Problem Statement:

Customer churn is when a company's customers stop doing business with that company. Businesses are very keen on measuring churn because keeping an existing customer is far less expensive than acquiring a new customer. New business involves working leads through a sales funnel, using marketing and sales budgets to gain additional customers. Existing customers will often have a higher volume of service consumption and can generate additional customer referrals.

Customer retention can be achieved with good customer service and products. But the most effective way for a company to prevent attrition of customers is to truly know them. The vast volumes of data collected about customers can be used to build churn prediction models. Knowing who is most likely to defect means that a company can prioritise focused marketing efforts on that subset of their customer base.

Preventing customer churn is critically important to the telecommunications sector, as the barriers to entry for switching services are so low.

Import Required Library

In [56]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
import scikitplot as skplt
from imblearn.over_sampling import SMOTE
pd.set_option('display.max_columns', None) # For display maximum columns
from sklearn.preprocessing import OrdinalEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_sco
from sklearn.metrics import classification_report, roc_auc_score, roc_curve, plot
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.linear_model import LogisticRegression
import xgboost as xgb
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Rading Data

In [2]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\csv file\Telecom_customer_churn.c
df.head()
```

Out[2]:

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

Check no of row and column

In [3]:
```
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (7043, 21)
```

Checking for Null values

In [4]:
```
print('================================\n')
print(df.isnull().sum())
print('\n================================')
```

```
================================

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

================================
```

There is null value

Fill NaN

In [5]:
```
df['TotalCharges'].fillna(df['TotalCharges'].mean(), inplace = True)
```

In [6]:
```
print('================================\n')
print(df.isnull().sum())
print('\n================================')
```

```
================================

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

================================
```

Nan are removed

Information about dataset

In [6]:
```
print('=====================================================\n')
print(df.info())
print('=====================================================')
```

```
=====================================================

<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
None
=====================================================
```

Categorical data present in our data set

Drop unwanted column

In [7]:
```
df = df.drop('customerID', axis = 1)
df.head(2)
```

Out[7]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService
0	Female	0	Yes	No	1	No	No phone service	DSL
1	Male	0	No	No	34	Yes	No	DSL

We drop the customerID column

Analysis of Data with respact to Churn

Gender column

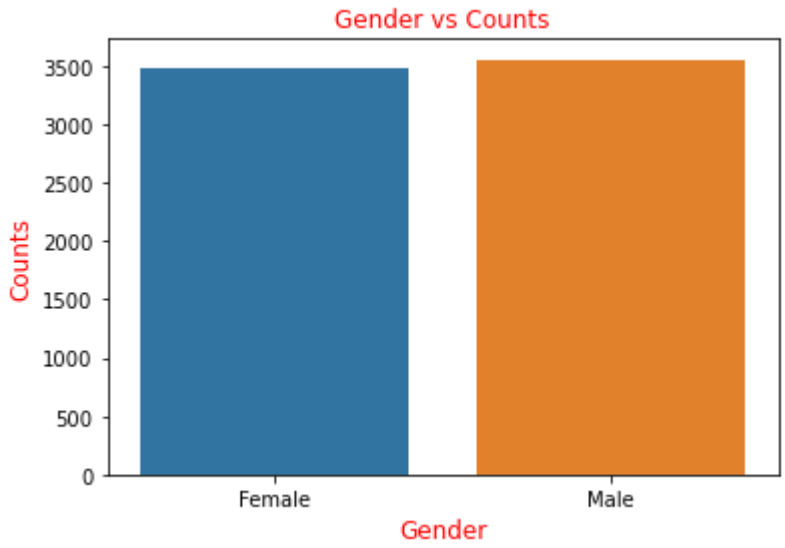
In [8]:
```
df['gender'].value_counts()
```

Out[8]:
```
Male      3555
Female    3488
Name: gender, dtype: int64
```

In [9]:
```
df['Churn'].value_counts()
```

Out[9]:
```
No     5174
Yes    1869
Name: Churn, dtype: int64
```

In [19]:
```
sns.countplot( x="gender", data=df)
plt.xlabel('Gender', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Gender vs Counts', c = 'r', fontsize = 12)
plt.show()
```

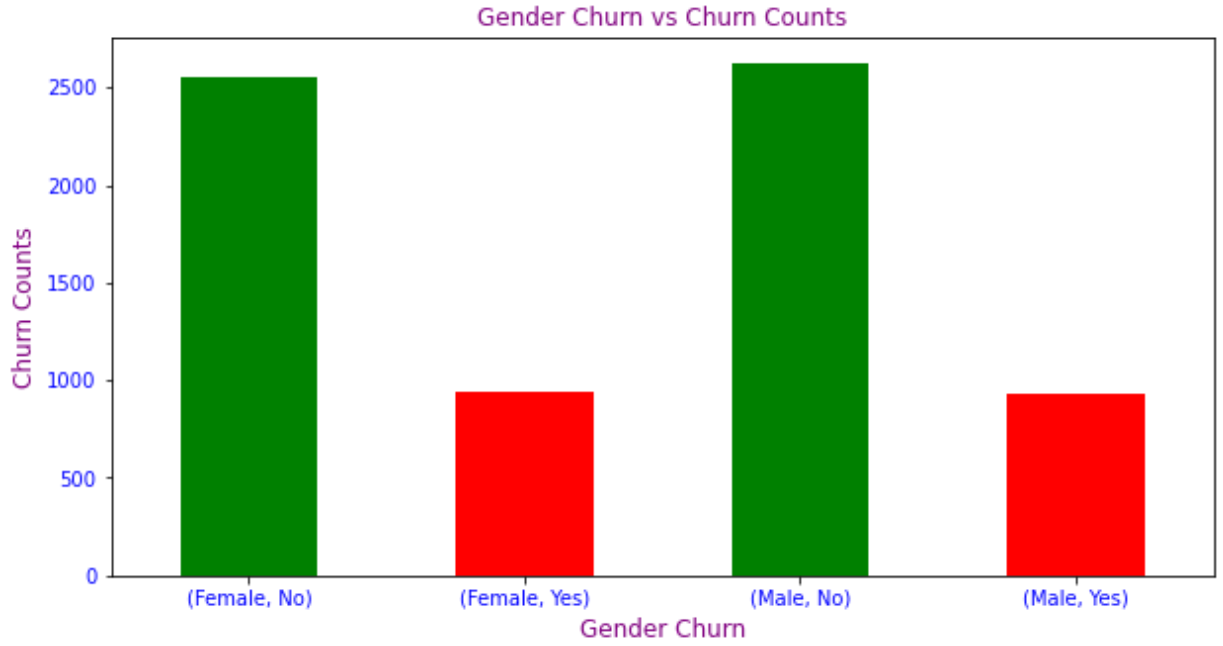


Male is highest in number

In [21]:
```
gn = df.groupby('gender')['Churn'].value_counts()
gn
```

Out[21]:
```
gender  Churn
Female  No       2549
        Yes       939
Male    No       2625
        Yes       930
Name: Churn, dtype: int64
```

In [24]:
```
gn.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Gender Churn', c = 'purple', fontsize = 12)
plt.ylabel('Churn Counts', c = 'purple', fontsize = 12 )
plt.title('Gender Churn vs Churn Counts', c = 'purple', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



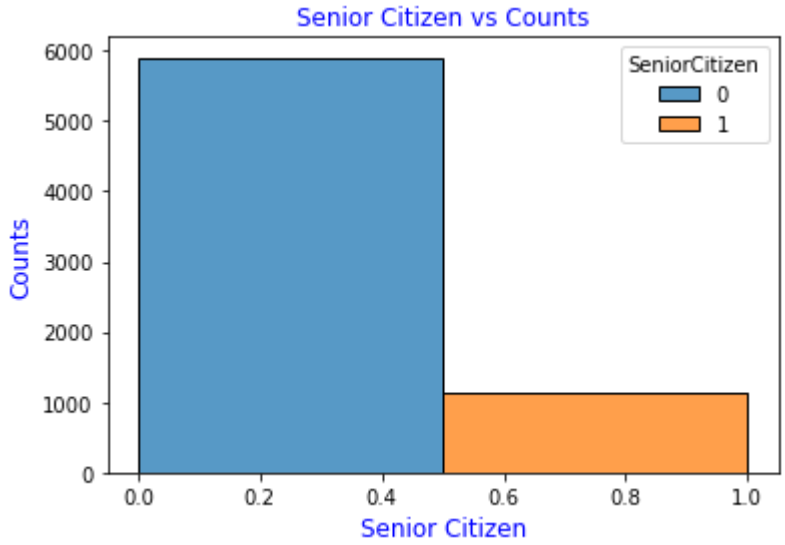
Female has highest no of churn

Senior Citizen column

In [25]:
```
df['SeniorCitizen'].value_counts()
```

Out[25]:
```
0    5901
1    1142
Name: SeniorCitizen, dtype: int64
```

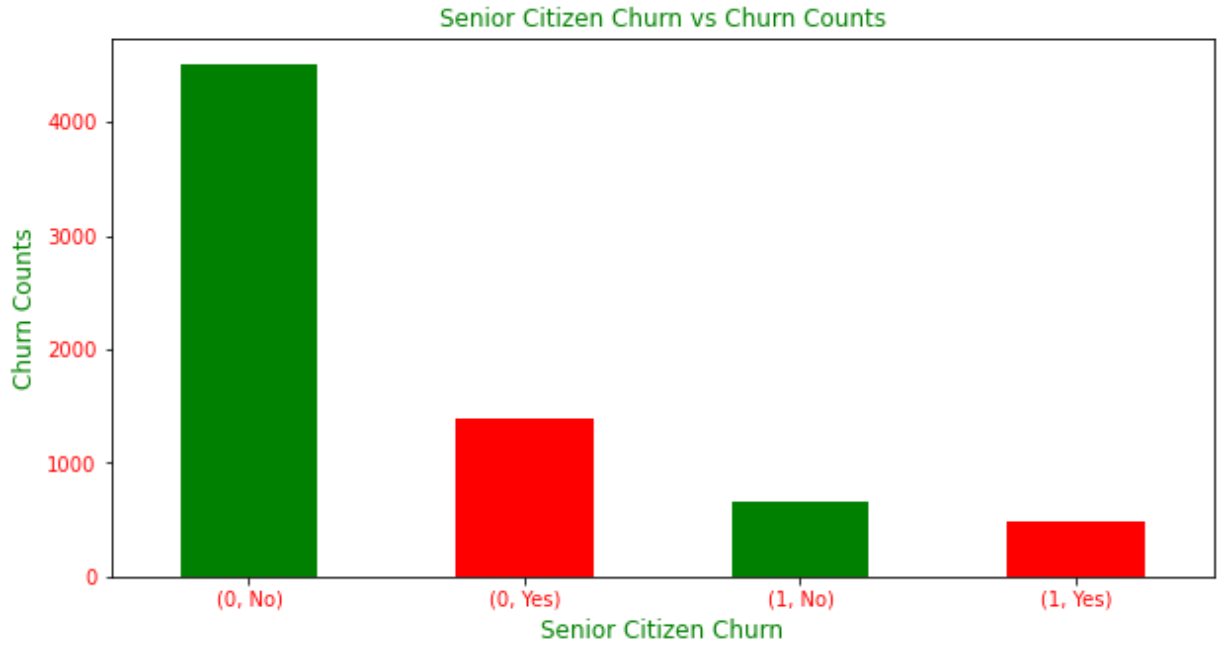
In [26]:
```
sns.histplot(binwidth=0.5, x="SeniorCitizen", hue="SeniorCitizen", data=df, stat=
plt.xlabel('Senior Citizen', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Senior Citizen vs Counts', c = 'b', fontsize = 12)
plt.show()
```



In [27]:
```
sc = df.groupby('SeniorCitizen')['Churn'].value_counts()
sc
```

Out[27]:
```
SeniorCitizen  Churn
0              No       4508
               Yes      1393
1              No        666
               Yes       476
Name: Churn, dtype: int64
```

In [28]:
```
sc.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Senior Citizen Churn', c = 'g', fontsize = 12)
plt.ylabel('Churn Counts', c = 'g', fontsize = 12 )
plt.title('Senior Citizen Churn vs Churn Counts', c = 'g', fontsize = 12)
plt.xticks(c = 'r')
plt.yticks(c = 'r')
plt.show()
```



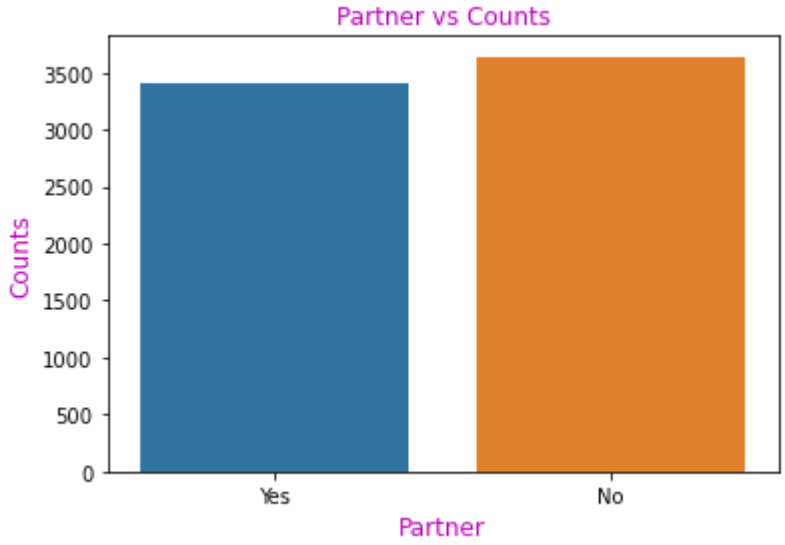
In Senior Citizen highest no of Not Churn 👍

Partner column

In [29]:
```
df['Partner'].value_counts()
```

Out[29]:
```
No     3641
Yes    3402
Name: Partner, dtype: int64
```

In [31]:
```
sns.countplot( x="Partner", data=df)
plt.xlabel('Partner', c = 'm', fontsize = 12)
plt.ylabel('Counts', c = 'm', fontsize = 12)
plt.title('Partner vs Counts', c = 'm', fontsize = 12)
plt.show()
```

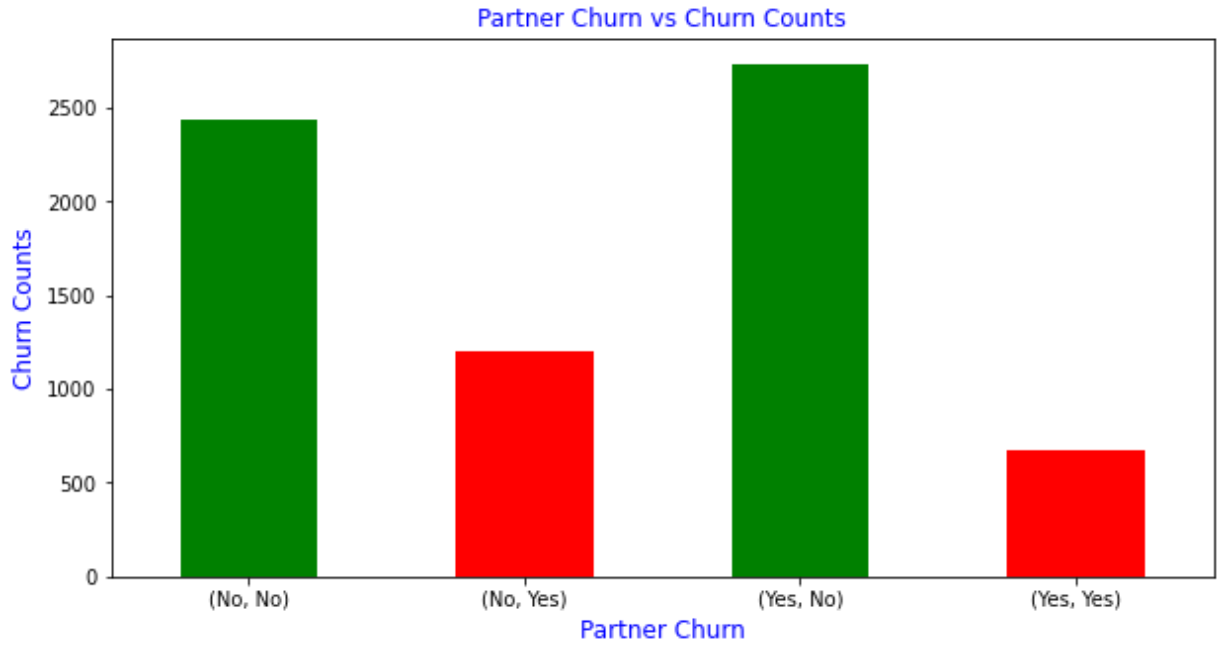


Person has No Partner count is high

In [33]:
```
p = df.groupby('Partner')['Churn'].value_counts()
p
```

Out[33]:
```
Partner  Churn
No       No       2441
         Yes      1200
Yes      No       2733
         Yes       669
Name: Churn, dtype: int64
```

In [35]:
```
p.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Partner Churn', c = 'b', fontsize = 12)
plt.ylabel('Churn Counts', c = 'b', fontsize = 12 )
plt.title('Partner Churn vs Churn Counts', c = 'b', fontsize = 12)
plt.xticks(c = 'k')
plt.yticks(c = 'k')
plt.show()
```



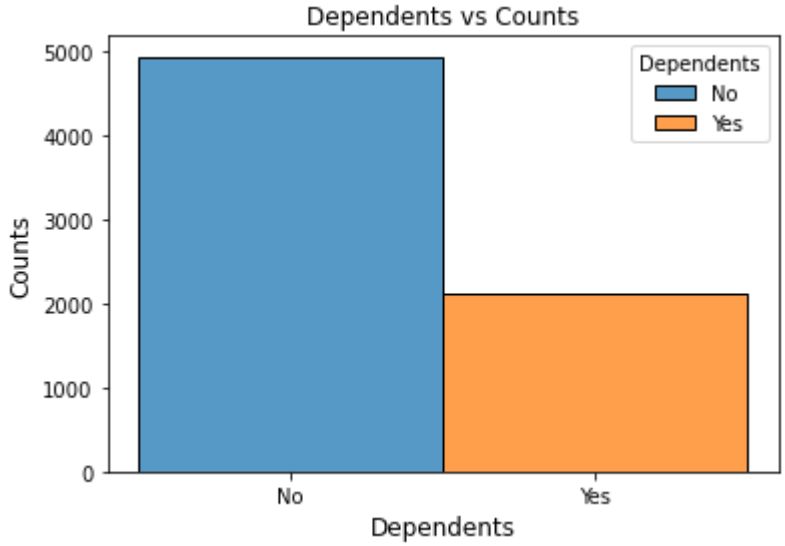
Person which has Partner no of Churn is high 👍

Dependents column

In [36]:
```
df['Dependents'].value_counts()
```

Out[36]:
```
No     4933
Yes    2110
Name: Dependents, dtype: int64
```

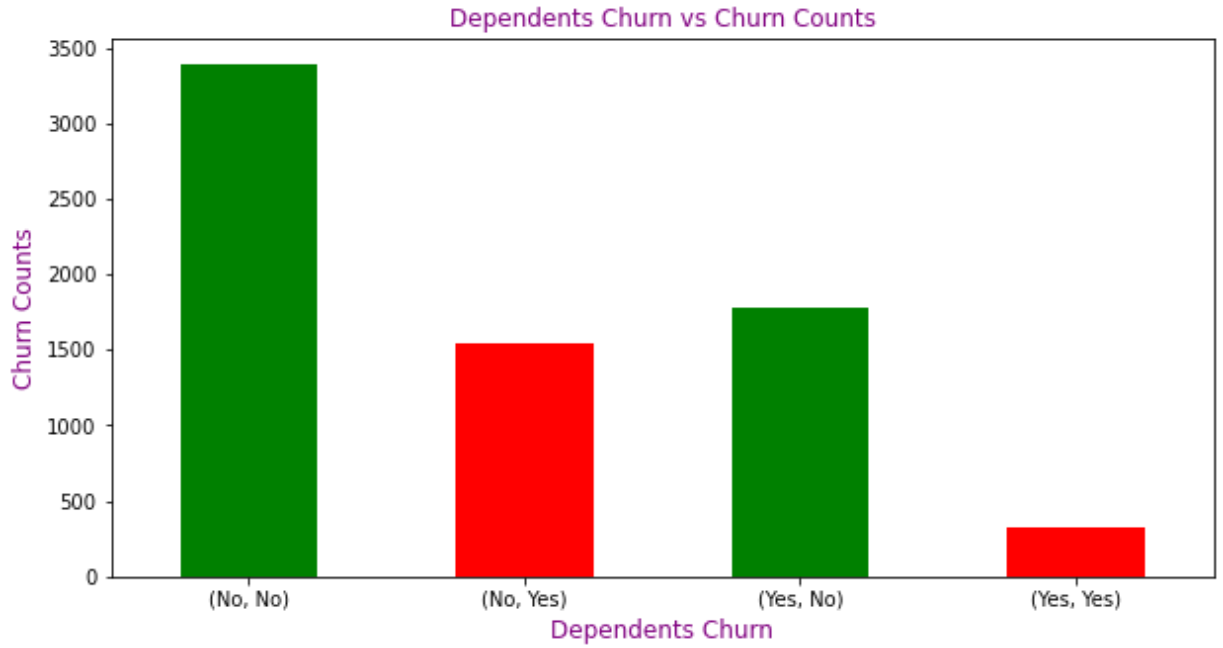
In [37]:
```
sns.histplot(binwidth=0.5, x="Dependents", hue="Dependents", data=df, stat="count
plt.xlabel('Dependents', c = 'k', fontsize = 12)
plt.ylabel('Counts', c = 'k', fontsize = 12)
plt.title('Dependents vs Counts', c = 'k', fontsize = 12)
plt.show()
```



In [38]:
```
d = df.groupby('Dependents')['Churn'].value_counts()
d
```

Out[38]:
```
Dependents  Churn
No          No       3390
            Yes      1543
Yes         No       1784
            Yes       326
Name: Churn, dtype: int64
```

In [40]:
```
d.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Dependents Churn', c = 'purple', fontsize = 12)
plt.ylabel('Churn Counts', c = 'purple', fontsize = 12 )
plt.title('Dependents Churn vs Churn Counts', c = 'purple', fontsize = 12)
plt.xticks(c = 'k')
plt.yticks(c = 'k')
plt.show()
```



Dependents person no of Churn is low

Tenure column

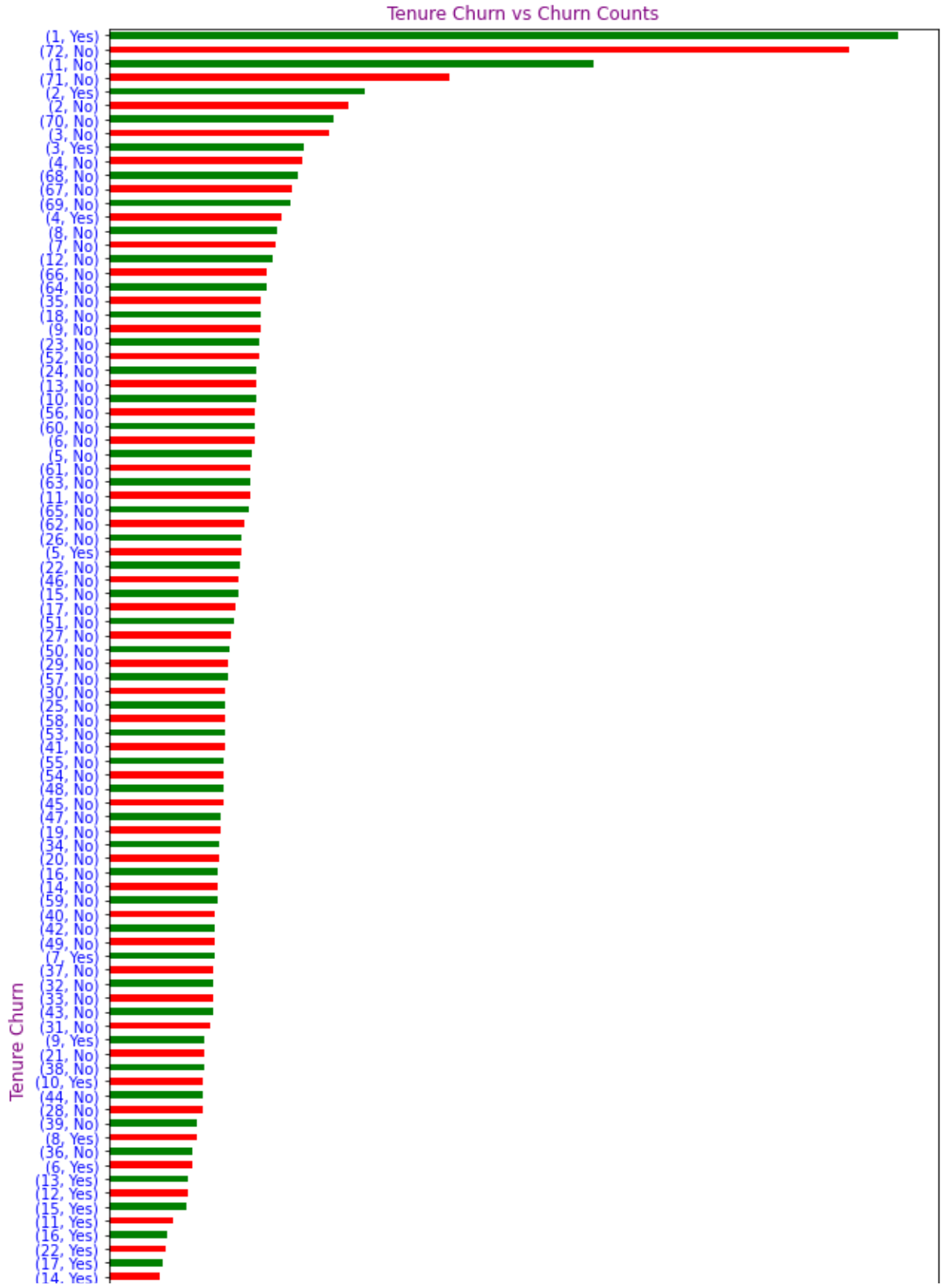
In [42]:
```
df['tenure'].value_counts()
```

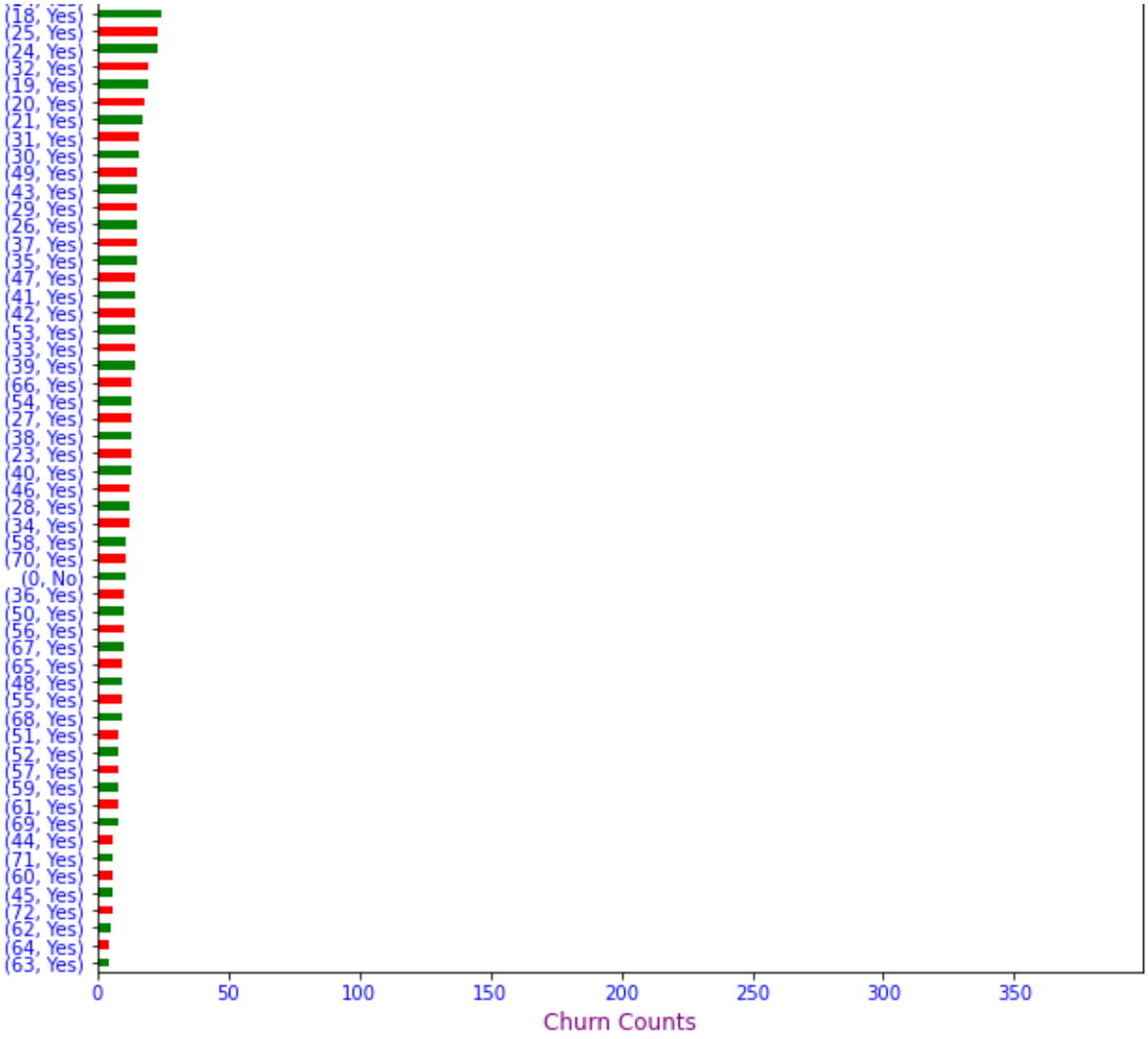
Out[42]:
```
1     613
72    362
2     238
3     200
4     176
     ...
28     57
39     56
44     51
36     50
0      11
Name: tenure, Length: 73, dtype: int64
```

In [57]:
```
tn = df.groupby('tenure')['Churn'].value_counts().sort_values()
tn
```

Out[57]:
```
tenure  Churn
63      Yes        4
64      Yes        4
62      Yes        5
72      Yes        6
45      Yes        6
                 ...
2       Yes      123
71      No       164
1       No       233
72      No       356
1       Yes      380
Name: Churn, Length: 145, dtype: int64
```

In [58]:
```
tn.plot.barh(figsize = (10,25), color = ['g','r'])
plt.ylabel('Tenure Churn', c = 'purple', fontsize = 12)
plt.xlabel('Churn Counts', c = 'purple', fontsize = 12 )
plt.title('Tenure Churn vs Churn Counts', c = 'purple', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```





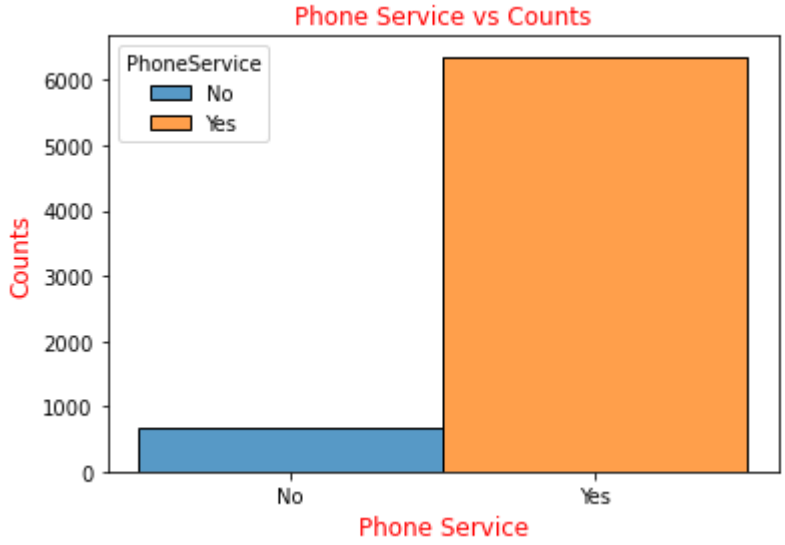
Person has year tenure has highest churn

Phone Service column

In [59]:
```
df['PhoneService'].value_counts()
```

Out[59]:
```
Yes    6361
No      682
Name: PhoneService, dtype: int64
```

In [62]:
```
sns.histplot(binwidth=0.5, x="PhoneService", hue="PhoneService", data=df, stat="c
plt.xlabel('Phone Service', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Phone Service vs Counts', c = 'r', fontsize = 12)
plt.show()
```

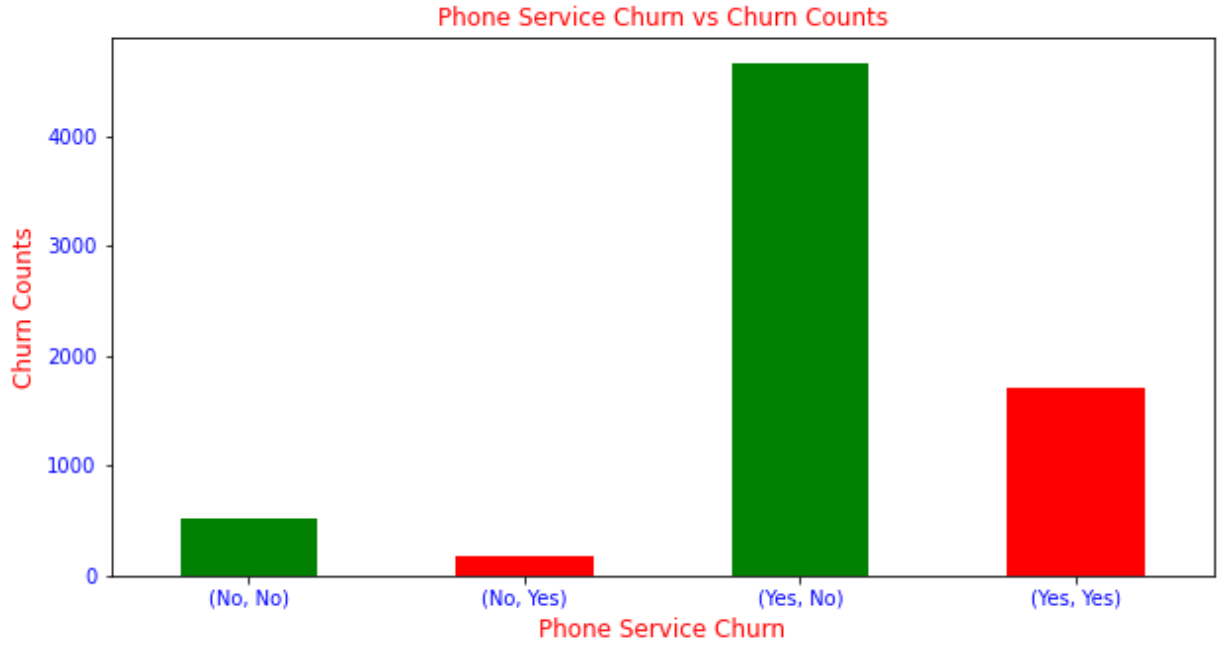


A person has Phone Service highest counts 👍

In [63]:
```
ps = df.groupby('PhoneService')['Churn'].value_counts()
ps
```

Out[63]:
```
PhoneService  Churn
No            No        512
              Yes       170
Yes           No       4662
              Yes      1699
Name: Churn, dtype: int64
```

In [64]:
```
ps.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Phone Service Churn', c = 'r', fontsize = 12)
plt.ylabel('Churn Counts', c = 'r', fontsize = 12 )
plt.title('Phone Service Churn vs Churn Counts', c = 'r', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



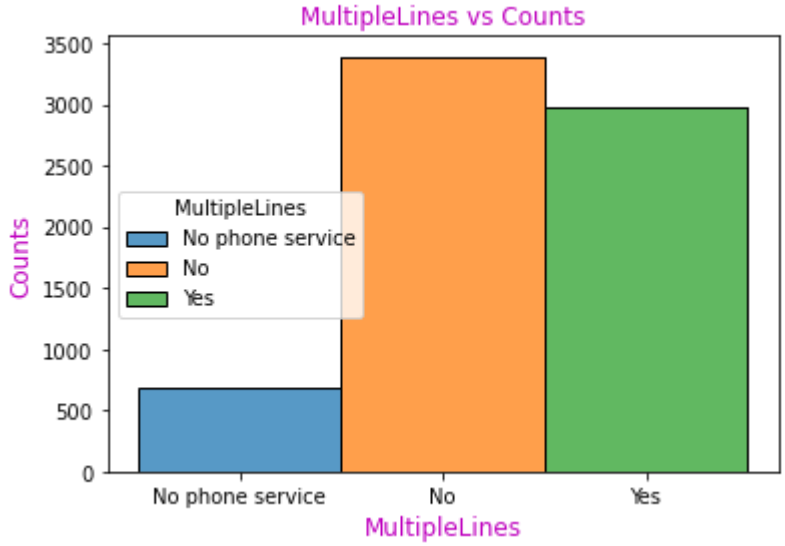
Person has Phone Service no of churn is low 👍

Multiple Lines column

In [66]:
```
df['MultipleLines'].value_counts()
```

Out[66]:
```
No                  3390
Yes                 2971
No phone service     682
Name: MultipleLines, dtype: int64
```

In [67]:
```
sns.histplot(binwidth=0.5, x="MultipleLines", hue="MultipleLines", data=df, stat=
plt.xlabel('MultipleLines', c= 'm', fontsize = 12)
plt.ylabel('Counts', c = 'm', fontsize = 12)
plt.title('MultipleLines vs Counts', c = 'm', fontsize = 12)
plt.show()
```

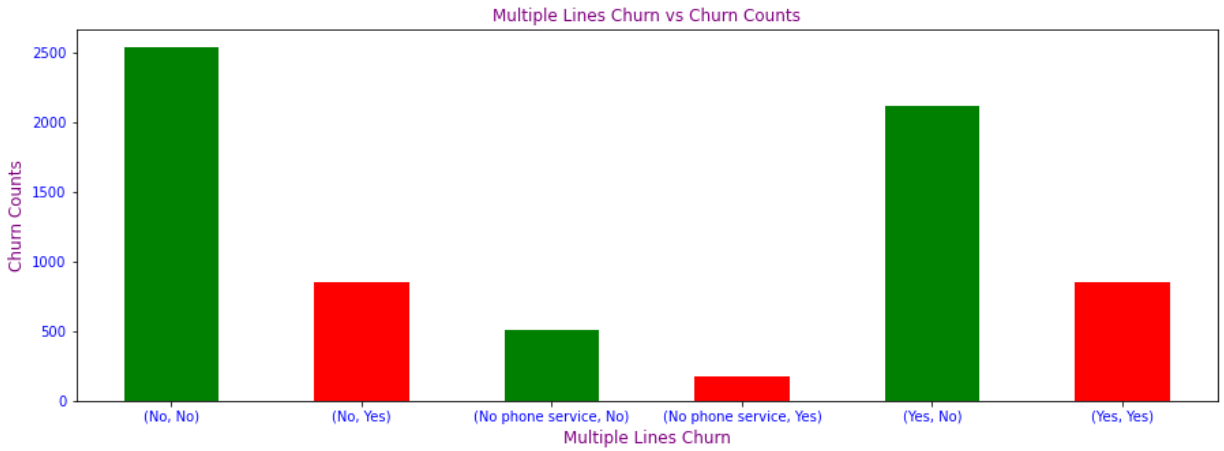


Person has no phone service count is highest

In [68]:
```
ml = df.groupby('MultipleLines')['Churn'].value_counts()
ml
```

Out[68]:
```
MultipleLines     Churn
No                No       2541
                  Yes       849
No phone service  No        512
                  Yes       170
Yes               No       2121
                  Yes       850
Name: Churn, dtype: int64
```

In [70]:
```
ml.plot.bar(figsize = (15,5), rot = 360, color = ['g','r'])
plt.xlabel('Multiple Lines Churn', c = 'purple', fontsize = 12)
plt.ylabel('Churn Counts', c = 'purple', fontsize = 12 )
plt.title('Multiple Lines Churn vs Churn Counts', c = 'purple', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```

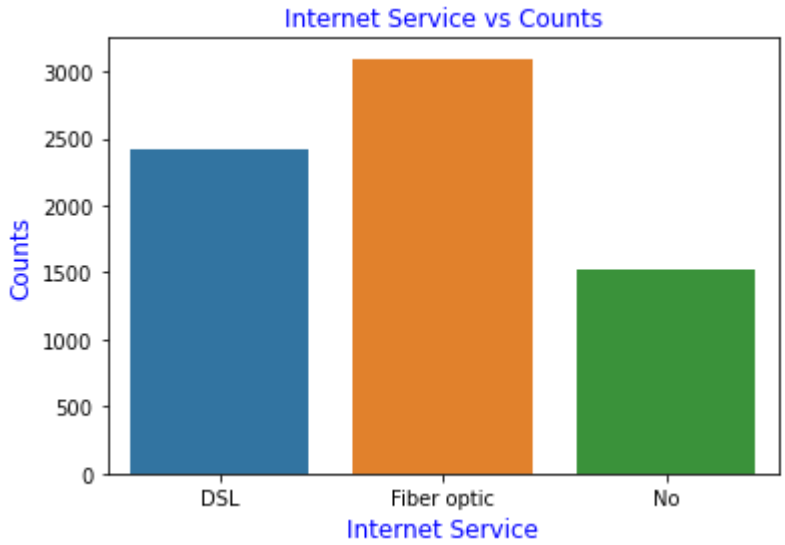


A person has Multiple Lines no of churn is low 👍

In [71]:
```
df['InternetService'].value_counts()
```

Out[71]:
```
Fiber optic    3096
DSL            2421
No             1526
Name: InternetService, dtype: int64
```

In [72]:
```
sns.countplot( x="InternetService", data=df)
plt.xlabel('Internet Service', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Internet Service vs Counts', c = 'b', fontsize = 12)
plt.show()
```

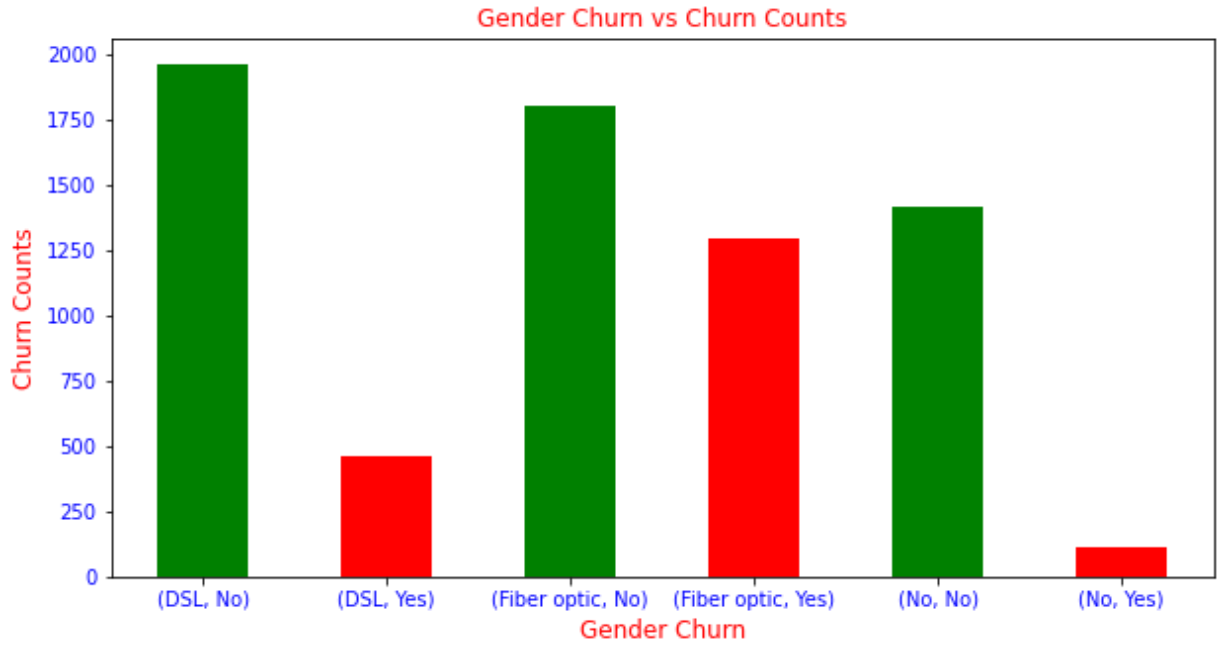


Fiber optic Internet Service count is highest 👍

In [73]:
```
ins = df.groupby('InternetService')['Churn'].value_counts()
ins
```

Out[73]:
```
InternetService  Churn
DSL              No       1962
                 Yes       459
Fiber optic      No       1799
                 Yes      1297
No               No       1413
                 Yes       113
Name: Churn, dtype: int64
```

In [74]:
```
ins.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Gender Churn', c = 'r', fontsize = 12)
plt.ylabel('Churn Counts', c = 'r', fontsize = 12 )
plt.title('Gender Churn vs Churn Counts', c = 'r', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



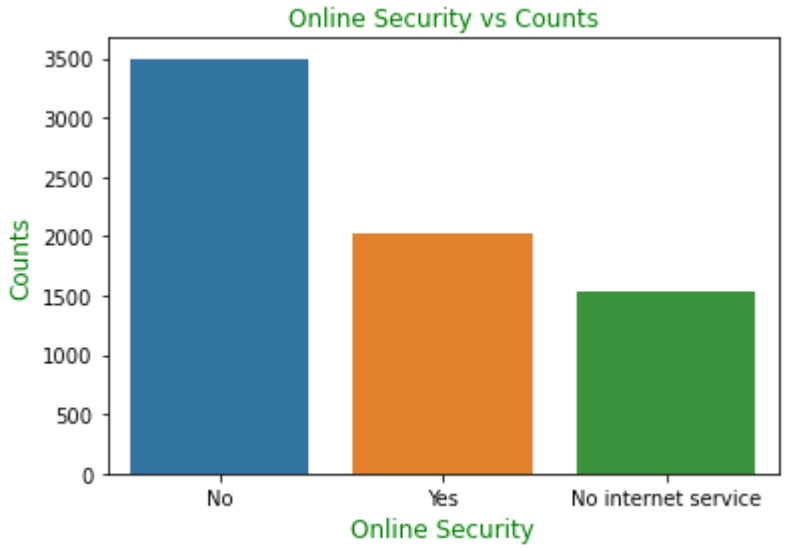
In fiber optic Internet Service has no of churn is low 👍

Online Security column

In [75]:
```
df['OnlineSecurity'].value_counts()
```

Out[75]:
```
No                     3498
Yes                    2019
No internet service    1526
Name: OnlineSecurity, dtype: int64
```

In [76]:
```
sns.countplot( x="OnlineSecurity", data=df)
plt.xlabel('Online Security', c = 'g', fontsize = 12)
plt.ylabel('Counts', c = 'g', fontsize = 12)
plt.title('Online Security vs Counts', c = 'g', fontsize = 12)
plt.show()
```

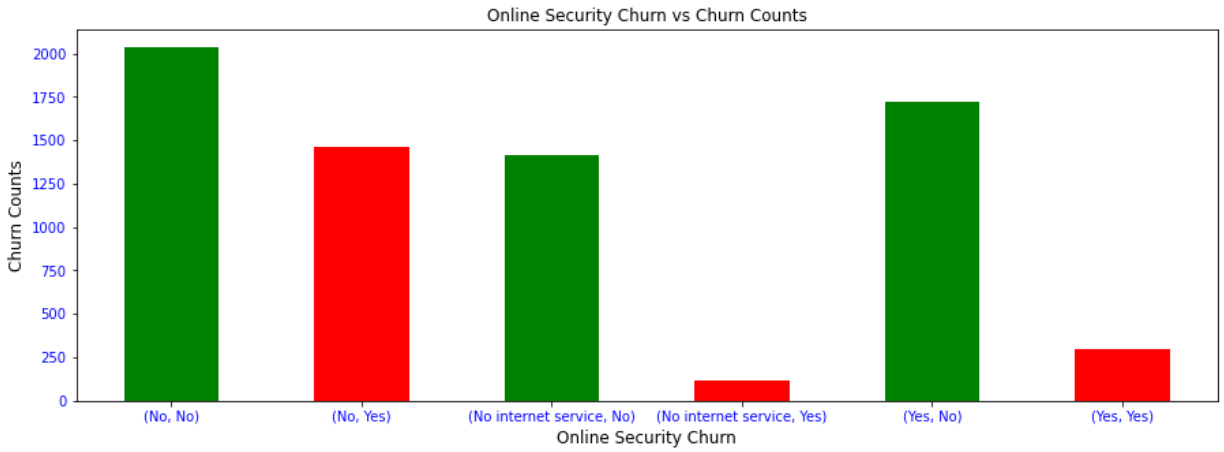


A person has no online security count has highest

In [77]:
```
os = df.groupby('OnlineSecurity')['Churn'].value_counts()
os
```

Out[77]:
```
OnlineSecurity       Churn
No                   No       2037
                     Yes      1461
No internet service  No       1413
                     Yes       113
Yes                  No       1724
                     Yes       295
Name: Churn, dtype: int64
```

In [80]:
```
os.plot.bar(figsize = (15,5), rot = 360, color = ['g','r'])
plt.xlabel('Online Security Churn', c = 'k', fontsize = 12)
plt.ylabel('Churn Counts', c = 'k', fontsize = 12 )
plt.title('Online Security Churn vs Churn Counts', c = 'k', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



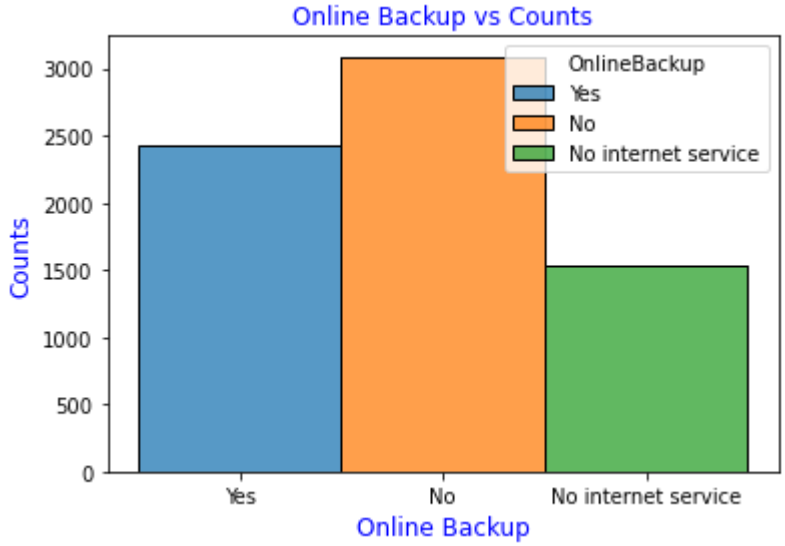
A person has no online security has highest no of churn

Online Backup column

In [82]:
```
df['OnlineBackup'].value_counts()
```

Out[82]:
```
No                     3088
Yes                    2429
No internet service    1526
Name: OnlineBackup, dtype: int64
```

In [83]:
```
sns.histplot(binwidth=0.5, x="OnlineBackup", hue="OnlineBackup", data=df, stat="c
plt.xlabel('Online Backup', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Online Backup vs Counts', c = 'b', fontsize = 12)
plt.show()
```



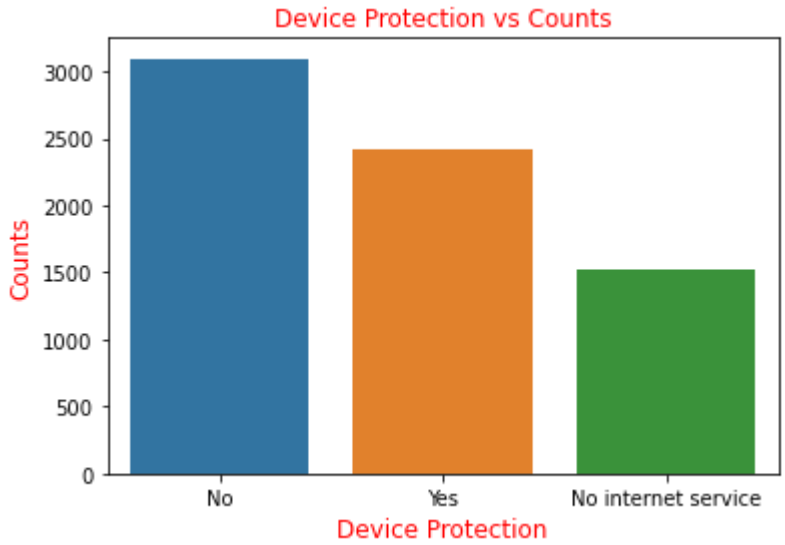
A person has No Online Backup counts is highest

Device Protection

In [84]:
```
df['DeviceProtection'].value_counts()
```

Out[84]:
```
No                  3095
Yes                 2422
No internet service    1526
Name: DeviceProtection, dtype: int64
```

In [85]:
```
sns.countplot(x = "DeviceProtection", data=df)
plt.xlabel('Device Protection', c = 'r', fontsize = 12)
plt.ylabel('Counts', c = 'r', fontsize = 12)
plt.title('Device Protection vs Counts', c = 'r', fontsize = 12)
plt.show()
```



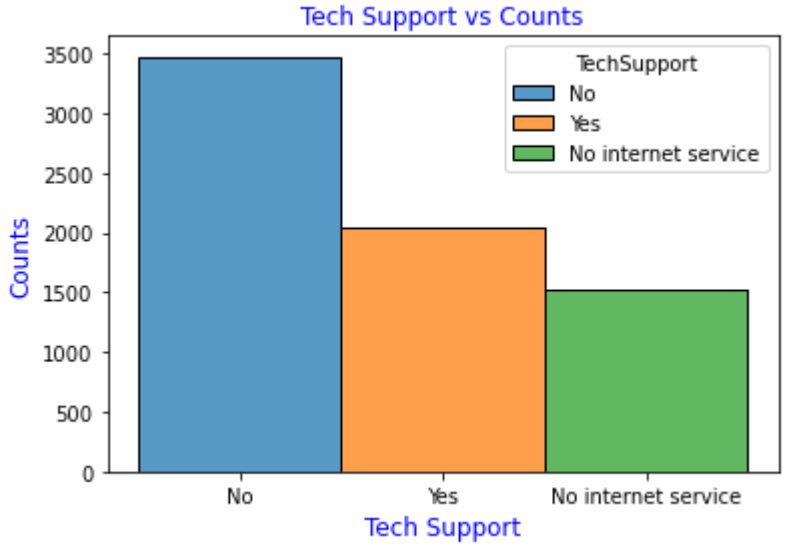
A person has No Device Protection counts is highest

Tech Support

In [86]:
```
df['TechSupport'].value_counts()
```

Out[86]:
```
No                     3473
Yes                    2044
No internet service    1526
Name: TechSupport, dtype: int64
```

In [87]:
```
sns.histplot(binwidth=0.5, x="TechSupport", hue="TechSupport", data=df, stat="cou
plt.xlabel('Tech Support', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Tech Support vs Counts', c = 'b', fontsize = 12)
plt.show()
```



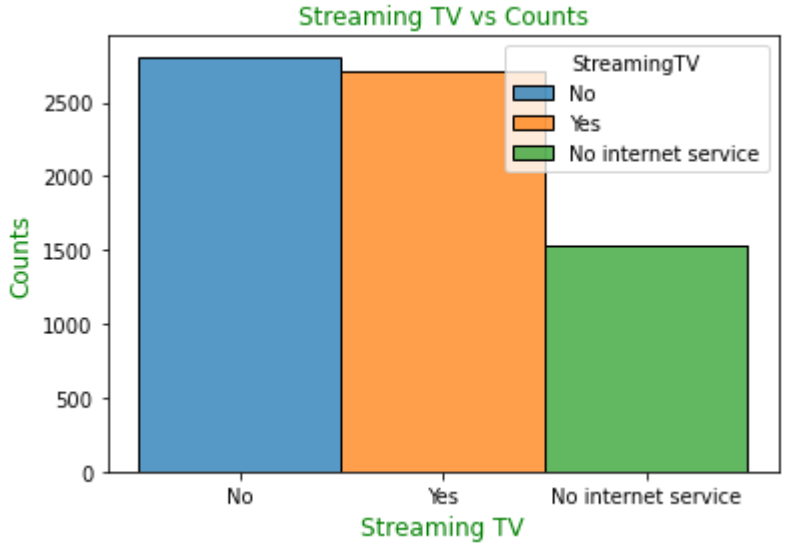
A person has No Tech Support counts is highest

Streaming TV column

In [88]:
```
df['StreamingTV'].value_counts()
```

Out[88]:
```
No                     2810
Yes                    2707
No internet service    1526
Name: StreamingTV, dtype: int64
```

In [89]:
```
sns.histplot(binwidth=0.5, x="StreamingTV", hue="StreamingTV", data=df, stat="cou
plt.xlabel('Streaming TV', c = 'g', fontsize = 12)
plt.ylabel('Counts', c = 'g', fontsize = 12)
plt.title('Streaming TV vs Counts', c = 'g', fontsize = 12)
plt.show()
```



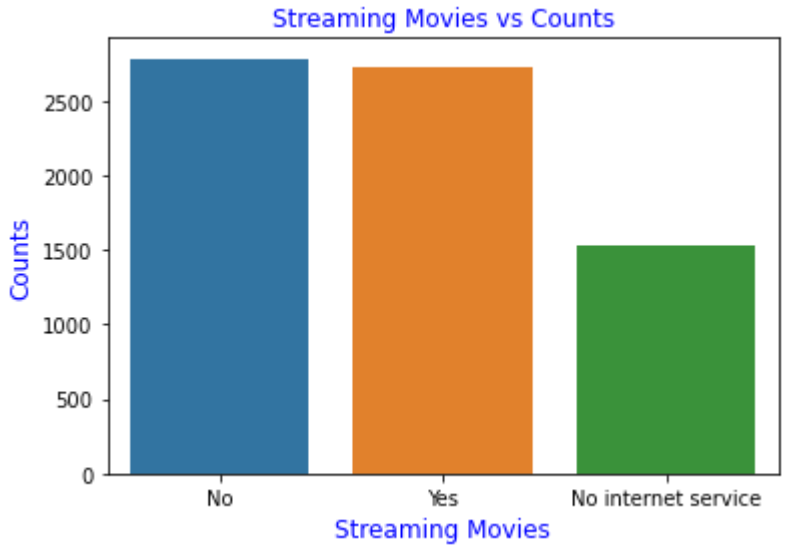
A person has Not Streaming TV live counts is highest count

Streaming Movies column

In [91]:
```
df['StreamingMovies'].value_counts()
```

Out[91]:
```
No                     2785
Yes                    2732
No internet service    1526
Name: StreamingMovies, dtype: int64
```

In [92]:
```
sns.countplot(x="StreamingMovies", data=df)
plt.xlabel('Streaming Movies', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Streaming Movies vs Counts', c = 'b', fontsize = 12)
plt.show()
```



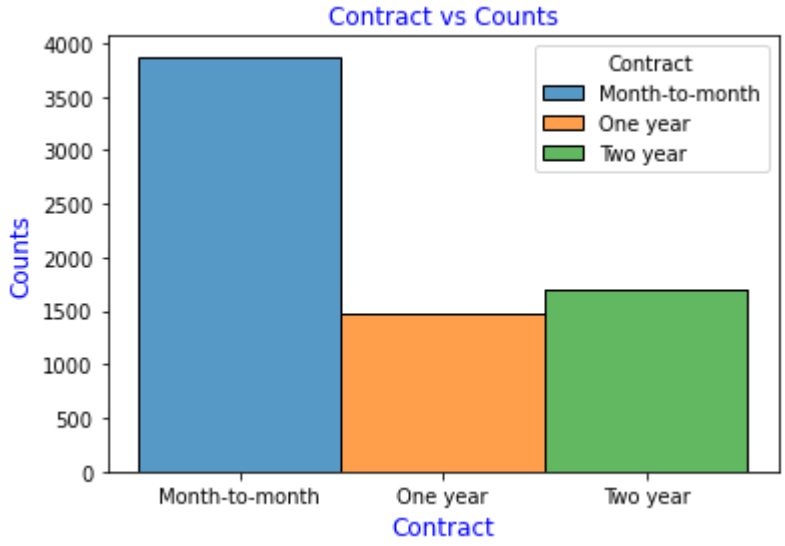
A person has Not Streaming Movies is highest count

Contract columns

In [93]:
```
df['Contract'].value_counts()
```

Out[93]:
```
Month-to-month    3875
Two year          1695
One year          1473
Name: Contract, dtype: int64
```

In [94]:
```
sns.histplot(binwidth=0.5, x="Contract", hue="Contract", data=df, stat="count", m
plt.xlabel('Contract', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Contract vs Counts', c = 'b', fontsize = 12)
plt.show()
```



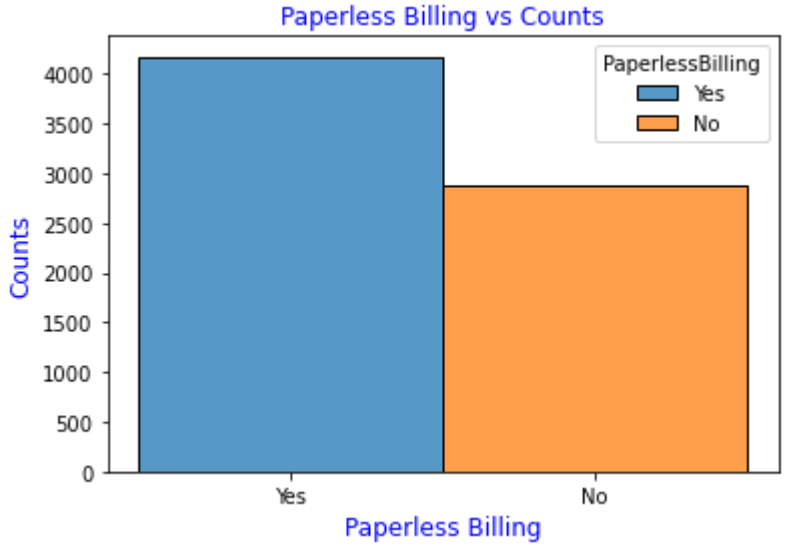
A person has Month to month contract counts is highest

Paperless Billing column

In [95]:
```
df['PaperlessBilling'].value_counts()
```

Out[95]:
```
Yes    4171
No     2872
Name: PaperlessBilling, dtype: int64
```

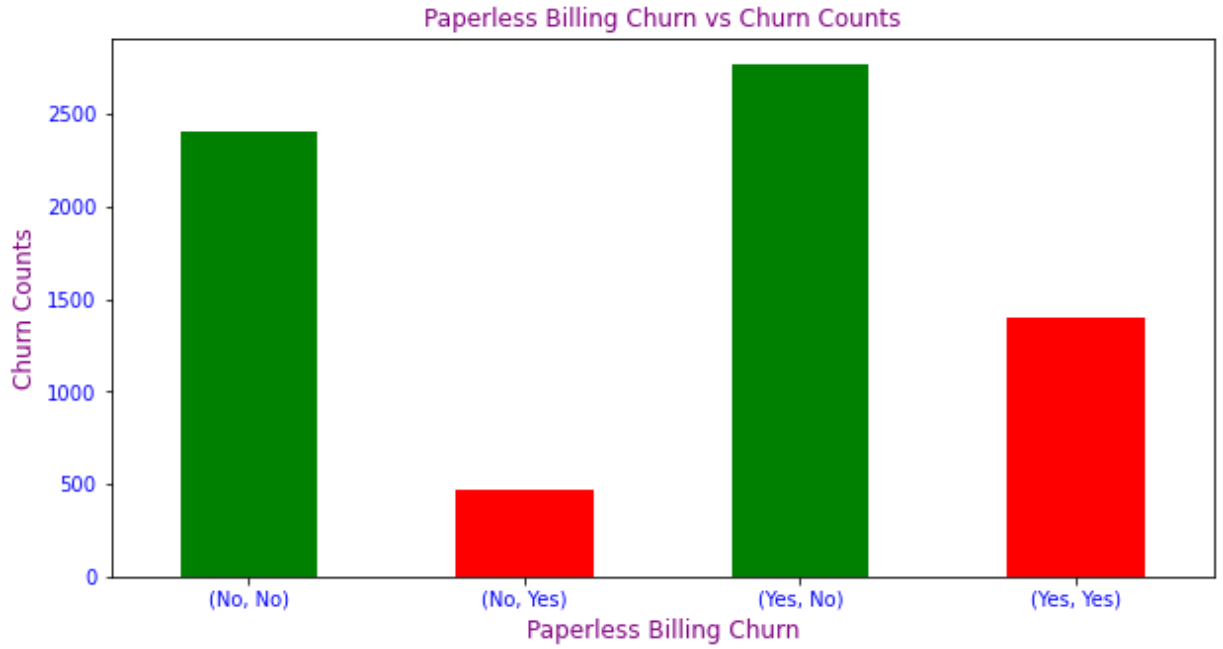
In [96]:
```
sns.histplot(binwidth=0.5, x="PaperlessBilling", hue="PaperlessBilling", data=df,
plt.xlabel('Paperless Billing', c = 'b', fontsize = 12)
plt.ylabel('Counts', c = 'b', fontsize = 12)
plt.title('Paperless Billing vs Counts', c = 'b', fontsize = 12)
plt.show()
```



In [97]:
```
pb = df.groupby('PaperlessBilling')['Churn'].value_counts()
pb
```

Out[97]:
```
PaperlessBilling  Churn
No                No       2403
                  Yes       469
Yes               No       2771
                  Yes      1400
Name: Churn, dtype: int64
```

In [98]:
```
pb.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Paperless Billing Churn', c = 'purple', fontsize = 12)
plt.ylabel('Churn Counts', c = 'purple', fontsize = 12 )
plt.title('Paperless Billing Churn vs Churn Counts', c = 'purple', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



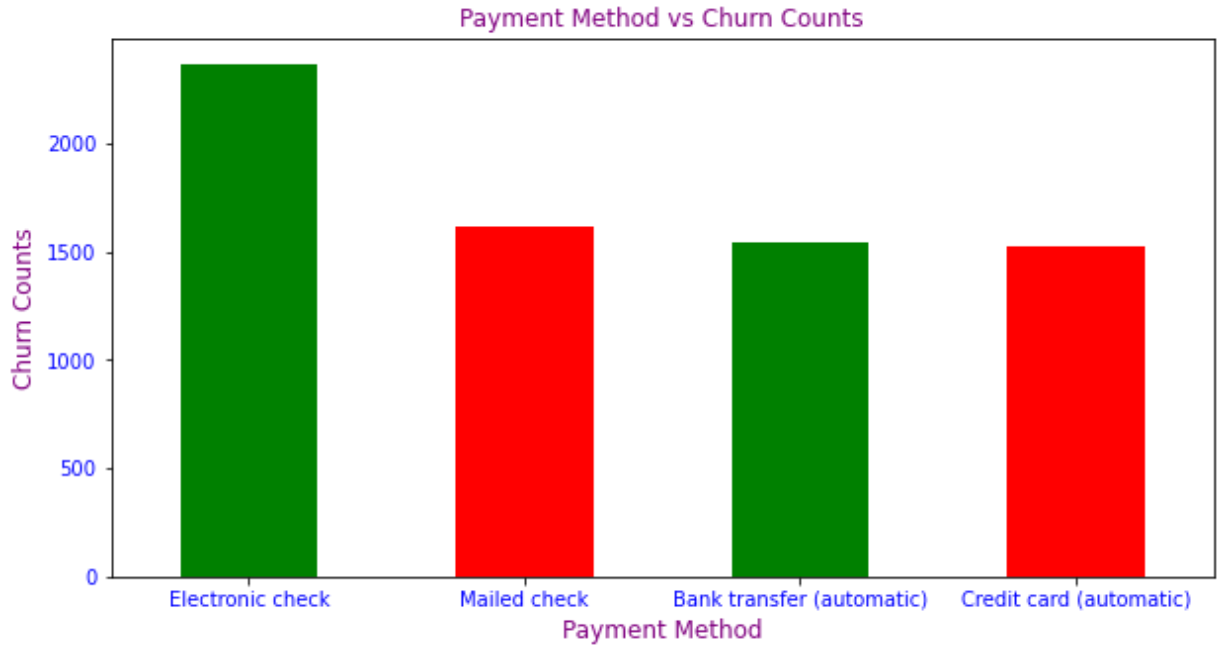
A person has Paperless Billing is lowest churn

Payment Method column

In [105]:
```
pm = df['PaymentMethod'].value_counts()
pm
```

Out[105]:
```
Electronic check             2365
Mailed check                 1612
Bank transfer (automatic)    1544
Credit card (automatic)      1522
Name: PaymentMethod, dtype: int64
```

In [109]:
```
pm.plot.bar(figsize = (10,5), rot = 360, color = ['g','r'])
plt.xlabel('Payment Method', c = 'purple', fontsize = 12)
plt.ylabel('Churn Counts', c = 'purple', fontsize = 12 )
plt.title('Payment Method vs Churn Counts', c = 'purple', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```

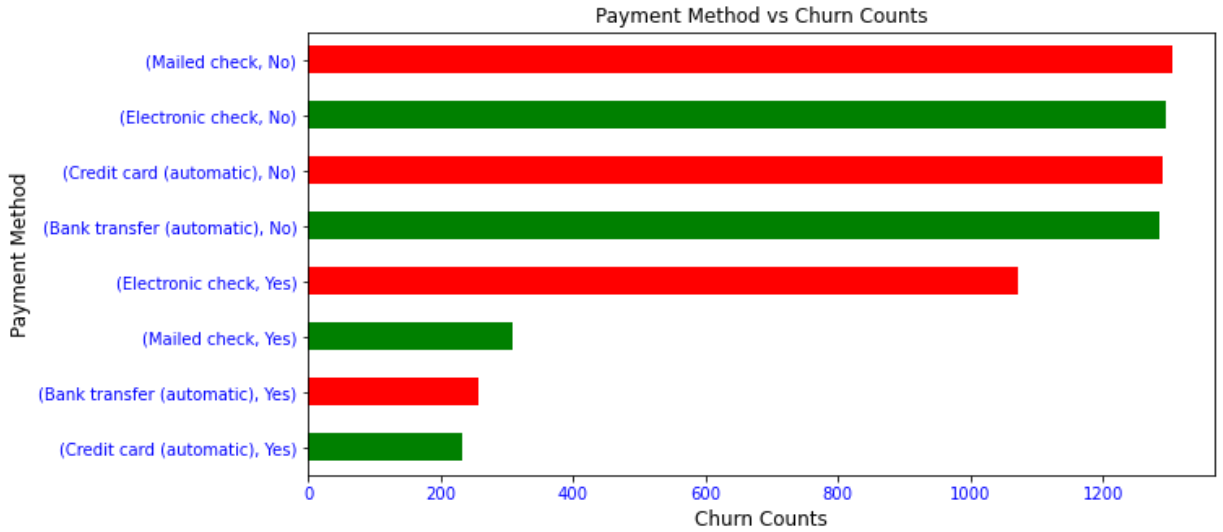


Electronic check payment method is highest

In [114]:
```
pmg = df.groupby('PaymentMethod')['Churn'].value_counts().sort_values()
pmg
```

Out[114]:
```
PaymentMethod              Churn
Credit card (automatic)    Yes       232
Bank transfer (automatic)  Yes       258
Mailed check               Yes       308
Electronic check           Yes      1071
Bank transfer (automatic)  No       1286
Credit card (automatic)    No       1290
Electronic check           No       1294
Mailed check               No       1304
Name: Churn, dtype: int64
```

In [115]:
```
pmg.plot.barh(figsize = (10,5), rot = 360, color = ['g','r'])
plt.ylabel('Payment Method', c = 'k', fontsize = 12)
plt.xlabel('Churn Counts', c = 'k', fontsize = 12 )
plt.title('Payment Method vs Churn Counts', c = 'k', fontsize = 12)
plt.xticks(c = 'b')
plt.yticks(c = 'b')
plt.show()
```



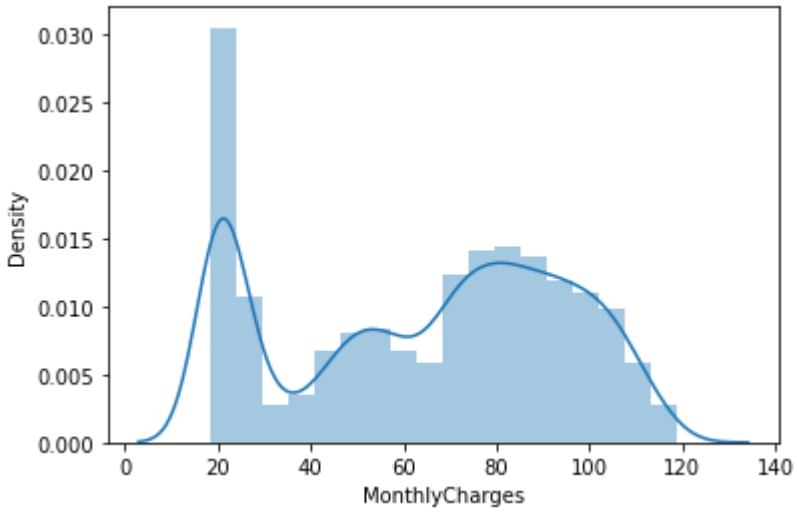
A person has No mailed check counts is highest churn

Monthly Charges column

In [119]:
```
df['MonthlyCharges'].value_counts()
```

Out[119]:
```
20.05     61
19.85     45
19.90     44
19.95     44
19.65     43
          ..
87.65      1
35.30      1
114.85     1
56.50      1
97.25      1
Name: MonthlyCharges, Length: 1585, dtype: int64
```

In [133]:
```
sns.distplot(df['MonthlyCharges'])
plt.show()
```



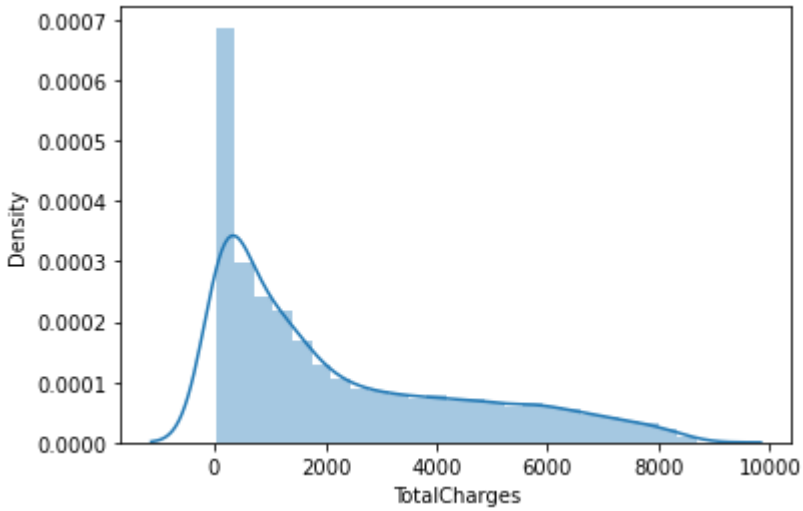
Above plot normaly distributed

Total Charges column

In [141]:
```
df['TotalCharges'].value_counts()
```

Out[141]:
```
2283.300441    11
20.200000      11
19.750000       9
19.650000       8
19.900000       8
               ..
1474.350000     1
6668.350000     1
6096.900000     1
140.700000      1
5867.000000     1
Name: TotalCharges, Length: 6531, dtype: int64
```

In [142]:
```
sns.distplot(df['TotalCharges'])
plt.show()
```



Above plot is skewed

Encoding Categorical Column

In [8]:
```
oe = OrdinalEncoder()
```

In [9]:
```
for i in df.columns:
    if df[i].dtypes == 'object':
        df[i] = oe.fit_transform(df[i].values.reshape(-1,1))
df.head(2)
```

Out[9]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService
0	0.0	0	1.0	0.0	1	0.0	1.0	0.0
1	1.0	0	0.0	0.0	34	1.0	0.0	0.0

In [10]:
```
print('=====================================================\n')
print(df.info())
print('=====================================================')
```

```
=====================================================

<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   float64
 1   SeniorCitizen     7043 non-null   int64  
 2   Partner           7043 non-null   float64
 3   Dependents        7043 non-null   float64
 4   tenure            7043 non-null   int64  
 5   PhoneService      7043 non-null   float64
 6   MultipleLines     7043 non-null   float64
 7   InternetService   7043 non-null   float64
 8   OnlineSecurity    7043 non-null   float64
 9   OnlineBackup      7043 non-null   float64
 10  DeviceProtection  7043 non-null   float64
 11  TechSupport       7043 non-null   float64
 12  StreamingTV       7043 non-null   float64
 13  StreamingMovies   7043 non-null   float64
 14  Contract          7043 non-null   float64
 15  PaperlessBilling  7043 non-null   float64
 16  PaymentMethod     7043 non-null   float64
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   float64
 19  Churn             7043 non-null   float64
dtypes: float64(18), int64(2)
memory usage: 1.1 MB
None
=====================================================
```

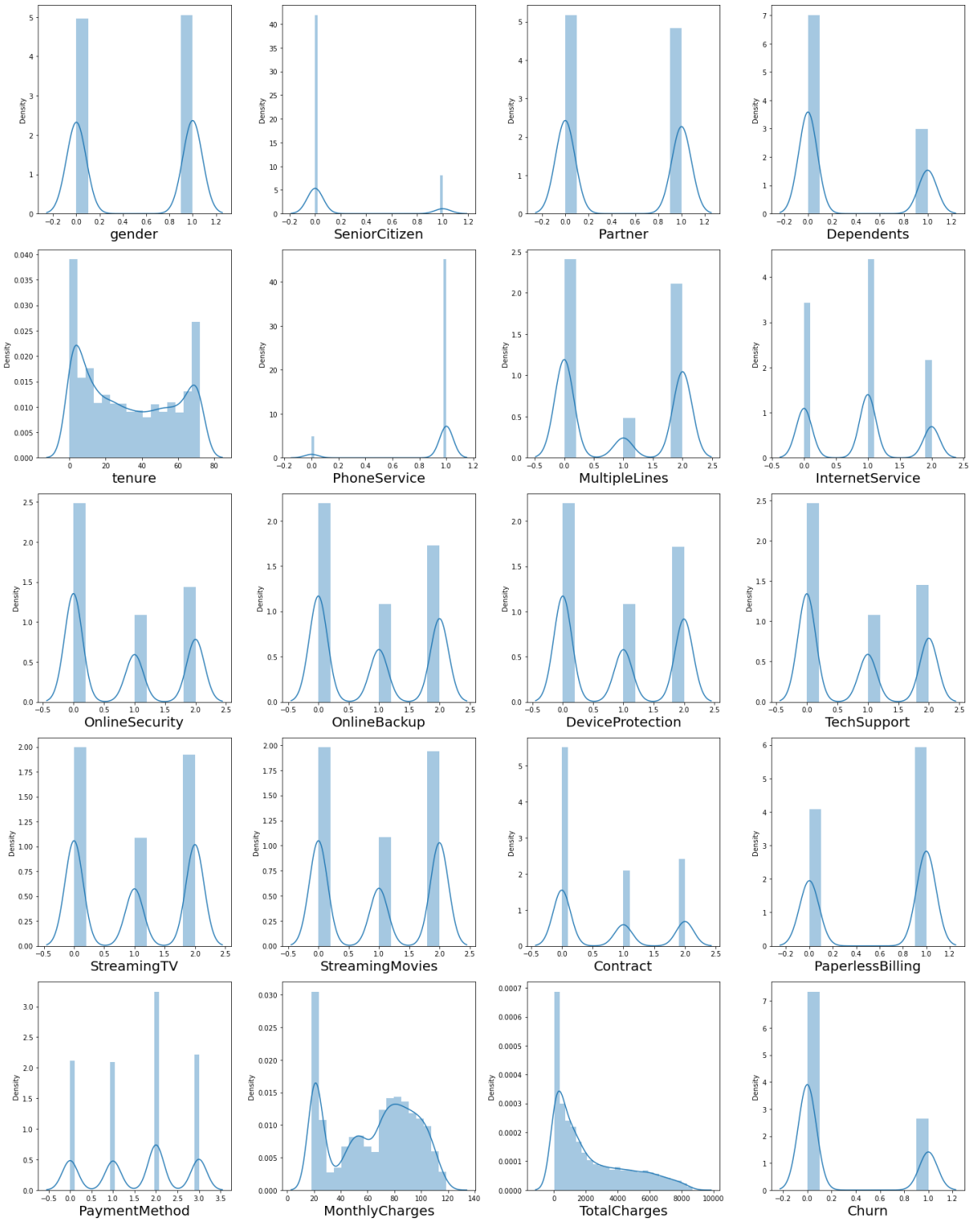
Data distribution

In [149]:
```
print('----------------------')
print('Distribution Plot :- ')
print('----------------------')

plt.figure(figsize = (20,25))
plotnumber = 1

for column in df:
    if plotnumber <=20:
        ax = plt.subplot(5,4, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```

```
----------------------
Distribution Plot :-
----------------------
```



Some columns are little skewed

Check skweness

In [150]:
```
df.skew()
```

Out[150]:
```
gender             -0.019031
SeniorCitizen       1.833633
Partner             0.067922
Dependents          0.875199
tenure              0.239540
PhoneService       -2.727153
MultipleLines       0.118719
InternetService     0.205423
OnlineSecurity      0.416985
OnlineBackup        0.182930
DeviceProtection    0.186847
TechSupport         0.402365
StreamingTV         0.028486
StreamingMovies     0.014657
Contract            0.630959
PaperlessBilling   -0.375396
PaymentMethod      -0.170129
MonthlyCharges     -0.220524
TotalCharges        0.962394
Churn               1.063031
dtype: float64
```

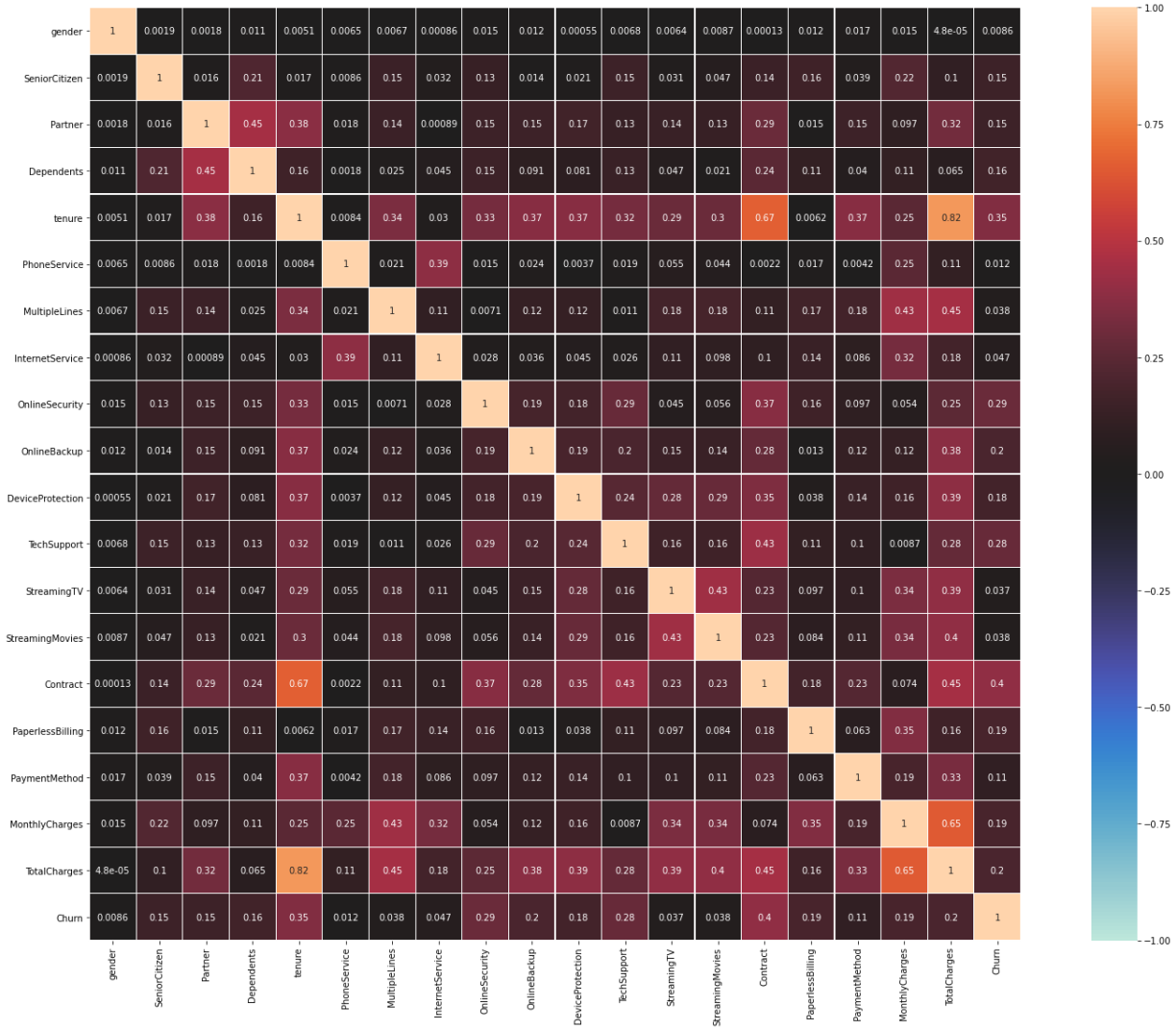
Skewness present in our dataset

Corelation of Feature vs Label using Heat map

In [152]:
```
print('-----------')
print('Heat Map :-')
print('-----------')
df_corr = df.corr().abs()

plt.figure(figsize = (22,16))
sns.heatmap(df_corr, vmin = -1, annot = True, square = True, center = 0, fmt = '.
plt.tight_layout()
```

```
-----------
Heat Map :-
-----------
```



Total charges has highest corelation with label

Spliting Dataset into features and label

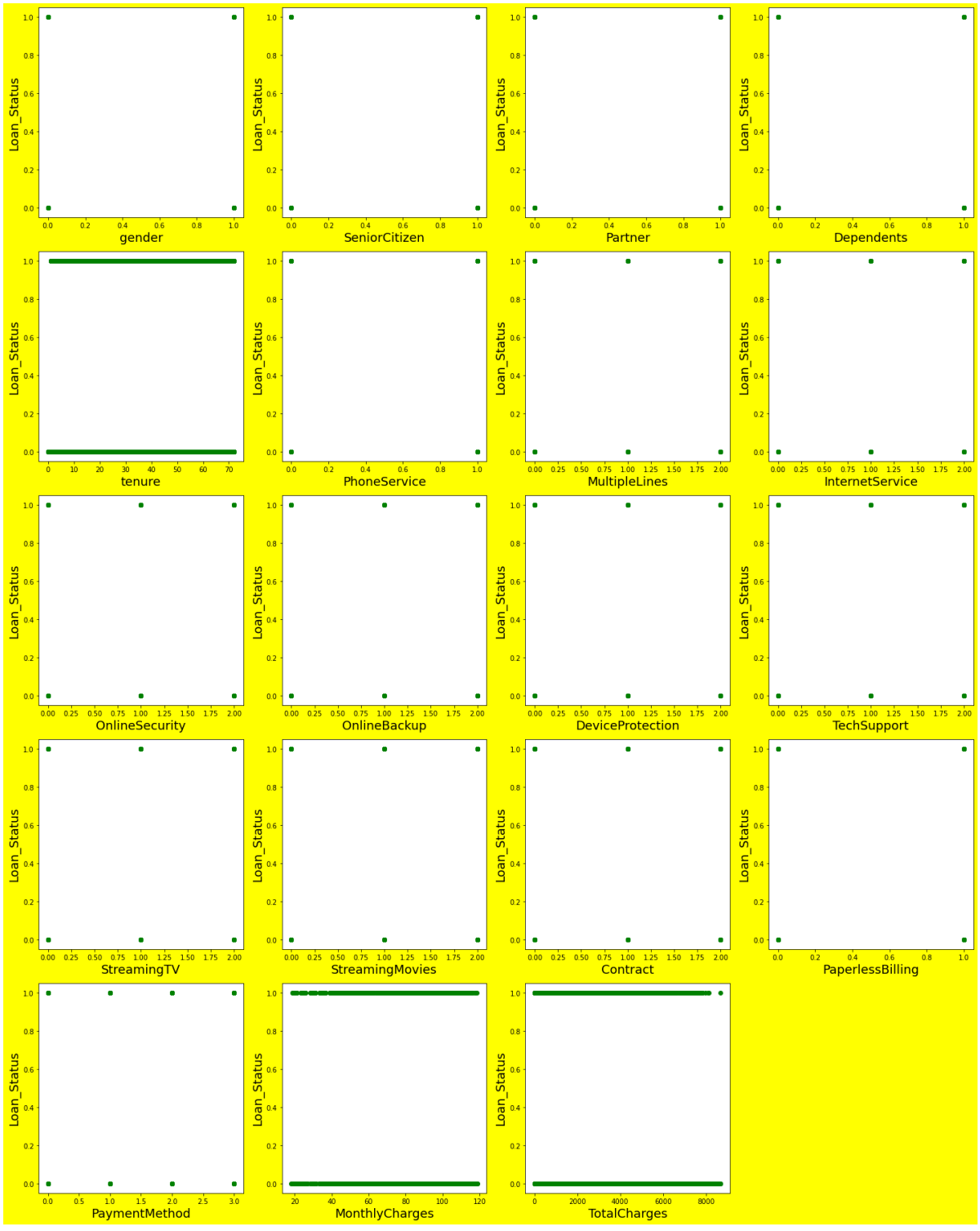
In [11]:
```
x = df.drop('Churn', axis = 1)
y = df. Churn
print('Data has been splited')
```

```
Data has been splited
```

In [156]:
```
# Let' see relation between features and label.
print('-----------------')
print('Scatter Plot :-')
print('-----------------')

plt.figure(figsize = (20,25), facecolor = 'yellow')
plotnumber = 1
for column in x:
    if plotnumber <=20:
        ax = plt.subplot(5,4, plotnumber)
        plt.scatter(x[column],y, c = 'g')
        plt.xlabel(column, fontsize = 18)
        plt.ylabel('Loan_Status', fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
-----------------
Scatter Plot :-
-----------------
```



Positive relation in feature and label

Checking for class imbalance

In [12]:
```
df['Churn'].value_counts()
```

Out[12]:
```
0.0    5174
1.0    1869
Name: Churn, dtype: int64
```

Handling Class Imbalance

In [13]:
```
sm = SMOTE()
x_over, y_over = sm.fit_resample(x,y)
```

In [14]:
```
print('----------------------')
print('Class are balanced :-')
print('----------------------')
print(y_over.value_counts())
print('----------------------')
```

```
----------------------
Class are balanced :-
----------------------
0.0    5174
1.0    5174
Name: Churn, dtype: int64
----------------------
```

Data Scaling

In [57]:
```
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[57]:
```
array([[0.        , 0.        , 1.        , ..., 0.66666667, 0.11542289,
        0.0012751 ],
       [1.        , 0.        , 0.        , ..., 1.        , 0.38507463,
        0.21586661],
       [1.        , 0.        , 0.        , ..., 1.        , 0.35422886,
        0.01031041],
       ...,
       [0.        , 0.        , 1.        , ..., 0.66666667, 0.11293532,
        0.03780868],
       [1.        , 1.        , 1.        , ..., 1.        , 0.55870647,
        0.03321025],
       [1.        , 0.        , 0.        , ..., 0.        , 0.86965174,
        0.78764136]])
```

Split data into train and test. Model will be bulit on training data and tested on test data

In [58]:
```
x_train, x_test, y_train, y_test = train_test_split(x_over, y_over, test_size = 0
print('Data has been splited.')
```

```
Data has been splited.
```

Model Bulding

Decision Tree model instantiaing, training and evaluating

In [59]:
```
bag_dt = BaggingClassifier(DecisionTreeClassifier(), n_estimators = 30, max_sampl
                           random_state= 3, oob_score = True)
```

In [60]:
```
bag_dt.oob_score
```

Out[60]:
```
True
```

In [61]:
```
bag_dt.fit(x_train, y_train)
print('Bagging DT score ------->', bag_dt.score(x_test, y_test))
```

```
Bagging DT score -------> 0.8465403942790878
```

In [62]:
```
y_pred = bag_dt.predict(x_test)
```

In [63]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.83      0.87      0.85      1298
         1.0       0.86      0.82      0.84      1289

    accuracy                           0.85      2587
   macro avg       0.85      0.85      0.85      2587
weighted avg       0.85      0.85      0.85      2587

-------------------------------------------------------------
```

Conclusion : Decision Tree model has 85% score

Cross Validation score to check if the model is overfitting

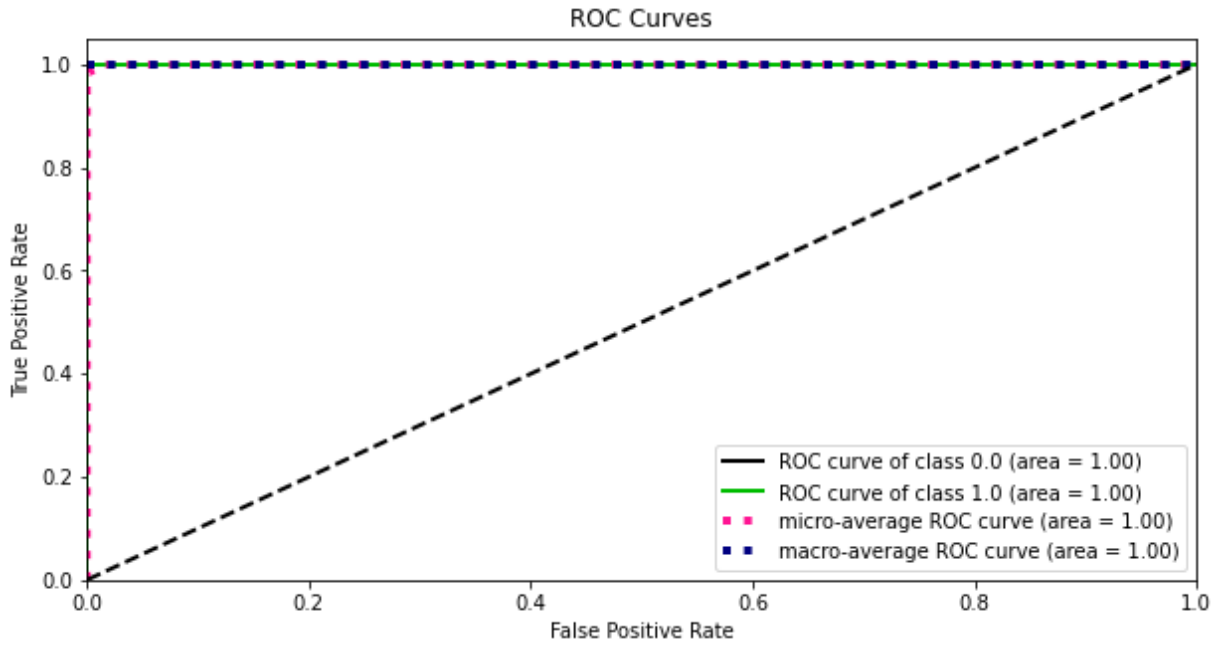
In [64]:
```
cv = cross_val_score(bag_dt, x, y, cv = 5)
print('Cross Validation score of Decision Tree model --->', cv.mean())
```

```
Cross Validation score of Decision Tree model ---> 0.78730795131944
```

Conclusion : Decision Tree model has 78% Cross Validation score

ROC, AUC Curve

In [65]:
```
prob = bag_dt.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



XGBoost model instantiaing, training and evaluating

In [66]:
```
bag_xgb = BaggingClassifier(xgb.XGBClassifier(eval_metric = 'mlogloss'), n_estima
                            random_state= 3, oob_score = True)
```

In [67]:
```
bag_xgb.oob_score
```

Out[67]:
```
True
```

In [68]:
```
bag_xgb.fit(x_train, y_train)
print('Bagging XGBoost score ------->', bag_xgb.score(x_test, y_test))
```

```
Bagging XGBoost score -------> 0.8612292230382682
```

In [69]:
```
y_pred = bag_xgb.predict(x_test)
```

In [70]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.87      0.86      1298
         1.0       0.87      0.85      0.86      1289

    accuracy                           0.86      2587
   macro avg       0.86      0.86      0.86      2587
weighted avg       0.86      0.86      0.86      2587

-------------------------------------------------------------
```

Conclusion : XGBoost model has 86% score

Cross Validation score to check if the model is overfitting

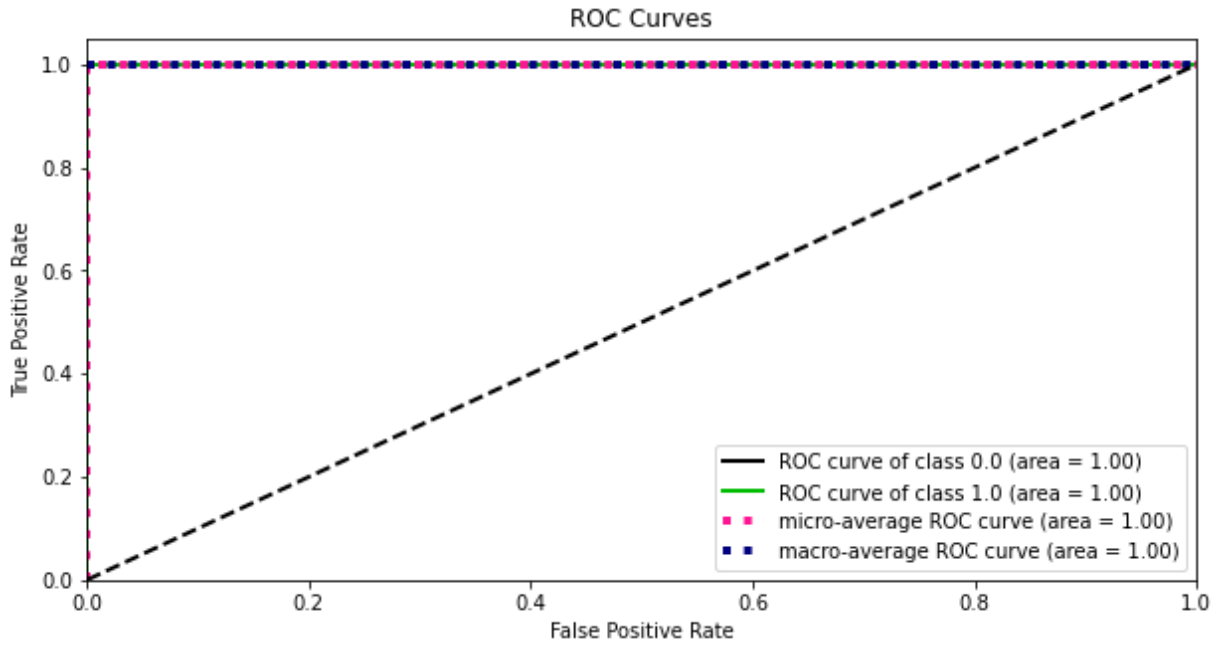
In [71]:
```
cv = cross_val_score(bag_xgb, x, y, cv = 5)
print('Cross Validation score of XGBoost model --->', cv.mean())
```

```
Cross Validation score of XGBoost model ---> 0.7968201577521131
```

Conclusion : XGBoost model has 79% Cross Validation score

ROC, AUC Curve

In [72]:
```
prob = bag_xgb.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Knn model instantiaing, training and evaluating

In [73]:
```
bag_Knn = BaggingClassifier(KNeighborsClassifier(n_neighbors = 5), n_estimators =
                            random_state= 3, oob_score = True)
```

In [74]:
```
bag_Knn.oob_score
```

Out[74]:
```
True
```

In [75]:
```
bag_Knn.fit(x_train, y_train)
print('Bagging KNN score ------->', bag_Knn.score(x_test, y_test))
```

```
Bagging KNN score -------> 0.7529957479706223
```

In [76]:
```
y_pred = bag_dt.predict(x_test)
```

In [77]:
```
print('------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.83      0.87      0.85      1298
         1.0       0.86      0.82      0.84      1289

    accuracy                           0.85      2587
   macro avg       0.85      0.85      0.85      2587
weighted avg       0.85      0.85      0.85      2587

------------------------------------------------------------
```

Conclusion : KNN model has 85% score

Cross Validation score to check if the model is overfitting

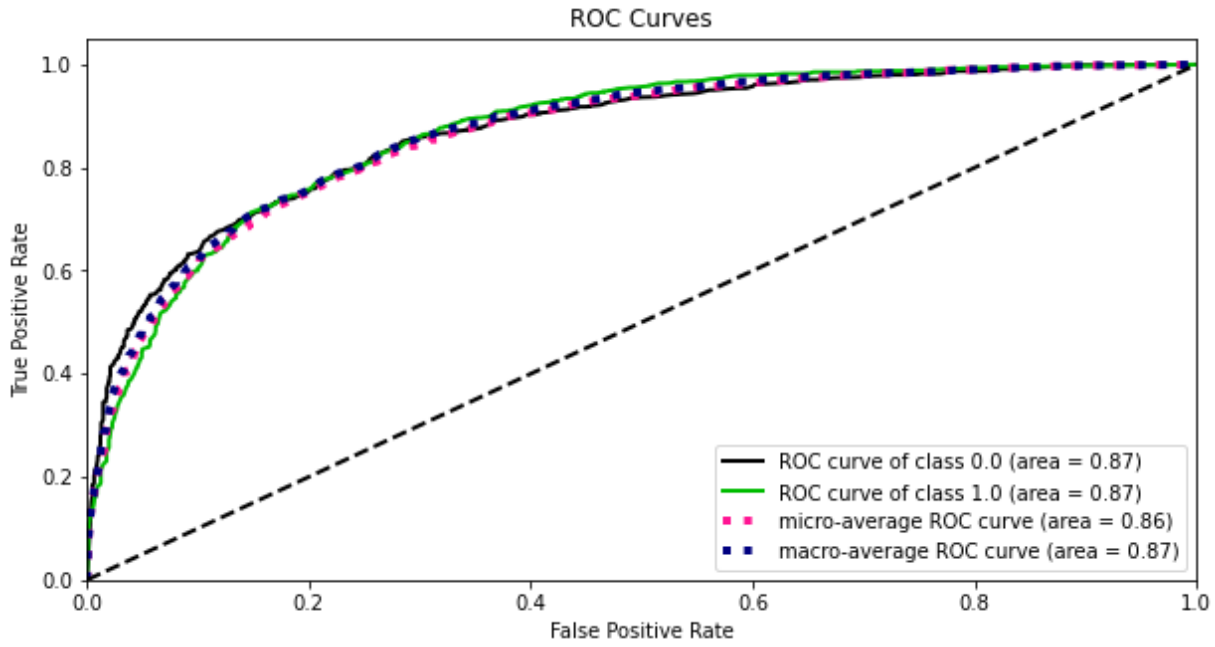
In [78]:
```
cv = cross_val_score(bag_Knn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.7826227700174205
```

Conclusion : Knn model has 78% Cross Validation score

ROC, AUC Curve

In [79]:
```
prob = bag_Knn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Random Forest model instantiaing, training and evaluating

In [90]:
```
bag_Rn = BaggingClassifier(RandomForestClassifier(), n_estimators = 10, max_sampl
                           random_state= 3, oob_score = True)
```

In [91]:
```
bag_Rn.oob_score
```

Out[91]: True

In [92]:
```
bag_Rn.fit(x_train, y_train)
print('Bagging Random Forest score ------->', bag_Rn.score(x_test, y_test))
```

```
Bagging Random Forest score -------> 0.8554310011596443
```

In [93]:
```
y_pred = bag_Rn.predict(x_test)
```

In [94]:
```
print('-------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-------------------------------------------------------------\n')
```

```
-------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.86      0.86      1298
         1.0       0.86      0.85      0.85      1289

    accuracy                           0.86      2587
   macro avg       0.86      0.86      0.86      2587
weighted avg       0.86      0.86      0.86      2587

-------------------------------------------------------------
```

Conclusion : Random Forest model has 86% score

Cross Validation score to check if the model is overfitting

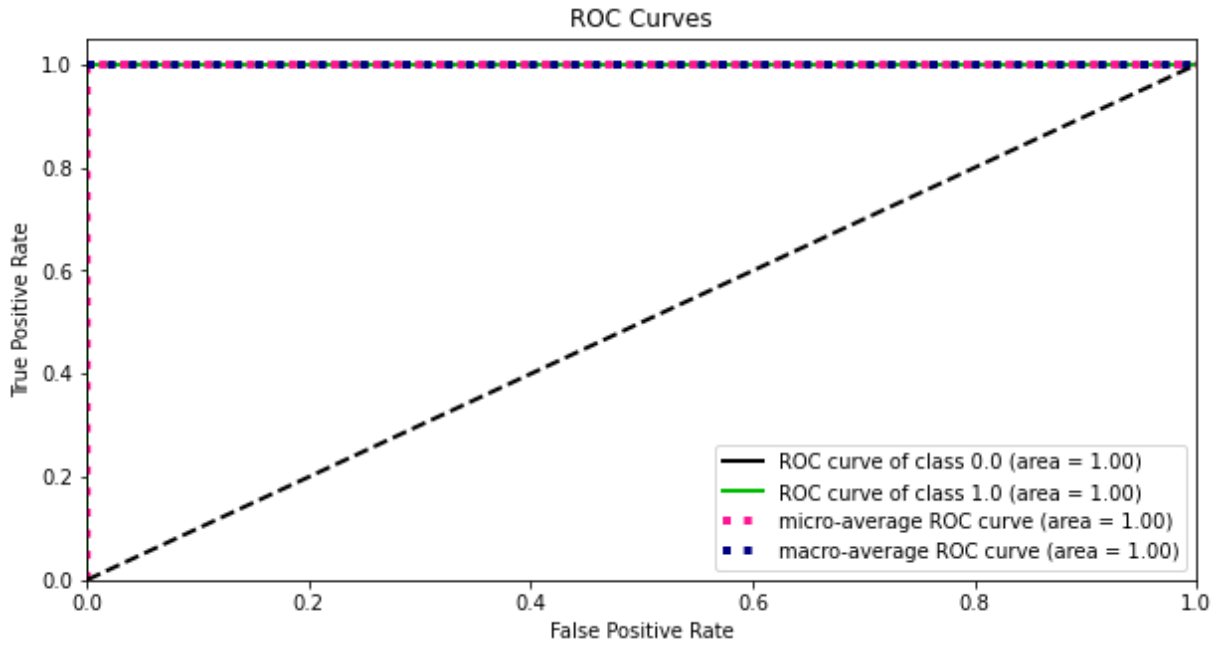
In [95]:
```
cv = cross_val_score(bag_Rn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.7968203593780244
```

Conclusion : Random Forest model has 79% Cross Validation score

ROC, AUC Curve

In [96]:
```
prob = bag_Rn.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Logistic Regression model instantiaing, training and evaluating

In [116]:
```
bag_Lr = BaggingClassifier(LogisticRegression(), n_estimators = 5, max_samples =
                           random_state= 3, oob_score = True)
```

In [117]:
```
bag_Lr.oob_score
```

Out[117]:
```
True
```

In [118]:
```
bag_Lr.fit(x_train, y_train)
print('Bagging Logostic Regression score ------->', bag_Lr.score(x_test, y_test))
```

```
Bagging Logostic Regression score -------> 0.7634325473521454
```

In [119]:
```
y_pred = bag_Lr.predict(x_test)
```

In [120]:
```
print('------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.79      0.72      0.75      1298
         1.0       0.74      0.80      0.77      1289

    accuracy                           0.76      2587
   macro avg       0.77      0.76      0.76      2587
weighted avg       0.77      0.76      0.76      2587

------------------------------------------------------------
```

Conclusion : Logistic Regression model has 76% score

Cross Validation score to check if the model is overfitting

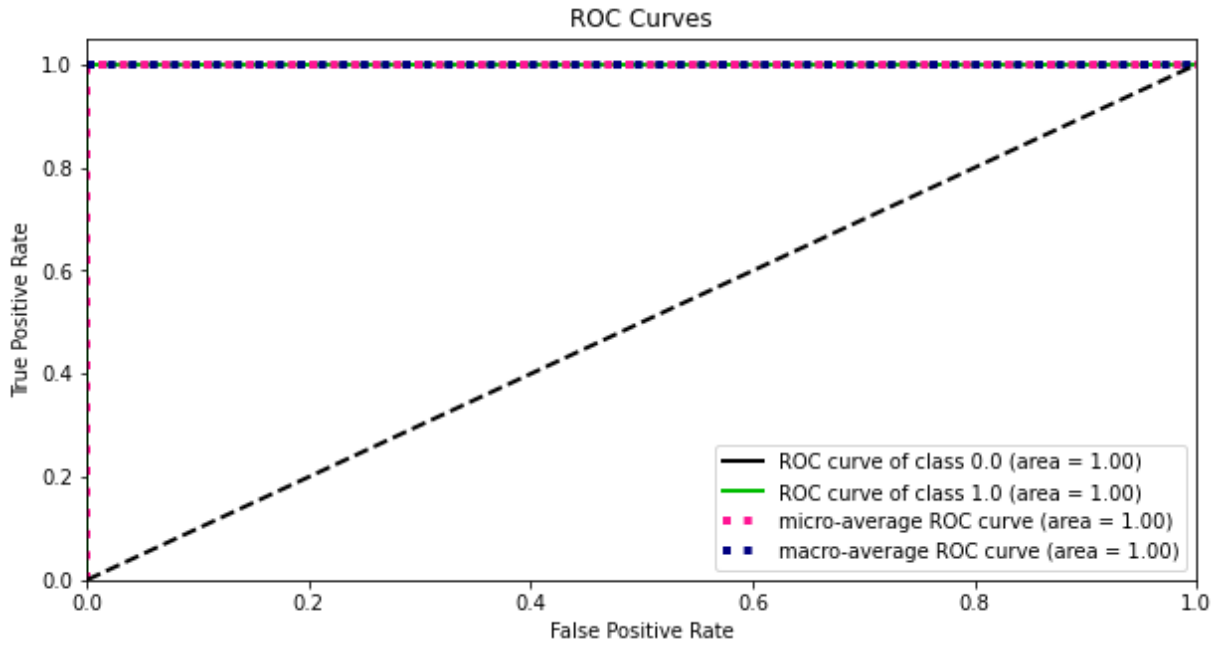
In [121]:
```
cv = cross_val_score(bag_Lr, x, y, cv = 5)
print('Cross Validation score of Logistic regression model --->', cv.mean())
```

```
Cross Validation score of Logistic regression model ---> 0.8025001613007291
```

Conclusion : Logistic Regression model has 80% Cross Validation score

ROC, AUC Curve

In [122]:
```
prob = bag_Lr.predict_proba(x_test) # calculating probability
skplt.metrics.plot_roc(y_pred,prob, figsize = (10,5))
plt.show()
```



Let's find ROC, AUC score

In [128]:
```
# DecisionTreeClassifier
roc_auc_score(y_test, bag_dt.predict(x_test))
```

Out[128]: 0.8464618838315436

In [129]:
```
# XGBoostClassifier
roc_auc_score(y_test, bag_xgb.predict(x_test))
```

Out[129]: 0.861188544529329

In [130]:
```
# KNeighborsClassifier
roc_auc_score(y_test, bag_Knn.predict(x_test))
```

Out[130]: 0.753136651122871

In [126]:
```
# RandomForestClassifier
roc_auc_score(y_test, bag_Rn.predict(x_test))
```

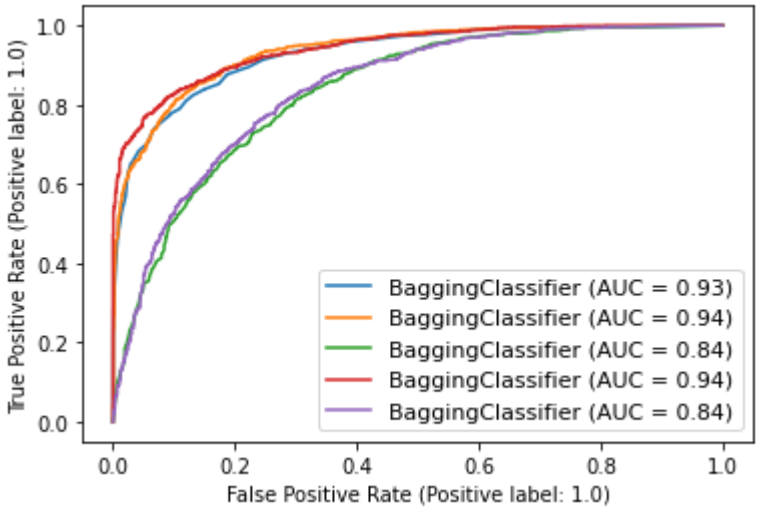
Out[126]: 0.8553996660135962

In [127]:
```
# LogisticRegressionClassifier
roc_auc_score(y_test, bag_Lr.predict(x_test))
```

Out[127]: 0.7635749216136062

Let's check ROC, AUC Curve for the fitted model

In [131]:
```
dis = plot_roc_curve(bag_dt, x_test, y_test)
plot_roc_curve(bag_Rn, x_test, y_test, ax = dis.ax_) # ax_ = Axes with confusion
plot_roc_curve(bag_Knn, x_test, y_test, ax = dis.ax_)
plot_roc_curve(bag_xgb, x_test, y_test, ax = dis.ax_)
plot_roc_curve(bag_Lr, x_test, y_test, ax = dis.ax_)
plt.legend(prop = {'size':11}, loc = 'lower right')
plt.show()
```



Looking ROC, AUC Curve we found XGBoost has best model so we do Hyperparameter Tuning on it.

In [132]:
```
param = {'n_estimators': [50,100,150], 'max_samples': [1.0], 'bootstrap': [True]}
```

In [133]:
```
grid_search = GridSearchCV(estimator = bag_xgb, param_grid = param, cv = 5 , n_jo
```

In [134]:
```
grid_search.fit(x_train, y_train)
```

Out[134]:
```
GridSearchCV(cv=5,
             estimator=BaggingClassifier(base_estimator=XGBClassifier(base_sc
ore=None,
                                                                      booster
=None,
                                                                      colsamp
le_bylevel=None,
                                                                      colsamp
le_bynode=None,
                                                                      colsamp
le_bytree=None,
                                                                      eval_me
tric='mlogloss',
                                                                      gamma=N
one,
                                                                      gpu_id=
None,
                                                                      importa
nce_type='gain',
                                                                      interac
tion_constraints=None,
                                                                      learnin
g_rate=None,
                                                                      max_del
ta_step=None,
                                                                      max_dep
th=None,
                                                                      min_chi
ld_weight=None,
                                                                      miss
i...
                                                                      monoton
e_constraints=None,
                                                                      n_estim
ators=100,
                                                                      n_jobs=
None,
                                                                      num_par
allel_tree=None,
                                                                      random_
state=None,
                                                                      reg_alp
ha=None,
                                                                      reg_lam
bda=None,
                                                                      scale_p
os_weight=None,
                                                                      subsamp
le=None,
                                                                      tree_me
thod=None,
                                                                      validat
e_parameters=None,
                                                                      verbosi
```

```
ty=None),
                                              max_samples=0.5, n_estimators=30,
                                              oob_score=True, random_state=3),
             n_jobs=-1,
             param_grid={'bootstrap': [True], 'max_samples': [1.0],
                         'n_estimators': [50, 100, 150]})
```

In [135]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```

```
{'bootstrap': True, 'max_samples': 1.0, 'n_estimators': 50}
```

In [137]:
```
hxgb = BaggingClassifier(base_estimator=xgb.XGBClassifier(eval_metric = 'mlogloss
hxgb.fit(x_train, y_train)
hxgb.score(x_test, y_test)
```

Out[137]:
```
0.860456126787785
```

In [139]:
```
y_pred = hxgb.predict(x_test)
```

In [140]:
```
print('------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------\n')
```

```
------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.87      0.86      1298
         1.0       0.87      0.85      0.86      1289

    accuracy                           0.86      2587
   macro avg       0.86      0.86      0.86      2587
weighted avg       0.86      0.86      0.86      2587

------------------------------------------------------------
```

After Hyperparameter Tuning model accuracy score 86%.

Saving The Model

In [148]:
```
# saving the model to the Local file system
filename = 'Customer Churn Analysis.pickle'
pickle.dump(hxgb, open(filename, 'wb'))
```

Predict Customer Churn

In [150]:
```
model = pickle.load(open('Customer Churn Analysis.pickle', 'rb'))
result = model.score(x_test, y_test)
print('Predicted Score --------->', result)
```

```
Predicted Score ---------> 0.860456126787785
```

In [159]:
```
Prediction = pd.DataFrame([model.predict(x_test)[:], y_test[:]], index = ['Predic
Prediction
```

Out[159]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Predicted	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0
Orginal	0.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0

Saving the predicted result in CSV file

In [160]:
```
Prediction.to_csv('Customer Churn Analysis Prediction.csv')
```

Final Conclusion : XGBoost is our best model.

In [ ]: