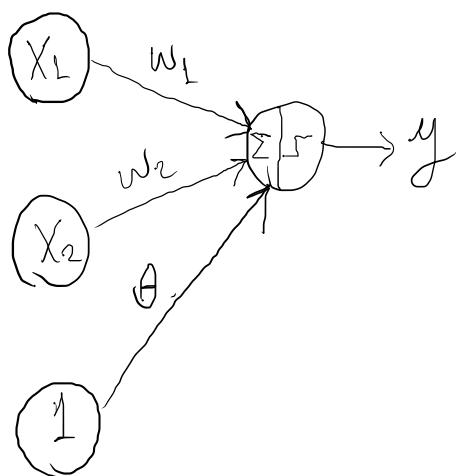


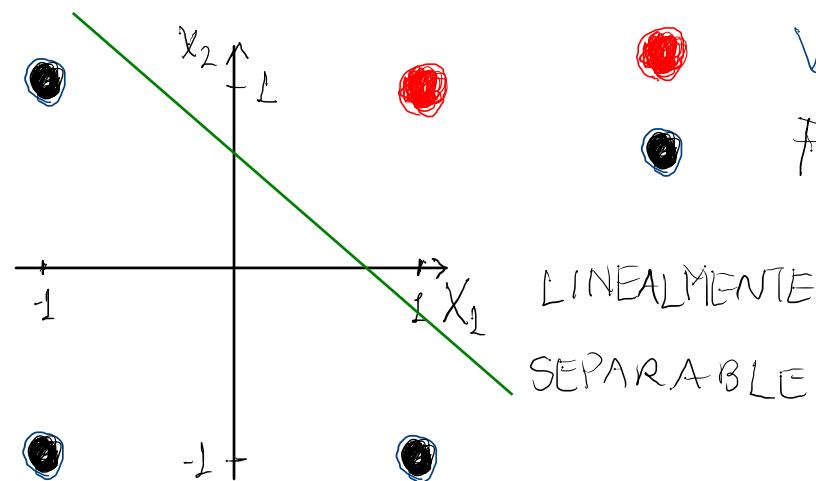
XOR		
x_1	x_2	$x_1 \oplus x_2$
1	1	-1
1	-1	1
-1	1	1
-1	-1	-1

$$V \Rightarrow 1$$

$$F \Rightarrow -1$$



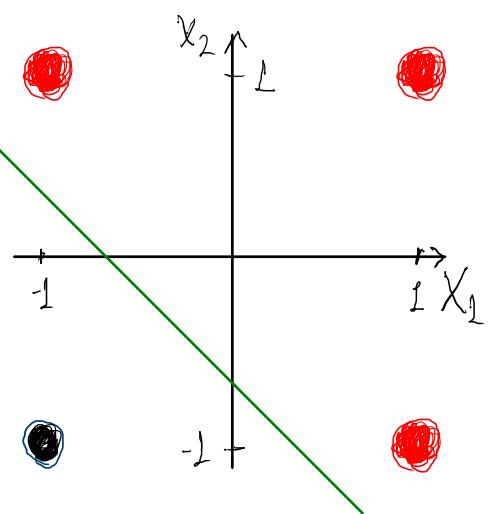
AND



Verdadero

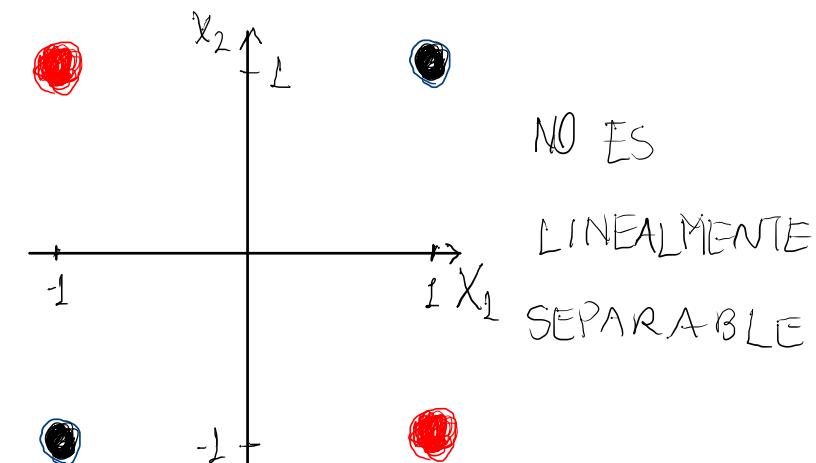
Falso

OR



Se usa la función signo

XOR



LINEALMENTE
SEPARABLE

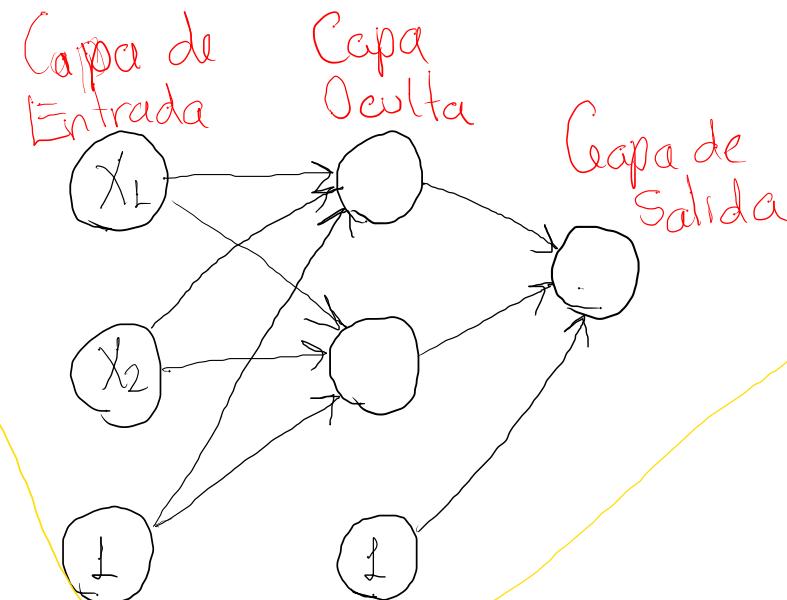
Perceptrón Simple
No puede resolver
XOR

XOR

$V \rightarrow 1$ $F \rightarrow 1$

x_1	x_2	$x_1 \text{ XOR } x_2$
1	1	-1
1	-1	1
-1	1	1
-1	-1	-1
XOR		

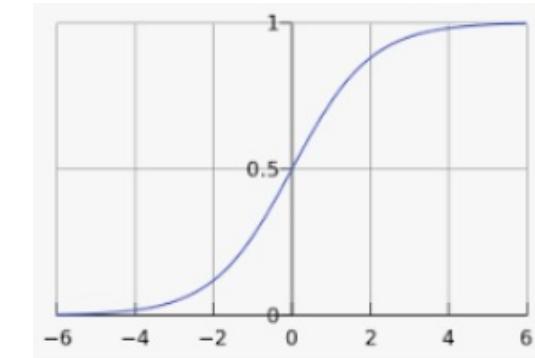
Modelo de Red Neuronal "Perceptrón Multicapa"
* Realmente usa Backpropagación (Retropropagación)



Función Sigmoidal

$$f(x) = \frac{1}{1+e^{-x}}$$

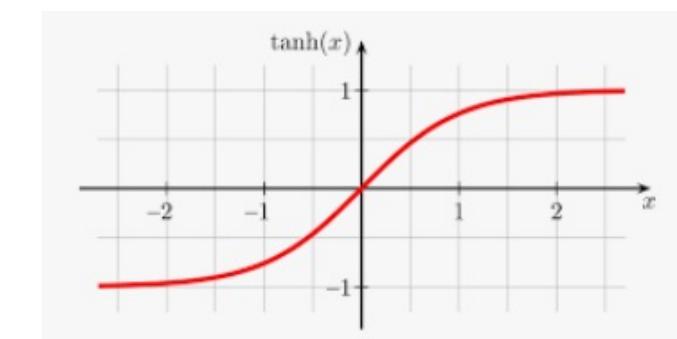
$$f'(x) = f(x)(1-f(x))$$



Función Tangente Hiperbólica

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$f'(x) = 1 - f^2(x)$$



$V \rightarrow 1$ $F \rightarrow 0$

x_1	x_2	$x_1 \text{ XOR } x_2$
1	1	0
1	0	1
0	1	1
0	0	0

XOR

$$V \rightarrow 1 \quad F \rightarrow 0$$

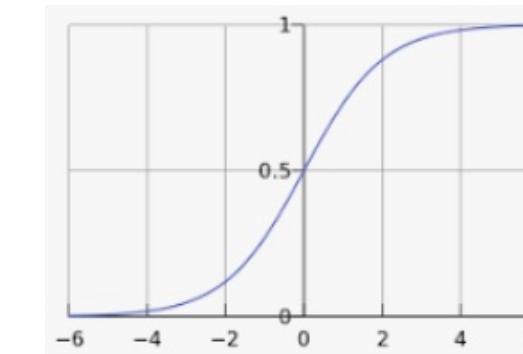
x_1	x_2	$x_1 \text{ XOR } x_2$
1	1	0
1	0	1
0	1	1
0	0	0

$x_1 = [1, 1, 0, 0]$
 $x_2 = [1, 0, 1, 0]$
 $z = [0, 1, 1, 0]$

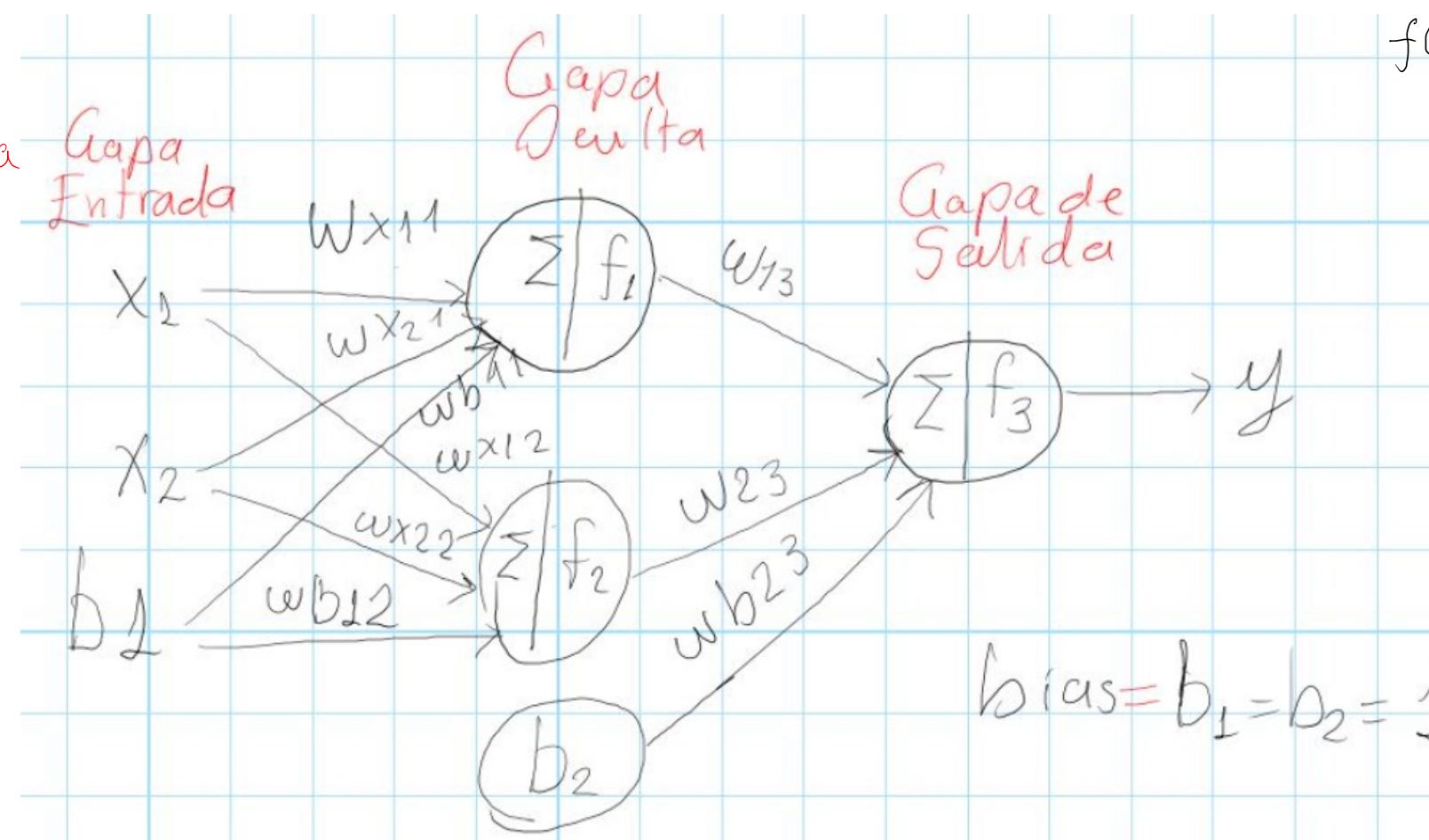
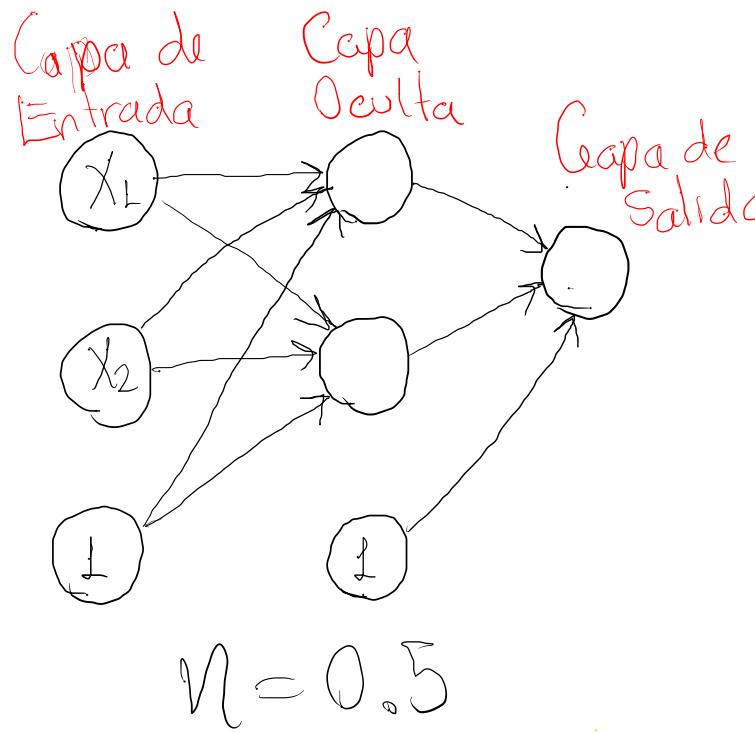
Modelo de Red Neuronal "Perceptrón Multicapa"
* Realmente usa Backpropagación (Retropropagación)

Función Sísmoide

$$f(x) = \frac{1}{1 + e^{-x}}$$



$$f'(x) = f(x)(1 - f(x))$$



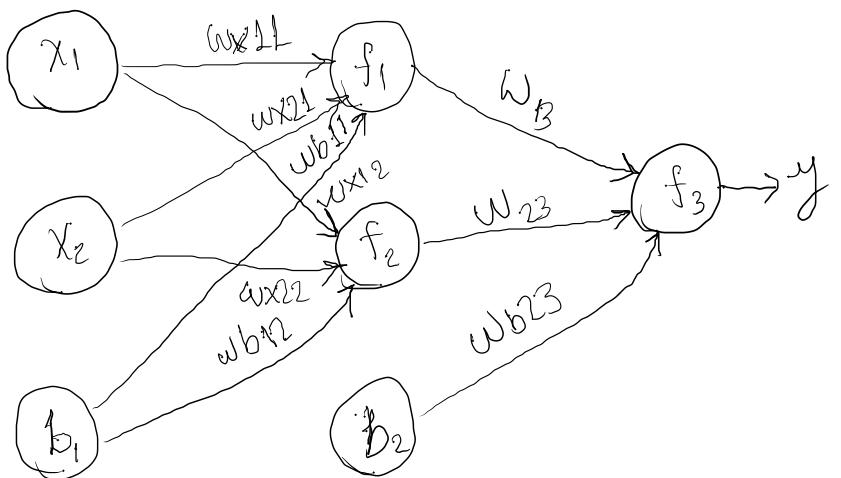
$$\text{bias} = b_1 = b_2 = 1$$

Neurona 1
 $wx_{11} = 0.909769237923872$
 $wx_{21} = 0.2940790407586785$
 $wb_{11} = 0.4594338793312195$
 Neurona 2
 $wx_{12} = 0.1363587105435612$
 $wx_{22} = 0.9950607203462696$
 $wb_{12} = 0.15464399620754732$
 Neurona 3
 $w_{13} = 0.6739395534640641$
 $w_{23} = 0.5980255545416808$
 $wb_{23} = 0.7146237169889224$

$$f_1 = f((x_1)(wx_{11}) + x_2(wx_{21}) + b_1(wb_{11})) = y_1$$

$$f_2 = f(x_1(wx_{12}) + x_2(wx_{22}) + b_1(wb_{12})) = y_2$$

$$f_3 = f(f_1 w_{13} + f_2 w_{23} + b_2 w_{b23}) = y$$



$$f = \frac{1}{1 + e^{-x}}$$

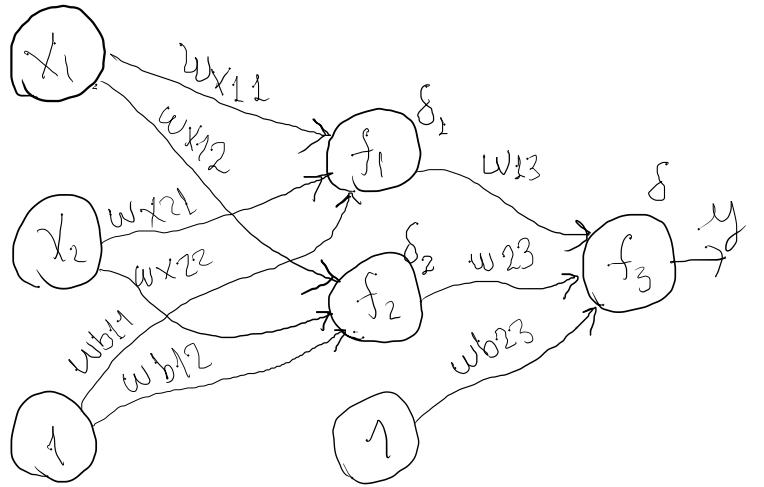
$$b_1 = b_2 = 1$$

x_1	x_2	XOR
1	1	0
1	0	1
0	1	1
0	0	0

rmse = 0.599430972279072
 $[0.8519188807951853, -0.16880249864585717, -0.16423634749611138, 0.8099606911859769]$

```

def rmse(lisX1, lisX2, lisZ):
    sum = 0
    e.clear()
    for i in range(0, len(lisX1)):
        y[i] = calcular_y(x1[i], x2[i])
        e.append(y[i] - z[i])
        print(e[i])
        sum = sum + e[i]*e[i]
    return math.sqrt(sum/len(lisX1))
  
```



$$y_1 = f_1$$

$$y_2 = f_2$$

$$y = f_3$$

$$\delta = \epsilon = z - y$$

$$\delta_1 = \delta w_{13}$$

$$\delta_2 = \delta w_{23}$$

$$w'_{(x1)2} = w_{(x1)2} + \eta \delta_2 \frac{df_2(e)}{de} x_1$$

η = tasa de aprendizaje

$$\left\{ \begin{array}{l} w_{x11} = w_{x11} + \eta \delta_1 f'(x_1) x_1 \\ w_{x12} = w_{x12} + \eta \delta_2 f'(x_1) x_1 \\ w_{x21} = w_{x21} + \eta \delta_1 f'(x_2) x_2 \\ w_{x22} = w_{x22} + \eta \delta_2 f'(x_2) x_2 \\ w_{b11} = w_{b11} + \eta \delta_1 f'(1) (1) \\ w_{b12} = w_{b12} + \eta \delta_2 f'(1) (1) \end{array} \right.$$

$$f(x) = \frac{1}{1 + e^{-x}}$$

$$f'(x) = f(x) - \hat{f}(x)$$

$$\left\{ \begin{array}{l} w_{13} = w_{13} + \eta \delta f'(y_1) y_1 \\ w_{23} = w_{23} + \eta \delta f'(y_2) y_2 \\ w_{b23} = w_{b23} + \eta \delta f'(1) (1) \end{array} \right.$$