

OPTIMIZING FLIGHT BOOKING DECISIONS

THROUGH MACHINE LEARNING

PRICE PREDICTIONS

INTRODUCTION

OVERVIEW

- People who work frequently travel through flight will have better knowledge on best discount and right time to buy the ticket.
- For the business purpose many airline companies change prices according to the seasons or time.
- They will increase the price when people travel more. Estimating the highest prices of the airline data for the route is collected with features such as Duration, Destination, Arrival and Departure.
- Features are taken from chosen dataset and in the price where in the airline price ticket costs vary overtime.

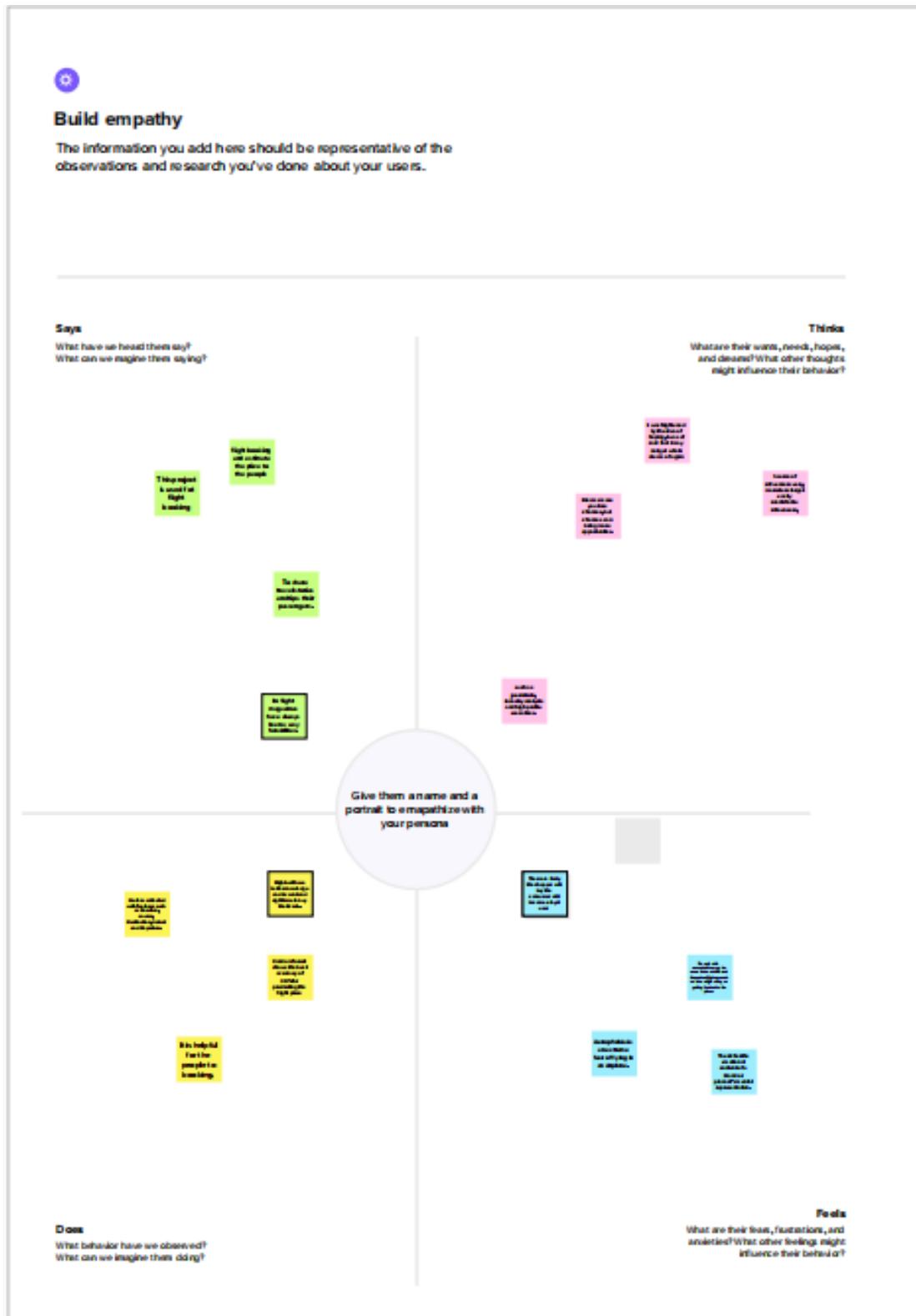
- We have implemented flight price prediction for users by using KNN, decision tree and random forest algorithms.
- Random Forest show the best accuracy of 80% for predicting the flight price. Also, we have done correlation tests and metrics for the statistical analysis.

PURPOSE

- ✓ Airline tickets are important document that confirm a passenger has a seat on a flight.
- ✓ The ticket includes important information about the passenger and the flight that they will take.
- ✓ The ticket is exchanged for a boarding pass during the check-in process, and this gives the passengers permission to board the plane.

PROBLEM DEFINITION & DESIGN THINKING

EMPATHY MAP



IDEATION & BRAINSTORMING MAP

①

Choose your best "How Might We" Questions.

From the top 10 ideation questions that you just used and in this group, determine which to begin by selecting one question to focus the rest of the group on at this time. In this round you will be 10 new generation ideas in 10 minutes you are trying to implement.

10 minutes

**1. How might we...
use design thinking?**

**2. How might we...
design better experiences?**

**3. How might we...
use our culture right?**

**4. How might we...
use our people as right strategy?**

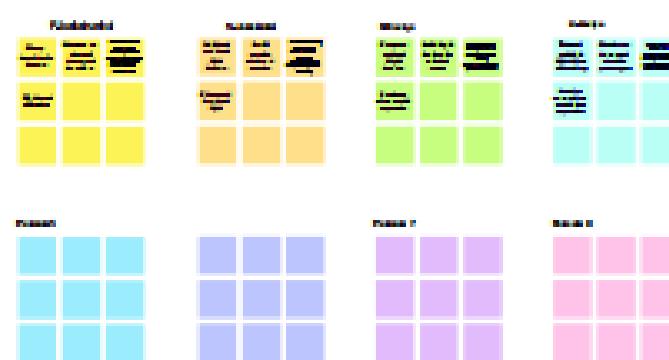
**5. How might we...
design better products?**

②

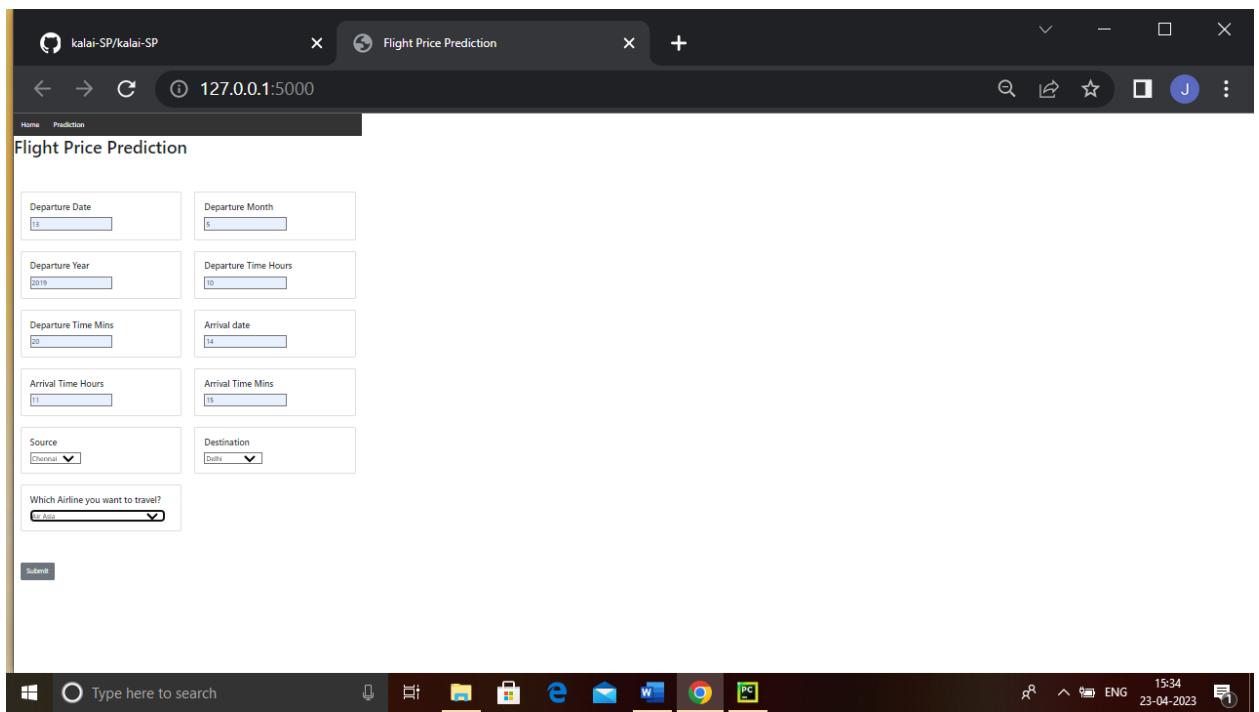
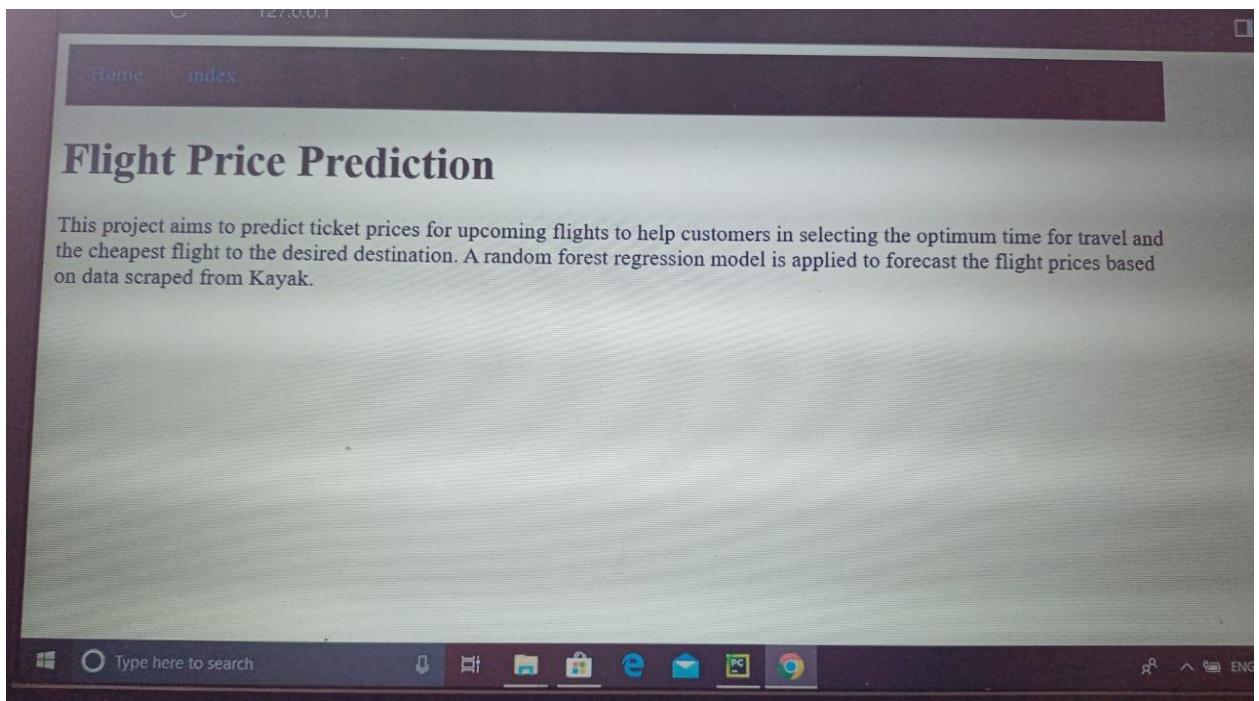
Brainstorm notes

Please each person write in the "Note ideation space" 10 randomly brainstorming ideas and placing them into the template. This "Silent, no talking" writing approach and one person speaking and writing for 10 seconds and 10 minutes, followed by a three break. Because big people like to go for speed.

10 minutes



RESULT



Flight Price Prediction

Based on the given input, we can get the flight price as 4824.76 INR.



ADVANTAGES

- They're called budget airline for a reason lower rates that make for appealing flight fares for budget travelers.
- First remember these airline serve fewer routes.
- Speaking of routers. The best budget airline fly both national and international routes.
- To take advantages of the promotion make it a habit to always check a booking website for new promo fares and discount packages.

DISADVANTAGE

- Many budget airline don't use major airports for takeoff and landing.
- Beware of hidden charges aside from the original fare advertised on the website.
- Another possible issue you might face with promotional tickets is that dates or destinations may be limited.
- Also the flight status might be delayed as well.

APPLICATION

- Fare Arena
- Kayak
- Air India
- IndiGo-Book flight ticket
- Kicci.com-Book cheap & flights
- Vistara-India's Best Airline
- Last minute flight Booking
- Expedia.

CONCLUSION

- ❖ Flight ticket booking app development latest trend in the market as the travel is rising globally, and people are relying app for easy trips. Machine learning algorithms are applied on the dataset to predict the dynamic fare of flight.
- ❖ This gives the predicted values of flight fare to get a flight ticket at minimum cost.
- ❖ Data is collected from the websites which sell the flight tickets so only limited information can be accessed, The values of R-squared obtained from the algorithm give the accuracy of the model.
- ❖ In the future. If more data could be accessed such as the current availability of seats. The predicted results will be more accurate. Finally. We have created the entire process of predicting an airline ticket and given a proof of our prediction based on the previous trends with our prediction.

FUTURE SCOPE

- Air ticketing is very dynamic and booming work sphere with great future scope on a global level.
- The Air ticketing industry is one of the industry is one of the largest and most profitable industries in the word and contributes substantially to the foreign exchange earned.

APPENDIX

A. Source Code

Flight Booking Decisions through machine learning price predictions

```
import numpy as np
import pandas as pd
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
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report, confusion_matrix
import warnings
import pickle
from scipy import stats
warnings.filterwarnings('ignore')
plt.style.use('fivethirtyeight')
```

[2] data=pd.read_excel("Data_Train.csv")
data.head()

Type here to search

Flight Booking Decisions through machine learning price predictions

```
from scipy import stats
warnings.filterwarnings('ignore')
plt.style.use('fivethirtyeight')
```

[78] data=pd.read_excel("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
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	No info	13302

```
category=['Airline','Source','Destination','Additional_Info']
category
```

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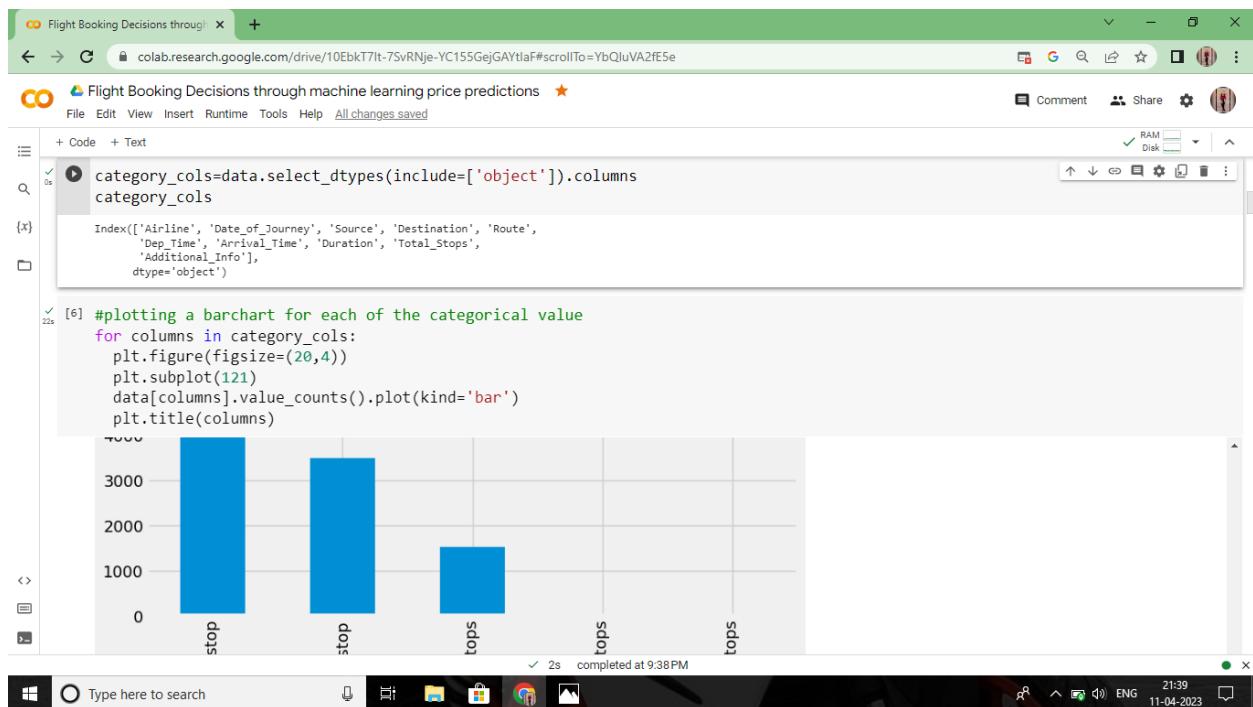
Flight Booking Decisions through machine learning price predictions

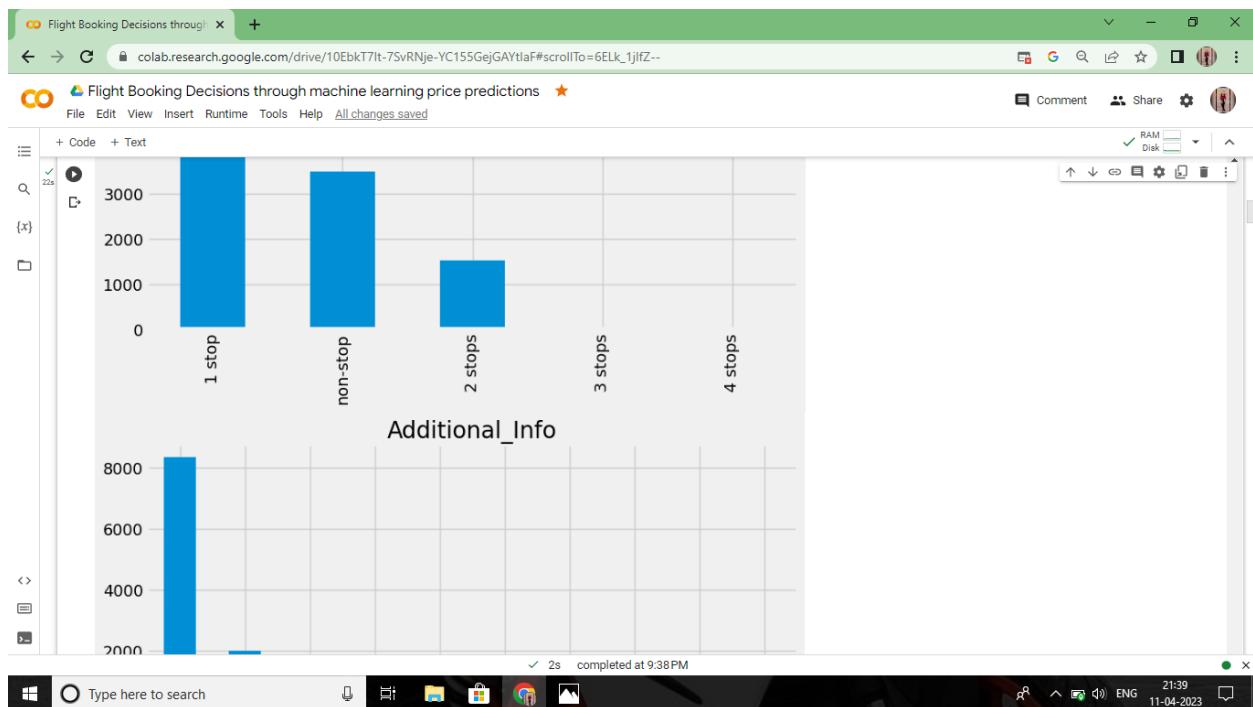
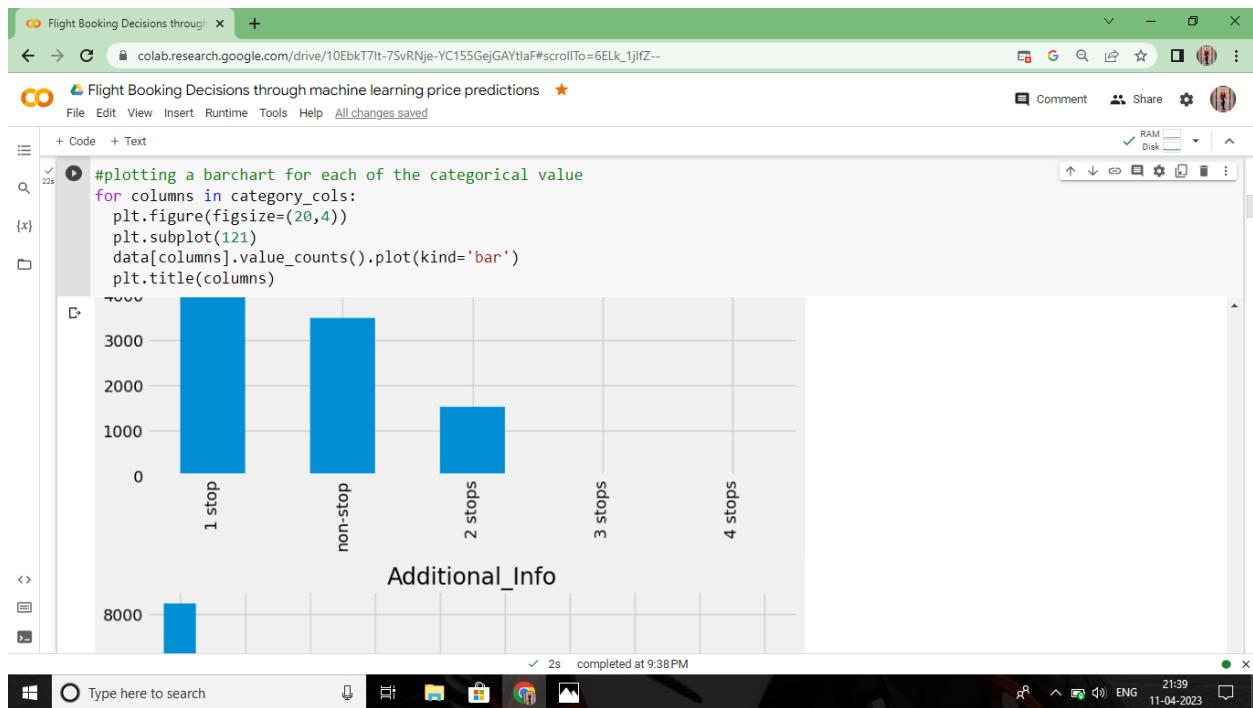
```
[3] category=['Airline','Source','Destination','Additional_Info']
category
['Airline', 'Source', 'Destination', 'Additional_Info']

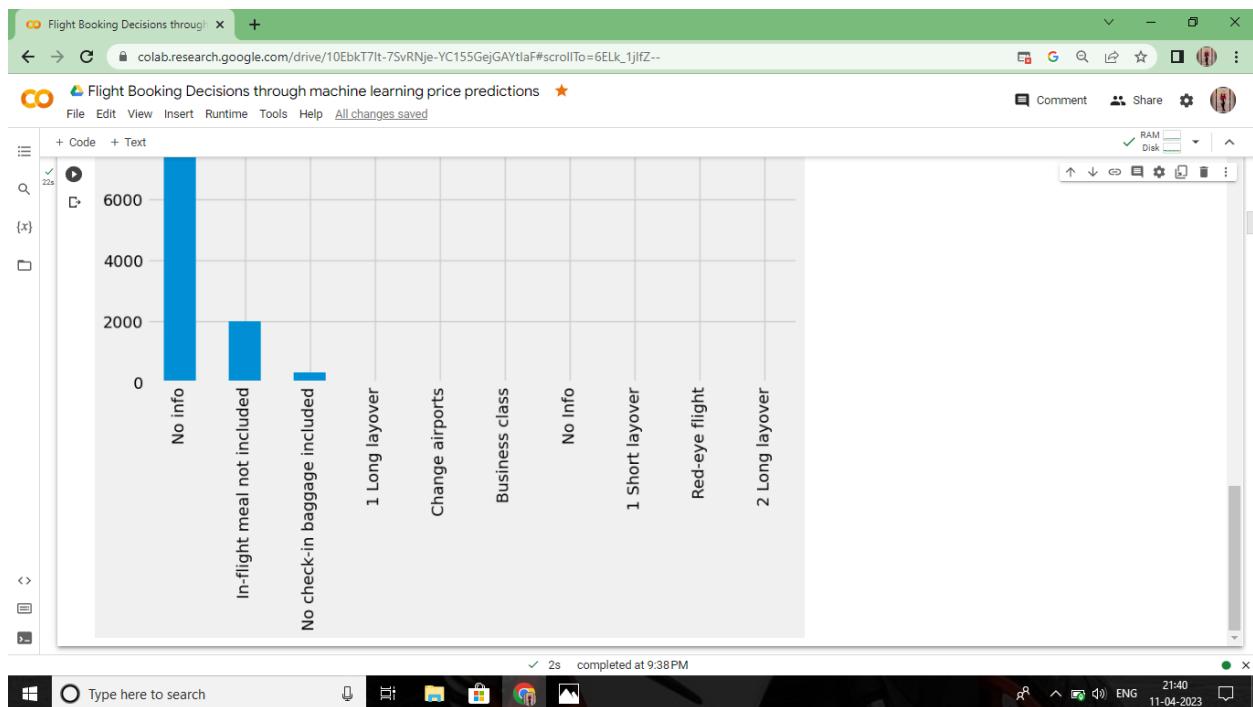
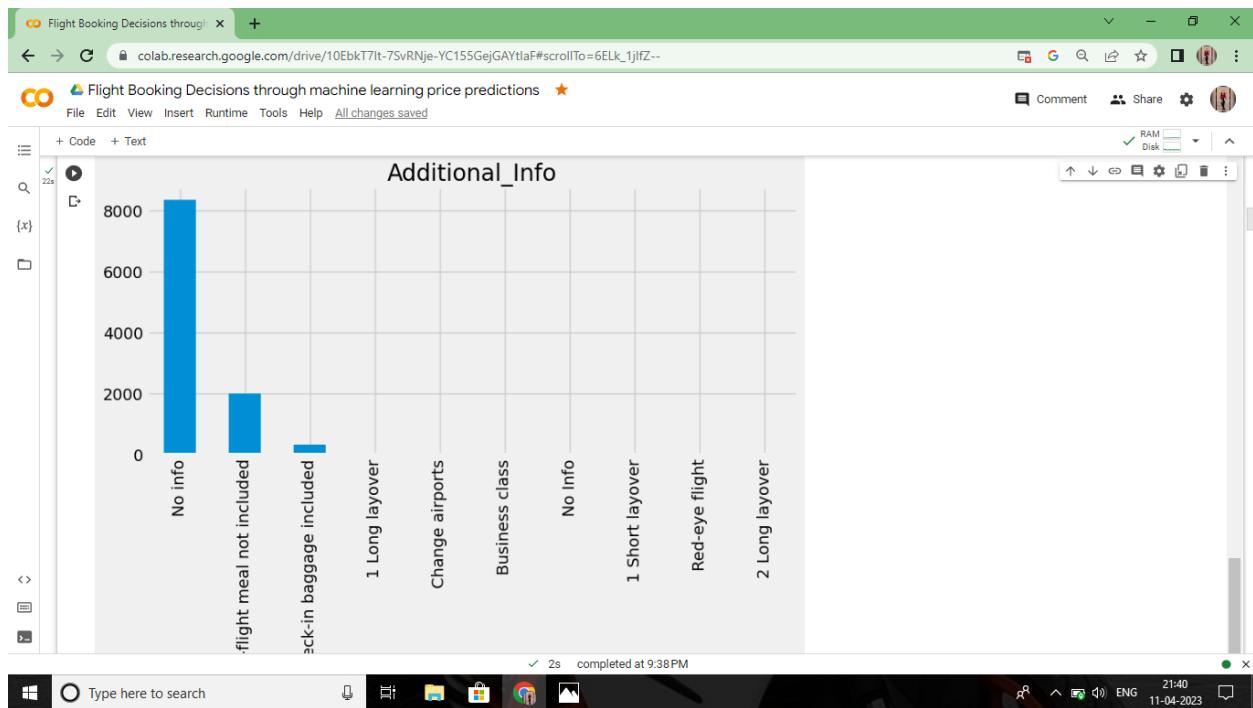
[4] for i in category:
    print(i,data[i].unique())

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']
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']

category_cols=data.select_dtypes(include=['object']).columns
category_cols
```







Flight Booking Decisions through machine learning price predictions

```
[x] 0 data.Date_of_Journey=data.Date_of_Journey.str.split('/')
data.Date_of_Journey
```

```
[x] 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
```

```
[x] 0 [8] data.Total_Stops.unique()
array(['non-stop', '2 stops', '1 stop', '3 stops', nan, '4 stops'],
      dtype=object)
```

```
[x] 0 [ ] data.Route=data.Route.str.split('->')
data.Route
```

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Flight Booking Decisions through machine learning price predictions

```
[x] 0 data.Total_Stops.unique()
array(['non-stop', '2 stops', '1 stop', '3 stops', nan, '4 stops'],
      dtype=object)
```

```
[x] 0 [79] data.Route=data.Route.str.split('->')
data.Route
```

```
[x] 0 [0] [BLR → DEL]
1 [CCU → IXN → 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
```

```
[x] 0 [0] 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]
```

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Flight Booking Decisions through machine learning price predictions

```
[9] data['City6']=data.Route.str[5]

[10] data.Date_of_Journey=data.Date_of_Journey.str.split('/')
    data.Date_of_Journey
    0      NaN
    1      NaN
    2      NaN
    3      NaN
    4      NaN
    ..
   10678    NaN
   10679    NaN
   10680    NaN
   10681    NaN
   10682    NaN
Name: Date_of_Journey, Length: 10683, dtype: float64

[11] data.Dep_Time=data.Dep_Time.str.split(':')
[12] data['Dep_Time_Hour']=data.Dep_Time.str[0]
    data['Dep_Time_Mins']=data.Dep_Time.str[1]

[13] data.Arrival_Time=data.Arrival_Time.str.split('')
```

Flight Booking Decisions through machine learning price predictions

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

[13] data.Arrival_Time=data.Arrival_Time.str.split('')

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

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

[16] 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]

[17] 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]
```

Flight Booking Decisions through machine learning price predictions

```
[1] 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]

[2] 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]

[3] 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)

[4] data.Additional_Info.replace('No Info','No Info',inplace=True)

[5] data.isnull().sum()

Airline          0
Date_of_Journey 10683
Source           0
Destination      0
Route            1
Dep_Time         0
Arrival_Time     0
Duration          0
dtype: int64
```

Flight Booking Decisions through machine learning price predictions

```
[1] '1 Long layover', 'Change airports', 'Business class',
    'Red-eye flight', '2 Long layover', dtype=object

[2] data.Additional_Info.replace('No Info','No Info',inplace=True)

[3] data.isnull().sum()

Airline          0
Date_of_Journey 10683
Source           0
Destination      0
Route            1
Dep_Time         0
Arrival_Time     0
Duration          0
Total_Stops      1
Additional_Info   0
Price             0
City1            1
City2            1
City3            1
City4            1
City5            1
City6            1
Dep_Time_Hour    0
Dep_Time_Mins    0
Arrival_date      0
Time_of_Arrival   0
Travel_Hours      0
Travel_Mins       0
dtype: int64
```

Flight Booking Decisions through machine learning price predictions

```

[21] travel_hours
      Travel_Mins
      dtype: int64

[x] [22] data.drop(['city4','city5','city6'],axis=1,inplace=True)

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

[24] data.isnull().sum()

      Airline      0
      Source      0
      Destination      0
      Total_Stops      1
      Additional_Info      0
      Price      0
      City1      1
      City2      1
      City3      1
      Dep_Time_Hour      0
      Dep_Time_Mins      0
      Arrival_date      0
      Travel_Hours      0
      Travel_Mins      0
      dtype: int64

```

Replacing Missing Values

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21:41 11-04-2023

Flight Booking Decisions through machine learning price predictions

```

[1] data['City1'].fillna('None',inplace=True)

[25] data['Arrival_date'].fillna(data['Dep_Time_Hour'],inplace=True)

[26] data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 14 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   Total_Stops     10682 non-null   object  
 4   Additional_Info 10683 non-null   object  
 5   Price           10683 non-null   int64  
 6   City1           10682 non-null   object  
 7   City2           10682 non-null   object  
 8   City3           10682 non-null   object  
 9   Dep_Time_Hour   10683 non-null   object  
 10  Dep_Time_Mins   10683 non-null   object  
 11  Arrival_date    10683 non-null   object  
 12  Travel_Hours    10683 non-null   object  
 13  Travel_Mins     10683 non-null   object  
dtypes: int64(1), object(13)
memory usage: 1.1+ MB

```

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Flight Booking Decisions through machine learning price predictions ★

```
[28]: 6   City1      10682 non-null object
      7   City2      10682 non-null object
      8   City3      10682 non-null object
      9   Dep_Time_Hour 10683 non-null object
     10  Dep_Time_Mins 10683 non-null object
     11  Arrival_date 10683 non-null object
     12  Travel_Hours 10683 non-null object
     13  Travel_Mins  10683 non-null object
dtypes: int64(1), object(13)
memory usage: 1.1+ MB
```

```
data.Dep_Time_Hour=data.Dep_Time_Hour.astype('int64')
data.Dep_Time_Mins=data.Dep_Time_Mins.astype('int64')
data.Arrival_date=data.Arrival_date.astype('int64')
data.head()
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Travel_Hours	Travel_Mins
0	IndiGo	Banglore	New Delhi	[]	No info	3897	BLR → DEL	NaN	NaN	22	20	0	2	h
1	Air India	Kolkata	Banglore	[]	No info	7662	CCU → IXR → BBI → BLR	NaN	NaN	5	50	1	7	h
2	Jet Airways	Delhi	Cochin	[]	No info	13882	DEL → LKO → BOM → COK	NaN	NaN	9	25	0	1	9
3	IndiGo	Kolkata	Banglore	[]	No info	6218	CCU → NAG → BLR	NaN	NaN	18	5	2	5	h
4	IndiGo	Banglore	New Delhi	[]	No info	13302	BLR → NAG → DEL	NaN	NaN	16	50	2	4	h

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Flight Booking Decisions through machine learning price predictions ★

```
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```

```
+ Code + Text
```

```
4   IndiGo  Banglore  New Delhi  [ ]  No info  13302  BLR → NAG → DEL  NaN  NaN  16  50  2  4  h
```

```
data[data['Airline']=='Air India']
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Travel_Hours	Travel_Mins
1	Air India	Kolkata	Banglore	[]	No info	7662	CCU → IXR → BBI → BLR	NaN	NaN	5	50	1	7	h
10	Air India	Delhi	Cochin	[]	No info	8907	DEL → BLR → COK	NaN	NaN	9	45	2	1	3
12	Air India	Chennai	Kolkata	[]	No info	4667	MAA → CCU	NaN	NaN	11	40	1	2	h
15	Air India	Delhi	Cochin	[]	No info	14011	DEL → AMD → BOM → COK	NaN	NaN	16	40	1	2	6
18	Air India	Delhi	Cochin	[]	No info	13381	DEL → CCU → BOM → COK	NaN	NaN	20	15	1	2	3
...
10670	Air India	Kolkata	Banglore	[]	No info	11411	CCU → IXR → DEL → BLR	NaN	NaN	5	50	2	1	7
10671	Air India	Mumbai	Hyderabad	[]	No info	3100	BOM → HYD	NaN	NaN	21	5	2	1	h
10675	Air India	Mumbai	Hyderabad	[]	No info	3100	BOM → HYD	NaN	NaN	6	20	0	1	h
10679	Air India	Kolkata	Banglore	[]	No info	4145	CCU → BLR	NaN	NaN	20	45	2	2	h
10682	Air India	Delhi	Cochin	[]	No info	11753	DEL → GOI → BOM → COK	NaN	NaN	10	55	1	8	h

1751 rows × 14 columns

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Flight Booking Decisions through machine learning price predictions

```
[30] categorical=['Airline','Source','Destination','Additional_Info','city1']
     numerical=['Total_Stops','date','Month','Year','Dep_Time_Hour','Dep_Time_Mins','Arrival_Time_Hour',
                'Arrival_Time_Mins','Travel_Hours','Travel_Mins']

Label Encoding

[31] 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.head()
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Travel_Hours	Travel_Mins
0	3	0	5	[]	No info	3897	B	L	R	22	20	0	2	h

Flight Booking Decisions through machine learning price predictions

```
[31] 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.head()
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Travel_Hours	Travel_Mins
0	3	0	5	[]	No info	3897	B	L	R	22	20	0	2	h
1	1	3	0	[]	No info	7662	C	C	U	05	50	1	7	h
2	4	2	1	[]	No info	13882	D	E	L	09	25	0	1	9
3	3	3	0	[]	No info	6218	C	C	U	18	05	2	5	h
4	3	0	5	[]	No info	13302	B	L	R	16	50	2	4	h

Flight Booking Decisions through machine learning price predictions ★

[34] data.head()

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Travel_Hours	Travel_Mins
0	3	0	5	[]	No info	3897	B	L	R	22	20	0	2	h
1	1	3	0	[]	No info	7662	C	C	U	05	50	1	7	h
2	4	2	1	[]	No info	13882	D	E	L	09	25	0	1	9
3	3	3	0	[]	No info	6218	C	C	U	18	05	2	5	h
4	3	0	5	[]	No info	13302	B	L	R	16	50	2	4	h

[35] data=data[['Airline','Source','Destination','Dep_Time_Hour','Dep_Time_Mins','Arrival_date','Price']]

[36] data.head()

	Airline	Source	Destination	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Price
0	3	0	5	22	20	0	3897
1	1	3	0	05	50	1	7662
2	4	2	1	09	25	0	13882
3	3	3	0	18	05	2	6218
4	3	0	5	16	50	2	13302

Flight Booking Decisions through machine learning price predictions ★

[36] data.describe()

	Airline	Source	Destination	Price
count	10682.000000	10682.000000	10682.000000	10682.000000
mean	3.966205	1.952069	1.435967	9086.292735
std	2.352090	1.177110	1.474773	4610.886695
min	0.000000	0.000000	0.000000	1759.000000
25%	3.000000	2.000000	0.000000	5277.000000
50%	4.000000	2.000000	1.000000	8372.000000
75%	4.000000	3.000000	2.000000	12373.000000
max	11.000000	4.000000	5.000000	79512.000000

Flight Booking Decisions through machine learning price predictions

```
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[36] 0 3 0 5 22 20 0 3897
     1 1 3 0 05 50 1 7662
{x} 2 4 2 1 09 25 0 13882
    3 3 3 0 18 05 2 6218
    4 3 0 5 16 50 2 13302

data.describe()

   Airline  Source  Destination  Price
count 10682.000000 10682.000000 10682.000000 10682.000000
mean 3.966205 1.952069 1.435967 9086.292735
std 2.352090 1.177110 1.474773 4610.885695
min 0.000000 0.000000 0.000000 1759.000000
25% 3.000000 2.000000 0.000000 5277.000000
50% 4.000000 2.000000 1.000000 8372.000000
75% 4.000000 3.000000 2.000000 12373.000000
max 11.000000 4.000000 5.000000 79512.000000
```

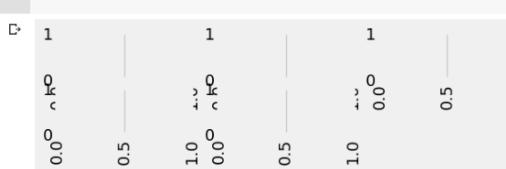
Milestone 3: Exploratory Data Analysis

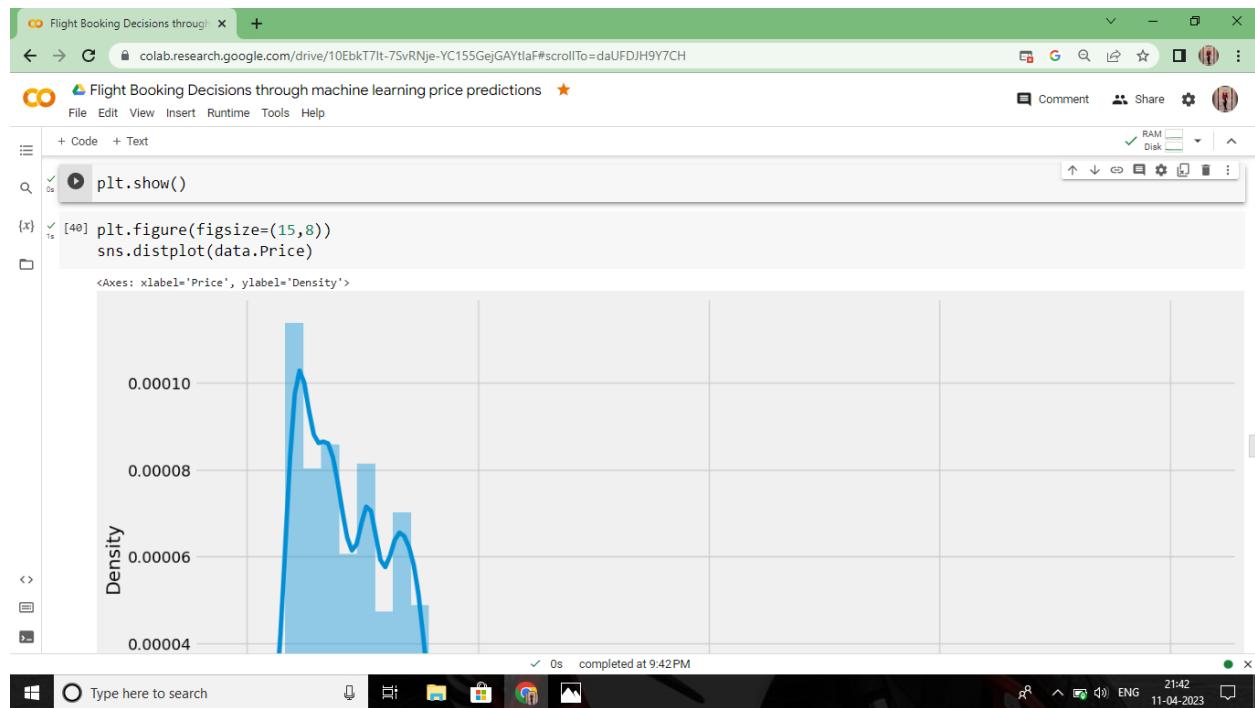
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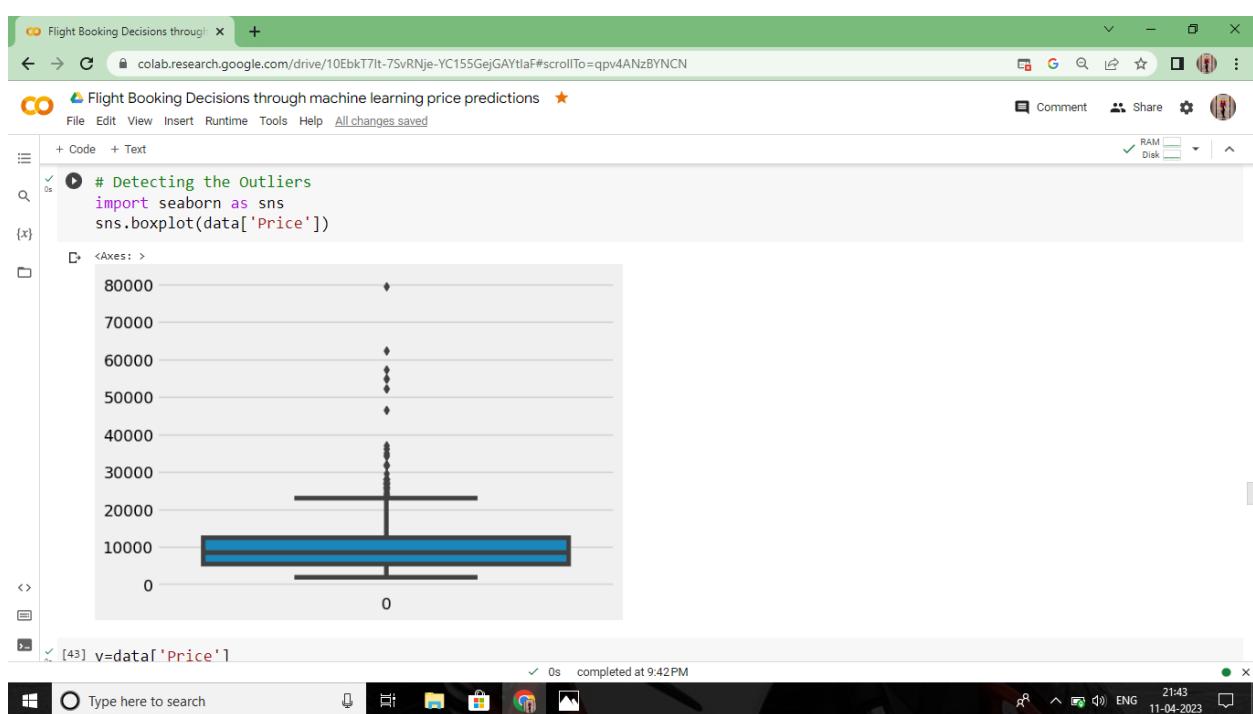
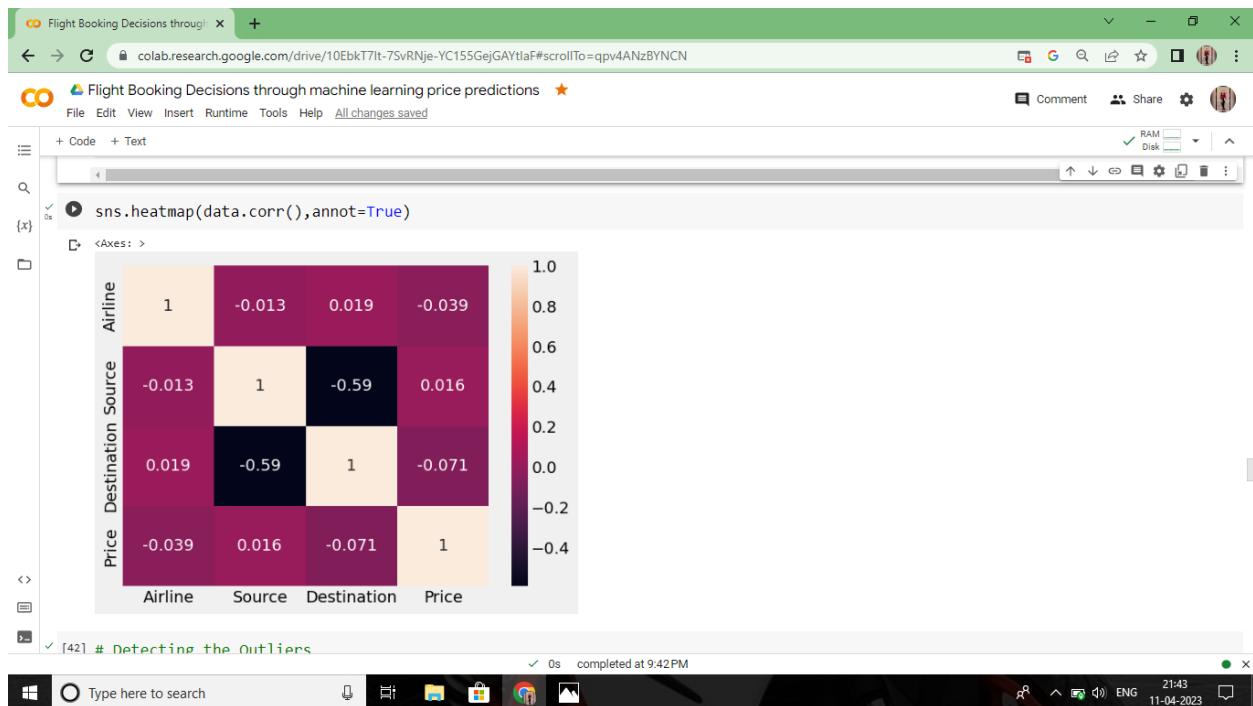
```
+ Code + Text
[38] import seaborn as sns
{x} C=1
plt.figure(figsize=(20,45))

for i in categorical:
    plt.subplot(6,3,C)

    plt.xticks(rotation=90)
    plt.tight_layout(pad=3.0)
    C=C+1
```







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

[44] ### Scaling the Data

[45] from sklearn.preprocessing import StandardScaler
     ss=StandardScaler

[46] x_scaled=ss.fit_transform

[47] data.head()

Airline Source Destination Dep_Time_Hour Dep_Time_Mins Arrival_date Price
0 3 0 5 22 20 0 3897
1 1 3 0 05 50 1 7662
2 4 2 1 09 25 0 13882
3 3 3 0 18 05 2 6218
4 3 0 5 16 50 2 13302
```

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```
[48] 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)

[49] x_train.head()

Airline Source Destination Dep_Time_Hour Dep_Time_Mins Arrival_date
10005 6 2 1 08 30 1
3684 4 2 1 11 30 1
1034 8 2 1 15 45 2
3909 6 2 1 12 50 0
3088 1 2 1 17 15 1

[50] x_train.shape
(8545, 6)

[51] from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, AdaBoostRegressor
     rfr=RandomForestRegressor()
     gb=GradientBoostingRegressor()
     ad=AdaBoostRegressor()
```

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```
[51] from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, AdaBoostRegressor
    rfr=RandomForestRegressor()
    gb=GradientBoostingRegressor()
    ad=AdaBoostRegressor()

Milestone 4: Model Building

[ ] from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error

Regression Model

[71] from sklearn.neighbors import KNeighborsRegressor
    from sklearn.svm import SVR
    from sklearn.tree import DecisionTreeRegressor

[52] from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error

[72] knn=KNeighborsRegressor()
    svr=SVR()
    dt=DecisionTreeRegressor()

[74] for i in [knn,svr,dt]:
```

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```
[74] 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 Score for train data',r2_score(y_train,i.predict(x_train)))
        print('Mean Squared Error is',mean_absolute_error(y_test,y_pred))
        print('Mean Squared Error is',mean_squared_error(y_test,y_pred))
        print('Root Mean Squared Error is',(mean_squared_error(y_test,y_pred,squared=False)))

KNeighborsRegressor()
R2 Score is 0.5723000556363665
R2 Score for train data 0.6651092826489714
Mean Squared Error is 1814.9600374356573
Mean Squared Error is 9041141.594010295
Root Mean Squared Error is 3006.8491139414186
SVR()
R2 Score is -0.03251945438100873
R2 Score for train data -0.02447186805496515
Mean Squared Error is 3627.11085776008436
Mean Squared Error is 21826451.39833652
Root Mean Squared Error is 4671.878786295044
DecisionTreeRegressor()
R2 Score is 0.63399082382534257
R2 Score for train data 0.7321334660000298
Mean Squared Error is 1746.012685649692
```

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```
[74] R2 Score is -0.03251945438190873
[74] R2 Score for train data -0.02447186805496515
[74] Mean Squared Error is 3627.118577608436
[74] Mean Squared Error is 21826451.393833652
[74] Root Mean Squared Error is 4671.878786295044
[74] DecisionTreeRegressor()
[74] R2 Score is 0.6339902382534257
[74] R2 Score for train data 0.7321334660000298
[74] Mean Squared Error is 1746.012685649692
[74] Mean Squared Error is 7737088.381751089
[74] Root Mean Squared Error is 2781.5622196440418

[55] from sklearn.model_selection import cross_val_score

[56] for i in range(2,5):
    cv=cross_val_score(rfr,x,y,cv=i)
    print(rfr.cv.mean())

[57] from sklearn.model_selection import RandomizedSearchCV

[58] param_grid={'n_estimators':[10,30,50,70,100],'max_depth':[None,1,2,3],'max_features':['auto','sqrt']}

[59] rfr=RandomForestRegressor()
```

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```
[59] rfr=RandomForestRegressor()

rfr.fit(x_train,y_train)

[60] gb=GradientBoostingRegressor()
gb_res=RandomizedSearchCV(estimator=gb,param_distributions=param_grid, cv=3, verbose=2, n_jobs=-1)

[61] gb_res.fit(x_train,y_train)
Fitting 3 folds for each of 10 candidates, totalling 30 fits
  >   RandomizedSearchCV
  >   estimator: GradientBoostingRegressor
      >     GradientBoostingRegressor
```

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```
+ Code + Text
gb_res.fit(x_train,y_train)
Fitting 3 folds for each of 10 candidates, totalling 30 fits
RandomizedSearchCV
estimator: GradientBoostingRegressor
GradientBoostingRegressor

Accuracy

[62] 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))

train accuracy 0.6064933937571388
test accuracy 0.45852312577640075

[75] knn=KNeighborsRegressor(n_neighbors=2,algorithm='auto',metric_params=None,n_jobs=-1)
knn.fit(x_train,y_train)
y_train_pred=knn.predict(x_train)
y_test_pred=knn.predict(x_test)
v test nred=knn.npredict(x test)

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Flight Booking Decisions through machine learning price predictions

```
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knn=KNeighborsRegressor(n_neighbors=2,algorithm='auto',metric_params=None,n_jobs=-1)
knn.fit(x_train,y_train)
y_train_pred=knn.predict(x_train)
y_test_pred=knn.predict(x_test)
print("train accuracy",r2_score(y_train_pred,y_train))
print("test accuracy",r2_score(y_test_pred,y_test))

train accuracy 0.5082560160438218
test accuracy 0.28385693588182304

[76] predicted_values=pd.DataFrame({'Actual':y_test,'Predicted':y_pred})

[77] predicted_values
```

	Actual	Predicted
6075	16655	19069.857143
3544	4959	5496.333333
9291	9187	8928.000000
5032	3858	3657.230769
2483	12898	12821.529412
...
9797	7408	12319.470588

```
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```

Flight Booking Decisions through machine learning price predictions

```
+ Code + Text
[77] predicted_values
Actual Predicted
6075 16655 19069.857143
3544 4959 5496.333333
9291 9187 8928.000000
5032 3858 3657.230769
2483 12898 12821.529412
...
9797 7408 12319.470588
9871 4622 4903.714286
10063 7452 7104.100000
8803 7060 6244.185185
8618 13731 11612.809524
2137 rows × 2 columns

[66] prices=rfr.predict(x_test)
[67] price_list=pd.DataFrame({'Price':prices})
```

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```
+ Code + Text
[67] price_list=pd.DataFrame({'Price':prices})
price_list
Price
0 19682.818124
1 5572.503719
2 9060.359167
3 3639.000300
4 13129.288745
...
2132 12017.435099
2133 4616.344545
2134 7158.664772
2135 6213.834415
2136 11593.775334
2137 rows × 1 columns

[] import numpy as np
[] from matplotlib import pyplot as plt
```

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+ Code + Text

```
import numpy as np
from matplotlib import pyplot as plt

ys = 200 + np.random.randn(100)
x = [x for x in range(len(ys))]

plt.plot(x, ys, '-')
plt.fill_between(x, ys, 195, where=(ys > 195), facecolor='g', alpha=0.6)

plt.title("Sample Visualization")
plt.show()
```

Sample Visualization

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