

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

sns.set()
```

## Importing dataset

Since data is in form of excel file we have to use pandas read\_excel to load the data After loading it is important to check the complete information of data as it can indicate many of the hidden information such as null values in a column or a row Check whether any null values are there or not. if it is present then following can be done, Imputing data using Imputation method in sklearn Filling NaN values with mean, median and mode using fillna() method Describe data --> which can give statistical analysis

```
In [3]: train_data = pd.read_excel("Data_Train.xlsx")
```

```
In [4]: pd.set_option('display.max_columns', None)
```

```
In [5]: train_data.head()
```

```
Out[5]:
```

	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

```
In [6]: train_data.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
```

```
In [7]: train_data["Duration"].value_counts()
```

```
Out[7]:
```

2h 50m	550
1h 30m	386
2h 45m	337
2h 55m	337
2h 35m	329
...	
31h 30m	1
30h 25m	1
42h 5m	1
4h 10m	1
47h 40m	1

Name: Duration, Length: 368, dtype: int64

```
In [8]: train_data.dropna(inplace = True)
```

```
In [9]: train_data.isnull().sum()
```

```
Out[9]: 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
```

## EDA

From description we can see that Date\_of\_Journey is a object data type, Therefore, we have to convert this datatype into timestamp so as to use this column properly for prediction

For this we require pandas to\_datetime to convert object data type to datetime dtype.

.dt.day method will extract only day of that date .dt.month method will extract only month of that date

```
In [10]: train_data["Journey_day"] = pd.to_datetime(train_data.Date_of_Journey, format="%d/%m/%Y").dt.day
```

```
In [11]: train_data["Journey_month"] = pd.to_datetime(train_data["Date_of_Journey"], format = "%d/%m/%Y").dt.month
```

```
In [12]: train_data.head()
```

```
Out[12]:
```

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	Journey_d
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897	2
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	1
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	No info	13302	

```
In [13]: # Since we have converted Date_of_Journey column into integers, Now we can drop as it is of no use.
```

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

```
In [14]: # Departure time is when a plane leaves the gate.
# Similar to Date_of_Journey we can extract values from Dep_Time
```

```
# Extracting Hours
train_data["Dep_hour"] = pd.to_datetime(train_data["Dep_Time"]).dt.hour
```

```
# Extracting Minutes
train_data["Dep_min"] = pd.to_datetime(train_data["Dep_Time"]).dt.minute
```

```
# Now we can drop Dep_Time as it is of no use
train_data.drop(["Dep_Time"], axis = 1, inplace = True)
```

```
In [15]: train_data.head()
```

Out[15]:	Airline	Source	Destination	Route	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	Journey_day	Journey_month	Dep_hour
0	IndiGo	Banglore	New Delhi	BLR → DEL	01:10 22 Mar	2h 50m	non-stop	No info	3897	24	3	22
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	13:15	7h 25m	2 stops	No info	7662	1	5	5
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	04:25 10 Jun	19h	2 stops	No info	13882	9	6	9
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	23:30	5h 25m	1 stop	No info	6218	12	5	18
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	21:35	4h 45m	1 stop	No info	13302	1	3	16

```
In [16]: # Arrival time is when the plane pulls up to the gate.
# Similar to Date_of_Journey we can extract values from Arrival_Time

# Extracting Hours
train_data["Arrival_hour"] = pd.to_datetime(train_data.Arrival_Time).dt.hour

# Extracting Minutes
train_data["Arrival_min"] = pd.to_datetime(train_data.Arrival_Time).dt.minute

# Now we can drop Arrival Time as it is of no use
train_data.drop(["Arrival_Time"], axis = 1, inplace = True)
```

```
In [17]: train_data.head()
```

Out[17]:	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	Journey_day	Journey_month	Dep_hour	Dep_min	A
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	24	3	22	20	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	7662	1	5	5	50	
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	19h	2 stops	No info	13882	9	6	9	25	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	5h 25m	1 stop	No info	6218	12	5	18	5	
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	4h 45m	1 stop	No info	13302	1	3	16	50	

```
In [18]: # Time taken by plane to reach destination is called Duration
# It is the difference between Departure Time and Arrival time

# Assigning and converting Duration column into list
duration = list(train_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 duration
    duration_mins.append(int(duration[i].split(sep = "m")[0].split()[-1])) # Extracts only minutes from duration

```

```
In [19]: # Adding duration_hours and duration_mins list to train_data dataframe
```

```

train_data["Duration_hours"] = duration_hours
train_data["Duration_mins"] = duration_mins

```

```
In [20]: train_data.drop(["Duration"], axis = 1, inplace = True)
```

```
In [21]: train_data.head()
```

```
Out[21]:
```

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

## Handling Categorical Data

One can find many ways to handle categorical data. Some of them categorical data are,

Nominal data --> data are not in any order --> OneHotEncoder is used in this case  
 Ordinal data --> data are in order --> LabelEncoder is used in this case

```
In [22]: train_data["Airline"].value_counts()
```

```
Out[22]:
```

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
Vistara Premium economy	3
Trujet	1

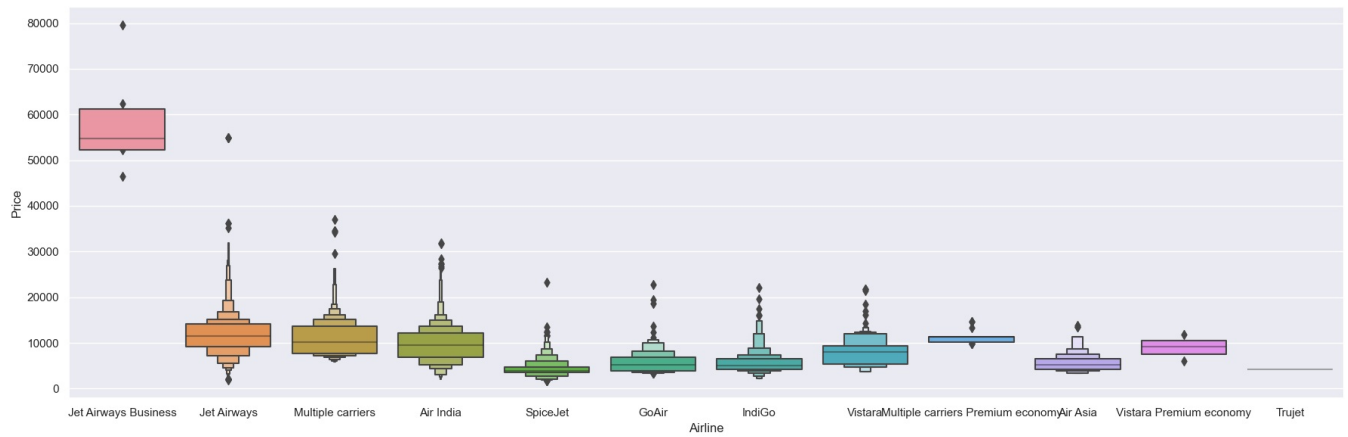
Name: Airline, dtype: int64

```

In [23]: # From graph we can see that Jet Airways Business have the highest Price.
# Apart from the first Airline almost all are having similar median

# Airline vs Price
sns.catplot(y = "Price", x = "Airline", data = train_data.sort_values("Price", ascending = False), kind="boxen"
plt.show()

```



In [24]: # As Airline is Nominal Categorical data we will perform OneHotEncoding

```
Airline = train_data[["Airline"]]
Airline = pd.get_dummies(Airline, drop_first= True)
Airline.head()
```

Out[24]:

	Airline_Air India	Airline_GoAir	Airline_IndiGo	Airline_Jet Airways	Airline_Jet Airways Business	Airline_Multiple carriers	Airline_Multiple carriers Premium economy	Airline_SpiceJet	Airline_Trujet	Airline_V
0	0	0	1	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	0	0	
2	0	0	0	1	0	0	0	0	0	
3	0	0	1	0	0	0	0	0	0	
4	0	0	1	0	0	0	0	0	0	

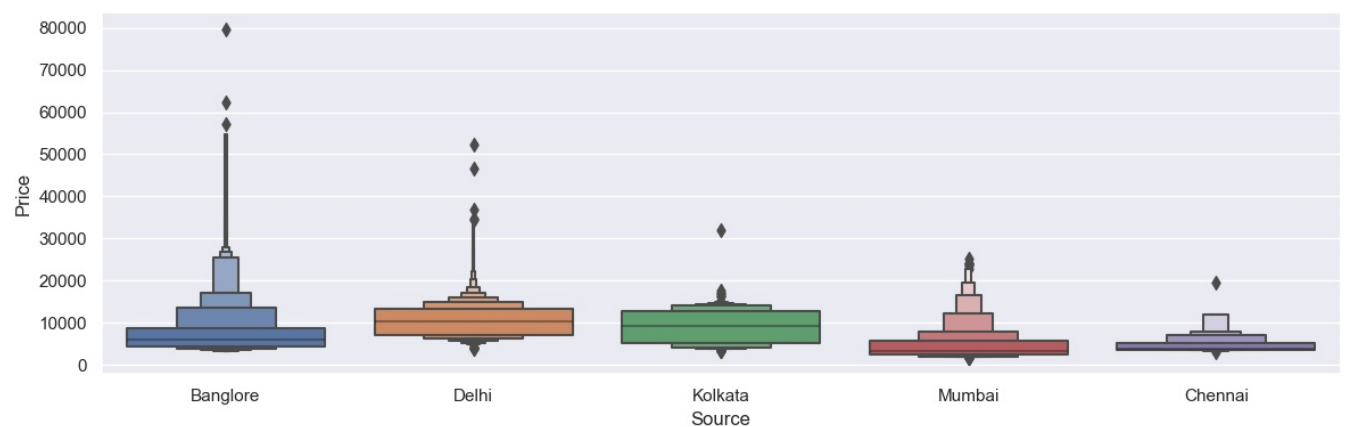
In [25]: train\_data["Source"].value\_counts()

Out[25]:

```
Delhi      4536
Kolkata    2871
Bangalore  2197
Mumbai     697
Chennai    381
Name: Source, dtype: int64
```

In [26]: # Source vs Price

```
sns.catplot(y = "Price", x = "Source", data = train_data.sort_values("Price", ascending = False), kind="boxen", plt.show())
```



In [27]: # As Source is Nominal Categorical data we will perform OneHotEncoding

```
Source = train_data[["Source"]]
Source = pd.get_dummies(Source, drop_first= True)
Source.head()
```

Out[27]:

	Source_Chennai	Source_Delhi	Source_Kolkata	Source_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 [28]: train\_data["Destination"].value\_counts()

Out[28]:

```
Cochin      4536
Bangalore   2871
Delhi       1265
New Delhi   932
Hyderabad   697
Kolkata     381
Name: Destination, dtype: int64
```

In [29]: # As Destination is Nominal Categorical data we will perform OneHotEncoding

```
Destination = train_data[["Destination"]]
Destination = pd.get_dummies(Destination, drop_first = True)
Destination.head()
```

Out[29]:

	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

In [30]: train\_data["Route"]

Out[30]:

```
0          BLR → DEL
1      CCU → IXR → BBI → BLR
2      DEL → LKO → BOM → COK
3          CCU → NAG → BLR
4          BLR → NAG → DEL
...
10678          CCU → BLR
10679          CCU → BLR
10680          BLR → DEL
10681          BLR → DEL
10682      DEL → GOI → BOM → COK
Name: Route, Length: 10682, dtype: object
```

In [31]: # Additional\_Info contains almost 80% no\_info
# Route and Total\_Stops are related to each other

```
train_data.drop(["Route", "Additional_Info"], axis = 1, inplace = True)
```

In [32]: train\_data["Total\_Stops"].value\_counts()

Out[32]:

```
1 stop      5625
non-stop    3491
2 stops     1520
3 stops       45
4 stops        1
Name: Total_Stops, dtype: int64
```

In [33]: # As this is case of Ordinal Categorical type we perform LabelEncoder
# Here Values are assigned with corresponding keys

```
train_data.replace({"non-stop": 0, "1 stop": 1, "2 stops": 2, "3 stops": 3, "4 stops": 4}, inplace = True)
```

In [34]: train\_data.head()

Out[34]:

	Airline	Source	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration
0	IndiGo	Banglore	New Delhi	0	3897	24	3	22	20	1	10	
1	Air India	Kolkata	Banglore	2	7662	1	5	5	50	13	15	
2	Jet Airways	Delhi	Cochin	2	13882	9	6	9	25	4	25	
3	IndiGo	Kolkata	Banglore	1	6218	12	5	18	5	23	30	
4	IndiGo	Banglore	New Delhi	1	13302	1	3	16	50	21	35	

```
In [35]: # Concatenate dataframe --> train_data + Airline + Source + Destination

data_train = pd.concat([train_data, Airline, Source, Destination], axis = 1)
```

```
In [36]: data_train.head()
```

Out[36]:

	Airline	Source	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_
0	IndiGo	Banglore	New Delhi	0	3897	24	3	22	20	1	10	
1	Air India	Kolkata	Banglore	2	7662	1	5	5	50	13	15	
2	Jet Airways	Delhi	Cochin	2	13882	9	6	9	25	4	25	
3	IndiGo	Kolkata	Banglore	1	6218	12	5	18	5	23	30	
4	IndiGo	Banglore	New Delhi	1	13302	1	3	16	50	21	35	

```
In [37]: data_train.drop(["Airline", "Source", "Destination"], axis = 1, inplace = True)
```

```
In [38]: data_train.head()
```

Out[38]:

	Total_Stops	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_mins	Airline_Inc
0	0	3897	24	3	22	20	1	10	2	50	
1	2	7662	1	5	5	50	13	15	7	25	
2	2	13882	9	6	9	25	4	25	19	0	
3	1	6218	12	5	18	5	23	30	5	25	
4	1	13302	1	3	16	50	21	35	4	45	

```
In [39]: data_train.shape
```

Out[39]: (10682, 30)

## Test set

```
In [41]: test_data = pd.read_excel("Test_set.xlsx")
```

```
In [42]: test_data.head()
```

Out[42]:

	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

```
In [43]: # Preprocessing
```

```
print("Test data Info")
print("-"*75)
print(test_data.info())

print()
print()

print("Null values :")
print("-"*75)
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.day
test_data["Journey_month"] = pd.to_datetime(test_data["Date_of_Journey"], format = "%d/%m/%Y").dt.month
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 duration
    duration_mins.append(int(duration[i].split(sep = "m")[0].split()[-1]))    # Extracts only minutes from duration

# 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()

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

print()

print("Destination")
print("-"*75)
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}, inplace = True)

# 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)

```



# Test data Info

```
<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
```

## Null values :

```
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
```

## Source

```
Delhi      1145
Kolkata    710
Banglore   555
Mumbai     186
Chennai    75
Name: Source, dtype: int64
```

## Destination

```
Cochin      1145
Banglore    710
Delhi        317
New Delhi   238
Hyderabad   186
Kolkata      75
Name: Destination, dtype: int64
```

Shape of test data : (2671, 28)

In [44]: data\_test.head()

Out[44]:

	Total_Stops	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_mins	Air India	GoAir	Ir
0	1	6	6	17	30	4	25	10	55	0	0	
1	1	12	5	6	20	10	20	4	0	0	0	
2	1	21	5	19	15	19	0	23	45	0	0	
3	1	21	5	8	0	21	0	13	0	0	0	
4	0	24	6	23	55	2	45	2	50	0	0	

# Feature Selection

Finding out the best feature which will contribute and have good relation with target variable. Following are some of the feature selection methods,

heatmap featureimportance SelectKBest

```
In [45]: data_train.shape
```

```
Out[45]: (10682, 30)
```

```
In [46]: data_train.columns
```

```
Out[46]: Index(['Total_Stops', 'Price', 'Journey_day', 'Journey_month', 'Dep_hour',
              'Dep_min', 'Arrival_hour', 'Arrival_min', 'Duration_hours',
              'Duration_mins', 'Airline_Air India', 'Airline_GoAir', 'Airline_IndiGo',
              'Airline_Jet Airways', 'Airline_Jet Airways Business',
              'Airline_Multiple carriers',
              'Airline_Multiple carriers Premium economy', 'Airline_SpiceJet',
              'Airline_Trujet', 'Airline_Vistara', 'Airline_Vistara Premium economy',
              'Source_Chennai', 'Source_Delhi', 'Source_Kolkata', 'Source_Mumbai',
              'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad',
              'Destination_Kolkata', 'Destination_New Delhi'],
              dtype='object')
```

```
In [48]: X = data_train.loc[:, ['Total_Stops', 'Journey_day', 'Journey_month', 'Dep_hour',
                                'Dep_min', 'Arrival_hour', 'Arrival_min', 'Duration_hours',
                                'Duration_mins', 'Airline_Air India', 'Airline_GoAir', 'Airline_IndiGo',
                                'Airline_Jet Airways', 'Airline_Jet Airways Business',
                                'Airline_Multiple carriers',
                                'Airline_Multiple carriers Premium economy', 'Airline_SpiceJet',
                                'Airline_Trujet', 'Airline_Vistara', 'Airline_Vistara Premium economy',
                                'Source_Chennai', 'Source_Delhi', 'Source_Kolkata', 'Source_Mumbai',
                                'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad',
                                'Destination_Kolkata', 'Destination_New Delhi']]
X.head()
```

```
Out[48]:
```

	Total_Stops	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_mins	Airline_Air India	Airl
0	0	24	3	22	20	1	10	2	50	0	
1	2	1	5	5	50	13	15	7	25	1	
2	2	9	6	9	25	4	25	19	0	0	
3	1	12	5	18	5	23	30	5	25	0	
4	1	1	3	16	50	21	35	4	45	0	

```
In [49]: y = data_train.iloc[:, 1]
y.head()
```

```
Out[49]: 0    3897
1    7662
2   13882
3    6218
4   13302
Name: Price, dtype: int64
```

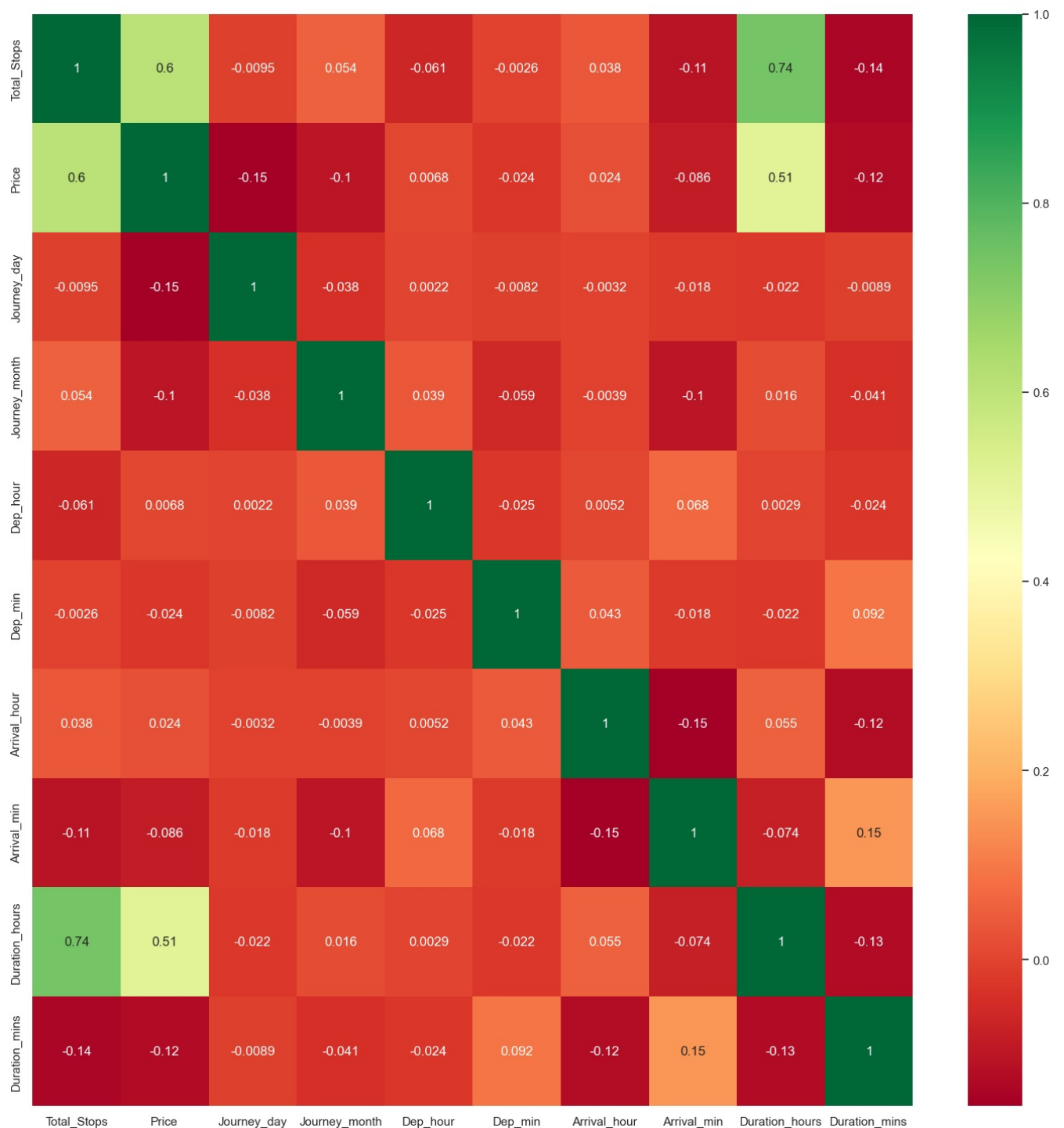
```
In [50]: # Finds correlation between Independent and dependent attributes
```

```
plt.figure(figsize = (18,18))
sns.heatmap(train_data.corr(), annot = True, cmap = "RdYlGn")

plt.show()
```

C:\Users\HP\AppData\Local\Temp\ipykernel\_16092\3228867913.py:4: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric\_only to silence this warning.

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



In [51]: # Important feature using ExtraTreesRegressor

```
from sklearn.ensemble import ExtraTreesRegressor
selection = ExtraTreesRegressor()
selection.fit(X, y)
```

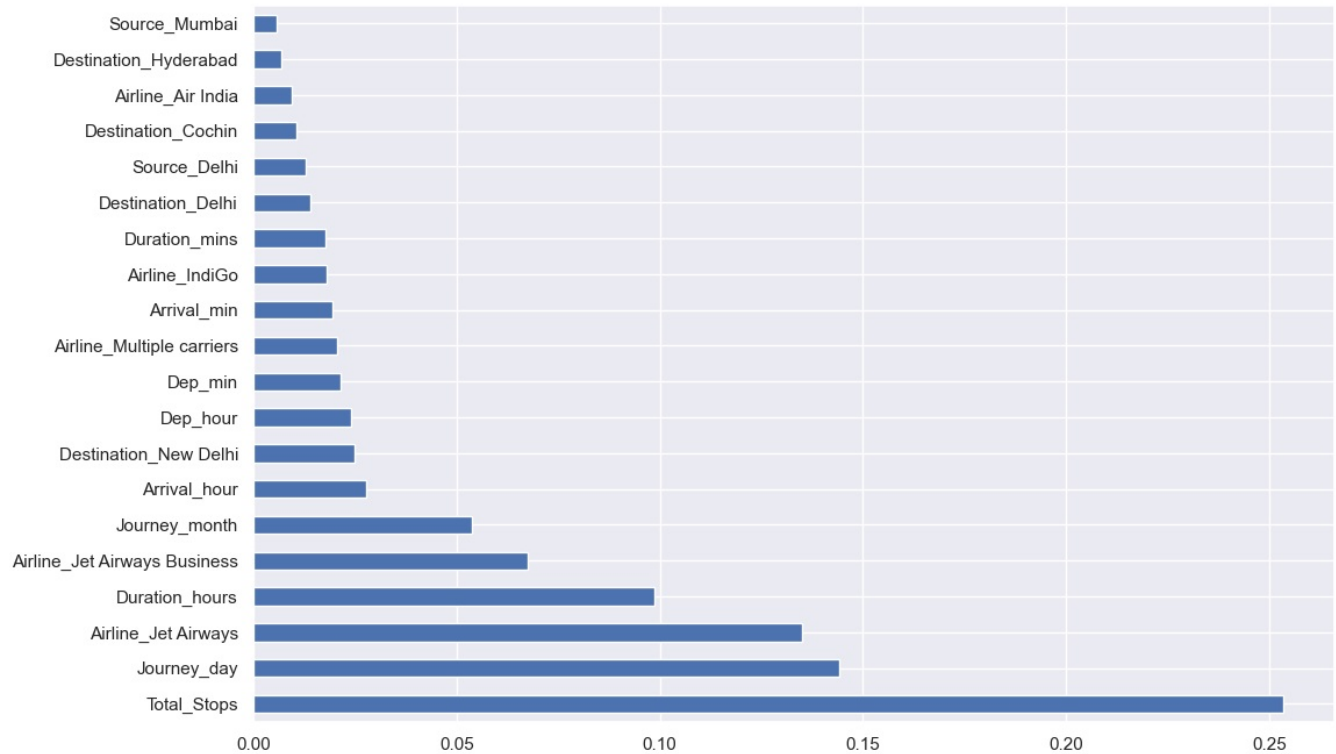
Out[51]: **ExtraTreesRegressor**  
ExtraTreesRegressor()

In [52]: print(selection.feature\_importances\_)

```
[2.53470796e-01 1.44094068e-01 5.36331525e-02 2.39955361e-02
2.13409191e-02 2.77962739e-02 1.94331763e-02 9.85932605e-02
1.77649302e-02 9.46535510e-03 1.83641379e-03 1.80382821e-02
1.35071199e-01 6.75795840e-02 2.05349566e-02 8.26382052e-04
3.07806504e-03 1.11001738e-04 4.98111153e-03 8.03756456e-05
4.50273490e-04 1.27076352e-02 3.13285406e-03 5.54249137e-03
1.04585774e-02 1.39380875e-02 6.77032032e-03 4.24529024e-04
2.48503928e-02]
```

```
In [53]: #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')
```



## Fitting model using Random Forest

Split dataset into train and test set in order to prediction w.r.t  $X_{test}$  If needed do scaling of data Scaling is not done in Random forest  
 Import model Fit the data Predict w.r.t  $X_{test}$  In regression check RSME Score Plot graph

```
In [54]: 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)
```

```
In [55]: from sklearn.ensemble import RandomForestRegressor
reg_rf = RandomForestRegressor()
reg_rf.fit(X_train, y_train)
```

```
Out[55]: ▼ RandomForestRegressor
RandomForestRegressor()
```

```
In [56]: y_pred = reg_rf.predict(X_test)
```

```
In [57]: reg_rf.score(X_train, y_train)
```

```
Out[57]: 0.9532348142789775
```

```
In [58]: reg_rf.score(X_test, y_test)
```

```
Out[58]: 0.797010031600254
```

```
In [59]: sns.distplot(y_test-y_pred)
plt.show()
```

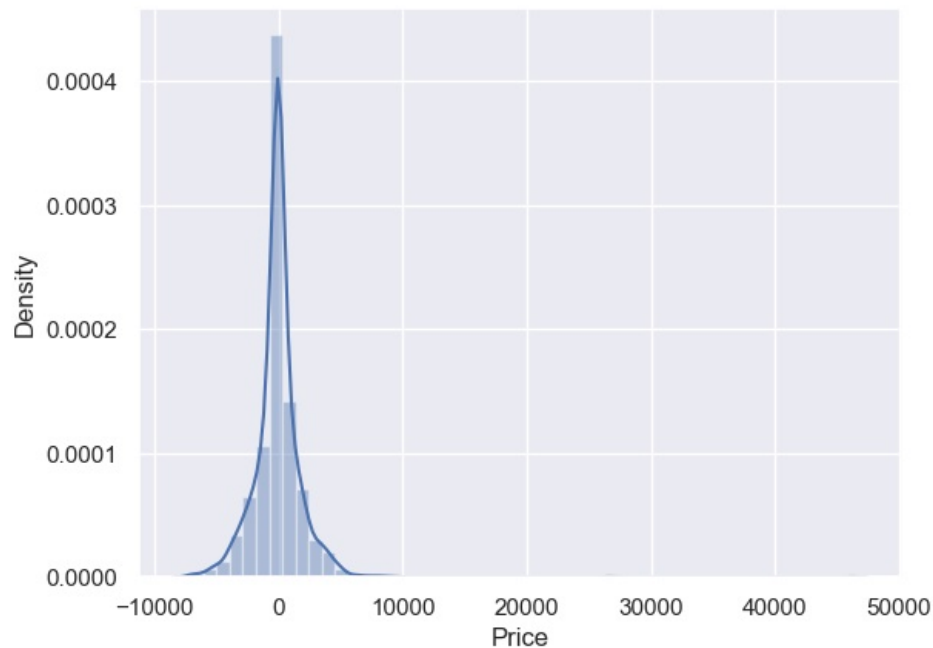
C:\Users\HP\AppData\Local\Temp\ipykernel\_16092\3453123835.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

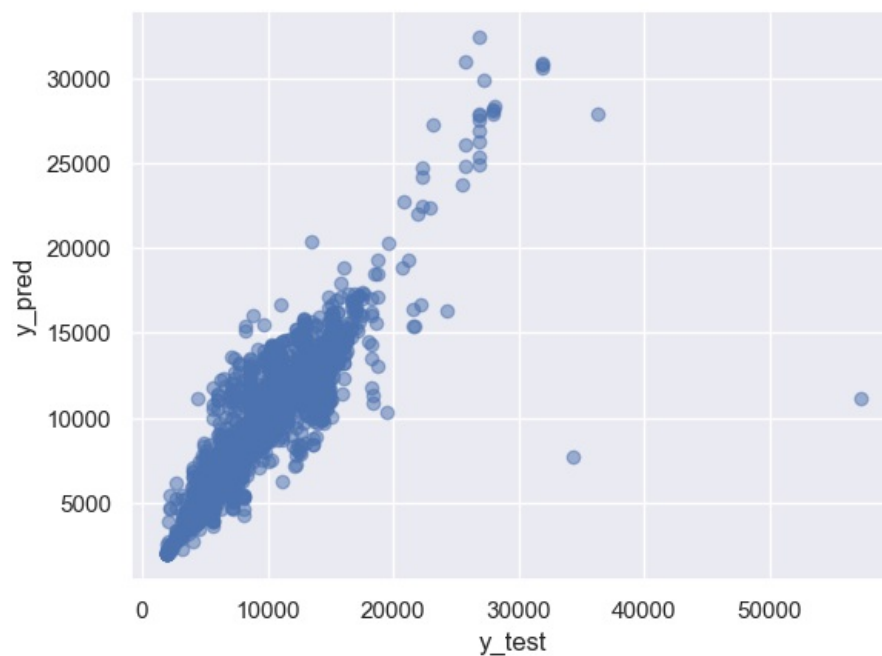
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(y_test-y_pred)
```



```
In [60]: plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```



```
In [61]: from sklearn import metrics
```

```
In [62]: 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: 1173.3705151589168
MSE: 4376881.131875144
RMSE: 2092.0996945354073
```

```
In [63]: # RMSE/(max(DV)-min(DV))
2090.5509/(max(y)-min(y))
```

```
Out[63]: 0.026887077025966846
```

```
In [64]: metrics.r2_score(y_test, y_pred)
```

```
Out[64]: 0.797010031600254
```

# Hyperparameter Tuning

Choose following method for hyperparameter tuning RandomizedSearchCV --> Fast GridSearchCV Assign hyperparameters in form of dictionary Fit the model Check best paramters and best score

```
In [65]: from sklearn.model_selection import RandomizedSearchCV
```

```
In [66]: #Randomized Search CV
```

```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1200, num = 12)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(5, 30, num = 6)]
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10, 15, 100]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 5, 10]
```

```
In [67]: # Create the random grid
```

```
random_grid = {'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 [69]: # Random search of parameters, using 5 fold cross validation,
# search across 100 different combinations
```

```
rf_random = RandomizedSearchCV(estimator = reg_rf, param_distributions = random_grid,scoring='neg_mean_squared_
```

```
In [70]: rf_random.fit(X_train,y_train)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time = 9.8s
```

```
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time = 9.7s
```

```
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time = 9.8s
```

```
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time = 9.4s
```

```
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time = 9.3s
```

```
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=1100; total time = 15.3s
```

```
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=1100; total time = 15.5s
```

```
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=1100; total time = 15.3s
```

```
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=1100; total time = 15.6s
```

```
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=1100; total time = 15.3s
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
```

```
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5, min_samples_split=100, n_estimators=300; total time = 8.4s
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
```

```
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5, min_samples_split=100, n_estimators=300; total time = 8.4s
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
```

```
[CV] END max_depth=15, max_features=auto, min_samples_leaf=5, min_samples_split=100, n_estimators=300; total time = 8.2s
```

[illegible]

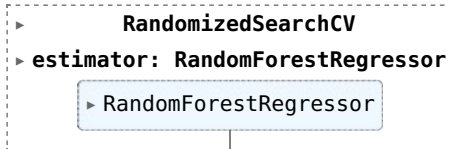
```

[CV] END max_depth=20, max_features=auto, min_samples_leaf=10, min_samples_split=5, n_estimators=700; total time= 24.3s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samples_split=2, n_estimators=1000; total time= 27.4s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samples_split=2, n_estimators=1000; total time= 27.4s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samples_split=2, n_estimators=1000; total time= 26.7s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samples_split=2, n_estimators=1000; total time= 26.7s
[CV] END max_depth=25, max_features=sqrt, min_samples_leaf=1, min_samples_split=2, n_estimators=1000; total time= 27.0s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=15, n_estimators=1100; total time= 7.2s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=15, n_estimators=1100; total time= 7.6s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=15, n_estimators=1100; total time= 7.3s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=15, n_estimators=1100; total time= 7.1s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=15, n_estimators=1100; total time= 7.1s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time= 4.0s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time= 3.9s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time= 3.9s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time= 3.9s
[CV] END max_depth=15, max_features=sqrt, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time= 4.0s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=700; total time= 5.5s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=700; total time= 4.5s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=700; total time= 4.6s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=700; total time= 4.6s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=700; total time= 4.6s
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1, min_samples_split=15, n_estimators=700; total time= 30.9s
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1, min_samples_split=15, n_estimators=700; total time= 30.6s
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1, min_samples_split=15, n_estimators=700; total time= 30.5s
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1, min_samples_split=15, n_estimators=700; total time= 31.1s
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
[CV] END max_depth=20, max_features=auto, min_samples_leaf=1, min_samples_split=15, n_estimators=700; total time= 31.5s
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\ensemble\_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(

```



Out[70]:



```
In [71]: rf_random.best_params_
```

```
Out[71]: {'n_estimators': 700,
          'min_samples_split': 15,
          'min_samples_leaf': 1,
          'max_features': 'auto',
          'max_depth': 20}
```

```
In [72]: prediction = rf_random.predict(X_test)
```

```
In [73]: plt.figure(figsize = (8,8))
          sns.distplot(y_test-prediction)
          plt.show()
```

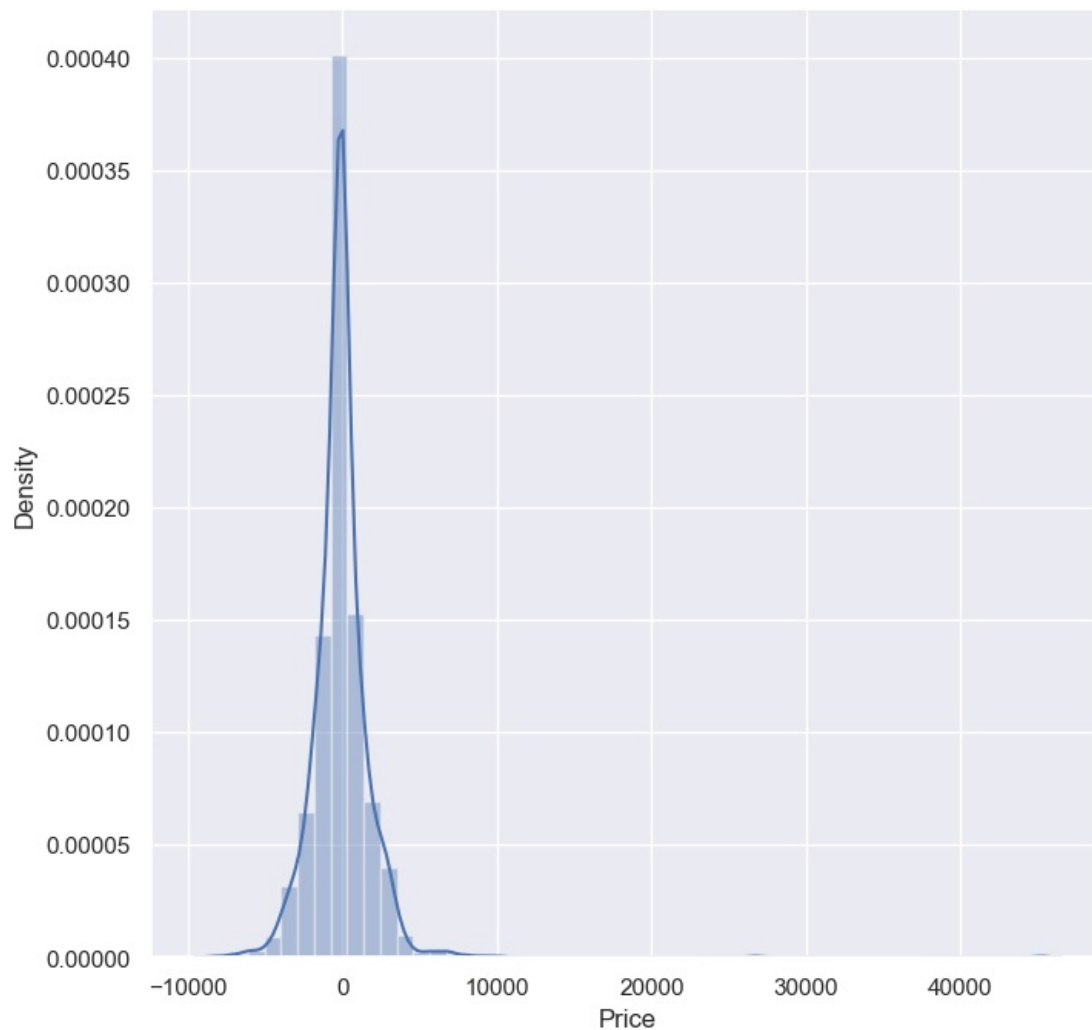
C:\Users\HP\AppData\Local\Temp\ipykernel\_16092\1574001921.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

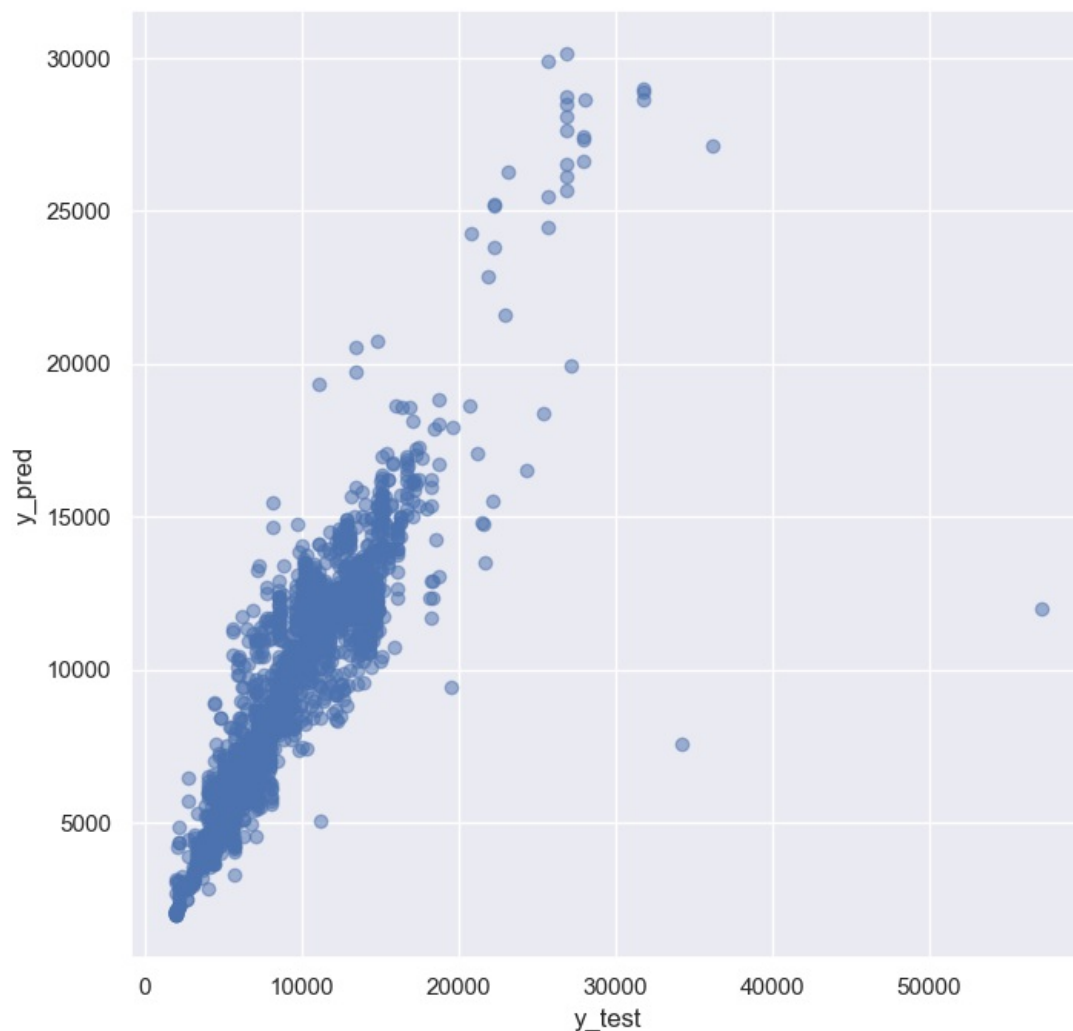
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(y_test-prediction)
```



```
In [74]: plt.figure(figsize = (8,8))
          plt.scatter(y_test, prediction, alpha = 0.5)
          plt.xlabel("y_test")
          plt.ylabel("y_pred")
          plt.show()
```



```
In [75]: 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: 1164.475741487747
MSE: 4051298.9496157276
RMSE: 2012.7838805037484
```

## Save the model to reuse it again

```
In [88]: import pickle
# open a file, where you want to store the data
file = open('flight_rf.pkl', 'wb')

# dump information to that file
pickle.dump(reg_rf, file)
```

```
In [92]: model = open('flight_rf.pkl', 'rb')
forest = pickle.load(model)
```

```
In [93]: y_prediction = forest.predict(X_test)
```

```
In [94]: metrics.r2_score(y_test, y_prediction)
```

```
Out[94]: 0.797010031600254
```

```
In [ ]:
```