

DSAA 5002 - Data Mining and Knowledge Discovery in Data Science

(Fall Semester 2023)

Homework 3

Deadline: 22 Nov 2023 11:59pm

(Please hand in via Canvas.) Full Mark: 100 Marks

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Q1 [20 Marks]

Apply the agglomerative hierarchical clustering algorithm with the following distance matrix and the single linkage. Plot the cluster tree and mark out all the merging levels.

	1	2	3	4
2	2.33			
3	3.15	1.30		
4	1.90	1.50	3.70	
5	3.01	0.47	1.40	1.82

Table 1 : distance matrix

\Rightarrow

	1	(2,5)	3
(2,5)	2.33		
3	3.15	1.30	
4	1.90	1.50	3.70

\Rightarrow

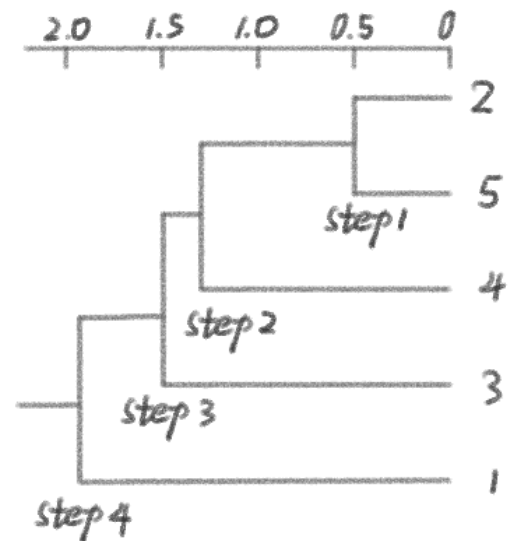
	1	(2,3,5)
(2,3,5)	2.33	
4	1.90	1.50

\Rightarrow

	1
(2,3,4,5)	1.90

\Rightarrow (1, 2, 3, 4, 5)

Cluster Tree:



Q2 [20 Marks]

Use the similarity matrix in Table 2 to perform single-link hierarchical clustering. Show your results by drawing a dendrogram. The dendrogram should clearly show the order in which the clusters are merged.

	p1	p2	p3	p4	p5
p1	1.00	0.10	0.41	0.55	0.35
p2	0.10	1.00	0.64	0.47	0.98
p3	0.41	0.64	1.00	0.44	0.85
p4	0.55	0.47	0.44	1.00	0.76
p5	0.35	0.98	0.85	0.76	1.00

Table 2: Similarity matrix for Q2

⇒

	P_1	(P_2, P_5)	P_3	P_4
P_1	1.0			
(P_2, P_5)	0.35	1.0		
P_3	0.41	0.85	1.0	
P_4	0.55	0.76	0.44	1.0

⇒

	P_1	(P_2, P_3, P_5)	P_4
P_1	1.0		
(P_2, P_3, P_5)	0.41	1.0	
P_4	0.55	0.76	1.0

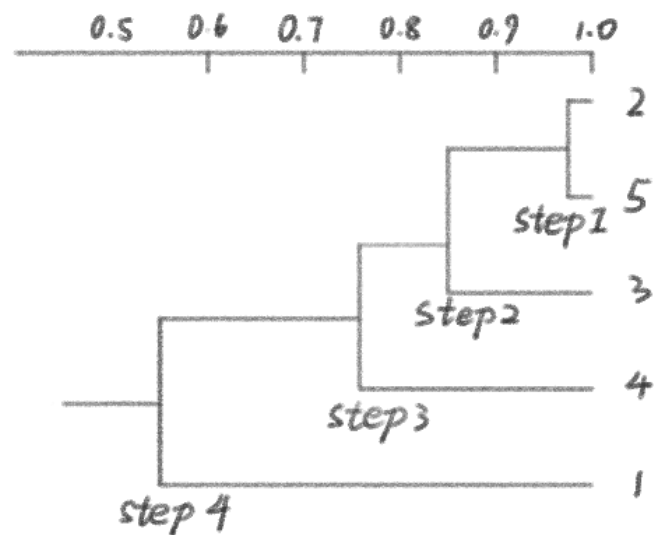
⇒

	P_1	(P_2, P_3, P_4, P_5)
P_1	1.0	
(P_2, P_3, P_4, P_5)	0.55	1.0

⇒

	$(P_1, P_2, P_3, P_4, P_5)$
$(P_1, P_2, P_3, P_4, P_5)$	1.0

Cluster Tree:



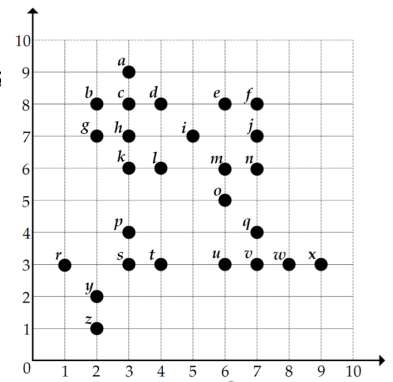
Q3 [30 Marks]

Apply DBSCAN with parameters $\text{MinPts}=4$ and $\text{Eps} = \sqrt{2}$ to get clustering results

First, for every data point, answer if it is a core, a border, or an outlier.

Second, for data points that are not outliers, show the clusters detected.

Third, show your detailed steps of DBSCAN process, including the content of the queue you maintain, whenever a new core is found.



1st. for each data point P , we calculate the $\sqrt{2}$ -neighborhood of P — $N(P)$, and judge its type with $\text{MinPts}=4$:

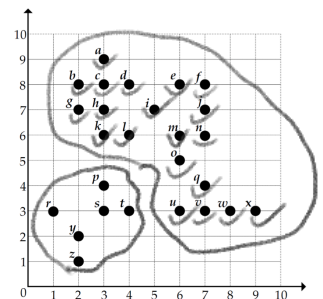
$N(a) = \{a, b, c, d\}$ core	$N(n) = \{j, m, n, o\}$ core
$N(b) = \{a, b, c, g, h\}$ core	$N(o) = \{m, n, o, q\}$ core
$N(c) = \{a, b, c, d, g, h\}$ core	$N(p) = \{p, s, t\}$ border
$N(d) = \{a, c, d, h, i\}$ core	$N(q) = \{o, q, u, v, w\}$ core
$N(e) = \{e, f, i, j\}$ core	$N(r) = \{r, y\}$ border
$N(f) = \{e, f, j\}$ border	$N(s) = \{p, s, t, y\}$ core
$N(g) = \{b, c, g, h, k\}$ core	$N(t) = \{p, s, t\}$ border
$N(h) = \{b, c, d, g, h, k, l\}$ core	$N(u) = \{q, u, v\}$ border
$N(i) = \{d, e, i, l, m\}$ core	$N(v) = \{q, u, v, w\}$ core
$N(j) = \{e, f, j, m, n\}$ core	$N(w) = \{q, v, w, x\}$ core
$N(k) = \{g, h, k, l\}$ core	$N(x) = \{w, x\}$ border
$N(l) = \{h, i, k, l\}$ core	$N(y) = \{r, s, y, z\}$ core
$N(m) = \{z, j, m, n, o\}$ core	$N(z) = \{y, z\}$ border

core points: $\{a, b, c, d, e, g, h, i, j, k, l, m, n, o, q, s, v, w, y\}$

border points: $\{f, p, r, t, u, x, z\}$ outlier: \emptyset

2nd. Clusters detected: [unprocessed points] = $\{a, b, c, \dots, x, y, z\}$

- 1° ① Arbitrary select a point, here we choose 'a'
- ② Retrieve all the points density-reachable from 'a': $\{b, c, d, e, f, g, h, i, j, k, l, m, n, o, q, u, v, w, x\}$
- ③ Here, 'a' is a core point, a cluster is formed:
Cluster_1 = $\{a, b, c, d, e, f, g, h, i, j, k, l, m, n, o, q, u, v, w, x\}$
- ④ [unprocessed points] = $\{p, r, s, t, y, z\}$



- 2° ① Next, select a point from [unprocessed points], here we choose 'p'
- ② Here, 'p' is a border point, just visit the next point
- ③ Then visit next point from [unprocessed points], here we choose 's'
- ④ Retrieve all the points density-reachable from 's': $\{p, r, t, y, z\}$
- ⑤ Here p is a core point, a cluster is formed:
Cluster_2 = $\{p, r, s, t, y, z\}$
- ⑥ [unprocessed points] = \emptyset , the algorithm stops here.

Q4 [20 Marks] Fuzzy Cluster

Assume there are 2 clusters in which the data is to be divided, initializing the data point randomly. Each data point lies in both clusters with some membership value which can be assumed anything in the initial state.

The table below represents the values of the data points along with their membership (gamma) in each cluster.

Cluster	(1,3)	(2,5)	(4,8)	(7,9)	(9,12)
1)	0.8	0.7	0.5	0.3	0.1
2)	0.2	0.3	0.5	0.7	0.9

Please work out the centroids, the distance of each point from centroid, and the cluster membership value.

Here, we have:

5 Data Points: $O = \{O_1, O_2, O_3, O_4, O_5\} = \{(1,3), (2,5), (4,8), (7,9), (9,12)\} \Rightarrow O_i = (x_i^{(0)}, y_i^{(0)})$

2 Clusters: $C = \{C_1, C_2\}$, with their centroids $\{c_1, c_2\} \Rightarrow C_j = (x_j^{(c)}, y_j^{(c)})$

\Rightarrow ① the distance of each point from centroid:

$$\text{dist}(O_i, C_j)^2 = (x_i^{(0)} - x_j^{(c)})^2 + (y_i^{(0)} - y_j^{(c)})^2$$

② Cluster membership value

$$W_{ij} = \frac{\frac{1}{\text{dist}(O_i, C_j)^2}}{\sum_{j=1}^2 \frac{1}{\text{dist}(O_i, C_j)^2}} \Rightarrow \begin{cases} W_{i1} = \frac{\text{dist}(O_i, C_2)^2}{\text{dist}(O_i, C_1)^2 + \text{dist}(O_i, C_2)^2} \\ W_{i2} = \frac{\text{dist}(O_i, C_1)^2}{\text{dist}(O_i, C_1)^2 + \text{dist}(O_i, C_2)^2} \end{cases}$$

$$\textcircled{3} \text{SSE}(C_j) = \sum_{i=1}^5 W_{ij}^2 \text{dist}(O_i, C_j)^2$$

0° We randomly set the centroid: $C_1 = O_1 = (1, 3)$, $C_2 = O_2 = (2, 5)$

1° In E-Step, we use centroid $C_1 = (x_1^{(c)}, y_1^{(c)})$ & $C_2 = (x_2^{(c)}, y_2^{(c)})$, to calculate W_{i1}, W_{i2} .

$$\begin{cases} W_{i1} = \frac{(x_i^{(0)} - x_2^{(c)})^2 + (y_i^{(0)} - y_2^{(c)})^2}{(x_i^{(0)} - x_1^{(c)})^2 + (y_i^{(0)} - y_1^{(c)})^2 + (x_i^{(0)} - x_2^{(c)})^2 + (y_i^{(0)} - y_2^{(c)})^2} \\ W_{i2} = \frac{(x_i^{(0)} - x_1^{(c)})^2 + (y_i^{(0)} - y_1^{(c)})^2}{(x_i^{(0)} - x_1^{(c)})^2 + (y_i^{(0)} - y_1^{(c)})^2 + (x_i^{(0)} - x_2^{(c)})^2 + (y_i^{(0)} - y_2^{(c)})^2} \end{cases}$$

2° In M-Step, we do optimization on $\text{SSE}(C_1)$ & $\text{SSE}(C_2)$ for $C_1 = (x_1^{(c)}, y_1^{(c)})$ & $C_2 = (x_2^{(c)}, y_2^{(c)})$, to get new c_1^* & c_2^* .

$$\frac{\partial SSE(c_j)}{\partial (x_j^{(c)}, y_j^{(c)})} = \left[\frac{\partial SSE(c_j)}{\partial x_j^{(c)}}, \frac{\partial SSE(c_j)}{\partial y_j^{(c)}} \right]$$

$$\Rightarrow \begin{cases} \frac{\partial SSE(c_j)}{\partial x_j^{(c)}} = -2 \sum_{i=1}^5 w_{ij}^2 (x_i^{(0)} - x_j^{(c)}) \\ \frac{\partial SSE(c_j)}{\partial y_j^{(c)}} = -2 \sum_{i=1}^5 w_{ij}^2 (y_i^{(0)} - y_j^{(c)}) \end{cases}$$

when $\frac{\partial SSE(c_j)}{\partial (x_j^{(c)}, y_j^{(c)})} = 0$, it is easy to prove from the second derivative of $SSE(c_j)$ that the stationary point $(x_j^{(c)}, y_j^{(c)})$ here is the Minimum Point:

$$\begin{cases} -2 \sum_{i=1}^5 w_{ij}^2 (x_i^{(0)} - x_j^{(c)}) = 0 \Rightarrow x_j^{(c)} = \frac{\sum_{i=1}^5 w_{ij}^2 x_i^{(0)}}{\sum_{i=1}^5 w_{ij}^2} \\ -2 \sum_{i=1}^5 w_{ij}^2 (y_i^{(0)} - y_j^{(c)}) = 0 \Rightarrow y_j^{(c)} = \frac{\sum_{i=1}^5 w_{ij}^2 y_i^{(0)}}{\sum_{i=1}^5 w_{ij}^2} \end{cases}$$

$$\Rightarrow C_j^* = \left(\frac{\sum_{i=1}^5 w_{ij}^2 x_i^{(0)}}{\sum_{i=1}^5 w_{ij}^2}, \frac{\sum_{i=1}^5 w_{ij}^2 y_i^{(0)}}{\sum_{i=1}^5 w_{ij}^2} \right)$$

so that, centroid will be renewed as below

$$\begin{cases} C_1^* = \left(\frac{\sum_{i=1}^5 w_{i1}^2 x_i^{(0)}}{\sum_{i=1}^5 w_{i1}^2}, \frac{\sum_{i=1}^5 w_{i1}^2 y_i^{(0)}}{\sum_{i=1}^5 w_{i1}^2} \right) \\ C_2^* = \left(\frac{\sum_{i=1}^5 w_{i2}^2 x_i^{(0)}}{\sum_{i=1}^5 w_{i2}^2}, \frac{\sum_{i=1}^5 w_{i2}^2 y_i^{(0)}}{\sum_{i=1}^5 w_{i2}^2} \right) \end{cases}$$

3° Cycle through E-step & M-step until the change of centroids is sufficiently small.

★ Programming to implement the specific calculation process of the EM Algorithm above:

```

1 import numpy as np
2
3 # Distance definition
4 def calculate_squared_distance(point, centroid):
5     return np.sum((point - centroid) ** 2)

```

```

1 # Calculate the centroid position with given membership
2 # Data points
3 points = np.array([[1.0, 3.0], [2.0, 5.0], [4.0, 8.0], [7.0, 9.0], [9.0, 12.0]])
4
5 # Initial membership
6 membership = np.array([[0.8, 0.7, 0.5, 0.3, 0.1],
7                        [0.2, 0.3, 0.5, 0.7, 0.9]]).T
8
9 #M-step: Update centroid position
10 for i in range(2):
11     # Centroid that will optimize SSE
12     centroids_numerator = np.sum(membership[:, i][:, None] ** 2 * points, axis=0).astype(float)
13     centroids_denominator = np.sum(membership[:, i]** 2).astype(float)
14     centroids[i] = centroids_numerator / centroids_denominator
15
16 print("Centroids with given membership:")
17 print(centroids)

```

Centroids with given membership in output:

```

Centroids with given membership:
[[2. 25675676  4. 93243243]
 [7. 10714286  9. 94047619]]

```

```

1 # Iterative Execution of EM Algorithm
2 iter_time = 0
3 while 1:
4     iter_time += 1
5
6     # Calculate the square distance from each point to each center point
7     squared_distances = np.array([[calculate_squared_distance(point, centroid) \
8                                   for centroid in centroids] \
9                                   for point in points])
10
11     # E-step: Update membership based on square distance
12     new_membership_denominator = np.sum(squared_distances, axis=1)
13
14     new_membership_numerator = squared_distances
15     new_membership_numerator[:, [0, 1]] = new_membership_numerator[:, [1, 0]]
16
17     new_membership = new_membership_numerator / new_membership_denominator[:, None]
18
19     mean_change_of_membership = np.mean(np.abs(new_membership - membership))
20     membership = new_membership
21
22     #M-step: Update centroid position
23     for i in range(len(centroids)):
24         # New centroid that will optimize SSE
25         centroids_numerator = np.sum(new_membership[:, i][:, None] ** 2 * points, axis=0).astype(float)
26         centroids_denominator = np.sum(new_membership[:, i]** 2).astype(float)
27         centroids[i] = centroids_numerator / centroids_denominator
28
29     print(f"Iteration {iter_time}:")
30     print("Distance:")
31     print(squared_distances)
32     print("New Membership:")
33     print(membership)
34     print("New Centroids:")
35     print(centroids)
36     print("Mean change of Membership:")
37     print(mean_change_of_membership)
38     print("-----")
39
40     # Two shutdown criteria
41     if mean_change_of_membership < 0.00001:
42         break
43     if iter_time > 20:
44         break

```

The Iteration 1 to 3 in output shows below:

Iteration 1: Distance: [[8. 54674036e+01 5. 31373265e+00] [5. 04912132e+01 7. 04894083e-02] [1. 34197846e+01 1. 24488678e+01] [8. 95975057e-01 3. 90434624e+01] [7. 82454649e+00 9. 54218408e+01]] New Membership: [[0. 94146655 0. 05853345] [0. 99860587 0. 00139413] [0. 51876628 0. 48123372] [0. 02243334 0. 97756666] [0. 07578518 0. 92421482]] New Centroids: [[1. 85854048 4. 57240718] [7. 48562706 10. 12986197]] Mean change of Membership: 0. 15212403662985943 -----	Iteration 2: Distance: [[92. 89829012 3. 20955612] [56. 40758811 0. 20284641] [16. 68590803 16. 33424136] [1. 51242172 46. 03818409] [5. 79074164 106. 16957904]] New Membership: [[0. 96660464 0. 03339536] [0. 9964168 0. 0035832] [0. 50532503 0. 49467497] [0. 03180657 0. 96819343] [0. 05172137 0. 94827863]] New Centroids: [[1. 81711109 4. 50607855] [7. 50785987 10. 17469156]] Mean change of Membership: 0. 014841089128195067 -----	Iteration 3: Distance: [[93. 82843918 2. 93594314] [57. 11395318 0. 27740675] [17. 0343643 16. 97249107] [1. 63782192 47. 05766741] [5. 55823304 107. 75275173]] New Membership: [[0. 96965884 0. 03034116] [0. 9951664 0. 0048336] [0. 50090972 0. 49909028] [0. 03363396 0. 96636604] [0. 04905291 0. 95094709]] New Centroids: [[1. 80965236 4. 49365897] [7. 50554914 10. 17718346]] Mean change of Membership: 0. 0026431543367460945 -----
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