assignment

August 24, 2023

1 Machine Learning Intern Assessment Assignment

1.1 Customer Churn Prediction

1.1.1 Import Libraries

[1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error


import warnings
warnings.filterwarnings('ignore')
```

1.1.2 Meet and Greet Data

In this phase we will import csv and analyze it

[3]:
```
customer = pd.read_excel("D:\Data Analysis\Machine Learning Intern␣
↪Task\customer_churn_large_dataset.xlsx")
```

[4]:
```
cust_copy = customer.copy()
```

[5]:
```
cust_copy.head()
```

[5]:
```
   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
```

[6]:
```python
print("The shape of customer churn dataset: ", cust_copy.shape)
cust_copy.info()
```

```
The shape of customer churn dataset:  (100000, 9)
<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
```

[43]:
```python
print("Sum of all the null values in customer churn dataset: \n", cust_copy.
 ↪isnull().sum())
```

```
Sum of all the null values in customer churn dataset:
 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
```

[8]:
```python
cust_copy.dtypes
```

[8]:
```
CustomerID                      int64
Name                           object
Age                             int64
Gender                         object
Location                       object
Subscription_Length_Months      int64
Monthly_Bill                  float64
Total_Usage_GB                  int64
Churn                           int64
dtype: object
```

1.1.3 Statistical Paramteres

[9]:
```python
cust_copy.describe()
```

[9]:
```
          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
```

1.1.4 Correlation of Data

[10]:
```python
cust_copy.corr()
```

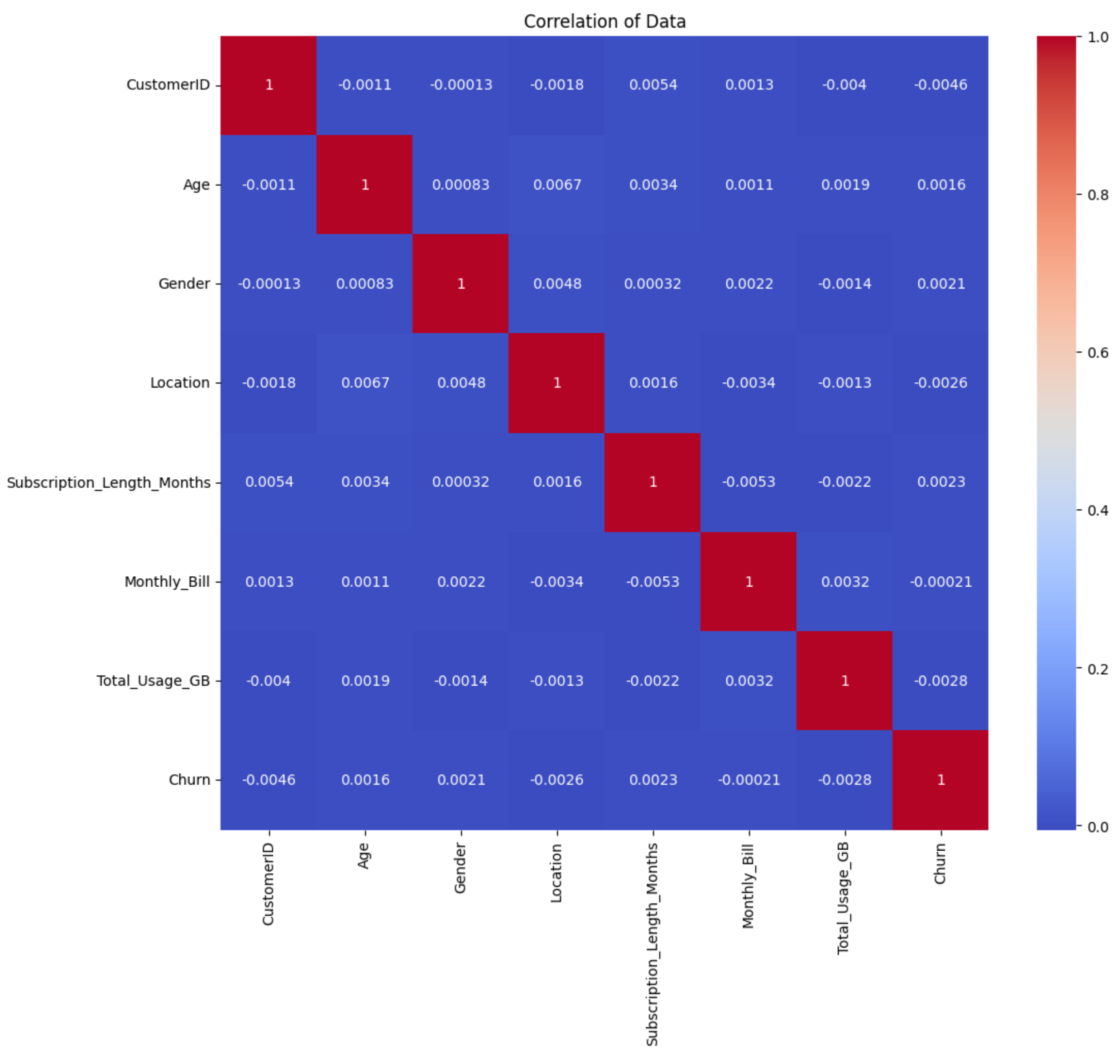
[10]:
```
                            CustomerID       Age  Subscription_Length_Months  \
CustomerID                    1.000000 -0.001085                    0.005444
Age                          -0.001085  1.000000                    0.003382
Subscription_Length_Months    0.005444  0.003382                    1.000000
Monthly_Bill                  0.001265  0.001110                   -0.005294
```

```
Total_Usage_GB              -0.004025  0.001927                          -0.002203
Churn                       -0.004586  0.001559                           0.002328

                           Monthly_Bill  Total_Usage_GB     Churn
CustomerID                     0.001265       -0.004025 -0.004586
Age                            0.001110        0.001927  0.001559
Subscription_Length_Months    -0.005294       -0.002203  0.002328
Monthly_Bill                   1.000000        0.003187 -0.000211
Total_Usage_GB                 0.003187        1.000000 -0.002842
Churn                         -0.000211       -0.002842  1.000000
```

[45]:

```python
plt.figure(figsize=(12,10))
sns.heatmap(cust_copy.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation of Data")
plt.show()
```

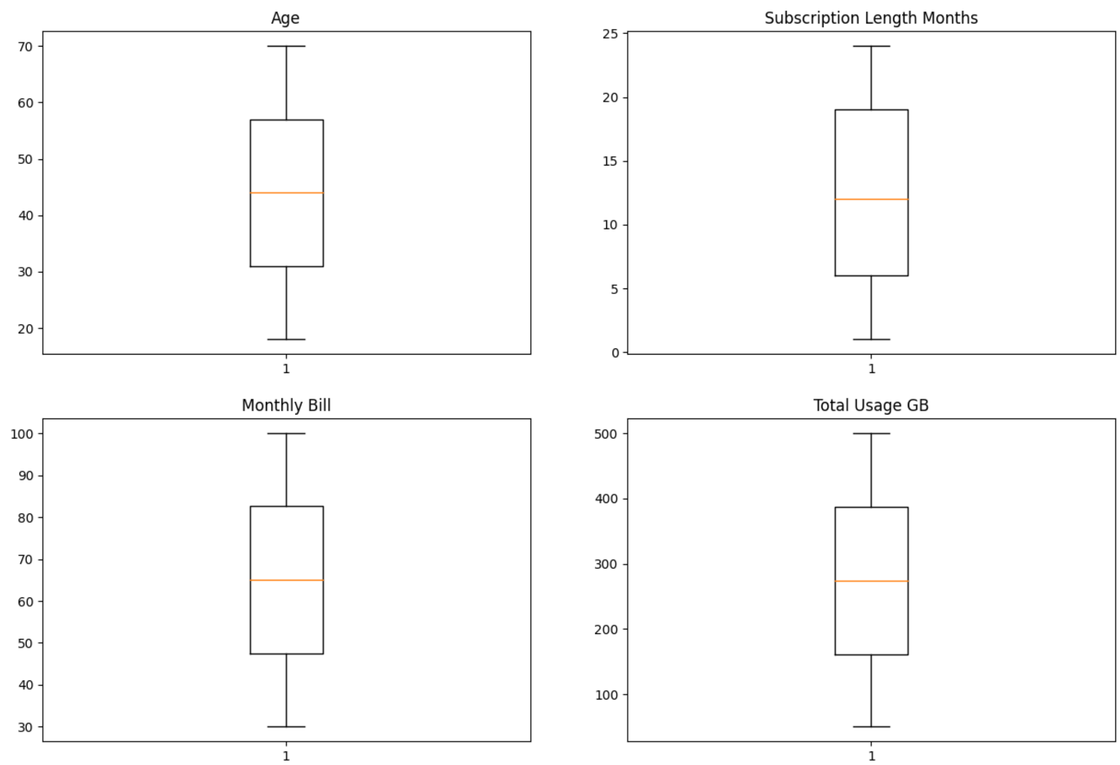


- In this correlation we can see that mostly are not much correlated with each other

1.1.5 Feature Engineering

Handling Outliers

[12]:
```
fig, ax = plt.subplots(2, 2, figsize=(15,10))
ax[0, 0].boxplot(cust_copy['Age'])
ax[0, 0].set_title('Age')
ax[0, 1].boxplot(cust_copy['Subscription_Length_Months'])
ax[0, 1].set_title('Subscription Length Months')
ax[1, 0].boxplot(cust_copy['Monthly_Bill'])
ax[1, 0].set_title('Monthly Bill')
ax[1, 1].boxplot(cust_copy['Total_Usage_GB'])
ax[1, 1].set_title('Total Usage GB')
plt.show()
```



- We can see that there are not a single outliers in our dataset
- So we don't have to remove outliers, procced to enocoding phase

Label Encoding

- So we Encode the Gender column with Label encoder

```
[13]: le = LabelEncoder()
      cust_copy['Gender'] = le.fit_transform(cust_copy['Gender'])
```

```
[14]: # cust_copy['Gender'] = cust_copy['Gender'].map({'Male':0, 'Female':1})
```

Encode through Mapping

- In this phase we encode location column through mapping
- For this we find out unique values of it
- Mapping enocding is efficient method for encoding

```
[15]: cust_copy.Location.unique()
```

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

```
[16]: cust_copy['Location'] = cust_copy['Location'].map({'Los Angeles':0, 'New York':
       ↪1, 'Miami':2, 'Chicago':3, 'Houston':4})
```

```
[17]: cust_copy.head()
```

```
[17]:    CustomerID        Name  Age  Gender  Location  Subscription_Length_Months  \
      0           1  Customer_1   63       1         0                          17
      1           2  Customer_2   62       0         1                           1
      2           3  Customer_3   24       0         0                           5
      3           4  Customer_4   36       0         2                           3
      4           5  Customer_5   46       0         2                          19

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

- So we encode all the necessary columns, now move forward

Feature Selection

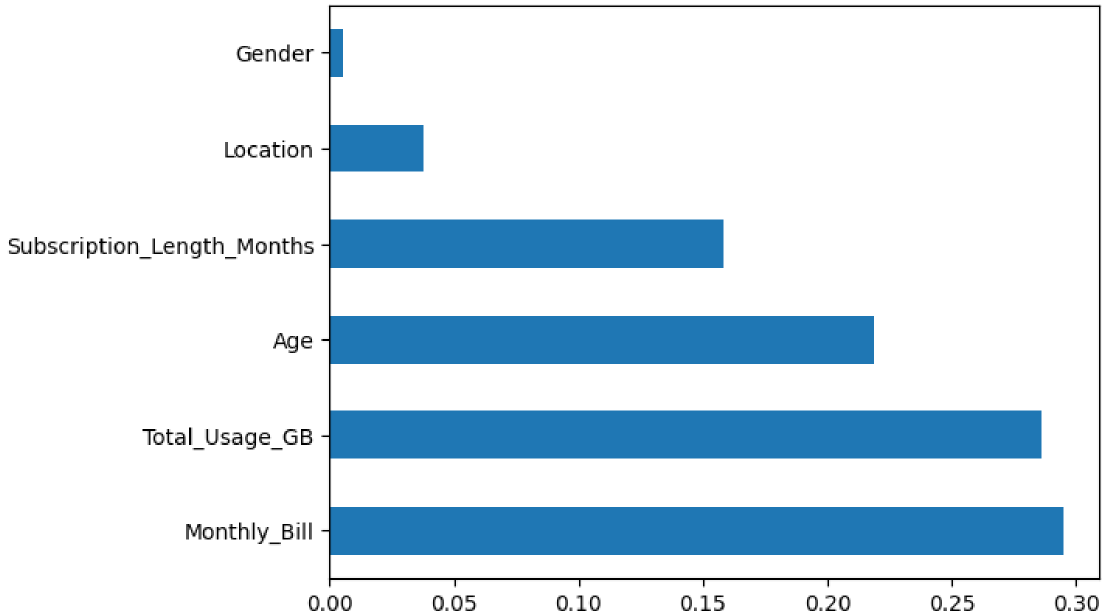
- First, we'll find out which feature are most important for our model to work well. Then, we'll remove any unnecessary feature to make our model perform even better.

```
[18]: x = cust_copy.drop(['Name', 'CustomerID', 'Churn'], axis=1)
      y = cust_copy['Churn']
```

```
[19]: et = ExtraTreesClassifier()
      et.fit(x,y)
```

```
[19]: ExtraTreesClassifier()
```

[20]:
```
feature_imp = pd.Series(et.feature_importances_, index=x.columns)
feature_imp.nlargest(6).plot(kind='barh')
plt.show()
```



- From the bar plot we can see the importances of features based on it's impact towards output.
- Let's take up the top 6 features, and from that we select 4

1.1.6 Train Test Split

- Let's drop the required and split the data into train and test

[21]:
```
x = cust_copy.drop(['Name', 'CustomerID', 'Gender', 'Location', 'Churn'],␣
↪axis=1)
y = cust_copy['Churn']
```

[22]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=.8,␣
↪random_state=124587)
```

[23]:
```
len(x_train)
```

[23]: 80000

[24]:
```
len(x_test)
```

[24]: 20000

1.1.7 Model Selection

- Let's do the process and select the best model

[25]:
```
lr_cv = LogisticRegression(random_state=0)
dt_cv = DecisionTreeClassifier()
rf_cv = RandomForestClassifier()
kn_cv = KNeighborsClassifier()
bn_cv = BernoulliNB()

cv_dict = {0: 'Logistic Regression', 1: 'Decision Tree Classifier', 2: 'Random␣
↪Forest Classifier', 3:'KNeighbour Classifier', 4:'Bernoulib'}

cv_model = [lr_cv, dt_cv, rf_cv, kn_cv, bn_cv]

for i,model in enumerate(cv_model):

    score = cross_val_score(model, x, y, cv=10, scoring='accuracy').mean()

    print("{} Test Accuracy: {}".format(cv_dict[i], score))
```

```
Logistic Regression Test Accuracy: 0.50011
Decision Tree Classifier Test Accuracy: 0.5027699999999999
Random Forest Classifier Test Accuracy: 0.50038
KNeighbour Classifier Test Accuracy: 0.50205
Bernoulib Test Accuracy: 0.50221
```

Logistic Regression with Hypyerparameter tuning

- Let's fit the model in Logistic Regression to figure out Accuracy of our mode

[29]:
```
from sklearn.model_selection import GridSearchCV
param_grid = {'C': np.logspace(-4, 4, 50), 'penalty':['l1','l2']}
clf = GridSearchCV(LogisticRegression(random_state=0),␣
↪param_grid,cv=5,verbose=0,n_jobs=-1)
best_model = clf.fit(x_train,y_train)
print(best_model.best_estimator_)
print("The mean accuracy of the model is:",best_model.score(x_test,y_test))
```

```
LogisticRegression(C=0.0020235896477251557, random_state=0)
The mean accuracy of the model is: 0.50275
```

- The accuracy of this model is not much, let's try more

[32]:
```
lr = LogisticRegression(C=0.0020235896477251557, random_state=0)
lr.fit(x_train,y_train)
lr_predict = lr.predict(x_test)
lr.score(x_train,y_train)
```

[32]: 0.5042125

[38]:
```
print("Logistic Regrssion Mean Absolute Error: ",␣
↪mean_absolute_error(y_test,lr_predict))
print("Logistic Regrssion Mean Square Error: ",␣
↪mean_squared_error(y_test,lr_predict))
print("Logistic Regrssion Test Score: ", lr.score(x_test,y_test))
```

```
Logistic Regrssion Mean Absolute Error:  0.49725
Logistic Regrssion Mean Square Error:  0.49725
Logistic Regrssion Test Score:  0.50275
```

Decision Tree Classifier

[31]:
```
dt = DecisionTreeClassifier()
dt.fit(x_train,y_train)
dt_predict = dt.predict(x_test)
dt.score(x_train,y_train)
```

[31]: 0.9999875

[37]:
```
print("Decision Tree Classifier Mean Absolute Error: ",␣
↪mean_absolute_error(y_test,dt_predict))
print("Decision Tree Classifier Mean Square Error: ",␣
↪mean_squared_error(y_test,dt_predict))
print("Decision Tree Classifier Test Score: ", dt.score(x_test,y_test))
```

```
Decision Tree Classifier Mean Absolute Error:  0.4896
Decision Tree Classifier Mean Square Error:  0.4896
Decision Tree Classifier Test Score:  0.5104
```

Random Forest Classifier

[33]:
```
rf = RandomForestClassifier()
rf.fit(x_train,y_train)
rf_predict = rf.predict(x_test)
rf.score(x_train,y_train)
```

[33]: 0.9999875

[39]:
```
print("Random Forest Classifier Mean Absolute Error: ",␣
↪mean_absolute_error(y_test,rf_predict))
print("Random Forest Classifier Mean Square Error: ",␣
↪mean_squared_error(y_test,rf_predict))
print("Random Forest Classifier Test Score: ", rf.score(x_test,y_test))
```

```
Random Forest Classifier Mean Absolute Error:  0.50035
Random Forest Classifier Mean Square Error:  0.50035
Random Forest Classifier Test Score:  0.49965
```

KNeighbour Classifier

[34]:
```
kn = KNeighborsClassifier()
kn.fit(x_train,y_train)
kn_predict = kn.predict(x_test)
kn.score(x_train,y_train)
```

[34]: 0.6842375

[40]:
```
print("KNeighbour Classifier Mean Absolute Error: ",␣
 ↪mean_absolute_error(y_test,kn_predict))
print("KNeighbour Classifier Mean Square Error: ",␣
 ↪mean_squared_error(y_test,kn_predict))
print("KNeighbour Classifier Test Score: ", kn.score(x_test,y_test))
```

```
KNeighbour Classifier Mean Absolute Error:  0.4914
KNeighbour Classifier Mean Square Error:  0.4914
KNeighbour Classifier Test Score:  0.5086
```

BernoulliNB Classifier

[35]:
```
bn = BernoulliNB()
bn.fit(x_train,y_train)
bn_predict = bn.predict(x_test)
bn.score(x_train,y_train)
```

[35]: 0.501175

[41]:
```
print("Bernoulib Classifier Mean Absolute Error: ",␣
 ↪mean_absolute_error(y_test,bn_predict))
print("Bernoulib Classifier Mean Square Error: ",␣
 ↪mean_squared_error(y_test,bn_predict))
print("Bernoulib Classifier Test Score: ", bn.score(x_test,y_test))
```

```
Bernoulib Classifier Mean Absolute Error:  0.49365
Bernoulib Classifier Mean Square Error:  0.49365
Bernoulib Classifier Test Score:  0.50635
```

- From all of this Decision Tree has best accuracy
- So we try that as user input prediction

1.1.8 User Input Prediction

[42]:
```
def predication():
    age = int(input("Enter your age: "))
    months = int(input("Enter the months of subsciption: "))
    bill = float(input("Enter the bill amount: "))
    gb = float(input("Enter the GB used: "))

    col = [age, months, bill, gb]
```

```
    dt_pre = dt.predict([col])

    print("Churn Prediction: ", dt_pre)

predict = predication()

predict
```

```
Enter your age: 63
Enter the months of subsciption: 17
Enter the bill amount: 73.36
Enter the GB used: 236
Churn Prediction:  [0]
```

- It Predicted correct and We built accurate model of Churn Prediction

1.1.9 Conclusion

After analyzing the data for Churn Predication we can say that Age, Length of Monthly Subscription, Bill Amount, GB used are major feature for prediction of Churn.

- For making customer not to churn we have to understand the need of customer
- Provide better service to customers
- Deliver good quality of service
- Continuously Make imporvement in service