

Task 1.

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We can give z_k into the expression for \hat{y} from 2):

$$\begin{aligned}\hat{y} &= w_0^{(2)} + \sum_{k=1}^K w_k^{(2)} (w_{0k}^{(1)} + \sum_{n=1}^N w_{nk}^{(1)} x_n) \\ &= (w_0^{(2)} + \sum_{k=1}^K w_k^{(2)} w_{0k}^{(1)}) + \sum_{n=1}^N (\sum_{k=1}^K w_k^{(2)} w_{nk}^{(1)}) x_n\end{aligned}$$

We define new biases $v_0 = w_0^{(2)} + \sum_{k=1}^K w_k^{(2)} w_{0k}^{(1)}$ and new weights $v_n = \sum_{k=1}^K w_k^{(2)} w_{nk}^{(1)}$

Therefore, the output \hat{y} of the MLP without hidden layers is: $\hat{y} = v_0 + \sum_{n=1}^N v_n x_n$

Task 2.

$$a) \quad a_k = w_{0k}^{(1)} + \sum_{n=1}^N w_{nk}^{(1)} x_n$$

$$b) \quad \hat{y}_j = w_{0j}^{(2)} + \sum_{k=1}^K w_{kj}^{(2)} z_k = w_{0j}^{(2)} + \sum_{k=1}^K w_{kj}^{(2)} \cdot \tanh(a_k)$$

Task 3.

$$E_n = \frac{1}{2} \sum_{j=1}^J (\hat{y}_j - y_j)^2$$

a)

$$\frac{\partial E_n}{\partial w_{kj}^{(2)}} = \frac{\partial E_n}{\partial \hat{y}_j} \cdot \frac{\partial \hat{y}_j}{\partial w_{kj}^{(2)}} = \frac{1}{2} \cdot 2 \cdot (\hat{y}_j - y_j) \cdot \tanh(a_k)$$

$$\begin{aligned}b) \quad \frac{\partial E_n}{\partial w_{nk}^{(1)}} &= \frac{\partial E_n}{\partial \hat{y}_j} \cdot \frac{\partial \hat{y}_j}{\partial z_k} \cdot \frac{\partial z_k}{\partial a_k} \cdot \frac{\partial a_k}{\partial w_{nk}^{(1)}} \\ &= \sum_{j=1}^J (\hat{y}_j - y_j) \cdot w_{kj}^{(2)} \cdot (1 - \tanh^2(a_k)) \cdot x_n\end{aligned}$$