```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

```
print("****************************************************ANALYSIS***
*******************************************************\n\n\t\t\t\
tProject topic:-Flight Price Prediction\n\n\t(1)Took Data set from
kaggle\n\n\t(2)I will be doing Exeploratary Data Analysis using
Numpy,pandas,matplotlib and seaborn.\n\n\t(3)Will be making prediction
models using number of machine learning regression algorithms.")
```

```
****************************************************ANALYSIS*********
************************************************

                      Project topic:-Flight Price Prediction

     (1)Took Data set from kaggle

     (2)I will be doing Exeploratary Data Analysis using
Numpy,pandas,matplotlib and seaborn.

     (3)Will be making prediction models using number of machine
learning regression algorithms.
```

```
print("*******************************************Data set
description****************************************************\n\n\
tThe objective of the study is to analyse the flight booking dataset
obtained from “Ease My Trip” website and to conduct various
statistical hypothesis tests in order to get meaningful information
from it. The 'Linear Regression' statistical algorithm would be used
to train the dataset and predict a continuous target variable.
'Easemytrip' is an internet platform for booking flight tickets, and
hence a platform that potential passengers use to buy tickets. A
thorough study of the data will aid in the discovery of valuable
insights that will be of enormous value to passengers\n\n\n\tDataset
contains information about flight booking options from the website
Easemytrip for flight travel between India's top 6 metro cities. There
are 300261 datapoints and 11 features in the cleaned dataset.")
```

```
*******************************************Data set
description****************************************************

     The objective of the study is to analyse the flight booking
dataset obtained from “Ease My Trip” website and to conduct various
statistical hypothesis tests in order to get meaningful information
from it. The 'Linear Regression' statistical algorithm would be used
to train the dataset and predict a continuous target variable.
```

'Easemytrip' is an internet platform for booking flight tickets, and hence a platform that potential passengers use to buy tickets. A thorough study of the data will aid in the discovery of valuable insights that will be of enormous value to passengers

Dataset contains information about flight booking options from the website Easemytrip for flight travel between India's top 6 metro cities. There are 300261 datapoints and 11 features in the cleaned dataset.

```
df=pd.read_csv("Clean_Dataset.csv")
```

```
df.head()
```

```
   Unnamed: 0   airline   flight source_city departure_time stops  \
0           0  SpiceJet  SG-8709       Delhi        Evening  zero   
1           1  SpiceJet  SG-8157       Delhi  Early_Morning  zero   
2           2   AirAsia   I5-764       Delhi  Early_Morning  zero   
3           3   Vistara   UK-995       Delhi        Morning  zero   
4           4   Vistara   UK-963       Delhi        Morning  zero   

    arrival_time destination_city    class  duration  days_left  price  

0          Night           Mumbai  Economy      2.17          1   5953  

1        Morning           Mumbai  Economy      2.33          1   5953  

2  Early_Morning           Mumbai  Economy      2.17          1   5956  

3      Afternoon           Mumbai  Economy      2.25          1   5955  

4        Morning           Mumbai  Economy      2.33          1   5955  
```

FEATURES

The various features of the cleaned dataset are explained below:

1) Airline: The name of the airline company is stored in the airline column. It is a categorical feature having 6 different airlines.

2) Flight: Flight stores information regarding the plane's flight code. It is a categorical feature.

3) Source City: City from which the flight takes off. It is a categorical feature having 6 unique cities.

4) Departure Time: This is a derived categorical feature obtained created by grouping time periods into bins. It stores information about the departure time and have 6 unique time labels.

5) Stops: A categorical feature with 3 distinct values that stores the number of stops between the source and destination cities.

6) Arrival Time: This is a derived categorical feature created by grouping time intervals into bins. It has six distinct time labels and keeps information about the arrival time.

7) Destination City: City where the flight will land. It is a categorical feature having 6 unique cities.

8) Class: A categorical feature that contains information on seat class; it has two distinct values: Business and Economy.

9) Duration: A continuous feature that displays the overall amount of time it takes to travel between cities in hours.

10)Days Left: This is a derived characteristic that is calculated by subtracting the trip date by the booking date.

11) Price: Target variable stores information of the ticket price.

Exploratry Data Analysis

```
print("\t\t\t\t\t(1)Data set has 300153 rows and 12 columns with no null values\n\n\t\t\t\t\t(2)There are 8 categorical columns and 4 numerical columns\n\n")
df.info()
```

```
                      (1)Data set has 300153 rows and 12 columns with 
no null values

                      (2)There are 8 categorical columns and 4 
numerical columns


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300153 entries, 0 to 300152
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   Unnamed: 0        300153 non-null  int64  
 1   airline           300153 non-null  object 
 2   flight            300153 non-null  object 
 3   source_city       300153 non-null  object 
 4   departure_time    300153 non-null  object 
 5   stops             300153 non-null  object 
 6   arrival_time      300153 non-null  object 
 7   destination_city  300153 non-null  object 
 8   class             300153 non-null  object 
 9   duration          300153 non-null  float64
 10  days_left         300153 non-null  int64  
```

```
 11  price             300153 non-null  int64  
dtypes: float64(1), int64(3), object(8)
memory usage: 27.5+ MB
```

```
#Deleting columns that are not important for analysis.

df.drop(["Unnamed: 0","flight"],axis=1,inplace=True)

df
```

```
         airline source_city departure_time stops   arrival_time  \
0       SpiceJet       Delhi        Evening  zero          Night   
1       SpiceJet       Delhi  Early_Morning  zero        Morning   
2        AirAsia       Delhi  Early_Morning  zero  Early_Morning   
3        Vistara       Delhi        Morning  zero      Afternoon   
4        Vistara       Delhi        Morning  zero        Morning   
...          ...         ...            ...   ...            ...   
300148   Vistara     Chennai        Morning   one        Evening   
300149   Vistara     Chennai      Afternoon   one          Night   
300150   Vistara     Chennai  Early_Morning   one          Night   
300151   Vistara     Chennai  Early_Morning   one        Evening   
300152   Vistara     Chennai        Morning   one        Evening   

       destination_city     class  duration  days_left  price  
0                Mumbai   Economy      2.17          1   5953  
1                Mumbai   Economy      2.33          1   5953  
2                Mumbai   Economy      2.17          1   5956  
3                Mumbai   Economy      2.25          1   5955  
4                Mumbai   Economy      2.33          1   5955  
...                 ...       ...       ...        ...    ...  
300148        Hyderabad  Business     10.08         49  69265  
300149        Hyderabad  Business     10.42         49  77105  
300150        Hyderabad  Business     13.83         49  79099  
300151        Hyderabad  Business     10.00         49  81585  
300152        Hyderabad  Business     10.08         49  81585  

[300153 rows x 10 columns]
```

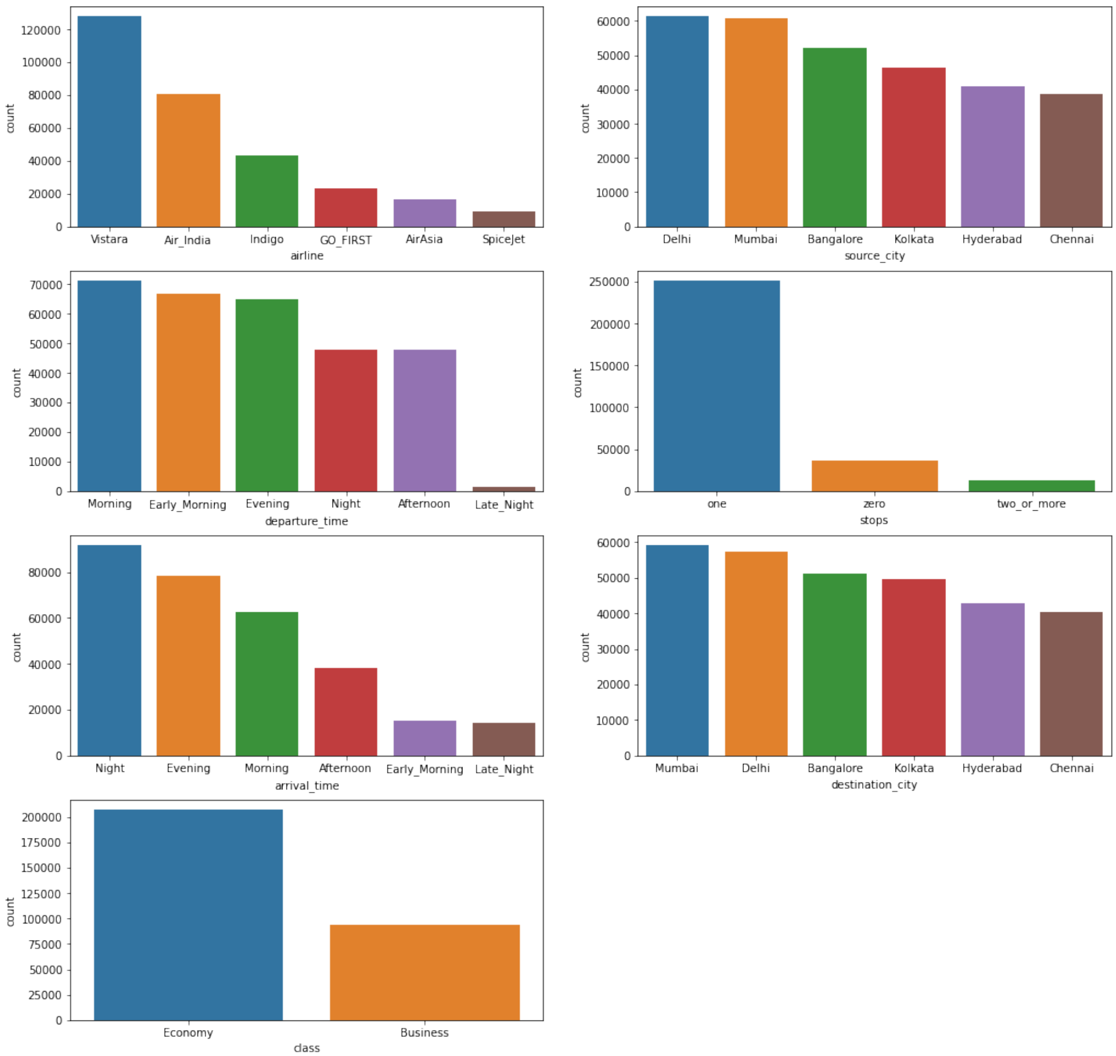
Univariate Analysis

```
cat_cols=df.select_dtypes(include="O")
cat_cols.columns
```

```
Index(['airline', 'source_city', 'departure_time', 'stops', 
'arrival_time',
       'destination_city', 'class'],
      dtype='object')
```

```
plt.figure(figsize=(17,17))
count=1
for i in cat_cols:
```

```
    plt.subplot(4,2,count)
    sns.countplot(df[i],order=df[i].value_counts().index)
    count+=1
plt.show()
```




```
print("*************************************************ANALYSIS******
***********************************************\n\n\n\t(1)Most number
of people prefer Vistara Airlines followed by Air_india and very less
people travel by spicejet\n\n\t(2)Maximum number of people travel from
Mumbai and Delhi to diffrent locations.\n\n\t(3)Higly preferred time
of departure is Morning,Early morning and Evening ,least preferred is
late nigh boarding\n\n\t(4)Maximum flights have only 1 stop between
source and destination city\n\n\t(5)Max flights have arrival time of
night and least is of Late night\n\n\t(6)Maximum people have travelled
to Mumbai and Delhi\n\n\t(7)Most preferred class is economy class")
```

```
*************************************************ANALYSIS*************
***************************************
```

(1)Most number of people prefer Vistara Airlines followed by Air_india and very less people travel by spicejet

(2)Maximum number of people travel from Mumbai and Delhi to differnt locations.

(3)Higly preferred time of departure is Morning,Early morning and Evening ,least preferred is late nigh boarding

(4)Maximum flights have only 1 stop between source and destination city

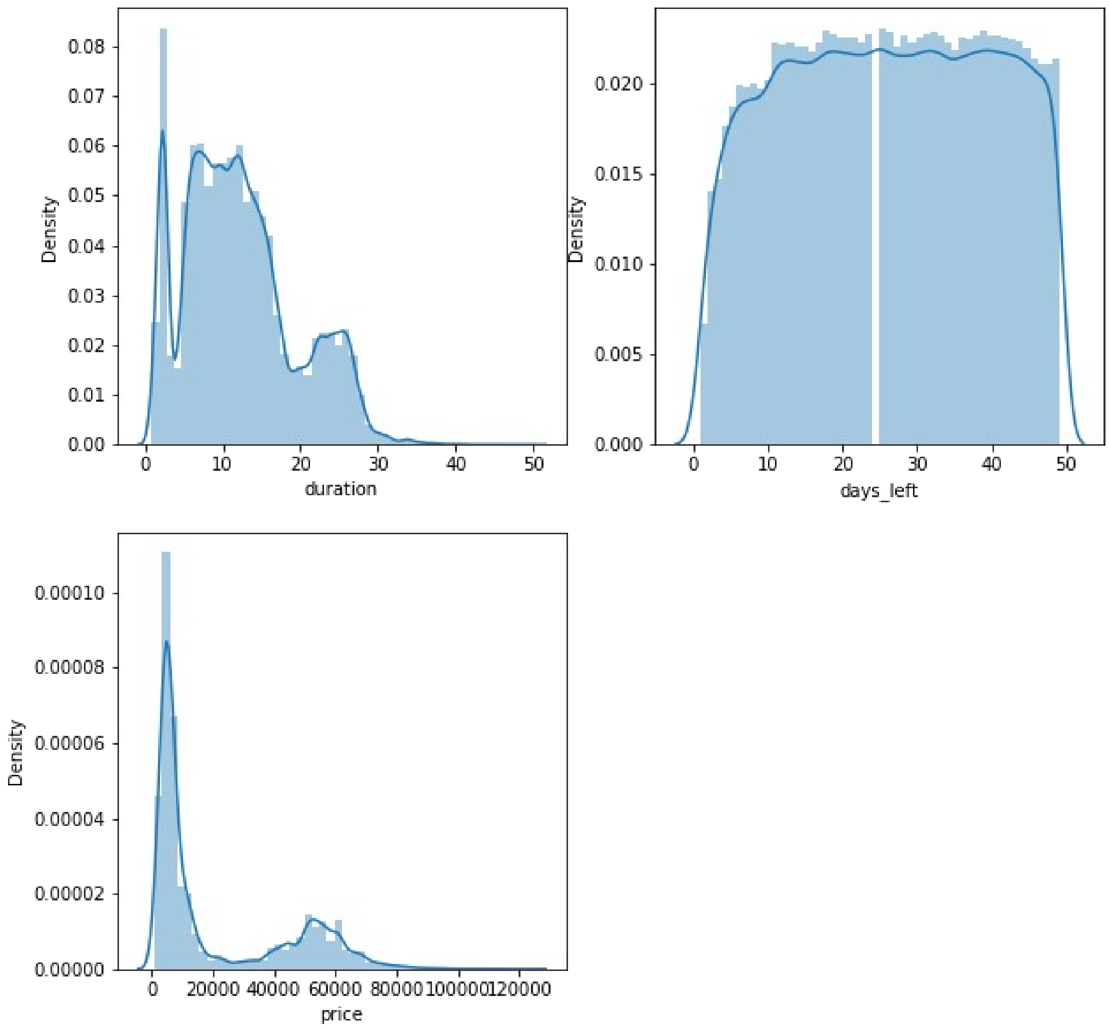
(5)Max flights have arrival time of night and least is of Late night

(6)Maximum people have travelled to Mumbai and Delhi

(7)Most preferred class is economy class

```
num_cols=df.select_dtypes(include=["int","float"])
```

```
plt.figure(figsize=(10,10))
count=1
for i in num_cols:
    plt.subplot(2,2,count)
    sns.distplot(df[i])
    count+=1
plt.show()
```




```
df.describe()
```

	duration	days_left	price
count	300153.000000	300153.000000	300153.000000
mean	12.221021	26.004751	20889.660523
std	7.191997	13.561004	22697.767366
min	0.830000	1.000000	1105.000000
25%	6.830000	15.000000	4783.000000
50%	11.250000	26.000000	7425.000000
75%	16.170000	38.000000	42521.000000
max	49.830000	49.000000	123071.000000

```
print("*************************************************ANALYSIS******
***********************************************\n\n\t(1)Min duration
of flight is 0.83 hours and max duration of flight is 49 hours.\n\n\
t(2)Days left column is Normally distributed with mean=median=26\n\n\
t(3)Price columns is Right Skeweed with mean>median")
```

```
*************************************************ANALYSIS*************
****************************************
```

(1)Min duration of flight is 0.83 hours and max duration of flight is 49 hours.

(2)Days left column is Normally distributed with mean=median=26

(3)Price columns is Right Skeweed with mean>median

BIVARIATE ANALYSIS.

```
print("**************************************************ANALYSIS*******************************************************\n\n\t(1)Vistara airlines have costliest tickets followed by Air_India.\n\n\t(2)Almost All cities in my dataset are costing equal fare price.\n\n\t(3)Highest fare is for night departure of flights and least is for late night.\n\n\t(4)One stop flights cost very high.\n\n\t(5)Destination cities donot have much impact on ticket fare.\n\n\t(6)Business class tickets are costlier than economy class.")
plt.figure(figsize=(17,17))
count=1
for i in cat_cols:
    plt.subplot(4,2,count)
    sns.barplot(x=df[i],y=df["price"],ci=False)
    count+=1
plt.show()
```

ANALYSIS

(1)Vistara airlines have costliest tickets followed by Air_India.

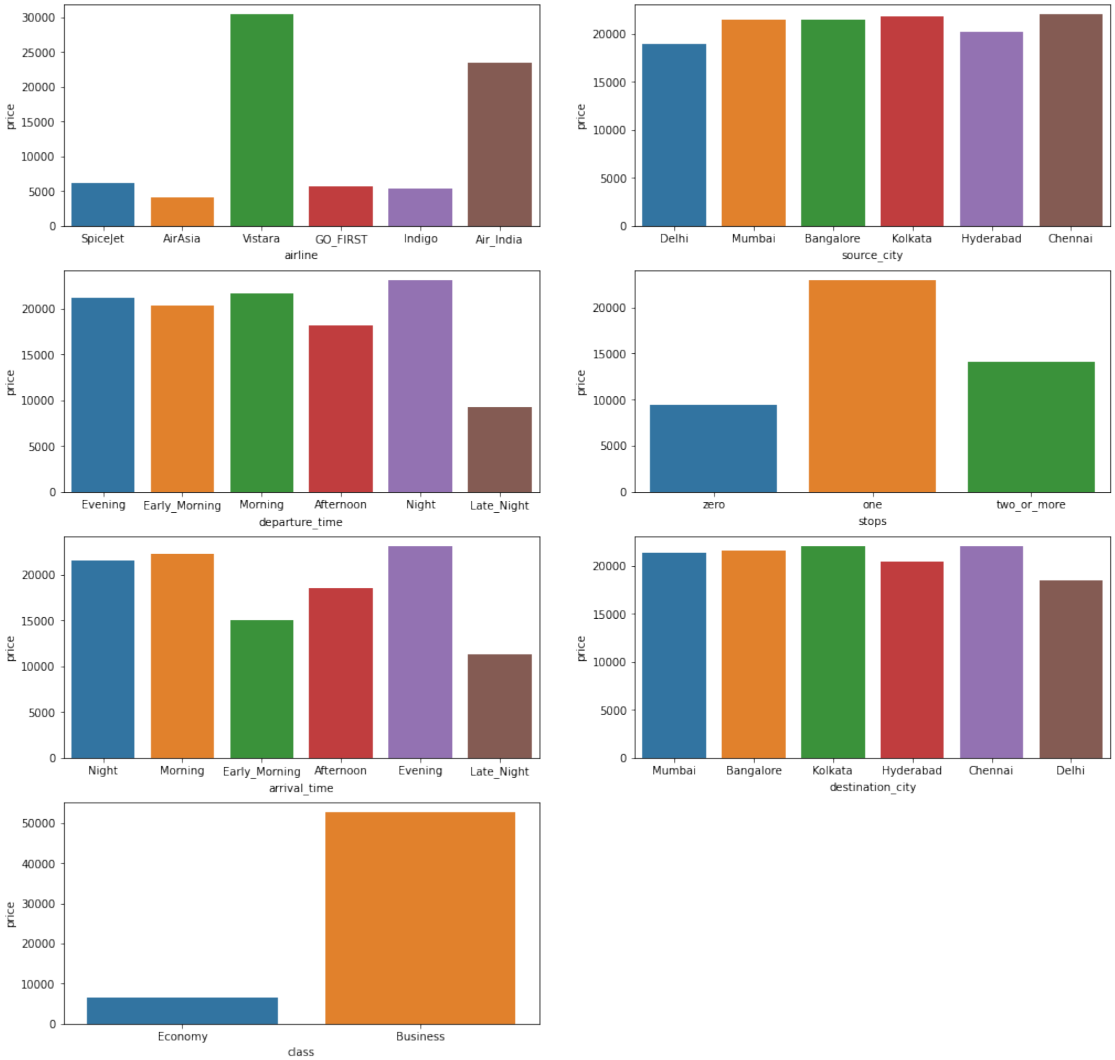
(2)Almost All cities in my dataset are costing equal fare price.

(3)Highest fare is for night departure of flights and least is for late night.

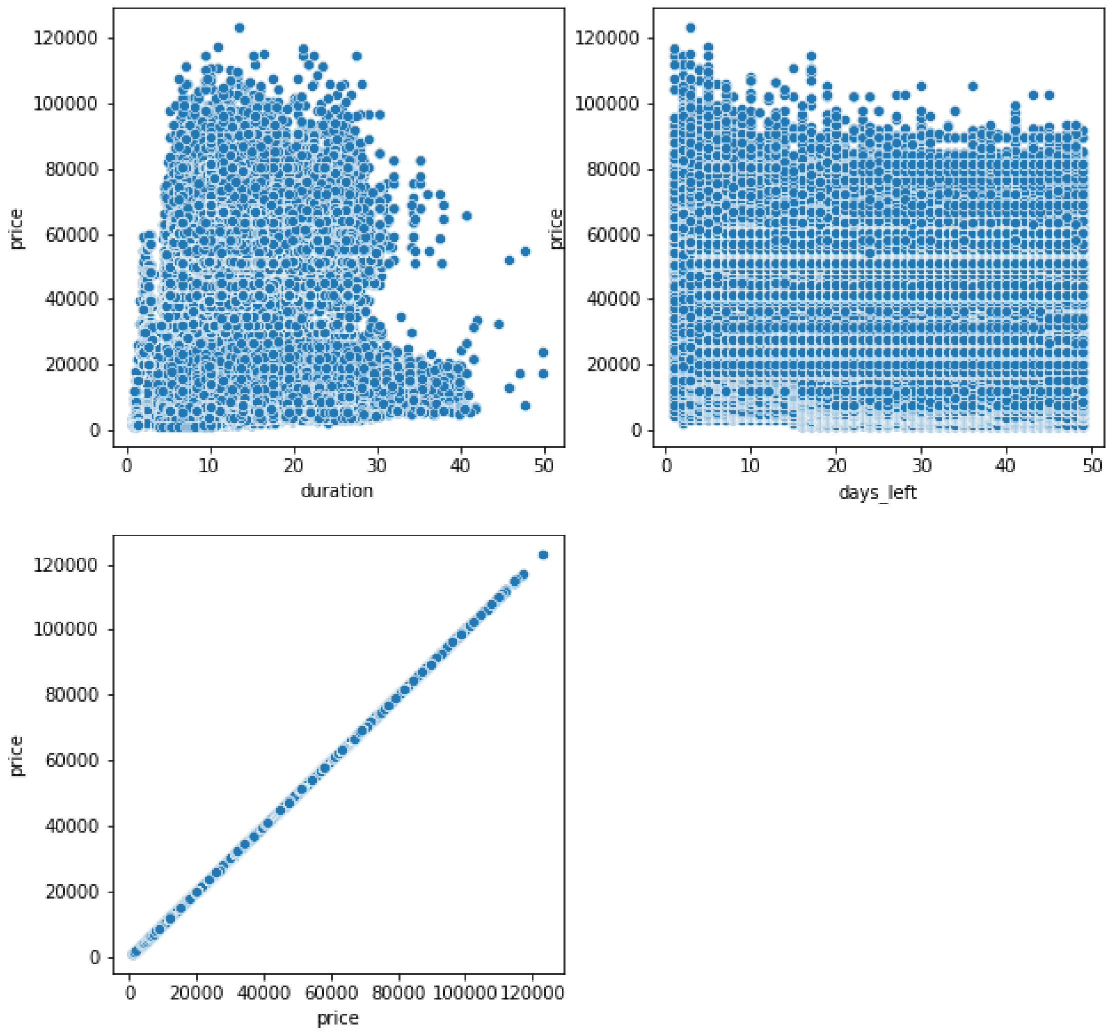
(4)One stop flights cost very high.

(5)Destination cities donot have much impact on ticket fare.

(6)Business class tickets are costlier than economy class.




```
plt.figure(figsize=(10,10))
count=1
for i in num_cols:
    plt.subplot(2,2,count)
    sns.scatterplot(x=df[i],y=df["price"])
    count+=1
plt.show()
```

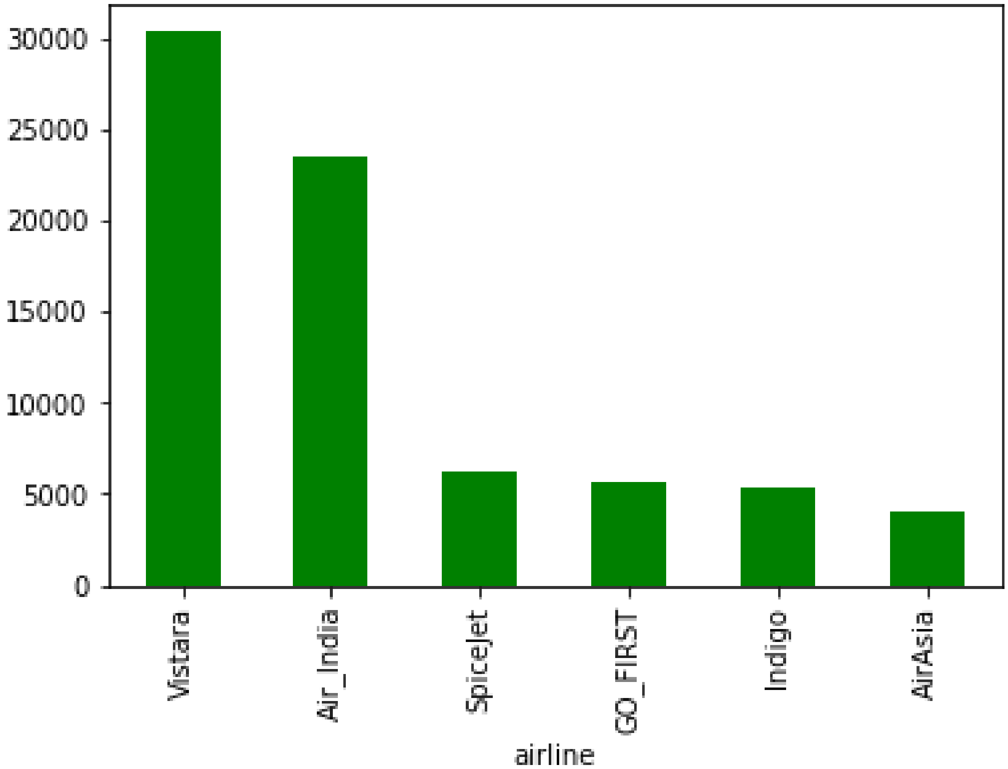


Q1)Does price vary with Airlines?

```
df.groupby("airline")["price"].mean().sort_values(ascending=False)
```

```
airline
Vistara      30396.536302
Air_India    23507.019112
SpiceJet      6179.278881
GO_FIRST      5652.007595
Indigo        5324.216303
AirAsia       4091.072742
Name: price, dtype: float64
```

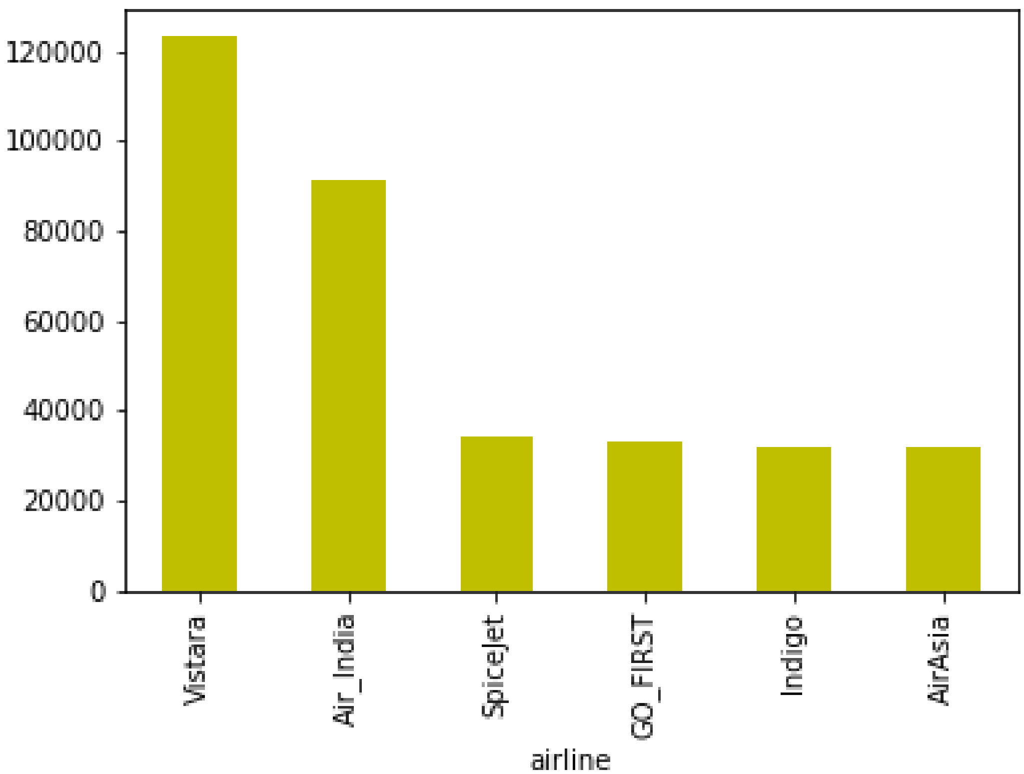
```
df.groupby("airline")
["price"].mean().sort_values(ascending=False).plot(kind="bar",color="g
")
plt.show()
```




```
df.groupby("airline")["price"].max().sort_values(ascending=False)
```

```
airline
Vistara      123071
Air_India     90970
SpiceJet      34158
GO_FIRST      32803
Indigo        31952
AirAsia       31917
Name: price, dtype: int64
```

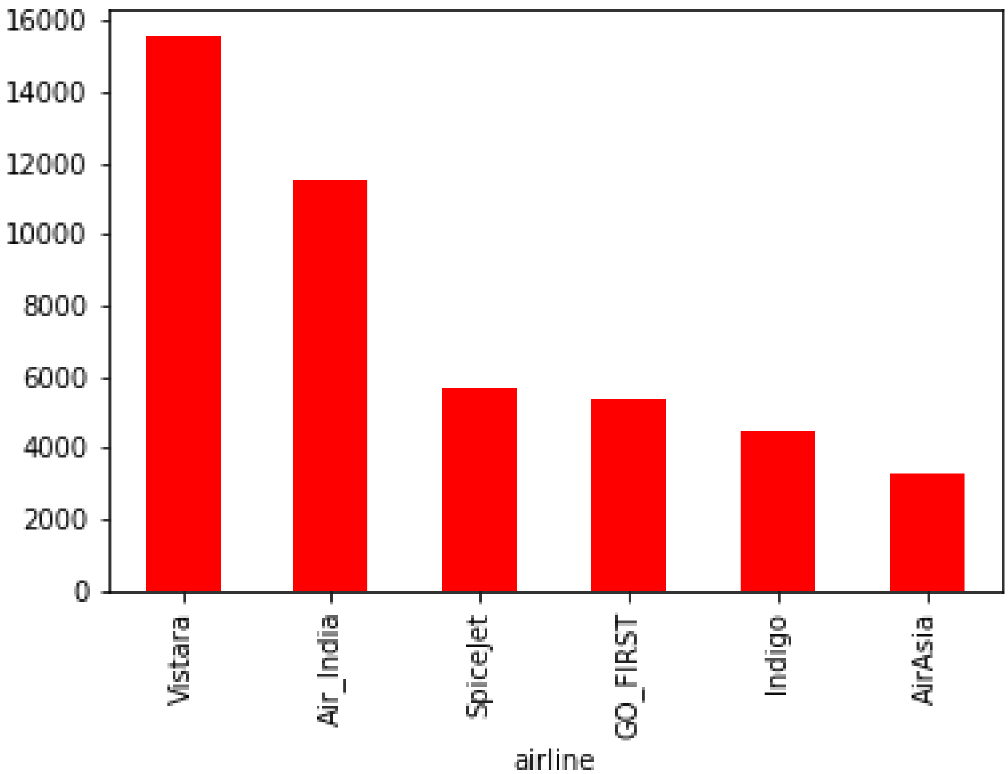
```
df.groupby("airline")
["price"].max().sort_values(ascending=False).plot(kind="bar",color="y"
)
plt.show()
```




```
df.groupby("airline")["price"].median().sort_values(ascending=False)
```

```
airline
Vistara      15543.0
Air_India    11520.0
SpiceJet      5654.0
GO_FIRST      5336.0
Indigo        4453.0
AirAsia       3276.0
Name: price, dtype: float64
```

```
df.groupby("airline")
["price"].median().sort_values(ascending=False).plot(kind="bar",color=
"r")
plt.show()
```




```
print("Air lines has impact on flight price\n\nVistara airlines has
costliest ticket followed by Airindia rest all have almost same cost
for highest ticket.\n\nHere mean is misleading because of outliers
median shows that average cost of ticket for vistara is around 15k
which is pocket friendly.")
```

```
Air lines has impact on flight price

Vistara airlines has costliest ticket followed by Airindia rest all
have almost same cost for highest ticket.

Here mean is misleading because of outliers median shows that average
cost of ticket for vistara is around 15k which is pocket friendly.
```

How is the price affected when tickets are bought in just 1 or 2 days before departure?

```
df["days_left"].unique()
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
34,
       35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49],
      dtype=int64)
```

```
df1=df[(df["price"])&(df["days_left"]<3)].sort_values(by="price",ascen
ding=False)
```

```
df1.groupby("airline")["price"].mean().sort_values(ascending=False)
```

```
airline
Vistara      39093.937182
Air_India    29542.800224
GO_FIRST     15673.372549
SpiceJet     12625.446602
Indigo       12290.087719
AirAsia       9831.534483
Name: price, dtype: float64
```

```
df1.groupby("airline")["price"].median().sort_values(ascending=False)
```

```
airline
Vistara      21843.0
Air_India    19279.0
GO_FIRST     14579.0
SpiceJet     12123.0
Indigo       11735.0
AirAsia       8393.0
Name: price, dtype: float64
```

```
df1.groupby("airline")["class"].count().sort_values(ascending=False)
```

```
airline
Vistara      1178
Air_India     891
Indigo        513
AirAsia       116
SpiceJet      103
GO_FIRST      102
Name: class, dtype: int64
```

```
A=df.groupby("airline")["price"].median().sort_values(ascending=False)
```

```
B=df1.groupby("airline")
["price"].median().sort_values(ascending=False)
```

```
d={"median_price_full_data":A,"Median_cost_2days_prior":B}
```

```
df2=pd.DataFrame(d)
```

```
df2["% increase in median flight
Price"]=((df2["Median_cost_2days_prior"]-
df2["median_price_full_data"])/df2["median_price_full_data"])*100
```

%Hike in fare price of flight 2days prior to departure day.

```
df2.sort_values(by="% increase in median flight
Price",ascending=False)
```

```
           median_price_full_data  Median_cost_2days_prior  \
airline
GO_FIRST                   5336.0                  14579.0
Indigo                     4453.0                  11735.0
AirAsia                    3276.0                   8393.0
SpiceJet                   5654.0                  12123.0
Air_India                 11520.0                  19279.0
Vistara                   15543.0                  21843.0

           % increase in median flight Price
airline
GO_FIRST                          173.219640
Indigo                            163.530204
AirAsia                           156.196581
SpiceJet                          114.414574
Air_India                          67.352431
Vistara                            40.532716
```

```
print("\n\tHere we can clearly see that every airline hikes there
ticket prices as departure date comes near\n\n\tGO_FIRST has highest
hike which is 173% more from normal days\n\n\tLeast hike is by Vistara
which is 40% but Vistara already has high cost of prices")
```

```

     Here we can clearly see that every airline hikes there ticket
prices as departure date comes near

     GO_FIRST has highest hike which is 173% more from normal days

     Least hike is by Vistara which is 40% but Vistara already has
high cost of prices
```

Does ticket price change based on the departure time and arrival time?

```
df.head()
```

```
    airline source_city departure_time stops   arrival_time
destination_city  \
0  SpiceJet       Delhi        Evening  zero          Night
Mumbai
1  SpiceJet       Delhi  Early_Morning  zero        Morning
Mumbai
2   AirAsia       Delhi  Early_Morning  zero  Early_Morning
Mumbai
```

```
3   Vistara       Delhi        Morning  zero      Afternoon
Mumbai
4   Vistara       Delhi        Morning  zero        Morning
Mumbai

     class  duration  days_left  price
0  Economy      2.17          1   5953
1  Economy      2.33          1   5953
2  Economy      2.17          1   5956
3  Economy      2.25          1   5955
4  Economy      2.33          1   5955
```

```
df.groupby("departure_time")
["price"].median().sort_values(ascending=False)
```

```
departure_time
Morning          8112.0
Night            7813.0
Evening          7425.0
Early_Morning    7212.0
Afternoon        6663.0
Late_Night       4499.0
Name: price, dtype: float64
```

```
df.groupby("arrival_time")
["price"].median().sort_values(ascending=False)
```

```
arrival_time
Evening          8854.0
Morning          7687.0
Night            7584.0
Afternoon        6714.0
Early_Morning    5800.0
Late_Night       4867.0
Name: price, dtype: float64
```

```
print("\n(1)Fare of flights has impact of arrival and departure time\
n\n(2)For departure Morning tickets are costly and Late night are
cheapest\n\n(3)For Arrival timings of evening tickes are costliest and
cheapest for arrival time of night")
```

```
(1)Fare of flights has impact of arrival and departure time

(2)For departure Morning tickets are costly and Late night are
cheapest

(3)For Arrival timings of evening tickes are costliest and cheapest
for arrival time of night
```

How the price changes with source_city and destination_city

```
df.groupby("source_city")
["price"].median().sort_values(ascending=False)
```

```
source_city
Kolkata      7958.0
Chennai      7846.0
Bangalore    7488.0
Mumbai       7413.0
Hyderabad    6855.0
Delhi        6840.0
Name: price, dtype: float64
```

```
df.groupby("destination_city")
["price"].median().sort_values(ascending=False)
```

```
destination_city
Chennai      7900.0
Kolkata      7767.0
Hyderabad    7548.0
Mumbai       7496.0
Bangalore    7425.0
Delhi        6521.0
Name: price, dtype: float64
```

```
print("(1)Kolkata is the costliest city to take a flight from,
followed by chennai ,bangalore and mumbai\n\n(2)Flights to Chennai are
costliest followed by kolkata\n\n(3)Flights to and from Delhi are
cheapest")
```

```
(1)Kolkata is the costliest city to take a flight from, followed by
chennai ,bangalore and mumbai

(2)Flights to Chennai are costliest followed by kolkata

(3)Flights to and from Delhi are cheapest
```

Q)How does the ticket price vary between Economy and Business class?

```
df.groupby("class")["price"].max()
```

```
class
Business    123071
Economy      42349
Name: price, dtype: int64
```

```
df.groupby("class")["price"].mean()
```

```
class
Business    52540.081124
Economy      6572.342383
Name: price, dtype: float64
```

```
print("\n\tThere is huge impact of class on fare price of flight\n\n\
tBuisness class has 699% higher rates than economy class")
```

```
	There is huge impact of class on fare price of flight

	Buisness class has 699% higher rates than economy class
```

Q)Find out which airline charge what for Different Classes

```
df.groupby(["airline","class"])["price"].median()
```

```
airline    class
AirAsia    Economy      3276.0
Air_India  Business    49613.0
           Economy      6082.0
GO_FIRST   Economy      5336.0
Indigo     Economy      4453.0
SpiceJet   Economy      5654.0
Vistara    Business    56588.0
           Economy      6461.0
Name: price, dtype: float64
```

```
print("(1)It can be seen that only 2 airlines provide Business class
Air_India and Vistara\n\n(2)Vistara charges highest amongst both
Classes")
```

```
(1)It can be seen that only 2 airlines provide Business class
Air_India and Vistara

(2)Vistara charges highest amongst both Classes
```

Q)How number of stops impact Fare price of flight

```
df.groupby("stops")["price"].median().sort_values(ascending=False)
```

```
stops
two_or_more    8307.0
one            7959.0
zero           4499.0
Name: price, dtype: float64
```

```
print("\n\t(1) Flights with 2 or more stops are costly and flights
with zero stops have cheapest fare price")
```

```
     (1) Flights with 2 or more stops are costly and flights with zero
stops have cheapest fare price
```

Q)Find all details of Flight with highest Ticket price

```
df[df["price"]==max(df["price"])]

        airline source_city departure_time stops arrival_time  \
261377  Vistara     Kolkata        Morning   one        Night

       destination_city     class  duration  days_left   price
261377            Delhi  Business      13.5          3  123071

print("\nIt was a flight of vistara airlines booked just 3 days prior
to boaring time , which took off from kolkata and went to delhi it
costed 123071 ruppes for the Business class")


It was a flight of vistara airlines booked just 3 days prior to
boaring time , which took off from kolkata and went to delhi it costed
123071 ruppes for the Business class

df.head(2)

    airline source_city departure_time stops arrival_time
destination_city  \
0  SpiceJet       Delhi        Evening  zero        Night
Mumbai
1  SpiceJet       Delhi  Early_Morning  zero      Morning
Mumbai

     class  duration  days_left  price
0  Economy      2.17          1   5953
1  Economy      2.33          1   5953
```

Q)Find Bussiest source and destinatioin cities

```
df.groupby("source_city")
["stops"].count().sort_values(ascending=False)

source_city
Delhi        61343
Mumbai       60896
Bangalore    52061
Kolkata      46347
Hyderabad    40806
Chennai      38700
Name: stops, dtype: int64
```

```
df.groupby("destination_city")
["stops"].count().sort_values(ascending=False)
```

```
destination_city
Mumbai       59097
Delhi        57360
Bangalore    51068
Kolkata      49534
Hyderabad    42726
Chennai      40368
Name: stops, dtype: int64
```

```
print("********************************Top 2 busisest cities are Delhi
and Mumbai*******************************************")
```

```
********************************Top 2 busisest cities are Delhi and
Mumbai******************************************
```

Encoding Categorical Features

```
for i in cat_cols:
    print(i)
    print(df[i].unique())
```

```
airline
['SpiceJet' 'AirAsia' 'Vistara' 'GO_FIRST' 'Indigo' 'Air_India']
source_city
['Delhi' 'Mumbai' 'Bangalore' 'Kolkata' 'Hyderabad' 'Chennai']
departure_time
['Evening' 'Early_Morning' 'Morning' 'Afternoon' 'Night' 'Late_Night']
stops
['zero' 'one' 'two_or_more']
arrival_time
['Night' 'Morning' 'Early_Morning' 'Afternoon' 'Evening' 'Late_Night']
destination_city
['Mumbai' 'Bangalore' 'Kolkata' 'Hyderabad' 'Chennai' 'Delhi']
class
['Economy' 'Business']
```

```
def stops(i):
        if i=="zero":
            return(0)
        elif i=="one":
            return(1)
        else:
            return(2)
```

```
df["stops"]=df["stops"].apply(stops)
```

```
def class_(i):
        if i=="Economy":
```

```
            return(0)
        else:
            return(1)
```

```
df["class"]=df["class"].map(class_)
```

```
from sklearn.preprocessing import LabelEncoder
```

```
le=LabelEncoder()
```

```
for i in cat_cols:
    df[i]=le.fit_transform(df[i])
```

```
df1=df.copy()
```

Linear regression is sensitive to scale

Feature scaling

```
from sklearn.preprocessing import StandardScaler
```

```
sc=StandardScaler()
```

```
df["duration"]=sc.fit_transform(df[["duration"]])
```

```
df["days_left"]=sc.fit_transform(df[["days_left"]])
```

Log transformation on target variable

```
df["price"]=np.log(df["price"])
```

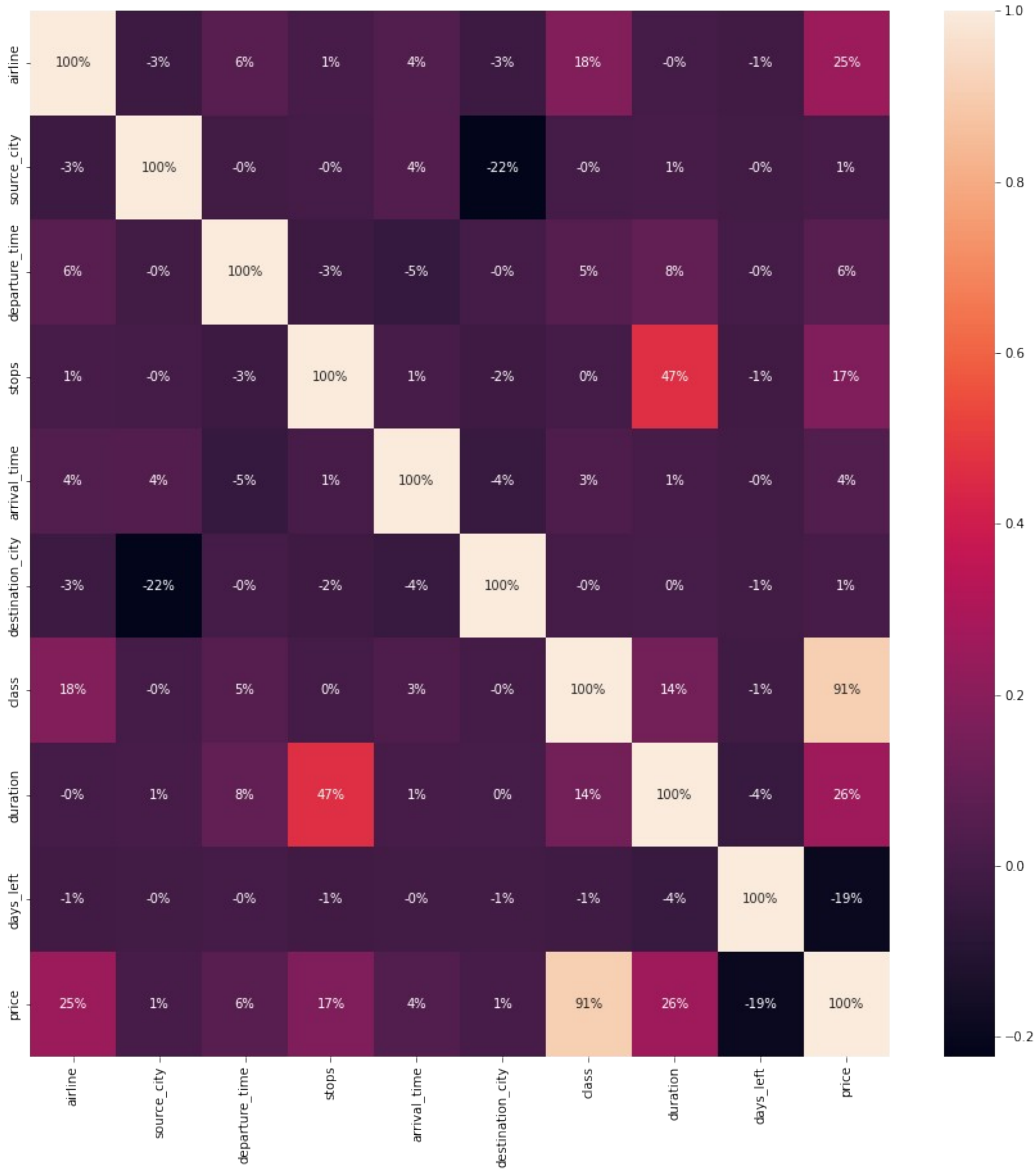
```
df.head()
```

```
   airline  source_city  departure_time  stops  arrival_time  \
0        4            2               2      0             5   
1        4            2               1      0             4   
2        0            2               1      0             1   
3        5            2               4      0             0   
4        5            2               4      0             4   

   destination_city  class  duration  days_left     price  
0                 5      0 -1.397531  -1.843875  8.691651  
1                 5      0 -1.375284  -1.843875  8.691651  
2                 5      0 -1.397531  -1.843875  8.692154  
3                 5      0 -1.386407  -1.843875  8.691986  
4                 5      0 -1.375284  -1.843875  8.691986  
```

```
plt.figure(figsize=(15,15))
sns.heatmap(df.corr(),annot=True,fmt=".0%")
```

```
<AxesSubplot:>
```



Spliting Data

```
X=df.drop("price",axis=1)
y=df["price"]

from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,rand
om_state=987)
```

Model Building

LinearRegression

```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()

lr.fit(X_train,y_train)

LinearRegression()

y_pred_train=lr.predict(X_train)
y_pred_test=lr.predict(X_test)

from sklearn.metrics import r2_score,mean_squared_error

print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y_train,y_pred_train)),
2))
print("R2 Score:",round(r2_score(y_train,y_pred_train),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y_test,y_pred_test)),2)
)
print("R2 Score:",round(r2_score(y_test,y_pred_test),2))

Train Data
RMSE: 0.35
R2 Score: 0.9
Test Data
RMSE: 0.35
R2 Score: 0.9

from sklearn.model_selection import cross_val_score
model_cv=cross_val_score(lr,X,y,cv=5)
model_cv

array([ 0.44868062,  0.44655593,  0.43131663,  0.90710316, -
0.43132839])

df1.head(3)

   airline  source_city  departure_time  stops  arrival_time  \
0        4            2               2      0             5
1        4            2               1      0             4
2        0            2               1      0             1

   destination_city  class  duration  days_left  price
0                 5      0      2.17          1   5953
1                 5      0      2.33          1   5953
2                 5      0      2.17          1   5956
```

Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor

dt=DecisionTreeRegressor()

X1=df1.drop("price",axis=1)
y1=df1["price"]

X1_train,X1_test,y1_train,y1_test=train_test_split(X1,y1,test_size=0.2
0,random_state=987)

dt.fit(X1_train,y1_train)

DecisionTreeRegressor()

y_pred_train1=dt.predict(X1_train)
y_pred_test1=dt.predict(X1_test)

print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train1)
),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train1),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test1)),
2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test1),2))

Train Data
RMSE: 594.44
R2 Score: 1.0
Test Data
RMSE: 3453.58
R2 Score: 0.98

param_grid={
     "max_depth":np.arange(1,50),
     "min_samples_leaf":np.arange(1,50),
     "min_samples_split":np.arange(2,50,2),
}

from sklearn.model_selection import RandomizedSearchCV
rand_reg=RandomizedSearchCV(dt,param_distributions=param_grid,cv=5,sco
ring=mean_squared_error,n_jobs=-1)
rand_reg.fit(X1_train,y1_train)

RandomizedSearchCV(cv=5, estimator=DecisionTreeRegressor(), n_jobs=-1,
                   param_distributions={'max_depth': array([ 1,  2,
3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
34,
       35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49]),
                                        'min_samples_leaf': array([ 1,
```

```
2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
34,
       35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49]),
                                        'min_samples_split':
array([ 2,  4,  6,  8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30, 32,
34,
       36, 38, 40, 42, 44, 46, 48])},
                   scoring=<function mean_squared_error at
0x0000014B2BD39990>)
```

```
rand_reg.best_params_
```

```
{'min_samples_split': 28, 'min_samples_leaf': 30, 'max_depth': 45}
```

```
y_train_pred=rand_reg.predict(X1_train)
y_test_pred=rand_reg.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y_train,y_train_pred)),
2))
print("R2 Score:",round(r2_score(y_train,y_train_pred),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y_test,y_test_pred)),2)
)
print("R2 Score:",round(r2_score(y_test,y_test_pred),2))
```

```
Train Data
RMSE: 30703.75
R2 Score: -761354434.17
Test Data
RMSE: 30641.64
R2 Score: -758052851.35
```

RandomForestRegressor

```
from sklearn.ensemble import RandomForestRegressor
```

```
rt=RandomForestRegressor()
```

```
rt.fit(X1_train,y1_train)
```

```
RandomForestRegressor()
```

```
y_pred_train2=rt.predict(X1_train)
y_pred_test2=rt.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train2)
),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train2),2))
print("Test Data")
```

```
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test2)),
2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test2),2))
```

```
Train Data
RMSE: 1136.44
R2 Score: 1.0
Test Data
RMSE: 2735.24
R2 Score: 0.99
```

Hyper parameter tuning

```
param_grid={
     "max_depth":np.arange(1,20),
     "n_estimators":(50,100,150,200),
     "max_samples":[0.25,0.5,0.75],
     "max_features":[0.5,0.75]
}
```

```
from sklearn.model_selection import RandomizedSearchCV
rand_reg1=RandomizedSearchCV(rt,param_distributions=param_grid,cv=5,sc
oring=mean_squared_error,n_jobs=-1)
rand_reg1.fit(X1_train,y1_train)
```

```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(), n_jobs=-1,
                   param_distributions={'max_depth': array([ 1,  2,
3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19]),
                                        'max_features': [0.5, 0.75],
                                        'max_samples': [0.25, 0.5,
0.75],
                                        'n_estimators': (50, 100, 150,
200)},
                   scoring=<function mean_squared_error at
0x0000014B2BD39990>)
```

```
rand_reg1.best_params_
```

```
{'n_estimators': 50, 'max_samples': 0.75, 'max_features': 0.5,
'max_depth': 5}
```

```
y_pred_train_rand=rand_reg1.predict(X1_train)
y_pred_test_rand=rand_reg1.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train_r
and)),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train_rand),2))
```

```
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test_ran
d)),2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test_rand),2))
```

```
Train Data
RMSE: 5503.55
R2 Score: 0.94
Test Data
RMSE: 5460.65
R2 Score: 0.94
```

ADA BOOST REGRESSOR

```
from sklearn.ensemble import AdaBoostRegressor
```

```
ada=AdaBoostRegressor()
```

```
ada.fit(X1_train,y1_train)
```

```
AdaBoostRegressor()
```

```
y_pred_train6=ada.predict(X1_train)
y_pred_test6=ada.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train6)
),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train6),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test6)),
2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test6),2))
```

```
Train Data
RMSE: 5980.24
R2 Score: 0.93
Test Data
RMSE: 5962.09
R2 Score: 0.93
```

HYPER PARAMETER TUNING

```
param_grid={'n_estimators':[20,50,70,100,120],
            'learning_rate':(0.1,0.01,0.001,1,),
             "loss":["linear", "square", "exponential"]}
```

```
from sklearn.model_selection import GridSearchCV
grid_clf=GridSearchCV(ada,param_grid=param_grid,cv=10,scoring=mean_squ
ared_error,n_jobs=-1)
grid_clf.fit(X1_train,y1_train)
```

```
GridSearchCV(cv=10, estimator=AdaBoostRegressor(), n_jobs=-1,
             param_grid={'learning_rate': (0.1, 0.01, 0.001, 1),
                         'loss': ['linear', 'square', 'exponential'],
                         'n_estimators': [20, 50, 70, 100, 120]},
             scoring=<function mean_squared_error at
0x00000267851C3520>)
```

```
grid_clf.best_params_
```

```
{'learning_rate': 0.1, 'loss': 'linear', 'n_estimators': 20}
```

```
y_pred_train_grid=grid_clf.predict(X1_train)
y_pred_test_grid=grid_clf.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train_g
rid)),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train_grid),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test_gri
d)),2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test_grid),2))
```

```
Train Data
RMSE: 5804.57
R2 Score: 0.93
Test Data
RMSE: 5780.93
R2 Score: 0.93
```

GradientBoostingRegressor

```
from sklearn.ensemble import GradientBoostingRegressor
```

```
gb_reg=GradientBoostingRegressor()
```

```
gb_reg.fit(X1_train,y1_train)
```

```
GradientBoostingRegressor()
```

```
y_pred_train3=gb_reg.predict(X1_train)
y_pred_test3=gb_reg.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train3)
```

```
),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train3),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test3)),
2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test3),2))
```

```
Train Data
RMSE: 4956.09
R2 Score: 0.95
Test Data
RMSE: 4934.23
R2 Score: 0.95
```

HYPER PARAMETER TUNING

```
param_grid={'n_estimators':[50,100,120,150],
            'learning_rate':(0.1,0.01,0.001)
           }
```

```
from sklearn.model_selection import GridSearchCV
grid_clf1=GridSearchCV(gb_reg,param_grid=param_grid,cv=10,scoring=mean
_squared_error,n_jobs=-1)
grid_clf1.fit(X1_train,y1_train)
```

```
GridSearchCV(cv=10, estimator=GradientBoostingRegressor(), n_jobs=-1,
             param_grid={'learning_rate': (0.1, 0.01, 0.001),
                         'n_estimators': [50, 100, 120, 150]},
             scoring=<function mean_squared_error at
0x000002599906CCA0>)
```

```
grid_clf1.best_params_
```

```
{'learning_rate': 0.1, 'n_estimators': 50}
```

```
y_pred_train_grid1=grid_clf1.predict(X1_train)
y_pred_test_grid1=grid_clf1.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train_g
rid1)),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train_grid1),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test_gri
d1)),2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test_grid1),2))
```

```
Train Data
RMSE: 5170.12
R2 Score: 0.95
```

```
Test Data
RMSE: 5140.48
R2 Score: 0.95
```

XGBOOST

```
pip install xgboost
```

```
Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: xgboost in c:\users\avina\appdata\
roaming\python\python310\site-packages (1.7.2)
Requirement already satisfied: scipy in c:\users\avina\appdata\
roaming\python\python310\site-packages (from xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\users\avina\appdata\
roaming\python\python310\site-packages (from xgboost) (1.23.1)
Note: you may need to restart the kernel to use updated packages.

WARNING: You are using pip version 22.0.4; however, version 22.3.1 is
available.
You should consider upgrading via the 'C:\Program Files\Python310\
python.exe -m pip install --upgrade pip' command.
```

```
import xgboost as xgb
```

```
xgb_reg = xgb.XGBRegressor()
xgb_reg.fit(X1_train, y1_train)
```

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1,
colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4,
max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1,
missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=0,
             num_parallel_tree=1, predictor='auto',
random_state=0, ...)
```

```
y_pred_train4=xgb_reg.predict(X1_train)
y_pred_test4=xgb_reg.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train4)
```

```
),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train4),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test4)),
2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test4),2))
```

```
Train Data
RMSE: 3426.53
R2 Score: 0.98
Test Data
RMSE: 3480.54
R2 Score: 0.98
```

HYPER PARAMETER TUNING

```
param_grid={'n_estimators':[50,100,120,150],
            'learning_rate':[0.1,0.01,0.001],
            "gamma":np.arange(1,30)}
```

```
from sklearn.model_selection import GridSearchCV
grid_clf2=GridSearchCV(xgb_reg,param_grid=param_grid,cv=10,scoring=mea
n_squared_error,n_jobs=-1)
grid_clf2.fit(X1_train,y1_train)
```

```
GridSearchCV(cv=10,
             estimator=XGBRegressor(base_score=0.5, booster='gbtree',
                                    callbacks=None,
colsample_bylevel=1,
                                    colsample_bynode=1,
colsample_bytree=1,
                                    early_stopping_rounds=None,
                                    enable_categorical=False,
eval_metric=None,
                                    feature_types=None, gamma=0,
gpu_id=-1,
                                    grow_policy='depthwise',
                                    importance_type=None,
                                    interaction_constraints='',
                                    learning_rate=0.300000012...
                                    min_child_weight=1, missing=nan,
                                    monotone_constraints='()',
n_estimators=100,
                                    n_jobs=0, num_parallel_tree=1,
                                    predictor='auto',
random_state=0, ...),
             n_jobs=-1,
             param_grid={'gamma': array([ 1,  2,  3,  4,  5,  6,  7,
8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29]),
```

```
                         'learning_rate': [0.1, 0.01, 0.001],
                         'n_estimators': [50, 100, 120, 150]},
             scoring=<function mean_squared_error at
0x000001E45766E830>)
```

```
grid_clf2.best_params_
```

```
{'gamma': 1, 'learning_rate': 0.1, 'n_estimators': 50}
```

```
y_pred_train_grid2=grid_clf2.predict(X1_train)
y_pred_test_grid2=grid_clf2.predict(X1_test)
```

```
print("Train Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_train,y_pred_train_g
rid2)),2))
print("R2 Score:",round(r2_score(y1_train,y_pred_train_grid2),2))
print("Test Data")
print("RMSE:",round(np.sqrt(mean_squared_error(y1_test,y_pred_test_gri
d2)),2))
print("R2 Score:",round(r2_score(y1_test,y_pred_test_grid2),2))
```

```
Train Data
RMSE: 4431.94
R2 Score: 0.96
Test Data
RMSE: 4419.87
R2 Score: 0.96
```

```
d={"Algorithm":["Linear Regression","DecisionTree
Regressor","RandomForest Regressor","AdaBoost
Regressor","GradientBoosting Regressor","XGBOOST
Regressor"],"TRAIN_RMSE":
[0.35,594.44,1136.44,5980.24,4956.09,3426.53],"TRAIN_R2":
[0.90,1.0,1.0,0.93,0.95,0.98],"TEST_RMSE":
[0.35,3448.83,2740.57,5962.09,4934.23,3480.54],"TEST_R2_SCORE":
[0.9,0.98,0.99,0.93,0.95,0.98],"TRAIN_Regularized_RMSE":
["-","-",0.94,0.93,0.95,0.96],"TRAIN_Regularized_R2_SCORE":
["-","-",0.94,0.93,0.95,0.96],"TEST_Regularized_RMSE":
["-","-",5460.65,5780.93,5140.48,4419.87],"TEST_Regularized_R2_SCORE":
["-","-",0.94,0.93,0.95,0.96]}
```

```
Model=pd.DataFrame(d)
```

```
Model
```

```
                    Algorithm  TRAIN_RMSE  TRAIN_R2  TEST_RMSE
TEST_R2_SCORE  \
0           Linear Regression        0.35      0.90       0.35
0.90
1      DecisionTree Regressor      594.44      1.00    3448.83
0.98
2      RandomForest Regressor     1136.44      1.00    2740.57
```

```
0.99
3          AdaBoost Regressor     5980.24      0.93    5962.09
0.93
4  GradientBoosting Regressor     4956.09      0.95    4934.23
0.95
5           XGBOOST Regressor     3426.53      0.98    3480.54
0.98

  TRAIN_Regularized_RMSE TRAIN_Regularized_R2_SCORE
TEST_Regularized_RMSE  \
0                      -                          -
-
1                      -                          -
-
2                   0.94                       0.94
5460.65
3                   0.93                       0.93
5780.93
4                   0.95                       0.95
5140.48
5                   0.96                       0.96
4419.87

  TEST_Regularized_R2_SCORE
0                         -
1                         -
2                      0.94
3                      0.93
4                      0.95
5                      0.96
```

Best Prediction Model is given by XGBOOST Regressor