

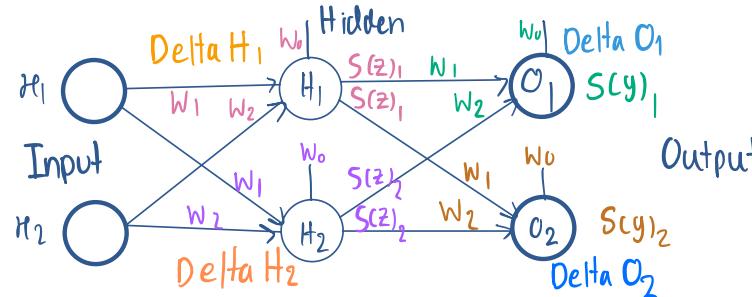
BNN

- Backpropagation Neural Network

output 2 in
target 2 in

1 more
↓
 XOR
(
not Target 1

X0	X1	X2	Target 1		Target 2		H1				H2				O1				O2			
			W0	W1	W0	W1	W2	Z1	S(Z)1	W0	W1	W2	Z2	S(Z)2	W0	W1	W2	Y1	S(Y)1	W0	W1	W2
0	0	0	0.0789	0.0636	0.0923	0.0789	0.5197	0.0964	0.0581	0.0983	0.0964	0.5241	0.0609	0.0727	0.0109	0.1044	0.5261	0.0382	0.0932	0.0485	0.1121	0.528
0	1	1	0.079	0.0636	0.0923	0.1713	0.5427	0.0967	0.0581	0.0983	0.1951	0.5486	0.0215	0.0522	-0.0097	0.0445	0.5111	0.0735	0.1116	0.067	0.1708	0.5426
1	0	1	0.0784	0.0636	0.0916	0.1419	0.5354	0.096	0.0581	0.0976	0.1541	0.5384	0.0582	0.0721	0.0104	0.1024	0.5256	0.0331	0.0897	0.0449	0.1052	0.5263
1	1	0	0.0781	0.0633	0.0916	0.2331	0.558	0.0956	0.0577	0.0976	0.2509	0.5624	0.0936	0.0911	0.0295	0.1611	0.5402	-0.0063	0.0686	0.0237	0.0453	0.5113



$$\eta = 0.3$$

At first iteration
W0, W1, W2
have been randomized

Following iterations

$$W_i \leftarrow W_i + \Delta W_i$$

Underlying Sigmoid Function
Backpropagation
Algorithm

$$Z_1 = w_0 + w_1 H_1 + w_2 H_2$$

$$S(Z)_1 = \frac{1}{1 + e^{-Z_1}}$$

$$Z_2 = w_0 + w_1 H_1 + w_2 H_2$$

$$S(Z)_2 = \frac{1}{1 + e^{-Z_2}}$$

$$Y_1 = w_0 + S(Z)_1 w_1 + S(Z)_2 w_2$$

$$S(Y)_1 = \frac{1}{1 + e^{-Y_1}}$$

$$Y_2 = w_0 + S(Z)_1 w_1 + S(Z)_2 w_2$$

$$S(Y)_2 = \frac{1}{1 + e^{-Y_2}}$$

η	δ	Δ
0.3		
Delta O1	Delta O2	Delta W0 (O1)
-0.131159031	0.117632619	-0.039347709
0.122156205	-0.134664834	-0.020449524
		Delta W1 (O1)
		-0.020621512
		Delta W2 (O1)
		0.035289786
		Delta W0 (O2)
		0.018340567
		Delta W1 (O2)
		0.018494818
		Delta W2 (O2)
		-0.04039945
		-0.021925515
		-0.022163793

$$\delta = (\text{Target} - \text{Output}) \cdot \text{diff sigmoid} = \text{Output} \cdot (1 - \text{Output})$$

$$\Delta O_1 = (\text{Target}_1 - S(Y)_1) \times S(Y)_1 \times (1 - S(Y)_1)$$

$$\Delta O_2 = (\text{Target}_2 - S(Y)_2) \times S(Y)_2 \times (1 - S(Y)_2)$$

$$\Delta W_0(O_1) = \eta \times \Delta O_1 \times 1$$

$$\Delta W_1(O_1) = \eta \times \Delta O_1 \times S(Z)_1$$

$$\Delta W_2(O_1) = \eta \times \Delta O_1 \times S(Z)_2$$

$$\Delta W_0(O_2) = \eta \times \Delta O_2 \times 1$$

$$\Delta W_1(O_2) = \eta \times \Delta O_2 \times S(Z)_1$$

$$\Delta W_2(O_2) = \eta \times \Delta O_2 \times S(Z)_2$$

Delta H1	δ	Delta H2	Δ	Delta W0 (H1)	Delta W1 (H1)	Delta W2 (H1)	Delta W0 (H2)	Delta W1 (H2)	Delta W2 (H2)
0.000358065	0.001067162	0.00010742	0	0	0	0	0.000320149	0	0
-0.002145474	-0.002529187	-0.000643642	0	-0.000643642	-0.000758756	-0.000758756	0	0	-0.000758756

$$\Delta H_1 = (\Delta O_1 \times w_1 + \Delta O_2 \times w_1) \times S(Z)_1 \times (1 - S(Z)_1)$$

$$\Delta H_2 = (\Delta O_1 \times w_2 + \Delta O_2 \times w_2) \times S(Z)_2 \times (1 - S(Z)_2)$$

↳ $\eta \times \Delta H_1 / H_1$

$$\Delta W_0(H_1) = \eta \times \Delta H_1 \times 1$$

$$\Delta W_1(H_1) = \eta \times \Delta H_1 \times w_1$$

$$\Delta W_2(H_1) = \eta \times \Delta H_1 \times w_2$$

$$\Delta W_0(H_2) = \eta \times \Delta H_2 \times 1$$

$$\Delta W_1(H_2) = \eta \times \Delta H_2 \times w_1$$

$$\Delta W_2(H_2) = \eta \times \Delta H_2 \times w_2$$

Backpropagation Algorithm: Operational Summary

Given A training set \mathcal{T} comprising vectors $X_k \in \mathbb{R}^n$
 and desired output vectors $D_k \in \mathbb{R}^p$
 and an $n-q-p$ architecture neural network \mathcal{N}

~~Initial random weight init~~

Initialize \rightsquigarrow Randomize weights w_{ih}^1 to small values, set $\Delta w_{ih}^0 = 0$, $i = 0, \dots, n$; $h = 1, \dots, q$
 \rightsquigarrow Randomize weights w_{hj}^1 to small values, set $\Delta w_{hj}^0 = 0$, $h = 0, \dots, q$; $j = 1, \dots, p$
 \rightsquigarrow Set $k = 1$, η , α , and the error tolerance τ as desired.

Iterate \circlearrowleft Repeat
 {

\rightsquigarrow Select a training pair $(X_k, D_k) \in \mathcal{T}$

forward pass
 ↴

\rightsquigarrow Compute signals on forward pass in the following sequence:

$$\mathcal{S}(x_i^k) = x_i^k, \quad i = 1, \dots, n$$

$$\mathcal{S}(x_0^k) = 1$$

$$z_h^k = \sum_{i=0}^n w_{ih}^k x_i^k, \quad h = 1, \dots, q$$

$$\mathcal{S}(z_h^k) = \frac{1}{1 + \exp(-z_h^k)}, \quad h = 1, \dots, q$$

$$\mathcal{S}(z_0^k) = 1$$

$$y_j^k = \sum_{h=0}^q w_{hj}^k \mathcal{S}(z_h^k), \quad j = 1, \dots, p$$

$$\mathcal{S}(y_j^k) = \frac{1}{1 + \exp(-y_j^k)}, \quad j = 1, \dots, p$$

Hidden

Output

Backpropagation Algorithm: Operational Summary (contd.)

$$b(y) = \frac{1}{1+e^{-y}}$$

$$\frac{d\delta(y)}{dy} = \delta(y)(1-\delta(y))$$

Delta Output

~ Compute deltas/errors at output neurons:

$$\delta_j^k = (d_j^k - S(y_j^k))S'(y_j^k) \quad j = 1, \dots, p$$

$$\Delta w_{hj}^k = \eta \delta_j^k S(x_h^k) z_h \quad h = 0, \dots, q; j = 1, \dots, p$$

(Learning Rate \times delta \times input value)

Delta Hidden

~ Compute deltas/errors at hidden neurons:

$$\delta_h^k = \left(\sum_{j=1}^p \delta_j^k w_{hj}^k \right) S'(z_h^k) \quad h = 1, \dots, q$$

$$\Delta w_{ih}^k = \eta \delta_h^k x_i^k \quad i = 0, \dots, n; h = 1, \dots, q$$

W in hidden
W output

~ Update weights:

$$w_{hj}^{k+1} = w_{hj}^k + \Delta w_{hj}^k + \alpha \Delta w_{hj}^{k-1} \quad h = 0, \dots, q; j = 1, \dots, p$$

$$w_{ih}^{k+1} = w_{ih}^k + \Delta w_{ih}^k + \alpha \Delta w_{ih}^{k-1} \quad i = 0, \dots, n; h = 1, \dots, q$$

~ Collect pattern error \mathcal{E}_k term momentum (backward)

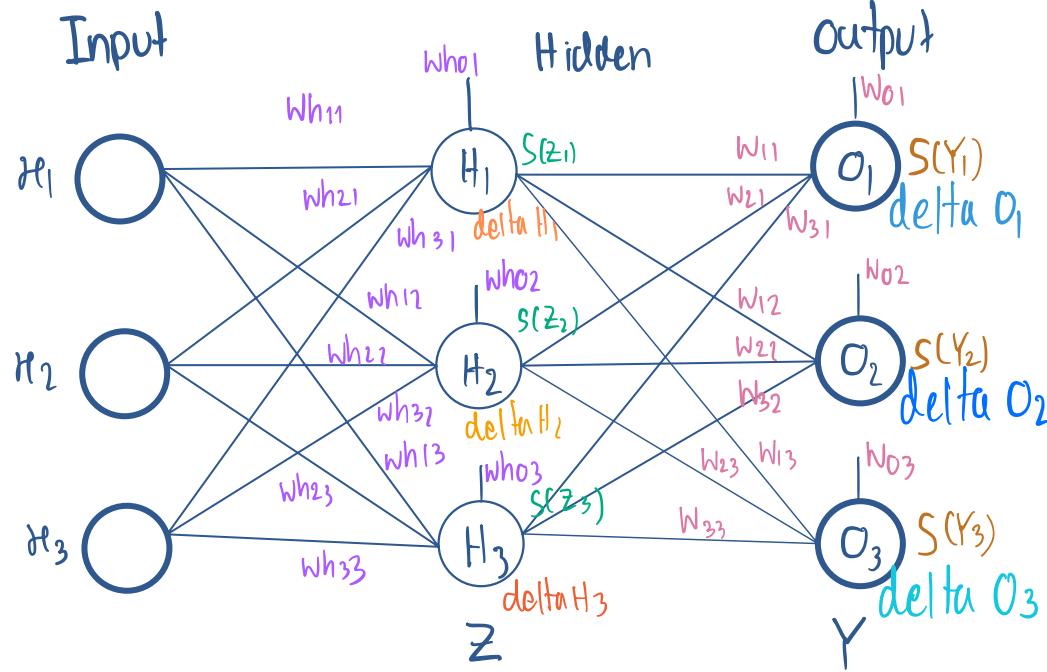
} until ($\mathcal{E}_{av} = \frac{1}{Q} \sum_{k=1}^Q \mathcal{E}_k < \tau$)

q ikh hidden node

p iIH output node

Tradicional
Statistical approach

Learning Rate \times Delta Output \times Input value



$$z_1 = w_{h11} \cdot h_1 + w_{h21} \cdot h_2 + w_{h31} \cdot h_3$$

$$z_2 = w_{h12} \cdot h_1 + w_{h22} \cdot h_2 + w_{h32} \cdot h_3$$

$$z_3 = w_{h13} \cdot h_1 + w_{h23} \cdot h_2 + w_{h33} \cdot h_3$$

$$S(z_1) = \frac{1}{1 + e^{-z_1}} ; S(z_2) = \frac{1}{1 + e^{-z_2}} ; S(z_3) = \frac{1}{1 + e^{-z_3}}$$

$$y_1 = w_{o1} + S(z_1)w_{11} + S(z_2)w_{21} + S(z_3)w_{31}$$

$$y_2 = w_{o2} + S(z_1)w_{12} + S(z_2)w_{22} + S(z_3)w_{32}$$

$$y_3 = w_{o3} + S(z_1)w_{13} + S(z_2)w_{23} + S(z_3)w_{33}$$

$$S(y_1) = \frac{1}{1 + e^{-y_1}} ; S(y_2) = \frac{1}{1 + e^{-y_2}} ; S(y_3) = \frac{1}{1 + e^{-y_3}}$$

δ

$$\delta_{O1} = (\text{target}_1 - S(Y_1)) \times S(Y_1) \times (1 - S(Y_1))$$

$$\delta_{O2} = (\text{target}_2 - S(Y_2)) \times S(Y_2) \times (1 - S(Y_2))$$

$$\delta_{O3} = (\text{target}_3 - S(Y_3)) \times S(Y_3) \times (1 - S(Y_3))$$

Δ

$$\delta_{W_{01}(O_1)} = \eta \times \delta_{O1} \times 1$$

$$\delta_{W_{11}(O_1)} = \eta \times \delta_{O1} \times S(z_1)$$

$$\delta_{W_{21}(O_1)} = \eta \times \delta_{O1} \times S(z_2)$$

$$\delta_{W_{31}(O_1)} = \eta \times \delta_{O1} \times S(z_3)$$

$$\delta_{W_{02}(O_2)} = \eta \times \delta_{O2} \times 1$$

$$\delta_{W_{12}(O_2)} = \eta \times \delta_{O2} \times S(z_1)$$

$$\delta_{W_{22}(O_2)} = \eta \times \delta_{O2} \times S(z_2)$$

$$\delta_{W_{32}(O_2)} = \eta \times \delta_{O2} \times S(z_3)$$

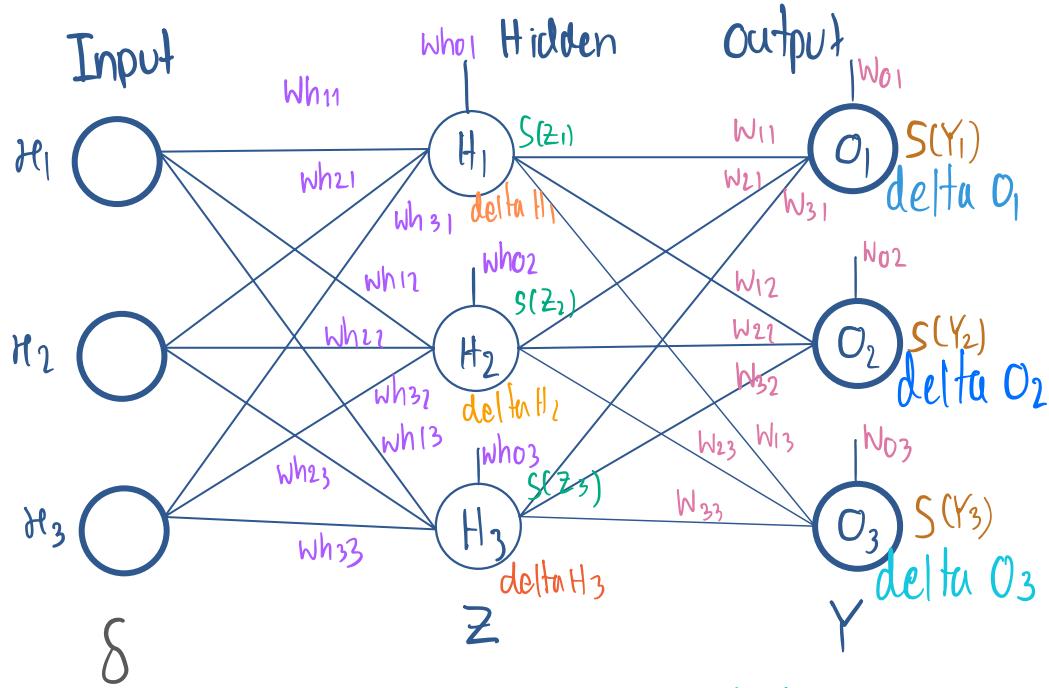
$$\delta_{W_{03}(O_3)} = \eta \times \delta_{O3} \times 1$$

$$\delta_{W_{13}(O_3)} = \eta \times \delta_{O3} \times S(z_1)$$

$$\delta_{W_{23}(O_3)} = \eta \times \delta_{O3} \times S(z_2)$$

$$\delta_{W_{33}(O_3)} = \eta \times \delta_{O3} \times S(z_3)$$

understanding backpropagation
using python



$$\delta = \text{delta } H_1 = (\text{delta } O_1 \times w_{11} + \text{delta } O_2 \times w_{12} + \text{delta } O_3 \times w_{13}) \times S(z_1) \times (1 - S(z_1))$$

$$\delta = \text{delta } H_2 = (\text{delta } O_1 \times w_{21} + \text{delta } O_2 \times w_{22} + \text{delta } O_3 \times w_{23}) \times S(z_2) \times (1 - S(z_2))$$

$$\delta = \text{delta } H_3 = (\text{delta } O_1 \times w_{31} + \text{delta } O_2 \times w_{32} + \text{delta } O_3 \times w_{33}) \times S(z_3) \times (1 - S(z_3))$$

columns

x_0	H_1	H_2	H_3
H_1, H_2, H_3	Target 1	Target 2	Target 3
$w_{01}, w_{11}, w_{21}, w_{31}, Y_1, S(Y_1)$	$w_{02}, w_{12}, w_{22}, w_{32}, Y_2, S(Y_2)$	$w_{03}, w_{13}, w_{23}, w_{33}, Y_3, S(Y_3)$	$\text{delta } O_1, \text{delta } O_2, \text{delta } O_3$
$w_{01}, w_{11}, w_{21}, w_{31}, Y_1, S(Y_1)$	$w_{02}, w_{12}, w_{22}, w_{32}, Y_2, S(Y_2)$	$w_{03}, w_{13}, w_{23}, w_{33}, Y_3, S(Y_3)$	$\text{delta } O_1, \text{delta } O_2, \text{delta } O_3$
$\text{delta } w_{01}(O_1), \text{delta } w_{11}(O_1), \text{delta } w_{21}(O_1), \text{delta } w_{31}(O_1)$	$\text{delta } w_{02}(O_2), \text{delta } w_{12}(O_2), \text{delta } w_{22}(O_2), \text{delta } w_{32}(O_2)$	$\text{delta } w_{03}(O_3), \text{delta } w_{13}(O_3), \text{delta } w_{23}(O_3), \text{delta } w_{33}(O_3)$	$\text{delta } H_1, \text{delta } H_2, \text{delta } H_3$
$\text{delta } w_{01}(H_1), \text{delta } w_{11}(H_1), \text{delta } w_{21}(H_1), \text{delta } w_{31}(H_1)$	$\text{delta } w_{02}(H_2), \text{delta } w_{12}(H_2), \text{delta } w_{22}(H_2), \text{delta } w_{32}(H_2)$	$\text{delta } w_{03}(H_3), \text{delta } w_{13}(H_3), \text{delta } w_{23}(H_3), \text{delta } w_{33}(H_3)$	$\text{delta } H_1, \text{delta } H_2, \text{delta } H_3$

↑
Top Left Submatrix Subgroup

$$\begin{aligned}\text{delta } w_{01}(H_1) &= h \times \text{delta } H_1 \times 1 \\ \text{delta } w_{11}(H_1) &= h \times \text{delta } H_1 \times h_1 \\ \text{delta } w_{21}(H_1) &= h \times \text{delta } H_1 \times h_2 \\ \text{delta } w_{31}(H_1) &= h \times \text{delta } H_1 \times h_3 \\ \\ \text{delta } w_{02}(H_2) &= h \times \text{delta } H_2 \times 1 \\ \text{delta } w_{12}(H_2) &= h \times \text{delta } H_2 \times h_1 \\ \text{delta } w_{22}(H_2) &= h \times \text{delta } H_2 \times h_2 \\ \text{delta } w_{32}(H_2) &= h \times \text{delta } H_2 \times h_3 \\ \\ \text{delta } w_{03}(H_3) &= h \times \text{delta } H_3 \times 1 \\ \text{delta } w_{13}(H_3) &= h \times \text{delta } H_3 \times h_1 \\ \text{delta } w_{23}(H_3) &= h \times \text{delta } H_3 \times h_2 \\ \text{delta } w_{33}(H_3) &= h \times \text{delta } H_3 \times h_3\end{aligned}$$