

## Assignment-2

(Q-1) Linear regression:

Loss function,  $L = \frac{1}{2} (y - \hat{y})^2$

Out system:

Input (2 features)  $\rightarrow$  1 hidden layer  $\rightarrow$  1 output.

$y \rightarrow$  Target

$\hat{y} \rightarrow$  Prediction

output:  $a_2 = \hat{y}$

Backward propagation:

Output Layer:

Chain rule:

$$\frac{\partial L}{\partial \omega_2} = \frac{\partial L}{\partial a_2} \frac{\partial a_2}{\partial z_2} \frac{\partial z_2}{\partial \omega_2}$$

$$\frac{\partial L}{\partial a_2} = (y - a_2) (-1)$$

$$\frac{\partial a_2}{\partial z_2} = 1$$

$$\frac{\partial z_2}{\partial \omega_2} = a_1$$

$$\frac{\partial L}{\partial \omega_2} = \boxed{(a_2 - y)} \cdot a_1$$

$$\frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial a_2} \frac{\partial a_2}{\partial z_2} \frac{\partial z_2}{\partial b_2}$$

$$\frac{\partial L}{\partial a_2} = (y - a_2) (-1)$$

$$\frac{\partial a_2}{\partial z_2} = 1$$

$$\frac{\partial z_2}{\partial b_2} = 1$$

$$\frac{\partial L}{\partial b_2} = \boxed{(a_2 - y)}$$

hidden Layer:

Similarly,

$$\frac{\partial L}{\partial \omega_1} = \frac{\partial L}{\partial a_2} \frac{\partial a_2}{\partial z_2} \frac{\partial z_2}{\partial a_1} \frac{\partial a_1}{\partial z_1} \frac{\partial z_1}{\partial \omega_1}$$

$$= \boxed{(a_2 - y)} \cdot \omega_2 \cdot a_1 \cdot (1 - a_1) \cdot x$$

$$\frac{\partial L}{\partial b_1} = \boxed{(a_2 - y)} \cdot \omega_2 \cdot a_1 \cdot (1 - a_1) \cdot 1$$

Forward passes:

$$a_2 = g(z_2) = \hat{y}$$

$$z_2 = \omega_2 a_1 + b_2$$

$$a_1 = g(z_1) = \frac{1}{1 + e^{-z_1}}$$

$$z_1 = \omega_1 x + b_1$$

$$g'(z_1) = g(z_1)(1 - g(z_1))$$

Binary classification:

output sigmoid  
 $a_2 \neq \hat{y} \Rightarrow a_2 = \sigma(z_2)$

Loss function,  $L = - [y \times \log(\hat{y}) + (1-y) \times \log(1-\hat{y})]$

$$\frac{\partial L}{\partial \omega_2} = \frac{\partial L}{\partial a_2} \frac{\partial a_2}{\partial z_2} \frac{\partial z_2}{\partial \omega_2}$$

$$\frac{\partial L}{\partial a_2} = -\frac{y}{a_2} - \frac{(1-y)(-1)}{1-a_2} = \frac{a_2 - y}{a_2(1-a_2)}$$

$$\frac{\partial a_2}{\partial z_2} = a_2(1-a_2)$$

$$\begin{aligned} \frac{\partial L}{\partial \omega_2} &= \frac{a_2 - y}{a_2(1-a_2)} \cdot \cancel{a_2} \cdot a_2 \cdot (1-a_2) \cdot a_1 \\ &= (a_2 - y) \cdot a_1^T \end{aligned}$$

F.P.

$$\begin{aligned} a_2 &= g(z_2) \\ &= \frac{1}{1+e^{-z_2}} \end{aligned}$$

$$z_2 = \omega_2 a_1 + b_2$$

$$\begin{aligned} a_1 &= g(z_1) \\ &= \frac{1}{1+e^{-z_1}} \end{aligned}$$

$$\begin{aligned} z_1 &= \omega_1 x + b_1 \\ g'(z_1) &= g(z_1)(1-g(z_1)) \end{aligned}$$

Similarly,  $\frac{\partial L}{\partial b_2} = (a_2 - y)$

$$\frac{\partial L}{\partial \omega_1} = (a_2 - y) \omega_2 a_1 (1-a_1) x$$

$$\frac{\partial L}{\partial b_1} = (a_2 - y) \cdot \omega_1 \cdot a_1 (1-a_1) \cdot 1$$

The main difference for the update rule for regression & <sup>binary</sup>classification is the loss function (Mean Square Error & log loss) and the activation function in output layer (Linear & sigmoid). Each pair provides the same update for both cases. So we can update rule for this given system we have same