

Feedforward

Backpropagation



O_{in}
 $\begin{bmatrix} 0.49 & -0.49 & 0.57 \\ 0.43 & -0.45 & 0.55 \\ 0.37 & -0.41 & 0.50 \end{bmatrix}$

O_{out}
 $\begin{bmatrix} 0.62 & 0.38 & 0.64 \\ 0.61 & 0.39 & 0.63 \\ 0.59 & 0.40 & 0.62 \end{bmatrix}$

Y
 $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

W_2
 $\begin{bmatrix} 0.0 & -0.1 & 0.2 \\ 0.6 & -0.5 & 0.5 \end{bmatrix}$

W_2^T
 $\begin{bmatrix} 0.0 & 0.6 \\ -0.1 & -0.5 \\ 0.2 & 0.5 \end{bmatrix}$

H_{out}^T
 $\begin{bmatrix} 0.81 & 0.97 & 0.97 \\ 0.81 & 0.71 & 0.62 \end{bmatrix}$

O_{delta}
 $\begin{bmatrix} -0.09 & 0.09 & 0.15 \\ 0.15 & -0.15 & 0.15 \\ 0.14 & 0.10 & -0.09 \end{bmatrix}$

O_{error}
 $\begin{bmatrix} -0.38 & 0.38 & 0.64 \\ 0.61 & -0.61 & 0.63 \\ 0.59 & 0.40 & -0.38 \end{bmatrix}$

$W_{2-update}$
 $\begin{bmatrix} 0.023 & 0.003 & 0.020 \\ 0.013 & 0.003 & 0.019 \end{bmatrix}$

H_{in}
 $\begin{bmatrix} 1.47 & 1.42 \\ 3.42 & 0.91 \\ 3.62 & 0.47 \end{bmatrix}$

H_{out}
 $\begin{bmatrix} 0.81 & 0.81 \\ 0.97 & 0.71 \\ 0.97 & 0.62 \end{bmatrix}$

W_1
 $\begin{bmatrix} 0.7 & 0.4 \\ -0.8 & 0.0 \\ 0.3 & -0.4 \\ 0.1 & 0.1 \end{bmatrix}$

X^T
 $\begin{bmatrix} 4.9 & 6.4 & 5.8 \\ 3.0 & 3.2 & 2.7 \\ 1.4 & 4.5 & 5.1 \\ 0.2 & 1.5 & 1.9 \end{bmatrix}$

H_{delta}
 $\begin{bmatrix} 0.003 & -0.004 \\ 0.001 & 0.049 \\ -0.001 & -0.003 \end{bmatrix}$

H_{error}
 $\begin{bmatrix} 0.021 & -0.024 \\ 0.045 & 0.240 \\ -0.028 & -0.011 \end{bmatrix}$

$W_{1-update}$
 $\begin{bmatrix} 0.002 & 0.031 \\ 0.001 & 0.015 \\ 0.000 & 0.022 \\ 0.000 & 0.007 \end{bmatrix}$

X
 $\begin{bmatrix} 4.9 & 3.0 & 1.4 & 0.2 \\ 6.4 & 3.2 & 4.5 & 1.5 \\ 5.8 & 2.7 & 5.1 & 1.9 \end{bmatrix}$

x_1 x_2 x_3 x_4

$\frac{\partial MSE}{\partial W_2}(W_2):$

$O_{error} = O_{out} - Y$

$O_{delta} = O_{error} \odot O_{out} \odot (1 - O_{out})$

$W_{2-update} = \frac{1}{N} (H_{out}^T \cdot O_{delta})$

$\frac{\partial MSE}{\partial W_1}(W_1):$

$H_{error} = O_{delta} \cdot W_2^T$

$H_{delta} = H_{error} \odot H_{out} \odot (1 - H_{out})$

$W_{1-update} = \frac{1}{N} (X^T \cdot H_{delta})$

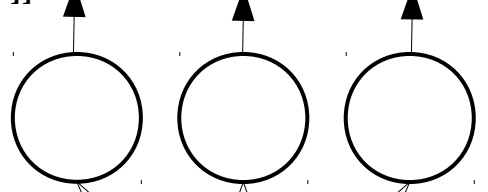
Feedforward

Backpropagation

Y
 $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$
MSE = 0.138

O_{in}
 $\begin{bmatrix} 0.49 & -0.49 & 0.57 \\ 0.43 & -0.45 & 0.55 \\ 0.37 & -0.41 & 0.50 \end{bmatrix}$

O_{out}
 $\begin{bmatrix} 0.62 & 0.38 & 0.64 \\ 0.61 & 0.39 & 0.63 \\ 0.59 & 0.40 & 0.62 \end{bmatrix}$



H_{out}^T
 $\begin{bmatrix} 0.81 & 0.97 & 0.97 \\ 0.81 & 0.71 & 0.62 \end{bmatrix}$

O_{delta}
 $\begin{bmatrix} -0.09 & 0.09 & 0.15 \\ 0.15 & -0.15 & 0.15 \\ 0.14 & 0.10 & -0.09 \end{bmatrix}$

O_{error}
 $\begin{bmatrix} -0.38 & 0.38 & 0.64 \\ 0.61 & -0.61 & 0.63 \\ 0.59 & 0.40 & -0.38 \end{bmatrix}$

W_{2-update}
 $\begin{bmatrix} 0.023 & 0.003 & 0.020 \\ 0.013 & 0.003 & 0.019 \end{bmatrix}$

W₂
 $\begin{bmatrix} 0.0 & -0.1 & 0.2 \\ 0.6 & -0.5 & 0.5 \end{bmatrix}$

W₂^T
 $\begin{bmatrix} 0.0 & 0.6 \\ -0.1 & -0.5 \end{bmatrix}$

H_{in}
 $\begin{bmatrix} 1.47 & 1.42 \\ 3.42 & 0.91 \\ 3.62 & 0.47 \end{bmatrix}$

H_{out}
 $\begin{bmatrix} 0.81 & 0.81 \\ 0.97 & 0.71 \\ 0.97 & 0.62 \end{bmatrix}$

Gradient Descent:

$$W_i := W_i - \alpha \cdot \frac{\partial \text{MSE}}{\partial W_i}(W_i)$$

X^T
 $\begin{bmatrix} 9 & 6.4 & 5.8 \\ 0 & 3.2 & 2.7 \\ 4 & 4.5 & 5.1 \\ 2 & 1.5 & 1.9 \end{bmatrix}$

H_{delta}
 $\begin{bmatrix} 0.003 & -0.004 \\ 0.001 & 0.049 \\ -0.001 & -0.003 \end{bmatrix}$

H_{error}
 $\begin{bmatrix} 0.021 & -0.024 \\ 0.045 & 0.240 \\ -0.028 & -0.011 \end{bmatrix}$

W_{1-update}
 $\begin{bmatrix} 0.002 & 0.031 \\ 0.001 & 0.015 \\ 0.000 & 0.022 \\ 0.000 & 0.007 \end{bmatrix}$

W₁
 $\begin{bmatrix} 0.7 & 0.4 \\ -0.8 & 0.0 \\ 0.3 & -0.4 \\ 0.1 & 0.1 \end{bmatrix}$

X
 $\begin{bmatrix} 4.9 & 3.0 & 1.4 & 0.2 \\ 6.4 & 3.2 & 4.5 & 1.5 \\ 5.8 & 2.7 & 5.1 & 1.9 \end{bmatrix}$

x₁ x₂ x₃ x₄

$\frac{\partial \text{MSE}}{\partial W_2}(W_2):$

- O_{error} = O_{out} - Y
- O_{delta} = O_{error} ⊙ O_{out} ⊙ (1 - O_{out})
- W_{2-update} = $\frac{1}{N}$ (H_{out}^T • O_{delta})

$\frac{\partial \text{MSE}}{\partial W_1}(W_1):$

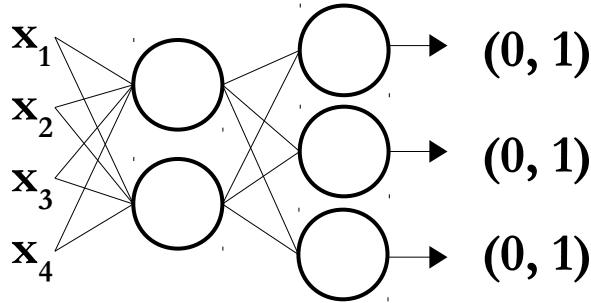
- H_{error} = O_{delta} • W₂^T
- H_{delta} = H_{error} ⊙ H_{out} ⊙ (1 - H_{out})
- W_{1-update} = $\frac{1}{N}$ (X^T • H_{delta})

Deep Learning

How does the algorithm make a decision?



Feedforward



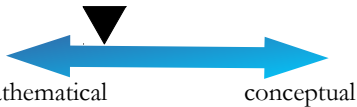
$$H_{in} = XW_1$$

$$H_{out} = \text{sigmoid}(H_{in})$$

$$O_{in} = H_{out} W_2$$

$$O_{out} = \text{sigmoid}(O_{in})$$

How do you determine the right parameters for the algorithm?



Cost function/Loss function:

$$\text{Mean Squared Error} = \frac{1}{2N} \sum_e \sum_n (O_{out,e,n} - Y_{e,n})^2$$

Gradient Descent:

$$W_i := W_i - \alpha \cdot \frac{\partial \text{MSE}}{\partial W_i}(W_i)$$

Chain Rule:

$$\frac{\partial Z}{\partial X} = \frac{\partial Z}{\partial Y} \cdot \frac{\partial Y}{\partial X}$$

Backpropagation

$$\frac{\partial \text{MSE}}{\partial W_1}(W_1) = \frac{\partial \text{MSE}}{\partial O_{out}} \frac{\partial O_{out}}{\partial O_{in}} \frac{\partial O_{in}}{\partial H_{out}} \frac{\partial H_{out}}{\partial H_{in}} \frac{\partial H_{in}}{\partial W_1}$$

$$\frac{\partial \text{MSE}}{\partial W_2}(W_2) = \frac{\partial \text{MSE}}{\partial O_{out}} \frac{\partial O_{out}}{\partial O_{in}} \frac{\partial O_{in}}{\partial W_2}$$