Perfect Code

```
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.preprocessing import StandardScaler

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

```
df = pd.read_csv('uber.csv')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 89353 entries, 0 to 89352
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         89353 non-null  int64
 1   key                89353 non-null  object
 2   fare_amount        89353 non-null  float64
 3   pickup_datetime    89353 non-null  object
 4   pickup_longitude   89353 non-null  float64
 5   pickup_latitude    89352 non-null  float64
 6   dropoff_longitude  89351 non-null  float64
 7   dropoff_latitude   89351 non-null  float64
 8   passenger_count    89352 non-null  float64
dtypes: float64(6), int64(1), object(2)
memory usage: 6.1+ MB
```

```
df.head()
```

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

```
df.describe()
```

	Unnamed: 0	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude
count	8.935300e+04	89353.000000	89353.000000	89352.000000	89351.000000
mean	2.771803e+07	11.387451	-72.538401	39.946244	-72.571011
std	1.600435e+07	9.916748	11.704086	8.352747	15.273303

Cleaning

50% 2.776538e+07 8.500000 73.981783 40.752648 73.980108

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

```
df.isna().sum()
```

```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      1
dropoff_longitude    2
dropoff_latitude     2
passenger_count      1
dtype: int64
```

Remove null rows

```
df.dropna(axis=0,inplace=True)
```

```
df.isna().sum()
```

```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

```
df.dtypes #Checking Datatypes.
```

```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count      float64
dtype: object
```

Fix data type of pickup_datetime from Object to DateTime

```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime, errors='coerce')
```

Outliers

```
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
```

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

```
df.head()
```

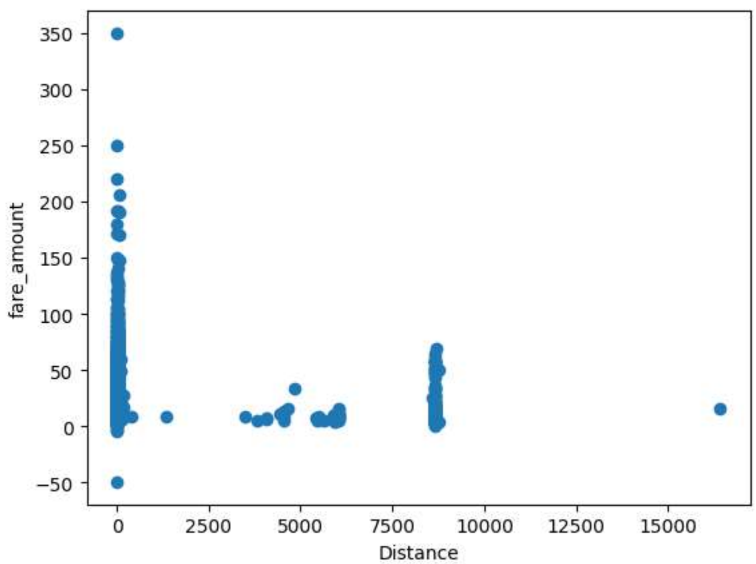
	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	c
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	

Outlier

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

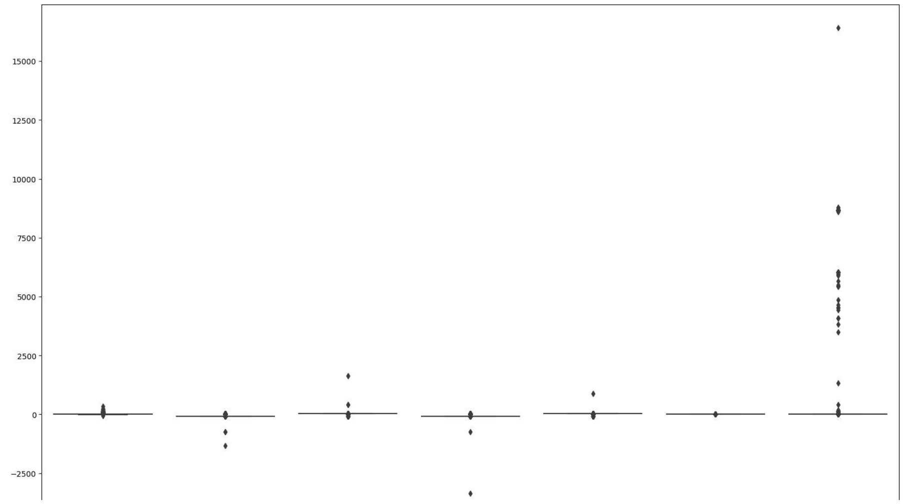
```
plt.scatter(df['Distance'], df['fare_amount'])
plt.xlabel("Distance")
plt.ylabel("fare_amount")
```

```
Text(0, 0.5, 'fare_amount')
```




```
plt.figure(figsize=(20,12))
sns.boxplot(data = df)
```

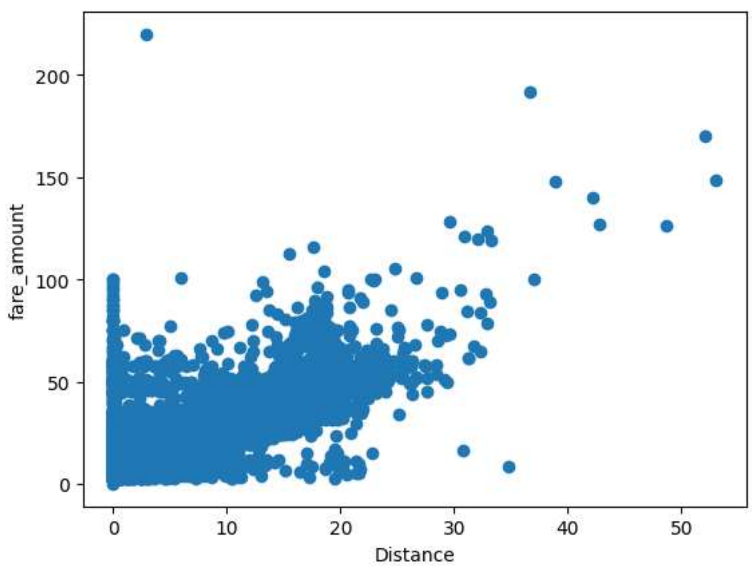
```
<Axes: >
```




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

```
Text(0, 0.5, 'fare_amount')
```



Correlation Matrix

To find to variables that have the most inter-dependence

```
corr = df.corr()
```

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

```
<ipython-input-18-a30339eb0752>:1: FutureWarning: The default value of numeric_only in D
  corr = df.corr()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dro
fare_amount	1.000000	0.013000	-0.012626	0.012630	
dropoff_longitude	0.012630	0.999992	-0.961417	1.000000	

Standardization

For more accurate results on our linear regression model

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

```
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)

X_train, X_test, y_train, y_test = train_test_split(x_std, y_std, test_size=0.2, random_state=0)
```

```
[[-0.39962371]
 [-0.37886439]
 [ 0.1608779 ]
 ...
 [-0.58645758]
 [-0.62797622]
 [-0.08823393]]
[[-0.43810617]
 [-0.22327866]
 [ 0.49222952]
 ...
 [-0.50344926]
 [-0.54681286]
 [-0.01567781]]
```

Simple Linear regression

Training the simple linear regression model in the training set

```
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: 0.7121509
```

```
y_pred = l_reg.predict(X_test)

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

result.sample(10)
```

	Actual	Predicted
14659	-0.254308	0.004877
737	-0.347725	-0.268805
2716	-0.399624	-0.572226
5241	-0.399624	-0.271634

```
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: 0.2688319980473103
Mean Absolute % Error: 1.486868094432629
Mean Squared Error: 0.29294149194855795
Root Mean Squared Error: 0.5412406968702168
R Squared (R²): 0.8438903188970259
```

Random Forest Regressor

Training the RandomForestRegressor model on the training set

```
rf_reg = RandomForestRegressor(n_estimators=100, random_state=10)

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

```
<ipython-input-26-23bf85fdec00>:4: DataConversionWarning: A column-vector y was passed w
  rf_reg.fit(X_train, y_train)
        RandomForestRegressor
RandomForestRegressor(random_state=10)
```

```
# 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)
```

	Actual	Predicted
6792	-0.295827	-0.380837
15315	0.482647	0.499566
6953	-0.503420	-0.374920
2868	-0.752532	-0.699803
13910	-0.254308	-0.487851
6241	0.171258	1.801528
16054	-0.669495	-0.626419
12708	-0.140132	-0.170752
2783	0.451508	0.646023
11177	-0.326966	-0.086885

```
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: 0.30668367770368754
Mean Absolute % Error: 1.662898917718992
Mean Squared Error: 0.3363309914144848
Root Mean Squared Error: 0.5799405067888298
R Squared (R²): 0.8182393502379268
```