In [2]:
```
#importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
C:\Users\CODEINE\AppData\Local\Temp\ipykernel_7848\3140943007.py:2: DeprecationWa
rning:
Pyarrow will become a required dependency of pandas in the next major release of
pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better i
nteroperability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

In [3]:
```
#loading data
df = pd.read_csv("Flyzy Flight Cancellation.csv")
```

In [4]:
```
df.head()
```

Out[4]:

	Flight ID	Airline	Flight_Distance	Origin_Airport	Destination_Airport	Scheduled_Dep
0	7319483	Airline D	475	Airport 3	Airport 2	
1	4791965	Airline E	538	Airport 5	Airport 4	
2	2991718	Airline C	565	Airport 1	Airport 2	
3	4220106	Airline E	658	Airport 5	Airport 3	
4	2263008	Airline E	566	Airport 2	Airport 2	

In [5]:
```
df.tail()
```

Out[5]:

	Flight ID	Airline	Flight_Distance	Origin_Airport	Destination_Airport	Scheduled_I
2995	1265781	Airline D	395	Airport 2	Airport 3	
2996	5440150	Airline E	547	Airport 1	Airport 4	
2997	779080	Airline C	461	Airport 1	Airport 3	
2998	4044431	Airline B	464	Airport 3	Airport 3	
2999	2806578	Airline A	369	Airport 1	Airport 2	

In [6]:
```
df.shape
```

Out[6]:
```
(3000, 14)
```

In [7]:
```
df.columns
```

Out[7]:
```
Index(['Flight ID', 'Airline', 'Flight_Distance', 'Origin_Airport',
       'Destination_Airport', 'Scheduled_Departure_Time', 'Day_of_Week',
       'Month', 'Airplane_Type', 'Weather_Score',
       'Previous_Flight_Delay_Minutes', 'Airline_Rating', 'Passenger_Load',
       'Flight_Cancelled'],
      dtype='object')
```

Observation: Most of the column names consist of multiple words seperated by underscores,but 'Flight ID' does not follow this format, therefore we need to change it to keep consistancy.

In [8]:
```
#Changing column name
df.rename(columns={'Flight ID' : 'Flight_ID'}, inplace =True)
```

In [9]:
```
df.head(2)
```

Out[9]:

	Flight_ID	Airline	Flight_Distance	Origin_Airport	Destination_Airport	Scheduled_Dep
0	7319483	Airline D	475	Airport 3	Airport 2	
1	4791965	Airline E	538	Airport 5	Airport 4	

CHECKING DATA TYPES OF EACH COLUMN

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 14 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Flight_ID                       3000 non-null   int64
 1   Airline                         3000 non-null   object
 2   Flight_Distance                 3000 non-null   int64
 3   Origin_Airport                  3000 non-null   object
 4   Destination_Airport             3000 non-null   object
 5   Scheduled_Departure_Time        3000 non-null   int64
 6   Day_of_Week                     3000 non-null   int64
 7   Month                           3000 non-null   int64
 8   Airplane_Type                   3000 non-null   object
 9   Weather_Score                   3000 non-null   float64
 10  Previous_Flight_Delay_Minutes   3000 non-null   float64
 11  Airline_Rating                  3000 non-null   float64
 12  Passenger_Load                  3000 non-null   float64
 13  Flight_Cancelled                3000 non-null   int64
dtypes: float64(4), int64(6), object(4)
memory usage: 328.3+ KB
```

Observation: This results indicate that all columns have the correct data types according to the data they contain

In [11]:
```
df.describe()
```

Out[11]:

	Flight_ID	Flight_Distance	Scheduled_Departure_Time	Day_of_Week	Mo
count	3.000000e+03	3000.000000	3000.000000	3000.000000	3000.000
mean	4.997429e+06	498.909333	11.435000	3.963000	6.381
std	2.868139e+06	98.892266	6.899298	2.016346	3.473
min	3.681000e+03	138.000000	0.000000	1.000000	1.000
25%	2.520313e+06	431.000000	6.000000	2.000000	3.000
50%	5.073096e+06	497.000000	12.000000	4.000000	6.000
75%	7.462026e+06	566.000000	17.000000	6.000000	9.000
max	9.999011e+06	864.000000	23.000000	7.000000	12.000

In [12]:
```
#Checking for duplicates entries
duplicates = df[df.duplicated()]
```

In [13]:
```
duplicates
```

Out[13]:

Flight_ID	Airline	Flight_Distance	Origin_Airport	Destination_Airport	Scheduled_Depa

No duplicates on the dataset

CHECKING FOR MISSING VALUES

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
Flight_ID                         0
Airline                           0
Flight_Distance                   0
Origin_Airport                    0
Destination_Airport               0
Scheduled_Departure_Time          0
Day_of_Week                       0
Month                             0
Airplane_Type                     0
Weather_Score                     0
Previous_Flight_Delay_Minutes     0
Airline_Rating                    0
Passenger_Load                    0
Flight_Cancelled                  0
dtype: int64
```

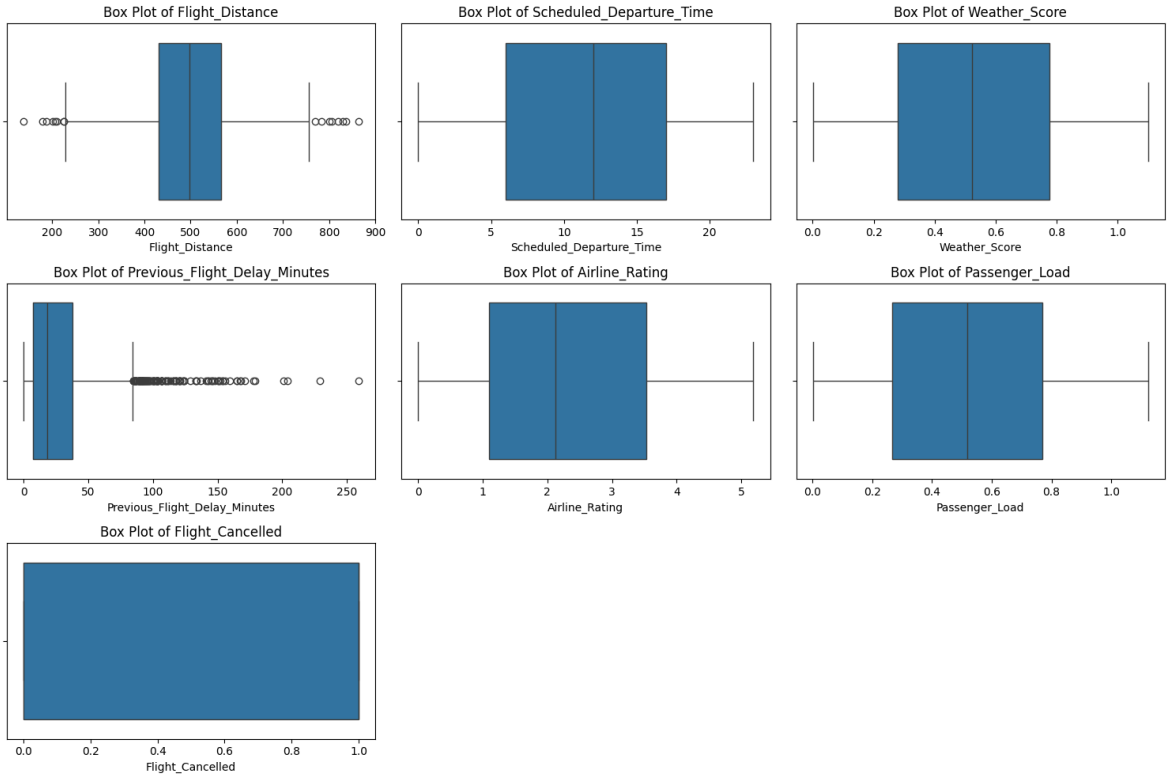
There are no missing values

CHECKING FOR OUTLIERS

In [15]:
```
#Used boxplot to visually check outliers
```

In [16]:
```
columns_to_check =['Flight_Distance',
          'Scheduled_Departure_Time',
          'Weather_Score',
          'Previous_Flight_Delay_Minutes',
          'Airline_Rating', 'Passenger_Load',
          'Flight_Cancelled'
         ]
```

In [17]:
```
plt.figure(figsize =(15,10))
for i, col in enumerate(columns_to_check, 1):
    plt.subplot(3,3, i)
    sns.boxplot(x=df[col])
    plt.title(f'Box Plot of {col}')
plt.tight_layout()
plt.show()
```



This plots shows that the following columns have outliers and have to be handled

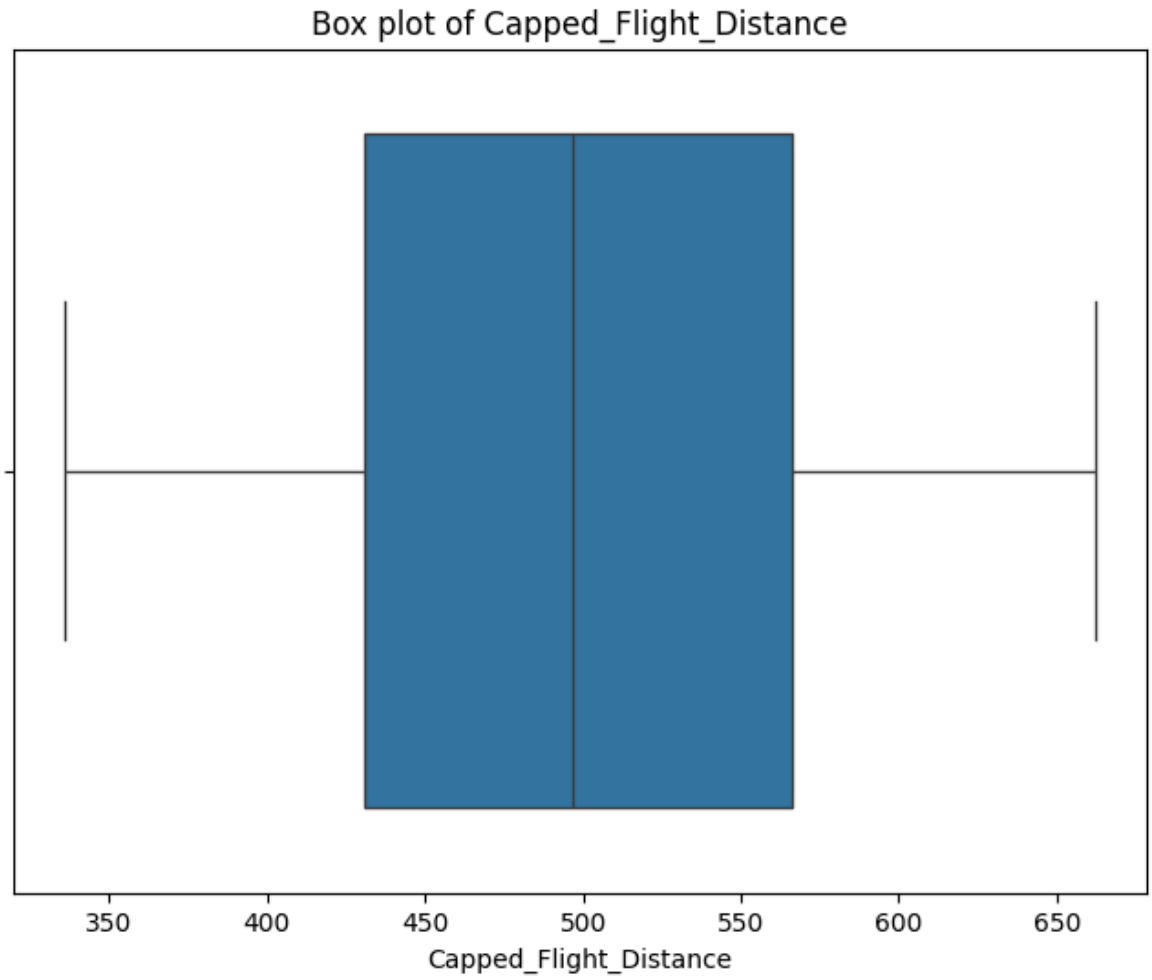
1. Flight_Distance
2. Previous_Flight_Delay_Minutes

1. Handling outliers for Flight_Distance column using Capping method Because it reduces the impact of extreme outliers, which can distort the analysis.

In [18]:
```
#Handling outliers on Flight Distance using Capping approach

#applying threshold
cap_max = df['Flight_Distance'].quantile(0.95)
cap_min =df['Flight_Distance'].quantile(0.05)
#Apply capping
df['Capped_Flight_Distance'] = np.clip(df['Flight_Distance'], cap_min, cap_max)
```

In [19]:
```
#Plotting transformed column
plt.figure(figsize =(8,6))
sns.boxplot(x=df['Capped_Flight_Distance'])
plt.title('Box plot of Capped_Flight_Distance')
plt.show()
```

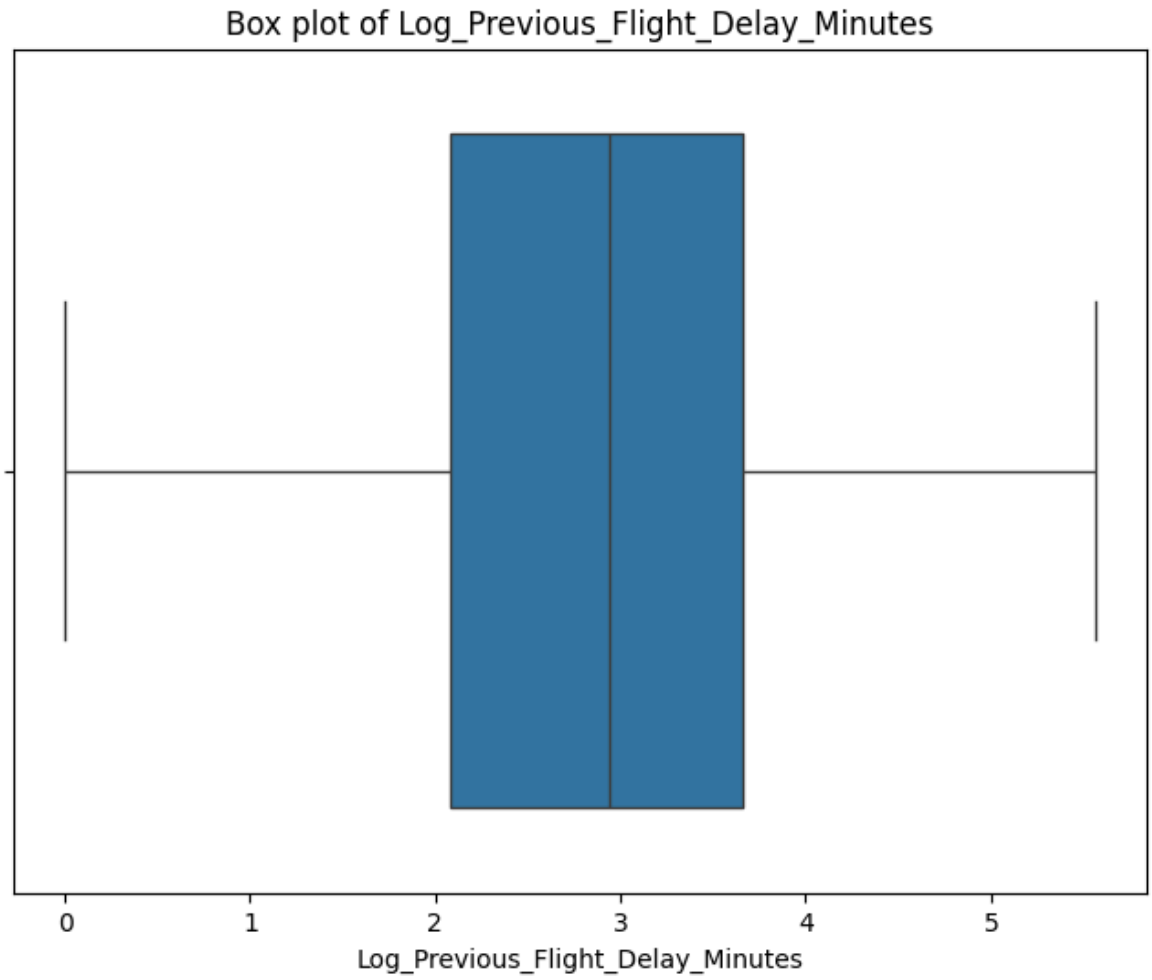


The results shows no more outliers for Flight_Distance

2. Handling Outliers for Previous_Flight_Delay_Minutes Using Log Transformation because data is skewed, compressing the range of delay times, reducing the impact of extreme values.

In [20]:
```
#creating a new column and applying the log
df['Log_Previous_Flight_Delay_Minutes'] = np.log1p(df['Previous_Flight_Delay_Min
```

In [21]:
```
#Plotting transformed column
plt.figure(figsize =(8,6))
sns.boxplot(x=df['Log_Previous_Flight_Delay_Minutes'])
plt.title('Box plot of Log_Previous_Flight_Delay_Minutes')
plt.show()
```



Now the outliers were handled and not showing on the plot

In [22]:
```
df.head(2)
```

Out[22]:

	Flight_ID	Airline	Flight_Distance	Origin_Airport	Destination_Airport	Scheduled_Dep
0	7319483	Airline D	475	Airport 3	Airport 2	
1	4791965	Airline E	538	Airport 5	Airport 4	

Preprocessing and Model Building

Encoding and Feature Scaling

In [80]:
```
#Cyclical data Month and Day of Week
df['Day_of_Week_sin'] =np.sin(2*np.pi *df['Day_of_Week']/7)
df['Day_of_Week_cos'] =np.cos(2*np.pi *df['Day_of_Week']/7)
df['Months_sin'] = np.sin(2*np.pi*df['Month'] /12)
df['Months_cos'] = np.cos(2*np.pi*df['Month'] /12)

df.drop(['Day_of_Week','Month'], axis =1).head()
```

Out[80]:

	Flight_ID	Airline	Flight_Distance	Origin_Airport	Destination_Airport	Scheduled_Dep
0	7319483	Airline D	475	Airport 3	Airport 2	
1	4791965	Airline E	538	Airport 5	Airport 4	
2	2991718	Airline C	565	Airport 1	Airport 2	
3	4220106	Airline E	658	Airport 5	Airport 3	
4	2263008	Airline E	566	Airport 2	Airport 2	

In [82]:
```
#One hot encoding for categorial variables
categorical_columns =['Airline', 'Origin_Airport', 'Destination_Airport','Airpla
df_encoded =pd.get_dummies(df, columns =categorical_columns, drop_first =True)
```

In [88]:
```
df_encoded.head()
```

Out[88]:

	Flight_ID	Flight_Distance	Scheduled_Departure_Time	Day_of_Week	Month	Weather
0	7319483	475	4	6	1	0.
1	4791965	538	12	1	6	0.
2	2991718	565	17	3	9	0.
3	4220106	658	1	1	8	0.
4	2263008	566	19	7	12	0.

5 rows × 31 columns

In [89]:
```
#Numerical columns to scale
numerical_features = [ 'Weather_Score','Scheduled_Departure_Time', 'Airline_Rati
       'Passenger_Load', 'Capped_Flight_Distance',
       'Log_Previous_Flight_Delay_Minutes','Flight_Distance','Previous_Flight_De
#apply standard scaler
from sklearn.preprocessing import StandardScaler
#initialise standard scaler
scaler =StandardScaler()

#apply scaler
df_encoded[numerical_features]= scaler.fit_transform(df_encoded[numerical_featur
```

In [90]:
```
df_encoded.head()
```

Out[90]:

	Flight_ID	Flight_Distance	Scheduled_Departure_Time	Day_of_Week	Month	Weather
0	7319483	-0.241812	-1.077826	6	1	-1.
1	4791965	0.395351	0.081906	1	6	-1.
2	2991718	0.668421	0.806738	3	9	-1.
3	4220106	1.608995	-1.512725	1	8	0.
4	2263008	0.678535	1.096671	7	12	-0.

5 rows × 31 columns

Splitting the data

In [91]:
```
#splitting the data
from sklearn.model_selection import train_test_split

#Dropping original columns (to use only the transformed ones) and also target co
X =df_encoded.drop(['Flight_Cancelled', 'Flight_ID','Flight_Distance','Previous_

#Target variable
y = df_encoded['Flight_Cancelled']

#Splitting the data
X_train, X_test, y_train,y_test = train_test_split(X,y,test_size =0.2, random_st
```

In [92]:
```
X.head()
```

Out[92]:

	Scheduled_Departure_Time	Weather_Score	Airline_Rating	Passenger_Load	Capped_F
0	-1.077826	-1.028402	-0.115698	-0.130868	
1	0.081906	-1.595333	-0.501109	-1.204954	
2	0.806738	-1.479818	1.460975	-0.876504	
3	-1.512725	0.456663	-0.922060	-0.039946	
4	1.096671	-0.064724	1.040989	-1.678862	

5 rows × 25 columns

In [93]:
```
y.head()
```

Out[93]:
```
0    0
1    1
2    0
3    1
4    0
Name: Flight_Cancelled, dtype: int64
```

Model Building

In [117…
```
#Iporting Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
import sklearn.metrics as metrics
from sklearn.metrics import roc_auc_score
```

In [118…
```
#create lr model
lr =LogisticRegression()

#train the model using training data
lr.fit(X_train,y_train)

#predict
y_pred = lr.predict(X_test)
```

Model Evaluation

In [119…
```
#Confusion matrix
metrics.confusion_matrix(y_test,y_pred)
```

Out[119…
```
array([[102,  85],
       [ 55, 358]], dtype=int64)
```

In [120…
```
accuracy =accuracy_score(y_test,y_pred)
print(f"Accuracy: {accuracy: .2f}")
```

```
Accuracy:  0.77
```

In [121…
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.55      0.59       187
           1       0.81      0.87      0.84       413

    accuracy                           0.77       600
   macro avg       0.73      0.71      0.71       600
weighted avg       0.76      0.77      0.76       600
```

In [122…
```
#roc_auc
roc_auc_score(y_test,y_pred)
```

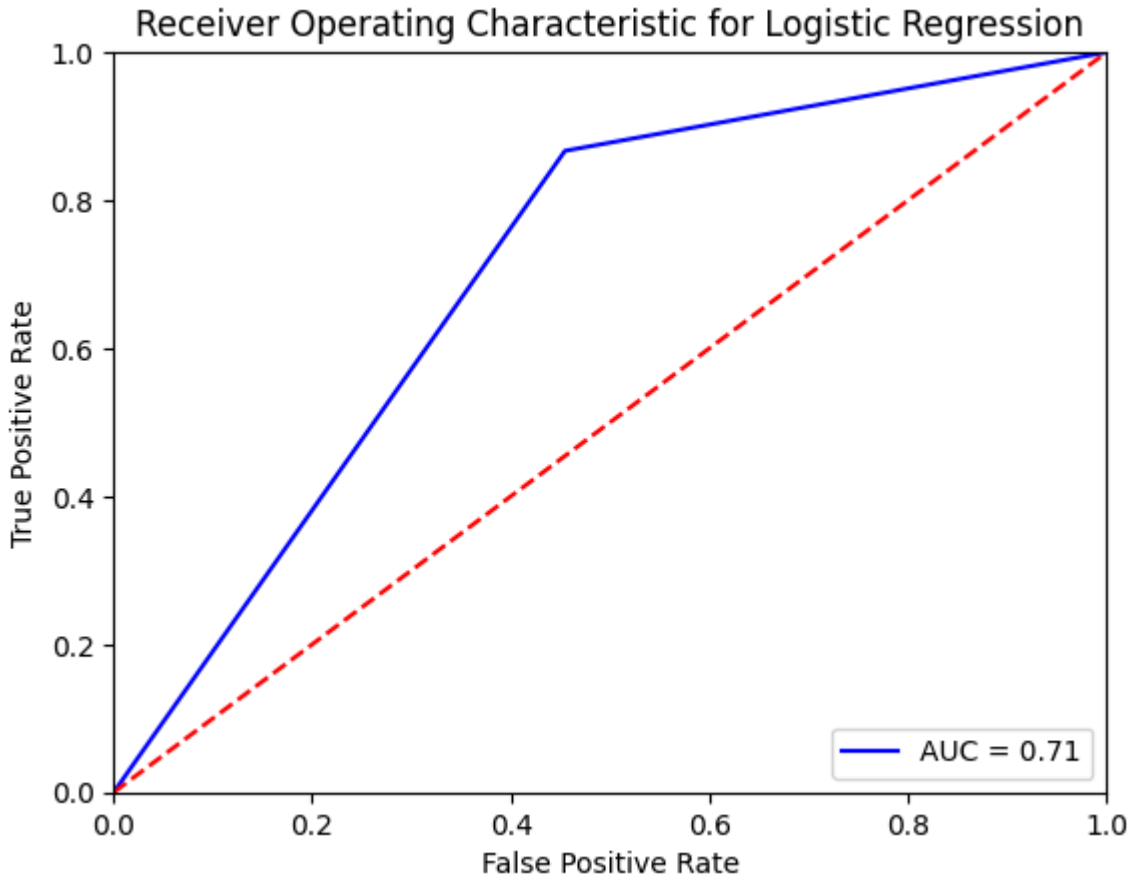
Out[122…
```
0.7061413163108079
```

In [123…
```
fpr, tpr, threshold = metrics.roc_curve(y_test, y_pred)
print(fpr)
print(tpr)
print(threshold)
roc_auc = metrics.auc(fpr, tpr)
print(roc_auc)

# method I: plt
plt.title('Receiver Operating Characteristic for Logistic Regression')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
```

```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
[0.         0.45454545 1.        ]
[0.         0.86682809 1.        ]
[inf  1.  0.]
0.7061413163108079
```



Our model achived an accuracy of 77%, we can try other classification methods to see how they perform

Example : Testing random Forest classifier

In [124…
```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
import sklearn.metrics as metrics
```

In [125…
```
randm=RandomForestClassifier(max_depth=5)
```

In [126…
```
print(cross_val_score(randm, X_train, y_train, cv=5).mean())
```

```
0.9708333333333334
```

In [127…
```
randm.fit(X_train,y_train)
ypred1=randm.predict(X_test)
```

In [128…
```
metrics.confusion_matrix(y_test,ypred1)
```

Out[128…
```
array([[186,   1],
       [  8, 405]], dtype=int64)
```

In [129…
```
print(classification_report(y_test,ypred1))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.98       187
           1       1.00      0.98      0.99       413

    accuracy                           0.98       600
   macro avg       0.98      0.99      0.98       600
weighted avg       0.99      0.98      0.99       600
```

This model already shows high accuracy than the logistic regression we used.

We will further explore other models.

In [ ]: