A Flight Price Prediction Model ¶

A Flight Price Prediction designed to analyze and predict the cost of airline tickets.The model is trained using historical data to identify patterns and relationships between these factors and the price of tickets. Once the model is trained, it can be used to make predictions on future ticket prices.

The model typically consists of several components, including data collection, data preprocessing, feature extraction, model training, and prediction. The data collection process involves gathering relevant data from various sources, such as airlines, travel agencies, and online travel portals. The data is then preprocessed to remove any inconsistencies and ensure its accuracy.

This Data is of Airline Operations from 01-03-2019 to 09-06-2019.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df = pd.read_excel("Data_Train.xlsx")
```

In [3]:
```
df.head()
```

Out[3]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	T
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	

This Data is of Airline Operations from 01-03-2019 to 09-06-2019

In [4]:
```
df["Date_of_Journey"].max()
```

Out[4]: '9/06/2019'

In [5]:
```
df["Date_of_Journey"].min()
```

Out[5]: '01/03/2019'

In [6]:
```
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
```

Null Values

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
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
```

Droping Null Values

As they are less than 3% of data we are drop null values.

In [8]:
```
df.dropna(inplace=True)
```

Converting Date of Journey into Numerical attributes

In [9]:
```
df["Journey_day"] = pd.to_datetime(df.Date_of_Journey, format="%d/%m/%Y").dt.
df["Journey_month"] = pd.to_datetime(df["Date_of_Journey"], format = "%d/%m/%
```

In [10]:
```
df.drop(["Date_of_Journey"], axis = 1, inplace = True)
```

Converting Depature Time into Numerical attributes

In [11]:
```
df["Dep_hour"] = pd.to_datetime(df["Dep_Time"]).dt.hour
df["Dep_min"] = pd.to_datetime(df["Dep_Time"]).dt.minute
df.drop(["Dep_Time"], axis = 1, inplace = True)
```

Converting Arrival Time into Numerical attributes

In [12]:
```
df["Arrival_hour"] = pd.to_datetime(df.Arrival_Time).dt.hour
df["Arrival_min"] = pd.to_datetime(df.Arrival_Time).dt.minute
df.drop(["Arrival_Time"], axis = 1, inplace = True)
```

Converting Duration of Flight into Numerical attributes

In [13]:
```
duration = list(df["Duration"])
```

In [14]:
```
len(duration[0].split())
```

Out[14]:
```
2
```

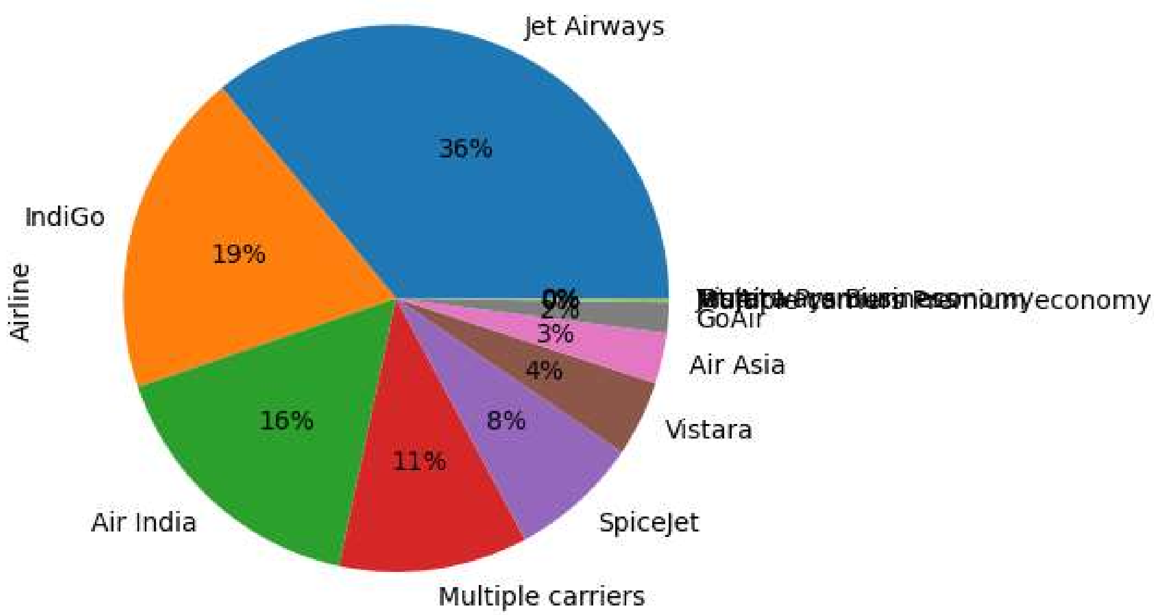
In [15]:
```
duration = list(df["Duration"])

for i in range(len(duration)):
    if len(duration[i].split()) != 2:
        if "h" in duration[i]:
            duration[i] = duration[i].strip() + " 0m"
        else:
            duration[i] = "0h " + duration[i]

duration_hours = []
duration_mins = []

for i in range(len(duration)):
    duration_hours.append(int(duration[i].split(sep = "h")[0]))
    duration_mins.append(int(duration[i].split(sep = "m")[0].split()[-1]))


df["Duration_hours"] = duration_hours
df["Duration_mins"] = duration_mins
```

In [16]:
```
df.drop(["Duration"], axis = 1, inplace = True)
```

Number of flight operations by specific Airline

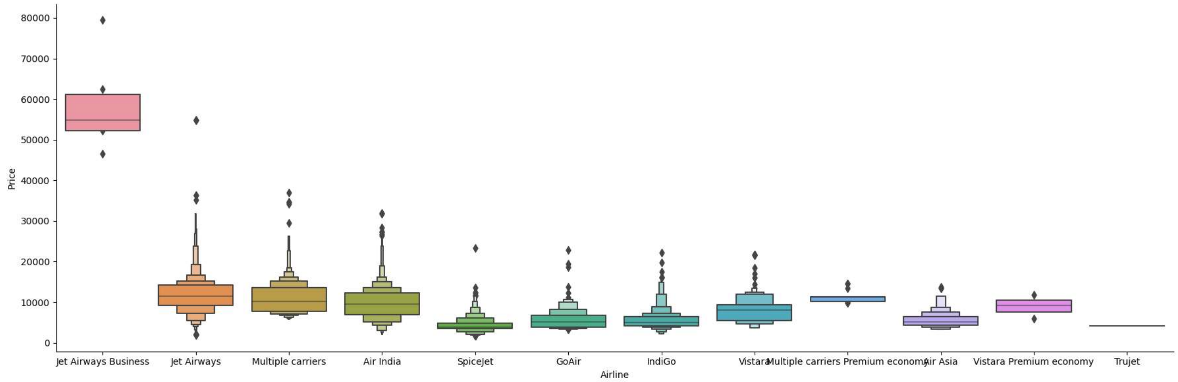
In [17]:
```
print(df["Airline"].value_counts())
df["Airline"].value_counts().plot(kind='pie', y='SOURCE', autopct='%1.0f%%')
plt.show()
```

```
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: Airline, dtype: int64
```



Outliers between Airlines Compared to price

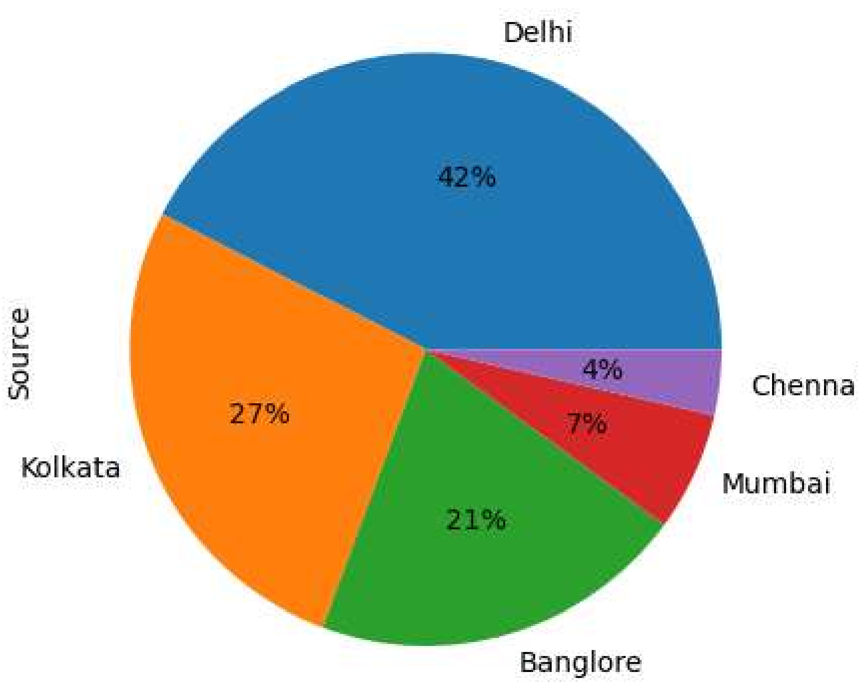
In [18]:
```
sns.catplot(y = "Price", x = "Airline", data = df.sort_values("Price", ascend
plt.show()
```



Number of Airline Operations from Source

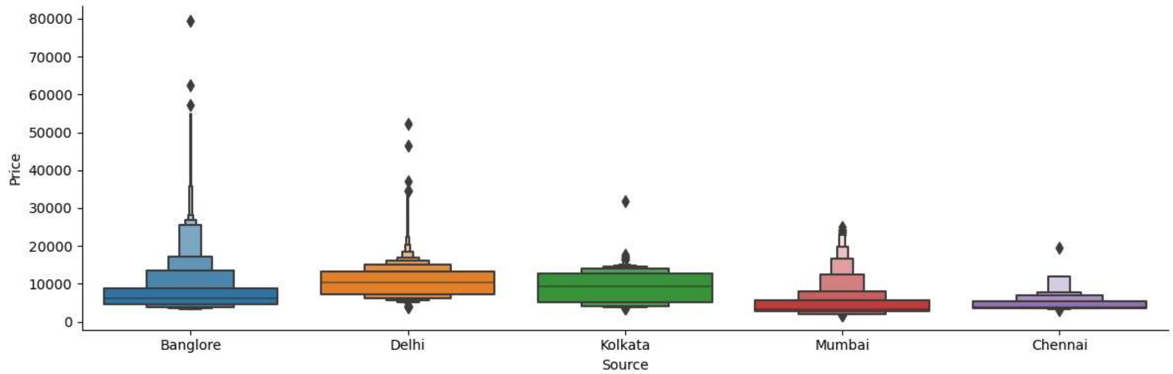
In [19]:
```
print(df["Source"].value_counts())
df["Source"].value_counts().plot(kind='pie', y='SOURCE', autopct='%1.0f%%')
plt.show()
```

```
Delhi       4536
Kolkata     2871
Banglore    2197
Mumbai       697
Chennai      381
Name: Source, dtype: int64
```



Outliers in source city compared to price

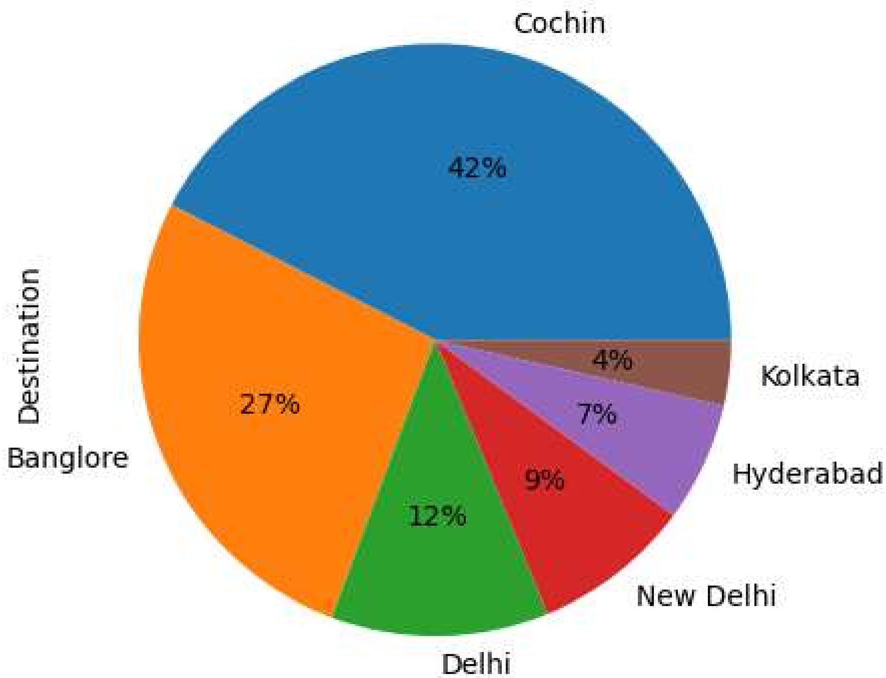
In [20]:
```
sns.catplot(y = "Price", x = "Source", data = df.sort_values("Price", ascendi
plt.show()
```



Number of Airline Operations from Destination Cities

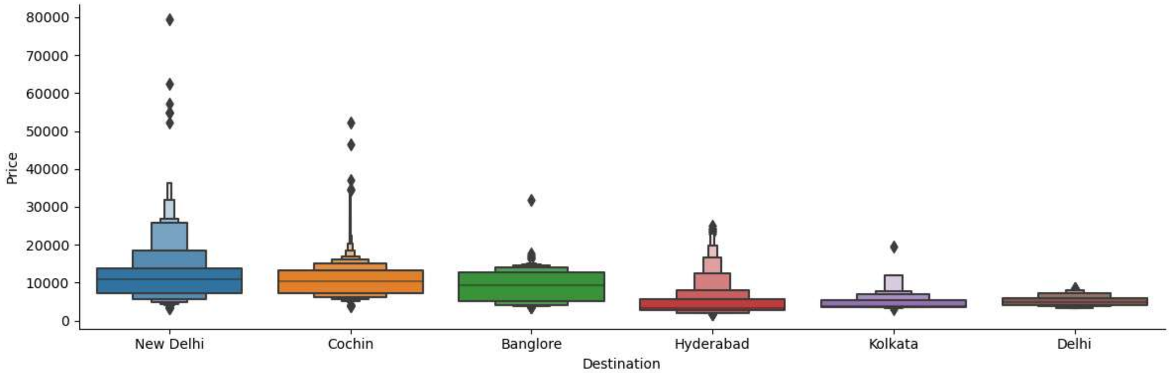
In [21]:
```
print(df["Destination"].value_counts())
df["Destination"].value_counts().plot(kind='pie', y='DESTINATION', autopct='%
plt.show()
```

```
Cochin       4536
Banglore     2871
Delhi        1265
New Delhi     932
Hyderabad     697
Kolkata       381
Name: Destination, dtype: int64
```



Outliers in Destination city compared to price

In [22]:
```
sns.catplot(y = "Price", x = "Destination", data = df.sort_values("Price", as
plt.show()
```



Droping Route and Additional info

Additional_Info contains almost 80% no_info

Route and Total_Stops are related to each other

In [23]:
```
df["Additional_Info"].value_counts()
```

Out[23]:
```
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
No Info                            3
1 Short layover                    1
Red-eye flight                     1
2 Long layover                     1
Name: Additional_Info, dtype: int64
```

In [24]:
```
df.drop(["Route", "Additional_Info"],axis=1,inplace=True)
```

Converting Total Stops column into Numerical attributes

In [25]:
```
df["Total_Stops"].value_counts()
```

Out[25]:
```
1 stop      5625
non-stop    3491
2 stops     1520
3 stops       45
4 stops        1
Name: Total_Stops, dtype: int64
```

In [26]:
```
df.replace({"non-stop": 0, "1 stop": 1, "2 stops": 2, "3 stops": 3, "4 stops"
```

In [27]:
```
df.head()
```

Out[27]:

	Airline	Source	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_hour
0	IndiGo	Banglore	New Delhi	0	3897	24	3	22
1	Air India	Kolkata	Banglore	2	7662	1	5	5
2	Jet Airways	Delhi	Cochin	2	13882	9	6	9
3	IndiGo	Kolkata	Banglore	1	6218	12	5	18
4	IndiGo	Banglore	New Delhi	1	13302	1	3	16

The least ticket prices during whole period.

In [28]:
```
TM = df["Price"].min()
df[df["Price"]==TM]
```

Out[28]:

	Airline	Source	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_ho
4066	SpiceJet	Mumbai	Hyderabad	0	1759	21	3	[illegible]
4274	SpiceJet	Mumbai	Hyderabad	0	1759	27	3	[illegible]
4839	SpiceJet	Mumbai	Hyderabad	0	1759	3	4	[illegible]
10513	SpiceJet	Mumbai	Hyderabad	0	1759	27	3	

The Max ticket prices during whole period.

In [29]:
```
TMX = df["Price"].max()
df[df["Price"]==TMX]
```

Out[29]:

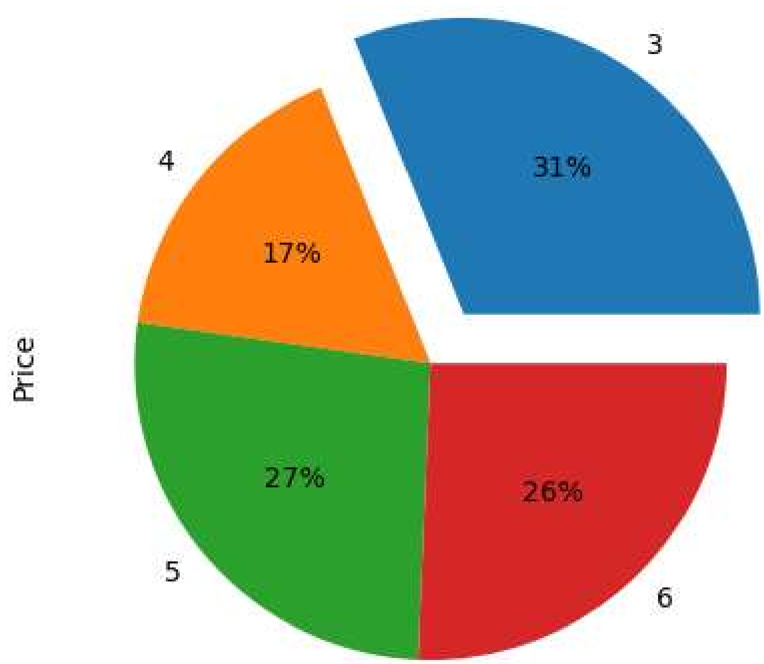
	Airline	Source	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_h
2924	Jet Airways Business	Banglore	New Delhi	1	79512	1	3	

Average prices of flight by months

In [30]:
```
A = df.groupby(["Journey_month"],sort=True).mean()
print(A["Price"])
expl = [0.2,0,0,0]
A["Price"].plot(kind='pie', y='Price', autopct='%1.0f%%',explode = expl)
```

```
Journey_month
3    10673.205580
4     5770.847081
5     9127.722944
6     8828.796134
Name: Price, dtype: float64
```

Out[30]: <AxesSubplot:ylabel='Price'>

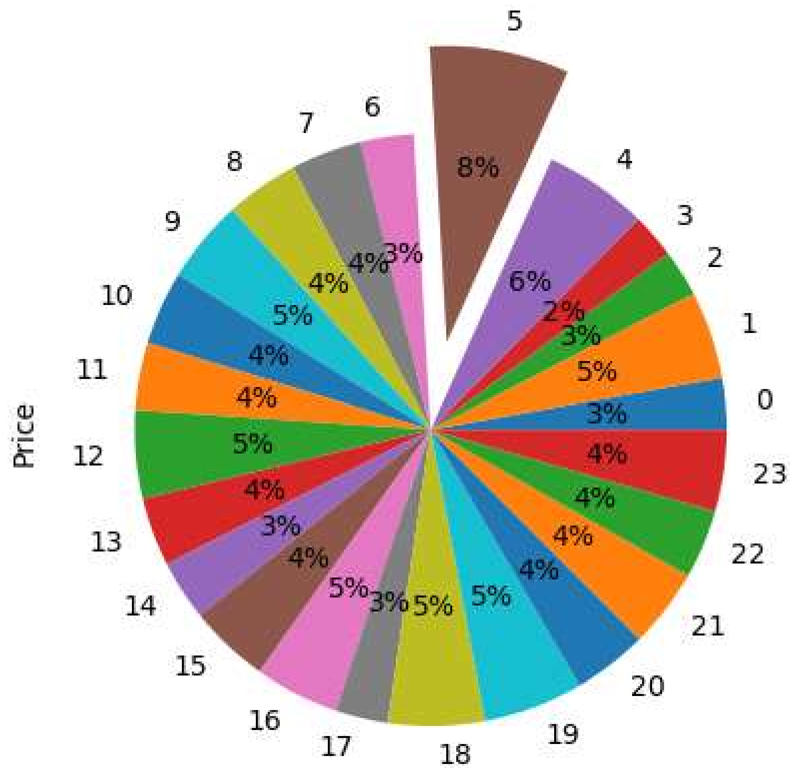


Average prices of flight by Hours

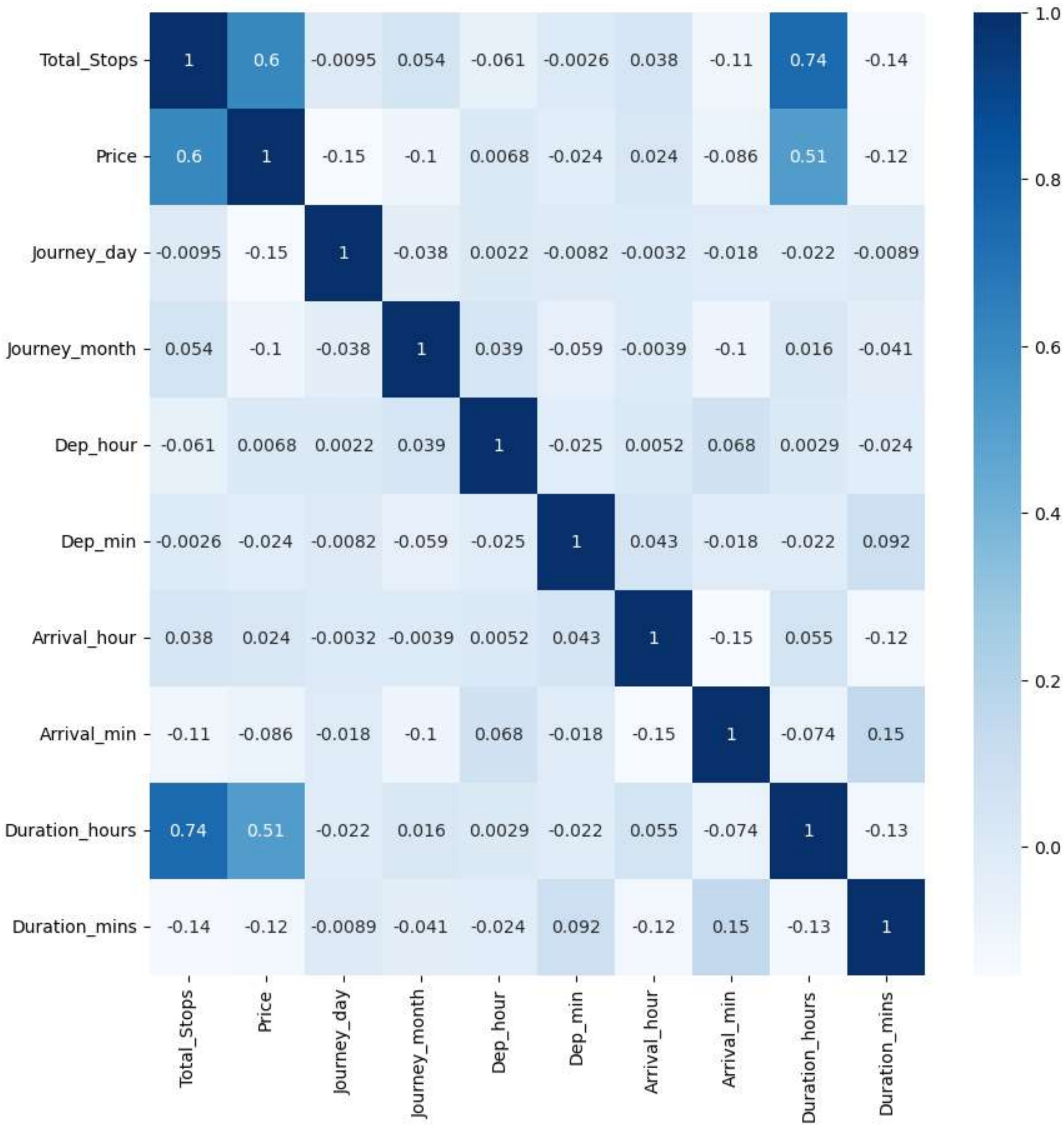
In [31]:
```
A = df.groupby(["Arrival_hour"],sort=True).mean()
print(A["Price"])
expl = [0,0,0,0,0,0.3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
A["Price"].plot(kind='pie', y='Price', autopct='%1.0f%%',explode = expl)
```

```
Arrival_hour
0      5642.447205
1      9657.563327
2      5151.886076
3      4934.638298
4     11485.781623
5     15369.855072
6      5799.423077
7      7837.741007
8      8047.191083
9      9203.018405
10     8124.470588
11     7415.758389
12     9686.433668
13     7575.480519
14     6623.430508
15     8925.412088
16     9272.121622
17     5820.633508
18    10591.204280
19    10972.746617
20     8267.570292
21     8672.246088
22     7575.047913
23     8946.379381
Name: Price, dtype: float64
```

Out[31]: <AxesSubplot:ylabel='Price'>

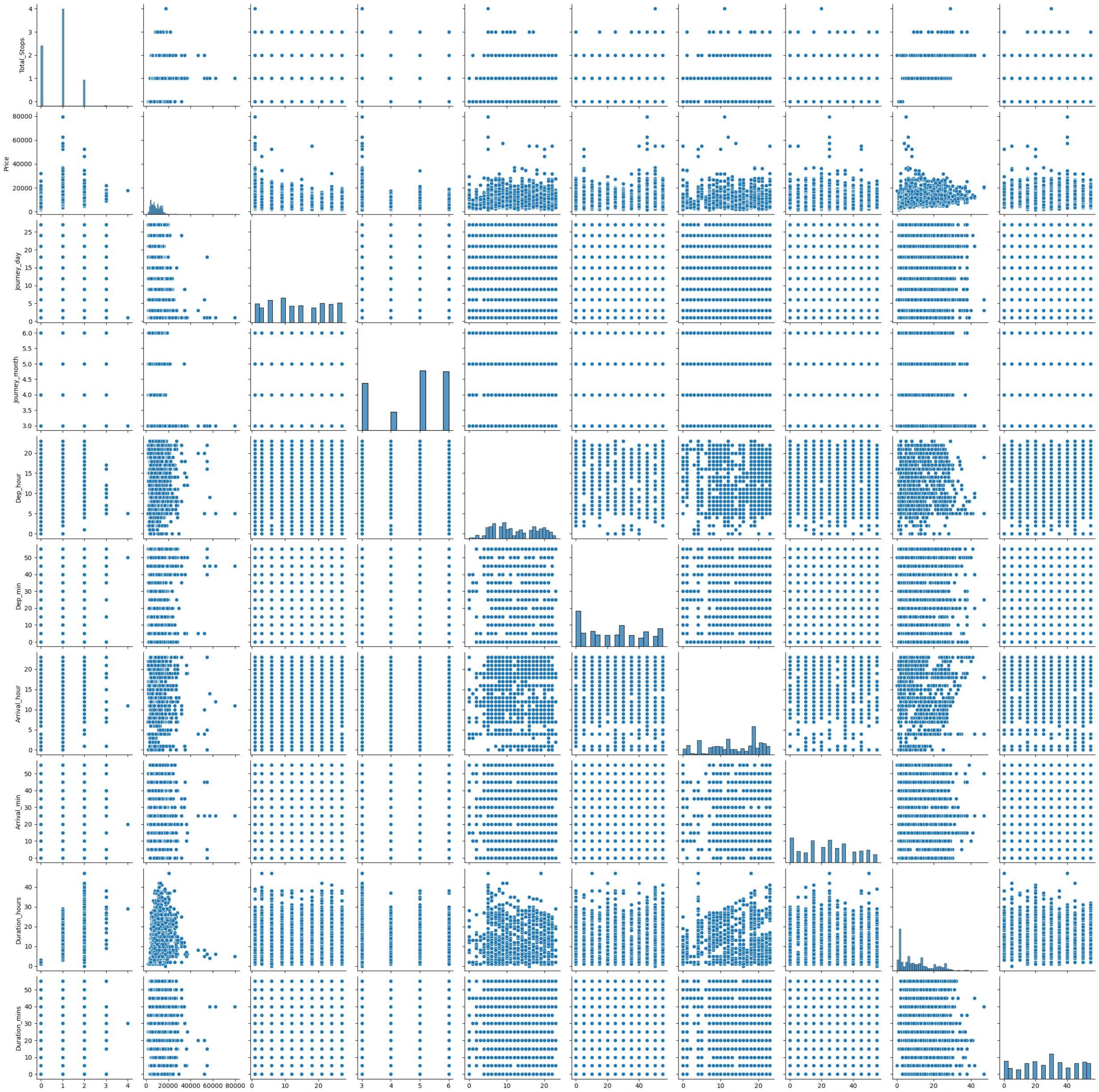

Price
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
3%
5%
3%
2%
6%
8%
3%
4%
4%
5%
4%
4%
5%
4%
3%
4%
5%
3%
5%
5%
4%
4%
4%
4%

In [32]:
```
plt.figure(figsize = (10,10))
sns.heatmap(df.corr(), annot = True, cmap = "Blues")
plt.show()
```



In [33]:
```
sns.pairplot(df)
```

Out[33]: <seaborn.axisgrid.PairGrid at 0x1b126975310>



Encoding Categorical Values

In [34]:
```
from sklearn.preprocessing import OrdinalEncoder
OE = OrdinalEncoder()

df[["Source","Destination","Airline"]] = OE.fit_transform(df[["Source","Desti
```

Spliting X and Y

In [35]:
```
df.columns
```

Out[35]:
```
Index(['Airline', 'Source', 'Destination', 'Total_Stops', 'Price',
       'Journey_day', 'Journey_month', 'Dep_hour', 'Dep_min', 'Arrival_hou
r',
       'Arrival_min', 'Duration_hours', 'Duration_mins'],
      dtype='object')
```

In [36]:
```
X = df.loc[:,['Airline','Source', 'Destination', 'Total_Stops','Journey_day',
       'Arrival_min', 'Duration_hours', 'Duration_mins']]
```

In [37]:
```
Y = df.iloc[:,4]
Y
```

Out[37]:
```
0         3897
1         7662
2        13882
3         6218
4        13302
         ...
10678     4107
10679     4145
10680     7229
10681    12648
10682    11753
Name: Price, Length: 10682, dtype: int64
```

Spliting Training and Testing Data

In [38]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(X,Y,test_size=0.2,random_state=1
```

Scaling Data Using Standard Scaler

In [39]:
```
from sklearn.preprocessing import StandardScaler

ss = StandardScaler()
xtrain = ss.fit_transform(xtrain)
xtest = ss.fit_transform(xtest)
```

Created a Function to implement Algorithms

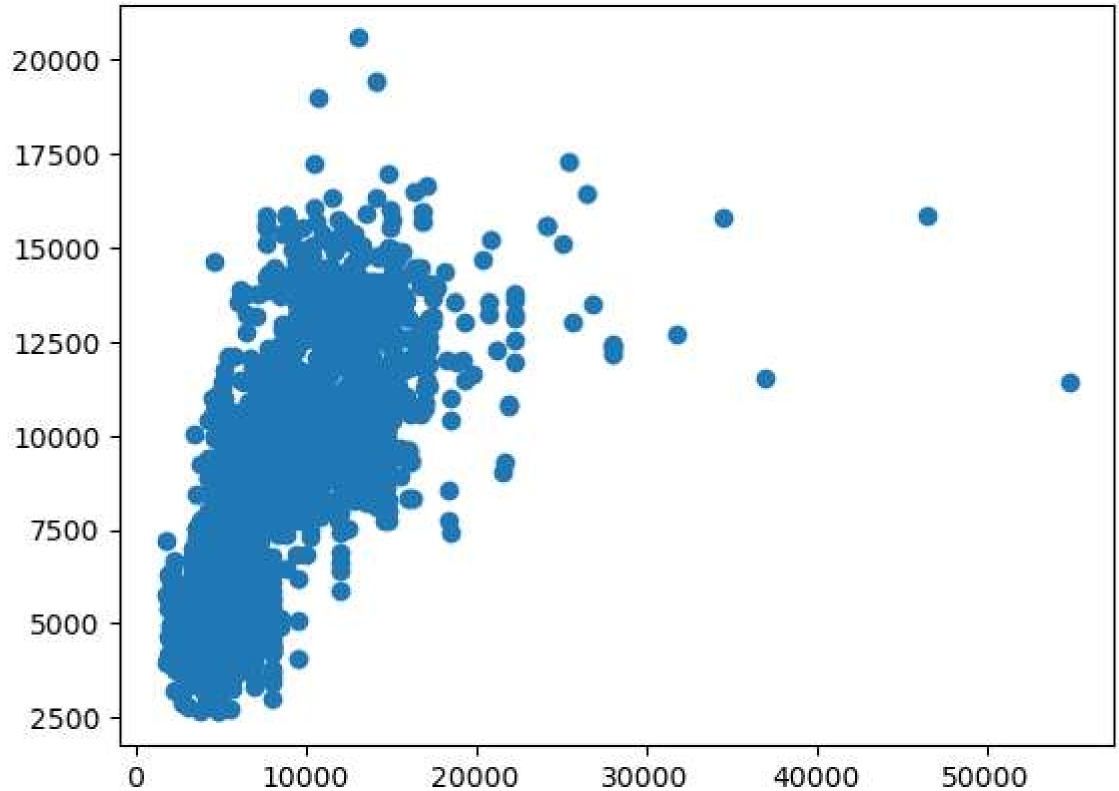
In [40]:
```
def mymodel(model):

    model.fit(xtrain,ytrain)
    ypred = model.predict(xtest)
    training = model.score(xtrain,ytrain)
    testing = model.score(xtest,ytest)
    print()
    mae=mean_absolute_error(ytest,ypred)
    mse=mean_squared_error(ytest,ypred)
    rmse=np.sqrt(mse)
    r2=r2_score(ytest,ypred)
    print(f"MAE:- {mae}\nMSE:- {mse}\nRMSE:- {rmse}\nAccuracy:- {r2}")
    print()
    print(f"Training Error of model is {training}")
    print(f"Testing Error of model is {testing}")
    print()
    print(plt.scatter(ytest,ypred))
    plt.show()
    print()
    print(sns.distplot((ytest-ypred)))
    plt.show()
    return model
```

Created a Model using LINEAR REGRESSION

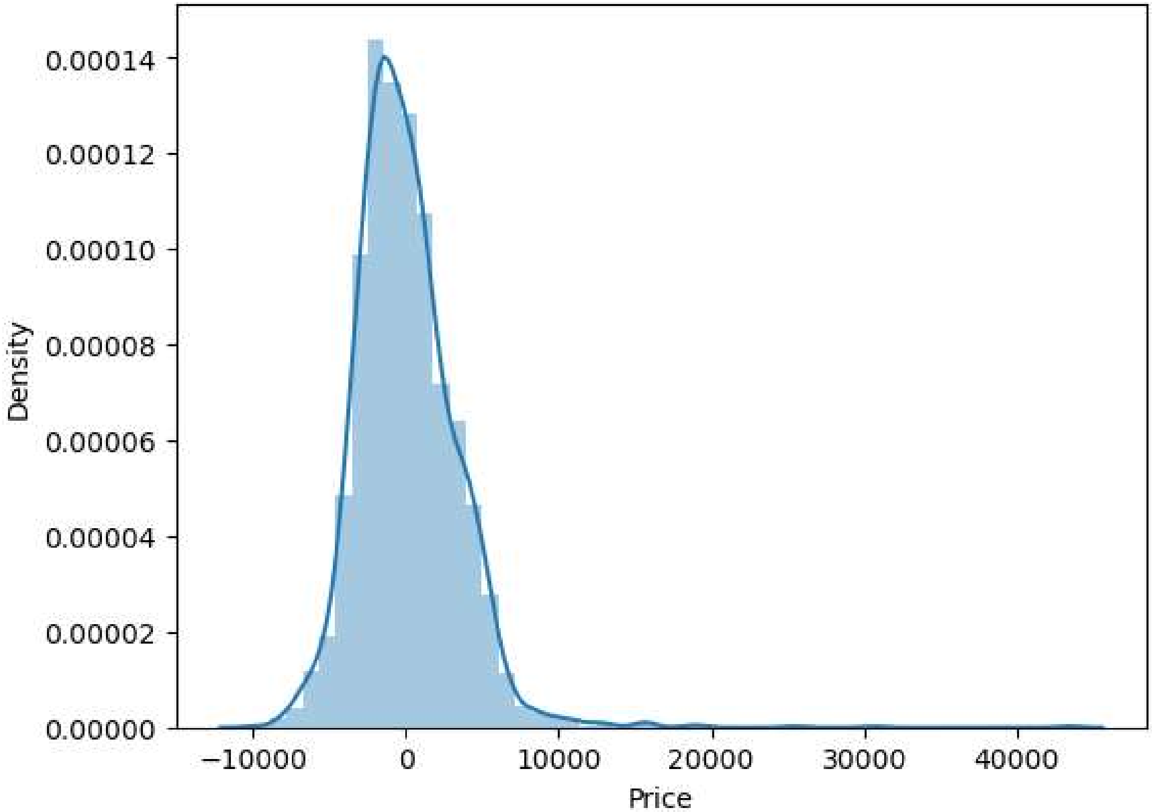
In [41]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
```

In [42]:
```
mymodel(LinearRegression())
```

```
MAE:- 2447.7319425947207
MSE:- 11391461.013739957
RMSE:- 3375.1238516149238
Accuracy:- 0.4446086023196977

Training Error of model is 0.4345788822406066
Testing Error of model is 0.4446086023196977

<matplotlib.collections.PathCollection object at 0x000001B12F2C8760>
```




```
AxesSubplot(0.125,0.11;0.775x0.77)
```

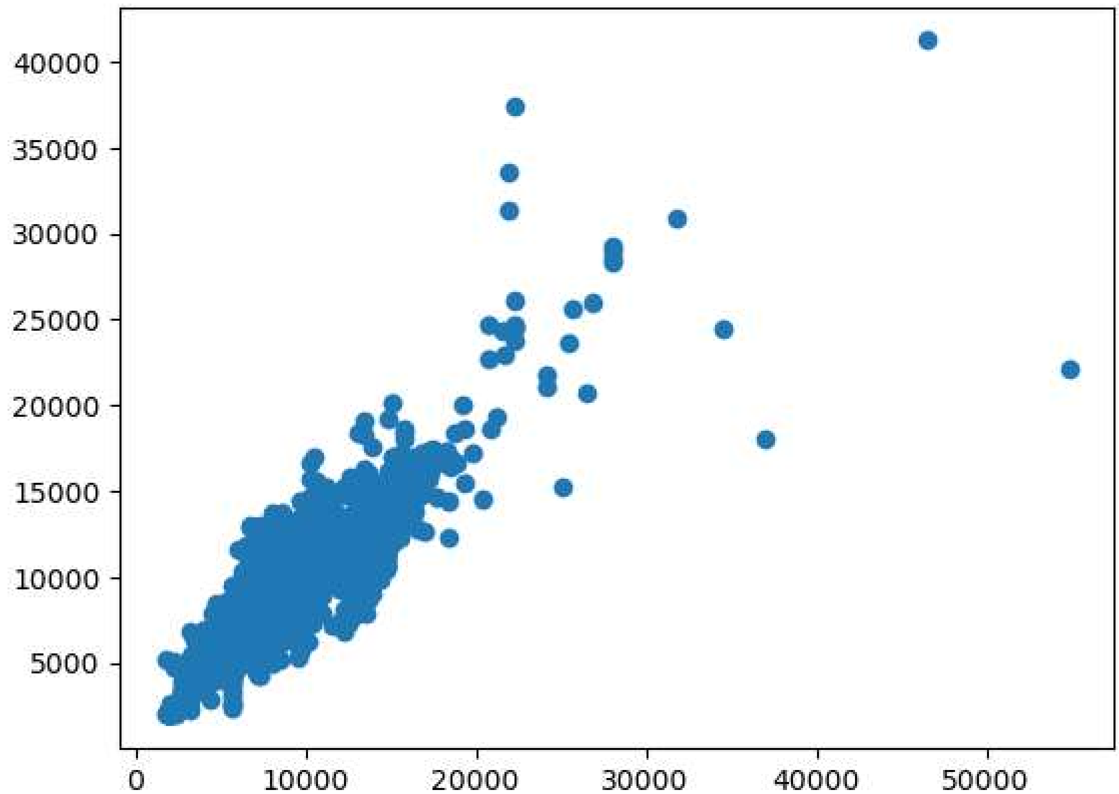


Out[42]:
```
LinearRegression()
```

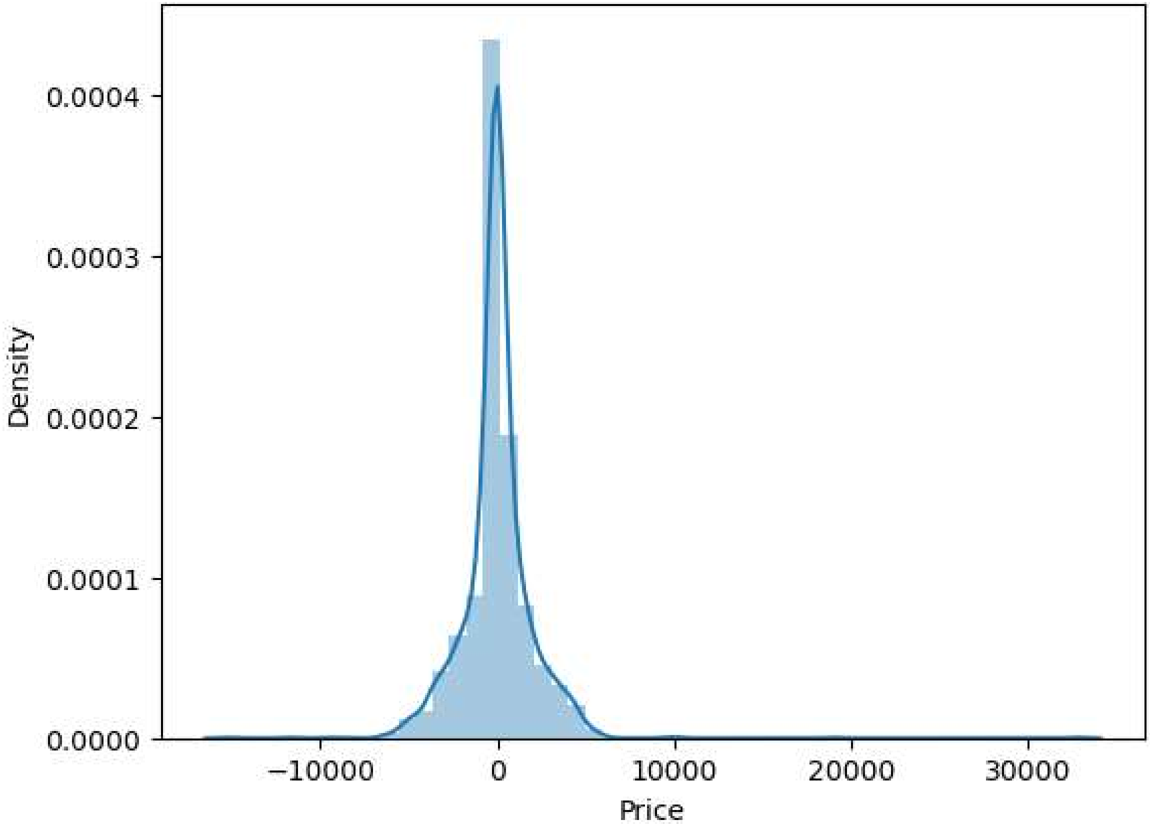
Created a Model Using RANDOM FOREST REGRESSOR

In [43]:
```
from sklearn.ensemble import RandomForestRegressor
mymodel(RandomForestRegressor())
```

```
MAE:- 1213.5347153642385
MSE:- 4032674.3712970787
RMSE:- 2008.1519791333221
Accuracy:- 0.8033867075730882

Training Error of model is 0.9527439236868568
Testing Error of model is 0.8033867075730882

<matplotlib.collections.PathCollection object at 0x000001B132619DF0>
```




```
AxesSubplot(0.125,0.11;0.775x0.77)
```



Out[43]:
```
RandomForestRegressor()
```

Implementing Hyperparameter Tunning using RANDOMIZED SEARCH CV

In [44]:
```
from sklearn.model_selection import RandomizedSearchCV

n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1200, num = 1
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(5, 30, num = 6)]
min_samples_split = [2, 5, 10, 15, 100]
min_samples_leaf = [1, 2, 5, 10]

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}

rf_random = RandomizedSearchCV(estimator = RandomForestRegressor(), param_dis

mymodel(rf_random)
```

```
[CV] END max_depth=25, max_features=auto, min_samples_leaf=2, min_samples
_split=10, n_estimators=400; total time=  12.6s
[CV] END max_depth=25, max_features=auto, min_samples_leaf=2, min_samples
_split=10, n_estimators=400; total time=  12.5s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1, min_samples
_split=100, n_estimators=1000; total time=   7.8s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1, min_samples
_split=100, n_estimators=1000; total time=   7.7s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1, min_samples
_split=100, n_estimators=1000; total time=   7.6s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1, min_samples
_split=100, n_estimators=1000; total time=   7.7s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1, min_samples
_split=100, n_estimators=1000; total time=   7.9s
[CV] END max_depth=20, max_features=sqrt, min_samples_leaf=5, min_samples
_split=10, n_estimators=700; total time=   8.0s
[CV] END max_depth=20, max_features=sqrt, min_samples_leaf=5, min_samples
_split=10, n_estimators=700; total time=   7.7s
[CV] END max_depth=20, max_features=sqrt, min_samples_leaf=5, min_samples
_split=10, n_estimators=700; total time=   7.8s
```

In [45]:
```
rf_random.best_params_
```

Out[45]:
```
{'n_estimators': 400,
 'min_samples_split': 10,
 'min_samples_leaf': 2,
 'max_features': 'auto',
 'max_depth': 25}
```

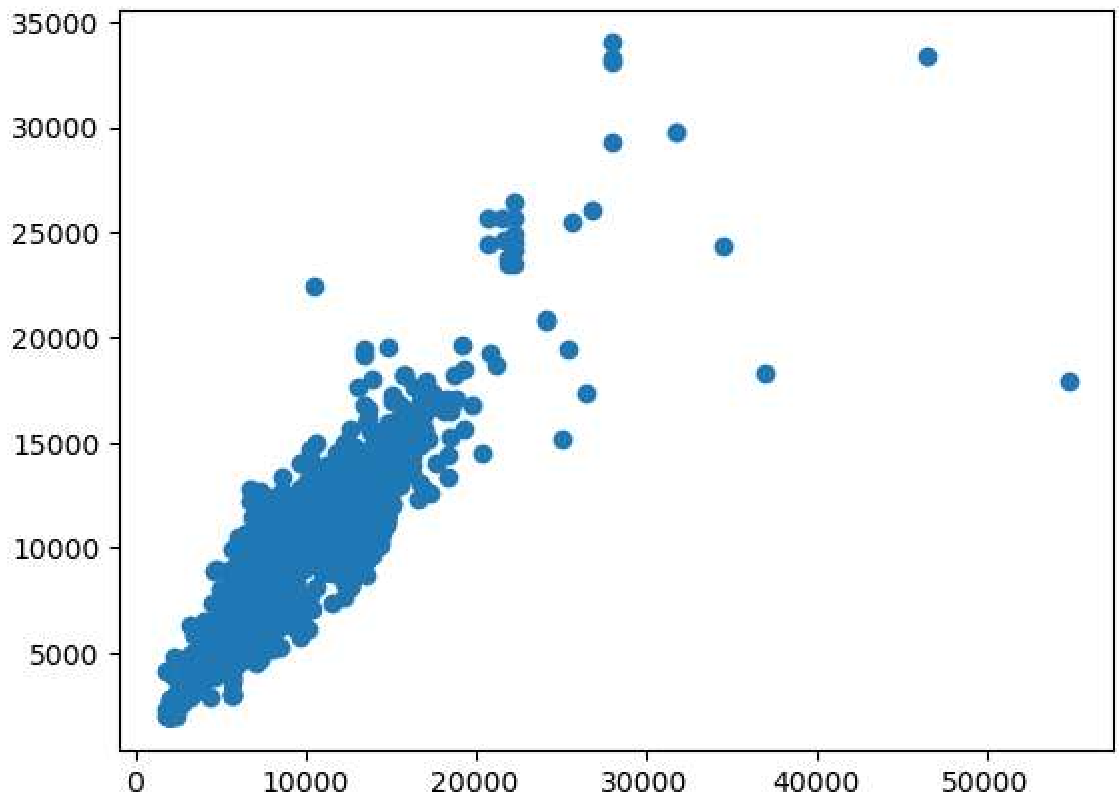
In [46]:
```
Best_rf = rf_random.best_estimator_
```

The Final Model Using RANDOM FOREST REGRESSOR and parameters from

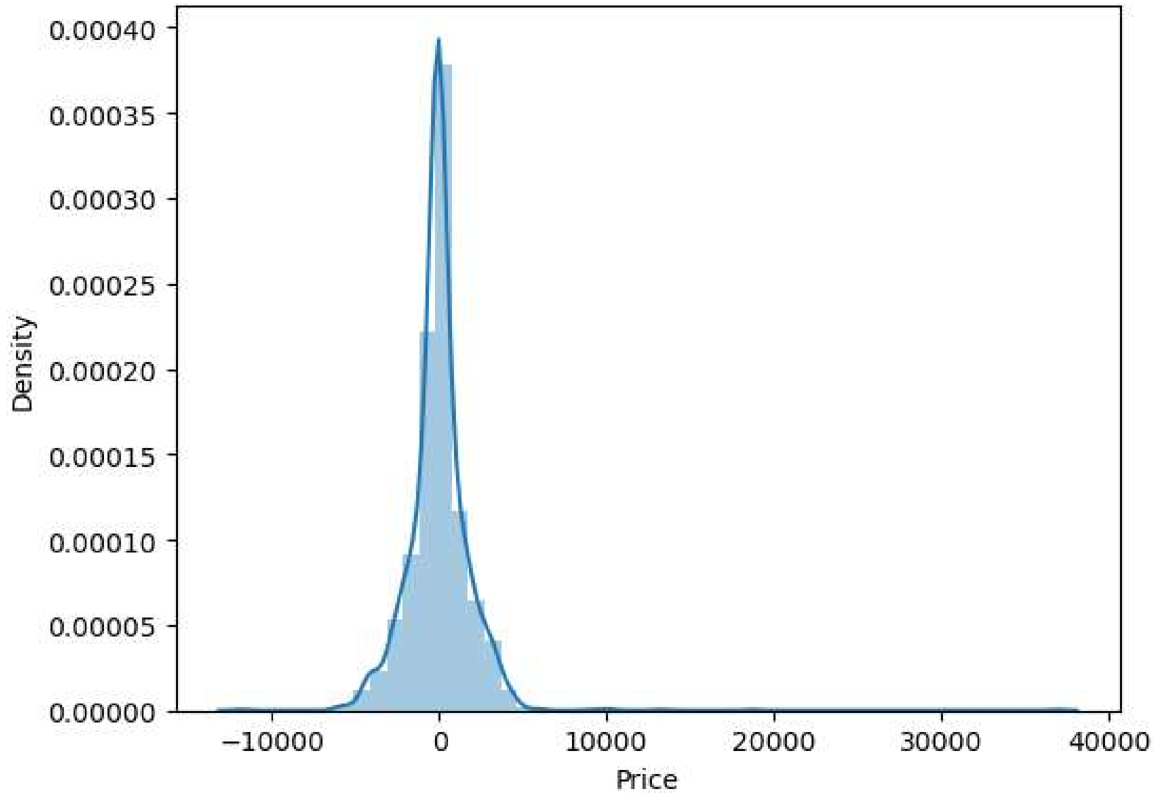
Hyperparameter Tunning using RANDOMIZED SEARCH CV

In [47]:
```
mymodel(Best_rf)
```

```
MAE:- 1163.0400932090806
MSE:- 3639611.1308344803
RMSE:- 1907.7764886994703
Accuracy:- 0.8225505305659389

Training Error of model is 0.8964367686335428
Testing Error of model is 0.8225505305659389

<matplotlib.collections.PathCollection object at 0x000001B12F3315E0>
```




```
AxesSubplot(0.125,0.11;0.775x0.77)
```



Out[47]:
```
RandomForestRegressor(max_depth=25, min_samples_leaf=2, min_samples_split=1
0,
                      n_estimators=400)
```

Conclusion :-

The Best Predicting Model is RANDOM FOREST REGRESSOR with Hyperparameter Tunning using RANDOMIZED SEARCH CV giving an Accuracy Rate of 82%.

In [ ]:

In [ ]: