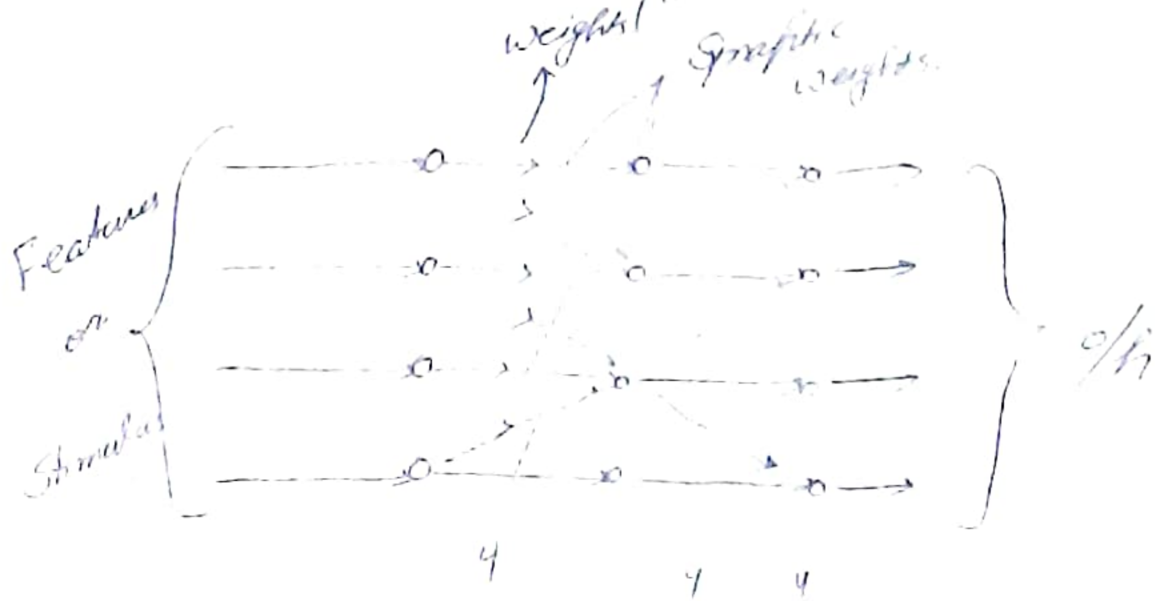
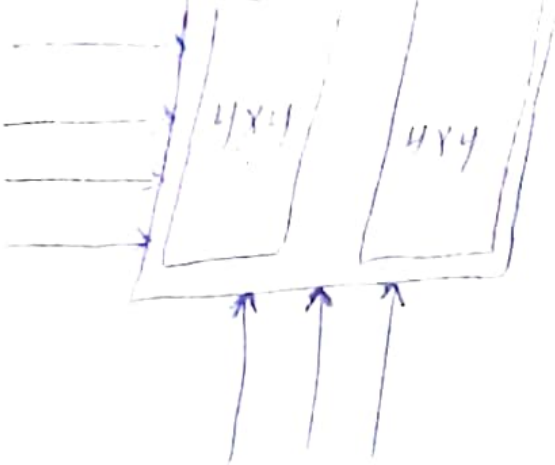
Neural N/w → It is a massively parallel distributed processor made up of simple processing unit which has a natural propensity for storing experimental knowledge & making it available to use. It resemble to brain in two way. 1. knowledge is acquire by the N/w from its environment for learning Process.

2. internural connection strain is known as ~~connecting~~ senaptic weight are used to store

→ neuron (represented by 'o')



[1x4] [4x4]



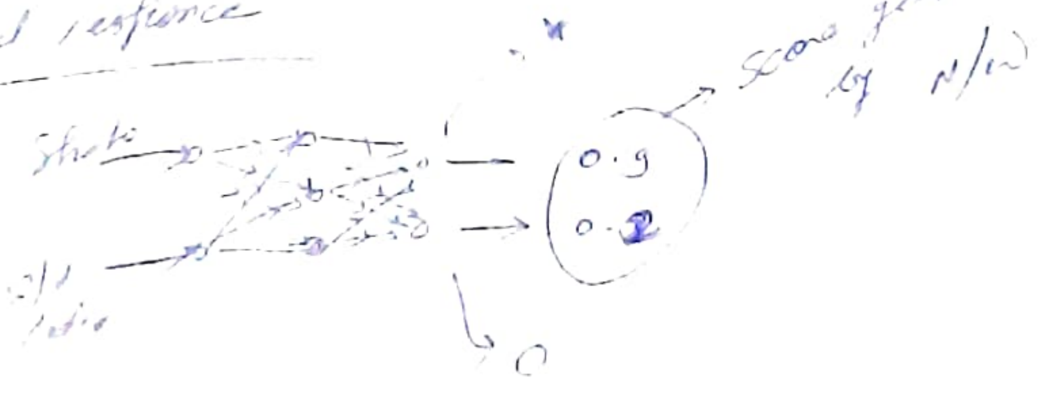
* Benefits of N/W -

1. Non linearity —

2. Input-output mapping.

3. Adaptivity

4. Evidential response



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5. Contextual information :- related to features.

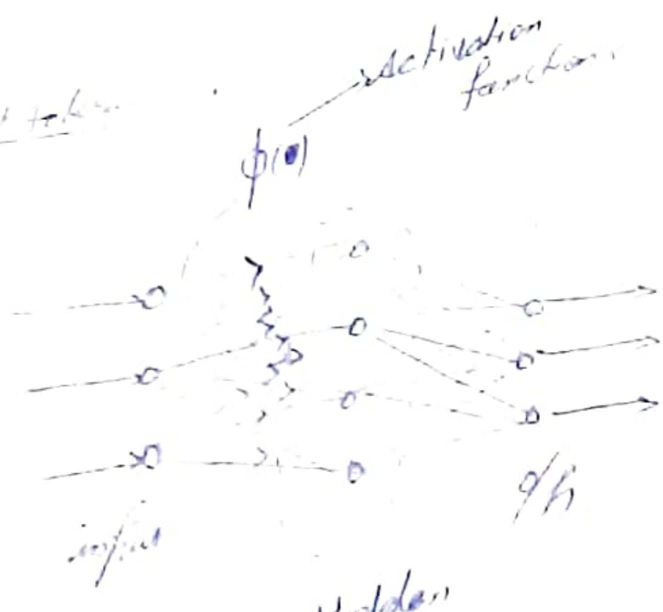
6. Fault tolerance :-

7. VLSI implementability

8. Uniformity of analysis & design.

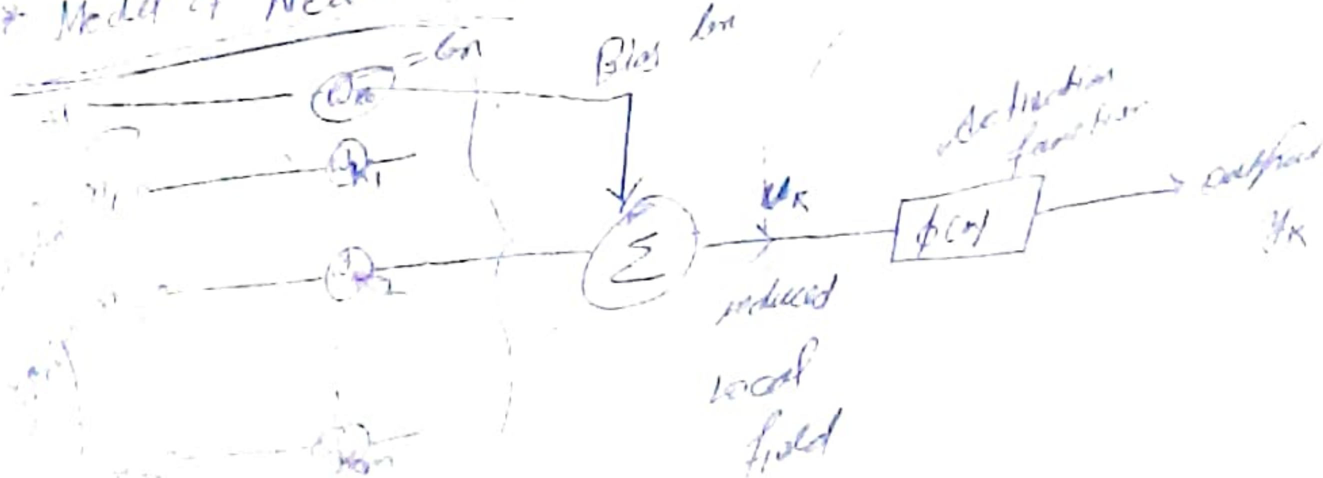
9. Neuro biological analogy.

6. fault tol...



for kth neuron model

* Model of Neuron :→



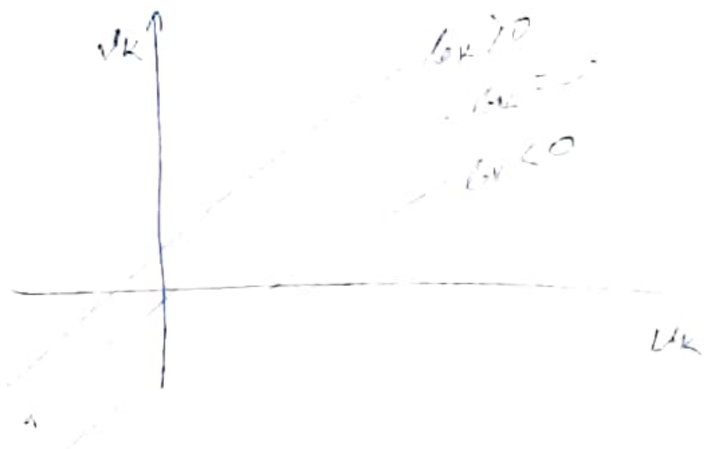
$$u_k = \sum_{j=1}^{m} w_{kj} x_j$$

induced local field
or linear

$$v_k = u_k + b_k$$

$$y_k = \phi(u_k + b_k)$$

$$= \phi(v_k)$$



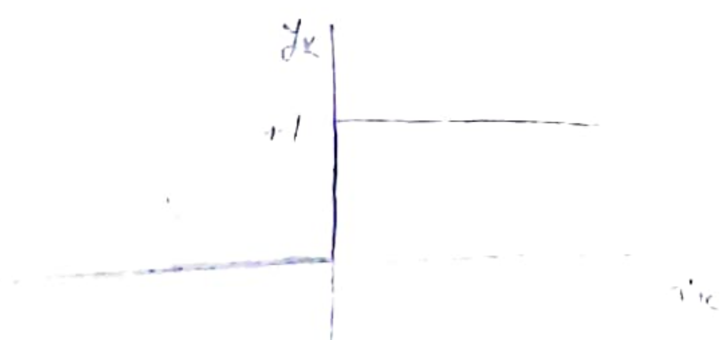
Q2

$$u_k = \sum_{j=0}^{m} w_{kj} x_j$$

$$y_k = \phi(v_k)$$

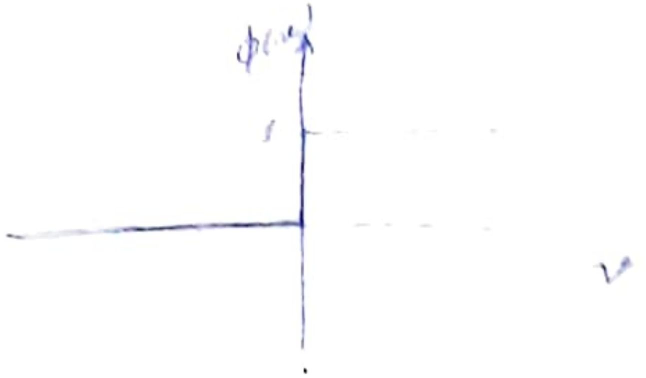
$x_0 = +1$

$w_{k0} = b_k$



$\phi(v) =$

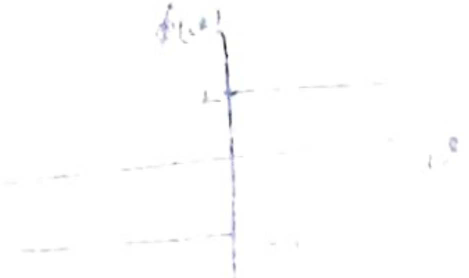
$\{ 0 \quad \text{if } v < 0$



$$y = \begin{cases} 1 & \text{if } v \geq 0 \\ 0 & \text{if } v < 0 \end{cases}$$

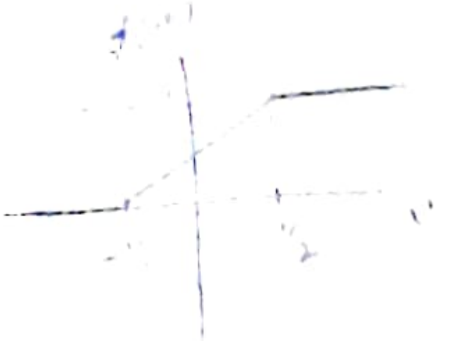
McCulloch Pitts model

• ... threshold.



• Piecewise linear activation function

$\phi(v) = \{ 1 \quad v \geq 1/2$



• Sigmoid activation function :→

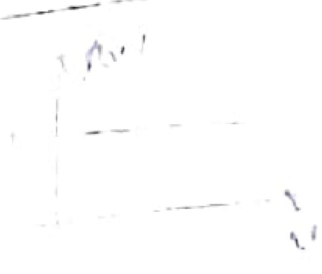
$$\phi(v) = \frac{1}{1 + \exp(-av)}$$

* Sigmoid

$$\varphi(v) = \frac{1}{1+\exp(-av)}$$

a = the slope parameter. it is defined as a strictly increasing function that exhibit the best to balance b/w linear & Non linear behavior. 'a' defines the slope parameter of sigmoid func^n. as slope parameter ↑ to ∞ the sigmoid func^n become threshold func^n. The sigmoid function is differentiable but threshold func^n is not. The sigmoid func^n ranges from 0 to +1. At some time desirable to have activation function ranges from -1 to +1 which antisymmetric form of activation func^n

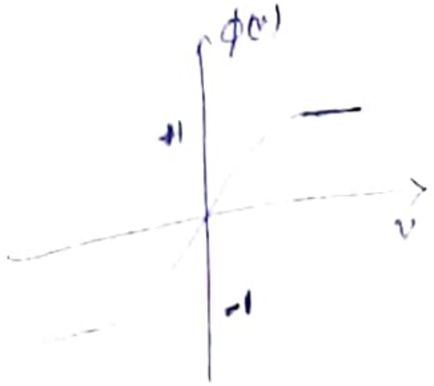
* Signum function



$$\varphi(v) = \begin{cases} 1 & \text{if } v > 0 \\ 0 & \text{if } v = 0 \\ -1 & \text{if } v < 0 \end{cases}$$

Tan hyperbolic activation function :-

$$\phi = \tanh(av)$$



$$= \frac{e^{av} - e^{-av}}{e^{av} + e^{-av}}$$

* Stochastic Model of Neuron :-

$$P(v) = \frac{1}{1 + exp(-v/T)}$$

where T is the Pseudo ___ that is used to control the Noise level and ___

. we should think T as a parameter that control thermal fluctuation representing the effect of synaptic Noise. Not that when $T \to 0$. that stochastic neuron reduces to noise less i.e deterministic form. namely

* Directed Graph

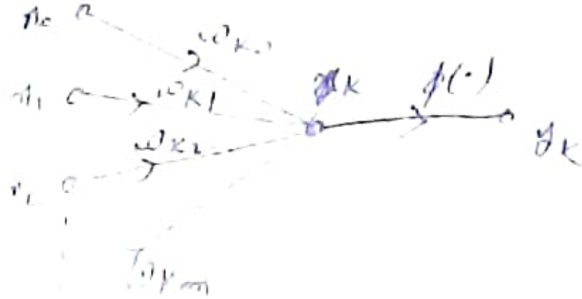
1) (i) Synaptic links : $x_j \xrightarrow{w_{kj}} y_k = w_{kj} x_j$

(ii) Activation link :- $x_j \xrightarrow{\varphi(x_j)} y_j = \varphi(x_j)$

2. A node signal equals the algebraic sum of all signal internode via incoming links.

3. The signal at node is transmitted to each outgoing link originating from that node with the transmission being entirely independent of the transfer function of outgoing link.

Synaptic divergence or fan out.

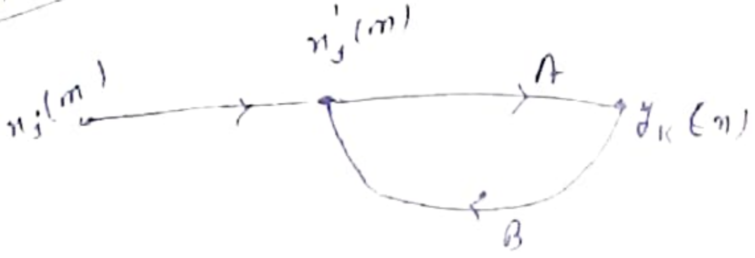


1) functional description

2) complete description.

3) Architectural graph.

Feedback



$$y_k(n) = A\, x_j'(n)$$

$$x_j'(n) = x_j(n) + B\, y_k(n)$$

* i) Single-Layer feed forward N/W
ii) Multi-Layer feed forward N/W
iii) Re-current N/W

i)

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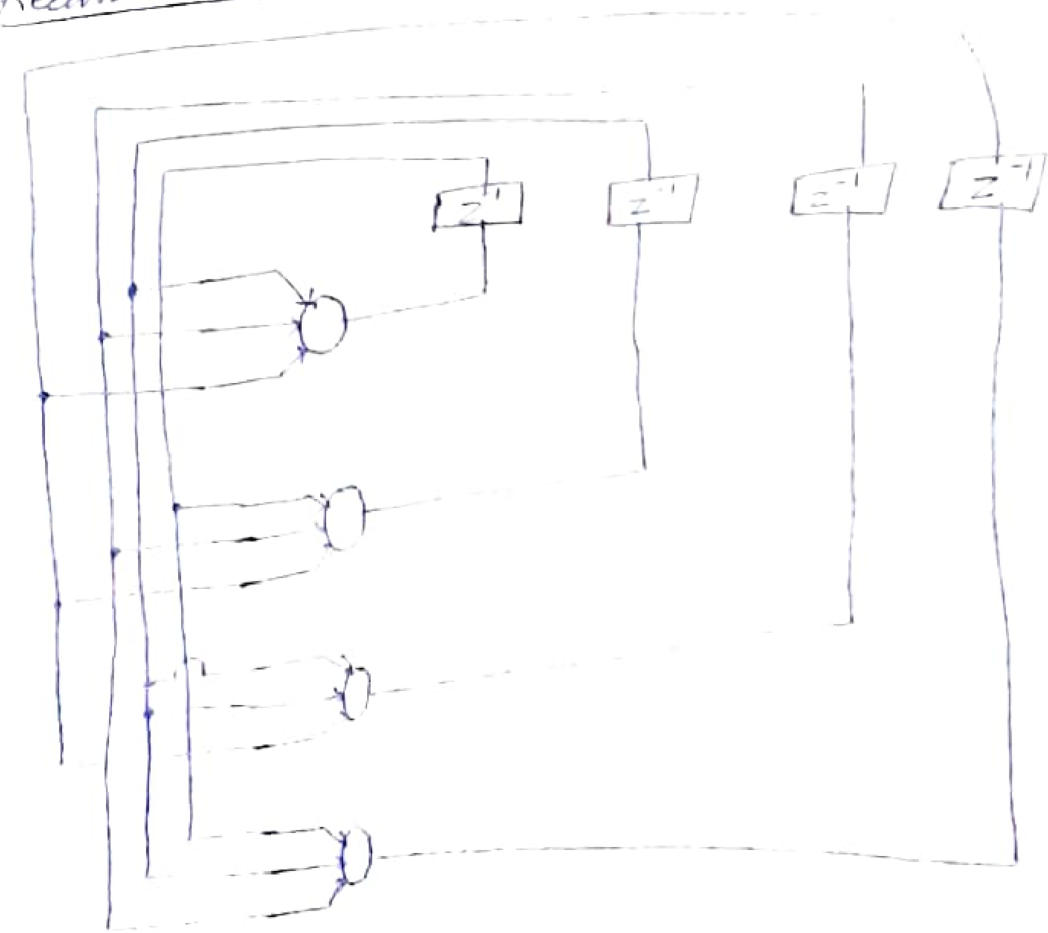
* MLP

* Recurrent Network :-



Recurrent N/w discriminate itself from feed forward in that it atleast one feedback loop

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* Knowledge Representation.

Rule 1: ~~Theorem~~

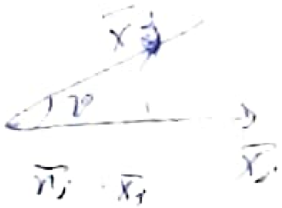
Similar ~~input~~ inputs from similar classes should usually ~~represent~~ produce similar representation.

$$x_i = [x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}]$$

$$d(x_i, x_j) = \|x_i - x_j\|$$

$$= \left[\sum_{k=0}^{m} (x_{ik} - x_{jk})^2\right]^{1/2}$$

* Dot product or inner product based measure.



$$\cos\theta = \frac{\bar{x}_i \cdot \bar{x}_j}{\|\vec{x}_i\| \, \|\vec{x}_j\|} = \frac{\bar{x}_i^T x_j}{(\quad)}$$

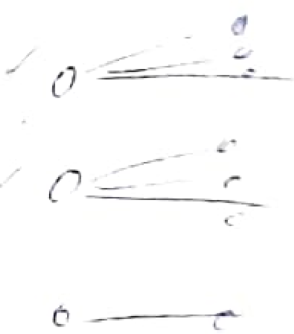
- $\|x_i\| = \|x_j\| = 1$

- $d^2(x_i, x_j) = (x_i - x_j)^T (x_i - x_j)$

$$= 2 - 2x_i^T x_j$$

Rule 2: items to be categorized as separate classes should be given widely different representation in the N/W. 2nd rule is exact opposite of rule 1.

Rule 3: if a particular feature is important, then there should be large no. of neurons involved in the representation of that item in the N/W.



Rule 4: Prior information & invariances should be build into the design of a neural N/W, thereby simplifying the N/W design by not having to ~~learn~~ learn them.

* How to build invariance in Neural N/w

1. invariance by Structure
2. invariances by training
3. " features space

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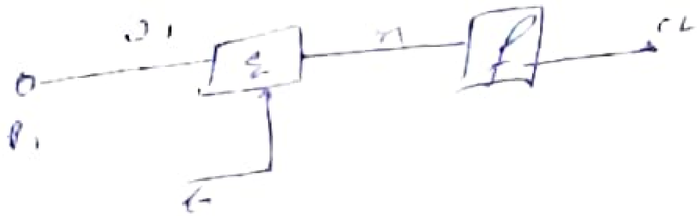
Q1: Input to a single i/p neuron is 2.0. its weight is 2.3 & bias is 3. what is net i/p to the transfer function. Also find out the o/p of the neuron if it has the following transfer function

i) Hard limiting
ii) linear
iii) log sigmoid fun

Soln:

$$\text{net i/p} = 2 \times 2.3 + 3$$
$$= 7.6$$

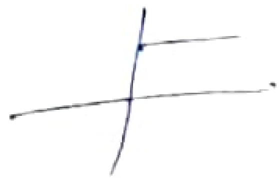


$x_1 = 2.0$

$w_1 = 2.3$

$b = 3$

$$n = w_1 x_1 + b$$
$$= 7.6.$$

i)  $a \to 1.$

ii)  $a \to 7.6$

iii) $a = \dfrac{1}{1+e^{-7.6}}$

Q3. Given two input neuron with the following parameters $p = [-5 \;\; 6]^T$, $w = [3, 2]$, $b = 1.2$

calculate the output of it for the following transfer function.

i) Symmetric hard limit func^n

ii) saturating linear func^n

iii) tan - hyperbolic

Q)

$n = pw + b$

2×1

$= [3 \quad 2] \begin{bmatrix} -5 \\ 6 \end{bmatrix} + 1.2$

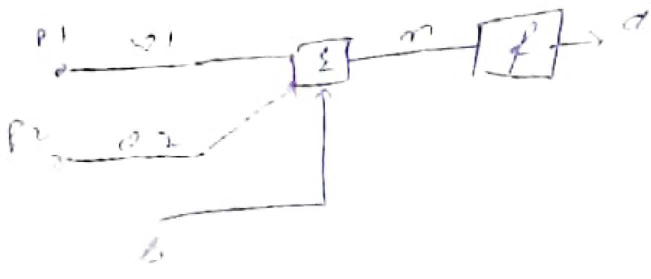
$n = -3 + 1.2 = -1.8$

$a = f(n)$

i) -1

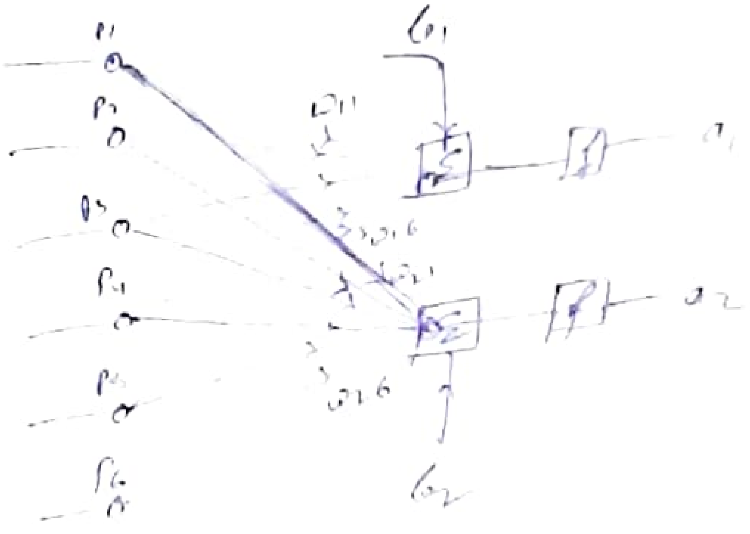
ii) 0

iii) tanh $\dfrac{e^{+n} - e^{-n}}{e^{+n} + e^{-n}}$



Q3: A single layer neural N/w have 6 i/p & 2 o/p. The o/p are limited to 0 to 1 with which is continuous in range. 1) How many neurons are required for the N/w architecture.
2) What are dimensions of wt. matrix.
3) What kind of T.F would be used.

Sol:



i) 8

2 × 2

Sigmoid

Ans i) 8

ii) 2 × 6

iii) Sigmoid

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* Learning

1. Error correction learning:

2. memory based learning:

3. Hebbian learning.

4. competitive learning.

5. Boltzman learning.

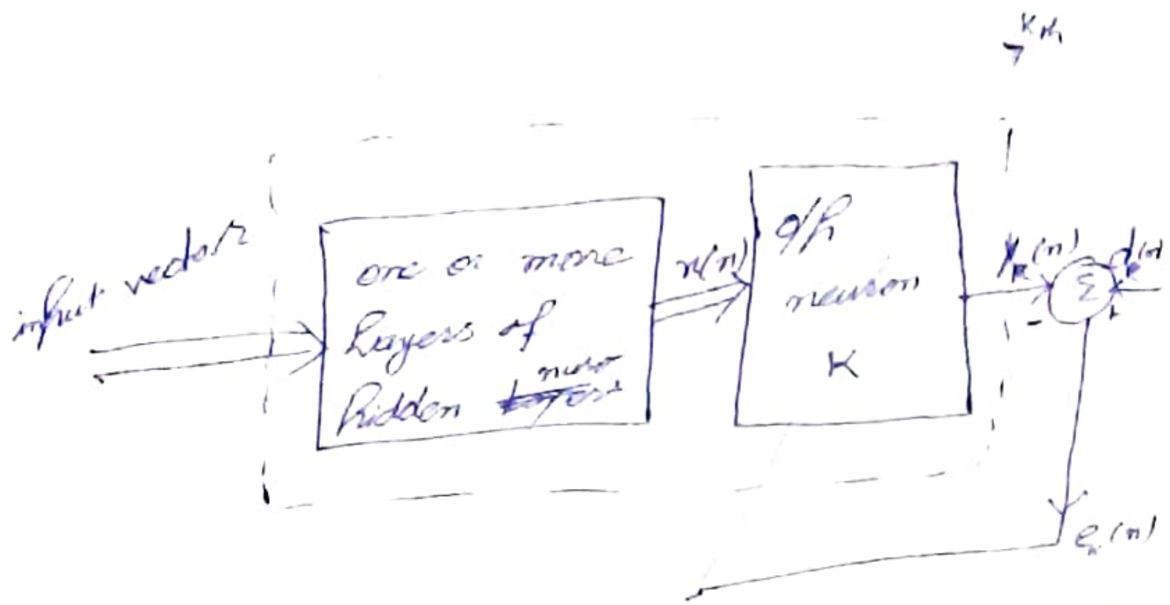
* Learning is a process by which the free parame of a neural N/w are adapted through a process of emulation by the environment by which the N/w is . The type of learning is determined by the manner in which parameter changes takes place. The definitio of learning process implies the following sequen of event.

1. The neural N/w

2. undergoes the changes in its free parameter as a result of this stimulation.

3. The neural N/w respond in a new way to the environment ~~th~~ because of changes that occur in its internal structure.

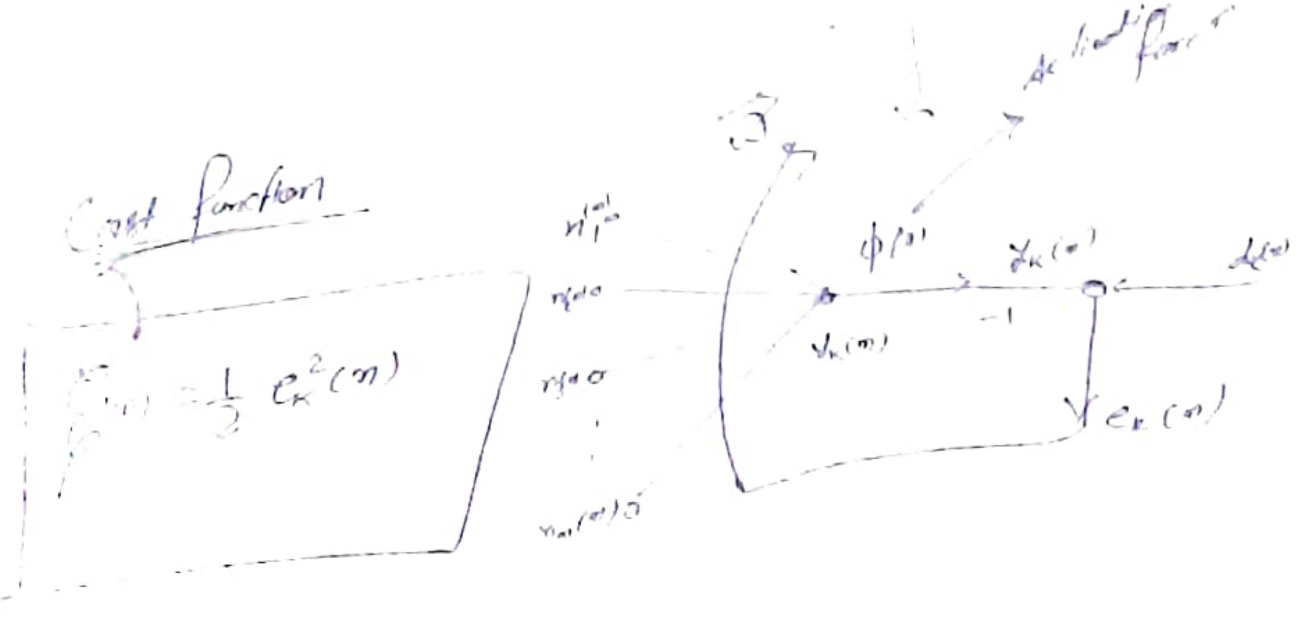
1. Error - Correction learning :-



MLP - feed forward neural n/w highlighting the only neuron in the o/p n/w.

$$e_k(n) = d_k(n) - y_k(n)$$

Cost function



• Delta rule or widrow - Hoff rule

$$\Delta \omega_{kj}(n) = \eta\, e_k(n)\, x_j(n)$$

$$\omega_{kj}(n+1) = \omega_{kj}(n) + \Delta \omega_{kj}(n)$$

$$= \omega_{kj}(n) + \eta\, e_k(n)\, x_j(n)$$

(2) Memory based Learning :- $\Rightarrow$

$$\{(x_i, d_i)\}_{i=1}^{N}$$

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3. Hebbian Learning :-

$$x_j \xrightarrow{w_{jk}} x_k$$

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

$$= \eta \, x_j(n) \, x_k(n)$$

↓

<u>learning rate</u>

Hebb's hypothesis can be defined by expanding restating it as a two part rule

1.) if two neuron on the either side of synaptic connection

then the strength of that synaptic is ~~[illegible]~~ increase.

2.) if two neuron on either side of a ~~[illegible]~~ synaptic are activated asynchronously then that synaptic ... weaken or ... such can be

... is called

can be defined as

& non-hebbian

... synaptic increases strength with truly ... presynaptic & postsynaptic signals.

and [illegible] for these signals
[illegible] correlated [illegible] only correlated.
[illegible] only correlated
[illegible] signals is an [illegible]
[illegible]

[illegible] the other hand doesn't
[illegible] mechanism of either kind.

[illegible]

[illegible] Hebb's hypothesis

[illegible]

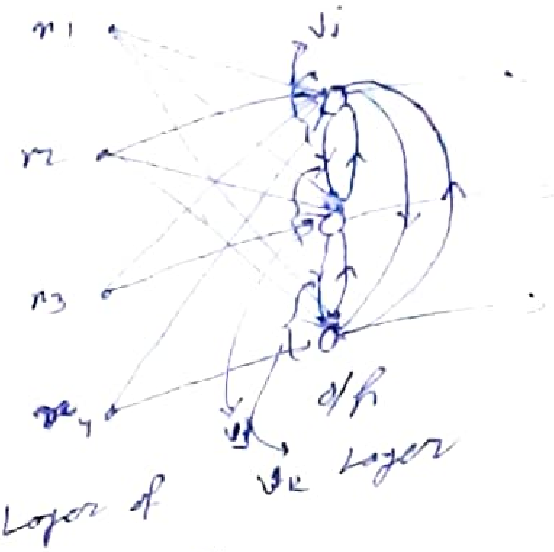
I_k

[illegible]

[illegible] → and [illegible] figure

[illegible]

4. Competitive learning :-
→ competition among neurons.



$$y_k = \begin{cases} 1 & \text{if } v_k > v_j \text{ for all } j. \\ 0 & \end{cases}$$

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

$$v_j = \sum_{m=1}^{4} w_{jm} \, x_m$$

$$v_k = \sum_{m=1}^{4} w_{km} \, x_k$$

$$\Delta w_{kj} = \begin{cases} \eta (x_j - w_{kj}) & \text{if neuron } k \text{ wins the competition.} \\ 0 & \end{cases}$$

Boltzmann learning :-