

# Neural Network

## Lecture 9

### NN Models:-

→ There are different available NN Models.

1) McCulloch-Pitts Neuron (earliest)

↳ M-P Neuron (1943)

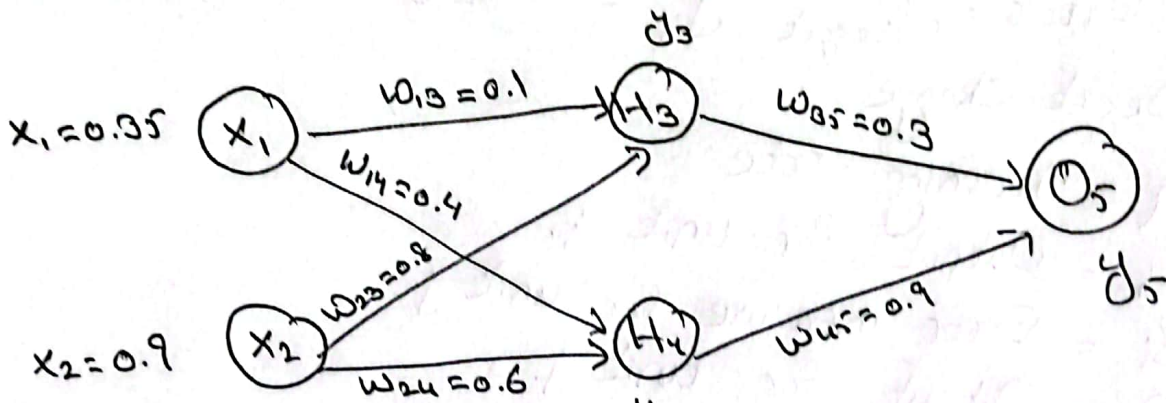
2) Perception NN

↳ Various types such as Rosenblatt (1962), Block (1962), Minsky-Papert (1969)

3) Adaptive Linear NN

4) Multiple Adaptive Linear NN

### Gradient Decent:-



Activation Function (AF) = Sigmoid AF

Actual Output  
Learning Rate

$$y = 0.5$$
$$= 1$$

Forward Pass (propagation):

Compute  $\hat{y}_3$ ,  $\hat{y}_4$  &  $\hat{y}_5$

$$a_{ij} = \sum_j (w_{ij} * x_i)$$

$$\hat{y}_j = F(a_j) = \frac{1}{1 + e^{-a_j}}$$

$$a_1 = (w_{13} * x_1) + (w_{23} * x_2) \\ = (0.1 * 0.35) + (0.8 * 0.9) = 0.755$$

$$y_3 = f(a_1) = 1 / (1 + e^{-0.755}) = 0.68$$

$$a_2 = (w_{14} * x_1) + (w_{24} * x_2) \\ = (0.4 * 0.35) + (0.6 * 0.9) = 0.68$$

$$y_4 = f(a_2) = 1 / (1 + e^{-0.68}) = 0.6337$$

$$a_3 = (w_{35} * y_3) + (w_{45} * y_4) \\ = (0.3 * 0.68) + (0.9 * 0.6337) = 0.801$$

$$y_5 = f(a_3) = 1 / (1 + e^{-0.801}) = \boxed{0.69} \text{ (Network Output)}$$

So

$$\text{Error} = y_{\text{target}} - y_5 = 0.5 - 0.69 = -0.19$$

Now Weight Change

$\eta$  = learning rate

$t_j$  = Output for unit  $j$ .

$\delta_j$  = Error measure for unit  $j$

$O_j$  = Output for unit  $j$ .

$$\Delta w_{ij} = \eta \delta_j O_i$$

$$\delta_j = O_j (1 - O_j) (t_j - O_j)$$

$\therefore$  if  $j$  is output unit

$$\delta_j = O_j (1 - O_j) \sum_k \delta_k w_{kj}$$

$\therefore$  if  $j$  is hidden unit

Backward pass (propagation):

Compute  $\delta_3$ ,  $\delta_4$  &  $\delta_5$

For output unit

$$\delta_5 = y_5 (1 - y_5) (y_{\text{target}} - y_5)$$

$$= 0.69 (1 - 0.69) (0.5 - 0.69)$$

$$= -0.0406$$

For hidden unit:

$$\begin{aligned} \delta_3 &= y_3(1-y_3)(w_{35} \times \delta_5) \\ &= 0.68(1-0.68)(\cancel{0.3} \times -0.0406) \\ &= -0.00265 \end{aligned}$$

$$\begin{aligned} \delta_4 &= y_4(1-y_4)(w_{45} \times \delta_5) \\ &= 0.6637 \times (1-0.6637)(0.9 \times -0.0406) \\ &= -0.0082 \end{aligned}$$

Compute New Weights  
 $\Delta w_{ji} = \eta \delta_j O_i$

$$\begin{aligned} \Delta w_{45} &= \eta \delta_5 y_4 \\ &= 1 \times (-0.0406) \times 0.6637 = -0.0269 \end{aligned}$$

$$\begin{aligned} w_{45}(\text{New}) &= \Delta w_{45} + w_{45}(\text{Old}) = -0.0269 + (0.9) \\ &= 0.8731 \end{aligned}$$

$$\begin{aligned} \Delta w_{14} &= \eta \delta_4 x_1 \\ &= 1 \times (-0.0082) \times 0.35 = -0.00287 \end{aligned}$$

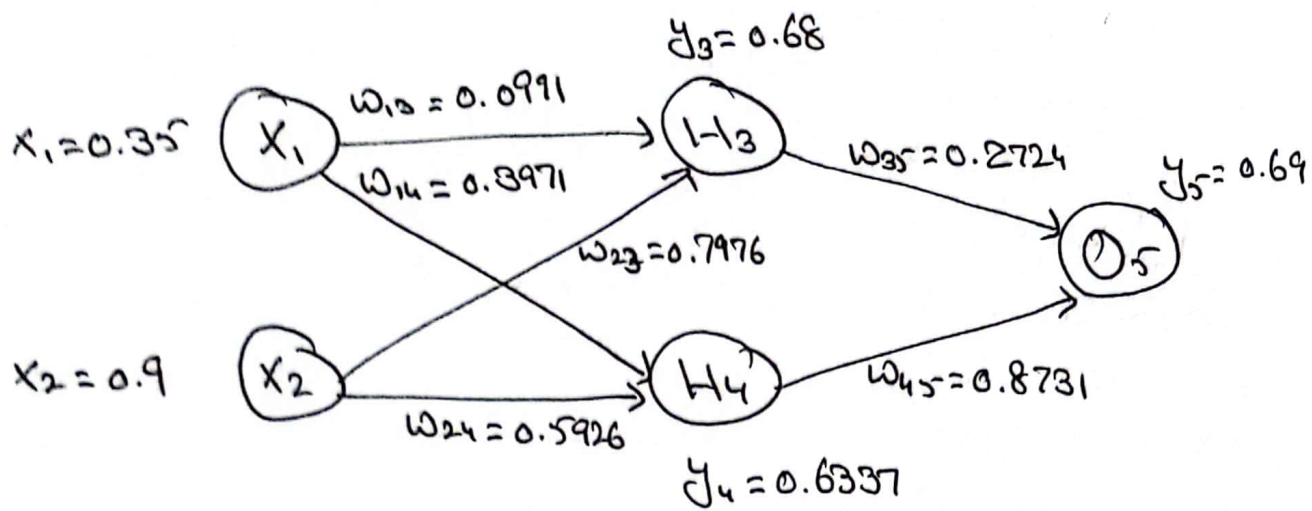
$$\begin{aligned} \Delta w_{14}(\text{New}) &= \Delta w_{14} + w_{14}(\text{Old}) \\ &= -0.00287 + 0.4 = 0.3971 \end{aligned}$$

Similarly

i	j	$w_{ij}$	$\delta_j$	$x_i$	$\eta$	Updated $w_{ij}$
1	3	0.1	-0.00265	0.35	1	0.6991
2	3	0.8	-0.00265	0.9	1	0.7976
1	4	0.4	-0.0082	0.35	1	0.3971
2	4	0.6	-0.0082	0.9	1	0.5926
3	5	0.3	-0.0406	0.68	1	0.2724
4	5	0.9	-0.0406	0.6337	1	0.8731



The Update Neural Network is



Forward pass (propagation):

$$a_j = \sum_i (w_{ij} \times x_i)$$

$$y_{ij} = F(a_j) = \frac{1}{1 + e^{-a_j}}$$

$$\begin{aligned} a_1 &= (w_{13} \times x_1) + (w_{23} \times x_2) \\ &= (0.0991 \times 0.35) + (0.7976 \times 0.9) = 0.7525 \\ y_3 &= f(a_1) = 1 / (1 + e^{-0.7525}) = 0.6797 \end{aligned}$$

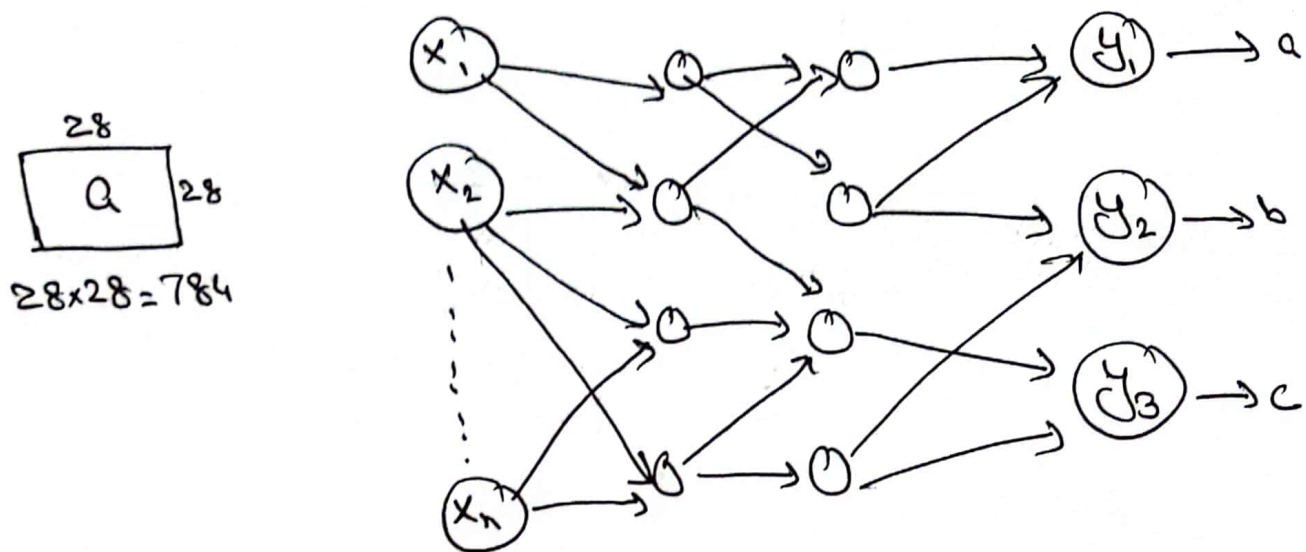
$$\begin{aligned} a_2 &= (w_{14} \times x_1) + (w_{24} \times x_2) \\ &= (0.3971 \times 0.35) + (0.5926 \times 0.9) = 0.6723 \\ y_4 &= f(a_2) = 1 / (1 + e^{-0.6723}) = 0.6620 \end{aligned}$$

$$\begin{aligned} a_3 &= (w_{35} \times y_3) + (w_{45} \times y_4) \\ &= (0.2724 \times 0.6797) + (0.8731 \times 0.6620) \\ &= 0.7631 \\ y_5 &= f(a_3) = 1 / (1 + e^{-0.7631}) \\ &= \boxed{0.6820} \text{ (Network Output)} \end{aligned}$$

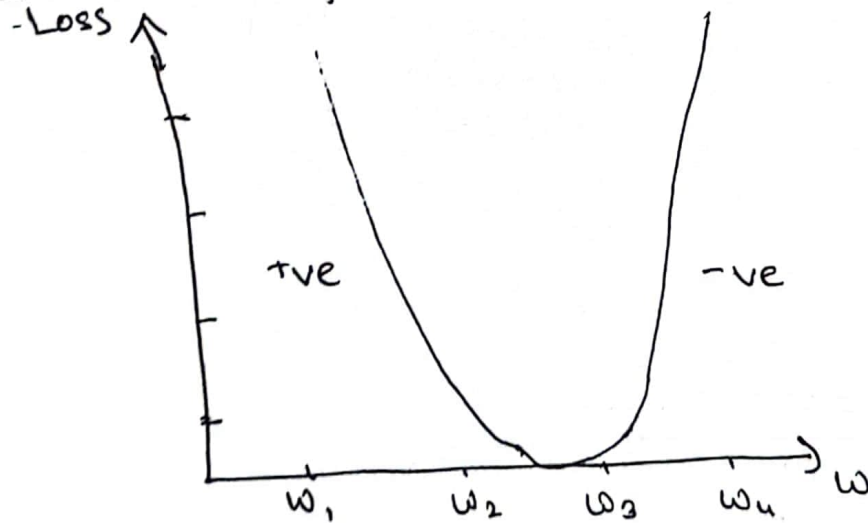
$$\begin{aligned} \text{Error} &= y_{\text{target}} - y_5 \\ &= 0.5 - 0.6820 \\ &= -0.182 \end{aligned}$$

## Gradient Decent:

- Three types (Batch, Stochastic, mini-Batch)
- Choice is between Accuracy & Time

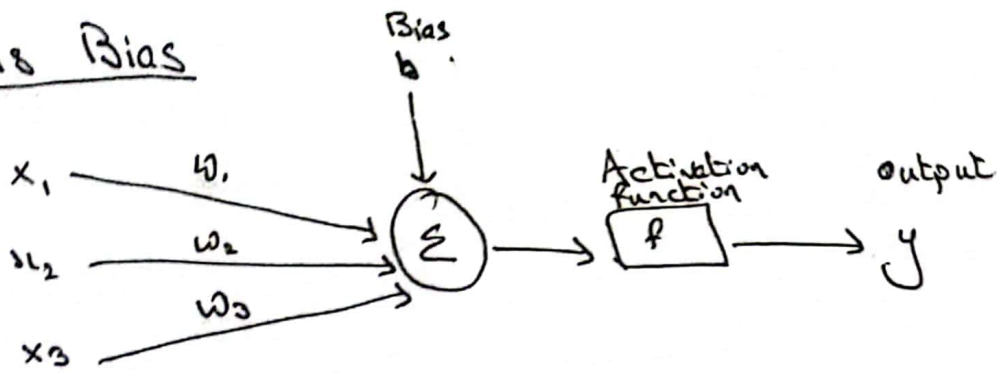


$$\text{Loss} = \left[ \text{(actual Output)} - \text{(predicted Output)} \right]$$



Every Learning Step = 1 iteration.

# What is Bias



→ Bias can shift the AF.  $y = mx + c$

→ Used to control AF (triggering, delay, steepness).

$$y = \text{sum}(\text{weight} \times \text{inputs}) + \text{bias}$$

$$y = \underset{\substack{\uparrow \\ \text{weight}}}{m} x + \underset{\substack{\uparrow \\ \text{Bias}}}{c}$$

