In [ ]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import pylab
from sklearn.model_selection import train_test_split
from sklearn import metrics

from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
from sklearn import preprocessing
```

# Loading the Dataset

First we load the dataset and find out the number of columns, rows, NULL values, etc.

In [ ]:
```python
df = pd.read_csv('uber.csv')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         200000 non-null  int64
 1   key                200000 non-null  object
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

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

Out[ ]:

| | Unnamed: 0 | key | fare_amount | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | pa |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 24238194 | 2015-05-07 19:52:06.0000003 | 7.5 | 2015-05-07 19:52:06 UTC | -73.999817 | 40.738354 | -73.999512 | 40.723217 | |
| **1** | 27835199 | 2009-07-17 20:04:56.0000002 | 7.7 | 2009-07-17 20:04:56 UTC | -73.994355 | 40.728225 | -73.994710 | 40.750325 | |
| **2** | 44984355 | 2009-08-24 21:45:00.00000061 | 12.9 | 2009-08-24 21:45:00 UTC | -74.005043 | 40.740770 | -73.962565 | 40.772647 | |
| **3** | 25894730 | 2009-06-26 08:22:21.0000001 | 5.3 | 2009-06-26 08:22:21 UTC | -73.976124 | 40.790844 | -73.965316 | 40.803349 | |
| **4** | 17610152 | 2014-08-28 17:47:00.000000188 | 16.0 | 2014-08-28 17:47:00 UTC | -73.925023 | 40.744085 | -73.973082 | 40.761247 | |

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

Out[ ]:

| | Unnamed: 0 | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passenger_count |
|---|---|---|---|---|---|---|---|
| **count** | 2.000000e+05 | 200000.000000 | 200000.000000 | 200000.000000 | 199999.000000 | 199999.000000 | 200000.000000 |
| **mean** | 2.771250e+07 | 11.359955 | -72.527638 | 39.935885 | -72.525292 | 39.923890 | 1.684535 |
| **std** | 1.601382e+07 | 9.901776 | 11.437787 | 7.720539 | 13.117408 | 6.794829 | 1.385997 |
| **min** | 1.000000e+00 | -52.000000 | -1340.648410 | -74.015515 | -3356.666300 | -881.985513 | 0.000000 |
| **25%** | 1.382535e+07 | 6.000000 | -73.992065 | 40.734796 | -73.991407 | 40.733823 | 1.000000 |
| **50%** | 2.774550e+07 | 8.500000 | -73.981823 | 40.752592 | -73.980093 | 40.753042 | 1.000000 |
| **75%** | 4.155530e+07 | 12.500000 | -73.967154 | 40.767158 | -73.963658 | 40.768001 | 2.000000 |
| **max** | 5.542357e+07 | 499.000000 | 57.418457 | 1644.421482 | 1153.572603 | 872.697628 | 208.000000 |

# Cleaning

In [ ]:
```
df = df.drop(['Unnamed: 0', 'key'], axis=1)
```

In [ ]:
```
df.isna().sum()
```

Out[ ]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

Remove null rows

In [ ]:
```
df.dropna(axis=0,inplace=True)
```

In [ ]:
```
df.dtypes
```

Out[ ]:
```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

Fix data type of `pickup_datetime` from `Object` to `DateTime`

In [ ]:
```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime, errors='coerce')
```

Separating the date and time into separate columns for more usability.

In [ ]:
```
df= df.assign(
    second = df.pickup_datetime.dt.second,
    minute = df.pickup_datetime.dt.minute,
    hour = df.pickup_datetime.dt.hour,
    day= df.pickup_datetime.dt.day,
    month = df.pickup_datetime.dt.month,
    year = df.pickup_datetime.dt.year,
    dayofweek = df.pickup_datetime.dt.dayofweek
)
df = df.drop('pickup_datetime',axis=1)
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 199999 entries, 0 to 199999
Data columns (total 13 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   fare_amount        199999 non-null  float64
 1   pickup_longitude   199999 non-null  float64
 2   pickup_latitude    199999 non-null  float64
 3   dropoff_longitude  199999 non-null  float64
 4   dropoff_latitude   199999 non-null  float64
 5   passenger_count    199999 non-null  int64  
 6   second             199999 non-null  int64  
 7   minute             199999 non-null  int64  
 8   hour               199999 non-null  int64  
 9   day                199999 non-null  int64  
 10  month              199999 non-null  int64  
 11  year               199999 non-null  int64  
 12  dayofweek          199999 non-null  int64  
dtypes: float64(5), int64(8)
memory usage: 21.4 MB
```

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

Out[ ]:

| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passenger_count | second | minute | hour | day | mon |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 7.5 | -73.999817 | 40.738354 | -73.999512 | 40.723217 | 1 | 6 | 52 | 19 | 7 | |
| **1** | 7.7 | -73.994355 | 40.728225 | -73.994710 | 40.750325 | 1 | 56 | 4 | 20 | 17 | |
| **2** | 12.9 | -74.005043 | 40.740770 | -73.962565 | 40.772647 | 1 | 0 | 45 | 21 | 24 | |
| **3** | 5.3 | -73.976124 | 40.790844 | -73.965316 | 40.803349 | 3 | 21 | 22 | 8 | 26 | |
| **4** | 16.0 | -73.925023 | 40.744085 | -73.973082 | 40.761247 | 5 | 0 | 47 | 17 | 28 | |

# Haversine Formula

Calculatin the distance between the pickup and drop co-ordinates using the Haversine formual for accuracy.

$$d = 2r sin^{-1}\left(\sqrt{sin^2\left(\frac{\Phi_2-\Phi_1}{2}\right) + cos(\Phi_1)cos(\Phi_2)sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)}\right)$$

In [ ]:
```
incorrect_coordinates = df.loc[
    (df.pickup_latitude > 90) |(df.pickup_latitude < -90) |
    (df.dropoff_latitude > 90) |(df.dropoff_latitude < -90) |
    (df.pickup_longitude > 180) |(df.pickup_longitude < -180) |
    (df.dropoff_longitude > 90) |(df.dropoff_longitude < -90)
]

df.drop(incorrect_coordinates, inplace = True, errors = 'ignore')
```

In [ ]:
```
def distance_transform(longitude1, latitude1, longitude2, latitude2):
    long1, lati1, long2, lati2 = map(np.radians, [longitude1, latitude1, longitude2, latitude2])
    dist_long = long2 - long1
    dist_lati = lati2 - lati1
    a = np.sin(dist_lati/2)**2 + np.cos(lati1) * np.cos(lati2) * np.sin(dist_long/2)**2
    c = 2 * np.arcsin(np.sqrt(a)) * 6371
    # long1,lati1,long2,lati2 = longitude1[pos],latitude1[pos],longitude2[pos],latitude2[pos]
    # c = sqrt((long2 - long1) ** 2 + (lati2 - lati1) ** 2)asin

    return c
```

In [ ]:
```
df['Distance'] = distance_transform(
    df['pickup_longitude'],
    df['pickup_latitude'],
    df['dropoff_longitude'],
    df['dropoff_latitude']
)
```

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

Out[ ]:

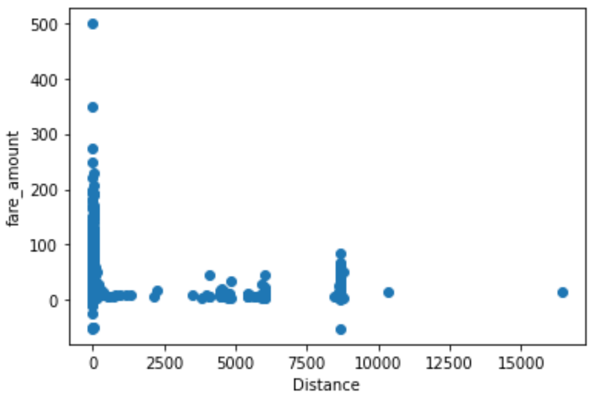
| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passenger_count | second | minute | hour | day | mon |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 7.5 | -73.999817 | 40.738354 | -73.999512 | 40.723217 | 1 | 6 | 52 | 19 | 7 | |
| **1** | 7.7 | -73.994355 | 40.728225 | -73.994710 | 40.750325 | 1 | 56 | 4 | 20 | 17 | |
| **2** | 12.9 | -74.005043 | 40.740770 | -73.962565 | 40.772647 | 1 | 0 | 45 | 21 | 24 | |
| **3** | 5.3 | -73.976124 | 40.790844 | -73.965316 | 40.803349 | 3 | 21 | 22 | 8 | 26 | |
| **4** | 16.0 | -73.925023 | 40.744085 | -73.973082 | 40.761247 | 5 | 0 | 47 | 17 | 28 | |

# Outliers

We can get rid of the trips with very large distances that are outliers as well as trips with 0 distance.

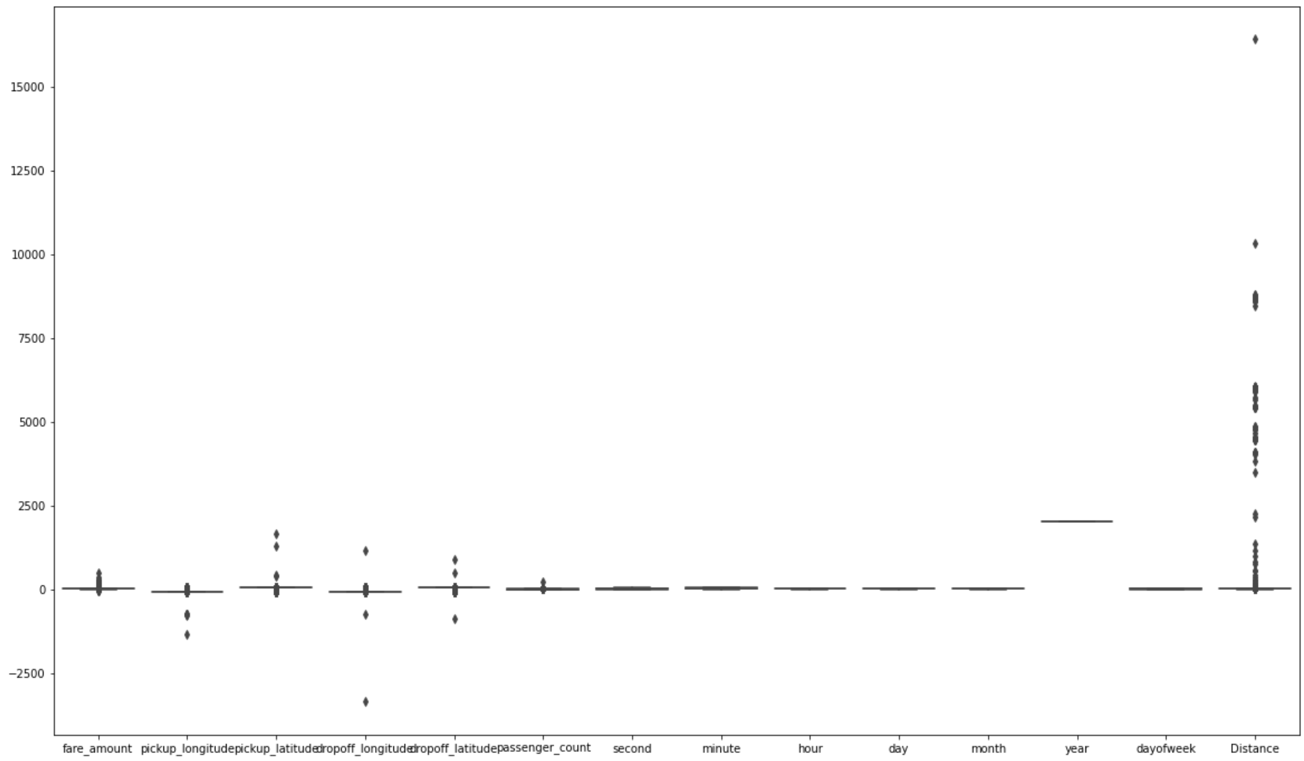
In [ ]:
```
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[ ]:
```
Text(0, 0.5, 'fare_amount')
```




In [ ]:
```
plt.figure(figsize=(20,12))
sns.boxplot(data = df)
```

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

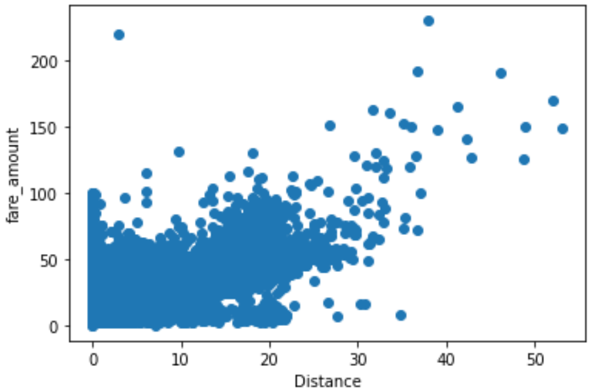



In [ ]:
```
df.drop(df[df['Distance'] >= 60].index, inplace = True)
df.drop(df[df['fare_amount'] <= 0].index, inplace = True)

df.drop(df[(df['fare_amount']>100) & (df['Distance']<1)].index, inplace = True )
df.drop(df[(df['fare_amount']<100) & (df['Distance']>100)].index, inplace = True )
```

In [ ]:
```python
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[ ]:
```
Text(0, 0.5, 'fare_amount')
```




# Coorelation Matrix

To find the two variables that have the most inter-dependence

In [ ]:
```python
corr = df.corr()

corr.style.background_gradient(cmap='BuGn')
```

Out[ ]:

| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passenger_count | second | mini |
|---|---|---|---|---|---|---|---|---|
| **fare_amount** | 1.000000 | 0.005885 | -0.006253 | 0.005501 | -0.006142 | 0.011693 | -0.000995 | -0.0077 |
| **pickup_longitude** | 0.005885 | 1.000000 | -0.973204 | 0.999992 | -0.981941 | -0.000649 | -0.014677 | 0.0027 |
| **pickup_latitude** | -0.006253 | -0.973204 | 1.000000 | -0.973206 | 0.991076 | -0.001190 | 0.016809 | -0.0022 |
| **dropoff_longitude** | 0.005501 | 0.999992 | -0.973206 | 1.000000 | -0.981942 | -0.000650 | -0.014638 | 0.0028 |
| **dropoff_latitude** | -0.006142 | -0.981941 | 0.991076 | -0.981942 | 1.000000 | -0.001035 | 0.017202 | -0.0025 |
| **passenger_count** | 0.011693 | -0.000649 | -0.001190 | -0.000650 | -0.001035 | 1.000000 | -0.202987 | 0.0007 |
| **second** | -0.000995 | -0.014677 | 0.016809 | -0.014638 | 0.017202 | -0.202987 | 1.000000 | 0.0018 |
| **minute** | -0.007795 | 0.002796 | -0.002295 | 0.002803 | -0.002593 | 0.000733 | 0.001893 | 1.0000 |
| **hour** | -0.020692 | 0.001547 | -0.001823 | 0.001316 | -0.001460 | 0.013226 | -0.013419 | 0.0013 |
| **day** | 0.001059 | 0.005300 | -0.008901 | 0.005307 | -0.008900 | 0.003146 | -0.002100 | -0.0012 |
| **month** | 0.023759 | -0.002667 | 0.004098 | -0.002656 | 0.004143 | 0.009921 | -0.049734 | -0.0016 |
| **year** | 0.121195 | 0.005907 | -0.008466 | 0.005878 | -0.008553 | 0.004841 | 0.083106 | -0.0026 |
| **dayofweek** | 0.006181 | 0.003006 | -0.004787 | 0.003082 | -0.004648 | 0.033360 | -0.000113 | -0.0024 |
| **Distance** | 0.857729 | -0.117044 | 0.110843 | -0.117282 | 0.109486 | 0.007784 | -0.000350 | -0.0079 |

# Standardization

For more accurate results on our linear regression model

In [ ]:
```python
X = df['Distance'].values.reshape(-1, 1)        #Independent Variable
y = df['fare_amount'].values.reshape(-1, 1)     #Dependent Variable
```

In [ ]:
```python
from sklearn.preprocessing import StandardScaler
std = StandardScaler()
y_std = std.fit_transform(y)
print(y_std)

x_std = std.fit_transform(X)
print(x_std)
```

```
[[-0.39820843]
 [-0.37738556]
 [ 0.1640092 ]
 ...
 [ 2.03806797]
 [ 0.3305922 ]
 [ 0.28894645]]
[[-0.43819769]
 [-0.22258873]
 [ 0.49552213]
 ...
 [ 2.67145829]
 [ 0.07874908]
 [ 0.60173174]]
```

# Splitting the Dataset

Training and Test Set

In [ ]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x_std, y_std, test_size=0.2, random_state=0)
```

# Simple Linear Regression

Training the simple linear regression model on the training set

In [ ]:

```
from sklearn.linear_model import LinearRegression
l_reg = LinearRegression()
l_reg.fit(X_train, y_train)

print("Training set score: {:.2f}".format(l_reg.score(X_train, y_train)))
print("Test set score: {:.7f}".format(l_reg.score(X_test, y_test)))
```

```
Training set score: 0.74
Test set score: 0.7340468
```

In [ ]:

```
y_pred = l_reg.predict(X_test)

result = pd.DataFrame()
result[['Actual']] = y_test
result[['Predicted']] = y_pred

result.sample(10)
```

Out[ ]:

| | Actual | Predicted |
|---|---|---|
| **6607** | 0.278535 | 0.256442 |
| **4656** | 0.747050 | 0.539006 |
| **38102** | -0.294094 | -0.360193 |
| **33546** | -0.137922 | -0.618219 |
| **26106** | -0.335740 | -0.255066 |
| **10178** | -0.377386 | -0.257612 |
| **4447** | 0.372238 | 0.351430 |
| **30142** | -0.335740 | -0.253503 |
| **37765** | 0.330592 | 0.189662 |
| **12811** | 0.642935 | 0.832901 |

In [ ]:

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Absolute % Error:', metrics.mean_absolute_percentage_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
print('R Squared (R²):', np.sqrt(metrics.r2_score(y_test, y_pred)))
```

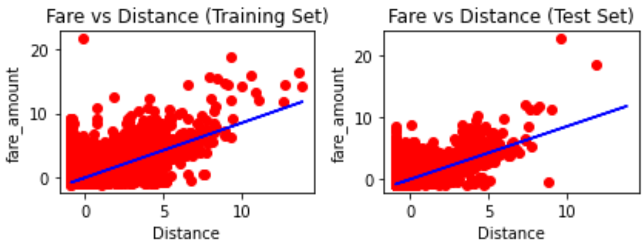
```
Mean Absolute Error: 0.26621298757938955
Mean Absolute % Error: 1.983074763340738
Mean Squared Error: 0.2705243510778542
Root Mean Squared Error: 0.5201195546005305
R Squared (R²): 0.8567653080822022
```

### Visualization

In [ ]:
```
plt.subplot(2, 2, 1)
plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, l_reg.predict(X_train), color ="blue")
plt.title("Fare vs Distance (Training Set)")
plt.ylabel("fare_amount")
plt.xlabel("Distance")

plt.subplot(2, 2, 2)
plt.scatter(X_test, y_test, color = 'red')
plt.plot(X_train, l_reg.predict(X_train), color ="blue")
plt.ylabel("fare_amount")
plt.xlabel("Distance")
plt.title("Fare vs Distance (Test Set)")

plt.tight_layout()
plt.show()
```




In [ ]:
```
cols = ['Model', 'RMSE', 'R-Squared']

# create a empty dataframe of the colums
# columns: specifies the columns to be selected
result_tabulation = pd.DataFrame(columns = cols)

# compile the required information
linreg_metrics = pd.DataFrame([[
     "Linear Regresion model",
     np.sqrt(metrics.mean_squared_error(y_test, y_pred)),
     np.sqrt(metrics.r2_score(y_test, y_pred))
]], columns = cols)

result_tabulation = pd.concat([result_tabulation, linreg_metrics], ignore_index=True)

result_tabulation
```

Out[ ]:

| | Model | RMSE | R-Squared |
|---|---|---|---|
| 0 | Linear Regresion model | 0.52012 | 0.856765 |

# RandomForestRegressor

Training the RandomForestRegressor model on the training set

In [ ]:
```
rf_reg = RandomForestRegressor(n_estimators=100, random_state=10)

# fit the regressor with training dataset
rf_reg.fit(X_train, y_train)
```

Out[ ]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=10)
```

In [ ]:
```
# predict the values on test dataset using predict()
y_pred_RF = rf_reg.predict(X_test)

result = pd.DataFrame()
result[['Actual']] = y_test
result['Predicted'] = y_pred_RF

result.sample(10)
```

Out[ ]:

| | Actual | Predicted |
|---|---|---|
| **36840** | -0.502323 | -0.461350 |
| **20708** | -0.419031 | 0.031472 |
| **14255** | -0.814666 | -0.783328 |
| **15882** | -0.460677 | -0.280559 |
| **4628** | 0.747050 | 1.350747 |
| **14809** | 0.226478 | -0.074751 |
| **25913** | -0.658494 | -0.661410 |
| **30875** | -0.460677 | -0.408620 |
| **28673** | -0.502323 | -0.307421 |
| **32829** | -0.554380 | -0.447350 |

In [ ]:

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred_RF))
print('Mean Absolute % Error:', metrics.mean_absolute_percentage_error(y_test, y_pred_RF))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred_RF))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred_RF)))
print('R Squared (R²):', np.sqrt(metrics.r2_score(y_test, y_pred_RF)))
```

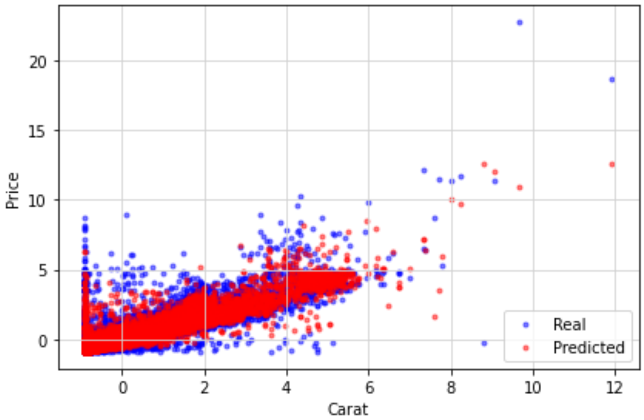
```
Mean Absolute Error: 0.3077087698385678
Mean Absolute % Error: 2.161623761570947
Mean Squared Error: 0.33297733033643484
Root Mean Squared Error: 0.5770418791876677
R Squared (R²): 0.8201518783882692
```

### Visualization

In [ ]:

```
# Build scatterplot
plt.scatter(X_test, y_test, c = 'b', alpha = 0.5, marker = '.', label = 'Real')
plt.scatter(X_test, y_pred_RF, c = 'r', alpha = 0.5, marker = '.', label = 'Predicted')
plt.xlabel('Carat')
plt.ylabel('Price')
plt.grid(color = '#D3D3D3', linestyle = 'solid')
plt.legend(loc = 'lower right')


plt.tight_layout()
plt.show()
```




In [ ]:

```
# compile the required information
random_forest_metrics = pd.DataFrame([[
     "Random Forest Regressor model",
     np.sqrt(metrics.mean_squared_error(y_test, y_pred_RF)),
     np.sqrt(metrics.r2_score(y_test, y_pred_RF))
]], columns = cols)

result_tabulation = pd.concat([result_tabulation, random_forest_metrics], ignore_index=True)

result_tabulation
```

Out[ ]:

| | Model | RMSE | R-Squared |
|---|---|---|---|
| **0** | Linear Regresion model | 0.520120 | 0.856765 |
| **1** | Random Forest Regressor model | 0.577042 | 0.820152 |