In [4]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [5]:
```python
!pip install plotly
```

```
Requirement already satisfied: plotly in /Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages (5.10.0)
Requirement already satisfied: tenacity>=6.2.0 in /Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages (from plotly) (8.1.0)
```

In [38]:
```python
## This makes visualisation more interactive

import plotly
import cufflinks as cf
from cufflinks.offline import go_offline
from plotly.offline import download_plotlyjs,init_notebook_mode,plot,iplot
```

In [7]:
```python
train_data = pd.read_excel('Data_Train.xlsx')
```

In [10]:
```python
train_data.head(7)
```

Out[10]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	No info	7662
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	No info	6218
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	No info	13302
5	SpiceJet	24/06/2019	Kolkata	Banglore	CCU → BLR	09:00	11:25	2h 25m	non-stop	No info	3873
6	Jet Airways	12/03/2019	Banglore	New Delhi	BLR → BOM → DEL	18:55	10:25 13 Mar	15h 30m	1 stop	In-flight meal not included	11087

In [11]:
```python
## information of the data (which are Flight Tickets)

train_data.info()
```

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

In [12]:
```python
## Finding missing values

train_data.isnull().sum()
```

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]:
```python
## This is the shape of the dataframe which has 10683 columns and 11 rows

train_data.shape
```

Out[13]:
```
(10683, 11)
```

In [14]:
```python
# locating all the rows where we have missing value [only 1 row indicates a mising values]

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

Out[14]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
9039	Air India	6/05/2019	Delhi	Cochin	NaN	09:45	09:25 07 May	23h 40m	NaN	No info	7480

In [15]:
```python
## Removing the missing values and update the dataframe

train_data.dropna(inplace=True)
```

In [16]:
```python
## The missing values are gone and updated in the dataframe

train_data.isnull().sum()
```

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
```

DATA PRE-PROCESSING

In [17]:
```python
## Creating a copy of the train_data and storing it in 'data'

data = train_data.copy()
```

In [18]:
```python
data.head(2)
```

Out[18]:

	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

In [19]:
```python
data.dtypes
```

Out[19]:
```
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 [20]:
```python
def change_into_datetime(col):
    data[col]=pd.to_datetime(data[col])
```

In [21]:
```python
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]:
```python
for feature in ['Date_of_Journey','Dep_Time', 'Arrival_Time']:
    change_into_datetime(feature)
```

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

Out[23]:
```
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
```

Cleaning Date_of_Journey

In [24]:
```python
data['journey_day']=data['Date_of_Journey'].dt.day
```

In [25]:
```python
data['journey_month']=data['Date_of_Journey'].dt.month
```

In [26]:
```python
data['journey_year']=data['Date_of_Journey'].dt.year
```

In [27]:
```python
## I have updated (and cleaned date_of_journey in) the dataframe with extra rows [jorney day, journey month,
                                                                                   #journey year]
data.head(2)
```

Out[27]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	jour
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	2022-12-18 22:20:00	2022-03-22 01:10:00	2h 50m	non-stop	No info	3897	
1	Air India	2019-01-05	Kolkata	Banglore	CCU → IXR → BBI → BLR	2022-12-18 05:50:00	2022-12-18 13:15:00	7h 25m	2 stops	No info	7662	

In [28]:
```python
## after updating the dataframe I removed the Date_of_Journey

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

In [29]:
```python
data.head(2)
```

Out[29]:

	Airline	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	journey_day	journey_
0	IndiGo	Banglore	New Delhi	BLR → DEL	2022-12-18 22:20:00	2022-03-22 01:10:00	2h 50m	non-stop	No info	3897	24	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	2022-12-18 05:50:00	2022-12-18 13:15:00	7h 25m	2 stops	No info	7662	5	

Cleaning Dep_Time and Arrival_Time then featurize it

In [30]:
```python
## This is a fuction which extract hours and minutes

def extract_hour_min(df,col):
    df[col+'_hour']=df[col].dt.hour
    df[col+'_minute']=df[col].dt.minute
    df.drop(col,axis=1,inplace=True)
    return df.head(2)
```

In [31]:
```python
## The dataframe has been updated with new features [Dep_time_hour and minute]

extract_hour_min(data,'Dep_Time')
```

Out[31]:

	Airline	Source	Destination	Route	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	journey_day	journey_month	jour
0	IndiGo	Banglore	New Delhi	BLR → DEL	2022-03-22 01:10:00	2h 50m	non-stop	No info	3897	24	3	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	2022-12-18 13:15:00	7h 25m	2 stops	No info	7662	5	1	

In [32]:
```python
## The dataframe has been updated with new features [arrival_time_hour and minute]

extract_hour_min(data,'Arrival_Time')
```

Out[32]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	journey_day	journey_month	journey_year	Dep
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	24	3	2019	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	7662	5	1	2019	

DATA ANALYSIS: analysing when most of the flight takeoff

In [33]:
```python
### Converting the flight Dep_Time into proper time i.e. mid_night, morning, afternoon and evening.

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 mrng'

    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 [36]:
```python
## This counts the number of flights in departure time which is categorised by early morning, evening, noon....

data['Dep_Time_hour'].apply(flight_dep_time).value_counts()
```

Out[36]:
```
Early mrng    2880
Evening       2357
Morning       2209
Noon          1731
Night         1040
Late night     465
Name: Dep_Time_hour, dtype: int64
```

In [42]:
```python
## This is an interactive visualisation of the number of flights in each category

data['Dep_Time_hour'].apply(flight_dep_time).value_counts().plot(kind='bar')
```

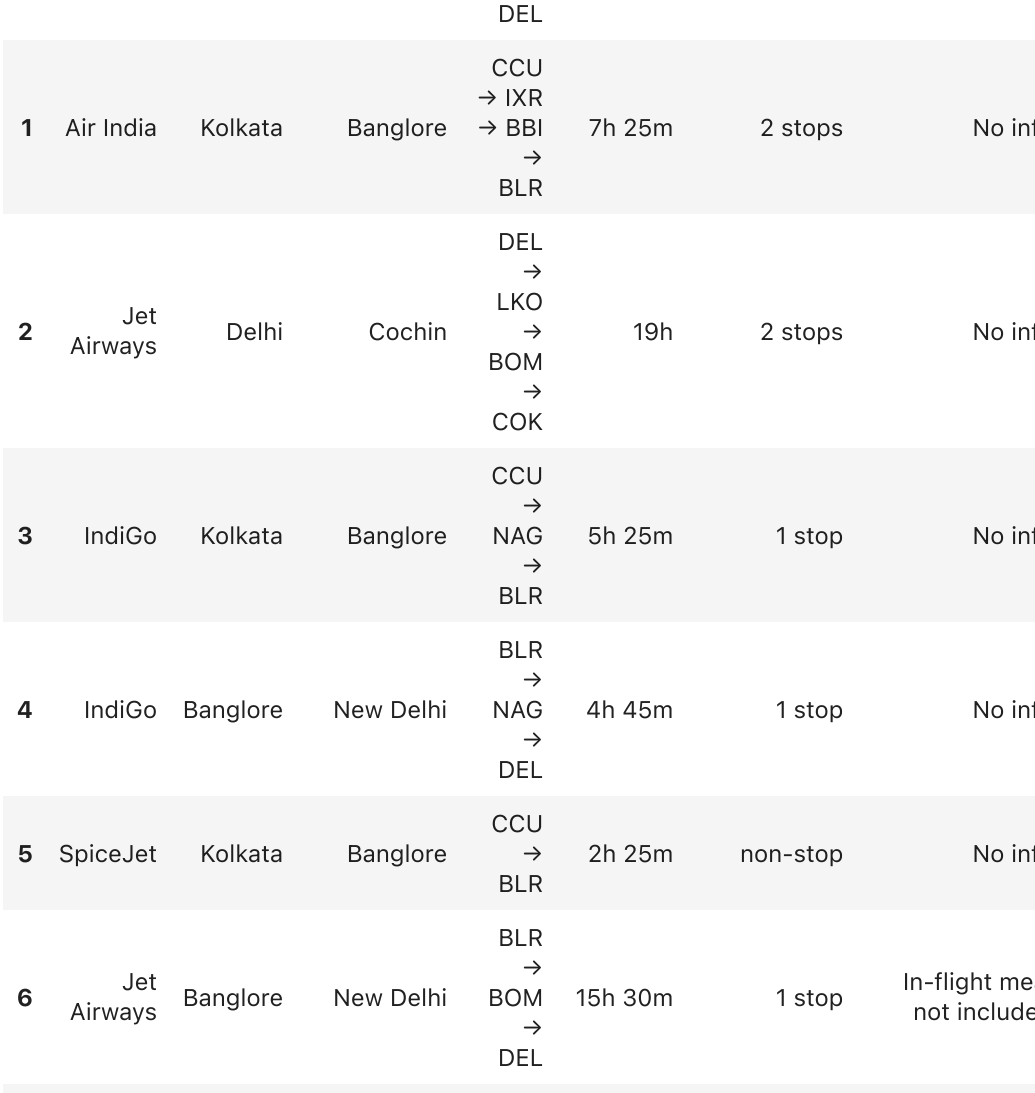
Out[42]:
```
<AxesSubplot:>
```

DATA ANALYSIS: analysis of Airports with the Most no of Departures

In [261]:
```python
## This shows Delhi is the Busiest Airport with 4536 flights followed by Kolkata and Bangalore Airports.

count = train_data.Source.value_counts()
departure = np.array(['Delhi','Kolkata','Bangalore','Mumbai','Chennai'])
count
```

Out[261]:
```
Delhi       4536
Kolkata     2871
Banglore    2197
Mumbai       697
Chennai      381
Name: Source, dtype: int64
```

In [257]:
```python
count = train_data.Source.value_counts()
departure = np.array(['Delhi','Kolkata','Bangalore','Mumbai','Chennai'])

fig, ax = plt.subplots()

ax.bar(departure,count)
ax.set_title("Airports with Most no of Departure",fontdict={'size':13})
ax.set_xlabel("Airports",fontdict={'size':14})
ax.set_ylabel("Count",fontdict={'size':12})
ax.grid()

fig.set_size_inches(8,8)
plt.show()
```



DATA PRE-PROCESSING: Focusing on duration and extracting new features.

In [48]:
```python
## I am focusing on the duration in this dataframe.

data.head(10)
```

Out[48]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	journey_day	journey_month	journey_year	D
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	24	3	2019	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	7662	5	1	2019	
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	19h	2 stops	No info	13882	6	9	2019	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	5h 25m	1 stop	No info	6218	5	12	2019	
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	4h 45m	1 stop	No info	13302	3	1	2019	
5	SpiceJet	Kolkata	Banglore	CCU → BLR	2h 25m	non-stop	No info	3873	24	6	2019	
6	Jet Airways	Banglore	New Delhi	BLR → BOM → DEL	15h 30m	1 stop	In-flight meal not included	11087	3	12	2019	
7	Jet Airways	Banglore	New Delhi	BLR → BOM → DEL	21h 5m	1 stop	No info	22270	3	1	2019	
8	Jet Airways	Banglore	New Delhi	BLR → BOM → DEL	25h 30m	1 stop	In-flight meal not included	11087	3	12	2019	
9	Multiple carriers	Delhi	Cochin	DEL → BOM → COK	7h 50m	1 stop	No info	8625	27	5	2019	

In [49]:
```python
def preprocess_duration(x):
    if 'h' not in x:
        x='0h '+x
    elif 'm' not in x:
        x=x+' 0m'
    return x
```

In [50]:
```python
data['Duration']=data['Duration'].apply(preprocess_duration)
```

In [51]:
```python
## This shows the duration of each flight.

data['Duration']
```

Out[51]:
```
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 [52]:
```python
data['Duration'][0].split(' ')[0]
```

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

In [54]:
```python
int(data['Duration'][0].split(' ')[0][0:-1])
```

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

In [55]:
```python
data['Duration_hours']=data['Duration'].apply(lambda x:int(x.split(' ')[0][0:-1]))
```

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

In [57]:
```python
## The dataframe has been updated with new features [Duration_hours and Duration_min]

data.head(3)
```

Out[57]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	journey_day	journey_month	journey_year	De
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	24	3	2019	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	7662	5	1	2019	
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	19h 0m	2 stops	No info	13882	6	9	2019	

DATA ANALYSIS: analysing if Duration of flights affects price or not.

In [59]:
```python
## This shows the total duration of each flight (array '0' shows 170 minutes...etc), using the 'eval' function

data['Duration'].str.replace('h','*60').str.replace(' ','+').str.replace('m','*1').apply(eval)
```

Out[59]:
```
0         170
1         445
2        1140
3         325
4         285
         ... 
10678     150
10679     155
10680     180
10681     160
10682     500
Name: Duration, Length: 10682, dtype: int64
```

In [60]:
```python
data['Duration_total_mins']=data['Duration'].str.replace('h','*60').str.replace(' ','+').str.replace('m','*1').
```

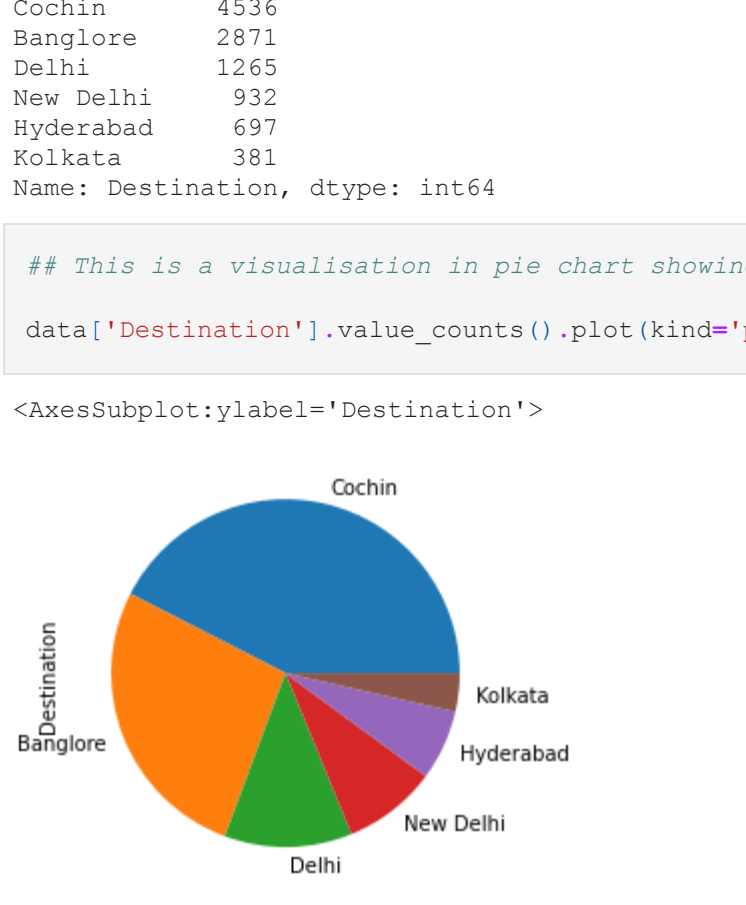
In [61]:
```python
## This dataframe is updated and shows the a new feature [Duration_Total_Time]

data.head(2)
```

Out[61]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	journey_day	journey_month	journey_year	Dep
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	24	3	2019	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	7662	5	1	2019	

In [62]:
```python
## This is a visualisation, It Plot data and regression model fits across a FacetGrid
## It also shows that As the duration of minutes increases Flight price also increases.

sns.lmplot(x='Duration_total_mins',y='Price',data=data)
```

Out[62]:
```
<seaborn.axisgrid.FacetGrid at 0x7f9e2ba1f8b0>
```



DATA ANALYSIS: Identifying which city has the maximum final destination of flights.

In [64]:
```python
## This shows all the unique destination

data['Destination'].unique()
```

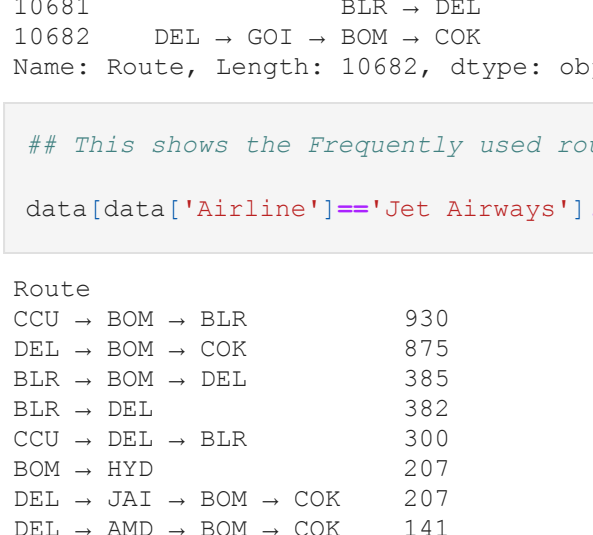
Out[64]:
```
array(['New Delhi', 'Banglore', 'Cochin', 'Kolkata', 'Delhi', 'Hyderabad'],
      dtype=object)
```

In [65]:
```python
## This shows/counts the max number of flight in each destination

data['Destination'].value_counts()
```

Out[65]:
```
Cochin       4536
Banglore     2871
Delhi        1265
New Delhi     932
Hyderabad     697
Kolkata       381
Name: Destination, dtype: int64
```

In [66]:
```python
## This is a visualisation in pie chart showing each destination with a different colour...

data['Destination'].value_counts().plot(kind='pie')
```

Out[66]:
```
<AxesSubplot:ylabel='Destination'>
```



DATA ANALYSIS: Identifying which Route 'Jet Airways' uses the most. (Jet Airways is an airline)

In [70]:
```python
## This shows all the unique Airlines in the data.

data['Airline'].unique()
```

Out[70]:
```
array(['IndiGo', 'Air India', 'Jet Airways', 'SpiceJet',
       'Multiple carriers', 'GoAir', 'Vistara', 'Air Asia',
       'Vistara Premium economy', 'Jet Airways Business',
       'Multiple carriers Premium economy', 'Trujet'], dtype=object)
```

In [71]:
```python
## This shows all the Route in the data.

data['Route']
```

Out[71]:
```
0                    BLR → DEL
1        CCU → IXR → BBI → BLR
2        DEL → LKO → BOM → COK
3              CCU → NAG → BLR
4              BLR → NAG → DEL
                 ...          
10678                CCU → BLR
10679                CCU → BLR
10680                BLR → DEL
10681                BLR → DEL
10682    DEL → GOI → BOM → COK
Name: Route, Length: 10682, dtype: object
```

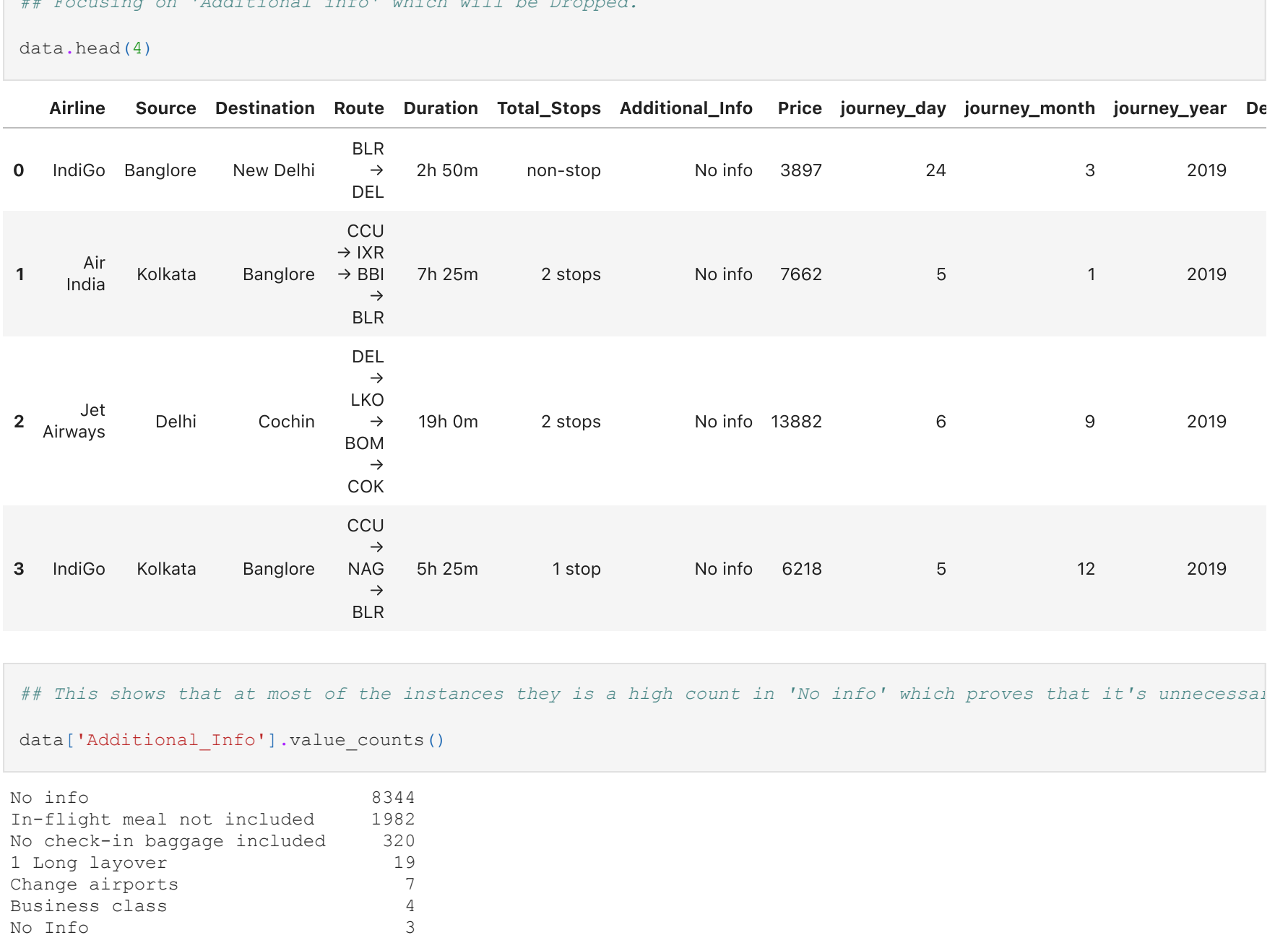
In [72]:
```python
## This shows the Frequently used routes by 'Jet Airways'

data[data['Airline']=='Jet Airways'].groupby('Route').size().sort_values(ascending=False)
```

Out[72]:
```
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
```

DATA ANALYSIS: Comparing Airline and Price

In [75]:
```python
## This is a disdribution boxplot which shows the airline and price.

plt.figure(figsize=(15,7))
sns.boxplot(y='Price',x='Airline',data=data)
plt.xticks(rotation='vertical')
```

Out[75]:
```
(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')])
```



DATA PRE-PROCESSING: removing some of the un-necessary features['Additional info' Route','Duration_total_mins..]

In [77]:
```python
## Focusing on 'Additional info' which will be Dropped.

data.head(4)
```

Out[77]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	journey_day	journey_month	journey_year	De
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	24	3	2019	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	7h 25m	2 stops	No info	7662	5	1	2019	
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	19h 0m	2 stops	No info	13882	6	9	2019	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	5h 25m	1 stop	No info	6218	5	12	2019	

In [81]:
```python
## This shows that at most of the instances they is a high count in 'No info' which proves that it's unnecessa

data['Additional_Info'].value_counts()
```

Out[81]:
```
No info                         8344
In-flight meal not included     1982
No check-in baggage included     320
1 Long layover                    19
Change airports                    7
Business class                     4
No Info                            3
1 Short layover                    1
2 Long layover                     1
Red-eye flight                     1
Name: Additional_Info, dtype: int64
```

In [82]:
```python
## Additional_Info contains almost 80% 'No_info',so I can drop this column
## I can drop Route as well because Total_stops feature can represent the 'Route' which means I dont need it.
## I can drop Duration_total_mins as I have already extracted "Duration_hours" and "Duration_mins"

data.drop(columns=['Additional_Info','Route','Duration_total_mins','journey_year'],axis=1,inplace=True)
```

In [85]:
```python
## This shows that the selected coluwns have been dropped.

data.columns
```

Out[85]:
```
Index(['Airline', 'Source', 'Destination', 'Duration', 'Total_Stops', 'Price',
       'journey_day', 'journey_month', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute', 'Duration_hours',
       'Duration_mins'],
      dtype='object')
```

In [86]:
```python
## This further shows the columns have been dropped in the dataframe

data.head(4)
```

Out[86]:

	Airline	Source	Destination	Duration	Total_Stops	Price	journey_day	journey_month	Dep_Time_hour	Dep_Time_minute	Arriv
0	IndiGo	Banglore	New Delhi	2h 50m	non-stop	3897	24	3	22	20	
1	Air India	Kolkata	Banglore	7h 25m	2 stops	7662	5	1	5	50	
2	Jet Airways	Delhi	Cochin	19h 0m	2 stops	13882	6	9	9	25	
3	IndiGo	Kolkata	Banglore	5h 25m	1 stop	6218	5	12	18	5	

DATA PRE-PROCESSING: Separating categorical data & numerical data

categorical data are those whose data-type is 'object'

Numerical data are those whose data-type is either int of float

In [88]:
```python
cat_col=[col for col in data.columns if data[col].dtype=='object']
```

In [89]:
```python
num_col=[col for col in data.columns if data[col].dtype!='object']
```

In [90]:
```python
## This shows all the categorial columns in the dataset

cat_col
```

Out[90]:
```
['Airline', 'Source', 'Destination', 'Duration', 'Total_Stops']
```

In [91]:
```python
## This shows all the Numerical  columns in the dataset

num_col
```

Out[91]:
```
['Price',
 'journey_day',
 'journey_month',
 'Dep_Time_hour',
 'Dep_Time_minute',
 'Arrival_Time_hour',
 'Arrival_Time_minute',
 'Duration_hours',
 'Duration_mins']
```

DATA PRE-PROCESSING: Handling categorical Data

I will be using 2 basic Encoding Techniques to convert Categorical data into some numerical format

if data belongs to Nominal data (ie data is not in any order) -->> OneHotEncoder is used in this case

if data belongs to Ordinal data (ie data is in order) -->> LabelEncoder is used in this case

In [93]:
```python
## applying one-hot encoding on 'Source' feature
```

In [94]:
```python
## This shows all the unique Sources in the data.

data['Source'].unique()
```

Out[94]:
```
array(['Banglore', 'Kolkata', 'Delhi', 'Chennai', 'Mumbai'], dtype=object)
```

In [95]:
```python
## The ML Model will not understand what this features mean so I apply an encoding.

data['Source']
```

Out[95]:
```
0        Banglore
1         Kolkata
2           Delhi
3         Kolkata
4        Banglore
           ...
10678     Kolkata
10679     Kolkata
10680    Banglore
10681    Banglore
10682       Delhi
Name: Source, Length: 10682, dtype: object
```

In [96]:
```python
## when ever we have 'Banglore' it says 1 else it says 0

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

Out[96]:
```
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 [97]:
```python
for category in data['Source'].unique():
    data['Source_'+category]=data['Source'].apply(lambda x: 1 if x==category else 0)
```

In [98]:
```python
data.head(3)
```

Out[98]:

	Airline	Source	Destination	Duration	Total_Stops	Price	journey_day	journey_month	Dep_Time_hour	Dep_Time_minute	Arriv
0	IndiGo	Banglore	New Delhi	2h 50m	non-stop	3897	24	3	22	20	
1	Air India	Kolkata	Banglore	7h 25m	2 stops	7662	5	1	5	50	
2	Jet Airways	Delhi	Cochin	19h 0m	2 stops	13882	6	9	9	25	

DATA PRE-PROCESSING: Performing Target Guided Mean Encoding

Target encoding is great for High-cardinality features: A feature with a large number of categories can be troublesome to encode: a one-hot encoding would generate too many features and alternatives,like a label encoding, might not be appropriate for that feature.

In [100…
```python
airlines=data.groupby(['Airline'])['Price'].mean().sort_values().index
```

In [101…
```python
dict1={key:index for index,key in enumerate(airlines,0)}
```

In [102…
```python
## dict1 stores each airline as a numerical from 0 to 11

dict1
```

Out[102…
```
{'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 [103…
```python
data['Airline']=data['Airline'].map(dict1)
```

In [104…
```python
data['Airline']
```

Out[104…
```
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 [114…
```python
## This dataframe is updated and shows the Airline column is now numerical

data.head(3)
```

Out[114…

	Airline	Source	Destination	Duration	Total_Stops	Price	journey_day	journey_month	Dep_Time_hour	Dep_Time_minute	Arriva
0	3	Banglore	2	2h 50m	non-stop	3897	24	3	22	20	
1	7	Kolkata	3	7h 25m	2 stops	7662	5	1	5	50	
2	10	Delhi	4	19h 0m	2 stops	13882	6	9	9	25	

In [106…
```python
## I will be focusing on 'New Delhi' and 'Delhi' which i will consider both as one/ the same...

data['Destination'].unique()
```

Out[106…
```
array(['New Delhi', 'Banglore', 'Cochin', 'Kolkata', 'Delhi', 'Hyderabad'],
      dtype=object)
```

In [107…
```python
data['Destination'].replace('New Delhi','Delhi',inplace=True)
```

In [108…
```python
## This shows i have updated the airline and their is only one Delhi

data['Destination'].unique()
```

Out[108…
```
array(['Delhi', 'Banglore', 'Cochin', 'Kolkata', 'Hyderabad'],
      dtype=object)
```

In [109…
```python
dest=data.groupby(['Destination'])['Price'].mean().sort_values().index
```

In [110…
```python
dict2={key:index for index,key in enumerate(dest,0)}
```

In [111…
```python
## dict2 stores each Destination as a numerical from 0 to 11

dict2
```

Out[111…
```
{'Kolkata': 0, 'Hyderabad': 1, 'Delhi': 2, 'Banglore': 3, 'Cochin': 4}
```

In [112…
```python
data['Destination']=data['Destination'].map(dict2)
```

In [113…
```python
data['Destination']
```

Out[113…
```
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 [115…
```python
## This dataframe is updated and shows that Destination column is in a numerical format

data.head(3)
```

Out[115…

	Airline	Source	Destination	Duration	Total_Stops	Price	journey_day	journey_month	Dep_Time_hour	Dep_Time_minute	Arriva
0	3	Banglore	2	2h 50m	non-stop	3897	24	3	22	20	
1	7	Kolkata	3	7h 25m	2 stops	7662	5	1	5	50	
2	10	Delhi	4	19h 0m	2 stops	13882	6	9	9	25	

In [116…
```python
## This feature ('Total_Stops') also needs a manual encoding

data['Total_Stops'].unique()
```

Out[116…
```
array(['non-stop', '2 stops', '1 stop', '3 stops', '4 stops'],
      dtype=object)
```

In [117…
```python
stops={'non-stop':0, '2 stops':2, '1 stop':1, '3 stops':3, '4 stops':4}
```

In [120…
```python
data['Total_Stops']=data['Total_Stops'].map(stops)
```

In [121…
```python
data['Total_Stops']
```

Out[121…
```
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
```

In [122…
```python
## This dataframe is updated and shows that Total Stops column is in a numerical format

data.head(3)
```

Out[122…

	Airline	Source	Destination	Duration	Total_Stops	Price	journey_day	journey_month	Dep_Time_hour	Dep_Time_minute	Arriva
0	3	Banglore	2	2h 50m	0	3897	24	3	22	20	
1	7	Kolkata	3	7h 25m	2	7662	5	1	5	50	
2	10	Delhi	4	19h 0m	2	13882	6	9	9	25	

DATA PRE-PROCESSING: Performing Outlier detection

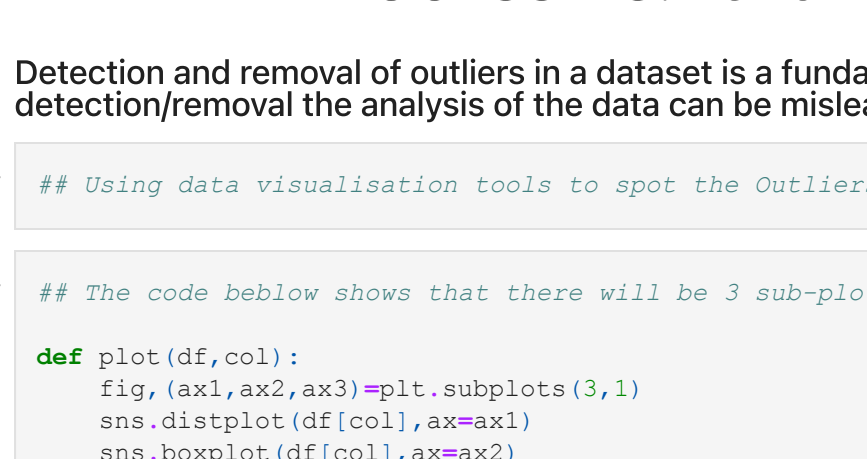
Detection and removal of outliers in a dataset is a fundamental preprocessing task, without outlier detection/removal the analysis of the data can be misleading

In [124…
```python
## Using data visualisation tools to spot the Outliers
```

In [135…
```python
## The code beblow shows that there will be 3 sub-plots which are distribution, box, and histogram

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 [136…
```python
## This shows 3 plots and I can identify the outliers for 'Price'

plot(data,'Price')
```

```
/Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning:

Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be
`data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

/Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use eith
er `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histo
grams).
```



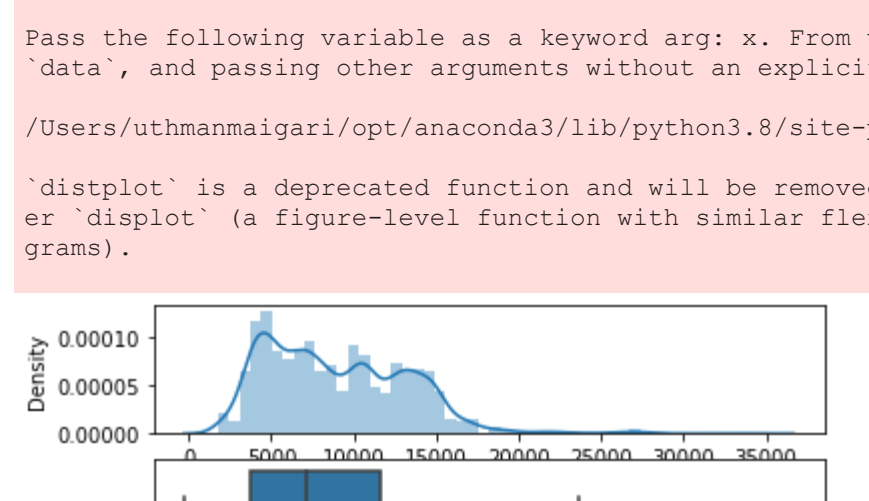
Dealing with outliers. Statistical imputation , i.e impute it with mean , median or mode of data..

As there is some outliers in price feature,so we replace it with median.

In [137…
```python
data['Price']=np.where(data['Price']>=35000,data['Price'].median(),data['Price'])
```

In [138…
```python
## once we deal with the outlier the data becomes less skewed

plot(data,'Price')
```

```
/Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use eith
er `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histo
grams).

/Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning:

Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be
`data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

/Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use eith
er `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histo
grams).
```



In [ ]:
```python
## I will be dropping 'Source' and 'Duration' column
```

In [139…
```python
data.head(2)
```

Out[139…

	Airline	Source	Destination	Duration	Total_Stops	Price	journey_day	journey_month	Dep_Time_hour	Dep_Time_minute	Arriv
0	3	Banglore	2	2h 50m	0	3897.0	24	3	22	20	
1	7	Kolkata	3	7h 25m	2	7662.0	5	1	5	50	

In [140…
```python
data.drop(columns=['Source','Duration'],axis=1,inplace=True)
```

In [276…
```python
data.columns
```

Out[276…
```
Index(['Airline', 'Destination', 'Total_Stops', 'Price', 'journey_day',
       'journey_month', 'Dep_Time_hour', 'Dep_Time_minute',
       'Arrival_Time_hour', 'Arrival_Time_minute', 'Duration_hours',
       'Duration_mins', 'Source_Banglore', 'Source_Kolkata', 'Source_Delhi',
       'Source_Chennai', 'Source_Mumbai'],
      dtype='object')
```

In [141…
```python
data.head(2)
```

Out[141…

	Airline	Destination	Total_Stops	Price	journey_day	journey_month	Dep_Time_hour	Dep_Time_minute	Arrival_Time_hour	Arriva
0	3	2	0	3897.0	24	3	22	20	1	
1	7	3	2	7662.0	5	1	5	50	13	

In [142…
```python
## As shown below this is a datatype of all the feature in the updated dataset
## which contains either float or integers. because this is what a ML algorithm needs

data.dtypes
```

Out[142…
```
Airline                  int64
Destination              int64
Total_Stops              int64
Price                  float64
journey_day              int64
journey_month            int64
Dep_Time_hour            int64
Dep_Time_minute          int64
Arrival_Time_hour        int64
Arrival_Time_minute      int64
Duration_hours           int64
Duration_mins            int64
Source_Banglore          int64
Source_Kolkata           int64
Source_Delhi             int64
Source_Chennai           int64
Source_Mumbai            int64
dtype: object
```

PERFORMING A FEATURE SELECTION

In [144…
```python
from sklearn.feature_selection import mutual_info_regression
```

In [145…
```python
## I need an independent feature and dependent feature.
## The 'Price' is my dependant (y) feature because it is reliant on the other features in the data.
## Hence the rest are independent (X) feature because they're not reliant on anything.
```

In [146…
```python
## The independant feature will be stored in 'x' while dependant will be stored in 'y'
```

In [147…
```python
X=data.drop(['Price'],axis=1)
```

In [148…
```python
y=data['Price']
```

In [149…
```python
X.dtypes
```

Out[149…
```
Airline                int64
Destination            int64
Total_Stops            int64
journey_day            int64
journey_month          int64
Dep_Time_hour          int64
Dep_Time_minute        int64
Arrival_Time_hour      int64
Arrival_Time_minute    int64
Duration_hours         int64
Duration_mins          int64
Source_Banglore        int64
Source_Kolkata         int64
Source_Delhi           int64
Source_Chennai         int64
Source_Mumbai          int64
dtype: object
```

In [151…
```python
## This shows all the mutual info regression Ill be getting

mutual_info_regression(X,y)
```

Out[151…
```
array([0.97769957, 1.00643463, 0.79256914, 0.18936692, 0.23257204,
       0.34034511, 0.25306132, 0.40479393, 0.34055364, 0.46188285,
       0.33637078, 0.37883112, 0.45315163, 0.520379  , 0.14153736,
       0.20897449])
```

In [152…
```python
## I have stored the mutual info regression in a pandas dataframe structure..

imp=pd.DataFrame(mutual_info_regression(X,y),index=X.columns)
imp.columns=['importance']
```

In [153…
```python
## This are all the importance values with respect to each of their features.
## 'Destination' has the promising score..

imp.sort_values(by='importance',ascending=False)
```

Out[153…

	importance
Destination	1.010642
Airline	0.985671
Total_Stops	0.796401
Source_Delhi	0.513507
Duration_hours	0.466363
Source_Kolkata	0.454341
Arrival_Time_hour	0.398595
Source_Banglore	0.387523
Duration_mins	0.347905
Arrival_Time_minute	0.347512
Dep_Time_hour	0.335869
Dep_Time_minute	0.257251
journey_month	0.236032
Source_Mumbai	0.205206
journey_day	0.196459
Source_Chennai	0.142494

BUILDING AN ML MODEL

In [155…
```python
from sklearn.model_selection import train_test_split
```

In [156…
```python
## Train test split is a model validation procedure that allows you to simulate how a model would....
## .....perform on new/unseen data.

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

BUILDING A RANDOM FOREST MODEL

In [158…
```python
from sklearn.ensemble import RandomForestRegressor
```

In [159…
```python
ml_model=RandomForestRegressor()
```

In [160…
```python
model=ml_model.fit(X_train,y_train)
```

In [161…
```python
y_pred=model.predict(X_test)
```

In [162…
```python
## This shows all the pridictions I end up getting.

y_pred
```

Out[162…
```
array([16723.03,  6447.62,  8872.98, ...,  3482.32,  6274.14,  7118.83])
```

In [163…
```python
y_pred.shape
```

Out[163…
```
(2671,)
```

In [164…
```python
len(X_test)
```

Out[164…
```
2671
```

In [188…
```python
forest= (model)
forest.predict(X_test)
```

Out[188…
```
array([16723.03,  6447.62,  8872.98, ...,  3482.32,  6274.14,  7118.83])
```

In [ ]:
```python
## Defining my own Evaluation Metric
```

In [186…
```python
## MAPE measures the average magnitude of error produced by a model, or how far off predictions are on average.

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 [187…
```python
mape(y_test,forest.predict(X_test))
```

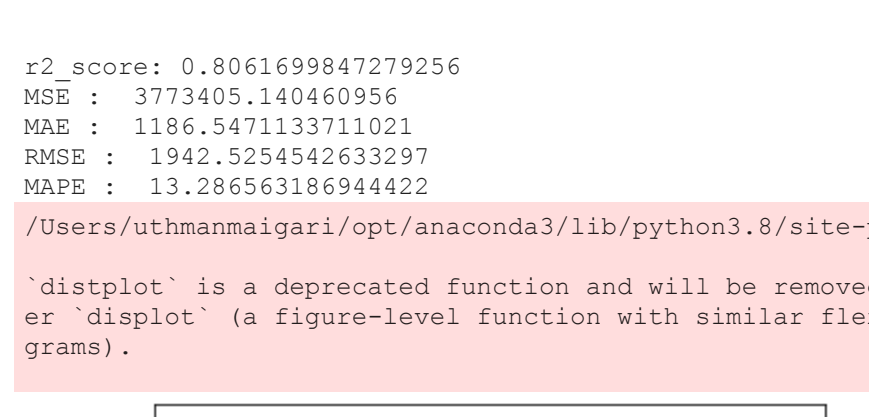
Out[187…
```
13.209839963739245
```

Automating My ML Pipeline

In [246…
```python
def predict(ml_model):

    from sklearn import metrics

    print('Model is: {}'.format(ml_model))
    model=ml_model.fit(X_train,y_train)
    print('\n')

    print('Training_Accuracy_score: {}'.format(model.score(X_train,y_train)))
    y_prediction=model.predict(X_test)
    print('Predictions are : {}'.format(y_prediction))
    print('\n')

    r2_score=metrics.r2_score(y_test,y_prediction)
    print('r2_score: {}'.format(r2_score))
    print('MSE : ', metrics.mean_squared_error(y_test,y_prediction))
    print('MAE : ', metrics.mean_absolute_error(y_test,y_prediction))
    print('RMSE : ', np.sqrt(metrics.mean_squared_error(y_test,y_prediction)))
    print('MAPE : ', mape(y_test,y_prediction))

    sns.distplot(y_test-y_prediction)
```

In [247…
```python
predict(RandomForestRegressor())
```

```
Model is: RandomForestRegressor()


Training_Accuracy_score: 0.9519794499765041
Predictions are : [16728.49  6393.05  8771.28 ...  3529.56  6241.19  6975.3 ]


r2_score: 0.8061699847279256
MSE :  3773405.140460956
MAE :  1186.5471133711021
RMSE :  1942.5254542633297
MAPE :  13.286563186944422
/Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use eith
er `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histo
grams).
```



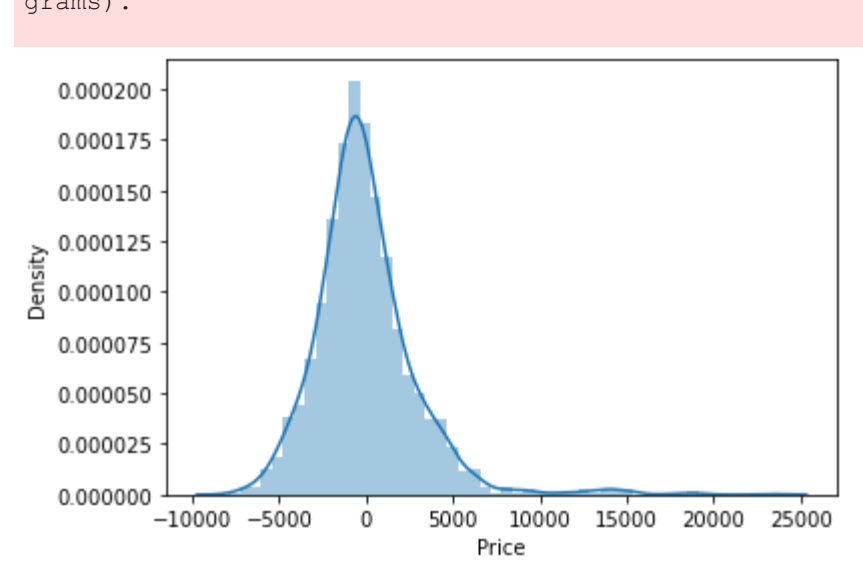
BUILD/AUTOMATE MY LINEAR REGRESSION MODEL

In [249…
```python
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
from sklearn.linear_model import LinearRegression
```

In [279…
```python
def predict(ml_model):
    print('Model is: {}'.format(ml_model))
    model= ml_model.fit(X_train,y_train)

    print('\n')
    print("Training Accuracy score: {}".format(model.score(X_train,y_train)))
    predictions = model.predict(X_test)
    print("Predictions are: {}".format(predictions))

    print('\n')

    r2score=r2_score(y_test,predictions)
    print("r2 score is: {}".format(r2score))
    print('MAE:{}'.format(mean_absolute_error(y_test,predictions)))
    print('MSE:{}'.format(mean_squared_error(y_test,predictions)))
    print('RMSE:{}'.format(np.sqrt(mean_squared_error(y_test,predictions))))
    print('MAPE : ', mape(y_test,predictions))

    sns.distplot(y_test-predictions)
```

In [280…
```python
predict(LinearRegression())
```

```
Model is: LinearRegression()


Training Accuracy score: 0.5794483128817276
Predictions are: [12816.72571495  8820.27264273  8909.99897771 ...  4190.62345641
  9411.25977293  8261.70381625]


r2 score is: 0.555713367195872
MAE:2061.784107595206
MSE:8649194.304132724
RMSE:2940.951258374189
MAPE :  24.94861105877553
/Users/uthmanmaigari/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use eith
er `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histo
grams).
```



Hyperparameter Optimization: To improve the ML model

In [197…
```python
## RandomizedSearchCV is a fast way to Hypertune model

from sklearn.model_selection import RandomizedSearchCV
```

In [198…
```python
### initialise the estimator

reg_rf=RandomForestRegressor()
```

In [199…
```python
## This returns an array that are equally spaced

np.linspace(start=1000,stop=1200,num=6)
```

Out[199…
```
array([1000., 1040., 1080., 1120., 1160., 1200.])
```

In [200…
```python
# Number of trees in random forest
n_estimators=[int(x) for x in np.linspace(start=1000,stop=1200,num=6)]

# Number of features to consider at every split
max_features=["auto", "sqrt"]

# Maximum number of levels in tree
max_depth=[int(x) for x in np.linspace(start=5,stop=30,num=4)]

# Minimum number of samples required to split a node
min_samples_split=[5,10,15,100]
```

In [201…
```python
# Create the grid or hyper-parameter space

random_grid={
    'n_estimators':n_estimators,
    'max_features':max_features,
    'max_depth':max_depth,
    'min_samples_split':min_samples_split
}
```

In [202…
```python
random_grid
```

Out[202…
```
{'n_estimators': [1000, 1040, 1080, 1120, 1160, 1200],
 'max_features': ['auto', 'sqrt'],
 'max_depth': [5, 13, 21, 30],
 'min_samples_split': [5, 10, 15, 100]}
```

In [203…
```python
 rf_Random=RandomizedSearchCV(reg_rf,param_distributions=random_grid,cv=3,verbose=2,n_jobs=-1)
```

In [204…
```python
rf_Random.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

Out[204…
```
RandomizedSearchCV(cv=3, estimator=RandomForestRegressor(), n_jobs=-1,
                   param_distributions={'max_depth': [5, 13, 21, 30],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_split': [5, 10, 15, 100],
                                        'n_estimators': [1000, 1040, 1080, 1120,
                                                         1160, 1200]},
                   verbose=2)
```

In [205…
```python
### to get your best model..
### This are typically parameters for my random forest model considering this use case

rf_Random.best_params_
```

Out[205…
```
{'n_estimators': 1120,
 'min_samples_split': 15,
 'max_features': 'auto',
 'max_depth': 21}
```

In [218…
```python
pred2=rf_Random.predict(X_test)
```

In [219…
```python
from sklearn import metrics
```

In [282…
```python
## This shows the accuracy has greatly improved with the error parameters declining....
## .....after the hypertuning is done.

print('Model is: {}'.format(ml_model))
model=ml_model.fit(X_train,y_train)
print('\n')

print('Training_Accuracy_score: {}'.format(model.score(X_train,y_train)))
y_prediction=model.predict(X_test)
print('Predictions are : {}'.format(y_prediction))
print('\n')

print('r2_score: ', metrics.r2_score(y_test,pred2))
print('MSE : ', metrics.mean_squared_error(y_test,pred2))
print('MAE : ', metrics.mean_absolute_error(y_test,pred2))
print('RMSE : ', np.sqrt(metrics.mean_squared_error(y_test,pred2)))
print('MAPE : ', mape(y_test,pred2))
```

```
Model is: RandomForestRegressor()


Training_Accuracy_score: 0.9516275830922576
Predictions are : [16712.04  6343.8   8788.78 ...  3496.04  6271.1   7070.78]


r2_score:  0.8283998807085746
MSE :  3340642.4249055255
MAE :  1152.027121877014
RMSE :  1827.7424394332822
MAPE :  12.909939018229052
```

In [ ]:

In [ ]: