flightpriceprediction

September 8, 2023

1 1.Busines Case:- To predict the flight ticket prices based on given data

1.1 2.IMPORT LIABRARIES

[127]:
```
#import libraries
import numpy as np
import pandas as pd
import seaborn as sns
import datetime as dt
from datetime import datetime
from datetime import datetime, timedelta
import time
import re
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
sns.set()
```

[3]:
```
from IPython.display import Image
Image("Flightpic.jpg")
```

[3]:

1.2 3.LOAD DATA

[129]:
```
#import data
data=pd.read_excel("Flight_Fare.xlsx")
```

[130]:
```
data.head(4)
```

[130]:

	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

1.3 4.DOMAIN ANALYSIS

1.Airline: This column represents the name of the airline company operating the flight.

2.Date_of_Journey: This column indicates the date when the journey is scheduled to begin.

3.Source: The starting location or city from which the flight originates.

4.Destination: The final destination or city where the flight is scheduled to arrive.

5.Route: The sequence of connecting cities or airports that the flight will pass through from source to destination.

6.Dep_Time: The departure time of the flight from the source airport.

7.Arrival_Time: The expected arrival time of the flight at the destination airport.

8.Duration: The duration of the flight, indicating the time taken to travel from source to destination.

9.Total_Stops: The number of stops or layovers during the journey. It can be a direct flight or have one or more layovers.

10.Additional_Info: Any additional information or notes about the flight that might not be covered by other columns. This could include special services, amenities, or instructions.

11.Price: The fare or price of the flight ticket. This is the target variable for prediction in your analysis.

1.4 5.BASIC CHECKS

[131]:
```
# to see the first five data
data.head()
```

[131]:
```
       Airline Date_of_Journey    Source Destination                  Route  \
0       IndiGo      24/03/2019  Banglore   New Delhi              BLR → DEL
1    Air India       1/05/2019   Kolkata    Banglore  CCU → IXR → BBI → BLR
2  Jet Airways       9/06/2019     Delhi      Cochin  DEL → LKO → BOM → COK
3       IndiGo      12/05/2019   Kolkata    Banglore        CCU → NAG → BLR
4       IndiGo      01/03/2019  Banglore   New Delhi        BLR → NAG → DEL

  Dep_Time  Arrival_Time Duration Total_Stops Additional_Info  Price
0    22:20  01:10 22 Mar   2h 50m    non-stop         No info   3897
1    05:50         13:15   7h 25m     2 stops         No info   7662
2    09:25  04:25 10 Jun      19h     2 stops         No info  13882
3    18:05         23:30   5h 25m      1 stop         No info   6218
4    16:50         21:35   4h 45m      1 stop         No info  13302
```

[132]:
```
# to see the bottom five data
data.tail()
```

[132]:
```
           Airline Date_of_Journey    Source Destination  \
10678     Air Asia       9/04/2019   Kolkata    Banglore
10679    Air India      27/04/2019   Kolkata    Banglore
10680  Jet Airways      27/04/2019  Banglore       Delhi
10681      Vistara      01/03/2019  Banglore   New Delhi
10682    Air India       9/05/2019     Delhi      Cochin

                      Route Dep_Time Arrival_Time Duration Total_Stops  \
10678              CCU → BLR    19:55        22:25   2h 30m    non-stop
10679              CCU → BLR    20:45        23:20   2h 35m    non-stop
10680              BLR → DEL    08:20        11:20       3h    non-stop
10681              BLR → DEL    11:30        14:10   2h 40m    non-stop
10682  DEL → GOI → BOM → COK    10:55        19:15   8h 20m     2 stops

      Additional_Info  Price
10678         No info   4107
10679         No info   4145
10680         No info   7229
10681         No info  12648
10682         No info  11753
```

[133]:
```
# to see the number of rows and columns
data.shape
```

[133]:
```
(10683, 11)
```

[134]:
```
# to see the size of the data
data.size
```

[134]:
```
117513
```

[135]:
```
# name of all the columns
data.columns
```

[135]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info', 'Price'],
      dtype='object')
```

[136]:
```
# to see the data types of all the columns
data.dtypes
```

[136]:
```
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
```

[137]:
```
# to see the statistical parameters of categorical columns
data.describe(include=["O"])
```

[137]:

	Airline	Date_of_Journey	Source	Destination	Route	\
count	10683	10683	10683	10683	10682	
unique	12	44	5	6	128	
top	Jet Airways	18/05/2019	Delhi	Cochin	DEL → BOM → COK	
freq	3849	504	4537	4537	2376	

	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info
count	10683	10683	10683	10682	10683
unique	222	1343	368	5	10
top	18:55	19:00	2h 50m	1 stop	No info
freq	233	423	550	5625	8345

[138]:
```
# to see the statistical parameters of numerical columns
data.describe(include=["int64"])
```

[138]:
```
              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
```

[139]:
```
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
```

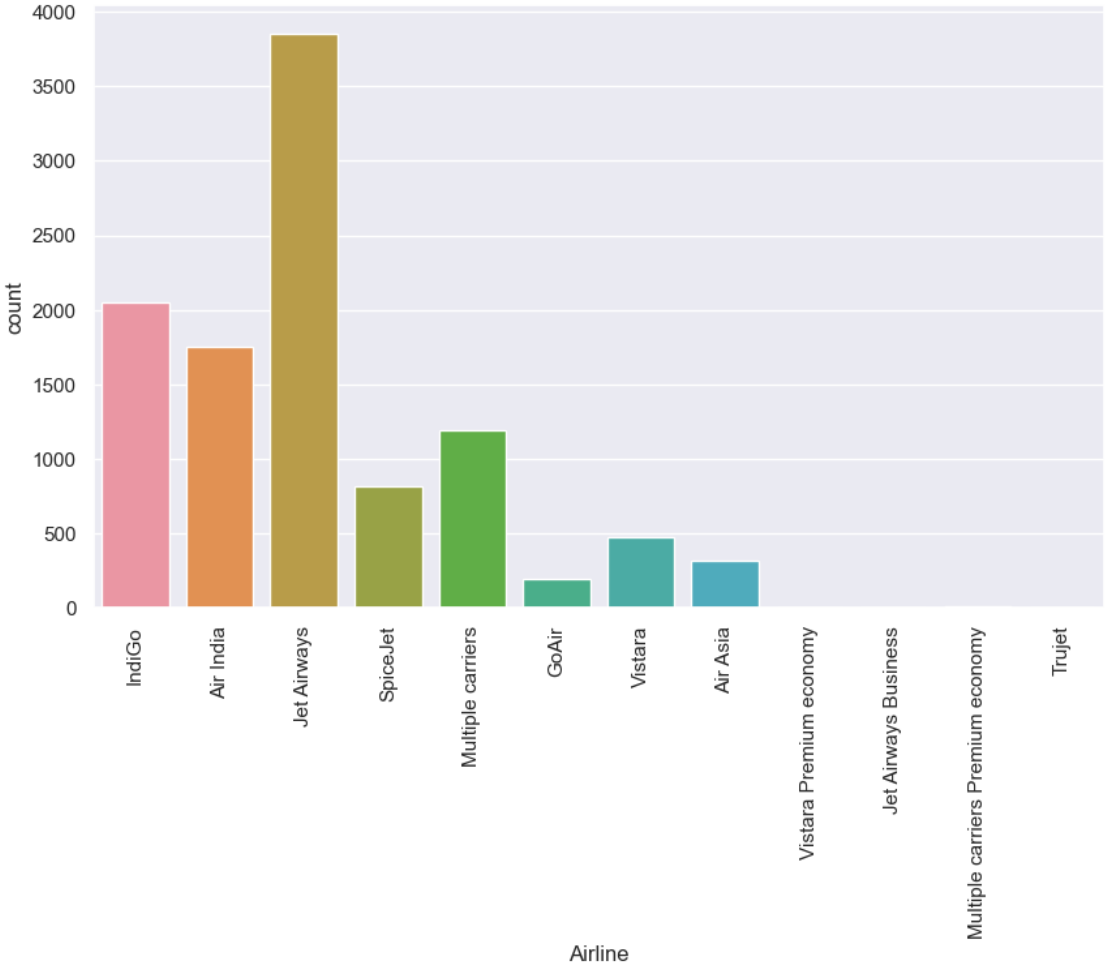
1.5 6.EXPLORATORY DATA ANALYSIS

1.5.1 UNIVARIATE

[140]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="Airline",data=data)
plt.xticks(rotation=90)
```

[140]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11]),
 [Text(0, 0, 'IndiGo'),
  Text(1, 0, 'Air India'),
  Text(2, 0, 'Jet Airways'),
  Text(3, 0, 'SpiceJet'),
  Text(4, 0, 'Multiple carriers'),
  Text(5, 0, 'GoAir'),
  Text(6, 0, 'Vistara'),
  Text(7, 0, 'Air Asia'),
```

```
Text(8, 0, 'Vistara Premium economy'),
Text(9, 0, 'Jet Airways Business'),
Text(10, 0, 'Multiple carriers Premium economy'),
Text(11, 0, 'Trujet')])
```



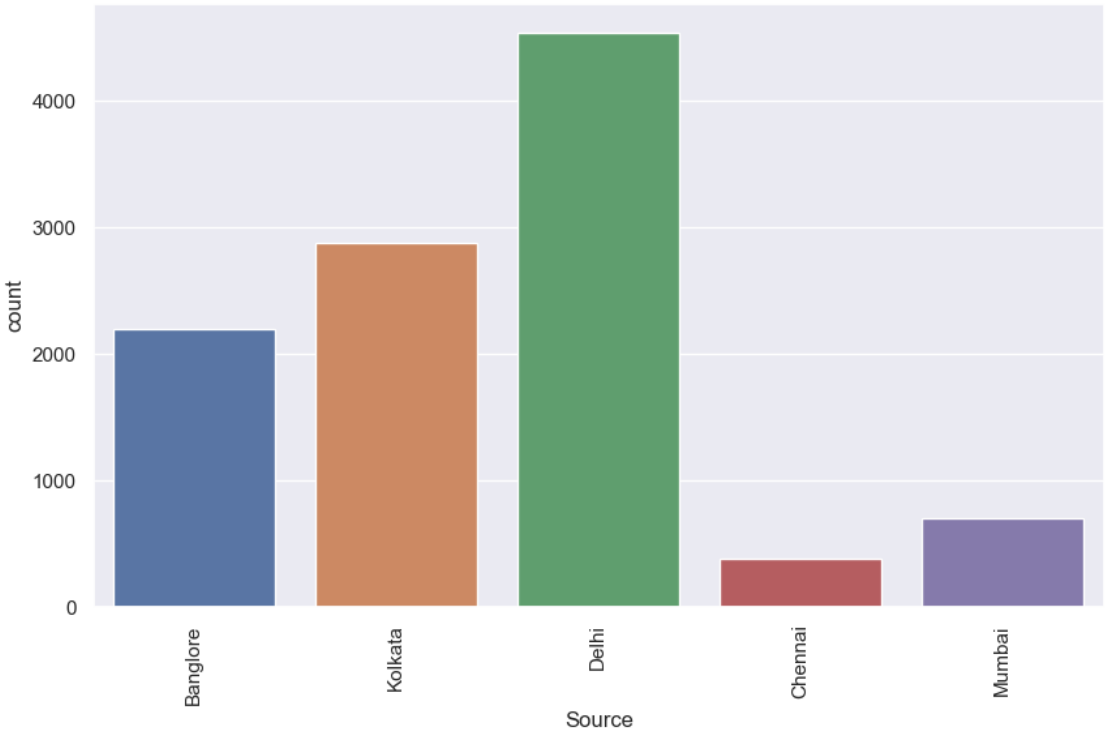
1.5.2 Insights

- Jet Airways is the costliest among all the flights
- Jet Airways has the highest share followed by Indigo

[141]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="Source",data=data)
plt.xticks(rotation=90)
```

[141]:
```
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'Banglore'),
  Text(1, 0, 'Kolkata'),
```

```
Text(2, 0, 'Delhi'),
Text(3, 0, 'Chennai'),
Text(4, 0, 'Mumbai')])
```

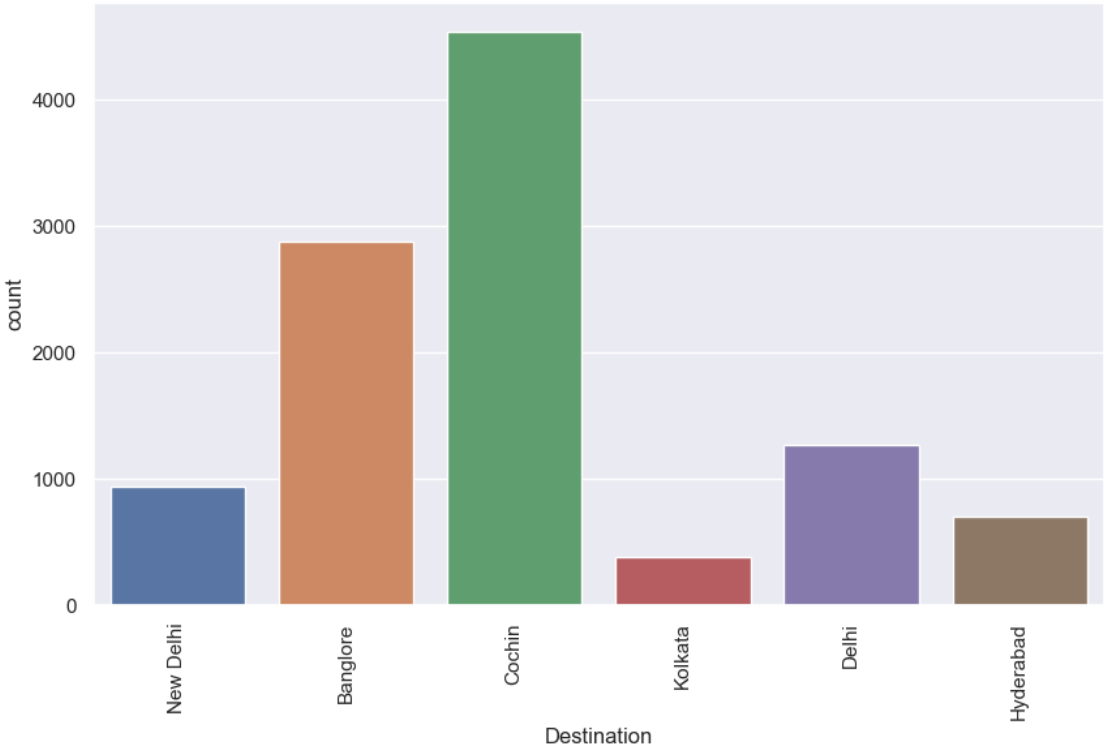


1.5.3 Insights

- Delhi has highest take off or originating point for all the flights followed by Kolkata and Banglore respectively.

[142]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="Destination",data=data)
plt.xticks(rotation=90)
```

[142]:
```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'New Delhi'),
  Text(1, 0, 'Banglore'),
  Text(2, 0, 'Cochin'),
  Text(3, 0, 'Kolkata'),
  Text(4, 0, 'Delhi'),
  Text(5, 0, 'Hyderabad')])
```

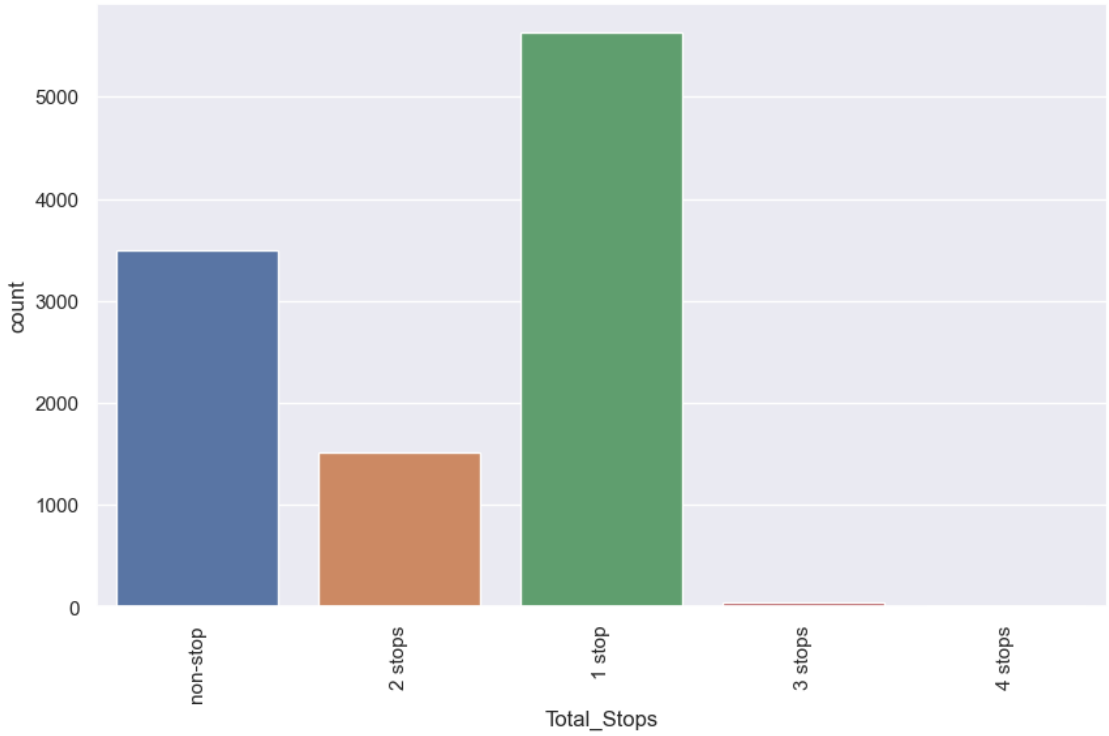


1.5.4 Insights

- Cochin has the highest landing or arrival of the flights from different places followed by Banglore

[143]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="Total_Stops",data=data)
plt.xticks(rotation=90)
```

[143]:
```
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'non-stop'),
  Text(1, 0, '2 stops'),
  Text(2, 0, '1 stop'),
  Text(3, 0, '3 stops'),
  Text(4, 0, '4 stops')])
```

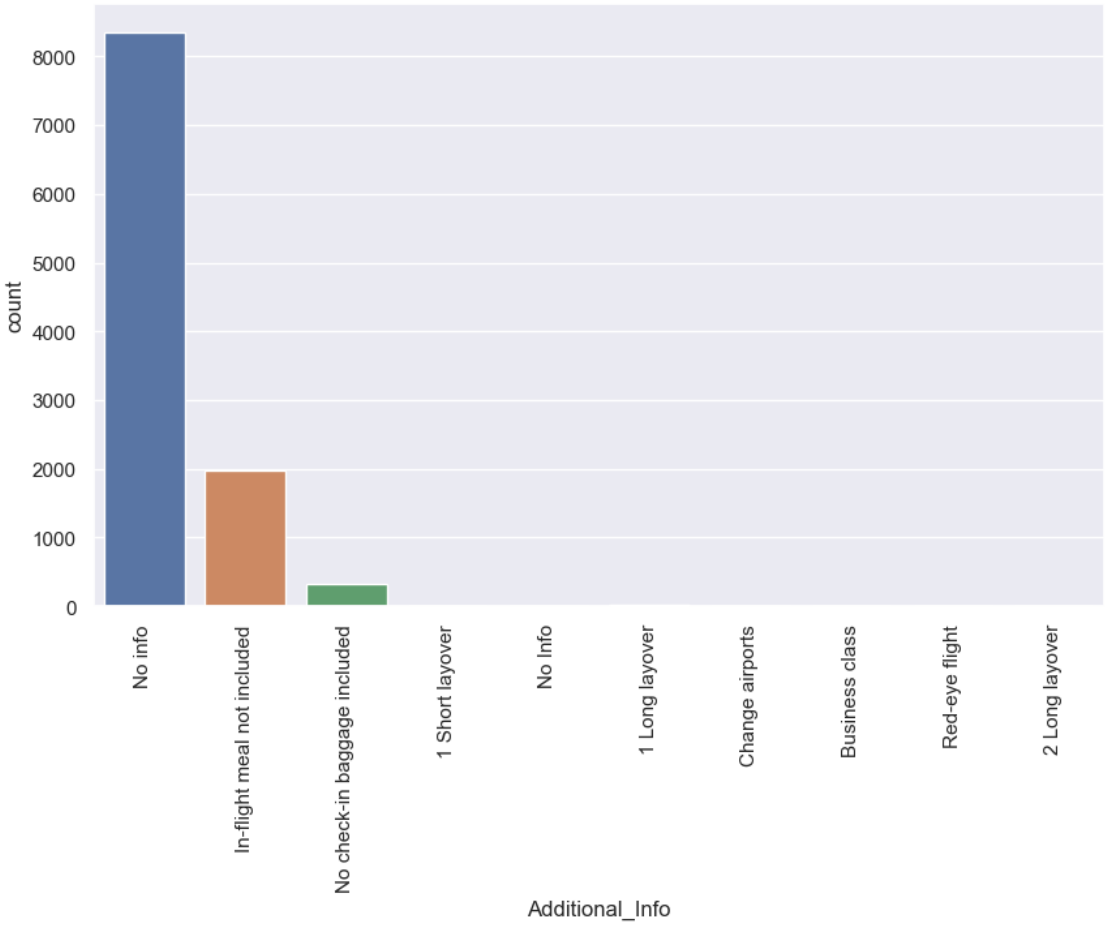


1.5.5 Insights

- Most flights have single stop in between taking off and landing at the destination followed by non-stop.

[144]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="Additional_Info",data=data)
plt.xticks(rotation=90)
```

[144]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'No info'),
  Text(1, 0, 'In-flight meal not included'),
  Text(2, 0, 'No check-in baggage included'),
  Text(3, 0, '1 Short layover'),
  Text(4, 0, 'No Info'),
  Text(5, 0, '1 Long layover'),
  Text(6, 0, 'Change airports'),
  Text(7, 0, 'Business class'),
  Text(8, 0, 'Red-eye flight'),
  Text(9, 0, '2 Long layover')])
```



1.5.6 Insights

- Most of the flights do not have any extra information
- There are few flights with extra information of "in-flight meal not included"

[145]:
```
# sweetviz is used for univariate
!pip install sweetviz
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: sweetviz in
c:\users\shashank\appdata\roaming\python\python310\site-packages (2.1.4)
Requirement already satisfied: matplotlib>=3.1.3 in
c:\programdata\anaconda3\lib\site-packages (from sweetviz) (3.7.0)
Requirement already satisfied: importlib-resources>=1.2.0 in
c:\users\shashank\appdata\roaming\python\python310\site-packages (from sweetviz)
(5.12.0)
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3 in
c:\programdata\anaconda3\lib\site-packages (from sweetviz) (1.5.3)
Requirement already satisfied: tqdm>=4.43.0 in
```

```
c:\programdata\anaconda3\lib\site-packages (from sweetviz) (4.64.1)
Requirement already satisfied: jinja2>=2.11.1 in
c:\programdata\anaconda3\lib\site-packages (from sweetviz) (3.1.2)
Requirement already satisfied: scipy>=1.3.2 in
c:\programdata\anaconda3\lib\site-packages (from sweetviz) (1.10.0)
Requirement already satisfied: numpy>=1.16.0 in
c:\programdata\anaconda3\lib\site-packages (from sweetviz) (1.23.5)
Requirement already satisfied: MarkupSafe>=2.0 in
c:\programdata\anaconda3\lib\site-packages (from jinja2>=2.11.1->sweetviz)
(2.1.1)
Requirement already satisfied: pyparsing>=2.3.1 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(3.0.9)
Requirement already satisfied: pillow>=6.2.0 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(9.4.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(1.4.4)
Requirement already satisfied: fonttools>=4.22.0 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(4.25.0)
Requirement already satisfied: cycler>=0.10 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(0.11.0)
Requirement already satisfied: packaging>=20.0 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(22.0)
Requirement already satisfied: contourpy>=1.0.1 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(1.0.5)
Requirement already satisfied: python-dateutil>=2.7 in
c:\programdata\anaconda3\lib\site-packages (from matplotlib>=3.1.3->sweetviz)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in
c:\programdata\anaconda3\lib\site-packages (from
pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3->sweetviz) (2022.7)
Requirement already satisfied: colorama in c:\programdata\anaconda3\lib\site-
packages (from tqdm>=4.43.0->sweetviz) (0.4.6)
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\site-
packages (from python-dateutil>=2.7->matplotlib>=3.1.3->sweetviz) (1.16.0)
```

[146]:
```
import sweetviz as sv
my_report=sv.analyze(data)
my_report.show_html("my_report.html")
```

```
                                             |                                  ␣
↪           | [  0%]   00:00 ->…
```

```
Report my_report.html was generated! NOTEBOOK/COLAB USERS: the web browser MAY
not pop up, regardless, the report IS saved in your notebook/colab files.
```

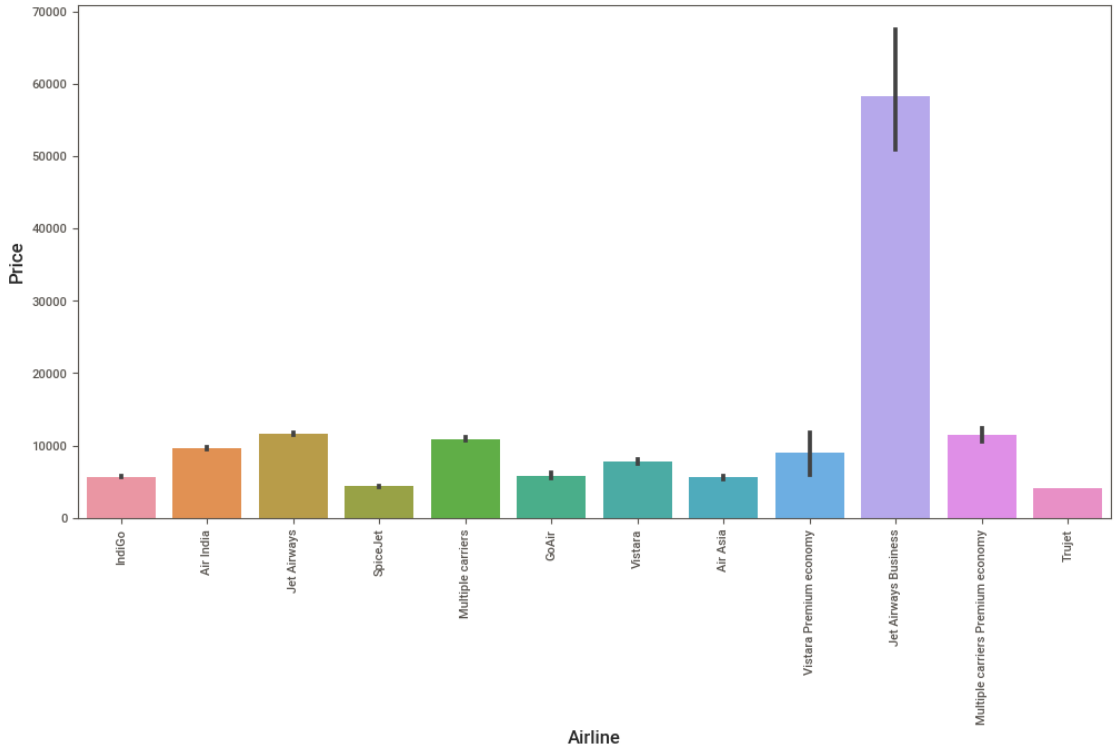
1.5.7 Insights

- The majority of prices are within the 20,000 range, but there are some outliers.
- The most frequent airline is Jet Airways. However, Jet Airways Business has a much higher average price than the other lines.
- The most flights depart from Delhi, and the average price is the highest.
- Cochin is the most heavily trafficked destination. New Delhi, on the other hand, has the highest average price.
- A little more than half of the flights make single stop between the origin and destination, around one-third is direct flight.

1.5.8 BYVARIATE

[147]:
```
plt.figure(figsize=(12,6))
sns.barplot(x="Airline",y="Price",data=data)
plt.xticks(rotation=90)
```

[147]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11]),
 [Text(0, 0, 'IndiGo'),
  Text(1, 0, 'Air India'),
  Text(2, 0, 'Jet Airways'),
  Text(3, 0, 'SpiceJet'),
  Text(4, 0, 'Multiple carriers'),
  Text(5, 0, 'GoAir'),
  Text(6, 0, 'Vistara'),
  Text(7, 0, 'Air Asia'),
  Text(8, 0, 'Vistara Premium economy'),
  Text(9, 0, 'Jet Airways Business'),
  Text(10, 0, 'Multiple carriers Premium economy'),
  Text(11, 0, 'Trujet')])
```



1.5.9 Insights

- Jet Airways Business has the highest price when compared to others.

1.6 7.DATA PREPROCESSING

1.6.1 Null Value

[148]:
```
# check the null value present in the data
data.isnull().sum()
```

[148]:
```
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
```

1.6.2 Insights

- There are only two null values
- 1 in Route
- 1 in Total_Stops

[149]:
```
# We drop the null value
data.dropna(inplace=True)
```

[150]:
```
# we have removed one row with null value
data.shape
```

[150]:
```
(10682, 11)
```

[151]:
```
data.isnull().sum()
```

[151]:
```
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
```

1.7 Extracting Date and Month from Date of Journey column

1.7.1 Converting into Datetime:

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

1.7.2 Date

[152]:
```
data["journey_Date"]= pd.to_datetime(data['Date_of_Journey'], format= "%d/%m/
↪%Y").dt.day
```

1.7.3 Month

[153]:
```
data["journey_Month"]= pd.to_datetime(data['Date_of_Journey'], format= "%d/%m/
↪%Y").dt.month
```

[154]:
```
data.head(3)
```

[154]:
```
        Airline Date_of_Journey    Source Destination                  Route  \
0        IndiGo      24/03/2019  Banglore   New Delhi              BLR → DEL
1    Air India       1/05/2019   Kolkata    Banglore  CCU → IXR → BBI → BLR
2  Jet Airways       9/06/2019     Delhi      Cochin  DEL → LKO → BOM → COK

  Dep_Time  Arrival_Time Duration Total_Stops Additional_Info  Price  \
0    22:20  01:10 22 Mar   2h 50m    non-stop         No info   3897
1    05:50         13:15   7h 25m     2 stops         No info   7662
2    09:25  04:25 10 Jun      19h     2 stops         No info  13882

   journey_Date  journey_Month
0            24              3
1             1              5
2             9              6
```

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

[155]:
```
# droping date of journey column as we have allready extracted data and month
data.drop(['Date_of_Journey'],axis=1,inplace=True)
```

- Departure time is when a plane leaves the Source .
- Similar to Date of Journey we can extract values from Departure Time
- So we will be extracting Hour & Minutes from Departure Time Column

1.7.4 Hours

[156]:
```
# Extracting Hours
data['Dep_hour']=pd.to_datetime(data['Dep_Time']).dt.hour #pd.to_datetime
```

1.7.5 Minutes

[157]:
```
#Extracting minutes
data['Dep_min']=pd.to_datetime(data['Dep_Time']).dt.minute
```

[158]:
```
#Now we will drop the dep_time as we dont need it anymore
data.drop(['Dep_Time'],axis=1,inplace=True)
```

[159]:
```
data.head(5)
```

[159]:
```
        Airline    Source Destination                  Route  Arrival_Time  \
0        IndiGo  Banglore   New Delhi              BLR → DEL  01:10 22 Mar
1     Air India   Kolkata    Banglore  CCU → IXR → BBI → BLR         13:15
2   Jet Airways     Delhi      Cochin  DEL → LKO → BOM → COK  04:25 10 Jun
3        IndiGo   Kolkata    Banglore        CCU → NAG → BLR         23:30
4        IndiGo  Banglore   New Delhi        BLR → NAG → DEL         21:35

  Duration Total_Stops Additional_Info  Price  journey_Date  journey_Month  \
0   2h 50m    non-stop         No info   3897            24              3
1   7h 25m     2 stops         No info   7662             1              5
2      19h     2 stops         No info  13882             9              6
3   5h 25m      1 stop         No info   6218            12              5
4   4h 45m      1 stop         No info  13302             1              3

   Dep_hour  Dep_min
0        22       20
1         5       50
2         9       25
3        18        5
4        16       50
```

- Arrival time is when a plane reaches the destination.
- Similar to Date of Journey we can extract values from Arrival Time
- So we will be extracting Hour & Minutes from Arrival Time Column

[160]:
```
# Extracting Hours
data['Arrival_hour']=pd.to_datetime(data['Arrival_Time']).dt.hour #pd.
 ↪to_datetime

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

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

[161]:
```
data.head(3)
```

[161]:
```
        Airline    Source Destination                  Route Duration  \
0        IndiGo  Banglore   New Delhi              BLR → DEL   2h 50m
1     Air India   Kolkata    Banglore  CCU → IXR → BBI → BLR   7h 25m
2   Jet Airways     Delhi      Cochin  DEL → LKO → BOM → COK      19h

  Total_Stops Additional_Info  Price  journey_Date  journey_Month  Dep_hour  \
0    non-stop         No info   3897            24              3        22
1     2 stops         No info   7662             1              5         5
2     2 stops         No info  13882             9              6         9
```

```
   Dep_min  Arrival_hour  Arrival_min
0       20             1           10
1       50            13           15
2       25             4           25
```

1.7.6 "Duration" column:

- Here we are trying to extract the hours and minutes from the feature "duration".

[162]:
```
# Assigning and converting Duration column into list to extract hours and␣
 ↪minutes seperately

duration = list(data["Duration"])
for i in range(len(duration)):
    if len(duration[i].split()) !=2:
        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]))
```

- Adding "duration_hours" and "duration_mins" list to data frame and dropping the column "duration" from it.

[163]:
```
data["Duration_hours"] = duration_hours
data["Duration_mins"] = duration_mins

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

[164]:
```
data.head(4)
```

[164]:
```
       Airline    Source Destination                  Route Total_Stops  \
0       IndiGo  Banglore   New Delhi              BLR → DEL    non-stop
1    Air India   Kolkata    Banglore  CCU → IXR → BBI → BLR     2 stops
2  Jet Airways     Delhi      Cochin  DEL → LKO → BOM → COK     2 stops
3       IndiGo   Kolkata    Banglore        CCU → NAG → BLR      1 stop

  Additional_Info  Price  journey_Date  journey_Month  Dep_hour  Dep_min  \
0         No info   3897            24              3        22       20
1         No info   7662             1              5         5       50
```

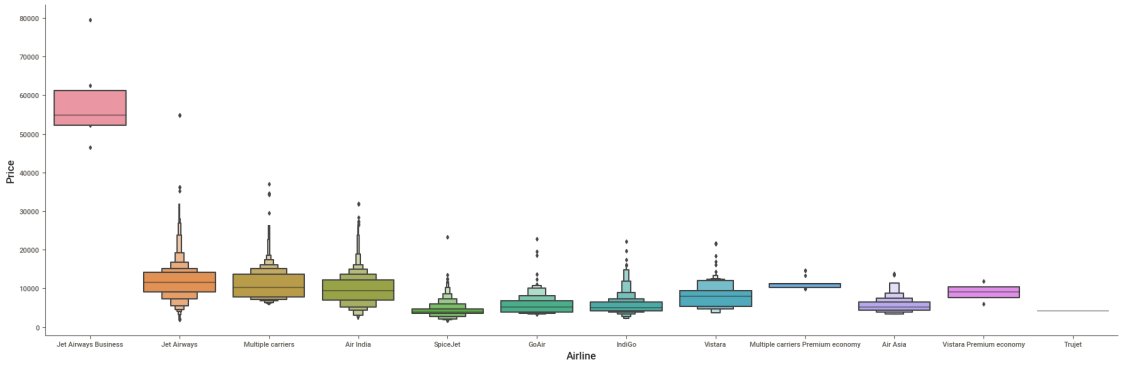
```
2         No info  13882             9              6         9        25
3         No info   6218            12              5        18         5

   Arrival_hour  Arrival_min  Duration_hours  Duration_mins
0             1           10               2             50
1            13           15               7             25
2             4           25              19              0
3            23           30               5             25
```

1.8 Converting categorical columns to numerical using One Hot Encoder

[165]:
```
cat_col=data.select_dtypes(include=["O"])
cat_col.head()
```

[165]:
```
       Airline    Source Destination                  Route Total_Stops  \
0       IndiGo  Banglore   New Delhi              BLR → DEL    non-stop
1    Air India   Kolkata    Banglore  CCU → IXR → BBI → BLR     2 stops
2  Jet Airways     Delhi      Cochin  DEL → LKO → BOM → COK     2 stops
3       IndiGo   Kolkata    Banglore        CCU → NAG → BLR      1 stop
4       IndiGo  Banglore   New Delhi        BLR → NAG → DEL      1 stop

  Additional_Info
0         No info
1         No info
2         No info
3         No info
4         No info
```

[166]:
```
# Airline vs Price
sns.catplot(x="Airline",y="Price",data=data.
 ↪sort_values("Price",ascending=False),kind="boxen",height=6,aspect=3)
plt.show()
```



1.8.1 Insights

- From the graph above we can understand that JetAirways has the highest price and rest are quite in the same range

[167]:
```
data2=data.copy()
```

[168]:
```
#OneHotEncoding
df1=pd.get_dummies(data2["Airline"],drop_first=True)
data2=pd.concat([data2,df1],axis=1).drop(["Airline"],axis=1)
```

[169]:
```
data2.head(3)
```

[169]:
```
     Source Destination                  Route Total_Stops Additional_Info  \
0  Banglore   New Delhi              BLR → DEL    non-stop         No info
1   Kolkata    Banglore  CCU → IXR → BBI → BLR     2 stops         No info
2     Delhi      Cochin  DEL → LKO → BOM → COK     2 stops         No info

   Price  journey_Date  journey_Month  Dep_hour  Dep_min  …  GoAir  IndiGo  \
0   3897            24              3        22       20  …      0       1
1   7662             1              5         5       50  …      0       0
2  13882             9              6         9       25  …      0       0

   Jet Airways  Jet Airways Business  Multiple carriers  \
0            0                     0                  0
1            0                     0                  0
2            1                     0                  0

   Multiple carriers Premium economy  SpiceJet  Trujet  Vistara  \
0                                  0         0       0        0
1                                  0         0       0        0
2                                  0         0       0        0

   Vistara Premium economy
0                        0
1                        0
2                        0

[3 rows x 25 columns]
```

[170]:
```
#OneHotEncoding
df2=pd.get_dummies(data2["Source"],drop_first=True)
data2=pd.concat([data2,df2],axis=1).drop(["Source"],axis=1)
```

[171]:
```
data2.head(3)
```

[171]:
```
  Destination                  Route Total_Stops Additional_Info  Price  \
0   New Delhi              BLR → DEL    non-stop         No info   3897
```

```
1    Banglore  CCU → IXR → BBI → BLR     2 stops         No info   7662
2      Cochin  DEL → LKO → BOM → COK     2 stops         No info  13882

   journey_Date  journey_Month  Dep_hour  Dep_min  Arrival_hour  …  \
0            24              3        22       20             1  …
1             1              5         5       50            13  …
2             9              6         9       25             4  …

   Multiple carriers  Multiple carriers Premium economy  SpiceJet  Trujet  \
0                  0                                  0         0       0
1                  0                                  0         0       0
2                  0                                  0         0       0

   Vistara  Vistara Premium economy  Chennai  Delhi  Kolkata  Mumbai
0        0                        0        0      0        0       0
1        0                        0        0      0        1       0
2        0                        0        0      1        0       0

[3 rows x 28 columns]
```

[172]:
```
#OneHotEncoding
df3=pd.get_dummies(data2["Destination"],drop_first=True)
data2=pd.concat([data2,df3],axis=1).drop(["Destination"],axis=1)
```

[173]:
```
data2.head(4)
```

[173]:
```
                  Route Total_Stops Additional_Info  Price  journey_Date  \
0             BLR → DEL    non-stop         No info   3897            24
1  CCU → IXR → BBI → BLR     2 stops         No info   7662             1
2  DEL → LKO → BOM → COK     2 stops         No info  13882             9
3        CCU → NAG → BLR      1 stop         No info   6218            12

   journey_Month  Dep_hour  Dep_min  Arrival_hour  Arrival_min  …  \
0              3        22       20             1           10  …
1              5         5       50            13           15  …
2              6         9       25             4           25  …
3              5        18        5            23           30  …

   Vistara Premium economy  Chennai  Delhi  Kolkata  Mumbai  Cochin  Delhi  \
0                        0        0      0        0       0       0      0
1                        0        0      0        1       0       0      0
2                        0        0      1        0       0       1      0
3                        0        0      0        1       0       0      0

   Hyderabad  Kolkata  New Delhi
0          0        0          1
1          0        0          0
```

```
2          0        0          0
3          0        0          0

[4 rows x 32 columns]
```

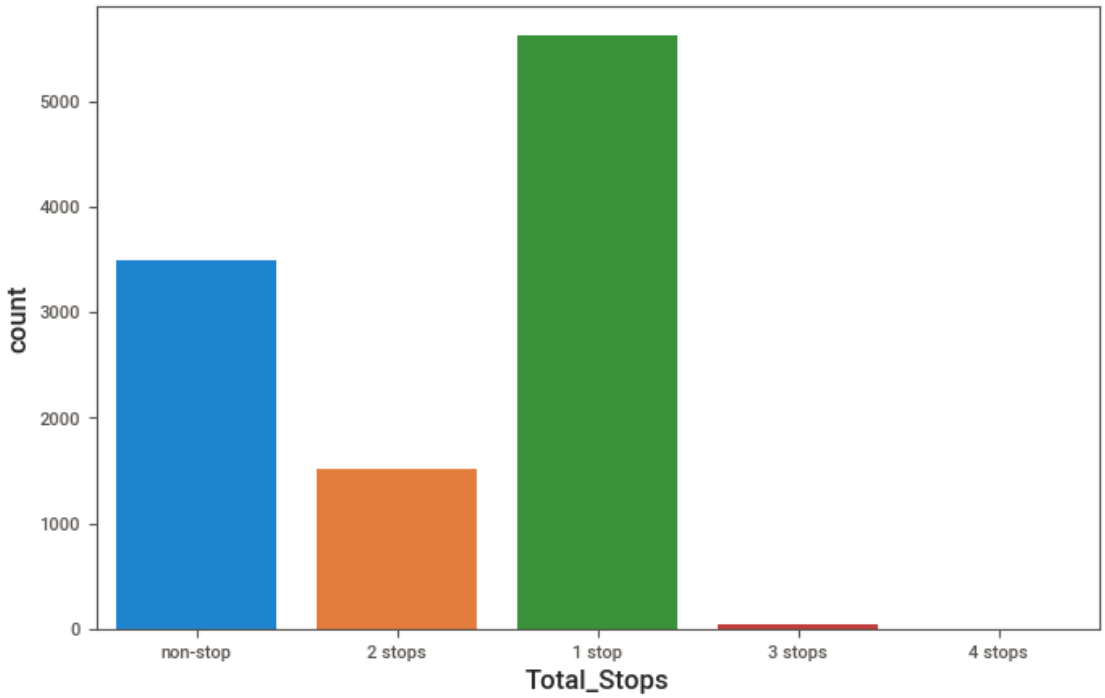
[174]:
```
# droping column, because Additinal_info since 80 % has no information
# Route---> is related to no of stops
data2.drop(["Route", "Additional_Info"], axis = 1, inplace = True)
```

[175]:
```
data2.head(5)
```

[175]:
```
  Total_Stops  Price  journey_Date  journey_Month  Dep_hour  Dep_min  \
0    non-stop   3897            24              3        22       20
1     2 stops   7662             1              5         5       50
2     2 stops  13882             9              6         9       25
3      1 stop   6218            12              5        18        5
4      1 stop  13302             1              3        16       50

   Arrival_hour  Arrival_min  Duration_hours  Duration_mins  …  \
0             1           10               2             50  …
1            13           15               7             25  …
2             4           25              19              0  …
3            23           30               5             25  …
4            21           35               4             45  …

   Vistara Premium economy  Chennai  Delhi  Kolkata  Mumbai  Cochin  Delhi  \
0                        0        0      0        0       0       0      0
1                        0        0      0        1       0       0      0
2                        0        0      1        0       0       1      0
3                        0        0      0        1       0       0      0
4                        0        0      0        0       0       0      0

   Hyderabad  Kolkata  New Delhi
0          0        0          1
1          0        0          0
2          0        0          0
3          0        0          0
4          0        0          1

[5 rows x 30 columns]
```

[176]:
```
plt.figure(figsize=(8,5))
sns.countplot(data=data,x="Total_Stops")
```

[176]:
```
<Axes: xlabel='Total_Stops', ylabel='count'>
```



[177]:
```
data2['Total_Stops'].value_counts()
```

[177]:
```
1 stop      5625
non-stop    3491
2 stops     1520
3 stops       45
4 stops        1
Name: Total_Stops, dtype: int64
```

[178]:
```
# Based on the observation from above countplot and value counts we can manualy␣
↪encode the total_stop column

data2.replace({'non-stop':0,'1 stop':1,'2 stops':2,'3 stops':3,'4 stops':
↪4},inplace=True)
df=data2
df.head()
```

[178]:

	Total_Stops	Price	journey_Date	journey_Month	Dep_hour	Dep_min	\
0	0	3897	24	3	22	20	
1	2	7662	1	5	5	50	
2	2	13882	9	6	9	25	
3	1	6218	12	5	18	5	
4	1	13302	1	3	16	50	

```
   Arrival_hour  Arrival_min  Duration_hours  Duration_mins  … \
0             1           10               2             50  …
1            13           15               7             25  …
2             4           25              19              0  …
3            23           30               5             25  …
4            21           35               4             45  …

   Vistara Premium economy  Chennai  Delhi  Kolkata  Mumbai  Cochin  Delhi  \
0                        0        0      0        0       0       0      0
1                        0        0      0        1       0       0      0
2                        0        0      1        0       0       1      0
3                        0        0      0        1       0       0      0
4                        0        0      0        0       0       0      0

   Hyderabad  Kolkata  New Delhi
0          0        0          1
1          0        0          0
2          0        0          0
3          0        0          0
4          0        0          1

[5 rows x 30 columns]
```

[179]:
```
x=df.drop("Price",axis=1)
x.head()
```

[179]:
```
   Total_Stops  journey_Date  journey_Month  Dep_hour  Dep_min  Arrival_hour  \
0            0            24              3        22       20             1
1            2             1              5         5       50            13
2            2             9              6         9       25             4
3            1            12              5        18        5            23
4            1             1              3        16       50            21

   Arrival_min  Duration_hours  Duration_mins  Air India  …  \
0           10               2             50          0  …
1           15               7             25          1  …
2           25              19              0          0  …
3           30               5             25          0  …
4           35               4             45          0  …

   Vistara Premium economy  Chennai  Delhi  Kolkata  Mumbai  Cochin  Delhi  \
0                        0        0      0        0       0       0      0
1                        0        0      0        1       0       0      0
2                        0        0      1        0       0       1      0
3                        0        0      0        1       0       0      0
4                        0        0      0        0       0       0      0
```

```
   Hyderabad  Kolkata  New Delhi
0          0        0          1
1          0        0          0
2          0        0          0
3          0        0          0
4          0        0          1

[5 rows x 29 columns]
```

1.9 Scaling

[180]:
```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
x=scaler.fit_transform(x)
print(x)
```

```
[[0.         0.88461538 0.         … 0.         0.         1.        ]
 [0.5        0.         0.66666667 … 0.         0.         0.        ]
 [0.5        0.30769231 1.         … 0.         0.         0.        ]
 …
 [0.         1.         0.33333333 … 0.         0.         0.        ]
 [0.         0.         0.         … 0.         0.         1.        ]
 [0.5        0.30769231 0.66666667 … 0.         0.         0.        ]]
```

1.10 8.FEATURE ENGINEERING

[181]:
```
data2=df.iloc[0:10,0:10]
data2
```

[181]:
```
   Total_Stops  Price  journey_Date  journey_Month  Dep_hour  Dep_min  \
0            0   3897            24              3        22       20
1            2   7662             1              5         5       50
2            2  13882             9              6         9       25
3            1   6218            12              5        18        5
4            1  13302             1              3        16       50
5            0   3873            24              6         9        0
6            1  11087            12              3        18       55
7            1  22270             1              3         8        0
8            1  11087            12              3         8       55
9            1   8625            27              5        11       25

   Arrival_hour  Arrival_min  Duration_hours  Duration_mins
0             1           10               2             50
1            13           15               7             25
2             4           25              19              0
3            23           30               5             25
4            21           35               4             45
```

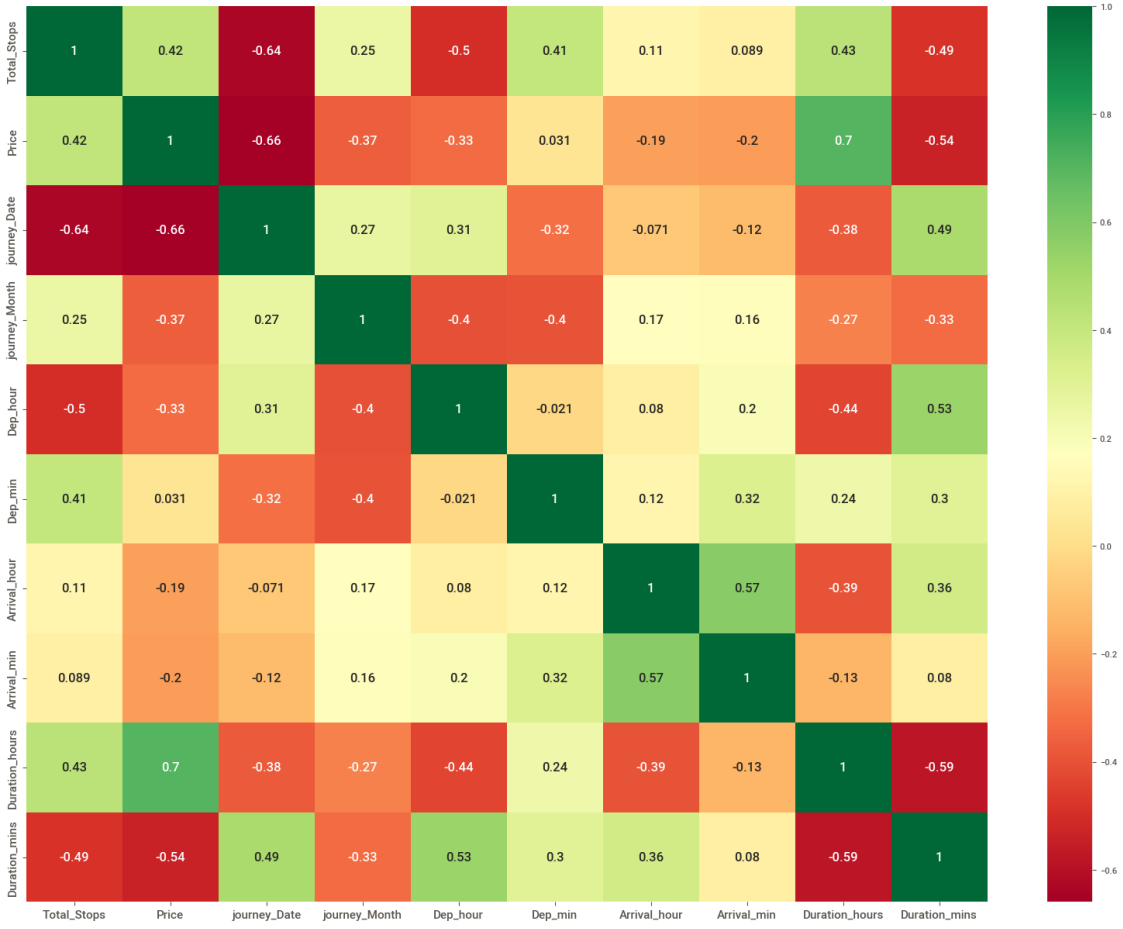
```
5             11           25              2            25
6             10           25             15            30
7              5            5             21             5
8             10           25             25            30
9             19           15              7            50
```

[182]:
```
data2.corr()
```

[182]:
```
                 Total_Stops     Price  journey_Date  journey_Month  Dep_hour  \
Total_Stops         1.000000  0.415321     -0.639003       0.253185 -0.502264
Price               0.415321  1.000000     -0.659511      -0.366571 -0.333911
journey_Date       -0.639003 -0.659511      1.000000       0.267372  0.305646
journey_Month       0.253185 -0.366571      0.267372       1.000000 -0.400946
Dep_hour           -0.502264 -0.333911      0.305646      -0.400946  1.000000
Dep_min             0.405355  0.031325     -0.319999      -0.399323 -0.020904
Arrival_hour        0.112469 -0.193463     -0.071263       0.166297  0.080281
Arrival_min         0.088946 -0.203835     -0.117263       0.162142  0.201823
Duration_hours      0.430101  0.703591     -0.378853      -0.271248 -0.438518
Duration_mins      -0.490055 -0.542767      0.487520      -0.332520  0.528181

                   Dep_min  Arrival_hour  Arrival_min  Duration_hours  \
Total_Stops       0.405355      0.112469     0.088946        0.430101
Price             0.031325     -0.193463    -0.203835        0.703591
journey_Date     -0.319999     -0.071263    -0.117263       -0.378853
journey_Month    -0.399323      0.166297     0.162142       -0.271248
Dep_hour         -0.020904      0.080281     0.201823       -0.438518
Dep_min           1.000000      0.116379     0.322526        0.239471
Arrival_hour      0.116379      1.000000     0.573010       -0.393844
Arrival_min       0.322526      0.573010     1.000000       -0.134939
Duration_hours    0.239471     -0.393844    -0.134939        1.000000
Duration_mins     0.304109      0.362001     0.080203       -0.585949

                 Duration_mins
Total_Stops          -0.490055
Price                -0.542767
journey_Date          0.487520
journey_Month        -0.332520
Dep_hour              0.528181
Dep_min               0.304109
Arrival_hour          0.362001
Arrival_min           0.080203
Duration_hours       -0.585949
Duration_mins         1.000000
```

[183]:
```
# Heatmap- to find the correlation between independent to independent and␣
 ↪independent to dependent variables
plt.figure(figsize=(20,15))
```

```
sns.heatmap(data2.corr(),annot = True, cmap = "RdYlGn")
plt.tick_params(labelsize=11)
```



1.10.1 Insights

- we have to drop the column if the independent columns are highly related but we dont have any.
- We see that there are few cells which shows high correlation but thats between independent and dependent columns

1.11 9.MODEL CREATION

[184]:
```
# for the model creation we have to separate the independent and dependent
x=df.drop("Price",axis=1)
y=df["Price"]
```

[185]:
```
## creating training and testing data
from sklearn.model_selection import train_test_split
```

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
↪25,random_state=42)
```

[186]:
```
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(8011, 29)
(8011,)
(2671, 29)
(2671,)
```

1.12 LINEAR REGRESSION

[187]:
```
## importing the model library
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
y_pred=lr.predict(x_test)
```

[188]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[189]:
```
mse=mean_squared_error(y_test,y_pred)
print(mse)
mae=mean_absolute_error(y_test,y_pred)
print(mae)
```

```
7835152.949901841
1949.458356115105
```

[190]:
```
import math
rmse=math.sqrt(mae)
print(rmse)
```

```
44.15267099638599
```

[191]:
```
lr_score=r2_score(y_test,y_pred)
lr_score
```

[191]: 0.6198931301596473

[192]:
```
# adjusted r2 score
adj_r2=1-(1-lr_score)*(2671-1)/(2671-13-1)
adj_r2
```

[192]: 0.6180333675296419

1.13 KNN

[193]:
```
# for the model creation we have to separate the independent and dependent
x=df.drop("Price",axis=1)
y=df["Price"]
```

[194]:
```
from sklearn.model_selection import train_test_split## splitting the training␣
 ↪and testing data
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
 ↪25,random_state=42)
```

[195]:
```
from sklearn.neighbors import KNeighborsRegressor
KNN=KNeighborsRegressor(n_neighbors=5)
KNN.fit(x_train,y_train)
y_pred=KNN.predict(x_test)
```

[196]:
```
(y_test!=y_pred).sum()
```

[196]: 2639

[197]:
```
len(y_test)
```

[197]: 2671

[198]:
```
(y_test!=y_pred).sum()/len(y_test)
```

[198]: 0.9880194683639086

[199]:
```
## taking optimal k to determine how many nearest neighbors  to create
# create a list to store the error values for each k
ERROR_RATE=[]
for i in range(1,13):
    KNN=KNeighborsRegressor(n_neighbors=i)
    KNN.fit(x_train,y_train)
    y_pred=KNN.predict(x_test)
    error_rate=(y_test!=y_pred).sum()/len(y_test)
    ERROR_RATE.append(error_rate)
```

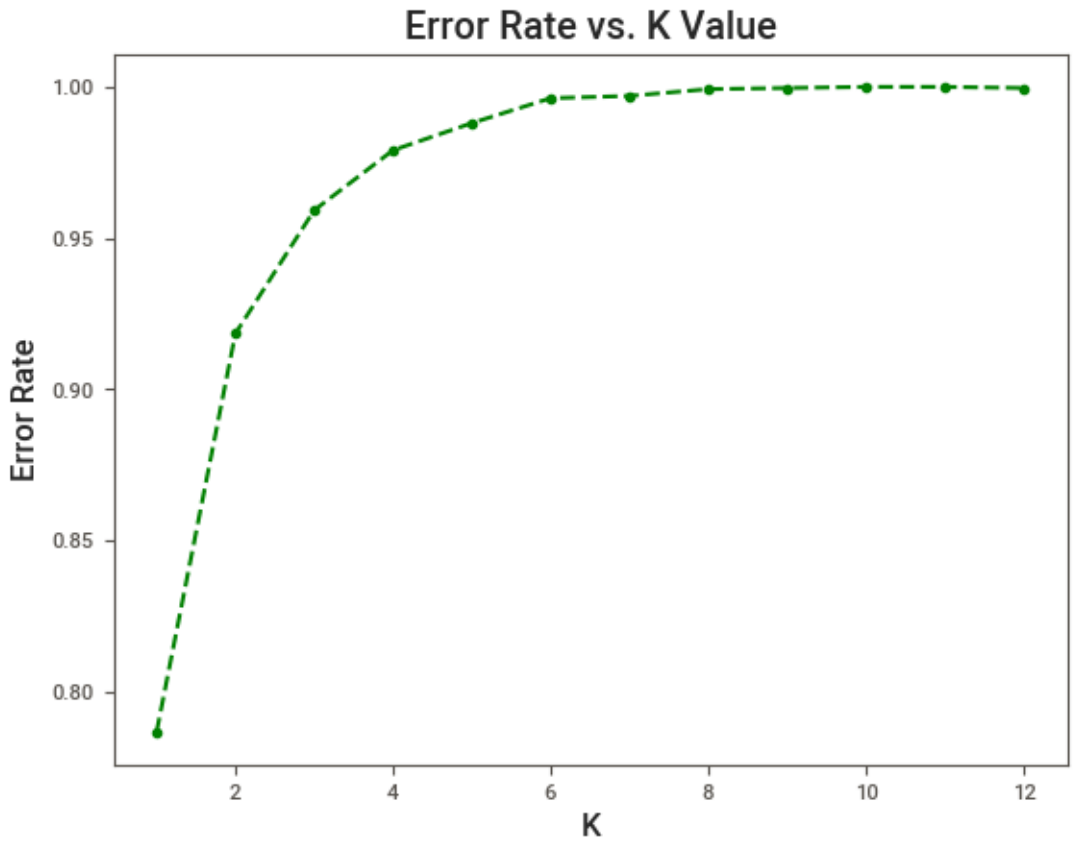
[200]:
```
ERROR_RATE
```

[200]:
```
[0.7865967802321228,
 0.9183826282291276,
 0.9591913141145638,
 0.9790340696368401,
 0.9880194683639086,
 0.9962560838637214,
 0.9970048670909771,
```

```
0.9992512167727443,
0.9996256083863722,
1.0,
1.0,
0.9996256083863722]
```

[201]:
```
# Lets plot the k-value and error rate
plt.plot(range(1,13),ERROR_RATE,color='green',marker='o',linestyle='--')
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

[201]: Text(0, 0.5, 'Error Rate')



[202]:
```
from sklearn.neighbors import KNeighborsRegressor
KNN=KNeighborsRegressor(n_neighbors=4)
KNN.fit(x_train,y_train)
y_pred=KNN.predict(x_test)
```

[203]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[204]:
```
mse=mean_squared_error(y_test,y_pred)
mse
```

[204]: 8908715.681299139

[205]:
```
mae=mean_absolute_error(y_test,y_pred)
mae
```

[205]: 1845.3384500187196

[206]:
```
knn_score=r2_score(y_test,y_pred)
knn_score
```

[206]: 0.5678113683844929

[207]:
```
adj_r2=1-(1-knn_score)*(2671-1)/(2671-13-1)
adj_r2
```

[207]: 0.5656967834349251

1.14 DECISION TREE

[208]:
```
# for the model creation we have to separate the independent and dependent
x=df.drop("Price",axis=1)
y=df["Price"]
```

[209]:
```
from sklearn.model_selection import train_test_split# preparing training and␣
 ↪testing data
x_train,x_test,y_train,y_test=train_test_split(x,y, test_size=0.
 ↪25,random_state=42)
```

[210]:
```
from sklearn.tree import DecisionTreeRegressor#importing decision tree from␣
 ↪sklearn.tree
dt=DecisionTreeRegressor()#object creation for decision tree
dt.fit(x_train,y_train)#training the model
y_pred=dt.predict(x_test)#prediction
```

[211]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[212]:
```
mse=mean_squared_error(y_test,y_pred)
mse
```

[212]: 5930858.2890817

[213]:
```
mae=mean_absolute_error(y_test,y_pred)
mae
```

[213]:
```
1350.9729190066143
```

[214]:
```
dt_score=r2_score(y_test,y_pred)
dt_score
```

[214]:
```
0.7122762000762477
```

[215]:
```
adj_r2=1-(1-dt_score)*(2671-1)/(2671-13-1)
adj_r2
```

[215]:
```
0.7108684434337904
```

1.15 RANDOM FOREST

[216]:
```
# for the model creation we have to separate the independent and dependent
x=df.drop("Price",axis=1)
y=df["Price"]
```

[217]:
```
# Splitting the Data into Train & Test Split
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
 ↪25,random_state=42)
```

[218]:
```
x.shape
```

[218]:
```
(10682, 29)
```

[219]:
```
y.shape
```

[219]:
```
(10682,)
```

[220]:
```
from sklearn.ensemble import RandomForestRegressor
random_forest=RandomForestRegressor()
random_forest.fit(x_train,y_train)
y_pred=random_forest.predict(x_test)
```

[221]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[222]:
```
#Mean absolute error
MAE=mean_absolute_error(y_test,y_pred)
MAE
```

[222]:
```
1159.2350776537098
```

[223]:
```
#Mean Squared error
MSE=mean_squared_error(y_test,y_pred)
MSE
```

[223]: 4118971.092235592

[224]:
```
#Root mean squared error
RMSE=np.sqrt(MSE)
RMSE
```

[224]: 2029.524843956238

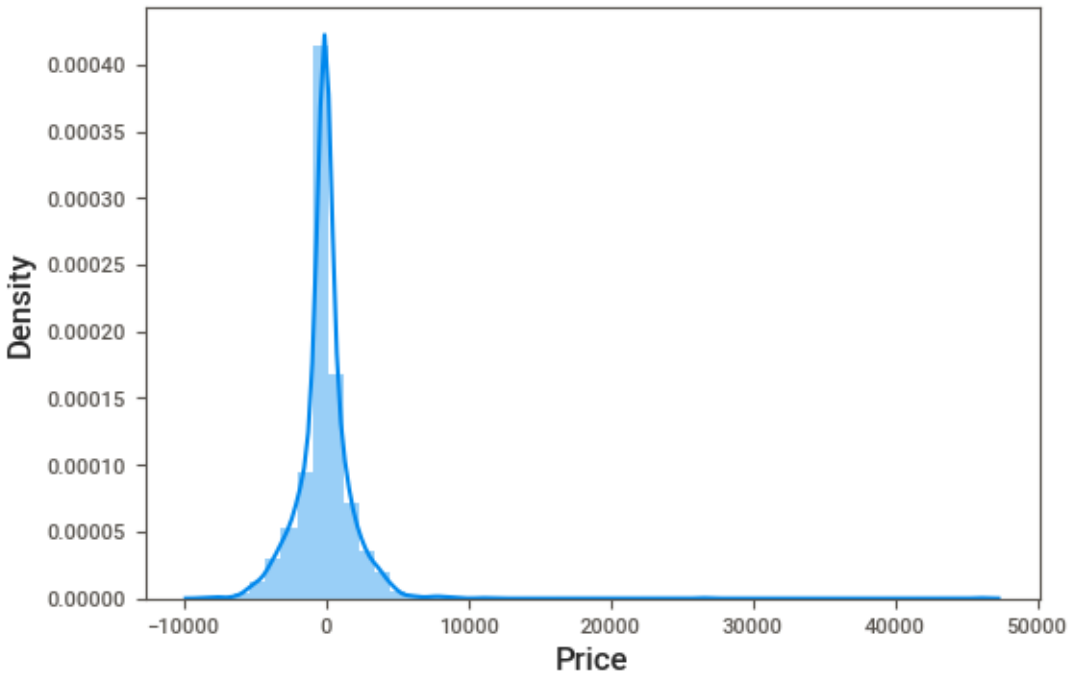
[233]:
```
r2=r2_score(y_test,y_pred)
r2
```

[233]: 0.8001763055752238

[234]:
```
adj_r2=1-(1-r2)*(2671-1)/(2671-13-1)
adj_r2
```

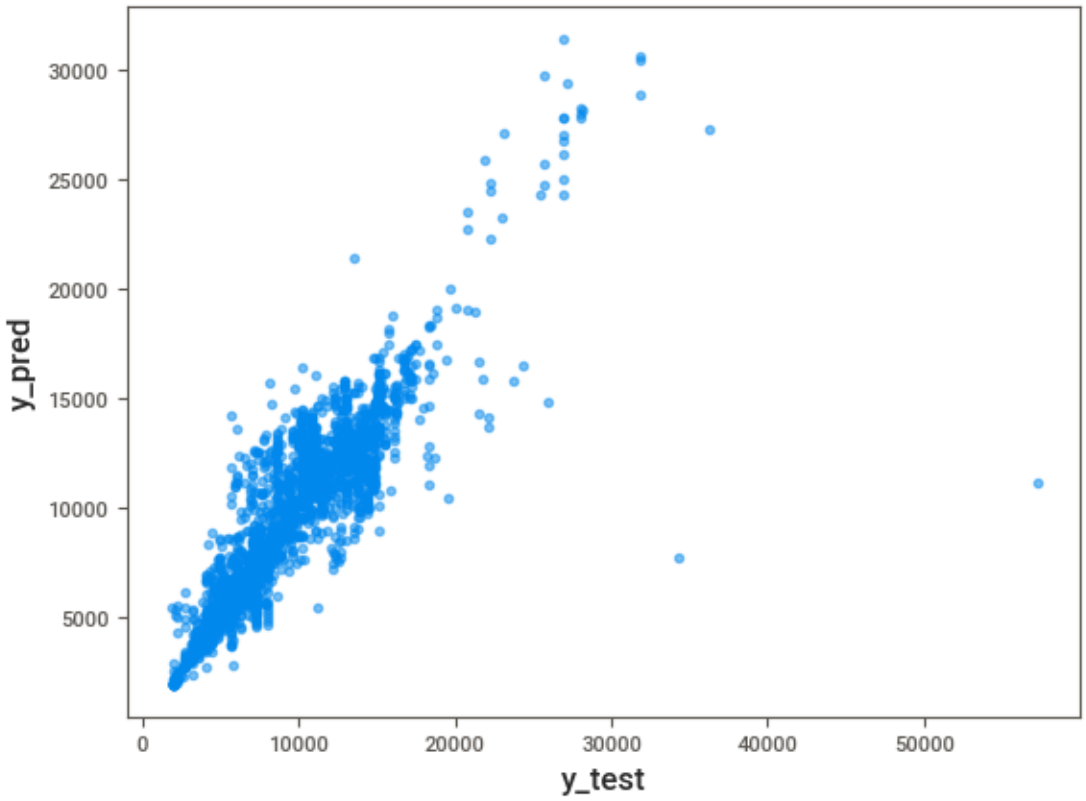
[234]: 0.7991986209581662

[235]:
```
plt.figure(figsize=(6,4))
sns.distplot(y_test-y_pred)
plt.show()
```



[236]:
```
plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
```

```
plt.ylabel("y_pred")
plt.figure(figsize=(6,4))
plt.show()
```




```
<Figure size 600x400 with 0 Axes>
```

1.16 HYPER PARAMETERTUNING

[237]:
```
from sklearn.model_selection import RandomizedSearchCV
```

[238]:
```
n_estimators=[int(x)for x in np.linspace(start=100,stop=1200,num=12)]
max_features=['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(5, 30, num=6)]
min_samples_split=[2,3,10,15,100]
min_samples_leaf=[1,2,5,10]
```

[239]:
```
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}
```

[240]:
```
rf_random=RandomizedSearchCV(estimator=random_forest,param_distributions=random_grid,scoring='
```

[241]:
```
rf_random.fit(x_train,y_train)
```

```
Fitting 4 folds for each of 100 candidates, totalling 400 fits
```

[241]:
```
RandomizedSearchCV(cv=4, estimator=RandomForestRegressor(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'max_depth': [5, 10, 15, 20, 25, 30],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 5, 10],
                                        'min_samples_split': [2, 3, 10, 15,
                                                              100],
                                        'n_estimators': [100, 200, 300, 400,
                                                         500, 600, 700, 800,
                                                         900, 1000, 1100,
                                                         1200]},
                   random_state=42, scoring='neg_mean_squared_error',
                   verbose=2)
```

[242]:
```
rf_random.best_params_
```

[242]:
```
{'n_estimators': 500,
 'min_samples_split': 10,
 'min_samples_leaf': 1,
 'max_features': 'auto',
 'max_depth': 20}
```

[243]:
```
from sklearn.ensemble import RandomForestRegressor
random_forest=RandomForestRegressor(n_estimators= 500,
 min_samples_split= 10,
 min_samples_leaf= 1,
 max_features= 'auto',
 max_depth= 20)
random_forest.fit(x_train,y_train)
y_pred=random_forest.predict(x_test)
```

[244]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[245]:
```
MAE=mean_absolute_error(y_test,y_pred)
MAE
```

[245]:
```
1132.3857159768027
```

[246]:
```
MSE=mean_squared_error(y_test,y_pred)
MSE
```

[246]: 3832499.572301327

[247]:
```
#Root mean squared error
RMSE=np.sqrt(MSE)
RMSE
```

[247]: 1957.6770858089255

[248]:
```
random_forest.score(x_train,y_train)
```

[248]: 0.9109941911759742

[249]:
```
random_forest.score(x_test,y_test)
```

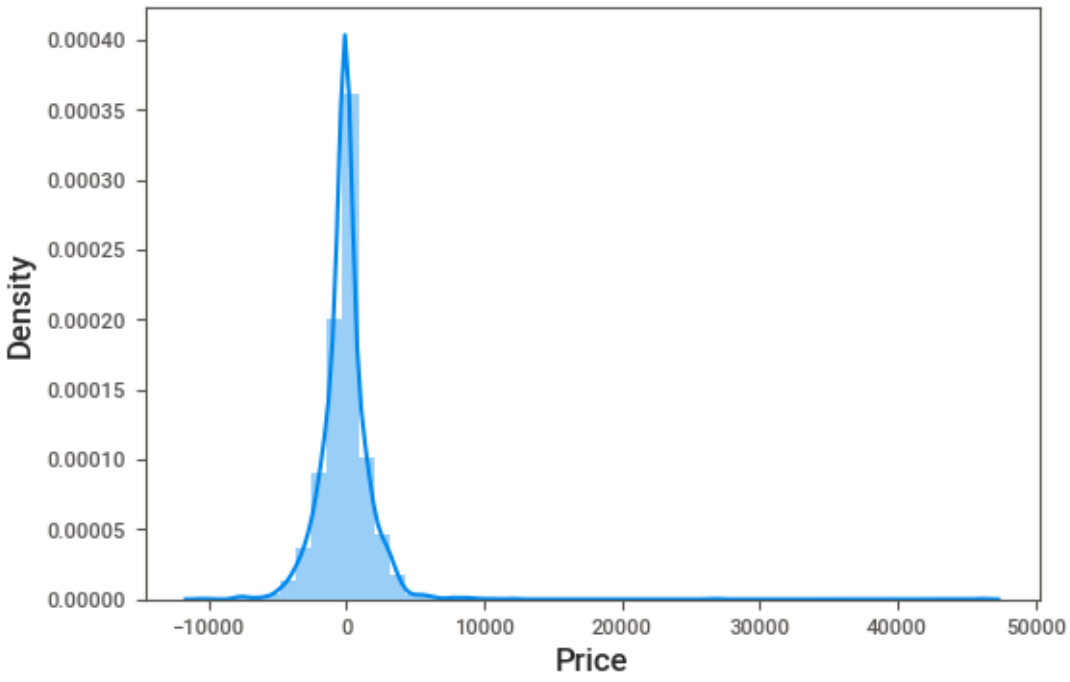
[249]: 0.8140739018872378

[250]:
```
# R2 score
rf_score=metrics.r2_score(y_test,y_pred)
rf_score
```

[250]: 0.8140739018872378

[251]:
```
prediction=rf_random.predict(x_test)
```

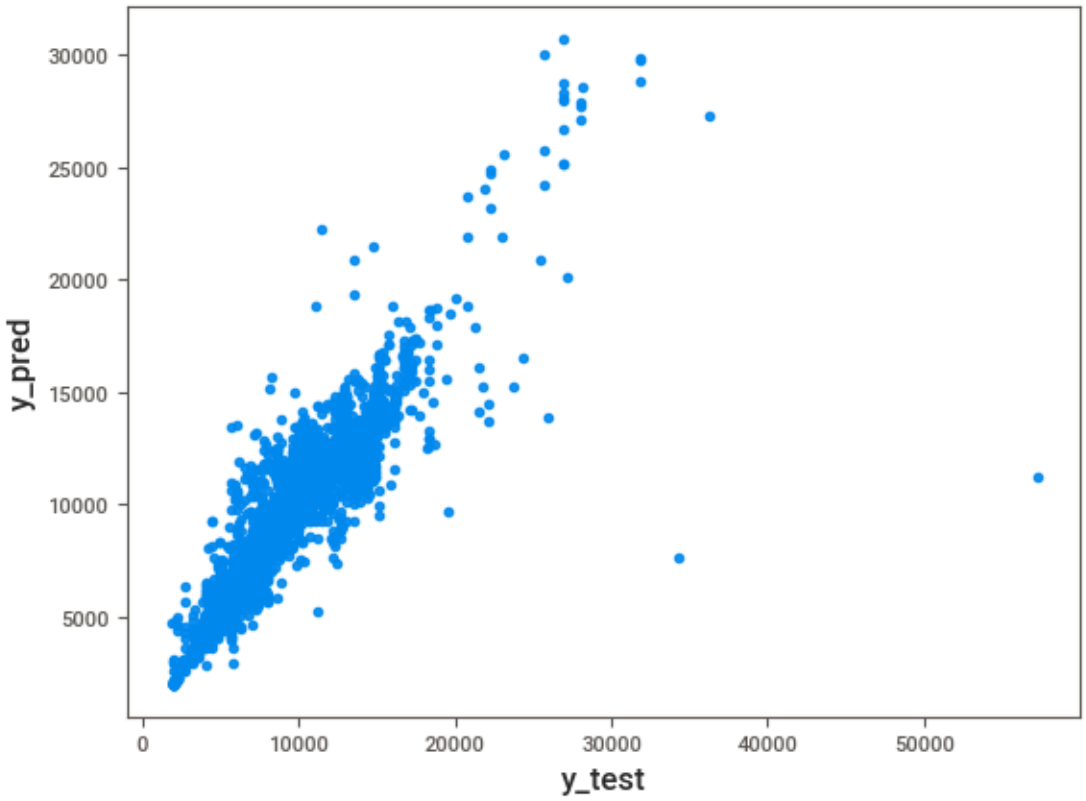
[252]:
```
plt.figure(figsize=(6,4))
sns.distplot(y_test-prediction)
plt.show()
```



1.16.1 Insight:

- We see the normal distribution in the curve

[253]:
```
plt.scatter(y_test, y_pred, alpha = 0.9)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.figure(figsize=(6,4))

plt.show()
```




```
<Figure size 600x400 with 0 Axes>
```

1.16.2 Insight:

- We can see the observation in linearly scattered

1.17 GRADIENT BOOSTING

[254]:
```
# for the model creation we have to separate the independent and dependent
x=df.drop("Price",axis=1)
y=df["Price"]
```

[255]:
```
# Splitting the Data into Train & Test Split
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
 ↪25,random_state=42)
```

[256]:
```
## importing the model library
from sklearn.ensemble import GradientBoostingRegressor
gbm=GradientBoostingRegressor(n_estimators=100) ## object creation
gbm.fit(x_train,y_train) ## fitting the data
y_hat=gbm.predict(x_test)#predicting the price
```

[257]:
```
## evaluatin the model
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[258]:
```
mse=mean_squared_error(y_test,y_hat)
mse
```

[258]: 4306336.397248144

[259]:
```
mae=mean_absolute_error(y_test,y_hat)
mae
```

[259]: 1488.1156304342967

[260]:
```
gb_score=r2_score(y_test,y_hat)
gb_score
```

[260]: 0.7910866502665936

[261]:
```
adj_r2=1-(1-gb_score)*(2671-1)/(2671-13-1)
adj_r2
```

[261]: 0.7900644923642473

1.18 HYPER PARAMETERTUNINIG

[272]:
```
from sklearn.model_selection import RandomizedSearchCV
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
```

```
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'subsample': [0.8, 0.9, 1.0]
}
```

[274]:
```
rsc=RandomizedSearchCV(estimator=gb_regressor,param_distributions=param_grid,scoring='neg_mean
```

[278]:
```
rsc.fit(x_train, y_train)
```

```
Fitting 4 folds for each of 100 candidates, totalling 400 fits
```

[278]:
```
RandomizedSearchCV(cv=4, estimator=GradientBoostingRegressor(random_state=42),
                   n_iter=100, n_jobs=-1,
                   param_distributions={'learning_rate': [0.01, 0.1, 0.2],
                                        'max_depth': [3, 4, 5],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [100, 200, 300],
                                        'subsample': [0.8, 0.9, 1.0]},
                   random_state=42, scoring='neg_mean_squared_error',
                   verbose=2)
```

[279]:
```
rsc.best_params_
```

[279]:
```
{'subsample': 0.9,
 'n_estimators': 300,
 'min_samples_split': 10,
 'min_samples_leaf': 2,
 'max_depth': 5,
 'learning_rate': 0.1}
```

[291]:
```
## importing the model library
from sklearn.ensemble import GradientBoostingRegressor
gradient_boost=GradientBoostingRegressor(n_estimators= 300,
                                         min_samples_split= 10,
                                         min_samples_leaf= 2,
                                         subsample= 0.9,
                                         learning_rate= 0.1,
                                         max_depth= 5)
gradient_boost.fit(x_train,y_train)
y_hat=gradient_boost.predict(x_test)
```

[292]:
```
## evaluatin the model
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[293]:
```
mse=mean_squared_error(y_test,y_hat)
mse
```

[293]: 3052127.0810980895

[294]:
```
mae=mean_absolute_error(y_test,y_hat)
mae
```

[294]: 1165.4653521509392

[295]:
```
gbst_score=r2_score(y_test,y_hat)
gbst_score
```

[295]: 0.8519321219931385

1.19 10.RESULT

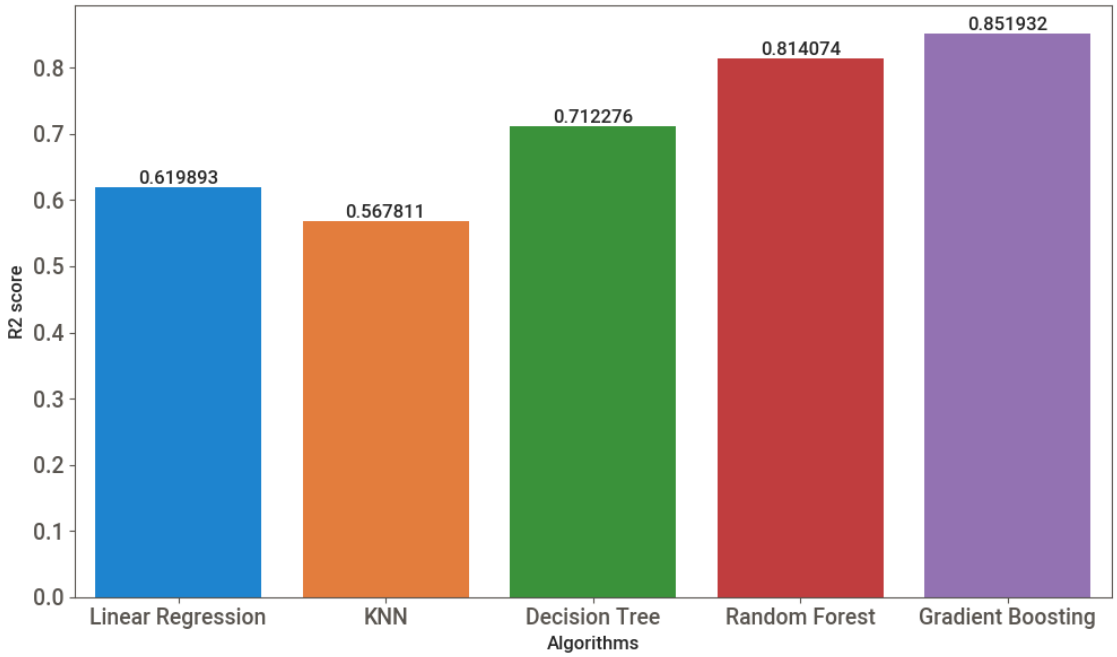
1.19.1 Comparison of the Best Models Evaluated by Cross Validation

- LinearRegressor - CV: 0.61
- KNeighborsRegressor - CV: 0.56
- DecisionTreeRegressor - CV: 0.70
- RandomForestRegressor - CV: 0.81
- GradientBoostingRegressor - CV: 0.85

[298]:
```
scores = [lr_score,knn_score,dt_score,rf_score,gbst_score]
algorithms = ["Linear Regression","KNN","Decision Tree","Random␣
 ↪Forest","Gradient Boosting"]

for i in range(len(algorithms)):
    print("The R2 score achieved using "+algorithms[i]+" is: "+str(scores[i])+"␣
 ↪%")
```

```
The R2 score achieved using Linear Regression is: 0.6198931301596473 %
The R2 score achieved using KNN is: 0.5678113683844929 %
The R2 score achieved using Decision Tree is: 0.7122762000762477 %
The R2 score achieved using Random Forest is: 0.8140739018872378 %
The R2 score achieved using Gradient Boosting is: 0.8519321219931385 %
```

[306]:
```
plt.figure(figsize=(10,6))
plt.xlabel("Algorithms")
plt.ylabel("R2 score")
ax=sns.barplot(x=algorithms,y=scores)
for label in ax.containers:
    ax.bar_label(label)
plt.tight_layout()
plt.tick_params(labelsize=14)
```



1.20 Conclusion

- The best model is Gradient Boosting with a r2_score of 0.85.
- The second best model followed by Gradient Boosting is Random Forest with a r2_score of 0.81.
- Some of the best features which has high impact on price are Total_Stops, Duration,Airline and Route.