Churn Analysis

November 22, 2024

[5]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.ticker as mtick
import matplotlib.pyplot as plt
%matplotlib inline
```

[6]:
```
telco_base_data=pd.read_csv('churn.csv')
#loading the file
```

[7]:
```
telco_base_data.head()
#looking at the top 5 records of  the data
```

[7]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	…	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	7590-VHVEG	Female	0	Yes	No	1	No	…	No	No	No	No	Month-to-month	Yes	Electronic check	29.85	29.85	No
1	5575-GNVDE	Male	0	No	No	34	Yes	…	Yes	No	No	No	One year	No	Mailed check	56.95	1889.5	No
2	3668-QPYBK	Male	0	No	No	2	Yes	…	No	No	No	No	Month-to-month	Yes	Mailed check	53.85	108.15	Yes
3	7795-CFOCW	Male	0	No	No	45	No	…	Yes	Yes	No	No	One year	No	Bank transfer (automatic)	42.30	1840.75	No
4	9237-HQITU	Female	0	No	No	2	Yes	…	No	No	No	No	Month-to-month	Yes	Electronic check	70.70	151.65	Yes

```
3  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

[8]:
```
telco_base_data.shape

#checking no. of rows and columns
```

[8]:
```
(7043, 21)
```

[9]:
```
telco_base_data.columns.values
#checking columns
```

[9]:
```
array(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
       'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges',
       'TotalCharges', 'Churn'], dtype=object)
```

[10]:
```
telco_base_data.dtypes
#checking data types of columns
```

[10]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

[11]:
```
telco_base_data.describe()
#viewing statictics of numerical data
```

[11]:

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

[12]:
```
telco_base_data['Churn'].value_counts()
#count of YES and NO
```

[12]:
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

[13]:
```
#clearly it is a imbalance data as no. of NO is much greater than no. of YES
```

[14]:
```
100*telco_base_data['Churn'].value_counts()/len(telco_base_data['Churn'])
#YES ,NO percentage
```

[14]:
```
Churn
No     73.463013
Yes    26.536987
Name: count, dtype: float64
```

[15]:
```
#Yes:NO ratio is appx 27:73 , highly imbalanced
```

[16]:
```
telco_base_data.info(verbose=True)
#viewing no of non null objects in each column
```

```
<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
```

[17]:
```
telco_base_data.TotalCharges=pd.to_numeric(telco_base_data.
 ↪TotalCharges,errors='coerce')
telco_base_data.isnull().sum()
#converting onject data into numeric and again finding null values
```

[17]:
```
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
```

[18]:
```
#11 values are null values, viewing in records
```

[19]:
```
telco_base_data.loc[telco_base_data['TotalCharges'].isnull()==True]
```

[19]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	\
488	4472-LVYGI	Female	0	Yes	Yes	0	
753	3115-CZMZD	Male	0	No	Yes	0	
936	5709-LVOEQ	Female	0	Yes	Yes	0	
1082	4367-NUYAO	Male	0	Yes	Yes	0	
1340	1371-DWPAZ	Female	0	Yes	Yes	0	
3331	7644-OMVMY	Male	0	Yes	Yes	0	
3826	3213-VVOLG	Male	0	Yes	Yes	0	
4380	2520-SGTTA	Female	0	Yes	Yes	0	
5218	2923-ARZLG	Male	0	Yes	Yes	0	
6670	4075-WKNIU	Female	0	Yes	Yes	0	
6754	2775-SEFEE	Male	0	No	Yes	0	

	PhoneService	MultipleLines	InternetService	OnlineSecurity	…	\
488	No	No phone service	DSL	Yes	…	
753	Yes	No	No	No internet service	…	
936	Yes	No	DSL	Yes	…	
1082	Yes	Yes	No	No internet service	…	
1340	No	No phone service	DSL	Yes	…	
3331	Yes	No	No	No internet service	…	
3826	Yes	Yes	No	No internet service	…	
4380	Yes	No	No	No internet service	…	
5218	Yes	No	No	No internet service	…	
6670	Yes	Yes	DSL	No	…	
6754	Yes	Yes	DSL	Yes	…	

	DeviceProtection	TechSupport	StreamingTV	\
488	Yes	Yes	Yes	
753	No internet service	No internet service	No internet service	
936	Yes	No	Yes	
1082	No internet service	No internet service	No internet service	
1340	Yes	Yes	Yes	
3331	No internet service	No internet service	No internet service	
3826	No internet service	No internet service	No internet service	
4380	No internet service	No internet service	No internet service	
5218	No internet service	No internet service	No internet service	
6670	Yes	Yes	Yes	
6754	No	Yes	No	

	StreamingMovies	Contract	PaperlessBilling	\
488	No	Two year	Yes	
753	No internet service	Two year	No	
936	Yes	Two year	No	
1082	No internet service	Two year	No	
1340	No	Two year	No	
3331	No internet service	Two year	No	
3826	No internet service	Two year	No	

```
4380  No internet service  Two year              No
5218  No internet service  One year             Yes
6670                   No  Two year              No
6754                   No  Two year             Yes

                  PaymentMethod MonthlyCharges  TotalCharges  Churn
488   Bank transfer (automatic)          52.55           NaN     No
753                Mailed check          20.25           NaN     No
936                Mailed check          80.85           NaN     No
1082               Mailed check          25.75           NaN     No
1340    Credit card (automatic)          56.05           NaN     No
3331               Mailed check          19.85           NaN     No
3826               Mailed check          25.35           NaN     No
4380               Mailed check          20.00           NaN     No
5218               Mailed check          19.70           NaN     No
6670               Mailed check          73.35           NaN     No
6754  Bank transfer (automatic)          61.90           NaN     No

[11 rows x 21 columns]
```

[20]:
```
#only 11 missing valuess, ie. 0.15% so dropping these rows
telco_base_data.dropna(how='any',inplace=True)
```

[21]:
```
# creating bins/groups for tenure for easy analysis
```

[22]:
```
#finding max of tenure
print(telco_base_data['tenure'].max())
```

```
72
```

[23]:
```
#making groups of 12 months
labels=["{0}-{1}".format(i,i+11) for i in range(1,72,12)]
telco_base_data['tenure_group']=pd.cut(telco_base_data.tenure,range(1,80,12),␣
 ↪right=False,labels=labels)
```

[24]:
```
telco_base_data['tenure_group'].value_counts()
```

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

[25]:
```
# removing useless columns , for ex - name, customer id
```

[26]:
```
telco_base_data.drop(columns=['customerID', 'tenure'], axis=1, inplace=True)
telco_base_data.head()
```

[26]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	\
0	Female	0	Yes	No	No	No phone service	
1	Male	0	No	No	Yes	No	
2	Male	0	No	No	Yes	No	
3	Male	0	No	No	No	No phone service	
4	Female	0	No	No	Yes	No	

	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	\
0	DSL	No	Yes	No	No	
1	DSL	Yes	No	Yes	No	
2	DSL	Yes	Yes	No	No	
3	DSL	Yes	No	Yes	Yes	
4	Fiber optic	No	No	No	No	

	StreamingTV	StreamingMovies	Contract	PaperlessBilling	\
0	No	No	Month-to-month	Yes	
1	No	No	One year	No	
2	No	No	Month-to-month	Yes	
3	No	No	One year	No	
4	No	No	Month-to-month	Yes	

	PaymentMethod	MonthlyCharges	TotalCharges	Churn	tenure_group
0	Electronic check	29.85	29.85	No	1-12
1	Mailed check	56.95	1889.50	No	25-36
2	Mailed check	53.85	108.15	Yes	1-12
3	Bank transfer (automatic)	42.30	1840.75	No	37-48
4	Electronic check	70.70	151.65	Yes	1-12

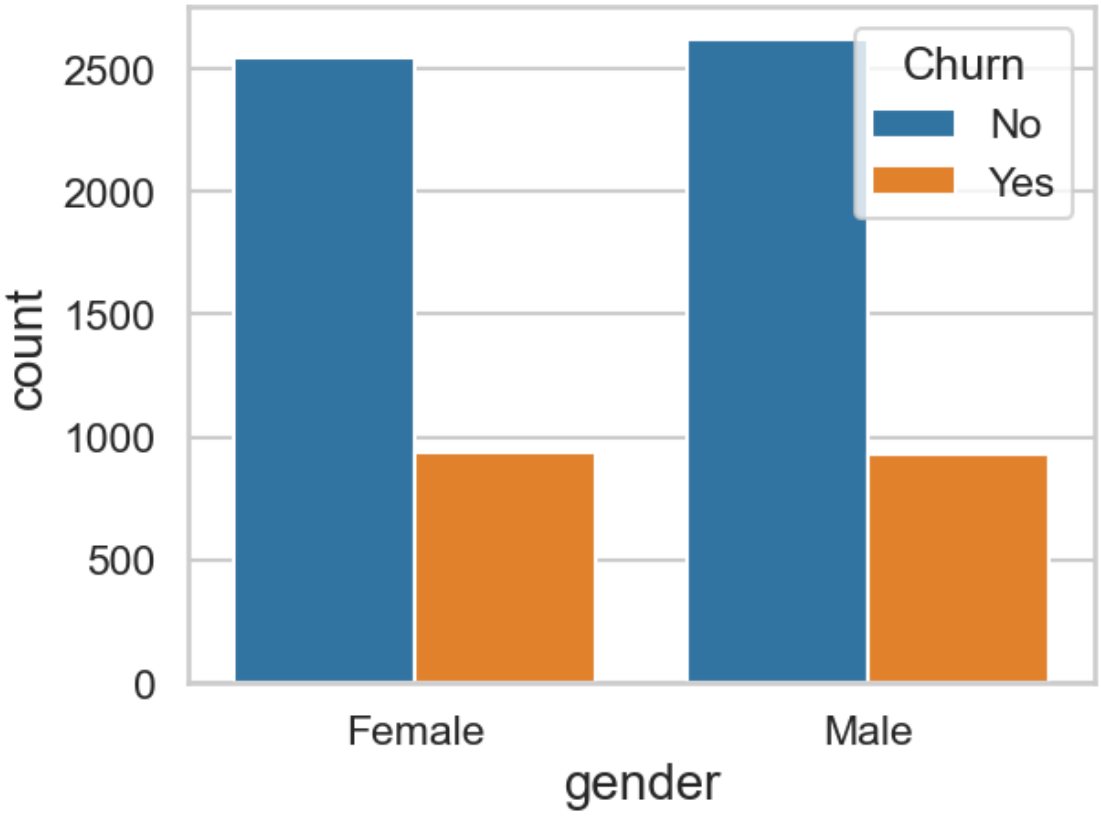
[27]:
```
# data exploration
```

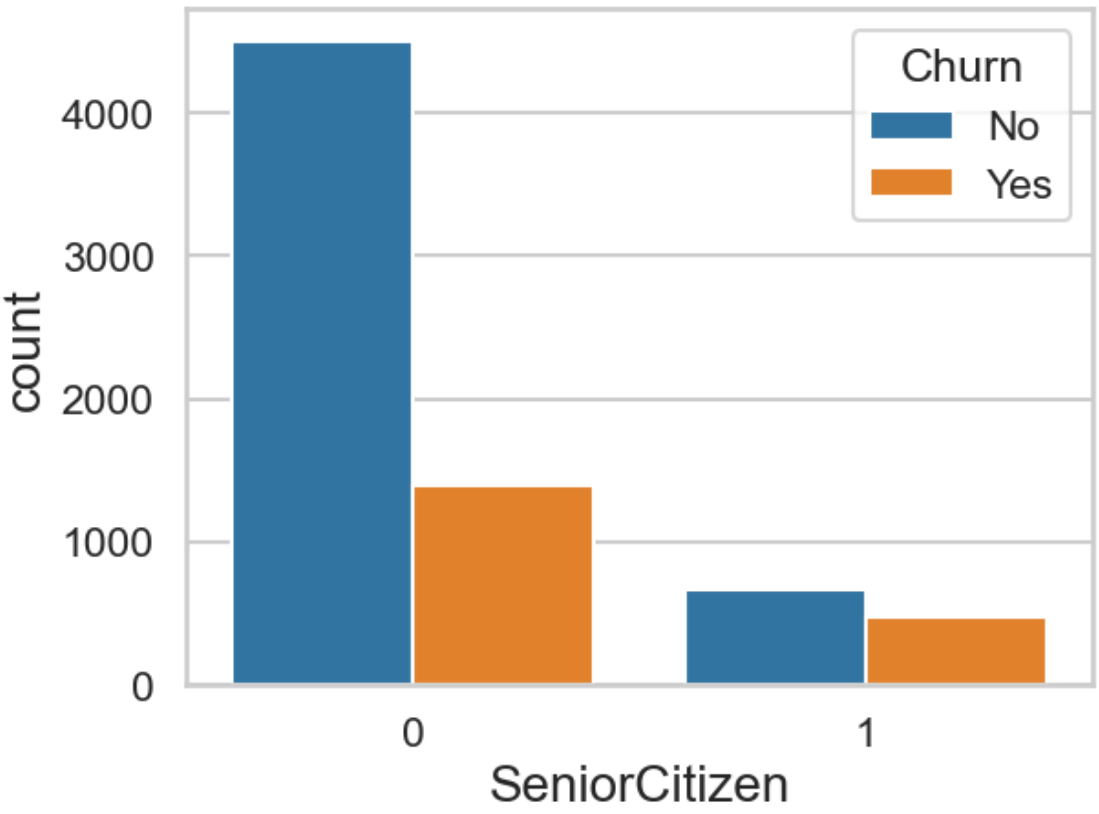
[28]:
```
#univariate analysis
```

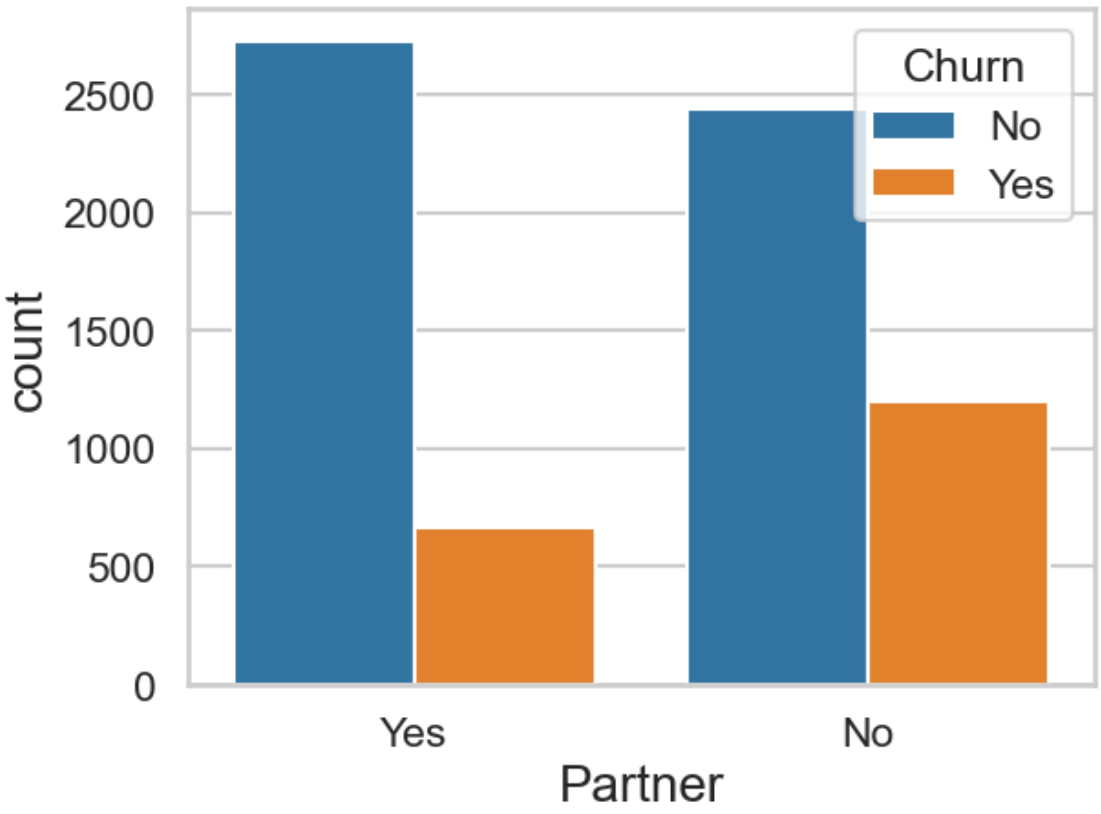
[151]:
```
#plotting count of churners and non churners wrt each column
for i, predictor in enumerate(telco_base_data.
 ↪drop(columns=['Churn','TotalCharges','MonthlyCharges'])):
   plt.figure(i)
   sns.countplot(data=telco_base_data,x=predictor,hue='Churn')
```

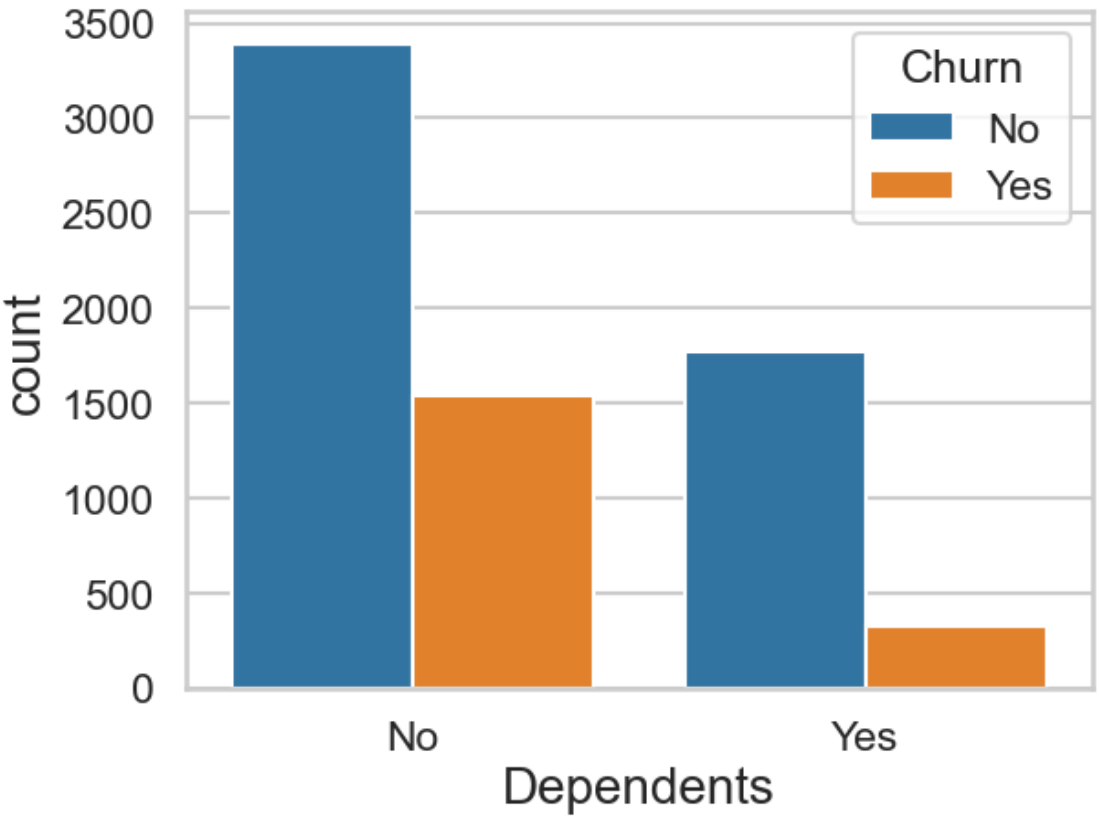
```
C:\Users\Aditya\anaconda3\Lib\site-packages\seaborn\categorical.py:641:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_vals = vals.groupby(grouper)
C:\Users\Aditya\anaconda3\Lib\site-packages\seaborn\categorical.py:641:
FutureWarning: The default of observed=False is deprecated and will be changed
```

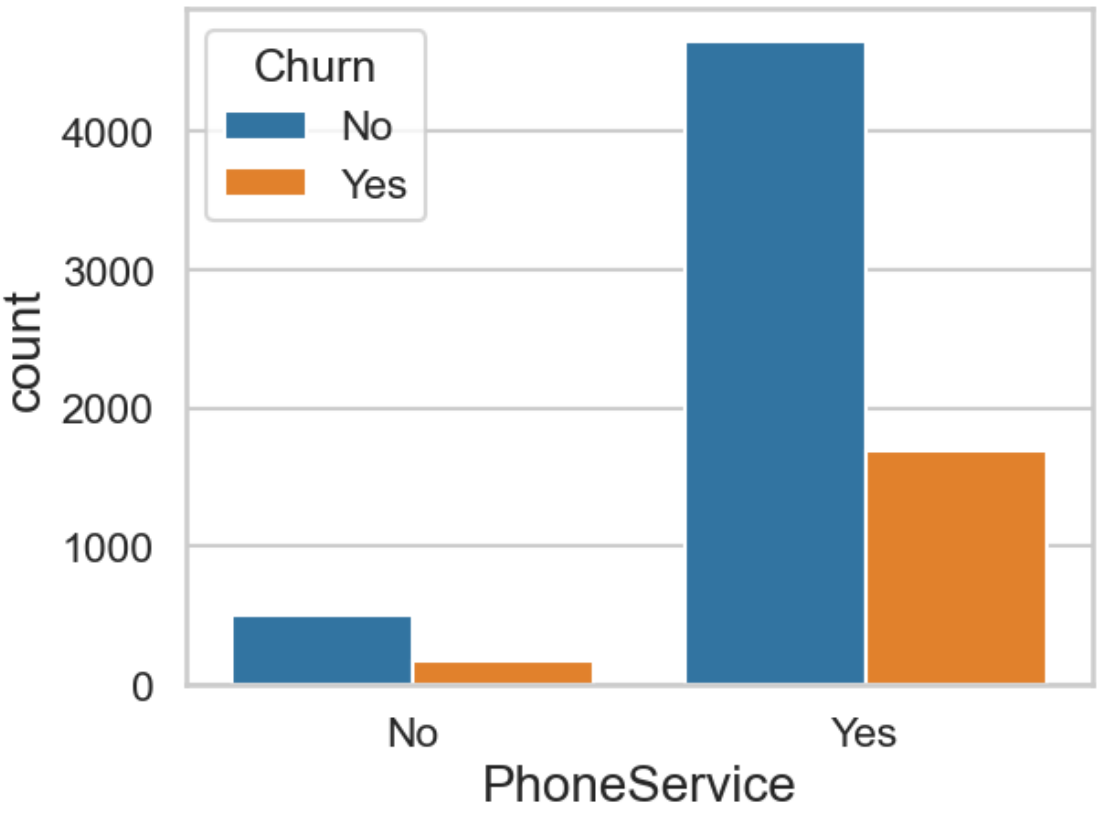
```
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_vals = vals.groupby(grouper)
```

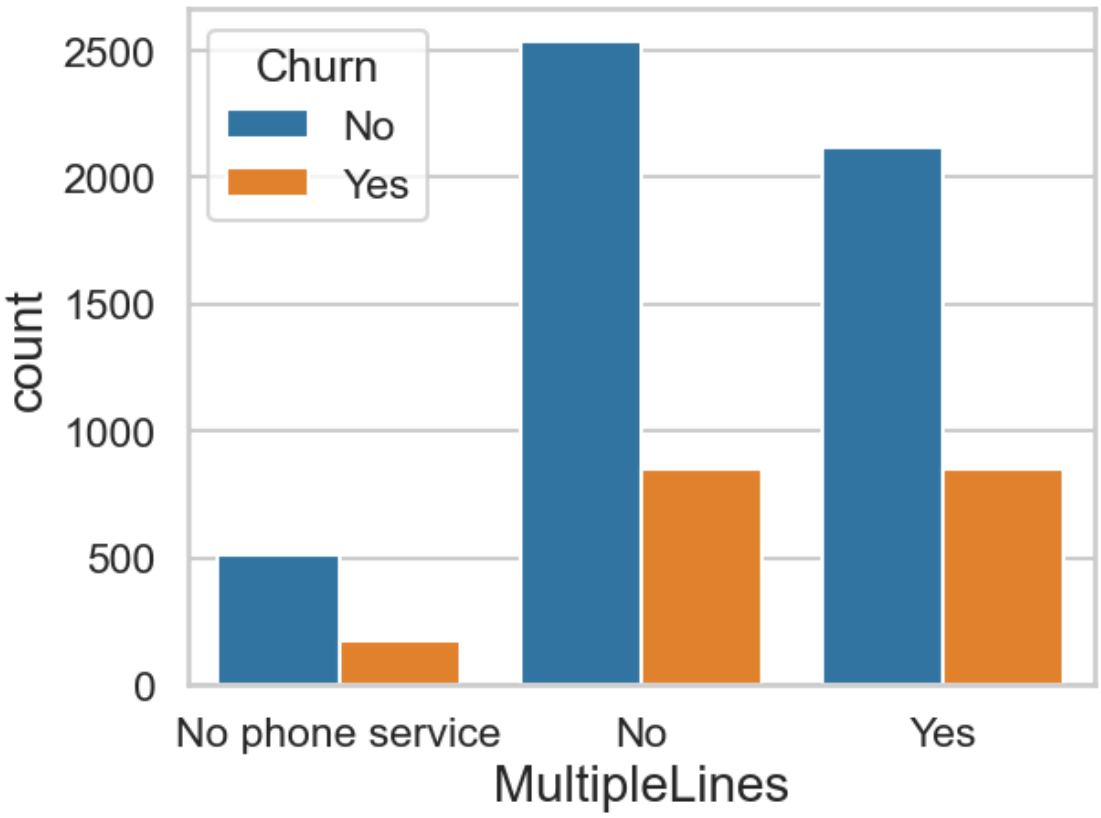


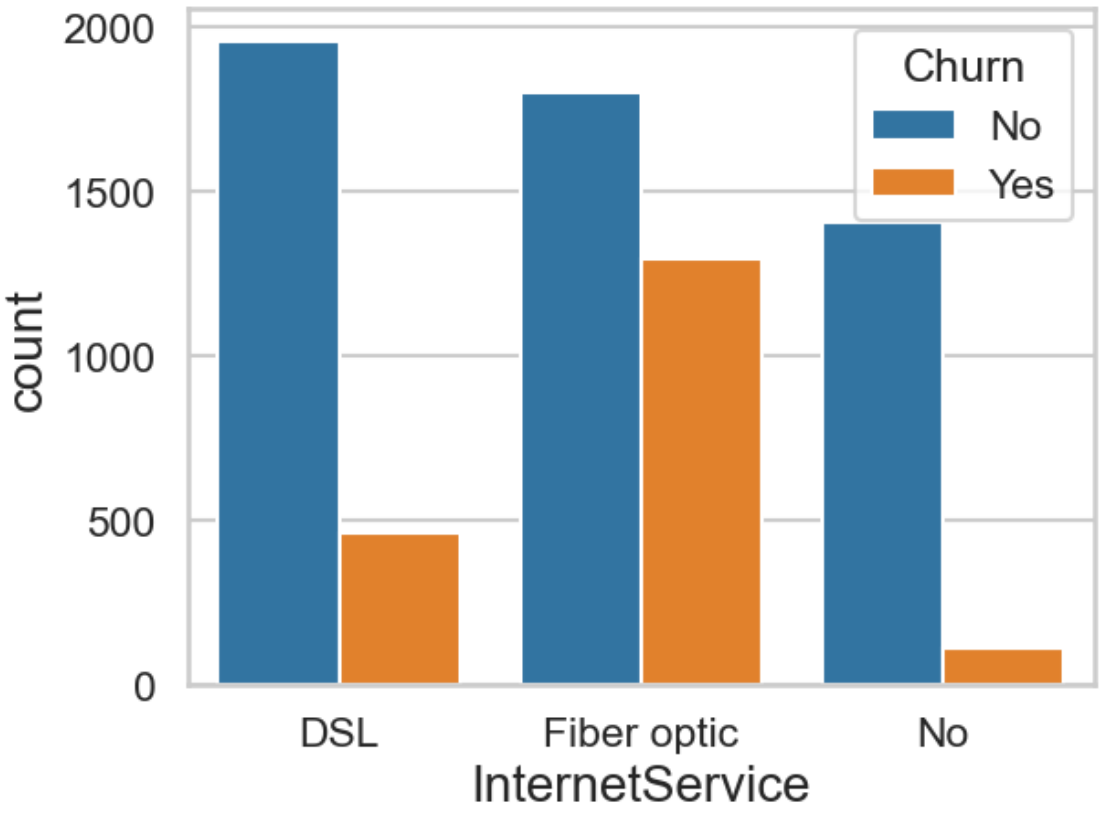

Churn
No
Yes
4000
3000
2000
1000
0
count
0
1
SeniorCitizen

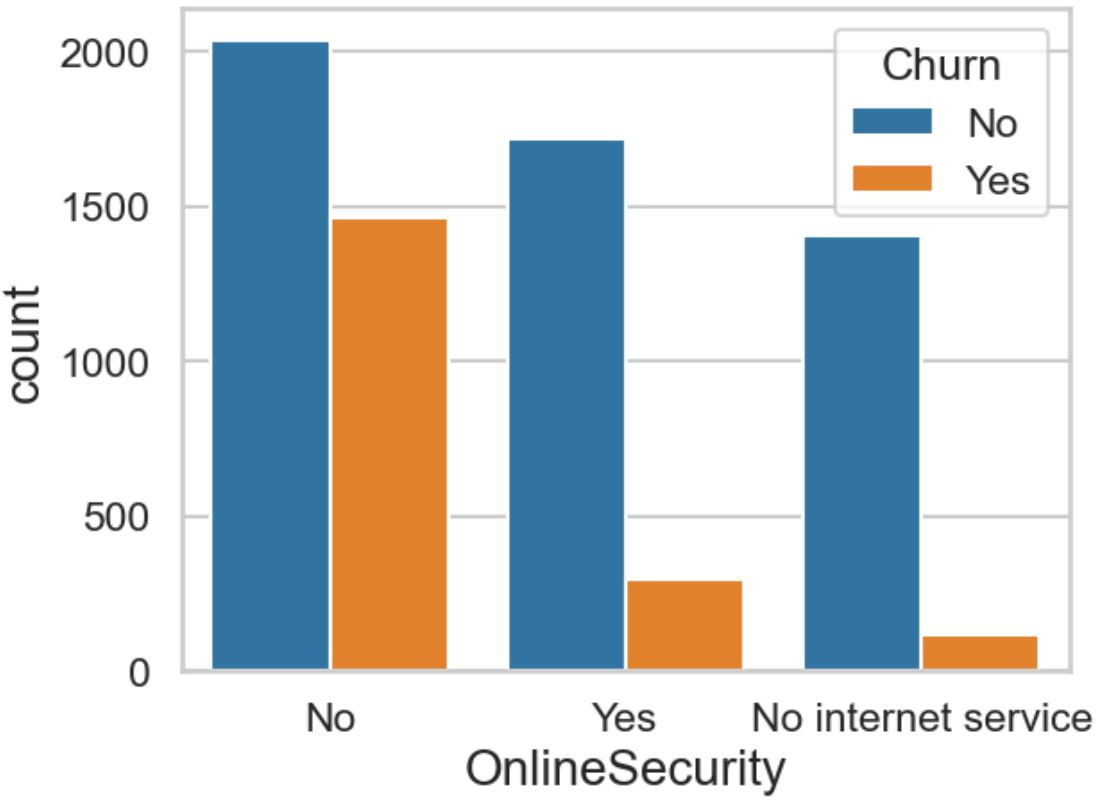

Churn
No
Yes
2500
2000
1500
1000
500
0
count
Yes
No
Partner

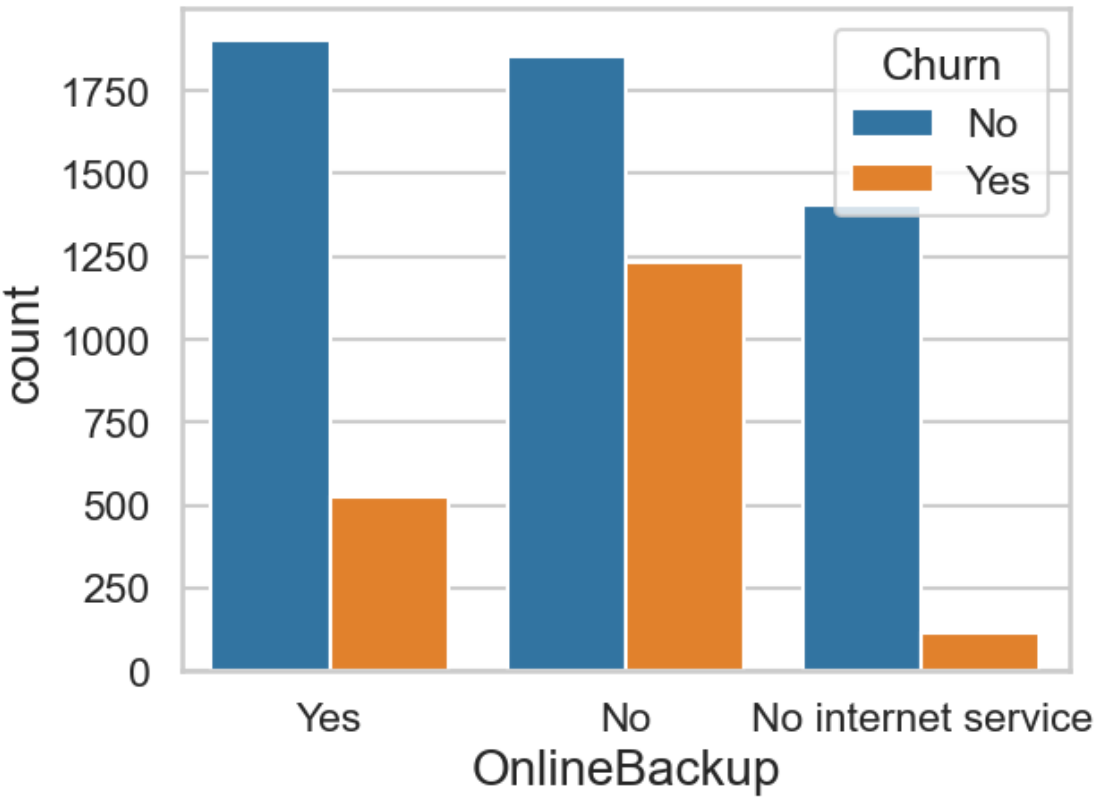

3500
3000
2500
2000
1500
1000
500
0
count
Churn
No
Yes
No
Yes
Dependents

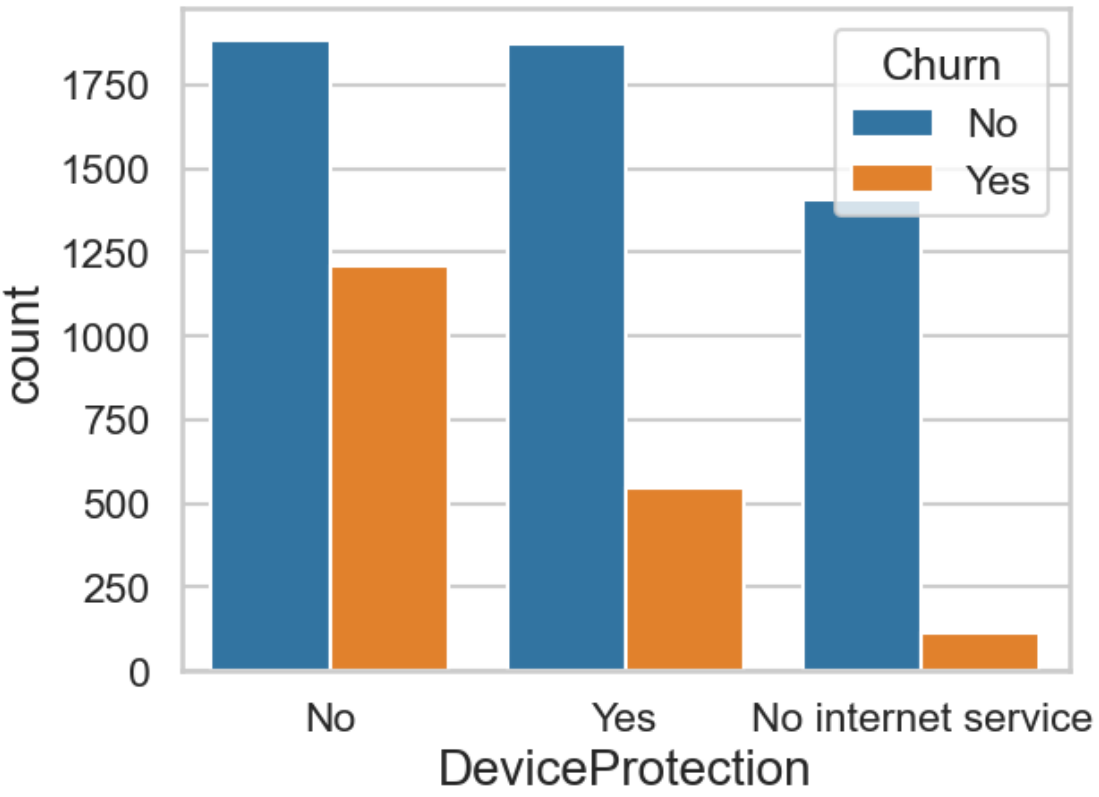

Churn
No
Yes
4000
3000
2000
1000
0
count
No
Yes
PhoneService

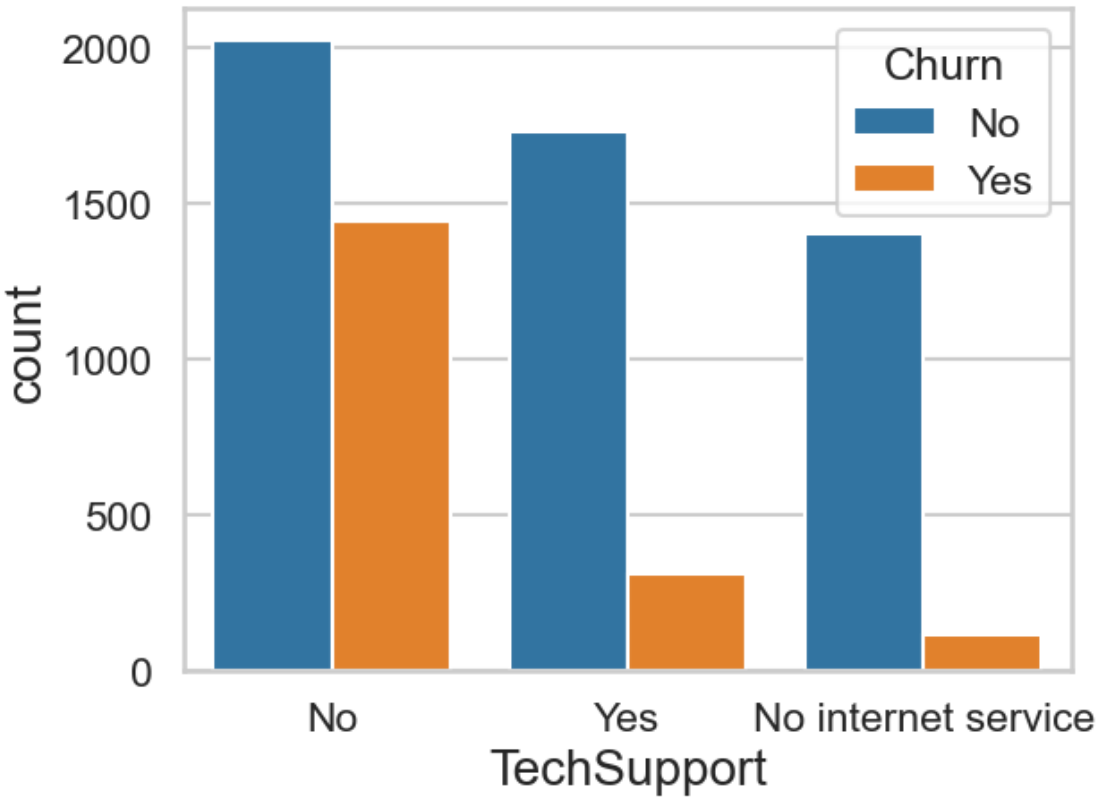

Churn
No
Yes
2500
2000
1500
1000
500
0
count
No phone service
No
Yes
MultipleLines

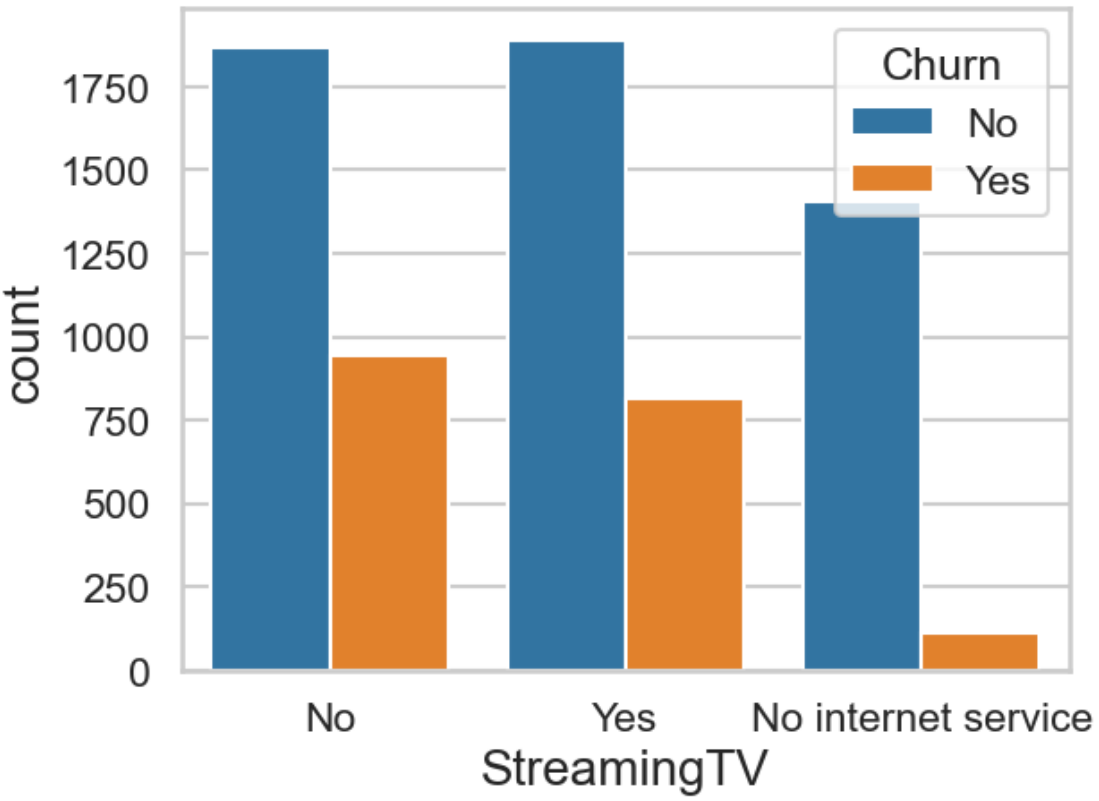

2000
1500
1000
500
0
count
Churn
No
Yes
DSL
Fiber optic
No
InternetService

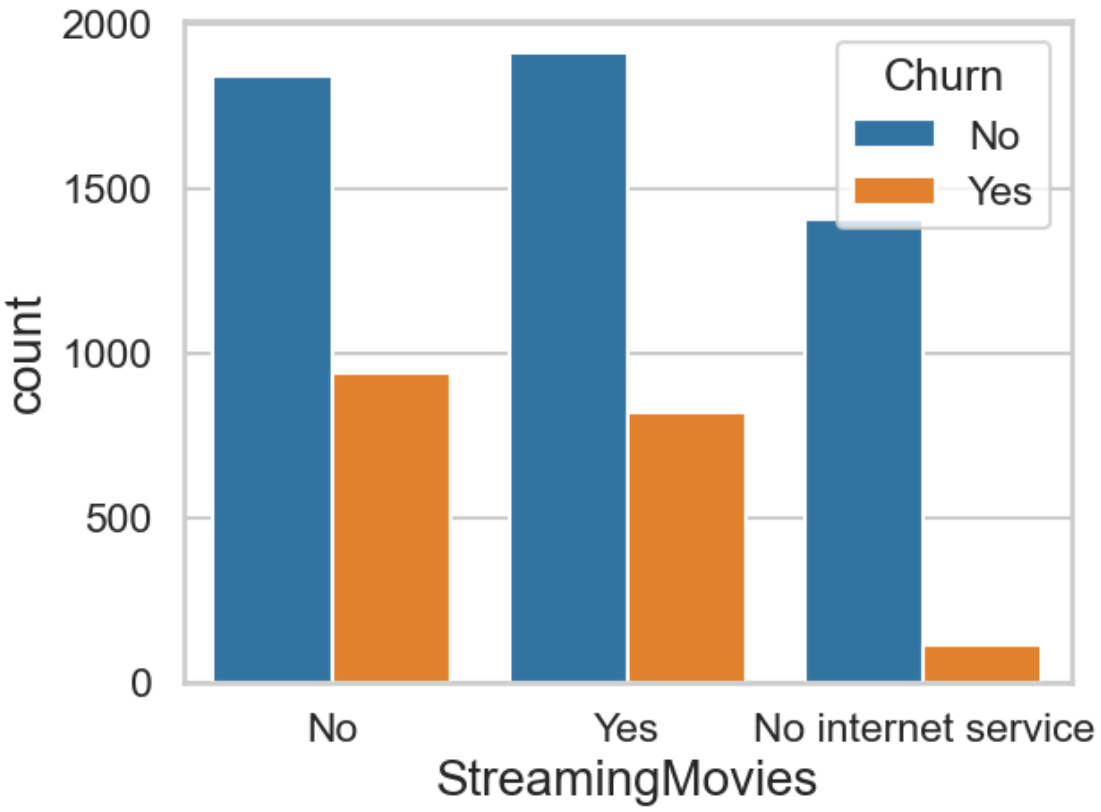

Churn
No
Yes
2000
1500
1000
500
0
count
No
Yes
No internet service
OnlineSecurity

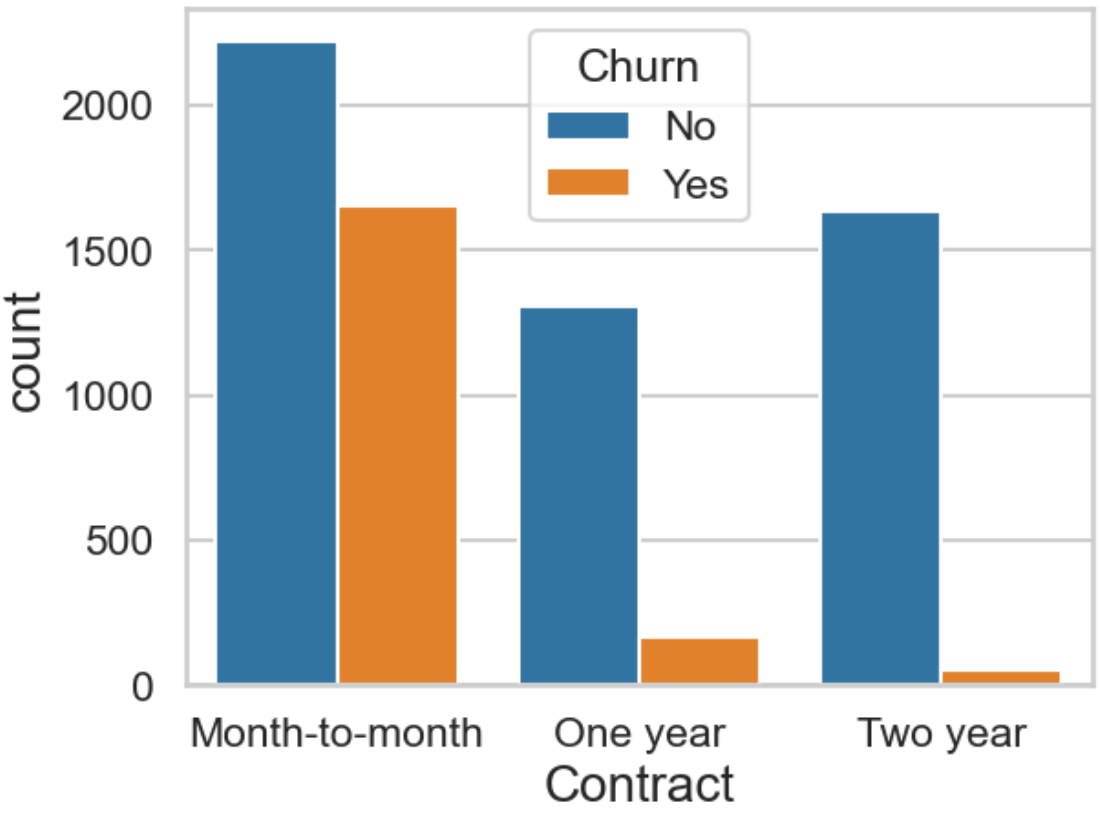

Churn
No
Yes
count
1750
1500
1250
1000
750
500
250
0
Yes
No
No internet service
OnlineBackup

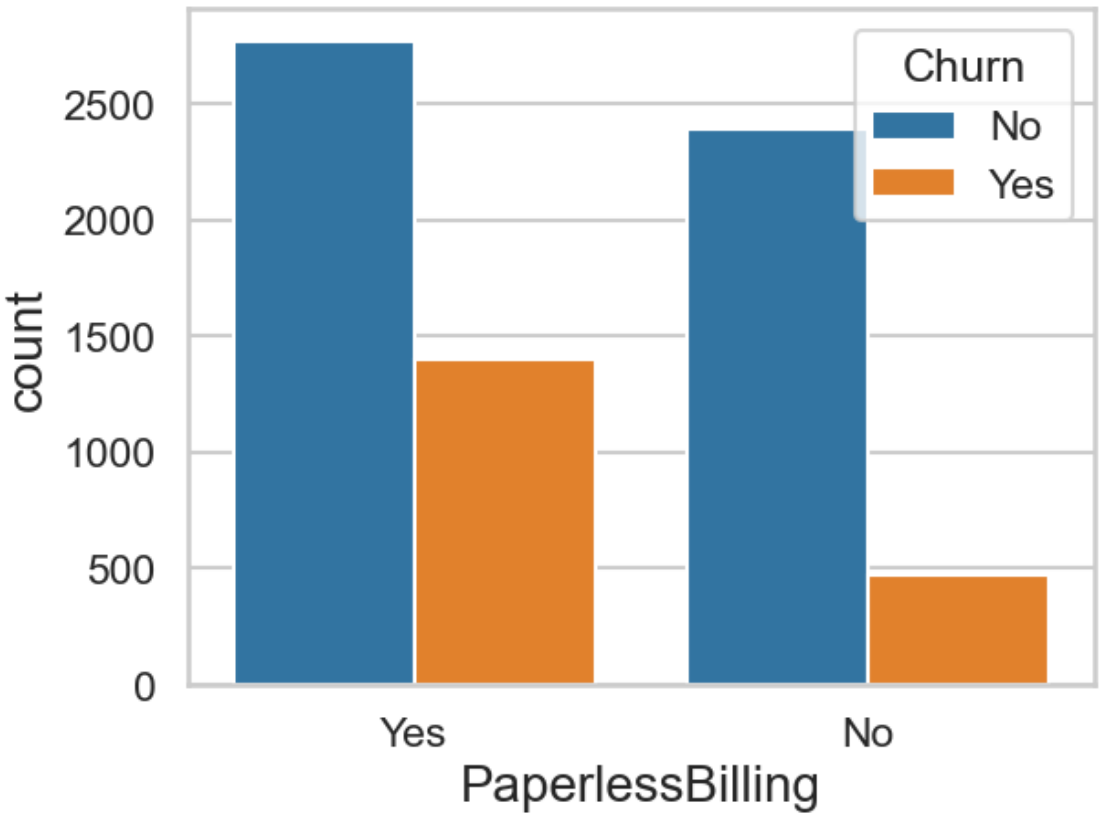

Churn
No
Yes
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
DeviceProtection

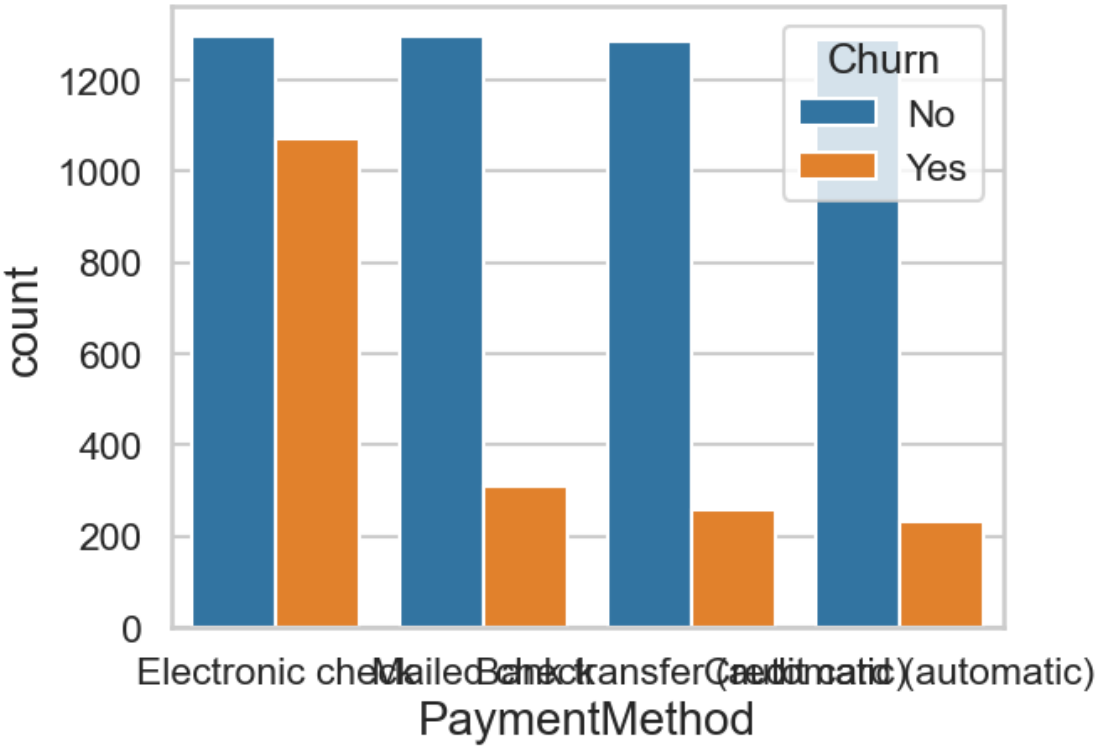

Churn
No
Yes
2000
1500
1000
500
0
count
No
Yes
No internet service
TechSupport

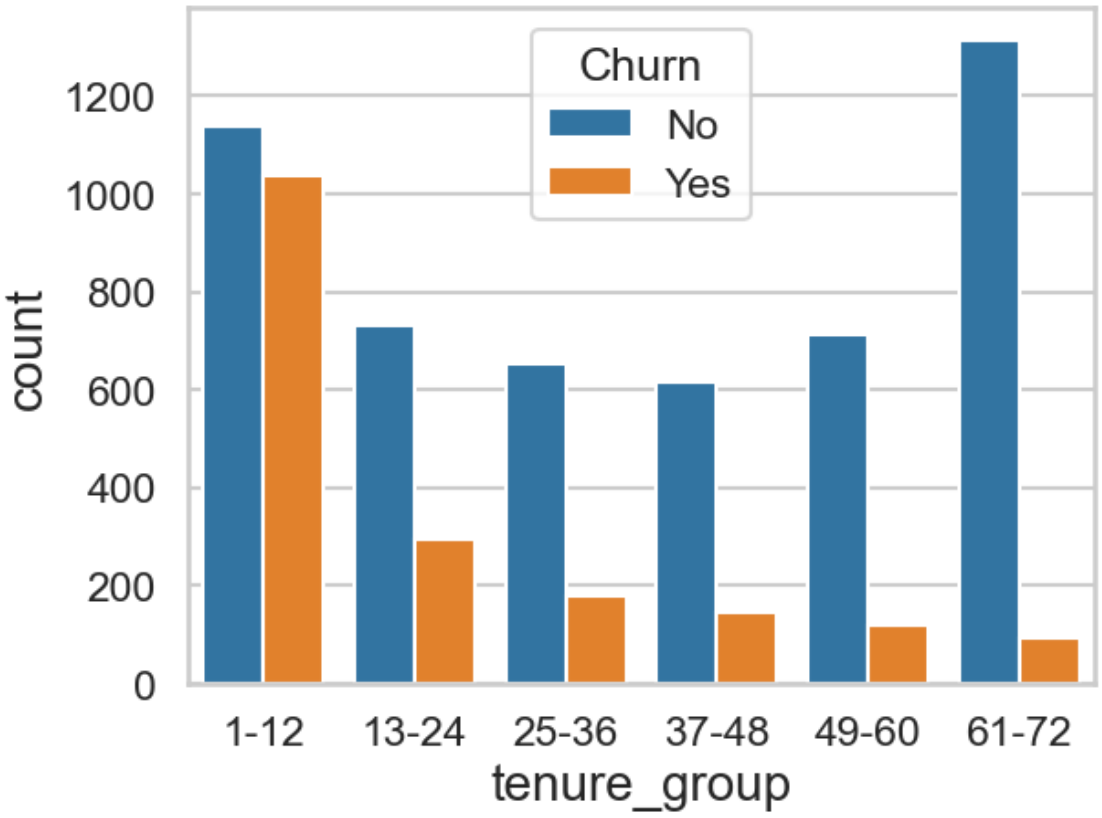

Churn
No
Yes
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
StreamingTV


2000
1500
1000
500
0
count
Churn
No
Yes
No
Yes
No internet service
StreamingMovies


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


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


Churn
No
Yes
1200
1000
800
600
400
200
0
count
Electronic check
Mailed check
Bank transfer (automatic)
Credit card (automatic)
PaymentMethod



[31]:
```
#one hot encoding
'''telco_data_dummies=pd.get_dummies(telco_base_data)
telco_data_dummies.head()'''
```

[31]:
```
'telco_data_dummies=pd.get_dummies(telco_base_data)\ntelco_data_dummies.head()'
```

[32]:
```
#relationship bw monthly charges and total charges
#sns.
 ↪lmplot(data=telco_data_dummies,x='MonthlyCharges',y='TotalCharges',fit_reg=False)
```

[33]:
```
#total charges increases as monthly charges increases, highly correlated
```

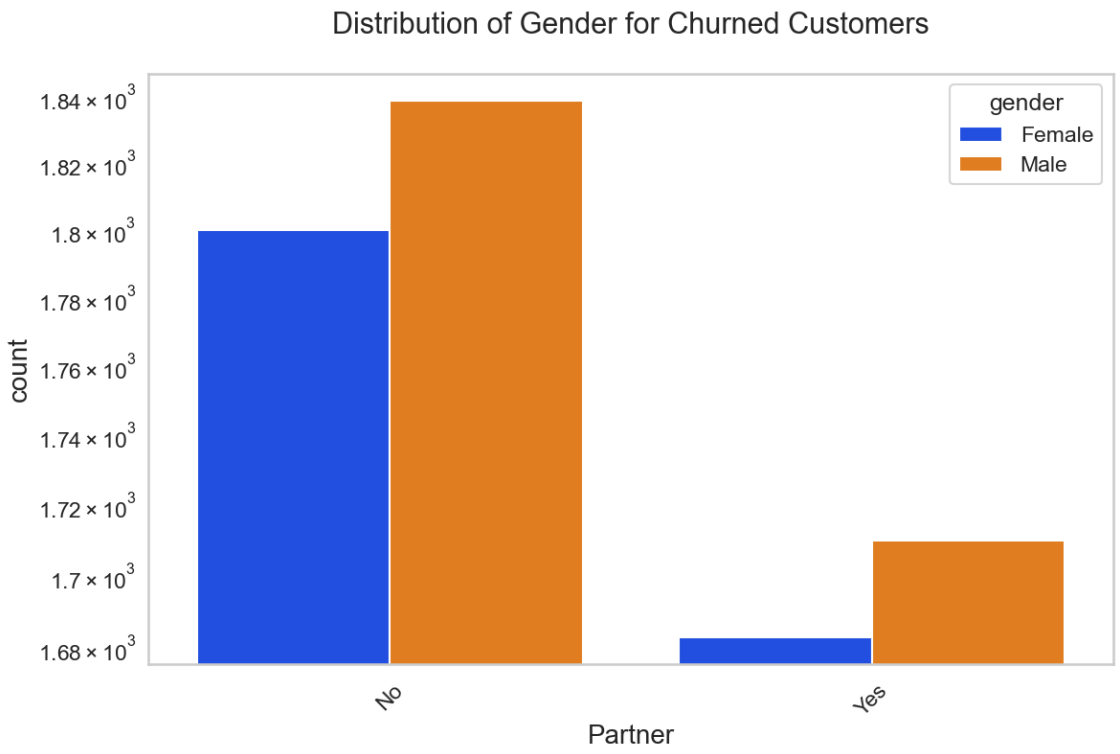
[34]:
```
#plt.figure(figsize=(12,12))
#sns.heatmap(telco_data_dummies.corr(),cmap="brg_r")
```

[35]:
```
#bivariate analysis
```

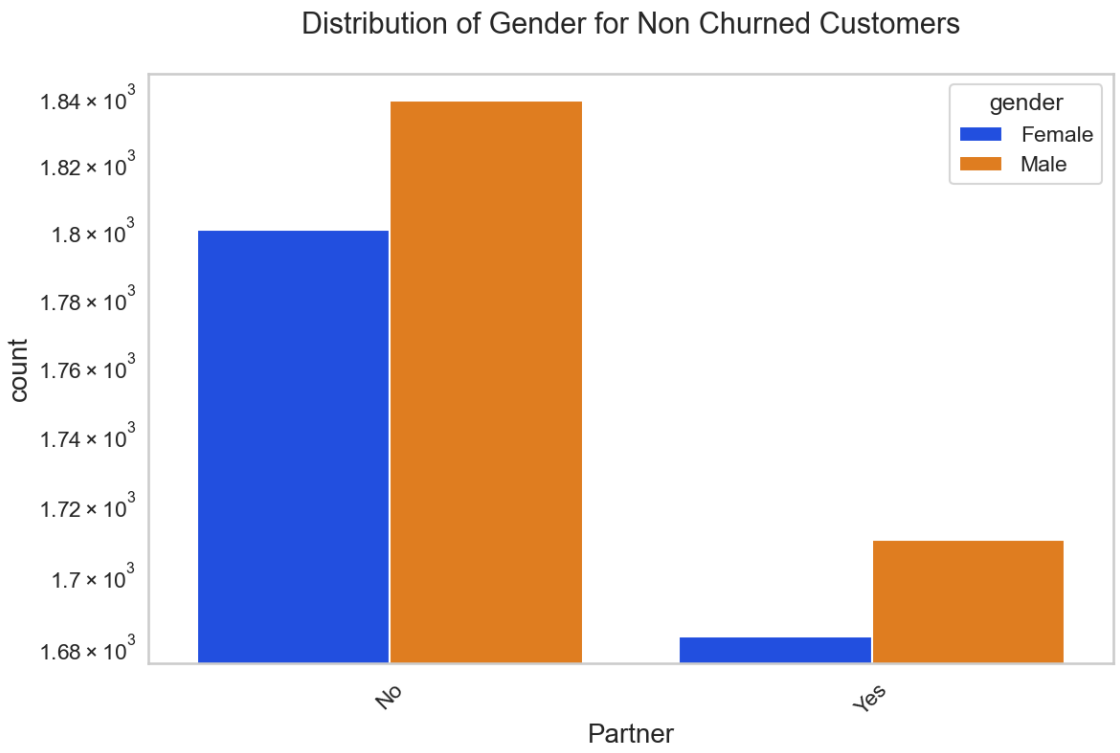
[36]:
```
new_df1_target0=telco_base_data.loc[telco_base_data["Churn"]==0]
new_df1_target1=telco_base_data.loc[telco_base_data["Churn"]==1]
```

[37]:
```
def uniplot(df,col,title,hue =None):

    sns.set_style('whitegrid')
    sns.set_context('talk')
    plt.rcParams["axes.labelsize"] = 20
    plt.rcParams['axes.titlesize'] = 22
    plt.rcParams['axes.titlepad'] = 30


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

    plt.show()
```

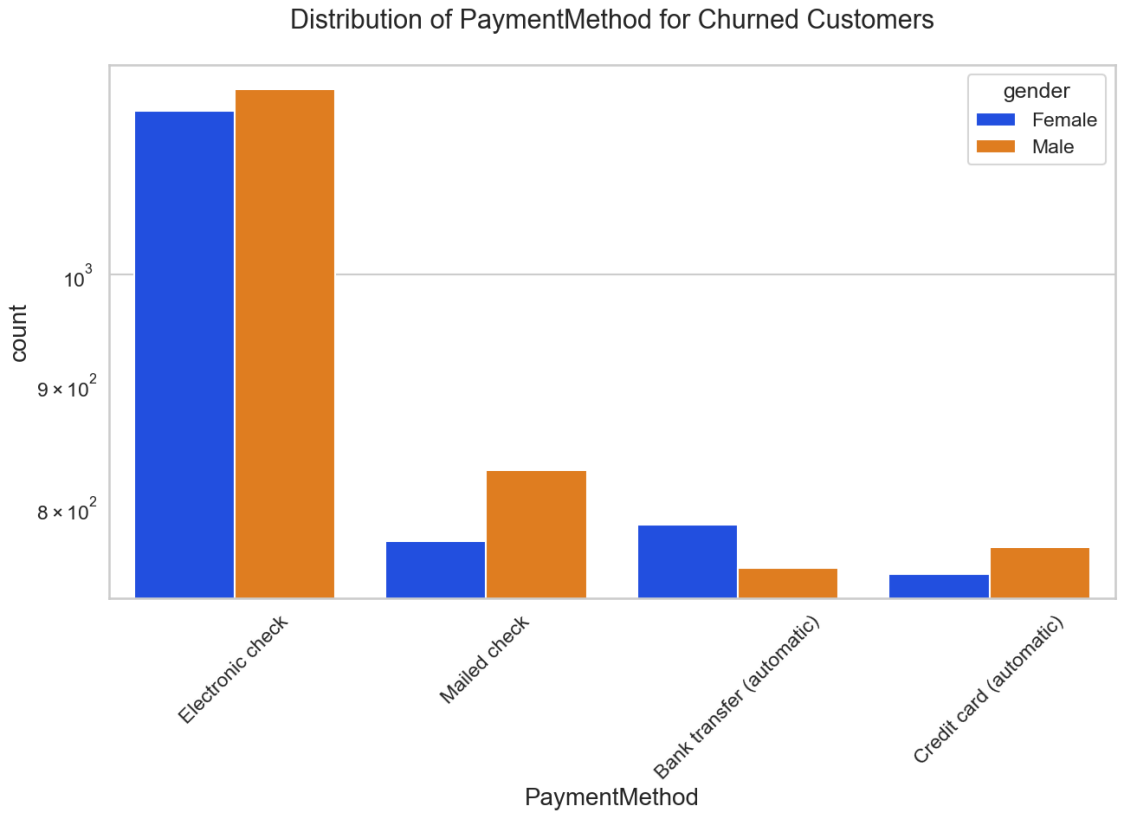
[38]:
```
uniplot(telco_base_data,col='Partner',title='Distribution of Gender for Churned␣
 ↪Customers',hue='gender')
```



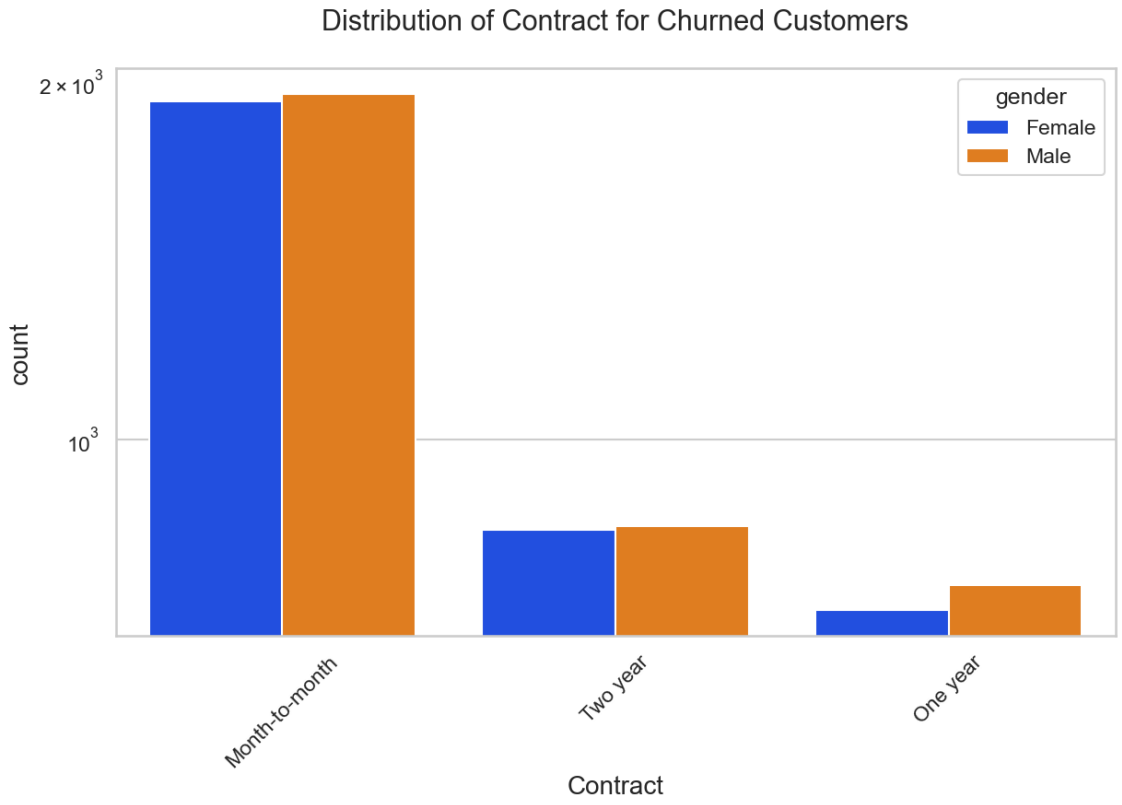
[39]:
```
uniplot(telco_base_data,col='Partner',title='Distribution of Gender for Non␣
↪Churned Customers',hue='gender')
```



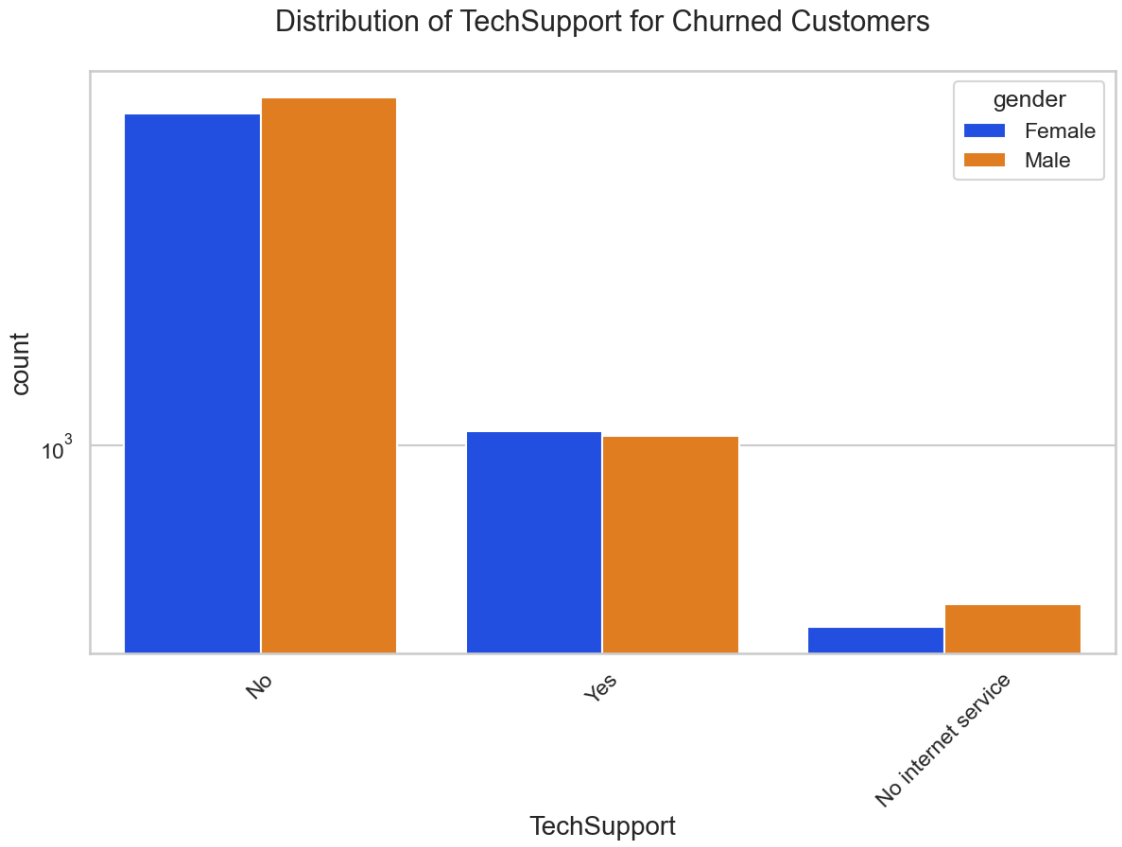
[40]:
```
uniplot(telco_base_data,col='PaymentMethod',title='Distribution of␣
↪PaymentMethod for Churned Customers',hue='gender')
```



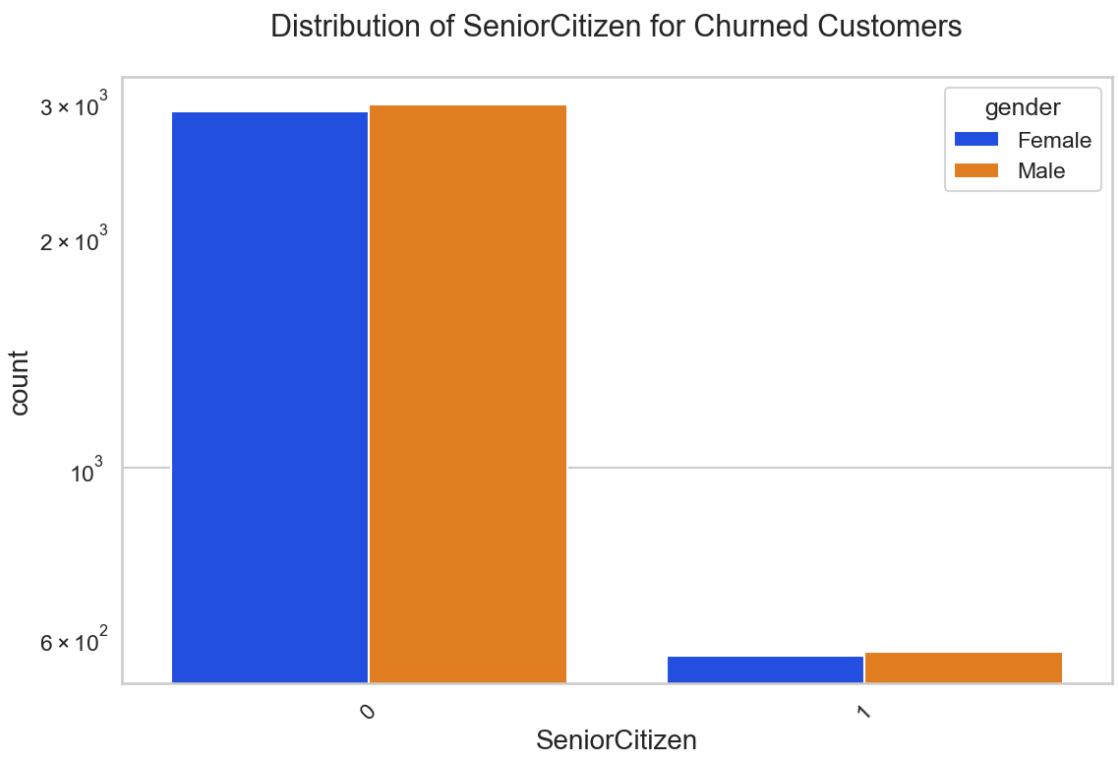
[41]:
```
uniplot(telco_base_data,col='Contract',title='Distribution of Contract for␣
↪Churned Customers',hue='gender')
```



[42]:
```
uniplot(telco_base_data,col='TechSupport',title='Distribution of TechSupport␣
↪for Churned Customers',hue='gender')
```



[43]:
```
uniplot(telco_base_data,col='SeniorCitizen',title='Distribution of␣
↪SeniorCitizen for Churned Customers',hue='gender')
```



[44]:
```
#Electronic check medium are the highest churners
#Contract Type - Monthly customers are more likely to churn because of no␣
 ↪contract terms, as they are free to go customers.
#No Online security, No Tech Support category are high churners
#Non senior Citizens are high churners
```

1 Model building

[46]:
```
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.metrics import recall_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from imblearn.combine import SMOTEENN
```

[ ]:
```
```

[47]:
```
#reading the database

df=pd.read_csv("tel_churn.csv")
df.head()
```

[47]:

	Unnamed: 0	SeniorCitizen	MonthlyCharges	TotalCharges	Churn	\
0	0	0	29.85	29.85	0	
1	1	0	56.95	1889.50	0	
2	2	0	53.85	108.15	1	
3	3	0	42.30	1840.75	0	
4	4	0	70.70	151.65	1	

	gender_Female	gender_Male	Partner_No	Partner_Yes	Dependents_No	…	\
0	1	0	0	1	1	…	
1	0	1	1	0	1	…	
2	0	1	1	0	1	…	
3	0	1	1	0	1	…	
4	1	0	1	0	1	…	

	PaymentMethod_Bank transfer (automatic)	\
0	0	
1	0	
2	0	
3	1	
4	0	

	PaymentMethod_Credit card (automatic)	PaymentMethod_Electronic check	\
0	0	1	
1	0	0	
2	0	0	
3	0	0	
4	0	1	

	PaymentMethod_Mailed check	tenure_group_1 - 12	tenure_group_13 - 24	\
0	0	1	0	
1	1	0	0	
2	1	1	0	
3	0	0	0	
4	0	1	0	

	tenure_group_25 - 36	tenure_group_37 - 48	tenure_group_49 - 60	\
0	0	0	0	
1	1	0	0	
2	0	0	0	
3	0	1	0	
4	0	0	0	

	tenure_group_61 - 72
0	0
1	0
2	0
3	0

```
4                     0

[5 rows x 52 columns]
```

[93]:
```
#deleting extra column unnamed
df=df.drop('Unnamed: 0',axis=1)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
Cell In[93], line 2
      1 #deleting extra column unnamed
----> 2 df=df.drop('Unnamed: 0',axis=1)

File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:5344, in DataFrame.
 ↪drop(self, labels, axis, index, columns, level, inplace, errors)
   5196 def drop(
   5197     self,
   5198     labels: IndexLabel | None = None,
   (…)
   5205     errors: IgnoreRaise = "raise",
   5206 ) -> DataFrame | None:
   5207     """
   5208     Drop specified labels from rows or columns.
   5209
   (…)
   5342             weight  1.0     0.8
   5343     """
-> 5344     return super().drop(
   5345         labels=labels,
   5346         axis=axis,
   5347         index=index,
   5348         columns=columns,
   5349         level=level,
   5350         inplace=inplace,
   5351         errors=errors,
   5352     )

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:4711, in NDFrame.
 ↪drop(self, labels, axis, index, columns, level, inplace, errors)
   4709 for axis, labels in axes.items():
   4710     if labels is not None:
-> 4711         obj = obj._drop_axis(labels, axis, level=level, errors=errors)
   4713 if inplace:
   4714     self._update_inplace(obj)

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:4753, in NDFrame.
 ↪_drop_axis(self, labels, axis, level, errors, only_slice)
```

```
   4751         new_axis = axis.drop(labels, level=level, errors=errors)
   4752     else:
-> 4753         new_axis = axis.drop(labels, errors=errors)
   4754     indexer = axis.get_indexer(new_axis)
   4756 # Case for non-unique axis
   4757 else:

File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:7000, in Index.
 ↪drop(self, labels, errors)
   6998 if mask.any():
   6999     if errors != "ignore":
-> 7000         raise KeyError(f"{labels[mask].tolist()} not found in axis")
   7001     indexer = indexer[~mask]
   7002 return self.delete(indexer)

KeyError: "['Unnamed: 0'] not found in axis"
```

[95]:
```
#creating x variable
x=df.drop('Churn',axis=1)
x
```

[95]:

	SeniorCitizen	MonthlyCharges	TotalCharges	gender_Female	gender_Male	\
0	0	29.85	29.85	1	0	
1	0	56.95	1889.50	0	1	
2	0	53.85	108.15	0	1	
3	0	42.30	1840.75	0	1	
4	0	70.70	151.65	1	0	
…	…	…	…	…	…	
7027	0	84.80	1990.50	0	1	
7028	0	103.20	7362.90	1	0	
7029	0	29.60	346.45	1	0	
7030	1	74.40	306.60	0	1	
7031	0	105.65	6844.50	0	1	

	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	\
0	0	1	1	0	1	
1	1	0	1	0	0	
2	1	0	1	0	0	
3	1	0	1	0	1	
4	1	0	1	0	0	
…	…	…	…	…	…	
7027	0	1	0	1	0	
7028	0	1	0	1	0	
7029	0	1	0	1	1	
7030	0	1	1	0	0	
7031	1	0	1	0	0	

```
      …  PaymentMethod_Bank transfer (automatic)  \
0     …                                        0
1     …                                        0
2     …                                        0
3     …                                        1
4     …                                        0
…   …                                        …
7027  …                                        0
7028  …                                        0
7029  …                                        0
7030  …                                        0
7031  …                                        1

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                         0                               1
1                                         0                               0
2                                         0                               0
3                                         0                               0
4                                         0                               1
…                                       …                               …
7027                                      0                               0
7028                                      1                               0
7029                                      0                               1
7030                                      0                               0
7031                                      0                               0

      PaymentMethod_Mailed check  tenure_group_1 - 12  tenure_group_13 - 24  \
0                              0                    1                     0
1                              1                    0                     0
2                              1                    1                     0
3                              0                    0                     0
4                              0                    1                     0
…                            …                    …                     …
7027                           1                    0                     1
7028                           0                    0                     0
7029                           0                    1                     0
7030                           1                    1                     0
7031                           0                    0                     0

      tenure_group_25 - 36  tenure_group_37 - 48  tenure_group_49 - 60  \
0                        0                     0                     0
1                        1                     0                     0
2                        0                     0                     0
3                        0                     1                     0
4                        0                     0                     0
…                      …                     …                     …
7027                     0                     0                     0
```

```
7028                    0                    0                    0
7029                    0                    0                    0
7030                    0                    0                    0
7031                    0                    0                    0

      tenure_group_61 - 72
0                         0
1                         0
2                         0
3                         0
4                         0
…                       …
7027                      0
7028                      1
7029                      0
7030                      0
7031                      1

[7032 rows x 50 columns]
```

[97]:
```
#creating y variable
y=df['Churn']
y
```

[97]:
```
0       0
1       0
2       1
3       0
4       1
       ..
7027    0
7028    0
7029    0
7030    1
7031    0
Name: Churn, Length: 7032, dtype: int64
```

[98]:
```
#Train Test Split 80:20 ratio
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
```

2 Decision Tree Classifier

[100]:
```
#calling decision tree classifier
model_dt=DecisionTreeClassifier(criterion = "gini",random_state =␣
 ↪100,max_depth=6, min_samples_leaf=8)
```

[101]:
```
#fitting
model_dt.fit(x_train,y_train)
```

[101]:
```
DecisionTreeClassifier(max_depth=6, min_samples_leaf=8, random_state=100)
```

[102]:
```
#predicted values
y_pred=model_dt.predict(x_test)
y_pred
```

[102]:
```
array([0, 1, 0, …, 0, 0, 0], dtype=int64)
```

[103]:
```
#comparing predicted and actual values
print(classification_report(y_test, y_pred, labels=[0,1]))
```

```
              precision    recall  f1-score   support

           0       0.84      0.87      0.86      1042
           1       0.59      0.53      0.56       365

    accuracy                           0.78      1407
   macro avg       0.72      0.70      0.71      1407
weighted avg       0.78      0.78      0.78      1407
```

[104]:
```
#upsampling to improve performance

from imblearn.over_sampling import SMOTE

oversample = SMOTE()
X_resampled, y_resampled= oversample.fit_resample(x, y)
```

[105]:
```
xr_train,xr_test,yr_train,yr_test=train_test_split(X_resampled,␣
 ↪y_resampled,test_size=0.2)
```

[106]:
```
model_dt_smote=DecisionTreeClassifier(criterion = "gini",random_state =␣
 ↪100,max_depth=6, min_samples_leaf=8)
```

[107]:
```
# values improved
model_dt_smote.fit(xr_train,yr_train)
yr_predict = model_dt_smote.predict(xr_test)
model_score_r = model_dt_smote.score(xr_test, yr_test)
print(model_score_r)
print(metrics.classification_report(yr_test, yr_predict))
```

```
0.8291384317521782
              precision    recall  f1-score   support

           0       0.83      0.82      0.82      1012
           1       0.83      0.84      0.83      1054
```

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

[108]:
```
print(metrics.confusion_matrix(yr_test, yr_predict))
```

```
[[825 187]
 [166 888]]
```

3 random forest classifier

[110]:
```
from sklearn.ensemble import RandomForestClassifier
```

[111]:
```
model_rf=RandomForestClassifier(n_estimators=100, criterion='gini',␣
↪random_state = 100,max_depth=6, min_samples_leaf=8)
```

[112]:
```
model_rf.fit(x_train,y_train)
```

[112]:
```
RandomForestClassifier(max_depth=6, min_samples_leaf=8, random_state=100)
```

[113]:
```
y_pred=model_rf.predict(x_test)
```

[114]:
```
model_rf.score(x_test,y_test)
```

[114]:
```
0.8052594171997157
```

[115]:
```
print(classification_report(y_test, y_pred, labels=[0,1]))
# results are not very good
```

```
              precision    recall  f1-score   support

           0       0.84      0.92      0.87      1042
           1       0.67      0.49      0.57       365

    accuracy                           0.81      1407
   macro avg       0.75      0.70      0.72      1407
weighted avg       0.79      0.81      0.79      1407
```

[123]:
```
from imblearn.combine import SMOTEENN
sm = SMOTEENN()
X_resampled1, y_resampled1 = sm.fit_resample(x,y)
```

[125]:
```
xr_train1,xr_test1,yr_train1,yr_test1=train_test_split(X_resampled1,␣
↪y_resampled1,test_size=0.2)
```

[126]:
```
model_rf_smote=RandomForestClassifier(n_estimators=100, criterion='gini',␣
↪random_state = 100,max_depth=6, min_samples_leaf=8)
```

[127]:
```
model_rf_smote.fit(xr_train1,yr_train1)
```

[127]:
```
RandomForestClassifier(max_depth=6, min_samples_leaf=8, random_state=100)
```

[128]:
```
yr_predict1 = model_rf_smote.predict(xr_test1)
```

[129]:
```
model_score_r1 = model_rf_smote.score(xr_test1, yr_test1)
```

[130]:
```
print(model_score_r1)
print(metrics.classification_report(yr_test1, yr_predict1))
```

```
0.9426860564585116
              precision    recall  f1-score   support

           0       0.95      0.91      0.93       493
           1       0.94      0.97      0.95       676

    accuracy                           0.94      1169
   macro avg       0.94      0.94      0.94      1169
weighted avg       0.94      0.94      0.94      1169
```

[131]:
```
print(metrics.confusion_matrix(yr_test1, yr_predict1))
```

```
[[448  45]
 [ 22 654]]
```

[133]:
```
#With RF Classifier, also we are able to get quite good results, infact better␣
↪than Decision Tree
```

4 saving model with pickle

[136]:
```
import pickle
```

[137]:
```
filename = 'model.sav'
```

[138]:
```
pickle.dump(model_rf_smote, open(filename, 'wb'))
```

[139]:
```
load_model = pickle.load(open(filename, 'rb'))
```

[140]:
```
model_score_r1 = load_model.score(xr_test1, yr_test1)
```

[141]:
```
model_score_r1
```

[141]:
```
0.9426860564585116
```

[ ]:

[ ]:

[ ]: