Title of the Project : # Telecom Churn Prediction

Photo credit: Superoffice.com

Customers are the most important resources for any companies or businesses. What if these customers leave the company due to high charges, better competitor offers, poor customer services or something unknown? Hence, Customer churn rate is one of the important metrics for companies to evaluate their performance.

Churn is a one of the biggest problems in the telecom industry. Research has shown that the average monthly churn rate among the top 4 wireless carriers in the US is 1.9% - 2%. churn refers to the number of customers who stop using a company's products or services over a period of time. Customer churn refers to the percentage of customers who stop using a company's service during a given timeframe. It can happen for various reasons including dissatisfaction with the product, better offers from competitors or changes in customer needs.

Customer churn rate is a KPI to understand the leaving customers. Churn rate represents the percentage of customers that company lost over all the customers at the beginning of the interval.

For example, If company had 400 customers at the beginning of the month and only 360 at the end of the month, means company's churn rate is 10%, because company lost 10% of the customer base. Companies always try to minimize the churn rate to as close as 0%.

Deliverables of the project:

To create a classification filter (Using all classification models and compare their performances) to determine Churn from Telecom dataset. Compare the performance of the filters. Reducing churn is particularly important in competitive industries as acquiring new customers can often be more expensive than retaining existing ones "churn 0" represents a customer who has not churned (meaning they are still actively using a service), while "churn 1" indicates a customer who has churned (stopped using the service)whether or not the customer left the bank. (0=No,1=Yes) Model will be evaluated by classification/Logistic Regression

Table of contents

5) Retention plan

In [ ]:
```
__author__ = "Alok Miglani"
__email__ = "alokmiglani@gmail.com"
```

1. Introduction

Dataset, Features and Target value

Dataset: Source: https://www.kaggle.com/datasets/blastchar/telco-customer-churn

Main objective here is to analyze churn customers' behavior and develop strategies to increase customer retention. Assumption — Here, data source has not provided any information related to time; So I have assumed that all the records are specific to the particular month.

Dataset has information related to,

Demographic:

- Gender - Male / Female
- Age range - In terms of Partner, Dependent and Senior Citizen

Services:

- Phone service - If customer has Phone service, then services related to Phone like;
  - Multiline Phone service
- Internet Service - If customer has Internet service, then services related to Internet like;
  - Online security
  - Online backup
  - Device protection
  - Tech support
  - Streaming TV
  - Streaming Movies

Account type:

- Tenure - How long customer is with the company?
- Contract type - What kind of contract they have with a company? Like
  - Monthly bases
  - On going bases - If on going bases, then One month contract or Two year contract
- Paperless billing - Customer is paperless billion option or not?
- Payment method - What kind of payment method customer has?
  - Mailed check
  - Electronic check
  - Credit card (Automatic)
  - Bank transfer (Automatic)

Usage:

- Monthly charges
- Total charges

Target:

- Churn - Whether customer left the company or still with the company?

Problem Description

Why customers leaving the company?

The reasons behind the customer leaving company could be

- High charges
- Better offer from competitor
- Poor customer service
- Some unknown reasons

How to detect the churn customer?

- Monitoring usage

- Analysing complains
- Analyzing competitors offers

How to prevent customers from leaving a company?

Once you detect high risk customers, apply

- Retention plans
- Improve customer service

In [ ]:
```
Import Libraries
```

In [114…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import LabelEncoder
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, cross_val_score
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.svm import SVC
import pickle
```

Importing Dataset The data set includes information about: • Customers who left within the last month – the column is called Churn • Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies • Customer account information – how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges • Demographic info about customers – gender, age range, and if they have partners and dependents

Dataset: Source: https://www.kaggle.com/datasets/blastchar/telco-customer-churn

In [3]:
```
df = pd.read_csv("Telco_Customer_Churn.csv")
df.head(5)
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	..
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 [4]:
```
df.tail()
```

Out[4]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	Fiber optic	No
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	Yes

5 rows × 21 columns

Dataset knowledge

In [7]:
```
df.shape
```

Out[7]:
```
(7043, 21)
```

In [8]:
```
df.columns
```

Out[8]:
```
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 [9]:
```
df.duplicated().sum()
```

Out[9]:
```
0
```

In [10]:
```
df.nunique()
```

Out[10]:
```
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        6531
Churn                  2
dtype: int64
```

In [11]:
```
# dropping customerID column as this is not required for modelling
df = df.drop(columns=["customerID"])
```

In [12]:
```
df.head(5)
```

Out[12]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes
1	Male	0	No	No	34	Yes	No	DSL	Yes	No
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No

In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            7043 non-null   object 
 1   SeniorCitizen     7043 non-null   int64  
 2   Partner           7043 non-null   object 
 3   Dependents        7043 non-null   object 
 4   tenure            7043 non-null   int64  
 5   PhoneService      7043 non-null   object 
 6   MultipleLines     7043 non-null   object 
 7   InternetService   7043 non-null   object 
 8   OnlineSecurity    7043 non-null   object 
 9   OnlineBackup      7043 non-null   object 
 10  DeviceProtection  7043 non-null   object 
 11  TechSupport       7043 non-null   object 
 12  StreamingTV       7043 non-null   object 
 13  StreamingMovies   7043 non-null   object 
 14  Contract          7043 non-null   object 
 15  PaperlessBilling  7043 non-null   object 
 16  PaymentMethod     7043 non-null   object 
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   object 
 19  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(17)
memory usage: 1.1+ MB
```

In [14]:
```
df.columns
```

Out[14]:
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [15]:
```
df.isnull().sum()
```

Out[15]:
```
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 [16]:
```
df["gender"].unique()
```

Out[16]:
```
array(['Female', 'Male'], dtype=object)
```

In [17]:
```
df["SeniorCitizen"].unique()
```

Out[17]:
```
array([0, 1], dtype=int64)
```

In [18]:
```
for col in df.columns:
    print(col, df[col].unique())
    print("-"*50)
```

```
gender ['Female' 'Male']
--------------------------------------------------
SeniorCitizen [0 1]
--------------------------------------------------
Partner ['Yes' 'No']
--------------------------------------------------
Dependents ['No' 'Yes']
--------------------------------------------------
tenure [ 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]
--------------------------------------------------
PhoneService ['No' 'Yes']
--------------------------------------------------
MultipleLines ['No phone service' 'No' 'Yes']
--------------------------------------------------
InternetService ['DSL' 'Fiber optic' 'No']
--------------------------------------------------
OnlineSecurity ['No' 'Yes' 'No internet service']
--------------------------------------------------
OnlineBackup ['Yes' 'No' 'No internet service']
--------------------------------------------------
DeviceProtection ['No' 'Yes' 'No internet service']
--------------------------------------------------
TechSupport ['No' 'Yes' 'No internet service']
--------------------------------------------------
StreamingTV ['No' 'Yes' 'No internet service']
--------------------------------------------------
StreamingMovies ['No' 'Yes' 'No internet service']
--------------------------------------------------
Contract ['Month-to-month' 'One year' 'Two year']
--------------------------------------------------
PaperlessBilling ['Yes' 'No']
--------------------------------------------------
PaymentMethod ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
--------------------------------------------------
MonthlyCharges [29.85 56.95 53.85 ... 63.1  44.2  78.7 ]
--------------------------------------------------
TotalCharges ['29.85' '1889.5' '108.15' ... '346.45' '306.6' '6844.5']
--------------------------------------------------
Churn ['No' 'Yes']
--------------------------------------------------
```

In [19]:
```
numerical_features_list = ["tenure", "MonthlyCharges", "TotalCharges"]

for col in df.columns:
  if col not in numerical_features_list:
    print(col, df[col].unique())
    print("-"*50)
```

```
gender ['Female' 'Male']
--------------------------------------------------
SeniorCitizen [0 1]
--------------------------------------------------
Partner ['Yes' 'No']
--------------------------------------------------
Dependents ['No' 'Yes']
--------------------------------------------------
PhoneService ['No' 'Yes']
--------------------------------------------------
MultipleLines ['No phone service' 'No' 'Yes']
--------------------------------------------------
InternetService ['DSL' 'Fiber optic' 'No']
--------------------------------------------------
OnlineSecurity ['No' 'Yes' 'No internet service']
--------------------------------------------------
OnlineBackup ['Yes' 'No' 'No internet service']
--------------------------------------------------
DeviceProtection ['No' 'Yes' 'No internet service']
--------------------------------------------------
TechSupport ['No' 'Yes' 'No internet service']
--------------------------------------------------
StreamingTV ['No' 'Yes' 'No internet service']
--------------------------------------------------
StreamingMovies ['No' 'Yes' 'No internet service']
--------------------------------------------------
Contract ['Month-to-month' 'One year' 'Two year']
--------------------------------------------------
PaperlessBilling ['Yes' 'No']
--------------------------------------------------
PaymentMethod ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
--------------------------------------------------
Churn ['No' 'Yes']
--------------------------------------------------
```

In [20]:
```
df.describe().T
```

Out[20]:

	count	mean	std	min	25%	50%	75%	max
SeniorCitizen	7043.0	0.162147	0.368612	0.00	0.0	0.00	0.00	1.00
tenure	7043.0	32.371149	24.559481	0.00	9.0	29.00	55.00	72.00
MonthlyCharges	7043.0	64.761692	30.090047	18.25	35.5	70.35	89.85	118.75

In [21]:
```
df[df["TotalCharges"]==" "]
```

Out[21]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBack
488	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	
753	Male	0	No	Yes	0	Yes	No	No	No internet service	No inter serv
936	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	Y
1082	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No inter serv
1340	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	Y
3331	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No inter serv
3826	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No inter serv
4380	Female	0	Yes	Yes	0	Yes	No	No	No internet service	No inter serv
5218	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No inter serv
6670	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	Y
6754	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	Y

In [22]:
```
len(df[df["TotalCharges"]==" "])
```

Out[22]: 11

In [23]:
```
df["TotalCharges"] = df["TotalCharges"].replace({" ": "0.0"})
```

In [24]:
```
df["TotalCharges"] = df["TotalCharges"].astype(float)
```

In [25]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            7043 non-null   object 
 1   SeniorCitizen     7043 non-null   int64  
 2   Partner           7043 non-null   object 
 3   Dependents        7043 non-null   object 
 4   tenure            7043 non-null   int64  
 5   PhoneService      7043 non-null   object 
 6   MultipleLines     7043 non-null   object 
 7   InternetService   7043 non-null   object 
 8   OnlineSecurity    7043 non-null   object 
 9   OnlineBackup      7043 non-null   object 
 10  DeviceProtection  7043 non-null   object 
 11  TechSupport       7043 non-null   object 
 12  StreamingTV       7043 non-null   object 
 13  StreamingMovies   7043 non-null   object 
 14  Contract          7043 non-null   object 
 15  PaperlessBilling  7043 non-null   object 
 16  PaymentMethod     7043 non-null   object 
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   float64
 19  Churn             7043 non-null   object 
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

In [26]:
```
# checking the class distribution of target column
df["Churn"].value_counts()
```

Out[26]:
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

Insights:

Customer ID removed as it is not required for modelling No mmissing values in the dataset Missing values in the TotalCharges column were replaced with 0 Class imbalance identified in the target

In [27]:
```
df.describe()
```

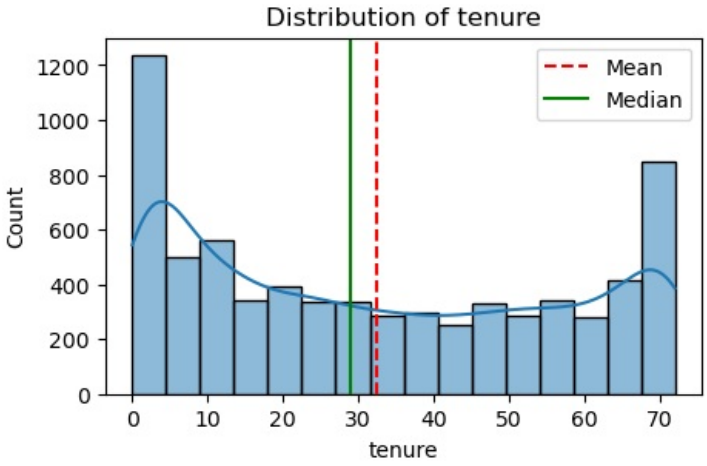
Out[27]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692	2279.734304
std	0.368612	24.559481	30.090047	2266.794470
min	0.000000	0.000000	18.250000	0.000000
25%	0.000000	9.000000	35.500000	398.550000
50%	0.000000	29.000000	70.350000	1394.550000
75%	0.000000	55.000000	89.850000	3786.600000
max	1.000000	72.000000	118.750000	8684.800000

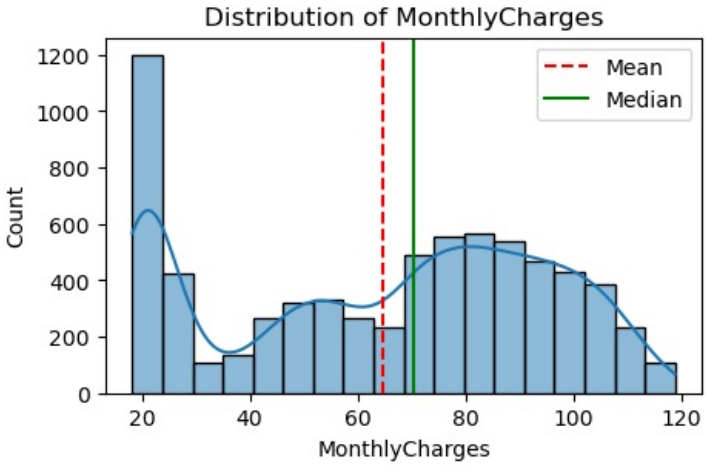
Numerical Features - Analysis Understand the distribution of the numerical features

In [28]:
```
def plot_histogram(df, column_name):

  plt.figure(figsize=(5, 3))
  sns.histplot(df[column_name], kde=True)
  plt.title(f"Distribution of {column_name}")

  # calculate the mean and median values for the columns
  col_mean = df[column_name].mean()
  col_median = df[column_name].median()

  # add vertical lines for mean and median
  plt.axvline(col_mean, color="red", linestyle="--", label="Mean")
  plt.axvline(col_median, color="green", linestyle="-", label="Median")
  plt.legend()
  plt.show()
```

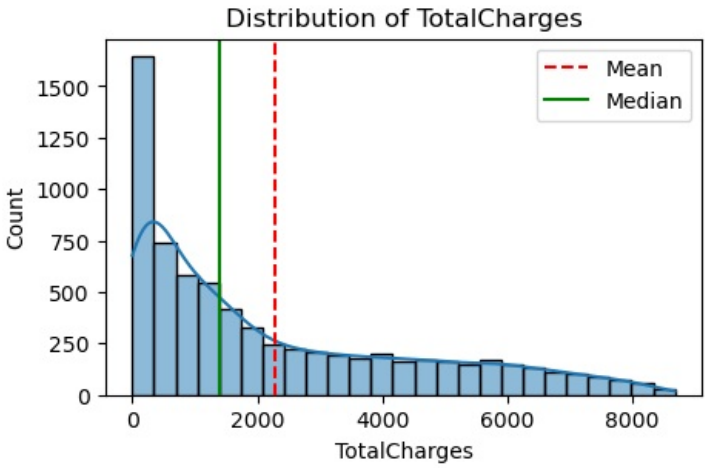
In [29]:
```
plot_histogram(df, "tenure")
```



In [30]:
```
plot_histogram(df, "MonthlyCharges")
```



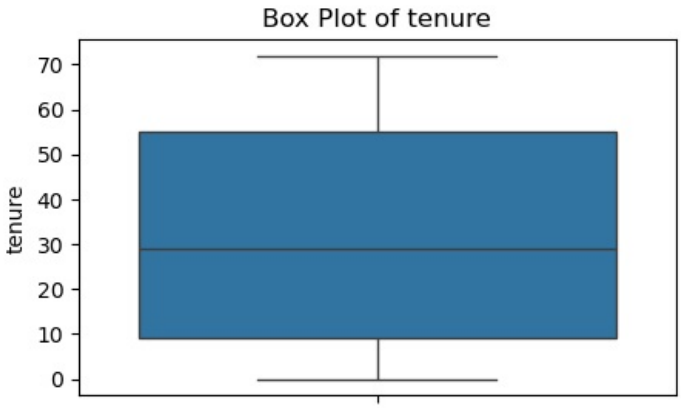
In [31]:
```
plot_histogram(df, "TotalCharges")
```



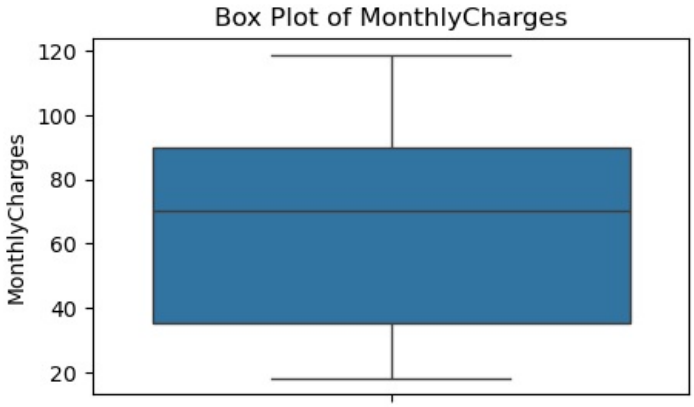
Box Plot for numerical features

In [32]:
```
def plot_boxplot(df, column_name):
    plt.figure(figsize=(5, 3))
    sns.boxplot(y=df[column_name])
    plt.title(f"Box Plot of {column_name}")
    plt.ylabel(column_name)
    plt.show()
```

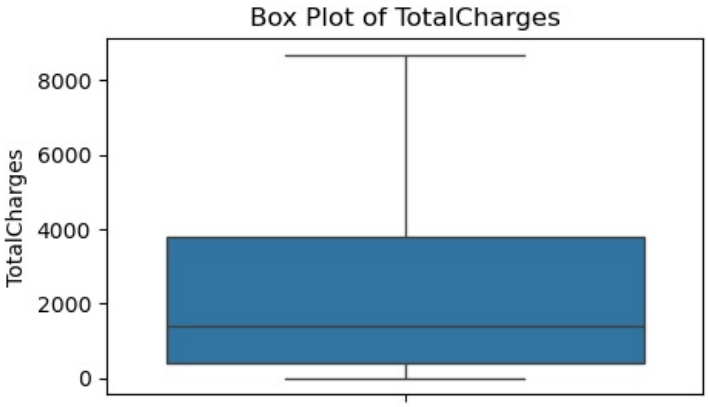
In [33]:
```
plot_boxplot(df, "tenure")
```



In [34]:
```
plot_boxplot(df, "MonthlyCharges")
```

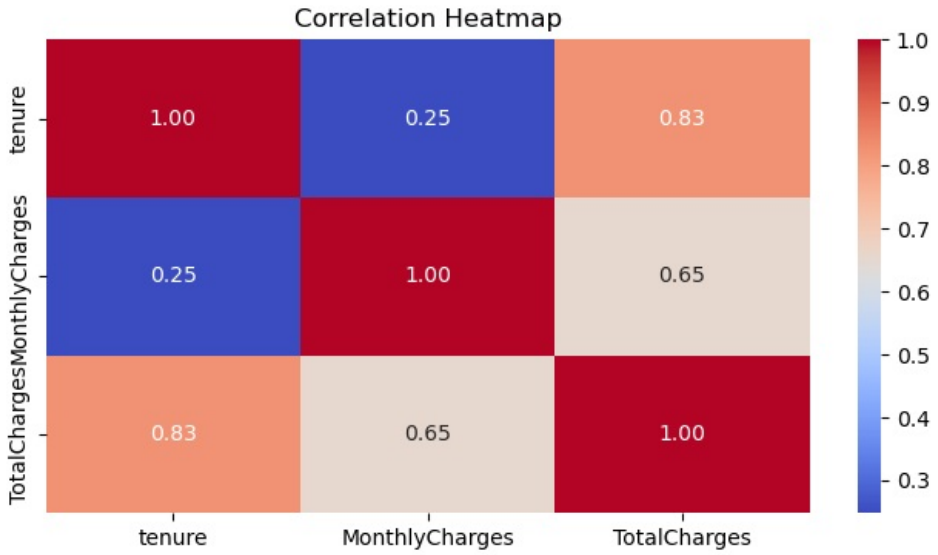


In [35]:
```
plot_boxplot(df, "TotalCharges")
```



corelation

In [36]:
```
# correlation matrix - heatmap
plt.figure(figsize=(8, 4))
sns.heatmap(df[["tenure", "MonthlyCharges", "TotalCharges"]].corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```

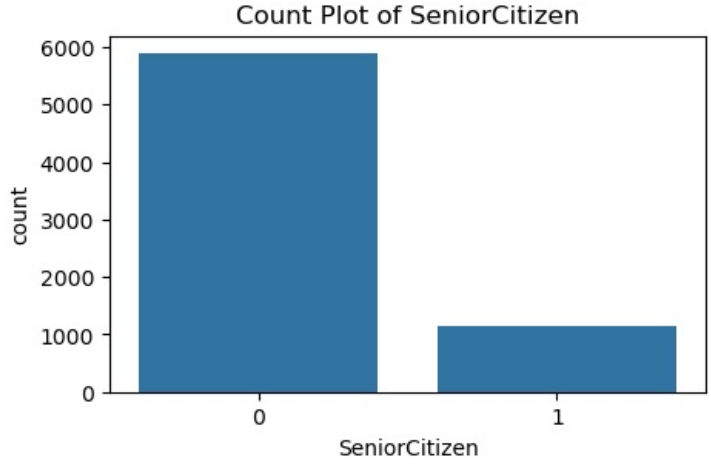


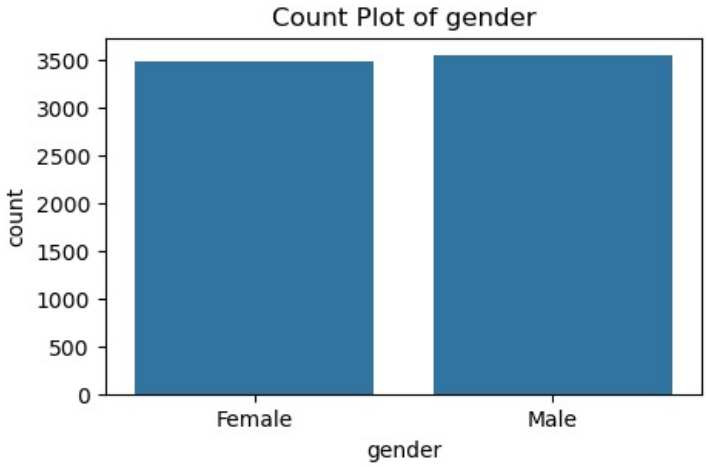
Categorical features - Analysis

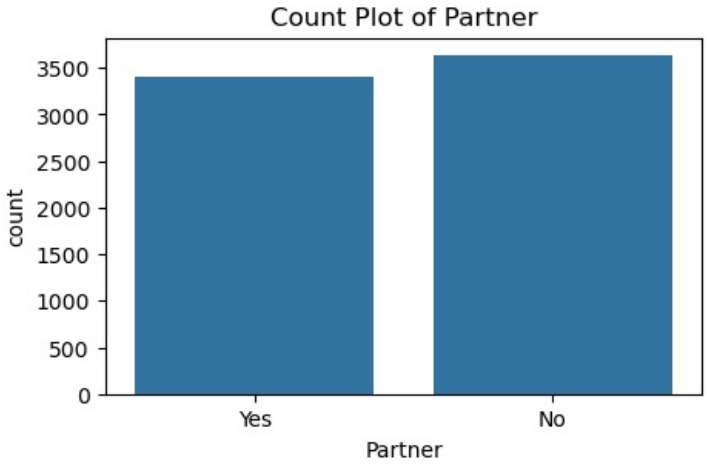
In [37]:
```
df.info()
```

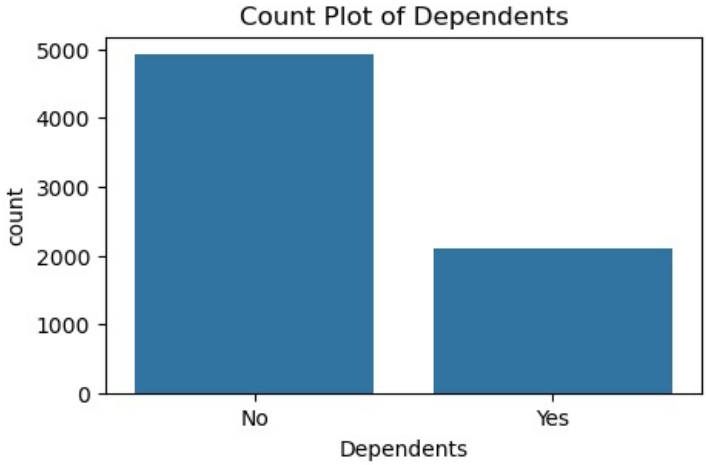
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   gender            7043 non-null   object
 1   SeniorCitizen     7043 non-null   int64
 2   Partner           7043 non-null   object
 3   Dependents        7043 non-null   object
 4   tenure            7043 non-null   int64
 5   PhoneService      7043 non-null   object
 6   MultipleLines     7043 non-null   object
 7   InternetService   7043 non-null   object
 8   OnlineSecurity    7043 non-null   object
 9   OnlineBackup      7043 non-null   object
 10  DeviceProtection  7043 non-null   object
 11  TechSupport       7043 non-null   object
 12  StreamingTV       7043 non-null   object
 13  StreamingMovies   7043 non-null   object
 14  Contract          7043 non-null   object
 15  PaperlessBilling  7043 non-null   object
 16  PaymentMethod     7043 non-null   object
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   float64
 19  Churn             7043 non-null   object
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

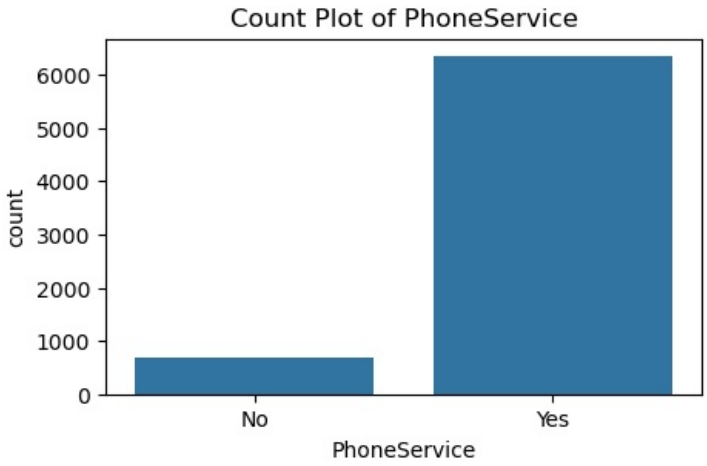
In [38]:
```
object_cols = df.select_dtypes(include="object").columns.to_list()
object_cols = ["SeniorCitizen"] + object_cols
for col in object_cols:
  plt.figure(figsize=(5, 3))
  sns.countplot(x=df[col])
  plt.title(f"Count Plot of {col}")
  plt.show()
```

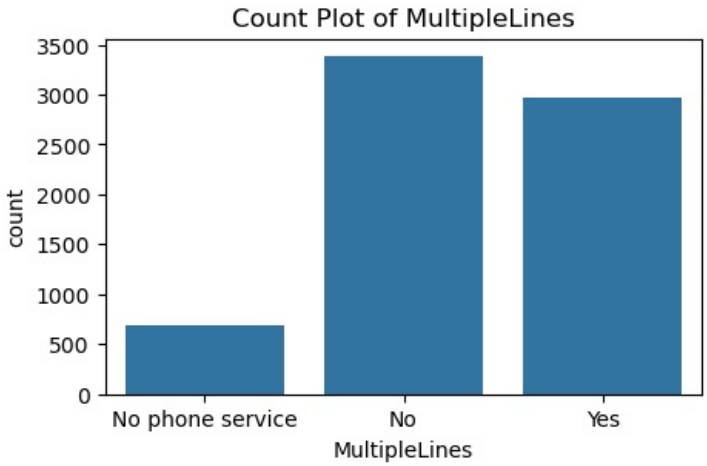


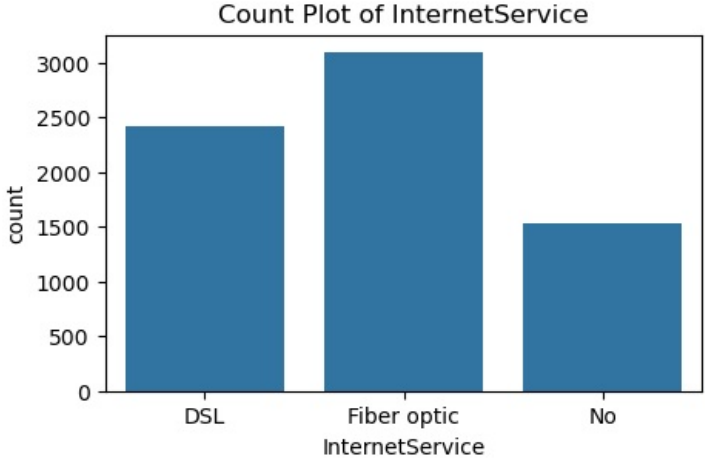

Count Plot of gender
count
3500
3000
2500
2000
1500
1000
500
0
Female
Male
gender

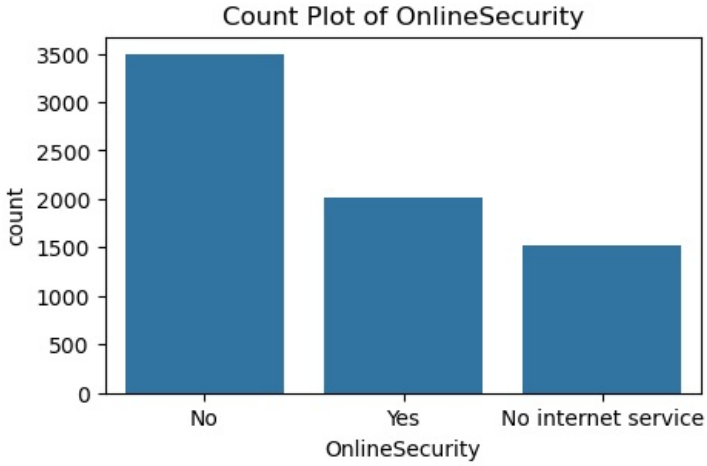

Count Plot of Partner
count
3500
3000
2500
2000
1500
1000
500
0
Yes
No
Partner

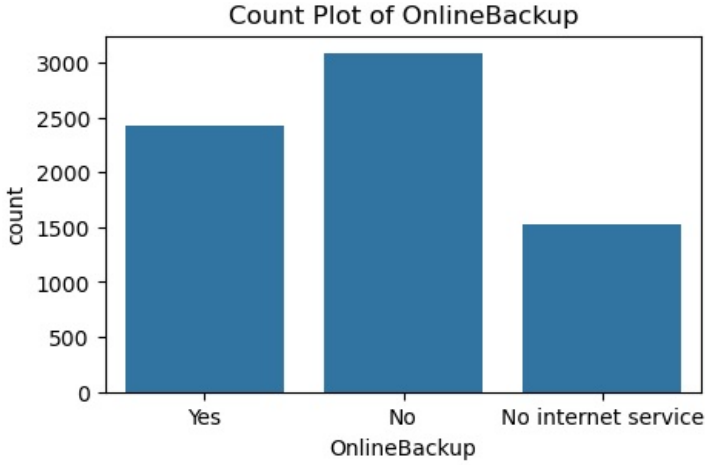

Count Plot of Dependents
count
5000
4000
3000
2000
1000
0
No
Yes
Dependents

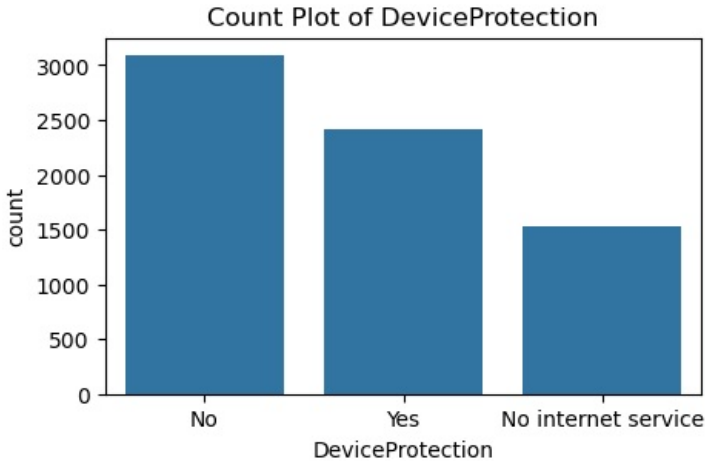

Count Plot of PhoneService
count
6000
5000
4000
3000
2000
1000
0
No
Yes
PhoneService

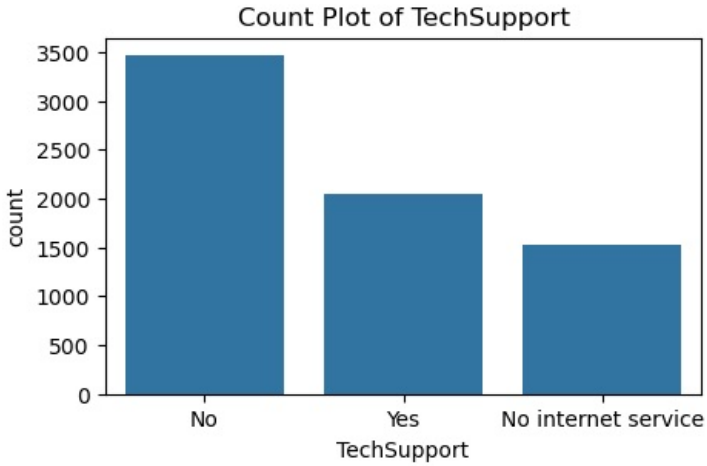

Count Plot of MultipleLines
count
3500
3000
2500
2000
1500
1000
500
0
No phone service
No
Yes
MultipleLines

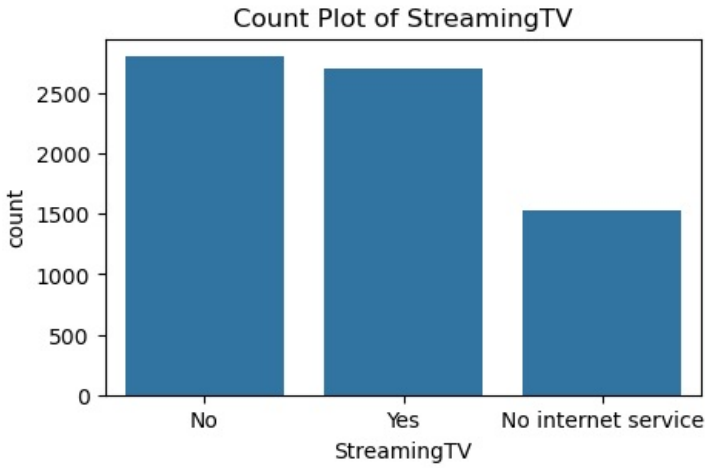

Count Plot of InternetService
count
3000
2500
2000
1500
1000
500
0
DSL
Fiber optic
No
InternetService

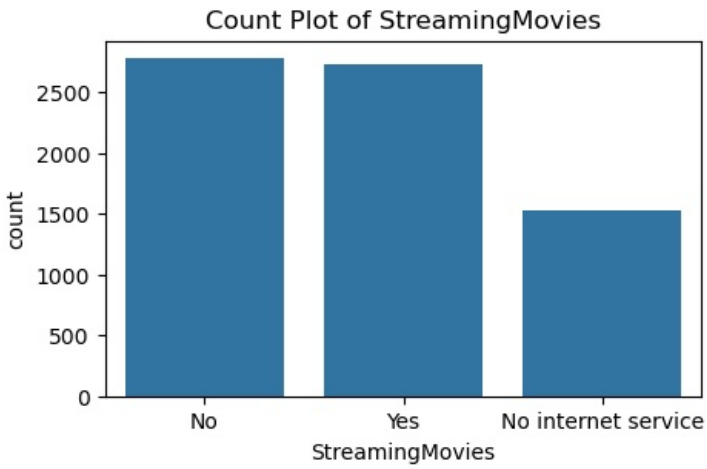

Count Plot of OnlineSecurity
count
3500
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service
OnlineSecurity

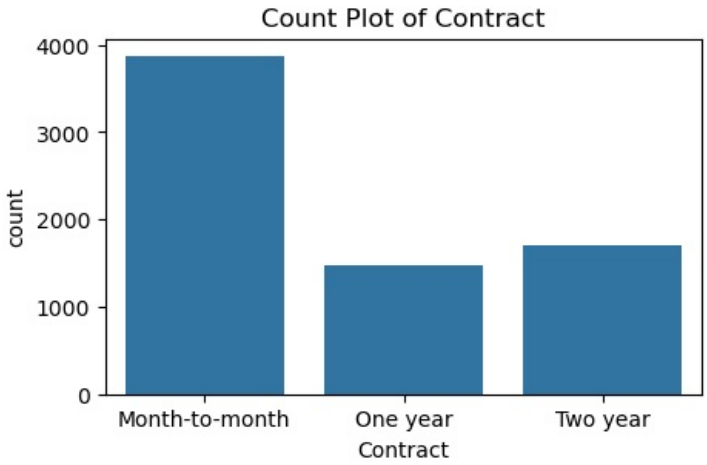

Count Plot of OnlineBackup
count
3000
2500
2000
1500
1000
500
0
Yes
No
No internet service
OnlineBackup

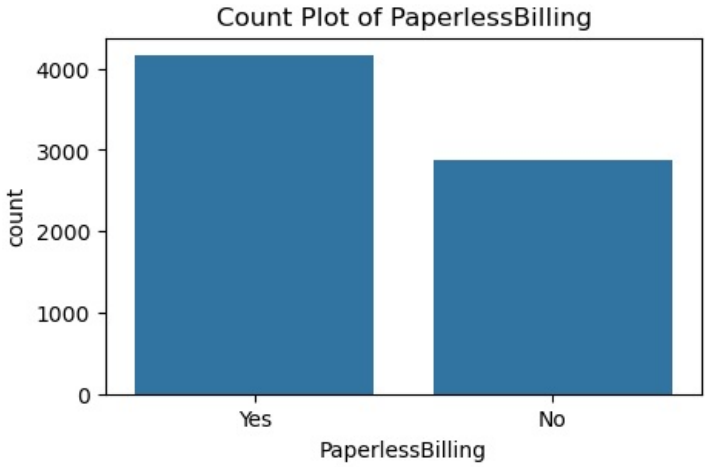

Count Plot of DeviceProtection
count
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service
DeviceProtection

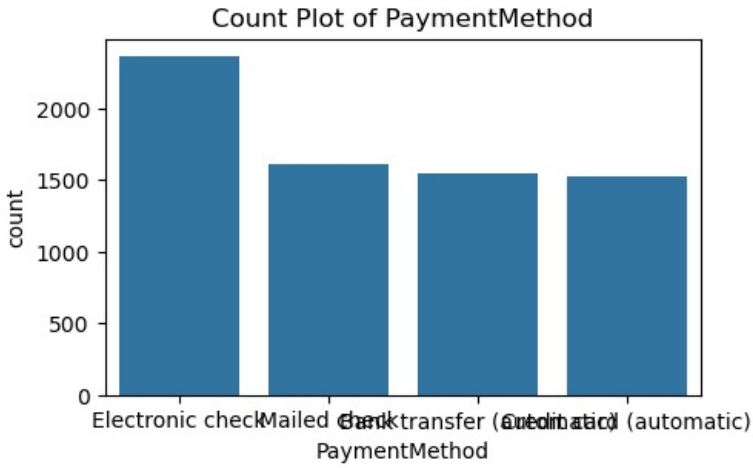

Count Plot of TechSupport
count
3500
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service
TechSupport

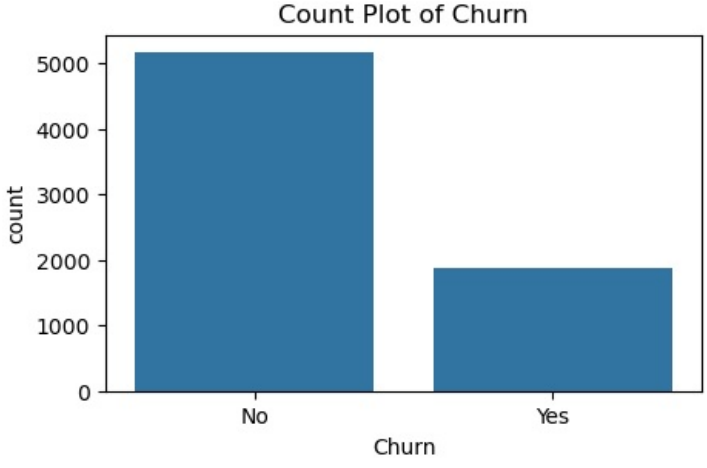

Count Plot of StreamingTV
count
2500
2000
1500
1000
500
0
No
Yes
No internet service
StreamingTV


Count Plot of StreamingMovies
count
2500
2000
1500
1000
500
0
No
Yes
No internet service
StreamingMovies





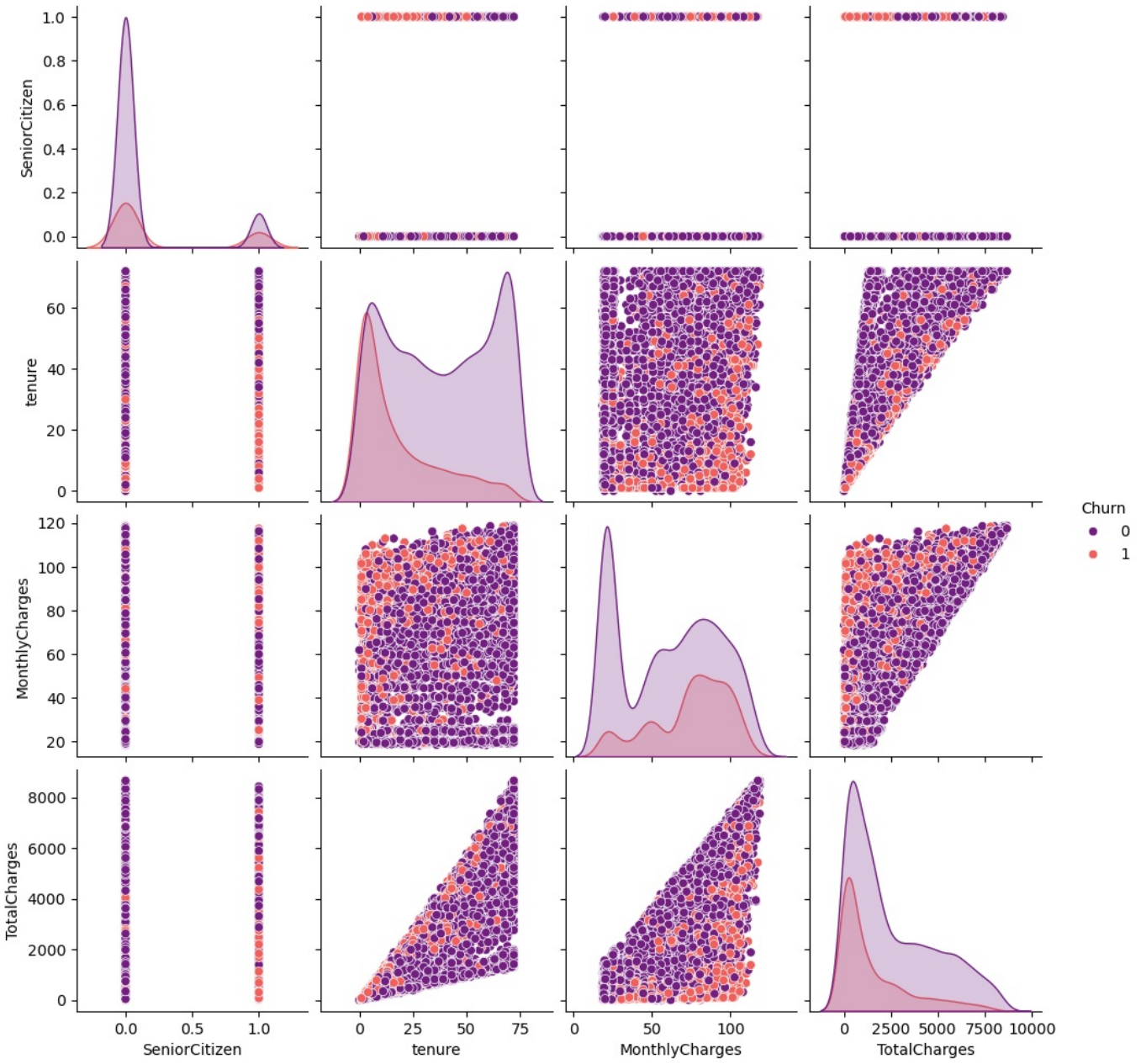




In [ ]:
```
Distribution
```

In [46]:
```
plt.figure(dpi=200, figsize=(8,6))
sns.pairplot(df,hue="Churn",palette="magma")
plt.show()
```

```
<Figure size 1600x1200 with 0 Axes>
```

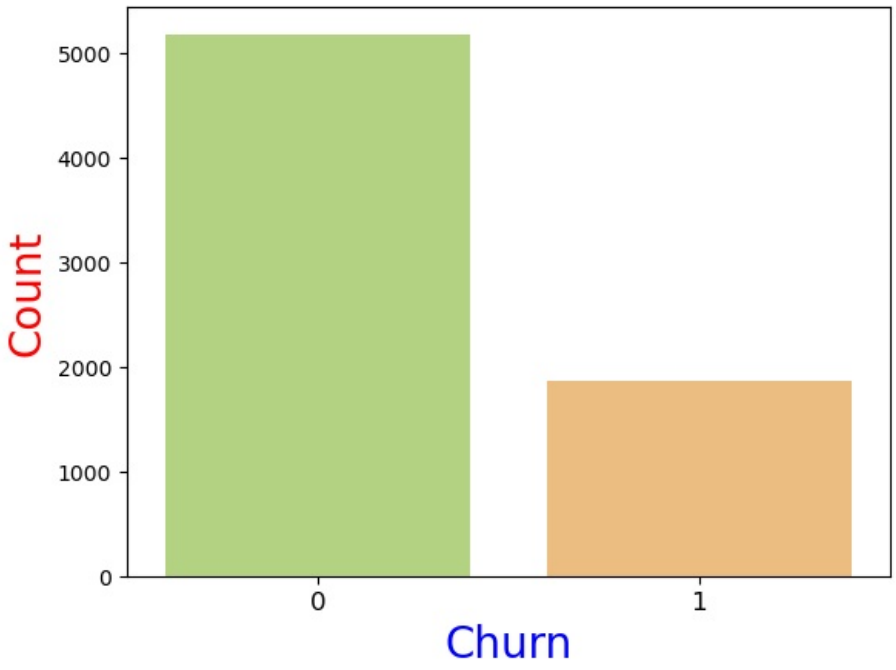


Churn is high when Monthly Charges are high. Churn is high at starting tenure and churn is low as tenure increases.

In [47]:
```
df['Churn'].value_counts()
```

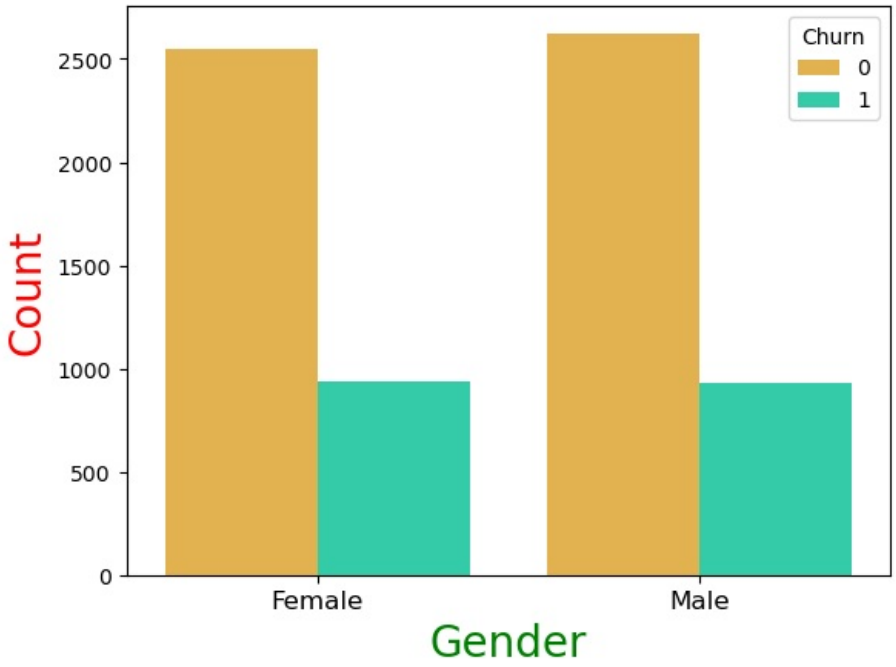
Out[47]:
```
Churn
0    5174
1    1869
Name: count, dtype: int64
```

In [48]:
```
sns.countplot(x= "Churn", data= df, palette= "RdYlGn_r")
plt.xticks(fontsize = 12)
plt.xlabel("Churn", fontsize = 20, c= "b")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



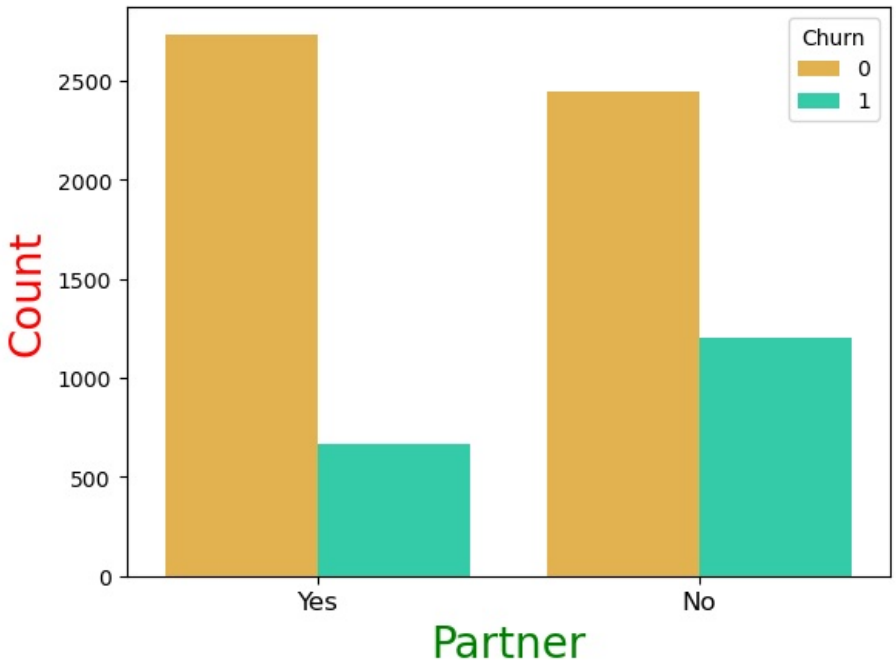
Here we can see Churn data is imbalance. It shows No churn is high.

In [49]:
```
sns.countplot(x= "gender", data= df, hue = "Churn", palette= "turbo_r")
plt.xticks(fontsize = 12)
plt.xlabel("Gender", fontsize = 20, c= "g")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



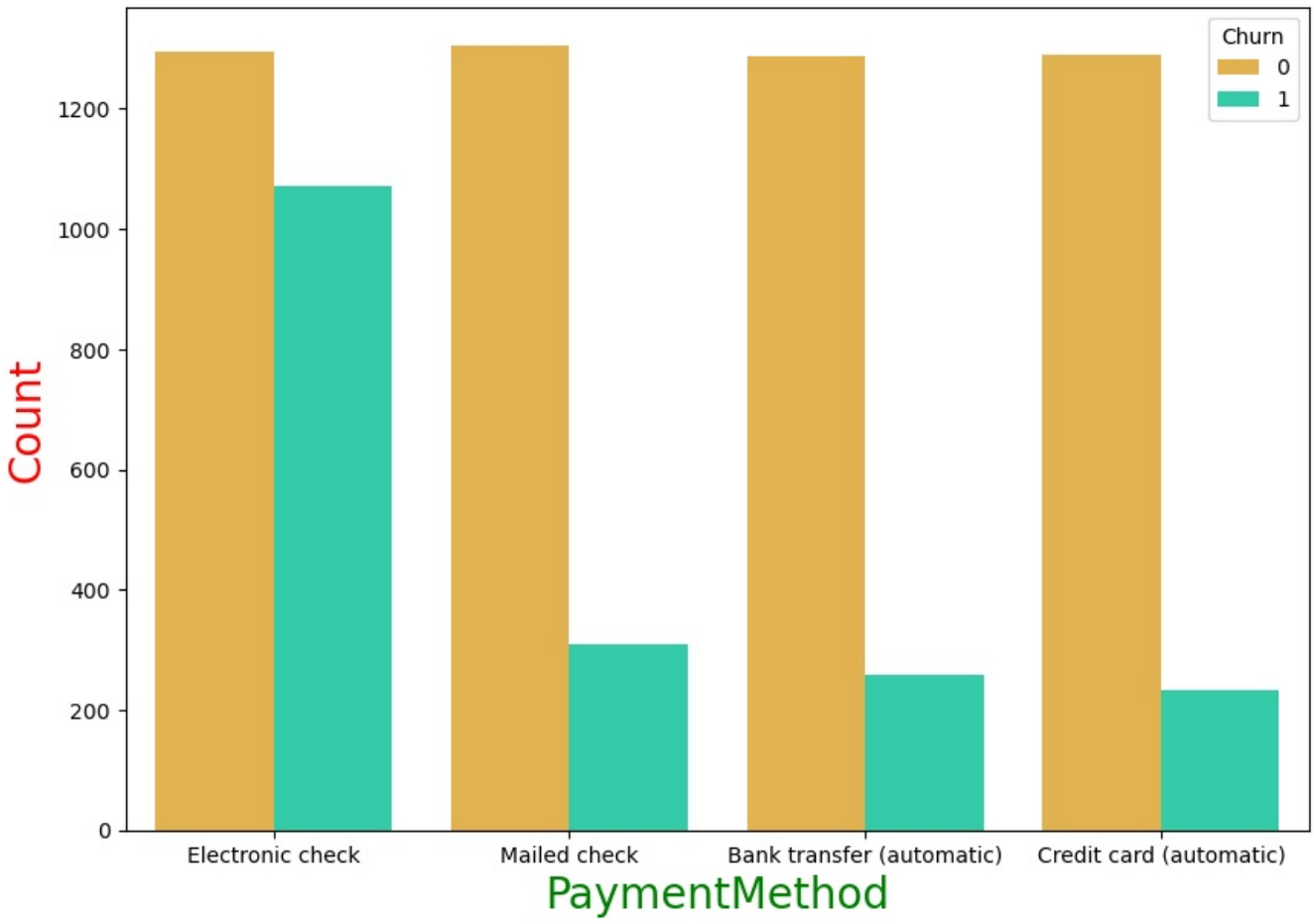
In [ ]:
```
Churn in male and female is approximately same whereas in the No-churn male are more than female
```

In [50]:
```
sns.countplot(x="Partner",hue="Churn",palette="turbo_r",data=df)
plt.xticks(fontsize = 12)
plt.xlabel("Partner", fontsize = 20, c= "g")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



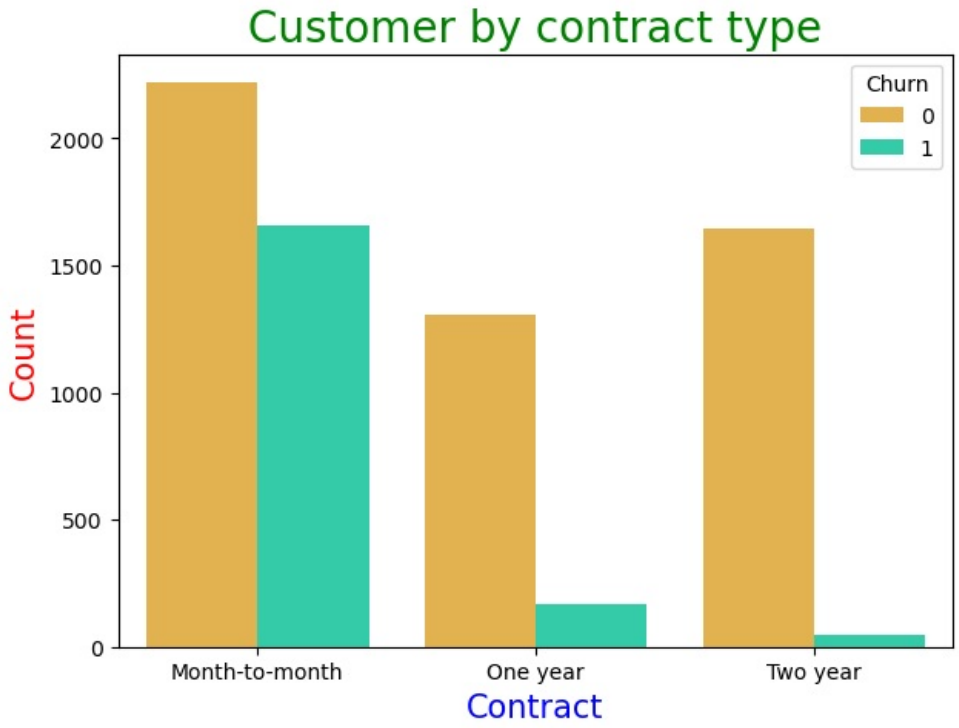
People have partners are less churn.

In [51]:
```
plt.figure(figsize= (10, 7))
sns.countplot(x="PaymentMethod",hue="Churn",palette="turbo_r",data=df)
plt.xticks(fontsize = 10)
plt.xlabel("PaymentMethod", fontsize = 20, c= "g")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



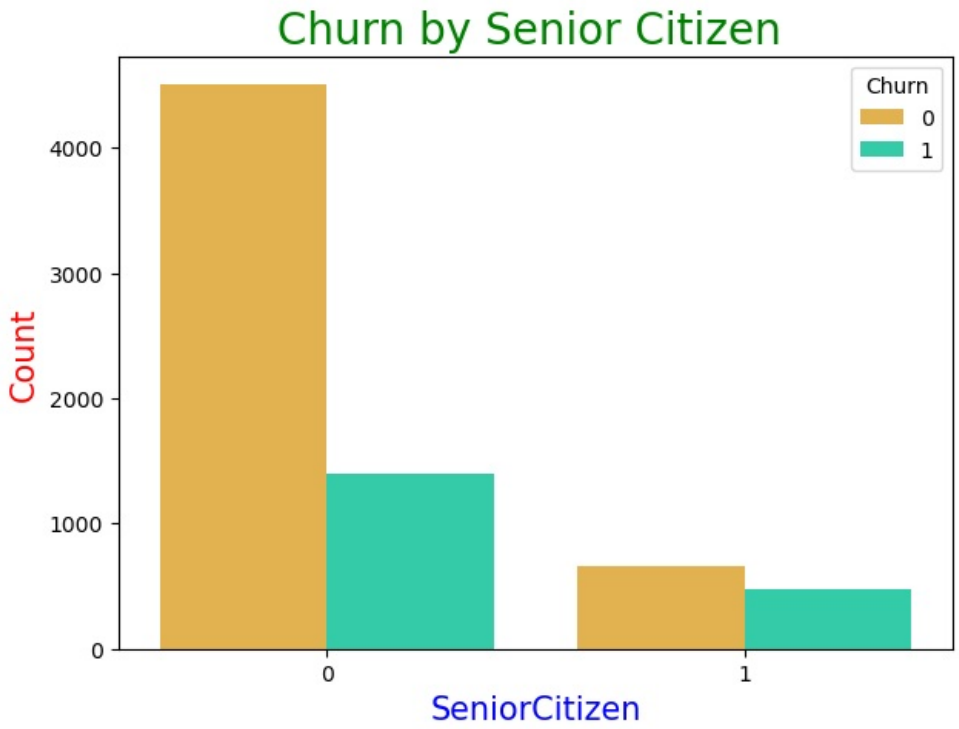
In Electronic check payment have high churn.

In [52]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "Contract", data= df ,palette="turbo_r", hue="Churn")
plt.xlabel("Contract", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Customer by contract type", fontsize = 20, c= "g")
plt.show()
```



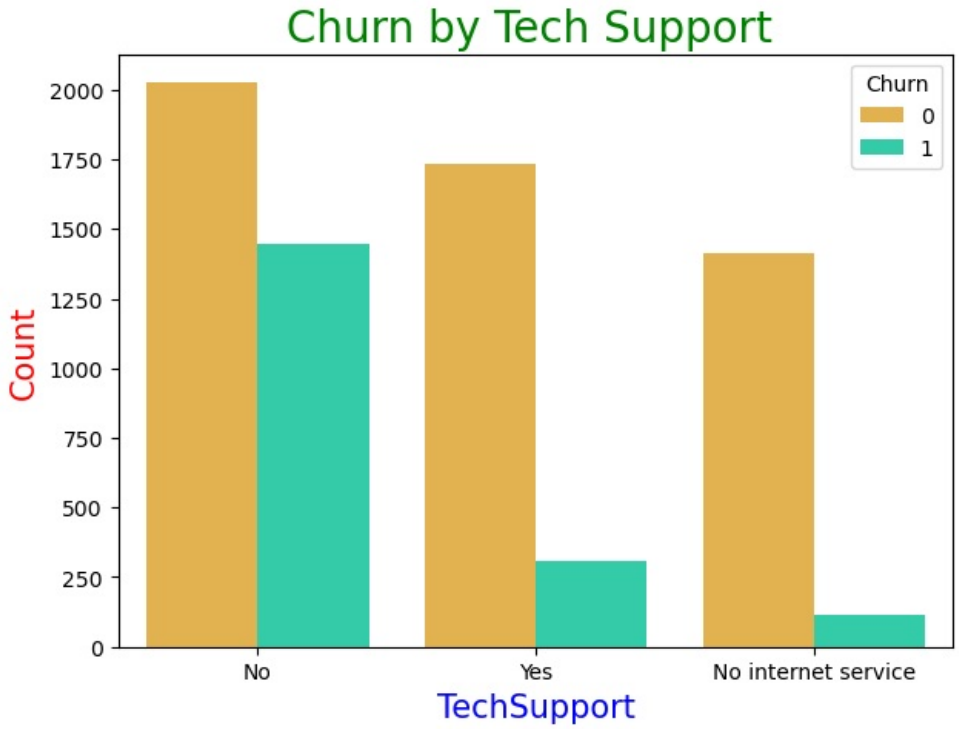
In [ ]:
```
Month to Month contract has high churn
```

In [53]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "SeniorCitizen", data= df ,palette="turbo_r", hue="Churn")
plt.xlabel("SeniorCitizen", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Churn by Senior Citizen ", fontsize = 20, c= "g")
plt.show()
```



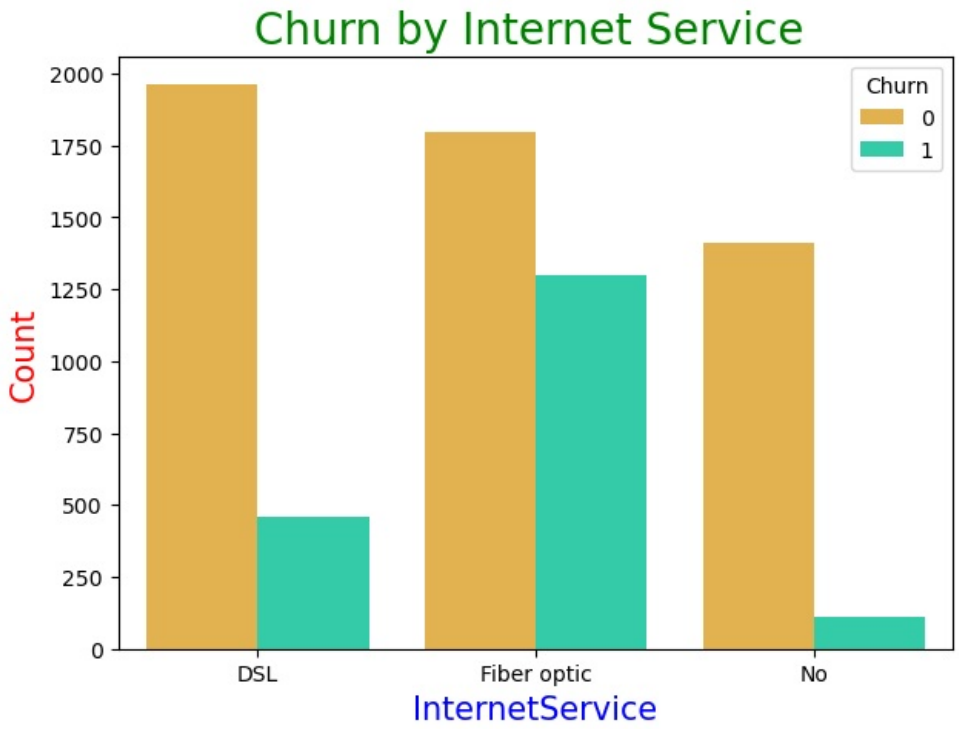
In [ ]:
```
Here we can see Senior Citizen has low churn
```

In [54]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "TechSupport", data= df ,palette="turbo_r", hue="Churn")
plt.xlabel("TechSupport", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Churn by Tech Support ", fontsize = 20, c= "g")
plt.show()
```



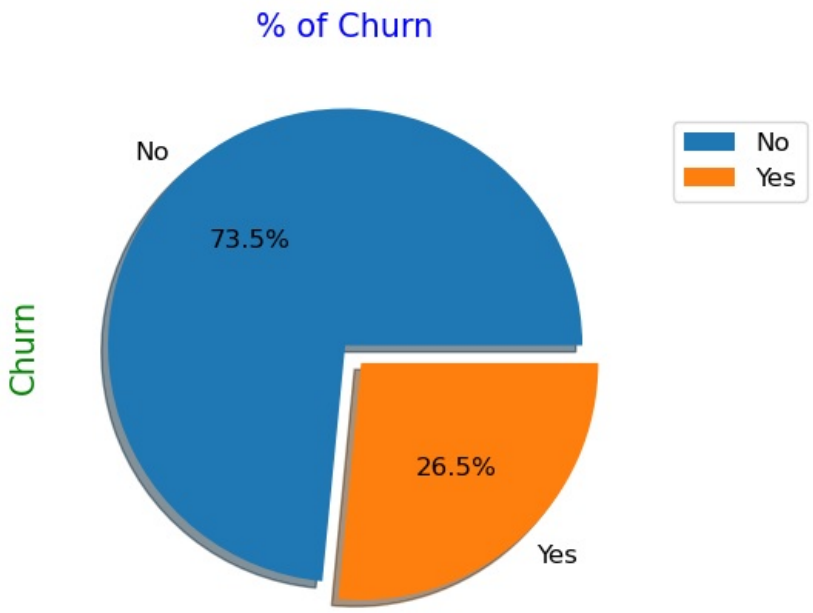
In [ ]:
```
No Tech support category has high Churn
```

In [55]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "InternetService", data= df ,palette="turbo_r", hue="Churn")
plt.xlabel("InternetService", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Churn by Internet Service ", fontsize = 20, c= "g")
plt.show()
```



In [ ]:
```
No Internet service has low churn
```

In [56]:
```
ax = (df['Churn'].value_counts()*100.0 /len(df))\
.plot.pie(autopct='%.1f%%', labels = ['No', 'Yes'],figsize =(5,5), fontsize = 12, explode = (0, 0.1), shadow=Tr
ax.set_ylabel('Churn',fontsize = 15, c = "g")
ax.set_title('% of Churn', fontsize = 15, c= "b")
plt.legend(loc='upper right', bbox_to_anchor =(1.3,0.9), fontsize=12)
plt.show()
df.Churn.value_counts()
```



Out[56]:
```
Churn
0    5174
1    1869
Name: count, dtype: int64
```

Here we can see Churn is 26.5% and No Churn is 73.5%. Data is imbalance.

In [ ]:
```
Label Encoding of Target Column
```

In [59]:
```
df["Churn"] = df["Churn"].replace({"Yes": 1, "No": 0})
```

In [60]:
```
df.head()
```

Out[60]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes
1	Male	0	No	No	34	Yes	No	DSL	Yes	No
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No

In [61]:
```
# identifying columns with object data type
object_columns = df.select_dtypes(include="object").columns
```

In [62]:
```
df.columns
```

Out[62]:
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [63]:
```
# initialize a dictionary to save the encoders
encoders = {}

# apply label encoding and store the encoders
for column in object_columns:
  label_encoder = LabelEncoder()
  df[column] = label_encoder.fit_transform(df[column])
  encoders[column] = label_encoder

# save the encoders to a pickle file
with open("encoders.pkl", "wb") as f:
  pickle.dump(encoders, f)
```

In [64]:
```
encoders
```

Out[64]:
```
{'gender': LabelEncoder(),
 'Partner': LabelEncoder(),
 'Dependents': LabelEncoder(),
 'PhoneService': LabelEncoder(),
 'MultipleLines': LabelEncoder(),
 'InternetService': LabelEncoder(),
 'OnlineSecurity': LabelEncoder(),
 'OnlineBackup': LabelEncoder(),
 'DeviceProtection': LabelEncoder(),
 'TechSupport': LabelEncoder(),
 'StreamingTV': LabelEncoder(),
 'StreamingMovies': LabelEncoder(),
 'Contract': LabelEncoder(),
 'PaperlessBilling': LabelEncoder(),
 'PaymentMethod': LabelEncoder()}
```

In [65]:
```
df.head()
```

Out[65]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	0	0	1	0	1	0	1	0	0	2
1	1	0	0	0	34	1	0	0	2	0
2	1	0	0	0	2	1	0	0	2	2
3	1	0	0	0	45	0	1	0	2	0
4	0	0	0	0	2	1	0	1	0	0

In [ ]:
```
Traianing and test data split
```

In [66]:
```
# splitting the features and target
X = df.drop(columns=["Churn"])
y = df["Churn"]
```

In [67]:
```
# split training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [71]:
```
y_train.shape
```

Out[71]:
```
(5634,)
```

In [72]:
```
X_train.shape
```

Out[72]:
```
(5634, 19)
```

In [74]:
```
y_train.value_counts()
```

Out[74]:
```
Churn
0    4138
1    1496
Name: count, dtype: int64
```

In [ ]:
```
Synthetic Minority Oversampling TEchnique (SMOTE)
```

In [79]:
```
smote = SMOTE(random_state=42)
```

In [81]:
```
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

In [82]:
```
print(y_train_smote.shape)
```

```
(8276,)
```

In [83]:
```
y_train_smote.value_counts()
```

Out[83]:
```
Churn
0    4138
1    4138
Name: count, dtype: int64
```

In [ ]:
```
Building a Model
```

In [84]:
```
# dictionary of models
models = {
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42)
}
```

In [85]:
```
# dictionary to store the cross validation results
```

```
cv_scores = {}

# perform 5-fold cross validation for each model
for model_name, model in models.items():
  print(f"Training {model_name} with default parameters")
  scores = cross_val_score(model, X_train_smote, y_train_smote, cv=5, scoring="accuracy")
  cv_scores[model_name] = scores
  print(f"{model_name} cross-validation accuracy: {np.mean(scores):.2f}")
  print("-"*70)
```

```
Training Decision Tree with default parameters
Decision Tree cross-validation accuracy: 0.78
----------------------------------------------------------------------
Training Random Forest with default parameters
Random Forest cross-validation accuracy: 0.84
----------------------------------------------------------------------
Training XGBoost with default parameters
XGBoost cross-validation accuracy: 0.83
----------------------------------------------------------------------
```

In [86]:
```
cv_scores
```

Out[86]:
```
{'Decision Tree': array([0.69202899, 0.70574018, 0.82537764, 0.83806647, 0.84350453]),
 'Random Forest': array([0.73067633, 0.77039275, 0.90392749, 0.89969789, 0.90030211]),
 'XGBoost': array([0.70833333, 0.76132931, 0.90453172, 0.88821752, 0.90755287])}
```

In [ ]:
```
Random Forest gives the highest accuracy compared to other models with default parameters
```

In [89]:
```
rfc = RandomForestClassifier(random_state=42)
rfc.fit(X_train_smote, y_train_smote)
```

Out[89]:

▾ RandomForestClassifier

RandomForestClassifier(random_state=42)

In [90]:
```
y_test.value_counts()
```

Out[90]:
```
Churn
0    1036
1     373
Name: count, dtype: int64
```

In [ ]:
```
Model Evaluation
```

In [91]:
```
# evaluate on test data
y_test_pred = rfc.predict(X_test)

print("Accuracy Score:\n", accuracy_score(y_test, y_test_pred))
print("Confsuion Matrix:\n", confusion_matrix(y_test, y_test_pred))
print("Classification Report:\n", classification_report(y_test, y_test_pred))
```

```
Accuracy Score:
 0.7785663591199432
Confsuion Matrix:
 [[878 158]
 [154 219]]
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.85      0.85      1036
           1       0.58      0.59      0.58       373

    accuracy                           0.78      1409
   macro avg       0.72      0.72      0.72      1409
weighted avg       0.78      0.78      0.78      1409
```

In [92]:
```
# save the trained model as a pickle file
model_data = {"model": rfc, "features_names": X.columns.tolist()}


with open("customer_churn_model.pkl", "wb") as f:
  pickle.dump(model_data, f)
```

In [ ]:
```
 Load the saved model and build a Predictive System
```

In [93]:
```
# load teh saved model and the feature names

with open("customer_churn_model.pkl", "rb") as f:
  model_data = pickle.load(f)

loaded_model = model_data["model"]
```

```
feature_names = model_data["features_names"]
```

In [94]:
```
print(loaded_model)
```

```
RandomForestClassifier(random_state=42)
```

In [95]:
```
print(feature_names)
```

```
['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure', 'PhoneService', 'MultipleLines', 'InternetService
', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contr
act', 'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges', 'TotalCharges']
```

In [96]:
```
input_data = {
    'gender': 'Female',
    'SeniorCitizen': 0,
    'Partner': 'Yes',
    'Dependents': 'No',
    'tenure': 1,
    'PhoneService': 'No',
    'MultipleLines': 'No phone service',
    'InternetService': 'DSL',
    'OnlineSecurity': 'No',
    'OnlineBackup': 'Yes',
    'DeviceProtection': 'No',
    'TechSupport': 'No',
    'StreamingTV': 'No',
    'StreamingMovies': 'No',
    'Contract': 'Month-to-month',
    'PaperlessBilling': 'Yes',
    'PaymentMethod': 'Electronic check',
    'MonthlyCharges': 29.85,
    'TotalCharges': 29.85
}


input_data_df = pd.DataFrame([input_data])

with open("encoders.pkl", "rb") as f:
  encoders = pickle.load(f)


# encode categorical featires using teh saved encoders
for column, encoder in encoders.items():
  input_data_df[column] = encoder.transform(input_data_df[column])

# make a prediction
prediction = loaded_model.predict(input_data_df)
pred_prob = loaded_model.predict_proba(input_data_df)

print(prediction)

# results
print(f"Prediction: {'Churn' if prediction[0] == 1 else 'No Churn'}")
print(f"Prediciton Probability: {pred_prob}")
```

```
[0]
Prediction: No Churn
Prediciton Probability: [[0.79 0.21]]
```

In [97]:
```
encoders
```

Out[97]:
```
{'gender': LabelEncoder(),
 'Partner': LabelEncoder(),
 'Dependents': LabelEncoder(),
 'PhoneService': LabelEncoder(),
 'MultipleLines': LabelEncoder(),
 'InternetService': LabelEncoder(),
 'OnlineSecurity': LabelEncoder(),
 'OnlineBackup': LabelEncoder(),
 'DeviceProtection': LabelEncoder(),
 'TechSupport': LabelEncoder(),
 'StreamingTV': LabelEncoder(),
 'StreamingMovies': LabelEncoder(),
 'Contract': LabelEncoder(),
 'PaperlessBilling': LabelEncoder(),
 'PaymentMethod': LabelEncoder()}
```

In [ ]:
```
Logistic Regression Model
```

In [102…
```
log_reg=LogisticRegression()
log_reg.fit(X_train_smote,y_train_smote)
y_train_pred=log_reg.predict(X_train_smote)
y_test_pred=log_reg.predict(X_test)
```

In [104…
```
accuracy = accuracy_score(y_train_smote, y_train_pred)
accuracy = accuracy_score(y_test, y_test_pred)
conf_matrix = confusion_matrix(y_test, y_test_pred)
class_report = classification_report(y_test, y_test_pred)
```

In [106…
```
accuracy = accuracy_score(y_train_smote, y_train_pred)
print(f"Logistic Regression Accuracy: {accuracy * 100:.2f}%")
```

```
Logistic Regression Accuracy: 78.99%
```

In [107…
```
print(conf_matrix)
```

```
[[785 251]
 [ 83 290]]
```

In [109…
```
print(class_report)
```

```
              precision    recall  f1-score   support

           0       0.90      0.76      0.82      1036
           1       0.54      0.78      0.63       373

    accuracy                           0.76      1409
   macro avg       0.72      0.77      0.73      1409
weighted avg       0.81      0.76      0.77      1409
```

In [ ]:
```
Random Forest Model
```

In [110…
```
rf=RandomForestClassifier()
rf.fit(X_train_smote,y_train_smote)
y_train_pred=rf.predict(X_train_smote)
y_test_pred=rf.predict(X_test)
```

In [111…
```
accuracy = accuracy_score(y_test, y_test_pred)
```

In [112…
```
print(f"Random Forest Accuracy: {accuracy * 100:.2f}%")
```

```
Random Forest Accuracy: 77.71%
```

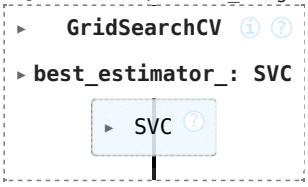
In [ ]:
```
Hyperparameter Tuning
```

In [126…
```
from sklearn.model_selection import GridSearchCV
```

In [128…
```
param_grid = {'C':[0.1,1,10],'gamma':[1,0.1,0.01],'kernel':['rbf'],'class_weight':['balanced']}
grid = GridSearchCV(SVC(),param_grid,refit=True,verbose=2,cv=2)
grid.fit(X_train,y_train)
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.5s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.4s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.5s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.5s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.3s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.4s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.5s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   1.5s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.5s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   1.5s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.6s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   1.4s
```

Out[128…



In [129…
```
print(grid.best_estimator_)
```

```
SVC(C=10, class_weight='balanced', gamma=0.1)
```

In [131…
```
grid_predictions = grid.predict(X_test)
```

In [132…
```
confusion_matrix(y_test, grid_predictions)
```

Out[132…
```
array([[982,  54],
       [270, 103]], dtype=int64)
```

In [133…
```
print(classification_report(y_test, grid_predictions))
```

```
              precision    recall  f1-score   support

           0       0.78      0.95      0.86      1036
           1       0.66      0.28      0.39       373

    accuracy                           0.77      1409
   macro avg       0.72      0.61      0.62      1409
weighted avg       0.75      0.77      0.73      1409
```

In [ ]:
```
Model Evaluation
we have used Hyperparameter tuning
overall accuracy of 77%
recall is 95% and precision=78%
```

Retention Plan We should focus on below Churn is high when Monthly Charges are high. Churn is high at starting tenure People have partners are less churn. In Electronic check payment have high churn. Month to Month contract has high churn Senior Citizen has low churn No Tech support category has high Churn No Internet service has low churn