Flight Forecast - Flight Price Prediction

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Overview

In this Machine Learning Project, we will be **analyzing the flight fare prediction using Machine Learning dataset** using essential exploratory data analysis techniques then will **draw some predictions about the price of the flight based on some features** such as what type of airline it is, what is the arrival time, what is the departure time, what is the duration of the flight, source, destination and more.

In this Project, we do prediction using machine learning which leads to below takeaways:

EDA: Learn the complete process of EDA

Data analysis: Learn to withdraw some insights from the dataset both mathematically and visualize it.

Data visualization: Visualising the data to get better insight from it.

Feature engineering: We will also see what kind of stuff we can do in the feature engineering part.

About the dataset

1. **Airline:** So this column will have all the types of airlines like Indigo, Jet Airways, Air India, and many more.
2. **Date_of_Journey:** This column will let us know about the date on which the passenger's journey will start.
3. **Source:** This column holds the name of the place from where the passenger's journey will start.
4. **Destination:** This column holds the name of the place to where passengers wanted to travel.
5. **Route:** Here we can know about that what is the route through which passengers have opted to travel from his/her source to their destination.
6. **Arrival_Time:** Arrival time is when the passenger will reach his/her destination.
7. **Duration:** Duration is the whole period that a flight will take to complete its journey from source to destination.
8. **Total_Stops:** This will let us know in how many places flights will stop there for the flight in the whole journey.
9. **Additional_Info:** In this column, we will get information about food, kind of food, and other amenities.
10. **Price:** Price of the flight for a complete journey including all the expenses before onboarding.

Importing Libraries

 # This Python 3 environment comes with many helpful analytics libraries installed

 # It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python

 # For example, here's several helpful packages to load

```python
import numpy as np # linear algebra

import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)



# Input data files are available in the read-only "../input/" directory

# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory



import os

for dirname, _, filenames in os.walk('/kaggle/input'):

    for filename in filenames:

        print(os.path.join(dirname, filename))



# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"

# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns



sns.set()
```

Exploratory Data Analysis (EDA)

Now here we will be looking at the kind of columns our dataset has.

```python
train_df.columns
```

Output:

```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',

       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',

       'Additional_Info', 'Price'],

      dtype='object')
```

Here we can get more information about our dataset

train_df.info()

Output:

```
<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
```

To know more about the dataset

train_df.describe()

Output:

	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

Now while using the IsNull function we will gonna see the number of null values in our dataset

train_df.isnull().head()

Output:

Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min
False	False	False	False	False	False	False	False	False	False	False	False	False	False
False	False	False	False	False	False	False	False	False	False	False	False	False	False
False	False	False	False	False	False	False	False	False	False	False	False	False	False
False	False	False	False	False	False	False	False	False	False	False	False	False	False
False	False	False	False	False	False	False	False	False	False	False	False	False	False

Now while using the IsNull function and sum function we will gonna see the number of null values in our dataset

train_df.isnull().sum()

Output:

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 NAN values

train_df.dropna(inplace = True)

Duplicate values

train_df[train_df.duplicated()].head()

Output:

Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min
Vistara	Banglore	New Delhi	BLR → DEL	175	non-stop	No info	7608	3	3	21	10	0	5
Air Asia	Banglore	New Delhi	BLR → DEL	165	non-stop	No info	4482	24	3	23	25	2	10

Here we will be removing those repeated values from the dataset and keeping the in-place attribute to be true so that there will be no changes.

train_df.drop_duplicates(keep='first',inplace=True)

train_df.head()

Output:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	No info	7662
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	No info	6218
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	No info	13302

train_df.shape

Output:

(10462, 11)

Checking the Additional_info column and having the count of unique types of values.

train_df["Additional_Info"].value_counts()

Output:

```
No info                         8182
In-flight meal not included     1926
No check-in baggage included     318
1 Long layover                    19
Change airports                    7
Business class                     4
No Info                            3
1 Short layover                    1
2 Long layover                     1
Red-eye flight                     1
Name: Additional_Info, dtype: int64
```

Checking the different Airlines

train_df["Airline"].unique()

Output:

array(['IndiGo', 'Air India', 'Jet Airways', 'SpiceJet',

'Multiple carriers', 'GoAir', 'Vistara', 'Air Asia',

'Vistara Premium economy', 'Jet Airways Business',

'Multiple carriers Premium economy', 'Trujet'], dtype=object)

Checking the different Airline Routes

train_df["Route"].unique()

Output: See the code**.**

Now let’s look at our testing dataset

test_df = pd.read_excel("Test_set.xlsx")

test_df.head(10)

Output:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info
0	Jet Airways	6/06/2019	Delhi	Cochin	DEL → BOM → COK	17:30	04:25 07 Jun	10h 55m	1 stop	No info
1	IndiGo	12/05/2019	Kolkata	Banglore	CCU → MAA → BLR	06:20	10:20	4h	1 stop	No info
2	Jet Airways	21/05/2019	Delhi	Cochin	DEL → BOM → COK	19:15	19:00 22 May	23h 45m	1 stop	In-flight meal not included
3	Multiple carriers	21/05/2019	Delhi	Cochin	DEL → BOM → COK	08:00	21:00	13h	1 stop	No info
4	Air Asia	24/06/2019	Banglore	Delhi	BLR → DEL	23:55	02:45 25 Jun	2h 50m	non-stop	No info
5	Jet Airways	12/06/2019	Delhi	Cochin	DEL → BOM → COK	18:15	12:35 13 Jun	18h 20m	1 stop	In-flight meal not included
6	Air India	12/03/2019	Banglore	New Delhi	BLR → TRV → DEL	07:30	22:35	15h 5m	1 stop	No info
7	IndiGo	1/05/2019	Kolkata	Banglore	CCU → HYD → BLR	15:15	20:30	5h 15m	1 stop	No info
8	IndiGo	15/03/2019	Kolkata	Banglore	CCU → BLR	10:10	12:55	2h 45m	non-stop	No info
9	Jet Airways	18/05/2019	Kolkata	Banglore	CCU → BOM → BLR	16:30	22:35	6h 5m	1 stop	No info

Now here we will be looking at the kind of columns our testing data has.

test_df.columns

Output:

Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',

'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',

'Additional_Info'],

dtype='object')

Information about the dataset

test_df.info()

Output:

```
<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
```

To know more about the testing dataset

test_df.describe()

Output:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info
count	2671	2671	2671	2671	2671	2671	2671	2671	2671	2671
unique	11	44	5	6	100	199	704	320	5	6
top	Jet Airways	9/05/2019	Delhi	Cochin	DEL → BOM → COK	10:00	19:00	2h 50m	1 stop	No info
freq	897	144	1145	1145	624	62	113	122	1431	2148

Now while using the IsNull function and sum function we will gonna see the number of null values in our testing data

test_df.isnull().sum()

Output:

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

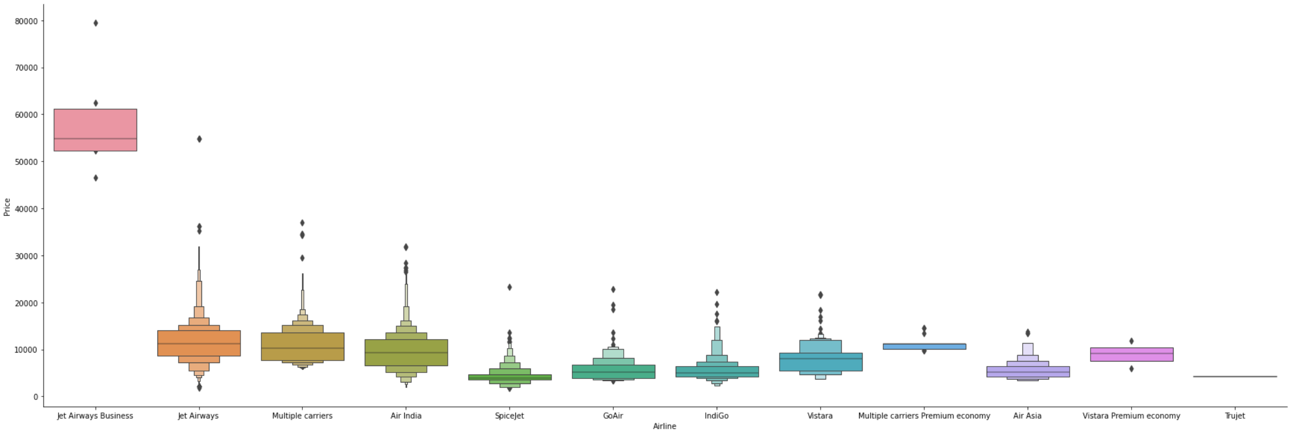
Data Visualization

Plotting Price vs Airline plot

sns.catplot(y = "Price", x = "Airline", data = train_df.sort_values("Price", ascending = False), kind="boxen", height = 8, aspect = 3)

plt.show()

Output:



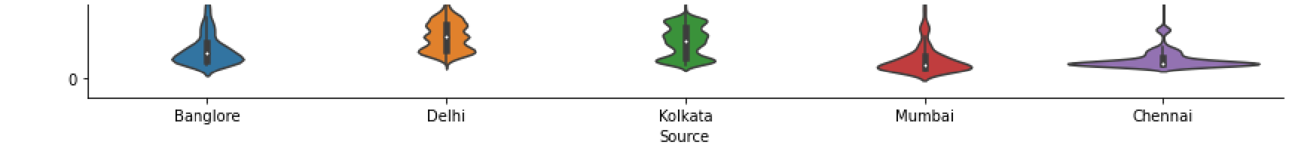
Inference: Here with the help of the cat plot we are trying to plot the boxplot between the price of the flight and airline and we can conclude that **Jet Airways has the most outliers in terms of price**.

Plotting Violin plot for Price vs Source

sns.catplot(y = "Price", x = "Source", data = train_df.sort_values("Price", ascending = False), kind="violin", height = 4, aspect = 3)

plt.show()

Output:



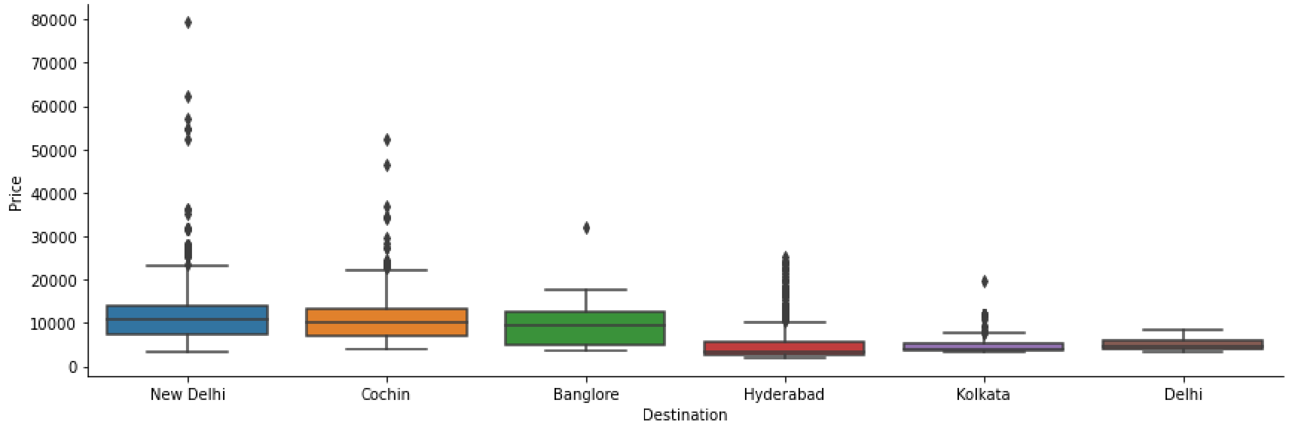
Inference: Now with the help of cat plot only we are plotting a box plot between the price of the flight and the source place i.e. **the place from where passengers will travel to the destination and we can see that Banglore as the source location has the most outliers while Chennai has the least.**

Plotting Box plot for Price vs Destination

sns.catplot(y = "Price", x = "Destination", data = train_df.sort_values("Price", ascending = False), kind="box", height = 4, aspect = 3)

plt.show()

Output:



Inference: Here we are plotting the box plot with the help of a cat plot between the price of the flight and the destination to which the passenger is travelling and figured out that **New Delhi has the most outliers and Kolkata has the least.**

Feature Engineering

Let's see our processed data first

train_df.head()

Output:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	No info	7662
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	No info	6218
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	No info	13302

Here first we are dividing the features and labels and then converting the hours in minutes.

train_df['Duration'] = train_df['Duration'].str.replace("h", '*60').str.replace(' ','+').str.replace('m','*1').apply(eval)

test_df['Duration'] = test_df['Duration'].str.replace("h", '*60').str.replace(' ','+').str.replace('m','*1').apply(eval)

Date_of_Journey: Here we are organizing the format of the date of journey in our dataset for better preprocessing in the model stage.

train_df["Journey_day"] = train_df['Date_of_Journey'].str.split('/').str[0].astype(int)

train_df["Journey_month"] = train_df['Date_of_Journey'].str.split('/').str[1].astype(int)

train_df.drop(["Date_of_Journey"], axis = 1, inplace = True)

Dep_Time: Here we are converting departure time into hours and minutes

train_df["Dep_hour"] = pd.to_datetime(train_df["Dep_Time"]).dt.hour

train_df["Dep_min"] = pd.to_datetime(train_df["Dep_Time"]).dt.minute

train_df.drop(["Dep_Time"], axis = 1, inplace = True)

Arrival_Time: Similarly we are converting the arrival time into hours and minutes.

Now after final preprocessing let's see our dataset

train_df.head()

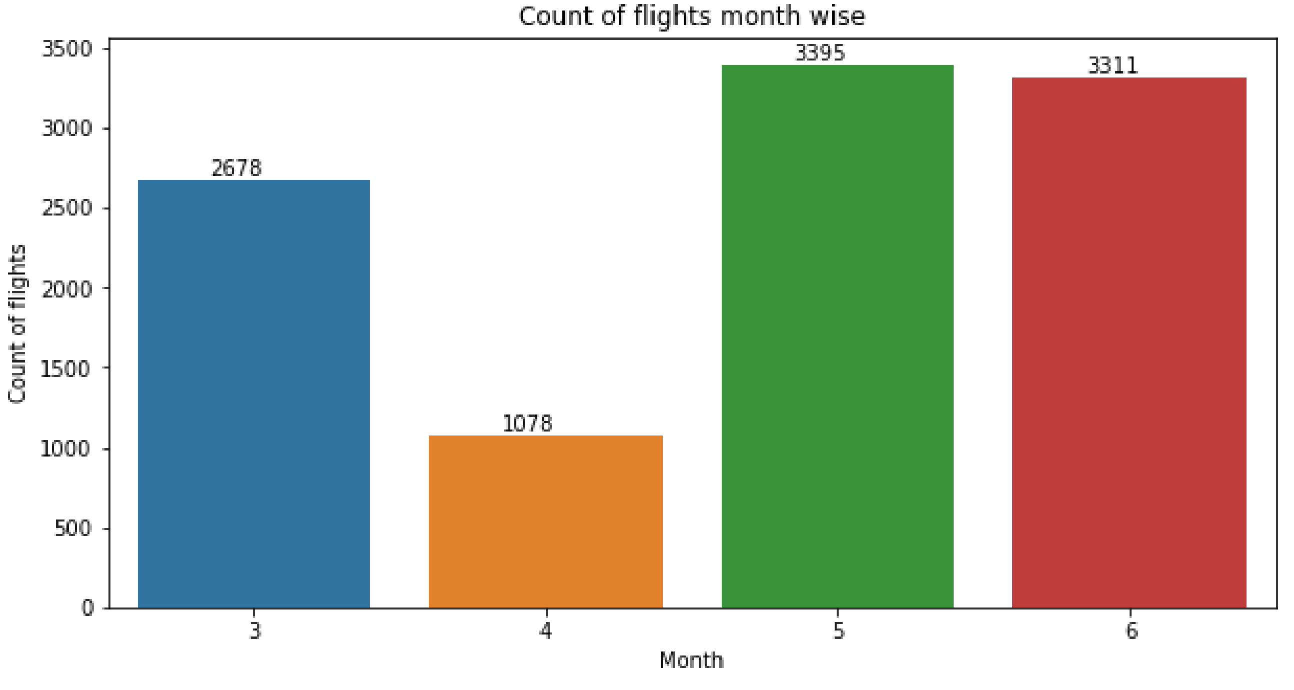
Output:

Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min
IndiGo	Banglore	New Delhi	BLR → DEL	170	non-stop	No info	3897	24	3	22	20	1	10
Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	445	2 stops	No info	7662	1	5	5	50	13	15
Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	1140	2 stops	No info	13882	9	6	9	25	4	25
IndiGo	Kolkata	Banglore	CCU → NAG → BLR	325	1 stop	No info	6218	12	5	18	5	23	30
IndiGo	Banglore	New Delhi	BLR → NAG → DEL	285	1 stop	No info	13302	1	3	16	50	21	35

Plotting Bar chart for Months (Duration) vs Number of Flights

```
plt.figure(figsize = (10, 5))

plt.title('Count of flights month wise')

ax=sns.countplot(x = 'Journey_month', data = train_df)

plt.xlabel('Month')

plt.ylabel('Count of flights')

for p in ax.patches:

    ax.annotate(int(p.get_height()), (p.get_x()+0.25, p.get_height()+1), va='bottom', color= 'black')
```

Output:



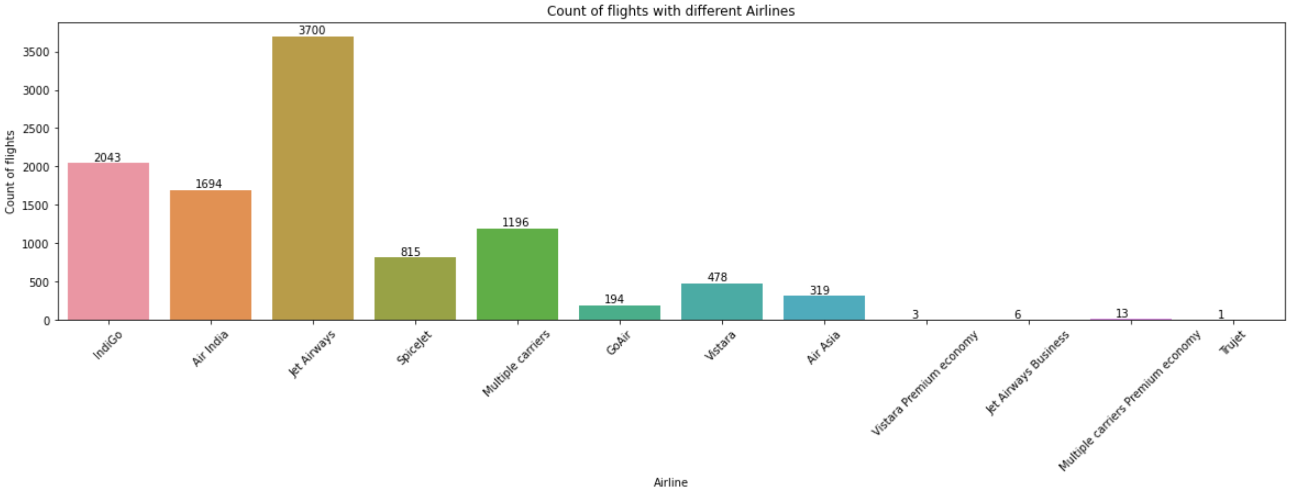
Inference: Here in the above graph we have plotted the count plot for journey in a month vs several flights and got to see that **May has the most number of flights.**

Plotting Bar chart for Types of Airline vs Number of Flights

```
plt.figure(figsize = (20,5))

plt.title('Count of flights with different Airlines')

ax=sns.countplot(x = 'Airline', data =train_df)

plt.xlabel('Airline')

plt.ylabel('Count of flights')

plt.xticks(rotation = 45)

for p in ax.patches:
```

ax.annotate(int(p.get_height()), (p.get_x()+0.25, p.get_height()+1), va='bottom', color= 'black')

Output:



Inference: Now from the above graph we can see that between the type of airline and **count of flights we can see that Jet Airways has the most flight boarded.**

Plotting Ticket Prices VS Airlines

plt.figure(figsize = (15,4))

plt.title('Price VS Airlines')

plt.scatter(train_df['Airline'], train_df['Price'])

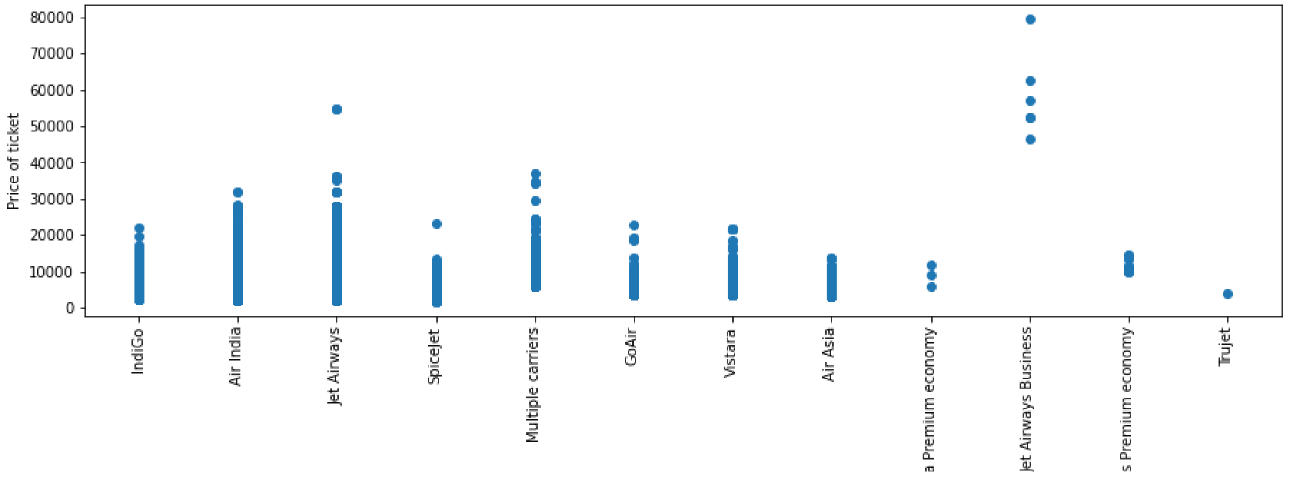
plt.xticks

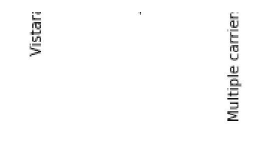
plt.xlabel('Airline')

plt.ylabel('Price of ticket')

plt.xticks(rotation = 90)

Output:





Correlation between all Features

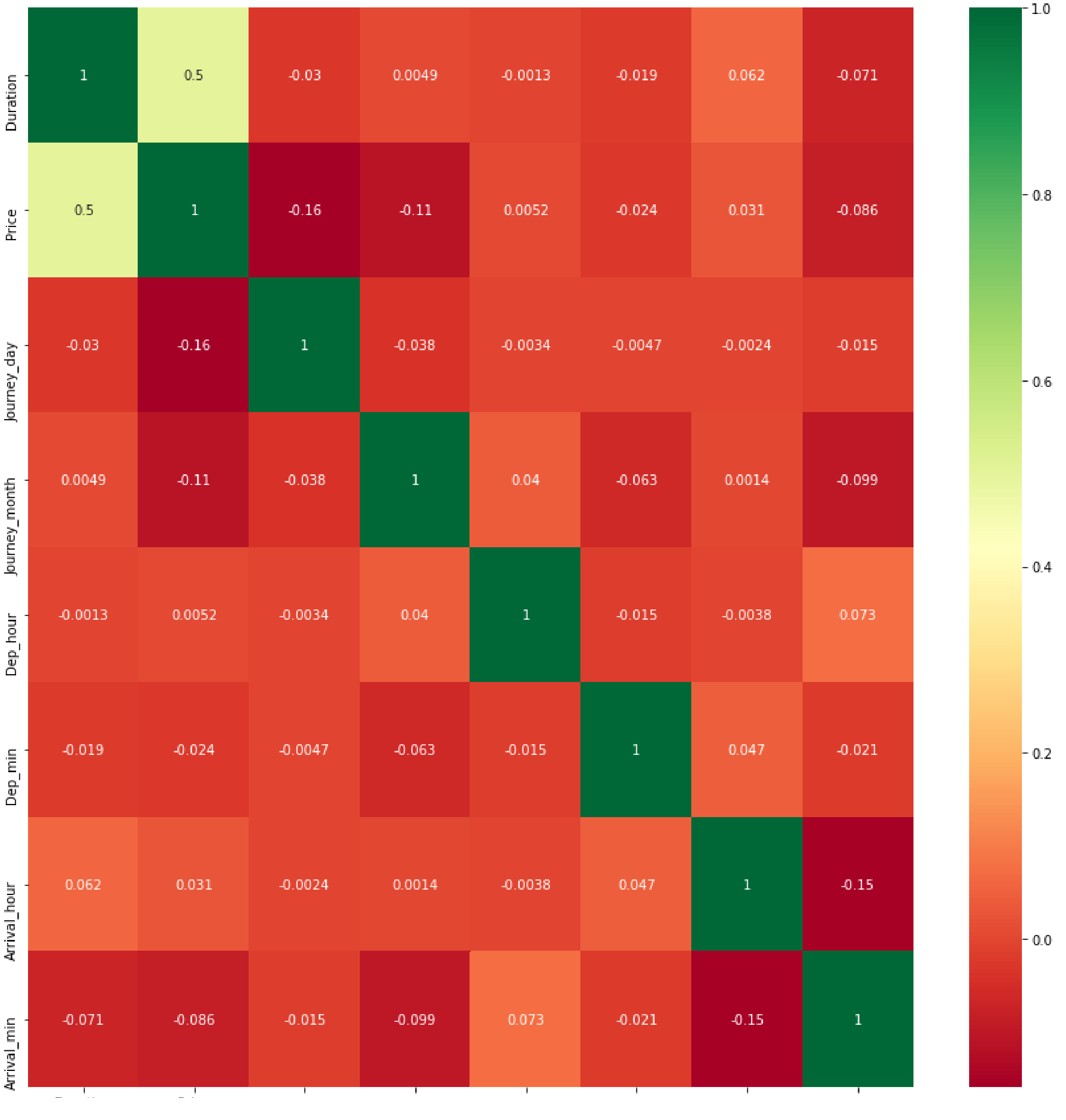
Plotting Correlation

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

sns.heatmap(train_df.corr(), annot = True, cmap = "RdYlGn")

plt.show()

Output:



Duration	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min

Dropping the Price column as it is of no use

data = train_df.drop(["Price"], axis=1)

Dealing with Categorical Data and Numerical Data

train_categorical_data = data.select_dtypes(exclude=['int64', 'float','int32'])

train_numerical_data = data.select_dtypes(include=['int64', 'float','int32'])

test_categorical_data = test_df.select_dtypes(exclude=['int64', 'float','int32','int32'])

test_numerical_data = test_df.select_dtypes(include=['int64', 'float','int32'])

train_categorical_data.head()

Output:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info
0	IndiGo	Banglore	New Delhi	BLR → DEL	non-stop	No info
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	2 stops	No info
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	2 stops	No info
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	1 stop	No info
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	1 stop	No info

Label Encode and Hot Encode for Categorical Columns

Output:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info
0	3	0	5	18	4	8
1	1	3	0	84	1	8
2	4	2	1	118	1	8
3	3	3	0	91	0	8
4	3	0	5	29	0	8

Concatenating both Categorical Data and Numerical Data

X = pd.concat([train_categorical_data, train_numerical_data], axis=1)

y = train_df['Price']

test_set = pd.concat([test_categorical_data, test_numerical_data], axis=1)

X.head()

Output:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info	Duration	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min
0	3	0	5	18	4	8	170	24	3	22	20	1	10
1	1	3	0	84	1	8	445	1	5	5	50	13	15
2	4	2	1	118	1	8	1140	9	6	9	25	4	25
3	3	3	0	91	0	8	325	12	5	18	5	23	30
4	3	0	5	29	0	8	285	1	3	16	50	21	35

y.head()

Output:

0 3897

1 7662

2 13882

3 6218

4 13302

Name: Price, dtype: int64

Conclusion

So as we saw that we have done a complete EDA process, getting data insights, feature engineering, and data visualization as well so after all these steps one can go for the prediction using machine learning model-making steps.