

- Kohonen self organizing networks
  - also known as Kohonen Feature maps or topology-preserving maps.
  - competition based n/w paradigm for data clustering.
  - N/w of this type impose a neighborhood constraint on the o/p units, such that a certain topological property in the i/p data is reflected in the o/p unit's weights.
  - Similar to competitive learning n/w.
  - For Kohonen Feature maps, we update not only the winning unit's weights but also all of the weights in a neighborhood around the winning units. The neighborhood size decreases slowly with each iteration.

Step 1: Select the winning o/p unit as the one with the largest similarity measure (or smallest dissimilarity measure) bet<sup>n</sup> all weight vectors  $w_i$  & the i/p vector  $x$ .

If Euclidean distance is chosen as the dissimilarity measure, then the winning unit  $c$  satisfies the following eq<sup>n</sup>.

$$\|x - w_c\| = \min_i \|x - w_i\|,$$

where the index  $c$  refers to the winning unit



Step 2: Let  $NB_c$  denote a set of index' corresponding to a neighborhood around winner  $c$ .  
The weights of the winner & its neighboring units are then updated by

$$\Delta w_i = \eta (x - w_i), i \in NB_c$$

where  $\eta \Rightarrow$  small positive learning rate.

Neighborhood fun<sup>n</sup>  $\Omega_c(i)$  around winning unit  $c$ .

(Gaussian function)

$$\Omega_c(i) = \exp\left(\frac{-\|p_i - p_c\|^2}{2\sigma^2}\right)$$

where  $p_i$  &  $p_c \Rightarrow$  positions of the o/p. units  $i$  &  $c$ .

$\sigma \Rightarrow$  scope of neighborhood.

By using neighborhood function, updated formula can be rewritten as

$$\Delta w_i = \eta \Omega_c(i) (x - w_i)$$

where  $i \Rightarrow$  index for all o/p units

## Kohonen's Self Organizing maps.

Steps. Action.

1. Initialise weights, set max value for R, set learning rate  $\alpha$ .

2. while stopping condition false do steps 3 to 9

3. For each i/p vector  $x$  do step 4 to 8.

4. For each  $j$  neuron, compute the Euclidean distance.

$$D(j) = \sqrt{\sum_{i=1}^n (x_i - w_{ij})^2}$$

5. Find the index  $J$  such that  $D(J)$  is min.

6. For all neurons  $j$  within a specified neighbourhood of  $J$  & for all  $i$

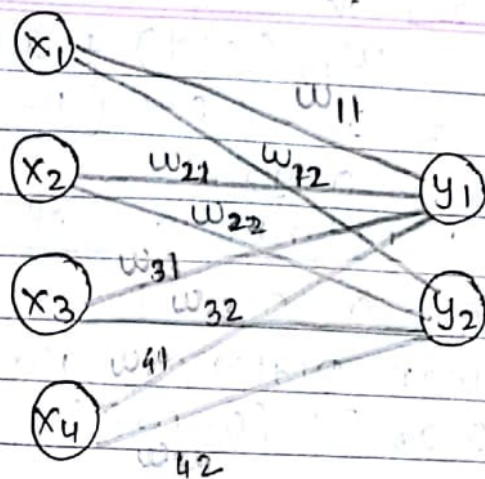
$$w_{ij}(\text{new}) = w_{ij}(\text{old}) + \alpha(x_i - w_{ij}(\text{old}))$$

7. Update learning rate  $\alpha$ . It is a decreasing function of the no of epochs.

8. Reduce radius of topological neighbourhood at specified times.

9. Test stopping condition. Typically this is a small value of the learning rate with which, the weight updates are insignificant.





initial weight matrix.

$w_{11}$	$w_{12}$
$w_{21}$	$w_{22}$
$w_{31}$	$w_{32}$
$w_{41}$	$w_{42}$

consider simple e.g in which there are only 4 i/p training patterns

0.2	0.8
0.6	0.4
0.5	0.7
0.9	0.3

$x_1$     $x_2$     $x_3$     $x_4$

1	1	0	0
0	0	0	1
1	0	0	0
0	0	1	1

Let the learning time rate  $t+1$  be given by

$$\alpha(t+1) = \frac{\alpha(t)}{2}$$

& suppose  $\alpha(t=0) = 0.6$ .

Let topological radius  $R=0$ .

• For vector 1100, i.e.  $x_1$

using Euclidean distance algorithm,

$$D(1) = (1 - 0.2)^2 + (1 - 0.6)^2 + (0 - 0.5)^2 + (0 - 0.9)^2$$

$$= 1.86$$

$$D(2) = (1 - 0.8)^2 + (1 - 0.4)^2 + (0 - 0.7)^2 + (0 - 0.3)^2$$

$$= 0.98$$

$\therefore J=2$  as  $D(1) > D(2)$

$$\begin{bmatrix} 0.08 & 0.92 \\ 0.6 & 0.76 \\ 0.5 & 0.28 \\ 0.9 & 0.12 \end{bmatrix}$$

$$\begin{aligned} \therefore w_{12}(\text{new}) &= w_{12}(\text{old}) + \alpha(x_1 - w_{12}(\text{old})) \\ &= 0.8 + 0.6(1 - 0.8) \\ &= 0.92 \end{aligned}$$

Do this for all neighbours of  $w_{12}$

• For  $x_2 = 0 \ 0 \ 0 \ 1$

using Euclidean distance algorithm,

$$\begin{aligned} D(1) &= (0 - 0.08)^2 + (0 - 0.6)^2 + (0 - 0.5)^2 + (1 - 0.9)^2 \\ &= 0.66 \end{aligned}$$

$$\begin{aligned} D(2) &= (0 - 0.92)^2 + (0 - 0.76)^2 + (0 - 0.28)^2 + (0 - 0.12)^2 \\ &= 2.2768 \end{aligned}$$

$$\therefore J = 1 \quad \text{as } D(1) < D(2)$$

$$\begin{aligned} \therefore w_{21}(\text{new}) &= w_{21}(\text{old}) + \alpha(x_2 - w_{21}(\text{old})) \\ &= 0.6 + 0.6(0 - 0.6) \\ &= 0.24 \end{aligned}$$

$w_{11}$	$w_{12}$	$0.08$	$0.92$
$w_{21}$	$w_{22}$	$0.24$	$0.76$
$w_{31}$	$w_{32}$	$0.20$	$0.28$
$w_{41}$	$w_{42}$	$0.96$	$0.12$

$$\begin{aligned} w_{31}(\text{new}) &= w_{31}(\text{old}) + \alpha(x_3 - w_{31}(\text{old})) \\ &= 0.5 + 0.6(0 - 0.5) \\ &= 0.20 \end{aligned}$$

$$\begin{aligned} w_{41}(\text{new}) &= w_{41}(\text{old}) + \alpha(x_4 - w_{41}(\text{old})) \\ &= 0.9 + 0.6(1 - 0.9) \\ &= 0.96 \end{aligned}$$

$$\begin{aligned} w_{11}(\text{new}) &= w_{11}(\text{old}) + \alpha(x_1 - w_{11}(\text{old})) \\ &= 0.2 + 0.6(0 - 0.2) \\ &= 0.08 \end{aligned}$$



• For vector 1000 ~~23~~

using Euclidean distance method.

$$D(1) = (1 - 0.08)^2 + (0 - 0.24)^2 + (0 - 0.20)^2 + (0 - 0.96)^2$$

$$= 1.8656$$

$$D(2) = (1 - 0.92)^2 + (0 - 0.76)^2 + (0 - 0.28)^2 + (0 - 0.12)^2$$

$$= 0.6768$$

$$\therefore D(2) < D(1), \quad J = 2$$

$$\therefore w_{12}(\text{new}) = w_{12}(\text{old}) + \alpha (x_i - w_{12}(\text{old}))$$

$$= 0.92 + 0.6(1 - 0.92)$$

$$= 0.968$$

$$w_{22}(\text{new}) = w_{22}(\text{old}) + \alpha (x_2 - w_{22}(\text{old}))$$

$$= 0.76 + 0.6(0 - 0.76)$$

$$= 0.304$$

$$w_{32}(\text{new}) = w_{23}(\text{old}) + \alpha (x_3 - w_{23}(\text{old}))$$

$$= 0.28 + 0.6(0 - 0.28)$$

$$= 0.112$$

$$w_{42}(\text{new}) = w_{24}(\text{old}) + \alpha (x_4 - w_{24}(\text{old}))$$

$$= 0.12 + 0.6(0 - 0.12)$$

$$= 0.048$$

$$\begin{bmatrix} w_{11} & w_{21} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \\ w_{41} & w_{42} \end{bmatrix} = \begin{bmatrix} 0.08 & 0.968 \\ 0.24 & 0.304 \\ 0.20 & 0.112 \\ 0.96 & 0.048 \end{bmatrix}$$

• For vector 0011 i.e.  $x_4$

$$D(1) = (-0.08)^2 + (-0.24)^2 + (1-0.20)^2 + (1-0.96)^2$$

$$= 0.7056$$

$$D(2) = (-0.968)^2 + (-0.304)^2 + (1-0.112)^2$$

$$+ (0-0.048)^2$$

$$= 2.724$$

$$\therefore D(1) < D(2) \quad \therefore J = 1$$

$$w_{11}(\text{new}) = w_{11}(\text{old}) + \alpha(x_1 - w_{11}(\text{old}))$$

$$= 0.08 + 0.6(0 - 0.08)$$

$$= 0.032$$

$$w_{21}(\text{new}) = w_{21}(\text{old}) + \alpha(x_2 - w_{21}(\text{old}))$$

$$= 0.24 + 0.6(0 - 0.24)$$

$$= 0.096$$

$$w_{31}(\text{new}) = w_{31}(\text{old}) + \alpha(x_3 - w_{31}(\text{old}))$$

$$= 0.20 + 0.6(1 - 0.20)$$

$$= 0.68$$

$$w_{41}(\text{new}) = w_{41}(\text{old}) + \alpha(x_4 - w_{41}(\text{old}))$$

$$= 0.96 + 0.6(1 - 0.96)$$

$$= 0.984$$

$w_{11}$	$w_{12}$	$0.032$	$0.968$
$w_{21}$	$w_{22}$	$0.096$	$0.304$
$w_{31}$	$w_{32}$	$0.68$	$0.112$
$w_{41}$	$w_{42}$	$0.984$	$0.048$



Step 2:

Now reduce learning rate

$$\alpha(1) = \frac{\alpha(0)}{2} = \frac{0.6}{2} = 0.3.$$

It can be shown that after 100 presentations of all the i/p vector, the final weight matrix is

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \\ w_{41} & w_{42} \end{bmatrix} = \begin{bmatrix} 6.7 \times 10^{-17} & 1 \\ 2 \times 10^{-16} & 0.49 \\ 0.51 & 2.3 \times 10^{-16} \\ 1 & 1 \times 10^{-16} \end{bmatrix}$$

This matrix seems to converge to .

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \\ w_{41} & w_{42} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0.5 \\ 0.5 & 0 \\ 1 & 0 \end{bmatrix}$$

cluster1

cluster2

Test n/w .

Suppose the i/p patten is 1100 . then.

$$D(1) = (0-1)^2 + (0-1)^2 + (0.5-0)^2 + (1-0)^2$$

$$= 3.25$$

$$D(2) = (1-1)^2 + (0.5-1)^2 + (0-0)^2 + (0-0)^2$$

$$= 0.25.$$

$\therefore$  neuron 2 is winner.

$x_1$	$x_2$	$x_3$	$x_4$	cluster
1	1	0	0	2
0	0	0	1	1
1	0	0	0	2
0	0	1	1	1