

Statistical Data Analysis

Exercise 2

December 12, 2022

Here we can define the following variables for each $L \in \{I, H, O\}$, where I stands for the input layer, H stands for the hidden layer and O stands for the output layer. For the index $k \in \mathbb{N}$ the following is assumed $0 \leq k \leq N_L$.

N_L is the number of neurons in layer L .

w_{ji}^L is the weight in layer L for neuron j with the incoming neuron i .

$O_k^{L'}$ is the output of the k -th neuron in layer $L' \in \{H, O\}$ which is produced by the perceptron with the activation function:

$$O_k^{L'} = \text{sig}(x_k^{L'})$$

$x_k^{L'}$ is the input of the k -th neuron in layer $L' \in \{H, O\}$. If $(L-1)$ represents the previous layer, then:

$$x_k^{L'} = \sum_{n=1}^{N_L} w_{nk}^L O_n^{(L-1)} + b_k^O$$

$\text{sig}(x)$ is the sigmoid function of x . It is the activation function for every neuron in the hidden and output layer.

t_k is the k -th target value

b_k^L is the bias of the k -th neuron in layer L

Here ...

$$O_k = \text{sig}(x_k) \tag{1}$$

Where ...

$$x_k = \sum_{l=1}^{N_O} w_{lk}^O O_l^H + b_k \tag{2}$$

And ...

$$\frac{\delta}{\delta w_{ji}^O} \text{sig}(x_k) = \text{sig}(x_k)(1 - \text{sig}(x_k)) \frac{\delta}{\delta w_{ji}^O}(x_k) \tag{3}$$

Because of (1) only O_i is influenced by w_{ji} , so,

$$\frac{\delta}{\delta w_{ji}^O} \sum_{k=1}^{N_O} (O_k - t_k)^2 = 2(O_i - t_i) \frac{\delta}{\delta w_{ji}^O}(O_i - t_i) = 2(O_i - t_i) \frac{\delta}{\delta w_{ji}^O} O_i \tag{4}$$

Because we are looking at a weight w_{ji}^H of the hidden layer, every O_k is influenced by w_{ji}^H , therefore (also (4)):

$$\frac{\delta}{\delta w_{ji}^O} \sum_{k=1}^{N_O} (O_k - t_k)^2 = 2 \sum_{l=1}^{N_O} (O_k - t_k) \frac{\delta}{\delta w_{ji}^O} (O_k) \quad (5)$$

Only O_i^H is influenced by w_{ji}^H because:

$$O_i^H = \text{sig}(x_i^H) \text{ with } x_i^H = \sum_{k=1}^{N_H} w_{li}^O O_l^H + b_i^O \quad (6)$$

Also, the following holds:

$$\frac{\delta O_i^H}{\delta w_{ji}^H} = \text{sig}(x_i^H)(1 - \text{sig}(x_i^H)) \frac{\delta}{\delta w_{ji}^H} \sum_{j=1}^{N_H} (O_j^I w_{ji}^H + b_j) = \text{sig}(x_i^H)(1 - \text{sig}(x_i^H)) O_j^I \quad (7)$$

..... [Because $\forall l \neq j : \frac{\delta}{\delta w_{ji}^O} w_{lk}^O \cdot O_l^H + b_k^O = 0$]

Now, we have to **determine** $\frac{\delta E}{\delta w_{ji}^H}$

$$\begin{aligned} \frac{\delta E}{\delta w_{ji}^H} &= \frac{\delta}{\delta w_{ji}^H} \frac{1}{2} \sum_{k \in N_O} (O_k - t_k)^2 \\ &= \sum_{k \in N_O} (O_k - t_k) * \frac{\delta}{\delta w_{ji}^H} O_k && \langle \text{from (5)} \rangle \\ &= \sum_{k \in N_O} (O_k - t_k) * \frac{\delta}{\delta w_{ji}^H} \text{sig}(x_k) && \langle \text{from (1)} \rangle \\ &= \sum_{k \in N_O} (O_k - t_k) * \text{sig}(x_k) * (1 - \text{sig}(x_k)) * \frac{\delta}{\delta w_{ji}^H} \sum_{l=1}^{N_H} w_{lk}^O O_l^H + b_k^O && \langle \text{from (2) and (3)} \rangle \\ &= \sum_{k \in N_O} (O_k - t_k) * \text{sig}(x_k) * (1 - \text{sig}(x_k)) * w_{ik}^O \frac{\delta}{\delta w_{ji}^H} O_i^H && \langle \text{from (6)} \rangle \\ &= \sum_{k \in N_O} (O_k - t_k) * \text{sig}(x_k) * (1 - \text{sig}(x_k)) * w_{ik} * \text{sig}(x_i^H) * (1 - \text{sig}(x_i^H)) * O_j^I && \langle \text{from (7)} \rangle \end{aligned}$$