

11

Mohamed Ehab Fathy

2002597

1) a) - First layer

$$y_1 = w_1^T x + b_1 = \begin{bmatrix} 2 & 2 \\ 1 & -1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} 9 \\ -2 \\ 5 \end{bmatrix}$$

- Second layer

$$y_2 = w_2^T y_1 + b_2 = [3 \ 1 \ 2] \begin{bmatrix} 9 \\ -2 \\ 5 \end{bmatrix} + 1 = 36$$

② using relu : $a_1 = \begin{bmatrix} 9 \\ 0 \\ 5 \end{bmatrix}$

$$y_2 = [3 \ 1 \ 2] \begin{bmatrix} 9 \\ 0 \\ 5 \end{bmatrix} + 1 = 38$$

$$a_2 = 38$$

③

$$y = w_2^T (\overbrace{w_1^T x + b_1}^{y_1}) + b_2, \quad J = (\hat{y} - y)^2$$

$$* \frac{\partial J}{\partial b_1} = \frac{\partial J}{\partial y} * \frac{\partial y}{\partial b_1}$$

$$= 2(\hat{y} - y) * 1 = 2 * (32 - 36) = -8$$

$$* \frac{\partial J}{\partial w_{21}^2} = \frac{\partial J}{\partial y} * \frac{\partial y}{\partial w_{21}^2} = 2 * (\hat{y} - y) * y_2$$

$$= 2 * -4 * -2 = 16$$

[2]

$$\times \frac{\partial J}{\partial b_2'} = \frac{\partial J}{\partial y} \times \frac{\partial y}{\partial y_2'} \times \frac{\partial y_2'}{\partial b_2'}$$

$$= 2 \times (\hat{y} - y) \times w_{21}^2 \times 1$$

$$= 2 \times (-4) \times 1 \times 1 = -8$$

$$\times \frac{\partial J}{\partial w_{13}^{[1]}} = \frac{\partial J}{\partial y^2} \times \frac{\partial y^2}{\partial y_3'} \times \frac{\partial y_3'}{\partial w_{13}^{[1]}}$$

$$= 2 (\hat{y} - y) \times w_{31}^2 \times x_1 = 2 \times -4 \times 2 \times 1$$

$$= -16$$

$$1) d) \times b_2'(t+1) = b_2'(t) - 2 \times \frac{\partial J}{\partial b_2'}$$

$$= 1 - 2 \times -8 = 17$$

$$\times w_{13}^{[1]} = 3 - 2 \times -16 = 35$$

e) yes, because using a sample that's not used to train the model is a good indicator of out-of-sample error

3

2

$$\begin{aligned} \text{(a)} \quad \frac{\partial F}{\partial x_1} &= \frac{\partial F}{\partial g_1} * \frac{\partial g_1}{\partial x_1} + \frac{\partial F}{\partial g_2} * \frac{\partial g_2}{\partial x_1} \\ &= \cos g_1 * e^{x_2} + 2g_2 * 1 \end{aligned}$$

$$\begin{aligned} \text{(b)} \quad \frac{\partial F}{\partial x_2} &= \frac{\partial F}{\partial g_1} * \frac{\partial g_1}{\partial x_2} + \frac{\partial F}{\partial g_2} * \frac{\partial g_2}{\partial x_2} \\ &= \cos g_1 * x_1 e^{x_2} + 2g_2 * 2x_2 \end{aligned}$$

$$\begin{aligned} \text{(3)} \quad \text{(1-)} \quad \frac{\partial F}{\partial z} &= \frac{e^{-z}}{(1+e^{-z})^2} = \frac{1}{1+e^{-z}} \left(1 - \frac{1}{1+e^{-z}} \right) \\ &= F(z)(1-F(z)) \end{aligned}$$

$$\text{(2)} \quad \text{let } z = w^T x$$

$$\frac{\partial F}{\partial w} = \frac{\partial F}{\partial z} * \frac{\partial z}{\partial w} = F(w)(1-F(w)) * x$$

$$\text{(3)} \quad \frac{\partial J(w)}{\partial w} = \frac{1}{2} \sum_{i=1}^m \frac{|w^T x^i - y^i|}{w^T x^i - y^i} * x^i$$

$$(4) \quad \frac{\partial J(w)}{\partial w} = \frac{1}{2} \sum_{i=1}^m 2(w^T x^i - y^i) \cdot x^i + 2\lambda w$$

$$(5) \quad \text{let } z_i = w^T x^i$$

$$\text{let } \sigma(z) = \frac{1}{1 + e^{-z}}$$

$$J(z) = \sum_{i=1}^m \left[y^i \log(\sigma(z_i)) + (1 - y^i) \log(1 - \sigma(z_i)) \right]$$

$$\frac{\partial J}{\partial w} = \frac{\partial J}{\partial \sigma} * \frac{\partial \sigma}{\partial z} * \frac{\partial z}{\partial w}$$

$$= \sum_{i=1}^m \left[\frac{y_i}{\sigma(z_i) \ln(10)} + \frac{(1 - y_i)}{(1 - \sigma(z_i)) \ln(10)} \right] * \sigma(z_i) (1 - \sigma(z_i)) * x^i$$

$$6) \quad \frac{\partial f(w)}{\partial w} = (1 - \tanh^2[w^T x]) x$$