

loss / cost =  $(y_{true} - y_{predicted})^2$

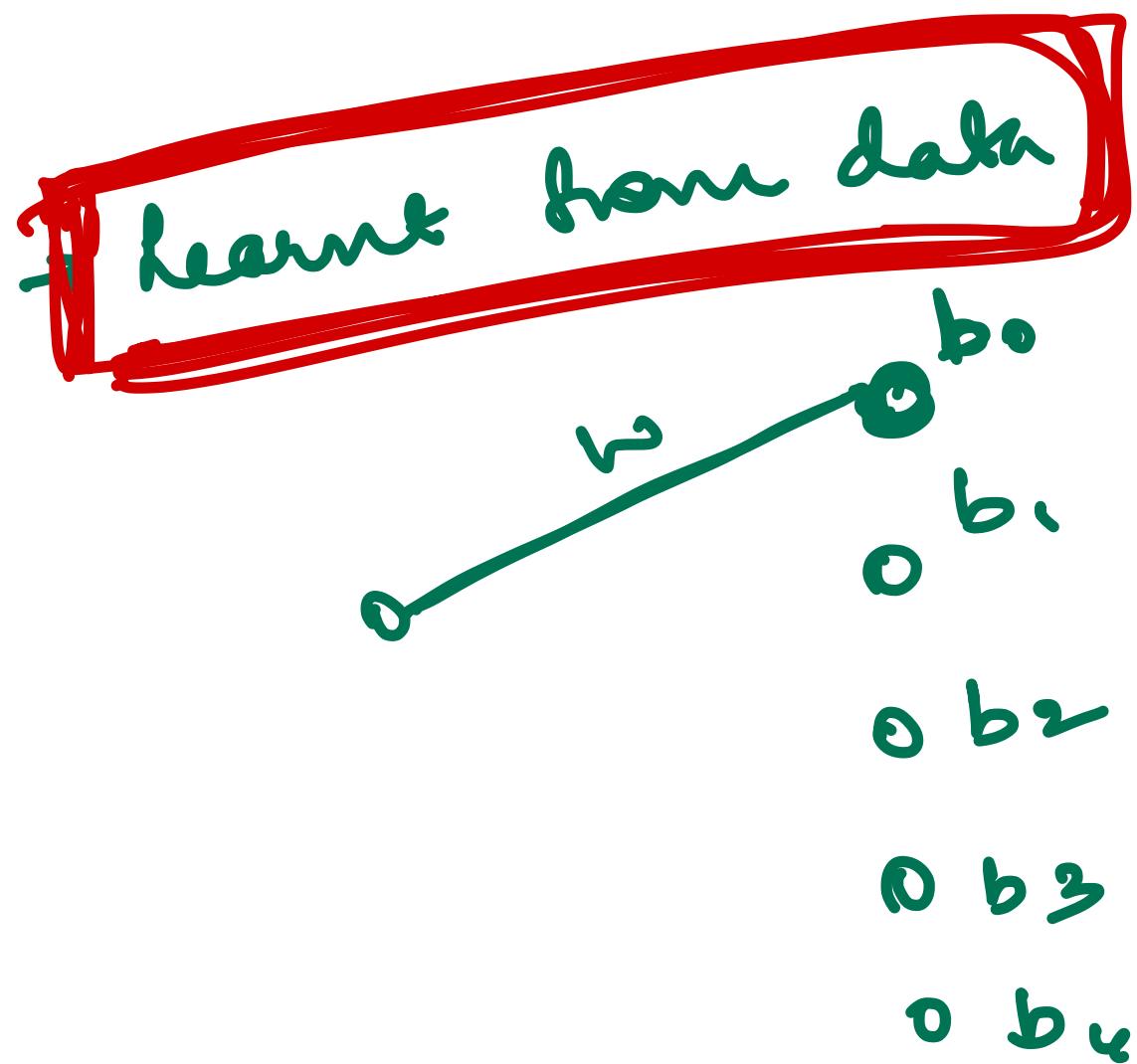
minimize

Errors

$w \rightarrow$  weight } Parameters

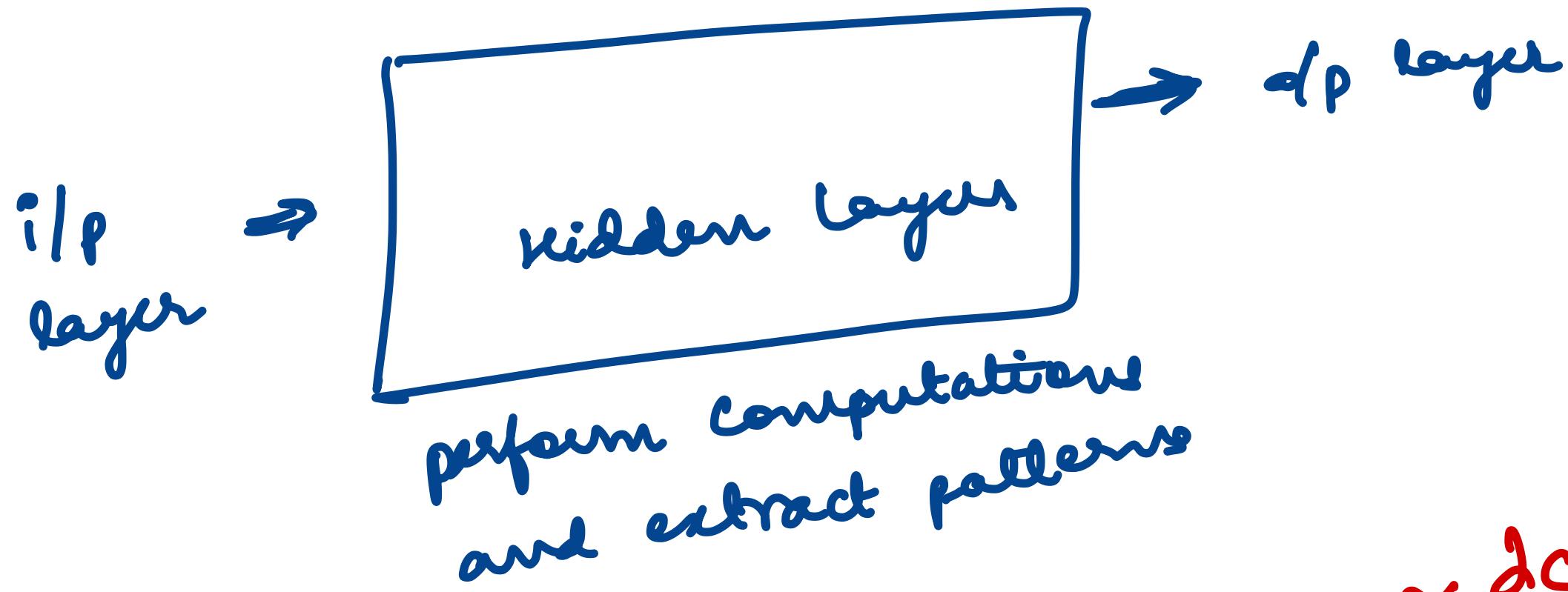
$b \rightarrow$  bias

Parameters  $\rightarrow$  weight  $w \rightarrow$  for every connection  
Bias  $b \rightarrow$  func should not  
always pass through  
origin



APT3  $\rightarrow$  175 B  
APT4  $\rightarrow$  1 Trillion  
Human  $\rightarrow$  100B

NN  $\rightarrow$  computational model inspired by  
human brain  
 $\rightarrow$  layers of interconnected nodes



$w \leftarrow w - \alpha \frac{\delta c}{\delta w}$

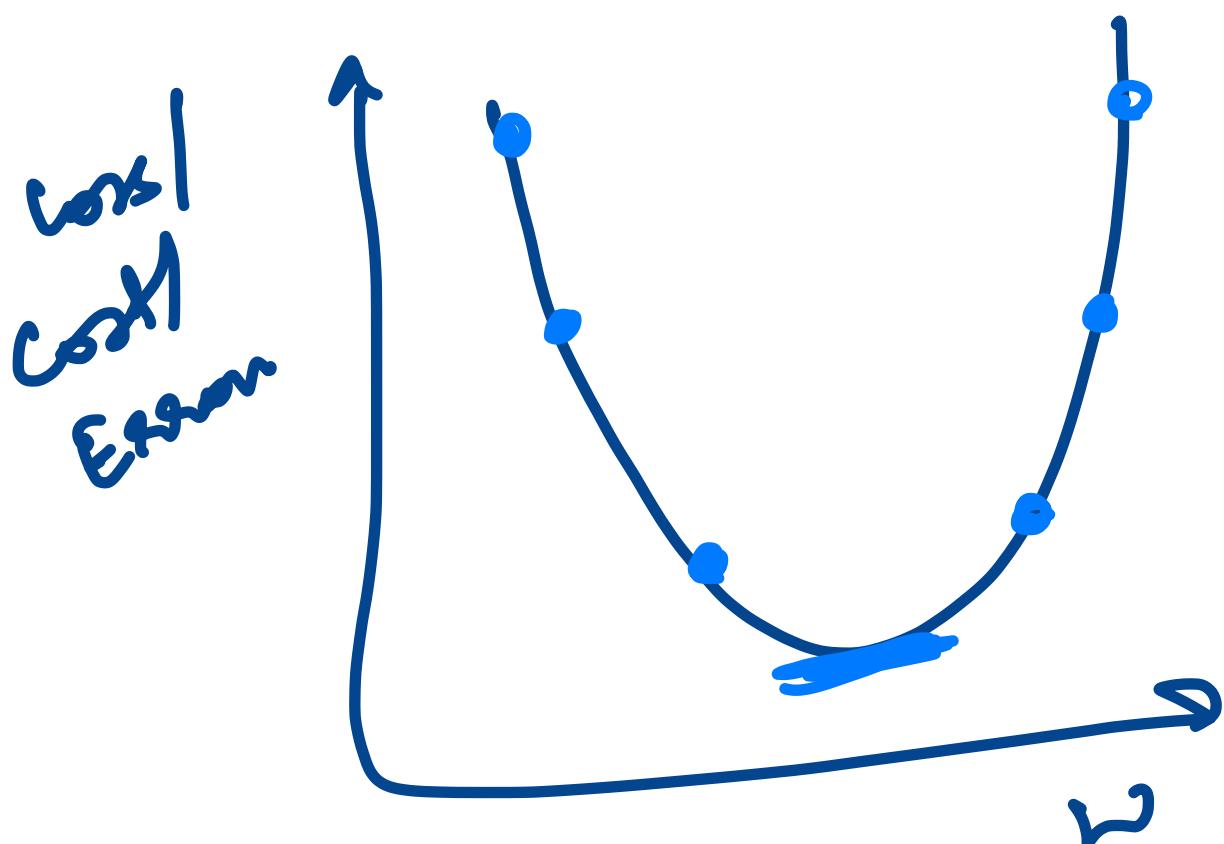
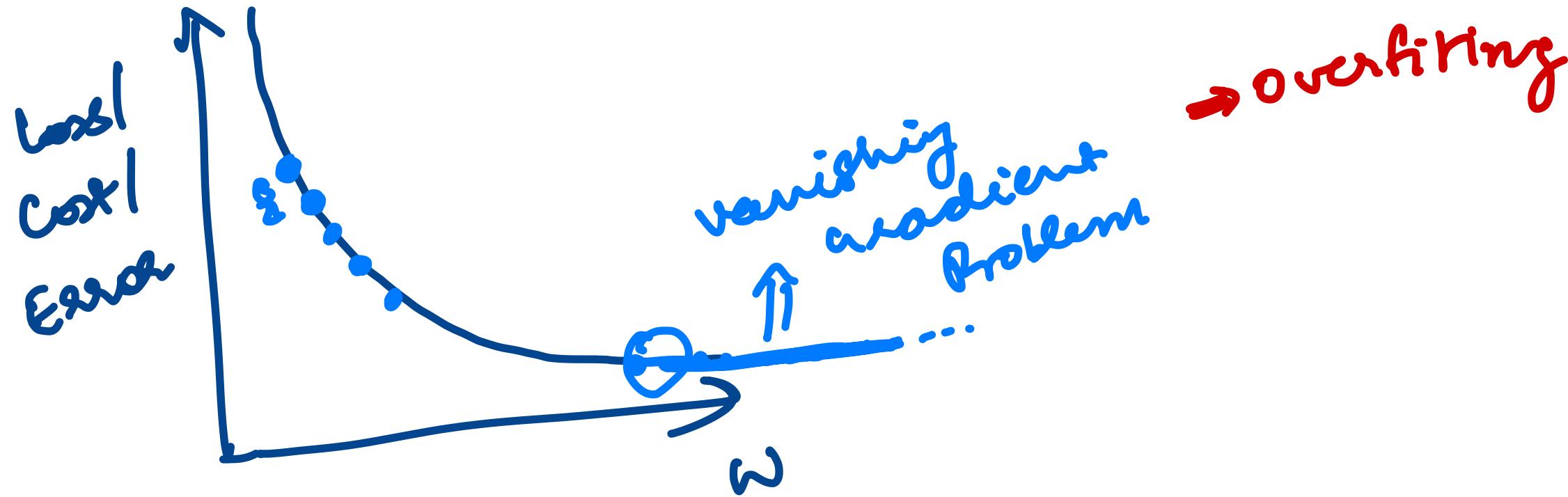
$\downarrow$

0.1  
0.00001  
0.0001

vanishing gradient  
problem

$$, b = b - \alpha \frac{\delta c}{\delta b}$$

Exploding  
gradient  
problem



Aim  $\rightarrow$  generalisation  
Goal  $\rightarrow$  model should perform well on training data & testing data (unseen)  
Overfitting underfitting

DSA Interview

face recognition

Spam Detection

Self Driving Car

remembers the  
questions  
without understanding  
hair, hair length  
glasses, background  
color, clothes  
black male

STOP sign 



Summary

oval  
2 eyes  
, nose

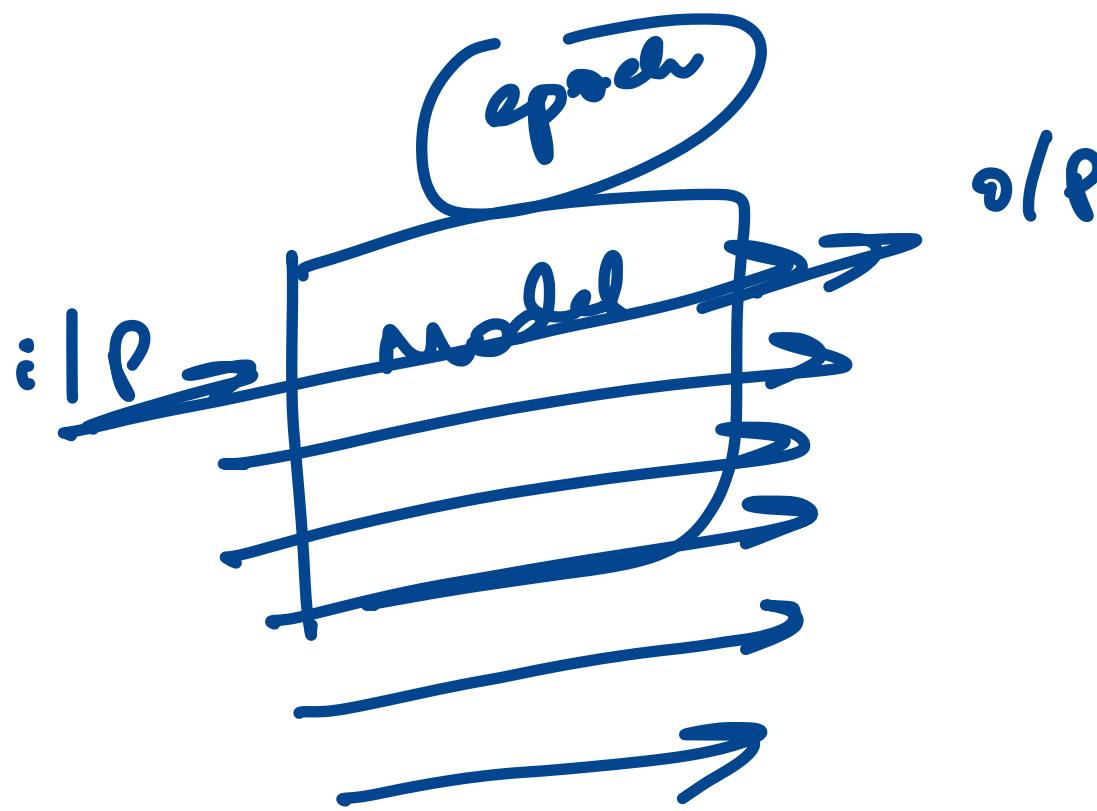
"hit"  
"foul"

Anything  
that is Red

$\Rightarrow$  Training data  
loss  $\rightarrow$  minimum

$\Rightarrow$  Testing  
loss  $\rightarrow$  more

Training Data X  
loss  $\uparrow$   
Testing Data X  
loss  $\uparrow$



No. of epochs?  
No. of hidden layers?  
weights initialisation?  
bias initialisation?

$$w = w - \alpha \frac{\partial C}{\partial w}$$

learning rate?

0.01, 0.001  
0.0001 → learning slow, Settings of  
neurons per layers  
No. of

## Hyper Parameters of Model

- Manually Set
- Not learnt from data

## Trial and Error

→ Set before training

gradients  $\rightarrow$  weight, bias

Algos  $\rightarrow$   $w \leftarrow w - \alpha \frac{\partial C}{\partial w}$   
learning rate

{ Stochastic Gradient Descent  
mini batch SGD  
Adaptive learning method  
: Adam

No. of doses  $\underbrace{x}$  v.s  $\underbrace{\text{Health}}_{y}$

$$\hat{y} = \underbrace{\sum_{i=1}^n}_{z = w_1x + b} w_1x + b$$

$$c = (y - \hat{y})^2 \quad \sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\frac{\partial c}{\partial w} = \frac{\partial c}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial w}$$

$$= -2(y - \hat{y}) \frac{\sigma(z)(1 - \sigma(z))x}{\sigma'(z)}$$

$$\frac{\partial c}{\partial b} = \frac{\partial c}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial b}$$

$$= -2(y - \hat{y}) \sigma(z)(1 - \sigma(z))$$

loss function  
cost function  
error function

$y_{true}, \hat{y}_{predicted}$

Regression

MSE  $\rightarrow$  Mean Squared Error

$$(y - \hat{y})^2$$

MAE  $\rightarrow$  Mean Absolute Error

Huber loss

Classification

Binary Cross Entropy

Categorical Cross Entropy

Sparse Categorical Entropy

Adam

## Training Steps

### ① **Forward Pass**

ip to o/p

calculate  $y_{predicted}$

$$L = \text{loss}(y_{true}, y_{pred})$$

↓  
loss function (cost function)

error function

### ② **Gradient Computation** **Backward Propagation**

use chain rule

$$\frac{\partial L}{\partial w} \cdot \frac{\partial L}{\partial b}$$

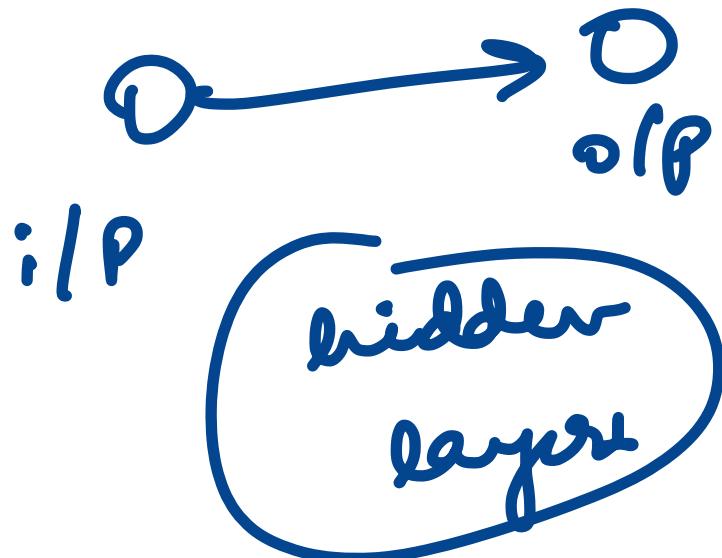
③ Optimization /  
update weights & biases

Optimization Algo

$$w = w - \alpha \frac{\partial C}{\partial w}$$

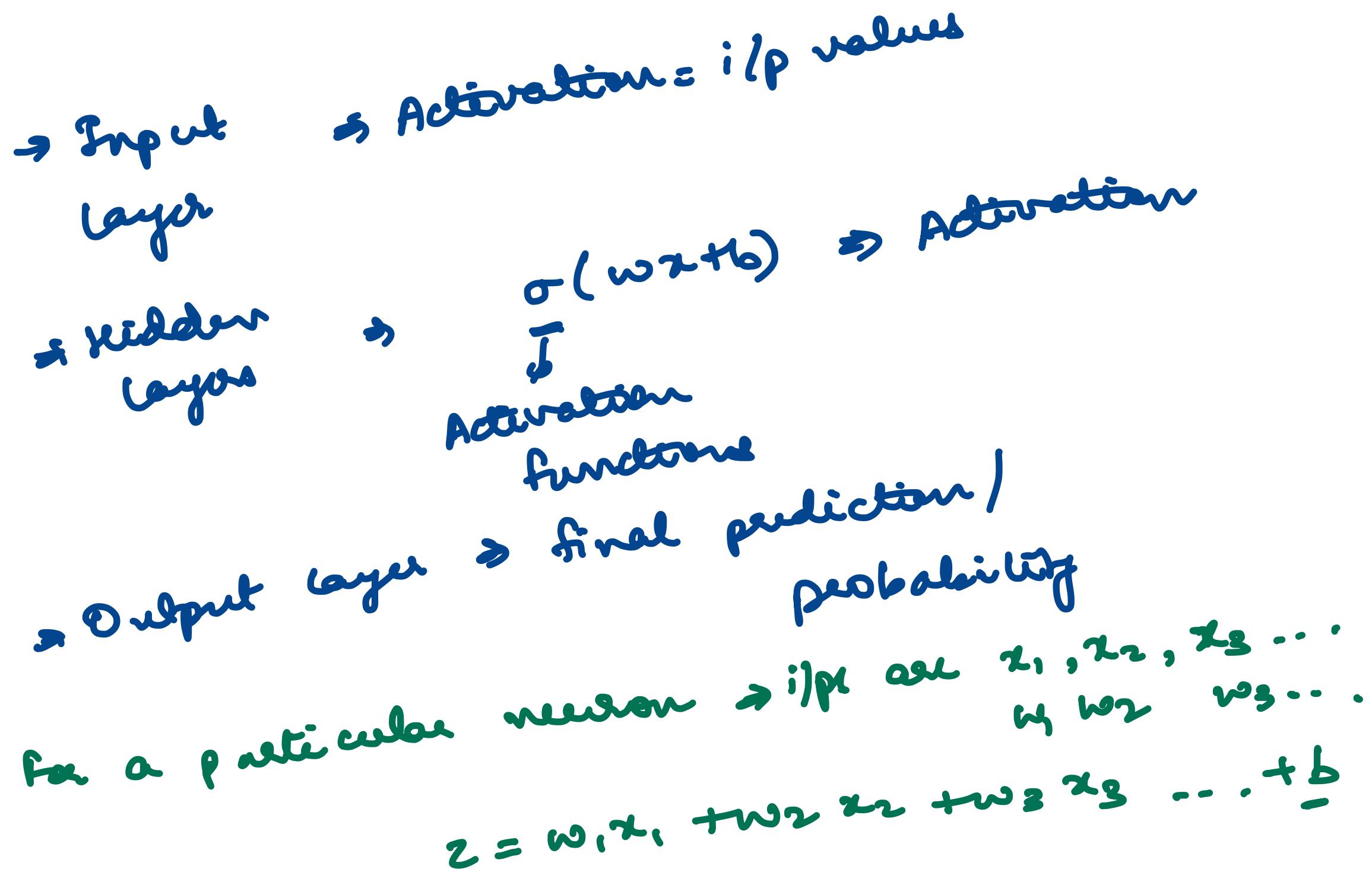
$$b = b - \alpha \frac{\partial C}{\partial b}$$

Gradient  
Descent.



## Activation

value that a neuron/node produces after applying activation function



## Activation funcs

Sigmoid  $\frac{1}{1+e^{-z}}$

ReLU  $\max(0, z)$

Tanh  $\frac{e^z - e^{-z}}{e^z + e^{-z}}$

Softmax  $\frac{e^{z_i}}{\sum_j e^{z_j}}$

- ① loss function  
cost/ error
- ② Optimization  
algo
- ③ Activation  
function

28 pixels x 28 pixels

78u pixels

0 0

1 0

2 0

.

.

.

:

181 0

182 0

183 0

11p layer

0 0

0 1

0 2

0 3

0 4

0 5

0 6

0 7

0 8

0 9

TensorFlow  
PyTorch } → Training, Creating,  
Texting models

Keras → wrapper on TensorFlow  
API

