In [7]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [8]:

```
data=pd.read_csv('CustomerChurn.csv')
```

Q: To show a record of table

In [80]:

```
data.head(1)
```

Out[80]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Intern
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	

1 rows × 22 columns

Q: To check how many customers are churned?

In [9]:

```
data['Churn'].value_counts()
```

Out[9]:

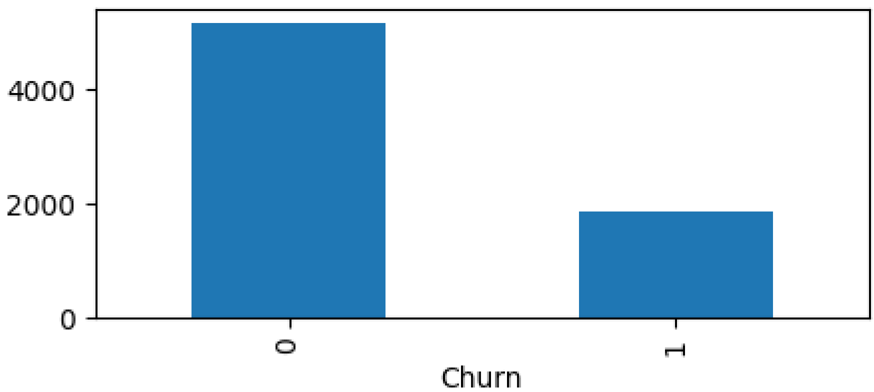
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

In [83]:

```
plt.figure(figsize=(5, 2))
data['Churn'].value_counts().plot(kind='bar')
```

Out[83]:

```
<Axes: xlabel='Churn'>
```



Conclusion: Almost 26.5% (1869) people are churned.

Q: To convert TotalCharges datatype to numeric

In [10]:

```
data['TotalCharges']=pd.to_numeric(data['TotalCharges'], errors='coerce')
```

Q: Divide customers into bins based on tenure(eg: for tenure < 12 months, assign tenure group of 1-12 fo tenure between 1 to 2 yrs, tenure group of 13-24)

In [11]:

```
data['tenure'].max() # to get max tenure
```

Out[11]:

```
72
```

In [12]:

```
labels = ["{0} - {1}".format(i, i+11) for i in range(1,72,12)] #to divide the tenure int
print(labels)
```

```
['1 - 12', '13 - 24', '25 - 36', '37 - 48', '49 - 60', '61 - 72']
```

In [13]:

```
data['tenure_group']=pd.cut(data['tenure'], range(1,80,12),right=False,labels=labels) #t
```

In [14]:

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

Out[14]:

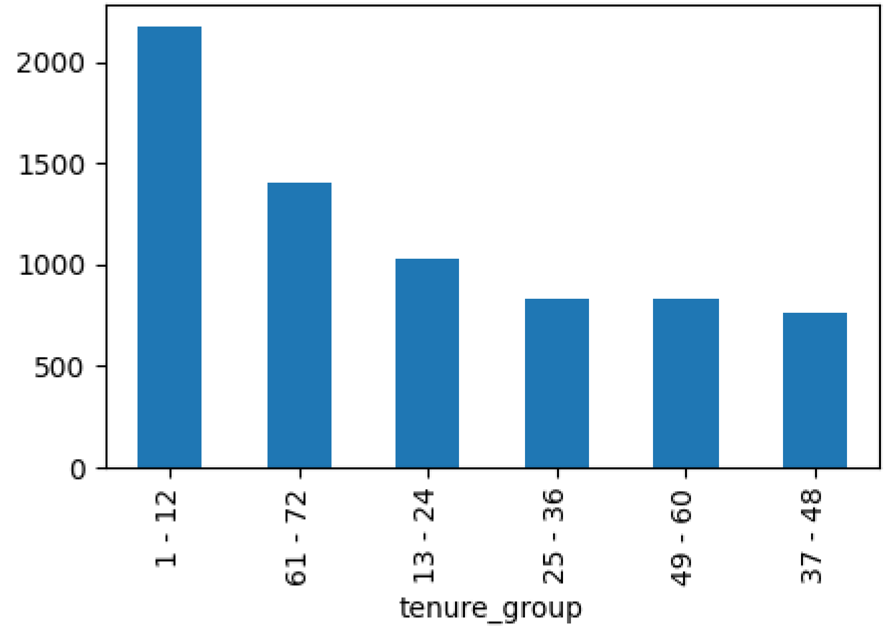
```
tenure_group
1 - 12     2175
61 - 72    1407
13 - 24    1024
25 - 36     832
49 - 60     832
37 - 48     762
Name: count, dtype: int64
```

In [86]:

```
plt.figure(figsize=(5, 3))
data['tenure_group'].value_counts().plot(kind='bar')
```

Out[86]:

```
<Axes: xlabel='tenure_group'>
```



Conclusion: Customers with age range of 1-12 have higher chance of churn(31%)

Q: Remove columns customerID & tenure

In [15]:

```
data.drop(columns=['customerID','tenure'],axis=1).head(1)
```

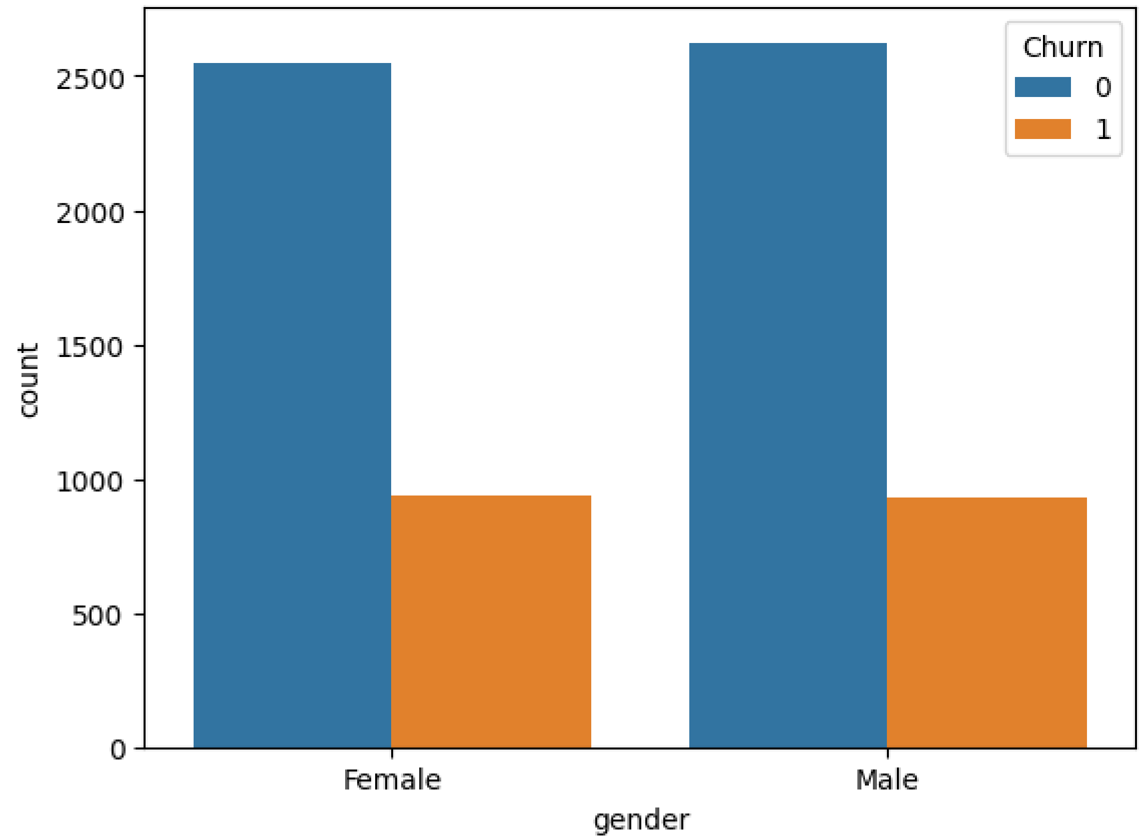
Out[15]:

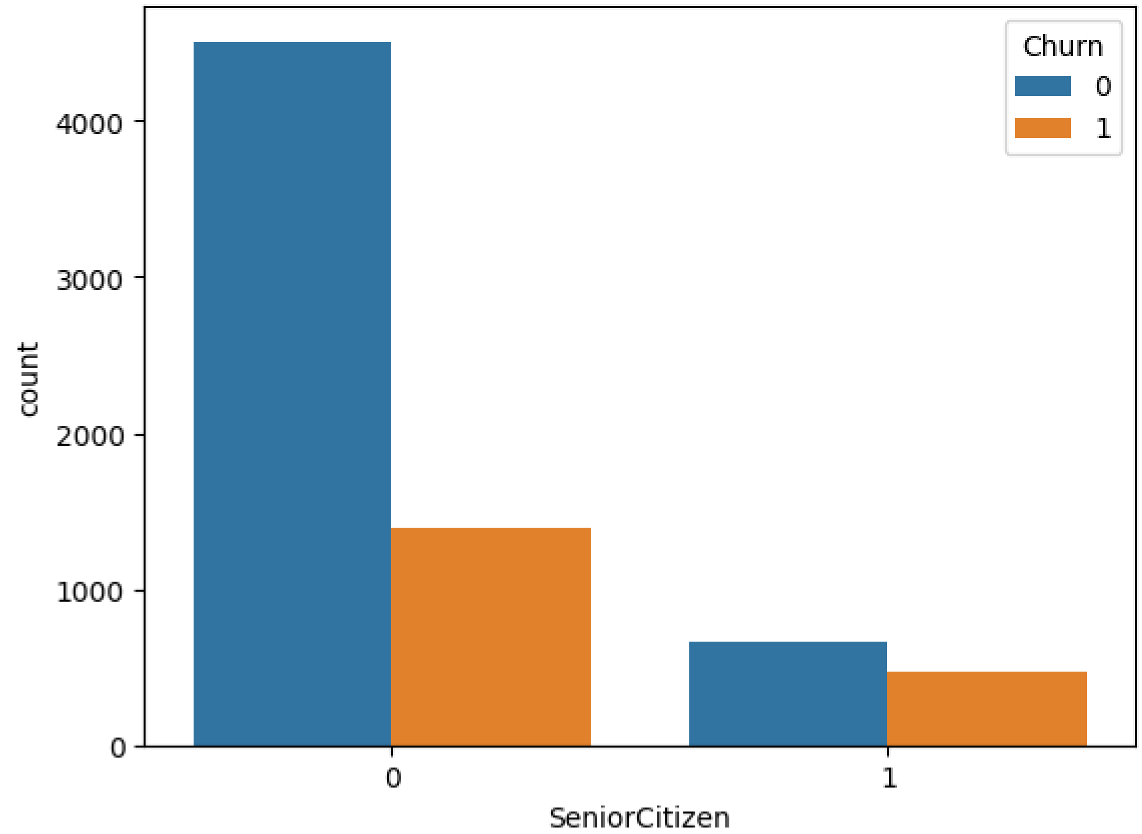
	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSec
0	Female	0	Yes	No	No	No phone service	DSL	

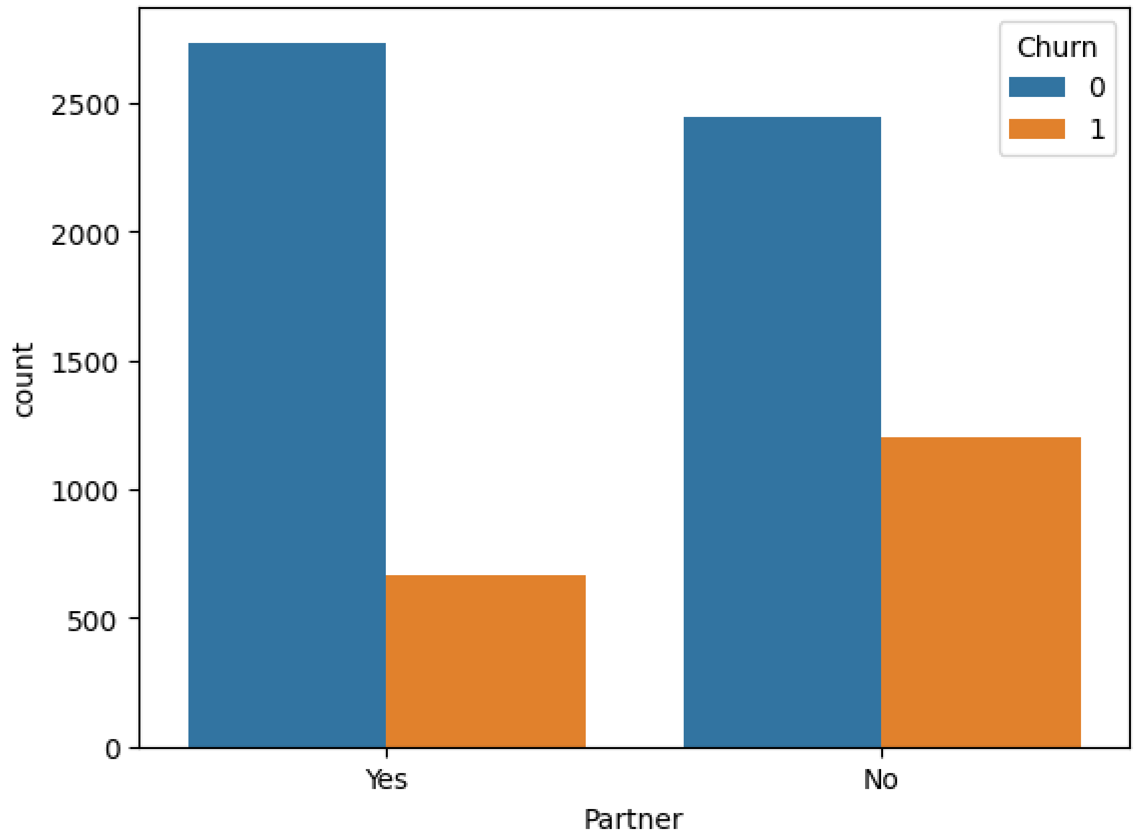
Q: Univariate analysis for every non-numeric columns

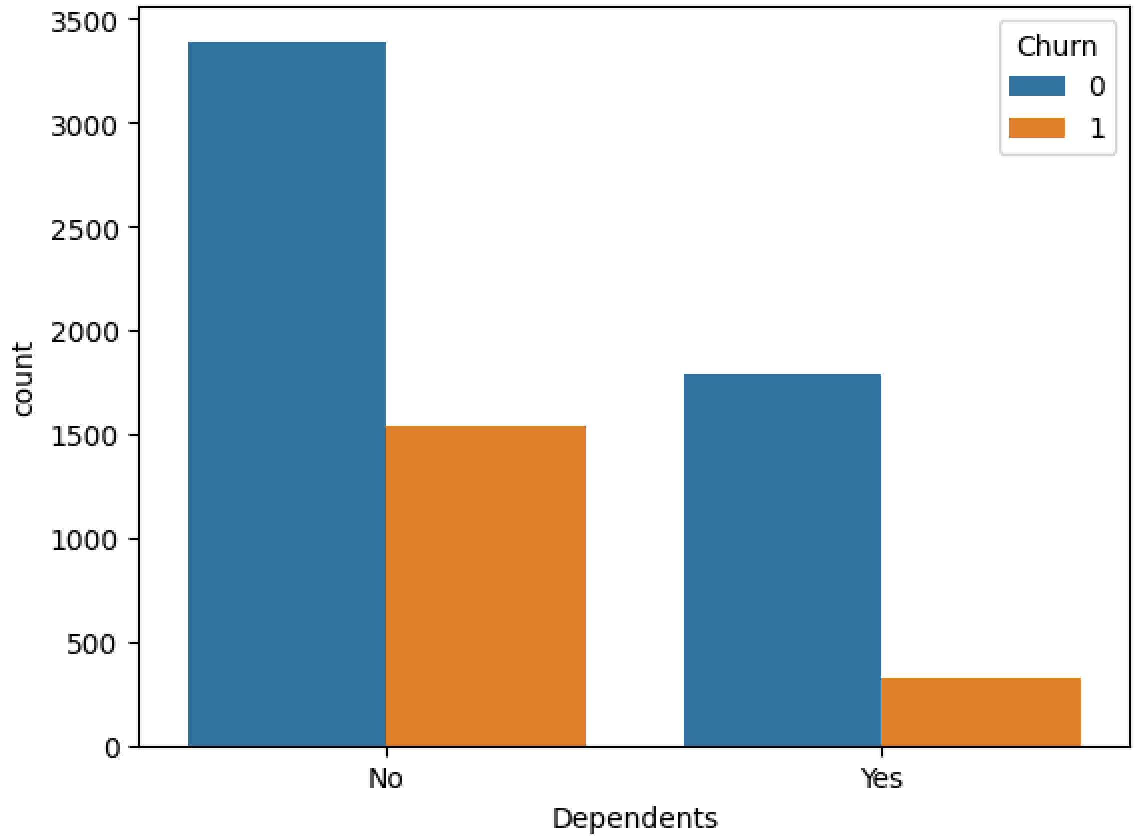
In [81]:

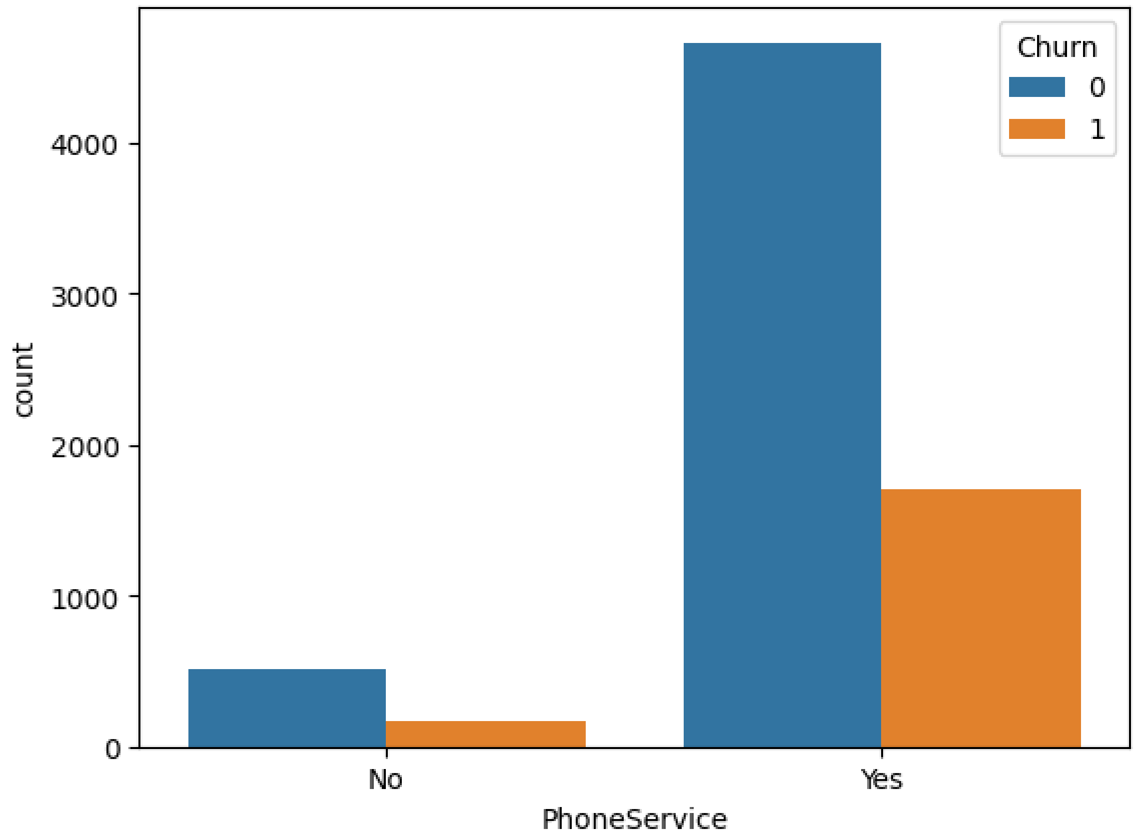
```
for i, predictor in enumerate(data.drop(columns=['Churn','TotalCharges','MonthlyCharges'
    sns.countplot(data,x=predictor,hue='Churn')
    plt.show()
```

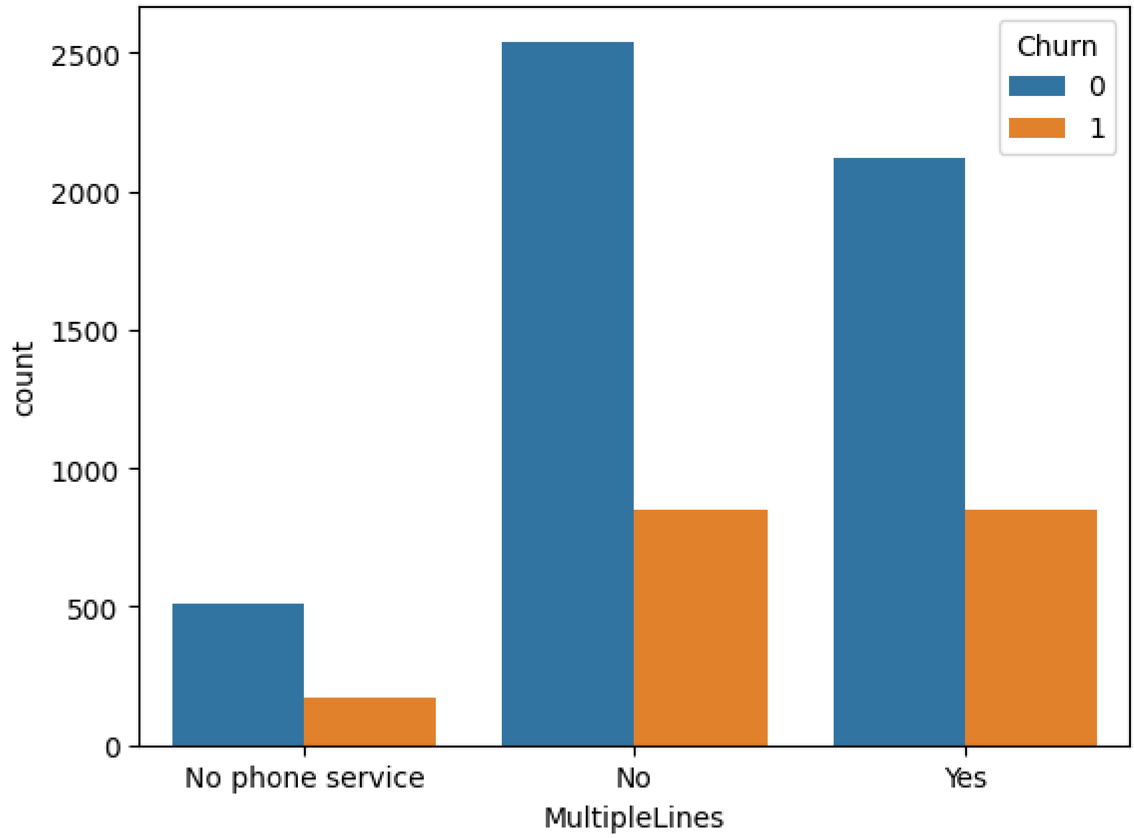

Churn
0
1
count
2500
2000
1500
1000
500
0
Female
Male
gender

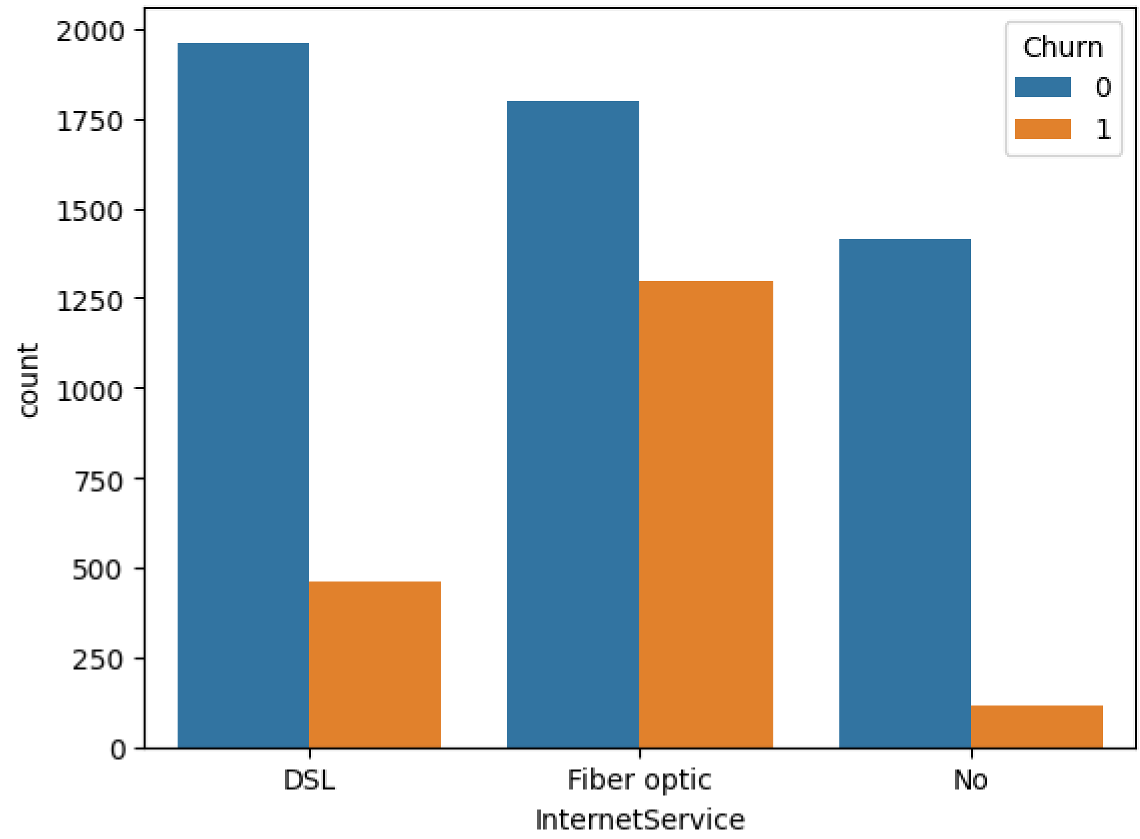

Churn
0
1
count
4000
3000
2000
1000
0
0
1
SeniorCitizen


Churn
0
1
count
2500
2000
1500
1000
500
0
Yes
No
Partner

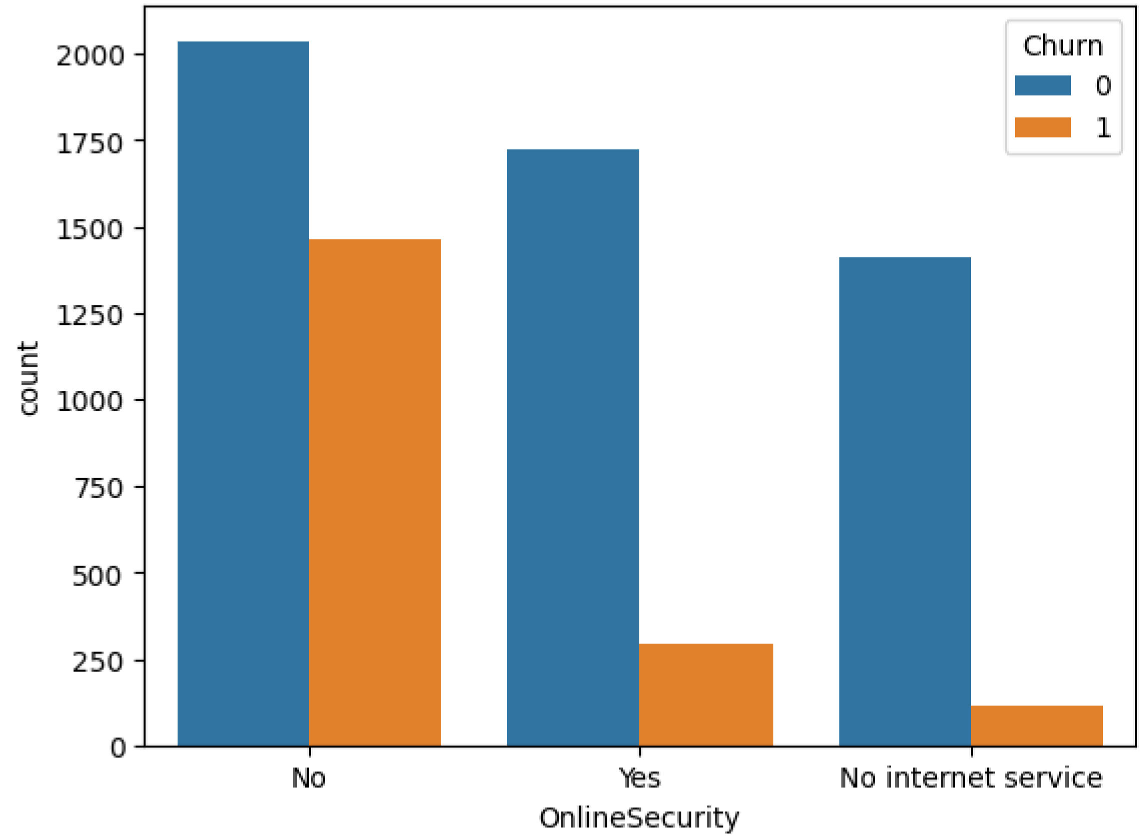

Churn
0
1
count
3500
3000
2500
2000
1500
1000
500
0
No
Yes
Dependents


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

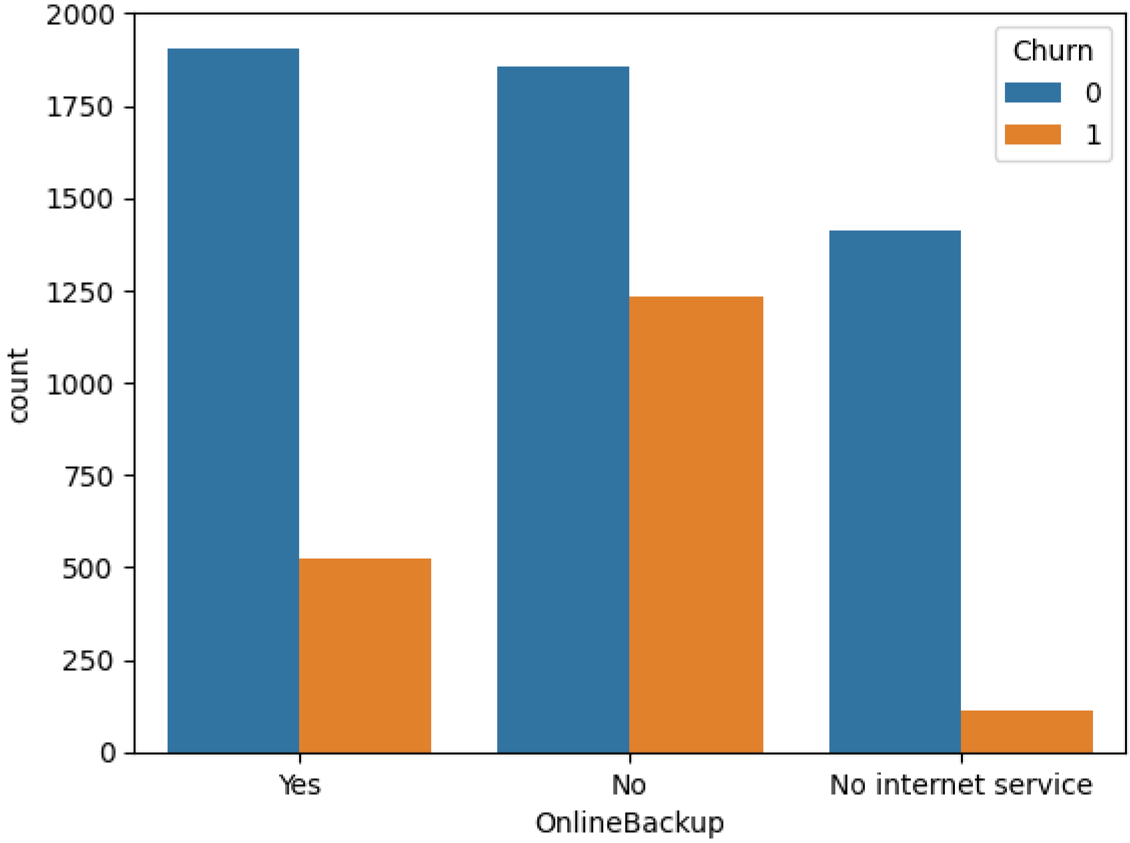

Churn
0
1
2500
2000
1500
1000
500
0
count
No phone service
No
Yes
MultipleLines



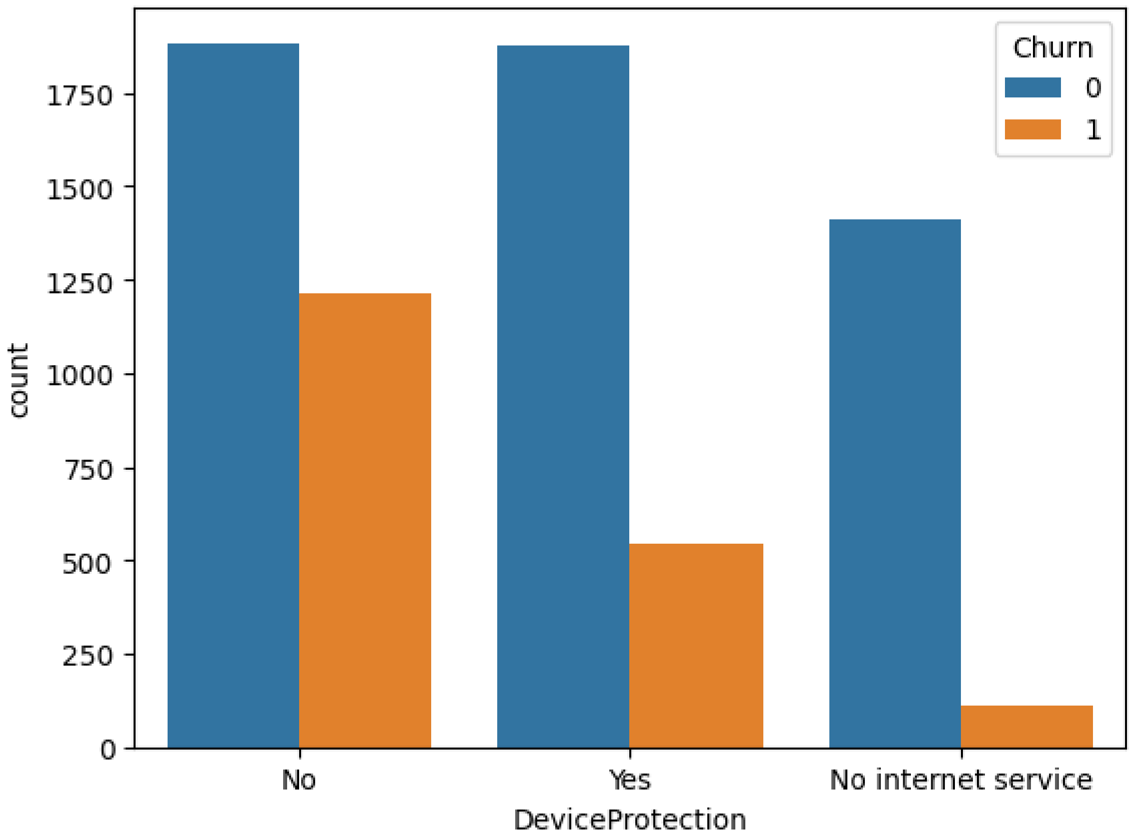
Churn
0
1
2000
1750
1500
1250
1000
750
500
250
0
count
DSL
Fiber optic
No
InternetService



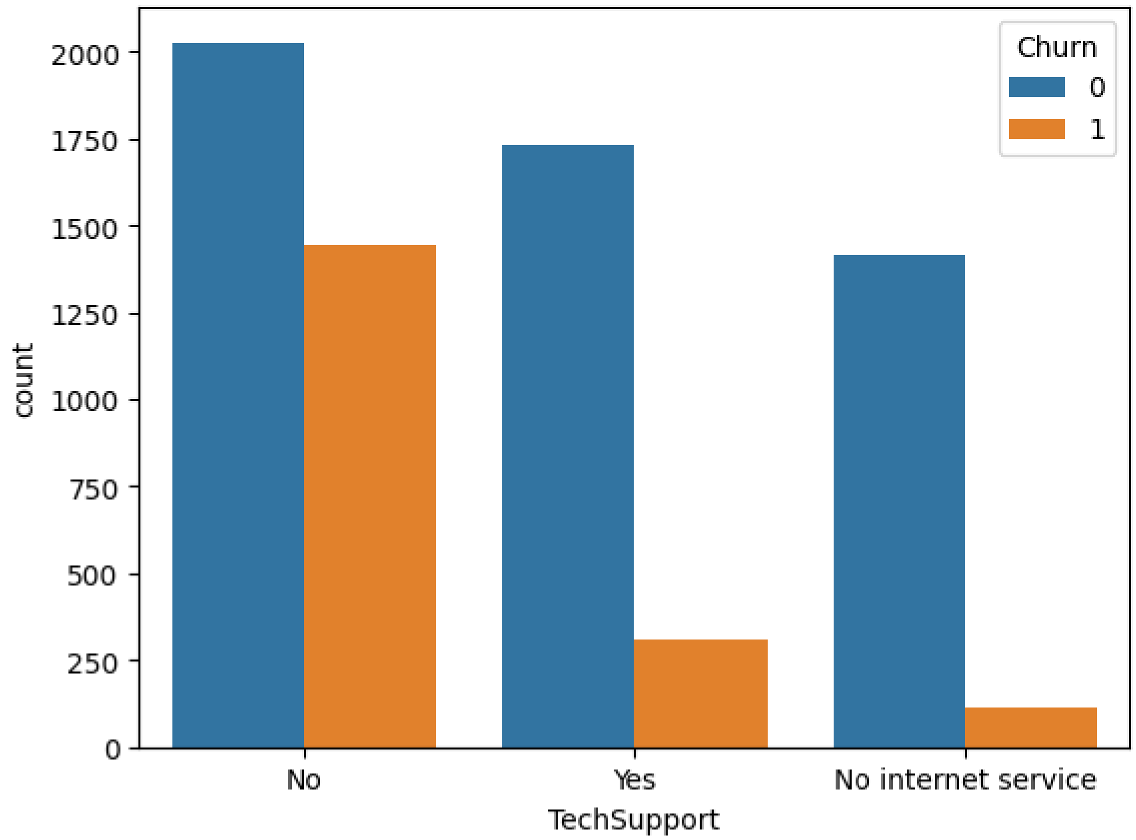
Churn
0
1
2000
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
OnlineSecurity

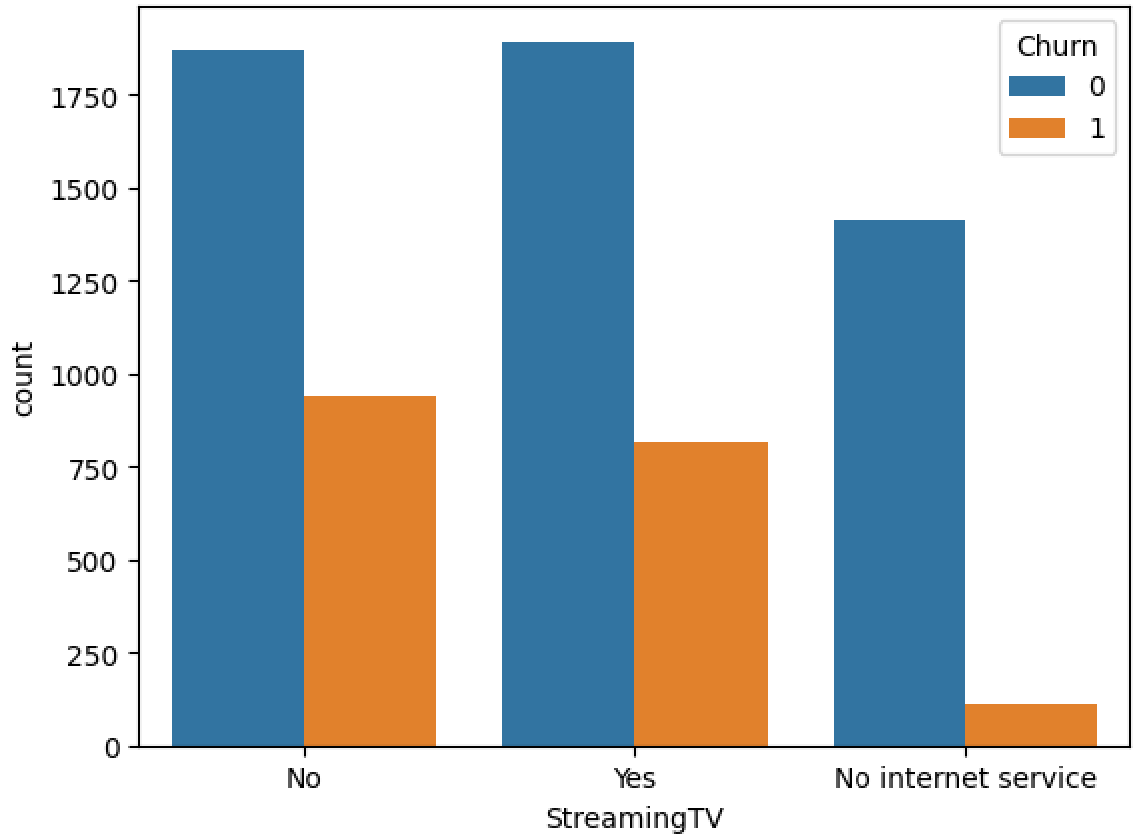


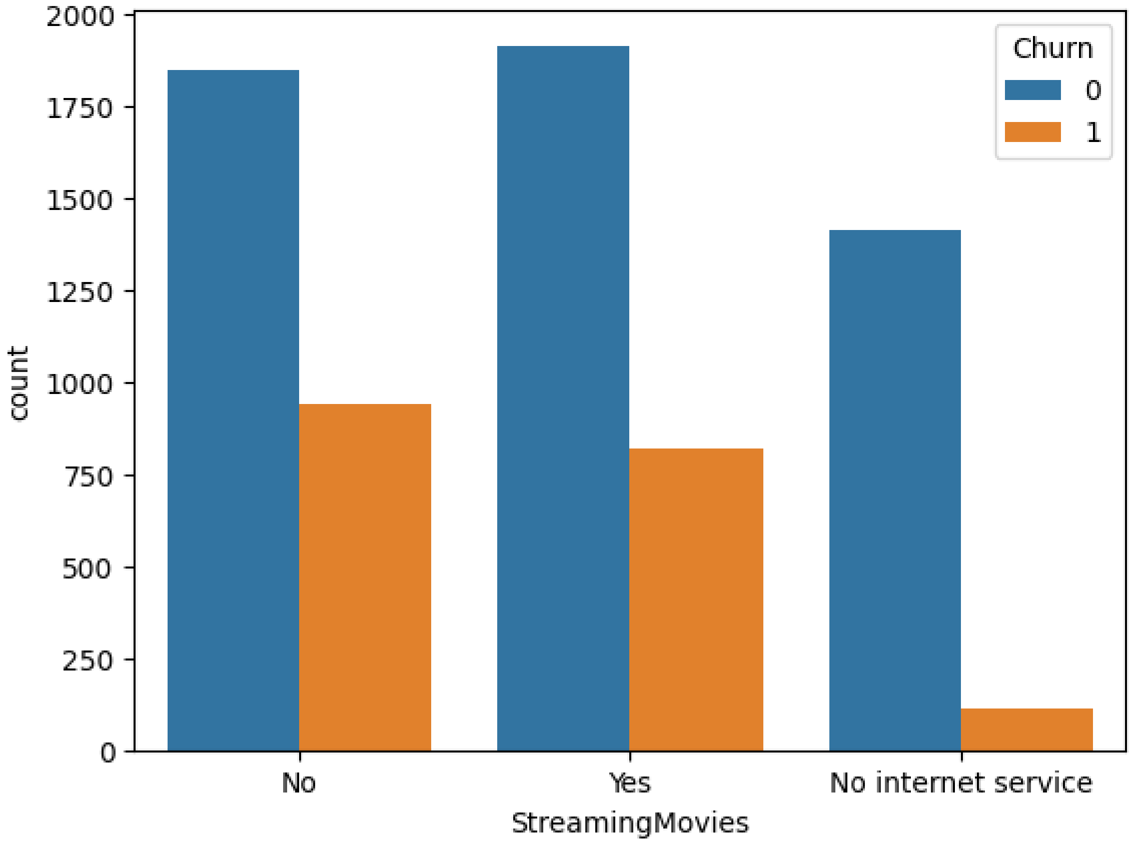
Churn
0
1
count
OnlineBackup
Yes
No
No internet service

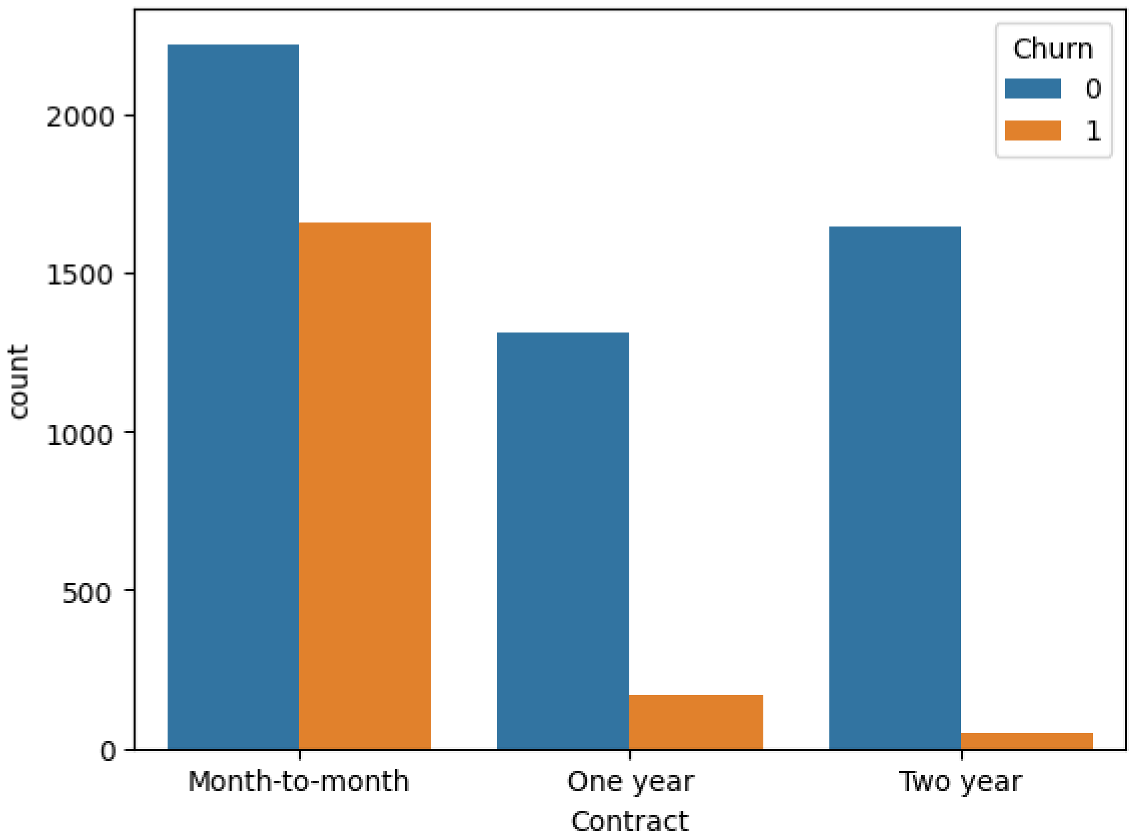


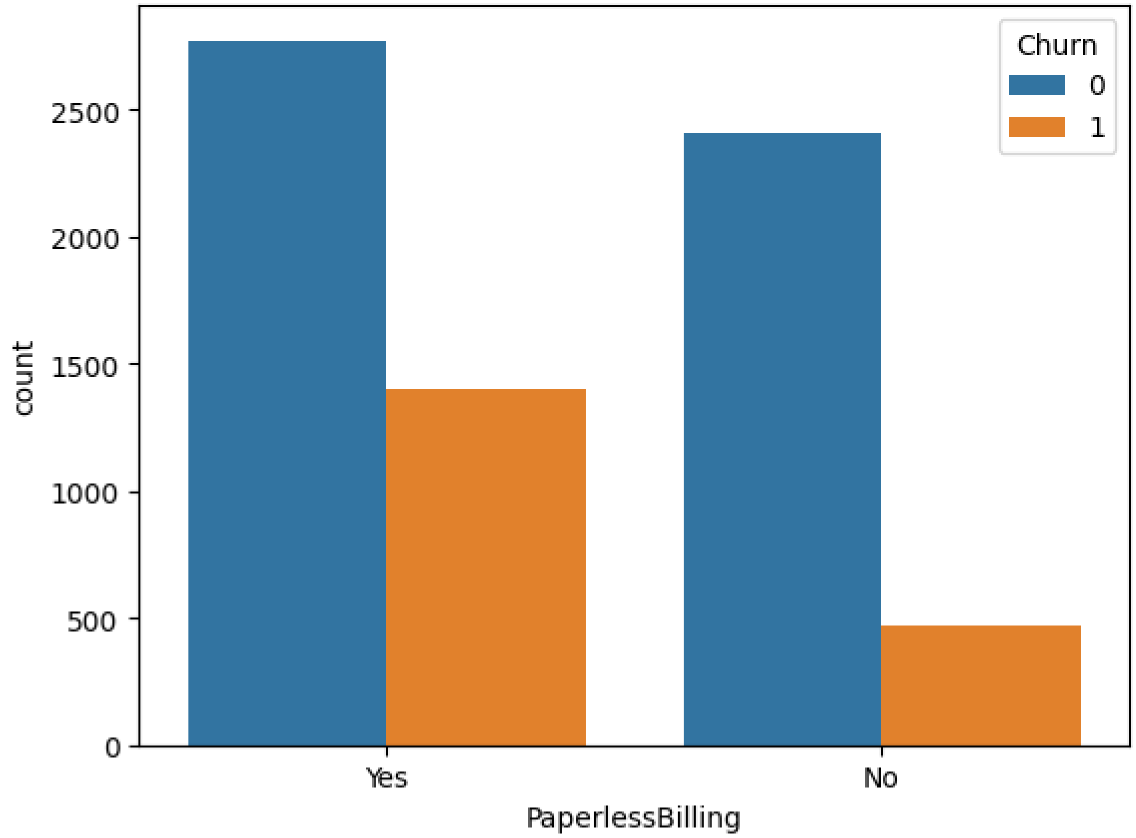
Churn
0
1
count
DeviceProtection
No
Yes
No internet service

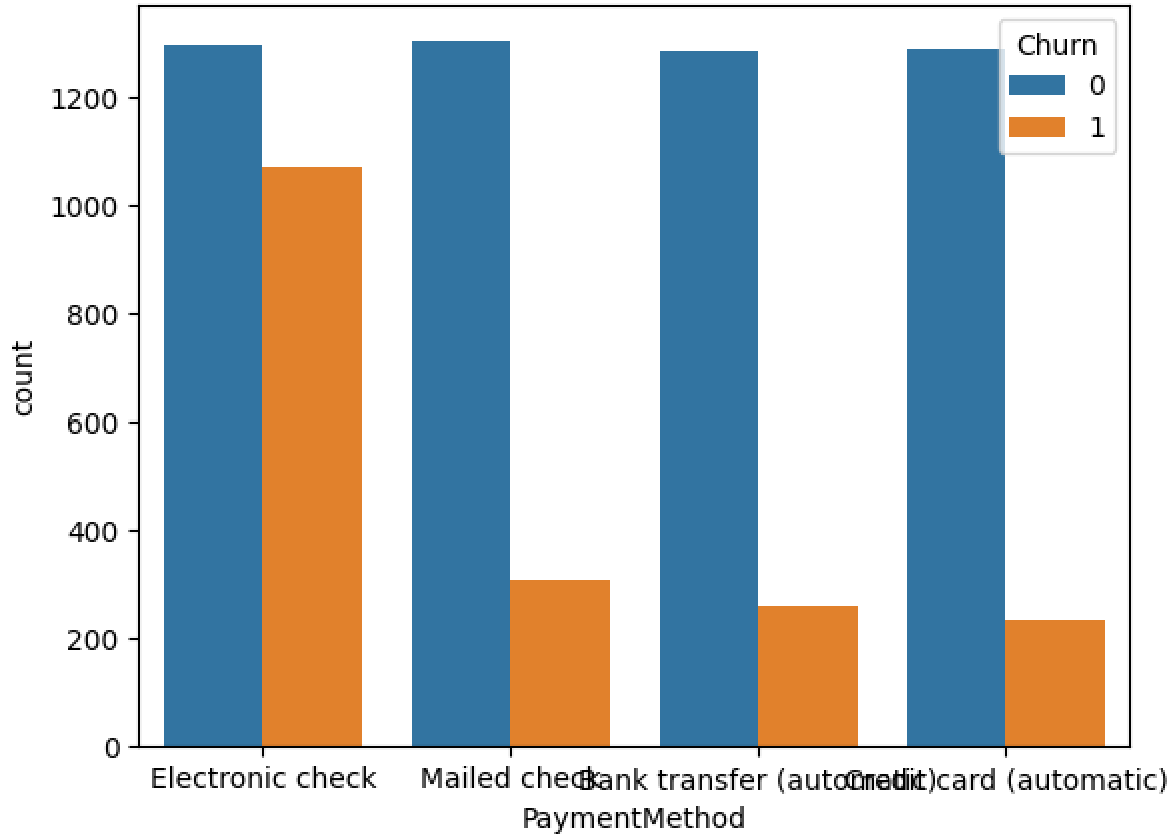

Churn
0
1
2000
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
TechSupport

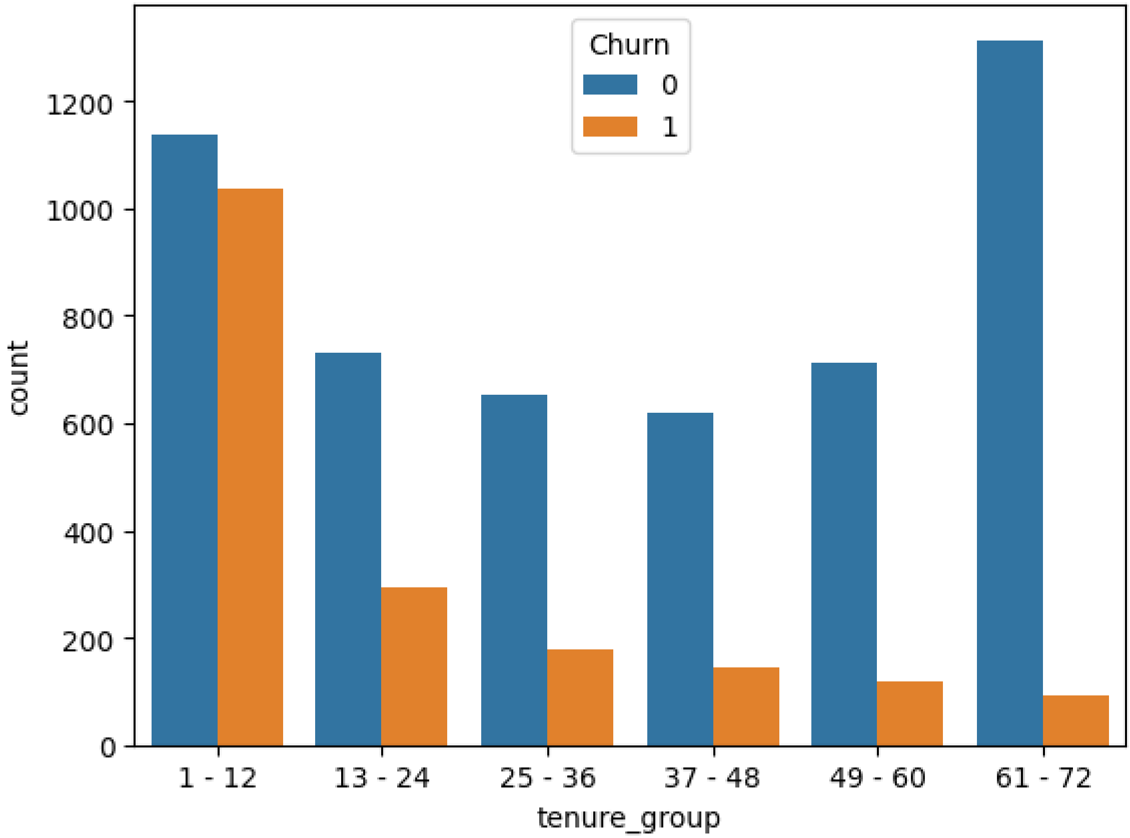

Churn
0
1
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
StreamingTV


2000
1750
1500
1250
1000
750
500
250
0
count
Churn
0
1
No
Yes
No internet service
StreamingMovies


2000
1500
1000
500
0
count
Churn
0
1
Month-to-month
One year
Two year
Contract


Churn
0
1
2500
2000
1500
1000
500
0
count
Yes
No
PaperlessBilling


Churn
0
1
1200
1000
800
600
400
200
0
count
Electronic check
PaymentMethod



Conclusions:

1) Senior Citizen are most likely to churn

2) People with no partners are more likely to churn

3) Monthly Contracted People are more likely to churn beacuse they are free customers

4) People who pay via Electronic Check are more likely to churn

Q: Show churn with respect to payment method?

In [32]:

```
pd.crosstab(data['PaymentMethod'],data['Churn'])
```

Out[32]:

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

Q: Convert column 'Churn' into binary numeric variable (Yes=1, No=0)

In [36]:

```
data['Churn']=data['Churn'].map({'Yes':1,'No':0})
```

Q: Relationship between Monthly Charges & Total Charges

In [41]:

```
data['MonthlyCharges'].corr(data['TotalCharges'])
```

Out[41]:

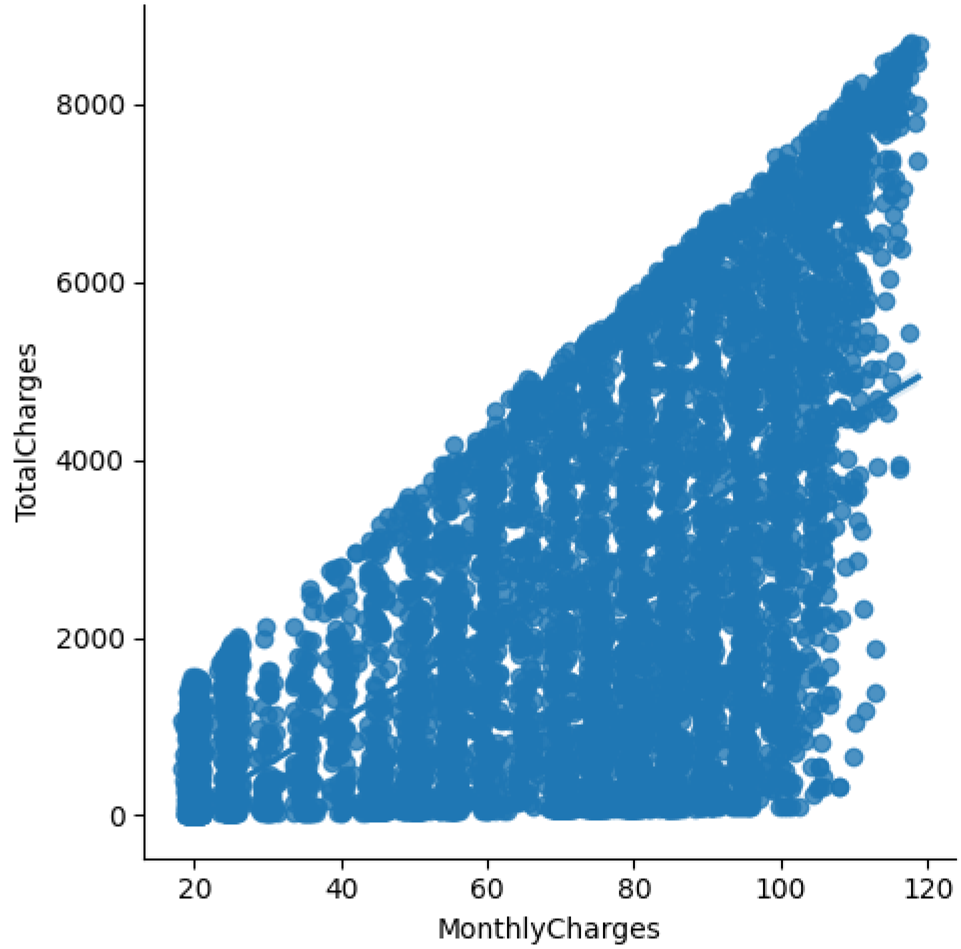
```
0.6510648032262025
```

In [40]:

```
sns.lmplot(data,x='MonthlyCharges',y='TotalCharges')
```

Out[40]:

```
<seaborn.axisgrid.FacetGrid at 0x1f140afd3d0>
```



Conclusion: Total Charges & Monthly Charges are +ve Co-Related

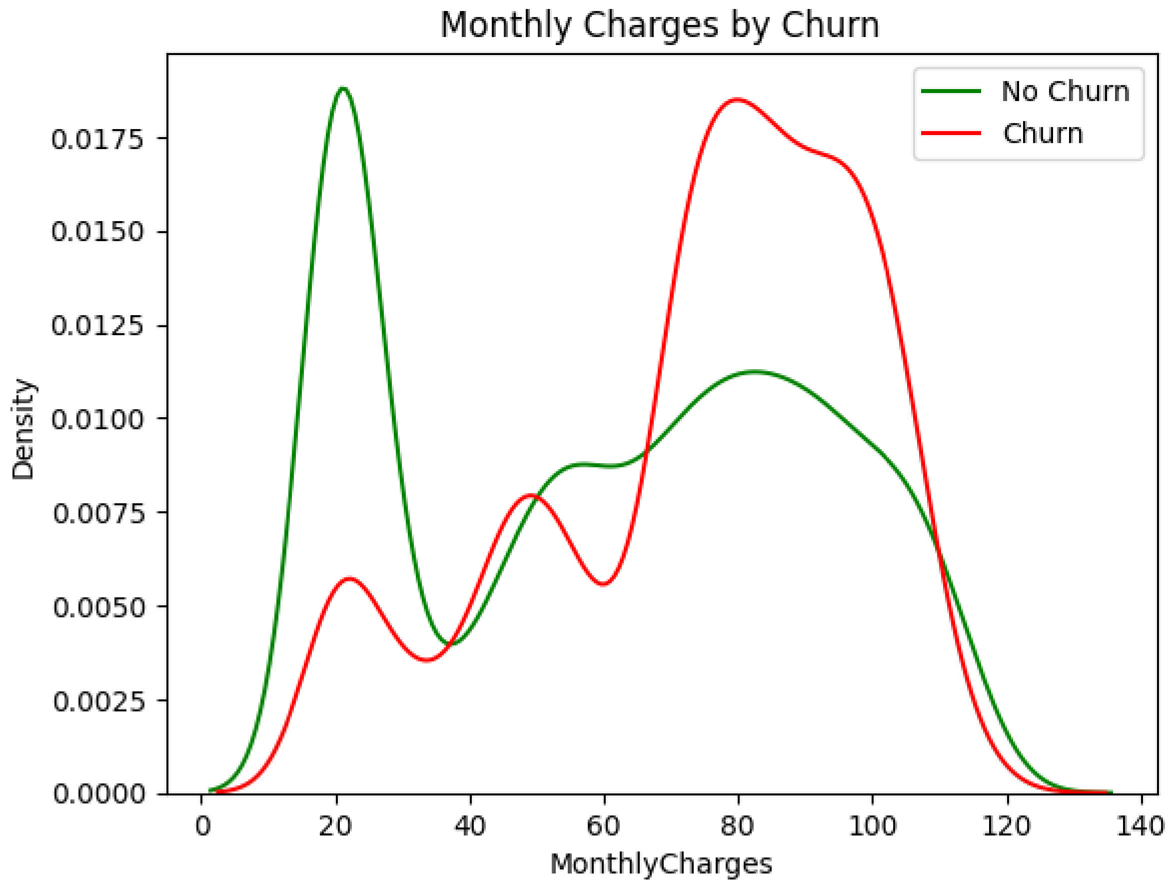
Q: Show Churn by Monthly Charges & Total Charges

In [51]:

```
ch=sns.kdeplot(data['MonthlyCharges'][(data['Churn']==0)],color='Green')
ch=sns.kdeplot(data['MonthlyCharges'][(data['Churn']==1)],color='Red')
ch.legend(['No Churn','Churn'])
ch.set_title('Monthly Charges by Churn')
```

Out[51]:

```
Text(0.5, 1.0, 'Monthly Charges by Churn')
```



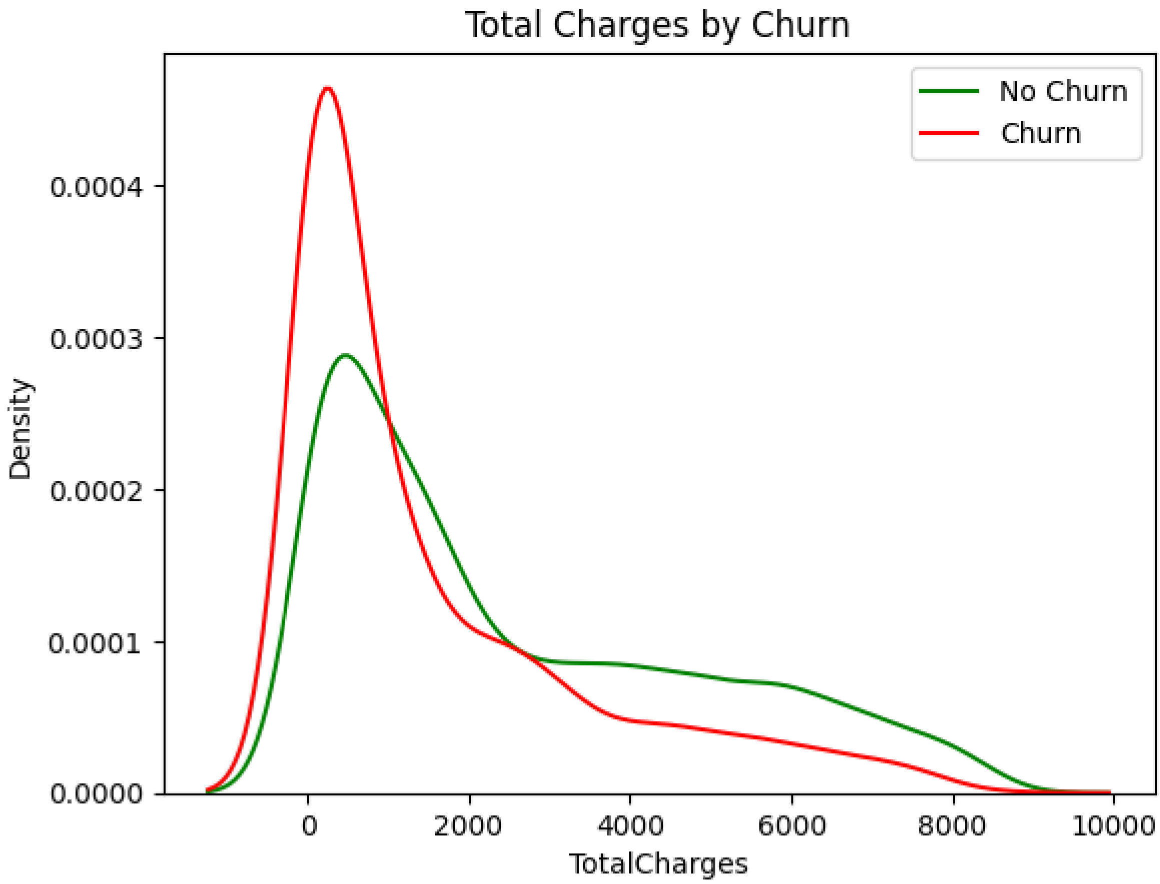
Conclusion: Churn is higher when Monthly Charges is higher

In [52]:

```
ch=sns.kdeplot(data['TotalCharges'][(data['Churn']==0)],color='Green')
ch=sns.kdeplot(data['TotalCharges'][(data['Churn']==1)],color='Red')
ch.legend(['No Churn','Churn'])
ch.set_title('Total Charges by Churn')
```

Out[52]:

```
Text(0.5, 1.0, 'Total Charges by Churn')
```



Conclusion: Churn is higher when Total Charges is low

Q: Show churn w.r.t gender

In [62]:

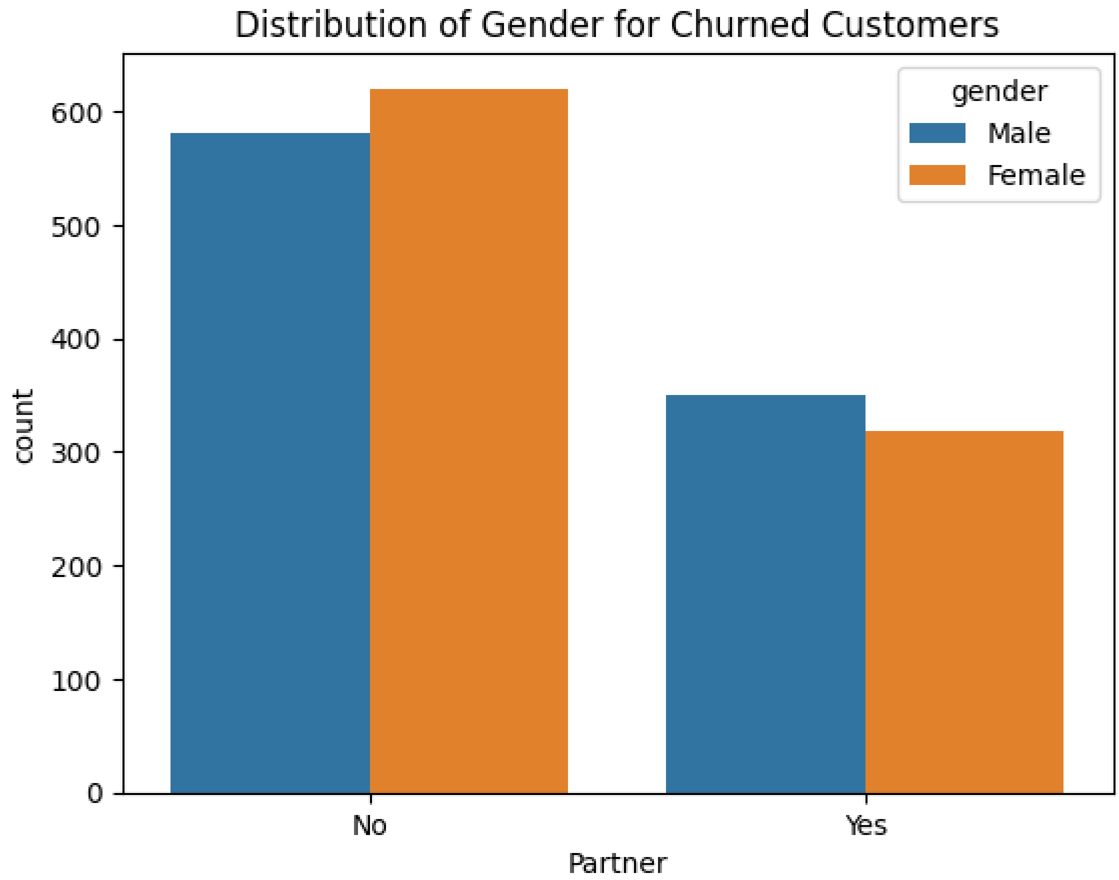
```
churn_z=data.loc[data['Churn']==0]
churn_o=data.loc[data['Churn']==1]
```

In [70]:

```
def uniplot(data,col,title,hue=None):
    plt.title(title)
    ax= sns.countplot(data,x=col,order=data[col].value_counts().index, hue=hue)
    plt.show()
```

In [71]:

```
uniplot(churn_o,col='Partner',title='Distribution of Gender for Churned Customers',hue='
```

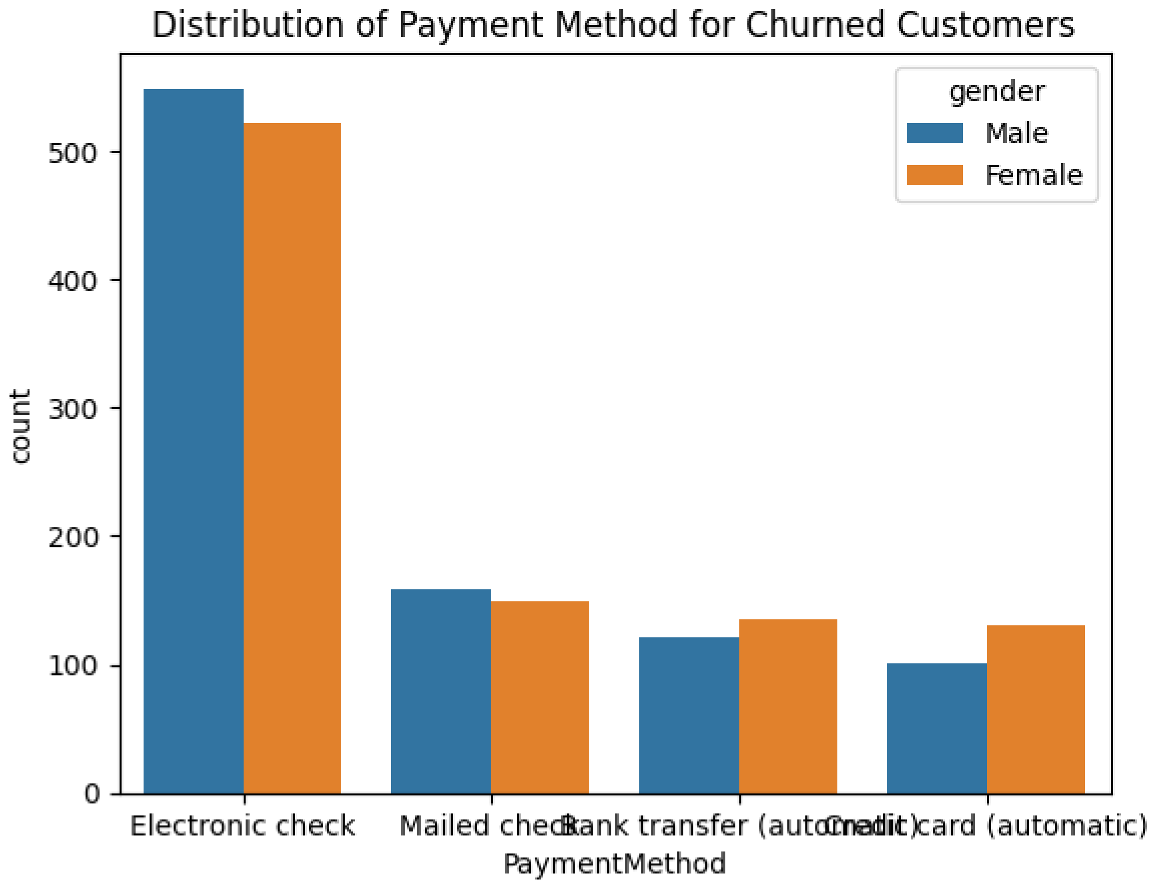


Conclusion: Female with no Partner have higher churn rate whereas Male with Partner have higher Churn rate

Q: Show churn w.r.t Payment Method

In [74]:

```
uniplot(churn_o,col='PaymentMethod',title='Distribution of Payment Method for Churned Cu
```



Conclusion: Male who pays via Electronic Check have higher Churn rate whereas Female who pays via 'Credit card (automatic)' have higher churn rate