

# Assignment 03

Q No: 01

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$$① S_n^k = f \left( \sum_{i=1}^M w_i^k a_i + w_i^k \right)$$

$$\text{for } S_1' \rightarrow w_1^1 = w_1^k = -2$$
$$w_1 = [0.2, 0.4, 0.6]$$
$$a = [3, 5, 2]$$

$$S_1' = f([0.2 \times 3 + 0.4 \times 5 + 0.6 \times 2] - 2)$$

$$S_1' = f([3.8] - 2)$$

$$S_1' = f(1.8)$$

$$S_1' = \frac{1}{(1 + e^{-1.8})} = \boxed{0.858}$$

$$\text{for } S_2' \rightarrow w_2^1 = w_2^k = 2$$

$$w_2 = [0.1, 0.9, 0.7]$$

$$a = [3, 5, 2]$$

$$S_2' = f([0.1 \times 3 + 0.9 \times 5 + 0.7 \times 2] + 2)$$

$$S_2' = f([6.2] + 2)$$

$$S_2' = f(8.2)$$

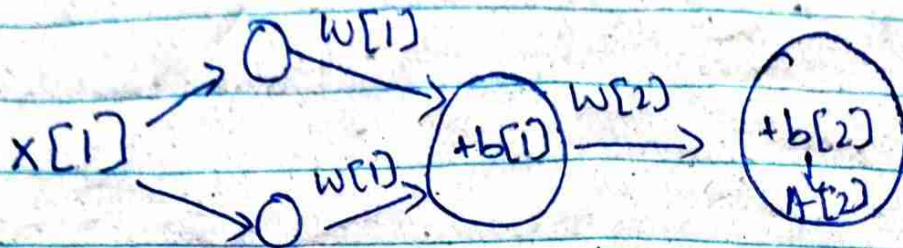
$$S_2' = \frac{1}{(1 + e^{-8.2})} = \boxed{0.998}$$

①



Hidden layer

Output layer



- where  $x[1]$  is input matrix of size  $(n \times m)$
- $w[1]$  &  $w[2]$  are weights associated with inputs
- $b[1]$  &  $b[2]$  represents bias on  $z[1]$  &  $z[2]$
- $A[2]$  is activation energy on layer  $z[2]$
- $z[1]$  hidden layers having  $p$  no of neurons
- $z[2]$  output layers having  $q$  no of neurons.

$$\partial L / \partial b[1]$$

$$\text{Chain Rule} \Rightarrow \frac{dz}{dx} = \frac{dz}{dy} \cdot \frac{dy}{dx}$$



- The loss  $L$  depends on  $Z[2]$  which depends on  $A[2]$  and  $A[2]$  depends on  $Z[1]$  which itself depends on  $B[1]$

$$\therefore \frac{\partial L}{\partial B[1]} = \frac{\partial L}{\partial B[2]} \frac{\partial L}{\partial Z[2]} \frac{\partial Z[2]}{\partial A[2]}$$

$$\frac{\partial A[2]}{\partial Z[1]} \frac{Z[1]}{\partial B[1]}$$

- In the above ~~equation~~ equations we replace the symbols with exact function which are missing.

- Back propagation allows updation of weights and biases based on error rate in forward pass.

- Back propagation reduces computational and memory cost for neural training.



Qno: 02

Initial Matrix

	A	B	C	D	E	F	
A	0	0	0	0	0	0	
B	0	0	0	0	0	0	Starting Pos $\Rightarrow$ B
C	0	0	0	0	0	0	Next Step $\Rightarrow$ F
D	0	0	0	0	0	0	Exploration rate $= 0.8$
E	0	0	0	0	0	0	reward $= 100$
F	0	0	0	0	0	0	

$$Q(\text{State}, \text{action}) = R(\text{state}, \text{action}) + \gamma \cdot \text{Max}$$

$$+ \gamma \cdot \text{Max} [Q(\text{next state}, \text{allocation})]$$

$$Q(B, F) = R(B, F) + \gamma \cdot \text{Max} [Q(F, B) + Q(F, E) + Q(F, F)]$$

$$Q(B, F) = R(B, F) + 0.8 \cdot \text{Max}(0, 0, 0)$$

$$Q(B, F) = 100 + 0.8(0) = 100$$

Updated Matrix  $Q$

	A	B	C	D	E	F
A	0	0	0	0	0	0
B	0	0	0	0	0	100
C	0	0	0	0	0	0
D	0	0	0	0	0	0
E	0	0	0	0	0	0
F	0	0	0	0	0	0