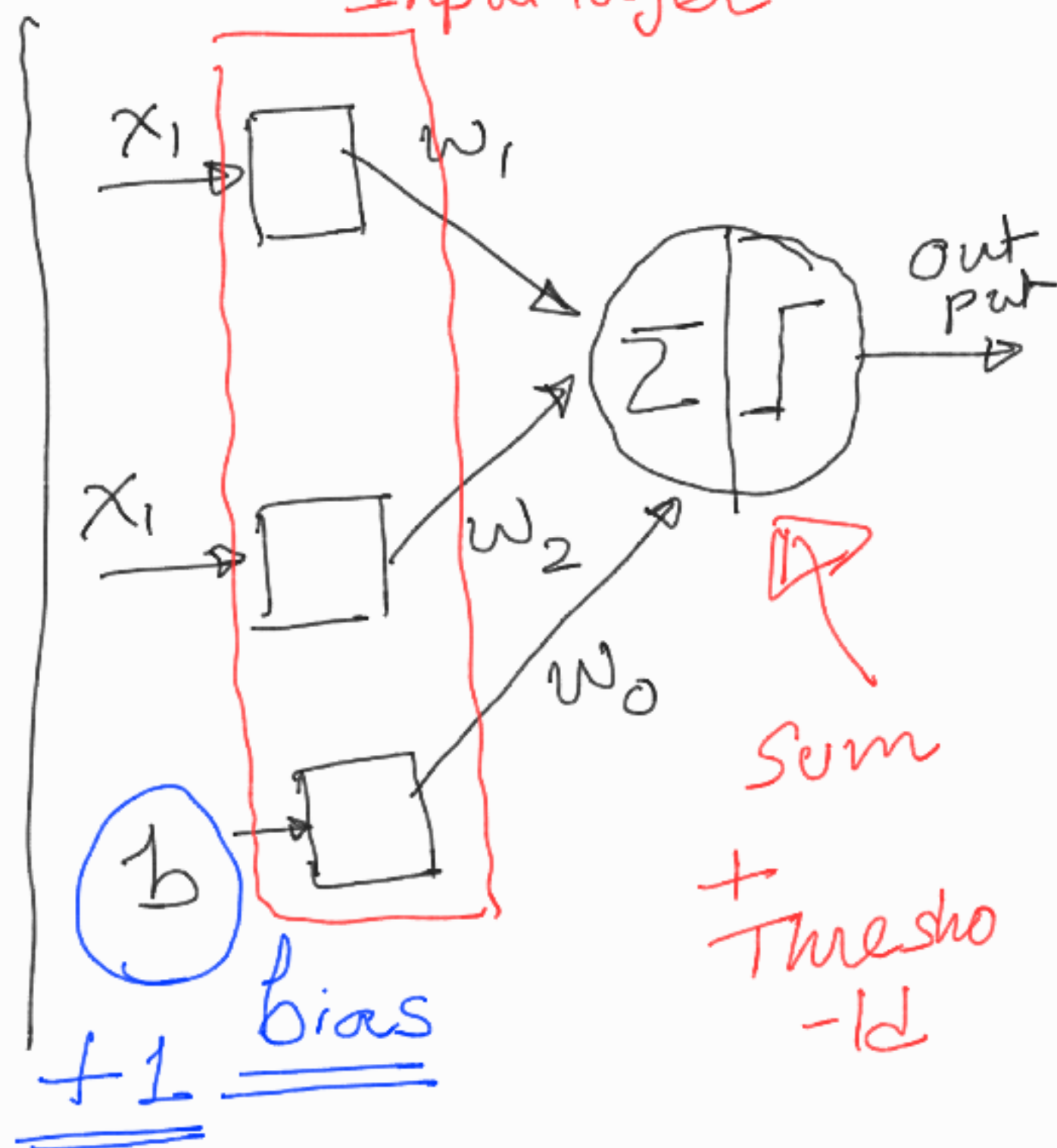
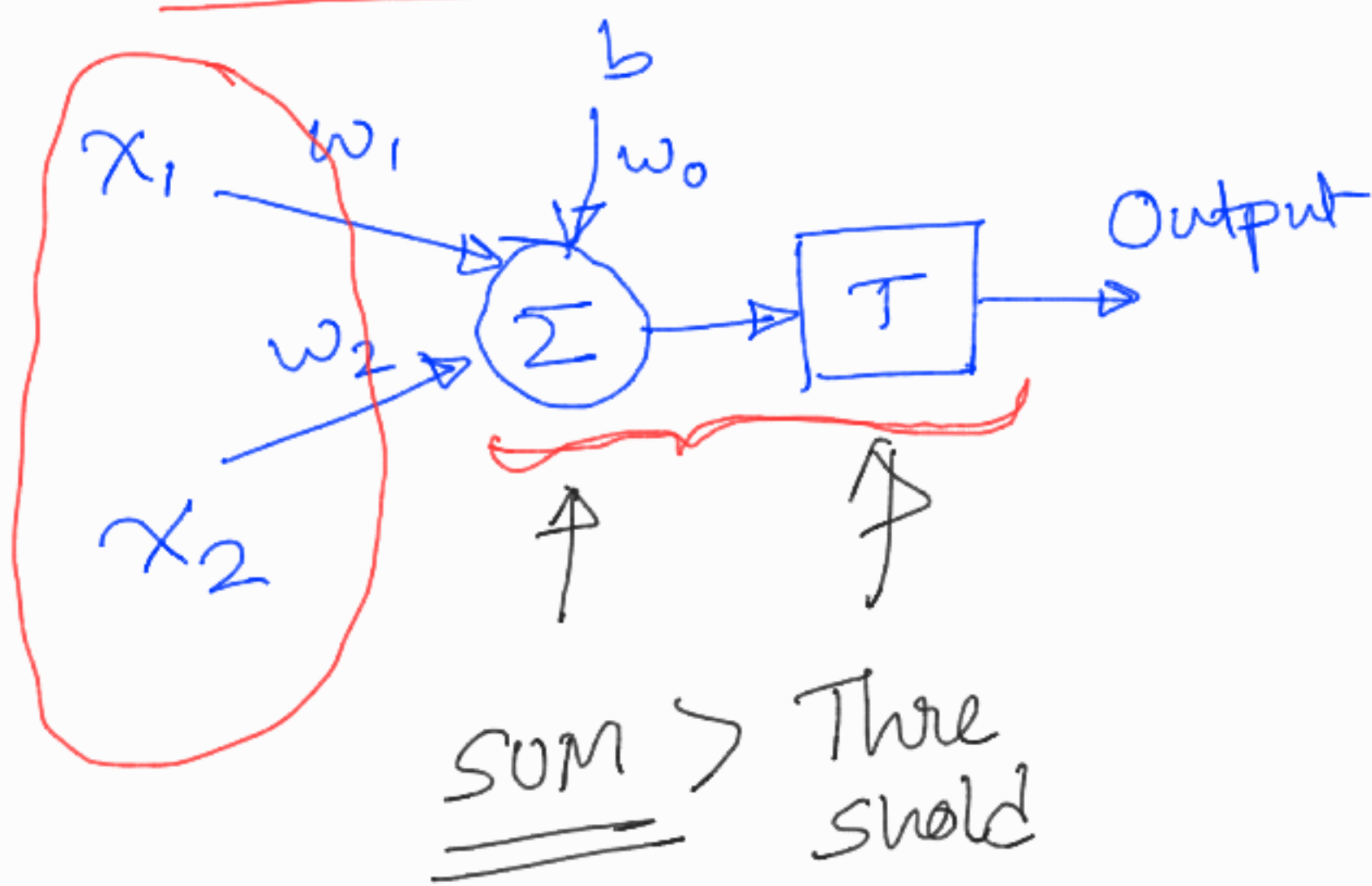
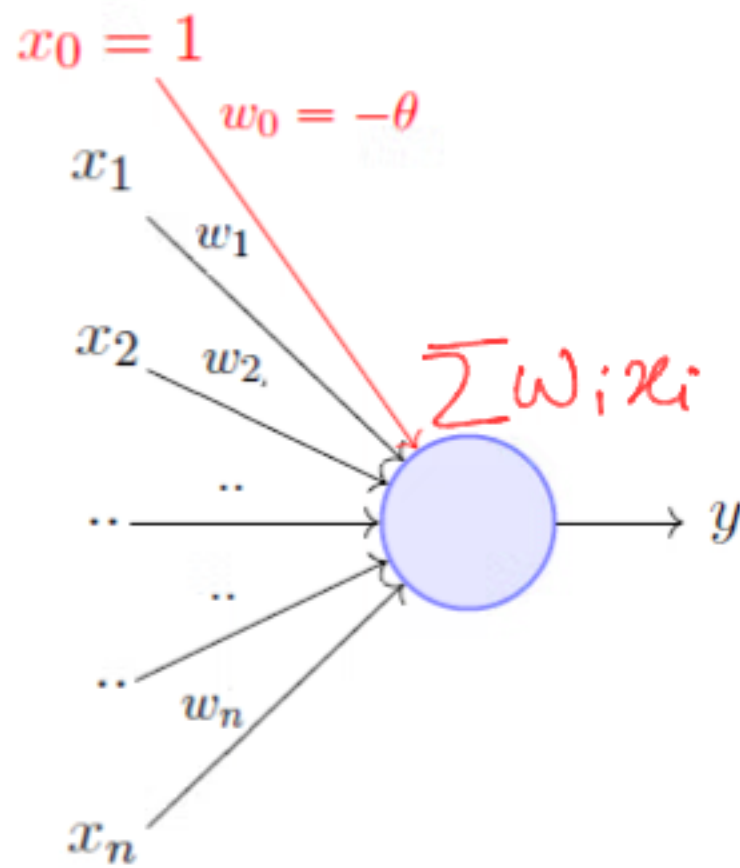


## Perceptron (Equivalent representations)



# Perceptron Learning :



A more accepted convention,

$$y = 1 \quad \text{if} \quad \sum_{i=0}^n w_i * x_i \geq 0$$

$$= 0 \quad \text{if} \quad \sum_{i=0}^n w_i * x_i < 0$$

where,  $x_0 = 1$  and  $w_0 = -\theta$

Bias

we can draw a  
Linearly Separable: line to separate two classes.

OR Gate using a single perceptron

$x_1$	$x_2$	OR	Class Label - Desired	Computed output - Actual
0	0	0	$w_0 + \sum_{i=1}^2 w_i x_i < 0$	$< 0$
1	0	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$	$\geq 0$
0	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$	$\geq 0$
1	1	1	$w_0 + \sum_{i=1}^2 w_i x_i \geq 0$	$\geq 0$

$$w_0 + w_1 \cdot 0 + w_2 \cdot 0 < 0 \Rightarrow w_0 < 0$$

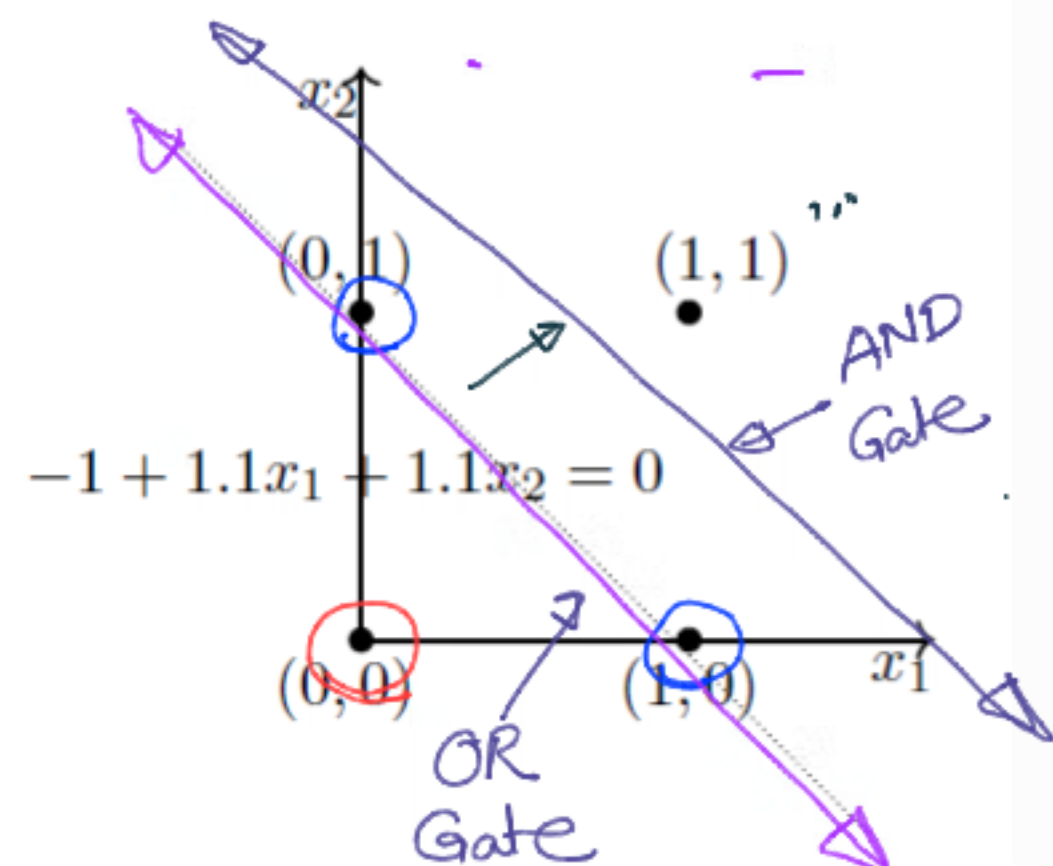
$$w_0 + w_1 \cdot 0 + w_2 \cdot 1 \geq 0 \Rightarrow w_2 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 0 \geq 0 \Rightarrow w_1 > -w_0$$

$$w_0 + w_1 \cdot 1 + w_2 \cdot 1 \geq 0 \Rightarrow w_1 + w_2 > -w_0$$

One possible solution is

$$w_0 = -1, w_1 = 1.1, w_2 = 1.1$$



(Image source: Towards data science)



### Algorithm: Perceptron Learning Algorithm

*Start with initial values for parameter*

```
P ← inputs with label 1;
N ← inputs with label 0;
Initialize w randomly;
while !convergence do
    Pick random x ∈ P ∪ N;
    if x ∈ P1 and w.x < 0 then
        w = w + x;
    end
    if x ∈ N0 and w.x ≥ 0 then
        w = w - x;
    end
end
//the algorithm converges when all the
//inputs are classified correctly
```

*Calculate errors*

*for x ∈ P  
wx ≥ 0  
for x ∈ N  
wx < 0*

*Class Label we know/want*

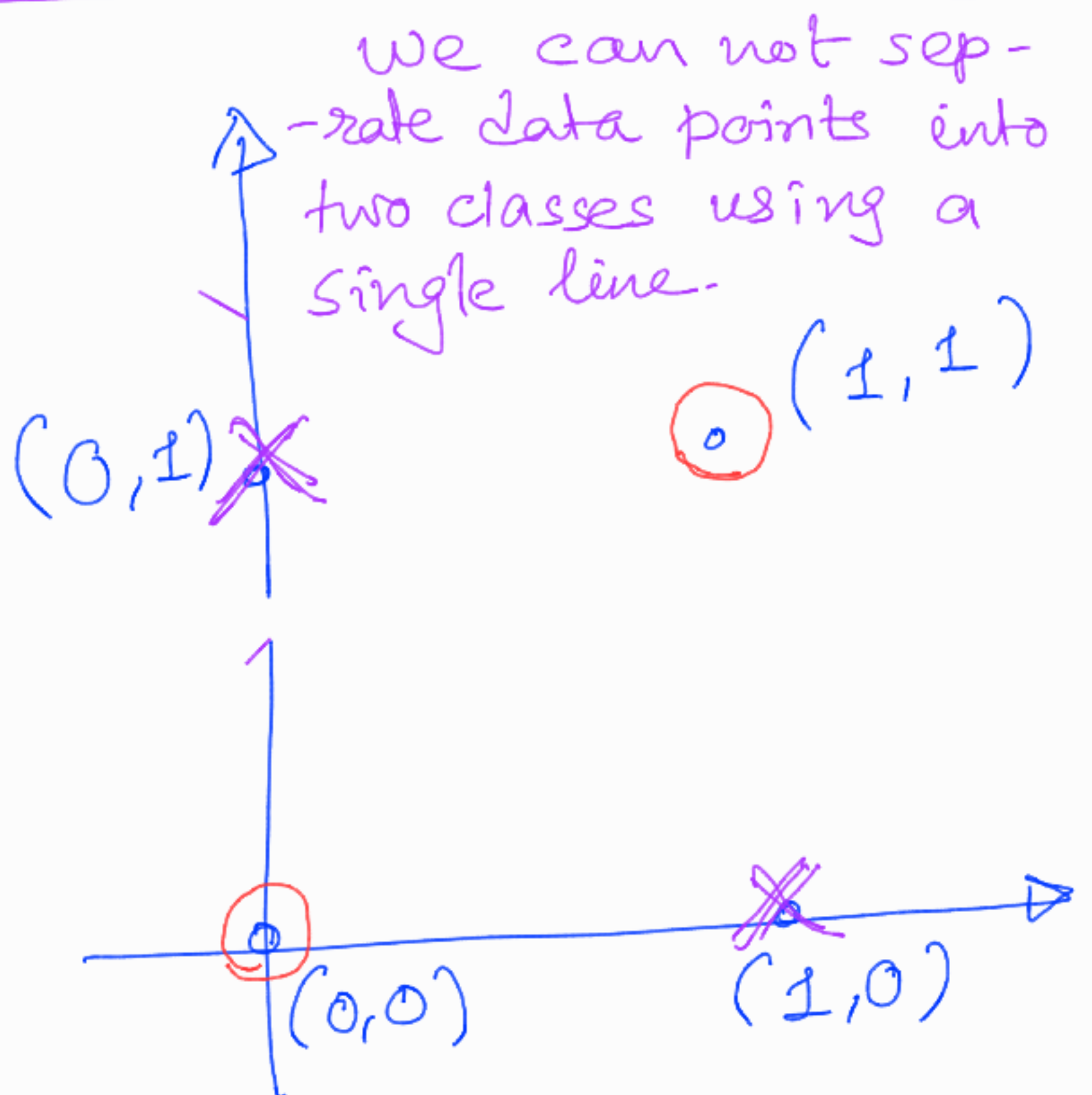
*Computed w are parameters.*

*Learning happens by changing w*

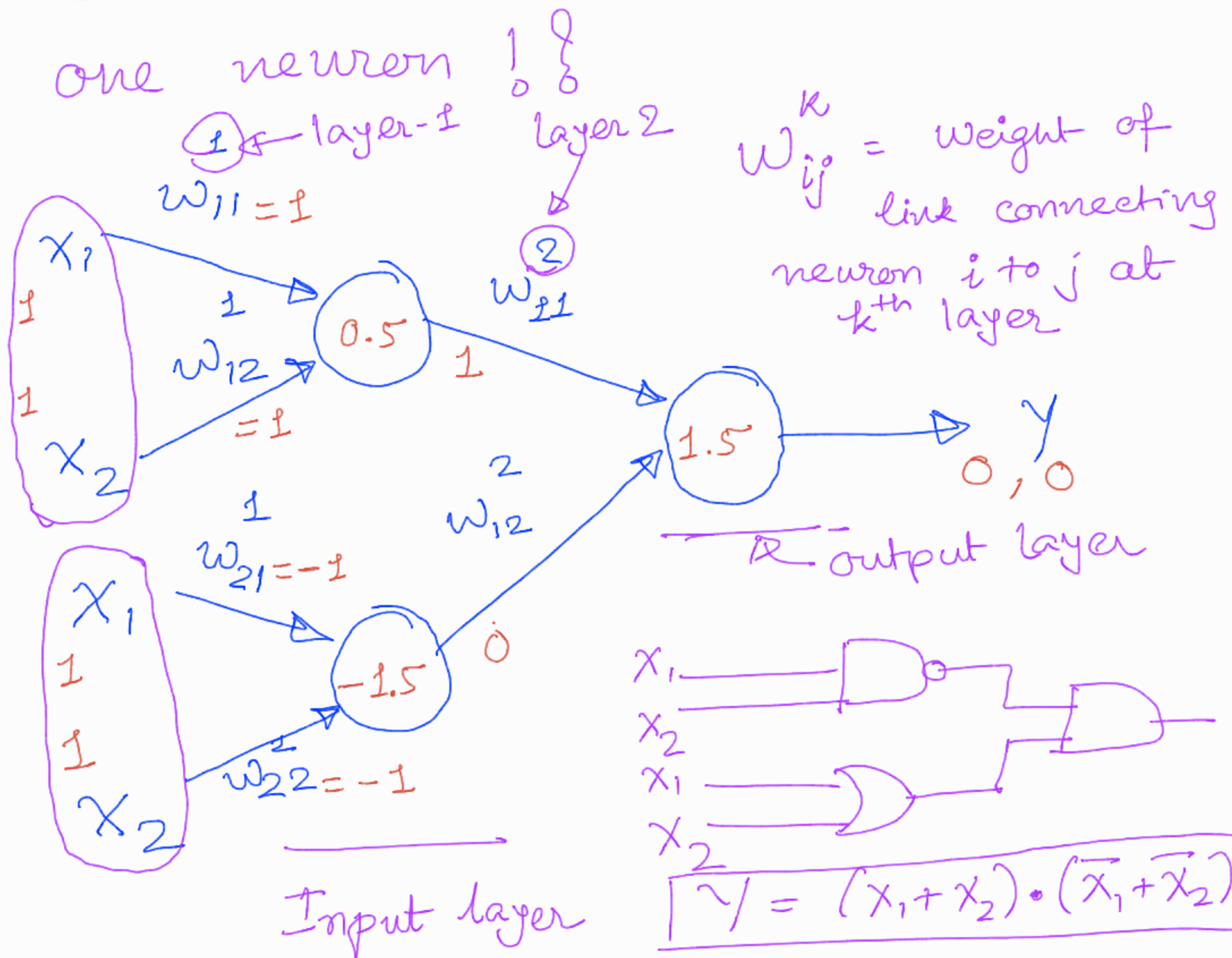
(Image source: Towards data science)

XOR : Linearly 'NOT' separable

$x_1$	$x_2$	$y$
0	0	0
1	0	1
0	1	1
1	1	0



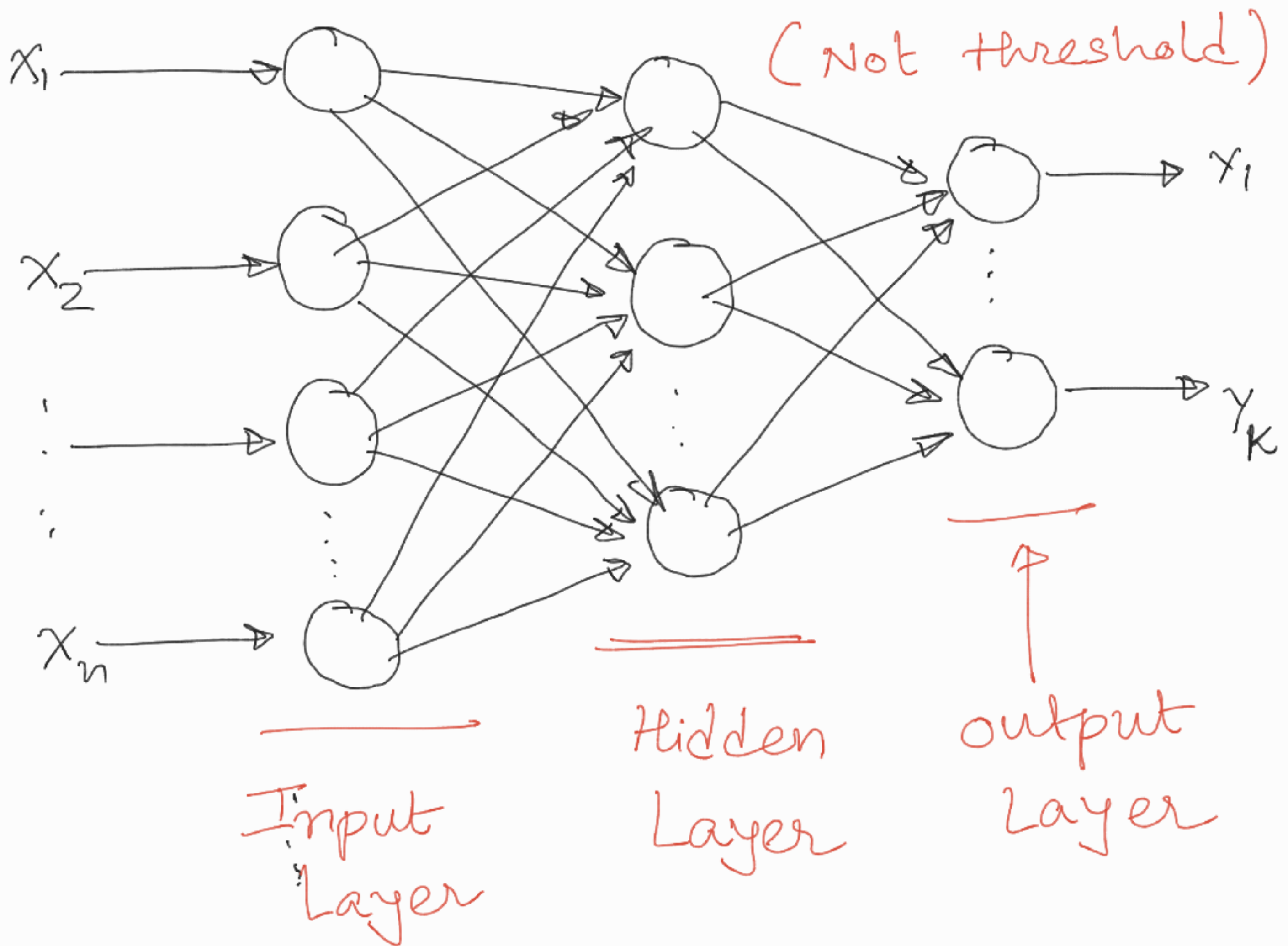
Can be solved with more than one neuron





# Multilayered Feed forward neural network

activation function: Non Linear



Hidden layer + Non linear activation

↳ Can model any  
non linear function

$$y = f(x)$$