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

Flight ticket prices can be something hard to guess, today we might see a price, check out the price of the same flight tomorrow, it will be a different story. We might have often heard travellers saying that flight ticket prices are so unpredictable. Here i will be provided with prices of flight tickets for various airlines between the months of March and June of 2019 and between various cities.

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***.**

```
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.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
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 inline
```

- 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.

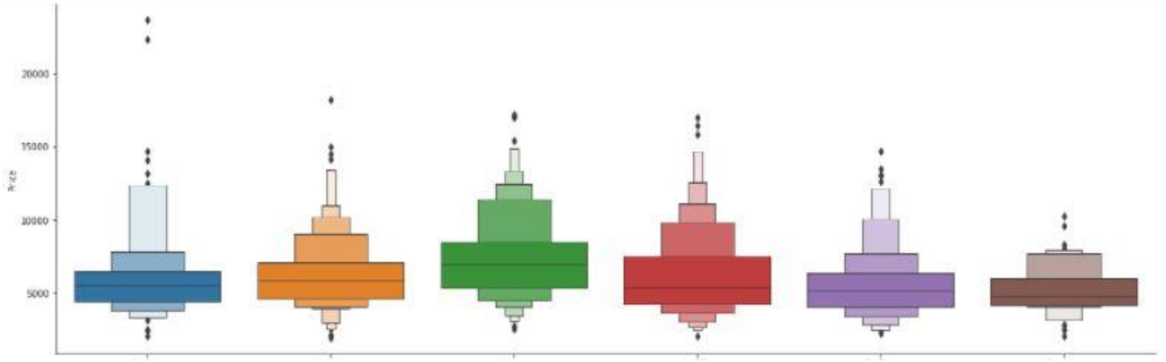
Cat Plot

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
```

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



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

Bar Plot

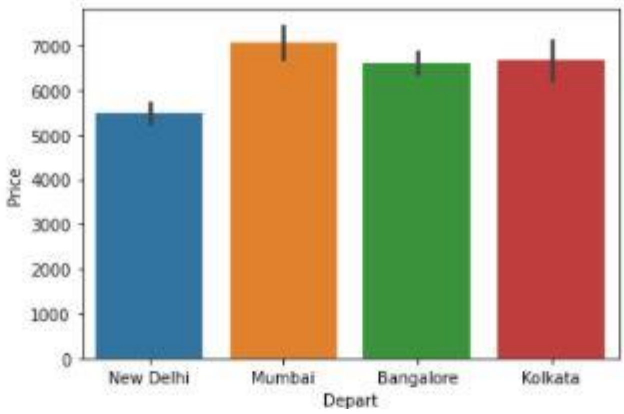
Departure

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

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

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

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



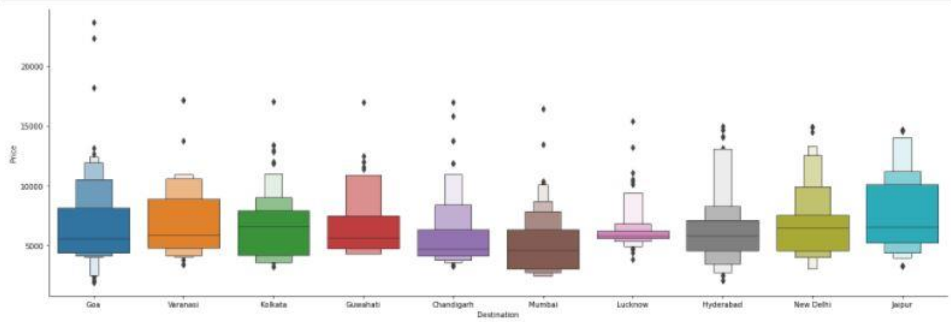
Flight price from Mumbai is high as compared to other state.

Cat Plot

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()
```



Destination do affect the price of the flight.

Jaipur, Goa and New Delhi flight price is high as compared to other state.

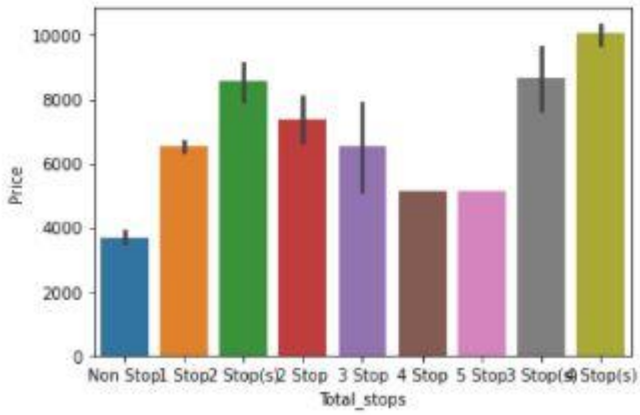
Total Stops

```
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
5 Stop         1
4 Stop         1
Name: Total_stops, dtype: int64
```

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

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



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.

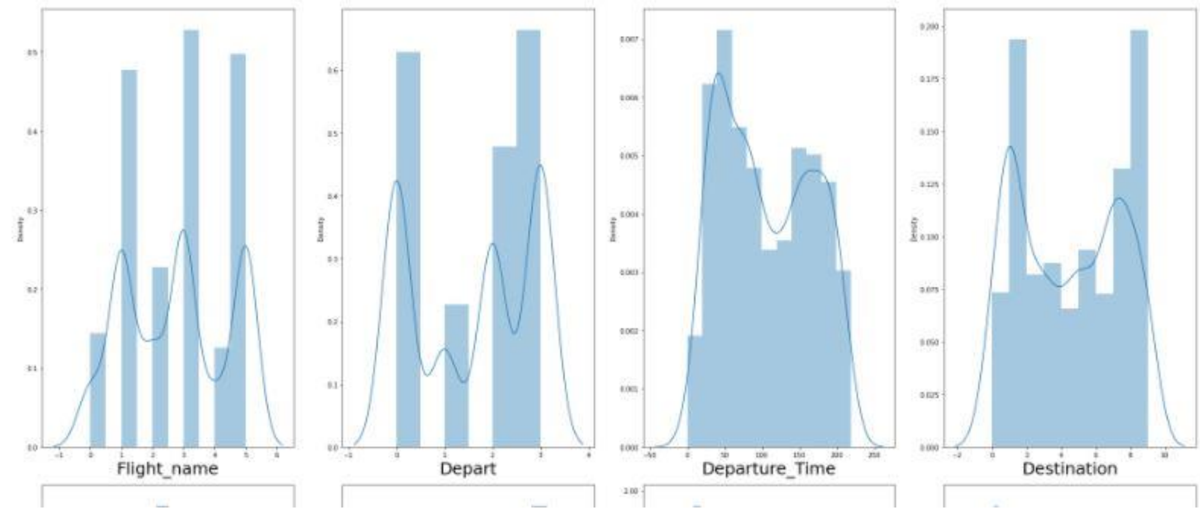
There are outliers in the dataset which i will remove it soon.

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

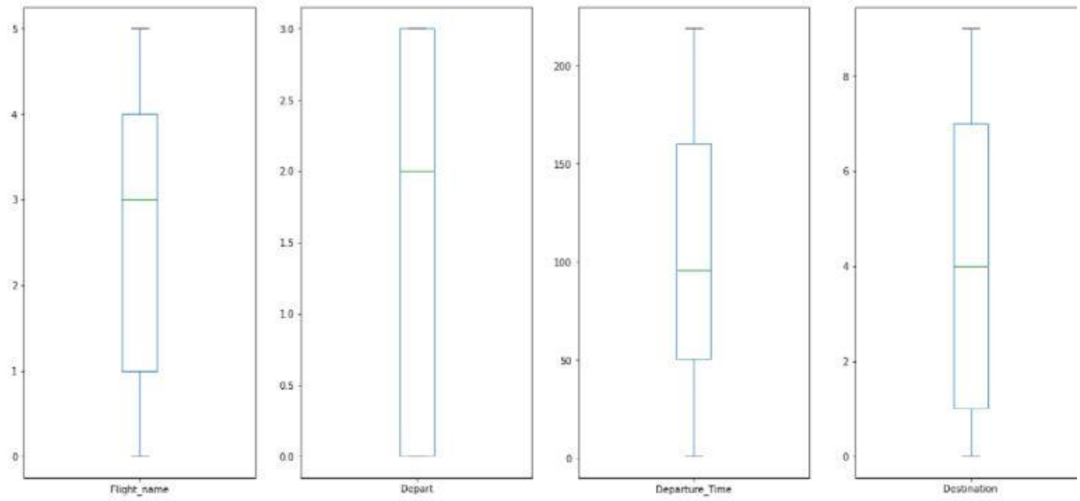
```
# Replacing continous columns with mean
df['Departure_Time']=df['Departure_Time'].replace(0,df['Departure_Time'].mean())
df['Arrival_Time']=df['Arrival_Time'].replace(0,df['Arrival_Time'].mean())
df['Duration']=df['Duration'].replace(0,df['Duration'].mean())
```

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

Box Plot

```
In [107]: df.plot(kind='box',subplots=True,layout=(2,4),figsize=(20,20))

Out[107]: Flight_name         AxesSubplot(0.125,0.536818;0.168478x0.343182)
          Depart           AxesSubplot(0.327174,0.536818;0.168478x0.343182)
          Departure_Time   AxesSubplot(0.529348,0.536818;0.168478x0.343182)
          Destination      AxesSubplot(0.731522,0.536818;0.168478x0.343182)
          Arrival_Time            AxesSubplot(0.125,0.125;0.168478x0.343182)
          Duration             AxesSubplot(0.327174,0.125;0.168478x0.343182)
          Total_stops          AxesSubplot(0.529348,0.125;0.168478x0.343182)
          Price                AxesSubplot(0.731522,0.125;0.168478x0.343182)
          dtype: object
```



There are no outliers in the dataset.

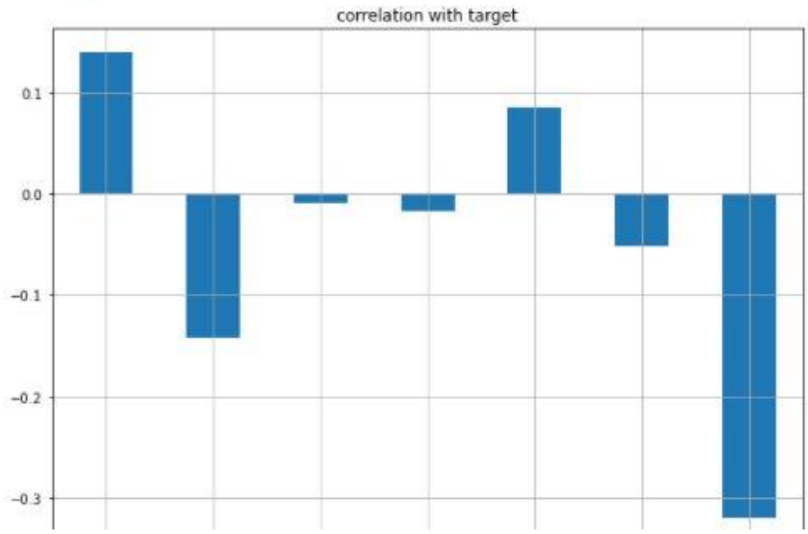
Visualize the correlation

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

```
Flight_name       0.140438
Depart           -0.141651
Departure_Time   -0.009117
Destination      -0.016628
Arrival_Time      0.085731
Duration         -0.050965
Total_stops      -0.319448
dtype: float64
```

correlation

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



The above plot gives me an clear idea that few columns are positively correlated and few are negatively correlated with label.

However i will use all the columns for model prediction.

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([[-1.67141879,  1.13828063, -1.57233836, ..., -1.54271178,
         0.30071996,  2.26302128],
       [-0.4571241 ,  1.13828063, -1.09311968, ..., -1.0700766 ,
         0.30071996,  2.26302128],
       [ 0.15002324,  1.13828063, -1.04354534, ..., -1.01943712,
         0.30071996,  2.26302128],
       ...,
       [ 1.36431793, -0.47569004,  0.74113112, ..., -0.44552297,
        -0.79960891,  0.16470157],
       [ 1.36431793, -0.47569004, -0.48170275, ..., -1.10383626,
        -0.35947736,  0.16470157],
       [ 1.36431793, -0.47569004,  0.74113112, ...,  0.90486326,
         0.01777825,  0.16470157]])
```

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	1.017104	Flight_name
1	1.039108	Depart
2	1.049731	Departure_Time
3	1.027024	Destination
4	1.031894	Arrival_Time
5	1.032525	Duration
6	1.019838	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

```
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.

Linear Regression model

```
rg = LinearRegression()
rg.fit(x_train,y_train)
```

```
LinearRegression()
```

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

```
0.14706355029372165
```

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

```
0.11949209738011568
```

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

```
array([3529.57500421, 7069.85813283, 6986.08924918, 6443.01477347,
       5630.19054029, 7062.9066522 , 7457.69203746, 6270.33571725,
       5436.29453016, 7447.40023519, 7609.90787591, 6959.25771574,
       6145.24072538, 7290.06806022, 3807.35574869, 6947.06936823,
       7262.39157445, 4369.60259254, 7139.03100957, 6852.66226128,
```

MSE

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

```
7956678.739333792
```

RMSE

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

```
2820.7585397076778
```

r2 score

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

```
0.11949209738011568
```

Linear Regression accuracy score 11%

Decision Tree Regressor

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

```
DecisionTreeRegressor()
```

```
dt.score(x_train,y_train)
```

```
0.9987444324558606
```

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

```
0.1243511924515116
```

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

```
array([ 4500. ,  4294. ,  4996. ,  6354. ,  6311. ,  4683. ,  5717. ,
        4661. ,  5806. ,  5595. ,  5702. ,  7830. ,  6354. ,  5959. ,
        4932. ,  5614. ,  6258. ,  5141. ,  4919. ,  6483. ,  5345. ,
        7461. ,  4903. ,  6295. ,  3988. ,  3597. ,  3295. ,  5896. ,
        4405. ,  3994. ,  5975. , 11372. ,  7004. ,  9745. ,  4448. ,
        4180. ,  4788. ,  4788. , 12990. ,  3515. ,  5660. ,  4888. ,
        6339. ,  3435. ,  9745. ,  5934. ,  6803. ,  6266. ,  5168. ,
```

MSE

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

```
7912769.697368421
```

RMSE

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

```
2812.9645744958148
```

r2 score

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

```
0.1243511924515116
```

Decision Tree Regression accuracy score 12%

Random Forest Regressor

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

```
RandomForestRegressor()
```

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

```
0.9317795359603639
```

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

```
0.5554022967852575
```

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

```
array([ 4782.52      , 4744.79      , 7205.95      , 6367.3       ,
        7135.07      , 5823.26      , 5784.67      , 5821.12      ,
        8403.81      , 6912.06      , 5258.17      , 7073.83      ,
        6276.41      , 6126.79      , 5061.47      , 5318.75      ,
        9237.82      , 5102.94      , 7481.47      , 5986.91      ,
        5328.5       , 7434.03      , 6406.99      , 5357.25      ,
        4246.77      , 3874.02      , 4593.99      , 5918.        ,
```

MSE ¶

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

```
4017591.531205741
```

RMSE

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

```
2004.393058061652
```

r2 score

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

```
0.5554022967852575
```

Random Forest Regression accuracy score 55%

Hyperparameter Tuning in Random Forest Regressor Model

```
#Randomized Search CV

# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1200, num = 12)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(5, 30, num = 6)]
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10, 15, 100]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 5, 10]
```

```
# Create the random grid

random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf}
```

```
# Random search of parameters, using 5 fold cross validation,
# search across 100 different combinations
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid,scoring='neg_mean_squared_error', n_iter = 10,
```

MSE

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

```
7482401.250526629
```

RMSE

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

```
2735.397823082893
```

r2 score

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

```
0.17197694572079236
```

I have tried to improve the accuracy score by using hyper parameter tuning in random forest algorithm.

Hyper parameter is reducing the accuracy score.

AdaBoost Regressor Model

```
ada = AdaBoostRegressor()
ada.fit(x_train,y_train)
```

```
AdaBoostRegressor()
```

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

```
0.18713105690613063
```

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

```
0.17197694572079236
```

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

```
array([5763.2       , 7018.29639175, 8269.21044776, 6944.79126214,
       8390.6122449 , 8271.63987138, 8269.21044776, 7643.39053254,
       8271.63987138, 8553.69310345, 8066.0625    , 8271.63987138,
       6944.79126214, 8066.0625    , 5209.46666667, 6944.79126214,
       8328.73271028, 5209.46666667, 7643.39053254, 6944.79126214,
       8328.73271028, 8271.63987138, 6419.9760479 , 8328.73271028,
```

MSE

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

```
7482401.250526629
```

RMSE

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

```
2735.397823082893
```

r2 score

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

```
0.17197694572079236
```

```
# AdaBoost Regression accuracy score 17%
```

AdaBoost Regression accuracy score 17%

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
```

```
1.4374302493910474
```

```
# now we have best parameter lets use the lasso regularization
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train,y_train)
```

```
Lasso(alpha=1.4374302493910474)
```

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

```
0.11940278317806119
```

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

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 Random Forest Regressor Model

filename = 'finalized_model.pickle'
pickle.dump(rf,open(filename,'wb'))
loaded_model = pickle.load(open(filename,'rb'))
```

```
# The best model is Random Forest classifier whose accuracy score is 55%.
```

The best model is Random Forest classifier whose accuracy score is 55%.

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

- I have managed out how to prepare a model that gives users for a novel best approach at future lodging value predictions.
- I have train dataset from which I had to extract information.
- I had used pandas library to read the Dataset which provide me to explore & visualize the Data properly based on Rows & Columns.
- I did exploratory data analysis on main data frame and tried to see all visualizations.
- Based on visualization knowledge, I use various EDA TECHNIQUES to plot the count plot.
- After from all these I split the Features & Labels into 2 parts.
- On this data, I have applied our machine learning regressor models such as Linear regression, Decision Tree Regressor, Random forest classifier and Ada Boost train dataset.
- After which I found Random forest Regressor has the High accuracy score 55% and best among all the regressor models.