Artificial Intelligence

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Clustering in Machine Learning

- Clustering or cluster analysis is a machine learning technique, which groups the unlabeled dataset. It can be defined as ***"A way of grouping the data points into different clusters, consisting of similar data points. The objects with the possible similarities remain in a group that has less or no similarities with another group."***

- It does it by finding some similar patterns in the unlabeled dataset such as shape, size, color, behavior, etc., and divides them as per the presence and absence of those similar patterns.

- It is an unsupervised learning method, hence no supervision is provided to the algorithm, and it deals with the unlabeled dataset.

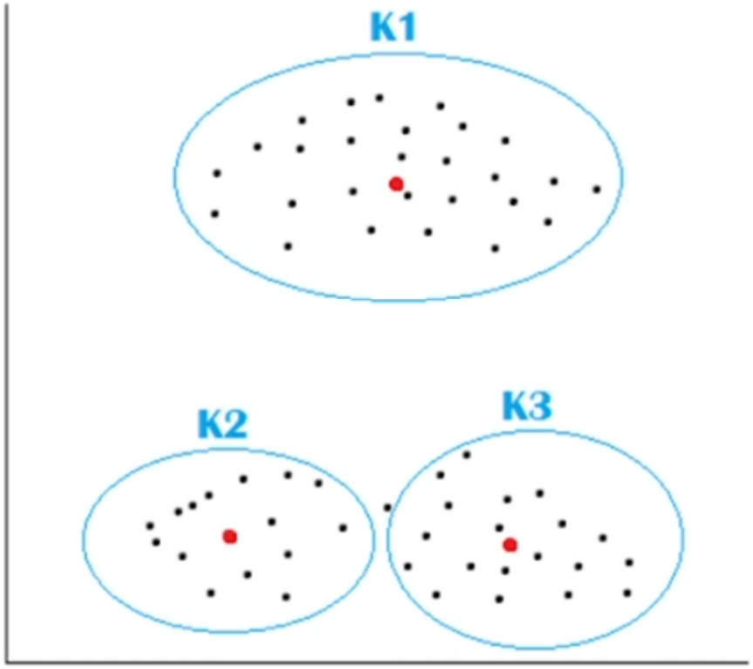
- After applying this clustering technique, each cluster or group is provided with a cluster-ID. ML systems can use this to simplify the processing of large and complex datasets.

Clustering in Machine Learning

- Let's understand the clustering technique with the real-world example of Mall: When we visit any shopping mall, we can observe that the things with similar usage are grouped together. Such as the t-shirts are grouped in one section, and trousers are at other sections, similarly, at vegetable sections, apples, bananas, Mangoes, etc., are grouped in separate sections, so that we can easily find out the things. The clustering technique also works in the same way. Other examples of clustering are grouping documents according to the topic.

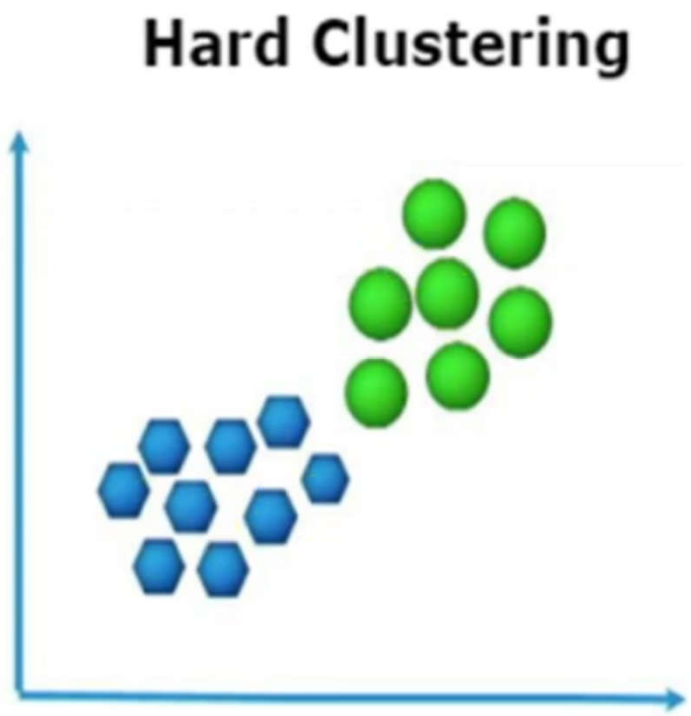
Clustering

- Clustering is a **distance-based unsupervised machine learning algorithm** where data points that are close to each other are grouped in a given number of clusters/groups.



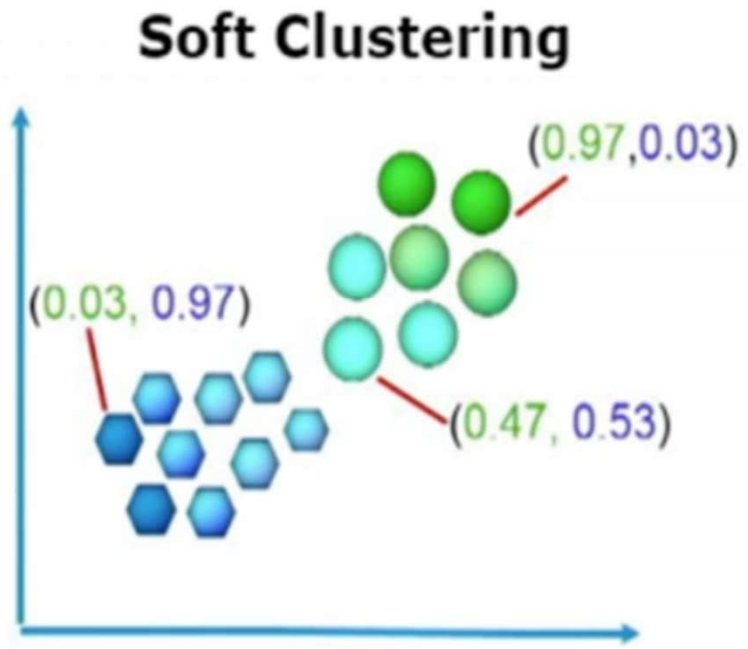
Clustering

- In hard clustering each datapoint is assigned only a single cluster.
- The K-Means, K-Medoid clustering algorithms are hard clustering algorithms.



Clustering

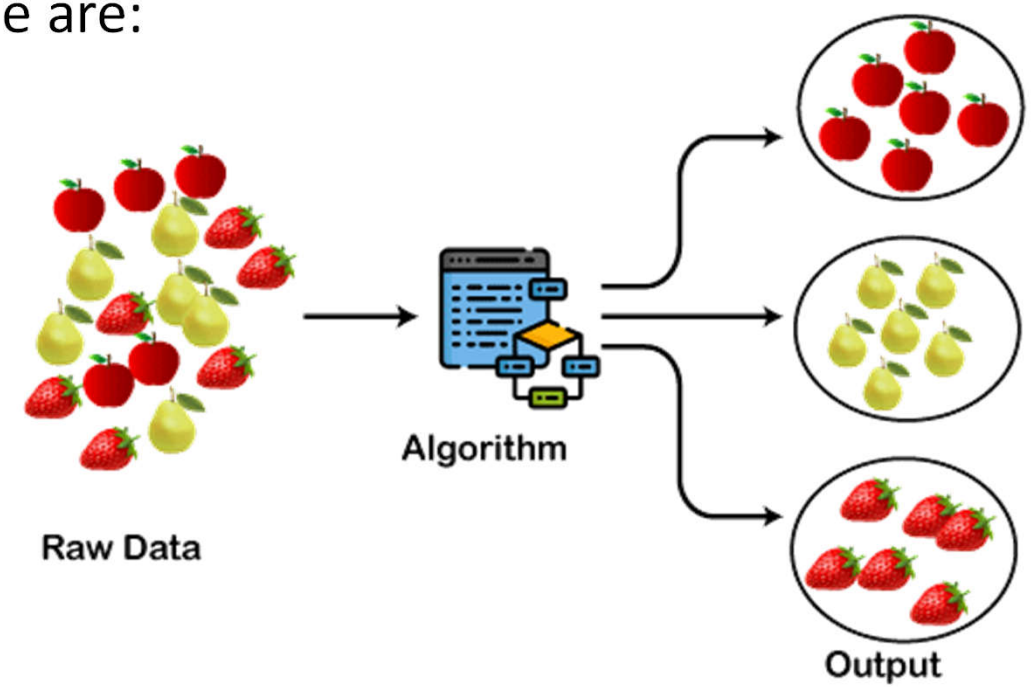
- On the other hand in soft clustering each data point belongs to a cluster with a certain probability also known as Membership Value.
- FCM (Fuzzy C-means clustering) algorithm is an example of soft clustering.



Clustering in Machine Learning

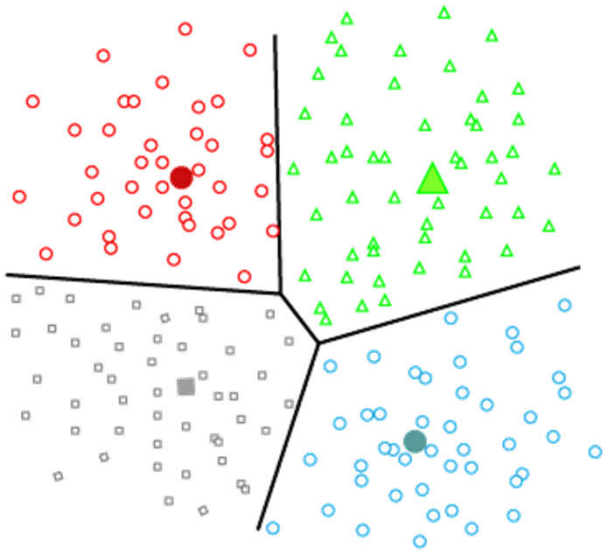
- The clustering technique can be widely used in various tasks. Some most common uses of this technique are:

- Market Segmentation
- Statistical data analysis
- Social network analysis
- Image segmentation
- Anomaly detection, etc.



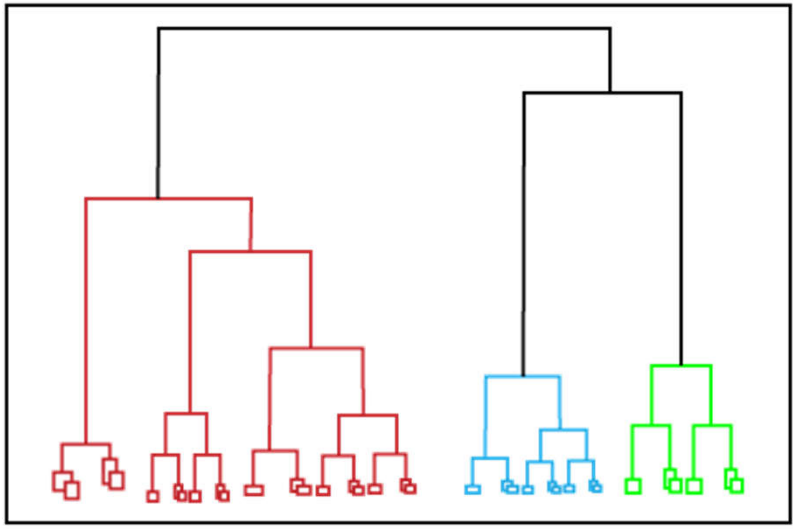
Partition Clustering

- It is a type of clustering that divides the data into non-hierarchical groups. It is also known as the **centroid-based method**. The most common example of partitioning clustering is the **K-Means Clustering algorithm**.
- In this type, the dataset is divided into a set of k groups, where K is used to define the number of pre-defined groups. The cluster center is created in such a way that the distance between the data points of one cluster is minimum as compared to another cluster centroid.



Hierarchical clustering

- Hierarchical clustering can be used as an alternative for the partitioned clustering as there is no requirement of pre-specifying the number of clusters to be created. In this technique, the dataset is divided into clusters to create a tree-like structure, which is also called a **dendrogram**. The observations or any number of clusters can be selected by cutting the tree at the correct level. The most common example of this method is the **Agglomerative Hierarchical algorithm**.



Solved Example 1
K-Mean clustering

Solved Example 1 K-Mean clustering

i	x	y
X1	2	6
X2	3	4
X3	3	8
X4	4	7
X5	6	2
X6	6	4
X7	7	3
X8	7	4
X9	8	5
X10	7	6

- Apply K-Medoid clustering algorithm to form two clusters.
- Use Manhattan distance to find the between data point and medoid.

Solved Example 1 K-Mean clustering

Step 1

- Select two medoids
- C1=(3, 4)
- C2=(7, 4)
- $Manhattan\ Dist = |x_1 - x_2| + |y_1 - y_2|$
- $Mdist[(2,6),(3,4)] = |2-3| + |6-4| = 3$
- $Mdist[(3,4),(3,4)] = |3-3| + |4-4| = 0$

i	x	y	C1	C2	Cluster
X1	2	6	3		
X2	3	4	0		
X3	3	8	4		
X4	4	7	4		
X5	6	2	5		
X6	6	4	3		
X7	7	3	5		
X8	7	4	4		
X9	8	5	6		
X10	7	6	6		

Solved Example 1 K-Mean clustering

Step 1

- Select two medoids
- C1=(3, 4)
- C2=(7, 4)
- $\boldsymbol{Manhattan\ Dist} = |x_1 - x_2| + |y_1 - y_2|$

$|2-7| + |6-4| = 5+2 = 7$

$|3-7| + |4-4| = 4+0 = 4$

i	x	y	C1	C2	Cluster
X1	2	6	3	7	
X2	3	4	0	4	
X3	3	8	4	8	
X4	4	7	4	6	
X5	6	2	5	3	
X6	6	4	3	1	
X7	7	3	5	1	
X8	7	4	4	0	
X9	8	5	6	2	
X10	7	6	6	2	

Solved Example 1 K-Mean clustering

If C1 < C2 then result is C1 otherwise C2

Step 2

- **Cluster are**
- **C1: {(2,6), (3,4), (3,8), (4,7)}**
- **C2: {(6, 2), (6, 4), (7, 3), (7, 4), (8, 5), (7,6)}**

i	x	y	C1	C2	Cluster
X1	2	6	3	7	C1
X2	3	4	0	4	C1
X3	3	8	4	8	C1
X4	4	7	4	6	C1
X5	6	2	5	3	C2
X6	6	4	3	1	C2
X7	7	3	5	1	C2
X8	7	4	4	0	C2
X9	8	5	6	2	C2
X10	7	6	6	2	C2

Solved Example 1 K-Mean clustering

- C1: {(2,6), **(3,4),** (3,8), (4,7)}
- C2: {(6, 2), (6, 4), (7, 3), **(7, 4),** (8, 5), (7,6)}
- **Calculate the Total Cost**
- $\boldsymbol{Cost(c,x)} = \sum_i |\boldsymbol{c_i} - \boldsymbol{x_i}|$

$= |3-2| + |4-6| = 1+2 = 3$

- $Total\ Cost = \{Cost\big((3,4),(2,6)\big) + Cost\big((3,4),(3,8)\big) + Cost\big((3,4),(4,7)\big) +$

  $Cost\big((7,4),(6,2)\big) + Cost\big((7,4),(6,4)\big) + Cost\big((7,4),(7,3)\big) + Cost\big((7,4),(8,5)\big) +$

  $Cost\big((7,4),(7,6)\big)\}$

$\boldsymbol{Total\ Cost} = \mathbf{3+4+4+2+3+1+1+2} = \mathbf{20}$

Solved Example 1 K-Mean clustering

Step 3

- **Randomly select one non-medoid point and recalculate the cost.**
- C1=(3, 4) and C2=(7, 4)
- **O=(7, 3)**
- **Swap C2 with O**
- **New Medoids**
- **C1=(3, 4) and O=(7, 3)**

i	x	y	C1	C2	Cluster
X1	2	6			
X2	3	4			
X3	3	8			
X4	4	7			
X5	6	2			
X6	6	4			
X7	7	3			
X8	7	4			
X9	8	5			
X10	7	6			

Solved Example 1 K-Mean clustering

- **New Medoids**
- **C1=(3, 4) and O=(7, 3)**
- $Manhattan\ Dist = |x_1 - x_2| + |y_1 - y_2|$
- $Mdist[(2,6),(7,3)] = |2-7| + |6-3| = 8$

i	x	y	C1	O	Cluster
X1	2	6	3		
X2	3	4	0		
X3	3	8	4		
X4	4	7	4		
X5	6	2	5		
X6	6	4	3		
X7	7	3	5		
X8	7	4	4		
X9	8	5	6		
X10	7	6	6		

Solved Example 1 K-Mean clustering

- **New Medoids**
- **C1=(3, 4) and O=(7, 3)**
- $Manhattan\ Dist = |x_1 - x_2| + |y_1 - y_2|$
- $Mdist[(2,6),(7,3)] = |2-7| + |6-3| = 8$

i	x	y	C1	O	Cluster
X1	2	6	3	8	
X2	3	4	0	5	
X3	3	8	4	9	
X4	4	7	4	7	
X5	6	2	5	2	
X6	6	4	3	2	
X7	7	3	5	0	
X8	7	4	4	1	
X9	8	5	6	3	
X10	7	6	6	3	

Solved Example 1 K-Mean clustering

- **New Cluster are**
- **C1: {(2,6), (3,4), (3,8), (4,7)}**
- **O: {(6, 2), (6, 4), (7, 3), (7, 4), (8, 5), (7,6)}**

i	x	y	C1	O	Cluster
X1	2	6	3	8	C1
X2	3	4	0	5	C1
X3	3	8	4	9	C1
X4	4	7	4	7	C1
X5	6	2	5	2	O
X6	6	4	3	2	O
X7	7	3	5	0	O
X8	7	4	4	1	O
X9	8	5	6	3	O
X10	7	6	6	3	O

Solved Example 1 K-Mean clustering

- C1: {(2,6), **(3,4),** (3,8), (4,7)}
- O: {(6, 2), (6, 4), **(7, 3),** (7, 4), (8, 5), (7,6)}
- **Calculate the Total Cost**
- $\boldsymbol{Cost(c, x)} = \sum_i |\boldsymbol{c_i} - \boldsymbol{x_i}|$
- $Current\ Total\ Cost = \{Cost\big((3,4),(2,6)\big) + Cost\big((3,4),(3,8)\big) + Cost\big((3,4),(4,7)\big) + Cost\big((7,3),(6,2)\big) + Cost\big((7,3),(6,4)\big) + Cost\big((7,3),(7,4)\big) + Cost\big((7,3),(8,5)\big) + Cost\big((7,3),(7,6)\big)\}$
- $\boldsymbol{Current\ Total\ Cost = 3 + 4 + 4 + 2 + 2 + 1 + 3 + 3 = 22}$

Solved Example 1 K-Mean clustering

Step 4

- **Cost of Swapping of medoid C2 with O**
- $S = Current\ Total\ Cost - Previous\ Total\ Cost$
- $S = 22 - 20 = 2 > 0$
- **Hence Swapping C2 with O is not a good Idea.**

Solved Example 2
K-Mean clustering

Solved Example 2 K-Mean clustering

- 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.

Solved Example 2 K-Mean clustering

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

Data Points			Distance to						Cluster	New Cluster
			2	10	5	8	1	2		
A1	2	10								
A2	2	5								
A3	8	4								
B1	5	8								
B2	7	5								
B3	6	4								
C1	1	2								
C2	4	9								

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

ED

Solved Example 2 K-Mean clustering

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

Data Points			Distance to						Cluster	New Cluster
			2	10	5	8	1	2		
A1	2	10	0.00							
A2	2	5	5.00							
A3	8	4	8.49							
B1	5	8	3.61							
B2	7	5	7.07							
B3	6	4	7.21							
C1	1	2	8.06							
C2	4	9	2.24							

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

Solved Example 2 K-Mean clustering

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

Data Points			Distance to						Cluster	New Cluster
			2	10	5	8	1	2		
A1	2	10	0.00		3.61		8.06			
A2	2	5	5.00		4.24		3.16			
A3	8	4	8.49		5.00		7.28			
B1	5	8	3.61		0.00		7.21			
B2	7	5	7.07		3.61		6.71			
B3	6	4	7.21		4.12		5.39			
C1	1	2	8.06		7.21		0.00			
C2	4	9	2.24		1.41		7.62			

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

Solved Example 2 K-Mean clustering

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

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

Data Points			Distance to						Cluster	New Cluster
			2	10	5	8	1	2		
A1	2	10	0.00		3.61		8.06		1	
A2	2	5	5.00		4.24		3.16		3	
A3	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	
B3	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	

$\frac{30}{5} = 6$

Solved Example 2 K-Mean clustering

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

Data Points			Distance to						Cluster	New Cluster
			2	10	6	6	1.5	3.5		
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		1.41		5.70		2	2
B3	6	4	7.21		2.00		4.53		2	2
C1	1	2	8.06		6.40		1.58		3	3
C2	4	9	2.24		3.61		6.04		2	1

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

Solved Example 2 K-Mean clustering

Current Centroids:
A1: (3, 9.5)
B1: (6.5, 5.25)
C1: (1.5, 3.5)

New Centroids:
A1: (3.67, 9)
B1: (7, 4.33)
C1: (1.5, 3.5)

Data Points			Distance to			Cluster	New Cluster
			3 9.5	6.5 5.25	1.5 3.5		
A1	2	10	1.12	6.54	6.52	1	
A2	2	5	4.61	4.51	1.58	3	
A3	8	4	7.43	1.95	6.52	2	
B1	5	8	2.50	3.13	5.70	1	
B2	7	5	6.02	0.56	5.70	2	
B3	6	4	6.26	1.35	4.53	2	
C1	1	2	7.76	6.39	1.58	3	
C2	4	9	1.12	4.51	6.04	1	

Solved Example 2 K-Mean clustering

Current Centroids:
A1: (3.67, 9)
B1: (7, 4.33)
C1: (1.5, 3.5)

Data Points			Distance to						Cluster	New Cluster
			3.67	9	7	4.33	1.5	3.5		
A1	2	10	1.94		7.56		6.52		1	1
A2	2	5	4.33		5.04		1.58		3	3
A3	8	4	6.62		1.05		6.52		2	2
B1	5	8	1.67		4.18		5.70		1	1
B2	7	5	5.21		0.67		5.70		2	2
B3	6	4	5.52		1.05		4.53		2	2
C1	1	2	7.49		6.44		1.58		3	3
C2	4	9	0.33		5.55		6.04		1	1

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