K-means clustering

0. load the data from the files

load the data from the files

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

dataset = pd.read_csv('data-kmeans.csv')
data = dataset.values
print(data.shape)

(200, 2)
```

1. define a function to compute a distance between two points aaa and bbb

```
def compute_distance(a, b):
    #distance between a and b#
    dist = np.sum((a - b) ** 2)
    return np.sqrt(dist)

temp_a = np.array([0, 0]);
temp_b = np.array([5, 2]);
print(compute_distance(temp_a, temp_b));

5.385164807134504
```

2. define a function to compute a centroid from a given set of points ZZZ

```
In [37]: def compute_centroid(Z):
    #centroid of a set of points in P#
    center = sum(Z, 0.0) / len(Z)
    return center
```

3. define a function to determine the label of point zzz with a set of centroids MMM

```
def compute_label(z, M):
    # label of point z with a set of centroids M #
    dist_list = np.zeros(len(M))
    for i in range(0, len(M)):
        dist_list[i] = compute_distance(z, M[i])

label = dist_list.argmin()

return label

temp_z = np.array([0, 0])
 temp_M = np.array([[1, 10], [0, 1], [100, 100]])

print(compute_label(temp_z, temp_M))
```

4. define a function to compute the loss with a set of clusters CCC and a set of centroids MMM

```
def compute_loss(C, M):
    # compute loss #
loss = 0
```

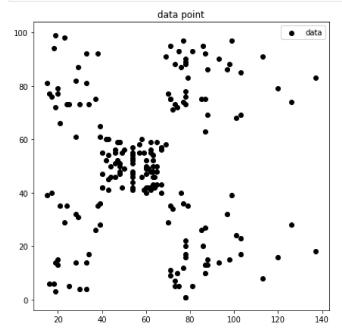
```
for c in C:
    loss = loss + compute_distance(c, M)

if(len(C) == 0):
    return 0
    return loss / len(C)

temp_c = np.array([[5, 5], [1, 2]])
temp_m = np.array([0, 0])
print(compute_loss(temp_c, temp_m))
```

4.653567894682633

5. plot the data points



6. Visualise the initial condition of the point labels

initialise the label of each point randomly, k = 5

```
In [104]: import random as rand

K = 5
init_label_list = np.zeros(len(data))
for i in range(len(data)):
    init_label_list[i] = rand.randint(0, K-1)

init_M_list = np.zeros([K, 2])

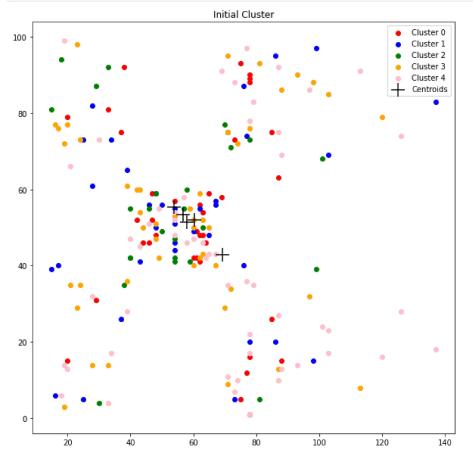
for i in range(K):
    init_M_list[i] = compute_centroid(data[init_label_list == i])
```

visualise the centroid of each cluster as well use different colors for different cluster labels

```
In [105]:
    cluster0_list = data[init_label_list == 0]
    cluster1_list = data[init_label_list == 1]
    cluster2_list = data[init_label_list == 2]
    cluster3_list = data[init_label_list == 3]
    cluster4_list = data[init_label_list == 4]

    plt.figure(figsize = (10, 10))
    plt.scatter(cluster0_list[:, 0], cluster0_list[:, 1], c = 'red', marker = 'o', label = 'Cluster 0')
    plt.scatter(cluster1_list[:, 0], cluster1_list[:, 1], c = 'blue', marker = 'o', label = 'Cluster 1')
    plt.scatter(cluster2_list[:, 0], cluster2_list[:, 1], c = 'green', marker = 'o', label = 'Cluster 2')
    plt.scatter(cluster3_list[:, 0], cluster3_list[:, 1], c = 'orange', marker = 'o', label = 'Cluster 3')
    plt.scatter(cluster4_list[:, 0], cluster4_list[:, 1], c = 'pink', marker = 'o', label = 'Cluster 4')
```

```
plt.scatter(init_M_list[:, 0], init_M_list[:, 1], c = 'black', marker = '+', s = 350, label = 'Centroids')
plt.title('Initial Cluster')
plt.legend(loc = 'upper right')
plt.show()
```



7. Optimisation

```
def compute_k_means(init_label_list, init_M_list, data, K, max_iter):
    # return loss_list, label_list, M_list, dist_M_list #
    loss_list = np.empty(1)
    prev_label_list = init_label_list
    cur_label_list = np.zeros(len(prev_label_list))
    prev_M_list = init_M_list
    cur_M_list = np.zeros([K, prev_M_list.shape[1]])
    dist_M_list = np.zeros([1, K])
    zero_point = np.array([0, 0])
    # compute first loss
    loss = 0
    for i in range(K):
        loss += compute_loss(data[prev_label_list == i], prev_M_list)
    loss_list[0] = loss / K
    # compute first dist
    for i in range(K):
        dist_M_list[0][i] = compute_distance(zero_point, prev_M_list[i])
    iter = 0
    while iter != max_iter :
        iter = iter + 1
        for i in range(K):
            cur_M_list[i] = compute_centroid(data[prev_label_list == i])
        for i in range(len(data)):
            cur_label_list[i] = compute_label(data[i], cur_M_list)
        loss = np.zeros(1)
        for i in range(K):
            loss[0] += compute_loss(data[cur_label_list == i], cur_M_list[i])
```

```
loss_list = np.append(loss_list, loss / K, axis = 0)

dist = np.zeros([1, K])
for i in range(K):
    dist[0][i] = compute_distance(zero_point, cur_M_list[i])

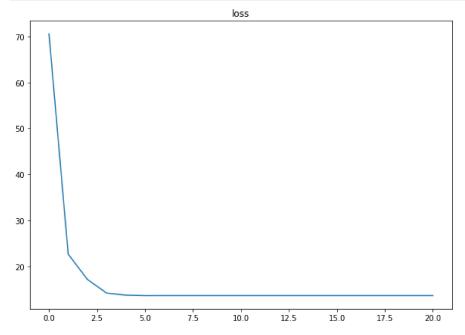
dist_M_list = np.append(dist_M_list, dist, axis = 0)

prev_M_list = cur_M_list
prev_label_list = cur_label_list

return loss_list, label_list, cur_M_list, dist_M_list
loss_list, label_list, M_list, dist_M_list = compute_k_means(init_label_list, init_M_list, data, K = 5, max_iter = 20)
```

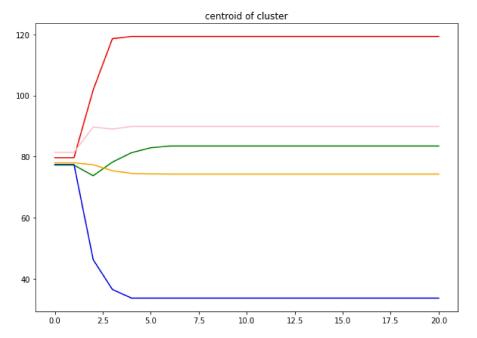
plot the loss curve

```
In [110]: plt.figure(figsize = (10, 7))
plt.plot(loss_list)
plt.title('loss')
plt.show()
```

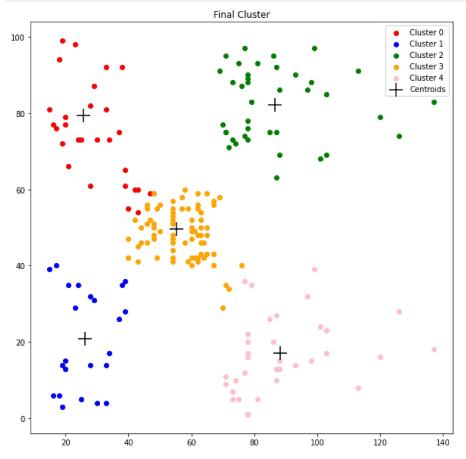


Plot the centroid of each clsuter

```
In [108]:
plt.figure(figsize = (10, 7))
plt.plot(dist_M_list[:, 0], c = 'red', label = 'Cluster 0')
plt.plot(dist_M_list[:, 1], c = 'blue', label = 'Cluster 1')
plt.plot(dist_M_list[:, 2], c = 'green', label = 'Cluster 2')
plt.plot(dist_M_list[:, 3], c = 'orange', label = 'Cluster 3')
plt.plot(dist_M_list[:, 4], c = 'pink', label = 'Cluster 4')
plt.title('centroid of cluster')
plt.show()
```



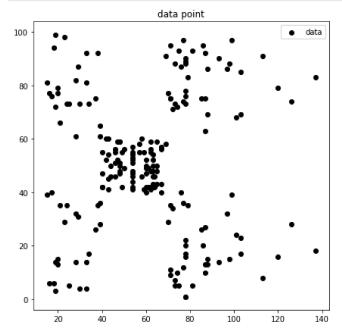
plot the final clustering result



[Output]

1. plot the data points

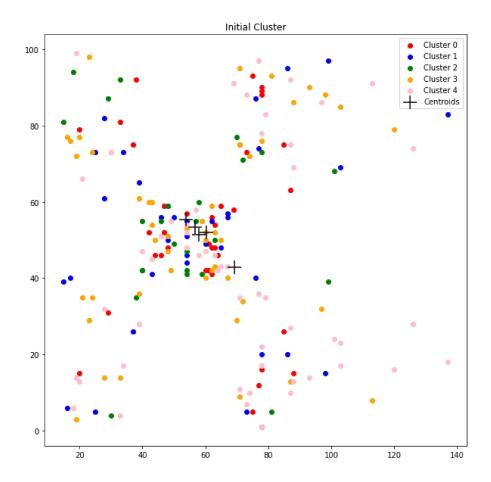
```
In [43]:
    plt.figure(figsize = (7, 7))
    plt.scatter(x, y, c = 'black', marker = 'o', label = 'data')
    plt.title('data point')
    plt.legend(loc = 'upper right')
    plt.show()
```



2. Visualise the initial condition of the point labels [1pt]

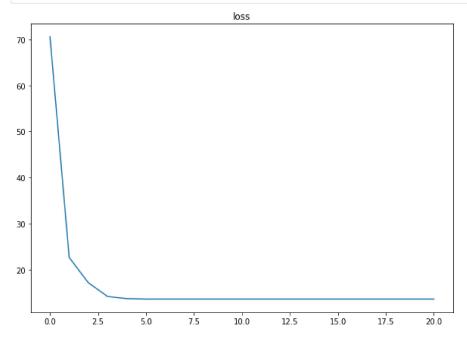
```
In [112]:
    clusterO_list = data[init_label_list == 0]
    cluster1_list = data[init_label_list == 1]
    cluster2_list = data[init_label_list == 2]
    cluster3_list = data[init_label_list == 3]
    cluster4_list = data[init_label_list == 4]

    plt.figure(figsize = (10, 10))
    plt.scatter(cluster0_list[:, 0], cluster0_list[:, 1], c = 'red', marker = 'o', label = 'Cluster 0')
    plt.scatter(cluster1_list[:, 0], cluster1_list[:, 1], c = 'blue', marker = 'o', label = 'Cluster 1')
    plt.scatter(cluster2_list[:, 0], cluster2_list[:, 1], c = 'green', marker = 'o', label = 'Cluster 2')
    plt.scatter(cluster3_list[:, 0], cluster3_list[:, 1], c = 'orange', marker = 'o', label = 'Cluster 3')
    plt.scatter(cluster4_list[:, 0], cluster4_list[:, 1], c = 'pink', marker = 'o', label = 'Cluster 4')
    plt.scatter(init_M_list[:, 0], init_M_list[:, 1], c = 'black', marker = '+', s = 350, label = 'Centroids')
    plt.legend(loc = 'upper right')
    plt.legend(loc = 'upper right')
    plt.show()
```

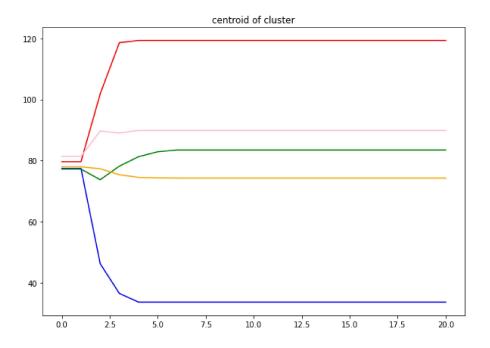


3. Plot the loss curve [5pt]

```
In [113]: plt.figure(figsize = (10, 7))
plt.plot(loss_list)
plt.title('loss')
plt.show()
```



4. Plot the centroid of each clsuter [5pt]



5. Plot the final clustering result [5pt]

```
In [115]:
    cluster0_list = data[label_list == 0]
    cluster1_list = data[label_list == 1]
    cluster2_list = data[label_list == 2]
    cluster3_list = data[label_list == 3]
    cluster4_list = data[label_list == 4]

    plt.figure(figsize = (10, 10))
    plt.scatter(cluster0_list[:, 0], cluster0_list[:, 1], c = 'red', marker = 'o', label = 'Cluster 0')
    plt.scatter(cluster1_list[:, 0], cluster1_list[:, 1], c = 'blue', marker = 'o', label = 'Cluster 1')
    plt.scatter(cluster2_list[:, 0], cluster2_list[:, 1], c = 'green', marker = 'o', label = 'Cluster 2')
    plt.scatter(cluster3_list[:, 0], cluster3_list[:, 1], c = 'orange', marker = 'o', label = 'Cluster 3')
    plt.scatter(cluster4_list[:, 0], cluster4_list[:, 1], c = 'pink', marker = 'o', label = 'Cluster 4')
    plt.scatter(M_list[:, 0], M_list[:, 1], c = 'black', marker = '+', s = 300, label = 'Centroids')
    plt.title('Final Cluster')
    plt.legend(loc = 'upper right')
    plt.show()
```

