In [1]:
```
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 [2]:
```
df = pd.read_csv('uber.csv')
```

In [3]:
```
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 [4]:
```
df.head()
```

Out[4]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
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
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	1
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	1
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	3
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	5

In [5]:
```
df.describe()
```

Out[5]:

	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 [6]:
```
df = df.drop(['Unnamed: 0', 'key'], axis=1)
```

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

Out[7]:

```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
```

Remove null rows

In [8]:
```python
df.dropna(axis=0,inplace=True)
```

In [9]:
```python
df.dtypes
```

Out[9]:
```
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 [10]:
```python
df.pickup_datetime = pd.to_datetime(df.pickup_datetime, errors='coerce')
```

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

In [11]:
```python
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 [12]:
```python
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 [13]:
```python
df.head()
```

Out[13]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	second	minute	hour	day	month	year	dayofweek
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1	6	52	19	7	5	2015	3
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1	56	4	20	17	7	2009	4
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1	0	45	21	24	8	2009	0
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3	21	22	8	26	6	2009	4
4	16.0	-73.925023	40.744085	-73.973082	40.761247	5	0	47	17	28	8	2014	3

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 [14]:
```python
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 [15]:
```
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 [16]:
```
df['Distance'] = distance_transform(
    df['pickup_longitude'],
    df['pickup_latitude'],
    df['dropoff_longitude'],
    df['dropoff_latitude']
)
```

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

Out[17]:

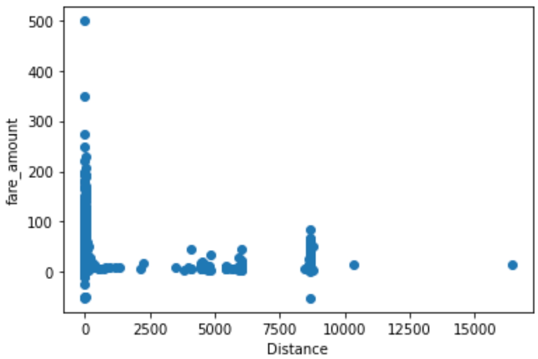
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	second	minute	hour	day	month	year	dayofweek
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1	6	52	19	7	5	2015	3
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1	56	4	20	17	7	2009	4
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1	0	45	21	24	8	2009	0
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3	21	22	8	26	6	2009	4
4	16.0	-73.925023	40.744085	-73.973082	40.761247	5	0	47	17	28	8	2014	3

Outliers

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

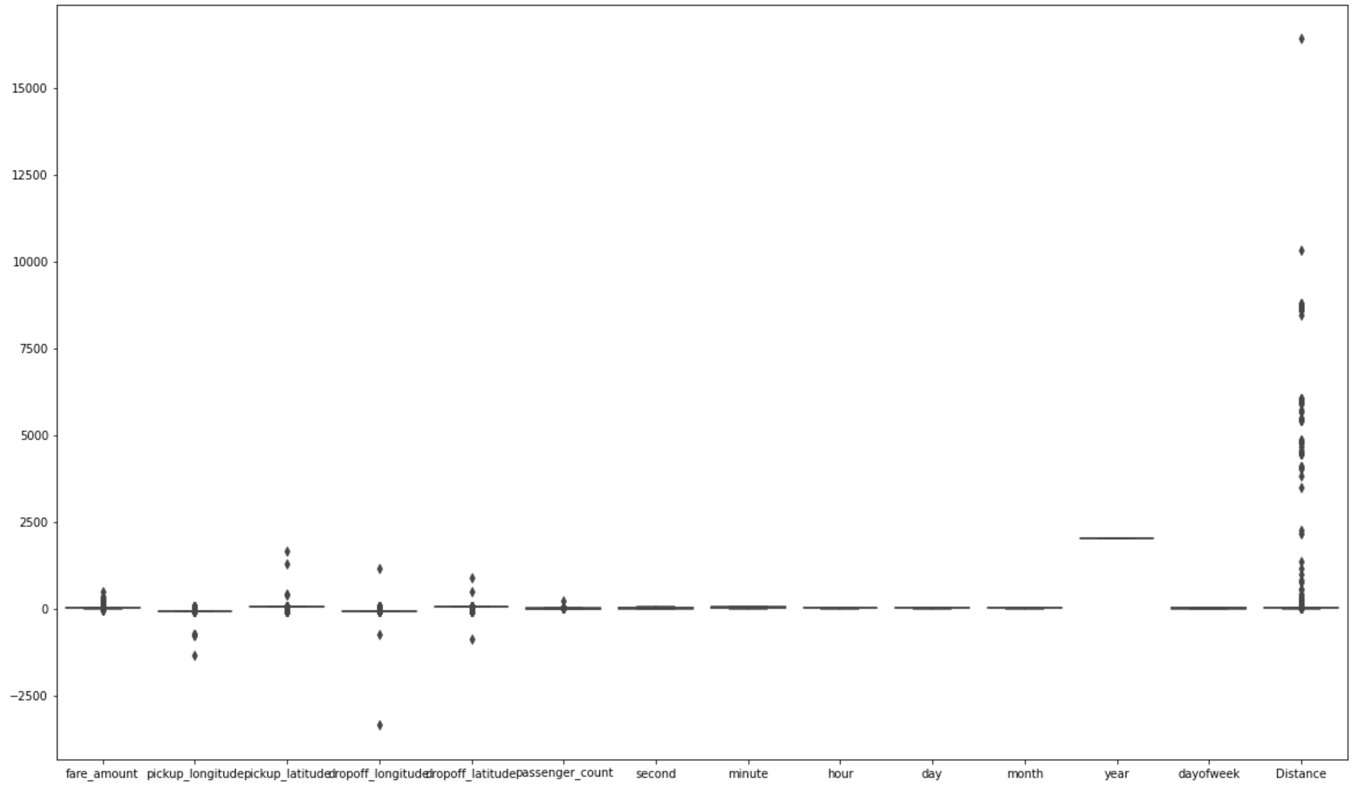
In [18]:
```
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[18]: Text(0, 0.5, 'fare_amount')



In [19]:
```
plt.figure(figsize=(20,12))
sns.boxplot(data = df)
```

Out[19]: <AxesSubplot:>

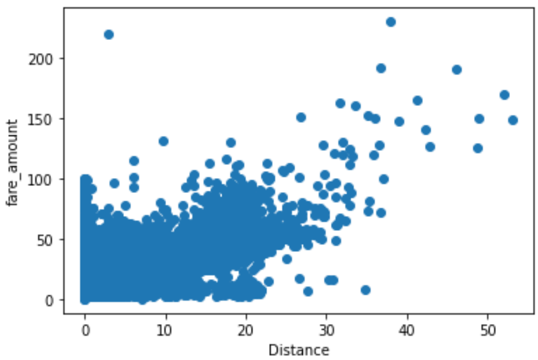


In [20]:
```
df.drop(df[df['Distance'] >= 60].index, inplace = True)
df.drop(df[df['fare_amount'] <= 0].index, inplace = True)

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 [21]:
```
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[21]: Text(0, 0.5, 'fare_amount')



Coorelation Matrix

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

In [22]:
```
corr = df.corr()

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

Out[22]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	second	minute	hour	
fare_amount	1.000000	0.005885	-0.006253	0.005501	-0.006142	0.011693	-0.000995	-0.007795	-0.020692	0.00
pickup_longitude	0.005885	1.000000	-0.973204	0.999992	-0.981941	-0.000649	-0.014677	0.002796	0.001547	0.00
pickup_latitude	-0.006253	-0.973204	1.000000	-0.973206	0.991076	-0.001190	0.016809	-0.002295	-0.001823	-0.00
dropoff_longitude	0.005501	0.999992	-0.973206	1.000000	-0.981942	-0.000650	-0.014638	0.002803	0.001316	0.00
dropoff_latitude	-0.006142	-0.981941	0.991076	-0.981942	1.000000	-0.001035	0.017202	-0.002593	-0.001460	-0.00
passenger_count	0.011693	-0.000649	-0.001190	-0.000650	-0.001035	1.000000	-0.202987	0.000733	0.013226	0.00

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	second	minute	hour	
second	-0.000995	-0.014677	0.016809	-0.014638	0.017202	-0.202987	1.000000	0.001893	-0.013419	-0.002
minute	-0.007795	0.002796	-0.002295	0.002803	-0.002593	0.000733	0.001893	1.000000	0.001352	-0.00
hour	-0.020692	0.001547	-0.001823	0.001316	-0.001460	0.013226	-0.013419	0.001352	1.000000	0.004
day	0.001059	0.005300	-0.008901	0.005307	-0.008900	0.003146	-0.002100	-0.001255	0.004849	1.000
month	0.023759	-0.002667	0.004098	-0.002656	0.004143	0.009921	-0.049734	-0.001606	-0.003989	-0.01
year	0.121195	0.005907	-0.008466	0.005878	-0.008553	0.004841	0.083106	-0.002687	0.002171	-0.01
dayofweek	0.006181	0.003006	-0.004787	0.003082	-0.004648	0.033360	-0.000113	-0.002405	-0.086995	0.00

Standardization

For more accurate results on our linear regression model

In [23]:
```
X = df['Distance'].values.reshape(-1, 1)        #Independent Variable
y = df['fare_amount'].values.reshape(-1, 1)     #Dependent Variable
```

In [24]:
```
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 [25]:
```
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 [26]:
```
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 [27]:
```
y_pred = l_reg.predict(X_test)

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

result.sample(10)
```

Out[27]:

	Actual	Predicted
1537	0.330592	0.026083
15346	-0.335740	0.233531
3541	-0.710552	-0.265730
36499	-0.044220	0.134647
29055	-0.502323	-0.233261
32339	-0.710552	-0.492669

	Actual	Predicted
5033	0.455529	0.879378
20741	-0.419031	-0.777099
25517	-0.668906	-0.397673

In [28]:
```
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)))
```

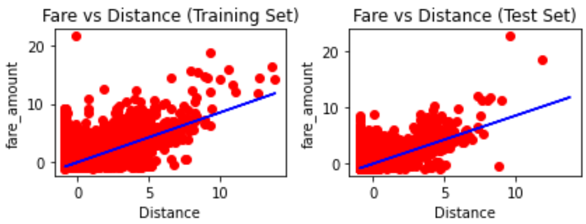
```
Mean Absolute Error: 0.26621298757938955
Mean Absolute % Error: 1.983074763340738
Mean Squared Error: 0.2705243510778542
Root Mean Squared Error: 0.5201195546005305
R Squared (R²): 0.8567653080822022
```

Visualization

In [29]:
```
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 [30]:
```
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[30]:

	Model	RMSE	R-Squared
0	Linear Regresion model	0.52012	0.856765

RandomForestRegressor

Training the RandomForestRegressor model on the training set

In [31]:
```
rf_reg = RandomForestRegressor(n_estimators=100, random_state=10)

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

Out[31]:
```
▾        RandomForestRegressor
RandomForestRegressor(random_state=10)
```

In [32]:
```
# 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[32]:

	Actual	Predicted
16558	-0.606437	-0.763858
31259	0.330592	-0.495868
23833	-0.606437	-0.706491
21759	-0.450266	-0.439750
23057	-0.710552	-0.357291
9115	-0.346151	-0.391545
28306	-0.242037	-0.340113
19079	-0.242037	-0.356042
9708	4.005830	3.895468
34415	-0.242037	-0.044532

In [33]:

```
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)))
```

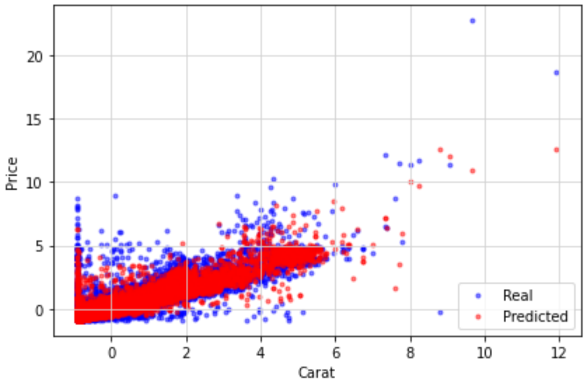
```
Mean Absolute Error: 0.3077087698385678
Mean Absolute % Error: 2.161623761570947
Mean Squared Error: 0.33297733033643484
Root Mean Squared Error: 0.5770418791876677
R Squared (R²): 0.8201518783882692
```

Visualization

In [34]:

```
# 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 [35]:

```
# compile the required information
linreg_metrics = pd.DataFrame([[
     "Linear Regresion 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, linreg_metrics], ignore_index=True)

result_tabulation
```

Out[35]:

	Model	RMSE	R-Squared
0	Linear Regresion model	0.520120	0.856765
1	Linear Regresion model	0.577042	0.820152