Importing all the necessary library required for implementing the project.

```
!pip install numpy
!pip install pandas
!pip install matplotlib
!pip install sklearn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (1.21.6)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (1.3.5)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.7/dist-packages (from pandas) (1.21.6)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from pandas) (2022.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.7.3->pandas) (1.15.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (3.2.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib) (0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplot
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib) (1.4.2)
Requirement already satisfied: numpy>=1.11 in /usr/local/lib/python3.7/dist-packages (from matplotlib) (1.21.6)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1->matplotlib)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1->matplotlib) (1.15
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: sklearn in /usr/local/lib/python3.7/dist-packages (0.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (from sklearn) (1.0.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->sklearn) (3.1
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->sklearn) (1.4.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->sklearn) (1.1.0)
Requirement already satisfied: numpy>=1.14.6 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->sklearn) (1.21.6)
```

```
import sys
```

```
import os
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split # to split the data into two parts i.e t
from sklearn.preprocessing import StandardScaler     # for normalization of the features
from sklearn.preprocessing import MinMaxScaler       # for scaling the features

from sklearn import metrics # for the check the error and accuracy of the model
from sklearn.metrics import mean_squared_error,r2_score,confusion_matrix
```

Connecting the jupyter notebook to google drive

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

Dataset on which machine learning will be applied.

```
!ls /content/gdrive/MyDrive/8th_semester_project
```

```
bead_size_prediction_dataset.xlsx  household_power_consumption.txt
household_dataset_description.pdf
```

Loading the dataset into the pandas dataframe.

```
my_dataset = pd.read_csv('/content/gdrive/MyDrive/8th_semester_project/household_power_consum
my_dataset
```

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Glol
0	16/12/2006	17:24:00	4.216	0.418	234.84	
1	16/12/2006	17:25:00	5.360	0.436	233.63	
2	16/12/2006	17:26:00	5.374	0.498	233.29	
3	16/12/2006	17:27:00	5.388	0.502	233.74	
4	16/12/2006	17:28:00	3.666	0.528	235.68	
...	...	...	...	...	...	
2075254	26/11/2010	20:58:00	0.946	0.000	240.43	
2075255	26/11/2010	20:59:00	0.944	0.000	240.00	
2075256	26/11/2010	21:00:00	0.938	0.000	239.82	
2075257	26/11/2010	21:01:00	0.934	0.000	239.70	
2075258	26/11/2010	21:02:00	0.932	0.000	239.55	

2075259 rows × 9 columns

```
my_dataset.shape
```

```
(2075259, 9)
```

```
my_dataset.drop_duplicates(keep=False,inplace=True)
```

```
my_dataset.shape
```

```
(2075259, 9)
```

```
dataset = my_dataset.sample(frac =.05)
```

```
dataset.shape
```

```
(103763, 9)
```

```
dataset
```

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Glob
1528022	11/11/2009	20:26:00	2.528	0.068	240.83	
793011	19/6/2008	10:15:00	0.234	0.114	237.85	

Exploratory Data Analysis

```
dataset = dataset.drop(["Date","Time"], inplace = False,axis=1)
dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_me
1528022	2.528	0.068	240.83	10.4	
793011	0.234	0.114	237.85	1.0	
1079781	0.706	0.130	245.73	3.0	
1150151	0.422	0.072	242.13	1.8	
1321406	0.532	0.000	239.73	2.6	
...	...	...	...	...	
42366	0.214	0.000	244.86	0.8	
190706	NaN	NaN	NaN	NaN	
1781604	0.882	0.152	238.97	3.8	
1893606	1.060	0.432	238.69	4.8	
32540	1.154	0.132	239.10	4.8	

103763 rows × 7 columns

```
dataset.head()
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_me
1528022	2.528	0.068	240.83	10.4	
793011	0.234	0.114	237.85	1.0	
1079781	0.706	0.130	245.73	3.0	
1150151	0.422	0.072	242.13	1.8	
1321406	0.532	0.000	239.73	2.6	

```
dataset.tail()
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_me
42366	0.214	0.000	244.86	0.8	
190706	NaN	NaN	NaN	NaN	
1781604	0.882	0.152	238.97	3.8	
1893606	1.060	0.432	238.69	4.8	
32540	1.154	0.132	239.10	4.8	

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 103763 entries, 1528022 to 32540
Data columns (total 7 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   Global_active_power    102434 non-null  float64
 1   Global_reactive_power  102434 non-null  float64
 2   Voltage                102434 non-null  float64
 3   Global_intensity       102434 non-null  float64
 4   Sub_metering_1         102434 non-null  float64
```

```
 5   Sub_metering_2         102434 non-null  float64
 6   Sub_metering_3         102434 non-null  float64
dtypes: float64(7)
memory usage: 6.3 MB
```

```
dataset.dtypes
```

```
Global_active_power      float64
Global_reactive_power    float64
Voltage                  float64
Global_intensity         float64
Sub_metering_1           float64
Sub_metering_2           float64
Sub_metering_3           float64
dtype: object
```

```
dataset.columns
```

```
Index(['Global_active_power', 'Global_reactive_power', 'Voltage',
       'Global_intensity', 'Sub_metering_1', 'Sub_metering_2',
       'Sub_metering_3'],
      dtype='object')
```

```
dataset.describe()
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Su
count	102434.000000	102434.000000	102434.000000	102434.000000	1
mean	1.085795	0.123507	240.858032	4.603536	

```
dataset.shape
```

```
(103763, 7)
```

25%	0.308000	0.048000	239.020000	1.400000

```
dataset.isnull().sum()
```

```
Global_active_power      1329
Global_reactive_power    1329
Voltage                  1329
Global_intensity         1329
Sub_metering_1           1329
Sub_metering_2           1329
Sub_metering_3           1329
dtype: int64
```

```
for j in range(0,7):
        dataset.iloc[:,j]=dataset.iloc[:,j].fillna(dataset.iloc[:,j].mean())
```

```
dataset.shape
```

```
(103763, 7)
```

```
dataset.isnull().sum()
```

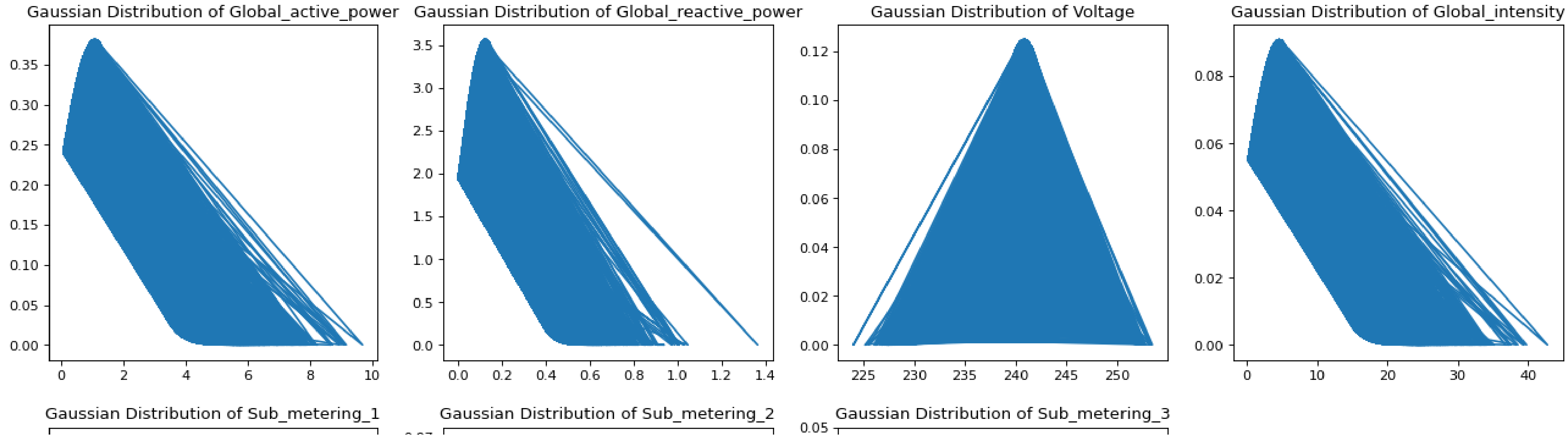
```
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
dtype: int64
```

Data visulization

```
from scipy.stats import norm
import statistics

import matplotlib as mpl
mpl.rcParams['agg.path.chunksize'] = 10000

plt.figure(figsize=(20,10),dpi=80)

x_axis = dataset['Global_active_power'].to_numpy()#[:1037630]
mean = statistics.mean(x_axis)
sd = statistics.stdev(x_axis)
plt.subplot(2,4,1)
plt.plot(x_axis, norm.pdf(x_axis, mean, sd))
plt.title("Gaussian Distribution of Global_active_power")

x_axis = dataset['Global_reactive_power'].to_numpy()#[:1037630]
mean = statistics.mean(x_axis)
sd = statistics.stdev(x_axis)
plt.subplot(2,4,2)
```

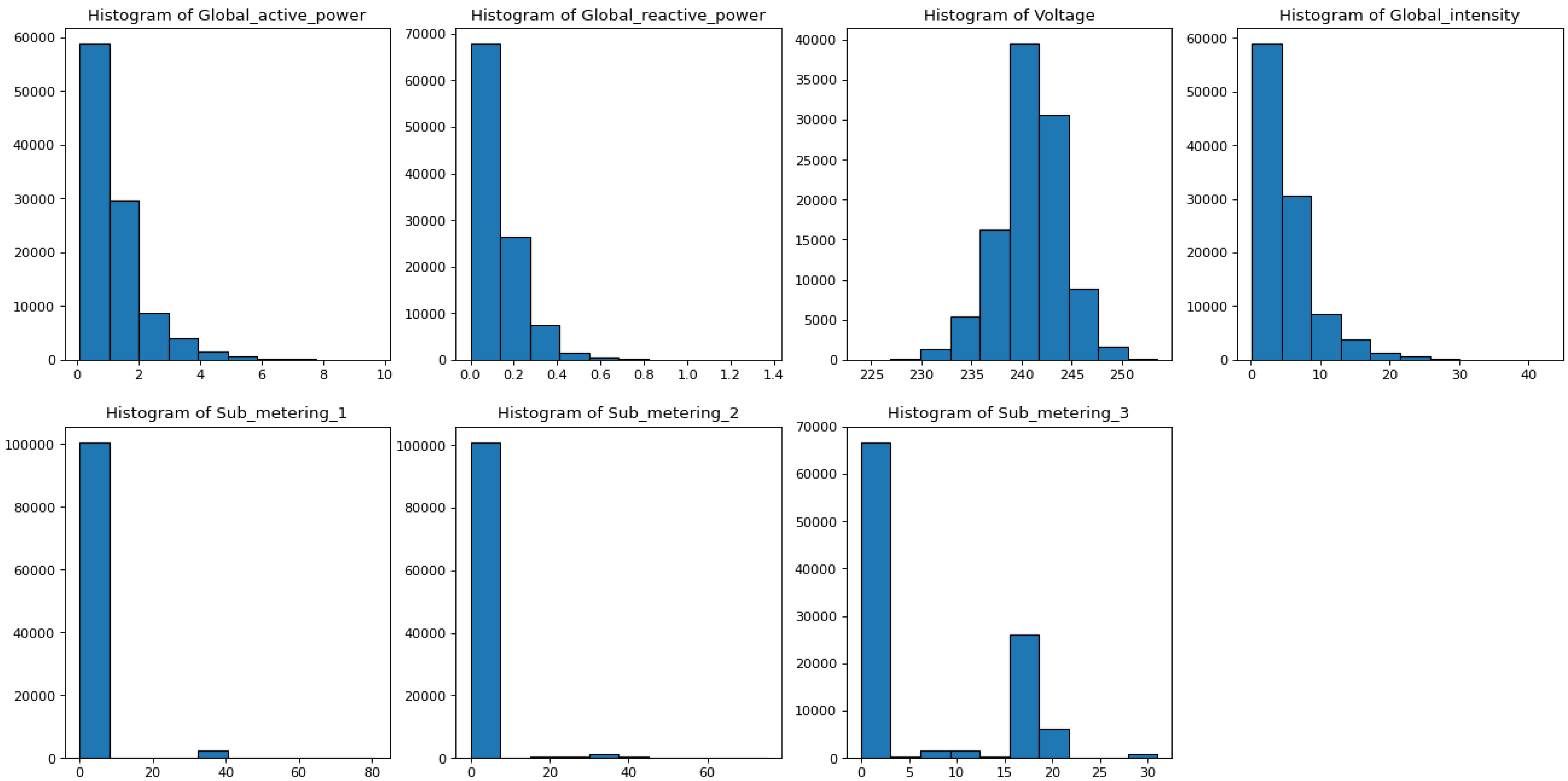
```
plt.plot(x_axis, norm.pdf(x_axis, mean, sd))
plt.title("Gaussian Distribution of Global_reactive_power")

x_axis = dataset['Voltage'].to_numpy()#[:1037630]
mean = statistics.mean(x_axis)
sd = statistics.stdev(x_axis)
plt.subplot(2,4,3)
plt.plot(x_axis, norm.pdf(x_axis, mean, sd))
plt.title("Gaussian Distribution of Voltage")

x_axis = dataset['Global_intensity'].to_numpy()#[:1037630]
mean = statistics.mean(x_axis)
sd = statistics.stdev(x_axis)
plt.subplot(2,4,4)
plt.plot(x_axis, norm.pdf(x_axis, mean, sd))
plt.title("Gaussian Distribution of Global_intensity")

x_axis = dataset['Sub_metering_1'].to_numpy()#[:1037630]
mean = statistics.mean(x_axis)
sd = statistics.stdev(x_axis)
plt.subplot(2,4,5)
plt.plot(x_axis, norm.pdf(x_axis, mean, sd))
plt.title("Gaussian Distribution of Sub_metering_1")

x_axis = dataset['Sub_metering_2'].to_numpy()#[:1037630]
mean = statistics.mean(x_axis)
sd = statistics.stdev(x_axis)
plt.subplot(2,4,6)
```

```
plt.plot(x_axis, norm.pdf(x_axis, mean, sd))
plt.title("Gaussian Distribution of Sub_metering_2")

x_axis = dataset['Sub_metering_3'].to_numpy()#[:1037630]
mean = statistics.mean(x_axis)
sd = statistics.stdev(x_axis)
plt.subplot(2,4,7)
plt.plot(x_axis, norm.pdf(x_axis, mean, sd))
plt.title("Gaussian Distribution of Sub_metering_3")

plt.show()
```




```
plt.figure(figsize=(20,10), dpi=80)

plt.subplot(2,4,1)
x = dataset['Global_active_power'].to_numpy()
plt.hist(x,edgecolor='black')
plt.title("Histogram of Global_active_power")

plt.subplot(2,4,2)
x = dataset['Global_reactive_power'].to_numpy()
plt.hist(x,edgecolor='black')
plt.title("Histogram of Global_reactive_power")

plt.subplot(2,4,3)
x = dataset['Voltage'].to_numpy()
plt.hist(x,edgecolor='black')
plt.title("Histogram of Voltage")
```

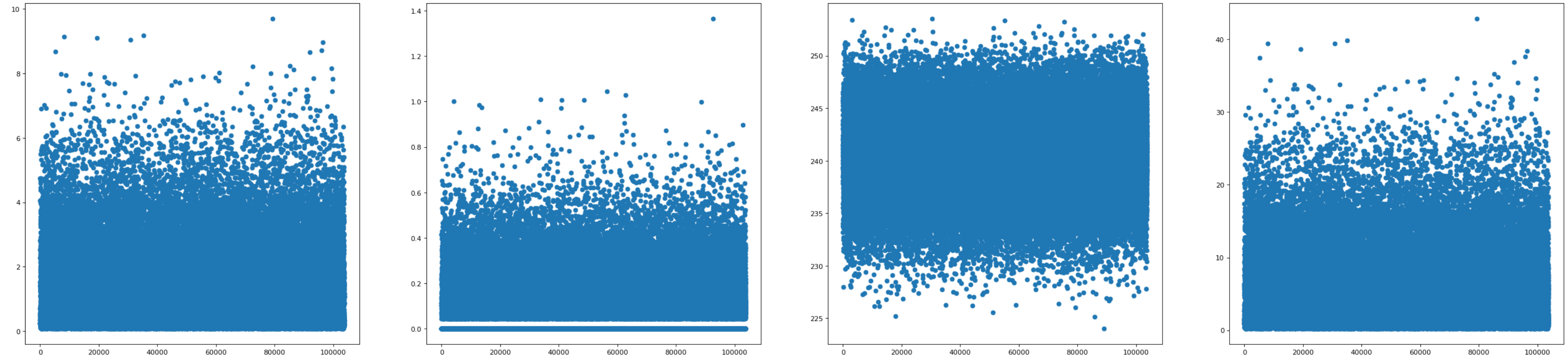
```
plt.subplot(2,4,4)
x = dataset['Global_intensity'].to_numpy()
plt.hist(x,edgecolor='black')
plt.title("Histogram of Global_intensity")

plt.subplot(2,4,5)
x = dataset['Sub_metering_1'].to_numpy()
plt.hist(x,edgecolor='black')
plt.title("Histogram of Sub_metering_1")

plt.subplot(2,4,6)
x = dataset['Sub_metering_2'].to_numpy()
plt.hist(x,edgecolor='black')
plt.title("Histogram of Sub_metering_2")

plt.subplot(2,4,7)
x = dataset['Sub_metering_3'].to_numpy()
plt.hist(x,edgecolor='black')
plt.title("Histogram of Sub_metering_3")

plt.show()
```




```
plt.figure(figsize=(40,20), dpi=80)


x = np.arange(1,103764)
y = dataset['Global_active_power'].to_numpy()
plt.subplot(2,4,1)
plt.scatter(x, y)
```

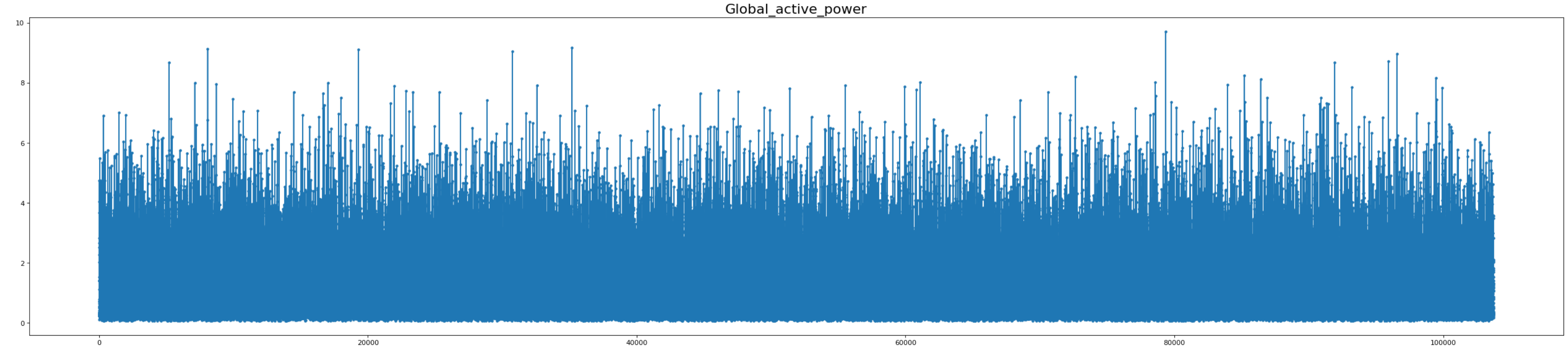
```
x = np.arange(1,103764)
y = dataset['Global_reactive_power'].to_numpy()
plt.subplot(2,4,2)
plt.scatter(x, y)

x = np.arange(1,103764)
y = dataset['Voltage'].to_numpy()
plt.subplot(2,4,3)
plt.scatter(x, y)

x = np.arange(1,103764)
y = dataset['Global_intensity'].to_numpy()
plt.subplot(2,4,4)
plt.scatter(x, y)

x = np.arange(1,103764)
y = dataset['Sub_metering_1'].to_numpy()
plt.subplot(2,4,5)
plt.scatter(x, y)

x = np.arange(1,103764)
y = dataset['Sub_metering_2'].to_numpy()
plt.subplot(2,4,6)
plt.scatter(x, y)

x = np.arange(1,103764)
y = dataset['Sub_metering_3'].to_numpy()
plt.subplot(2,4,7)
```

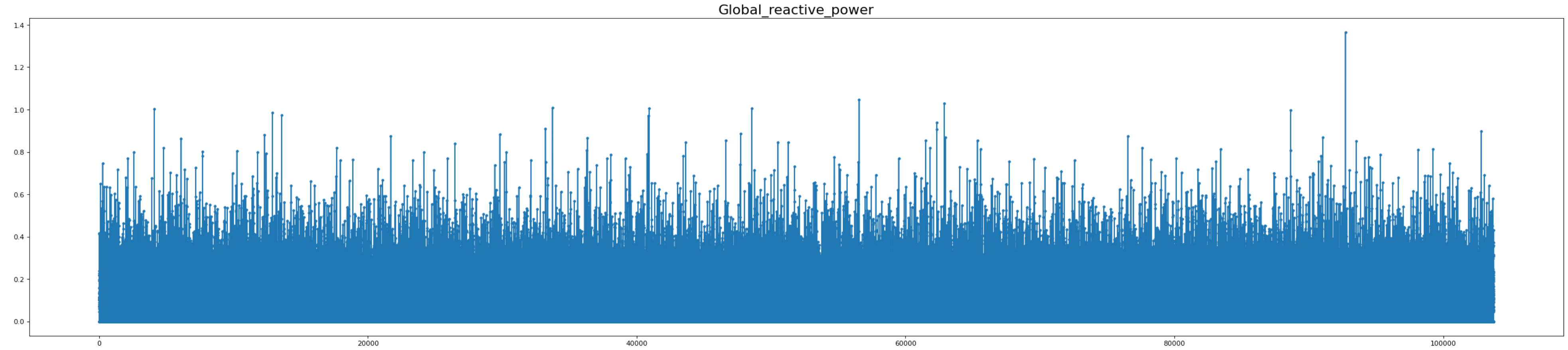
```
plt.scatter(x, y)

plt.show()
```

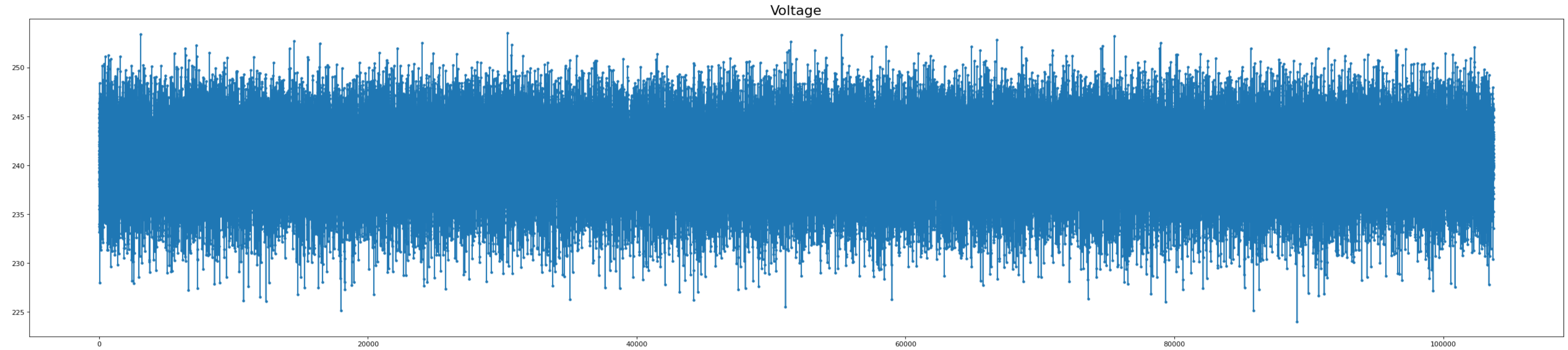


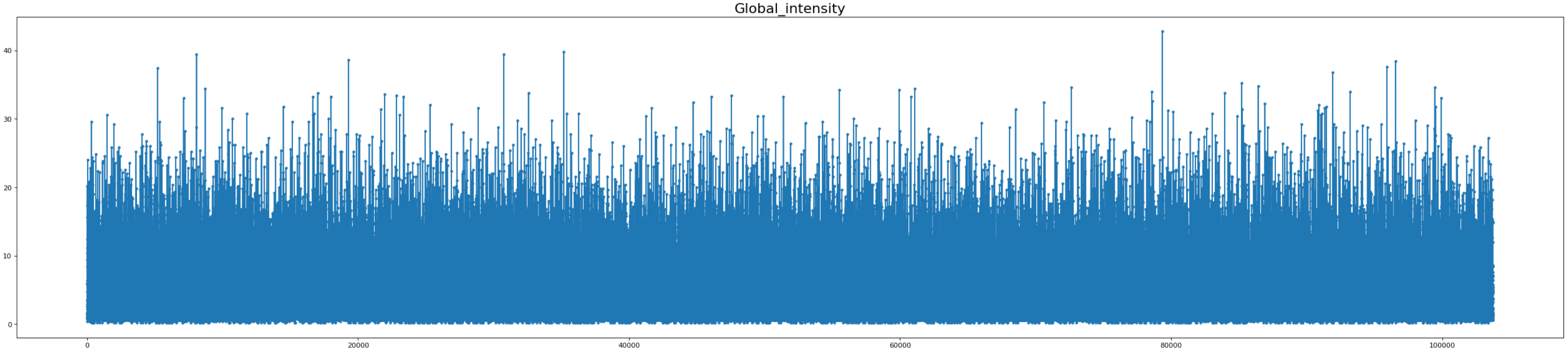
```
plt.figure(figsize=(40,80), dpi=80)

ypoints = dataset['Global_active_power'].to_numpy()
plt.subplot(8,1,1)
plt.plot(ypoints, marker = '.')
plt.title('Global_active_power',fontsize=20)

ypoints = dataset['Global_reactive_power'].to_numpy()
plt.subplot(8,1,2)
plt.plot(ypoints, marker = '.')
plt.title('Global_reactive_power',fontsize=20)

ypoints = dataset['Voltage'].to_numpy()
plt.subplot(8,1,3)
plt.plot(ypoints, marker = '.')
plt.title('Voltage',fontsize=20)
```

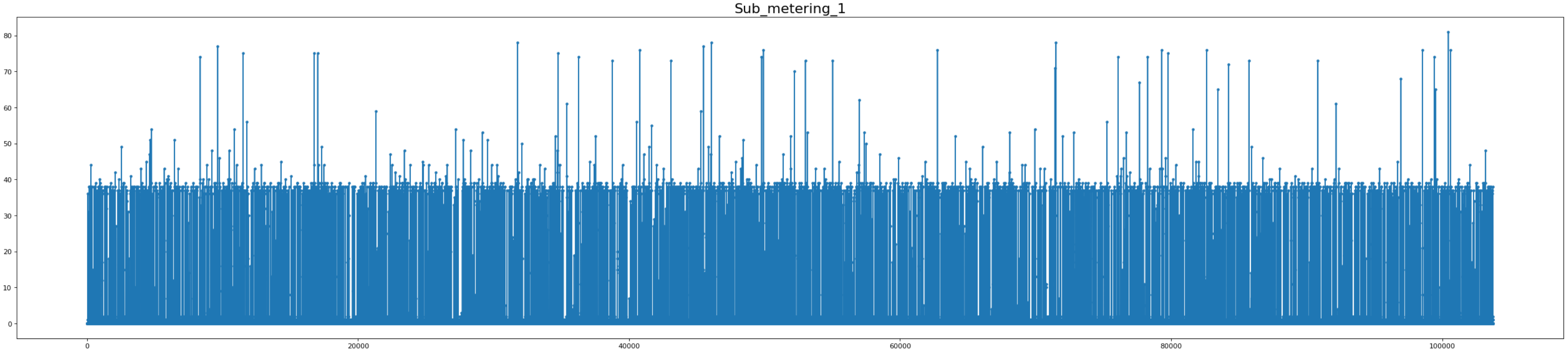
```
ypoints = dataset['Global_intensity'].to_numpy()
plt.subplot(8,1,4)
plt.plot(ypoints, marker = '.')
plt.title('Global_intensity',fontsize=20)

ypoints = dataset['Sub_metering_1'].to_numpy()
plt.subplot(8,1,5)
plt.plot(ypoints, marker = '.')
plt.title('Sub_metering_1',fontsize=20)


ypoints = dataset['Sub_metering_2'].to_numpy()
plt.subplot(8,1,6)
plt.plot(ypoints, marker = '.')
plt.title('Sub_metering_2',fontsize=20)

ypoints = dataset['Sub_metering_3'].to_numpy()
plt.subplot(8,1,7)
plt.plot(ypoints, marker = '.')
plt.title('Sub_metering_3',fontsize=20)

plt.show()
```

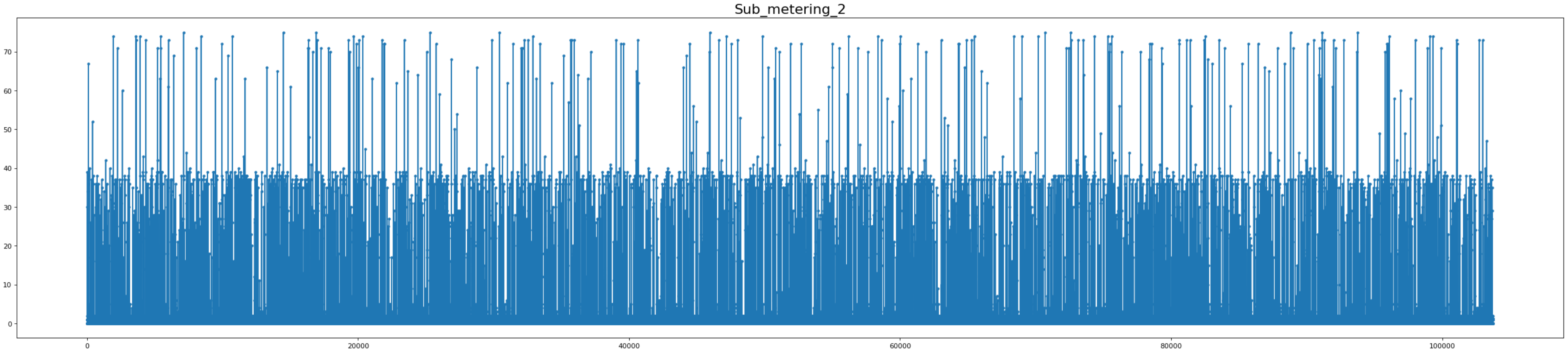

Global_active_power
10
8
6
4
2
0
0
20000
40000
60000
80000
100000

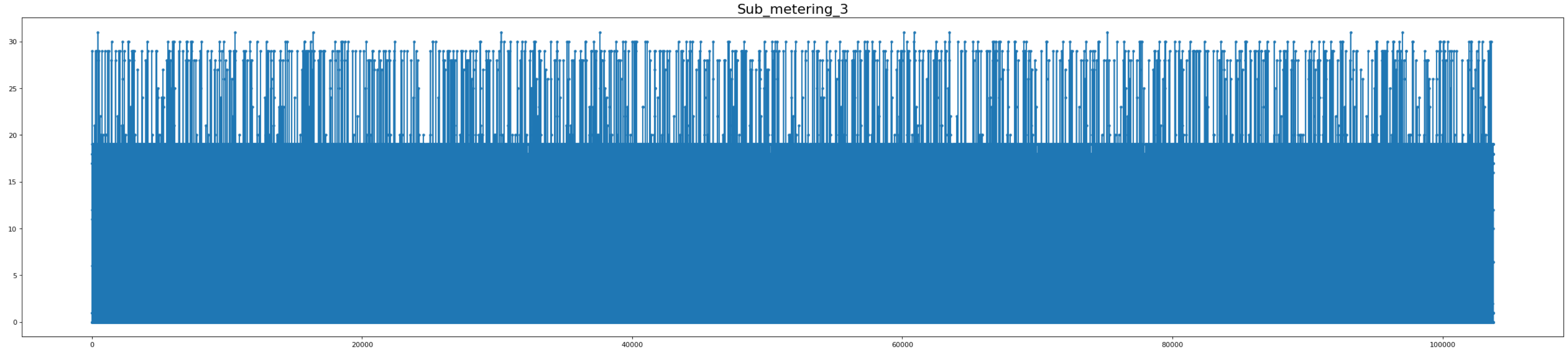

Global_reactive_power
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
20000
40000
60000
80000
100000


Voltage
250
245
240
235
230
225
0
20000
40000
60000
80000
100000


Global_intensity
0
10
20
30
40
0
20000
40000
60000
80000
100000


Sub_metering_1
0
10
20
30
40
50
60
70
80
0
20000
40000
60000
80000
100000

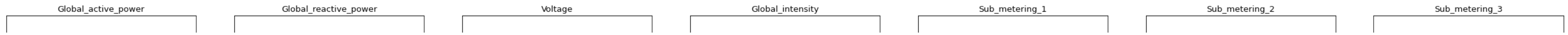

Sub_metering_2
0
10
20
30
40
50
60
70
0
20000
40000
60000
80000
100000


Sub_metering_3
30
25
20
15
10
5
0
0
20000
40000
60000
80000
100000

```
import seaborn as sns
import pandas as pd

plt.figure(figsize=(40,10), dpi=80)

plt.subplot(1,7,1)
sns.violinplot(dataset["Global_active_power"])
plt.title("Global_active_power")

plt.subplot(1,7,2)
sns.violinplot(dataset["Global_reactive_power"])
plt.title("Global_reactive_power")

plt.subplot(1,7,3)
sns.violinplot(dataset["Voltage"])
plt.title("Voltage")

plt.subplot(1,7,4)
sns.violinplot(dataset["Global_intensity"])
plt.title("Global_intensity")

plt.subplot(1,7,5)
sns.violinplot(dataset["Sub_metering_1"])
plt.title("Sub_metering_1")

plt.subplot(1,7,6)
```

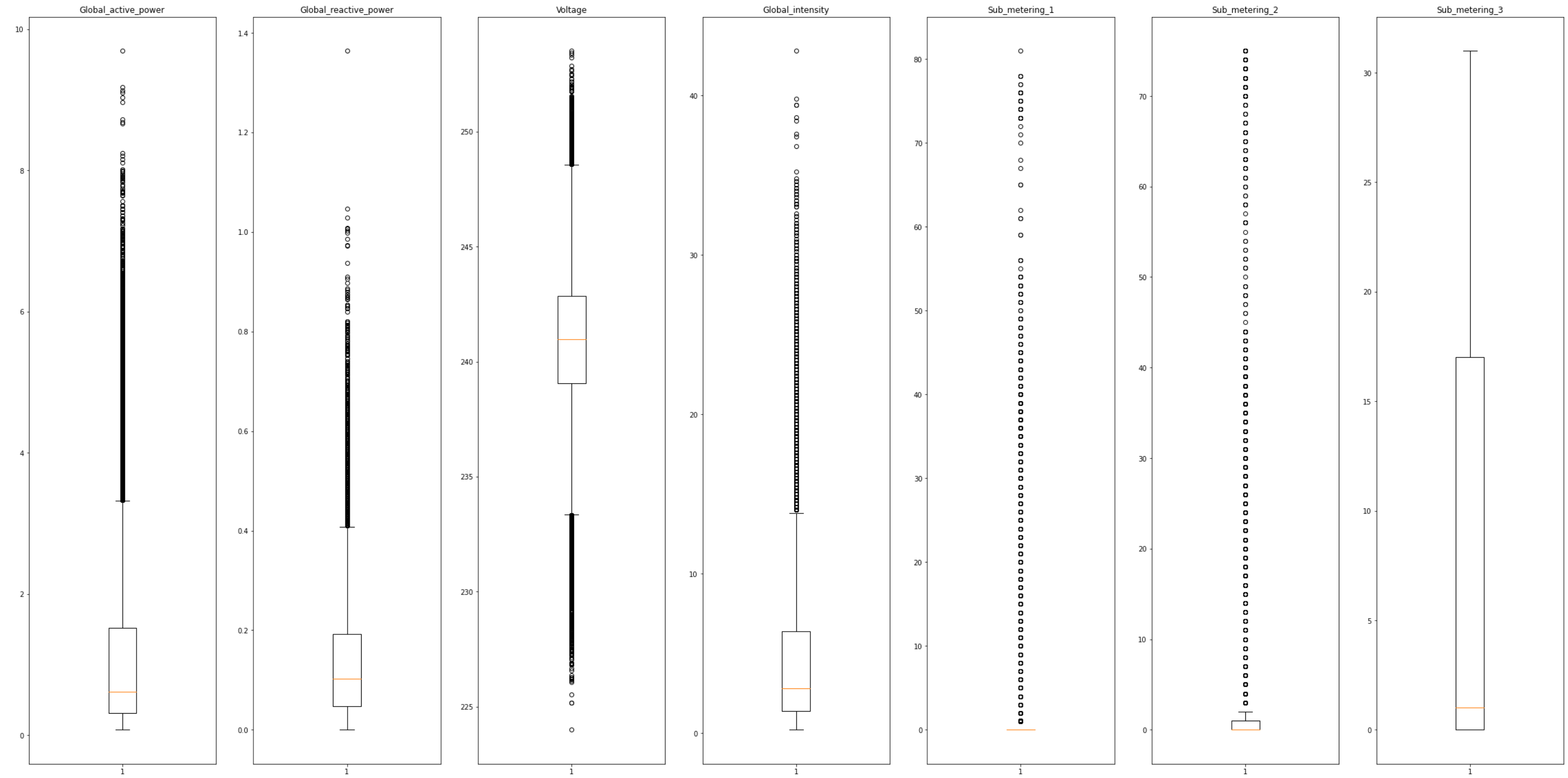
```
sns.violinplot(dataset["Sub_metering_2"])
plt.title("Sub_metering_2")

plt.subplot(1,7,7)
sns.violinplot(dataset["Sub_metering_3"])
plt.title("Sub_metering_3")

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
```




```
import matplotlib.pyplot as plt
import numpy as np

fig = plt.figure(figsize =(40,20))
np.random.seed(10)

data = dataset['Global_active_power'].to_numpy()
plt.subplot(1,7,1)
plt.boxplot(data)
plt.title('Global_active_power')

data = dataset['Global_reactive_power'].to_numpy()
plt.subplot(1,7,2)
plt.boxplot(data)
plt.title('Global_reactive_power')

data = dataset['Voltage'].to_numpy()
```

```
plt.subplot(1,7,3)
plt.boxplot(data)
plt.title('Voltage')

data = dataset['Global_intensity'].to_numpy()
plt.subplot(1,7,4)
plt.boxplot(data)
plt.title('Global_intensity')

data = dataset['Sub_metering_1'].to_numpy()
plt.subplot(1,7,5)
plt.boxplot(data)
plt.title('Sub_metering_1')

data = dataset['Sub_metering_2'].to_numpy()
plt.subplot(1,7,6)
plt.boxplot(data)
plt.title('Sub_metering_2')

data = dataset['Sub_metering_3'].to_numpy()
plt.subplot(1,7,7)
plt.boxplot(data)
plt.title('Sub_metering_3')

plt.show()
```


Global_active_power
Global_reactive_power
Voltage
Global_intensity
Sub_metering_1
Sub_metering_2
Sub_metering_3

Splitting dataset into training dataset and test dataset respectively.

```
from sklearn.model_selection import train_test_split

training_dataset, testing_dataset = train_test_split(dataset, test_size=0.1, random_state=25)
```

```
dataset.shape
```

```
(103763, 7)
```

```
training_dataset.shape
```

```
(93386, 7)
```

```
testing_dataset.shape
```

```
(10377, 7)
```

```
dataset.shape[0] == training_dataset.shape[0]+testing_dataset.shape[0]
```

```
True
```

Creation of the target variable in the training dataset with the help of available features in the dataframe

```
training_dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	1.348	0.084	241.19	5.6	1.0	0.0	18.0
401411	0.286	0.212	237.63	1.4	0.0	1.0	0.0
696281	0.268	0.000	243.93	1.0	0.0	0.0	1.0
1085652	0.378	0.116	249.62	1.6	0.0	0.0	0.0
474897	3.536	0.496	236.83	15.2	0.0	0.0	17.0
...	...	...	...	...	...	...	...
1677877	6.546	0.092	234.48	27.8	0.0	73.0	17.0
1114970	0.374	0.156	248.47	1.6	0.0	0.0	0.0
873524	0.174	0.146	237.91	0.8	0.0	0.0	0.0
1805780	0.924	0.404	238.19	4.2	0.0	0.0	1.0
773390	0.420	0.214	236.24	2.0	0.0	0.0	0.0

93386 rows × 7 columns

```
training_dataset["active_energy_per_minute_in_Wh"] = (training_dataset['Global_active_power']
```

```
training_dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	1.348	0.084	241.19	5.6	1.0	0.0	18.0
401411	0.286	0.212	237.63	1.4	0.0	1.0	0.0
696281	0.268	0.000	243.93	1.0	0.0	0.0	1.0
1085652	0.378	0.116	249.62	1.6	0.0	0.0	0.0
474897	3.536	0.496	236.83	15.2	0.0	0.0	17.0
...	...	...	...	...	...	...	...
1677877	6.546	0.092	234.48	27.8	0.0	73.0	17.0
1114970	0.374	0.156	248.47	1.6	0.0	0.0	0.0
873524	0.174	0.146	237.91	0.8	0.0	0.0	0.0
1805780	0.924	0.404	238.19	4.2	0.0	0.0	1.0
773390	0.420	0.214	236.24	2.0	0.0	0.0	0.0

93386 rows × 8 columns

Creation of the target variable in the testing dataset with the help of available features in the dataframe.

```
testing_dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
696294	0.266	0.000	243.85	1.0	0.0	0.0	1.0
1953000	0.630	0.000	246.69	2.6	0.0	0.0	1.0
1787586	1.554	0.204	245.88	6.2	0.0	0.0	19.0
1546288	1.980	0.000	240.85	8.2	0.0	0.0	18.0
1722499	2.704	0.000	238.62	11.2	0.0	0.0	18.0
...	...	...	...	...	...	...	...

```
testing_dataset["active_energy_per_minute_in_Wh"] = (testing_dataset['Global_active_power']*1
```

```
testing_dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
696294	0.266	0.000	243.85	1.0	0.0	0.0	1.0

Performing segmentation using K-means clustering algorithm.

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

```
clustering_dataset = training_dataset.copy()
clustering_dataset.head()
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	1.348	0.084	241.19	5.6	1.0	0.0	18.0
401411	0.286	0.212	237.63	1.4	0.0	1.0	0.0
696281	0.268	0.000	243.93	1.0	0.0	0.0	1.0
1085652	0.378	0.116	249.62	1.6	0.0	0.0	0.0
474897	3.536	0.496	236.83	15.2	0.0	0.0	17.0

```
clustering_dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	1.348	0.084	241.19	5.6	1.0	0.0	18.0
401411	0.286	0.212	237.63	1.4	0.0	1.0	0.0
696281	0.268	0.000	243.93	1.0	0.0	0.0	1.0
1085652	0.378	0.116	249.62	1.6	0.0	0.0	0.0
474897	3.536	0.496	236.83	15.2	0.0	0.0	17.0
...	...	...	...	...	...	...	...
1677877	6.546	0.092	234.48	27.8	0.0	73.0	17.0
1114970	0.374	0.156	248.47	1.6	0.0	0.0	0.0
873524	0.174	0.146	237.91	0.8	0.0	0.0	0.0
1805780	0.924	0.404	238.19	4.2	0.0	0.0	1.0
773390	0.420	0.214	236.24	2.0	0.0	0.0	0.0

93386 rows × 8 columns

```
sc = MinMaxScaler()

clustering_dataset['Global_active_power'] = sc.fit_transform(clustering_dataset['Global_activ

clustering_dataset['Global_reactive_power'] = sc.fit_transform(clustering_dataset['Global_rea

clustering_dataset['Voltage'] = sc.fit_transform(clustering_dataset['Voltage'].to_numpy().res

clustering_dataset['Global_intensity'] = sc.fit_transform(clustering_dataset['Global_intensit

clustering_dataset['Sub_metering_1'] = sc.fit_transform(clustering_dataset['Sub_metering_1'].
```

```
clustering_dataset['Sub_metering_2'] = sc.fit_transform(clustering_dataset['Sub_metering_2'].

clustering_dataset['Sub_metering_3'] = sc.fit_transform(clustering_dataset['Sub_metering_3'].


clustering_dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	0.132252	0.080306	0.582459	0.126761	0.012346	0.000000	0.580645
401411	0.021834	0.202677	0.461903	0.028169	0.000000	0.013333	0.000000
696281	0.019963	0.000000	0.675246	0.018779	0.000000	0.000000	0.032258
1085652	0.031399	0.110899	0.867931	0.032864	0.000000	0.000000	0.000000
474897	0.359742	0.474187	0.434812	0.352113	0.000000	0.000000	0.548387
...	...	...	...	...	...	...	...
1677877	0.672697	0.087954	0.355232	0.647887	0.000000	0.973333	0.548387
1114970	0.030984	0.149140	0.828987	0.032864	0.000000	0.000000	0.000000
873524	0.010189	0.139579	0.471385	0.014085	0.000000	0.000000	0.000000
1805780	0.088168	0.386233	0.480867	0.093897	0.000000	0.000000	0.032258
773390	0.035766	0.204589	0.414832	0.042254	0.000000	0.000000	0.000000

93386 rows × 8 columns

```
k_rng = range(1,10)
sse = []
```

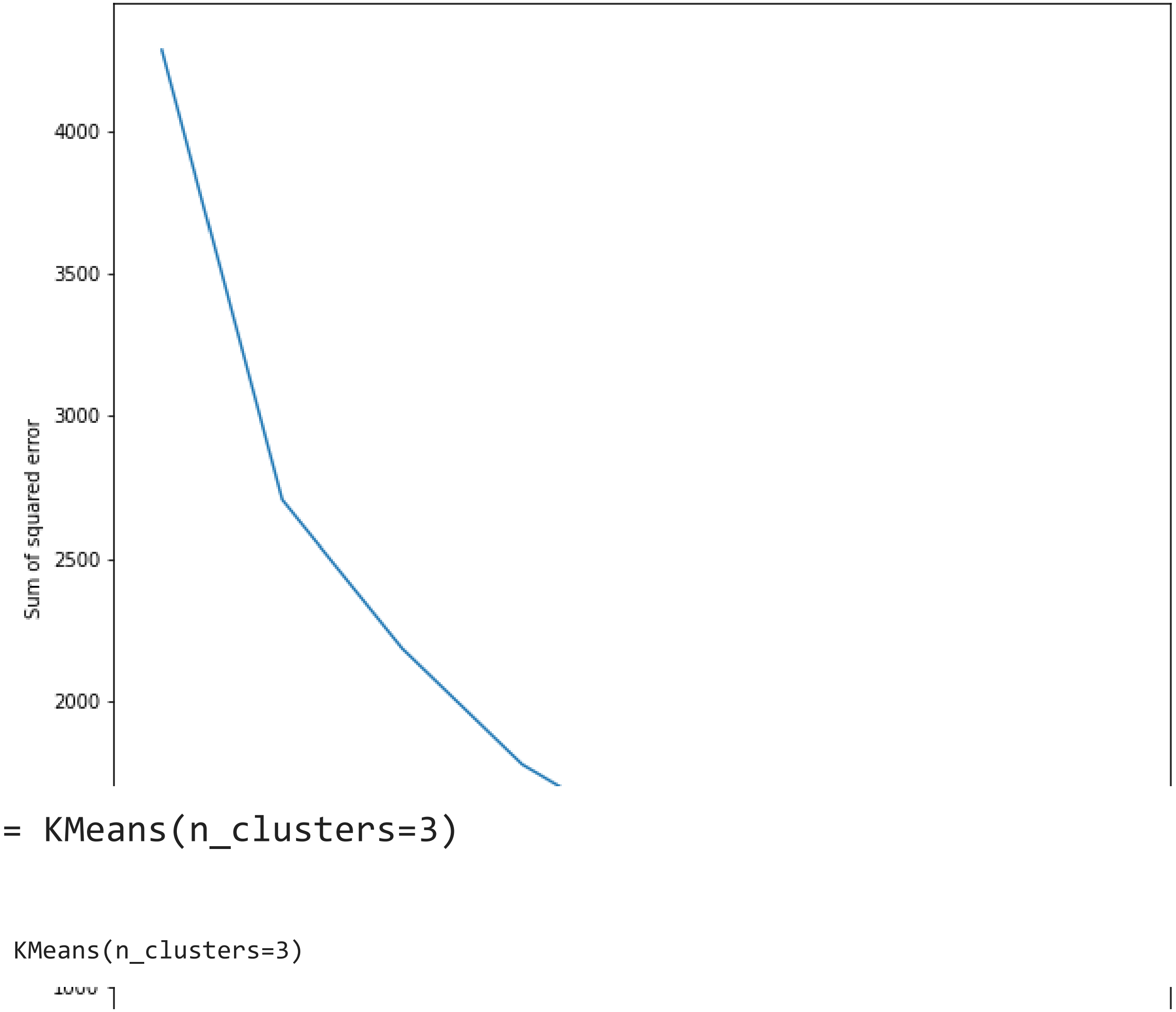
```
for k in k_rng:
  KM = KMeans(n_clusters=k)
  KM.fit(clustering_dataset[['Global_active_power', 'Global_reactive_power', 'Voltage',
                             'Global_intensity']])
  sse.append(KM.inertia_)
```

```
sse
```

```
[4282.613148306373,
 2705.5459098482434,
 2184.587990962694,
 1777.7238689964763,
 1529.0325298003072,
 1353.90815717943,
 1206.1778920002967,
 1084.466999094875,
 1003.7456194574811]
```

```
plt.figure(figsize=(10,10))
plt.xlabel('K')
plt.ylabel('Sum of squared error')
plt.plot(k_rng,sse)
```

```
[<matplotlib.lines.Line2D at 0x7f5e2bb14490>]
```




```
km = KMeans(n_clusters=3)
km
```

```
KMeans(n_clusters=3)
```

```
y_predicted = km.fit_predict(clustering_dataset[['Global_active_power', 'Global_reactive_powe
                                                 'Global_intensity', 'Sub_metering_1', 'Sub_met
                                                 'Sub_metering_3']])
y_predicted
```

```
array([0, 1, 1, ..., 1, 1, 1], dtype=int32)
```

```
clustering_dataset['cluster'] = y_predicted
clustering_dataset
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	0.132252	0.080306	0.582459	0.126761	0.012346	0.000000	0.580645
401411	0.021834	0.202677	0.461903	0.028169	0.000000	0.013333	0.000000
696281	0.019963	0.000000	0.675246	0.018779	0.000000	0.000000	0.032258
1085652	0.031399	0.110899	0.867931	0.032864	0.000000	0.000000	0.000000
474897	0.359742	0.474187	0.434812	0.352113	0.000000	0.000000	0.548387
...	...	...	...	...	...	...	...
1677877	0.672697	0.087954	0.355232	0.647887	0.000000	0.973333	0.548387
1114970	0.030984	0.149140	0.828987	0.032864	0.000000	0.000000	0.000000
873524	0.010189	0.139579	0.471385	0.014085	0.000000	0.000000	0.000000
1805780	0.088168	0.386233	0.480867	0.093897	0.000000	0.000000	0.032258
773390	0.035766	0.204589	0.414832	0.042254	0.000000	0.000000	0.000000

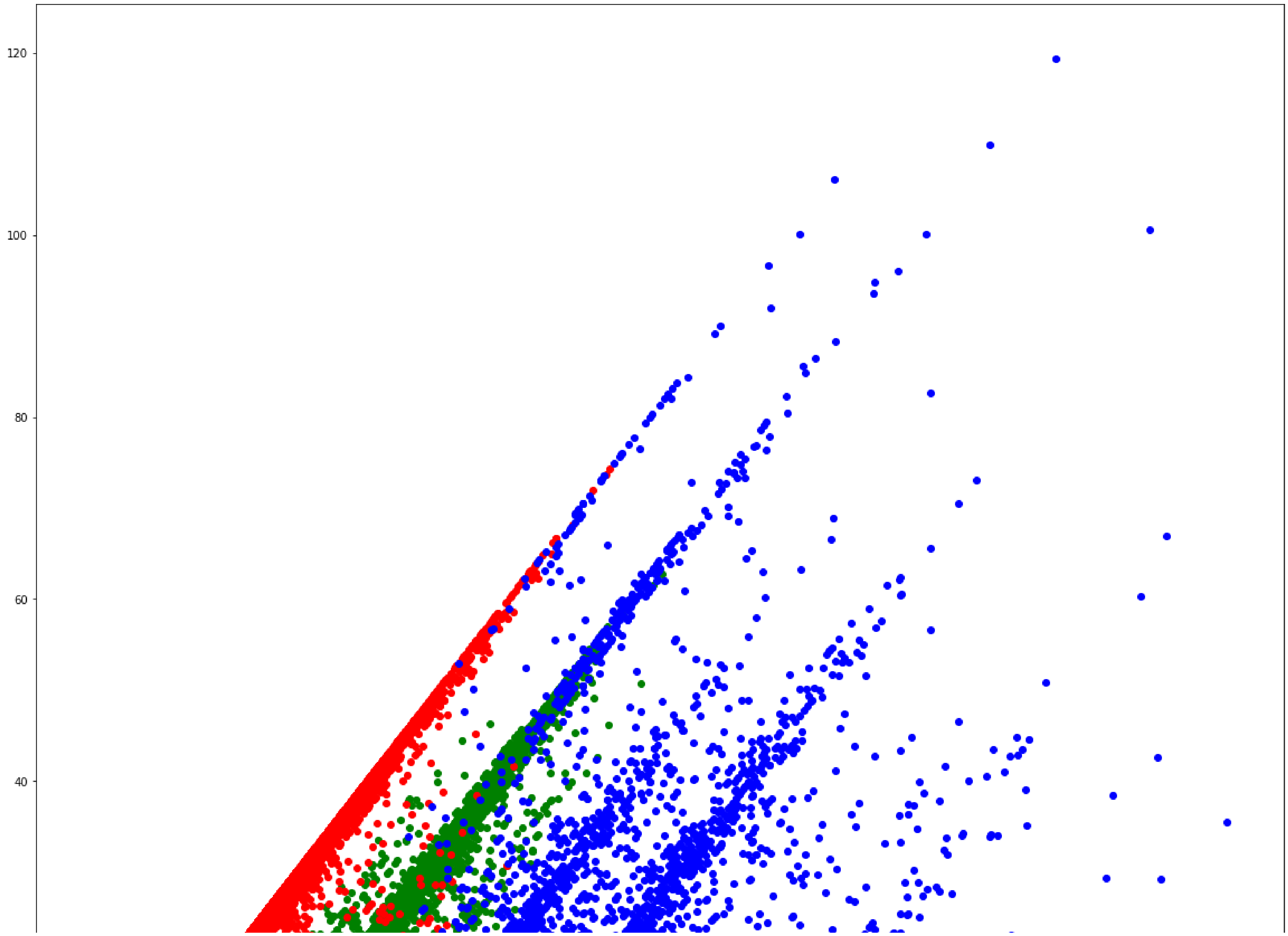
93386 rows × 9 columns

```
km.cluster_centers_
```

```
array([[0.17662204, 0.12524244, 0.53842678, 0.16912945, 0.00237614,
        0.00745483, 0.57747216],
       [0.04897228, 0.10901652, 0.59579662, 0.05104554, 0.00221747,
        0.00905642, 0.01719687],
       [0.42633057, 0.19967411, 0.43704665, 0.41129531, 0.2663664 ,
        0.20273521, 0.40370177]])
```

```
df1 = clustering_dataset[clustering_dataset.cluster == 0]
df2 = clustering_dataset[clustering_dataset.cluster == 1]
df3 = clustering_dataset[clustering_dataset.cluster == 2]
```

```
plt.figure(figsize=(20,20))
plt.scatter(df1.Global_active_power,df1.active_energy_per_minute_in_Wh,color='green')
plt.scatter(df2.Global_active_power,df2.active_energy_per_minute_in_Wh,color='red')
plt.scatter(df3.Global_active_power,df3.active_energy_per_minute_in_Wh,color='blue')
plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:,6],color='black',marker='*',label=
plt.show()
```


120
100
80
60
40

Scaling/ Normalizing the features in the training dataset

```
X_train = training_dataset[training_dataset.columns.tolist()[:-1]].copy()
X_train
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	1.348	0.084	241.19	5.6	1.0	0.0	18.0
401411	0.286	0.212	237.63	1.4	0.0	1.0	0.0
696281	0.268	0.000	243.93	1.0	0.0	0.0	1.0
1085652	0.378	0.116	249.62	1.6	0.0	0.0	0.0
474897	3.536	0.496	236.83	15.2	0.0	0.0	17.0
...	...	...	...	...	...	...	...
1677877	6.546	0.092	234.48	27.8	0.0	73.0	17.0
1114970	0.374	0.156	248.47	1.6	0.0	0.0	0.0
873524	0.174	0.146	237.91	0.8	0.0	0.0	0.0
1805780	0.924	0.404	238.19	4.2	0.0	0.0	1.0
773390	0.420	0.214	236.24	2.0	0.0	0.0	0.0

93386 rows × 7 columns

```
sctr = MinMaxScaler()

X_train['Global_active_power'] = sctr.fit_transform(X_train['Global_active_power'].to_numpy()
```

```
X_train['Global_reactive_power'] = sctr.fit_transform(X_train['Global_reactive_power'].to_num

X_train['Voltage'] = sctr.fit_transform(X_train['Voltage'].to_numpy().reshape(-1,1))

X_train['Global_intensity'] = sctr.fit_transform(X_train['Global_intensity'].to_numpy().resha

X_train['Sub_metering_1'] = sctr.fit_transform(X_train['Sub_metering_1'].to_numpy().reshape(-

X_train['Sub_metering_2'] = sctr.fit_transform(X_train['Sub_metering_2'].to_numpy().reshape(-

X_train['Sub_metering_3'] = sctr.fit_transform(X_train['Sub_metering_3'].to_numpy().reshape(-

X_train
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
1440973	0.132252	0.080306	0.582459	0.126761	0.012346	0.000000	0.580645

```
Y_train = training_dataset[training_dataset.columns.tolist()[-1:]].copy()
Y_train
```

	active_energy_per_minute_in_Wh
1440973	3.466667
401411	3.766667
696281	3.466667
1085652	6.300000
474897	41.933333
...	...
1677877	19.100000
1114970	6.233333
873524	2.900000
1805780	14.400000
773390	7.000000

93386 rows × 1 columns

Scaling/ Normalizing the features in the testing dataset

```
X_test = testing_dataset[testing_dataset.columns.tolist()[:-1]].copy()
X_test
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
696294	0.266	0.000	243.85	1.0	0.0	0.0	1.0
1953000	0.630	0.000	246.69	2.6	0.0	0.0	1.0
1787586	1.554	0.204	245.88	6.2	0.0	0.0	19.0
1546288	1.980	0.000	240.85	8.2	0.0	0.0	18.0
1722499	2.704	0.000	238.62	11.2	0.0	0.0	18.0
...	...	...	...	...	...	...	...
1671759	0.344	0.070	247.68	1.4	0.0	0.0	1.0
1401804	0.156	0.000	243.91	0.6	0.0	0.0	1.0
1977546	0.236	0.088	244.35	1.0	0.0	2.0	0.0
1284552	0.394	0.156	228.47	1.8	0.0	2.0	1.0
1303477	0.910	0.212	239.69	3.8	1.0	1.0	0.0

10377 rows × 7 columns

```
sctt = MinMaxScaler()

X_test['Global_active_power'] = sctt.fit_transform(X_test['Global_active_power'].to_numpy().r

X_test['Global_reactive_power'] = sctt.fit_transform(X_test['Global_reactive_power'].to_numpy

X_test['Voltage'] = sctt.fit_transform(X_test['Voltage'].to_numpy().reshape(-1,1))

X_test['Global_intensity'] = sctt.fit_transform(X_test['Global_intensity'].to_numpy().reshape

X_test['Sub_metering_1'] = sctt.fit_transform(X_test['Sub_metering_1'].to_numpy().reshape(-1,
```

```
X_test['Sub_metering_2'] = sctt.fit_transform(X_test['Sub_metering_2'].to_numpy().reshape(-1,

X_test['Sub_metering_3'] = sctt.fit_transform(X_test['Sub_metering_3'].to_numpy().reshape(-1,


X_test
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
696294	0.023701	0.000000	0.683864	0.023669	0.000000	0.000000	0.033333
1953000	0.069592	0.000000	0.787779	0.071006	0.000000	0.000000	0.033333
1787586	0.186082	0.149560	0.758141	0.177515	0.000000	0.000000	0.633333
1546288	0.239788	0.000000	0.574094	0.236686	0.000000	0.000000	0.600000
1722499	0.331064	0.000000	0.492499	0.325444	0.000000	0.000000	0.600000
...	...	...	...	...	...	...	...
1671759	0.033535	0.051320	0.824003	0.035503	0.000000	0.000000	0.033333
1401804	0.009834	0.000000	0.686059	0.011834	0.000000	0.000000	0.033333
1977546	0.019919	0.064516	0.702159	0.023669	0.000000	0.027027	0.000000
1284552	0.039839	0.114370	0.121112	0.047337	0.000000	0.027027	0.033333
1303477	0.104892	0.155425	0.531650	0.106509	0.012987	0.013514	0.000000

10377 rows × 7 columns

```
Y_test = testing_dataset[testing_dataset.columns.tolist()[-1:]].copy()
Y_test
```

	active_energy_per_minute_in_Wh
696294	3.433333
1953000	9.500000
1787586	6.900000
1546288	15.000000
1722499	27.066667
...	...
1671759	4.733333
1401804	1.600000
1977546	1.933333
1284552	3.566667
1303477	13.166667

10377 rows × 1 columns

Linear Regression Model

```
#Fitting the model on training set
from sklearn.linear_model import LinearRegression

reg = LinearRegression()
model1 = reg.fit(X_train,Y_train)

print(f'Regression score : {model1.score(X_train,Y_train)}')
print(f'Regression coefficient : {model1.coef_}')
```

```
Regression score : 1.0
Regression coefficient : [[ 1.60300000e+02 -2.84217094e-14  2.48689958e-14  4.65405492e-13
  -8.10000000e+01 -7.50000000e+01 -3.10000000e+01]]
```

```
target1 = Y_test.to_numpy().flatten()
target1
```

```
array([ 3.43333333,  9.5       ,  6.9       , ...,  1.93333333,
        3.56666667, 13.16666667])
```

```
predicted1 = model1.predict(X_test).flatten()
predicted1
```

```
array([ 4.03267776, 11.38885527, 11.46222895, ...,  2.4327057 ,
        4.59243843, 16.01532512])
```

```
predicted1 - target1
```

```
array([0.59934443, 1.88885527, 4.56222895, ..., 0.49937237, 1.02577176,
       2.84865845])
```

```
from sklearn.metrics import mean_squared_error,r2_score
```

```
mse1 = mean_squared_error(target1,predicted1)
r2_scr1 = r2_score(target1,predicted1)

print(f"value of mse : {mse1}")
print(f"value of r2_score : {r2_scr1}")
```

```
value of mse : 21.219513887994836
```

```
value of r2_score : 0.7612794175528509
```

```
import pickle

#saving the model into the disk
filename = f'linear_model_{r2_scr1}_{mse1}.sav'
pickle.dump(model1, open(filename, 'wb'))


#load the model from disk
#loaded_model = pickle.load(open(filename, 'rb'))
#result = loaded_model.score(X_test, Y_test)
#print(result)
```

Support Vector Machine Model

```
from sklearn import svm

svr1 = svm.SVR(kernel='linear')

svr1.fit(X_train,Y_train.to_numpy().flatten())

predicted2 = svr1.predict(X_test)
target2 = Y_test.to_numpy().flatten()


mse2 = mean_squared_error(target2,predicted2)
r2_scr2 = r2_score(target2,predicted2)
```

```
print(f"value of mse : {mse2}")
print(f"value of r2_score : {r2_scr2}")

filename = f'svm_svr1_linear_model_{r2_scr2}_{mse2}.sav'
pickle.dump(svr1, open(filename, 'wb'))
```

```
value of mse : 23.089427705219222
value of r2_score : 0.7402427944742079
```

```
from sklearn import svm

svr2 = svm.SVR(kernel='poly')

svr2.fit(X_train,Y_train.to_numpy().flatten())

predicted3 = svr2.predict(X_test)
target3 = Y_test.to_numpy().flatten()


mse3 = mean_squared_error(target3,predicted3)
r2_scr3 = r2_score(target3,predicted3)

print(f"value of mse : {mse3}")
print(f"value of r2_score : {r2_scr3}")

filename = f'svm_svr2_poly_model_{r2_scr3}_{mse3}.sav'
pickle.dump(svr2, open(filename, 'wb'))
```

```
value of mse : 58.68205425161569
value of r2_score : 0.3398239825811269
```

Decision Tree Regression Model

```
from sklearn.tree import DecisionTreeRegressor


regressor1 = DecisionTreeRegressor(random_state = 0)
regressor1.fit(X_train,Y_train.to_numpy().flatten())


predicted4 = regressor1.predict(X_test)
target4 = Y_test.to_numpy().flatten()


mse4 = mean_squared_error(target4,predicted4)
r2_scr4 = r2_score(target4,predicted4)

print(f"value of mse : {mse4}")
print(f"value of r2_score : {r2_scr4}")

filename = f'decision_tree_model_{r2_scr4}_{mse4}.sav'
pickle.dump(regressor1, open(filename, 'wb'))
```

```
value of mse : 25.3096945136599
value of r2_score : 0.7152646828880185
```

Random Forest Model

```
from sklearn.ensemble import RandomForestRegressor

regressor2 = RandomForestRegressor(n_estimators = 100, random_state = 0)
regressor2.fit(X_train,Y_train.to_numpy().flatten())

predicted5 = regressor2.predict(X_test)
target5 = Y_test.to_numpy().flatten()



mse5 = mean_squared_error(target5,predicted5)
r2_scr5 = r2_score(target5,predicted5)

print(f"value of mse : {mse5}")
print(f"value of r2_score : {r2_scr5}")

filename = f'random_forest_model_{r2_scr5}_{mse5}.sav'
pickle.dump(regressor2, open(filename, 'wb'))
```

```
value of mse : 23.70021669477456
value of r2_score : 0.73337138808344
```

Xgboost Regression Model

```
import xgboost as xg
from xgboost import XGBRegressor
```

```
regressor3 = XGBRegressor()
regressor3.fit(X_train,Y_train)

predicted6 = regressor3.predict(X_test)
target6 = Y_test.to_numpy().flatten()


mse6 = mean_squared_error(target6,predicted6)
r2_scr6 = r2_score(target6,predicted6)

print(f"value of mse : {mse6}")
print(f"value of r2_score : {r2_scr6}")

filename = f'xgboost_model_{r2_scr6}_{mse6}.sav'
pickle.dump(regressor3, open(filename, 'wb'))
```

```
[03:20:27] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
value of mse : 20.31091849734466
value of r2_score : 0.7715011607091595
```

Double-click (or enter) to edit

Evaluation of machine learning models on scikit-learn mean-sqaured-error & r2_score performance metrics:

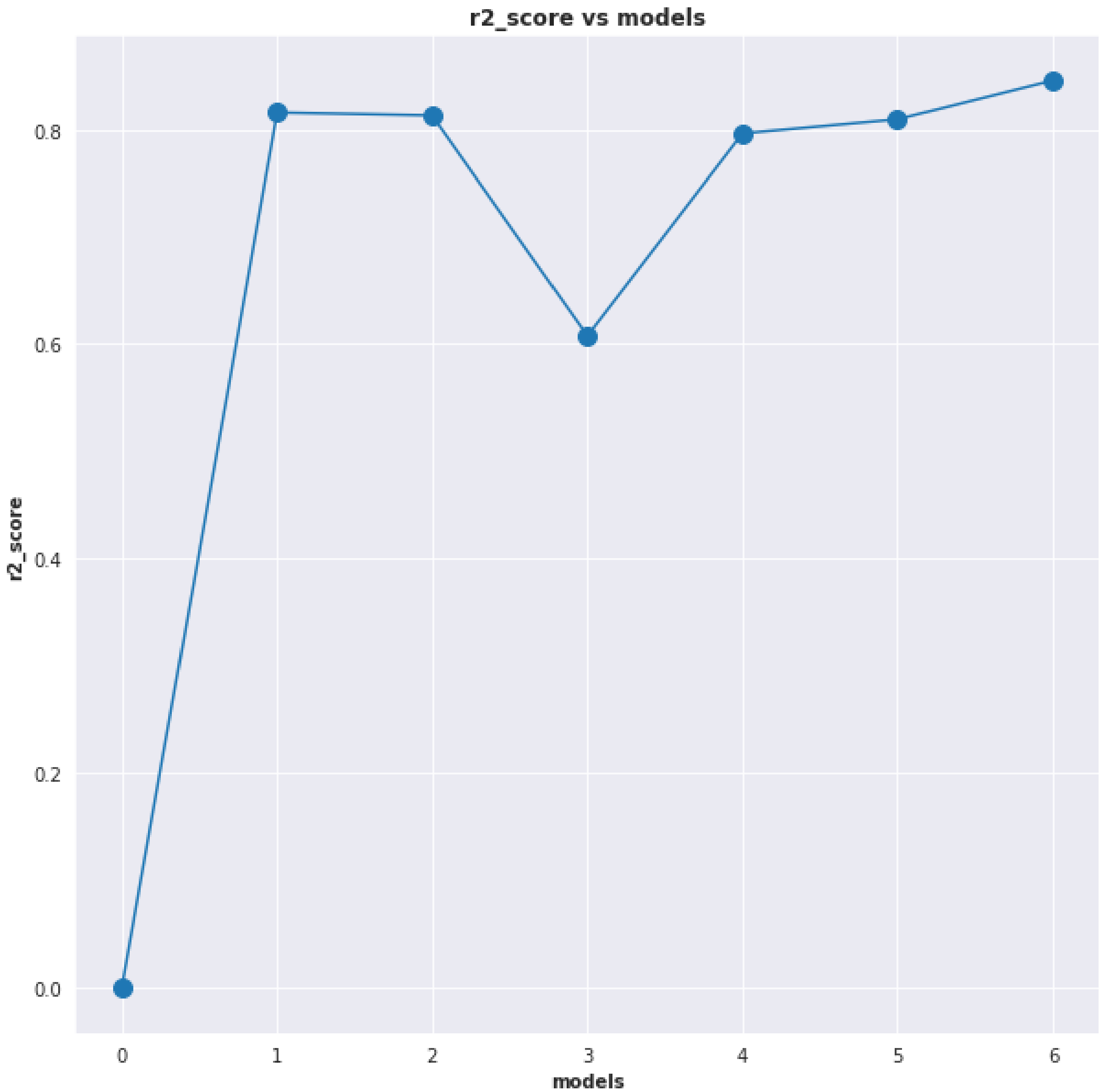
```
model = ["zero_point","linear_regression_model","linear_kernel_svm_model","poly_kernel_svm_mo
         "random_forest_model","xgboost_model"]

mse = [0,mse1,mse2,mse3,mse4,mse5,mse6]
```

```
r2_scr = [0,r2_scr1,r2_scr2,r2_scr3,r2_scr4,r2_scr5,r2_scr6]

print(model)
print(mse)
print(r2_scr)
```

```
['zero_point', 'linear_regression_model', 'linear_kernel_svm_model', 'poly_kernel_svm_model', 'decision_tree_model', 'random_fo
[0, 15.142193612381762, 15.360562178574126, 32.22943014152453, 16.743579167842157, 15.662564533880547, 12.686506695482702]
[0, 0.8156753007770728, 0.8130171178668877, 0.6076737513047541, 0.7961817638162978, 0.8093408676001526, 0.8455681791756802]
```

Plot of r2_score of the models:

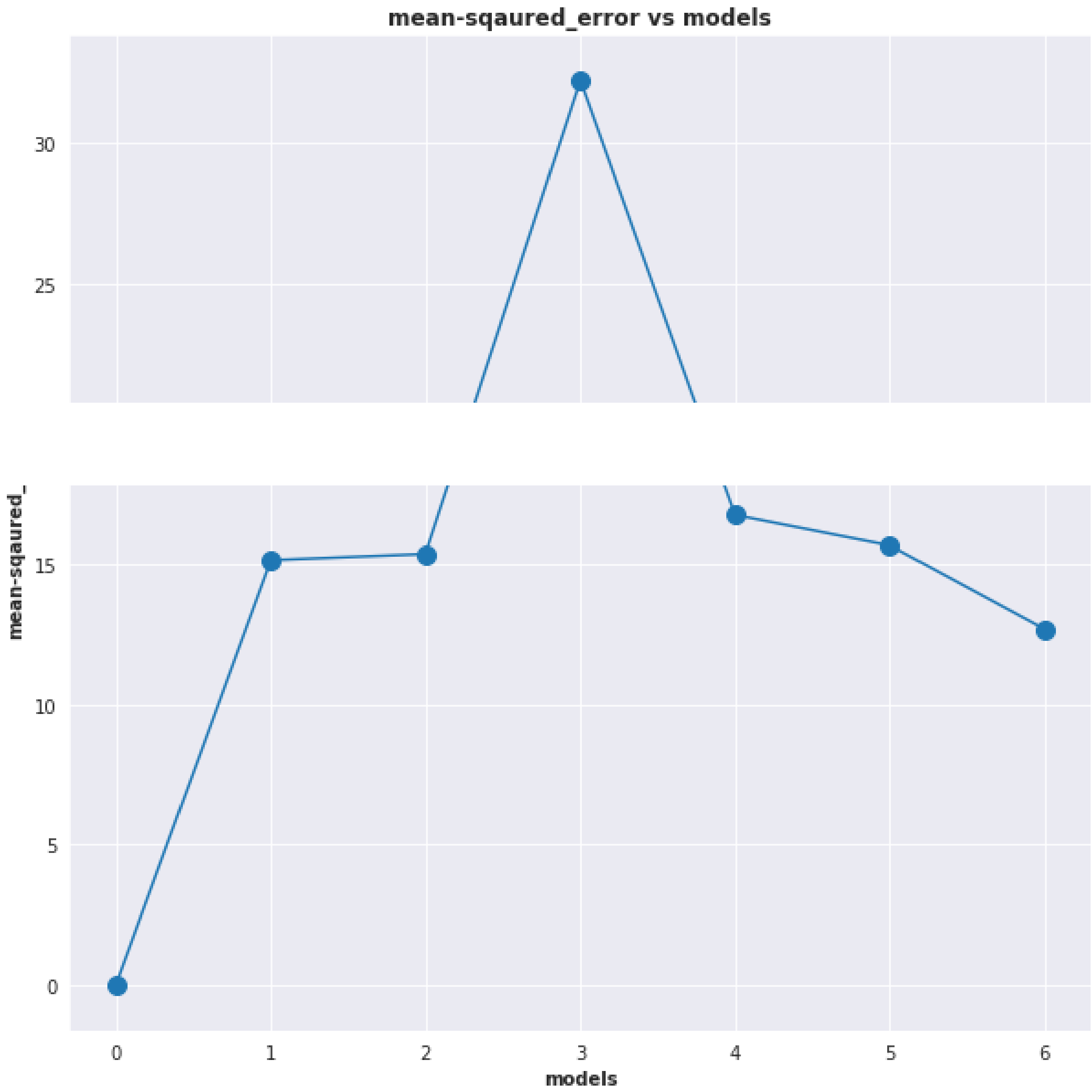
```
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

plt.figure(figsize=(10,10))

sns.set_style("darkgrid")
plt.plot(r2_scr,marker = 'o',markersize=10,linewidth=1.5)

plt.title("r2_score vs models",fontweight="bold")
plt.xlabel("models",fontweight="bold")
plt.ylabel("r2_score",fontweight="bold")

plt.show()
```



Plot of mse of the models:

```
import matplotlib.pyplot as plt
```

```
import numpy as np
import seaborn as sns

plt.figure(figsize=(10,10))

sns.set_style("darkgrid")
plt.plot(mse,marker = 'o',markersize=10,linewidth=1.5)

plt.title("mean-sqaured_error vs models",fontweight="bold")
plt.xlabel("models",fontweight="bold")
plt.ylabel("mean-sqaured_error",fontweight="bold")
plt.show()
```



✓ 5s completed at 8:50 AM