TP1_ELFILALI_NGUYEN

December 21, 2018

1 TP Clustering

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1.1 Partie DBSCAN

On import les dépendances ainsi que le dataSet

```
In [2]: from sklearn import cluster
        import numpy as np
        from sklearn import metrics
        import matplotlib.pyplot as plt
        from sklearn.datasets.samples_generator import make_blobs

        data = np.genfromtxt("cham-data/t4.8k.dat",delimiter=" ")
```

On crée une méthode qui prend en entré le dataSet ainsi que d'autre paramètres

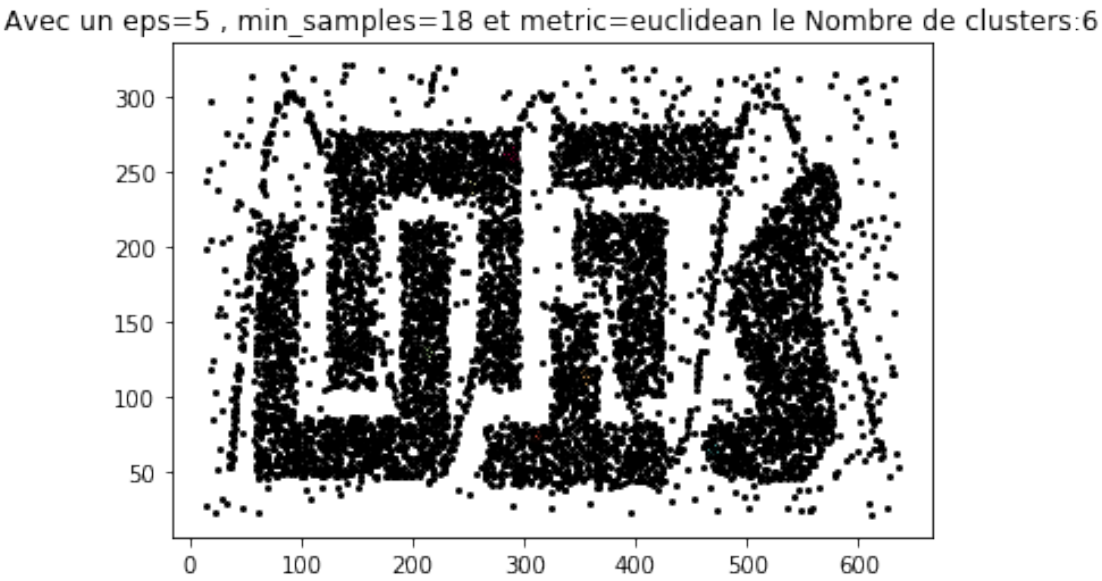
```
In [3]: def meth_dbscan(dataSet,Scores,met='euclidean',minSamples = 18,distance = 10):
            clustering = cluster.DBSCAN(eps=distance,min_samples=minSamples,metric=met).fit(da
            labels = clustering.labels_

            score = metrics.silhouette_score(dataSet, labels)

            Scores.append(score)

            print("Silhouette Coefficient: %0.3f" % score)

            core_samples_mask = np.zeros_like(clustering.labels_, dtype=bool)
            core_samples_mask[clustering.core_sample_indices_] = True

            n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
            unique_labels = set(labels)
            colors = [plt.cm.Spectral(each)
                      for each in np.linspace(0, 1, len(unique_labels))]
            for k, col in zip(unique_labels, colors):
                if k == -1:
                    col = [0, 0, 0, 1]
```

```
            class_member_mask = (labels == k)

            xy = dataSet[class_member_mask & core_samples_mask]
            plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col),
                     markeredgecolor='k', markersize=5)

            xy = dataSet[class_member_mask & ~core_samples_mask]
            plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col),
                     markeredgecolor='k', markersize=2)

        plt.title('Avec un eps='+str(distance)+' , min_samples='+str(minSamples)+' et metri
        plt.show()
```

On teste plusieurs valeur pour la distance (eps) et on obtient le résultat suivant

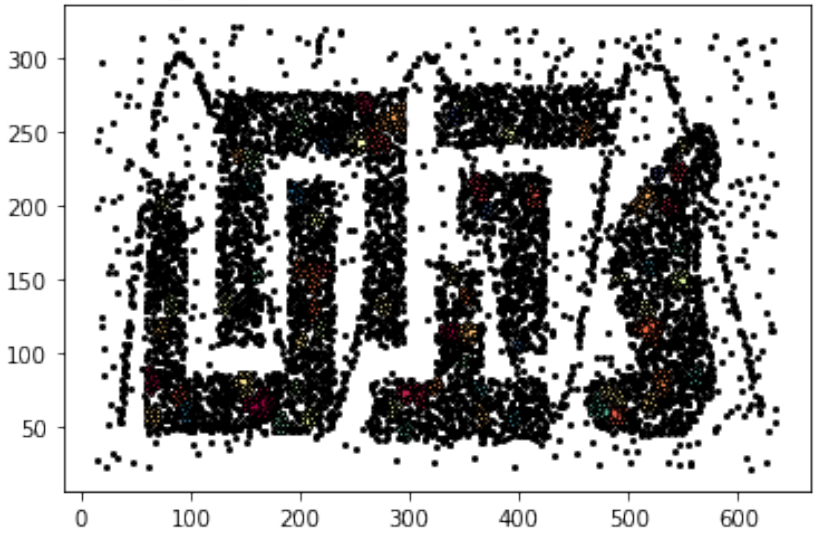
```
In [4]: Scores = []

        for i in range(5,30):
            meth_dbscan(dataSet=data,distance=i,Scores = Scores)
```

```
Silhouette Coefficient: -0.596
```



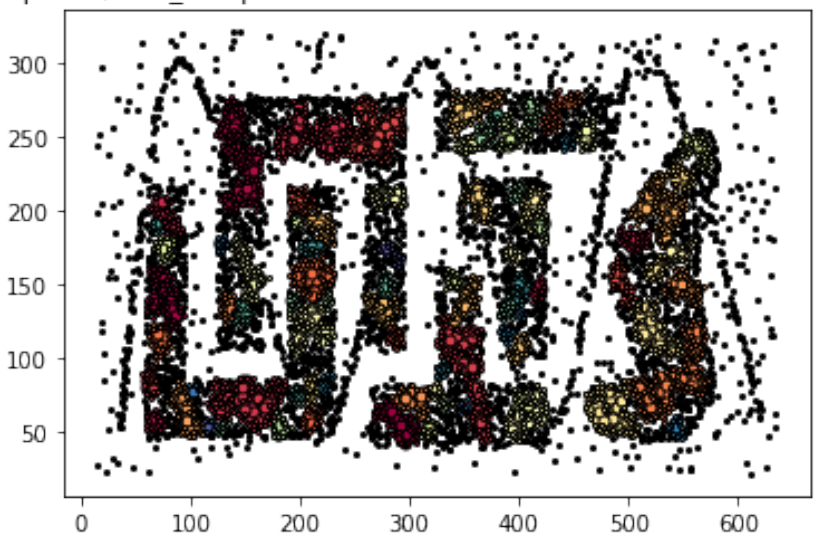

```
Silhouette Coefficient: -0.527
```

Avec un eps=6 , min_samples=18 et metric=euclidean le Nombre de clusters:69

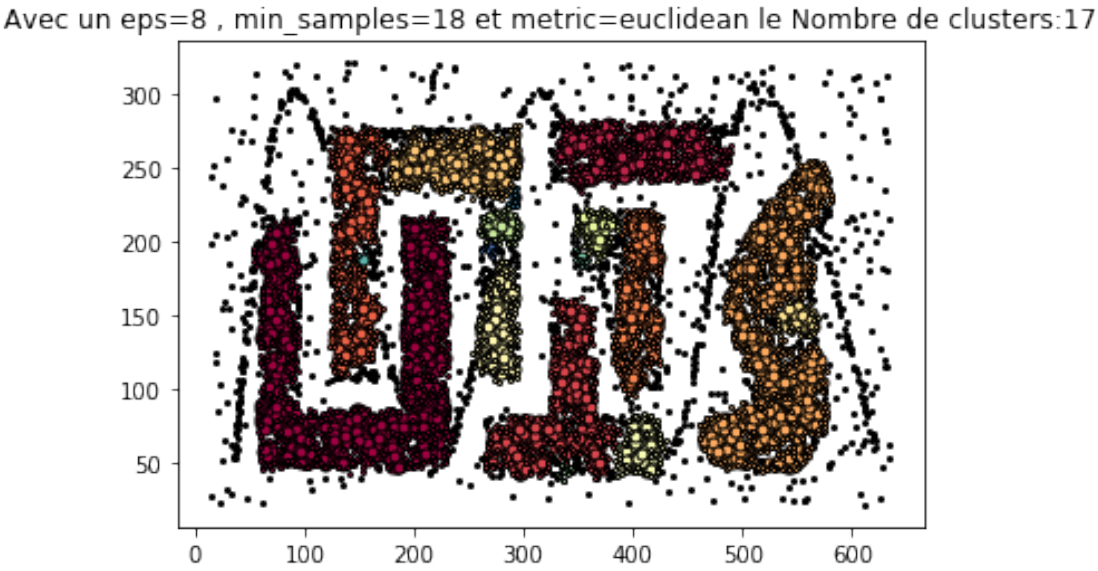



```
Silhouette Coefficient: -0.105
```

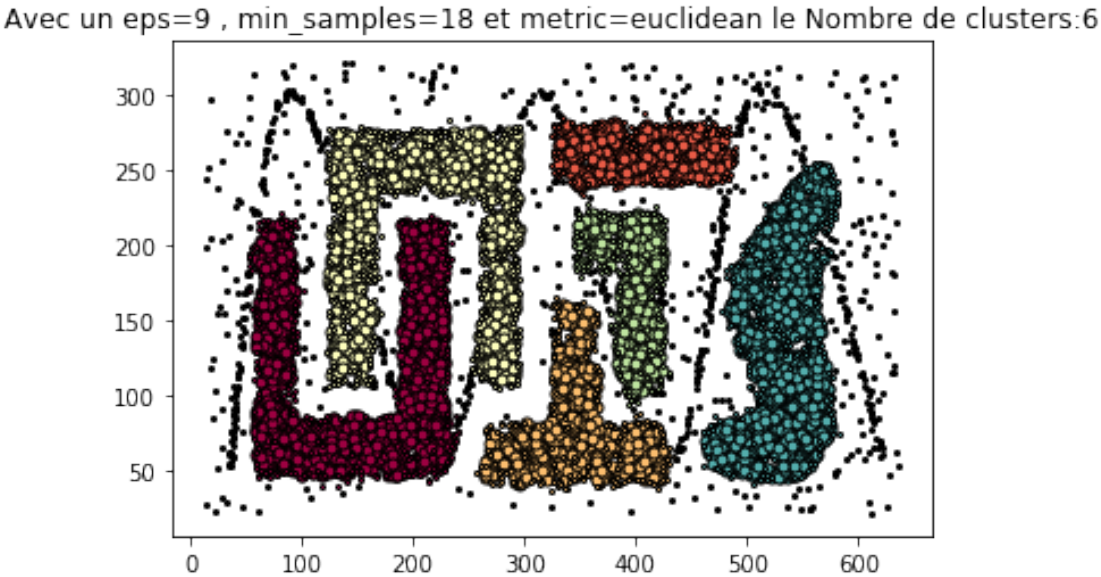
Avec un eps=7 , min_samples=18 et metric=euclidean le Nombre de clusters:85



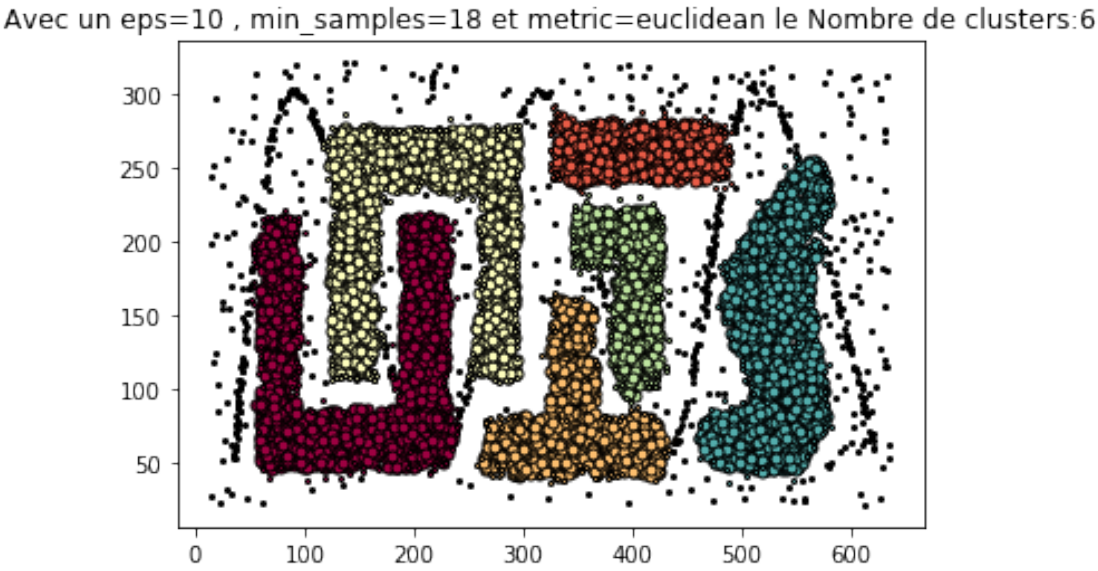

```
Silhouette Coefficient: -0.106
```



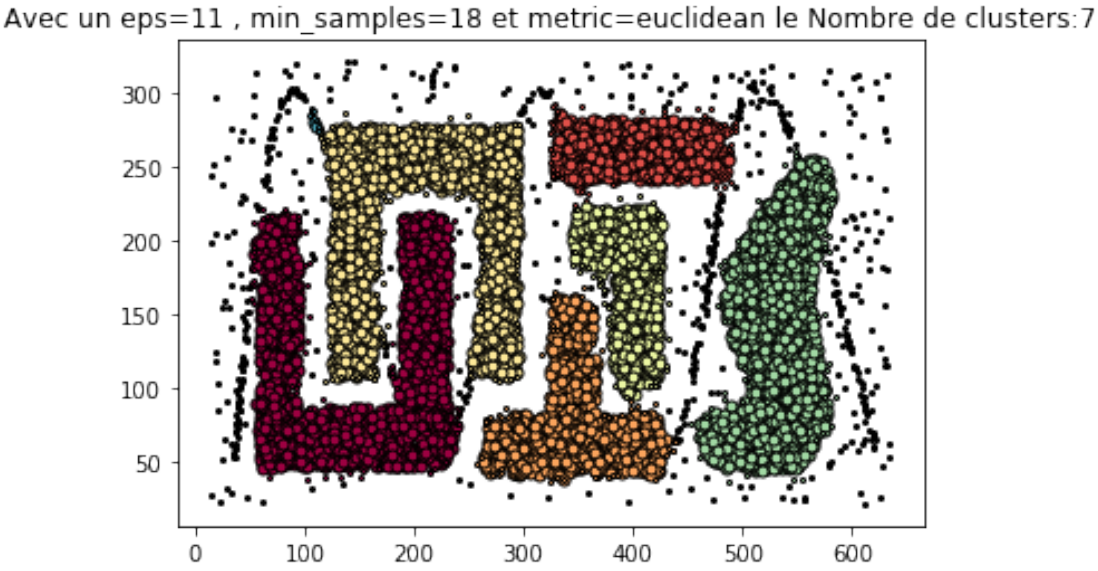

```
Silhouette Coefficient: 0.237
```



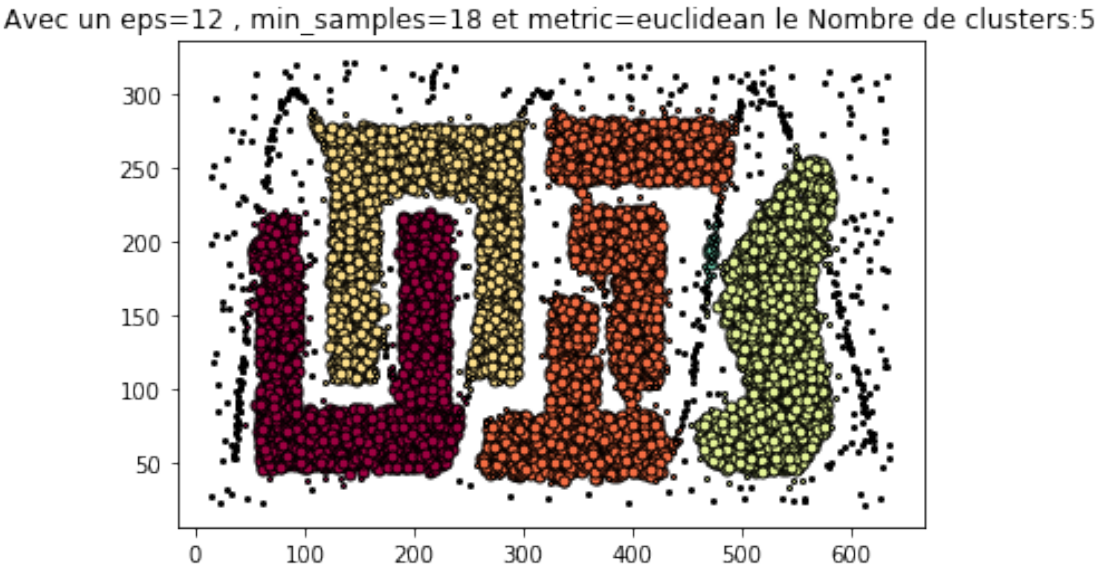

```
Silhouette Coefficient: 0.246
```



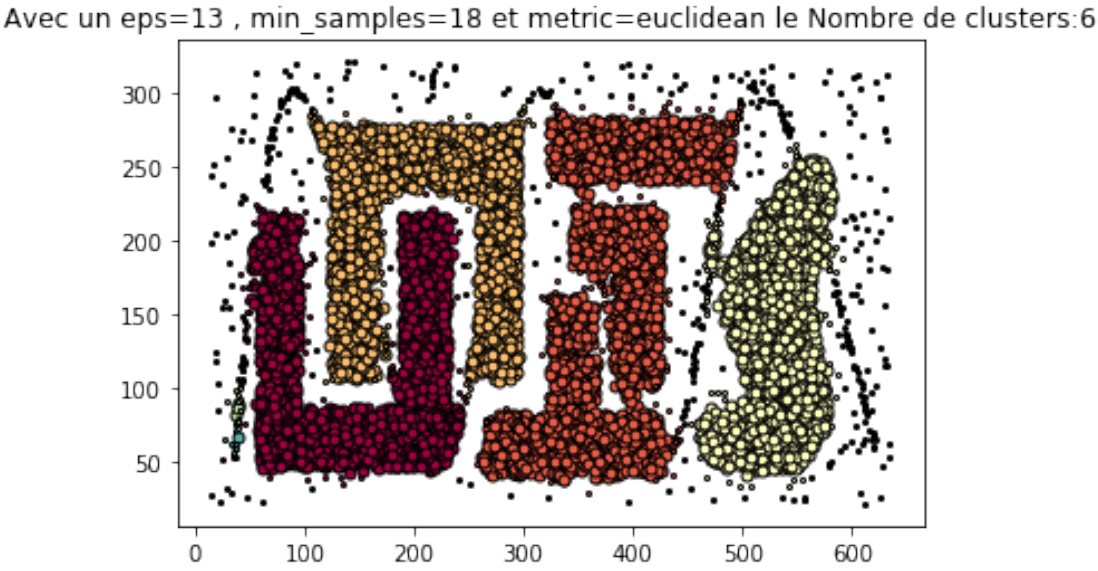

```
Silhouette Coefficient: 0.199
```



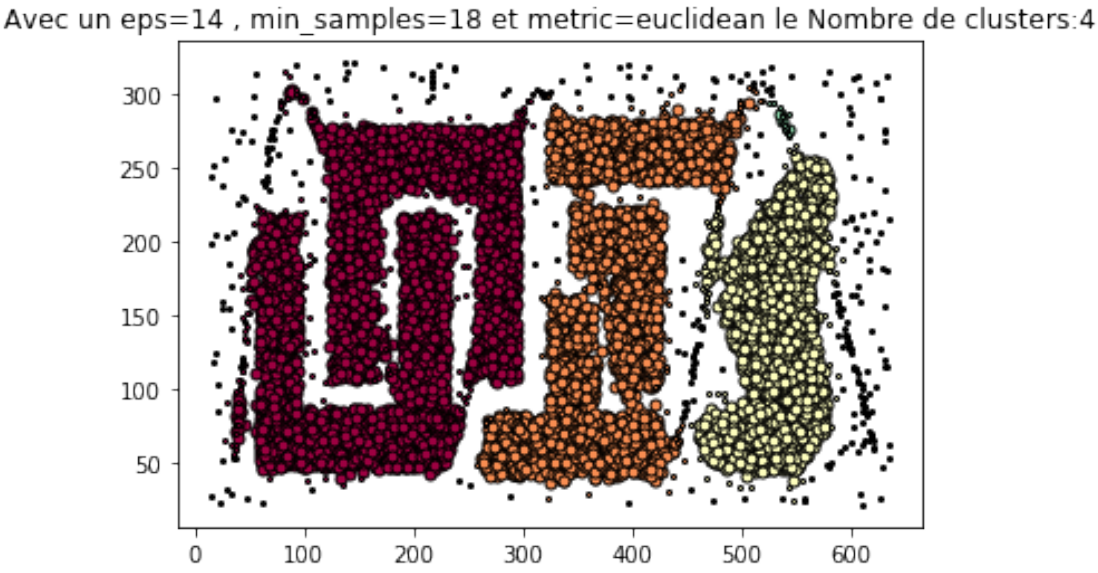

```
Silhouette Coefficient: 0.105
```



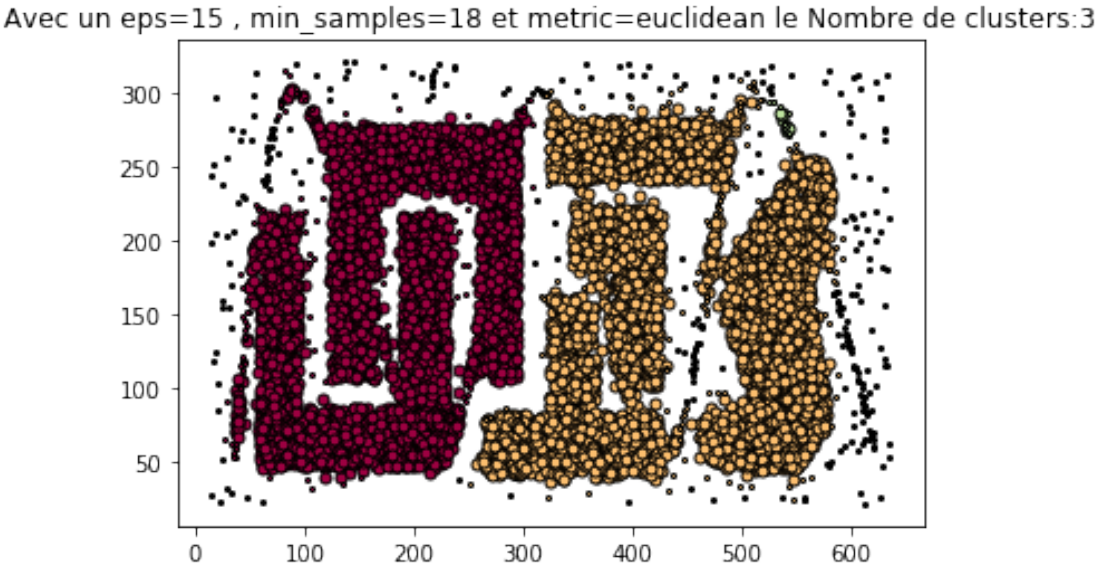

```
Silhouette Coefficient: 0.199
```



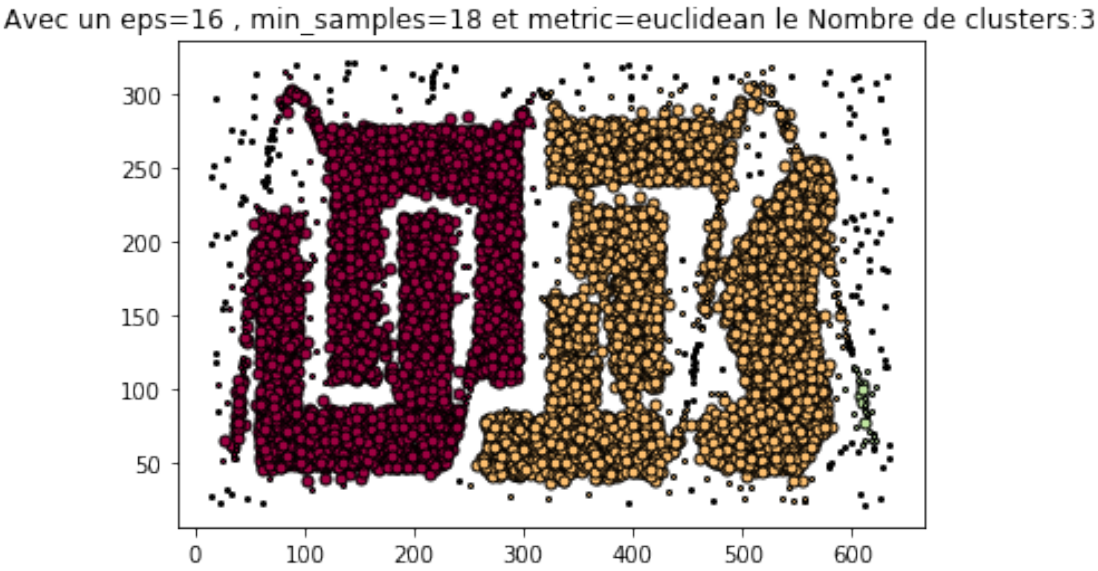

```
Silhouette Coefficient: 0.305
```



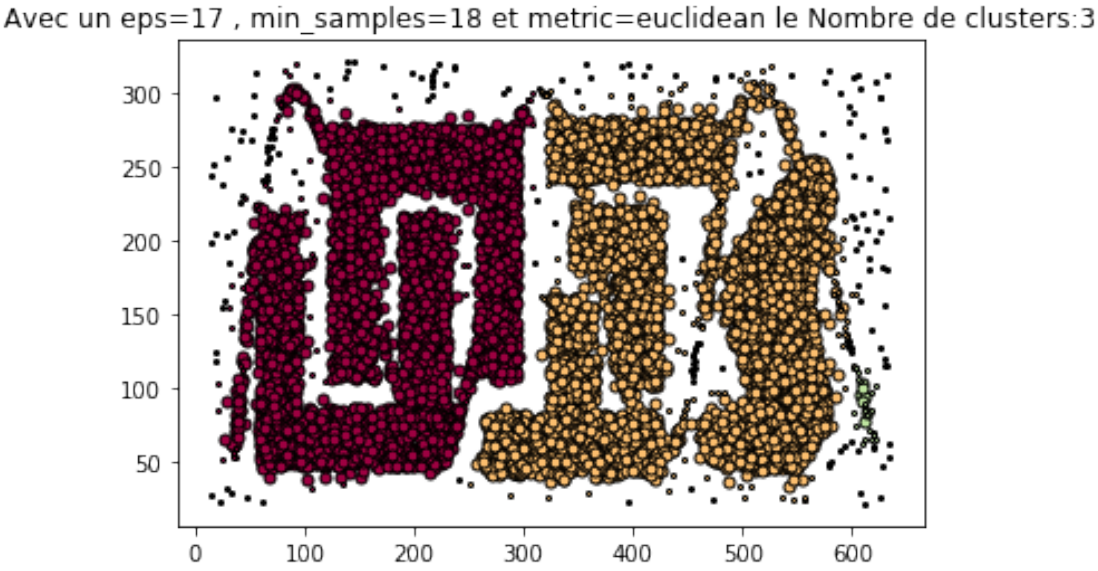

```
Silhouette Coefficient: 0.277
```




```
Silhouette Coefficient: 0.283
```

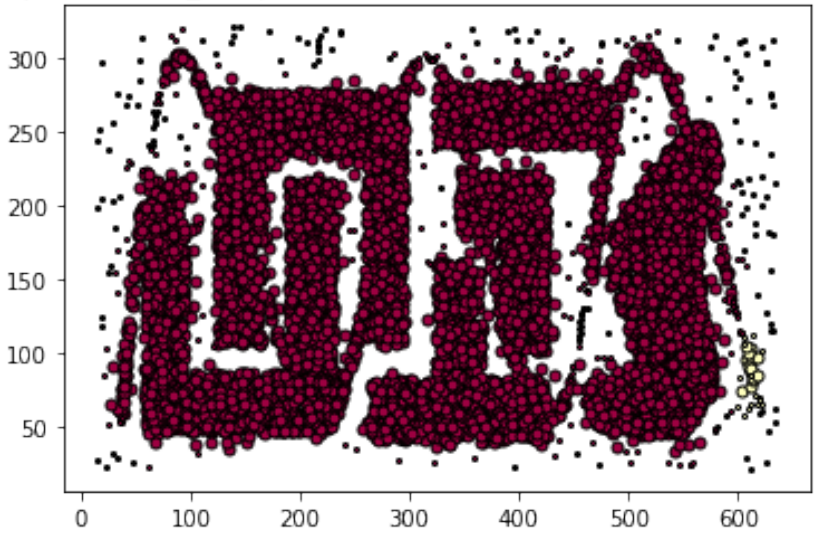


Silhouette Coefficient: 0.287



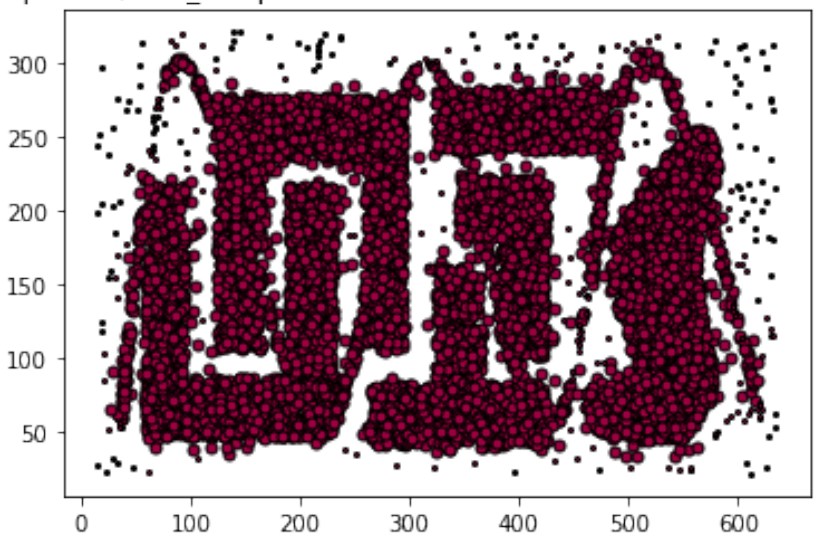
Silhouette Coefficient: 0.092

Avec un eps=18 , min_samples=18 et metric=euclidean le Nombre de clusters:2

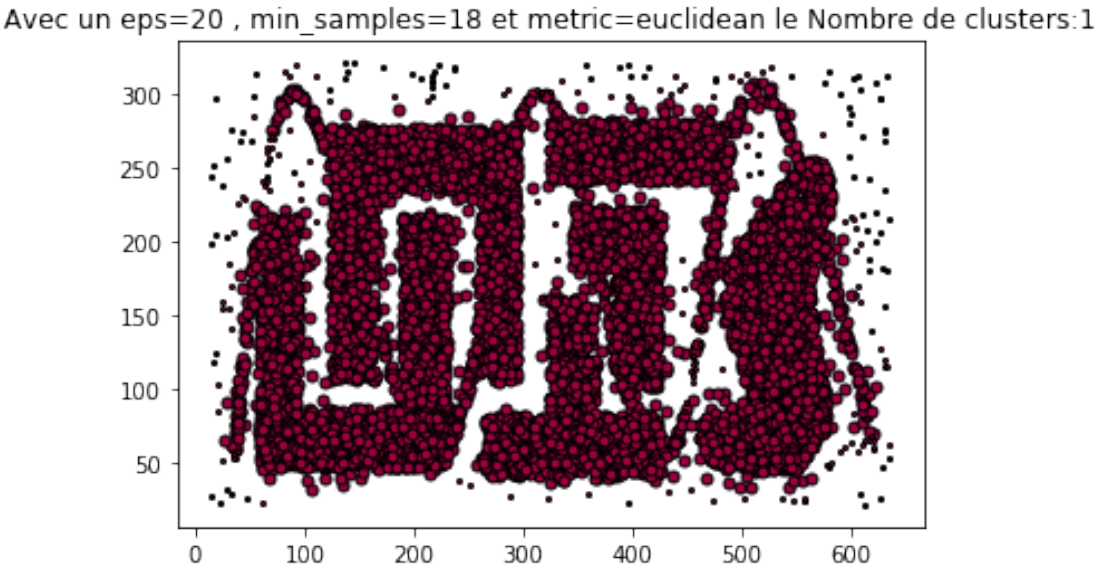



```
Silhouette Coefficient: 0.272
```

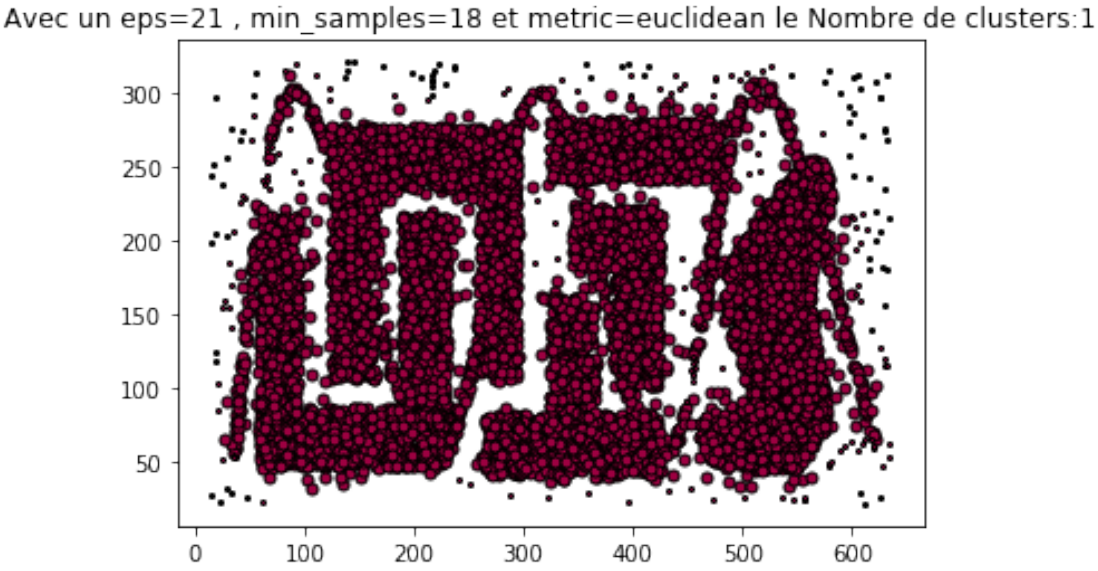
Avec un eps=19 , min_samples=18 et metric=euclidean le Nombre de clusters:1



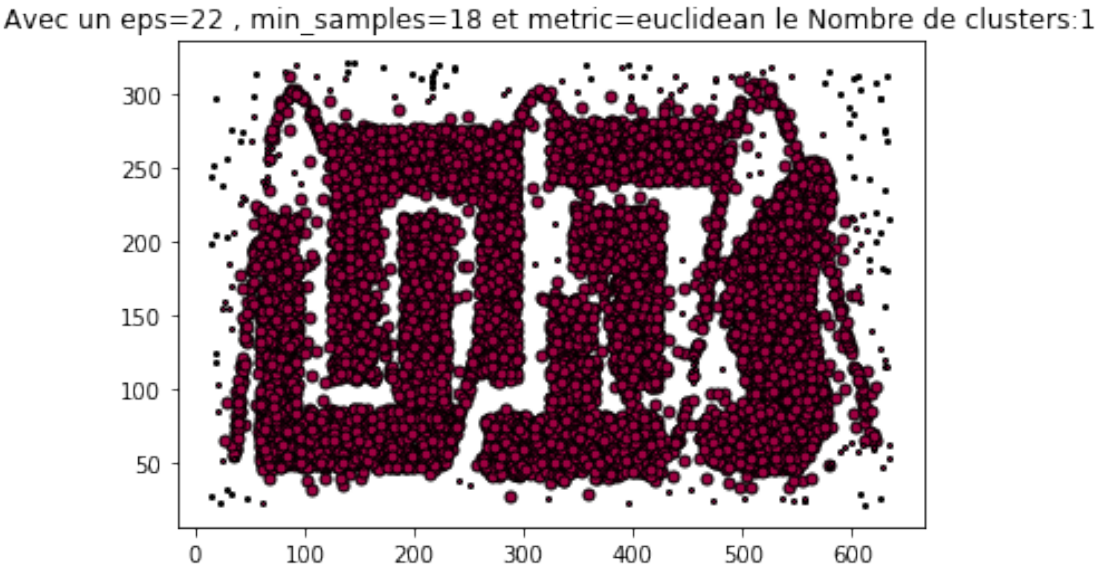

```
Silhouette Coefficient: 0.277
```



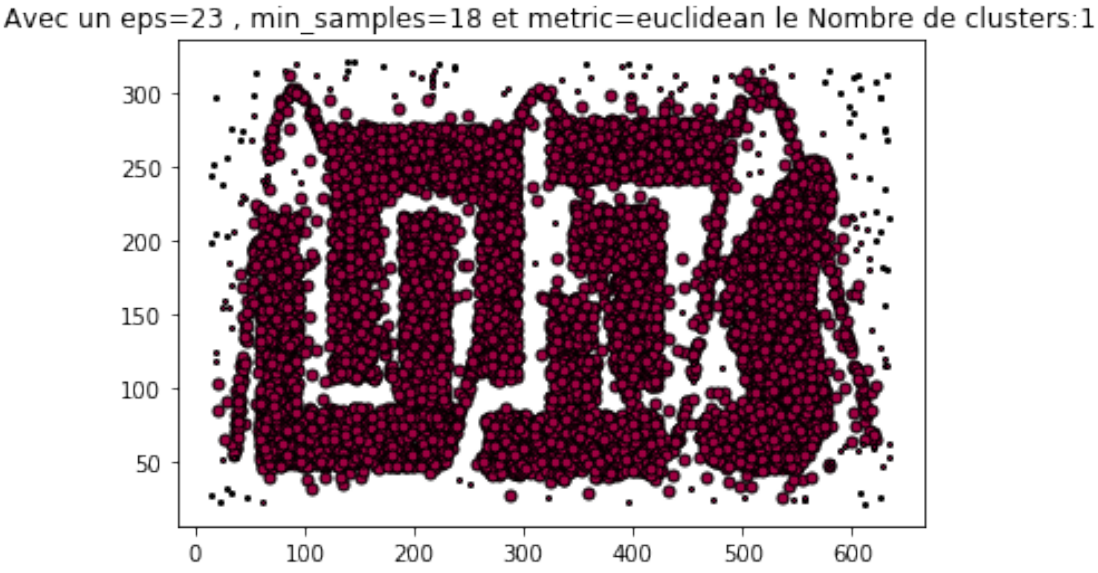

```
Silhouette Coefficient: 0.285
```



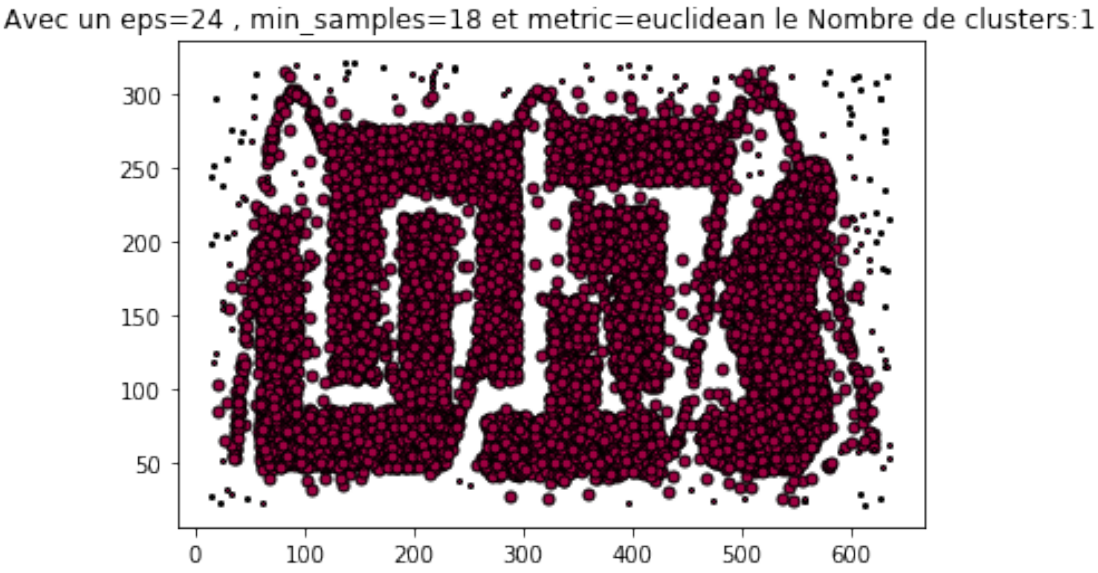

```
Silhouette Coefficient: 0.291
```



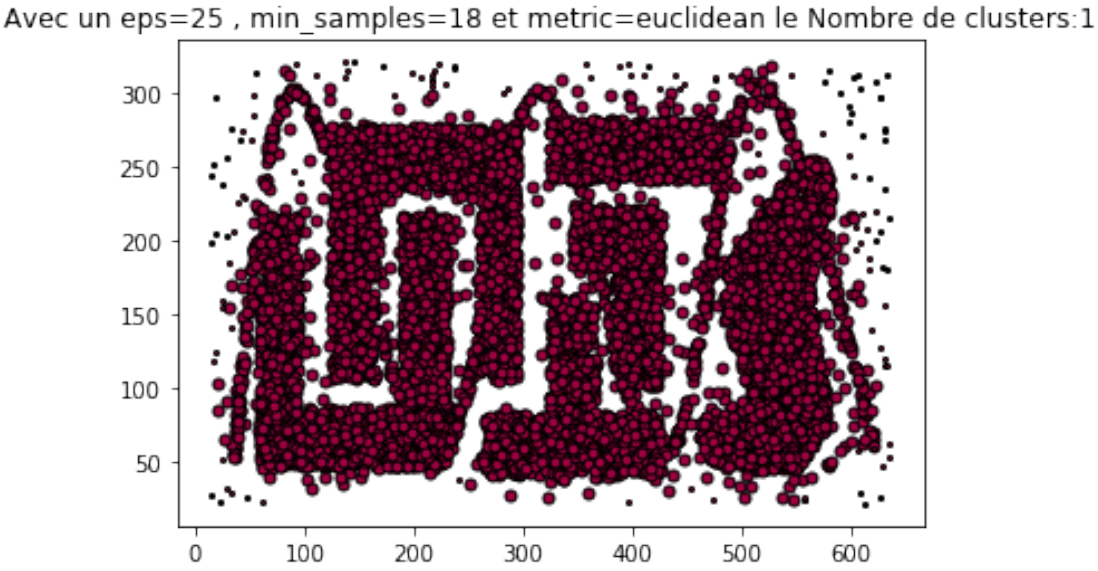

```
Silhouette Coefficient: 0.316
```



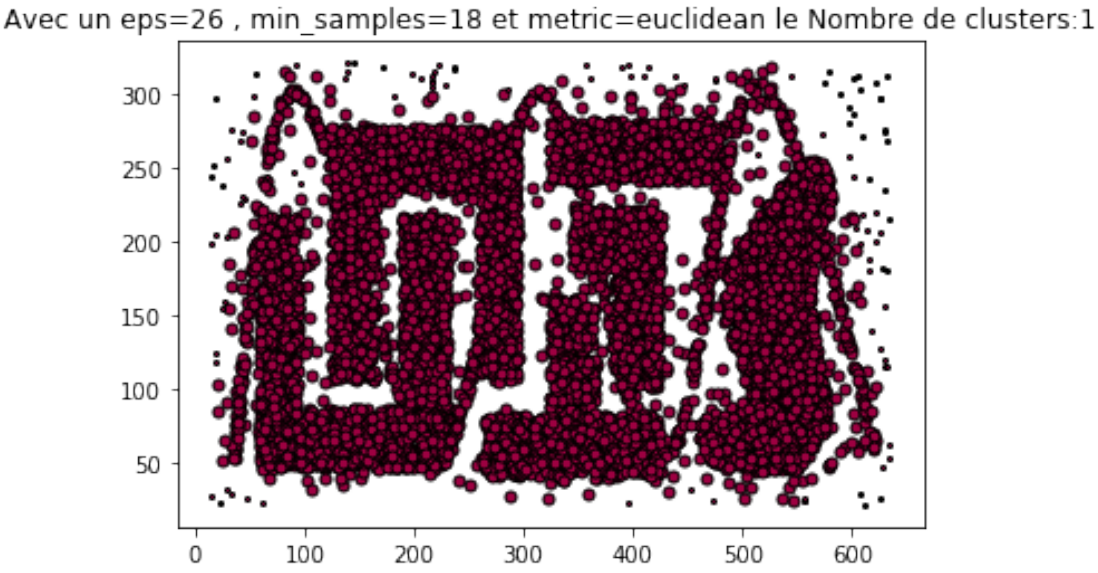

```
Silhouette Coefficient: 0.323
```



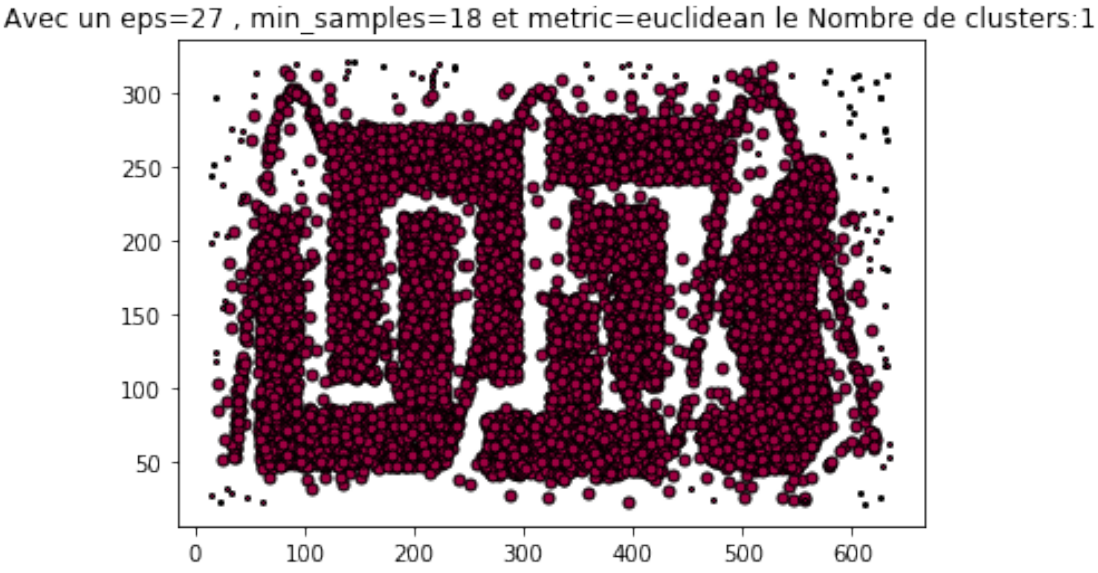

```
Silhouette Coefficient: 0.325
```



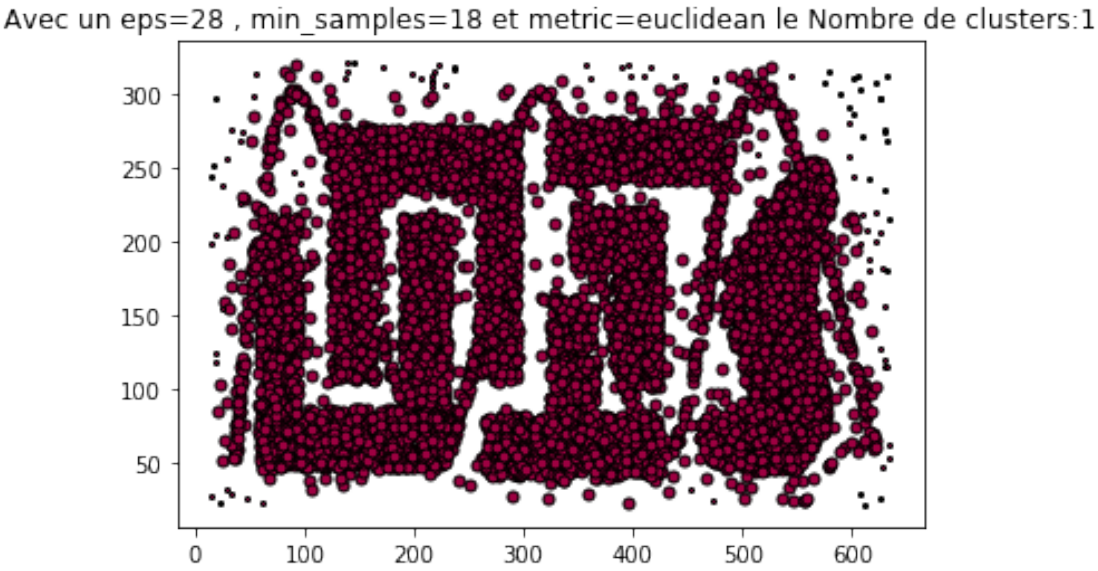

```
Silhouette Coefficient: 0.311
```



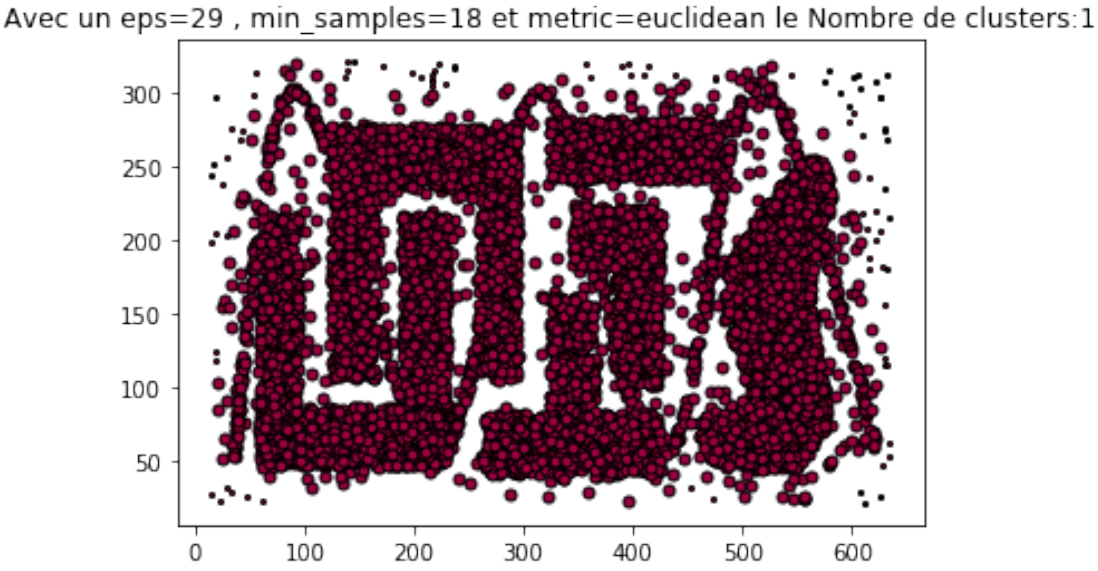

```
Silhouette Coefficient: 0.303
```




```
Silhouette Coefficient: 0.309
```



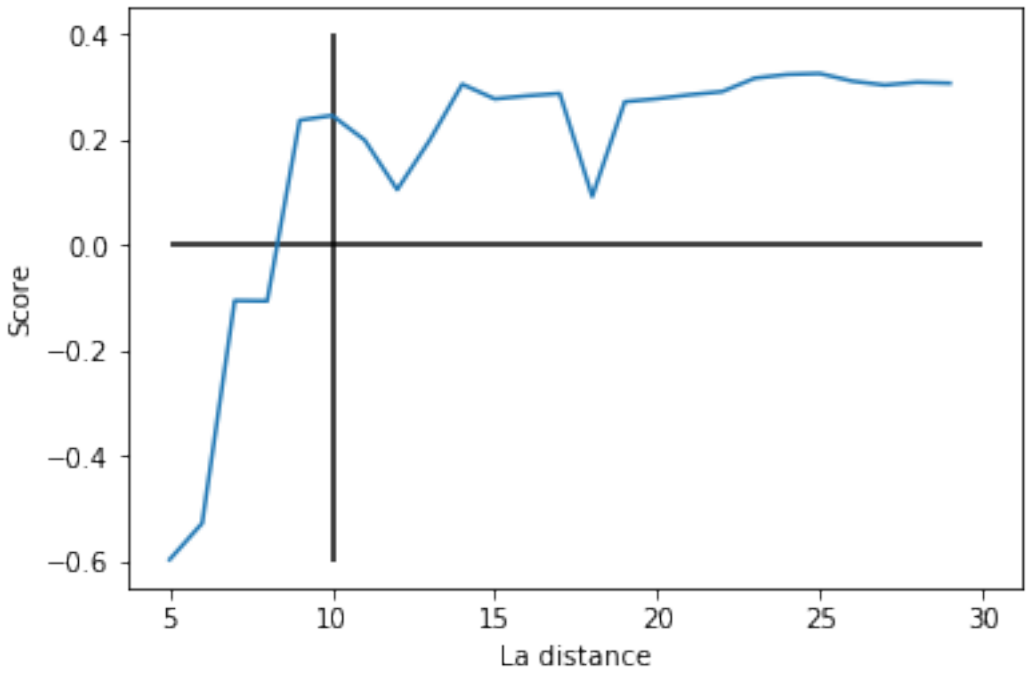

```
Silhouette Coefficient: 0.307
```



Pour les valeurs 9 et 10 comme distance on a eu un meilleur nombre de clusters mais pour une distance 10 on a un meilleur score

```
In [5]: plt.plot(range(5,30),Scores)
        plt.hlines(y=0,xmin=5, xmax=30)
        plt.vlines(x=10,ymin=-0.6,ymax=0.4)
```

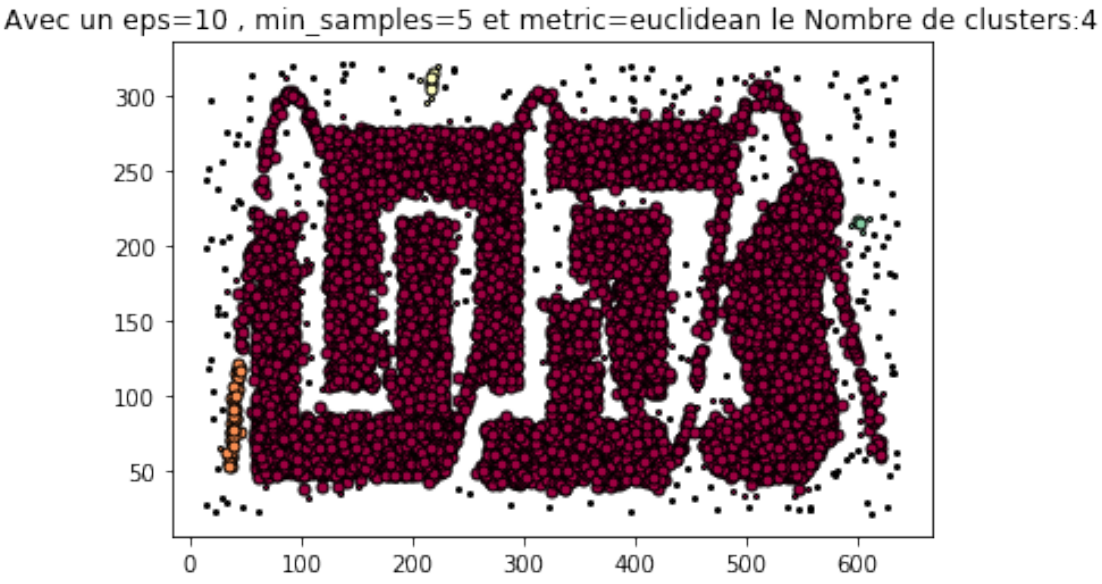
```
plt.xlabel('La distance')
plt.ylabel('Score')
plt.show()
```



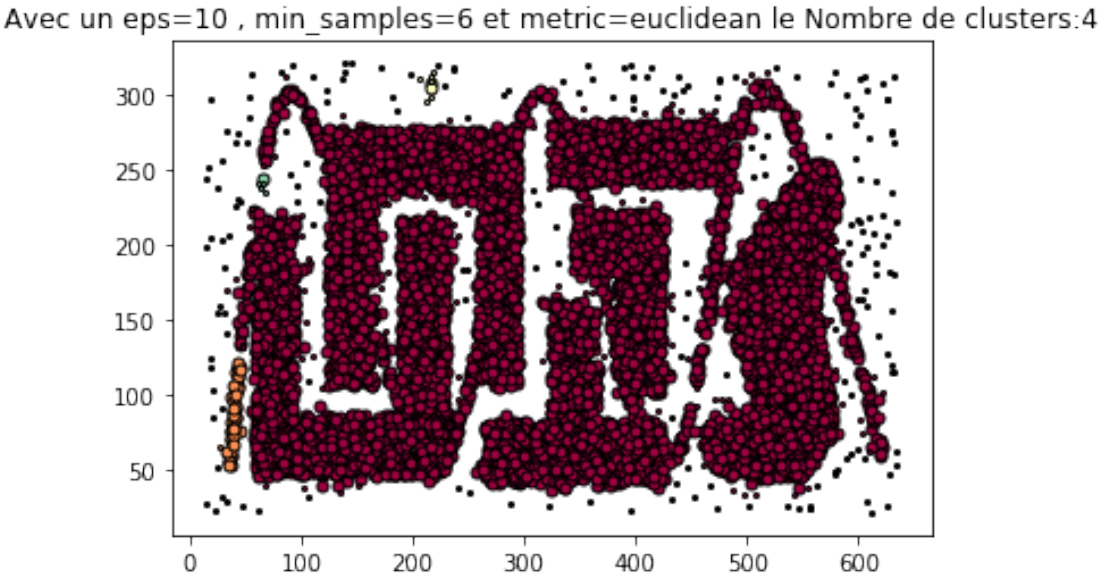
On teste plusieurs valeur pour le minSamples et on obtient le résultat suivant

```
In [6]: ScoresSamples = []

        for i in range(5,30):
            meth_dbscan(dataSet=data,minSamples=i,Scores = ScoresSamples)
```

```
Silhouette Coefficient: -0.295
```

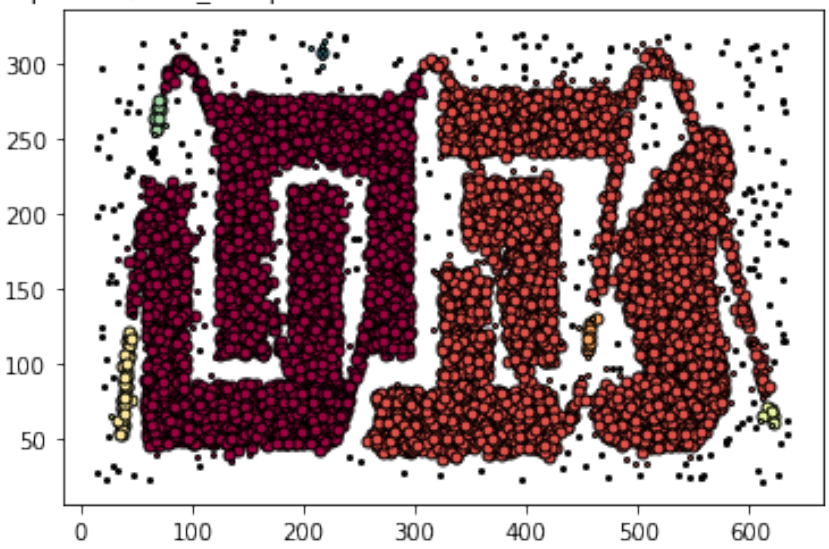



```
Silhouette Coefficient: -0.156
```



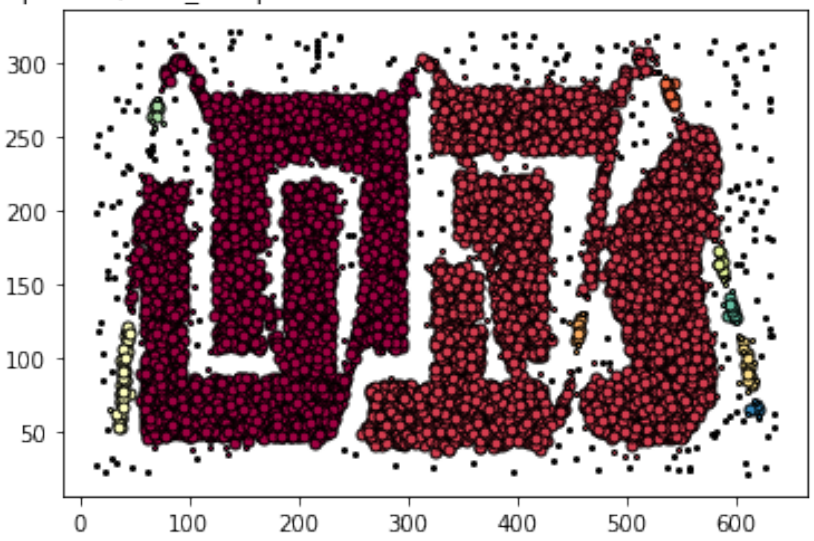

```
Silhouette Coefficient: -0.219
```

Avec un eps=10 , min_samples=7 et metric=euclidean le Nombre de clusters:7



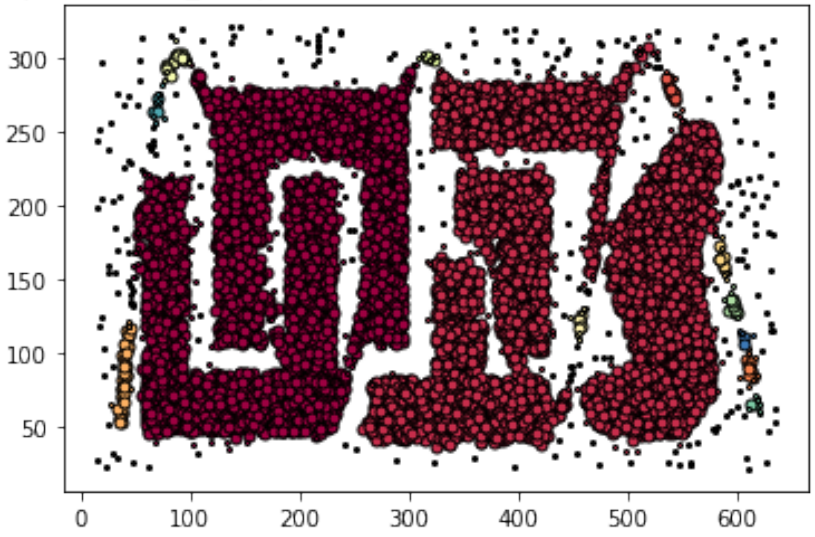

```
Silhouette Coefficient: -0.194
```

Avec un eps=10 , min_samples=8 et metric=euclidean le Nombre de clusters:10



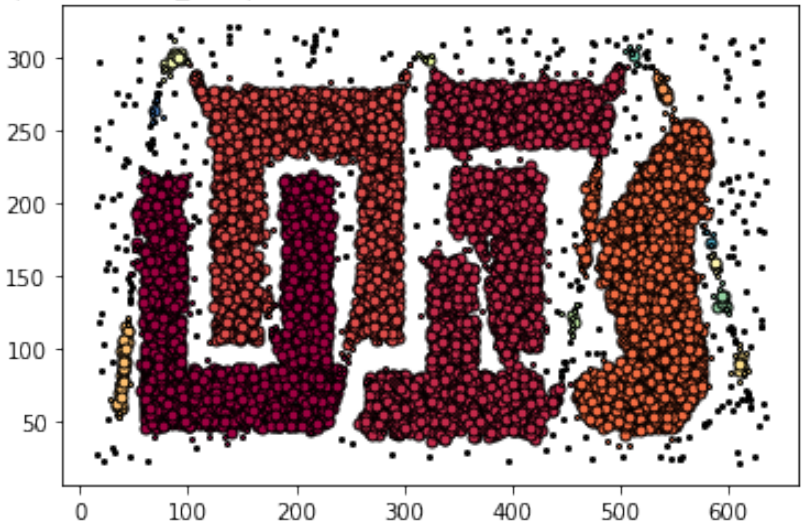

```
Silhouette Coefficient: -0.272
```

Avec un eps=10 , min_samples=9 et metric=euclidean le Nombre de clusters:13

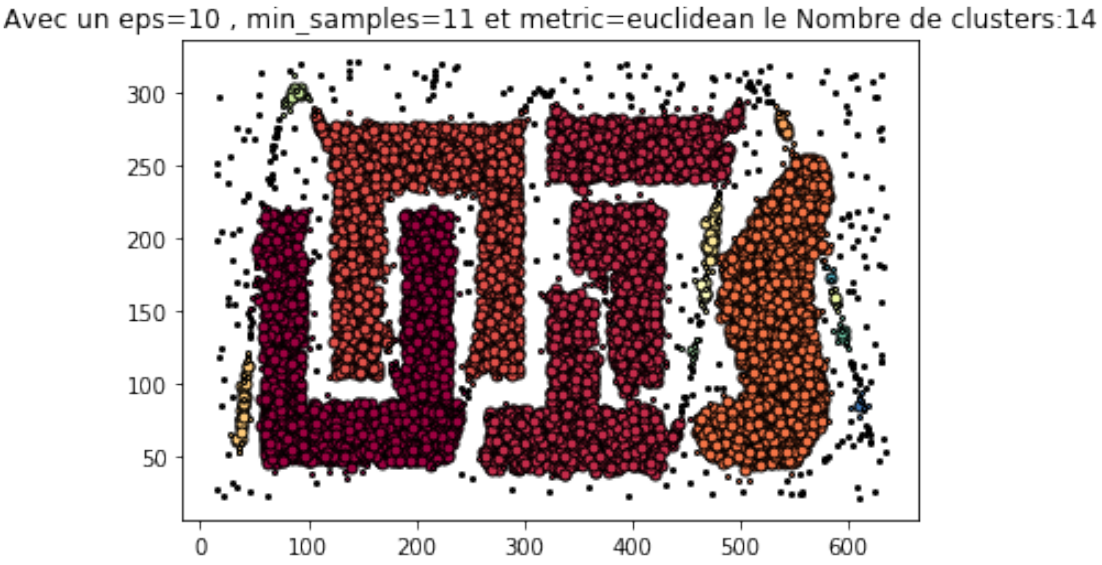



```
Silhouette Coefficient: -0.158
```

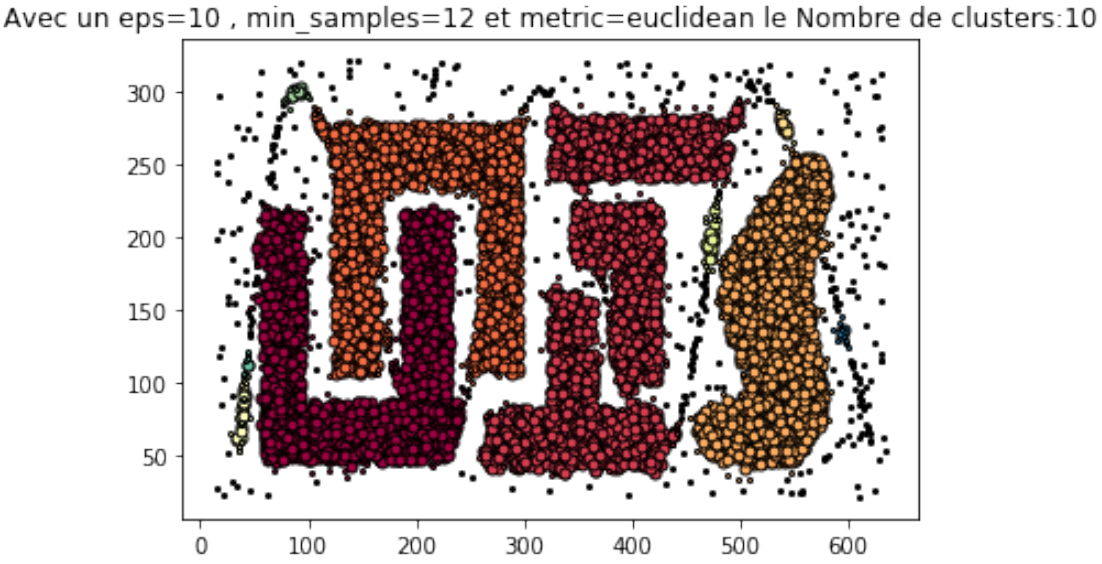
Avec un eps=10 , min_samples=10 et metric=euclidean le Nombre de clusters:15



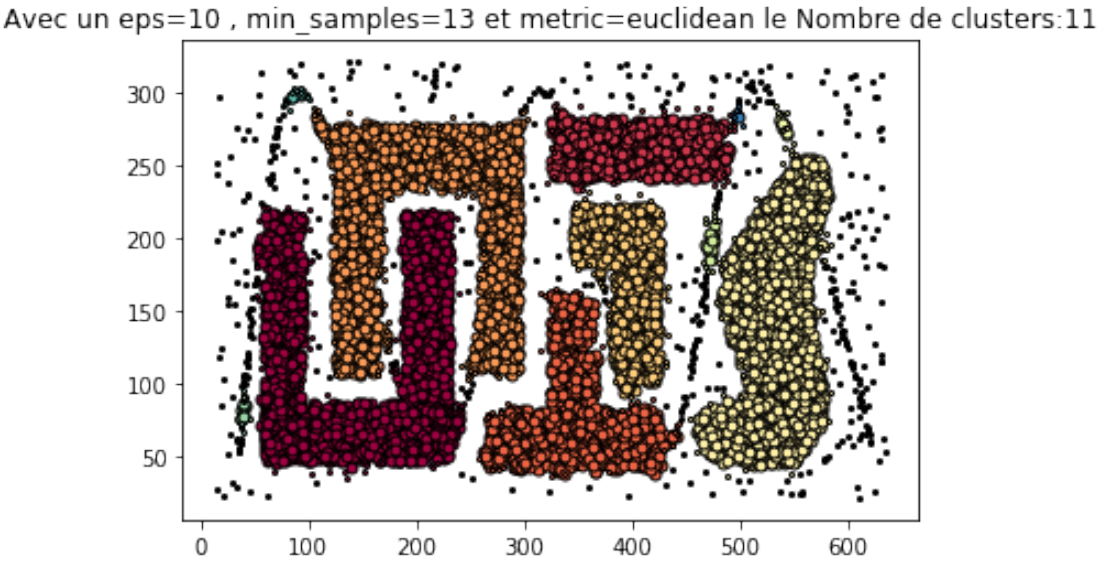

```
Silhouette Coefficient: -0.115
```



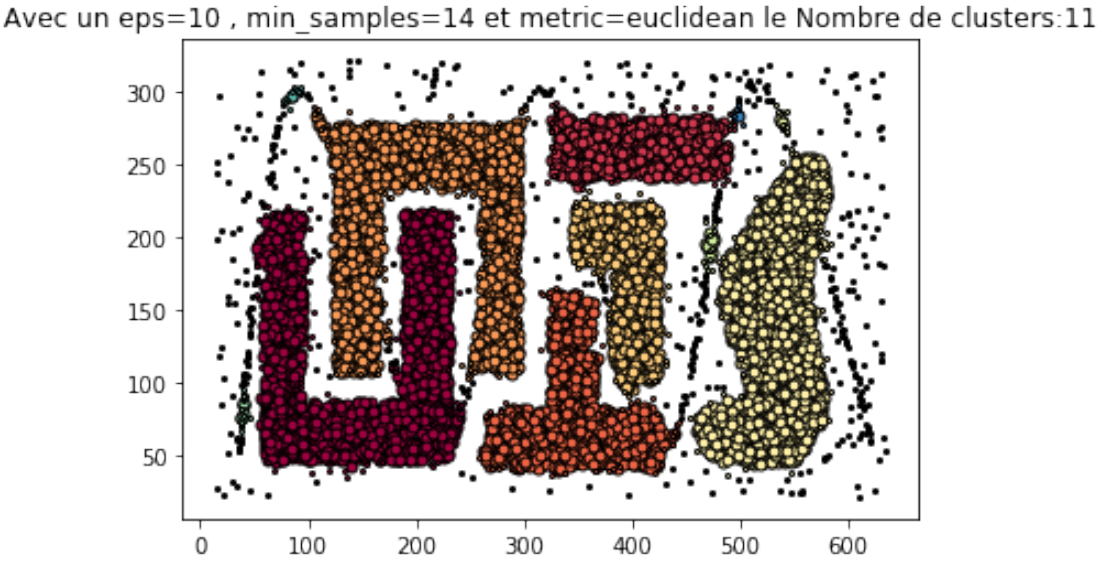

```
Silhouette Coefficient: -0.047
```



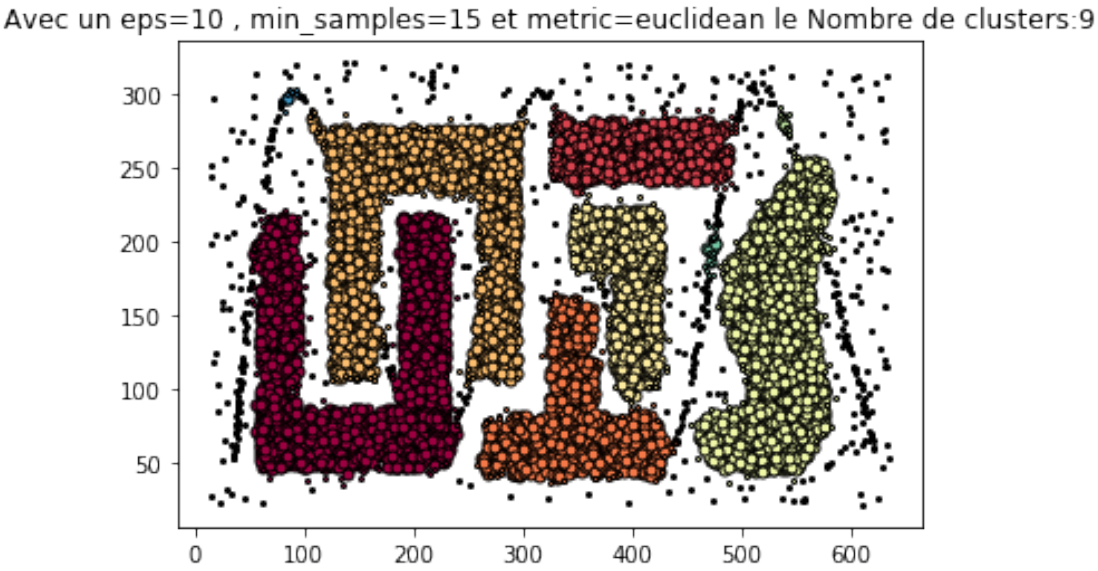

```
Silhouette Coefficient: 0.062
```



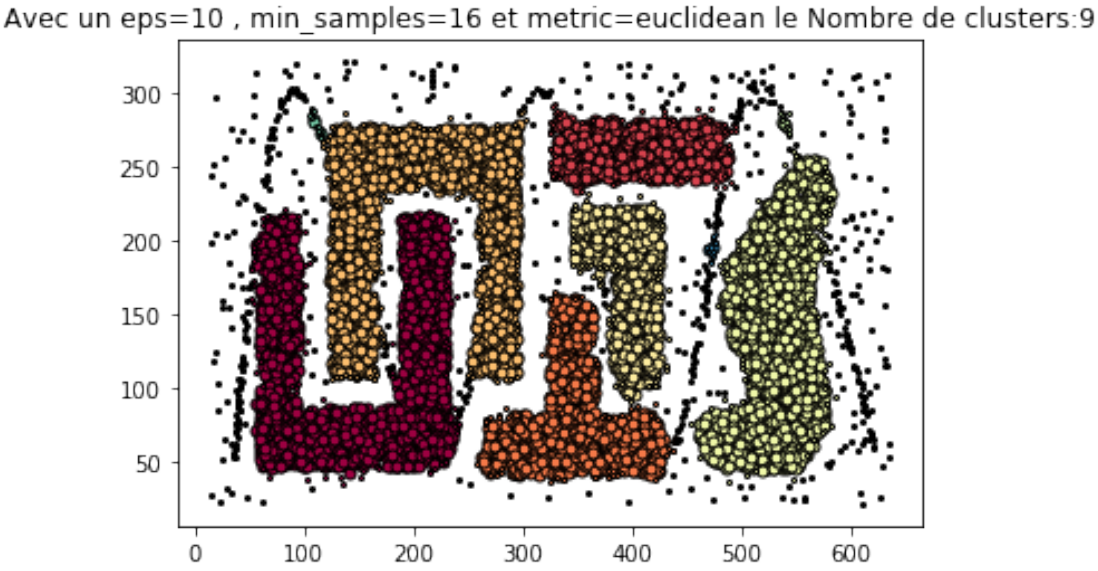

```
Silhouette Coefficient: 0.058
```



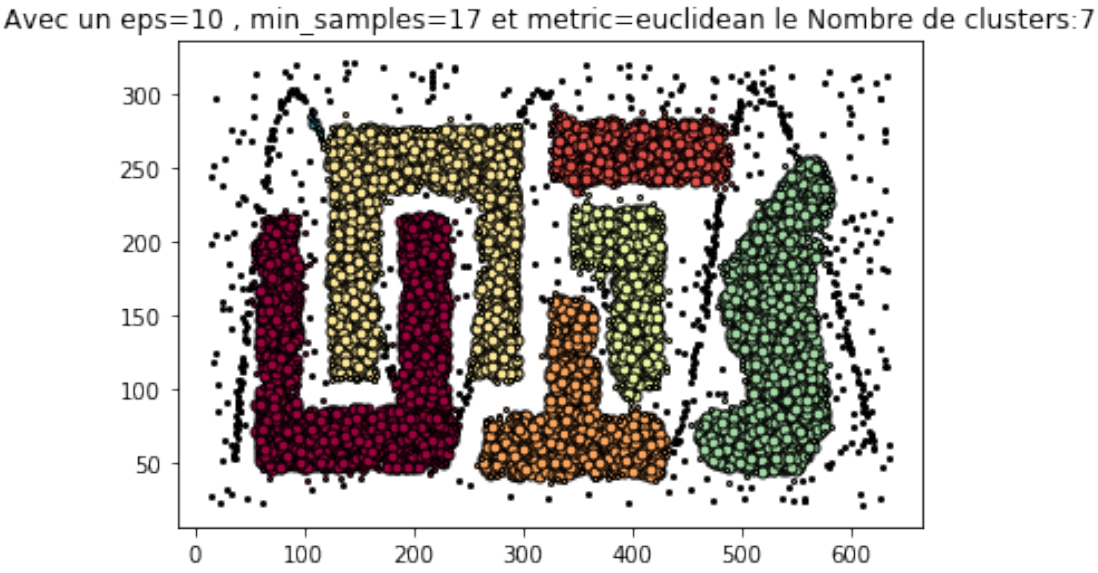

```
Silhouette Coefficient: 0.129
```



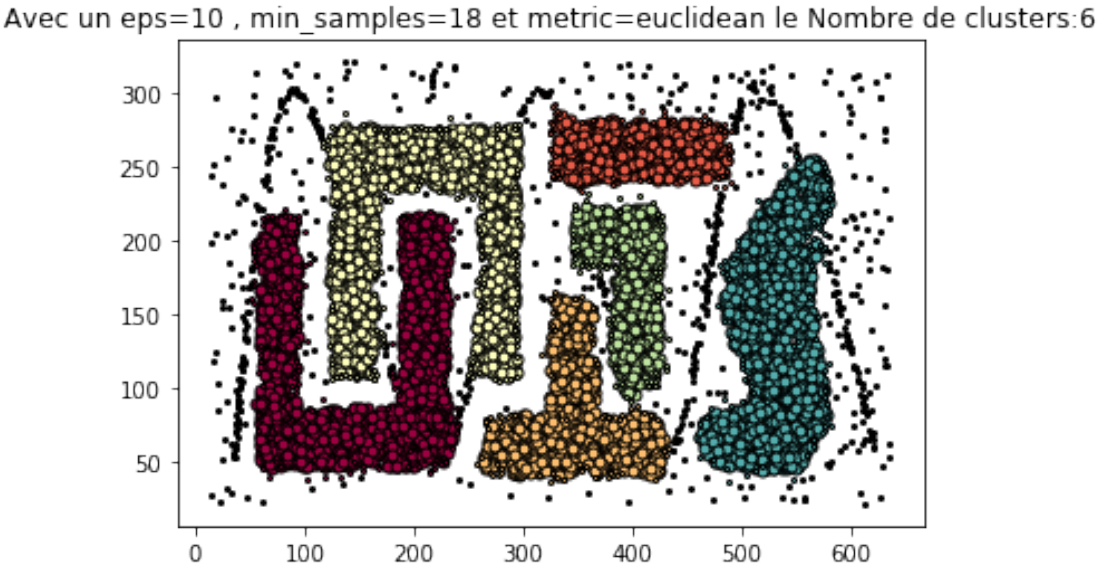

```
Silhouette Coefficient: 0.103
```



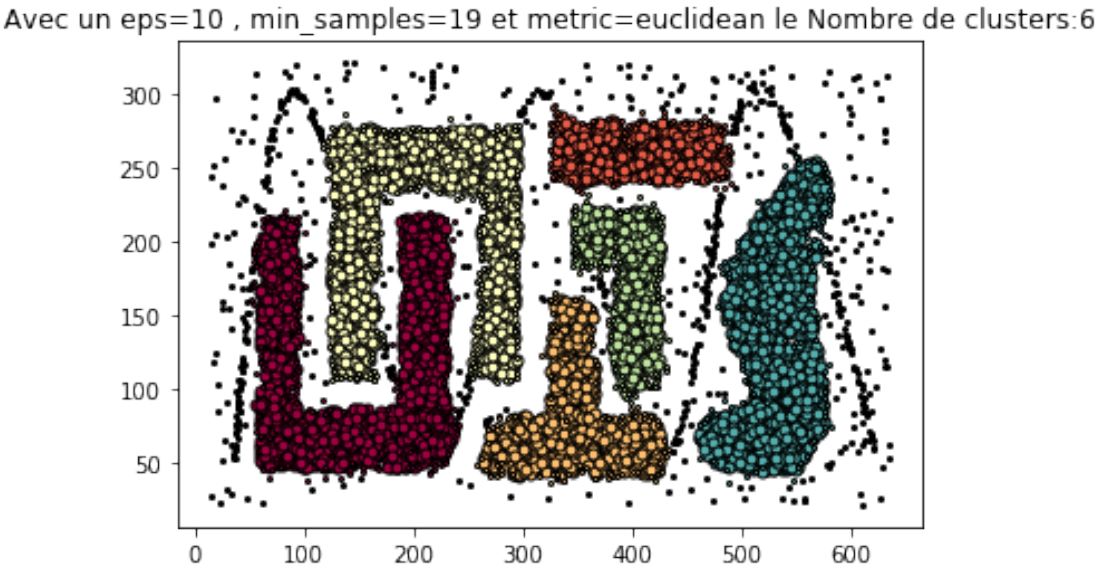

```
Silhouette Coefficient: 0.193
```



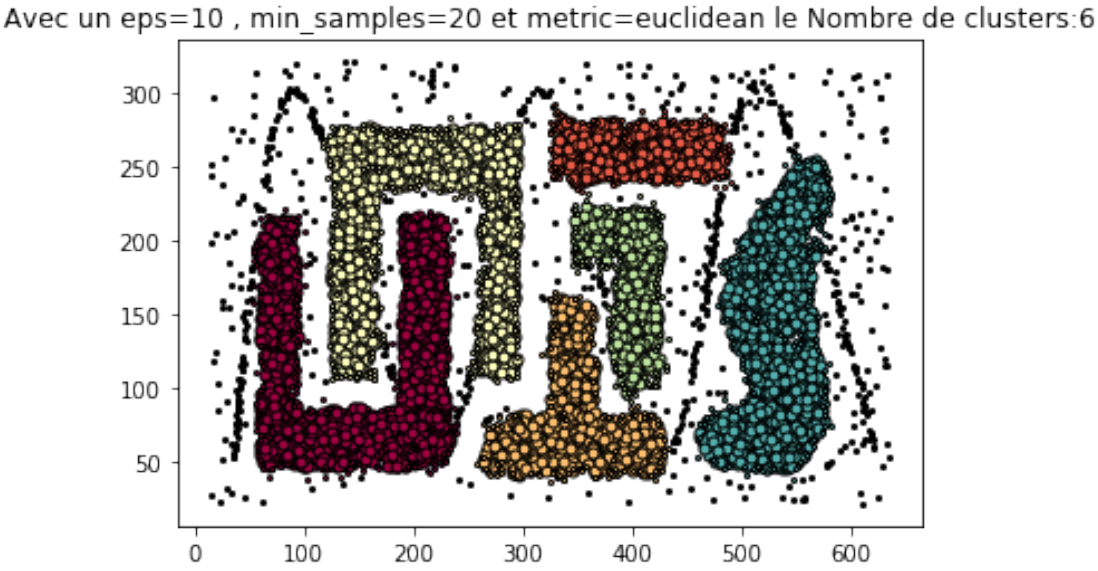

```
Silhouette Coefficient: 0.246
```



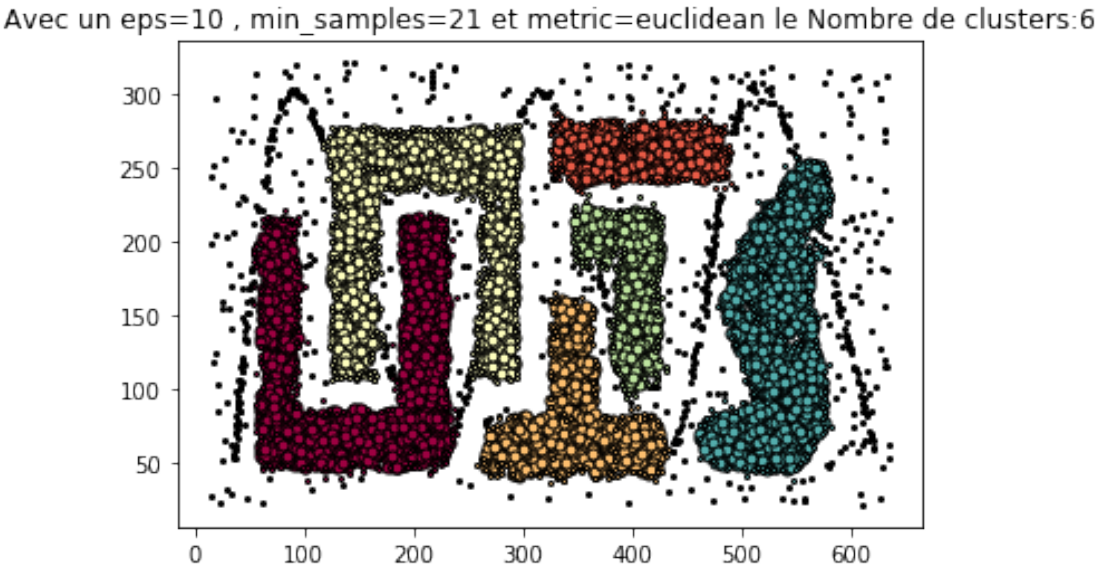

```
Silhouette Coefficient: 0.244
```



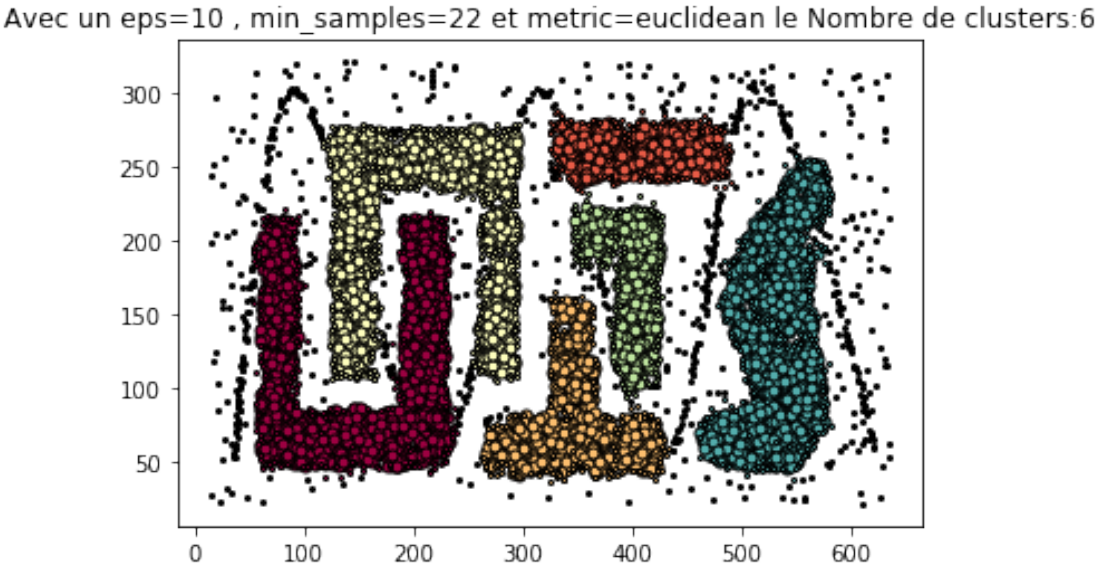

```
Silhouette Coefficient: 0.243
```



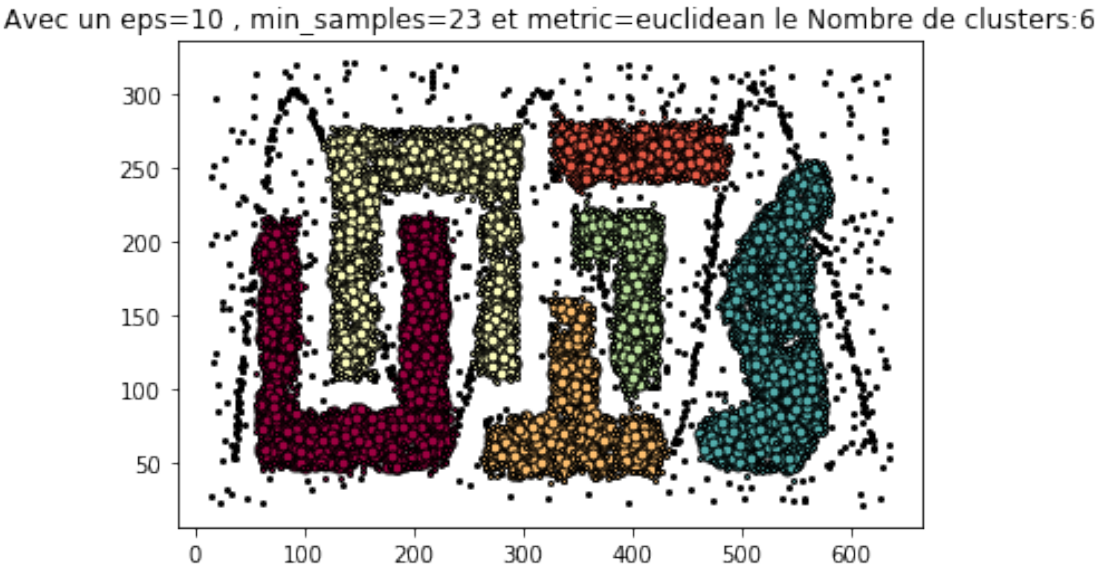

```
Silhouette Coefficient: 0.241
```



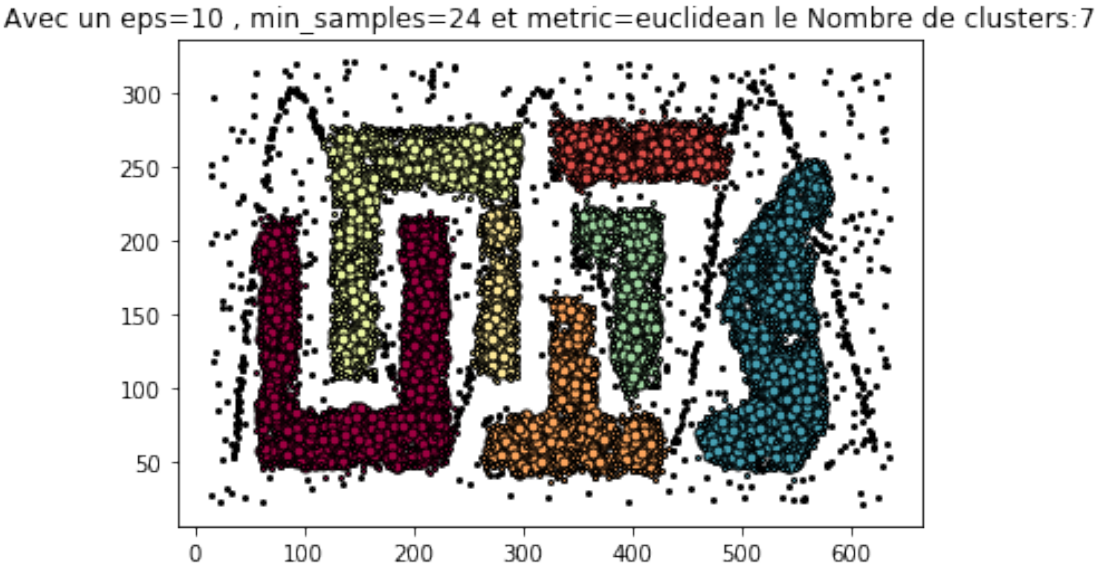

```
Silhouette Coefficient: 0.238
```



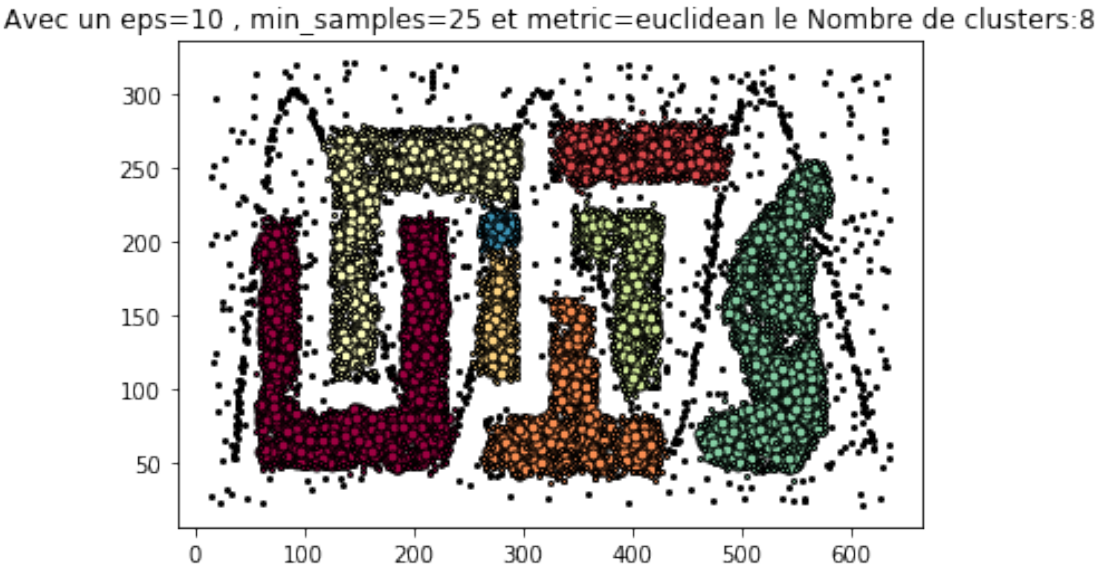

```
Silhouette Coefficient: 0.235
```



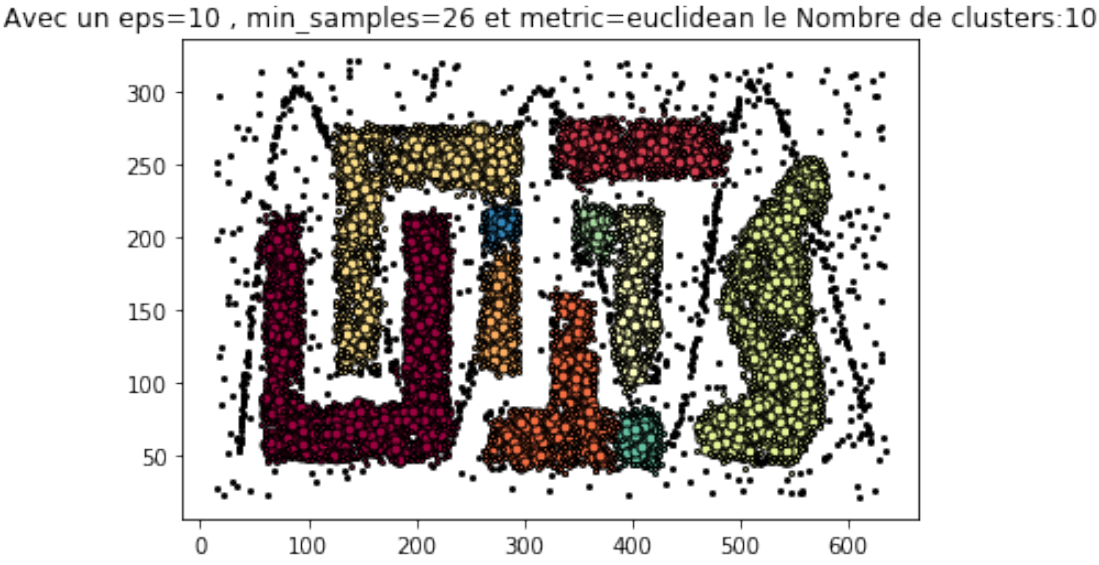

```
Silhouette Coefficient: 0.223
```



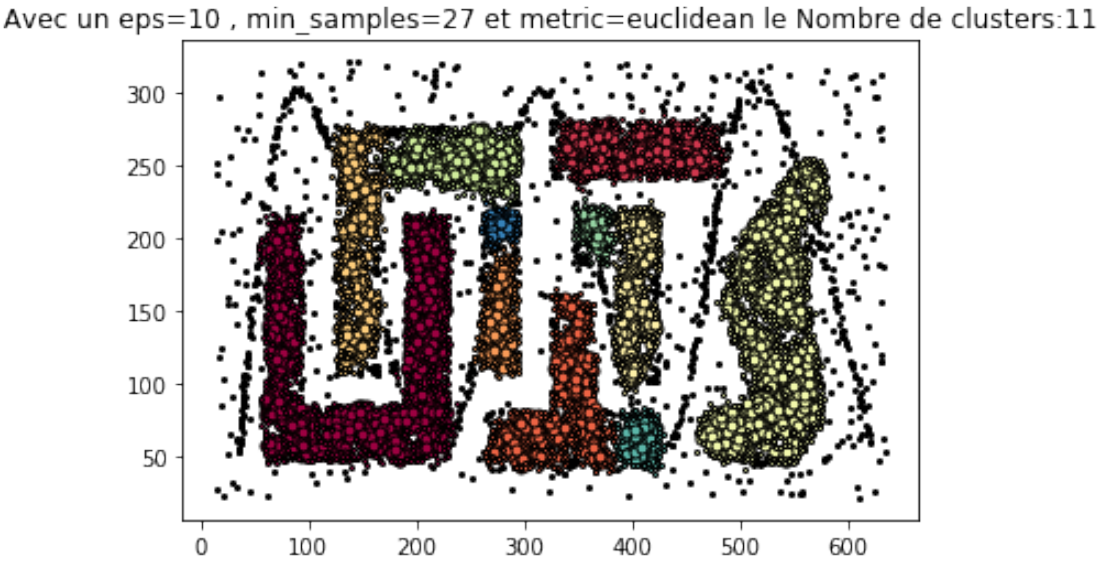

```
Silhouette Coefficient: 0.168
```



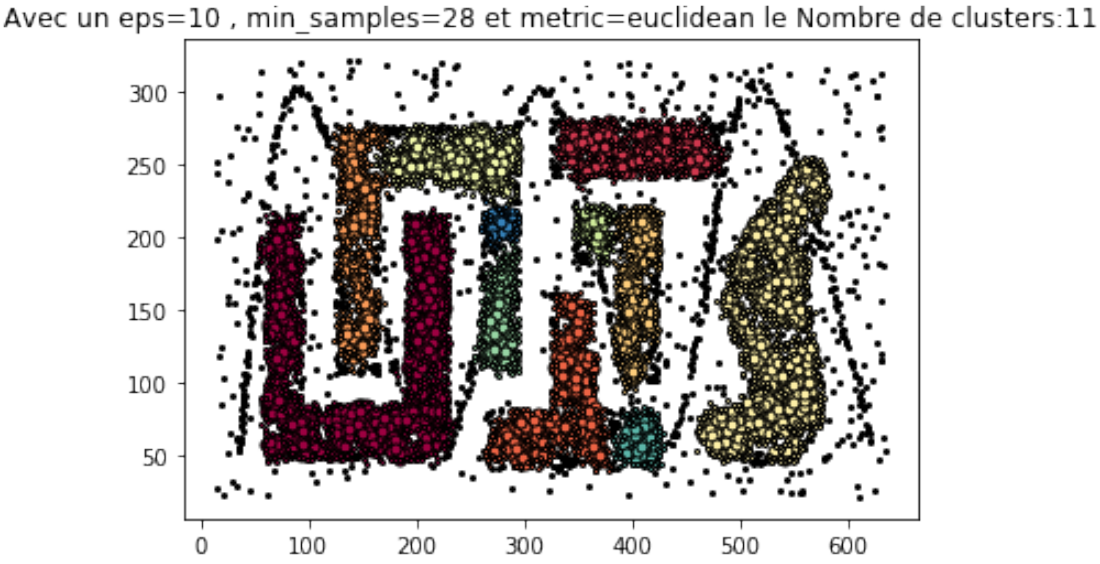

```
Silhouette Coefficient: 0.115
```



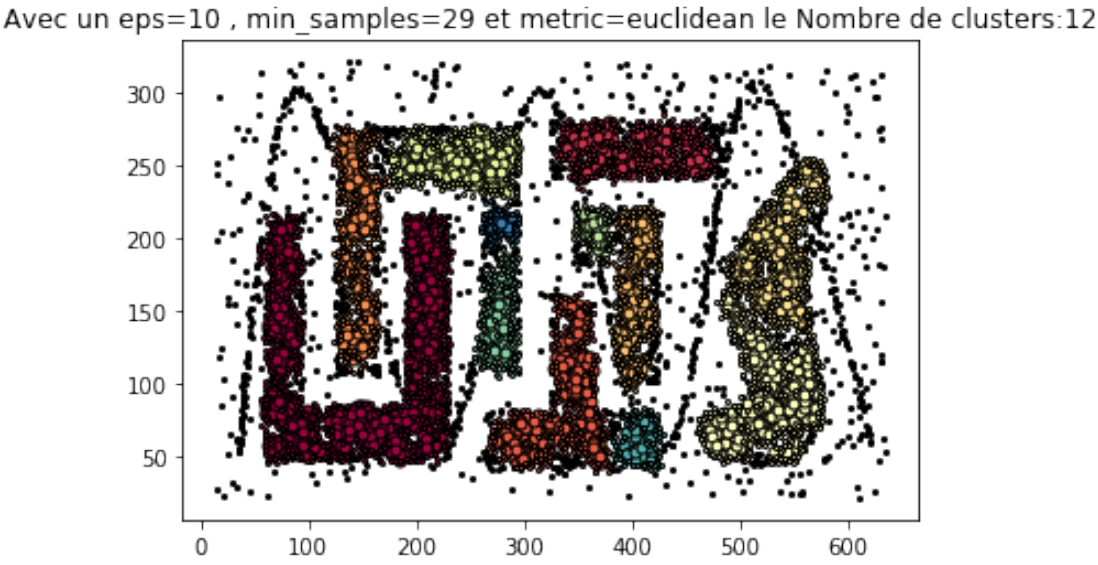

```
Silhouette Coefficient: 0.125
```




```
Silhouette Coefficient: 0.114
```

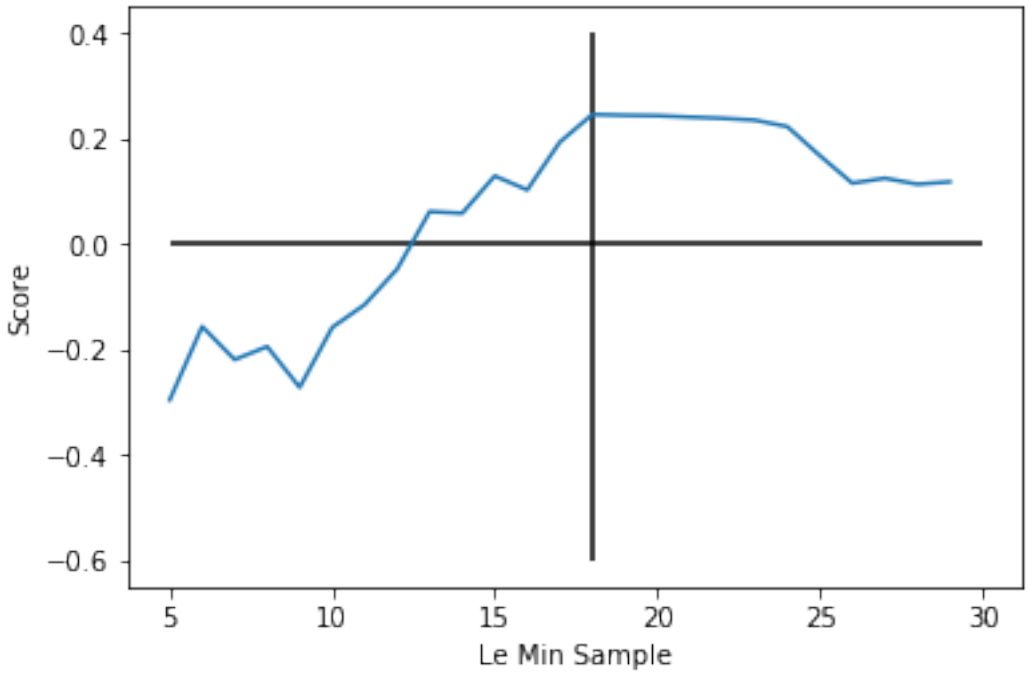



```
Silhouette Coefficient: 0.118
```



Pour les valeurs de 19 jusqu'à 23 comme minSamples on a eu un meilleur nombre de clusters mais pour un minSamples 18 on a un meilleur score

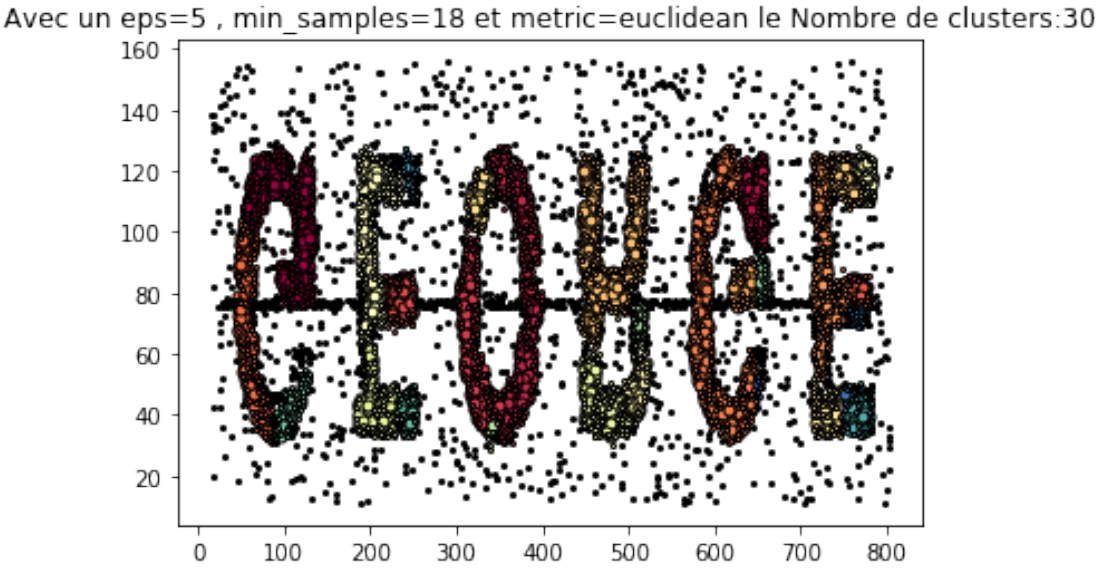
```
In [7]: plt.plot(range(5,30),ScoresSamples)
        plt.hlines(y=0,xmin=5, xmax=30)
        plt.vlines(x=18,ymin=-0.6,ymax=0.4)
        plt.xlabel('Le Min Sample')
        plt.ylabel('Score')
        plt.show()
```



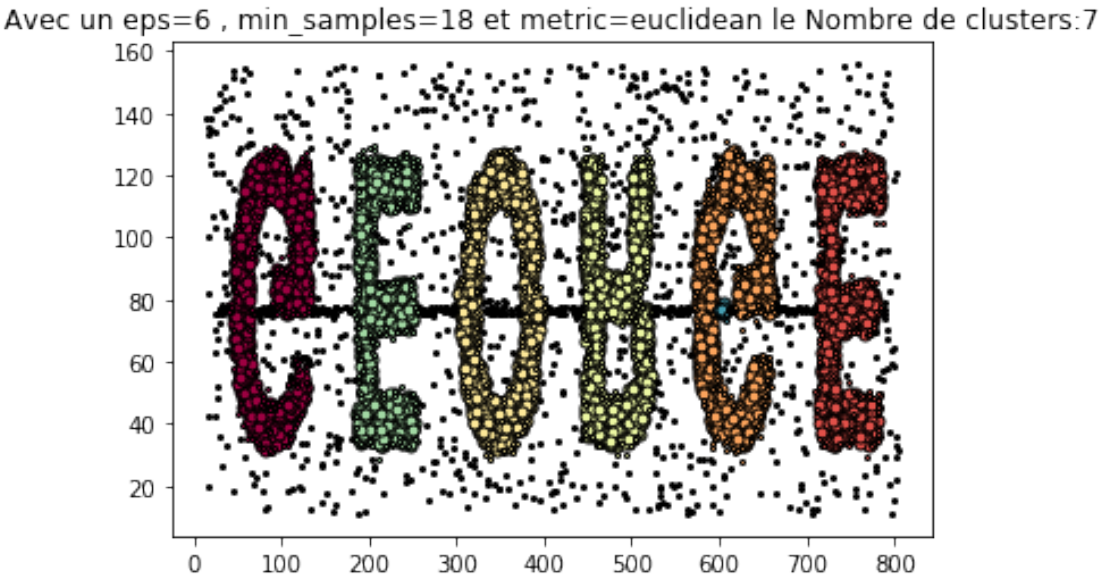
On réalise les même etapes avec un autre DataSet

```
In [9]: Scores_2 = []
        data_2 = np.genfromtxt("cham-data/t5.8k.dat",delimiter=" ")
        for i in range(5,25):
            meth_dbscan(dataSet=data_2,distance=i,Scores = Scores_2)
```

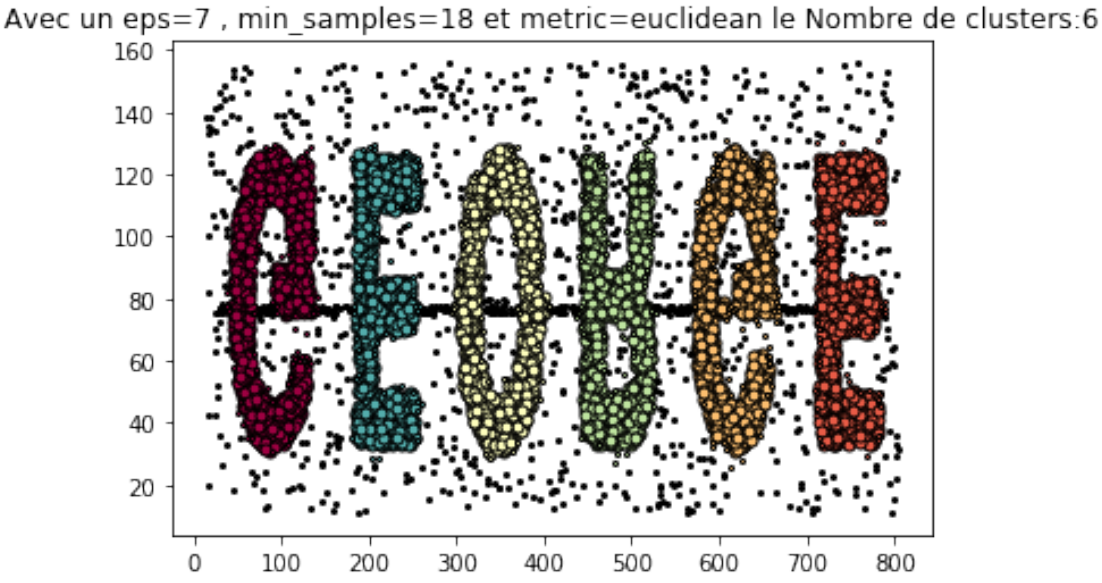
```
Silhouette Coefficient: 0.035
```




```
Silhouette Coefficient: 0.296
```

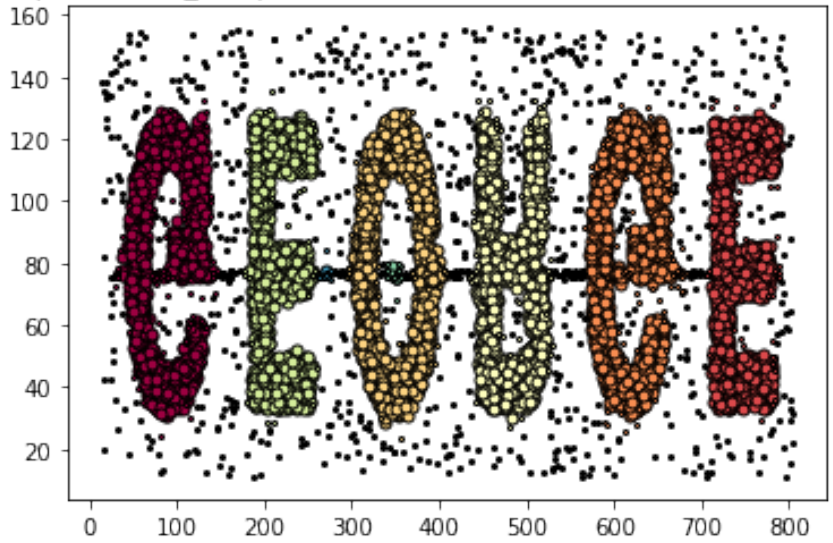



```
Silhouette Coefficient: 0.440
```



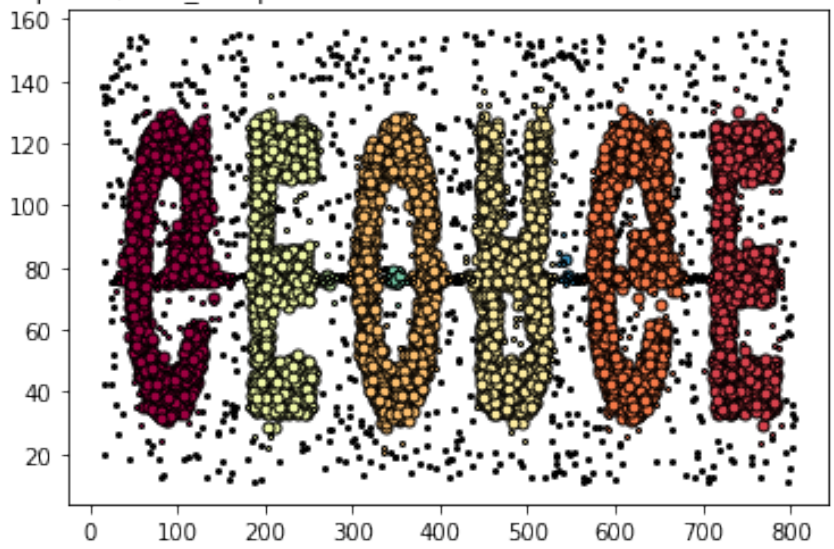

```
Silhouette Coefficient: 0.293
```

Avec un eps=8 , min_samples=18 et metric=euclidean le Nombre de clusters:8



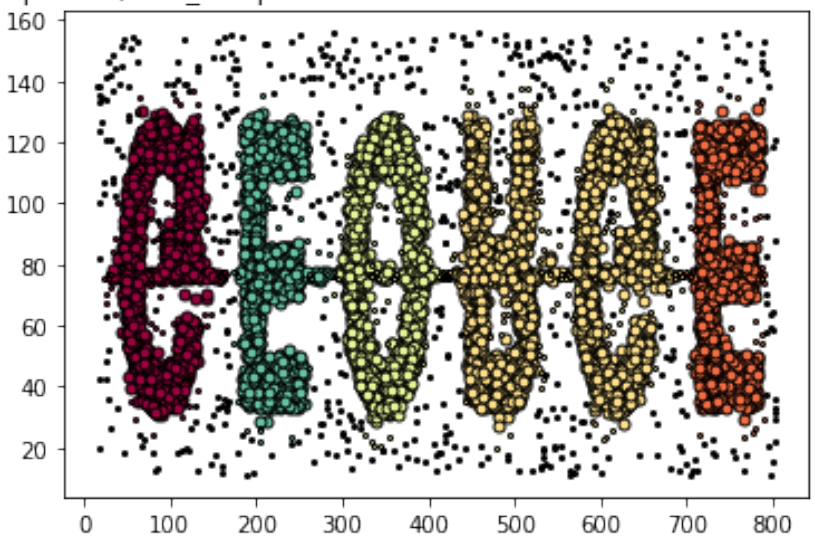

```
Silhouette Coefficient: 0.210
```

Avec un eps=9 , min_samples=18 et metric=euclidean le Nombre de clusters:9



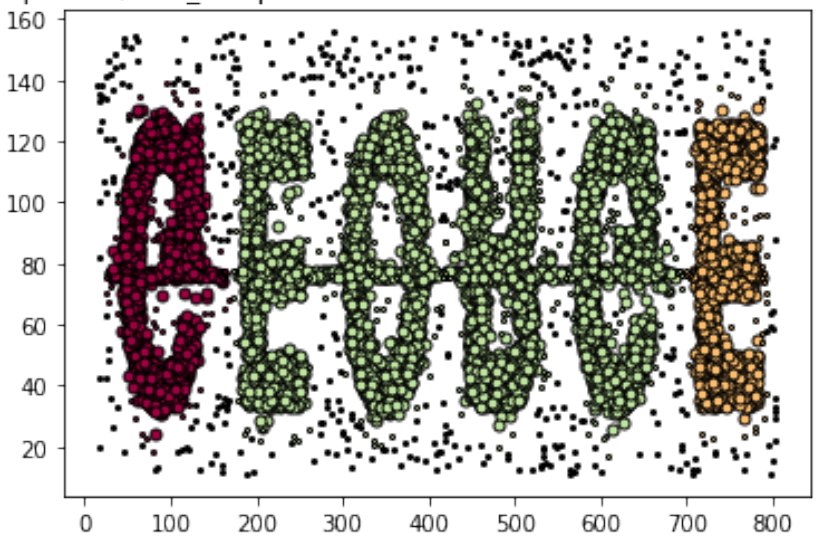

```
Silhouette Coefficient: 0.421
```

Avec un eps=10 , min_samples=18 et metric=euclidean le Nombre de clusters:5

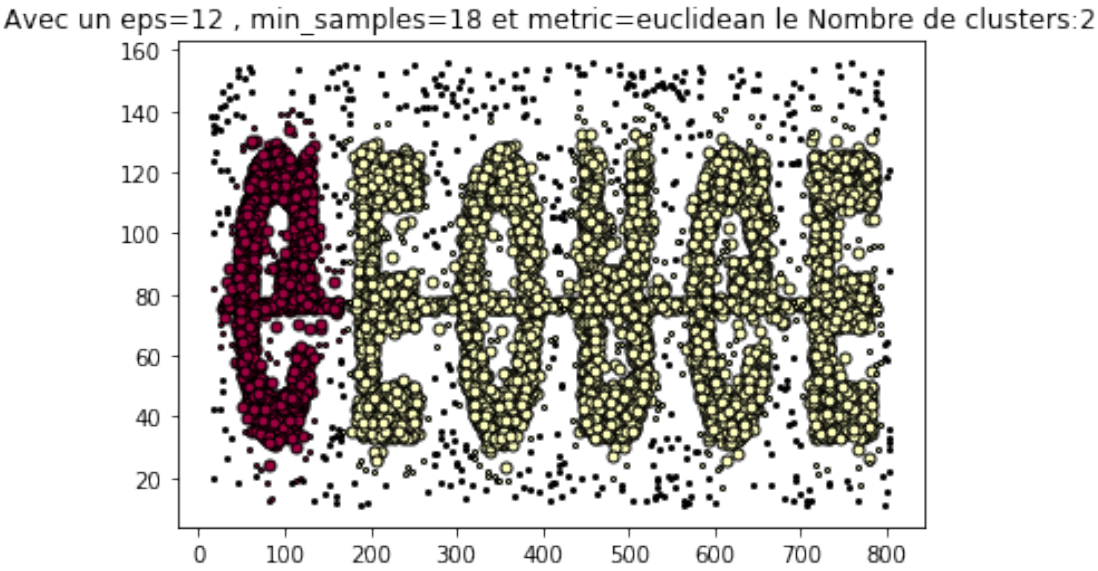



```
Silhouette Coefficient: 0.217
```

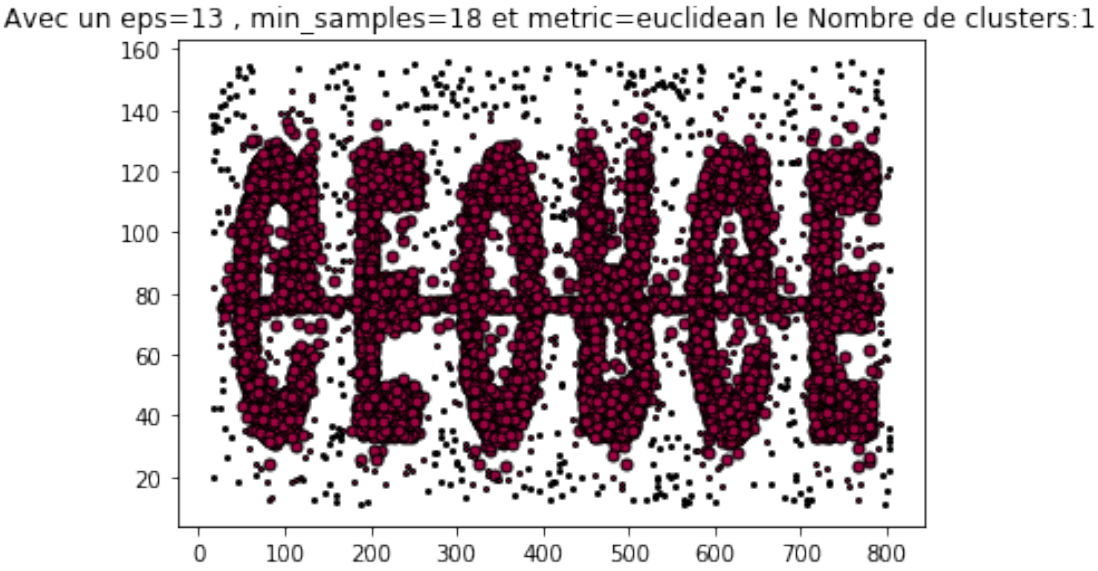
Avec un eps=11 , min_samples=18 et metric=euclidean le Nombre de clusters:3



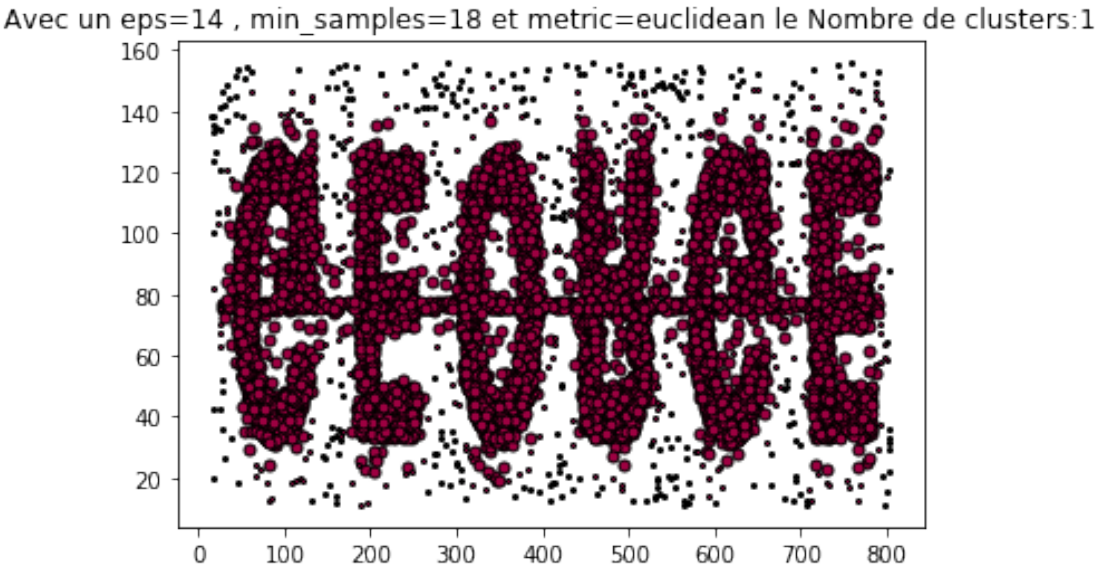

```
Silhouette Coefficient: 0.176
```



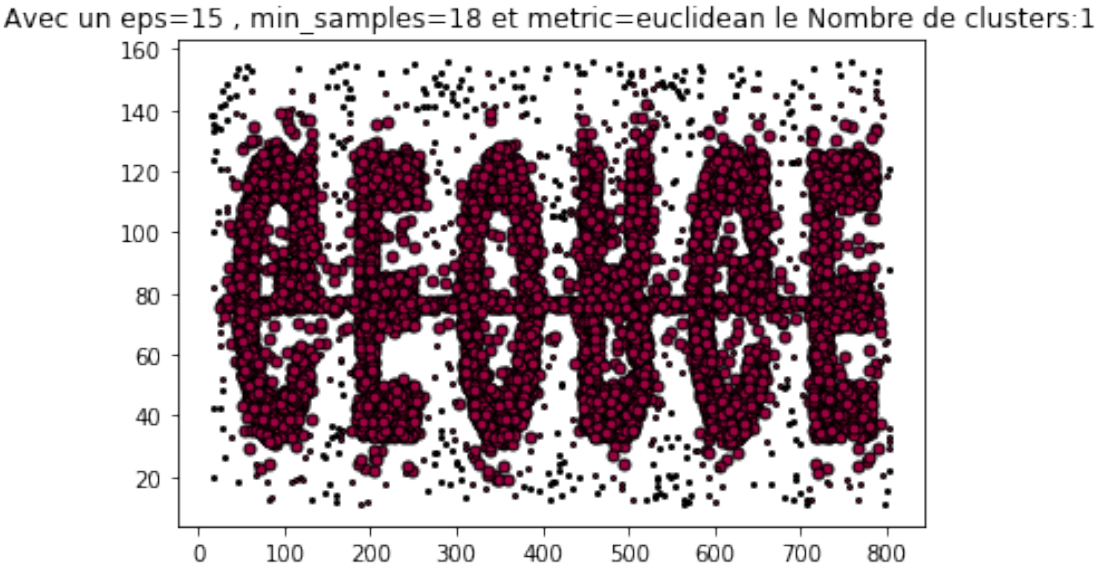

```
Silhouette Coefficient: 0.028
```



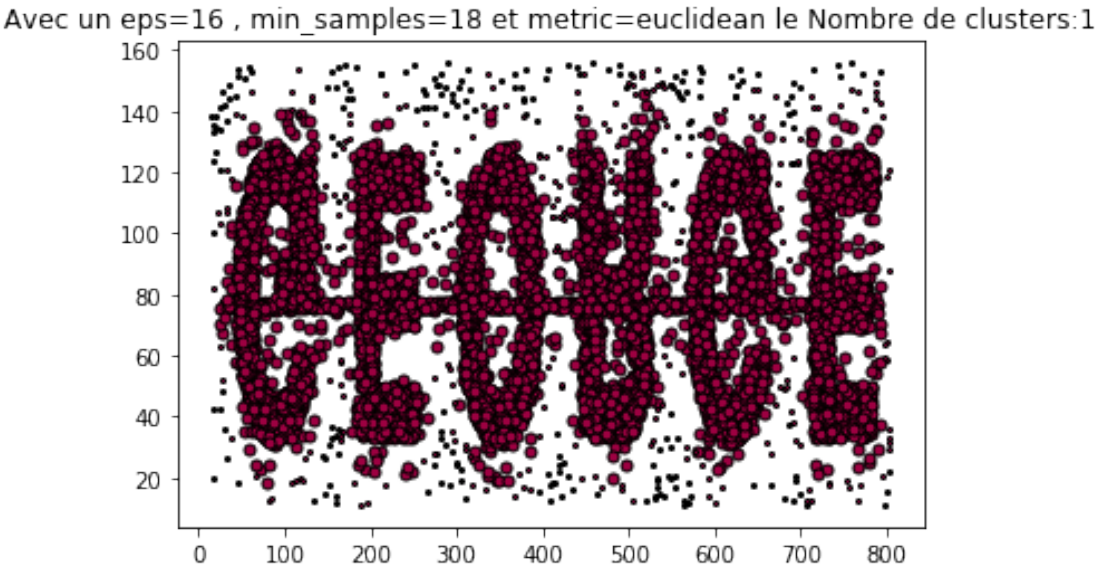

```
Silhouette Coefficient: 0.021
```



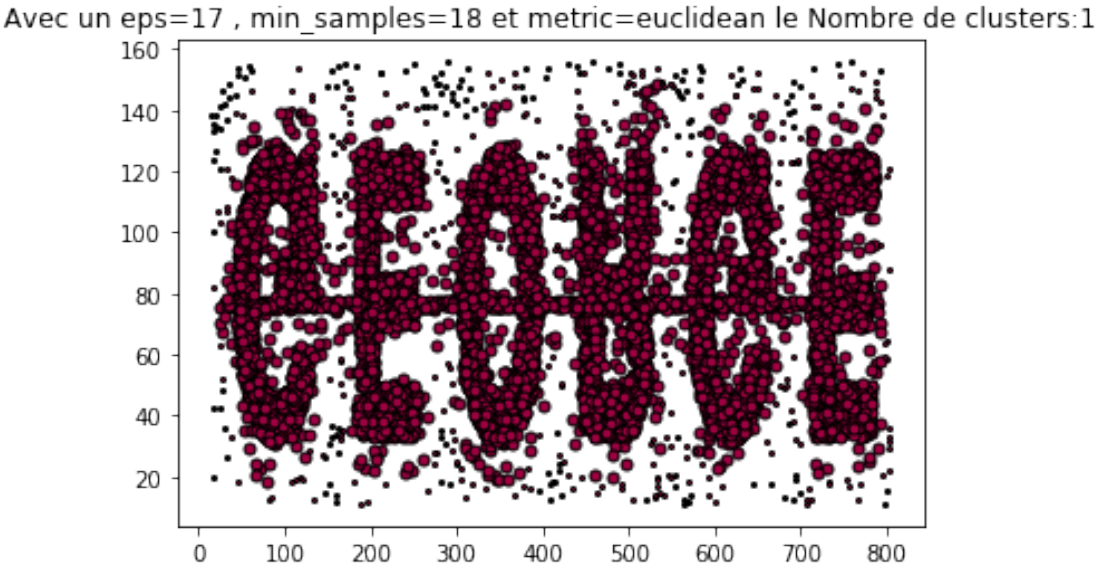
Silhouette Coefficient: 0.011



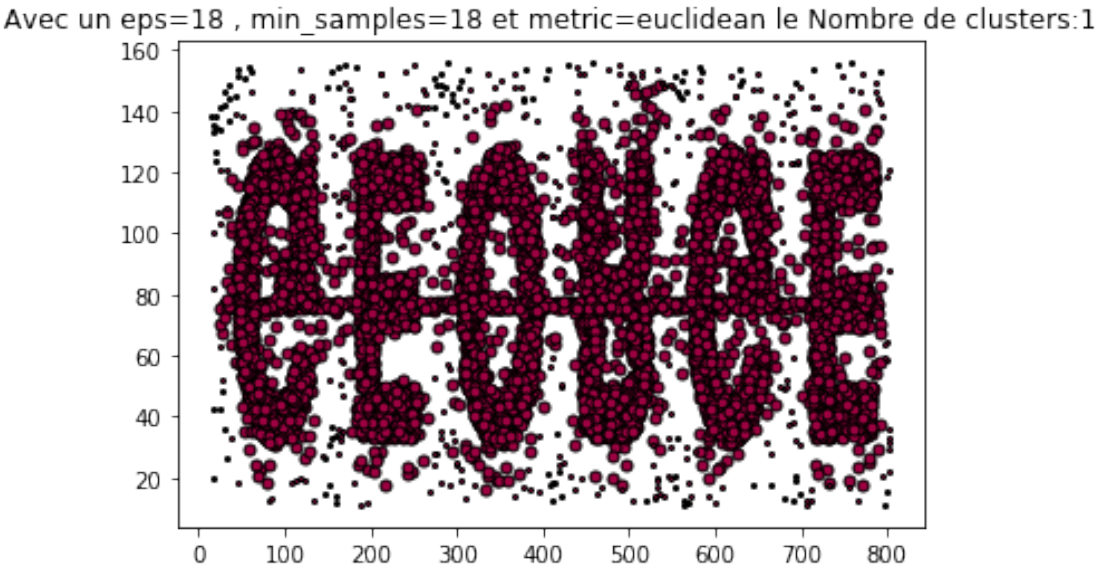
Silhouette Coefficient: 0.024



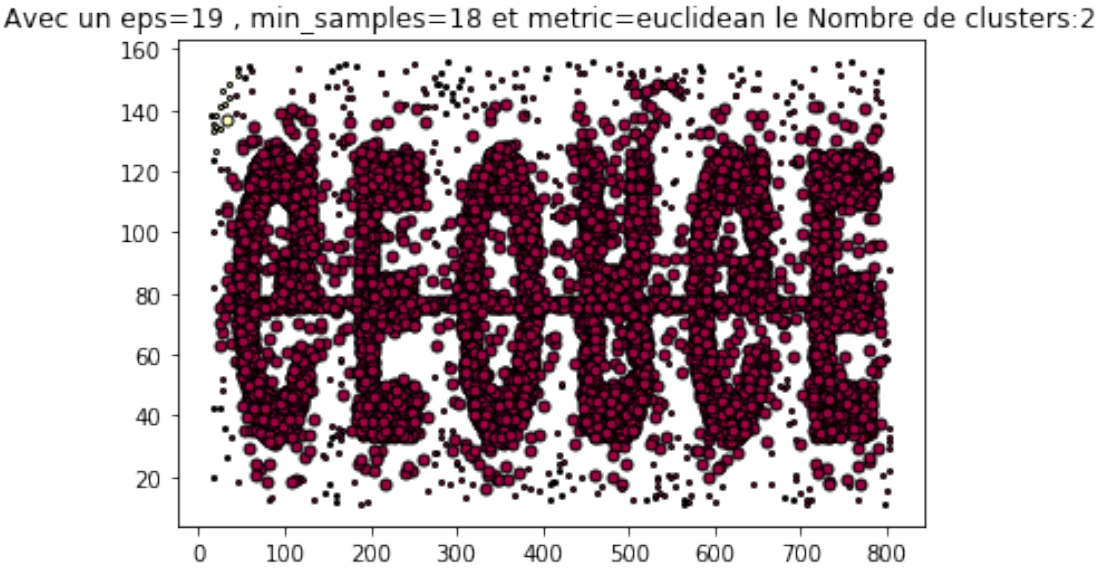
Silhouette Coefficient: 0.051



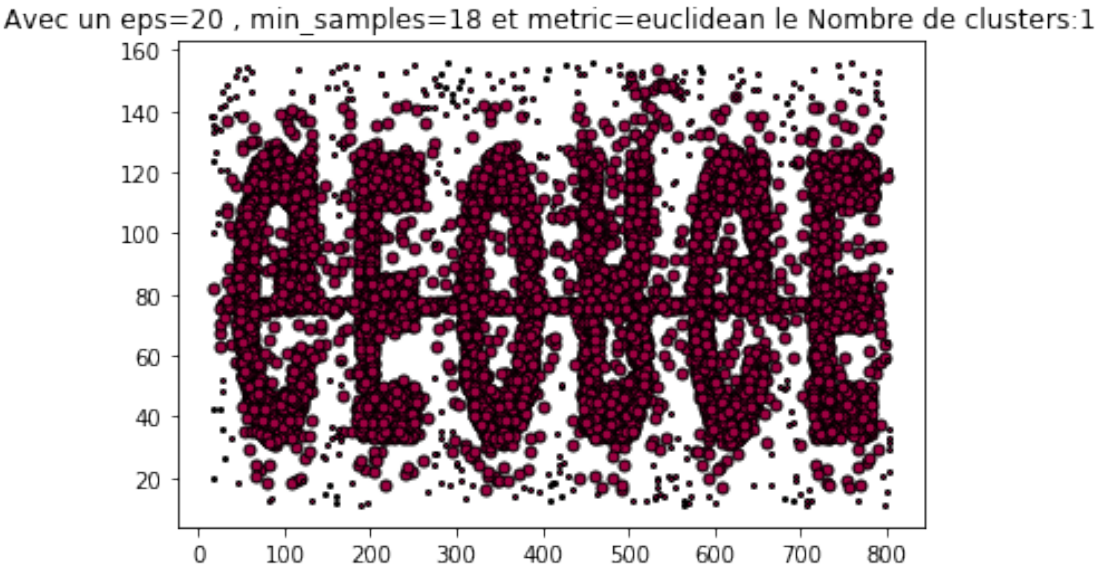
Silhouette Coefficient: 0.086



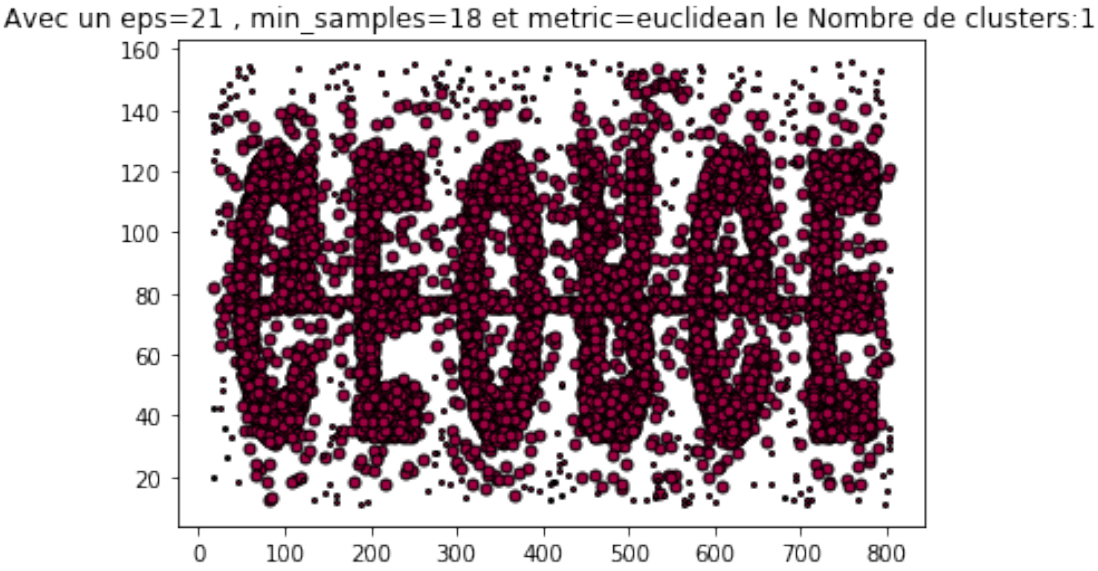

```
Silhouette Coefficient: -0.055
```



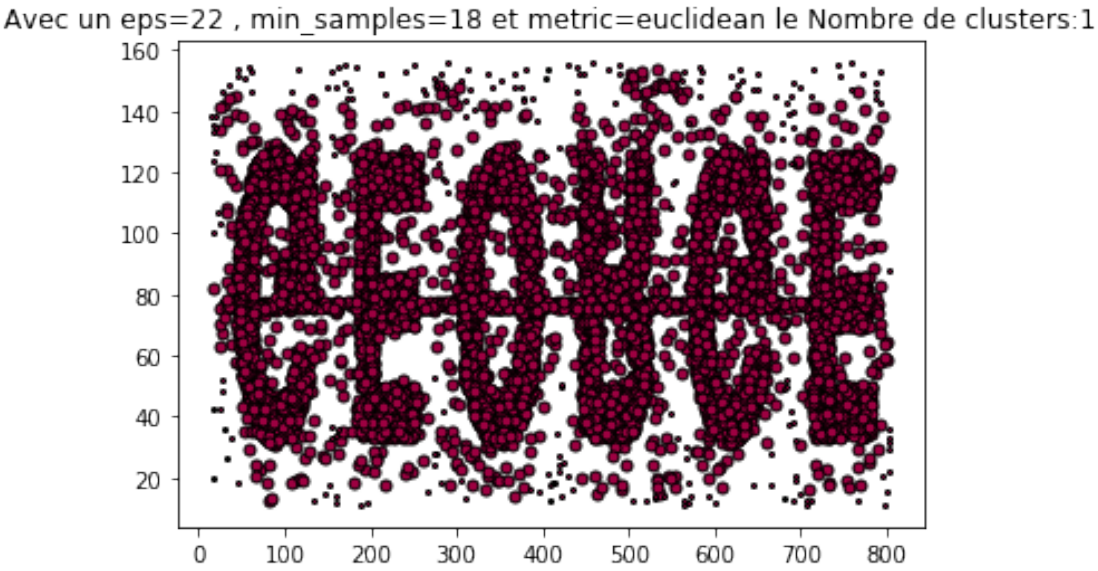

```
Silhouette Coefficient: 0.010
```



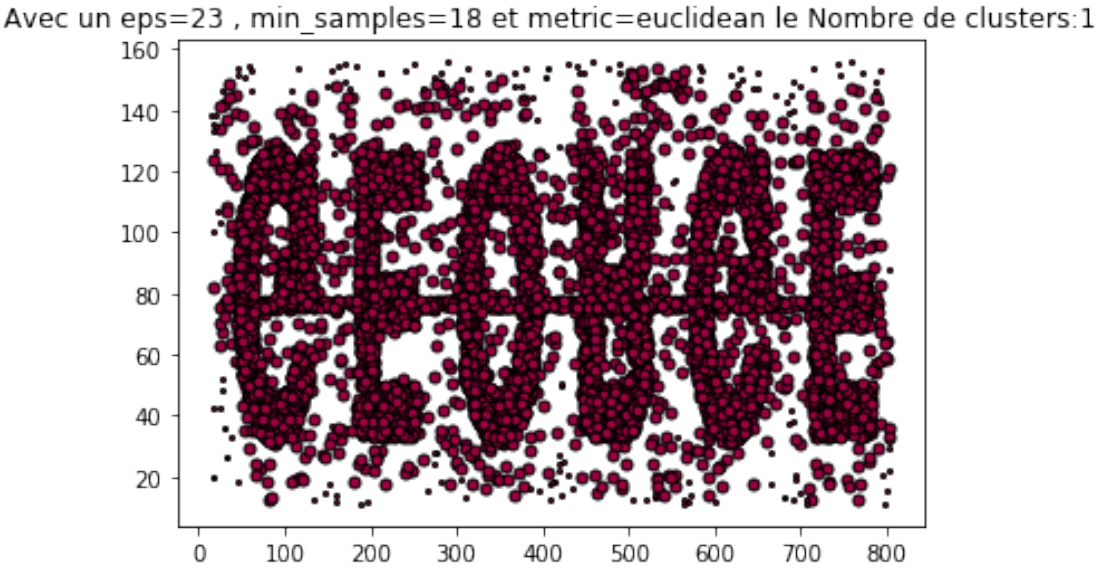
Silhouette Coefficient: 0.021



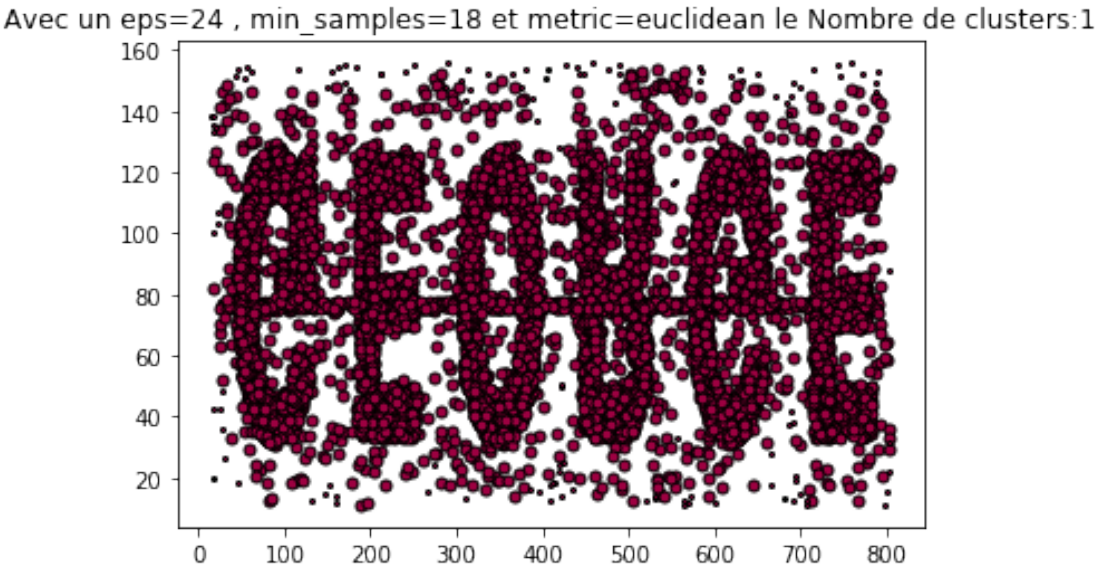
Silhouette Coefficient: 0.077



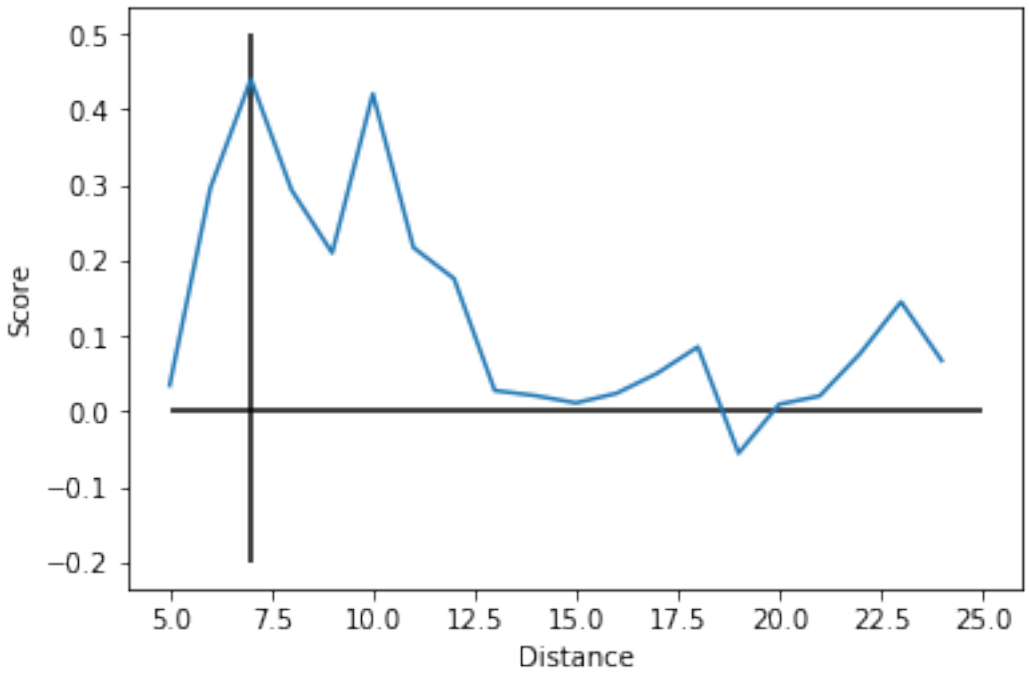
Silhouette Coefficient: 0.145



Silhouette Coefficient: 0.068

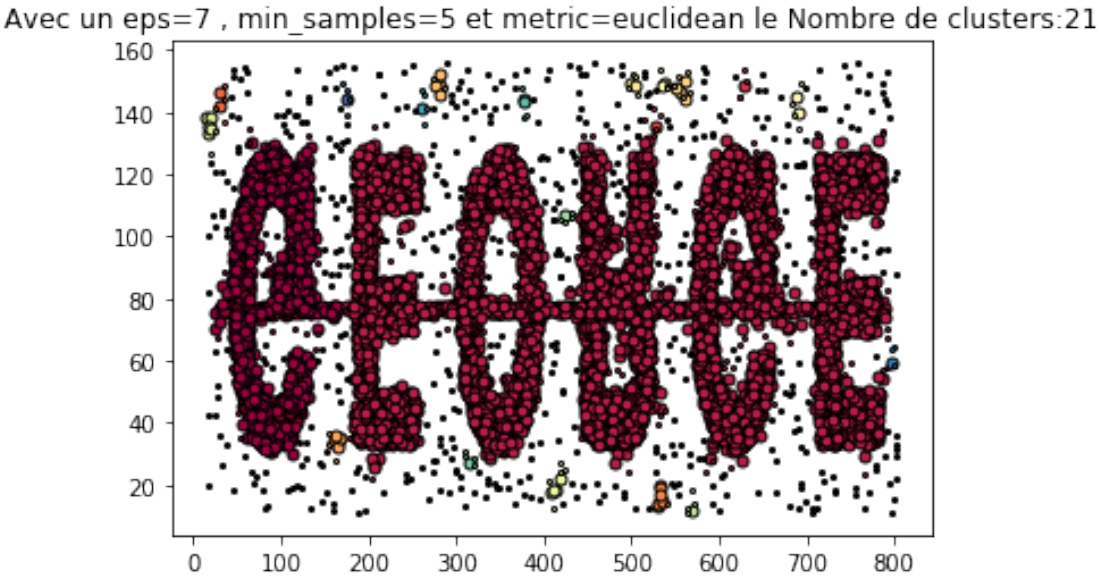



```
In [10]: plt.plot(range(5,25),Scores_2)
         plt.hlines(y=0,xmin=5, xmax=25)
         plt.vlines(x=7,ymin=-0.2,ymax=0.5)
         plt.xlabel('Distance')
         plt.ylabel('Score')
         plt.show()
```

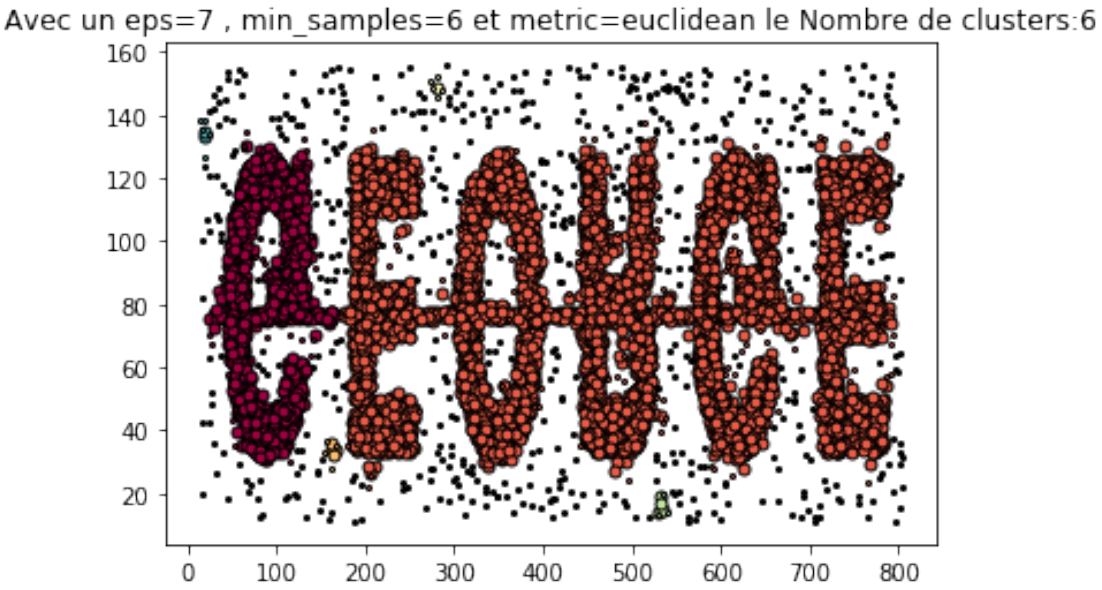


```
In [11]: ScoresSamples_2 = []
         data_2 = np.genfromtxt("cham-data/t5.8k.dat",delimiter=" ")
         for i in range(5,25):
             meth_dbscan(dataSet=data_2,minSamples=i,distance=7,Scores = ScoresSamples_2)
```

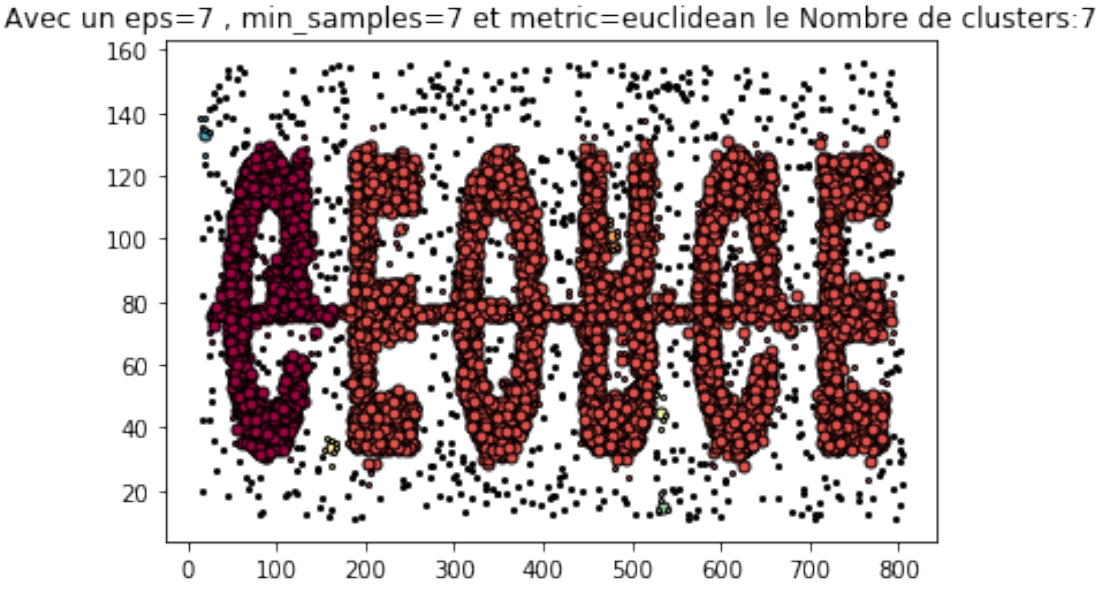
```
Silhouette Coefficient: -0.594
```



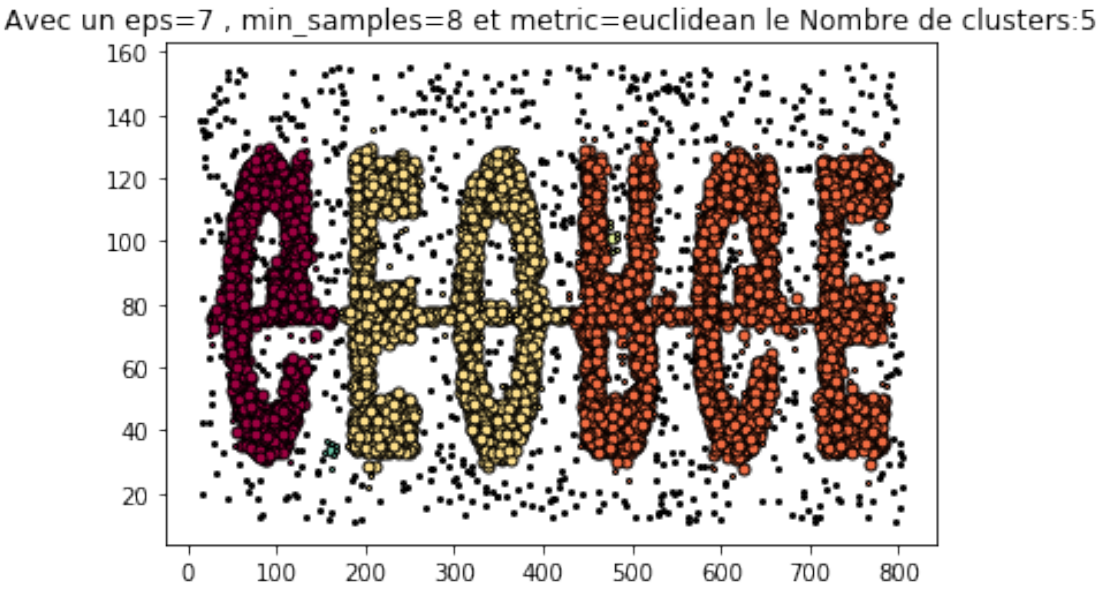

```
Silhouette Coefficient: -0.361
```



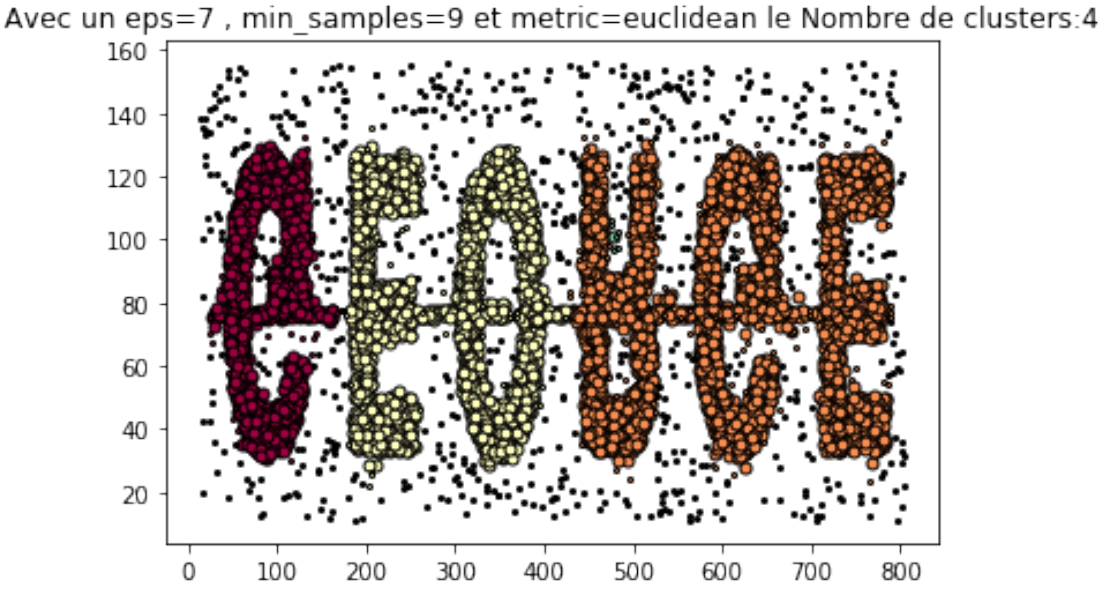

```
Silhouette Coefficient: -0.398
```




```
Silhouette Coefficient: 0.004
```

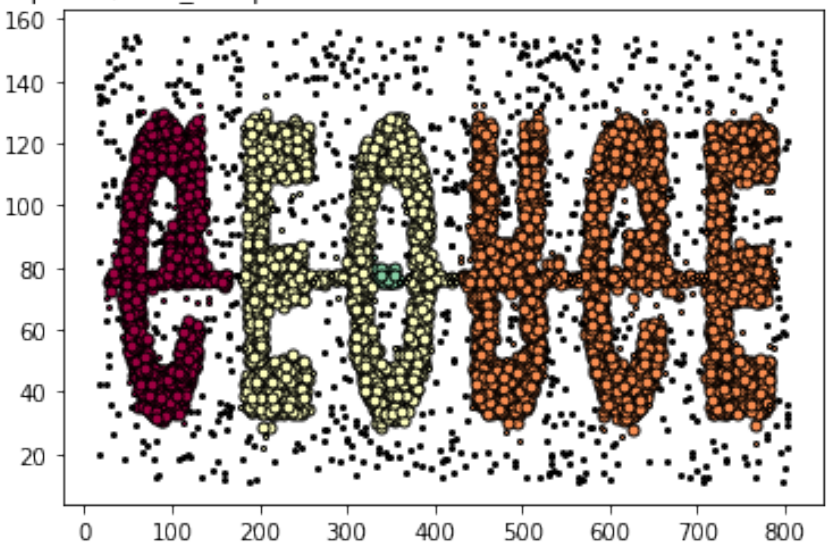



```
Silhouette Coefficient: 0.122
```



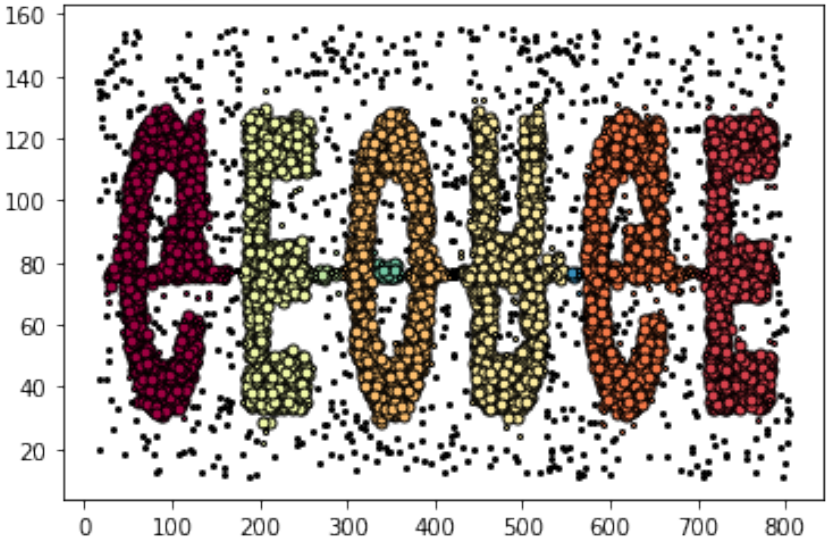

```
Silhouette Coefficient: 0.171
```

Avec un eps=7 , min_samples=10 et metric=euclidean le Nombre de clusters:4



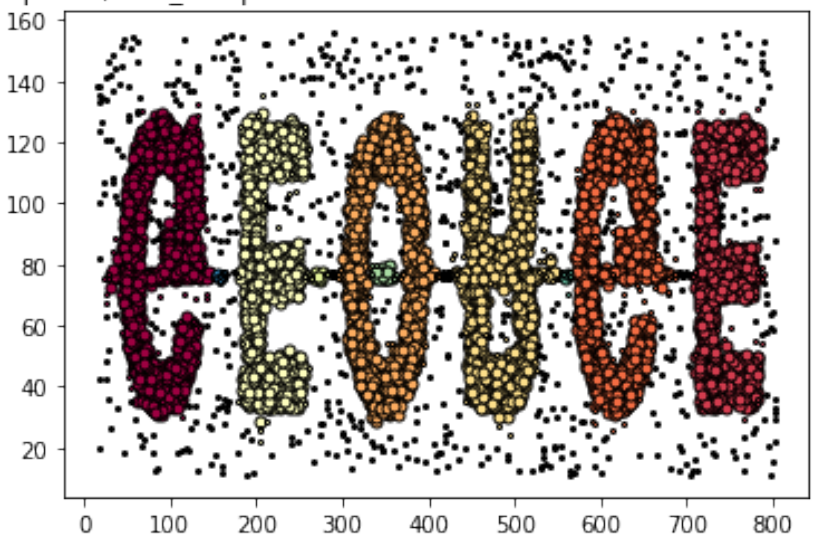

```
Silhouette Coefficient: 0.198
```

Avec un eps=7 , min_samples=11 et metric=euclidean le Nombre de clusters:9



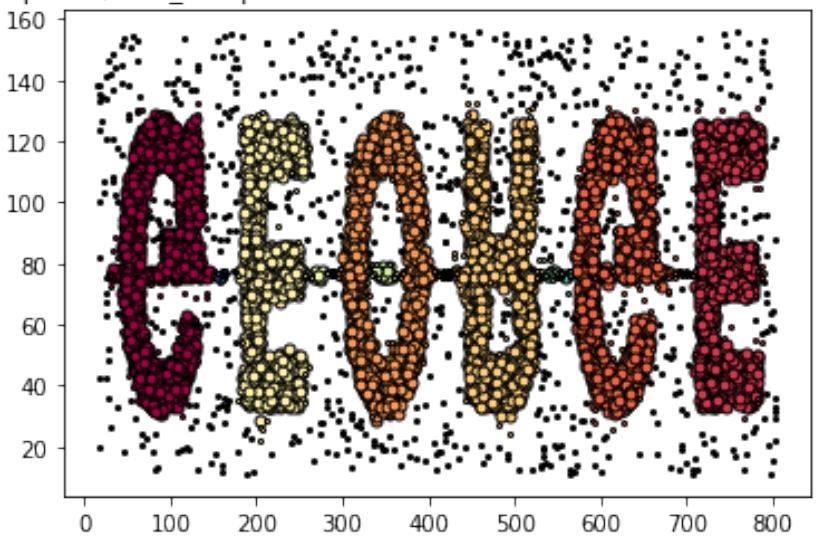

```
Silhouette Coefficient: 0.110
```

Avec un eps=7 , min_samples=12 et metric=euclidean le Nombre de clusters:10



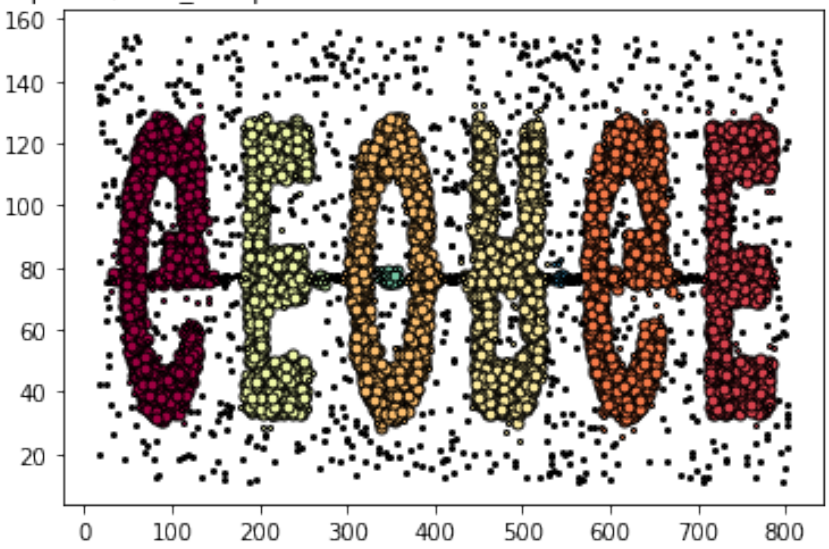
Silhouette Coefficient: 0.090

Avec un eps=7 , min_samples=13 et metric=euclidean le Nombre de clusters:11



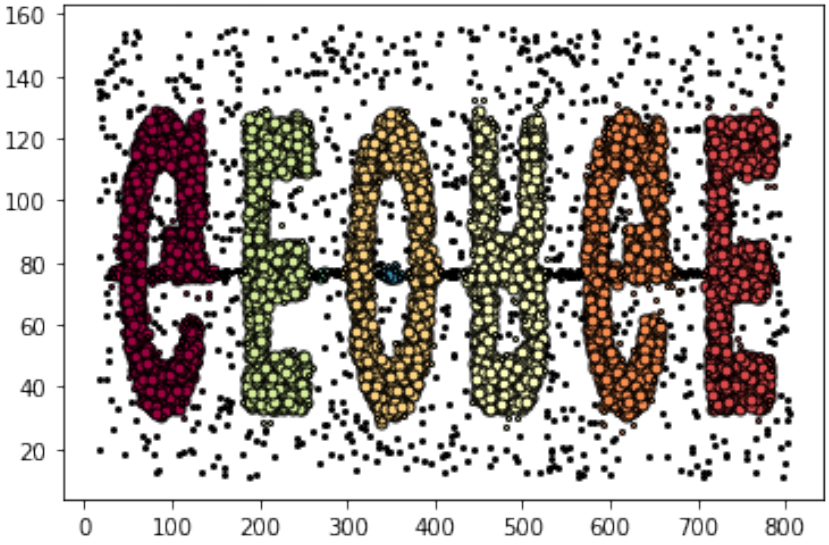
Silhouette Coefficient: 0.193

Avec un eps=7 , min_samples=14 et metric=euclidean le Nombre de clusters:9



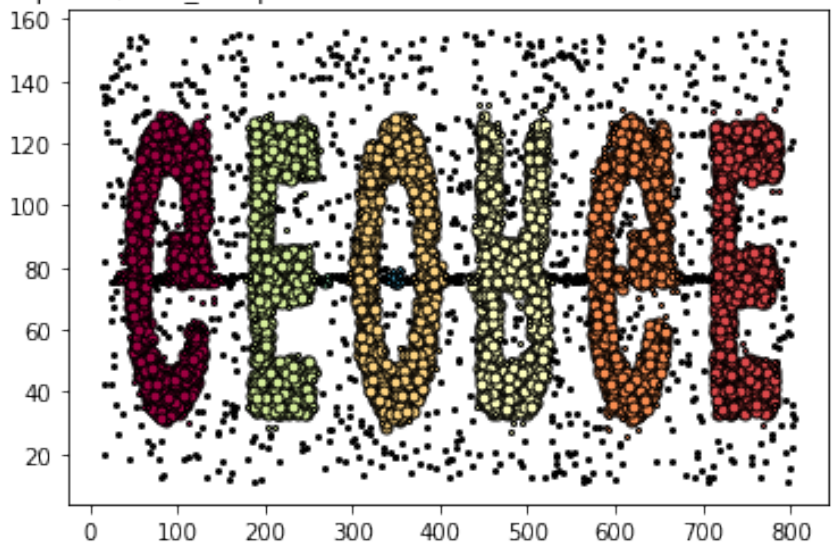

```
Silhouette Coefficient: 0.289
```

Avec un eps=7 , min_samples=15 et metric=euclidean le Nombre de clusters:8



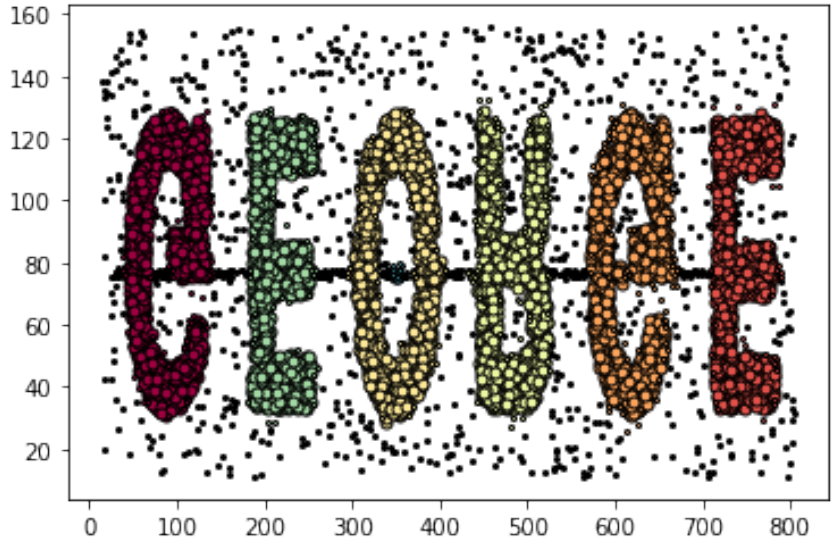

```
Silhouette Coefficient: 0.281
```

Avec un eps=7 , min_samples=16 et metric=euclidean le Nombre de clusters:8

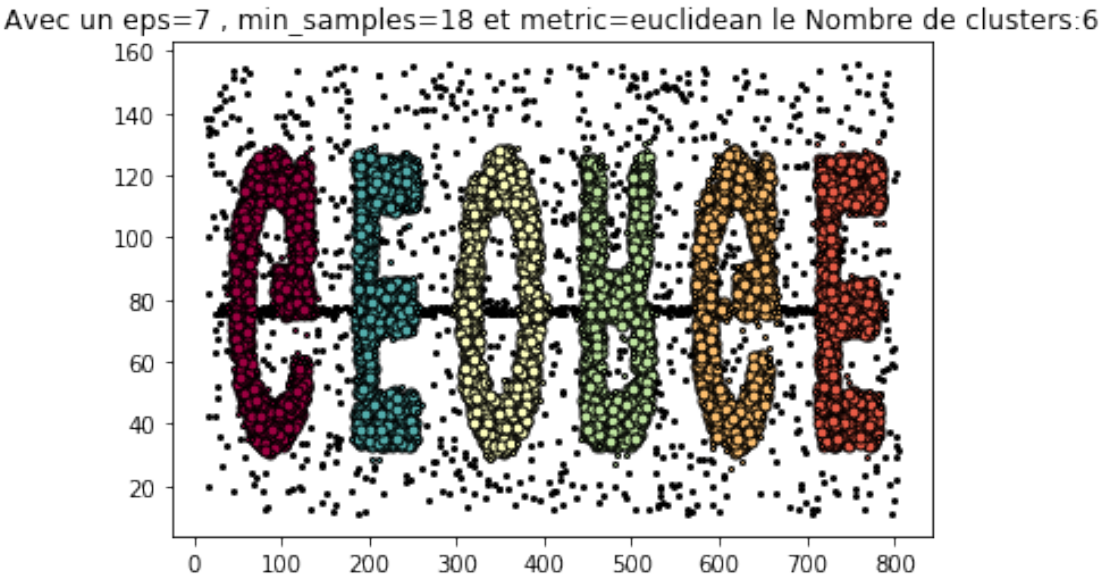



```
Silhouette Coefficient: 0.327
```

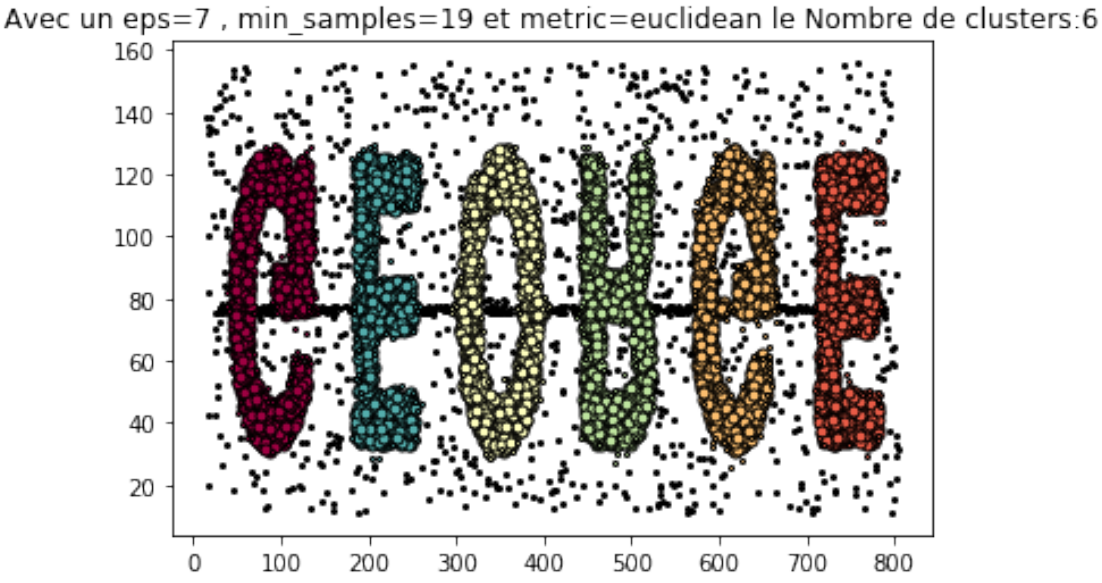
Avec un eps=7 , min_samples=17 et metric=euclidean le Nombre de clusters:7



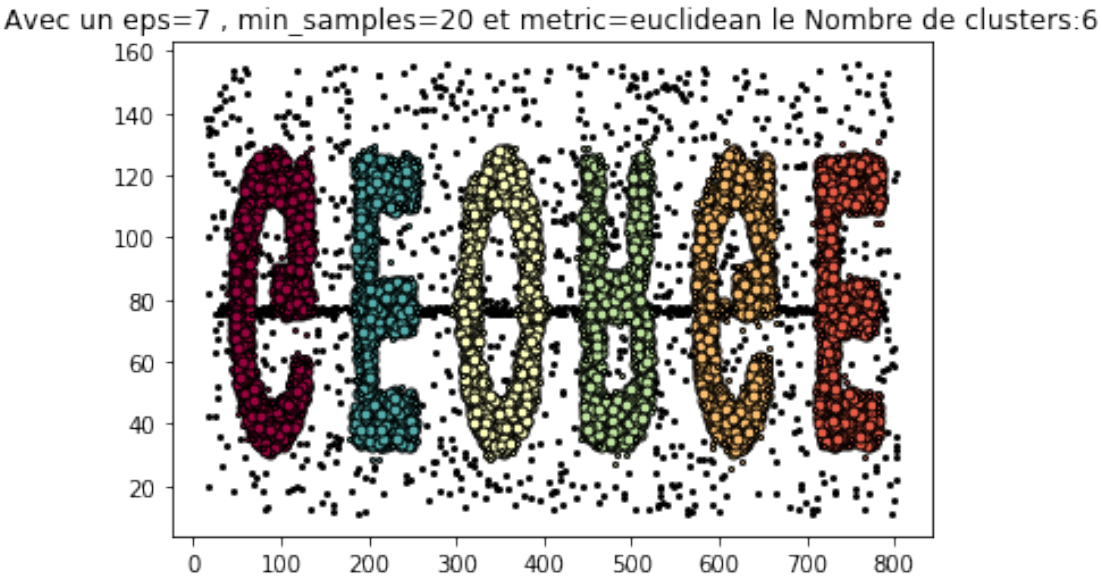

```
Silhouette Coefficient: 0.440
```



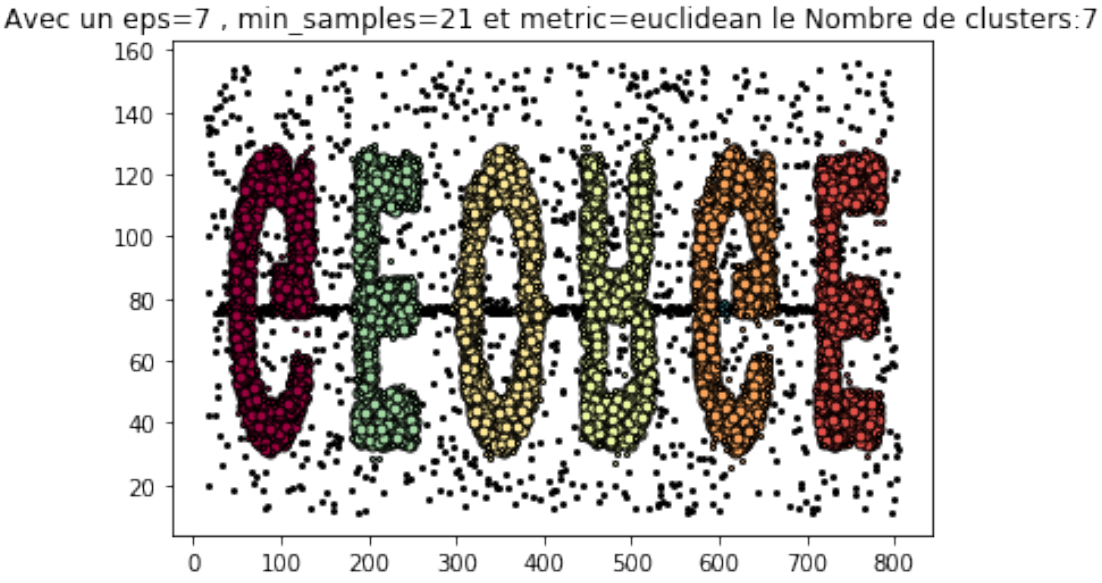

```
Silhouette Coefficient: 0.438
```



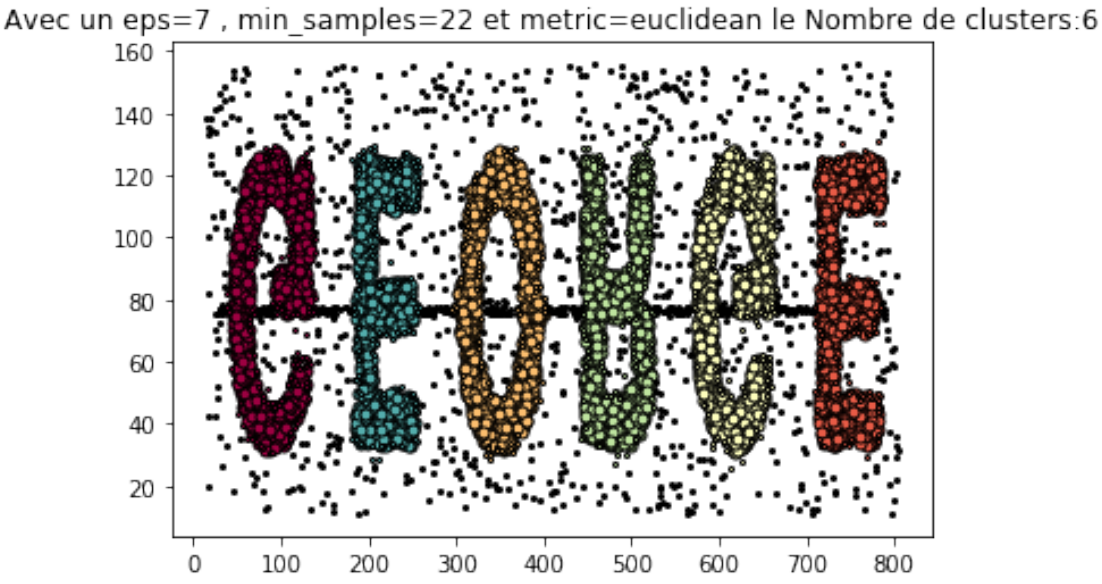

```
Silhouette Coefficient: 0.436
```



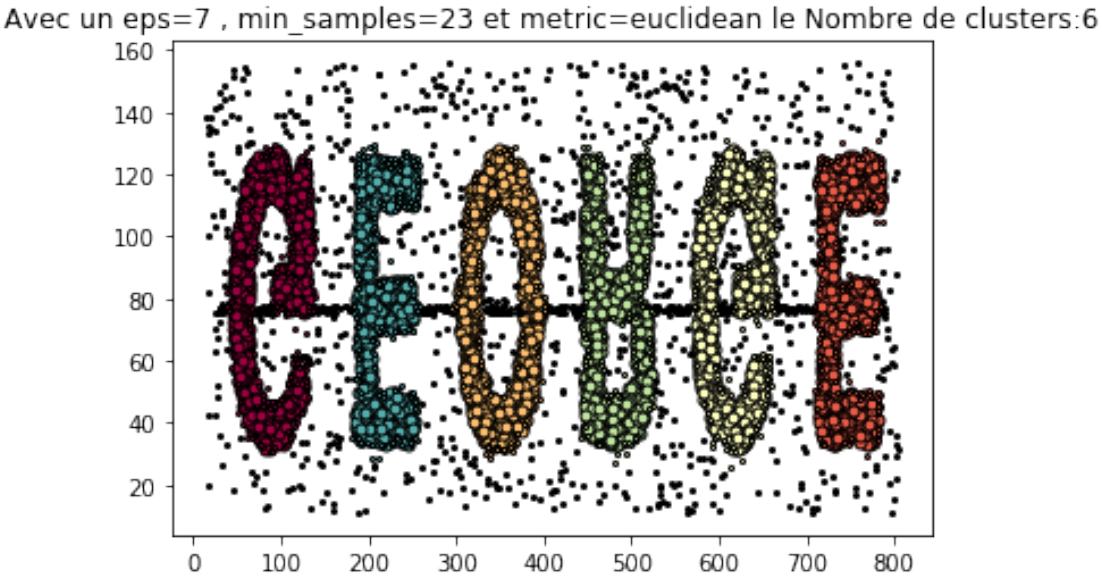

```
Silhouette Coefficient: 0.307
```



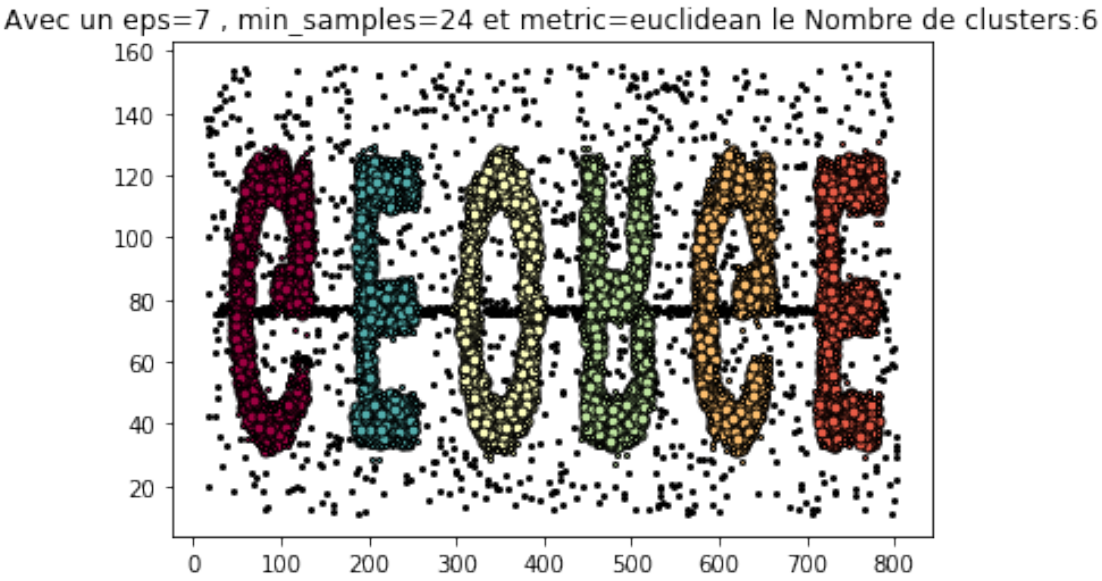

```
Silhouette Coefficient: 0.430
```



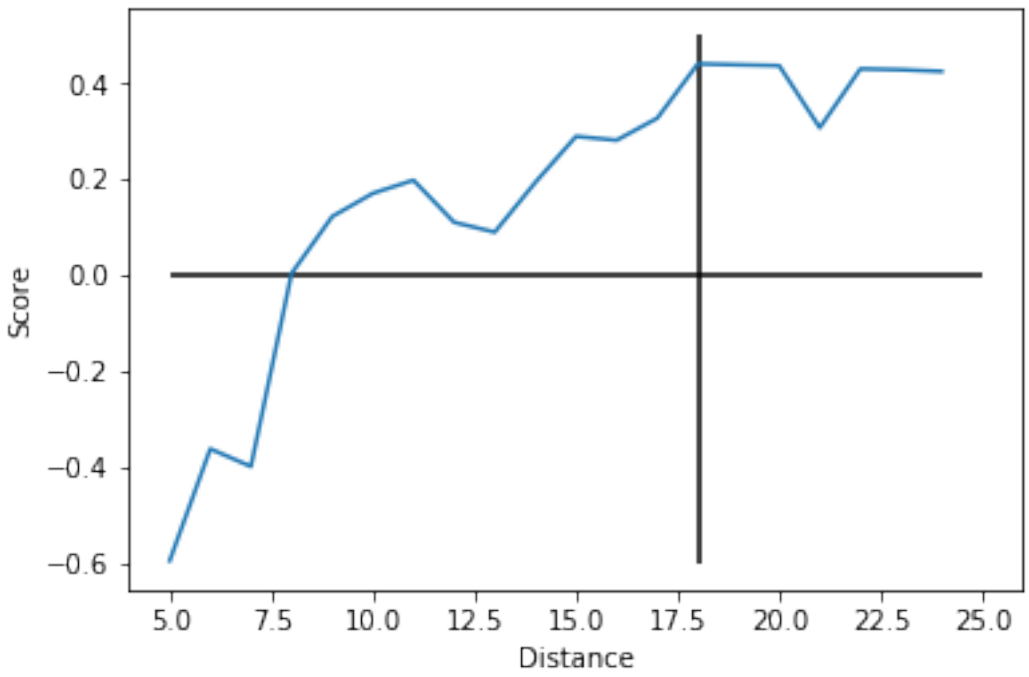

```
Silhouette Coefficient: 0.428
```



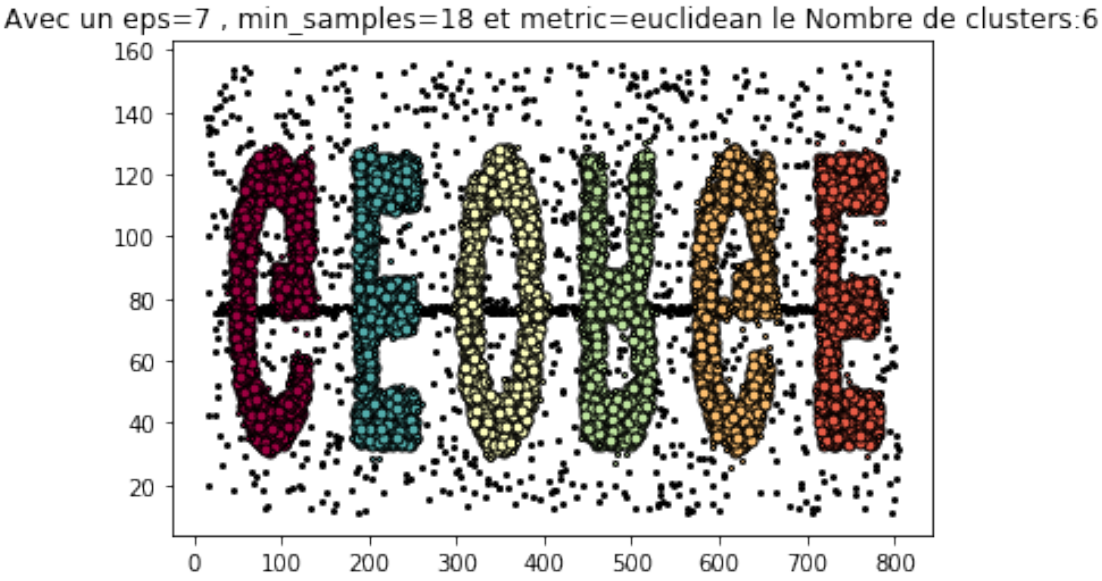

```
Silhouette Coefficient: 0.424
```




```
In [12]: plt.plot(range(5,25),ScoresSamples_2)
         plt.hlines(y=0,xmin=5, xmax=25)
         plt.vlines(x=18,ymin=-0.6,ymax=0.5)
         plt.xlabel('Distance')
         plt.ylabel('Score')
         plt.show()
```



```
In [13]: meth_dbscan(dataSet=data_2,minSamples=18,distance=7,Scores = ScoresSamples)

Silhouette Coefficient: 0.440
```



1.2 Partie SNN

On import les données et ensuite on crée notre matrice des plus proches voisins qui contient des 0 et 1

1.2.1 Méthode 1

```
In [4]: from scipy.spatial.distance import pdist,squareform
        from sklearn.neighbors import NearestNeighbors

        data_2 = np.genfromtxt("cham-data/t4.8k.dat",delimiter=" ")

        res=np.array(squareform(pdist(data_2, metric='euclidean')))

        res = (1/(1+res))

        res_data = res.copy()

        idx = np.argpartition(res, kth=5)
```

```
        for i in range(len(res)):
            res[i,idx[i][:5]] = 1
            res[i,idx[i][5:]] = 0
```

```
In [5]: res2 = res
        print(res2)
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 ...
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
```

Ensuite on crée la matrice qui représente le schéma de Jarvis – Patrick

```
In [6]: multi = np.linalg.matrix_power(res2,2)
```

```
In [17]: multi2 = multi.copy()
         multi2 = multi2 + multi2.T
         multi2[np.where(multi2 > 1)] = 1

         multi2 = np.multiply((res_data),multi2)

         multi2[np.where(multi2 < 0.02)] = 0
```

Pour un nombre de voisin 5 et un threshold 0.02 on obtient 5 cluster bien distinct

```
In [18]: import networkx as nx

         mulit2 = multi2[:200,:200]

         G = nx.from_numpy_matrix(multi2)

         nx.draw(G, node_size=5)
```

1.2.2 Methode 2

```
In [1]: import numpy as np
        from numpy import linalg as la

        # scikit-learn
        from sklearn import datasets, metrics
        from sklearn.cluster import DBSCAN
        from sklearn.neighbors import kneighbors_graph, NearestNeighbors

        # scipy
        from scipy.spatial.distance import pdist,squareform
        from scipy.sparse import csgraph as csg

        # plot
        import matplotlib.pyplot as plt
        import networkx as nx
        from networkx.drawing.nx_pydot import write_dot # Write to file
```

```
In [2]: dataset = np.loadtxt('cham-data/t4.8k.dat')
```

Paramètre

```
In [3]: X = dataset
        k = 10
```

```
threshold_percentage = 0.4 # min = 0, max = 1
symmetric = True
n_clusters = 100
noise_percentage = 0.05 # Percentage of linking power to be ignored
```

Construct similarity mattrix (save in file to avoid learn time)

```
In [5]: # similarity_graph = kneighbors_graph(
        #     X,
        #     n_neighbors = X.shape[0] - 1,
        #     mode='distance',
        #     metric='euclidean',
        #      p=2) # n x n

        # similarity_matrix = similarity_graph.toarray()
        similarity_matrix = np.array(squareform(pdist(X, metric='euclidean')))
        similarity_matrix = 1 / (1 + similarity_matrix)
        np.save('similarity_matrix', similarity_matrix)
```

(check point)

```
In [6]: similarity_matrix = np.load('similarity_matrix.npy')
        print("similarity_matrix loaded, dimension",similarity_matrix.shape)
```

```
similarity_matrix loaded, dimension (8000, 8000)
```

Sparsify the similarity matrix using k-nn sparsification

```
In [7]: neigh = NearestNeighbors(n_neighbors = k, n_jobs=-1)
        neigh.fit(similarity_matrix)
        k_neighbor_indices = neigh.kneighbors(return_distance = False)
        np.save('k_neighbor_indices', k_neighbor_indices)
```

(check point)

```
In [8]: k_neighbor_indices = np.load('k_neighbor_indices.npy')
        print("k_neighbor_indices loaded, dimension",k_neighbor_indices.shape)
```

```
k_neighbor_indices loaded, dimension (8000, 10)
```

Construct the shared nearest neighbor graph from k-nn sparsified similarity matrix

```
In [9]: linking_matrix = np.zeros(similarity_matrix.shape)
        linking_matrix[np.arange(similarity_matrix.shape[0])[:, None], k_neighbor_indices] = 1
        if symmetric :
            linking_matrix = (linking_matrix + linking_matrix.T)
            linking_matrix = linking_matrix + linking_matrix.T
            linking_matrix[ np.where(linking_matrix > 1) ] = 1
        np.save('linking_matrix', linking_matrix)
```

```
In [10]: # Verify that we don't have 0 every where
         print(np.sum(linking_matrix, axis=1))
         print(np.sum(linking_matrix))
```

```
[10. 12. 10. ... 10. 11. 14.]
93796.0
```

(check point)

```
In [11]: linking_matrix = np.load('linking_matrix.npy')
         print("linking_matrix loaded, dimension",linking_matrix.shape)
```

```
linking_matrix loaded, dimension (8000, 8000)
```

For every point in the graph, calculate the total strength of links coming out of the point. (Steps 1-4 are identical to the Jarvis – Patrick scheme.)

```
In [12]: shared_matrix = la.matrix_power(linking_matrix, 2)
         np.fill_diagonal(shared_matrix, 0)
         shared_matrix = np.multiply((k + 1 - similarity_matrix), shared_matrix)
         np.save('shared_matrix', shared_matrix)
```

(check point)

```
In [13]: shared_matrix = np.load('shared_matrix.npy')
         print("shared_matrix loaded, dimension",shared_matrix.shape)
```

```
shared_matrix loaded, dimension (8000, 8000)
```

Identify representative points by choosing the points that have high total link strength.

Identify noise points by choosing the points that have low total link strength and remove them.

```
In [14]: linking_power = np.sum(shared_matrix, axis=0)

         noise_threshold = noise_percentage * (np.max(linking_power) - np.min(linking_power)) +
         noises = np.where(linking_power < noise_threshold)[0]
```

Remove all links that have weight smaller than a threshold.

```
In [15]: threshold = threshold_percentage * np.max(shared_matrix)
         cutted_shared_matrix = shared_matrix.copy()
         cutted_shared_matrix[np.where(shared_matrix < threshold)] = 0
```

Take connected components of points to form clusters, where every point in a cluster is either a representative point or is connected to a representative point

```
In [16]: # Test if we have Strongly connected graph
         nb_cluster, _labels = csg.connected_components(cutted_shared_matrix, directed=False)
         print('Detect cluster by Strongly connected components: nb cluster = ', nb_cluster)
```

```
Detect cluster by Strongly connected components: nb cluster =  1398
```

```
In [17]: # ignore noises:
         # Caution: bewhare to affect noises when you are not sure about the noises threshold
         _labels[noises] = -1
```

Debug show shared matrix

```
In [19]: def show_graph(matrix):
             G = nx.from_numpy_matrix(matrix)
             nx.draw(G, node_size=10)
```

```
In [20]: show_graph(shared_matrix)
```

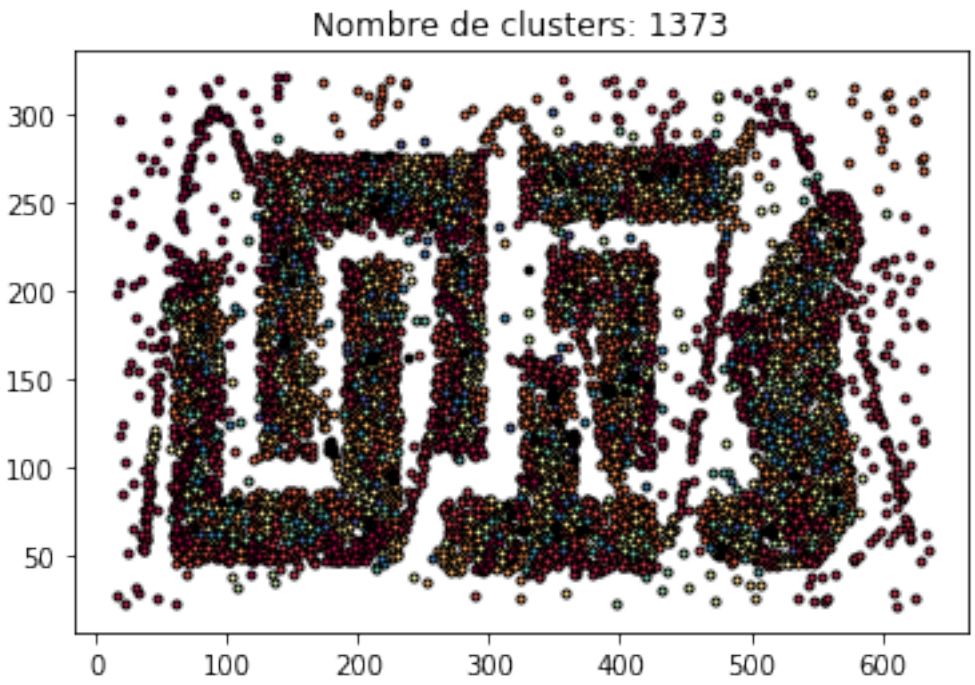
```
c:\users\moham\appdata\local\programs\python\python36\lib\site-packages\networkx\drawing\nx_py
  if cb.is_numlike(alpha):
```

Visualize

```
In [22]: # labels = clustering.labels_
         labels = _labels
         n_clusters = len(set(labels)) - (1 if -1 in labels else 0)
         print("Nombre de cluster:",n_clusters)
```

```
Nombre de cluster: 1373
```

```
In [23]: unique_labels = set(labels)
         colors = [plt.cm.Spectral(each) for each in np.linspace(0, 1, len(unique_labels))]
         # core_samples_mask = np.zeros_like(labels, dtype=bool)
         # core_samples_mask[clustering.core_sample_indices_] = True

         for k, col in zip(unique_labels, colors):

             if k == -1:
                 # Black used for noise.
                 col = [0, 0, 0, 1]

             class_member_mask = (labels == k)

             # afficher les données de cluster
         #     xy = dataset[class_member_mask & core_samples_mask]
             xy = dataset[class_member_mask]
             plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col), markeredgecolor='k'

             # noises
         #     xy = dataset[class_member_mask & ~core_samples_mask]
         #     xy = dataset[class_member_mask]
         #     plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col), markeredgecolor='

         plt.title('Nombre de clusters: %d' % n_clusters)
         plt.show()
```



Pour la deuxième méthode on peut avoir une représentation des clusters par rapport aux données entré en revanche la méthode une nous donne seulement un visuel sur le nombre de clusters