First we read the datasets

we simply define some colors for the clusters corresponding to each dataset(for example dataset 1 will have 2 clusters later)

In [ ]:
```
import pandas as pd
df1 = pd.read_csv("./first_clustering_dataset.csv", header=None)
df2 = pd.read_csv("./second_clustering_dataset.csv", header=None)
df3 = pd.read_csv("./third_clustering_dataset.csv", header=None)

df1_color_set = {0: "#4682b4", 1: "#ad0a51"}
df2_color_set = {0: "#8a2e22", 1: "#8a5322", 2: "#8a7222", 3: "#878a22",
                 4: "#698a22", 5: "#3e8a22", 6: "#22878a", 7: "#22668a", 8: "#223f8a"}
df2_color_set2 ={0: "#4682b4", 1: "#ad0a51", 2: "#0aad8a"}
df3_color_set = {0: "#4682b4", 1: "#ad0a51", 2: "#0aad8a", 3: "#9f0aad", 4: "#0a64ad"}
df3_color_set2 ={0: "#4682b4", 1: "#ad0a51"}
```

Just a quick review of the datasets

In [ ]:
```
print(df1)
print("============================================")
df1.describe()
```

```
            0         1
0   -0.125391 -1.268829
1    0.062522  1.278778
2   -0.048762  0.200549
3    0.105585 -0.496629
4    0.011886 -0.739317
..        ...       ...
395  0.248226 -1.088287
396  0.205768 -0.421411
397  0.269167  0.695011
398  0.211597  0.977275
399  0.261713 -0.993928

[400 rows x 2 columns]
============================================
```

Out[ ]:

	0	1
count	400.000000	400.000000
mean	0.124219	-0.012087
std	0.139098	0.988992
min	-0.135468	-3.286417
25%	-0.000858	-0.727178
50%	0.135032	0.028863
75%	0.251976	0.639484
max	0.365536	2.967989

In [ ]:
```
print(df2)
print("============================================")
df2.describe()
```

```
             0          1
0     1.047961   0.357217
1     0.201221   0.295197
2     0.163506  -1.846756
3     0.876857   1.499314
4     1.389838   0.092843
..         ...        ...
445  12.353425  21.892071
446  12.398762  21.301938
447  12.713268  19.627323
448  13.503682  20.372600
449  12.546129  19.866065

[450 rows x 2 columns]
============================================
```

Out[ ]:

	0	1
count	450.000000	450.000000
mean	12.973701	6.685215
std	8.610405	7.634260
min	-2.655059	-2.243070
25%	5.687410	0.154821
50%	12.872814	4.359575
75%	20.514214	14.873280
max	28.847761	23.683402

In [ ]:
```
print(df3)
print("============================================")
df3.describe()
```

```
            0         1
0    0.315715  0.230080
1   -0.420268  0.609144
2    0.102944 -1.117928
3   -0.105657 -0.112488
4   -0.674778  0.130790
..        ...       ...
495  1.618047  2.610644
496  1.997595  1.888732
497  2.870525  1.726396
498  1.760763  2.430575
499  2.541713  1.661525

[500 rows x 2 columns]
============================================
```

Out[ ]:

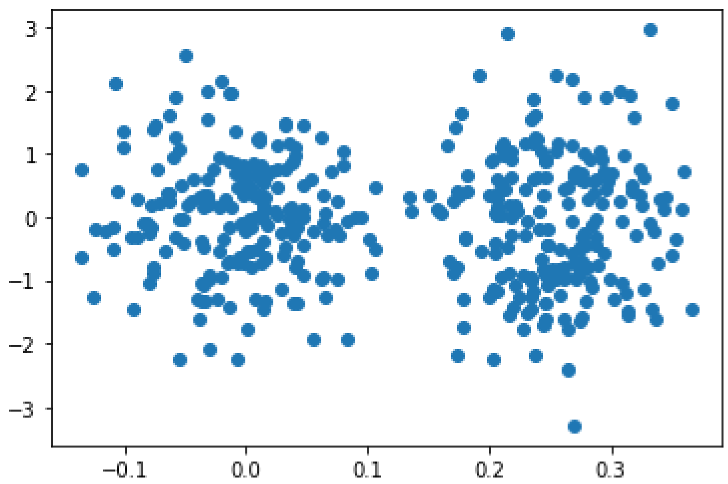
	0	1
count	500.000000	500.000000
mean	2.048625	1.208745
std	1.649316	1.104357
min	-1.295953	-1.511252
25%	0.460990	0.169674
50%	2.020882	1.657572
75%	3.676495	2.121065
max	4.998794	3.005554

Now first plots of datasets

For the first data set it seems to have 2 clusters. so 2 is our guess. we'll see later if 2 is a good guess

In [ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.scatter(x=df1[0], y=df1[1])
```

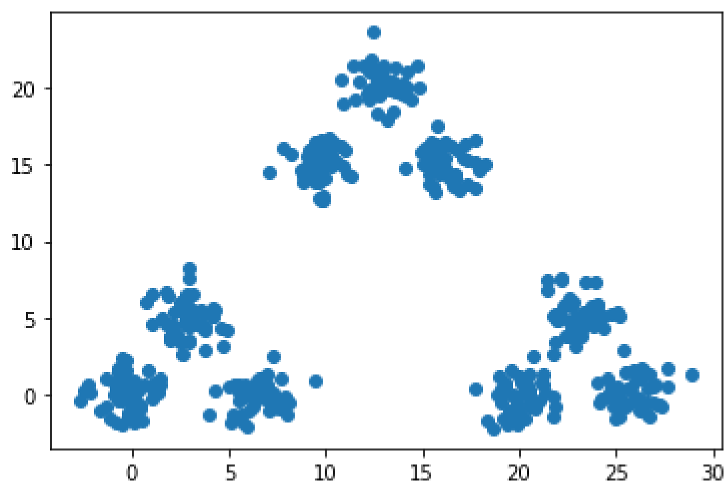
Out[ ]: <matplotlib.collections.PathCollection at 0x7f91338b6550>



For the second data set it seems to have 9 clusters. so 9 is our guess. but in another way it also may have 3 clusters. we'll see later if 9 or 3 is a good guess

In [ ]:
```
plt.scatter(x=df2[0], y=df2[1])
```

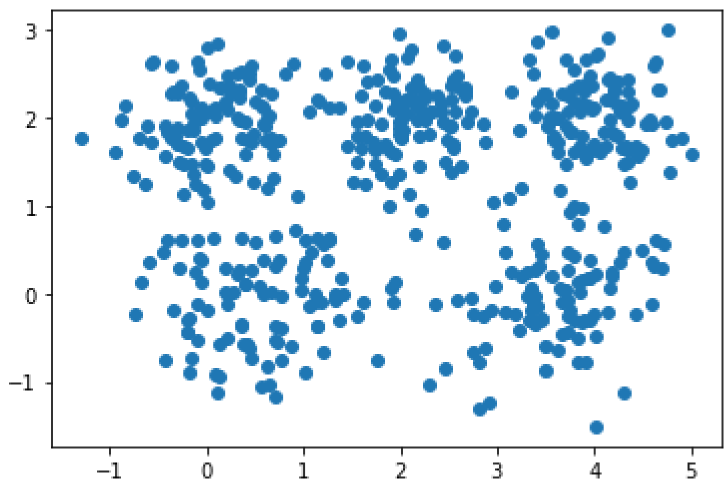
Out[ ]: <matplotlib.collections.PathCollection at 0x7f91338c2a00>



For the third data set it seems to have 5 clusters. so 5 is our guess. we'll see later if 5 is a good guess

In [ ]:
```
plt.scatter(x=df3[0], y=df3[1])
```

Out[ ]: <matplotlib.collections.PathCollection at 0x7f9133b8e6a0>



Here we define the main function for KMeans model. it gets the dataset as "df", number of desired clusters as "n_clusters" and the corresponding color set.

Then it fits the model. predict the data. and plot some stuff and measures it with silhouette_score and prints all we need

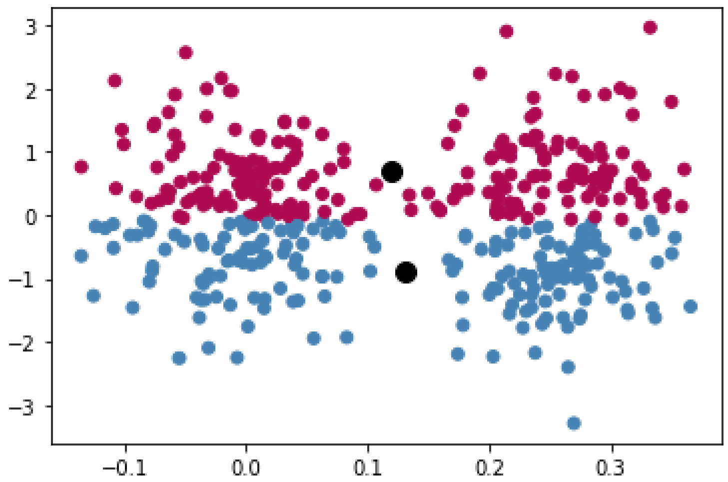
In [ ]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
def reportSilhouetteScore(df, labels):
    print(f"silhouette_score: {silhouette_score(df, labels)}")


def runKMeans(df, n_clusters, color_set):
    model = KMeans(n_clusters=n_clusters, random_state=42)
    labels = model.fit_predict(df)
    plotKMeansClusteringResult(df, model, color_set)
    print(f"SSE: {model.inertia_}")
    reportSilhouetteScore(df, labels)

def plotKMeansClusteringResult(df, model, color_set):
    plt.scatter(df[0], df[1], c=[color_set[c] for c in model.predict(df)])
    plt.scatter(model.cluster_centers_[:, 0], model.cluster_centers_[:, 1], s=100, c='black')
```

And here we just need to all the function we mentioned earlier.

First dataset

In [ ]:
```
runKMeans(df1, 2, df1_color_set)
```

```
SSE: 146.88856005335137
silhouette_score: 0.5362906097948957
```

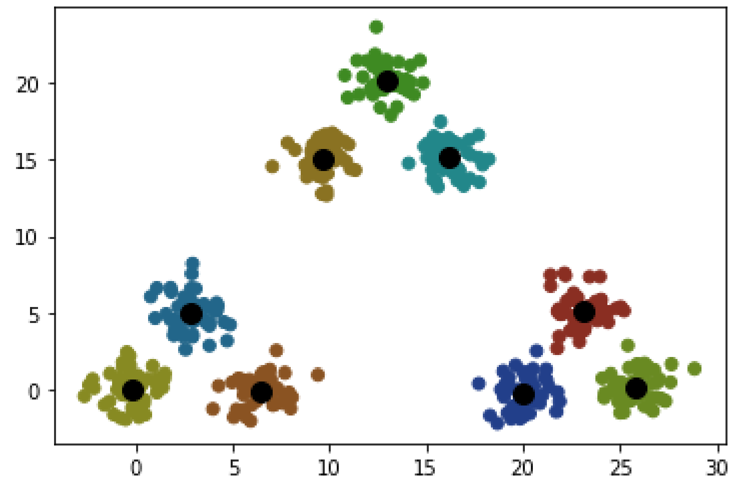


not good!

Second dataset (for 9 clusters)

In [ ]:
```
runKMeans(df2, 9, df2_color_set)
```

```
SSE: 859.3931951407194
silhouette_score: 0.6925519321164127
```

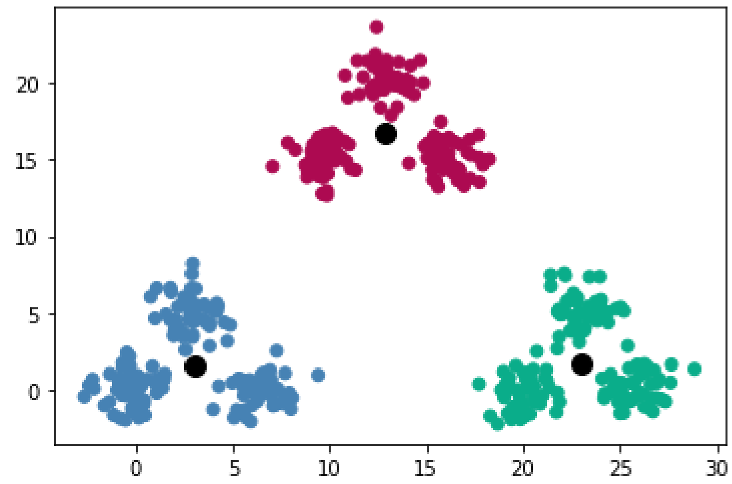


seems pretty good!

Second dataset (with 3 clusters)

In [ ]:
```
runKMeans(df2, 3, df2_color_set2)
```

```
SSE: 6487.004526263209
silhouette_score: 0.7240379233766401
```

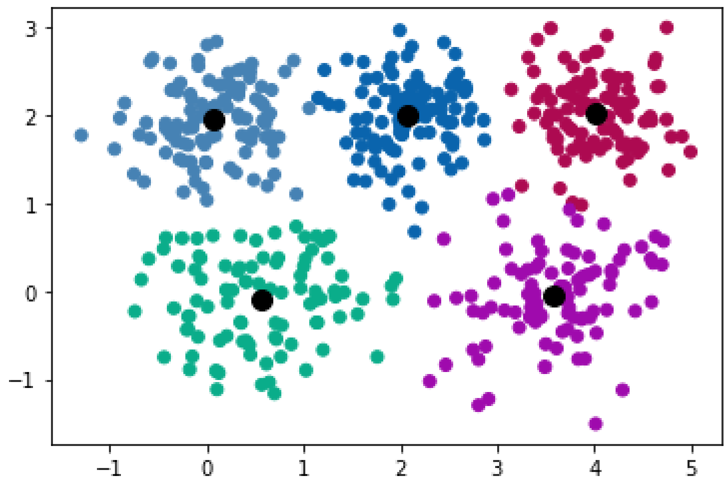


pretty good again!

Third dataset:

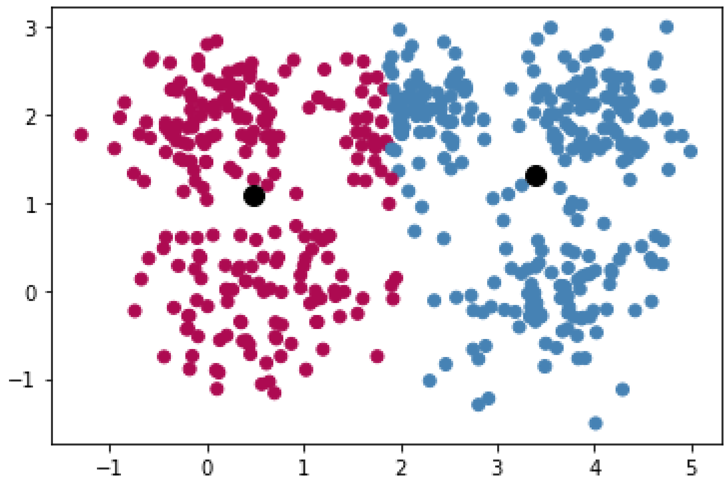
In [ ]:
```
runKMeans(df3, 5, df3_color_set)
```

```
SSE: 222.3659877692909
silhouette_score: 0.5604142087131664
```



In [ ]:
```
runKMeans(df3, 2, df3_color_set2)
```

```
SSE: 908.1713254614044
silhouette_score: 0.4597651234688414
```



pretty good again!

So far Kmean has woked very well!

To make sure if the guessed n_clusters are correct we need to draw the Knee point plot:

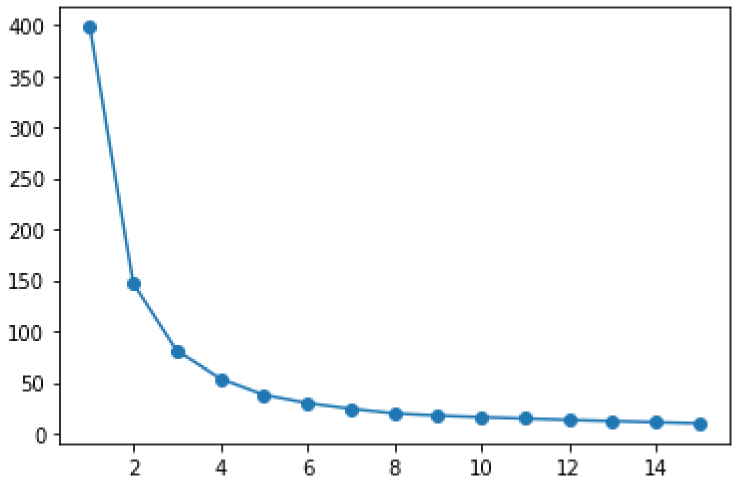
To do this we just define a function that creates the model 200 times with k=0, ... 16 and then calculates the mean of it and the plot it

```
In [ ]: def drawKneePoint(df):
            Ys = []
            for k in range(1, 16):
                l = []
                for i in range(20): #20 is enough. most are the same!
                    model = KMeans(n_clusters=k, random_state=i)
                    model.fit(df)
                    l.append(model.inertia_)
                Ys.append(sum(l)/len(l))
            plt.scatter(x=[i for i in range(1, 16)], y=Ys)
            plt.plot([i for i in range(1, 16)], Ys)
```

Now we just call the function

First dataset

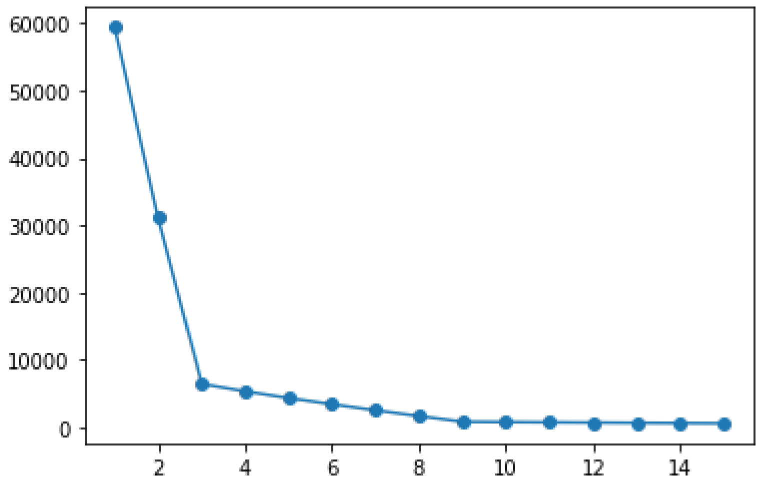
```
In [ ]: drawKneePoint(df1)
```



K=2 is the knee point

Second dataset

```
In [ ]: drawKneePoint(df2)
```

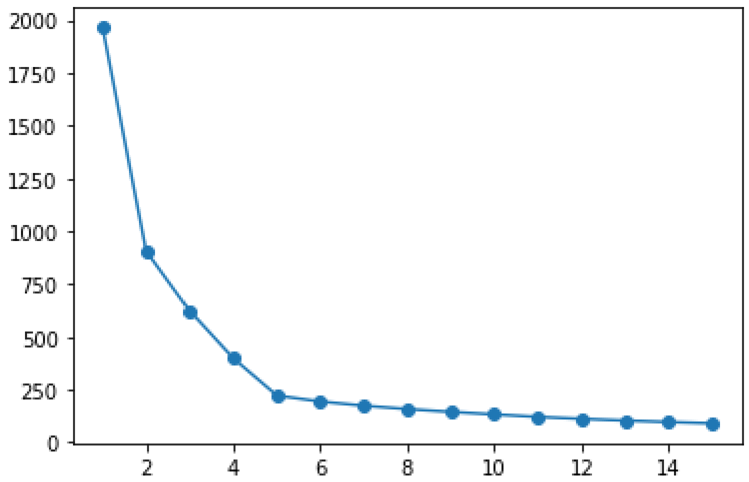


K=3 is the knee point

Also K=9 can be a knee point(as we can guess by eye)

Third dataset

```
In [ ]: drawKneePoint(df3)
```



K=2 and K=5 are knee points.

we'll see the score for them later

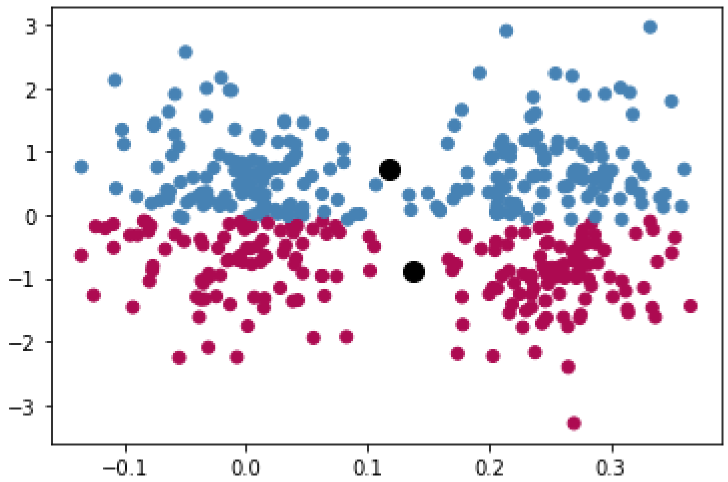
Now we go for the FCM model. Just the same we just define a function that does all the stuff for us and later we just call it with the three datasets

In [ ]:
```
from fcmeans import FCM
def runFCM(X, n_clusters, color_set):
    model = FCM(n_clusters=n_clusters, random_state=42)
    model.fit(X)
    labels = model.predict(X)
    # print(labels)
    plotFCMClusteringResult(X, model, color_set)
    reportSilhouetteScore(X, labels)

def plotFCMClusteringResult(X, model, color_set):
    plt.scatter(X[:, 0], X[:, 1], c=[color_set[c] for c in model.predict(X)])
    plt.scatter(model.centers[:, 0], model.centers[:, 1], s=100, c='black')
```

First dataset

In [ ]:
```
runFCM(df1.values, 2, df1_color_set)
```

```
silhouette_score: 0.5362906097948957
```

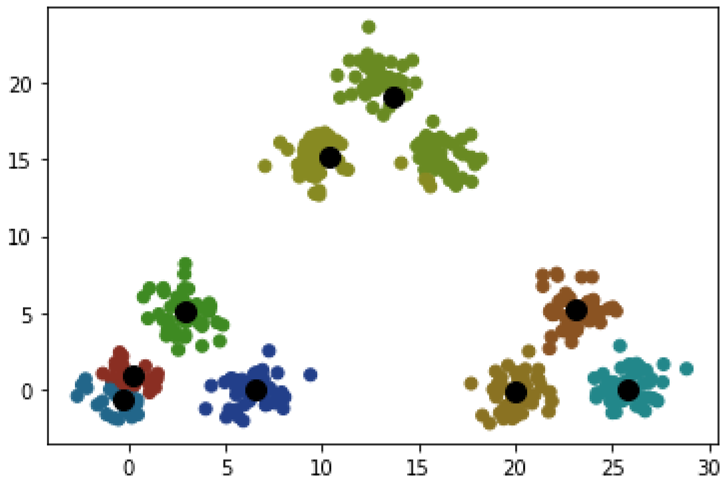


Not good!

Second dataset(9 clusters)

In [ ]:
```
runFCM(df2.values, 9, df2_color_set)
```

```
silhouette_score: 0.5681960198683133
```

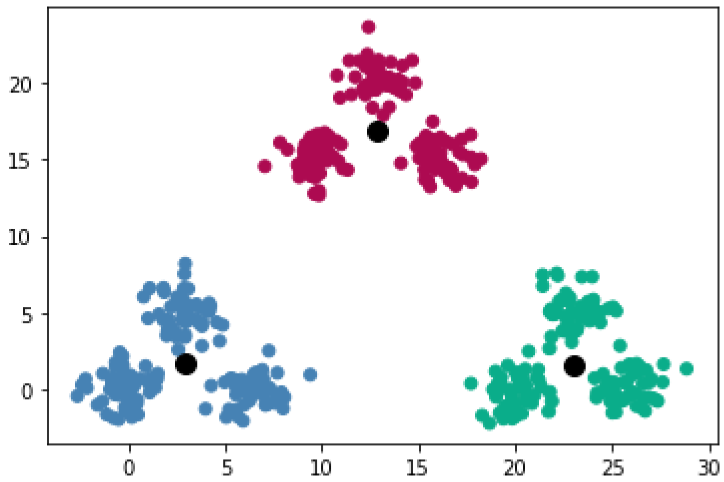


seems good but centroids are not much percise and also one cluster is merged with another one

Second dataset(3 clusters)

In [ ]:
```
runFCM(df2.values, 3, df2_color_set2)
```

```
silhouette_score: 0.7240379233766401
```

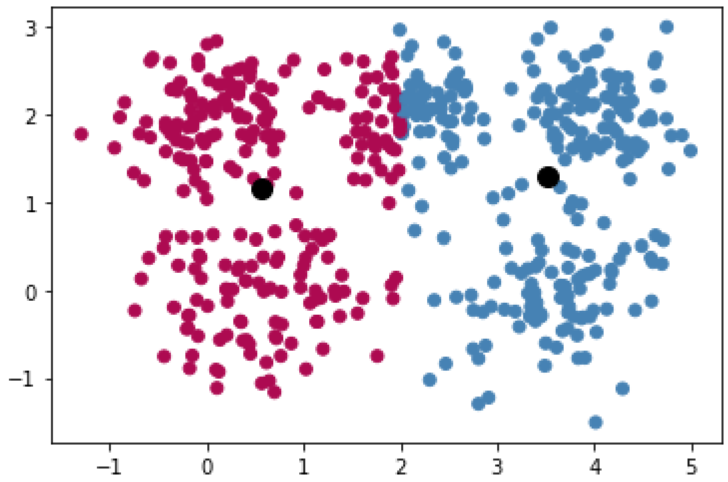


Pretty good

Third dataset

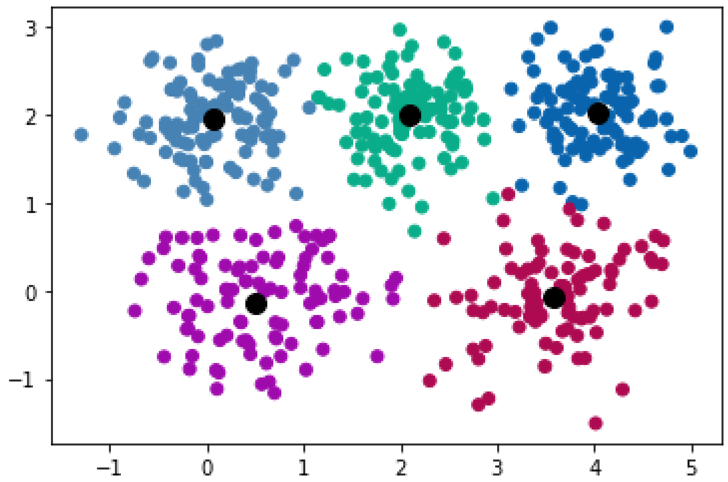
In [ ]:
```
runFCM(df3.values, 2, df3_color_set2)
```

```
silhouette_score: 0.45534072562474137
```



In [ ]:
```
runFCM(df3.values, 5, df3_color_set)
```

```
silhouette_score: 0.5605130818892635
```



it seems that our guess got more score! (56 compare to 45)

it proves that in the knee point plot k=5 is better!

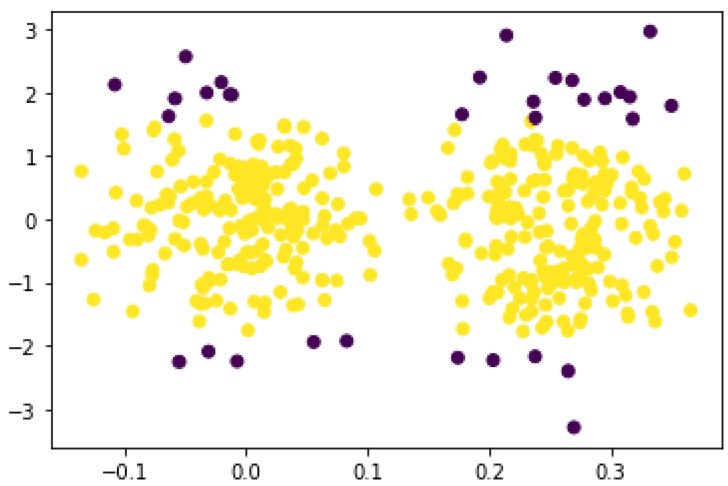
At the end, again we define a function ...

In [ ]:
```
from sklearn.cluster import DBSCAN
def runDBScan(df, **params):
    model = DBSCAN(**params)
    labels = model.fit_predict(df)

    plotDBScanClusteringResult(df, labels)
    reportSilhouetteScore(df, labels)


def plotDBScanClusteringResult(df, labels):
    plt.scatter(df[0], df[1], c=labels)
```

First dataset

In [ ]:
```
runDBScan(df1, eps=0.32, min_samples=33)
```

```
silhouette_score: 0.503987643756188
```

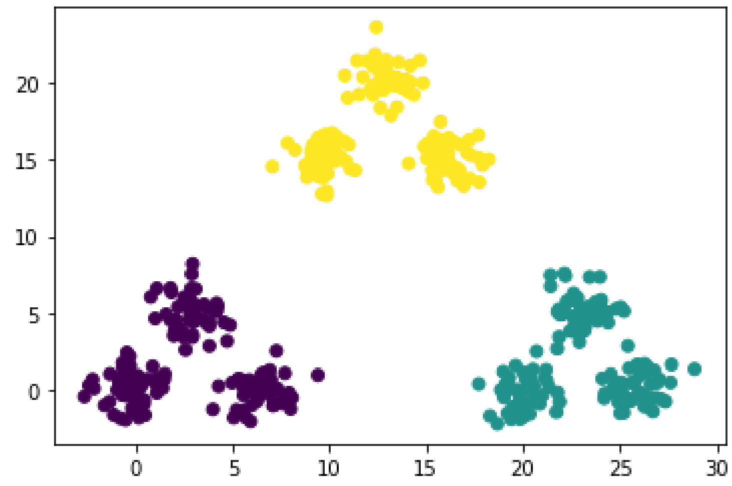


Very Bad!!!

Second dataset

In [ ]:
```
runDBScan(df2, eps=2.9, min_samples=20)
```

```
silhouette_score: 0.7240379233766401
```

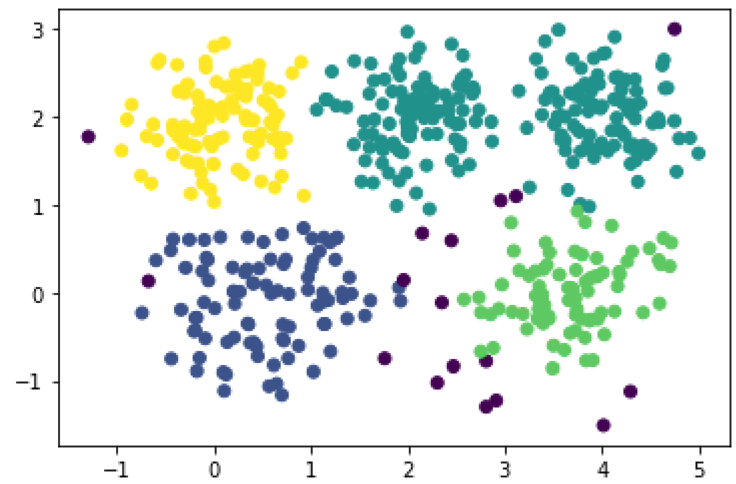


Bad!

Third dataset

```
In [ ]: runDBScan(df3, eps=0.55, min_samples=20)
```

```
silhouette_score: 0.43974768868065206
```



Bad again!

Conclusion

Before the comparison we should say that we didn't need to repeat running model 200 times because the results were the same.(even when setting the "random_state" each time with a different number)

Comparison

K-Means SSE	SSE
Dataset(I) 2 clusters	146.88856005335137
Dataset(II) 9 clusters	859.3931951407194
Dataset(II) 3 clusters	6487.00452626321
Dataset(III) 5 clusters	222.36598776929088
Dataset(III) 2 clusters	908.1713254614045

Silhoutter Score	K-Means	FCM	result of comparison
Dataset(I) 2 clusters	0.5362906097948957	0.5362906097948957	both the same
Dataset(II) 9 clusters	0.6925519321164127	0.5681960198683133	K-Means better
Dataset(II) 3 clusters	0.7240379233766401	0.7240379233766401	both the same
Dataset(III) 5 clusters	0.5604142087131664	0.5605130818892635	K-Means a bit better
Dataset(III) 2 clusters	0.4597651234688414	0.45534072562474137	K-Means a bit better

Silhoutter Score	DBSCAN
Dataset(I)	0.503987643756188
Dataset(II)	0.7240379233766401
Dataset(III)	0.43974768868065206

In compare to DBSCAN; for the second data set all three models were the same. For Other dataset K-Means were better a bit.