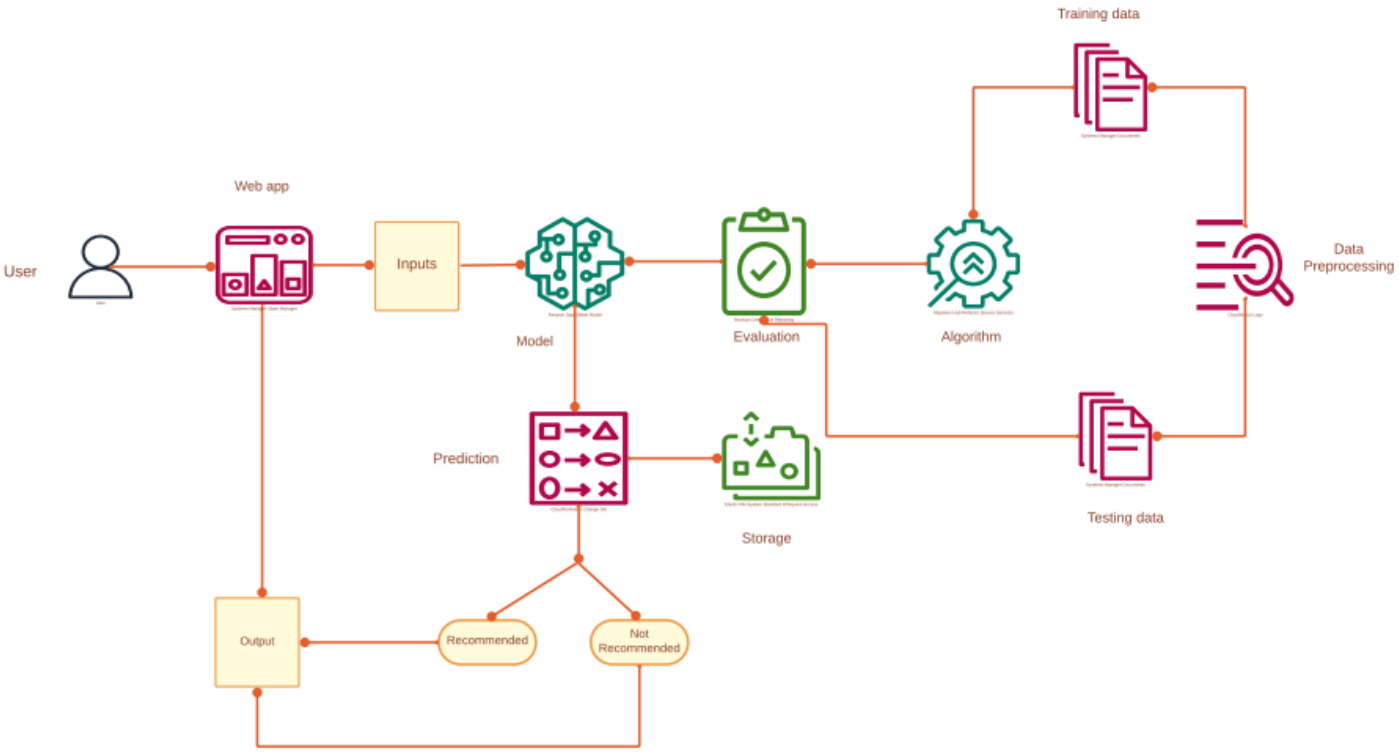
Airline Review Classification Using Machine Learning

In this present interconnected world, the airline industry serves as a critical catalyst for global travel and business. With the increasing accessibility of air travel, the significance of the service quality delivered by airlines cannot be overstated, as it profoundly influences the overall passenger experience. This endeavor is dedicated to the creation of a sophisticated airline review classification system, leveraging state-of-the-art models such as the Decision Tree Classifier, Random Forest Classifier, and XGBoost Classifier.

The expansion of social media platforms, travel-centric websites, and online discussion forums has given rise to an abundance of user-generated content, prominently featuring airline reviews. Harnessing actionable insights from this extensive repository of unstructured text data holds immense potential for furnishing airlines with valuable feedback to enhance their services and augment passenger satisfaction.

Throughout this report, we will delve into the methodology employed to preprocess the raw text data, the process of selecting pertinent features, the training and evaluation of the classification model, and the subsequent interpretation of the obtained results.

Solution Architecture:



Project Flow:

- User interacts with the UI to enter the input.
- Entered input is analyzed by the model and then integrated.
- Once model analyses the input the prediction is showcased on the UI to accomplish this, we must complete allthe activities listed below,

➢ 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
  - Testing model with multiple evaluation metrics

➢ Model Deployment
  - Save the best model
  - Integrate with Web Framework

Milestone 1: Data Collection & Preprocessing

ML depends heavily on data. It is the most crucial aspect that makes algorithm training possible. So, this sectionallows you to download the required dataset.

Activity 1: Collect the dataset

The dataset I have used is **Airline Reviews** csv file from Kaggle.
https://www.kaggle.com/datasets/khushipitroda/airline-reviews

Activity 1.1: Importing the libraries

1.Collect the Dataset

Importing the libraries

In [4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc
import pickle
from scipy import stats
```

In [5]:
```
import warnings
warnings.filterwarnings('ignore')
```

Activity 1.2: 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 pandaswe have a function called read_csv() to read the dataset. As a parameter we have to give the directory of the csv file.

```
In [6]: data = pd.read_csv("C:\Internship\self\Airline_Reviews.csv")
```

```
In [7]: data.head()
```

Out[7]:

	Unnamed: 0	Airline Name	Overall_Rating	Review_Title	Review Date	Verified	Review	Aircraft	Type Of Traveller	Seat Type	Route	Date Flown	Seat Comfort	Cabin Staff Service	F Beve
0	0	AB Aviation	9	"pretty decent airline"	11th November 2019	True	Moroni to Moheli. Turned out to be a pretty ...	NaN	Solo Leisure	Economy Class	Moroni to Moheli	November 2019	4.0	5.0	
1	1	AB Aviation	1	"Not a good airline"	25th June 2019	True	Moroni to Anjouan. It is a very small airline...	E120	Solo Leisure	Economy Class	Moroni to Anjouan	June 2019	2.0	2.0	
2	2	AB Aviation	1	"flight was fortunately short"	25th June 2019	True	Anjouan to Dzaoudzi. A very small airline an...	Embraer E120	Solo Leisure	Economy Class	Anjouan to Dzaoudzi	June 2019	2.0	1.0	
3	3	Adria Airways	1	"I will never fly again with Adria"	28th September 2019	False	Please do a favor yourself and do not fly wi...	NaN	Solo Leisure	Economy Class	Frankfurt to Pristina	September 2019	1.0	1.0	
4	4	Adria Airways	1	"it ruined our last days of holidays"	24th September 2019	True	Do not book a flight with this airline! My fr...	NaN	Couple Leisure	Economy Class	Sofia to Amsterdam via Ljubljana	September 2019	1.0	1.0	

Activity 2: Data Preparation

Preprocessing the data has the following steps:

- Handling Missing values
- Handling categorical data

Activity 2.1: Handling missing values

In [48]:
```
data.shape
```

Out[48]:
```
(23171, 20)
```

In [46]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23171 entries, 0 to 23170
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Unnamed: 0              23171 non-null  int64  
 1   Airline Name            23171 non-null  object 
 2   Overall_Rating          23171 non-null  object 
 3   Review_Title            23171 non-null  object 
 4   Review Date             23171 non-null  object 
 5   Verified                23171 non-null  bool   
 6   Review                  23171 non-null  object 
 7   Aircraft                7129 non-null   object 
 8   Type Of Traveller       19433 non-null  object 
 9   Seat Type               22075 non-null  object 
 10  Route                   19343 non-null  object 
 11  Date Flown              19417 non-null  object 
 12  Seat Comfort            19016 non-null  float64
 13  Cabin Staff Service     18911 non-null  float64
 14  Food & Beverages        14500 non-null  float64
 15  Ground Service          18378 non-null  float64
 16  Inflight Entertainment  10829 non-null  float64
 17  Wifi & Connectivity     5920 non-null   float64
 18  Value For Money         22105 non-null  float64
 19  Recommended             23171 non-null  object 
dtypes: bool(1), float64(7), int64(1), object(11)
memory usage: 3.4+ MB
```

In the above dataset check also for any unnecessary values, upon checking the Overall_Rating column we foundsome irrelevant value, so we replace it with relevant value. And later fill all the null values.

```
nar['Overall_Rating']=nar['Overall_Rating'].replace(['1','2','3','4,','5','6','7','8','9','n'],['1','2','3','4','5','6','7','8','9','10'])
```

```
nar['Overall_Rating'].value_counts()
```

```
1     11595
2      2296
9      1768
8      1757
3      1356
7      1192
4       859
n       842
5       830
6       676
Name: Overall_Rating, dtype: int64
```

In Left image we can see that there is a Value ‘n’. We replaced it with 10 alongside we also replaced the rest of values with the respective same value but in the string format. The right image is of column after replacing the old values with new values.

```
nar['Overall_Rating'].value_counts()
```

```
1     11595
2      2296
9      1768
8      1757
3      1356
7      1192
4       859
10      842
5       830
6       676
Name: Overall_Rating, dtype: int64
```

i) Filling the null values with median and mode depending on the values(Mode for Categorical and median for Numerical)

```
nar['Type Of Traveller']=nar['Type Of Traveller'].fillna(nar['Type Of Traveller'].mode()[0])
nar['Seat Type']=nar['Seat Type'].fillna(nar['Seat Type'].mode()[0])
nar['Seat Comfort']=nar['Seat Comfort'].fillna(nar['Seat Comfort'].mode()[0])
nar['Route']=nar['Route'].fillna(nar['Route'].mode()[0])
nar['Date Flown']=nar['Date Flown'].fillna(nar['Date Flown'].mode()[0])
nar['Food & Beverages']=nar['Food & Beverages'].fillna(nar['Food & Beverages'].mode()[0])
nar['Ground Service']=nar['Ground Service'].fillna(nar['Ground Service'].mode()[0])
#For the above columns we are using mode instead of median even though numerical values are present
#because the column consists of categories(0 to 5).So its considered as categorical data
```

Later , we will modify the existing columns depending on our requirement. In our dataset I have modified the Date flown and Route columns.

```
nar[['Month Flown','Year Flown']]=nar['Date Flown'].str.split(expand=True)
```

```
nar['Origin']=nar.Route.str.split(' to ',expand=True)[0]
nar['Destination']=nar.Route.str.split(' to ',expand=True)[1]
# Route column has 3 values i.e., eg. Place A to Place B via Place C ,so inorder to chose
#,we gave indices for Moroni as 0 & Moheli as 1,and then run the split function again to remove 'via'
nar['Destination']=nar.Destination.str.split(' via ',expand=True)[0]
```

```
del nar['Route']
del nar['Date Flown']
```

```
nar['Origin']=nar['Origin'].replace(['Tel Avivito Malta (MLA)','Bangalore toChennai','JFK toTLV via Baku','Krabi toBangkok','Hong Kong To Shanghai',
                                     'Edinburgh To Fuerteventura','Nuremburg toHamburg','Mumbai toJaipur','Sydney to- New York via Soul',
                                     'London Gatwick - Bangkok','SIN toi MFM','Jakartato Yogyakarta','Cardiff-Malta return','KIV-LIS',
                                    'GRR-ORD','LCY-FRA','NAP-RMF return','LEB-BOS','Bucharest-Brussels','Da Nang - Hong Kong ','New-York',
                                    'LHR-DXB','Dublin - Charlotte','Kansas City via Dallas Ft Worth','Sydney via Singapore',
                                     'Geneva via Brussels','Nursultan via Dubai','Denpasar Medan via Jakarta',
                                     'Auckland Denpasar via Sydney / Melbourne','Lima via Santiago','Manila via Los Angeles',
                                    'Dar es Salaam via Kigali','Singapore via Sydney','Grand Rapidsvto Orlando via Chicago',
                                    'Toronto via Varadero','Bangkok via Mumbai','A Coruna via Bilbao','LHR-DXB ',
                                     'Paris Orly  Los Angeles','Newark Los Angeles','Honolulu Seattle ','San {Paulo'],
                                    ['Tel Aviv(MLA)','Bangalore','JFK','Krabi','Hong Kong','Edinburgh','Nuremburg','Mumbai',
                                     'Sydney','London Gatwick','SIN','Jakarta','Cardiff','KIV','GRR','LCY','NAP','LEB','Bucharest',
                                    'Da Nang','New York','LHR','Dublin','Kansas City','Sydney','Geneva','Nursultan','Denpasar Medan',
                                    'Auckland Denpasar','Lima','Manila','Dar es Salaam','Singapore','Grand Rapidsvto Orlando',
                                    'Toronto','Bangkok','A Coruna','LHR','Paris Orly','Newark','Honolulu','San Paulo'])
```

```
#Destination recorrections
j=0
row_num=[2172,3788,5112,5368,7000,8314,9107,10589,12993,17759,20572,
        20930,2225,2380,4339,5182,5785,6382,10991,12573,17051,21497,
         4293,6215,9787,10207,12372,13556,16022,17217,17732,18774,
        19462,20112,22449,11584,10001,12258,10886]
new_des=['Malta','Chennai','TLV','Bangkok','Shanghai','Fuerteventura','Hamburg',
        'Jaipur','New York','Bangkok','MFM','Yogyakarta','Malta','LIS','ORD','FRA',
        'RMF','BOS','Brussels','Hong Kong','DXB','Charlotte','Dallas Ft Worth',
        'Brussels','Dubai','Jakarta','Sydney / Melbourne','Santiago','Los Angeles','Kigali',
        'Sydney','Chicago','Varadero','Mumbai','Bilbao','Dallas','Los Angeles','Los Angeles','Seattle ']
for i in row_num:
    nar.at[i,'Destination']=new_des[j]
    j+=1
```

```
new_column_order=['Airline Name','Seat Type','Type Of Traveller','Origin',
                  'Destination','Month Flown', 'Year Flown','Verified', 'Seat Comfort',
                   'Food & Beverages','Ground Service','Overall_Rating','Recommended']
```

```
# Reordering the columns of given data to our desired manner
nar=nar.reindex(columns=new_column_order)
```

After correcting all the values in the respective features as shown in the above images, we shall re order the columns for our convenience. The resultant dataset looks as below.

```
nar.head()
```

	Airline Name	Seat Type	Type Of Traveller	Origin	Destination	Month Flown	Year Flown	Verified	Seat Comfort	Food & Beverages	Ground Service	Overall_Rating	Recommended
0	AB Aviation	Economy Class	Solo Leisure	Moroni	Moheli	November	2019	True	4.0	4.0	4.0	9	yes
1	AB Aviation	Economy Class	Solo Leisure	Moroni	Anjouan	June	2019	True	2.0	1.0	1.0	1	no
2	AB Aviation	Economy Class	Solo Leisure	Anjouan	Dzaoudzi	June	2019	True	2.0	1.0	1.0	1	no
3	Adria Airways	Economy Class	Solo Leisure	Frankfurt	Pristina	September	2019	False	1.0	1.0	1.0	1	no
4	Adria Airways	Economy Class	Couple Leisure	Sofia	Amsterdam	September	2019	True	1.0	1.0	1.0	1	no

Activity 2.2: Handling Categorical Values

```
from sklearn.preprocessing import LabelEncoder
le1=LabelEncoder()
le2=LabelEncoder()
le3=LabelEncoder()
le4=LabelEncoder()
le5=LabelEncoder()
le6=LabelEncoder()
le7=LabelEncoder()
le8=LabelEncoder()
le9=LabelEncoder()
le10=LabelEncoder()
```

```
nar['Airline Name']=le1.fit_transform(nar['Airline Name'])
nar['Seat Type']=le2.fit_transform(nar['Seat Type'])
nar['Type Of Traveller']=le3.fit_transform(nar['Type Of Traveller'])
nar['Origin']=le4.fit_transform(nar['Origin'])
nar['Destination']=le5.fit_transform(nar['Destination'])
nar['Month Flown']=le6.fit_transform(nar['Month Flown'])
nar['Year Flown']=le7.fit_transform(nar['Year Flown'])
nar['Verified']=le8.fit_transform(nar['Verified'])
nar['Overall_Rating']=le9.fit_transform(nar['Overall_Rating'])
nar['Recommended']=le10.fit_transform(nar['Recommended'])
```

As we can see our dataset has categorical data, we must convert the categorical data to integer encoding or binary encoding. To convert the categorical features into numerical features we use encoding techniques. There are several techniques but, in our project, we are using label encoding. But prior encoding we need to doEDA.

- In our project, categorical features are Airline Name, Seat Type, Type Of Traveller, Origin, Destination, Month Flown, Year Flown, Verified, Overall_Rating, Recommended. Label encoding is done for those columns.

Dataset will be converted as below image

```
nar.head()
```

	Airline Name	Seat Type	Type Of Traveller	Origin	Destination	Month Flown	Year Flown	Verified	Seat Comfort	Food & Beverages	Ground Service	Overall_Rating	Recommended
0	0	1	3	1271	1545	9	6	1	4.0	4.0	4.0	9	1
1	0	1	3	1271	107	6	6	1	2.0	1.0	1.0	0	0
2	0	1	3	79	672	6	6	1	2.0	1.0	1.0	0	0
3	4	1	3	628	1927	11	6	0	1.0	1.0	1.0	0	0
4	4	1	1	1826	99	11	6	1	1.0	1.0	1.0	0	0

Milestone 3: Exploratory Data Analysis

Activity 1: Descriptive statistical

```
nar.describe()
```

	Seat Comfort	Food & Beverages	Ground Service
count	23171.000000	23171.000000	23171.000000
mean	2.328126	1.972207	2.073713
std	1.465062	1.422340	1.523264
min	0.000000	0.000000	1.000000
25%	1.000000	1.000000	1.000000
50%	2.000000	1.000000	1.000000
75%	4.000000	3.000000	3.000000
max	5.000000	5.000000	5.000000

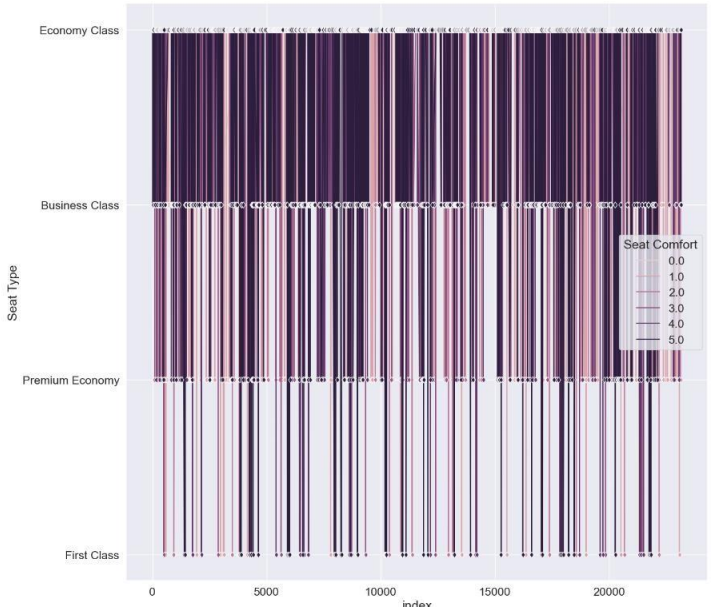
Descriptive analysis is to study the basic features of datawith the statistical process.
Here pandas have a worthy function called describe. Withthis describe function we can understand the unique, top and frequent values of categorical features. And we can find mean, std, min, max and percentile values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

Activity 2: Visual analysis

Visual analysis is the process of using visual representations, such as charts, plots, and graphs, to explore andunderstand data. It is a way to quickly identify patterns, trends, and outliers in the data, which can help to gain insights and make informed decisions.

Activity 2.1: Univariate analysis

```
#line plot in seaborn
sns.set(rc={'figure.figsize':[15,15]})
```



Seaborn package provides a wonderful function distplot. With the help of distplot, we can find the distribution of the feature. To make multiple graphs in a single plot, we use subplot. Matplotlib function have many plots. We are using bar plot for our dataset.

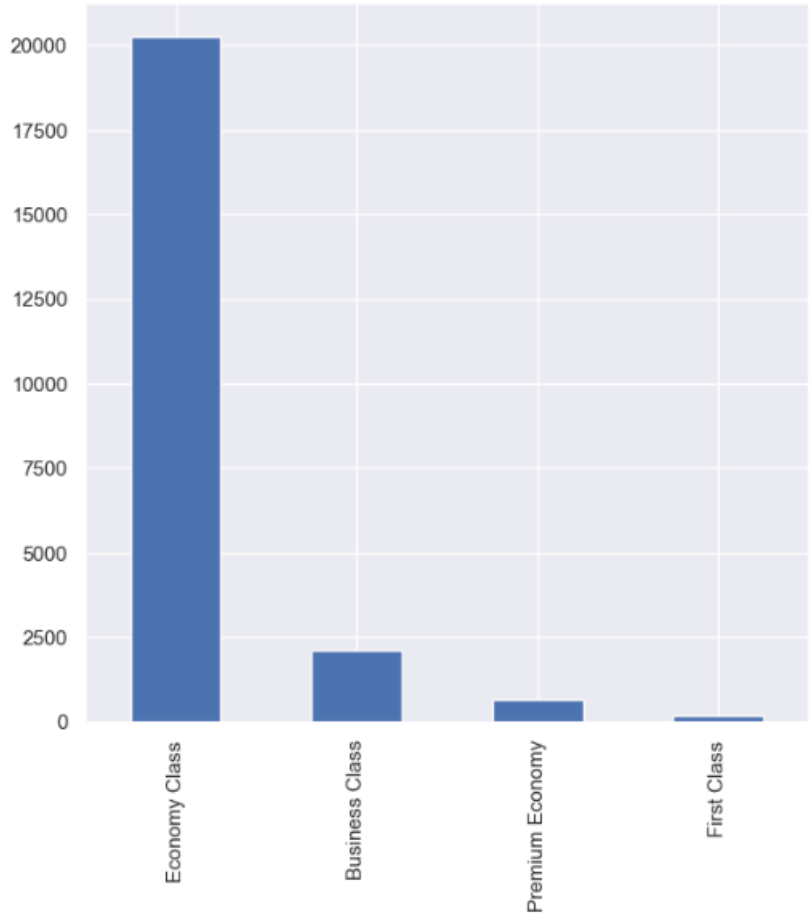
Note: In our dataset we used lineplot, bar plot, pieplot and not using distplot and countplot because our dataset is not having continuous values

In [51]:
```
ndata['Seat Type'].value_counts()
```

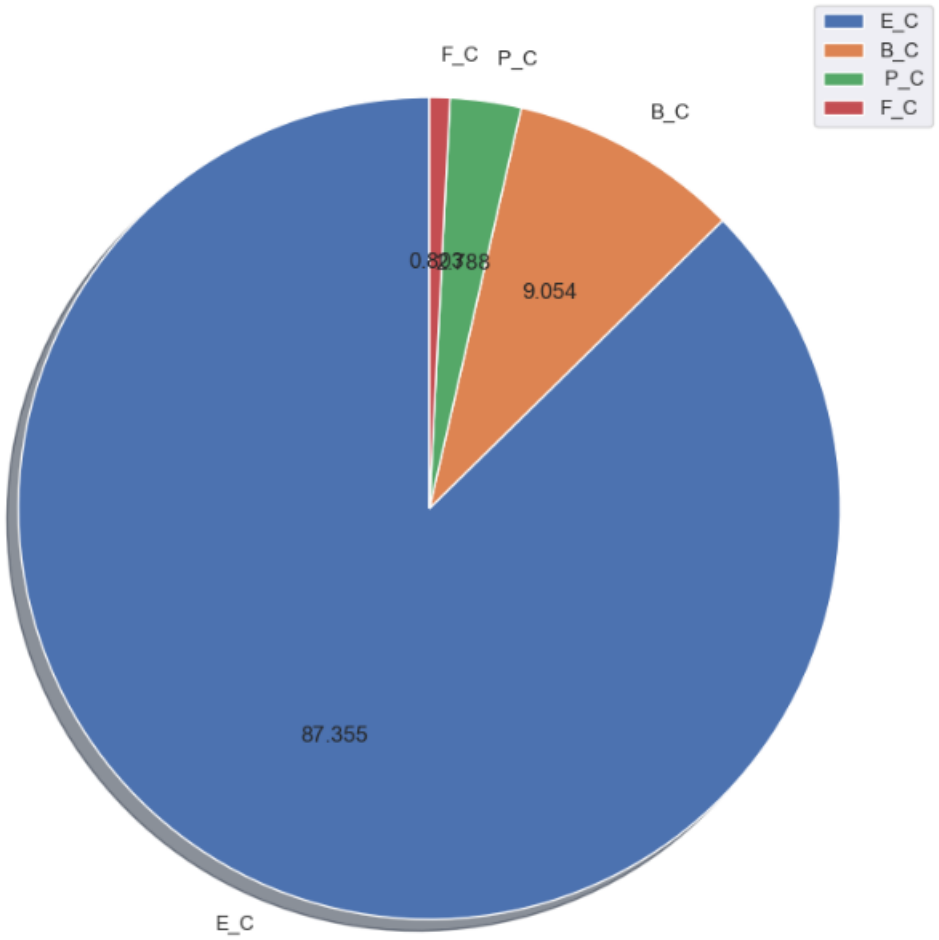
Out[51]:
```
Economy Class      20241
Business Class      2098
Premium Economy      646
First Class          186
Name: Seat Type, dtype: int64
```

In [52]:
```
ndata['Seat Type'].value_counts().plot.bar()
```

Out[52]: <AxesSubplot:>



In [53]:
```
plt.figure(figsize=(10,10))
labels = ['E_C','B_C',' P_C','F_C']
plt.pie(ndata['Seat Type'].value_counts(),startangle=90,autopct='%.3f',
        labels=labels,shadow=True)
plt.legend(labels,loc='best')
#plt.axis('equal')
plt.show()
```

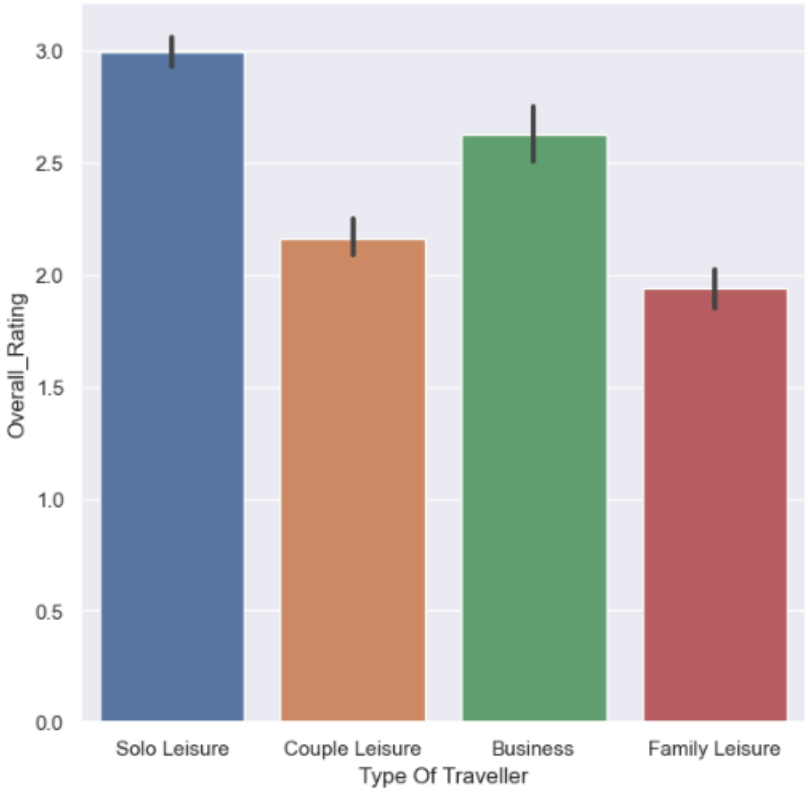


Activity 2.2: Bivariate analysis

To find the relation between two features we use bivariate analysis. Here we are visualizing the relationship between Type Of Traveller, Overall_Rating.

```
In [55]: #Bivariate analysis
         sns.barplot(data=ndata,x='Type Of Traveller',y='Overall_Rating')
```

```
Out[55]: <AxesSubplot:xlabel='Type Of Traveller', ylabel='Overall_Rating'>
```

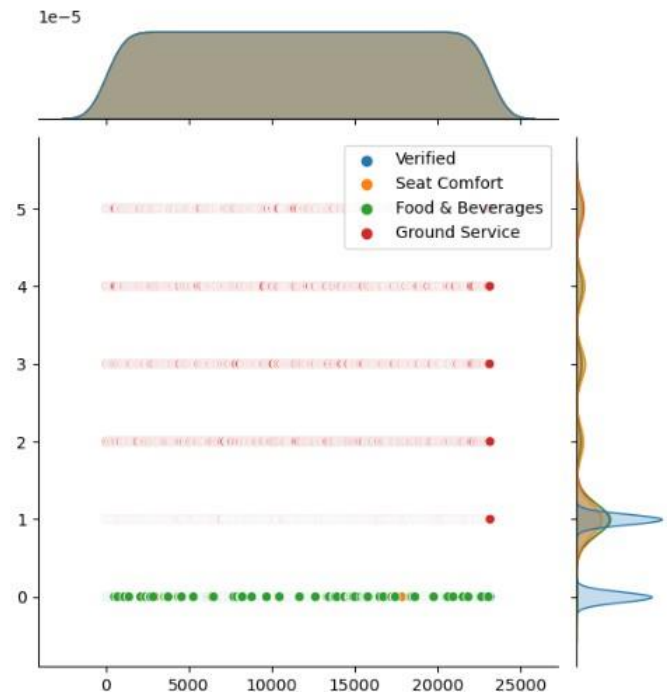


Activity 2.3: Multivariate analysis

In simple words, multivariate analysis is to find the relation between multiple features. Here we have used jointplot and heatmap(for finding correlation) from seaborn package.

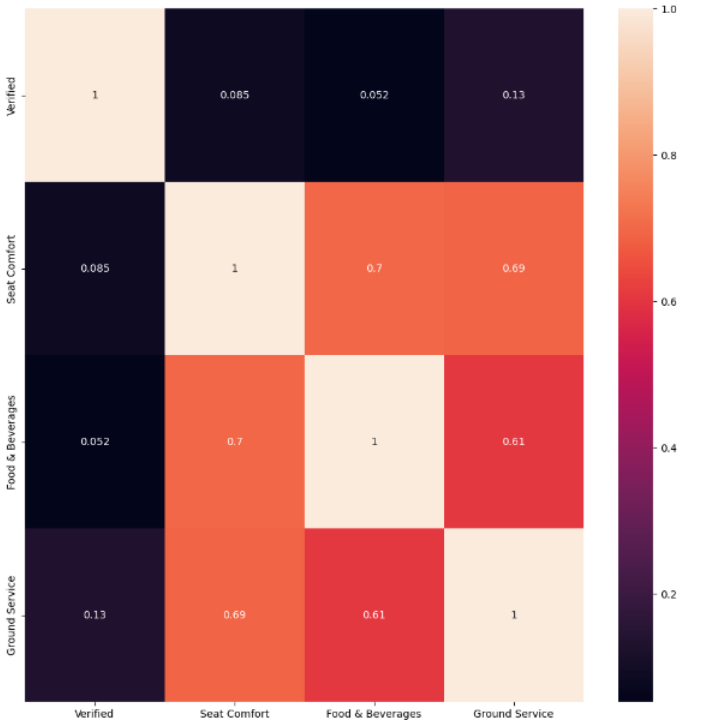
```
sns.jointplot(nar)
```

```
<seaborn.axisgrid.JointGrid at 0x22d3c45c510>
```




```
plt.subplots(figsize=(12,12))
sns.heatmap(nar.corr(),annot=True)
```

```
<Axes: >
```



Milestone 4: Model Building

Activity 4.1: Splitting data into train and test

```
X=nar.iloc[:,0:12].values
y=nar.iloc[:,12:13].values
```

```
X
```

```
array([[  0.,   1.,   3., ...,   4.,   4.,   9.],
       [  0.,   1.,   3., ...,   1.,   1.,   0.],
       [  0.,   1.,   3., ...,   1.,   1.,   0.],
       ...,
       [487.,   1.,   0., ...,   2.,   1.,   3.],
       [487.,   0.,   0., ...,   3.,   1.,   6.],
       [487.,   1.,   3., ...,   1.,   1.,   0.]])
```

```
y
```

```
array([[1],
       [0],
       [0],
       ...,
       [0],
       [1],
       [0]])
```

Now let's split the Dataset into train and test sets. First split the dataset into X and y and then split the dataset. Here X and y variables are created.

On X variable, nar is passed with dropping the target variable. And on y target variable is passed.

Basically, in target variable some values repeat more often than the other kind of values. To remove that imbalanced data, we will use SMOTE(Synthetic Minority Over Sampling Technique).

After checking ,we got to know that there is an imbalance of values in target variable.

```
nar.Recommended.value_counts()
```

```
0    15364
1     7807
Name: Recommended, dtype: int64
```

```
# As the values are over_sampling we need to use smote technique
from imblearn.over_sampling import SMOTE
smote=SMOTE(sampling_strategy='auto',random_state=50)
```

```
X,y=smote.fit_resample(X,y)
```

```
np.count_nonzero(y==1)
```

```
15364
```

```
np.count_nonzero(y==0)
```

```
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=1)
```

```
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
X_train=ss.fit_transform(X_train)
X_test=ss.transform(X_test)
import pickle
pickle.dump(ss,open('ar_ss.pkl','wb'))
```

We can observe that after doing SMOTE the count of each value in target variable became equal.

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.

After splitting the train and test data, we shall use StandardScaler function to remove the outliers of our dataset. And also save that model with the help of pickle function

Activity 2: Training the model in multiple algorithms

Now our data is cleaned and it's time to build the model. We can train our data on different algorithms. For thisproject we are applying three classification algorithms. The best model is saved based on its performance.

Activity 2.1: Decision tree model

```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier(criterion='entropy',random_state=50)
```

```
dtc.fit(X_train,y_train)
```

```
DecisionTreeClassifier(criterion='entropy', random_state=50)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
pred_dt=dtc.predict(X_test)
pred_dt
```

```
array([1, 0, 0, ..., 1, 1, 0])
```

sklearn.metrics section

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc

fpr_dt,tpr_dt,threshold_dt=roc_curve(y_test,pred_dt)

print(classification_report(y_test,pred_dt))


roc_auc_dt=auc(fpr_dt,tpr_dt)
print("roc_auc_dt :",roc_auc_dt)

cm_dt=confusion_matrix(y_test,pred_dt)
print("cm_dt:",cm_dt)

as_dt=accuracy_score(y_test,pred_dt)
print("as_dt:",as_dt)
```

```
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      3116
           1       0.95      0.95      0.95      3030

    accuracy                           0.95      6146
   macro avg       0.95      0.95      0.95      6146
weighted avg       0.95      0.95      0.95      6146

roc_auc_dt : 0.9508299546257578
cm_dt: [[2970  146]
 [ 156 2874]]
as_dt: 0.9508623494956069
```

A function named Decision Tree is created and train and test data are passed as the parameters. Inside the function, DecisionTreeClassifier algorithm is initialized and training data is passed to the model with the **fit()** function. Test data is predicted with **predict()** function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

Activity 2.2: K-Nearest Neighbors

```
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=5)
```

```
knn.fit(X_train,y_train)
```

```
KNeighborsClassifier()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
pred_knn=knn.predict(X_test)
pred_knn
```

```
array([1, 0, 0, ..., 1, 1, 0])
```

sklearn.metrics section

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc
fpr_knn,tpr_knn,threshold_knn=roc_curve(y_test,pred_knn)

print(classification_report(y_test,pred_knn))


roc_auc_knn=auc(fpr_knn,tpr_knn)
print("roc_auc_knn :",roc_auc_knn)

cm_knn=confusion_matrix(y_test,pred_knn)
print("cm_knn:",cm_knn)

as_knn=accuracy_score(y_test,pred_knn)
print("as_knn:",as_knn)
```

```
              precision    recall  f1-score   support

           0       0.95      0.93      0.94      3116
           1       0.93      0.95      0.94      3030

    accuracy                           0.94      6146
   macro avg       0.94      0.94      0.94      6146
weighted avg       0.94      0.94      0.94      6146

roc_auc_knn : 0.9419214995954025
cm_knn: [[2897  219]
 [ 139 2891]]
as_knn: 0.941750732183534
```

A function named KNeighborsClassifier is created and train and test data are passed as the parameters. Inside the function, KNeighborsClassifier algorithm is initialized and training data is passed to the model with the **fit()** function. Test data is predicted with **predict()** function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

Activity 2.3: LogisticRegression

```
from sklearn.linear_model import LogisticRegression
Lr=LogisticRegression()
```

```
Lr.fit(X_train,y_train)
```

```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
pred_Lr=Lr.predict(X_test)
pred_Lr
```

```
array([1, 0, 0, ..., 1, 1, 0])
```

sklearn.metrics section

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc
fpr_Lr,tpr_Lr,threshold_Lr=roc_curve(y_test,pred_Lr)

print(classification_report(y_test,pred_Lr))


roc_auc_Lr=auc(fpr_Lr,tpr_Lr)
print("roc_auc_Lr :",roc_auc_Lr)

cm_Lr=confusion_matrix(y_test,pred_Lr)
print("cm_Lr:",cm_Lr)

as_Lr=accuracy_score(y_test,pred_Lr)
print("as_Lr:",as_Lr)
```

```
              precision    recall  f1-score   support

           0       0.93      0.92      0.92      3116
           1       0.92      0.92      0.92      3030

    accuracy                           0.92      6146
   macro avg       0.92      0.92      0.92      6146
weighted avg       0.92      0.92      0.92      6146

roc_auc_Lr : 0.9217793184966763
cm_Lr: [[2863  253]
 [ 228 2802]]
as_Lr: 0.9217377155873739
```

A function named Logistic Regression is created and train and test data are passed as the parameters. Inside the function, LogisticRegression algorithm is initialized and training data is passed to the model with the **fit()** function. Test data is predicted with **predict()** function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

Activity 2.4: Naive Bayes Classification

```
from sklearn.naive_bayes import GaussianNB
gnb=GaussianNB()
```

```
gnb.fit(X_train,y_train)
```

```
GaussianNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
pred_nb=gnb.predict(X_test)
```

sklearn.metrics section

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc
fpr_gnb,tpr_gnb,threshold_gnb=roc_curve(y_test,pred_Lr)

print(classification_report(y_test,pred_Lr))


roc_auc_nb=auc(fpr_gnb,tpr_gnb)
print("roc_auc_nb :",roc_auc_nb)

cm_nb=confusion_matrix(y_test,pred_nb)
print("cm_nb:",cm_nb)

as_nb=accuracy_score(y_test,pred_nb)
print("as_nb:",as_nb)
```

```
              precision    recall  f1-score   support

           0       0.93      0.92      0.92      3116
           1       0.92      0.92      0.92      3030

    accuracy                           0.92      6146
   macro avg       0.92      0.92      0.92      6146
weighted avg       0.92      0.92      0.92      6146

roc_auc_nb : 0.9217793184966763
cm_nb: [[2754  362]
 [ 203 2827]]
as_nb: 0.9080702896192646
```

A function named GaussianNB is created and train and test data are passed as the parameters. Inside the function, GaussianNB algorithm is initialized and training data is passed to the model with the **fit()** function. Test data is predicted with **predict()** function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

Activity 2.5: Random Forest Classification

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(n_estimators=10,criterion='entropy',random_state=2)
```

```
rfc.fit(X_train,y_train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=2)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
pred_rfc=rfc.predict(X_test)
pred_rfc
```

```
array([1, 0, 0, ..., 1, 1, 0])
```

sklearn.metrics section

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc
fpr_rfc,tpr_rfc,threshold_rfc=roc_curve(y_test,pred_rfc)

print(classification_report(y_test,pred_rfc))


roc_auc_rfc=auc(fpr_rfc,tpr_rfc)
print("roc_auc_rfc :",roc_auc_rfc)

cm_rfc=confusion_matrix(y_test,pred_rfc)
print("cm_rfc:",cm_rfc)

as_rfc=accuracy_score(y_test,pred_rfc)
print("as_rfc:",as_rfc)
```

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.96      3116
           1       0.96      0.96      0.96      3030

    accuracy                           0.96      6146
   macro avg       0.96      0.96      0.96      6146
weighted avg       0.96      0.96      0.96      6146

roc_auc_rfc : 0.9612088359028457
cm_rfc: [[3010  106]
 [ 132 2898]]
as_rfc: 0.9612756264236902
```

A function named RandomForestClassifier is created and train and test data are passed as the parameters. Inside the function, RandomForestClassifier algorithm is initialized and training data is passed to the model with the **fit()** function. Test data is predicted with **predict()** function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

Activity 2.6: Support Vector Machine

```
from sklearn.svm import SVC
svc=SVC()
```

```
svc.fit(X_train,y_train)
```

```
SVC()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
pred_svc=svc.predict(X_test)
pred_svc
```

```
array([1, 0, 0, ..., 1, 1, 0])
```

sklearn.metrics section

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc
fpr_svc,tpr_svc,threshold_svc=roc_curve(y_test,pred_svc)

print(classification_report(y_test,pred_svc))


roc_auc_svc=auc(fpr_svc,tpr_svc)
print("roc_auc_svc :",roc_auc_svc)

cm_svc=confusion_matrix(y_test,pred_svc)
print("cm_svc:",cm_svc)

as_svc=accuracy_score(y_test,pred_svc)
print("as_svc:",as_svc)
```

```
              precision    recall  f1-score   support

           0       0.93      0.95      0.94      3116
           1       0.95      0.93      0.94      3030

    accuracy                           0.94      6146
   macro avg       0.94      0.94      0.94      6146
weighted avg       0.94      0.94      0.94      6146

roc_auc_svc : 0.9397692946444837
cm_svc: [[2971  145]
 [ 224 2806]]
as_svc: 0.9399609502115197
```

A function named SVC is created and train and test data are passed as the parameters. Inside the function, SVC algorithm is initialized and training data is passed to the model with the **fit()** function. Test data is predicted with **predict()** function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

Activity 2.7: XGBoost Classifier

```
from xgboost import XGBClassifier
xgb=XGBClassifier()
```

```
xgb.fit(X_train,y_train)
```

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
pred_xgb=xgb.predict(X_test)
```

sklearn.metrics section

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score,roc_curve,auc
fpr_xgb,tpr_xgb,threshold_xgb=roc_curve(y_test,pred_xgb)

print(classification_report(y_test,pred_xgb))


roc_auc_xgb=auc(fpr_xgb,tpr_xgb)
print("roc_auc_xgb :",roc_auc_xgb)

cm_xgb=confusion_matrix(y_test,pred_xgb)
print("cm_xgb:",cm_xgb)

as_xgb=accuracy_score(y_test,pred_xgb)
print("as_xgb:",as_xgb)
```

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.96      3116
           1       0.97      0.96      0.96      3030

    accuracy                           0.96      6146
   macro avg       0.96      0.96      0.96      6146
weighted avg       0.96      0.96      0.96      6146

roc_auc_xgb : 0.9631753708105085
cm_xgb: [[3013  103]
 [ 123 2907]]
as_xgb: 0.9632281158477058
```

A function named XGBClassifier is created and train and test data are passed as the parameters. Inside the function, XGBClassifier algorithm is initialized and training data is passed to the model with the **fit()** function. Test data is predicted with **predict()** function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done. Let us check the training accuracy also for this algorithm. We get to know that there is no issue of overfitting and at the same time both the testing and training accuracies are best. So will test this model.

```
pred_xgb1=xgb.predict(X_train)
```

```
print(classification_report(y_train,pred_xgb1))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99     12248
           1       0.99      0.98      0.99     12334

    accuracy                           0.99     24582
   macro avg       0.99      0.99      0.99     24582
weighted avg       0.99      0.99      0.99     24582
```

Activity 2: Testing the model

```
xgb.predict([[4,71,1,3,900,1133,1,6,1,5,5,5]])
```

```
array([1])
```

```
# As there is a very less difference between accuracies of training and testing models ,there is no issue of overfitting
```

```
com=pd.DataFrame({'Model':['DecisionTree Classification','K-Nearest Neighbours',
                           'Logistic Regression','Naive Bayes Classification',
                           'RandomForest Classification','Support Vector Machine','XGBClassifier'],
                  'roc_auc':[roc_auc_dt,roc_auc_knn,roc_auc_Lr,roc_auc_nb,roc_auc_rfc,roc_auc_svc,roc_auc_xgb],
                   'accuracy':[as_dt,as_knn,as_Lr,as_nb,as_rfc,as_svc,as_xgb]})
```

```
com
```

	Model	roc_auc	accuracy
0	DecisionTree Classification	0.950830	0.950862
1	K-Nearest Neighbours	0.941921	0.941751
2	Logistic Regression	0.921779	0.921738
3	Naive Bayes Classification	0.921779	0.908070
4	RandomForest Classification	0.961209	0.961276
5	Support Vector Machine	0.939769	0.939961
6	XGBClassifier	0.963175	0.963228

```
maxi=0
for i in range(len(com['Model'])):
    if com.iloc[i:i+1,1:2].values>maxi:
        maxi=com.iloc[i:i+1,1:2].values
        model=com.iloc[i:i+1,0:1].values
    else:
        pass
print('Best accuracy score is:',maxi,'by',model)
maxi=0
for i in range(len(com['Model'])):
    if com.iloc[i:i+1,2:3].values>maxi:
        maxi=com.iloc[i:i+1,2:3].values
        model=com.iloc[i:i+1,0:1].values
    else:
        pass
print('Best roc_auc is:',maxi,'by',model)
```

```
Best accuracy score is: [[0.96317537]] by [['XGBClassifier']]
Best roc_auc is: [[0.96322812]] by [['XGBClassifier']]
```

Here we have tested with XGBoost algorithm. You can test with all algorithm. With the help of predict() function.

Milestone 6: Model Deployment

Activity 1: Save 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.

```
import pickle
pickle.dump(xgb,open('ar_xgb.pkl','wb'))
```

Activity 2: Integrate with Web Framework

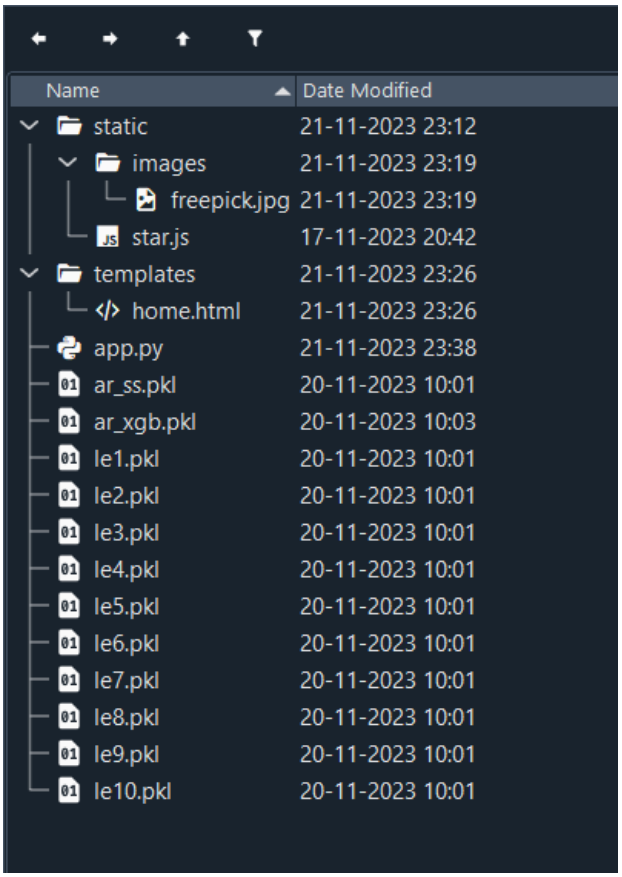
This section has the following tasks

- Building HTML Pages
- Building server-side script
- Run the web application

Activity 2.1: Building Html Pages:

For this project I created one HTML file namely index.html and saved them in the templates folder.

- **ar_xgb.pkl** is the saved model. This model is used for flask integration.
- **ar_ss.pkl** is pickle file of Standard Scaler Feature.
- **[le1.pkl, le2.pkl, le3.pkl, le4.pkl, le5.pkl, le6.pkl, le7.pkl, le8.pkl, le9.pkl, le10.pkl]** arethe pickle files of Label encoding.



Activity 2.2: Build Python code:

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.

```
# -*- coding: utf-8 -*-
"""
Created on Wed Nov 15 22:18:08 2023

@author: ramir
"""

from flask import Flask,render_template,request
import pickle

model = pickle.load(open('ar_xgb.pkl','rb'))
ss1 = pickle.load(open('ar_ss.pkl','rb'))
le1 = pickle.load(open('le1.pkl','rb'))
le2 = pickle.load(open('le2.pkl','rb'))
le3 = pickle.load(open('le3.pkl','rb'))
le4 = pickle.load(open('le4.pkl','rb'))
le5 = pickle.load(open('le5.pkl','rb'))
le6 = pickle.load(open('le6.pkl','rb'))
le7 = pickle.load(open('le7.pkl','rb'))
le8 = pickle.load(open('le8.pkl','rb'))
le9 = pickle.load(open('le9.pkl','rb'))
le10 = pickle.load(open('le10.pkl','rb'))

app = Flask(__name__)
```

Render HTML page:

```
@app.route('/')
def home():
    return render_template('home.html')
@app.route('/guest',methods=['POST'])
```

Here I will be using a declared constructor to route to the HTML page which is created earlier. In the above example, '/' URL is bound with the index.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:

```
def Guest():
    Airline_name = request.form['Airline name']
    Seat_Type = request.form['Seat Type']
    Type_Of_Traveller= request.form['Type Of Traveller']
    Origin=request.form['Origin']
    Destination=request.form['Destination']
    Month_Flown=request.form['Month Flown']
    Year_Flown=request.form['Year Flown']
    Verified =request.form['Verified']
    S_C=request.form['S_C']
    F_B=request.form['F_B']
    G_S=request.form['G_S']
    O_R=request.form['O_R']

    data=[[Airline_name,Seat_Type,Type_Of_Traveller,Origin,Destination,
           Month_Flown,Year_Flown,Verified,S_C,F_B,G_S,O_R]]
    encoded_data=[
        le1.transform([Airline_name])[0],
        le2.transform([Seat_Type])[0],
        le3.transform([Type_Of_Traveller])[0],
        le4.transform([Origin])[0],
        le5.transform([Destination])[0],
        le6.transform([Month_Flown])[0],
        le7.transform([Year_Flown])[0],
        le8.transform([Verified])[0],
        [S_C][0],[F_B][0],[G_S][0],
        le9.transform([O_R])[0]
        ]
    print(encoded_data)

    prediction=model.predict(ss1.transform([encoded_data]))
    print(prediction)
    if prediction ==1:
        a="Recommended"
        return render_template('home.html', y=a)
    else:
        b="Not Recommended"
        return render_template('home.html', y=b)
```

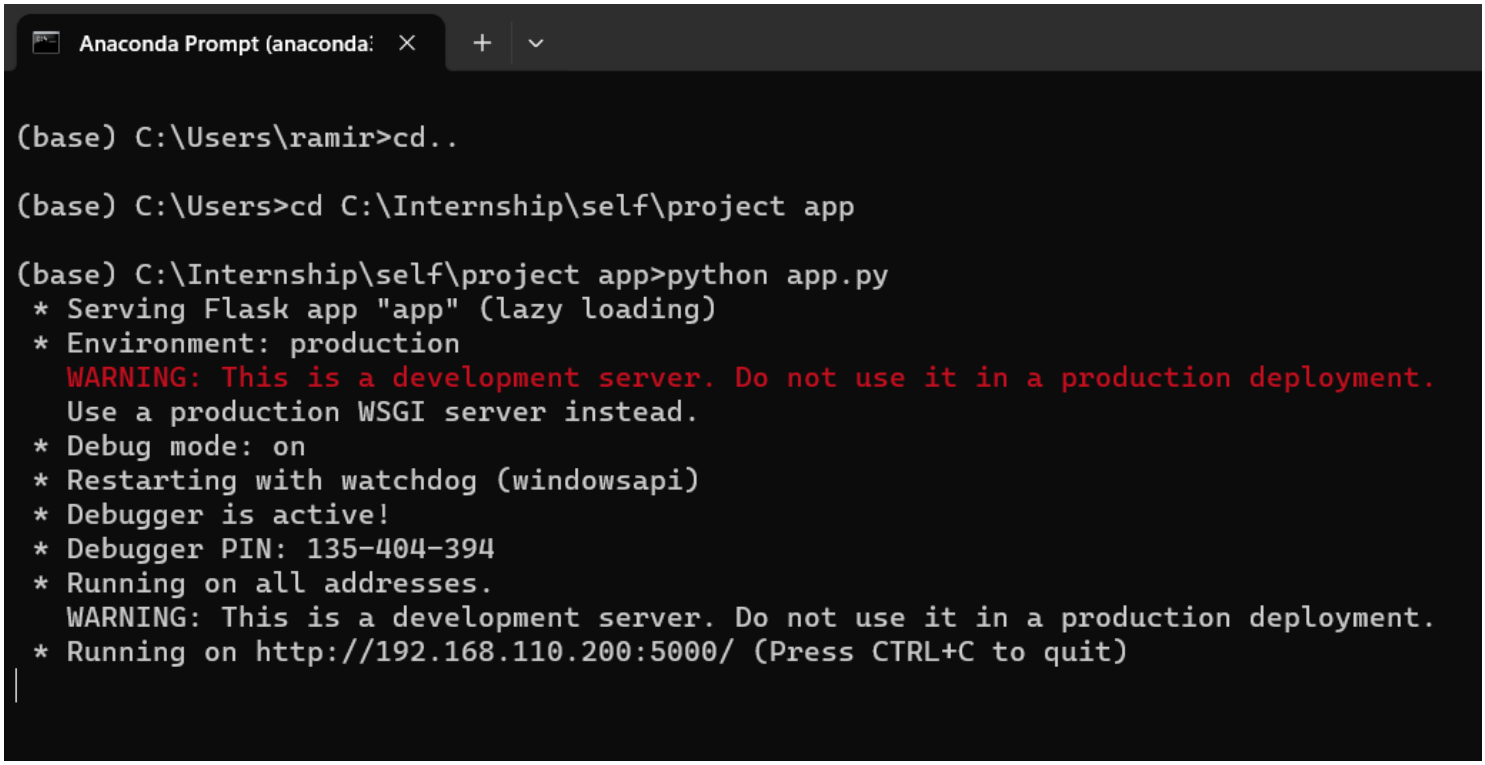
Here we are routing our app to Guest() function. This function retrieves all the values from the HTML page using Post request. That is stored in an array. This array is passed to the model.predict() function. This function returns the prediction.

```
if __name__ == '__main__':
    app.debug = True
    app.run(host='0.0.0.0',port=5000)
```

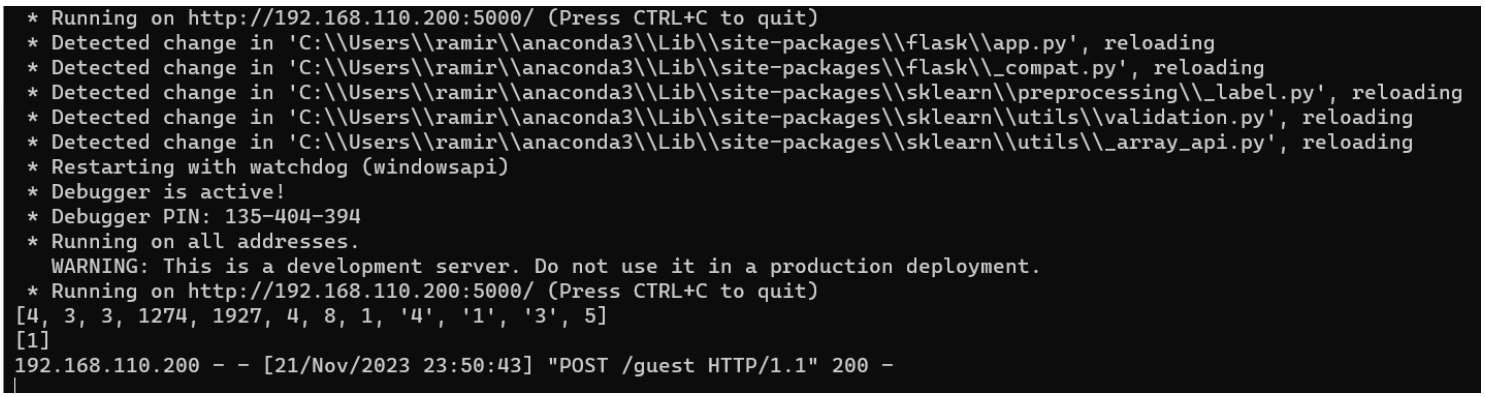
And this prediction value will be rendered to the text that we have mentioned in the index.html page. Set app.run(debug=True) so that we can edit.

Activity 2.3: Run the web application

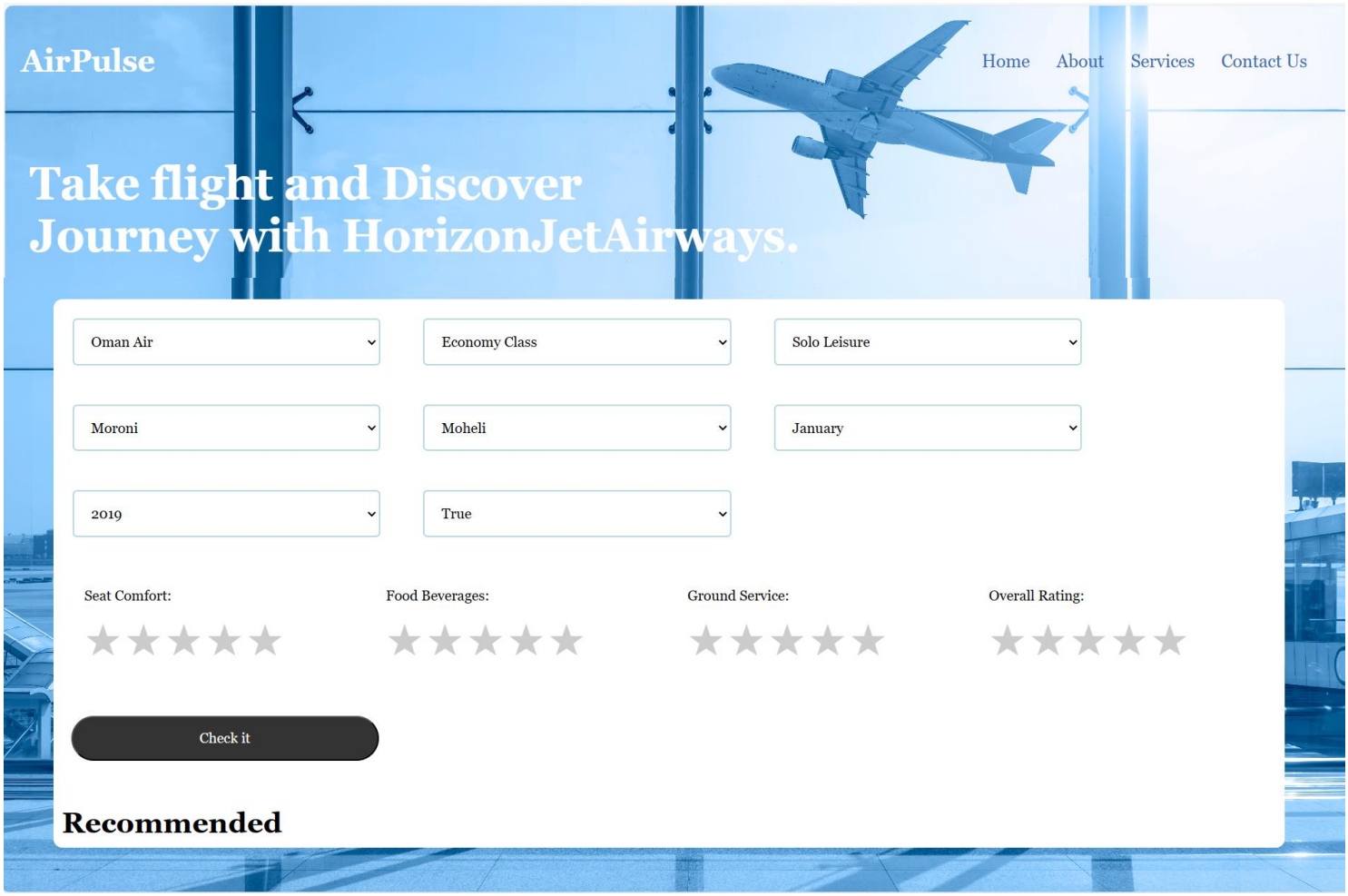
- Opened anaconda prompt from the start menu
- After Navigating to the folder where your python script is.
- After typing python app.py, the link is displayed where web app is running.
- Navigate to the link to view web page.



Enter the inputs, click on the Check It button, and see the result/prediction on the web



Now, in the web browser, writing the localhost URL (http://127.0.0.1:5000/) to get the below result.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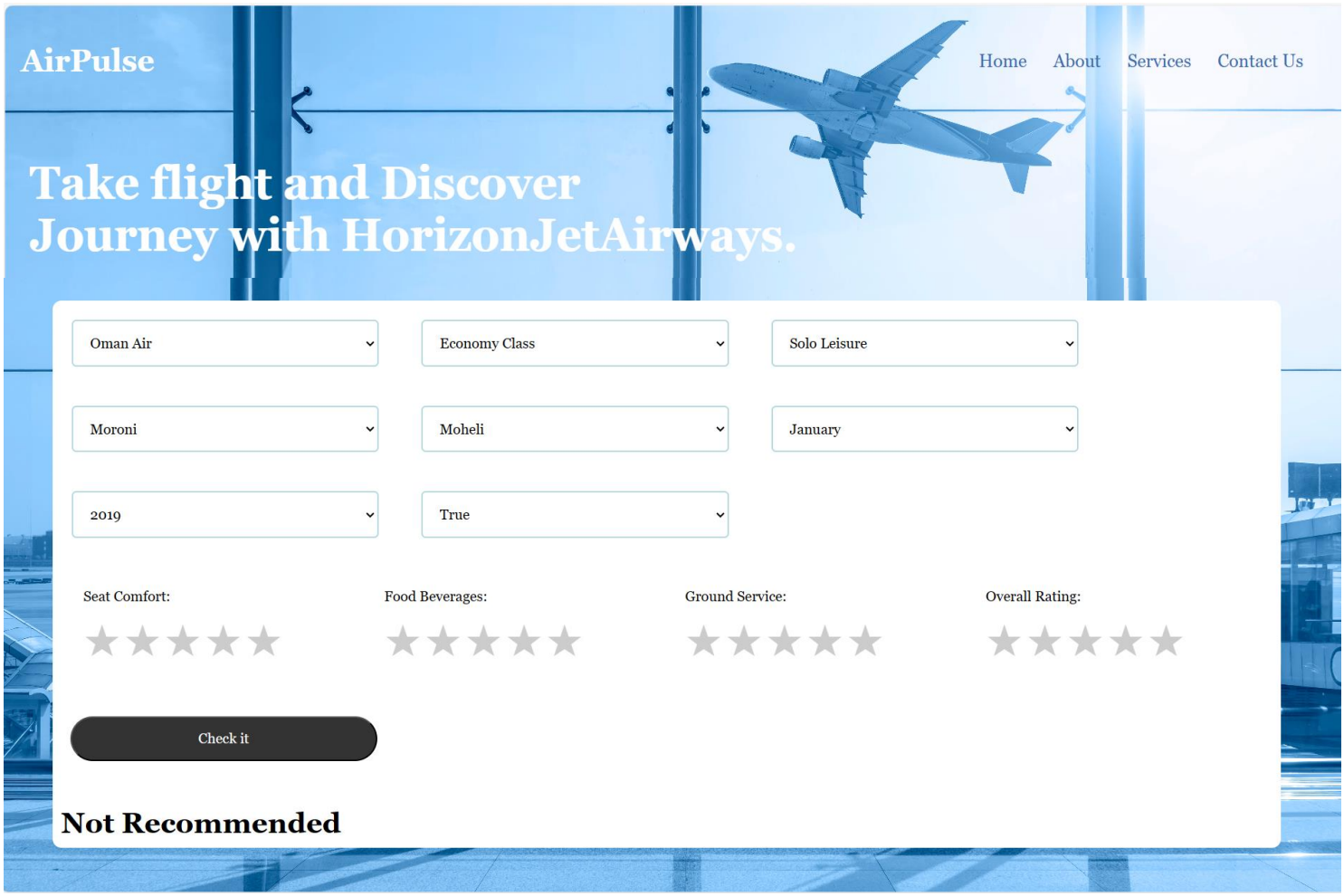
Journey with HorizonJetAirways.
Oman Air
Economy Class
Solo Leisure
Moroni
Moheli
January
2019
True
Seat Comfort:
Food Beverages:
Ground Service:
Overall Rating:
Check it
Recommended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Take flight and Discover
Journey with HorizonJetAirways.
Oman Air
Economy Class
Solo Leisure
Moroni
Moheli
January
2019
True
Seat Comfort:
Food Beverages:
Ground Service:
Overall Rating:
Check it
Not Recommended