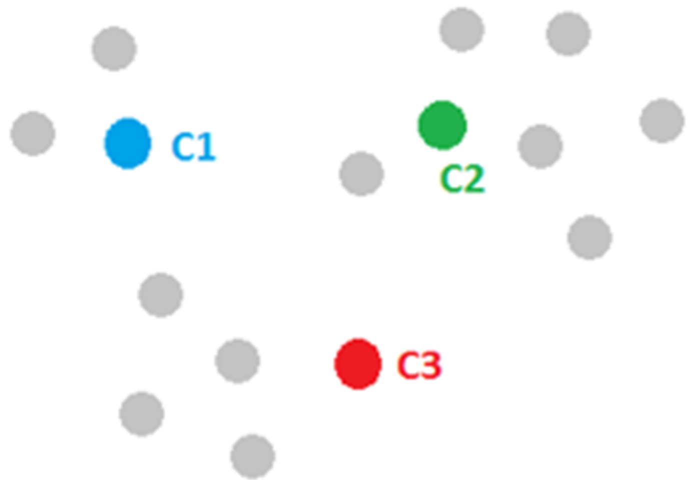
Sample no.	Points	Cluster 1 (2, 10)	Cluster 2 (5, 8)	Cluster 3 (1, 2)	Clusters
1	(2, 10)				
2	(2, 5)				
3	(8, 4)				
4	(5, 8)				
5	(7, 5)				
6	(6, 4)				
7	(1, 2)				
8	(4, 9)				

Let's calculate **Euclidean Distance** for sample number 1 to each distance means.

- **Distance from Cluster 1** $\sqrt{(2-2)^2+(10-10)^2}$ = 0

- **Distance from Cluster 2** $\sqrt{(5-2)^2+(8-10)^2}$ = 3.60

- **Distance from Cluster 3** $\sqrt{(1-2)^2+(2-10)^2}$ = 8.06

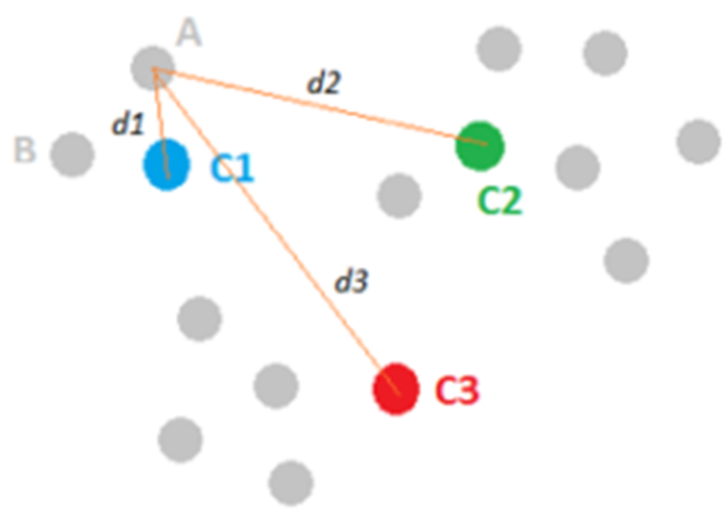

C1
C2
C3

Sample no.	Points	Cluster 1 (2, 10)	Cluster 2 (5, 8)	Cluster 3 (1, 2)	Clusters
1	(2, 10)	$\boxed{0}$	3.60	8.06	1
2	(2, 5)				
3	(8, 4)				
4	(5, 8)				
5	(7, 5)				
6	(6, 4)				
7	(1, 2)				
8	(4, 9)				

Similarly, we calculate the **Euclidean distance** for all the Sample numbers and **fill up** the table.

Iteration 1

Sample no.	Points	Cluster 1 (2, 10)	Cluster 2 (5, 8)	Cluster 3 (1, 2)	Clusters
1	(2, 10)	0	3.60	$\boxed{8.06}$	1
2	(2, 5)	5	$\boxed{4.24}$	3.16	3
3	(8, 4)	8.48	$\boxed{5}$	7.28	2
4	(5, 8)	3.60	$\boxed{0}$	7.21	2
5	(7, 5)	7.07	$\boxed{3.60}$	6.7	2
6	(6, 4)	7.21	4.12	5.38	2
7	(1, 2)	8.06	$\boxed{7.21}$	$\boxed{0}$	3
8	(4, 9)	2.23	1.41	7.61	2


A
B
d1
d2
d3
C1
C2
C3

(2, 10)

(8, 4) (5, 8) (7, 5)
(6, 4) (4, 9)

(2, 5) (1, 2)

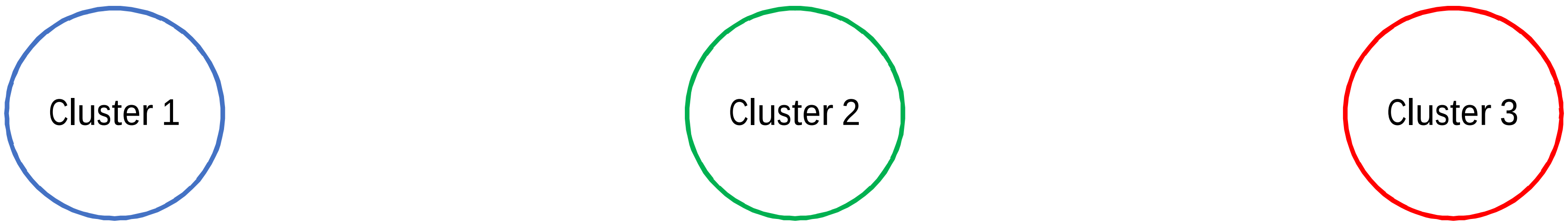
Cluster 1

Cluster 2

Cluster 3

STEP 2

- Re-compute **the centres** of the new clusters.
- We do so, **by taking mean** of all points in each cluster.



Mean = (2, 10)

- Since, we have only **one point** in Cluster 1 so the center remains the same.

INSAID

New, updated **centroids**

Cluster 1

Cluster 2

Cluster 3

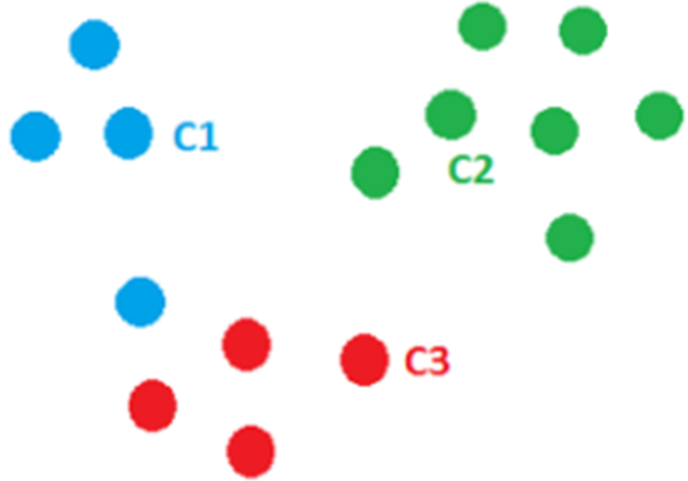
Mean $\boxed{= (2, 10)}$

Mean = ((8+5+7+6+4)/5 , (4+8+5+4+9)/5

$\boxed{= (6, 6)}$

Mean = ((2+1)/2 , (5+2)/2

$\boxed{= (1.5, 3.5)}$

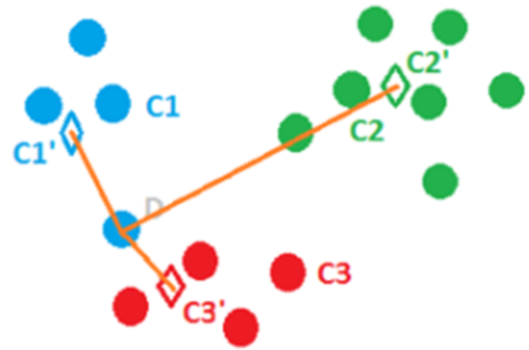

C1
C2
C3

Iteration 2

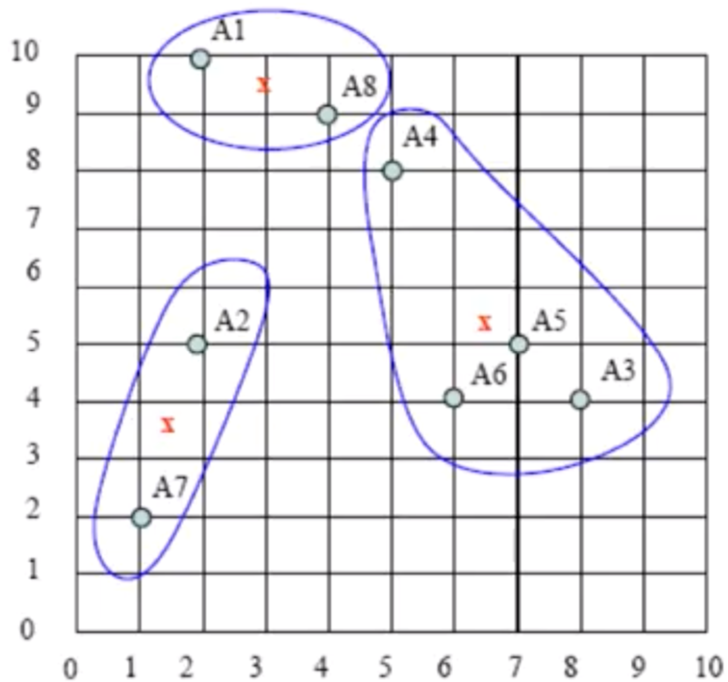
Sample no.	Points	Cluster 1 (2, 10)	Cluster 2 (6, 6)	Cluster 3 (1.5, 3.5)	Clusters
1	(2, 10)	0	5.65	6.51	1
2	(2, 5)	5	4.12	1.58	3
3	(8, 4)	8.48	2.82	6.51	2
4	(5, 8)	3.60	2.23	5.70	2
5	(7, 5)	7.07	1.41	5.70	2
6	(6, 4)	7.21	2	4.52	2
7	(1, 2)	8.06	6.40	1.58	3
8	(4, 9)	2.23	3.60	6.04	1

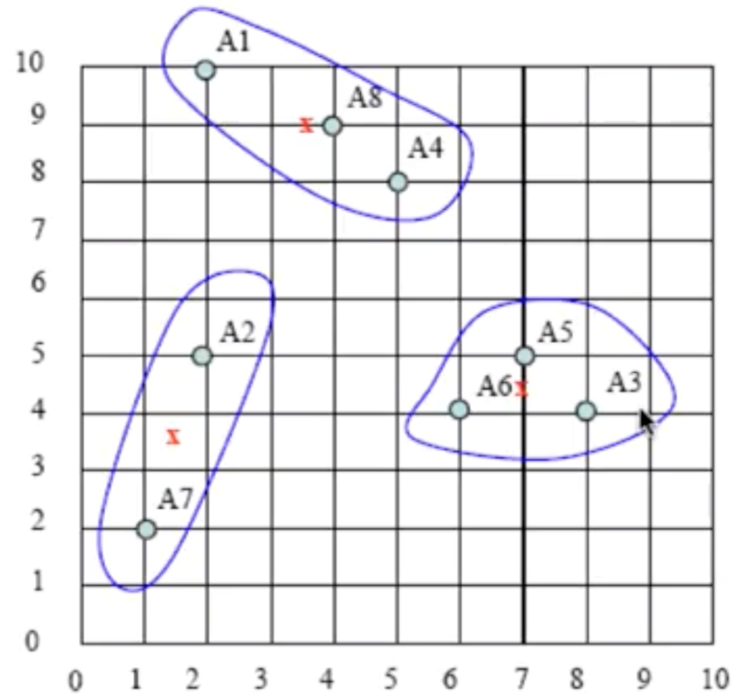
STEP 3

- We **re-compute the centres** of the new clusters.
- We do so, **by taking mean** of all points in each cluster.
- We keep doing these **iterations** until we get **the same mean** value.

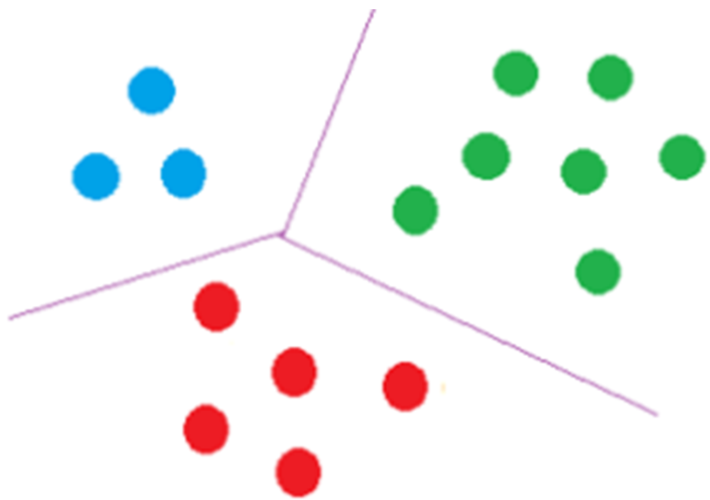


After two more iterations the **updated centroids** and the **points**





Final Figure



AGENDA

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- Unsupervised Learning
- Why Clustering?
- Types of Clustering
    - Partitioning Clustering
- K Means Clustering
- Challenges in K Means Clustering
- Elbow Method
- Euclidean Distance
- **Illustration of K Means algorithm**
- Applications of K Means

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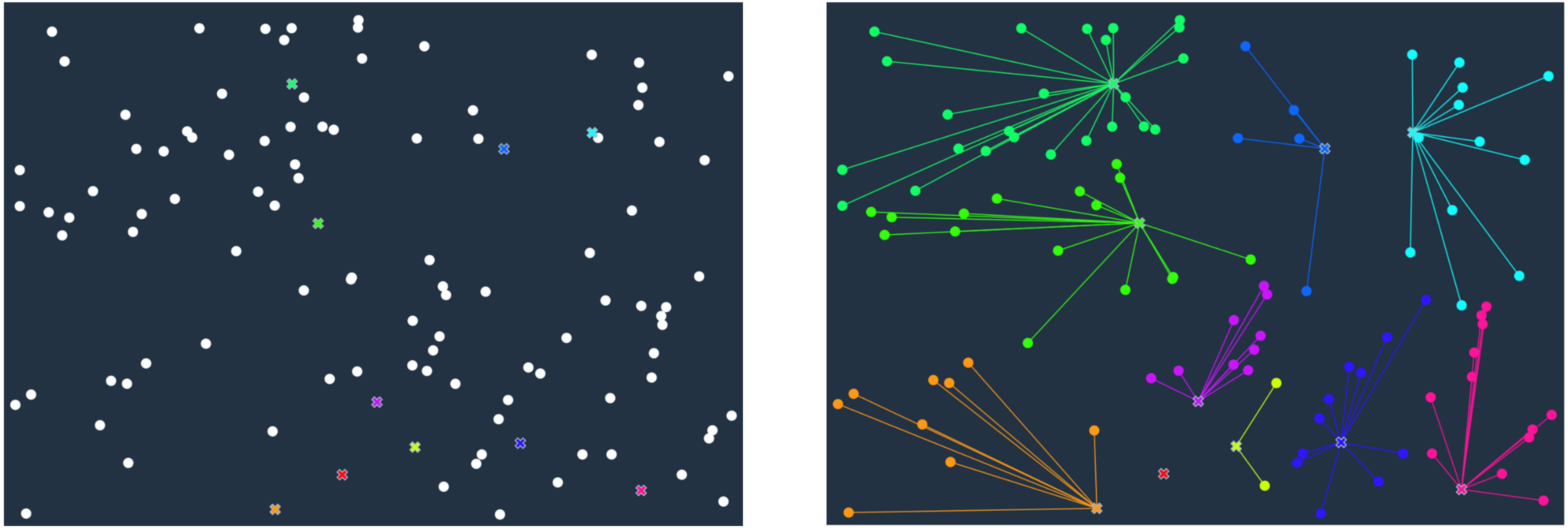
    - Divisive Clustering
- Applications
- Density Based Clustering
- Distance metrics
    - Manhattan
    - Minkowski
    - Mahalanobis

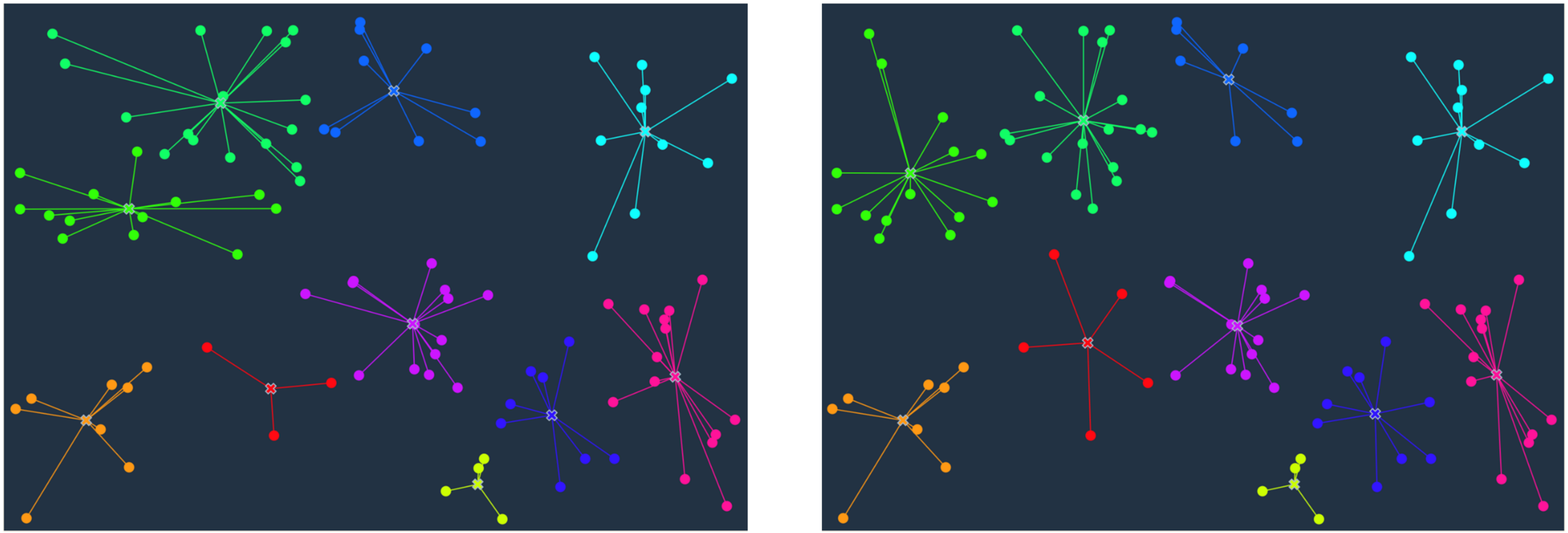
Illustration

Illustration

K = 10



Illustrating the relocating of centroids



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