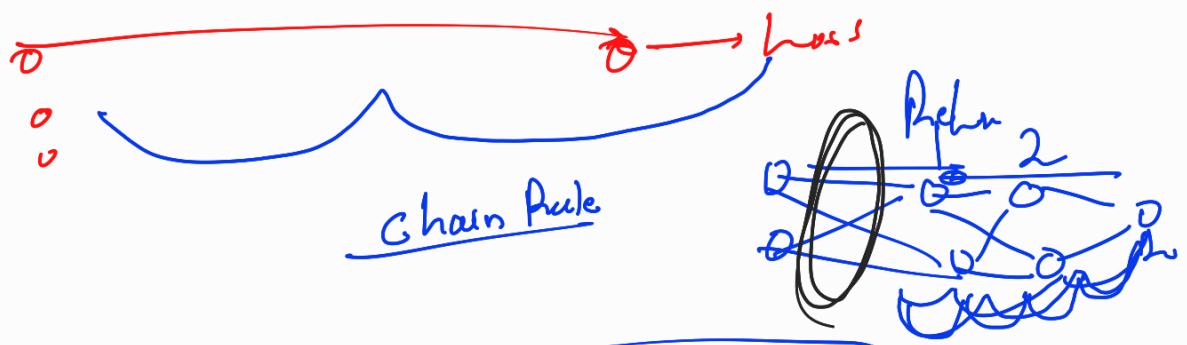
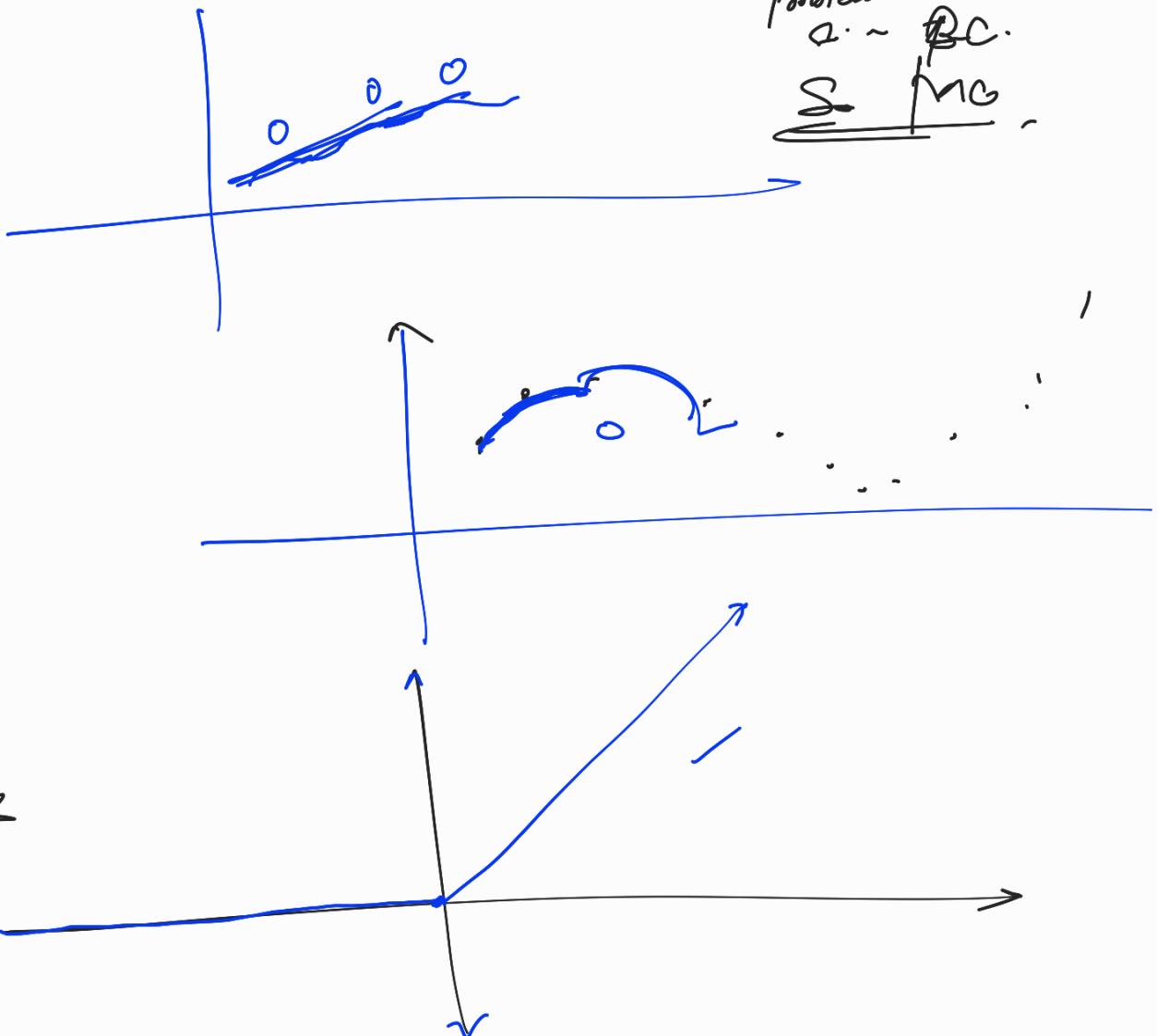


26/4/2024

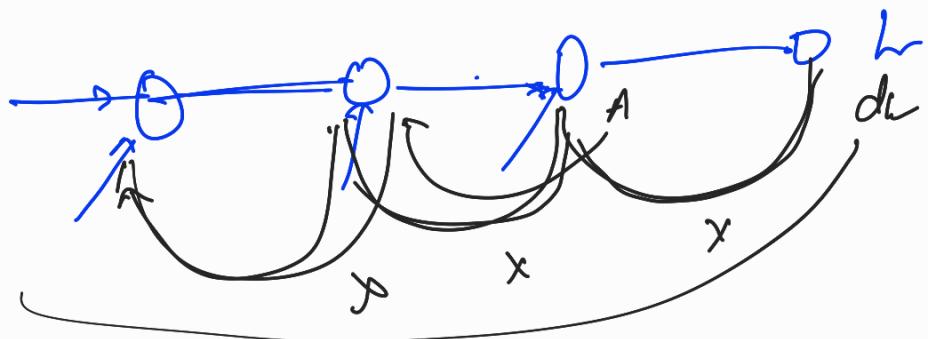
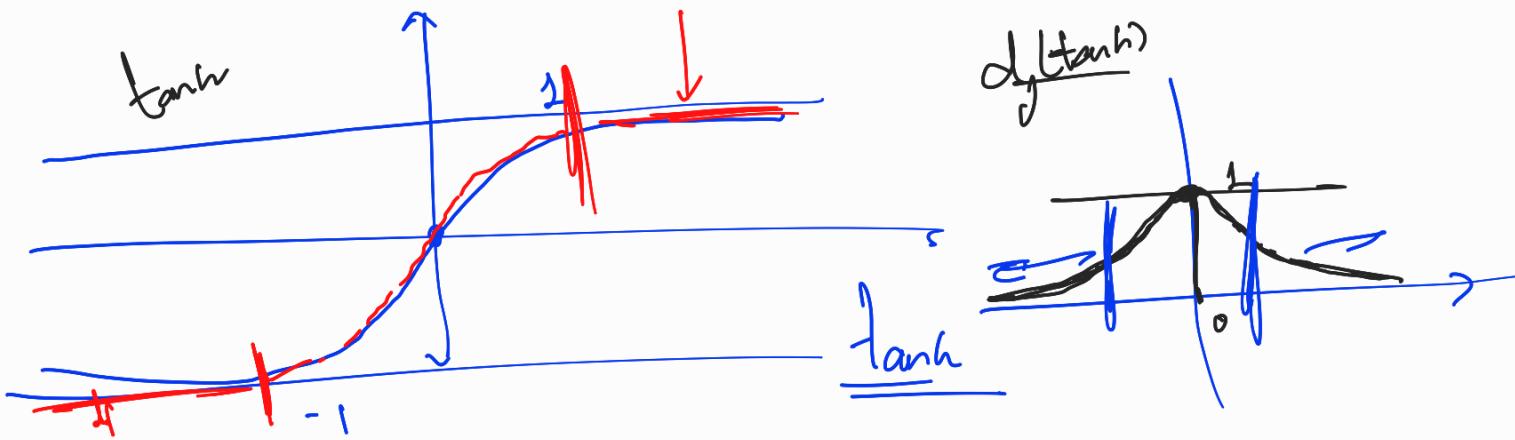
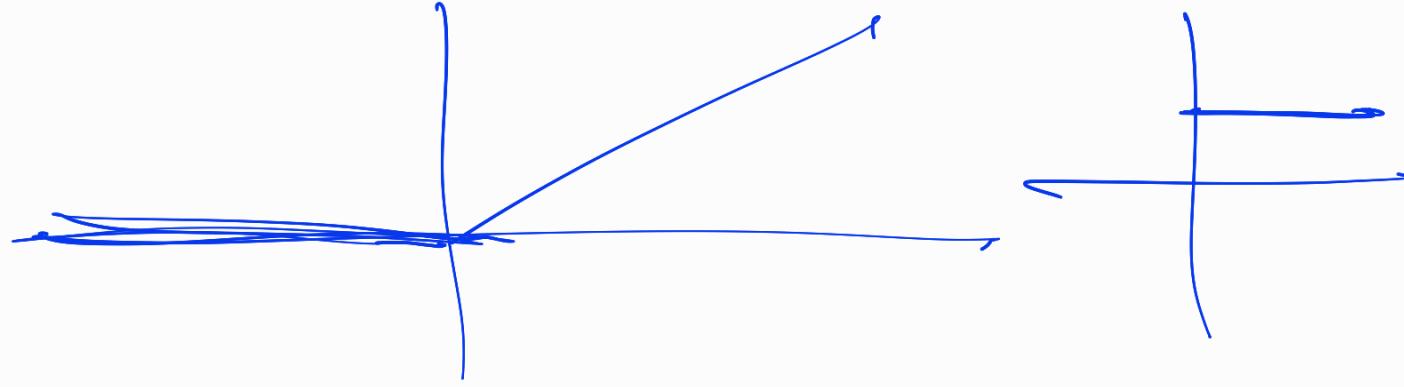
- Activation functions
- Handout FP, BP looklike for a 1HL NN. (activation functions)
- Activation functions → Functions which are applied at the Neuron output in HL /  $O_L$  to specifically bring in Non-linearity in the system.

$\text{HL} \rightarrow \text{Activations} \rightarrow \text{Non-linearity}$   
 $\text{OL} \rightarrow \text{Activations} \rightarrow$  Restrict the output specific  
 Problem  
 $\alpha \sim \text{BC}$   
 $\beta \sim \text{MC}$



$$\Delta w_{i+1} = \Delta w_i - \frac{\partial h}{\partial w} c$$

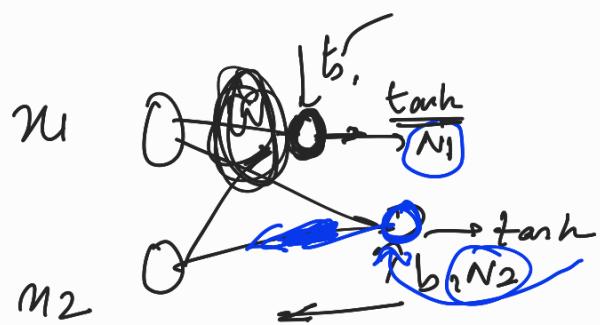
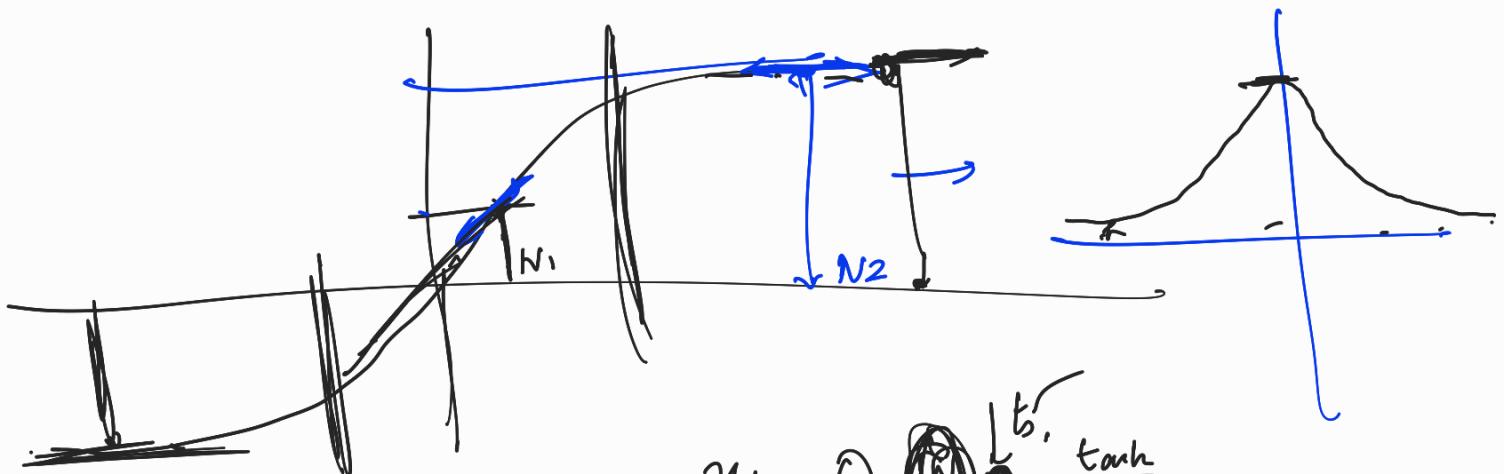
$$w_{i+1} = w_i - \frac{\partial h}{\partial w} c$$



$$w_i^{t+1} = w_i - \alpha \frac{dh}{dw}$$

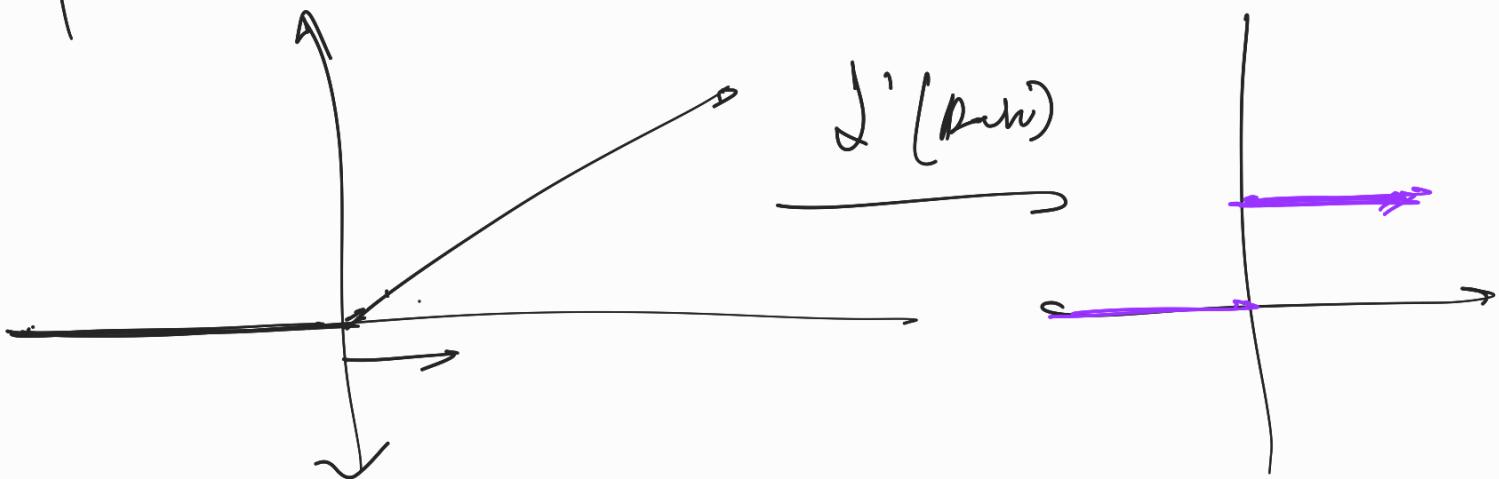
$\downarrow f$

$$\left( \begin{array}{c} x \\ x \\ x \end{array} \right)$$

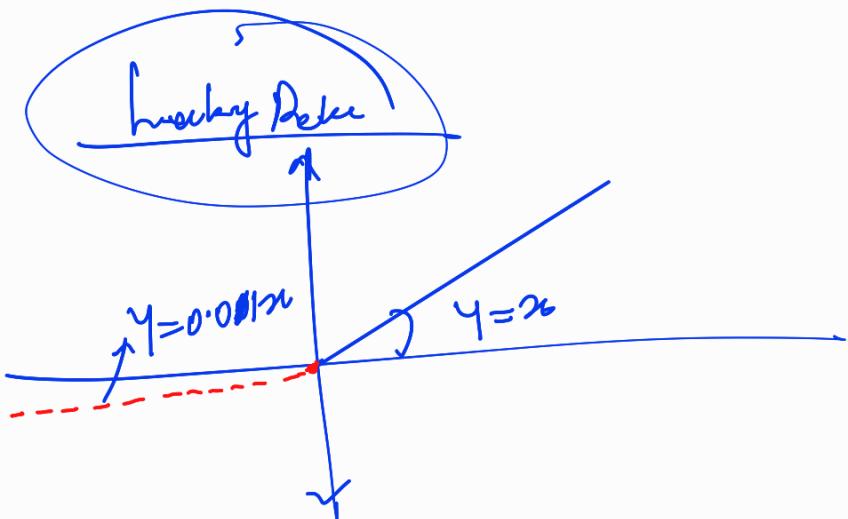
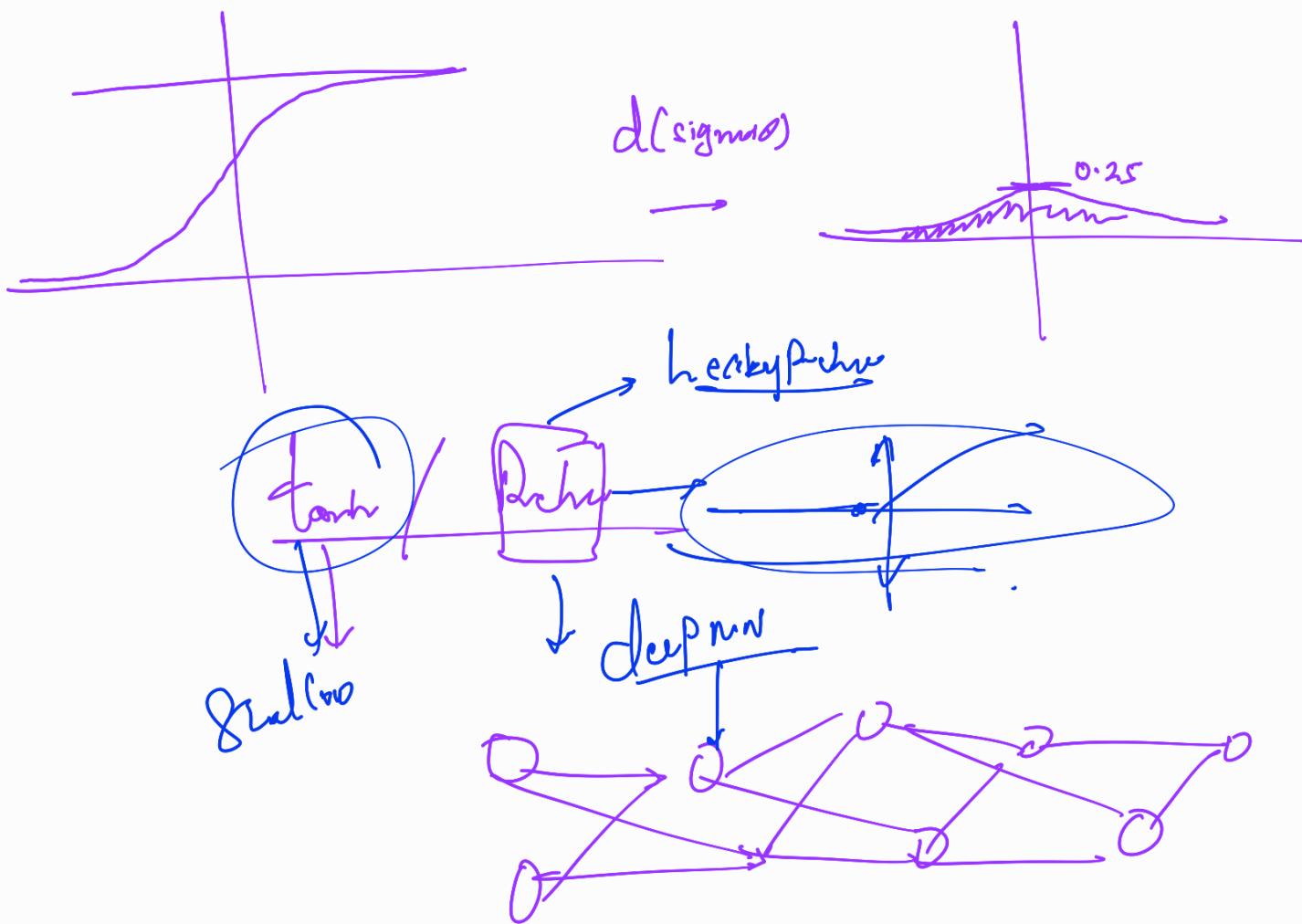


$$w_{it1} = w_i - \alpha \frac{dh}{d\omega}$$

Rehr



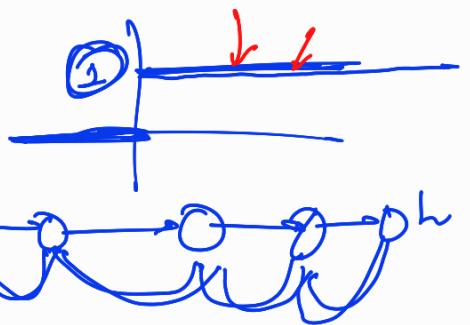
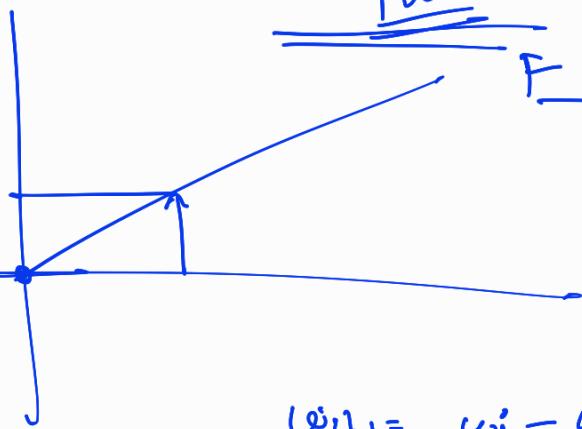
$$w_{it1} = w_i - \alpha \frac{dh}{d\omega}$$



Activation function

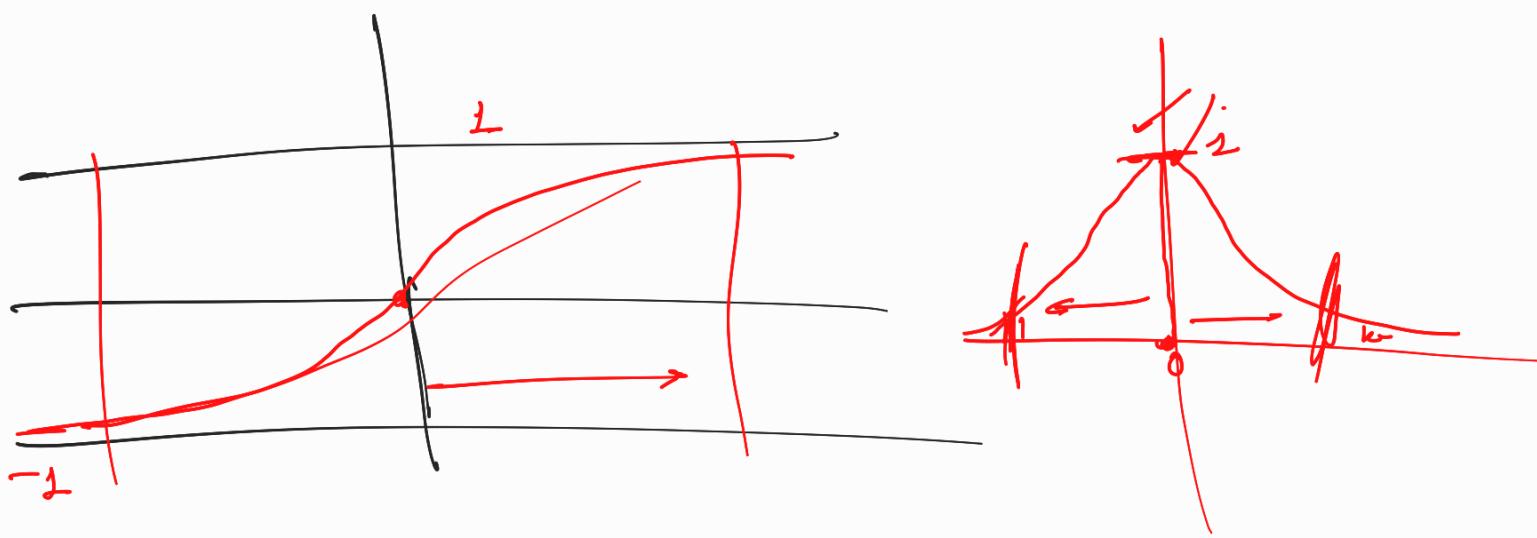
ReLU

$F$

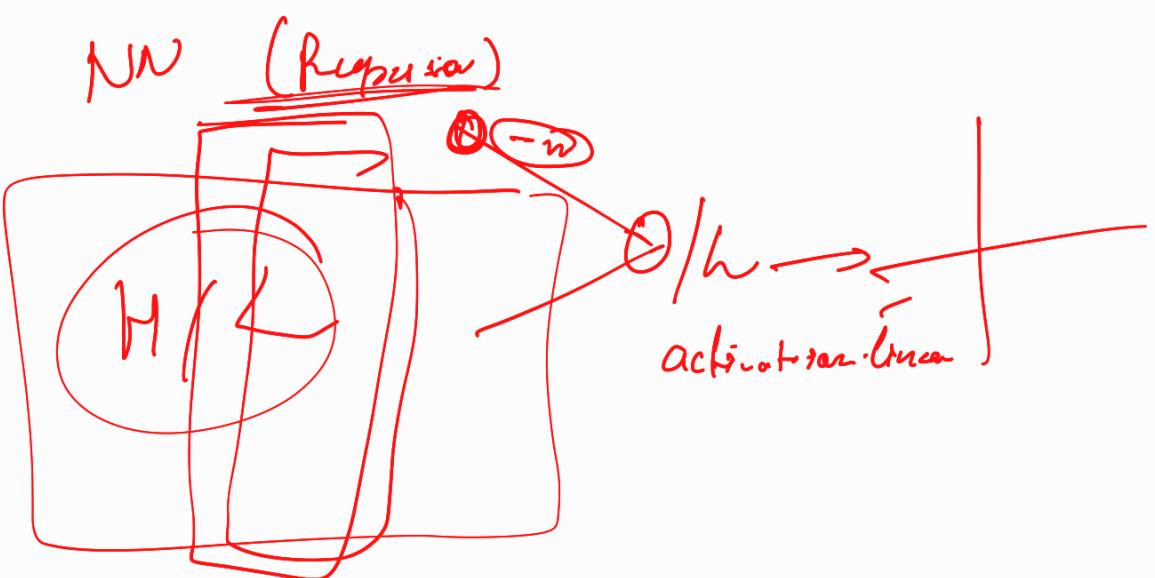
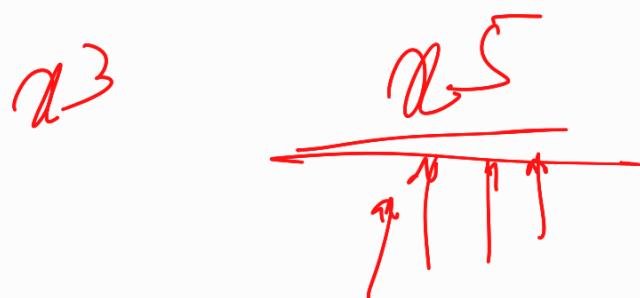


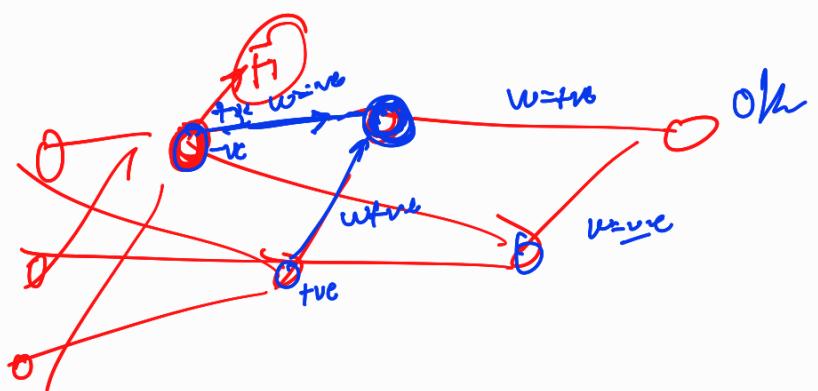
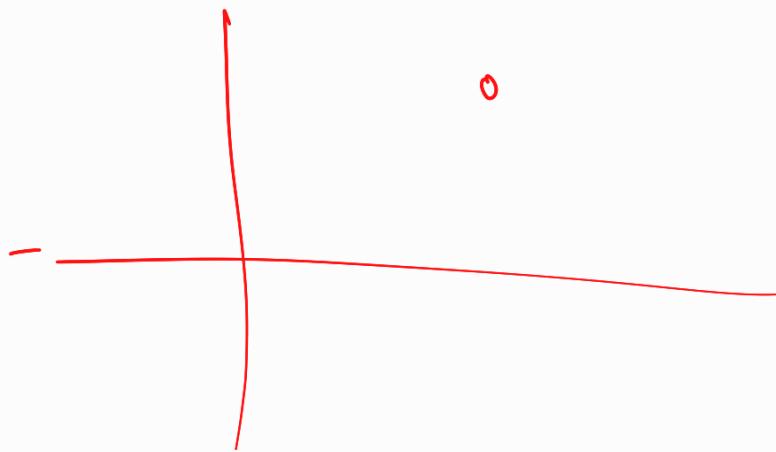
A diagram illustrating a weight update step. A red oval encloses a blue line segment with arrows indicating a gradient descent step. The formula below shows the update rule:

$$w_{j+1} = w_j - \alpha \frac{dJ}{dw_j}$$

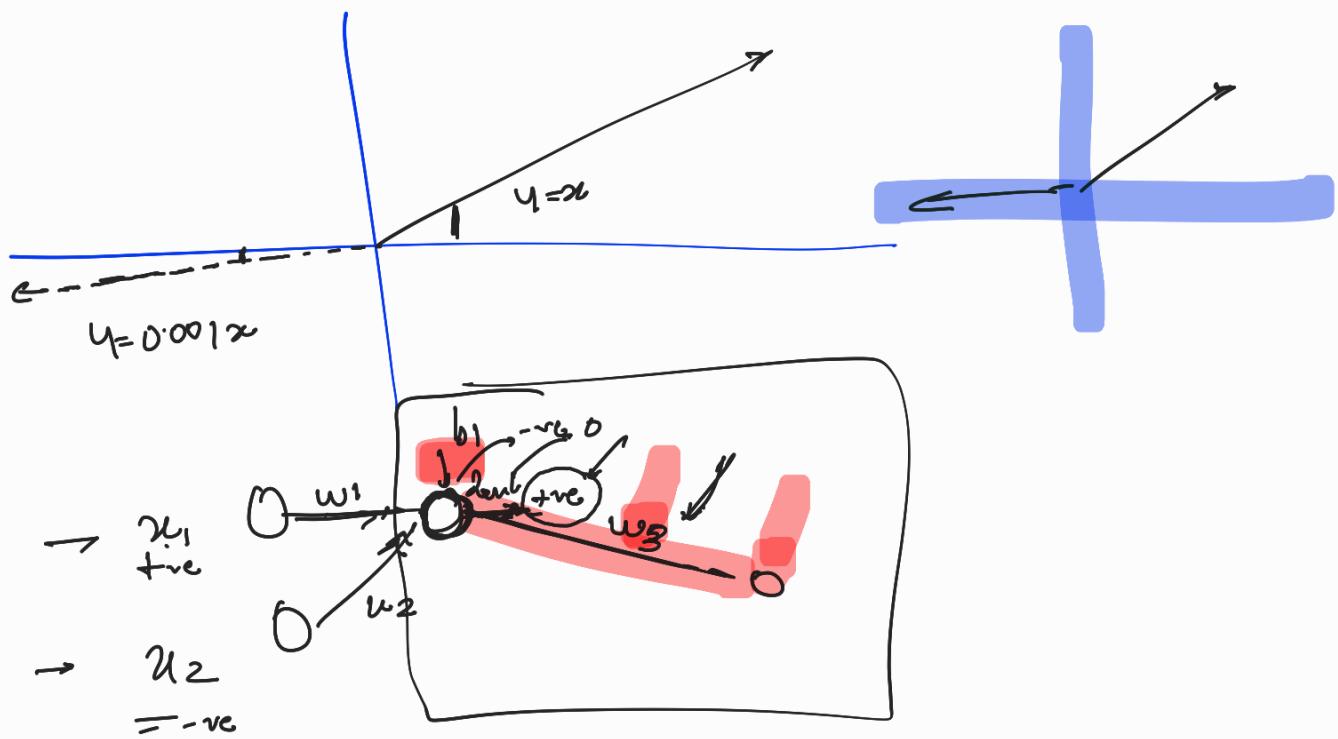


$\text{tanh}$   
 $\checkmark$   
 Shallow  
 networks  
 $v_i$  Relu  
 $\downarrow$   
Deep

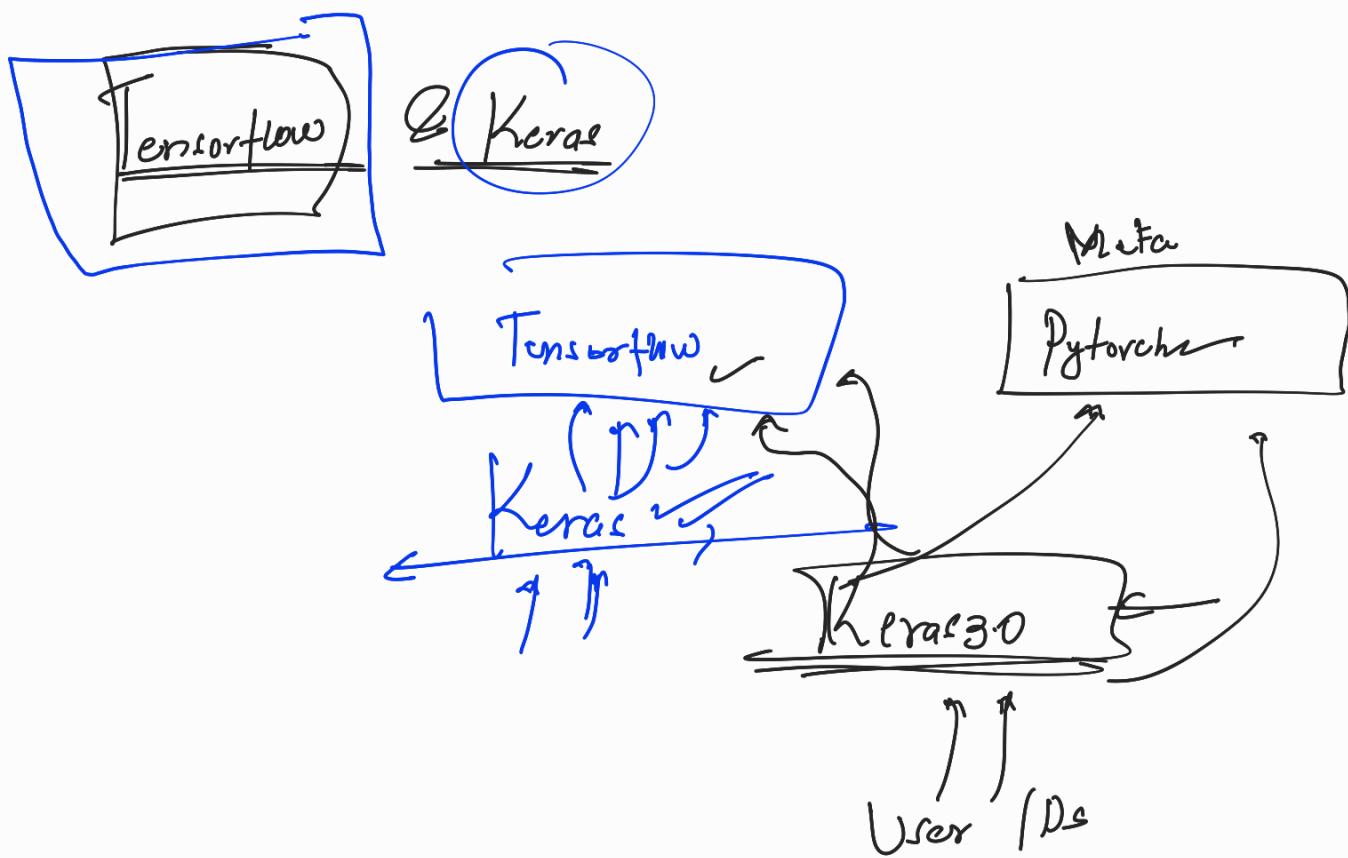
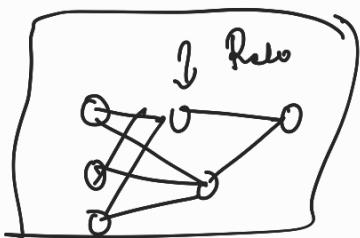




Leaky ReLU



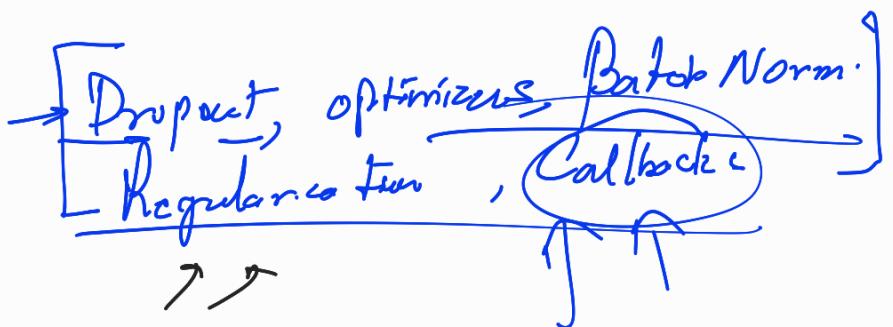
Break 1

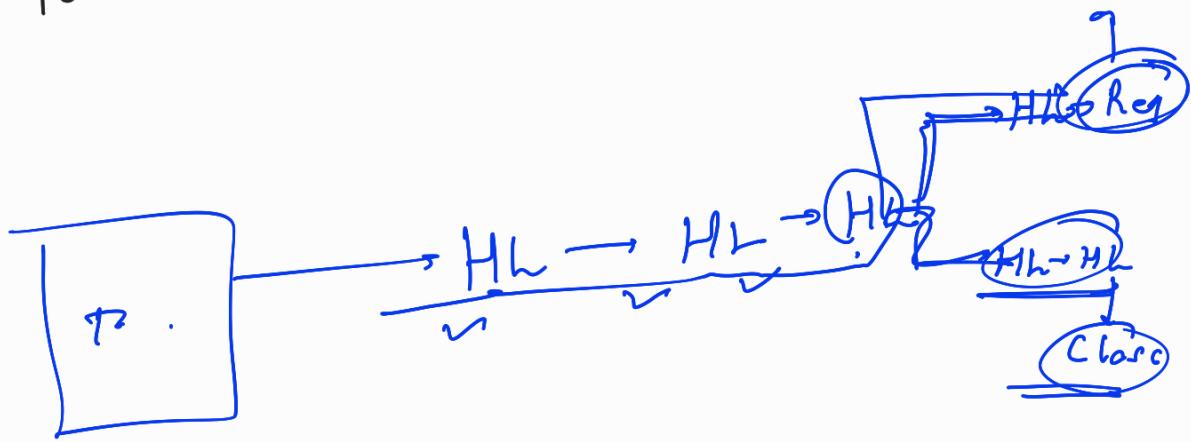
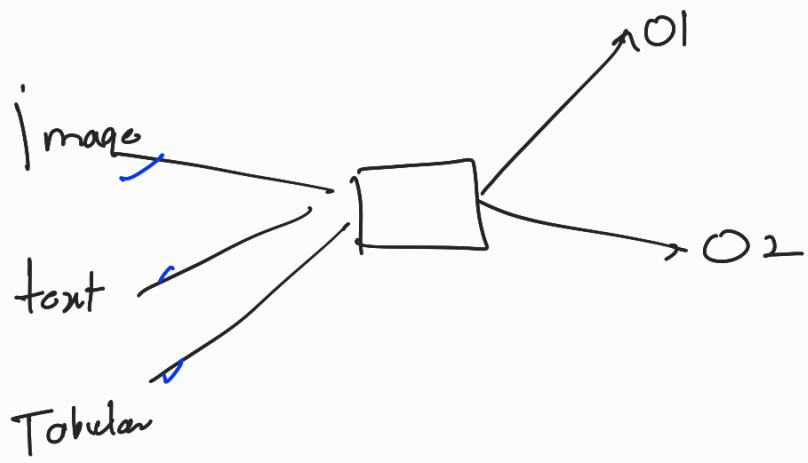


①  Simple code on how to implement a nn from scratch

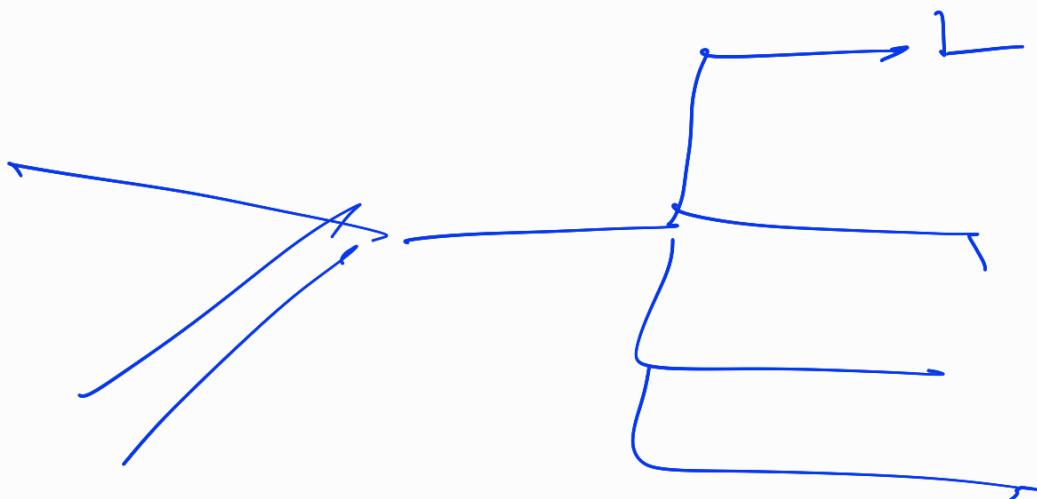
in Keras →

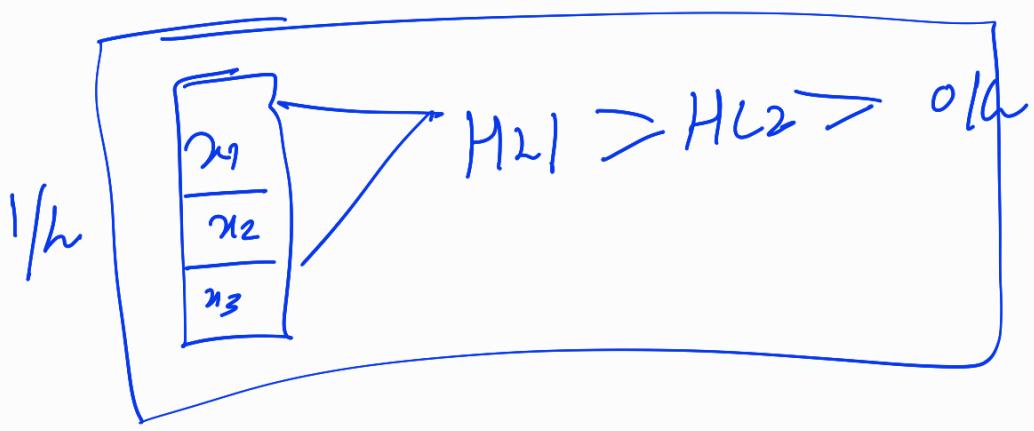
→ improving nn





$I/k \rightarrow H_h \rightarrow H_L \rightarrow H_l \rightarrow O/L$

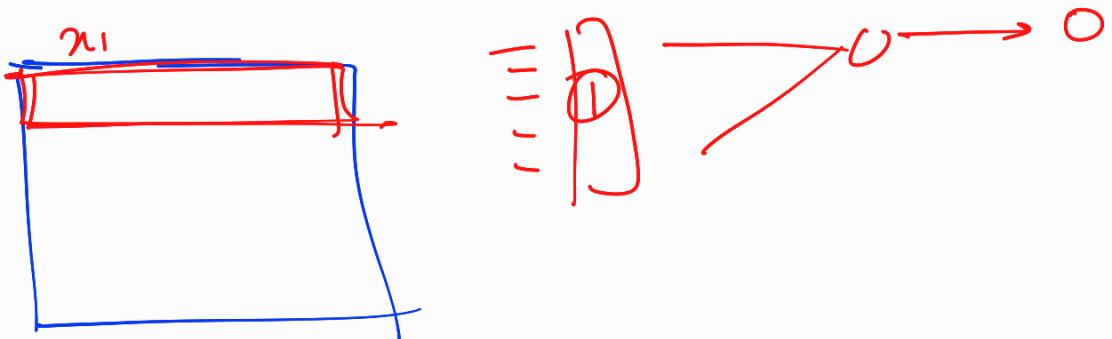




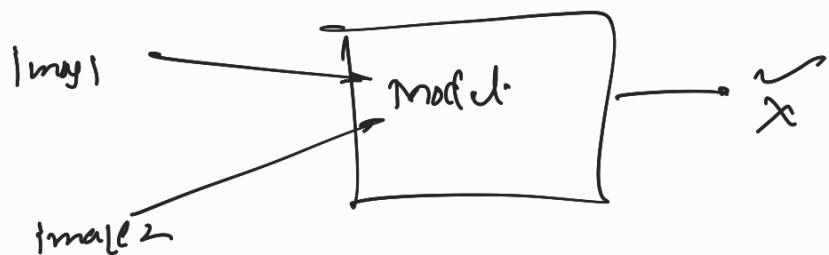
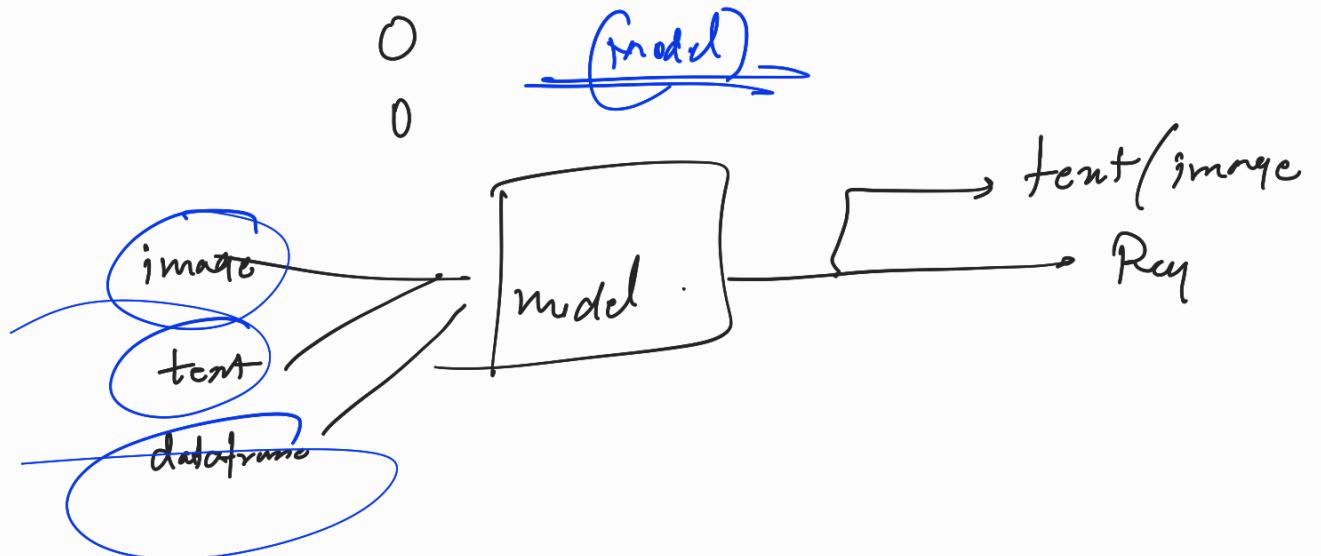
Sequential ()

3/05/2024

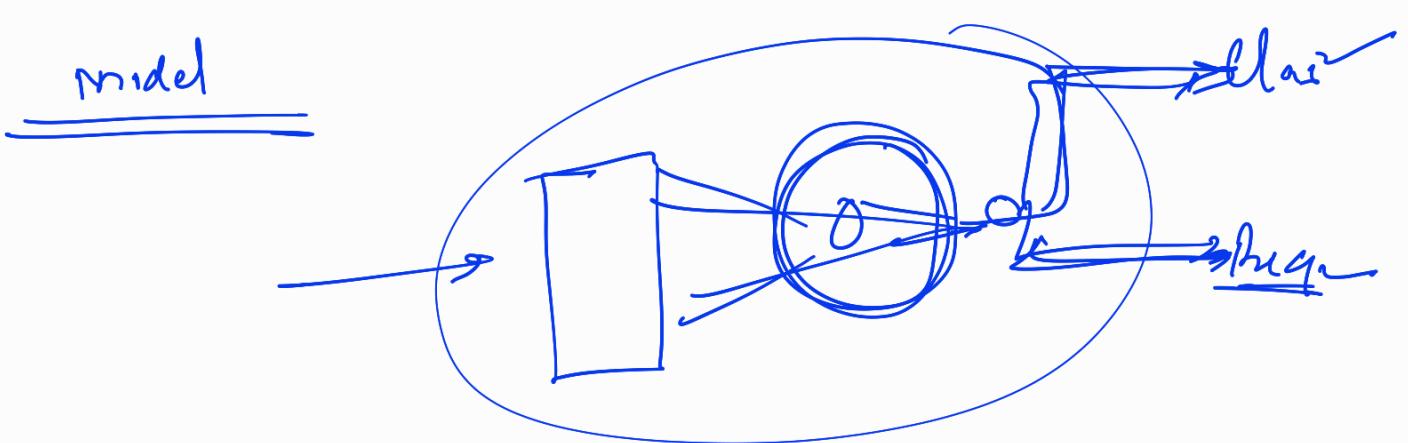
Sequential

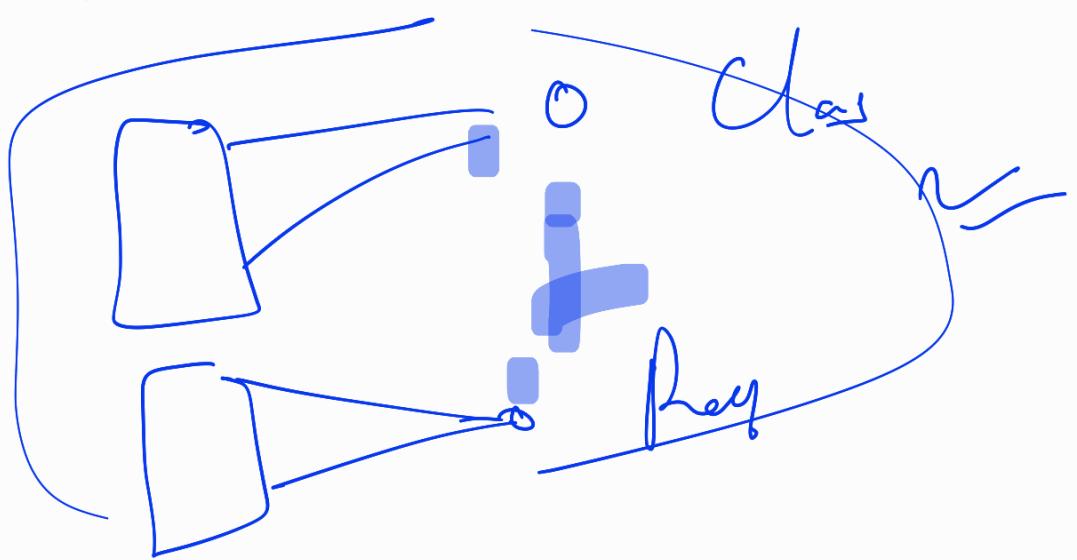
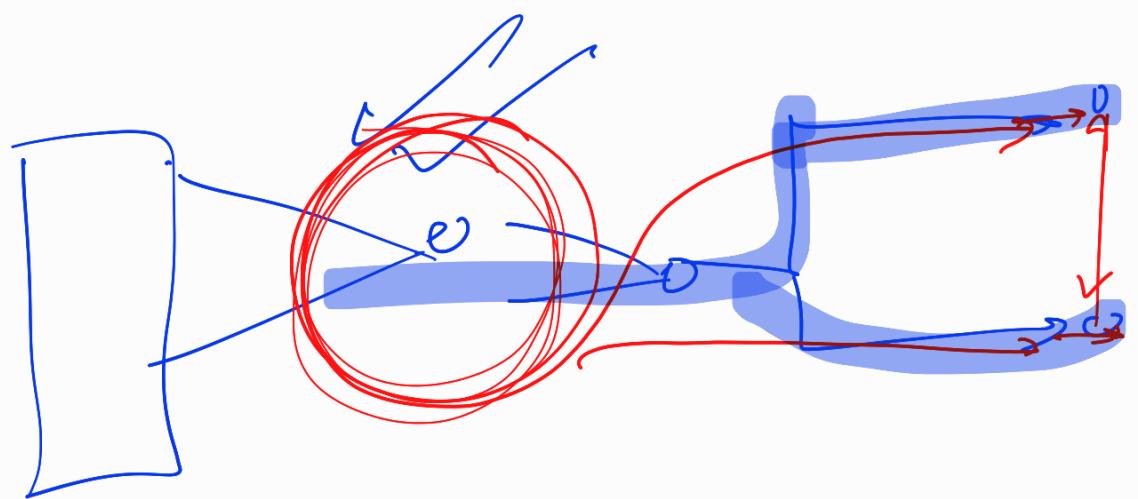
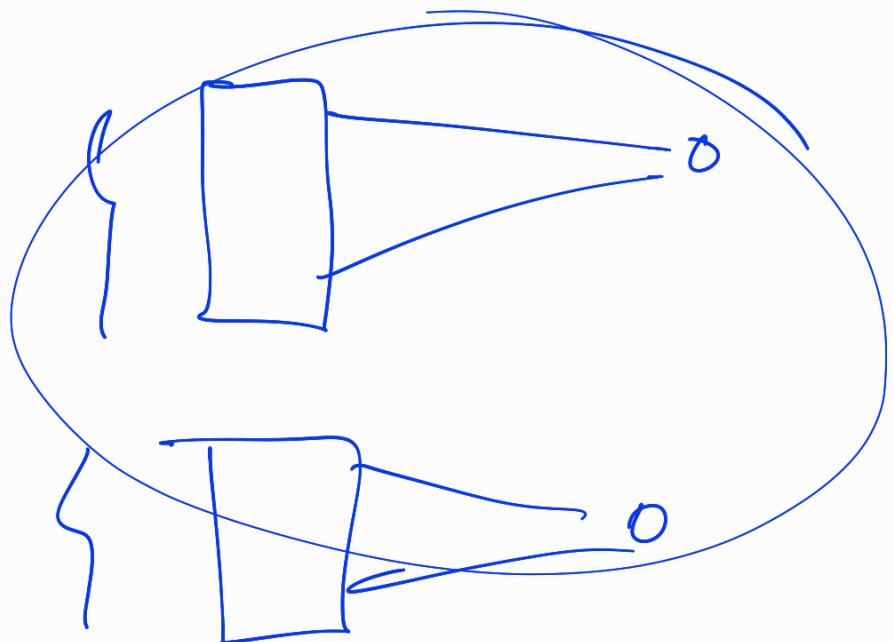


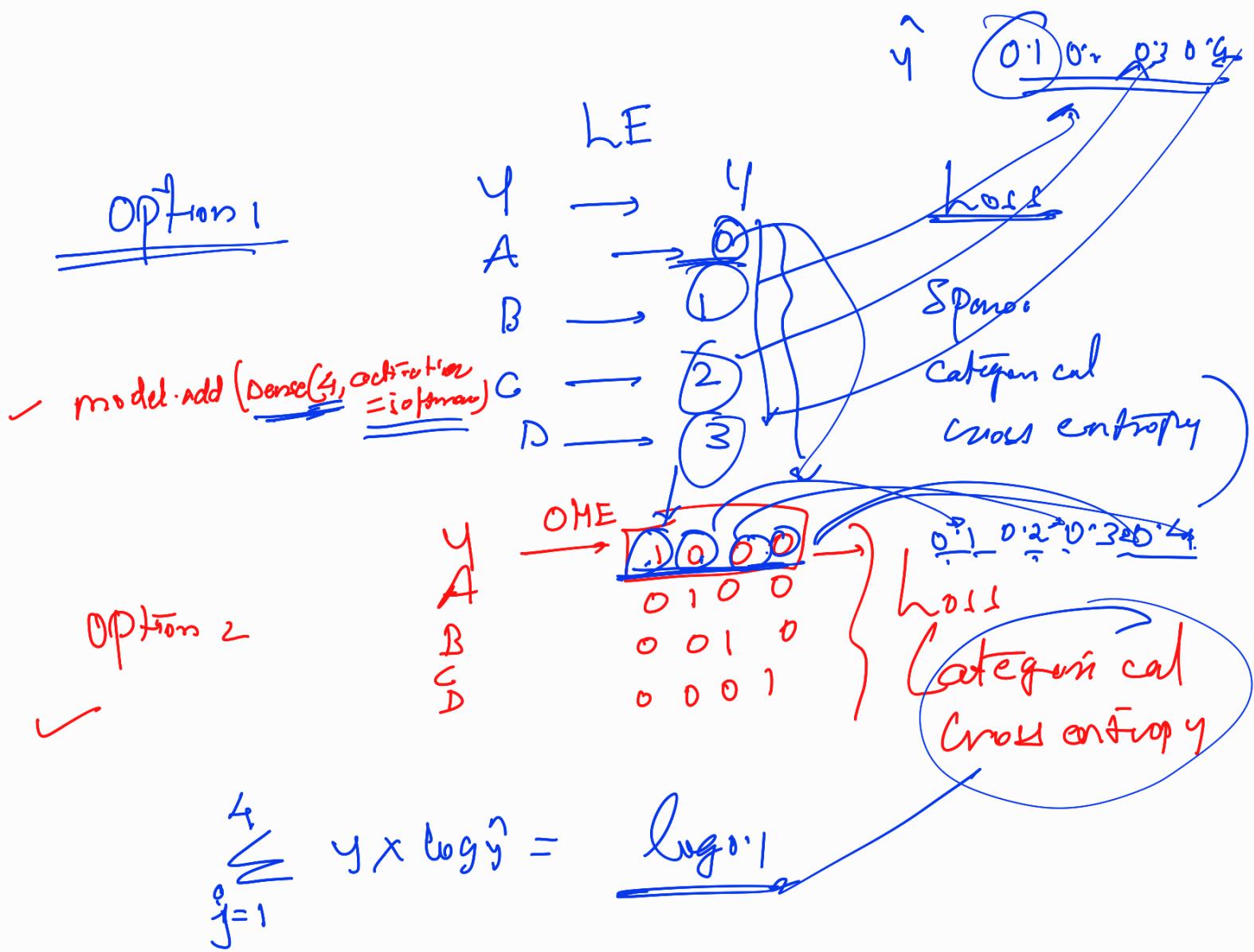
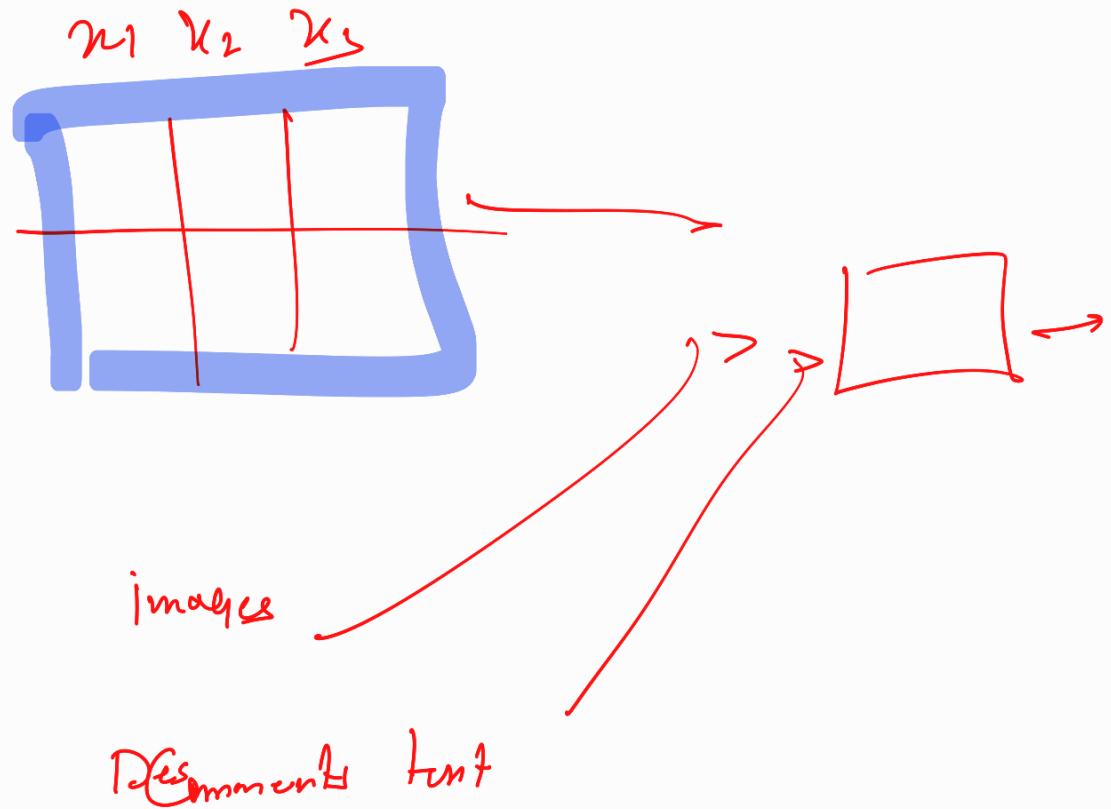
Multimodality

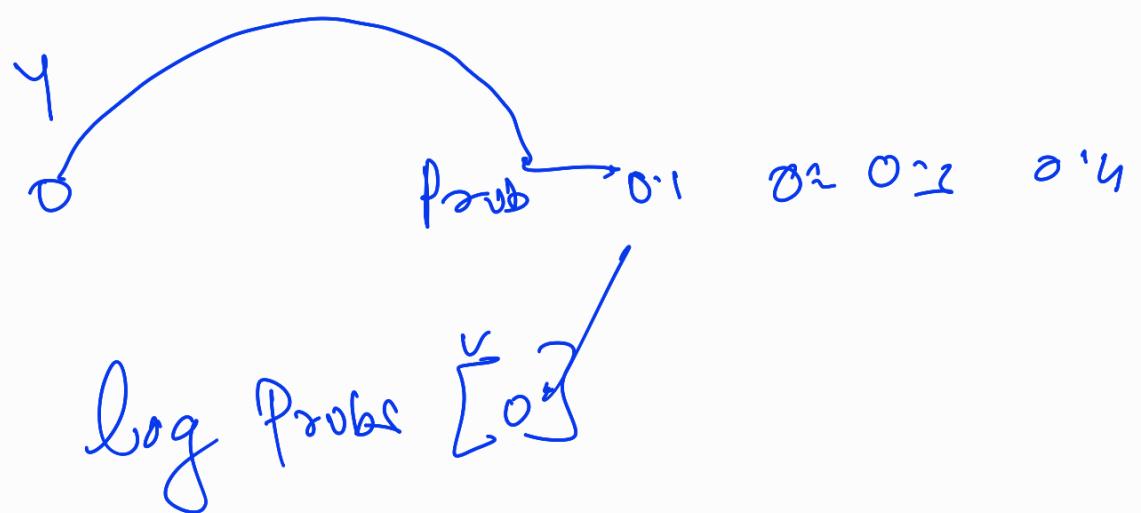


Semantical ()

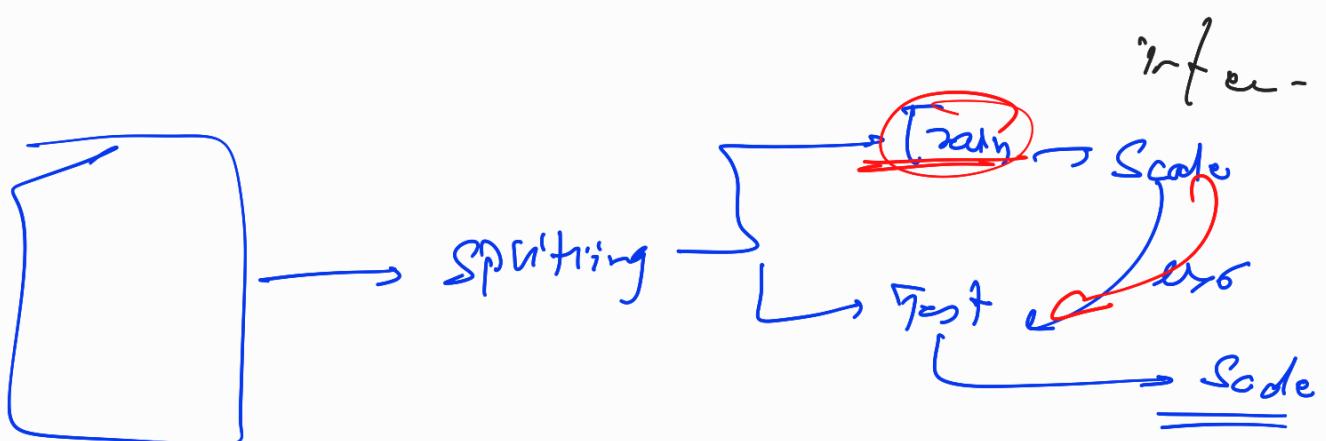
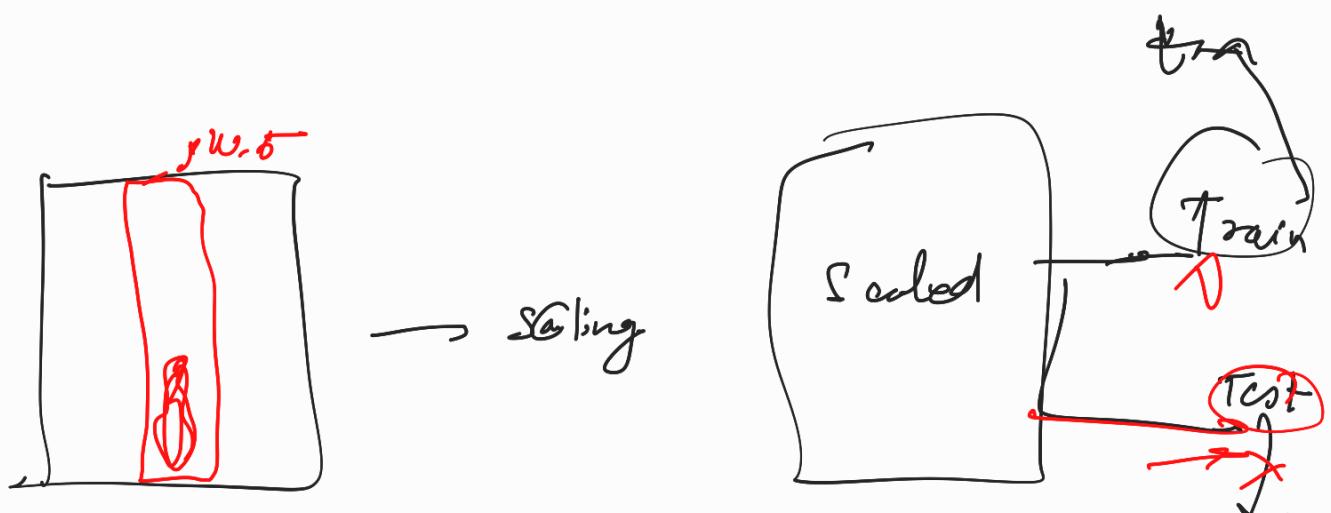


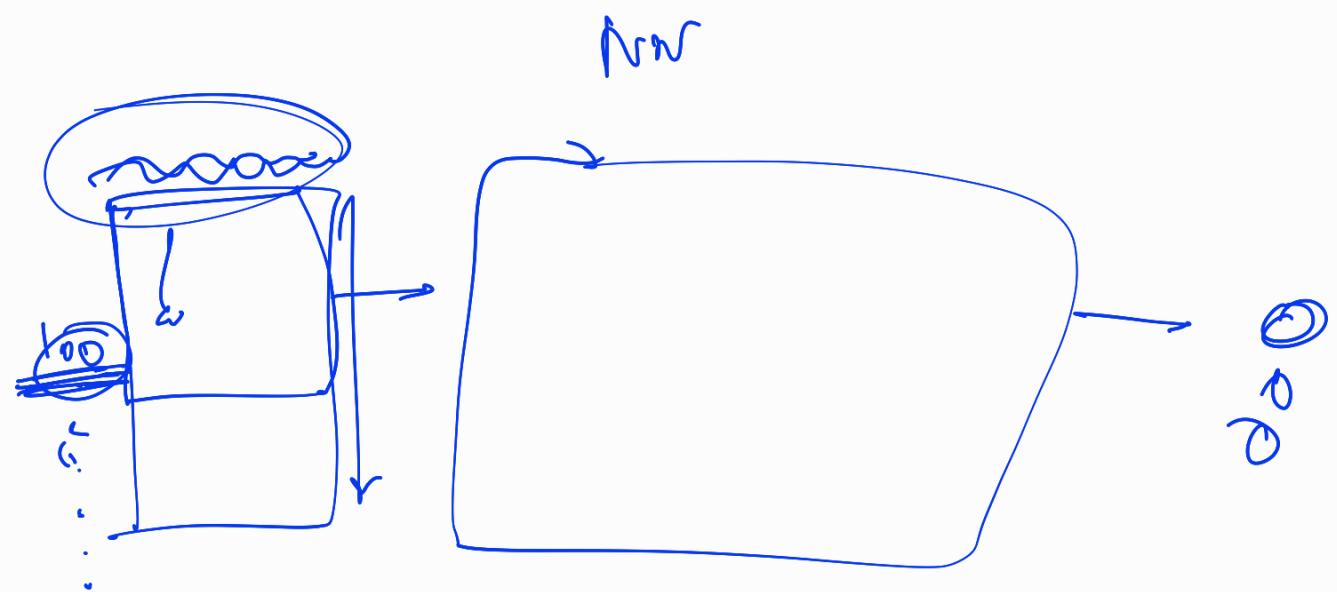






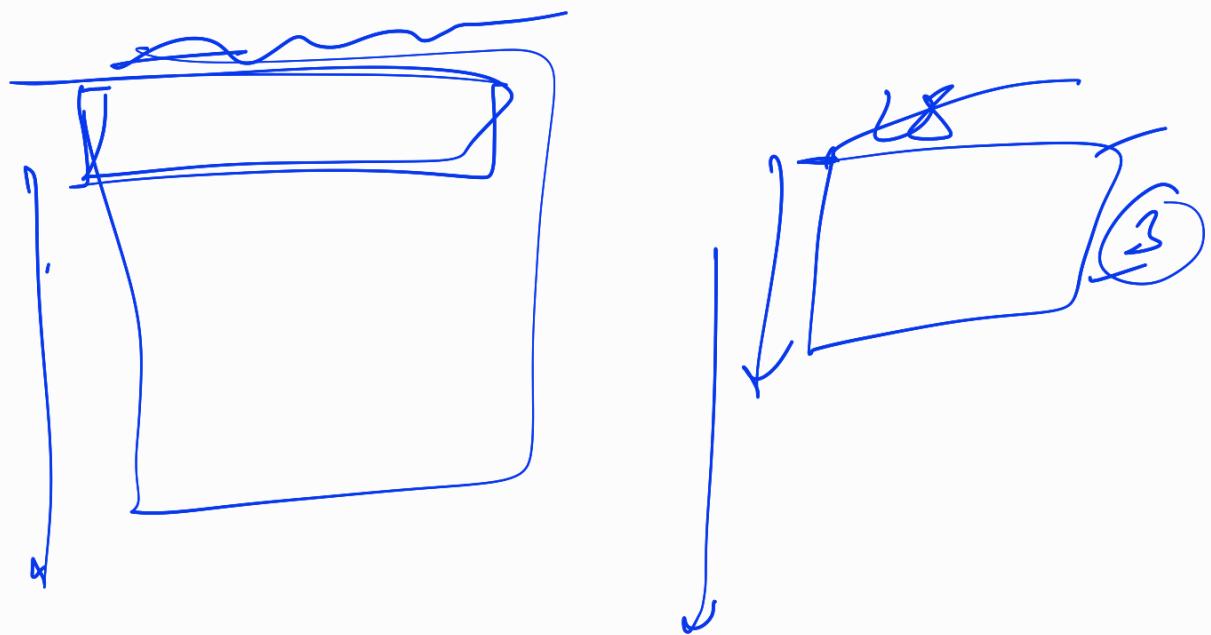
→  $1x \log 0.1 + 0x \dots \dots \dots$

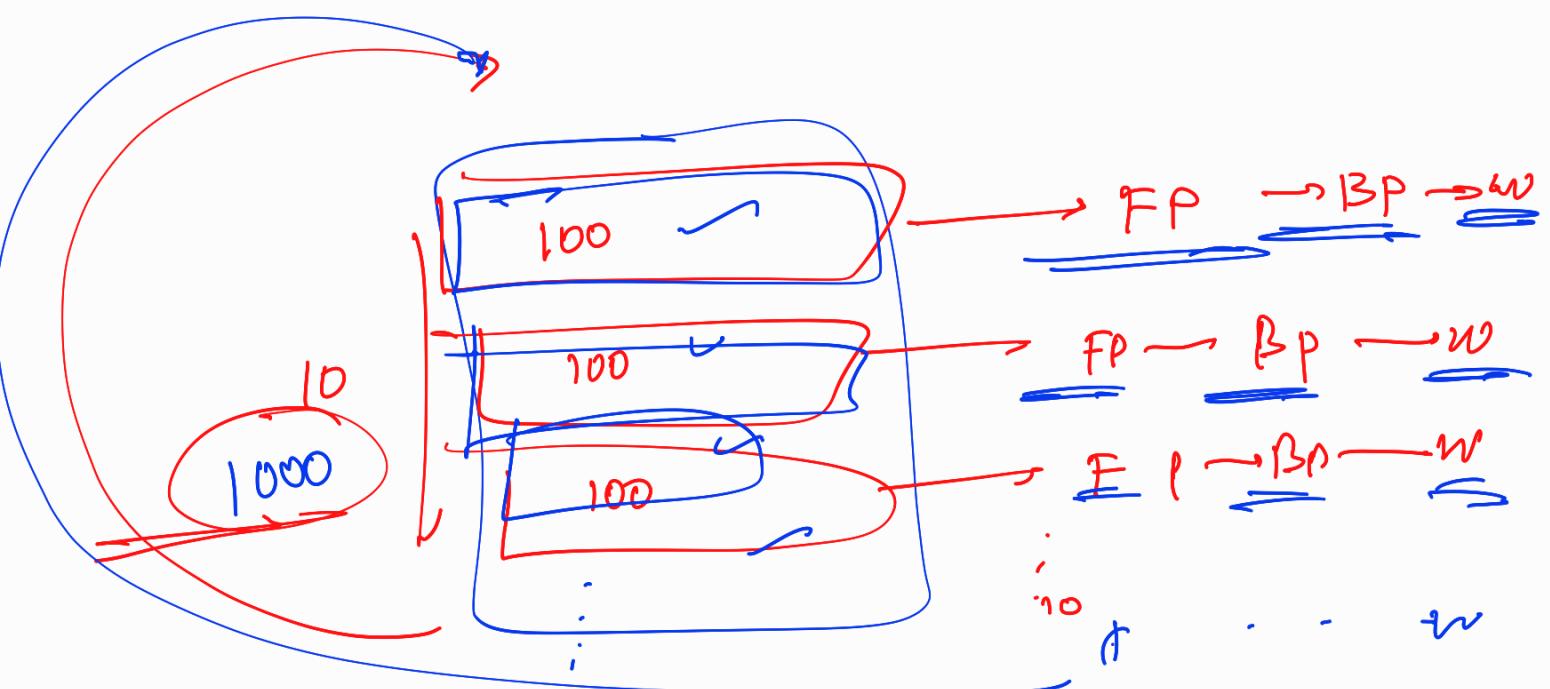
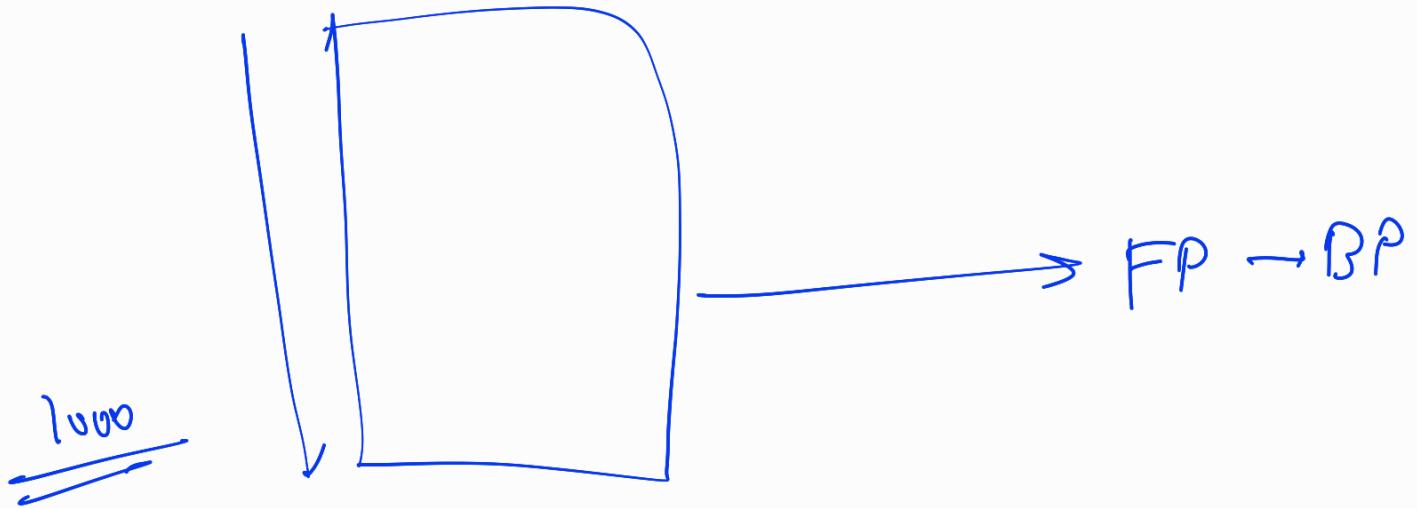


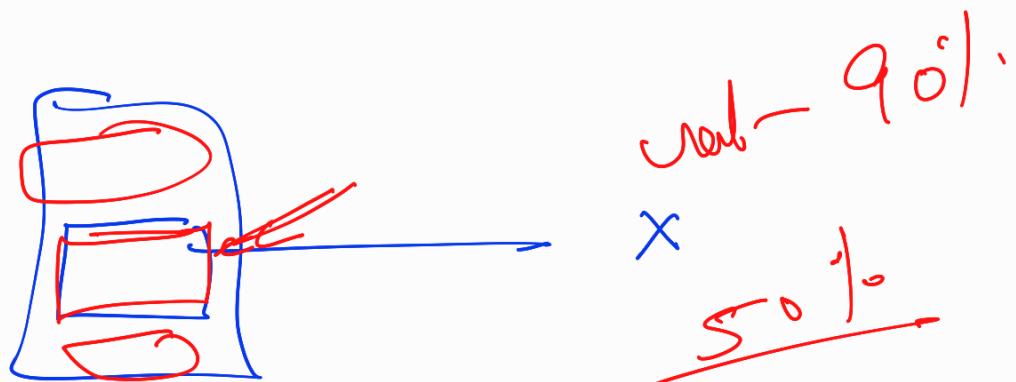
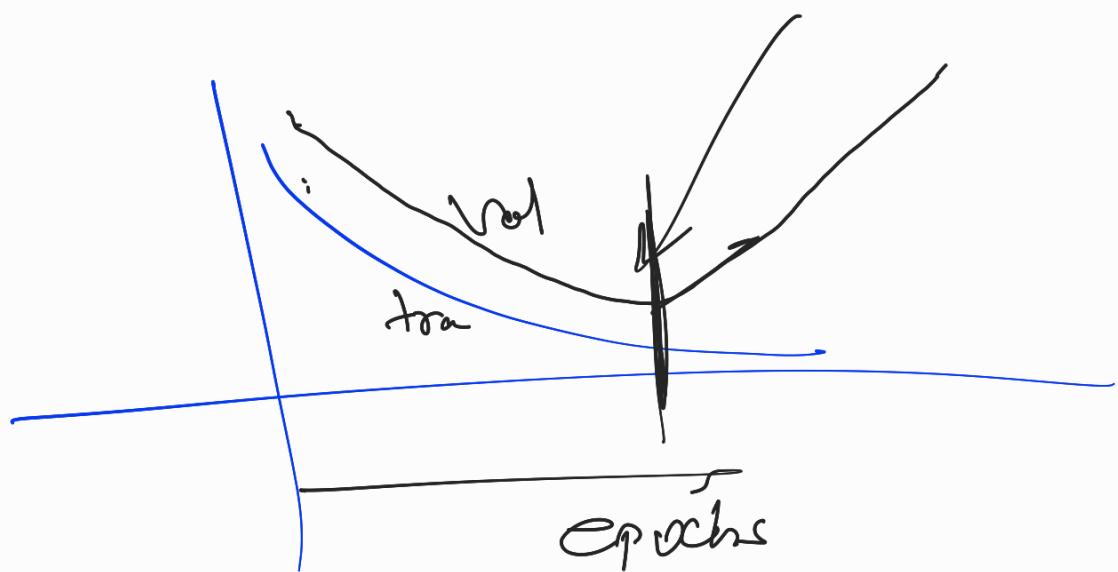
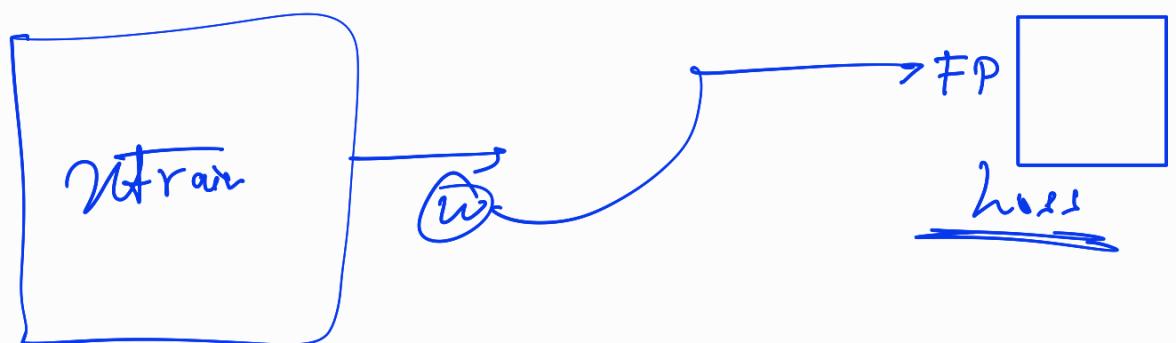
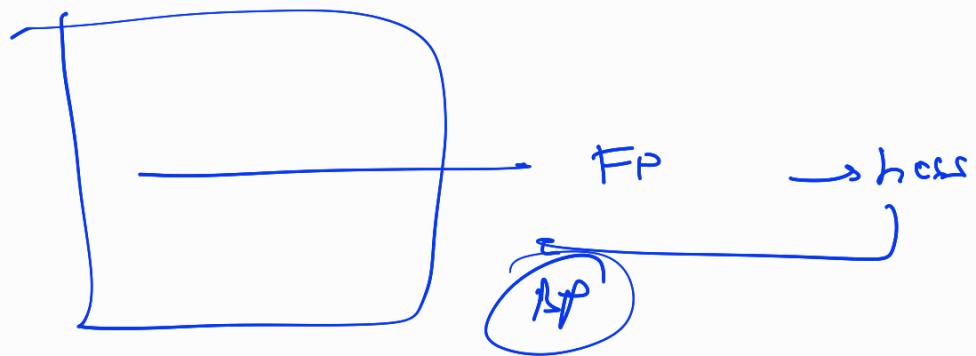


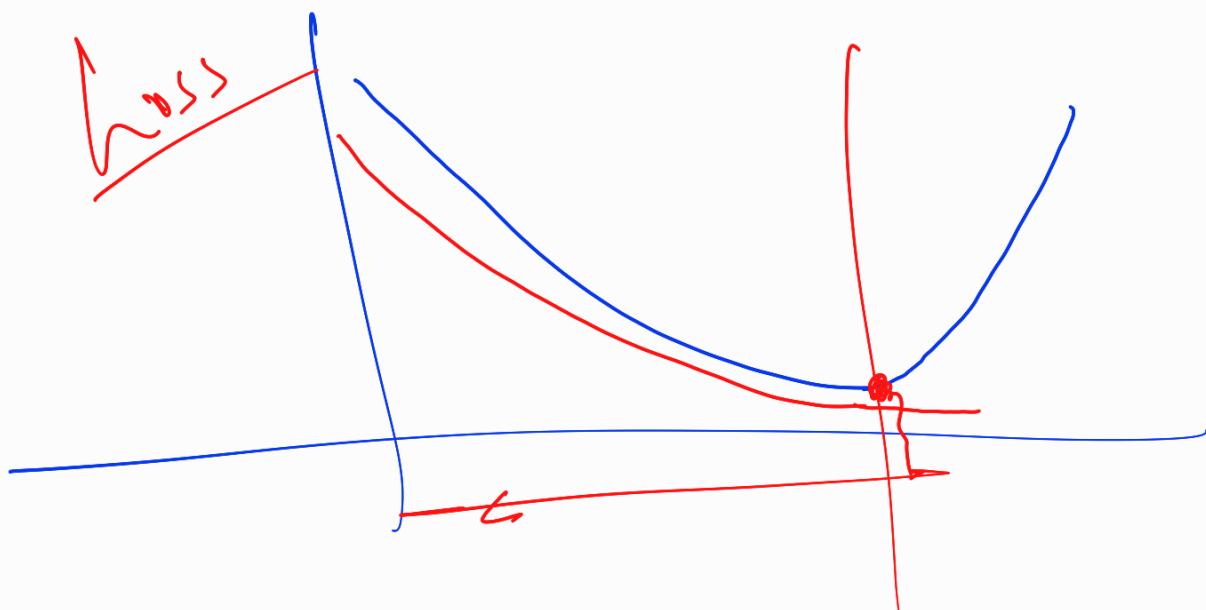
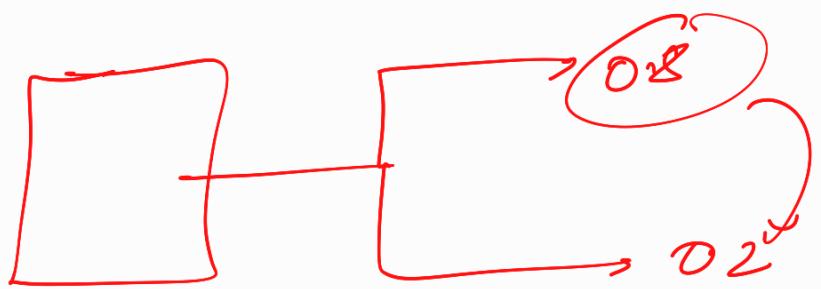
20,00 ♂

$$20,000 \times \frac{28}{28} \times \underline{\underline{28}} \times \underline{\underline{3}}$$

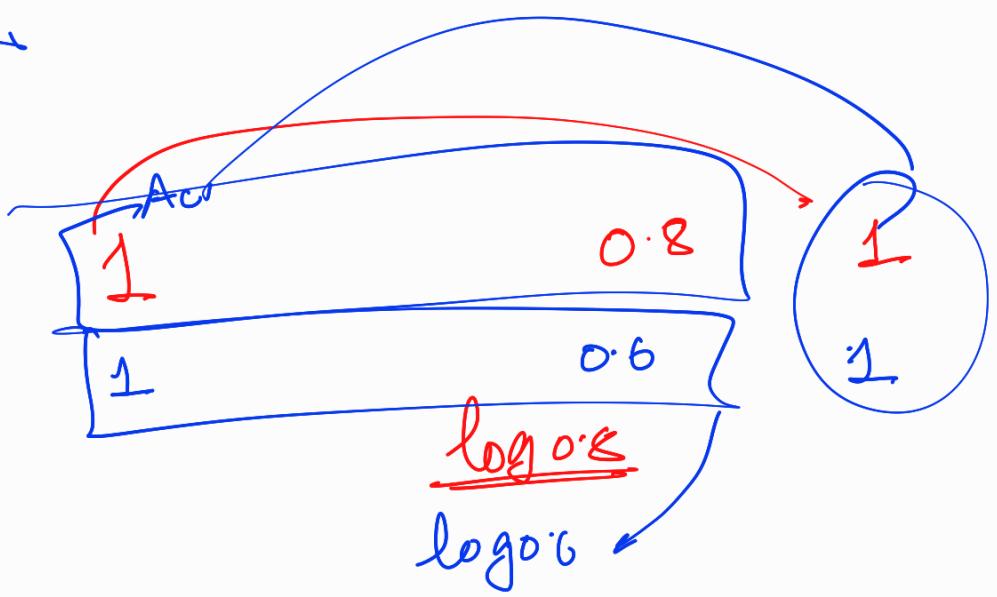


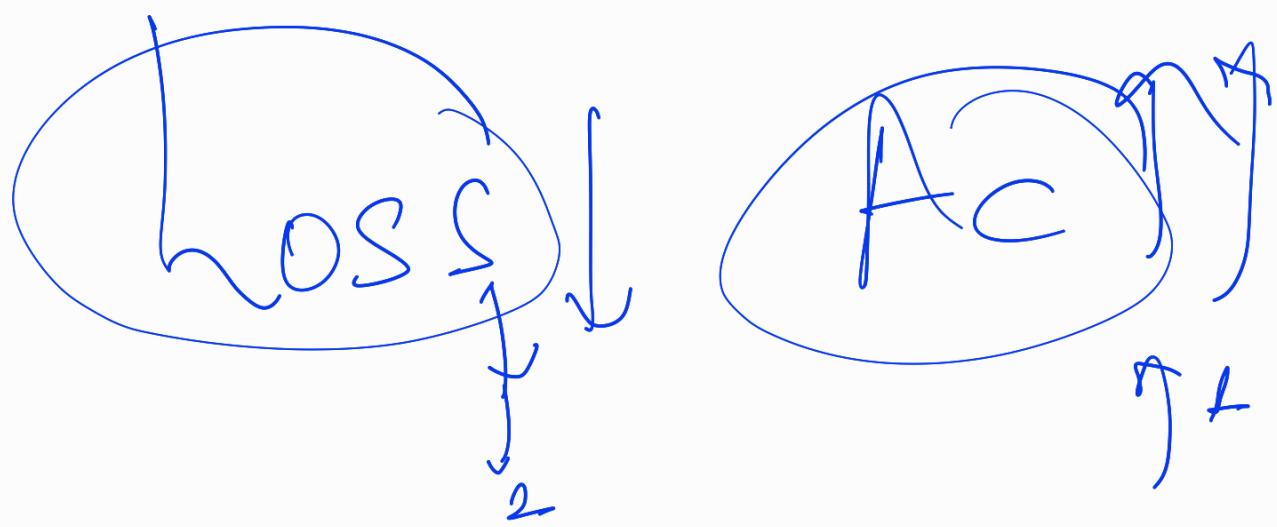




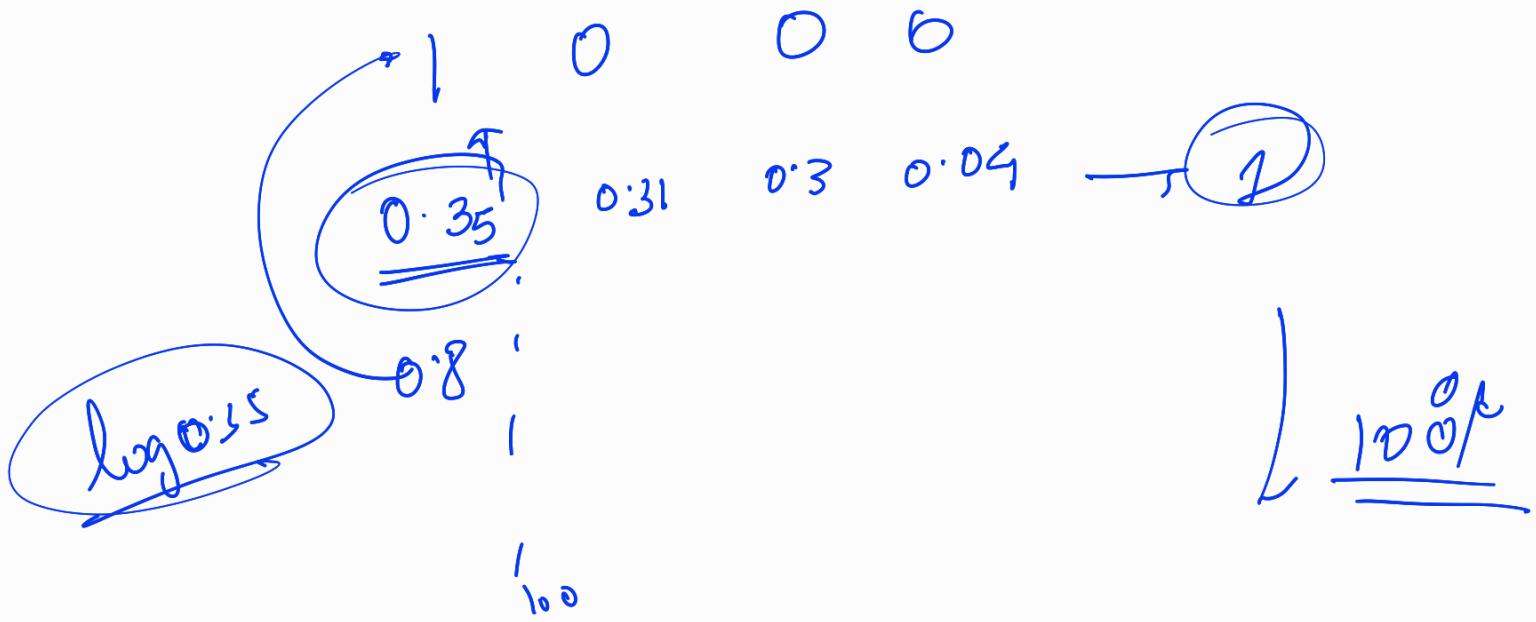


$$0.68 \times = 6.32$$





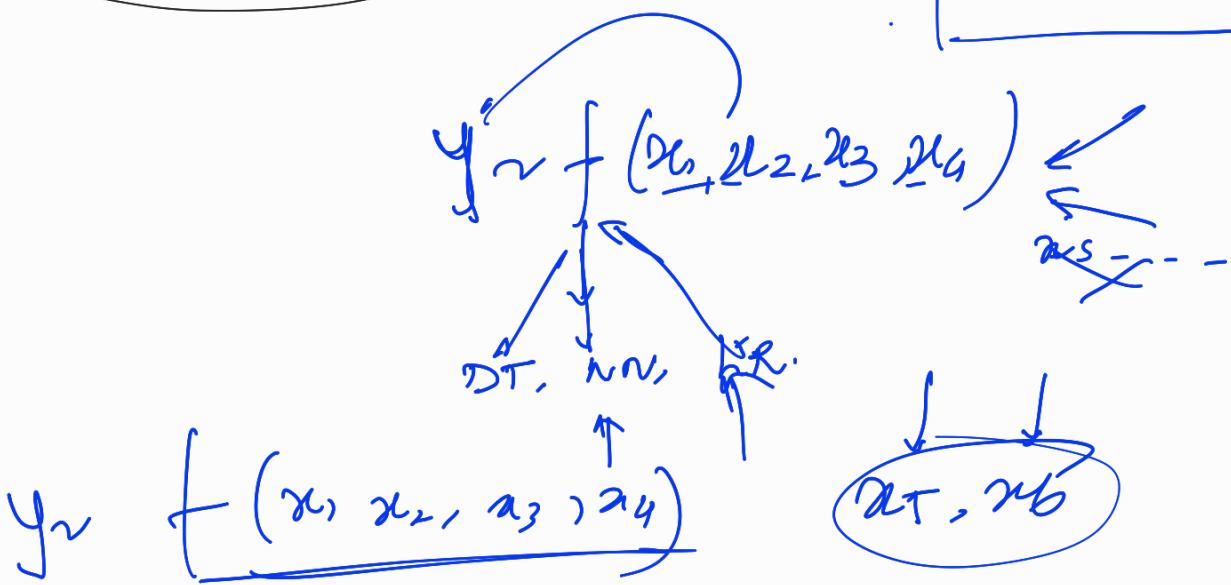
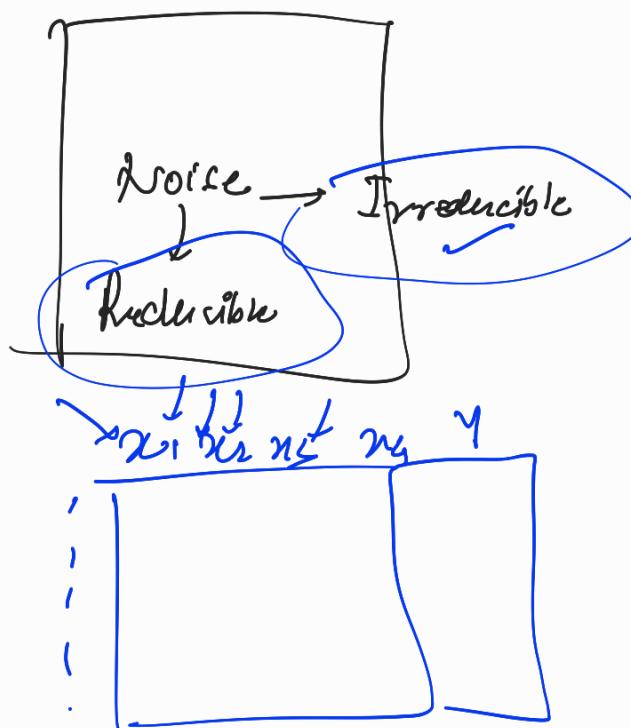
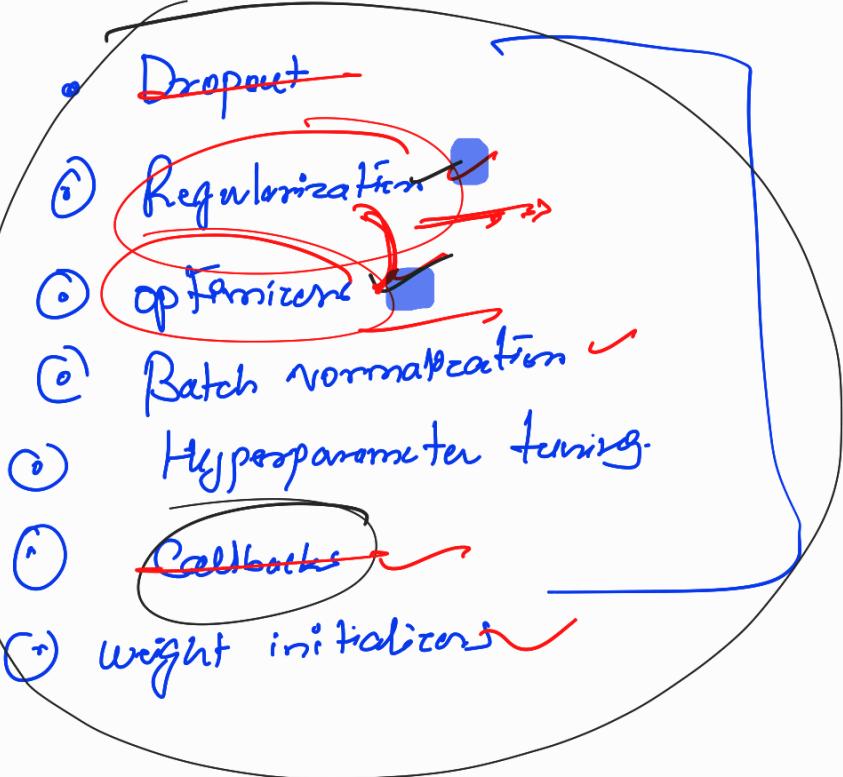
loss → hog loss

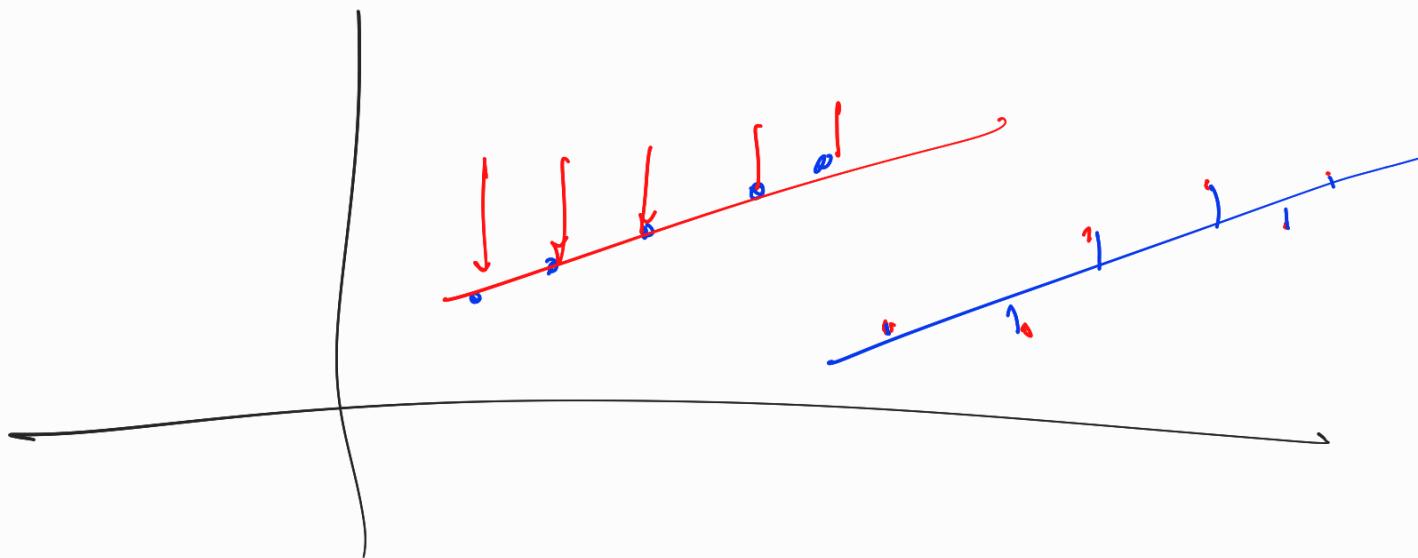
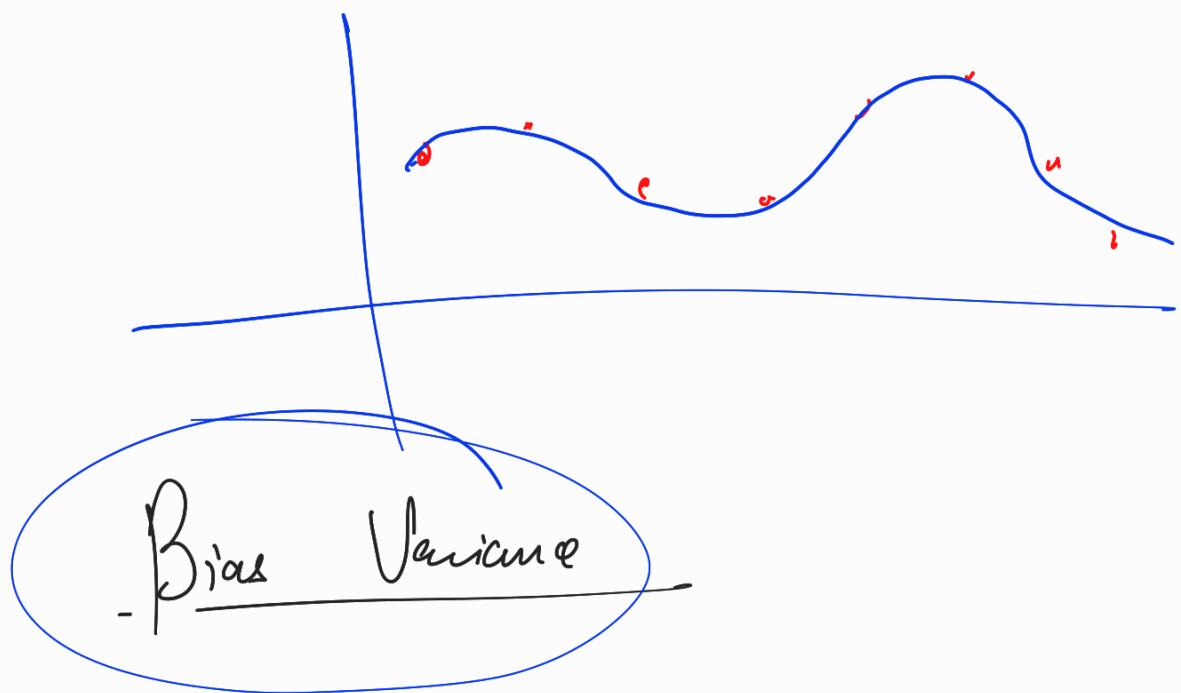
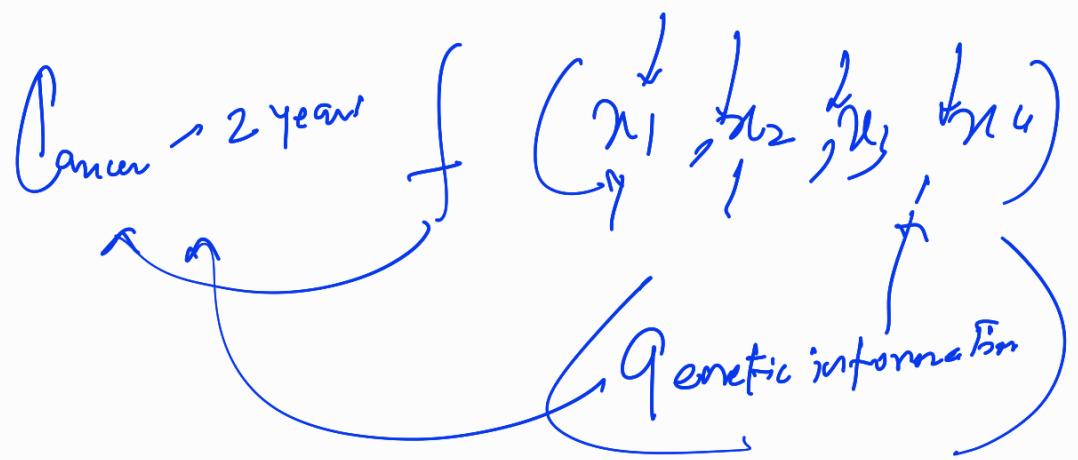


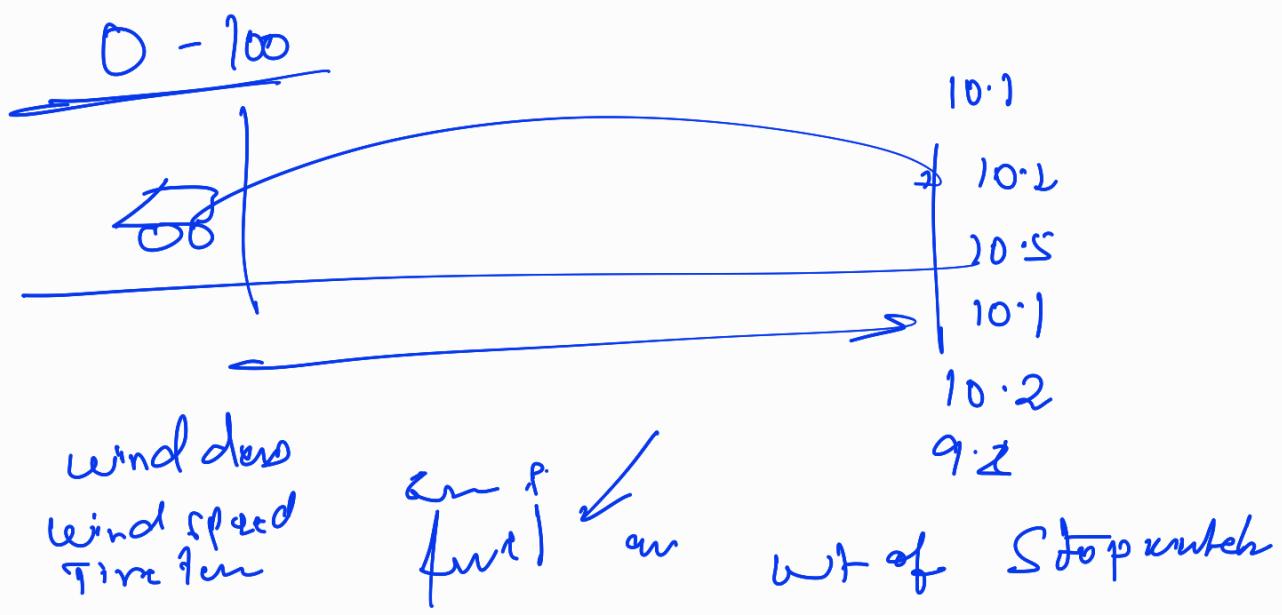
Trained → loss

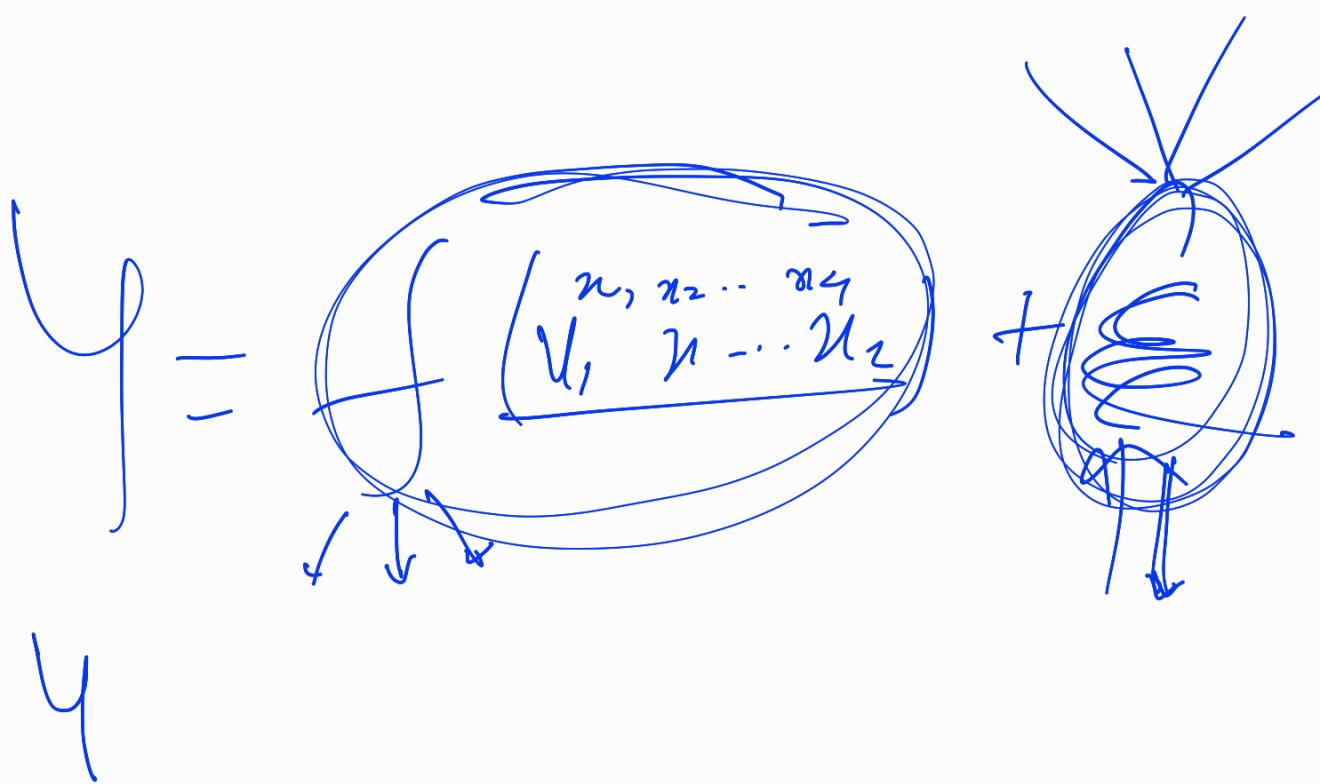
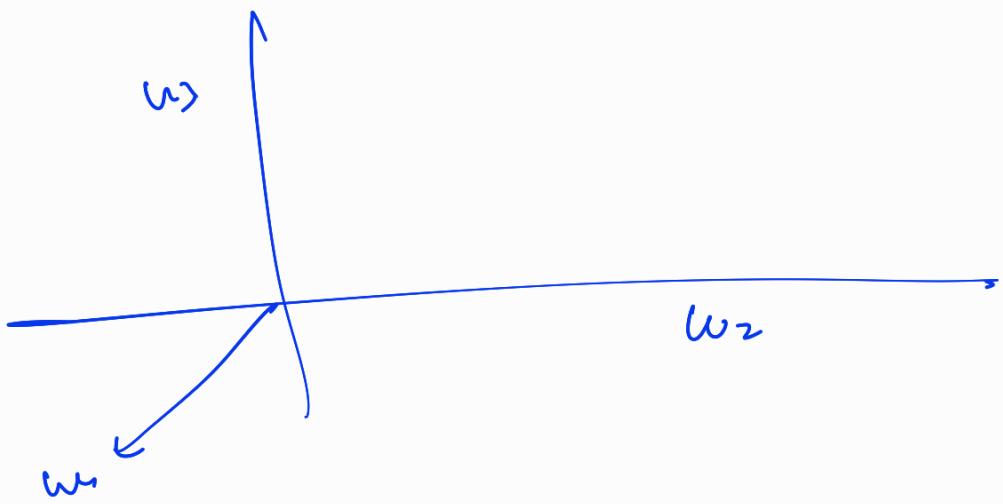
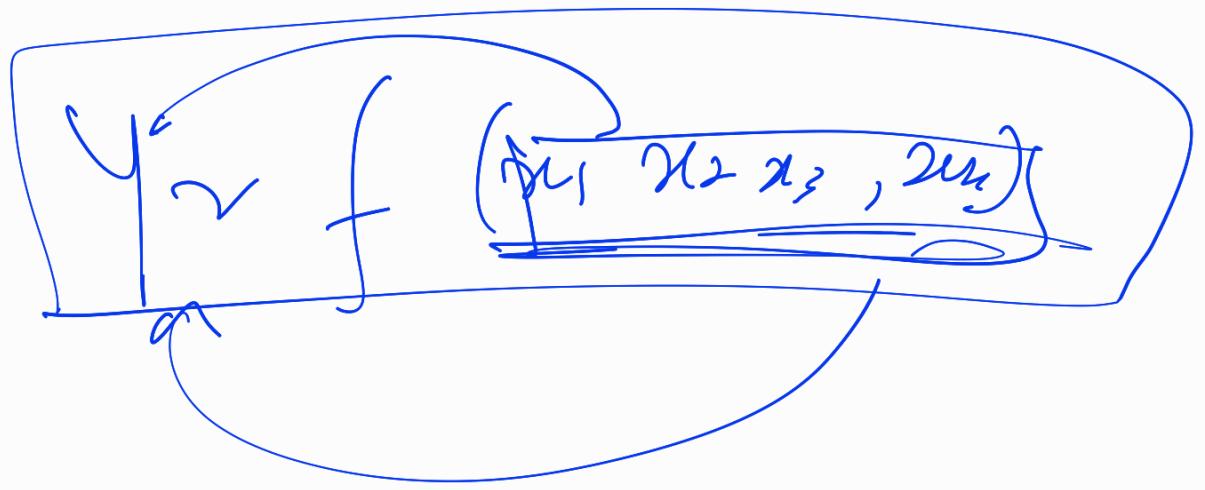
Accuracy

6/5/2024



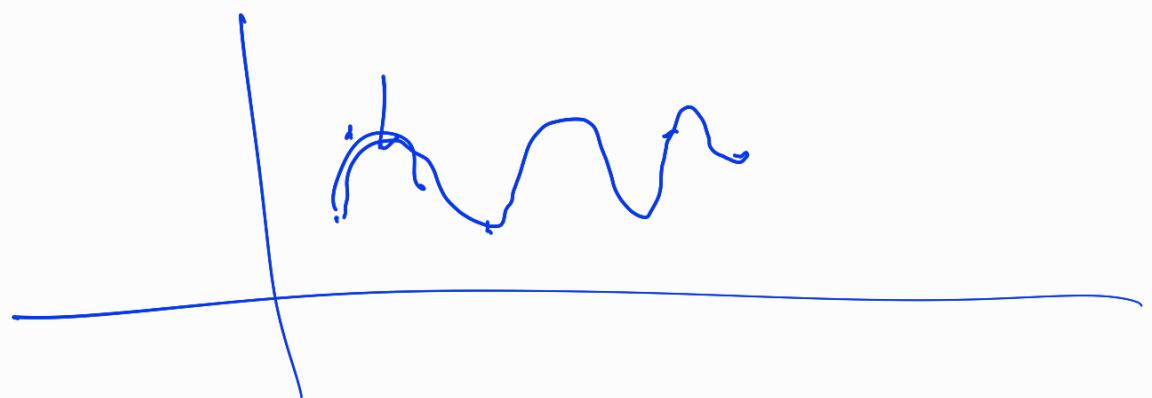
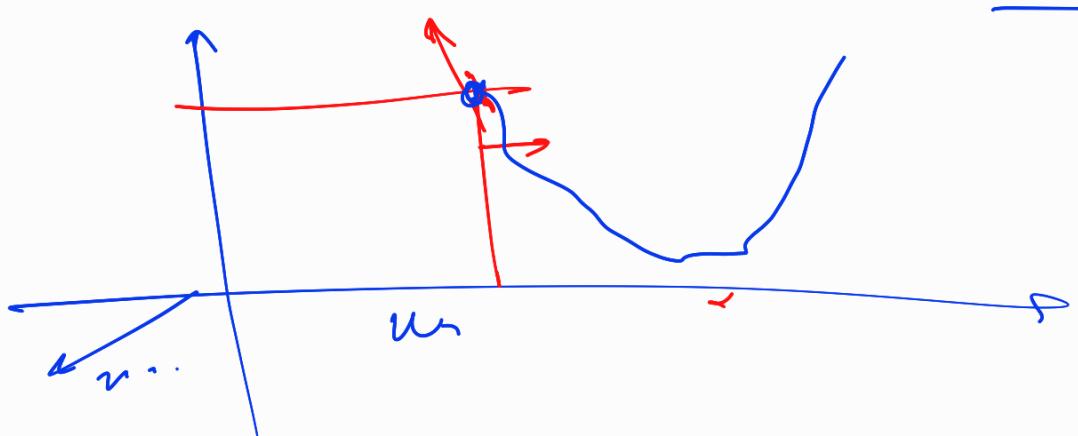
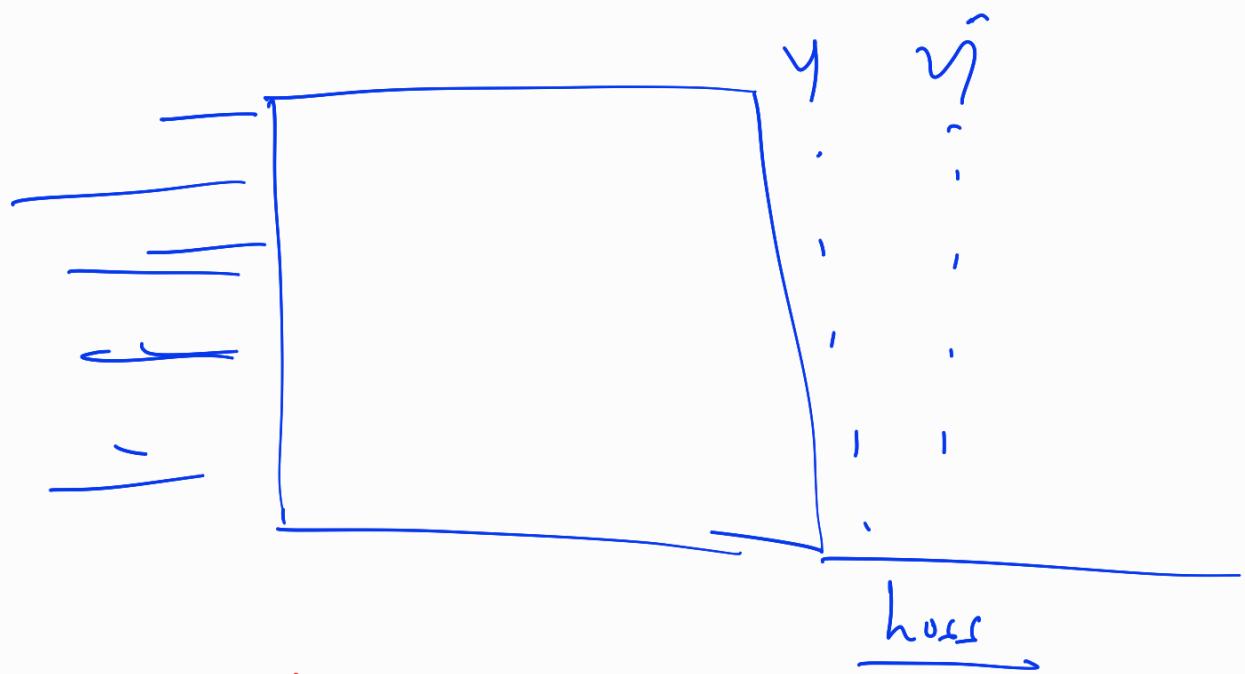




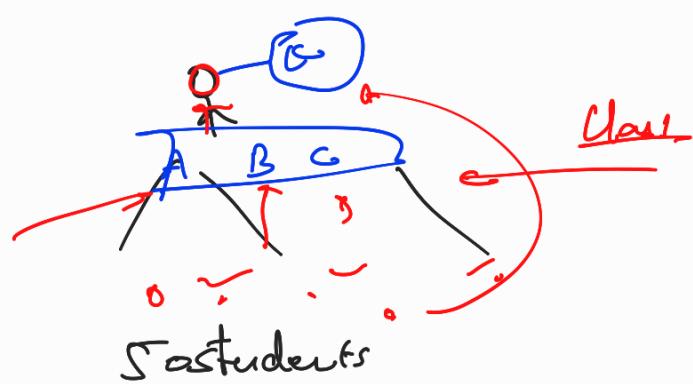




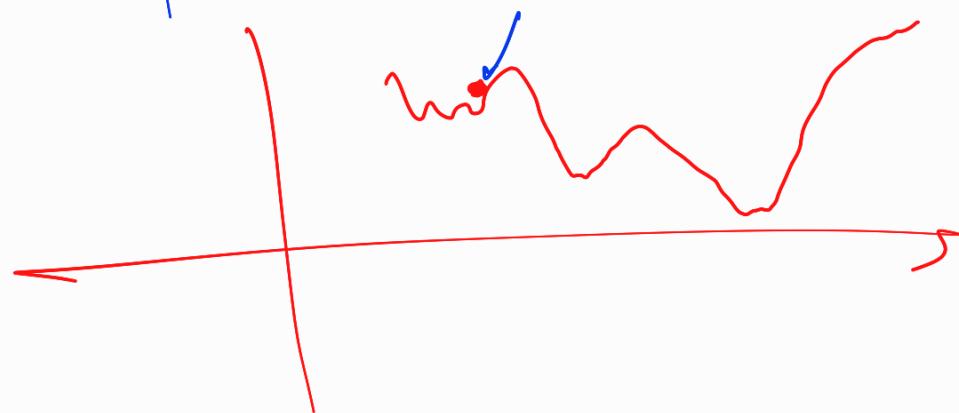
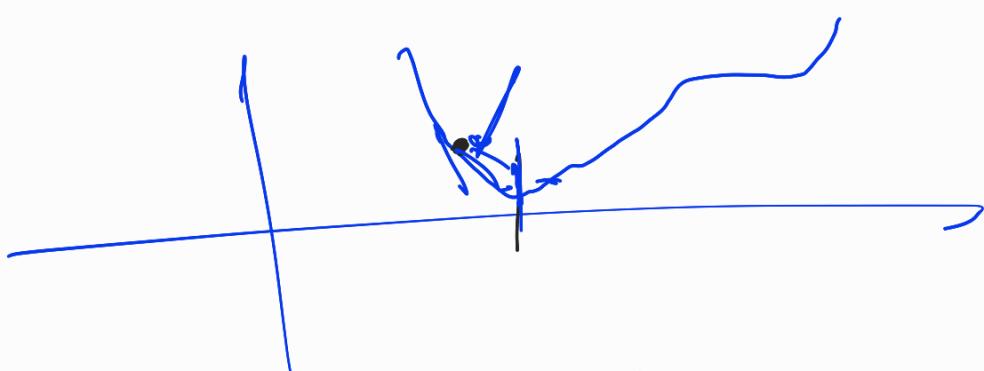
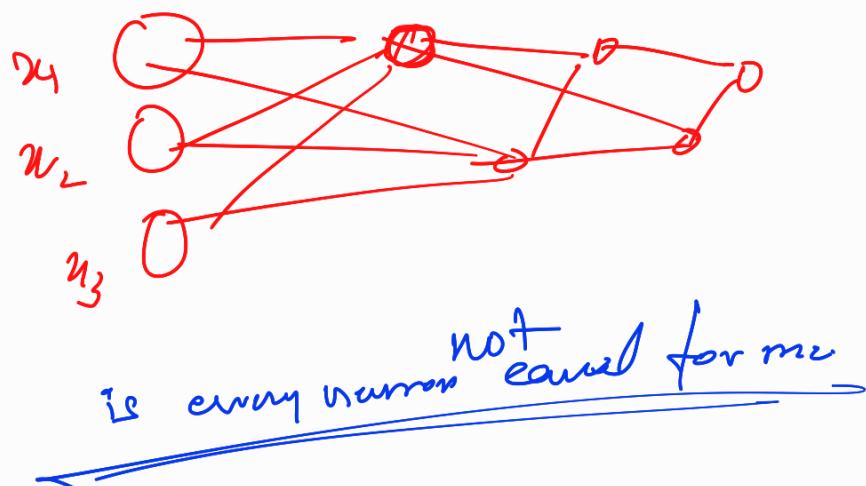
$$\begin{array}{ccc}
 \chi_0 & , & \chi^2 \\
 n_1 & \longrightarrow & n^2 \\
 n_5 & \downarrow & \\
 \text{Temp} & \leftarrow & \text{pt} \\
 & & \text{wind}
 \end{array}$$



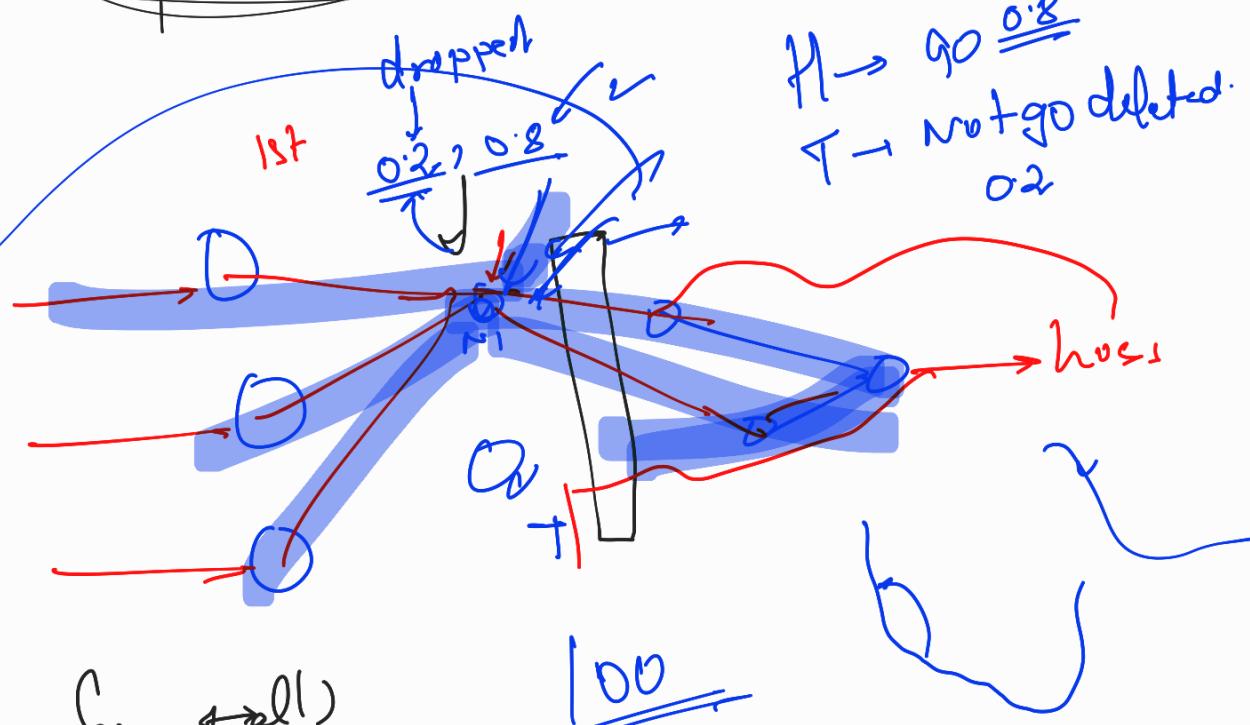
Drop out:



Cold calling



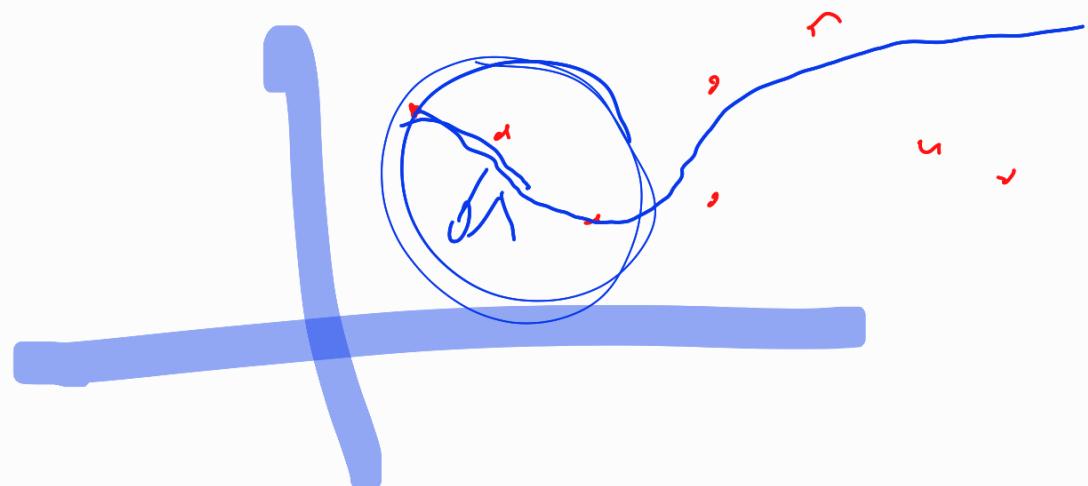
OPTimizers

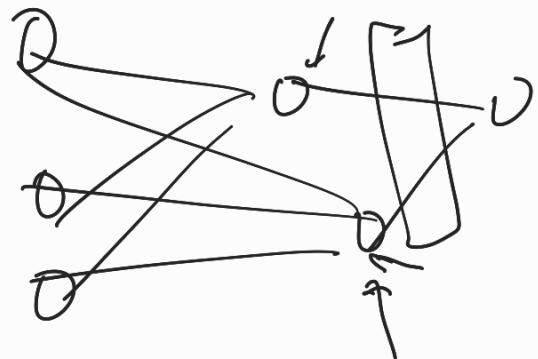


model = Sequential()

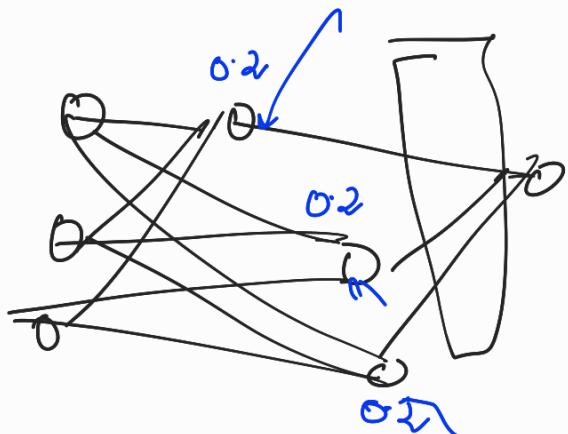
model.add(Dense(2))

model.add(Dropout( $\frac{0.2}{dropout\_rate}$ )  
at HGP

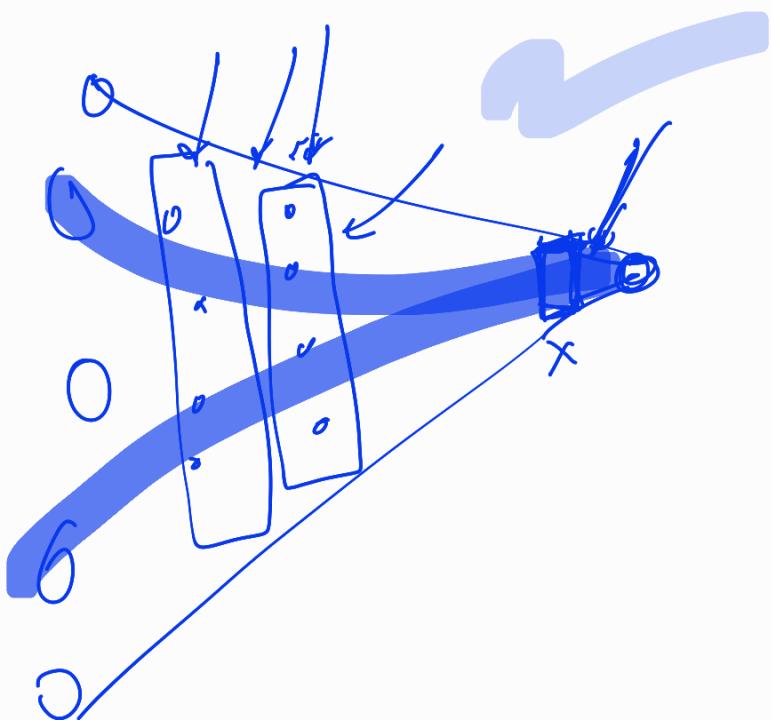




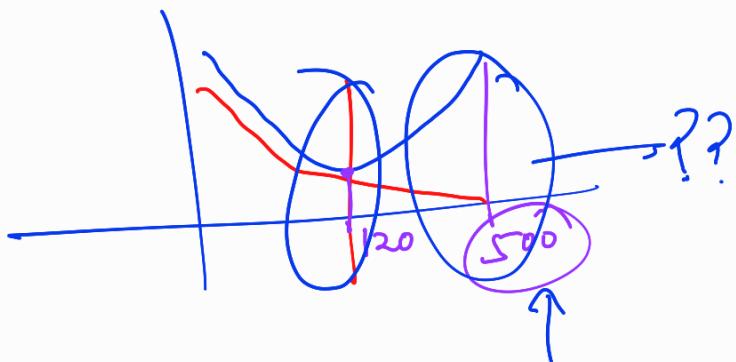
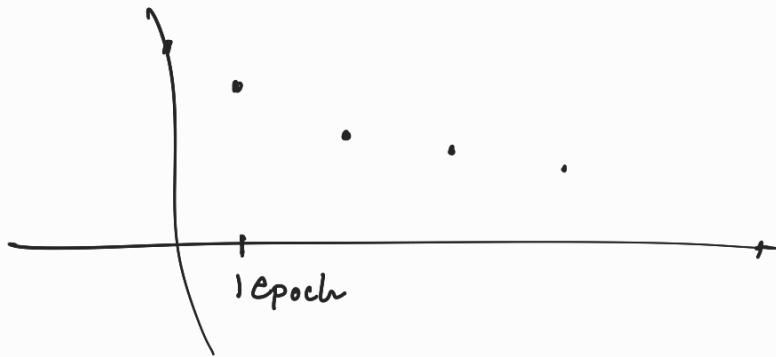
100 1 →



3L<sub>2</sub> 0.2 x 0.2

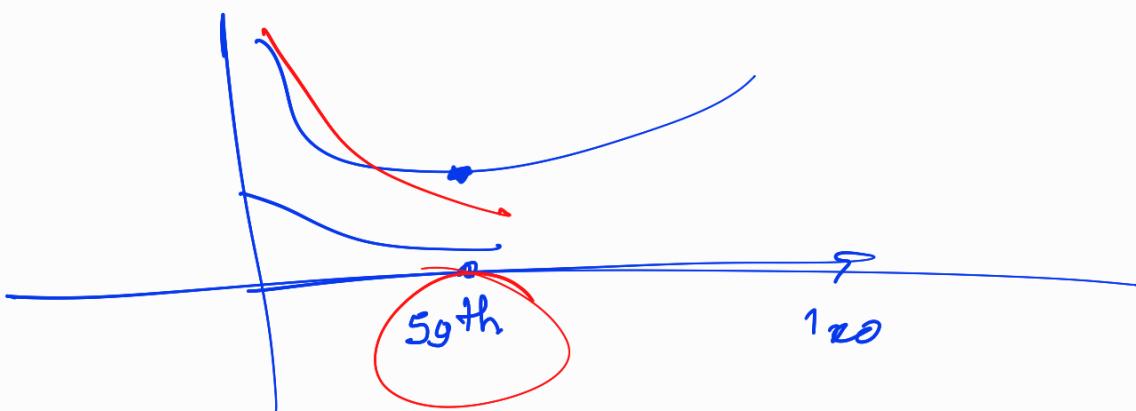


## Callbacks

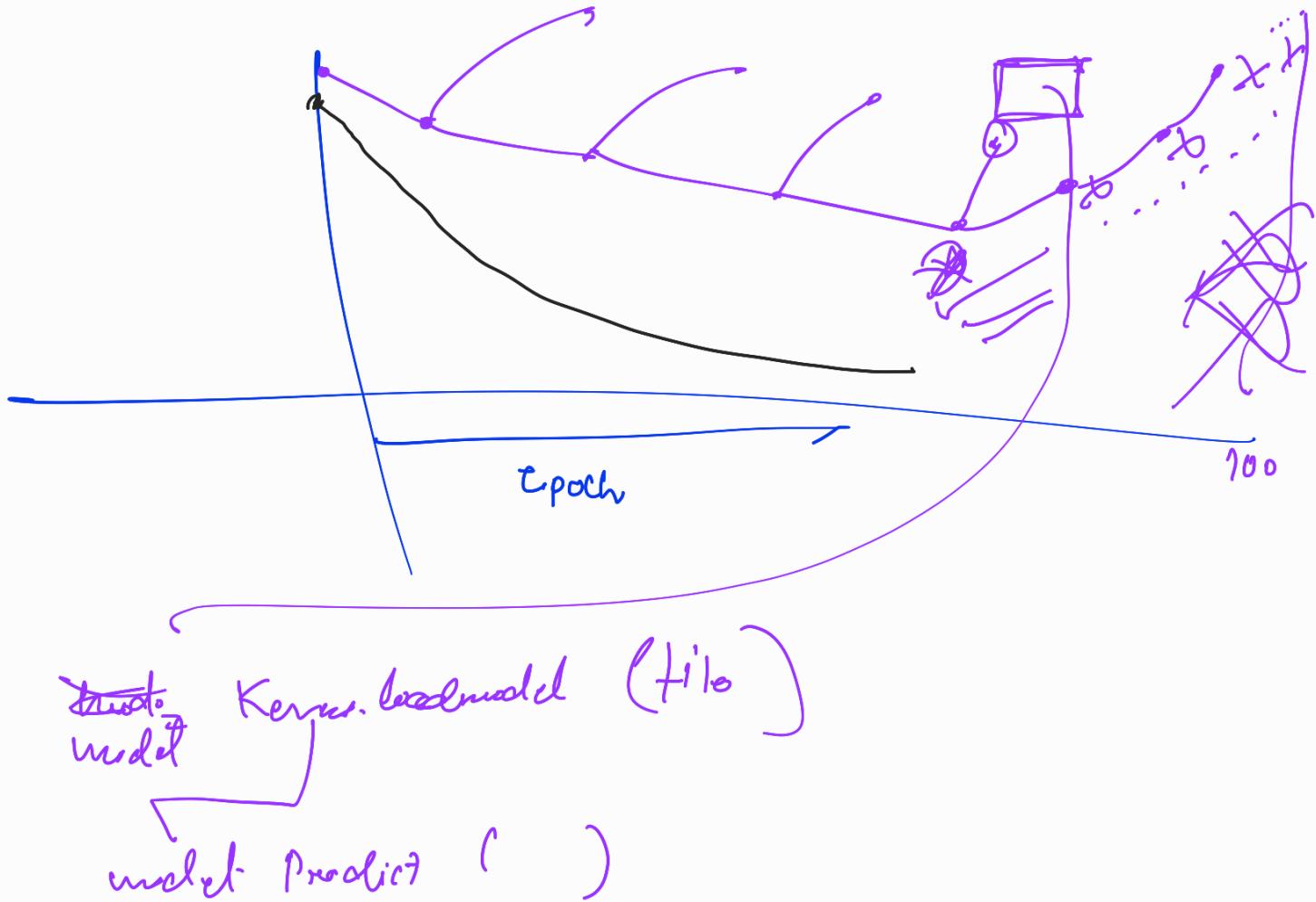


~~Epochs=500~~  
~~Model Checkpoint~~

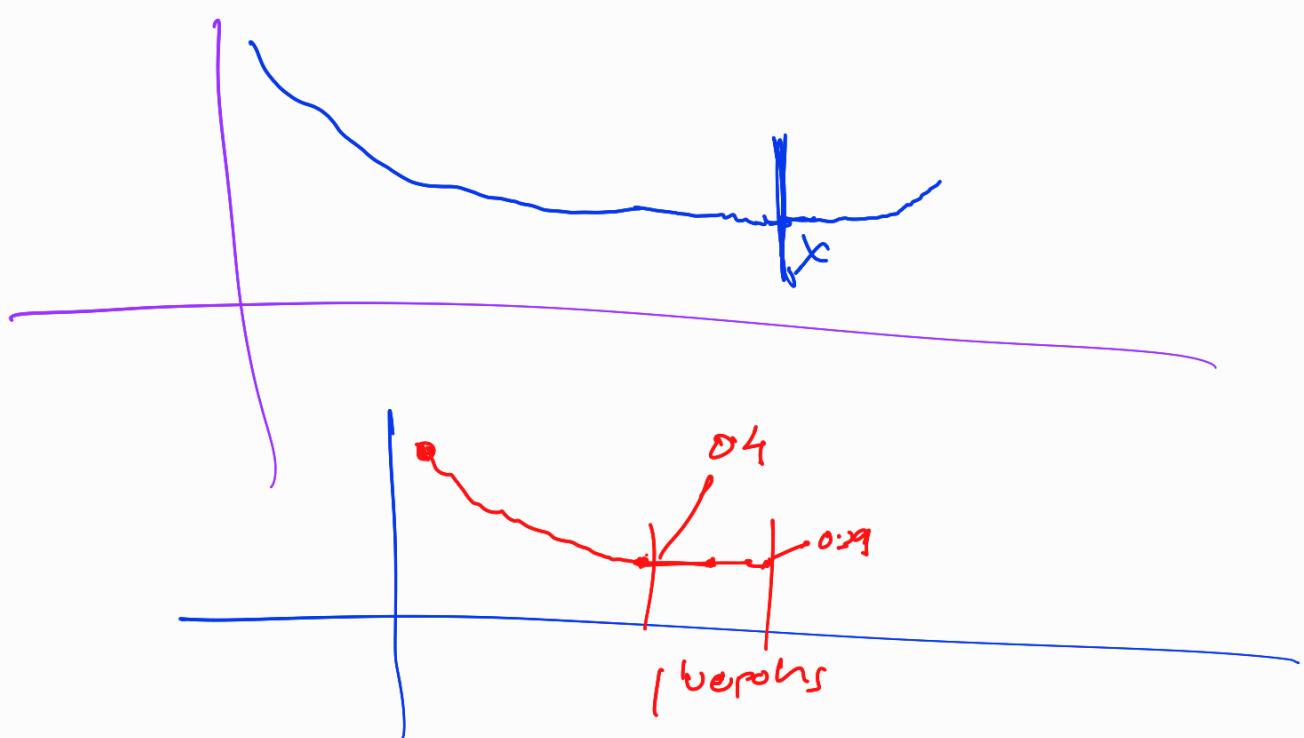
after every epoch and if my val-loss  
has reduced from the previous epoch's val-loss  
of the model  
I will save the weights at a particular  
file path else will continue .

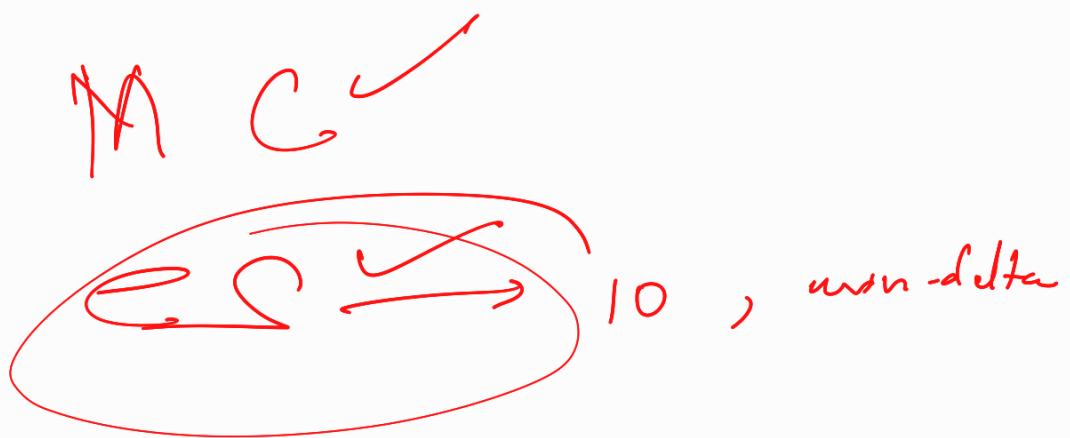


Epochs 60



Early stopping





Weight initializations

5af/hr

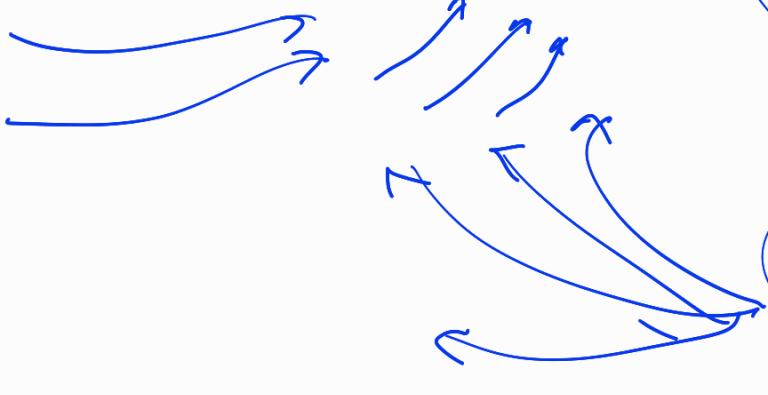
18 inches.

Weight initializations

1 inch

1 inch

$L_1$



10 verticals

5af/hr