⇒ update the weight
→ To decrease the error, subtract this from actual weight

η = learning rate (eta)
→ How far to go?

⇒ Unsupervised Learning:

⇒ (2) Competitive Neural Network:
→ form of unsupervised learning in ANN, nodes compete for the right to respond to the subset of input data
→ increasing the specialization of each node in the n/w.

⇒ (1) Hebbian Learning
→ Proposed by Donald Hebb

$A \xrightarrow{w_{AB}} B$

1. Neuron A is near B, fires or excites B, metabolic changes happen both in A and B, (A efficiency in B increases)
2. If A and B are simultaneously excited (synaptic strength increases)
3. If A and B are activated unsynchronised, (strength of synapse decreased)

Pre A | Post A |
---|---|---
1 | 1 | → +ve
0 | 1 | } → -ve
1 | 0 |

Features

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→ 1. Time dependant
2. Local $A \longrightarrow B$
3. strongly interactive (True between Post/Pre)
4. Correlational (+ve, -ve, uncorelated)

(Same Time → ↑ w_{kj}) (unsync A B → ↓ w_{kj}) (uncorelated → No excitation)

~~UNSUPERVISED LEARNING~~

⇒ ~~Self-organizing Map~~ (SOM)

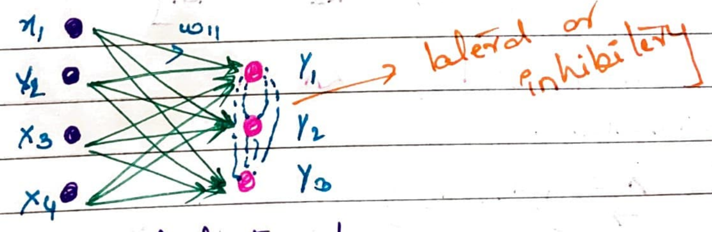
⇒ classification of Synaptic
1. Hebbian → w_{kj} ↑ with +ve correlation
2. Anti-Hebbian → w_{kj} ↑ with -ve "
3. Non-Hebbian →

⇒ Mathematical model

$$\Delta w_{kj} = F(x_j, y_k)$$

Activity Product Rule $= \eta x_i y_k$
↳ learning parameter

⇒ (2) competitive



→ All i/p connected to o/p
→ one i/p is trying to inhibit the o/p neuron
→ only one o/p will become the competitor
→ and by not sharing the weights
→ if o/p → winner
Higher chances for the same neuron to win.

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→ Basic Elements

1. All input neurons are structurally similar, initial weights

2. A limit is imposed on the strength of each neuron.

3. neuron compete for the right to respond

→ Network Architecture

$\Rightarrow V_k = \sum x_j w_{kj}$

→ o/p of neuron is set to one, others to zero

$$y_k = \begin{cases} 1, & V_k > V_j, \forall j, j \neq k \quad (\text{o/}\ldots \\ 0, & \end{cases}$$

→ Synaptic weights of not winning neuron is not updated.

$$\Delta w_{kj} = \begin{cases} \eta(x_j - w_{kj}) & \rightarrow K \text{ wins competition} \\ 0 & \rightarrow K \text{ loses competition} \end{cases}$$

approach ⇑

$\vec{X} = \{x_1, x_2 \ldots x_n\}$

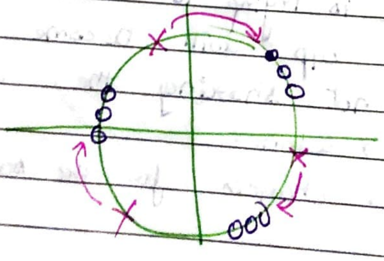
$W_k = \{w_{k1}, w_{k2} \ldots w_{kn}\}$ →

$\sum w_{kj} = 1$, $\sum X = 1$

two dimensional

→ $X = \{x_1, x_2\}$

$\vec{w}_k = \{w_{k1}, w_{k2}\}$; $\sum w_{kj} = 1$



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