

$$f(x) = w_2^T \pi(w_1^T x)$$

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

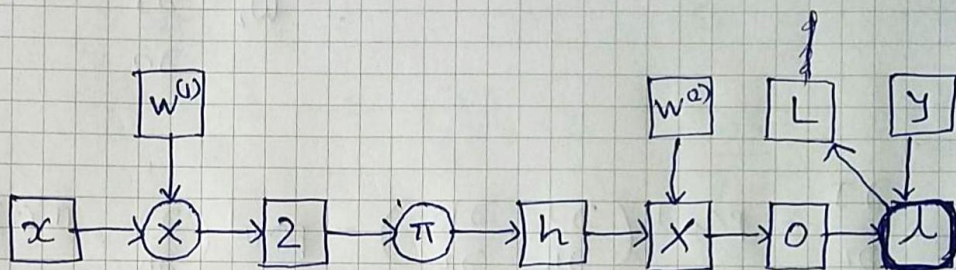
$$\lambda = \frac{1}{2} (y - f(x))^2, \quad \hat{y} = f(x)$$

$$\lambda = \frac{1}{2} (y - \hat{y})^2$$

$$z = w_1^T x, \quad h = \pi(z)$$

$$o = w_2^T h$$

a)



* Computational graph *

b) ^{a)} gradient matrix σ_1 of λ with respect to w_1 .

$$\sigma_1 = \frac{\partial L}{\partial w_1} \quad J = L \quad \frac{\partial J}{\partial L} = 1$$

$$\frac{\partial J}{\partial o} = \text{prod} \left(\frac{\partial J}{\partial L}, \frac{\partial L}{\partial o} \right) = \frac{\partial L}{\partial o}$$

$$f(x) = o = \hat{y} \quad \frac{\partial L}{\partial \hat{y}} = \frac{\partial}{\partial \hat{y}} \frac{1}{2} (y - \hat{y})^2 = -(y - \hat{y})$$

$$\frac{\partial J}{\partial w_2} = \text{prod} \left(\frac{\partial J}{\partial o}, \frac{\partial o}{\partial w_2} \right)$$

$$\frac{\partial}{\partial w_2} w_2^T h = h^T$$

$$= \text{prod} \left(\frac{\partial J}{\partial o}, h^T \right) = \frac{\partial J}{\partial o} h^T$$

$$\sigma_2 = \cancel{w_2} h^T (y - \hat{y})$$

— (c)

$$\frac{\partial J}{\partial h} = \text{prod} \left(\frac{\partial J}{\partial o}, \frac{\partial o}{\partial h} \right) = \text{prod} \left(\frac{\partial J}{\partial o}, w_2 \right)$$

$$= w_2^T \frac{\partial J}{\partial o}$$

$$\frac{\partial J}{\partial z} = \text{prod} \left(\frac{\partial J}{\partial h}, \frac{\partial h}{\partial z} \right) = \text{prod} \left(\frac{\partial J}{\partial h}, \pi'(z) \right)$$

$$= \frac{\partial J}{\partial h} \odot \pi'(z)$$

$$\pi'(z) = \frac{e^{-z}}{(1 + e^{-z})^2}$$

$$\frac{\partial J}{\partial w_1} = \text{prod} \left(\frac{\partial J}{\partial z}, \frac{\partial z}{\partial w_1} \right) = \text{prod} \left(\frac{\partial J}{\partial z}, x \right)$$

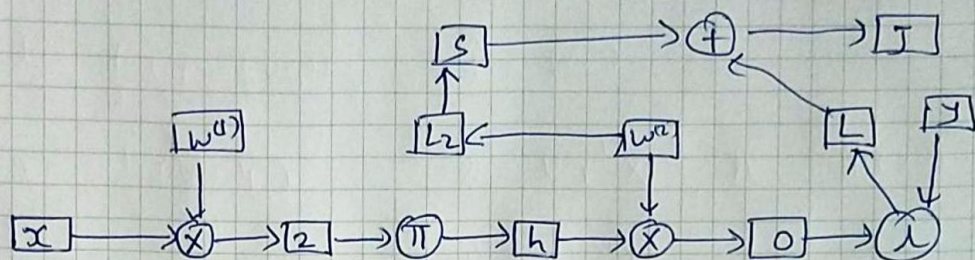
$$\sigma_1 = \frac{\partial J}{\partial z} x^T$$

$$\sigma_1 = \frac{\partial J}{\partial w_1} = \left[w_2^T (-(y - \hat{y}) \odot \pi'(z)) \right] x^T$$

— (b)

D) gradient with L_2 regularization on w_2 .

$$L = J + \|w_2\|_2^2$$



* Computational graph with L_2 *

$$J = S + L$$

$$S = \frac{\lambda}{2} (\|w^{(2)}\|_2^2)$$

$$\tilde{g}_L = \frac{\partial J}{\partial w_2}$$

$$\frac{\partial J}{\partial L} = 1$$

$$\frac{\partial J}{\partial S} = 1$$

$$\frac{\partial S}{\partial w^{(2)}} = \lambda w^{(2)}$$

$$\tilde{g}_2 = g_2 + \frac{\partial S}{\partial w^{(2)}}$$

(prev.
calculated
 g_L grad)

$$\tilde{g}_2 = -(y - \hat{y}) h^T + \lambda w^{(2)}$$