Welcome to Telco Churn Customers analysis and Prediction

Description of dataset

Context

"Predict behavior to retain customers. You can analyze all relevant customer data and develop focused customer retention programs." [IBM Sample Data Sets]

Content

Each row represents a customer, each column contains customer's attributes described on the column Metadata.

The data set includes information about:

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

Inspiration

To explore this type of models and learn more about the subject.

Objectives:

I will explore the data and try to answer some questions like:

- What's the % of Churn Customers and customers that keep in with the active services.
- We can see different patterns in Churn Customers based on the type of service provided?
- We have difference pattern of churn between genders ?
- What's the difference between customers that pay monthly and by year?
- what's the most profitable service types?
- What's the amount lose in revenue?
- What's the mean age of papeless customers? they are more propense to churn?
- A lot of other questions that will raise trought the exploration

After EDA

I will build a pipeline to find a model that better fits our data. With the best models I will predict the result and verify the scores of the models. I hope you enjoy the Kernel.

Importing Libraries

```
import numpy as np # linear algebra
from scipy import stats # statistic library
import pandas as pd # To table manipulations
import seaborn as sns
import matplotlib.pyplot as plt

# Standard plotly imports
import plotly.plotly as py
import plotly.graph_objs as go
import plotly.tools as tls
from plotly.offline import iplot, init_notebook_mode
import cufflinks
import cufflinks as cf
import plotly.figure_factory as ff

# Using plotly + cufflinks in offline mode
init_notebook_mode(connected=True)
cufflinks.go_offline(connected=True)

import os

#Importing the auxiliar and preprocessing librarys
from sklearn.metrics import accuracy_score, confusion_matrix,
```

```
classification_report
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.utils.multiclass import unique_labels
from sklearn.model_selection import train_test_split, KFold,
cross_validate

#Models
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.svm import SVC
from sklearn.linear_model import RidgeClassifier, SGDClassifier,
LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier, ExtraTreesClassifier
from sklearn.ensemble import BaggingClassifier, VotingClassifier,
RandomTreesEmbedding

def binary_ploting_distributions(df, cat_col):
    from plotly import tools

    fig = tools.make_subplots(rows=1,
                              cols=2,
                              print_grid=True,
                              horizontal_spacing=0.15,
                              subplot_titles=("Distribution of and %
Churn",
                                              f'Mean Monthly Charges
of {cat_col}')
                             )

    tmp_churn = df[df['Churn'] == 1]
    tmp_no_churn = df[df['Churn'] == 0]
    tmp_attr = round(tmp_churn[cat_col].value_counts().sort_index() /
df_train[cat_col].value_counts().sort_index(),2)*100

    trace1 = go.Bar(
        x=tmp_churn[cat_col].value_counts().sort_index().index,
        y=tmp_churn[cat_col].value_counts().sort_index().values,
        name='Yes_Churn',opacity = 0.8, marker=dict(
            color='seagreen',
            line=dict(color='#000000',width=1)))
```

```
    trace2 = go.Bar(
        x=tmp_no_churn[cat_col].value_counts().sort_index().index,
        y=tmp_no_churn[cat_col].value_counts().sort_index().values,
        name='No_Churn', opacity = 0.8,
        marker=dict(
            color='indianred',
            line=dict(color='#000000',
                      width=1)
        )
    )

    trace3 =  go.Scatter(
        x=tmp_attr.sort_index().index,
        y=tmp_attr.sort_index().values,
        yaxis = 'y2',
        name='% Churn', opacity = 0.6,
        marker=dict(
            color='black',
            line=dict(color='#000000',
                      width=2 )
        )
    )

    df_tmp = (df_train.groupby(['Churn', cat_col])
['MonthlyCharges'].mean().reset_index())

    tmp_churn = df_tmp[df_tmp['Churn'] == 1]
    tmp_no_churn = df_tmp[df_tmp['Churn'] == 0]

    df_tmp = (df_train.groupby(['Churn', cat_col])
['MonthlyCharges'].mean()).unstack('Churn').reset_index()
    df_tmp['diff_rate'] = round((df_tmp[1] / df_tmp[0]) - 1,2) * 100

    trace4 = go.Bar(
        x=tmp_churn[cat_col],
        y=tmp_churn['MonthlyCharges'], showlegend=False,
        name='Mean Charge Churn',opacity = 0.8, marker=dict(
            color='seagreen',
            line=dict(color='#000000',width=1)))

    trace5 = go.Bar(
        x=tmp_no_churn[cat_col],
        y=tmp_no_churn['MonthlyCharges'],showlegend=False,
        name='Mean Charge NoChurn', opacity = 0.8,
        marker=dict(
            color='indianred',
            line=dict(color='#000000',
                      width=1)
        )
    )
```

```
    trace6 =  go.Scatter(
        x=df_tmp[cat_col],
        y=df_tmp['diff_rate'],
        yaxis = 'y2',
        name='% Diff Churn', opacity = 0.6,
        marker=dict(
            color='black',
            line=dict(color='#000000',
                      width=5 )
        )
    )

    fig.append_trace(trace1, 1, 1)
    fig.append_trace(trace2, 1, 1)
    fig.append_trace(trace3, 1, 1)
    fig.append_trace(trace4, 1, 2)
    fig.append_trace(trace5, 1, 2)
    fig.append_trace(trace6, 1, 2)

    fig['data'][2].update(yaxis='y3')
    fig['data'][5].update(yaxis='y4')

    fig['layout']['xaxis'].update(autorange=True,
                                   tickfont=dict(size= 10),
                                   title= f'{cat_col}',
                                   type= 'category',
                                  )
    fig['layout']['yaxis'].update(title= 'Count')

    fig['layout']['xaxis2'].update(autorange=True,
                                   tickfont=dict(size= 10),
                                   title= f'{cat_col}',
                                   type= 'category',
                                  )
    fig['layout']['yaxis2'].update( title= 'Mean Monthly Charges' )

    fig['layout']['yaxis3']=dict(range= [0, 100], #right y-axis in
subplot (1,1)
                              overlaying= 'y',
                              anchor= 'x',
                              side= 'right',
                              showgrid= False,
                              title= '%Churn Ratio'
                             )

    #Insert a new key, yaxis4, and the associated value:
    fig['layout']['yaxis4']=dict(range= [-20, 100], #right y-axis in
the subplot (1,2)
                              overlaying= 'y2',
```

```
                              anchor= 'x2',
                              side= 'right',
                              showgrid= False,
                              title= 'Monhtly % Difference'
                             )
    fig['layout']['title'] = f"{cat_col} Distributions"
    fig['layout']['height'] = 500
    fig['layout']['width'] = 1000

    iplot(fig)

def plot_dist_churn(df, col, binary=None):
    tmp_churn = df[df[binary] == 1]
    tmp_no_churn = df[df[binary] == 0]
    tmp_attr = round(tmp_churn[col].value_counts().sort_index() /
df[col].value_counts().sort_index(),2)*100
    print(f'Distribution of {col}: ')
    trace1 = go.Bar(
        x=tmp_churn[col].value_counts().sort_index().index,
        y=tmp_churn[col].value_counts().sort_index().values,
        name='Yes_Churn',opacity = 0.8, marker=dict(
            color='seagreen',
            line=dict(color='#000000',width=1)))

    trace2 = go.Bar(
        x=tmp_no_churn[col].value_counts().sort_index().index,
        y=tmp_no_churn[col].value_counts().sort_index().values,
        name='No_Churn', opacity = 0.8,
        marker=dict(
            color='indianred',
            line=dict(color='#000000',
                      width=1)
        )
    )

    trace3 =  go.Scatter(
        x=tmp_attr.sort_index().index,
        y=tmp_attr.sort_index().values,
        yaxis = 'y2',
        name='% Churn', opacity = 0.6,
        marker=dict(
            color='black',
            line=dict(color='#000000',
                      width=2 )
        )
    )

    layout = dict(title =  f'Distribution of {str(col)} feature by
Target - With Churn Rates',
              xaxis=dict(),
```

```
             yaxis=dict(title= 'Count'),
             yaxis2=dict(range= [0, 100],
                         overlaying= 'y',
                         anchor= 'x',
                         side= 'right',
                         zeroline=False,
                         showgrid= False,
                         title= 'Percentual Churn Ratio'
                        ))

    fig = go.Figure(data=[trace1, trace2, trace3], layout=layout)
    iplot(fig)


def plot_distribution(df, var_select=None, bins=1.0):
    # Calculate the correlation coefficient between the new variable
and the target
    tmp_churn = df[df['Churn'] == 1]
    tmp_no_churn = df[df['Churn'] == 0]
    corr = df_train['Churn'].corr(df_train[var_select])
    corr = np.round(corr,3)
    tmp1 = tmp_churn[var_select].dropna()
    tmp2 = tmp_no_churn[var_select].dropna()
    hist_data = [tmp1, tmp2]

    group_labels = ['Yes_churn', 'No_churn']
    colors = ['seagreen','indianred', ]

    fig = ff.create_distplot(hist_data,
                             group_labels,
                             colors = colors,
                             show_hist = True,
                             curve_type='kde',
                             bin_size = bins
                            )

    fig['layout'].update(title = var_select+' '+'(corr target ='+
str(corr)+')')

    iplot(fig, filename = 'Density plot')

def monthly_charges(df, col, binary=None):
    #(df_train.groupby(['Churn', 'tenure'])
['MonthlyCharges'].mean()).unstack('Churn').reset_index()
    df_tmp = (df_train.groupby([binary, col])
['MonthlyCharges'].mean().reset_index())

    tmp_churn = df_tmp[df_tmp['Churn'] == 1]
    tmp_no_churn = df_tmp[df_tmp['Churn'] == 0]
```

```
    df_tmp = (df_train.groupby([binary, col])
['MonthlyCharges'].mean()).unstack('Churn').reset_index()
    df_tmp['diff_rate'] = round((df_tmp[1] / df_tmp[0]) - 1,2) * 100

    trace1 = go.Bar(
        x=tmp_churn[col],
        y=tmp_churn['MonthlyCharges'],
        name='Mean Charge\nChurn',opacity = 0.8, marker=dict(
            color='seagreen',
            line=dict(color='#000000',width=1)))

    trace2 = go.Bar(
        x=tmp_no_churn[col],
        y=tmp_no_churn['MonthlyCharges'],
        name='Mean Charge No Churn', opacity = 0.8,
        marker=dict(
            color='indianred',
            line=dict(color='#000000',
                      width=1)
        )
    )

    trace3 =  go.Scatter(
        x=df_tmp[col],
        y=df_tmp['diff_rate'],
        yaxis = 'y2',
        name='% Diff Churn', opacity = 0.6,
        marker=dict(
            color='black',
            line=dict(color='#000000',
                      width=5 )
        )
    )

    layout = dict(title =  f'Mean Monthly Charges of {str(col)}
feature by Churn or Not Churn Customers - With Churn Ratio',
              xaxis=dict(),
              yaxis=dict(title= 'Mean Monthly Charges'),
              yaxis2=dict(range= [0, 100],
                          overlaying= 'y',
                          anchor= 'x',
                          side= 'right',
                          zeroline=False,
                          showgrid= False,
                          title= '% diff Monthly Charges Mean'
                         ))

    fig = go.Figure(data=[trace1, trace2, trace3], layout=layout)
    iplot(fig)
```

Importing the dataset

```
df_train = pd.read_csv('../input/WA_Fn-UseC_-Telco-Customer-
Churn.csv')

def resumetable(df):
    print(f"Dataset Shape: {df.shape}")
    summary = pd.DataFrame(df.dtypes,columns=['dtypes'])
    summary = summary.reset_index()
    summary['Name'] = summary['index']
    summary = summary[['Name','dtypes']]
    summary['Missing'] = df.isnull().sum().values
    summary['Uniques'] = df.nunique().values
    summary['First Value'] = df.loc[0].values
    summary['Second Value'] = df.loc[1].values
    summary['Third Value'] = df.loc[2].values

    #for name in summary['Name'].value_counts().index:
    #    summary.loc[summary['Name'] == name, 'Entropy'] =
round(stats.entropy(df[name].value_counts(normalize=True), base=10),2)


    return summary

#pd.DataFrame(df_train.dtypes,columns=['dtypes'])

resumetable(df_train)

Dataset Shape: (7043, 21)

                Name   dtypes       ...        Second Value     Third
Value
0         customerID   object       ...          5575-GNVDE       3668-
QPYBK
1             gender   object       ...                Male
Male
2      SeniorCitizen    int64       ...                   0
0
3            Partner   object       ...                  No
No
4         Dependents   object       ...                  No
No
5             tenure    int64       ...                  34
2
6       PhoneService   object       ...                 Yes
Yes
7      MultipleLines   object       ...                  No
No
8    InternetService   object       ...                 DSL
DSL
9     OnlineSecurity   object       ...                 Yes
```

```
Yes
10        OnlineBackup   object        ...                        No
Yes
11    DeviceProtection   object        ...                       Yes
No
12         TechSupport   object        ...                        No
No
13         StreamingTV   object        ...                        No
No
14     StreamingMovies   object        ...                        No
No
15            Contract   object        ...                  One year  Month-to-
month
16    PaperlessBilling   object        ...                        No
Yes
17       PaymentMethod   object        ...              Mailed check    Mailed
check
18      MonthlyCharges  float64        ...                     56.95
53.85
19        TotalCharges   object        ...                    1889.5
108.15
20               Churn   object        ...                        No
Yes

[21 rows x 7 columns]
```

Very interesting.

- We can see that we have one entry for each CustomerId
- The dataset don't have missing values
- Some features are categorical
- The target the we will use to guide the exploration is Churn

Let's investigate the data further.

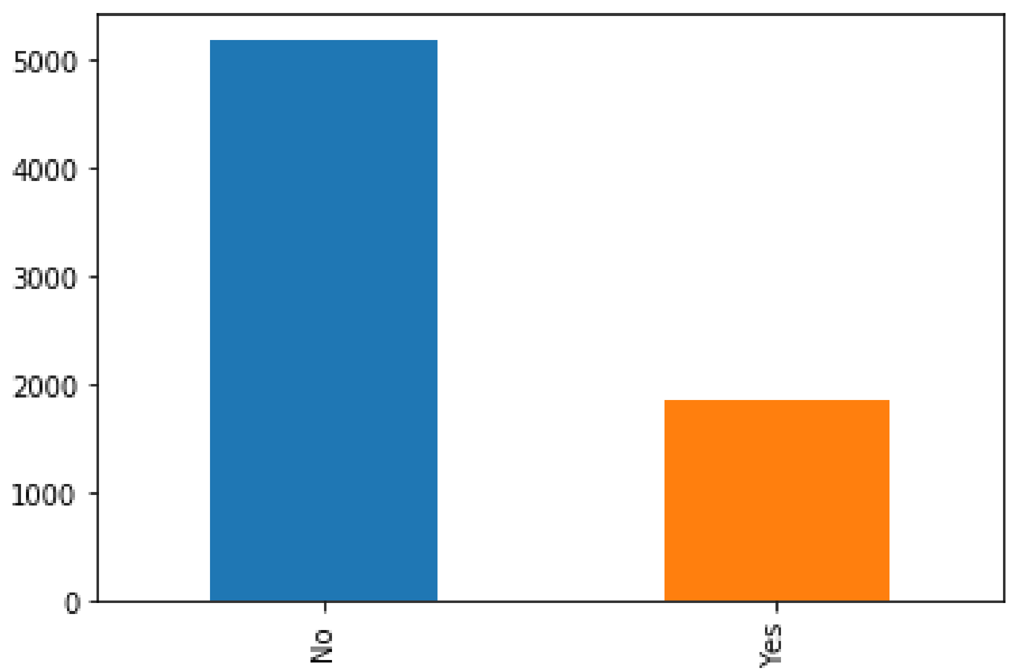
- I will get all categorical features and see their distribution by the target
- I will calculate the Churn Rate for each value in categories

```
#CATEGORICAL VARIABLES
cat_features = ['gender', 'SeniorCitizen', 'Partner', 'Dependents',
                'PaperlessBilling', 'PhoneService', 'Contract',
'StreamingMovies',
                'StreamingTV', 'TechSupport', 'OnlineBackup',
'OnlineSecurity',
                'InternetService', 'MultipleLines',
'DeviceProtection', 'PaymentMethod']
```

Understanding the Churn Distribution

- Let's known our target feature

```
df_train['Churn'].value_counts(normalize=True)

No      0.73463
Yes     0.26537
Name: Churn, dtype: float64

print("CUSTOMERS %CHURN:")
print(round(df_train['Churn'].value_counts(normalize=True) * 100,2))
# df_train.groupby('Churn')['customerID'].count().iplot(kind='bar',
title='Churn (Target) Distribution',
#
xTitle='Customer Churn?', yTitle='Count')

df_train.Churn.value_counts().plot.bar()

CUSTOMERS %CHURN:
No      73.46
Yes     26.54
Name: Churn, dtype: float64

<matplotlib.axes._subplots.AxesSubplot at 0x7f5e2f5d8c50>
```



We have 26.5% of our data that is about the Churned customers, and I will try to understand the pattern of these groups I will filter the dataset and set an dataset for Churn and Non Churn Customers.

- Also, I will see if monthly Charges has some difference to Churn and Non-Churn Customers.

- I have the hipotesis that maybe Churn customers has a highest mean value of no churn customers

Monthly Charges Distribution

Let's see the distribution of Monthly Charges by Churn and No Churn Customers.

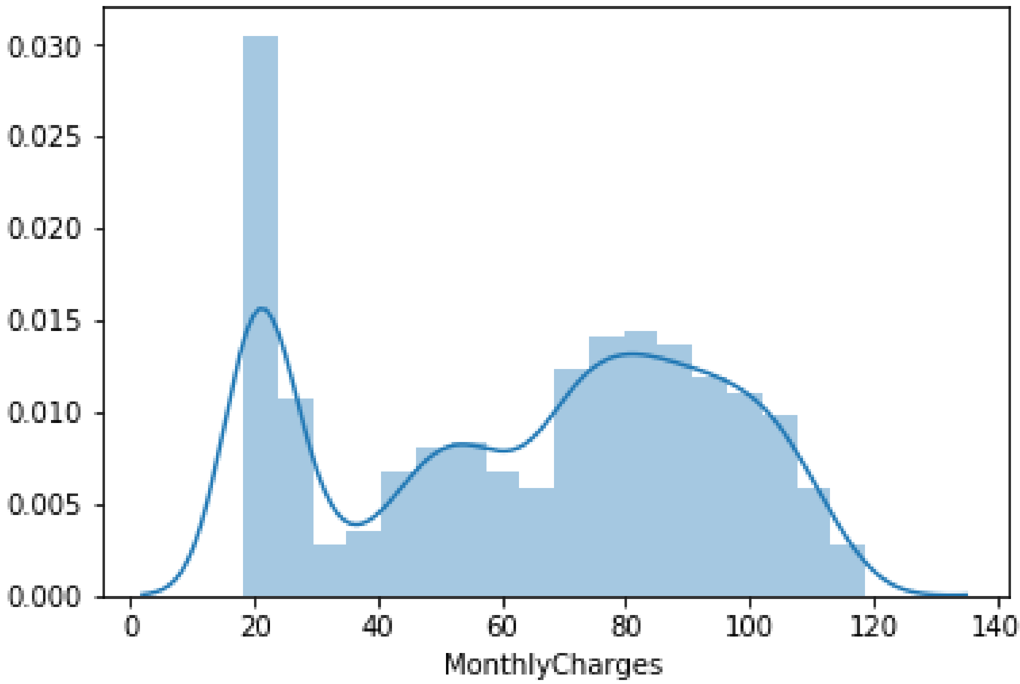
```
df_train['TotalCharges'].isnull().sum()
```

```
0
```

```
#df_train['TotalCharges'].fillna(df_train['MonthlyCharges'],
inplace=True)
#df_train['Churn'] = df_train.Churn.replace({'Yes': 1, 'No': 0})
print(f"The mininum value in Monthly Charges is
{df_train['MonthlyCharges'].min()} and the maximum is
{df_train['MonthlyCharges'].max()}")
print(f"The mean Monthly Charges of Churn Customers is
{round(df_train[df_train['Churn'] != 0]['MonthlyCharges'].mean(),2)}\
      \nThe mean Monthly Charges of Non-churn Customers is
{round(df_train[df_train['Churn'] == 0]['MonthlyCharges'].mean(),2)}")

#plot_distribution(df_train, 'MonthlyCharges', bins=4.0)
sns.distplot(df_train['MonthlyCharges'])
```

```
The mininum value in Monthly Charges is 18.25 and the maximum is
118.75
The mean Monthly Charges of Churn Customers is 64.76
The mean Monthly Charges of Non-churn Customers is nan
```

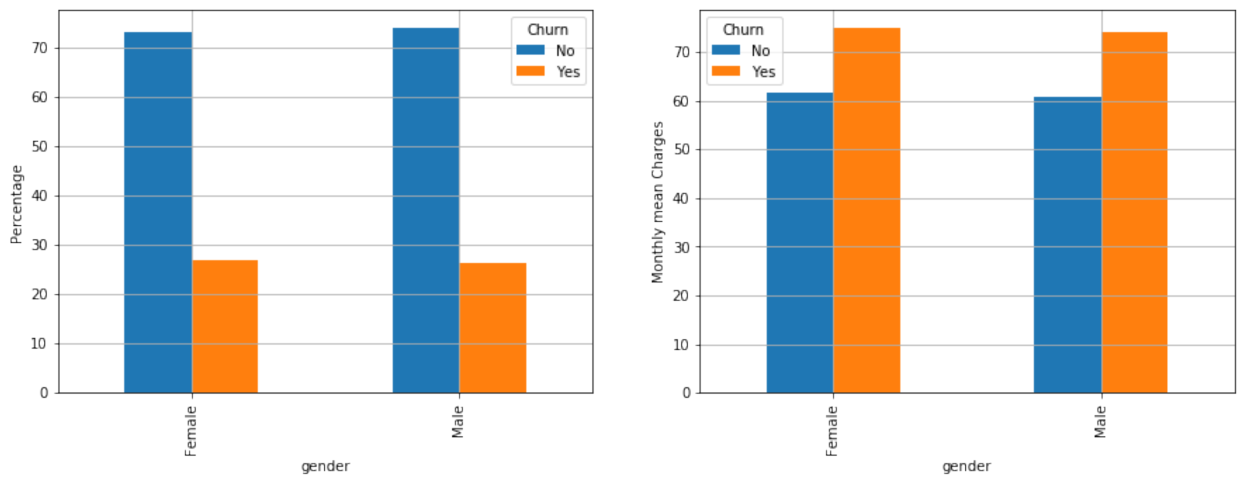
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5e2ecda4a8>
```

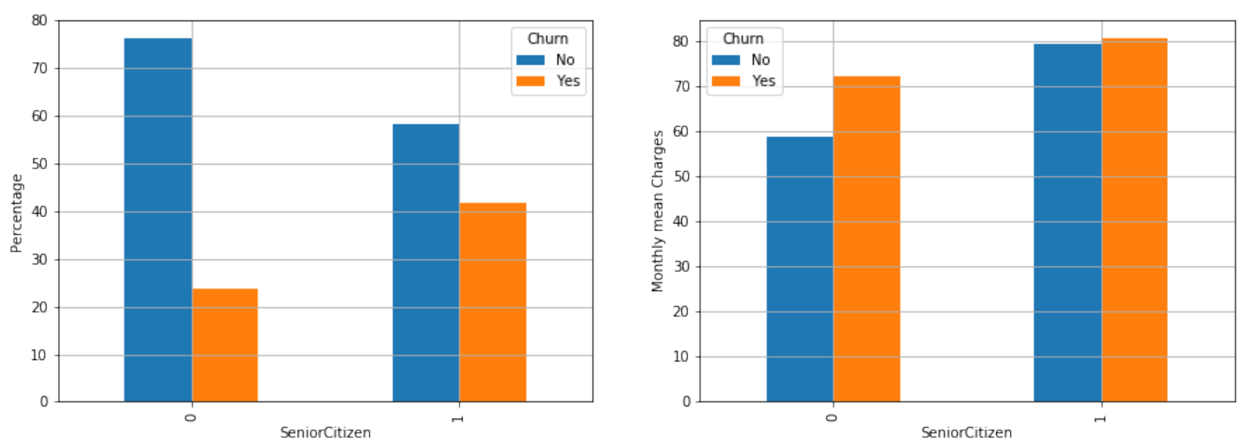


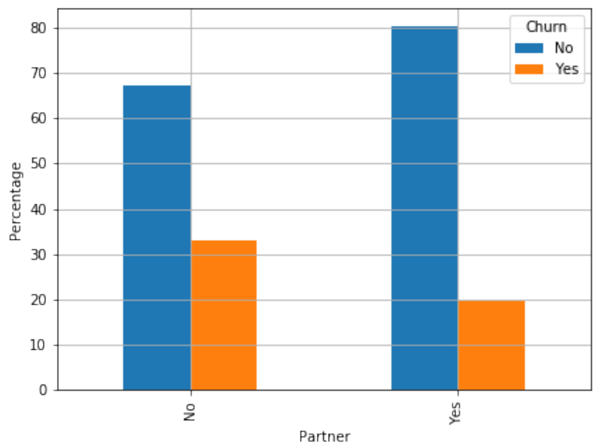
Ploting all categorical features

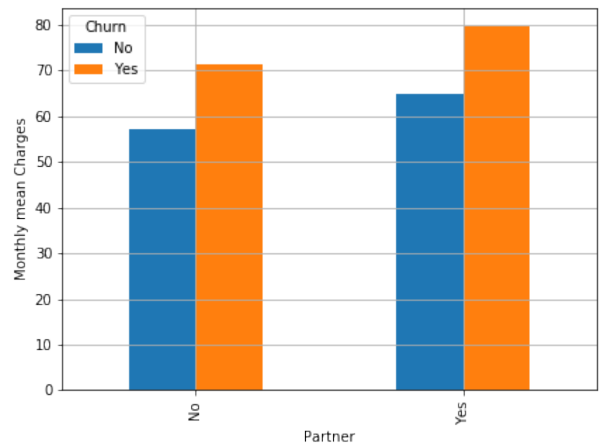
```
df_train.head()

   customerID  gender  SeniorCitizen  ...   MonthlyCharges
TotalCharges  Churn
0  7590-VHVEG  Female              0  ...            29.85
29.85     No
1  5575-GNVDE    Male              0  ...            56.95
1889.5     No
2  3668-QPYBK    Male              0  ...            53.85
108.15    Yes
3  7795-CFOCW    Male              0  ...            42.30
1840.75     No
4  9237-HQITU  Female              0  ...            70.70
151.65    Yes

[5 rows x 21 columns]

## I did some modifications but you can see the original on IBM
df_plot=df_train
df_plot['Churn'] = df_plot.Churn.replace({1: 'Yes Churn', 0: 'No
Churn'})
for col in cat_features:
    df_pivot = pd.pivot_table(
    df_train,
    values="MonthlyCharges",
    index=col,
```

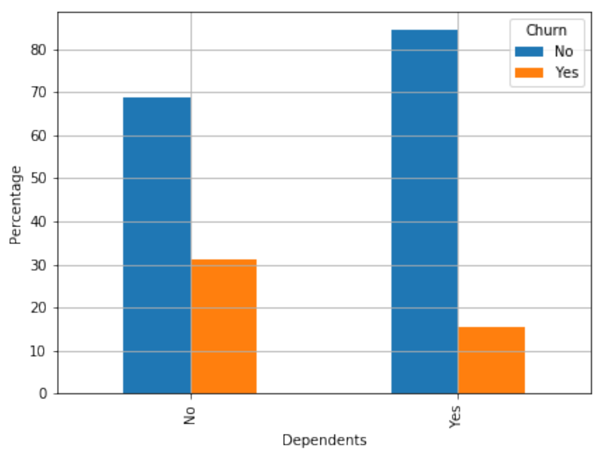
```
    columns="Churn",
    aggfunc=np.mean
    )
    fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(15, 5))
    ax1 =
round((df_plot.groupby(col).Churn.value_counts(normalize=True)*100),2)
.unstack(level=1).plot(kind='bar',ax=axes[0],grid=True)
    ax1.set_ylabel("Percentage")
    ax2 = df_pivot.plot(kind="bar",ax=axes[1],grid=True)
    ax2.set_ylabel('Monthly mean Charges')
```

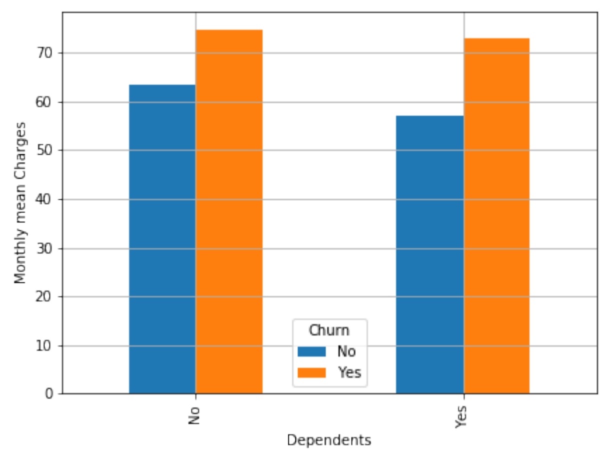


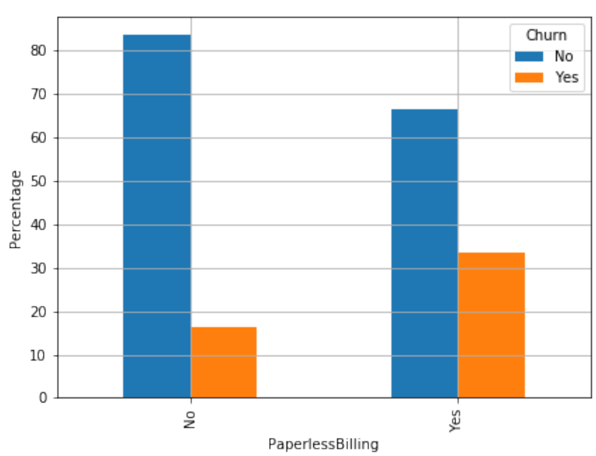


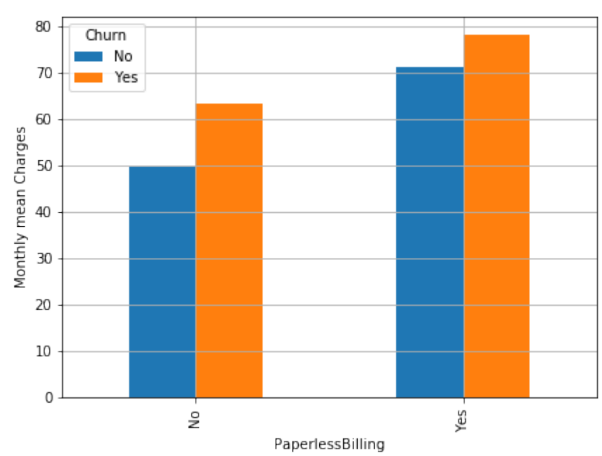

Percentage
Churn
No
Yes
Partner

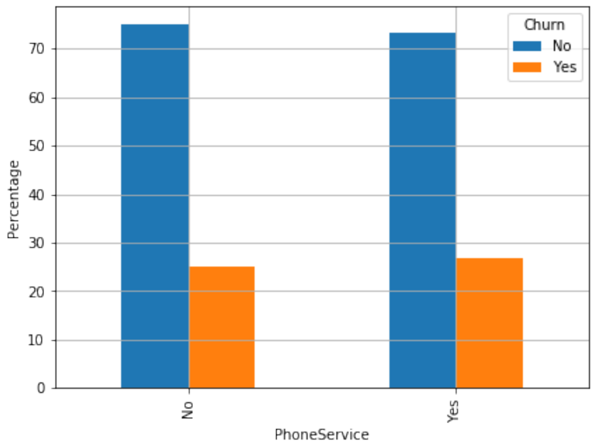

Monthly mean Charges
Churn
No
Yes
Partner

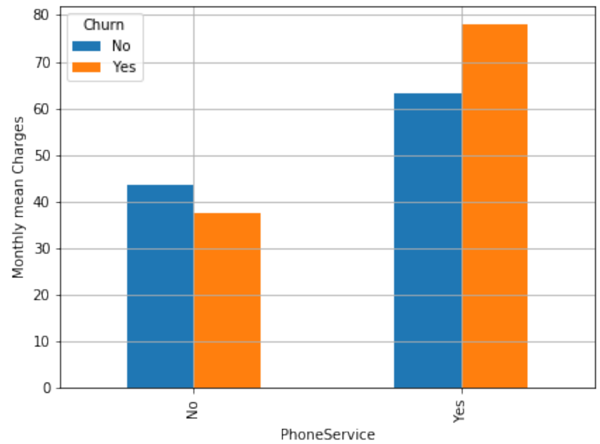

Percentage
Churn
No
Yes
Dependents

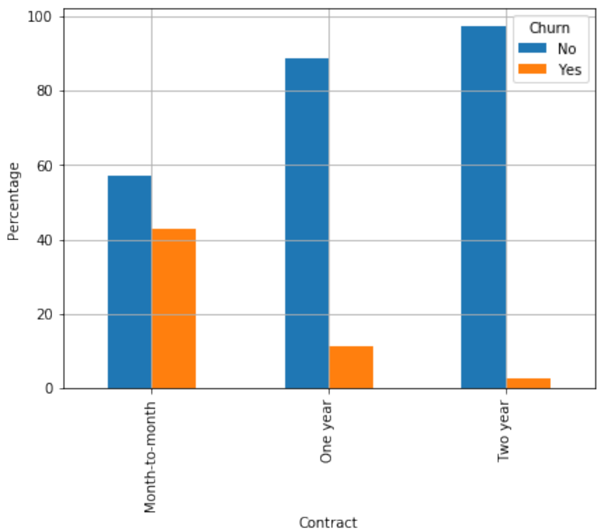

Monthly mean Charges
Churn
No
Yes
Dependents

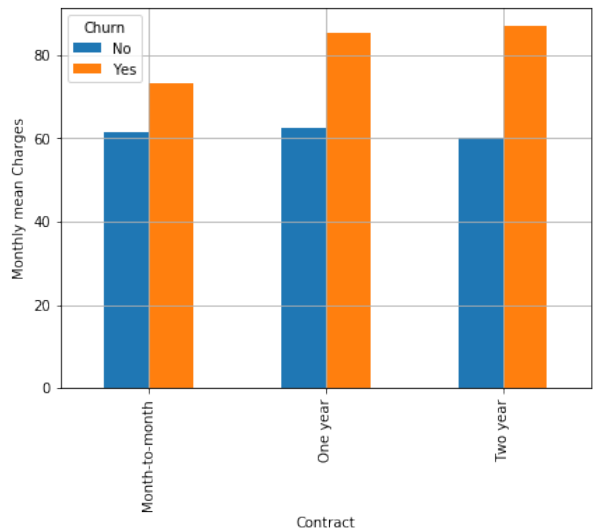

Percentage
Churn
No
Yes
PaperlessBilling

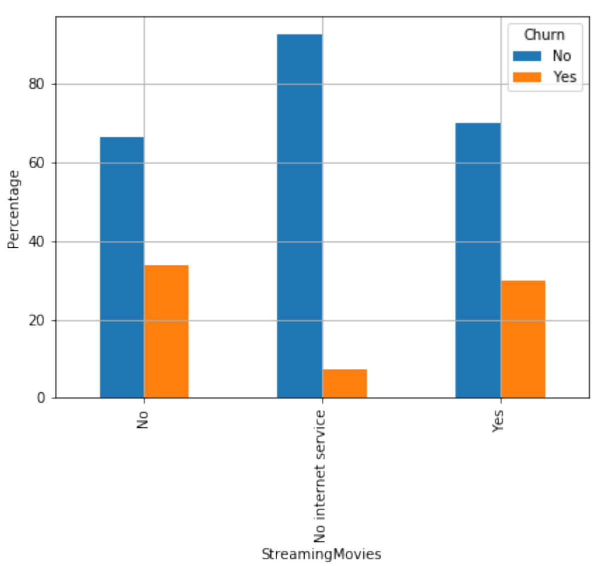

Monthly mean Charges
Churn
No
Yes
PaperlessBilling

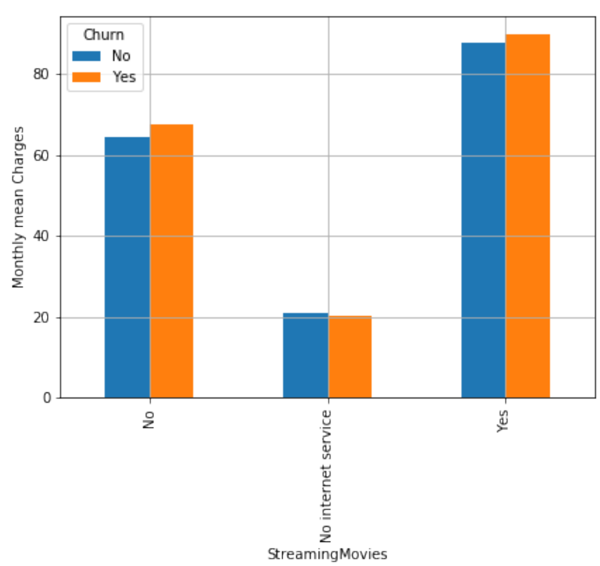

Churn
No
Yes
Percentage
0
10
20
30
40
50
60
70
No
Yes
PhoneService

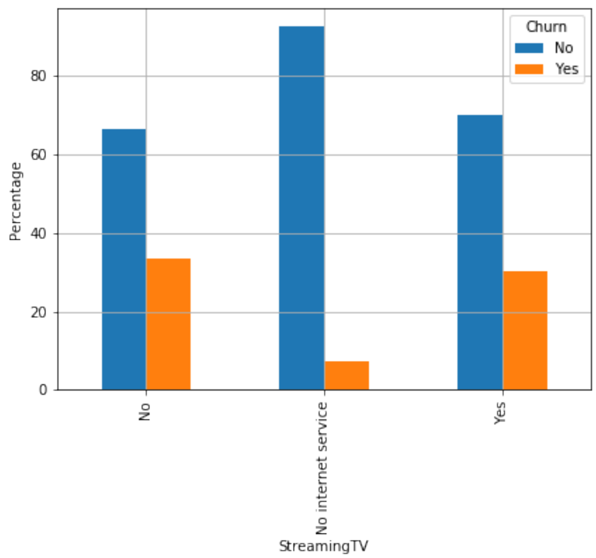

Churn
No
Yes
Monthly mean Charges
0
10
20
30
40
50
60
70
80
No
Yes
PhoneService

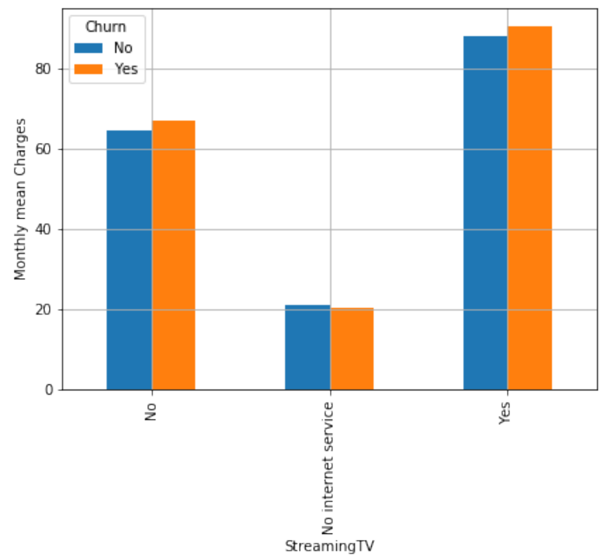

Churn
No
Yes
Percentage
0
20
40
60
80
100
Month-to-month
One year
Two year
Contract

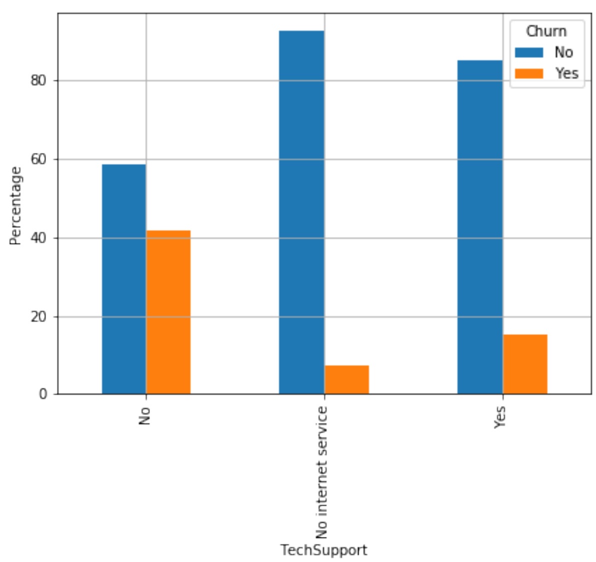

Churn
No
Yes
Monthly mean Charges
0
20
40
60
80
Month-to-month
One year
Two year
Contract

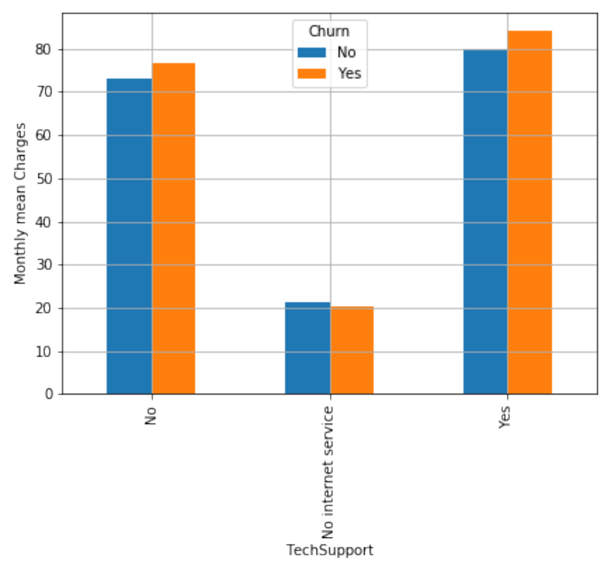

Churn
No
Yes
Percentage
0
20
40
60
80
No
No internet service
Yes
StreamingMovies

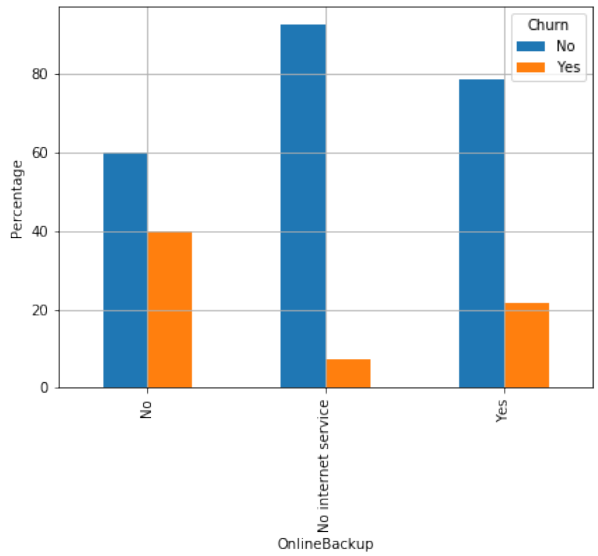

Churn
No
Yes
Monthly mean Charges
0
20
40
60
80
No
No internet service
Yes
StreamingMovies

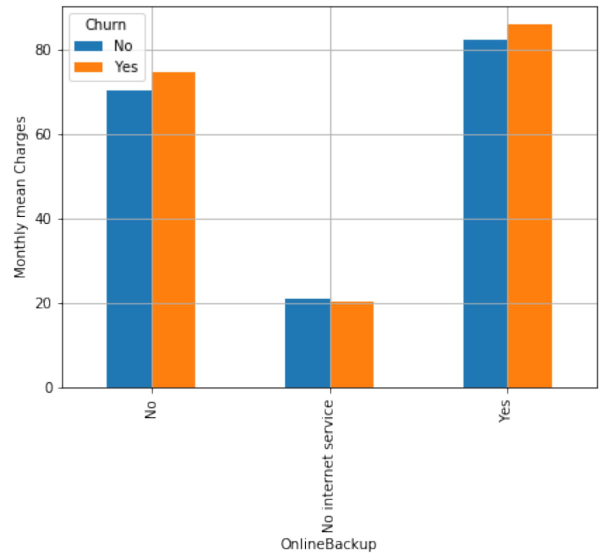

Churn
No
Yes
Percentage
0
20
40
60
80
No
No internet service
Yes
StreamingTV

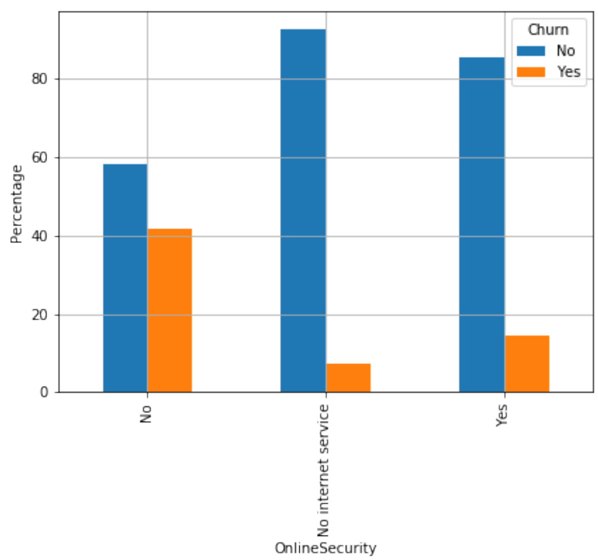

Churn
No
Yes
Monthly mean Charges
0
20
40
60
80
No
No internet service
Yes
StreamingTV

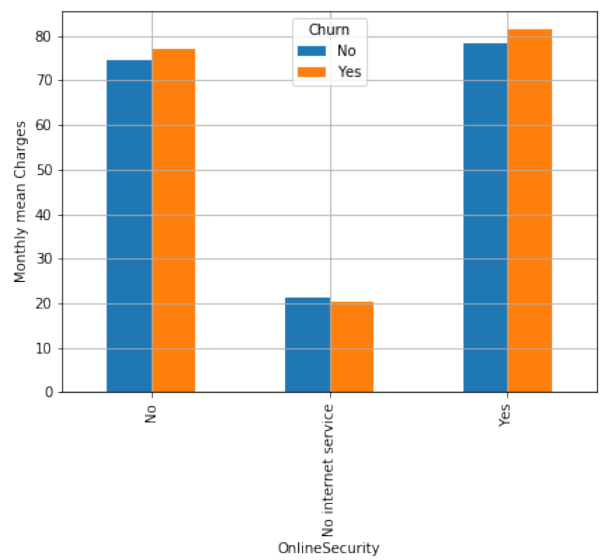

Churn
No
Yes
Percentage
0
20
40
60
80
No
No internet service
Yes
TechSupport

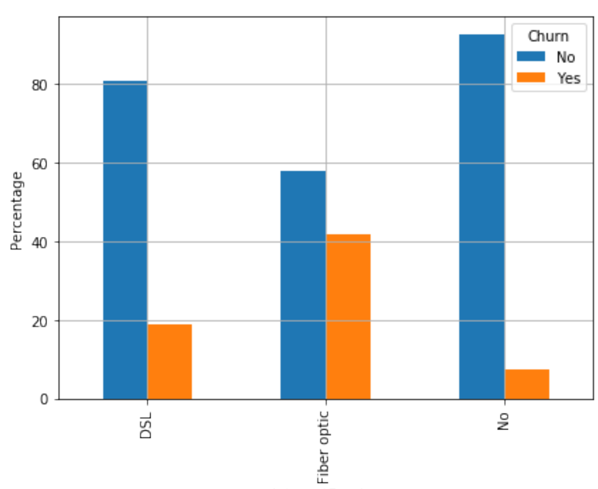

Churn
No
Yes
Monthly mean Charges
0
10
20
30
40
50
60
70
80
No
No internet service
Yes
TechSupport

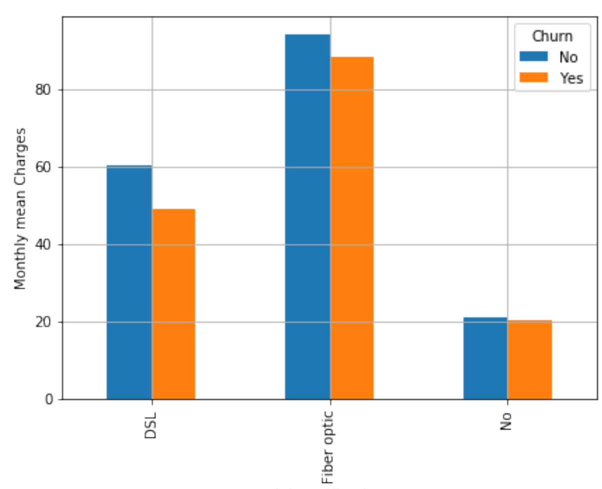

Churn
No
Yes
Percentage
0
20
40
60
80
No
No internet service
Yes
OnlineBackup

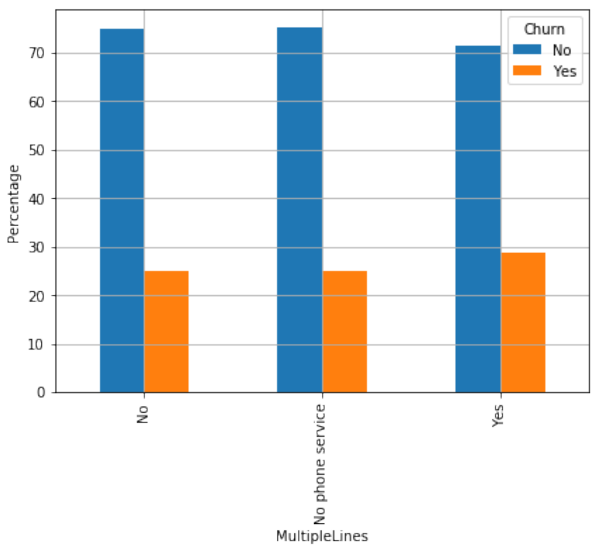

Churn
No
Yes
Monthly mean Charges
0
20
40
60
80
No
No internet service
Yes
OnlineBackup

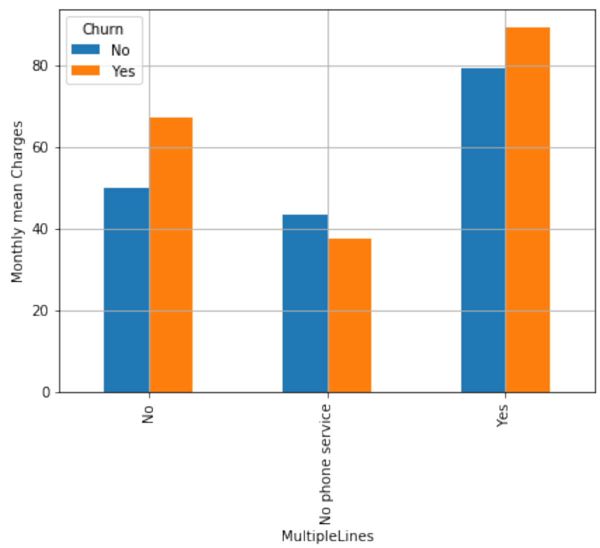

Churn
No
Yes
Percentage
0
20
40
60
80
No
No internet service
Yes
OnlineSecurity

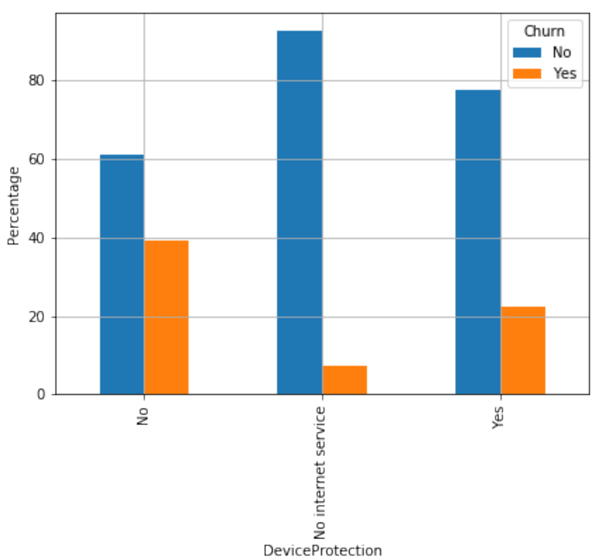

Churn
No
Yes
Monthly mean Charges
0
10
20
30
40
50
60
70
80
No
No internet service
Yes
OnlineSecurity

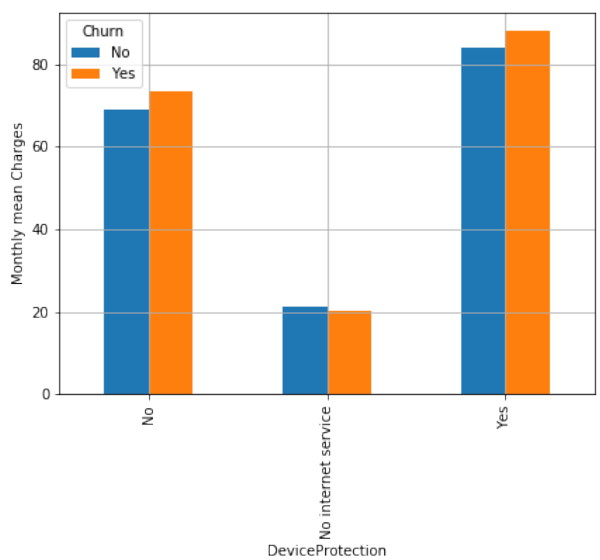

Churn
No
Yes
Percentage
0
20
40
60
80
DSL
Fiber optic
No
InternetService

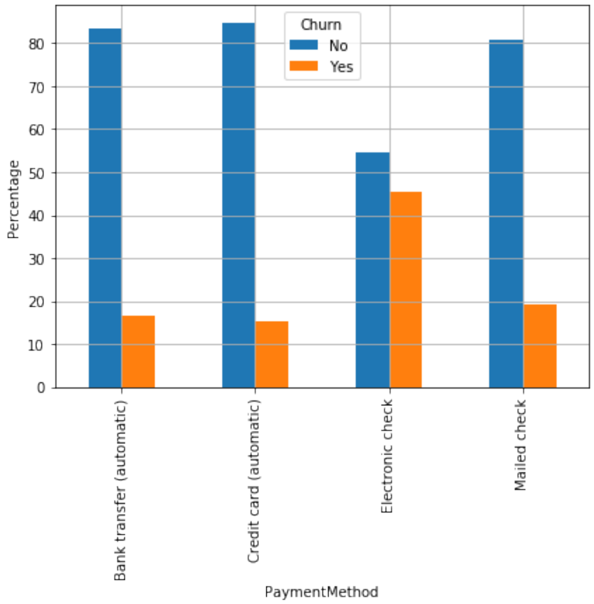

Churn
No
Yes
Monthly mean Charges
0
20
40
60
80
DSL
Fiber optic
No
InternetService

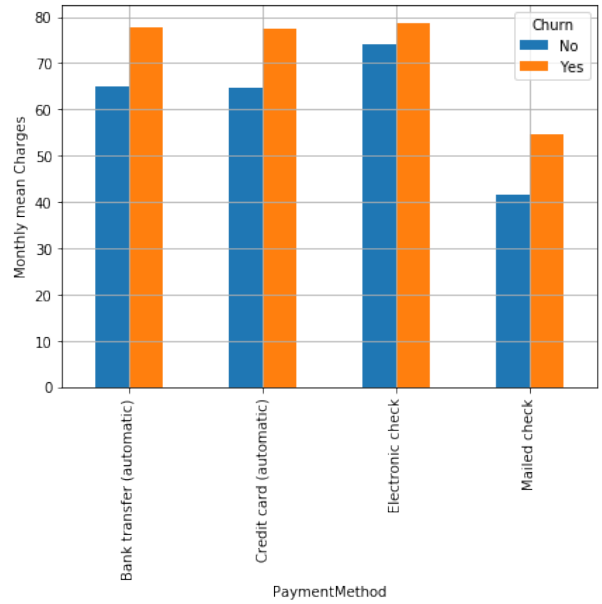

Churn
No
Yes
Percentage
0
10
20
30
40
50
60
70
No
No phone service
Yes
MultipleLines


Churn
No
Yes
Monthly mean Charges
0
20
40
60
80
No
No phone service
Yes
MultipleLines


Churn
No
Yes
Percentage
0
20
40
60
80
No
No internet service
Yes
DeviceProtection


Churn
No
Yes
Monthly mean Charges
0
20
40
60
80
No
No internet service
Yes
DeviceProtection





Analyzing the outputs we can note that:

- Gender, PhoneService, MultipleLines don't have a clear difference Churn Rates between the values in categories
- The other features seems that could be possible to help algorithmn predict Churn Customers
- The features with the churn ratio values higher or equal to 40%: -- Internet service -- online Security -- online Backup -- tech support -- contract -- seniorcitzen

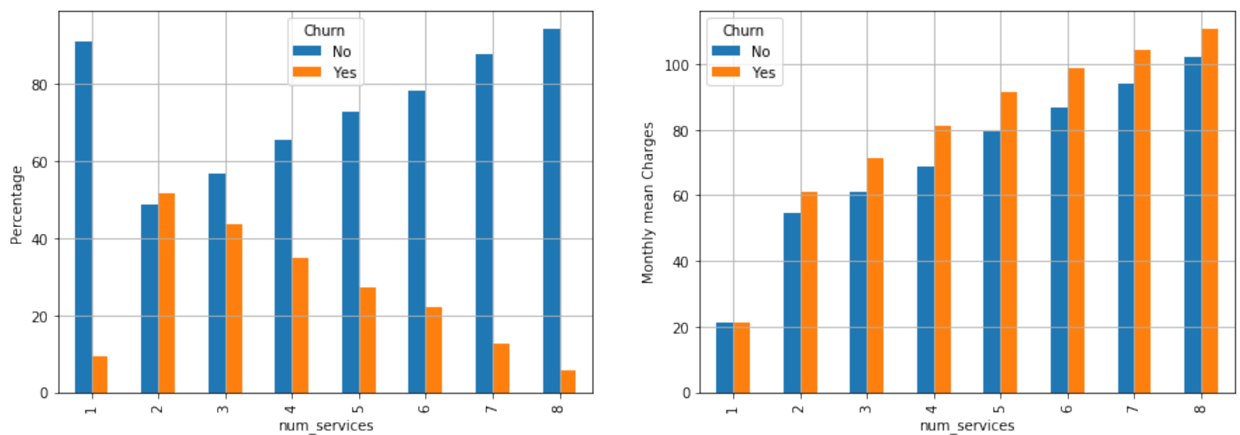
We can see that in some categories, the churn customers have highest mean of monthly charges.

Understanding the distribution of Total services provided for each Customer and the Churn % Rate

```
df_train['internet']= np.where(df_train.InternetService != 'No',
'Yes', 'No')

df_train['num_services'] = (df_train[['PhoneService',
'OnlineSecurity',
                                      'OnlineBackup',
'DeviceProtection',
                                      'TechSupport', 'StreamingTV',
                                      'StreamingMovies', 'internet']]
== 'Yes').sum(axis=1)

df_pivot = pd.pivot_table(
    df_train,
    values="MonthlyCharges",
    index='num_services',
    columns="Churn",
```

```
    aggfunc=np.mean
    )
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(15, 5))
ax1 = 
round((df_plot.groupby('num_services').Churn.value_counts(normalize=True)*100),2).unstack(level=1).plot(kind='bar',ax=axes[0],grid=True)
ax1.set_ylabel("Percentage")
ax2 = df_pivot.plot(kind="bar",ax=axes[1],grid=True)
ax2.set_ylabel('Monthly mean Charges')
```

```
Text(0, 0.5, 'Monthly mean Charges')
```



We have 22% of customers with only one service contracted... Of people with 1 service contract, 95% are Phone Service and 5% of total are DSL;

Altought we have some part of our sample with one service, we can see that people with two services are more propense to left.

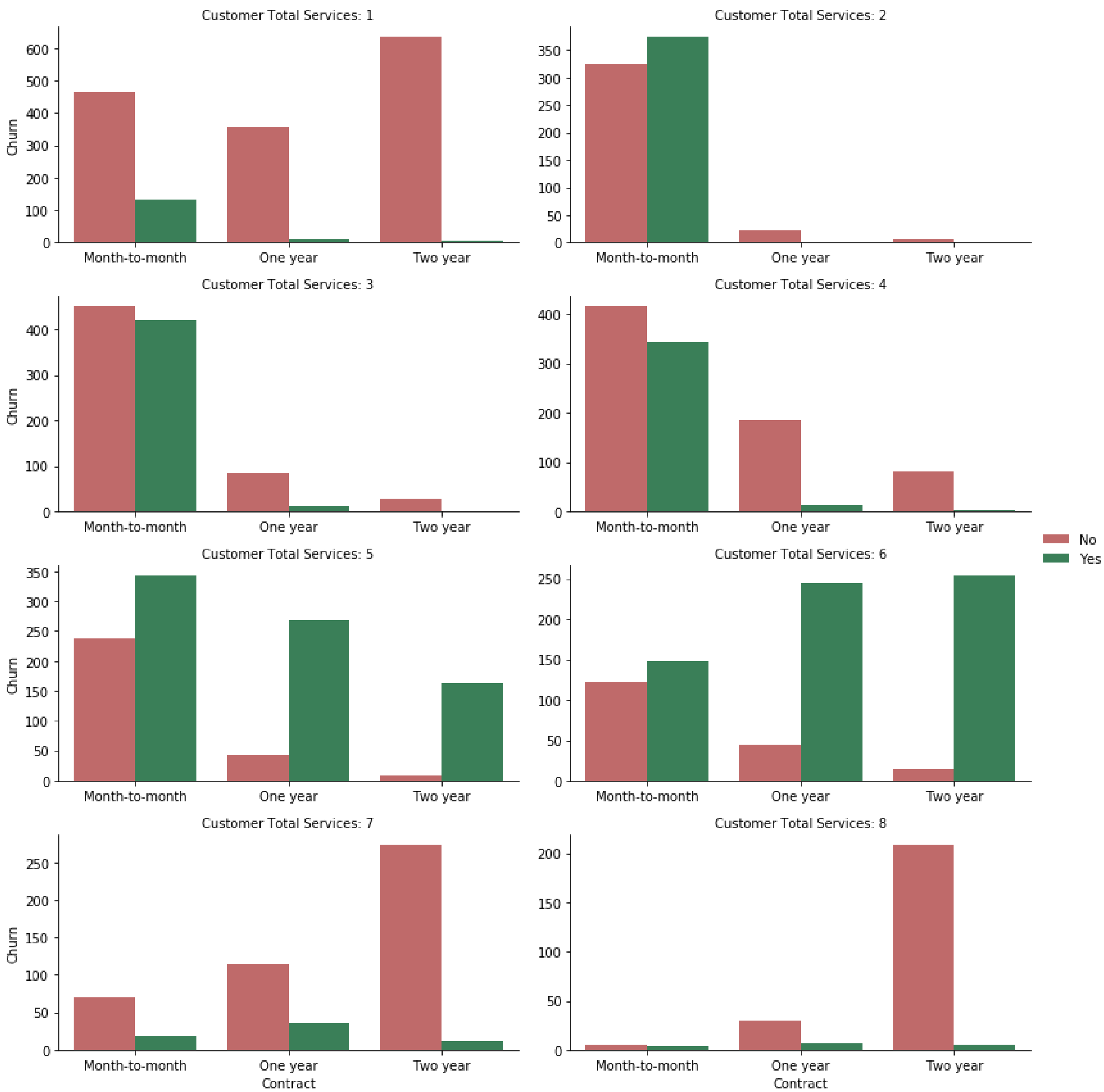
100% of Customers with total of services 2+ has internet (DSL or Fiber)

Based on Num Services

- I thought in see what's the Contract Type and the Churn distribution by each group

```
def countplot(x, hue, **kwargs):
    sns.countplot(x=x, hue=hue, **kwargs, order=['Month-to-month', 
'One year', 'Two year'])

print("TOTAL NUMBER OF SERVICES BY CONTRACT AND CHURN")
grid = sns.FacetGrid(data=df_train,col='num_services', col_wrap=2,
                     aspect=1.9, height=3, sharey=False, sharex=False)
fig = grid.map(countplot,'Contract','Churn', palette=['indianred', 
'seagreen'] )
fig.set_titles('Customer Total Services: {col_name}', fontsize=18)
fig.add_legend()

plt.show()
```

```
TOTAL NUMBER OF SERVICES BY CONTRACT AND CHURN
```



Very cool and meaningful visualization.

We can see difference in Contract feature in different total services that a customer has.

Knowning the Numerical Features

- The total features is object because it contains blank space.
- When exploring the dataset, I noted that these values occurs in customers with tenure 0, that don't have generated the first bill.

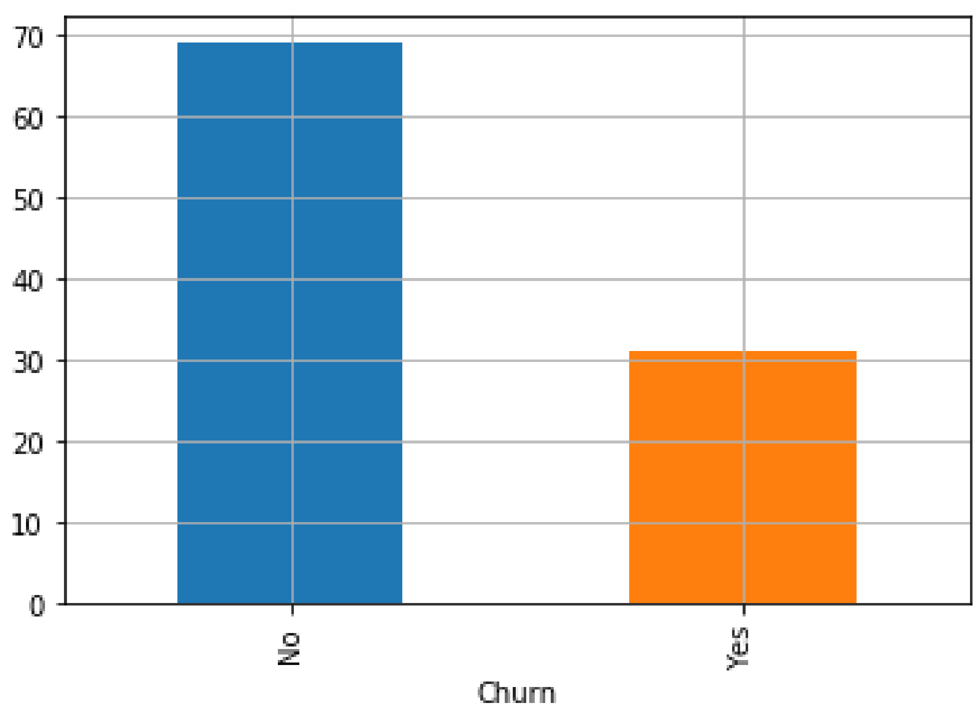
```
df_train.loc[df_train['TotalCharges'] == ' ', 'TotalCharges']=np.nan
df_train['TotalCharges'] = df_train['TotalCharges'].astype(float)
```

- I will fill this Na's values with zero

Total of the Monthly Revenue Lose

```
df_train.head()
print("Total Amount of Monthly Charges by each group: ")
print(round(df_train.groupby('Churn')['MonthlyCharges'].sum() ))
round(df_train.groupby('Churn')
['MonthlyCharges'].sum(normalize=True)/
df_train['MonthlyCharges'].sum()*100 ).plot(kind='bar',grid=True,)
```

```
Total Amount of Monthly Charges by each group:
Churn
No     316986.0
Yes    139131.0
Name: MonthlyCharges, dtype: float64

<matplotlib.axes._subplots.AxesSubplot at 0x7f5e290e35f8>
```



We can see that when we consider the amount of customers, the churn represents 26.5% of total customers, but when we consider Monthly Charges we can see that the ratio is 31% of total revenue was "lost" by people who left.

Distribution of Total Charges

- To better view the Total Charges I will use the log of Total Charges

```
df_convert=df_train
df_convert['Churn']=df_convert.Churn.replace({'Yes':1,"No":0})
df_convert.head()
```

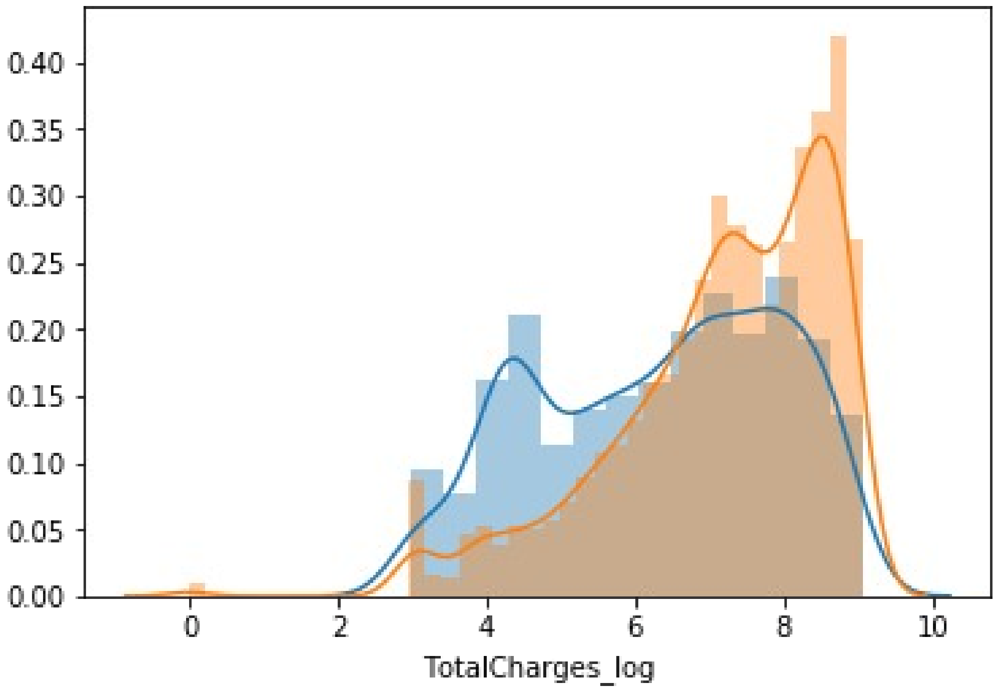
```
   customerID  gender  SeniorCitizen      ...       Churn  internet
num_services
0  7590-VHVEG  Female              0      ...           0       Yes
2
1  5575-GNVDE    Male              0      ...           0       Yes
4
2  3668-QPYBK    Male              0      ...           1       Yes
4
3  7795-CFOCW    Male              0      ...           0       Yes
4
4  9237-HQITU  Female              0      ...           1       Yes
2

[5 rows x 23 columns]
```

```
df_convert['TotalCharges_log'] = np.log(df_convert['TotalCharges']+1)
print(f"The mininum value in Total Charges is
{df_convert['TotalCharges'].min()} and the maximum is
{df_convert['TotalCharges'].max()}")
print(f"The mean Total Charges of Churn Customers is
{round(df_convert[df_convert['Churn'] != 0]
['TotalCharges'].mean(),2)}\
      \nThe mean Total Charges of Non-churn Customers is
{round(df_convert[df_convert['Churn'] == 0]
['TotalCharges'].mean(),2)}")

#plot_distribution(df_train, 'TotalCharges_log', bins=.25)
```

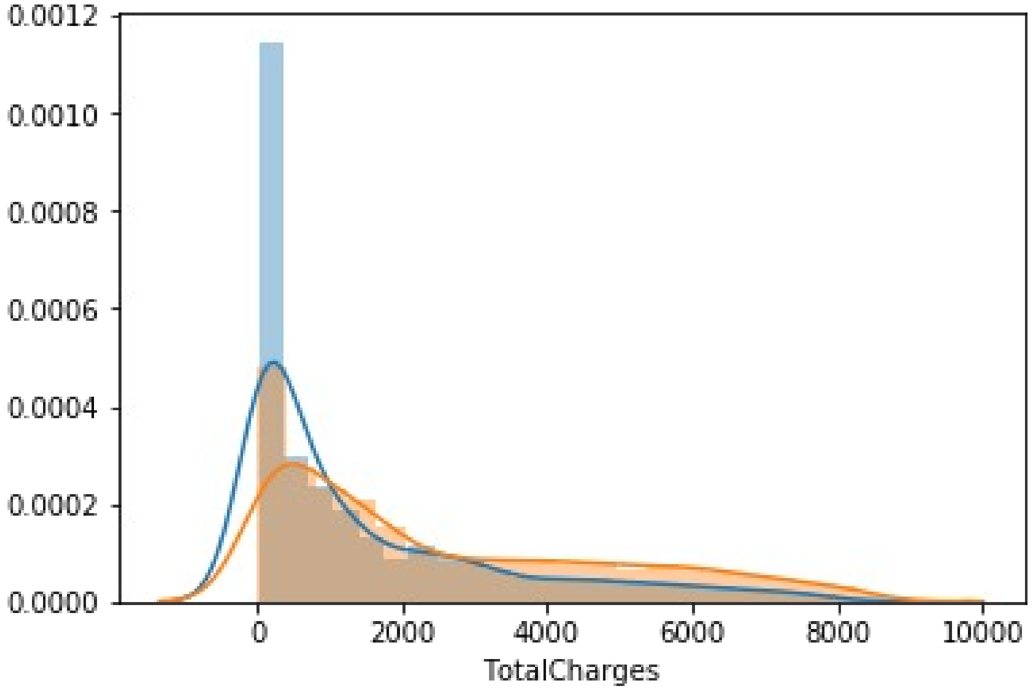
```
The mininum value in Total Charges is 18.8 and the maximum is 8684.8
The mean Total Charges of Churn Customers is 1531.8
The mean Total Charges of Non-churn Customers is 2555.34
```

```
tmp_churn_log = df_convert[df_convert['Churn'] == 1]
['TotalCharges_log']
tmp_no_churn_log = df_convert[df_convert['Churn'] == 0]
['TotalCharges_log']

tmp_churn = df_convert[df_convert['Churn'] == 1]['TotalCharges']
tmp_no_churn = df_convert[df_convert['Churn'] == 0]['TotalCharges']

sns.distplot(tmp_churn_log,label="Churn")
tmp_no_churn_log=tmp_no_churn_log.replace(np.nan,0)
sns.distplot(tmp_no_churn_log,label="No Churn")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5e2891b780>
```




```
sns.distplot(tmp_churn,label="Churn")
tmp_no_churn=tmp_no_churn.replace(np.nan,0)
sns.distplot(tmp_no_churn,label="No Churn")

<matplotlib.axes._subplots.AxesSubplot at 0x7f5e2887d400>
```



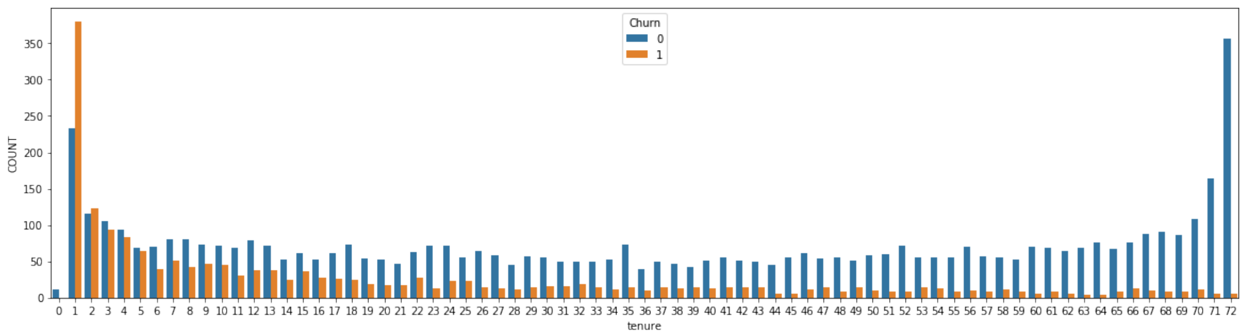
We can note that churn customers has lower values in Total Charges.... I think that it's a signal of a different tenure values; Let's check what tenure feature says.

Tenure feature

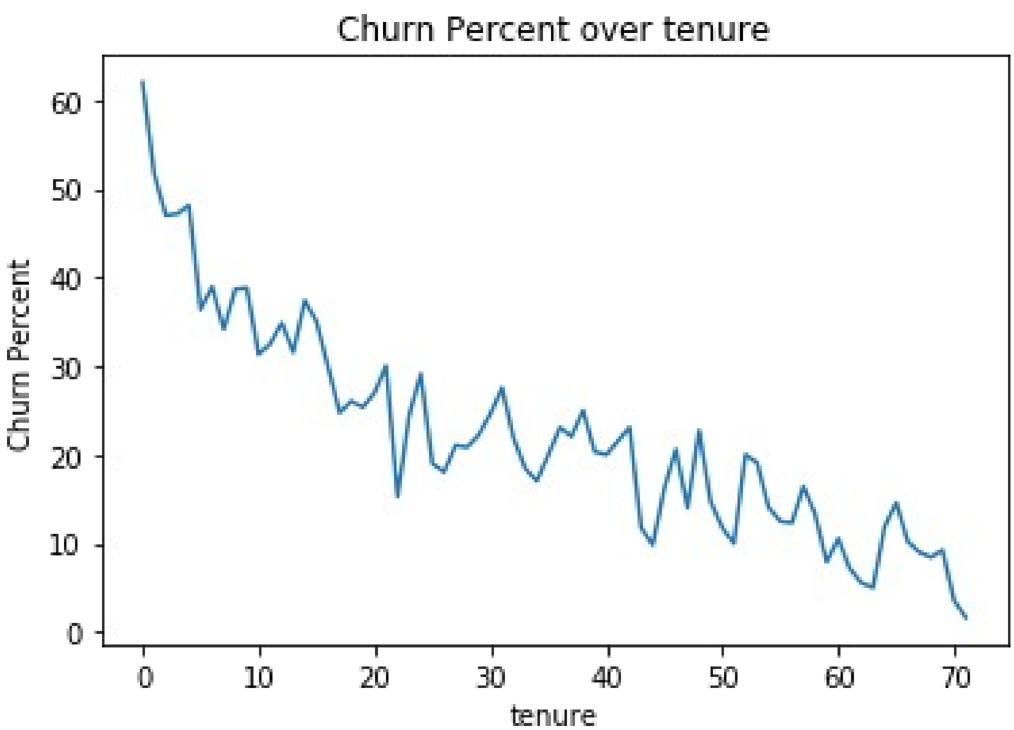
- Let's understand the distribution and churn probabilities by Tenure

```
print(f"The mininum value in Tenure is {df_train['tenure'].min()} and
the maximum is {df_train['tenure'].max()}")
print(f"The mean Tenure of Churn Customers is
{round(df_train[df_train['Churn'] != 0]['tenure'].mean())}\
      \nThe mean Tenure of Non-churn Customers is
{round(df_train[df_train['Churn'] == 0]['tenure'].mean())}")

The mininum value in Tenure is 0 and the maximum is 72
The mean Tenure of Churn Customers is 18
The mean Tenure of Non-churn Customers is 38

#one=df_train.groupby('tenure')['Churn'].count()

temp=df_train.groupby(['tenure','Churn'])
['Churn'].count().reset_index(name='COUNT')
sum_val=temp.groupby('tenure')['COUNT'].sum().reset_index(name='SUM')
tenure_sum=pd.merge(temp,sum_val,on='tenure')
tenure_sum['percent']=(tenure_sum['COUNT']*100.0)/tenure_sum['SUM']
churn_percent=temp[temp['Churn']==1]['Churn']/temp[temp['Churn']==1]
['COUNT'].sum()

line_tenure=tenure_sum[tenure_sum['Churn']==1]
['percent'].reset_index(name='Percent')
```

```
nums=np.arange(0,72,1)
line_tenure['tenure'] = nums.tolist()

fig, ax = plt.subplots(figsize=(20, 5))
sns.barplot(data=temp,x='tenure',y='COUNT',hue='Churn')
#tenure_sum[tenure_sum['Churn']==1]
['percent'].reset_index(name='Percent').plot(kind='line')

<matplotlib.axes._subplots.AxesSubplot at 0x7f5e2874be80>
```




```
plt=sns.lineplot(data=line_tenure,x='tenure',y='Percent')
plt.set(ylabel='Churn Percent',title='Churn Percent over tenure')

[Text(0, 0.5, 'Churn Percent'), Text(0.5, 1.0, 'Churn Percent over
tenure')]
```



We can see that the mean of two groups has different... To afirm it, we need to do a statistc test, but it's a very insightful visualization.

Mean Monthly Charges by tenure with Churn Rate of tenure values

```
fig, ax = plt.subplots(figsize=(20, 5))
monthly_mean=df_train.groupby(['tenure','Churn'])
['MonthlyCharges'].mean().reset_index(name='mean_monthly')
sns.barplot(data=monthly_mean,x='tenure',y='mean_monthly',hue='Churn')
```

```
----------------------------------------------------------------------
-----
AttributeError                            Traceback (most recent call
last)
<ipython-input-31-bd5804e2cbe0> in <module>
----> 1 fig, ax = plt.subplots(figsize=(20, 5))
      2 monthly_mean=df_train.groupby(['tenure','Churn'])
['MonthlyCharges'].mean().reset_index(name='mean_monthly')
      3
sns.barplot(data=monthly_mean,x='tenure',y='mean_monthly',hue='Churn')

AttributeError: 'AxesSubplot' object has no attribute 'subplots'
```

```
fig, ax = plt.subplots(figsize=(20, 5))
monthly_mean=df_train.groupby(['tenure','Churn'])
['MonthlyCharges'].mean().reset_index(name='mean_monthly')
sns.barplot(data=monthly_mean,x='tenure',y='mean_monthly',hue='Churn')
```

```
month_list=np.arange(0,73,1)
print(month_list)
temp_month=monthly_mean[monthly_mean['tenure']==1]['mean_monthly']
#for i in range(0,73,1):
#    temp_month=monthly_mean[monthly_mean['tenure']==i]
['mean_monthly'].reset_index()
#    #(temp_month[2]-temp_month[1])/temp_month[1]
print(monthly_mean)
monthly_mean.groupby('tenure')
```

```
lol=monthly_mean.groupby('tenure')
```

```
lol['mean_monthly'].head()
```