Matrizen in Neuronalen Netzwerken

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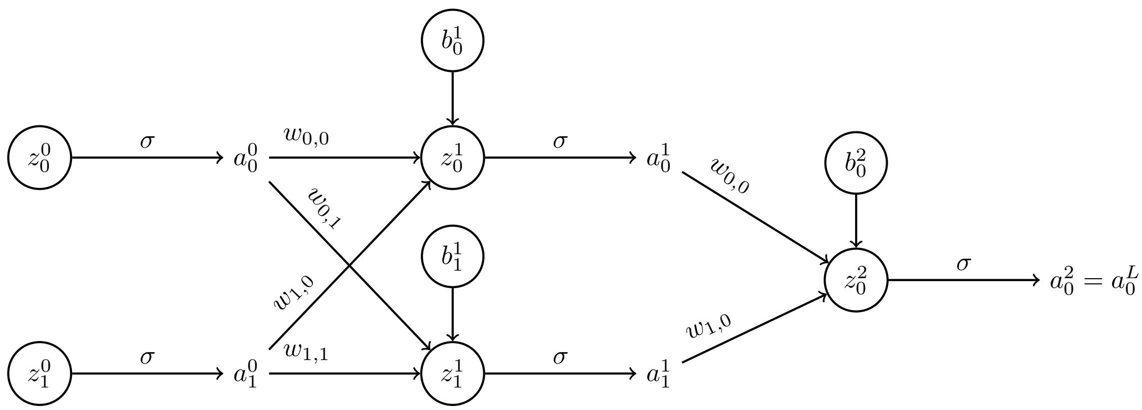
1 Feed-Forward

1.1 Grafik



1.2 Formeln

$$z_0^1 = a_0^0 \cdot w_{0,0} + a_1^0 \cdot w_{1,0} + b^1$$

allgemein:

$$z_0^1 = b^1 + \sum_{j=0}^{n^1} a_j^0 \cdot w_{j,0}$$

$$a_j^l = \sigma(z_j^l)$$

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

1.3 Matrizendarstellung

$$\vec{z}^l = \begin{pmatrix} z_0^l \\ z_1^l \\ ... \\ z_j^l \end{pmatrix} \qquad \vec{a}^l = \begin{pmatrix} a_0^l \\ a_1^l \\ ... \\ a_j^l \end{pmatrix} \qquad \vec{b}^l = \begin{pmatrix} b_0^l \\ b_1^l \\ ... \\ b_j^l \end{pmatrix} \qquad W^l = \begin{pmatrix} w_{0,0}^l & w_{1,0}^l & ... & w_{j,0}^l \\ w_{0,1}^l & w_{1,1}^l & ... & w_{j,1}^l \\ ... & ... & ... & ... \\ w_{0,i}^l & w_{1,i}^l & ... & w_{j,i}^l \end{pmatrix}$$

$$\vec{a}^l = \vec{z}^{l-1} \cdot W^l + \vec{b}^l$$

$$\begin{pmatrix} a_0^l \\ a_1^l \\ ... \\ a_j^l \end{pmatrix} = \begin{pmatrix} z_0^{l-1} \\ z_1^{l-1} \\ ... \\ z_j^{l-1} \end{pmatrix} \cdot \begin{pmatrix} w_{0,0}^l & w_{1,0}^l & ... & w_{j,0}^l \\ w_{0,1}^l & w_{1,1}^l & ... & w_{j,1}^l \\ ... & ... & ... & ... \\ w_{0,i}^l & w_{1,i}^l & ... & w_{j,i}^l \end{pmatrix} + \begin{pmatrix} b_0^l \\ b_1^l \\ ... \\ b_j^l \end{pmatrix}$$

$$\begin{pmatrix} a_0^l \\ a_1^l \\ ... \\ a_j^l \end{pmatrix} = \begin{pmatrix} w_{0,0}^l \cdot z_0^{l-1} + w_{1,0}^l \cdot z_1^{l-1} + ... + w_{j,0}^l \cdot z_j^{l-1} \\ w_{0,1}^l \cdot z_0^{l-1} + w_{1,1}^l \cdot z_1^{l-1} + ... + w_{j,1}^l \cdot z_j^{l-1} \\ ... \\ w_{0,i}^l \cdot z_0^{l-1} + w_{1,i}^l \cdot z_1^{l-1} + ... + w_{j,i}^l \cdot z_j^{l-1} \end{pmatrix} + \begin{pmatrix} b_0^l \\ b_1^l \\ ... \\ b_j^l \end{pmatrix}$$

2 Backpropagation

2.1 Verlustfunktion

$$E_j = \frac{1}{2}(y_j - a_j^L)^2$$

$$E = \frac{1}{2}\sum_j (y_j - a_j^L)^2$$

$$\frac{dE_j}{da_j^L} = (a_j^L - y_j)$$

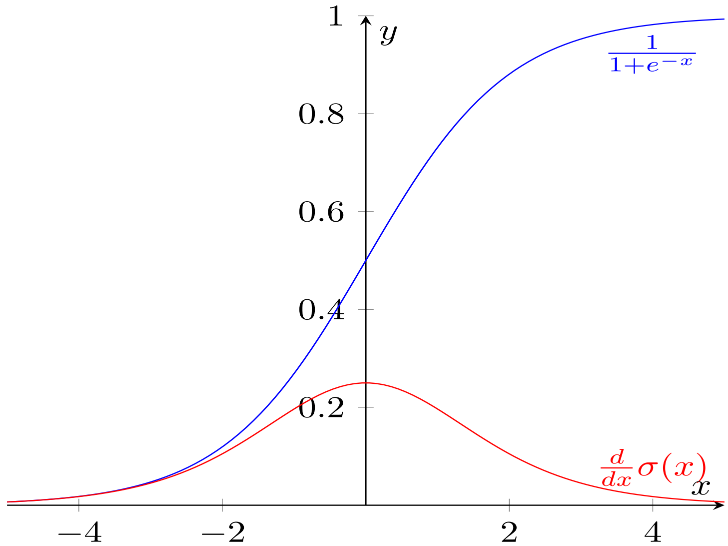
2.2 Ableitung der sigmoid Funktion

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

$$\frac{d}{dx}\sigma(x) = \frac{0(\cdot 1 + e^{-x}) - 1 \cdot e^{-x} \cdot -1}{(1+e^{-x})^2} = \frac{e^{-x}}{(1+e^{-x})^2} = \frac{1+e^{-x}-1}{(1+e^{-x})^2}$$

$$= \frac{1+e^{-x}}{(1+e^{-x})^2} - \frac{1}{(1+e^{-x})^2} = \frac{1}{1+e^{-x}} - \frac{1}{(1+e^{-x})^2}$$

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



2.3 Fehler(δ)

-Zwischenwert zur leichteren Berechnung des Gradienten

$$\delta_j^l = \frac{\partial E}{\partial z_j^l} \qquad \frac{\partial E}{\partial w_{j,i}^l} = \delta_i^l \cdot a_j^{l-1} \qquad \frac{\partial E}{\partial b_j^l} = \delta_j^l$$

Berechnung des Fehlers des letzten Layers durch Anwendung der Kettenregel:

$$\delta_j^L = \frac{\partial E}{\partial z_j^L} = \frac{\partial E}{\partial a_j^L} \cdot \frac{\partial a_j^L}{\partial z_j^L}$$

Einsetzen der Ableitungen:

$$= \frac{\partial E}{\partial a_j^L} \cdot \sigma(z_j^L) \cdot (1 - \sigma(z_j^L))$$

$$= (a_j^L - y_j) \cdot \sigma(z_j^L) \cdot (1 - \sigma(z_j^L))$$

Berechnung des Fehlers des vorletzten Layers:

$$\delta_j^{L-1} = \frac{\partial E}{\partial z_j^{L-1}} = \frac{\partial E}{\partial a_j^{L-1}} \cdot \frac{\partial a_j^{L-1}}{\partial z_j^{L-1}}$$

$$\frac{\partial a_j^{L-1}}{\partial z_j^{L-1}} = \sigma'(z_j^{L-1})$$

$$\frac{\partial E}{\partial a_j^{L-1}} = \sum_{i=0}^{n^L} \frac{\partial E}{\partial z_i^L} \cdot \frac{\partial z_i^L}{\partial a_j^{L-1}} = \sum_{i=0}^{n^L} \delta_i^L \cdot \frac{\partial z_i^L}{\partial a_j^{L-1}}$$

$$\frac{\partial z_i^L}{\partial a_j^{L-1}} = \frac{\partial}{\partial a_j^{L-1}} (\sum_{p=0}^{n^L} a_p^{L-1} \cdot w_{p,i}^L + b_p^L) = w_{j,i}^L$$

$$\frac{\partial E}{\partial a_j^{L-1}} = \sum_{i=0}^{n^L} \delta_j^L \cdot w_{j,i}^L$$

Zusammenführen der Einzelergebnisse:

$$\delta_j^l = [\sum_{i=0}^{n^l+1} \delta_j^l + 1 \cdot w_{j,i}^l + 1] \cdot \sigma'(z_j^l)$$

Allgemein:

$$\delta_j^l = [\sum_{i=0}^{n^{l+1}} \delta_j^{l+1} \cdot w_{j,i}^{l+1}] \cdot \sigma'(z_j^l)$$