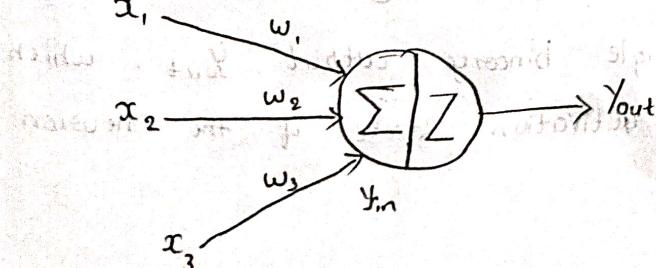


↳ McCulloch-Pitts (MCP) Neuron Model

MLDB

- i) Give the architecture of the MCP neural network model.
- Ans: The MCP Neural Network Model refers to the McCulloch-Pitts Neural Network, which is one of the earliest models of artificial neurons. The neurons are connected by directed weighted paths. McCulloch-Pitts neuron allows binary activation, it either fires with an activation of 1 or does not fire with an activation of 0. If  $w > 0$ , then the connected path is said to be excitatory else it is known as inhibitory. Excitatory connections have positive weights and inhibitory connections have negative weights. Each neuron has a fixed threshold for firing. If  $\sum w_i x_i > \text{threshold}$ , it fires.
- If the net input to the neuron is greater than the threshold, it fires.



$$y_{in} = \sum_{i=1}^n x_i w_i + y_{in}$$

$$\text{Activation function} = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} > 0 \\ 0 & \text{if } y_{in} \leq 0 \end{cases} \quad \theta = \text{threshold}$$

- i) Input layer: A layer of binary inputs  $x_1, x_2, x_3 \dots x_n$ . Each input represents a feature of variable and takes a binary values of 0 or 1.
- ii) Weights: Each input is associated with a weight which represents the importance of the input. The weight sum of inputs is calculated as  $y_{in} = \sum_{i=1}^n x_i w_i$ .
- iii) Summation function: Computed the linear combination weighted sum of inputs.
- iv) Threshold function: A threshold  $\theta$  is applied to the weighted sum  $y_{in}$ . If  $y_{in} > \theta$ , the neuron fires (output = 1). If  $y_{in} < \theta$ , the neuron does not fire (output = 0).
- $$y_{out} = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} > \theta \\ 0 & \text{if } y_{in} \leq \theta \end{cases}$$
- v) Output: A single binary output  $y_{out}$ , which represents the activation state of the neuron.

2) Generate the output of logic NOT, NAND and NOR function using MCP neuron.

NOT function

Input	Output	$y_{in} = x_1 w_1 + b$
0	1	$0 = (1 \times 0) + (0 + 1) = 1$
1	0	$1 = (1 \times 1) + (1 \times 0) = 1$

$$w_1 = 1 \quad b = 0$$

$$x_1 = 0 \quad y_{in_1} = 1 \times 0 + 0 = 0$$

$$x_1 = 1 \quad y_{in_2} = 1 \times 1 + 0 = 1$$

Activation function =  $y_{out} = f(y_{in}) = \begin{cases} 0 & \text{if } y_{in} \geq 1 \\ 1 & \text{if } y_{in} < 1 \end{cases}$

threshold =  $\theta = 1$

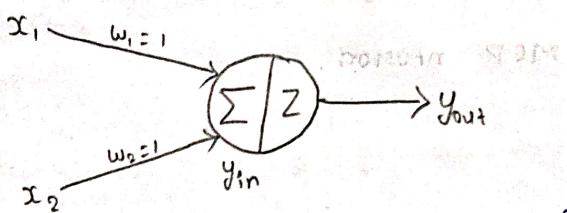


$$y_{out_1} = f(y_{in_1}) = f(0) = 1$$

$$y_{out_2} = f(y_{in_2}) = f(1) = 0$$

Nand function

$x_1$	$x_2$	Nand ( $x_1, x_2$ )	$y_{in} = x_1 + x_2$	$y_{out}$
0	0	1	0	1
0	1	1	1	1
1	0	1	1	1
1	1	0	2	0



$$y_{in} = x_1 w_1 + x_2 w_2 + b$$

$$w_1 = w_2 = 1, b = 0$$

$$\text{threshold } \theta = 1$$

Activation function =  $\begin{cases} 1 & y_{in} \geq 1 \\ 0 & y_{in} < 1 \end{cases}$

$$x_1 = 0 \quad x_2 = 0 \Rightarrow y_{in} = (1+0) + (0 \times 1) = 0$$

$$x_1 = 0 \quad x_2 = 1 \Rightarrow y_{in} = (0 \times 1) + (1 \times 1) = 1$$

$$x_1 = 1 \quad x_2 = 0 \Rightarrow y_{in} = (1 \times 1) + (0 \times 1) = 1$$

$$x_1 = 1 \quad x_2 = 1 \Rightarrow y_{in} = (1 \times 1) + (1 \times 1) = 2$$

### NOR Function

For all  $(x_1, x_2)$ ,  $y_{in} = 1 - (x_1 \oplus x_2)$  is called NOR function.

$$x_1 \text{ and } x_2 \quad y_{in} = x_1 w_1 + x_2 w_2 + b \quad \text{NOR}(x_1, x_2)$$

0	0	0	1
0	1	1	0
1	0	1	0
1	1	2	0

$$y_{in} = x_1 w_1 + x_2 w_2 + b$$

$$w_1 = 1 \quad w_2 = 1 \quad b = 0 \quad \theta = 1$$

$$x_1 = 0 \quad x_2 = 0 \Rightarrow y_{in} = (0 \times 1) + (1 \times 0) = 0$$

$$x_1 = 0 \quad x_2 = 1 \Rightarrow y_{in} = (1 \times 0) + (1 \times 1) = 1$$

$$x_1 = 1 \quad x_2 = 0 \Rightarrow y_{in} = (1 \times 1) + (0 \times 1) = 1$$

$$x_1 = 1 \quad x_2 = 1 \Rightarrow y_{in} = (1 \times 1) + (1 \times 1) = 2$$

Activation function

$$y_{out} = f(y_{in})$$

$$= \begin{cases} 0 & \text{if } y_{in} \leq 1 \\ 1 & \text{if } y_{in} > 1 \end{cases}$$

③ write the limitations of MCP neuron model

→ MCP neuron model is a foundational concept in neural networks but it has several limitations that make it less suitable for modeling complex or real-world neural networks.

Binary Output :- MCP neuron produces only binary outputs (0/1), which is overly simplistic. In real biological neurons, the output is more continuous (analog) and can vary in response to different stimuli.

Input :- This limitation makes the MCP model less flexible when trying to model complex behaviour such as graded response that occurs in actual neural systems.

\* Lack of learning mechanism :- MCP neuron model does not include a mechanism for learning or adaptation. In other words, it cannot adjust its weights or bias based on experience or feedback.

Input :- In practical neural networks, learning through adjustments to weights (such as via backpropagation) is essential for improving performance, without learning,

\* No Temporal Dynamics:- The MCP model does not account for the temporal dependencies of neurons or their interactions over time. It operates in a static function, where the output only depends on the current input and not on previous status or sequence.

\* Inflexibility in Input Representation:- MCP model ensures that all inputs are independent and binary. It doesn't have the flexibility to process continuous or real valued inputs in a natural way.

\* Simplified Activation Function:- The activation function in the MCP model is a simple threshold function, which only determines whether the neuron fires or not based on the weighted sum of inputs. It lacks the more sophisticated activation functions like the Sigmoid, ReLU or tanh functions, that are commonly used in modern neural networks.

\* Limited Expressions:- MCP neuron model can only represent limited practical applicability. Due to its simplicity, the MCP model cannot address modern machine learning tasks like image recognition, natural language processing, or speech synthesis.