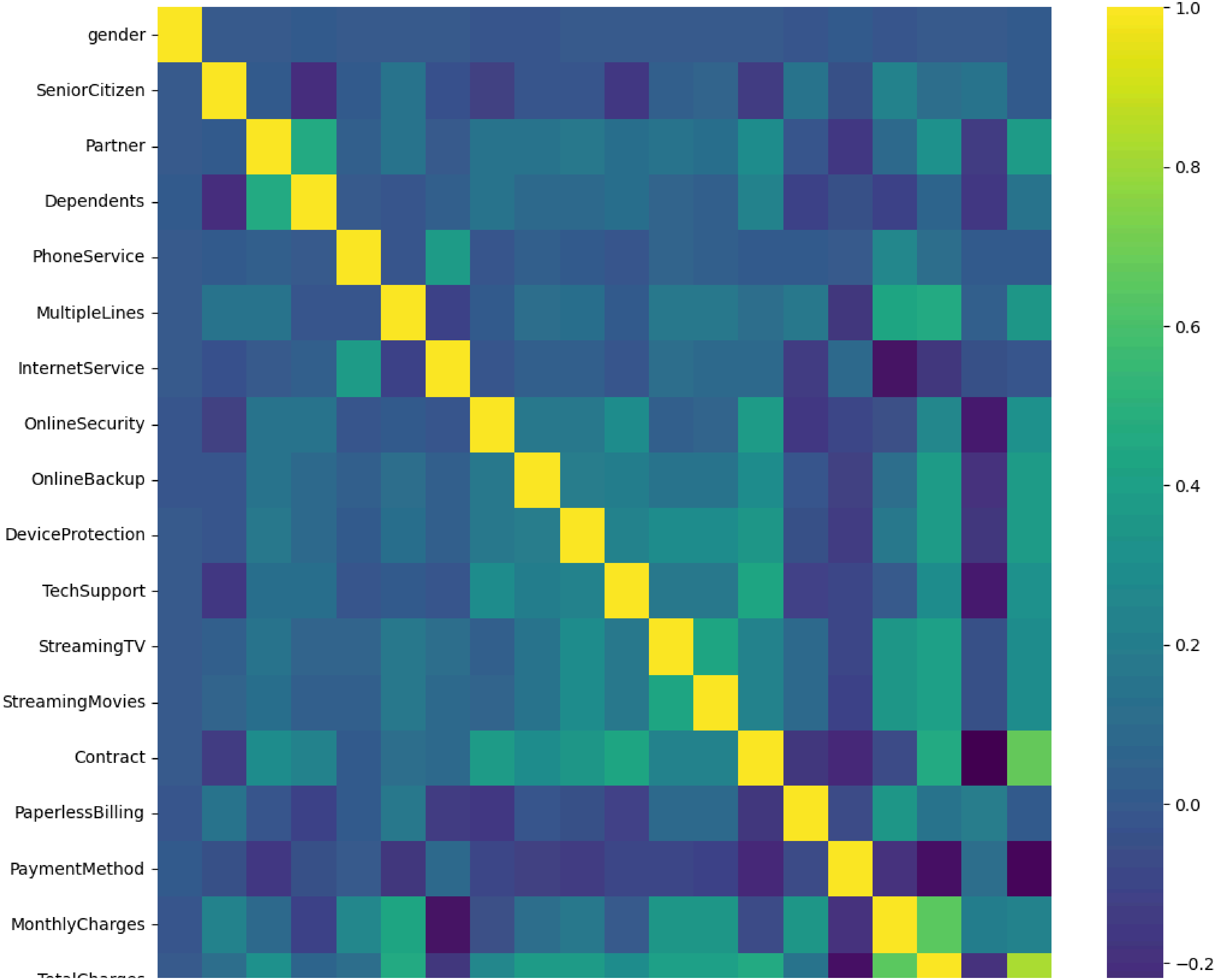
LOW Churn is seens in case of Long term contracts, Subscriptions without internet service and The customers engaged for 5+ years

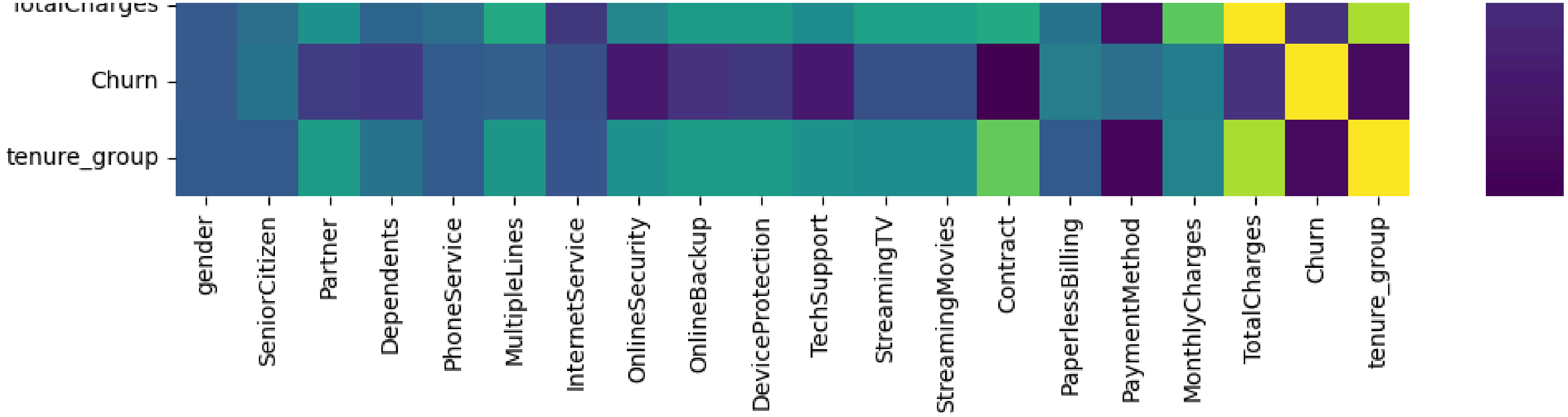
Factors like Gender, Availability of PhoneService and # of multiple lines have alomost NO impact on Churn

This is also evident from the Heatmap below

In [40]:
```
plt.figure(figsize=(12,12))
sns.heatmap(telco_data.corr(), cmap="viridis")
```

Out[40]: <Axes: >


gender
SeniorCitizen
Partner
Dependents
PhoneService
MultipleLines
InternetService
OnlineSecurity
OnlineBackup
DeviceProtection
TechSupport
StreamingTV
StreamingMovies
Contract
PaperlessBilling
PaymentMethod
MonthlyCharges
1.0
0.8
0.6
0.4
0.2
0.0
−0.2



Bivariate Analysis

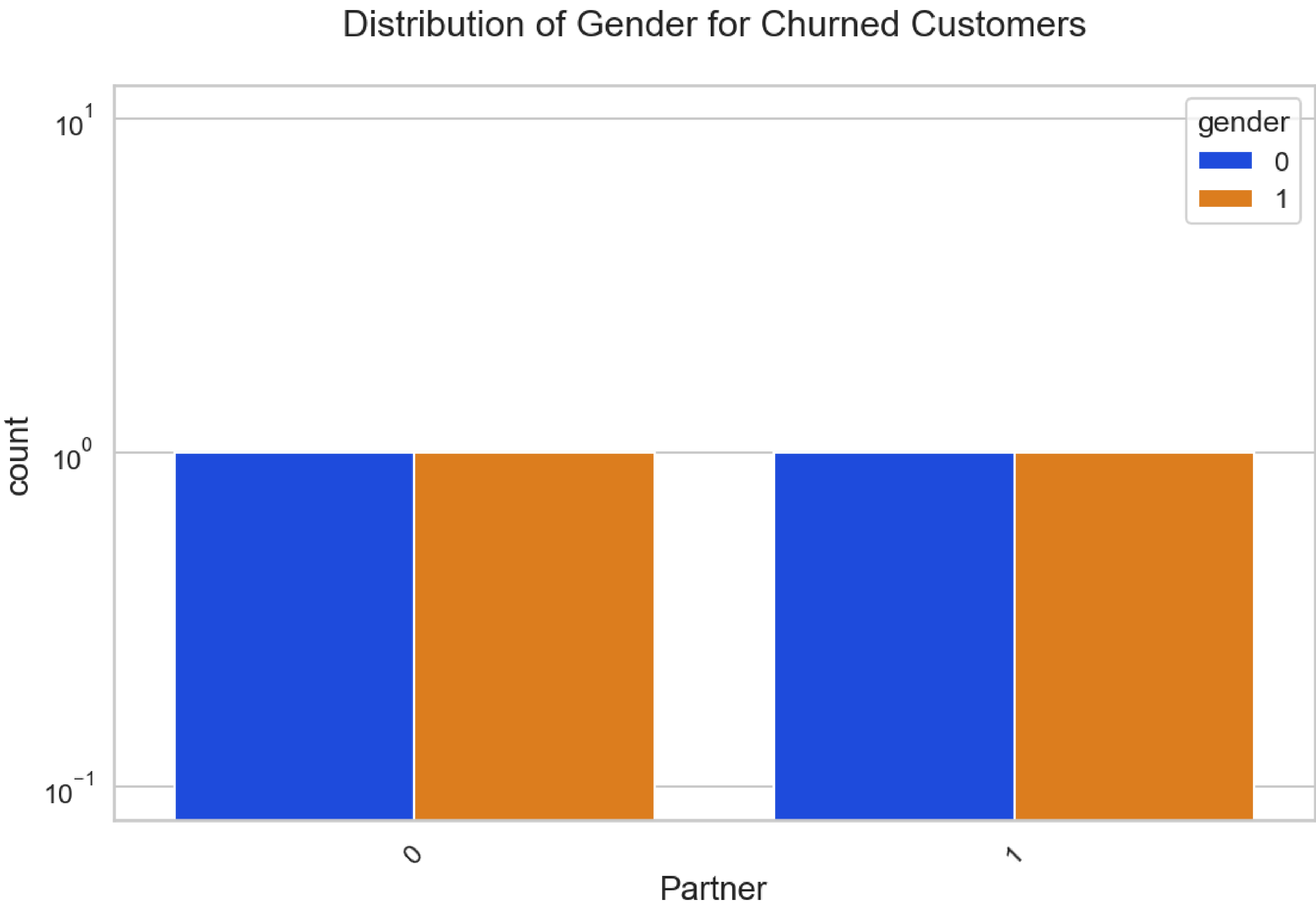
In [41]:

```
new_df1_target0 = telco_data.loc[telco_data["Churn"]==0]
new_df1_target1 = telco_data.loc[telco_data["Churn"]==1]
```

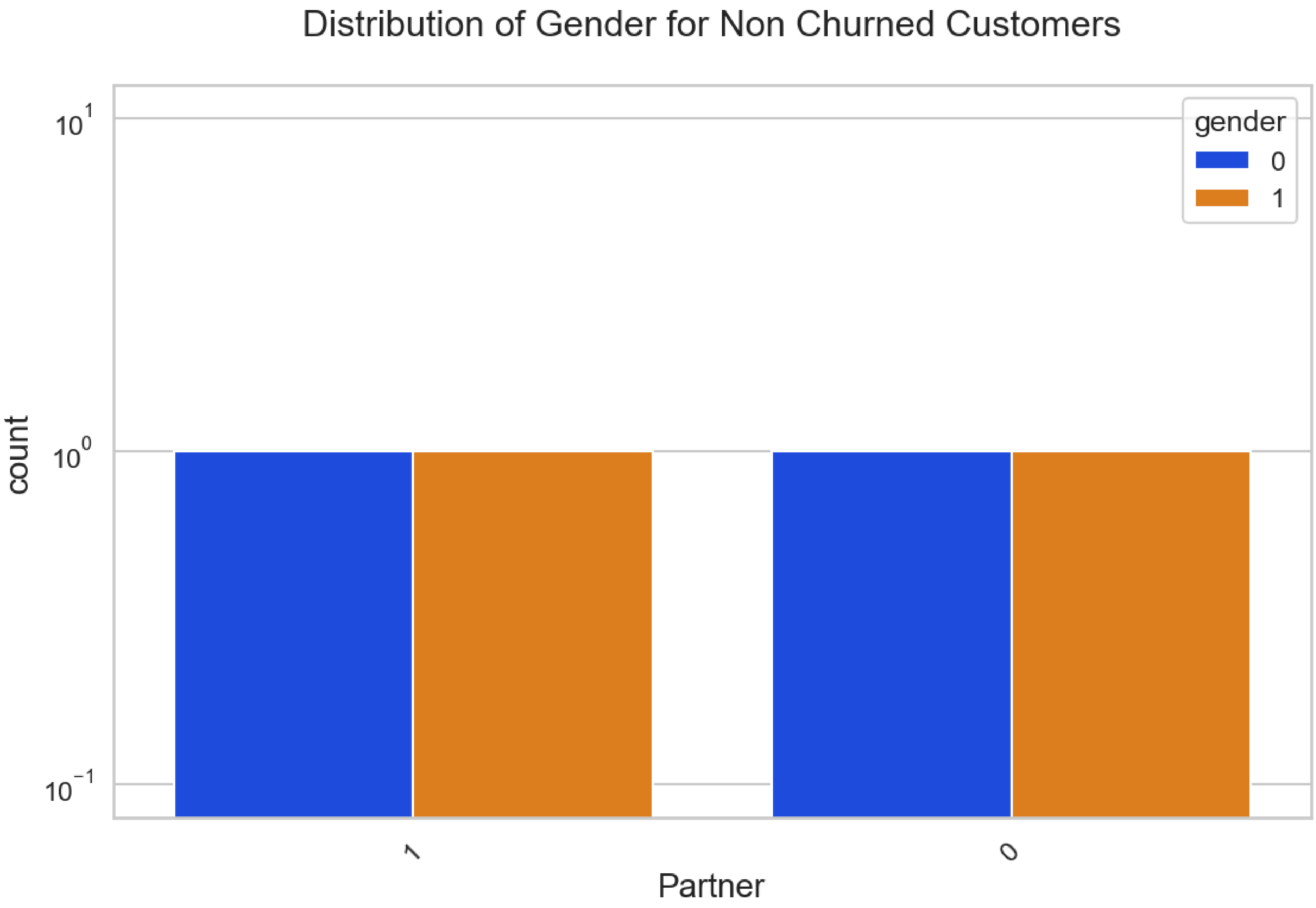
In [42]:

```
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()) + 7 + 4*len(temp.unique())
    fig.set_size_inches(width , 8)
    plt.xticks(rotation=45)
    plt.yscale('log')
    plt.title(title)
    ax = sns.countplot(data = df, x= col, order=df[col].value_counts().index,hue = hue,palette='bright')

    plt.show()
```

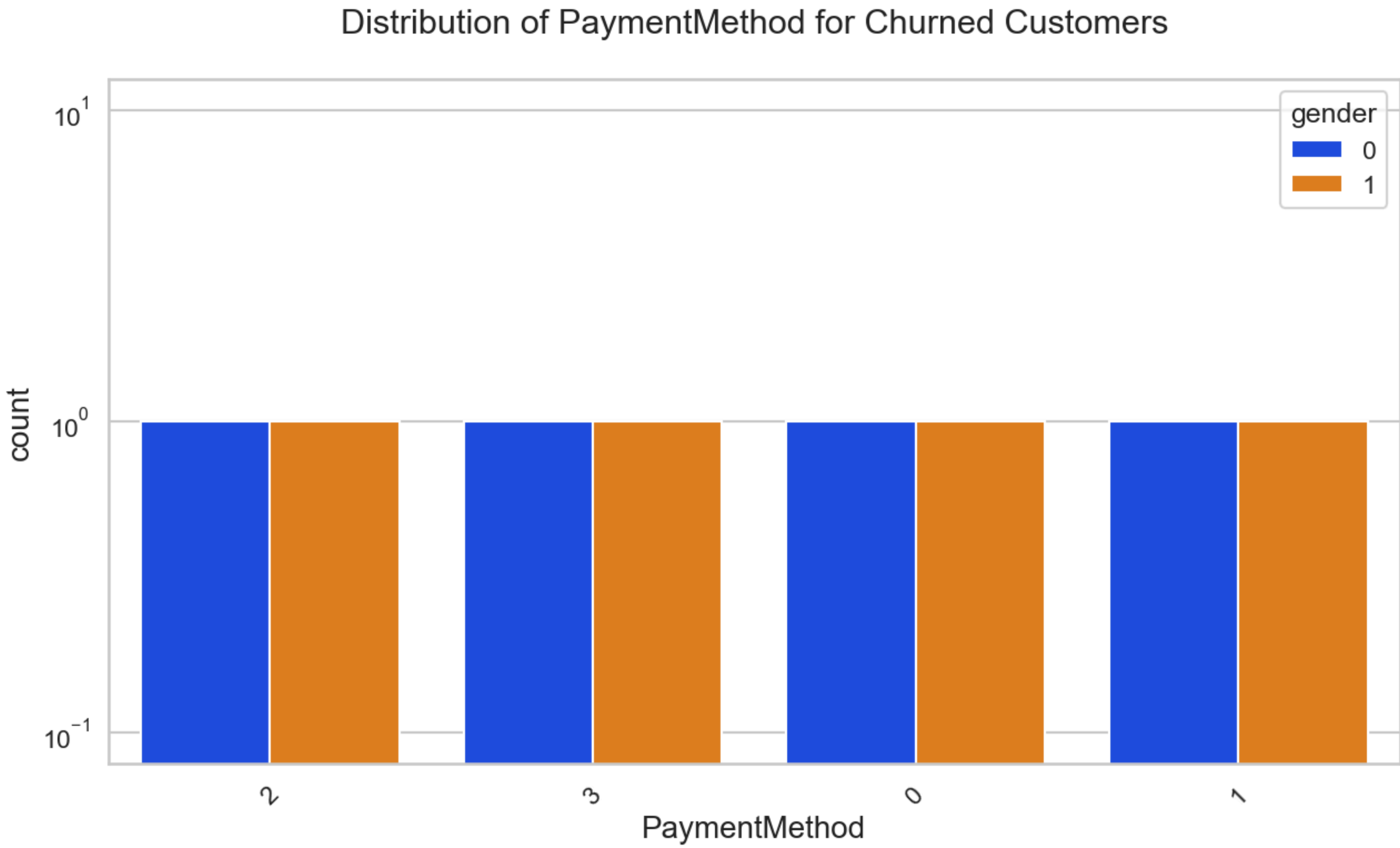
In [43]:
```
uniplot(new_df1_target1,col='Partner',title='Distribution of Gender for Churned Customers',hue='gender')
```



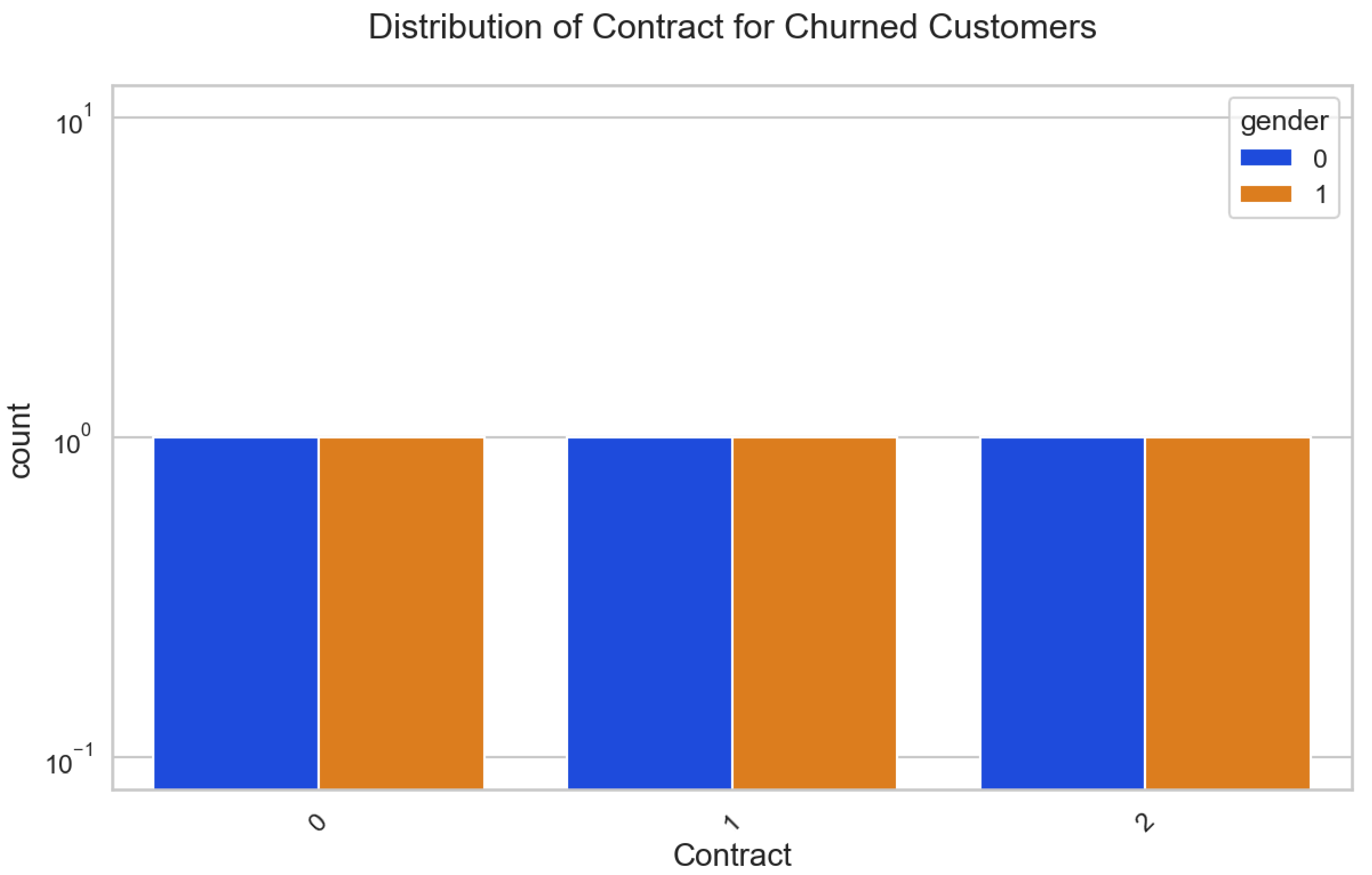
In [44]:
```
uniplot(new_df1_target0,col='Partner',title='Distribution of Gender for Non Churned Customers',hue='gender')
```



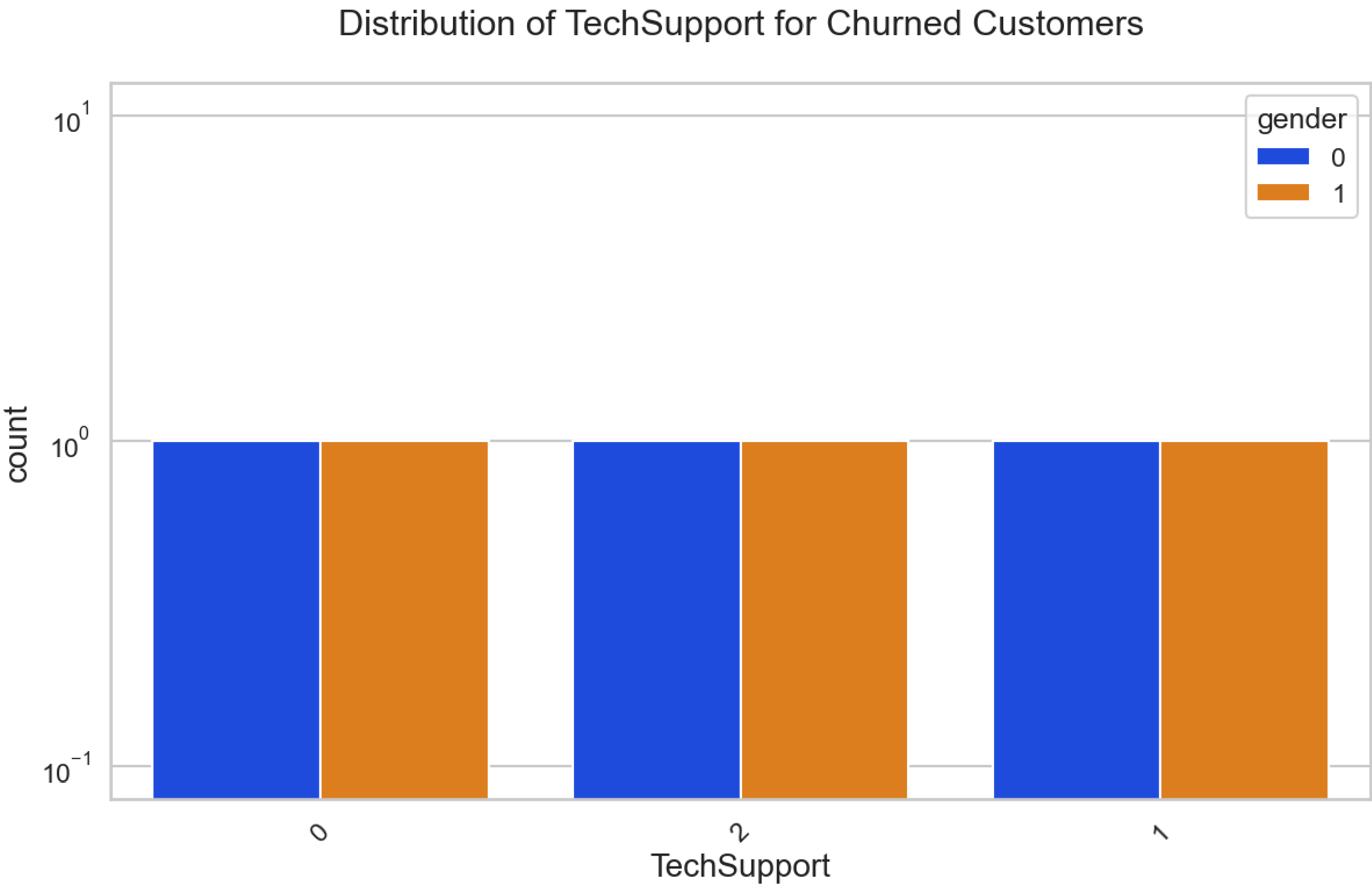
In [45]:
```
uniplot(new_df1_target1,col='PaymentMethod',title='Distribution of PaymentMethod for Churned Customers',hue='gend
```



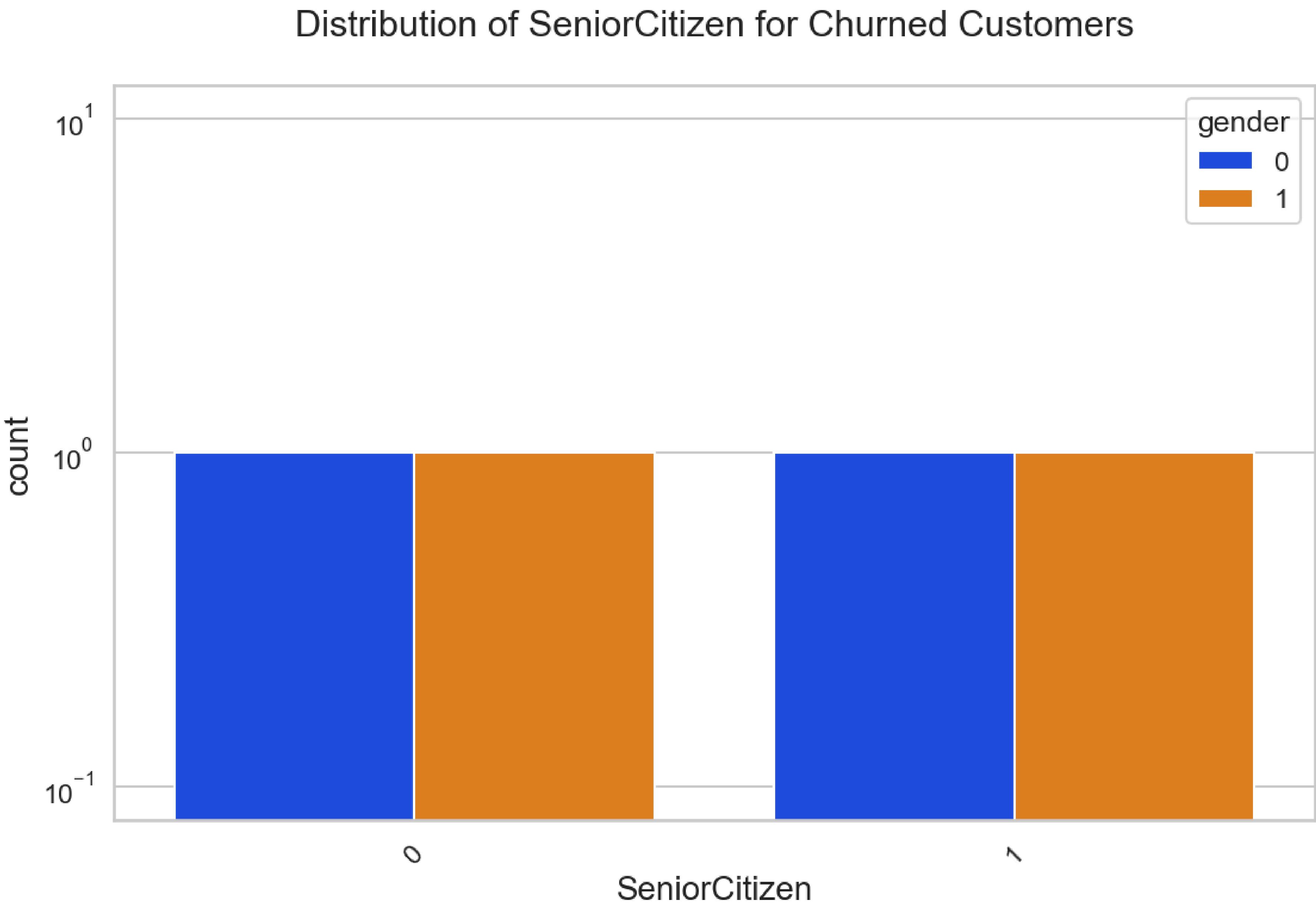
In [46]:
```
uniplot(new_df1_target1,col='Contract',title='Distribution of Contract for Churned Customers',hue='gender')
```



In [47]:
```
uniplot(new_df1_target1,col='TechSupport',title='Distribution of TechSupport for Churned Customers',hue='gender')
```



In [48]:
```
uniplot(new_df1_target1,col='SeniorCitizen',title='Distribution of SeniorCitizen for Churned Customers',hue='gend
```



In [49]:
```
X=telco_data.drop('Churn',axis=1)
y=telco_data['Churn']
```

In [50]:
```
X
```

Out[50]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	T
0	0	0	1	0	0	1	0	0	2	0	
1	1	0	0	0	1	0	0	2	0	2	
2	1	0	0	0	1	0	0	2	2	0	
3	1	0	0	0	0	1	0	2	0	2	
4	0	0	0	0	1	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	
7038	1	0	1	1	1	2	0	2	0	2	
7039	0	0	1	1	1	2	1	0	2	2	
7040	0	0	1	1	0	1	0	2	0	0	
7041	1	1	1	0	1	2	1	0	0	0	
7042	1	0	0	0	1	0	1	2	0	2	

7032 rows × 19 columns

In [51]:
```
telco_data['Churn'].value_counts()/len(telco_data) #data is highly imbalancing
```

Out[51]:
```
Churn
0    0.734215
1    0.265785
Name: count, dtype: float64
```

Train Test Split

In [52]:
```
from sklearn.model_selection  import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
```

In [53]:
```
print('Traing data shape')

print(X_train.shape)
print(y_train.shape)

print('Testing Data shape')

print(X_test.shape)
print(y_test.shape)
```

```
Traing data shape
(5625, 19)
(5625,)
Testing Data shape
(1407, 19)
(1407,)
```

In [54]:
```
print(y_test.value_counts())

print(y_train.value_counts())
```

```
Churn
0    1033
1     374
Name: count, dtype: int64
Churn
0    4130
1    1495
Name: count, dtype: int64
```

Decision Tree

In [55]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [56]:
```
model_dtc=DecisionTreeClassifier(criterion = "gini",random_state = 100,max_depth=6, min_samples_leaf=8)
```

In [57]:
```
model_dtc.fit(X_train,y_train)
```

Out[57]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=6, min_samples_leaf=8, random_state=100)
```

In [58]:
```
model_dtc.score(X_test,y_test)
```

Out[58]:
```
0.7619047619047619
```

In [59]:
```
y_pred=model_dtc.predict(X_test)
y_pred[:10]
```

Out[59]:
```
array([0, 0, 1, 0, 0, 1, 0, 1, 0, 0], dtype=int64)
```

In [60]:
```
print(y_test[:10])
```

```
2481    0
6784    0
6125    1
3052    0
4099    0
3223    0
3774    0
3469    0
3420    0
1196    0
Name: Churn, dtype: int64
```

In [61]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred, labels=[0,1]))
```

```
              precision    recall  f1-score   support

           0       0.84      0.83      0.84      1033
           1       0.55      0.56      0.56       374

    accuracy                           0.76      1407
   macro avg       0.70      0.70      0.70      1407
weighted avg       0.76      0.76      0.76      1407
```

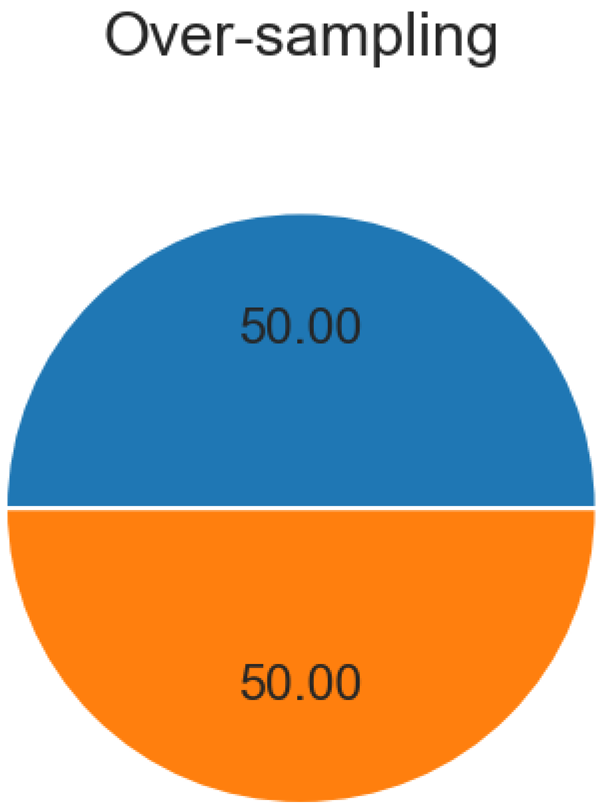
''' As you can see that the accuracy is quite low, and as it's an imbalanced dataset, we shouldn't consider Accuracy as our metrics to measure the model, as Accuracy is cursed in imbalanced datasets. Hence, we need to check recall, precision & f1 score for the minority class, and it's quite evident that the precision, recall & f1 score is too low for Class 1, i.e. churned customers. Hence, moving ahead to call SMOTEENN (UpSampling + ENN)'''

'''main advantage of using SMOTEENN is that it addresses both overfitting and underfitting issues that can arise from class imbalance. By generating synthetic samples and removing noisy ones'''

Balancing the Datasets

In [62]:

```
from imblearn.over_sampling import SMOTE

smote=SMOTE()

X_ovs,y_ovs=smote.fit_resample(X,y)



fig, oversp = plt.subplots()
oversp.pie( y_ovs.value_counts(), autopct='%.2f')
oversp.set_title("Over-sampling")
plt.show()

```



In [63]:
```
Xr_train,Xr_test,yr_train,yr_test=train_test_split(X_ovs, y_ovs,test_size=0.2,random_state=42)
```

Logistic Regression

In [64]:
```
from sklearn.linear_model  import LogisticRegression

model_lr=LogisticRegression(max_iter=1000)
```

In [65]:
```
model_lr.fit(Xr_train,yr_train)
```

Out[65]:
```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

In [66]:
```
y_pred=model_lr.predict(Xr_test)
y_pred[:10]
```

Out[66]:
```
array([1, 0, 0, 1, 0, 1, 1, 0, 1, 0], dtype=int64)
```

In [67]:
```
model_lr.score(Xr_test,yr_test)
```

Out[67]:
```
0.8049370764762827
```

In [68]:
```
from sklearn.metrics import accuracy_score, classification_report

report = classification_report(y_pred, yr_test, labels=[0, 1])

print(report)
```

```
              precision    recall  f1-score   support

           0       0.77      0.83      0.80       966
           1       0.84      0.78      0.81      1100

    accuracy                           0.80      2066
   macro avg       0.81      0.81      0.80      2066
weighted avg       0.81      0.80      0.81      2066
```

In [69]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(yr_test,y_pred)
```

Out[69]:
```
array([[800, 237],
       [166, 863]], dtype=int64)
```

Decision Tree classifier

In [70]:
```
from sklearn.tree import DecisionTreeClassifier

model_dtc=DecisionTreeClassifier(criterion = "gini",random_state = 100,max_depth=6, min_samples_leaf=8)
```

In [71]:
```
model_dtc.fit(Xr_train,yr_train)
```

Out[71]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=6, min_samples_leaf=8, random_state=100)
```

In [72]:
```
y_pred=model_dtc.predict(Xr_test)
y_pred[:10]
```

Out[72]:
```
array([1, 0, 0, 1, 0, 1, 1, 0, 1, 0], dtype=int64)
```

In [73]:
```
yr_test[:10]
```

Out[73]:
```
4139    1
1692    0
2692    0
7704    1
321     0
9752    1
39      1
3813    0
7396    1
2613    0
Name: Churn, dtype: int64
```

In [74]:
```
model_dtc.score(Xr_test,yr_test)
```

Out[74]:
```
0.7981606969990319
```

In [75]:
```
print(classification_report(yr_test, y_pred, labels=[0,1]))
```

```
              precision    recall  f1-score   support

           0       0.81      0.78      0.80      1037
           1       0.79      0.81      0.80      1029

    accuracy                           0.80      2066
   macro avg       0.80      0.80      0.80      2066
weighted avg       0.80      0.80      0.80      2066
```

In [76]:
```
confusion_matrix(yr_test,y_pred)
```
Out[76]:
```
array([[812, 225],
       [192, 837]], dtype=int64)
```

Random Forest Classifier

In [77]:
```
from sklearn.ensemble import RandomForestClassifier

model_rfc=RandomForestClassifier(n_estimators=100, random_state = 100,max_depth=6, min_samples_leaf=8,class_weigh
```

In [78]:
```
model_rfc.fit(Xr_train,yr_train)
```
Out[78]:
```
RandomForestClassifier
RandomForestClassifier(class_weight='balanced', max_depth=6, min_samples_leaf=8,
                       random_state=100)
```

In [79]:
```
y_pred=model_rfc.predict(Xr_test)
y_pred[:10]
```
Out[79]:
```
array([1, 0, 0, 1, 0, 1, 1, 0, 1, 0], dtype=int64)
```

In [80]:
```
yr_test[:10]
```

Out[80]:
```
4139    1
1692    0
2692    0
7704    1
321     0
9752    1
39      1
3813    0
7396    1
2613    0
Name: Churn, dtype: int64
```

In [81]:
```
model_rfc.score(Xr_test,yr_test)
```

Out[81]:
```
0.81945788964182
```

In [82]:
```
report_rfc=classification_report(y_pred,yr_test)
print(report_rfc)
```

```
              precision    recall  f1-score   support

           0       0.77      0.85      0.81       936
           1       0.87      0.79      0.83      1130

    accuracy                           0.82      2066
   macro avg       0.82      0.82      0.82      2066
weighted avg       0.82      0.82      0.82      2066
```

In [83]:
```
confusion_matrix(yr_test,y_pred)
```

Out[83]:
```
array([[800, 237],
       [136, 893]], dtype=int64)
```

AdaBoost

In [84]:
```
from sklearn.ensemble import  AdaBoostClassifier
```

In [85]:
```
model_abc=AdaBoostClassifier(n_estimators=100)
```

In [86]:
```
model_abc.fit(Xr_train,yr_train)
```

Out[86]:
```
        AdaBoostClassifier
AdaBoostClassifier(n_estimators=100)
```

In [87]:
```
y_pred=model_abc.predict(Xr_test)
```

In [88]:
```
print(classification_report(y_pred,yr_test))
```

```
              precision    recall  f1-score   support

           0       0.78      0.86      0.82       948
           1       0.87      0.80      0.83      1118

    accuracy                           0.83      2066
   macro avg       0.83      0.83      0.83      2066
weighted avg       0.83      0.83      0.83      2066
```

In [89]:
```
confusion_matrix(yr_test,y_pred)
```

Out[89]:
```
array([[814, 223],
       [134, 895]], dtype=int64)
```

GradientBoostingClassifer

In [90]:
```
from sklearn.ensemble import GradientBoostingClassifier
model_gbc=GradientBoostingClassifier()
model_gbc
```

Out[90]:
```
▾ GradientBoostingClassifier
GradientBoostingClassifier()
```

In [91]:
```
model_gbc.fit(Xr_train,yr_train)
```

Out[91]:
```
▾ GradientBoostingClassifier
GradientBoostingClassifier()
```

In [92]:
```
y_pred_gbc=model_gbc.predict(Xr_test)
y_pred_gbc[:10]
```

Out[92]:
```
array([1, 0, 0, 1, 0, 1, 1, 0, 1, 0], dtype=int64)
```

In [93]:
```
yr_test[:10]
```

Out[93]:
```
4139    1
1692    0
2692    0
7704    1
321     0
9752    1
39      1
3813    0
7396    1
2613    0
Name: Churn, dtype: int64
```

In [94]:
```
print(classification_report(y_pred_gbc,yr_test))
```

```
              precision    recall  f1-score   support

           0       0.80      0.85      0.82       967
           1       0.86      0.81      0.83      1099

    accuracy                           0.83      2066
   macro avg       0.83      0.83      0.83      2066
weighted avg       0.83      0.83      0.83      2066
```

In [95]:
```
confusion_matrix(yr_test,y_pred)
```

Out[95]:
```
array([[814, 223],
       [134, 895]], dtype=int64)
```

Xgboost

In [96]:
```
from xgboost import XGBClassifier

model_xgb=XGBClassifier(class_weight={0:1, 1:2})

model_xgb
```

Out[96]:
```
XGBClassifier
    colsample_bynode=None, colsample_bytree=None, device=None,
    early_stopping_rounds=None, enable_categorical=False,
    eval_metric=None, feature_types=None, gamma=None,
    grow_policy=None, importance_type=None,
    interaction_constraints=None, learning_rate=None, max_bin=None,
    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, ...)
```

In [97]:
```
model_xgb.fit(Xr_train,yr_train)
```

```
C:\Users\sumit\anaconda3\Lib\site-packages\xgboost\core.py:160: UserWarning: [15:14:45] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-0b3782d1791676daf-1\xgboost\xgboost-ci-windows\src\learner.cc:742:
Parameters: { "class_weight" } are not used.

  warnings.warn(smsg, UserWarning)
```

Out[97]:

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              class_weight={0: 1, 1: 2}, colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, device=None,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              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,
```

In [98]:
```
y_pred=model_xgb.predict(Xr_test)
y_pred[:10]
```

Out[98]:
```
array([0, 0, 0, 1, 0, 1, 1, 0, 1, 0])
```

In [99]:
```
yr_test[:10]
```

Out[99]:
```
4139    1
1692    0
2692    0
7704    1
321     0
9752    1
39      1
3813    0
7396    1
2613    0
Name: Churn, dtype: int64
```

In [100]:
```
print(classification_report(y_pred,yr_test))
```

```
              precision    recall  f1-score   support

           0       0.84      0.85      0.84      1026
           1       0.85      0.84      0.84      1040

    accuracy                           0.84      2066
   macro avg       0.84      0.84      0.84      2066
weighted avg       0.84      0.84      0.84      2066
```

In [101]:
```
from sklearn.metrics import confusion_matrix

# Assuming y_pred and y_test are your predicted and true labels respectively
cm = confusion_matrix(yr_test, y_pred)

print("Confusion Matrix:")
print(cm)
```

```
Confusion Matrix:
[[867 170]
 [159 870]]
```

GradientBoostingClassifier and adaboost has accuracy i go with Gradientboostingclassifier /finding the best hyperparameter

In [102]:

```python
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import GradientBoostingClassifier
import time

# Define your GradientBoostingClassifier and param_dist
model = GradientBoostingClassifier()
param_dist = {
    'learning_rate': [0.1, 0.5, 1.0],
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, 7],  # Example: Adding max_depth parameter
    'min_samples_split': [2, 5, 10]  # Example: Adding min_samples_split parameter
}

# Create RandomizedSearchCV object with fewer iterations
random_search = RandomizedSearchCV(estimator=model, param_distributions=param_dist, n_iter=5, cv=10, scoring='acc

# Start the timer
start_time = time.time()

# Fit the RandomizedSearchCV object
random_search.fit(Xr_train, yr_train)

# Stop the timer
end_time = time.time()

# Calculate the total time taken
total_time = end_time - start_time

print("RandomizedSearchCV took {:.2f} seconds to complete.".format(total_time))

# Get the best parameters
best_params = random_search.best_params_
print("Best Parameters:", best_params)
```

```
RandomizedSearchCV took 227.54 seconds to complete.
Best Parameters: {'n_estimators': 100, 'min_samples_split': 5, 'max_depth': 7, 'learning_rate': 0.1}
```

final model

In [103]:
```python
from sklearn.ensemble import GradientBoostingClassifier

# Define the best hyperparameters obtained from GridSearchCV
best_params = {
    'n_estimators': 100, 'min_samples_split':5 , 'max_depth': 7, 'learning_rate': 0.1
}

# Create Gradient Boosting Classifier with the best hyperparameters
final_gb_classifier = GradientBoostingClassifier(**best_params)

# Train the final model on the entire training data
final_gb_classifier.fit(Xr_train, yr_train)
```

Out[103]:
```
GradientBoostingClassifier
GradientBoostingClassifier(max_depth=7, min_samples_split=5)
```

In [104]:
```python
from sklearn.model_selection import cross_val_score

# trained model with tuned hyperparameters
# X_train and y_train are your training data
# cv=10 indicates 10-fold cross-validation
cv_scores = cross_val_score(final_gb_classifier, Xr_train, yr_train, cv=10, scoring='accuracy')

# Print the cross-validation scores
print("Cross-validation scores:", cv_scores)
print("Mean CV score:", cv_scores.mean())

```

```
Cross-validation scores: [0.83898305 0.8559322  0.84261501 0.8535109  0.84382567 0.86561743
 0.82687651 0.83535109 0.83656174 0.86440678]
Mean CV score: 0.8463680387409201
```

In [105]:
```
y_pred=final_gb_classifier.predict(Xr_test)
y_pred[:10]
```

Out[105]:
```
array([1, 0, 0, 1, 0, 1, 1, 0, 1, 0], dtype=int64)
```

In [106]:
```
yr_test[:10]
```

Out[106]:
```
4139    1
1692    0
2692    0
7704    1
321     0
9752    1
39      1
3813    0
7396    1
2613    0
Name: Churn, dtype: int64
```

In [107]:
```
print(classification_report(y_pred,yr_test))
```

```
              precision    recall  f1-score   support

           0       0.83      0.85      0.84      1011
           1       0.85      0.83      0.84      1055

    accuracy                           0.84      2066
   macro avg       0.84      0.84      0.84      2066
weighted avg       0.84      0.84      0.84      2066
```

In [108]:
```
confusion_matrix(y_pred,yr_test)
```

Out[108]:
```
array([[861, 150],
       [176, 879]], dtype=int64)
```

Electronic check medium are the highest churners

Contract Type - Monthly customers are more likely to churn because of no contract terms, as they are free to go customers.

No Online security, No Tech Support category are high churners

Non senior Citizens are high churners

Pickle file

In [109]:
```
import os
import pickle
from sklearn.ensemble import GradientBoostingClassifier

# Change directory if needed
#os.chdir('D:\\Datasets')

# Assuming final_gb_classifier is your trained model
# Define and train Gradient Boosting Classifier
best_params = {
    'n_estimators': 100,
    'min_samples_split': 5,
    'max_depth': 7,
    'learning_rate': 0.1
}

final_gb_classifier = GradientBoostingClassifier(**best_params)

# Train the final model on the entire training data (assuming Xr_train and yr_train are defined)
final_gb_classifier.fit(X_train, y_train)

# Dumping the model to a file
with open('final_gb_classifier.pkl', 'wb') as file:
    pickle.dump(final_gb_classifier, file)

# Load the saved model
#with open('final_gb_classifier.pkl', 'rb') as file:
  #  loaded_model = pickle.load(file)
```

Checking accuravy with our features

In [110]:

```
import pickle
import pandas as pd

# Load the saved model from the pickle file
with open('final_gb_classifier.pkl', 'rb') as file:
    loaded_model = pickle.load(file)

# Prepare your own data for testing
# Create a DataFrame with your feature data
your_features = pd.DataFrame({
    'gender': [1, 0, 0, 0, 0],
    'SeniorCitizen': [0, 0, 0, 0, 0],
    'Partner': [0, 0, 0, 1, 1],
    'Dependents': [0, 0, 0, 0, 1],
    'PhoneService': [1, 0, 1, 1, 1],
    'MultipleLines': [0, 0, 0, 2, 2],
    'InternetService': [1, 0, 1, 1, 0],
    'OnlineSecurity': [0, 0, 0, 2, 2],
    'OnlineBackup': [0, 0, 1, 2, 2],
    'DeviceProtection': [0, 0, 0, 0, 2],
    'TechSupport': [0, 0, 0, 2, 2],
    'StreamingTV': [0, 1, 0, 0, 0],
    'StreamingMovies': [0, 1, 0, 0, 0],
    'Contract': [2, 0, 0, 1, 2],
    'PaperlessBilling': [0, 1, 0, 0, 0],
    'PaymentMethod': [1, 1, 1, 0, 0],
    'MonthlyCharges': [90.407734, 58.273891, 74.379767, 108.55, 64.35],
    'TotalCharges': [707.535237, 3264.466697, 1146.937795, 5610.7, 1558.65],
    'tenure_group': [0, 4, 1, 4, 2]
})
# Make predictions using the loaded model on your own data
predictions = loaded_model.predict(your_features)

# Print the predictions
print("Predictions:", predictions)
```

```
Predictions: [0 0 0 1 0]
```