

Input layer Hidden layer !

Hidde layer 2

Feedbrund:

A1 = Ji(Zi) ; where J1 = actichu, fuction

$$A_2 = g_2(Z_2)$$

 $Az = g_2(Z_2)$; where $g_2 = activation$ Romation

$$Z_3 = A_2 \cdot W_3 + b_3$$

$$A_2 = 93(Z_1) = 4$$

 $A_3 = g_3(Z_3) = \hat{y}$; where $g_3 = achieation Anchion$

gilgz -> ReLU actuator

g3 -> Sigmoid activation

Loss: Cross-entropy,
$$L = -\frac{1}{m} \sum_{i=0}^{m} (y^{(i)} \log (\hat{y}^{(i)}) + (-y^{(i)} \log (1-\hat{y}^{(i)}))$$

$$\frac{\partial L}{\partial \hat{g}} = \frac{-9}{9} + \frac{1-9}{1-\hat{g}}$$

Activation functions:

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

$$\frac{d\sigma(x)}{dx} = \frac{d}{dx} \left(\frac{1}{1+e^{-x}} \right) = -(1+e^{-x})^{-2} (-e^{-x})$$

$$= \frac{e^{-x}}{(1+e^{-x})^{2}}$$

$$= \frac{1}{1+e^{-x}} \cdot \frac{e^{-x}}{1+e^{-x}}$$

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

$$= \frac{1}{1+e^{-x}} \cdot \left(1 - \frac{1}{1+e^{-x}} \right)$$

$$= \sigma(x) \cdot (1 - \sigma(x))$$

Backpropegation:

$$\frac{\partial L}{\partial z_{3}} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial g}{\partial z_{3}} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial g}{\partial z_{3}}$$

$$= \left(\frac{-y}{\hat{y}} + \frac{1-y}{1-\hat{y}}\right) \cdot \left(\hat{g}(1-\hat{y})\right)$$

$$= \frac{-y(1-\hat{y}) + (1-y)\hat{y}}{\hat{g}(1-\hat{y})} \cdot \hat{g}(1-\hat{y})$$

$$= \hat{y} + y \cdot y + \hat{y} - y \cdot \hat{y}$$

$$= \hat{y} - y$$

$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial z_3} \cdot \frac{\partial z_3}{\partial w_3} = \frac{\partial L}{\partial z_3} \cdot \frac{\partial (A_8 \cdot w_3 + b_3)}{\partial w_3}$$

$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial z_3} \cdot \frac{\partial (A_8 \cdot w_3 + b_3)}{\partial w_3}$$

$$\frac{\partial L}{\partial b_3} = \frac{\partial L}{\partial z_3} \cdot \frac{\partial z_3}{\partial b_3} = \frac{9-9}{3} \cdot \frac{\partial z_3}{\partial b_3} = 1$$

$$\frac{\partial L}{\partial A_2} = \frac{\partial L}{\partial A_2$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial z_2} \cdot \frac{\partial Z_2}{\partial w_2} = \frac{\partial L}{\partial z_2} \cdot A_1$$

$$\frac{\partial L}{\partial z} = \frac{\partial L}{\partial A_1} \cdot \frac{\partial A_1}{\partial z_1} = \frac{\partial L}{\partial A_2} \cdot \frac{\partial z_2}{\partial A_1} \cdot \frac{\partial A_1}{\partial z_1}$$

$$= \frac{\partial L}{\partial z_2} \cdot \frac{\partial z_2}{\partial A_1} \cdot \frac{\partial A_1}{\partial z_1}$$

$$= \frac{\partial L}{\partial z_2} \cdot \frac{\partial z_2}{\partial A_1} \cdot \frac{\partial A_1}{\partial z_1}$$

Update parameters:
$$\theta := \theta - \alpha \frac{\partial L}{\partial v}$$
; where $x = learning$ rate

 $w_3 = w_3 - \alpha \frac{\partial L}{\partial w_3}$
 $w_4 = w_2 - \alpha \frac{\partial L}{\partial w_2}$
 $w_5 = b_3 - \alpha \frac{\partial L}{\partial b_2}$
 $w_6 = b_1 - \alpha \frac{\partial L}{\partial b_1}$
 $w_8 = b_1 - \alpha \frac{\partial L}{\partial b_2}$