Layer

input :
$$x \in \mathbb{R}^m \to Wx + b \in \mathbb{R}^n$$

 $\to f(Wx + b) \in \mathbb{R}^n$: output (1)

Network

input:
$$x_1 \rightarrow y_1 = f_1(W_1x_1 + b_1)$$
 (2)

$$x_2 = y_1 \rightarrow y_2 = f_2(W_2x_2 + b_2)$$
 (3)

:

$$x_N = y_{N-1} \rightarrow y_N = f_N(W_N x_N + b_N)$$
: output (4)

Training

Training data: a collection of pairs (x, y_{true})

Loss function:
$$L = \frac{1}{N_{\text{samples}}} \sum_{x \in \text{samples}} ||y_N(x) - y_{\text{true}}||^2 \quad \text{(for example)} \quad (5)$$

Parameters repeatedly updated according to

$$W \to W - r \frac{\partial L}{\partial W} \Big|_{\text{batch}}$$
 (6)

$$b \rightarrow b - r \frac{\partial L}{\partial b} \Big|_{\text{batch}}$$
 (7)

where "batch" is a randomly selected subset of the training data.

Gradient

Let λ_n denote a parameter (W or b) in the n-th layer. Then

$$\frac{\partial L}{\partial \lambda_n} = \frac{\partial L}{\partial y_N^i} \frac{\partial y_N^i}{\partial x_N^j} \frac{\partial y_{N-1}^j}{\partial x_{N-1}^k} \cdots \frac{\partial y_n^l}{\partial \lambda_n}$$
 (8)

and introducing the notation

$$(J_{f_m})^i_j := \frac{\partial f_m^i(x)}{\partial x^j} \bigg|_{x = W_m x_m + b_m} \tag{9}$$

the derivatives in Eq. (8) are given by

$$\frac{\partial y_m^i}{\partial x_m^j} = (J_{f_m})^i_{\ k} (W_m)^k_{\ j} \tag{10}$$

$$\frac{\partial y_n^i}{\partial (W_n)^j_k} = (J_{f_n})^i_{\ j} x_n^k \tag{11}$$

$$\frac{\partial y_n^i}{\partial b_n^j} = (J_{f_n})_j^i \tag{12}$$