Flight Fare Prediction

October 29, 2025

1 Flight Fare Prediction

1.1 Importing Libraries

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
sns.set_style('whitegrid')
sns.set_context('notebook')
plt.rcParams['figure.figsize'] = (10,6)
```

[2]:
```
pd.set_option('display.max_columns',None) #displays max number of cols
```

1.2 Data Insepction

[3]:
```
df=pd.read_excel("Data_Train.xlsx")
```

[4]:
```
df.columns
```

[4]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info', 'Price'],
      dtype='object')
```

[5]:
```
df.shape
```

[5]:
```
(10683, 11)
```

[6]:
```
df.head()
```

[6]:
```
       Airline Date_of_Journey    Source Destination                  Route  \
0       IndiGo      24/03/2019  Banglore   New Delhi              BLR → DEL
1    Air India       1/05/2019   Kolkata    Banglore  CCU → IXR → BBI → BLR
2  Jet Airways       9/06/2019     Delhi      Cochin  DEL → LKO → BOM → COK
3       IndiGo      12/05/2019   Kolkata    Banglore        CCU → NAG → BLR
```

```
4       IndiGo      01/03/2019  Banglore   New Delhi        BLR → NAG → DEL

   Dep_Time  Arrival_Time Duration Total_Stops Additional_Info  Price
0     22:20  01:10 22 Mar   2h 50m    non-stop         No info   3897
1     05:50         13:15   7h 25m     2 stops         No info   7662
2     09:25  04:25 10 Jun      19h     2 stops         No info  13882
3     18:05         23:30   5h 25m      1 stop         No info   6218
4     16:50         21:35   4h 45m      1 stop         No info  13302
```

[7]:
```
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
```

[8]:
```
df.describe()
```

[8]:

	Price
count	10683.000000
mean	9087.064121
std	4611.359167
min	1759.000000
25%	5277.000000
50%	8372.000000
75%	12373.000000
max	79512.000000

[9]:
```
df.describe(include = 'object')
```

[9]:
```
            Airline Date_of_Journey Source Destination            Route  \
count         10683           10683  10683       10683            10682
unique           12              44      5           6              128
top     Jet Airways      18/05/2019  Delhi      Cochin  DEL → BOM → COK
```

```
freq           3849             504   4537        4537              2376

       Dep_Time Arrival_Time Duration Total_Stops Additional_Info
count     10683        10683    10683       10682           10683
unique      222         1343      368           5              10
top       18:55        19:00   2h 50m      1 stop         No info
freq        233          423      550        5625            8345
```

1.3 Data Cleaning

[10]:
```python
df.isnull().sum()
```

[10]:
```
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
```

[11]:
```python
df.duplicated().sum()
```

[11]:
```
np.int64(220)
```

[12]:
```python
df = df.drop_duplicates()
```

[13]:
```python
df.dropna(inplace = True)
```

[14]:
```python
df['Price'].skew()  ## Right Skew
```

[14]:
```
np.float64(1.8574899082173875)
```

[15]:
```python
df.nunique().sort_values(ascending = True)
```

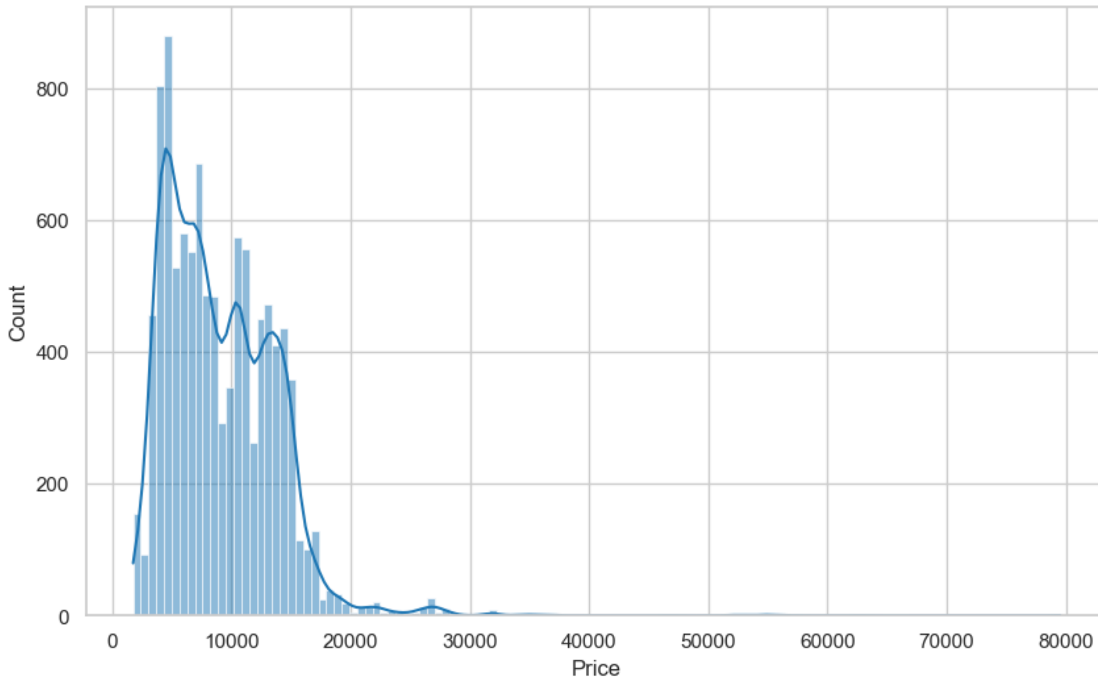
[15]:
```
Source                5
Total_Stops           5
Destination           6
Additional_Info      10
Airline              12
Date_of_Journey      44
Route               128
Dep_Time            222
Duration            368
```

```
Arrival_Time        1343
Price               1870
dtype: int64
```

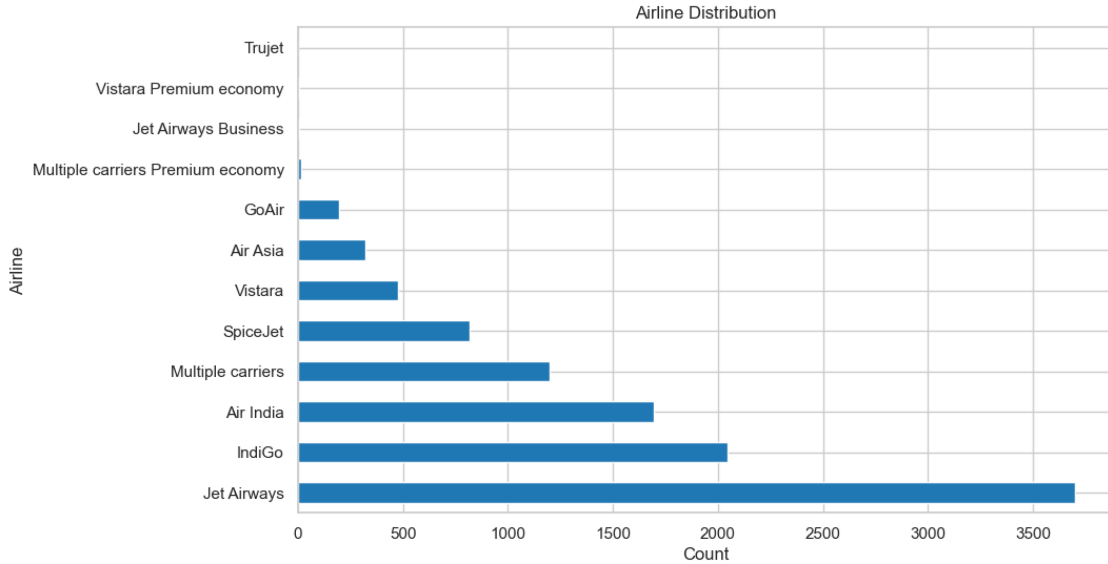
1.4 Data Preprocessing & EDA

[16]:
```
sns.histplot( x ='Price', data = df, kde = True)
```

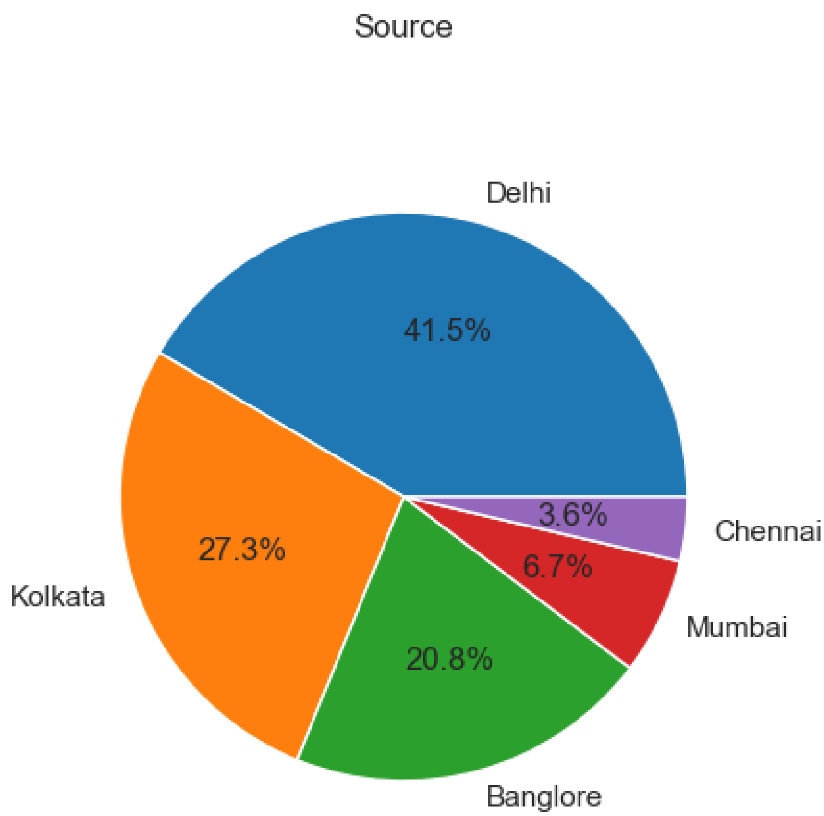
[16]:
```
<Axes: xlabel='Price', ylabel='Count'>
```



[17]:
```
# Calculate counts by Airline
df['Airline'].value_counts().plot(kind='barh')
plt.xlabel("Count")
plt.title("Airline Distribution")
plt.show()
```



[18]:
```
# Calculate counts by Source
Source_var = df['Source'].value_counts()
plt.pie(Source_var, labels=Source_var.index, autopct='%1.1f%%', radius=0.8)
plt.title('Source')
plt.show()
```



[19]:
```
# Since date and time are strings, convert them to datetime using to_datetime()
df["Journey_day"] = pd.to_datetime(df["Date_of_Journey"], format="%d/%m/%Y").dt.
  ↪day
df["Journey_month"] = pd.to_datetime(df["Date_of_Journey"], format="%d/%m/%Y").
  ↪dt.month
df["Journey_year"] = pd.to_datetime(df["Date_of_Journey"], format="%d/%m/%Y").
  ↪dt.year
```

[20]:
```
# Since we have converted Date_of_Journey into features, drop the original␣
  ↪column
df.drop(["Date_of_Journey"], axis=1, inplace=True)
```

[21]:
```
# Extract hour and minute from Dep_Time
df["Dep_hour"] = pd.to_datetime(df["Dep_Time"]).dt.hour
df["Dep_min"] = pd.to_datetime(df["Dep_Time"]).dt.minute

# Drop the original Dep_Time column
```

```
df.drop(["Dep_Time"], axis=1, inplace=True)
```

[22]:
```
# Extract hour and minute from Arrival_Time
df["Arrival_hour"] = pd.to_datetime(df["Arrival_Time"]).dt.hour
df["Arrival_min"] = pd.to_datetime(df["Arrival_Time"]).dt.minute

# Drop the original Arrival_Time column
df.drop(["Arrival_Time"], axis=1, inplace=True)
```

[23]:
```
df.drop(["Route"], axis=1, inplace=True)
```

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

[25]:
```
df['Journey_year'].value_counts()
```

[25]:
```
Journey_year
2019    10462
Name: count, dtype: int64
```

[26]:
```
df.drop(["Journey_year"], axis=1, inplace = True)
```

[27]:
```
# Fill missing hours/minutes and split Duration
duration = df["Duration"].str.replace('h', 'h ').str.replace('  ', ' ')
duration = duration.apply(lambda x: x if 'h' in x else '0h ' + x)
duration = duration.apply(lambda x: x if 'm' in x else x + ' 0m')

df["Duration_hours"] = duration.str.extract(r'(\d+)h').astype(int)
df["Duration_mins"] = duration.str.extract(r'(\d+)m').astype(int)
```

[28]:
```
df.drop(["Duration"], axis=1, inplace=True)
```

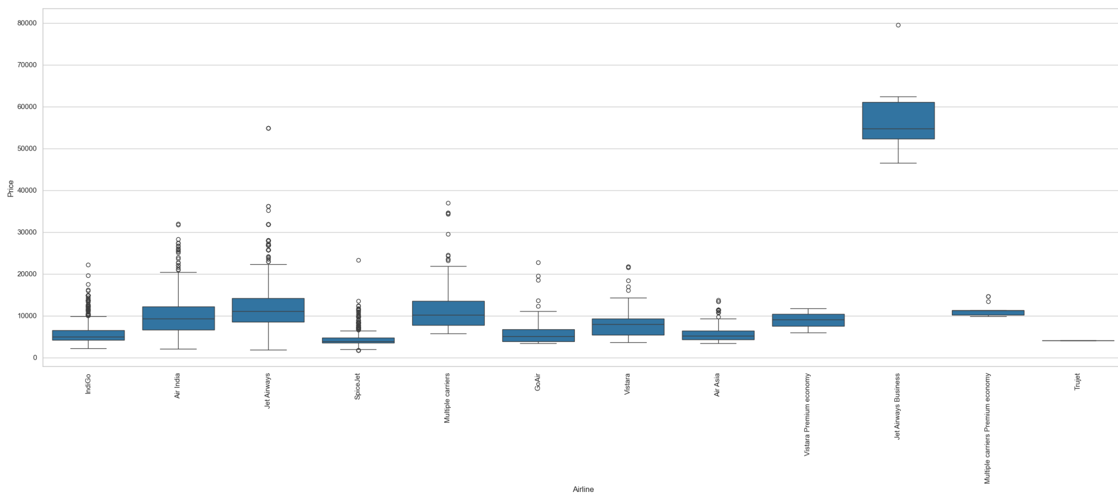
[29]:
```
df.replace({"non-stop": 0, "1 stop": 1, "2 stops": 2, "3 stops": 3, "4 stops":␣
↪4}, inplace=True)
```

[30]:
```
df['Airline'].value_counts().sort_values(ascending = True)
```

[30]:
```
Airline
Trujet                                1
Vistara Premium economy               3
Jet Airways Business                  6
Multiple carriers Premium economy    13
GoAir                               194
Air Asia                            319
Vistara                             478
SpiceJet                            815
Multiple carriers                  1196
Air India                          1694
IndiGo                             2043
```

```
Jet Airways                          3700
Name: count, dtype: int64
```

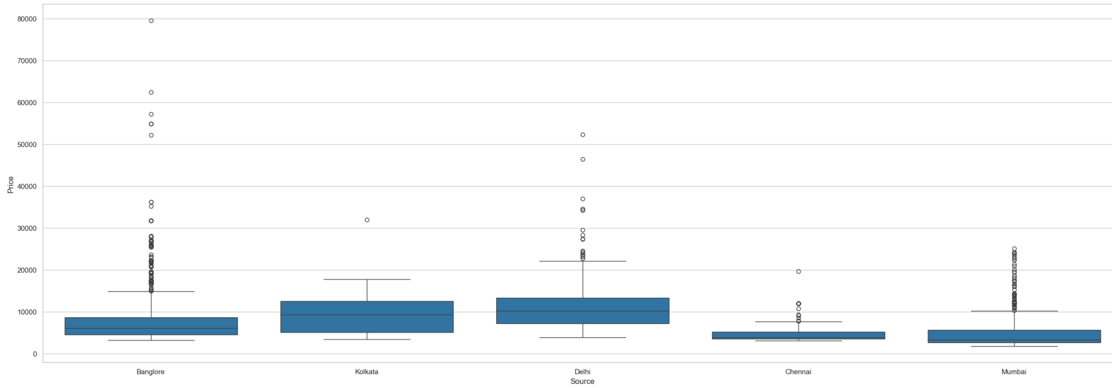
[31]:
```python
# Price by Airline
plt.figure(figsize = (30,10))
sns.boxplot(x="Airline", y="Price", data=df)
plt.xticks(rotation=90)
plt.show()
```



[32]:
```python
df['Source'].value_counts().sort_values(ascending = True)
```

[32]:
```
Source
Chennai      381
Mumbai       697
Banglore    2179
Kolkata     2860
Delhi       4345
Name: count, dtype: int64
```

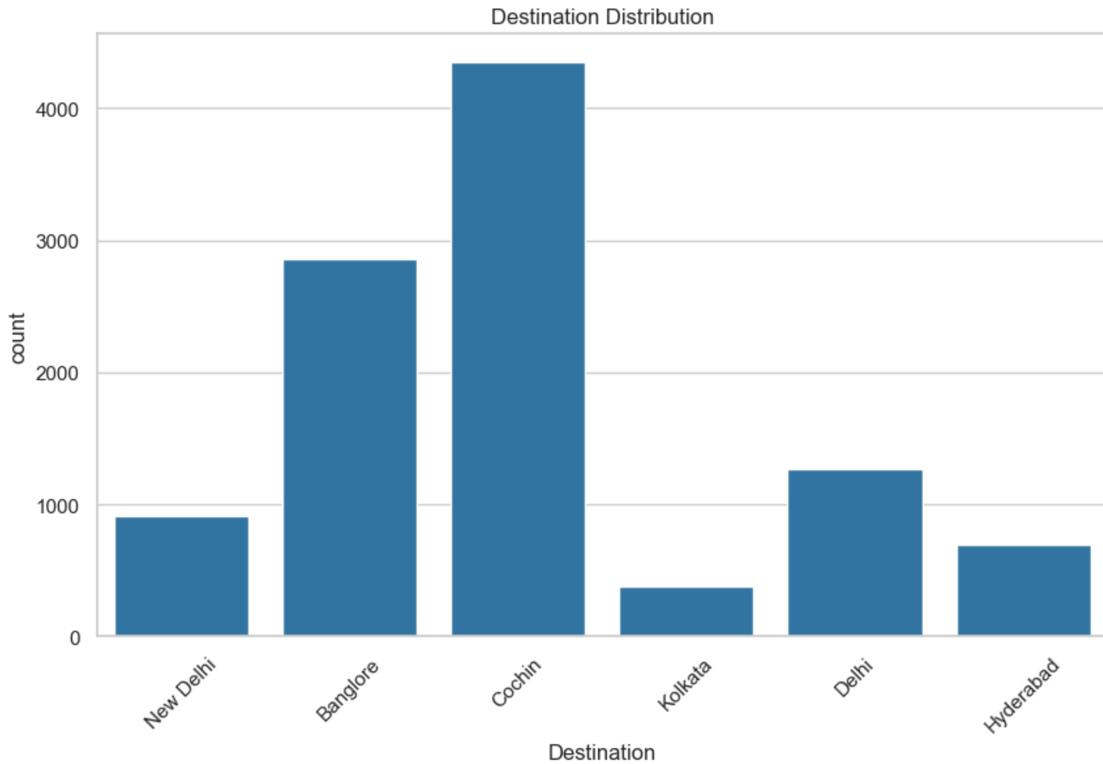
[33]:
```python
# Source vs Price
plt.figure(figsize=(30,10))
sns.boxplot(y = df["Price"], x = df["Source"])
plt.show()
```



[34]:
```
df['Destination'].value_counts().sort_values(ascending = True)
```

[34]:
```
Destination
Kolkata       381
Hyderabad     697
New Delhi     914
Delhi        1265
Banglore     2860
Cochin       4345
Name: count, dtype: int64
```

[35]:
```
sns.countplot(x="Destination", data=df)
plt.title("Destination Distribution")
plt.xticks(rotation=45)
plt.show()
```

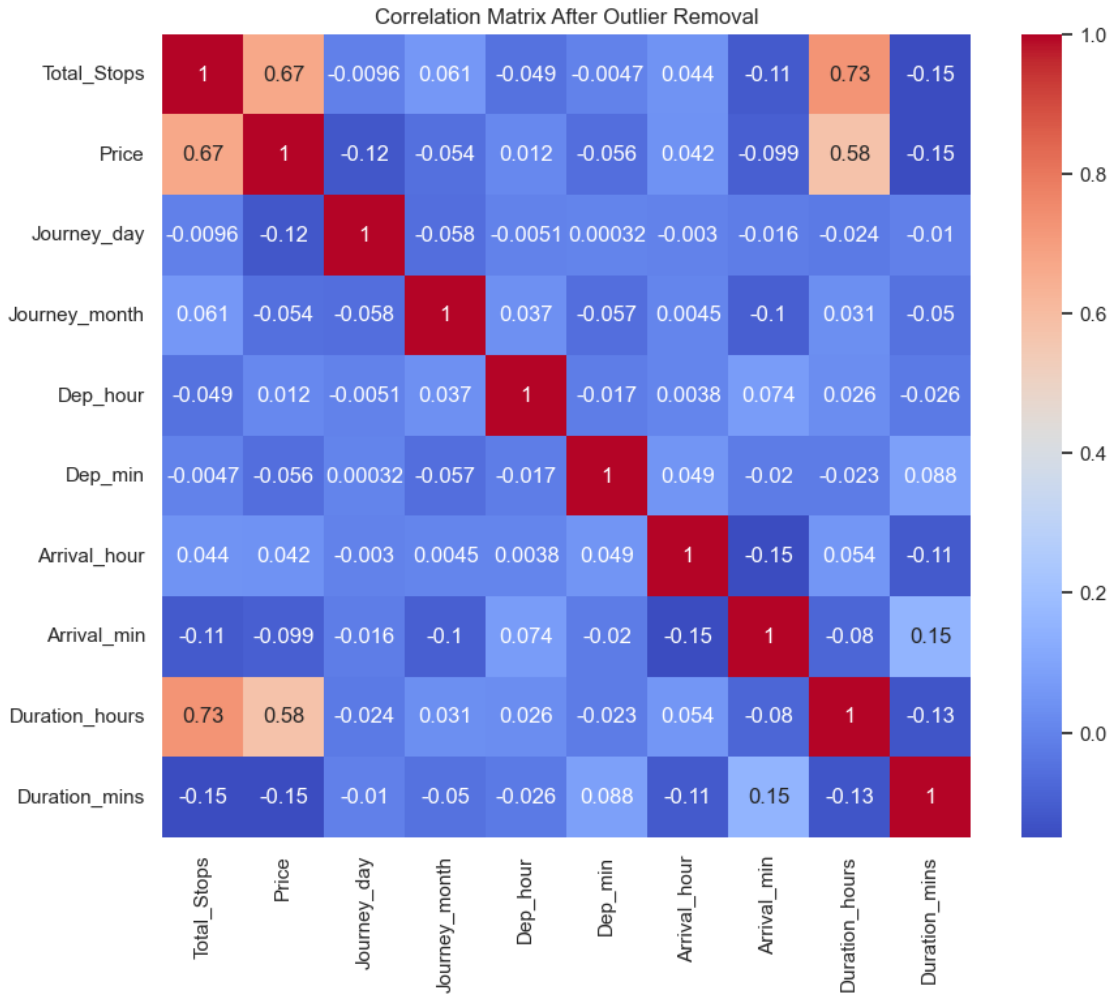


1.4.1 Outliers Detection

[36]:
```
numeric_cols = df.select_dtypes(include='number').columns
Q1 = df[numeric_cols].quantile(0.25)
Q3 = df[numeric_cols].quantile(0.75)
IQR = Q3 - Q1
df_outliers_removed = df[~((df[numeric_cols] < (Q1 - 1.5 * IQR)) |␣
↪(df[numeric_cols] > (Q3 + 1.5 * IQR))).any(axis=1)]
```

1.4.2 Correlation

[37]:
```
numeric_cols = df_outliers_removed.select_dtypes(include='number')
corr_matrix = numeric_cols.corr()
plt.figure(figsize=(10,8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix After Outlier Removal')
plt.show()
```



[38]:
```
df = df_outliers_removed
df.head()
```

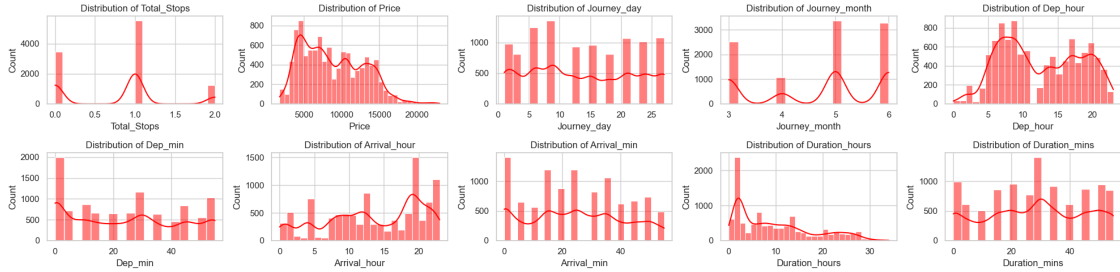
[38]:
```
       Airline    Source Destination  Total_Stops  Price  Journey_day  \
0       IndiGo  Banglore   New Delhi            0   3897           24
1    Air India   Kolkata    Banglore            2   7662            1
2  Jet Airways     Delhi      Cochin            2  13882            9
3       IndiGo   Kolkata    Banglore            1   6218           12
4       IndiGo  Banglore   New Delhi            1  13302            1

   Journey_month  Dep_hour  Dep_min  Arrival_hour  Arrival_min  \
0              3        22       20             1           10
1              5         5       50            13           15
2              6         9       25             4           25
3              5        18        5            23           30
4              3        16       50            21           35
```

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

1.4.3 OneHot Encoding

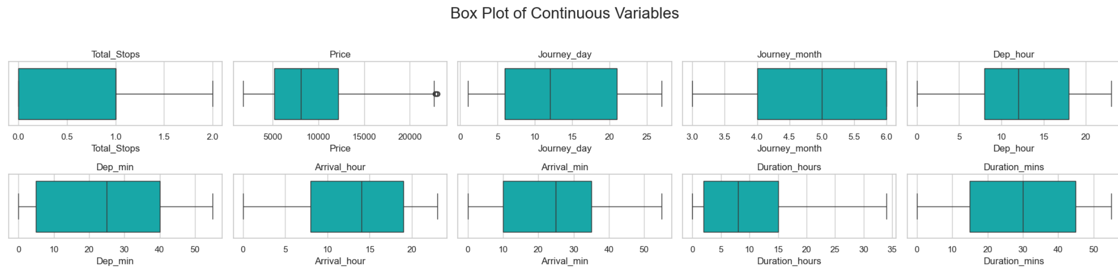
[39]:
```python
categorical_cols = df.select_dtypes(include='object').columns

# Apply one-hot encoding using get_dummies
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
```

[40]:
```python
numeric_cols = df.select_dtypes(include='number').columns[:10]
cols = 5
rows = 2

plt.figure(figsize=(20, 5))
for i, col in enumerate(numeric_cols):
    plt.subplot(rows, cols, i+1)
    sns.histplot(df[col], color='red', kde=True)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```



[41]:
```python
plt.figure(figsize=(20, 5))

numeric_cols = df.select_dtypes(include='number').columns

for i, col in enumerate(numeric_cols[:10]):
    ax = plt.subplot(2, 5, i + 1)
    sns.boxplot(x=df[col], ax=ax, color='c')
    ax.set_title(col)
plt.suptitle('Box Plot of Continuous Variables', fontsize=20)
```

```
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

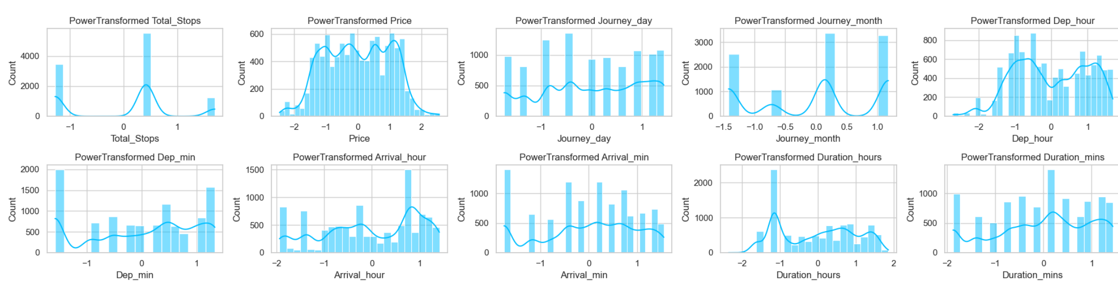


1.4.4 Power Transformer

[42]:
```
from sklearn.preprocessing import PowerTransformer
```

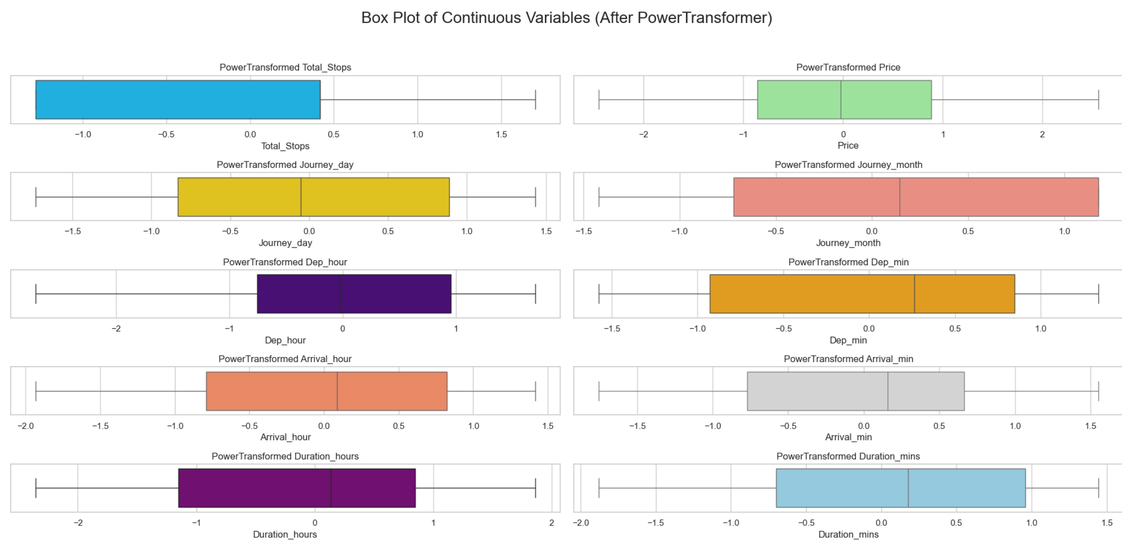
[43]:
```
numeric_cols = df.select_dtypes(include='number').columns

pt = PowerTransformer()
df_transformed = df.copy()
df_transformed[numeric_cols] = pt.fit_transform(df[numeric_cols])
```

[44]:
```
cols = 5
rows = 2
plt.figure(figsize=(20, 5))
for i, col in enumerate(numeric_cols[:cols*rows]):
    plt.subplot(rows, cols, i+1)
    sns.histplot(df_transformed[col], color='deepskyblue', kde=True)
    plt.title(f'PowerTransformed {col}')
plt.tight_layout()
plt.show()
```



[45]:
```
plt.figure(figsize=(20, 10))
```

```
colors = ["deepskyblue", "lightgreen", "gold", "salmon", "indigo", "orange",␣
↪"coral", "lightgrey", "purple", "skyblue"]

for i, col in enumerate(numeric_cols[:10]):
    ax = plt.subplot(5, 2, i + 1)
    sns.boxplot(x=df_transformed[col], ax=ax, color=colors[i % len(colors)])
    ax.set_title(f'PowerTransformed {col}')
plt.suptitle('Box Plot of Continuous Variables (After PowerTransformer)',␣
↪fontsize=20)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```



[46]:
```
df = df_transformed
```

[47]:
```
df.shape
```

[47]: (10272, 29)

[48]:
```
df.columns
```

[48]:
```
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_IndiGo',
       'Airline_Jet Airways', 'Airline_Multiple carriers',
       'Airline_Multiple carriers Premium economy', 'Airline_SpiceJet',
       'Airline_Trujet', 'Airline_Vistara', 'Airline_Vistara Premium economy',
       'Source_Chennai', 'Source_Delhi', 'Source_Kolkata', 'Source_Mumbai',
       'Destination_Cochin', 'Destination_Delhi', 'Destination_Hyderabad',
       'Destination_Kolkata', 'Destination_New Delhi'],
```

```
      dtype='object')
```

[49]:
```
df.head()
```

[49]:
```
   Total_Stops     Price  Journey_day  Journey_month  Dep_hour   Dep_min  \
0    -1.279796 -1.341609     1.165861      -1.419075  1.553919  0.029354
1     1.701334 -0.129416    -1.734038       0.144376 -1.366553  1.181361
2     1.701334  1.197707    -0.421134       1.176325 -0.561804  0.261548
3     0.417439 -0.534557    -0.054377       0.144376  0.954777 -0.927348
4     0.417439  1.093037    -1.734038      -1.419075  0.641055  1.181361

   Arrival_hour  Arrival_min  Duration_hours  Duration_mins  \
0     -1.792980    -0.770154       -1.153004       1.204606
1     -0.058930    -0.428486       -0.006545      -0.098596
2     -1.365973     0.157025        1.130917      -1.877946
3      1.414746     0.418743       -0.350235      -0.098596
4      1.118798     0.665869       -0.564826       0.959172

   Airline_Air India  Airline_GoAir  Airline_IndiGo  Airline_Jet Airways  \
0              False          False            True                False
1               True          False           False                False
2              False          False           False                 True
3              False          False            True                False
4              False          False            True                False

   Airline_Multiple carriers  Airline_Multiple carriers Premium economy  \
0                      False                                      False
1                      False                                      False
2                      False                                      False
3                      False                                      False
4                      False                                      False

   Airline_SpiceJet  Airline_Trujet  Airline_Vistara  \
0             False           False            False
1             False           False            False
2             False           False            False
3             False           False            False
4             False           False            False

   Airline_Vistara Premium economy  Source_Chennai  Source_Delhi  \
0                            False           False         False
1                            False           False         False
2                            False           False          True
3                            False           False         False
4                            False           False         False

   Source_Kolkata  Source_Mumbai  Destination_Cochin  Destination_Delhi  \
```

```
0          False          False            False             False
1           True          False            False             False
2          False          False             True             False
3           True          False            False             False
4          False          False            False             False

   Destination_Hyderabad  Destination_Kolkata  Destination_New Delhi
0                  False                False                   True
1                  False                False                  False
2                  False                False                  False
3                  False                False                  False
4                  False                False                   True
```

[50]:
```
X = df.drop("Price", axis=1)
```

[51]:
```
y = df["Price"]
```

1.5 Feature Selection

[52]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import r_regression  # Correlation
```

[53]:
```
rs = SelectKBest(score_func=r_regression, k='all')
rs.fit(X, y)
```

[53]:
```
SelectKBest(k='all', score_func=<function r_regression at 0x000001C408942480>)
```

[54]:
```
feature_scores = pd.Series(rs.scores_, index=X.columns)*100
print(feature_scores.sort_values(ascending=False))
```

```
Total_Stops                                71.638619
Duration_hours                             71.345716
Airline_Jet Airways                        45.419042
Source_Delhi                               35.365598
Destination_Cochin                         35.365598
Airline_Multiple carriers                  18.576788
Destination_New Delhi                      11.344666
Airline_Air India                           6.782248
Source_Kolkata                              6.302605
Arrival_hour                                6.054419
Airline_Multiple carriers Premium economy   2.549822
Dep_hour                                    1.288436
Airline_Vistara Premium economy             0.244035
Airline_Trujet                             -1.227814
Journey_month                              -2.999336
Airline_Vistara                            -3.968974
Dep_min                                    -8.728755
Airline_GoAir                             -10.221739
```

```
Journey_day                              -10.415706
Arrival_min                              -11.225003
Duration_mins                            -15.623295
Destination_Kolkata                      -21.245660
Source_Chennai                           -21.245660
Destination_Hyderabad                    -32.215020
Source_Mumbai                            -32.215020
Destination_Delhi                        -34.286294
Airline_SpiceJet                         -36.705815
Airline_IndiGo                           -38.958689
dtype: float64
```

[55]:
```python
from sklearn.ensemble import ExtraTreesRegressor
selection = ExtraTreesRegressor()
selection.fit(X, y)
```

[55]:
```
ExtraTreesRegressor()
```

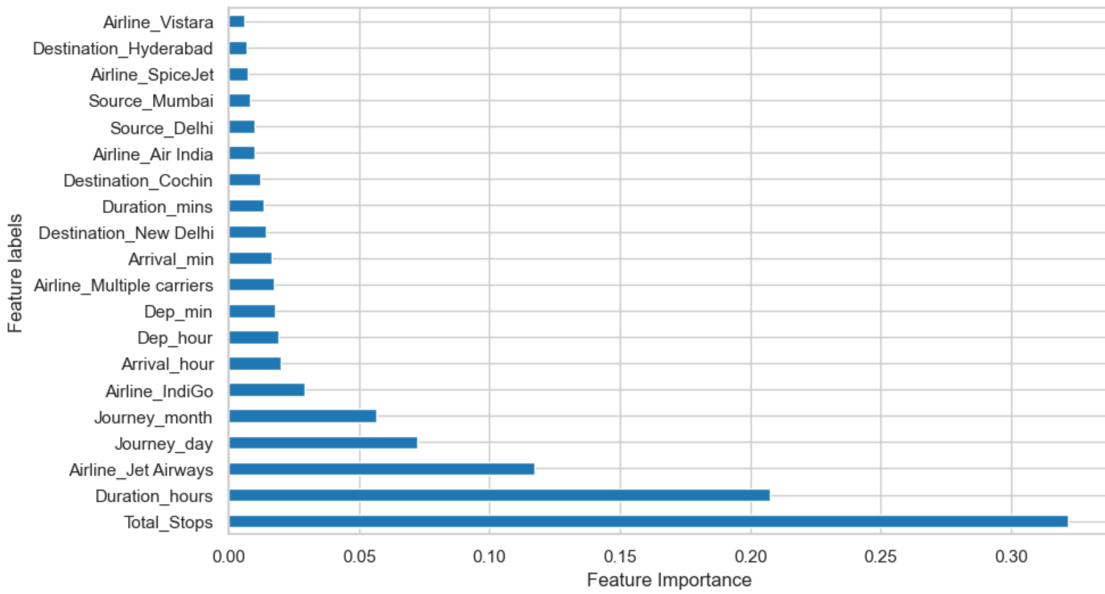
[56]:
```python
feature_importances = pd.Series(selection.feature_importances_, index=X.columns)
```

[57]:
```python
print(feature_importances.sort_values(ascending=False))
```

```
Total_Stops                                 0.321978
Duration_hours                              0.207699
Airline_Jet Airways                         0.117053
Journey_day                                 0.072339
Journey_month                               0.056649
Airline_IndiGo                              0.028906
Arrival_hour                                0.019820
Dep_hour                                    0.018950
Dep_min                                     0.017983
Airline_Multiple carriers                   0.017511
Arrival_min                                 0.016376
Destination_New Delhi                       0.014258
Duration_mins                               0.013298
Destination_Cochin                          0.012037
Airline_Air India                           0.009931
Source_Delhi                                0.009874
Source_Mumbai                               0.008007
Airline_SpiceJet                            0.007439
Destination_Hyderabad                       0.007003
Airline_Vistara                             0.006088
Destination_Delhi                           0.005941
Source_Kolkata                              0.005351
Airline_GoAir                               0.002172
Airline_Multiple carriers Premium economy   0.001191
Source_Chennai                              0.000912
Destination_Kolkata                         0.000864
```

```
Airline_Trujet                              0.000200
Airline_Vistara Premium economy             0.000169
dtype: float64
```

[58]:
```
feature_importances.nlargest(20).plot(kind='barh')
plt.ylabel("Feature labels")
plt.xlabel("Feature Importance")
plt.show()
```



[59]:
```
top_features = feature_importances.nlargest(20).index
X1 = X[top_features]
```

[60]:
```
X1.columns
```

[60]:
```
Index(['Total_Stops', 'Duration_hours', 'Airline_Jet Airways', 'Journey_day',
       'Journey_month', 'Airline_IndiGo', 'Arrival_hour', 'Dep_hour',
       'Dep_min', 'Airline_Multiple carriers', 'Arrival_min',
       'Destination_New Delhi', 'Duration_mins', 'Destination_Cochin',
       'Airline_Air India', 'Source_Delhi', 'Source_Mumbai',
       'Airline_SpiceJet', 'Destination_Hyderabad', 'Airline_Vistara'],
      dtype='object')
```

1.6 Model Building

[62]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
```

```python
from sklearn import metrics
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from math import sqrt
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
```

[63]:
```python
X_train, X_test, y_train, y_test = train_test_split(X1, y, test_size = 0.2,␣
↪random_state = 42)
```

[64]:
```python
model_comparison={}
```

1.7 Linear Regression

[65]:
```python
lr = LinearRegression()
lr.fit(X_train, y_train)
```

[65]:
```
LinearRegression()
```

[66]:
```python
y_pred_lr = lr.predict(X_test)
```

[67]:
```python
print("R2 Score:", r2_score(y_test, y_pred_lr))
print("MSE:", mean_squared_error(y_test, y_pred_lr))
print("RMSE:",np.sqrt(mean_squared_error(y_test, y_pred_lr)))
print("MAE:", mean_absolute_error(y_test, y_pred_lr))
```

```
R2 Score: 0.6996677932341544
MSE: 0.2894823923034944
RMSE: 0.5380356793963523
MAE: 0.41351684471712313
```

[68]:
```python
model_comparison['LinearRegression'] = {
    'R2': r2_score(y_test, y_pred_lr),
    'MSE': mean_squared_error(y_test, y_pred_lr),
    'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_lr)),
    'MAE': mean_absolute_error(y_test, y_pred_lr)
}
```

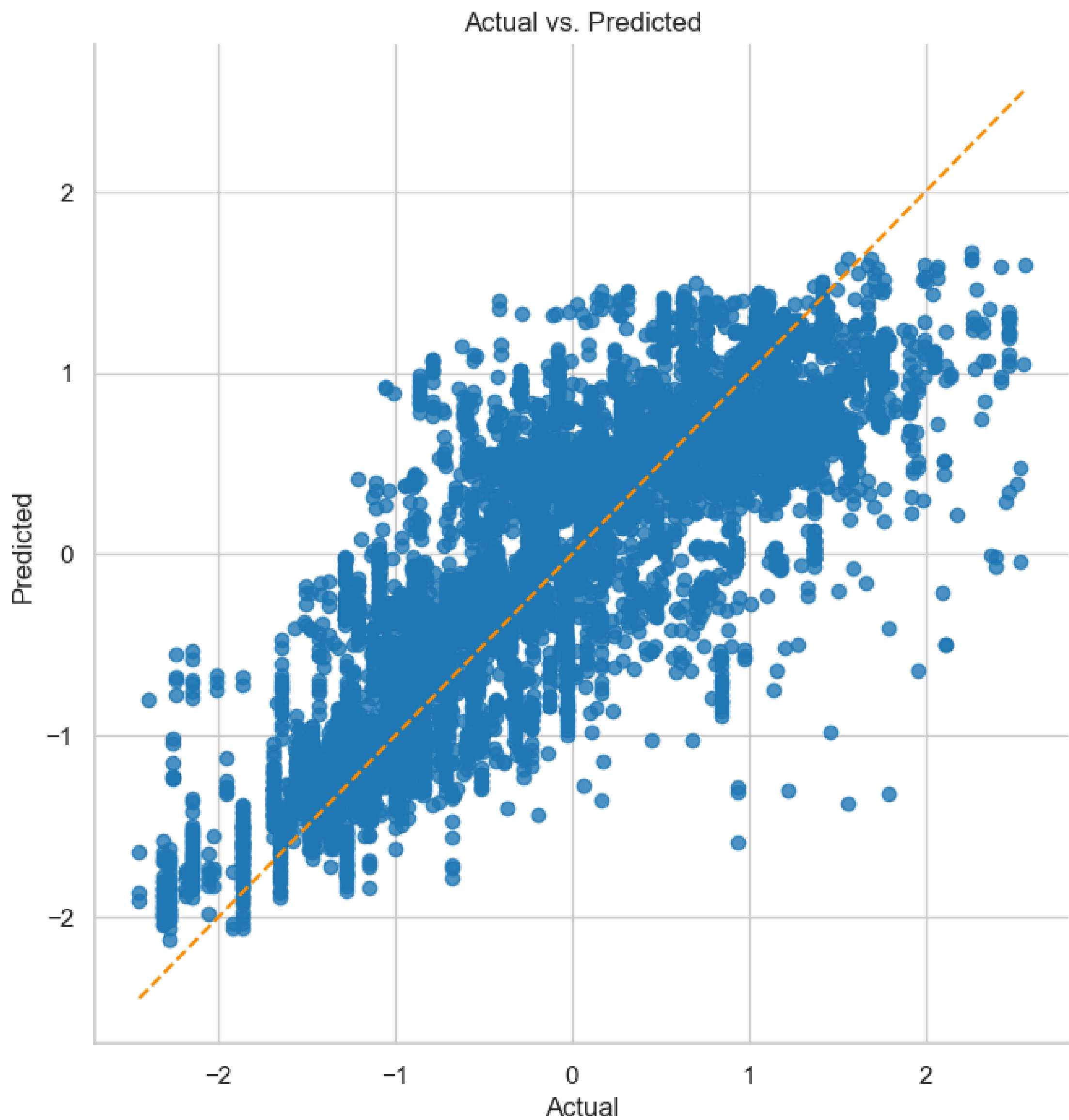
Checking linearity assumption

[69]:
```python
def calculate_residuals(lr, features, label):
    # Creates predictions on the features with the model and calculates␣
↪residuals
    predictions = lr.predict(features)
    df_results = pd.DataFrame({'Actual': label, 'Predicted': predictions})
    df_results['Residuals'] = df_results['Actual'] - df_results['Predicted']
    return df_results
```

[70]:
```python
def linear_assumption(lr, features, label):
    print('Assumption 1: Linear Relationship between the Target and the␣
↪Feature\n')
    print('Checking with a scatter plot of actual vs. predicted.',
           'Predictions should follow the diagonal line.')
    df_results = calculate_residuals(lr, features, label)
    sns.lmplot(x='Actual', y='Predicted', data=df_results, fit_reg=False,␣
↪height=7)

    line_coords = np.linspace(df_results[['Actual', 'Predicted']].min().min(),
                              df_results[['Actual', 'Predicted']].max().max(),␣
↪100)
    plt.plot(line_coords, line_coords, color='darkorange', linestyle='--')
    plt.title('Actual vs. Predicted')
    plt.show()
```

[71]:
```python
linear_assumption(lr, X_train, y_train)
```

```
Assumption 1: Linear Relationship between the Target and the Feature

Checking with a scatter plot of actual vs. predicted. Predictions should follow
the diagonal line.
```



Normality assumption

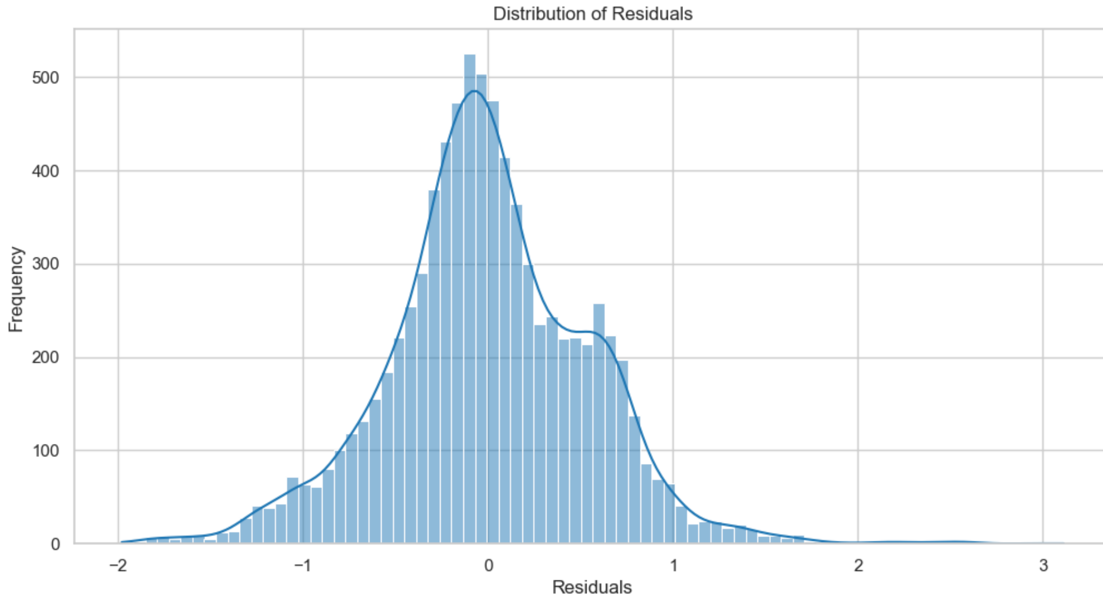
[72]:
```
from statsmodels.stats.diagnostic import normal_ad
```

[73]:
```
def normal_errors_assumption(lr, X_train, y_train, p_value_thresh=0.05):
    """
    Checks normality of residuals for linear regression using Anderson-Darling␣
 ↪test,
    and plots the residual distribution.
    """
    y_pred = lr.predict(X_train)
    residuals = y_train - y_pred
```

```
    print('Assumption 2: The error terms are normally distributed\n')
    print('Using the Anderson-Darling test for normal distribution...')

    # Perform Anderson-Darling test
    p_value = normal_ad(residuals)[1]
    print('p-value from the test - below 0.05 generally means non-normal:',␣
↪p_value)

    if p_value < p_value_thresh:
        print('Residuals are NOT normally distributed')
        print('Assumption NOT satisfied')
        print('Confidence intervals will likely be affected.')
        print('Try performing nonlinear transformations on variables.')
    else:
        print('Residuals are normally distributed')
        print('Assumption satisfied')


    plt.figure(figsize=(12, 6))
    plt.title('Distribution of Residuals')
    sns.histplot(residuals, kde=True)
    plt.xlabel('Residuals')
    plt.ylabel('Frequency')
    plt.show()
```

[74]:
```
normal_errors_assumption(lr, X_train, y_train)
```

```
Assumption 2: The error terms are normally distributed

Using the Anderson-Darling test for normal distribution…
p-value from the test - below 0.05 generally means non-normal: 0.0
Residuals are NOT normally distributed
Assumption NOT satisfied
Confidence intervals will likely be affected.
Try performing nonlinear transformations on variables.
```



Multicollinearity assumption

[75]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

[76]:
```
def calc_vif(X):
    """
    Calculates Variance Inflation Factor (VIF) for each feature column after
    cleaning data of NaN and infinite values.
    """
    # Keep only numeric columns
    X_numeric = X.select_dtypes(include=[np.number])
    # Replace infinite values with NaN, then drop rows with NaN
    X_clean = X_numeric.replace([np.inf, -np.inf], np.nan).dropna()

    vif = pd.DataFrame()
    vif["variables"] = X_clean.columns
    vif["VIF"] = [variance_inflation_factor(X_clean.values, i) for i in␣
 ↪range(X_clean.shape[1])]
    return vif
```

[77]:
```
vif_result = calc_vif(X_train)
print(vif_result)
```

```
         variables       VIF
0      Total_Stops  3.523610
1   Duration_hours  3.560112
2      Journey_day  1.004596
3    Journey_month  1.023563
```

```
4    Arrival_hour  1.048141
5        Dep_hour  1.018130
6         Dep_min  1.020159
7     Arrival_min  1.088331
8   Duration_mins  1.080899
```

Autocorrelation assumption

[78]:
```python
from statsmodels.stats.stattools import durbin_watson
```

[79]:
```python
def autocorrelation_assumption(lr, X_train, y_train):
    """
    Checks autocorrelation of residuals using Durbin-Watson test.
    Assumes the residuals should not be correlated for classical linear␣
 ↪regression.
    """
    y_pred = lr.predict(X_train)
    residuals = y_train - y_pred

    print('Assumption 4: No Autocorrelation\n')
    print('Performing Durbin-Watson Test')
    print('Values between 1.5 and 2.5 generally show no autocorrelation')
    print('0 - 1.5: positive autocorrelation')
    print('2.5 - 4: negative autocorrelation')
    print('-------------------------------------')

    dw_value = durbin_watson(residuals)
    print('Durbin-Watson:', dw_value)
    if dw_value < 1.5:
        print('Signs of positive autocorrelation\nAssumption not satisfied')
    elif dw_value > 2.5:
        print('Signs of negative autocorrelation\nAssumption not satisfied')
    else:
        print('Little to no autocorrelation\nAssumption satisfied')
```

[80]:
```python
autocorrelation_assumption(lr, X_train, y_train)
```

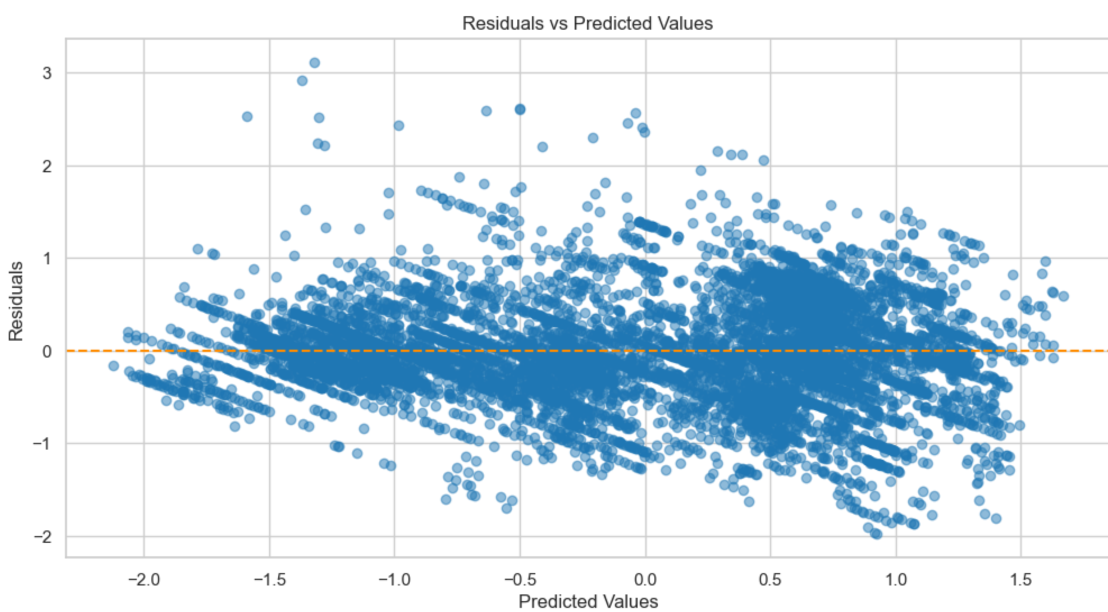
```
Assumption 4: No Autocorrelation

Performing Durbin-Watson Test
Values between 1.5 and 2.5 generally show no autocorrelation
0 - 1.5: positive autocorrelation
2.5 - 4: negative autocorrelation
-------------------------------------
Durbin-Watson: 2.0240255305437818
Little to no autocorrelation
Assumption satisfied
```

Homoscedasticity assumption

[81]:
```python
def homoscedasticity_assumption(lr, X_train, y_train):
    """
    Checks for constant variance in residuals (homoscedasticity) for linear␣
    ↪regression.
    """
    y_pred = lr.predict(X_train)
    residuals = y_train - y_pred

    print('Assumption 5: Homoscedasticity of Error Terms\n')
    print('Residuals should show constant variance.')

    plt.figure(figsize=(12, 6))
    plt.scatter(y_pred, residuals, alpha=0.5)
    plt.axhline(0, color='darkorange', linestyle='--')
    plt.xlabel('Predicted Values')
    plt.ylabel('Residuals')
    plt.title('Residuals vs Predicted Values')
    plt.show()
```

[82]:
```python
homoscedasticity_assumption(lr, X_train, y_train)
```

```
Assumption 5: Homoscedasticity of Error Terms

Residuals should show constant variance.
```



1.8 DecisionTree

[83]:
```
dt = DecisionTreeRegressor(random_state = 0)
dt.fit(X_train,y_train)
```

[83]:
```
DecisionTreeRegressor(random_state=0)
```

[84]:
```
y_pred_dt = dt.predict(X_test)
```

[85]:
```
print("R2 Score:", r2_score(y_test, y_pred_dt))
print("MSE:", mean_squared_error(y_test, y_pred_dt))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_dt)))
print("MAE:", mean_absolute_error(y_test, y_pred_dt))
```

```
R2 Score: 0.7294295241083384
MSE: 0.26079583502304704
RMSE: 0.5106817355487143
MAE: 0.32367563608328814
```

[86]:
```
model_comparison['DecisionTree'] = {
    'R2': r2_score(y_test, y_pred_dt),
    'MSE': mean_squared_error(y_test, y_pred_dt),
    'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_dt)),
    'MAE': mean_absolute_error(y_test, y_pred_dt)
}
```

1.9 Random Forest

linearity assumption is violated so random forest(non-linear data) is used

[87]:
```
rf = RandomForestRegressor()
rf.fit(X_train, y_train)
```

[87]:
```
RandomForestRegressor()
```

[88]:
```
y_pred_rf = rf.predict(X_test)
```

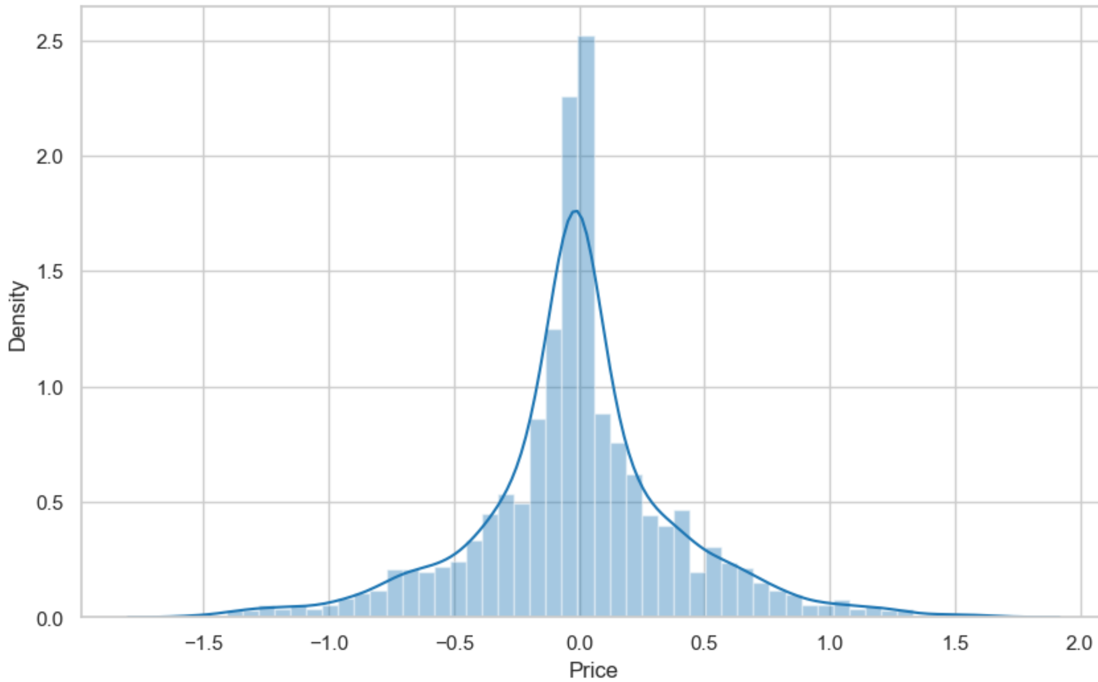
[89]:
```
print("R2 Score:", r2_score(y_test, y_pred_rf))
print("MSE:", mean_squared_error(y_test, y_pred_rf))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_rf)))
print("MAE:", mean_absolute_error(y_test, y_pred_rf))
```

```
R2 Score: 0.8285372103248156
MSE: 0.1652685174217815
RMSE: 0.406532307967991
MAE: 0.274294791564093
```

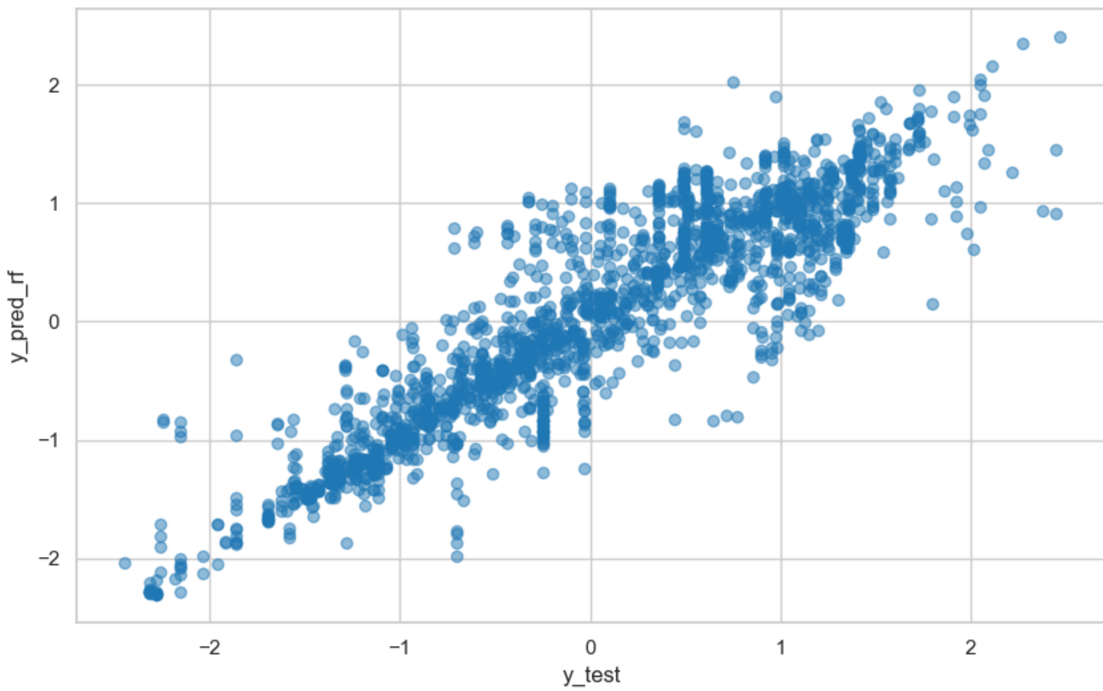
[90]:
```
model_comparison['Random Forest'] = {
    'R2': r2_score(y_test, y_pred_rf),
```

```
    'MSE': mean_squared_error(y_test, y_pred_rf),
    'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_rf)),
    'MAE': mean_absolute_error(y_test, y_pred_rf)
}
```

[91]:
```
sns.distplot(y_test-y_pred_rf)
plt.show()
```



[92]:
```
plt.scatter(y_test, y_pred_rf, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred_rf")
plt.show()
```



1.10 Hyperparameter Tuning

[93]:
```
n_estimators = [int(x) for x in np.linspace(start=100, stop=1200, num=12)]

max_features = ['sqrt', 'log2']

max_depth = [int(x) for x in np.linspace(5, 30, num=6)]
max_depth.append(None)
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
}
```

[94]:
```
rf_random = RandomizedSearchCV(
    estimator= rf,
    param_distributions=random_grid,
    n_iter=100,
    scoring='neg_mean_squared_error',
```

```
    cv=5,
    verbose=2,
    random_state=0,
    n_jobs=-1
)
```

[95]:
```
rf_random.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

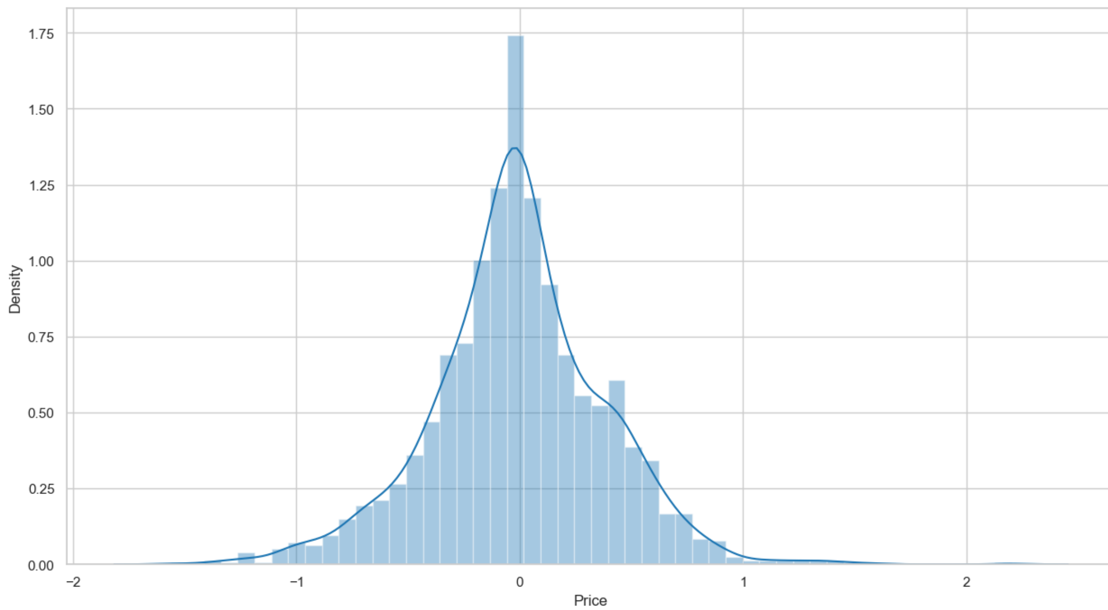
[95]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'max_depth': [5, 10, 15, 20, 25, 30,
                                                      None],
                                        'max_features': ['sqrt', 'log2'],
                                        'min_samples_leaf': [1, 2, 5, 10],
                                        'min_samples_split': [2, 5, 10, 15,
                                                              100],
                                        'n_estimators': [100, 200, 300, 400,
                                                         500, 600, 700, 800,
                                                         900, 1000, 1100,
                                                         1200]},
                   random_state=0, scoring='neg_mean_squared_error', verbose=2)
```

[96]:
```
rf_random.best_params_
```

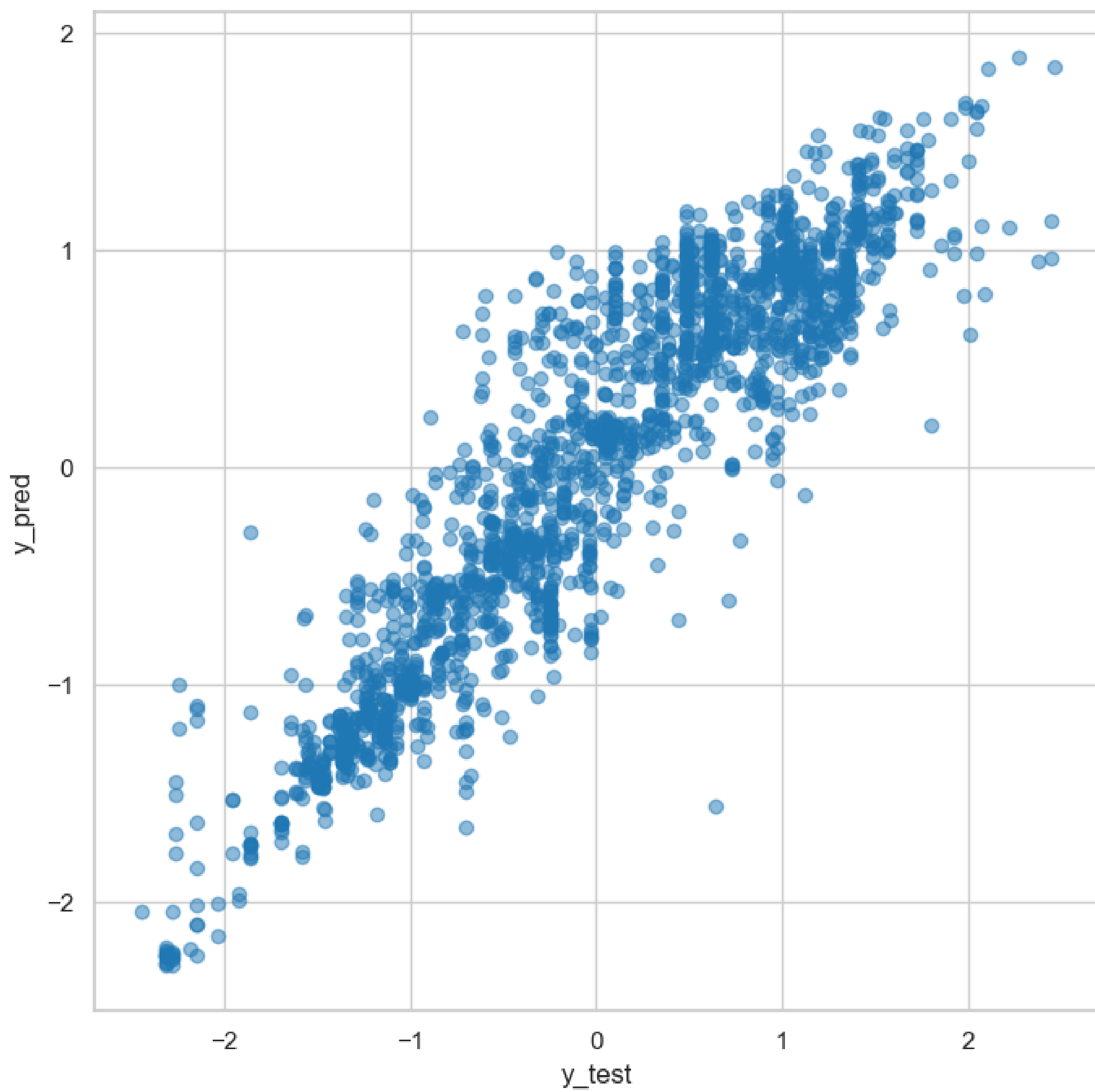
[96]:
```
{'n_estimators': 1200,
 'min_samples_split': 10,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': None}
```

[97]:
```
prediction = rf_random.predict(X_test)
```

[98]:
```
plt.figure(figsize = (15,8))
sns.distplot(y_test-prediction)
plt.show()
```



[99]:
```
plt.figure(figsize = (8,8))
plt.scatter(y_test, prediction, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```



[100]:
```
print("R2 Score:", r2_score(y_test, prediction))
print("MSE:", mean_squared_error(y_test, prediction))
print("RMSE:", np.sqrt(mean_squared_error(y_test, prediction)))
print("MAE:", mean_absolute_error(y_test, prediction))
```

```
R2 Score: 0.8450821434477532
MSE: 0.14932128727785154
RMSE: 0.38642112685236496
MAE: 0.2864533781987897
```

[101]:
```
model_comparison['R F After Tunning'] = {
    'R2': r2_score(y_test, prediction),
    'MSE': mean_squared_error(y_test, prediction),
```

```
    'RMSE': np.sqrt(mean_squared_error(y_test, prediction)),
    'MAE': mean_absolute_error(y_test, prediction)
}
```

1.11 Gradient Boosting

[103]:
```
from sklearn.ensemble import GradientBoostingRegressor
```

[104]:
```
gb = GradientBoostingRegressor()
gb.fit(X_train, y_train)
```

[104]:
```
GradientBoostingRegressor()
```

[105]:
```
gb_pred = gb.predict(X_test)
```

[106]:
```
print("R2 Score:", r2_score(y_test, gb_pred))
print("MSE:", mean_squared_error(y_test, gb_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, gb_pred)))
print("MAE:", mean_absolute_error(y_test, gb_pred))
```

```
R2 Score: 0.804530790509146
MSE: 0.1884076802632153
RMSE: 0.434059535390268
MAE: 0.3399156002433246
```

[107]:
```
model_comparison['Gradient Boosting'] = {
    'R2': r2_score(y_test, gb_pred),
    'MSE': mean_squared_error(y_test, gb_pred),
    'RMSE': np.sqrt(mean_squared_error(y_test, gb_pred)),
    'MAE': mean_absolute_error(y_test, gb_pred)
}
```

1.12 XGboost

[108]:
```
import xgboost as xgb
```

[110]:
```
xgbr = xgb.XGBRegressor()
xgbr.fit(X_train, y_train)
```

[110]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             feature_weights=None, gamma=None, grow_policy=None,
             importance_type=None, interaction_constraints=None,
             learning_rate=None, max_bin=None, max_cat_threshold=None,
             max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
             max_leaves=None, min_child_weight=None, missing=nan,
```

```
             monotone_constraints=None, multi_strategy=None, n_estimators=None,
             n_jobs=None, num_parallel_tree=None, …)
```

[111]:
```
xgb_pred = xgbr.predict(X_test)
```

[112]:
```
print("R2 Score:", r2_score(y_test, xgb_pred))
print("MSE:", mean_squared_error(y_test, xgb_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, xgb_pred)))
print("MAE:", mean_absolute_error(y_test, xgb_pred))
```

```
R2 Score: 0.8598120469312733
MSE: 0.13512351693304991
RMSE: 0.3675915082439336
MAE: 0.2618111561175429
```

[113]:
```
model_comparison['XGBoost'] = {
    'R2': r2_score(y_test, xgb_pred),
    'MSE': mean_squared_error(y_test, xgb_pred),
    'RMSE': np.sqrt(mean_squared_error(y_test, xgb_pred)),
    'MAE': mean_absolute_error(y_test, xgb_pred)
}
```

[114]:
```
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7, 10],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'subsample': [0.6, 0.8, 1.0],
    'colsample_bytree': [0.6, 0.8, 1.0]
}
```

[115]:
```
grid_search = GridSearchCV(estimator=xgbr,
                           param_grid=param_grid,
                           scoring='neg_mean_squared_error',
                           cv=3,
                           verbose=2,
                           n_jobs=-1)
grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 432 candidates, totalling 1296 fits
```

[115]:
```
GridSearchCV(cv=3,
             estimator=XGBRegressor(base_score=None, booster=None,
                                    callbacks=None, colsample_bylevel=None,
                                    colsample_bynode=None,
                                    colsample_bytree=None, device=None,
                                    early_stopping_rounds=None,
                                    enable_categorical=False, eval_metric=None,
                                    feature_types=None, feature_weights=None,
```

```
                                      gamma=None, grow_policy=None,
                                      importance_type=None,
                                      interaction_constraints=None…
                                      min_child_weight=None, missing=nan,
                                      monotone_constraints=None,
                                      multi_strategy=None, n_estimators=None,
                                      n_jobs=None, num_parallel_tree=None, …),
             n_jobs=-1,
             param_grid={'colsample_bytree': [0.6, 0.8, 1.0],
                         'learning_rate': [0.01, 0.05, 0.1, 0.2],
                         'max_depth': [3, 5, 7, 10],
                         'n_estimators': [100, 200, 300],
                         'subsample': [0.6, 0.8, 1.0]},
             scoring='neg_mean_squared_error', verbose=2)
```

[120]:
```python
print("Best parameters:", grid_search.best_params_)
best_xgbr = grid_search.best_estimator_

xgb_tuned_pred = best_xgbr.predict(X_test)

print("R2 Score:", r2_score(y_test, xgb_tuned_pred))
print("MSE:", mean_squared_error(y_test, xgb_tuned_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, xgb_tuned_pred)))
print("MAE:", mean_absolute_error(y_test, xgb_tuned_pred))
```

```
Best parameters: {'colsample_bytree': 0.6, 'learning_rate': 0.1, 'max_depth': 5,
'n_estimators': 300, 'subsample': 1.0}
R2 Score: 0.8682099711306163
MSE: 0.1270289765113342
RMSE: 0.3564112463311648
MAE: 0.2655487590505811
```

[122]:
```python
model_comparison['XgBoost After Tunning'] = {
    'R2': r2_score(y_test, xgb_tuned_pred),
    'MSE': mean_squared_error(y_test, xgb_tuned_pred),
    'RMSE': np.sqrt(mean_squared_error(y_test, xgb_tuned_pred)),
    'MAE': mean_absolute_error(y_test, xgb_tuned_pred)
}
```

1.13 Model Comparision

[123]:
```python
df_model_comparison = pd.DataFrame(model_comparison).T
df_model_comparison
```

[123]:

	R2	MSE	RMSE	MAE
LinearRegression	0.699668	0.289482	0.538036	0.413517
DecisionTree	0.729430	0.260796	0.510682	0.323676
Random Forest	0.828537	0.165269	0.406532	0.274295

R F After Tunning	0.845082	0.149321	0.386421	0.286453
Gradient Boosting	0.804531	0.188408	0.434060	0.339916
XGBoost	0.859812	0.135124	0.367592	0.261811
XgBoost After Tunning	0.868210	0.127029	0.356411	0.265549