customer-churn-prediction-1

August 24, 2023

```
[1]: import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     import plotly.express as px
     import plotly.graph_objects as go
     from plotly.subplots import make_subplots
     import warnings
     warnings.filterwarnings('ignore')
[2]: from sklearn.preprocessing import StandardScaler
     from sklearn.preprocessing import LabelEncoder
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.naive_bayes import GaussianNB
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.svm import SVC
     from sklearn.neural_network import MLPClassifier
     from sklearn.ensemble import AdaBoostClassifier
     from sklearn.ensemble import GradientBoostingClassifier
     from sklearn.ensemble import ExtraTreesClassifier
     from sklearn.linear_model import LogisticRegression
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import accuracy score
     from sklearn import metrics
     from sklearn.metrics import roc curve
     from sklearn.metrics import recall_score, confusion_matrix, precision_score, u
      →f1_score, accuracy_score, classification_report
[3]: #loading data
     df=pd.read_excel("C:\\Users\\pavan\\Downloads\\customer.xlsx")
[4]: df
[4]:
                                                         Location \
            CustomerID
                                   Name Age Gender
                     1
                             Customer_1
                                          63
     0
                                                Male Los Angeles
```

| 1 | | | 2 | C11 | stome | r 2 | 62 | Fer | nale | N | ew Yor | k | | | |
|-----|-------|----------|-------|----------|-------|------|--------|-------|--------|-------|--------|------|------|-----|--|
| 2 | | | 3 | | stome | _ | 24 | | | | Angele | | | | |
| 3 | | | 4 | | stome | _ | 36 | | nale | | Miam | | | | |
| 4 | | | 5 | | stome | _ | 46 | | nale | | Miam | | | | |
| ••• | | ••• | | | | | ••• | | ••• | | | | | | |
| 9 | 9995 | 99 | 996 | Custom | er_99 | 996 | 33 | 1 | Male |] | Housto | n | | | |
| 9 | 9996 | 99 | 997 | Custom | er_99 | 997 | 62 | Fer | nale | N | ew Yor | k | | | |
| 9 | 9997 | 99 | 998 | Custom | er_99 | 998 | 64 | ľ | Male | (| Chicag | 0 | | | |
| 9 | 9998 | 99 | 999 | Custom | er_99 | 999 | 51 | Fer | nale | N | ew Yor | k | | | |
| 9 | 9999 | 100 | 000 | Custome | r_100 | 000 | 27 | Fer | nale | Los | Angele | s | | | |
| | | Subscri | ntior | n_Length | Mont | hs | Mont] | hlv I | Rill | Tota | l_Usag | e GR | Chu | ırn | |
| 0 | | Dubberr | Poloi | | | 17 | 110110 | - | 3.36 | 1000. | _0006 | 236 | OIIC | 0 | |
| 1 | | | | | | 1 | | | 3.76 | | | 172 | | 0 | |
| 2 | | | | | | 5 | | | 5.47 | | | 460 | | 0 | |
| 3 | | | | | | 3 | | | 7.94 | | | 297 | | 1 | |
| 4 | | | | | | 19 | | | 3.14 | | | 266 | | 0 | |
| | | | | | ••• | | | ••• | | | ••• | ••• | | | |
| | 9995 | | | | | 23 | | 55 | 5.13 | | | 226 | | 1 | |
| | 9996 | | | | | 19 | | | 1.65 | | | 351 | | 0 | |
| | 9997 | | | | | 17 | | | 3.11 | | | 251 | | 1 | |
| | 9998 | | | | | 20 | | | 9.25 | | | 434 | | 1 | |
| 9 | 9999 | | | | | 19 | | | 6.57 | | | 173 | | 1 | |
| [| 10000 | 0 rows x | 9 c | olumns] | | | | | | | | | | | |
| : d | f.hea | d() | | | | | | | | | | | | | |
| | ~ | | | | | | | | | | | | | | |
| : | | tomerID | a . | Name | Age | | der | | Locat | | \ | | | | |
| 0 | | 1 | | tomer_1 | 63 | | ale | | Ange | | | | | | |
| 1 | | 2 | | tomer_2 | 62 | Fem | | | New Yo | | | | | | |
| 2 | | | | tomer_3 | | | | Los | Ange | | | | | | |
| 3 | | 4 | | tomer_4 | 36 | | ale | | | ami | | | | | |
| 4 | | 5 | Cust | tomer_5 | 46 | Fem | ale | | Mia | ami | | | | | |
| | Sub | scriptio | n_Ler | ngth_Mon | ths | Mont | hly_ | Bill | Tota | al_Us | age_GB | Chu | ırn | | |
| 0 | | - | | • | 17 | | - | 3.36 | | | 236 | | 0 | | |
| 1 | | | | | 1 | | 48 | 8.76 | | | 172 | | 0 | | |

[6]: df.shape

[5]

[5]

[6]: (100000, 9)

[7]: df.info()

85.47

97.94

58.14

```
RangeIndex: 100000 entries, 0 to 99999
     Data columns (total 9 columns):
          Column
                                       Non-Null Count
                                                        Dtype
                                       _____
          CustomerID
                                                        int64
      0
                                       100000 non-null
      1
          Name
                                       100000 non-null
                                                        object
                                       100000 non-null
      2
          Age
                                                        int64
      3
          Gender
                                       100000 non-null
                                                        object
      4
          Location
                                       100000 non-null
                                                        object
      5
                                       100000 non-null
          Subscription_Length_Months
                                                        int64
      6
          Monthly_Bill
                                       100000 non-null
                                                        float64
      7
          Total_Usage_GB
                                       100000 non-null
                                                        int64
          Churn
                                       100000 non-null
                                                        int64
     dtypes: float64(1), int64(5), object(3)
     memory usage: 6.9+ MB
 [8]: df.columns.values
 [8]: array(['CustomerID', 'Name', 'Age', 'Gender', 'Location',
             'Subscription_Length_Months', 'Monthly_Bill', 'Total_Usage_GB',
             'Churn'], dtype=object)
 [9]: df.dtypes
 [9]: CustomerID
                                      int64
      Name
                                     object
      Age
                                      int64
      Gender
                                     object
      Location
                                     object
                                      int64
      Subscription_Length_Months
     Monthly_Bill
                                    float64
      Total_Usage_GB
                                      int64
                                      int64
      Churn
      dtype: object
[10]: df = df.drop(['CustomerID'], axis = 1)
      df.head()
[10]:
               Name Age Gender
                                     Location
                                               Subscription_Length_Months
      0 Customer 1
                            Male Los Angeles
                                                                        17
                      63
                                     New York
      1 Customer 2
                      62 Female
                                                                         1
      2 Customer 3
                      24 Female Los Angeles
                                                                         5
      3 Customer 4
                      36 Female
                                        Miami
                                                                         3
      4 Customer_5
                      46 Female
                                        Miami
                                                                        19
         Monthly_Bill Total_Usage_GB
```

<class 'pandas.core.frame.DataFrame'>

```
0
      0
                73.36
                                   236
      1
                48.76
                                   172
                                            0
      2
                85.47
                                   460
                                            0
      3
                97.94
                                   297
                                            1
      4
                58.14
                                   266
                                            0
[11]: df['Total_Usage_GB'] = pd.to_numeric(df.Total_Usage_GB, errors='coerce')
      df.isnull().sum()
[11]: Name
                                     0
                                     0
      Age
      Gender
                                     0
      Location
                                     0
      Subscription_Length_Months
                                     0
      Monthly Bill
                                     0
      Total_Usage_GB
                                     0
      Churn
                                     0
      dtype: int64
[12]: df[np.isnan(df['Total_Usage_GB'])]
[12]: Empty DataFrame
      Columns: [Name, Age, Gender, Location, Subscription_Length_Months, Monthly_Bill,
      Total Usage GB, Churn]
      Index: []
[13]: df[df['Age'] == 0].index
[13]: Int64Index([], dtype='int64')
[14]: df.drop(labels=df[df['Age'] == 0].index, axis=0, inplace=True)
      df[df['Age'] == 0].index
[14]: Int64Index([], dtype='int64')
[15]: df.fillna(df["Total_Usage_GB"].mean())
[15]:
                              Age Gender
                                                         Subscription_Length_Months
                        Name
                                               Location
                  Customer 1
                                63
                                      Male Los Angeles
                                                                                   17
      0
      1
                  Customer 2
                                62 Female
                                               New York
                                                                                   1
      2
                  Customer_3
                                24 Female Los Angeles
                                                                                   5
      3
                  Customer 4
                                36 Female
                                                  Miami
                                                                                   3
                  Customer_5
                                46 Female
                                                  Miami
                                                                                   19
      4
      99995
              Customer_99996
                                33
                                      Male
                                                Houston
                                                                                  23
              Customer_99997
                                62 Female
                                               New York
      99996
                                                                                   19
              Customer_99998
      99997
                                      Male
                                                Chicago
                                                                                   17
                                64
```

```
99998
                                                                                    20
              Customer_99999
                                51
                                    Female
                                                New York
      99999
             Customer_100000
                                27
                                                                                    19
                                    Female
                                            Los Angeles
             Monthly_Bill Total_Usage_GB
                                             Churn
      0
                     73.36
                                        236
                                                 0
      1
                     48.76
                                        172
                                                 0
                     85.47
      2
                                        460
                                                 0
      3
                     97.94
                                        297
                                                 1
      4
                     58.14
                                        266
                                                 0
                                         •••
                     55.13
      99995
                                        226
                                                 1
      99996
                     61.65
                                        351
                                                 0
      99997
                     96.11
                                        251
                                                 1
                     49.25
      99998
                                        434
                                                 1
      99999
                     76.57
                                        173
                                                 1
      [100000 rows x 8 columns]
[16]: df.isnull().sum()
[16]: Name
                                     0
      Age
                                     0
      Gender
                                     0
      Location
                                      0
      Subscription_Length_Months
                                     0
      Monthly_Bill
                                      0
      Total_Usage_GB
                                      0
      Churn
                                      0
      dtype: int64
[17]: df["Monthly_Bill"].describe(include=['object', 'bool'])
[17]: count
               100000.000000
                   65.053197
      mean
      std
                   20.230696
      min
                   30.000000
      25%
                   47.540000
      50%
                   65.010000
      75%
                   82.640000
                   100.000000
      max
      Name: Monthly_Bill, dtype: float64
[18]: numerical_cols = ['Age', 'Monthly_Bill', 'Total_Usage_GB']
      df[numerical_cols].describe()
[18]:
                                             Total_Usage_GB
                        Age
                              Monthly_Bill
      count 100000.000000
                            100000.000000
                                              100000.000000
```

```
15.280283
                                20.230696
                                               130.463063
      std
     min
                 18.000000
                                30.000000
                                                50.000000
      25%
                 31.000000
                                47.540000
                                               161.000000
      50%
                 44.000000
                                65.010000
                                               274.000000
      75%
                 57.000000
                                82.640000
                                               387.000000
                 70.000000
                               100.000000
                                               500.000000
     max
[19]: g_labels = ['Male', 'Female']
      c_labels = ['No', 'Yes']
      # Create subplots: use 'domain' type for Pie subplot
      fig = make_subplots(rows=1, cols=2, specs=[[{'type':'domain'}, {'type':
       fig.add_trace(go.Pie(labels=g_labels, values=df['Gender'].value_counts(),_

¬name="Gender"),
                    1, 1)
      fig.add_trace(go.Pie(labels=c_labels, values=df['Age'].value_counts(),_

¬name="Age"),
                    1, 2)
      # Use `hole` to create a donut-like pie chart
      fig.update_traces(hole=.4, hoverinfo="label+percent+name", textfont_size=16)
      fig.update_layout(
          title_text="customer_churn_prediction",
          # Add annotations in the center of the donut pies.
          annotations=[dict(text='Gender', x=0.16, y=0.5, font_size=20,_
       ⇒showarrow=False),
                       dict(text='Age', x=0.84, y=0.5, font_size=20,__
       ⇒showarrow=False)])
      fig.show()
[20]: df["Gender"][df["Gender"]=="No"].groupby(by=df["Age"]).count()
[20]: Series([], Name: Gender, dtype: int64)
[21]: df["Age"][df["Age"]=="Yes"].groupby(by=df["Gender"]).count()
[21]: Series([], Name: Age, dtype: int64)
[22]: plt.figure(figsize=(6, 6))
      labels =["Churn: Yes", "Churn:No"]
      values = [1869, 5163]
      labels gender = ["F","M","F","M"]
      sizes\_gender = [939,930, 2544,2619]
      colors = ['#ff6666', '#66b3ff']
      colors_gender = ['#c2c2f0','#ffb3e6', '#c2c2f0','#ffb3e6']
```

44.027020

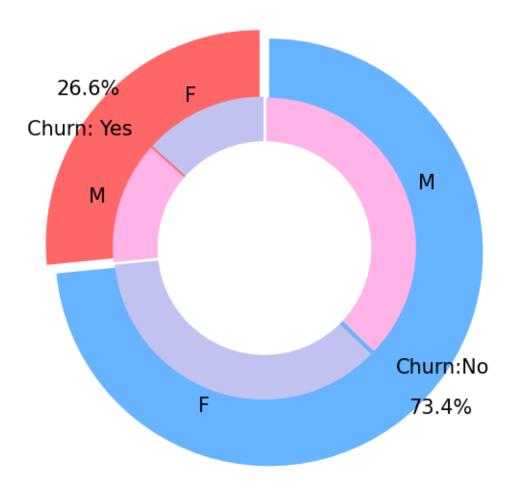
mean

65.053197

274.393650

```
explode = (0.3, 0.3)
explode_gender = (0.1,0.1,0.1,0.1)
textprops = {"fontsize":15}
#Plot
plt.pie(values, labels=labels,autopct='%1.1f%%',pctdistance=1.08,__
 ⇔labeldistance=0.8,colors=colors, startangle=90,frame=True,⊔
explode=explode,radius=10, textprops =textprops, counterclock = True, )
plt.pie(sizes_gender,labels=labels_gender,colors=colors_gender,startangle=90,__
 ⇔explode=explode_gender,radius=7, textprops =textprops, counterclock = True, )
#Draw circle
centre_circle = plt.Circle((0,0),5,color='black', fc='white',linewidth=0)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
plt.title('Churn Distribution w.r.t Gender: Male(M), Female(F)', fontsize=15, __
 \hookrightarrowy=1.1)
# show plot
plt.axis('equal')
plt.tight_layout()
plt.show()
```

Churn Distribution w.r.t Gender: Male(M), Female(F)



```
[24]: labels = df['Monthly_Bill'].unique()
values = df['Monthly_Bill'].value_counts()

fig = go.Figure(data=[go.Pie(labels=labels, values=values, hole=.3)])
fig.update_layout(title_text="<b>Payment Method Distribution</b>")
fig.show()

[25]: fig = px.histogram(df, x="Churn", color="Monthly_Bill", title="<b>Customer_U
→Payment Method distribution w.r.t. Churn</b>")
```

fig.update_layout(width=700, height=500, bargap=0.1)

fig.show()

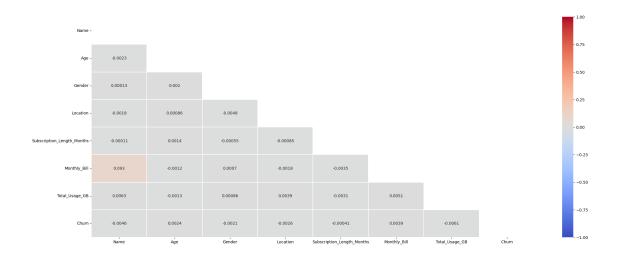
```
[26]: df["Subscription_Length_Months"].unique()
[26]: array([17, 1, 5, 3, 19, 15, 10, 12, 20, 13, 8, 23, 2, 4, 18, 9, 14,
             16, 6, 7, 24, 22, 11, 21], dtype=int64)
[27]: df[df["Gender"]=="Male"][["Subscription_Length_Months", "Churn"]].value_counts()
[27]: Subscription_Length_Months
                                   Churn
                                             1109
      2
                                   1
                                             1089
      14
                                   0
                                             1088
                                   0
      21
                                             1088
      20
                                   0
                                             1087
      22
                                   0
                                             1083
                                   0
      15
                                             1079
      22
                                   1
                                             1067
      10
                                   1
                                             1067
      2
                                   0
                                             1059
      20
                                   1
                                             1058
      13
                                   1
                                             1058
      5
                                   0
                                             1056
      14
                                   1
                                             1056
                                             1056
      11
                                   1
                                   0
                                             1050
      16
                                             1049
                                   1
      18
                                   1
                                             1046
      7
                                   1
                                             1044
      9
                                   0
                                             1042
      10
                                   0
                                             1040
      12
                                   1
                                             1040
      16
                                             1038
                                   0
      3
                                             1037
                                   1
      24
                                   0
                                             1037
      17
                                   0
                                             1034
      7
                                   0
                                             1034
      4
                                   0
                                             1030
      8
                                   1
                                             1027
      19
                                             1025
                                   1
                                             1024
      9
                                   1
      5
                                   1
                                             1024
      24
                                   1
                                             1024
      8
                                   0
                                             1022
      6
                                   0
                                             1020
                                   0
                                             1018
      18
      23
                                   0
                                             1016
      19
                                   0
                                             1012
                                             1011
      1
```

```
3
                                              1010
                                    0
      23
                                              1006
                                    1
      12
                                    0
                                              1001
      6
                                    1
                                              1000
      4
                                              1000
                                    1
      13
                                               994
                                    0
      15
                                    1
                                               980
      21
                                    1
                                               977
      17
                                    1
                                               972
      dtype: int64
[28]: df[df["Gender"]=="Female"][["Subscription_Length_Months", "Churn"]].
       ⇔value_counts()
[28]: Subscription_Length_Months Churn
                                              1124
      5
                                    0
                                              1099
      1
                                    0
                                              1098
      20
                                    0
                                              1081
      18
                                    0
                                              1081
      16
                                    1
                                              1080
      20
                                    1
                                              1077
      22
                                              1072
                                    1
      7
                                    1
                                              1071
      12
                                    0
                                              1069
                                    0
                                              1062
      16
      7
                                    0
                                              1062
      21
                                    1
                                              1061
                                              1060
      2
                                    0
      24
                                    1
                                              1059
                                              1058
      11
                                    0
      9
                                    0
                                              1055
      13
                                    0
                                              1053
      14
                                    0
                                              1052
      4
                                    0
                                              1050
      3
                                              1049
                                    1
      17
                                              1049
                                    1
      13
                                    1
                                              1049
      19
                                    1
                                              1047
      12
                                              1045
                                    1
      22
                                    0
                                              1045
      8
                                    0
                                              1044
      23
                                    1
                                              1042
```

```
15
                                  0
                                           1034
                                           1029
                                  1
      1
                                  1
                                           1029
      21
                                  0
                                           1028
      18
                                  1
                                           1026
      19
                                  0
                                           1022
      2
                                  1
                                           1020
     23
                                  0
                                           1019
      4
                                  1
                                           1018
      14
                                  1
                                           1017
     8
                                           1013
                                  1
      9
                                  1
                                           1013
      10
                                  1
                                           1010
                                  0
      17
                                           1009
      24
                                  0
                                            993
      5
                                  1
                                            992
      dtype: int64
[29]: fig = go.Figure()
      fig.add_trace(go.Bar(
        x = [['Churn:No', 'Churn:No', 'Churn:Yes', 'Churn:Yes'],
             ["Female", "Male", "Female", "Male"]],
       y = [965, 992, 219, 240],
       name = 'DSL',
      ))
      fig.add_trace(go.Bar(
        x = [['Churn:No', 'Churn:No', 'Churn:Yes'],
             ["Female", "Male", "Female", "Male"]],
       y = [889, 910, 664, 633],
       name = 'Fiber optic',
      ))
      fig.add_trace(go.Bar(
       x = [['Churn:No', 'Churn:No', 'Churn:Yes'],
             ["Female", "Male", "Female", "Male"]],
       y = [690, 717, 56, 57],
       name = 'No Internet',
      ))
      fig.update_layout(title_text="<b>Churn Distribution w.r.t. Internet Service and_

Gender</b>")
      fig.show()
```

```
[30]: color_map = {"Yes": "#FF97FF", "No": "#AB63FA"}
     fig = px.histogram(df, x="Churn", color="Subscription_Length_Months", __
       ⇔barmode="group", title="<b>Dependents distribution</b>",□
       →color_discrete_map=color_map)
     fig.update layout(width=700, height=500, bargap=0.1)
     fig.show()
[31]: color_map = {"Yes": '#FFA15A', "No": '#00CC96'}
     fig = px.histogram(df, x="Churn", color="Monthly Bill", barmode="group", __
       →title="<b>Chrun distribution w.r.t. Partners</b>",□
      ⇔color_discrete_map=color_map)
     fig.update_layout(width=700, height=500, bargap=0.1)
     fig.show()
[32]: color_map = {"Yes": '#00CC96', "No": '#B6E880'}
     fig = px.histogram(df, x="Churn", color="Age", title="<b>Chrun distribution w.r.
      ot. Senior Citizen</b>", color_discrete_map=color_map)
     fig.update_layout(width=700, height=500, bargap=0.1)
     fig.show()
[33]: color map = {"Yes": "#FF97FF", "No": "#AB63FA"}
     fig = px.histogram(df, x="Churn", color="Age", barmode="group", title="<b>Churn_
      fig.update_layout(width=700, height=500, bargap=0.1)
     fig.show()
[34]: color map = {"Yes": '#FFA15A', "No": '#00CC96'}
     fig = px.histogram(df, x="Churn", color="Total_Usage_GB", title="<b>Chrun_
       distribution w.r.t. Paperless Billing</b>", color_discrete_map=color_map)
     fig.update_layout(width=700, height=500, bargap=0.1)
     fig.show()
[35]: | fig = px.histogram(df, x="Churn", color="Gender",barmode="group", ___
      stitle="<b>Chrun distribution w.r.t. TechSupport</b>")
     fig.update_layout(width=700, height=500, bargap=0.1)
     fig.show()
[36]: plt.figure(figsize=(25, 10))
     corr = df.apply(lambda x: pd.factorize(x)[0]).corr()
     mask = np.triu(np.ones_like(corr, dtype=bool))
     ax = sns.heatmap(corr, mask=mask, xticklabels=corr.columns, yticklabels=corr.
       →columns, annot=True, linewidths=.2, cmap='coolwarm', vmin=-1, vmax=1)
```



```
[37]: def object_to_int(dataframe_series):
    if dataframe_series.dtype=='object':
        dataframe_series = LabelEncoder().fit_transform(dataframe_series)
    return dataframe_series
[38]: df = df.apply(lambda x: object_to_int(x))
    df.head()
```

```
[38]:
                                        Subscription_Length_Months
          Name
                Age
                     Gender
                            Location
                                                                    Monthly_Bill \
             0
                 63
                                                                 17
                                                                            73.36
      0
                          1
                                     2
                                     4
                                                                            48.76
      1 11112
                 62
                          0
                                                                 1
                                     2
                                                                 5
                                                                            85.47
      2 22223
                 24
                          0
      3 33334
                                                                 3
                                                                            97.94
                 36
                          0
                                     3
      4 44445
                          0
                                     3
                                                                 19
                                                                            58.14
                 46
```

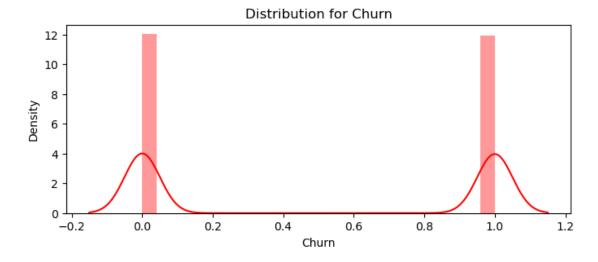
```
Total_Usage_GB Churn
0 236 0
1 172 0
2 460 0
3 297 1
4 266 0
```

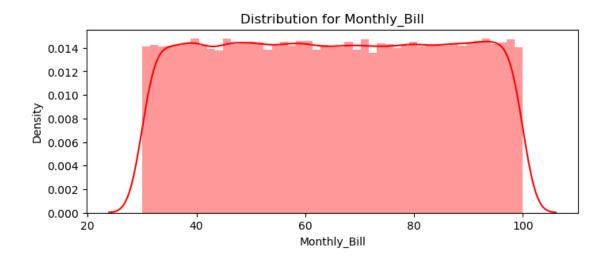
```
[39]: plt.figure(figsize=(14,7))
df.corr()['Churn'].sort_values(ascending = False)
```

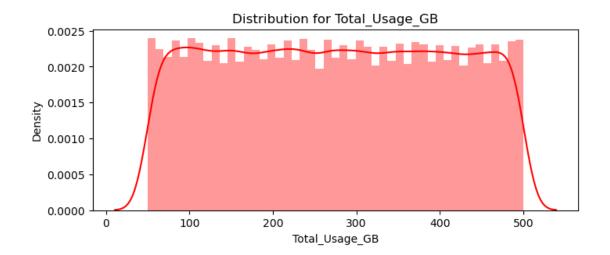
```
[39]: Churn 1.000000
Location 0.006405
Subscription_Length_Months 0.002328
Gender 0.002121
Age 0.001559
Monthly_Bill -0.000211
```

-0.001418

Name







```
[44]: knn_model = KNeighborsClassifier(n_neighbors = 11)
knn_model.fit(X_train,y_train)
predicted_y = knn_model.predict(X_test)
accuracy_knn = knn_model.score(X_test,y_test)
print("KNN accuracy:",accuracy_knn)
```

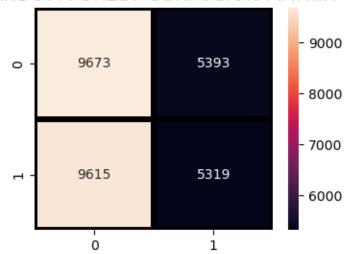
KNN accuracy: 0.49773333333333336

[45]: print(classification_report(y_test, predicted_y))

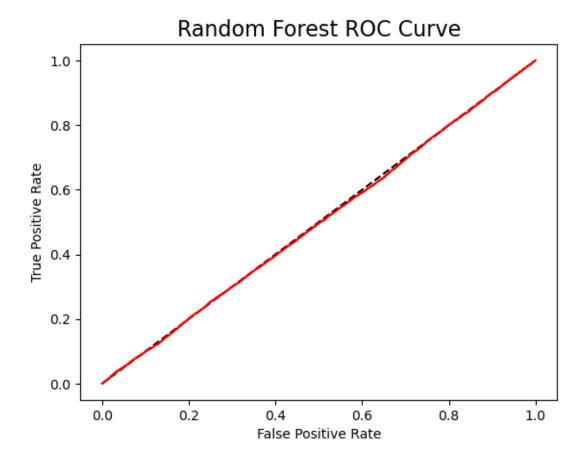
| | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 0.50 | 0.50 | 0.50 | 15066 |
| 1 | 0.50 | 0.49 | 0.49 | 14934 |

```
0.50
                                                       30000
         accuracy
                                             0.50
                                                       30000
        macro avg
                         0.50
                                   0.50
     weighted avg
                         0.50
                                   0.50
                                             0.50
                                                       30000
[46]: svc_model = SVC(random_state = 1)
      svc_model.fit(X_train,y_train)
      predict_y = svc_model.predict(X_test)
      accuracy_svc = svc_model.score(X_test,y_test)
      print("SVM accuracy is :",accuracy_svc)
     SVM accuracy is: 0.5022
[47]: print(classification_report(y_test, predict_y))
                   precision
                                 recall f1-score
                                                    support
                0
                         0.50
                                   1.00
                                             0.67
                                                       15066
                         0.00
                                   0.00
                1
                                             0.00
                                                       14934
         accuracy
                                             0.50
                                                       30000
        macro avg
                         0.25
                                   0.50
                                             0.33
                                                       30000
     weighted avg
                         0.25
                                   0.50
                                             0.34
                                                       30000
[48]: model_rf = RandomForestClassifier(n_estimators=500 , oob_score = True, n_jobs =__
       ⊶-1,
                                         random_state =50, max_features = "auto",
                                         max_leaf_nodes = 30)
      model_rf.fit(X_train, y_train)
      # Make predictions
      prediction_test = model_rf.predict(X_test)
      print (metrics.accuracy_score(y_test, prediction_test))
     0.4997333333333333
[49]: print(classification_report(y_test, prediction_test))
                   precision
                                 recall f1-score
                                                    support
                0
                                   0.64
                                             0.56
                         0.50
                                                       15066
                1
                        0.50
                                   0.36
                                             0.41
                                                       14934
         accuracy
                                             0.50
                                                       30000
                                   0.50
                                             0.49
        macro avg
                         0.50
                                                       30000
     weighted avg
                         0.50
                                   0.50
                                             0.49
                                                       30000
```

RANDOM FOREST CONFUSION MATRIX



```
[51]: y_rfpred_prob = model_rf.predict_proba(X_test)[:,1]
    fpr_rf, tpr_rf, thresholds = roc_curve(y_test, y_rfpred_prob)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.plot(fpr_rf, tpr_rf, label='Random Forest',color = "r")
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Random Forest ROC Curve',fontsize=16)
    plt.show();
```



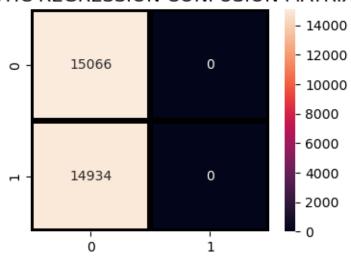
```
[52]: lr_model = LogisticRegression()
lr_model.fit(X_train,y_train)
accuracy_lr = lr_model.score(X_test,y_test)
print("Logistic Regression accuracy is :",accuracy_lr)
```

Logistic Regression accuracy is : 0.5022

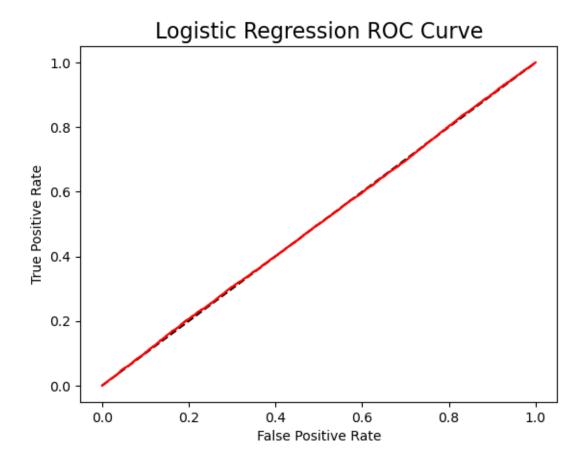
```
[53]: lr_pred= lr_model.predict(X_test)
report = classification_report(y_test,lr_pred)
print(report)
```

| support | f1-score | recall | precision | |
|---------|----------|--------|-----------|--------------|
| 15066 | 0.67 | 1.00 | 0.50 | 0 |
| 14934 | 0.00 | 0.00 | 0.00 | 1 |
| 30000 | 0.50 | | | accuracy |
| 30000 | 0.33 | 0.50 | 0.25 | macro avg |
| 30000 | 0.34 | 0.50 | 0.25 | weighted avg |

LOGISTIC REGRESSION CONFUSION MATRIX



```
[55]: y_pred_prob = lr_model.predict_proba(X_test)[:,1]
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.plot(fpr, tpr, label='Logistic Regression',color = "r")
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Logistic Regression ROC Curve',fontsize=16)
    plt.show();
```



```
[56]: dt_model = DecisionTreeClassifier()
    dt_model.fit(X_train,y_train)
    predictdt_y = dt_model.predict(X_test)
    accuracy_dt = dt_model.score(X_test,y_test)
    print("Decision Tree accuracy is :",accuracy_dt)
```

Decision Tree accuracy is : 0.4982

[57]: print(classification_report(y_test, predictdt_y))

| support | f1-score | recall | precision | |
|---------|----------|--------|-----------|--------------|
| 15066 | 0.50 | 0.50 | 0.50 | 0 |
| 14934 | 0.50 | 0.49 | 0.50 | 1 |
| 30000 | 0.50 | | | accuracy |
| 30000 | 0.50 | 0.50 | 0.50 | macro avg |
| 30000 | 0.50 | 0.50 | 0.50 | weighted avg |

```
[58]: a_model = AdaBoostClassifier()
a_model.fit(X_train,y_train)
a_preds = a_model.predict(X_test)
print("AdaBoost Classifier accuracy")
metrics.accuracy_score(y_test, a_preds)
```

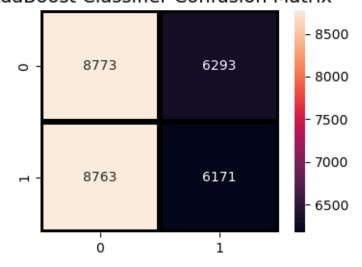
AdaBoost Classifier accuracy

[58]: 0.4981333333333333

[59]: print(classification_report(y_test, a_preds))

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.50 | 0.58 | 0.54 | 15066 |
| 1 | 0.50 | 0.41 | 0.45 | 14934 |
| accuracy | | | 0.50 | 30000 |
| macro avg | 0.50 | 0.50 | 0.49 | 30000 |
| weighted avg | 0.50 | 0.50 | 0.49 | 30000 |

AdaBoost Classifier Confusion Matrix



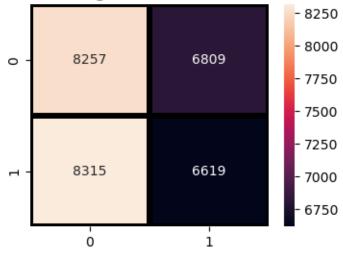
```
[61]: gb = GradientBoostingClassifier()
    gb.fit(X_train, y_train)
    gb_pred = gb.predict(X_test)
    print("Gradient Boosting Classifier", accuracy_score(y_test, gb_pred))
```

Gradient Boosting Classifier 0.4958666666666667

```
[62]: print(classification_report(y_test, gb_pred))
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| | - | | | |
| 0 | 0.50 | 0.55 | 0.52 | 15066 |
| 1 | 0.49 | 0.44 | 0.47 | 14934 |
| | | | | |
| accuracy | | | 0.50 | 30000 |
| macro avg | 0.50 | 0.50 | 0.49 | 30000 |
| weighted avg | 0.50 | 0.50 | 0.49 | 30000 |

Gradient Boosting Classifier Confusion Matrix



```
[64]: from sklearn.ensemble import VotingClassifier clf1 = GradientBoostingClassifier()
```

```
clf2 = LogisticRegression()
clf3 = AdaBoostClassifier()
eclf1 = VotingClassifier(estimators=[('gbc', clf1), ('lr', clf2), ('abc',
clf3)], voting='soft')
eclf1.fit(X_train, y_train)
predictions = eclf1.predict(X_test)
print("Final Accuracy Score ")
print(accuracy_score(y_test, predictions))
```

Final Accuracy Score 0.4968

```
[65]: print(classification_report(y_test, predictions))
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.50 | 0.61 | 0.55 | 15066 |
| 1 | 0.49 | 0.38 | 0.43 | 14934 |
| accuracy | | | 0.50 | 30000 |
| macro avg | 0.50 | 0.50 | 0.49 | 30000 |
| weighted avg | 0.50 | 0.50 | 0.49 | 30000 |



