OPTIMIZING FLIGHT BOOKING DECISIONS THROUGH MACHINE LEARNING PRICE PREDICTION

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CLASS : BSC COMPUTER SCIENCE

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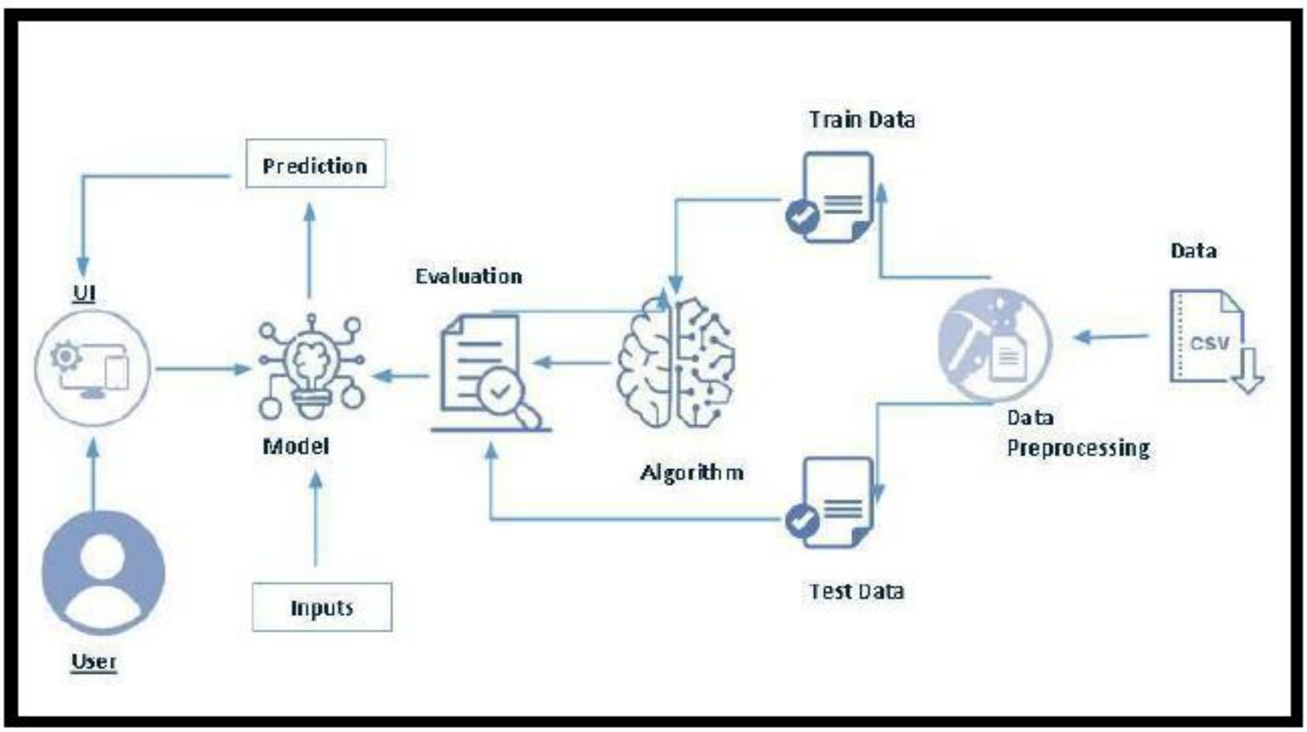
1.INTRODUCTION

FLIGHT PRICE PREDICTION THROUGH MACHINE LEARNING:

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

Technical Architecture:



1.1.OVERVIEW

- User interacts with the UI to enter the input.
- Entered input is analysed by the model which is integrated.

- Once model analyses the input the prediction is showcased on the UI

To accomplish this, we have to complete all the activities listed below,

- Define Problem / Problem Understanding
    - Specify the business problem
    - Business requirements
    - Literature Survey
    - Social or Business Impact.

- Data Collection & Preparation
    - Collect the dataset
    - Data Preparation

- Exploratory Data Analysis
    - Descriptive statistical
    - Visual Analysis

- Model Building
    - Training the model in multiple algorithms
    - Testing the model

- Performance Testing & Hyperparameter Tuning
    - Testing model with multiple evaluation metrics
    - Comparing model accuracy before & after applying hyperparameter tuning
- Model Deployment
    - Save the best model
    - Integrate with Web Framework
- Project Demonstration & Documentation

○ Record explanation Video for project end to end solution

○ Project Documentation-Step by step project development procedure

1.2.PURPOSE

Flights price prediction is a crucial task in the travel industry, as it allows both travel agencies and customers to plan their trips more efficiently and cost-effectively. By analyzing various data sources such as historical flight prices, seasonal patterns, and market trends, predictive models can estimate the probability of future prices for different routes and dates. This information can help travel companies to optimize their pricing strategies and provide personalized offers to their customers, while also enabling travelers to make informed decisions about their travel plans. Additionally, flights price prediction can contribute to reducing the risk of overbooking, cancellations, and revenue loss for airlines, leading to a more efficient and reliable air travel industry.

2.PROBLEM DEFINITION & DESIGN THINKING

The business requirements for a machine learning model to predict personal loan approval include theability to accurately predict loan approval based on applicant information, Minimise the number of falsepositives (approved loans that default) and false negatives (rejected loans that would have beensuccessful). Provide an explanation for the model's decision, to comply with regulations and improve Transparency.

As the data is increasing daily due to digitization in the banking sector, people want to apply for loans throughthe internet. Machine Learning (ML), as a typical method for information investigation, has gotten moreconsideration increasingly. Individuals of various businesses are utilising ML calculations to take care of theissues dependent on their industry information. Banks are facing a significant problem in the approval of theloan. Daily there are so many applications that are challenging to manage by the bank employees, and alsothe chances of some mistakes are high.Most banks earn profit from the loan, but it is risky to choosedeserving customers from the number of applications.There are various algorithms that have been used withvarying levels of success. Logistic regression, decision tree, random forest, and neural networks have allbeen used and have been able to accurately predict loan defaults. Commonly used features in these studiesinclude credit score, income, and employment history, sometimes also other features like age, occupation,and education level.

Flight price prediction is a challenging problem in the domain of travel and tourism. This problem involves predicting the future price of a flight ticket with respect to various factors that influence the pricing model of airlines. In this paper, we provide a comprehensive overview of the problem of flight price prediction and discuss various approaches that have been proposed in the literature to address this problem. The pricing model of airlines is influenced by a variety of factors, such as the date and time of travel, the destination and departure location, the type of airline, the availability of seats, and the demand-supply dynamics of the market. These factors are typically used to build predictive models that can forecast the future price of flight tickets. Various approaches have been proposed in the literature to address the problem of flight price prediction. These approaches can be broadly categorized into two groups: traditional statistical models and machine learning models.

Traditional statistical models involve using regression analysis to model the relationship between various factors and flight prices.

2.1 EMPATHY MAP

In the ideation phase we have empathized as our client flight price prediction with machine learning and we have acquired the details which are represented in the Empathy Map given below.

Template

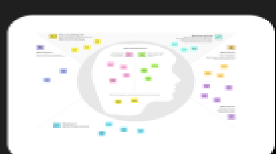
Empathy map canvas

Use this framework to empathize with a customer, user, or any person who is affected by a team's work. Document and discuss your observations and note your assumptions to gain more empathy for the people you serve.

Originally created by Dave Gray at

XPLANE

Share template feedback



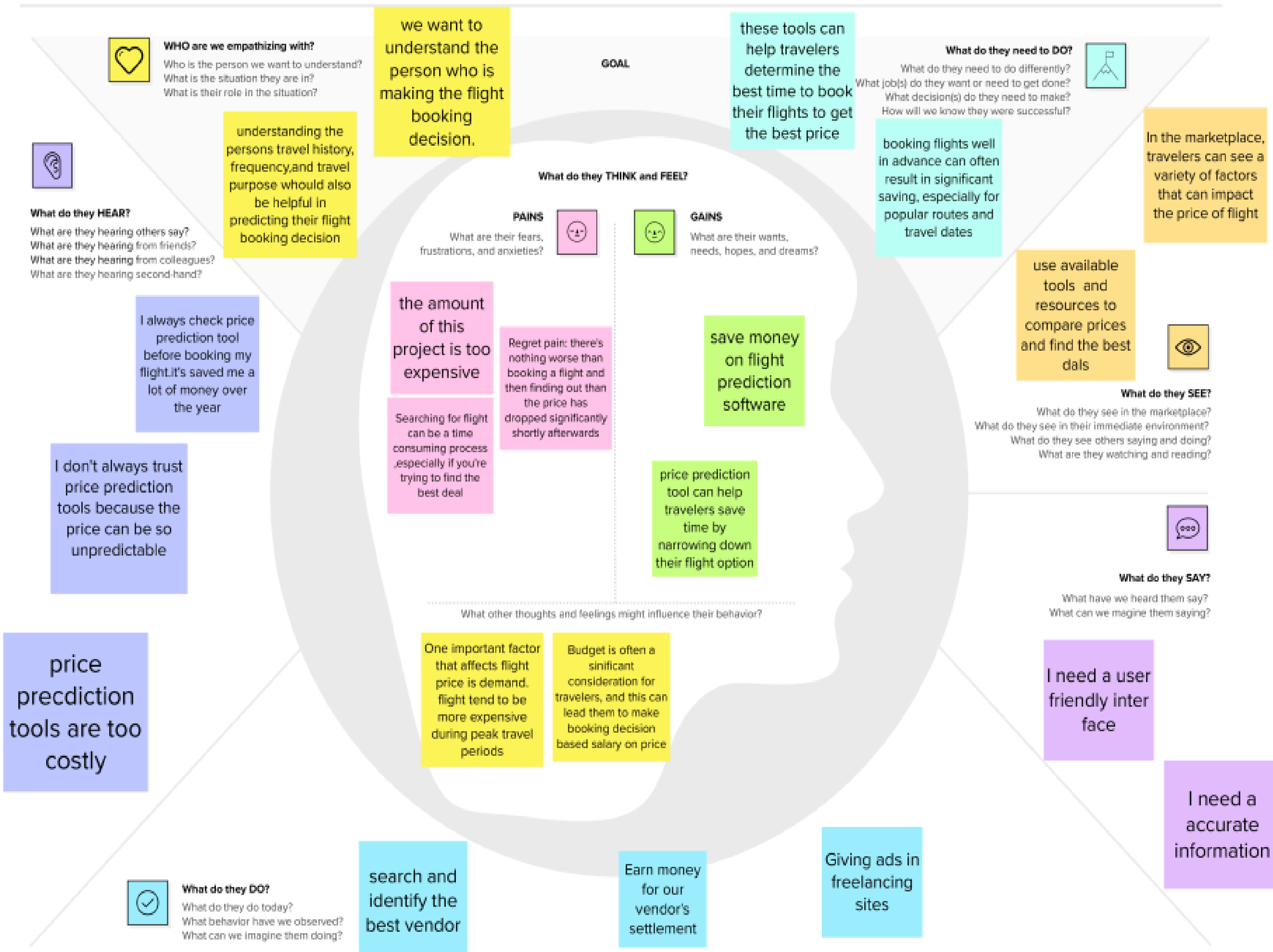
Need some inspiration?

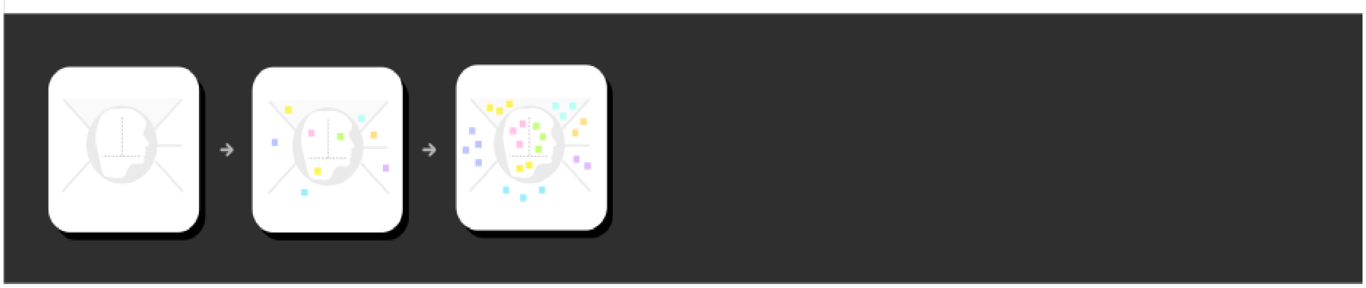
See a finished version of this template to kickstart your work.

Open example →

Develop shared understanding and empathy

Summarize the data you have gathered related to the people that are impacted by your work. It will help you generate ideas, prioritize features, or discuss decisions.

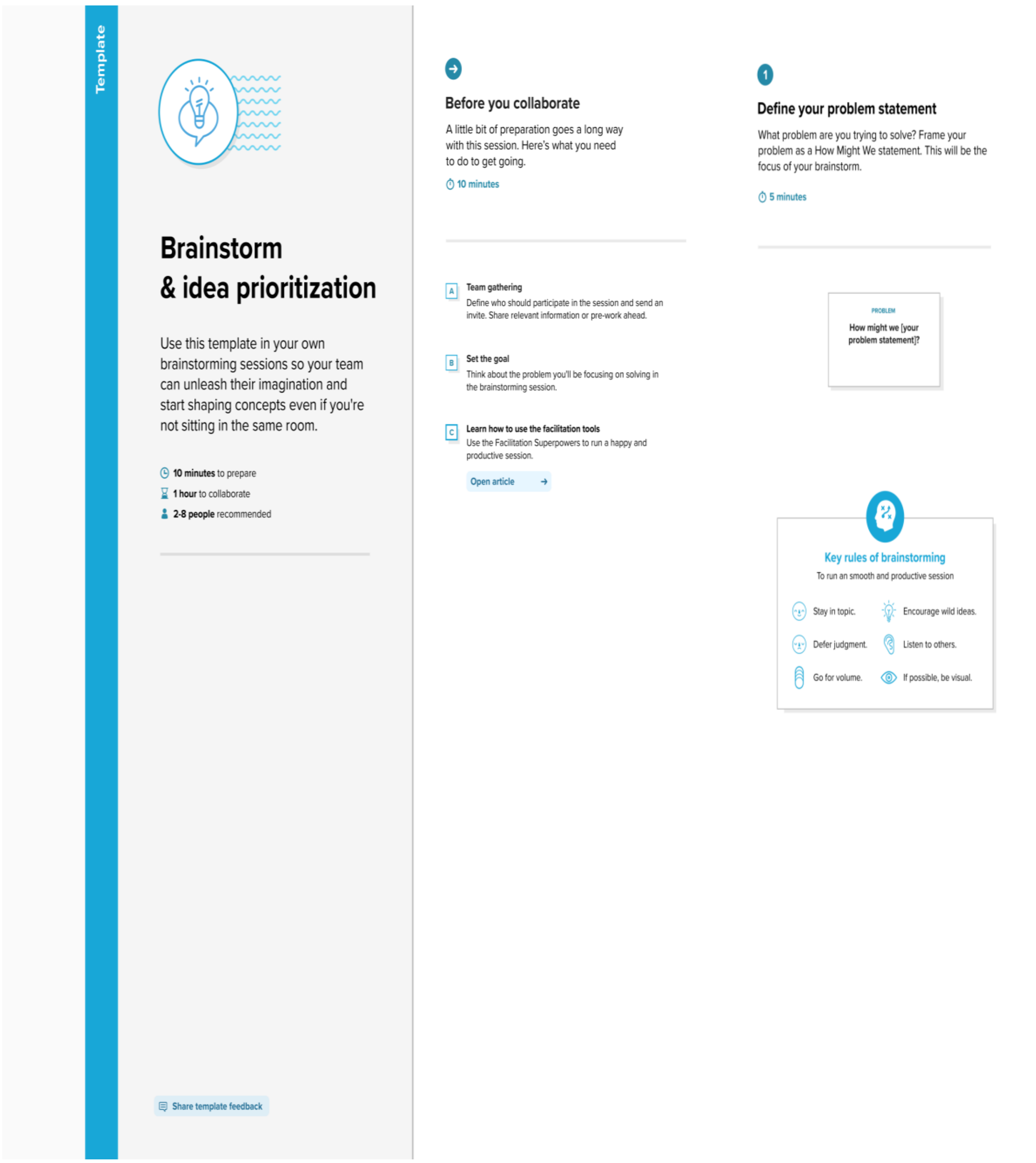




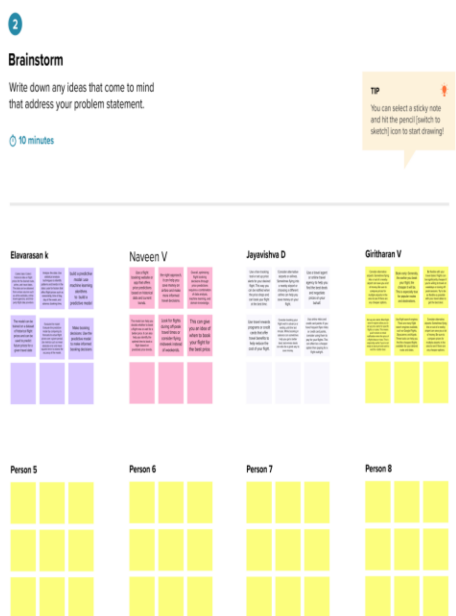
2.2 IDEATION & BRAINSTORMING MAP

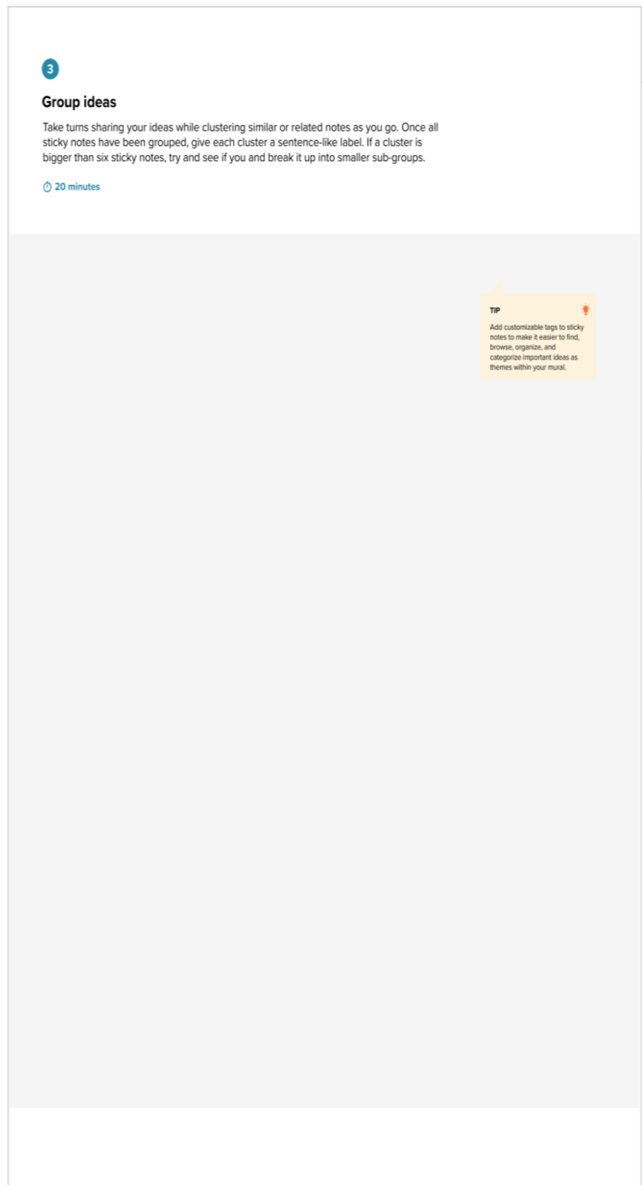
Under this activity our team members have gathered and discussed various idea to solve our project problem. Each member contributed 6 to 10 ideas after gathering all ideas we have assessed the impact and feasibility of each point. Finally, we have assign the priority for each point based on the impact value

STEP 1:Team Gathering, collaboration and Select the Problem.

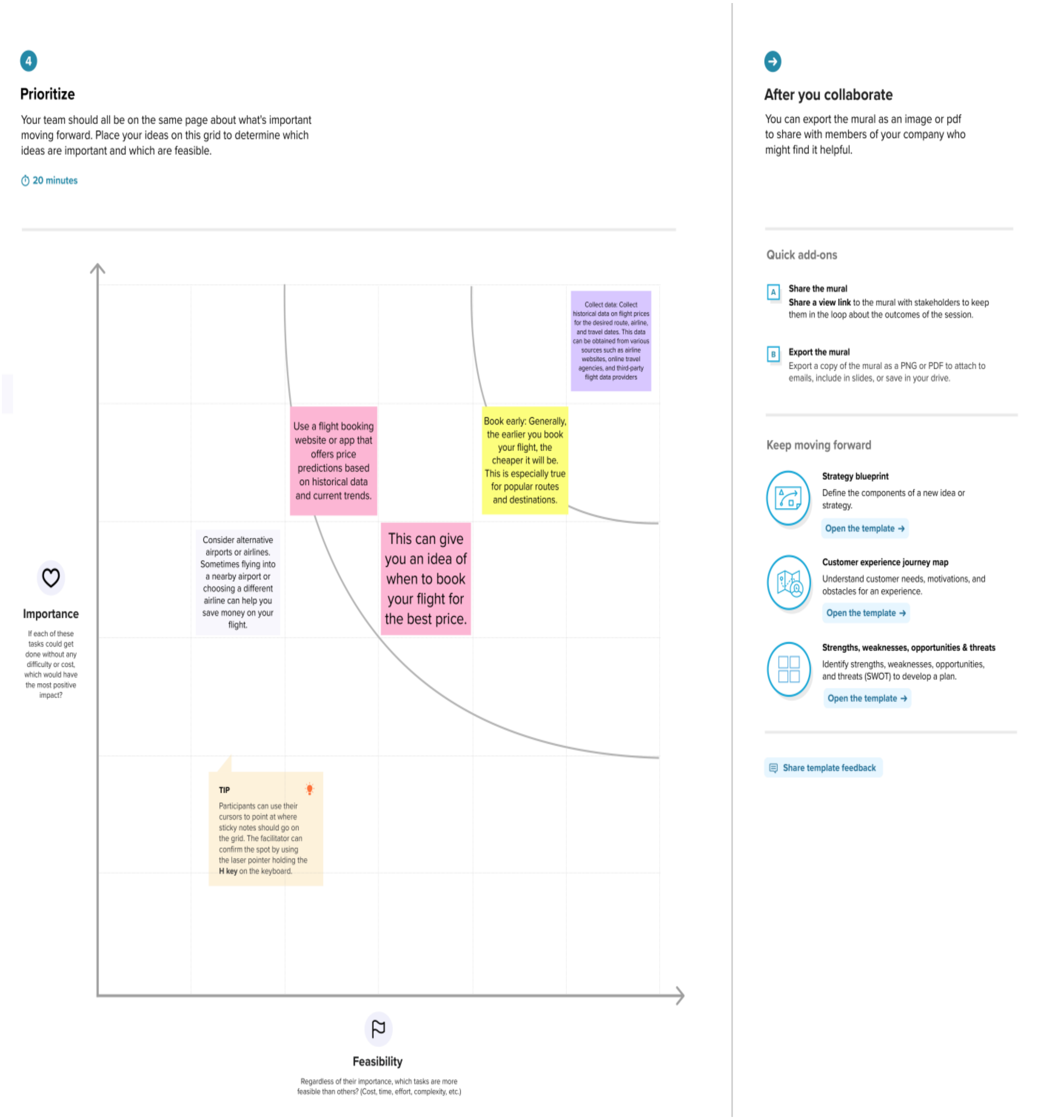


<u>STEP-2: Brainstorm, Idea Listing and Grouping</u>





STEP-3: Idea Prioritization



3.RESULT

Integrate with web FrameWork

Building HTML pages

```
<!DOCTYPE html>
<html>
<head>
<title>Flight Price Prediction</title>
</head>

<body bgcolor='black' text='white'>
<h1>
<b>
<i>
<font size=15>
Flight Price Prediction
</font>
</i>
</b>
</h1>
<div style="background-color:white">
<hr>
<hr></div>
<h2> Optimize Flight Booking</h2>
<h4>

<form action="{{url_for('predict')}}" method="post">

<p> airline </p>
```

```
 <p> source </p>
 <p> Destination </p>
 <p> Date: <input type='text' name=' date' placeholder='  ' required='required' /></p>
 <p>Month : <input type='text' name='month ' placeholder='  ' required='required' /></p>
 <p>Year : <input type='text' name='year' placeholder='  ' required='required' /></p>
 <p> Dep_Time_Hour : <input type='text' name='Dep_Time_Hour' placeholder='  '
required='required' /></p>
 <p> Dep_Time_Mins : <input type='text' name='Dep_Time_Mins' placeholder='  '
required='required' /></p>
 <p>  Arrival_Time : <input type='text' name=' Arrival_Time' placeholder='  '
required='required' /></p>
 <p>  Arrival_Time_Hour : <input type='text' name=' Arrival_Time_Hour' placeholder='  '
required='required' /></p>
 <p>  Arrival_Time_Mins : <input type='text' name='Credit_History' placeholder='  '
required='required' /></p>
 <p> Source : <input type='text' name='Source' placeholder='  ' required='required' /></p>
 <p> Destination : <input type='text' name='Destination' placeholder='  ' required='required'
/></p>
<label>airlines</lable>
<select>
<option value="Airline">airline
</option>
<option value="Indigo">indigo
</option>
<option value="AirIndia">airindia
</option>
<option value="Jet Airways">Jet airways
</option>
</select>
 <button type="submit" class="btn btn-primary btn-block btn-large">submit</button>
</form>
```

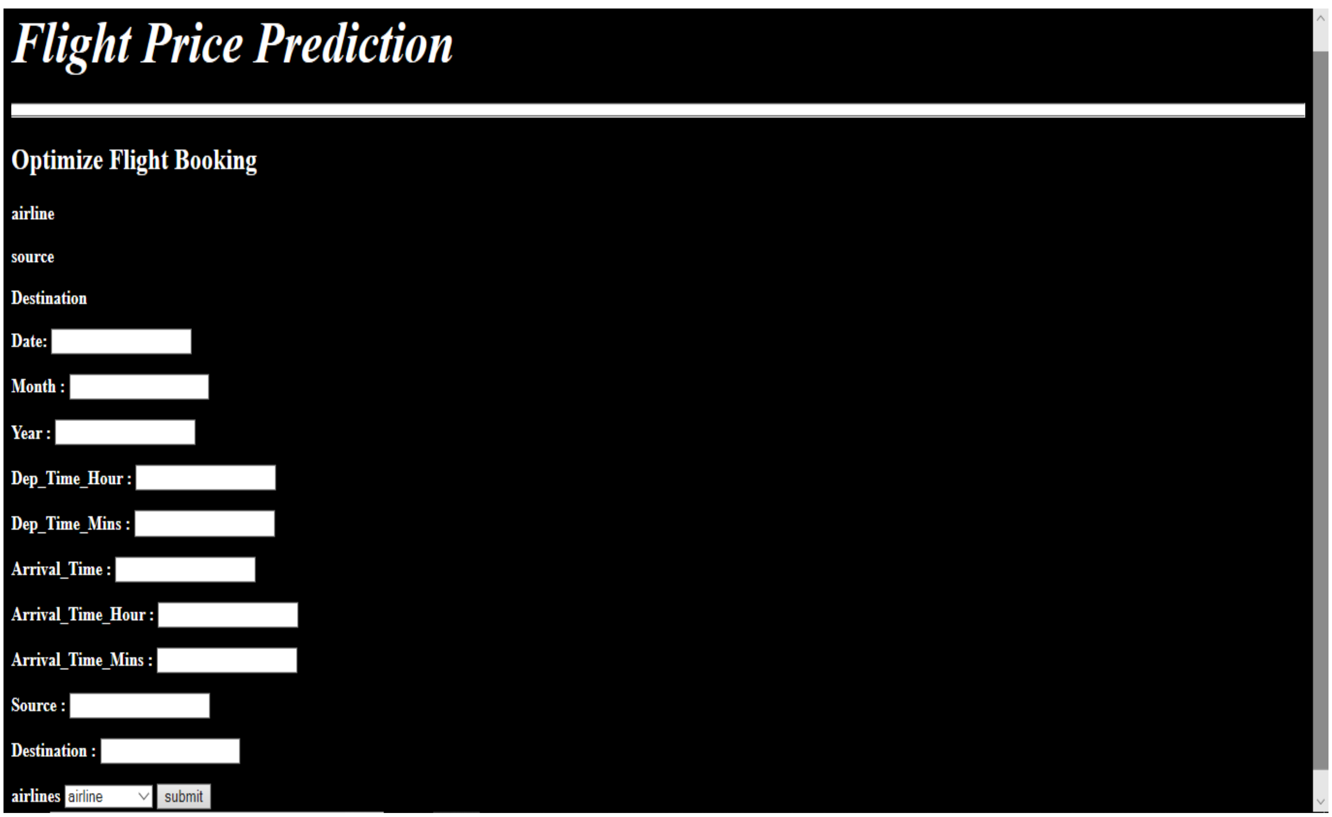
```
</h4>
<h2>
</h2>
</body>
</html>
```

Building Python Code

```
import flask
from flask import Flask, render_template, request
import pickle
import numpy as np
import sklearn
from flask_ngrok import run_with_ngrok
import warnings

warnings.filterwarnings('ignore')

app = Flask(__name__)
run_with_ngrok(app)

pickle.dump(rf,open('rf.pkl','wb'))



@app.route('/', methods=['GET'])
def home():
    return render_template('index.html')



@app.route('/', methods=['GET', "POST"])
```

```
def predict():
    input_values = [float(x) for x in request.form.values()]
    inp_features = [input_values]
    print(inp_features )
    prediction = model.predict(inp_features)
    if prediction == 1:
        return render_template('index.html', prediction_text='Eligible to loan, Loan will be sanctioned')
    else:
        return render_template('index.html', prediction_text='Not eligible to loan')



app.run()
```

Run the Web Application



4.ADVANTAGES & DISADVANTAGES

Advantages:

- Save money: With flight price prediction, you can save money by booking flights at the right time when the prices are low.
- Time-saving: You don't have to spend hours searching for the best flight deals when you use flight price prediction tools.
- Convenience: Flight price prediction tools make it easy to find the best flight deals without leaving your home.
- Greater accuracy: Flight price prediction tools use algorithms that are designed to accurately predict flight prices.
- More options: You can explore more flight options when you use flight price prediction tools.
- Avoid last-minute rush: By using flight price prediction tools, you can avoid the last-minute rush to book flights.
- Flexibility: Flight price prediction tools allow you to be flexible with your travel plans and help you find the best deals.
- Personalization: Flight price prediction tools can personalize recommendations based on your preferences and travel history.
- Real-time updates: Flight price prediction tools provide real-time updates on flight prices, making it easy to book flights at the right time.
- Multiple airlines: Flight price prediction tools allow you to compare prices from multiple airlines, helping you find the best deals.
- Multiple destinations: You can explore flight options to multiple destinations when you use flight price prediction tools.
- Multiple dates: Flight price prediction tools allow you to compare prices for flights on multiple dates, helping you find the cheapest one.
- Easy to use: Flight price prediction tools are easy to use, even for those who are not tech-savvy.
- Accessible: Flight price prediction tools are accessible from anywhere, anytime.
- User-friendly: Flight price prediction tools have an easy-to-use interface that allows you to find the best deals quickly.
- Customizable: Flight price prediction tools allow you to customize your search based on your preferences.
- Multilingual: Flight price prediction tools are available in multiple languages, making them accessible to a global audience.
- Comprehensive: Flight price prediction tools provide comprehensive information on flight prices, including taxes and fees.
- Reliable: Flight price prediction tools use reliable data to predict flight prices, ensuring that you get accurate information.

- Historical data: Flight price prediction tools use historical data to make predictions, which helps to increase the accuracy of the predictions.
- Advanced algorithms: Flight price prediction tools use advanced algorithms to make predictions, making them more accurate.
- Machine learning: Flight price prediction tools use machine learning to learn from past data and make predictions based on that data.
- Data visualization: Flight price prediction tools provide data visualization, making it easy to understand the data and make informed decisions.
- Email notifications: Flight price prediction tools send email notifications when prices drop, helping you book flights at the right time.
- Price alerts: Flight price prediction tools allow you to set up price alerts, so you don't miss out on the best deals.
- Mobile app: Flight price prediction tools have mobile apps, making it easy to access information on the go.
- Customer support: Flight price predict n tools provide customer support to help you with any questions or issues.
- Free to use: Many flight price prediction tools are free to use, making them accessible to everyone.
- Low cost: Even paid flight price prediction tools are affordable and offer great value for money.
- Faster bookings: Flight price prediction tools help you book flights faster, without wasting time on searching for deals.
- Reduced stress: Flight price prediction tools reduce the stress of booking flights by providing accurate information and deals.
- Better planning: Flight price prediction tools help you plan your travel better by providing information on the best times to book flights.

Disadvantages:

While flights price prediction can be useful in helping travelers find the best deals on airfare, there are several disadvantages to consider:

- Inaccuracy: Flight prices are influenced by many variables, such as fuel costs, demand, and availability, making it difficult to accurately predict prices.
- Limited scope: Flight price prediction tools typically only analyze a specific route or airline, which may not provide a comprehensive view of the available options.
- Time constraints: Price predictions are only valid for a limited period of time, which means that travelers must act quickly to take advantage of the predicted prices.
- False expectations: Predicted prices may lead travelers to set unrealistic expectations, causing disappointment when actual prices are different.
- Potential for manipulation: Airlines may use price prediction tools to manipulate prices and generate more revenue, rather than offering the best deal to customers.

- Reliance on data: Price prediction tools rely on historical data, which may not be an accurate predictor of future prices due to changing market conditions.
- Overall, while flights price prediction can be a useful tool, it should be used with caution and in conjunction with other research and comparison methods to ensure the best possible deal.

5.APPLICATIONS

- Airline ticket booking websites: Flight price prediction solutions can be integrated into airline ticket booking websites to provide users with real-time price estimates for their desired routes and dates of travel.
- Travel planning apps: Travel planning apps can incorporate flight price prediction solutions to help users find the best deals on flights and plan their trips accordingly.
- Travel blogs and forums: Flight price prediction solutions can be used to provide readers with up-to-date information on the cheapest flights to popular destinations. Social media platforms: Social media platforms can use flight price prediction solutions to help users find the best deals on flights and share them with their friends and followers.
- Travel agencies: Travel agencies can use flight price prediction solutions to provide their clients with real-time information on flight prices and availability.
- Corporate travel management: Flight price prediction solutions can be used by corporate travel managers to help their employees save money on business travel.
- Hotel booking websites: Flight price prediction solutions can be integrated into hotel booking websites to help users find the best deals on flights and hotels for their trips.
- Vacation rental websites: Vacation rental websites can use flight price prediction solutions to help users plan their trips and find the best deals on flights and accommodations.
- Tour operators: Tour operators can use flight price prediction solutions to help their customers plan their trips and find the best deals on flights and tours.
- Airline loyalty programs: Airline loyalty programs can use flight price prediction solutions to offer members exclusive deals and discounts on flights.
- Airport websites: Flight price prediction solutions can be integrated into airport websites to provide travelers with real-time information on flight prices and availability.
- Business intelligence platforms: Business intelligence platforms can use flight price prediction solutions to provide companies with insights into market trends and consumer behavior in the airline industry.
- Financial institutions: Financial institutions can use flight price prediction solutions to offer customers travel-related financial products and services, such as travel loans and insurance.
- Mobile apps: Flight price prediction solutions can be integrated into mobile apps to provide users with real-time information on flight prices and availability.
- Online travel agencies: Online travel agencies can use flight price prediction solutions to help customers find the best deals on flights, hotels, and other travel-related products and services.
- Price comparison websites: Flight price prediction solutions can be used by price comparison websites to help users find the best deals on flights from multiple airlines and travel providers.

- Travel insurance companies: Travel insurance companies can use flight price prediction solutions to offer customers policies that cover flight cancellations, delays, and other related issues.
- Transportation and logistics companies: Transportation and logistics companies can use flight price prediction solutions to optimize their supply chains and logistics operations.
- Academic research: Flight price prediction solutions can be used by researchers to study consumer behavior and market trends in the airline industry.
- Government agencies: Government agencies can use flight price prediction solutions to monitor market trends and consumer behavior in the airline industry, and to inform policies related to air travel and transportation.

6.CONCLUSION

We learn that ML models can be used to predict prices based on earlier data more correctly. The presented paper reflects the dynamic change in the cost of flight tickets from which we get the information about the increase or decrease in the price as per the days, weekends, and the time of the day. With the Ml algorithm applied on various datasets, better results can be obtained for prediction.we have developed machine learning model using python programming language And the reports are shown above.

7.FUTURE SCOPE

- Incorporating advanced machine learning techniques: The future of flight price prediction will involve more sophisticated machine learning algorithms. Techniques like deep learning and neural networks can help improve prediction accuracy.
- Big data analytics: With the increasing amount of data available, big data analytics will play a crucial role in flight price prediction. This will help to identify patterns and trends that might be missed by traditional methods.
- Integration of social media data: Social media data can be used to predict demand for flights. By analyzing social media data, airlines can get a better understanding of customer preferences and behavior.
- Personalized pricing: With the help of AI, airlines can offer personalized pricing to customers. This will involve analyzing customer data to understand their preferences and offer them customized pricing options.
- Real-time pricing: The future of flight price prediction will involve real-time pricing. This will allow airlines to adjust their pricing based on demand, supply, and other factors in real-time.
- Blockchain technology: Blockchain technology can be used to create a secure and transparent system for flight price prediction. This can help to prevent fraud and increase transparency
- Predictive analytics: Predictive analytics can be used to forecast future trends and patterns in flight pricing. This can help airlines to make more informed decisions about pricing.
- Natural Language Processing (NLP): NLP can be used to analyze customer feedback and reviews. This can help airlines to understand customer sentiment and improve their pricing strategies.
- Cloud computing: Cloud computing can be used to store and analyze large amounts of data. This can help airlines to make more accurate predictions about flight pricing.
- IoT sensors: IoT sensors can be used to gather data about flight demand, weather conditions, and other factors that can affect pricing. This data can be used to improve prediction accuracy.
- Collaborative filtering: Collaborative filtering can be used to recommend flights to customers based on their past behavior and preferences.
- Multi-modal prediction: Multi-modal prediction can be used to predict flight prices based on various factors like weather conditions, fuel prices, and flight demand.
- Dynamic pricing: Dynamic pricing can be used to adjust flight prices in real-time based on demand, supply, and other factors.
- Pricing optimization: Pricing optimization can be used to find the optimal price for flights based on various factors like demand, competition, and costs.

- Price comparison engines: Price comparison engines can be used to compare flight prices across multiple airlines and booking websites.
- Mobile apps: Mobile apps can be used to provide real-time flight pricing information to customer
- Chatbots: Chatbots can be used to provide personalized pricing information to customers and assist them in booking flights
- Customer segmentation: Customer segmentation can be used to group customers based on their preferences and behavior. This can help airlines to offer customized pricing options to different segments.
- Integration with travel agencies: Flight price prediction can be integrated with travel agencies to provide customers with a seamless booking experience.
- Data visualization: Data visualization can be used to represent flight pricing information in an easy-to-understand format. This can help customers to make more informed decisions about their travel plans

8.APPENDIX

SOURCE CODE:

Importing the libraries:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.metrics import f1_score,confusion_matrix,classification_report
from scipy import stats
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor,RandomForestRegressor
from sklearn.model_selection import train_test_split
import pickle
import warnings
warnings.filterwarnings('ignore')
```

Read the Dataset:

```
data=pd.read_excel('/content/Data_Train.xlsx')
data.head()
data.isnull().sum()


data.dropna(inplace=True)
```

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

data.Date_of_Journey

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

data.Total_Stops.unique()

data.Route=data.Route.str.split('→')

Data.Route

data['City1']=data.Route.str[0]
data['City2']=data.Route.str[1]
data['City3']=data.Route.str[2]
data['City4']=data.Route.str[3]
data['City5']=data.Route.str[4]
data['City6']=data.Route.str[5]

data.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]

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

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

data.Arrival_Time_Mins=data.Arrival_Time_Mins.str.split(' ')
data['Arrival_Time_Mins']=data.Arrival_Time_Mins.str[0]
data['Arrival_Day']=data.Arrival_Time_Mins.str[1]

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

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

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

data.Total_Stops=data.Total_Stops.str.split(' ')
data.Total_Stops=data.Total_Stops.str[0]
data.Total_Stops.replace('non-stop',0,inplace=True)

data.Total_Stops

data.Total_Stops.isnull().sum()

data.Additional_Info.unique()

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

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

data.drop(['City4','City5','City6'],axis=1,inplace=True)

data.isnull().sum()

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

data.isnull().sum()

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

data['City3'].fillna('None',inplace=True)

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

data.info()

data.head(3)

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_Mins=data.Dep_Time_Mins.astype('int64')
data.Arrival_Time_Hour=data.Arrival_Time_Hour.astype('int64')
```

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

data.info()

data.Arrival_Time_Mins=data.Arrival_Time_Mins.astype('int64')

data.Arrival_Day=data.Arrival_Day.astype('int64')

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

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

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

column=[column for column in data.columns if data[column].dtype=='object']
Column

continuous_col =[column for column in data.columns if data[column].dtype!='object']
continuous_co

categorical = data[column]
Categorical

numerical=data[continuous_col]

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.Additional_Info=le.fit_transform(data.Additional_Info)
data.City1=le.fit_transform(data.City1)
data.City2=le.fit_transform(data.City2)
data.City3=le.fit_transform(data.City3)
data.head()
```

Categorical

```
fdata=data.copy()
```

```
Fdata
```

```
fdata.drop(['Additional_Info','City1','City2','City3'],axis=1,inplace=True)
Fdata
```

```
fdata.drop(['Total_Stops','Travel_Hours','Travel_Mins'],axis=1,inplace=True)
Fdata
```

Exploratory Data Analysis

```
fdata.describe()
```

Categorical

```
import seaborn as sns
c=1
plt.figure(figsize=(20,45))
for i in categorical:
```

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

plt.show()

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

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

sns.boxplot(data['Price'])

x=fdata.drop('Price',axis=1)
y=fdata['Price']

from sklearn.preprocessing import StandardScaler
ss=StandardScaler()

xscaled=ss.fit_transform(x)

xscaled=pd.DataFrame(xscaled,columns=x.columns)
xscaled.head()

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,random_state=123)
```

```
x_train.head()

from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
def predict(ml_model):
    print('Model is: {}'.format(ml_model))
    model= ml_model.fit(x_train,y_train)
    print("Training score: {}".format(model.score(x_train,y_train)))
    predictions = model.predict(x_test)
    print("Predictions are: {}".format(predictions))
    print('\n')
    r2score=r2_score(y_test,predictions)
    print("r2 score is: {}".format(r2score))

    print('MAE:{}'.format(mean_absolute_error(y_test,predictions)))
    print('MSE:{}'.format(mean_squared_error(y_test,predictions)))
    print('RMSE:{}'.format(np.sqrt(mean_squared_error(y_test,predictions))))

    sns.distplot(y_test-predictions)

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor,RandomForestRegressor

predict(RandomForestRegressor())

predict(LogisticRegression())

predict(KNeighborsRegressor())
```

```
predict(DecisionTreeRegressor())

from sklearn.svm import SVR
predict(SVR())

predict(GradientBoostingRegressor())
```

Hypertunning the model

```
from sklearn.model_selection import RandomizedSearchCV
random_grid = {
    'n_estimators' : [100, 120, 150, 180, 200,220],
    'max_features':['auto','sqrt'],
    'max_depth':[5,10,15,20],
    }

rf=RandomForestRegressor()
rf_random=RandomizedSearchCV(estimator=rf,param_distributions=random_grid,cv=3,verbose
=2,n_jobs=-1,)

rf_random.fit(x_train,y_train)

# best parameter
rf_random.best_params_

#predicting the values
prediction = rf_random.predict(x_test)
```

```
#distribution plot between actual value and predicted value
sns.displot(y_test-prediction)

r2_score(y_test,prediction)

pickle.dump(rf,open("rf.pkl",'wb'))
```