problem statement: FLIGHT PRICE PREDICTION Anyone who has booked a flight ticket knows how unexpectedly the prices vary. The cheapest available ticket on a given flight gets more and less expensive over time. This usually happens as an attempt to maximize revenue based on -

1. Time of purchase patterns (making sure last-minute purchases are expensive)
2. Keeping the flight as full as they want it (raising prices on a flight which is filling up in order to reduce sales and hold back inventory for those expensive last-minute expensive purchases) So, you have to work on a project where you collect data of flight fares with other features and work to make a model to predict fares of flights.

In [1]:

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df=pd.read_csv('Flight_price_dataset.csv')
df
```

Out[2]:

| | Unnamed: 0 | Airlines | Aerplane | Date | Depature_Time | Arrival_time | Source | Destination | Stop |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | Air India | AI-887 | Sun, 7 Aug 2022 | 07:00 | 09:05 | New Delhi | Mumbai | No Sto |
| **1** | 1 | Air India | AI-665 | Sun, 7 Aug 2022 | 08:00 | 10:10 | New Delhi | Mumbai | No Sto |
| **2** | 2 | Air India | AI-805 | Sun, 7 Aug 2022 | 20:00 | 22:10 | New Delhi | Mumbai | No Sto |
| **3** | 3 | Air India | AI-678 | Sun, 7 Aug 2022 | 09:00 | 11:15 | New Delhi | Mumbai | No Sto |
| **4** | 4 | Air India | AI-624 | Sun, 7 Aug 2022 | 19:00 | 21:15 | New Delhi | Mumbai | No Sto |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | . |
| **1516** | 1516 | Air India Business | AI-865 | Sun, 14 Aug 2022 | 10:00 | 12:35 | New Delhi | Mumbai | No Sto |
| **1517** | 1517 | Air India Business | AI-636 | Sun, 14 Aug 2022 | 14:30 | 18:10 | New Delhi | Mumbai | Sto |
| **1518** | 1518 | Air India Business | AI-441 | Sun, 14 Aug 2022 | 17:55 | 22:10 | New Delhi | Mumbai | Sto |
| **1519** | 1519 | Air India Business | AI-475/646 | Sun, 14 Aug 2022 | 12:55 | 13:35\n+ 1 day | New Delhi | Mumbai | Sto |
| **1520** | 1520 | Vistara Business | UK-927 | Sun, 14 Aug 2022 | 09:30 | 11:35 | New Delhi | Mumbai | No Sto |

1521 rows × 11 columns

In [3]:

```
#Dataset Shape
df.shape
```

Out[3]:

```
(1521, 11)
```

There are 1521 rows and 11 columns present in the dataset

In [4]:

```
df.columns
```

Out[4]:

```
Index(['Unnamed: 0', 'Airlines', 'Aerplane', 'Date', 'Depature_Time',
       'Arrival_time', 'Source', 'Destination', 'Stops', 'Duration', 'Price'],
      dtype='object')
```

In [5]:

```
df.dtypes
```

Out[5]:

```
Unnamed: 0        int64
Airlines         object
Aerplane         object
Date             object
Depature_Time    object
Arrival_time     object
Source           object
Destination      object
Stops            object
Duration         object
Price             int64
dtype: object
```

Here we are having 2 integer columns unnamed and Price and the remaining are object type

The Date column is of object type we should change it to Date datatype Depature_Time and Arrival_time is also object type we should change it to Date_Time type Stops column should also change

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1521 entries, 0 to 1520
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Unnamed: 0     1521 non-null   int64 
 1   Airlines       1521 non-null   object
 2   Aerplane       1521 non-null   object
 3   Date           1521 non-null   object
 4   Depature_Time  1521 non-null   object
 5   Arrival_time   1521 non-null   object
 6   Source         1521 non-null   object
 7   Destination    1521 non-null   object
 8   Stops          1521 non-null   object
 9   Duration       1521 non-null   object
 10  Price          1521 non-null   int64 
dtypes: int64(2), object(9)
memory usage: 77.3+ KB
```

There are 2 integer type of columns and 9 object type of columns present in the data

**Data Integrity Checking**

Dataset contains white spaces,?,missing values now we will check for them

In [7]:
```

df.duplicated().sum()
```

Out[7]: 0

In [8]:
```
df.isin([' ','?','-','null','NA']).sum().any()
```

Out[8]: False

In [9]:
```
df.isnull().sum()
```

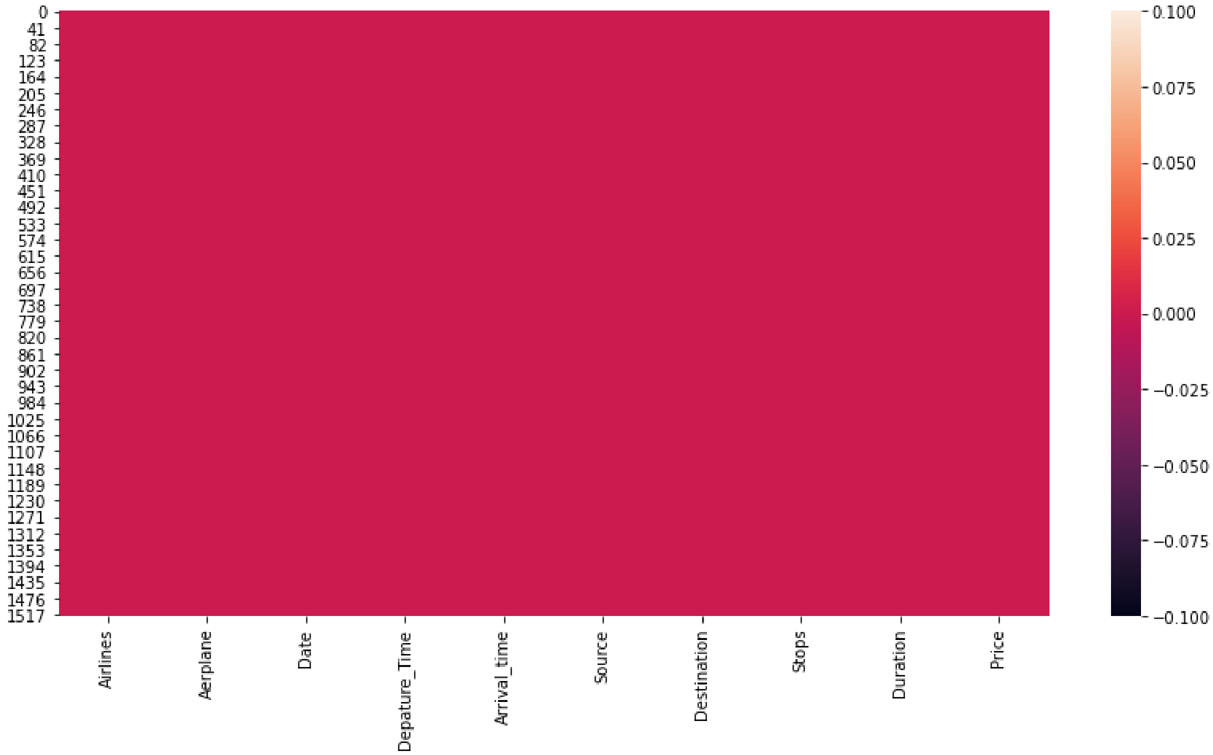
Out[9]:
```
Unnamed: 0       0
Airlines         0
Aerplane         0
Date             0
Depature_Time    0
Arrival_time     0
Source           0
Destination      0
Stops            0
Duration         0
Price            0
dtype: int64
```

There are no null values present in the dataset

In [10]:
```
# droping unnamed:0 column
df.drop(columns='Unnamed: 0',inplace=True)
```

In [11]:
```
plt.figure(figsize=(14,7))
sns.heatmap(df.isnull())
```

Out[11]:
```
<AxesSubplot:>
```




There is no missing values present in the dataset

**Data Preprocessing**

convert Duration column hr & minutes format to minutes

In [12]:
```
df['Duration']=df['Duration'].map(lambda x: x.replace('05m','5m'))
```

In [13]:
```
#convertion of Duration column from hr & minutes format to minutes
df['Duration']=df['Duration'].str.replace('h','*60').str.replace(' ','+').st
```

In [14]:
```
#Convert Duration column into numeric datatype
df['Duration']=pd.to_numeric(df['Duration'])
```

Create new column for day & date

In [15]:
```
df['Day']=df['Date'].map(lambda x:x[:3])
df['Date']=df['Date'].map(lambda x:x[4:])
```

In [16]:
```
categorical=['Airlines','Day','Stops','Aerplane']
```

In [17]:
```
pd.set_option('display.max_rows',None)
for i in categorical:
    print(i)
    print(df[i].value_counts())
    print("="*100)
```

```
Airlines
IndiGo                 326
Vistara                288
Vistara Business       255
Air India              196
Air India Business     173
Go First               121
SpiceJet               110
Air Asia                52
Name: Airlines, dtype: int64
============================================================================
======================
Day
Mon    251
Sun    247
Sat    228
Fri    206
Wed    201
Tue    198
```

In [18]:
```
df.describe()
```

Out[18]:

| | Duration | Price |
|---|---|---|
| **count** | 1521.000000 | 1521.000000 |
| **mean** | 525.943458 | 17769.464168 |
| **std** | 434.662695 | 12869.727263 |
| **min** | 120.000000 | 8465.000000 |
| **25%** | 135.000000 | 8579.000000 |
| **50%** | 385.000000 | 11843.000000 |
| **75%** | 760.000000 | 22297.000000 |
| **max** | 1705.000000 | 74713.000000 |

describe method tells us minimum price is 8465 and maximum price is 74713

In [19]:
```
df.describe(include=object)
```

Out[19]:

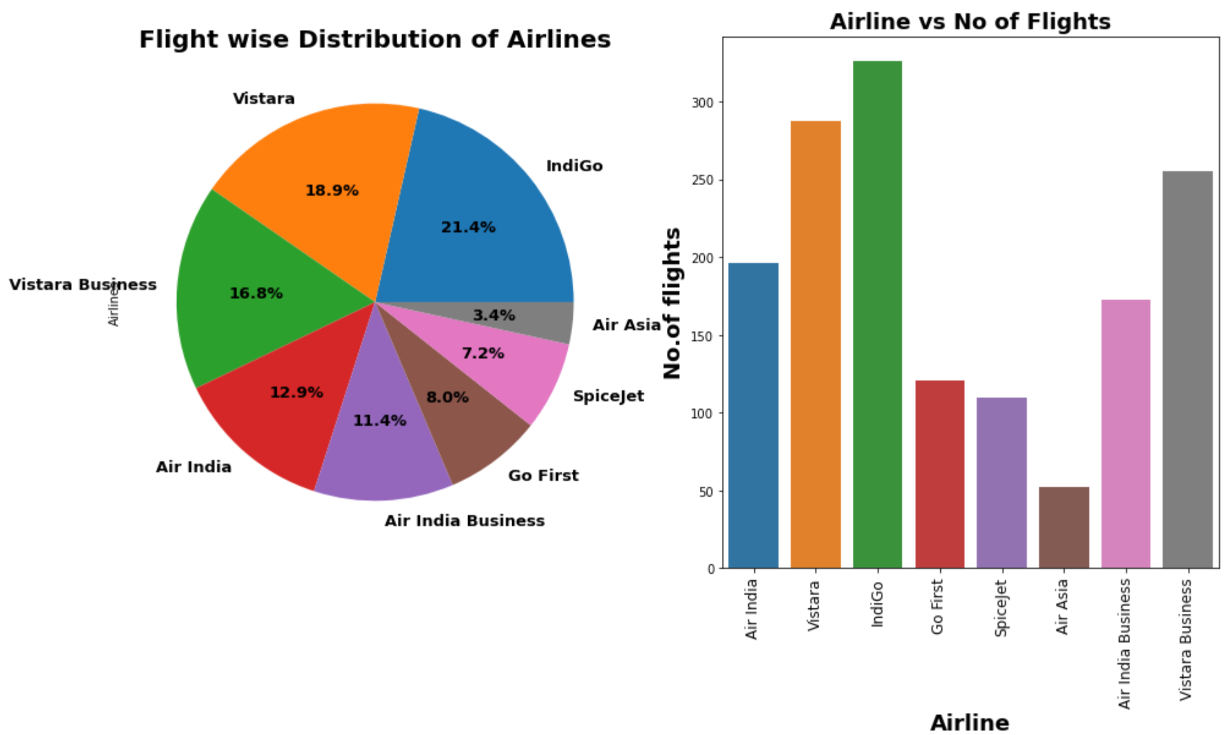
| | Airlines | Aerplane | Date | Depature_Time | Arrival_time | Source | Destination | Stops | Day |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 1521 | 1521 | 1521 | 1521 | 1521 | 1521 | 1521 | 1521 | 1521 |
| **unique** | 8 | 255 | 9 | 114 | 145 | 1 | 1 | 3 | 7 |
| **top** | IndiGo | AI-665 | 13 Aug 2022 | 07:20 | 08:40\n+ 1 day | New Delhi | Mumbai | 1 Stop | Mon |
| **freq** | 326 | 17 | 228 | 55 | 45 | 1521 | 1521 | 975 | 251 |

# EDA

Exploring Airlines types

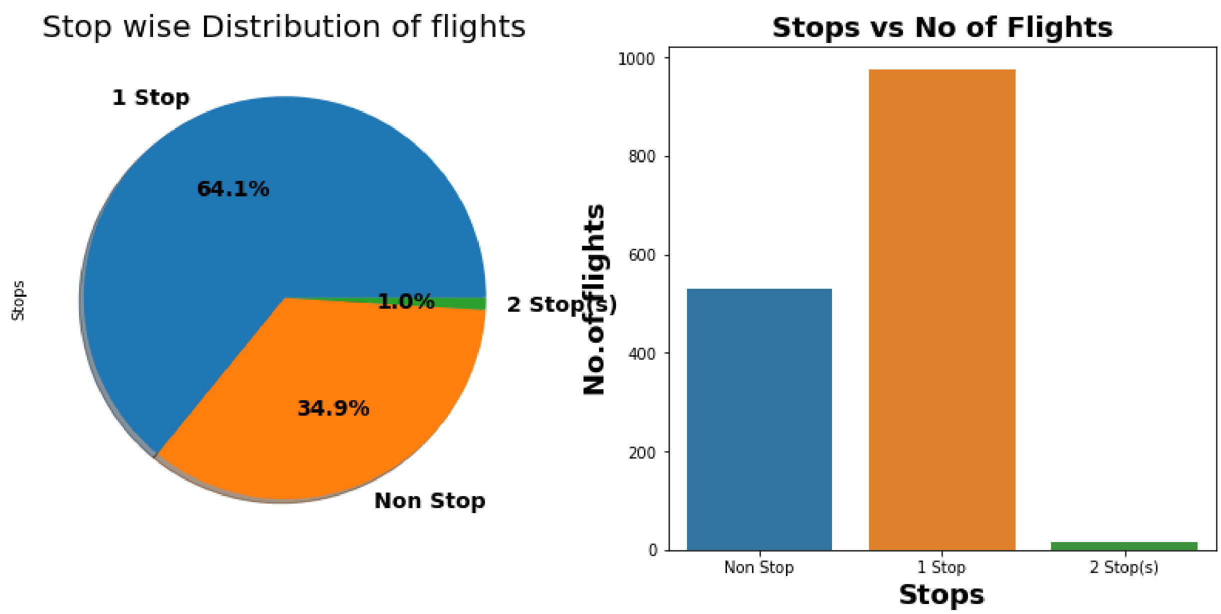
In [20]:
```
#plt.rcparams["figure.autolayout"]
f,ax=plt.subplots(1,2,figsize=(16,8))
df['Airlines'].value_counts().plot.pie(autopct='%2.1f%%',textprops={ 'fontsi
ax[0].set_title("Flight wise Distribution of Airlines",fontsize=20,fontweigh
sns.countplot('Airlines',data=df,ax=ax[1])
ax[1].set_title('Airline vs No of Flights',fontsize=18,fontweight='bold')
ax[1].set_xlabel("Airline",fontsize=18,fontweight='bold')
ax[1].set_ylabel("No.of flights",fontsize=18,fontweight='bold')
plt.xticks(fontsize=12,rotation=90)
plt.show()

```



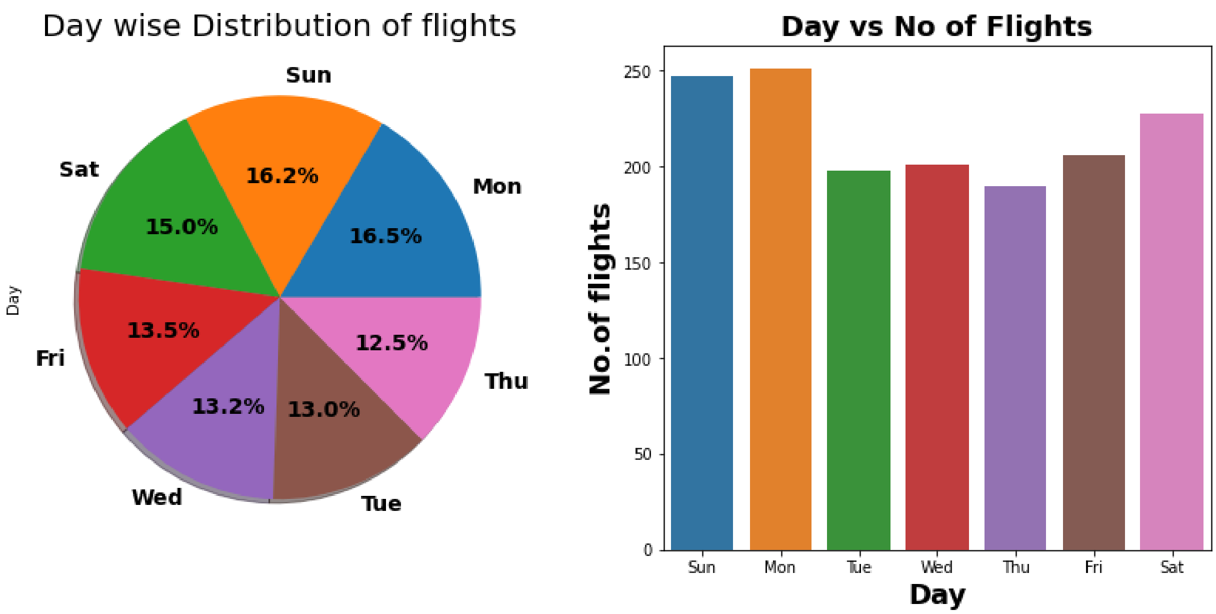

we observe that maximum number of flights run by Vistara premium Economy while minimum flights run by AirAsia

In [21]:
```
#counting No.of Stops
f,ax=plt.subplots(1,2,figsize=(14,6))
df['Stops'].value_counts().plot.pie(autopct='%2.1f%%',textprops={ 'fontsize'
ax[0].set_title("Stop wise Distribution of flights",fontsize=20)
sns.countplot('Stops',data=df,ax=ax[1])
ax[1].set_title('Stops vs No of Flights',fontsize=18,fontweight='bold')
ax[1].set_xlabel("Stops",fontsize=18,fontweight='bold')
ax[1].set_ylabel("No.of flights",fontsize=18,fontweight='bold')
plt.show()
```




64.1% of flights are taking single stop in there way and 34.9% flights are Non stop flights and 1% flights are taking 2 stops

In [22]:
```
#Day-wise distribution of flights
f,ax=plt.subplots(1,2,figsize=(14,6))
df['Day'].value_counts().plot.pie(autopct='%2.1f%%',textprops={ 'fontsize':1
ax[0].set_title("Day wise Distribution of flights",fontsize=20)
sns.countplot('Day',data=df,ax=ax[1])
ax[1].set_title('Day vs No of Flights',fontsize=18,fontweight='bold')
ax[1].set_xlabel("Day",fontsize=18,fontweight='bold')
ax[1].set_ylabel("No.of flights",fontsize=18,fontweight='bold')
plt.show()
```




Monday There are more number of flights run and on Thursday less number of flights run

In [23]:
```
#plotting Day  vs price
plt.figure(figsize =(14S,7))
sns.barplot(x=df['Day'],y=df['Price'])
plt.title("Day Vs Price",fontsize=20,fontweight ='bold')
plt.xlabel('Day',fontsize = 20,fontweight ='bold')
plt.ylabel('Avg. Price of Flights',fontsize = 20,fontweight ='bold')
plt.tight_layout()
plt.show()
df['Price'].value_counts()
```

```
29512     3
37048     3
40891     3
14852     3
16541     3
10007     3
44081     2
17293     2
40411     2
34860     2
39470     2
10292     2
11730     2
47418     2
10364     2
40292     2
12412     2
20340     2
39965     2
44076     2
```

In [ ]:
```

```

```
Do airfares change frequently?
Do they move in small increments or in large jumps?
Do they tend to go up or down overtime?
What is the best time to buy so that the consumer can save the most by taking the least risk?
Does price increase as we get near to departure date?
Is Indigo cheaper than JetAirways?
Are morning flights expensive?
```

In [24]:
```
df['Airlines'].value_counts()
```

Out[24]:
```
IndiGo               326
Vistara              288
Vistara Business     255
Air India            196
Air India Business   173
Go First             121
SpiceJet             110
Air Asia              52
Name: Airlines, dtype: int64
```

## 6.Is Indigo Cheaper than SpiceJet

In [25]:
```
df.groupby('Airlines')['Price'].mean()
```

Out[25]:
```
Airlines
Air Asia               10214.826923
Air India              12284.112245
Air India Business     33655.433526
Go First               10209.090909
IndiGo                  9146.190184
SpiceJet               10408.590909
Vistara                12297.715278
Vistara Business       36715.541176
Name: Price, dtype: float64
```

In [26]:
```
p=df.sort_values('Price')
```

## 7. Are morning flights expensive?

In [27]:
```
df.groupby('Depature_Time')['Price'].value_counts()
```

Out[27]:
```
Depature_Time  Price
00:15          8579     15
02:10          8579      6
02:40          8579      4
04:45          8579      6
05:00          14852     3
               19220     1
05:05          8579      8
05:15          12504    10
               8579      6
               31996     4
               39682     2
               40292     2
05:20          13094     7
               8579      4
               14955     4
               10364     1
               13934     1
05:30          8579      5
```

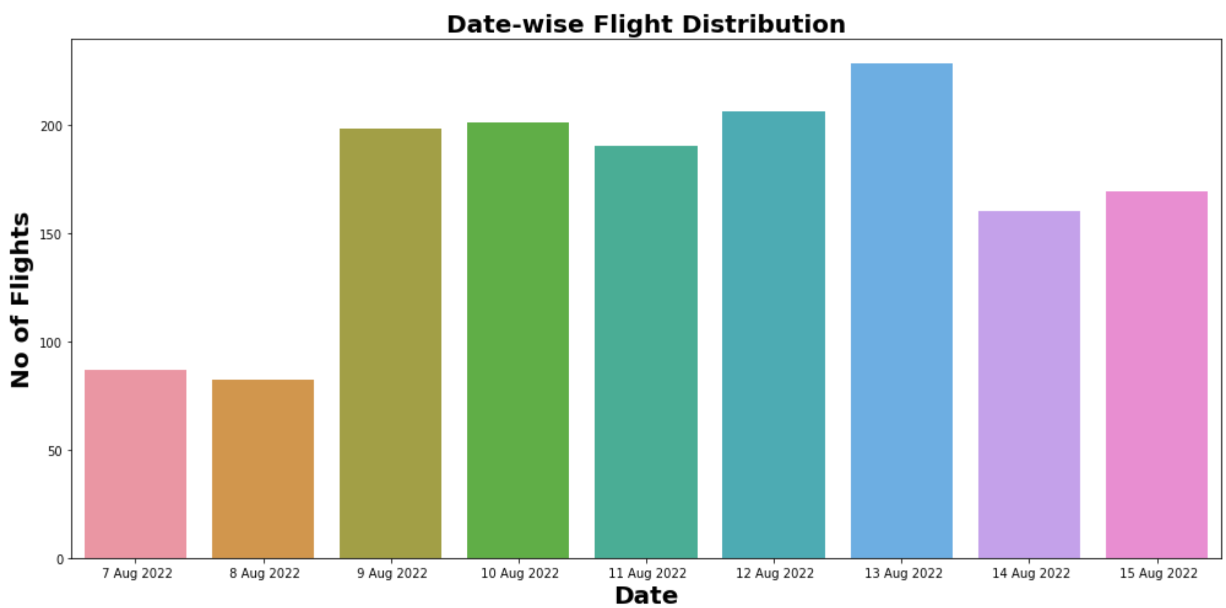
Flights price are less at midnight and early in the morning

Tuesday Around Midnight is the Cheapest Time to Book

In [28]:
```
df.groupby('Day')['Price'].count()
```

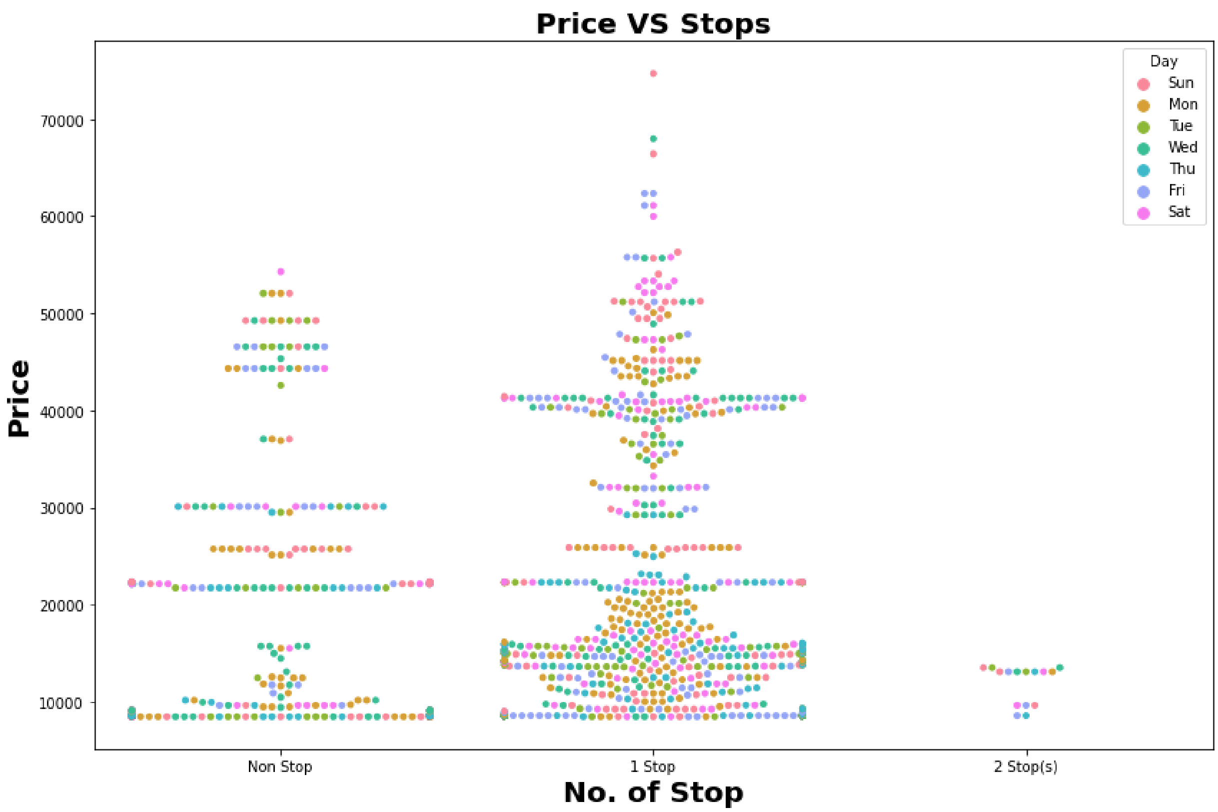
Out[28]:
```
Day
Fri    206
Mon    251
Sat    228
Sun    247
Thu    190
Tue    198
Wed    201
Name: Price, dtype: int64
```

In [29]:
```
plt.rcParams["figure.autolayout"] = True
sns.set_palette('mako')
plt.figure(figsize =(14,7))
sns.countplot(x=df['Date'])
plt.title("Date-wise Flight Distribution",fontsize=20,fontweight ='bold')
plt.xlabel('Date',fontsize = 20,fontweight ='bold')
plt.ylabel('No of Flights',fontsize = 20,fontweight ='bold')
plt.tight_layout()
plt.show()
```

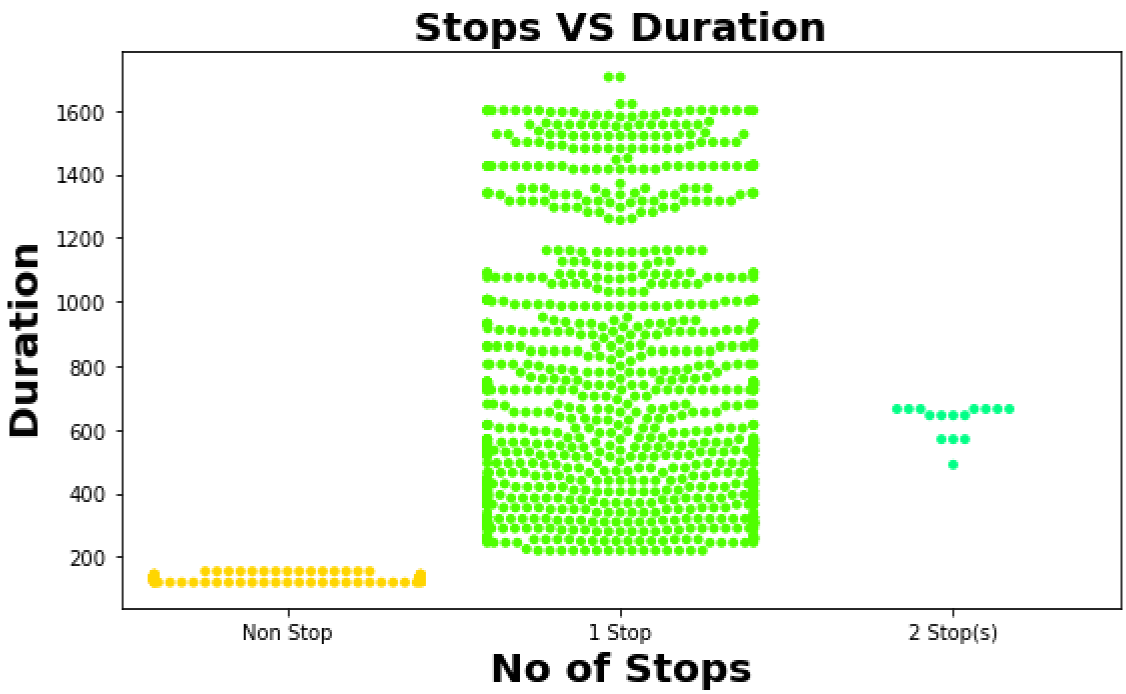



we can observe that maximum flights scheduled at 13-Aug and minimum flights scheduled on 8-Aug

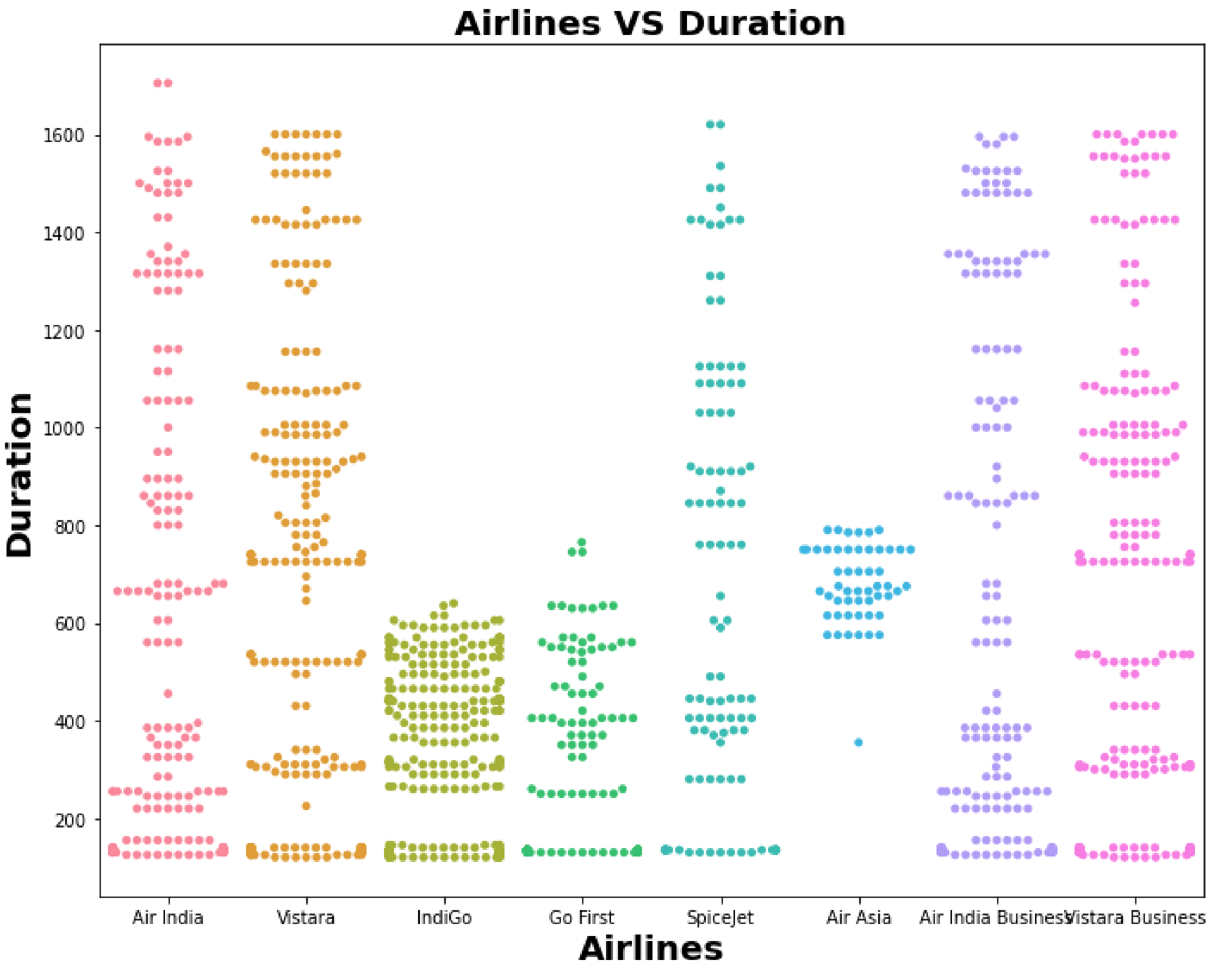
In [30]:
```
plt.rcParams["figure.autolayout"] = True
sns.set_palette('mako')
plt.figure(figsize =(12,8))
sns.swarmplot(y=df['Price'],x=df['Stops'], hue= df['Day'])
plt.title("Price VS Stops",fontsize=20,fontweight ='bold')
plt.xlabel('No. of Stop',fontsize = 20,fontweight ='bold')
plt.ylabel('Price',fontsize = 20,fontweight ='bold')
plt.tight_layout()
plt.show()
```



In [31]:
```
plt.rcParams["figure.autolayout"] = True
sns.set_palette('hsv')
plt.figure(figsize =(8,5))
sns.swarmplot(y=df['Duration'],x=df['Stops'])
plt.title("Stops VS Duration",fontsize=20,fontweight ='bold')
plt.xlabel('No of Stops',fontsize = 20,fontweight ='bold')
plt.ylabel('Duration ',fontsize = 20,fontweight ='bold')
plt.tight_layout()
plt.show()
```



In [32]:
```
plt.rcParams["figure.autolayout"] = True
sns.set_palette('rainbow_r')
plt.figure(figsize =(10,8))
sns.swarmplot(x=df['Airlines'],y=df['Duration'])
plt.title("Airlines VS Duration",fontsize=20,fontweight ='bold')
plt.xlabel('Airlines',fontsize = 20,fontweight ='bold')
plt.ylabel('Duration',fontsize = 20,fontweight ='bold')
plt.tight_layout()
plt.show()
```




## Feature Engineering

## Feature Engineering

1. Encoding categeorical data

In [33]:
```
#Dropping unnecesary columns
df.drop(columns=['Depature_Time','Arrival_time','Source','Destination'],inpl
```

In [34]:
```
#Let's sort columns by their datatypes
df.columns.to_series().groupby(df.dtypes).groups
```

Out[34]:
```
{int64: ['Duration', 'Price'], object: ['Airlines', 'Aerplane', 'Date', 'Stop
s', 'Day']}
```

In [35]:
```
categeorical=['Airlines','Aerplane','Date','Stops','Day']
Numerical=['Duration','Price']
```

In [36]:
```
df['Aerplane']=df['Aerplane'].map(lambda x: str(x).replace('-',''))
df['Aerplane']=df['Aerplane'].map(lambda x: str(x).replace('/',''))
```

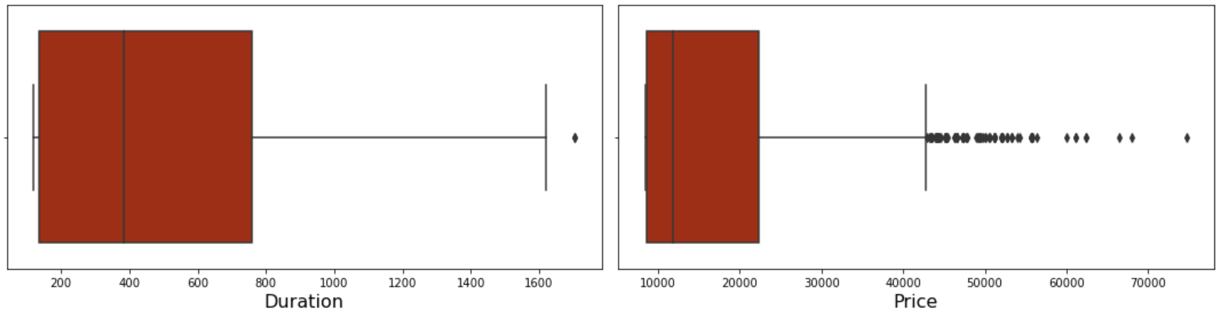
In [37]:
```
#using label encoder for Transforming categeorical data
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for i in categeorical:
    df[i]=le.fit_transform(df[i])
df.head()
```

Out[37]:

| | Airlines | Aerplane | Date | Stops | Duration | Price | Day |
|---|---|---|---|---|---|---|---|
| **0** | 1 | 103 | 6 | 2 | 125 | 8465 | 3 |
| **1** | 1 | 84 | 6 | 2 | 130 | 8465 | 3 |
| **2** | 1 | 89 | 6 | 2 | 130 | 8465 | 3 |
| **3** | 1 | 85 | 6 | 2 | 135 | 8465 | 3 |
| **4** | 1 | 82 | 6 | 2 | 135 | 8465 | 3 |

## 2. Outliers Detection and removal

In [38]:
```
plt.figure(figsize=(15,4))
plt_num = 1
for i in Numerical:
    if plt_num <= 2:
        ax = plt.subplot(1,2,plt_num)
        sns.boxplot(df[i], palette='gnuplot')
        plt.xlabel(i, fontsize= 16)
    plt_num += 1
plt.show()
```




From the above graph we can observe that There are outliers present in the price column, since the data is realistic and error free we will proceed for building ML model without removing outliers

# Correlation

In [39]:
```
df.corr()
```

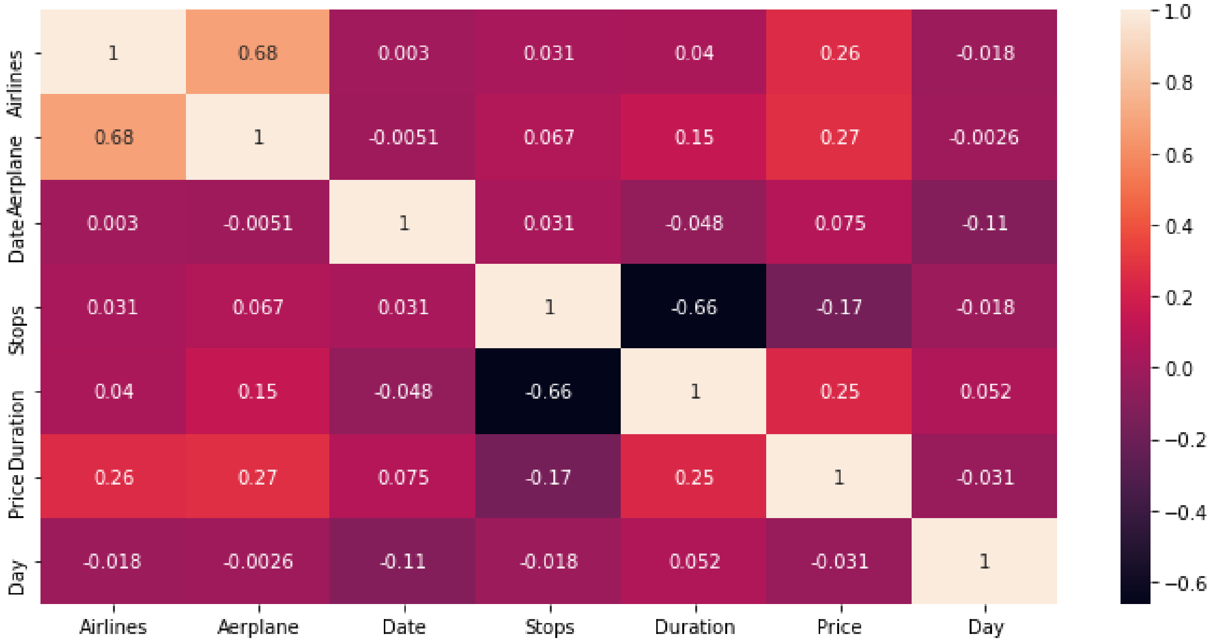
Out[39]:

| | Airlines | Aerplane | Date | Stops | Duration | Price | Day |
|---|---|---|---|---|---|---|---|
| **Airlines** | 1.000000 | 0.682672 | 0.003009 | 0.031016 | 0.039892 | 0.257065 | -0.018240 |
| **Aerplane** | 0.682672 | 1.000000 | -0.005075 | 0.066818 | 0.146583 | 0.274997 | -0.002604 |
| **Date** | 0.003009 | -0.005075 | 1.000000 | 0.031381 | -0.048494 | 0.075017 | -0.107706 |
| **Stops** | 0.031016 | 0.066818 | 0.031381 | 1.000000 | -0.662088 | -0.166766 | -0.018455 |
| **Duration** | 0.039892 | 0.146583 | -0.048494 | -0.662088 | 1.000000 | 0.246610 | 0.052209 |
| **Price** | 0.257065 | 0.274997 | 0.075017 | -0.166766 | 0.246610 | 1.000000 | -0.031221 |
| **Day** | -0.018240 | -0.002604 | -0.107706 | -0.018455 | 0.052209 | -0.031221 | 1.000000 |

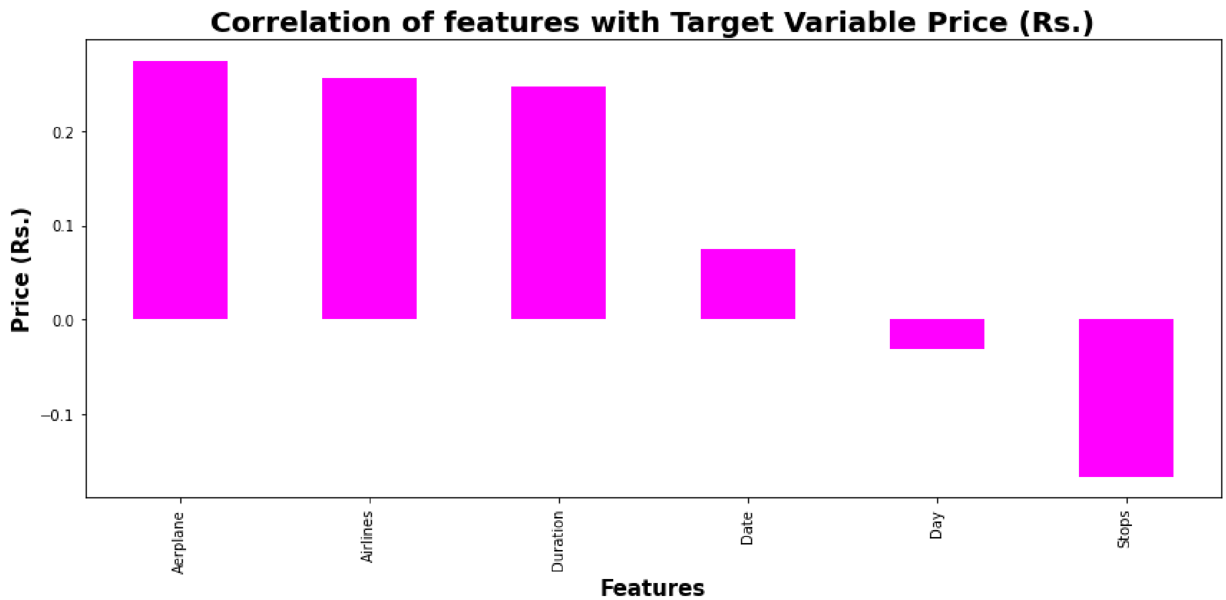
In [40]:

```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),annot=True)
```

Out[40]: <AxesSubplot:>



In [41]:
```
plt.figure(figsize = (12,6))
df.corr()['Price'].drop(['Price']).sort_values(ascending=False).plot(kind='b
plt.xlabel('Features',fontsize=15,fontweight='bold')
plt.ylabel('Price (Rs.)',fontsize=15,fontweight='bold')
plt.title('Correlation of features with Target Variable Price (Rs.)',fontsiz
plt.show()
```




Airlines and Aeroplane are 26% and 27% correlated with price column and all the other columns are poorly correlated with price

## Skewness

In [42]:
```
df.skew()
```

Out[42]:
```
Airlines   -0.229666
Aerplane    0.101154
Date        0.330741
Stops       0.610989
Duration    1.003800
Price       1.492503
Day         0.108128
dtype: float64
```

we can see all the columns are under the threshold value of skewness i.e -0.5-+0.5 The Duration is above the threshold value

## seperating target variable

In [ ]:
```
x=df.drop(['Price'],axis=1)
y=df['Price']
```

# Transforming data to remove skewness we use powerTransformation method

In [44]:
```
from sklearn.preprocessing import power_transform
x=power_transform(x,method='yeo-johnson')
x
```

Out[44]:
```
array([[-1.46108244, -0.1986708 ,  0.94704414,  1.34603883, -1.25774029,
         0.15285874],
       [-1.46108244, -0.44585067,  0.94704414,  1.34603883, -1.20843635,
         0.15285874],
       [-1.46108244, -0.37886408,  0.94704414,  1.34603883, -1.20843635,
         0.15285874],
       ...,
       [-0.99453226, -0.80742074,  0.30590934, -0.74778627, -0.38609333,
         0.15285874],
       [-0.99453226, -0.73096452,  0.30590934, -0.74778627,  1.54763809,
         0.15285874],
       [ 1.34765059,  1.15630847,  0.30590934,  1.34603883, -1.25774029,
         0.15285874]])
```

# scaling the data using StandardScaler

In [45]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x=sc.fit_transform(x)
x
```

Out[45]:
```
array([[-1.46108244, -0.1986708 ,  0.94704414,  1.34603883, -1.25774029,
         0.15285874],
       [-1.46108244, -0.44585067,  0.94704414,  1.34603883, -1.20843635,
         0.15285874],
       [-1.46108244, -0.37886408,  0.94704414,  1.34603883, -1.20843635,
         0.15285874],
       ...,
       [-0.99453226, -0.80742074,  0.30590934, -0.74778627, -0.38609333,
         0.15285874],
       [-0.99453226, -0.73096452,  0.30590934, -0.74778627,  1.54763809,
         0.15285874],
       [ 1.34765059,  1.15630847,  0.30590934,  1.34603883, -1.25774029,
         0.15285874]])
```

In [46]:
```
pd.DataFrame(x).skew()
```

Out[46]:
```
0   -0.226505
1   -0.237270
2   -0.119992
3    0.592574
4    0.037567
5   -0.155961
dtype: float64
```

# Checking VIF

In [47]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif=pd.DataFrame()
vif["vif"]=[variance_inflation_factor(x,i) for i in range(x.shape[1])]
vif['Features']=pd.DataFrame(x).columns
vif
```

Out[47]:

| | vif | Features |
|---|---|---|
| 0 | 1.627605 | 0 |
| 1 | 1.757096 | 1 |
| 2 | 1.041977 | 2 |
| 3 | 4.102141 | 3 |
| 4 | 4.150025 | 4 |
| 5 | 1.041209 | 5 |

All the features are lessthan the cutoff value of vif i.e<5

# Model Building

since our target variable continuous variable so we use regression model

In [57]:
```
from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import SGDRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
```

In [103]:
```
#creating a function to run all the regressors
def regressor(model,x,y):
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random

    #training the model
    model.fit(x_train,y_train)

    #predicting the model
    pred=model.predict(x_test)

    print("Mean Squared Error is:",mean_squared_error(y_test,pred))

    print('Mean absolute error :', mean_absolute_error(y_test,pred))

    print('Root Mean squared error :', np.sqrt(mean_squared_error(y_test, pr

    print("r2_score is:",r2_score(y_test,pred))

    print("cross_validation_score is:",cross_val_score(model,x_train,y_train

```

# LinearRegression

In [104]:
```
model=LinearRegression()
regressor(model,x,y)
```

```
Mean Squared Error is: 158425632.10147795
Mean absolute error : 9465.07957596196
Root Mean squared error : 12586.72443892683
r2_score is: 0.1147413697703511
cross_validation_score is: 0.1360295732706547
```

# Support Vector Regressor

In [105]:
```
model=SVR(kernel='rbf')
regressor(model,x,y)
```

```
Mean Squared Error is: 222408560.446919
Mean absolute error : 9373.908605320747
Root Mean squared error : 14913.368514420845
r2_score is: -0.24278562099390744
cross_validation_score is: -0.2130841144204668
```

In [106]:
```
model=SVR(kernel='poly')
regressor(model,x,y)
```

```
Mean Squared Error is: 221899185.90483028
Mean absolute error : 9359.75847910728
Root Mean squared error : 14896.280942061689
r2_score is: -0.23993931258142487
cross_validation_score is: -0.21193738746425378
```

In [107]:
```
model=SVR(kernel='linear')
regressor(model,x,y)
```

```
Mean Squared Error is: 220876786.05114457
Mean absolute error : 9052.340346266967
Root Mean squared error : 14861.924035976788
r2_score is: -0.23422629580494103
cross_validation_score is: -0.2022495135393517
```

# DecissionTreeRegressor

In [108]:
```
model=DecisionTreeRegressor(random_state=63)
regressor(model,x,y)
```

```
Mean Squared Error is: 33590423.2
Mean absolute error : 2564.937704918033
Root Mean squared error : 5795.724562123359
r2_score is: 0.8123017618019097
cross_validation_score is: 0.8448283365180489
```

# RandomForestRegressor

In [109]:
```
model=RandomForestRegressor()
regressor(model,x,y)
```

```
Mean Squared Error is: 25035376.16151639
Mean absolute error : 2351.9494098360656
Root Mean squared error : 5003.536365563499
r2_score is: 0.8601060793380212
cross_validation_score is: 0.9202471941836606
```

# KNN

In [110]:
```
model=KNeighborsRegressor()
regressor(model,x,y)
```

```
Mean Squared Error is: 40797719.06963934
Mean absolute error : 3861.632786885246
Root Mean squared error : 6387.309219823269
r2_score is: 0.7720284753104292
cross_validation_score is: 0.7341759542606537
```

# SGDRegressor

In [111]:
```
model=SGDRegressor()
regressor(model,x,y)
```

```
Mean Squared Error is: 158453316.65834534
Mean absolute error : 9502.235432641428
Root Mean squared error : 12587.824143129159
r2_score is: 0.11458667262591904
cross_validation_score is: 0.13698461099081888
```

# GradientBoostRegressor

In [112]:
```
model=GradientBoostingRegressor()
regressor(model,x,y)
```

```
Mean Squared Error is: 22428274.88701833
Mean absolute error : 2716.1451342803516
Root Mean squared error : 4735.849964580628
r2_score is: 0.8746741695675984
cross_validation_score is: 0.9069393244105013
```

# AdaBoostRegressor

In [113]:
```
model=AdaBoostRegressor()
regressor(model,x,y)
```

```
Mean Squared Error is: 33010145.75996408
Mean absolute error : 4421.682935308756
Root Mean squared error : 5745.445653729925
r2_score is: 0.8155442649556313
cross_validation_score is: 0.8235625442494718
```

we are getting GradientBoostingRegressor r2_score as 87% and crossvalidation score as 90% so we accept this model and perform Hyper parameter tuning

# Hyper Parameter Tuning

In [114]:

```
# creating parameters list to pass into GridSearchCV
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_sta
parameters = {'loss' : ['squared_error', 'absolute_error', 'huber', 'quantil
              'learning_rate': [0.1 , 0.5 , 1, 1.5],
              'criterion': ['friedman_mse', 'squared_error', 'mse'],
              'max_depth' : [3 , 4 ,5 ],
              'max_features' : ['auto', 'sqrt', 'log2']}
GCV = GridSearchCV(GradientBoostingRegressor(), parameters, cv=5)
GCV.fit(x_train,y_train)
```

Out[114]:

```
GridSearchCV(cv=5, estimator=GradientBoostingRegressor(),
             param_grid={'criterion': ['friedman_mse', 'squared_error', 'mse'],
                         'learning_rate': [0.1, 0.5, 1, 1.5],
                         'loss': ['squared_error', 'absolute_error', 'huber',
                                  'quantile'],
                         'max_depth': [3, 4, 5],
                         'max_features': ['auto', 'sqrt', 'log2']})
```

**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 [115]:

```
GCV.best_params_
```

Out[115]:

```
{'criterion': 'friedman_mse',
 'learning_rate': 0.1,
 'loss': 'squared_error',
 'max_depth': 5,
 'max_features': 'auto'}
```

In [116]:

```
final_model=GradientBoostingRegressor(criterion='mse',learning_rate=0.1,loss
```

In [117]:

```
final_fit=final_model.fit(x_train,y_train)
```

In [118]:

```
final_pred=final_model.predict(x_test)
```

In [119]:

```
best_r2=r2_score(y_test,final_pred,multioutput='variance_weighted')*100
print('Best r2_score:',best_r2)
```

```
Best r2_score: 88.21518610750367
```

In [121]:

```
print("cross_validation_score is:",cross_val_score(final_model,x_train,y_tra
```

```
cross_validation_score is: 0.922484471405728
```

In [122]:
```
df=pd.DataFrame({"Actual":y_test,"Predicted":final_pred})
df
```

Out[122]:

| | Actual | Predicted |
|---|---|---|
| **954** | 8579 | 9367.413124 |
| **1311** | 44081 | 41626.423239 |
| **202** | 8465 | 8713.261420 |
| **1170** | 25881 | 24128.287848 |
| **1446** | 22337 | 22529.838562 |
| **1452** | 30104 | 33029.163973 |
| **137** | 9105 | 10078.062505 |
| **1444** | 22337 | 22892.443204 |
| **1384** | 39184 | 32348.452648 |
| **67** | 8578 | 8532.859401 |
| **44** | 8579 | 8769.800928 |
| **265** | 8714 | 9658.100886 |

**conclusion: After Hyper parameter tuning we are getting GradientBoostingRegressor r2_score as 88% and cross validation score as 92% so we accept this model**

## Saving the model

In [124]:
```
import pickle
filename='flight_price_prediction.pkl'
pickle.dump(GCV,open(filename,'wb'))
```

In [ ]:
```

```