FLIP ROBO

Flight Price Prediction

Submitted by

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ACKNOWLEDGMENT

Working on this project has an incredible experience that will have an impact on my career.

It is pleasant gratification to present Flight Price Prediction.

I have completed this project by taking the help from Google, Bing and You tube.

INTRODUCTION

The tourism industry is changing fast and this is attracting a lot more travellers each year. The airline industry is considered as one of the most sophisticated industry in using complex pricing strategies. Now-a-days flight prices are quite unpredictable. The ticket prices change frequently. Customers are seeking to get the lowest price for their ticket, while airline companies are trying to keep their overall revenue as high as possible. Using technology it is actually possible to reduce the uncertainty of flight prices. So here we will be predicting the flight prices using efficient machine learning techniques.

Flight_name: Name of flight

Depart: The source from which the service begins.

Departure Time: The time when the journey starts from the source.

Arrival_Time: Time of arrival at the destination.

Duration : Total duration of the flight.

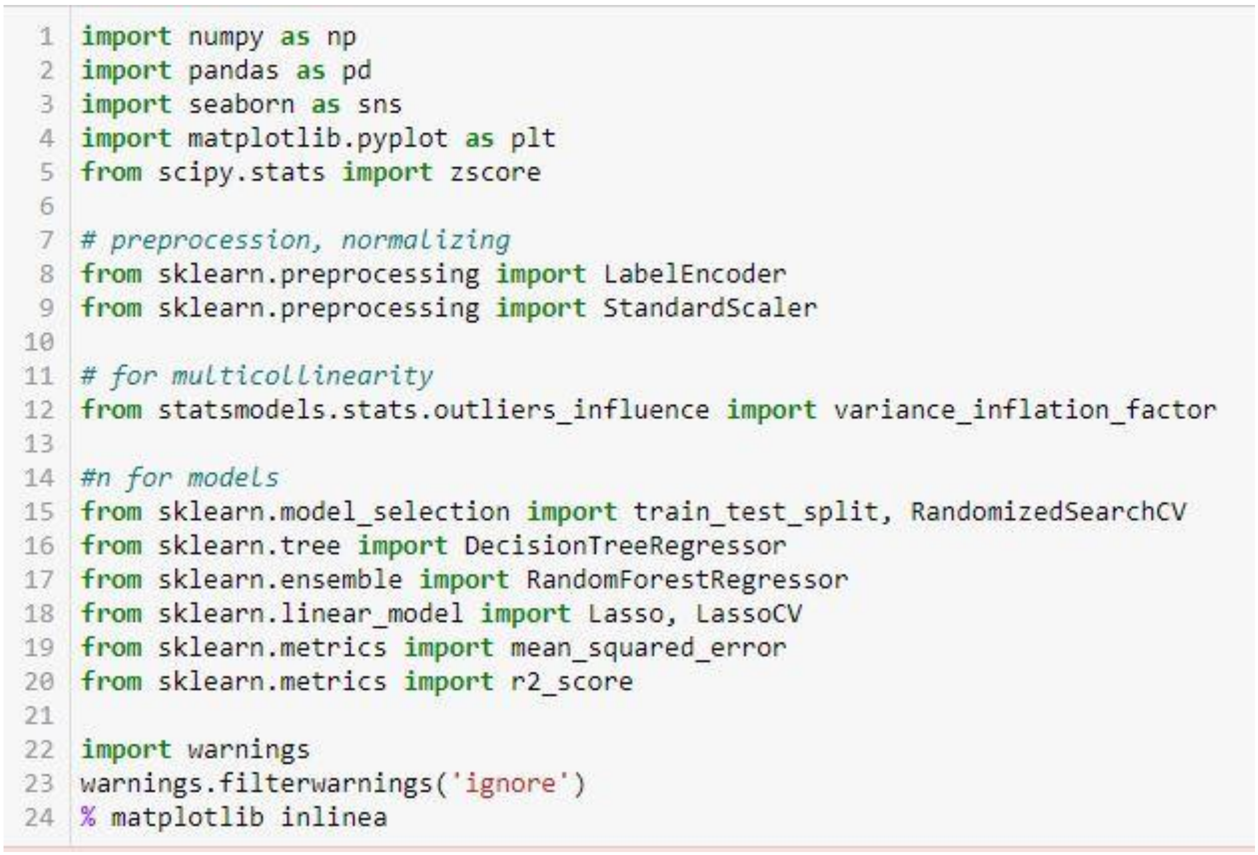
Destination: The destination where the service ends.

Total_stops : Total stops between the source and destination.

Price: The price of the ticket.

Importing Libraries

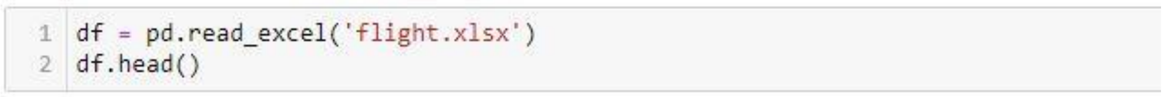
I am importing all the library which I required for EDA, visualization, prediction and finding all matrices. The reason of doing this is that it become easier to use all the import statement at one go and we do not require to import the statement again at each point.



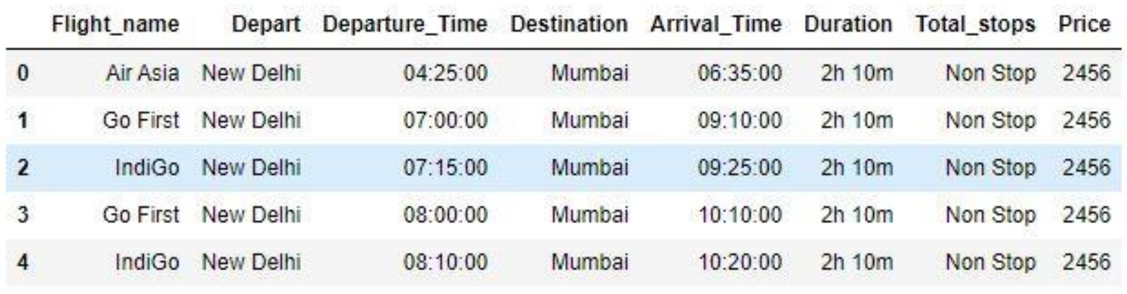
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import zscore

# preprocession, normalizing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler

# for multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor

#n for models
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import Lasso, LassoCV
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

import warnings
warnings.filterwarnings('ignore')
% matplotlib inlinea
```

- Data Sources and their formats

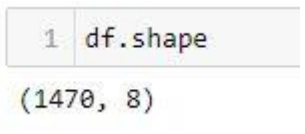
  Now I am going to upload or read the files/data-sets using pandas. For this I used read csv method.



```
df = pd.read_excel('flight.xlsx')
df.head()
```



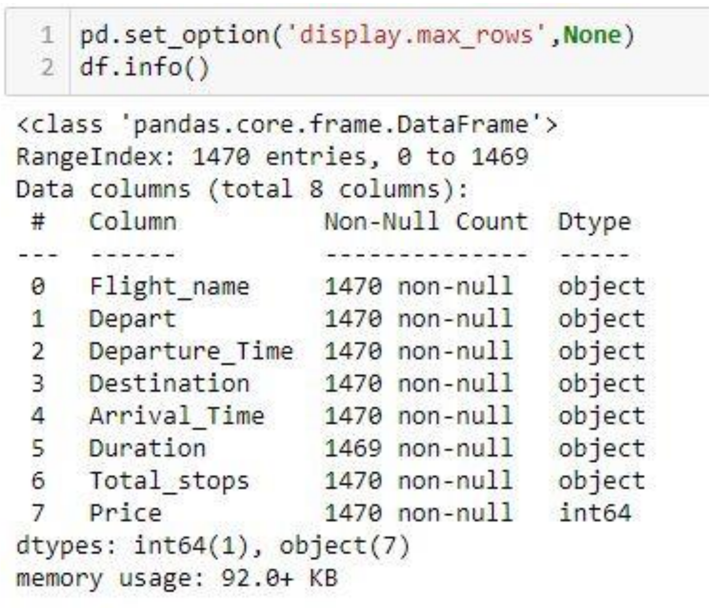
	Flight_name	Depart	Departure_Time	Destination	Arrival_Time	Duration	Total_stops	Price
0	Air Asia	New Delhi	04:25:00	Mumbai	06:35:00	2h 10m	Non Stop	2456
1	Go First	New Delhi	07:00:00	Mumbai	09:10:00	2h 10m	Non Stop	2456
2	IndiGo	New Delhi	07:15:00	Mumbai	09:25:00	2h 10m	Non Stop	2456
3	Go First	New Delhi	08:00:00	Mumbai	10:10:00	2h 10m	Non Stop	2456
4	IndiGo	New Delhi	08:10:00	Mumbai	10:20:00	2h 10m	Non Stop	2456



```
df.shape
```

```
(1470, 8)
```

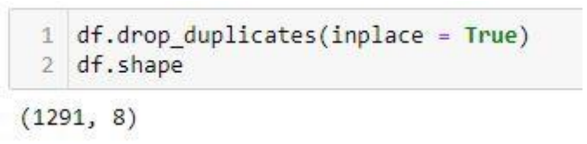
There are 1470 rows and 8 columns in the dataset.



```
pd.set_option('display.max_rows',None)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Flight_name     1470 non-null   object
 1   Depart          1470 non-null   object
 2   Departure_Time  1470 non-null   object
 3   Destination     1470 non-null   object
 4   Arrival_Time    1470 non-null   object
 5   Duration        1469 non-null   object
 6   Total_stops     1470 non-null   object
 7   Price           1470 non-null   int64 
dtypes: int64(1), object(7)
memory usage: 92.0+ KB
```

It is a mixed dataset as 6 columns are object type and 1 columns are integers type.

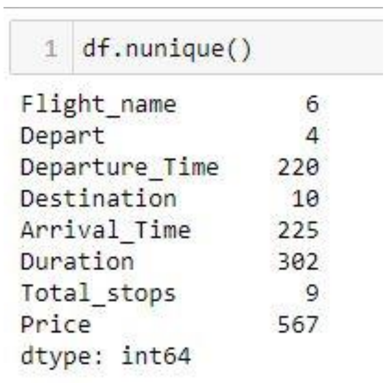


```
df.drop_duplicates(inplace = True)
df.shape
```

```
(1291, 8)
```

There are few duplicates value in the dataset.

Now there are 1291 rows and 8 columns in the dataset.



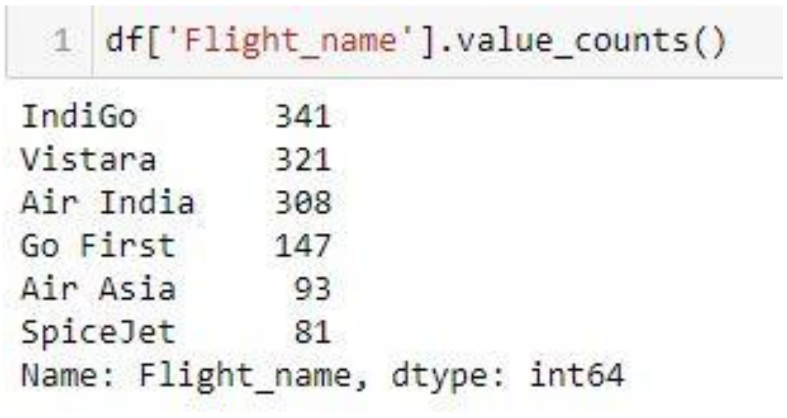
```
df.nunique()
```

```
Flight_name         6
Depart              4
Departure_Time    220
Destination        10
Arrival_Time      225
Duration          302
Total_stops         9
Price             567
dtype: int64
```

There are few columns which are categorical in nature and few columns are continuous in nature.

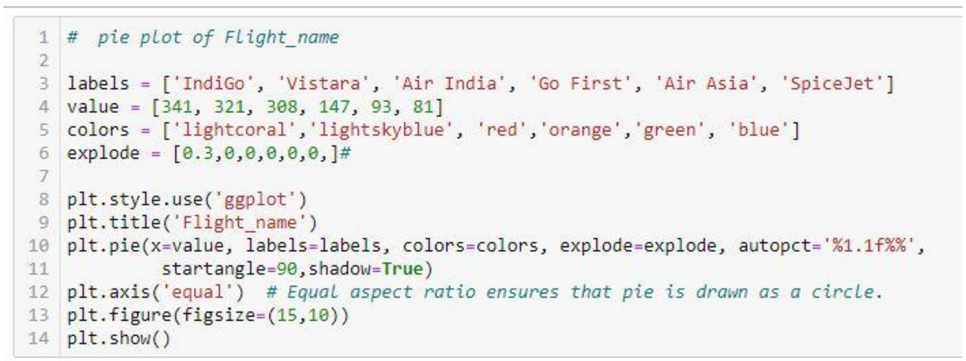
Data Visualizations

Flight Name

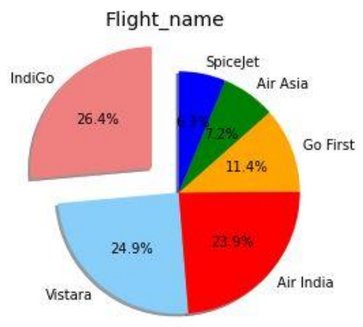


```
df['Flight_name'].value_counts()
```

```
IndiGo       341
Vistara      321
Air India    308
Go First     147
Air Asia      93
SpiceJet      81
Name: Flight_name, dtype: int64
```



```
#  pie plot of Flight_name

labels = ['IndiGo', 'Vistara', 'Air India', 'Go First', 'Air Asia', 'SpiceJet']
value = [341, 321, 308, 147, 93, 81]
colors = ['lightcoral','lightskyblue', 'red','orange','green', 'blue']
explode = [0.3,0,0,0,0,0,]#

plt.style.use('ggplot')
plt.title('Flight_name')
plt.pie(x=value, labels=labels, colors=colors, explode=explode, autopct='%1.1f%%',
         startangle=90,shadow=True)
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.figure(figsize=(15,10))
plt.show()
```



```
<Figure size 1080x720 with 0 Axes>
```

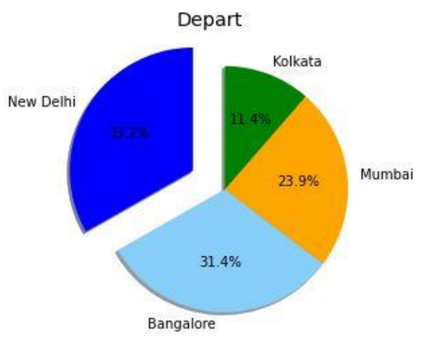
Indigo flight price is high as compared to other flight service.

Departure

```
df["Depart"].value_counts()
```

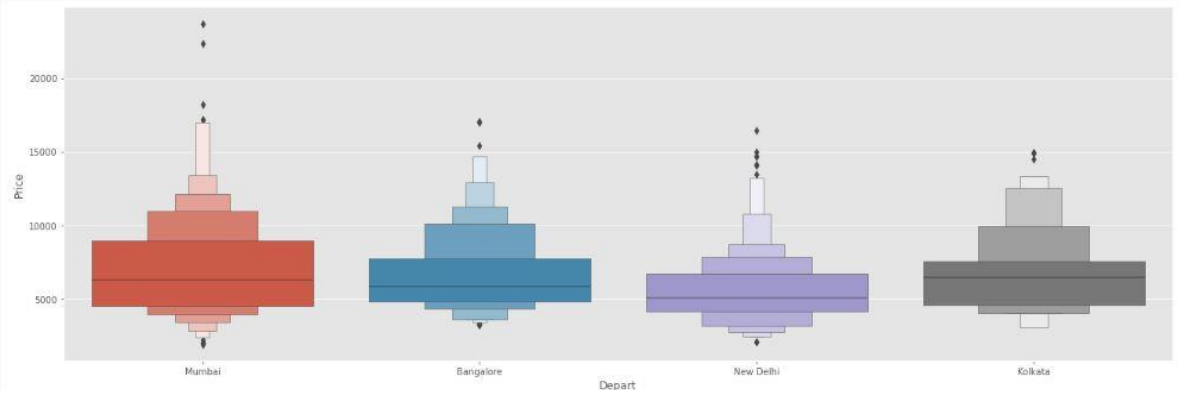
```
New Delhi    429
Bangalore    406
Mumbai       309
Kolkata      147
Name: Depart, dtype: int64
```

```
#  pie plot of Depart

labels = ['New Delhi', 'Bangalore', 'Mumbai', 'Kolkata']
value = [429, 406, 309, 147]
colors = ['blue','lightskyblue','orange','green']
explode = [0.3,0,0,0]#

plt.style.use('ggplot')
plt.title('Depart')
plt.pie(x=value, labels=labels, colors=colors, explode=explode, autopct='%1.1f%%',
          startangle=90,shadow=True)
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.figure(figsize=(15,10))
plt.show()
```



```
<Figure size 1080x720 with 0 Axes>
```

```
# Depart vs Price
sns.catplot(y = "Price", x = "Depart", data = df.sort_values("Price", ascending = False), kind="boxen", height = 6, aspect =
plt.show()
```

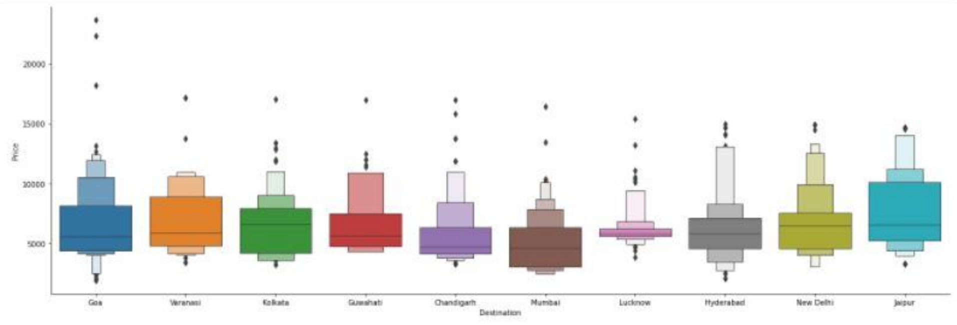


Flight price from Mumbai is high as compared to other state.

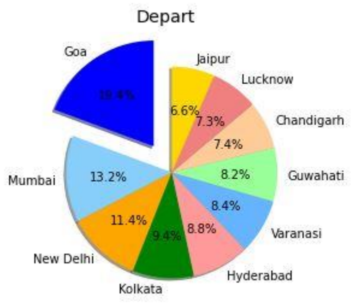
Destination

```
Goa           250
Mumbai        171
New Delhi     147
Kolkata       121
Hyderabad     113
Varanasi      109
Guwahati      106
Chandigarh     95
Lucknow        94
Jaipur         85
Name: Destination, dtype: int64
```

```
sns.catplot(y = "Price", x = "Destination", data = df.sort_values("Price", ascending = False), kind="boxen", height = 6, aspect
plt.show()
```



```
#  pie plot of Destination

labels = ['Goa', 'Mumbai', 'New Delhi', 'Kolkata', 'Hyderabad', 'Varanasi', 'Guwahati', 'Chandigarh', 'Lucknow', 'Jaipur']
value = [250, 171, 147, 121, 113, 109, 106, 95, 94, 85]
colors = ['blue','lightskyblue','orange','green','#ff9999','#66b3ff','#99ff99','#ffcc99','lightcoral','gold']
explode = [0.3,0,0,0,0,0,0,0,0,0]#

plt.style.use('ggplot')
plt.title('Depart')
plt.pie(x=value, labels=labels, colors=colors, explode=explode, autopct='%1.1f%%',
          startangle=90,shadow=True)
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.figure(figsize=(15,10))
plt.show()
```



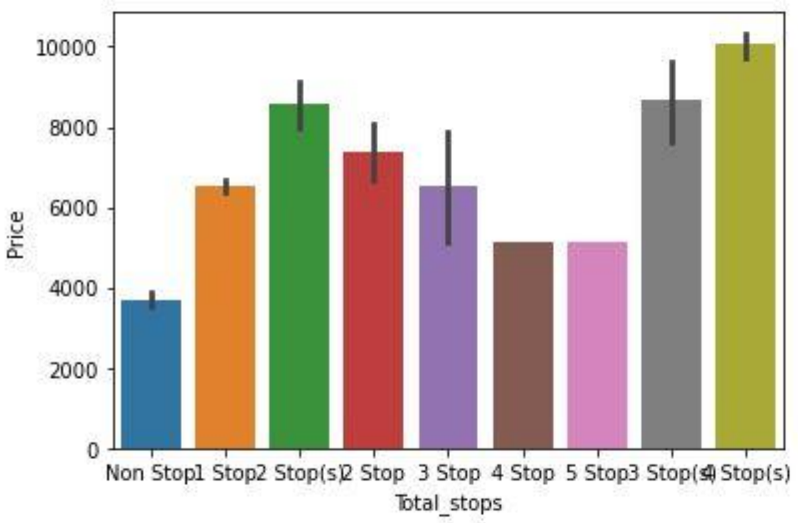
```
<Figure size 1080x720 with 0 Axes>
```

From the above plots and charts I can see Goa destination flight prices are more higher rather than others in this dataset.

Total Stops

```
sns.barplot(df['Total_stops'],df['Price'])
```

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

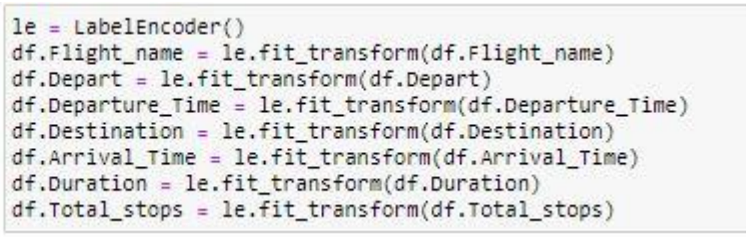


```
df["Total_stops"].value_counts()
```

```
1 Stop       906
Non Stop     194
2 Stop(s)    118
2 Stop        38
3 Stop(s)     28
4 Stop(s)      3
3 Stop         2
4 Stop         1
5 Stop         1
Name: Total_stops, dtype: int64
```

The flight that have no stop is cheapest among others.

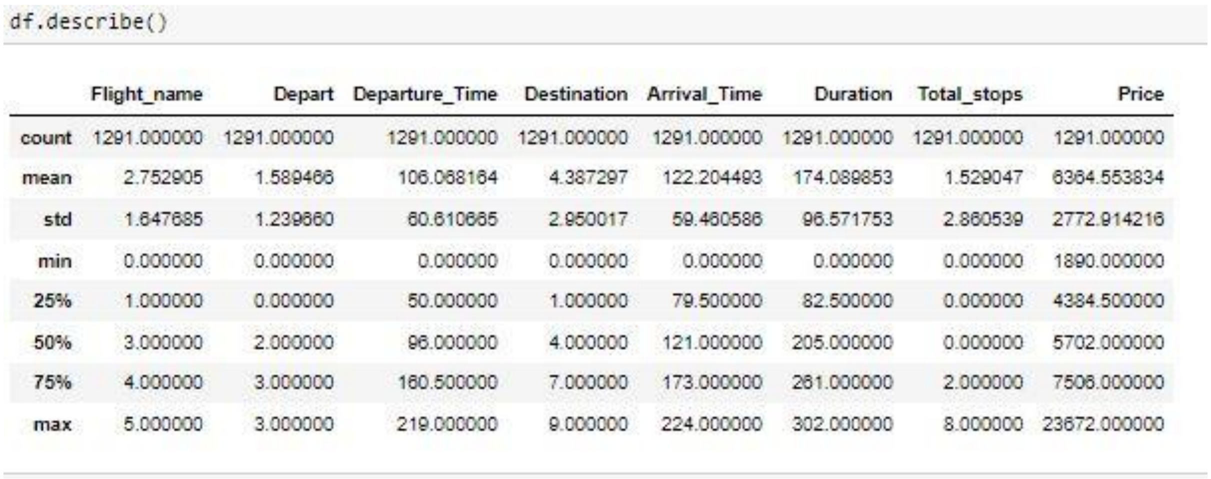
Label Encoder



```
le = LabelEncoder()
df.Flight_name = le.fit_transform(df.Flight_name)
df.Depart = le.fit_transform(df.Depart)
df.Departure_Time = le.fit_transform(df.Departure_Time)
df.Destination = le.fit_transform(df.Destination)
df.Arrival_Time = le.fit_transform(df.Arrival_Time)
df.Duration = le.fit_transform(df.Duration)
df.Total_stops = le.fit_transform(df.Total_stops)
```

I have used label encoder to convert the strings values into integers.

It will help me in model building.



```
df.describe()
```

	Flight_name	Depart	Departure_Time	Destination	Arrival_Time	Duration	Total_stops	Price
count	1291.000000	1291.000000	1291.000000	1291.000000	1291.000000	1291.000000	1291.000000	1291.000000
mean	2.752905	1.589466	106.068164	4.387297	122.204493	174.089853	1.529047	6364.553834
std	1.647685	1.239660	60.610665	2.950017	59.460586	96.571753	2.860539	2772.914216
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1890.000000
25%	1.000000	0.000000	50.000000	1.000000	79.500000	82.500000	0.000000	4384.500000
50%	3.000000	2.000000	96.000000	4.000000	121.000000	205.000000	0.000000	5702.000000
75%	4.000000	3.000000	160.500000	7.000000	173.000000	261.000000	2.000000	7506.000000
max	5.000000	3.000000	219.000000	9.000000	224.000000	302.000000	8.000000	23672.000000

Total number of counts in each columns is matching as there is no missing values.

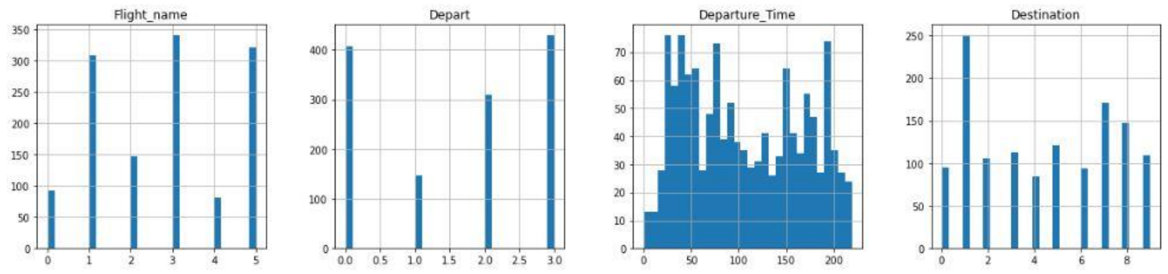
The difference between the mean and 50% is not much.

There are outliers in the dataset which i will remove it soon.

Histogram Plot

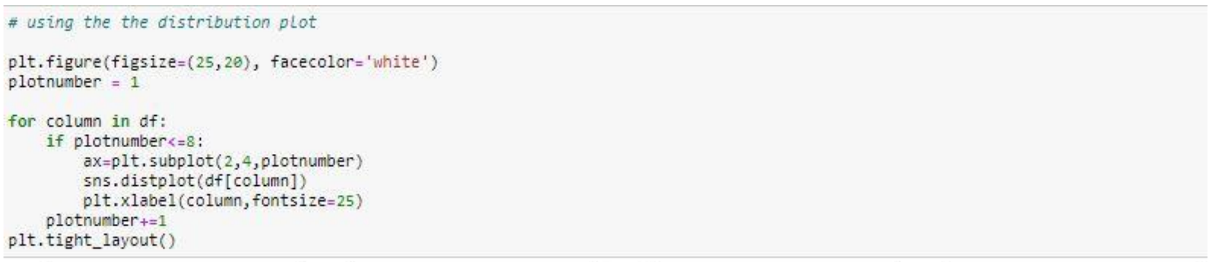
```python
# using the the histogrom plot

df.hist(figsize=(20,20),grid=True,layout=(4,4),bins=30)
```

```
array([[<AxesSubplot:title={'center':'Flight_name'}>,
        <AxesSubplot:title={'center':'Depart'}>,
        <AxesSubplot:title={'center':'Departure_Time'}>,
        <AxesSubplot:title={'center':'Destination'}>],
       [<AxesSubplot:title={'center':'Arrival_Time'}>,
        <AxesSubplot:title={'center':'Duration'}>,
        <AxesSubplot:title={'center':'Total_stops'}>,
        <AxesSubplot:title={'center':'Price'}>],
       [<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>],
       [<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>]],
      dtype=object)
```

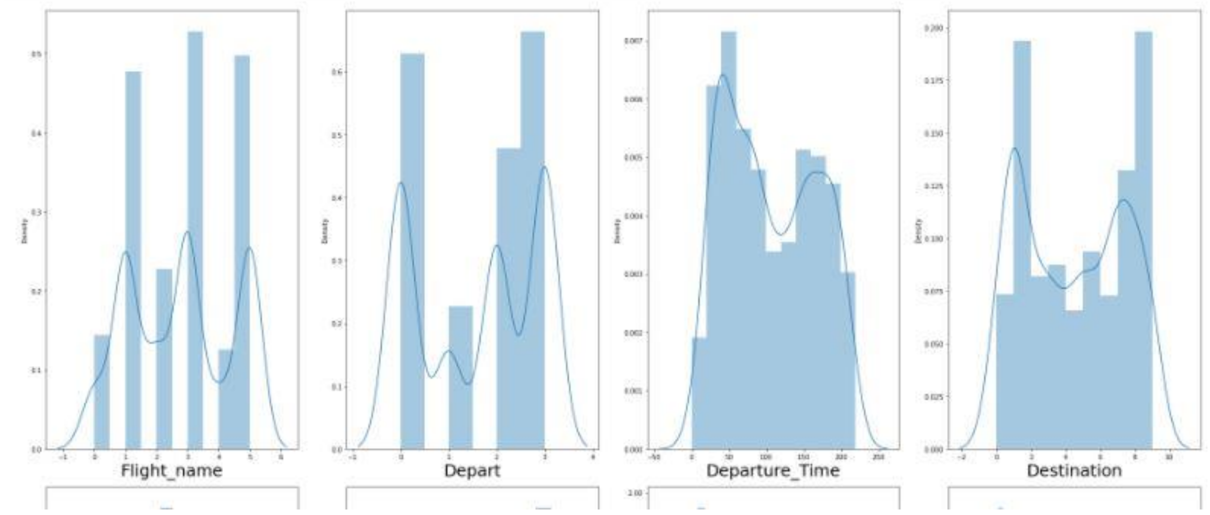


By making Histogram Plot I can see there are some skewness in this dataset.From plotting this histogram, I used the bin size as 30, we can take any bin size (suited as per as data).

Distribution Plot

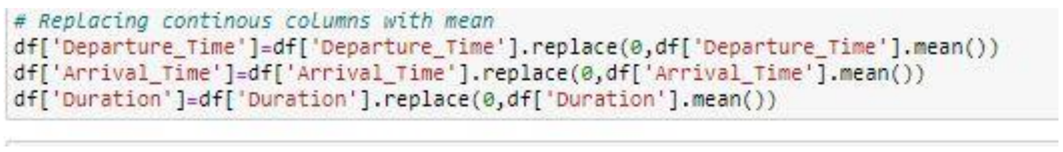


```
# using the the distribution plot

plt.figure(figsize=(25,20), facecolor='white')
plotnumber = 1

for column in df:
    if plotnumber<=8:
        ax=plt.subplot(2,4,plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column,fontsize=25)
    plotnumber+=1
plt.tight_layout()
```



The dataset is normally distributed as there is no skewness in the dataset.

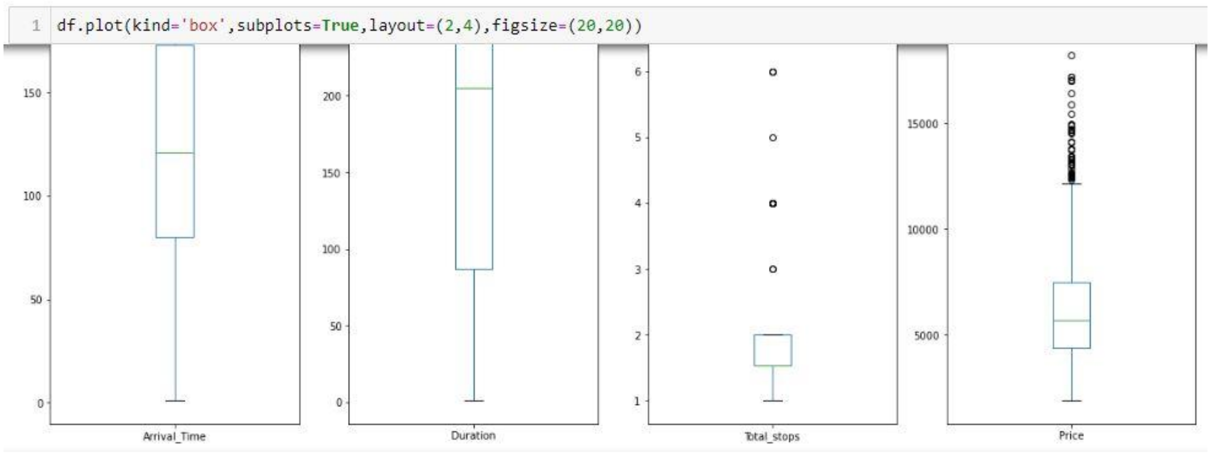
Replacing zero values from different columns



```
# Replacing continous columns with mean
df['Departure_Time']=df['Departure_Time'].replace(0,df['Departure_Time'].mean())
df['Arrival_Time']=df['Arrival_Time'].replace(0,df['Arrival_Time'].mean())
df['Duration']=df['Duration'].replace(0,df['Duration'].mean())
```

There are few zero values that got replaced with the help of mean.

Box Plot



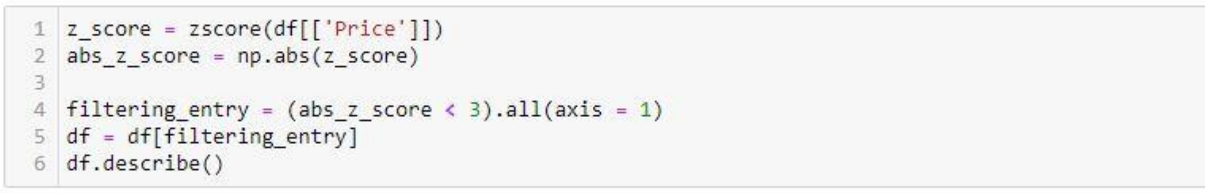
```
df.plot(kind='box',subplots=True,layout=(2,4),figsize=(20,20))
```

From above image I can clear see that there are few number of black dots in the column which are referring to the outliers, so it means most of the data are outside the distribution.

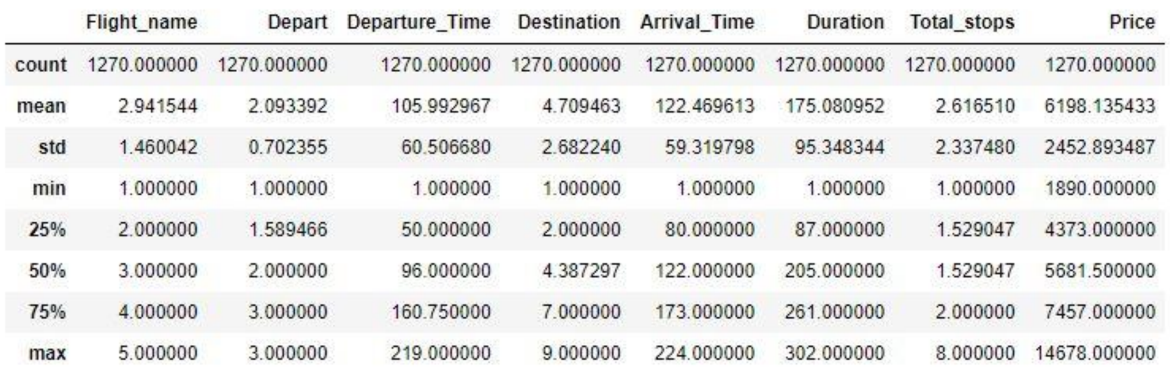
So now I detect the outliers now the second step is to remove the outliers, there are different way to remove the outliers that are zscore values.

There are outliers in Price which is continuous in nature.

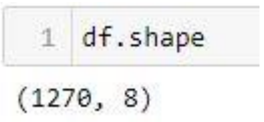
Z score



```
z_score = zscore(df[['Price']])
abs_z_score = np.abs(z_score)

filtering_entry = (abs_z_score < 3).all(axis = 1)
df = df[filtering_entry]
df.describe()
```



	Flight_name	Depart	Departure_Time	Destination	Arrival_Time	Duration	Total_stops	Price
count	1270.000000	1270.000000	1270.000000	1270.000000	1270.000000	1270.000000	1270.000000	1270.000000
mean	2.941544	2.093392	105.992967	4.709463	122.469613	175.080952	2.616510	6198.135433
std	1.460042	0.702355	60.506680	2.682240	59.319798	95.348344	2.337480	2452.893487
min	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1890.000000
25%	2.000000	1.589466	50.000000	2.000000	80.000000	87.000000	1.529047	4373.000000
50%	3.000000	2.000000	96.000000	4.387297	122.000000	205.000000	1.529047	5681.500000
75%	4.000000	3.000000	160.750000	7.000000	173.000000	261.000000	2.000000	7457.000000
max	5.000000	3.000000	219.000000	9.000000	224.000000	302.000000	8.000000	14678.000000



```
df.shape
```

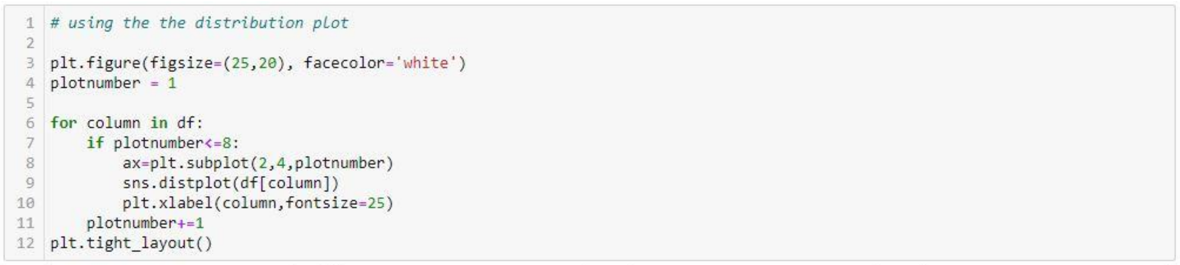
```
(1270, 8)
```

I am using zscore value then I again check if there are some of the outliers then I will remove it by replacing the outliers with the mean value of that column.

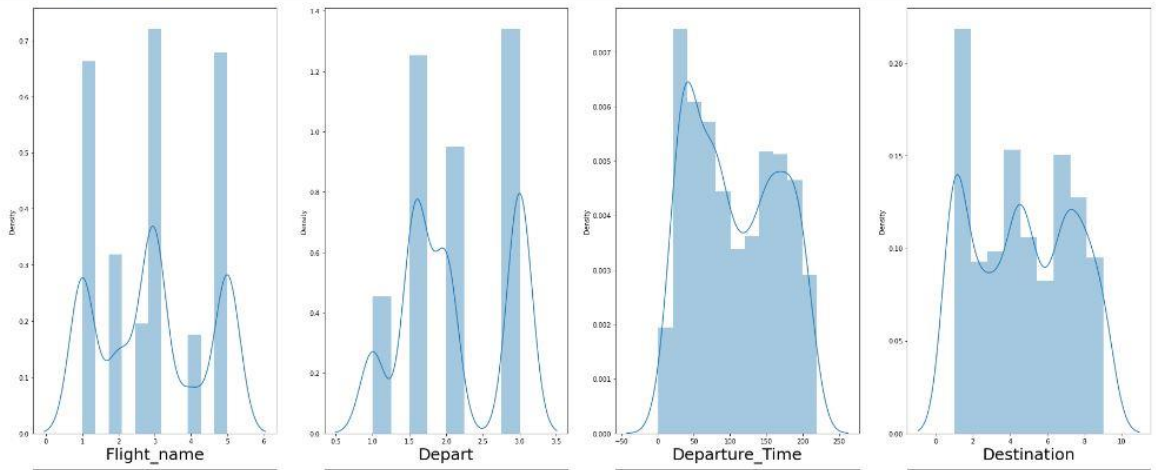
So, I first find the zscore value and then I decide to make one threshold value as 3 which is standard of industry recommend value and then I remove all the outliers which zscore value is greater than 3.

After, removing the outlier’s final there are 1270 and 8 column presents in the data set.

After Removing Skewness making Distribution Plot



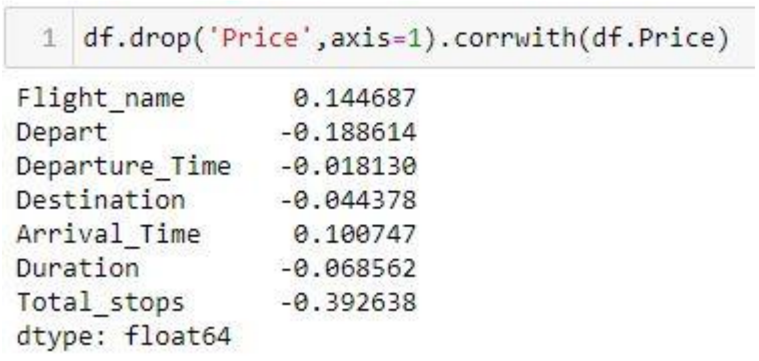
```python
# using the the distribution plot

plt.figure(figsize=(25,20), facecolor='white')
plotnumber = 1

for column in df:
    if plotnumber<=8:
        ax=plt.subplot(2,4,plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column,fontsize=25)
    plotnumber+=1
plt.tight_layout()
```



Hence After Removing Outliers I make distribution plot which shows few outliers are removed.

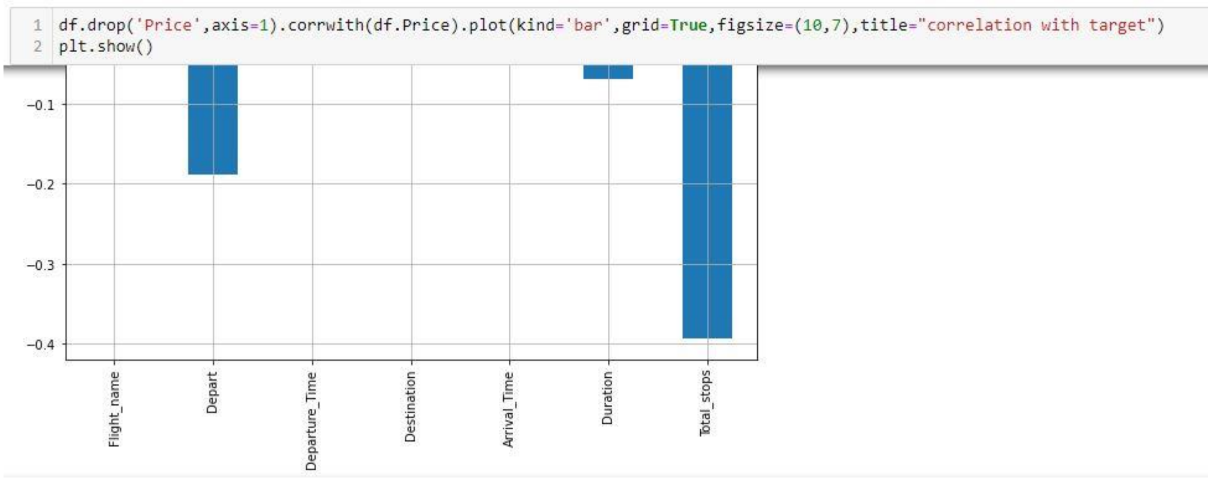
Finding correlation of features vs target using corrwith

Visualize the correlation



```
df.drop('Price',axis=1).corrwith(df.Price)
```

```
Flight_name       0.144687
Depart           -0.188614
Departure_Time   -0.018130
Destination      -0.044378
Arrival_Time      0.100747
Duration         -0.068562
Total_stops      -0.392638
dtype: float64
```

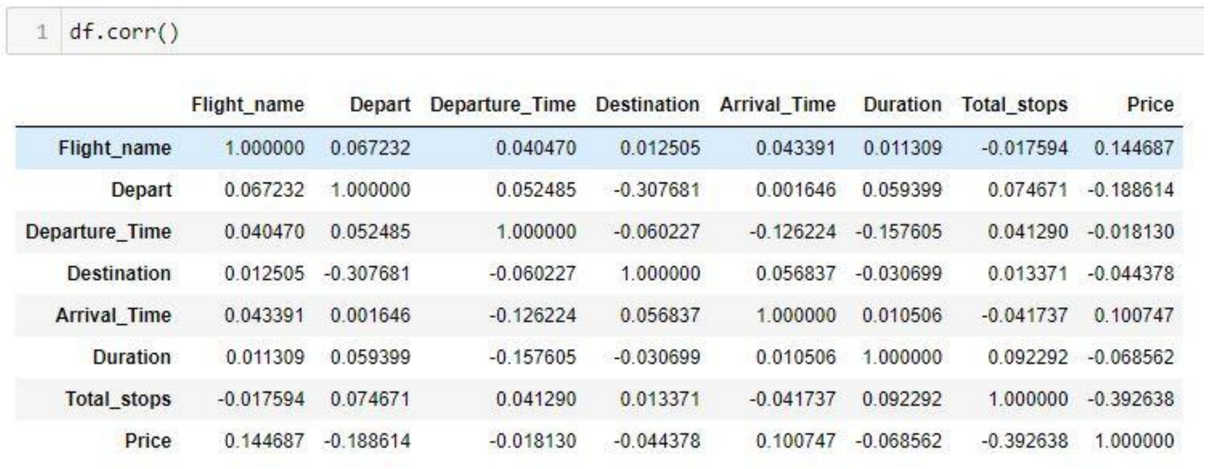


```
df.drop('Price',axis=1).corrwith(df.Price).plot(kind='bar',grid=True,figsize=(10,7),title="correlation with target")
plt.show()
```

I have checked the relationship between label and different features.

Most of the features are in minus value only 2 columns are positively related to target value.

Correlation



```
df.corr()
```

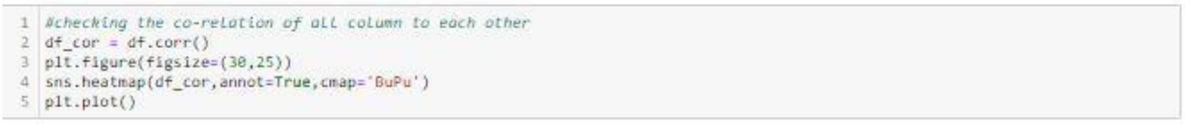
	Flight_name	Depart	Departure_Time	Destination	Arrival_Time	Duration	Total_stops	Price
Flight_name	1.000000	0.067232	0.040470	0.012505	0.043391	0.011309	-0.017594	0.144687
Depart	0.067232	1.000000	0.052485	-0.307681	0.001646	0.059399	0.074671	-0.188614
Departure_Time	0.040470	0.052485	1.000000	-0.060227	-0.126224	-0.157605	0.041290	-0.018130
Destination	0.012505	-0.307681	-0.060227	1.000000	0.056837	-0.030699	0.013371	-0.044378
Arrival_Time	0.043391	0.001646	-0.126224	0.056837	1.000000	0.010506	-0.041737	0.100747
Duration	0.011309	0.059399	-0.157605	-0.030699	0.010506	1.000000	0.092292	-0.068562
Total_stops	-0.017594	0.074671	0.041290	0.013371	-0.041737	0.092292	1.000000	-0.392638
Price	0.144687	-0.188614	-0.018130	-0.044378	0.100747	-0.068562	-0.392638	1.000000

Now I am finding the correlation value of each column, this value is categorized into mainly 2 parts that are:

Positive correlated value

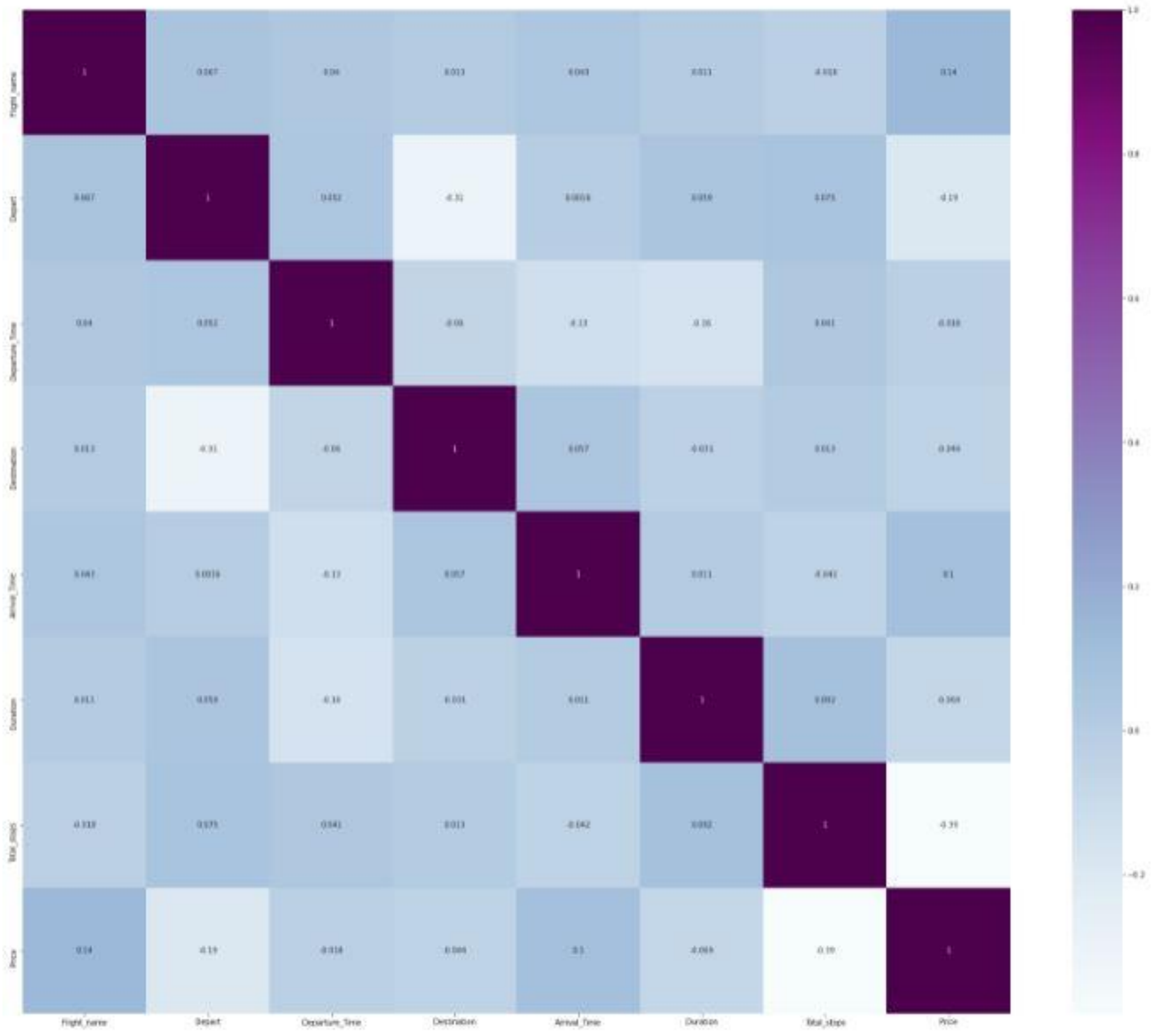
Negative correlated value The most the value is positive means that column is much co related and vice versa.

Heat map



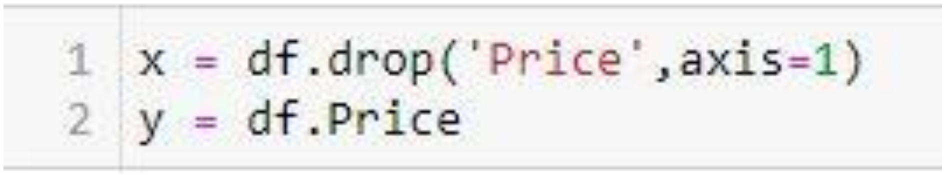
```
#checking the co-relation of all column to each other
df_cor = df.corr()
plt.figure(figsize=(30,25))
sns.heatmap(df_cor,annot=True,cmap='BuPu')
plt.plot()
```

```
[]
```



I am using sea born heatmap to plot the correlated matrix and plot the corr value in the heatmap graph.

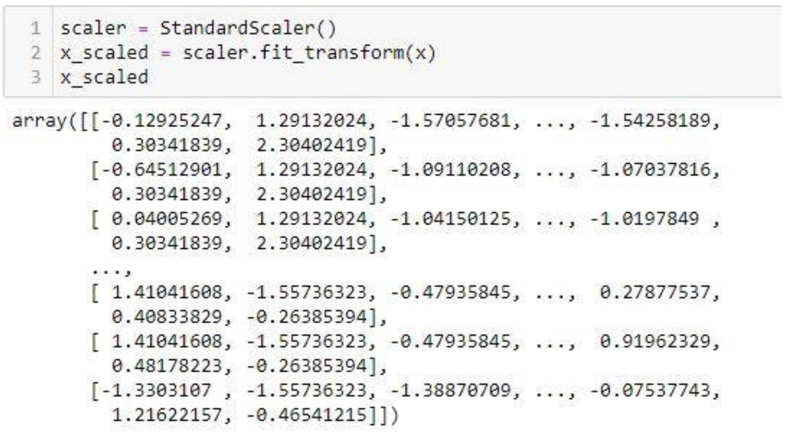
Machine Learning



```
x = df.drop('Price',axis=1)
y = df.Price
```

I have divided dataset into feature and label.

Standard Scaler

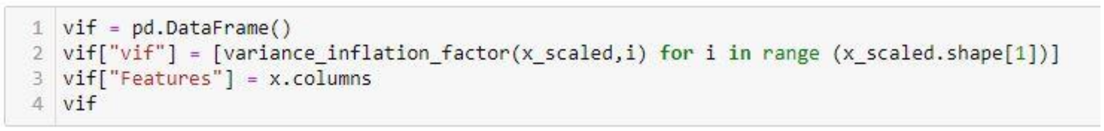


```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

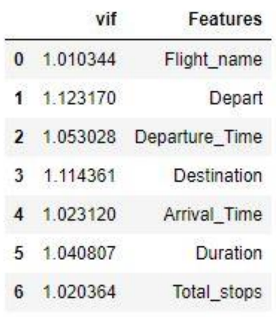
```
array([[-0.12925247,  1.29132024, -1.57057681, ..., -1.54258189,
         0.30341839,  2.30402419],
       [-0.64512901,  1.29132024, -1.09110208, ..., -1.07037816,
         0.30341839,  2.30402419],
       [ 0.04005269,  1.29132024, -1.04150125, ..., -1.0197849 ,
         0.30341839,  2.30402419],
       ...,
       [ 1.41041608, -1.55736323, -0.47935845, ...,  0.27877537,
         0.40833829, -0.26385394],
       [ 1.41041608, -1.55736323, -0.47935845, ...,  0.91962329,
         0.48178223, -0.26385394],
       [-1.3303107 , -1.55736323, -1.38870709, ..., -0.07537743,
         1.21622157, -0.46541215]])
```

Standard scaler is basically scaling the date in one range so that it will be easy for Model building.

VIF - variance inflation factor



```
vif = pd.DataFrame()
vif["vif"] = [variance_inflation_factor(x_scaled,i) for i in range (x_scaled.shape[1])]
vif["Features"] = x.columns
vif
```



	vif	Features
0	1.010344	Flight_name
1	1.123170	Depart
2	1.053028	Departure_Time
3	1.114361	Destination
4	1.023120	Arrival_Time
5	1.040807	Duration
6	1.020364	Total_stops

VIF is used to detect the severity of multicollinearity in the ordinary least square (OLS) regression analysis.

Multicollinearity is a phenomenon when two or more independent variables are highly intercorrelated.

From the above stats i can say that none of the features are highly intercorrelated it means Multicollinearity doesn't exist.

Model Building

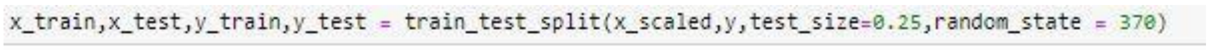
A machine learning model is built by learning and generalizing from training data, then applying that acquired knowledge to new data it has never seen before to make predictions and full fill its purpose. Lack of data will prevent you from building the model, and access to data isn't enough.

So in this dataset while predicting Price label first, I have used these Algorithms for Model Building:

a)Random Forest Regressor Model

b)Decision Tree Regressor Model

Train Test Split



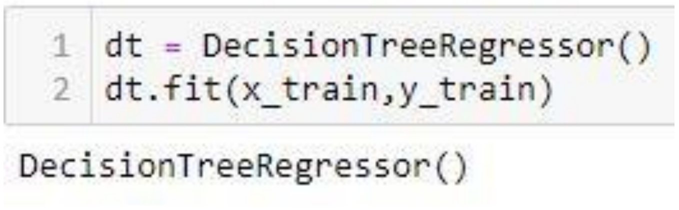
```
x_train,x_test,y_train,y_test = train_test_split(x_scaled,y,test_size=0.25,random_state = 370)
```

For model prediction i am dividing the dataset into 2 parts.

One part is used for training purpose i.e 75% dataset.

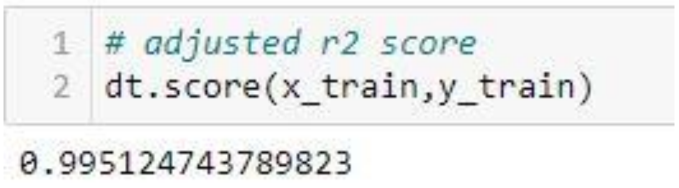
other part is used for testing purpose i.e 25% dataset.

Decision Tree Regressor



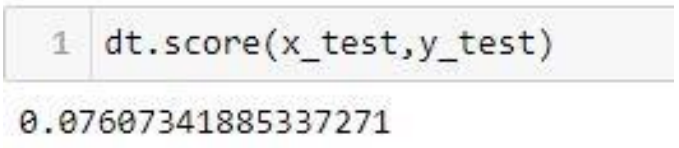
```
dt = DecisionTreeRegressor()
dt.fit(x_train,y_train)
```

```
DecisionTreeRegressor()
```



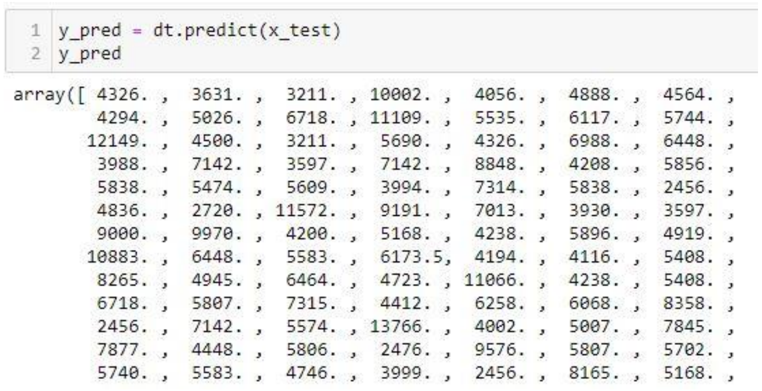
```
# adjusted r2 score
dt.score(x_train,y_train)
```

```
0.995124743789823
```



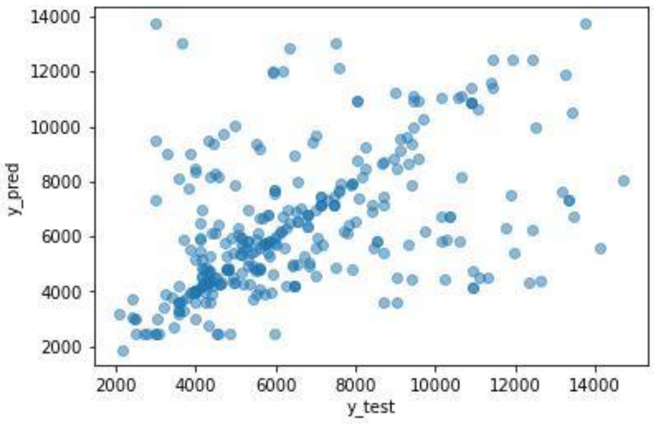
```
dt.score(x_test,y_test)
```

```
0.07607341885337271
```



```
y_pred = dt.predict(x_test)
y_pred
```

```
array([ 4326. ,  3631. ,  3211. , 10002. ,  4056. ,  4888. ,  4564. ,
        4294. ,  5026. ,  6718. , 11109. ,  5535. ,  6117. ,  5744. ,
       12149. ,  4500. ,  3211. ,  5690. ,  4326. ,  6988. ,  6448. ,
        3988. ,  7142. ,  3597. ,  7142. ,  8848. ,  4208. ,  5856. ,
        5838. ,  5474. ,  5609. ,  3994. ,  7314. ,  5838. ,  2456. ,
        4836. ,  2720. , 11572. ,  9191. ,  7013. ,  3930. ,  3597. ,
        9000. ,  9970. ,  4200. ,  5168. ,  4238. ,  5896. ,  4919. ,
       10883. ,  6448. ,  5583. ,  6173.5,  4194. ,  4116. ,  5408. ,
        8265. ,  4945. ,  6464. ,  4723. , 11066. ,  4238. ,  5408. ,
        6718. ,  5807. ,  7315. ,  4412. ,  6258. ,  6068. ,  8358. ,
        2456. ,  7142. ,  5574. , 13766. ,  4002. ,  5007. ,  7845. ,
        7877. ,  4448. ,  5806. ,  2476. ,  9576. ,  5807. ,  5702. ,
        5740. ,  5583. ,  4746. ,  3999. ,  2456. ,  8165. ,  5168. ,
plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```



MSE

```
mean_squared_error(y_test,y_pred)
```

```
6662980.154874214
```

RMSE

```
np.sqrt(mean_squared_error(y_test,y_pred))
```

```
2581.2749088142887
```

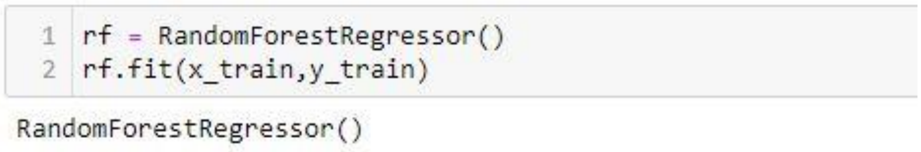
r2 Score

```
r2_score(y_test,y_pred)
```

```
0.07607341885337271
```

Decision Tree Regression accuracy score 76.07%

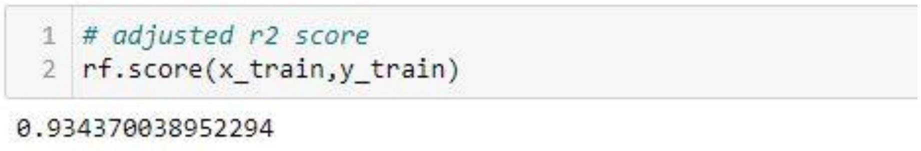
Random Forest Regressor



```
rf = RandomForestRegressor()
rf.fit(x_train,y_train)
```

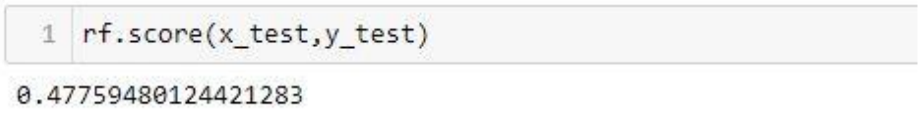
```
RandomForestRegressor()
```

First I have to fit the Training data of RandomForestRegressor.



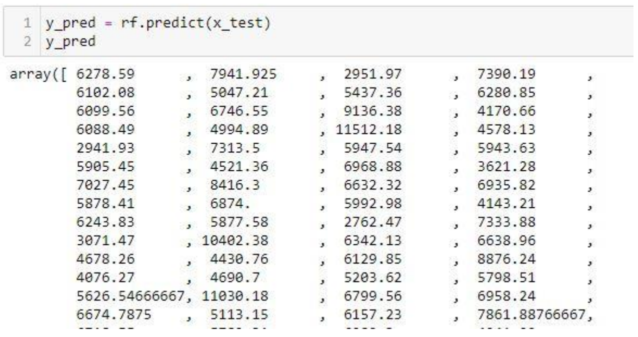
```
# adjusted r2 score
rf.score(x_train,y_train)
```

```
0.934370038952294
```



```
rf.score(x_test,y_test)
```

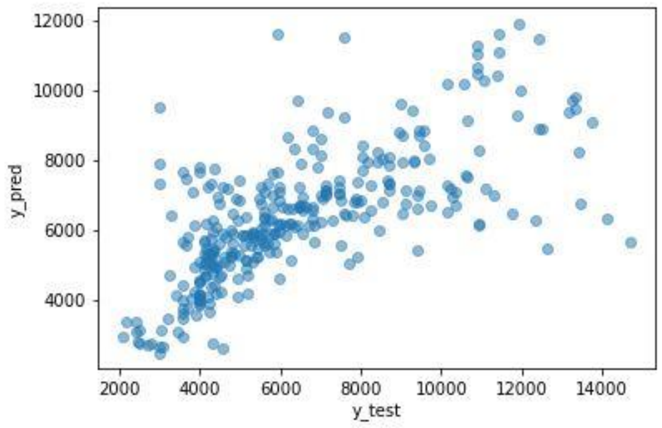
```
0.47759480124421283
```



```
y_pred = rf.predict(x_test)
y_pred
```

```
array([ 6278.59      ,  7941.925     ,  2951.97      ,  7390.19      ,
        6102.08      ,  5047.21      ,  5437.36      ,  6280.85      ,
        6099.56      ,  6746.55      ,  9136.38      ,  4170.66      ,
        6088.49      ,  4994.89      , 11512.18      ,  4578.13      ,
        2941.93      ,  7313.5       ,  5947.54      ,  5943.63      ,
        5905.45      ,  4521.36      ,  6968.88      ,  3621.28      ,
        7027.45      ,  8416.3       ,  6632.32      ,  6935.82      ,
        5878.41      ,  6874.       ,  5992.98      ,  4143.21      ,
        6243.83      ,  5877.58      ,  2762.47      ,  7333.88      ,
        3071.47      , 10402.38      ,  6342.13      ,  6638.96      ,
        4678.26      ,  4430.76      ,  6129.85      ,  8876.24      ,
        4076.27      ,  4690.7       ,  5203.62      ,  5798.51      ,
        5626.54666667, 11030.18      ,  6799.56      ,  6958.24      ,
        6674.7875    ,  5113.15      ,  6157.23      ,  7861.88766667,
```

```python
plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```



MSE

```python
mean_squared_error(y_test,y_pred)
```

```
3767372.3682602113
```

RMSE

```python
np.sqrt(mean_squared_error(y_test,y_pred))
```

```
1940.9720163516556
```

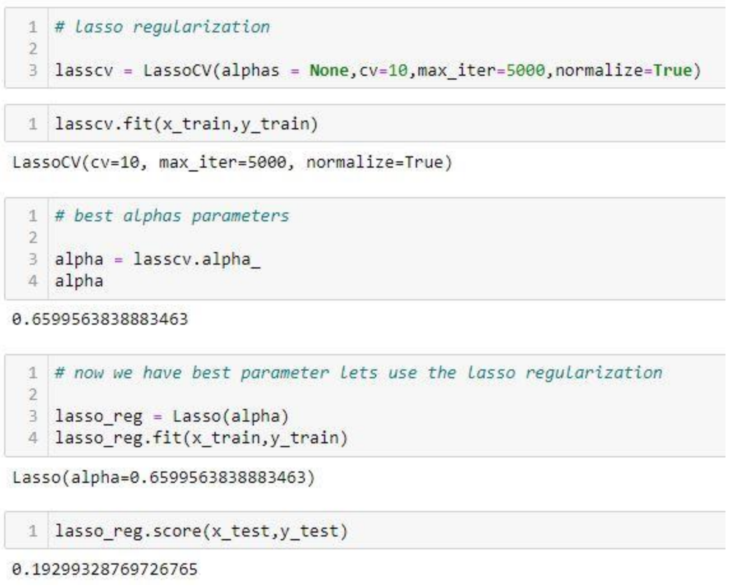
r2 Score

```python
r2_score(y_test,y_pred)
```

```
0.47759480124421283
```

Random Forest Regression accuracy score 47.77%

Lasso Regularization



```
# lasso regularization

lasscv = LassoCV(alphas = None,cv=10,max_iter=5000,normalize=True)
```

```
lasscv.fit(x_train,y_train)
```

```
LassoCV(cv=10, max_iter=5000, normalize=True)
```

```
# best alphas parameters

alpha = lasscv.alpha_
alpha
```

```
0.6599563838883463
```

```
# now we have best parameter lets use the lasso regularization

lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train,y_train)
```

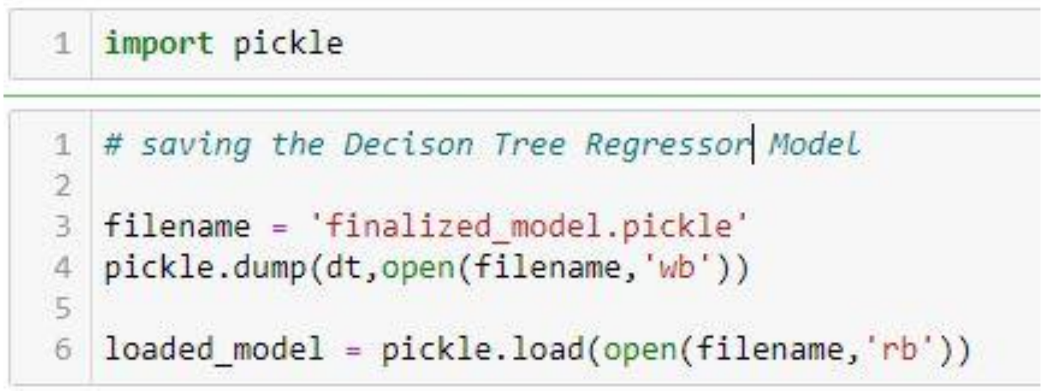
```
Lasso(alpha=0.6599563838883463)
```

```
lasso_reg.score(x_test,y_test)
```

```
0.19299328769726765
```

I have used lasso for increasing accuracy score for linear regression but it is neither improving nor reducing the score.

Saving the Best Model



```
import pickle
```

```
# saving the Decison Tree Regressor Model

filename = 'finalized_model.pickle'
pickle.dump(dt,open(filename,'wb'))

loaded_model = pickle.load(open(filename,'rb'))
```

The best model is Random Forest classifier whose accuracy score is 76.07%.

Interpretation of the Results

- I have used visualization tool such as cat Plot and Bar Plot to understand the data in a better way.
- I used describe method for five-point summary analysis and also found the number of rows and columns in dataset.
- I have done the model building with 4 algorithms and the best model is Random Forest Regressor with an accuracy score of 55%

CONCLUSION

The overall survey for the dynamic price changes in the flight tickets is presented. This gives the information about the highs and lows in the airfares according to the days, weekend and time of the day that is morning, evening and night. Also the machine learning models in the computational intelligence field that are evaluated before on different datasets are studied. Their accuracy and performances are evaluated and compared in order to get better result. For the prediction of the ticket prices perfectly different prediction models are tested for the better prediction accuracy. As the pricing models of the company are developed in order to maximize the revenue management. So to get result with maximum accuracy regression analysis is used. From the studies , the feature that influences the prices of the ticket are to be considered. In future the details about number of available seats can improve the performance of the model.

I'll briefly discuss how I approached this problem of predicting flight price prediction.

a) I have flight price prediction dataset from which I had to extract information.

b) I have done 1 label as the dataset speaks:

Price

c) I had used pandas library to read the Dataset which provide me to explore & visualize the Data properly based on Rows & Columns.

d) After from all datasets, I pre-processed the data using replacing all zeros and filling all missing values.

e) I did exploratory data analysis on main data frame and tried to see all visualizations.

f) Based on visualization knowledge, I use various EDA TECHNIQUES to plot the graphs and Box Plot.

g) I use VIF and Standard Scalar to scaled the data and by VIF I make a relationship between Features & Features.

h) After from all these i split the Features & Labels into 2 parts.

i) On this data, I have applied our machine learning models such as Random Forest Repressor and Decision Tree Regressor According to the above 4 model prediction the best model is Decision Tree Regressor - 76.07%.