FCM

June 8, 2021

1 Fuzzy C-means

implementing FCM algorithm and implying it on different datasets

[1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from matplotlib import style
```

[2]:
```
def read_dataset(path, name):
    df = pd.read_csv(path + name, header=None)
    return df
```

[3]:
```
def initialize_membership_matrix(df, c):
    membership_matrix = np.random.dirichlet(np.ones(c),size=len(df))
    df_membership_matrix = pd.DataFrame(membership_matrix)
    return df_membership_matrix
```

[4]:
```
def find_centroids(df, c, membership_matrix, m):
    centroids = np.zeros((c, len(df.columns)))

    for i in range(c):
        sum_membership = sum(np.power(membership_matrix[i], m))
        for j in range (len(df.columns)):
            c = sum(np.multiply(np.power(membership_matrix[i], m), df[j]))/
 ↪sum_membership
            centroids[i, j] = c

    return centroids
```

[5]:
```
def calculate_membership_matrix(df, centroids, m):
    EuclidianDistance = pd.DataFrame()
    inverse_EuclidianDistance = pd.DataFrame()
    membership_matrix = pd.DataFrame()
    for i in range(0, len(centroids)):
        x = 0
        for j in range(0, len(df.columns)):
            x = np.add(x, np.power((df.iloc[ : , j] - centroids[i,j]), 2))
```

```
        x = np.sqrt(x)
        EuclidianDistance[len(EuclidianDistance.columns)] = x

    inverse_EuclidianDistance = np.power((1 / EuclidianDistance), 1/(m-1))
    sum = inverse_EuclidianDistance.sum(axis=1)

    for i in range(len(centroids)):
        membership_matrix[len(membership_matrix.columns)] = np.power(1 /␣
↪EuclidianDistance[i], 1/(m-1)) / sum
    #to handle devison by zero
    membership_matrix.replace(np.inf, 1, inplace=True)

    return membership_matrix
```

1.1 Fuzzy C-means algorithm

[6]:
```
def c_means(df, c, m, max_it):
    #initialing weights randomly
    membership_matrix = initialize_membership_matrix(df, c)
    centroids = np.zeros((c, len(df.columns)))
    for i in range(max_it):
        temp_centroids = find_centroids(df, c, membership_matrix, m)
        # print(np.array_equal(centroids, temp_centroids))
        if np.array_equal(centroids, temp_centroids):
            # print("clustering finished, it", i)
            minvalue_series = membership_matrix.idxmin(axis = 1)
            return centroids, membership_matrix, minvalue_series
        centroids = temp_centroids
        membership_matrix = calculate_membership_matrix(df, centroids, m)
    minvalue_series = membership_matrix.idxmax(axis = 1)
    return centroids, membership_matrix, minvalue_series
```

1.2 Cost function

we calculate cost according to distances and memberships

[7]:
```
#Calculate cost
def cost_calculate(df, centroids, membership_matrix, m):
    EuclidianDistance = pd.DataFrame()
    cost = 0

    for i in range(0, len(centroids)):
        x = 0
        for j in range(0, len(df.columns)):
            x = np.add(x, np.power((df.iloc[ : , j] - centroids[i,j]), 2))
        x = np.sqrt(x)
        EuclidianDistance[len(EuclidianDistance.columns)] = x
```

```
    # print(EuclidianDistance)
    # print(membership_matrix)
    cost = ((np.multiply(EuclidianDistance, np.power(membership_matrix, m)).
↪sum(axis=1)).sum())/len(df)
    # print(cost)
    return cost
```

1.3 ploting elbow method

ploting elbow method per different numbers of c

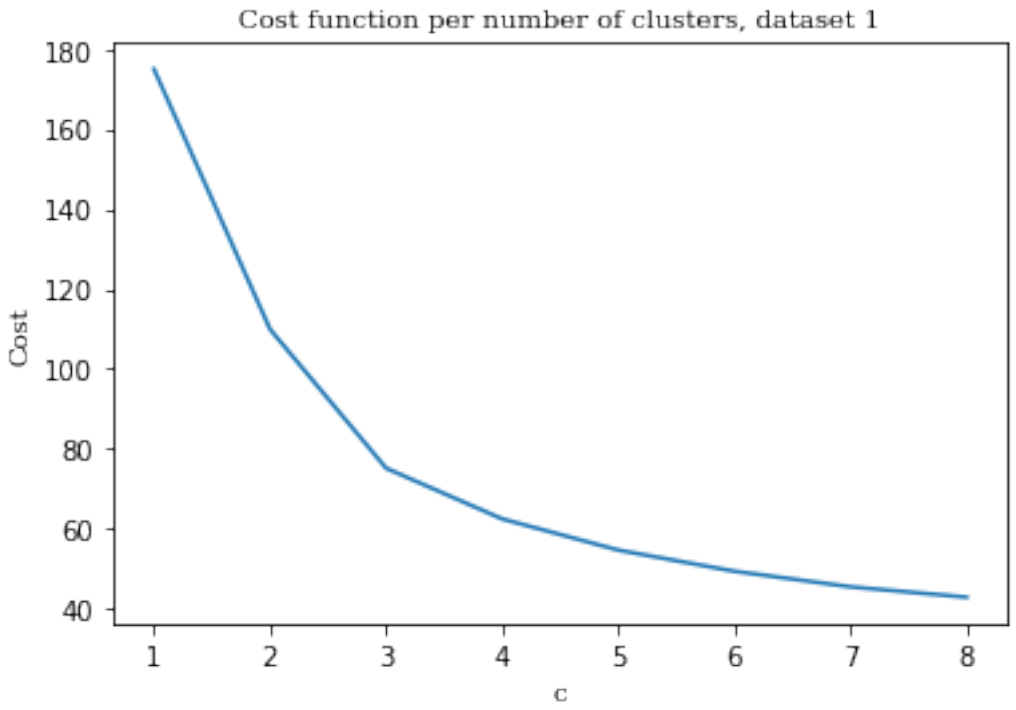
[8]:
```
def plot_cost(df, dataset_name, c, m):
    axis = []
    c_list = []
    for i in range(1,c + 1):

        centroids, membership_matrix, minvalue_seri = c_means(df, i, m, 100)
        cost = cost_calculate(df, centroids, membership_matrix, m)

        axis.append(cost)
        c_list.append(i)

    #plot
    font1 = {'family':'serif','color':'black','size':10}

    plt.xlabel("c", fontdict = font1)
    plt.ylabel("Cost", fontdict = font1)
    plt.title('Cost function per number of clusters, dataset␣
↪'+str(dataset_name), fontdict = font1)

    plt.plot(c_list, axis, label = "Cost Function")
    plt.show()
```

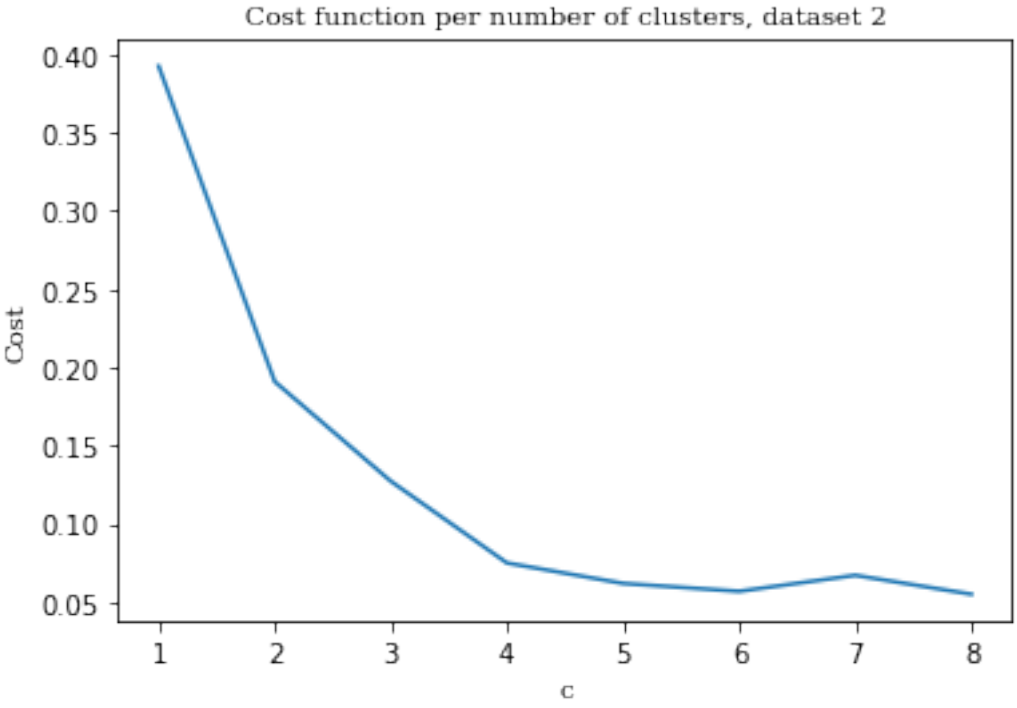
[9]:
```
our_datasets = []
our_datasets.append(read_dataset("datasets/", "data1.csv"))
our_datasets.append(read_dataset("datasets/", "data2.csv"))
our_datasets.append(read_dataset("datasets/", "data3.csv"))
our_datasets.append(read_dataset("datasets/", "data4.csv"))
```

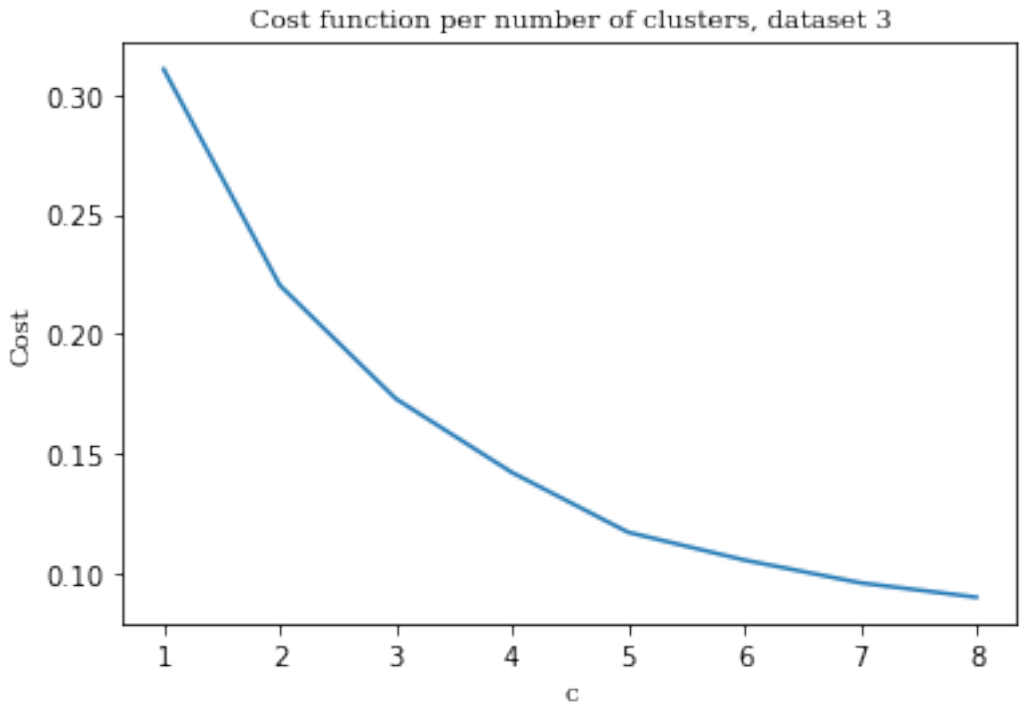
1.4 Elbow method

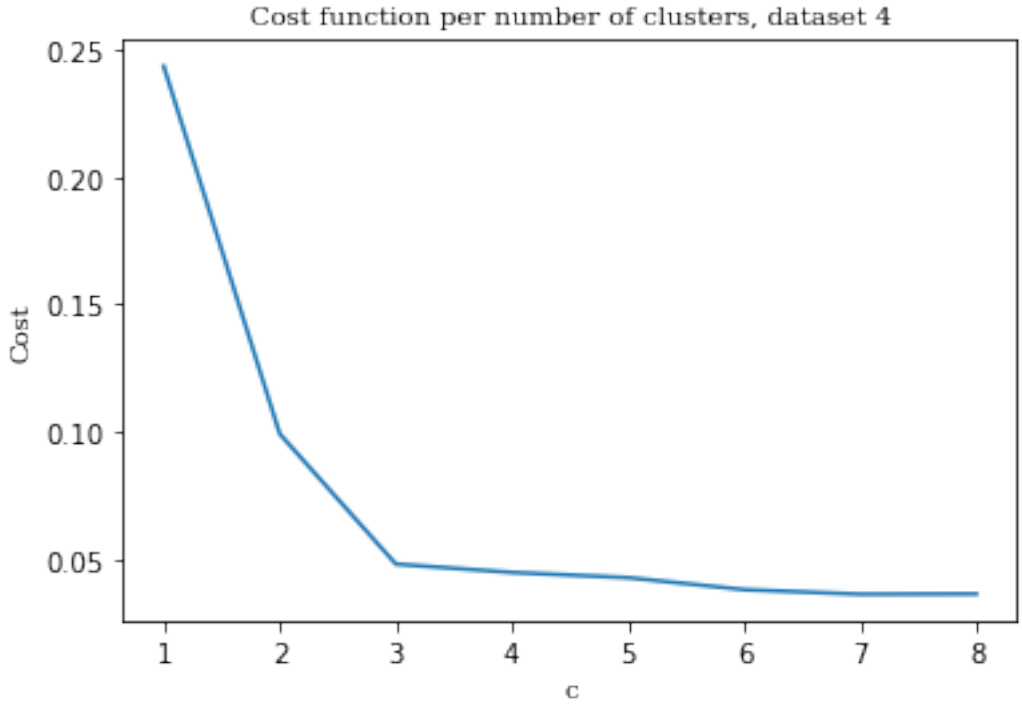
we used elbow method in order to find a good number of clusters.

[10]:
```
c = 8
m = 1.25

for i in range(0, len(our_datasets)):
    plot_cost(our_datasets[i], i + 1, c, m)
```


Cost function per number of clusters, dataset 1
Cost
180
160
140
120
100
80
60
40
1
2
3
4
5
6
7
8
c


Cost function per number of clusters, dataset 2
Cost
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
1
2
3
4
5
6
7
8
c



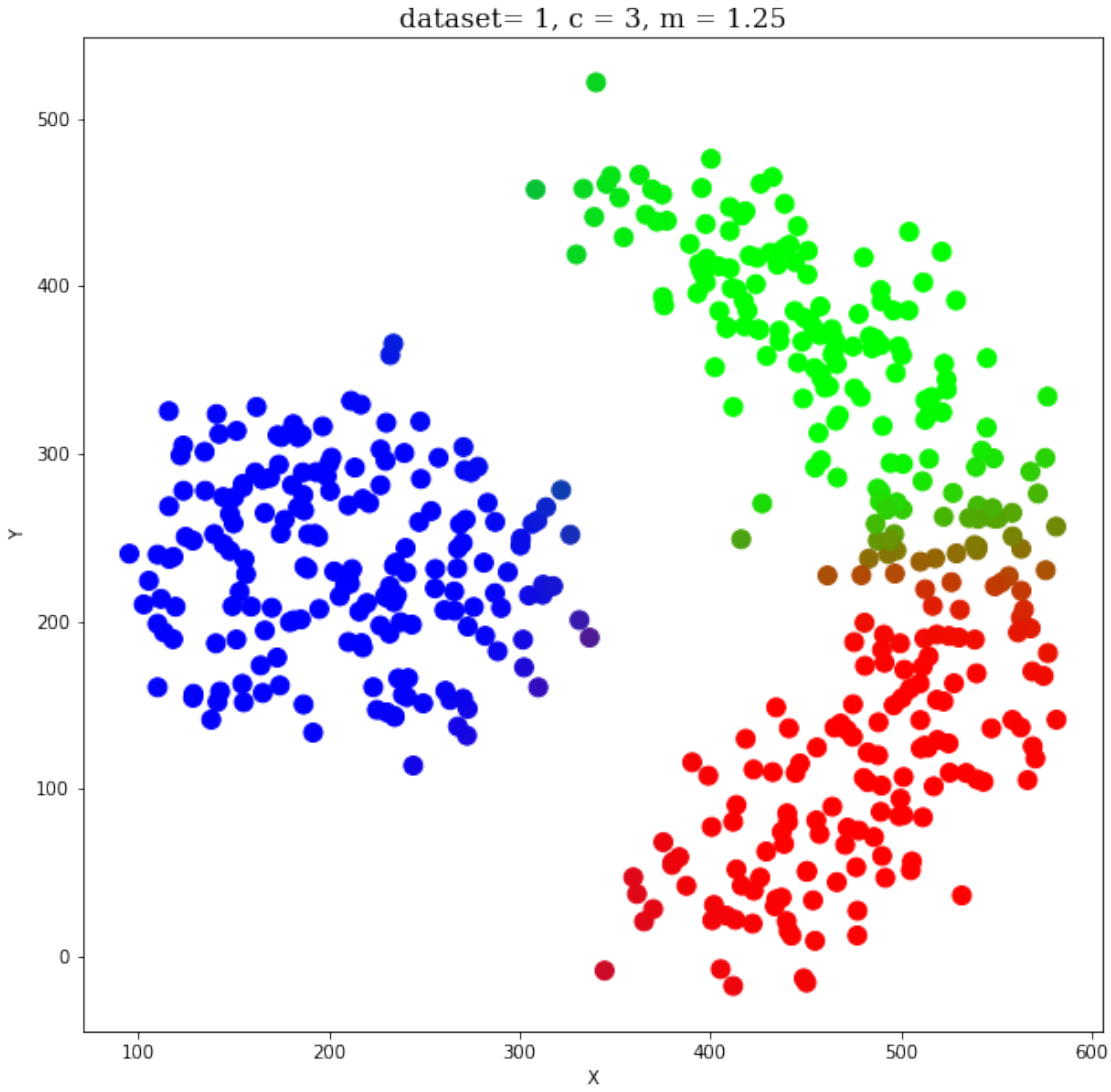


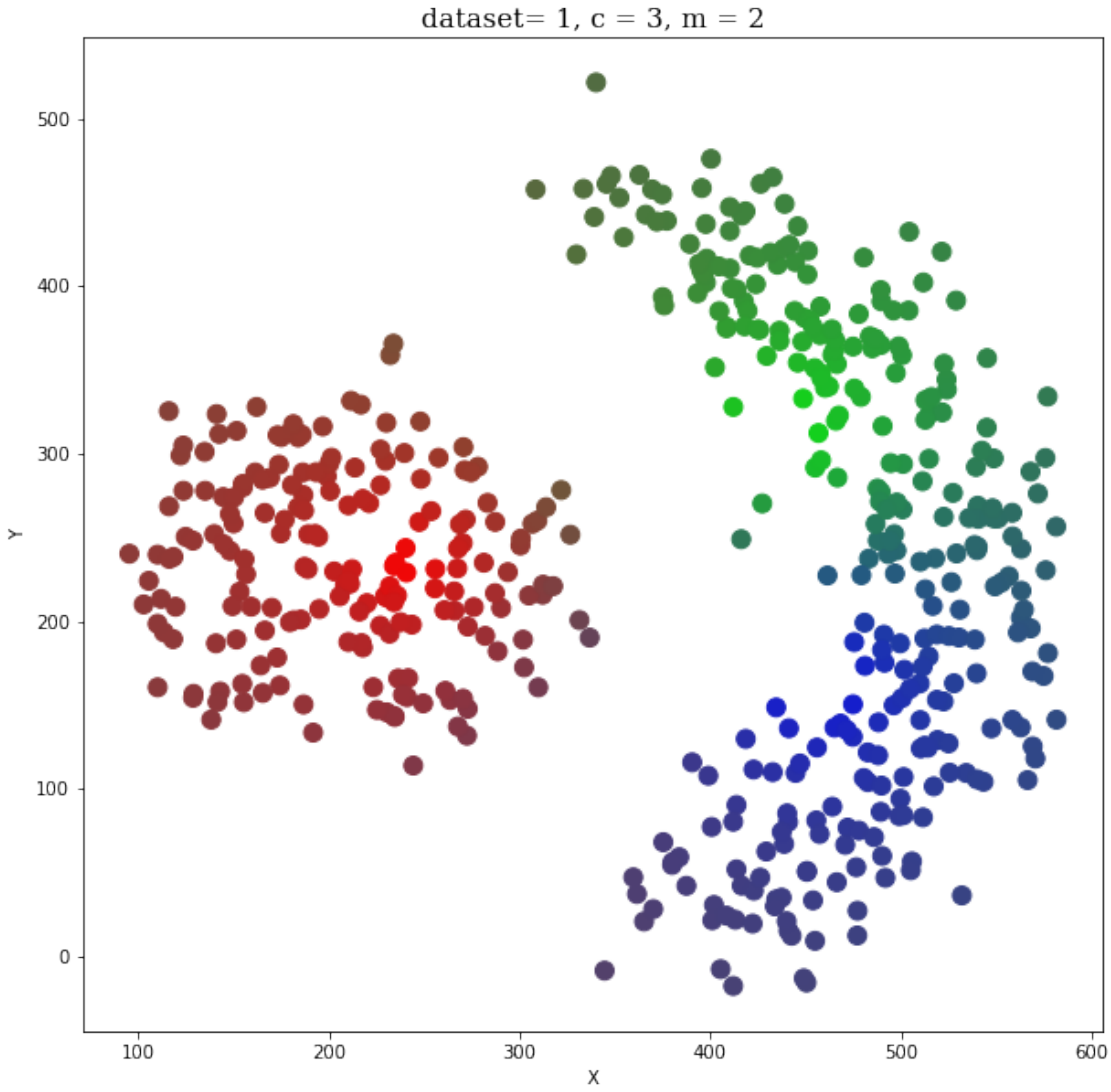
looking at the charts we would find out: On dataset 1, c = 3, On dataset 2, c = 4, On dataset 3, c

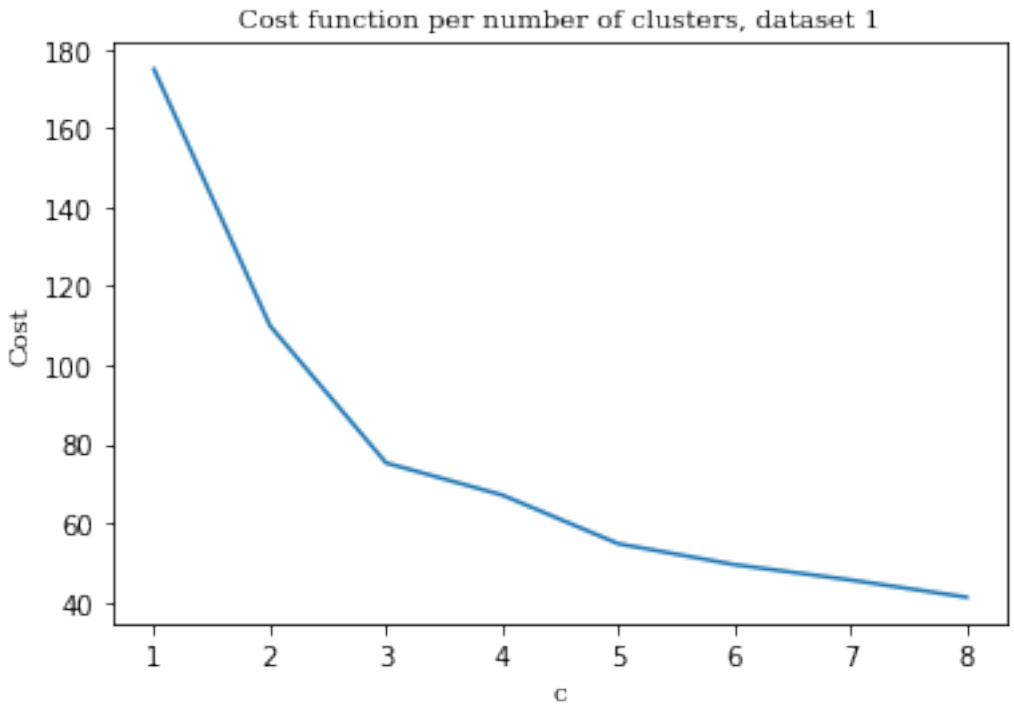
= 5, On dataset 4, c = 3, can be appropriate.

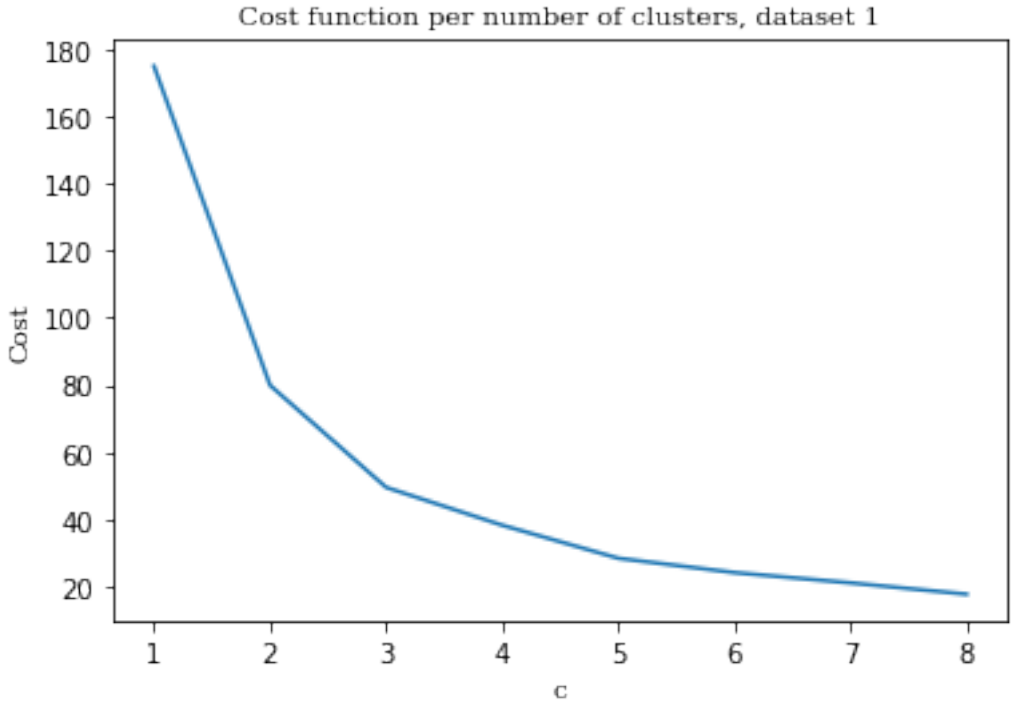
1.5 Running algortihm with different value m

[20]:
```
df = our_datasets[0]
c = 3
max_it = 100

font1 = {'family':'serif','color':'black','size':15}

m = 1.25
centroids, membership_matrix, minvalue_seri = c_means(df, c, m, max_it)
df_clustered = df.copy()
df_clustered.loc[:, "Cluster"] = minvalue_seri

fig, ax = plt.subplots(figsize=(10, 10))
ax.scatter(x = df[0], y = df[1], s=100, c= membership_matrix)
plt.xlabel("X")
plt.ylabel("Y")
plt.title('dataset= 1' + ', c = '+ str(c) + ', m = ' + str(m), fontdict = font1)
plt.show()

m = 2
centroids, membership_matrix, minvalue_seri = c_means(df, c, m, max_it)
df_clustered = df.copy()
df_clustered.loc[:, "Cluster"] = minvalue_seri

fig, ax = plt.subplots(figsize=(10, 10))
ax.scatter(x = df[0], y = df[1], s=100, c= membership_matrix)
plt.xlabel("X")
plt.ylabel("Y")
plt.title('dataset= 1' + ', c = '+ str(c) + ', m = ' + str(m), fontdict = font1)
plt.show()

m = 1.25
c = 8
plot_cost(our_datasets[0], 1, c, m)

m = 2
c = 8
plot_cost(our_datasets[0], 1, c, m)
```


dataset= 1, c = 3, m = 1.25
500
400
300
200
100
0
Y
100
200
300
400
500
600
X


dataset= 1, c = 3, m = 2
500
400
300
200
100
0
Y
100
200
300
400
500
600
X





looking at colours, we can find out by increasing m, usually m can be between 1.25 and 2, our

clustering got more fuzzy.