

Note

Exercise-2

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

N_L = the number of neurons in layer L

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

O_k^L = the output of the k -th neuron in layer $L \in \{H, O\}$

which is produced by perception with the activation function $O_k^L = \text{sig}(x_k^L)$

x_k^L = the input of the k -th neuron in layer $L \in \{H, O\}$

$$x_k^L = \sum_{n=1}^{N_{L-1}} w_{nk}^{L-1} O_n^{L-1} + b_k \text{ with } (L-1) \text{ representing}$$

the previous layer

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

t_k = the k -th target value

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

$$\frac{\delta E}{\delta \omega_{ji}^H} = \frac{\delta}{\delta \omega_{ji}^H} \frac{1}{2} \sum_{k \in N_o} (O_k - t_k)^2$$

$$\stackrel{(1)}{=} \sum_{k \in N_o} (O_k - t_k) * \frac{\delta}{\delta \omega_{ji}^H} O_k$$

$$= \sum_{k \in N_o} (O_k - t_k) * \frac{\delta}{\delta \omega_{ji}^H} \text{sig}(x_k) \left[\because O_k = \text{sig}(x_k) \right]$$

$$= \sum_{k \in N_o} (O_k - t_k) * \text{sig}(x_k) * (1 - \text{sig}(x_k)) * \frac{\delta}{\delta \omega_{ji}^H} \sum_{l=1}^{N_H} \omega_{lk} O_l^H + b_k$$

$$\left[x_k = \sum_{l=1}^{N_H} \omega_{lk} \cdot O_l^H + b_k \text{ and} \right.$$

$$\left. \frac{\delta}{\delta \omega_{ji}^H} \text{sig}(x_k) = \text{sig}(x_k) (1 - \text{sig}(x_k)) \cdot \frac{\delta}{\delta \omega_{ji}^H} (x_k) \right]$$

$$\stackrel{(2)}{=} \sum_{k \in N_o} (O_k - t_k) * \text{sig}(x_k) * (1 - \text{sig}(x_k)) * \omega_{ik} \frac{\delta}{\delta \omega_{ji}^H} O_i^H$$

$$\stackrel{(3)}{=} \sum_{k \in N_o} (O_k - t_k) * \text{sig}(x_k) * (1 - \text{sig}(x_k)) * \omega_{ik} * \text{sig}(x_i^H) * (1 - \text{sig}(x_i^H)) * O_j^I$$

The following properties explain the equation -
 Because we are looking at a weight w_{ji}^H of the hidden layer, every O_k is influenced by w_{ji}^H , therefore

$$\frac{\delta}{\delta w_{ji}} \sum_{k \in N_o} (O_k - t_k)^2 = 2 (O_i - t_i) \frac{\delta}{\delta w_{ji}} (O_i - t_i)$$

$$= 2 (O_i - t_i) \frac{\delta}{\delta w_{ji}} O_i$$

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

only O_i^H is influenced by w_{ji}^H because

$$O_i^H = \text{sig}(\chi_i^H) \text{ with } \chi_i^H = \sum_{k \in N_H} w_{ki} O_k^H + b_i \quad (2)$$

Equivalent to $\frac{\delta \chi_k}{\delta w_{ji}} = \frac{\delta}{\delta w_{ji}} \sum_{l=1}^{N_o} w_{lk} O_l^H + b_k = O_j^H$

the following holds

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

$$= \text{sig}(\chi_i^H) (1 - \text{sig}(\chi_i^H)) O_j^I \quad (3)$$