Airlines Tickets Fare Predictor by Patrick BENIE

March 11, 2021

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[3]:
```
train_data = pd.read_excel('/Users/patrickslearningprogams/Desktop/Python␣
↪Projects/Airlines Ticket Fare/Data_Train.xlsx')
```

[4]:
```
train_data.head()
```

[4]:

	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

[ ]:
```

```

[5]:
```
# Deal with missing values
```

[6]:
```
train_data.shape # Gives you the shape of your table, 10683rows and 11columns
```

[6]:
```
(10683, 11)
```

[7]:
```
# cleaning the data
```

[8]:
```
# Checking for missing values in the dataset
train_data.isna().sum()
```

[8]:
```
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
```

[9]:
```
# removing missing values
train_data.dropna(inplace=True)
```

[10]:
```
train_data.isna().sum()
```

[10]:
```
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
```

[11]:
```
# check different data types
train_data.dtypes
```

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

[ ]:

[12]:
```
# create function to give appropiate datetime type
def chante_to_datetime(col):
    train_data[col]=pd.to_datetime(train_data[col])
```

[13]:
```
train_data.columns
```

[13]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info', 'Price'],
      dtype='object')
```

[14]:
```
# apply function
for i in ['Date_of_Journey','Dep_Time', 'Arrival_Time']:
    chante_to_datetime(i)
```

[15]:
```
train_data.dtypes
```

[15]:
```
Airline                    object
Date_of_Journey    datetime64[ns]
Source                     object
Destination                object
Route                      object
Dep_Time           datetime64[ns]
Arrival_Time       datetime64[ns]
Duration                   object
Total_Stops                object
Additional_Info            object
Price                       int64
dtype: object
```

[ ]:

[16]:
```
#splitting date of journey into days and months
train_data['Journey_day'] = train_data['Date_of_Journey'].dt.day
train_data['Journey_month'] = train_data['Date_of_Journey'].dt.month
```

[17]:
```
train_data.head()
```

[17]:

	Airline	Date_of_Journey	Source	Destination	Route	\
0	IndiGo	2019-03-24	Banglore	New Delhi	BLR → DEL	
1	Air India	2019-01-05	Kolkata	Banglore	CCU → IXR → BBI → BLR	
2	Jet Airways	2019-09-06	Delhi	Cochin	DEL → LKO → BOM → COK	
3	IndiGo	2019-12-05	Kolkata	Banglore	CCU → NAG → BLR	
4	IndiGo	2019-01-03	Banglore	New Delhi	BLR → NAG → DEL	

```
             Dep_Time        Arrival_Time Duration Total_Stops  \
0 2021-03-11 22:20:00 2021-03-22 01:10:00   2h 50m    non-stop
1 2021-03-11 05:50:00 2021-03-11 13:15:00   7h 25m     2 stops
2 2021-03-11 09:25:00 2021-06-10 04:25:00      19h     2 stops
3 2021-03-11 18:05:00 2021-03-11 23:30:00   5h 25m      1 stop
4 2021-03-11 16:50:00 2021-03-11 21:35:00   4h 45m      1 stop

  Additional_Info  Price  Journey_day  Journey_month
0         No info   3897           24              3
1         No info   7662            5              1
2         No info  13882            6              9
3         No info   6218            5             12
4         No info  13302            3              1
```

[18]:
```
#dropping Date_of_Journey from the table
train_data.drop('Date_of_Journey', axis=1, inplace=True)
```

[ ]:
```

```

[19]:
```
#create functions to extract hours and minutes from Dep_time and Arrival_time␣
↪and drop them from the table
def extract_hour(df,col):
    df[col+'_hour']=df[col].dt.hour

def extract_minute(df,col):
    df[col+'_minute']=df[col].dt.minute

def drop_column(df,col):
    df.drop(col,axis=1,inplace=True)
```

[ ]:
```

```

[20]:
```
#apply the functions to Dep_Time
extract_hour(train_data, 'Dep_Time')
extract_minute(train_data, 'Dep_Time')
drop_column(train_data, 'Dep_Time')
```

[21]:
```
#apply the functions to Arrival_Time
extract_hour(train_data, 'Arrival_Time')
extract_minute(train_data, 'Arrival_Time')
drop_column(train_data, 'Arrival_Time')
```

[22]:
```
train_data.head()
```

[22]:
```
       Airline    Source Destination                  Route Duration  \
0       IndiGo  Banglore   New Delhi              BLR → DEL   2h 50m
1    Air India   Kolkata    Banglore  CCU → IXR → BBI → BLR   7h 25m
```

```
2  Jet Airways     Delhi      Cochin  DEL → LKO → BOM → COK      19h
3       IndiGo   Kolkata    Banglore        CCU → NAG → BLR   5h 25m
4       IndiGo  Banglore   New Delhi        BLR → NAG → DEL   4h 45m

  Total_Stops Additional_Info  Price  Journey_day  Journey_month  \
0    non-stop         No info   3897           24              3
1     2 stops         No info   7662            5              1
2     2 stops         No info  13882            6              9
3      1 stop         No info   6218            5             12
4      1 stop         No info  13302            3              1

   Dep_Time_hour  Dep_Time_minute  Arrival_Time_hour  Arrival_Time_minute
0             22               20                  1                   10
1              5               50                 13                   15
2              9               25                  4                   25
3             18                5                 23                   30
4             16               50                 21                   35
```

[ ]:

[23]:
```
#creating a standard of 0h 00m by assigning '0h' or '0m' to missing hours or␣
 ↪minutes
#using the split function to access data separately
duration=list(train_data['Duration'])

for i in range(len(duration)):
    if len(duration[i].split(' '))==2:
        pass
    else:
        if 'h' in duration[i]:
            duration[i]=duration[i] + ' 0m'
        else:
            duration[i]='0h '+ duration[i]
```

[24]:
```
train_data['Duration'] =duration
```

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

[25]:
```
       Airline    Source Destination                  Route Duration  \
0       IndiGo  Banglore   New Delhi              BLR → DEL   2h 50m
1    Air India   Kolkata    Banglore  CCU → IXR → BBI → BLR   7h 25m
2  Jet Airways     Delhi      Cochin  DEL → LKO → BOM → COK   19h 0m
3       IndiGo   Kolkata    Banglore        CCU → NAG → BLR   5h 25m
4       IndiGo  Banglore   New Delhi        BLR → NAG → DEL   4h 45m

  Total_Stops Additional_Info  Price  Journey_day  Journey_month  \
0    non-stop         No info   3897           24              3
```

```
1     2 stops         No info   7662            5              1
2     2 stops         No info  13882            6              9
3      1 stop         No info   6218            5             12
4      1 stop         No info  13302            3              1

   Dep_Time_hour  Dep_Time_minute  Arrival_Time_hour  Arrival_Time_minute
0             22               20                  1                   10
1              5               50                 13                   15
2              9               25                  4                   25
3             18                5                 23                   30
4             16               50                 21                   35
```

[ ]:

[26]:
```
#functions to access the hours and minutes of the 'Duration' data
def hour(x):
    return x.split(' ')[0][0:-1]

def minute(x):
    return x.split(' ')[1][0:-1]
```

[27]:
```
train_data['Duration_hours'] = train_data['Duration'].apply(hour)
train_data['Duration_mins'] = train_data['Duration'].apply(minute)
```

[28]:
```
train_data.head()
```

[28]:
```
       Airline    Source Destination                  Route Duration  \
0       IndiGo  Banglore   New Delhi              BLR → DEL   2h 50m
1    Air India   Kolkata    Banglore  CCU → IXR → BBI → BLR   7h 25m
2  Jet Airways     Delhi      Cochin  DEL → LKO → BOM → COK   19h 0m
3       IndiGo   Kolkata    Banglore        CCU → NAG → BLR   5h 25m
4       IndiGo  Banglore   New Delhi        BLR → NAG → DEL   4h 45m

  Total_Stops Additional_Info  Price  Journey_day  Journey_month  \
0    non-stop         No info   3897           24              3
1     2 stops         No info   7662            5              1
2     2 stops         No info  13882            6              9
3      1 stop         No info   6218            5             12
4      1 stop         No info  13302            3              1

   Dep_Time_hour  Dep_Time_minute  Arrival_Time_hour  Arrival_Time_minute  \
0             22               20                  1                   10
1              5               50                 13                   15
2              9               25                  4                   25
3             18                5                 23                   30
4             16               50                 21                   35
```

```
  Duration_hours Duration_mins
0              2            50
1              7            25
2             19             0
3              5            25
4              4            45
```

[29]:
```
drop_column(train_data, 'Duration')
```

[30]:
```
train_data.dtypes
```

[30]:
```
Airline               object
Source                object
Destination           object
Route                 object
Total_Stops           object
Additional_Info       object
Price                  int64
Journey_day            int64
Journey_month          int64
Dep_Time_hour          int64
Dep_Time_minute        int64
Arrival_Time_hour      int64
Arrival_Time_minute    int64
Duration_hours        object
Duration_mins         object
dtype: object
```

[31]:
```
#changing duration hours and minutes datatype from object to int
train_data['Duration_hours']=train_data['Duration_hours'].astype(int)
train_data['Duration_mins']=train_data['Duration_mins'].astype(int)
```

[32]:
```
train_data.dtypes
```

[32]:
```
Airline               object
Source                object
Destination           object
Route                 object
Total_Stops           object
Additional_Info       object
Price                  int64
Journey_day            int64
Journey_month          int64
Dep_Time_hour          int64
Dep_Time_minute        int64
Arrival_Time_hour      int64
Arrival_Time_minute    int64
```

```
Duration_hours          int64
Duration_mins           int64
dtype: object
```

[33]:
```
#differentiating categorical columns from numerical columns
#assigning all columns of type object to cat_col
cat_col = [col for col in train_data.columns if train_data[col].dtypes=='O']
cat_col
```

[33]:
```
['Airline', 'Source', 'Destination', 'Route', 'Total_Stops', 'Additional_Info']
```

[34]:
```
cont_col = [col for col in train_data.columns if train_data[col].dtypes!='O']
cont_col
```

[34]:
```
['Price',
 'Journey_day',
 'Journey_month',
 'Dep_Time_hour',
 'Dep_Time_minute',
 'Arrival_Time_hour',
 'Arrival_Time_minute',
 'Duration_hours',
 'Duration_mins']
```

[ ]:
```

```

[35]:
```
# in this next section we will handle Categorical data
# and perform feature encoding data on data
## two kinds of categorical data: Nominal data [normal data i.e name of␣
 ↪countries (doesnt have any hierachy)] -
#perform Onehot encoding
#ordinal data [ data with some kind of order i.e good, better, best]
#perform labelEncoding
```

[ ]:
```

```

[36]:
```
categorical = train_data[cat_col]
```

[37]:
```
categorical.head()
```

[37]:

	Airline	Source	Destination	Route	Total_Stops
0	IndiGo	Banglore	New Delhi	BLR → DEL	non-stop
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	2 stops
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	2 stops
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	1 stop
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	1 stop

```
  Additional_Info
0         No info
1         No info
2         No info
3         No info
4         No info
```

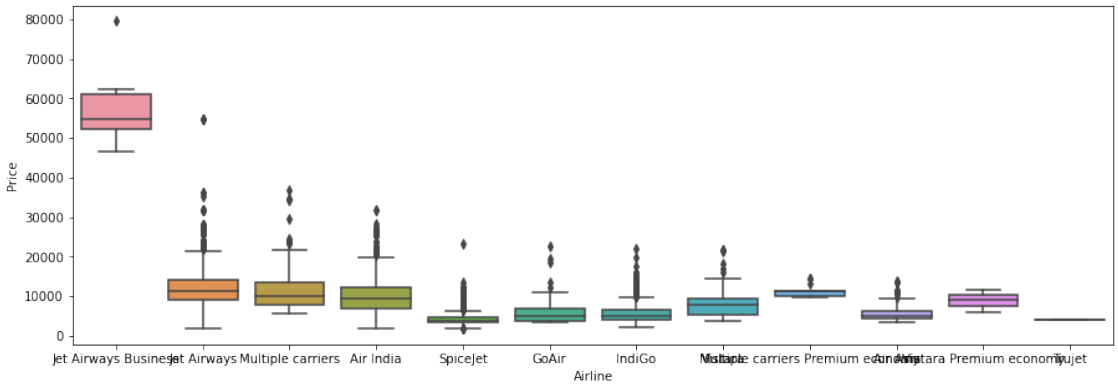
[38]:
```
#get a count of every feature of the airline column
categorical['Airline'].value_counts()
```

[38]:
```
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
```

[ ]:
```

```

[39]:
```
#find the relation about the airline with the price using a plot
#sort the values in descending order according to the price
plt.figure(figsize=(15,5)) #setting the display windows
sns.boxplot(x='Airline', y='Price', data=train_data.
 ↪sort_values('Price',ascending=False))
```

[39]:
```
<AxesSubplot:xlabel='Airline', ylabel='Price'>
```



[40]:
```
#using onehot encoding for the machine learning to understand the data
#machine learning doesnt understang string only numerical data
Airline = pd.get_dummies(categorical['Airline'], drop_first=True) #drop_first␣
↪to avoid duplicates
```

[41]:
```
Airline.head()
```

[41]:

	Air India	GoAir	IndiGo	Jet Airways	Jet Airways Business	\
0	0	0	1	0	0	
1	1	0	0	0	0	
2	0	0	0	1	0	
3	0	0	1	0	0	
4	0	0	1	0	0	

	Multiple carriers	Multiple carriers Premium economy	SpiceJet	Trujet	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Vistara	Vistara Premium economy
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

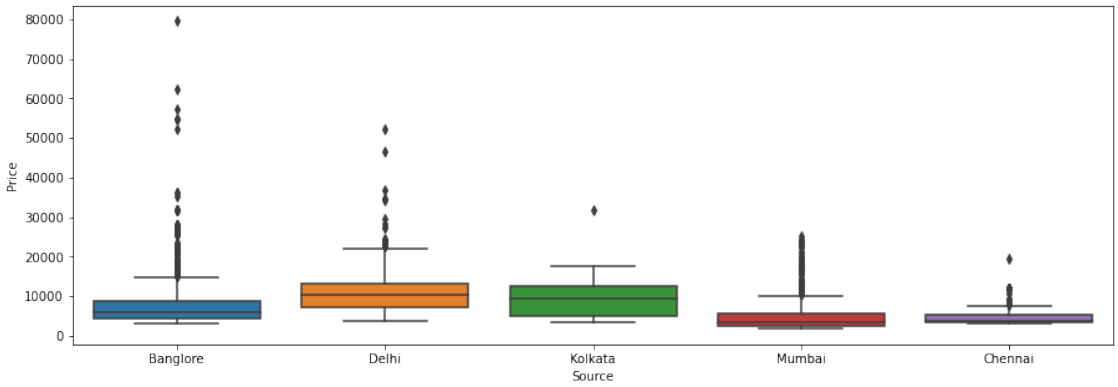
[ ]:
```

```

[42]:
```
categorical['Source'].value_counts()
```

[42]:
```
Delhi       4536
Kolkata     2871
Banglore    2197
Mumbai       697
Chennai      381
Name: Source, dtype: int64
```

[43]:
```
plt.figure(figsize=(15,5))
sns.boxplot(x='Source', y='Price', data=train_data.
↪sort_values('Price',ascending=False))
```

[43]:
```
<AxesSubplot:xlabel='Source', ylabel='Price'>
```



[44]:
```
Source = pd.get_dummies(categorical['Source'], drop_first=True)
Source.head()
```

[44]:

	Chennai	Delhi	Kolkata	Mumbai
0	0	0	0	0
1	0	0	1	0
2	0	1	0	0
3	0	0	1	0
4	0	0	0	0

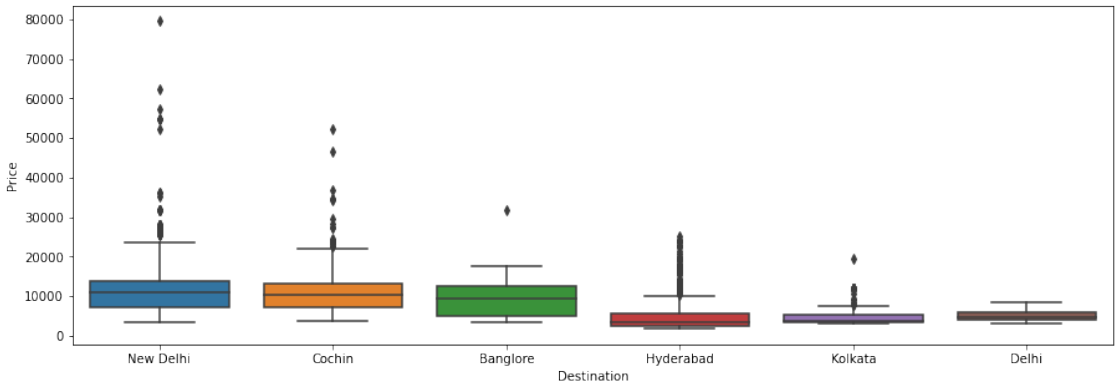
[ ]:
```

```

[45]:
```
categorical['Destination'].value_counts()
```

[45]:
```
Cochin       4536
Banglore     2871
Delhi        1265
New Delhi     932
Hyderabad     697
Kolkata       381
Name: Destination, dtype: int64
```

[46]:
```
plt.figure(figsize=(15,5))
sns.boxplot(x='Destination', y='Price', data=train_data.
 ↪sort_values('Price',ascending=False))
```

[46]:
```
<AxesSubplot:xlabel='Destination', ylabel='Price'>
```



[47]:
```
Destination = pd.get_dummies(categorical['Destination'], drop_first=True)
Destination.head()
```

[47]:

	Cochin	Delhi	Hyderabad	Kolkata	New Delhi
0	0	0	0	0	1
1	0	0	0	0	0
2	1	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	1

[ ]:
```

```

[48]:
```
#access the 'Route' column
categorical['Route']
```

[48]:
```
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
```

[49]:
```
#remove the arrows as machine learning will not comprehend them
categorical['Route'].str.split('→')
```

[49]:
```
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
```

[50]:
```
#access first element of the lists
categorical['Route'].str.split('→').str[0]
```

[50]:
```
0         BLR
1         CCU
2         DEL
3         CCU
4         BLR
          …
10678     CCU
10679     CCU
10680     BLR
10681     BLR
10682     DEL
Name: Route, Length: 10682, dtype: object
```

[51]:
```
import warnings
from warnings import filterwarnings
filterwarnings ('ignore')
```

[52]:
```
categorical['Route_1'] = categorical['Route'].str.split('→').str[0]
categorical['Route_2'] = categorical['Route'].str.split('→').str[1]
categorical['Route_3'] = categorical['Route'].str.split('→').str[2]
categorical['Route_4'] = categorical['Route'].str.split('→').str[3]
categorical['Route_5'] = categorical['Route'].str.split('→').str[4]
```

[53]:
```
categorical.head()
```

[53]:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info	Route_1	Route_2	Route_3	Route_4	Route_5
0	IndiGo	Banglore	New Delhi	BLR → DEL	non-stop	No info	BLR	DEL			
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	2 stops	No info	CCU	IXR	BBI	BLR	
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	2 stops	No info	DEL	LKO	BOM	COK	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	1 stop	No info	CCU	NAG	BLR		
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	1 stop	No info	BLR	NAG	DEL		

```
0         No info    BLR      DEL     NaN     NaN     NaN
1         No info    CCU      IXR     BBI     BLR     NaN
2         No info    DEL      LKO     BOM     COK     NaN
3         No info    CCU      NAG      BLR    NaN     NaN
4         No info    BLR      NAG      DEL    NaN     NaN
```

[54]:
```
drop_column(categorical, 'Route')
```

[55]:
```
categorical.head()
```

[55]:
```
       Airline    Source Destination Total_Stops Additional_Info Route_1  \
0       IndiGo  Banglore   New Delhi    non-stop         No info    BLR
1    Air India   Kolkata    Banglore     2 stops         No info    CCU
2  Jet Airways     Delhi      Cochin     2 stops         No info    DEL
3       IndiGo   Kolkata    Banglore      1 stop         No info    CCU
4       IndiGo  Banglore   New Delhi      1 stop         No info    BLR

  Route_2 Route_3 Route_4 Route_5
0     DEL     NaN     NaN     NaN
1    IXR      BBI      BLR     NaN
2    LKO      BOM      COK     NaN
3    NAG       BLR     NaN     NaN
4    NAG       DEL     NaN     NaN
```

[ ]:
```

```

[56]:
```
#check for missing values
#Route_3,4,5 contain missing values
categorical.isnull().sum()
```

[56]:
```
Airline              0
Source               0
Destination          0
Total_Stops          0
Additional_Info      0
Route_1              0
Route_2              0
Route_3           3491
Route_4           9116
Route_5          10636
dtype: int64
```

[57]:
```
#replace missing values with None using fillna method
#inplace=True to update dataframe
for i in ['Route_3','Route_4','Route_5']:
    categorical[i].fillna('None', inplace=True)
```

[58]:
```
#no missing values anymore
categorical.isnull().sum()
```

[58]:
```
Airline            0
Source             0
Destination        0
Total_Stops        0
Additional_Info    0
Route_1            0
Route_2            0
Route_3            0
Route_4            0
Route_5            0
dtype: int64
```

[ ]:
```

```

[59]:
```
for i in categorical.columns:
    print(f'{i} has total {len(categorical[i].value_counts())} categories')
```

```
Airline has total 12 categories
Source has total 5 categories
Destination has total 6 categories
Total_Stops has total 5 categories
Additional_Info has total 10 categories
Route_1 has total 5 categories
Route_2 has total 45 categories
Route_3 has total 30 categories
Route_4 has total 14 categories
Route_5 has total 6 categories
```

[60]:
```
#because of the high number of categories in Route_2,3,4 using onehot encoding␣
 ↪will create a whole lot more number
#of columns.and the data will become huge. So we need to be using labelEncoding
```

[61]:
```
from sklearn.preprocessing import LabelEncoder
```

[62]:
```
encoder = LabelEncoder()
```

[63]:
```
categorical.columns
```

[63]:
```
Index(['Airline', 'Source', 'Destination', 'Total_Stops', 'Additional_Info',
       'Route_1', 'Route_2', 'Route_3', 'Route_4', 'Route_5'],
      dtype='object')
```

[64]:
```
for i in ['Route_1', 'Route_2', 'Route_3', 'Route_4', 'Route_5']:
    categorical[i]=encoder.fit_transform(categorical[i])
```

[65]:
```
categorical.head()
```

[65]:
```
        Airline    Source Destination Total_Stops Additional_Info  Route_1  \
0        IndiGo  Banglore   New Delhi    non-stop         No info        0
1     Air India   Kolkata    Banglore     2 stops         No info        2
2   Jet Airways     Delhi      Cochin     2 stops         No info        3
3        IndiGo   Kolkata    Banglore      1 stop         No info        2
4        IndiGo  Banglore   New Delhi      1 stop         No info        0

   Route_2  Route_3  Route_4  Route_5
0       13       29       13        5
1       25        1        3        5
2       32        4        5        5
3       34        3       13        5
4       34        8       13        5
```

[66]:
```
#drop Additional_info column since there is no info provided
drop_column(categorical, 'Additional_Info')
```

[67]:
```
#to see every unique item on the 'Total_Stops' column
categorical['Total_Stops'].unique()
```

[67]:
```
array(['non-stop', '2 stops', '1 stop', '3 stops', '4 stops'],
      dtype=object)
```

[68]:
```
#create a dictionnary to assign stops to number
dict = {'non-stop':0, '2 stops':2, '1 stop':1, '3 stops':3, '4 stops':4}
```

[69]:
```
#map dict to Total_Stops and update column
categorical['Total_Stops']=categorical['Total_Stops'].map(dict)
```

[70]:
```
categorical.head()
```

[70]:
```
        Airline    Source Destination  Total_Stops  Route_1  Route_2  Route_3  \
0        IndiGo  Banglore   New Delhi            0        0       13       29
1     Air India   Kolkata    Banglore            2        2       25        1
2   Jet Airways     Delhi      Cochin            2        3       32        4
3        IndiGo   Kolkata    Banglore            1        2       34        3
4        IndiGo  Banglore   New Delhi            1        0       34        8

   Route_4  Route_5
0       13        5
1        3        5
2        5        5
3       13        5
4       13        5
```

[ ]:

[71]:
```
#now we need to concatenate all the dataframes we've created (categorical +␣
 ↪continuous)
#concatenate in a vertical fashion(axis=1)
data_train=pd.
 ↪concat([categorical,Airline,Source,Destination,train_data[cont_col]],axis=1)
```

[72]:
```
data_train.head()
```

[72]:

	Airline	Source	Destination	Total_Stops	Route_1	Route_2	Route_3	\
0	IndiGo	Banglore	New Delhi	0	0	13	29	
1	Air India	Kolkata	Banglore	2	2	25	1	
2	Jet Airways	Delhi	Cochin	2	3	32	4	
3	IndiGo	Kolkata	Banglore	1	2	34	3	
4	IndiGo	Banglore	New Delhi	1	0	34	8	

	Route_4	Route_5	Air India	…	New Delhi	Price	Journey_day	\
0	13	5	0	…	1	3897	24	
1	3	5	1	…	0	7662	5	
2	5	5	0	…	0	13882	6	
3	13	5	0	…	0	6218	5	
4	13	5	0	…	1	13302	3	

	Journey_month	Dep_Time_hour	Dep_Time_minute	Arrival_Time_hour	\
0	3	22	20	1	
1	1	5	50	13	
2	9	9	25	4	
3	12	18	5	23	
4	1	16	50	21	

	Arrival_Time_minute	Duration_hours	Duration_mins
0	10	2	50
1	15	7	25
2	25	19	0
3	30	5	25
4	35	4	45

[5 rows x 38 columns]

[73]:
```
drop_column(data_train, 'Airline')
drop_column(data_train, 'Source')
drop_column(data_train, 'Destination')
```

[74]:
```
data_train.head()
```

[74]:
```
   Total_Stops  Route_1  Route_2  Route_3  Route_4  Route_5  Air India  GoAir  \
0            0        0       13       29       13        5          0      0
1            2        2       25        1        3        5          1      0
2            2        3       32        4        5        5          0      0
3            1        2       34        3       13        5          0      0
4            1        0       34        8       13        5          0      0

   IndiGo  Jet Airways  …  New Delhi  Price  Journey_day  Journey_month  \
0       1            0  …          1   3897           24              3
1       0            0  …          0   7662            5              1
2       0            1  …          0  13882            6              9
3       1            0  …          0   6218            5             12
4       1            0  …          1  13302            3              1

   Dep_Time_hour  Dep_Time_minute  Arrival_Time_hour  Arrival_Time_minute  \
0             22               20                  1                   10
1              5               50                 13                   15
2              9               25                  4                   25
3             18                5                 23                   30
4             16               50                 21                   35

   Duration_hours  Duration_mins
0               2             50
1               7             25
2              19              0
3               5             25
4               4             45

[5 rows x 35 columns]
```

[75]:
```
#to display all the columns
pd.set_option('display.max_columns',35)
data_train.head()
```

[75]:
```
   Total_Stops  Route_1  Route_2  Route_3  Route_4  Route_5  Air India  GoAir  \
0            0        0       13       29       13        5          0      0
1            2        2       25        1        3        5          1      0
2            2        3       32        4        5        5          0      0
3            1        2       34        3       13        5          0      0
4            1        0       34        8       13        5          0      0

   IndiGo  Jet Airways  Jet Airways Business  Multiple carriers  \
0       1            0                     0                  0
1       0            0                     0                  0
2       0            1                     0                  0
3       1            0                     0                  0
4       1            0                     0                  0
```

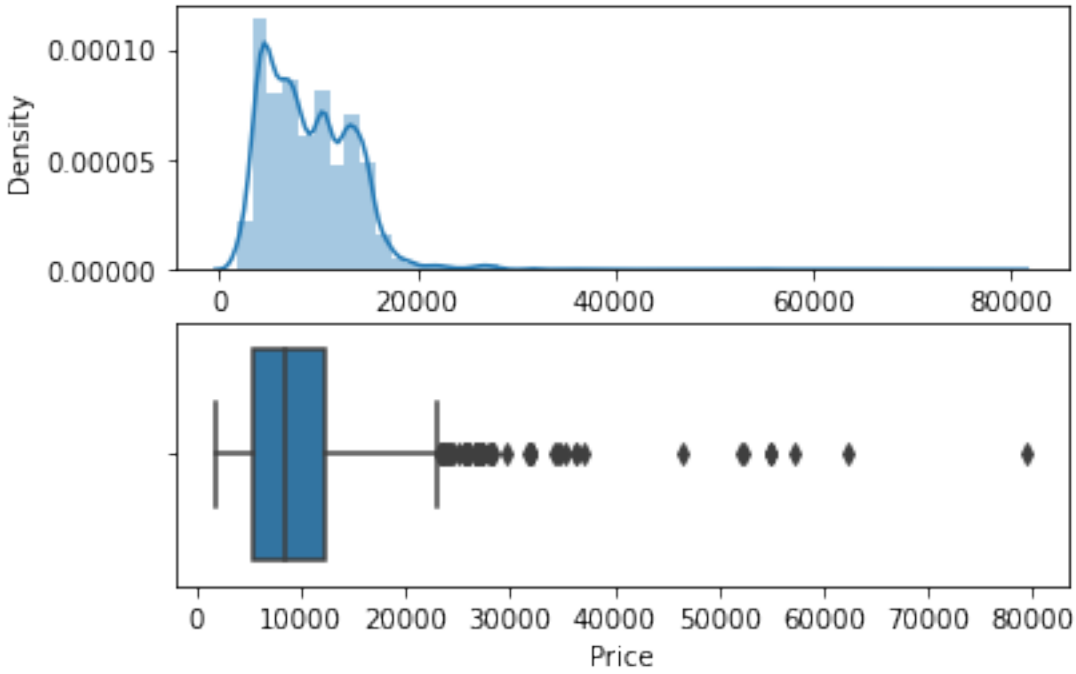
```
   Multiple carriers Premium economy  SpiceJet  Trujet  Vistara  \
0                                  0         0       0        0
1                                  0         0       0        0
2                                  0         0       0        0
3                                  0         0       0        0
4                                  0         0       0        0

   Vistara Premium economy  Chennai  Delhi  Kolkata  Mumbai  Cochin  Delhi  \
0                        0        0      0        0       0       0      0
1                        0        0      0        1       0       0      0
2                        0        0      1        0       0       1      0
3                        0        0      0        1       0       0      0
4                        0        0      0        0       0       0      0

   Hyderabad  Kolkata  New Delhi  Price  Journey_day  Journey_month  \
0          0        0          1   3897           24              3
1          0        0          0   7662            5              1
2          0        0          0  13882            6              9
3          0        0          0   6218            5             12
4          0        0          1  13302            3              1

   Dep_Time_hour  Dep_Time_minute  Arrival_Time_hour  Arrival_Time_minute  \
0             22               20                  1                   10
1              5               50                 13                   15
2              9               25                  4                   25
3             18                5                 23                   30
4             16               50                 21                   35

   Duration_hours  Duration_mins
0               2             50
1               7             25
2              19              0
3               5             25
4               4             45
```

[ ]:

[76]:
```
#in this section we'll have to deal with Outlier detection & outlier imputation␣
 ↪if available in data...
#separate independent and dependent features
```

[77]:
```
#check for outliers
def plot(df,col):
    fig,(ax1,ax2)=plt.subplots(2,1)
    sns.distplot(df[col],ax=ax1)
    sns.boxplot(df[col],ax=ax2)
```

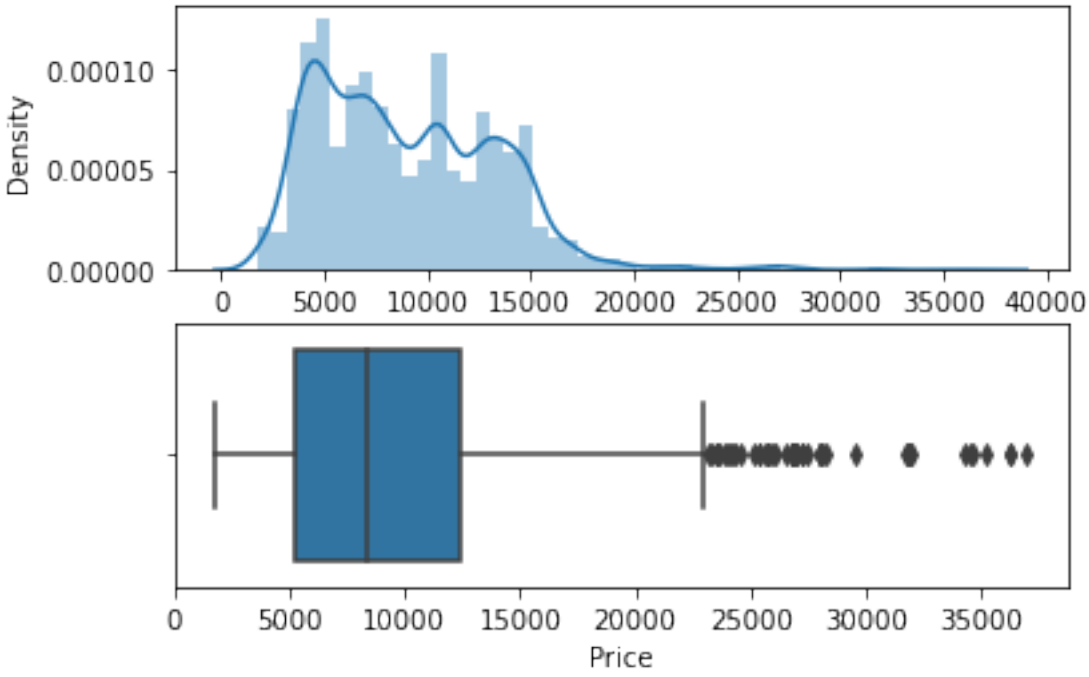
[78]:
```
plot(data_train, 'Price')
```



[ ]:
```

```

[79]:
```
#replace outliers with median using the 'where' numpy function
data_train['Price']=np.where(data_train['Price']>=40000, data_train['Price'].
 ↪median(),data_train['Price'])
```

[80]:
```
plot(data_train, 'Price')
```



[81]:
```
#now we separate independent and dependent features
```

[82]:
```
#indepencies stay on x variable
X=data_train.drop('Price',axis=1)
X.head()
```

[82]:

	Total_Stops	Route_1	Route_2	Route_3	Route_4	Route_5	Air India	GoAir
0	0	0	13	29	13	5	0	0
1	2	2	25	1	3	5	1	0
2	2	3	32	4	5	5	0	0
3	1	2	34	3	13	5	0	0
4	1	0	34	8	13	5	0	0

	IndiGo	Jet Airways	Jet Airways Business	Multiple carriers
0	1	0	0	0
1	0	0	0	0
2	0	1	0	0
3	1	0	0	0
4	1	0	0	0

	Multiple carriers Premium economy	SpiceJet	Trujet	Vistara
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0

```
4                                    0         0       0         0

   Vistara Premium economy  Chennai  Delhi  Kolkata  Mumbai  Cochin  Delhi  \
0                        0        0      0        0       0       0      0
1                        0        0      0        1       0       0      0
2                        0        0      1        0       0       1      0
3                        0        0      0        1       0       0      0
4                        0        0      0        0       0       0      0

   Hyderabad  Kolkata  New Delhi  Journey_day  Journey_month  Dep_Time_hour  \
0          0        0          1           24              3             22
1          0        0          0            5              1              5
2          0        0          0            6              9              9
3          0        0          0            5             12             18
4          0        0          1            3              1             16

   Dep_Time_minute  Arrival_Time_hour  Arrival_Time_minute  Duration_hours  \
0               20                  1                   10               2
1               50                 13                   15               7
2               25                  4                   25              19
3                5                 23                   30               5
4               50                 21                   35               4

   Duration_mins
0             50
1             25
2              0
3             25
4             45
```

[83]:
```
X.shape
```

[83]:
```
(10682, 34)
```

[84]:
```
#depencies on y variable
y=data_train['Price']
y
```

[84]:
```
0         3897.0
1         7662.0
2        13882.0
3         6218.0
4        13302.0
          ...
10678     4107.0
10679     4145.0
10680     7229.0
```

```
10681    12648.0
10682    11753.0
Name: Price, Length: 10682, dtype: float64
```

[ ]:

[85]:
```
#for this section we will apply feature seclection on data...
#find the best features which will contribute most and that have a good␣
 ↪relationship with the target variable
#Select important features to avoid issues of multiple dimensions and multiple␣
 ↪columns
```

[86]:
```
from sklearn.feature_selection import mutual_info_classif
```

[87]:
```
#this will return some kind of priority, or importance with respect to the␣
 ↪target variable
mutual_info_classif(X,y)
```

[87]:
```
array([2.14042775, 2.01009681, 2.82783103, 2.29801653, 1.47042035,
       0.68856276, 0.75613213, 0.09606386, 0.6770895 , 0.90714433,
       0.00305658, 0.56916562, 0.00605294, 0.31494933, 0.        ,
       0.22651447, 0.01092568, 0.16158929, 1.53651999, 0.88505005,
       0.30052424, 1.5442354 , 0.41868123, 0.29158328, 0.16279016,
       0.37356045, 1.09698381, 0.85858848, 1.42884175, 1.20332063,
       1.85594904, 1.52834219, 1.77158555, 1.06586197])
```

[88]:
```
#these numbers represent the importance with respect to the target variable
```

[89]:
```
imp = pd.DataFrame(mutual_info_classif(X,y),index=X.columns)
imp
```

[89]:

	0
Total_Stops	2.185548
Route_1	2.010874
Route_2	2.752543
Route_3	2.339646
Route_4	1.511860
Route_5	0.747055
Air India	0.777524
GoAir	0.086267
IndiGo	0.675871
Jet Airways	0.927195
Jet Airways Business	0.028651
Multiple carriers	0.573235
Multiple carriers Premium economy	0.015077
SpiceJet	0.330892
Trujet	0.000000

```
Vistara                          0.220221
Vistara Premium economy          0.000000
Chennai                          0.159924
Delhi                            1.525373
Kolkata                          0.881817
Mumbai                           0.295559
Cochin                           1.528811
Delhi                            0.419388
Hyderabad                        0.296560
Kolkata                          0.174056
New Delhi                        0.358589
Journey_day                      1.087641
Journey_month                    0.885879
Dep_Time_hour                    1.406186
Dep_Time_minute                  1.213520
Arrival_Time_hour                1.829344
Arrival_Time_minute              1.540630
Duration_hours                   1.785375
Duration_mins                    1.089092
```

[90]:
```
#dataframe sorted on a basis of importance
imp.columns=['importance']
imp.sort_values(by='importance',ascending=False)
```

[90]:
```
                                 importance
Route_2                            2.752543
Route_3                            2.339646
Total_Stops                        2.185548
Route_1                            2.010874
Arrival_Time_hour                  1.829344
Duration_hours                     1.785375
Arrival_Time_minute                1.540630
Cochin                             1.528811
Delhi                              1.525373
Route_4                            1.511860
Dep_Time_hour                      1.406186
Dep_Time_minute                    1.213520
Duration_mins                      1.089092
Journey_day                        1.087641
Jet Airways                        0.927195
Journey_month                      0.885879
Kolkata                            0.881817
Air India                          0.777524
Route_5                            0.747055
IndiGo                             0.675871
Multiple carriers                  0.573235
Delhi                              0.419388
```

```
New Delhi                                 0.358589
SpiceJet                                  0.330892
Hyderabad                                 0.296560
Mumbai                                    0.295559
Vistara                                   0.220221
Kolkata                                   0.174056
Chennai                                   0.159924
GoAir                                     0.086267
Jet Airways Business                      0.028651
Multiple carriers Premium economy         0.015077
Trujet                                    0.000000
Vistara Premium economy                   0.000000
```

[ ]:

[91]:
```
#in this section we will apply machine learning algorithm to our data and␣
↪automate predictions
```

[92]:
```
#use train_test_split to split our data into training data and testing data
from sklearn.model_selection import train_test_split
```

[93]:
```
#0.2 means that 20% of our data will be used as testing data the rest is␣
↪training data
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2)
```

[150]:
```
#define a function to predict the data using whatever machine learning model␣
↪that will be passed onto it
from sklearn import metrics #use it to check metrics
import pickle
def predict(ml_model,dump):
    model=ml_model.fit(X_train,y_train)
    print(f'Training Score: {model.score(X_train,y_train)}')
    predictions=model.predict(X_test)
    print(f'Predictions are: {predictions}')
    print('\n')
    r2_score=metrics.r2_score(y_test,predictions)
    print(f'r2 score is: {r2_score}') #Prediction Accuracy

    print('MEA:',metrics.mean_absolute_error(y_test,predictions))
    print('MSA: ',metrics.mean_squared_error(y_test,predictions))
    print('RMSA: ',np.sqrt(metrics.mean_absolute_error(y_test,predictions)))
    sns.distplot(y_test-predictions)

    if dump==1:
        file=open('/Users/patrickslearningprogams/Desktop/Python Projects/
↪Airlines Ticket Fare/model.pkl','wb')
        pickle.dump(model,file)
```

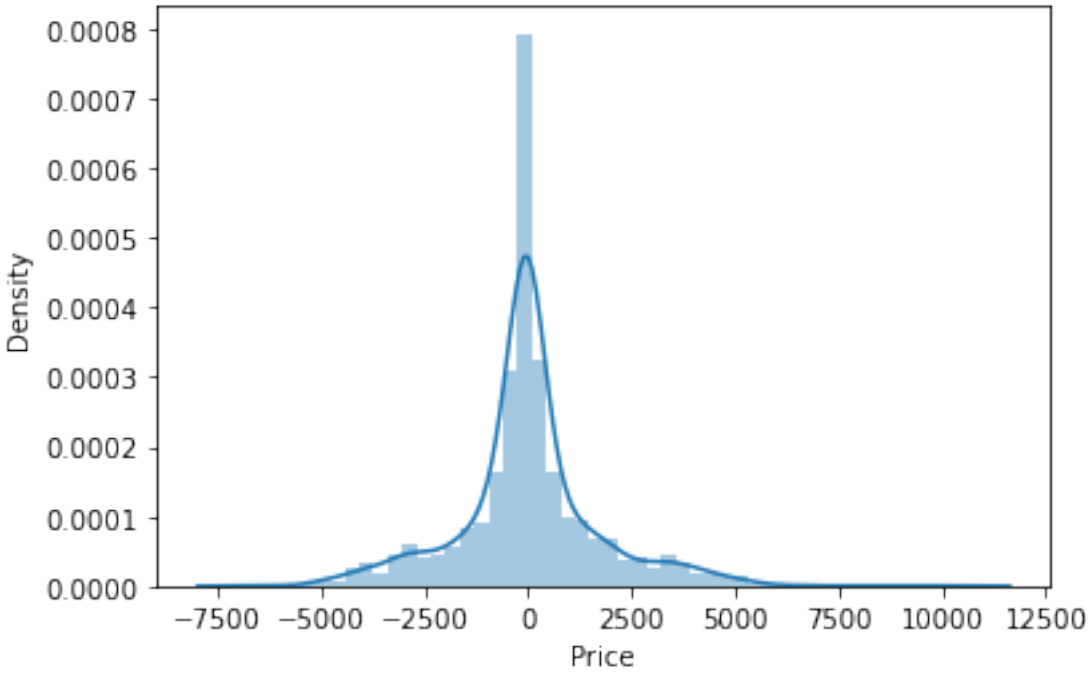
[ ]:

[ ]:

[95]:
```
from sklearn.ensemble import RandomForestRegressor
```

[151]:
```
predict(RandomForestRegressor(),1)
```

```
Training Score: 0.9538147768498436
Predictions are: [ 2932.85       13354.675      12293.94033333 …  3625.58
  5294.76       11135.38      ]


r2 score is: 0.8413825253244394
MEA: 1110.137875675305
MSA:  2996697.404316219
RMSA:  33.31873160363859
```

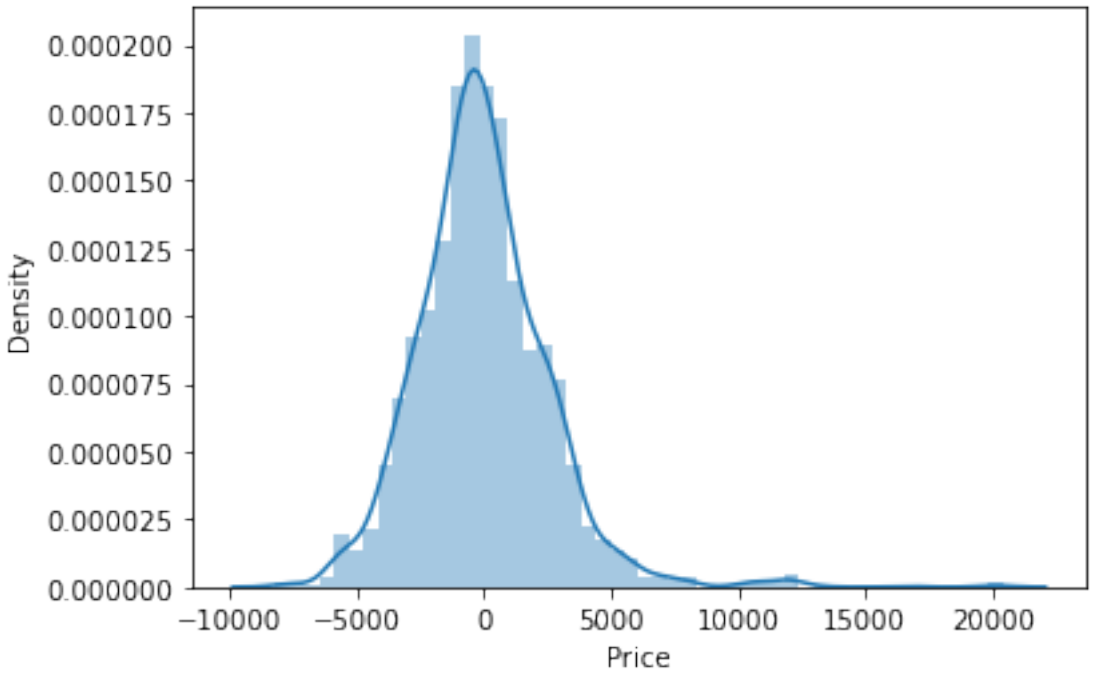


[ ]:

[97]:
```
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
```

[98]:
```
#Linear Regression
predict(LinearRegression(),0)
```

```
Training Score: 0.6102213511031335
Predictions are: [ 3371.60264176 11154.04978018 12038.10293558 …
5202.57683696
  6949.84784593 10553.93865388]


r2 score is: 0.6374844008761719
MEA: 1904.9461718855964
MSA:  6848864.270097325
RMSA:  43.64568904125122
```

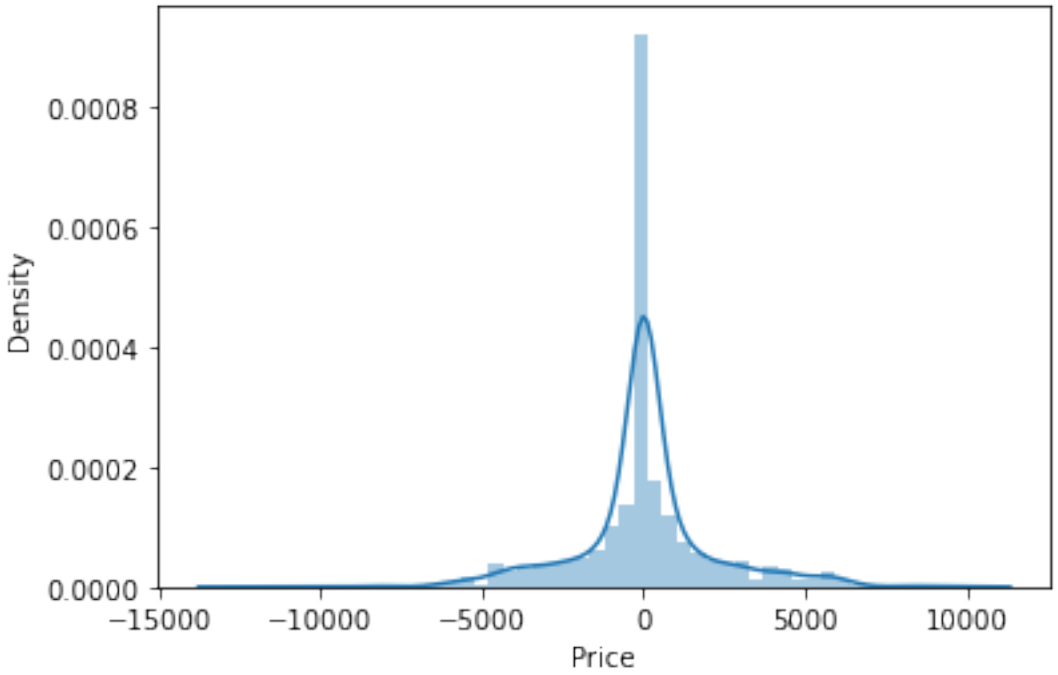


[ ]:

[99]:
```
#Decision Tree Regressor
predict(DecisionTreeRegressor(),0)
```

```
Training Score: 0.9685100635502201
Predictions are: [ 2754. 13033. 14151. …  3540.  5192. 10697.]


r2 score is: 0.7608211724957166
MEA: 1250.5585478084543
```

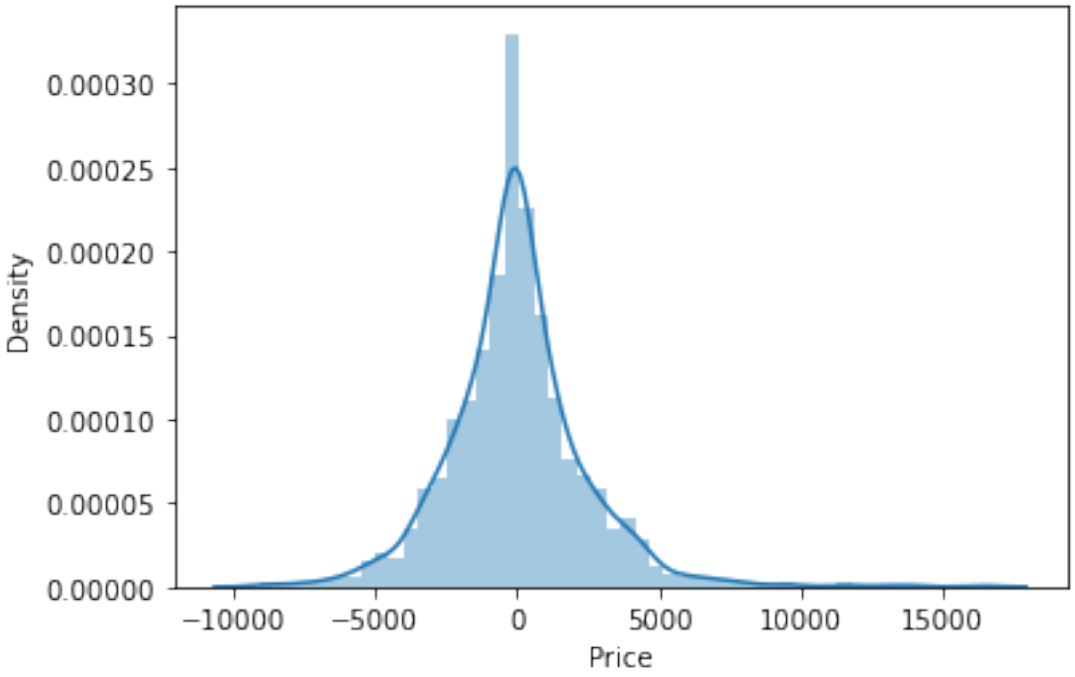
```
MSA:  4518711.2770237345
RMSA:  35.36323723598356
```



[ ]:

[100]:
```
#KNN
predict(KNeighborsRegressor(),0)
```

```
Training Score: 0.7677027459797942
Predictions are: [ 2754.   13579.   11251.4 …  3602.    5942.    8616. ]


r2 score is: 0.6856653077535626
MEA: 1681.6349087505848
MSA:  5938601.394759008
RMSA:  41.0077420586721
```



[ ]:

[104]:
```
#Hypertune models using cross validation
```

[112]:
```
from sklearn.ensemble import RandomForestRegressor
```

[113]:
```
reg_rf=RandomForestRegressor()
```

[105]:
```
from sklearn.model_selection import RandomizedSearchCV
```

[ ]:

[107]:
```
n_estimators=[int(x) for x in np.linspace(start=100,stop=1200,num=6)]
max_depth=[int(x) for x in np.linspace(start=5,stop=30,num=4)]
```

[111]:
```
random_grid={
    'n_estimators': n_estimators, #number of decision trees
    'max_features': ['auto', 'sqrt'],#number of features to consider at every␣
 ↪split of decision tree
    'max_depth': max_depth, #maximum number of levels in our decision tree
    'min_samples_split': [5,10,15,100]#minimum number of splits required to␣
 ↪split a node
}
random_grid
```

[111]:
```
{'n_estimators': [100, 320, 540, 760, 980, 1200],
 'max_features': ['auto', 'sqrt'],
 'max_depth': [5, 13, 21, 30],
 'min_samples_split': [5, 10, 15, 100]}
```

[114]:
```
rf_random=RandomizedSearchCV(estimator=reg_rf,param_distributions=random_grid,cv=3,verbose=2,r
```

[116]:
```
rf_random.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:  1.7min finished
```

[116]:
```
RandomizedSearchCV(cv=3, estimator=RandomForestRegressor(), n_jobs=-1,
                   param_distributions={'max_depth': [5, 13, 21, 30],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_split': [5, 10, 15, 100],
                                        'n_estimators': [100, 320, 540, 760,
                                                         980, 1200]},
                   verbose=2)
```

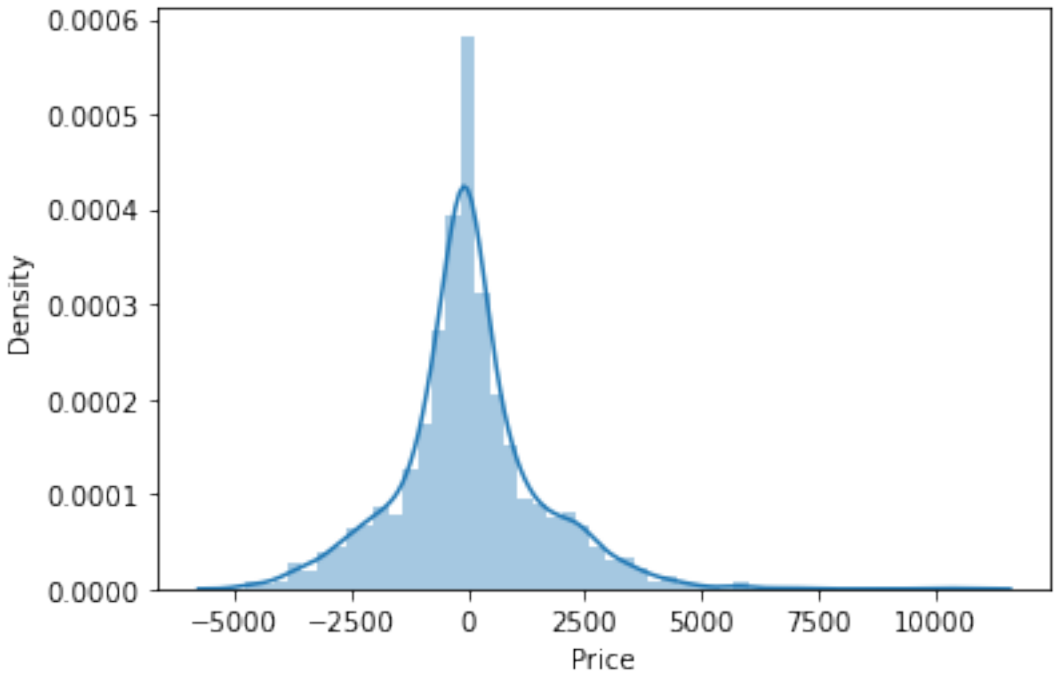
[ ]:
```

```

[119]:
```
#best parameters selected by the cross validation
rf_random.best_params_
```

[119]:
```
{'n_estimators': 1200,
 'min_samples_split': 10,
 'max_features': 'auto',
 'max_depth': 13}
```

[120]:
```
#predict on test data
prediction=rf_random.predict(X_test)
#distribution between actual data and prediction
sns.distplot(y_test-prediction)
```

[120]:
```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```



[121]:
```
#chech the prediction accuracy
metrics.r2_score(y_test,prediction)
```

[121]:
```
0.8755079508939131
```

[ ]:
```

```

[130]:
```
file=open('/Users/patrickslearningprogams/Desktop/Python Projects/Airlines␣
↪Ticket Fare/rf_random.pkl','wb')
```

[131]:
```
pickle.dump(rf_random,file)
```

[155]:
```
model=open('/Users/patrickslearningprogams/Desktop/Python Projects/Airlines␣
↪Ticket Fare/model.pkl','rb')
forrest=pickle.load(model)
predictions2=forrest.predict(X_test)
predictions2
```

[155]:
```
array([ 2932.85      , 13354.675     , 12293.94033333, …,
        3625.58      ,  5294.76      , 11135.38      ])
```

[156]:
```
metrics.r2_score(y_test,predictions2)
```

[156]:
```
0.8413825253244394
```

[ ]: