

$$1) h^{(1)} = W^{(1)} x + b^{(1)}$$

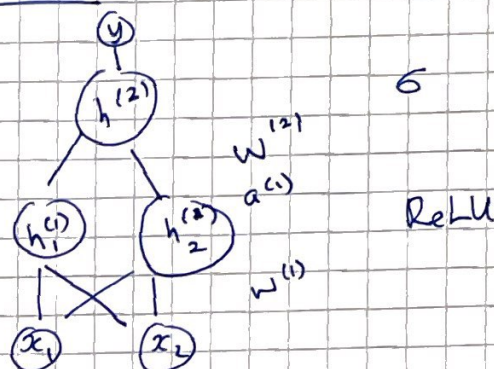
$$a^{(1)} = \text{ReLU}(h^{(1)})$$

$$h^{(2)} = (W^{(2)})^T a^{(1)} + b^{(2)}$$

$$y = \sigma(h^{(2)})$$

$$J = \frac{1}{2} (t - y)^2$$

Find  $\frac{\partial J}{\partial W_{1,2}^{(1)}}$



$$\frac{\partial J}{\partial W^{(1)}} = \frac{\partial J}{\partial y} \frac{\partial y}{\partial h^{(2)}} \frac{\partial h^{(2)}}{\partial a^{(1)}} \frac{\partial a^{(1)}}{\partial h^{(1)}} \frac{\partial h^{(1)}}{\partial W^{(1)}}$$

①      ②      ③      ④      ⑤

$$① \frac{\partial J}{\partial y} = -(t - y)$$

$$② \frac{\partial y}{\partial h^{(2)}} = \sigma(h^{(2)}) (1 - \sigma(h^{(2)}))$$

$$③ \frac{\partial h^{(2)}}{\partial a^{(1)}} = W^{(2)T}$$

$$④ h^{(1)} = \begin{bmatrix} 0.75 & 0.5 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0.5 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0.75 + 0.25 \\ -1 + 0.5 \end{bmatrix} = \begin{bmatrix} 1 \\ -0.5 \end{bmatrix}$$

Dimensions

$$① J, y, \frac{\partial J}{\partial y} : 1 \times 1$$

$$② h^{(2)} \text{ is } \mathbb{R}, \frac{\partial y}{\partial h} : 1 \times 1$$

$$③ a^{(1)} : 2 \times 1, \frac{\partial h^{(2)}}{\partial a^{(1)}} = 1 \times 2$$

$$④ \overset{a^{(1)}}{2} \times \overset{h^{(2)}}{(2 \times 1)} \Rightarrow 2 \times 2$$

$$⑤ \overset{h^{(1)}}{2} \times \overset{W}{(2 \times 2)}.$$

$$\text{ReLU}^{(x)} = \max\{0, x\}$$

$$\frac{\partial a^{(1)}}{\partial h^{(1)}} = \begin{bmatrix} \begin{cases} 1 & \text{if } h_1^{(1)} \geq 0 \\ 0 & \text{else} \end{cases} \\ \begin{cases} 1 & \text{if } h_2^{(1)} \geq 0 \\ 0 & \text{else} \end{cases} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Not  
2x2



$$(4) \frac{\partial a^{(1)}}{\partial h^{(1)}} = \begin{bmatrix} \frac{\partial a_1^{(1)}}{\partial h_1^{(1)}} & \frac{\partial a_1^{(1)}}{\partial h_2^{(1)}} \\ \frac{\partial a_2^{(1)}}{\partial h_1^{(1)}} & \frac{\partial a_2^{(1)}}{\partial h_2^{(1)}} \end{bmatrix}$$

Since  $h_1 = \begin{bmatrix} 1 \\ -0.5 \end{bmatrix}$

$$= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$

$$(5) \frac{\partial h^{(1)}}{\partial w^{(1)}} = \begin{bmatrix} \frac{\partial h_1^{(1)}}{\partial w^{(1)}} \\ \frac{\partial h_2^{(1)}}{\partial w^{(1)}} \end{bmatrix}$$

$\nwarrow 2 \times 2$   
 $\nearrow 2 \times 2$

$\therefore$  We see that  $\frac{\partial a^{(1)}}{\partial h^{(1)}}$  has 0's everywhere except first element, only need to find  $\frac{\partial h_1^{(1)}}{\partial w^{(1)}}$

~~$$\frac{\partial h^{(1)}}{\partial w^{(1)}}$$~~

$$h^{(1)} = \begin{bmatrix} w_{1,1}^{(1)} & w_{1,2}^{(1)} \\ w_{2,1}^{(1)} & w_{2,2}^{(1)} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$= \begin{bmatrix} w_{1,1}^{(1)} x_1 + w_{1,2}^{(1)} x_2 \\ w_{2,1}^{(1)} x_1 + w_{2,2}^{(1)} x_2 \end{bmatrix} = \begin{bmatrix} h_1^{(1)} \\ h_2^{(1)} \end{bmatrix}$$

$$\frac{\partial h_1^{(1)}}{\partial w^{(1)}} = \begin{bmatrix} x_1 & x_2 \\ 0 & 0 \end{bmatrix}$$

$$\frac{\partial h_1^{(1)}}{\partial w_{2,1}^{(1)}} = 0$$

Now that gradients are computed, just sum:

abuse  
of  
notation

$$\frac{\partial J}{\partial W^{(1)}} = -(t-y) \sigma(h^2) (1-\sigma(h^2)) W^{(2)T} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \\ 0 & 0 \end{bmatrix}$$

$$h^{(2)} = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + (-1) = 0$$

$$\sigma(0) = 0.5$$

$$t = 1, y = \sigma(0) = 0.5$$

$$\frac{\partial J}{\partial W^{(1)}} = -(0.5) \frac{1}{2} (1 - \frac{1}{2}) \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \\ 0 & 0 \end{bmatrix}$$

$$W^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$x = \begin{bmatrix} 1 \\ 0.5 \end{bmatrix}$$

$$= -\frac{1}{8} \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \\ 0 & 0 \end{bmatrix}$$

$$= -\frac{1}{8} \begin{bmatrix} x_1 & x_2 \\ 0 & 0 \end{bmatrix}$$

$$\Rightarrow \frac{\partial J}{\partial W_{1,2}^{(1)}} = -\frac{1}{8} x_2 = -\frac{1}{8} \cdot 0.5 = -\frac{1}{16}$$

$$= 0.125/2 = 0.0625$$

Question 2

$$E(v, h) = -b^T v - c^T h - v^T W h$$

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

$$p(x|\theta) = ? \quad \frac{\partial \log p(x|\theta)}{\partial c_z} = \sum_{i=1}^n \sigma(c_z + v_i^T W_{:,z})$$

$$- \sum_v p(v) \sigma(c_z + v^T W_{:,z})$$