# **IMPORTING LIBERARIES**

```
In [94]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.metrics import mean_absolute_error,mean_squared_error,explained_v
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

### **IMPORTING FILE**

In [93]: train\_data=pd.read\_excel('Data\_Train.xlsx')
 train\_data.head()

### Out[93]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	То
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	
1	Air India	1/05/2019	Kolkata	Banglore	CCU  IXR  BBI  BLR	05:50	13:15	7h 25m	
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL  → LKO  → BOM  → COK	09:25	04:25 10 Jun	19h	
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	
4									•

```
In [4]: |train_data.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
                                                object
                               10683 non-null
         4
                                                object
              Route
                                10682 non-null
         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 [5]:
        train_data.describe()
Out[5]:
                      Price
         count 10683.000000
         mean
                9087.064121
           std
                4611.359167
           min
                1759.000000
          25%
                5277.000000
          50%
                8372.000000
          75%
               12373.000000
          max 79512.000000
        Checking Null Values
In [6]: |train_data.isnull().sum()
Out[6]: Airline
                            0
                            0
        Date_of_Journey
        Source
                            0
                            0
        Destination
                            1
        Route
                            0
        Dep Time
        Arrival_Time
                            0
                            0
        Duration
        Total_Stops
                            1
                            0
        Additional_Info
        Price
                            0
        dtype: int64
```

```
In [7]: train_data.isnull().any()
Out[7]: Airline
                            False
        Date_of_Journey
                            False
        Source
                            False
        Destination
                            False
        Route
                            True
        Dep_Time
                            False
        Arrival_Time
                           False
        Duration
                           False
        Total_Stops
                            True
        Additional_Info
                            False
        Price
                            False
        dtype: bool
        NULL VALUE TREATMENT
In [8]: train_data.dropna(inplace=True)
        RECHECKING NULL VALUE
In [9]: train_data.isnull().sum()
Out[9]: Airline
                            0
        Date_of_Journey
                            0
                            0
        Source
        Destination
                            0
        Route
                            0
                            0
        Dep_Time
                            0
        Arrival_Time
                            0
        Duration
        Total Stops
                            0
                            0
        Additional_Info
        Price
                            0
        dtype: int64
```

NULL VALUE HAS BEEN PROPERLY TREATED

FEATURE REMODELING

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '24/03/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '24/06/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '27/05/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '18/04/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '24/04/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '15/04/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '21/03/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '15/05/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '18/06/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache array = maybe cache(arg, format, cache, convert listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '15/06/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarni ng: Parsing '18/05/2019' in DD/MM/YYYY format. Provide format or specify infe r\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '27/06/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '21/05/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '15/03/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarni

ng: Parsing '24/05/2019' in DD/MM/YYYY format. Provide format or specify infe  $r_{datetime}$  format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '21/04/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarni ng: Parsing '21/06/2019' in DD/MM/YYYY format. Provide format or specify infe r datetime format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '27/03/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache\_array = \_maybe\_cache(arg, format, cache, convert\_listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '18/03/2019' in DD/MM/YYYY format. Provide format or specify infer\_datetime\_format=True for consistent parsing.

cache array = maybe cache(arg, format, cache, convert listlike)

D:\Anaconda3\lib\site-packages\pandas\core\tools\datetimes.py:1047: UserWarning: Parsing '27/04/2019' in DD/MM/YYYY format. Provide format or specify infer datetime format=True for consistent parsing.

cache array = maybe cache(arg, format, cache, convert listlike)

Checking converted Date of Journey to datetime format

### In [11]: train data.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10682 entries, 0 to 10682
Data columns (total 11 columns):

memory usage: 1001.4+ KB

```
#
    Column
                      Non-Null Count Dtype
- - -
0
    Airline
                      10682 non-null object
1
    Date of Journey
                     10682 non-null datetime64[ns]
2
                      10682 non-null object
    Source
3
    Destination
                      10682 non-null object
4
    Route
                      10682 non-null object
5
    Dep_Time
                      10682 non-null object
6
    Arrival Time
                      10682 non-null object
7
    Duration
                      10682 non-null object
8
    Total_Stops
                      10682 non-null object
9
    Additional Info 10682 non-null object
10 Price
                      10682 non-null int64
dtypes: datetime64[ns](1), int64(1), object(9)
```

# In [12]: train\_data.head()

## Out[12]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	То
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	
1	Air India	2019-01-05	Kolkata	Banglore	CCU  → IXR  → BBI  → BLR	05:50	13:15	7h 25m	
2	Jet Airways	2019-09-06	Delhi	Cochin	DEL  → LKO  → BOM  → COK	09:25	04:25 10 Jun	19h	
3	IndiGo	2019-12-05	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	
4	IndiGo	2019-01-03	Banglore	New Delhi	$\begin{array}{c} BLR \\ \to \\ NAG \\ \to \\ DEL \end{array}$	16:50	21:35	4h 45m	
4									•

Extracting the month and day from the Date of Journey column

In [14]: train\_data.head()

Out[14]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	То
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	
1	Air India	2019-01-05	Kolkata	Banglore	CCU  IXR  BBI  BLR	05:50	13:15	7h 25m	
2	Jet Airways	2019-09-06	Delhi	Cochin	DEL  → LKO  → BOM  → COK	09:25	04:25 10 Jun	19h	
3	IndiGo	2019-12-05	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	
4	IndiGo	2019-01-03	Banglore	New Delhi	$\begin{array}{c} BLR \\ \to \\ NAG \\ \to \\ DEL \end{array}$	16:50	21:35	4h 45m	
4									•

Dropping the date\_of\_journey column as it will not be further used anymore

```
In [15]: train_data.drop('Date_of_Journey',axis=1,inplace=True)
```

# In [16]: train\_data.head()

### Out[16]:

	Airline	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additio
0	IndiGo	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	
1	Air India	Kolkata	Banglore	CCU  → IXR  → BBI  → BLR	05:50	13:15	7h 25m	2 stops	
2	Jet Airways	Delhi	Cochin	DEL  → LKO  → BOM  → COK	09:25	04:25 10 Jun	19h	2 stops	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	
4									•

Same as converting Dep\_Time and Arrival\_Time to datetime format

```
In [17]: train_data['Dep_Time']=pd.to_datetime(train_data['Dep_Time'])
    train_data['Arrival_Time']=pd.to_datetime(train_data['Arrival_Time'])
```

# In [18]: train\_data.head()

## Out[18]:

	Airline	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additio
0	IndiGo	Banglore	New Delhi	BLR → DEL	2023-05- 11 22:20:00	2023-03-22 01:10:00	2h 50m	non-stop	
1	Air India	Kolkata	Banglore	CCU  → IXR  → BBI  → BLR	2023-05- 11 05:50:00	2023-05-11 13:15:00	7h 25m	2 stops	
2	Jet Airways	Delhi	Cochin	DEL  → LKO  → BOM  → COK	2023-05- 11 09:25:00	2023-06-10 04:25:00	19h	2 stops	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	2023-05- 11 18:05:00	2023-05-11 23:30:00	5h 25m	1 stop	
4	IndiGo	Banglore	New Delhi	$\begin{array}{c} BLR \\ \to \\ NAG \\ \to \\ DEL \end{array}$	2023-05- 11 16:50:00	2023-05-11 21:35:00	4h 45m	1 stop	
4									•

## In [19]: train\_data.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10682 entries, 0 to 10682
Data columns (total 12 columns):

Data	COTUMNIS (COLAT 12	COTUMNS):	
#	Column	Non-Null Count	Dtype
0	Airline	10682 non-null	object
1	Source	10682 non-null	object
2	Destination	10682 non-null	object
3	Route	10682 non-null	object
4	Dep_Time	10682 non-null	<pre>datetime64[ns]</pre>
5	Arrival_Time	10682 non-null	<pre>datetime64[ns]</pre>
6	Duration	10682 non-null	object
7	Total_Stops	10682 non-null	object
8	Additional_Info	10682 non-null	object
9	Price	10682 non-null	int64
10	day_of_journey	10682 non-null	int64
11	month_of_journey	10682 non-null	int64
dtype	es: datetime64[ns]	(2), int64(3), o	bject(7)
memor	ry usage: 1.1+ MB		

```
In [20]: train_data['Dep_time_hr']=train_data['Dep_Time'].dt.hour
    train_data['Dep_time_minute']=train_data['Dep_Time'].dt.minute
    train_data['Arr_time_hr']=train_data['Arrival_Time'].dt.hour
    train_data['Arr_time_minute']=train_data['Arrival_Time'].dt.minute
```

Dropping the dep\_time and arrival\_time columns

In [21]: train\_data.drop(['Dep\_Time','Arrival\_Time'],axis=1,inplace=True)

In [22]: train\_data.head()

Out[22]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	day_of_j
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	
1	Air India	Kolkata	Banglore	CCU  → IXR  → BBI  → BLR	7h 25m	2 stops	No info	7662	
2	Jet Airways	Delhi	Cochin	DEL  → LKO  → BOM  → COK	19h	2 stops	No info	13882	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	5h 25m	1 stop	No info	6218	
4	IndiGo	Banglore	New Delhi	$\begin{array}{c} BLR \\ \to \\ NAG \\ \to \\ DEL \end{array}$	4h 45m	1 stop	No info	13302	
4									•

**DURATION** 

```
In [23]: def duration_preprocess(value):
    lst=value.split()
    if len(lst)==2:  # if both the hours and minutes are present return it
        return value
    else:
        if 'h' in value: # if only hour is present append 0m
            return value+' 0m'
        else:  # if only minute is present add 0h in the front
            return '0h '+value
```

Applying the function on the entire Duration column

```
In [24]: train_data['Duration']=train_data['Duration'].apply(duration_preprocess)
```

**Checking Data** 

```
In [25]: train_data.head()
```

Out[25]:

	Airline	Source	Destination	Route	Duration	Total_Stops	Additional_Info	Price	day_of_j
0	IndiGo	Banglore	New Delhi	BLR → DEL	2h 50m	non-stop	No info	3897	
1	Air India	Kolkata	Banglore	CCU  IXR  BBI  BLR	7h 25m	2 stops	No info	7662	
2	Jet Airways	Delhi	Cochin	DEL	19h 0m	2 stops	No info	13882	
3	IndiGo	Kolkata	Banglore	$\begin{array}{c} CCU \\ \to \\ NAG \\ \to \\ BLR \end{array}$	5h 25m	1 stop	No info	6218	
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	4h 45m	1 stop	No info	13302	
4									•

Extracting the hours and minutes from duration

```
In [26]: | train_data['duration_hours']=train_data['Duration'].apply(lambda x:int(x.split)
          train_data['duration_minutes']=train_data['Duration'].apply(lambda x:int(x.spl
          Dropping the duration column
In [27]: | train_data.drop('Duration',axis=1,inplace=True)
          Remaining columns having object datatype
In [28]:
          train data.select dtypes(['object']).columns
Out[28]: Index(['Airline', 'Source', 'Destination', 'Route', 'Total_Stops',
                 'Additional_Info'],
                dtype='object')
          Value Count of Total Stop
In [29]: train data['Total Stops'].value counts()
Out[29]: 1 stop
                      5625
          non-stop
                      3491
                      1520
          2 stops
          3 stops
                         45
          4 stops
                         1
          Name: Total_Stops, dtype: int64
          Mapping non-stop to 0, 1 stop to 1, 2 stops to 2, 3 stops to 3, and 4 stops to 4
In [30]: train_data['Total_Stops']=train_data['Total_Stops'].map({'non-stop':0,'1 stop'
```

In [31]: train\_data.head()

Out[31]:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info	Price	day_of_journey	m
0	IndiGo	Banglore	New Delhi	BLR → DEL	0	No info	3897	24	
1	Air India	Kolkata	Banglore	$\begin{array}{c} CCU \\ \to \\ IXR \\ \to \\ BBI \\ \to \\ BLR \end{array}$	2	No info	7662	5	
2	Jet Airways	Delhi	Cochin	DEL  → LKO  → BOM  → COK	2	No info	13882	6	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	1	No info	6218	5	
4	IndiGo	Banglore	New Delhi	$\begin{array}{c} BLR \\ \to \\ NAG \\ \to \\ DEL \end{array}$	1	No info	13302	3	
4									•

Remaining columns having object datatype

```
In [32]: train_data.select_dtypes(['object']).columns
```

More Information

```
In [33]: | train_data['Additional_Info'].value_counts()
Out[33]: No info
                                           8344
         In-flight meal not included
                                           1982
         No check-in baggage included
                                           320
         1 Long layover
                                             19
         Change airports
                                              7
         Business class
                                              4
                                              3
         No Info
                                              1
         1 Short layover
         Red-eye flight
                                              1
         2 Long layover
                                              1
         Name: Additional_Info, dtype: int64
```

Almost 80% of the values have no-info in the additional info column and hence does not provide any necessary insights

In [34]: train\_data.drop('Additional\_Info',inplace=True,axis=1)
 train\_data.head()

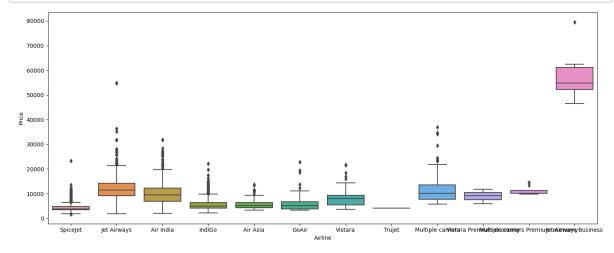
### Out[34]:

	Airline	Source	Destination	Route	Total_Stops	Price	day_of_journey	month_of_journey
0	IndiGo	Banglore	New Delhi	BLR → DEL	0	3897	24	3
1	Air India	Kolkata	Banglore	CCU  → IXR  → BBI  → BLR	2	7662	5	1
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	2	13882	6	9
3	IndiGo	Kolkata	Banglore	$\begin{array}{c} CCU \\ \to \\ NAG \\ \to \\ BLR \end{array}$	1	6218	5	12
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	1	13302	3	1
4								•

Remaining columns having object Datatype

```
In [35]: train_data.select_dtypes(['object']).columns
Out[35]: Index(['Airline', 'Source', 'Destination', 'Route'], dtype='object')
         AIRLINES DATA VALUE COUNT
In [36]: |train_data['Airline'].value_counts()
Out[36]: 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
                                                   1
          Trujet
         Name: Airline, dtype: int64
In [37]: plt.figure(figsize=(15,5))
          sns.barplot(x='Airline',y='Price',data=train_data.sort_values('Price',ascendin')
          plt.tight layout()
           30000
           20000
           10000
```

Airline



### Descriptional Data For Various Airlines

In [39]: train\_data.groupby('Airline').describe()['Price'].sort\_values('mean',ascending

## Out[39]:

	count	mean	std	min	25%	50%	75%	max
Airline								
Trujet	1.0	4140.000000	NaN	4140.0	4140.0	4140.0	4140.00	4140.0
SpiceJet	818.0	4338.284841	1849.922514	1759.0	3574.5	3873.0	4760.00	23267.0
Air Asia	319.0	5590.260188	2027.362290	3383.0	4282.0	5162.0	6451.00	13774.0
IndiGo	2053.0	5673.682903	2264.142168	2227.0	4226.0	5000.0	6494.00	22153.0
GoAir	194.0	5861.056701	2703.585767	3398.0	3898.0	5135.0	6811.25	22794.0
Vistara	479.0	7796.348643	2914.298578	3687.0	5403.0	7980.0	9345.00	21730.0
Vistara Premium economy	3.0	8962.333333	2915.405518	5969.0	7547.0	9125.0	10459.00	11793.0
Air India	1751.0	9612.427756	3901.734561	2050.0	6891.0	9443.0	12219.00	31945.0
Multiple carriers	1196.0	10902.678094	3721.234997	5797.0	7723.0	10197.0	13587.00	36983.0
Multiple carriers Premium economy	13.0	11418.846154	1717.153936	9845.0	10161.0	11269.0	11269.00	14629.0
Jet Airways	3849.0	11643.923357	4258.940578	1840.0	9134.0	11467.0	14151.00	54826.0
Jet Airways Business	6.0	58358.666667	11667.596748	46490.0	52243.0	54747.0	61122.50	79512.0

```
In [40]: Airline=pd.get_dummies(train_data['Airline'],drop_first=True)
    Airline.head()
```

## Out[40]:

	Air India	GoAir	IndiGo	Jet Airways	Jet Airways Business	Multiple carriers	Multiple carriers Premium economy	SpiceJet	Trujet	Vistara	Vista Premi econo
0	0	0	1	0	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	0	0	0	
2	0	0	0	1	0	0	0	0	0	0	
3	0	0	1	0	0	0	0	0	0	0	
4	0	0	1	0	0	0	0	0	0	0	
4											<b>•</b>

Concatinating the Airline dataframe with the train\_data dataframe

In [41]: train\_data=pd.concat([train\_data,Airline],axis=1)
 train\_data.head()

### Out[41]:

	Airline	Source	Destination	Route	Total_Stops	Price	day_of_journey	month_of_journey
0	IndiGo	Banglore	New Delhi	BLR → DEL	0	3897	24	3
1	Air India	Kolkata	Banglore	CCU  IXR  BBI  BLR	2	7662	5	1
2	Jet Airways	Delhi	Cochin	DEL  → LKO  → BOM  → COK	2	13882	6	9
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	1	6218	5	12
4	IndiGo	Banglore	New Delhi	$\begin{array}{c} BLR \\ \to \\ NAG \\ \to \\ DEL \end{array}$	1	13302	3	1
5 r	ows × 25	columns						
4								•

Dropping the Airline column

In [42]: train\_data.drop('Airline',axis=1,inplace=True)

Source And Destination Related Value Count

```
In [43]: train_data['Source'].value_counts()
```

Out[43]: Delhi 4536 Kolkata 2871 Banglore 2197 Mumbai 697 Chennai 381

Name: Source, dtype: int64

```
In [44]: | train_data['Destination'].value_counts()
Out[44]: Cochin
                       4536
          Banglore
                       2871
          Delhi
                       1265
          New Delhi
                        932
         Hyderabad
                        697
                        381
          Kolkata
          Name: Destination, dtype: int64
          WE ARE USING ONE HOT ENCODING AS THERE ARE CATEGORICAL VALUES ONLY 5-6
          VALUES ARE THERE AND THAT WOULD BE REPETATIVE ONLY
In [45]: | train_data=pd.get_dummies(data=train_data,columns=['Source','Destination'],drd
In [46]: train_data.head()
Out[46]:
             Route Total_Stops Price day_of_journey month_of_journey Dep_time_hr Dep_time_minute
              BLR
                                               24
                                                                3
                                                                           22
                                                                                          20
          0
                            0
                               3897
              DEL
              CCU
               IXR
          1
                            2
                               7662
                                                5
                                                                1
                                                                            5
                                                                                          50
               BBI
               BLR
               DEL
              LKO
                            2 13882
                                                6
                                                                9
                                                                            9
                                                                                          25
              BOM
              COK
              CCU
              NAG
                               6218
                                                5
                                                               12
                                                                           18
                                                                                           5
              BLR
               BLR
              NAG
                            1 13302
                                                3
                                                                1
                                                                           16
                                                                                          50
              DEL
          5 rows × 31 columns
```

```
In [47]: train data.columns
Out[47]: Index(['Route', 'Total_Stops', 'Price', 'day_of_journey', 'month_of_journey',
                   'Dep_time_hr', 'Dep_time_minute', 'Arr_time_hr', 'Arr_time_minute',
                   'duration_hours', 'duration_minutes', 'Air India', 'GoAir', 'IndiGo',
                   'Jet Airways', 'Jet Airways Business', 'Multiple carriers',
                   'Multiple carriers Premium economy', 'SpiceJet', 'Trujet', 'Vistara',
                   'Vistara Premium economy', 'Source_Chennai', 'Source_Delhi',
                   'Source_Kolkata', 'Source_Mumbai', 'Destination_Cochin',
                   'Destination_Delhi', 'Destination_Hyderabad', 'Destination_Kolkata',
                   'Destination New Delhi'],
                  dtype='object')
           Remaining columns of object datatype
In [48]: | train data.select dtypes(['object']).columns
Out[48]: Index(['Route'], dtype='object')
           Route
In [49]:
           route=train_data.select_dtypes(['object'])
           route.head()
Out[49]:
                                 Route
            0
                            BLR \rightarrow DEL
            1
                \mathsf{CCU} \to \mathsf{IXR} \to \mathsf{BBI} \to \mathsf{BLR}
            2 DEL \rightarrow LKO \rightarrow BOM \rightarrow COK
            3
                     \mathsf{CCU} \to \mathsf{NAG} \to \mathsf{BLR}
                      \mathsf{BLR} \to \mathsf{NAG} \to \mathsf{DEL}
In [50]: | train_data['Total_Stops'].value_counts()
Out[50]: 1
                 5625
           0
                 3491
           2
                 1520
           3
                   45
           4
           Name: Total_Stops, dtype: int64
           There are maximum 4 stops for a flight and hence the number of routes would be 5 (a -> b -> c
```

There are maximum 4 stops for a flight and hence the number of routes would be 5 (a -> b -> c -> d -> e -> f)

```
In [51]: | route['Route 1']=route['Route'].str.split('→').str[0]
             route['Route_2']=route['Route'].str.split('→').str[1]
             route['Route 3']=route['Route'].str.split('→').str[2]
             route['Route 4']=route['Route'].str.split('→').str[3]
             route['Route 5']=route['Route'].str.split('→').str[4]
In [52]: route.head()
Out[52]:
                                        Route Route_1 Route_2 Route_3 Route_4 Route_5
              0
                                  BLR \rightarrow DEL
                                                     BLR
                                                                DEL
                                                                          NaN
                                                                                     NaN
                                                                                                NaN
              1
                   \mathsf{CCU} \to \mathsf{IXR} \to \mathsf{BBI} \to \mathsf{BLR}
                                                    CCU
                                                                IXR
                                                                           BBI
                                                                                     BLR
                                                                                                NaN
               2 \quad \mathsf{DEL} \to \mathsf{LKO} \to \mathsf{BOM} \to \mathsf{COK} 
                                                     DEL
                                                               LKO
                                                                          BOM
                                                                                     COK
                                                                                                NaN
              3
                         \mathsf{CCU} \to \mathsf{NAG} \to \mathsf{BLR}
                                                    CCU
                                                               NAG
                                                                          BLR
                                                                                     NaN
                                                                                                NaN
                          \mathsf{BLR} \to \mathsf{NAG} \to \mathsf{DEL}
                                                    BLR
                                                               NAG
                                                                          DEL
                                                                                     NaN
                                                                                                NaN
In [53]: # fill the NaN values with None
             route.fillna('None',inplace=True)
             route.head()
Out[53]:
                                        Route Route_1 Route_2 Route_3 Route_4 Route_5
              0
                                  \mathsf{BLR} \to \mathsf{DEL}
                                                     BLR
                                                               DEL
                                                                         None
                                                                                    None
                                                                                               None
              1
                   CCU \rightarrow IXR \rightarrow BBI \rightarrow BLR
                                                    CCU
                                                                                     BLR
                                                                IXR
                                                                           BBI
                                                                                               None
              2 DEL \rightarrow LKO \rightarrow BOM \rightarrow COK
                                                     DEL
                                                               LKO
                                                                          BOM
                                                                                     COK
                                                                                               None
                         \mathsf{CCU} \to \mathsf{NAG} \to \mathsf{BLR}
                                                    CCU
                                                               NAG
                                                                          BLR
              3
                                                                                    None
                                                                                               None
                          \mathsf{BLR} \to \mathsf{NAG} \to \mathsf{DEL}
                                                     BLR
                                                               NAG
                                                                          DEL
                                                                                    None
                                                                                               None
```

#### HENCE DATA HAS BEEN SEGREGATED PROPERLY

HERE IN ROUTE WE CAN SEE TOO MANY CATEGORIES SO WE CAN USE LABEL ENCODING NOT ONE HOT ENCODING

Out[58]:

	Route	Route_1	Route_2	Route_3	Route_4	Route_5
0	$BLR \to DEL$	0	13	29	13	5
1	$CCU \to IXR \to BBI \to BLR$	2	25	1	3	5
2	$DEL \to LKO \to BOM \to COK$	3	32	4	5	5
3	$CCU \to NAG \to BLR$	2	34	3	13	5
4	$BLR \to NAG \to DEL$	0	34	8	13	5

Dropping the Route column

```
In [59]: route.drop('Route',inplace=True,axis=1)
route.head(2)
```

Out[59]:

	Route_1	Route_2	Route_3	Route_4	Route_5
0	0	13	29	13	5
1	2	25	1	3	5

Concatinating route and train\_data

In [60]:	<pre>train_data=pd.concat([train_data,route],axis=1) train_data.head(2)</pre>												
Out[60]:													
		Route	Total	_Stops	Price	day_of_j	ourney	month_of_j	ourney	Dep_t	ime_hr	Dep_time_	minute
	0	BLR → DEL		0	3897		24		3		22		20
	1	CCU  → IXR  → BBI  → BLR		2	7662		5		1		5		50
	2 r	ows × 3	6 colu	ımns									
	4												•
	Dro	opping t	he ro	ute colu	ımn froi	m train_c	data						
In [61]:		nin_dat nin_dat			oute',	inplace	=True,	axis=1)					
Out[61]:													
		Total_S	tops	Price	day_of_	journey	month_	_of_journey	Dep_tir	ne_hr	Dep_tir	me_minute	Arr_tin
	0		0	3897		24		3		22		20	
	1		2	7662		5		1		5		50	
	2 rc	ows × 3	5 colu	ımns									
	4												<b>&gt;</b>

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10682 entries, 0 to 10682
Data columns (total 35 columns):

#	Column	Non-Null Count	
0	Total_Stops	10682 non-null	
1	Price	10682 non-null	int64
2	day_of_journey	10682 non-null	int64
3	month_of_journey	10682 non-null	int64
4	Dep_time_hr	10682 non-null	int64
5	Dep_time_minute	10682 non-null	int64
6	Arr_time_hr	10682 non-null	int64
7	Arr_time_minute	10682 non-null	int64
8	duration_hours	10682 non-null	int64
9	duration_minutes	10682 non-null	int64
10	Air India	10682 non-null	uint8
11	GoAir	10682 non-null	uint8
12	IndiGo	10682 non-null	uint8
13	Jet Airways	10682 non-null	uint8
14	Jet Airways Business	10682 non-null	uint8
15	Multiple carriers	10682 non-null	uint8
16	Multiple carriers Premium economy	10682 non-null	uint8
17	SpiceJet	10682 non-null	uint8
18	Trujet	10682 non-null	uint8
19	Vistara	10682 non-null	uint8
20	Vistara Premium economy	10682 non-null	uint8
21	Source_Chennai	10682 non-null	uint8
22	Source_Delhi	10682 non-null	uint8
23	Source_Kolkata	10682 non-null	uint8
24	Source_Mumbai	10682 non-null	uint8
25	Destination_Cochin	10682 non-null	uint8
26	Destination_Delhi	10682 non-null	uint8
27	Destination_Hyderabad	10682 non-null	uint8
28	Destination_Kolkata	10682 non-null	uint8
29	Destination_New Delhi	10682 non-null	uint8
30	Route_1	10682 non-null	int32
31	Route_2	10682 non-null	int32
32	Route_3	10682 non-null	int32
33	Route_4	10682 non-null	int32
34	Route_5	10682 non-null	int32
dtvne	es: int32(5), int64(10), uint8(20)		

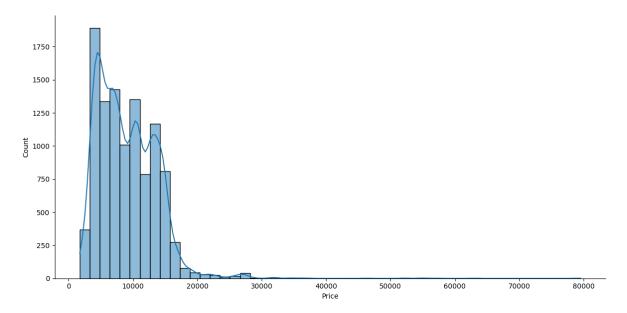
dtypes: int32(5), int64(10), uint8(20)

memory usage: 1.3 MB

**Outlier Detection** 

In [63]: sns.displot(train\_data['Price'],bins=50,aspect=2,height=6,kde=True)

Out[63]: <seaborn.axisgrid.FacetGrid at 0x1f890e899a0>



In [64]: train\_data[train\_data['Price']>40000]

### Out[64]:

	Total_Stops	Price	day_of_journey	month_of_journey	Dep_time_hr	Dep_time_minute	Α
657	1	52229	3	1	5	45	_
1478	1	54826	18	3	18	40	
2618	1	54826	18	3	22	50	
2924	1	79512	3	1	5	45	
5372	1	62427	3	1	5	45	
5439	1	54826	3	1	16	55	
7351	2	46490	3	3	20	5	
9715	2	52285	3	6	20	5	
10364	1	57209	3	1	9	45	

9 rows × 35 columns

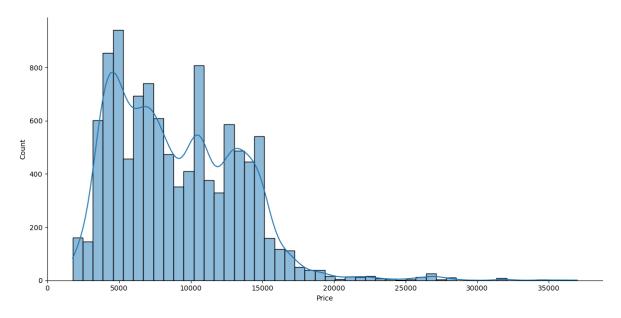
There are some outliers in the dataset where the airfare is over 40000, which could negatively impact the accuracy of machine learning models. To address this issue, it may be better to replace those outliers with the median price of the entire dataset.

Replacing airfare of more than 40000 with the median price

```
In [65]: train_data['Price']=np.where(train_data['Price']>40000,train_data['Price'].med
```

```
In [66]: sns.displot(train_data['Price'],bins=50,aspect=2,height=6,kde=True)
```

Out[66]: <seaborn.axisgrid.FacetGrid at 0x1f89106db80>



#### MACHINE LEARNING PART

Spliting Data into Target and Feature

```
In [68]: X=train_data.drop('Price',axis=1) # all columns except the price column
y=train_data['Price'] # the price column for which we are predic

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) #
```

#### **DEFINING METRICS**

```
In [75]: # Defining a function that prints out all the metrics
def metrics(y_true,y_pred):
    print(f'MAE: ',mean_absolute_error(y_true,y_pred))
    print(f'MSE: ',mean_squared_error(y_true,y_pred))
    print(f'RMSE: ',mean_squared_error(y_true,y_pred)**0.5)
    print(f'Explained Variance Score: ',explained_variance_score(y_true,y_pred)

# function for calculating the accuracy
def accuracy(y_true,y_predictions):
    errors = abs(y_predictions - y_true)
    mape = 100 * np.mean(errors / y_true)
    accuracy_model = 100 - mape
    return accuracy_model
```

```
In [76]: # creating an instance of the Random Forest model
    model_random_forest=RandomForestRegressor(n_estimators=500,min_samples_split=3
    # fitting the model
    model_random_forest.fit(X_train,y_train)

Out[76]: RandomForestRegressor(min_samples_split=3, n_estimators=500)

In [78]: # making predictions on the test data
    from sklearn.metrics import mean_absolute_error,mean_squared_error,explained_v
    predictions_random_forest=model_random_forest.predict(X_test)

    metrics(y_test,predictions_random_forest)

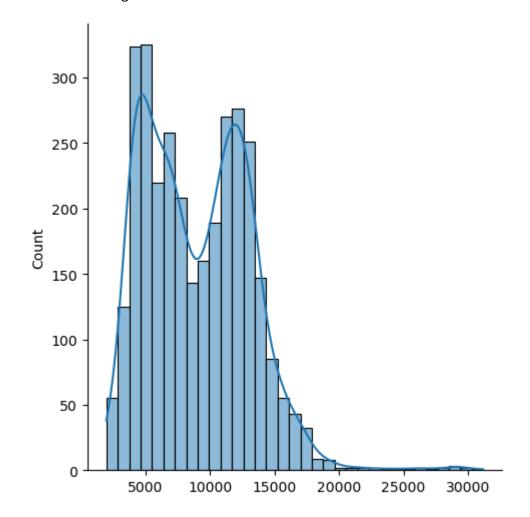
MAE: 1121.4502692460148
    MSE: 3464535.372052645
    RMSE: 1861.3262400913616
    Explained Variance Score: 0.8223326516728537

In [79]: accuracy(y_test,predictions_random_forest)
```

Out[79]: 87.61937955758866

```
In [86]: sns.displot(predictions_random_forest,kde=True)
```

Out[86]: <seaborn.axisgrid.FacetGrid at 0x1f895f9d820>



In [ ]:	
In [ ]:	