Assesment Report CLO-2 Case Based

K-Means Algorithm

Created by:

Muhammad Rizky Aulia Gobel – 1304211002

IF-45-02.1PJJ

Long-Distance Informatics major

Informatic faculty

Telkom University

Bandung

2023

Statement

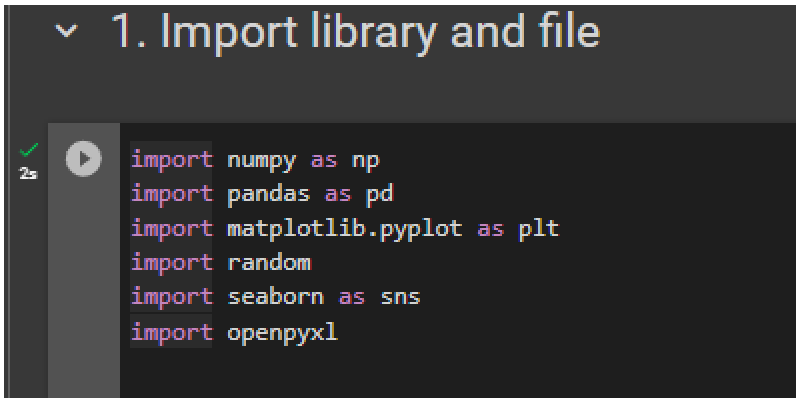
I do this assignment honestly and follow the rule of conduct of academic ethics in case I do not follow the rule I am ready to get a 0 (zero) mark for my assignment.

Rizky

Muhammad Rizky Aulia Gobel

Import library

For this assignment, the author used several libraries as follows

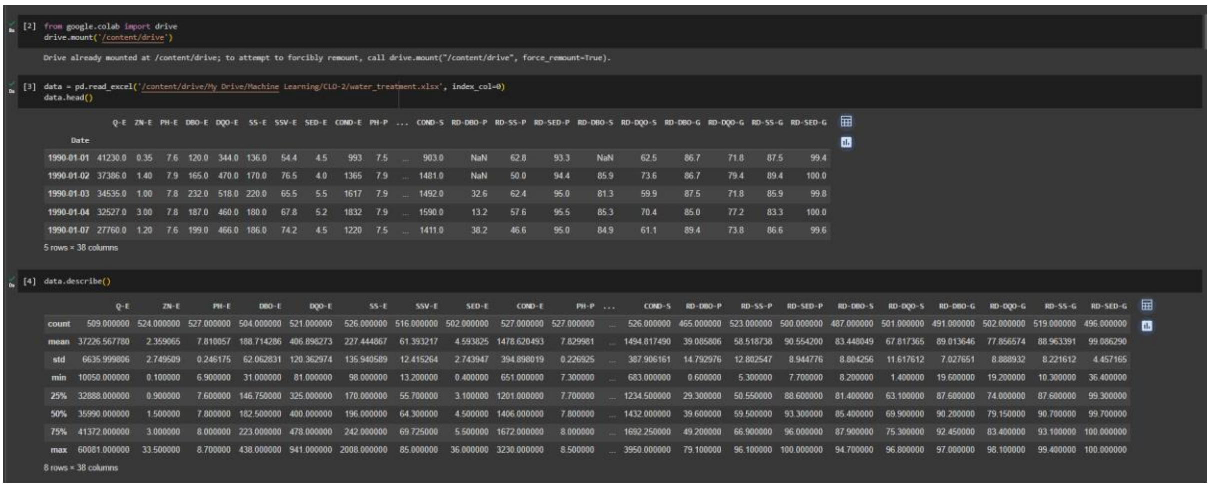


1. Import library and file

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

Overview the dataset

To run an .xlsx file, the author uses Google Colab mount to mount to the author's drive. Then, the author creates a variable called data that is used to read the water-treatment file that has been converted to an .xlsx file previously. Then, the author runs data.head() which is used to display the first 5 rows.



```
[2] from google.colab import drive
    drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
[3] data = pd.read_excel('/content/drive/My Drive/Machine Learning/CLO-2/water_treatment.xlsx', index_col=0)
    data.head()
```

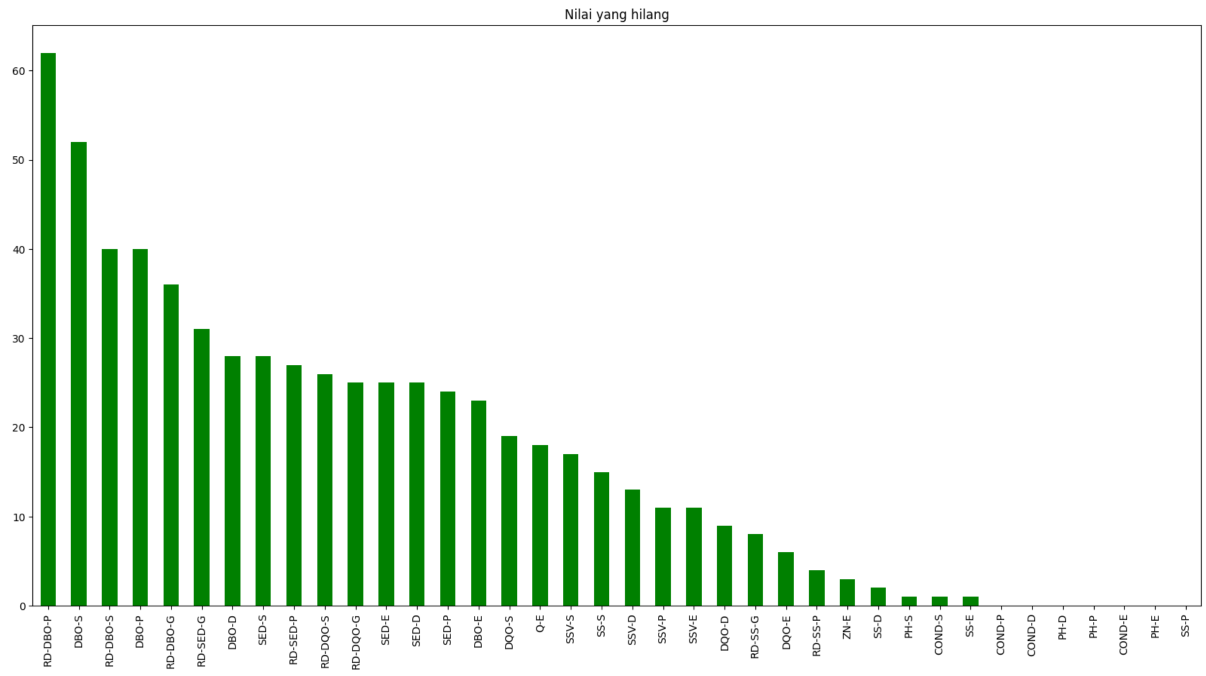
```
                Q-E  ZN-E  PH-E  DBO-E  DQO-E   SS-E  SSV-E  SED-E  COND-E  PH-P  ...  COND-S  RD-DBO-P  RD-SS-P  RD-SED-P  RD-DBO-S  RD-DQO-S  RD-DBO-G  RD-DQO-G  RD-SS-G  RD-SED-G
Date
1990-01-01  41230.0  0.35   7.6  120.0  344.0  136.0   54.4    4.5     993   7.5  ...   903.0       NaN     62.8      93.3       NaN      62.5      86.7      71.8     87.5      99.4
1990-01-02  37386.0  1.40   7.9  165.0  470.0  170.0   76.5    4.0    1365   7.9  ...  1481.0       NaN     50.0      94.4      85.9      73.6      86.7      79.4     89.4     100.0
1990-01-03  34535.0  1.00   7.8  232.0  518.0  220.0   65.5    5.5    1617   7.9  ...  1492.0      32.6     62.4      95.0      81.3      59.9      87.5      71.8     85.9      99.8
1990-01-04  32527.0  3.00   7.8  187.0  460.0  180.0   67.8    5.2    1832   7.9  ...  1590.0      13.2     57.6      95.5      85.3      70.4      85.0      77.2     83.3     100.0
1990-01-07  27760.0  1.20   7.6  199.0  466.0  186.0   74.2    4.5    1220   7.5  ...  1411.0      38.2     46.6      95.0      84.9      61.1      89.4      73.8     86.6      99.6
5 rows × 38 columns
```

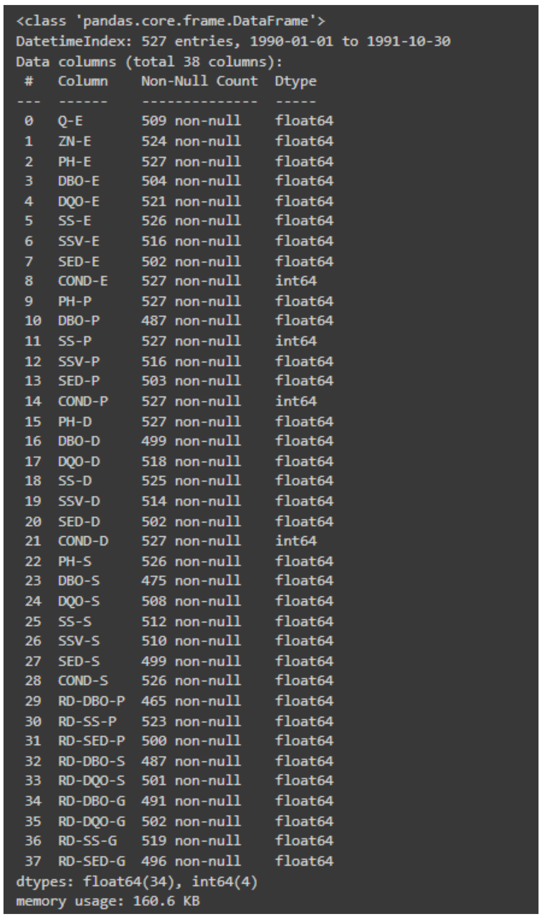
```
[4] data.describe()
```

```
                Q-E        ZN-E        PH-E       DBO-E       DQO-E         SS-E       SSV-E       SED-E       COND-E        PH-P  ...       COND-S    RD-DBO-P     RD-SS-P    RD-SED-P    RD-DBO-S    RD-DQO-S    RD-DBO-G    RD-DQO-G     RD-SS-G    RD-SED-G
count    509.000000  524.000000  527.000000  504.000000  521.000000   526.000000  516.000000  502.000000   527.000000  527.000000  ...   526.000000  465.000000  523.000000  500.000000  487.000000  501.000000  491.000000  502.000000  519.000000  496.000000
mean   37226.567780    2.359065    7.810057  188.714286  406.898273   227.444867   61.393217    4.593825  1478.620493    7.829981  ...  1494.817490   39.085806   58.518738   90.554200   83.448049   67.817365   89.013646   77.856574   88.963391   99.086290
std     6635.999806    2.749509    0.246175   62.062831  120.362974   135.940589   12.415264    2.743947   394.898019    0.226925  ...   387.906161   14.792976   12.802547    8.944776    8.804256   11.617612    7.027651    8.888932    8.221612    4.457165
min    10050.000000    0.100000    6.900000   31.000000   81.000000    98.000000   13.200000    0.400000   651.000000    7.300000  ...   683.000000    0.600000    5.300000    7.700000    8.200000    1.400000   19.600000   19.200000   10.300000   36.400000
25%    32888.000000    0.900000    7.600000  146.750000  325.000000   170.000000   55.700000    3.100000  1201.000000    7.700000  ...  1234.500000   29.300000   50.550000   88.600000   81.400000   63.100000   87.600000   74.000000   87.600000   99.300000
50%    35990.000000    1.500000    7.800000  182.500000  400.000000   196.000000   64.300000    4.500000  1406.000000    7.800000  ...  1432.000000   39.600000   59.500000   93.300000   85.400000   69.900000   90.200000   79.150000   90.700000   99.700000
75%    41372.000000    3.000000    8.000000  223.000000  478.000000   242.000000   69.725000    5.500000  1672.000000    8.000000  ...  1692.250000   49.200000   66.900000   96.000000   87.900000   75.300000   92.450000   83.400000   93.100000  100.000000
max    60081.000000   33.500000    8.700000  438.000000  941.000000  2008.000000   85.000000   36.000000  3230.000000    8.500000  ...  3950.000000   79.100000   96.100000  100.000000   94.700000   96.800000   97.000000   98.100000   99.400000  100.000000
8 rows × 38 columns
```

Preprocessing

The author then ran data.describe() to check the contents of the dataset as a whole. What surprised the author was that the values in the count series had different values. There were some with 526 data points, 527 data points, 509 data points, and so on.



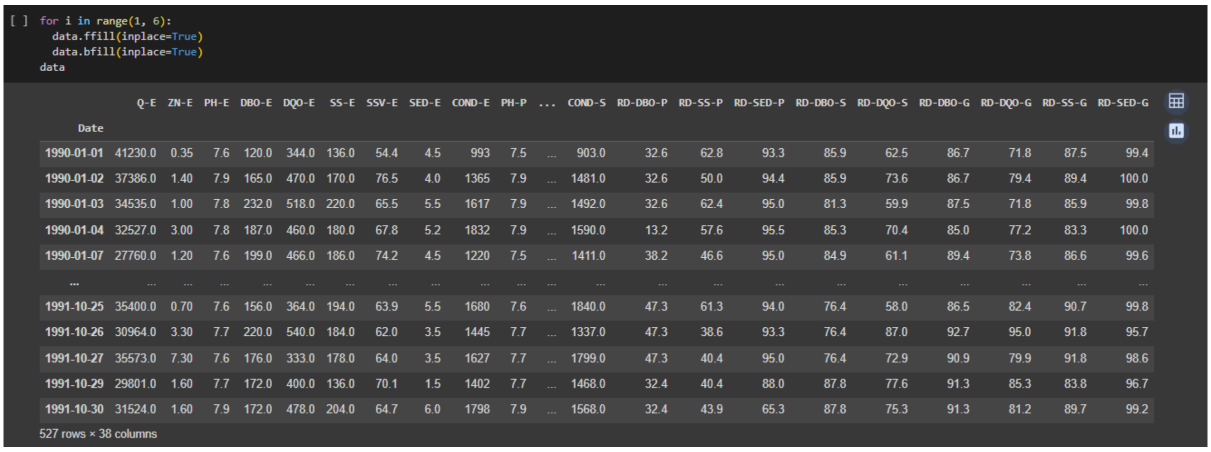

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 527 entries, 1990-01-01 to 1991-10-30
Data columns (total 38 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Q-E       509 non-null    float64
 1   ZN-E      524 non-null    float64
 2   PH-E      527 non-null    float64
 3   DBO-E     504 non-null    float64
 4   DQO-E     521 non-null    float64
 5   SS-E      526 non-null    float64
 6   SSV-E     516 non-null    float64
 7   SED-E     502 non-null    float64
 8   COND-E    527 non-null    int64
 9   PH-P      527 non-null    float64
 10  DBO-P     487 non-null    float64
 11  SS-P      527 non-null    int64
 12  SSV-P     516 non-null    float64
 13  SED-P     503 non-null    float64
 14  COND-P    527 non-null    int64
 15  PH-D      527 non-null    float64
 16  DBO-D     499 non-null    float64
 17  DQO-D     518 non-null    float64
 18  SS-D      525 non-null    float64
 19  SSV-D     514 non-null    float64
 20  SED-D     502 non-null    float64
 21  COND-D    527 non-null    int64
 22  PH-S      526 non-null    float64
 23  DBO-S     475 non-null    float64
 24  DQO-S     508 non-null    float64
 25  SS-S      512 non-null    float64
 26  SSV-S     510 non-null    float64
 27  SED-S     499 non-null    float64
 28  COND-S    526 non-null    float64
 29  RD-DBO-P  465 non-null    float64
 30  RD-SS-P   523 non-null    float64
 31  RD-SED-P  500 non-null    float64
 32  RD-DBO-S  487 non-null    float64
 33  RD-DQO-S  501 non-null    float64
 34  RD-DBO-G  491 non-null    float64
 35  RD-DQO-G  502 non-null    float64
 36  RD-SS-G   519 non-null    float64
 37  RD-SED-G  496 non-null    float64
dtypes: float64(34), int64(4)
memory usage: 160.6 KB
```

The author filled in the missing data using the bfill and ffill methods. The methods work as follows:

bfill fills in the missing data from top to bottom.

ffill fills in the missing data from bottom to top.

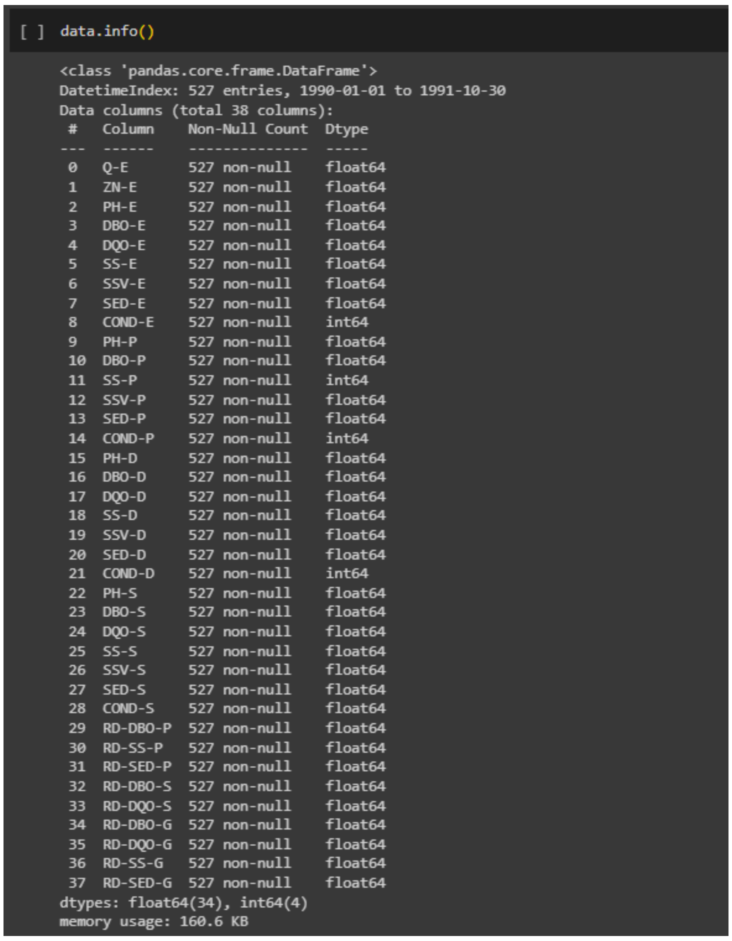
The results are then displayed as follows:



```
[ ] for i in range(1, 6):
      data.ffill(inplace=True)
      data.bfill(inplace=True)
    data
```

	Q-E	ZN-E	PH-E	DBO-E	DQO-E	SS-E	SSV-E	SED-E	COND-E	PH-P	...	COND-S	RD-DBO-P	RD-SS-P	RD-SED-P	RD-DBO-S	RD-DQO-S	RD-DBO-G	RD-DQO-G	RD-SS-G	RD-SED-G
Date																					
1990-01-01	41230.0	0.35	7.6	120.0	344.0	136.0	54.4	4.5	993	7.5	...	903.0	32.6	62.8	93.3	85.9	62.5	86.7	71.8	87.5	99.4
1990-01-02	37386.0	1.40	7.9	165.0	470.0	170.0	76.5	4.0	1365	7.9	...	1481.0	32.6	50.0	94.4	85.9	73.6	86.7	79.4	89.4	100.0
1990-01-03	34535.0	1.00	7.8	232.0	518.0	220.0	65.5	5.5	1617	7.9	...	1492.0	32.6	62.4	95.0	81.3	59.9	87.5	71.8	85.9	99.8
1990-01-04	32527.0	3.00	7.8	187.0	460.0	180.0	67.8	5.2	1832	7.9	...	1590.0	13.2	57.6	95.5	85.3	70.4	85.0	77.2	83.3	100.0
1990-01-07	27760.0	1.20	7.6	199.0	466.0	186.0	74.2	4.5	1220	7.5	...	1411.0	38.2	46.6	95.0	84.9	61.1	89.4	73.8	86.6	99.6
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1991-10-25	35400.0	0.70	7.6	156.0	364.0	194.0	63.9	5.5	1680	7.6	...	1840.0	47.3	61.3	94.0	76.4	58.0	86.5	82.4	90.7	99.8
1991-10-26	30964.0	3.30	7.7	220.0	540.0	184.0	62.0	3.5	1445	7.7	...	1337.0	47.3	38.6	93.3	76.4	87.0	92.7	95.0	91.8	95.7
1991-10-27	35573.0	7.30	7.6	176.0	333.0	178.0	64.0	3.5	1627	7.7	...	1799.0	47.3	40.4	95.0	76.4	72.9	90.9	79.9	91.8	98.6
1991-10-29	29801.0	1.60	7.7	172.0	400.0	136.0	70.1	1.5	1402	7.7	...	1468.0	32.4	40.4	88.0	87.8	77.6	91.3	85.3	83.8	96.7
1991-10-30	31524.0	1.60	7.9	172.0	478.0	204.0	64.7	6.0	1798	7.9	...	1568.0	32.4	43.9	65.3	87.8	75.3	91.3	81.2	89.7	99.2

527 rows × 38 columns

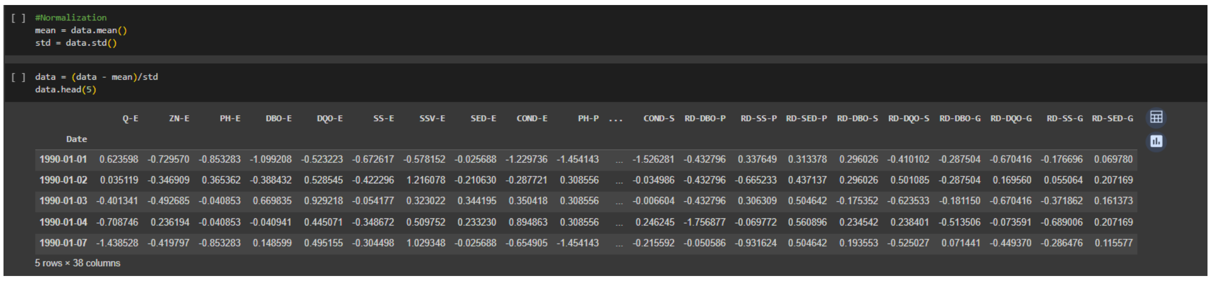


```
[ ] data.info()

    <class 'pandas.core.frame.DataFrame'>
    DatetimeIndex: 527 entries, 1990-01-01 to 1991-10-30
    Data columns (total 38 columns):
     #   Column    Non-Null Count  Dtype
    ---  ------    --------------  -----
     0   Q-E       527 non-null    float64
     1   ZN-E      527 non-null    float64
     2   PH-E      527 non-null    float64
     3   DBO-E     527 non-null    float64
     4   DQO-E     527 non-null    float64
     5   SS-E      527 non-null    float64
     6   SSV-E     527 non-null    float64
     7   SED-E     527 non-null    float64
     8   COND-E    527 non-null    int64
     9   PH-P      527 non-null    float64
     10  DBO-P     527 non-null    float64
     11  SS-P      527 non-null    int64
     12  SSV-P     527 non-null    float64
     13  SED-P     527 non-null    float64
     14  COND-P    527 non-null    int64
     15  PH-D      527 non-null    float64
     16  DBO-D     527 non-null    float64
     17  DQO-D     527 non-null    float64
     18  SS-D      527 non-null    float64
     19  SSV-D     527 non-null    float64
     20  SED-D     527 non-null    float64
     21  COND-D    527 non-null    int64
     22  PH-S      527 non-null    float64
     23  DBO-S     527 non-null    float64
     24  DQO-S     527 non-null    float64
     25  SS-S      527 non-null    float64
     26  SSV-S     527 non-null    float64
     27  SED-S     527 non-null    float64
     28  COND-S    527 non-null    float64
     29  RD-DBO-P  527 non-null    float64
     30  RD-SS-P   527 non-null    float64
     31  RD-SED-P  527 non-null    float64
     32  RD-DBO-S  527 non-null    float64
     33  RD-DQO-S  527 non-null    float64
     34  RD-DBO-G  527 non-null    float64
     35  RD-DQO-G  527 non-null    float64
     36  RD-SS-G   527 non-null    float64
     37  RD-SED-G  527 non-null    float64
    dtypes: float64(34), int64(4)
    memory usage: 160.6 KB
```

If you look at the first page, the rows 1990-01-01 and 1990-01-02 have NaN values. The NaN values are located in RD-DBO-P and RD-DBO-S, and on 1990-01-02, they are located in RD-DBO-P. After running bfill and ffill, the values are immediately filled in with the values below them. For example, the value of RD-DBO-S on row 1990-01-01 is filled in with the same value as RD-DBO-S on row 1990-01-02. In addition, with data.info(), the non-null values are the same from Q-E to RD-SED-G, indicating that there are no more missing values and the dataset is ready to be used.

Now author can perform normalization, normalization will standardize the data so that it has a mean of 0 and a standard deviation of 1. This is important for many machine learning algorithms, as they often assume that the data is normally distributed, the method that is used is Z-Score, here’s the code:



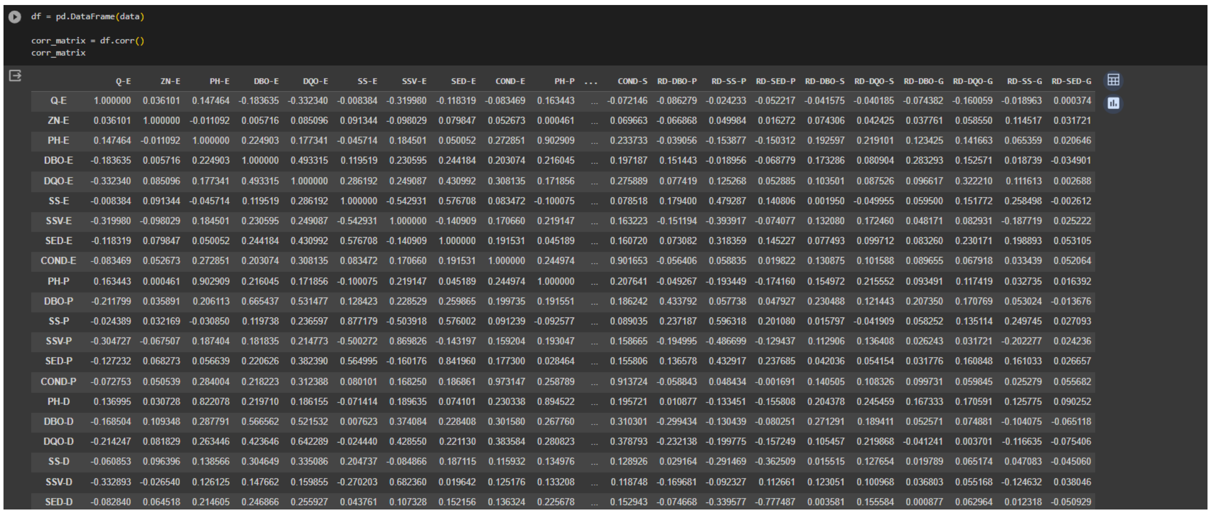
```
[ ] #Normalization
    mean = data.mean()
    std = data.std()
```

```
[ ] data = (data - mean)/std
    data.head(5)
```

	Q-E	ZN-E	PH-E	DBO-E	DQO-E	SS-E	SSV-E	SED-E	COND-E	PH-P	...	COND-S	RD-DBO-P	RD-SS-P	RD-SED-P	RD-DBO-S	RD-DQO-S	RD-DBO-G	RD-DQO-G	RD-SS-G	RD-SED-G
Date																					
1990-01-01	0.623598	-0.729570	-0.853283	-1.099208	-0.523223	-0.672617	-0.578152	-0.025688	-1.229736	-1.454143	...	-1.526281	-0.432796	0.337649	0.313378	0.296026	-0.410102	-0.287504	-0.670416	-0.176696	0.069780
1990-01-02	0.035119	-0.346909	0.365362	-0.388432	0.528545	-0.422296	1.216078	-0.210630	-0.287721	0.308556	...	-0.034986	-0.432796	-0.665233	0.437137	0.296026	0.501085	-0.287504	0.169560	0.055064	0.207169
1990-01-03	-0.401341	-0.492685	-0.040853	0.669835	0.929218	-0.054177	0.323022	0.344195	0.350418	0.308556	...	-0.006604	-0.432796	0.306309	0.504642	-0.175352	-0.623533	-0.181150	-0.670416	-0.371862	0.161373
1990-01-04	-0.708746	0.236194	-0.040853	-0.040941	0.445071	-0.348672	0.509752	0.233230	0.894863	0.308556	...	0.246245	-1.756877	-0.069772	0.560896	0.234542	0.238401	-0.513506	-0.073591	-0.689006	0.207169
1990-01-07	-1.438528	-0.419797	-0.853283	0.148599	0.495155	-0.304498	1.029348	-0.025688	-0.654905	-1.454143	...	-0.215592	-0.050586	-0.931624	0.504642	0.193553	-0.525027	0.071441	-0.449370	-0.286476	0.115577

5 rows × 38 columns

After that, author will create the correlation matrix, correlation matrix is a table that summarizes the correlation between every pair of variables in a dataset. It is used to identify relationships between variables and can be used to inform feature selection and model building.

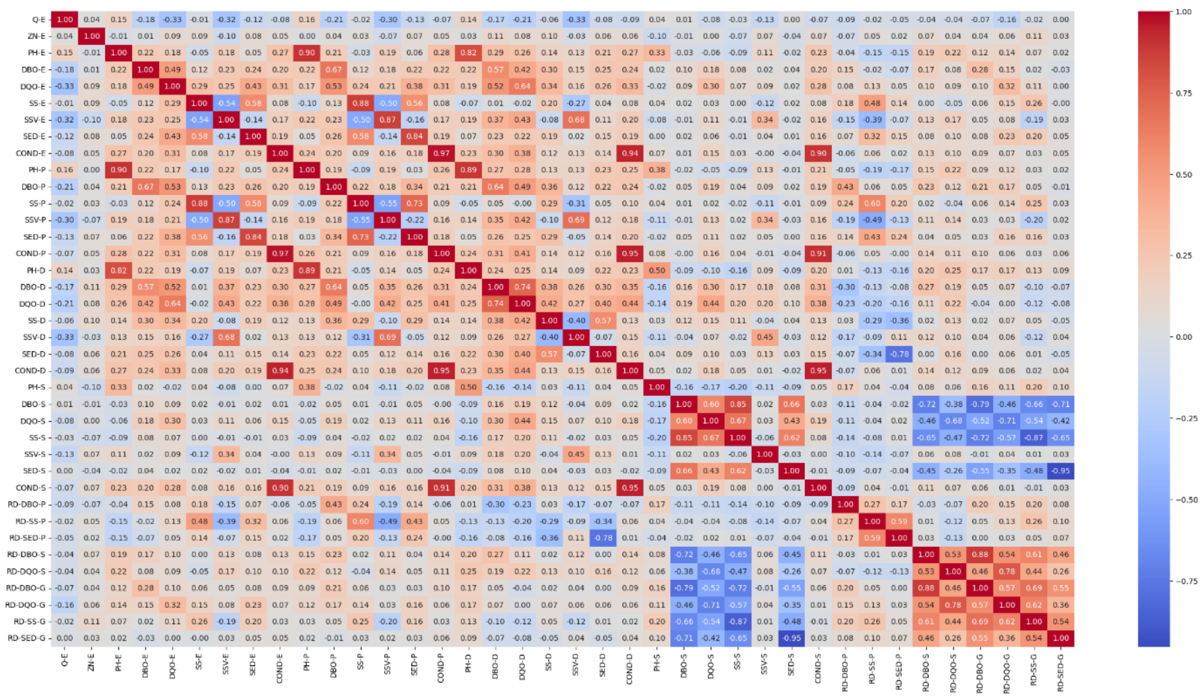


```
df = pd.DataFrame(data)

corr_matrix = df.corr()
corr_matrix
```

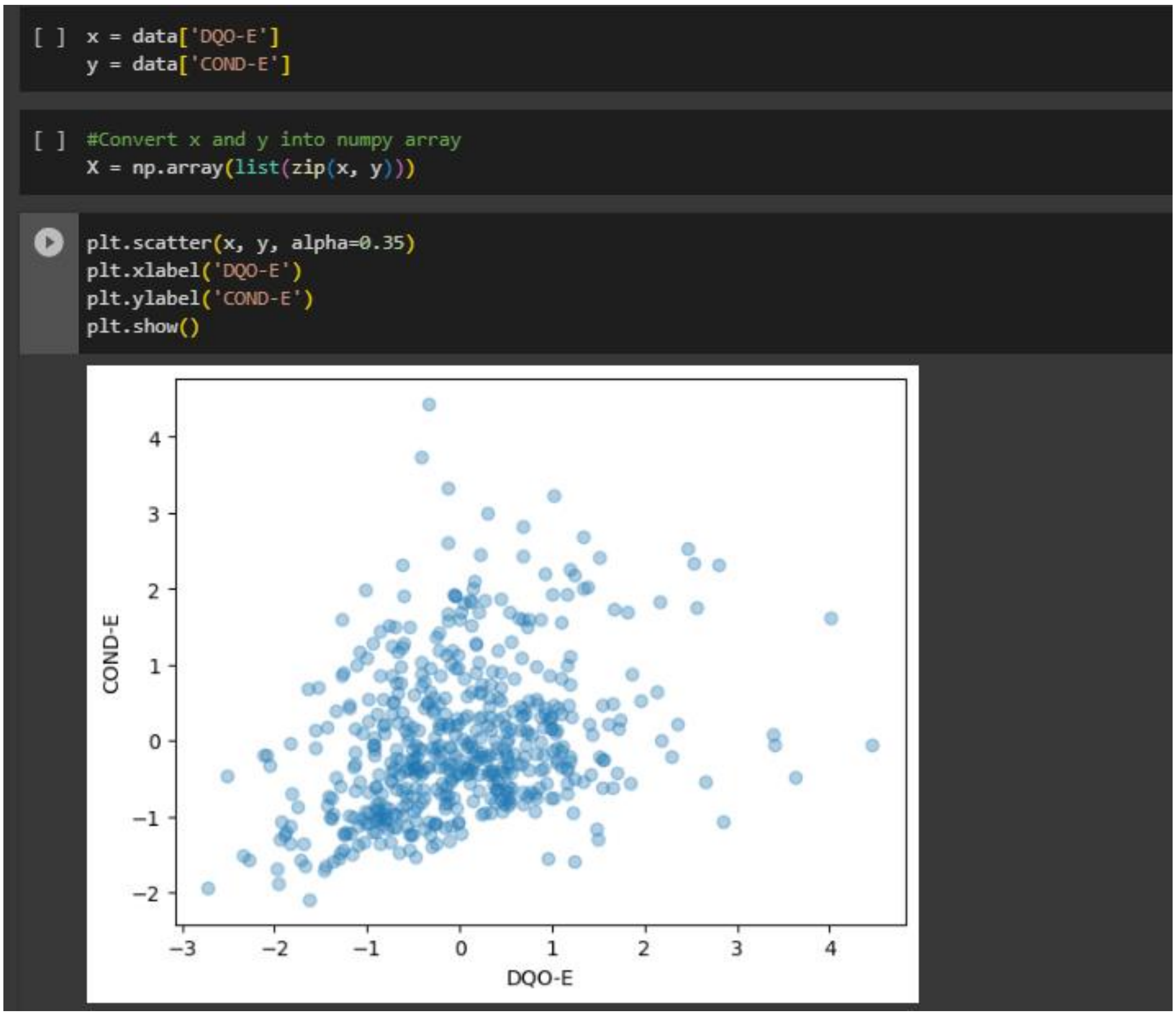
	Q-E	ZN-E	PH-E	DBO-E	DQO-E	SS-E	SSV-E	SED-E	COND-E	PH-P	...	COND-S	RD-DBO-P	RD-SS-P	RD-SED-P	RD-DBO-S	RD-DQO-S	RD-DBO-G	RD-DQO-G	RD-SS-G	RD-SED-G
Q-E	1.000000	0.036101	0.147464	-0.183635	-0.332340	-0.008384	-0.319980	-0.118319	-0.083469	0.163443	...	-0.072146	-0.086279	-0.024233	-0.052217	-0.041575	-0.040185	-0.074382	-0.160059	-0.018963	0.000374
ZN-E	0.036101	1.000000	-0.011092	0.005716	0.085096	0.091344	-0.098029	0.079847	0.052673	0.000461	...	0.069663	-0.066868	0.049984	0.016272	0.074306	0.042425	0.037761	0.058550	0.114517	0.031721
PH-E	0.147464	-0.011092	1.000000	0.224903	0.177341	-0.045714	0.184501	0.050052	0.272851	0.902909	...	0.233733	-0.039056	-0.153877	-0.150312	0.192597	0.219101	0.123425	0.141663	0.065359	0.020646
DBO-E	-0.183635	0.005716	0.224903	1.000000	0.493315	0.119519	0.230595	0.244184	0.203074	0.216045	...	0.197187	0.151443	-0.018956	-0.068779	0.173286	0.080904	0.283293	0.152571	0.018739	-0.034901
DQO-E	-0.332340	0.085096	0.177341	0.493315	1.000000	0.286192	0.249087	0.430992	0.308135	0.171856	...	0.275889	0.077419	0.125268	0.052885	0.103501	0.087526	0.096617	0.322210	0.111613	0.002688
SS-E	-0.008384	0.091344	-0.045714	0.119519	0.286192	1.000000	-0.542931	0.576708	0.083472	-0.100075	...	0.078518	0.179400	0.479287	0.140806	0.001950	-0.049955	0.059500	0.151772	0.258498	-0.002612
SSV-E	-0.319980	-0.098029	0.184501	0.230595	0.249087	-0.542931	1.000000	-0.140909	0.170660	0.219147	...	0.163223	-0.151194	-0.393917	-0.074077	0.132080	0.172460	0.048171	0.082931	-0.187719	0.025222
SED-E	-0.118319	0.079847	0.050052	0.244184	0.430992	0.576708	-0.140909	1.000000	0.191531	0.045189	...	0.160720	0.073082	0.318359	0.145227	0.077493	0.099712	0.083260	0.230171	0.198893	0.053105
COND-E	-0.083469	0.052673	0.272851	0.203074	0.308135	0.083472	0.170660	0.191531	1.000000	0.244974	...	0.901653	-0.056406	0.058835	0.019822	0.130875	0.101588	0.089655	0.067918	0.033439	0.052064
PH-P	0.163443	0.000461	0.902909	0.216045	0.171856	-0.100075	0.219147	0.045189	0.244974	1.000000	...	0.207641	-0.049267	-0.193449	-0.174160	0.154972	0.215552	0.093491	0.117419	0.032735	0.016392
DBO-P	-0.211799	0.035891	0.206113	0.665437	0.531477	0.128423	0.228529	0.259865	0.199735	0.191551	...	0.186242	0.433792	0.057738	0.047927	0.230488	0.121443	0.207350	0.170769	0.053024	-0.013676
SS-P	-0.024389	0.032169	-0.030850	0.119738	0.236597	0.877179	-0.503918	0.576002	0.091239	-0.092577	...	0.089035	0.237187	0.596318	0.201080	0.015797	-0.041909	0.058252	0.135114	0.249745	0.027093
SSV-P	-0.304727	-0.067507	0.187404	0.181835	0.214773	-0.500272	0.869826	-0.143197	0.159204	0.193047	...	0.158665	-0.194995	-0.486699	-0.129437	0.112906	0.136408	0.026243	0.031721	-0.202277	0.024236
SED-P	-0.127232	0.068273	0.056639	0.220626	0.382390	0.564995	-0.160176	0.841960	0.177300	0.028464	...	0.155806	0.136578	0.432917	0.237685	0.042036	0.054154	0.031776	0.160848	0.161033	0.026657
COND-P	-0.072753	0.050539	0.284004	0.218223	0.312388	0.080101	0.168250	0.186861	0.973147	0.258789	...	0.913724	-0.058843	0.048434	-0.001691	0.140505	0.108326	0.099731	0.059845	0.025279	0.055682
PH-D	0.136995	0.030728	0.822078	0.219710	0.186155	-0.071414	0.189635	0.074101	0.230338	0.894522	...	0.195721	0.010877	-0.133451	-0.155808	0.204378	0.245459	0.167333	0.170591	0.125775	0.090252
DBO-D	-0.168504	0.109348	0.287791	0.566562	0.521532	0.007623	0.374084	0.228408	0.301580	0.267760	...	0.310301	-0.299434	-0.130439	-0.080251	0.271291	0.189411	0.052571	0.074881	-0.104075	-0.065118
DQO-D	-0.214247	0.081829	0.263446	0.423646	0.642289	-0.024440	0.428550	0.221130	0.383584	0.280823	...	0.378793	-0.232138	-0.199775	-0.157249	0.105457	0.219868	-0.041241	0.003701	-0.116635	-0.075406
SS-D	-0.060853	0.096396	0.138566	0.304649	0.335086	0.204737	-0.084866	0.187115	0.115932	0.134976	...	0.128926	0.029164	-0.291469	-0.362509	0.015515	0.127654	0.019789	0.065174	0.047083	-0.045060
SSV-D	-0.332893	-0.026540	0.126125	0.147662	0.159855	-0.270203	0.682360	0.019642	0.125176	0.133208	...	0.118748	-0.169681	-0.092327	0.112661	0.123051	0.100968	0.036803	0.055168	-0.124632	0.038046
SED-D	-0.082840	0.064518	0.214605	0.246866	0.255927	0.043761	0.107328	0.152156	0.136324	0.225678	...	0.152943	-0.074668	-0.339577	-0.777487	0.003581	0.155584	0.000877	0.062964	0.012318	-0.050929

And here’s the heatmap:



Algorithm(K-Means)

Before performing k-means clustering, author will choose 2 column from the dataset, the column that author pick is DQO-E and COND-E, and then DQO-E and COND-E will be converted into numPy array, then visualized with scatterplot

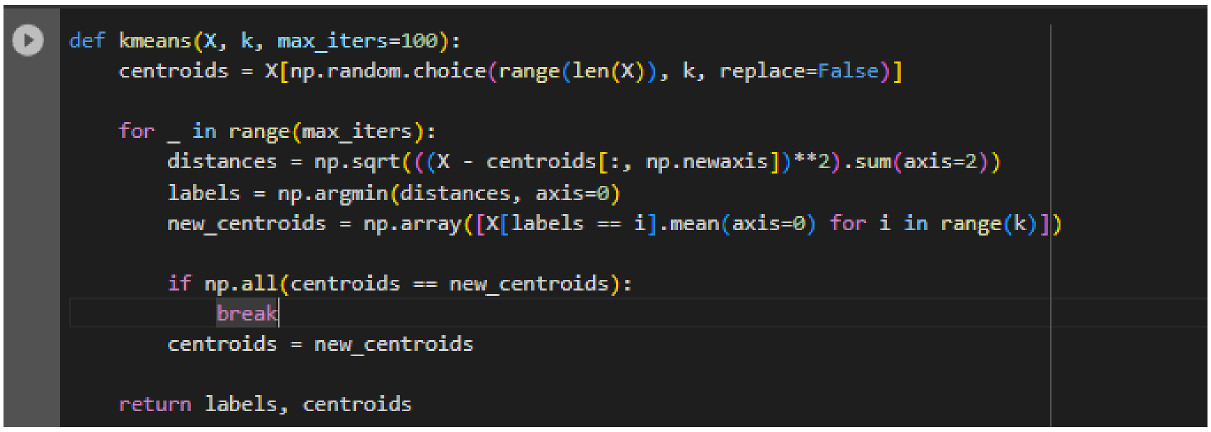


```
[ ] x = data['DQO-E']
    y = data['COND-E']
```

```
[ ] #Convert x and y into numpy array
    X = np.array(list(zip(x, y)))
```

```
plt.scatter(x, y, alpha=0.35)
plt.xlabel('DQO-E')
plt.ylabel('COND-E')
plt.show()
```

Then onto the K-Means, here's the code that author create:



```
def kmeans(X, k, max_iters=100):
    centroids = X[np.random.choice(range(len(X)), k, replace=False)]

    for _ in range(max_iters):
        distances = np.sqrt(((X - centroids[:, np.newaxis])**2).sum(axis=2))
        labels = np.argmin(distances, axis=0)
        new_centroids = np.array([X[labels == i].mean(axis=0) for i in range(k)])

        if np.all(centroids == new_centroids):
            break
        centroids = new_centroids

    return labels, centroids
```

def kmeans(X, k, max_iters=100) = function, X is the data points to cluster and represented numPy array, k is clusters to identify, and max_iters= is the maximum number to run the clustering algorithm

centroids = X[np.random.choice(range(len(X)), k, replace=False)] = initial centroid selection

```
    for _ in range(max_iters):
        distances = np.sqrt(((X - centroids[:, np.newaxis])**2).sum(axis=2))
        labels = np.argmin(distances, axis=0)
        new_centroids = np.array([X[labels == i].mean(axis=0) for i in range(k)])

        if np.all(centroids == new_centroids):
            break
        centroids = new_centroids
```

= The clustering algorithm, it iterates until convergence or the maximum number of iterations is reached, each iteration involves the following steps:

1.Calculate distances;

2.Assign data points;

3.Recompute centroids, and

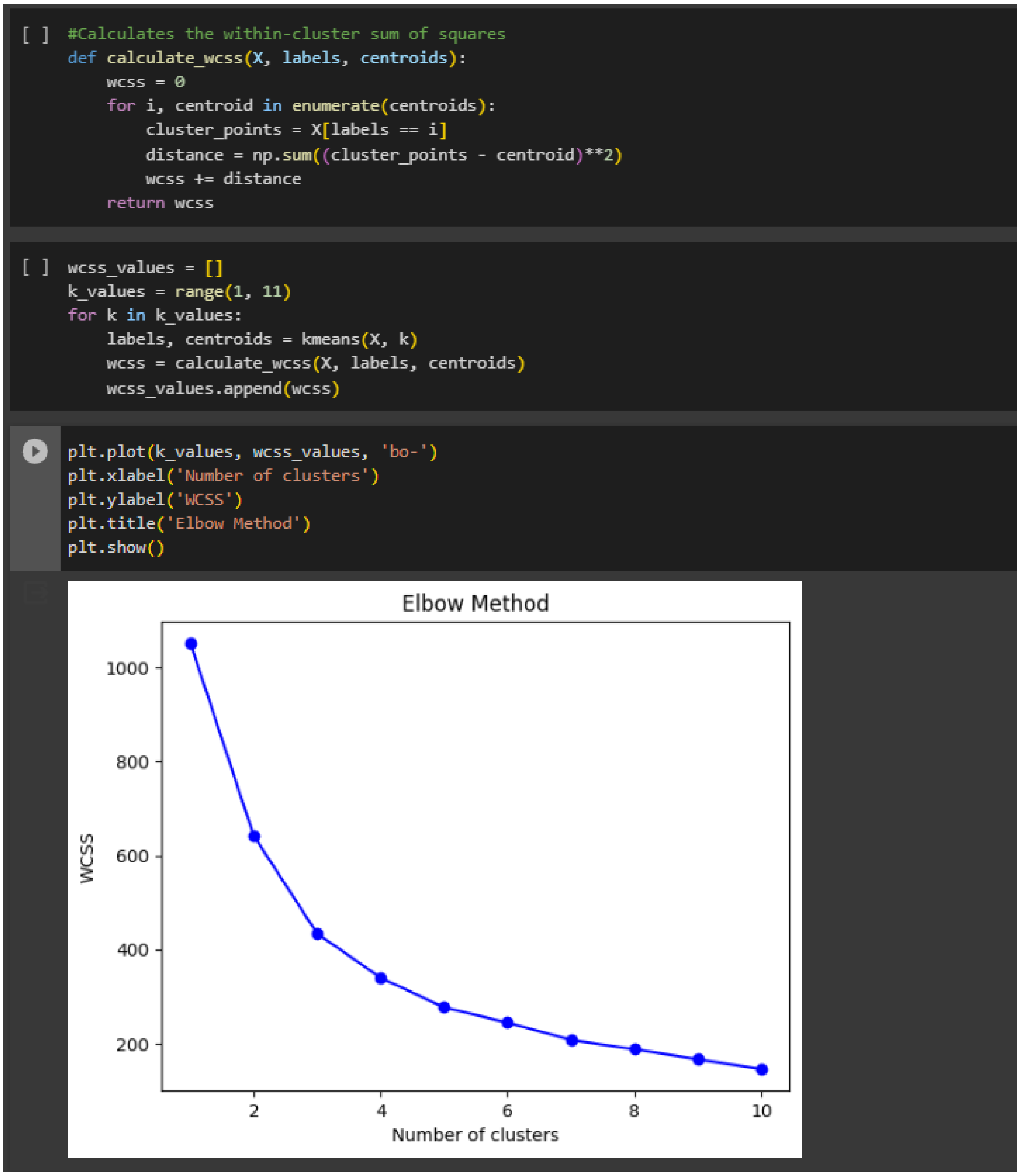
4.Check for convergence

then ended with

```
    return labels, centroids
```

Elbow method

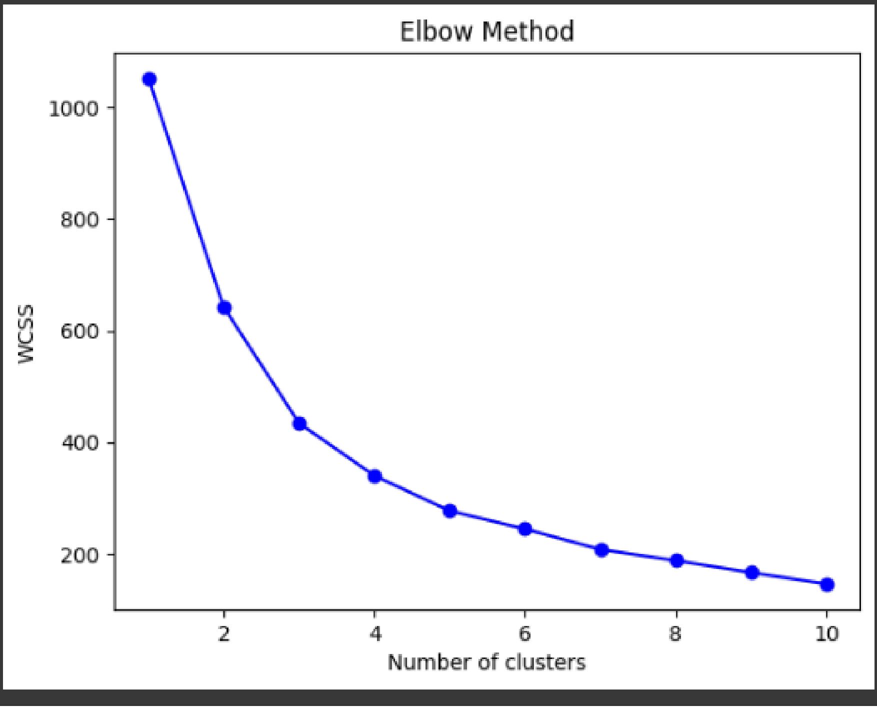
Elbow method is a method used in clustering to determine the optimum number of clusters in dataset, It is a heuristic method, doesn't guarantee that the optimum number will be found but it's relatively simple and effective method to quickly get the idea of the optimal numbers of clusters.



```
[ ] #Calculates the within-cluster sum of squares
    def calculate_wcss(X, labels, centroids):
        wcss = 0
        for i, centroid in enumerate(centroids):
            cluster_points = X[labels == i]
            distance = np.sum((cluster_points - centroid)**2)
            wcss += distance
        return wcss
```

```
[ ] wcss_values = []
    k_values = range(1, 11)
    for k in k_values:
        labels, centroids = kmeans(X, k)
        wcss = calculate_wcss(X, labels, centroids)
        wcss_values.append(wcss)
```

```
plt.plot(k_values, wcss_values, 'bo-')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.title('Elbow Method')
plt.show()
```



def calculate_wcss(X, labels, centroids) = Define the function to calculate wcss, takes 3 arguments, X = data points to cluster, labels = an array of labels indicating the cluster assignment for each data point, and centroids = the final centroids representating centers of the cluster

for i, centroid in enumerate(centroids):

cluster_points = X[labels == i]

distance = np.sum((cluster_points - centroid)**2)

wcss += distance

    return wcss

= Calculation within wcss, a measure of how tightly the data points within each cluster are grouped together

wcss_values = [] = Create empty list

k_values = range(1, 11) = define range of k values to test

for k in k_values:

    labels, centroids = kmeans(X, k) = run the k-means function to obtain the cluster labels and centroids to the current k value

    wcss = calculate_wcss(X, labels, centroids) = calculate the wcss for the resulting clusters using the calculate_wcss() function

    wcss_values.append(wcss) = append the calculated wcss to the wcss_values list

= Calculating WCSS for Different k Values

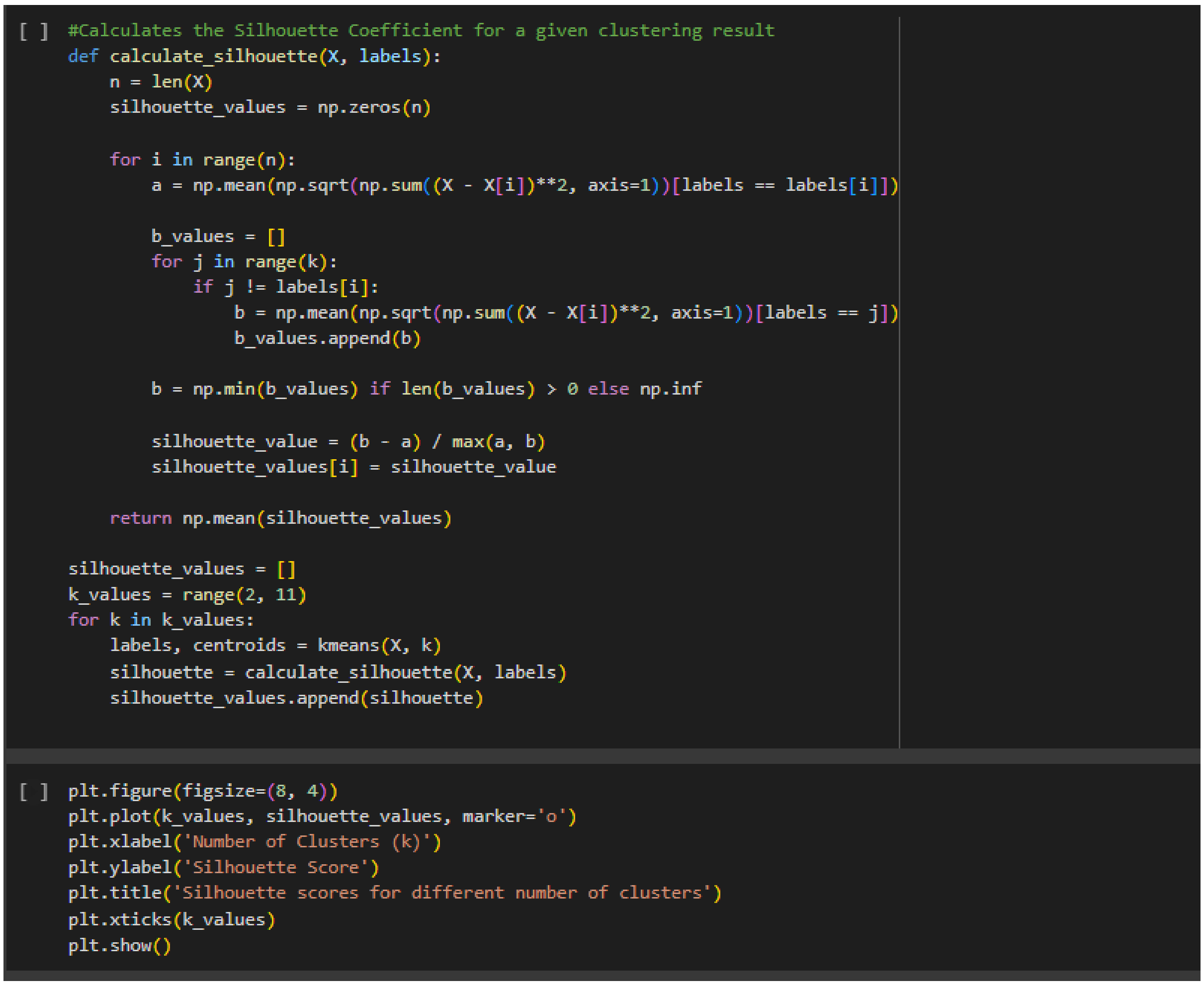
Author decide that third cluster is the optimum, because it's resembles human-elbow, and for the silhouette method, here's the code:

Silhouette method

Silhouette method is a method used in cluster analysis to assess the quality of clustering algorithms. It measures how well each data point is assigned to its cluster based on two parameters that is:

-Cohesion

-Separation



```
[ ] #Calculates the Silhouette Coefficient for a given clustering result
    def calculate_silhouette(X, labels):
        n = len(X)
        silhouette_values = np.zeros(n)

        for i in range(n):
            a = np.mean(np.sqrt(np.sum((X - X[i])**2, axis=1))[labels == labels[i]])

            b_values = []
            for j in range(k):
                if j != labels[i]:
                    b = np.mean(np.sqrt(np.sum((X - X[i])**2, axis=1))[labels == j])
                    b_values.append(b)

            b = np.min(b_values) if len(b_values) > 0 else np.inf

            silhouette_value = (b - a) / max(a, b)
            silhouette_values[i] = silhouette_value

        return np.mean(silhouette_values)

    silhouette_values = []
    k_values = range(2, 11)
    for k in k_values:
        labels, centroids = kmeans(X, k)
        silhouette = calculate_silhouette(X, labels)
        silhouette_values.append(silhouette)
```

```
[ ] plt.figure(figsize=(8, 4))
    plt.plot(k_values, silhouette_values, marker='o')
    plt.xlabel('Number of Clusters (k)')
    plt.ylabel('Silhouette Score')
    plt.title('Silhouette scores for different number of clusters')
    plt.xticks(k_values)
    plt.show()
```

def calculate_silhouette(X, labels) = define the function for calculating silhouette

silhouette_values = initialize empty list

for i in range(n):

    a = np.mean(np.sqrt(np.sum((X - X[i])**2, axis=1))[labels == labels[i]])

= Calculate the cohesion by averaging the distances between current data point and other data points in the same cluster

```
    b_values = []

    for j in range(k):

        if j != labels[i]:

            b = np.mean(np.sqrt(np.sum((X - X[i])**2, axis=1))[labels == j])

            b_values.append(b)


    b = np.min(b_values) if len(b_values) > 0 else np.inf
```

= Calculate the separation by finding the minimum average distance between current data point and data points in all other clusters

silhouette_value = (b - a) / max(a, b)

silhouette_values[i] = silhouette_value

= calculate the silhouette coefficient using the formula, then store the result silhouette_values[i]

silhouette_values = [] = Create empty list

k_values = range(2, 11) = define range of k values to test

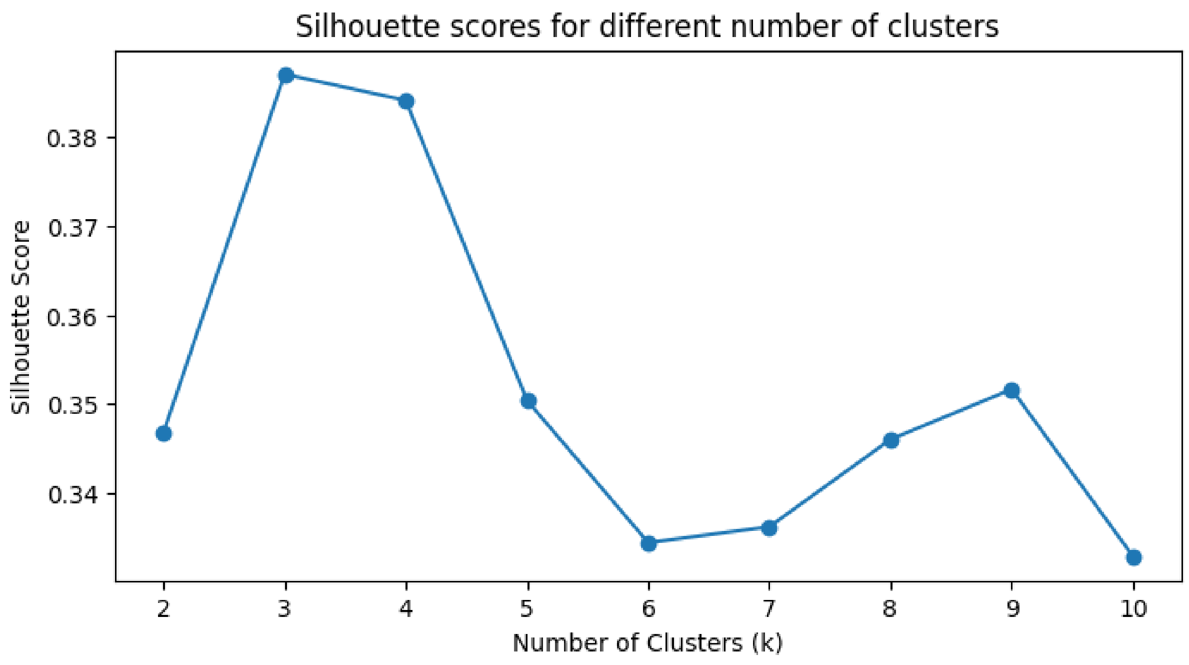
for k in k_values:

   labels, centroids = kmeans(X, k) = run the k-means to obtain cluster labels for the current value(k)

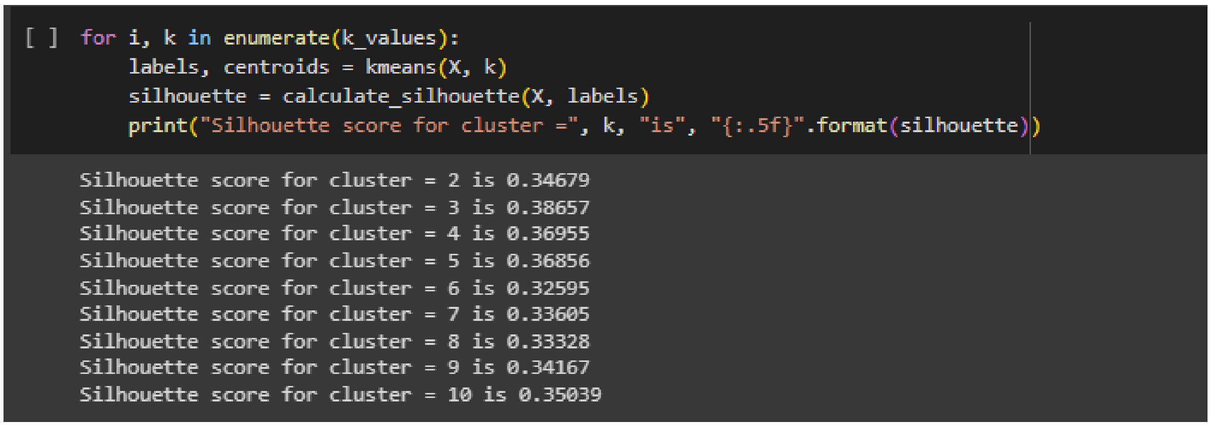
   silhouette = calculate_silhouette(X, labels) = calculate average silhouette coefficient for the resulting clusters using the calculate_silhouette function

   silhouette_values.append(silhouette) = append the calculated average silhouette coefficient to the silhouette_value s

= Evaluating Silhouette for Different Cluster Numbers



Because author is curious what's the score, then author create this code



```
[ ]  for i, k in enumerate(k_values):
         labels, centroids = kmeans(X, k)
         silhouette = calculate_silhouette(X, labels)
         print("Silhouette score for cluster =", k, "is", "{:.5f}".format(silhouette))
```

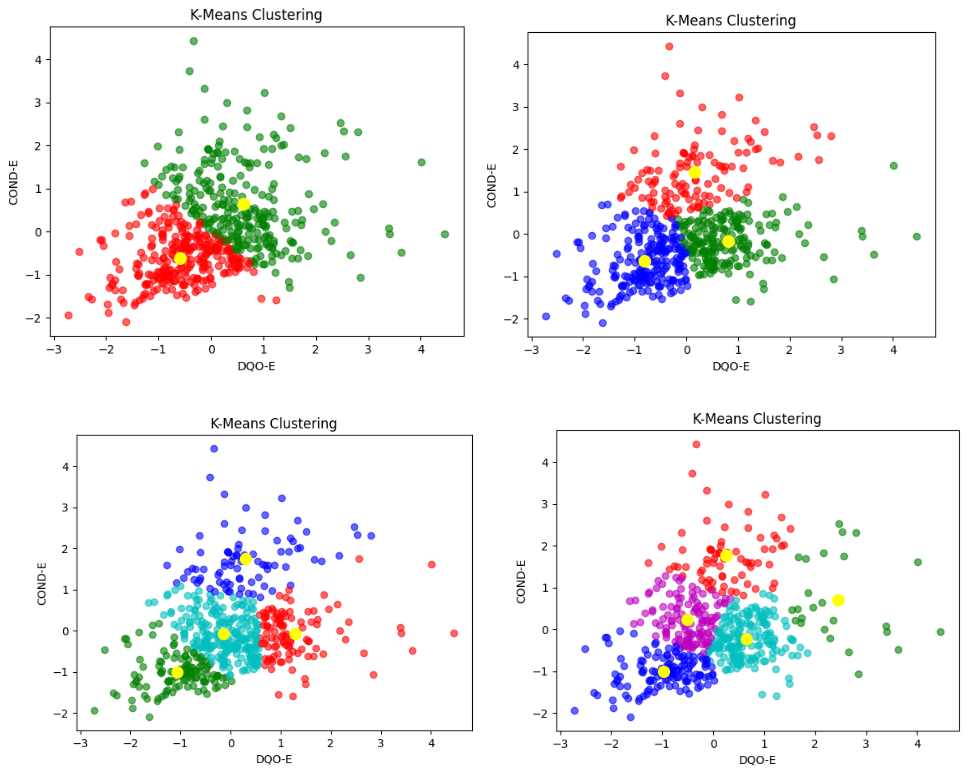
```
Silhouette score for cluster = 2 is 0.34679
Silhouette score for cluster = 3 is 0.38657
Silhouette score for cluster = 4 is 0.36955
Silhouette score for cluster = 5 is 0.36856
Silhouette score for cluster = 6 is 0.32595
Silhouette score for cluster = 7 is 0.33605
Silhouette score for cluster = 8 is 0.33328
Silhouette score for cluster = 9 is 0.34167
Silhouette score for cluster = 10 is 0.35039
```

With this, we know that third cluster is the most optimum cluster for silhouette method

Author conclude that elbow method and silhouette method has the same cluster which is 3.

Evaluate the results

Author create a test from second cluster to fifth cluster, and here's the result:



From left up -> right up -> bottom left -> bottom right : second cluster -> third cluster -> forth cluster -> fifth cluster.

Author conclude that the second cluster is the closest to 0.

During working for this assignment, troubles that author have met:

-Some of the column won’t work really well with elbows method as they sometime spiked or drop randomly

-Creating kmeans without sklearn

-Choosing what pre-processing that suitable for this case

LINKS

Video Presentation:https://www.youtube.com/watch?v=PbY9aTiKtZU

GDrive:https://drive.google.com/drive/folders/1lOa5vJnLr0by2lKfXpB_e6st4GBlU6Ph?usp=sharing