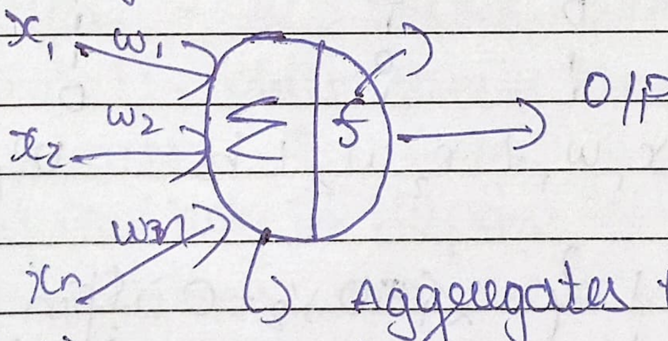
1) MC culloch-Pitts (MCP) Neuron model.

Give the architecture of the MCP neural network model.

1943

The Mcculloch pitt neural network is considered to be the first neural network. The neurons are connected by directed weighted paths. Mcculloch-pitt neuron allows binary activation (1 on or OFF), it either fires with an activation 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.

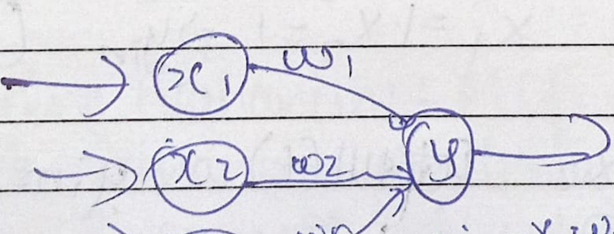
Excitatory connections have positive weights and inhibitory connections have negative weights. Each neuron has a fixed threshold for firing. That is, if the net input to the neuron is greater than the threshold, it fires.



$$O/P = \begin{cases} 1 & \text{if } x > T \\ 0 & \text{if } x < T \end{cases}$$

Σ → Aggregates the weighted i/p into single numeric value

$\Sigma\; x_1 w_1 + x_2 w_2 + \dots + x_n w_n$.



$y_{in} = x_1 w_1 + x_2 w_2 + x_n w_n$

$$y = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} \geq \theta \rightarrow \text{threshold} \\ 0 & \text{if } y_{in} < \theta \end{cases}$$

Generate the output of logic NOT, NAND, and NOR functions using MCP neuron model.

NOT

Input	output
0	1
1	0

$x_1\ w_1 \to (\Sigma | f) \to$

$y_{in} = x_1 w_1 + b$.

$w_1 = 1 \quad b = 0 \quad$ Threshold $\theta = 0.5$

$\begin{cases} 1 & \text{if } y_{in} \geq 0.5 \\ 0 & \text{if } y_{in} < 0.5 \end{cases}$

$x = 0 \quad y_{in} = 1 \times 0 + 0 = 0 \Rightarrow 1$

$x = 1 \quad y_{in} = 1 \times 1 + 0 = 1 \to 0$.

NAND

Input x_1	x_2	output (t)
0	0	1
0	1	1
1	0	1
1	1	0

$y_{in} = x_1 w_1 + x_2 w_2 + b \quad w_1 = w_2 = 1 \quad b = 0, \quad \theta = 1$

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

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

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

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

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

NOR

Inputs x_1	x_2	Output (t)
0	0	1
0	1	0
1	0	0
1	1	0

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

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

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

$x_1 = 0\ x_2 = 1 \quad y_{2in} = (1 \times 0) + (1 \times 1) = 1$

$x_1 = 1\ x_2 = 0 \quad y_{3in} = (1 \times 1) + (1 \times 0) = 1$

$x_1 = 1\ x_2 = 1 \quad y_{4in} = (1 \times 1) + (1 \times 1) = 1$

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

$y_1 < 1 \to y_{in} = 0 \to 1 = t = 1$

$y_2 \geq 1 \to y_{in} = 1 \to 0 \neq t = 0$

$y_3 \geq 1 \to y_{in} \to 0 \neq t\ 0$

$y_4 \geq 1 \to y_{in} \to 0 \neq t\ 0$

3) MCP neuron model is a foundational concept in neural network but it has several limitations that make it less suitable for modelling complex or real world neural networks.

* Binary output → MCP neuron produces only binary outputs (0 or 1), which overly simplistic. In real biological neurons, the output is more continuous (analog) and can vary in response to different stimuli.
Impact: This limitations make the MCP model less flexible when trying to model complex behaviors such as graded responses 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 biases based on experience or feedback.
Impact: In practical neural networks, learning through adjustments to weights (such as via backpropagation) is essential for improving performance. without learning, the

• No Temporal Dynamics.
The MCP model does not account for the temporal dynamics of neurons or their interactions over time. It operates in a static fashion, where the output only depends on the current input and not on previous states or sequences.

* Inflexibility in Input Representation: MCP model assumes 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 Expressiveness: MCP neuron model can only represent linearly separable functions, meaning it can only solve problems that can be divided into two distinct classes by a straight line (or hyperplane in higher dimensions). Complex tasks (like XOR (exclusive OR), which are not linearly separable, cannot be solved by a single MCP neuron.

• No interactions Between Neurons: MCP model treats each neuron in isolations, with no communication or interaction between neurons. It does not support the concept of a neural network where neurons are interconnected and work together to process information.