

points:

if weight matrix  $W$  is initialized too large, the output of the matrix multiply too could probably have a very large range, which in turn will make all the outputs in the vector  $z$  almost binary either '1' or '0'.

1. sigmoid,  $\sigma(z) = \frac{1}{1+e^{-z}}$

2. local gradient, is a derivative that measures how much the output of the sigmoid function changes with respect to its input  $z$ .

$$\sigma'(z) = \frac{d}{dz} \left( \frac{1}{1+e^{-z}} \right)$$

$$f(g(z)); \text{ where } f(u) = \frac{1}{u}, g(z) = 1 + e^{-z}$$

$$f'(u) = -\frac{1}{u^2} \quad g'(z) = \frac{d}{dz} (1 + e^{-z}) = -e^{-z}$$

$$\frac{d\sigma(z)}{dz} = f'(g(z)) \cdot g'(z) = -\frac{1}{(1+e^{-z})^2} \cdot (-e^{-z})$$

$$\frac{d\sigma(z)}{dz} = \frac{-e^{-z}}{(1+e^{-z})^2}$$

$$\text{we know, } \sigma(2) = \frac{1}{1+e^{-2}}$$

or written as, Subtract the sigmoid from 1.

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

$$\text{Express 1 with common denominator, } 1 = \frac{1+e^{-2}}{1+e^{-2}}$$

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

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

$$= \boxed{\frac{d\sigma(2)}{dz} = \sigma(2) \times (1-\sigma(2))}$$

If  $\sigma(2)$  is close to 1 or 0, the term  $\sigma(2) \times (1-\sigma(2))$  becomes very small approaching to zero.

In;

→ Back propagation, gradients are propagated backward through the network by multiplying them together (as per the chain rule)

→ If local gradient is small, when you multiply it with other gradients in the backward pass, the overall gradient becomes effectively zero.

→ This causes the entire backward pass to have nearly zero gradients, preventing the network from learning.

ReLU (Non-linear) activation function.

$$\text{ReLU}(z) = \max(0, z) \quad \begin{cases} z & \text{if } z > 0 \\ 0 & \text{if } z \leq 0 \end{cases}$$

$z = \text{np.maximum}(0, \text{np.dot}(w, x))$  #forward pass

$dW = \text{np.outer}(z > 0, x)$  #representing backward pass:  
 ↓ which elements in  $z$  are greater than zero that pass through ReLU  
 (how much each weight should be adjusted) local gradient for  $w$ .

Calculates dot product between weight matrix ' $w$ ' and input vector ' $x$ '.

→ if any negative value it return '0'.

→  $\text{np.outer}(z > 0, x)$ : Outer product ( $z > 0$ ) (a vector of 'True' or 'False') and the input vector  $x$ .

The outer product is used to determine how much each weight ' $w$ ' should be adjusted based on the input ' $x$ ' and the result ' $z$ '.

Chain Rule:  $F(x) = f(g(x))$  for all  $x$ ,

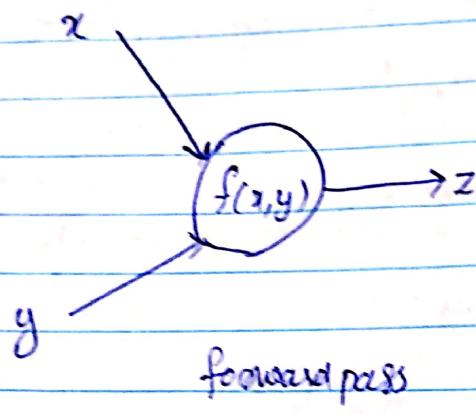
$$F'(x) = f'(g(x)) \cdot g'(x)$$

Leibniz notation,  $\frac{dz}{dx} = \frac{dz}{dy} \cdot \frac{dy}{dx}$   $z$  dependent on  $y$   
 $y \parallel$  on  $x$

Sigmoid function:-  $z = \frac{1}{1 + \text{np.exp}(-\text{np.dot}(w, x))}$  #forward pass

Computes the gradient of  $z$  w.r.t input  $x$ ;  $dz = \text{np.dot}(w.T, z * (1 - z))$  #backward pass  
 local gradient of sigmoid function

output  $z$  w.r.t gradients  $w$ ,  $dW = \text{np.outer}(z * (1 - z), x)$  #backward pass,  
 local gradient  $w$



forward pass

$$\frac{dL}{dx} = \frac{dL}{dz} \frac{dz}{dx}$$

$$\frac{dL}{dy} = \frac{dL}{dz} \frac{dz}{dy}$$



backward pass

$$\frac{dL}{dz}$$