#### K-Means Clustering – Solved Example

- · Suppose that the data mining task is to cluster points into three clusters,
- · where the points are
- A1(2, 10), A2(2, 5), A3(8, 4), B1(5, 8), B2(7, 5), B3(6, 4), C1(1, 2), C2(4, 9).
- The distance function is Euclidean distance.
- Suppose initially we assign A1, B1, and C1 as the center of each cluster, respectively.

#### K-Means Clustering - Solved Example

Initial Centroids: A1: (2, 10) B1: (5, 8) C1: (1, 2)

Da	ıta Poi	nts		 Dist	ance to		Cluster	New
	Data Points						Cluster	Cluster
A1	2	10						
A2	2	5						
А3	8	4						
B1	5	8						
B2	7	5						
ВЗ	6	4						
C1	1	2						

#### K-Means Clustering - Solved Example

Initial Centroids: A1: (2, 10) B1: (5, 8) C1: (1, 2)

Do	ata Poir	-t-			Dista	nce to			Cluster	New
Da	ita Poii	ILS	2	10	5	8	1	2	Cluster	Cluster
A1	2	10	0.0	00	3.	61	8.	06	1	
A2	2	5	5.0	00	4.	24	3.	16	3	
А3	8	4	8.4	49	5.	00	7.	28	2	
B1	5	8	3.	61	0.	00	7.	21	2	
B2	7	5	7.0	07	3.	61	6.	71	2	
В3	6	4	7.	21	4.	12	5.	39	2	
C1	1	2	8.0	06	7.	21	0.	00	3 .	
C2	4	9	2.:	24	1.	41	7.	62	2	

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

### K-Means Clustering – Solved Example

**Initial Centroids:** 

A1: (2, 10) B1: (5, 8) C1: (1, 2)

New Centroids	5:

A1: (2, 10) B1: (6, 6) -

C1: (1.5, 3.5) ~

Do	to Doi:	a+c			Distar	nce to			Cluster	New
Da	Data Points		2 10		5	8	1	2	Cluster	Cluster
A1	2	10	0.	00	3.	61	8.	06	1	
A2	2	5	5.	00	4.	24	3.	16	3	
АЗ	8	4	8.	49	5.	00	7.	28	2	
B1	5	8	3.	61	0.	00	7.	21	2	
B2	7	5	7.	07	3.	61	6.	71	2	
ВЗ	6	4	7.	21	4.	12	5.	39	2	
C1	1	2	8.	06	7.	21	0.	00	3	
C2	4	9	2.	24	1.	41	7.	62	2	

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

## **K-Means** Clustering – Solved Example

**Current Centroids:** 

A1: (2, 10) B1: (6, 6) C1: (1.5, 3.5)

Do	ita Poir	a+c				Cluster	New			
Da	ita Poir	its	2	2 10 6 6 1.5 1.5				Cluster	Cluster	
A1	2	10	0.	00	5.	66	6.	52	1	1
A2	2	5	5.	00	4.	12	1.	58	3	3
A3	8	4	8.	49	2.	83	6.	52	2	2
B1	5	8	3.	61	2.:	24	5.	70	2	2
B2	7	5	7.	07	1.4	41	5.	70	2	2
В3	6	4	7.	21	2.	00	4.	53	2	2
C1	1	2	8.	06	6.4	40	1.	58	3	3
C2	4	9	2.	24	3.	61	6.	04	2	1

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

#### K-Means Clustering - Solved Exa Suggested: Machine Learning (i)

**Current Centroids:** A1: (2, 10)

B1: (6, 6)

C1: (1.5, 3.5)

		+- D-!-				Distar	nce to			Cluster	New
:	Da	ita Poir	its	2	10	6	6	1.5	1.5	Cluster	Cluster
	A1	2	10	0.	00	5.	66	6.	52	1	
	A2	2	5	5.	00	4.	12	1.	58	3	
	A3	8	4	8.	49	2.	83	6.	52	2	
	B1	5	8	3.	61	2.	24	5.	70	2	
	B2	7	5	7.	07	1.	41	5.	70	2	
	В3	6	4	7.	21	2.	00	4.	53	2	
	C1	1	2	8.	06	6.	40	1.	58	3	
Ī	C2	4	9	2	24	3	61	6	04	1	)

**New Centroids:** A1: (3, 9.5)

B1: (6.5, 5.25)

C1: (1.5, 3.5)

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

# **K-Means** Clustering – Solved Example

**Current Centroids:** 

A1: (3, 9.5) B1: (6.5, 5.25)

C1: (1.5, 3.5)

	Da	ta Poir	-t-c			Distar	nce to			Cluster	New
	υa	ta Poli	its	3	9.5	6.5	5.25	1.5	3.5	Cluster	Cluster
A1	L	2	10	1.	12	6.	54	6.	52	1	
A2	2	2	5	4.	61	4.	51	1.5	58	3	
A3	3	8	4	7.	43	1.	95	6.5	52	2	
B1		5	8	2.	50	3.	13	5.	70	1	
B2	2	7	5	6.	02	0.	56	5.	70	2	
В3	3	6	4	6.	26	1.	35	4.5	53	2	
C1		1	2	7.	76	6.	39	1.5	58	3	
C2	2	4	9	1.	12	4.	51	6.0	04	1	

New Centroids:

A1: (3.67, 9) B1: (7, 4.33)

C1: (1.5, 3.5)

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

## K-Means Clustering - Solved Example

**Current Centroids:** 

A1: (3.67, 9) B1: (7, 4.33)

C1: (1.5, 3.5)

. D.	ata Poir	atc			Dista	nce to			Cluster	New
: Da	ata Poli	11.5	3.67	9	7	4.33	1.5	3.5	Cluster	Cluster
-A1	2	10	1.9	94	7	.56	6.	52	1	1
A2	2	5	4.3	33	5	.04	1.	58	3.	3
А3	8	4	6.6	52	1	.05	6.	52	2	2
B1	5	8	1.6	57	4	.18	5.	70	1	1
B2	7	5	5.2	21	0	.67	5.	70	2	2
В3	6	4	5.5	52	1	.05	4.	53	2	2
C1	1	2	7.4	19	6	.44	1.	58	3	3
C2	4	9	0.3	33	5	.55	6.	04	1	1

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

## Agglomerative Hierarchical Cougested: K Means Clustering Algorithm - Solved Numerical Exa... (i)

- Consider the following set of 6 one dimensional data points:
- 18, 22, 25, 42, 27, 43
- Apply the agglomerative hierarchical clustering algorithm to build the hierarchical clustering dendogram.
- Merge the clusters using Min distance and update the proximity matrix accordingly.
- Clearly show the proximity matrix corresponding to each iteration of the algorithm.

### **Agglomerative Hierarchical Clustering Solved Example**

• Step - 1

	18	22	25	27	42	43
18	0	4	7	9	24	25
22	4	0	3	5	20	21
25	7	3	0	2	17	18
27	9	5	2	0	15	16
42	24	20	17	15	0	1
43	25	21	18	16	1	0

## **Agglomerative Hierarchical Clustering Solved Example**

• Step - 2

	18	22	25	27	42, 43
18	0	4	7	9	24
22	4	0	3	5	20
25	7	3	0	2	17
27	9	5	2	0	15
42, 43	24	20	17	15	0

# **Agglomerative Hierarchical Clustering Solved Example**

• Step – 3

	18	22	25, 27	42, 43
18	0	4	7	24
22	4	0	3	20
25, 27	7	3	0	15
42, 43	24	20	15	0

# **Agglomerative Hierarchical Clustering Solved Example**

• Step – 4

	18	22, 25, 27	42, 43
18	0	4	24
22, 25, 27	4 🔉	0	15
42, 43	24	15	0

# **Agglomerative Hierarchical Clustering Solved Example**

• Step – 5

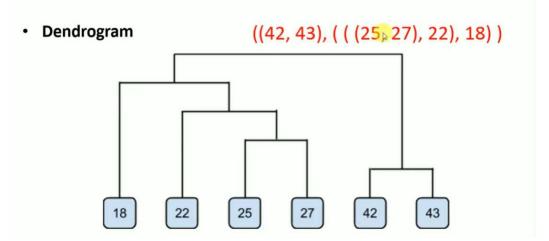
	18, 22, 25, 27	42, 43
18, 22, 25, 27	0	15
42, 43	15	0

# **Agglomerative Hierarchical Clustering Solved Example**

• Step - 6

	18, 22, 25, 27, 42, 43
18, 22, 25, 27, 42, 43	0

# **Agglomerative Hierarchical Clustering Solved Example**



Sample No.	х	Υ
P1	0.40	0.53
P2	0.22	0.38
Р3	0.35	0.32
P4	0.26	0.19
P5	0.08	0.41
P6	0.45	0.30

## Clusters using a Single Link Technique Example - 1

#### Step 1: Compute the distance matrix

- So we have to find the Euclidean distance between each and every points.
- Let  $A(x_1, y_1)$  and  $B(x_2, y_2)$  are two points.
- · Then Euclidean distance between

$$d(A,B) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

#### Clusters using a Single Link Technique Example - 1

Sample No.	х	Y	$d(p_1, p_2) = \sqrt{(0.22 - 0.40)^2 + (0.38 - 0.53)^2}$
P1	0.40	0.53	= 0.23
P2	0.22	0.38	$d(p_1, p_3) = \sqrt{(0.35 - 0.40)^2 + (0.32 - 0.53)^2}$
Р3	0.35	0.32	
P4	0.26	0.19	= 0.22
P5	0.08	0.41	$d(p_2, p_3) = \sqrt{(0.35 - 0.22)^2 + (0.32 - 0.38)^2}$
P6	0.45	0.30	
= 0.14			

# Clusters using a Single Lin Suggested: Salary Prediction End to End Machine Learning Project ... (i)

Sample No.	x	Y	
P1	0.40	0.53	
P2	0.22	0.38	
Р3	0.35	0.32	
P4	0.26	0.19	
P5	0.08	0.41	
P6	0.45	0.30	

$$\begin{pmatrix} P1 & P2 & P3 & P4 & P5 & P6 \\ P1 & 0 & & & & \\ P2 & 0.23 & 0 & & & \\ P3 & 0.22 & 0.14 & 0 & & \\ P4 & 0.37 & 0.19 & 0.13 & 0 & & \\ P5 & 0.34 & 0.14 & 0.28 & 0.23 & 0 & \\ P6 & 0.24 & 0.24 & 0.10 & 0.22 & 0.39 & 0 \end{pmatrix}$$

## Clusters using a Single Link Technique Example - 1

Step 2: Merging the two closest members.

- Here the minimum value is 0.10 and hence we combine P3 and P6
  (as 0.10 came in the P6 row and P3 column).
- Now, form clusters of elements corresponding to the minimum value and update the distance matrix.

#### Now we will update the Distance Matrix:

$$\begin{pmatrix} P1 & P2 & P3 & P4 & P5 & P6 \\ P1 & 0 & & & & & \\ P2 & 0.23 & 0 & & & & & \\ P3 & 0.22 & 0.14 & 0 & & & & \\ P4 & 0.37 & 0.19 & 0.13 & 0 & & \\ P5 & 0.34 & 0.14 & 0.28 & 0.23 & 0 & \\ P6 & 0.24 & 0.24 & 0.10 & 0.22 & 0.39 & 0 \end{pmatrix} \begin{pmatrix} P1 & P2 & P3, P6 & P4 & P5 \\ P1 & 0 & & & & \\ P2 & 0.23 & 0 & & & \\ P3, P6 & 0.22 & 0.14 & 0 & & \\ P4 & 0.37 & 0.19 & 0.13 & 0 & \\ P5 & 0.34 & 0.14 & 0.28 & 0.23 & 0 \end{pmatrix}$$

(P3, P6)

## Clusters using a Single Link Technique Example - 1

#### Now we will update the Distance Matrix:

$$\begin{pmatrix} P1 & P2 & P3, P6 & P4 & P5 \\ P1 & 0 & & & & \\ P2 & 0.23 & 0 & & & \\ P3, P6 & 0.22 & 0.14 & 0 & & \\ P4 & 0.37 & 0.19 & 0.13 & 0 & \\ P5 & 0.34 & 0.14 & 0.28 & 0.23 & 0 \end{pmatrix} \begin{pmatrix} P1 & P2 & P3, R6, P4 & P5 \\ P1 & 0 & & & \\ P2 & 0.23 & 0 & & \\ P3, P6, P4 & 0.22 & 0.14 & 0 & \\ P5 & 0.34 & 0.14 & 0.28 & 0 \end{pmatrix}$$

{(P3, P6), P4}

#### Now we will update the Distance Matrix:

$$\begin{pmatrix} P1 & P2 & P3, P6, P4 & P5 \\ P1 & 0 & & & \\ P2 & 0.23 & 0 & & \\ P3, P6, P4 & 0.22 & 0.14 & 0 & \\ P5 & 0.34 & 0.14 & 0.28 & 0 \end{pmatrix} \begin{pmatrix} P1 & P2, P5 & P3, P6, P4 \\ P1 & 0 & & \\ P2, P5 & 0.23 & 0 & \\ P3, P6, P4 & 0.22 & 0.14 & 0 \end{pmatrix}$$

{(P3, P6), P4} and (P2, P5)

## Clusters using a Single Link Technique Example - 1

#### Now we will update the Distance Matrix:

$$\begin{pmatrix} P1 & P2, P5 & P3, P6, P4 \\ P1 & 0 & & & \\ P_{2}^{2}, P5 & 0.23 & 0 & & \\ P3, P6, P4 & 0.22 & 0.14 & 0 \end{pmatrix}$$

$$\begin{pmatrix} P1 & P2, P5, P3, P6, P4 \\ P1 & 0 \\ P2, P5, P3, P6, P4 & 0.22 & 0 \end{pmatrix}$$
 [{(P3, P6), P4}, (P2, P5)]

Now we will update the Distance Matrix:

$$\begin{pmatrix} P1 & P2, P5 & P3, P6, P4 \\ P1 & 0 & & & \\ P2, P5 & 0.23 & 0 & & \\ P3, P6, P4 & 0.22 & 0.14 & 0 \end{pmatrix}$$
 
$$\begin{pmatrix} P1 & P2, P5, P3, P6, P4 \\ P1 & 0 & & \\ P2, P5, P3, P6, P4 & 0.22 & 0 \end{pmatrix}$$
 [{(P3, P6), P4}, (P2, P5)], P1

# Clusters using a Single Link Technique Example - 1

So now we have reached to the solution, the dendrogram for those question will be as follows:

[{(P3, P6), P4}, (P2, P5)], P1



Dendogram of the cluster formed \*\*