```
import pandas as pd

import numpy as np

from pandas._libs import sparse

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn. model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier

from sklearn.tree import DecisionTreeClassifier
```

+ Code + Text

```
from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import f1_score

from sklearn.metrics import classification_report,confusion_matrix

import warnings

from scipy import stats

warnings.filterwarnings('ignore')

plt.style.use('fivethirtyeight')

from sklearn.datasets import load_breast_cancer

iris=load_iris()
x=iris.data
y=iris.target
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 1)



from google.colab import files
ubloaded=files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving Data_Train.csv to Data_Train (1).csv

```
data=pd.read_csv("Data_Train.csv")
data.head()
```

| | 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 |

```
category = ['Airline','Source','Price','Destination','Additional_Info','Dep_Time']
for i in category:
```

```
print(i,data[i].unique())
```

```
Airline ['IndiGo' 'Air India' 'Jet Airways' 'SpiceJet' 'Multiple carriers' 'GoAir'
 'Vistara' 'Air Asia' 'Vistara Premium economy' 'Jet Airways Business'
 'Multiple carriers Premium economy' 'Trujet']
Source ['Banglore' 'Kolkata' 'Delhi' 'Chennai' 'Mumbai']
Price [ 3897  7662 13882 ...  9790 12352 12648]
Destination ['New Delhi' 'Banglore' 'Cochin' 'Kolkata' 'Delhi' 'Hyderabad']
Additional_Info ['No info' 'In-flight meal not included' 'No check-in baggage included'
 '1 Short layover' 'No Info' '1 Long layover' 'Change airports'
 'Business class' 'Red-eye flight' '2 Long layover']
Dep_Time ['22:20' '05:50' '09:25' '18:05' '16:50' '09:00' '18:55' '08:00' '08:55'
 '11:25' '09:45' '20:20' '11:40' '21:10' '17:15' '16:40' '08:45' '14:00'
 '20:15' '16:00' '14:10' '22:00' '04:00' '21:25' '21:50' '07:00' '07:05'
 '09:50' '14:35' '10:35' '15:05' '14:15' '06:45' '20:55' '11:10' '05:45'
 '19:00' '23:05' '11:00' '09:35' '21:15' '23:55' '19:45' '08:50' '15:40'
 '06:05' '15:00' '13:55' '05:55' '13:20' '05:05' '06:25' '17:30' '08:20'
 '19:55' '06:30' '14:05' '02:00' '09:40' '08:25' '20:25' '13:15' '02:15'
 '16:55' '20:45' '05:15' '19:50' '20:00' '06:10' '19:30' '04:45' '12:55'
 '18:15' '17:20' '15:25' '23:00' '12:00' '14:45' '11:50' '11:30' '14:40'
 '19:10' '06:00' '23:30' '07:35' '13:05' '12:30' '15:10' '12:50' '18:25'
 '16:30' '00:40' '06:50' '13:00' '19:15' '01:30' '17:00' '10:00' '19:35'
 '15:30' '12:10' '16:10' '20:35' '22:25' '21:05' '05:35' '05:10' '06:40'
 '15:15' '00:30' '08:30' '07:10' '05:30' '14:25' '05:25' '10:20' '17:45'
 '13:10' '22:10' '04:55' '17:50' '21:20' '06:20' '15:55' '20:30' '17:25'
 '09:30' '07:30' '02:35' '10:55' '17:10' '09:10' '18:45' '15:20' '22:50'
 '14:55' '14:20' '13:25' '22:15' '11:05' '16:15' '20:10' '06:55' '19:05'
 '07:55' '07:45' '10:10' '08:15' '11:35' '21:00' '17:55' '16:45' '18:20'
 '03:50' '08:35' '19:20' '20:05' '17:40' '04:40' '17:35' '09:55' '05:00'
 '18:00' '02:55' '20:40' '22:55' '22:40' '21:30' '08:10' '17:05' '07:25'
 '15:45' '09:15' '15:50' '11:45' '22:05' '18:35' '00:25' '19:40' '20:50'
 '22:45' '10:30' '23:25' '11:55' '10:45' '11:15' '12:20' '14:30' '07:15'
 '01:35' '18:40' '09:20' '21:55' '13:50' '01:40' '00:20' '04:15' '13:45'
 '18:30' '06:15' '02:05' '12:15' '13:30' '06:35' '10:05' '08:40' '03:05'
 '21:35' '16:35' '02:30' '16:25' '05:40' '15:35' '13:40' '07:20' '04:50'
 '12:45' '10:25' '12:05' '11:20' '21:40' '03:00']
```

```
data.Date_of_Journey=data.Date_of_Journey.str.split('/')
```

```
data.Date_of_Journey
```

```
0        [24, 03, 2019]
1         [1, 05, 2019]
2         [9, 06, 2019]
3        [12, 05, 2019]
4        [01, 03, 2019]
              ...
10678     [9, 04, 2019]
10679    [27, 04, 2019]
10680    [27, 04, 2019]
10681    [01, 03, 2019]
10682     [9, 05, 2019]
Name: Date_of_Journey, Length: 10683, dtype: object
```

```
data['Date']=data.Date_of_Journey.str[0]
data['Month']=data.Date_of_Journey.str[1]
data['Year']=data.Date_of_Journey.str[2]
```

```
data.Total_Stops.unique()
```

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

```
data.Route.str.split('@')
data.Route
```

```
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: 10683, dtype: object
```

```
data['city1']=data.Route.str[0]
data['city2']=data.Route.str[1]
data['city3']=data.Route.str[2]
data['city4']=data.Route.str[3]
data['city5']=data.Route.str[4]
data['city6']=data.Route.str[5]
```

```
data["Price"]
```

```
0         3897
1         7662
2        13882
3         6218
4        13302
         ...
10678     4107
10679     4145
10680     7229
10681    12648
10682    11753
Name: Price, Length: 10683, dtype: int64
```

```
my_data={'Dep_Time'}
```

```
data["Dep_Time"]
```

```
0        22:20
1        05:50
2        09:25
3        18:05
4        16:50
         ...
10678    19:55
10679    20:45
10680    08:20
10681    11:30
10682    10:55
Name: Dep_Time, Length: 10683, dtype: object
```

```
data.Dep_Time=data.Dep_Time.str.split(':')
```

```
data['Dep_Time_Hour'] = data.Dep_Time.str[0]
data['Dep_Time_Hour'] = data.Dep_Time.str[1]
```

```
data.Arrival_Time=data.Arrival_Time.str.split('  ')
```

```
data['Arrival_date']=data.Arrival_Time.str[1]
data['Time_of_Arrival']=data.Arrival_Time.str[0]
```

```
data['Time_of_Arrival']=data.Time_of_Arrival.str.split(':')
```

```
data['Arrival_Time_Hour']=data.Time_of_Arrival.str[0]
data['Arrival_Time_Mins']=data.Time_of_Arrival.str[1]
```

```
data.Duration=data.Duration.str.split(' ')
```

```
data['Travel_Hours']=data.Duration.str[0]
data['Travel_Hours']=data['Travel_Hours'].str.split('h')
data['Travel_Hours']=data['Travel_Hours'].str[0]
data.Travel_Hours=data.Travel_Hours
data['Travel_Mins']=data.Duration.str[1]

data.Travel_Mins=data.Travel_Mins.str.split('m')
data.Travel_Mins=data.Travel_Mins.str[0]
```

```
data.Total_Stops.replace('non_stop',0,inplace=True)
data.Total_Stops=data.Total_Stops.str.split(':')
data.Total_Stops=data.Total_Stops.str[0]
```

```
data.Total_Stops.replace('non_stop',0,inplace=True)
data.Total_Stops=data.Total_Stops.str.split('  ')
data.Total_Stops=data.Total_Stops.str[0]
```

```
data.Additional_Info.unique()
```

```
array(['No info', 'In-flight meal not included',
       'No check-in baggage included', '1 Short layover', 'No Info',
       '1 Long layover', 'Change airports', 'Business class',
       'Red-eye flight', '2 Long layover'], dtype=object)
```

```
data.Additional_Info.replace('No Info','No info',inplace=True)
```

```
data.isnull().sum()
```

```
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
Date                   0
Month                  0
Year                   0
city1                  1
city2                  1
city3                  1
city4                  1
city5                  1
city6                  1
Dep_Time_Hour          0
Arrival_date       10683
Time_of_Arrival        0
Arrival_Time_Hour      0
Arrival_Time_Mins      0
Travel_Hours           0
Travel_Mins         1032
dtype: int64
```

```
data.drop(['city4','city5','city6'], axis=1, inplace=True)
```

```
data.drop(['Date_of_Journey','Route','Dep_Time','Duration'],axis=1, inplace=True)
```

```
data.drop(['Time_of_Arrival'],axis=1,inplace=True)
```

```
data.isnull().sum()
```

```
Airline                0
Source                 0
Destination            0
Arrival_Time           0
Total_Stops            1
Additional_Info        0
Price                  0
Date                   0
Month                  0
Year                   0
city1                  1
city2                  1
city3                  1
Dep_Time_Hour          0
Arrival_date       10683
Arrival_Time_Hour      0
Arrival_Time_Mins      0
Travel_Hours           0
Travel_Mins         1032
dtype: int64
```

```
data['city3'].fillna('None',inplace=True)
```

```
data['Arrival_date'].fillna(data['Date'],inplace=True)
```

```
data['Travel_Mins'].fillna(0,inplace=True)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Airline            10683 non-null  object
 1   Source             10683 non-null  object
 2   Destination        10683 non-null  object
 3   Arrival_Time       10683 non-null  object
 4   Total_Stops        10682 non-null  object
 5   Additional_Info    10683 non-null  object
 6   Price              10683 non-null  int64 
 7   Date               10683 non-null  object
 8   Month              10683 non-null  object
 9   Year               10683 non-null  object
 10  city1              10682 non-null  object
 11  city2              10682 non-null  object
 12  city3              10683 non-null  object
 13  Dep_Time_Hour      10683 non-null  object
 14  Arrival_date       0 non-null      float64
 15  Arrival_Time_Hour  10683 non-null  object
 16  Arrival_Time_Mins  10683 non-null  object
 17  Travel_Hours       10683 non-null  object
 18  Travel_Mins        10683 non-null  object
dtypes: float64(1), int64(1), object(17)
memory usage: 1.5+ MB
```

```
data.Travel_Mins=data.Travel_Mins.astype('int64')
```

```
data.Date=data.Date.astype('int64')
data.Month=data.Month.astype('int64')
data.Year=data.Year.astype('int64')
data.Dep_Time_Hour=data.Dep_Time_Hour.astype('int64')
data.Dep_Time_Hour=data.Dep_Time_Hour.astype('int64')
data.Arrival_Time_Hour=data.Arrival_Time_Hour.astype('int64')
data.Arrival_Time_Mins=data.Arrival_Time_Mins.astype('int64')
```

```
data[data['Travel_Hours']=='5m']
```

| | Airline | Source | Destination | Arrival_Time | Total_Stops | Additional_Info | Price | Date | Month | Year | city1 | city2 | city3 | Dep_Time_H |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **6474** | Air India | Mumbai | Hyderabad | [16:55] | 2 stops | No info | 17327 | 6 | 3 | 2019 | B | O | M | |

```
data.drop(index=6474,inplace=True,axis=0)
```

```
data.Travel_Hours=data.Travel_Hours.astype('int64')
```

```
categorical=['Airline','Source','Destination','Additional_Info','City1','Price']
numerical=['Total_stops','Date','Month','Year','Dep_Time_Hour','Dep_Time_Mins','Arrival_date','Arrival_Time_Hour','Arrival_Time_Mins','Travel
```

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

```
data.Airline=le.fit_transform(data.Airline)
data.source=le.fit_transform(data.Source)
data.Destination=le.fit_transform(data.Destination)
data.Total_Stops=le.fit_transform(data.Total_Stops)
data.cityt1=le.fit_transform(data.city1)
data.city2=le.fit_transform(data.city2)
data.city3=le.fit_transform(data.city3)
data.Additional_Info=le.fit_transform(data.Additional_Info)
data.head()
```

| | Airline | Source | Destination | Arrival_Time | Total_Stops | Additional_Info | Price | Date | Month | Year | city1 | city2 | city3 | Dep_Time_Hou |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | Banglore | 5 | [01:10 22 Mar] | 4 | 7 | 3897 | 24 | 3 | 2019 | B | 3 | 4 | 2 |
| **1** | 1 | Kolkata | 0 | [13:15] | 1 | 7 | 7662 | 1 | 5 | 2019 | C | 1 | 5 | 5 |
| **2** | 4 | Delhi | 1 | [04:25 10 Jun] | 1 | 7 | 13882 | 9 | 6 | 2019 | D | 2 | 1 | 2 |
| **3** | 3 | Kolkata | 0 | [23:30] | 0 | 7 | 6218 | 12 | 5 | 2019 | C | 1 | 5 | |
| **4** | 3 | Banglore | 5 | [21:35] | 0 | 7 | 13302 | 1 | 3 | 2019 | B | 3 | 4 | 5 |

```
data.head()
```

| | Airline | Source | Destination | Arrival_Time | Total_Stops | Additional_Info | Price | Date | Month | Year | city1 | city2 | city3 | Dep_Time_Hou |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | Banglore | 5 | [01:10 22 Mar] | 4 | 7 | 3897 | 24 | 3 | 2019 | B | 3 | 4 | 2 |
| **1** | 1 | Kolkata | 0 | [13:15] | 1 | 7 | 7662 | 1 | 5 | 2019 | C | 1 | 5 | 5 |
| **2** | 4 | Delhi | 1 | [04:25 10 Jun] | 1 | 7 | 13882 | 9 | 6 | 2019 | D | 2 | 1 | 2 |
| **3** | 3 | Kolkata | 0 | [23:30] | 0 | 7 | 6218 | 12 | 5 | 2019 | C | 1 | 5 | |
| **4** | 3 | Banglore | 5 | [21:35] | 0 | 7 | 13302 | 1 | 3 | 2019 | B | 3 | 4 | 5 |

```
data=data[['Airline','Source','Destination','Date','Month','Year','Dep_Time_Hour','Arrival_Time_Mins','Arrival_Time']]
```

```
data.head()
```

| | Airline | Source | Destination | Date | Month | Year | Dep_Time_Hour | Arrival_Time_Mins | Arrival_Time |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | Banglore | 5 | 24 | 3 | 2019 | 20 | 10 22 Mar | [01:10 22 Mar] |
| **1** | 1 | Kolkata | 0 | 1 | 5 | 2019 | 50 | 15 | [13:15] |
| **2** | 4 | Delhi | 1 | 9 | 6 | 2019 | 25 | 25 10 Jun | [04:25 10 Jun] |
| **3** | 3 | Kolkata | 0 | 12 | 5 | 2019 | 5 | 30 | [23:30] |
| **4** | 3 | Banglore | 5 | 1 | 3 | 2019 | 50 | 35 | [21:35] |

```
data.describe()
```

| | Airline | Destination | Date | Month | Year | Dep_Time_Hour |
|---|---|---|---|---|---|---|
| **count** | 10682.000000 | 10682.000000 | 10682.000000 | 10682.000000 | 10682.0 | 10682.000000 |
| **mean** | 3.966205 | 1.435967 | 13.509081 | 4.708762 | 2019.0 | 24.408819 |
| **std** | 2.352090 | 1.474773 | 8.479363 | 1.164294 | 0.0 | 18.767225 |
| **min** | 0.000000 | 0.000000 | 1.000000 | 3.000000 | 2019.0 | 0.000000 |
| **25%** | 3.000000 | 0.000000 | 6.000000 | 3.000000 | 2019.0 | 5.000000 |
| **50%** | 4.000000 | 1.000000 | 12.000000 | 5.000000 | 2019.0 | 25.000000 |
| **75%** | 4.000000 | 2.000000 | 21.000000 | 6.000000 | 2019.0 | 40.000000 |
| **max** | 11.000000 | 5.000000 | 27.000000 | 6.000000 | 2019.0 | 55.000000 |

```
import seaborn as sns
c=1
plt.figure(figsize=(20,45))
```

```
<Figure size 2000x4500 with 0 Axes>
<Figure size 2000x4500 with 0 Axes>
```

```
for i in categorical:
  plt.subplot(6,3,c)
  sns.countplot(data[i])
  plt.xticks(rotation=90)
  plt.tight_layout(pad=3.0)
  c=c+1
```

```
  plt.show()
```

```
from sklearn.datasets import load_iris
```

```
iris=load_iris()
```

```
df=pd.DataFrame(iris.data,columns=iris.feature_names)
```

```
price_list=pd.DataFrame({'price:prices'})
```

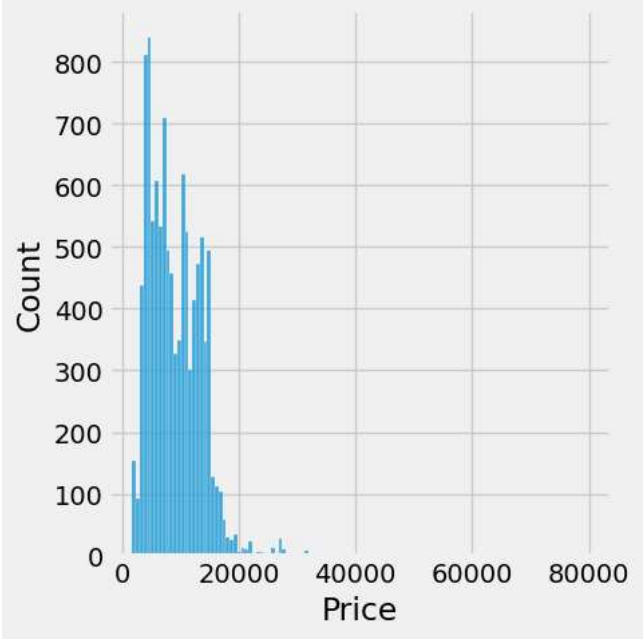
```
price_list
```

| | 0 |
|---|---|
| 0 | price:prices |

```
Price
```

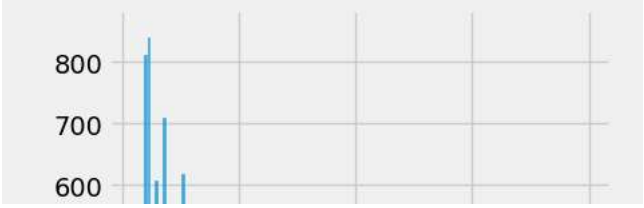
```
sns.displot(data.Price)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd58ceddc10>
```



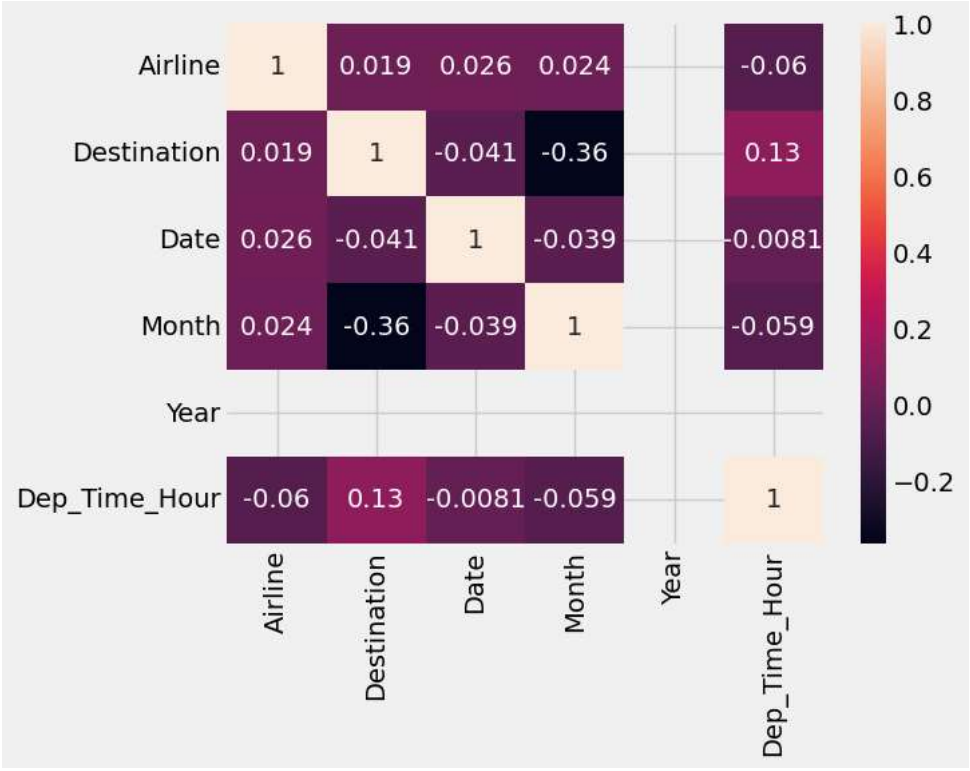

```
plt.figure(figsize=(15,8))
sns.displot(data.Price)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd5cc4028b0>
<Figure size 1500x800 with 0 Axes>
```



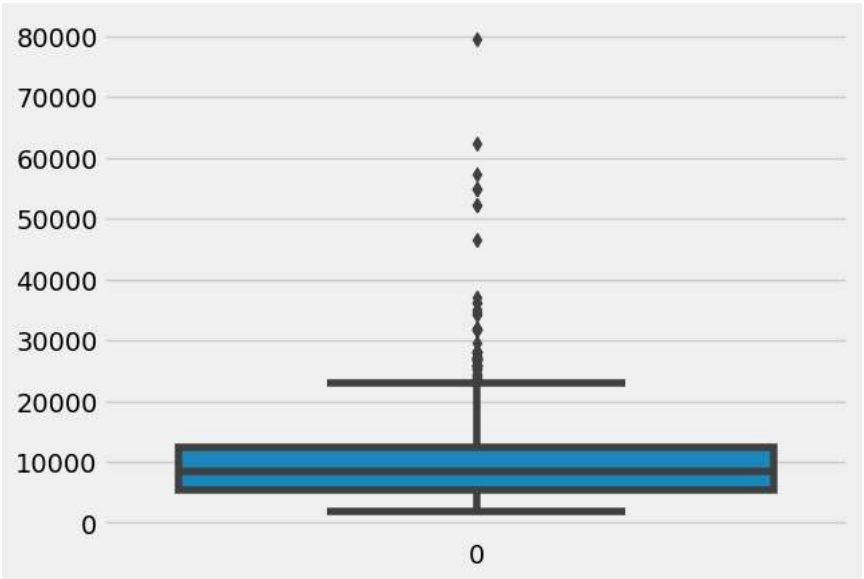

```
sns.heatmap(data.corr(),annot=True)
```

```
<Axes: >
```




```
import seaborn as sns
sns.boxplot(data['Price'])
```

```
<Axes: >
```




```
y = data['Price']
x = data.drop(columns=['Price'],axis=1)
```

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
```

```
knn.fit(x,y)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=1)
```

```
print(x_scaled)
```

```
[[-9.00681170e-01  1.01900435e+00 -1.34022653e+00 -1.31544430e+00]
 [-1.14301691e+00 -1.31979479e-01 -1.34022653e+00 -1.31544430e+00]
 [-1.38535265e+00  3.28414053e-01 -1.39706395e+00 -1.31544430e+00]
 [-1.50652052e+00  9.82172869e-02 -1.28338910e+00 -1.31544430e+00]
 [-1.02184904e+00  1.24920112e+00 -1.34022653e+00 -1.31544430e+00]
 [-5.37177559e-01  1.93979142e+00 -1.16971425e+00 -1.05217993e+00]
 [-1.50652052e+00  7.88807586e-01 -1.34022653e+00 -1.18381211e+00]
 [-1.02184904e+00  7.88807586e-01 -1.28338910e+00 -1.31544430e+00]
 [-1.74885626e+00 -3.62176246e-01 -1.34022653e+00 -1.31544430e+00]
 [-1.14301691e+00  9.82172869e-02 -1.28338910e+00 -1.44707648e+00]
 [-5.37177559e-01  1.47939788e+00 -1.28338910e+00 -1.31544430e+00]
 [-1.26418478e+00  7.88807586e-01 -1.22655167e+00 -1.31544430e+00]
 [-1.26418478e+00 -1.31979479e-01 -1.34022653e+00 -1.44707648e+00]
 [-1.87002413e+00 -1.31979479e-01 -1.51073881e+00 -1.44707648e+00]
 [-5.25060772e-02  2.16998818e+00 -1.45390138e+00 -1.31544430e+00]
 [-1.73673948e-01  3.09077525e+00 -1.28338910e+00 -1.05217993e+00]
 [-5.37177559e-01  1.93979142e+00 -1.39706395e+00 -1.05217993e+00]
 [-9.00681170e-01  1.01900435e+00 -1.34022653e+00 -1.18381211e+00]
 [-1.73673948e-01  1.70959465e+00 -1.16971425e+00 -1.18381211e+00]
 [-9.00681170e-01  1.70959465e+00 -1.28338910e+00 -1.18381211e+00]
 [-5.37177559e-01  7.88807586e-01 -1.16971425e+00 -1.31544430e+00]
 [-9.00681170e-01  1.47939788e+00 -1.28338910e+00 -1.05217993e+00]
 [-1.50652052e+00  1.24920112e+00 -1.56757623e+00 -1.31544430e+00]
 [-9.00681170e-01  5.58610819e-01 -1.16971425e+00 -9.20547742e-01]
 [-1.26418478e+00  7.88807586e-01 -1.05603939e+00 -1.31544430e+00]
 [-1.02184904e+00 -1.31979479e-01 -1.22655167e+00 -1.31544430e+00]
 [-1.02184904e+00  7.88807586e-01 -1.22655167e+00 -1.05217993e+00]
 [-7.79513300e-01  1.01900435e+00 -1.28338910e+00 -1.31544430e+00]
 [-7.79513300e-01  7.88807586e-01 -1.34022653e+00 -1.31544430e+00]
 [-1.38535265e+00  3.28414053e-01 -1.22655167e+00 -1.31544430e+00]
 [-1.26418478e+00  9.82172869e-02 -1.22655167e+00 -1.31544430e+00]
 [-5.37177559e-01  7.88807586e-01 -1.28338910e+00 -1.05217993e+00]
 [-7.79513300e-01  2.40018495e+00 -1.28338910e+00 -1.44707648e+00]
 [-4.16009689e-01  2.63038172e+00 -1.34022653e+00 -1.31544430e+00]
 [-1.14301691e+00  9.82172869e-02 -1.28338910e+00 -1.31544430e+00]
 [-1.02184904e+00  3.28414053e-01 -1.45390138e+00 -1.31544430e+00]
 [-4.16009689e-01  1.01900435e+00 -1.39706395e+00 -1.31544430e+00]
 [-1.14301691e+00  1.24920112e+00 -1.34022653e+00 -1.44707648e+00]
 [-1.74885626e+00 -1.31979479e-01 -1.39706395e+00 -1.31544430e+00]
 [-9.00681170e-01  7.88807586e-01 -1.28338910e+00 -1.31544430e+00]
 [-1.02184904e+00  1.01900435e+00 -1.39706395e+00 -1.18381211e+00]
 [-1.62768839e+00 -1.74335684e+00 -1.39706395e+00 -1.18381211e+00]
 [-1.74885626e+00  3.28414053e-01 -1.39706395e+00 -1.31544430e+00]
 [-1.02184904e+00  1.01900435e+00 -1.22655167e+00 -7.88915558e-01]
 [-9.00681170e-01  1.70959465e+00 -1.05603939e+00 -1.05217993e+00]
 [-1.26418478e+00 -1.31979479e-01 -1.34022653e+00 -1.18381211e+00]
 [-9.00681170e-01  1.70959465e+00 -1.22655167e+00 -1.31544430e+00]
 [-1.50652052e+00  3.28414053e-01 -1.34022653e+00 -1.31544430e+00]
 [-6.58345429e-01  1.47939788e+00 -1.28338910e+00 -1.31544430e+00]
 [-1.02184904e+00  5.58610819e-01 -1.34022653e+00 -1.31544430e+00]
 [ 1.40150837e+00  3.28414053e-01  5.35408562e-01  2.64141916e-01]
 [ 6.74501145e-01  3.28414053e-01  4.21733708e-01  3.95774101e-01]
 [ 1.28034050e+00  9.82172869e-02  6.49083415e-01  3.95774101e-01]
 [-4.16009689e-01 -1.74335684e+00  1.37546573e-01  1.32509732e-01]
 [ 7.95669016e-01 -5.92373012e-01  4.78571135e-01  3.95774101e-01]
 [-1.73673948e-01 -5.92373012e-01  4.21733708e-01  1.32509732e-01]
 [ 5.53333275e-01  5.58610819e-01  5.35408562e-01  5.27406285e-01]
 [-1.14301691e+00 -1.51316008e+00 -2.60315415e-01 -2.62386821e-01]
```

```
x_scaled = scaler.fit_transform(x)
```

```
x_scaled = pd.DataFrame(x_scaled,columns=x.columns)
x_scaled.head()
```

```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)


from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)


x_train.head()
```

| | Airline | Date_of_Journey | Source | Destination | Route | Dep_Time | Arrival_Time | Duration | Total_Stops | Additional_Info |
|---|---|---|---|---|---|---|---|---|---|---|
| **8990** | Jet Airways | 12/03/2019 | Mumbai | Hyderabad | BOM → VNS → DEL → HYD | 06:30 | 16:35 | 10h 5m | 2 stops | No info |
| **3684** | Jet Airways | 9/05/2019 | Delhi | Cochin | DEL → BOM → COK | 11:30 | 12:35 10 May | 25h 5m | 1 stop | In-flight meal not included |
| **1034** | SpiceJet | 24/04/2019 | Delhi | Cochin | DEL → MAA → COK | 15:45 | 22:05 | 6h 20m | 1 stop | No info |
| | Multiple | | | | DEL → BOM → | | | | | |

```
from sklearn.ensemble import AdaBoostRegressor


rfr = RandomForestRegressor()


gb = GradientBoostingRegressor()


ad = AdaBoostRegressor()


from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor,  AdaBoostRegressor

rfr=RandomForestRegressor()
gb=GradientBoostingRegressor()
ad=AdaBoostRegressor()


from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error

for i in [rfr,gb,ad]:
  i.fit(x_train,y_train)
  y_pred=i.predict(x_test)
  test_score=r2_score(y_test,y_pred)
  train_score=r2_score(y_train, i.predict(x_train))
  if abs(train_score-test_score)<=0.2:
    print(i)
    print("R2 score is",r2_score(y_test,y_pred))
    print("r2 for train data",r2_score(y_train, i.predict(x_train)))
    print("Mean Absolute Error is",mean_absolute_error(y_pred,y_test))
    print("Mean Squred Error is",mean_squared_error(y_pred,y_test))
    print("Root Mean Squared Error is", (mean_squared_error(y_pred,y_test,squared=False)))



from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error

knn=KNeighborsRegressor()
svr=SVR()
dt=DecisionTreeRegressor()


for i in [knn,svr,dt]:
  i.fit(x_train,y_train)
  y_pred=i.predict(x_test)
  test_score=r2_score(y_test,y_pred)
  train_score=r2_score(y_train,i.predict(x_train))
  if abs(train_score-test_score)<=0.1:
    print(i)
    print('R2 score is',r2_score(y_test,y_pred))
    print("R2 for train data",r2_score(y_train, i.predict(x_train)))
    print('Mean Absolute Error is',mean_absolute_error(y_pred,y_test))
    print('Mean Squred Error is',mean_squared_error(y_pred,y_test))
```

```
    print('Root Mean Squared Error is', (mean_squared_error(y_pred,y_test,squared=False)))
```

```
from sklearn.model_selection import cross_val_score
for i in range(2,5):
  cv=cross_val_score(rfr,x,y,cv=i)
  print(rfr,cv.mean())
```

```
    RandomForestRegressor(max_features='sqrt', n_estimators=10) -2.0431999999999997
    RandomForestRegressor(max_features='sqrt', n_estimators=10) 0.0
    RandomForestRegressor(max_features='sqrt', n_estimators=10) 0.38848557692307695
```

```
from sklearn.model_selection import RandomizedSearchCV
```

```
param_grid={'n_estimators':[10,30,50,70,100],'max_depth':[None,1,2,3],
            'max_features':['auto','sqrt']}
rfr=RandomForestRegressor()
rf_res=RandomizedSearchCV(estimator=rfr,param_distributions=param_grid,cv=3,verbose=2,n_jobs=-1)

rf_res.fit(x_train,y_train)
```

```
gb=GradientBoostingRegressor()
gb_res=RandomizedSearchCV(estimator=gb,param_distributions=param_grid,cv=3,verbose=2,n_jobs=-1)
gb_res.fit(x_train,y_train)
```

```
rfr=RandomForestRegressor(n_estimators=10,max_features='sqrt',max_depth=None)
rfr.fit(x_train,y_train)
y_train_pred=rfr.predict(x_train)
y_test_pred=rfr.predict(x_test)
print("train accuracy",r2_score(y_train_pred,y_train))
print("test accuracy",r2_score(y_test_Pred,y_test))
```

```
price_list=pd.DataFrame({'price:prices'})
```

```
price_list
```

| | 0 |
|---|---|
| 0 | price:prices |

```
import pickle
pickle.dump(rfr,open('model1.pkl','wb'))
```

```
import pickle
pickle.dump(rfr,open('model1.pkl','wb'))
```