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ASSIGNMENT-2

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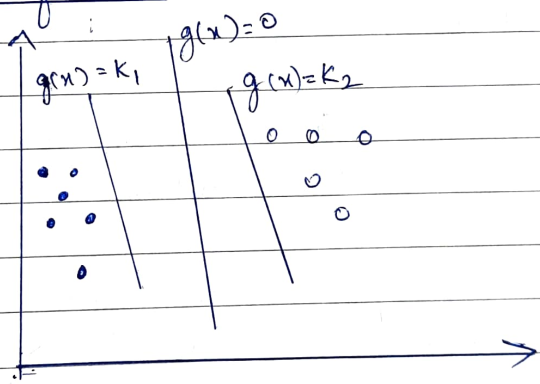
Q.1] With mathematical evidence explain how SVM will be considered a minimization problem with respect to weight vector.

Ans • SVM or Support Vector Machine is the classifier that maximizes the margin.

• The goal of a classifier is to find a line or (n-1) dimension hyper plane that seperates the two classes present in the n-dimensional space.

→ Formulation of SVM



$$g(x) = w^T x + b$$

• The goal is to optimize k such that
At the optimum,

$$\frac{\partial J}{\partial w} = 0 \quad \text{and} \quad \frac{\partial J}{\partial b} = 0$$

$$\Rightarrow w_0 = \sum_{i=1}^{N} \alpha_i \alpha_i x_i \quad \text{and}$$

$$\sum_{i=1}^{N} \alpha_i d_i = 0$$

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Maximize k such that,
$-w^T x + b \geq k$, for $d_i = 1$
$-w^T x + b \leq k$, for $d_i = -1$

→ Value of $g(x)$ depends upon $\|w\|$ i.e. weight

(1) Keep $\|w\| = 1$ & maximize $g(x)$ (or)

(2) $g(x) \geq 1$ & maximize $\|w\|$.

→ We use approach (2) and formulate as;
$\phi(w) = \frac{1}{2} w^T w$ – minimize subject to $d(w^T + x) \geq |x|$

→ Integrating constants in Lagrangian form;
minimize:

$$J(w, b, \alpha) = \frac{1}{2} w^T w - \sum_{i=1}^{N} \alpha_i d_i (w^T x_i + n) + \sum_{i=1}^{N} \alpha_i$$

J → saddle point.

In dual form,

$$J(w, b, \alpha) = \frac{1}{2} w^T \cdot w - \sum_{i=1}^{N} \alpha_i d_i (w^T x_i + b) + \sum_{i=1}^{N} \alpha_i$$

* When 'd' is maximized then C_1 and C_2 clusters are separated. Alternatively we can ~~do~~ say that this SVM problem works when the weight vector $\|w\|$ is minimized

$$\uparrow d = \frac{d}{\|w\| \downarrow}$$

Hence proved, SVM is considered as a minimization problem with respect to weight vector.

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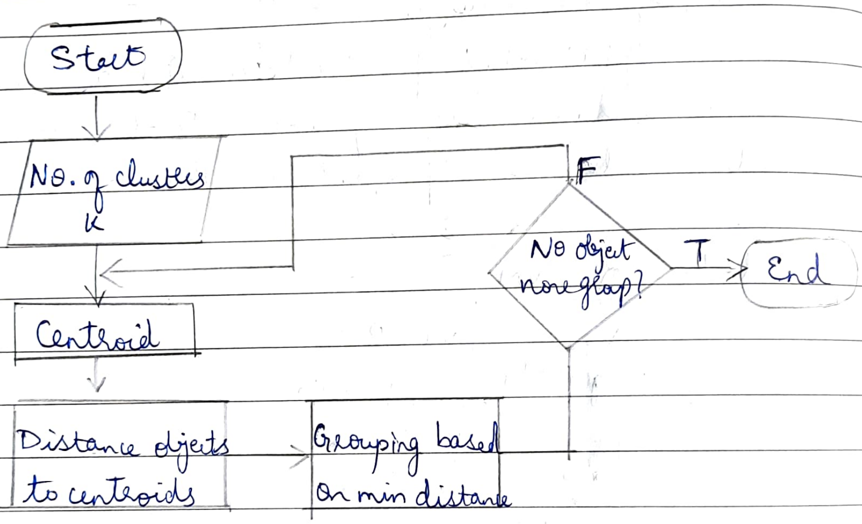
Q.2] With the help of suitable diagrams & flow chart explain K-means in detail.

Ans • K-means clustering is an algorithm to cluster n objects based on attributes into k partitions, where k < n.

• It assumes that the object attributes from a vector space.

→ **Flowchart :**



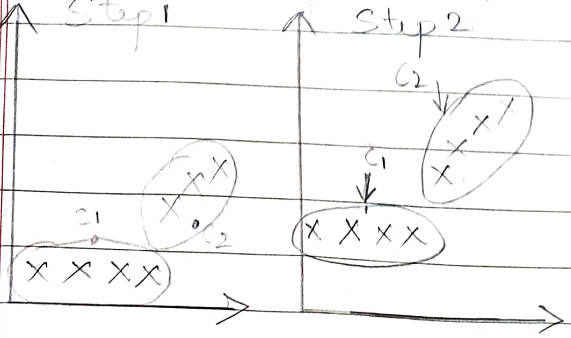
Step1: For each data point place it in a cluster whose current centroid to which is the nearest.

Step2: After all data points are assigned, update the location of centroid of the K-clusters.

Step3: Reassign all the points to the closest centroid.

Step4: Repeat ② & ③ until all points are clustered / converge.

Example:



- If there is no change in clusters then it remains same.

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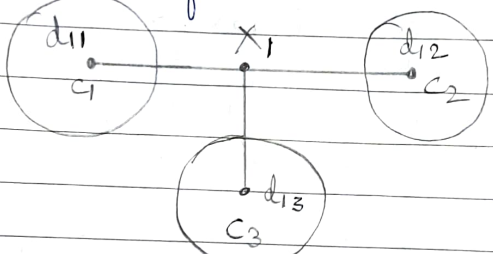
Q.3] Explain fuzzy k-means algorithm in detail.

Ans: In fuzzy clustering, instead of putting each data points into separate clusters a probability of that point to be in that cluster assigned.

- Each data point can belong to multiple clusters along with its probability score or likelihood.
- Here fuzzy set theory is used to obtain the optimal values of the centroid.



In this technique the particular vector (x_1) belongs to all clusters with different membership value.

→ Algorithm:-

1. Initializes the membership values (m_{ij}) randomly.
2. Compute the centroids of the clusters
3. Update the membership value m, using new centroids, $M_{11} = \dfrac{1}{\left[\dfrac{(x_1-c_1)^2}{(x_1-c_1)^2}\right]^2 + \left[\dfrac{(x_1-c_1)^2}{(x_1-c_2)^2}\right]^2 + \cdots + \left[\dfrac{(x_1-c_1)^2}{(x_1-c_6)^2}\right]^2}$
4. Compute the sum of squared errors between ~~two~~ previous membership value & current membership value.

$$\left[m_{11}^{old} - m_{11}^{new}\right]^2 + \left[m_{12}^{old} - m_{12}^{new}\right]^2 + \cdots$$

* If computed value is less than the threeshold value then goto step 2.
* If computed value is less than the threeshold stop the iteration.

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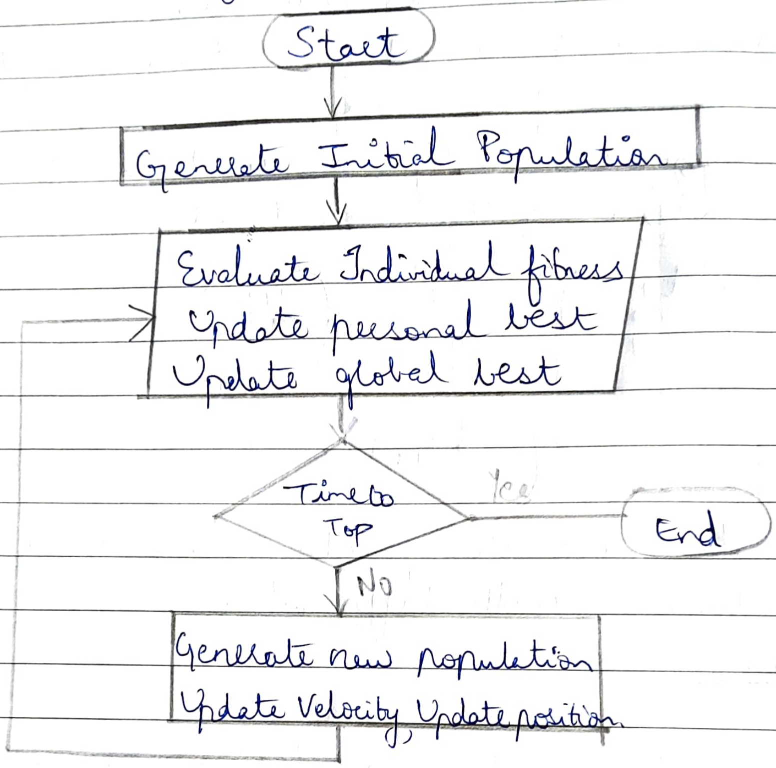
Q.4) With the help of suitable diagrams & flow chart explain Particle Swarm Algorithm

Ans • Flowchart of Particle Swarm Algorithm:



- Here the location is represented as particles and the population is called swarm of particles
- Each particle has 2 properties, velocity and position
- Each moves to a new position and once a new position is reached the best position of each particle & the best position of the swarm are updated as needed.
- The velocity of each particle is then adjusted based on the experiences of the particle.

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- The process is repeated until a stopping criterion is met.
- Each particle is initialized with a random position and velocity.
- Each particle is then evaluated for fitness value which is calculated & compared against the previous fitness value of the swarm & with scores & are updated where appropriate.
- When stopping criterion is not met the velocity & position are updated to get a new swarm.

Q.5] In Ant colony Optimization, assume that six ants have the cost functions C1, C2, C3, C4, C5, C6. Consider the following are the orders selected by the six ants along with the corresponding cost as given below.

Ant	Order									Cost
A1	9	6	8	5	7	1	4	2	3	C1
A2	1	4	6	3	7	2	9	8	5	C2
A3	4	1	7	9	3	2	8	6	5	C3
A4	5	7	2	1	3	6	9	4	8	C4
A5	8	2	9	1	4	3	7	6	5	C5
A6	3	9	5	2	1	8	7	6	4	C6

Design the pheromone matrix from the above data

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Any Pheromone Matrix

	1	2	3	4	5	6	7	8	9
1	$1/c_2$	$1/c_3$	0	$\frac{1}{c_4}+\frac{1}{c_5}$	$1/c_6$	$1/c_1$	0	0	0
2	0	$1/c_5$	$1/c_4$	$1/c_6$	0	$\frac{1}{c_2}+\frac{1}{c_3}$	0	$1/c_1$	0
3	$1/c_6$	0	0	$1/c_2$	$\frac{1}{c_3}+\frac{1}{c_4}$	$1/c_5$	0	0	$1/c_1$
4	$1/c_3$	$1/c_2$	0	0	$1/c_5$	0	$1/c_1$	$1/c_4$	$1/c_6$
5	$1/c_4$	0	$1/6$	$1/c_1$	0	0	0	0	$\frac{1}{c_2}+\frac{1}{c_3}+\frac{1}{c_5}$
6	0	$1/c_1$	$1/c_2$	0	0	$1/c_4$	0	$\frac{1}{c_3}+\frac{1}{c_5}+\frac{1}{c_6}$	0
7	0	$1/c_4$	$1/c_3$	0	$\frac{1}{c_1}+\frac{1}{c_2}$	0	$\frac{1}{c_5}+\frac{1}{c_6}$	0	0
8	$1/c_5$	0	$1/c_1$	0	0	$1/c_6$	$1/c_3$	$1/c_2$	$1/c_4$
9	$1/c_1$	$1/c_6$	$1/c_5$	$1/c_3$	0	0	$\frac{1}{c_2}+\frac{1}{c_4}$	0	0