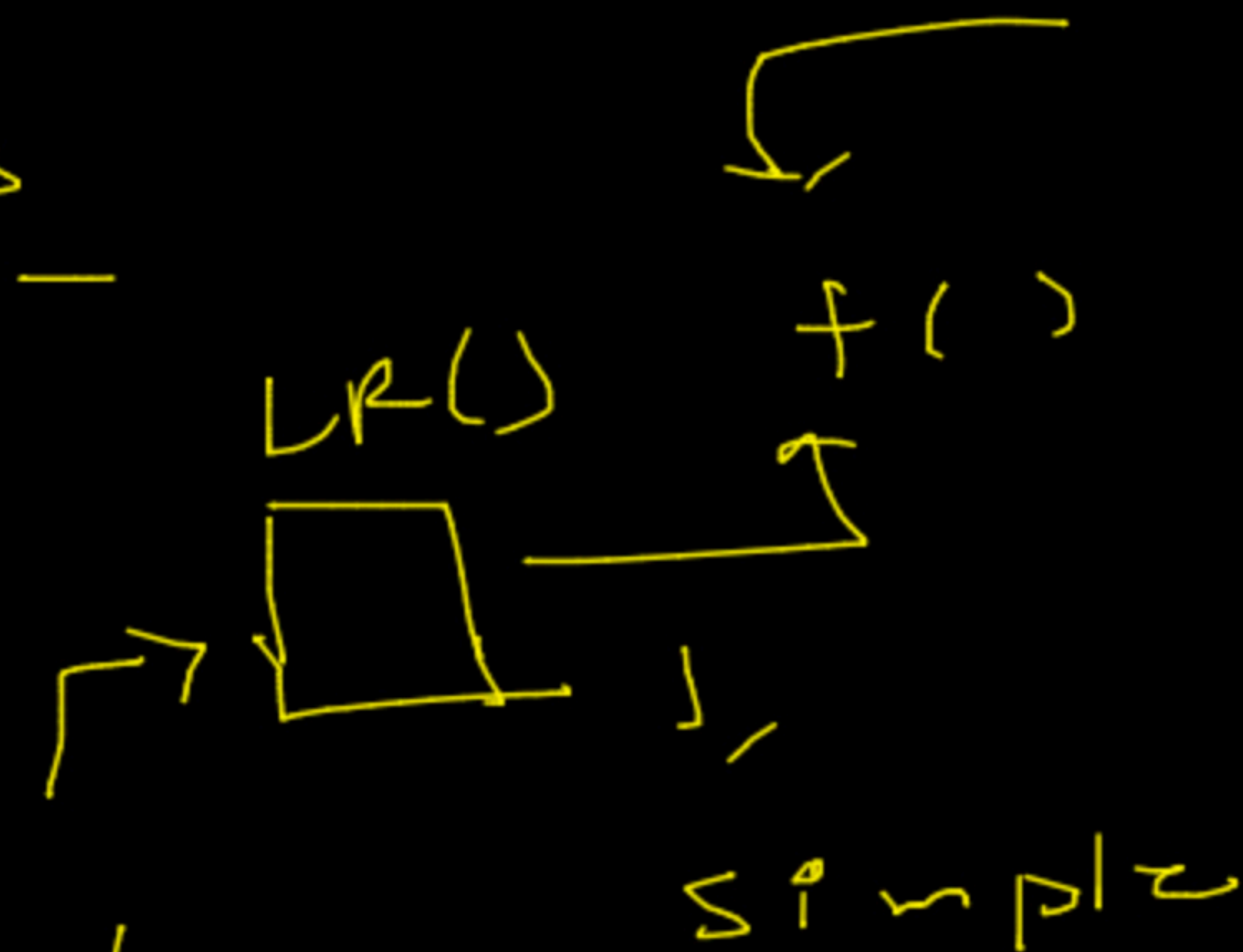


image/audio/video, pdf,

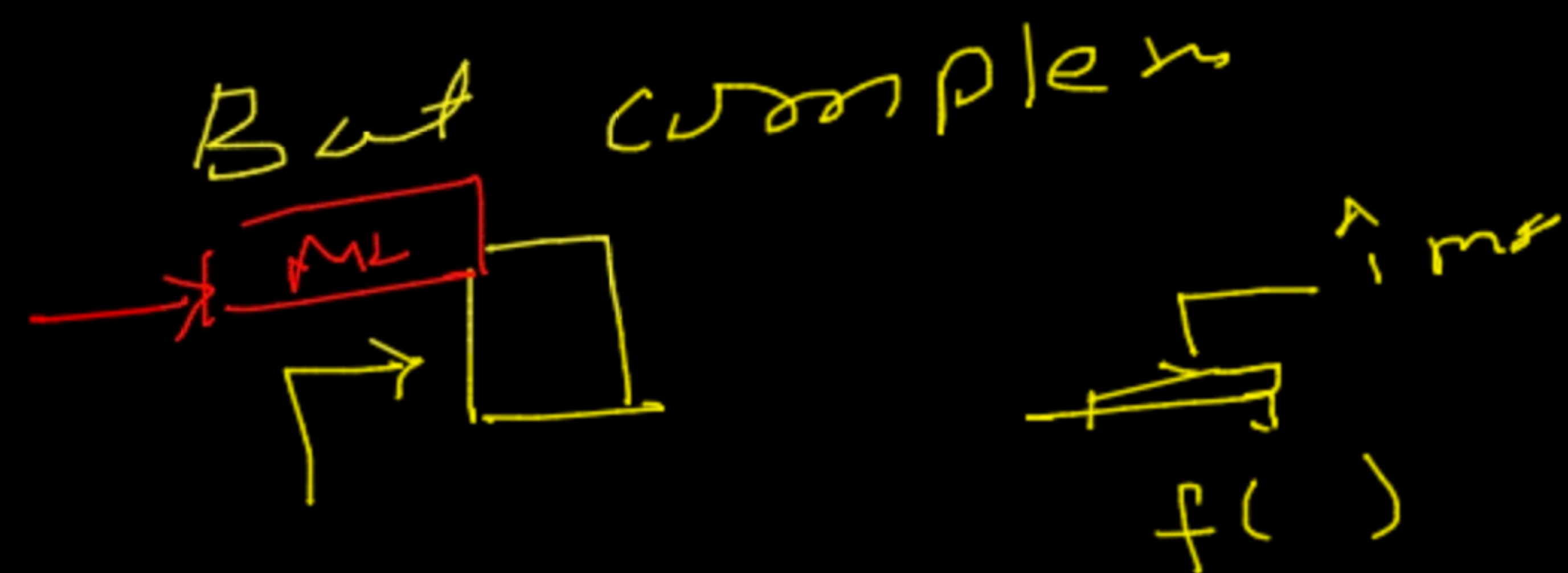
Data

↳ {  $f_1$     $f_2$     $f_3$     $f_4$    Sales

$D_x$  {  $D_{train}(x_{train}, y_{train})$   
           $D_{test}$



text → vectorization



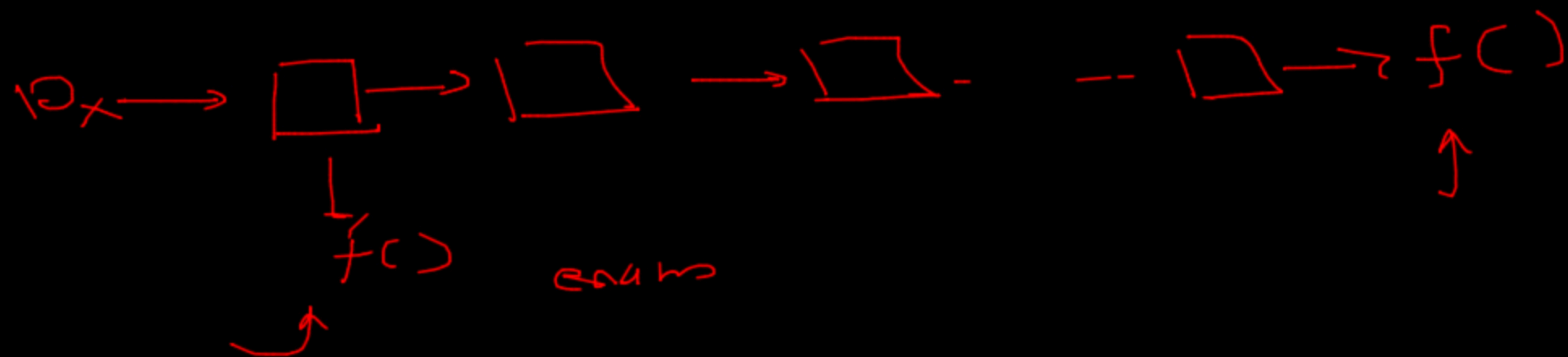
audio/video  
↓

image → [ - - - ]  
          ↑  
          vectorization

↓  
↓  
↓  
Real Fake

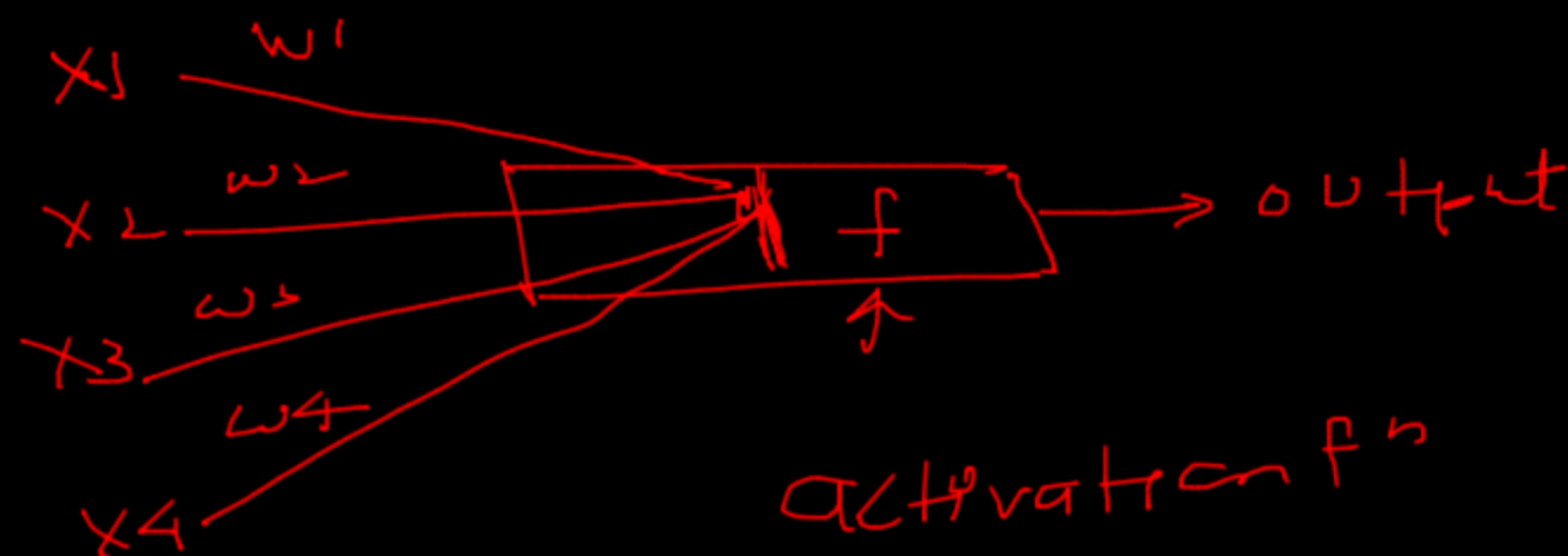
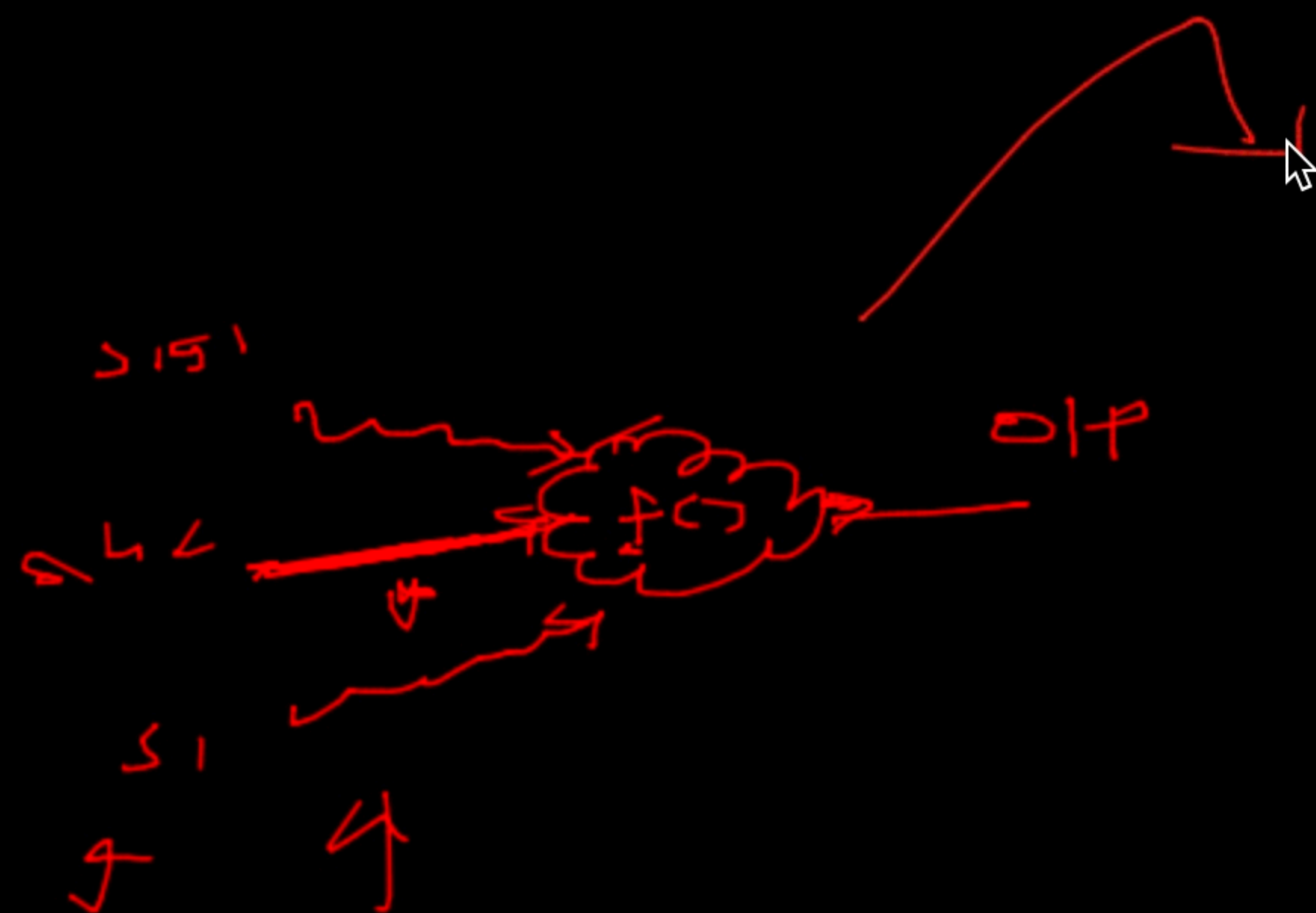
WOW





11

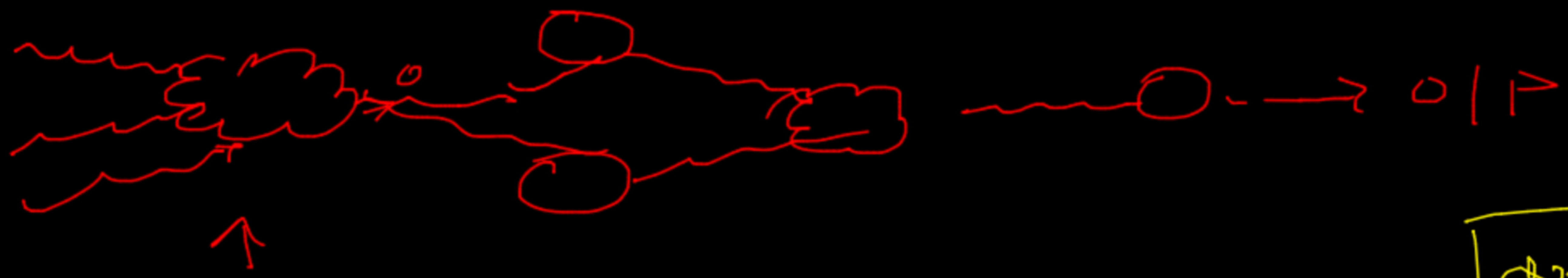
(957)



Human brain  $\rightarrow$  math

$[w_1, w_2, w_3, w_4]$

#



layer

1986 → Hallen

1986 → NT

Backpropagation

AI window

1986 1990 2006 2012  
↑ D = 12  
for 1 2

SSJ  
↑  
↓  
↑  
↓

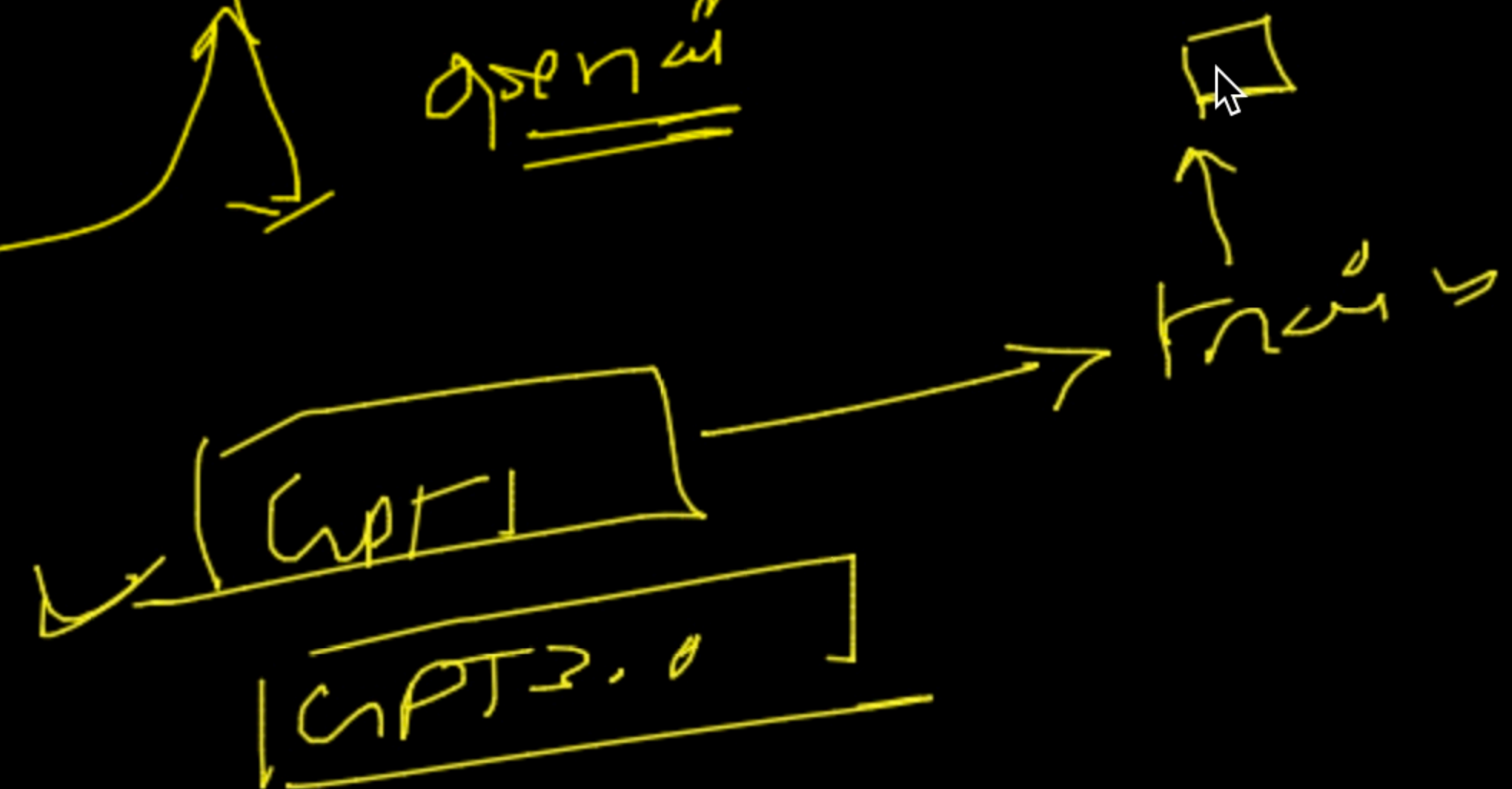
deg

F(L)  
→ (deg)

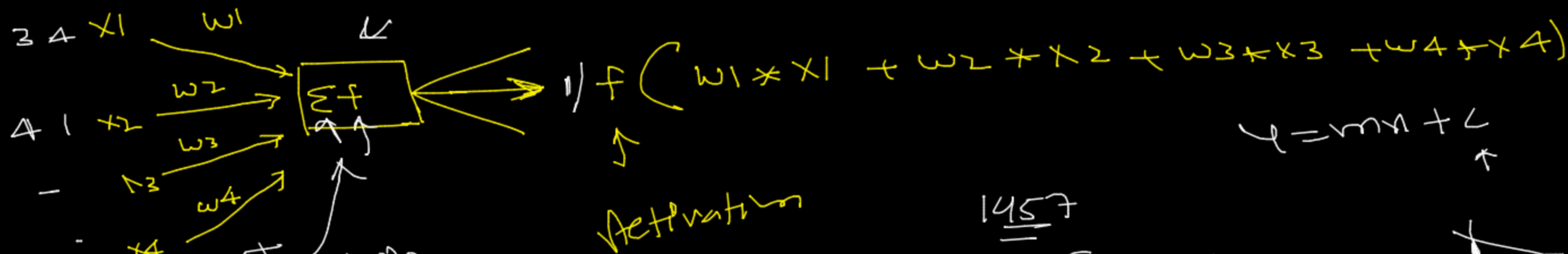
↑  
□



2012







$$y = mx + c$$

mathematically

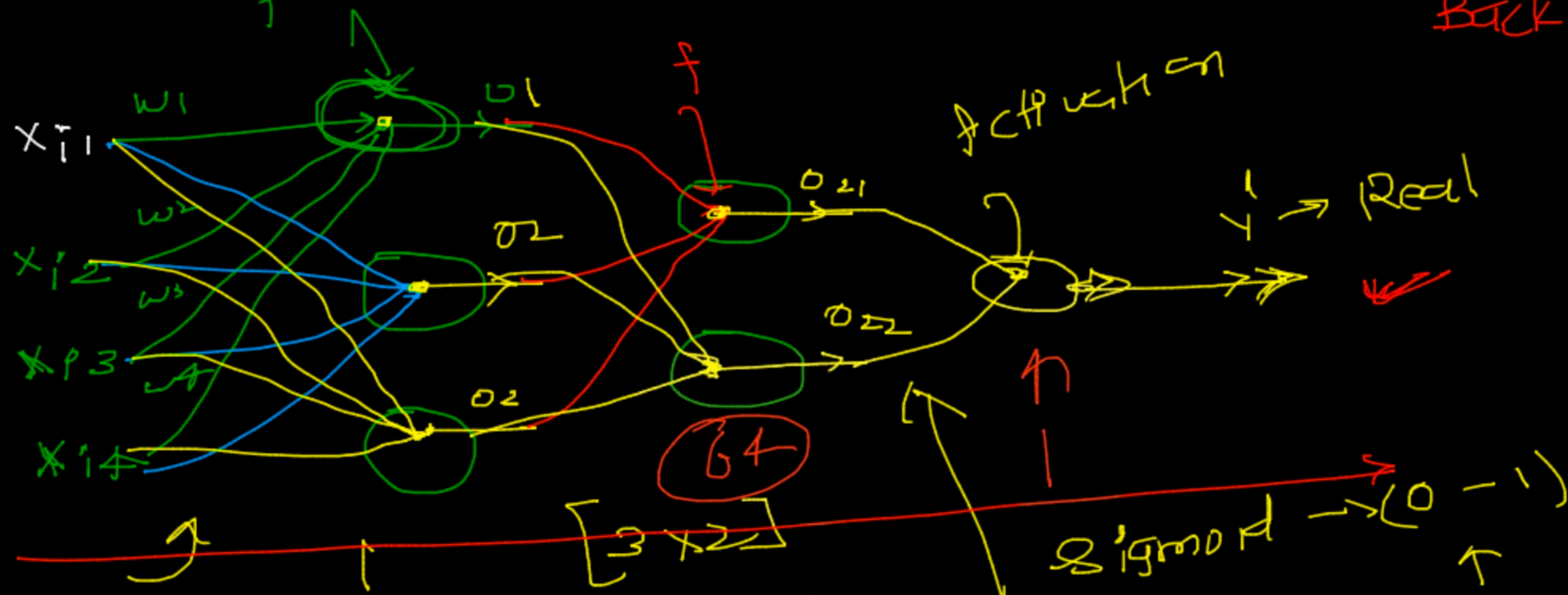
Diagram illustrating the mathematical representation of a perceptron. The output is labeled "output". The activation function  $f$  is applied to the weighted sum of inputs, represented as  $f\left(\sum_{i=1}^n w_i \cdot x_i^T\right)$ . The term  $\sum_{i=1}^n w_i \cdot x_i^T$  is labeled "activation". The term  $w_i$  is labeled "weight". The term  $x_i^T$  is labeled "input". The term  $b$  is labeled "same". The output is labeled "perceptron". The output is labeled "LR → sigmoid".

$$f(x) = \begin{cases} 1 & \text{if } w^T x + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

identity  $f$



# MLP



Backpropagation

Activation

Real

Feed

Forward

Sigmoid  $\rightarrow (0-1)$

$[4, 3]$

Layers

$[1]$

$2 \times 1$

Initially

12 weights  $\rightarrow$   $\begin{bmatrix} w_1 & w_2 & w_3 & w_4 \\ w_5 & w_6 & w_7 & w_8 \\ w_9 & w_{10} & w_{11} & w_{12} \end{bmatrix}$

20

found out Random

20 parameters

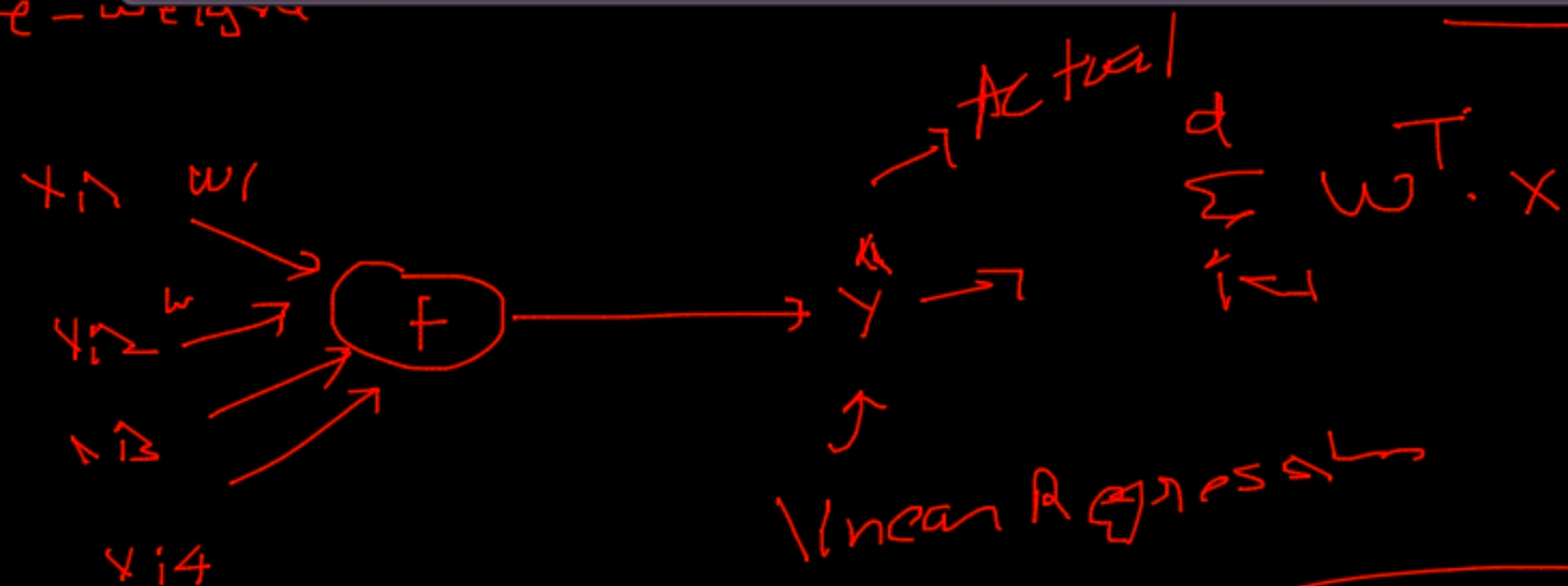
78 parameters

$\begin{bmatrix} 0 & 0 & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \end{bmatrix}$

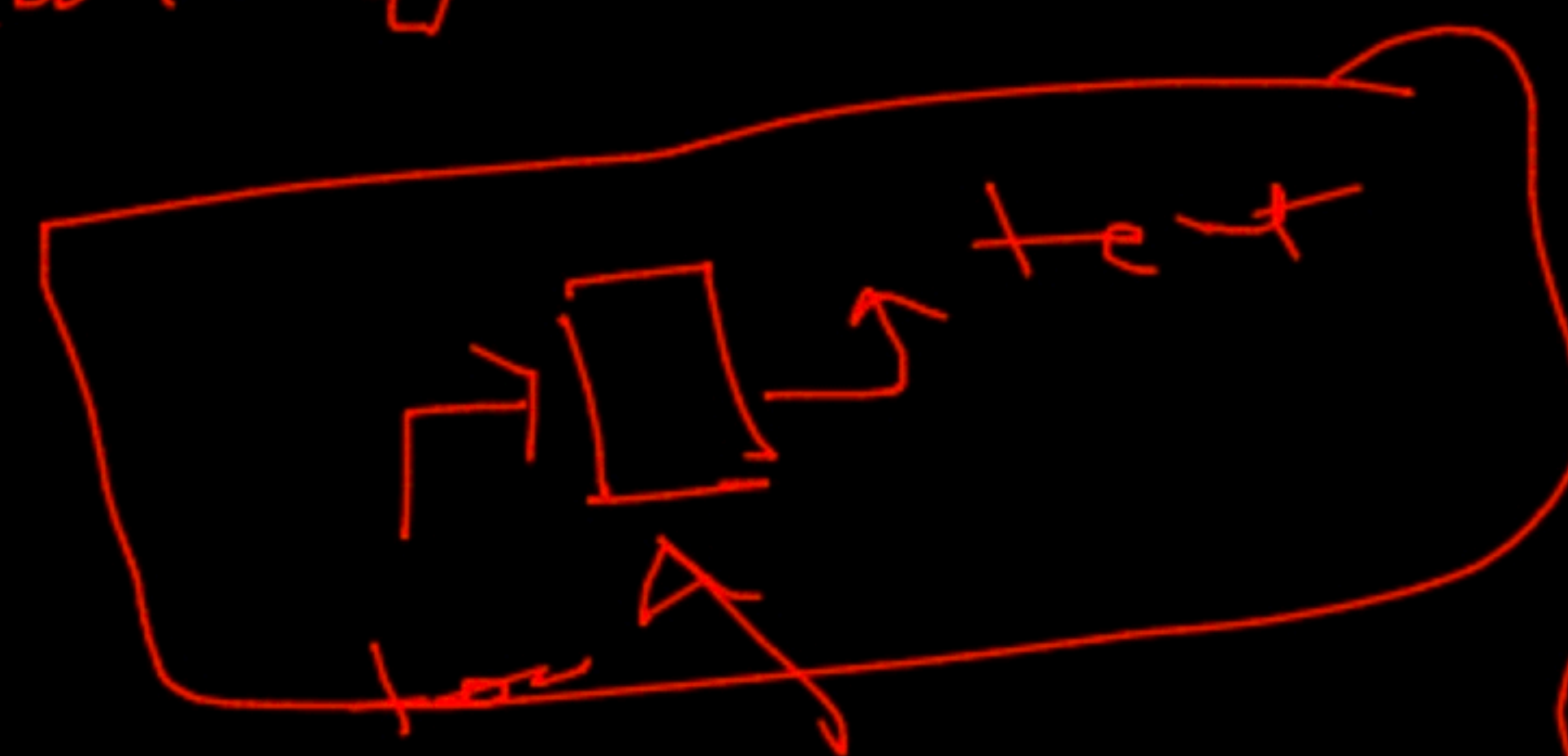


# Train a single Neuron model

↳ edge-weights



Linear Regression

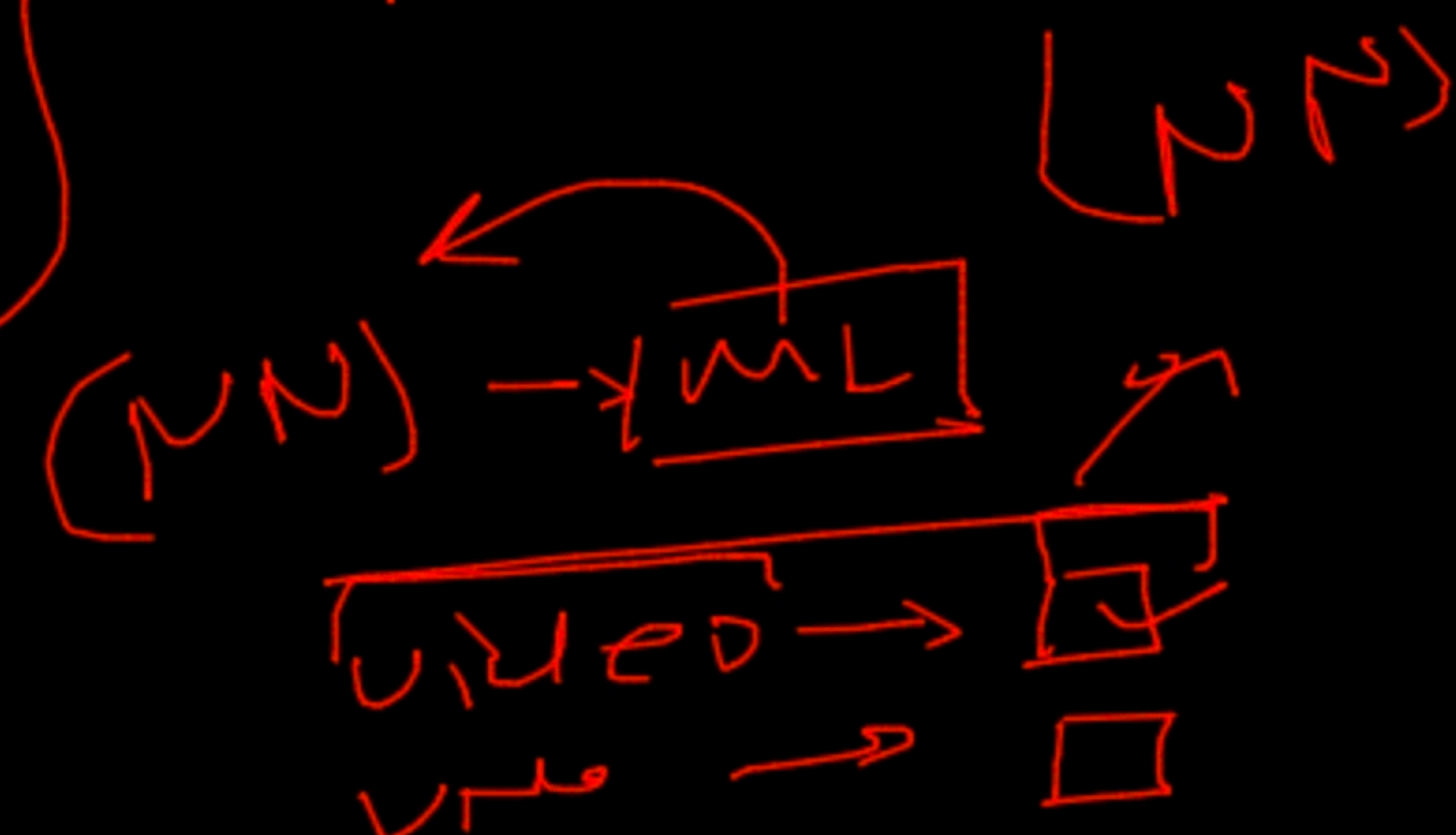


$$(y - \hat{y})$$

loss

Linear Regression

$$L = \min_{w_i} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \text{reg}$$



ie- (Step 1) define loss f<sup>n</sup>

$$d_i = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \text{reg}$$



$$w^* = \underset{w}{\operatorname{argmin}} \sum_{i=1}^n (y - \hat{y})^2 \rightarrow \text{reg}$$

Step 3  $\rightarrow$  using SGD algorithm

$\downarrow$

'NN'

$\uparrow$

'sequential'

$\uparrow$

$\downarrow$

$f(x)$

$$f = \sin x$$

$\nearrow \quad \uparrow$

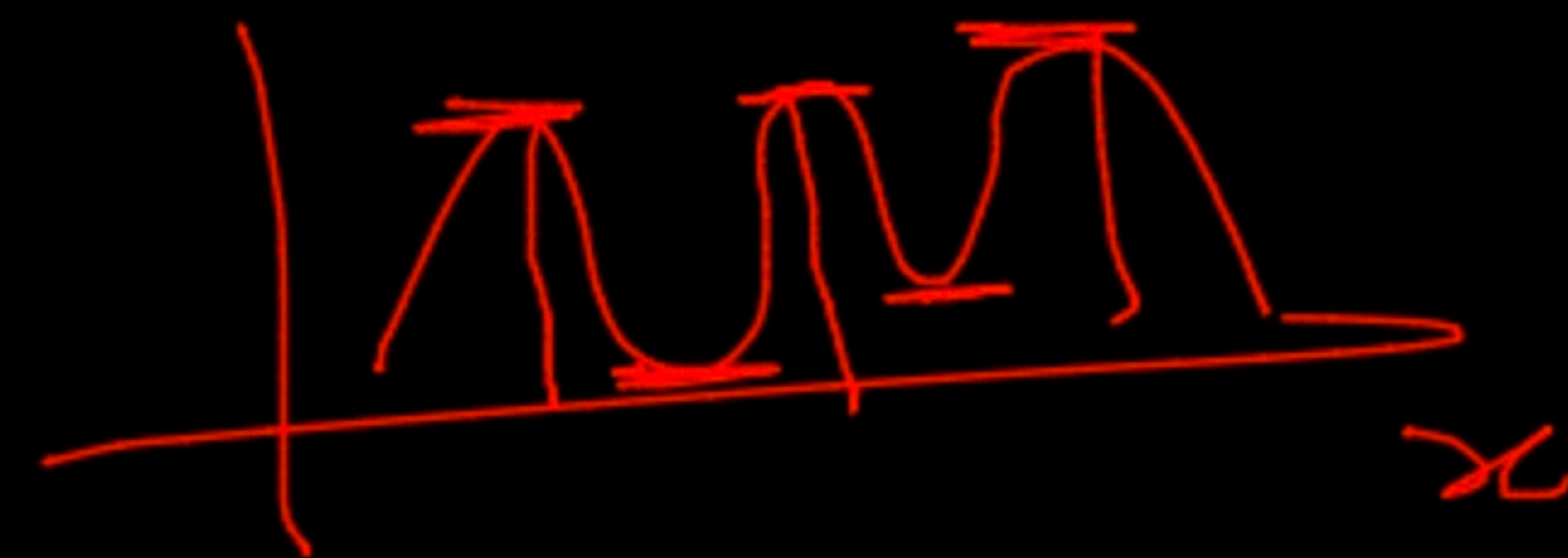
max

$\uparrow$

$$|x| =$$

$$|x| <$$

$f$



maxima? }  $\rightarrow$  ~~min~~

$\downarrow$

derivative