Flight Booking Price Prediction

Agenda

01 Importing the Libraries

02 Loading the Data

03 Data Visualization

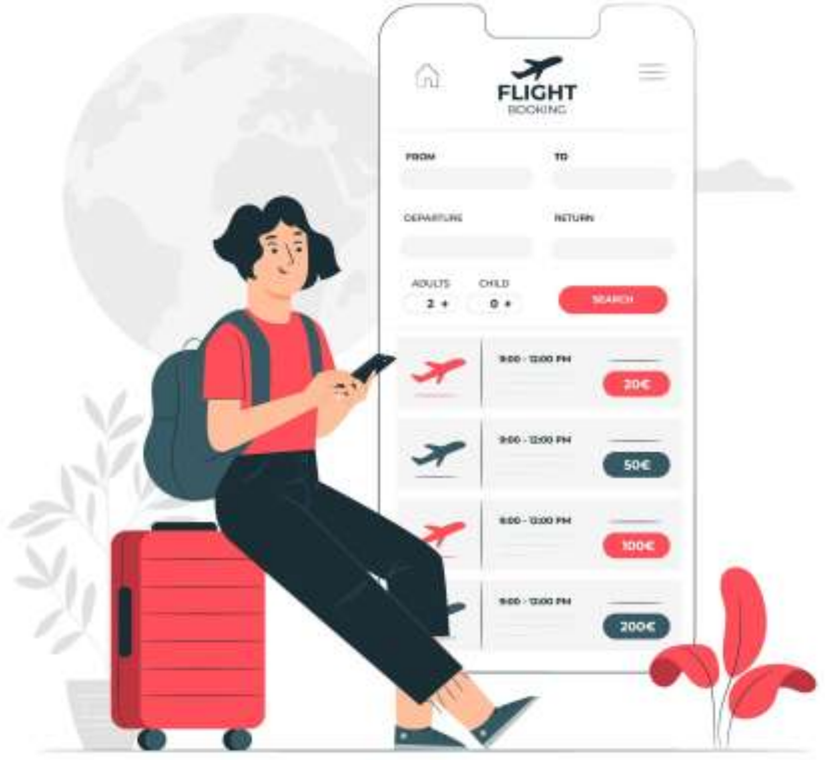
04 One Hot Encoding

05 Feature Selection

06 Implementing ML Algorithms

Problem Statement

The objective is to analyze the flight booking dataset obtained from a platform which is used to book flight tickets. A thorough study of the data will aid in the discovery of valuable insights that will be of enormous value to passengers. Apply EDA, statistical methods and Machine learning algorithms in order to get meaningful information from it.



Dataset Information

Flight booking price prediction dataset contains around 3 lacs records with 11 attributes .

Dataset Information

Attributes	Description
Airline	Name of the airline company
Flight	Plane's flight code
Source City	City from which the flight takes off
Departure Time	Time of Departure
Stops	Number of stops between the source and destination cities
Arrival Time	Time of Arrival
Destination City	City where the flight will land
Class	Contains information on seat class
Duration	Overall amount of time taken to travel between cities in hours.
Days left	Subtracting the trip date by the booking date.
Price	Ticket price

Importing the Libraries

We start off this project by importing all the necessary libraries that will be required for the process.

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

Loading the Data

Loading the data and removing unnecessary column from the dataframe

```
import pandas as pd
df=pd.read_csv("Flight_Booking.csv")
df=df.drop(columns=["Unnamed: 0"])
df.head()
```

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Economy	2.17	1	5953
1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Economy	2.33	1	5953
2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Economy	2.17	1	5956
3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Economy	2.25	1	5955
4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mumbai	Economy	2.33	1	5955

Loading the Data

```
df.shape
df.info()
df.describe()
```

Checking the shape of a dataframe and datatypes of all columns along with calculating the statistical data.

```
(300153, 11)
```

```
<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
```

	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

Missing Values

Checking out the missing values in a dataframe

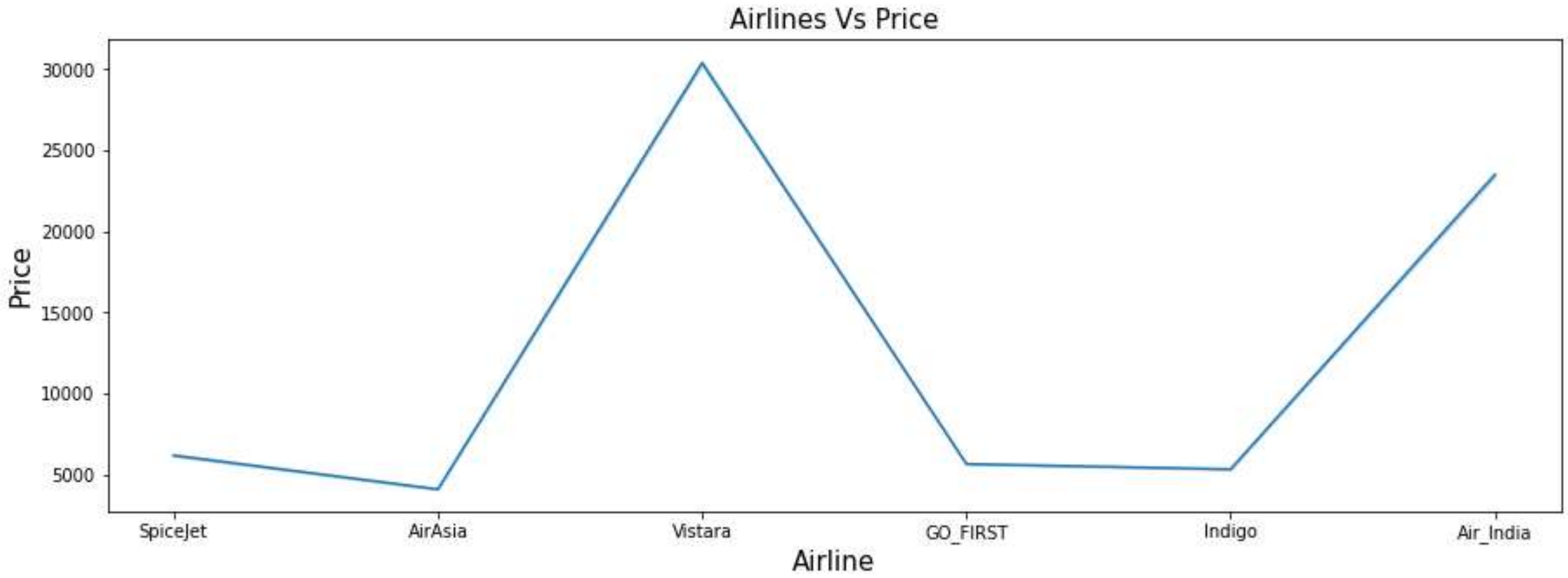
```
df.isnull().sum()
```

```
airline             0
flight              0
source_city         0
departure_time      0
stops               0
arrival_time        0
destination_city    0
class               0
duration            0
days_left           0
price               0
dtype: int64
```

Data Visualization

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

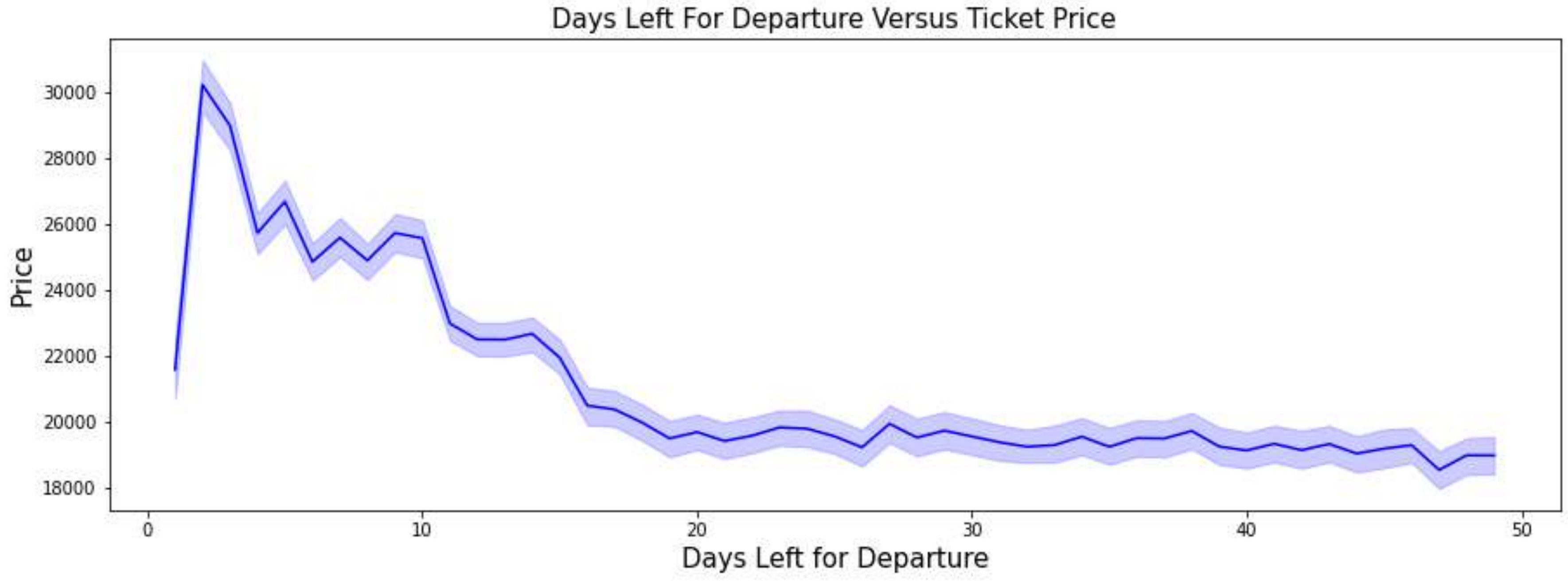
There is a variation in price with different airlines



Data Visualization

```
plt.figure(figsize=(15,5))
sns.lineplot(data=df,x='days_left',y='price',color='blue')
plt.title('Days Left For Departure Versus Ticket Price',fontsize=15)
plt.xlabel('Days Left for Departure',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```

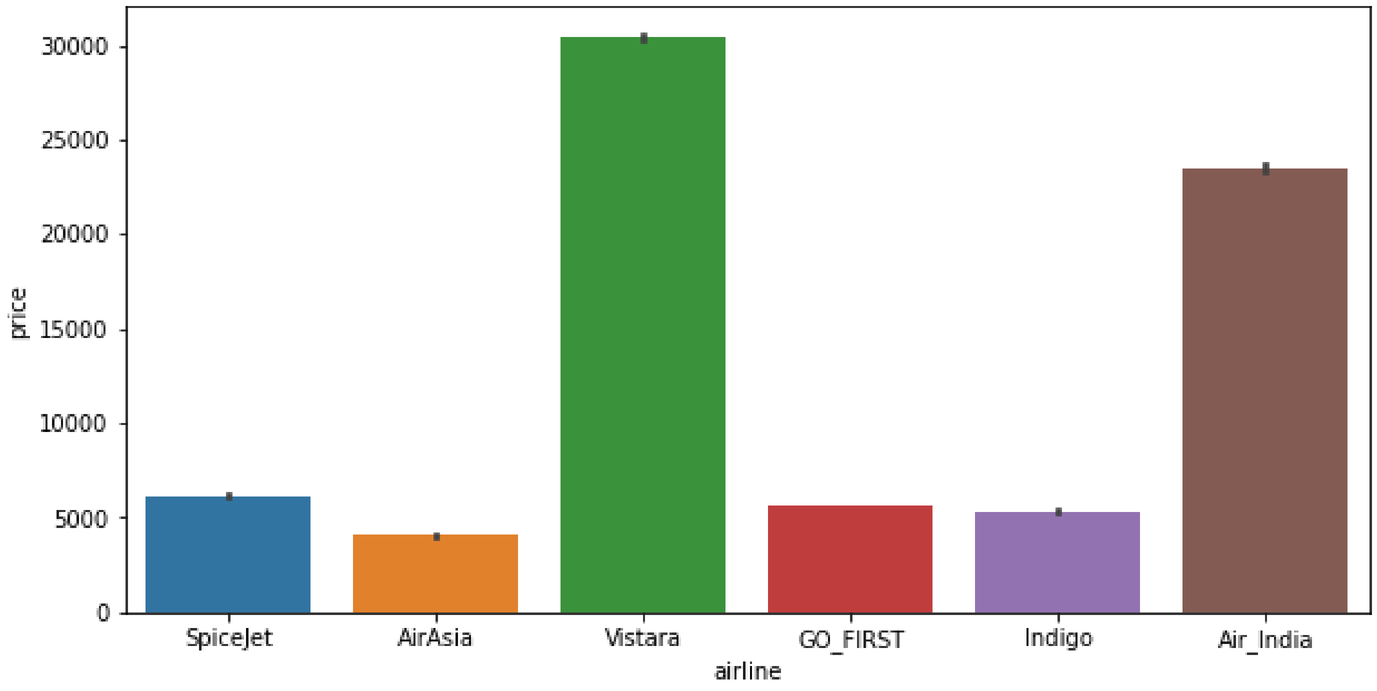
The price of the ticket increases as the days left for departure decreases



Data Visualization

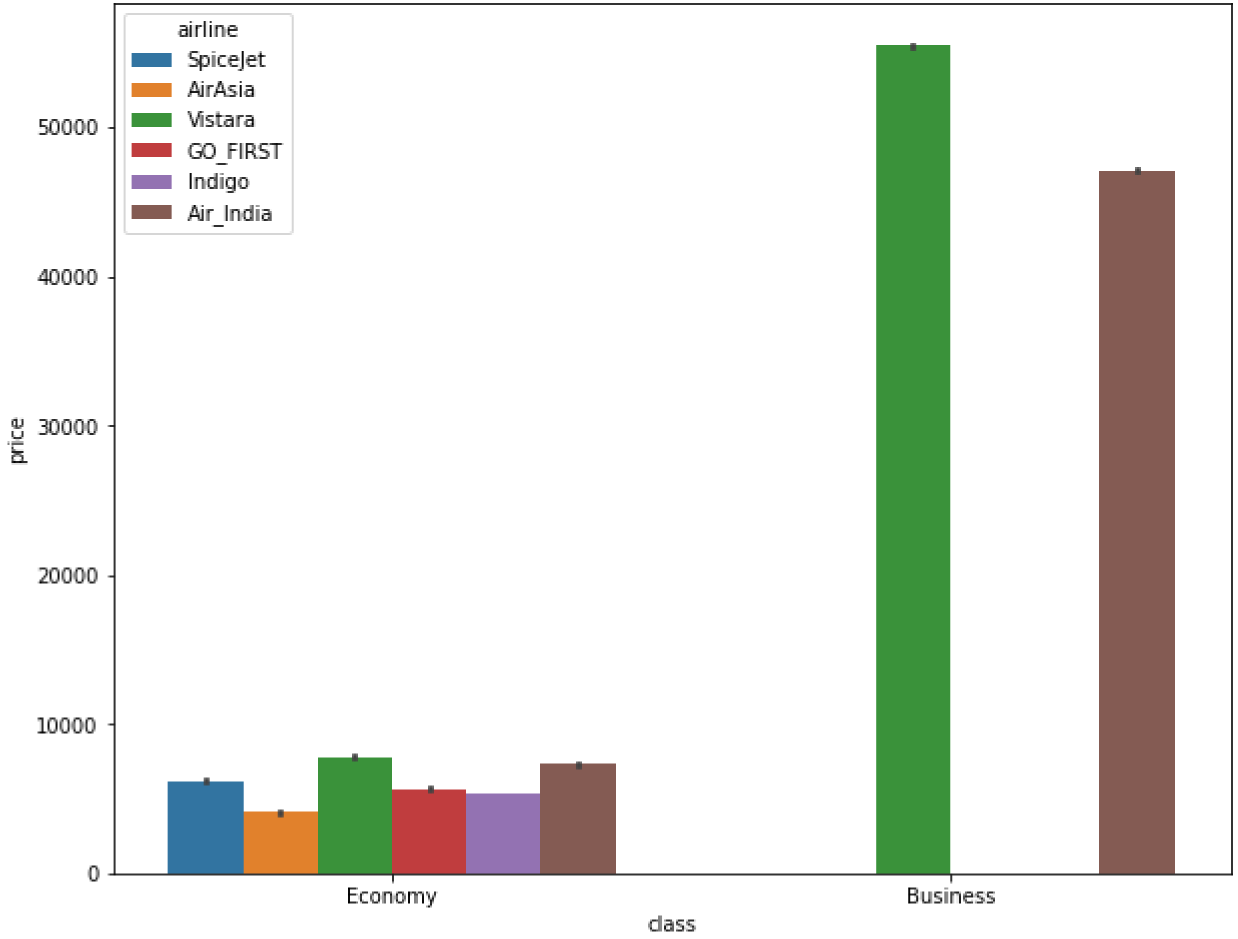
```
plt.figure(figsize=(10,5));
sns.barplot(x='airline',y='price',data=df)
```

Price range of all the flights



Data Visualization

```
plt.figure(figsize=(10,8));
sns.barplot(x='class',y='price',data=df,hue='airline')
```

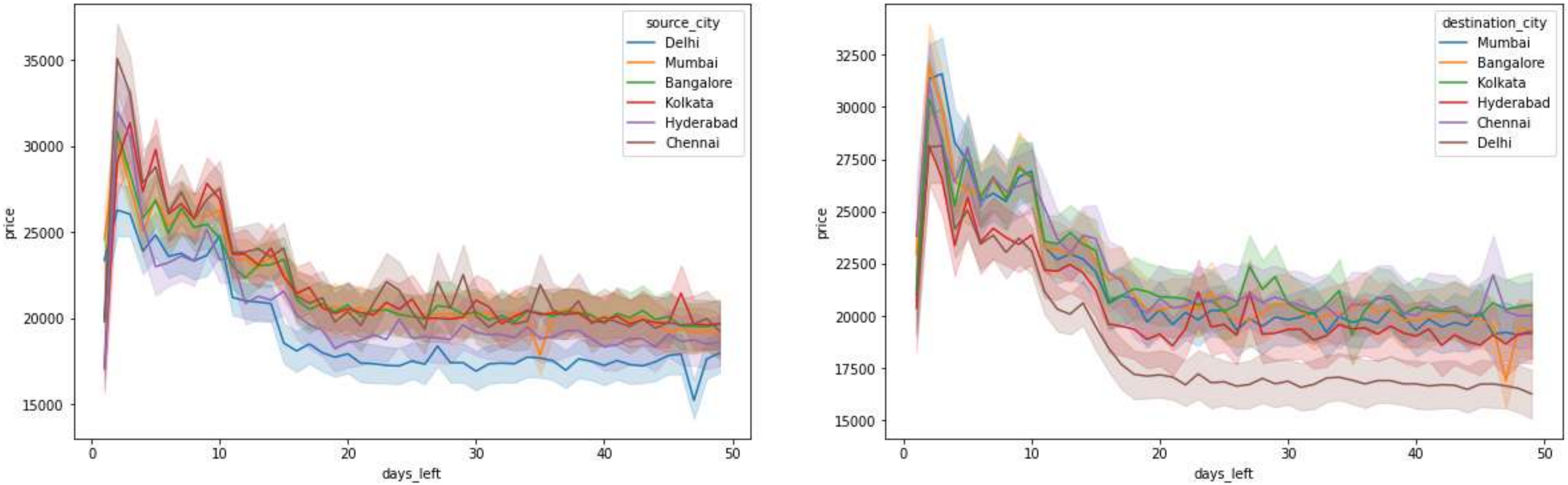


Range of price of all the flights of Economy and Business class

Data Visualization

```
fig,ax=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(x='days_left',y='price',data=df,hue='source_city',ax=ax[0])
sns.lineplot(x='days_left',y='price',data=df,hue='destination_city',ax=ax[1])
plt.show()
```

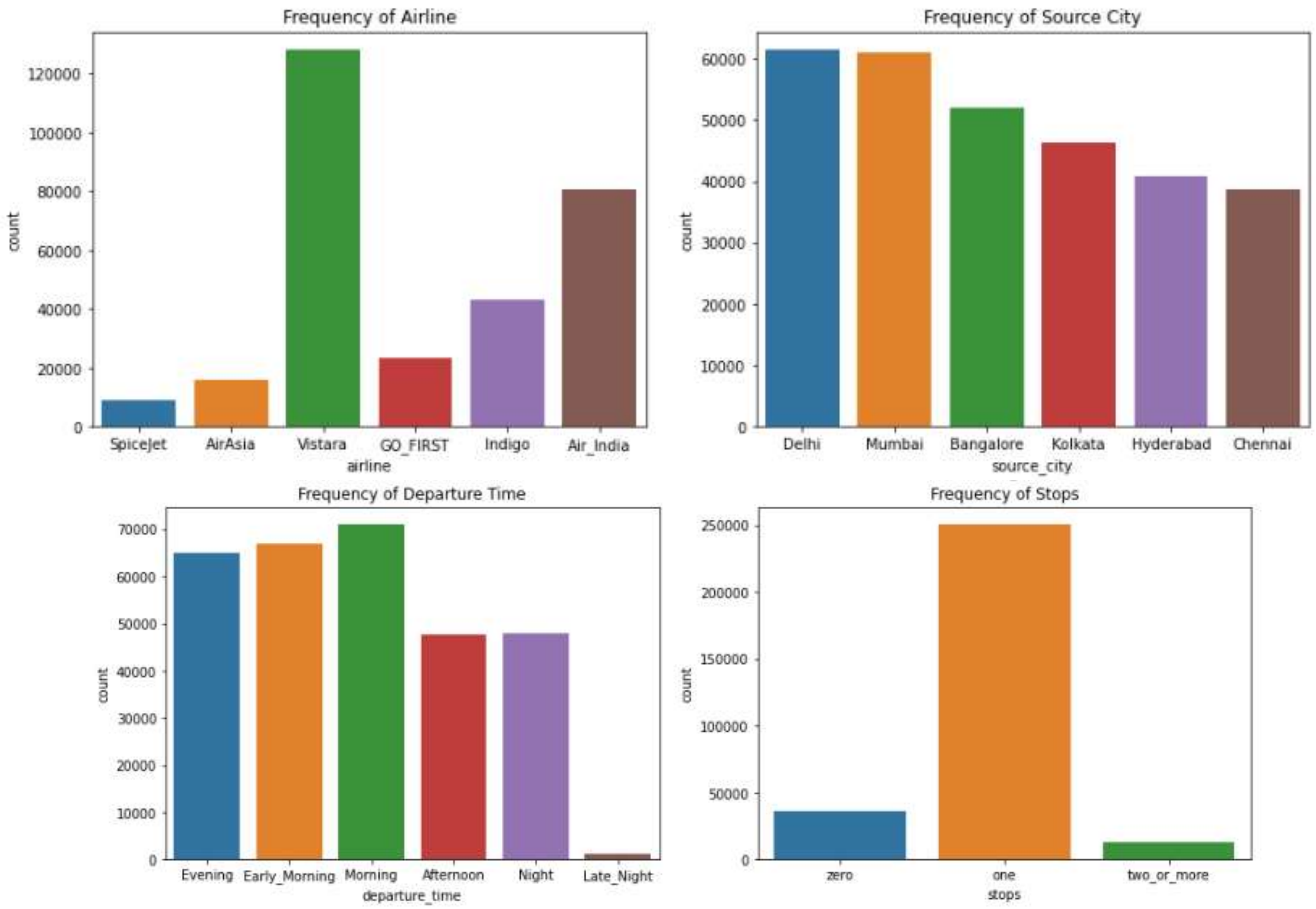
Range of price of flights with source and destination city according to the days left



Data Visualization

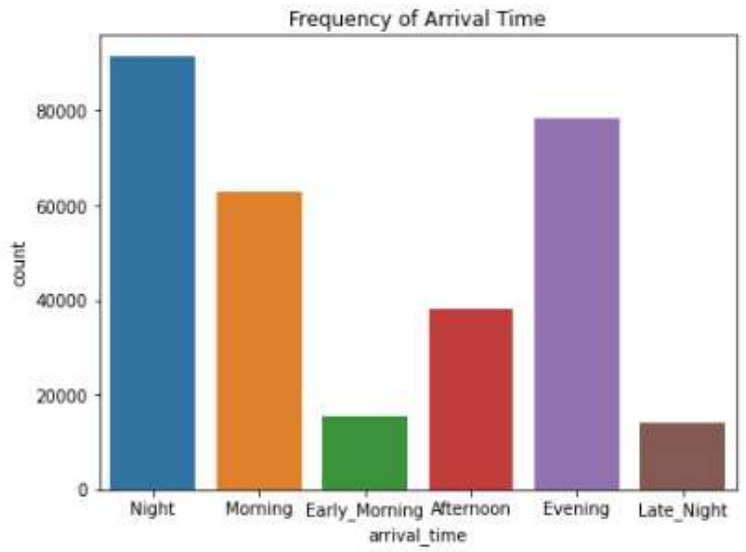
```
plt.figure(figsize=(15,23))

plt.subplot(4, 2, 1)
sns.countplot(x=df["airline"], data=df)
plt.title("Frequency of Airline")

plt.subplot(4, 2, 2)
sns.countplot(x=df["source_city"], data=df)
plt.title("Frequency of Source City")

plt.subplot(4, 2, 3)
sns.countplot(x=df["departure_time"], data=df)
plt.title("Frequency of Departure Time")

plt.subplot(4, 2, 4)
sns.countplot(x=df["stops"], data=df)
plt.title("Frequency of Stops")

plt.subplot(4, 2, 5)
sns.countplot(x=df["arrival_time"], data=df)
plt.title("Frequency of Arrival Time")

plt.subplot(4, 2, 6)
sns.countplot(x=df["destination_city"], data=df)
plt.title("Frequency of Destination City")

plt.subplot(4, 2, 7)
sns.countplot(x=df["class"], data=df)
plt.title("Class Frequency")

plt.show()
```

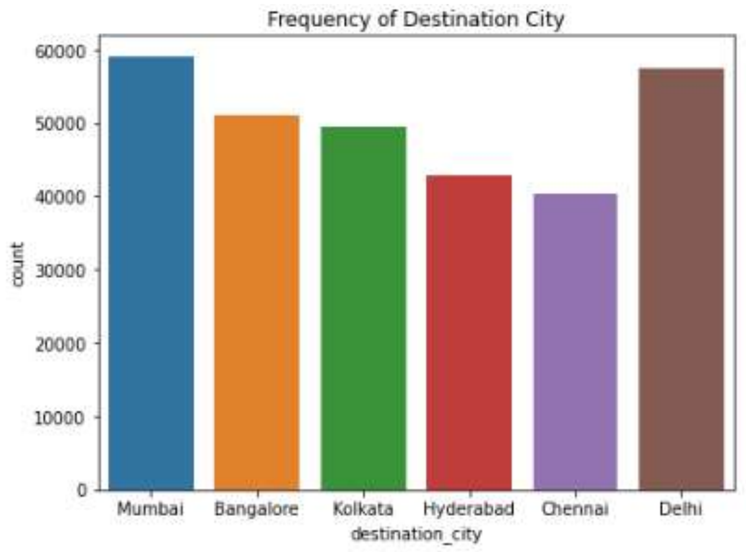
Visualization of categorical features with countplot

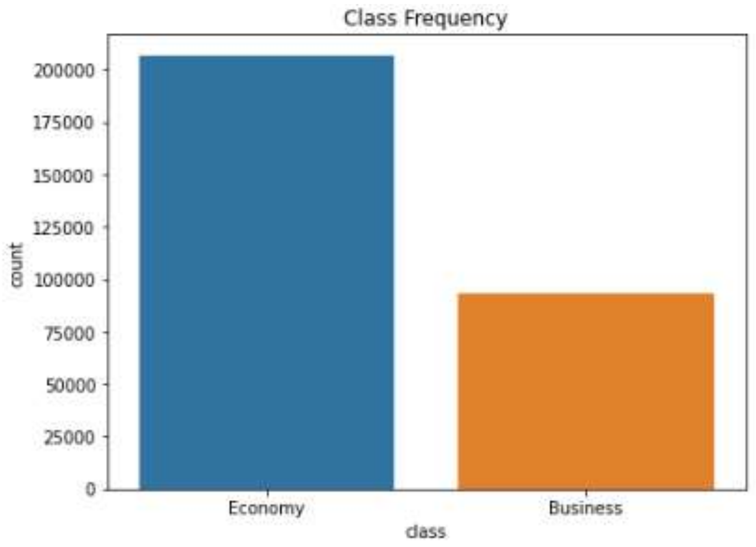


Data Visualization

Visualization of categorical features with countplot







Label Encoding

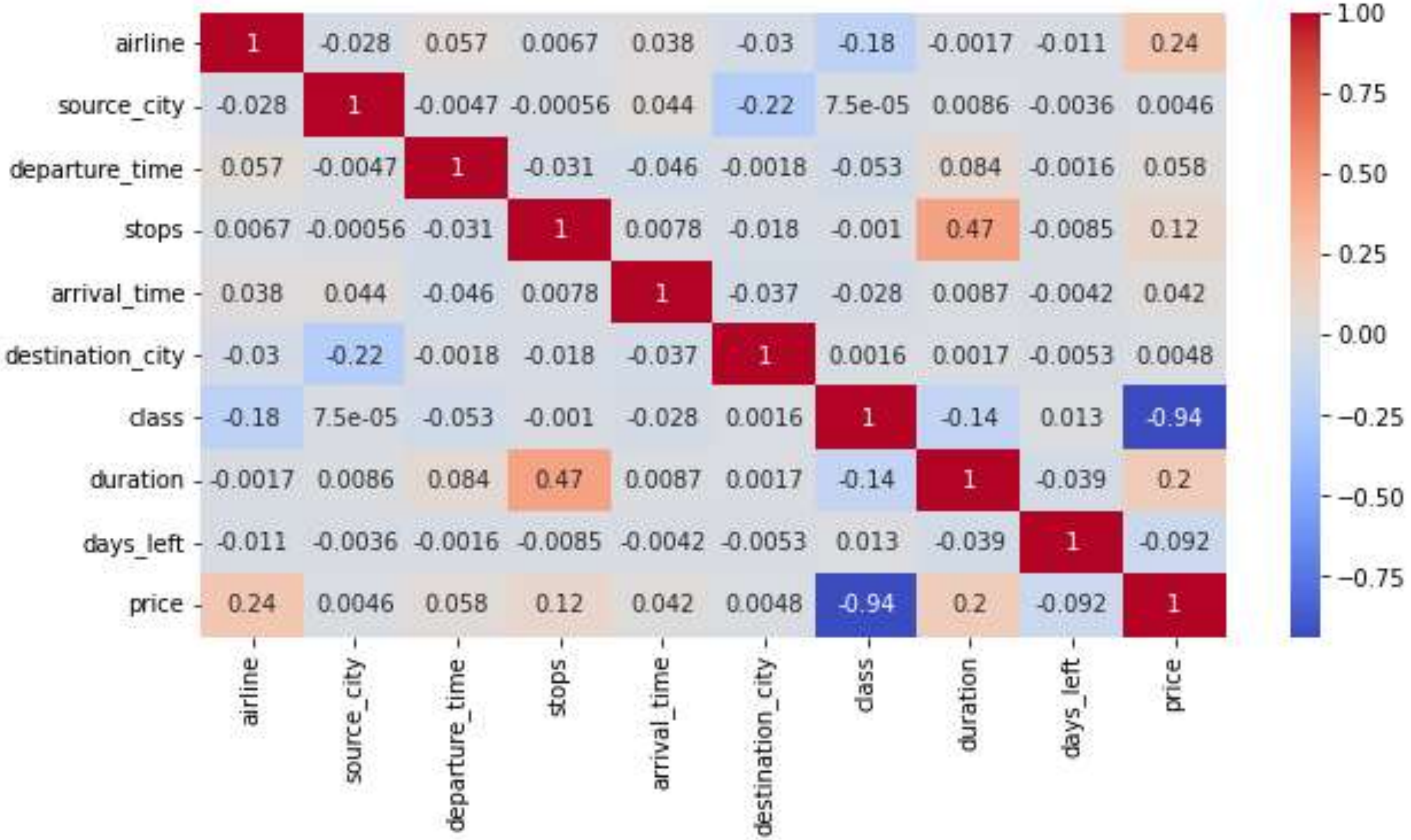
Performing One Hot Encoding for categorical features of a dataframe

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df["airline"]=le.fit_transform(df["airline"])
df["source_city"]=le.fit_transform(df["source_city"])
df["departure_time"]=le.fit_transform(df["departure_time"])
df["stops"]=le.fit_transform(df["stops"])
df["arrival_time"]=le.fit_transform(df["arrival_time"])
df["destination_city"]=le.fit_transform(df["destination_city"])
df["class"]=le.fit_transform(df["class"])
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  int64
 1   flight            300153 non-null  object
 2   source_city       300153 non-null  int64
 3   departure_time    300153 non-null  int64
 4   stops             300153 non-null  int64
 5   arrival_time      300153 non-null  int64
 6   destination_city  300153 non-null  int64
 7   class             300153 non-null  int64
 8   duration          300153 non-null  float64
 9   days_left         300153 non-null  int64
 10  price             300153 non-null  int64
dtypes: float64(1), int64(9), object(1)
memory usage: 25.2+ MB
```

Feature Selection

```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),annot=True,cmap="coolwarm")
plt.show()
```



Plotting the correlation graph to see the correlation between features and dependent variable.

Feature Selection

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
col_list = []
for col in df.columns:
    if ((df[col].dtype != 'object') & (col != 'price') ):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]
print(vif_data)
```

```
          feature       VIF
          airline  3.461766
      source_city  2.933064
   departure_time  2.746367
            stops  7.464236
     arrival_time  3.684695
 destination_city  2.893218
            class  2.917521
         duration  5.037943
        days_left  4.035735
```

Selecting the features using VIF. VIF should be less than 5. So drop the stops feature.

Feature Selection

```
df=df.drop(columns=["stops"])

from statsmodels.stats.outliers_influence import variance_inflation_factor
col_list = []
for col in df.columns:
    if ((df[col].dtype != 'object') & (col != 'price') ):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]
print(vif_data)
```

Dropping the stops column. All features are having VIF less than 5.

```
          feature       VIF
          airline  3.370020
      source_city  2.895803
   departure_time  2.746255
     arrival_time  3.632792
 destination_city  2.857808
            class  2.776721
         duration  3.429344
        days_left  3.950132
```

Linear Regression

Applying standardization and implementing Linear Regression Model to predict the price of a flight.

```
X = df.drop(columns=["price"])
y = df['price']
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x_train=sc.fit_transform(x_train)
x_test=sc.transform(x_test)
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
y_pred=lr.predict(x_test)
difference=pd.DataFrame(np.c_[y_test,y_pred],columns=["Actual_Value","Predicted_Value"])
difference
```

	Actual_Value	Predicted_Value
0	7366.0	4673.755319
1	64831.0	51713.744720
2	6195.0	6610.897658
3	60160.0	55489.844234
4	6578.0	5120.342596
...	...	...
60026	5026.0	4960.777767
60027	3001.0	4693.865426
60028	6734.0	4974.962678
60029	5082.0	2729.650066
60030	66465.0	59638.748598

Linear Regression

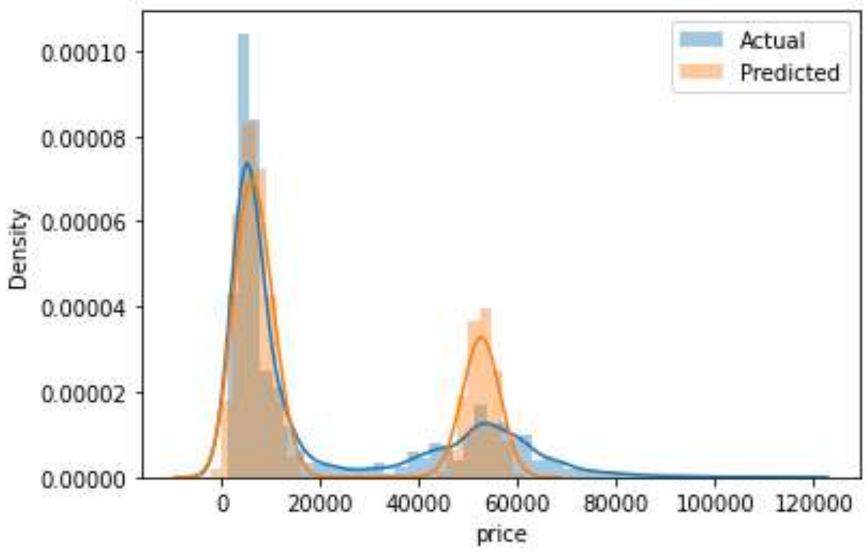
Calculating r2 score,MAE, MAPE, MSE, RMSE. Root Mean square error(RMSE) of the Linear regression model is 7259.93 and Mean absolute percentage error(MAPE) is 34 percent. Lower the RMSE and MAPE better the model.

```
from sklearn.metrics import r2_score
r2_score(y_test,y_pred)
from sklearn import metrics
mean_abs_error= metrics.mean_absolute_error(y_test,y_pred)
mean_abs_error
from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(y_test, y_pred)
mean_sq_error=metrics.mean_squared_error(y_test,y_pred)
mean_sq_error
root_mean_sq_error = np.sqrt(metrics.mean_squared_error(y_test,y_pred))
root_mean_sq_error
```

```
0.89775273751232l
4468.42667354211З
0.3476580461068184
52706651.33334208
7259.93466453673З
```

Linear Regression

```
sns.distplot(y_test,label="Actual")
sns.distplot(y_pred,label="Predicted")
plt.legend()
```



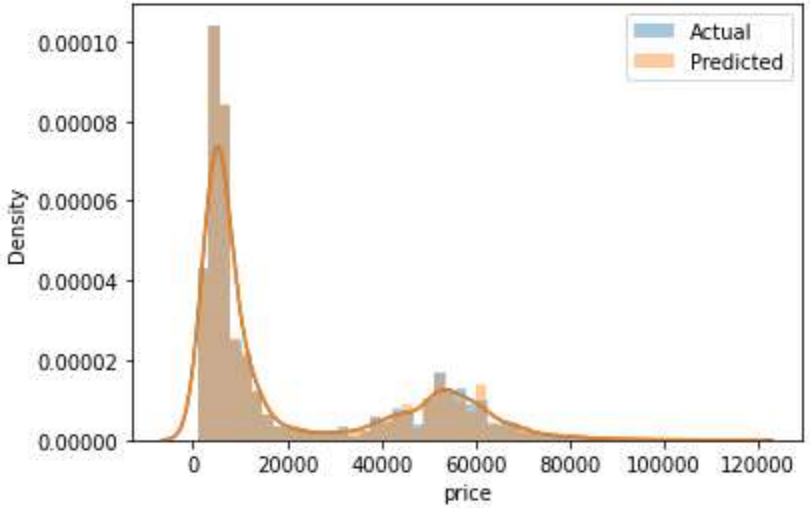
Plotting the graph of actual and predicted price of flight

Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor
dt=DecisionTreeRegressor()
dt.fit(x_train,y_train)
y_pred=dt.predict(x_test)
r2_score(y_test,y_pred)
mean_abs_error= metrics.mean_absolute_error(y_test,y_pred)
mean_abs_error
from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(y_test, y_pred)
mean_sq_error=metrics.mean_squared_error(y_test,y_pred)
mean_sq_error
root_mean_sq_error = np.sqrt(metrics.mean_squared_error(y_test,y_pred))
root_mean_sq_error
```

```
0.9745774442285287
1219.455742310917
0.07732296917115203
13104876.849009493
3620.0658625237047
```

Mean absolute percentage error is 7.7 percent and RMSE is 3620 which is less than the linear regression model



Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor
rfr=RandomForestRegressor()
rfr.fit(x_train,y_train)
y_pred=rfr.predict(x_test)
r2_score(y_test,y_pred)
mean_abs_error= metrics.mean_absolute_error(y_test,y_pred)
mean_abs_error
from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(y_test, y_pred)
mean_sq_error=metrics.mean_squared_error(y_test,y_pred)
mean_sq_error
root_mean_sq_error = np.sqrt(metrics.mean_squared_error(y_test,y_pred))
root_mean_sq_error
```

```
sns.distplot(y_test,label="Actual")
sns.distplot(y_pred,label="Predicted")
plt.legend()
```

```
0.9845246238799552
1122.6731295238862
0.07319114674216119
7977282.066694117
2824.4082684155487
```

Mean absolute percentage error is 7.3 percent and RMSE is 2824 which is less than the linear regression and decision tree model