Sasta_ticket_case

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1 SastaTicket: Flight Price Prediction Model

Participant

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Instructions - Ahmed is a customer of Sastaticket.pk. He is planning to fly from Karachi to Islamabad for his brother's wedding and is currently in the process of choosing tickets. Ahmed has to go to Islamabad but Ahmed also wants to save some money in the process, so he chooses to wait instead of buy now, simply because ticket prices are just too high.
- Is this the right decision? Won't ticket prices increase in the future? Perhaps there is a sweet-spot Ahmed is hoping to find and maybe he just might find it.
- This is the problem that you will be tackling in this competition. Can you predict future prices accurately to such a degree that you can now tell Ahmed - with confidence - that he has made the wrong decision.
- Your task boils down to generating optimal predictions for flight prices of multiple airlines. If successful, your model will contribute greatly to Sastaticket's rich and diverse set of operating algorithms.

Summary 1. Find Cheapest and expenses flights at specific time.
2. You have to go through EDA(Exploratory Data Analysis) Process.
3. Apply an appropriate Machine Learning Model.
4. Find a sweet spot for cheap ticket

1.0.1 1. Importing Relevant Libraries

[ ]:
```
# Importing Libraries
import pandas as pd
from pandas import MultiIndex, Int16Dtype

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Reproductability : *A good practice to set the seed to reproduce the Same Results*

[ ]:
```
SEED = 10
np.random.seed(SEED)
```

1.0.2 2. Loading Train and Test Data_Sets

[ ]:
```
# Loading Data_Sets into Data_Frames
df=  pd.read_csv('sastaTicket_train.csv')
df1= pd.read_csv('sastaticket_test.csv')
```

Interpreting Data_Set

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  5000 non-null   int64
 1   f1          5000 non-null   object
 2   f2          5000 non-null   object
 3   f3          5000 non-null   object
 4   f4          5000 non-null   object
 5   f5          5000 non-null   object
 6   f6          5000 non-null   object
 7   f7          5000 non-null   bool
 8   f8          5000 non-null   float64
 9   f9          5000 non-null   int64
 10  f10         5000 non-null   object
 11  target      5000 non-null   float64
dtypes: bool(1), float64(2), int64(2), object(7)
memory usage: 434.7+ KB
```

Renaming The Columns for Ease

[ ]:
```
# Renaming Our Columns
df.rename({'f1': 'Buying_Time', 'f2': 'Origin' , 'f3':'Destination', 'f4':␣
↪'Depart_Time', 'f5':'Arrival_Time' , 'f6':'Airline',
       'f7': 'Ticket_Refunded', 'f8':'Bag_Weight', 'f9':'Bag_Pieces' , 'f10':
↪'Airline_No.','target':'Fare'}
         , axis=1, inplace=True)
df1.rename({'f1': 'Buying_Time', 'f2': 'Origin' , 'f3':'Destination', 'f4':␣
↪'Depart_Time', 'f5':'Arrival_Time' , 'f6':'Airline',
       'f7': 'Ticket_Refunded', 'f8':'Bag_Weight', 'f9':'Bag_Pieces' , 'f10':
↪'Airline_No.'}
         , axis=1, inplace=True)
```

Dropping Unnecessary Columns

```
[ ]: df.drop(['Origin','Destination','Airline_No.','Unnamed: 0'],axis=1,inplace=True)
     df1.drop(['Origin','Destination','Airline_No.','Unnamed:␣
      ↪0'],axis=1,inplace=True)
```

1.0.3 3. Data Munging

Type Casting

```
[ ]: df[['Arrival_Time','Depart_Time','Buying_Time']] =␣
      ↪df[['Arrival_Time',"Depart_Time",'Buying_Time']].apply(pd.to_datetime)
     df1[['Arrival_Time','Depart_Time','Buying_Time']] =␣
      ↪df1[['Arrival_Time',"Depart_Time",'Buying_Time']].apply(pd.to_datetime)
```

Feature Engineering

```
[ ]: date_format_string= '%Y/%m/%d %.f'


     f1= pd.to_datetime(df['Buying_Time'], date_format_string)
     f2= pd.to_datetime(df['Depart_Time'], date_format_string)
     f3= pd.to_datetime(df['Arrival_Time'], date_format_string)

     f11= pd.to_datetime(df1['Buying_Time'], date_format_string)
     f22= pd.to_datetime(df1['Depart_Time'], date_format_string)
     f33= pd.to_datetime(df1['Arrival_Time'], date_format_string)


         # Feature Engineering
     diff = f2-f1
     df['Days_to_Depart'] = diff
     df['Days_to_Depart'] = df['Days_to_Depart'].dt.days.values

     df['hrs_to_Depart'] = diff
     df['hrs_to_Depart'] = df['hrs_to_Depart'].dt.components['hours']


     df['min_to_Depart'] = diff
     df['min_to_Depart'] = df['min_to_Depart'].dt.components['minutes']



         # Feature Engineering
     diff1 = f22-f11
     df1['Days_to_Depart'] = diff
     df1['Days_to_Depart'] = df1['Days_to_Depart'].dt.days.values
```

```
df1['hrs_to_Depart'] = diff
df1['hrs_to_Depart'] = df1['hrs_to_Depart'].dt.components['hours']


df1['min_to_Depart'] = diff
df1['min_to_Depart'] = df1['min_to_Depart'].dt.components['minutes']
```

Again Dropping unuseful columns

[ ]:
```
df.drop(['Buying_Time','Depart_Time','Arrival_Time'],axis=1,inplace=True)
 ↪# Again Removing Unnecssary Columns
df1.
 ↪drop(['Buying_Time','Depart_Time','Arrival_Time','hrs_to_Depart','min_to_Depart'],axis=1,in
```

1.0.4 4. Doing Statistical Analysis

Checking Missing Values

[ ]:
```
df.isnull().sum()
```

[ ]:
```
Airline            0
Ticket_Refunded    0
Bag_Weight         0
Bag_Pieces         0
Fare               0
Days_to_Depart     0
hrs_to_Depart      0
min_to_Depart      0
dtype: int64
```

[ ]:
```
df.describe(include='all')
```

[ ]:
```
       Airline Ticket_Refunded   Bag_Weight   Bag_Pieces          Fare  \
count     5000            5000  5000.000000  5000.000000   5000.000000
unique       4               2          NaN          NaN           NaN
top      alpha            True          NaN          NaN           NaN
freq      2211            4968          NaN          NaN           NaN
mean       NaN             NaN    22.727400     0.944000  10084.847000
std        NaN             NaN     8.902075     0.606084   3374.189875
min        NaN             NaN     0.000000     0.000000   4990.000000
25%        NaN             NaN    20.000000     1.000000   7796.000000
50%        NaN             NaN    20.000000     1.000000   9150.000000
75%        NaN             NaN    32.000000     1.000000  11245.000000
max        NaN             NaN    45.000000     2.000000  35000.000000

        Days_to_Depart  hrs_to_Depart  min_to_Depart
count      5000.000000     5000.00000    5000.000000
```

```
unique          NaN         NaN         NaN
top             NaN         NaN         NaN
freq            NaN         NaN         NaN
mean      14.971600    11.84600   29.700000
std       18.918498     7.27294   17.462812
min        0.000000     0.00000    0.000000
25%        4.000000     5.00000   14.000000
50%       10.000000    12.00000   30.000000
75%       19.000000    18.00000   45.000000
max      243.000000    23.00000   59.000000
```

Dropping Duplicate Values

[ ]:
```
df.drop_duplicates(keep=False,inplace=True)
```

***Making list of Categorical Column and Numerical Ones**

[ ]:
```
cat_cols= ['Airline','Ticket_Refunded','Bag_Weight','Bag_Pieces']
num_cols= ['Days_to_Depart','hrs_to_Depart','min_to_Depart']
```

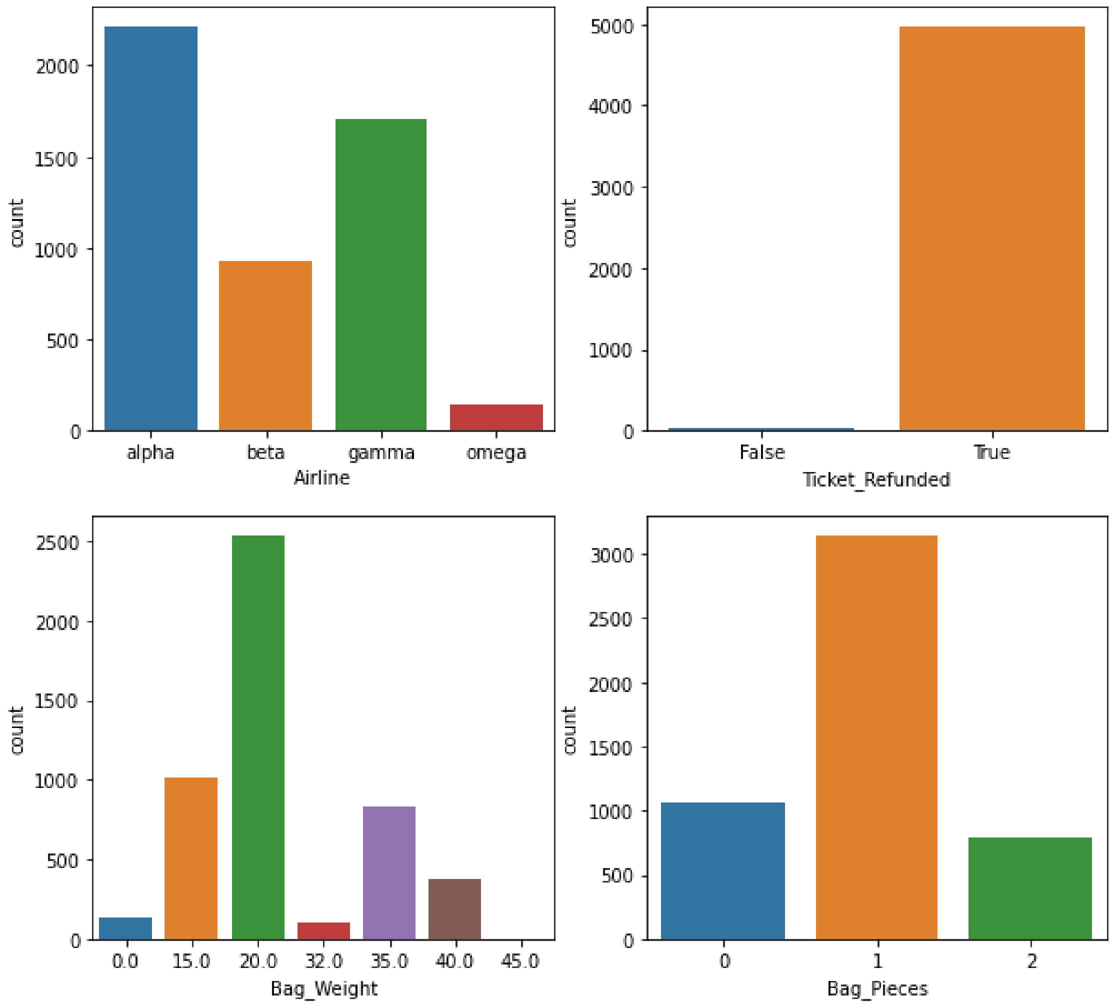
1.0.5 5. PLOTTING and VISUALIZATION

Count Plot

[ ]:
```
# Categorical Count Plotting
plt.figure (figsize=(10,30))
c=1
for i in cat_cols:
    plt.subplot(6,2,c)
    sns.countplot(df[i])
    c=c+1
plt.show()
```

```
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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(
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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(
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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(
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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(
```

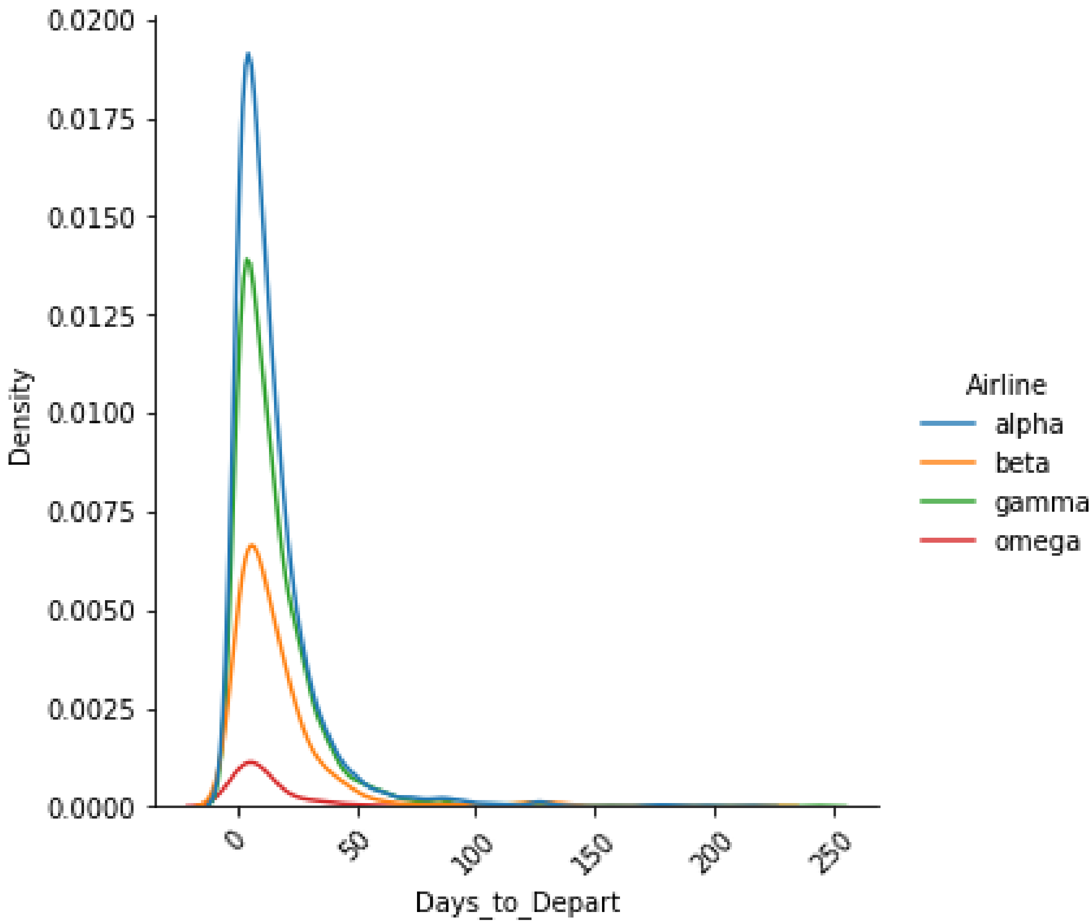


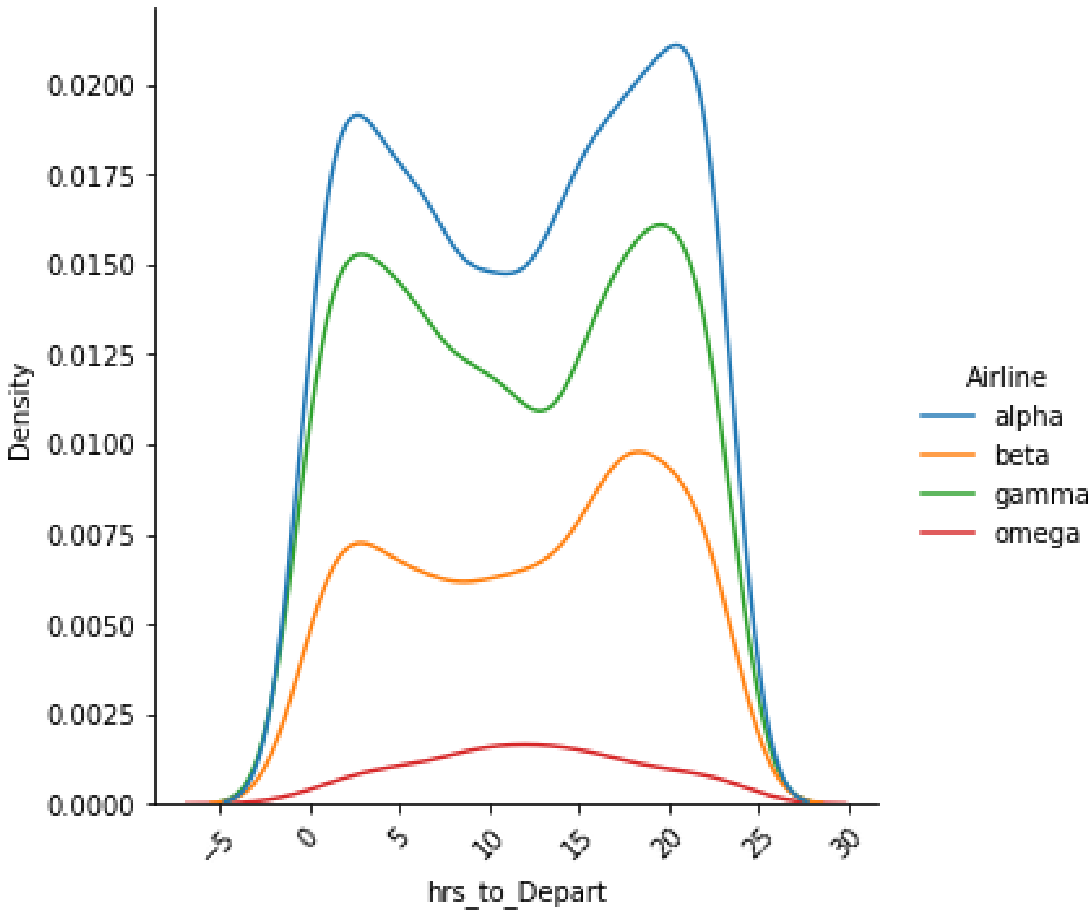
Results:
1. **Alpha** has higher number of flights
2. Mostly Tickets are Refund-able
3. Most Passengers have 2 piece of Bag and the avg weight is 20.

Dist Plot

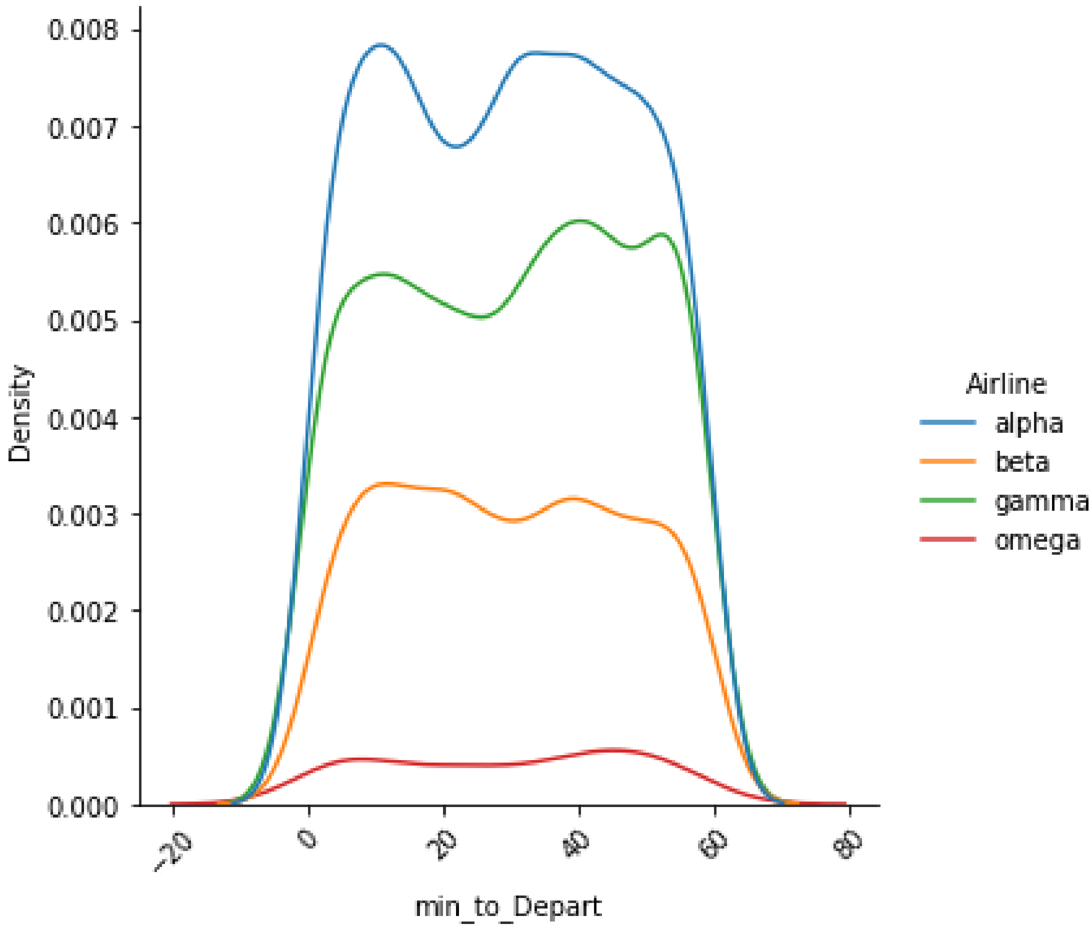
[ ]:
```python
# plotting numerical data
c=1
plt.figure(figsize=(10,8))
for i in num_cols:
    sns.displot(df,
        x=df[i],
        hue="Airline",
        kind="kde",
        warn_singular=False)
    plt.xticks(rotation=45)
plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```





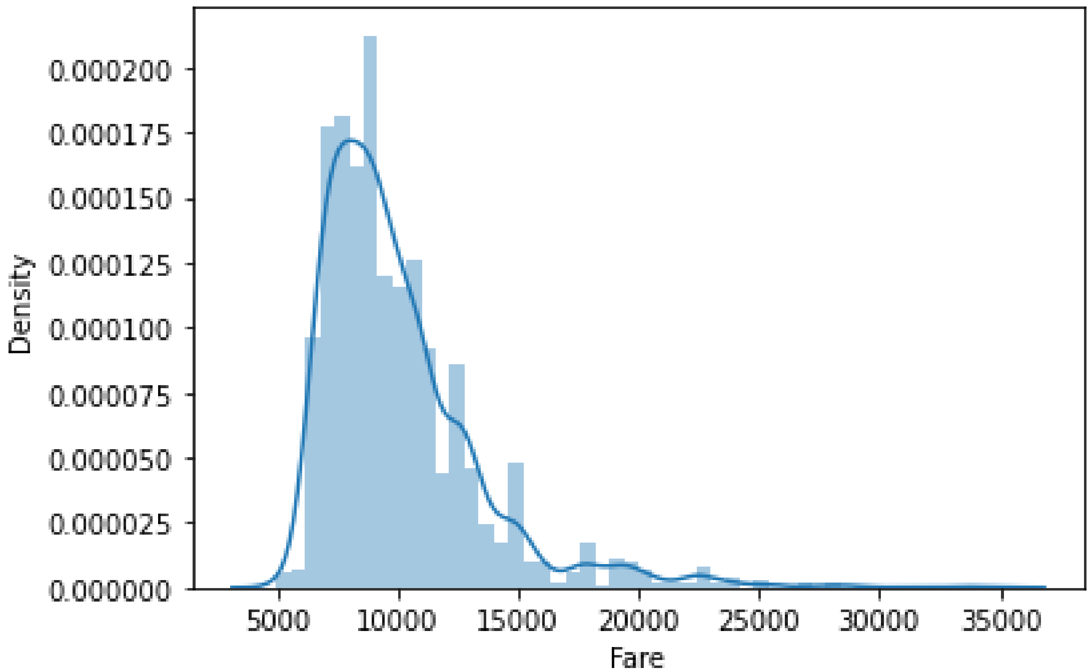
Density
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
0.0200
−5
0
5
10
15
20
25
30
hrs_to_Depart
Airline
alpha
beta
gamma
omega



[ ]:
```
sns.distplot(df['Fare'])
```

```
c:\Users\DELL\AppData\Local\Programs\Python\Python310\lib\site-
packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[ ]:
```
<AxesSubplot:xlabel='Fare', ylabel='Density'>
```



Result: *Looks Right Skewed.*

1.0.6 6. Normalization Test

[ ]:
```
# Importing Library
from scipy.stats import shapiro

stat, p = shapiro(df['Fare'])

print ("stat = %.3f , p-value=%.3f" %(stat,p))

if p > 0.05:
    print('H1: Probably Gaussian or Normal distribution')
else:
    print('H0: Probably NO Gaussian or Normal distribution')
```

```
stat = 0.823 , p-value=0.000
H0: Probably NO Gaussian or Normal distribution
```

Normalizing The Data

[ ]:
```
df['Fare']=np.log(df['Fare'])

# df['Days_to_Depart'] = (df['Days_to_Depart']-df['Days_to_Depart'].mean()) /␣
↪df['Days_to_Depart'].std()
```

```
# df['hrs_to_Depart']=    (df['hrs_to_Depart']-df['hrs_to_Depart'].mean()) /␣
↪df['hrs_to_Depart'].std()
# df['Bag_Weight']=   (df['Bag_Weight']-df['Bag_Weight'].mean()) /␣
↪df['Bag_Weight'].std()
# df['Fare'] = (df['Fare']-df['Fare'].mean()) / df['Fare'].std()
# df['min_to_Depart']= (df['min_to_Depart']-df['min_to_Depart'].mean()) /␣
↪df['min_to_Depart'].std()
df.head(5)
```

[ ]:

```
  Airline  Ticket_Refunded  Bag_Weight  Bag_Pieces      Fare  Days_to_Depart  \
0   alpha             True        35.0           1  9.591854               8
1   alpha             True        35.0           1  9.180603              11
2    beta             True        20.0           0  8.814925              17
3   gamma             True        20.0           1  9.354008              21
4   gamma             True        32.0           1  9.175231               1

   hrs_to_Depart  min_to_Depart
0              1              7
1             20             48
2             21              7
3              5             53
4              1             21
```

1.0.7 7. Checking Outliers and removing them on percentage basis

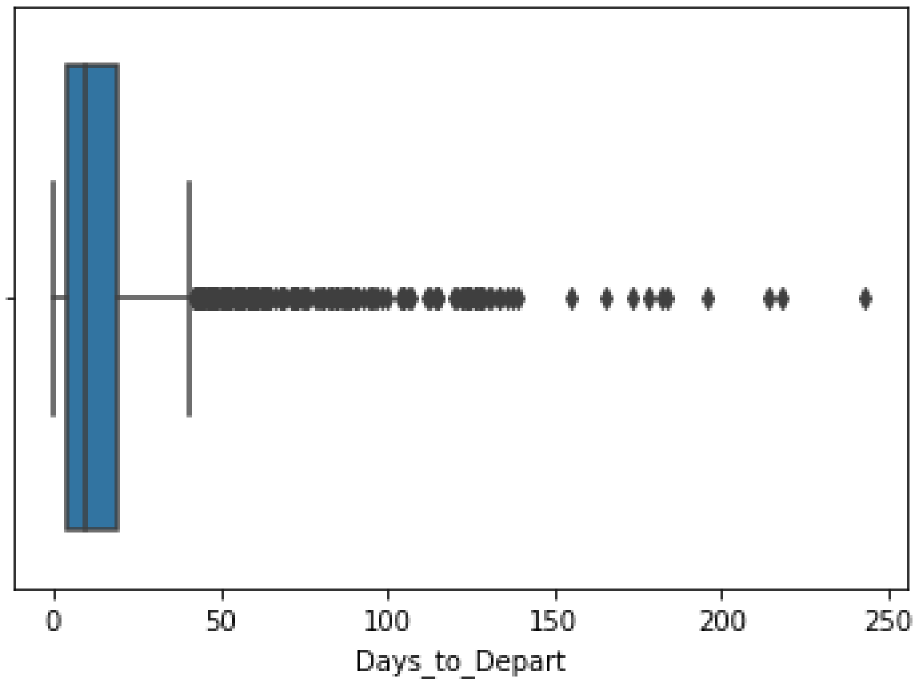
[ ]:

```
sns.boxplot(df['Days_to_Depart'])
```

```
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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='Days_to_Depart'>
```

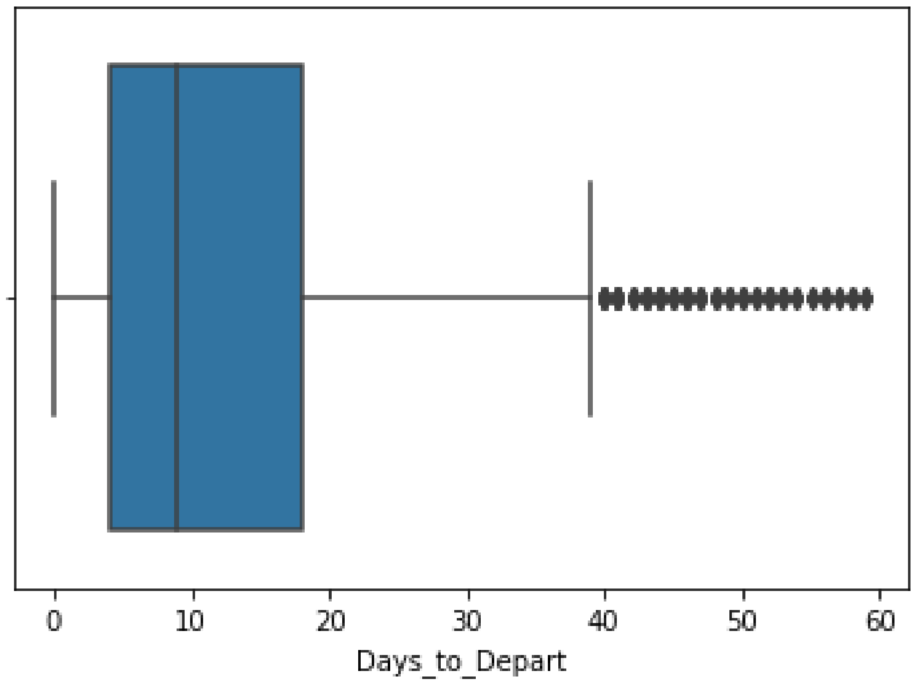


[ ]:
```
df = df[df['Days_to_Depart'] < 60]              # Removing Days to depart a␣
↪Flight as there less numbers that buy tickets way before the flight Depart
```

[ ]:
```
sns.boxplot(df['Days_to_Depart'])
```

```
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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(
```

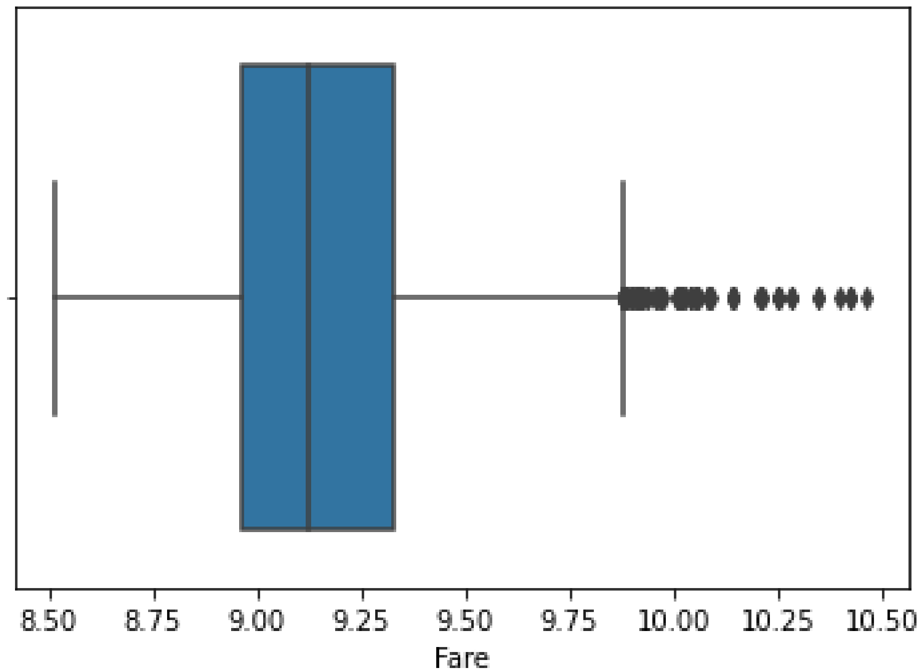
[ ]: <AxesSubplot:xlabel='Days_to_Depart'>



[ ]:
```
sns.boxplot(df['Fare'])
```

```
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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(
```

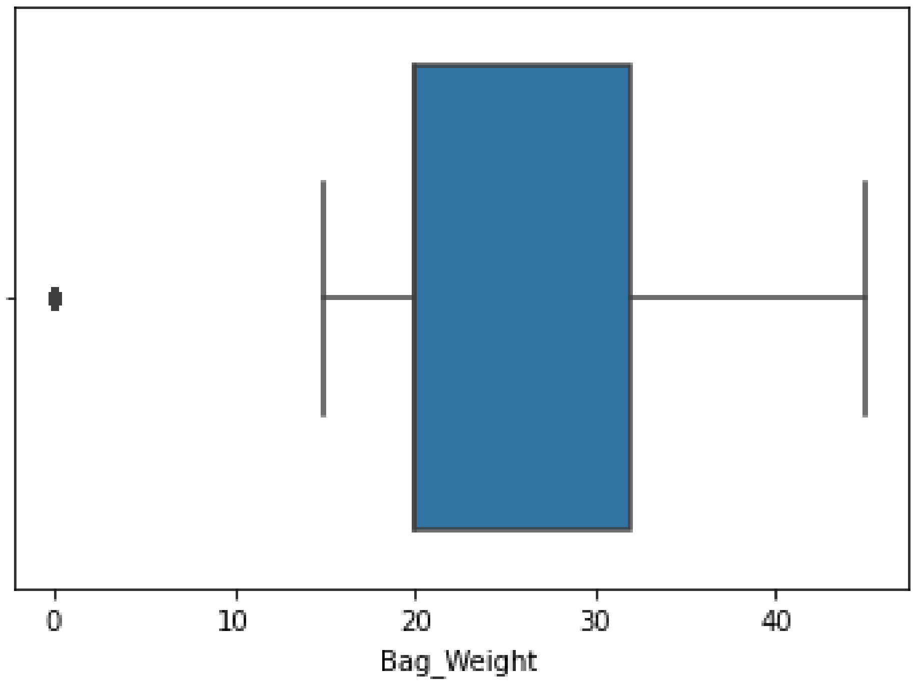
[ ]: <AxesSubplot:xlabel='Fare'>



[ ]:
```
sns.boxplot(df['Bag_Weight'])
```

```
c:\Users\DELL\AppData\Local\Programs\Python\Python310\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='Bag_Weight'>



Since Data isn't normal we can check the coorelation as well.

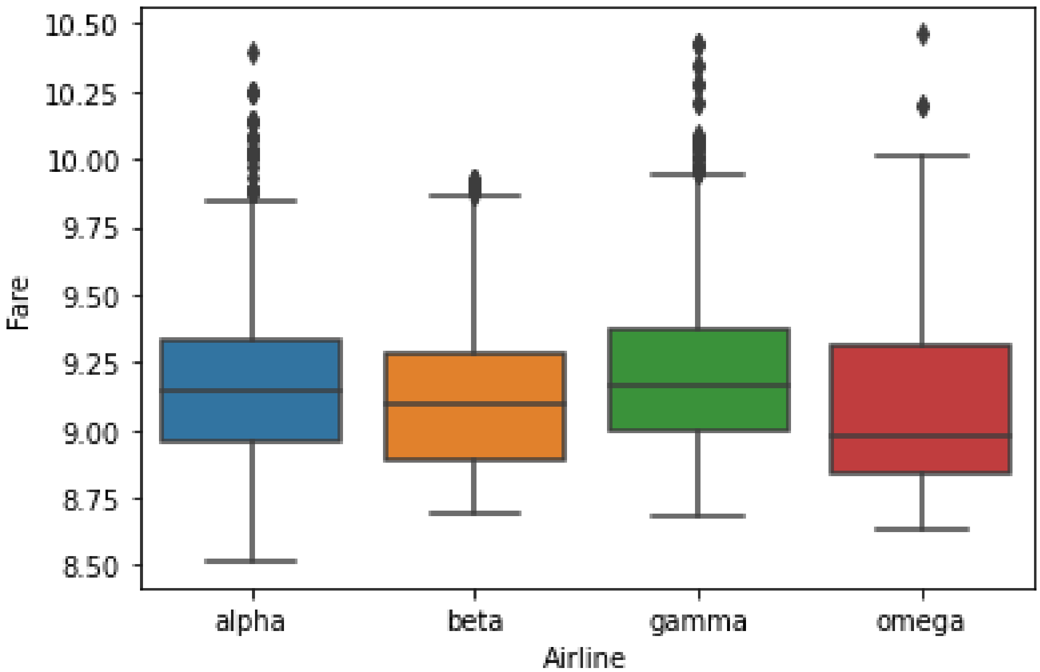
[ ]:
```
corr= df.corr(method='pearson')    # Correlation range from 1 to -1
corr.style.background_gradient(cmap='Accent')
```

[ ]: <pandas.io.formats.style.Styler at 0x2120a8cbf40>

Result: *Fare has slight Corelation between Bag_weight,Pieces,Days_to_Depart.*

[ ]:
```
sns.boxplot(data=df , x="Airline",y='Fare')
```

[ ]: <AxesSubplot:xlabel='Airline', ylabel='Fare'>



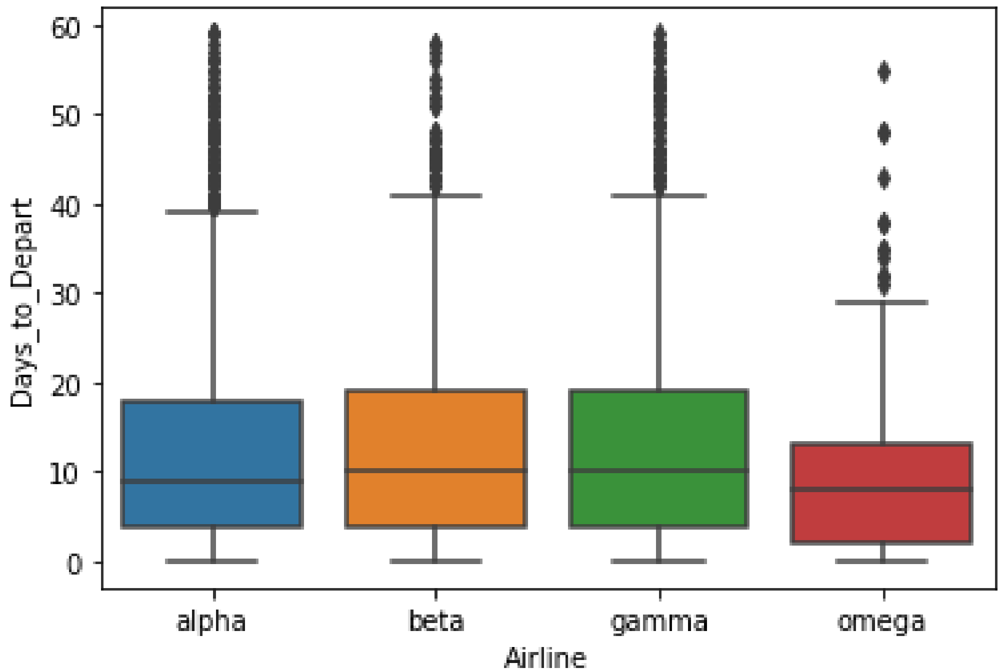
Omega Has relatively Low Fare from Other Airlines but on the other hand they have low no. of flights

[ ]:
```
df['Airline'].value_counts()
```

[ ]:
```
alpha    2148
gamma    1663
beta      902
omega     143
Name: Airline, dtype: int64
```

[ ]:
```
sns.boxplot(data=df,x='Airline',y='Days_to_Depart')
```

[ ]: <AxesSubplot:xlabel='Airline', ylabel='Days_to_Depart'>



Less Days for Omega flight to Departure.

1.0.8 8. Applying Machine_Learning Models

Encoding

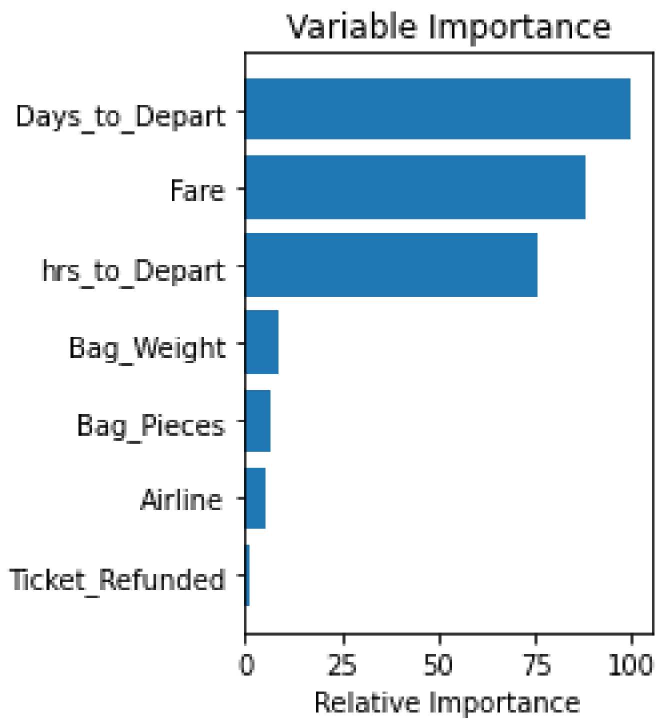
[ ]:
```
from sklearn.preprocessing import LabelEncoder  as le      # Importing Encoder
```

[ ]:
```
df['Airline'] = le().fit_transform(df['Airline'])
df['Ticket_Refunded'] = le().fit_transform(df['Ticket_Refunded'])

df1['Airline'] = le().fit_transform(df1['Airline'])
df1['Ticket_Refunded'] = le().fit_transform(df1['Ticket_Refunded'])
```

Important Feature

[ ]:
```
from sklearn.ensemble import ExtraTreesRegressor

df_name = df.columns
clf = ExtraTreesRegressor(n_estimators=250,
                              random_state=SEED)

clf.fit(df[df_name[0:7]],df[df_name[7]])



# Plot feature importance
```

```
feature_importance = clf.feature_importances_
# make importances relative to max importance
feature_importance = 100.0 * (feature_importance / feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
plt.subplot(1, 2, 2)
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, df.columns[sorted_idx])
#boston.feature_names[sorted_idx])

plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```



Splittin into X and Y

[ ]:
```
X= df[['Airline','Ticket_Refunded','Bag_Weight','Bag_Pieces','Days_to_Depart']]
y= df['Fare']
```

[ ]:
```
X.shape
```

[ ]: (4856, 5)

[ ]:
```
# Making df1 Data_Frame equal ot our test data_frame
df1 = df1.sample(4856)
```

[ ]:
```
df1.head()
```

[ ]:

	Airline	Ticket_Refunded	Bag_Weight	Bag_Pieces	Days_to_Depart
758	2	0	20.0	1	3
4009	0	0	20.0	1	41
1820	3	0	20.0	1	25
1056	0	0	20.0	1	8
1552	3	0	20.0	1	61

1.0.9 *Machine Learning Modeling*

Importing Models

[ ]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor

# For Classification
# from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
# from sklearn.naive_bayes import GaussianNB



from pandas import set_option
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
# For Classification
# from pandas.tools.plotting import scatter_matrix
# from sklearn.model_selection import StratifiedKFold


from sklearn.metrics import
↪mean_squared_error,mean_absolute_error,explained_variance_score,max_error,r2_score,median_a
```

Models Function

```
[ ]: # Initial Algorithms to fit the data on
def GetBasedModel():
    basedModels = []
    basedModels.append(('Linear Regression', LinearRegression()))
    basedModels.append(('K-Nearest Neigbour', KNeighborsRegressor()))
    basedModels.append(('Decision Tree', DecisionTreeRegressor()))
    basedModels.append(('Support Vector Machine', SVR()))
    basedModels.append(('Ada Boost', AdaBoostRegressor()))
    basedModels.append(('Gradient Boost'  , GradientBoostingRegressor()))
    basedModels.append(('Random Forest'   , RandomForestRegressor()))
    basedModels.append(('Extra Tree Classifier'   , ExtraTreesRegressor()))
    # max_depth = 12, eta = 0.3,n_estimators = 100, objective = 'reg:
↪squarederror',gamma = 0.01



    return basedModels
```

Metrics Function

```
[ ]: def evaluate_metrics(X_test,y_test,y_pred,model):
    mean_abs_error = mean_absolute_error(y_test,y_pred)
    mean_sq_error = mean_squared_error(y_test,y_pred)
    root_mean_sq_error = mean_squared_error(y_test,y_pred)**0.5
    r2_scr = r2_score(y_test,y_pred)
    median_abs_score = median_absolute_error(y_test,y_pred)
    explained_variance = explained_variance_score(y_test,y_pred)
    max_err = max_error(y_test,y_pred)

    metric_name = ["Mean Absolute Error (MAE)","Mean Square Error (MSE)","Root␣
↪Mean Squared Error (RMSE)","R2 Score","Median Absolute Error","Explained␣
↪Variance Score", "Max Error"]

    return metric_name, mean_abs_error, mean_sq_error, root_mean_sq_error,␣
↪r2_scr, median_abs_score, explained_variance, max_err
```

Model Tuning Function

```
[ ]: def BasedLine2(X_train, y_train, X_test, y_test, models):
    results = []
    names = []
    metric_values = []
    metric_names = []

    for name, model in models:
        kfold = KFold(n_splits=10, random_state=SEED, shuffle=True)
        cv_results = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='neg_root_mean_squared_error')
```

```
        # For scoring Parameters visit: https://scikit-learn.org/stable/modules/
↪model_evaluation.html#scoring-parameter
        results.append(abs(cv_results))
        names.append(name)
        # print(f"{name} {abs(cv_results.mean()):.3f} [{cv_results.std():.3f}]")
        # print(abs(cv_results))

        model.fit(X_train, y_train)
        global y_pred
        y_pred = model.predict(X_test)
        m_n, mean_abs_error, mean_sq_error, root_mean_sq_error, r2_scr,␣
↪median_abs_score, explained_variance, max_err = evaluate_metrics(X_test,␣
↪y_test, y_pred, models)

        metric_names.append(m_n)
        metric_values.append((mean_abs_error.mean(), mean_sq_error.mean(),␣
↪root_mean_sq_error.mean(), r2_scr.mean(), median_abs_score.mean(),␣
↪explained_variance.mean(), max_err.mean()))

    return names, results, metric_names, metric_values
```

Models Visualization Function

[ ]:
```
# Importing Plotting Libraries
import plotly.offline as py
import plotly.graph_objs as go
import plotly.tools as tls
import plotly.express as px
```

[ ]:
```
class PlotBoxR(object):

    def __Trace(self,nameOfFeature,value):

        trace = go.Box(
            y = value,
            name = nameOfFeature,
            marker = dict(
                color = 'rgb(0, 128, 128)',
            )
        )
        return trace

    def PlotResult(self,names,results):

        data = []

        for i in range(len(names)):
```

```
            data.append(self.__Trace(names[i],results[i]))

        py.iplot(data)
```

Splitting Data into Traing and Test

[ ]:
```
X_train,X_test,y_train,y_test =train_test_split(X, y, test_size=0.2,␣
↪random_state=42)   # Random sample of 42 from dataset

# X_train, y_train =␣
↪df[['Airline','Ticket_Refunded','Bag_Weight','Bag_Pieces','Days_to_Depart']].
↪values, df['Fare'].values
```

Model Training and Evaluation

[ ]:
```
import warnings
warnings.filterwarnings("ignore")

models = GetBasedModel()
names, results, metric_names, metric_values = BasedLine2(X_train, y_train,␣
↪X_test, y_test, models)
PlotBoxR().PlotResult(names, results)
pd.DataFrame(metric_values, columns=metric_names[0], index=names)
```

[ ]:
```
                        Mean Absolute Error (MAE)  Mean Square Error (MSE)  \
Linear Regression                        0.213384                 0.072262
K-Nearest Neigbour                       0.214714                 0.078296
Decision Tree                            0.202936                 0.071014
Support Vector Machine                   0.199066                 0.067219
Ada Boost                                0.228907                 0.081062
Gradient Boost                           0.201709                 0.068009
Random Forest                            0.203060                 0.070503
Extra Tree Classifier                    0.203051                 0.070932

                        Root Mean Squared Error (RMSE)  R2 Score  \
Linear Regression                             0.268815  0.079847
K-Nearest Neigbour                            0.279815  0.003001
Decision Tree                                 0.266485  0.095729
Support Vector Machine                        0.259265  0.144062
Ada Boost                                     0.284715 -0.032221
Gradient Boost                                0.260785  0.134002
Random Forest                                 0.265525  0.102236
Extra Tree Classifier                         0.266331  0.096777

                        Median Absolute Error  Explained Variance Score  \
Linear Regression                    0.188443                  0.081683
K-Nearest Neigbour                   0.174715                  0.003704
```

```
Decision Tree                        0.172438                   0.097744
Support Vector Machine               0.155954                   0.148536
Ada Boost                            0.196691                   0.059423
Gradient Boost                       0.170139                   0.136039
Random Forest                        0.173752                   0.104034
Extra Tree Classifier                0.172977                   0.098593

                        Max Error
Linear Regression        1.031586
K-Nearest Neigbour       1.177087
Decision Tree            1.016442
Support Vector Machine   1.084740
Ada Boost                1.065866
Gradient Boost           1.040108
Random Forest            1.014378
Extra Tree Classifier    1.016442
```

[ ]:
```python
# another way of Importing Models
# from sklearn.linear_model import LinearRegression
# from sklearn.tree import DecisionTreeRegressor
# from sklearn.neighbors import KNeighborsRegressor
# from sklearn.svm import SVR
# from sklearn.model_selection import train_test_split
# from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error



# lr = LinearRegression()
# dt = DecisionTreeRegressor()
# knn = KNeighborsRegressor()
# svr =  SVR()
```

For Root Mean Square Error Calculation: `rms= mean_squared_error(y_test,y_pred, squared=False)`

Model Looping on basis of scores

[ ]:
```python
# X_train,X_test,y_train,y_test =train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)               # Random sample of 42 from dataset



# for i in [lr,dt,knn,svr]:                          # Reading all Models
#         i.fit(X_train,y_train)                     # Fitting the Models
#         pred = i.predict(X_test)                   # Predicting the values
#         test_score = r2_score(y_test, pred)        # test score
#         train_score =  r2_score(y_train, i.predict(X_train))       # train␣
 ↪score
#         if abs(train_score-test_score) <= 0.1:
```

```
#               print(i)
#               print('R2 Score: ', r2_score(y_test,pred))
#               print('Mean Absolute Error: ', mean_absolute_error(y_test,pred))
#               print('Mean Squared Error: ', mean_squared_error(y_test,pred))
#               print('Root Mean Square Error: ', mean_squared_error(y_test,pred,␣
↪squared=False))
```

Final prediciton on given values for Linear Regression

[ ]:
```
lr = LinearRegression().fit(X,y)                         # Fitting Original X and y
pred = lr.predict(df1)

# To save the predicted model
res = pd.DataFrame(pred)
res.index = X.index          # it's important for comparison
res.columns = ['Prediction']
res.to_csv('Prediction_results.csv')
```

[ ]:
```
df3 = pd.read_csv('Prediction_results.csv')         # Reading Predicted File
df3.head()
```

[ ]:

	Unnamed: 0	Prediction
0	0	9.316368
1	1	9.249922
2	2	9.211446
3	3	9.235493
4	4	9.182590

[ ]:
```
df3['Prediction']=np.exp(df3['Prediction'])         # Converting to Original␣
↪Values
```

[ ]:
```
df3.head()
```

[ ]:

	Unnamed: 0	Prediction
0	0	11118.530379
1	1	10403.750141
2	2	10011.066418
3	3	10254.720420
4	4	9726.311281

[ ]:
```
df3.to_csv('Without_log_pred.csv')           # Original Values CSV
```

2 The End