

→ One of the most popular ML

→ Different types of NN:

- CNN: Image data

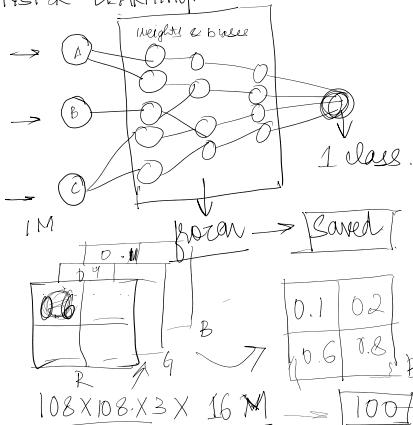
- RNN: Text data

- ANN: DL

- Transformers & Convolutions

- FNN

### \* TRANSFER LEARNING:



$$\begin{array}{c} \text{---} \\ \theta_1, \theta_2 \end{array}$$

[VGG-16]  
for any img classification

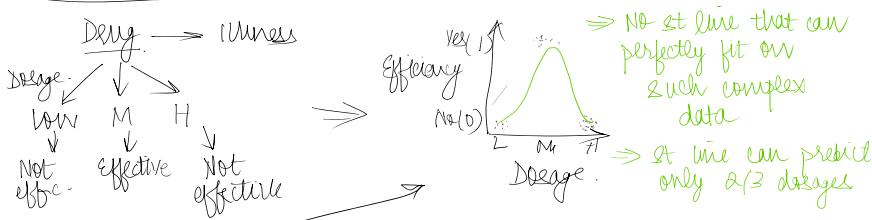
### # Neural Networks

1. What is NN?
2. What NN does?
3. How NN fits on data?
4. Backpropagation (GFG blog)
5. Variations

because.

ya [BLACK BOX] → it is difficult to understand what happens inside a NN

### EXAMPLE :



\* NN as shown can squiggle to any complex data -



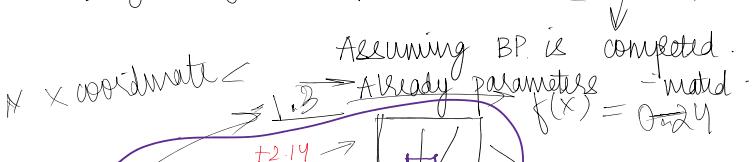
### \* Concept & Composition of NN

NN consist of nodes & connections b/w nodes.

→ Node: represents parameter values that were estimated when NN will fit to a data

↓  
similar to slope & intercept of LR

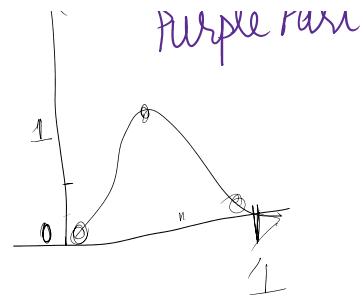
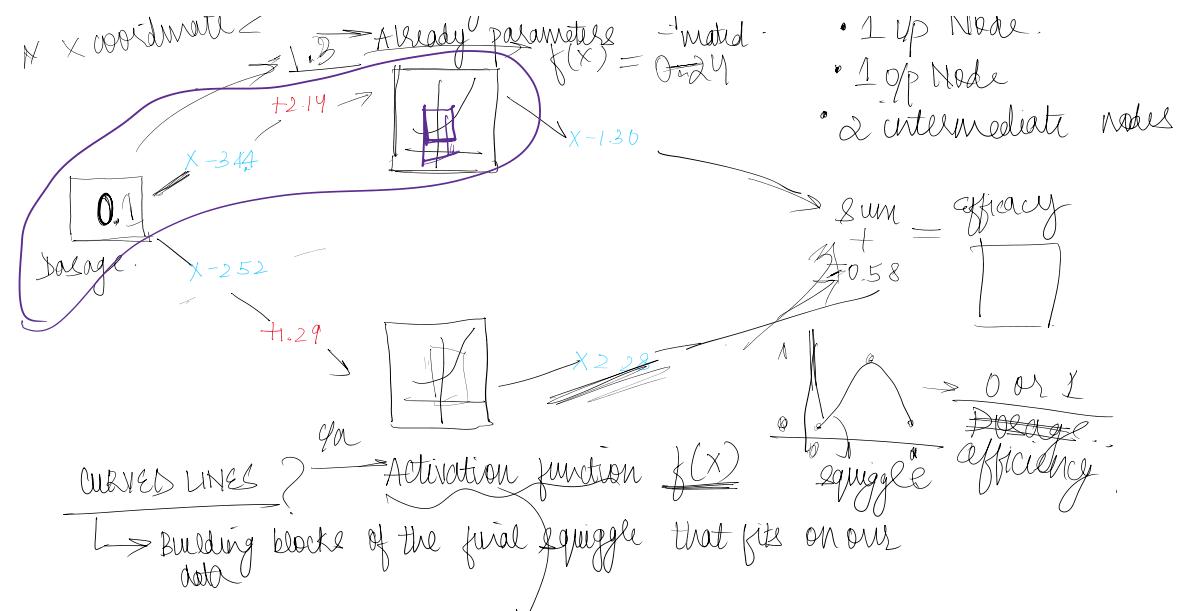
→ NN starts w/ unknown parameters & these are estimated during fitting using a process of BACKPROPAGATION.



- Components
- 1 ip Node
  - 1 op Node



Purple Part



which one you want to use  
 you can decide while building the NN

$$\rightarrow \text{Sigmoid: } f(x) = \frac{e^x}{e^x + 1}$$

$$\rightarrow \text{ReLU (Rectified Linear Unit): } f(x) = \max(0, x)$$

$$\rightarrow \text{Softplus: } f(x) = \log(1 + e^x)$$

## BACK PROPOGATION

→ helps evaluate weights & biases  
 most optimal value

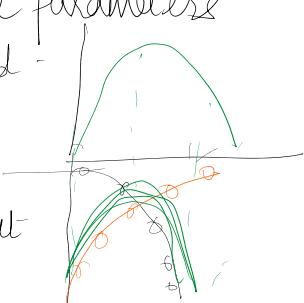
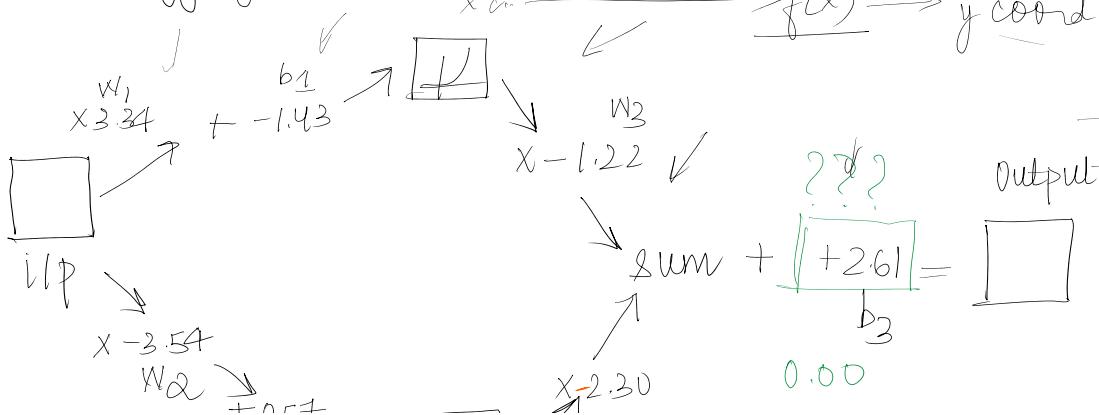
### \* Basic Idea

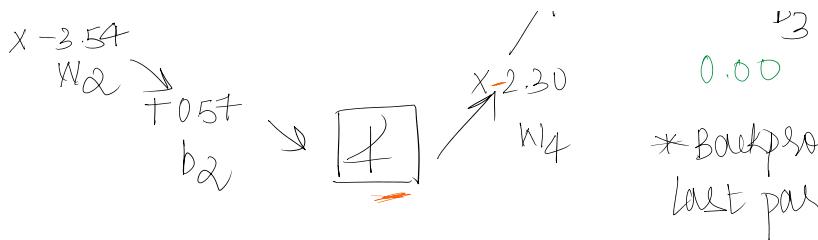
Main 2 steps:

(1) Using chain rule calculate derivatives

$$\frac{d \text{SSR}}{d \text{bias}} = \frac{d \text{SSR}}{d \text{Predicted}} \times \frac{d \text{Predicted}}{d \text{Bias}}$$

(2) Plugging derivative to grad. Descent to optimize parameters

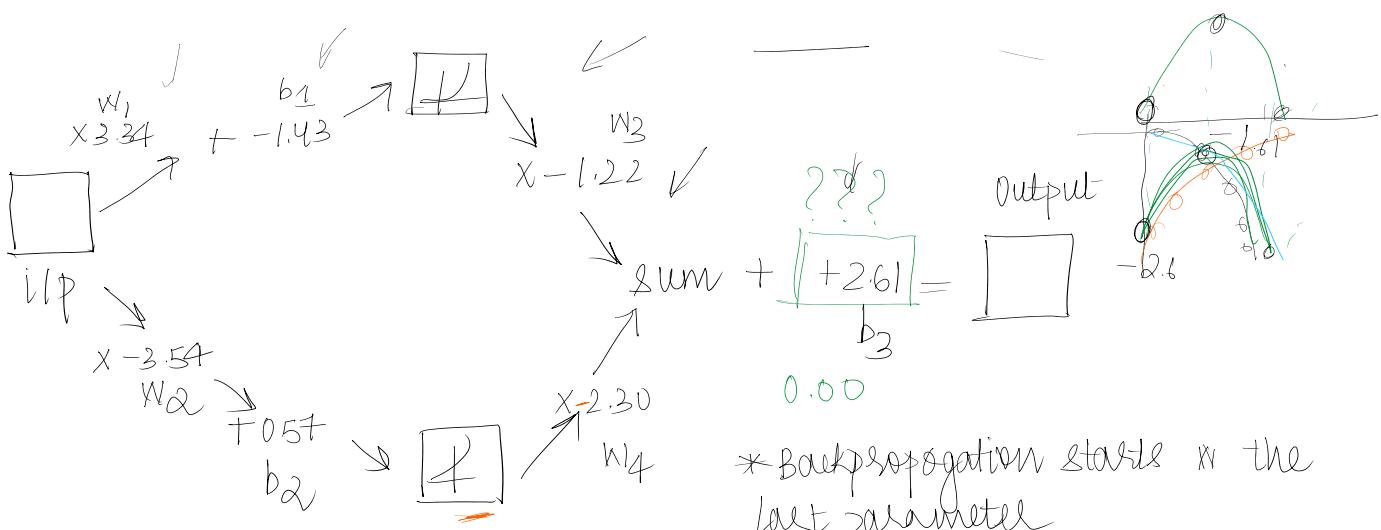




\* Backpropagation starts in the last parameter

- \* While understanding the main concept, we start in estimating Bias,  $b_3$
- \* In order to estimate last value we assume we already have optimal values for all other  $w$  &  $b$ .
- \* Dosage (0 - 1)  
Efficacy (0, 1)

## UNDERSTANDING PREDICTION OF $B_3$



\* Backpropagation starts in the last parameter

Residual: Difference b/w observed & predicted value

$$\text{Residual} = \text{Obs} - \text{Pred}$$

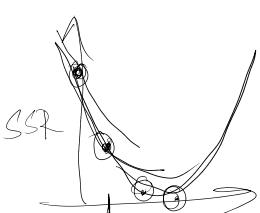
$$SSR = (0 - -2.6)^2 = 2.6$$

$$= 1 - (-1.61) = 2$$

$$= 0 - (-2.61) =$$

$$= (0 - -2.6)^2 + (1 - (-1.61))^2 + (0 - (-2.61))^2$$

$$= 120.4 \rightarrow SSR \text{ in } b_3 = 0$$



$$\boxed{\text{let } b_3 = 4}$$

$$\boxed{\text{Let } b_3 = 4}$$

$$SSR = (0 - 1.6)^2 + (1 - 0.6)^2 + (0 - 1.6)^2 \\ = 7.8.$$

$$\boxed{b_3 = 2.9}$$

$$SSR = 1.1$$

$$b_3 = 3$$

$$SSR = 0.42$$

Generalizing:

$$\underline{SSR} = \frac{(ob_1 - \text{pred}_1)^2 + (ob_2 - \text{pred}_2)^2}{\dots} \\ = \sum_{i=1}^{n=3} (ob_i - \underline{\text{pred}_i})^2$$

$$\text{pred}_i = \text{green squiggle}_i = \text{blue}_i + \text{orange}_i + b_3$$

$$\boxed{\frac{d(-x)}{dx} = -1}$$

$$\frac{dSSR}{db_3} = \frac{dSSR}{d\text{predicted}} \times \frac{d\text{predicted}}{db_3}$$

$$\frac{dSSR}{d\text{predicted}} = \frac{d}{d\text{predicted}} \sum_{i=1}^3 (ob_i - \text{pred}_i)^2$$

$$= \sum_{i=1}^{n=3} 2 \times (ob_i - \text{pred}_i) \times \frac{d}{d\text{predicted}} (ob_i - \text{pred}_i)$$

$$\frac{dSSR}{db_3} = \sum_{i=1}^3 -2 \times (ob_i - \text{pred}_i) \times \frac{d\text{pred}}{db_3} = -1$$

$$\frac{d\text{pred}}{db_3} = \frac{d \text{green squiggle}}{db_3}$$

$$= \frac{d}{db_3} [\text{blue} + \text{orange} + b_3] = 1$$

$$\frac{dSIR}{db_3} = \sum_{i=1}^{N=3} -2x_i (obs_i - pred_i)$$

lr —————  
gn —————