churn

July 19, 2022

1 Telecom Churn Case Study

[ ]:
```python
# Import necessary libraries
import numpy as np
import pandas as pd

# set the max columns to none
pd.set_option('display.max_columns', None)
```

[ ]:
```python
# Read the data
churn_data = pd.read_csv('churn_data.csv')
customer_data = pd.read_csv('customer_data.csv')
internet_data = pd.read_csv('internet_data.csv')
```

[ ]:
```python
print('Churn data')
churn_data.head()
```

```
Churn data
```

[ ]:
```
   customerID  tenure PhoneService        Contract PaperlessBilling  \
0  7590-VHVEG       1           No  Month-to-month              Yes
1  5575-GNVDE      34          Yes        One year               No
2  3668-QPYBK       2          Yes  Month-to-month              Yes
3  7795-CFOCW      45           No        One year               No
4  9237-HQITU       2          Yes  Month-to-month              Yes

              PaymentMethod  MonthlyCharges TotalCharges Churn
0          Electronic check           29.85        29.85    No
1              Mailed check           56.95       1889.5    No
2              Mailed check           53.85       108.15   Yes
3 Bank transfer (automatic)           42.30      1840.75    No
4          Electronic check           70.70       151.65   Yes
```

[ ]:
```python
print('Internet data')
internet_data.head()
```

```
Internet data
```

```
[ ]:    customerID     MultipleLines InternetService OnlineSecurity OnlineBackup  \
     0  7590-VHVEG  No phone service             DSL             No          Yes
     1  5575-GNVDE                No             DSL            Yes           No
     2  3668-QPYBK                No             DSL            Yes          Yes
     3  7795-CFOCW  No phone service             DSL            Yes           No
     4  9237-HQITU                No     Fiber optic             No           No

       DeviceProtection TechSupport StreamingTV StreamingMovies
     0               No          No          No              No
     1              Yes          No          No              No
     2               No          No          No              No
     3              Yes         Yes          No              No
     4               No          No          No              No
```

```
[ ]: print('Customer data')
     customer_data.head()
```

```
     Customer data
```

```
[ ]:    customerID  gender  SeniorCitizen Partner Dependents
     0  7590-VHVEG  Female              0     Yes         No
     1  5575-GNVDE    Male              0      No         No
     2  3668-QPYBK    Male              0      No         No
     3  7795-CFOCW    Male              0      No         No
     4  9237-HQITU  Female              0      No         No
```

```
[ ]: # Merge all data
     df1 = pd.merge(customer_data, internet_data, how='inner', on='customerID')
     data = pd.merge(churn_data, df1, how='inner', on='customerID')
```

2 View all data

Merging on customerID as it is common in all datasets

```
[ ]: data.head()
```

```
[ ]:    customerID  tenure PhoneService        Contract PaperlessBilling  \
     0  7590-VHVEG       1           No  Month-to-month              Yes
     1  5575-GNVDE      34          Yes        One year               No
     2  3668-QPYBK       2          Yes  Month-to-month              Yes
     3  7795-CFOCW      45           No        One year               No
     4  9237-HQITU       2          Yes  Month-to-month              Yes

                    PaymentMethod  MonthlyCharges TotalCharges Churn  gender  \
     0           Electronic check           29.85        29.85    No  Female
     1               Mailed check           56.95       1889.5    No    Male
     2               Mailed check           53.85       108.15   Yes    Male
```

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

   SeniorCitizen Partner Dependents     MultipleLines InternetService  \
0              0     Yes         No  No phone service             DSL
1              0      No         No                No             DSL
2              0      No         No                No             DSL
3              0      No         No  No phone service             DSL
4              0      No         No                No     Fiber optic

  OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV  \
0             No          Yes               No          No          No
1            Yes           No              Yes          No          No
2            Yes          Yes               No          No          No
3            Yes           No              Yes         Yes          No
4             No           No               No          No          No

  StreamingMovies
0              No
1              No
2              No
3              No
4              No
```

[ ]:
```
print('Total entries of data :',data.shape)
```

```
Total entries of data : (7043, 21)
```

[ ]:
```
data.describe()
```

[ ]:

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

Looking at all details that have numerical values. - Comparing the mean and 50% median we can see that they are almost the same. This is a good indicator of no outliers - There is a steady increase in the values of percentiles. This is also a good indicator of no outliers

3 Clean up data

There are a lot of columns with 'Yes' and 'No' entries. It is useful to convert them into 1 and 0, so that it can be used in the model

[ ]:
```
cols = ['PhoneService', 'PaperlessBilling', 'Churn', 'Partner', 'Dependents',␣
 ↪'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',␣
 ↪'StreamingTV', 'StreamingMovies']
for i in cols:
    print(data[i].value_counts())
    print()
```

```
Yes    6361
No      682
Name: PhoneService, dtype: int64

Yes    4171
No     2872
Name: PaperlessBilling, dtype: int64

No     5174
Yes    1869
Name: Churn, dtype: int64

No     3641
Yes    3402
Name: Partner, dtype: int64

No     4933
Yes    2110
Name: Dependents, dtype: int64

No                     3498
Yes                    2019
No internet service    1526
Name: OnlineSecurity, dtype: int64

No                     3088
Yes                    2429
No internet service    1526
Name: OnlineBackup, dtype: int64

No                     3095
Yes                    2422
No internet service    1526
Name: DeviceProtection, dtype: int64

No                     3473
```

```
Yes                    2044
No internet service    1526
Name: TechSupport, dtype: int64

No                     2810
Yes                    2707
No internet service    1526
Name: StreamingTV, dtype: int64

No                     2785
Yes                    2732
No internet service    1526
Name: StreamingMovies, dtype: int64
```

We can observe that 'No internet service' can be seen at many columns. Let us see if this info is present in the 'InternetService' column

[ ]:
```
print(data.InternetService.value_counts())
```

```
Fiber optic    3096
DSL            2421
No             1526
Name: InternetService, dtype: int64
```

As the number is exact (1526), we don't need this info as it is present in another column already. So, we are going to replace 'No internet service' with 0

[ ]:
```
data['PhoneService'].value_counts()
data.replace('Yes', 1, inplace=True)
data.replace('No', 0, inplace=True)
data.replace('No internet service', 0, inplace=True)
data.head()
```

[ ]:
```
   customerID  tenure  PhoneService        Contract  PaperlessBilling  \
0  7590-VHVEG       1             0  Month-to-month                 1
1  5575-GNVDE      34             1        One year                 0
2  3668-QPYBK       2             1  Month-to-month                 1
3  7795-CFOCW      45             0        One year                 0
4  9237-HQITU       2             1  Month-to-month                 1

               PaymentMethod  MonthlyCharges TotalCharges  Churn  gender  \
0           Electronic check           29.85        29.85      0  Female
1               Mailed check           56.95       1889.5      0    Male
2               Mailed check           53.85       108.15      1    Male
3  Bank transfer (automatic)           42.30      1840.75      0    Male
4           Electronic check           70.70       151.65      1  Female

   SeniorCitizen  Partner  Dependents     MultipleLines InternetService  \
```

```
0              0        1           0  No phone service             DSL
1              0        0           0                 0             DSL
2              0        0           0                 0             DSL
3              0        0           0  No phone service             DSL
4              0        0           0                 0     Fiber optic

   OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
0               0             1                 0            0            0
1               1             0                 1            0            0
2               1             1                 0            0            0
3               1             0                 1            1            0
4               0             0                 0            0            0

   StreamingMovies
0                0
1                0
2                0
3                0
4                0
```

[ ]:
```python
data.gender.value_counts()
```

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

Since there are only 2 values for gender we can also replace them as Male=1 and Female=0

[ ]:
```python
data.replace('Male', 1, inplace=True)
data.replace('Female', 0, inplace=True)
data.head()
```

[ ]:
```
   customerID  tenure  PhoneService        Contract  PaperlessBilling  \
0  7590-VHVEG       1             0  Month-to-month                 1
1  5575-GNVDE      34             1        One year                 0
2  3668-QPYBK       2             1  Month-to-month                 1
3  7795-CFOCW      45             0        One year                 0
4  9237-HQITU       2             1  Month-to-month                 1

              PaymentMethod  MonthlyCharges TotalCharges  Churn  gender  \
0          Electronic check           29.85        29.85      0       0
1              Mailed check           56.95       1889.5      0       1
2              Mailed check           53.85       108.15      1       1
3  Bank transfer (automatic)           42.30      1840.75      0       1
4          Electronic check           70.70       151.65      1       0

   SeniorCitizen  Partner  Dependents     MultipleLines InternetService  \
```

```
0               0         1            0  No phone service             DSL
1               0         0            0                 0             DSL
2               0         0            0                 0             DSL
3               0         0            0  No phone service             DSL
4               0         0            0                 0     Fiber optic

   OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
0               0             1                 0            0            0
1               1             0                 1            0            0
2               1             1                 0            0            0
3               1             0                 1            1            0
4               0             0                 0            0            0

   StreamingMovies
0                0
1                0
2                0
3                0
4                0
```

It is better to convert categorical variables using one-hot encoding

```
[ ]: cols = ['Contract', 'PaymentMethod', 'MultipleLines', 'InternetService']
     for i in cols:
         print(data[i].value_counts())
         print()
```

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

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

0                    3390
1                    2971
No phone service      682
Name: MultipleLines, dtype: int64

Fiber optic    3096
DSL            2421
0              1526
Name: InternetService, dtype: int64
```

[ ]:
```
data.PhoneService.value_counts()
```

[ ]:
```
1    6361
0     682
Name: PhoneService, dtype: int64
```

'No phone service' can be predicted from the column 'PhoneService' as it is an exact match. So, 'No phone service' can be replaced with 0 in column 'MultipleLines'

[ ]:
```
data.replace('No phone service', 0, inplace=True)
data.head()
```

[ ]:
```
   customerID  tenure  PhoneService        Contract  PaperlessBilling  \
0  7590-VHVEG       1             0  Month-to-month                 1
1  5575-GNVDE      34             1        One year                 0
2  3668-QPYBK       2             1  Month-to-month                 1
3  7795-CFOCW      45             0        One year                 0
4  9237-HQITU       2             1  Month-to-month                 1

               PaymentMethod  MonthlyCharges TotalCharges  Churn  gender  \
0           Electronic check           29.85        29.85      0       0
1               Mailed check           56.95       1889.5      0       1
2               Mailed check           53.85       108.15      1       1
3  Bank transfer (automatic)           42.30      1840.75      0       1
4           Electronic check           70.70       151.65      1       0

   SeniorCitizen  Partner  Dependents  MultipleLines InternetService  \
0              0        1           0              0             DSL
1              0        0           0              0             DSL
2              0        0           0              0             DSL
3              0        0           0              0             DSL
4              0        0           0              0     Fiber optic

   OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
0               0             1                 0            0            0
1               1             0                 1            0            0
2               1             1                 0            0            0
3               1             0                 1            1            0
4               0             0                 0            0            0

   StreamingMovies
0                0
1                0
2                0
3                0
4                0
```

```
[ ]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   tenure            7043 non-null   int64
 2   PhoneService      7043 non-null   int64
 3   Contract          7043 non-null   object
 4   PaperlessBilling  7043 non-null   int64
 5   PaymentMethod     7043 non-null   object
 6   MonthlyCharges    7043 non-null   float64
 7   TotalCharges      7043 non-null   object
 8   Churn             7043 non-null   int64
 9   gender            7043 non-null   int64
 10  SeniorCitizen     7043 non-null   int64
 11  Partner           7043 non-null   int64
 12  Dependents        7043 non-null   int64
 13  MultipleLines     7043 non-null   int64
 14  InternetService   7043 non-null   object
 15  OnlineSecurity    7043 non-null   int64
 16  OnlineBackup      7043 non-null   int64
 17  DeviceProtection  7043 non-null   int64
 18  TechSupport       7043 non-null   int64
 19  StreamingTV       7043 non-null   int64
 20  StreamingMovies   7043 non-null   int64
dtypes: float64(1), int64(15), object(5)
memory usage: 1.2+ MB
```

Strangely the column 'TotalCharges' is an object and not number. But we know that they are numbers. So, convert them into numbers

```
[ ]: # data['TotalCharges'] = pd.to_numeric(data['TotalCharges'], errors='raise')
print('The above command is commented out because it will throw and error')
data.info()
```

```
The above command is commented out because it will throw and error
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   tenure            7043 non-null   int64
 2   PhoneService      7043 non-null   int64
 3   Contract          7043 non-null   object
```

```
 4   PaperlessBilling  7043 non-null   int64
 5   PaymentMethod     7043 non-null   object
 6   MonthlyCharges    7043 non-null   float64
 7   TotalCharges      7043 non-null   object
 8   Churn             7043 non-null   int64
 9   gender            7043 non-null   int64
 10  SeniorCitizen     7043 non-null   int64
 11  Partner           7043 non-null   int64
 12  Dependents        7043 non-null   int64
 13  MultipleLines     7043 non-null   int64
 14  InternetService   7043 non-null   object
 15  OnlineSecurity    7043 non-null   int64
 16  OnlineBackup      7043 non-null   int64
 17  DeviceProtection  7043 non-null   int64
 18  TechSupport       7043 non-null   int64
 19  StreamingTV       7043 non-null   int64
 20  StreamingMovies   7043 non-null   int64
dtypes: float64(1), int64(15), object(5)
memory usage: 1.2+ MB
```

Apparently there is an empty string at position 488. Convert it to 0. Let us see where these entries are

[ ]:
```
empties = []
for i in range(data.shape[0]):
    if data.TotalCharges[i] == ' ':
        empties.append(i)
empties
```

[ ]:
```
[488, 753, 936, 1082, 1340, 3331, 3826, 4380, 5218, 6670, 6754]
```

[ ]:
```
for i in empties:
    data.TotalCharges.iloc[i] = 0
```

```
/tmp/ipykernel_2511/1912021023.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data.TotalCharges.iloc[i] = 0
```

[ ]:
```
data['TotalCharges'] = pd.to_numeric(data['TotalCharges'], errors='raise')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
```

```
 0   customerID        7043 non-null   object
 1   tenure            7043 non-null   int64
 2   PhoneService      7043 non-null   int64
 3   Contract          7043 non-null   object
 4   PaperlessBilling  7043 non-null   int64
 5   PaymentMethod     7043 non-null   object
 6   MonthlyCharges    7043 non-null   float64
 7   TotalCharges      7043 non-null   float64
 8   Churn             7043 non-null   int64
 9   gender            7043 non-null   int64
 10  SeniorCitizen     7043 non-null   int64
 11  Partner           7043 non-null   int64
 12  Dependents        7043 non-null   int64
 13  MultipleLines     7043 non-null   int64
 14  InternetService   7043 non-null   object
 15  OnlineSecurity    7043 non-null   int64
 16  OnlineBackup      7043 non-null   int64
 17  DeviceProtection  7043 non-null   int64
 18  TechSupport       7043 non-null   int64
 19  StreamingTV       7043 non-null   int64
 20  StreamingMovies   7043 non-null   int64
dtypes: float64(2), int64(15), object(4)
memory usage: 1.4+ MB
```

[ ]:

4 Exploratory Data Analysis

[ ]:
```
data.head()
```

[ ]:
```
   customerID  tenure  PhoneService        Contract  PaperlessBilling  \
0  7590-VHVEG       1             0  Month-to-month                 1
1  5575-GNVDE      34             1        One year                 0
2  3668-QPYBK       2             1  Month-to-month                 1
3  7795-CFOCW      45             0        One year                 0
4  9237-HQITU       2             1  Month-to-month                 1

               PaymentMethod  MonthlyCharges  TotalCharges  Churn  gender  \
0           Electronic check           29.85         29.85      0       0
1               Mailed check           56.95       1889.50      0       1
2               Mailed check           53.85        108.15      1       1
3  Bank transfer (automatic)           42.30       1840.75      0       1
4           Electronic check           70.70        151.65      1       0

   SeniorCitizen  Partner  Dependents  MultipleLines InternetService  \
0              0        1           0              0             DSL
```

```
1              0          0          0            0             DSL
2              0          0          0            0             DSL
3              0          0          0            0             DSL
4              0          0          0            0     Fiber optic

   OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
0               0             1                 0            0            0
1               1             0                 1            0            0
2               1             1                 0            0            0
3               1             0                 1            1            0
4               0             0                 0            0            0

   StreamingMovies
0                0
1                0
2                0
3                0
4                0
```

[ ]:
```python
# Import necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns
# %matplotlib inline
```

[ ]:
```python
# sns.scatterplot(data=data, x = 'tenure', y='MonthlyCharges', hue='Churn',␣
↪alpha=0.25)
print('The median of tenure for churned customers is :',data[data['Churn'] ==␣
↪1].tenure.median())
print('The median of tenure for NON-churned customers is :',data[data['Churn']␣
↪== 0].tenure.median())
```

```
The median of tenure for churned customers is : 10.0
The median of tenure for NON-churned customers is : 38.0
```

Customers with less tenure tend to churn easily

[ ]:
```python
data[data['Churn'] == 1].gender.value_counts()
```

[ ]:
```
0    939
1    930
Name: gender, dtype: int64
```

There is no gender bias for Churn

[ ]:
```python
print(data[data['Churn'] == 1].SeniorCitizen.value_counts())
```

```
0    1393
1     476
```

```
Name: SeniorCitizen, dtype: int64
```

Senior Citizen are less likely to Churn

[ ]:
```
data[data['Churn'] == 1].Partner.value_counts()
```

[ ]:
```
0    1200
1     669
Name: Partner, dtype: int64
```

People with a partner are less likely to Churn

[ ]:
```
data[data['Churn'] == 1].Dependents.value_counts()
```

[ ]:
```
0    1543
1     326
Name: Dependents, dtype: int64
```

People with dependents are less likely to Churn

[ ]:
```
churned_number = data[data['Churn'] == 1].shape[0]
print('Among the people who churned')
print('Customers availing Online Security :', round(data[data['Churn'] == 1].
 ↪OnlineSecurity.sum()*100/churned_number, 2), '%')
print('Customers availing Online Backup :', round(data[data['Churn'] == 1].
 ↪OnlineBackup.sum()*100/churned_number, 2), '%')
print('Customers availing Device Protection :', round(data[data['Churn'] == 1].
 ↪DeviceProtection.sum()*100/churned_number, 2), '%')
print('Customers availing Tech Support:', round(data[data['Churn'] == 1].
 ↪TechSupport.sum()*100/churned_number, 2), '%')
print('Customers availing Online Security :', round(data[data['Churn'] == 1].
 ↪OnlineSecurity.sum()*100/churned_number, 2), '%')
print('Customers availing Streaming TV :', round(data[data['Churn'] == 1].
 ↪StreamingTV.sum()*100/churned_number, 2), '%')
print('Customers availing Streaming Movies :', round(data[data['Churn'] == 1].
 ↪StreamingMovies.sum()*100/churned_number, 2), '%')
print()
print()
print('Among the people who did not churn')
churned_number = data[data['Churn'] == 0].shape[0]
print('Customers availing Online Security :', round(data[data['Churn'] == 0].
 ↪OnlineSecurity.sum()*100/churned_number, 2), '%')
print('Customers availing Online Backup :', round(data[data['Churn'] == 0].
 ↪OnlineBackup.sum()*100/churned_number, 2), '%')
print('Customers availing Device Protection :', round(data[data['Churn'] == 0].
 ↪DeviceProtection.sum()*100/churned_number, 2), '%')
print('Customers availing Tech Support:', round(data[data['Churn'] == 0].
 ↪TechSupport.sum()*100/churned_number, 2), '%')
```

```
print('Customers availing Online Security :', round(data[data['Churn'] == 0].
    OnlineSecurity.sum()*100/churned_number, 2), '%')
print('Customers availing Streaming TV :', round(data[data['Churn'] == 0].
    StreamingTV.sum()*100/churned_number, 2), '%')
print('Customers availing Streaming Movies :', round(data[data['Churn'] == 0].
    StreamingMovies.sum()*100/churned_number, 2), '%')
```

```
Among the people who churned
Customers availing Online Security : 15.78 %
Customers availing Online Backup : 27.98 %
Customers availing Device Protection : 29.16 %
Customers availing Tech Support: 16.59 %
Customers availing Online Security : 15.78 %
Customers availing Streaming TV : 43.55 %
Customers availing Streaming Movies : 43.77 %


Among the people who did not churn
Customers availing Online Security : 33.32 %
Customers availing Online Backup : 36.84 %
Customers availing Device Protection : 36.28 %
Customers availing Tech Support: 33.51 %
Customers availing Online Security : 33.32 %
Customers availing Streaming TV : 36.59 %
Customers availing Streaming Movies : 36.99 %
```

- Potentially customers like to avail all services are not happy with Streaming TV and Streaming Movies
- Customers who churn contact very less tech support

[ ]:
```
print('Internet Service preference among churned customers in Percentage')
print(round(data[data['Churn'] == 1].InternetService.value_counts()*100/
    data[data['Churn'] == 1].shape[0],2))
print()
print()
print('Internet Service preference among NON-churned customers in Percentage')
print(round(data[data['Churn'] == 0].InternetService.value_counts()*100/
    data[data['Churn'] == 0].shape[0],2))
```

```
Internet Service preference among churned customers in Percentage
Fiber optic    69.40
DSL            24.56
0               6.05
Name: InternetService, dtype: float64


Internet Service preference among NON-churned customers in Percentage
DSL            37.92
```

```
Fiber optic    34.77
0              27.31
Name: InternetService, dtype: float64
```

Customers with Fiber Optic internet service tend to churn

```
[ ]: print('Payment Method preference among churned customers in Percentage')
     print(round(data[data['Churn'] == 1].PaymentMethod.value_counts()*100/
      ↪data[data['Churn'] == 1].shape[0],2))
     print()
     print()
     print('Payment Method preference among NON-churned customers in Percentage')
     print(round(data[data['Churn'] == 0].PaymentMethod.value_counts()*100/
      ↪data[data['Churn'] == 0].shape[0],2))
```

```
Payment Method preference among churned customers in Percentage
Electronic check             57.30
Mailed check                 16.48
Bank transfer (automatic)    13.80
Credit card (automatic)      12.41
Name: PaymentMethod, dtype: float64


Payment Method preference among NON-churned customers in Percentage
Mailed check                 25.20
Electronic check             25.01
Credit card (automatic)      24.93
Bank transfer (automatic)    24.86
Name: PaymentMethod, dtype: float64
```

Customers who churn tend to have Electronic check

```
[ ]: print('Contract preference among churned customers in Percentage')
     print(round(data[data['Churn'] == 1].Contract.value_counts()*100/
      ↪data[data['Churn'] == 1].shape[0],2))
     print()
     print()
     print('Contract preference among NON-churned customers in Percentage')
     print(round(data[data['Churn'] == 0].Contract.value_counts()*100/
      ↪data[data['Churn'] == 0].shape[0],2))
```

```
Contract preference among churned customers in Percentage
Month-to-month    88.55
One year           8.88
Two year           2.57
Name: Contract, dtype: float64


Contract preference among NON-churned customers in Percentage
```

```
Month-to-month    42.91
Two year          31.83
One year          25.26
Name: Contract, dtype: float64
```

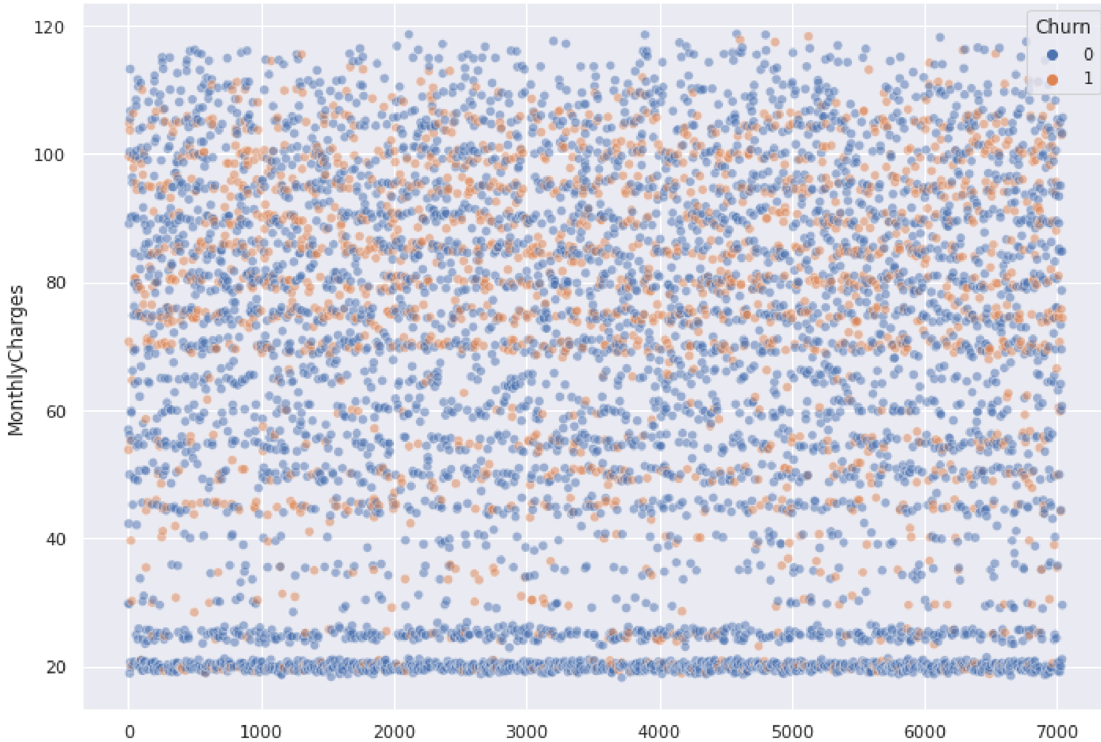
Customers who churn tend to follow a Month-to-Month contract

[ ]:
```
data.head()
```

[ ]:
```
   customerID  tenure  PhoneService        Contract  PaperlessBilling  \
0  7590-VHVEG       1             0  Month-to-month                 1
1  5575-GNVDE      34             1        One year                 0
2  3668-QPYBK       2             1  Month-to-month                 1
3  7795-CFOCW      45             0        One year                 0
4  9237-HQITU       2             1  Month-to-month                 1

               PaymentMethod  MonthlyCharges  TotalCharges  Churn  gender  \
0           Electronic check           29.85         29.85      0       0
1               Mailed check           56.95       1889.50      0       1
2               Mailed check           53.85        108.15      1       1
3  Bank transfer (automatic)           42.30       1840.75      0       1
4           Electronic check           70.70        151.65      1       0

   SeniorCitizen  Partner  Dependents  MultipleLines InternetService  \
0              0        1           0              0             DSL
1              0        0           0              0             DSL
2              0        0           0              0             DSL
3              0        0           0              0             DSL
4              0        0           0              0     Fiber optic

   OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
0               0             1                 0            0            0
1               1             0                 1            0            0
2               1             1                 0            0            0
3               1             0                 1            1            0
4               0             0                 0            0            0

   StreamingMovies
0                0
1                0
2                0
3                0
4                0
```

[ ]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.scatterplot(data=data, x=data.index, y='MonthlyCharges', hue='Churn',␣
 ↪alpha=0.5)
```

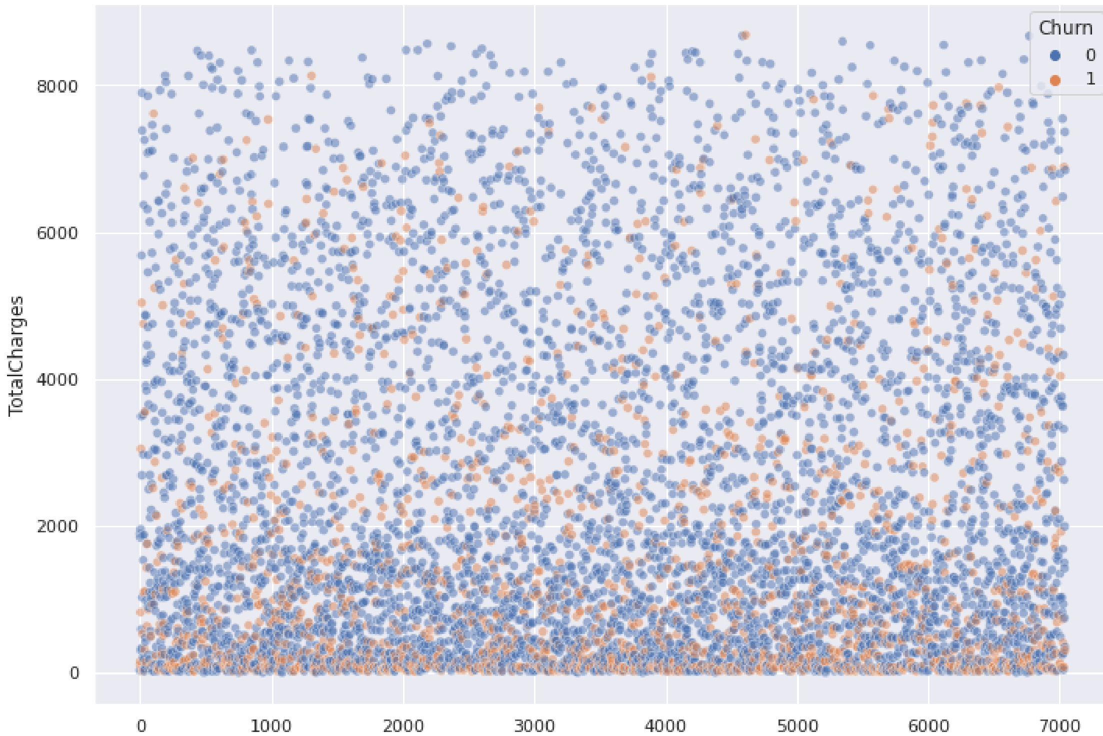
[ ]: <AxesSubplot:ylabel='MonthlyCharges'>



Bands of churning can be observed here

```
[ ]: sns.set(rc={'figure.figsize':(11.7,8.27)})
     sns.scatterplot(data=data, x=data.index, y='TotalCharges', hue='Churn', alpha=0.
      ↪5)
```

[ ]: <AxesSubplot:ylabel='TotalCharges'>

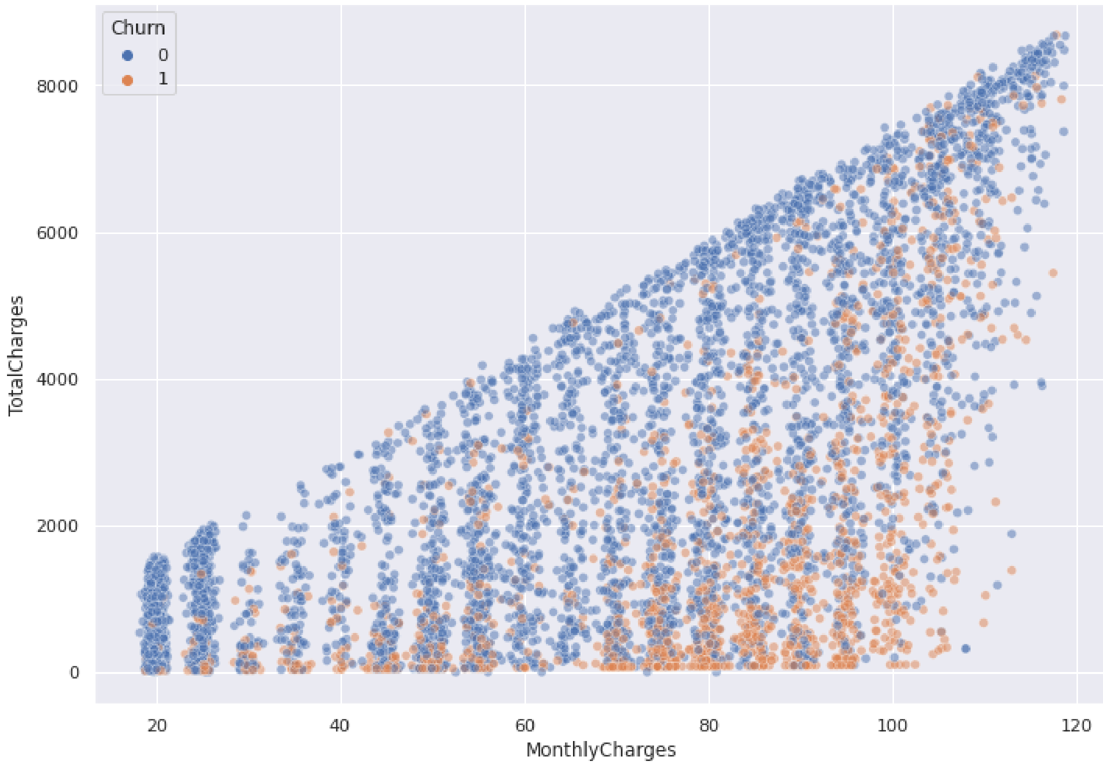


[ ]:
```
for i in range(8000):
    threshold = i
    business_below = data[data.TotalCharges <= threshold].TotalCharges.sum()
    business_above = data[data.TotalCharges > threshold].TotalCharges.sum()
    if abs(business_below - business_above) < 10000:
        break

print('Total business due to customers having Total charges <=', threshold,␣
 ↪'=', business_below)
print('Total business due to customers having Total charges >', threshold, '=',␣
 ↪business_above)
```

```
Total business due to customers having Total charges <= 4736 = 8024013.4
Total business due to customers having Total charges > 4736 = 8032155.300000001
```

[ ]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.scatterplot(data=data, x='MonthlyCharges', y='TotalCharges', hue='Churn',␣
 ↪alpha=0.5)
```

[ ]: <AxesSubplot:xlabel='MonthlyCharges', ylabel='TotalCharges'>



- There is a linear pattern betwen MonthlyCharges and TotalCharges. This is expected
- Vertical bands can be observed hinting that MonthlyCharges is a discrete variable and not a continuous variable
- Churning density in low MonthlyCharges and low TotalCharges is less

[ ]:

```

```

4.1 Dummy variables

[ ]:

```
# We won't include column'MultipleLines' as it is now a numeric column
cols = ['Contract', 'PaymentMethod', 'InternetService']

# create dummy variables
dummy1 = pd.get_dummies(data[cols], drop_first=True)

# adding this to the main dataset
data = pd.concat([data, dummy1], axis=1)
data.head()
```

[ ]:

```
  customerID  tenure  PhoneService        Contract  PaperlessBilling  \
0  7590-VHVEG       1             0  Month-to-month                 1
1  5575-GNVDE      34             1        One year                 0
```

```
2  3668-QPYBK       2             1  Month-to-month                1
3  7795-CFOCW      45             0        One year                0
4  9237-HQITU       2             1  Month-to-month                1

             PaymentMethod  MonthlyCharges  TotalCharges  Churn  gender  \
0         Electronic check           29.85         29.85      0       0
1             Mailed check           56.95       1889.50      0       1
2             Mailed check           53.85        108.15      1       1
3  Bank transfer (automatic)         42.30       1840.75      0       1
4         Electronic check           70.70        151.65      1       0

   SeniorCitizen  Partner  Dependents  MultipleLines InternetService  \
0              0        1           0              0             DSL
1              0        0           0              0             DSL
2              0        0           0              0             DSL
3              0        0           0              0             DSL
4              0        0           0              0     Fiber optic

   OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
0               0             1                 0            0            0
1               1             0                 1            0            0
2               1             1                 0            0            0
3               1             0                 1            1            0
4               0             0                 0            0            0

   StreamingMovies  Contract_One year  Contract_Two year  \
0                0                  0                  0
1                0                  1                  0
2                0                  0                  0
3                0                  1                  0
4                0                  0                  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  InternetService_DSL  \
0                           0                    1
1                           1                    1
2                           1                    1
3                           0                    1
4                           0                    0

   InternetService_Fiber optic
```

```
0                            0
1                            0
2                            0
3                            0
4                            1
```

[ ]:
```
# dropping the original columns corresponding to the dummy columns created
data.drop(labels=cols, axis=1, inplace=True)
data.head()
```

[ ]:
```
   customerID  tenure  PhoneService  PaperlessBilling  MonthlyCharges  \
0  7590-VHVEG       1             0                 1           29.85
1  5575-GNVDE      34             1                 0           56.95
2  3668-QPYBK       2             1                 1           53.85
3  7795-CFOCW      45             0                 0           42.30
4  9237-HQITU       2             1                 1           70.70

   TotalCharges  Churn  gender  SeniorCitizen  Partner  Dependents  \
0         29.85      0       0              0        1           0
1       1889.50      0       1              0        0           0
2        108.15      1       1              0        0           0
3       1840.75      0       1              0        0           0
4        151.65      1       0              0        0           0

   MultipleLines  OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  \
0              0               0             1                 0            0
1              0               1             0                 1            0
2              0               1             1                 0            0
3              0               1             0                 1            1
4              0               0             0                 0            0

   StreamingTV  StreamingMovies  Contract_One year  Contract_Two year  \
0            0                0                  0                  0
1            0                0                  1                  0
2            0                0                  0                  0
3            0                0                  1                  0
4            0                0                  0                  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  InternetService_DSL  \
0                           0                    1
```

```
1                          1                    1
2                          1                    1
3                          0                    1
4                          0                    0

   InternetService_Fiber optic
0                            0
1                            0
2                            0
3                            0
4                            1
```

4.2 Checking for Outliers

[ ]:
```
data.describe(percentiles=[.25, .5, .75, .9, .95, .99])
```

[ ]:
```
            tenure  PhoneService  PaperlessBilling  MonthlyCharges  \
count  7043.000000   7043.000000       7043.000000     7043.000000
mean     32.371149      0.903166          0.592219       64.761692
std      24.559481      0.295752          0.491457       30.090047
min       0.000000      0.000000          0.000000       18.250000
25%       9.000000      1.000000          0.000000       35.500000
50%      29.000000      1.000000          1.000000       70.350000
75%      55.000000      1.000000          1.000000       89.850000
90%      69.000000      1.000000          1.000000      102.600000
95%      72.000000      1.000000          1.000000      107.400000
99%      72.000000      1.000000          1.000000      114.729000
max      72.000000      1.000000          1.000000      118.750000

       TotalCharges        Churn       gender  SeniorCitizen      Partner  \
count   7043.000000  7043.000000  7043.000000    7043.000000  7043.000000
mean    2279.734304     0.265370     0.504756       0.162147     0.483033
std     2266.794470     0.441561     0.500013       0.368612     0.499748
min        0.000000     0.000000     0.000000       0.000000     0.000000
25%      398.550000     0.000000     0.000000       0.000000     0.000000
50%     1394.550000     0.000000     1.000000       0.000000     0.000000
75%     3786.600000     1.000000     1.000000       0.000000     1.000000
90%     5973.690000     1.000000     1.000000       1.000000     1.000000
95%     6921.025000     1.000000     1.000000       1.000000     1.000000
99%     8039.256000     1.000000     1.000000       1.000000     1.000000
max     8684.800000     1.000000     1.000000       1.000000     1.000000

        Dependents  MultipleLines  OnlineSecurity  OnlineBackup  \
count  7043.000000    7043.000000     7043.000000   7043.000000
mean      0.299588       0.421837        0.286668      0.344881
std       0.458110       0.493888        0.452237      0.475363
min       0.000000       0.000000        0.000000      0.000000
```

```
25%       0.000000       0.000000        0.000000      0.000000
50%       0.000000       0.000000        0.000000      0.000000
75%       1.000000       1.000000        1.000000      1.000000
90%       1.000000       1.000000        1.000000      1.000000
95%       1.000000       1.000000        1.000000      1.000000
99%       1.000000       1.000000        1.000000      1.000000
max       1.000000       1.000000        1.000000      1.000000

       DeviceProtection  TechSupport  StreamingTV  StreamingMovies  \
count       7043.000000  7043.000000  7043.000000      7043.000000
mean           0.343888     0.290217     0.384353         0.387903
std            0.475038     0.453895     0.486477         0.487307
min            0.000000     0.000000     0.000000         0.000000
25%            0.000000     0.000000     0.000000         0.000000
50%            0.000000     0.000000     0.000000         0.000000
75%            1.000000     1.000000     1.000000         1.000000
90%            1.000000     1.000000     1.000000         1.000000
95%            1.000000     1.000000     1.000000         1.000000
99%            1.000000     1.000000     1.000000         1.000000
max            1.000000     1.000000     1.000000         1.000000

       Contract_One year  Contract_Two year  \
count        7043.000000        7043.000000
mean            0.209144           0.240664
std             0.406726           0.427517
min             0.000000           0.000000
25%             0.000000           0.000000
50%             0.000000           0.000000
75%             0.000000           0.000000
90%             1.000000           1.000000
95%             1.000000           1.000000
99%             1.000000           1.000000
max             1.000000           1.000000

       PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
count                            7043.000000                     7043.000000
mean                                0.216101                        0.335794
std                                 0.411613                        0.472301
min                                 0.000000                        0.000000
25%                                 0.000000                        0.000000
50%                                 0.000000                        0.000000
75%                                 0.000000                        1.000000
90%                                 1.000000                        1.000000
95%                                 1.000000                        1.000000
99%                                 1.000000                        1.000000
max                                 1.000000                        1.000000
```

```
       PaymentMethod_Mailed check  InternetService_DSL  \
count                 7043.000000          7043.000000
mean                     0.228880             0.343746
std                      0.420141             0.474991
min                      0.000000             0.000000
25%                      0.000000             0.000000
50%                      0.000000             0.000000
75%                      0.000000             1.000000
90%                      1.000000             1.000000
95%                      1.000000             1.000000
99%                      1.000000             1.000000
max                      1.000000             1.000000

       InternetService_Fiber optic
count                  7043.000000
mean                      0.439585
std                       0.496372
min                       0.000000
25%                       0.000000
50%                       0.000000
75%                       1.000000
90%                       1.000000
95%                       1.000000
99%                       1.000000
max                       1.000000
```

At all percentiles the value increase is gradual so there are no outliers

[ ]:
```
## Checking for Null values
```

[ ]:
```
data.isnull().sum()
```

[ ]:
```
customerID                          0
tenure                              0
PhoneService                        0
PaperlessBilling                    0
MonthlyCharges                      0
TotalCharges                        0
Churn                               0
gender                              0
SeniorCitizen                       0
Partner                             0
Dependents                          0
MultipleLines                       0
OnlineSecurity                      0
OnlineBackup                        0
DeviceProtection                    0
```

```
TechSupport                                 0
StreamingTV                                 0
StreamingMovies                             0
Contract_One year                           0
Contract_Two year                           0
PaymentMethod_Credit card (automatic)       0
PaymentMethod_Electronic check              0
PaymentMethod_Mailed check                  0
InternetService_DSL                         0
InternetService_Fiber optic                 0
dtype: int64
```

There are no null values

5 Test Train Split

[ ]:
```
# Import necessary libraries
from sklearn.model_selection import train_test_split
```

- We don't need the column 'CustomerID' as it is not useful in prediction
- We will split the column 'Churn' as y (dependant variable) and rest of them as X (independant variable)

[ ]:
```
y = data['Churn']
y.head()
```

[ ]:
```
0    0
1    0
2    1
3    0
4    1
Name: Churn, dtype: int64
```

[ ]:
```
X = data.drop(['Churn','customerID'], axis=1)
X.head()
```

[ ]:
```
   tenure  PhoneService  PaperlessBilling  MonthlyCharges  TotalCharges  \
0       1             0                 1           29.85         29.85
1      34             1                 0           56.95       1889.50
2       2             1                 1           53.85        108.15
3      45             0                 0           42.30       1840.75
4       2             1                 1           70.70        151.65

   gender  SeniorCitizen  Partner  Dependents  MultipleLines  OnlineSecurity  \
0       0              0        1           0              0               0
1       1              0        0           0              0               1
2       1              0        0           0              0               1
```

```
3       1              0        0           0              0              1
4       0              0        0           0              0              0

   OnlineBackup  DeviceProtection  TechSupport  StreamingTV  StreamingMovies  \
0             1                 0            0            0                0
1             0                 1            0            0                0
2             1                 0            0            0                0
3             0                 1            1            0                0
4             0                 0            0            0                0

   Contract_One year  Contract_Two year  \
0                  0                  0
1                  1                  0
2                  0                  0
3                  1                  0
4                  0                  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  InternetService_DSL  \
0                           0                    1
1                           1                    1
2                           1                    1
3                           0                    1
4                           0                    0

   InternetService_Fiber optic
0                            0
1                            0
2                            0
3                            0
4                            1
```

[ ]:
```
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7,␣
 ↪test_size=0.3, random_state=100)
```

5.1 Feature Scaling

[ ]:
```
# Import necessary libraries
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

Columns 'tenure', 'MonthlyCharges', 'TotalCharges' have data of different proportiones which can cause unequal influences on the model. So, we standardise them

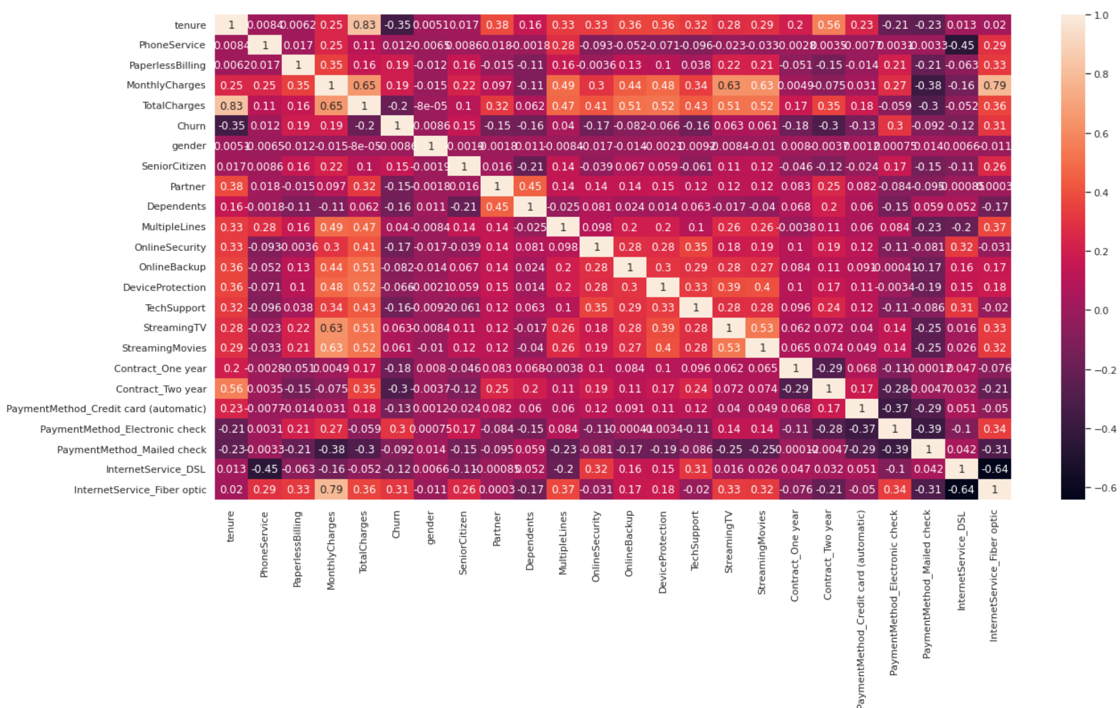
[ ]:
```
cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
X_train[cols] = scaler.
 ↪fit_transform(X_train[['tenure','MonthlyCharges','TotalCharges']])

X_train.head()
```

[ ]:
```
        tenure  PhoneService  PaperlessBilling  MonthlyCharges  TotalCharges  \
877   0.754422             0                 0       -0.145568      0.350963
5792 -0.710751             1                 1        1.051796     -0.377957
5334  0.673024             1                 1        1.437668      1.329866
878   1.120716             1                 0        0.006794      0.776103
6578 -0.914247             1                 0        0.298268     -0.701925

      gender  SeniorCitizen  Partner  Dependents  MultipleLines  \
877        0              0        0           1              0
5792       0              1        0           0              0
5334       0              0        1           1              1
878        0              0        0           0              1
6578       0              0        0           1              1

      OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  \
877                1             0                 1            1
5792               1             0                 1            1
5334               0             1                 1            1
878                1             0                 1            1
6578               1             0                 1            1

      StreamingTV  StreamingMovies  Contract_One year  Contract_Two year  \
877             1                1                  1                  0
5792            0                1                  0                  0
5334            1                1                  0                  1
878             0                0                  1                  0
6578            0                1                  1                  0

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
877                                       0                               0
5792                                      0                               0
5334                                      0                               0
878                                       0                               1
```

```
6578                                        1                                0

      PaymentMethod_Mailed check  InternetService_DSL  \
877                            0                    1
5792                           1                    0
5334                           0                    0
878                            0                    1
6578                           0                    1

      InternetService_Fiber optic
877                             0
5792                            1
5334                            1
878                             0
6578                            0
```

5.2 Checking Correlations

[ ]:
```python
# Let's see the correlation matrix
plt.figure(figsize = (20,10))        # Size of the figure
sns.heatmap(data.corr(),annot = True)
plt.show()
```



There are no big clusters of high correlations (>0.5 or < -0.5). So we will ignore for now and proceed further on. The big factors will be taken care of during VIF anyway …

6 Model building

```
[ ]: # Imposrt necessary libraries
import statsmodels.api as sm
```

```
[ ]: # Logistic regression model
# GLM is Generalised Linear Models
# Binomial family because the classification is binomial - Churn or Non-Churn
logm1 = sm.GLM(y_train,(sm.add_constant(X_train)), family = sm.families.
 ↪Binomial())
logm1.fit().summary()
```

```
[ ]: <class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                 4930
Model:                            GLM   Df Residuals:                     4906
Model Family:                Binomial   Df Model:                           23
Link Function:                  Logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -2008.0
Date:                Tue, 19 Jul 2022   Deviance:                       4016.1
Time:                        05:53:36   Pearson chi2:                 5.77e+03
No. Iterations:                     7   Pseudo R-squ. (CS):             0.2885
Covariance Type:            nonrobust
================================================================================
=========================
                                          coef    std err          z
P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
-------------------------
const                                  -5.1683      2.493     -2.073
0.038     -10.054      -0.282
tenure                                 -1.3441      0.179     -7.500
0.000      -1.695      -0.993
PhoneService                            0.4097      0.786      0.521
0.602      -1.131       1.950
PaperlessBilling                        0.3453      0.090      3.828
0.000       0.169       0.522
MonthlyCharges                         -1.5336      1.162     -1.320
0.187      -3.812       0.744
TotalCharges                            0.6103      0.190      3.215
0.001       0.238       0.982
gender                                 -0.0411      0.078     -0.525
```

```
0.600      -0.195      0.112
SeniorCitizen                               0.2950      0.103      2.877
0.004       0.094      0.496
Partner                                     0.0272      0.094      0.289
0.772      -0.157      0.212
Dependents                                 -0.2207      0.108     -2.049
0.040      -0.432     -0.010
MultipleLines                               0.5539      0.215      2.577
0.010       0.133      0.975
OnlineSecurity                             -0.0429      0.217     -0.198
0.843      -0.467      0.382
OnlineBackup                               -0.0206      0.211     -0.097
0.922      -0.435      0.394
DeviceProtection                            0.2014      0.213      0.944
0.345      -0.217      0.620
TechSupport                                -0.2538      0.219     -1.159
0.247      -0.683      0.175
StreamingTV                                 0.7001      0.397      1.764
0.078      -0.078      1.478
StreamingMovies                             0.6689      0.396      1.688
0.091      -0.108      1.445
Contract_One year                          -0.6736      0.129     -5.205
0.000      -0.927     -0.420
Contract_Two year                          -1.3372      0.207     -6.452
0.000      -1.743     -0.931
PaymentMethod_Credit card (automatic)      -0.1531      0.138     -1.108
0.268      -0.424      0.118
PaymentMethod_Electronic check              0.2733      0.114      2.396
0.017       0.050      0.497
PaymentMethod_Mailed check                 -0.0916      0.139     -0.660
0.509      -0.364      0.180
InternetService_DSL                         2.1794      0.977      2.231
0.026       0.264      4.094
InternetService_Fiber optic                 4.2015      1.930      2.177
0.029       0.419      7.984
================================================================================
=========================
"""
```

The p>|z| needs to be as close to 0 as possible. Apparently there are many variables that have p>|z| close to 1. So there is a need for feature elimination

7 Recursive Feature Elimination

[ ]:
```
# Import necessary libraries
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
logreg = LogisticRegression()
```

[ ]:
```
rfe = RFE(logreg, n_features_to_select=15)             # Finding 15 top features
rfe = rfe.fit(X_train, y_train)
```

[ ]:
```
rfe.support_
```

[ ]:
```
array([ True,  True,  True,  True,  True, False,  True, False, False,
        True,  True,  True, False,  True, False, False,  True,  True,
       False,  True, False,  True,  True])
```

[ ]:
```
rfe.ranking_
```

[ ]:
```
array([1, 1, 1, 1, 1, 8, 1, 9, 2, 1, 1, 1, 3, 1, 6, 7, 1, 1, 4, 1, 5, 1,
       1])
```

[ ]:
```
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

[ ]:
```
[('tenure', True, 1),
 ('PhoneService', True, 1),
 ('PaperlessBilling', True, 1),
 ('MonthlyCharges', True, 1),
 ('TotalCharges', True, 1),
 ('gender', False, 8),
 ('SeniorCitizen', True, 1),
 ('Partner', False, 9),
 ('Dependents', False, 2),
 ('MultipleLines', True, 1),
 ('OnlineSecurity', True, 1),
 ('OnlineBackup', True, 1),
 ('DeviceProtection', False, 3),
 ('TechSupport', True, 1),
 ('StreamingTV', False, 6),
 ('StreamingMovies', False, 7),
 ('Contract_One year', True, 1),
 ('Contract_Two year', True, 1),
 ('PaymentMethod_Credit card (automatic)', False, 4),
 ('PaymentMethod_Electronic check', True, 1),
 ('PaymentMethod_Mailed check', False, 5),
 ('InternetService_DSL', True, 1),
 ('InternetService_Fiber optic', True, 1)]
```

[ ]:
```
print('These are the columns that RFE feels to be significant')
cols = X_train.columns[rfe.support_]
cols
```

```
These are the columns that RFE feels to be significant
```

[ ]:
```
Index(['tenure', 'PhoneService', 'PaperlessBilling', 'MonthlyCharges',
       'TotalCharges', 'SeniorCitizen', 'MultipleLines', 'OnlineSecurity',
       'OnlineBackup', 'TechSupport', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check', 'InternetService_DSL',
       'InternetService_Fiber optic'],
      dtype='object')
```

8 Iteration2 with StatsModel

[ ]:
```
X_train_sm = sm.add_constant(X_train[cols])
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                 4930
Model:                            GLM   Df Residuals:                     4914
Model Family:                Binomial   Df Model:                           15
Link Function:                  Logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -2013.4
Date:                Tue, 19 Jul 2022   Deviance:                       4026.7
Time:                        05:53:37   Pearson chi2:                 5.83e+03
No. Iterations:                     7   Pseudo R-squ. (CS):             0.2870
Covariance Type:            nonrobust
================================================================================
==================
                                     coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
------------------
const                             -1.1953      0.381     -3.138      0.002
-1.942      -0.449
tenure                            -1.3454      0.176     -7.639      0.000
-1.691      -1.000
PhoneService                      -0.8813      0.179     -4.913      0.000
-1.233      -0.530
PaperlessBilling                   0.3623      0.090      4.038      0.000
```

```
0.186       0.538
MonthlyCharges                     0.4036      0.165      2.440      0.015
0.079       0.728
TotalCharges                       0.6046      0.188      3.208      0.001
0.235       0.974
SeniorCitizen                      0.3300      0.101      3.283      0.001
0.133       0.527
MultipleLines                      0.2363      0.099      2.380      0.017
0.042       0.431
OnlineSecurity                    -0.3684      0.103     -3.565      0.000
-0.571      -0.166
OnlineBackup                      -0.3406      0.095     -3.568      0.000
-0.528      -0.154
TechSupport                       -0.5774      0.109     -5.285      0.000
-0.792      -0.363
Contract_One year                 -0.6967      0.129     -5.409      0.000
-0.949      -0.444
Contract_Two year                 -1.3658      0.206     -6.616      0.000
-1.770      -0.961
PaymentMethod_Electronic check     0.3619      0.083      4.339      0.000
0.198       0.525
InternetService_DSL                0.5788      0.229      2.527      0.012
0.130       1.028
InternetService_Fiber optic        1.0172      0.338      3.008      0.003
0.354       1.680
================================================================================
==================
"""
```

Now that everything looks satisfactory, let us go with predictions

9 Predictions

[ ]:
```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]

# Reshaping to lose the index values
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

[ ]:
```
array([0.04227204, 0.45993782, 0.09399225, 0.0271777 , 0.12154661,
       0.46119626, 0.7428697 , 0.04231436, 0.70426688, 0.07369918])
```

[ ]:
```
# Create a dataframe with actual and predicted data
y_train_pred_final = pd.DataFrame({'Churn':y_train.values, 'Churn_Prob':
 ↪y_train_pred})
```

```
y_train_pred_final['the_index'] = y_train.index


y_train_pred_final.head()
```

[ ]:

	Churn	Churn_Prob	the_index
0	0	0.042272	877
1	1	0.459938	5792
2	1	0.093992	5334
3	0	0.027178	878
4	0	0.121547	6578

[ ]:
```
y_train_pred_final['prediction'] = y_train_pred_final.Churn_Prob.map(lambda x:␣
↪1 if x > 0.5 else 0)
y_train_pred_final.head(10)
```

[ ]:

	Churn	Churn_Prob	the_index	prediction
0	0	0.042272	877	0
1	1	0.459938	5792	0
2	1	0.093992	5334	0
3	0	0.027178	878	0
4	0	0.121547	6578	0
5	1	0.461196	3090	0
6	1	0.742870	3043	1
7	0	0.042314	5028	0
8	1	0.704267	4463	1
9	1	0.073699	2822	0

10 Metrics

[ ]:
```
# Import necessary libraries
from sklearn import metrics
```

10.0.1 We don’t go with percentage error because of class imbalance

10.1 Confusion Matrix

[ ]:
```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Churn,␣
↪y_train_pred_final.prediction )
print(confusion)
```

```
[[3259  368]
 [ 552  751]]
```

```
[ ]: #                 Confusion Matrix

     #                       Actual
     #              True                 False
     # P  T
     # r  r
     # e  u
     # d  e      True Positive    | False Positive
     # i  ----------------------------------------
     # c  F      False Negative   | True Negative
     # t  a
     # e  l
     # d  s
     #    e
```

```
[ ]: # Let's check the overall accuracy:
     # accuracy = correctly predicted labels / total labels = (TP + FN)/ (TP + FP +␣
      ↪FN + TN)
     print('Accuracy :')
     acc = metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.
      ↪prediction)
     acc = round(acc*100, 2)
     print(acc, '%')
```

```
Accuracy :
81.34 %
```

11 Variance Inflation Factor (VIF)

```
[ ]: # Import ncessary libraries
     from statsmodels.stats.outliers_influence import variance_inflation_factor
```

```
[ ]: vif = pd.DataFrame()
     vif['Features'] = X_train[cols].columns

     # THis method not working due to shallow copy
     # for i in range(X_train[cols].shape[1]):
     #     print(X_train[cols].columns[i])
     #     z = variance_inflation_factor(X_train[cols].values, i)
     #     print(z)
     #     vif['VIF_me'] = z

     vif['VIF'] = [variance_inflation_factor(X_train[cols].values, i) for i in␣
      ↪range(X_train[cols].shape[1])]

     vif['VIF'] = round(vif['VIF'], 2)
```

```
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[ ]:

	Features	VIF
4	TotalCharges	10.30
14	InternetService_Fiber optic	8.90
1	PhoneService	7.67
0	tenure	6.82
3	MonthlyCharges	6.34
13	InternetService_DSL	3.45
11	Contract_Two year	3.10
2	PaperlessBilling	2.90
6	MultipleLines	2.58
9	TechSupport	2.25
8	OnlineBackup	2.24
7	OnlineSecurity	2.07
12	PaymentMethod_Electronic check	1.95
10	Contract_One year	1.91
5	SeniorCitizen	1.33

Let us drop TotalCharges

[ ]:
```
cols = cols.drop('TotalCharges', 1)
cols
```

[ ]:
```
Index(['tenure', 'PhoneService', 'PaperlessBilling', 'MonthlyCharges',
       'SeniorCitizen', 'MultipleLines', 'OnlineSecurity', 'OnlineBackup',
       'TechSupport', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check', 'InternetService_DSL',
       'InternetService_Fiber optic'],
      dtype='object')
```

12 Iteration3 with StatsModel

[ ]:
```
X_train_sm = sm.add_constant(X_train[cols])
logm3 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()

# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]

# Reshaping to lose the index values
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

```python
# Create a dataframe with actual and predicted data
y_train_pred_final = pd.DataFrame({'Churn':y_train.values, 'Churn_Prob':
 ↪y_train_pred})
y_train_pred_final['the_index'] = y_train.index


y_train_pred_final.head()

y_train_pred_final['prediction'] = y_train_pred_final.Churn_Prob.map(lambda x:␣
 ↪1 if x > 0.5 else 0)
y_train_pred_final.head(10)

print('Accuracy :')
acc = metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.
 ↪prediction)
acc = round(acc*100, 2)
print(acc, '%')
```

```
Accuracy :
80.83 %
```

Clearly, the accuracy did not take a big hit. So, it is OK

[ ]:
```python
vif = pd.DataFrame()
vif['Features'] = X_train[cols].columns

# THis method not working due to shallow copy
# for i in range(X_train[cols].shape[1]):
#     print(X_train[cols].columns[i])
#     z = variance_inflation_factor(X_train[cols].values, i)
#     print(z)
#     vif['VIF_me'] = z

vif['VIF'] = [variance_inflation_factor(X_train[cols].values, i) for i in␣
 ↪range(X_train[cols].shape[1])]

vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[ ]:

	Features	VIF
13	InternetService_Fiber optic	8.78
1	PhoneService	7.67
3	MonthlyCharges	3.93
12	InternetService_DSL	3.37
10	Contract_Two year	3.10
2	PaperlessBilling	2.90

```
5                   MultipleLines  2.58
0                          tenure  2.52
8                     TechSupport  2.21
7                    OnlineBackup  2.18
6                  OnlineSecurity  2.04
11  PaymentMethod_Electronic check  1.94
9                Contract_One year  1.90
4                   SeniorCitizen  1.33
```

[ ]:
```
cols = cols.drop('InternetService_Fiber optic', 1)
cols
```

[ ]:
```
Index(['tenure', 'PhoneService', 'PaperlessBilling', 'MonthlyCharges',
       'SeniorCitizen', 'MultipleLines', 'OnlineSecurity', 'OnlineBackup',
       'TechSupport', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check', 'InternetService_DSL'],
      dtype='object')
```

13 Iteration4 with StatsModel

[ ]:
```
X_train_sm = sm.add_constant(X_train[cols])
logm4 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm4.fit()
res.summary()

# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]

# Reshaping to lose the index values
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]

# Create a dataframe with actual and predicted data
y_train_pred_final = pd.DataFrame({'Churn':y_train.values, 'Churn_Prob':
 ↪y_train_pred})
y_train_pred_final['the_index'] = y_train.index


y_train_pred_final.head()

y_train_pred_final['prediction'] = y_train_pred_final.Churn_Prob.map(lambda x:␣
 ↪1 if x > 0.5 else 0)
y_train_pred_final.head(10)

print('Accuracy :')
```

```
acc = metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.
↪prediction)
acc = round(acc*100, 2)
print(acc, '%')
```

```
Accuracy :
80.71 %
```

Clearly, the accuracy did not take a big hit. So, it is OK

```
[ ]: vif = pd.DataFrame()
vif['Features'] = X_train[cols].columns

# THis method not working due to shallow copy
# for i in range(X_train[cols].shape[1]):
#     print(X_train[cols].columns[i])
#     z = variance_inflation_factor(X_train[cols].values, i)
#     print(z)
#     vif['VIF_me'] = z

vif['VIF'] = [variance_inflation_factor(X_train[cols].values, i) for i in␣
↪range(X_train[cols].shape[1])]

vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[ ]:

	Features	VIF
1	PhoneService	5.33
10	Contract_Two year	3.09
2	PaperlessBilling	2.63
5	MultipleLines	2.58
0	tenure	2.40
3	MonthlyCharges	2.29
12	InternetService_DSL	2.27
8	TechSupport	2.21
7	OnlineBackup	2.16
6	OnlineSecurity	2.04
9	Contract_One year	1.89
11	PaymentMethod_Electronic check	1.79
4	SeniorCitizen	1.29

```
[ ]: cols = cols.drop('PhoneService', 1)
cols
```

```
[ ]: Index(['tenure', 'PaperlessBilling', 'MonthlyCharges', 'SeniorCitizen',
       'MultipleLines', 'OnlineSecurity', 'OnlineBackup', 'TechSupport',
       'Contract_One year', 'Contract_Two year',
```

```
 'PaymentMethod_Electronic check', 'InternetService_DSL'],
dtype='object')
```

14 Iteration5 with StatsModel

```
[ ]: X_train_sm = sm.add_constant(X_train[cols])
logm5 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm5.fit()
res.summary()

# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]

# Reshaping to lose the index values
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]

# Create a dataframe with actual and predicted data
y_train_pred_final = pd.DataFrame({'Churn':y_train.values, 'Churn_Prob':
 ↪y_train_pred})
y_train_pred_final['the_index'] = y_train.index


y_train_pred_final.head()

y_train_pred_final['prediction'] = y_train_pred_final.Churn_Prob.map(lambda x:␣
 ↪1 if x > 0.5 else 0)
y_train_pred_final.head(10)

print('Accuracy :')
acc = metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.
 ↪prediction)
acc = round(acc*100, 2)
print(acc, '%')
```

```
Accuracy :
80.87 %
```

The accuracy did not take a big hit. So, it is OK

```
[ ]: vif = pd.DataFrame()
vif['Features'] = X_train[cols].columns

# THis method not working due to shallow copy
# for i in range(X_train[cols].shape[1]):
#     print(X_train[cols].columns[i])
```

```
#     z = variance_inflation_factor(X_train[cols].values, i)
#     print(z)
#     vif['VIF_me'] = z

vif['VIF'] = [variance_inflation_factor(X_train[cols].values, i) for i in␣
 ↪range(X_train[cols].shape[1])]

vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[ ]:

	Features	VIF
9	Contract_Two year	2.53
1	PaperlessBilling	2.29
11	InternetService_DSL	2.21
2	MonthlyCharges	2.19
7	TechSupport	2.18
4	MultipleLines	2.10
6	OnlineBackup	2.10
5	OnlineSecurity	2.00
0	tenure	1.95
10	PaymentMethod_Electronic check	1.70
8	Contract_One year	1.61
3	SeniorCitizen	1.28

All VIF are below 3, so this is an acceptable model

[ ]:
```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Churn,␣
 ↪y_train_pred_final.prediction )
print(confusion)
tn, fp, fn, tp = confusion_matrix(y_train_pred_final.Churn, y_train_pred_final.
 ↪prediction ).ravel()
print(tn, fp, fn, tp)


#                  Confusion Matrix

#                      Predicted
#               False               True
#    F
#    a
# A  l
# c  s
# t  e     True Negative    |   False Positive
#    ---------------------------------------
# u  T     False Negative   |   True Positive
```

```
# a   r
# l   u
#     e
#
```

```
[[3267  360]
 [ 583  720]]
3267 360 583 720
```

Are we concerned about True predictions ?

[ ]:
```
# Sensitivity
# sensitivity = Trues that are correctly predicted / Total Trues
sensitivity = tp / (tp + fn)
print('Sensitivity : ', round(sensitivity*100, 2), '%')
```

```
Sensitivity :  55.26 %
```

Are we concerned about False predictions ?

[ ]:
```
# Specificity
# Specificity = Falses that are correctly predicted / Total Falses
specificity = tn / (tn + fp)
print('Specificity : ', round(specificity*100, 2), '%')
```

```
Specificity :  90.07 %
```

This may be concerning to us :

We are under-estimating the churn cases and over-estimating the non-churn cases

15 Finding Optimal Cut-Off point

[ ]:
```
# Let's create columns with different probability cutoffs
numbers = [i/100 for i in range(0,101, 5)]
for i in numbers:
    y_train_pred_final[i]= y_train_pred_final.Churn_Prob.map(lambda x: 1 if x >␣
 ↪i else 0)
y_train_pred_final.head()
```

[ ]:
```
   Churn  Churn_Prob  the_index  prediction  0.0  0.05  0.1  0.15  0.2  0.25  \
0      0    0.026667        877           0    1     0    0     0    0     0
1      1    0.491507       5792           0    1     1    1     1    1     1
2      1    0.076346       5334           0    1     1    0     0    0     0
3      0    0.038487        878           0    1     0    0     0    0     0
4      0    0.145008       6578           0    1     1    1     0    0     0

   0.3  0.35  0.4  0.45  0.5  0.55  0.6  0.65  0.7  0.75  0.8  0.85  0.9  \
0    0     0    0     0    0     0    0     0    0     0    0     0    0
```

```
1     1     1     1     1     0     0     0     0     0     0     0     0     0
2     0     0     0     0     0     0     0     0     0     0     0     0     0
3     0     0     0     0     0     0     0     0     0     0     0     0     0
4     0     0     0     0     0     0     0     0     0     0     0     0     0

   0.95  1.0
0     0    0
1     0    0
2     0    0
3     0    0
4     0    0
```

[ ]:
```
# numbers = [i/100 for i in range(0,101, 5)]
# numbers
```

[ ]:
```
# Now let's calculate accuracy sensitivity and specificity for various␣
↪probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

# TP = confusion[1,1] # true positive
# TN = confusion[0,0] # true negatives
# FP = confusion[0,1] # false positives
# FN = confusion[1,0] # false negatives

num = numbers
for i in num:
    cm1 = metrics.confusion_matrix(y_train_pred_final.Churn,␣
↪y_train_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
print(cutoff_df)
```

```
      prob  accuracy     sensi     speci
0.00  0.00  0.264300  1.000000  0.000000
0.05  0.05  0.517039  0.976209  0.352082
0.10  0.10  0.608925  0.935533  0.491591
0.15  0.15  0.665720  0.908672  0.578439
0.20  0.20  0.716836  0.851880  0.668321
0.25  0.25  0.747667  0.815810  0.723187
0.30  0.30  0.765720  0.762855  0.766749
0.35  0.35  0.785801  0.716807  0.810587
0.40  0.40  0.797160  0.665388  0.844500
```

```
0.45  0.45  0.803854  0.615503  0.871519
0.50  0.50  0.808722  0.552571  0.900744
0.55  0.55  0.803448  0.470453  0.923077
0.60  0.60  0.797363  0.382195  0.946512
0.65  0.65  0.788235  0.295472  0.965261
0.70  0.70  0.776268  0.207214  0.980700
0.75  0.75  0.758621  0.112817  0.990626
0.80  0.80  0.745436  0.046048  0.996691
0.85  0.85  0.738540  0.011512  0.999724
0.90  0.90  0.735700  0.000000  1.000000
0.95  0.95  0.735700  0.000000  1.000000
1.00  1.00  0.735700  0.000000  1.000000
```

The best cut-off is 0.3

16 Iteration6 The final iteration

[ ]:
```
X_train_sm = sm.add_constant(X_train[cols])
logm6 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm6.fit()
res.summary()

# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]

# Reshaping to lose the index values
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]

# Create a dataframe with actual and predicted data
y_train_pred_final = pd.DataFrame({'Churn':y_train.values, 'Churn_Prob':
 ↪y_train_pred})
y_train_pred_final['the_index'] = y_train.index


y_train_pred_final.head()

y_train_pred_final['prediction'] = y_train_pred_final.Churn_Prob.map(lambda x:␣
 ↪1 if x > 0.3 else 0)
y_train_pred_final.head(10)

print('Accuracy :')
acc = metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.
 ↪prediction)
acc = round(acc*100, 2)
print(acc, '%')
```

```
confusion = metrics.confusion_matrix(y_train_pred_final.Churn,␣
 ↪y_train_pred_final.prediction )
print('Confusion Matrix')
print(confusion)
```

```
Accuracy :
76.57 %
Confusion Matrix
[[2781  846]
 [ 309  994]]
```

[ ]:

```
tn, fp, fn, tp = confusion_matrix(y_train_pred_final.Churn, y_train_pred_final.
 ↪prediction ).ravel()

sensitivity = tp / (tp + fn)
print('Sensitivity : ', round(sensitivity*100, 2), '%')

specificity = tn / (tn + fp)
print('Specificity : ', round(specificity*100, 2), '%')
```

```
Sensitivity :  76.29 %
Specificity :  76.67 %
```

17 Making Predictions on Test Case

[ ]:

```
X_test.head()
```

[ ]:

```
      tenure  PhoneService  PaperlessBilling  MonthlyCharges  TotalCharges  \
4880      50             1                 0           20.55       1067.65
1541      72             1                 0           19.85       1434.10
1289      63             1                 0           68.80       4111.35
5745      61             1                 1           24.20       1445.20
4873       7             1                 0           19.30        144.95

      gender  SeniorCitizen  Partner  Dependents  MultipleLines  \
4880       1              0        1           0              0
1541       1              0        0           0              0
1289       1              0        0           0              1
5745       0              0        1           1              1
4873       0              0        0           0              0

      OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  \
4880               0             0                 0            0
1541               0             0                 0            0
1289               1             1                 1            1
```

```
5745              0             0                 0            0
4873              0             0                 0            0

      StreamingTV  StreamingMovies  Contract_One year  Contract_Two year  \
4880            0                0                  0                  1
1541            0                0                  0                  1
1289            0                0                  1                  0
5745            0                0                  0                  1
4873            0                0                  0                  0

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
4880                                      0                               0
1541                                      0                               0
1289                                      0                               0
5745                                      0                               0
4873                                      0                               0

      PaymentMethod_Mailed check  InternetService_DSL  \
4880                           1                    0
1541                           0                    0
1289                           0                    1
5745                           1                    0
4873                           1                    0

      InternetService_Fiber optic
4880                            0
1541                            0
1289                            0
5745                            0
4873                            0
```

[ ]:
```
y_test.head()
```

[ ]:
```
4880    0
1541    0
1289    0
5745    0
4873    0
Name: Churn, dtype: int64
```

'tenure', 'MonthlyCharges' and 'TotalCharges' need to be scaled because they were scaled during training

[ ]:
```
X_test[['tenure', 'MonthlyCharges', 'TotalCharges']] = scaler.
 ↪transform(X_test[['tenure', 'MonthlyCharges', 'TotalCharges']])
X_test.head()
```

```
[ ]:       tenure  PhoneService  PaperlessBilling  MonthlyCharges  TotalCharges  \
4880  0.713723             1                 0       -1.457203     -0.536573
1541  1.609107             1                 0       -1.480388     -0.374711
1289  1.242814             1                 0        0.140938      0.807839
5745  1.161415             1                 1       -1.336307     -0.369808
4873 -1.036345             1                 0       -1.498605     -0.944133

      gender  SeniorCitizen  Partner  Dependents  MultipleLines  \
4880       1              0        1           0              0
1541       1              0        0           0              0
1289       1              0        0           0              1
5745       0              0        1           1              1
4873       0              0        0           0              0

      OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  \
4880               0             0                 0            0
1541               0             0                 0            0
1289               1             1                 1            1
5745               0             0                 0            0
4873               0             0                 0            0

      StreamingTV  StreamingMovies  Contract_One year  Contract_Two year  \
4880            0                0                  0                  1
1541            0                0                  0                  1
1289            0                0                  1                  0
5745            0                0                  0                  1
4873            0                0                  0                  0

      PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
4880                                      0                               0
1541                                      0                               0
1289                                      0                               0
5745                                      0                               0
4873                                      0                               0

      PaymentMethod_Mailed check  InternetService_DSL  \
4880                           1                    0
1541                           0                    0
1289                           0                    1
5745                           1                    0
4873                           1                    0

      InternetService_Fiber optic
4880                            0
1541                            0
1289                            0
5745                            0
```

```
4873                             0
```

[ ]:
```
# Removing unwanted columns
X_test = X_test[cols]
```

[ ]:
```
X_test_sm = sm.add_constant(X_test)
X_test_sm.head()
```

[ ]:
```
      const    tenure  PaperlessBilling  MonthlyCharges  SeniorCitizen  \
4880    1.0  0.713723                 0       -1.457203              0
1541    1.0  1.609107                 0       -1.480388              0
1289    1.0  1.242814                 0        0.140938              0
5745    1.0  1.161415                 1       -1.336307              0
4873    1.0 -1.036345                 0       -1.498605              0

      MultipleLines  OnlineSecurity  OnlineBackup  TechSupport  \
4880              0               0             0            0
1541              0               0             0            0
1289              1               1             1            1
5745              1               0             0            0
4873              0               0             0            0

      Contract_One year  Contract_Two year  PaymentMethod_Electronic check  \
4880                  0                  1                               0
1541                  0                  1                               0
1289                  1                  0                               0
5745                  0                  1                               0
4873                  0                  0                               0

      InternetService_DSL
4880                    0
1541                    0
1289                    1
5745                    0
4873                    0
```

[ ]:
```
y_test_pred = res.predict(X_test_sm)
y_test_pred.head()
```

[ ]:
```
4880    0.010738
1541    0.005194
1289    0.018975
5745    0.014021
4873    0.156611
dtype: float64
```

[ ]:
```
final_df = pd.DataFrame(zip(y_test.index, y_test, round(y_test_pred,2),␣
↪y_test_pred.map(lambda x: 1 if x > 0.3 else 0)))
final_df = final_df.rename(columns={0:'Sl. No.', 1:'Actual Churn', 2:
↪'Churn_Prob', 3:'Predicted Churn'})
final_df.head(10)
```

[ ]:

	Sl. No.	Actual Churn	Churn_Prob	Predicted Churn
0	4880	0	0.01	0
1	1541	0	0.01	0
2	1289	0	0.02	0
3	5745	0	0.01	0
4	4873	0	0.16	0
5	4168	0	0.02	0
6	1557	0	0.33	1
7	2892	0	0.19	0
8	664	0	0.01	0
9	1588	0	0.26	0

[ ]:
```
print('Accuracy :')
acc = metrics.accuracy_score(final_df['Actual Churn'], final_df['Predicted␣
↪Churn'])
acc = round(acc*100, 2)
print(acc, '%')

confusion = metrics.confusion_matrix(final_df['Actual Churn'],␣
↪final_df['Predicted Churn'])
print('Confusion Matrix')
print(confusion)
```

```
Accuracy :
73.54 %
Confusion Matrix
[[1134  413]
 [ 146  420]]
```

[ ]:
```
tn, fp, fn, tp = metrics.confusion_matrix(final_df['Actual Churn'],␣
↪final_df['Predicted Churn']).ravel()

sensitivity = tp / (tp + fn)
print('Sensitivity : ', round(sensitivity*100, 2), '%')

specificity = tn / (tn + fp)
print('Specificity : ', round(specificity*100, 2), '%')
```

```
Sensitivity :  74.2 %
Specificity :  73.3 %
```