Ju- 24 05/03/21 Introduction to Neural Net works Introdu. to NN I standard activation functions NN architecture -> Learning paradigms. Model of a biological newron 7 dendrites Soma an arti ficial newson wt5 Mynaphes Borne 14, 12...an are n inputs to artificial neuron W1, W2. - wo are weights attached to input ! links

$$I = w_1 \approx 1 + w_2 \approx 1 + \cdots + w_n \approx n$$

$$= \begin{cases} w_2 \approx 1 \\ 2 = 1 \end{cases}$$

$$= \begin{cases} v_1 \approx 1 \\ v_2 \approx 1 \end{cases}$$

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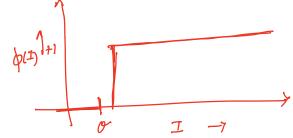
$$= \begin{cases} v_1 \approx 1 \\ v_3 \approx 1 \end{cases}$$

$$= \begin{cases} v_1 \approx 1 \end{cases}$$

$$= \begin{cases} v_1$$

To generate the final OIP Y, the sum is passed to a non-linear filter à which releases the O/P.

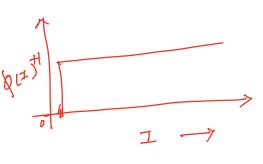
standard activation functione



2. Heaviside function:

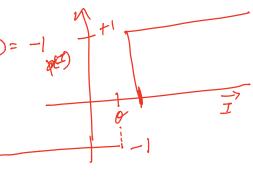
9/ I > 0, then
$$\varphi(I) = 1$$

else $\varphi(I) = 0$ $\varphi(I)^{\dagger}$



I 7 0 Fresh 9

else (if
$$I \leq 0$$
) then $b(I) = -1$



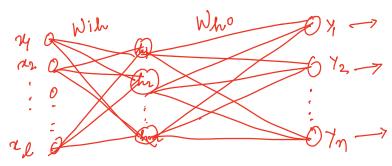
yigh sigmoidal function:

$$\phi(I) = \frac{1}{1 + e^{-\lambda I}}$$

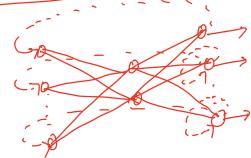
A - Rigmoidal gain

* sigmoidal functions are differentiable -57 Hyperbolie tangent function: which can per duce negative ofprolver. Q(I) = tanh(I) f, fe fg fy < 0.4 0.5 0.6 0.77 NN architecturs. muttilayered feed forward Single lay great Jeed to NN Wnm

24 mubbilagered FFNN:



34 Recurrent NN:



Learning methods:

NN Learning

Supervised learning

(Error based)

Crov (correction (Stochastic) Hebbian Competition

(Gratticut descent)

Back propagation

Jessey

Jess