Ans 1

(a) LSTMs
(b) DROPOUT
(c) VALIDATION
(d) EPSILON=1
(e) 0.5
(f) TRANSFER LEARNING
(g) BPTT
(h) LOGSIGMOID
(i) RPROP
(j) PRODUCER ACCURACY, OMISSION ERROR
(k) HADMARD
(l) SIGMOID
(m) RESIDUAL
(n) CUTOUT/DROPBLOCK

Ans 2.

(i) Case A : 1x1x256x64+4x4x64x256=2,78,528
(ii) Case B: 4x4x256x256= 10,48,576
(iii) Case B is slower, more weights to be trained

Ans 3

(i)

	X

X=(3,2,1)(-1,01,1)+(6,7,8)(-1,0,1)+(7,6,5)(-1,01,1)=-2

Ans 4

$Loss_{DOG}$ =max(0, (1.49-(-0.39)+1)+max(0,(4.21-(-0.39)+1)

=max(0,2.88)+max(0,5.6)= 2.88+5.6=8.48

[High Loss as very wrong prediction)

$Loss_{CAT}$ =max(0, (-4.61-3.28+1)+max(0,(1.46 - 3.28+1)

=max(0, -6.89)+max(0,-.82)= 0+0=0

Zero loss as correct prediction

Ans 5

(i) Sensitivity = TP/TAP= (3000/5000)x100=60%

(ii) Specificity=TN/(TAN)=(1800/20000)x100=90%

(iii) Overall error rate=[(18,000+3000)/(25000)]x100= 84%

Ans 6

$$\phi_i(x) = \exp(-\beta \|x - \mu_i\|^2); \beta = \frac{\mathrm{M}}{\mathrm{d}_{\max}^2}$$

$$\beta = 2/2 = 1$$

$$inputX = (x_1, x_2) : (1,1), \mu_1 = (0,0), \mu_2 = (1,1)$$

$$\varphi_1(X_4) = \exp(-[(x_1 - \mu_1)^2 + (x_2 - \mu_1)^2)]$$

$$\varphi_1(X_4) = \exp(-[(1-0)^2 + (1-0)^2)] = \exp(-2) = 0.1353$$

$$\varphi_2(X_4) = \exp(-[(x_1 - \mu_2)^2 + (x_2 - \mu_2)^2)]$$

$$\varphi_2(X_4) = \exp(-[(1-1)^2 + (1-1)^2)] = \exp(0) = 1.0$$

Output= 0.1x.1353+.1x1+.1x1=0.2135

Q7. i) It requires the objective fn to be differentiable everywhere in the search space.
ii) It suffers from local minima problem (not a good global optimization technique).

Q8. Decimal equivalent of 100111 is 39

$$\therefore x_1 = 5 + \frac{10-5}{2^6-1} \times 39 = 8.095$$

Q9. In Mamdani inference the output or consequent parts of the rules are described in terms of fuzzy sets whereas in Sugeno inference they are described as crisp functions of the input variables.

Q10.

$$\tilde{A} = \left\{ \frac{1}{1} + \frac{0.6}{2} + \frac{0.3}{3} + \frac{0}{4} \right\}, \quad \tilde{B} = \left\{ \frac{0}{1} + \frac{0.5}{2} + \frac{0.7}{3} + \frac{0.2}{4} \right\}$$

$$\therefore \bar{\tilde{A}} = \left\{ \frac{0}{1} + \frac{0.4}{2} + \frac{0.7}{3} + \frac{1}{4} \right\} \quad \& \quad \bar{\tilde{B}} = \left\{ \frac{1}{1} + \frac{0.5}{2} + \frac{0.3}{3} + \frac{0.8}{4} \right\}$$

$$\therefore \tilde{A} \cdot \bar{\tilde{B}} = \left\{ \frac{1}{1} + \frac{0.3}{2} + \frac{0.09}{3} + \frac{0}{4} \right\}$$

$$\bar{\tilde{A}} + \tilde{B} = \left\{ \frac{0}{1} + \frac{0.5}{2} + \frac{0.7}{3} + \frac{1}{4} \right\}$$

Q11.

$$\tilde{A} = \left\{ \frac{0.5}{2} + \frac{0.7}{3} + \frac{0.8}{4} + \frac{0.6}{5} \right\}$$

$$\tilde{B} = \left\{ \frac{1}{2} + \frac{0.9}{3} + \frac{0.6}{4} + \frac{0.2}{5} \right\}$$

'A Comfortable and Affordable House' is given by

$$\tilde{A} \cdot \tilde{B} = \left\{ \frac{0.5}{2} + \frac{0.7}{3} + \frac{0.6}{4} + \frac{0.2}{5} \right\}$$ (considering min. T-norm)

Hence, the family is most likely to buy a 3 roomed flat.

Q12. False.

Q13.

$$\begin{bmatrix} 1 & 0.8 & 0.5 & 0.1 \end{bmatrix} \circ \begin{bmatrix} 1 & 0.6 & 0.4 & 0.2 \\ 0.6 & 1 & 0.6 & 0.2 \\ 0.4 & 0.6 & 1 & 0.6 \\ 0.2 & 0.4 & 0.6 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0.8 & 0.6 & 0.5 \end{bmatrix}$$ (using Max-Min composition)

$\therefore$ 'An Approximately Small Number' is given by $\left\{ \frac{1}{1} + \frac{0.8}{2} + \frac{0.6}{3} + \frac{0.5}{4} \right\}$

~~Q13.~~

Q14. Fuzzy clustering is a constrained optimization problem since the membership value of each point to all the clusters must sum up to one.

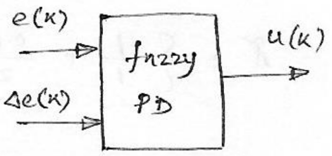
Q15. For a PD controller, $u(t) = K_p \cdot e(t) + K_D \dot{e}(t)$

$$\Rightarrow u(k) = K_p\, e(k) + K_D \cdot \frac{e(k) - e(k-1)}{T_s}$$

$$\simeq K_p\, e(k) + K_D' \,\Delta e(k)\,; \quad K_D' \triangleq \frac{K_D}{T_s}$$

For fuzzy PD controllers, the above linear fn usually becomes nonlinear.

$$\therefore \quad u(k) = f\left(e(k), \Delta e(k)\right)$$



For a PI controller, $u(t) = K_p\, e(t) + K_I \int e(t)\,dt$

$$\Rightarrow \dot{u}(t) = K_p\, \dot{e}(t) + K_I\, e(t)$$

$$\Rightarrow \frac{u(k) - u(k-1)}{T_s} \cong K_p \frac{e(k) - e(k-1)}{T_s} + K_I\, e(k)$$

$$\Rightarrow \Delta u(k) \cong K_p\, \Delta e(k) + K_I'\, e(k)\,; \quad K_I' = K_I \cdot T_s.$$

For a fuzzy PI controller, usually a nonlinear mapping is obtained as,

$$\Delta u(k) = f\left(e(k), \Delta e(k)\right).$$

Hence treating the o/p of a fuzzy PD controller as incremental control $\Delta u(k)$, it can be made to work like a fuzzy PI controller.

Q16. Clearly, all four rules will be activated for $x_1 = 5$ & $x_2 = 6$.

Clearly, weight of each rule is 0.5 if we consider minimum T-norm.

$$\therefore \quad y = \frac{0.5\,(x_1 + x_2) + 0.5\,(x_1^2 + x_2) + 0.5\,(-x_1 + x_2^2) + 0.5\,(x_1 - x_2)}{0.5 + 0.5 + 0.5 + 0.5}$$

$$= \frac{0.5}{2}\left(x_1 + x_2 + x_1^2 + \cancel{x_2} - \cancel{x_1} + x_2^2 + \cancel{x_1} - \cancel{x_2}\right)$$

$$= \frac{1}{4}\left(x_1 + x_2 + x_1^2 + x_2^2\right)$$

Ans 1 $P1 = [1\ -1\ 1\ 1\ -1]$

$P2 = [1\ 1\ 1\ -1\ -1]$

$w_{12} = w_{21} = (1)(-1) + (1)(1) = 0$

$w_{13} = w_{31} = (1)(1) + (1)(1) = 2$

$w_{14} = w_{41} = (1)(1) + (1)(-1) = 0$

$w_{15} = w_{51} = (1)(-1) + (1)(-1) = -2$

$w_{23} = w_{32} = (-1)(1) + (1)(1) = 0$

$w_{24} = w_{42} = (-1)(1) + (1)(-1) = -2$

$w_{25} = w_{52} = (-1)(-1) + (1)(-1) = 0$

$w_{34} = w_{43} = (1)(1) + (1)(-1) = 0$

$w_{35} = w_{53} = (1)(-1) + (1)(-1) = -2$

W =

	1	2	3	4	5
1	0	0	2	0	-2
2	0	0	0	-2	0
3	2	0	0	0	-2
4	0	-2	0	0	0
5	-2	0	-2	0	0

4M

node 3 $[1\ 1\ 1\ 1\ 1]\begin{bmatrix}2\\0\\0\\0\\-2\end{bmatrix} = 2-2 = 0 \geq 0$ unchanged

$\frac{1}{2}$

node 2 $[1\ 1\ 1\ 1\ 1]\begin{bmatrix}0\\0\\0\\-2\\0\end{bmatrix} = -2 < 0$ so changed

$[1\ -1\ 1\ 1\ 1]$

$\frac{1}{2}$

node 1 $[1\ -1\ 1\ 1\ 1]\begin{bmatrix}0\\0\\2\\0\\-2\end{bmatrix} = 2-2 = 0$ no change

$\frac{1}{2}$

node 5 $[1\ -1\ 1\ 1\ 1]\begin{bmatrix}-2\\0\\-2\\0\\0\end{bmatrix} = -2-2 = -4 < 0$ changed

$\frac{1}{2}$

$[1\ -1\ 1\ 1\ -1]$

node 4 $[1\ -1\ 1\ 1\ -1]\begin{bmatrix}0\\-2\\0\\0\\0\end{bmatrix} = +2 \geq 0$ no change

$\frac{1}{2}$

$[1\ -1\ 1\ 1\ -1]$

arrived at stable state

Synchronous

$$[1\ 1\ 1\ 1\ 1]\begin{bmatrix}0 & 0 & 2 & 0 & -2\\0 & 0 & 0 & -2 & 0\\2 & 0 & 0 & 0 & -2\\0 & -2 & 0 & 0 & 0\\-2 & 0 & -2 & 0 & 0\end{bmatrix} = 0, -2, 0, -2, -4$$

$= [1\ -1\ 1\ -1\ -1]$

2

Not a stable state

Ans.2 episode 1 S3—S6

$Q(3,6) = R(3,6) + 0.5 \max[Q(6,6)]$

$= 100 + 0.5 \max(0) = 100$ (1)

episode 2 (S2-S3-S6)

$Q(2,3) = R(2,3) + 0.5 \max[Q(3,6), Q(3,2)]$

$= 0 + 0.5 \max[100, 0]$

$= 0 + 50 = 50$ (1)

$Q(3,6) = R(3,6) + 0.5 \max[Q(6,6)]$

$= 100 + 0.5 \max[0] = 100$

episode 4 S1-S2-S5-S6

$Q(1,2) = R(1,2) + 0.5 \max[Q(2,1), Q(2,5), Q(2,3)]$

$= 0 + 0.5 \max[0, 0, 50]$

$= 25$ (1)

$Q(2,5) = R(2,5) + 0.5 \max[Q(5,6), Q(5,2), Q(5,4)]$

$= 0 + 0.5 \max[100, 0, 100] = 50$ (1)

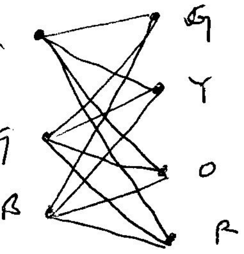
$Q(5,6) = 100$ (1)

episode 3 S5-S6

$Q(5,6) = R(5,6) + 0.5 \max[Q(6,6)]$

$= 100 + 0.5 \max[0] = 100$

1



1

	G	Y	O	R
R	0.4	0.5	0.6	0.7
G	0.4	0.5	0.6	0.7
B	0.4	0.5	0.6	0.7

$[255, 91, 71] \xrightarrow{\text{Normalize}} \frac{255-0}{255} = 1, \ \frac{91-0}{255} = 0.35, \ \frac{71-0}{255} = 0.27$

$d(G) = (1-.4)^2 + (.35-.4)^2 + (.27-.4)^2 = 0.37$ $\quad .606$

$d(Y) = (1-.5)^2 + (.35-.5)^2 + (.27-.5)^2 = 0.32$ $\quad .56$

$d(O) = (1-.6)^2 + (.35-.6)^2 + (.27-.6)^2 = 0.33$ $\quad .57$ 4

$d(R) = (1-.7)^2 + (.35-.7)^2 + (.27-.7)^2 = 0.39$ $\quad .62$

Winner node is Y

$W_{Y,new} = W_{Y,old} + \alpha (X - W_{Y,old})$

$= 0.5 + 0.5 [(1-.5), (.35-.5), (.27-.5)]$

$= 0.5 + 0.5 [\cancel{.25}\ .5, -.15, -.23]$

$= [0.75, .425, .385]$ 2

~~test~~ $x_1 = [0.1, 0.5, 1.0, 0.1]$

$z_1 = \sigma [W_z (h_{t-1}, x_t)] = \sigma [W_z (h_0, x_1)]$

$$= \sigma \underbrace{\begin{bmatrix} 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \end{bmatrix}}_{W_z}_{2\times6} \begin{bmatrix} 0.1 \\ 0.5 \\ 1.0 \\ 0.1 \\ 0 \\ 0 \end{bmatrix}_{6\times1}$$

$= \sigma \begin{pmatrix} 0.17 \\ 0.17 \end{pmatrix} = \begin{pmatrix} 0.5423 \\ 0.5423 \end{pmatrix}$ 2

$r_1 = z_1 = \sigma [W_r [h_0, x_1)] = \begin{pmatrix} 0.5423 \\ 0.5423 \end{pmatrix}$ $\frac{1}{2}$

$\tilde{h}_1 = \tanh [W [r_1 * h_0, x_1)]$

$r_1 * h_0 = \begin{pmatrix} .5423 \\ .5423 \end{pmatrix} * \begin{pmatrix} 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$

$$\tilde{h}_1 = \tanh \left[\begin{array}{cccc|cc} 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \end{array} \right] \begin{bmatrix} 0.1 \\ 0.5 \\ 1.0 \\ 0.1 \\ 0 \\ 0 \end{bmatrix} \begin{matrix} \\ \\ \\ \\ \left.\right\} r_1 * h_0 \end{matrix}$$

$= \tanh \begin{bmatrix} 0.17 \\ 0.17 \end{bmatrix} = \begin{bmatrix} .1683 \\ .1683 \end{bmatrix}$ 1

$h_1 = (1 - z_1) \underset{\begin{bmatrix} 0 \\ 0 \end{bmatrix}}{h_0} + z_1 * \tilde{h}_1 = \begin{pmatrix} .5423 \\ .5423 \end{pmatrix} * \begin{pmatrix} .1683 \\ .1683 \end{pmatrix}$

$= \begin{pmatrix} 0.0912 \\ 0.0912 \end{pmatrix}$ 2

$z_2 = \sigma [W_z (h_1, x_2)]$

$$z_2 = \sigma \left[\begin{array}{cccc|cc} 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \end{array} \right] \begin{bmatrix} .01 \\ .25 \\ 1.0 \\ .01 \\ .0912 \\ .0912 \end{bmatrix} \begin{matrix} \left.\right\} x_2 \\ \left.\right\} h_1 \end{matrix}$$ 2

$= \sigma \begin{bmatrix} .1452 \\ .1452 \end{bmatrix} = \begin{bmatrix} .5362 \\ .5362 \end{bmatrix}$

$r_2 = z_2$ $\frac{1}{2}$ $\qquad r_2 * h_1 = \begin{bmatrix} .5362 \\ .5362 \end{bmatrix} * \begin{bmatrix} .0912 \\ .0912 \end{bmatrix} = \begin{bmatrix} .0489 \\ .0489 \end{bmatrix}$

$$\tilde{h}_2 = \tanh \left[\begin{pmatrix} .1 & .1 & .1 & .1 & .1 & .1 \\ .1 & .1 & .1 & .1 & .1 & .1 \end{pmatrix} \begin{pmatrix} .01 \\ .25 \\ 1.0 \\ .01 \\ .0489 \\ .0489 \end{pmatrix} \right] \left.\right\} r_2 * h_1$$ 2

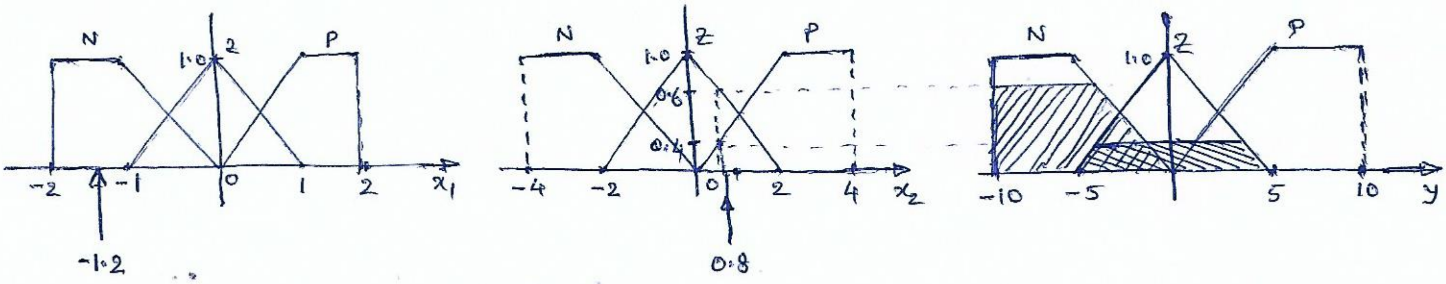
$= \tanh \begin{bmatrix} .13678 \\ .13678 \end{bmatrix} = \begin{bmatrix} .1359 \\ .1359 \end{bmatrix}$

$h_2 = (1 - z_2) h_1 + z_2 \cdot \tilde{h}_2$

$= \begin{pmatrix} 1-.5362 \\ 1-.5362 \end{pmatrix} * \begin{pmatrix} .0912 \\ .0912 \end{pmatrix} + \begin{pmatrix} .5362 \\ .5362 \end{pmatrix} \begin{pmatrix} .1359 \\ .1359 \end{pmatrix}$ 2

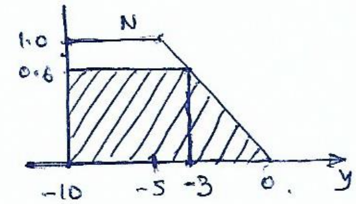
$= \begin{pmatrix} 0.11516 \\ 0.11516 \end{pmatrix}$

Q5.



Rule 3 & Rule 4 are activated. (1M)

Fuzzy o/p of Rule 3 $\longrightarrow$



(1M)

$A_{11} = 0.6 \times 7 = 4.2$

$A_{12} = \frac{1}{2} \times 3 \times 0.6 = 0.9$.

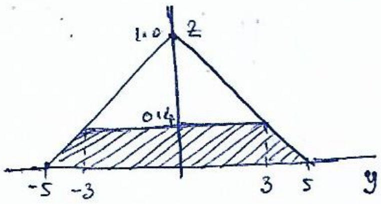
$y_{11} = \frac{-10 + (-3)}{2} = -6.5$

$y_{12} = \frac{2}{3} \times (-3) = -2$

$\therefore \quad A_1 = A_{11} + A_{12} = 5.1$ (2M)

$y_1 = \frac{y_{11} A_{11} + y_{12} A_{12}}{A_{11} + A_{12}} = \frac{-6.5 \times 4.2 - 2 \times 0.9}{5.1} \simeq -5.7$. (2M)

Fuzzy o/p of Rule 4 $\longrightarrow$



(1M)

$A_2 = \frac{1}{2}(10+6) \times 0.4 = 3.2$ (1M)

$y_2 = 0$. (1M)

Find crisp o/p, $y = \frac{A_1 y_1 + A_2 y_2}{A_1 + A_2} = \frac{5.1 \times (-5.7)}{5.1 + 3.2} = \cancel{-2.22}\ -3.5$ (1M)

Q6.

Particle.

1.> (i.e. $\begin{bmatrix} 2.8 \\ 1.7 \\ 7.0 \\ 3.0 \end{bmatrix}$)

Data Points	Dist. from $\underline{c}_1$ (i.e. $\begin{bmatrix} 2.8 \\ 1.7 \end{bmatrix}$)	Dist. from $\underline{c}_2$ (i.e. $\begin{bmatrix} 7 \\ 3 \end{bmatrix}$)	Cluster 1.	Cluster 2
1.>	3.44	5.15	Data pt. 1.> & 2>	Data pt. 3> & 4>
2.>	0	4.40		
3.>	4.58	1.14		
4.>	4.40	0		

2M

updating the 1st particle $\rightarrow$

$$\begin{bmatrix} \frac{2.3+2.8}{2} \\ \frac{5.1+1.7}{2} \\ \frac{6.7+7}{2} \\ \frac{4.1+3}{2} \end{bmatrix} = \begin{bmatrix} 2.55 \\ 3.4 \\ 6.85 \\ 3.55 \end{bmatrix}$$

1M

Fitness of 1st particle', $F_1 = \frac{1}{M_1+M_2}$ where

$$M_1 = \|\underline{x}_1 - \underline{c}_1\| + \|\underline{x}_2 - \underline{c}_1\|$$; x_1, x_2 being data points belonging to cluster 1.

$$= \left\| \begin{bmatrix} 2.3 \\ 5.1 \end{bmatrix} - \begin{bmatrix} 2.55 \\ 3.4 \end{bmatrix} \right\| + \left\| \begin{bmatrix} 2.8 \\ 1.7 \end{bmatrix} - \begin{bmatrix} 2.55 \\ 3.4 \end{bmatrix} \right\|$$

$$= 1.72 + 1.72 = 3.44.$$

& $$M_2 = \|\underline{x}_3 - \underline{c}_2\| + \|\underline{x}_4 - \underline{c}_2\|$$; x_3, x_4 being data points belonging to cluster 2.

$$= \left\| \begin{bmatrix} 6.7 \\ 4.1 \end{bmatrix} - \begin{bmatrix} 6.85 \\ 3.55 \end{bmatrix} \right\| + \left\| \begin{bmatrix} 7.0 \\ 3.0 \end{bmatrix} - \begin{bmatrix} 6.85 \\ 3.55 \end{bmatrix} \right\|$$

$$= 0.57 + 0.57 = 1.14.$$

$$\therefore F_1 = \frac{1}{3.44+1.14} = 0.2183.$$

2.5M

Particle	Data Pt.	Dist. from c_1 (i.e. $\begin{bmatrix}2.3\\5.1\end{bmatrix}$)	Dist. from c_2 (i.e. $\begin{bmatrix}2.8\\1.7\end{bmatrix}$)	Cluster 1.	Cluster 2
2.> (i.e. $\begin{bmatrix}2.3\\5.1\\2.8\\1.7\end{bmatrix}$)	1.>	0	3.44	Data pt: 1.> & 3>	Data pt. 2> & 4>
	2.>	3.44	0		
	3.>	4.51	4.58		
	4.>	5.15	4.40		

2M

updating the 2nd particle $\rightarrow$ $\begin{bmatrix}\frac{2.3+6.7}{2}\\ \frac{5.1+4.1}{2}\\ \frac{2.8+7}{2}\\ \frac{1.7+3}{2}\end{bmatrix} = \begin{bmatrix}4.5\\4.6\\4.9\\2.35\end{bmatrix}$ 1M

Fitness of 2nd particle, $F_2 = \frac{1}{M_1+M_2}$ where

$$M_1 = \|x_1 - c_1\| + \|x_3 - c_1\|$$; x_1, x_3 being data pts. belonging to cluster 1

$$= \left\|\begin{bmatrix}2.3\\5.1\end{bmatrix} - \begin{bmatrix}4.5\\4.6\end{bmatrix}\right\| + \left\|\begin{bmatrix}6.7\\4.1\end{bmatrix} - \begin{bmatrix}4.5\\4.6\end{bmatrix}\right\|$$

$$= 2.26 + 2.26 = 4.52$$

& $$M_2 = \|x_2 - c_2\| + \|x_4 - c_2\|$$; x_2, x_4 being data pts. belonging to cluster 2

$$= \left\|\begin{bmatrix}2.8\\1.7\end{bmatrix} - \begin{bmatrix}4.9\\2.35\end{bmatrix}\right\| + \left\|\begin{bmatrix}7\\3\end{bmatrix} - \begin{bmatrix}4.9\\2.35\end{bmatrix}\right\|$$

$$= 2.19 + 2.19 = 4.38$$

$$\therefore F_2 = \frac{1}{4.52+4.38} = 0.1124$$ 2.5M

Hence Particle 1 is G_{best} i.e. $G_{best} = \begin{bmatrix}2.55\\3.4\\6.85\\3.55\end{bmatrix}$ 1M

Velocity update for Particle 1 :

$$\underline{V}_1 = w \cdot \underline{V}_1(0) + c_1 \cdot r_1 \cdot (P_{best,1} - \underline{X}_1) + c_2 \cdot r_2 \cdot (\cancel{P_{best}}\ G_{best} - \underline{X}_1).$$

$$= 1 \times \underline{0} + 2 \times 0.3 \times \left\{ \begin{bmatrix} 2.55 \\ 3.4 \\ 6.85 \\ 3.55 \end{bmatrix} - \begin{bmatrix} 2.55 \\ 3.4 \\ 6.85 \\ 3.55 \end{bmatrix} \right\} + 2 \times 0.6 \left\{ \begin{bmatrix} 2.55 \\ 3.4 \\ 6.85 \\ 3.55 \end{bmatrix} - \begin{bmatrix} 2.55 \\ 3.4 \\ 6.85 \\ 3.55 \end{bmatrix} \right\}$$

$$= \underline{0}$$

Position update for Particle 1 :

$$\underline{X}_1(\text{new}) = \underline{X}_1(\text{old}) + \underline{V}_1 = \underline{X}_1(\text{old}) = \begin{bmatrix} 2.55 \\ 3.4 \\ 6.85 \\ 3.55 \end{bmatrix}.$$

1.5M

Velocity update for Particle 2 :

$$\underline{V}_2 = w \cdot \underline{V}_2(0) + c_1 \cdot r_1 \cdot (P_{best,2} - \underline{X}_2) + c_2 \cdot r_2 \cdot (G_{best} - \underline{X}_2).$$

$$= 1 \times \underline{0} + 2 \times 0.3 \left\{ \begin{bmatrix} 4.5 \\ 4.6 \\ 4.9 \\ 2.35 \end{bmatrix} - \begin{bmatrix} 4.5 \\ 4.6 \\ 4.9 \\ 2.35 \end{bmatrix} \right\} + 2 \times 0.6 \left\{ \begin{bmatrix} 2.55 \\ 3.4 \\ 6.85 \\ 3.55 \end{bmatrix} - \begin{bmatrix} 4.5 \\ 4.6 \\ 4.9 \\ 2.35 \end{bmatrix} \right\}$$

$$= \begin{bmatrix} -2.34 \\ -1.44 \\ 2.34 \\ 1.44 \end{bmatrix}$$

Position update for Particle 2 :

$$\underline{X}_2(\text{new}) = \underline{X}_2(\text{old}) + \underline{V}_2 = \begin{bmatrix} 4.5 \\ 4.6 \\ 4.9 \\ 2.35 \end{bmatrix} + \begin{bmatrix} -2.34 \\ -1.44 \\ 2.34 \\ 1.44 \end{bmatrix} = \begin{bmatrix} 2.16 \\ 3.16 \\ 7.24 \\ 3.79 \end{bmatrix}.$$

1.5M