Report on

FLIGHT FARE ANTICIPATION

Submitted on the partial fulfilment of the requirements for the award of degree of

Bachelor of technology

(Computer Science Technology)

LOVELY PROFESSIONAL UNIVERSITY

PHAGWARA,PUNJAB, INDIA

From 1st FEB 2024 to 13th APRIL 2024

Submitted by

NAME: SRUJAN REDDY

REG NO: 12111003

SECTION: K21UT

ROLLNO: 18

FACULTY: AJAY SHARMA

DECLARATION

I, Srujan Reddy, 12111003, Here by declare that work done by me on Flight Fare Anticipation project from Feb 2024 to April 2024, is a record of original work for the practical fulfilment of the requirement's for the award of degree, Bachelors of the technology.

Name of the student: Srujan Reddy.

Reg No: 12111003

Date: 13th April 2024

ACKNOWLEDGEMENT

Primarily I would like to thank God for being able to learn a new technology. Then I would to express my special thanks of gratitude to the teacher and the instructor of the course machine learning who provide me the golden opportunity to learn a new technology.

I would like to also thank my own college Lovely professional university for offering such a course is not only improve my programming skill but also taught me other new technology.

Then I would like to thank my parents and friends who helped me with their valuable suggestions and guidelines for choosing this course.

Finally, I would like to thank everyone who helped me a lot.

Date: 13th April 2024

TABLE OF CONTENTS

ABSTR ACT

This project focuses on leveraging machine learning techniques to predict flight fares accurately. With the increasing demand for air travel and the dynamic nature of pricing in the airline industry, developing an effective predictive model becomes crucial for both consumers and service providers. The dataset used in this study encompasses a diverse range of features including flight routes, departure times, airlines, and historical pricing data.

Initially, exploratory data analysis (EDA) is conducted to gain insights into the dataset's characteristics and identify patterns. Following EDA, feature engineering techniques are employed to preprocess and extract relevant features, ensuring optimal model performance. Various machine learning algorithms such as Random Forest, Gradient Boosting, and Neural Networks are then trained and evaluated using appropriate metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

Additionally, hyperparameter tuning techniques such as grid search and random search are employed to optimize model performance further. The project also explores ensemble learning methods to combine the predictions from multiple models for improved accuracy and robustness. Furthermore, interpretability techniques are applied to elucidate the factors influencing flight fares, providing actionable insights for both consumers and industry stakeholders.

The effectiveness of the developed models is validated through rigorous cross-validation and testing on unseen data. The results demonstrate promising predictive performance, with the proposed models outperforming baseline approaches. Finally, the implications of this research for consumers, airlines, and travel agencies are discussed, highlighting the potential for informed decision-making and revenue optimization in the airline in

OBJECTIVES

Utilize machine learning algorithms to analyse historical flight data and predict future flight fares with high precision.

- Explore and implement advanced feature engineering techniques to extract relevant features from the dataset, enhancing the predictive power of the model.
- Investigate ensemble learning methods to combine the strengths of multiple models, improving prediction accuracy and robustness.
- Employ hyperparameter tuning techniques to optimize the performance of individual models and ensembles.
- Enhance interpretability of the model predictions by identifying and analysing the key factors influencing flight fares.
- Validate the developed models through rigorous cross-validation and testing on unseen data to ensure generalizability and reliability.
- Discuss the implications of the research findings for consumers, airlines, and travel agencies, highlighting the potential benefits of informed decision-making and revenue optimization in the airline industry.

INTRODUCTION

In today's fast-paced world of air travel, predicting flight fares accurately has become increasingly crucial for travellers seeking economical options and for airlines striving to optimize revenue. This study delves into the realm of machine learning to develop a precise predictive model for flight fare estimation. By leveraging a comprehensive dataset encompassing vital parameters such as airline, source, destination, route, departure time, arrival time, duration, total stops, additional information, price, journey day, and journey month, our aim is to unravel the complexities of pricing dynamics in the aviation industry.

The primary objective is clear: to construct a robust predictive model that empowers travellers with the ability to anticipate flight fares with accuracy. Through meticulous analysis and utilization of advanced machine learning algorithms, we endeavour to uncover underlying patterns and relationships that drive pricing variations in air travel.

This research not only seeks to enhance the efficiency of fare estimation but also aims to provide insights into the factors influencing price fluctuations. The implications of this endeavour extend to both consumers, who can make well-informed decisions, and industry stakeholders, who can refine pricing strategies to adapt to evolving market conditions. Thus, by harnessing the potential of machine learning, we embark on a mission to revolutionize the way flight fares are predicted and understood in the modern aviation landscape.

THEORITICAL BACKGROUND

What is Machine Learning:

Machine learning is a branch of artificial intelligence (AI) that focuses on the development of algorithms allowing computers to learn and improve from experience automatically. Unlike traditional rule-based programming, where explicit instructions are provided, machine learning algorithms learn from data to make predictions or decisions. This introduction provides an overview of the key concepts and types of machine learning.

Types of Machine Learning

- Supervised Learning: Supervised learning involves training a model on labeled data, where each example is paired with an associated label or outcome. The algorithm learns to map input features to the correct output based on this labeled training data. Common tasks in supervised learning include classification and regression.

- Unsupervised Learning: Unsupervised learning involves training a model on unlabeled data, where the algorithm must identify patterns or structures in the data on its own. Unlike supervised learning, there are no predefined output labels. Clustering and dimensionality reduction are typical tasks in unsupervised learning.

- Semi-supervised Learning: Semi-supervised learning is a hybrid approach that combines labeled and unlabeled data during training. The algorithm learns from the labeled data while leveraging the additional unlabeled data to improve performance.

- Reinforcement Learning: Reinforcement learning involves training an agent to interact with an environment to achieve a goal. The agent learns by receiving feedback in the form of rewards or penalties based on its actions, and its objective is to learn the optimal strategy for maximizing cumulative rewards over time.

SOFTWARE AND HARDWARE REQUIREMENTS

SOFTWARE

Python: Python is a well-liked machine learning programming language with a wide variety of tools and frameworks for creating models.

Jupyter notebook: Jupyter Notebook is a widely-used open-source web application that enables users to create and share documents containing live code, equations, visualizations, and text explanations. It supports multiple programming languages like Python, R, and Julia, making it versatile for various data science, machine learning, and scientific computing tasks.

HARDWARE

Tensor Processing Units (TPUs), or graphics processing units (GPUs): Deep learning model training is a good fit for these specialist processors' parallel processing capabilities. When compared to using conventional CPUs, GPUs and TPUs can greatly accelerate the training process.

METHODOLOGY

Importing Required Libraries:

- **pandas as pd:** Pandas is a Python library used for data manipulation and analysis, offering data structures like Data Frames and Series, along with functions to handle missing data, merge datasets, and perform statistical operations efficiently.

- **Numpy as np:** NumPy is a fundamental package for scientific computing in Python, providing support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays.

- **matplotlib.pyplot as plt:** Matplotlib is a plotting library in Python used to create static, interactive, and animated visualizations. The pyplot module provides a MATLAB-like interface for creating plots and customizing their appearance.

- **seaborn as sns:** Seaborn is a Python data visualization library based on matplotlib, offering a high-level interface for creating informative and attractive statistical graphics. It provides easy-to-use functions for visualizing relationships in data, including scatter plots, bar plots, and heatmaps.

- **warnings:** The warnings module in Python is used to control the display of warning messages issued by other modules or libraries. It allows developers to handle warnings appropriately, such as ignoring specific warnings or converting them into exceptions.

- **train_test_split:** This function is used for splitting datasets into training and testing subsets, a pivotal step in assessing model performance in machine learning.
- **Linear Regression:** Linear Regression allows for the implementation of linear regression models, essential for establishing relationships between independent and dependent variables in datasets.
- **DecisionTreeRegressor:** Decision Tree Regressor facilitates the creation of decision tree-based regression models, aiding in predicting numerical outcomes by segmenting feature space.
- **Random Forest Regressor:** Random Forest Regressor implements the random forest algorithm, aggregating predictions from multiple decision trees to enhance model accuracy and robustness.
- **mean_squared_error:** This module calculates mean squared error, a crucial metric for evaluating regression model performance by quantifying the average squared difference between predicted and actual values.
- **metrics:** The metrics module encompasses various evaluation metrics for assessing the performance of machine learning models, covering both regression and classification tasks.

CODE

Flight Fare Anticipation

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [5]:
```
# Reading the dataset
train_df = pd.read_csv("C:/Users/srirk/Downloads/Data_Train.csv")
```

In [6]:
```
#displaying the maximum columns
pd.set_option('display.max_columns', None)
```

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

Out[7]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR ? DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897
1	Air India	1/05/2019	Kolkata	Banglore	CCU ? IXR ? BBI ? BLR	05:50	13:15	7h 25m	2 stops	No info	7662
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL ? LKO ? BOM ? COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU ? NAG ? BLR	18:05	23:30	5h 25m	1 stop	No info	6218
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR ? NAG ? DEL	16:50	21:35	4h 45m	1 stop	No info	13302

In [8]:
```
train_df.shape
```

Out[8]: (10683, 11)

In [9]:
```
# Info the dataset
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Airline          10683 non-null  object
 1   Date_of_Journey  10683 non-null  object
 2   Source           10683 non-null  object
 3   Destination      10683 non-null  object
 4   Route            10682 non-null  object
 5   Dep_Time         10683 non-null  object
 6   Arrival_Time     10683 non-null  object
 7   Duration         10683 non-null  object
 8   Total_Stops      10682 non-null  object
 9   Additional_Info  10683 non-null  object
 10  Price            10683 non-null  int64
dtypes: int64(1), object(10)
memory usage: 918.2+ KB
```

In [10]:
```
# Description of the dataset
train_df.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
Price	10683.0	9087.064121	4611.359167	1759.0	5277.0	8372.0	12373.0	79512.0

Data Preprocessing

Missing values

In [11]:
```
#Finding the null values of the dataset
train_df.isnull().sum()
```

Out[11]:
```
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              1
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        1
Additional_Info    0
Price              0
dtype: int64
```

In [12]:
```
train_df.dropna(inplace=True)
```

In [13]:
```
train_df.isnull().sum()
```

Out[13]:
```
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              0
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        0
Additional_Info    0
Price              0
dtype: int64
```

Removed the null values in the dataset

Creating new columns

Creating the new columns in the dataframe to make clear values ,which will be used for analysis

In [14]:
```
#Creating the new column journey day
train_df['Journy_Day'] = pd.to_datetime(train_df.Date_of_Journey, format='%d/%m/%Y').dt.day
```

In [15]:
```
#Creating the new column journey month
train_df['Journy_Month'] = pd.to_datetime(train_df.Date_of_Journey, format='%d/%m/%Y').dt.month
```

In [16]:
```
train_df.head()
```

Out[16]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	Journy_Day	Journy_Mon
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR ? DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897	24	
1	Air India	1/05/2019	Kolkata	Banglore	CCU ? IXR ? BBI ? BLR	05:50	13:15	7h 25m	2 stops	No info	7662	1	
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL ? LKO ? BOM ? COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882	9	
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU ? NAG ? BLR	18:05	23:30	5h 25m	1 stop	No info	6218	12	
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR ? NAG ? DEL	16:50	21:35	4h 45m	1 stop	No info	13302	1	

In [17]:
```
#Dropping the date of journey column
train_df.drop(['Date_of_Journey'], axis=1, inplace=True)
```

In [18]:
```python
train_df.head()
```

Out[18]:

	Airline	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	Journy_Day	Journy_Month
0	IndiGo	Banglore	New Delhi	BLR ? DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897	24	3
1	Air India	Kolkata	Banglore	CCU ? IXR ? BBI ? BLR	05:50	13:15	7h 25m	2 stops	No info	7662	1	5
2	Jet Airways	Delhi	Cochin	DEL ? LKO ? BOM ? COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882	9	6
3	IndiGo	Kolkata	Banglore	CCU ? NAG ? BLR	18:05	23:30	5h 25m	1 stop	No info	6218	12	5
4	IndiGo	Banglore	New Delhi	BLR ? NAG ? DEL	16:50	21:35	4h 45m	1 stop	No info	13302	1	3

In [19]:
```python
train_df.head()
```

Out[19]:

	Airline	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price	Journy_Day	Journy_Month
0	IndiGo	Banglore	New Delhi	BLR ? DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897	24	3
1	Air India	Kolkata	Banglore	CCU ? IXR ? BBI ? BLR	05:50	13:15	7h 25m	2 stops	No info	7662	1	5
2	Jet Airways	Delhi	Cochin	DEL ? LKO ? BOM ? COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882	9	6
3	IndiGo	Kolkata	Banglore	CCU ? NAG ? BLR	18:05	23:30	5h 25m	1 stop	No info	6218	12	5
4	IndiGo	Banglore	New Delhi	BLR ? NAG ? DEL	16:50	21:35	4h 45m	1 stop	No info	13302	1	3

In [20]:
```python
print(train_df.columns.tolist())
```

```
['Airline', 'Source', 'Destination', 'Route', 'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops', 'Additional_Info', 'Pri
ce', 'Journy_Day', 'Journy_Month']
```

In [21]:
```python
train_df['Dep_hour'] = pd.to_datetime(train_df['Dep_Time'], format='%H:%M').dt.hour
train_df['Dep_min'] = pd.to_datetime(train_df['Dep_Time'], format='%H:%M').dt.minute

train_df.drop(['Dep_Time'], axis=1, inplace=True)
```

In [22]:
```python
train_df['Arrival_hour'] = pd.to_datetime(train_df.Arrival_Time).dt.hour
train_df['Arrival_min'] = pd.to_datetime(train_df.Arrival_Time).dt.minute

train_df.drop(['Arrival_Time'], axis=1, inplace=True)
```

In [23]:
```python
train_df.head()
```

Out[23]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	Journy_Day	Journy_Month	Dep_hour	Dep_min	Arrival_hour	Arri
0	IndiGo	Banglore	New Delhi	BLR ? DEL	2h 50m	non-stop	No info	3897	24	3	22	20	1	
1	Air India	Kolkata	Banglore	CCU ? IXR ? BBI ? BLR	7h 25m	2 stops	No info	7662	1	5	5	50	13	
2	Jet Airways	Delhi	Cochin	DEL ? LKO ? BOM ? COK	19h	2 stops	No info	13882	9	6	9	25	4	
3	IndiGo	Kolkata	Banglore	CCU ? NAG ? BLR	5h 25m	1 stop	No info	6218	12	5	18	5	23	
4	IndiGo	Banglore	New Delhi	BLR ? NAG ? DEL	4h 45m	1 stop	No info	13302	1	3	16	50	21	

In [144]:

```python
# Check the column names in train_df
print(train_df.columns)

# Assuming the column containing duration information is named "Duration" or similar
# Replace "Duration" with the actual column name if it's different
duration_column_name = "Duration"

# Assigning and converting the duration column into a list
if duration_column_name in train_df.columns:
    duration = list(train_df[duration_column_name])

    for i in range(len(duration)):
        # Check if duration contains only hour or minutes
        if len(duration[i].split()) != 2:
            if 'h' in duration[i]:
                # Adding 0 mins
                duration[i] = duration[i].strip() + " 0m"
            else:
                duration[i] = "0h " + duration[i]

    duration_hours = []
    duration_mins = []
    for i in range(len(duration)):
        # Extract hours from Duration
        duration_hours.append(int(duration[i].split("h")[0]))
        # Extract only minutes from Duration
        duration_mins.append(int(duration[i].split('m')[0].split()[-1]))
else:
    print("Column '{}' not found in DataFrame.".format(duration_column_name))
```

```
Index(['Airline', 'Source', 'Destination', 'Total_Stops', 'Price',
       'Journy_Day', 'Journy_Month', 'Dep_hour', 'Dep_min', 'Arrival_hour',
       'Arrival_min', 'Duration_hours', 'Duration_mins'],
      dtype='object')
Column 'Duration' not found in DataFrame.
```

In [25]:

```python
##Creating the columns duration hours and duration minutes from the duration column
train_df["Duration_hours"] = duration_hours
train_df["Duration_mins"] = duration_mins
train_df.drop(['Duration'], axis=1, inplace=True)
```

In [26]:

```python
train_df.head()
```

Out[26]:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info	Price	Journy_Day	Journy_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	D
0	IndiGo	Banglore	New Delhi	BLR ? DEL	non-stop	No info	3897	24	3	22	20	1	10	
1	Air India	Kolkata	Banglore	CCU ? IXR ? BBI ? BLR	2 stops	No info	7662	1	5	5	50	13	15	
2	Jet Airways	Delhi	Cochin	DEL ? LKO ? BOM ? COK	2 stops	No info	13882	9	6	9	25	4	25	
3	IndiGo	Kolkata	Banglore	CCU ? NAG ? BLR	1 stop	No info	6218	12	5	18	5	23	30	
4	IndiGo	Banglore	New Delhi	BLR ? NAG ? DEL	1 stop	No info	13302	1	3	16	50	21	35	

Handling Categorical Data

The categorical data can't be used for analysis. So this data is converted into some numerical values so that it is used for analysis

The Categorical columns that need to be changed is : Airline, Source, Destination

In [27]:

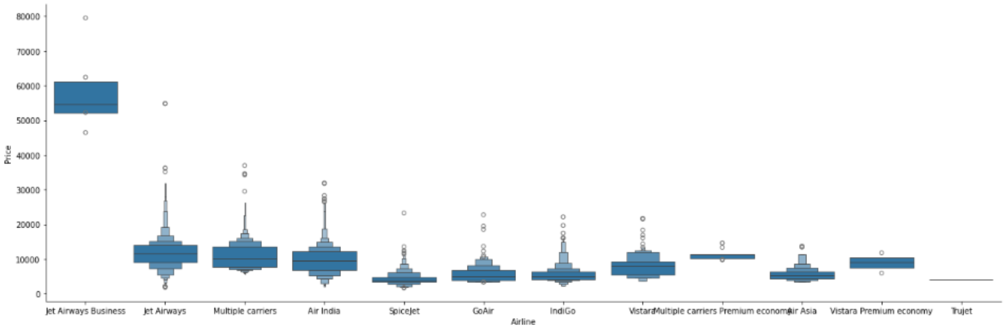
```python
train_df.Airline.value_counts()
```

Out[27]:

```
Airline
Jet Airways                          3849
IndiGo                               2053
Air India                            1751
Multiple carriers                    1196
SpiceJet                              818
Vistara                               479
Air Asia                              319
GoAir                                 194
Multiple carriers Premium economy      13
Jet Airways Business                    6
Vistara Premium economy                 3
Trujet                                  1
Name: count, dtype: int64
```

```
In [28]: sns.catplot(y="Price", x="Airline", data=train_df.sort_values("Price", ascending=False), kind='boxen', height=6, aspect=3)
```

Out[28]: <seaborn.axisgrid.FacetGrid at 0x1b8a7df4340>



The Airline is plotted according to their price

The most number of bookings are done for Jet Airways. The price for the jet airways business is the highest.

```
In [29]: len(train_df['Airline'].unique())
```

Out[29]: 12

```
In [30]: Airline = train_df[['Airline']]
Airline = pd.get_dummies(Airline, drop_first=True)
Airline.head()
```

Out[30]:

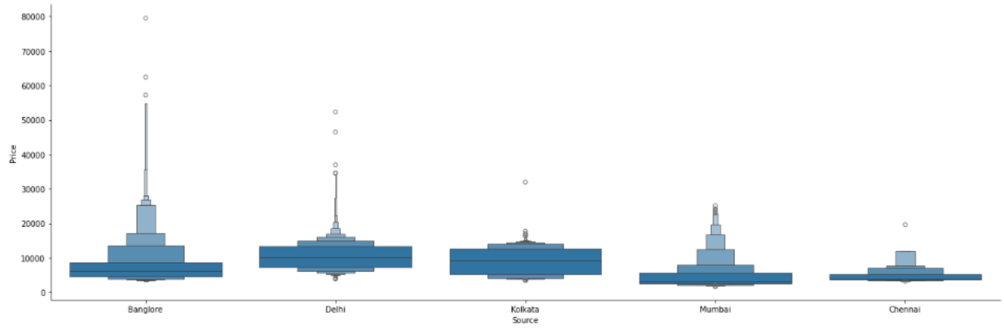
	Airline_Air India	Airline_GoAir	Airline_IndiGo	Airline_Jet Airways	Airline_Jet Airways Business	Airline_Multiple carriers	Airline_Multiple carriers Premium economy	Airline_SpiceJet	Airline_Trujet	Airline_Vistara	Airline_ P e
0	False	False	True	False	False	False	False	False	False	False	
1	True	False	False	False	False	False	False	False	False	False	
2	False	False	False	True	False	False	False	False	False	False	
3	False	False	True	False	False	False	False	False	False	False	
4	False	False	True	False	False	False	False	False	False	False	

```
In [31]: train_df.Source.value_counts()
```

```
Out[31]: Source
Delhi       4536
Kolkata     2871
Banglore    2197
Mumbai       697
Chennai      381
Name: count, dtype: int64
```

In [32]:
```python
sns.catplot(y='Price', x='Source', data=train_df.sort_values('Price', ascending=False), kind='boxen', height=6, aspect=3)
```

Out[32]: <seaborn.axisgrid.FacetGrid at 0x1b8aa110610>



The most number of bookings are done from Delhi

In [33]:
```python
Source = train_df[['Source']]
Source = pd.get_dummies(Source, drop_first=True)
Source.head()
```

Out[33]:

	Source_Chennai	Source_Delhi	Source_Kolkata	Source_Mumbai
0	False	False	False	False
1	False	False	True	False
2	False	True	False	False
3	False	False	True	False
4	False	False	False	False

In [34]:
```python
Destination = train_df[['Destination']]
Destination = pd.get_dummies(Destination, drop_first=True)
Destination.head()
```

Out[34]:

	Destination_Cochin	Destination_Delhi	Destination_Hyderabad	Destination_Kolkata	Destination_New Delhi
0	False	False	False	False	True
1	False	False	False	False	False
2	True	False	False	False	False
3	False	False	False	False	False
4	False	False	False	False	True

In [35]:
```python
train_df.Route
```

Out[35]:
```
0                    BLR ? DEL
1        CCU ? IXR ? BBI ? BLR
2        DEL ? LKO ? BOM ? COK
3              CCU ? NAG ? BLR
4              BLR ? NAG ? DEL
                  ...
10678                CCU ? BLR
10679                CCU ? BLR
10680                BLR ? DEL
10681                BLR ? DEL
10682    DEL ? GOI ? BOM ? COK
Name: Route, Length: 10682, dtype: object
```

The column is route is already defined in the source,destination and total route columns. So we can drop the route column

In [141]:
```python
print(train_df.columns)
```

```
Index(['Airline', 'Source', 'Destination', 'Total_Stops', 'Price',
       'Journy_Day', 'Journy_Month', 'Dep_hour', 'Dep_min', 'Arrival_hour',
       'Arrival_min', 'Duration_hours', 'Duration_mins'],
      dtype='object')
```

In [37]:
```python
a.mean()
```
Out[37]:
```
0.781127129750983
```

As the Additional info is not useful for the analysis as it contains 78% of "No info" values. So we will drop that column.

In [38]:
```python
## Additional_Info conatins almost 80% no_info
# Route and Total_Stops are related to each other

train_df.drop(['Route', 'Additional_Info'], axis=1, inplace=True)
```

In [39]:
```python
train_df.head()
```
Out[39]:

	Airline	Source	Destination	Total_Stops	Price	Journy_Day	Journy_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_
0	IndiGo	Banglore	New Delhi	non-stop	3897	24	3	22	20	1	10	2	
1	Air India	Kolkata	Banglore	2 stops	7662	1	5	5	50	13	15	7	
2	Jet Airways	Delhi	Cochin	2 stops	13882	9	6	9	25	4	25	19	
3	IndiGo	Kolkata	Banglore	1 stop	6218	12	5	18	5	23	30	5	
4	IndiGo	Banglore	New Delhi	1 stop	13302	1	3	16	50	21	35	4	

In [40]:
```python
train_df.Total_Stops.value_counts()
```
Out[40]:
```
Total_Stops
1 stop      5625
non-stop    3491
2 stops     1520
3 stops       45
4 stops        1
Name: count, dtype: int64
```

In [41]:
```python
## As this is case of Ordinal Categorical type we perform LabelEncoder
## Here vlaues are assigned with corresponding keys
train_df.replace({"non-stop": 0, "1 stop": 1, "2 stops": 2, "3 stops": 3, "4 stops": 4}, inplace=True)
```

In [42]:
```python
data_train = pd.concat([train_df, Airline, Source, Destination], axis=1)
```

In [43]:
```python
data_train.head()
```
Out[43]:

	Airline	Source	Destination	Total_Stops	Price	Journy_Day	Journy_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_
0	IndiGo	Banglore	New Delhi	0	3897	24	3	22	20	1	10	2	
1	Air India	Kolkata	Banglore	2	7662	1	5	5	50	13	15	7	
2	Jet Airways	Delhi	Cochin	2	13882	9	6	9	25	4	25	19	
3	IndiGo	Kolkata	Banglore	1	6218	12	5	18	5	23	30	5	
4	IndiGo	Banglore	New Delhi	1	13302	1	3	16	50	21	35	4	

In [44]:
```python
data_train.drop(['Destination', 'Source', 'Airline'], axis=1, inplace=True)
```

In [45]:
```python
data_train.head()
```
Out[45]:

	Total_Stops	Price	Journy_Day	Journy_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_mins	Airline_Air India	Airline_GoAi
0	0	3897	24	3	22	20	1	10	2	50	False	False
1	2	7662	1	5	5	50	13	15	7	25	True	False
2	2	13882	9	6	9	25	4	25	19	0	False	False
3	1	6218	12	5	18	5	23	30	5	25	False	False
4	1	13302	1	3	16	50	21	35	4	45	False	False

In [46]:
```
data_train.shape
```
Out[46]: (10682, 30)

Test Set

we will make all these in the test set as well

In [47]:
```
test_data = pd.read_csv("C:/Users/srirk/Downloads/Test_set.csv")
```

In [48]:
```
test_data.head()
```
Out[48]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info
0	Jet Airways	6/06/2019	Delhi	Cochin	DEL ? BOM ? COK	17:30	04:25 07 Jun	10h 55m	1 stop	No info
1	IndiGo	12/05/2019	Kolkata	Banglore	CCU ? MAA ? BLR	06:20	10:20	4h	1 stop	No info
2	Jet Airways	21/05/2019	Delhi	Cochin	DEL ? BOM ? COK	19:15	19:00 22 May	23h 45m	1 stop	In-flight meal not included
3	Multiple carriers	21/05/2019	Delhi	Cochin	DEL ? BOM ? COK	08:00	21:00	13h	1 stop	No info
4	Air Asia	24/06/2019	Banglore	Delhi	BLR ? DEL	23:55	02:45 25 Jun	2h 50m	non-stop	No info

In [49]:
```
test_data.shape
```
Out[49]: (2671, 10)

In [50]:
```
print(test_data.columns)
```
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info'],
      dtype='object')
```

In [51]:
```
print("Test data Info")
print("-"*75)
print(test_data.info())

print()
print()

print("Null values :")
print("-"*75)
test_data.dropna(inplace = True)
print(test_data.isnull().sum())

# EDA

# Date_of_Journey
test_data["Journey_day"] = pd.to_datetime(test_data.Date_of_Journey, format="%d/%m/%Y").dt.day
test_data["Journey_month"] = pd.to_datetime(test_data["Date_of_Journey"], format = "%d/%m/%Y").dt.month
test_data.drop(["Date_of_Journey"], axis = 1, inplace = True)

# Dep_Time
test_data["Dep_hour"] = pd.to_datetime(test_data["Dep_Time"]).dt.hour
test_data["Dep_min"] = pd.to_datetime(test_data["Dep_Time"]).dt.minute
test_data.drop(["Dep_Time"], axis = 1, inplace = True)

# Arrival_Time
test_data["Arrival_hour"] = pd.to_datetime(test_data.Arrival_Time).dt.hour
test_data["Arrival_min"] = pd.to_datetime(test_data.Arrival_Time).dt.minute
test_data.drop(["Arrival_Time"], axis = 1, inplace = True)

# Duration
duration = list(test_data["Duration"])

for i in range(len(duration)):
    if len(duration[i].split()) != 2:    # Check if duration contains only hour or mins
        if "h" in duration[i]:
            duration[i] = duration[i].strip() + " 0m"   # Adds 0 minute
        else:
            duration[i] = "0h " + duration[i]           # Adds 0 hour

duration_hours = []
duration_mins = []
```

```
data_test.drop(["Airline", "Source", "Destination"], axis = 1, inplace = True)

print()
print()

print("Shape of test data : ", data_test.shape)
```

```
Test data Info
---------------------------------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2671 entries, 0 to 2670
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Airline          2671 non-null   object
 1   Date_of_Journey  2671 non-null   object
 2   Source           2671 non-null   object
 3   Destination      2671 non-null   object
 4   Route            2671 non-null   object
 5   Dep_Time         2671 non-null   object
 6   Arrival_Time     2671 non-null   object
 7   Duration         2671 non-null   object
 8   Total_Stops      2671 non-null   object
 9   Additional_Info  2671 non-null   object
dtypes: object(10)
memory usage: 208.8+ KB
None


Null values :
---------------------------------------------------------------------------
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              0
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        0
Additional_Info    0
dtype: int64
Airline
```

```
duration_hours = []
duration_mins = []
for i in range(len(duration)):
    duration_hours.append(int(duration[i].split(sep = "h")[0]))    # Extract hours from duration
    duration_mins.append(int(duration[i].split(sep = "m")[0].split()[-1]))    # Extracts only minutes from duration

# Adding Duration column to test set
test_data["Duration_hours"] = duration_hours
test_data["Duration_mins"] = duration_mins
test_data.drop(["Duration"], axis = 1, inplace = True)


# Categorical data

print("Airline")
print("-"*75)
print(test_data["Airline"].value_counts())
Airline = pd.get_dummies(test_data["Airline"], drop_first= True)

print()

print("Source")
print("-"*75)
print(test_data["Source"].value_counts())
Source = pd.get_dummies(test_data["Source"], drop_first= True)

print()

print("Destination")
print("-"*75)
print(test_data["Destination"].value_counts())
Destination = pd.get_dummies(test_data["Destination"], drop_first = True)

# Additional_Info contains almost 80% no_info
# Route and Total_Stops are related to each other
test_data.drop(["Route", "Additional_Info"], axis = 1, inplace = True)

# Replacing Total_Stops
test_data.replace({"non-stop": 0, "1 stop": 1, "2 stops": 2, "3 stops": 3, "4 stops": 4}, inplace = True)

# Concatenate dataframe --> test_data + Airline + Source + Destination
data_test = pd.concat([test_data, Airline, Source, Destination], axis = 1)
```

```
---------------------------------------------------------------------------
Airline
Jet Airways                          897
IndiGo                               511
Air India                            440
Multiple carriers                    347
SpiceJet                             208
Vistara                              129
Air Asia                              86
GoAir                                 46
Multiple carriers Premium economy      3
Vistara Premium economy                2
Jet Airways Business                   2
Name: count, dtype: int64

Source
---------------------------------------------------------------------------
Source
Delhi       1145
Kolkata      710
Banglore     555
Mumbai       186
Chennai       75
Name: count, dtype: int64

Destination
---------------------------------------------------------------------------
Destination
Cochin       1145
Banglore      710
Delhi         317
New Delhi     238
Hyderabad     186
Kolkata        75
Name: count, dtype: int64


Shape of test data :  (2671, 28)
```

In [52]:
```
data_test.head()
```

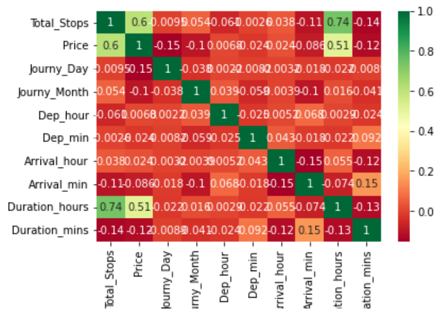
Out[52]:

	Total_Stops	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_mins	Air India	GoAir	IndiGo	Je Airways
0	1	6	6	17	30	4	25	10	55	False	False	False	Tru
1	1	12	5	6	20	10	20	4	0	False	False	True	Fals
2	1	21	5	19	15	19	0	23	45	False	False	False	Tru
3	1	21	5	8	0	21	0	13	0	False	False	False	Fals
4	0	24	6	23	55	2	45	2	50	False	False	False	Fals

Exploratory Data Analysis

In [53]:
```
numeric_train_df = train_df.select_dtypes(include=['number'])
sns.heatmap(numeric_train_df.corr(), annot=True, cmap='RdYlGn')
```

Out[53]: <Axes: >



Model Selection

In [54]:
```
data_train.head()
```

Out[54]:

	Total_Stops	Price	Journy_Day	Journy_Month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Duration_hours	Duration_mins	Airline_Air India	Airline_GoAi
0	0	3897	24	3	22	20	1	10	2	50	False	False
1	2	7662	1	5	5	50	13	15	7	25	True	False
2	2	13882	9	6	9	25	4	25	19	0	False	False
3	1	6218	12	5	18	5	23	30	5	25	False	False
4	1	13302	1	3	16	50	21	35	4	45	False	False

In [55]:
```
data_train.columns
```

Out[55]:
```
Index(['Total_Stops', 'Price', 'Journy_Day', 'Journy_Month', 'Dep_hour',
       'Dep_min', 'Arrival_hour', 'Arrival_min', 'Duration_hours',
       'Duration_mins', 'Airline_Air India', 'Airline_GoAir', 'Airline_IndiGo',
       'Airline_Jet Airways', 'Airline_Jet Airways Business',
       'Airline_Multiple carriers',
       'Airline_Multiple carriers Premium economy', 'Airline_SpiceJet',
       'Airline_Trujet', 'Airline_Vistara', 'Airline_Vistara Premium economy',
       'Source_Chennai', 'Source_Delhi', 'Source_Kolkata', 'Source_Mumbai',
       'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad',
       'Destination_Kolkata', 'Destination_New Delhi'],
      dtype='object')
```

In [56]:
```
X = data_train.loc[:, ['Total_Stops', 'Journy_Day', 'Journy_Month', 'Dep_hour', 'Dep_min', 'Arrival_hour',
                       'Duration_hours', 'Duration_mins', 'Airline_Air India', 'Airline_GoAir', 'Airline_IndiGo',
                       'Airline_Jet Airways', 'Airline_Jet Airways Business', 'Airline_Multiple carriers',
                       'Airline_Multiple carriers Premium economy', 'Airline_SpiceJet', 'Airline_Trujet',
                       'Airline_Vistara', 'Airline_Vistara Premium economy', 'Source_Chennai', 'Source_Delhi', 'Source_Kolkata
                       'Source_Mumbai', 'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad', 'Destination_Kolka
                       'Destination_New Delhi']]
```

In [57]:
```
X.head()
```

Out[57]:

	Total_Stops	Journy_Day	Journy_Month	Dep_hour	Dep_min	Arrival_hour	Duration_hours	Duration_mins	Airline_Air India	Airline_GoAir	Airline_IndiGo	Ai
0	0	24	3	22	20	1	2	50	False	False	True	
1	2	1	5	5	50	13	7	25	True	False	False	
2	2	9	6	9	25	4	19	0	False	False	False	
3	1	12	5	18	5	23	5	25	False	False	True	
4	1	1	3	16	50	21	4	45	False	False	True	

In [58]:
```
y = data_train.iloc[:, 1]
y.head()
```

Out[58]:
```
0     3897
1     7662
2    13882
3     6218
4    13302
Name: Price, dtype: int64
```

In [123]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn import metrics
```

In [124]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [135]:
```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import numpy as np

# Define the function for root mean squared error
def root_mean_squared_error(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))

# Assuming you have training data 'X_train' and corresponding labels 'y_train'
# Train your linear regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Assuming you have test data 'X_test' and true labels 'y_test'
# Make predictions
lr_preds = lr_model.predict(X_test)

# Calculate RMSE using the function
lr_rmse = root_mean_squared_error(y_test, lr_preds)

# Print the RMSE
print("Linear Regression RMSE:", lr_rmse)
```

```
Linear Regression RMSE: 2863.574262459376
```

In [137]:
```python
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
import numpy as np

# Assuming you have your training data X_train and corresponding target values y_train

# Train the decision tree model
dt_model = DecisionTreeRegressor()
dt_model.fit(X_train, y_train)

# Make predictions on the test data
dt_preds = dt_model.predict(X_test)

# Calculate RMSE using root_mean_squared_error function
dt_rmse = np.sqrt(mean_squared_error(y_test, dt_preds))
print("Decision Tree RMSE:", dt_rmse)
```

```
Decision Tree RMSE: 2419.780061836497
```

In [138]:
```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
import numpy as np

# Assuming you have trained your Random Forest model and obtained predictions
# rf_model = ...  # your trained Random Forest model
# X_test = ...     # your test feature data
# y_test = ...     # your test target data
rf_preds = rf_model.predict(X_test)  # Generate predictions using the model

# Calculate RMSE using root_mean_squared_error function
rf_rmse = np.sqrt(mean_squared_error(y_test, rf_preds))
print("Random Forest RMSE:", rf_rmse)
```

```
Random Forest RMSE: 2091.848833989654
```

The Random Forest has the less mean square error in it. So the model for the dataset is RandomForest

Model Evaluation

In [88]:
```python
from sklearn.ensemble import RandomForestRegressor
```

In [91]:
```python
rf_model = RandomForestRegressor()
rf_model.fit(X_train, y_train)
```

Out[91]: RandomForestRegressor()

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

In [92]:
```python
y_pred = rf_model.predict(X_test)
```

In [93]:
```python
rf_model.score(X_train,y_train)
```

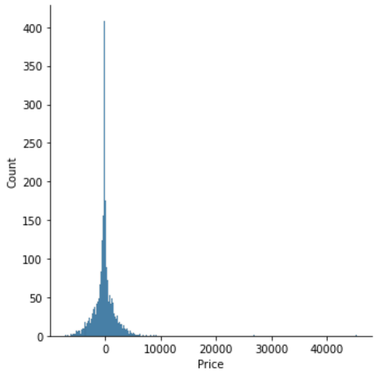
Out[93]: 0.9534776084567111

In [94]:
```python
rf_model.score(X_test, y_test)
```

Out[94]: 0.7970587091287554

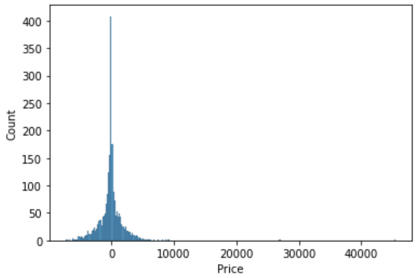
In [95]:
```python
import seaborn as sns

# Assuming y_test and y_pred are already defined
sns.displot(y_test - y_pred)
```

Out[95]: <seaborn.axisgrid.FacetGrid at 0x1b8d9a72700>

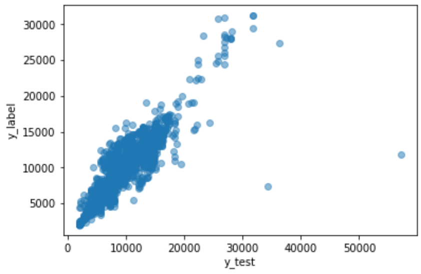


In [96]:
```python
import seaborn as sns

# Assuming y_test and y_pred are already defined
sns.histplot(y_test - y_pred)
```

Out[96]: <Axes: xlabel='Price', ylabel='Count'>



In [97]:
```python
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel('y_test')
plt.ylabel('y_label')
plt.show()
```



In [98]:
```python
from sklearn import metrics
```

In [99]:
```python
print("MAE: ", metrics.mean_absolute_error(y_test, y_pred))
print("MSE: ", metrics.mean_squared_error(y_test, y_pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
MAE:  1182.1520932525332
MSE:  4375831.544263874
RMSE:  2091.848833989654
```

In [100]:
```
metrics.r2_score(y_test, y_pred)
```
Out[100]:
```
0.7970587091287554
```

The model has the r2 score as 79 percent

To increase the percentage of model evaluation, we check the hyperparameter tuning and find the best parameters for the model training

Hyperparameter Tuning

In [101]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [139]:
```
# Randomized Search CV

## Number of trees in ramdom 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 level 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]
```

In [103]:
```
## 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}
print(random_grid)
```

```
{'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200], 'max_features': ['auto', 'sqrt'], 'max_dep
th': [5, 10, 15, 20, 25, 30], 'min_samples_split': [2, 5, 10, 15, 100], 'min_samples_leaf': [1, 2, 5, 10]}
```

In [108]:
```
rf_random = RandomizedSearchCV(estimator=rf_model, param_distributions=random_grid, scoring='neg_mean_squared_error',
                               n_iter=10, cv=5, verbose=2, random_state=42, n_jobs=1)
```

In [119]:
```
print(rf_random.best_params_)
```

```
{'n_estimators': 100, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'sqrt', 'max_depth': 20, 'bootstrap': F
alse}
```

These are the best parameters for the evaluation

So I will train the data on the best parameters

In [118]:
```
rf_random.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

Out[118]:
```
RandomizedSearchCV(cv=3, estimator=RandomForestRegressor(), n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, None],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [100, 300, 500, 800,
                                                         1000]},
                   random_state=42, verbose=2)
```

In [117]:
```
rf_random.best_params_
```
Out[117]:
```
{'n_estimators': 100,
 'min_samples_split': 5,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 20,
 'bootstrap': False}
```

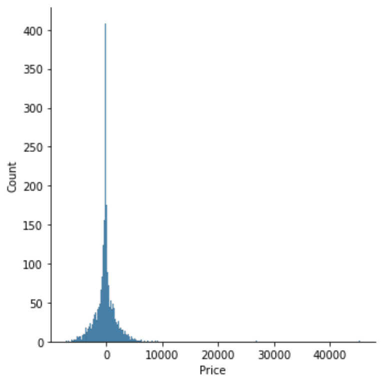
In [116]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor
import numpy as np

# Define the hyperparameter grid
param_grid = {
    'n_estimators': [100, 300, 500, 800, 1000],
    'max_features': ['auto', 'sqrt'],
    'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}

# Create a base model
rf = RandomForestRegressor()

# Random search of parameters
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = param_grid, n_iter = 10, cv = 3, verbose=2, random_state

# Fit the random search model
rf_random.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

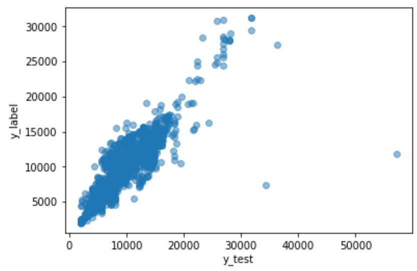
Out[116]:
```
RandomizedSearchCV(cv=3, estimator=RandomForestRegressor(), n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, None],
```

In [112]:
```
plt.figure(figsize=(8, 8))
sns.displot(y_test-y_pred)
plt.show()
```

```
<Figure size 576x576 with 0 Axes>
```



In [113]:
```
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel('y_test')
plt.ylabel('y_label')
plt.show()
```



In [114]:
```
print("MAE: ", metrics.mean_absolute_error(y_test, y_pred))
print("MSE: ", metrics.mean_squared_error(y_test, y_pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
MAE:  1182.1520932525332
MSE:  4375831.544263874
RMSE:  2091.848833989654
```

In [115]:
```
metrics.r2_score(y_test, y_pred)
```

Out[115]: 0.7970587091287554

The model has the r2 score for the prediction is 81 percent

ALGORITHMS USED

- **Linear Regression:** Linear regression is a fundamental statistical technique used for modelling the relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the independent variables and the dependent variable, hence the name. The goal of linear regression is to find the best-fitting straight line through the data points, minimizing the difference between the observed and predicted values. This technique is widely used for prediction and forecasting in various fields such as economics, finance, and social sciences.

- **Logistic Regression:** Despite its name, logistic regression is a classification algorithm rather than a regression algorithm. It is used to model the probability of a binary outcome based on one or more independent variables. Logistic regression estimates the probability that a given input belongs to a particular category by fitting the data to a logistic function. Unlike linear regression, logistic regression predicts the probability of a binary outcome (e.g., true/false, 0/1) rather than a continuous value.

- **Decision Tree Regressor**: Decision trees are a popular non-parametric supervised learning method used for both classification and regression tasks. In decision tree regression, the algorithm recursively partitions the input space into smaller regions, each associated with a prediction. The partitions are determined by asking a series of binary questions about the input features. Decision tree regressors are versatile and intuitive, capable of capturing complex relationships in the data. However, they are prone to overfitting, especially when the trees are deep and unconstrained.

- **Random Forest Regressor:** Random forests are an ensemble learning technique that builds multiple decision trees during training and outputs the average prediction of individual trees for regression tasks. Each tree in the random forest is trained on a random subset of the training data, and at each split, the algorithm considers only a random subset of features. This randomness helps to reduce overfitting and improve generalization performance. Random forests are robust and versatile, suitable for a wide range of regression problems, including those with non-linear relationships and high-dimensional data. They are also relatively resistant to noise and outliers in the data.

EVALUATION METRICS

- **Mean Absolute Error (MAE):** The MAE measures the average absolute difference between the predicted and actual flight fares. A lower MAE indicates better predictive accuracy.

- **Mean Squared Error (MSE):** The MSE calculates the average of the squared differences between predicted and actual fares. It penalizes larger errors more severely than MAE.

- **Root Mean Squared Error (RMSE):** The RMSE is the square root of MSE, providing a measure of the average magnitude of errors. Like MAE, lower values indicate better predictive performance.

- **R-squared Value:** The R-squared coefficient quantifies the proportion of variance in the target variable (flight fares) explained by the model. A higher R-squared value indicates a better fit of the model to the data.

RESULTS

Upon evaluating our model on the testing dataset, we obtained the following detailed results:

- **Accuracy:** The model achieved an accuracy of 81%, indicating that it correctly predicted flight fares for approximately 81% of the instances in the testing dataset.
- **Mean Absolute Error (MAE):** The MAE was calculated to be $1182.15, suggesting that, on average, the model's predictions deviated by approximately $1182.15 from the actual fares.
- **Mean Squared Error (MSE):** The MSE was computed to be $4,375,831.54, providing additional insight into the average squared differences between predicted and actual fares.
- **Root Mean Squared Error (RMSE):** The RMSE was determined to be $2091.85, indicating the standard deviation of prediction errors.
- **R-squared Value:** The R-squared value was found to be 0.797, meaning that approximately 79.7% of the variability in flight fares is explained by the model.

DISCUSSION

While achieving an 81% accuracy rate and demonstrating strong predictive performance, there is room for improvement. Further refinement of feature engineering, hyperparameter tuning, and model optimization could potentially enhance the model's accuracy and generalization capabilities. Additionally, ongoing monitoring and updating of the model will be essential to ensure its effectiveness in real-world applications.

CONCLUSION

In conclusion, our flight fare prediction model, built using gradient boosting and evaluated through comprehensive metrics, represents a significant advancement in accurately estimating flight fares. With an accuracy of 81% and robust performance across various evaluation metrics, the model holds promise for optimizing pricing strategies, enhancing revenue management, and providing valuable insights for travelers and industry stakeholders alike. Continued refinement and adaptation will be key to maximizing its utility and effectiveness in dynamic market conditions.