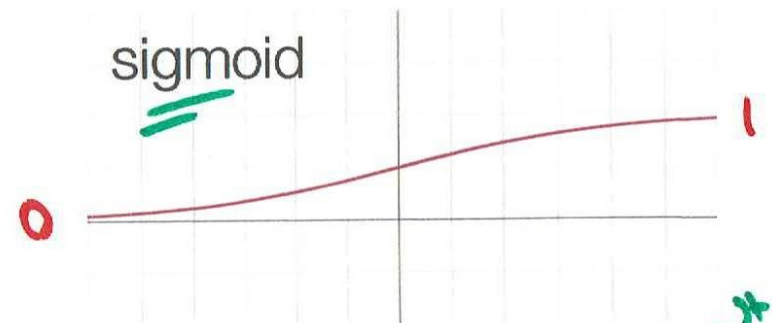
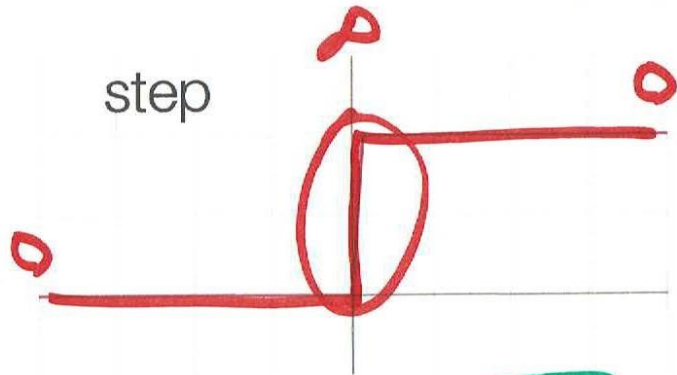
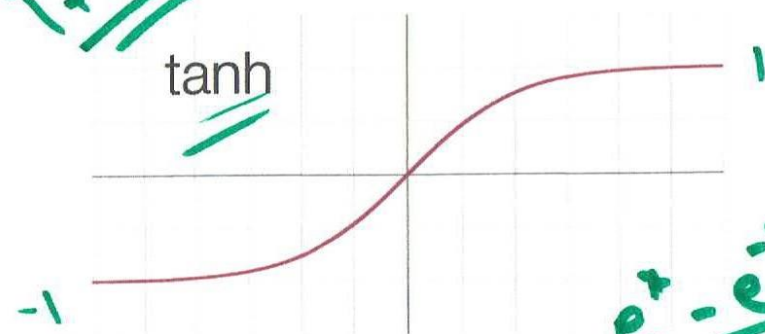
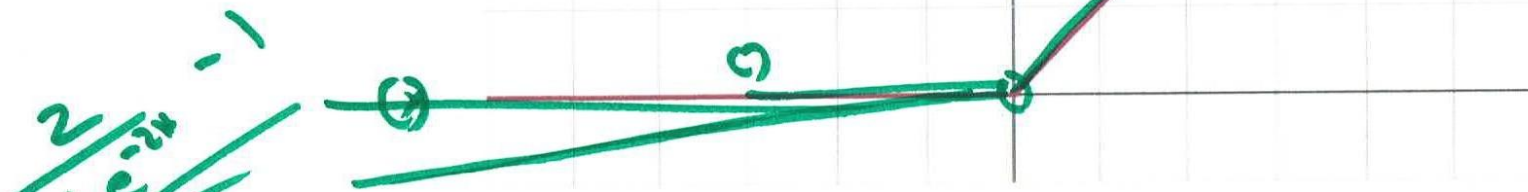


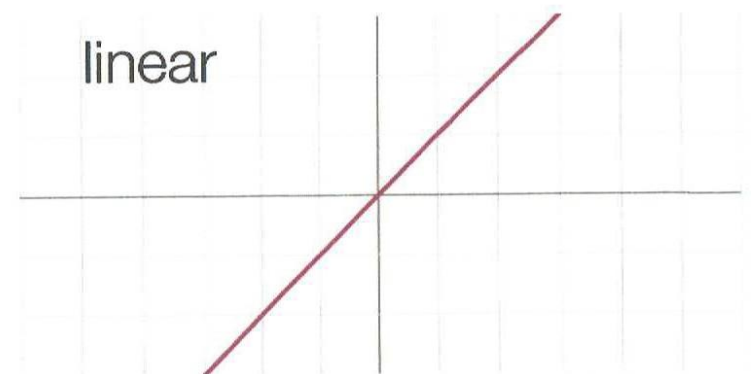
# Activation Functions

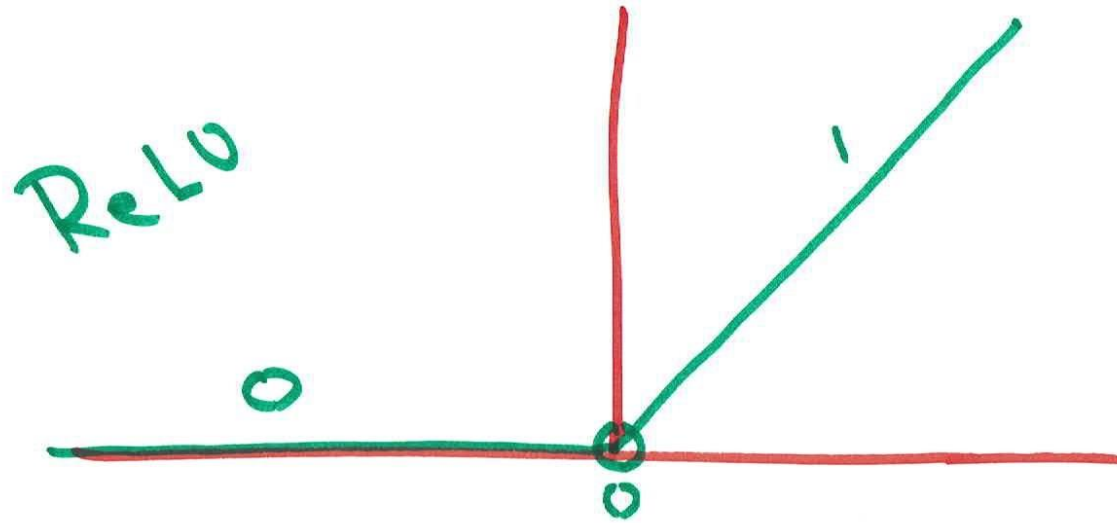


$$\frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1}$$



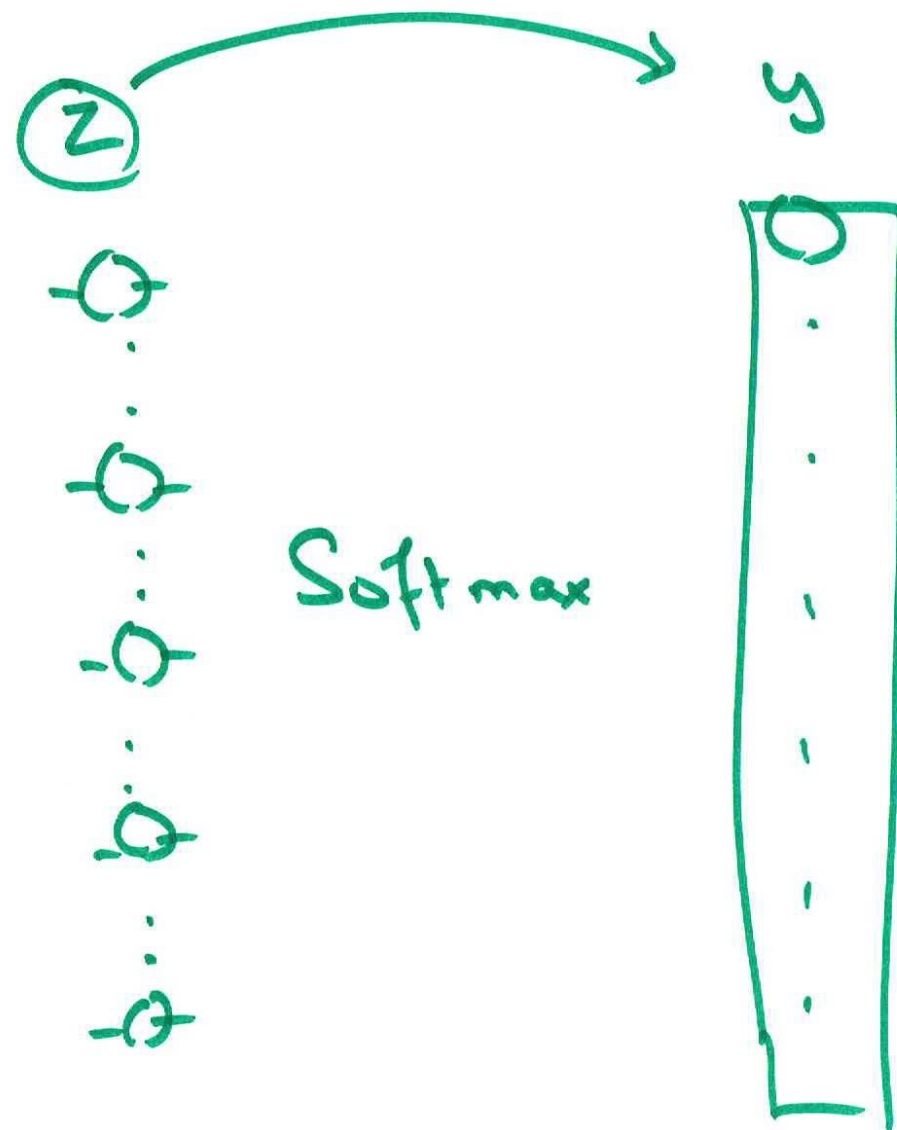
$$\frac{e^x - e^{-x}}{e^x + e^{-x}}$$





$$f(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

$$f(x) = \max(0, x)$$

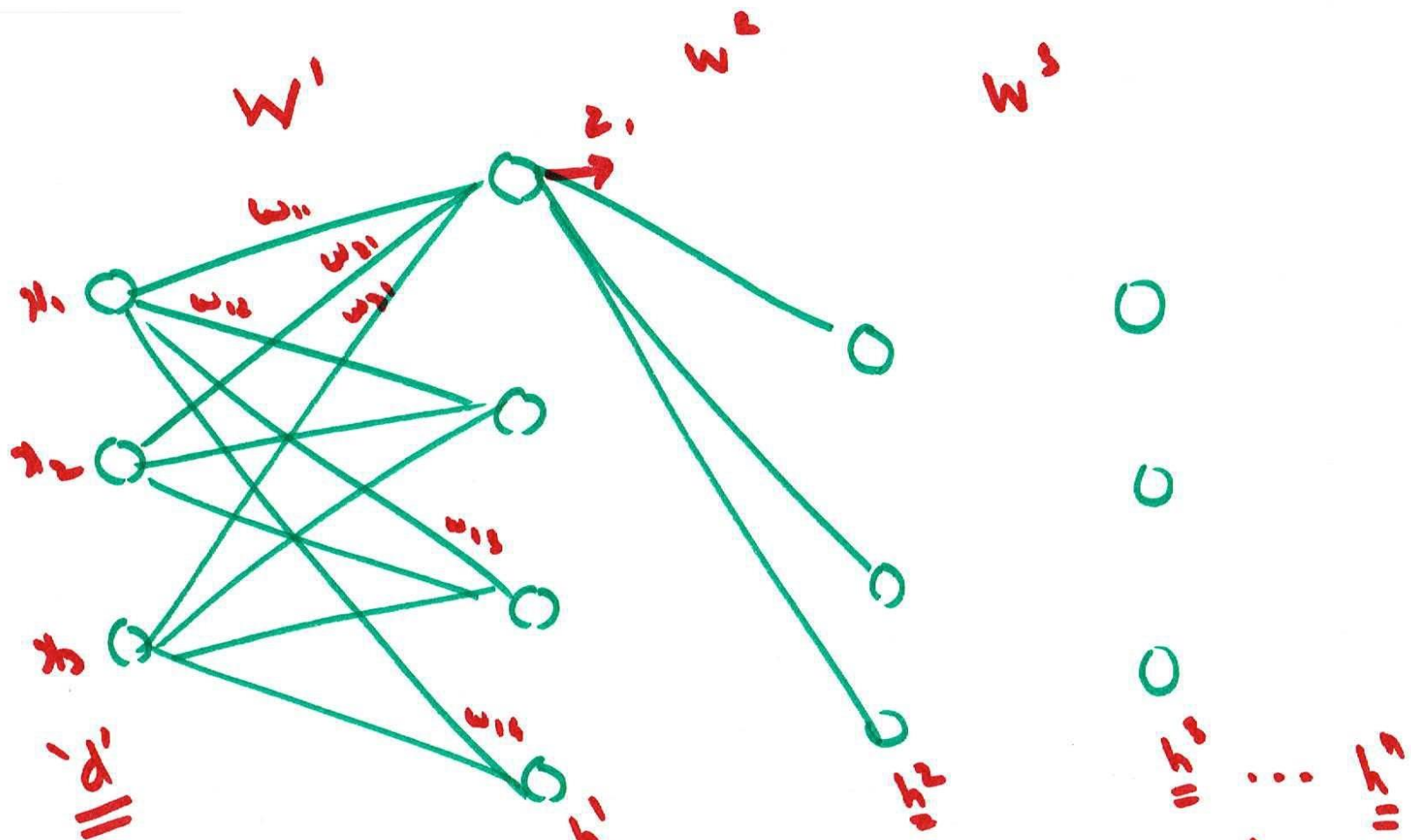


z

y

$$y_i = \frac{e^{z_i}}{\sum e^{z_i}}$$

$$\begin{aligned}\omega^{\text{new}} &= \omega^{\text{old}} - \eta \nabla_{\omega} l(\omega) \\ &= \omega^{\text{old}} - \frac{1}{N} \eta \sum \nabla_{\omega} l_i(\omega)\end{aligned}$$



$$z_1 = f(\omega_{11}x_1 + \omega_{21}x_2 + \omega_{31}x_3 + b)$$

$$z_j = f\left(\sum_i \omega_{ji} x_i + b_j\right)$$



$$X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix}$$

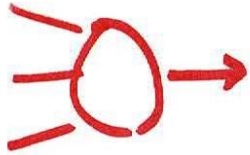
$$W' = \begin{pmatrix} w_{11} & w_{12} & w_{13} & \dots & w_{1d} \\ w_{21} & w_{22} & w_{23} & & \\ & & \ddots & & \\ w_{h'1} & w_{h'2} & w_{h'3} & \dots & w_{h'd} \end{pmatrix}$$

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix} \quad \begin{matrix} h' \times d \\ \text{matrix} \end{matrix}$$

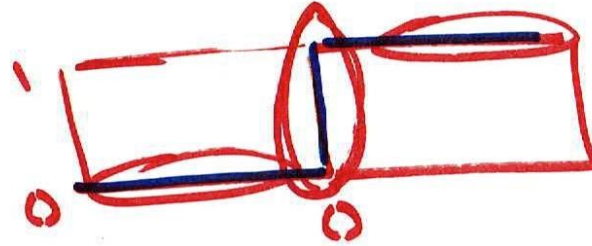
$$\hat{y} = f^n \left( f \left( W^3 f \left( W^2 f \left( W' X + b' \right) + b^2 \right) + b^3 \right) \dots \right)$$

Diagram illustrating the dimensions of the matrices and vectors in the nested function expression:

- $W'$  is an  $h' \times d$  matrix.
- $X$  is a vector of size  $d$ .
- $W'X + b'$  is a vector of size  $h'$ .
- $W^2$  is an  $h' \times h'$  matrix.
- $W^2 (W'X + b')$  is a vector of size  $h'$ .
- $W^3$  is an  $h' \times h'$  matrix.
- $W^3 (W^2 (W'X + b'))$  is a vector of size  $h'$ .
- $f$  is an activation function.
- $f(W^3 (W^2 (W'X + b')))$  is a vector of size  $h'$ .
- $W^4$  is an  $h' \times h'$  matrix.
- $W^4 (f(W^3 (W^2 (W'X + b'))))$  is a vector of size  $h'$ .
- $f(W^4 (f(W^3 (W^2 (W'X + b')))))$  is a vector of size  $h'$ .
- $\hat{y}$  is the final output vector of size  $h'$ .



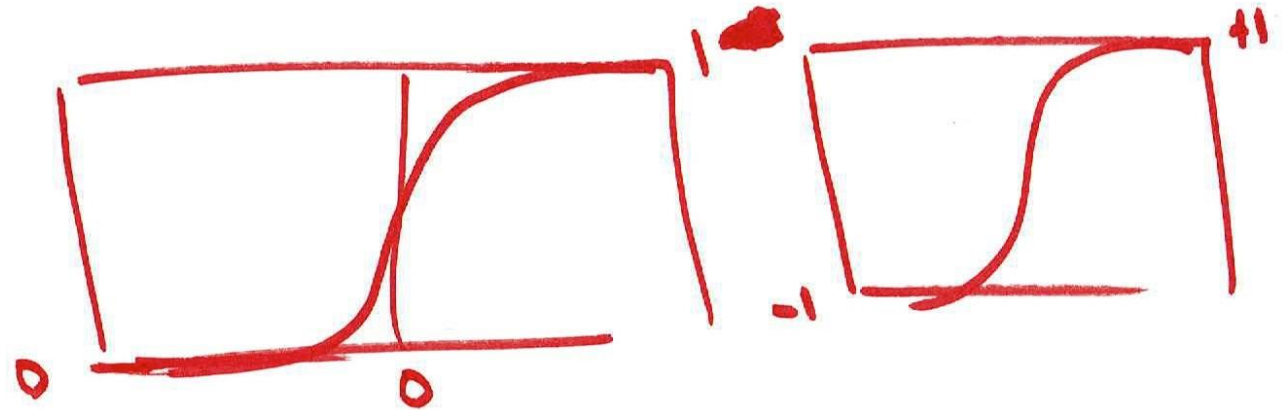
Step ( $w_1 x_1 + w_2 x_2 + w_3 x_3 + b$ )



Sigmoid

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

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



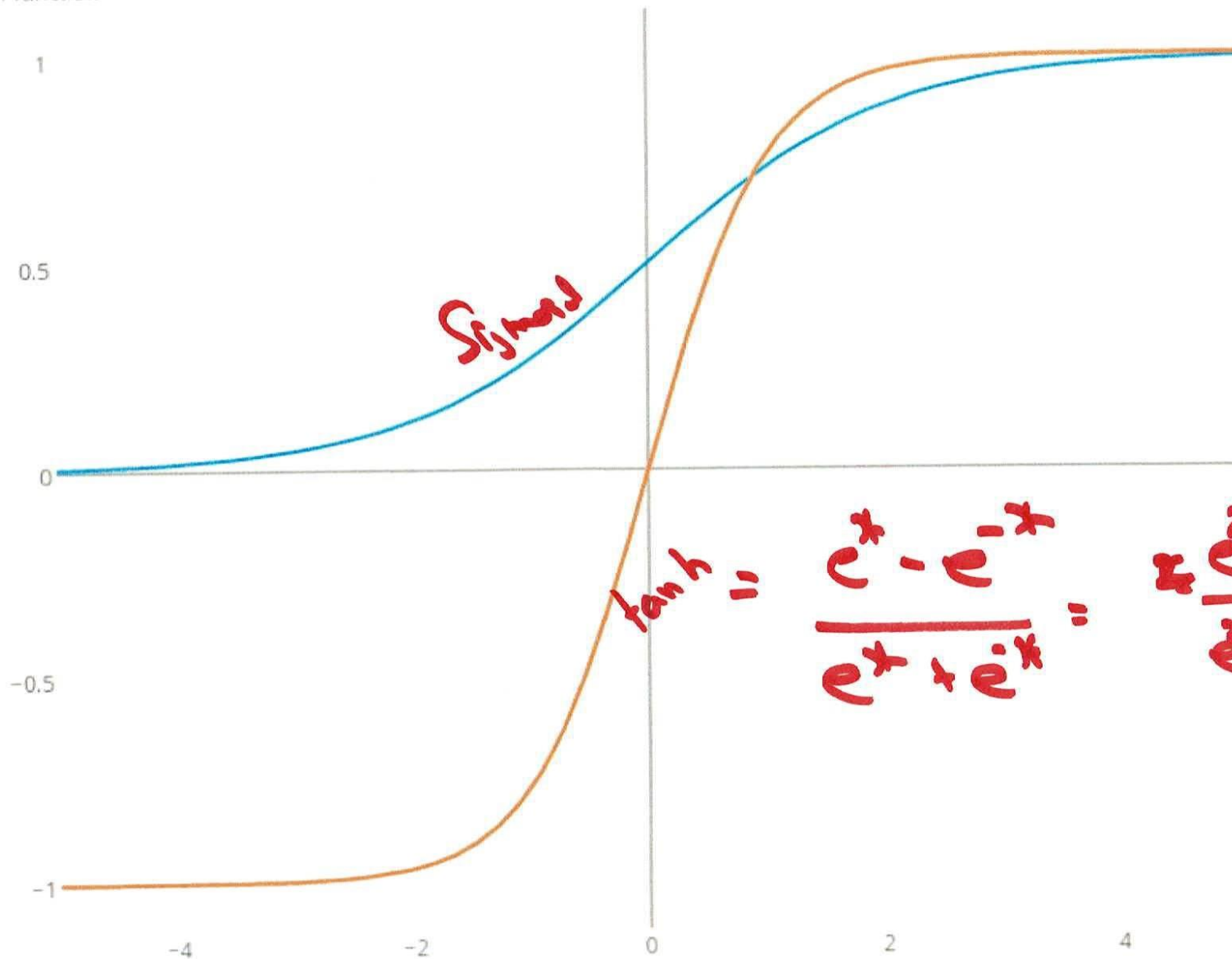
$$\boxed{2\sigma(x) = 1}$$

$$\boxed{\tanh = 2\sigma(2x) - 1}$$

↑

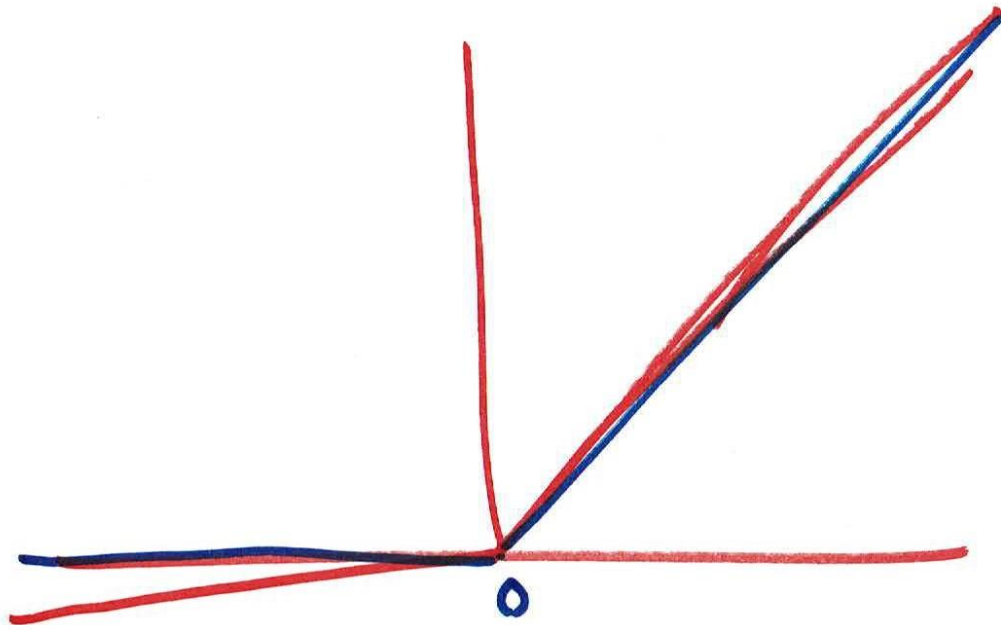


— Sigmoid function  
— Tanh function



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

ReLU



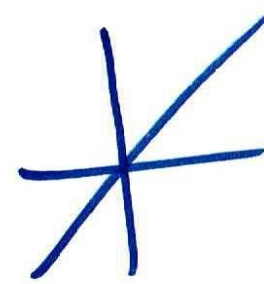
$$= \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

$$= \max(0, x)$$

$\max(0.01x, x)$

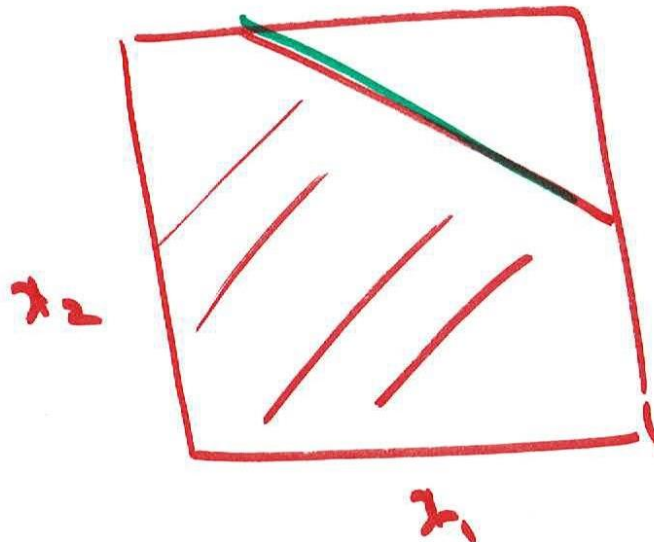
linear

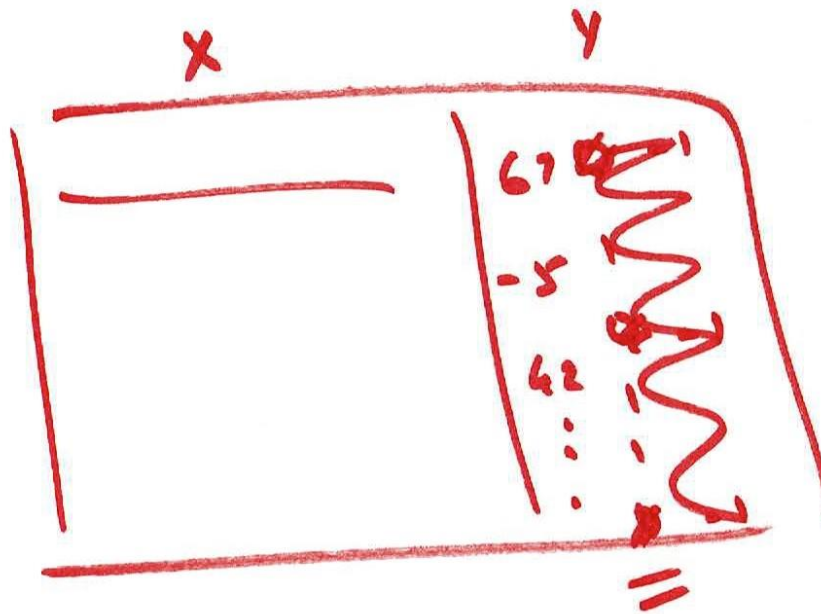
=  $\lambda$



$$\text{Step } = f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

$$f(w_1 x_1 + w_2 x_2 + b)$$





Classification  $\rightarrow$

Sigmoid, tanh  
Softmax

Reg  $\rightarrow$

linear

$$\hat{a} + \hat{b} (a + b x)$$

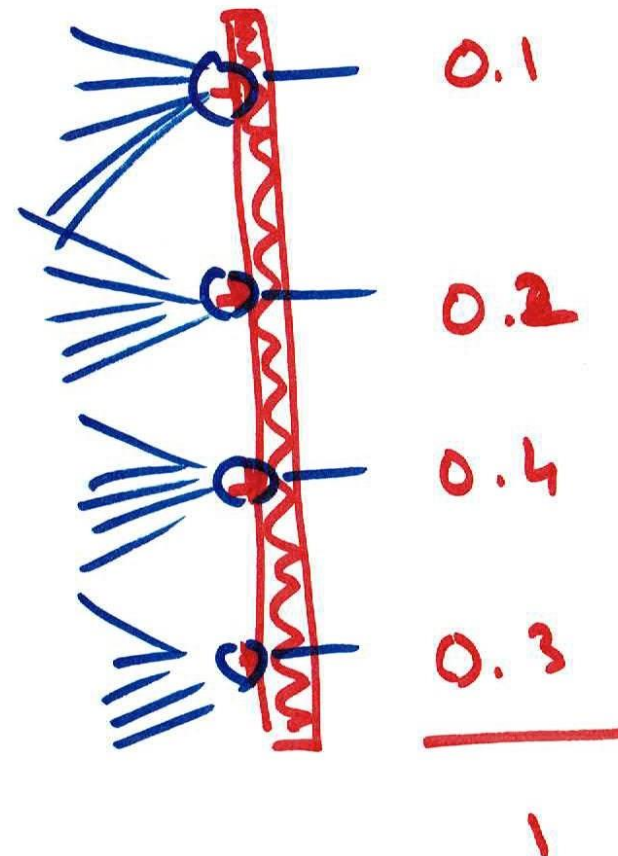
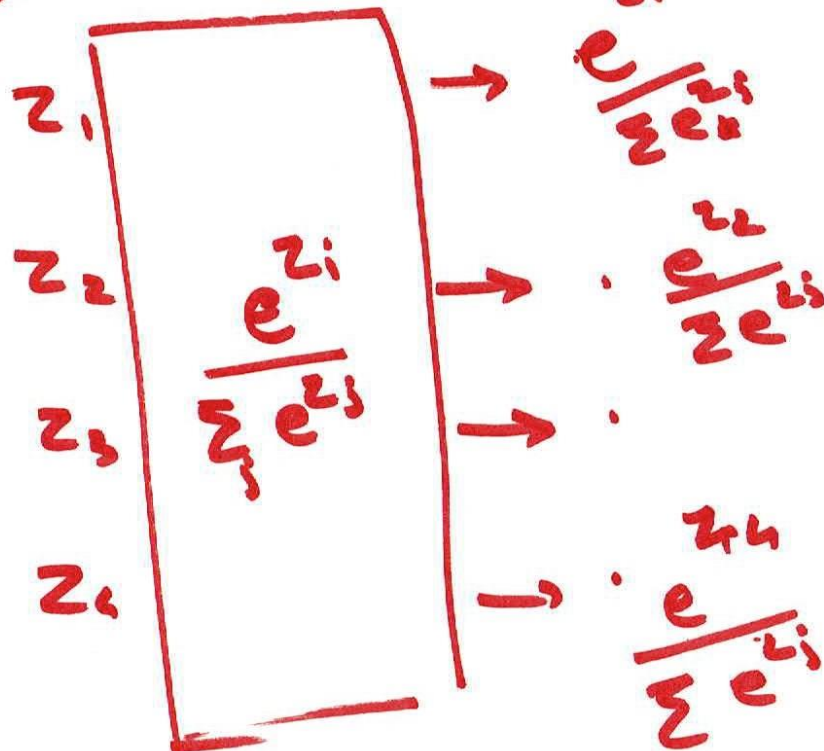
Output nodes

hidden layer

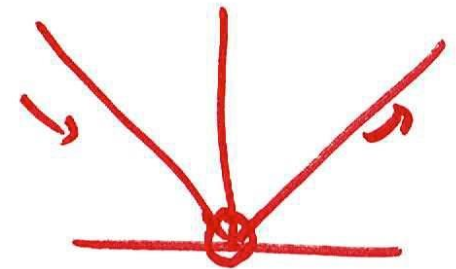
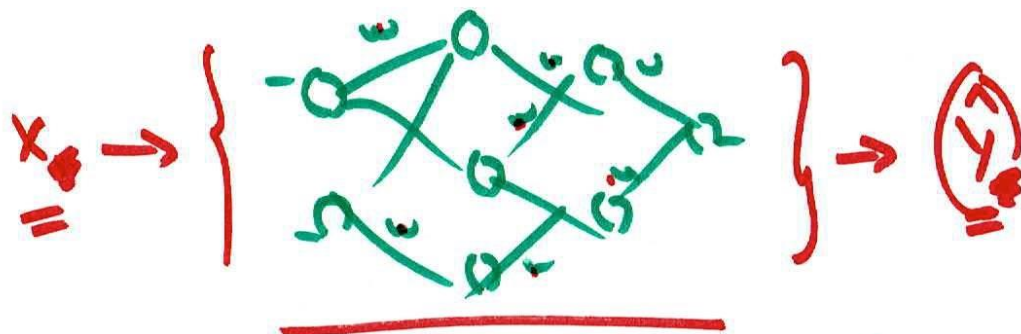
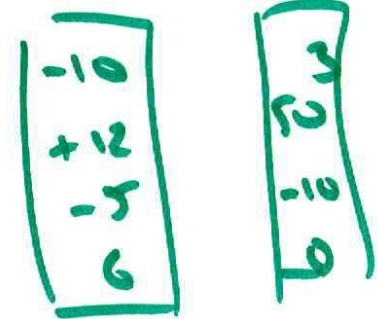
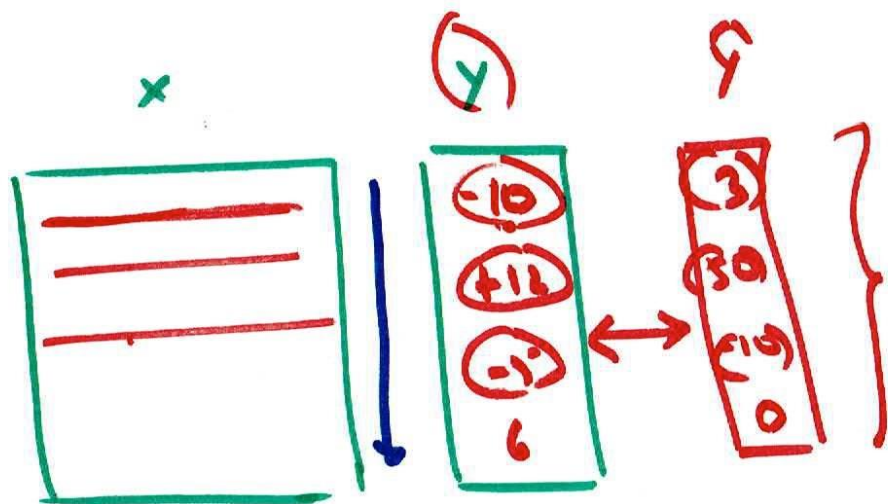
Sigmoid ✓  
tanh ✓

ReLU ✓  
~~linear~~

Softmax







Loss function  $L(y, \hat{y})$

Req

$$\frac{1}{N} \sum_i (y_i - \hat{y}_i)^2$$

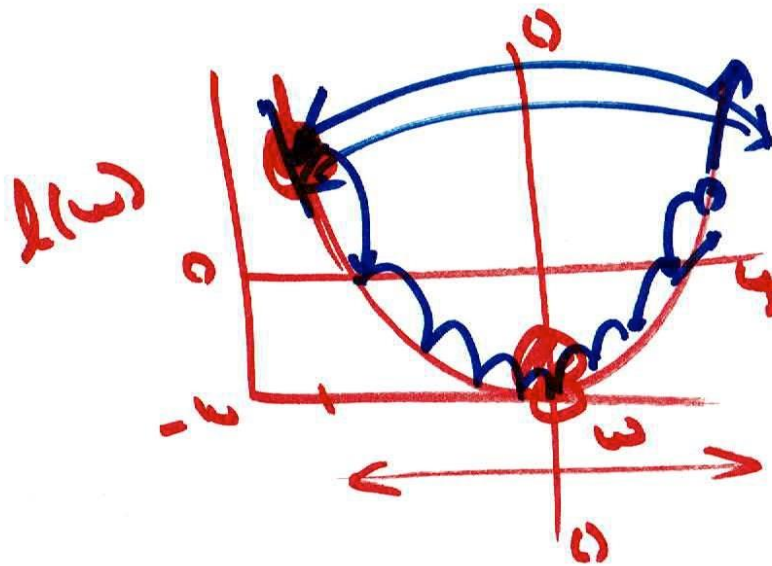
$$L(y, \hat{y}) = l(w)$$

$L_2$  loss  
MSE  
SSE

Classifier  $L(y, \hat{y}) = - (y_i \log(\hat{y}_i) + (1-y_i) \log(1-\hat{y}_i))$

Cross entropy loss

How min  $\underline{L(y, \hat{y})}$  by ~~changing~~  $w^1, w^2, \dots, w^n$



$$y = x^2 - 10 = -10$$

$$\frac{dy}{dx} = 2x = 0$$

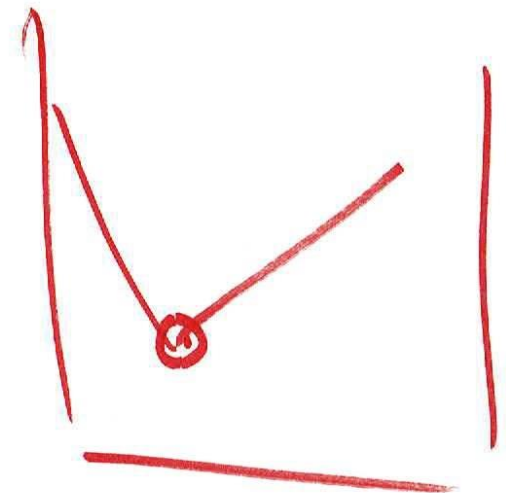
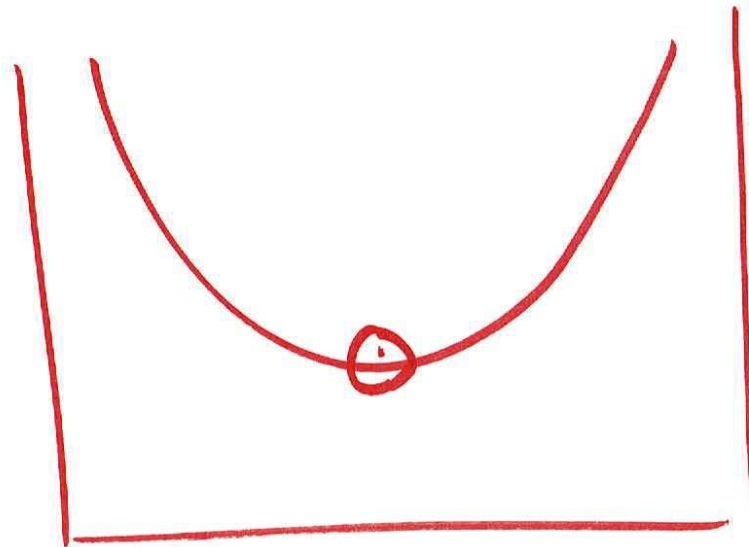
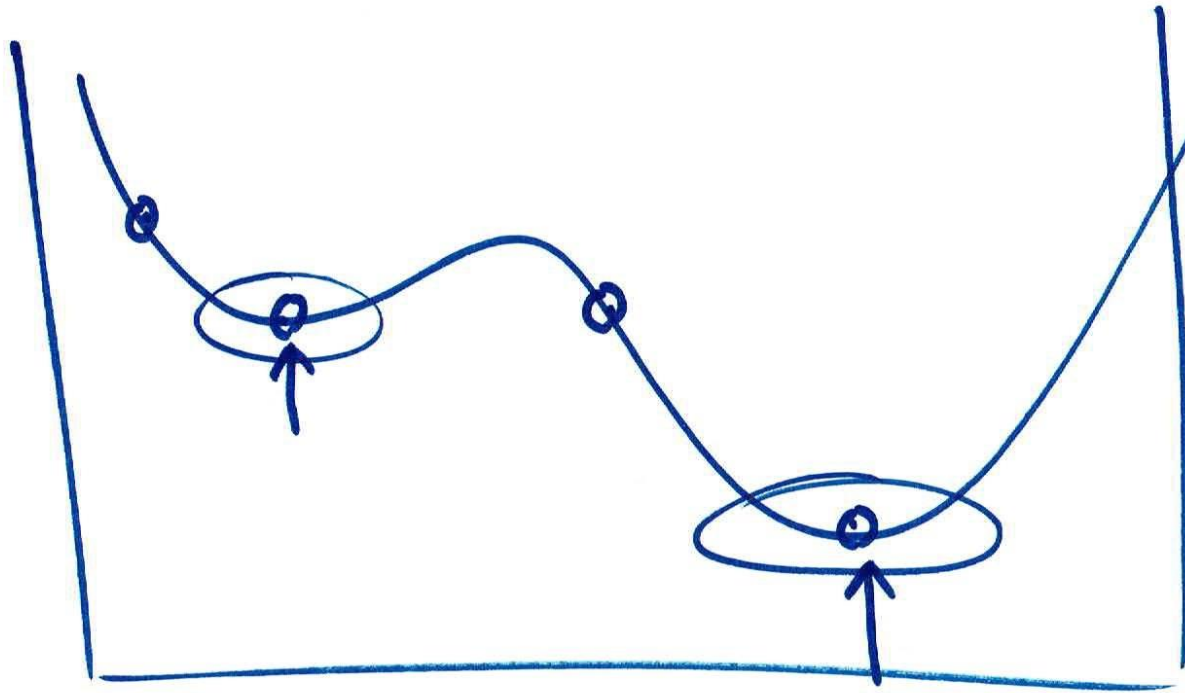
$$x = 0$$

$$\left( \frac{dL}{dw} \right) = \boxed{\quad} = 0$$

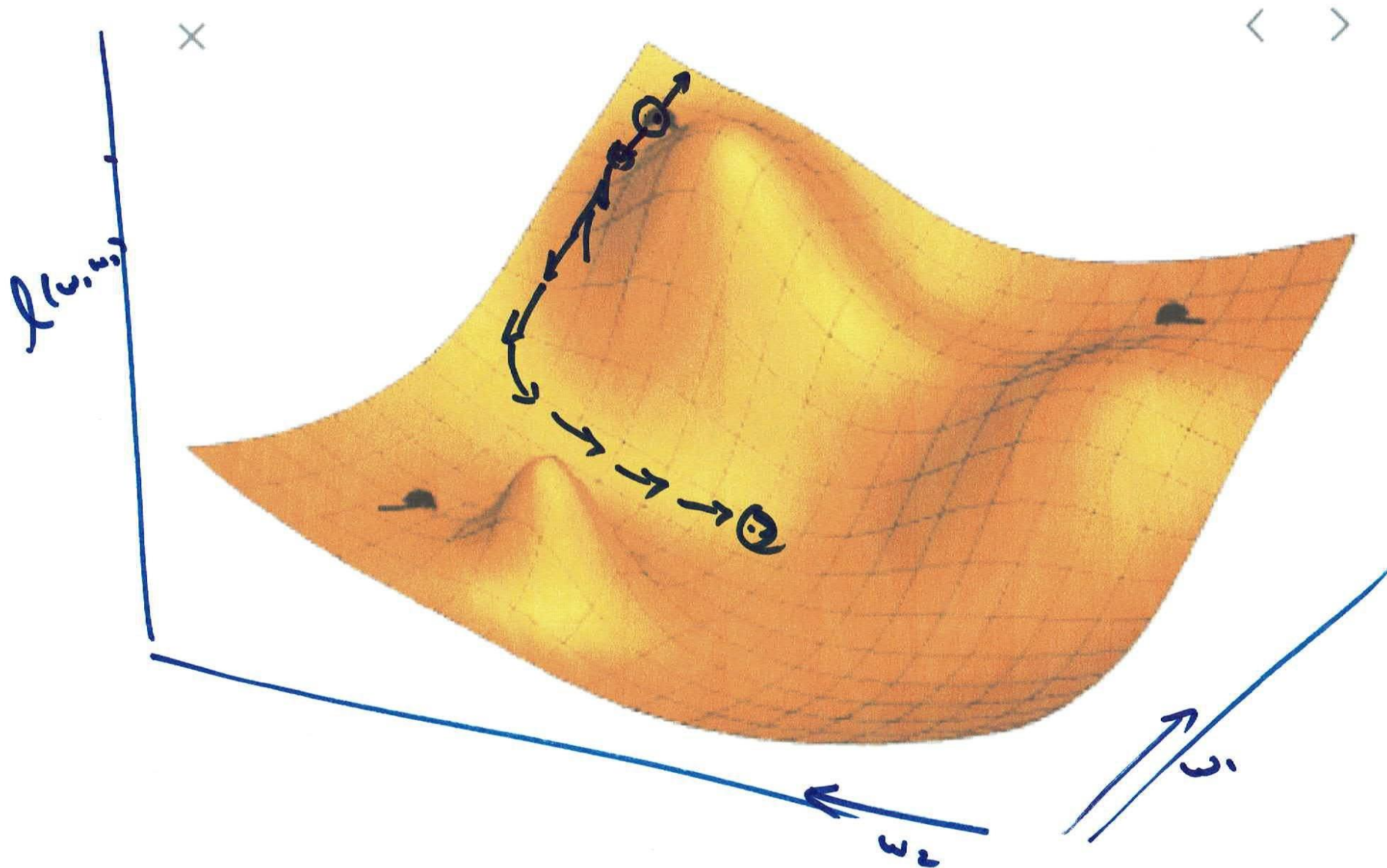
$$\frac{dL}{dw}$$

$$w_{new} = w - \eta \frac{\Delta L}{\Delta w}$$

learning rate







$$\omega^{\text{new}} = \omega^{\text{old}} - \frac{2 \nabla_{\omega} l(\omega)}{2}$$

$$= \omega^{\text{old}} - \frac{1}{N} \sum \nabla_{\omega} l_i(\omega) \leftarrow$$

SGD

$$\omega^{\text{new}} = \omega^{\text{old}} - \eta \nabla_{\omega} l_i(\omega) \leftarrow$$

$$\omega^{\text{new}} = \omega^{\text{old}} - \frac{1}{N} \eta \sum \nabla_{\omega} l_i(\omega)$$

over a min batch



Loss  
↓  
L:

Function of  $w$  ( $l(w)$ )  
↓

$$L = \frac{1}{2} \sum_i (y_i - \underbrace{f(\dots f(w^2 f'(w'x + b')) + b^2)}_{\text{Function of } w})^2$$

Chain Rule

$$f(g(h(x)))$$

$$\frac{df}{dx} = \left( \frac{df}{dy} \cdot \frac{dy}{dh} \right) \cdot \frac{dh}{dx}$$

Back Propagation