customer-churn-data-prediction-1

September 6, 2023

[426]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy import stats
```

[427]:
```
data=pd.read_csv("/content/customer_churn_large_dataset.csv")
```

[428]:
```
data.head()
```

[428]:
```
   CustomerID        Name  Age  Gender     Location  \
0           1  Customer_1   63    Male  Los Angeles
1           2  Customer_2   62  Female     New York
2           3  Customer_3   24  Female  Los Angeles
3           4  Customer_4   36  Female        Miami
4           5  Customer_5   46  Female        Miami

   Subscription_Length_Months  Monthly_Bill  Total_Usage_GB  Churn
0                          17         73.36             236      0
1                           1         48.76             172      0
2                           5         85.47             460      0
3                           3         97.94             297      1
4                          19         58.14             266      0
```

[429]:
```
data.tail()
```

[429]:
```
       CustomerID            Name  Age  Gender     Location  \
99995       99996   Customer_99996   33    Male      Houston
99996       99997   Customer_99997   62  Female     New York
99997       99998   Customer_99998   64    Male      Chicago
99998       99999   Customer_99999   51  Female     New York
99999      100000  Customer_100000   27  Female  Los Angeles

       Subscription_Length_Months  Monthly_Bill  Total_Usage_GB  Churn
99995                          23         55.13             226      1
99996                          19         61.65             351      0
99997                          17         96.11             251      1
99998                          20         49.25             434      1
```

```
99999                              19          76.57              173       1
```

[430]:
```python
data.shape
print("Number of Rows",data.shape[0])
print("Number of Columns",data.shape[1])
```

```
Number of Rows 100000
Number of Columns 9
```

[431]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 9 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   CustomerID                  100000 non-null  int64
 1   Name                        100000 non-null  object
 2   Age                         100000 non-null  int64
 3   Gender                      100000 non-null  object
 4   Location                    100000 non-null  object
 5   Subscription_Length_Months  100000 non-null  int64
 6   Monthly_Bill                100000 non-null  float64
 7   Total_Usage_GB              100000 non-null  int64
 8   Churn                       100000 non-null  int64
dtypes: float64(1), int64(5), object(3)
memory usage: 6.9+ MB
```

[432]:
```python
data.describe()
```

[432]:
```
          CustomerID            Age  Subscription_Length_Months  \
count  100000.000000  100000.000000               100000.000000
mean    50000.500000      44.027020                   12.490100
std     28867.657797      15.280283                    6.926461
min         1.000000      18.000000                    1.000000
25%     25000.750000      31.000000                    6.000000
50%     50000.500000      44.000000                   12.000000
75%     75000.250000      57.000000                   19.000000
max    100000.000000      70.000000                   24.000000

        Monthly_Bill  Total_Usage_GB          Churn
count  100000.000000   100000.000000  100000.000000
mean       65.053197      274.393650       0.497790
std        20.230696      130.463063       0.499998
min        30.000000       50.000000       0.000000
25%        47.540000      161.000000       0.000000
50%        65.010000      274.000000       0.000000
```

```
75%       82.640000    387.000000     1.000000
max      100.000000    500.000000     1.000000
```

#checking missing data

[433]:
```
headers =␣
↪["CustomerID","Name","Age","Gender","Location","Subscription_Length_Months","Monthly_Bill",
```

[434]:
```
data.isnull().sum()
```

[434]:
```
CustomerID                    0
Name                          0
Age                           0
Gender                        0
Location                      0
Subscription_Length_Months    0
Monthly_Bill                  0
Total_Usage_GB                0
Churn                         0
dtype: int64
```

[435]:
```
missing_data = data.isnull()
for column in headers :
  print(column)
  print(missing_data[column].value_counts())
  print(" ")
```

```
CustomerID
False    100000
Name: CustomerID, dtype: int64

Name
False    100000
Name: Name, dtype: int64

Age
False    100000
Name: Age, dtype: int64

Gender
False    100000
Name: Gender, dtype: int64

Location
False    100000
Name: Location, dtype: int64

Subscription_Length_Months
```

```
False    100000
Name: Subscription_Length_Months, dtype: int64

Monthly_Bill
False    100000
Name: Monthly_Bill, dtype: int64

Total_Usage_GB
False    100000
Name: Total_Usage_GB, dtype: int64

Churn
False    100000
Name: Churn, dtype: int64
```

#Dropping Irrelevent Features

[436]:
```python
data.columns
```

[436]:
```
Index(['CustomerID', 'Name', 'Age', 'Gender', 'Location',
       'Subscription_Length_Months', 'Monthly_Bill', 'Total_Usage_GB',
       'Churn'],
      dtype='object')
```

[437]:
```python
data = data.drop(['CustomerID', 'Name'],axis=1)
```

[438]:
```python
data.head(10)
```

[438]:
```
   Age  Gender     Location  Subscription_Length_Months  Monthly_Bill  \
0   63    Male  Los Angeles                          17         73.36
1   62  Female     New York                           1         48.76
2   24  Female  Los Angeles                           5         85.47
3   36  Female        Miami                           3         97.94
4   46  Female        Miami                          19         58.14
5   67    Male     New York                          15         82.65
6   30  Female      Chicago                           3         73.79
7   67  Female        Miami                           1         97.70
8   20  Female        Miami                          10         42.45
9   53  Female  Los Angeles                          12         64.49

   Total_Usage_GB  Churn
0             236      0
1             172      0
2             460      0
3             297      1
4             266      0
5             456      1
```

```
6              269      0
7              396      1
8              150      1
9              383      1
```

#Encoding Categorical Data

[439]:
```
data['Location'].unique()
```

[439]:
```
array(['Los Angeles', 'New York', 'Miami', 'Chicago', 'Houston'],
      dtype=object)
```

[440]:
```
data = pd.get_dummies(data, drop_first=True)
```

[441]:
```
data.head()
```

[441]:
```
   Age  Subscription_Length_Months  Monthly_Bill  Total_Usage_GB  Churn  \
0   63                          17         73.36             236      0
1   62                           1         48.76             172      0
2   24                           5         85.47             460      0
3   36                           3         97.94             297      1
4   46                          19         58.14             266      0

   Gender_Male  Location_Houston  Location_Los Angeles  Location_Miami  \
0            1                 0                     1               0
1            0                 0                     0               0
2            0                 0                     1               0
3            0                 0                     0               1
4            0                 0                     0               1

   Location_New York
0                  0
1                  1
2                  0
3                  0
4                  0
```

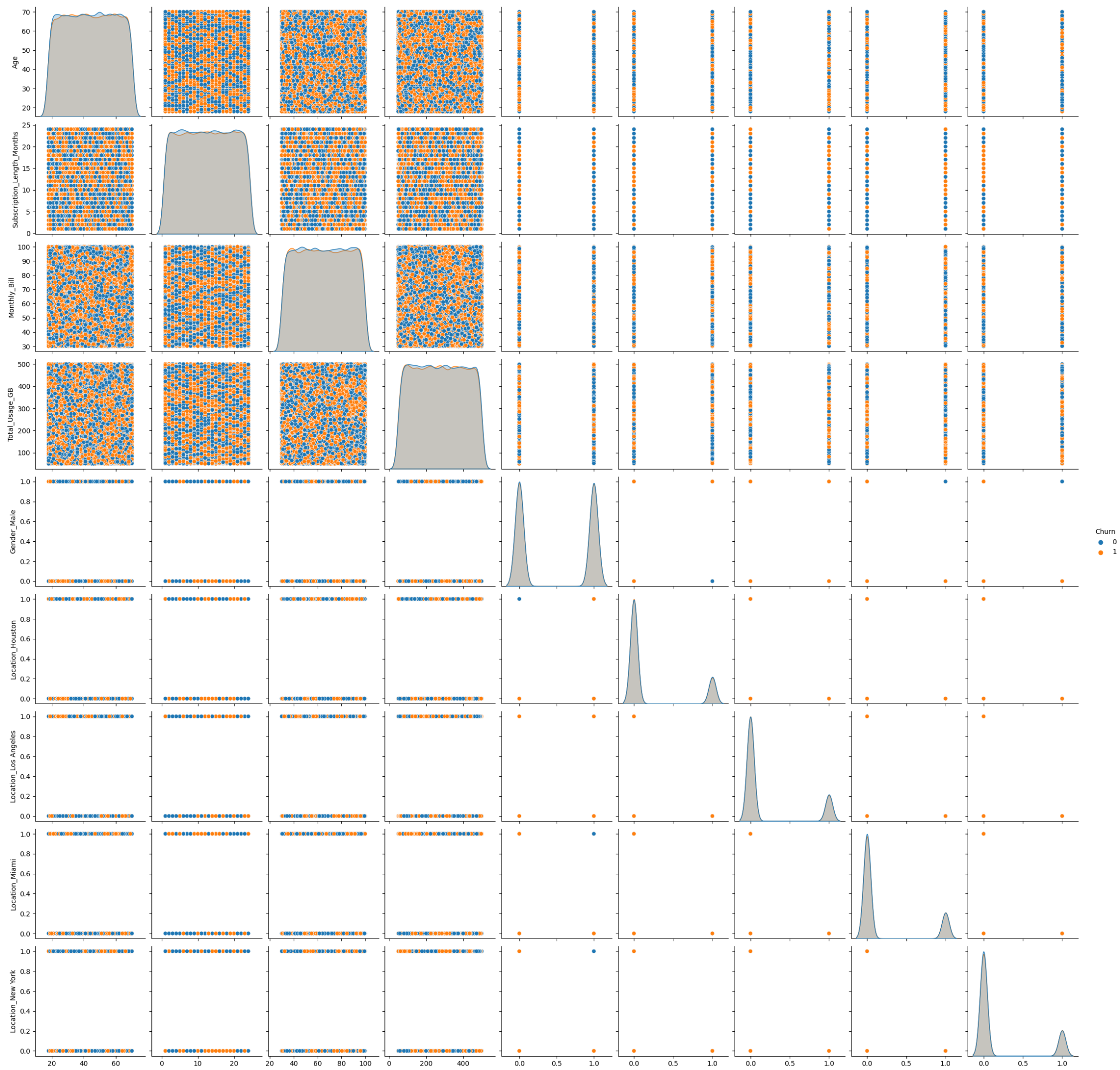
#Not Handling imbalanced

[442]:
```
data['Churn'].value_counts()
```

[442]:
```
0    50221
1    49779
Name: Churn, dtype: int64
```

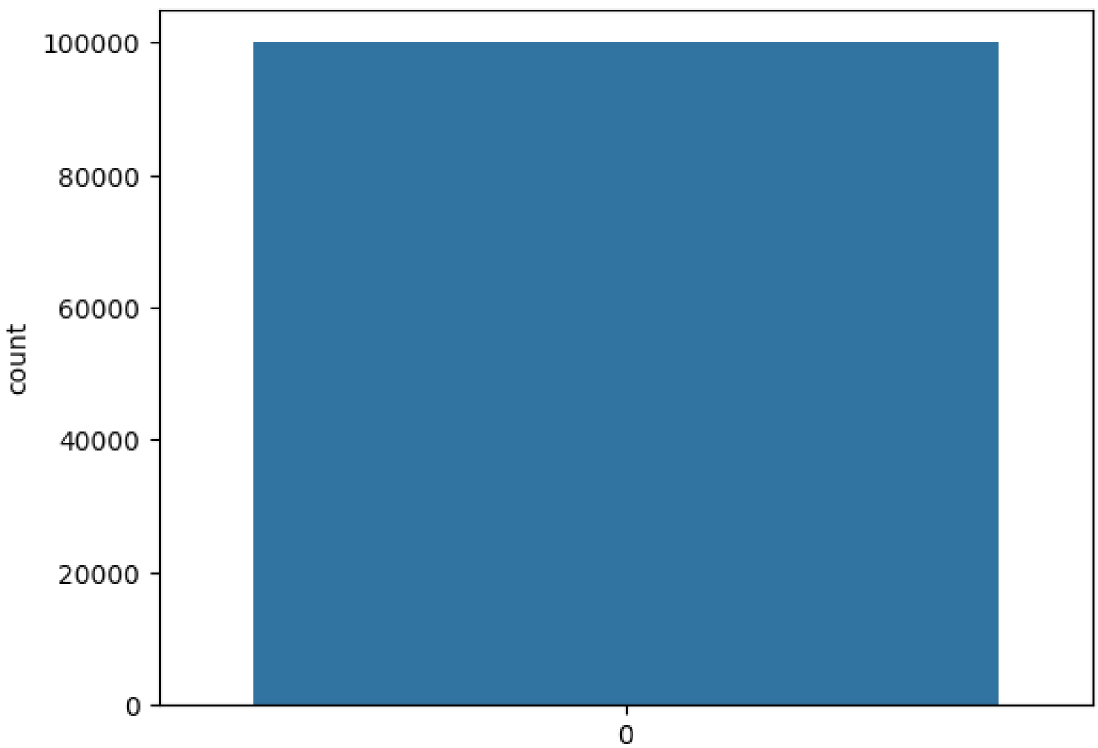
[443]:
```
import seaborn as sns
```

[504]:
```python
sns.pairplot(data, hue='Churn')
plt.show()
```



[478]:
```python
sns.countplot(data['Churn'])
```

[478]: <Axes: ylabel='count'>



#Diving into Target and Predictor Variables

[446]:
```
X= data.drop('Churn',axis=1)
y=data['Churn']
```

[447]:
```
y
```

[447]:
```
0        0
1        0
2        0
3        1
4        0
        ..
99995    1
99996    0
99997    1
99998    1
99999    1
Name: Churn, Length: 100000, dtype: int64
```

#Handling Imbalanced Data With SMOTE

[448]:
```
from imblearn.over_sampling import SMOTE
```

[449]:
```
X_res,y_res = SMOTE().fit_resample(X,y)
```

[450]:
```
y_res.value_counts()
```

[450]:
```
0    50221
1    50221
Name: Churn, dtype: int64
```

[451]:
```
from collections import Counter
print('original dataset shape {}'.format(Counter(y)))
print('Resampled dataset shape{}'.format(Counter(y_res)))
```

```
original dataset shape Counter({0: 50221, 1: 49779})
Resampled dataset shapeCounter({0: 50221, 1: 50221})
```

#Divide Data as Training Set and Testing Set

[480]:
```
from sklearn.model_selection import train_test_split
```

[482]:
```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res,test_size= 0.
↪20,random_state= 46)
```

[454]:
```
X_train
```

[454]:

	Age	Subscription_Length_Months	Monthly_Bill	Total_Usage_GB	\
67665	62	19	49.48	466	
65564	36	3	81.75	381	
52159	52	7	83.18	101	
39494	62	23	91.43	114	
51526	18	10	30.89	423	
…	…	…	…	…	
84410	56	20	42.91	130	
56692	27	18	47.15	315	
30248	69	23	74.57	464	
88901	44	7	85.85	376	
81085	62	24	73.85	328	

	Gender_Male	Location_Houston	Location_Los Angeles	Location_Miami	\
67665	0	1	0	0	
65564	1	0	1	0	
52159	1	0	0	1	
39494	0	1	0	0	
51526	0	0	1	0	
…	…	…	…	…	
84410	1	0	0	0	
56692	0	0	1	0	
30248	1	0	0	0	
88901	1	0	1	0	

```
81085           1               1                   0               0

        Location_New York
67665                   0
65564                   0
52159                   0
39494                   0
51526                   0
…                     …
84410                   0
56692                   0
30248                   0
88901                   0
81085                   0

[80353 rows x 9 columns]
```

[455]:
```
X_test
```

[455]:
```
        Age  Subscription_Length_Months  Monthly_Bill  Total_Usage_GB  \
42508   60                          12         42.04              51
49541   39                          21         77.67             456
70673   25                           9         94.84             315
70424   28                          19         71.24             273
34843   38                           8         44.21             298
…     …                          …           …             …
76177   69                           7         39.62             345
86183   54                           3         33.33             193
29963   44                           8         37.75             197
58207   20                           1         63.43             106
19501   28                           1         79.13             234

        Gender_Male  Location_Houston  Location_Los Angeles  Location_Miami  \
42508             0                 0                     0               0
49541             0                 0                     0               1
70673             0                 0                     0               0
70424             1                 0                     0               1
34843             0                 0                     0               1
…             …               …                   …            …
76177             1                 0                     1               0
86183             1                 0                     0               0
29963             1                 0                     0               0
58207             0                 1                     0               0
19501             0                 0                     0               1

        Location_New York
42508                   0
```

```
49541                  0
70673                  1
70424                  0
34843                  0
…                    …
76177                  0
86183                  1
29963                  0
58207                  0
19501                  0

[20089 rows x 9 columns]
```

[456]:
```
y_train
```

[456]:
```
67665    0
65564    1
52159    1
39494    1
51526    1
        ..
84410    0
56692    1
30248    0
88901    0
81085    0
Name: Churn, Length: 80353, dtype: int64
```

[457]:
```
y_test
```

[457]:
```
42508    0
49541    1
70673    1
70424    0
34843    0
        ..
76177    0
86183    0
29963    0
58207    0
19501    0
Name: Churn, Length: 20089, dtype: int64
```

#Feature Engineering

[458]:
```
from sklearn.preprocessing import LabelEncoder
```

[459]:
```
age_bins = [0, 30, 40, 50, 100]
age_labels = ['Young', 'Adult', 'Middle-aged', 'Senior']
data['Age_Group'] = pd.cut(data['Age'], bins=age_bins, labels=age_labels)
```

[460]:
```
data['Subscription_Length_Category'] = pd.
 ↪cut(data['Subscription_Length_Months'], bins=[0, 6, 12, 24, 100],␣
 ↪labels=['Short', 'Medium', 'Long', 'Very Long'])
```

[461]:
```
data
```

[461]:
```
       Age  Subscription_Length_Months  Monthly_Bill  Total_Usage_GB  Churn  \
0       63                          17         73.36             236      0
1       62                           1         48.76             172      0
2       24                           5         85.47             460      0
3       36                           3         97.94             297      1
4       46                          19         58.14             266      0
…      …                         …           …             …    …
99995   33                          23         55.13             226      1
99996   62                          19         61.65             351      0
99997   64                          17         96.11             251      1
99998   51                          20         49.25             434      1
99999   27                          19         76.57             173      1

       Gender_Male  Location_Houston  Location_Los Angeles  Location_Miami  \
0                1                 0                     1               0
1                0                 0                     0               0
2                0                 0                     1               0
3                0                 0                     0               1
4                0                 0                     0               1
…              …               …                   …             …
99995            1                 1                     0               0
99996            0                 0                     0               0
99997            1                 0                     0               0
99998            0                 0                     0               0
99999            0                 0                     1               0

       Location_New York    Age_Group Subscription_Length_Category
0                      0       Senior                         Long
1                      1       Senior                        Short
2                      0        Young                        Short
3                      0        Adult                        Short
4                      0  Middle-aged                         Long
…                    …          …                          …
99995                  0        Adult                         Long
99996                  1       Senior                         Long
99997                  0       Senior                         Long
99998                  1       Senior                         Long
```

```
99999                  0        Young                         Long

[100000 rows x 12 columns]
```

#Feature Scaling

[462]:
```python
from sklearn.preprocessing import StandardScaler
```

[463]:
```python
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

[464]:
```python
X_train
```

[464]:
```
array([[ 1.17834719e+00,  9.37438190e-01, -7.69791232e-01, …,
        -4.97439652e-01, -5.00688274e-01, -4.94128162e-01],
       [-5.25863760e-01, -1.37187720e+00,  8.26086176e-01, …,
         2.01029411e+00, -5.00688274e-01, -4.94128162e-01],
       [ 5.22881441e-01, -7.94548349e-01,  8.96805255e-01, …,
        -4.97439652e-01,  1.99725069e+00, -4.94128162e-01],
       …,
       [ 1.63717322e+00,  1.51476704e+00,  4.71007162e-01, …,
        -4.97439652e-01, -5.00688274e-01, -4.94128162e-01],
       [-1.49115950e-03, -7.94548349e-01,  1.02884717e+00, …,
         2.01029411e+00, -5.00688274e-01, -4.94128162e-01],
       [ 1.17834719e+00,  1.65909925e+00,  4.35400352e-01, …,
        -4.97439652e-01, -5.00688274e-01, -4.94128162e-01]])
```

[465]:
```python
X_test
```

[465]:
```
array([[ 1.04725404e+00, -7.28872908e-02, -1.13772826e+00, …,
        -4.97439652e-01, -5.00688274e-01, -4.94128162e-01],
       [-3.29224035e-01,  1.22610261e+00,  6.24314257e-01, …,
        -4.97439652e-01,  1.99725069e+00, -4.94128162e-01],
       [-1.24687609e+00, -5.05883926e-01,  1.47343775e+00, …,
        -4.97439652e-01, -5.00688274e-01,  2.02376646e+00],
       …,
       [-1.49115950e-03, -6.50216137e-01, -1.34988550e+00, …,
        -4.97439652e-01, -5.00688274e-01, -4.94128162e-01],
       [-1.57460896e+00, -1.66054162e+00, -7.99093033e-02, …,
        -4.97439652e-01, -5.00688274e-01, -4.94128162e-01],
       [-1.05023636e+00, -1.66054162e+00,  6.96516953e-01, …,
        -4.97439652e-01,  1.99725069e+00, -4.94128162e-01]])
```

##Logistic Regression

[466]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score
```

[467]:
```
log = LogisticRegression()
log.fit(X_train,y_train)
y_pred1 = log.predict(X_test)
```

[468]:
```
accurac=accuracy_score(y_test,y_pred1)
precision=precision_score(y_test,y_pred1)
recall=recall_score(y_test,y_pred1)
f1=f1_score(y_test,y_pred1)
```

[469]:
```
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

```
Accuracy: 0.50
Precision: 0.51
Recall: 0.51
F1-score: 0.51
```

#SVC

[471]:
```
from sklearn import svm
svm = svm.SVC()
svm.fit(X_train,y_train)
y_pred2 = svm.predict(X_test)
```

[473]:
```
accuracy=accuracy_score(y_test,y_pred2)
precision=precision_score(y_test,y_pred2)
recall =recall_score(y_test, y_pred2)
f1 =f1_score(y_test, y_pred2)
```

[474]:
```
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

```
Accuracy: 0.50
Precision: 0.51
Recall: 0.49
F1-score: 0.50
```

#KNeighbors Classifier

[475]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn.fit(X_train,y_train)
y_pred3 =knn.predict(X_test)
```

[476]:
```
accuracy=accuracy_score(y_test,y_pred3)
precision=precision_score(y_test,y_pred3)
recall =recall_score(y_test, y_pred3)
f1 =f1_score(y_test, y_pred3)
```

[477]:
```
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

```
Accuracy: 0.50
Precision: 0.50
Recall: 0.50
F1-score: 0.50
```

#Decision Tree Classifier

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(X_train,y_train)
y_pred4 = dt.predict(X_test)
```

[ ]:
```
accuracy=accuracy_score(y_test,y_pred4)
precision=precision_score(y_test,y_pred4)
recall =recall_score(y_test, y_pred4)
f1 =f1_score(y_test, y_pred4)
```

[ ]:
```
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

#Random Forest Classifier

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train,y_train)
y_pred5 = rf.predict(X_test)
```

[ ]:
```
accuracy=accuracy_score(y_test,y_pred5)
precision=precision_score(y_test,y_pred5)
recall =recall_score(y_test, y_pred5)
f1 =f1_score(y_test, y_pred5)
```

[ ]:
```
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

#Gradient Boosting Classifier

```
[ ]: from sklearn.ensemble import GradientBoostingClassifier
gbc = GradientBoostingClassifier()
gbc.fit(X_train,y_train)
y_pred6 = gbc.predict(X_test)
```

```
[ ]: accuracy=accuracy_score(y_test,y_pred6)
precision=precision_score(y_test,y_pred6)
recall =recall_score(y_test, y_pred6)
f1 =f1_score(y_test, y_pred6)
```

```
[ ]: print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

#Neural Network

```
[ ]: from sklearn.neural_network import MLPClassifier
#from sklearn.metrics import accuracy_score, precision_score
nn = MLPClassifier(random_state=42)
nn.fit(X_train, y_train)
y_pred7 = model.predict(X_test)
```

```
[ ]: accuracy = accuracy_score(y_test, y_pred7)
precision = precision_score(y_test, y_pred7)
recall =recall_score(y_test, y_pred7)
f1 =f1_score(y_test, y_pred7)
```

```
[ ]: print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

```
[483]: final_data=pd.DataFrame({'Models':
  ↪['LR','SVC','KNN','DT','RF','GBC','MLPC'],'ACC':
  ↪[accuracy_score(y_test,y_pred1),
                                                                    ␣
  ↪accuracy_score(y_test,y_pred2),
                                                                    ␣
  ↪accuracy_score(y_test,y_pred3),
                                                                    ␣
  ↪accuracy_score(y_test,y_pred4),
                                                                    ␣
  ↪accuracy_score(y_test,y_pred5),
```

```
↪accuracy_score(y_test,y_pred6),
↪accuracy_score(y_test,y_pred7)]})
```

[484]:
```
final_data
```

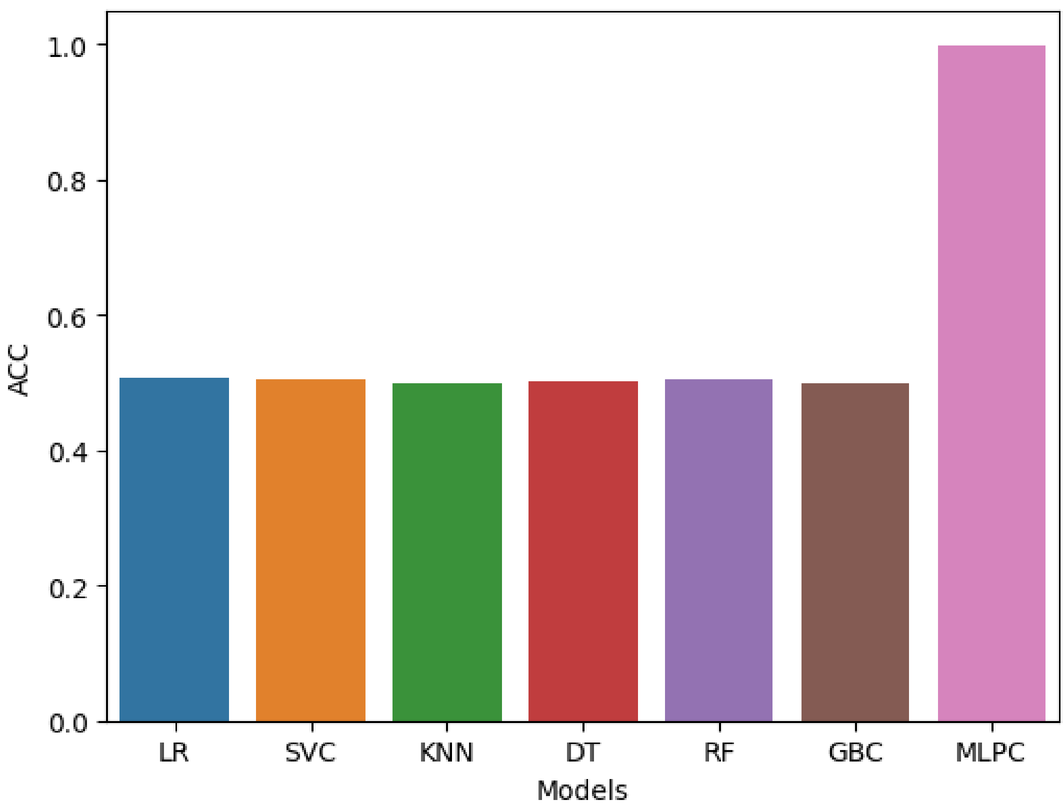
[484]:

	Models	ACC
0	LR	0.507143
1	SVC	0.504654
2	KNN	0.499228
3	DT	0.500274
4	RF	0.503659
5	GBC	0.499278
6	MLPC	0.998855

[485]:
```
import seaborn as sns
```

[486]:
```
sns.barplot(x='Models', y='ACC', data=final_data)
```

[486]: <Axes: xlabel='Models', ylabel='ACC'>



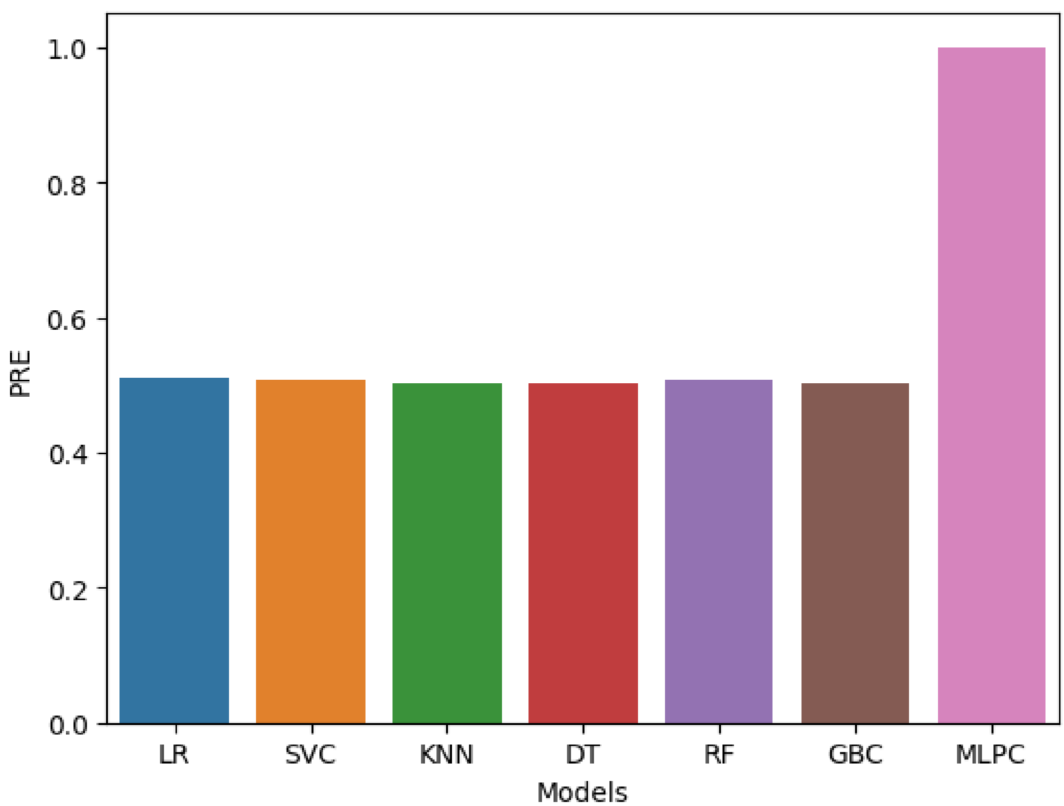
[487]:

```
final_data=pd.DataFrame({'Models':
↪['LR','SVC','KNN','DT','RF','GBC','MLPC'],'PRE':
↪[precision_score(y_test,y_pred1),
                                                                    ␣
↪precision_score(y_test,y_pred2),
                                                                    ␣
↪precision_score(y_test,y_pred3),
                                                                    ␣
↪precision_score(y_test,y_pred4),
                                                                    ␣
↪precision_score(y_test,y_pred5),
                                                                    ␣
↪precision_score(y_test,y_pred6),
                                                                     ␣
↪precision_score(y_test,y_pred7)]})
```

[488]:

```
sns.barplot(x='Models', y='PRE', data=final_data)
```

[488]: <Axes: xlabel='Models', ylabel='PRE'>



#Save The Model

[490]:
```
X_res = sc.fit_transform(X_res)
nn.fit(X_res,y_res)
```

[490]:
```
MLPClassifier(random_state=42)
```

[492]:
```
import joblib
```

[493]:
```
joblib.dump(rf,'churn_predict_model')
```

[493]:
```
['churn_predict_model']
```

[494]:
```
model = joblib.load('churn_predict_model')
```

[495]:
```
data.columns
```

[495]:
```
Index(['Age', 'Subscription_Length_Months', 'Monthly_Bill', 'Total_Usage_GB',
       'Churn', 'Gender_Male', 'Location_Houston', 'Location_Los Angeles',
       'Location_Miami', 'Location_New York', 'Age_Group',
       'Subscription_Length_Category'],
      dtype='object')
```

[496]:
```
model.predict(X_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has
feature names, but RandomForestClassifier was fitted without feature names
  warnings.warn(
```

[496]:
```
array([0, 0, 0, …, 0, 0, 1])
```

#GUI

[ ]:
```
!pip install -q gradio
```

[497]:
```
import gradio as gr
import joblib
import pandas as pd
import numpy as np

model = joblib.load('/content/churn_predict_model')

def predict_churn(age, subscription_months, monthly_bill, total_usage_gb):

    input_data = pd.DataFrame({
        'Age': [age],
        'Gender':[gender],
        'Location':[location],
        'Subscription_Length_Months': [subscription_months],
        'Monthly_Bill': [monthly_bill],
```

```
        'Total_Usage_GB': [total_usage_gb],
    })

    prediction = model.predict(input_data)

    return 'Churned' if prediction[0] == 1 else 'Not Churned'
iface = gr.Interface(
    fn=predict_churn,
    inputs=[
        gr.inputs.Number(label="Age"),
        gr.inputs.Number(label="Gender"),
        gr.inputs.Number(label="Location"),
        gr.inputs.Number(label="Subscription Months"),
        gr.inputs.Number(label="Monthly Bill"),
        gr.inputs.Number(label="Total Usage (GB)"),
    ],
    outputs=gr.outputs.Textbox(label="Churn Prediction"),
    title="Customer Churn Prediction",
)

iface.launch()
```

```
<ipython-input-497-65c4bbb9d77c>:31: GradioDeprecationWarning: Usage of
gradio.inputs is deprecated, and will not be supported in the future, please
import your component from gradio.components
  gr.inputs.Number(label="Age"),
<ipython-input-497-65c4bbb9d77c>:31: GradioDeprecationWarning: `optional`
parameter is deprecated, and it has no effect
  gr.inputs.Number(label="Age"),
<ipython-input-497-65c4bbb9d77c>:32: GradioDeprecationWarning: Usage of
gradio.inputs is deprecated, and will not be supported in the future, please
import your component from gradio.components
  gr.inputs.Number(label="Gender"),
<ipython-input-497-65c4bbb9d77c>:32: GradioDeprecationWarning: `optional`
parameter is deprecated, and it has no effect
  gr.inputs.Number(label="Gender"),
<ipython-input-497-65c4bbb9d77c>:33: GradioDeprecationWarning: Usage of
gradio.inputs is deprecated, and will not be supported in the future, please
import your component from gradio.components
  gr.inputs.Number(label="Location"),
<ipython-input-497-65c4bbb9d77c>:33: GradioDeprecationWarning: `optional`
parameter is deprecated, and it has no effect
  gr.inputs.Number(label="Location"),
<ipython-input-497-65c4bbb9d77c>:34: GradioDeprecationWarning: Usage of
gradio.inputs is deprecated, and will not be supported in the future, please
import your component from gradio.components
  gr.inputs.Number(label="Subscription Months"),
```

```
<ipython-input-497-65c4bbb9d77c>:34: GradioDeprecationWarning: `optional`
parameter is deprecated, and it has no effect
  gr.inputs.Number(label="Subscription Months"),
<ipython-input-497-65c4bbb9d77c>:35: GradioDeprecationWarning: Usage of
gradio.inputs is deprecated, and will not be supported in the future, please
import your component from gradio.components
  gr.inputs.Number(label="Monthly Bill"),
<ipython-input-497-65c4bbb9d77c>:35: GradioDeprecationWarning: `optional`
parameter is deprecated, and it has no effect
  gr.inputs.Number(label="Monthly Bill"),
<ipython-input-497-65c4bbb9d77c>:36: GradioDeprecationWarning: Usage of
gradio.inputs is deprecated, and will not be supported in the future, please
import your component from gradio.components
  gr.inputs.Number(label="Total Usage (GB)"),
<ipython-input-497-65c4bbb9d77c>:36: GradioDeprecationWarning: `optional`
parameter is deprecated, and it has no effect
  gr.inputs.Number(label="Total Usage (GB)"),
<ipython-input-497-65c4bbb9d77c>:38: GradioDeprecationWarning: Usage of
gradio.outputs is deprecated, and will not be supported in the future, please
import your components from gradio.components
  outputs=gr.outputs.Textbox(label="Churn Prediction"),
/usr/local/lib/python3.10/dist-packages/gradio/utils.py:1000: UserWarning:
Expected 4 arguments for function <function predict_churn at 0x7f8092853ac0>,
received 6.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/gradio/utils.py:1008: UserWarning:
Expected maximum 4 arguments for function <function predict_churn at
0x7f8092853ac0>, received 6.
  warnings.warn(
```

```
Colab notebook detected. To show errors in colab notebook, set debug=True in
launch()
Note: opening Chrome Inspector may crash demo inside Colab notebooks.

To create a public link, set `share=True` in `launch()`.
```

```
<IPython.core.display.Javascript object>
```

[497]: