Assignment 2 - Network Anomaly Detection

Presented By:-

Name1: Ali Hassan Ali Ahmed ElSharawy - **ID1:** 19016013

Name2: Ziad Mohamed Abuelkher - **ID2:** 19015733

Name3: Youssef Magdy Helmy - **ID3:** 19016937

Problem Statement:

The exponential growth of network traffic has led to an increase in network anomalies, such as cyber attacks, network failures, and hardware malfunctions. Network anomaly detection is a critical task for maintaining the security and stability of computer networks. The objective of this assignment is to help students understand how K-Means and Normalized Cut algorithms can be used for network anomaly detection.

Imports

In [2]:
```
from google.colab import drive
import os
import zipfile
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import numpy as np
import scipy
from sklearn.model_selection import train_test_split
import random
from sklearn.metrics import adjusted_rand_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics.pairwise import euclidean_distances
from sklearn.cluster import AgglomerativeClustering
import matplotlib.pyplot as plt
import random as rd
import pickle
from scipy.spatial.distance import cdist
from scipy.stats import entropy
from sklearn.cluster import SpectralClustering
```

Global Variables

data_labeled_kmeans --> np array for labeled data of Kmeans - 10% file

data_labeled_spectral --> np array for unlabeled data used in spectral clustering - 5M rows file

test_labeled --> np array for labeled tests dataset data_kmeans --> unlabeled data for kmeans.

data_spectral --> unlabeled data for spectral clustering.

data_spectral_labels --> labels of the spectral clustering dataset (last column).

test --> unlabeled test dataset.

kmeans_dict --> dictionary used to convert categorical data to numerical (in rows 1, 2, 3, 41)

spectral_dict --> same idea but on spectral data

test_dict --> same idea but on test dataset

1 Download Datset and Understand the Format

In [3]:
```
drive.mount('/content/drive')
```

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

In [4]:
```
path = "/content/drive/MyDrive/Lab2/Datasets"
os.chdir(path)
print("Current directory:", os.getcwd())
print("Files inside folder:", os.listdir())
```

```
Current directory: /content/drive/MyDrive/Lab2/Datasets
Files inside folder: ['corrected.gz', 'kddcup.data.gz', 'kddcup.data_10_percent.gz']
```

In [5]:
```
class Get_Data:
  def __init__(self, data_path_kmeans, data_path_spectral, test_path, printFlag):
    self.data_path_kmeans = data_path_kmeans
    self.data_path_spectral = data_path_spectral
    self.test_path = test_path
    self.printFlag = printFlag
    self.data_kmeans = 0
    self.data_spectral = 0
    self.test = 0
    self.encoded_dict_kmeansData = {}
    self.encoded_dict_spectralData = {}
    self.encoded_dict_test = {}

    self.getData()

  def _saveToDF(self, path):
    return pd.read_csv(path, header=None)

  def _getCatCols(self, df):
    data_cols = []
    for col in df.columns:
      if df[col].dtype == 'object':
        data_cols.append(col)
    if(self.printFlag):
      print("Columns containing categorical data: " + str(data_cols))
    return data_cols

# cat_cols = categorical columns
  def _encodeCategories(self, df, cat_cols):
```

```
    label_encoders = {}
    encodings_dict = {}
    for col in cat_cols:
      currentEncode = LabelEncoder()
      df[col] = np.array(currentEncode.fit_transform(df[col]))
      label_encoders[col] = df[col]
      encodings_dict[col] = dict(zip(currentEncode.inverse_transform(range(len(current

    print(df.to_numpy()[:6,41])
    print(encodings_dict[41])
    return df.to_numpy(), encodings_dict

  def getData(self):
    currentDF = [self._saveToDF(self.data_path_kmeans), self._saveToDF(self.data_path_

    if(self.printFlag):
      print(f"Head of stored data DF:\n{currentDF[0].head()}")
      print(f"Head of stored data DF:\n{currentDF[1].head()}")
      print(f"Head of stored test DF:\n{currentDF[2].head()}")

    dataToStore = []
    dictToStore = []

    for df in currentDF:
      colsOfCategories = self._getCatCols(df) # 1,2,3,41
      data, curDict = self._encodeCategories(df, colsOfCategories)
      dataToStore.append(data)
      dictToStore.append(curDict)

    self.data_kmeans = dataToStore[0]
    self.data_spectral = dataToStore[1]
    self.test = dataToStore[2]

    self.encoded_dict_kmeansData = dictToStore[0]
    self.encoded_dict_spectralData = dictToStore[1]
    self.encoded_dict_test = dictToStore[2]
    pass
```

Dataset is downloaded to our drive, in: 'MyDrive/Lab2/Datasets'.

There are 2 files that matter with us:

- The unlabled initial data, which has 4898431 rows (samples), and 42 columns (41 features + 1 labels).
- The labled corrected data, which has 311029 rows (samples), and 42 columns.

In [6]:
```
data_path_kmeans = '/content/drive/MyDrive/Lab2/Datasets/kddcup.data_10_percent.gz'
data_path_spectral = '/content/drive/MyDrive/Lab2/Datasets/kddcup.data.gz'
test_path = '/content/drive/MyDrive/Lab2/Datasets/corrected.gz'
getData = Get_Data(data_path_kmeans, data_path_spectral, test_path, True)
data_labeled_kmeans = getData.data_kmeans
data_labeled_spectral = getData.data_spectral
test = getData.test
```

```
Head of stored data DF:
   0    1     2   3    4     5   6   7   8   9   ...  32   33   34    35   36  \
0   0  tcp  http  SF  181  5450   0   0   0   0  ...   9  1.0  0.0  0.11  0.0
1   0  tcp  http  SF  239   486   0   0   0   0  ...  19  1.0  0.0  0.05  0.0
2   0  tcp  http  SF  235  1337   0   0   0   0  ...  29  1.0  0.0  0.03  0.0
3   0  tcp  http  SF  219  1337   0   0   0   0  ...  39  1.0  0.0  0.03  0.0
4   0  tcp  http  SF  217  2032   0   0   0   0  ...  49  1.0  0.0  0.02  0.0

    37   38   39   40       41
0  0.0  0.0  0.0  0.0  normal.
1  0.0  0.0  0.0  0.0  normal.
2  0.0  0.0  0.0  0.0  normal.
3  0.0  0.0  0.0  0.0  normal.
4  0.0  0.0  0.0  0.0  normal.

[5 rows x 42 columns]
Head of stored data DF:
   0    1     2   3    4      5   6   7   8   9   ...  32   33   34    35  \
0   0  tcp  http  SF  215  45076   0   0   0   0  ...   0  0.0  0.0  0.00
1   0  tcp  http  SF  162   4528   0   0   0   0  ...   1  1.0  0.0  1.00
2   0  tcp  http  SF  236   1228   0   0   0   0  ...   2  1.0  0.0  0.50
3   0  tcp  http  SF  233   2032   0   0   0   0  ...   3  1.0  0.0  0.33
4   0  tcp  http  SF  239    486   0   0   0   0  ...   4  1.0  0.0  0.25

    36   37   38   39   40       41
0  0.0  0.0  0.0  0.0  0.0  normal.
1  0.0  0.0  0.0  0.0  0.0  normal.
2  0.0  0.0  0.0  0.0  0.0  normal.
3  0.0  0.0  0.0  0.0  0.0  normal.
4  0.0  0.0  0.0  0.0  0.0  normal.

[5 rows x 42 columns]
Head of stored test DF:
   0    1        2   3    4    5   6   7   8   9   ...   32   33    34    35  \
0   0  udp  private  SF  105  146   0   0   0   0  ...  254  1.0  0.01  0.00
1   0  udp  private  SF  105  146   0   0   0   0  ...  254  1.0  0.01  0.00
2   0  udp  private  SF  105  146   0   0   0   0  ...  254  1.0  0.01  0.00
3   0  udp  private  SF  105  146   0   0   0   0  ...  254  1.0  0.01  0.00
4   0  udp  private  SF  105  146   0   0   0   0  ...  254  1.0  0.01  0.01

    36   37   38   39   40              41
0  0.0  0.0  0.0  0.0  0.0         normal.
1  0.0  0.0  0.0  0.0  0.0         normal.
2  0.0  0.0  0.0  0.0  0.0         normal.
3  0.0  0.0  0.0  0.0  0.0  snmpgetattack.
4  0.0  0.0  0.0  0.0  0.0  snmpgetattack.

[5 rows x 42 columns]
Columns containing categorical data: [1, 2, 3, 41]
[11. 11. 11. 11. 11. 11.]
{'back.': 0, 'buffer_overflow.': 1, 'ftp_write.': 2, 'guess_passwd.': 3, 'imap.': 4,
'ipsweep.': 5, 'land.': 6, 'loadmodule.': 7, 'multihop.': 8, 'neptune.': 9, 'nmap.':
10, 'normal.': 11, 'perl.': 12, 'phf.': 13, 'pod.': 14, 'portsweep.': 15, 'rootkit.':
16, 'satan.': 17, 'smurf.': 18, 'spy.': 19, 'teardrop.': 20, 'warezclient.': 21, 'war
ezmaster.': 22}
Columns containing categorical data: [1, 2, 3, 41]
[11. 11. 11. 11. 11. 11.]
{'back.': 0, 'buffer_overflow.': 1, 'ftp_write.': 2, 'guess_passwd.': 3, 'imap.': 4,
'ipsweep.': 5, 'land.': 6, 'loadmodule.': 7, 'multihop.': 8, 'neptune.': 9, 'nmap.':
10, 'normal.': 11, 'perl.': 12, 'phf.': 13, 'pod.': 14, 'portsweep.': 15, 'rootkit.':
```

```
16, 'satan.': 17, 'smurf.': 18, 'spy.': 19, 'teardrop.': 20, 'warezclient.': 21, 'war
ezmaster.': 22}
Columns containing categorical data: [1, 2, 3, 41]
[16. 16. 16. 28. 28. 28.]
{'apache2.': 0, 'back.': 1, 'buffer_overflow.': 2, 'ftp_write.': 3, 'guess_passwd.':
4, 'httptunnel.': 5, 'imap.': 6, 'ipsweep.': 7, 'land.': 8, 'loadmodule.': 9, 'mailbo
mb.': 10, 'mscan.': 11, 'multihop.': 12, 'named.': 13, 'neptune.': 14, 'nmap.': 15,
'normal.': 16, 'perl.': 17, 'phf.': 18, 'pod.': 19, 'portsweep.': 20, 'processtabl
e.': 21, 'ps.': 22, 'rootkit.': 23, 'saint.': 24, 'satan.': 25, 'sendmail.': 26, 'smu
rf.': 27, 'snmpgetattack.': 28, 'snmpguess.': 29, 'sqlattack.': 30, 'teardrop.': 31,
'udpstorm.': 32, 'warezmaster.': 33, 'worm.': 34, 'xlock.': 35, 'xsnoop.': 36, 'xter
m.': 37}
```

In [7]:

```python
kmeans_dict = getData.encoded_dict_kmeansData
spectral_dict = getData.encoded_dict_spectralData
test_dict = getData.encoded_dict_test
print(f"dictionary for Kmeans mappings:\n{kmeans_dict}")
print(f"dictionary for Spectral Clustering mappings:\n{spectral_dict}")
print(f"dictionary for Testing mappings:\n{test_dict}")

# del data_path_kmeans, data_path_spectral, test_path, getData
```

```
dictionary for Kmeans mappings:
{1: {'icmp': 0, 'tcp': 1, 'udp': 2}, 2: {'IRC': 0, 'X11': 1, 'Z39_50': 2, 'auth': 3,
'bgp': 4, 'courier': 5, 'csnet_ns': 6, 'ctf': 7, 'daytime': 8, 'discard': 9, 'domai
n': 10, 'domain_u': 11, 'echo': 12, 'eco_i': 13, 'ecr_i': 14, 'efs': 15, 'exec': 16,
'finger': 17, 'ftp': 18, 'ftp_data': 19, 'gopher': 20, 'hostnames': 21, 'http': 22,
'http_443': 23, 'imap4': 24, 'iso_tsap': 25, 'klogin': 26, 'kshell': 27, 'ldap': 28,
'link': 29, 'login': 30, 'mtp': 31, 'name': 32, 'netbios_dgm': 33, 'netbios_ns': 34,
'netbios_ssn': 35, 'netstat': 36, 'nnsp': 37, 'nntp': 38, 'ntp_u': 39, 'other': 40,
'pm_dump': 41, 'pop_2': 42, 'pop_3': 43, 'printer': 44, 'private': 45, 'red_i': 46,
'remote_job': 47, 'rje': 48, 'shell': 49, 'smtp': 50, 'sql_net': 51, 'ssh': 52, 'sunr
pc': 53, 'supdup': 54, 'systat': 55, 'telnet': 56, 'tftp_u': 57, 'tim_i': 58, 'time':
59, 'urh_i': 60, 'urp_i': 61, 'uucp': 62, 'uucp_path': 63, 'vmnet': 64, 'whois': 65},
3: {'OTH': 0, 'REJ': 1, 'RSTO': 2, 'RSTOS0': 3, 'RSTR': 4, 'S0': 5, 'S1': 6, 'S2': 7,
'S3': 8, 'SF': 9, 'SH': 10}, 41: {'back.': 0, 'buffer_overflow.': 1, 'ftp_write.': 2,
'guess_passwd.': 3, 'imap.': 4, 'ipsweep.': 5, 'land.': 6, 'loadmodule.': 7, 'multiho
p.': 8, 'neptune.': 9, 'nmap.': 10, 'normal.': 11, 'perl.': 12, 'phf.': 13, 'pod.': 1
4, 'portsweep.': 15, 'rootkit.': 16, 'satan.': 17, 'smurf.': 18, 'spy.': 19, 'teardro
p.': 20, 'warezclient.': 21, 'warezmaster.': 22}}
dictionary for Spectral Clustering mappings:
{1: {'icmp': 0, 'tcp': 1, 'udp': 2}, 2: {'IRC': 0, 'X11': 1, 'Z39_50': 2, 'aol': 3,
'auth': 4, 'bgp': 5, 'courier': 6, 'csnet_ns': 7, 'ctf': 8, 'daytime': 9, 'discard':
10, 'domain': 11, 'domain_u': 12, 'echo': 13, 'eco_i': 14, 'ecr_i': 15, 'efs': 16, 'e
xec': 17, 'finger': 18, 'ftp': 19, 'ftp_data': 20, 'gopher': 21, 'harvest': 22, 'host
names': 23, 'http': 24, 'http_2784': 25, 'http_443': 26, 'http_8001': 27, 'imap4': 2
8, 'iso_tsap': 29, 'klogin': 30, 'kshell': 31, 'ldap': 32, 'link': 33, 'login': 34,
'mtp': 35, 'name': 36, 'netbios_dgm': 37, 'netbios_ns': 38, 'netbios_ssn': 39, 'netst
at': 40, 'nnsp': 41, 'nntp': 42, 'ntp_u': 43, 'other': 44, 'pm_dump': 45, 'pop_2': 4
6, 'pop_3': 47, 'printer': 48, 'private': 49, 'red_i': 50, 'remote_job': 51, 'rje': 5
2, 'shell': 53, 'smtp': 54, 'sql_net': 55, 'ssh': 56, 'sunrpc': 57, 'supdup': 58, 'sy
stat': 59, 'telnet': 60, 'tftp_u': 61, 'tim_i': 62, 'time': 63, 'urh_i': 64, 'urp_i':
65, 'uucp': 66, 'uucp_path': 67, 'vmnet': 68, 'whois': 69}, 3: {'OTH': 0, 'REJ': 1,
'RSTO': 2, 'RSTOS0': 3, 'RSTR': 4, 'S0': 5, 'S1': 6, 'S2': 7, 'S3': 8, 'SF': 9, 'SH':
10}, 41: {'back.': 0, 'buffer_overflow.': 1, 'ftp_write.': 2, 'guess_passwd.': 3, 'im
ap.': 4, 'ipsweep.': 5, 'land.': 6, 'loadmodule.': 7, 'multihop.': 8, 'neptune.': 9,
'nmap.': 10, 'normal.': 11, 'perl.': 12, 'phf.': 13, 'pod.': 14, 'portsweep.': 15, 'r
ootkit.': 16, 'satan.': 17, 'smurf.': 18, 'spy.': 19, 'teardrop.': 20, 'warezclien
t.': 21, 'warezmaster.': 22}}
dictionary for Testing mappings:
{1: {'icmp': 0, 'tcp': 1, 'udp': 2}, 2: {'IRC': 0, 'X11': 1, 'Z39_50': 2, 'auth': 3,
'bgp': 4, 'courier': 5, 'csnet_ns': 6, 'ctf': 7, 'daytime': 8, 'discard': 9, 'domai
n': 10, 'domain_u': 11, 'echo': 12, 'eco_i': 13, 'ecr_i': 14, 'efs': 15, 'exec': 16,
'finger': 17, 'ftp': 18, 'ftp_data': 19, 'gopher': 20, 'hostnames': 21, 'http': 22,
'http_443': 23, 'icmp': 24, 'imap4': 25, 'iso_tsap': 26, 'klogin': 27, 'kshell': 28,
'ldap': 29, 'link': 30, 'login': 31, 'mtp': 32, 'name': 33, 'netbios_dgm': 34, 'netbi
os_ns': 35, 'netbios_ssn': 36, 'netstat': 37, 'nnsp': 38, 'nntp': 39, 'ntp_u': 40, 'o
ther': 41, 'pm_dump': 42, 'pop_2': 43, 'pop_3': 44, 'printer': 45, 'private': 46, 're
mote_job': 47, 'rje': 48, 'shell': 49, 'smtp': 50, 'sql_net': 51, 'ssh': 52, 'sunrp
c': 53, 'supdup': 54, 'systat': 55, 'telnet': 56, 'tftp_u': 57, 'tim_i': 58, 'time':
59, 'urp_i': 60, 'uucp': 61, 'uucp_path': 62, 'vmnet': 63, 'whois': 64}, 3: {'OTH':
0, 'REJ': 1, 'RSTO': 2, 'RSTOS0': 3, 'RSTR': 4, 'S0': 5, 'S1': 6, 'S2': 7, 'S3': 8,
'SF': 9, 'SH': 10}, 41: {'apache2.': 0, 'back.': 1, 'buffer_overflow.': 2, 'ftp_writ
e.': 3, 'guess_passwd.': 4, 'httptunnel.': 5, 'imap.': 6, 'ipsweep.': 7, 'land.': 8,
'loadmodule.': 9, 'mailbomb.': 10, 'mscan.': 11, 'multihop.': 12, 'named.': 13, 'nept
une.': 14, 'nmap.': 15, 'normal.': 16, 'perl.': 17, 'phf.': 18, 'pod.': 19, 'portswee
p.': 20, 'processtable.': 21, 'ps.': 22, 'rootkit.': 23, 'saint.': 24, 'satan.': 25,
'sendmail.': 26, 'smurf.': 27, 'snmpgetattack.': 28, 'snmpguess.': 29, 'sqlattack.':
30, 'teardrop.': 31, 'udpstorm.': 32, 'warezmaster.': 33, 'worm.': 34, 'xlock.': 35,
'xsnoop.': 36, 'xterm.': 37}}
```

store_data & load_saved_data are used to store and later retrieve kmeans result, instead of running hours to get them if we need to test.

In [ ]:
```
def store_data(name, obj):
  with open(f'/content/drive/MyDrive/Lab2/KmeansFinalResults/{name}.pkl', 'wb') as f:
    pickle.dump(obj, f)
```

In [ ]:
```
def load_saved_data(name):
  with open(f'/content/drive/My Drive/Lab2/KmeansFinalResults/{name}.pkl', 'rb') as f:
    data = pickle.load(f)
  return data
```

In [ ]:
```
# store_data("data_labeled_kmeans", data_labeled_kmeans)
# store_data("kmeans_dict", kmeans_dict)
# store_data("test_dict", test_dict)
# store_data("test_labeled", test)
```

In [ ]:
```
# print(data)
print(np.unique(data_labeled_kmeans[:,41]))
print(np.unique(data_labeled_spectral[:,41]))
```

```
[ 0.  1.  2.  3.  4.  5.  6.  7.  8.  9. 10. 11. 12. 13. 14. 15. 16. 17.
 18. 19. 20. 21. 22.]
[ 0.  1.  2.  3.  4.  5.  6.  7.  8.  9. 10. 11. 12. 13. 14. 15. 16. 17.
 18. 19. 20. 21. 22.]
```

"Change the categorical features to numerical"

Concerning this part: Columns containing categorical data are 4 columns: 2nd, 3rd, 4th and last one: [1, 2, 3, 41].

Now, all data is ready, where:

initial data --> stored in 'data' np array

test data --> stored in 'test' np array

All categories are mapped to unique values, so all our data is now numerical.

Last column in data is for labels, so we need to remove it:

In [8]:
```
print(data_labeled_spectral)
data_kmeans = data_labeled_kmeans[:,:-1]
data_spectral = data_labeled_spectral[:,:-1]
data_spectral_labels = data_labeled_spectral[:,-1]
test_labeled = test
test = test_labeled[:,:-1]
print(data_kmeans)
```

```
[[ 0.  1. 24. ...  0.  0. 11.]
 [ 0.  1. 24. ...  0.  0. 11.]
 [ 0.  1. 24. ...  0.  0. 11.]
 ...
 [ 0.  1. 24. ...  0.  0. 11.]
 [ 0.  1. 24. ...  0.  0. 11.]
 [ 0.  1. 24. ...  0.  0. 11.]]
[[0.0e+00 1.0e+00 2.2e+01 ... 0.0e+00 0.0e+00 0.0e+00]
 [0.0e+00 1.0e+00 2.2e+01 ... 0.0e+00 0.0e+00 0.0e+00]
 [0.0e+00 1.0e+00 2.2e+01 ... 0.0e+00 0.0e+00 0.0e+00]
 ...
 [0.0e+00 1.0e+00 2.2e+01 ... 1.0e-02 0.0e+00 0.0e+00]
 [0.0e+00 1.0e+00 2.2e+01 ... 1.0e-02 0.0e+00 0.0e+00]
 [0.0e+00 1.0e+00 2.2e+01 ... 1.0e-02 0.0e+00 0.0e+00]]
```

In [ ]:

```
# store_data("data_kmeans", data_kmeans)
# store_data("test", test)
```

---

2 Clustering Using K-Means

Functions used in Kmeans part:

- **create_randomized_centroids():** chooses k points from data points D to represent initial centroids for k-means.
- **Kmeans():** main algorithm to run k-means, taking 4 parameters: dataset, k, stopping conditions (epsilon, max iterations)
- **run_kmeans():** initialize stopping conditions, and calls Kmeans() on the kmeans' dataset, for a given value k, then prints the resulting centroids.
- **distance_centroids_clusters():** given k centroids and k clusters, it finds the sum of distances between all points and each's equivalent centroid.
- **get_centroids_with_random_restarts():** applies 3 random restarts on run_kmeans(), and chooses the best centroids according to the previous described function.

In [9]:

```
def create_randomized_centroids(D, k):
  centroids = set()
  randomRange = len(D) # number of rows (samples)
  while(len(centroids)<k):
    c = rd.randint(0,randomRange)
    centroids.add(tuple(D[c]))
  toReturn = np.array(list(centroids))
  print(f"({len(toReturn)},{len(toReturn[0])})")
  return toReturn
```

In [10]:

```
# D --> Dataset, k --> number of clusters we want, e --> stopping value

def Kmeans(D, k, e, max):
  centroids = create_randomized_centroids(D, k)
  iterationN = 0

  while True:
    iterationN += 1
```

```
    clusters = [[] for _ in range(k)]

    distances = cdist(D, centroids)
    closest_clusters_idxs = np.argmin(distances, axis=1)
    for i, cluster_idx in enumerate(closest_clusters_idxs):
      clusters[cluster_idx].append(D[i])

    newCentroids = []
    for i in range(k):
      newCentroids.append(np.mean(clusters[i], axis=0))
    newCentroids = np.array(newCentroids)

    totalNorm = np.sum(np.square(centroids - newCentroids))

    if(totalNorm < e):
      print(f"Total iterations number = {iterationN}")
      break;
    elif(iterationN >= max):
      print("MAX Number of Iterations! algorithm STOPPED")
      break;

    if(iterationN % 25 == 0):
      print(f"{iterationN}) dM = {totalNorm}")

    centroids = newCentroids

  return clusters, centroids
```

In [11]:

```
Ks = [7, 15, 23, 31, 45]
# clusters = [] # returned just to print data, but not stored
epsilon = 0.01

def run_Kmeans(k):
  max_itr = 300
  print(f"For K = {k}:")
  clusters, centroids = Kmeans(data_kmeans, k, epsilon, max_itr)
  for idx, cluster in enumerate(clusters):
    print(f"cluster {idx+1} ==> {len(cluster)}")
  print(f"Result Centroids:\n{centroids}\n============================\n\n")
  return clusters, centroids
```

In [12]:

```
def distance_centroids_clusters(centroids, clusters):
  distance = 0
  idx = 0
  for cluster in (clusters):
    currCluster = np.array(cluster)
    currCentroid = centroids[idx].reshape(1,41)
    distance += np.sum(np.sqrt(np.sum((currCentroid - currCluster)**2, axis=1)))
    idx+=1
  return distance
```

In [14]:

```
def get_centroids_with_random_restarts(k):
  centroids_arr = [[] for _ in range(3)]
  dists = [[] for _ in range(3)]

  clusters_run1, centroids_arr[0] = run_Kmeans(k)
  dists[0] = distance_centroids_clusters(centroids_arr[0], clusters_run1)
  del clusters_run1
```

```
    clusters_run2, centroids_arr[1] = run_Kmeans(k)
    dists[1] = distance_centroids_clusters(centroids_arr[1], clusters_run2)
    del clusters_run2

    clusters_run3, centroids_arr[2] = run_Kmeans(k)
    dists[2] = distance_centroids_clusters(centroids_arr[2], clusters_run3)
    del clusters_run3

    centroids = centroids_arr[dists.index(min(dists))]
    return centroids
```

Next, we run 5 runs, for each k value.

In [ ]:
```
centroids_k7 = get_centroids_with_random_restarts(7)
```

```
For K = 7:
(7,41)
25) dM = 5926807280.225866
Total iterations number = 31
cluster 1 ==> 295520
cluster 2 ==> 18
cluster 3 ==> 82
cluster 4 ==> 80
cluster 5 ==> 198298
cluster 6 ==> 1
cluster 7 ==> 22
Result Centroids:
[[9.32505372e-02 4.90719277e-02 1.52309944e+01 8.99827414e+00
  1.45093454e+03 7.33068239e+01 0.00000000e+00 8.76465711e-04
  0.00000000e+00 1.46901068e-02 0.00000000e+00 4.64323785e-02
  7.20461583e-03 0.00000000e+00 6.76807499e-06 8.07769750e-03
  8.02016886e-04 1.45513612e-04 4.50076987e-04 0.00000000e+00
  0.00000000e+00 0.00000000e+00 4.81956982e+02 4.81976525e+02
  6.53796044e-05 7.01510973e-05 3.08522698e-04 7.27161977e-04
  9.99230571e-01 1.29046886e-03 1.54218710e-02 2.48974474e+02
  2.48706550e+02 9.82012555e-01 3.14414308e-03 9.55429857e-01
  7.85671985e-04 3.51669176e-04 1.25818514e-04 7.66416812e-04
  4.22294039e-04]
 [5.52277778e+02 1.00000000e+00 2.12222222e+01 9.00000000e+00
  1.08944444e+02 5.00968983e+06 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.66666667e-01 1.11111111e-01
  1.00000000e+00 5.55555556e-02 1.11111111e-01 5.00000000e-01
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.11111111e+00 1.11111111e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  1.00000000e+00 0.00000000e+00 0.00000000e+00 4.39444444e+01
  2.61666667e+01 9.03333333e-01 2.22222222e-03 8.33888889e-01
  5.55555556e-04 4.16666667e-02 4.77777778e-02 4.27777778e-02
  0.00000000e+00]
 [3.66493902e+03 1.00000000e+00 1.97682927e+01 8.92682927e+00
  4.31342730e+06 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 1.95121951e+00 0.00000000e+00 9.39024390e-01
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.20731707e+00 1.50000000e+00
  1.21951220e-02 1.39024390e-02 1.21951220e-02 1.21951220e-02
  9.83780488e-01 3.25609756e-02 4.14634146e-02 5.38414634e+01
  4.23780488e+01 7.39390244e-01 3.68292683e-02 7.69878049e-01
  8.13414634e-02 7.80487805e-03 1.74390244e-02 6.46341463e-03
  4.87804878e-04]
 [6.02925000e+02 1.00000000e+00 4.16625000e+01 8.85000000e+00
  9.49040000e+03 3.92440237e+05 0.00000000e+00 0.00000000e+00
  3.75000000e-02 3.75000000e-02 2.50000000e-02 9.37500000e-01
  1.48250000e+01 2.50000000e-02 3.75000000e-02 1.60375000e+01
  2.50000000e-02 0.00000000e+00 1.00000000e-01 0.00000000e+00
  0.00000000e+00 0.00000000e+00 2.47500000e+00 3.61250000e+00
  1.87500000e-02 1.33750000e-02 1.25000000e-02 1.38750000e-02
  9.87500000e-01 2.50000000e-02 4.15000000e-02 1.27500000e+02
  1.05475000e+02 5.03875000e-01 4.00000000e-02 7.60000000e-02
  2.32500000e-02 1.25000000e-02 1.85000000e-02 1.60000000e-02
  2.38750000e-02]
 [1.17569000e+02 1.08953523e+00 3.55856752e+01 6.11909456e+00
  9.13025571e+01 1.25987117e+03 1.10935743e-04 1.47191561e-02
  2.01701351e-05 6.32737138e-02 3.52977364e-04 2.99228997e-01
  8.63281782e-03 2.62211756e-04 5.54678715e-05 9.72704765e-03
```

```
  1.49259000e-03 5.54678715e-05 1.80018456e-03 0.00000000e+00
  0.00000000e+00 3.45413563e-03 1.09599542e+02 1.14720618e+01
  4.40033230e-01 4.39834252e-01 1.42602502e-01 1.42688830e-01
  4.81882983e-01 5.03211590e-02 4.92205251e-02 2.08020901e+02
  9.93263326e+01 4.13846596e-01 7.22690898e-02 7.53781144e-02
  1.54308089e-02 4.39777927e-01 4.39329444e-01 1.43622455e-01
  1.42378462e-01]
 [2.00000000e+00 1.00000000e+00 1.70000000e+01 2.00000000e+00
  6.93375640e+08 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 1.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 5.70000000e+01 3.00000000e+00
  7.90000000e-01 6.70000000e-01 2.10000000e-01 3.30000000e-01
  5.00000000e-02 3.90000000e-01 0.00000000e+00 2.55000000e+02
  3.00000000e+00 1.00000000e-02 9.00000000e-02 2.20000000e-01
  0.00000000e+00 1.80000000e-01 6.70000000e-01 5.00000000e-02
  3.30000000e-01]
 [4.83636364e+01 1.00000000e+00 5.43181818e+01 9.00000000e+00
  5.57181818e+02 1.63601168e+06 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 9.54545455e-01
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.04545455e+00 1.04545455e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  1.00000000e+00 0.00000000e+00 0.00000000e+00 1.51545455e+02
  3.10909091e+01 2.27727273e-01 3.27272727e-02 5.50000000e-02
  4.31818182e-02 0.00000000e+00 0.00000000e+00 4.54545455e-04
  0.00000000e+00]]
============================


For K = 7:
(7,41)
25) dM = 6360173315.126939
Total iterations number = 31
cluster 1 ==> 198297
cluster 2 ==> 295521
cluster 3 ==> 18
cluster 4 ==> 22
cluster 5 ==> 82
cluster 6 ==> 80
cluster 7 ==> 1
Result Centroids:
[[1.17576069e+02 1.08954065e+00 3.55848029e+01 6.11892023e+00
  9.12687884e+01 1.25992710e+03 1.10942456e-04 1.47200468e-02
  2.01713557e-05 6.32775427e-02 3.52998724e-04 2.99186590e-01
  8.63334023e-03 2.62227624e-04 5.54712281e-05 9.72763627e-03
  1.48763748e-03 5.54712281e-05 1.80029349e-03 0.00000000e+00
  0.00000000e+00 3.45434466e-03 1.09606109e+02 1.14726653e+01
  4.40059858e-01 4.39860868e-01 1.42611132e-01 1.42697465e-01
  4.81854151e-01 5.03191613e-02 4.91982895e-02 2.08025441e+02
  9.93227417e+01 4.13835533e-01 7.22688741e-02 7.53814151e-02
  1.54310367e-02 4.39804489e-01 4.39355929e-01 1.43631046e-01
  1.42386927e-01]
 [9.32772057e-02 4.91105419e-02 1.52324063e+01 8.99827421e+00
  1.45090199e+03 7.33174775e+01 0.00000000e+00 8.76430121e-04
  0.00000000e+00 1.46895102e-02 0.00000000e+00 4.64710998e-02
  7.20432327e-03 0.00000000e+00 6.76780016e-06 8.07736949e-03
  8.05368219e-04 1.45507703e-04 4.50058711e-04 0.00000000e+00
```

```
 0.00000000e+00 0.00000000e+00 4.81937455e+02 4.81957014e+02
 6.53769495e-05 7.01482487e-05 3.08510170e-04 7.27132449e-04
 9.99228911e-01 1.29380036e-03 1.54381643e-02 2.48969765e+02
 2.48702894e+02 9.81996907e-01 3.14709475e-03 9.55391906e-01
 7.86113828e-04 3.51688735e-04 1.25881083e-04 7.66453368e-04
 4.22378408e-04]
[5.52277778e+02 1.00000000e+00 2.12222222e+01 9.00000000e+00
 1.08944444e+02 5.00968983e+06 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 1.66666667e-01 1.11111111e-01
 1.00000000e+00 5.55555556e-02 1.11111111e-01 5.00000000e-01
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 1.11111111e+00 1.11111111e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 1.00000000e+00 0.00000000e+00 0.00000000e+00 4.39444444e+01
 2.61666667e+01 9.03333333e-01 2.22222222e-03 8.33888889e-01
 5.55555556e-04 4.16666667e-02 4.77777778e-02 4.27777778e-02
 0.00000000e+00]
[4.83636364e+01 1.00000000e+00 5.43181818e+01 9.00000000e+00
 5.57181818e+02 1.63601168e+06 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 9.54545455e-01
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 1.04545455e+00 1.04545455e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 1.00000000e+00 0.00000000e+00 0.00000000e+00 1.51545455e+02
 3.10909091e+01 2.27727273e-01 3.27272727e-02 5.50000000e-02
 4.31818182e-02 0.00000000e+00 0.00000000e+00 4.54545455e-04
 0.00000000e+00]
[3.66493902e+03 1.00000000e+00 1.97682927e+01 8.92682927e+00
 4.31342730e+06 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 1.95121951e+00 0.00000000e+00 9.39024390e-01
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 1.20731707e+00 1.50000000e+00
 1.21951220e-02 1.39024390e-02 1.21951220e-02 1.21951220e-02
 9.83780488e-01 3.25609756e-02 4.14634146e-02 5.38414634e+01
 4.23780488e+01 7.39390244e-01 3.68292683e-02 7.69878049e-01
 8.13414634e-02 7.80487805e-03 1.74390244e-02 6.46341463e-03
 4.87804878e-04]
[6.02925000e+02 1.00000000e+00 4.16625000e+01 8.85000000e+00
 9.49040000e+03 3.92440237e+05 0.00000000e+00 0.00000000e+00
 3.75000000e-02 3.75000000e-02 2.50000000e-02 9.37500000e-01
 1.48250000e+01 2.50000000e-02 3.75000000e-02 1.60375000e+01
 2.50000000e-02 0.00000000e+00 1.00000000e-01 0.00000000e+00
 0.00000000e+00 0.00000000e+00 2.47500000e+00 3.61250000e+00
 1.87500000e-02 1.33750000e-02 1.25000000e-02 1.38750000e-02
 9.87500000e-01 2.50000000e-02 4.15000000e-02 1.27500000e+02
 1.05475000e+02 5.03875000e-01 4.00000000e-02 7.60000000e-02
 2.32500000e-02 1.25000000e-02 1.85000000e-02 1.60000000e-02
 2.38750000e-02]
[2.00000000e+00 1.00000000e+00 1.70000000e+01 2.00000000e+00
 6.93375640e+08 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 1.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 5.70000000e+01 3.00000000e+00
 7.90000000e-01 6.70000000e-01 2.10000000e-01 3.30000000e-01
 5.00000000e-02 3.90000000e-01 0.00000000e+00 2.55000000e+02
 3.00000000e+00 1.00000000e-02 9.00000000e-02 2.20000000e-01
 0.00000000e+00 1.80000000e-01 6.70000000e-01 5.00000000e-02
```

```
  3.30000000e-01]]
============================


For K = 7:
(7,41)
25) dM = 4094933789.262665
Total iterations number = 49
cluster 1 ==> 21
cluster 2 ==> 490339
cluster 3 ==> 69
cluster 4 ==> 3491
cluster 5 ==> 82
cluster 6 ==> 18
cluster 7 ==> 1
Result Centroids:
[[4.86666667e+01 1.00000000e+00 5.42380952e+01 9.00000000e+00
  5.47523810e+02 1.66558667e+06 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 9.52380952e-01
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.04761905e+00 1.04761905e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  1.00000000e+00 0.00000000e+00 0.00000000e+00 1.46619048e+02
  3.10476190e+01 2.32380952e-01 3.33333333e-02 5.76190476e-02
  4.52380952e-02 0.00000000e+00 0.00000000e+00 4.76190476e-04
  0.00000000e+00]
 [4.71886817e+01 4.63130610e-01 2.34110442e+01 7.83394549e+00
  9.08795907e+02 3.48874562e+02 4.48669186e-05 6.48123033e-03
  4.07881078e-06 3.42640500e-02 1.40718972e-04 1.41914064e-01
  4.79668148e-03 7.95368102e-05 8.15762156e-06 5.44317299e-03
  8.03525724e-04 1.08088486e-04 9.56481128e-04 0.00000000e+00
  0.00000000e+00 1.39699269e-03 3.34737861e+02 2.95044186e+02
  1.77972790e-01 1.77897944e-01 5.78520371e-02 5.81299468e-02
  7.89990782e-01 2.11255478e-02 2.84262113e-02 2.33308503e+02
  1.88320907e+02 7.52211266e-01 3.11080497e-02 6.05704768e-01
  6.53914945e-03 1.78041192e-01 1.77737892e-01 5.84974681e-02
  5.77712766e-02]
 [5.42449275e+02 1.00000000e+00 4.28260870e+01 8.92753623e+00
  1.09025362e+04 4.33171029e+05 0.00000000e+00 0.00000000e+00
  4.34782609e-02 1.44927536e-02 2.89855072e-02 9.42028986e-01
  1.71884058e+01 2.89855072e-02 4.34782609e-02 1.85942029e+01
  2.89855072e-02 0.00000000e+00 1.15942029e-01 0.00000000e+00
  0.00000000e+00 0.00000000e+00 2.04347826e+00 2.52173913e+00
  2.17391304e-02 1.55072464e-02 0.00000000e+00 1.59420290e-03
  9.85507246e-01 2.89855072e-02 3.73913043e-02 1.36753623e+02
  9.53188406e+01 4.71304348e-01 4.34782609e-02 8.04347826e-02
  2.15942029e-02 1.42028986e-02 1.95652174e-02 1.69565217e-02
  2.23188406e-02]
 [6.17052421e+01 1.00000000e+00 2.26362074e+01 8.97822973e+00
  3.59362647e+02 2.94946763e+04 0.00000000e+00 0.00000000e+00
  5.72901747e-04 2.57805786e-02 2.86450874e-04 9.98854197e-01
  4.26525351e-01 3.72386136e-03 2.57805786e-03 4.71784589e-01
  3.98166714e-02 2.86450874e-04 6.01546835e-03 0.00000000e+00
  0.00000000e+00 0.00000000e+00 5.94156402e+00 8.58693784e+00
  4.76367803e-03 4.37696935e-03 1.42938986e-03 2.73560584e-03
  9.99713549e-01 5.72901747e-04 1.09014609e-01 1.22375251e+02
  2.44210828e+02 9.82578058e-01 2.21712976e-03 8.09567459e-02
  2.47121169e-02 4.89258092e-03 2.93039244e-03 7.21856202e-03
  9.49584646e-03]
```

```
 [3.66493902e+03 1.00000000e+00 1.97682927e+01 8.92682927e+00
  4.31342730e+06 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 1.95121951e+00 0.00000000e+00 9.39024390e-01
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.20731707e+00 1.50000000e+00
  1.21951220e-02 1.39024390e-02 1.21951220e-02 1.21951220e-02
  9.83780488e-01 3.25609756e-02 4.14634146e-02 5.38414634e+01
  4.23780488e+01 7.39390244e-01 3.68292683e-02 7.69878049e-01
  8.13414634e-02 7.80487805e-03 1.74390244e-02 6.46341463e-03
  4.87804878e-04]
 [5.52277778e+02 1.00000000e+00 2.12222222e+01 9.00000000e+00
  1.08944444e+02 5.00968983e+06 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.66666667e-01 1.11111111e-01
  1.00000000e+00 5.55555556e-02 1.11111111e-01 5.00000000e-01
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 1.11111111e+00 1.11111111e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  1.00000000e+00 0.00000000e+00 0.00000000e+00 4.39444444e+01
  2.61666667e+01 9.03333333e-01 2.22222222e-03 8.33888889e-01
  5.55555556e-04 4.16666667e-02 4.77777778e-02 4.27777778e-02
  0.00000000e+00]
 [2.00000000e+00 1.00000000e+00 1.70000000e+01 2.00000000e+00
  6.93375640e+08 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 1.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 5.70000000e+01 3.00000000e+00
  7.90000000e-01 6.70000000e-01 2.10000000e-01 3.30000000e-01
  5.00000000e-02 3.90000000e-01 0.00000000e+00 2.55000000e+02
  3.00000000e+00 1.00000000e-02 9.00000000e-02 2.20000000e-01
  0.00000000e+00 1.80000000e-01 6.70000000e-01 5.00000000e-02
  3.30000000e-01]]
============================
```

In [ ]:
```
centroids_k15 = get_centroids_with_random_restarts(15)
```

For K = 15:

(15,41)

25) dM = 176552658.30320373

50) dM = 19549862.37463402

Total iterations number = 68

cluster 1 ==> 53067

cluster 2 ==> 237667

cluster 3 ==> 88

cluster 4 ==> 574

cluster 5 ==> 52

cluster 6 ==> 82

cluster 7 ==> 9928

cluster 8 ==> 185029

cluster 9 ==> 18

cluster 10 ==> 2340

cluster 11 ==> 20
cluster 12 ==> 1769
cluster 13 ==> 1
cluster 14 ==> 17
cluster 15 ==> 3369

For K = 15:
(15,41)
25) dM = 124287064.74056992
50) dM = 50880654.55105877
75) dM = 83302.82444131857
100) dM = 12206848.447218515
125) dM = 721334.3773999268
Total iterations number = 140
cluster 1 ==> 82
cluster 2 ==> 124
cluster 3 ==> 2340
cluster 4 ==> 6
cluster 5 ==> 24
cluster 6 ==> 3369
cluster 7 ==> 574
cluster 8 ==> 1
cluster 9 ==> 290813
cluster 10 ==> 10173
cluster 11 ==> 55
cluster 12 ==> 1883
cluster 13 ==> 184542
cluster 14 ==> 17
cluster 15 ==> 18

For K = 15:
(15,41)
25) dM = 44898125.237195335
50) dM = 8699896.736135526
Total iterations number = 69
cluster 1 ==> 53067
cluster 2 ==> 237667
cluster 3 ==> 20
cluster 4 ==> 17
cluster 5 ==> 52
cluster 6 ==> 88
cluster 7 ==> 18
cluster 8 ==> 185029
cluster 9 ==> 82

cluster 10 ==> 3369
cluster 11 ==> 1769
cluster 12 ==> 9928
cluster 13 ==> 1
cluster 14 ==> 2340
cluster 15 ==> 574

In [ ]:
```
centroids_k23 = get_centroids_with_random_restarts(23)
```

For K = 23: (23,41) 25) dM = 4018382044.442143 50) dM = 49871134.11411251 75) dM = 8926321558.06701 100) dM = 49600953.17906812 Total iterations number = 121 cluster 1 ==> 52793 cluster 2 ==> 3109 cluster 3 ==> 82 cluster 4 ==> 739 cluster 5 ==> 1 cluster 6 ==> 236191 cluster 7 ==> 5 cluster 8 ==> 56 cluster 9 ==> 20389 cluster 10 ==> 3088 cluster 11 ==> 748 cluster 12 ==> 1143 cluster 13 ==> 18 cluster 14 ==> 209 cluster 15 ==> 15 cluster 16 ==> 42 cluster 17 ==> 106 cluster 18 ==> 20 cluster 19 ==> 2271 cluster 20 ==> 164442 cluster 21 ==> 6887 cluster 22 ==> 266 cluster 23 ==> 1401

For K = 23: (23,41) 25) dM = 176315415.14432776 50) dM = 216641655.92633724 75) dM = 364482867.0527531 100) dM = 1150005352.5502946 125) dM = 0.37674285985942724 Total iterations number = 129 cluster 1 ==> 5 cluster 2 ==> 52793 cluster 3 ==> 18 cluster 4 ==> 163659 cluster 5 ==> 227911 cluster 6 ==> 573 cluster 7 ==> 903 cluster 8 ==> 56 cluster 9 ==> 1401 cluster 10 ==> 15 cluster 11 ==> 20421 cluster 12 ==> 1 cluster 13 ==> 2271 cluster 14 ==> 682 cluster 15 ==> 3366 cluster 16 ==> 106 cluster 17 ==> 42 cluster 18 ==> 6895 cluster 19 ==> 3109 cluster 20 ==> 9426 cluster 21 ==> 266 cluster 22 ==> 82 cluster 23 ==> 20

For K = 23: (23,41) 25) dM = 369533834.791988 50) dM = 23397387.3411346 75) dM = 8932741363.903055 100) dM = 4246883.8676567655 125) dM = 6187801659.386045 150) dM = 92941.46517563534 175) dM = 3667281.351634036 200) dM = 619723.9368142623 225) dM = 152.06420786243817 Total iterations number = 243 cluster 1 ==> 739 cluster 2 ==> 289907 cluster 3 ==> 10 cluster 4 ==> 2310 cluster 5 ==> 82 cluster 6 ==> 209 cluster 7 ==> 7194 cluster 8 ==> 21281 cluster 9 ==> 3621 cluster 10 ==> 62 cluster 11 ==> 20 cluster 12 ==> 27 cluster 13 ==> 1247 cluster 14 ==> 738 cluster 15 ==> 235 cluster 16 ==> 5 cluster 17 ==> 3088 cluster 18 ==> 1 cluster 19 ==> 161755 cluster 20 ==> 12 cluster 21 ==> 35 cluster 22 ==> 18 cluster 23 ==> 1425

In [ ]:
```
centroids_k31 = get_centroids_with_random_restarts(31)
```

For K = 31: (31,41) 25) dM = 3194024124.0092025 50) dM = 11925505.397964254 75) dM = 7629647.021045925 100) dM = 1756525.4763086035 125) dM = 515801005.57846195 150) dM = 624430.175885238 175) dM = 5822586.891821563 200) dM = 15818901.336138532 Total iterations number = 219 cluster 1 ==> 60 cluster 2 ==> 34941 cluster 3 ==> 10018 cluster 4 ==> 17859 cluster 5 ==> 227854 cluster 6 ==> 573 cluster 7 ==> 150630 cluster 8 ==> 12 cluster 9 ==> 1 cluster 10 ==> 105 cluster 11 ==> 3556 cluster 12 ==> 3364 cluster 13 ==> 711 cluster 14 ==> 5 cluster 15 ==> 18 cluster 16 ==> 10 cluster 17 ==> 186 cluster 18 ==>

19 cluster 19 ==> 2271 cluster 20 ==> 1082 cluster 21 ==> 20193 cluster 22 ==> 535 cluster 23 ==> 565 cluster 24 ==> 1798 cluster 25 ==> 43 cluster 26 ==> 1332 cluster 27 ==> 13 cluster 28 ==> 9623 cluster 29 ==> 5334 cluster 30 ==> 1228 cluster 31 ==> 82 Result Centroids: [[2.61783333e+02 1.00000000e+00 2.65333333e+01 ... 7.50000000e-03 7.50000000e-03 1.15000000e-02] [0.00000000e+00 1.14478693e-04 1.40014882e+01 ... 0.00000000e+00 0.00000000e+00 0.00000000e+00] [1.79716510e+00 1.00000000e+00 2.19703534e+01 ... 9.46296666e-04 4.46097025e-03 6.58315033e-03] ... [1.08997000e+01 1.00000000e+00 2.21361080e+01 ... 1.13798275e-03 6.76040495e-03 9.89313836e-03] [2.35586319e+00 1.00000000e+00 3.91986971e+01 ... 3.95765472e-03 9.57654723e-03 9.77198697e-04] [3.66493902e+03 1.00000000e+00 1.97682927e+01 ... 1.74390244e-02 6.46341463e-03 4.87804878e-04]]

For K = 31: (31,41) 25) dM = 743184423.806469 50) dM = 50415587.1304739 75) dM = 688839752.6036332 100) dM = 12442837.595616465 125) dM = 6526944.020444147 150) dM = 428568.5162675529 175) dM = 7831240.408963785 200) dM = 66607.47046130704 225) dM = 81429.22756300244 250) dM = 187882.00290442008 275) dM = 37221588.757800065 MAX Number of Iterations! algorithm STOPPED cluster 1 ==> 209 cluster 2 ==> 52795 cluster 3 ==> 12 cluster 4 ==> 151365 cluster 5 ==> 227904 cluster 6 ==> 3087 cluster 7 ==> 17 cluster 8 ==> 20157 cluster 9 ==> 41 cluster 10 ==> 13 cluster 11 ==> 18 cluster 12 ==> 682 cluster 13 ==> 10 cluster 14 ==> 1081 cluster 15 ==> 3489 cluster 16 ==> 10028 cluster 17 ==> 1334 cluster 18 ==> 1 cluster 19 ==> 2271 cluster 20 ==> 9628 cluster 21 ==> 106 cluster 22 ==> 82 cluster 23 ==> 905 cluster 24 ==> 5 cluster 25 ==> 209 cluster 26 ==> 76 cluster 27 ==> 1813 cluster 28 ==> 40 cluster 29 ==> 5299 cluster 30 ==> 606 cluster 31 ==> 738 Result Centroids: [[2.27332249e+04 1.71291866e+00 3.97894737e+01 ... 3.82775120e-04 2.52200957e-01 2.76507177e-01] [0.00000000e+00 1.36376551e-03 1.40177290e+01 ... 0.00000000e+00 0.00000000e+00 0.00000000e+00] [3.89166667e+01 1.00000000e+00 5.60000000e+01 ... 0.00000000e+00 0.00000000e+00 0.00000000e+00] ... [4.40169811e+00 1.00000000e+00 2.21535849e+01 ... 1.09433962e-03 6.40754717e-03 9.02452830e-03] [2.20841584e+01 1.00000000e+00 2.25379538e+01 ... 2.24422442e-03 9.76897690e-03 9.85148515e-03] [1.05996070e+04 1.90785908e+00 3.87520325e+01 ... 3.75338753e-03 3.13550136e-02 4.07452575e-02]]

For K = 31: (31,41) 25) dM = 87236541.37234738 50) dM = 58055614.31950802 75) dM = 30962830835.173763 100) dM = 9842411.41093181 125) dM = 1900942791.4920065 150) dM = 14705285.007585887 175) dM = 5704600.6607852 200) dM = 4328498.992352758 225) dM = 967.7896495506602 Total iterations number = 246 cluster 1 ==> 12 cluster 2 ==> 33986 cluster 3 ==> 10 cluster 4 ==> 20 cluster 5 ==> 2271 cluster 6 ==> 227855 cluster 7 ==> 5 cluster 8 ==> 105 cluster 9 ==> 9584 cluster 10 ==> 641 cluster 11 ==> 157048 cluster 12 ==> 6984 cluster 13 ==> 1210 cluster 14 ==> 18 cluster 15 ==> 62 cluster 16 ==> 1 cluster 17 ==> 35 cluster 18 ==> 11830 cluster 19 ==> 6848 cluster 20 ==> 82 cluster 21 ==> 1225 cluster 22 ==> 27 cluster 23 ==> 739 cluster 24 ==> 4459 cluster 25 ==> 233 cluster 26 ==> 21547 cluster 27 ==> 565 cluster 28 ==> 711 cluster 29 ==> 2612 cluster 30 ==> 209 cluster 31 ==> 3087 Result Centroids: [[3.89166667e+01 1.00000000e+00 5.60000000e+01 ... 0.00000000e+00 0.00000000e+00 0.00000000e+00] [0.00000000e+00 5.88477608e-05 1.40007650e+01 ...

0.00000000e+00 0.00000000e+00 0.00000000e+00] [3.20000000e+01 1.00000000e+00 4.52000000e+01 ... 0.00000000e+00 1.00000000e-03 0.00000000e+00] ... [1.50647014e+01 1.00000000e+00 2.22584227e+01 ... 1.55053599e-03 5.17228178e-03 8.18912711e-03] [2.27332249e+04 1.71291866e+00 3.97894737e+01 ... 3.82775120e-04 2.52200957e-01 2.76507177e-01] [3.18959864e+03 1.99546485e+00 3.98270165e+01 ... 0.00000000e+00 8.06608358e-04 9.78296080e-04]]

In [ ]:
```
centroids_k45 = get_centroids_with_random_restarts(45)
```

For K = 45: (45,41) 25) dM = 2458564268.439884 50) dM = 16101180.849004028 75) dM = 7758265.925369633 100) dM = 312768660.19861686 125) dM = 600884.0831698527 150) dM = 14686328.398945857 175) dM = 779317581.8920798 200) dM = 280909.7899030334 225) dM = 92489.47131992971 250) dM = 1994.485004599017 275) dM = 505.3507330533022 MAX Number of Iterations! algorithm STOPPED cluster 1 ==> 3870 cluster 2 ==> 52361 cluster 3 ==> 17 cluster 4 ==> 18 cluster 5 ==> 52793 cluster 6 ==> 200 cluster 7 ==> 557 cluster 8 ==> 2259 cluster 9 ==> 4682 cluster 10 ==> 227839 cluster 11 ==> 13 cluster 12 ==> 74 cluster 13 ==> 17694 cluster 14 ==> 899 cluster 15 ==> 781 cluster 16 ==> 21701 cluster 17 ==> 428 cluster 18 ==> 19159 cluster 19 ==> 2928 cluster 20 ==> 620 cluster 21 ==> 3513 cluster 22 ==> 40 cluster 23 ==> 12 cluster 24 ==> 1 cluster 25 ==> 82 cluster 26 ==> 487 cluster 27 ==> 7853 cluster 28 ==> 1296 cluster 29 ==> 19393 cluster 30 ==> 5 cluster 31 ==> 262 cluster 32 ==> 105 cluster 33 ==> 45 cluster 34 ==> 2271 cluster 35 ==> 5802 cluster 36 ==> 1175 cluster 37 ==> 11920 cluster 38 ==> 996 cluster 39 ==> 41 cluster 40 ==> 10 cluster 41 ==> 1870 cluster 42 ==> 577 cluster 43 ==> 24392 cluster 44 ==> 2339 cluster 45 ==> 641 Result Centroids: [[2.64780362e+00 9.33074935e-01 4.54855297e+01 ... 2.22997416e-03 5.82170543e-03 1.16279070e-03] [1.23045778e+00 1.04373484e+00 4.37942362e+01 ... 7.11427398e-01 2.13726247e-01 2.11326178e-01] [1.27135294e+03 1.00000000e+00 4.78235294e+01 ... 4.17647059e-02 4.52941176e-02 8.23529412e-03] ... [1.43137094e+00 1.45137750e+00 2.61582896e+01 ... 2.20441128e-03 2.16254100e-01 2.04163660e-01] [1.37049808e+01 1.00000000e+00 2.21421882e+01 ... 1.16645381e-03 7.41592167e-03 1.17156237e-02] [1.49083463e+03 1.99063963e+00 3.94524181e+01 ... 0.00000000e+00 7.02028081e-03 8.51794072e-03]]

For K = 45: (45,41) 25) dM = 163454900.29276264 50) dM = 38762963.84002216 75) dM = 688051596.695631 100) dM = 1269958.9733821794 125) dM = 22708796.10904589 150) dM = 2061889.0403148648 175) dM = 110035.1157206646 200) dM = 248339.53322846547 225) dM = 14980459.284923058 250) dM = 23667.67344113585 275) dM = 243.61028684220042 Total iterations number = 287 cluster 1 ==> 30317 cluster 2 ==> 3264 cluster 3 ==> 33986 cluster 4 ==> 10 cluster 5 ==> 2271 cluster 6 ==> 4468 cluster 7 ==> 18 cluster 8 ==> 41 cluster 9 ==> 227841 cluster 10 ==> 30000 cluster 11 ==> 10448 cluster 12 ==> 12606 cluster 13 ==> 1990 cluster 14 ==> 5616 cluster 15 ==> 56753 cluster 16 ==> 487 cluster 17 ==> 1299 cluster 18 ==> 818 cluster 19 ==> 903 cluster 20 ==> 429 cluster 21 ==> 265 cluster 22 ==> 82 cluster 23 ==> 2555 cluster 24 ==> 1148 cluster 25 ==> 6984 cluster 26 ==> 40 cluster 27 ==> 13 cluster 28 ==> 620 cluster 29 ==> 1018 cluster 30 ==> 28444 cluster 31 ==> 5 cluster 32 ==> 7519 cluster 33 ==> 576 cluster 34 ==> 12 cluster 35 ==> 2543 cluster 36 ==> 3724 cluster 37 ==> 105 cluster 38 ==> 200 cluster 39 ==> 17 cluster 40 ==> 74 cluster 41 ==> 1 cluster 42 ==> 11821 cluster 43 ==> 2088 cluster 44 ==> 557 cluster 45 ==> 45 Result Centroids: [[1.35237655e-03 1.00220998e+00 4.42017350e+01 ... 8.26186628e-01 1.72233071e-01 1.71603391e-01] [7.06801471e+00 1.00000000e+00 2.21755515e+01 ... 1.36948529e-03 6.45220588e-03 1.00490196e-02] [0.00000000e+00 5.88477608e-05 1.40007650e+01 ... 0.00000000e+00 0.00000000e+00 0.00000000e+00] ... [2.05977011e+02 1.21886973e+00 2.40383142e+01 ... 1.69540230e-03 1.20162835e-02 5.50766284e-03] [3.58707361e+00 1.00000000e+00 3.10377020e+01 ... 1.43626571e-03 1.39497307e-02 6.24775583e-03] [3.45650889e+04 1.13333333e+00 3.86888889e+01 ... 1.77777778e-03 7.40222222e-01 8.34222222e-01]]

For K = 45: (45,41) 25) dM = 3681628800.79655 50) dM = 11189683.287676465 75) dM = 5499578.289599714 100) dM = 1475022.5529326445 125) dM = 415667.6329125293 150) dM = 2024220.1512852132 175) dM = 376294.6710435486 200) dM = 355184.3130726231 225) dM = 14984748.237262001 250) dM = 33680.49315630928 275) dM = 750.1553095423969 Total iterations number = 288 cluster 1 ==> 2613 cluster 2 ==> 33779 cluster 3 ==> 903 cluster 4 ==> 3868 cluster 5 ==> 2543 cluster 6 ==> 7531 cluster 7 ==> 10513 cluster 8 ==> 227840 cluster 9 ==> 5 cluster 10 ==> 557 cluster 11 ==> 852 cluster 12 ==> 1018 cluster 13 ==> 59492 cluster 14 ==> 5118 cluster 15 ==> 200 cluster 16 ==> 74 cluster 17 ==> 7002 cluster 18 ==> 17 cluster 19 ==> 82 cluster 20 ==> 1 cluster 21 ==> 18 cluster 22 ==> 29612 cluster 23 ==> 13 cluster 24 ==> 1303 cluster 25 ==> 41 cluster 26 ==> 4468 cluster 27 ==> 266 cluster 28 ==> 12614 cluster 29 ==> 5733 cluster 30 ==> 1179 cluster 31 ==> 105 cluster 32 ==> 5805 cluster 33 ==> 2271 cluster 34 ==> 40 cluster 35 ==> 12 cluster 36 ==> 436 cluster 37 ==> 10 cluster 38 ==> 45 cluster 39 ==> 577 cluster 40 ==> 1162 cluster 41 ==> 1990 cluster 42 ==> 620 cluster 43 ==> 57942 cluster 44 ==> 3264 cluster 45 ==> 487 Result Centroids: [[2.57073211e+03 1.99885189e+00 3.98882511e+01 ... 0.00000000e+00 4.01836969e-04 8.03673938e-04] [0.00000000e+00 5.92083839e-05 1.40007697e+01 ... 0.00000000e+00 0.00000000e+00 0.00000000e+00] [3.29490587e+01 1.00000000e+00 2.24894795e+01 ... 1.31782946e-03 8.58250277e-03 1.02547065e-02] ... [4.73468296e+00 1.04388872e+00 4.18614649e+01 ... 6.54313279e-01 2.18004211e-01 2.15608194e-01] [7.06801471e+00 1.00000000e+00 2.21755515e+01 ... 1.36948529e-03 6.45220588e-03 1.00490196e-02] [2.70677618e+01 1.00000000e+00 2.25995893e+01 ... 2.64887064e-03 1.17043121e-02 1.19917864e-02]]

In [ ]:
```
# store_data("centroids_k7", centroids_k7)
# store_data("centroids_k15", centroids_k15)
# store_data("centroids_k23", centroids_k23)
# store_data("centroids_k31", centroids_k31)
# store_data("centroids_k45", centroids_k45)
```

Now, let's start working with the test set, and mapping each data point to a cluster, for each k.

Functions used in prediction part:

- **switch():** given a value k, it returns the equivalent centroids.

- **closest_centroid():** given a data point, and the array of centroids, it calculates all distances between the point and every centroid, then returns the index of the min distance (point is concidered part of cluster i).
- **test_kmeans():** applies closest_centroid for each point in the test dataset.

In [ ]:
```
def switch(argument):
  switcher = {
    7: centroids_k7,
    15: centroids_k15,
    23: centroids_k23,
    31: centroids_k31,
    45: centroids_k45
  }
  return switcher.get(argument, "Invalid argument")
```

In [21]:
```
def closest_centroid(point, centroids):
  distances = np.sqrt(np.sum((centroids - point)**2, axis=1))
  return np.argmin(distances)
```

In [ ]:
```
# This function returns indexes from 0 to k-1, each index represent a cluster (predict
def test_kmeans(k):
  centroids = switch(k)
  return np.apply_along_axis(closest_centroid, 1, test, centroids)
```

In [ ]:
```
# centroids_k7 = load_saved_data("centroids_k7")
# centroids_k15 = load_saved_data("centroids_k15")
# centroids_k23 = load_saved_data("centroids_k23")
# centroids_k31 = load_saved_data("centroids_k31")
# centroids_k45 = load_saved_data("centroids_k45")
# test = load_saved_data("test")
# test_labeled = load_saved_data("test_labeled")
```

In [ ]:
```
print(test.shape)
print(test_labeled.shape)
```

```
(311029, 41)
(311029, 42)
```

Calculated data here:

test_kmeans_clusters_k7, ..15, ..23, ..31, ..45, (predicted labels)
test_kmeans_true (actual labels (last column ofthe test dataset))

In [ ]:
```
test_kmeans_clusters_k7 = test_kmeans(7)
print(len(test_kmeans_clusters_k7))
print(test_kmeans_clusters_k7[:30])
```

```
311029
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 3 1 1 1 1 1]
```

In [ ]:
```
test_kmeans_clusters_k15 = test_kmeans(15)
print(test_kmeans_clusters_k15[:30])
```

```
[ 7  7  7  7  7  7  7  7  7  7  7  7  7  7  1 11  7  7  7  7 11  7  7 11
 11  0  7 13  1  7]
```

In [ ]:
```
test_kmeans_clusters_k23 = test_kmeans(23)
print(test_kmeans_clusters_k23[:30])
```

```
[ 3  3  3  3  3  3  3  3  3  3  3  3  3  3 19 18 10  3  3  3 17  3  3 17
 18  3  3 15  6  3]
```

In [ ]:
```
test_kmeans_clusters_k31 = test_kmeans(31)
print(test_kmeans_clusters_k31[:30])
```

```
[ 3  3  3  3  3  3  3  3  3  3  3  3  3  3 19 14 15  7  3  3 14  3  3 28
 26  3  3 20 22  3]
```

In [ ]:
```
test_kmeans_clusters_k45 = test_kmeans(45)
print(len(test_kmeans_clusters_k45))
print(test_kmeans_clusters_k45[:30])
```

```
311029
[42 42 42 42 42 42 42 42 42 42 42 42 42 42 35 40  8 12 42 42 18 42 42 18
 37 34 42 31 19 42]
```

In [ ]:
```
test_kmeans_true = test_labeled[:, -1].astype(int)
print(test_kmeans_true.shape)
```

```
(311029,)
```

---

3 Spectral Clustering

In [15]:
```
from sklearn.cluster import KMeans
from sklearn.metrics.pairwise import rbf_kernel
from scipy.spatial.distance import pdist, squareform

def spectral_clustering(data_matrix, k):

  data_matrix = data_matrix.astype(np.float32)

  sim_matrix = rbf_kernel(data_matrix, gamma=0.1)
  sim_matrix = sim_matrix.astype(np.float32)
  np.fill_diagonal(sim_matrix, 0)
  sim_matrix = sim_matrix + np.finfo(float).eps
  # print(sim_matrix)
  # sim matrix is symmetric so axis = 0 eq axis = 1

  degree_matrix = np.diag(np.sum(sim_matrix, axis = 0))
  # print(degree_matrix)

  L_matrix = degree_matrix - sim_matrix
  # print(L_matrix)

  eigen_values, eigen_vectors = scipy.linalg.eigh(L_matrix, degree_matrix)
  eigen_vectors = eigen_vectors[:,:k] / np.linalg.norm(eigen_vectors[:,:k], ord=2, axi

  # print(eigen_vectors)

  kmeans = KMeans(n_clusters=k)
  kmeans.fit(eigen_vectors)
  labels = kmeans.labels_
  centroids = kmeans.cluster_centers_
```

```
  return centroids , labels
```

work on 0.15 % of data we will suffle data and get percentage we want

In [16]:
```
def sub_data(total_data, percentage):
  rows = int((percentage/100) * total_data.shape[0])
  sampled_data = total_data[np.random.choice(total_data.shape[0], rows, replace=False)
  return sampled_data
```

In [17]:
```
data_labeled_spectral.shape[0]
```

Out[17]:
```
4898431
```

In [49]:
```
my_data = sub_data(data_labeled_spectral, 0.15)
```

In [ ]:
```
print("new data shape: ",my_data.shape)
print("unique labels : ",np.unique(my_data[:,-1]))
```

```
new data shape:  (7347, 42)
unique labels :  [ 0.  5.  9. 10. 11. 15. 17. 18. 21.]
```

In [50]:
```
my_labels = my_data[:,-1]
my_data = my_data[:,:-1]
print("labels for our training data : ", my_labels)
```

```
labels for our training data :  [ 9.  9. 11. ... 18. 18. 18.]
```

In [ ]:
```
spectral_centroids, spectral_labels = spectral_clustering(my_data, 45)


print('centroids')
print(spectral_centroids)
print('labels')
print(spectral_labels)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:
The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of
`n_init` explicitly to suppress the warning
  warnings.warn(
centroids
[[ 1.57751143e-04  6.44510761e-02  9.91084427e-03 ... -6.26195222e-02
   6.01242483e-03 -9.12979305e-01]
 [-4.08838063e-01  5.05626276e-02 -1.18001476e-01 ...  5.06272279e-02
  -1.01702824e-01  3.06695998e-01]
 [-2.39976570e-02  1.05117410e-02 -6.66158348e-02 ... -1.34442374e-01
  -3.59557092e-01 -6.38825521e-02]
 ...
 [ 2.36097947e-02 -4.30704981e-01 -1.65781118e-02 ... -7.00429976e-02
   9.63579565e-02 -4.30561453e-02]
 [ 3.03500220e-02  4.60218862e-02  2.65812129e-03 ...  1.79892965e-02
   3.98872644e-02 -7.57862814e-03]
 [ 5.20944595e-04  6.69089183e-02 -1.12795122e-02 ...  1.36796370e-01
   7.45478570e-02 -7.47838765e-02]]
labels
[11 16  3 ...  1 11  1]
```

Comparing the results of K-Means and Normalized Cut clustering in terms of the number of detected anomalies and their characteristics:

Let's run kmeans & clustering on k=23 and compare them:

In [57]:
```
def get_normal_val_in_dict(dictio):
  dict4 = dictio[41]
  normal = 0
  for key, value in dict4.items():
    if(key == 'normal.'):
      normal = value
  print(normal)
  return normal
```

In [47]:
```
def calculate_anomalies(labels, normal_val):
  n1 = len(labels)
  n2 = np.count_nonzero((labels==normal_val).astype(int))
  return n1-n2
```

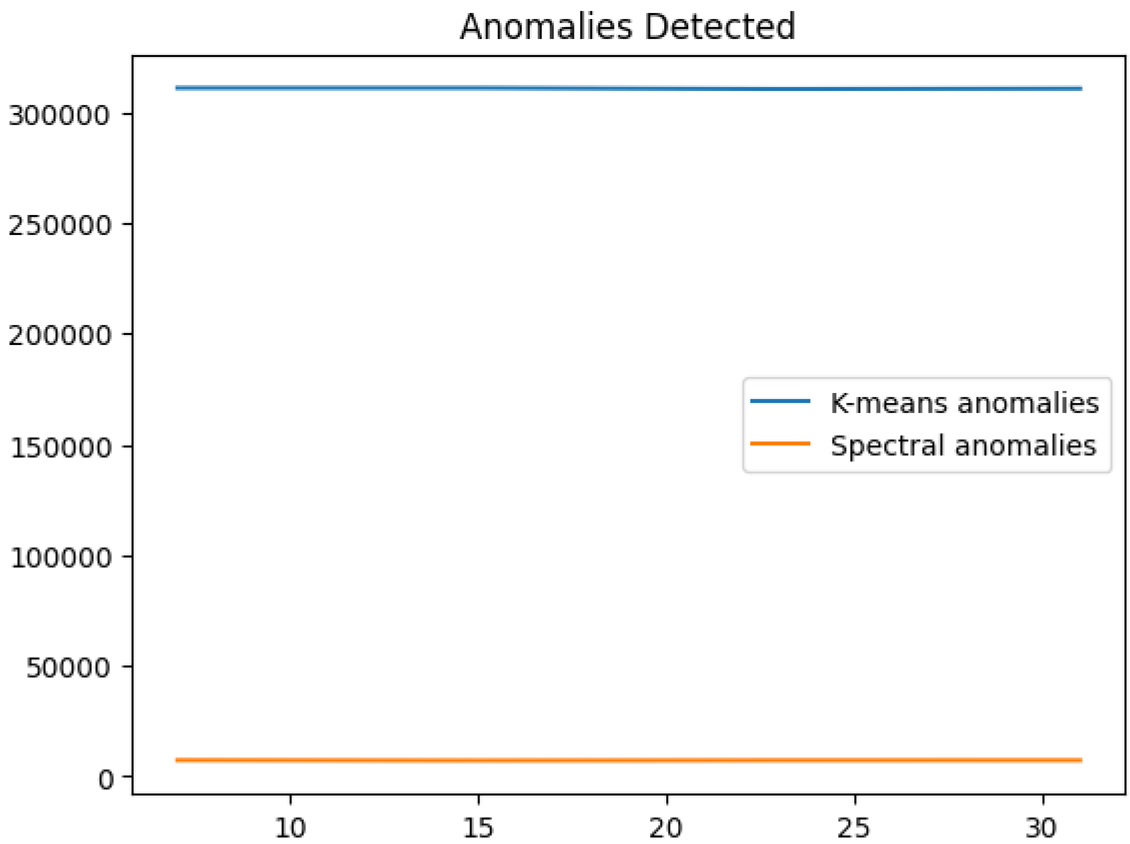
In [ ]:
```
kmeans_normal = get_normal_val_in_dict(test_dict)
spectral_normal = get_normal_val_in_dict(spectral_dict)
anomalies_kmeans = []
anomalies_spectral = []

for i in range(len(Ks)-1):
  _ , centroids_kmeans = run_Kmeans(Ks[i])
  Kmeans_labels = np.apply_along_axis(closest_centroid, 1, test, centroids_kmeans)

  _ , spectral_labels = spectral_clustering(my_data, Ks[i])

  anomalies_kmeans.append(calculate_anomalies(Kmeans_labels, kmeans_normal))
  anomalies_spectral.append(calculate_anomalies(spectral_labels, spectral_normal))
```

In [60]:
```
print(anomalies_kmeans)
print(anomalies_spectral)
```

```
[311029, 311029, 310564, 310766]
[7347, 7213, 7292, 7315]
```

K	K-means	Spectral-Clustering
7	311029	7347
15	311029	7213
23	310564	7292
31	310766	7315

In [65]:
```
fig, ax = plt.subplots()
ax.plot(Ks[:4], anomalies_kmeans, label='K-means anomalies')
ax.plot(Ks[:4], anomalies_spectral, label='Spectral anomalies')
ax.legend()
ax.set_title('Anomalies Detected')
plt.show()
```



4 validation and new technique

In [ ]:
```
def map_predicted_labels(y_true, y_pred):
    # Compute the adjusted Rand score between the true and predicted labels
    score = adjusted_rand_score(y_true, y_pred)
    print("Adjusted Rand score:", score)

    # Create a dictionary to map predicted labels to true labels
    label_map = {}
    true_labels = np.unique(y_true)
    pred_labels = np.unique(y_pred)
    for pred_label in pred_labels:
        best_match = -1
        for true_label in true_labels:
            intersect = np.intersect1d(np.where(y_pred == pred_label), np.where(y_true
            if len(intersect) > best_match:
                label_map[pred_label] = true_label
                best_match = len(intersect)

    # Map the predicted labels to the true labels
    y_mapped = np.vectorize(label_map.get)(y_pred)

    return y_mapped
```

In [ ]:
```
import numpy as np
from sklearn.metrics.cluster import contingency_matrix

def validation(labels_true, labels_pred_):
    """
```

```
    Validates the quality of clustering results using precision, recall, F-score, and

    Parameters:
    labels_true (array-like): True cluster labels.
    labels_pred (array-like): Predicted cluster labels.

    Returns:
    precision (float): Precision score.
    recall (float): Recall score.
    f_score (float): F-score.
    conditional_entropy (float): Conditional entropy.
    """
    # we first map prediction labels to true labels
    labels_pred = map_predicted_labels(labels_true, labels_pred_)
    contingency = contingency_matrix(labels_true, labels_pred)
    row_sums = np.sum(contingency, axis=1)
    col_sums = np.sum(contingency, axis=0)
    total_samples = np.sum(row_sums)

    # Precision
    precision = np.sum(np.max(contingency, axis=0)) / total_samples

    # Recall
    recall = np.sum(np.max(contingency, axis=1)) / total_samples

    # F-score
    f_score = 2 * precision * recall / (precision + recall)

    # Conditional entropy
    eps = np.finfo(float).eps
    row_prob = row_sums / total_samples
    col_prob = col_sums / total_samples
    joint_prob = contingency / total_samples
    entropy_row = -np.sum(row_prob * np.log2(row_prob + eps))
    entropy_col = -np.sum(col_prob * np.log2(col_prob + eps))
    entropy_joint = -np.sum(joint_prob * np.log2(joint_prob + eps))
    conditional_entropy = entropy_joint - entropy_col
    return precision, recall, f_score, conditional_entropy
```

In [ ]:

```
print("count of each cluster in total labeled data in kddcup.data_10_percent.gz : ")
for i in range(23):
  print("cluster "+str(i)+" : "+str(np.sum((data_spectral_labels==i) == True)))
```

```
count of each cluster in total labeled data in kddcup.data_10_percent.gz :
cluster 0 : 2203
cluster 1 : 30
cluster 2 : 8
cluster 3 : 53
cluster 4 : 12
cluster 5 : 12481
cluster 6 : 21
cluster 7 : 9
cluster 8 : 7
cluster 9 : 1072017
cluster 10 : 2316
cluster 11 : 972781
cluster 12 : 3
cluster 13 : 4
cluster 14 : 264
cluster 15 : 10413
cluster 16 : 10
cluster 17 : 15892
cluster 18 : 2807886
cluster 19 : 2
cluster 20 : 979
cluster 21 : 1020
cluster 22 : 20
```

In [ ]:

```
print("count of each cluster in sampled data : ")
for i in range(23):
  print("cluster "+str(i)+" : "+str(np.sum((my_labels==i) == True)))
```

```
count of each cluster in sampled data :
cluster 0 : 3
cluster 1 : 0
cluster 2 : 0
cluster 3 : 0
cluster 4 : 0
cluster 5 : 19
cluster 6 : 0
cluster 7 : 0
cluster 8 : 0
cluster 9 : 1562
cluster 10 : 3
cluster 11 : 1458
cluster 12 : 0
cluster 13 : 0
cluster 14 : 0
cluster 15 : 14
cluster 16 : 0
cluster 17 : 22
cluster 18 : 4264
cluster 19 : 0
cluster 20 : 0
cluster 21 : 2
cluster 22 : 0
```

In [ ]:

```
my_data.shape
```

Out[ ]:

```
(7347, 41)
```

In [ ]:

```
def dbscan(X, eps, min_samples):
    X = StandardScaler().fit_transform(X)
```

```
    # Initialize labels as -1 (unclassified)
    labels = np.full(X.shape[0], -1)

    # Initialize the core samples set
    core_samples = set()

    # Compute pairwise distances
    D = euclidean_distances(X)

    # Find all core samples
    for i in range(X.shape[0]):
        # Find all samples within eps distance
        neighbors = np.where(D[i] <= eps)[0]

        # Check if there are enough samples to form a dense region
        if len(neighbors) >= min_samples:
            core_samples.add(i)

    # Expand clusters from core samples
    cluster_id = 0
    for i in range(X.shape[0]):
        if labels[i] == -1 and i in core_samples:
            # Start a new cluster
            cluster_id += 1
            labels[i] = cluster_id

            # Expand the cluster using depth-first search
            stack = [i]
            while stack:
                j = stack.pop()

                # Find all samples within eps distance
                neighbors = np.where(D[j] <= eps)[0]

                # Check if there are enough samples to form a dense region
                if len(neighbors) >= min_samples:
                    for k in neighbors:
                        if labels[k] == -1:
                            # Add k to the current cluster
                            labels[k] = cluster_id
                            stack.append(k)
                        elif labels[k] == 0:
                            # Add k to the current cluster and mark as border
                            labels[k] = cluster_id

    return labels
```

In [ ]:
```
# l = [1,3,5,7,10,12,15,20]
# for i in l :
#   labels = dbscan(my_data, 0.3, i)
#   p,r,f,e = validation(my_labels,labels)
#   print(p)
#   print(r)
#   print(f)
#   print(e)
```

In [ ]:
```
labels = dbscan(my_data, 0.3, 10)
```

new technique validation

In [ ]:
```
p,r,f,e = validation(my_labels,labels)
print("percision : ",p)
print("recall : ",r)
print("F score : ",f)
print("coditional entropy : ",e)
```

```
Adjusted Rand score: 0.9060536967540196
percision :  0.9757724241186879
recall :  0.9843473526609501
F score :  0.9800411320361573
coditional entropy :  0.16006450379662795
```

spectral validation

In [ ]:
```
# validate spectral prediction
p,r,f,e = validation(my_labels,spectral_labels)
print("percision : ",p)
print("recall : ",r)
print("F score : ",f)
print("coditional entropy : ",e)
```

```
Adjusted Rand score: 0.6690520335926263
percision :  0.9865251122907309
recall :  0.9908806315502926
F score :  0.9886980750931333
coditional entropy :  0.11289811916537462
```

kmeans validation

In [ ]:
```
print(test_kmeans_true[:50])
```

```
[16 16 16 28 28 28 16 16 28 16 28 16 16 28 16 16 16 16 28 28 16 28 16 16
 16 16 16 16 16 28 28 16 28 16 16 16 16 16 16 16 16 16 16 16 16 16 16 16
 28 28]
```

In [ ]:
```
validation(test_kmeans_true, test_kmeans_clusters_k7)
```

```
Adjusted Rand score: 0.008635798848664 37
```

Out[ ]:
```
(0.5359210877442296, 0.991579563320462, 0.6957881134639783, 1.987249400277048)
```

In [ ]:
```
validation(test_kmeans_true, test_kmeans_clusters_k15)
```

```
Adjusted Rand score: 0.4200811832679274
```

Out[ ]:
```
(0.7464770166125988, 0.957418761594578, 0.8388906292802026, 0.9885101646439609)
```

In [ ]:
```
validation(test_kmeans_true, test_kmeans_clusters_k23)
```

```
Adjusted Rand score: 0.4604327580608341
```

Out[ ]:
```
(0.8033302360873101,
 0.9088252220854004,
 0.8528276760559445,
 0.7958765715502201)
```

In [ ]:
```
validation(test_kmeans_true, test_kmeans_clusters_k31)
```

```
Adjusted Rand score: 0.46679483124670096
```

Out[ ]:
```
(0.8232833594295066,
 0.8835381909725459,
 0.8523472062756677,
 0.7323634400505512)
```

In [ ]:
```python
validation(test_kmeans_true, test_kmeans_clusters_k45)
```

```
Adjusted Rand score: 0.38339176027161914
```

Out[ ]:
```
(0.9226760205639989, 0.981027492613229, 0.9509574749248086, 0.4667259162811004)
```

In [ ]:
```python
# rand_score_kmeans = [0.008635798848664437, 0.4200811832679274, 0.4604327580608341, 0.
precision_kmeans = [0.5359210877442296, 0.7464770166125988, 0.8033302360873101, 0.8232
recall_kmeans = [0.991579563320462, 0.957418761594578, 0.9088252220854004, 0.8835381909
f1score_kmeans = [0.6957881134639783, 0.8388906292802026, 0.8528276760559445, 0.852347
condEntropy_kmeans = [1.987249400277048, 0.9885101646439609, 0.7958765715502201, 0.732
```

In [ ]:
```python
# for i in range(len(Ks)):
Ks = [7, 15, 23, 31, 45]
fig, ax = plt.subplots()
# ax.plot(Ks, rand_score_kmeans, label='Rand Score')
ax.plot(Ks, precision_kmeans, label='Precision')
ax.plot(Ks, recall_kmeans, label='Recall')
ax.plot(Ks, f1score_kmeans, label='F1 Score')
ax.plot(Ks, condEntropy_kmeans, label='Conditional Entropy')
ax.legend()
ax.set_title('Kmeans Validation Measures')
plt.show()
```