

# Flight Price Prediction Project



Submitted by: Raghavulu Patnala

## **ACKNOWLEDGMENT**

Thanks for giving me the opportunity to work in Flip Robo Technologies as Intern and would like to express my gratitude to Data Trained Institute as well for trained me in Data Science Domain. This helps me to do my projects well and understand the concepts.

Resources Referred – Google, GitHub, Blogs for conceptual referring

#### INTRODUCTION

## Business Problem Framing

We need to predict the flight price here as we know already that flight prices will vary due to many factors like festive time and booking ticket at a last moment and based on airlines also prices will vary too.

Keeping the flight full as they want it because last minute purchases are expensive.

Depends on the route and the duration between the places. This is also one of the factors that they can raise the price of the ticket at any time.

#### Motivation for the Problem Undertaken

Due to the high price strategy, all cannot afford to travel in flight, and it is the fastest mode of travel now a days.

Here, Predicting the prices will help us to know the cheapest and best route and it will help us to find the price of the flight.

This will help the all kinds of people to conclude when the prices will be high and when it will be less.

## **Analytical Problem Framing**

• Mathematical/ Analytical Modelling of the Problem

Target variable is **Price** for our problem. Hence It is *Regression Problem as the data is continuous variable*.

Data Sources and their formats

Data has been collected by me from one of the official websites of flight and it has 2305 rows and 9 columns.

<pre>df = pd.read_excel("Flight_Price_Dataset.xlsx") df</pre>
---

	Unnamed:	AirlineName	Stops	Duration	Source	Destination	DepartureTime	ArrivalTime	Price
0	0	Air India	direct	2h 30m	BLR Bengaluru Intl	DEL Indira Gandhi Intl	13:20	15:50	7889
1	1	Air India	direct	2h 35m	BLR Bengaluru Intl	DEL Indira Gandhi Intl	10:25	13:00	6936
2	2	Vistara	direct	2h 35m	BLR Bengaluru Intl	DEL Indira Gandhi Intl	21:10	23:45	7484
3	3	SpiceJet	direct	2h 40m	BLR Bengaluru Intl	DEL Indira Gandhi Intl	21:55	00:35	7472
4	4	Vistara	direct	2h 40m	BLR Bengaluru Intl	DEL Indira Gandhi Intl	17:50	20:30	7484
	***	39963		***	(***)	***		***	***
2300	748	United Airlines	2 stops	41h 30m	LHR Heathrow	DEL Indira Gandhi Intl	10:25	09:25	1154916
2301	749	Air Canada	1 stop	36h 55m	LHR Heathrow	DEL Indira Gandhi Intl	15:00	09:25	1276588
2302	750	Air Canada	1 stop	40h 45m	LHR Heathrow	DEL Indira Gandhi Intl	11:10	09:25	1276588
2303	751	Austrian Airlines	3 stops	41h 40m	USM Ko Samui	LHR Heathrow	19:40	06:20	1595550
2304	752	Austrian Airlines	3 stops	46h 10m	USM Ko Samui	LHR Heathrow	19:40	10:50	1714796

2305 rows × 9 columns

Data doesn't have any null values or missing data. So, we are good to pre-process the data.

```
# Summary of each column and its datatype,
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2305 entries, 0 to 2304
Data columns (total 8 columns):
# Column Non-Null Count Dtype
     AirlineName 2305 non-null
Stops 2305 non-null
Duration 2305 non-null
Source 2305 non-null
Destination 2305 non-null
      object
dtypes: int64(1), object(7) memory usage: 144.2+ KB
information of the dataset is data type is 8 object type and no null values present in a dataset and total 2305
rows and 8 columns
# Checking if any null values in a dataset,
df.isnull().sum()
AirlineName
Stops
Duration
Source
Destination
DepartureTime
ArrivalTime
Price
dtype: int64
```

## Data Pre-processing Done

We can see that we have object datatypes for most of the columns in dataset.

So, we need to convert those categorical columns into numerical columns as pre- processing step for better model.

I am applying Datetime index to split the hour and minute from departure / arrival time and duration columns.

```
# splitting duration column which has string and integer,

df['Duration'] = df['Duration'].str.split(' ')

df['dur_hr'] = df['dur_hr'].str.split('h')

df['dur_hr'] = df['dur_hr'].str.split('h')

df['dur_min'] = df['Duration'].str[i]

df['dur_min'] = df['dur_min'].str.split('m')

df['dur_min'] = df['dur_min'].str[@]

# changing datatype into Int for duration hour and min column,

df['dur_hr'] = df['dur_min'].astype(int)

df['dur_min'] = df['dur_min'].astype(int)

# dropping duration columns,

df = df.drop(columns = ['Duration'], axis = 1)

df.head()
```

	AirlineName	Stops	Source	Destination	Price	dep_hr	dep_min	arr_hr	arr_min	dur_hr	dur_min
0	Air India	direct	BLR Bengaluru Intl	DEL Indira Gandhi Intl	7889	13	20	15	50	2	30
1	Air India	direct	BLR Bengaluru Intl	DEL Indira Gandhi Intl	6936	10	25	13	О	2	35
2	Vistara	direct	BLR Bengaluru Intl	DEL Indira Gandhi Intl	7484	21	10	23	45	2	35
3	SpiceJet	direct	BLR Bengaluru Intl	DEL Indira Gandhi Intl	7472	21	55	0	35	2	40
4	Vistara	direct	BLR Bengaluru Inti	DEL Indira Gandhi Intl	7484	17	50	20	30	2	40

As you can see from the above snap, we still have stops, departure and arrival place as categorical column. Applying **Label Encoder ()** Technique to rest of the column,

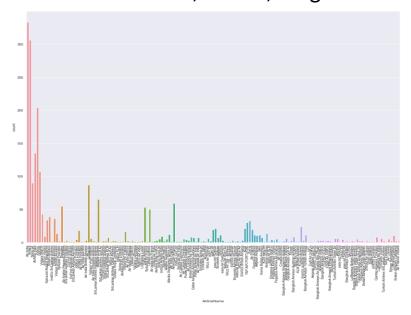
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
col = ['AirlineName', 'Stops', 'Source', 'Destination']
for i in col:
    df[col] = df[col].apply(le.fit_transform)
df
```

	AirlineName	Stops	Source	Destination	Price	dep_hr	dep_min	arr_hr	arr_min	dur_hr	dur_min
0	13	4	0	2	7889	13	20	15	50	2	30
1	13	4	0	2	6936	10	25	13	0	2	35
2	127	4	0	2	7484	21	10	23	45	2	35
3	109	4	0	2	7472	21	55	0	35	2	40
4	127	4	0	2	7484	17	50	20	30	2	40
	***		•••			***					***
2300	125	2	7	2	1154916	10	25	9	25	41	30
2301	5	1	7	2	1276588	15	0	9	25	36	55
2302	5	1	7	2	1276588	11	10	9	25	40	45
2303	29	3	10	9	1595550	19	40	6	20	41	40
2304	29	3	10	9	1714796	19	40	10	50	46	10

2305 rows × 11 columns

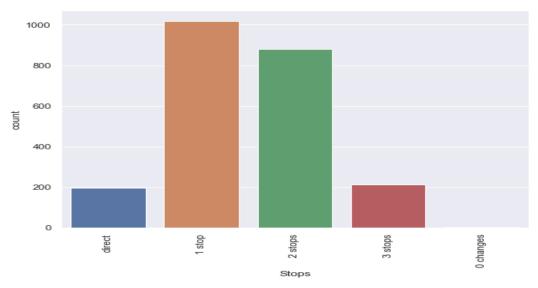
Data Inputs- Logic- Output Relationships

As we can see that there are different types airline names as per mentioned below chart, we can see most of the flights names are AirIndia, Vistara, Indigo

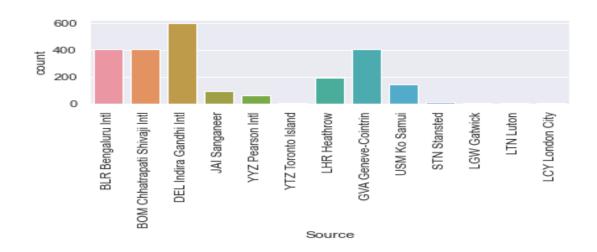


As we can see that there are stops such as – Direct, 1 /2/3 stops and either we can change or not change.

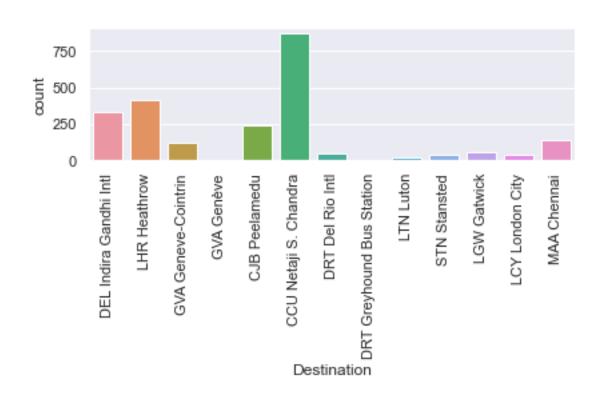
So as per the below chart, we can see that most of the flights has minimum 1 or 2 stops to proceed further.



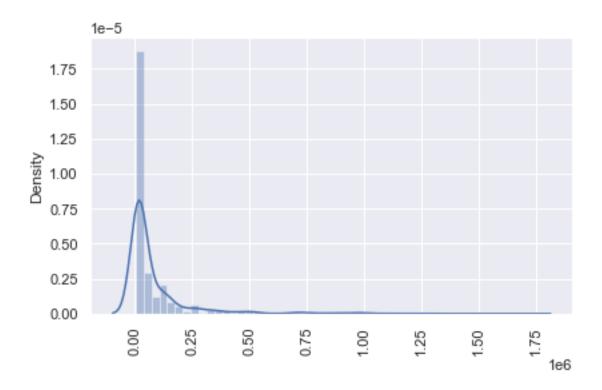
Passengers most booked departure place is DEL (Indhira Gandhi Intl)



# Most of the arrival place is CCU Netaji S Chandra



Target variable price has some skewness on right side and its because depends on place, price will be varying



Hardware and Software Requirements and Tools Used

**Libraries** – Scikit Learn, Pandas, NumPy

**Label Encoder** to encode the categorical values and convert into Numerical values.

Metric - MSE, RMSE, R2 Score

**Model Selection** – Train\_Test \_split for splitting the data into trainand test dataset.

**CV Score** to check the model is over fit or under fit.

**Grid Search CV** for hyper parameter tuning the model

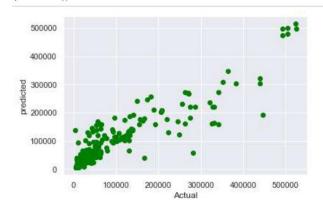
## **Model/s Development and Evaluation**

- Testing of Identified Approaches (Algorithms)
- 1. Random Forest Regressor
- 2. Gradient Boost Regressor
- 3. Ada Boost Regressor
- 4. K Neighbors Regressor

#### Run and evaluate selected models

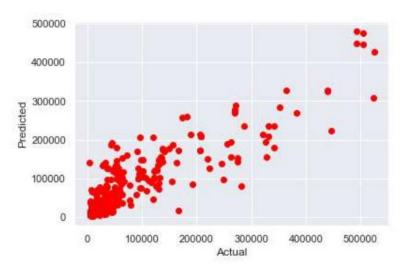
```
# SPLitting X and Y
x = df_new.drop(columns = ['Price'])
y = df_new['Price']
#Scaling the data for normalize the range of values to 0-1.
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x = scaler.fit_transform(x)
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.model_selection import train_test_split, cross_val_score, RandomizedSearchCV
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import AdaBoostRegressor
# Train test split
x train,x test,y train,y test = train test split(x,y, test size = 0.20, random state = 555
# Random Forest regressor
rfr = RandomForestRegressor()
rfr.fit(x_train,y_train)
y pred = rfr.predict(x test)
scr_rfr = cross_val_score(rfr,x,y,cv=5)
print("r2_Score", r2_score(y_test,y_pred))
print("CV Score", scr_rfr.mean())
print("MSE", mean_squared_error(y_test,y_pred))
print("RMSE",np.sqrt(mean_squared_error(y_test,y_pred)))
print("Train Score", rfr.score(x_train,y_train))
print("Test Score", rfr.score(x_test,y_test))
r2 Score 0.8604489217259426
CV Score 0.8311985772356756
MSE 1270851750.2627993
RMSE 35649.007703760835
Train Score 0.9766959077607412
Test Score 0.8604489217259426
plt.scatter(y_test,y_pred, color = 'green')
                                          #Scatter Matrix for Actual VS predicted f
plt.xlabel("Actual")
```





### # Gradient Boost Regression from sklearn.ensemble import GradientBoostingRegressor gb = GradientBoostingRegressor() gb.fit(x\_train,y\_train) y\_pred = gb.predict(x\_test) scr\_gb = cross\_val\_score(gb,x,y,cv = 5) print("r2\_Score", r2\_score(y\_test,y\_pred)) print("CV Score", scr\_gb.mean()) print("MSE", mean\_squared\_error(y\_test,y\_pred)) print("RMSE",np.sqrt(mean\_squared\_error(y\_test,y\_pred))) print("Train Score", gb.score(x\_train,y\_train)) print("Test Score", gb.score(x\_test,y\_test)) plt.scatter(y\_test,y\_pred, color = 'red') plt.xlabel("Actual") plt.ylabel("Predicted") plt.show()

r2\_Score 0.7957871144618289 CV Score 0.750327822503668 MSE 1859708332.0469546 RMSE 43124.33572876172 Train Score 0.8364313549319184 Test Score 0.7957871144618289



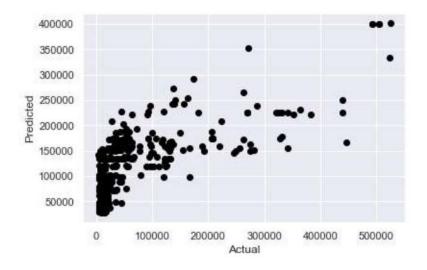
# #AdaBoostRegressor ab = AdaBoostRegressor() ab.fit(x\_train,y\_train) y\_pred = ab.predict(x\_test) scr\_ab = cross\_val\_score(ab,x,y,cv = 5) print("r2\_Score", r2\_score(y\_test,y\_pred)) print("CV Score", scr\_ab.mean()) print("MSE",mean\_squared\_error(y\_test,y\_pred)) print("RMSE",np.sqrt(mean\_squared\_error(y\_test,y\_pred)))

plt.scatter(y\_test,y\_pred, color = 'black')
plt.xlabel("Actual")
plt.ylabel("Predicted")

print("Train Score", ab.score(x\_train,y\_train))
print("Test Score", ab.score(x\_test,y\_test))

plt.show()

r2\_Score 0.21178847713732152 CV Score 0.23983500085952233 MSE 7178016865.1950655 RMSE 84723.17785113507 Train Score 0.25967663959613807 Test Score 0.21178847713732152



#### : # K Neighbors regression

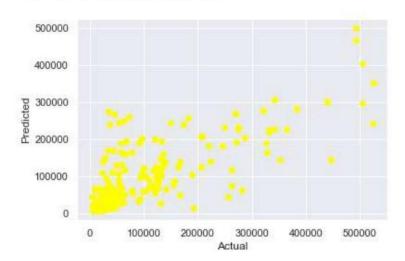
```
knr = KNeighborsRegressor(n_neighbors = 5)
knr.fit(x_train,y_train)
y_pred = knr.predict(x_test)

scr_knr = cross_val_score(knr,x,y,cv=5)

print("r2_Score", r2_score(y_test,y_pred))
print("CV Score", scr_knr.mean())
print("MSE",mean_squared_error(y_test,y_pred))
print("RMSE",np.sqrt(mean_squared_error(y_test,y_pred)))
print("Train Score", knr.score(x_train,y_train))
print("Test Score", knr.score(x_test,y_test))

plt.scatter(y_test,y_pred, color = 'yellow')
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.show()
```

r2\_Score 0.6906919227930592 CV Score 0.6288493939944896 MSE 2816780179.3469625 RMSE 53073.34716547433 Train Score 0.7627770313893869 Test Score 0.6906919227930592



## Visualizations

To visualize the graphs, we have used matplotlib library and seaborn library.

Correlation Matrix													1.0	
AirlineName	1	-0.064	-0.093	0.13	0.069	0.045	0.081	0.11	0.26	-0.031	-0.014			1.0
Stops	-0.064	1	0.096	-0.0076	0.0011	0.0031	-0.02	-0.0013	-0.052	0.056	-0.017		_	0.8
Source	-0.093	0.096	1	0.26	0.32	0.16	-0.074	-0.15	-0.1	0.35	0.016			0.0
Destination	0.13	-0.0076	0.26	1	0.17	0.12	-0.046	-0.072	-0.029	0.28	0.018		_	0.6
Price	0.069	0.0011	0.32	0.17	1	0.02	-0.041	-0.11	-0.045	0.45	-0.021			
dep_hr	0.045	0.0031	0.16	0.12	0.02	1	0.041	-0.12	0.0043	0.0075	0.061		-	0.4
dep_min	0.081	-0.02	-0.074	-0.046	-0.041	0.041	1	-0.054	0.037	-0.014	0.0011			
arr_hr	0.11	-0.0013	-0.15	-0.072	-0.11	-0.12	-0.054	1	0.13	-0.062	0.00084		-	0.2
arr_min	0.26	-0.052	-0.1	-0.029	-0.045	0.0043	0.037	0.13	1	0.018	-0.017			
dur_hr	-0.031	0.056	0.35	0.28	0.45	0.0075	-0.014	-0.062	0.018	1	0.013		-	0.0
dur_min	-0.014	-0.017	0.016	0.018	-0.021	0.061	0.0011	0.00084	-0.017	0.013	1			
	AirlineName	Stops	Source	Destination	Price	dep_hr	dep_min	arr_hr	arr_min	dur_hr	dur_min			

#### Interpretation of the Results

```
grid.best_params_

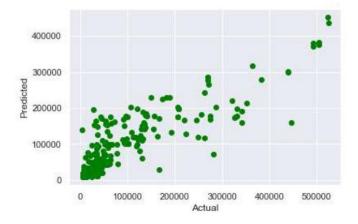
{'bootstrap': False,
   'criterion': 'mse',
   'max_depth': 10,
   'max_features': 'log2',
   'min_samples_leaf': 1,
   'min_samples_split': 10,
   'n_estimators': 100}
```

```
Fnal_model = RandomForestRegressor(bootstrap= 'True',criterion = 'mse',max_depth = 20,max_min_samples_split = 10 ,n_estimators = 100,min_samples_split = 1
```

accuracy score of the final model is : 0.8210548199147409

```
plt.scatter(y_test,y_pred, color = 'green')
plt.xlabel("Actual")
plt.ylabel("Predicted")
```

Text(0, 0.5, 'Predicted')



#### **CONCLUSION**

Key Findings and Conclusions of the Study

As this project is about predicting the prices of flight, it is a regression problem as the target variables are continuous range.

Used r2 score, MSE as a metrics to calculate the model accuracy.

Data is Collected by me from kayak.co for predicting the price of flight.

The dataset doesn't have any null or missing values.

 Learning Outcomes of the Study in respect of Data Science

Random forest and Gradient Boost Algorithm have high accuracy score and I have used GridSearch CV for Hyper parametertuning to check accuracy score finally I got after tuning 83%.

This is kind of different as the data is not present and we need to collect it to build a model but helps me to learn more and most important is that I am getting hands-on experience more on Data Science Concepts.

Thanks, Flip Robo and Data Trained for this wonderful Opportunity!!