Project Name : - Flight Fare Prediction

1) Problem statement.

- This dataset comprises of Flight Price taken from Kaggle
- Link of the dataset is as follows :- https://www.kaggle.com/datasets/nikhilmittal/flight-fare-prediction-mh
- A user can predict the price of the Flight Fare based on input features.
- Prediction results can be useful for traveller to get suggested price

2) Data Collection.

- This dataset comprises of Flight Fare data taken from Kaggle
- The data consists of 11 column and 10683 rows.

2.1 Import Data and Required Packages

Importing Pandas, Numpy, Matplotlib, Seaborn and Warings Library.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

Loading the Flight Fare Data

In [2]:
```
df=pd.read_excel("Data_train.xlsx")
df
```

Out[2]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Add
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Add
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	
...	...	...	...	...	...	...	...	...	...	
10678	Air Asia	9/04/2019	Kolkata	Banglore	CCU → BLR	19:55	22:25	2h 30m	non-stop	
10679	Air India	27/04/2019	Kolkata	Banglore	CCU → BLR	20:45	23:20	2h 35m	non-stop	
10680	Jet Airways	27/04/2019	Banglore	Delhi	BLR → DEL	08:20	11:20	3h	non-stop	
10681	Vistara	01/03/2019	Banglore	New Delhi	BLR → DEL	11:30	14:10	2h 40m	non-stop	
10682	Air India	9/05/2019	Delhi	Cochin	DEL → GOI → BOM → COK	10:55	19:15	8h 20m	2 stops	

10683 rows × 11 columns

Show Top 5 Records

In [3]:
```
df.head()
```

Out[3]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additiona
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	N
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	N
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	N
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	N
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	N

Shape of the DataSet

In [4]:
```
df.shape
```

Out[4]:
```
(10683, 11)
```

Summary of the DataSet

In [5]:
```python
# df.describe() Display summary statistics for a dataframe which has numerical columns
# since in this case we have only 1 numercial column df.describe() will come only for thes
df.describe()
```

Out[5]:

	Price
count	10683.000000
mean	9087.064121
std	4611.359167
min	1759.000000
25%	5277.000000
50%	8372.000000
75%	12373.000000
max	79512.000000

In [6]:
```python
#Check Null and Dtypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Airline          10683 non-null  object
 1   Date_of_Journey  10683 non-null  object
 2   Source           10683 non-null  object
 3   Destination      10683 non-null  object
 4   Route            10682 non-null  object
 5   Dep_Time         10683 non-null  object
 6   Arrival_Time     10683 non-null  object
 7   Duration         10683 non-null  object
 8   Total_Stops      10682 non-null  object
 9   Additional_Info  10683 non-null  object
 10  Price            10683 non-null  int64
dtypes: int64(1), object(10)
memory usage: 918.2+ KB
```

3. EXPLORING DATA

In [7]:
```python
# define numerical & categorical columns
numeric_features=[feature for feature in df.columns if df[feature].dtype != 'O']
categorical_features=[feature for feature in df.columns if df[feature].dtype == 'O']

#print columns
print(f'We have {len(numeric_features)} numerical features :{numeric_features}')
print(f'We have {len(categorical_features)} categorical features :{categorical_features}')
```

```
We have 1 numerical features :['Price']
We have 10 categorical features :['Airline', 'Date_of_Journey', 'Source', 'Destination',
'Route', 'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops', 'Additional_Info']
```

Feature Information

- **Airline:** Name of the Airline from which the Ticket is Booked.
- **Date_of_Journey:** Date of Journey of the Traveller.
- **Source:** Source from which the Airline Would Departure.
- **Destination:** Destination to Which Airline Would Arrive.
- **Route:** Route of the Airline from Source to Destination.
- **Dep_Time:** Time at which Flight Would Departure from the Source.
- **Arrival_Time:** Time at which Flight Would Arrive at the Destination.
- **Duration:** Duration that Airline Takes to fly from Source to Destination.
- **Total_Stops:** Total No of Stops that Airline takes Between Source and Destination.
- **Additional_Info:** Any Additional Info about the Airline.
- **Price:** Fare of the Ticket to fly from Source to Destination.

In [8]:

```
# proportion of count data of each categorical columns
for col in categorical_features:
    print(df[col].value_counts(normalize=True)*100)
    print('----------------------------')
```

```
Jet Airways                          36.029205
IndiGo                               19.217448
Air India                            16.399888
Multiple carriers                    11.195357
SpiceJet                              7.657025
Vistara                               4.483759
Air Asia                              2.986053
GoAir                                 1.815969
Multiple carriers Premium economy     0.121689
Jet Airways Business                  0.056164
Vistara Premium economy               0.028082
Trujet                                0.009361
Name: Airline, dtype: float64
----------------------------
18/05/2019    4.717776
6/06/2019     4.708415
21/05/2019    4.652251
9/06/2019     4.633530
12/06/2019    4.614809
9/05/2019     4.530563
21/03/2019    3.959562
15/05/2019    3.791070
27/05/2019    3.575775
27/06/2019    3.323037
24/06/2019    3.285594
1/06/2019     3.201348
3/06/2019     3.117102
15/06/2019    3.070299
24/03/2019    3.023495
6/03/2019     2.883085
27/03/2019    2.798839
24/05/2019    2.677151
6/05/2019     2.639708
1/05/2019     2.592905
12/05/2019    2.424413
1/04/2019     2.405691
3/03/2019     2.040625
9/03/2019     1.872133
15/03/2019    1.516428
18/03/2019    1.460264
01/03/2019    1.422821
12/03/2019    1.329215
9/04/2019     1.170083
3/04/2019     1.029673
```

```
21/06/2019    1.020313
18/06/2019    0.982870
09/03/2019    0.954788
6/04/2019     0.936067
03/03/2019    0.907985
06/03/2019    0.889263
27/04/2019    0.879903
24/04/2019    0.861181
3/05/2019     0.842460
15/04/2019    0.833099
21/04/2019    0.767575
18/04/2019    0.627165
12/04/2019    0.589722
1/03/2019     0.439951
Name: Date_of_Journey, dtype: float64
----------------------------
Delhi       42.469344
Kolkata     26.874473
Banglore    20.565384
Mumbai       6.524385
Chennai      3.566414
Name: Source, dtype: float64
----------------------------
Cochin       42.469344
Banglore     26.874473
Delhi        11.841243
New Delhi     8.724141
Hyderabad     6.524385
Kolkata       3.566414
Name: Destination, dtype: float64
----------------------------
DEL → BOM → COK          22.243026
BLR → DEL                14.529114
CCU → BOM → BLR           9.164950
CCU → BLR                 6.777757
BOM → HYD                 5.813518
                            ...
CCU → VTZ → BLR           0.009362
CCU → IXZ → MAA → BLR     0.009362
BOM → COK → MAA → HYD     0.009362
BOM → CCU → HYD           0.009362
BOM → BBI → HYD           0.009362
Name: Route, Length: 128, dtype: float64
----------------------------
18:55    2.181035
17:00    2.124871
07:05    1.918937
10:00    1.900215
07:10    1.890855
           ...
16:25    0.009361
01:35    0.009361
21:35    0.009361
04:15    0.009361
03:00    0.009361
Name: Dep_Time, Length: 222, dtype: float64
----------------------------
19:00           3.959562
21:00           3.369840
19:15           3.117102
16:10           1.441543
12:35           1.142001
                  ...
00:25 02 Jun    0.009361
08:55 13 Mar    0.009361
11:05 19 May    0.009361
```

```
12:30 22 May    0.009361
21:20 13 Mar    0.009361
Name: Arrival_Time, Length: 1343, dtype: float64
----------------------------
2h 50m     5.148367
1h 30m     3.613217
2h 45m     3.154545
2h 55m     3.154545
2h 35m     3.079659
             ...
31h 30m    0.009361
30h 25m    0.009361
42h 5m     0.009361
4h 10m     0.009361
47h 40m    0.009361
Name: Duration, Length: 368, dtype: float64
----------------------------
1 stop      52.658678
non-stop    32.681146
2 stops     14.229545
3 stops      0.421269
4 stops      0.009362
Name: Total_Stops, dtype: float64
----------------------------
No info                         78.114762
In-flight meal not included     18.552841
No check-in baggage included     2.995413
1 Long layover                   0.177853
Change airports                  0.065525
Business class                   0.037443
No Info                          0.028082
1 Short layover                  0.009361
Red-eye flight                   0.009361
2 Long layover                   0.009361
Name: Additional_Info, dtype: float64
----------------------------
```

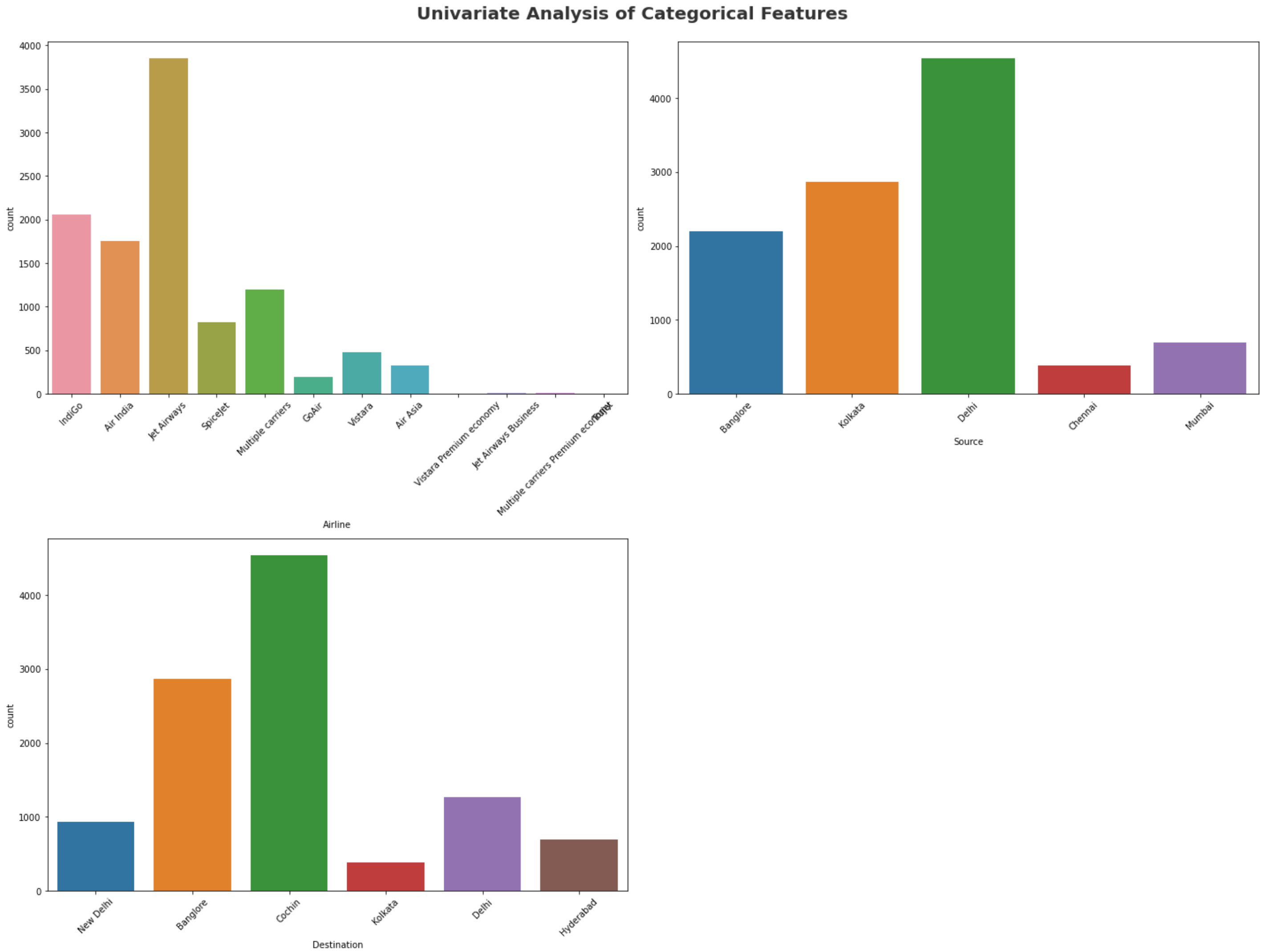
Univariate Analysis

- The term univariate analysis refers to the analysis of one variable prefix “uni” means “one.” The purpose of univariate analysis is to understand the distribution of values for a single variable.

Categorical Features

In [9]:

```
# categorical columns
plt.figure(figsize=(20,15))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fontweight='bold'
cat1 = [ 'Airline','Source', 'Destination']
for i in range(0, len(cat1)):
    plt.subplot(2,2,i+1)
    sns.countplot(x=df[cat1[i]])
    plt.xlabel(cat1[i])
    plt.xticks(rotation=45)
    plt.tight_layout()
```



Multivariate Analysis

- Multivariate analysis is the analysis of more than one variable.

Check Multicollinearity for Categorical features

- **A chi-squared test (also chi-square or χ2 test) is a statistical hypothesis test that is valid to perform when the test statistic is chi-squared distributed under the null hypothesis, specifically Pearson's chi-squared test**

- **A chi-square statistic is one way to show a relationship between two categorical variables.**

- **Here we test correlation of Categorical columns with Target column i.e Price**

In [10]:

```
from scipy.stats import chi2_contingency
chi2_test=[]
for feature in categorical_features:
    if chi2_contingency(pd.crosstab(df['Price'],df[feature]))[1] <0.05:
        chi2_test.append('Rejet Null Hypothesis')
    else:
        chi2_test.append('Fail to Reject Null Hypothesis')
result=pd.DataFrame(data=[categorical_features,chi2_test]).T
result.columns=['Column','Hypothesis Result']
result
```

Out[10]:

	Column	Hypothesis Result
0	Airline	Rejet Null Hypothesis
1	Date_of_Journey	Rejet Null Hypothesis
2	Source	Rejet Null Hypothesis
3	Destination	Rejet Null Hypothesis
4	Route	Rejet Null Hypothesis
5	Dep_Time	Rejet Null Hypothesis
6	Arrival_Time	Rejet Null Hypothesis
7	Duration	Rejet Null Hypothesis
8	Total_Stops	Rejet Null Hypothesis
9	Additional_Info	Rejet Null Hypothesis

Checking Null Values

In [11]:

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

Out[11]:

```
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              1
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        1
Additional_Info    0
Price              0
dtype: int64
```

Dropping the rows which has null values

In [12]:

```
df.dropna(inplace=True)
```

Now there are no null values

In [13]:

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

Out[13]:

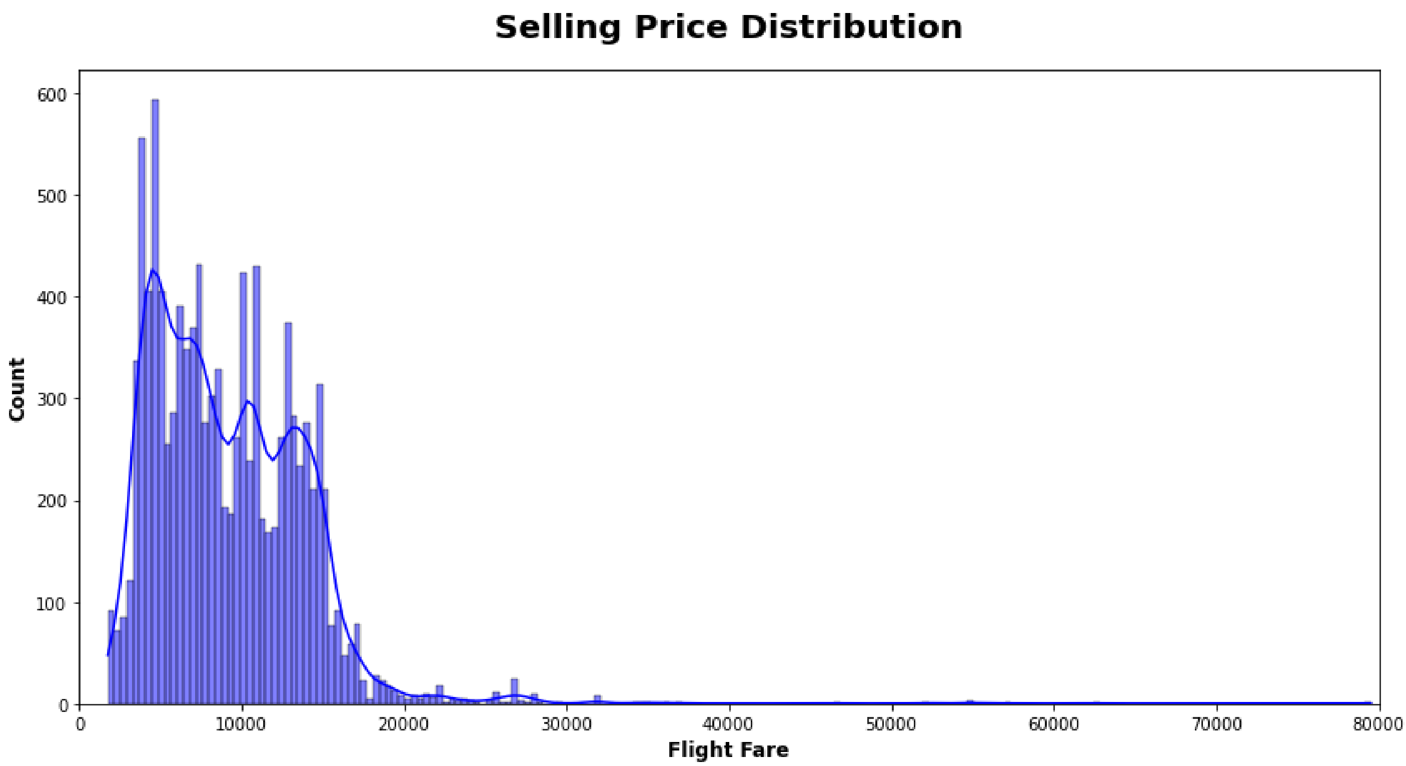
```
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              0
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        0
Additional_Info    0
Price              0
dtype: int64
```

Initial Analysis Report

Report

- **Jet Airways has highest customer footfall followed by Indigo and Air India .**
- **Jet Airways has a market Share of 36.03 % followed by Indigo which has a market share of 19.22 % and Air India Which has market share of 16.40 % .**
- **Delhi has the highest footfall for source and Cochin has the highest footfall for Destination .**

In [14]:
```
plt.subplots(figsize=(14,7))
sns.histplot(df.Price, bins=200, kde=True, color = 'b')
plt.title("Selling Price Distribution", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=12)
plt.xlabel("Flight Fare", weight="bold", fontsize=12)
plt.xlim(0,80000)
plt.show()
```



- From the chart it is clear that the Target Variable is Skewed

4.2 Top 10 Aviation Companies whose flight tickets are sold the most ?

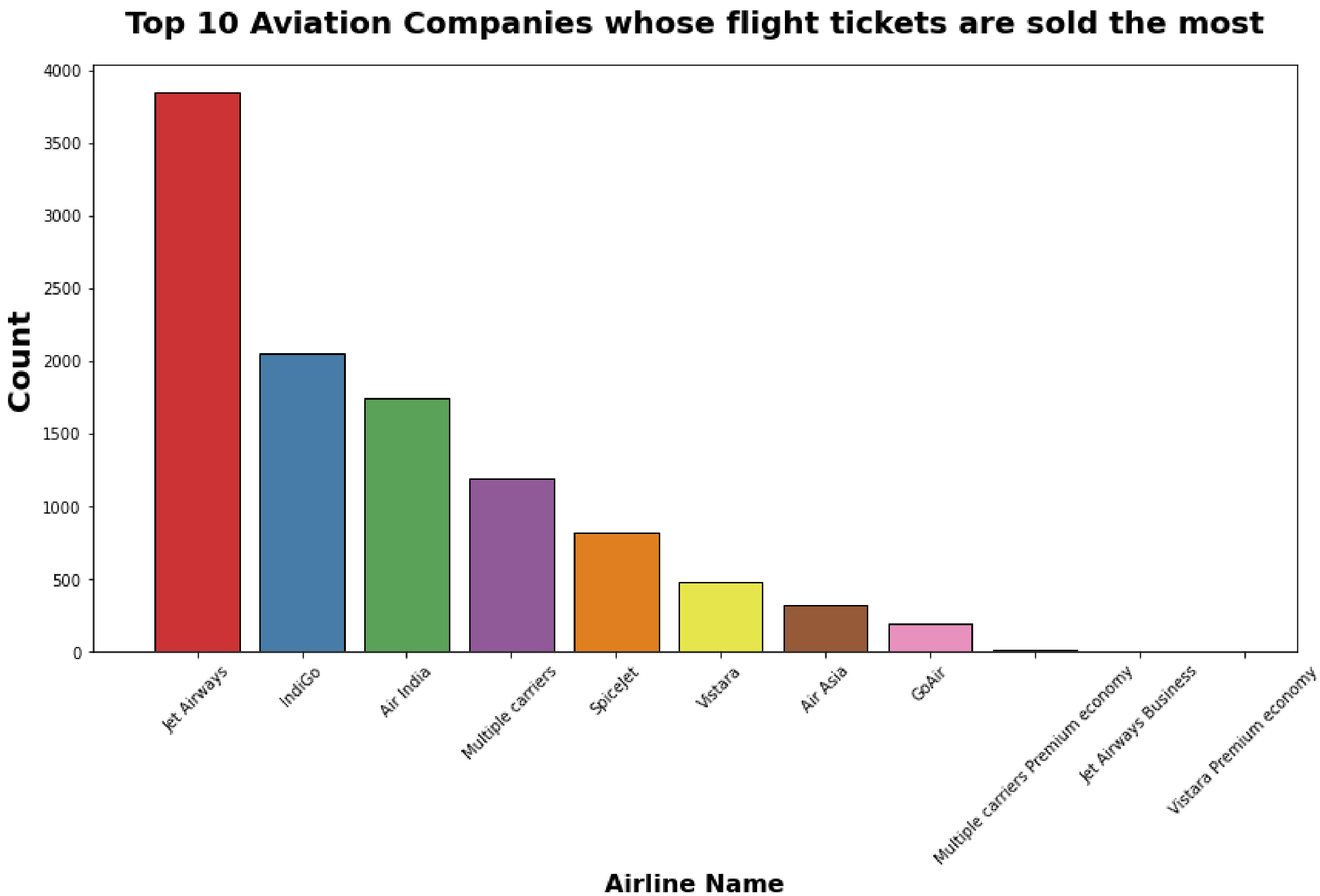
In [15]:
```
df.Airline.value_counts()[0:10]
```

Out[15]:
```
Jet Airways                          3849
IndiGo                               2053
Air India                            1751
Multiple carriers                    1196
SpiceJet                              818
Vistara                               479
Air Asia                              319
GoAir                                 194
Multiple carriers Premium economy      13
Jet Airways Business                    6
Name: Airline, dtype: int64
```

Most Sold Tickets are of Jet Airways Airline

In [16]:
```
plt.subplots(figsize=(14,7))
sns.countplot(x="Airline", data=df,ec = "black",palette="Set1",order = df['Airline'].value
```

```
plt.title("Top 10 Aviation Companies whose flight tickets are sold the most", weight="bolc
plt.ylabel("Count", weight="bold", fontsize=20)
plt.xlabel("Airline Name", weight="bold", fontsize=16)
plt.xticks(rotation= 45)
plt.xlim(-1,10.5)
plt.show()
```



Check mean price of Jet Airways whose flight tickets are sold the most

In [17]:
```
jet_airways = df[df['Airline'] == 'Jet Airways']['Price'].mean()
print(f'The mean price of Jet Airways Flight Tickets  is {jet_airways:.2f} Rupees')
```

```
The mean price of Jet Airways Flight Tickets  is 11643.92 Rupees
```

Report:

- As per the Chart these are top 10 aviation companies whose tickets are sold the most.
- Of the total flight tickets sold Jet Airways has the highest share followed by Indigo .
- Mean Price of Jet Airways Flight Ticket is Rs 11,643.92.
- This Feature has impact on the Target Variable.

In [18]:
```
## Costliest Aviation Companies and Costliest Flight Tickets
```

In [19]:
```
aviation_company_airline = df.groupby('Airline').Price.max()
aviation_company= aviation_company_airline.to_frame().sort_values('Price',ascending=False)
aviation_company
```

Out[19]:

Price

	Price
Airline	
Jet Airways Business	79512
Jet Airways	54826
Multiple carriers	36983
Air India	31945
SpiceJet	23267
GoAir	22794
IndiGo	22153
Vistara	21730
Multiple carriers Premium economy	14629
Air Asia	13774

In [20]:

```
plt.subplots(figsize=(14,7))
sns.barplot(x=aviation_company_airline.index, y=aviation_company_airline.values,ec = "blac
plt.title("Airlines Company vs Flight Ticket Price", weight="bold",fontsize=20, pad=20)
plt.ylabel("Flight Ticket Price", weight="bold", fontsize=15)
plt.xlabel("Airlines Name", weight="bold", fontsize=16)
plt.xticks(rotation=90)
plt.show()
```

Report:

- Costliest Flight Tickets Sold is of Jet Airways Business .
- Second Most Costliest Flight Tickets Sold is of Jet Airways .
- As can be seen, the airline's name is important. The most expensive option is 'JetAirways Business.' The cost of other carriers varies as well.
- We'll use one-hot encoding to handle the Airline variable because it's Nominal Categorical Data (airline names have no order of any kind).

Extracting Date & Month from Date of Journey Column

Converting into Datetime:

- We are going to extract the date and month from the date of the journey .
- For this, we require pandas to_datetime to convert the object data type to DateTime data type .
- .dt.day the method will extract only the day from the date.
- .dt.month the method will extract only the month of that date.

Date

In [21]:

```
df["journey_Date"]= pd.to_datetime(df['Date_of_Journey'], format= "%d/%m/%Y").dt.day
```

Month

In [22]:
```
df["journey_Month"]= pd.to_datetime(df['Date_of_Journey'], format= "%d/%m/%Y").dt.month
```

Checking the New Date & Month Column

In [23]:
```
df.head()
```

Out[23]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additiona
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	N
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	N
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	N
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	N
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	N

Since we have extracted Date of Journey column into Date & Month, Now we can drop it as Original Date of Journey column is of no use.

In [24]:
```
df.drop(['Date_of_Journey'],axis=1,inplace=True)
```

Departure time is when a plane leaves the Source .

Similar to Date of Journey we can extract values from Departure Time

So we will be extracting Hour & Minutes from Departure Time Column

In [25]:
```
# Extracting Hours
df['Dep_hour']=pd.to_datetime(df['Dep_Time']).dt.hour   #pd.to_datetime
```

```
#Extracting minutes
df['Dep_min']=pd.to_datetime(df['Dep_Time']).dt.minute

#Now we will drop the dep_time, no use
df.drop(['Dep_Time'],axis=1,inplace=True)
```

Arrival time is when a plane reaches the destination.

Similar to Date of Journey we can extract values from Arrival Time

So we will be extracting Hour & Minutes from Arrival Time Column

In [26]:

```
# Extracting Hours
df['Arrival_hour']=pd.to_datetime(df['Arrival_Time']).dt.hour   #pd.to_datetime

#Extracting minutes
df['Arrival_min']=pd.to_datetime(df['Arrival_Time']).dt.minute

#Now we will drop the dep_time, no use
df.drop(['Arrival_Time'],axis=1,inplace=True)
```

Let's look at the data.

In [27]:

```
df.head()
```

Out[27]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	journey_Date	journey_Mont
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	24	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	7662	1	
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	19h	2 stops	No info	13882	9	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	5h 25m	1 stop	No info	6218	12	
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	4h 45m	1 stop	No info	13302	1	

“Duration” column:

Here we are trying to extract the hours and minutes from the feature “duration”.

In [28]:

```
# Assigning and converting Duration column into list to extract hours ans minutes seperate
duration = list(df["Duration"])
for i in range(len(duration)):
    if len(duration[i].split()) !=2:  # Check if duration contains only hour or mins
        if "h" in duration[i]:
            duration[i] = duration[i].strip() + " 0m"    # Adds 0 minute
        else:
            duration[i] = "0h " + duration[i]            # Adds 0 hour

duration_hours = []
duration_mins = []
for i in range(len(duration)):
    duration_hours.append(int(duration[i].split(sep = "h")[0]))    # Extract hours from du
    duration_mins.append(int(duration[i].split(sep = "m")[0].split()[-1]))    # Extracts on
```

Adding “duration_hours” and “duration_mins” list to df data frame and dropping the column “duration” from it.

In [29]:

```
df["Duration_hours"] = duration_hours
df["Duration_mins"] = duration_mins

#we will remove the Durtaion column
df.drop(['Duration'],axis=1,inplace=True)
```

Handling Categorical Data:

Airline, Source, Destination, Route, Total_Stops, Additional_info are the categorical variables we have in our data.

Let’s handle each one by one.

Nominal data → are not in any order → OneHotEncoder is used in this case

Ordinal data → are in order → LabelEncoder is used in this case

Trying to find out unique values in column Airline and counts of the unique values as well.

One-hot encoding:

Another typical technique for dealing with categorical information is, one-hot encoding. It simply adds more characteristics to the categorical feature dependent on the number of unique values. Every category’s unique value will be added as a feature.

The method of constructing dummy variables is known as one-hot encoding.

Each category is represented as a single-hot vector in this encoding technique.

In [ ]:

```

```

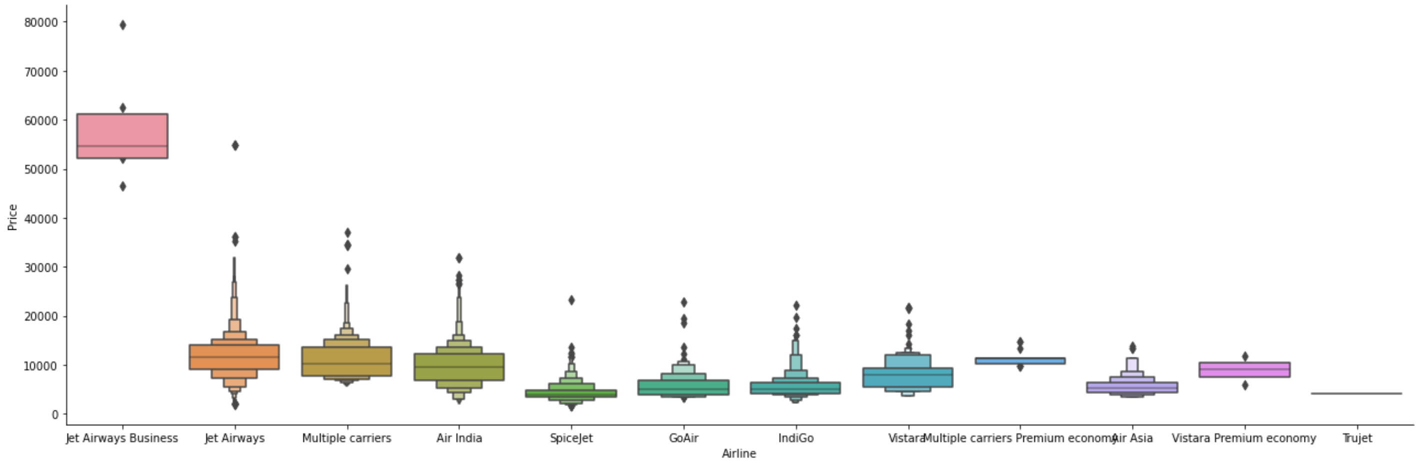
Boxplots

Airline vs Price:

- Let's see how the Airline variable is related to the Price variable.

Airline vs Price

In [30]:
```
sns.catplot(y = "Price", x = "Airline", data = df.sort_values("Price", ascending = False),
plt.show()
```



From the Above we can see that Jet Airways Business has premium flight fares as compared to other Airlines

In [31]:
```
#OneHotEncoding -----> Nominal data
Airline = df[["Airline"]]
Airline = pd.get_dummies(df['Airline'],drop_first=False)
Airline.head()
```

Out[31]:

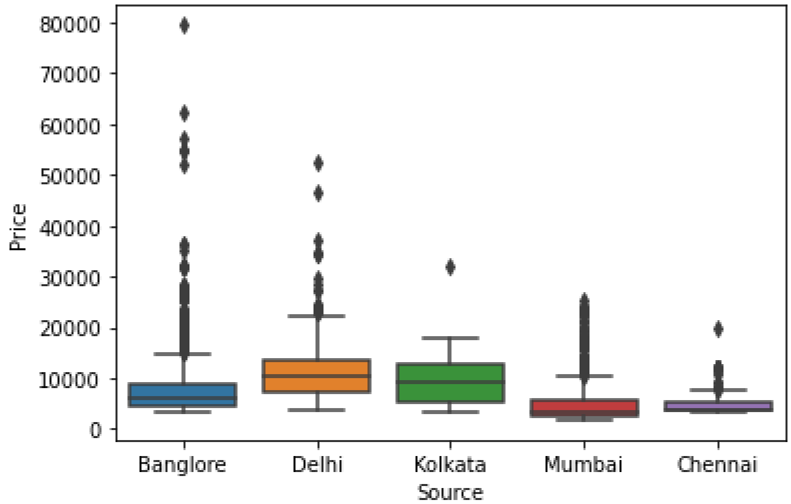
	Air Asia	Air India	GoAir	IndiGo	Jet Airways	Jet Airways Business	Multiple carriers	Multiple carriers Premium economy	SpiceJet	Trujet	Vistara	Vistara Premium economy
0	0	0	0	1	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	1	0	0	0	0	0	0	0
3	0	0	0	1	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0	0

Source vs Destination:

- Again, the variables 'Source' and 'Destination' are Nominal Categorical Data. To deal with these two variables, we'll employ One-Hot encoding once more.

Source vs Price

In [32]:
```
sns.boxplot(y = "Price", x = "Source", data = df.sort_values("Price", ascending = False))
plt.show()
```



From the Above we can see that Flights Originating From Banglore has high flight fares as compared to other sources from where flights are originating

In [33]:
```
#OneHotEncoding -----> Nominal data
Source = df[["Source"]]
Source = pd.get_dummies(df['Source'],drop_first=True)
Source.head()
```

Out[33]:

	Chennai	Delhi	Kolkata	Mumbai
0	0	0	0	0
1	0	0	1	0
2	0	1	0	0
3	0	0	1	0
4	0	0	0	0

In [34]:
```
# As Destination is Nominal Categorical data we will perform OneHotEncoding

Destination = df[["Destination"]]

Destination = pd.get_dummies(Destination, drop_first = True)

Destination.head()
```

Out[34]:

	Destination_Cochin	Destination_Delhi	Destination_Hyderabad	Destination_Kolkata	Destination_New Delhi
0	0	0	0	0	1
1	0	0	0	0	0
2	1	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	1

Variable route:

- The journey’s path is represented by the route variable.
- I opted to remove this field because the ‘Total Stops’ value captures whether the flight is direct or connected.

In [35]:

```
# droping column, because Additinal_info has since 80 % has no information
# Route---> is related to no of stops
df.drop(["Route", "Additional_Info"], axis = 1, inplace = True)
```

Total_Stops Variable:

- Non-stop refers to a flight with no stops, i.e. a straight flight. It is self-evident that other values have the same meaning. We can see that it’s Ordinal Categorical Data, thus we’ll use LabelEncoder to deal with it.

In [36]:

```
df['Total_Stops'].value_counts()
# As this is case of Ordinal Categorical type we perform LabelEncoder
#we replace the values in key values
df.replace({'non-stop':0,'1 stop':1,'2 stops':2,'3 stops':3,'4 stops':4},inplace=True)
df.head()
```

Out[36]:

	Airline	Source	Destination	Total_Stops	Price	journey_Date	journey_Month	Dep_hour	Dep_min	Arrival_hou
0	IndiGo	Banglore	New Delhi	0	3897	24	3	22	20	
1	Air India	Kolkata	Banglore	2	7662	1	5	5	50	
2	Jet Airways	Delhi	Cochin	2	13882	9	6	9	25	
3	IndiGo	Kolkata	Banglore	1	6218	12	5	18	5	
4	IndiGo	Banglore	New Delhi	1	13302	1	3	16	50	

Correlation:

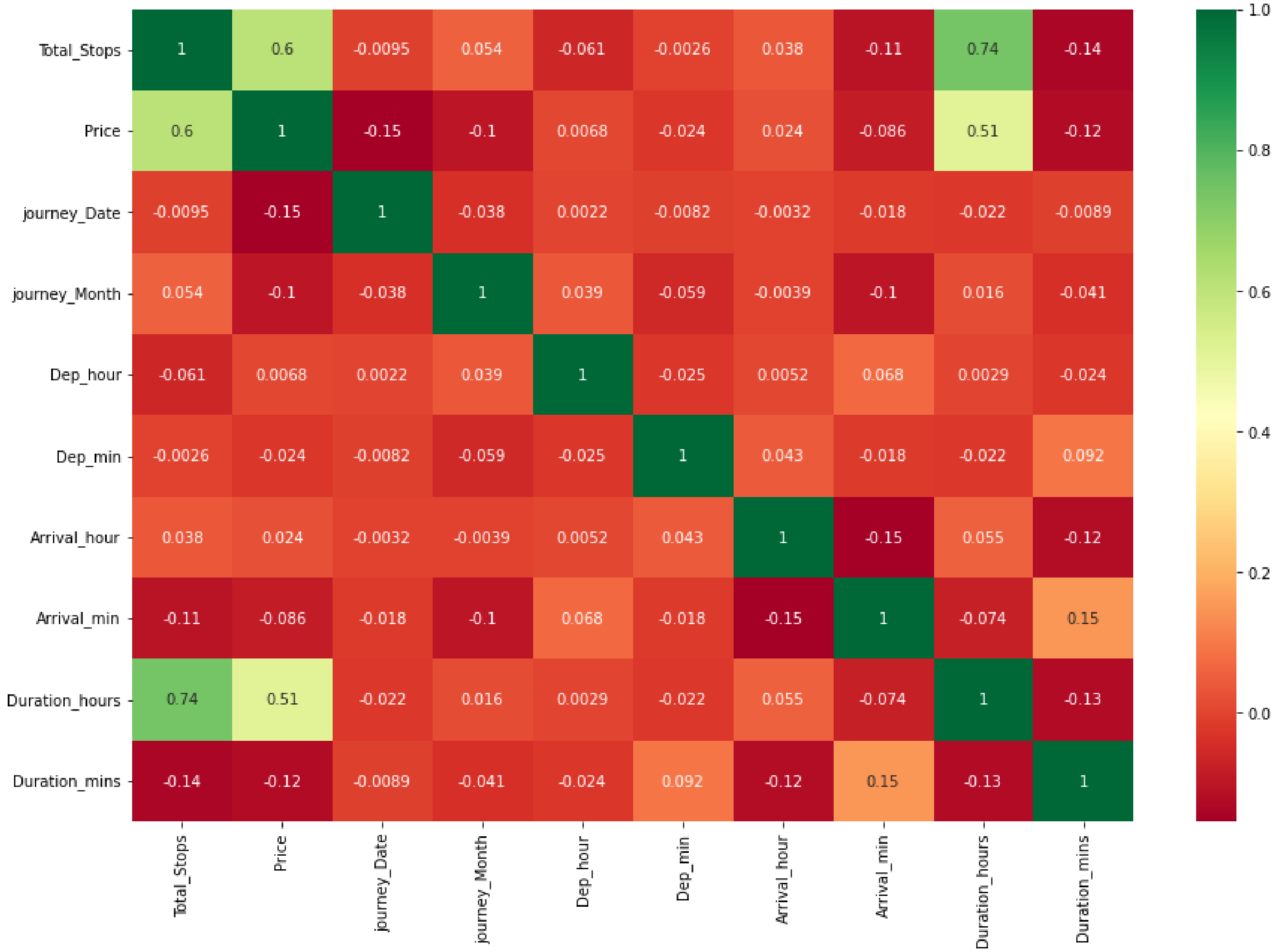
- Correlation is a technique for determining the link between two variables, which is useful in real life since it allows us to forecast the value of one variable using other factors that are connected with it. Because two variables are involved, it is a sort of bivariate statistic.

In [37]:

```
# Heatmap
plt.figure(figsize=(15,10))
sns.heatmap(df.corr(),annot = True, cmap = "RdYlGn")
```

Out[37]:

```
<AxesSubplot:>
```



Final Dataframe:

- Now we'll join all of the One-hot and Label-encoded features to the original data frame to make the final data frame. We'll also get rid of the old variables that we used to create the new encoded variables.

In [38]:

```
#Concatenate dataframe --> df+ Airline + Source + Destination
data_train=pd.concat([df,Airline , Source, Destination],axis=1)
# we have drop the varibles
data_train.drop(["Airline","Source","Destination"],axis=1,inplace=True)
data_train.head()
```

Out[38]:

	Total_Stops	Price	journey_Date	journey_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours
0	0	3897	24	3	22	20	1	10	2
1	2	7662	1	5	5	50	13	15	7
2	2	13882	9	6	9	25	4	25	19
3	1	6218	12	5	18	5	23	30	5
4	1	13302	1	3	16	50	21	35	4

5 rows × 31 columns

As a result, the final data frame has 30 variables, including the dependent variable 'Price.' For training, there are only 29variables.

Test Data:

We are going to repeat all these steps for test data as well.

Importing test data:

In [39]:

```
test_data= pd.read_excel("Test_Set.xlsx")
test_data.head()
```

Out[39]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Addition
0	Jet Airways	6/06/2019	Delhi	Cochin	DEL → BOM → COK	17:30	04:25 07 Jun	10h 55m	1 stop	
1	IndiGo	12/05/2019	Kolkata	Banglore	CCU → MAA → BLR	06:20	10:20	4h	1 stop	
2	Jet Airways	21/05/2019	Delhi	Cochin	DEL → BOM → COK	19:15	19:00 22 May	23h 45m	1 stop	In-flig not ir
3	Multiple carriers	21/05/2019	Delhi	Cochin	DEL → BOM → COK	08:00	21:00	13h	1 stop	
4	Air Asia	24/06/2019	Banglore	Delhi	BLR → DEL	23:55	02:45 25 Jun	2h 50m	non-stop	

In [40]:

```
# Preprocessing


print(test_data.info())


test_data.dropna(inplace = True)
print(test_data.isnull().sum())

# EDA

# Date_of_Journey
test_data["Journey_day"] = pd.to_datetime(test_data.Date_of_Journey, format="%d/%m/%Y").dt
test_data["Journey_month"] = pd.to_datetime(test_data["Date_of_Journey"], format = "%d/%m/
test_data.drop(["Date_of_Journey"], axis = 1, inplace = True)

# Dep_Time
test_data["Dep_hour"] = pd.to_datetime(test_data["Dep_Time"]).dt.hour
test_data["Dep_min"] = pd.to_datetime(test_data["Dep_Time"]).dt.minute
test_data.drop(["Dep_Time"], axis = 1, inplace = True)

# Arrival_Time
test_data["Arrival_hour"] = pd.to_datetime(test_data.Arrival_Time).dt.hour
test_data["Arrival_min"] = pd.to_datetime(test_data.Arrival_Time).dt.minute
test_data.drop(["Arrival_Time"], axis = 1, inplace = True)

# Duration
duration = list(test_data["Duration"])
```

```
for i in range(len(duration)):
    if len(duration[i].split()) != 2:    # Check if duration contains only hour or mins
        if "h" in duration[i]:
            duration[i] = duration[i].strip() + " 0m"   # Adds 0 minute
        else:
            duration[i] = "0h " + duration[i]           # Adds 0 hour

duration_hours = []
duration_mins = []
for i in range(len(duration)):
    duration_hours.append(int(duration[i].split(sep = "h")[0]))    # Extract hours from du
    duration_mins.append(int(duration[i].split(sep = "m")[0].split()[-1]))   # Extracts or

# Adding Duration column to test set
test_data["Duration_hours"] = duration_hours
test_data["Duration_mins"] = duration_mins
test_data.drop(["Duration"], axis = 1, inplace = True)


# Categorical data

print("Airline")
print("-"*75)
print(test_data["Airline"].value_counts())
Airline = pd.get_dummies(test_data["Airline"], drop_first= True)





print(test_data["Source"].value_counts())
Source = pd.get_dummies(test_data["Source"], drop_first= True)





print(test_data["Destination"].value_counts())
Destination = pd.get_dummies(test_data["Destination"], drop_first = True)

# Additional_Info contains almost 80% no_info
# Route and Total_Stops are related to each other
test_data.drop(["Route", "Additional_Info"], axis = 1, inplace = True)

# Replacing Total_Stops
test_data.replace({"non-stop": 0, "1 stop": 1, "2 stops": 2, "3 stops": 3, "4 stops": 4},

# Concatenate dataframe --> test_data + Airline + Source + Destination
data_test = pd.concat([test_data, Airline, Source, Destination], axis = 1)

data_test.drop(["Airline", "Source", "Destination"], axis = 1, inplace = True)

print()
print()

print("Shape of test data : ", data_test.shape)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2671 entries, 0 to 2670
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Airline          2671 non-null   object
 1   Date_of_Journey  2671 non-null   object
 2   Source           2671 non-null   object
 3   Destination      2671 non-null   object
 4   Route            2671 non-null   object
```

```
 5   Dep_Time         2671 non-null   object
 6   Arrival_Time     2671 non-null   object
 7   Duration         2671 non-null   object
 8   Total_Stops      2671 non-null   object
 9   Additional_Info  2671 non-null   object
dtypes: object(10)
memory usage: 208.8+ KB
None
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              0
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        0
Additional_Info    0
dtype: int64
Airline
---------------------------------------------------------------------------
Jet Airways                          897
IndiGo                               511
Air India                            440
Multiple carriers                    347
SpiceJet                             208
Vistara                              129
Air Asia                              86
GoAir                                 46
Multiple carriers Premium economy      3
Vistara Premium economy                2
Jet Airways Business                   2
Name: Airline, dtype: int64
Delhi       1145
Kolkata      710
Banglore     555
Mumbai       186
Chennai       75
Name: Source, dtype: int64
Cochin       1145
Banglore      710
Delhi         317
New Delhi     238
Hyderabad     186
Kolkata        75
Name: Destination, dtype: int64


Shape of test data :  (2671, 28)
```

5. Now we Will Build a Machine Learning Model Using Random Forest Algorithm

In [41]:

```
x= data_train[['Total_Stops', 'journey_Date', 'journey_Month', 'Dep_hour',
       'Dep_min', 'Arrival_hour', 'Arrival_min', 'Duration_hours',
       'Duration_mins', 'Air India', 'GoAir', 'IndiGo', 'Jet Airways',
       'Jet Airways Business', 'Multiple carriers',
       'Multiple carriers Premium economy', 'SpiceJet', 'Trujet', 'Vistara',
       'Vistara Premium economy', 'Chennai', 'Delhi', 'Kolkata', 'Mumbai',
       'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad',
       'Destination_Kolkata', 'Destination_New Delhi']]
x.head()
```

Out[41]:

	Total_Stops	journey_Date	journey_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Durati
0	0	24	3	22	20	1	10	2	
1	2	1	5	5	50	13	15	7	
2	2	9	6	9	25	4	25	19	
3	1	12	5	18	5	23	30	5	
4	1	1	3	16	50	21	35	4	

5 rows × 29 columns

In [42]:

```
y=data_train['Price']
```

Feature importance:

- In machine learning, the purpose of feature selection is to discover the best set of characteristics that allows one to develop usable models of the phenomena being examined.

In [43]:

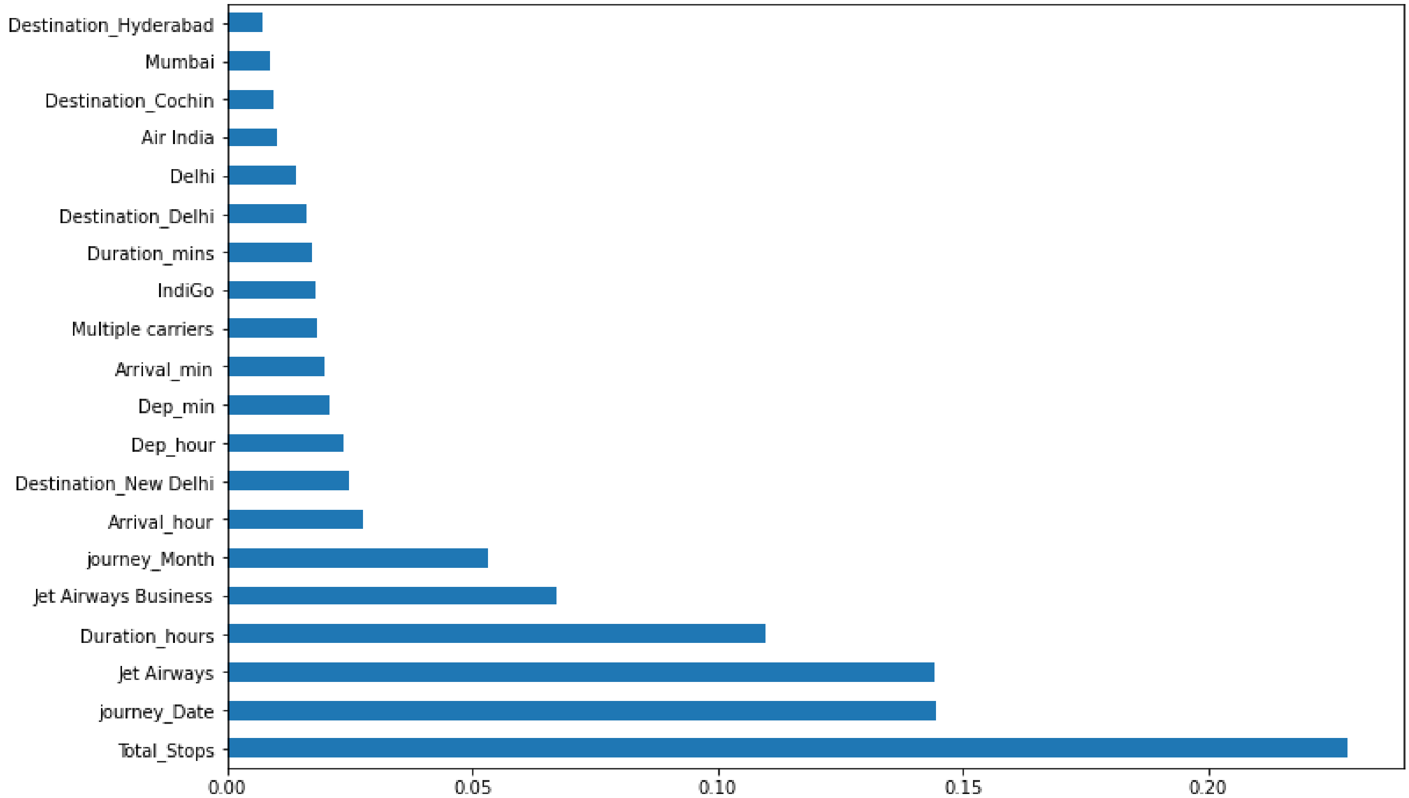
```
# Important feature using ExtraTreesRegressor
from sklearn.ensemble import ExtraTreesRegressor
selection = ExtraTreesRegressor()
selection.fit(x, y)
```

Out[43]:

```
▾ ExtraTreesRegressor
ExtraTreesRegressor()
```

In [44]:

```
#plot graph of feature importances for better visualization
plt.figure(figsize = (12,8))
feat_importances = pd.Series(selection.feature_importances_, index=x.columns)
feat_importances.nlargest(20).plot(kind='barh')
plt.show()
```

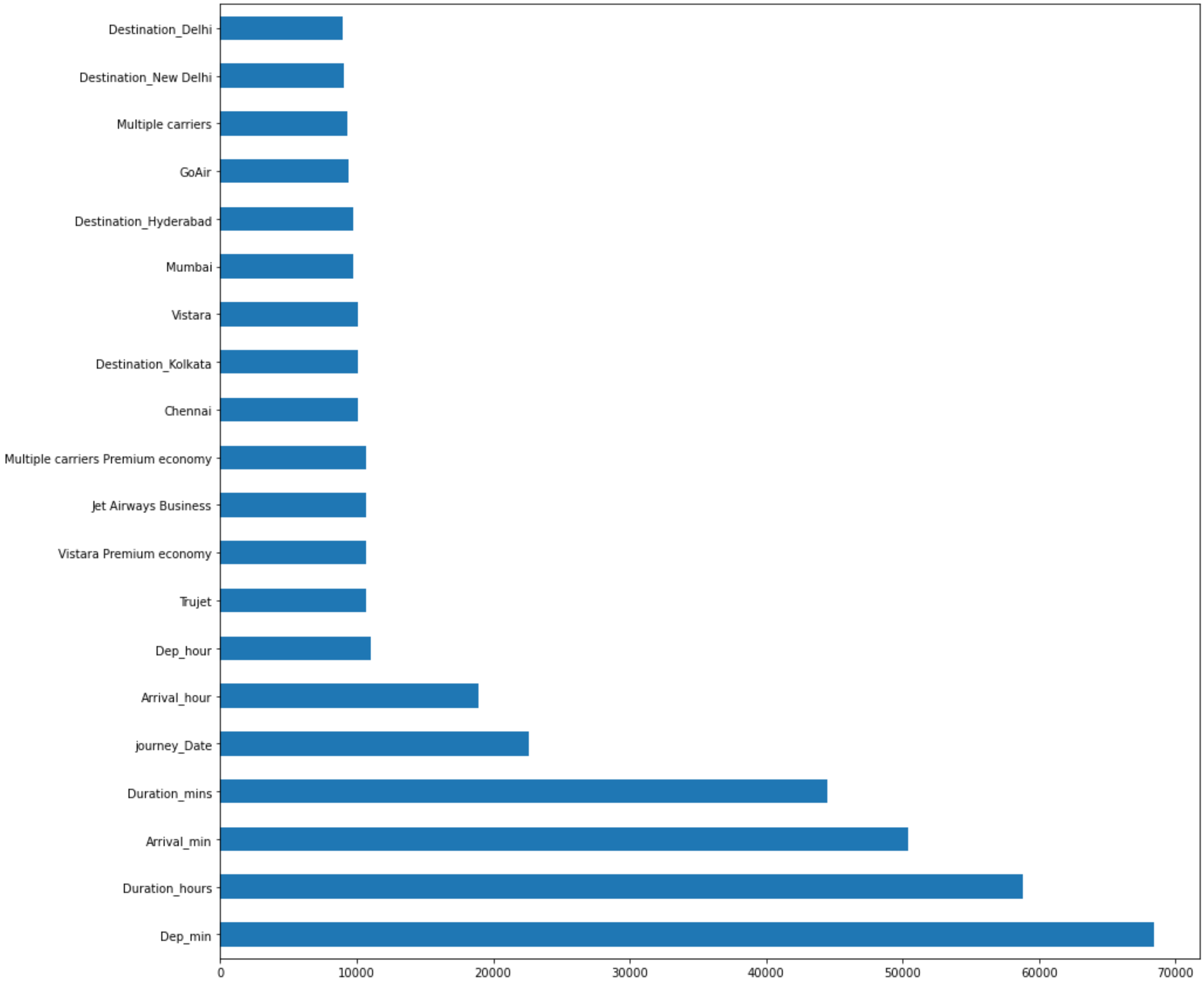


In [45]:

```
# import library
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
#Deifne feature selection
fs=SelectKBest(score_func=chi2)
# Applying feature selection
X_selected=fs.fit(x,y)
```

In [46]:

```
plt.figure(figsize=(15,15))
feat_importances = pd.Series(X_selected.scores_, index=x.columns)
feat_importances.nlargest(20).plot(kind='barh')
plt.show()
```



In [47]:
```
#Splitting the Data into Train & Test Split
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=32)
```

In [48]:
```
from sklearn.ensemble import RandomForestRegressor
random_forest=RandomForestRegressor()
```

In [49]:
```
random_forest.fit(x_train,y_train)
```

Out[49]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

R2 SCORE

In [50]:
```
random_forest.score(x_test,y_test)
```

Out[50]:
```
0.8164403978288426
```

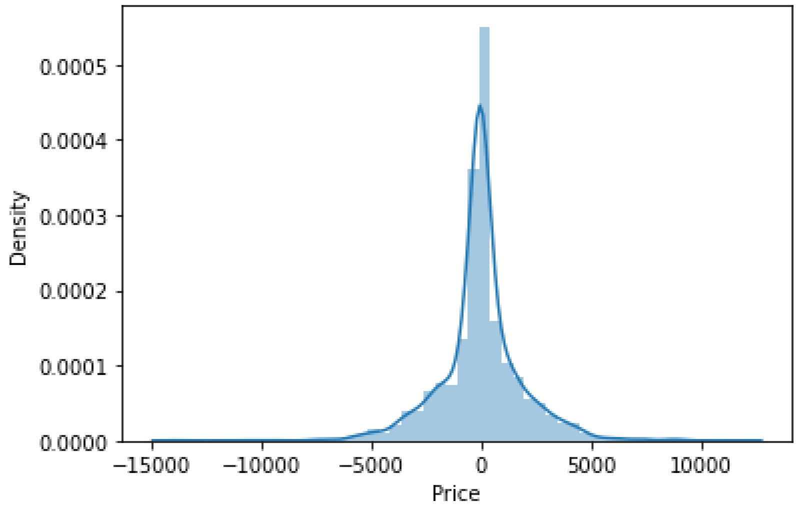
In [51]:
```
random_forest.score(x_train,y_train)
```

Out[51]: 0.9555361870581005

In [52]:
```
y_pred=random_forest.predict(x_test)
```

In [53]:
```
#Plotting the error graph and should be mean=0
sns.distplot(y_test-y_pred,kde=True)
```

Out[53]: <AxesSubplot:xlabel='Price', ylabel='Density'>



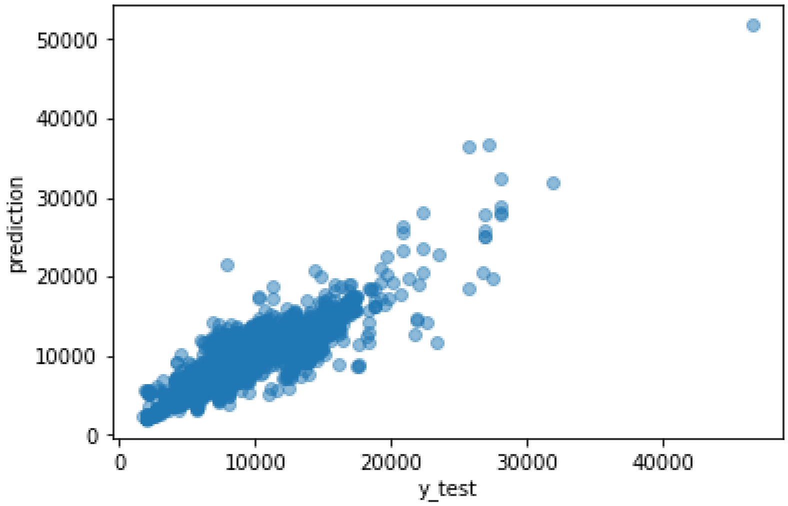
With an R2 score of 81 percent, With this model, we can also calculate the minimal values for mean absolute error, mean squared error, and root mean squared error (regression metrics). We will try to improve the accuracy by doing hyperparameter tuning.

In [54]:
```
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
MAE: 1183.4087125743447
MSE: 3448513.0710223014
RMSE: 1857.0172511375067
```

In [55]:
```
#Plotting scatter graph to check linear relations
plt.scatter(y_test,y_pred,alpha=0.5)
plt.xlabel('y_test')
plt.ylabel('prediction')
```

Out[55]: Text(0, 0.5, 'prediction')



Performing Hyperparameter Tuning for better Accuracy, it can be done using:-

- RandomizedSearchCV
- GridSearchCV

Here we will be using RandomizedSearchCV

In [56]:
```
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1200, num = 12)]
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(5, 30, num = 8)]
min_samples_split = [2, 5, 10, 15, 100, 120, 150, 200, 250]
min_samples_leaf = [1, 2, 5, 10,15,25,30,35]
```

In [57]:
```
random_grid_params = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf}
```

In [58]:
```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV, train_test_split
```

In [59]:
```
#random_search=RandomizedSearchCV(estimator=random_forest,param_distributions=random_grid_
#random_search
```

In [60]:
```
#random_search.fit(x_train,y_train)
```

In [61]:
```
#let's see the best parameters as per our grid search
#random_search.best_params_
```

We will pass these parameters into our random forest classifier.

In [62]:
```
random_forest_regresor=RandomForestRegressor(n_estimators=300,
 min_samples_split= 10,
 min_samples_leaf= 2,
 max_features= 'auto',
 max_depth= 15)
```

In [63]:

```
random_forest_regresor.fit(x_train,y_train)
```

Out[63]:

```
RandomForestRegressor
RandomForestRegressor(max_depth=15, max_features='auto', min_samples_leaf=2,
                      min_samples_split=10, n_estimators=300)
```

In [64]:

```
random_forest_regresor.score(x_train,y_train)
```

Out[64]:

```
0.8977195039073879
```

R2 SCORE

In [65]:

```
random_forest_regresor.score(x_test,y_test)
```

Out[65]:

```
0.8438132264416254
```

In [66]:

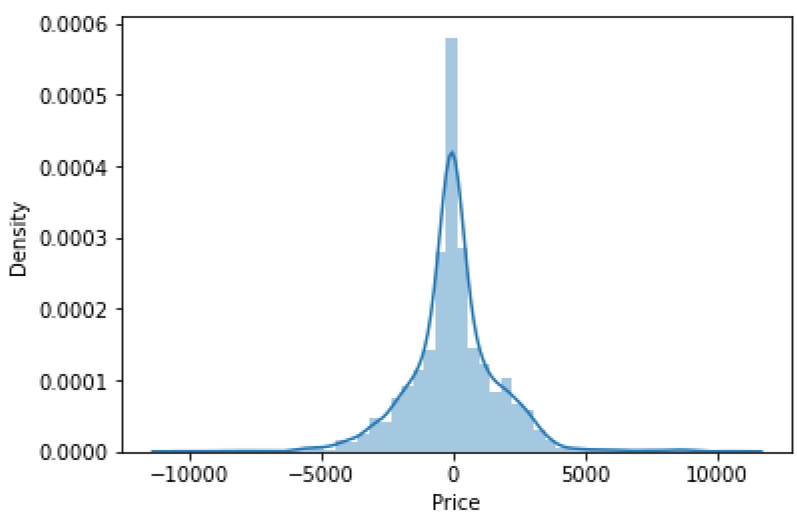
```
prediction=random_forest_regresor.predict(x_test)
```

In [67]:

```
#Plotting the error graph and should be mean=0
sns.distplot(y_test-prediction,kde=True)
```

Out[67]:

```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```

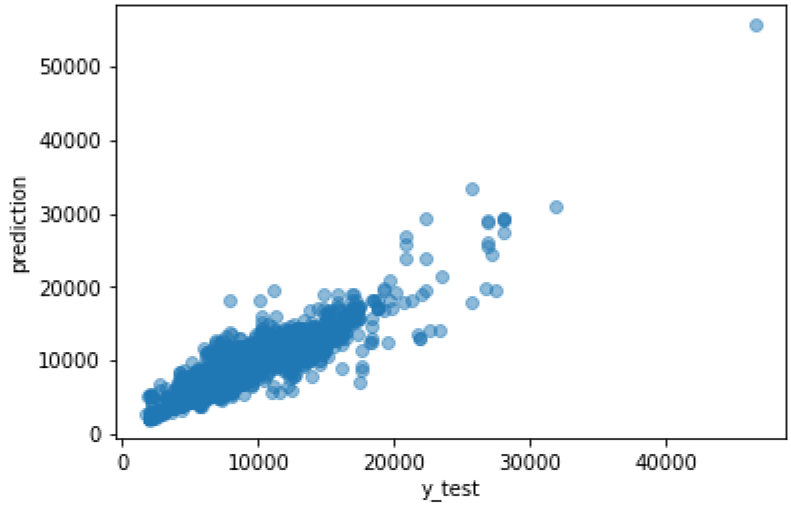


In [68]:

```
#Plotting scatter graph to check linear relations
plt.scatter(y_test,prediction,alpha=0.5)
plt.xlabel('y_test')
plt.ylabel('prediction')
```

Out[68]:

```
Text(0, 0.5, 'prediction')
```



In [69]:

```
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, prediction))
print('MSE:', metrics.mean_squared_error(y_test, prediction))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, prediction)))
```

```
MAE: 1143.7946947373855
MSE: 2934262.8975335998
RMSE: 1712.9690299400045
```

After hyper tuning, the R2 score for random forest Regressor is 84 percent, whereas, before hyper tuning, the R2 score for random forest Regressor was 81 percent. The value of MAE drops as well, indicating that we were successful in tunning our model.

Conclusion:

- So, we have used a random forest model for this data and improved accuracy by doing hyperparameter tuning.
- As a result, we were able to successfully train our regression model, the ‘Random forest model,’ to forecast fares of flight tickets with an R2 score of 84 percent and complete the required work.

Model Saving in Pickle Format

In [70]:

```
import pickle
file = open('flight_fare_pred.pkl', 'wb')
pickle.dump(random_forest_regresor, file)
```

Loading the Model Saved in Pickle Format

In [71]:

```
model = open('flight_fare_pred.pkl','rb')
flight_fare_pedictor = pickle.load(model)
```

Predicting Using the Loaded Model

In [72]:

```
flight_fare_pedictor.score(x_test,y_test)
```

Out[72]:

```
0.8438132264416254
```

In [73]:

```
x_test
```

Out[73]:

	Total_Stops	Journey_Date	Journey_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	D
8396	2	24	6	18	20	4	25	10	
9284	1	9	6	17	30	12	35	19	
10609	0	12	5	12	0	13	30	1	
10229	0	3	3	19	35	22	5	2	
3874	1	27	3	2	15	15	30	13	
...	...	...	...	...	...	...	...	...	
5803	0	24	3	23	30	2	20	2	
5663	1	6	5	11	35	18	50	7	
8332	0	27	6	11	30	14	5	2	
10453	2	24	6	9	40	12	35	26	
1080	0	21	6	15	15	18	10	2	

2671 rows × 29 columns

In [74]:

```
y_prediction = flight_fare_pedictor.predict(x_test)
```

In [75]:

```
y_prediction
```

Out[75]:

```
array([13631.15298391, 11409.16071819,  3144.10333994, ...,
        4904.74315097, 11165.70469196,  7591.92767134])
```