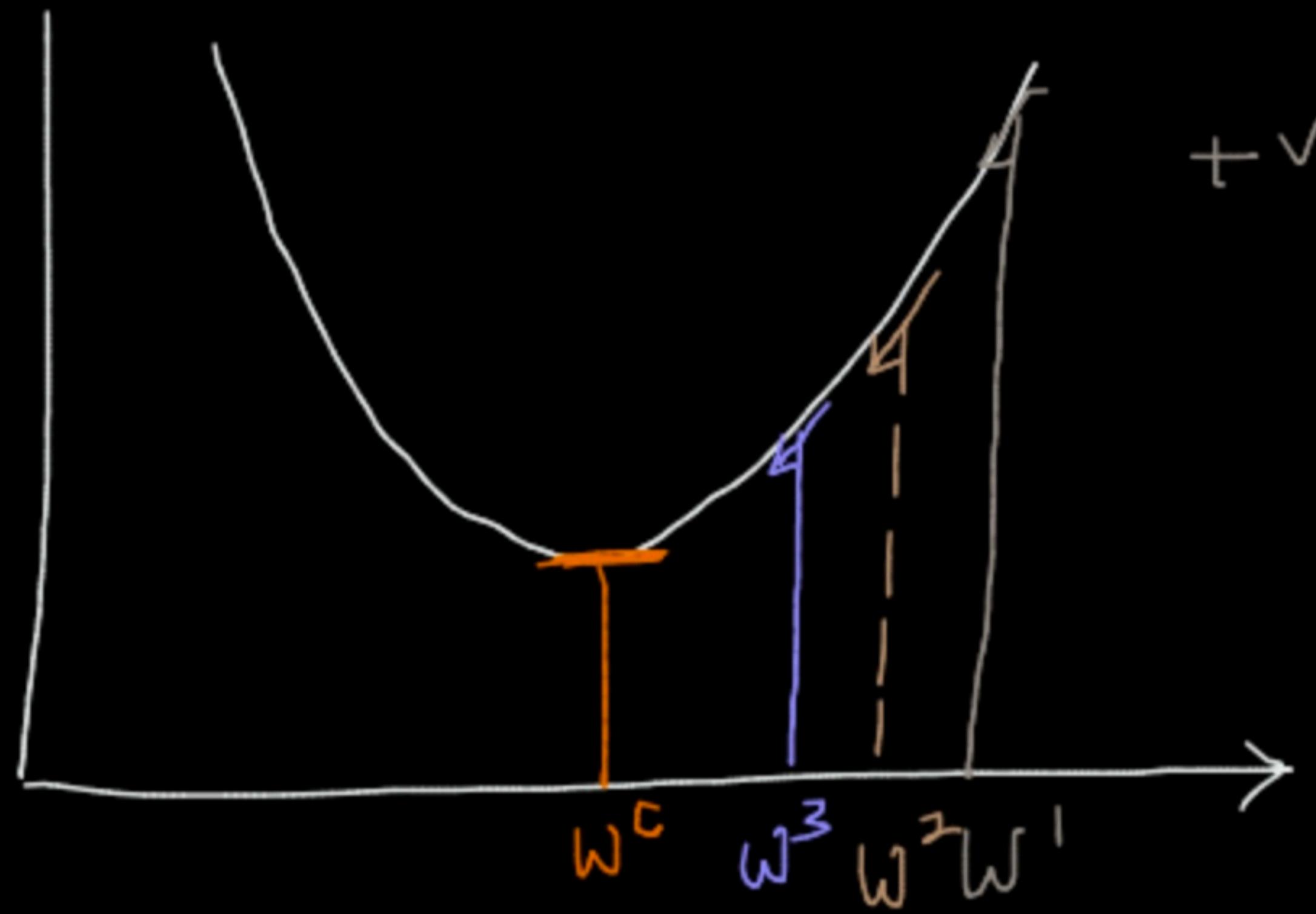


Gradient Descent Algorithm



$$\text{Loss} = (\hat{y} - y)^2$$

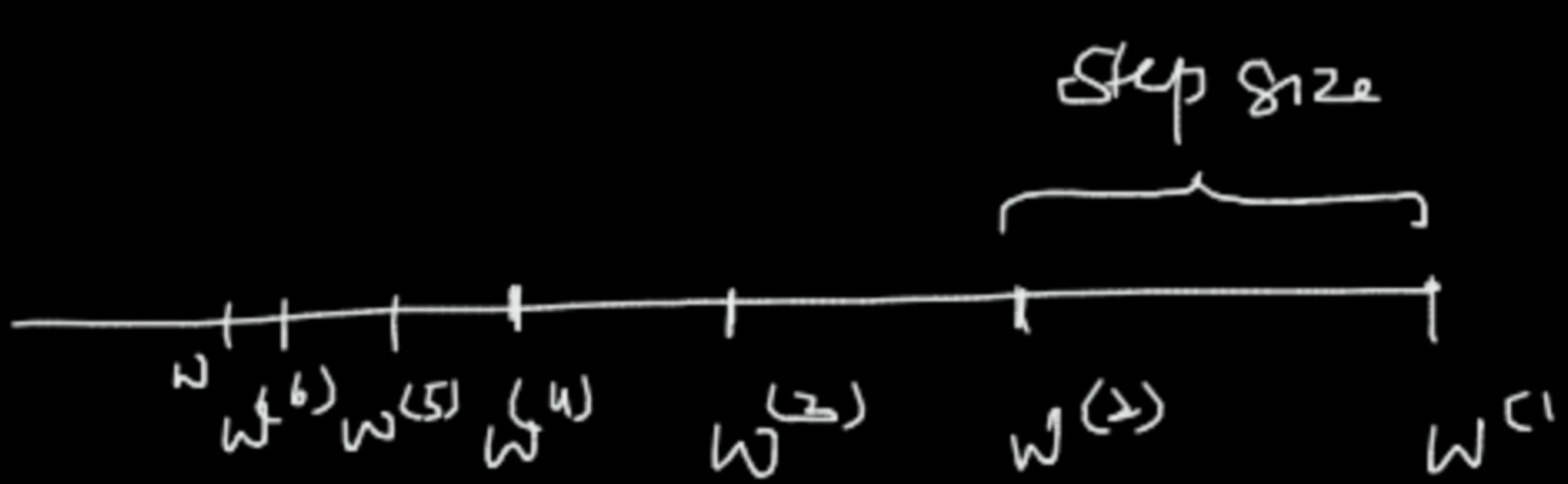
$$\hat{y} = w_1 x_1 + w_2 x_2 + b$$

$$\frac{\partial L}{\partial w_1}, \quad \frac{\partial L}{\partial w_2}, \quad \frac{\partial L}{\partial b}$$

$$w_1^{\text{new}} = w_1^{\text{old}} + \lambda \left[-\frac{\partial L}{\partial w_1} \right] w_1^{\text{old}}$$

$$w_2^{\text{new}} = w_2^{\text{old}} + \lambda \left[-\frac{\partial L}{\partial w_2} \right] w_2^{\text{old}}$$

$$w^{\text{new}} = w^{\text{old}} \quad \xrightarrow{\text{Step size}} \quad \xrightarrow{\lambda \rightarrow 0}$$



λ - learning rate

Step size $\left[\frac{\partial L}{\partial w} \right]$ optimizers

optimizers

1 Momentum — Gradient

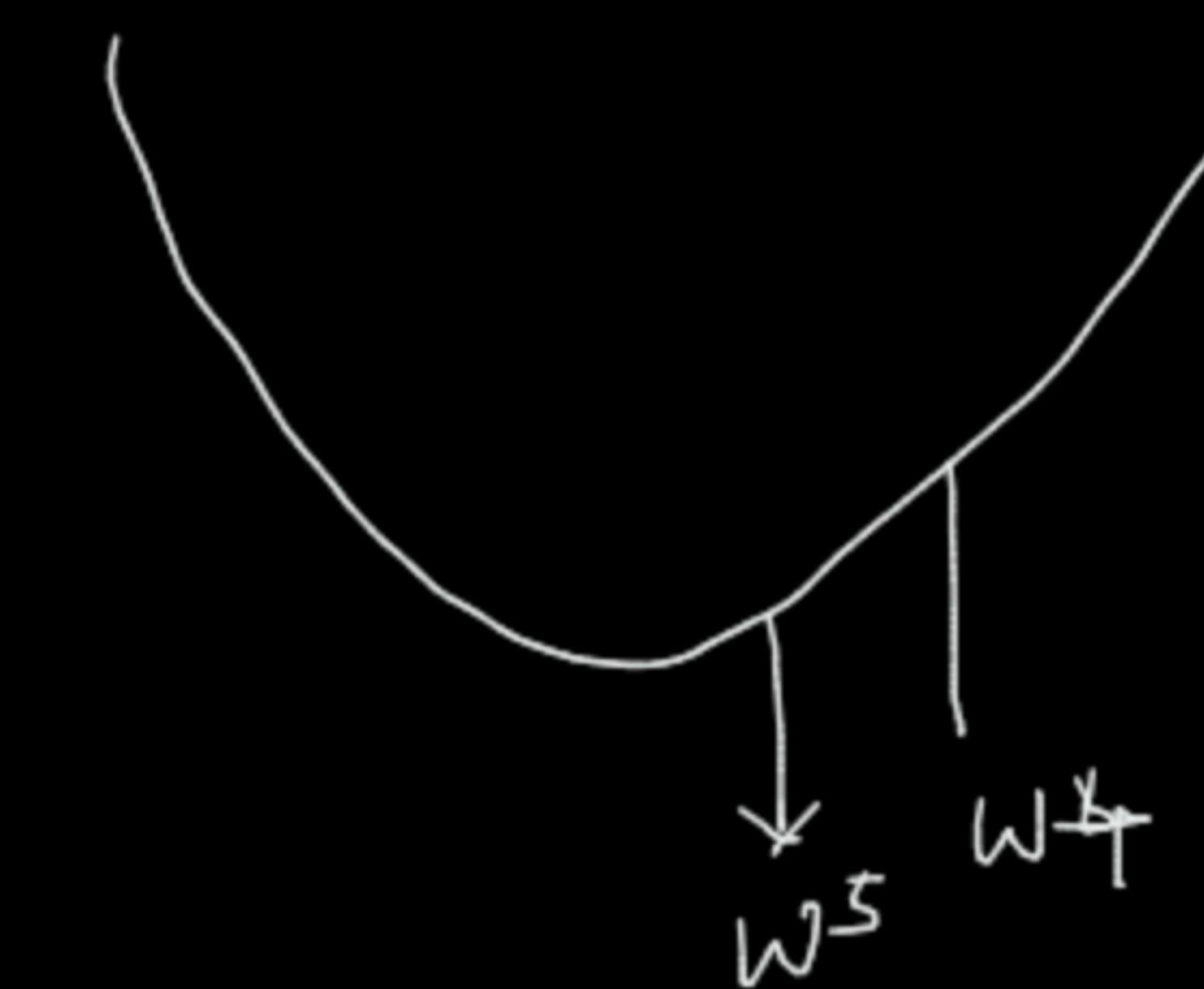


$$w^{new} = w^{old} + \left(\frac{\partial L}{\partial w} \right)$$

2 Nesterov Momentum

$$w^5 \rightarrow$$

$$w^6 \rightarrow$$

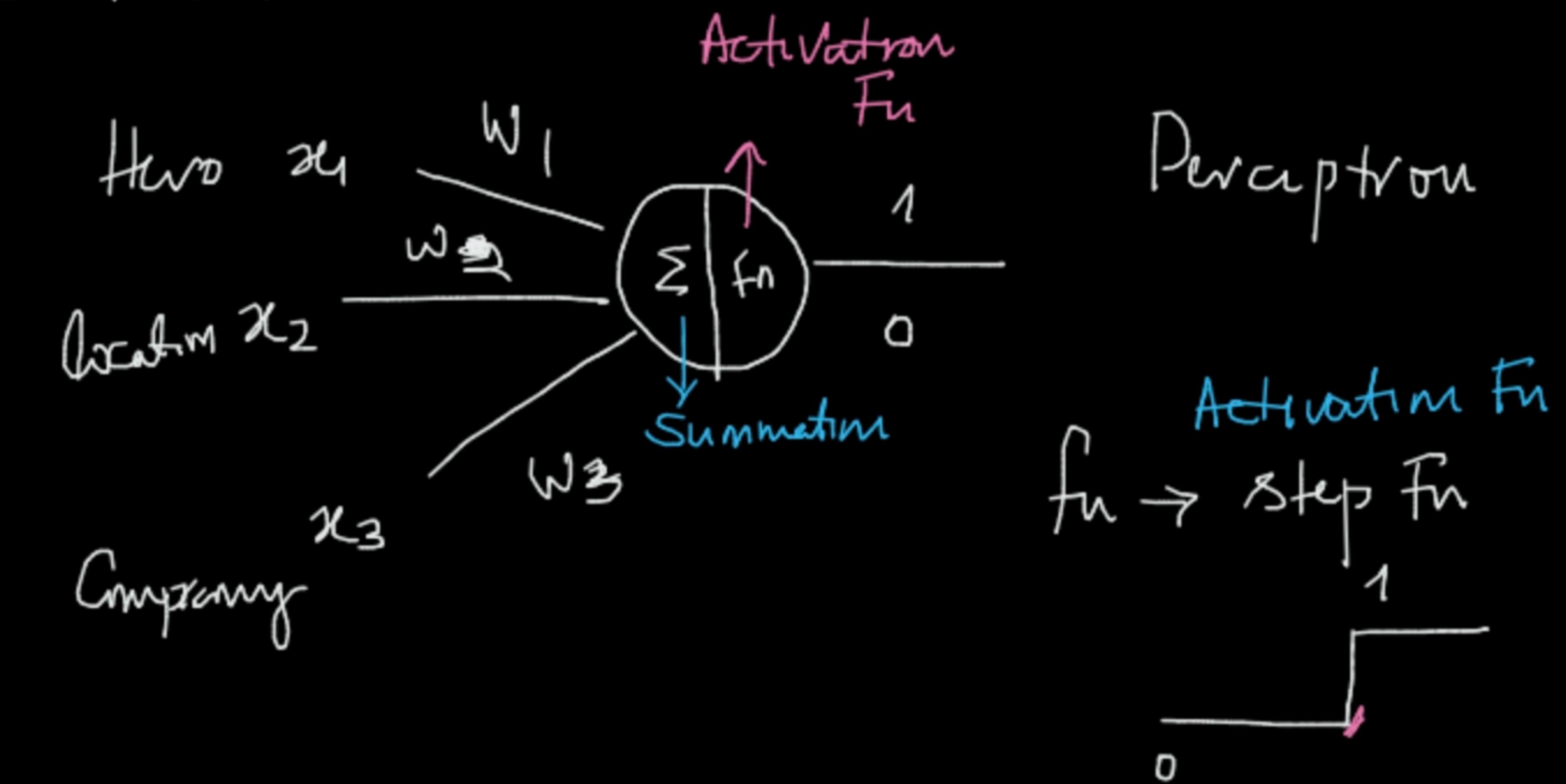
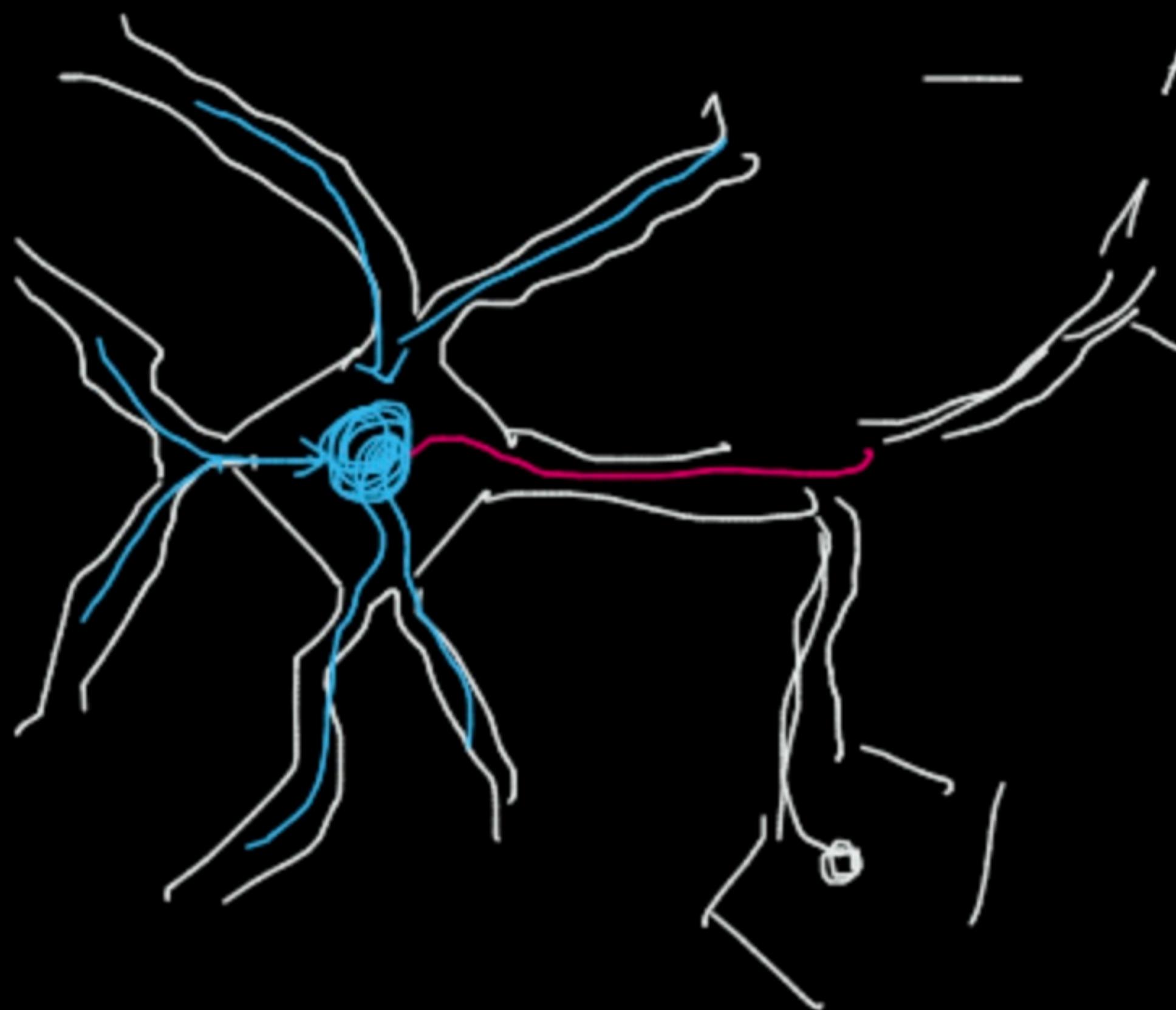


$$w^5 = w_4^{old} - \lambda \left[\frac{\partial L}{\partial w_4} + \underbrace{\frac{\partial L}{\partial w_5} + \frac{\partial L}{\partial w_6}}_{\text{Layer Step Size}} \right]$$

Layer Step Size

Neural Networks

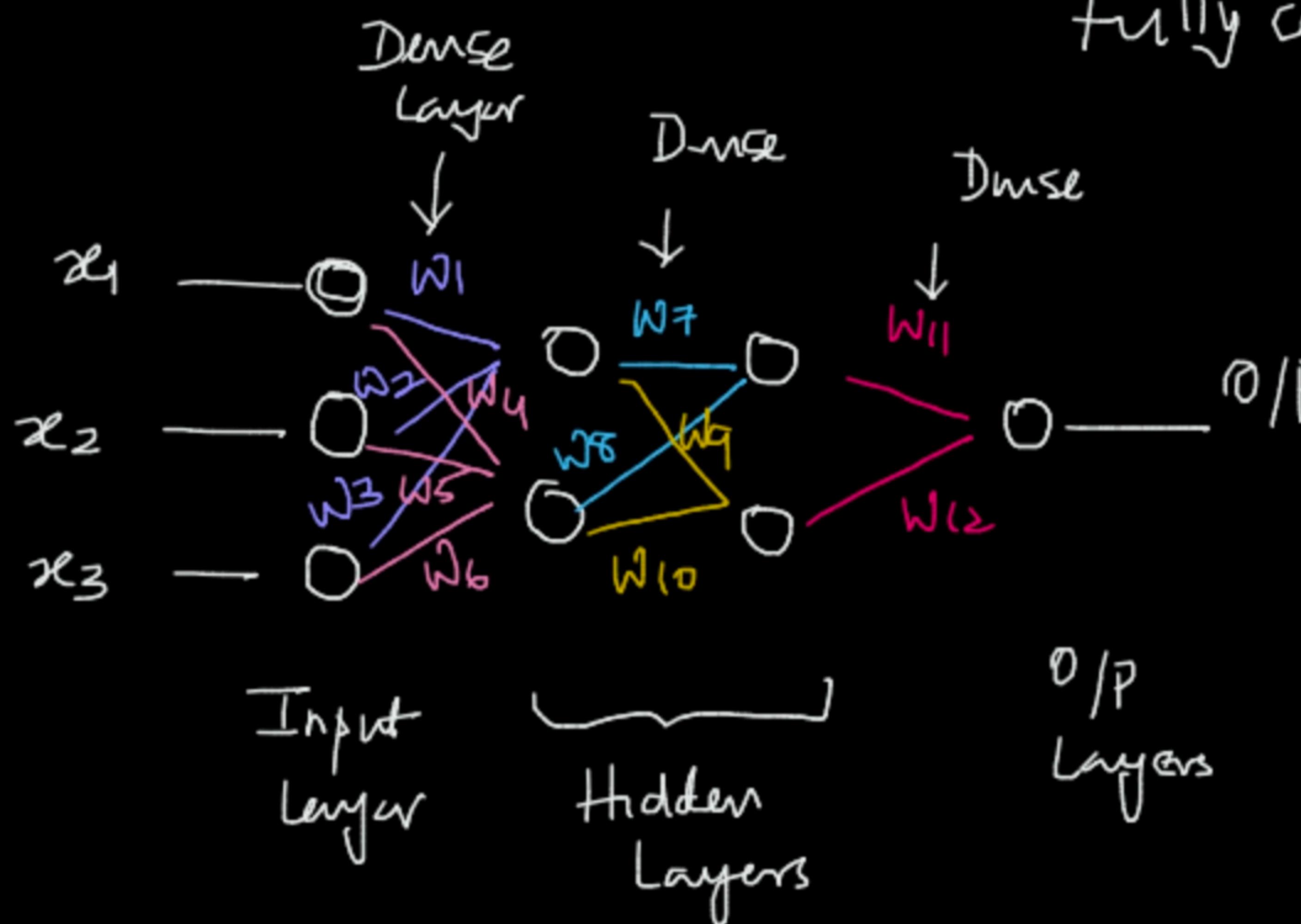
- Artificial Neurons
- Artificial Neural Networks



$$f_n(w_1 x_1 + w_2 x_2 + w_3 x_3 + b) \begin{cases} 1 & \geq 0 \\ 0 & < 0 \end{cases}$$

Activation
 $f_n \rightarrow \text{Step Fn}$

Fully connected / Dense Layer
Network



→ 12 weights / parameters

→ Artificial Neural Network
(ANN)

x_1	x_2	\bar{x}_3	y
			Regression
			Binary cl
			Multiclass cl

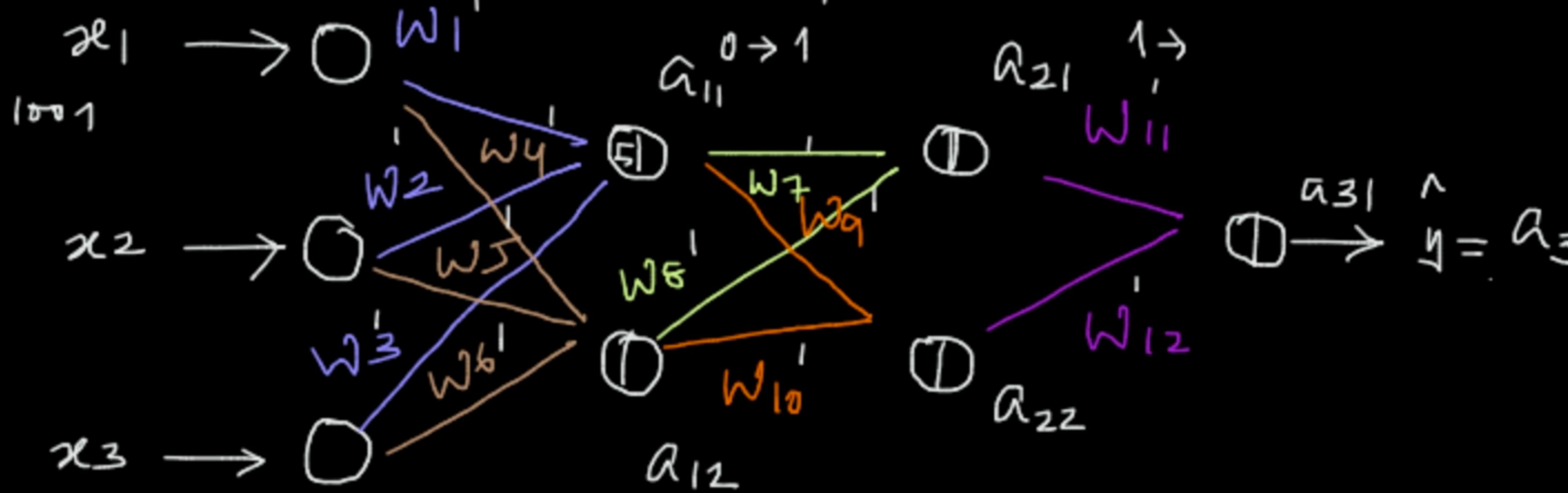
Soft max layers

Img → 0 → 0 → 0

H → 0.15 0.02 0.83

A → Hors

— Forward Propagation —



← Backward propagation —

$$a_{11} = f_n(w_1 x_1 + w_2 x_2 + w_3 x_3)$$

$$a_{12} = f_n(w_4 x_1 + w_5 x_2 + w_6 x_3)$$

$$a_{21} = f_n(w_7 a_{11} + w_8 a_{12})$$

$$a_{22} = f_n(w_9 a_{11} + w_{10} a_{12})$$

$$a_{31} = f_n(w_{11} a_{21} + w_{12} a_{22})$$

$$wss^{\checkmark} = (y - \hat{y})^2$$

$$L = (y - a_{31})^2 \downarrow$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial L}{\partial a_{31}} \frac{\partial a_{31}}{\partial w_{11}}$$

$$\frac{\partial L}{\partial w_7} = \frac{\partial L}{\partial a_{31}} \frac{\partial a_{31}}{\partial a_{21}} \frac{\partial a_{21}}{\partial w_7} \xrightarrow[2]{1} \xrightarrow[2]{3} \xrightarrow[2]{1} \rightarrow 24 \rightarrow \text{Exploding gradient}$$

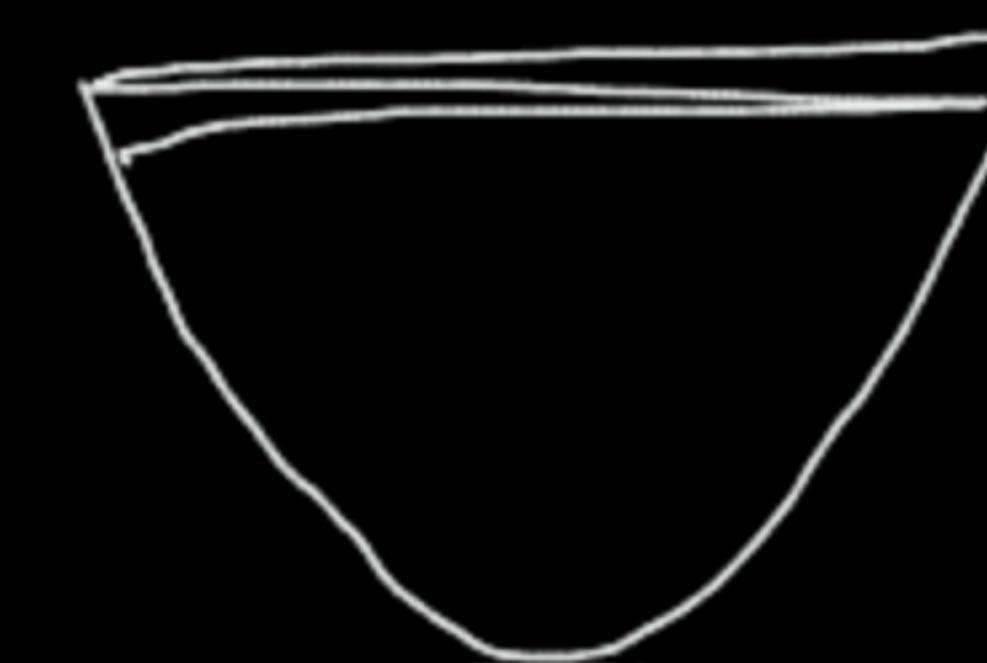
$$\left(\frac{\partial L}{\partial w_1} \right) = \left(\frac{\partial L}{\partial a_{31}} \right) \left(\frac{\partial a_{31}}{\partial a_{21}} \right) \left(\frac{\partial a_{21}}{\partial a_{11}} \right) \left(\frac{\partial a_{11}}{\partial w_1} \right)$$

$$0.2 \quad 0.1 \quad 0.01 \quad 0.002$$

$$= 0.000004$$

$$w_1^{(1)} \quad w_1^{(2)}$$

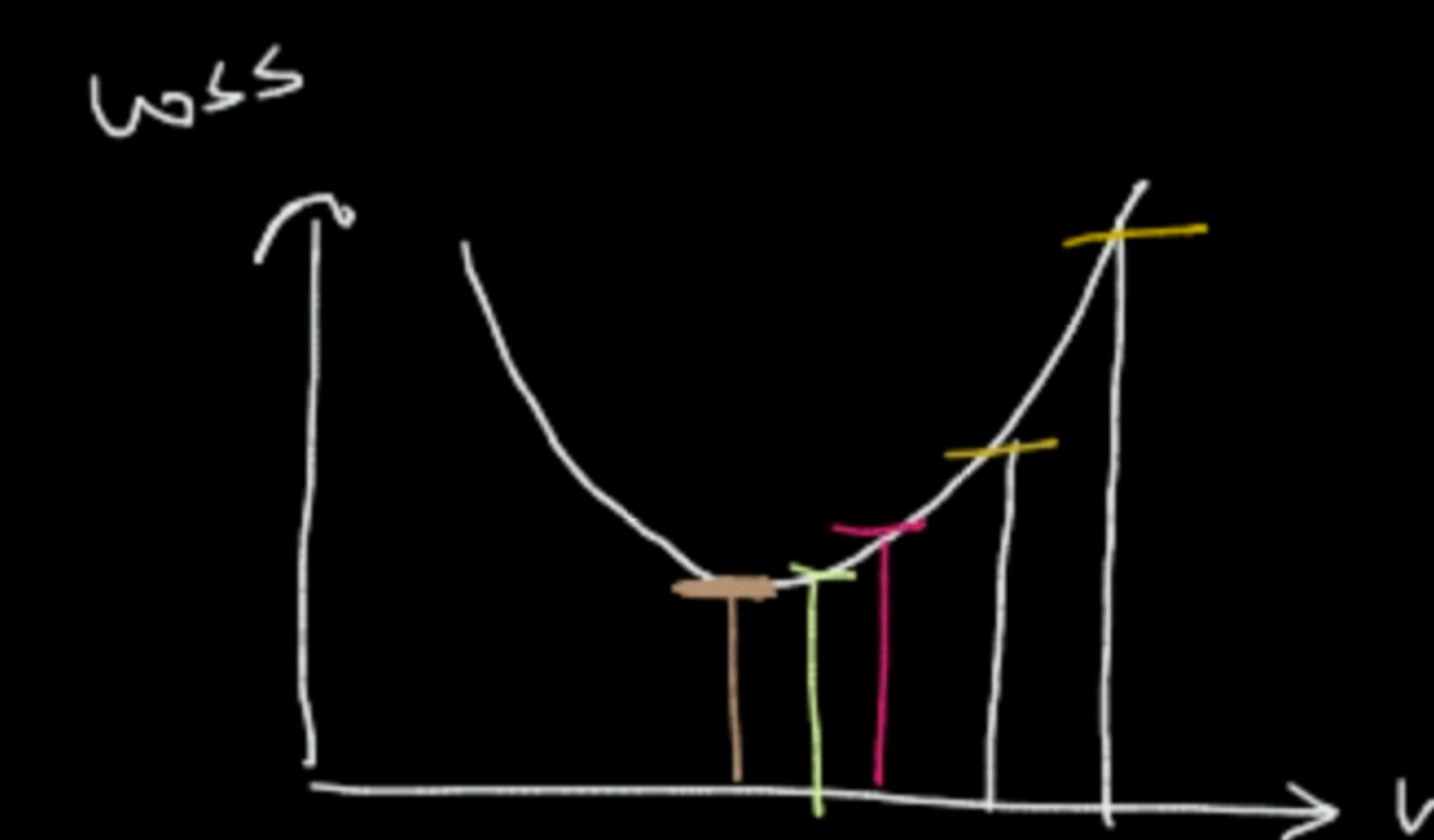
↳ Vanishing Gradients
— Never reach the min loss



Step 1 Randomly choose 12 weights

Step 2 Find the gradient of the loss fn w.r.t the weights

$$\frac{\partial L}{\partial w_1}, \frac{\partial L}{\partial w_2}, \frac{\partial L}{\partial w_3} \quad \frac{\partial L}{\partial w_{12}}$$



Step 3 Simultaneously update weights

$$w_1^{\text{new}} = w_1^{\text{old}} + -\lambda \left[\frac{\partial L}{\partial w_1} \right] w_1^{\text{old}}$$

$$w_2^{\text{new}} = w_2^{\text{old}} + -\lambda \left[\frac{\partial L}{\partial w_2} \right] w_2^{\text{old}}$$

$$\dots \dots \dots$$

$$w_{12}^{\text{new}} = w_{12}^{\text{old}} + -\lambda \left[\frac{\partial L}{\partial w_{12}} \right] w_{12}^{\text{old}}$$

	x_1	x_2	x_3	y	\hat{y}	$(y - \hat{y})^2$	\hat{y}	$(y - \hat{y})^2$	\hat{y}	$(y - \hat{y})^2$	\hat{y}
1	1000	3	5	47	20	27 ²	23	24 ²	30	17 ²	45

Step 4 Repeat steps 2 & 3 until convergence

↳ all weights are stable

3Blue1Brown

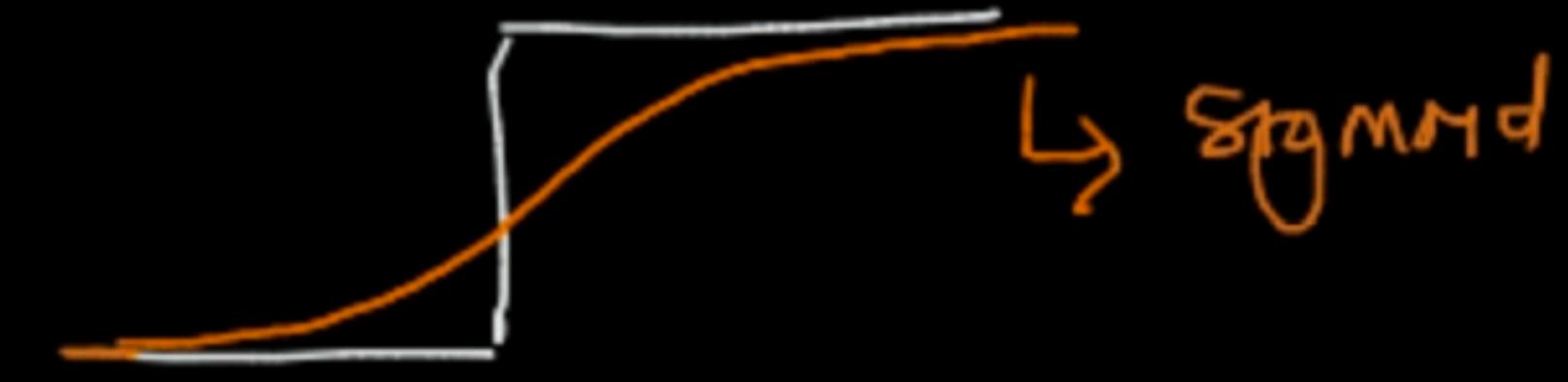
Composite Fn → $y = f(g(h(x)))$

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

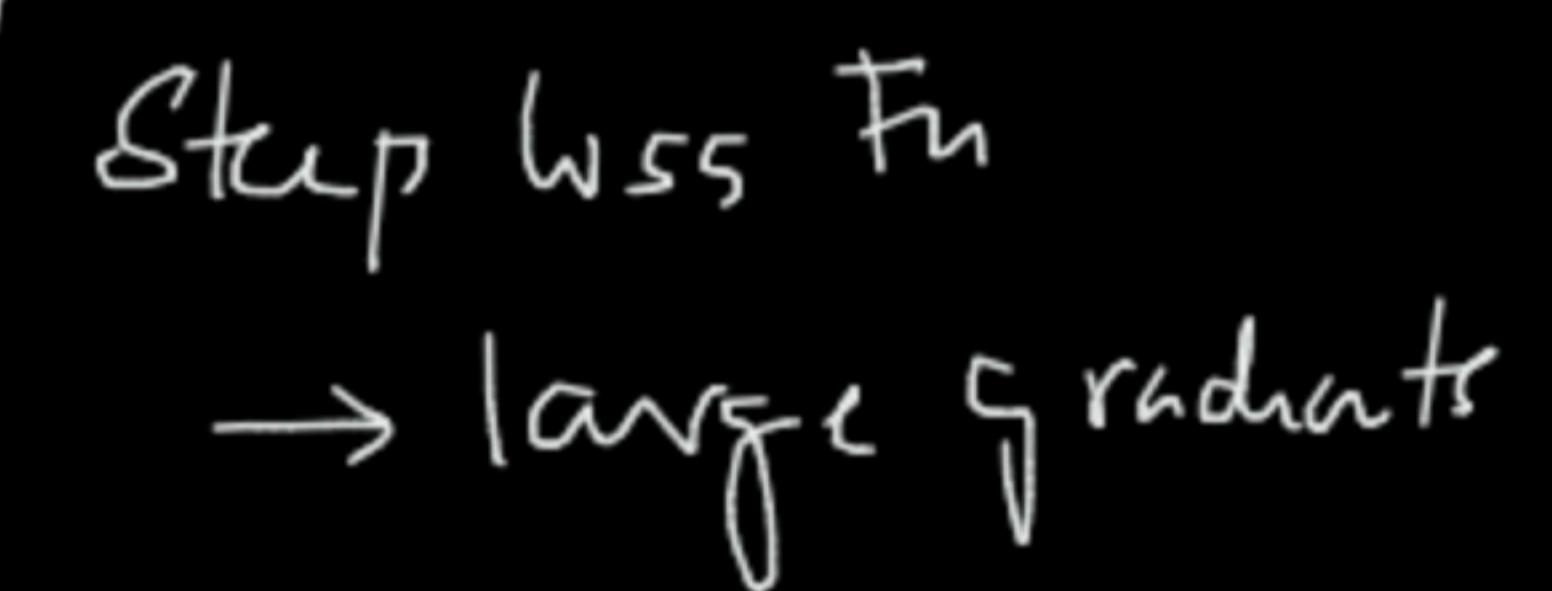
Chain Rule of differentiation

— product of multiple gradients

I/P $b - \Delta \rightarrow 0$
 $b \rightarrow 1$



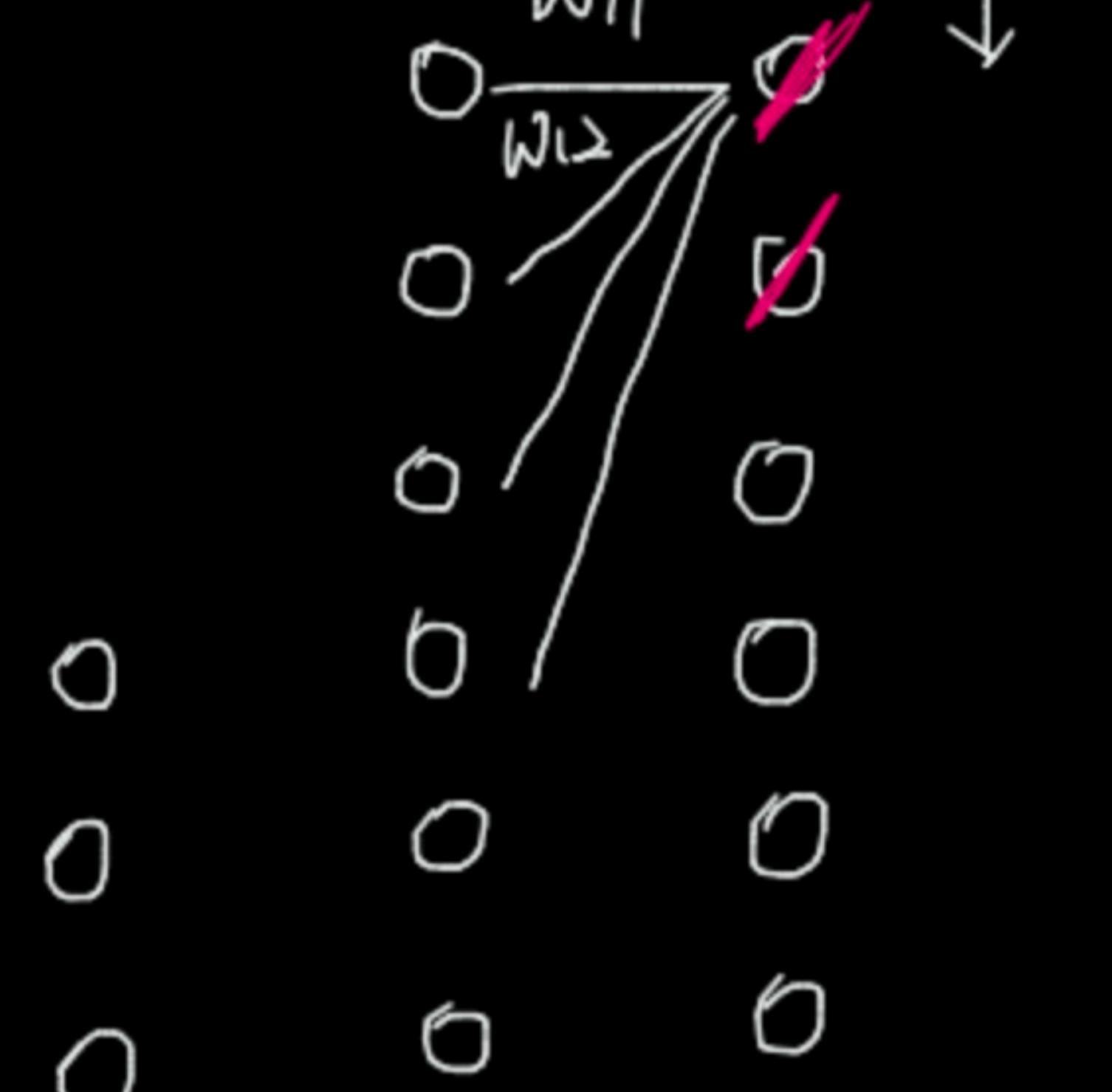
$$g(x) = \frac{1}{1 + e^{-x}}$$



Truncating \rightarrow Regularize

$$\hat{y} = w_1 x_1 + w_2 x_2 + w_3 x_3 + \dots + w_m x_m + b$$

\downarrow drop (20%)
 \downarrow drop (20%)
 w_{11} w_{12}



140 wts

\hookrightarrow 120 wts \rightarrow

softmax

0

0

1

0

↓
30 wt

10 wts

0 0

10 ↓ 10

1HL 10 wts
1dL 1HL 1dL

• Activation fn

- Step Fn $\begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$
- Sigmoid Fn $\sigma(x) = \frac{1}{1 + e^{-x}}$
- tanh $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
- ReLu $\begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases}$
- Leaky ReLu $\begin{cases} x & x \geq 0 \\ \alpha x & x < 0 \end{cases}$
- knene $\rightarrow x$

• optimizers

- Momentum
- Nesterov Momentum
- Adam
- RMSprop
- Adagrad

• Weight Initialization

- Normal
- uniform
- zero

• Network

- No of hidden layers
- No of units in HL

Gradient Descent

- learning rate
- Batch size
- Epochs

• Layers

- Dense layer
- Softmax
- dropout

• Regularization

L1 Reg

L2 Reg

• loss Fn

Ridgeless

- squared loss

Classification

- Binary cross entropy (2 class)

- Categorical cross entropy (Multidim)

