customer-churn-prediction

November 20, 2023

#IMPORTING THE DEPENDENCIES

[ ]:
```
# IMPORTING THE REQUIRED LIBRARIES
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
```

#LOADING THE DATASET

[ ]:
```
# READING THE EXCEL FILE AND CREATING THE DATAFRAME USING PANDAS FUNCTION.
customer_df = pd.read_excel('/content/customer_churn_large_dataset.xlsx')
customer_df.head()
```

[ ]:

	CustomerID	Name	Age	Gender	Location	Subscription_Length_Months	Monthly_Bill	Total_Usage_GB	Churn
0	1	Customer_1	63	Male	Los Angeles	17	73.36	236	0
1	2	Customer_2	62	Female	New York	1	48.76	172	0
2	3	Customer_3	24	Female	Los Angeles	5	85.47	460	0
3	4	Customer_4	36	Female	Miami	3	97.94	297	1
4	5	Customer_5	46	Female	Miami	19	58.14	266	0

#DATA EXPLORATION

EXPLORING THE DATASET'S FEATURES, DATATYPES, ATTRIBUTES PRESENT, UNIQUE VALUES, NULL VALUES, INFORMATION, DIMENTION ETC

[ ]:
```
# CHECKING THE INFORMATION OF THE DATASET SUCH AS DATA TYPES, AND COLUMN NAMES
customer_df.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
```

[ ]:
```
# CHECKING THE SHAPE/DIMENTION OF THE DATASET
customer_df.shape
```

[ ]:
```
(100000, 9)
```

[ ]:
```
# CHECKING FOR NULL VALUES IN THE DATASET
customer_df.isnull().sum()
```

[ ]:
```
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
```

[ ]:
```
# CHECKING THE STATISTICAL MEASURES OF THE DATASET
customer_df.describe()
```

[ ]:
```
          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
```

#DATA VISUALIZATION

LINE PLOT

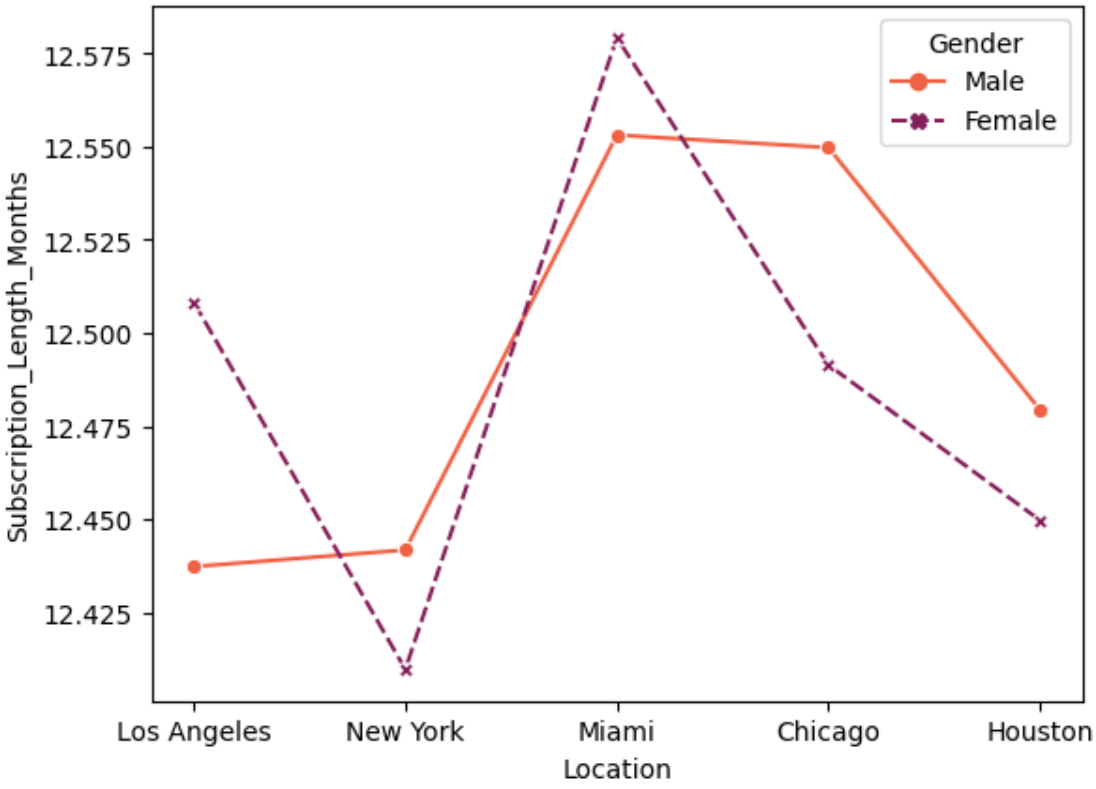
[ ]:
```
# CREAING THE LINE CHART TO UNDERSTAND THE "SUBSCRIPTION LENGTH" FOR MALE AND␣
↪FEMALE FOR DIFFERENT LOCATION.
sns.lineplot(data=customer_df, x='Location', y='Subscription_Length_Months',␣
↪ci=None,
             hue='Gender', style='Gender', palette='rocket_r', markers=True)
```

```
<ipython-input-36-2780a2e58cc6>:2: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.lineplot(data=customer_df, x='Location', y='Subscription_Length_Months',
ci=None,
```

[ ]:
```
<Axes: xlabel='Location', ylabel='Subscription_Length_Months'>
```

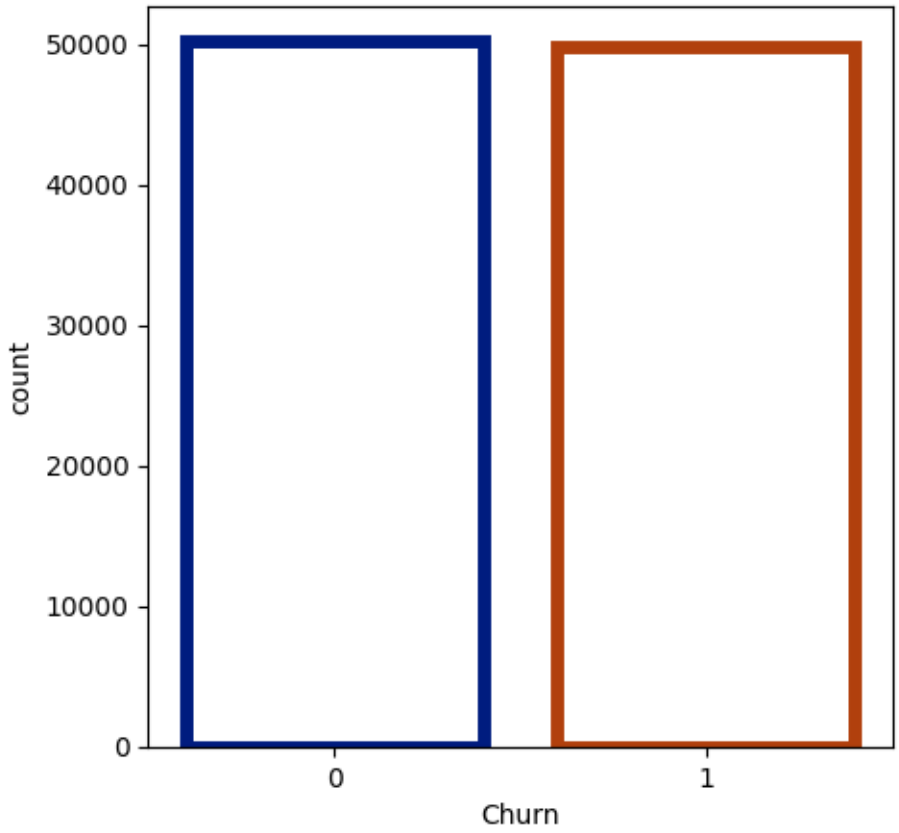


COUNT-PLOT

[ ]:
```
# COUNT PLOT HAS BEEN CREATED TO UNDERSTAND THE CUSTOMER CHURNED.
plt.figure(figsize=(5,5))

sns.countplot(data=customer_df, x='Churn', facecolor = (0,0,0,0), linewidth=5,␣
↪edgecolor=sns.color_palette('dark',3))
```

[ ]:
```
<Axes: xlabel='Churn', ylabel='count'>
```



#DATA PRE-PROCESSING

NOW WE WILL PRE-PROCESS THE DATASET BEFORE FEEDING IT TO OUR MACHINE LEARNING ALGORITHM

[ ]:
```
# HERE, WE ARE DROPPING THE COLUMNS SUCH AS "CUSTOMERID" AND "NAME" BECAUSE␣
↪THESE COLUMNS DOES NOT HOLD RELEVENCE.
customer_df.drop(['CustomerID', 'Name'], axis='columns', inplace=True )
customer_df.head()
```

[ ]:

	Age	Gender	Location	Subscription_Length_Months	Monthly_Bill	Total_Usage_GB	Churn
0	63	Male	Los Angeles	17	73.36	236	0
1	62	Female	New York	1	48.76	172	0
2	24	Female	Los Angeles	5	85.47	460	0
3	36	Female	Miami	3	97.94		
4	46	Female	Miami	19	58.14		

```
3              297       1
4              266       0
```

[ ]:
```
# FOR "CHURN" COLUMN WE ARE CHECKING THE COUNT OF LABELS '0' and '1'.
customer_df['Churn'].value_counts()
```

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

0——> Not Churned

1——> Churned

[ ]:
```
# HERE, WE ARE REPLACING THE GENDER COLUMN WITH NUMERICAL VARIABLES.
customer_df['Gender'].replace({'Female':1, 'Male':0}, inplace=True)
customer_df['Gender'].unique()
```

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

[ ]:
```
# NOW CHECKING FOR THE UNIQUE VALUES OF 'LOCATION' COLUMN
customer_df['Location'].unique()
```

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

[ ]:
```
# CONVERTING THE CATEGORICAL VARIABLES TO NUMERICAL VARIABLES FOR 'LOCATION'␣
 ↪COLUMN
customer_df.replace({'Location':{'Los Angeles':0, 'New York':1, 'Miami':2,␣
 ↪'Chicago':3, 'Houston':4}}, inplace=True)
```

SEPARATING THE TARGET VARIABLE FROM THE DATASET

[ ]:
```
# HERE, WE ARE DROPPING OUR TARGET VARIABLE FROM OUT DATASET AND STORING IT IN␣
 ↪DIFFERENT VARIABLE
X = customer_df.drop('Churn', axis='columns')
Y = customer_df['Churn']
```

#TRAIN TEST SPLIT

[ ]:
```
# NOW, SPLITTING THE DATASET INTO TRAINING DATA AND TESTING DATA
# TAKING 20% AS TEST DATA AND 80% AS TRAINING DATA

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=5)
```

[ ]:
```
# CHECKING THE DIMENTION OF OUR TRAIN DATASET
X_train.shape
```

[ ]: (80000, 6)

[ ]:
```
# CHECKING THE DIMENTION OF OUR TEST DATASET
Y_train.shape
```

[ ]: (80000,)

#DATA STANDARDIZATION

SCALING THE NUMERICAL VALUES OF OUR DATASET INTO A COMMON RANGE OF '0' TO '1'

[ ]:
```
# IMPORTING THE STANDARD SCALER FUNCTION
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

# FITTING OUR DATASET TO THE FUNCTION
standardized_data = scaler.fit_transform(X)

#STORING THE SCALED DATA TO 'X' VARIABLE AND 'CHURN' TO Y VARIABLE
X = standardized_data
Y = customer_df["Churn"]

# PRINTING THE VALUES OF 'X' AND 'Y'
print(X)
print(Y)
```

```
[[ 1.24167039 -1.00432937 -1.41489431  0.65111499  0.41060598 -0.29428898]
 [ 1.17622625  0.99568929 -0.70877818 -1.65887854 -0.80537409 -0.78485174]
 [-1.31065114  0.99568929 -1.41489431 -1.08138015  1.0092043   1.42268068]
 …
 [ 1.30711454 -1.00432937  0.70345407  0.65111499  1.5351404  -0.17931334]
 [ 0.45634069  0.99568929 -0.70877818  1.08423877 -0.78115335  1.22338955]
 [-1.11431871  0.99568929 -1.41489431  0.93986418  0.56927655 -0.7771867 ]]
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
```

#MODEL BUILDING

#1. LOGISTIC REGRESSION MODEL

[ ]:
```
# Using Logistic Regression model
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()

# FITTING OUR TRAINING DATA TO THE MODEL
model.fit(X_train, Y_train)
```

[ ]:
```
LogisticRegression()
```

#MODEL EVALUATION

ACCURACY OF TRAINING DATA

[ ]:
```
# PREDICTING VALUES FOR TRAINING DATASET
X_train_prediction = model.predict(X_train)

# CHECKING THE ACCURACY OF THE MODEL ON TRAINING DATA
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)

# DISPLAYING THE ACCURACY
print('Accuracy on training data: ', training_data_accuracy)
```

```
Accuracy on training data:  0.5042375
```

ACCURACY OF TESTING DATA

[ ]:
```
# PREDICTING VALUES FOR TESTING DATASET
X_test_prediction = model.predict(X_test)

# CHECKING THE ACCURACY OF THE MODEL ON TESTING DATA
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)

# DISPLAYING THE ACCURACY
print('Accuracy on test data: ', test_data_accuracy)
```

```
Accuracy on test data:  0.49475
```

ACCURACY OF LOGISTIC REGRESSION MODEL IS :-

ON TRAINING DATA——> 50%

ON TESTING DATA——-> 49%

#2. ARTIFICIAL NEURAL NETWORK

[ ]:
```
# USING NEURAL NETWORK MODEL
from sklearn.neural_network import MLPClassifier
model_3 = MLPClassifier()

# FITTING OUR TRAINING DATA TO THE MODEL
```

```
model_3.fit(X_train, Y_train)
```

[ ]:
```
MLPClassifier()
```

#MODEL EVALUATION

ACCURACY OF TRAINING DATA

[ ]:
```
# PREDICTING VALUES FOR TRAINING DATASET
X_train_prediction = model.predict(X_train)

# CHECKING THE ACCURACY OF THE MODEL ON TRAINING DATA
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)

# DISPLAYING THE ACCURACY
print('Accuracy on training data: ', training_data_accuracy)
```

```
Accuracy on training data:  0.5042375
```

ACCURACY ON TESTING DATA

[ ]:
```
# PREDICTING VALUES FOR TESTING DATASET
X_test_prediction = model.predict(X_test)

# CHECKING THE ACCURACY OF THE MODEL ON TESTING DATA
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)

# DISPLAYING THE ACCURACY
print('Accuracy on test data: ', test_data_accuracy)
```

```
Accuracy on test data:  0.49475
```

ACCURACY OF ARTIFICIAL NEURAL NETWORK IS:-

ON TRAINING DATA——-> 50%

ON TESTING DATA ——-> 49%

#HYPERPARAMETER TUNING

[ ]:
```
# USING "GridSearchCV" FOR TUNING THE HYPERPARAMETERS
# Grid Search Exhaustively search through all possible combinations of␣
 ↪hyperparameters.


# IMPORTING THE GRID SEARCH FROM SKLEARN
from sklearn.model_selection import GridSearchCV

# Defining the parameter grid
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
```

```
    'penalty': ['l2']  # Use only 'l2' penalty with 'lbfgs' solver
}

# Create a Logistic Regression classifier
logistic_regression = LogisticRegression(solver='lbfgs')

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=logistic_regression,␣
 ↪param_grid=param_grid, scoring='accuracy', cv=5)

# Perform grid search on the training data
grid_search.fit(X_train, Y_train)
```

[ ]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(),
             param_grid={'C': [0.01, 0.1, 1, 10, 100], 'penalty': ['l2']},
             scoring='accuracy')
```

CHECKING THE BEST PARAMETERS AND ACCURACY

[ ]:
```
# CHECKING FOR BEST MODEL AND BEST PARAMETERS
best_model = grid_search.best_estimator_
best_params = grid_search.best_params_

# USE THE BEST MODEL TO PREDICT LABELS ON TEST DATA
Y_pred = best_model.predict(X_test)

# CALCULATE THE ACCURACY OF THE MODEL
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(Y_test, Y_pred)

# DISPLAYING THE BEST PARAMETERS AND ACCURACY ACHIEVED
print("Best Parameters:", best_params)
print("Test Accuracy:", accuracy)
```

```
Best Parameters: {'C': 0.1, 'penalty': 'l2'}
Test Accuracy: 0.4948
```

#MAKING A PREDICTIVE SYSTEM

[ ]:
```
# SINCE, WE HAVE ENCODED THE GENDER COLUMN AS '1' FOR FEMALE AND '0' FOR MALE.
# SO, WILL TAKE THE INPUT IN THAT FORMAT ONLY.
# WE HAVE ALSO ENCODED THE 'LOCATION' COLUMN AS:-
# 'Los Angeles'---> 0, 'New York'---> 1, 'Miami'---> 2, 'Chicago'---> 3,␣
 ↪'Houston'---> 4

# TAKING THE INPUT DATA
input_data = (62, 1, 1, 19, 61.65, 351)
```

```
# Changing the input data to numpy array
input_data_as_numpy_array = np.asarray(input_data)

# Reshape the array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1, -1)

prediction = model.predict(input_data_reshaped)
print(prediction)

if (prediction[0]==0):
    print("The person is not likely to churn")
else:
    print("The person is likely to churn")
```

```
[0]
The person is not likely to churn

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but LogisticRegression was fitted with feature
names
  warnings.warn(
```

Our Model has predicted correctly (above) for this input data , let's check for one more instance.

[ ]:
```
import numpy as np

# Define the input data (example values)
input_data = [27, 1, 0, 19, 76.57, 173]  # Assuming 1 for Female, 1 for New York

# Convert the input data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# Reshape the array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1, -1)

# Make predictions using the best model obtained from hyperparameter tuning
prediction = best_model.predict(input_data_reshaped)

if prediction[0] == 0:
    print("The person is not likely to churn")
else:
    print("The person is likely to churn")
```

```
The person is likely to churn

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but LogisticRegression was fitted with feature
names
```

```
  warnings.warn(
```

For this instance also, our model has predicted correctly.

#SAVING THE TRAINED MODEL

[ ]:
```
# Importing the Pickle library to save the model
import pickle
```

[ ]:
```
# Saving the model with name "trained_model"
filename = 'trained_model'

# Saving the model, and writing it in binary.
pickle.dump(model, open(filename, 'wb'))
```

[ ]:
```
# Loading the Saved Model
loaded_model = pickle.load(open('trained_model', 'rb'))
```

[ ]:
```
import numpy as np

# Define the input data (example values)
input_data = [27, 1, 0, 19, 76.57, 173]  # Assuming 1 for Female, 1 for New York

# Convert the input data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# Reshape the array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1, -1)

# Make predictions using the best model obtained from hyperparameter tuning
prediction = best_model.predict(input_data_reshaped)

if prediction[0] == 0:
    print("The person is not likely to churn")
else:
    print("The person is likely to churn")
```

```
The person is likely to churn

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but LogisticRegression was fitted with feature
names
  warnings.warn(
```