Prediction Model for Flight Fare

Shreya Todmal

```
Life- Cycle of  this Data Science Project :
   a) Data collection
   b) Perform Data Cleaning / Data Preparation / Data Pre-processing
   c) Data visuaslisation(EDA)
   d) Perform feature engineering
       I)  Feature encoding
       II) checking outliers & impute it
       III)Feature selection or feature importance

   e) build machine leaning model
   f) Automate ML Pipeline
   g) Dump the appropriate model
```

Importing libraries

In [4]:
```
## import necessary packages !

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

Importing dataset

```
Since data is in form of excel file use pandas read_excel to load the
data
```

In [5]:
```
train_data = pd.read_excel(r"C:\Users\Shreya\Documents\Data Analytics Project\Flight F
```

In [6]:
```
train_data.head(4)
```

Out[6]:

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

In [7]:
```
train_data.tail(4)
```

Out[7]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Tot
10679	Air India	27/04/2019	Kolkata	Banglore	CCU → BLR	20:45	23:20	2h 35m	
10680	Jet Airways	27/04/2019	Banglore	Delhi	BLR → DEL	08:20	11:20	3h	
10681	Vistara	01/03/2019	Banglore	New Delhi	BLR → DEL	11:30	14:10	2h 40m	
10682	Air India	9/05/2019	Delhi	Cochin	DEL → GOI → BOM → COK	10:55	19:15	8h 20m	

Data Cleaning

1) Missing Values

In [8]:
```
train_data.info() # check if all non null values are same
```

```
<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
```

features belong to object data-type , ie.. in context to Python , they belong to string data-type

1 feature belong to int64 nature , ie Variations of int are : ('int64','int32','int16') in numpy library The only difference is that int64 has max range of storing numbers , then comes int32 , then 16 , then int8

That means that Int64's take up twice as much memory-and doing operations on them may be a lot slower in some machine architectures.

However, Int64's can represent numbers much more accurately than 32 bit floats.They also allow much larger numbers to be stored..

The memory usage of a DataFrame (including the index) is shown when calling the info(). A configuration option, display.memory_usage (see the list of options), specifies if the DataFrame's memory usage will be displayed when invoking the df.info() method..

memory usage: 918.2+ KB The + symbol indicates that the true memory usage could be higher, because pandas does not count the memory used by values in columns with dtype=object

Passing memory_usage='deep' will enable a more accurate memory usage report .

In [12]:
```
# After loading it is important to check null/missing values in a column or a row
# Missing value :  values which occur when no data is recorded for an observation..

train_data.isnull().sum()

# by-default axis is 0 , ie it computes total missing values column-wise !
```

Out[12]:
```
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
```

In [13]:
```
train_data['Total_Stops'].isnull()
```

Out[13]:
```
0        False
1        False
2        False
3        False
4        False
         ...
10678    False
10679    False
10680    False
10681    False
10682    False
Name: Total_Stops, Length: 10683, dtype: bool
```

In [14]:
```
# getting all the rows where we have missing value

train_data[train_data['Total_Stops'].isnull()]
```

Out[14]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_
9039	Air India	6/05/2019	Delhi	Cochin	NaN	09:45	09:25 07 May	23h 40m	

as we have 1 missing value , directly drop these

In [15]:
```
train_data.dropna(inplace=True)
```

In [16]:
```
train_data.isnull().sum() # check again for missing value
```

Out[16]:
```
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
```

In [17]:
```
train_data.dtypes
```

Out[17]:
```
Airline            object
Date_of_Journey    object
Source             object
Destination        object
Route              object
Dep_Time           object
Arrival_Time       object
Duration           object
Total_Stops        object
Additional_Info    object
Price               int64
dtype: object
```

In [19]:
```
# In order to more accurate memory usage ,leverage memory_usage="deep" in info()
train_data.info(memory_usage="deep")
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10682 entries, 0 to 10682
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Airline          10682 non-null  object
 1   Date_of_Journey  10682 non-null  object
 2   Source           10682 non-null  object
 3   Destination      10682 non-null  object
 4   Route            10682 non-null  object
 5   Dep_Time         10682 non-null  object
 6   Arrival_Time     10682 non-null  object
 7   Duration         10682 non-null  object
 8   Total_Stops      10682 non-null  object
 9   Additional_Info  10682 non-null  object
 10  Price            10682 non-null  int64 
dtypes: int64(1), object(10)
memory usage: 7.2 MB
```

2) Data Pre-process & extract Derived attributes from "Date_of_Journey"

Extract derived attributes from "Date_of_Journey" & fetch day , month , year

In [20]:
```
data = train_data.copy()
```

In [21]:
```
data.columns
```

Out[21]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info', 'Price'],
      dtype='object')
```

In [22]:
```
data.head(2)
```

Out[22]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_St
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-s
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 st

In [23]:
```
data.dtypes
```

Out[23]:
```
Airline            object
Date_of_Journey    object
Source             object
Destination        object
Route              object
Dep_Time           object
Arrival_Time       object
Duration           object
Total_Stops        object
Additional_Info    object
Price               int64
dtype: object
```

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,bcz our model will not be able to understand these string values,it just understand Time-stamp
For this we require pandas to_datetime to convert object data type to datetime dtype.

In [24]:
```
def change_into_Datetime(col):
    data[col] = pd.to_datetime(data[col])
```

In [25]:
```
import warnings
from warnings import filterwarnings
filterwarnings("ignore")
```

In [26]:
```
data.columns
```

Out[26]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info', 'Price'],
      dtype='object')
```

In [27]:
```
for feature in ['Dep_Time', 'Arrival_Time' , 'Date_of_Journey']:
    change_into_Datetime(feature)
```

In [28]:
```
data.dtypes
```

Out[28]:
```
Airline                  object
Date_of_Journey    datetime64[ns]
Source                   object
Destination              object
Route                    object
Dep_Time           datetime64[ns]
Arrival_Time       datetime64[ns]
Duration                 object
Total_Stops              object
Additional_Info          object
Price                     int64
dtype: object
```

In [29]:
```
data["Journey_day"] = data['Date_of_Journey'].dt.day
```

In [30]:
```
data["Journey_month"] = data['Date_of_Journey'].dt.month
```

In [31]:
```
data["Journey_year"] = data['Date_of_Journey'].dt.year
```

In [32]:
```
data.head(3)
```

Out[32]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_St
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2024-08-18 22:20:00	2024-03-22 01:10:00	2h 50m	non-s
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	2024-08-18 05:50:00	2024-08-18 13:15:00	7h 25m	2 st
2	Jet Airways	2019-06-09	Delhi	Cochin	DEL → LKO → BOM → COK	2024-08-18 09:25:00	2024-06-10 04:25:00	19h	2 st

3) clean Dep_Time & Arrival_Time & then extract Derived attributes

In [33]:
```
def extract_hour_min(df , col):
    df[col+"_hour"] = df[col].dt.hour
    df[col+"_minute"] = df[col].dt.minute
    return df.head(3)
```

In [34]:
```
data.columns
```

Out[34]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info', 'Price', 'Journey_day', 'Journey_month',
       'Journey_year'],
      dtype='object')
```

In [35]:
```
# Departure time is when a plane leaves the gate.

extract_hour_min(data , "Dep_Time")
```

Out[35]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_St
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2024-08-18 22:20:00	2024-03-22 01:10:00	2h 50m	non-s
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	2024-08-18 05:50:00	2024-08-18 13:15:00	7h 25m	2 st
2	Jet Airways	2019-06-09	Delhi	Cochin	DEL → LKO → BOM → COK	2024-08-18 09:25:00	2024-06-10 04:25:00	19h	2 st

In [36]:
```
extract_hour_min(data , "Arrival_Time")
```

Out[36]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_St
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2024-08-18 22:20:00	2024-03-22 01:10:00	2h 50m	non-s
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	2024-08-18 05:50:00	2024-08-18 13:15:00	7h 25m	2 st
2	Jet Airways	2019-06-09	Delhi	Cochin	DEL → LKO → BOM → COK	2024-08-18 09:25:00	2024-06-10 04:25:00	19h	2 st

In [37]:
```
# we have extracted derived attributes from ['Arrival_Time' , "Dep_Time"] , so lets dr
cols_to_drop = ['Arrival_Time' , "Dep_Time"]

data.drop(cols_to_drop , axis=1 , inplace=True )
```

In [38]:
```
data.head(3)
```

Out[38]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pri
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	38
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	76
2	Jet Airways	2019-06-09	Delhi	Cochin	DEL → LKO → BOM → COK	19h	2 stops	No info	138

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

Out[39]:
```
(10682, 16)
```

Data Analysis

1) Analyse when will most of the flights take-off..

In [40]:
```
data.columns
```

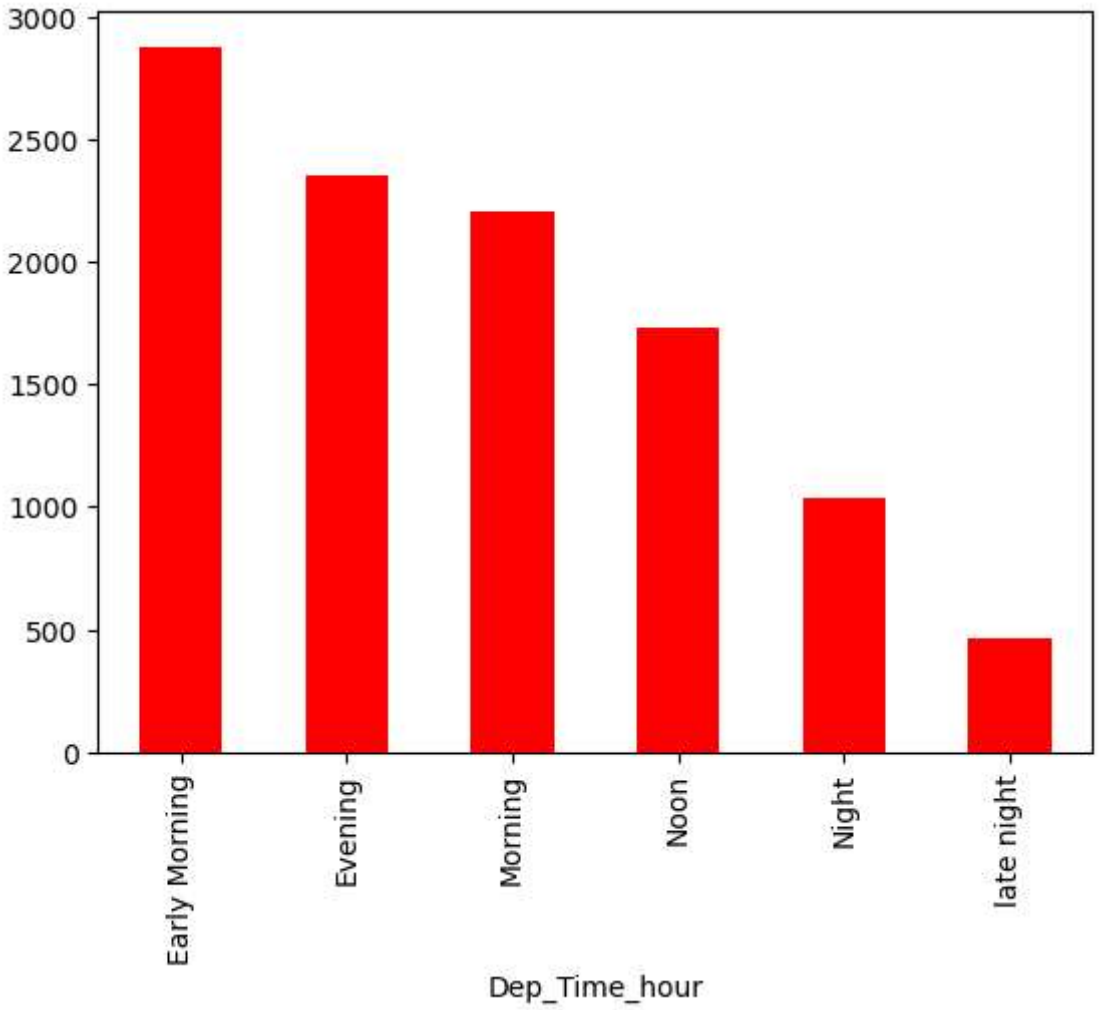
Out[40]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Duration', 'Total_Stops', 'Additional_Info', 'Price', 'Journey_day',
       'Journey_month', 'Journey_year', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute'],
      dtype='object')
```

In [41]:
```
# Converting the flight Dep_Time into proper time i.e. mid_night, morning, afternoon a

def flight_dep_time(x):
    '''
    This function takes the flight Departure time
    and convert into appropriate format.

    '''


    if (x>4) and (x<=8):
        return "Early Morning"

    elif (x>8) and (x<=12):
        return "Morning"

    elif (x>12) and (x<=16):
        return "Noon"

    elif (x>16) and (x<=20):
        return "Evening"
```

```
    elif (x>20) and (x<=24):
        return "Night"

    else:
        return "late night"
```

In [42]:
```
data['Dep_Time_hour'].apply(flight_dep_time).value_counts().plot(kind="bar" , color="r
```

Out[42]:
```
<Axes: xlabel='Dep_Time_hour'>
```



In [38]:
```
#### To make above graph interactive use Cufflinks & plotly
```

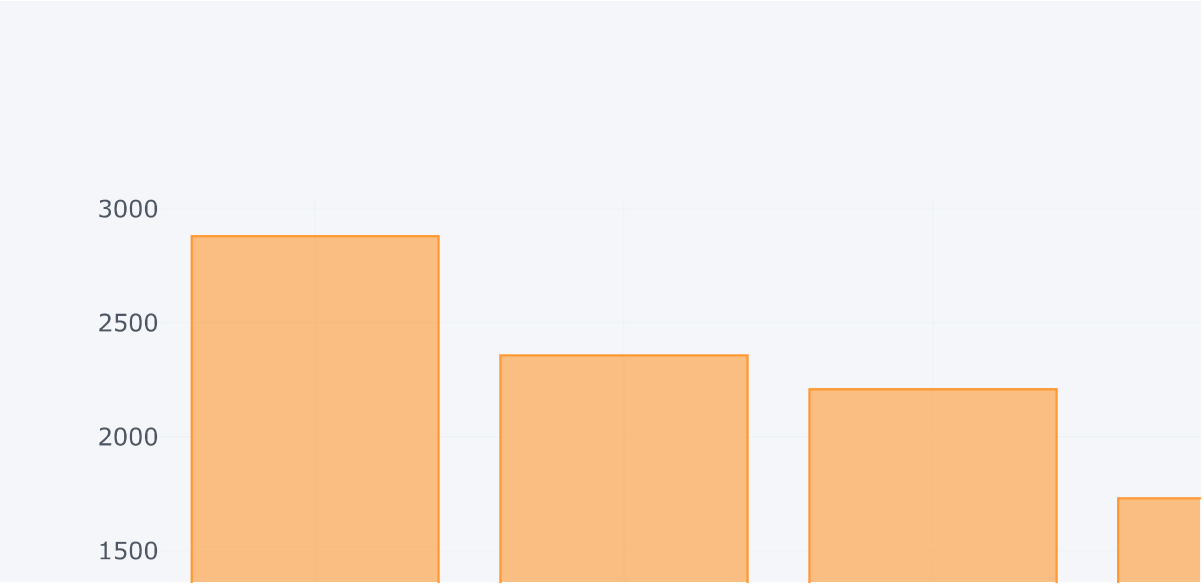
In [54]:
```
#!pip install plotly
#!pip install chart_studio
```

In [55]:
```
#!pip install cufflinks
```

In [43]:
```
# use Plotly interactive plots directly with Pandas dataframes

import plotly
import cufflinks as cf
from cufflinks.offline import go_offline
from plotly.offline import plot , iplot , init_notebook_mode , download_plotlyjs
init_notebook_mode(connected=True)
cf.go_offline()
```

```
# plot is a command of Matplotlib which is more old-school. It creates static charts
# iplot is an interactive plot. Plotly takes Python code and makes beautiful looking J
# It is available only in jupyter ntbk and google collab
```

In [44]:
```
data['Dep_Time_hour'].apply(flight_dep_time).value_counts().iplot(kind="bar")
```



2) Pre-process Duration Feature & extract meaningful features from it

Apply pre-processing on duration column,

```
-->> Once we pre-processed the Duration feature extract Duration
hours and minute from duration

-->> As ML model is not able to understand this duration as it
contains string values ,
thats why we have to convert this in hour &  minute for each of the
row
```

In [45]:
```
data.head(3)
```

Out[45]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pri
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	38
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	76
2	Jet Airways	2019-06-09	Delhi	Cochin	DEL → LKO → BOM → COK	19h	2 stops	No info	138

In [46]:
```
def preprocess_duration(x):
    if 'h' not in x:
        x = '0h' + ' ' + x
    elif 'm' not in x:
        x = x + ' ' +'0m'

    return x
```

In [47]:
```
data['Duration'] = data['Duration'].apply(preprocess_duration)
```

In [48]:
```
data['Duration']
```

Out[48]:
```
0        2h 50m
1        7h 25m
2        19h 0m
3        5h 25m
4        4h 45m
          ...
10678    2h 30m
10679    2h 35m
10680     3h 0m
10681    2h 40m
10682    8h 20m
Name: Duration, Length: 10682, dtype: object
```

Now after pre-processing duration feature , still ml_model is not able to understand duration
bcz it is string data so any how we have to convert it into numerical(integer of float) values

In [49]:
```
data['Duration'][0]
```

Out[49]:
```
'2h 50m'
```

In [50]:
```
'2h 50m'.split(' ')
```

Out[50]:
```
['2h', '50m']
```

In [51]:
```
'2h 50m'.split(' ')[0]
```

Out[51]:
```
'2h'
```

In [52]:
```
'2h 50m'.split(' ')[0][0:-1]
```

Out[52]:
```
'2'
```

In [53]:
```
type('2h 50m'.split(' ')[0][0:-1])
```

Out[53]:
```
str
```

In [54]:
```
int('2h 50m'.split(' ')[0][0:-1])
```

Out[54]:
```
2
```

In [55]:
```
int('2h 50m'.split(' ')[1][0:-1])
```

Out[55]:
```
50
```

In [56]:
```
data['Duration_hours'] = data['Duration'].apply(lambda x : int(x.split(' ')[0][0:-1]))
```

In [57]:
```
data['Duration_mins'] = data['Duration'].apply(lambda x : int(x.split(' ')[1][0:-1]))
```

In [58]:
```
data.head(2)
```

Out[58]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pric
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	389
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	766

In [59]:
```
pd.to_timedelta(data["Duration"]).dt.components.hours
```

Out[59]:
```
0         2
1         7
2        19
3         5
4         4
        ..
10678     2
10679     2
10680     3
10681     2
10682     8
Name: hours, Length: 10682, dtype: int64
```

In [60]:
```
data["Duration_hour"] = pd.to_timedelta(data["Duration"]).dt.components.hours
```

In [61]:
```
data["Duration_minute"] = pd.to_timedelta(data["Duration"]).dt.components.minutes
```

3) Analyse whether Duration impacts Price or not ?

In [63]:
```
data['Duration'] # convert duration into total minutes duration
```

Out[63]:
```
0        2h 50m
1        7h 25m
2        19h 0m
3        5h 25m
4        4h 45m
         ...
10678    2h 30m
10679    2h 35m
10680     3h 0m
10681    2h 40m
10682    8h 20m
Name: Duration, Length: 10682, dtype: object
```

In [64]:
```
eval('2*60') # explaination of below step, where elav function can be used to evaluate
```

Out[64]:
```
120
```

In [65]:
```
data['Duration_total_mins'] = data['Duration'].str.replace('h' ,"*60").str.replace(' '
```

In [66]:
```
data['Duration_total_mins']
```

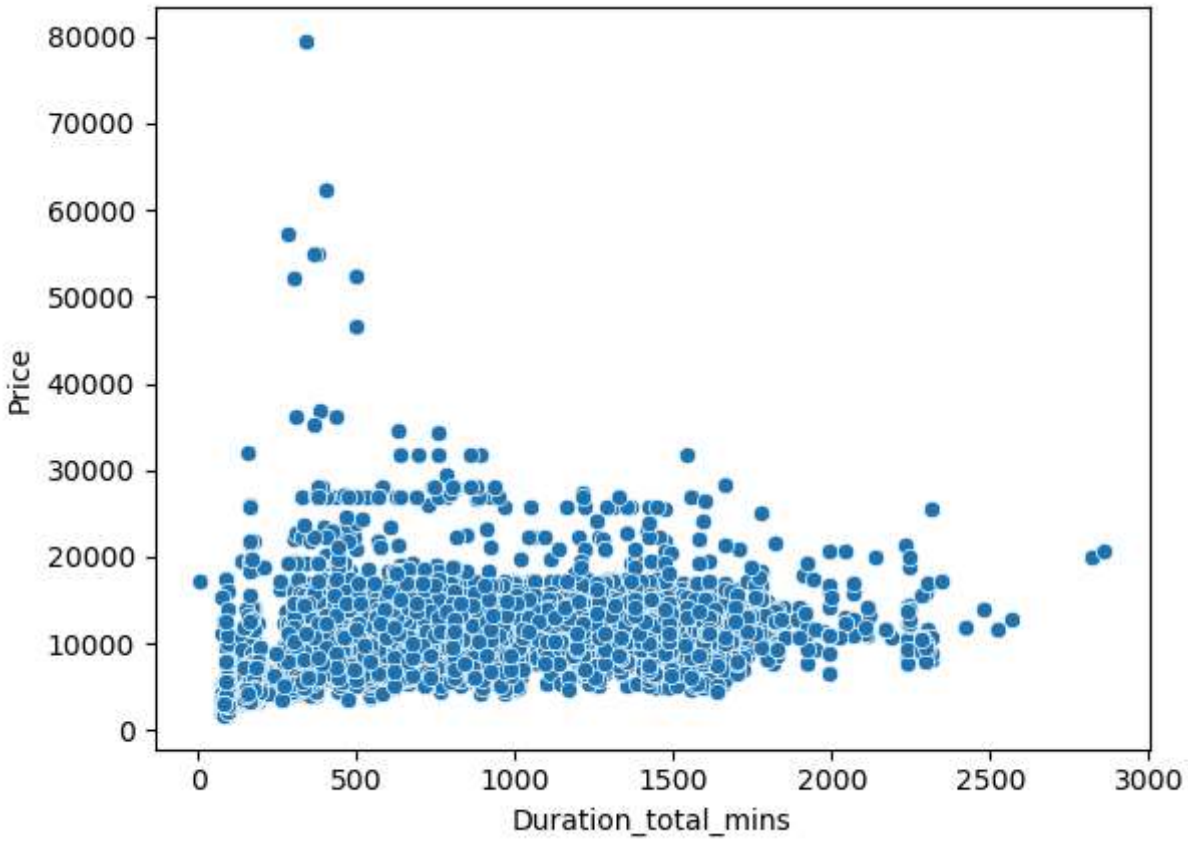
Out[66]:
```
0         170
1         445
2        1140
3         325
4         285
         ...
10678     150
10679     155
10680     180
10681     160
10682     500
Name: Duration_total_mins, Length: 10682, dtype: int64
```

In [67]:
```
data.columns
```

Out[67]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Duration', 'Total_Stops', 'Additional_Info', 'Price', 'Journey_day',
       'Journey_month', 'Journey_year', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute', 'Duration_hours',
       'Duration_mins', 'Duration_hour', 'Duration_minute',
       'Duration_total_mins'],
      dtype='object')
```

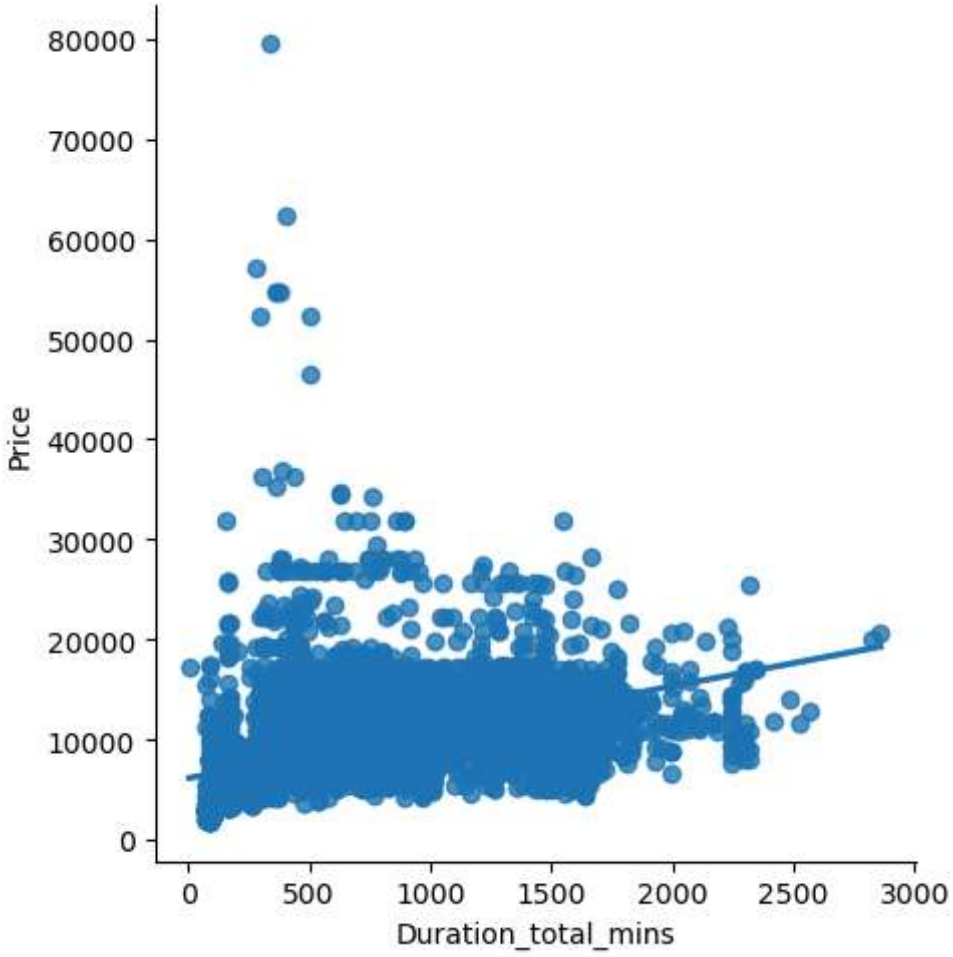
In [68]:
```
sns.scatterplot(x="Duration_total_mins" , y="Price" , data=data) # to be used when the
```

Out[68]:
```
<Axes: xlabel='Duration_total_mins', ylabel='Price'>
```



In [69]:
```
sns.lmplot(x="Duration_total_mins" , y="Price" , data=data) #regression plot

# pretty clear that As the duration of minutes increases Flight price also increases.
```

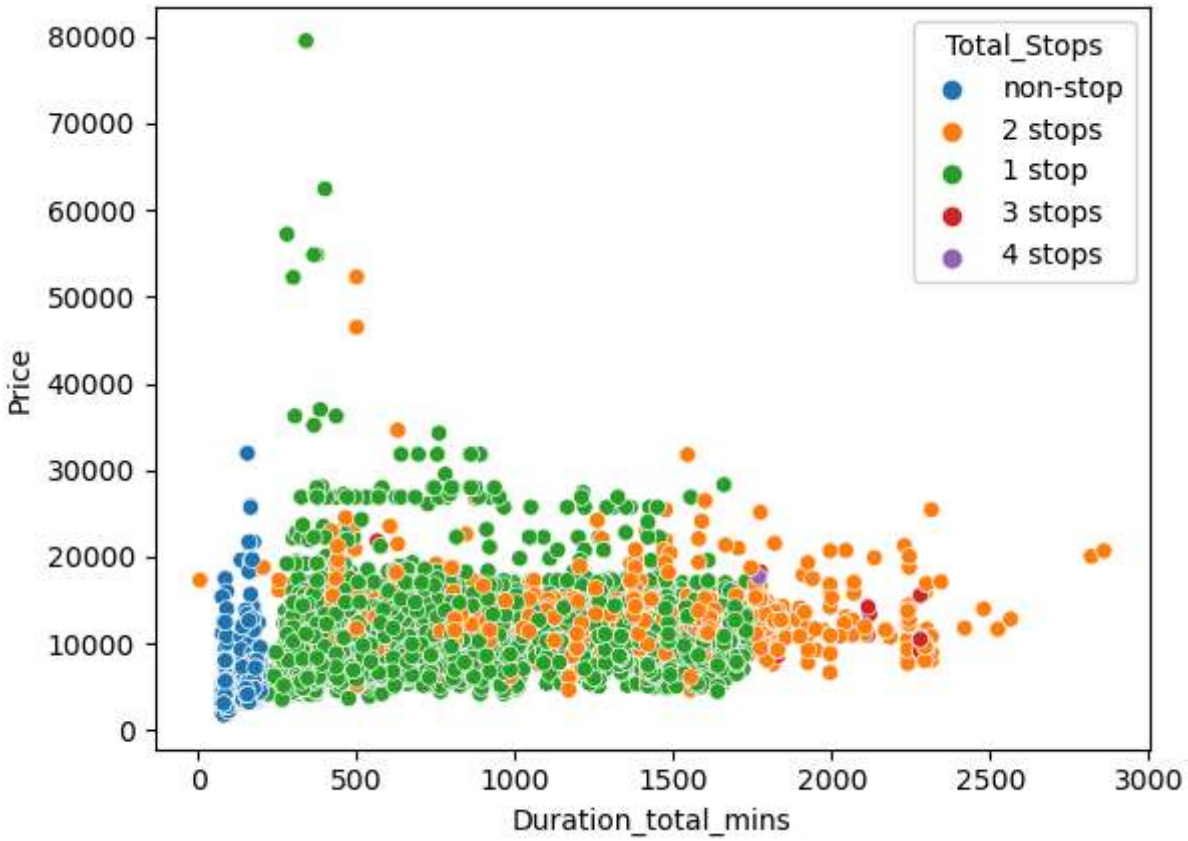
Out[69]:
```
<seaborn.axisgrid.FacetGrid at 0x206a16bf1d0>
```



In [70]:
```
# understand whether total stops affect price or not !
```

In [71]:
```
sns.scatterplot(x="Duration_total_mins" , y="Price" , hue="Total_Stops", data=data)
```

Out[71]:
```
<Axes: xlabel='Duration_total_mins', ylabel='Price'>
```



Non stops flights take less duration while their fare is also low, then as the stop increases, duration also increases and price also increases(in most of the cases)

4) which route Jet Airways is extremely used?

In [72]:
```
data['Airline']=='Jet Airways'
```

Out[72]:
```
0        False
1        False
2         True
3        False
4        False
         ...
10678    False
10679    False
10680     True
10681    False
10682    False
Name: Airline, Length: 10682, dtype: bool
```

In [73]:
```
data[data['Airline']=='Jet Airways'].groupby('Route').size().sort_values(ascending=Fal
```

Out[73]:
```
Route
CCU → BOM → BLR          930
DEL → BOM → COK          875
BLR → BOM → DEL          385
BLR → DEL                382
CCU → DEL → BLR          300
BOM → HYD                207
DEL → JAI → BOM → COK    207
DEL → AMD → BOM → COK    141
DEL → IDR → BOM → COK     86
DEL → NAG → BOM → COK     61
DEL → ATQ → BOM → COK     38
DEL → COK                 34
DEL → BHO → BOM → COK     29
DEL → BDQ → BOM → COK     28
DEL → LKO → BOM → COK     25
DEL → JDH → BOM → COK     23
CCU → GAU → BLR           22
DEL → MAA → BOM → COK     16
DEL → IXC → BOM → COK     13
BLR → MAA → DEL           10
BLR → BDQ → DEL            8
DEL → UDR → BOM → COK      7
BOM → DEL → HYD            5
CCU → BOM → PNQ → BLR      4
BLR → BOM → JDH → DEL      3
DEL → DED → BOM → COK      2
BOM → BDQ → DEL → HYD      2
DEL → CCU → BOM → COK      1
BOM → VNS → DEL → HYD      1
BOM → UDR → DEL → HYD      1
BOM → JDH → DEL → HYD      1
BOM → IDR → DEL → HYD      1
BOM → DED → DEL → HYD      1
dtype: int64
```

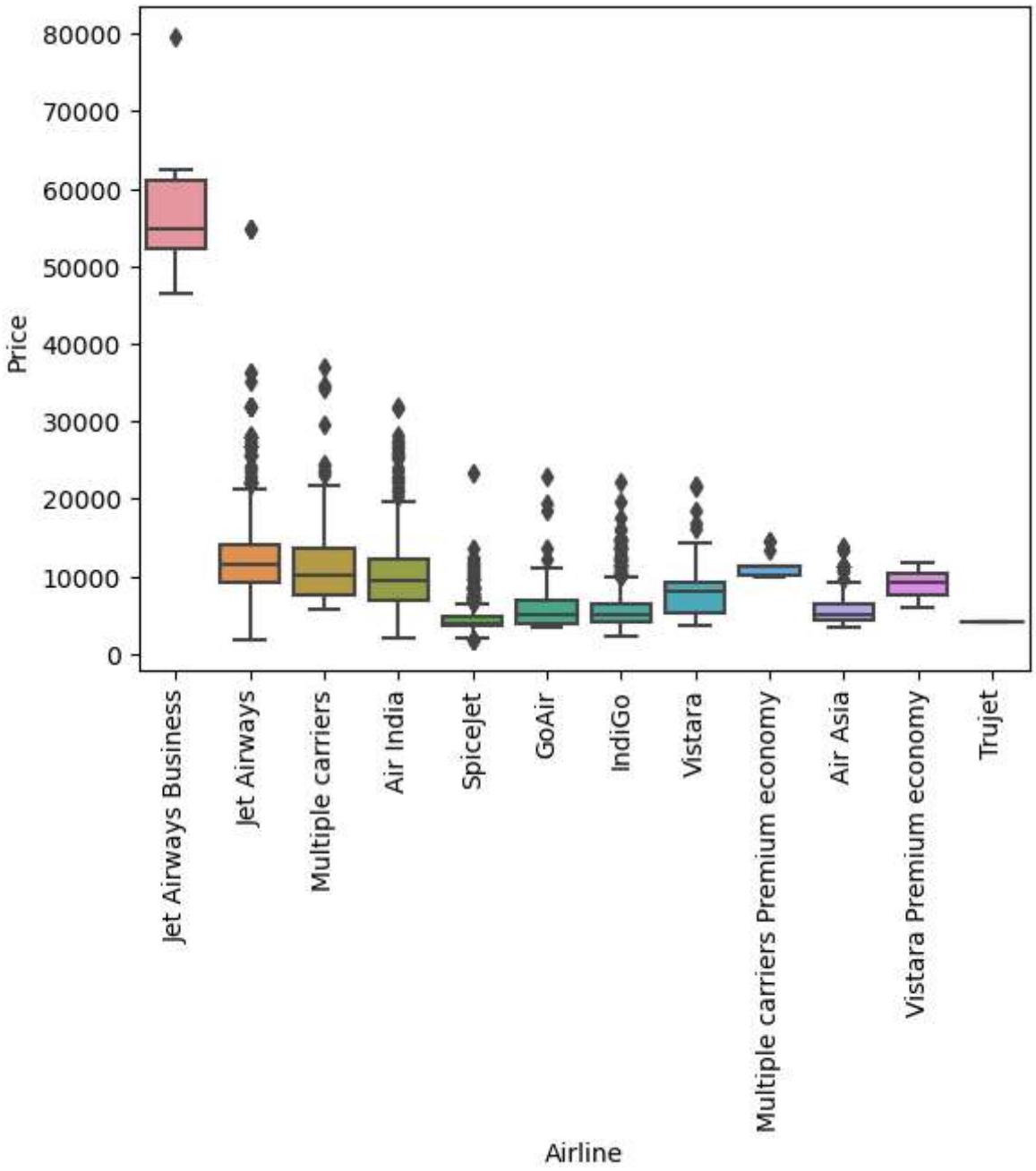
5) Performing Airline vs Price Analysis

ie find price distribution & 5-point summary of each Airline

In [74]:
```
data.columns
```

Out[74]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Duration', 'Total_Stops', 'Additional_Info', 'Price', 'Journey_day',
       'Journey_month', 'Journey_year', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute', 'Duration_hours',
       'Duration_mins', 'Duration_hour', 'Duration_minute',
       'Duration_total_mins'],
      dtype='object')
```

In [75]:
```
sns.boxplot(y='Price' , x='Airline' , data=data.sort_values('Price' , ascending=False))
plt.xticks(rotation="vertical")
plt.show()
```



Conclusion--> From graph we can see that Jet Airways Business have the highest Price., Apart from the first Airline almost all are having similar median

Feature Engineering

1) Applying one-hot Encoding on data

In [76]:
```
data.head(2)
```

Out[76]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pric
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	389
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	766

2 rows × 21 columns

Categorical data refers to a data type that can be stored into groups/categories/labels Examples of categorical variables are age group, educational level,blood type etc..

Numerical data refers to the data that is in the form of numbers, Examples of numerical data are height, weight, age etc..

Numerical data has two categories: discrete data and continuous data

Discrete data : It basically takes countable numbers like 1, 2, 3, 4, 5, and so on. In case of infinity, these numbers will keep going on... age of a fly : 8 , 9 day etc..

Continuous data : which is continuous in nature amount of sugar , 11.2 kg , temp of a city , your bank balance !

In [77]:
```
cat_col = [col for col in data.columns if data[col].dtype=="object"]
```

In [78]:
```
num_col = [col for col in data.columns if data[col].dtype!="object"]
```

2) Handling Categorical Data

```
We are using 2 basic Encoding Techniques to convert Categorical data
into some numerical format
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 [79]:
```
cat_col
```

Out[79]:
```
['Airline',
 'Source',
 'Destination',
 'Route',
 'Duration',
 'Total_Stops',
 'Additional_Info']
```

In [80]:
```
# Applying One-hot from scratch :
```

In [81]:
```
data['Source'].unique()
```

Out[81]:
```
array(['Banglore', 'Kolkata', 'Delhi', 'Chennai', 'Mumbai'], dtype=object)
```

In [82]:
```
data['Source'].apply(lambda x : 1 if x=='Banglore' else 0)
```

Out[82]:
```
0        1
1        0
2        0
3        0
4        1
        ..
10678    0
10679    0
10680    1
10681    1
10682    0
Name: Source, Length: 10682, dtype: int64
```

In [83]:
```
for sub_category in data['Source'].unique():
    data['Source_'+sub_category] = data['Source'].apply(lambda x : 1 if x==sub_categor
```

In [84]:
```
data.head(3)
```

Out[84]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pri
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	38
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	76
2	Jet Airways	2019-06-09	Delhi	Cochin	DEL → LKO → BOM → COK	19h 0m	2 stops	No info	138

3 rows × 26 columns

3) Perform target guided encoding on Data

```
We can use One-hot , but if we have more sub-categories , it creates
curse of dimensionality
Use Target Guided Mean Encoding in such case to get rid of curse of
dimensionality..
```

Now on 2 features , Airline & Destination , we can apply on-hot as there is no such order but total_stops is my ordinal data , it makes no sense if we apply on-hot on top of this.. similarly if

we have any feature which have more categories , it is not good to apply one-hot as it will create curse of dimensionality issue , which leads to usage of more resources of your pc..

So appplying mean Encoding or better techniques like Target Guided Ordinal Encoding

In [85]:
```
cat_col
```

Out[85]:
```
['Airline',
 'Source',
 'Destination',
 'Route',
 'Duration',
 'Total_Stops',
 'Additional_Info']
```

In [86]:
```
data.head(2)
```

Out[86]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pric
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	389
1	Air India	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	766

2 rows × 26 columns

In [87]:
```
data['Airline'].nunique()
```

Out[87]:
```
12
```

In [88]:
```
data.groupby(['Airline'])['Price'].mean().sort_values()
```

Out[88]:
```
Airline
Trujet                             4140.000000
SpiceJet                           4338.284841
Air Asia                           5590.260188
IndiGo                             5673.682903
GoAir                              5861.056701
Vistara                            7796.348643
Vistara Premium economy            8962.333333
Air India                          9612.427756
Multiple carriers                 10902.678094
Multiple carriers Premium economy 11418.846154
Jet Airways                       11643.923357
Jet Airways Business              58358.666667
Name: Price, dtype: float64
```

In [89]:
```
airlines = data.groupby(['Airline'])['Price'].mean().sort_values().index
```

In [90]:
```
airlines
```

Out[90]:
```
Index(['Trujet', 'SpiceJet', 'Air Asia', 'IndiGo', 'GoAir', 'Vistara',
       'Vistara Premium economy', 'Air India', 'Multiple carriers',
       'Multiple carriers Premium economy', 'Jet Airways',
       'Jet Airways Business'],
      dtype='object', name='Airline')
```

In [91]:
```
dict_airlines = {key:index for index , key in enumerate(airlines , 0)}
```

In [92]:
```
dict_airlines
```

Out[92]:
```
{'Trujet': 0,
 'SpiceJet': 1,
 'Air Asia': 2,
 'IndiGo': 3,
 'GoAir': 4,
 'Vistara': 5,
 'Vistara Premium economy': 6,
 'Air India': 7,
 'Multiple carriers': 8,
 'Multiple carriers Premium economy': 9,
 'Jet Airways': 10,
 'Jet Airways Business': 11}
```

In [93]:
```
data['Airline'] = data['Airline'].map(dict_airlines)
```

In [94]:
```
data['Airline']
```

Out[94]:
```
0         3
1         7
2        10
3         3
4         3
        ..
10678     2
10679     7
10680    10
10681     5
10682     7
Name: Airline, Length: 10682, dtype: int64
```

In [95]:
```
data.head(3)
```

Out[95]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pri
0	3	2019-03-24	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	38
1	7	2019-05-01	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	76
2	10	2019-06-09	Delhi	Cochin	DEL → LKO → BOM → COK	19h 0m	2 stops	No info	138

3 rows × 26 columns

In [96]:
```
# now perform Target Guided Mean encoding on 'Destination'
```

In [97]:
```
data['Destination'].unique()
```

Out[97]:
```
array(['New Delhi', 'Banglore', 'Cochin', 'Kolkata', 'Delhi', 'Hyderabad'],
      dtype=object)
```

till now , Delhi has only one Airport which is IGI & its second Airport is yet to build in Greater Noida (Jewar) which is neighbouring part of Delhi so we will consider New Delhi & Delhi as same

but in future , these conditions may change..

In [98]:
```
data['Destination'].replace('New Delhi' , 'Delhi' , inplace=True)
```

In [99]:
```
data['Destination'].unique()
```

Out[99]:
```
array(['Delhi', 'Banglore', 'Cochin', 'Kolkata', 'Hyderabad'],
      dtype=object)
```

In [100…
```
dest = data.groupby(['Destination'])['Price'].mean().sort_values().index
```

In [101…
```
dest
```

Out[101]:
```
Index(['Kolkata', 'Hyderabad', 'Delhi', 'Banglore', 'Cochin'], dtype='object', name
='Destination')
```

In [102…
```
dict_dest = {key:index for index , key in enumerate(dest , 0)}
```

In [103…
```
dict_dest
```

Out[103]:
```
{'Kolkata': 0, 'Hyderabad': 1, 'Delhi': 2, 'Banglore': 3, 'Cochin': 4}
```

In [104…
```
data['Destination'] = data['Destination'].map(dict_dest)
```

In [105…
```
data['Destination']
```

Out[105]:
```
0        2
1        3
2        4
3        3
4        2
        ..
10678    3
10679    3
10680    2
10681    2
10682    4
Name: Destination, Length: 10682, dtype: int64
```

In [106…
```
data.head(3)
```

Out[106]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pri
0	3	2019-03-24	Banglore	2	BLR → DEL	2h 50m	non-stop	No info	38
1	7	2019-05-01	Kolkata	3	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	76
2	10	2019-06-09	Delhi	4	DEL → LKO → BOM → COK	19h 0m	2 stops	No info	138

3 rows × 26 columns

4) Perform Label(Manual) Encoding on Data

In [107…
```
data.head(3)
```

Out[107]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pri
0	3	2019-03-24	Banglore	2	BLR → DEL	2h 50m	non-stop	No info	38
1	7	2019-05-01	Kolkata	3	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	76
2	10	2019-06-09	Delhi	4	DEL → LKO → BOM → COK	19h 0m	2 stops	No info	138

3 rows × 26 columns

In [108…
```
data['Total_Stops']
```

Out[108]:
```
0        non-stop
1         2 stops
2         2 stops
3          1 stop
4          1 stop
           ...
10678    non-stop
10679    non-stop
10680    non-stop
10681    non-stop
10682     2 stops
Name: Total_Stops, Length: 10682, dtype: object
```

In [109…
```
data['Total_Stops'].unique()
```

Out[109]:
```
array(['non-stop', '2 stops', '1 stop', '3 stops', '4 stops'],
      dtype=object)
```

In [ ]:
```
# As this is case of Ordinal Categorical type we perform Label encoding from scratch
# Here Values are assigned with corresponding key
```

In [110…
```
stop = {'non-stop':0, '2 stops':2, '1 stop':1, '3 stops':3, '4 stops':4}
```

In [111…
```
data['Total_Stops'] = data['Total_Stops'].map(stop)
```

In [112…
```
data['Total_Stops']
```

Out[112]:
```
0        0
1        2
2        2
3        1
4        1
        ..
10678    0
10679    0
10680    0
10681    0
10682    2
Name: Total_Stops, Length: 10682, dtype: int64
```

4) Remove Un-necessary features

In [113…
```
data.head(1)
```

Out[113]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pric
0	3	2019-03-24	Banglore	2	BLR → DEL	2h 50m	0	No info	389

1 rows × 26 columns

In [114…
```
data.columns
```

Out[114]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Duration', 'Total_Stops', 'Additional_Info', 'Price', 'Journey_day',
       'Journey_month', 'Journey_year', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute', 'Duration_hours',
       'Duration_mins', 'Duration_hour', 'Duration_minute',
       'Duration_total_mins', 'Source_Banglore', 'Source_Kolkata',
       'Source_Delhi', 'Source_Chennai', 'Source_Mumbai'],
      dtype='object')
```

In [115…
```
data['Additional_Info'].value_counts()/len(data)*100

# Additional_Info contains almost 80% no_info,so drop this column
```

Out[115]:
```
Additional_Info
No info                         78.112713
In-flight meal not included     18.554578
No check-in baggage included     2.995694
1 Long layover                   0.177869
Change airports                  0.065531
Business class                   0.037446
No Info                          0.028085
1 Short layover                  0.009362
Red-eye flight                   0.009362
2 Long layover                   0.009362
Name: count, dtype: float64
```

In [116…
```
data.head(4)
```

Out[116]:

	Airline	Date_of_Journey	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Pri
0	3	2019-03-24	Banglore	2	BLR → DEL	2h 50m	0	No info	38
1	7	2019-05-01	Kolkata	3	CCU → IXR → BBI → BLR	7h 25m	2	No info	76
2	10	2019-06-09	Delhi	4	DEL → LKO → BOM → COK	19h 0m	2	No info	138
3	3	2019-05-12	Kolkata	3	CCU → NAG → BLR	5h 25m	1	No info	62

4 rows × 26 columns

In [117…
```
data.columns
```

Out[117]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Duration', 'Total_Stops', 'Additional_Info', 'Price', 'Journey_day',
       'Journey_month', 'Journey_year', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute', 'Duration_hours',
       'Duration_mins', 'Duration_hour', 'Duration_minute',
       'Duration_total_mins', 'Source_Banglore', 'Source_Kolkata',
       'Source_Delhi', 'Source_Chennai', 'Source_Mumbai'],
      dtype='object')
```

In [118…
```
data['Journey_year'].unique()
```

Out[118]:
```
array([2019])
```

Drop Date_of_Journey as well as we have already extracted "Journey_hour" , "jpuney_month" , Journey_day".. Additional_Info contains almost 80% no_info , so we can drop this column .. Drop Duration_total_mins as we have already extracted "Duration_hours" & "Duration_mins" Drop "Source" feature as well as we have already perform feature encoding on this Feature Drop Journey_year as well , as it has constant values throughtout dataframe which is 2019..

In [119…
```
data.drop(columns=['Date_of_Journey' , 'Additional_Info' , 'Duration_total_mins' , 'So
```

In [120…
```
data.columns
```

Out[120]:
```
Index(['Airline', 'Destination', 'Route', 'Duration', 'Total_Stops', 'Price',
       'Journey_day', 'Journey_month', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute', 'Duration_hours',
       'Duration_mins', 'Duration_hour', 'Duration_minute', 'Source_Banglore',
       'Source_Kolkata', 'Source_Delhi', 'Source_Chennai', 'Source_Mumbai'],
      dtype='object')
```

In [121…
```
data.head(4)
```

Out[121]:

	Airline	Destination	Route	Duration	Total_Stops	Price	Journey_day	Journey_month	Dep_Time_
0	3	2	BLR → DEL	2h 50m	0	3897	24	3	
1	7	3	CCU → IXR → BBI → BLR	7h 25m	2	7662	1	5	
2	10	4	DEL → LKO → BOM → COK	19h 0m	2	13882	9	6	
3	3	3	CCU → NAG → BLR	5h 25m	1	6218	12	5	

4 rows × 21 columns

In [122…
```
data.drop(columns=['Route'] , axis=1 , inplace=True)

## drop Route bcz Route is directly related to Total stops & considering 2 same featur
```

In [126…
```
data.head(3)
```

Out[126]:

	Airline	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_Time_hour	Dep_Time_m
0	3	2	0	3897	24	3	22	
1	7	3	2	7662	1	5	5	
2	10	4	2	13882	9	6	9	

5) Perform 0utlier detection

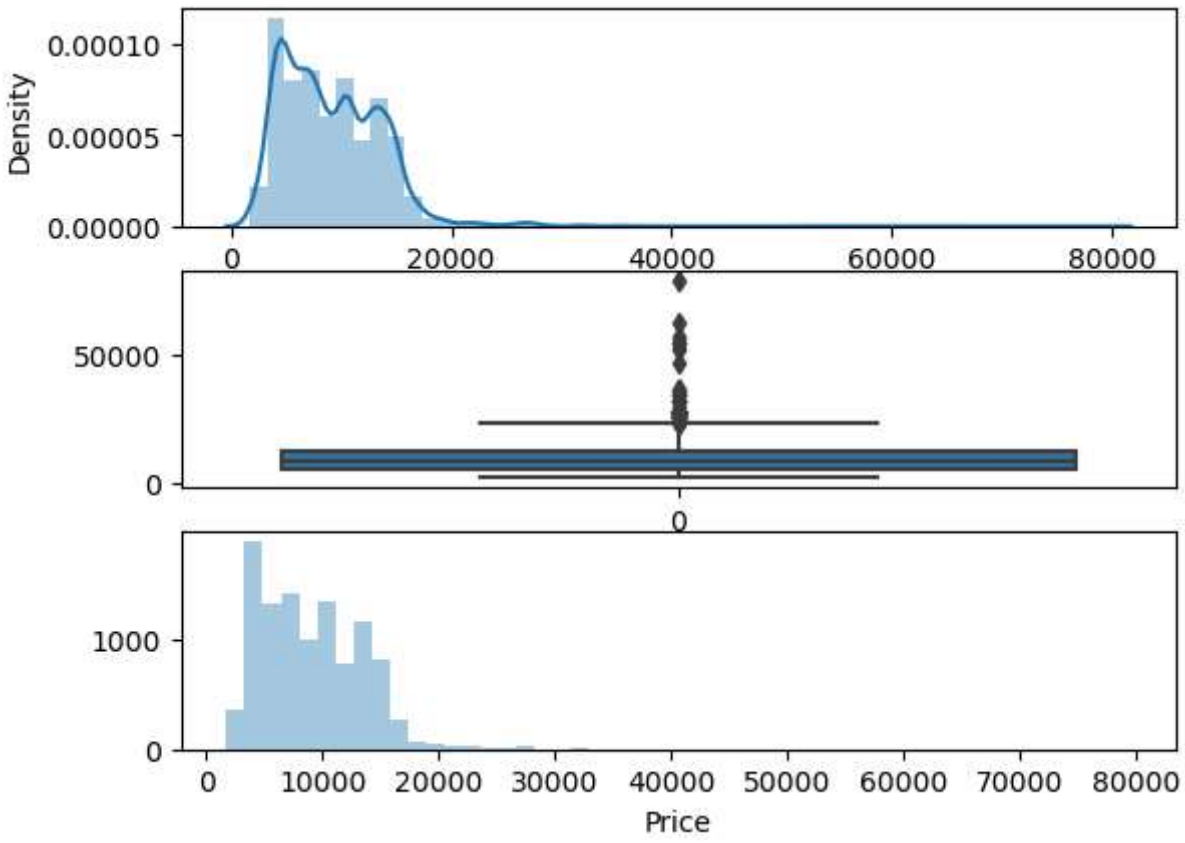
CAUSE FOR OUTLIERS * Data Entry Errors:- Human errors such as errors caused during data collection, recording, or entry can cause outliers in data. * Measurement Error:- It is the most common source of outliers. This is caused when the measurement instrument used turns out to be faulty.

Here the list of data visualization plots to spot the outliers.

1. Box and whisker plot (box plot).
2. Scatter plot.
3. Histogram.
4. Distribution Plot.

In [127…
```
def plot(df, col):
    fig , (ax1 , ax2 , ax3) = plt.subplots(3,1)

    sns.distplot(df[col] , ax=ax1)
    sns.boxplot(df[col] , ax=ax2)
    sns.distplot(df[col] , ax=ax3 , kde=False)
```

In [128…
```
plot(data , 'Price')
```



If Features are Skewed use the below Technique which is IQR
Data which are greater than IQR +1.5 IQR and data which are below than IQR - 1.5 IQR are outliers
where , IQR = 75th%ile data - 25th%ile data

& IQR +- 1.5 IQR will be changed depending upon the domain ie it could be sometimes IQR +- 3IQR

In [129…
```
q1 = data['Price'].quantile(0.25)
q3 = data['Price'].quantile(0.75)

iqr = q3- q1
```

```
maximum = q3 + 1.5*iqr
minimum = q1 - 1.5*iqr
```

In [130…
```
print(maximum)
```

```
23017.0
```

In [131…
```
print(minimum)
```

```
-5367.0
```

In [132…
```
print([price for price in data['Price'] if price> maximum or price<minimum])
```

```
[27430, 36983, 26890, 26890, 25139, 27210, 52229, 26743, 26890, 25735, 27992, 26890,
26890, 23583, 26890, 23533, 24115, 25735, 54826, 31783, 27992, 26890, 26890, 25430, 3
6235, 27210, 26890, 25735, 54826, 26890, 35185, 79512, 28097, 27992, 26890, 25735, 26
092, 31825, 25913, 25735, 27992, 31825, 23267, 62427, 54826, 31825, 25430, 26890, 362
35, 23843, 26890, 25735, 28322, 25735, 25735, 31825, 26890, 27992, 34273, 46490, 2952
8, 26890, 26890, 26890, 34503, 26890, 27992, 26890, 26890, 23170, 24528, 26890, 2799
2, 25735, 34608, 25703, 26890, 23528, 31825, 27282, 25735, 27992, 52285, 24017, 3194
5, 26890, 24318, 23677, 27992, 24210, 57209, 26890, 31825, 26480]
```

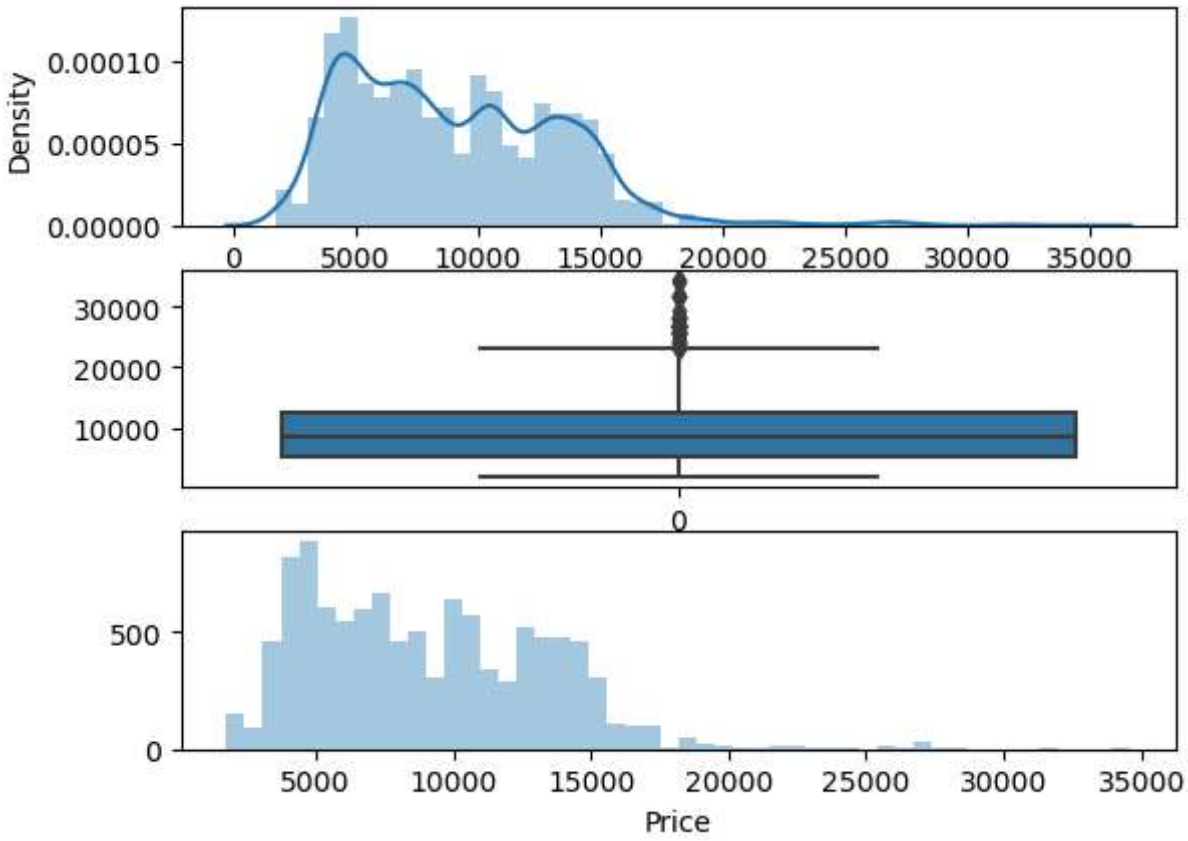
In [133…
```
len([price for price in data['Price'] if price> maximum or price<minimum])
```

Out[133]:
```
94
```

6) Deal with Outlier

In [134…
```
# wherever price >35K just replace replace it with median of Price

data['Price'] = np.where(data['Price']>=35000 , data['Price'].median() , data['Price']
```

In [135…
```
plot(data , 'Price')
```



Feature Selection

```
Feature Selection
Finding out the best feature which will contribute and have good
relation with target variable.


Q-> Why to apply Feature Selection?
To select important features ie to get rid of curse of dimensionality
ie..or to get rid of duplicate features
```

In [136…
```
X = data.drop(['Price'] , axis=1)
```

In [137…
```
y = data['Price']
```

In [138…
```
from sklearn.feature_selection import mutual_info_regression
```

In [139…
```
imp = mutual_info_regression(X , y)
```

Estimate mutual information for a continuous target variable.

Mutual information between two random variables is a non-negative value, which measures the dependency between the variables. If It is equal to zero it means two random variables are independent, and higher values mean higher dependency.

In [140…
```
imp
```

Out[140]:
```
array([0.9703245 , 1.00843625, 0.78757166, 0.23196788, 0.62690735,
       0.33440916, 0.2636411 , 0.38914304, 0.3522347 , 0.46376704,
       0.33497637, 0.42039949, 0.3478449 , 0.38981863, 0.45136283,
       0.52037359, 0.12622555, 0.18960283])
```

In [141…
```
imp_df = pd.DataFrame(imp , index=X.columns)
```

In [142…
```
imp_df.columns = ['importance']
```

In [143…
```
imp_df
```

Out[143]:

	importance
Airline	0.970325
Destination	1.008436
Total_Stops	0.787572
Journey_day	0.231968
Journey_month	0.626907
Dep_Time_hour	0.334409
Dep_Time_minute	0.263641
Arrival_Time_hour	0.389143
Arrival_Time_minute	0.352235
Duration_hours	0.463767
Duration_mins	0.334976
Duration_hour	0.420399
Duration_minute	0.347845
Source_Banglore	0.389819
Source_Kolkata	0.451363
Source_Delhi	0.520374
Source_Chennai	0.126226
Source_Mumbai	0.189603

In [144…
```
imp_df.sort_values(by='importance' , ascending=False)
```

Out[144]:

	importance
Destination	1.008436
Airline	0.970325
Total_Stops	0.787572
Journey_month	0.626907
Source_Delhi	0.520374
Duration_hours	0.463767
Source_Kolkata	0.451363
Duration_hour	0.420399
Source_Banglore	0.389819
Arrival_Time_hour	0.389143
Arrival_Time_minute	0.352235
Duration_minute	0.347845
Duration_mins	0.334976
Dep_Time_hour	0.334409
Dep_Time_minute	0.263641
Journey_day	0.231968
Source_Mumbai	0.189603
Source_Chennai	0.126226

Machine Learning Model

split dataset into train & test

In [145…
```
from sklearn.model_selection import train_test_split
```

In [170…
```
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.25, random_state=42)
```

In [171…
```
from sklearn.ensemble import RandomForestRegressor
```

In [172…
```
ml_model = RandomForestRegressor()
```

In [173…
```
ml_model.fit(X_train , y_train)
```

Out[173]:
```
RandomForestRegressor
RandomForestRegressor()
```

In [174…
```
y_pred = ml_model.predict(X_test)
```

In [175…
```
y_pred
```

Out[175]:
```
array([16930.72,  5372.24,  8890.42, ...,  3491.81,  6403.65,  6878.93])
```

In [176…
```
from sklearn import metrics
```

In [177…
```
metrics.r2_score(y_test , y_pred)
```

Out[177]:
```
0.8106484475983164
```

Automate ml pipeline & define Evaluation metric

1) make our own metric

In [161…
```
def mape(y_true , y_pred):
    y_true , y_pred = np.array(y_true) , np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

In [162…
```
mape(y_test , y_pred)
```

Out[162]:
```
13.262759339262784
```

2) Automate ml pipeline

Lets automate all the stuffs
just pass ml algo & get several results like--

Training score, predictions, r2_score, mse, mae, rmse,
mape,distribution of error

In [163…
```
from sklearn.model_selection import cross_val_score, KFold
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn import metrics
```

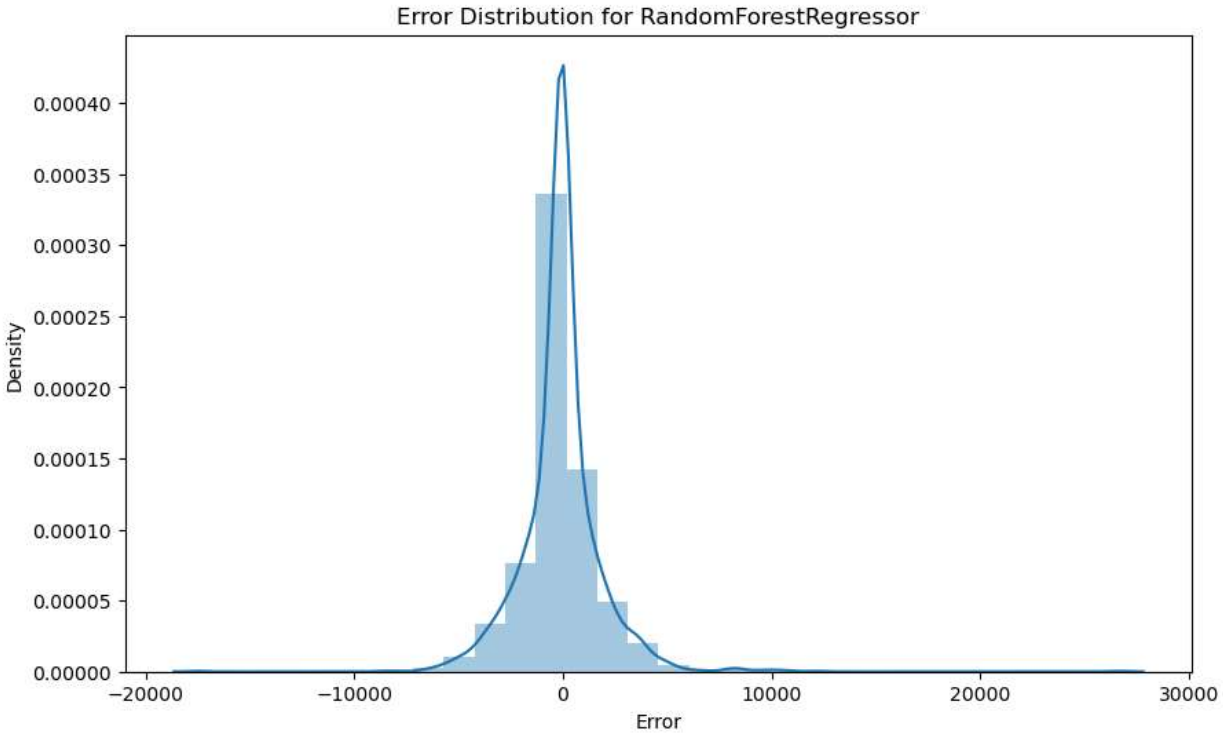
In [169…
```
def predict(mlmodel):
    model = mlmodel.fit(X_train , y_train)
    print('Training score : {}'.format(model.score(X_train , y_train)))
    y_predection = model.predict(X_test)
    print('predictions are : {}'.format(y_predection))
    print('\n')
    r2_score = metrics.r2_score(y_test , y_predection)
    print('r2 score : {}'.format(r2_score))
    print('MAE : {}'.format(metrics.mean_absolute_error(y_test , y_predection)))
    print('MSE : {}'.format(metrics.mean_squared_error(y_test , y_predection)))
    print('RMSE : {}'.format(np.sqrt(metrics.mean_squared_error(y_test , y_predection))
    print('MAPE : {}'.format(mape(y_test , y_predection)))
    # Plotting the distribution of errors
    plt.figure(figsize=(10, 6))
    sns.distplot(y_test - y_predection, bins=30, kde=True)
```

```
    plt.title(f'Error Distribution for {ml_model.__class__.__name__}')
    plt.xlabel('Error')
    plt.ylabel('Density')
    plt.show()

    # Cross-validation
    cv = KFold(n_splits=5, shuffle=True, random_state=42)
    cv_scores = cross_val_score(ml_model, X_train, y_train, cv=cv, scoring='r2')
    print(f'Cross-validated R2 scores: {cv_scores}')
    print(f'Mean CV R2 score: {cv_scores.mean():.4f}')
    print('-' * 50)
```

In [165…

```
predict(RandomForestRegressor())
```

```
Training score : 0.9515029799312105
predictions are : [16859.81  5402.85  8854.98 ...  3518.68  6279.77  6854.59]


r2 score : 0.8110384504791415
MAE : 1175.577388469667
MSE : 3678627.798231426
RMSE : 1917.9749211685294
MAPE : 13.174772900885989
```

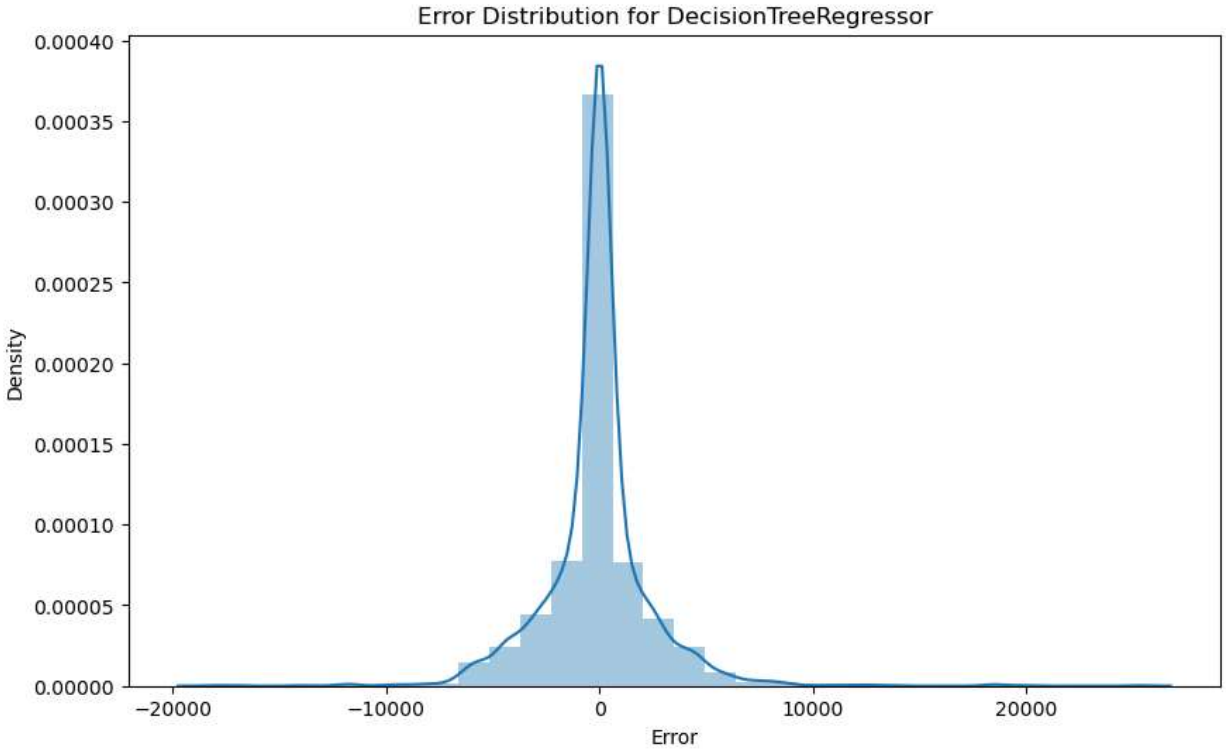



```
Cross-validated R2 scores: [0.81437113 0.78265293 0.81377621 0.81415118 0.80749271]
Mean CV R2 score: 0.8065
--------------------------------------------------
```

In [166…

```
predict(DecisionTreeRegressor())
```

```
Training score : 0.966591628243878
predictions are : [16840.  4959.  8085. ...  3419.  5797.  6442.]


r2 score : 0.6813523199496411
MAE : 1407.6086359665544
MSE : 6203305.469538459
RMSE : 2490.643585408892
MAPE : 15.512905195789797
```

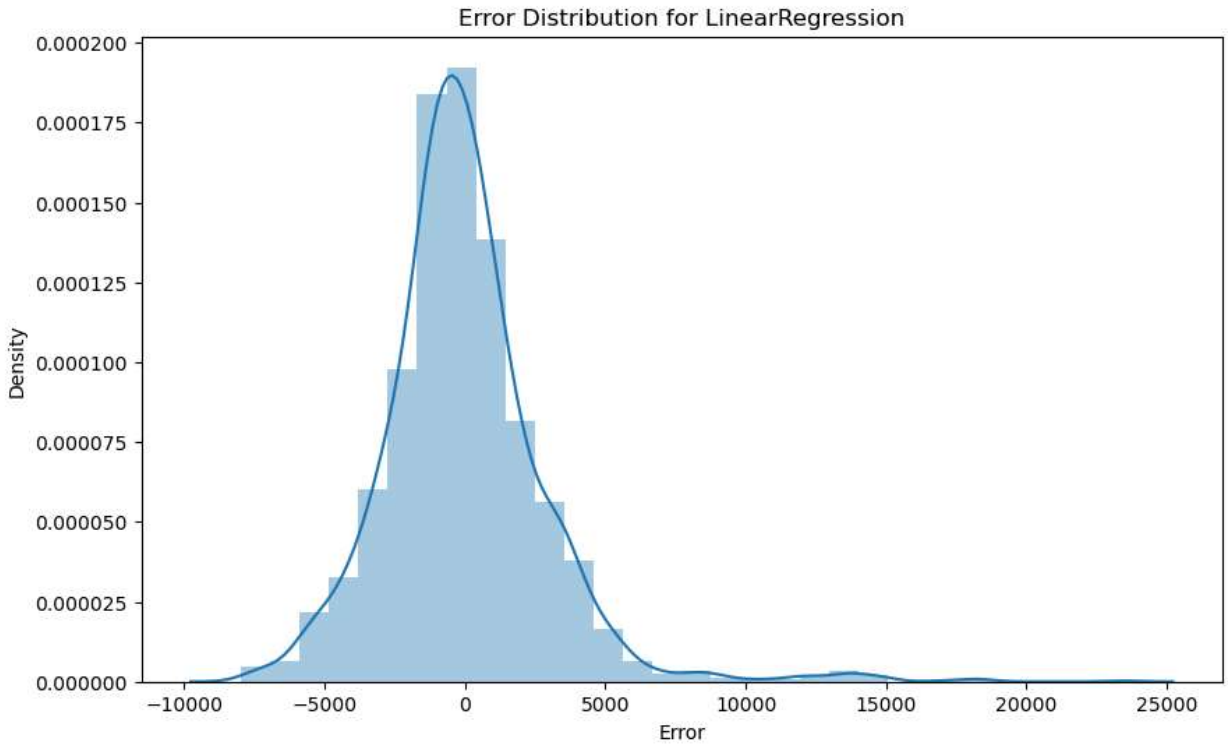



```
Cross-validated R2 scores: [0.68215263 0.6614025  0.72106648 0.7133294  0.66456947]
Mean CV R2 score: 0.6885
--------------------------------------------------
```

In [167…

```
# Apply LinearRegression
predict(LinearRegression())
```

```
Training score : 0.5974311101154715
predictions are : [12668.50092552  8108.02334286  9087.41658728 ...  3329.01067447
  8902.54439747  7581.7554673 ]


r2 score : 0.5725924273245007
MAE : 2012.5827755770702
MSE : 8320599.518819858
RMSE : 2884.5449413763445
MAPE : 24.829513004041935
```

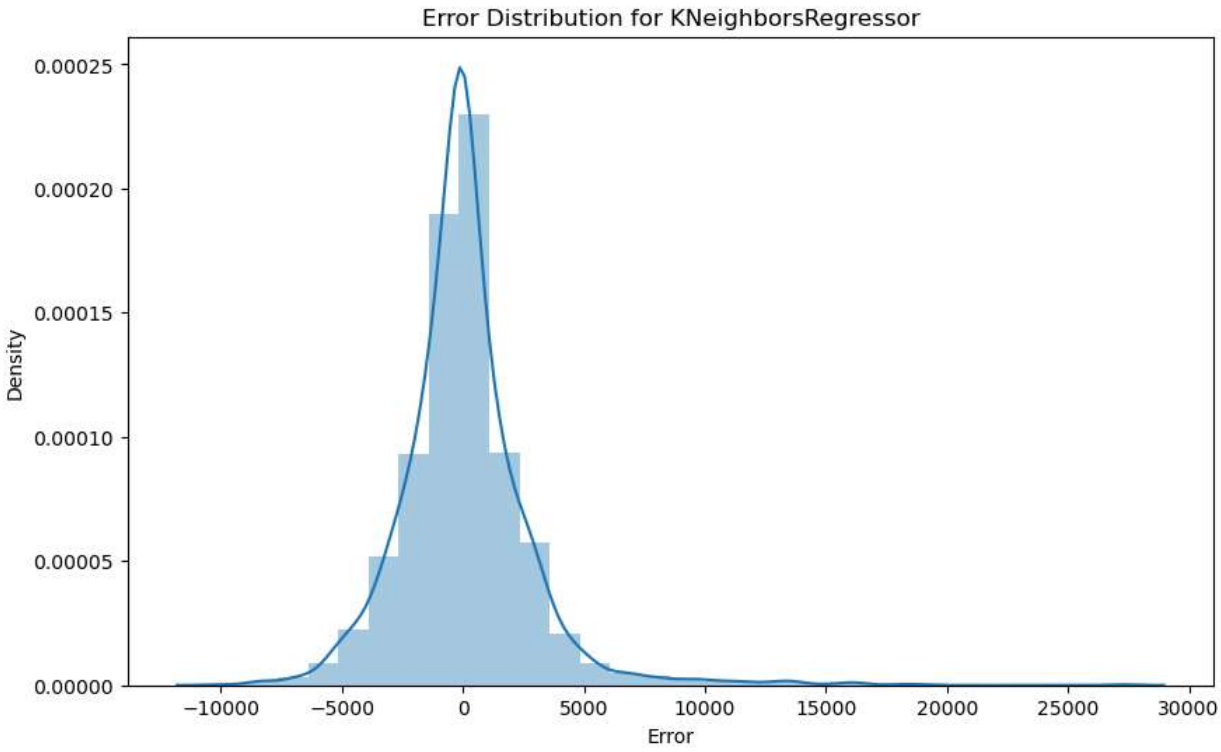



```
Cross-validated R2 scores: [0.56800856 0.61638543 0.58441762 0.61559058 0.59269228]
Mean CV R2 score: 0.5954
--------------------------------------------------
```

In [168…

```
# Apply KNeighborsRegressor
predict(KNeighborsRegressor())
```

```
Training score : 0.7730773965679995
predictions are : [16315.   5158.2  8536.  ...  4125.6 11656.4  8159.2]


r2 score : 0.629671023909574
MAE : 1746.0433545488581
MSE : 7209416.251037063
RMSE : 2685.0356144820616
MAPE : 19.657698932146968
```




```
Cross-validated R2 scores: [0.59094561 0.59957088 0.62058308 0.64303244 0.60554159]
Mean CV R2 score: 0.6119
--------------------------------------------------
```

Thus it is clear that RandomForestRegression is the best ML model for this kind of data set further saving the trained model as follows:

Save Model

dump ml model using pickle

```
advantage of dumping--
imagine in future we have new data & lets say we have to predict
price on this huge data

then to do prediction on this new data , we can use this pre-trained
model what we have dumped
```

In [154…
```
import pickle
```

In [155…
```
# open a file, where you want to store the data
file = open(r'C:\Users\Shreya\Documents\Data Analytics Project\Flight Fare prediction\
```

In [156…
```
# dump information to that file
pickle.dump(ml_model , file)
```

In [178…
```
model = open(r'C:\Users\Shreya\Documents\Data Analytics Project\Flight Fare predictior
```

In [179…
```
forest = pickle.load(model)
```

In [180…
```
y_pred2 = forest.predict(X_test)
```

In [181…
```
metrics.r2_score(y_test , y_pred2)
```

Out[181]:
```
0.808079501624755
```