

$$GT_{3 \times 4}$$

$$W = GT^T d$$

$$= (3 \times 4) (4 \times 1) = (3 \times 1)$$

$$W = \begin{bmatrix} -2.5018 \\ -2.5018 \\ +2.8404 \end{bmatrix} \begin{array}{l} \text{weights} \\ \text{bias} \end{array}$$

$3 \times 1$

Comparison between MLP & RBF:

RBF

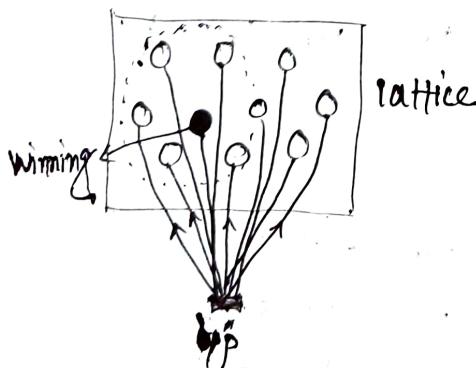
- (i) single hidden layer
- (ii) radial basis fn.s.
- (iii) hidden layer - non-linear
- (iv) compute Euclidean norm of i/p & centers
- (v) Local approximation to non-linear i/p - o/p mapping.

MLP

- (i) one or more hidden layers
- (ii) Activation fn.s.
- (iii) non-linear activations
- (iv) inner product of i/p & synaptic weights

- (v) Global approximation to non-linear i/p - o/p mapping.

## Self-Organizing Map (SOM)



competitive learning  
↓  
winner takes all

- (i) Competition
- (ii) Co-operation
- (iii) Synaptic adaptation

(i) competition:

$$\vec{x} = [x_1, x_2, \dots, x_m]$$

$$\vec{w}_j = [w_{j1}, w_{j2}, \dots, w_{jm}], j=1, 2, \dots, l$$

$\vec{w}^T \cdot \vec{x}$  → inner product

$l$ : total # neurons in networks

↳ best matching criterion

↳ maximize the inner product

equivalent to minimize the Euclidean distance

$$\min_j \|x - w_j\|$$

Affine projection Algorithm

23/10/25  
ADSP

Time  $n$

$$\begin{matrix} n+1 & n+2 & \cdots & n+p \\ y(n+1) & y(n+2) & \cdots & y(n+p) \\ \vec{x}(n+1) & \vec{x}(n+2) & \cdots & \vec{x}(n+p) \end{matrix} \quad \left. \begin{array}{l} \text{using this data, we need} \\ \text{to find } \vec{w}(n) \end{array} \right.$$

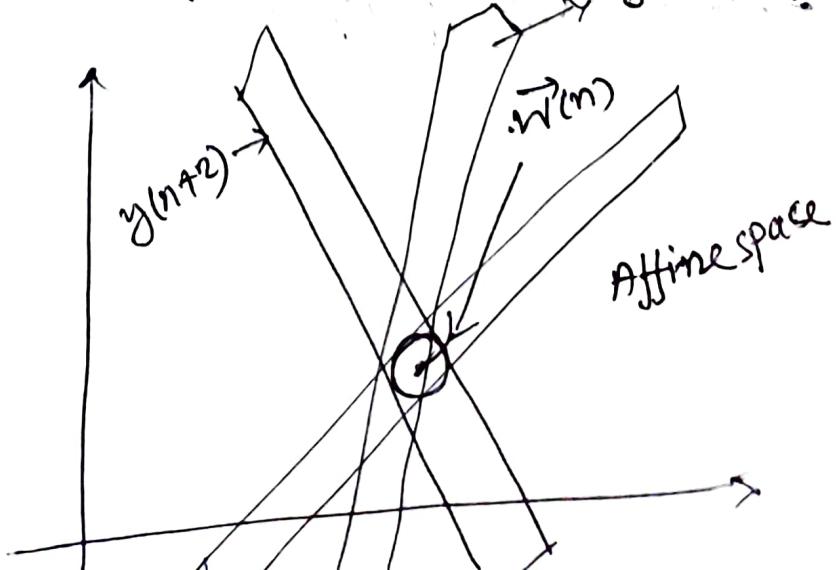
$$\text{total data} = N$$

$$\# \text{data in one batch} = p$$

$$\# \text{batch} = \frac{N}{p}$$

$$y(n+1) = \vec{x}^T(n+1) \vec{w}(n+1)$$

$$y(n+2) = \vec{x}^T(n+2) \vec{w}(n+1)$$



24/10/25  
soft computing

$$i(x) = \arg \min_j \|x - w_j\|, j=1, 2, \dots, l$$

winning neuron can be detected

### ② Co-operation process:

$$h_{ji}(x) = \exp\left(-\frac{d_{ji}}{2\sigma^2}\right)$$

$h_{ji}(x) \rightarrow$  topological neighbourhood centered on winning neuron  $i$ .  
 $d_{ji} \rightarrow$  lateral distance between winning neuron  $i$  & excited neuron  $j$

$$d_{ji}^2 = \|x_j - x_i\|^2; \quad x_j \rightarrow \text{position of the excited neuron } j$$

$x_i \rightarrow \text{position of the winning neuron } i$

### ③ Adaptive process:

$$\Delta w_j = \eta h_{ji}(x - w_j)$$

$$w_j^{(n+1)} = w_j^{(n)} + \eta^{(n)} h_{ji}(x)^{(n)} \cdot (\vec{x} - \vec{w}_j^{(n)})$$

## Summary of the algorithm:

(i) Initialization: weight vectors are to be initialized  $w_j(0)$ , where  $j = 1, 2, \dots, l$

$$\{x_i, y_i\}_{i=1}^N, \quad N: \# \text{ datapoints}$$

$l: \# \text{ neurons in lattice}$

(ii) Sampling: Draw a sample  $\vec{x}$  from the input space with certain probability.

(iii) Similarity Matching:

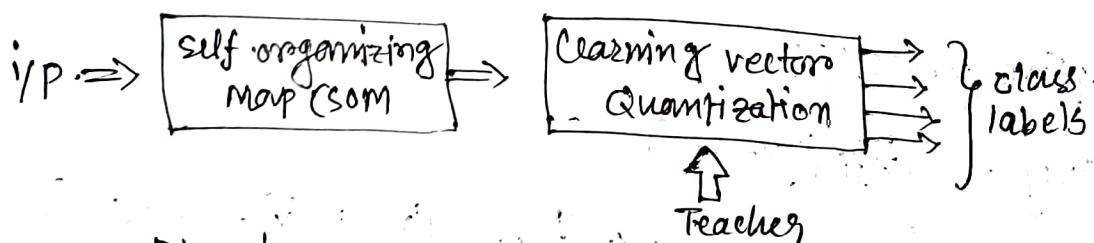
$$i(x) = \arg \min_j \|x(n) - w_j\|, \quad j = 1, 2, \dots, l$$

(iv) Updating:

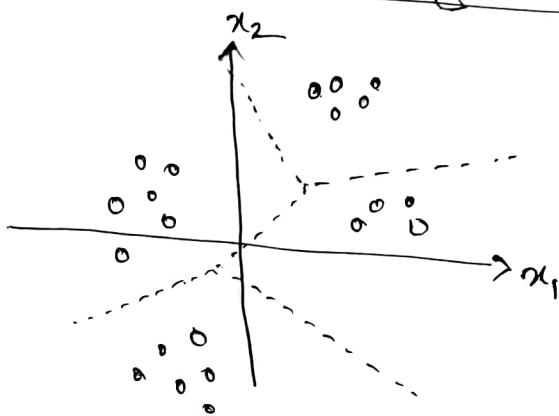
$$w_j(n+1) = w_j(n) + \eta(n) h_{j,i_x(n)}(x(n) - w_j(n))$$

(v) Continuation: continue until no noticeable changes in the feature map.

## \*Learning vector Quantization (LVQ):



Block diagram of improved pattern classification using SOM & LVQ



$$x = [x_1, x_2]^T$$

Voronoi diagram involving four cells

Code-book - NN rule

LVQ  $\rightarrow$  supervised learning technique

26/10/25  
Soft Computing

## LVQ algorithm:

① Assume, voronoi vectors -  $w_c \rightarrow$  closest to the i/p vector

$c_{w_i} \rightarrow$  class which associated voronoi vector  
 $w_c$

$c_{x_i} \rightarrow$  class label of i/p vector  $x_i$

$\rightarrow$  If  $c_{w_i} = c_{x_i}$ , then

$$w_c(n+1) = w_c(n) + \alpha_n [x_i - w_c(n)]$$

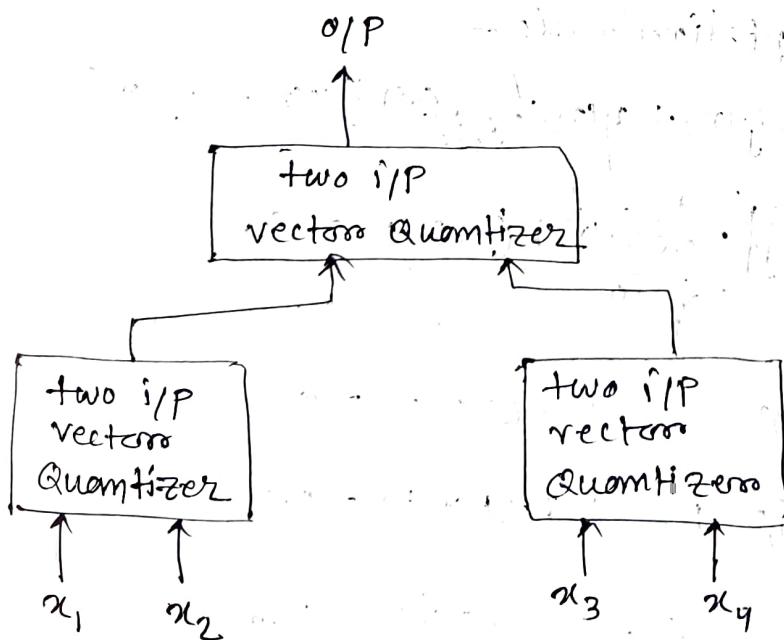
where,  $0 < \alpha_n < 1$

$\rightarrow$  If  $c_{w_i} \neq c_{x_i}$ , then

$$w_c(n+1) = w_c(n) - \alpha_n [x_i - w_c(n)]$$

② The other voronoi vectors are not modified.  
(Hierarchical vector Quantization)

## Two-stage Hierarchical LVQ:



### Example

Two dimensional NN:  $q$  neurons  $\rightarrow$  defined by coordinate values.

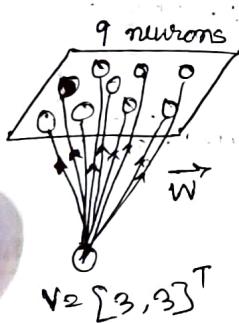
$$i_1 = [0, 0]; i_2 = [1, 0]; i_3 = [2, 0]; i_4 = [0, 1]; i_5 = [1, 1]; \\ i_6 = [2, 1]; i_7 = [0, 2]; i_8 = [1, 2]; i_9 = [2, 2]$$

At a certain step  $t$ , the weight vectors  $w_j$  are,

$$\vec{w}_1 = [4, 5]^T; \vec{w}_2 = [5, 3]^T; \vec{w}_3 = [4, 6]^T; \vec{w}_4 = [1, 1]^T; \\ \vec{w}_5 = [2, 2]^T; \vec{w}_6 = [0, 0]^T; \vec{w}_7 = [8, 4]^T; \vec{w}_8 = [3, 5]^T; \\ \vec{w}_9 = [5, 4]^T$$

$$\text{At time } t, \text{ we've input vector } v = [3, 3]^T$$

calculate weights at time  $(t+1)$ , using sum adaptation rule. Assume,  $\eta(t) = 1$ ;  $h(r, s, t) = 1$  if  $|i_r - i_s| = 0$



$$h(r, s, t) = 0.5 \text{ if } |i_r - i_s| = 1$$

$$h(r, s, t) = 0 \text{ otherwise}$$

Solution: sum adaptation rule -

$$w_j(n+1) = w_j(n) + \eta(n) h_{j, i_x}(n) [x(n) - w_j(n)]$$

$$\left| \begin{bmatrix} 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right| = \sqrt{(-1)^2 + 0^2} = \sqrt{1+0} = 1 \quad ; \quad h(1, 2, t) = 1 \\ \therefore h(1, 2, t) = 0.5$$

$$\left| \begin{bmatrix} 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 2 \\ 0 \end{bmatrix} \right| = \sqrt{(2)^2 + 0^2} = 2 \quad ; \quad h(1, 3, t) = 0$$

$$\left| \begin{bmatrix} 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right| = \sqrt{0^2 + (-1)^2} = 1 \quad ; \quad h(1, 4, t) = 0.5$$

$$\left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 4 \\ 5 \end{bmatrix} \right| = \sqrt{(-1)^2 + (-2)^2} = \sqrt{1+4} = \sqrt{5} = 2.236$$

$$\left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 5 \\ 3 \end{bmatrix} \right| = \sqrt{(-2)^2 + 0^2} = \sqrt{4+0} = 2$$

$$\left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 4 \\ 6 \end{bmatrix} \right| = \sqrt{(-1)^2 + (-3)^2} = \sqrt{1+9} = \sqrt{10} = 3.162$$

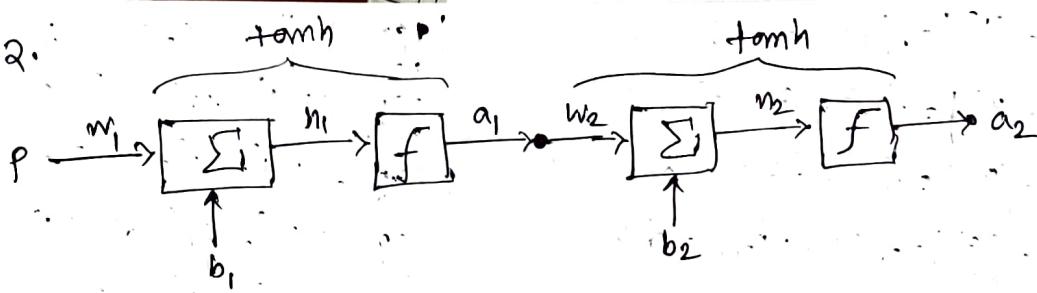
$$\begin{aligned} \left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right| &= \sqrt{2^2 + 2^2} = \sqrt{8} = 2.828 \\ \left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \end{bmatrix} \right| &= \sqrt{1^2 + 1^2} = \sqrt{2} = 1.414 \\ \left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \right| &= \sqrt{3^2 + 3^2} = \sqrt{18} = 4.242 \\ \left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 6 \\ 4 \end{bmatrix} \right| &= \sqrt{(-3)^2 + (-1)^2} = \sqrt{10} = 3.162 \\ \left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 9 \\ 5 \end{bmatrix} \right| &= \sqrt{0^2 + (-2)^2} = 2 \\ \left| \begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 5 \\ 4 \end{bmatrix} \right| &= \sqrt{(-2)^2 + (-1)^2} = \sqrt{5} = 2.236 \end{aligned}$$

$\xrightarrow{\text{winning}}$

$$\begin{aligned} \vec{w}_1 &= \begin{bmatrix} 4 \\ 5 \end{bmatrix} + 1 * 0 = \begin{bmatrix} 4 \\ 5 \end{bmatrix} \\ \vec{w}_2 &= \begin{bmatrix} 5 \\ 3 \end{bmatrix} + 1 * 0.5 (\begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 5 \\ 3 \end{bmatrix}) = \begin{bmatrix} 5 \\ 3 \end{bmatrix} + 0.5 \begin{bmatrix} -2 \\ 0 \end{bmatrix} = \begin{bmatrix} 5 \\ 3 \end{bmatrix} + \begin{bmatrix} -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 4 \\ 3 \end{bmatrix} \\ \vec{w}_3 &= \begin{bmatrix} 4 \\ 6 \end{bmatrix} + 1 * 0 = \begin{bmatrix} 4 \\ 6 \end{bmatrix} \\ \vec{w}_4 &= \begin{bmatrix} 1 \\ 1 \end{bmatrix} + 1 * 0.5 (\begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix}) = \begin{bmatrix} 1 \\ 1 \end{bmatrix} + 0.5 \begin{bmatrix} 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \\ \vec{w}_5 &= \begin{bmatrix} 2 \\ 2 \end{bmatrix} + 1 * 0.5 (\begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \end{bmatrix}) = \begin{bmatrix} 2 \\ 2 \end{bmatrix} + 0.5 \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2.5 \\ 2.5 \end{bmatrix} \\ \vec{w}_6 &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} + 1 * 0.5 (\begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix}) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + 0.5 \begin{bmatrix} 3 \\ 3 \end{bmatrix} = \begin{bmatrix} 1.5 \\ 1.5 \end{bmatrix} \\ \vec{w}_7 &= \begin{bmatrix} 6 \\ 4 \end{bmatrix} + 1 * 0.5 (\begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 6 \\ 4 \end{bmatrix}) = \begin{bmatrix} 6 \\ 4 \end{bmatrix} + 0.5 \begin{bmatrix} 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 6 \\ 4 \end{bmatrix} + \begin{bmatrix} 1.5 \\ 0.5 \end{bmatrix} = \begin{bmatrix} 7.5 \\ 4.5 \end{bmatrix} \\ \vec{w}_8 &= \begin{bmatrix} 3 \\ 5 \end{bmatrix} + 1 * 0.5 (\begin{bmatrix} 3 \\ 3 \end{bmatrix} - \begin{bmatrix} 3 \\ 5 \end{bmatrix}) = \begin{bmatrix} 3 \\ 5 \end{bmatrix} + 0.5 \begin{bmatrix} 0 \\ -2 \end{bmatrix} = \begin{bmatrix} 3 \\ 5 \end{bmatrix} + \begin{bmatrix} 0 \\ -1 \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \\ \vec{w}_9 &= \begin{bmatrix} 5 \\ 9 \end{bmatrix} + 1 * 0 = \begin{bmatrix} 5 \\ 9 \end{bmatrix} \end{aligned}$$

$$\begin{aligned} \left| \begin{bmatrix} 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= \sqrt{(-1)^2 + (-1)^2} = 2 \Rightarrow 0 \\ \left| \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= (0)^2 + (-1)^2 = 1 \Rightarrow 0.5 \\ \left| \begin{bmatrix} 2 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= 1^2 + (-1)^2 = 2 \Rightarrow 0 \\ \left| \begin{bmatrix} 0 \\ 1 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= (-1)^2 + 0^2 = 1 \Rightarrow 0.5 \\ \left| \begin{bmatrix} 2 \\ 1 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= (1)^2 + (0)^2 = 1 \Rightarrow 0.5 \\ \left| \begin{bmatrix} 0 \\ 2 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= (-1)^2 + (1)^2 = 2 \Rightarrow 0 \\ \left| \begin{bmatrix} 1 \\ 2 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= 0^2 + 1^2 = 1 \Rightarrow 0.5 \\ \left| \begin{bmatrix} 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right|^2 &= 1^2 + 1^2 = 2 \Rightarrow 0 \end{aligned}$$

Q.2.



$$\text{Initial weights: } w_1(0) = -1, b_1(0) = 1$$

$$w_2(0) = -2, b_2(0) = 1$$

An i/p pair is given: ( $p = -1, t = 1$ )

perform one iteration of BP algorithm with  $\eta = 1$

$\boxed{\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}; \nabla \tanh(z) = 1 - \tanh^2(z)}$

Forward pass:

$$z_1 = p_1 w_1 + b_1 = (-1) * (-1) + 1 = 2; \tanh(z_1) = \frac{e^2 - e^{-2}}{e^2 + e^{-2}}$$

$$a_1 = 0.964$$

$$z_2 = a_1 w_2 + b_2 = (0.964) * (-2) + 1 = -0.928; \tanh(z_2) = \frac{e^{-0.928} - e^{0.928}}{e^{-0.928} + e^{0.928}}$$

$$\text{Error} = 1 - 0.729 = 0.271; \mathcal{E} = \frac{1}{2} \text{error}^2 \quad a_2 = 0.729$$

Backward pass:

$$= \frac{1}{2} (t - a_2)^2$$

$$w_2(1) = w_2(0) - \eta * \frac{\partial \mathcal{E}}{\partial w_2(0)}; \frac{\partial \mathcal{E}}{\partial w_2} = \frac{\partial \mathcal{E}}{\partial a_2} \frac{\partial a_2}{\partial z_2} \frac{\partial z_2}{\partial w_2}$$

$$= -2 - 1 * (-0.452)$$

$$= -2 + 0.452 = 1.548$$

$$= -1 * (1 - 0.531) * 0.964$$

$$a_2 = \tanh(\cancel{z_2}); \frac{\partial a_2}{\partial z_2} = 1 - \tanh^2(z_2)$$

$$z_2 = a_1 w_2 + b_2; \frac{\partial z_2}{\partial w_2} = a_1$$

$$= -0.452$$

$$b_2(1) = b_2(0) - \eta * \frac{\partial \mathcal{E}}{\partial b_2(0)}; \frac{\partial \mathcal{E}}{\partial b_2} = \frac{\partial \mathcal{E}}{\partial a_2} * \frac{\partial a_2}{\partial z_2} * \frac{\partial z_2}{\partial b_2}$$

$$= 1 - 1 * (-0.469)$$

$$= 1.469$$

$$= -1 * (1 - 0.531) * 1$$

$$= -0.469$$

$$w_1(1) = w_1(0) - \eta \frac{\partial \ell}{\partial w_1(0)} \quad ; \quad \frac{\partial \ell}{\partial w_1} = \frac{\partial w_1}{\partial a_2} \frac{\partial a_2}{\partial z_2} \frac{\partial z_2}{\partial a_1} \frac{\partial a_1}{\partial z_1} \frac{\partial z_1}{\partial w_1}$$

Product  
Tap ( $a, b$ ) =  
29/10/25  
soft computing

→ Fuzzy set :-

$$P = \{x | x > 6 \text{ ft.}\} \text{ where } x = \text{height}$$

$x \rightarrow$  collection of objects → denoted by  $x$

then, fuzzy set

$$A = \{(x, \mu_A(x)) | x \in x\}$$

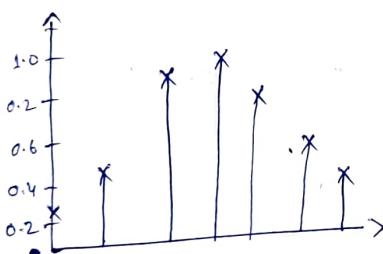
where,

$\mu_A(x) \rightarrow$  membership function for  
the fuzzy set  $A$

$$0 \leq \mu_A(x) \leq 1$$

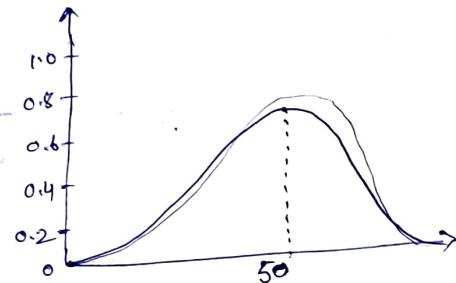
$x \rightarrow$  Universe of discourse / universe

MF on a discrete universe



$x = \# \text{children}$

$A = \text{sensible number}$   
of children in a  
family



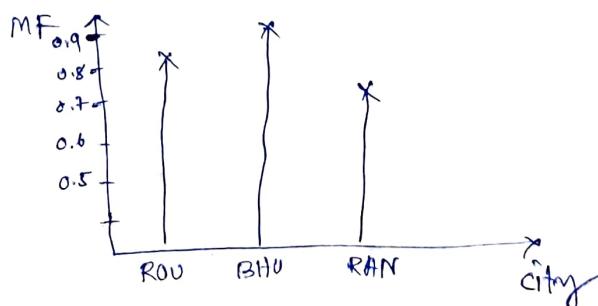
$x = \text{Age}$

$B = \text{about 50y old}$

Fuzzy set with discrete Universe:

Best city to live given by set  $C$

$$C = \{(Rourkela, 0.8), (Bhubaneswar, 0.9), (Ranchi, 0.7)\}$$



Sensible # students

$$B = \{(2, 0.1), (5, 0.2), (10, 0.3), (15, 0.6), (18, 0.7), (20, 0.8), \\ (22, 0.9), (50, 0.4), (60, 0.3)\}$$

Alternative Expression:

$$C = 0.8/\text{Rourkela} + 0.9/\text{Bhubaneswar} + 0.7/\text{Ranchi}$$

$$B = 0.1/2 + 0.2/5 + 0.3/10 + 0.6/15 + 0.7/18 + 0.8/20 + \\ 0.9/22 + 0.4/50 + 0.3/60$$

Fuzzy set with continuous Universe:

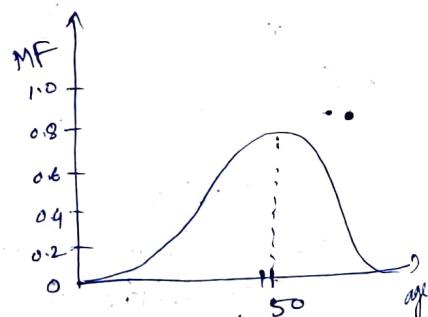
$X = \mathbb{R}^+$  be the set of possible ages of human in a village

$B \rightarrow$  Fuzzy set "about 50 years old".

$$B = \{(x, \mu_B(x)) | x \in X\}$$

where,

$$\mu_B(x) = \frac{1}{1 + \left(\frac{x-50}{10}\right)^4} \quad \leftarrow \text{Bell MF}$$



Linguistic variable and Linguistic values:

$x \rightarrow \text{age}$

fuzzy set can be defined as -

$$\begin{array}{ccc} \text{"young"} & & \text{"Middle age"} \\ \uparrow & & \uparrow \\ \mu_{\text{young}}(x) & & \mu_{\text{middle age}}(x) \end{array}$$

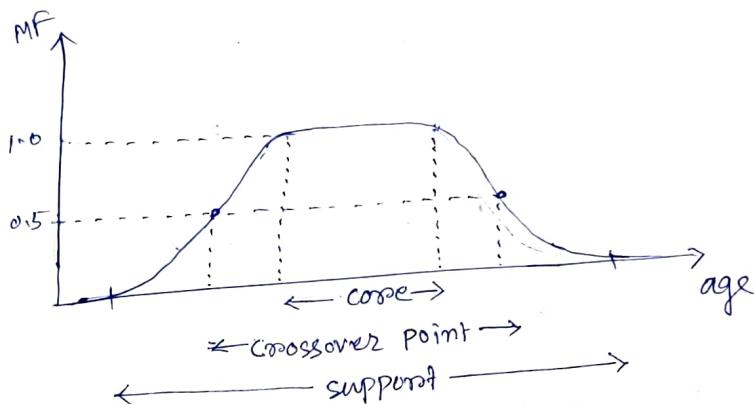
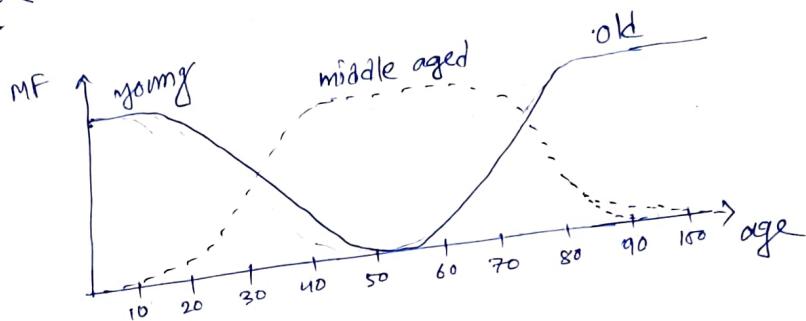
where,

"Age"  $\rightarrow$  Linguistic variable

"young", "middle age"  $\rightarrow$  Linguistic values

Basic Product

ap(a)



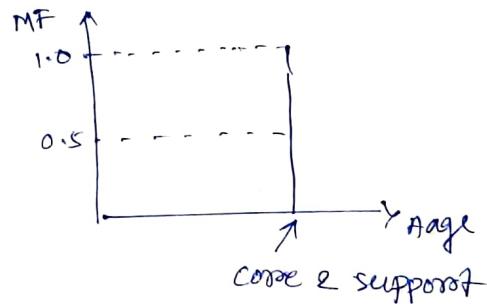
support:  $\text{support}(A) = \{x \mid \mu_A(x) > 0\}$

core:  $\text{core}(A) = \{x \mid \mu_A(x) = 1\}$

normality: normal fuzzy set  $\rightarrow$  el point  $x \in X$  s.t.  $\mu_A(x) = 1$

cross-over points:  $\text{crossover}(A) = \{x \mid \mu_A(x) = 0.5\}$

Fuzzy singleton: a fuzzy set whose support is a single point in  $X$  with  $\mu_A(x) = 1$



$\alpha$ -cut  $\geq$  strong  $\alpha$ -cut:

( $\alpha$ -level cut /  $\alpha$ -cut)  $\rightarrow A_\alpha = \{x \mid \mu_A(x) \geq \alpha\}$ ,  $\text{support}(A) = A_\alpha$

(strong  $\alpha$ -cut)  $\rightarrow A'_\alpha = \{x \mid \mu_A(x) > \alpha\}$ ,  $\text{core}(A) = A'_\alpha$

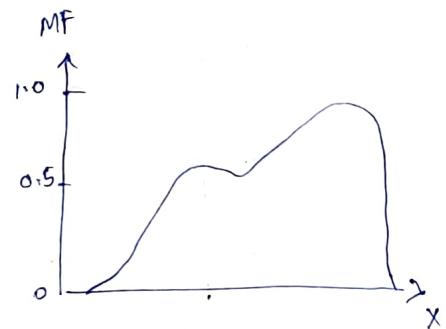
## Convexity:

Fuzzy set  $A$  is convex iff for any  $x_1, x_2 \in X$  and  $\lambda \in [0, 1]$

$$\mu_A(\lambda x_1 + (1-\lambda)x_2) \geq \min\{\mu_A(x_1), \mu_A(x_2)\}$$



Convex



## Bandwidth of normal and convex fuzzy set

$$\text{width}(A) = |x_2 - x_1| \quad \text{where, } \mu_A(x_1) = \mu_A(x_2) = 0.5$$

## Symmetry:

fuzzy set will be symmetric fuzzy set if its MF is symmetric around a central point  $x=c$

$$\mu_A(c+x) = \mu_A(c-x) \quad \forall x \in X$$

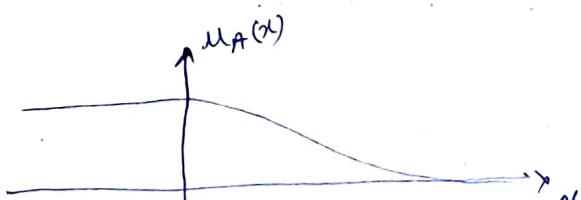
## open left, open right, closed Membership Function:

fuzzy set  $A$  is open left if  $\lim_{x \rightarrow +\infty} \mu_A(x) = 0$  and

$$\lim_{x \rightarrow -\infty} \mu_A(x) = 1$$

open right: if  $\lim_{x \rightarrow +\infty} \mu_A(x) = 1$  and  $\lim_{x \rightarrow -\infty} \mu_A(x) = 0$

closed MF: if  $\lim_{x \rightarrow +\infty} \mu_A(x) = 0$  &  $\lim_{x \rightarrow -\infty} \mu_A(x) = 0$



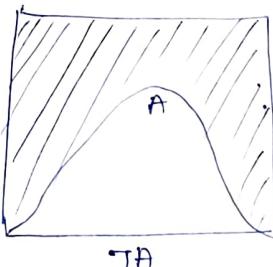
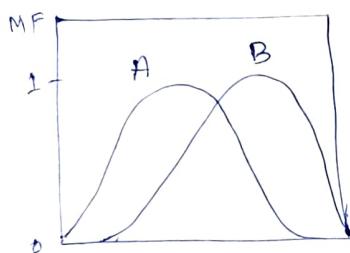
## Set theoretic operation:

① Subset / Containment: Fuzzy set A is contained in fuzzy set B (or fuzzy set A is subset of fuzzy set B) iff  $\mu_A(x) \leq \mu_B(x)$   $\forall x$ ,

$$A \subseteq B \Rightarrow \mu_A(x) \leq \mu_B(x)$$

② Union: The union of two fuzzy set A and B will be fuzzy set C or  $C = A \cup B$  or  $C = A \text{ OR } B$

$$\begin{aligned}\mu_C(x) &= \max(\mu_A(x), \mu_B(x)) \\ &= \mu_A(x) \vee \mu_B(x)\end{aligned}$$



③ Intersection:  $C = A \cap B \Rightarrow C = A \text{ AND } B$

$$\mu_C(x) = \min(\mu_A(x), \mu_B(x)) = \mu_A(x) \wedge \mu_B(x)$$

④ Complement: complement of fuzzy set A  $\rightarrow \bar{A}$  or NOT A  $\Rightarrow \bar{A}$

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x)$$

⑤ Cartesian product or co-product

Assume, A and B two fuzzy set in X and Y respectively.

Cartesian product of A and B  $\rightarrow A \times B$  in the product space

$$\mu_{A \times B}(x,y) = \min(\mu_A(x), \mu_B(y))$$

X  $\times$  Y

Cartesian co-product of A  $\Sigma$  B  $\rightarrow A + B$

$$\mu_{A+B}(x,y) = \max(\mu_A(x), \mu_B(y))$$

## MF formulation and parameterization:

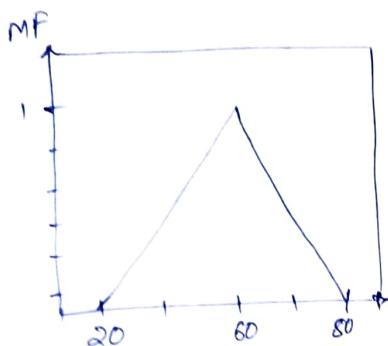
MF's in one dimension:

### ① Triangular MF's:

This MF is specified by 3 parameters ( $a, b, c$ )

triangle ( $a, b, c$ )

$$\text{triangle}(x; a, b, c) = \begin{cases} 0 &; x \leq a \\ \frac{x-a}{b-a} &; a \leq x \leq b \\ \frac{c-x}{c-b} &; b \leq x \leq c \\ 0 &; c \leq x \end{cases}$$



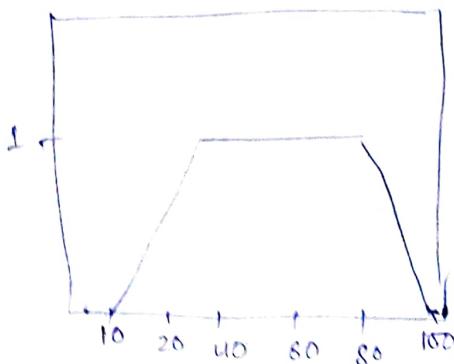
triangle ( $u; 20, 60, 80$ )

### ② Trapezoidal MF's:

specified by 4 parameters ( $a, b, c, d$ )

trapezoid ( $x; a, b, c, d$ )

$$\text{trapezoid}(x; a, b, c, d) = \begin{cases} 0 &; x \leq a \\ \frac{x-a}{b-a} &; a \leq x \leq b \\ 1 &; b \leq x \leq c \\ \frac{d-x}{d-c} &; c \leq x \leq d \\ 0 &; x \geq d \end{cases}$$

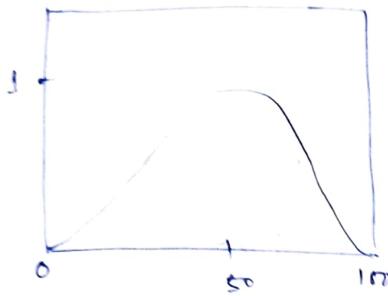


trapezoid ( $u; 10, 20, 60, 95$ )

### ④ Gaussian MF:

specified by two parameters  $(c, \sigma)$

$$\text{Gaussian}(x; c, \sigma) = e^{-\frac{1}{2} \left( \frac{x-c}{\sigma} \right)^2}$$

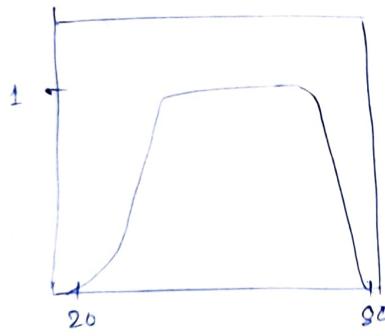


$$\text{Gaussian}(x; 50, 20)$$

### ⑤ Generalized Bell MF:

specified by 3 parameters of  $a, b, c$

$$\text{bell}(x; a, b, c) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}}$$



### ⑥ Sigmoidal / Mob MF:

$$\delta(x; a, c) = \frac{1}{1 + \exp(-a(x-c))}$$

$a$ : controls the slope @ crossover point  
 $c$ : cross over point

$c$ : cross over point

### ⑦ Closed and asymmetric MF based on Sigmoidal MF:

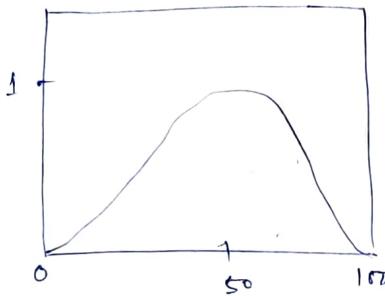
$$\mathcal{Z}_1 = \delta(x; 1, -5)$$

$$\mathcal{Z}_2 = \delta(x; 2, 5)$$

### ③ Gaussian MF:

specified by two parameters  $(c, \sigma)$

$$\text{Gaussian}(x; c, \sigma) = e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2}$$

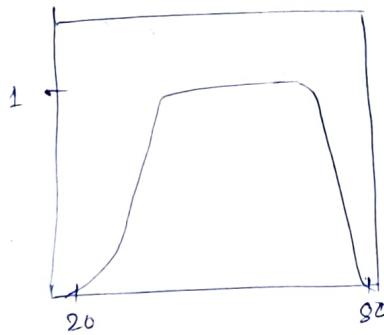


$$\text{Gaussian}(x; 50, 20)$$

### ④ Generalized Bell MF:

specified by 3 parameters of  $a, b, c$

$$\text{bell}(x; a, b, c) = \frac{1}{1 + |\frac{x-c}{a}|^{2b}}$$



### ⑤ Sigmoidal MF:

$$\delta(x; a, c) = \frac{1}{1 + \exp(-a(x-c))}$$

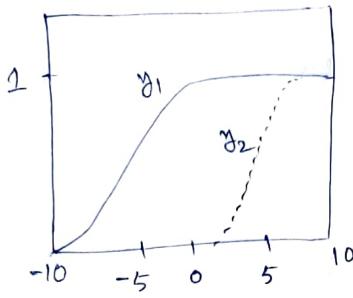
$a$ : controls the slope @ crossover point  $x=c$

$c$ : cross over point

### ⑥ Closed and asymmetric MF based on Sigmoidal MF:

$$y_1 = \delta(x; 1, -5)$$

$$y_2 = \delta(x; 2, 5)$$



⑦ Left-Right MF (3 parameters of  $\alpha, \beta, c$ )

$$LR(x; c, \alpha, \beta) = \begin{cases} F_L\left(\frac{c-x}{\alpha}\right) & ; x \leq c \\ F_R\left(\frac{x-c}{\beta}\right) & ; x > c \end{cases}$$

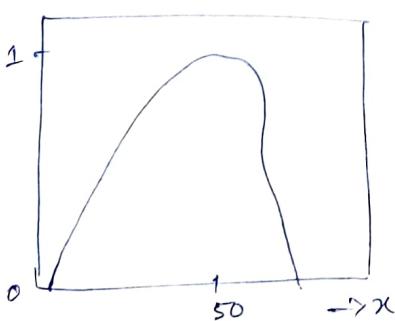
where,  $F_L(x) \geq F_R(x)$  monotonically decreasing function defined on  $(-\infty, \infty)$  with  $F_L(0) = F_R(0) = 1$

and  $\lim_{x \rightarrow \infty} F_L(x) = \lim_{x \rightarrow \infty} F_R(x) = 0$

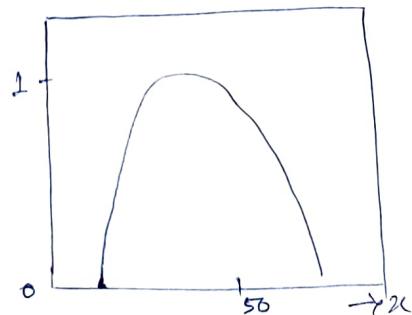
e.g.: L-R MF

$$F_L(x) = \sqrt{\max(0, 1-x^2)}$$

$$F_R(x) = e^{-x^3}$$

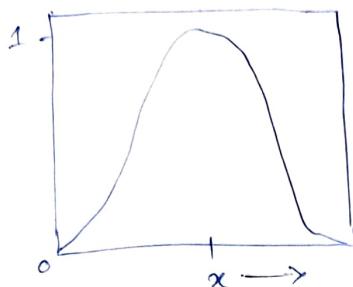


$$LR(x; 65, 60, 10)$$

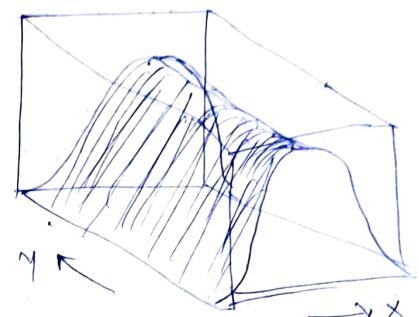


$$LR(x; 25, 10, 40)$$

2D-MF:



Base Fuzzy set A



Cylindrical Extension of A

Cylindrical Extension of 1D Fuzzy set:

A is a fuzzy set in x

Then its cylindrical extension in  $x \times y$  is a fuzzy set  $c(A)$

$$c(A) = \int_{x \times y} M_A(x) / (x, y)$$

Projection of Fuzzy sets:

$R \rightarrow$  2D fuzzy set on  $x \times y$

then projections of R onto x and y are defined as,

$$R_x = \int_x [\max_y M_R(x, y)] / x$$

$$R_y = \int_y [\max_x M_R(x, y)] / y \text{ respectively.}$$

Composite and Non-composite MFs:

e.g.: fuzzy set  $A \rightarrow M_A(x, y)$  is near  $(3, 4)$

$$M_A(x, y) = \exp \left[ - \left( \frac{x-3}{2} \right)^2 - (y-4)^2 \right]$$

$$M_A(x, y) = \exp \left[ - \left( \frac{x-3}{2} \right)^2 \right] \exp \left[ - \frac{(y-4)}{1} \right]^2$$

$$= \text{Gaussian}(x; 3, 2) \text{ Gaussian}(y; 4, 1)$$

Fuzzy set A  $\rightarrow$  composite MF

If, fuzzy set A is defined by following MF

$$M_A(x, y) = \frac{1}{1 + |x-3| |y-4|^{2.5}} \quad \left\{ \begin{array}{l} \text{non composite MF} \\ \hookrightarrow \end{array} \right.$$

Derivative of parameterized MF's :

Assume,  $y = \text{Gaussian}(x; \sigma, c) = e^{-\frac{1}{2} \left( \frac{x-c}{\sigma} \right)^2}$

$$\frac{\partial y}{\partial x} = -\frac{(x-c)}{\sigma^2} y$$

$$\frac{\partial y}{\partial \sigma} = \frac{(x-c)^2}{\sigma^3} y$$

$$\frac{\partial y}{\partial c} = \frac{(x-c)}{\sigma^2} y$$

10/25  
soft computing

Fuzzy rules and Fuzzy Reasoning :

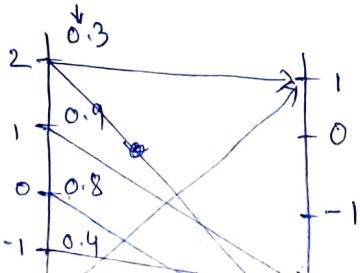
Extension principle :

$$A = M_A(x_1)/x_1 + M_A(x_2)/x_2 + \dots + M_A(x_n)/x_n$$

$$f(A) = B = M_A(x_1)/y_1 + M_A(x_2)/y_2 + \dots + M_A(x_n)/y_n$$

where,

$$y_i = f(x_i); i=1, 2, \dots, n$$



$$A = 0.1|-2 + 0.4|-1 + 0.8|0 + 0.9|2 + 0.3|2$$

$$f(x) = x^2 - 2$$