Optimizing Flight Booking Decisions through Machine Learning Price Predictions

BACHELOR OF SCIENCE

IN

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Submitted by

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1. INTRODUCTION:

1.1.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 duration. They will increase the price when people travel more. Estimating the highest prices of the airlines data for the route is collected with features such as Duration, Source, Destination, Arrival and Departure. Features are taken from chosen dataset and in the price wherein 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 shows the best accuracy of 80% for predicting the flight price. also, we have done correlation tests and metrics for the statistical analysis.

Collect The Dataset

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc. In this project we have used .csv data. This data is downloaded from kaggle.com.Please refer to the link given below to download the dataset. Link: https://www.kaggle.com/code/anshigupta01/flight-price-prediction/data As the dataset is downloaded. Let us read and understand the data properly with the help of some visualisation techniques and some analysing techniques

Importing The Libraries

Import the necessary libraries as shown in the image. (optional) Here we have used the visualization style as FiveThirtyEight.

```python
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, GradientBoost
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report, confusion_matri
import warnings
import pickle
from scipy import stats
warnings.filterwarnings('ignore')
plt.style.use('fivethirtyeight')
```

Read The Dataset

Our dataset format might be in .csv, excel files,.txt,.json, etc. We can read the dataset with the help of pandas.

In pandas we have a function called read_csv() to read the dataset. As a parameter

we have to give the directory of csv file.\

Importing the data set

```python
train_data = pd.read_excel("../input/flight-fare-prediction-mh/Data_Train.xl
sx")
pd.set_option('display.max_columns', None)
train_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

```
train_data.info()
```

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

```
train_data["Duration"].value_counts()
```

```
2h 50m     550
1h 30m     386
2h 55m     337
2h 45m     337
2h 35m     329
          ...
35h 35m      1
36h 25m      1
30h 25m      1
30h 10m      1
13h 35m      1
Name: Duration, Length: 368, dtype: int64
```

```
train_data.dropna(inplace = True)
```

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

```
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              0
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        0
Additional_Info    0
Price              0
dtype: int64
```

Data Preparation

As we have understood how the data is let'svv pre-process the collected data.The download data set is not suitable for training the machine learning model as it might have so much of randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps.

Handling missing values
Handling categorical data
Handling outliers
Scaling Techniques
Splitting dataset into training and test set

Note: These are the general steps of pre-processing the data before using it for machine learning. Depending on the condition of your dataset, you may or may not have to go through all these steps.

We have 1 missing value in Route column, and 1 missing value in Total stops column. We will meaningfully replace the missing values going further.

We now start exploring the columns available in our dataset. The first thing we do is to create a list of categorical columns, and check the unique values present in these columns.

1. Airline column has 12 unique values - 'IndiGo' , 'Air India', 'Jet Airways' , 'SpiceJet' , 'Multiple carriers' , 'GoAir', 'Vistara', 'Air Asia', 'Vistara Premium economy' , 'Jet Airways Business', 'Multiple carriers Premium economy', 'Trujet'.
2. Source column has 5 unique values – ‘Bangalore’, ‘Kolkata’, ‘Chennai’, ‘Delhi’ and ‘Mumbai’.
3. Destination column has 6 unique values - 'New Delhi', 'Banglore', 'Cochin', 'Kolkata', 'Delhi' , 'Hyderabad'.
4. Additional info column has 10 unique values - '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'.

We now split the Date column to extract the ‘Date’, ‘Month’ and ‘Year’ values and store them in new columns in our dataframe.

```
#We now split the Date column to extract the 'Date', 'Month' and 'Year' values, and store them in new columns in our dataframe.

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: 10682, dtype: object
```

```
#Treating the data_column


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

• Further, we split the Route column to create multiple columns with cities that the flight travels through. We check the maximum number of stops that a flight has, to confirm what should be the maximum number of cities in the longest route.

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

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

• Since the maximum number of stops is 4, there should be maximum 6 cities in any particular route. We split the data in route column, and store all the city names in separate columns.

```
#Since the maximum number of stops is 4, there should be maximum 6 cities in any particular route. We split the data in route col

data.Route=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: 10682, 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]
```

• In the similar manner, we split the Dep_time column, and create separate columns for departure hours and minutes.

```
#In the similar manner, we split the Dep_time column, and create separate columns for departure hours and minutes -
data.Dep_Time=data.Dep_Time.str.split(':')
```

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

• Further, for the arrival date and arrival time separation, we split the 'Arrival_Time' column, and create 'Arrival_date' column. We also split the time and divide it into 'Arrival_time_hours' and 'Arrival_time_minutes', similar to what we did with the 'Dep_time' column.

```
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]
```

• Next, we divide the ‘Duration’ column to ‘Travel_hours’ and ‘ Travel_mins’

```
#Next, we divide the ‘Duration’ column to ‘Travel_hours’ and ‘ Travel_mins’

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]
```

```
#We also treat the ‘Total_stops’ column, and replace non-stop flights with 0 value and extract the integer part of the ‘Total_Sto
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]
```

• We also treat the ‘Total_stops’ column, and replace non-stop flights with 0 value and extract the integer part of the ‘Total_Stops’ column.


```
#We also treat the ‘Total_stops’ column, and replace non-stop flights with 0 value and extract the integer part of the ‘Total_Sto
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]
```


• We proceed further to the ‘Additional_info’ column, where we observe that there are 2 categories signifying ‘No info’, which are divided into 2 categories since ‘I’ in ‘No Info’ is capital. We replace ‘No Info’ by ‘No info’ to merge it into a single category.

```
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)
```

• We now drop all the columns from which we have extracted the useful information (original columns). We also drop some columns like ‘city4’,'city5' and ‘city6’, since majority of the data in these columns was NaN(null). As a result, we now obtain 20 different columns, which we will be feeding to our ML model. But first, we treat the missing values and explore the contents in the columns and its impact on the flight price, to separate a list of final set of columns.

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

```
Airline                 0
Date_of_Journey         0
Source                  0
Destination             0
Route                   0
Dep_Time                0
Arrival_Time            0
Duration                0
Total_Stops             0
Additional_Info         0
Price                   0
City1                   0
City2                   0
City3                3491
City4                9116
City5               10636
City6               10681
Date                    0
Month                   0
Year                    0
Dep_Time_Hour           0
Dep_Time_Mins           0
Arrival_date         6348
Time_of_Arrival         0
Arrival_Time_Hour       0
Arrival_Time_Mins       0
Travel_Hours            0
Travel_Mins          1032
dtype: int64
```

```
#We also drop some columns like ‘city6’ and ‘city5’, since majority of the data in these columns was NaN(null)
data.drop(['City4','City5','City6'],axis=1,inplace=True)
```

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

• After dropping some columns, here we can see the meaningful columns to predict the flight price without the NaN values.

```
#Checking Null Values
data.isnull().sum()
```

```
Airline                 0
Source                  0
Destination             0
Total_Stops             0
Additional_Info         0
Price                   0
City1                   0
City2                   0
City3                3491
Date                    0
Month                   0
Year                    0
Dep_Time_Hour           0
Dep_Time_Mins           0
Arrival_date         6348
Arrival_Time_Hour       0
Arrival_Time_Mins       0
Travel_Hours            0
Travel_Mins          1032
dtype: int64
```

Replacing Missing Values

```
#filling City3 as None, the missing values are less
data['City3'].fillna('None',inplace=True)
```

```
#filling Arrival_Date as Departure_Date
data['Arrival_date'].fillna(data['Date'],inplace=True)
```

```
#filling Travel_Mins as Zero(0)
data['Travel_Mins'].fillna(0,inplace=True)
```

• Using the above steps, we were successfully able to treat all the missing values from our data. We again check the info in our data and find out that the dataset still has data types for multiple columns as ‘object’, where it should be ‘int’.

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10682 entries, 0 to 10682
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Airline            10682 non-null  object
 1   Source             10682 non-null  object
 2   Destination        10682 non-null  object
 3   Total_Stops        10682 non-null  object
 4   Additional_Info    10682 non-null  object
 5   Price              10682 non-null  int64 
 6   City1              10682 non-null  object
 7   City2              10682 non-null  object
 8   City3              10682 non-null  object
 9   Date               10682 non-null  object
 10  Month              10682 non-null  object
 11  Year               10682 non-null  object
 12  Dep_Time_Hour      10682 non-null  object
 13  Dep_Time_Mins      10682 non-null  object
 14  Arrival_date       10682 non-null  object
 15  Arrival_Time_Hour  10682 non-null  object
 16  Arrival_Time_Mins  10682 non-null  object
 17  Travel_Hours       10682 non-null  object
 18  Travel_Mins        10682 non-null  object
dtypes: int64(1), object(18)
memory usage: 1.6+ MB
```

• Hence, we try to change the datatype of the required columns

```
#changing the numerical columns from object to int
#data.Total_Stops=data.Total_Stops.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.Dep_Time_Mins=data.Dep_Time_Mins.astype('int64')
data.Arrival_date=data.Arrival_date.astype("int64")
data.Arrival_Time_Hour=data.Arrival_Time_Hour.astype('int64')
data.Arrival_Time_Mins=data.Arrival_Time_Mins.astype('int64')
#data.Travel_Hours=data.Travel_Hours.astype('int64')
data.Travel_Mins=data.Travel_Mins.astype('int64')
```

• During this step, we face issue converting the ‘Travel_hours’ column, saying that the column has data as ‘5m’, which is not allowing its conversion to ‘int’.

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

Price	City1	City2	City3	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_Time_Hour	Arrival_Time_Mins	Travel_Hours	Travel_Mins
17327	BOM	GOI	PNQ	6	3	2019	16	50	6	16	55	5m	0

• The data signifies that the flight time is ‘5m’, which is obviously wrong as the plane cannot fly from BOMBAY->GOA->PUNE->HYDERABAD in 5 mins! (The flight has ‘Total_stops’ as 2)

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

• We then convert the ‘Travel_hours’ column to ‘int’ data type, and the operation happens successfully.
• We now have a treated dataset with 10682 rows and 17 columns (16 independent and 1 dependent variable).

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

```
#Creating list of Different types of columns
categorical=['Airline','Source','Destination','Additional_Info','City1']
numerical=['Total_Stops','Date','Month','Year','Dep_Time_Hour','Dep_Time_Mins','Arrival_date','Arrival_Time_Hour',
           'Arrival_Time_Mins','Travel_Hours','Travel_Mins']
```

• We create separate lists of categorical columns and numerical columns for plotting and analyzing the data

Label Encoding

• label Encoding of the dataset and enables the mLabel encoding converts the data in machine readable form, but it assigns a unique number (starting from 0) to each class of data. it performs the conversion of categorical data into numeric format.
• In our dataset I have converted these variables'Airline','Source','Destination','Total_Stops','City1','City2','City3','Additional_Info' into number format. So that it helps the model in better structures. understanding odel to learn more complex.

```
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.City1	=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	Total_Stops	Additional_Info	Price	City1	City2	City3	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arri
0	3	0	5	4	7	3897	0	13	29	24	3	2019	22	20	22	
1	1	3	0	1	7	7662	2	25	1	1	5	2019	5	50	1	
2	4	2	1	1	7	13882	3	32	4	9	6	2019	9	25	10	
3	3	3	0	0	7	6218	2	34	3	12	5	2019	18	5	12	
4	3	0	5	0	7	13302	0	34	8	1	3	2019	16	50	1	

Output Columns

• Initially in our dataset we have 19 features. So, in that some features are not more important to get output (Price).
• So i removed some unrelated features and I selected important features. So, it makes easy to understand. Now we have only 12 Output Columns.

```
data.head()
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	City1	City2	City3	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arriv
0	3	0	5	4	7	3897	0	13	29	24	3	2019	22	20	22	
1	1	3	0	1	7	7662	2	25	1	1	5	2019	5	50	1	
2	4	2	1	1	7	13882	3	32	4	9	6	2019	9	25	10	
3	3	3	0	0	7	6218	2	34	3	12	5	2019	18	5	12	
4	3	0	5	0	7	13302	0	34	8	1	3	2019	16	50	1	

```
data = data[['Airline','Source','Destination','Date','Month','Year','Dep_Time_Hour','Dep_Time_Mins','Arrival_date','Arrival_Time_
```

```
data.head()
```

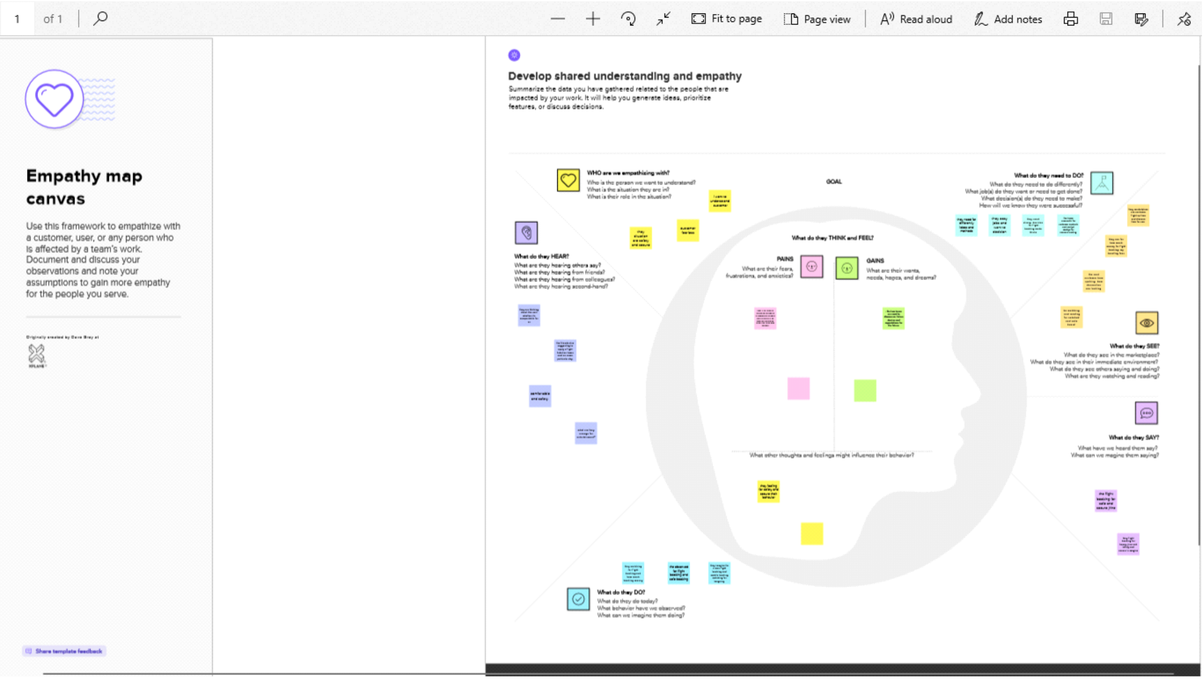
	Airline	Source	Destination	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_Time_Hour	Arrival_Time_Mins	Price
0	3	0	5	24	3	2019	22	20	22	1	10	3897
1	1	3	0	1	5	2019	5	50	1	13	15	7662
2	4	2	1	9	6	2019	9	25	10	4	25	13882
3	3	3	0	12	5	2019	18	5	12	23	30	6218
4	3	0	5	1	3	2019	16	50	1	21	35	13302

1.2 Purpose

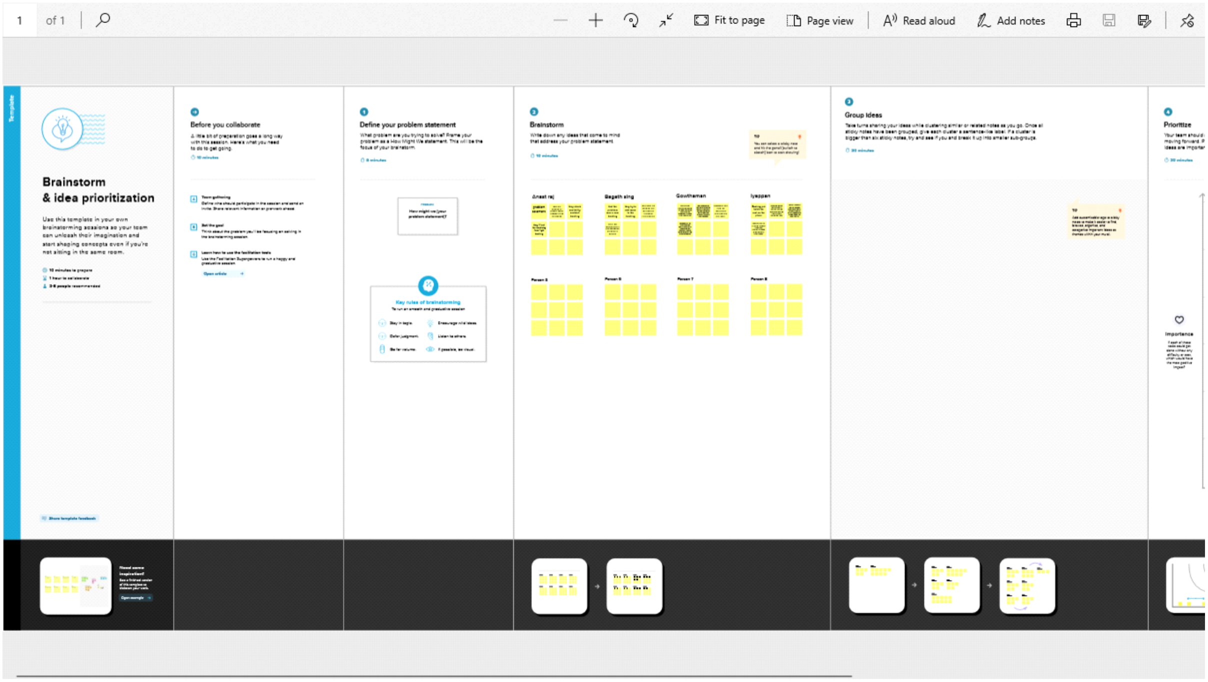
The Flight ticket prices increase or decrease every now and then depending on various factors like timing of the flights, destination, duration of flights. In the proposed system a predictive model will be created by applying machine learning algorithms to the collected historical data of flights. Optimal timing for airline ticket purchasing from the consumer's perspective is challenging principally because buyers have insufficient information for reasoning about future price movements. In this project we majorly targeted to uncover underlying trends of flight prices in India using historical data and also to suggest the best time to buy a flight ticket. The project implements the validations or contradictions towards myths regarding the airline industry, a comparison study among various models in predicting the optimal time to buy the flight ticket and the amount that can be saved if done so. Remarkably, the trends of the prices are highly sensitive to the route, month of departure, day of departure, time of departure, whether the day of departure is a holiday and airline carrier. Highly competitive routes like most business routes (tier 1 to tier 1 cities like Mumbai-Delhi) had a non-decreasing trend where prices increased as days to departure decreased, however other routes (tier 1 to tier 2 cities like Delhi - Guwahati) had a specific time frame where the prices are minimum. Moreover, the data also uncovered two basic categories of airline carriers operating in India – the economical group and the luxurious group, and in most cases, the minimum priced flight was a member of the economical group. The data also validated the fact that, there are certain time-periods of the day where the prices are expected to be maximum. The scope of the project can be extensively extended across the various routes to make significant savings on the purchase of flight prices across the Indian Domestic Airline market.

2. Problem Definition & Design Thinking:

2.1 Empathy map



2.2 Ideation & Brainstorming Map



3. RESULT:

The Best Model Saving the best model after comparing its performance using different evaluation metrics means selecting the model with the highest performance and saving its weights and configuration. This can be useful in avoiding the need to retrain the model every time it is needed and also to be able to use it in the future.

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

Integrate With Web Framework

In this section, we will be building a web application that is integrated to the model we built. A UI is provided for the uses where he has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.

This section has the following tasks

• Building HTML pages
• Building server side script
• Run the web application

Building Html Pages

For this project create two HTML files namely

• home.html
• predict.html
• submit.html

and save them in the templates folder.

Build Python Code

Import the libraries

```python
from flask import Flask, render_template, request
import numpy as np
import pickle
```

Load the saved model. Importing the flask module in the project is mandatory. An object of Flask class is our WSGI application. Flask constructor takes the name of the current module (__name__) as argument.

```python
model = pickle.load(open(r"model1.pkl",'rb'))
```

Render HTML page:

```python
@app.route("/home")
def home():
    return render_template('home.html')
```

Here we will be using a declared constructor to route to the HTML page which we have created earlier.

In the above example, '/' URL is bound with the home.html function. Hence, when the home page of the web server is opened in the browser, the html page will be rendered. Whenever you enter the values from the html page the values can be retrieved using POST Method.

Retrieves the value from UI:

```python
@app.route("/predict")
def home1():
    return render_template('predict.html')




@app.route("/pred", methods=['POST','GET'])
def predict():
    x = [[int(x) for x in request.form.values()]]
    print(x)

    x = np.array(x)
    print(x.shape)


    print(x)
    pred = model.predict(x)
    print(pred)
    return render_template('submit.html', prediction_text=pred)
```

Here we are routing our app to predict() function. This function retrieves all the values from the HTML page using Post request. That is stored in an array. This array is passed to the model.predict() function. This function returns the prediction.

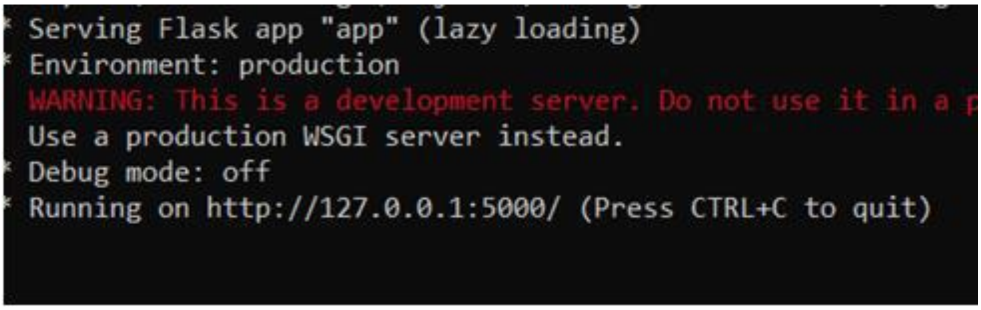
And this prediction value will be rendered to the text that we have mentioned in the submit.html page earlier.

Main Function:

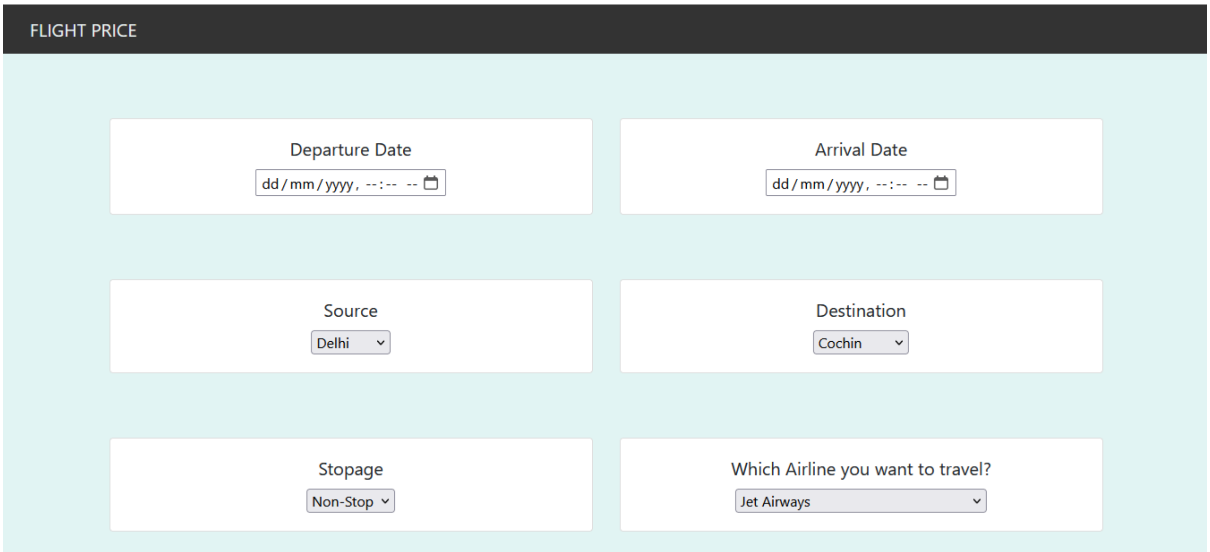
```python
if __name__ == "__main__":
    app.run(debug=False)
```

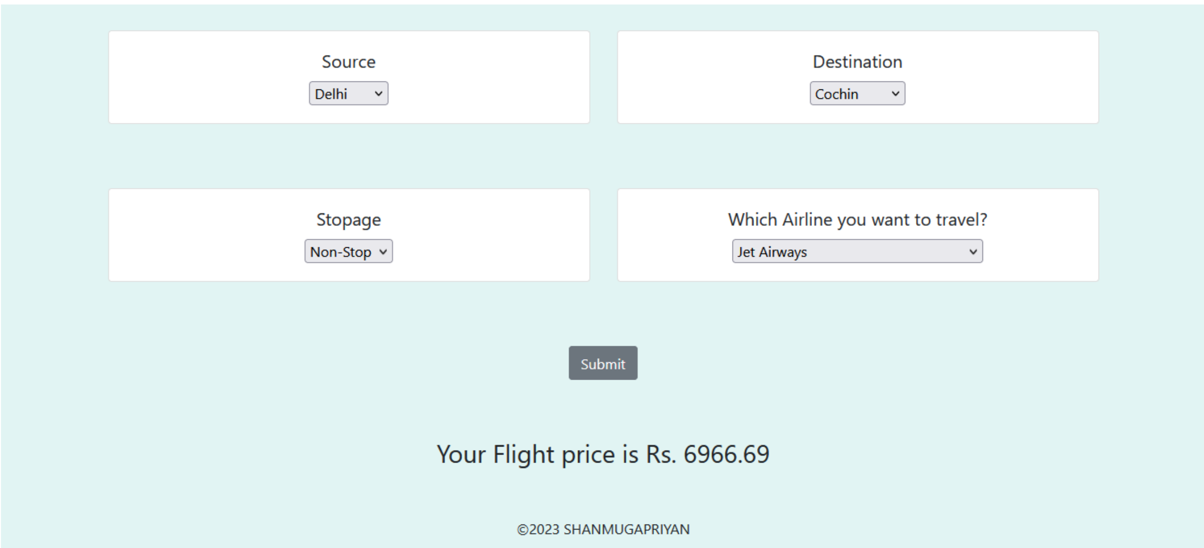
Run The Web Application

• Open anaconda prompt from the start menu
• Navigate to the folder where your python script is.
• Now type “python app.py” command
• Navigate to the localhost where you can view your web page.
• Click on the predict button from the top left corner, enter the inputs, click on the submit button, and see the result/prediction on the web.



Now,Go the web browser and write the localhost url (http://127.0.0.1:5000) to get the below result.





4.ADVANTAGES&DISADVANTAGES:

Advantages

Pricing automation. Businesses that implement dynamic pricing can completely or partially automate price adjustments – depending on their needs. Pricing tools evaluate a large number of internal (stock or inventory, KPIs, etc.) and external factors (competitor prices, demand, etc.) to generate prices that alignwith a company's pricing strategy.Increased competitiveness. The ability of a business to respond to current demand ,rationally use its inventory or stock, or develop a brand perception through specific pricing decisions allows it to stay afloat no matter what the current market condition is. For instance, an airline can secure itself from bad sales during a lowdemand season or before an upcoming departure day by putting tickets on sale.

Disadvantages

Customer alienation and backlash. Generally, people accept price drops and increases when booking accommodation or flights, which isn't the case for retailers and car rental companies in particular. "Customers don't like to feel like they've paid more than other people for the same product or service. Such a pricing strategy can l ead to bad reviews, complaints, or worse. One case for customer alienation is that when users put an item in the basket without purchasing the item and after a day or so, they'll get a discount code for the abandoned cart item," explains Kocak. Regular customers may get offended once they see that a seller gives a discount to shoppers that take their time before the checkout. Poising a rhetorical question that the customer must ponder, the expert asks, "So why are regular shoppers treated badly although they bring more value to the business?" "some issues" during implementation, thinks data scientist Stylianos Kampakis. The expert recalls cases when clients were charged preposterous fees for short rides due to extremely high demand, for instance, on the New Year's Eve.

5.APPLICATIONS:

Currently, everyone loves to travel by flights. Going along with the study, the charge of travelling through a plane change now and then which also includes the day and night time. Additionally, it changes with special times of the year or celebration seasons. There are a few unique elements upon which the cost of air transport depends. The salesperson has data regarding each of the variables, however, buyers can get confined information which is not sufficient to foresee the airfare costs. Considering the provisions, for example, time of theday, the number of days remaining and the time of take-off this will provide the perfect time to purchase the plane ticket. The motivation behind this paper is to concentrate on every component that impacts the variations in the costs of this means of transport and how these are connected with the diversity in the airfare. Subsequently, at that point, utilizing this data, construct a framework that can help purchasers when to purchase a ticket. Machine Learning algorithms prove to be the best solution for the above-discussed problems. In this project, there is an implementation of Artificial Neural Network (ANN), LR (Linear Regression), DT (Decision Tree), and RF (Random Forest).

6.CONCLUSION:

Machine Learning algorithms are applied on the dataset to predict the dynamic fare of flights. 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 predictions based on the previous trends with our prediction.

7.FUTURE SCOPE:

To evaluate the conventional algorithm, a dataset is built for route BOMBAY to DELHI and studied a trend of price variation for the period of limited days. Machine Learning algorithms are applied on the dataset to predict the dynamic fare of flights. 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.

8. APPENDIX:

Descriptive Statistical

Descriptive analysis is to study the basic features of data with the statistical process. Here pandas has a worthy function called describe. With this describe function we can understand the unique, top and frequent values of categorical features. And we can find mean, std, min, max and percentile values of continuous features.

```
data.describe()
```

	Price
count	10683.000000
mean	9087.064121
std	4611.359167
min	1759.000000
25%	5277.000000
50%	8372.000000
75%	12373.000000
max	79512.000000

Visual Analysis

- Plotting countplots for categorical data

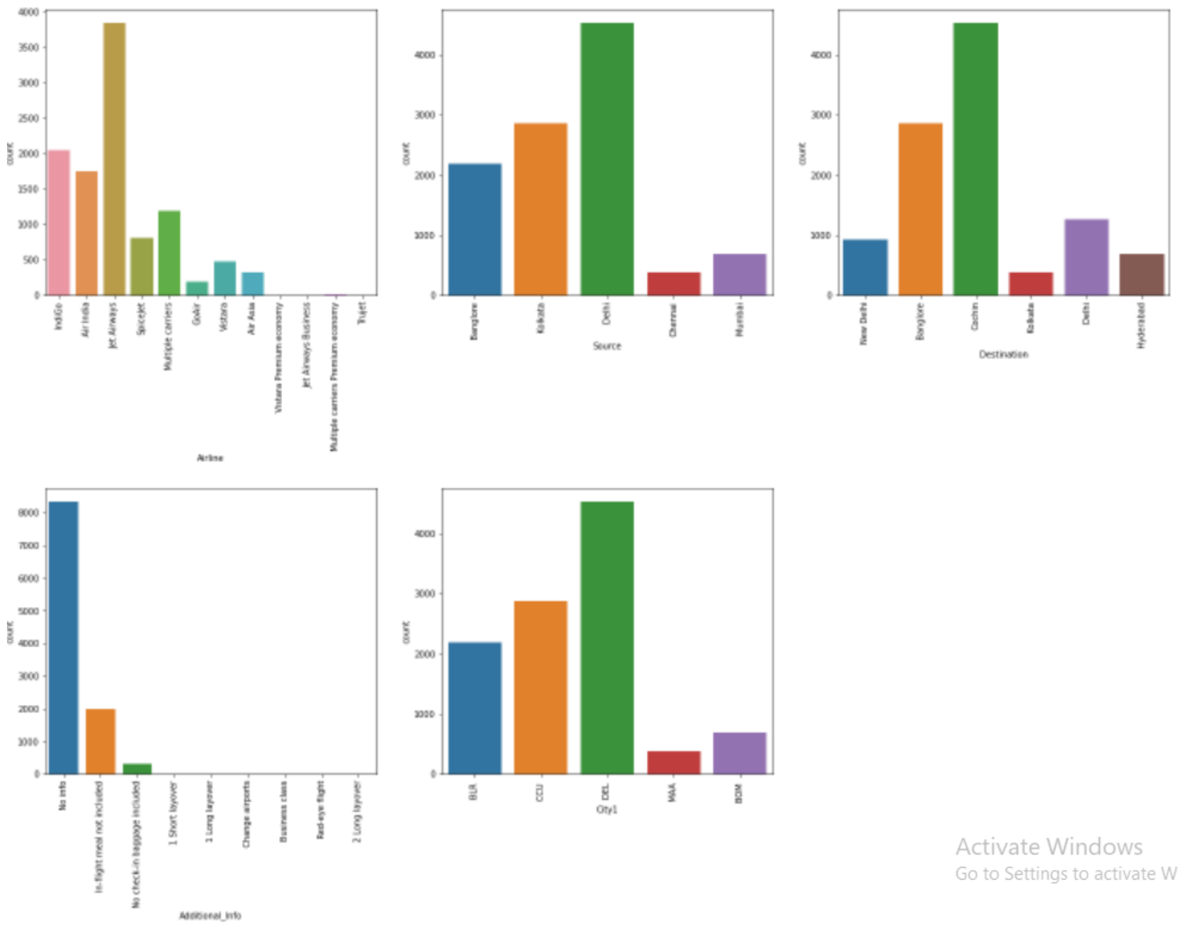
```python
#plotting Countplots for Categorical Data

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

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()
```

```
C:\Users\SmartBridge-PC\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an ex
plicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\SmartBridge-PC\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an ex
plicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\SmartBridge-PC\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an ex
plicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\SmartBridge-PC\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an ex
plicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\SmartBridge-PC\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an ex
plicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



We Now Plot Distribution Plots To Check The Distribution

In Numerical Data (Distribution Of 'Price' Column)

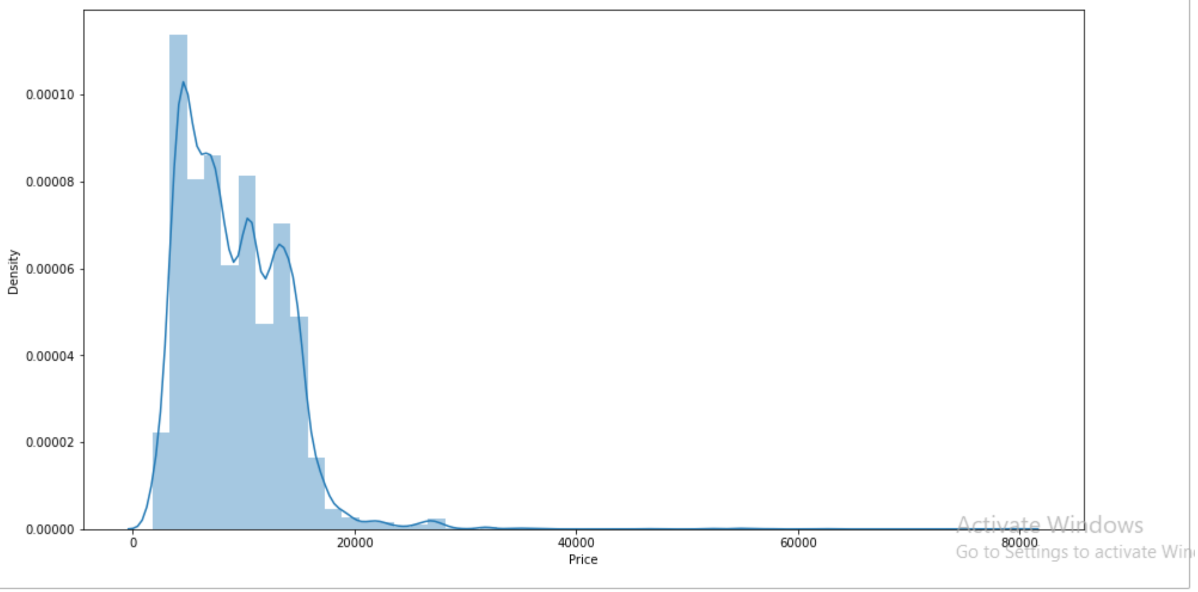
• The seaborn.displot() function is used to plot the displot. The displot represents the univariate distribution of data variable as an argument and returns the plot with the density distribution. Here, I used distribution(displot) on 'Price' column.

• It estimates the probability of distribution of continous variable across various data.

```
#Distribution of 'PRICE' Column
plt.figure(figsize=(15,8))
sns.distplot(data.Price)
```

```
C:\Users\SmartBridge-PC\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated fu
nction and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with si
milar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```



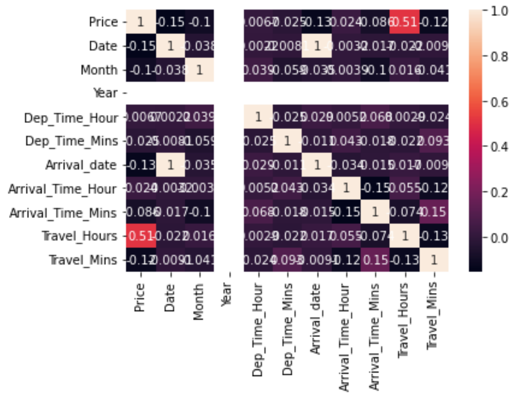
Checking The Correlation Using HeatMap

• Here, I 'm finding the correlation using HeatMap. It visualizes the data in 2-D colored maps making use of color variations. It describes the relationship variables in form of colors instead of numbers it will be plotted on both axes.

• So, by this heatmap we found that correlation between 'Arrival_date' and 'Date'. Remaining all columns don't have the any Correlation.

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

<AxesSubplot:>



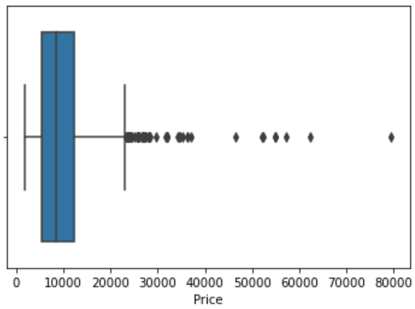
Outlier Detection For 'Price' Column

Sometimes it's best to keep outliers in your data. it captures the valuable information and they can effect on statistical results and detect any errors in your statistical process. Here, we are checking Outliers in the 'Price' column.

```
# Detecting the Outliers
import seaborn as sns
sns.boxplot(data['Price'])
```

```
C:\Users\SmartBridge-PC\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

<AxesSubplot:xlabel='Price'>



Scaling the Data

• We are taking two variables 'x' and 'y' to split the dataset as train and test.
• On x variable, drop is passed with dropping the target variable. And on y target variable('Price') is passed.
• Scaling the features makes the flow of gradient descent smooth and helps algorithms quickly reach the minima of the cost function.
• Without scaling features, the algorithm maybe biased toward the feature which has values higher in magnitude. it brings every feature in the same range and the model uses every feature wisely.

• We have popular techniques used to scale all the features but I used StandardScaler in which we transform the feature such that the changed features will have mean=0 and standard deviation=1.

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

```
### Scaling the Data
```

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

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

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

	Airline	Source	Destination	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_Time_Hour	Arrival_Time_Mins
0	-0.410934	-1.658354	2.416648	1.237192	-1.467619	0.0	1.654162	-0.234832	0.955658	-1.800328	-0.889941
1	-1.261305	0.890262	-0.973718	-1.475375	0.250165	0.0	-1.303018	1.363790	-1.524701	-0.050871	-0.586988
2	0.014251	0.040723	-0.295645	-0.531874	1.109057	0.0	-0.607211	0.031605	-0.461690	-1.362964	0.018919
3	-0.410934	0.890262	-0.973718	-0.178060	0.250165	0.0	0.958355	-1.034142	-0.225465	1.407010	0.321872
4	-0.410934	-1.658354	2.416648	-1.475375	-1.467619	0.0	0.610452	1.363790	-1.524701	1.115434	0.624825

Splitting data into train and test

Now let's split the Dataset into train and test sets.

For splitting training and testing data we are using train_test_split() function. From sklearn. As parameters, we are passing x, y, test_size, random_state.

```
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	Source	Destination	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_Time_Hour	Arrival_Time_Mins
10611	4	4	3	18	5	2019	7	5	18	8	30
1034	8	2	1	24	4	2019	15	45	24	22	5
8123	4	2	1	27	6	2019	2	15	27	12	35
4779	4	3	0	1	4	2019	6	30	1	18	15
3207	3	3	0	24	5	2019	18	5	24	23	30

Using Ensemble Techniques

RandomForestRegressor, GradientBoostingRegressor, AdaBoostRegressor
A function named RandomForest, GradientBoosting, AdaBoost is created and train and test data are passed as the parameters. Inside the function, RandomForest, GradientBoosting, AdaBoost algorithm is initialized and training data is passed to the model with .fit() function. Test data is predicted with .predict() function and saved in new variable. For evaluating the model, r2_score, mean_absolute_error, and mean_squared_error report is done.

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

```
RandomForestRegressor()
R2 score is 0.8227214297234019
R2 for train data 0.9510465962960551
Mean Absolute Error is 1182.0594710483324
Mean Squared Error is 3742662.8044006103
Root Mean Sqaured Error is 1934.596289772264
GradientBoostingRegressor()
R2 score is 0.7647464119441486
R2 for train data 0.7333243455087605
Mean Absolute Error is 1678.510006493234
Mean Squared Error is 4966617.523170804
Root Mean Sqaured Error is 2228.5909277323203
AdaBoostRegressor()
R2 score is 0.2582227532056507
R2 for train data 0.2911833713550127
Mean Absolute Error is 3276.5456982057563
Mean Squared Error is 15660223.942444455
Root Mean Sqaured Error is 3957.3008824355554
```


Regression Model

KNeighborsRegressor, SVR, DecisionTreeRegressor A function named KNN, SVR, DecisionTree is created and train and test data are passed as the parameters. Inside the function, KNN, SVR, DecisionTree algorithmis initialized and training data is passed to the model with .fit() function. Test data is predicted with .predict() function and saved in new variable. For evaluating the model, r2_score, mean_absolute_error, and mean_squared_error is done.

```
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 Score for train data',r2_score(y_train,i.predict(x_train)))
        print('Mean Absolute 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 0.7354576039734038
R2 Score for train data 0.7910150823510993
Mean Absolute Error is 1635.3106223678053
Mean Squared Error is 5584955.836743098
Root Mean Squared Error is 2363.2511158874117
SVR()
R2 Score is -0.007934481035057894
R2 Score for train data -0.012381130959185693
Mean Absolute Error is 3631.923243955232
Mean Squared Error is 21279271.857602067
Root Mean Squared Error is 4612.94611475162
```

Checking Cross Validation For RandomForestRegressor

We perform the cross validation of our model to check if the model has any overfitting issue, by checking the ability of the model to make predictions on new data, using k-folds. We test the cross validation for Random forest and Gradient Boosting Regressor.

```
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() 0.7916634416866438
RandomForestRegressor() 0.7929369032321089
RandomForestRegressor() 0.799914397784633
```

Hypertuning The Model

RandomSearch CV is a technique used to validate the model with different parameter combinations, by creating a random of parameters and trying all the combinations to compare which combination gave the best results. We apply random search on our model. From sklearn, cross_val_score is used to evaluate the score of the model. On the parameters, we have given rf (model name), x, y, cv (as 3 folds). Our model is performing well.

```
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)
```

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

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

```
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)
```

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

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

Now let's see the performance of all the models and save the best model

Accuracy

Checking Train and Test Accuracy by RandomSearchCV using RandomForestRegression Model

```
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 0.9299395776145483
test accuracy 0.7657841369272524
```

Checking Train and Test Accuracy by RandomSearchCV using KNN Model2

```
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 0.8829162343701471
test accuracy 0.6874228308668873
```

By Observing two models train and test accuracy we are getting good accuracy in RandomForestRegression

Evaluating Performance Of The Model And Saving The Model

From sklearn, cross_val_score is used to evaluate the score of the model. On the parameters, we have given rfr (model name), x, y, cv (as 3 folds). Our model is performing well. So, we are saving the model by pickle.dump().

Note: To understand cross validation, refer this link.

[https://towardsdatascience.com/cross-validation-explained-evaluating-estimatorperformance- e51e5430ff85](https://towardsdatascience.com/cross-validation-explained-evaluating-estimatorperformance-e51e5430ff85).

```
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 0.9299395776145483
test accuracy 0.7657841369272524
```

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

```
price_list
```

	Price
0	5852.800000
1	9121.900000
2	10931.640000
3	14780.700000
4	6064.600000
...	...
2132	7171.200000
2133	7381.200000
2134	7820.900000
2135	12388.673333
2136	13314.400000

2137 rows × 1 columns

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