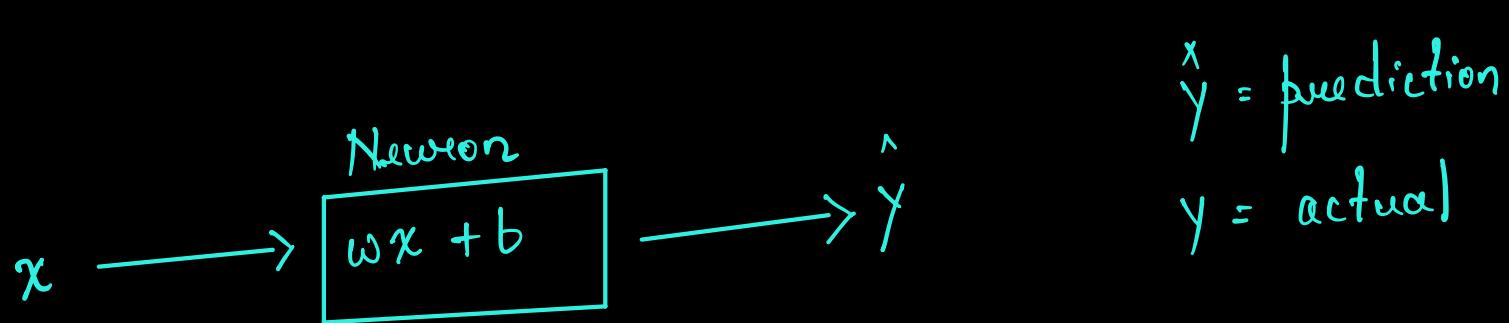
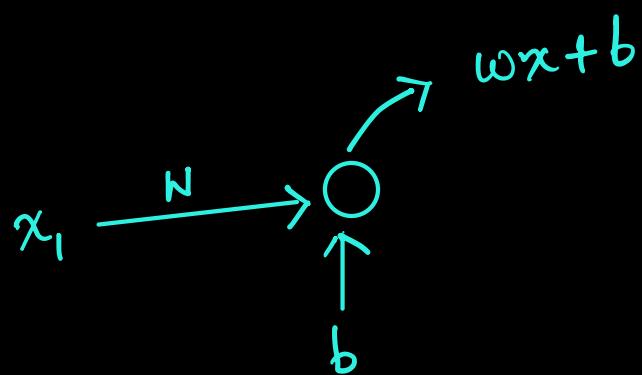


Today's Agenda

Perception Model



$$x = \begin{Bmatrix} x_0 \\ x_1 \\ x_2 \end{Bmatrix}$$



Loss Calculation

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

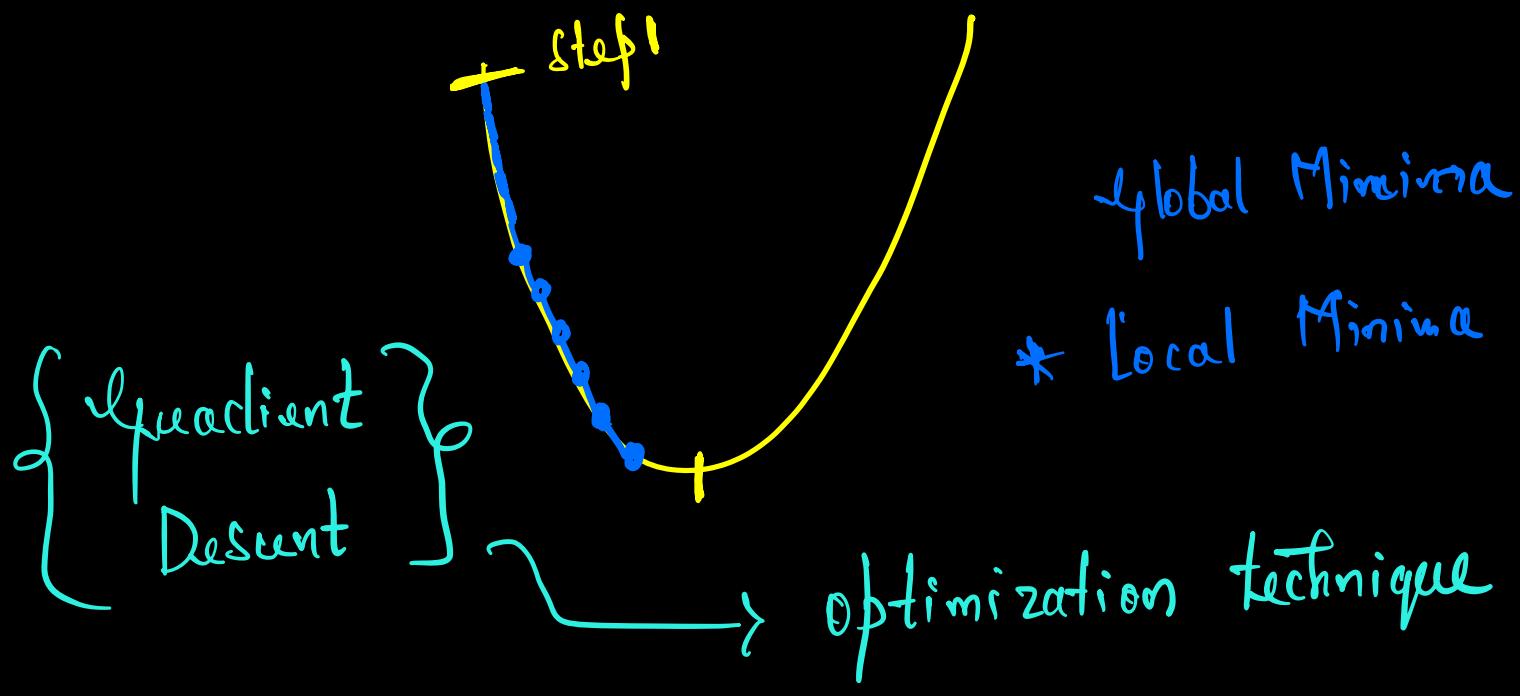
Error \rightarrow Reducing the error close to 0

$x \rightarrow$ Fixed

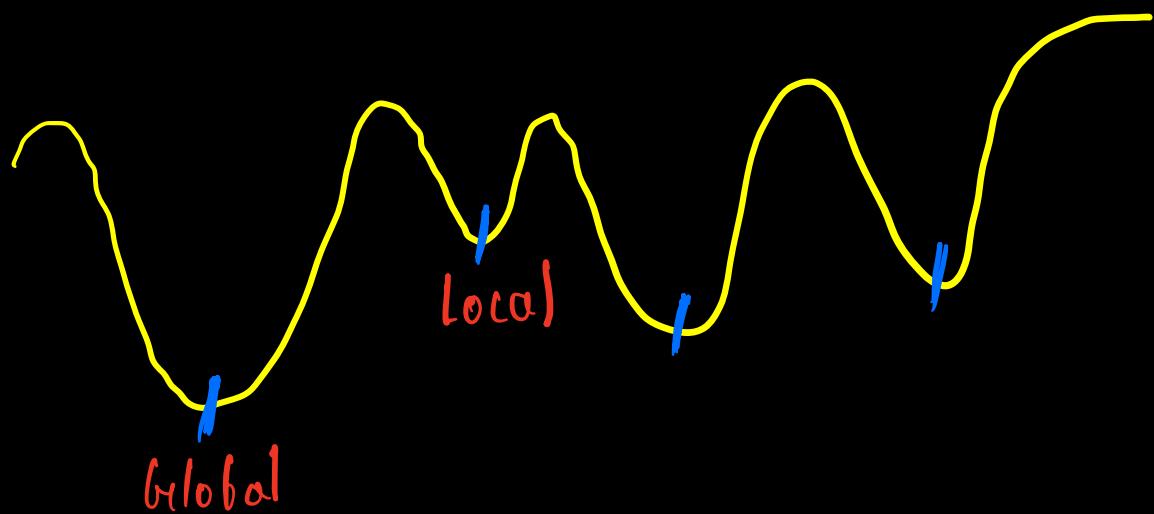
$\{w, b\} \rightarrow$ change / learnable params

Tune $\{w, b\}$ so that the loss comes close to L_{true} .

Update $w \& b$



$w \& b \approx \text{loss}(0)$ close



w & b Update Rule

$$L = E$$

$$\text{Loss} = \text{Enew}$$

$$w_x = w_{x'} - \eta \left\{ \frac{\partial L}{\partial w_x} \right\}$$

↓
New weight old weight

LR → Learning Rate
(0.01, 0.001, 0.0001)

$$\left(\frac{\partial L}{\partial w_x} \text{ over } \frac{\partial E}{\partial w_{x'}} \right)$$

Derivative of Enew w.r.t weight

Bias

$$b_{\text{new}} = \underline{b_{\text{old}}} - \eta \frac{\partial L}{\partial b_{\text{old}}}$$

LR → hyperparameter

Weight Update Rule

Forward Propagation

Input layer

I_1

I_2

$$w_1 = 0.11$$

$$w_2 = 0.21$$

$$w_3 = 0.12$$

$$w_4 = 0.08$$

$$w_5 = 0.14$$

$$w_6 = 0.15$$

$$X = [i_1, i_2] = [2, 3]$$

$$Y = 1$$

Hidden layer

t_{h1}

t_{h2}

Output

w_5

w_6

Nodes = 2

No of nodes
↓

hyperparameter

No of layers
↓

hyperparameter

Forward Propagation

(i) Input \rightarrow Hidden layer

$$x = \begin{bmatrix} 2, 3 \end{bmatrix} \quad w = \begin{bmatrix} 0.11 & 0.12 \\ 0.21 & 0.08 \end{bmatrix}$$

$$h_1 = 2 \times 0.11 + 3 \times 0.21 = 0.85$$

$$h_2 = 2 \times 0.12 + 3 \times 0.08 = 0.48$$

$$= \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} = \begin{bmatrix} 0.85 \\ 0.48 \end{bmatrix}$$

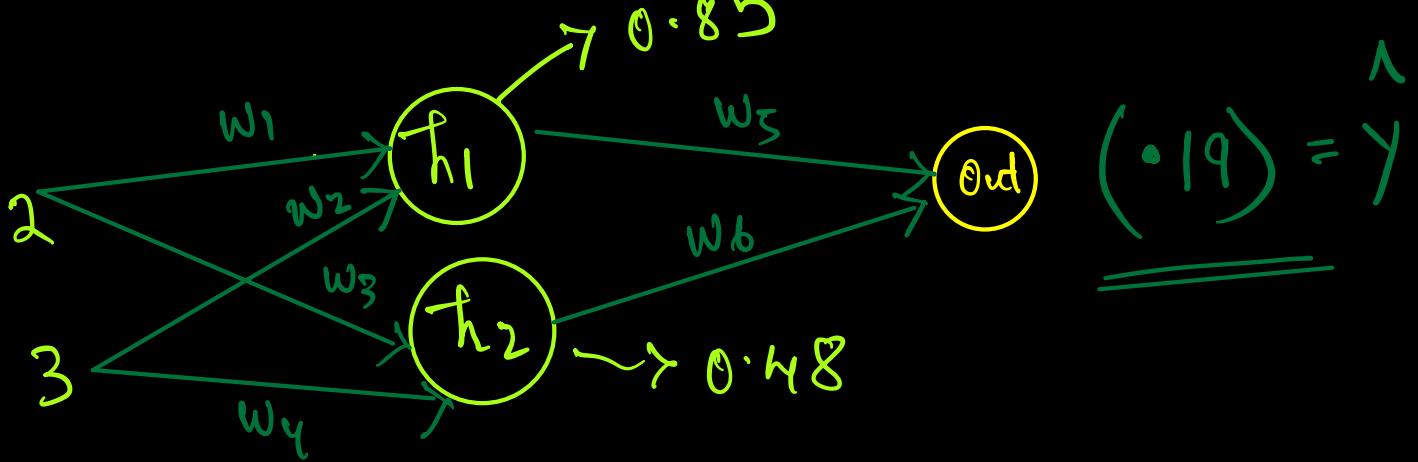
ii) Hidden Layer \rightarrow Output layer

$$= \begin{bmatrix} 0.85 & 0.48 \end{bmatrix} \begin{bmatrix} 0.14 \\ 0.15 \end{bmatrix}$$

$$= 0.85 \times 0.14 + 0.48 \times 0.15$$

$$= [0.191]$$

Calculate Error



Exercise Calculation

$$\begin{aligned}
 \text{Loss Function} &= \frac{1}{2} (\hat{y} - y)^2 \\
 &= \frac{1}{2} (0.19 - 1)^2
 \end{aligned}$$

$$E_{\text{loss}} = 0.327$$

Reducing the Error

$$\begin{aligned}
 \text{Prediction} &= \text{output} \\
 &= (h_1) w_5 + (h_2) w_6
 \end{aligned}$$

Phase, Output layer \rightarrow Hidden layer

Reverce

$$h_1 = i_1 w_1 + i_2 w_2$$

$$h_2 = i_1 w_3 + i_2 w_4$$

$$\text{Prediction} = (i_1 w_1 + i_2 w_2) w_5 + (i_1 w_3 + i_2 w_4) w_6$$

To change prediction value, weights.

How to change \rightarrow Backpropagation

- 1) Reduce the weight
- 2) Change the weight

Weight Update \rightarrow Gradient Descent

{ Iterative Optimization algorithm for finding the minimum of a function. }

Backprop with Gradient Descent

Weight Update :-

$$w_{\text{new}} = w_{\text{old}} - \eta \left(\frac{\partial E}{\partial w_{\text{old}}} \right)$$

As per our Network

$$* w_6 = w_6 - \eta \left(\frac{\partial E}{\partial w_6} \right)$$

$$* w_5 = w_5 - \eta \left(\frac{\partial E}{\partial w_5} \right)$$

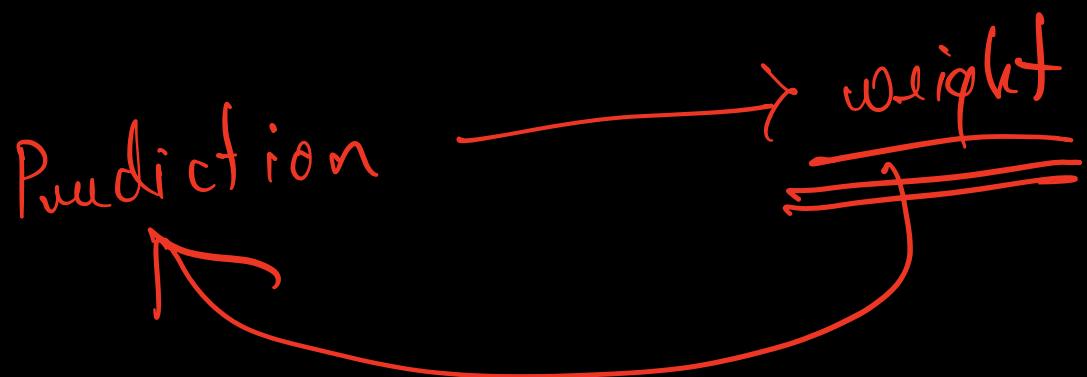
$$w_6 =$$

$$\eta = .001$$

* Chain Rule *

$$\frac{\partial E_{\text{new}}}{\partial w} = \frac{\partial E_{\text{new}}}{\partial \text{prediction}} * \frac{\partial \text{prediction}}{\partial w_6}$$

$$\text{Error} = \underbrace{(\hat{y} - y)^2}_{\text{Prediction}}$$



loss vs loss function

i) MSE (Regression)

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2$$

no of samples. → actual
→ predicted

2) Log loss (Binary Cross Entropy)

Logistic Regression

$$\text{loss} = -\frac{1}{n} \sum_{i=1}^n [y \log(\hat{y}) + (1-y) \log(1-\hat{y})]$$

Loss Function

i) Sample

Cost Function

i) Dataset

Average loss on
the entire dataset

Gradient Descent

Optimization Algorithm

Update

$$\theta = \theta - \alpha \frac{\partial J(\theta)}{\partial \theta}$$

$\theta(w, b)$

LR

$J(\theta)$: cost function

$$\alpha = 0.001$$

$$w_0 = 0.6$$

$$w_{\text{new}} = w_{\text{old}} - 0.001 \frac{\partial E}{\partial w_0}$$

$$= 0.6 - (0.001 \times 5)$$

$$= 0.6 - ()$$

$$w_{\text{new}} = ?$$

Gradient Descent Types

*1) Batch Gradient Descent : Full Dataset to be used every update

*2) SGD (Stochastic Gradient Descent)

*3) Mini Batch Gradient Descent

SGD \rightarrow One data point at a time
(SLOW) Very Slow

* Mini-Batch :- A small batch of dataset

Batch size :- (2^n) 8, 16, 32, 64, 128, 256,
 \downarrow
hardware
512, 1024

Framework :- Keras / PyTorch

Mini Batch Gradient Descent.
(SGD)

Data Terminologies

1) Batch :- Subset of your data

2) Iteration :- $1 \text{ update} = 1 \text{ batch}$
 weight

Batch :- 1000 training sample

Batch size :- 100

Total No of batches :- 10

Iterations :- 10 iterations

3) Epoch :- full cycle of the entire dataset

All students taught in a class $\rightarrow 1 \text{ epoch}$

1 epoch = Network has seen every

training sample once.

Total Samples :- 1000

Batch size :- 100

Total Batch :- 10

Total Iteration :- 10

1000
Epochs = 1 , $\frac{10 \text{ Iteration}}{10 \text{ Batch}}$

1000
Epoch = 2 , $\frac{20 \text{ Iteration}}{10 \text{ Batch}}$

Epoch = 10 , 100 iterations

4) Step

1 step = weight update

DL Frame works :- Tensorflow & Pytorch

1 weight update :- At every batch, the weight update takes place.