

COMPETITIVE LEARNING

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Winner - Takes - All Network

During learning process, there exist a competition b/w the clusters to accommodate an object in its partition (cluster). finally only one cluster (the output neuron) wins the competition & object is placed in the corresponding cluster. there can be only one winning neuron that is active at a time. The neural network of this type is also known as competitive net.

prototypes of cluster: $v = \{v_1, v_2, \dots, v_n\}$ where v is set of prototypes for n clusters.

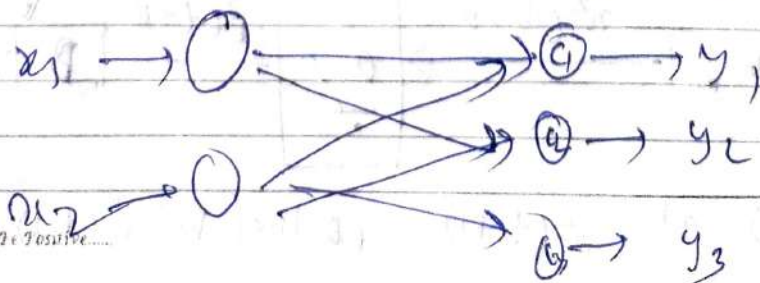
Winner-takes-all-network: Two layers (input & output).

Weights: Initially random weights. There is no bias values.

Activation function: Step function

$$f_i = \begin{cases} 1 & \text{if } i = \arg \min_j a_j \\ 0 & \text{otherwise} \end{cases}$$

If the distance b/w the object x_j & the cluster prototype v_i is minimum, then the neuron wins & will be active by setting a_i to 1.



Exy $x = \begin{bmatrix} .5 \\ .2 \end{bmatrix}$, $C_1 = \begin{bmatrix} .7 \\ .4 \end{bmatrix}$, $C_2 = \begin{bmatrix} .6 \\ .3 \end{bmatrix}$, $C_3 = \begin{bmatrix} .9 \\ .1 \end{bmatrix}$

$$d_1(x, C_1) = \sqrt{(.5 - .7)^2 + (.2 - .4)^2} = \sqrt{.08} = .2828$$

$$d_2(x, C_2) = .1414$$

$$d_3(x, C_3) = .4123$$

Here d_2 is minimum distance b/w object & cluster C_2 , therefore neuron corresponding to cluster C_2 in the output layer is winner neuron.

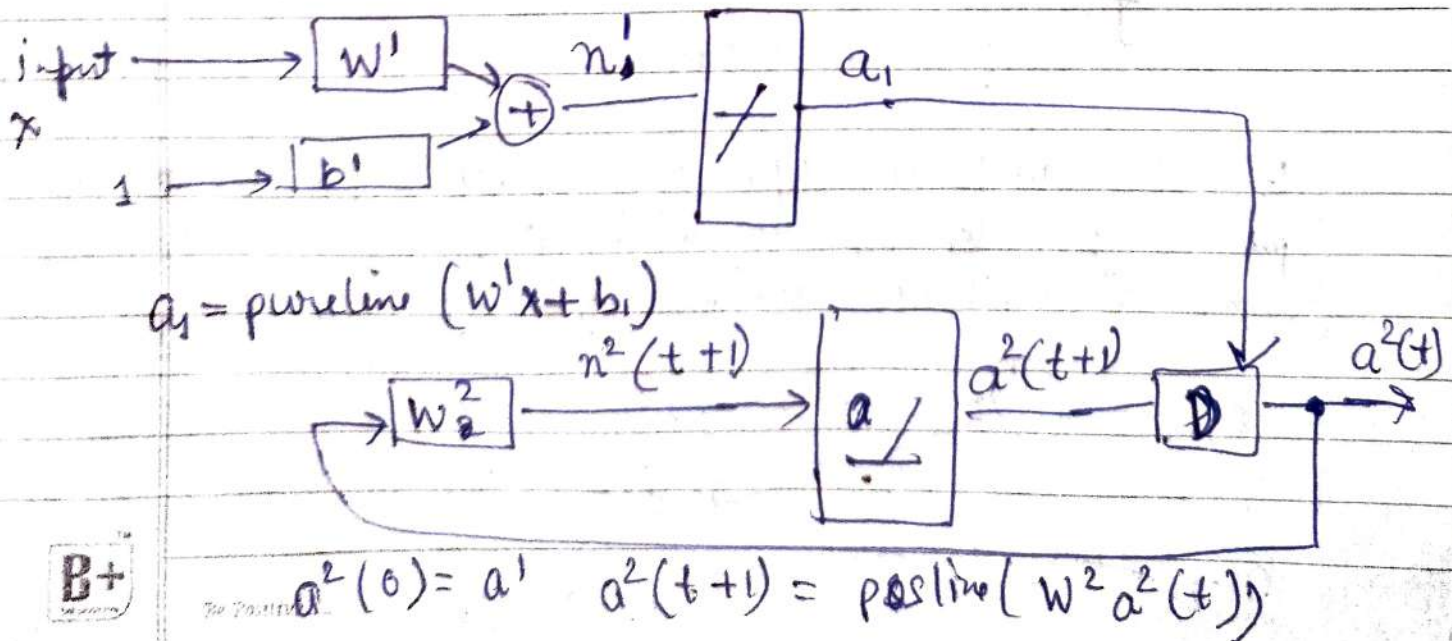
Hamming Network →

Feedforward
and
Layer

Hamming network consist of two layer.

Layer ① performs a correlation b/w the input vector & the ~~output~~ prototype vectors.

Layer ② performs a competition to determine which of the prototype vectors is closest to the input vector.



Competitive layer \rightarrow Second layer is competitive layer.

transfer functions for recurrent competitive layer

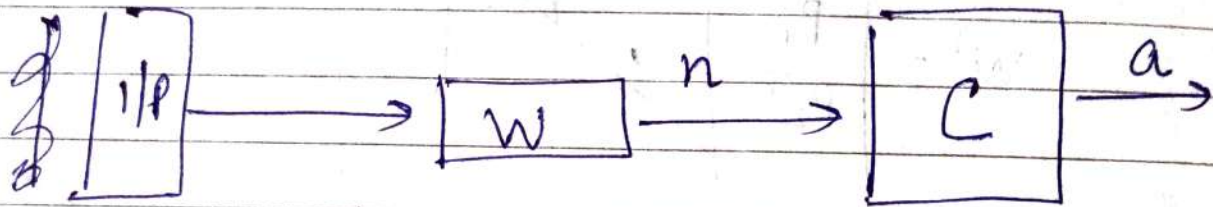
$$a = \text{compact}(n), \text{index}$$

It works by finding the i^{th} of the neuron with the largest net input, & setting its to 1 & all others output are set to 0.

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$$a_i = \begin{cases} 1, & \text{if } i = i^* \\ 0, & \text{if } i \neq i^* \end{cases}$$

where $n_{i^*} \geq n_i \forall i$,
~~and~~ $i^* \leq i \forall n_i = n_{i^*}$

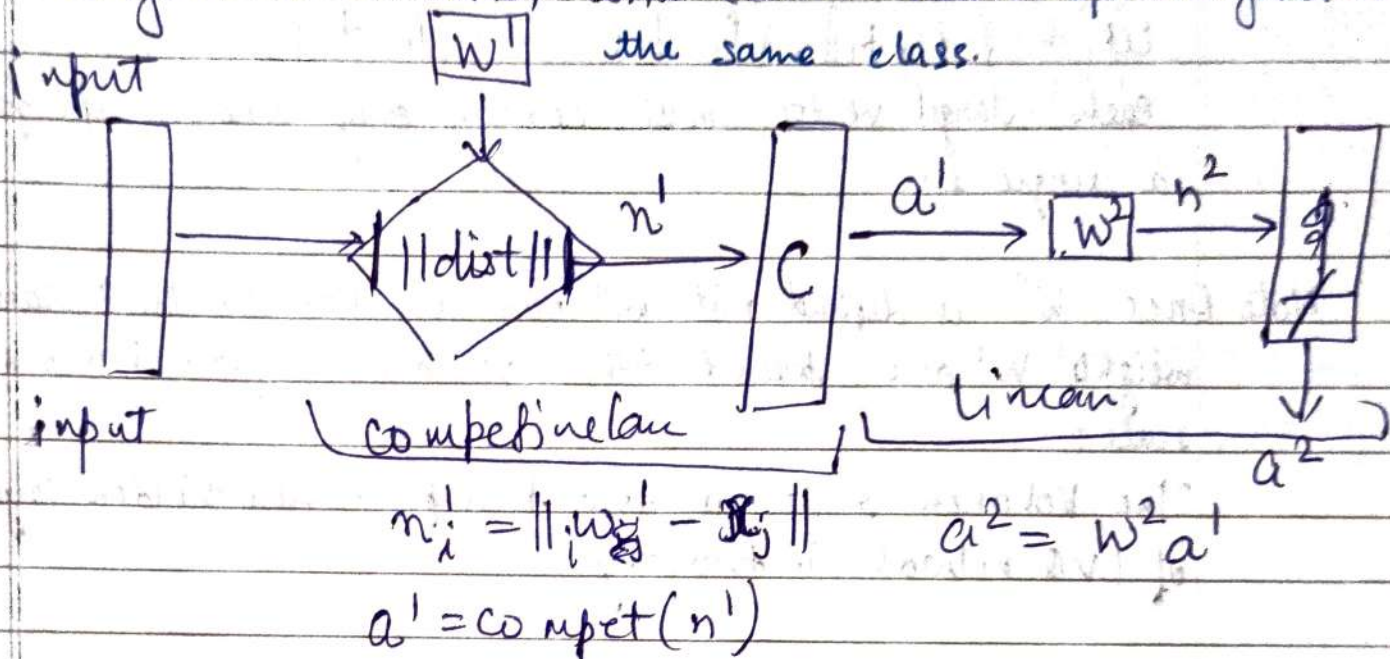


$$a = \text{comp}(Wp)^T$$

Learning Vector Quantization →

It is both supervised & unsupervised learning to form classifications.

In LVQ network, each neuron in the first layer is assigned to a class, with several neurons often assigned to the same class.



The net input of the first layer of the LVQ

$$n_i^1 = - \|w_i^1 - x_j\|$$

is the output of the first layer of LVQ.

$$a^1 = \text{compet}(n^1)$$

Therefore the neuron whose weight vector is closest to the input vector will output a 1, other 0.

The net input of the first layer of the LVD will be

$$n_i^1 = - \| w_{ij} - x_j \|$$

LVD Learning -

Let $\{p_1, t_1\}, \{p_2, t_2\} \dots \{p_q, t_q\}$

each target vector must contain only zero, except for a single 1.

Note Once w^2 is defined, it will never be altered. The hidden weights w^1 are trained with a variation of the Kohonen rule.

The Kohonen rule is used to improve the hidden layer of LVD network in two ways:

① p is classified correctly, then we move the weights w_{ij}^1 of the winning hidden neuron toward p .

$$w_{ij}(q) = w_{ij}(q-1) + \alpha_k (p(q) - w_{ij}(q-1))$$

if $a_k^2 = t_k = 1$

② p is classified incorrectly, so we move the weights away from p

$$w_{ij}(q) = w_{ij}(q-1) - \alpha_k (p(q) - w_{ij}(q-1))$$

if $a_k^1 = 1 \neq t_k = 0$

Ex → class 1: $\{P_1 = \begin{bmatrix} -1 \\ -1 \end{bmatrix}, P_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}\}$, class 2: $\{P_3 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, P_4 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}\}$

Solution - assignment target vectors to each input

$$\left\{ P_1 = \begin{bmatrix} -1 \\ -1 \end{bmatrix}, t_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\}, \left\{ P_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, t_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\},$$

$$\left\{ P_3 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, t_3 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}, \left\{ P_4 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, t_4 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

The output layer weight matrix will be

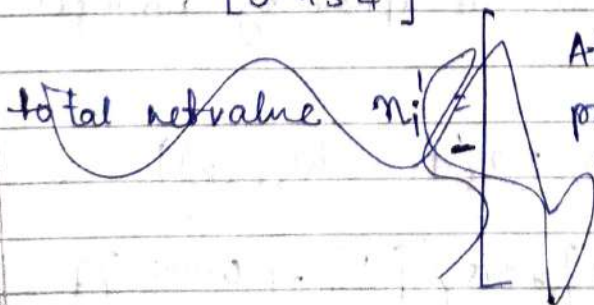
$$W^2 = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 1 \end{bmatrix}$$

W^2 connects hidden neuron 1 & 2 to output neuron 1.

The column vector W^1 are initially set to random values.

$${}_1W^1 = \begin{bmatrix} -0.543 \\ 0.840 \end{bmatrix}, {}_2W^1 = \begin{bmatrix} -0.969 \\ -0.249 \end{bmatrix}, {}_3W^1 = \begin{bmatrix} 0.997 \\ 0.894 \end{bmatrix}$$

$${}_4W^1 = \begin{bmatrix} 0.456 \\ 0.954 \end{bmatrix}$$



At each iteration of the training process, we present an input vector, find its response & then adjust the weight.

In this case we will begin by presenting p_2

$$a^1 = \text{compnet}(n^1) = \text{compnet} \begin{pmatrix} -||w_{11} - p_{21}|| \\ -||w_{22} - p_{21}|| \\ -||w_{33} - p_{21}|| \\ -||w_{44} - p_{21}|| \end{pmatrix}$$

$$= \text{compnet} \begin{pmatrix} -2.40 \\ -2.11 \\ -1.09 \\ -2.03 \end{pmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

Third hidden neuron has the closest weight vector to p_2

$$a_2 = W^{2T} \cdot a^1$$

$$= \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

This output indicates that p_2 is a member of class 2. This is correct so w_{33} is updated by moving it towards p_2

$$\begin{aligned} w_{33}^1(1) &= w_{33}(0) + \eta(p_2 - w_{33}(0)) \\ &= \begin{bmatrix} 0.997 \\ 0.094 \end{bmatrix} + 0.5 \left(\begin{bmatrix} 1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0.997 \\ 0.094 \end{bmatrix} \right) \\ &= \begin{bmatrix} 0.998 \\ -0.453 \end{bmatrix} \end{aligned}$$

Self Organising Map →

Kohonen rule.

$$\begin{aligned}
 {}_i w(a) &= {}_i w(a-1) + \eta (P(a) - {}_i w(a-1)) \\
 &= (1 - \alpha) {}_i w(a-1) + \alpha P(a)
 \end{aligned}$$

and

$$\begin{aligned}
 &\cancel{{}_i w(a) = {}_i w(a-1)} \quad \text{if } i \\
 &{}_i w(a) = {}_i w(a-1) \quad i \neq i^*
 \end{aligned}$$

the weight matrix that

$$P_1 = \begin{bmatrix} -0.1961 \\ 0.9806 \end{bmatrix}, P_2 = \begin{bmatrix} 0.1961 \\ 0.9806 \end{bmatrix}, P_3 = \begin{bmatrix} 0.9806 \\ 0.1961 \end{bmatrix}, P_4 = \begin{bmatrix} 0.9806 \\ -0.1961 \end{bmatrix}$$

$$P_5 = \begin{bmatrix} -0.5812 \\ -0.8137 \end{bmatrix}, P_6 = \begin{bmatrix} -0.8137 \\ -0.5812 \end{bmatrix}$$

$${}_1 w = \begin{bmatrix} w_{11} \\ w_{12} \end{bmatrix} = \begin{bmatrix} 0.7071 \\ -0.7071 \end{bmatrix}, {}_2 w = \begin{bmatrix} 0.7071 \\ 0.7071 \end{bmatrix}, {}_3 w = \begin{bmatrix} -1.0 \\ 0.0 \end{bmatrix}$$

$$w = \begin{bmatrix} {}_1 w \\ {}_2 w \\ {}_3 w \end{bmatrix} = \begin{bmatrix} 0.7071 & 0.7071 & -1.0 \\ -0.7071 & 0.7071 & 0.0 \end{bmatrix}$$

for P_2

$$a_1 = \text{compet} = (w^T \cdot P_2) = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

second neuron's weight vector is w_2

We apply Kohonen learning rule to winning neuron with $\eta = 0.5$

$${}_2w(1) = {}_2w(0) + \eta (P_2 - {}_2w(0)) = \begin{bmatrix} 0.4516 \\ 0.8438 \end{bmatrix}$$

${}_2w$ is closer to P_2

Self Organizing feature Map (SOFM) network first determines the winning neuron i^* using the same procedure as the competitive layer.

Next the weight vectors for all neuron within a certain neighborhood of the winning neuron are updated using the Kohonen rule:

$$i w(a) = i w(a-1) + \eta (P(a) - i w(a-1))$$

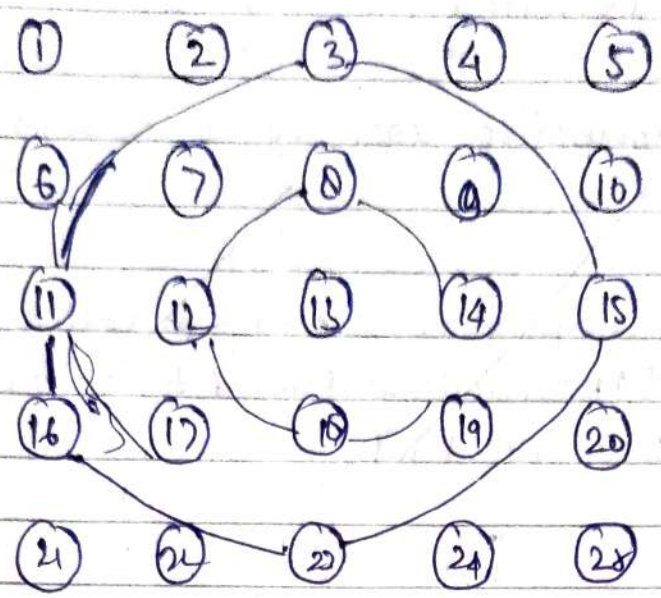
$$= (1 - \eta) i w(a-1) + \eta P(a)$$

$$i \in N_{i^*}(d),$$

where the neighborhood $N_{i^*}(d)$ contains the indices for all of the neurons that lie within a radius d of winning neuron i^* :

$$N_i(d) = \{j, d_{ij} \leq d\}$$



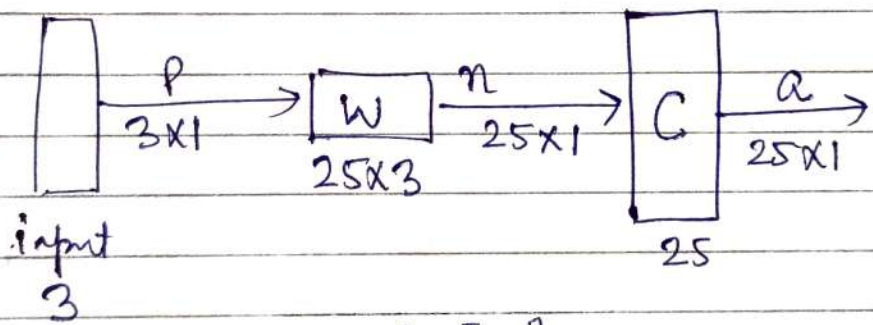


$$N_{13}(1) = \{0, 12, 13, 14, 20\}$$

$$N_{13}(2) = \{3, 7, 8, 9, 11, 12, 13, 14, 15, 17, 18, 19, 23\}$$

$N_{13}(1)$

Kohonen has suggested rectangular and hexagonal neighborhoods for different implementations.



featuremap

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

$$a = \text{compnet}(W^T P)$$