```
# Importing all the Required Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns',None)
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
# Lets see what is in the Data
df=pd.read_csv(r"C:\Users\neeth\OneDrive\文档\5th sem\AIML\PROJECT\
Clean_Dataset.csv")
df.head()
```

```
   Unnamed: 0   airline   flight source_city departure_time stops  \
0           0  SpiceJet  SG-8709       Delhi        Evening  zero
1           1  SpiceJet  SG-8157       Delhi  Early_Morning  zero
2           2   AirAsia   I5-764       Delhi  Early_Morning  zero
3           3   Vistara   UK-995       Delhi        Morning  zero
4           4   Vistara   UK-963       Delhi        Morning  zero

    arrival_time destination_city    class  duration  days_left  price

0          Night           Mumbai  Economy      2.17          1   5953

1        Morning           Mumbai  Economy      2.33          1   5953

2  Early_Morning           Mumbai  Economy      2.17          1   5956

3      Afternoon           Mumbai  Economy      2.25          1   5955

4        Morning           Mumbai  Economy      2.33          1   5955
```

```
# Droping the useless column 'Unnamed: 0'
df=df.drop('Unnamed: 0',axis=1)
```

```
# A Quick Information abou the Data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300153 entries, 0 to 300152
Data columns (total 11 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   airline           300153 non-null  object
 1   flight            300153 non-null  object
```

```
 2   source_city       300153 non-null  object 
 3   departure_time    300153 non-null  object 
 4   stops             300153 non-null  object 
 5   arrival_time      300153 non-null  object 
 6   destination_city  300153 non-null  object 
 7   class             300153 non-null  object 
 8   duration          300153 non-null  float64
 9   days_left         300153 non-null  int64  
 10  price             300153 non-null  int64  
dtypes: float64(1), int64(2), object(8)
memory usage: 25.2+ MB
```

```
# Stastical Description of Data
df.describe()
```

```
            duration      days_left          price
count  300153.000000  300153.000000  300153.000000
mean       12.221021      26.004751   20889.660523
std         7.191997      13.561004   22697.767366
min         0.830000       1.000000    1105.000000
25%         6.830000      15.000000    4783.000000
50%        11.250000      26.000000    7425.000000
75%        16.170000      38.000000   42521.000000
max        49.830000      49.000000  123071.000000
```

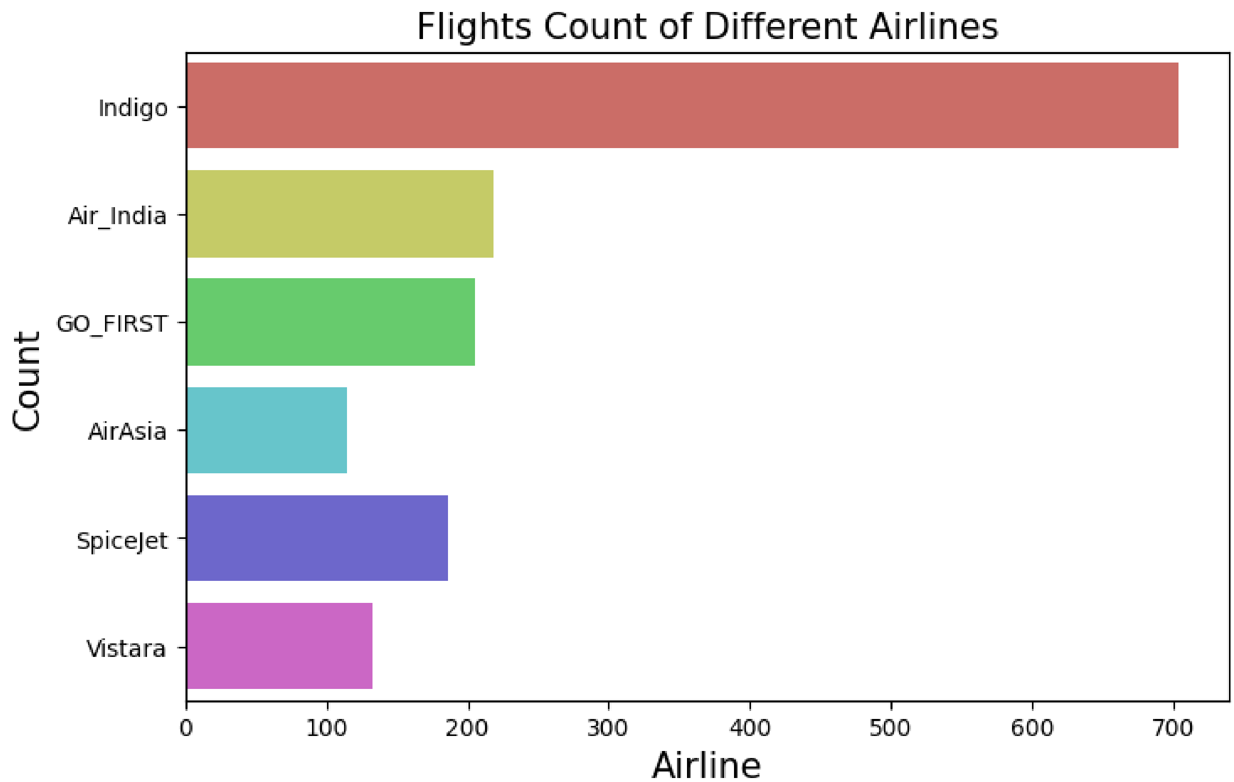
```
# Size of the data
df.shape
```

```
(300153, 11)
```

```
df1=df.groupby(['flight','airline'],as_index=False).count()
df1.airline.value_counts()
```

```
airline
Indigo       704
Air_India    218
GO_FIRST     205
SpiceJet     186
Vistara      133
AirAsia      115
Name: count, dtype: int64
```

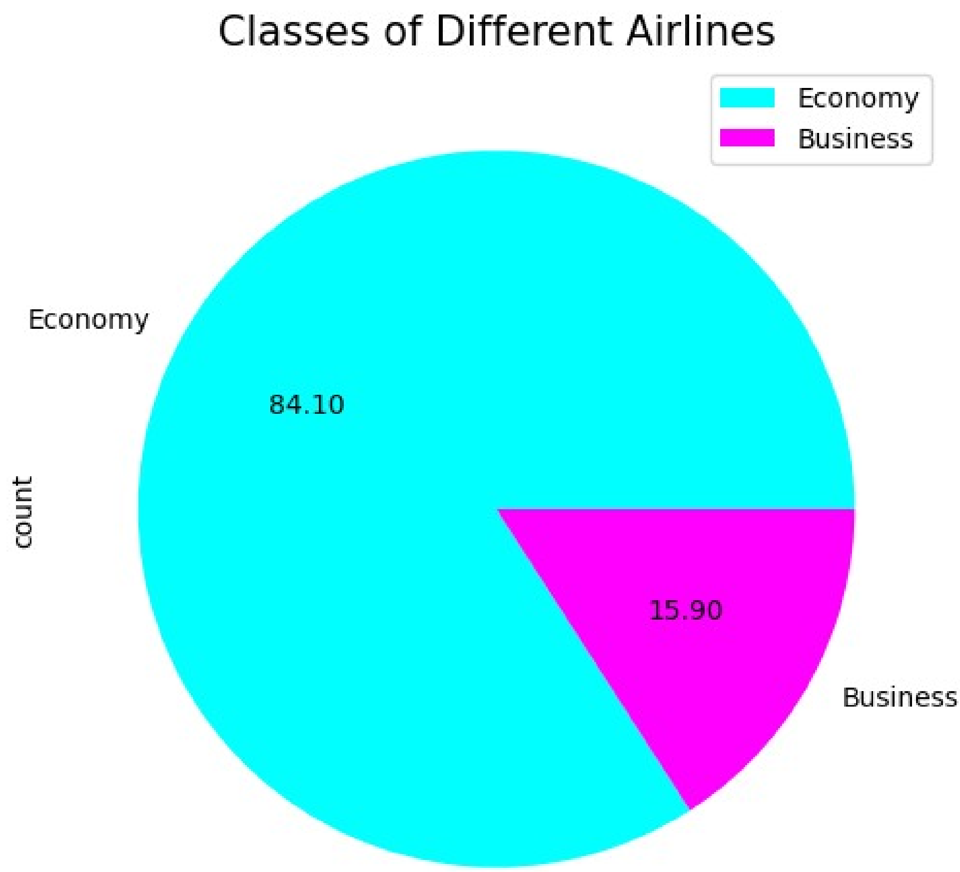
```
#Indigo becaming as a most popular Airline
plt.figure(figsize=(8,5))
sns.countplot(df1['airline'],palette='hls')
plt.title('Flights Count of Different Airlines',fontsize=15)
plt.xlabel('Airline',fontsize=15)
plt.ylabel('Count',fontsize=15)
plt.show()
```



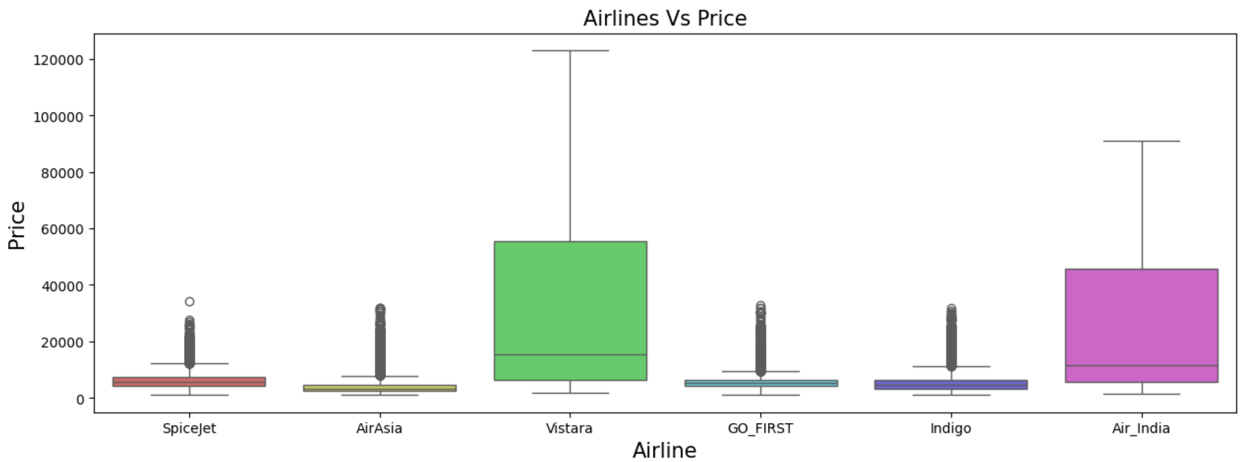

```
df2=df.groupby(['flight','airline','class'],as_index=False).count()
df2['class'].value_counts()
```

```
class
Economy     1560
Business     295
Name: count, dtype: int64
```

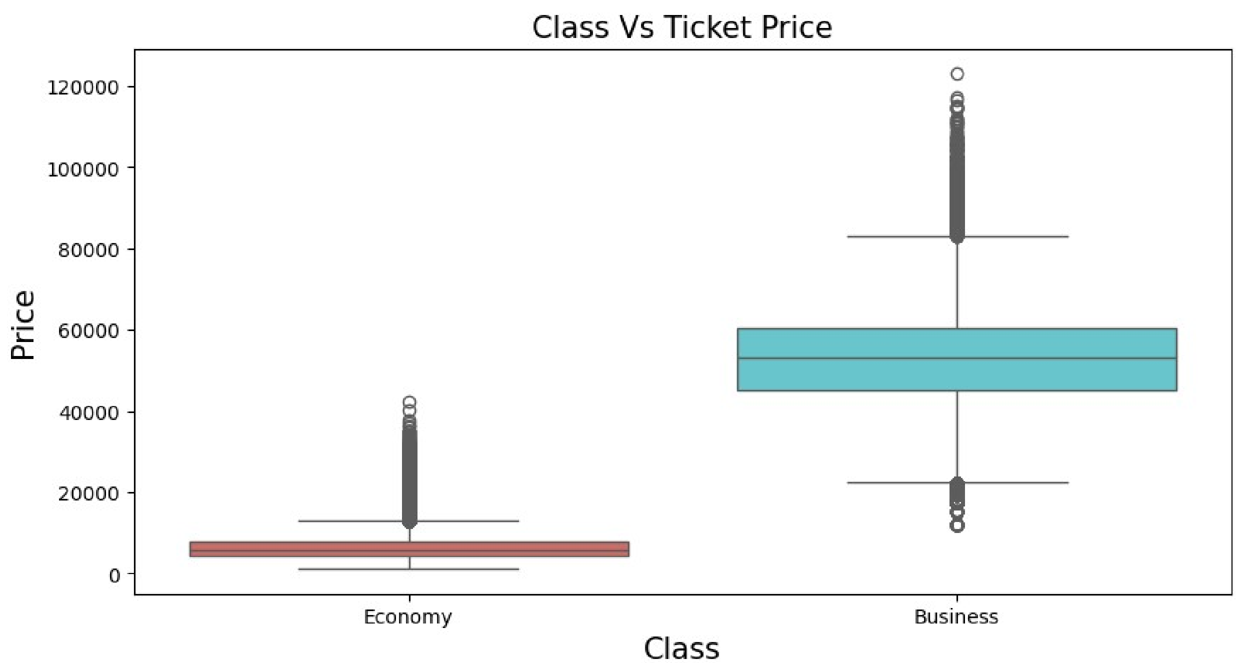
```
#Most of the Airlines has Economic Class as common

plt.figure(figsize=(8,6))
df2['class'].value_counts().plot(kind='pie',textprops={'color':'black'
},autopct='%.2f',cmap='cool')
plt.title('Classes of Different Airlines',fontsize=15)
plt.legend(['Economy','Business'])
plt.show()
```



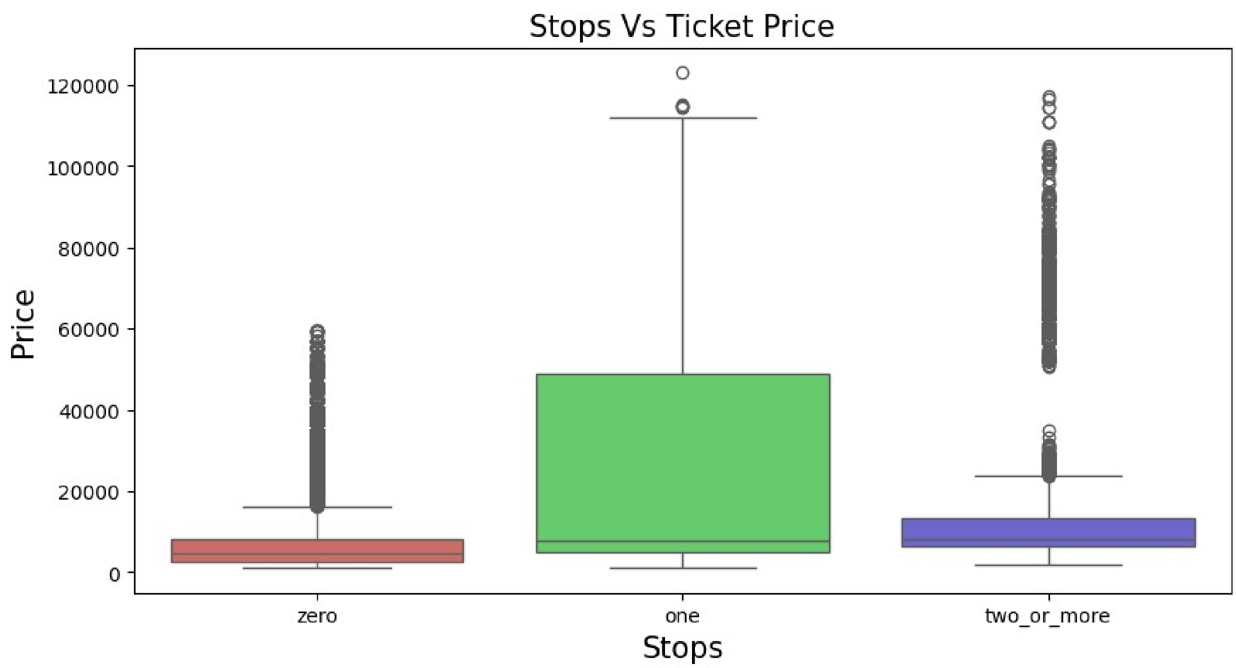

```
plt.figure(figsize=(15,5))
sns.boxplot(x=df['airline'],y=df['price'],palette='hls')
plt.title('Airlines Vs Price',fontsize=15)
plt.xlabel('Airline',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```



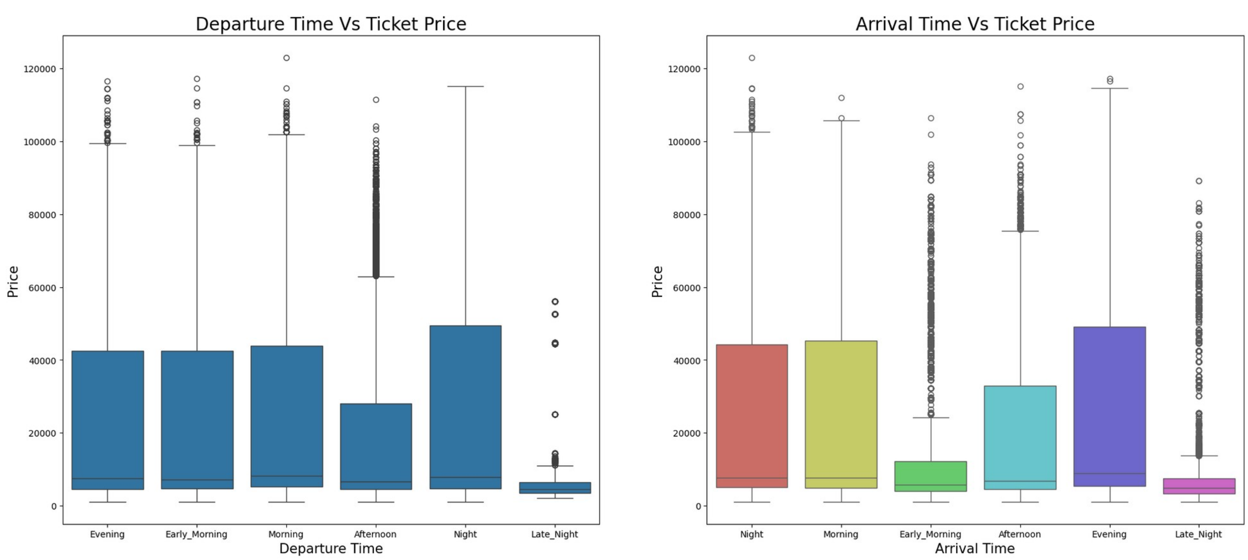

```
plt.figure(figsize=(10,5))
sns.boxplot(x='class',y='price',data=df,palette='hls')
plt.title('Class Vs Ticket Price',fontsize=15)
plt.xlabel('Class',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```



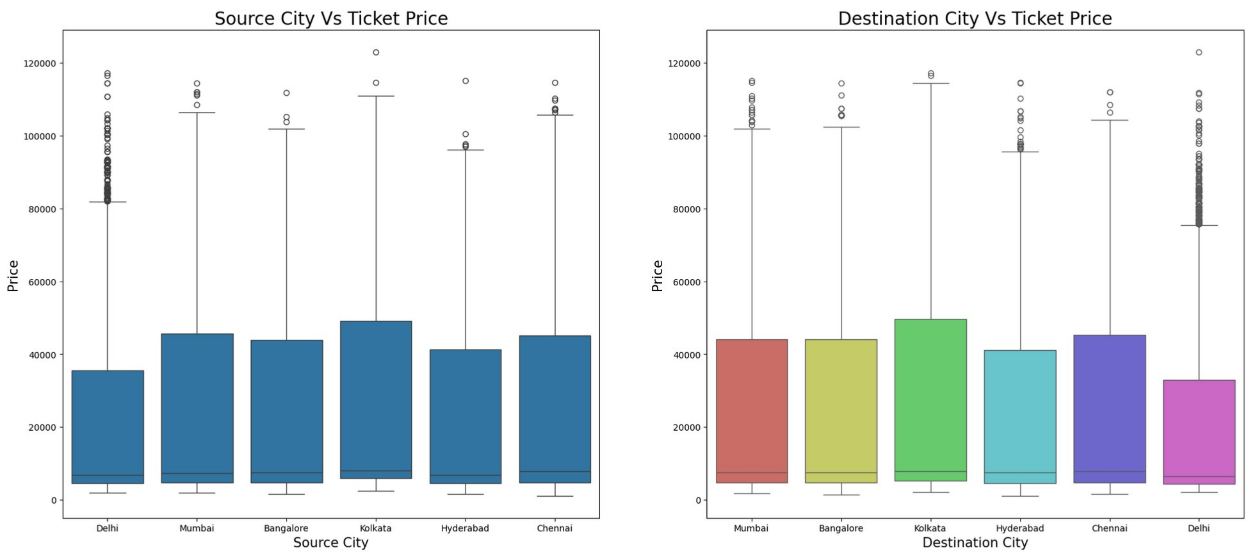

```
plt.figure(figsize=(10,5))
sns.boxplot(x='stops',y='price',data=df,palette='hls')
plt.title('Stops Vs Ticket Price',fontsize=15)
plt.xlabel('Stops',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```



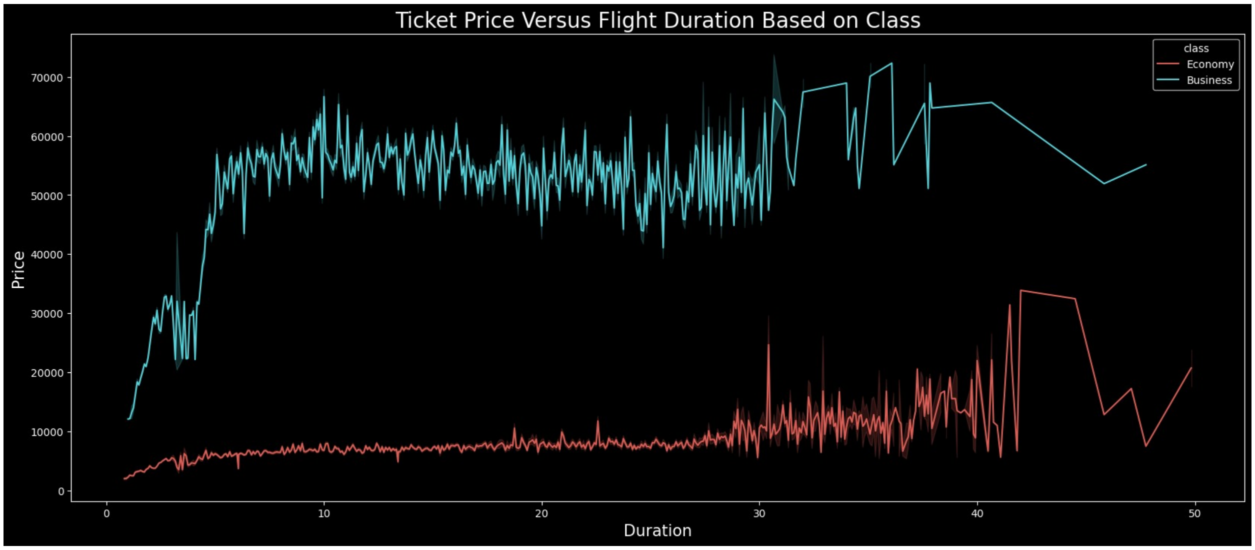

```
plt.figure(figsize=(24,10))
plt.subplot(1,2,1)
sns.boxplot(x='departure_time',y='price',data=df)
plt.title('Departure Time Vs Ticket Price',fontsize=20)
plt.xlabel('Departure Time',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.subplot(1,2,2)
sns.boxplot(x='arrival_time',y='price',data=df,palette='hls')
plt.title('Arrival Time Vs Ticket Price',fontsize=20)
plt.xlabel('Arrival Time',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```



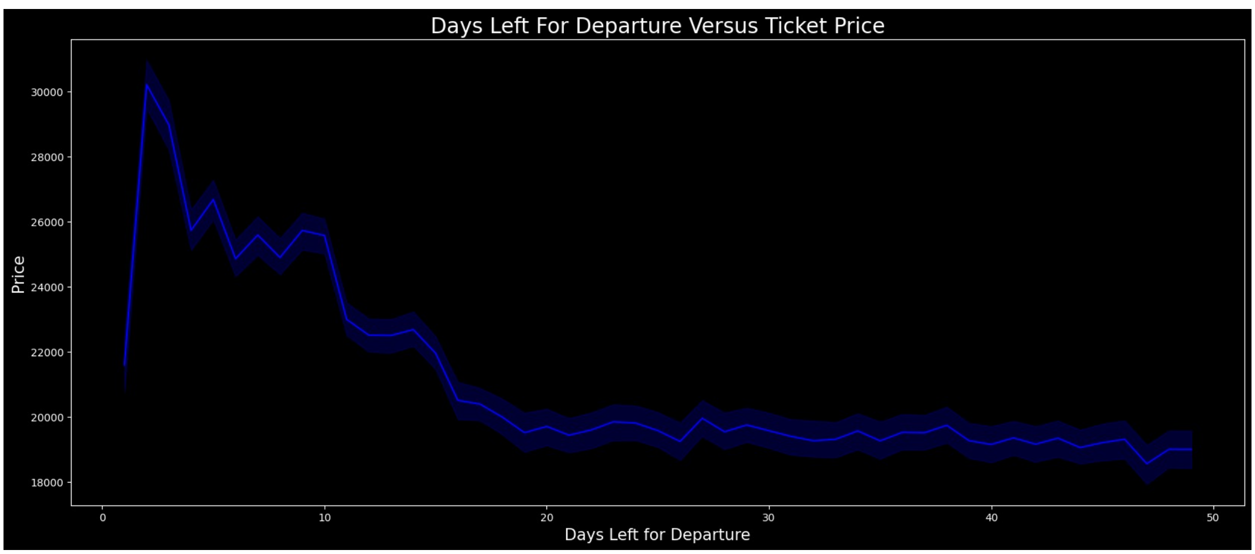
```
plt.figure(figsize=(24,10))
plt.subplot(1,2,1)
sns.boxplot(x='source_city',y='price',data=df)
plt.title('Source City Vs Ticket Price',fontsize=20)
plt.xlabel('Source City',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.subplot(1,2,2)
sns.boxplot(x='destination_city',y='price',data=df,palette='hls')
plt.title('Destination City Vs Ticket Price',fontsize=20)
plt.xlabel('Destination City',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```



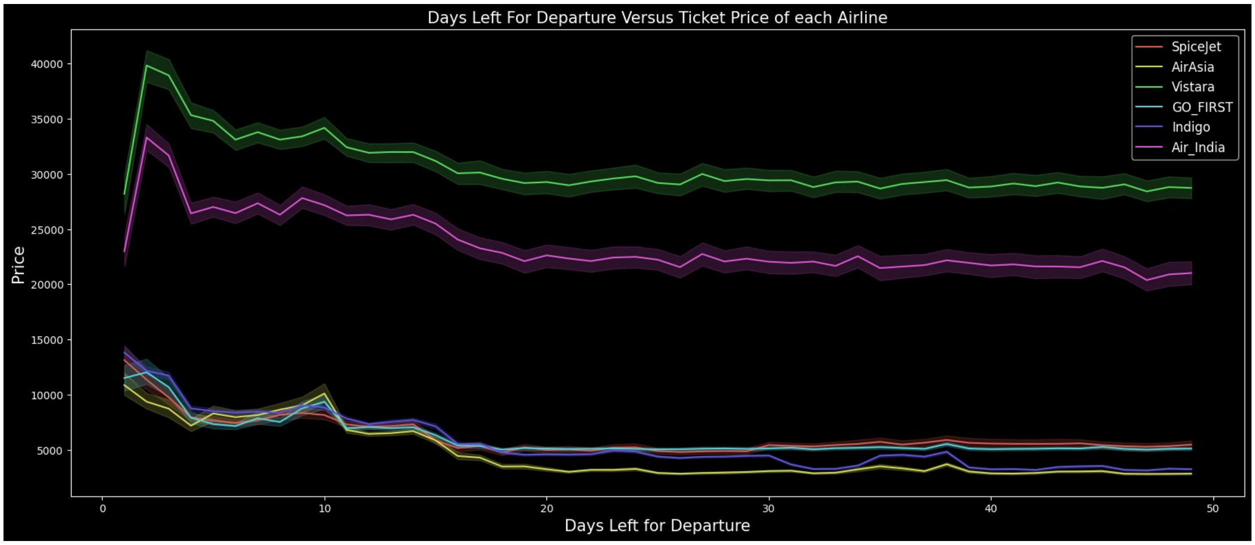

```
plt.style.use('dark_background')
plt.figure(figsize=(20,8))
sns.lineplot(data=df,x='duration',y='price',hue='class',palette='hls')
plt.title('Ticket Price Versus Flight Duration Based on
Class',fontsize=20)
plt.xlabel('Duration',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```




```
plt.figure(figsize=(20,8))
sns.lineplot(data=df,x='days_left',y='price',color='blue')
plt.title('Days Left For Departure Versus Ticket Price',fontsize=20)
plt.xlabel('Days Left for Departure',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```




```
plt.figure(figsize=(20,8))
sns.lineplot(data=df,x='days_left',y='price',color='blue',hue='airline
',palette='hls')
plt.title('Days Left For Departure Versus Ticket Price of each
Airline',fontsize=15)
plt.legend(fontsize=12)
plt.xlabel('Days Left for Departure',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```




```
df.groupby(['flight','source_city','destination_city','airline','class
'],as_index=False).count().groupby(['source_city','destination_city'],
as_index=False)['flight'].count().head(10)
```

	source_city	destination_city	flight
0	Bangalore	Chennai	106
1	Bangalore	Delhi	227
2	Bangalore	Hyderabad	132
3	Bangalore	Kolkata	171
4	Bangalore	Mumbai	175
5	Chennai	Bangalore	69
6	Chennai	Delhi	105
7	Chennai	Hyderabad	82
8	Chennai	Kolkata	110
9	Chennai	Mumbai	94

```
df.groupby(['airline','source_city','destination_city'],as_index=False
)['price'].mean().head(10)
```

	airline	source_city	destination_city	price
0	AirAsia	Bangalore	Chennai	2073.043478
1	AirAsia	Bangalore	Delhi	4807.092426
2	AirAsia	Bangalore	Hyderabad	2931.494792
3	AirAsia	Bangalore	Kolkata	4443.468160
4	AirAsia	Bangalore	Mumbai	3342.385350
5	AirAsia	Chennai	Bangalore	1914.760870
6	AirAsia	Chennai	Delhi	3697.314003
7	AirAsia	Chennai	Hyderabad	2053.182540
8	AirAsia	Chennai	Kolkata	3682.338762
9	AirAsia	Chennai	Mumbai	2691.100000

```
# Creating a Back up File
df_bk=df.copy()
```

```python
# Coverting the labels into a numeric form using Label Encoder
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for col in df.columns:
    if df[col].dtype=='object':
        df[col]=le.fit_transform(df[col])
```

```python
# storing the Dependent Variables in X and Independent Variable in Y
x=df.drop(['price'],axis=1)
y=df['price']
```

```python
# Splitting the Data into Training set and Testing Set
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,rand
om_state=42)
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((210107, 10), (90046, 10), (210107,), (90046,))
```

```python
# Scaling the values to convert the int values to Machine Languages
from sklearn.preprocessing import MinMaxScaler
mmscaler=MinMaxScaler(feature_range=(0,1))
x_train=mmscaler.fit_transform(x_train)
x_test=mmscaler.fit_transform(x_test)
x_train=pd.DataFrame(x_train)
x_test=pd.DataFrame(x_test)
```

```python
a={'Model Name':[], 'Mean_Absolute_Error_MAE':[] ,'Adj_R_Square':
[] ,'Root_Mean_Squared_Error_RMSE':
[] ,'Mean_Absolute_Percentage_Error_MAPE':
[] ,'Mean_Squared_Error_MSE':[] ,'Root_Mean_Squared_Log_Error_RMSLE':
[] ,'R2_score':[]}
Results=pd.DataFrame(a)
Results.head()
```

```
Empty DataFrame
Columns: [Model Name, Mean_Absolute_Error_MAE, Adj_R_Square,
Root_Mean_Squared_Error_RMSE, Mean_Absolute_Percentage_Error_MAPE,
Mean_Squared_Error_MSE, Root_Mean_Squared_Log_Error_RMSLE, R2_score]
Index: []
```

```python
# Build the Regression / Regressor models

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn import linear_model
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
import xgboost as xgb
from sklearn.neighbors import KNeighborsRegressor
```

```
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import BaggingRegressor
from sklearn.ensemble import GradientBoostingRegressor

# Create objects of Regression / Regressor models with default hyper-
parameters

modelmlg = LinearRegression()
modeldcr = DecisionTreeRegressor()
modelbag = BaggingRegressor()
modelrfr = RandomForestRegressor()
modelSVR = SVR()
modelXGR = xgb.XGBRegressor()
modelKNN = KNeighborsRegressor(n_neighbors=5)
modelETR = ExtraTreesRegressor()
modelRE=Ridge()
modelLO=linear_model.Lasso(alpha=0.1)
modelGBR = GradientBoostingRegressor(loss='squared_error',
learning_rate=0.1, n_estimators=100, subsample=1.0,
                                     criterion='friedman_mse',
min_samples_split=2, min_samples_leaf=1,
                                     min_weight_fraction_leaf=0.0,
max_depth=3, min_impurity_decrease=0.0,
                                     init=None, random_state=None,
max_features=None,
                                     alpha=0.9, verbose=0,
max_leaf_nodes=None, warm_start=False,
                                     validation_fraction=0.1,
n_iter_no_change=None, tol=0.0001, ccp_alpha=0.0)

# Evalution matrix for all the algorithms

MM = [modelmlg, modeldcr, modelrfr, modelKNN, modelETR, modelGBR,
modelXGR, modelbag,modelRE,modelLO]

for models in MM:

    # Fit the model with train data

    models.fit(x_train, y_train)

    # Predict the model with test data

    y_pred = models.predict(x_test)

    # Print the model name

    print('Model Name: ', models)

    # Evaluation metrics for Regression analysis
```

```
    from sklearn import metrics

    print('Mean Absolute Error (MAE):',
round(metrics.mean_absolute_error(y_test, y_pred),3))
    print('Mean Squared Error (MSE):',
round(metrics.mean_squared_error(y_test, y_pred),3))
    print('Root Mean Squared Error (RMSE):',
round(np.sqrt(metrics.mean_squared_error(y_test, y_pred)),3))
    print('R2_score:', round(metrics.r2_score(y_test, y_pred),6))
    print('Root Mean Squared Log Error (RMSLE):',
round(np.log(np.sqrt(metrics.mean_squared_error(y_test, y_pred))),3))

    # Define the function to calculate the MAPE - Mean Absolute
Percentage Error

    def MAPE (y_test, y_pred):
        y_test, y_pred = np.array(y_test), np.array(y_pred)
        return np.mean(np.abs((y_test - y_pred) / y_test)) * 100

    # Evaluation of MAPE

    result = MAPE(y_test, y_pred)
    print('Mean Absolute Percentage Error (MAPE):', round(result, 2),
'%')

    # Calculate Adjusted R squared values

    r_squared = round(metrics.r2_score(y_test, y_pred),6)
    adjusted_r_squared = round(1 - (1-r_squared)*(len(y)-1)/(len(y)-
x.shape[1]-1),6)
    print('Adj R Square: ', adjusted_r_squared)

print('-----------------------------------------------------------------------
--------------------------------------------')

#-----------------------------------------------------------------------
----------------------
    new_row = {'Model Name' : models,
               'Mean_Absolute_Error_MAE' :
metrics.mean_absolute_error(y_test, y_pred),
               'Adj_R_Square' : adjusted_r_squared,
               'Root_Mean_Squared_Error_RMSE' :
np.sqrt(metrics.mean_squared_error(y_test, y_pred)),
               'Mean_Absolute_Percentage_Error_MAPE' : result,
               'Mean_Squared_Error_MSE' :
metrics.mean_squared_error(y_test, y_pred),
               'Root_Mean_Squared_Log_Error_RMSLE':
np.log(np.sqrt(metrics.mean_squared_error(y_test, y_pred))),
               'R2_score' : metrics.r2_score(y_test, y_pred)}
```

```
    import pandas as pd
    Results = pd.concat([Results, pd.DataFrame([new_row])],
ignore_index=True)

    #-------------------------------------------------------------
```

```
Model Name:  LinearRegression()
Mean Absolute Error (MAE): 4630.296
Mean Squared Error (MSE): 49070241.265
Root Mean Squared Error (RMSE): 7005.015
R2_score: 0.904656
Root Mean Squared Log Error (RMSLE): 8.854
Mean Absolute Percentage Error (MAPE): 43.89 %
Adj R Square:  0.904653
----------------------------------------------------------------------
--------------------------------------
Model Name:  DecisionTreeRegressor()
Mean Absolute Error (MAE): 1270.674
Mean Squared Error (MSE): 14012980.306
Root Mean Squared Error (RMSE): 3743.392
R2_score: 0.972773
Root Mean Squared Log Error (RMSLE): 8.228
Mean Absolute Percentage Error (MAPE): 8.66 %
Adj R Square:  0.972772
----------------------------------------------------------------------
--------------------------------------
Model Name:  RandomForestRegressor()
Mean Absolute Error (MAE): 1172.282
Mean Squared Error (MSE): 8228203.693
Root Mean Squared Error (RMSE): 2868.485
R2_score: 0.984013
Root Mean Squared Log Error (RMSLE): 7.962
Mean Absolute Percentage Error (MAPE): 7.94 %
Adj R Square:  0.984012
----------------------------------------------------------------------
--------------------------------------
Model Name:  KNeighborsRegressor()
Mean Absolute Error (MAE): 1854.896
Mean Squared Error (MSE): 14590102.958
Root Mean Squared Error (RMSE): 3819.699
R2_score: 0.971651
Root Mean Squared Log Error (RMSLE): 8.248
Mean Absolute Percentage Error (MAPE): 11.13 %
Adj R Square:  0.97165
----------------------------------------------------------------------
--------------------------------------
Model Name:  ExtraTreesRegressor()
Mean Absolute Error (MAE): 1139.641
Mean Squared Error (MSE): 7773122.609
Root Mean Squared Error (RMSE): 2788.032
```

```
R2_score: 0.984897
Root Mean Squared Log Error (RMSLE): 7.933
Mean Absolute Percentage Error (MAPE): 7.59 %
Adj R Square:  0.984896
------------------------------------------------------------------------
--------------------------------------
Model Name:  GradientBoostingRegressor()
Mean Absolute Error (MAE): 2808.069
Mean Squared Error (MSE): 22221132.303
Root Mean Squared Error (RMSE): 4713.93
R2_score: 0.956824
Root Mean Squared Log Error (RMSLE): 8.458
Mean Absolute Percentage Error (MAPE): 20.67 %
Adj R Square:  0.956823
------------------------------------------------------------------------
--------------------------------------
Model Name:  XGBRegressor(base_score=None, booster=None,
callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None,
early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None,
feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None,
max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan,
monotone_constraints=None,
             multi_strategy=None, n_estimators=None, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
Mean Absolute Error (MAE): 1862.407
Mean Squared Error (MSE): 11680762.0
Root Mean Squared Error (RMSE): 3417.713
R2_score: 0.977304
Root Mean Squared Log Error (RMSLE): 8.137
Mean Absolute Percentage Error (MAPE): 14.23 %
Adj R Square:  0.977303
------------------------------------------------------------------------
--------------------------------------
Model Name:  BaggingRegressor()
Mean Absolute Error (MAE): 1207.99
Mean Squared Error (MSE): 8966813.523
Root Mean Squared Error (RMSE): 2994.464
R2_score: 0.982577
Root Mean Squared Log Error (RMSLE): 8.005
Mean Absolute Percentage Error (MAPE): 8.25 %
Adj R Square:  0.982576
```

```
--------------------------------------------------------------------------------------------------------------
Model Name:  Ridge()
Mean Absolute Error (MAE): 4630.313
Mean Squared Error (MSE): 49070187.277
Root Mean Squared Error (RMSE): 7005.012
R2_score: 0.904656
Root Mean Squared Log Error (RMSLE): 8.854
Mean Absolute Percentage Error (MAPE): 43.89 %
Adj R Square:  0.904653
--------------------------------------------------------------------------------------------------------------
Model Name:  Lasso(alpha=0.1)
Mean Absolute Error (MAE): 4630.179
Mean Squared Error (MSE): 49070111.63
Root Mean Squared Error (RMSE): 7005.006
R2_score: 0.904656
Root Mean Squared Log Error (RMSLE): 8.854
Mean Absolute Percentage Error (MAPE): 43.89 %
Adj R Square:  0.904653
--------------------------------------------------------------------------------------------------------------

Results

                                          Model Name  
Mean_Absolute_Error_MAE  \
0                                 LinearRegression()  
4630.295614   
1                            DecisionTreeRegressor()  
1267.046858   
2  (DecisionTreeRegressor(max_features=1.0, rando...  
1171.195628   
3                              KNeighborsRegressor()  
1854.469527   
4  (ExtraTreeRegressor(random_state=370408196), E...  
1148.979440   
5  ([DecisionTreeRegressor(criterion='friedman_ms...  
2808.074076   
6  XGBRegressor(base_score=None, booster=None, ca...  
1862.407227   
7  (DecisionTreeRegressor(random_state=510902622)...  
1210.905216   
8                                            Ridge()  
4630.313301   
9                                   Lasso(alpha=0.1)  
4630.179207   

   Adj_R_Square  Root_Mean_Squared_Error_RMSE  \
0      0.904653                   7005.015436   
```

```
1      0.972946                    3731.414789
2      0.984113                    2859.347334
3      0.971645                    3820.074173
4      0.984726                    2803.632993
5      0.956823                    4713.930286
6      0.977303                    3417.712978
7      0.982816                    2973.788019
8      0.904653                    7005.011583
9      0.904653                    7005.006183

   Mean_Absolute_Percentage_Error_MAPE  Mean_Squared_Error_MSE  \
0                            43.888567            4.907024e+07
1                             8.636776            1.392346e+07
2                             7.910083            8.175867e+06
3                            11.113824            1.459297e+07
4                             7.629837            7.860358e+06
5                            20.673080            2.222114e+07
6                            14.232981            1.168076e+07
7                             8.290388            8.843415e+06
8                            43.888754            4.907019e+07
9                            43.885459            4.907011e+07

   Root_Mean_Squared_Log_Error_RMSLE  R2_score
0                           8.854382  0.904656
1                           8.224543  0.972947
2                           7.958349  0.984114
3                           8.248025  0.971646
4                           7.938671  0.984727
5                           8.458277  0.956824
6                           8.136727  0.977304
7                           7.997592  0.982817
8                           8.854381  0.904656
9                           8.854380  0.904656
```

```
models=['LinearRegression','DecisionTreeRegressor','RandomForestRegres
sor','KNeighborsRegressor','ExtraTreesRegressor','GradientBoostingRegr
essor','XGBRegressor','BaggingRegressor','Ridge Regression','Lasso
Regression']
result=pd.DataFrame({'Model_Name':models})
result['Adj_R_Square']=Results['Adj_R_Square']
result['Mean_Absolute_Error_MAE']=Results['Mean_Absolute_Error_MAE']
result['Root_Mean_Squared_Error_RMSE']=Results['Root_Mean_Squared_Erro
r_RMSE']
result['Mean_Absolute_Percentage_Error_MAPE']=Results['Mean_Absolute_P
ercentage_Error_MAPE']
result['Mean_Squared_Error_MSE']=Results['Mean_Squared_Error_MSE']
result['Root_Mean_Squared_Log_Error_RMSLE']=Results['Root_Mean_Squared
_Log_Error_RMSLE']
result['R2_score']=Results['R2_score']
result=result.sort_values(by='Adj_R_Square',ascending=False).reset_ind
```

```
ex(drop=True)
result
```

```
                     Model_Name  Adj_R_Square  Mean_Absolute_Error_MAE  \
0         ExtraTreesRegressor      0.984726              1148.979440
1       RandomForestRegressor      0.984113              1171.195628
2            BaggingRegressor      0.982816              1210.905216
3                XGBRegressor      0.977303              1862.407227
4       DecisionTreeRegressor      0.972946              1267.046858
5         KNeighborsRegressor      0.971645              1854.469527
6   GradientBoostingRegressor      0.956823              2808.074076
7            LinearRegression      0.904653              4630.295614
8            Ridge Regression      0.904653              4630.313301
9            Lasso Regression      0.904653              4630.179207

   Root_Mean_Squared_Error_RMSE
Mean_Absolute_Percentage_Error_MAPE  \
0                    2803.632993                                  7.629837

1                    2859.347334                                  7.910083

2                    2973.788019                                  8.290388

3                    3417.712978                                 14.232981

4                    3731.414789                                  8.636776

5                    3820.074173                                 11.113824

6                    4713.930286                                 20.673080

7                    7005.015436                                 43.888567

8                    7005.011583                                 43.888754

9                    7005.006183                                 43.885459


   Mean_Squared_Error_MSE  Root_Mean_Squared_Log_Error_RMSLE  R2_score

0            7.860358e+06                           7.938671  0.984727

1            8.175867e+06                           7.958349  0.984114

2            8.843415e+06                           7.997592  0.982817

3            1.168076e+07                           8.136727  0.977304

4            1.392346e+07                           8.224543  0.972947

5            1.459297e+07                           8.248025  0.971646
```

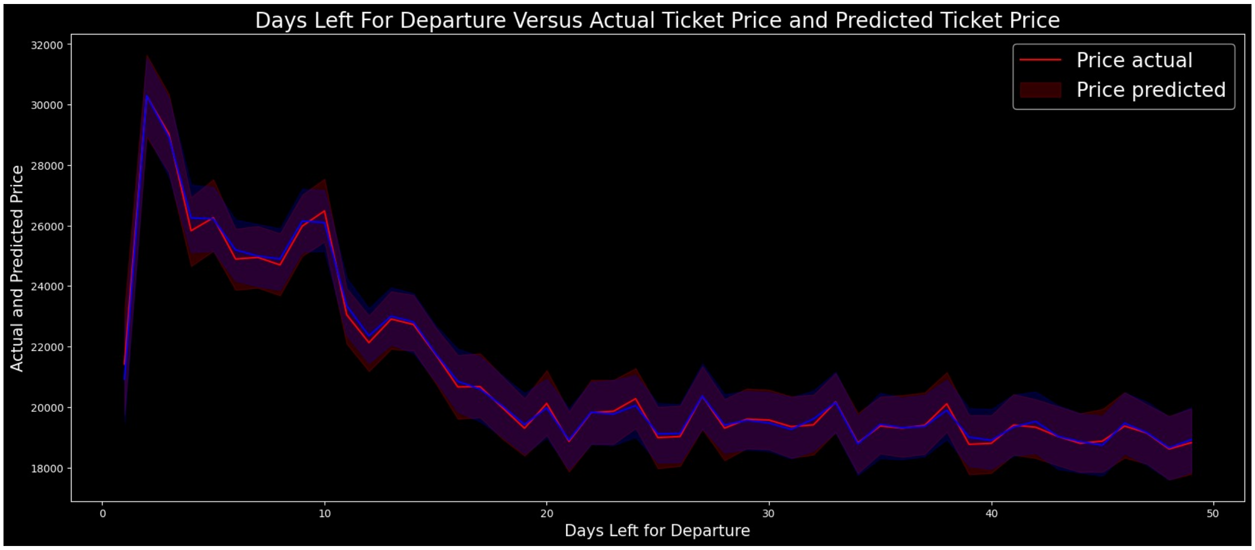
```
6           2.222114e+07                          8.458277  0.956824

7           4.907024e+07                          8.854382  0.904656

8           4.907019e+07                          8.854381  0.904656

9           4.907011e+07                          8.854380  0.904656
```

```python
#Trainig the model with
modelETR.fit(x_train, y_train)

# Predict the model with test data

y_pred = modelETR.predict(x_test)

out=pd.DataFrame({'Price_actual':y_test,'Price_pred':y_pred})
result=df_bk.merge(out,left_index=True,right_index=True)

result.sample(10)
```

```
          airline   flight source_city departure_time stops
arrival_time  \
172088   GO_FIRST   G8-123   Hyderabad  Early_Morning  zero
Early_Morning
172328    AirAsia   I5-510   Hyderabad  Early_Morning   one
Afternoon
267403    Vistara   UK-772     Kolkata        Morning   one
Morning
151587     Indigo   6E-345     Kolkata        Morning   one
Evening
226901    Vistara   UK-841      Mumbai        Morning   one
Evening
157140     Indigo  6E-7156   Hyderabad      Afternoon   one
Night
263123  Air_India   AI-773     Kolkata        Evening   one
Morning
260667    Vistara   UK-864   Bangalore        Evening   one
Evening
26986     AirAsia   I5-721       Delhi          Night   one
Morning
157987    Vistara   UK-874   Hyderabad        Morning   one
Late_Night

       destination_city     class  duration  days_left  price
Price_actual  \
172088          Kolkata   Economy      1.83         15   5292
5292
172328          Kolkata   Economy      6.00         17   2056
2056
```

```
267403        Bangalore  Business     22.42           3  75023
75023
151587          Chennai   Economy     10.00          39   3015
3015
226901            Delhi  Business      5.67          20  60813
60813
157140            Delhi   Economy      6.17          39   3243
3243
263123            Delhi  Business     17.50          34  53743
53743
260667          Chennai  Business     24.92          38  44280
44280
26986           Kolkata   Economy     12.25          40   3175
3175
157987            Delhi   Economy     16.42          45   5656
5656

        Price_pred
172088     5431.45
172328     3579.41
267403    68566.20
151587     3315.70
226901    54000.05
157140     3669.54
263123    53743.00
260667    44354.27
26986      2621.60
157987     5652.85
```

```
plt.figure(figsize=(20,8))
sns.lineplot(data=result,x='days_left',y='Price_actual',color='red')
sns.lineplot(data=result,x='days_left',y='Price_pred',color='blue')
plt.title('Days Left For Departure Versus Actual Ticket Price and
Predicted Ticket Price',fontsize=20)
plt.legend(labels=['Price actual','Price predicted'],fontsize=19)
plt.xlabel('Days Left for Departure',fontsize=15)
plt.ylabel('Actual and Predicted Price',fontsize=15)
plt.show()
```




```
plt.figure(figsize=(10,5))
sns.regplot(x='Price_actual',y='Price_pred',data=result,color='cyan')
plt.title('Actual Price  Vs  Predicted Price ',fontsize=20)
plt.xlabel('Actual Price',fontsize=15)
plt.ylabel('Predicted Price',fontsize=15)
plt.show()
```


```
import pandas as pd
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.linear_model import LinearRegression  # Import
```

```
LinearRegression

# Initialize Results DataFrame
Results = pd.DataFrame(columns=[
    'Model Name', 'Mean_Absolute_Error_MAE', 'Adj_R_Square',
    'Root_Mean_Squared_Error_RMSE',
'Mean_Absolute_Percentage_Error_MAPE',
    'Mean_Squared_Error_MSE', 'Root_Mean_Squared_Log_Error_RMSLE',
'R2_score'])

# Iterate through each model in the MM list
for models in MM:
    # Check if the current model is LinearRegression
    if isinstance(models, LinearRegression):
        # Fit the model with train data
        models.fit(x_train, y_train)

        # Predict the model with test data
        y_pred = models.predict(x_test)

        # Model evaluation
        mae = mean_absolute_error(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)
        rmse = np.sqrt(mse)
        r2 = r2_score(y_test, y_pred)

        # Calculate MAPE (Mean Absolute Percentage Error)
        def MAPE(y_test, y_pred):
            y_test, y_pred = np.array(y_test), np.array(y_pred)
            return np.mean(np.abs((y_test - y_pred) / y_test)) * 100

        mape = MAPE(y_test, y_pred)

        # Adjusted R-Square calculation
        adj_r2 = 1 - (1 - r2) * (len(y_test) - 1) / (len(y_test) -
x_test.shape[1] - 1)

        # RMSLE calculation
        rmsle = np.log(np.sqrt(mse))

        # Print evaluation metrics
        print(f"Model Name: {models}")
        print(f"Mean Absolute Error (MAE): {mae:.3f}")
        print(f"Mean Squared Error (MSE): {mse:.3f}")
        print(f"Root Mean Squared Error (RMSE): {rmse:.3f}")
        print(f"R2 Score: {r2:.6f}")
        print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
        print(f"Root Mean Squared Log Error (RMSLE): {rmsle:.3f}")
        print("-" * 100)
```

```python
        # Prepare new row as a DataFrame
        new_row = pd.DataFrame({
            'Model Name': [str(models)],
            'Mean_Absolute_Error_MAE': [mae],
            'Adj_R_Square': [adj_r2],
            'Root_Mean_Squared_Error_RMSE': [rmse],
            'Mean_Absolute_Percentage_Error_MAPE': [mape],
            'Mean_Squared_Error_MSE': [mse],
            'Root_Mean_Squared_Log_Error_RMSLE': [rmsle],
            'R2_score': [r2]
        })

        # Concatenate the new row with the existing Results DataFrame
        Results = pd.concat([Results, new_row], ignore_index=True)

# After the loop, you can check the Results DataFrame
print(Results)
```

```
Model Name: LinearRegression()
Mean Absolute Error (MAE): 4630.296
Mean Squared Error (MSE): 49070241.265
Root Mean Squared Error (RMSE): 7005.015
R2 Score: 0.904656
Mean Absolute Percentage Error (MAPE): 43.89%
Root Mean Squared Log Error (RMSLE): 8.854
----------------------------------------------------------------------
------------------------------
           Model Name  Mean_Absolute_Error_MAE  Adj_R_Square  \
0  LinearRegression()              4630.295614      0.904646

   Root_Mean_Squared_Error_RMSE
Mean_Absolute_Percentage_Error_MAPE  \
0                   7005.015436                            43.888567


   Mean_Squared_Error_MSE  Root_Mean_Squared_Log_Error_RMSLE  R2_score

0            4.907024e+07                           8.854382  0.904656
```

```python
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_iris
from sklearn.naive_bayes import GaussianNB

# Load a dataset (example: Iris dataset)
data = load_iris()
X = data.data  # Feature data
y = data.target  # Target labels

# Split the dataset into training and testing sets
```

```
x_train, x_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# List of models to train (in this case, Naive Bayes)
MM = [GaussianNB()]

# Iterate through each model in the MM list
for model in MM:
    # Fit the model with train data
    model.fit(x_train, y_train)

    # Predict the model with test data
    y_pred = model.predict(x_test)

    # Print or evaluate the results (you can add metrics like
accuracy, etc.)
    print(f'Model: {model.__class__.__name__}')
    print(f'Predictions: {y_pred}')
```

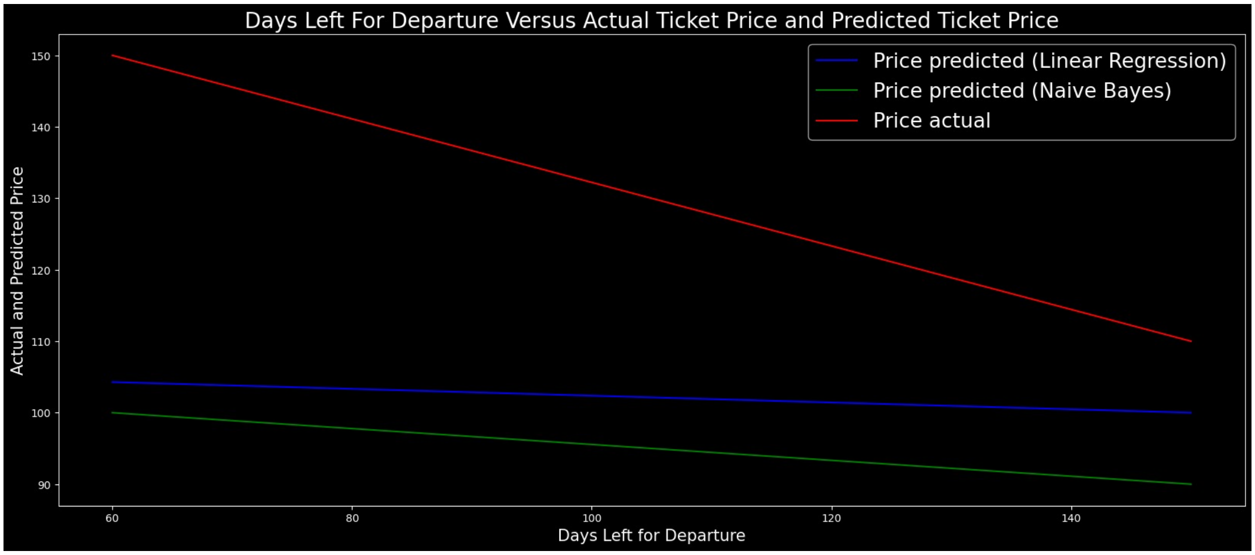
```
Model: GaussianNB
Predictions: [1 0 2 1 1 0 1 2 1 1 2 0 0 0 0 2 2 1 1 2 0 2 0 2 2 2 2 2
0 0 0 0 1 0 0 2 1
 0 0 0 2 1 1 0 0]
```

```
from sklearn.metrics import accuracy_score, confusion_matrix

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print(f'Confusion Matrix:\n{conf_matrix}')
```

```
Accuracy: 97.78%
Confusion Matrix:
[[19  0  0]
 [ 0 12  1]
 [ 0  0 13]]
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split

# Example DataFrame 'result' (replace this with your actual data)
import pandas as pd

result = pd.DataFrame({
    'days_left': [30, 60, 90, 120, 150],  # Example days_left
```

```
    'Price_actual': [100, 150, 120, 90, 110]  # Example actual prices
})

# Prepare the data
X = result[['days_left']]  # Feature: 'days_left'
y = result['Price_actual']  # Target: 'Price_actual'

# Split the dataset into train and test sets
x_train, x_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Fit the Linear Regression model
lr_model = LinearRegression()
lr_model.fit(x_train, y_train)
y_pred_lr = lr_model.predict(x_test)

# Fit the Naive Bayes model (GaussianNB is generally used for
classification)
nb_model = GaussianNB()
y_train_nb = y_train.astype(int)  # Naive Bayes expects integer labels
nb_model.fit(x_train, y_train_nb)
y_pred_nb = nb_model.predict(x_test)

# Plotting the results
plt.figure(figsize=(20, 8))

# Plot Linear Regression predictions
sns.lineplot(x=x_test['days_left'], y=y_pred_lr, color='blue',
label='Price predicted (Linear Regression)')

# Plot Naive Bayes predictions
sns.lineplot(x=x_test['days_left'], y=y_pred_nb, color='green',
label='Price predicted (Naive Bayes)')

# Plot actual prices for the test set
sns.lineplot(x=x_test['days_left'], y=y_test, color='red',
label='Price actual')

# Title and labels
plt.title('Days Left For Departure Versus Actual Ticket Price and
Predicted Ticket Price', fontsize=20)
plt.xlabel('Days Left for Departure', fontsize=15)
plt.ylabel('Actual and Predicted Price', fontsize=15)

# Show legend
plt.legend(fontsize=19)

# Display the plot
plt.show()
```




```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split

# Example DataFrame 'result' (replace this with your actual data)
import pandas as pd

result = pd.DataFrame({
    'days_left': [30, 60, 90, 120, 150],  # Example days_left
    'Price_actual': [100, 150, 120, 90, 110]  # Example actual prices
})

# Prepare the data
X = result[['days_left']]  # Feature: 'days_left'
y = result['Price_actual']  # Target: 'Price_actual'

# Split the dataset into train and test sets
x_train, x_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Fit the Linear Regression model
lr_model = LinearRegression()
lr_model.fit(x_train, y_train)
y_pred_lr = lr_model.predict(x_test)

# Fit the Naive Bayes model (GaussianNB is generally used for
classification)
nb_model = GaussianNB()
y_train_nb = y_train.astype(int)  # Naive Bayes expects integer labels
nb_model.fit(x_train, y_train_nb)
y_pred_nb = nb_model.predict(x_test)
```

```
# Add the predictions to the 'result' DataFrame (for comparison)
# Assuming you're interested in the Linear Regression predictions
result['Price_pred'] = lr_model.predict(X)

# Plotting the Actual vs Predicted prices
plt.figure(figsize=(10, 5))
sns.regplot(x='Price_actual', y='Price_pred', data=result,
color='cyan')
plt.title('Actual Price Vs Predicted Price', fontsize=20)
plt.xlabel('Actual Price', fontsize=15)
plt.ylabel('Predicted Price', fontsize=15)
plt.show()
```