Flight Price Prediction

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

sns.set()
```

Importing dataset

1. Since data is in form of excel file we have to use pandas read_excel to load the data
2. After loading it is important to check the complete information of data as it can indication many of the hidden infomation such as null values in a column or a row
3. Check whether any null values are there or not. if it is present then following can be done,
   A. Imputing data using Imputation method in sklearn
   B. Filling NaN values with mean, median and mode using fillna() method
4. Describe data --> which can give statistical analysis

In [2]:
```
train_data = pd.read_excel(r"C:/Users/mural/Google Drive/flight fare projec
t/Data_Train.xlsx")
```

In [3]:
```
pd.set_option('display.max_columns', None)
```

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

Out[4]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Tota
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	n
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	

In [5]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 11 columns):
Airline            10683 non-null object
Date_of_Journey    10683 non-null object
Source             10683 non-null object
Destination        10683 non-null object
Route              10682 non-null object
Dep_Time           10683 non-null object
Arrival_Time       10683 non-null object
Duration           10683 non-null object
Total_Stops        10682 non-null object
Additional_Info    10683 non-null object
Price              10683 non-null int64
dtypes: int64(1), object(10)
memory usage: 918.2+ KB
```

In [6]:
```
train_data.shape
```

Out[6]: (10683, 11)

In [7]:
```
train_data["Duration"].value_counts()
```

Out[7]:
```
2h 50m     550
1h 30m     386
2h 45m     337
2h 55m     337
2h 35m     329
          ...
42h 5m       1
37h 10m      1
30h 25m      1
33h 20m      1
47h 40m      1
Name: Duration, Length: 368, dtype: int64
```

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

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

Out[9]:
```
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
```

EDA

From description we can see that Date_of_Journey is a object data type,\ Therefore, we have to convert this datatype into timestamp so as to use this column properly for prediction

For this we require pandas **to_datetime** to convert object data type to datetime dtype.

.dt.day method will extract only day of that date\ **.dt.month method will extract only month of that date**

In [10]:
```
train_data["Journey_day"] = pd.to_datetime(train_data.Date_of_Journey, format="%d/%m/%Y").dt.day
```

In [11]:
```
train_data["Journey_month"] = pd.to_datetime(train_data["Date_of_Journey"], format = "%d/%m/%Y").dt.month
```

In [12]:
```
train_data.head()
```

Out[12]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Tota
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	n
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	

In [13]:
```
# Since we have converted Date_of_Journey column into integers, Now we can
 drop as it is of no use.

train_data.drop(["Date_of_Journey"], axis = 1, inplace = True)
```

In [14]:
```
# Departure time is when a plane leaves the gate.
# Similar to Date_of_Journey we can extract values from Dep_Time

# Extracting Hours
train_data["Dep_hour"] = pd.to_datetime(train_data["Dep_Time"]).dt.hour

# Extracting Minutes
train_data["Dep_min"] = pd.to_datetime(train_data["Dep_Time"]).dt.minute

# Now we can drop Dep_Time as it is of no use
train_data.drop(["Dep_Time"], axis = 1, inplace = True)
```

In [15]:
```
train_data.head()
```

Out[15]:

	Airline	Source	Destination	Route	Arrival_Time	Duration	Total_Stops	Additional_Info	Pric
0	IndiGo	Banglore	New Delhi	BLR → DEL	01:10 22 Mar	2h 50m	non-stop	No info	389
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	13:15	7h 25m	2 stops	No info	766
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	04:25 10 Jun	19h	2 stops	No info	1388
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	23:30	5h 25m	1 stop	No info	621
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	21:35	4h 45m	1 stop	No info	1330

In [16]:
```
# Arrival time is when the plane pulls up to the gate.
# Similar to Date_of_Journey we can extract values from Arrival_Time

# Extracting Hours
train_data["Arrival_hour"] = pd.to_datetime(train_data.Arrival_Time).dt.hou
r

# Extracting Minutes
train_data["Arrival_min"] = pd.to_datetime(train_data.Arrival_Time).dt.minu
te

# Now we can drop Arrival_Time as it is of no use
train_data.drop(["Arrival_Time"], axis = 1, inplace = True)
```

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

Out[17]:

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

In [18]:
```
# Time taken by plane to reach destination is called Duration
# It is the differnce betwwen Departure Time and Arrival time


# Assigning and converting Duration column into list
duration = list(train_data["Duration"])
#print(duration)

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

        else:
            duration[i] = "0h " + duration[i]           # Adds 0 hour

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

In [19]:
```
# Adding duration_hours and duration_mins list to train_data dataframe

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

In [20]:
```
train_data.drop(["Duration"], axis = 1, inplace = True)
```

In [21]:
```
train_data.head()
```

Out[21]:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info	Price	Journey_day	Journe
0	IndiGo	Banglore	New Delhi	BLR → DEL	non-stop	No info	3897	24	
1	Air India	Kolkata	Banglore	CCU → IXR → BBI → BLR	2 stops	No info	7662	1	
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	2 stops	No info	13882	9	
3	IndiGo	Kolkata	Banglore	CCU → NAG → BLR	1 stop	No info	6218	12	
4	IndiGo	Banglore	New Delhi	BLR → NAG → DEL	1 stop	No info	13302	1	

Handling Categorical Data

One can find many ways to handle categorical data. Some of them categorical data are,

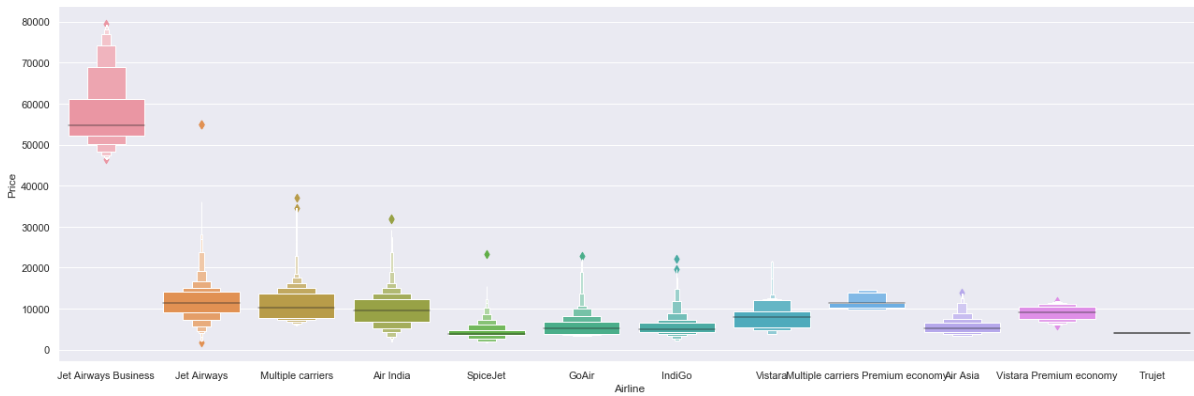
1. **Nominal data** --> data are not in any order --> **OneHotEncoder** is used in this case
2. **Ordinal data** --> data are in order --> **LabelEncoder** is used in this case

In [22]:
```
train_data["Airline"].value_counts()
```

Out[22]:
```
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
```

In [23]:
```
# From graph we can see that Jet Airways Business have the highest Price.
# Apart from the first Airline almost all are having similar median

# Airline vs Price
sns.catplot(y = "Price", x = "Airline", data = train_data.sort_values("Pric
e", ascending = False), kind="boxen", height = 6, aspect = 3)
plt.show()
```



In [24]:
```
# As Airline is Nominal Categorical data we will perform OneHotEncoding

Airline = train_data[["Airline"]]

Airline = pd.get_dummies(Airline, drop_first= True)

Airline.head()
```

Out[24]:

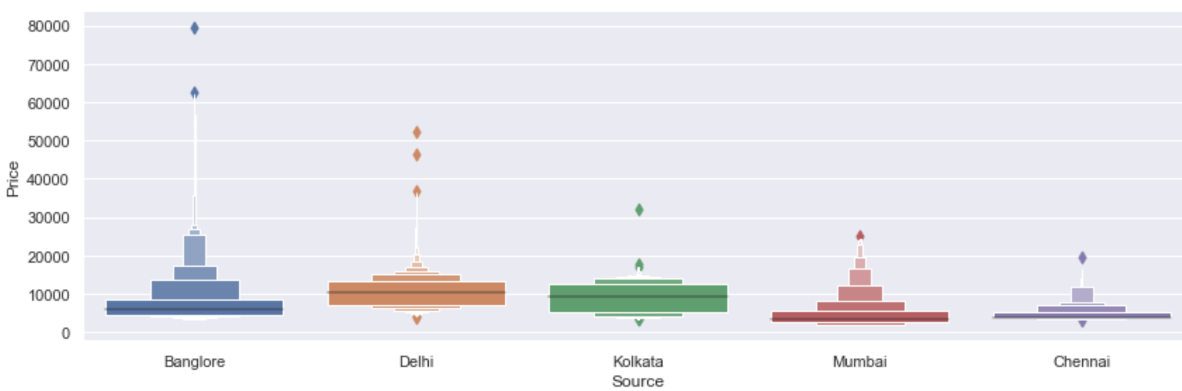
	Airline_Air India	Airline_GoAir	Airline_IndiGo	Airline_Jet Airways	Airline_Jet Airways Business	Airline_Multiple carriers	Airline_Multiple carriers Premium economy
0	0	0	1	0	0	0	0
1	1	0	0	0	0	0	0
2	0	0	0	1	0	0	0
3	0	0	1	0	0	0	0
4	0	0	1	0	0	0	0

In [25]:
```
train_data["Source"].value_counts()
```

Out[25]:
```
Delhi       4536
Kolkata     2871
Banglore    2197
Mumbai       697
Chennai      381
Name: Source, dtype: int64
```

In [26]:
```
# Source vs Price

sns.catplot(y = "Price", x = "Source", data = train_data.sort_values("Pric
e", ascending = False), kind="boxen", height = 4, aspect = 3)
plt.show()
```



In [27]:
```
# As Source is Nominal Categorical data we will perform OneHotEncoding

Source = train_data[["Source"]]

Source = pd.get_dummies(Source, drop_first= True)

Source.head()
```

Out[27]:

	Source_Chennai	Source_Delhi	Source_Kolkata	Source_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

In [28]:
```
train_data["Destination"].value_counts()
```

Out[28]:
```
Cochin       4536
Banglore     2871
Delhi        1265
New Delhi     932
Hyderabad     697
Kolkata       381
Name: Destination, dtype: int64
```

In [29]:
```
# As Destination is Nominal Categorical data we will perform OneHotEncoding

Destination = train_data[["Destination"]]

Destination = pd.get_dummies(Destination, drop_first = True)

Destination.head()
```

Out[29]:

	Destination_Cochin	Destination_Delhi	Destination_Hyderabad	Destination_Kolkata	Destination_N De
0	0	0	0	0	
1	0	0	0	0	
2	1	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

In [30]:
```
train_data["Route"]
```

Out[30]:
```
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
```

In [31]:
```
# Additional_Info contains almost 80% no_info
# Route and Total_Stops are related to each other

train_data.drop(["Route", "Additional_Info"], axis = 1, inplace = True)
```

In [32]:
```
train_data["Total_Stops"].value_counts()
```

Out[32]:
```
1 stop      5625
non-stop    3491
2 stops     1520
3 stops       45
4 stops        1
Name: Total_Stops, dtype: int64
```

In [33]:
```
# As this is case of Ordinal Categorical type we perform LabelEncoder
# Here Values are assigned with corresponding keys

train_data.replace({"non-stop": 0, "1 stop": 1, "2 stops": 2, "3 stops": 3,
"4 stops": 4}, inplace = True)
```

In [34]:
```
train_data.head()
```

Out[34]:

	Airline	Source	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_hour	De
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	

In [35]:
```
# Concatenate dataframe --> train_data + Airline + Source + Destination

data_train = pd.concat([train_data, Airline, Source, Destination], axis = 1
)
```

In [36]:
```
data_train.head()
```

Out[36]:

	Airline	Source	Destination	Total_Stops	Price	Journey_day	Journey_month	Dep_hour	De
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	

In [37]:
```
data_train.drop(["Airline", "Source", "Destination"], axis = 1, inplace = T
rue)
```

In [38]:
```
data_train.head()
```

Out[38]:

	Total_Stops	Price	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_mi
0	0	3897	24	3	22	20	1	1(
1	2	7662	1	5	5	50	13	1!
2	2	13882	9	6	9	25	4	2!
3	1	6218	12	5	18	5	23	3(
4	1	13302	1	3	16	50	21	3!

In [39]:
```
data_train.shape
```

Out[39]: (10682, 30)

Test set

In [40]:
```
test_data = pd.read_excel(r"C:/Users/mural/Google Drive/flight fare projec
t/Test_set.xlsx")
```

In [41]:
```
test_data.head()
```

Out[41]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Tota
0	Jet Airways	6/06/2019	Delhi	Cochin	DEL → BOM → COK	17:30	04:25 07 Jun	10h 55m	
1	IndiGo	12/05/2019	Kolkata	Banglore	CCU → MAA → BLR	06:20	10:20	4h	
2	Jet Airways	21/05/2019	Delhi	Cochin	DEL → BOM → COK	19:15	19:00 22 May	23h 45m	
3	Multiple carriers	21/05/2019	Delhi	Cochin	DEL → BOM → COK	08:00	21:00	13h	
4	Air Asia	24/06/2019	Banglore	Delhi	BLR → DEL	23:55	02:45 25 Jun	2h 50m	n

In [42]:
```
# Preprocessing

print("Test data Info")
print("-"*75)
print(test_data.info())

print()
print()

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

# EDA

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

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

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

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

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

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

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

```
# Categorical data

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

print()

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

print()

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

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

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

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

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

print()
print()

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

```
Test data Info
---------------------------------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2671 entries, 0 to 2670
Data columns (total 10 columns):
Airline            2671 non-null object
Date_of_Journey    2671 non-null object
Source             2671 non-null object
Destination        2671 non-null object
Route              2671 non-null object
Dep_Time           2671 non-null object
Arrival_Time       2671 non-null object
Duration           2671 non-null object
Total_Stops        2671 non-null object
Additional_Info    2671 non-null object
dtypes: object(10)
memory usage: 208.8+ KB
None


Null values :
---------------------------------------------------------------------------
Airline            0
Date_of_Journey    0
Source             0
Destination        0
Route              0
Dep_Time           0
Arrival_Time       0
Duration           0
Total_Stops        0
Additional_Info    0
dtype: int64
Airline
---------------------------------------------------------------------------
Jet Airways                          897
IndiGo                               511
Air India                            440
Multiple carriers                    347
SpiceJet                             208
Vistara                              129
Air Asia                              86
GoAir                                 46
Multiple carriers Premium economy      3
Jet Airways Business                   2
Vistara Premium economy                2
Name: Airline, dtype: int64

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

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


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

In [43]:
```
data_test.head()
```

Out[43]:

	Total_Stops	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Durat
0	1	6	6	17	30	4	25	
1	1	12	5	6	20	10	20	
2	1	21	5	19	15	19	0	
3	1	21	5	8	0	21	0	
4	0	24	6	23	55	2	45	

Feature Selection

Finding out the best feature which will contribute and have good relation with target variable. Following are some of the feature selection methods,

1. **heatmap**
2. **feature_importance_**
3. **SelectKBest**

In [44]:
```
data_train.shape
```

Out[44]: (10682, 30)

In [45]:
```
data_train.columns
```

Out[45]:
```
Index(['Total_Stops', 'Price', 'Journey_day', 'Journey_month', 'Dep_hour',
       'Dep_min', 'Arrival_hour', 'Arrival_min', 'Duration_hours',
       'Duration_mins', 'Airline_Air India', 'Airline_GoAir', 'Airline_Indi
Go',
       'Airline_Jet Airways', 'Airline_Jet Airways Business',
       'Airline_Multiple carriers',
       'Airline_Multiple carriers Premium economy', 'Airline_SpiceJet',
       'Airline_Trujet', 'Airline_Vistara', 'Airline_Vistara Premium econom
y',
       'Source_Chennai', 'Source_Delhi', 'Source_Kolkata', 'Source_Mumbai',
       'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad',
       'Destination_Kolkata', 'Destination_New Delhi'],
      dtype='object')
```

In [46]:
```
X = data_train.loc[:, ['Total_Stops', 'Journey_day', 'Journey_month', 'Dep_
hour',
       'Dep_min', 'Arrival_hour', 'Arrival_min', 'Duration_hours',
       'Duration_mins', 'Airline_Air India', 'Airline_GoAir', 'Airline_Indi
Go',
       'Airline_Jet Airways', 'Airline_Jet Airways Business',
       'Airline_Multiple carriers',
       'Airline_Multiple carriers Premium economy', 'Airline_SpiceJet',
       'Airline_Trujet', 'Airline_Vistara', 'Airline_Vistara Premium econom
y',
       'Source_Chennai', 'Source_Delhi', 'Source_Kolkata', 'Source_Mumbai',
       'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad',
       'Destination_Kolkata', 'Destination_New Delhi']]
X.head()
```

Out[46]:

	Total_Stops	Journey_day	Journey_month	Dep_hour	Dep_min	Arrival_hour	Arrival_min	Durat
0	0	24	3	22	20	1	10	
1	2	1	5	5	50	13	15	
2	2	9	6	9	25	4	25	
3	1	12	5	18	5	23	30	
4	1	1	3	16	50	21	35	

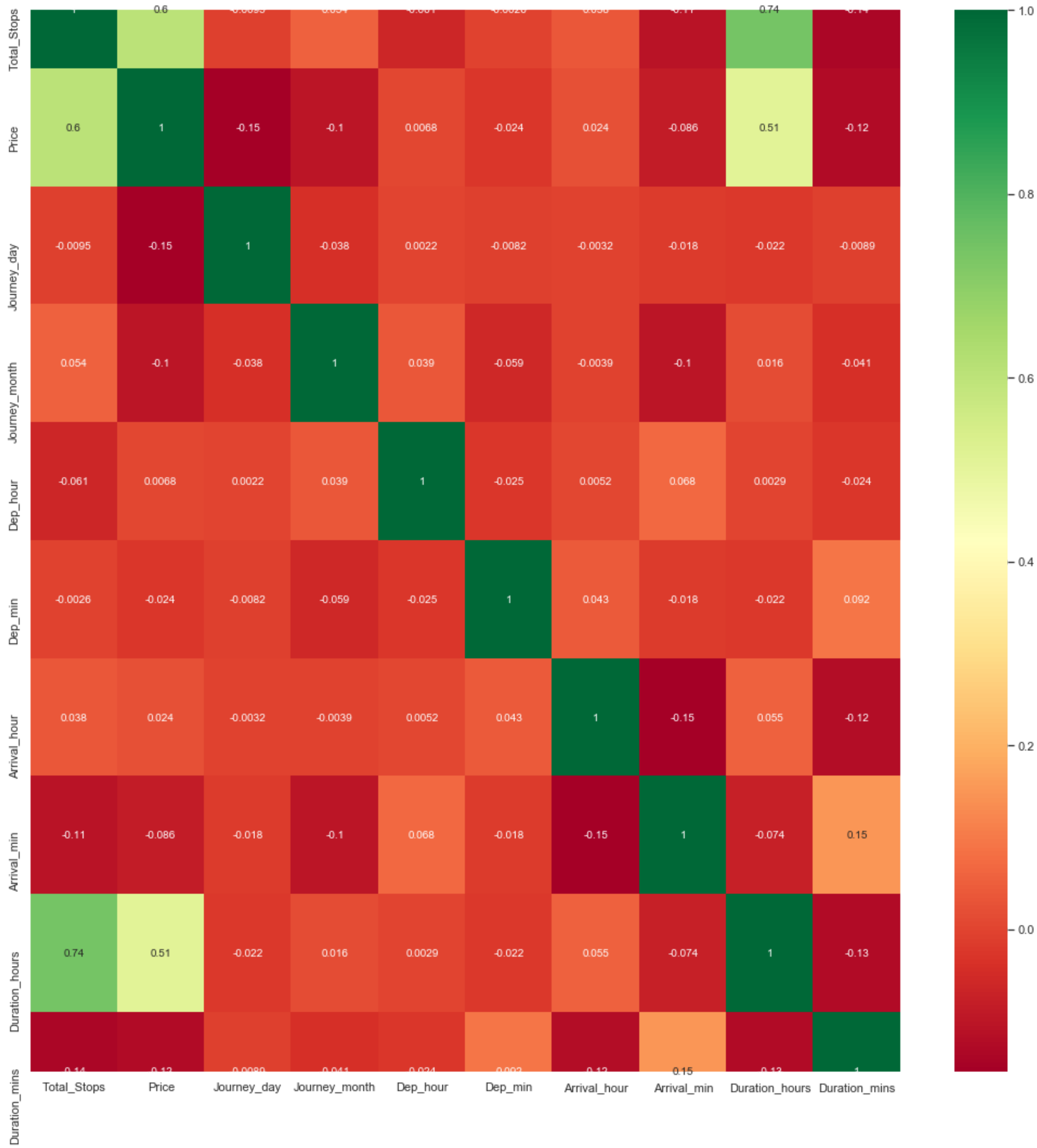
In [47]:
```
y = data_train.iloc[:, 1]
y.head()
```

Out[47]:
```
0     3897
1     7662
2    13882
3     6218
4    13302
Name: Price, dtype: int64
```

In [48]:
```
# Finds correlation between Independent and dependent attributes

plt.figure(figsize = (18,18))
sns.heatmap(train_data.corr(), annot = True, cmap = "RdYlGn")

plt.show()
```



In [49]:
```
# Important feature using ExtraTreesRegressor

from sklearn.ensemble import ExtraTreesRegressor
selection = ExtraTreesRegressor()
selection.fit(X, y)
```

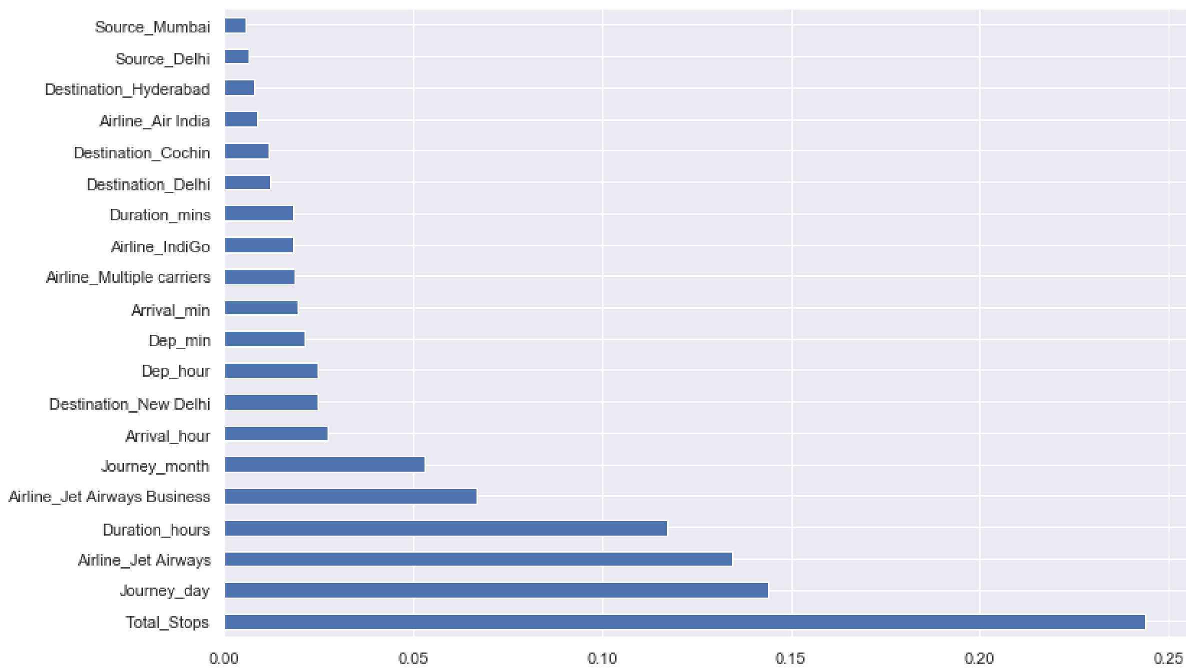
Out[49]:
```
ExtraTreesRegressor()
```

In [50]:
```
print(selection.feature_importances_)
```

```
[2.43919296e-01 1.43871358e-01 5.31100140e-02 2.45551021e-02
 2.13795945e-02 2.74170890e-02 1.93349879e-02 1.17280141e-01
 1.80312683e-02 8.81524030e-03 2.29686194e-03 1.82362808e-02
 1.34611637e-01 6.67236814e-02 1.85662608e-02 8.56434843e-04
 3.60441124e-03 9.33222411e-05 4.83092814e-03 8.72375702e-05
 5.27435156e-04 6.34458612e-03 3.31192043e-03 5.48976625e-03
 1.17491658e-02 1.20660149e-02 7.75170413e-03 4.63697538e-04
 2.46745636e-02]
```

In [51]:
```
#plot graph of feature importances for better visualization

plt.figure(figsize = (12,8))
feat_importances = pd.Series(selection.feature_importances_, index=X.column
s)
feat_importances.nlargest(20).plot(kind='barh')
plt.show()
```



Fitting model using Random Forest

1. Split dataset into train and test set in order to prediction w.r.t X_test
2. If needed do scaling of data
   - Scaling is not done in Random forest
3. Import model
4. Fit the data
5. Predict w.r.t X_test
6. In regression check **RSME** Score
7. Plot graph

In [52]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
random_state = 42)
```

In [53]:
```
from sklearn.ensemble import RandomForestRegressor
reg_rf = RandomForestRegressor()
reg_rf.fit(X_train, y_train)
```

Out[53]:
```
RandomForestRegressor()
```

In [54]:
```
y_pred = reg_rf.predict(X_test)
```

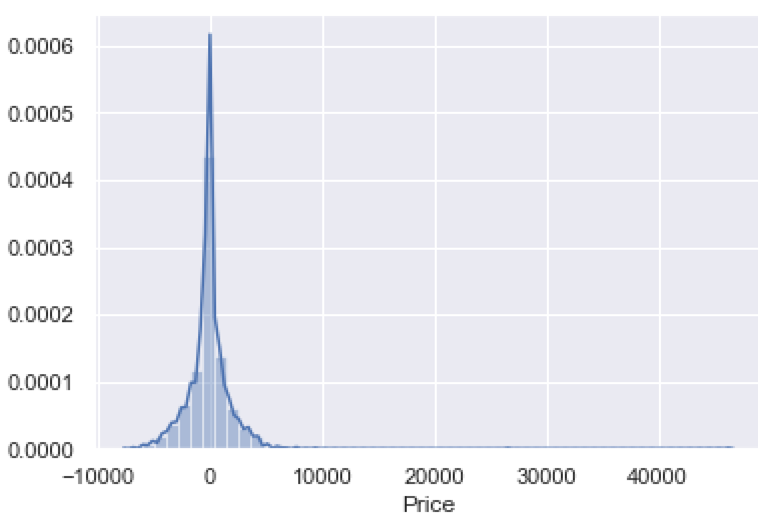
In [55]:
```
reg_rf.score(X_train, y_train)
```

Out[55]:
```
0.95292260137654
```

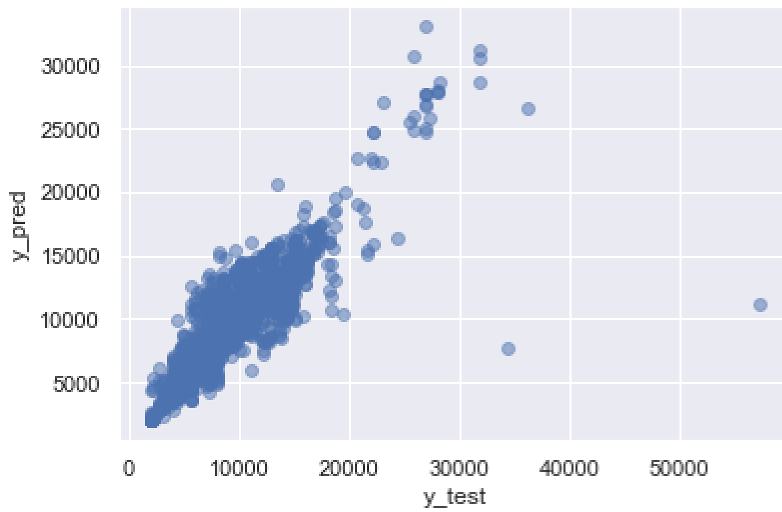
In [56]:
```
reg_rf.score(X_test, y_test)
```

Out[56]:
```
0.7962756059997153
```

In [57]:
```
sns.distplot(y_test-y_pred)
plt.show()
```



In [58]:
```
plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```



In [59]:
```
from sklearn import metrics
```

In [60]:
```
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
MAE: 1181.3115319573837
MSE: 4392716.858039867
RMSE: 2095.8809264936467
```

In [61]:
```
# RMSE/(max(DV)-min(DV))

2090.5509/(max(y)-min(y))
```

Out[61]: 0.026887077025966846

In [62]:
```
metrics.r2_score(y_test, y_pred)
```

Out[62]: 0.7962756059997153

In [ ]:

Hyperparameter Tuning

- Choose following method for hyperparameter tuning
  1. **RandomizedSearchCV** --> Fast
  2. **GridSearchCV**
- Assign hyperparameters in form of dictionery
- Fit the model
- Check best paramters and best score

In [63]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [64]:
```
#Randomized Search CV

# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1200, num = 
12)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(5, 30, num = 6)]
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10, 15, 100]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 5, 10]
```

In [65]:
```
# Create the random grid

random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf}
```

In [66]:
```
# Random search of parameters, using 5 fold cross validation,
# search across 100 different combinations
rf_random = RandomizedSearchCV(estimator = reg_rf, param_distributions = ra
ndom_grid,scoring='neg_mean_squared_error', n_iter = 10, cv = 5, verbose=2,
random_state=42, n_jobs = 1)
```

In [67]:
```
rf_random.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_feature
s=sqrt, max_depth=10

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent wor
kers.

[CV]  n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_featur
es=sqrt, max_depth=10, total=   2.9s
[CV] n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_feature
s=sqrt, max_depth=10

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.8s remaining:
0.0s
```

```
[CV]  n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_featur
es=sqrt, max_depth=10, total=   2.9s
[CV] n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_feature
s=sqrt, max_depth=10
[CV]  n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_featur
es=sqrt, max_depth=10, total=   3.0s
[CV] n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_feature
s=sqrt, max_depth=10
[CV]  n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_featur
es=sqrt, max_depth=10, total=   2.8s
[CV] n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_feature
s=sqrt, max_depth=10
[CV]  n_estimators=900, min_samples_split=5, min_samples_leaf=5, max_featur
es=sqrt, max_depth=10, total=   2.9s
[CV] n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=15
[CV]  n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_feat
ures=sqrt, max_depth=15, total=   4.5s
[CV] n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=15
[CV]  n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_feat
ures=sqrt, max_depth=15, total=   4.5s
[CV] n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=15
[CV]  n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_feat
ures=sqrt, max_depth=15, total=   4.7s
[CV] n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=15
[CV]  n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_feat
ures=sqrt, max_depth=15, total=   4.7s
[CV] n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=15
[CV]  n_estimators=1100, min_samples_split=10, min_samples_leaf=2, max_feat
ures=sqrt, max_depth=15, total=   4.8s
[CV] n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_featu
res=auto, max_depth=15
[CV]  n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_feat
ures=auto, max_depth=15, total=   3.1s
[CV] n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_featu
res=auto, max_depth=15
[CV]  n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_feat
ures=auto, max_depth=15, total=   3.0s
[CV] n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_featu
res=auto, max_depth=15
[CV]  n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_feat
ures=auto, max_depth=15, total=   2.9s
[CV] n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_featu
res=auto, max_depth=15
[CV]  n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_feat
ures=auto, max_depth=15, total=   2.8s
[CV] n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_featu
res=auto, max_depth=15
[CV]  n_estimators=300, min_samples_split=100, min_samples_leaf=5, max_feat
ures=auto, max_depth=15, total=   2.8s
[CV] n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_feature
s=auto, max_depth=15
[CV]  n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_featur
```

```
es=auto, max_depth=15, total=   5.4s
[CV] n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_feature
s=auto, max_depth=15
[CV]  n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_featur
es=auto, max_depth=15, total=   5.3s
[CV] n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_feature
s=auto, max_depth=15
[CV]  n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_featur
es=auto, max_depth=15, total=   5.3s
[CV] n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_feature
s=auto, max_depth=15
[CV]  n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_featur
es=auto, max_depth=15, total=   5.2s
[CV] n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_feature
s=auto, max_depth=15
[CV]  n_estimators=400, min_samples_split=5, min_samples_leaf=5, max_featur
es=auto, max_depth=15, total=   5.3s
[CV] n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featu
res=auto, max_depth=20, total=   8.1s
[CV] n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featu
res=auto, max_depth=20, total=   7.9s
[CV] n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featu
res=auto, max_depth=20, total=   8.0s
[CV] n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featu
res=auto, max_depth=20, total=   8.2s
[CV] n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=5, min_samples_leaf=10, max_featu
res=auto, max_depth=20, total=   8.1s
[CV] n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featur
es=sqrt, max_depth=25
[CV]  n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featu
res=sqrt, max_depth=25, total=   7.5s
[CV] n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featur
es=sqrt, max_depth=25
[CV]  n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featu
res=sqrt, max_depth=25, total=   7.2s
[CV] n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featur
es=sqrt, max_depth=25
[CV]  n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featu
res=sqrt, max_depth=25, total=   7.2s
[CV] n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featur
es=sqrt, max_depth=25
[CV]  n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featu
res=sqrt, max_depth=25, total=   7.3s
[CV] n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featur
es=sqrt, max_depth=25
[CV]  n_estimators=1000, min_samples_split=2, min_samples_leaf=1, max_featu
res=sqrt, max_depth=25, total=  12.3s
```

```
[CV] n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_feat
ures=sqrt, max_depth=5
[CV]  n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_fea
tures=sqrt, max_depth=5, total=   2.7s
[CV] n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_feat
ures=sqrt, max_depth=5
[CV]  n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_fea
tures=sqrt, max_depth=5, total=   2.5s
[CV] n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_feat
ures=sqrt, max_depth=5
[CV]  n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_fea
tures=sqrt, max_depth=5, total=   2.3s
[CV] n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_feat
ures=sqrt, max_depth=5
[CV]  n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_fea
tures=sqrt, max_depth=5, total=   2.5s
[CV] n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_feat
ures=sqrt, max_depth=5
[CV]  n_estimators=1100, min_samples_split=15, min_samples_leaf=10, max_fea
tures=sqrt, max_depth=5, total=   2.4s
[CV] n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featur
es=sqrt, max_depth=15
[CV]  n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featu
res=sqrt, max_depth=15, total=   1.5s
[CV] n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featur
es=sqrt, max_depth=15
[CV]  n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featu
res=sqrt, max_depth=15, total=   1.2s
[CV] n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featur
es=sqrt, max_depth=15
[CV]  n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featu
res=sqrt, max_depth=15, total=   1.2s
[CV] n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featur
es=sqrt, max_depth=15
[CV]  n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featu
res=sqrt, max_depth=15, total=   1.3s
[CV] n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featur
es=sqrt, max_depth=15
[CV]  n_estimators=300, min_samples_split=15, min_samples_leaf=1, max_featu
res=sqrt, max_depth=15, total=   1.4s
[CV] n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featur
es=sqrt, max_depth=5
[CV]  n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=5, total=   1.4s
[CV] n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featur
es=sqrt, max_depth=5
[CV]  n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=5, total=   1.4s
[CV] n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featur
es=sqrt, max_depth=5
[CV]  n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=5, total=   1.6s
[CV] n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featur
es=sqrt, max_depth=5
[CV]  n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=5, total=   1.6s
[CV] n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featur
```

```
es=sqrt, max_depth=5
[CV]  n_estimators=700, min_samples_split=10, min_samples_leaf=2, max_featu
res=sqrt, max_depth=5, total=   1.4s
[CV] n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featu
res=auto, max_depth=20, total=  13.3s
[CV] n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featu
res=auto, max_depth=20, total=  11.5s
[CV] n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featu
res=auto, max_depth=20, total=  10.5s
[CV] n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featu
res=auto, max_depth=20, total=  12.3s
[CV] n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featur
es=auto, max_depth=20
[CV]  n_estimators=700, min_samples_split=15, min_samples_leaf=1, max_featu
res=auto, max_depth=20, total=  11.8s

[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed:  4.1min finished
```

Out[67]:

```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(), n_jobs=1,
                   param_distributions={'max_depth': [5, 10, 15, 20, 25, 3
0],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 5, 10],
                                        'min_samples_split': [2, 5, 10, 15,
                                                              100],
                                        'n_estimators': [100, 200, 300, 40
0,
                                                         500, 600, 700, 80
0,
                                                         900, 1000, 1100,
                                                         1200]},
                   random_state=42, scoring='neg_mean_squared_error',
                   verbose=2)
```

In [68]:

```
rf_random.best_params_
```

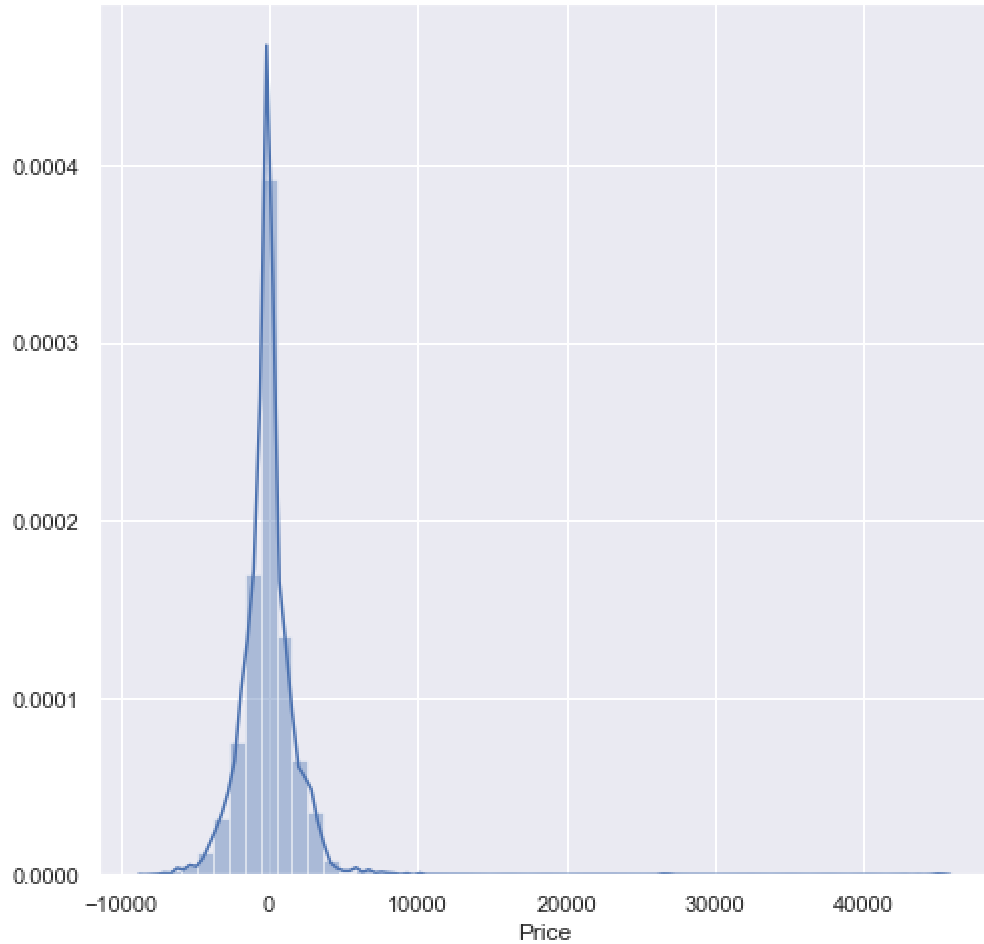
Out[68]:

```
{'n_estimators': 700,
 'min_samples_split': 15,
 'min_samples_leaf': 1,
 'max_features': 'auto',
 'max_depth': 20}
```

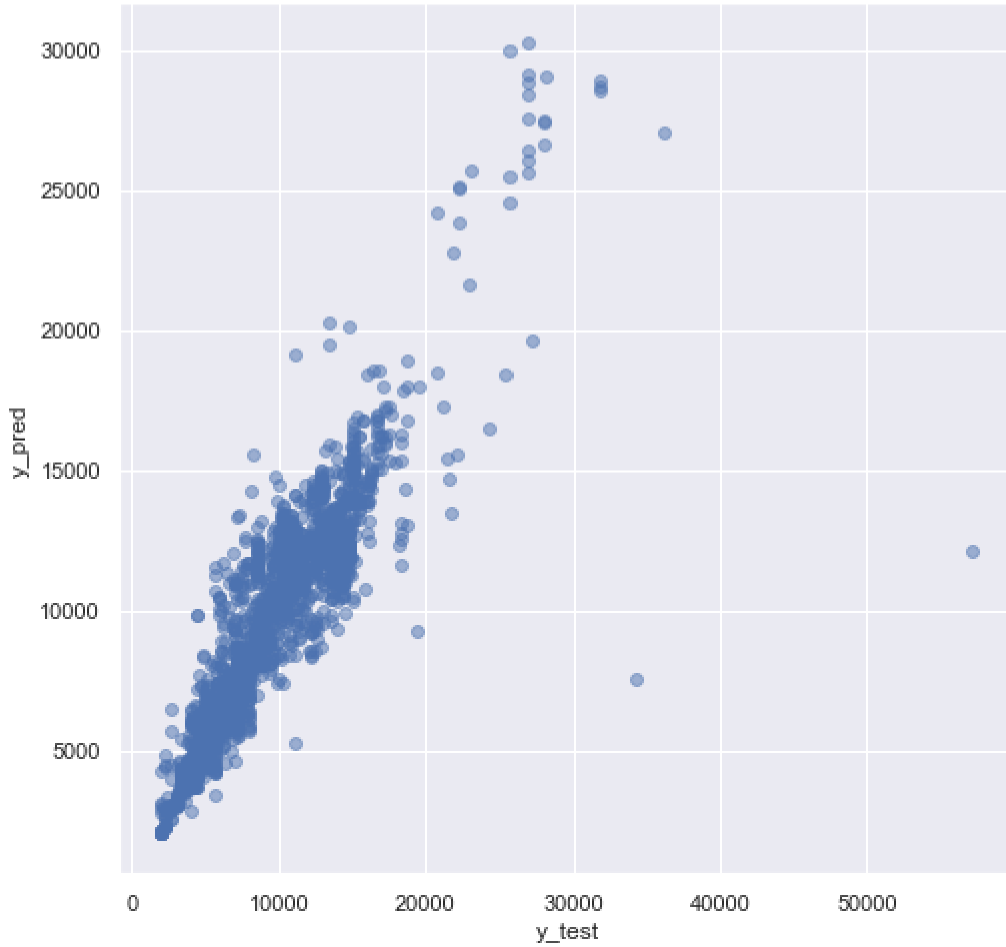
In [69]:

```
prediction = rf_random.predict(X_test)
```

In [70]:
```
plt.figure(figsize = (8,8))
sns.distplot(y_test-prediction)
plt.show()
```



In [71]:
```
plt.figure(figsize = (8,8))
plt.scatter(y_test, prediction, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```



In [72]:
```
print('MAE:', metrics.mean_absolute_error(y_test, prediction))
print('MSE:', metrics.mean_squared_error(y_test, prediction))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, prediction)))
```

```
MAE: 1163.8157755917616
MSE: 4045244.6928126826
RMSE: 2011.2793671722193
```

Save the model to reuse it again

In [73]:
```
#import pickle
# open a file, where you ant to store the data
#file = open('flight_price_rf.pkl', 'wb')

# dump information to that file
#pickle.dump(reg_rf, file)
```

In [74]:
```
#model = open('flight_price_rf.pkl','rb')
#forest = pickle.load(model)
```

In [75]:
```
#y_prediction = forest.predict(X_test)
```

In [76]:
```
#metrics.r2_score(y_test, prediction)
```

In [ ]:

export model

In [77]:
```
import sklearn.externals
import joblib
```

In [ ]:

In [78]:
```
import joblib
```

In [79]:
```
conda install -c anaconda scikit-learn
```

```
Note: you may need to restart the kernel to use updated packages.
```

In [80]:
```
#https://www.youtube.com/watch?v=sm5xeKal72I&t=1455s
joblib.dump(rf_random,'flight_price_pred_model.ml')
```

Out[80]:
```
['flight_price_pred_model.ml']
```