

Sigmoid function:

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

Net:

inputs = [2, 3, 1]

$$w_1 = \begin{bmatrix} 0.5 & 0.3 & -0.1 \\ 0.2 & 0.4 & 0.6 \\ -0.3 & 0.5 & 0.2 \end{bmatrix}$$

$$b_1 = [0.1 \quad 0.2 \quad 0.3]$$

$$w_2 = [0.9 \quad -0.5 \quad 0.4]$$

$$b_2 = 0.3$$

$$\text{actual} = 1$$

First layer: (hidden layer)

$$w_1 = \begin{bmatrix} 0.5 & 0.3 & -0.1 \\ 0.2 & 0.4 & 0.6 \\ -0.3 & 0.5 & 0.2 \end{bmatrix} \quad x = \begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix}$$

← classic matrix multiplication

$$z_1 = \begin{bmatrix} 0.5 & 0.3 & -0.1 \\ 0.2 & 0.4 & 0.6 \\ -0.3 & 0.5 & 0.2 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix} + \begin{bmatrix} 0.1 \\ 0.2 \\ 0.3 \end{bmatrix} = \begin{bmatrix} 1.9 \\ 2.4 \\ 1.4 \end{bmatrix}$$

$$z_1 = \text{np.dot}(w_1, x) + b_1$$

$$h = \sigma(z_1) = \begin{bmatrix} \frac{1}{1+e^{-1.9}} \\ \frac{1}{1+e^{-2.4}} \\ \frac{1}{1+e^{-1.4}} \end{bmatrix} = \begin{bmatrix} 0.86999 \\ 0.916527 \\ 0.402153 \end{bmatrix}$$

← hidden neuron 1
← hidden neuron 2
← hidden neuron 3

hidden layer activation

Second layer:

$$z_2 = w_2 \cdot h = \begin{bmatrix} 0.9 \\ -0.5 \\ 0.4 \end{bmatrix} \cdot \begin{bmatrix} 0.86999 \\ 0.916527 \\ 0.402153 \end{bmatrix} + [0.3] = 0.554 + 0.3 = 0.853$$

← predicted value

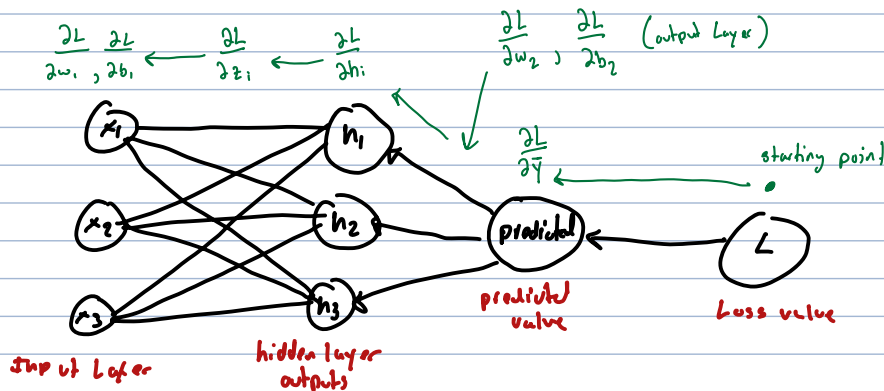
$$\text{predicted} = 0.853$$

$$\text{loss} = (1 - 0.853)^2 = 0.02006$$

Back propagation

We must move backward:

$$\text{let predicted} = \bar{y}, \text{ actual} = y$$



$$\bar{y} = w_{21}h_1 + w_{22}h_2 + w_{23}h_3 + b_2$$

$$\frac{\partial \bar{y}}{\partial h} = w$$

First output layer:

$$① \frac{\partial L}{\partial \bar{y}} = -2(y - \bar{y}) \quad ③ \frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial \bar{y}}$$

$$② \frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \bar{y}} \cdot h$$

Next, hidden layer:

$$④ \frac{\partial L}{\partial h} = \frac{\partial L}{\partial \bar{y}} \cdot \frac{\partial \bar{y}}{\partial h_i} = \frac{\partial L}{\partial \bar{y}} \cdot w_2$$

$$⑤ \frac{\partial L}{\partial z_i} = \frac{\partial L}{\partial h} \cdot \frac{\partial h}{\partial z_i} \quad \frac{\partial h}{\partial z} = \sigma'(z)$$
$$= \frac{\partial L}{\partial h} \cdot \sigma'(z)$$

$$⑥ \frac{\partial L}{\partial u_i} = \frac{\partial L}{\partial z_i} \cdot \frac{\partial z_i}{\partial u_i} = \frac{\partial L}{\partial z_i} \cdot x$$

$$z_i = w_1 x + b$$
$$\frac{\partial z_i}{\partial w_1} = x$$
$$\frac{\partial z_i}{\partial b_1} = 1$$

$$⑦ \frac{\partial L}{\partial b_i} = \frac{\partial L}{\partial z_i} \cdot \frac{\partial z_i}{\partial b_i} = \frac{\partial L}{\partial z_i}$$

After calculation of gradients:

$$\begin{aligned} w_1^{new} &= w_1 - \alpha \frac{\partial L}{\partial w_1} \\ b_1^{new} &= b_1 - \alpha \frac{\partial L}{\partial b_1} \\ w_2^{new} &= w_2 - \alpha \frac{\partial L}{\partial w_2} \\ b_2^{new} &= b_2 - \alpha \frac{\partial L}{\partial b_2} \end{aligned} \quad \left. \vphantom{\begin{aligned} w_1^{new} &= w_1 - \alpha \frac{\partial L}{\partial w_1} \\ b_1^{new} &= b_1 - \alpha \frac{\partial L}{\partial b_1} \\ w_2^{new} &= w_2 - \alpha \frac{\partial L}{\partial w_2} \\ b_2^{new} &= b_2 - \alpha \frac{\partial L}{\partial b_2} \end{aligned}} \right\} \text{Hidden Layer}$$

α : learning rate