In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import classification_report

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data = pd.read_csv("E:/BE/Assignments/LP3/ML Assignments/1/uber.csv")
data.head()
```

Out[2]:

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

In [3]:
```
df = data.copy()
df.head()
```

Out[3]:

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

In [4]:
```
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 [5]:
```
df.describe()
```

Out[5]:

	Unnamed: 0	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_la
count	2.000000e+05	200000.000000	200000.000000	200000.000000	199999.000000	199999.(
mean	2.771250e+07	11.359955	-72.527638	39.935885	-72.525292	39.9
std	1.601382e+07	9.901776	11.437787	7.720539	13.117408	6.7
min	1.000000e+00	-52.000000	-1340.648410	-74.015515	-3356.666300	-881.9
25%	1.382535e+07	6.000000	-73.992065	40.734796	-73.991407	40.7
50%	2.774550e+07	8.500000	-73.981823	40.752592	-73.980093	40.7
75%	4.155530e+07	12.500000	-73.967154	40.767158	-73.963658	40.7
max	5.542357e+07	499.000000	57.418457	1644.421482	1153.572603	872.6

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
Unnamed: 0           0
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [7]:
```
df = df.drop(['Unnamed: 0','key'],axis=1)
df.dropna(axis=0,inplace=True)
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

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 [9]:
```
def haversine (lon_1, lon_2, lat_1, lat_2):

    lon_1, lon_2, lat_1, lat_2 = map(np.radians, [lon_1, lon_2, lat_1, lat_2])  #


    diff_lon = lon_2 - lon_1
    diff_lat = lat_2 - lat_1


    km = 2 * 6371 * np.arcsin(np.sqrt(np.sin(diff_lat/2.0)**2 +
                                  np.cos(lat_1) * np.cos(lat_2) * np.sin(dif

    return km
```

In [10]:
```
df['Distance']= haversine(df['pickup_longitude'], df['dropoff_longitude'],
                             df['pickup_latitude'], df['dropoff_latitude'])

df['Distance'] = df['Distance'].astype(float).round(2)
```

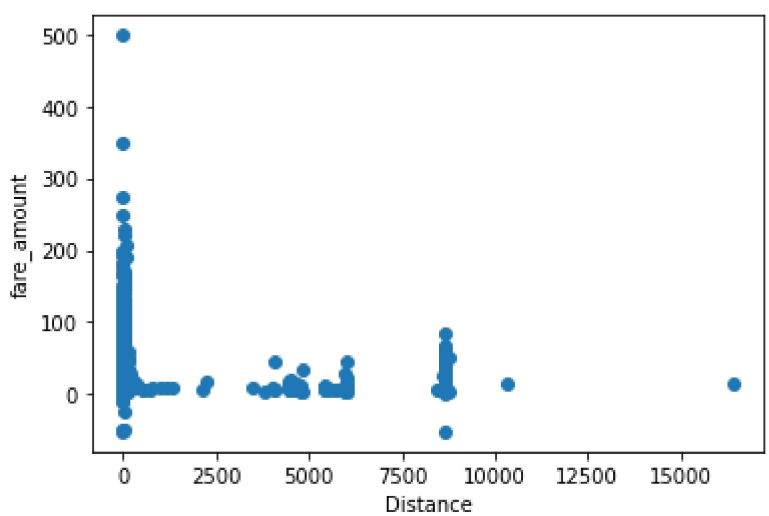
In [11]:
```
df.head()
```

Out[11]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitu
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723:
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750:
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772(
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803:
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761:

In [12]:
```
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[12]: Text(0, 0.5, 'fare_amount')



Outliers

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

In [13]:
```
df.drop(df[df['Distance'] > 60].index, inplace = True)
df.drop(df[df['Distance'] == 0].index, inplace = True)
df.drop(df[df['Distance'] < 0].index, inplace = True)

df.drop(df[df['fare_amount'] == 0].index, inplace = True)
df.drop(df[df['fare_amount'] < 0].index, inplace = True)
```

In [14]:
```
df.drop(df[df['Distance'] > 100].index, inplace = True)
df.drop(df[df['fare_amount'] > 100].index, inplace = True)
```

Also removing rows with non-plausible fare amounts and distance travelled

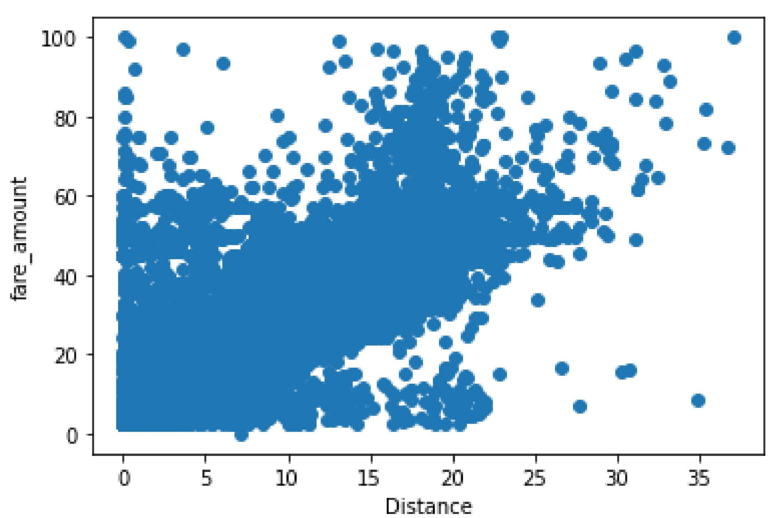
In [15]:
```
df.drop(df[(df['fare_amount']>100) & (df['Distance']<1)].index, inplace = True )
df.drop(df[(df['fare_amount']<100) & (df['Distance']>100)].index, inplace = True
```

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 193436 entries, 0 to 199999
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   fare_amount        193436 non-null  float64
 1   pickup_datetime    193436 non-null  object 
 2   pickup_longitude   193436 non-null  float64
 3   pickup_latitude    193436 non-null  float64
 4   dropoff_longitude  193436 non-null  float64
 5   dropoff_latitude   193436 non-null  float64
 6   passenger_count    193436 non-null  int64  
 7   Distance           193436 non-null  float64
dtypes: float64(6), int64(1), object(1)
memory usage: 17.3+ MB
```

In [17]:
```
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

Out[17]:
```
Text(0, 0.5, 'fare_amount')
```



Separating the date and time into separate columns for more usability

In [18]:
```
df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'])

df['Year'] = df['pickup_datetime'].apply(lambda time: time.year)
df['Month'] = df['pickup_datetime'].apply(lambda time: time.month)
df['Day'] = df['pickup_datetime'].apply(lambda time: time.day)
df['Day of Week'] = df['pickup_datetime'].apply(lambda time: time.dayofweek)
df['Day of Week_num'] = df['pickup_datetime'].apply(lambda time: time.dayofweek)
df['Hour'] = df['pickup_datetime'].apply(lambda time: time.hour)

day_map = {0:'Mon',1:'Tue',2:'Wed',3:'Thu',4:'Fri',5:'Sat',6:'Sun'}
df['Day of Week'] = df['Day of Week'].map(day_map)

df['counter'] = 1
```

Creating separate coumns for pickup and droppoff coordinates for more usability.

In [19]:
```
df['pickup'] = df['pickup_latitude'].astype(str) + "," + df['pickup_longitude'].a
df['drop off'] = df['dropoff_latitude'].astype(str) + "," + df['dropoff_longitude
```

In [20]:
```
df.head()
```

Out[20]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitu
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	40.723
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	40.750
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	40.772
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	40.803
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	40.761

Correlation

In [21]:
```
corr = df.corr()

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

Out[21]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitud
fare_amount	1.000000	0.012292	-0.008891	0.010831	-0.00904
pickup_longitude	0.012292	1.000000	-0.949099	0.999885	-0.99397
pickup_latitude	-0.008891	-0.949099	1.000000	-0.949096	0.95476
dropoff_longitude	0.010831	0.999885	-0.949096	1.000000	-0.99396
dropoff_latitude	-0.009044	-0.993976	0.954760	-0.993964	1.00000
passenger_count	0.014409	0.009176	-0.009219	0.009164	-0.00926
Distance	0.895513	0.005356	0.003243	0.004464	-0.00225
Year	0.124050	0.013480	-0.013693	0.013373	-0.01436
Month	0.024850	-0.007497	0.007602	-0.007452	0.00798
Day	0.000277	0.019531	-0.019393	0.019555	-0.02011
Day of Week_num	0.004881	0.008243	-0.008924	0.008543	-0.00891
Hour	-0.020270	0.001835	-0.001821	0.000937	-0.00101
counter	nan	nan	nan	nan	na

There is some correlation between the distance and fare amount.
Implementing simple linear regression model using these two varaibles.

In [22]:
```
X = df['Distance'].values.reshape(-1, 1)
y = df['fare_amount'].values.reshape(-1, 1)
```

In [23]:
```
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)
```

```
[[-0.40638221]
 [-0.38489719]
 [ 0.17371326]
 ...
 [ 2.10736482]
 [ 0.3455934 ]
 [ 0.30262337]]
[[-0.46769936]
 [-0.24942881]
 [ 0.472543  ]
 ...
 [ 2.65804681]
 [ 0.05279195]
 [ 0.57887993]]
```

In [24]:
```
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=0.3,
```

Linear Regression Model

In [25]:
```
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: 0.80
Test set score: 0.8050688
```

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

In [28]:
```
from sklearn import metrics

print('Mean Absolute Error:', metrics.mean_absolute_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_pr
```

```
Mean Absolute Error: 0.2438330049716194
Mean Squared Error: 0.1926995801043055
Root Mean Squared Error: 0.4389756030855308
```

In [29]:
```
print(l_reg.intercept_)
print(l_reg.coef_)
```

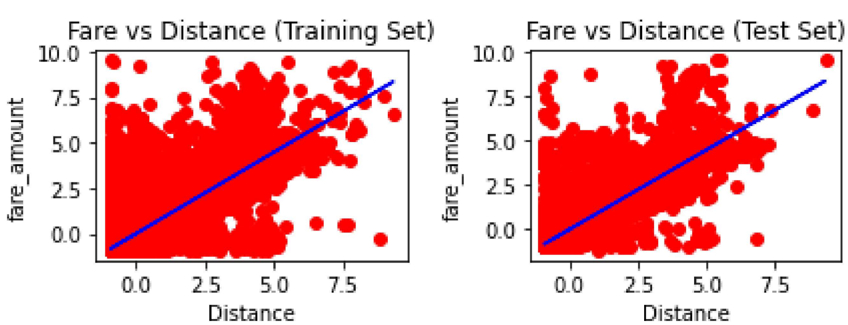
```
[0.00029241]
[[0.89503692]]
```

Plotting the linear regression line against the training and test set side by side.

In [30]:
```
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.rcParams["figure.figsize"] = (32,22)
plt.show()
```



Random Forest Model

In [31]:
```
from sklearn.ensemble import RandomForestRegressor

r_reg = RandomForestRegressor(n_estimators = 50, random_state = 0)

r_reg.fit(X_train, y_train)
```

Out[31]:
```
RandomForestRegressor(n_estimators=50, random_state=0)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [32]:
```
predictions = r_reg.predict(X_test)

print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, predictions))

print('Mean Squared Error:', metrics.mean_squared_error(y_test, predictions))

print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, pred
```

```
Mean Absolute Error: 0.24670010997672112
Mean Squared Error: 0.19753474247914912
Root Mean Squared Error: 0.4444488074898493
```

In [ ]: