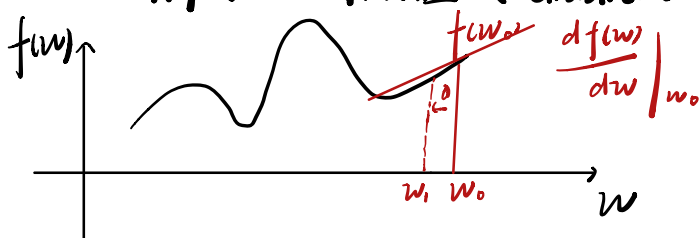


反向传播算法 (Back Propagation)

梯度下降法求局部极值 (Gradient Descent Method)



① 找一个 w_0 .

② 设 $k=0$, 假设 $\frac{df(w)}{dw} \Big|_{w_k} = 0$ 退出

否则: $w_{k+1} = w_k - a \frac{df(w)}{dw} \Big|_{w_k}$

原因如下:

泰勒展开:

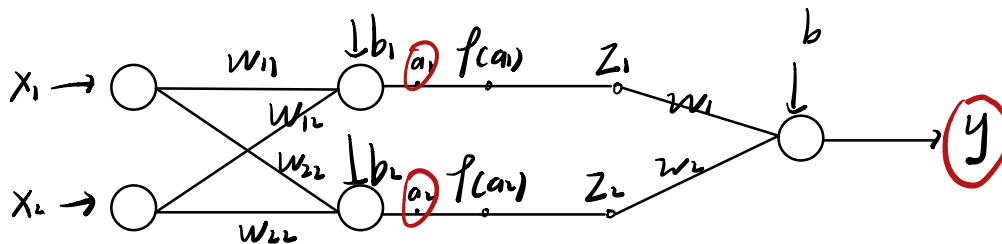
$$f(w + \Delta w) = f(w) + \frac{df(w)}{dw} \Big|_w \cdot \Delta w + o(\Delta w)$$

$$\begin{aligned} f(w_{k+1}) &= f\left(w_k - a \frac{df(w)}{dw} \Big|_{w_k}\right) \\ &= f(w_k) + \frac{df(w)}{dw} \Big|_{w_k} \cdot \left(-a \frac{df(w)}{dw} \Big|_{w_k}\right) \\ &\quad + o(\Delta w) \end{aligned}$$

$$= f(w_k) - \underbrace{a}_{>0} \underbrace{\left[\frac{df(w)}{dw} \Big|_{w_k}\right]^2}_{>0} + \underbrace{o(\Delta w)}_{\rightarrow 0}$$

$$< f(w_k)$$

BP:



输入: $\{(x_i, y_i) \mid i=1, \dots, N\}$

针对输入 (x, y)

定义 $E = \frac{1}{2} (y - \hat{y})^2$

① 随机取 $(w_{11}, w_{12}, w_{21}, w_{22}, b_1, b_2, w_1, w_2, b)$

② 对所有 w : 求 $\frac{\partial E}{\partial w}$ BP?

b : 求 $\frac{\partial E}{\partial b}$

③ $w^{(\text{新})} = w^{(\text{旧})} - \alpha \frac{\partial E}{\partial w}$
 $b^{(\text{新})} = b^{(\text{旧})} - \alpha \frac{\partial E}{\partial b}$

④ 当所有 $\frac{\partial E}{\partial w} / \frac{\partial E}{\partial b}$ 都为 0 时 退出

$$a_1 = w_{11}x_1 + w_{12}x_2 + b_1$$

$$a_2 = w_{21}x_1 + w_{22}x_2 + b_2$$

$$z_1 = f(a_1)$$

$$z_2 = f(a_2)$$

$$\hat{y} = w_1 z_1 + w_2 z_2 + b$$

$$\frac{dE}{dy} = (y - \hat{y})$$

$$\begin{aligned}\frac{\partial E}{\partial a_1} &= \frac{dE}{dy} \cdot \frac{\partial y}{\partial z_1} \cdot \frac{dz_1}{da_1} \\ &= (y - \hat{y}) w_1 \cdot f'(a_1)\end{aligned}$$

$$\begin{aligned}\frac{\partial E}{\partial a_2} &= \frac{dE}{dy} \cdot \frac{\partial y}{\partial z_2} \cdot \frac{dz_2}{da_2} \\ &= (y - \hat{y}) w_2 f'(a_2)\end{aligned}$$

$$\frac{\partial E}{\partial b} = \frac{dE}{dy} \cdot \frac{\partial y}{\partial b} = (y - \hat{y})$$

$$\frac{\partial E}{\partial w_1} = \frac{dE}{dy} \cdot \frac{\partial y}{\partial w_1} = (y - \hat{y}) z_1$$

$$\frac{\partial E}{\partial w_2} = \frac{dE}{dy} \cdot \frac{\partial y}{\partial w_2} = (y - \hat{y}) z_2$$

$$\frac{\partial E}{\partial w_{11}} = \frac{\partial E}{\partial a_1} \cdot \frac{\partial a_1}{\partial w_{11}} = (y - \hat{y}) w_1 f'(a_1) x_1$$

$$\frac{\partial E}{\partial w_{12}} = \frac{\partial E}{\partial a_1} \cdot \frac{\partial a_1}{\partial w_{12}} = (y - \hat{y}) w_1 f'(a_1) x_2$$

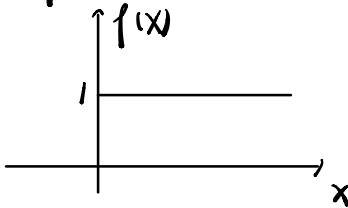
$$\frac{\partial E}{\partial b_1} = (y - \hat{y}) w_1 f'(a_1)$$

$$\frac{\partial E}{\partial w_{21}} = (y - \hat{y}) w_2 f'(a_2) x_1$$

$$\frac{\partial E}{\partial w_{22}} = (y - \hat{y}) w_2 f'(a_2) x_2$$

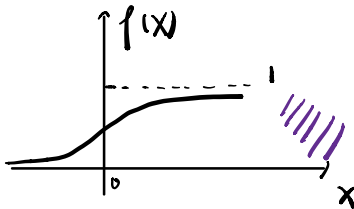
$$\frac{\partial E}{\partial b_2} = (y-1)w_2 f'(a_2)$$

若 $f(x)$ 取阶跃函数



$$f'(x) = 0$$

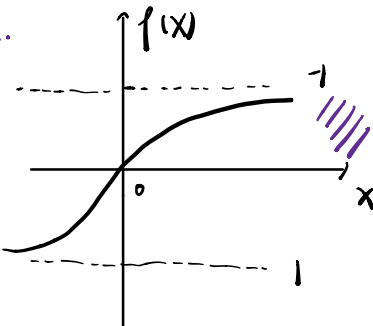
1.



$$f(x) = \frac{1}{1 + e^{-x}} \quad (\text{Sigmoid})$$

$$f'(x) = f(x) [1 - f(x)]$$

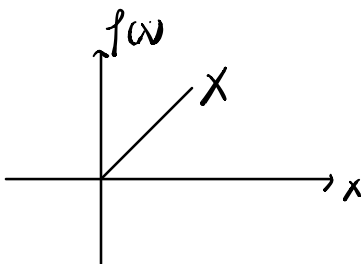
2.



$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$f'(x) = 1 - [f(x)]^2$$

3.



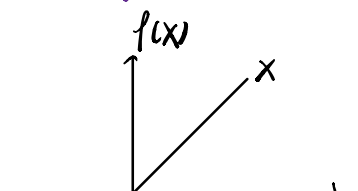
ReLU(x)

Rectified Linear Units

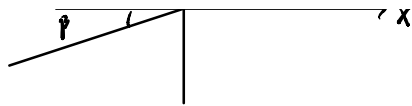
$$f(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases} = \max(x, 0)$$

$$f'(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$$

4.



$$f(x) = \begin{cases} x & x > 0 \\ \lambda x & x \leq 0 \end{cases}$$



$$f'(x) = \begin{cases} 1 & x > 0 \\ \beta & x \leq 0 \end{cases}$$

Leak $\text{ReLU}(x)$