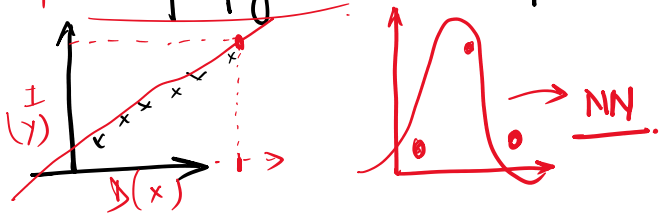
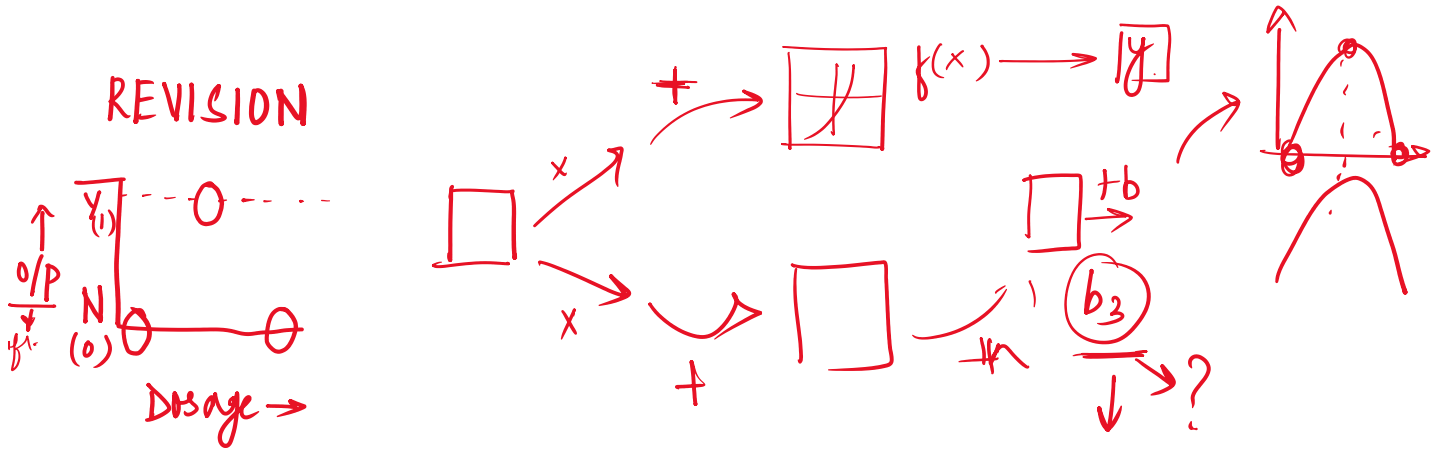


\* Backpropagation: It helps in optimizing weights & biases

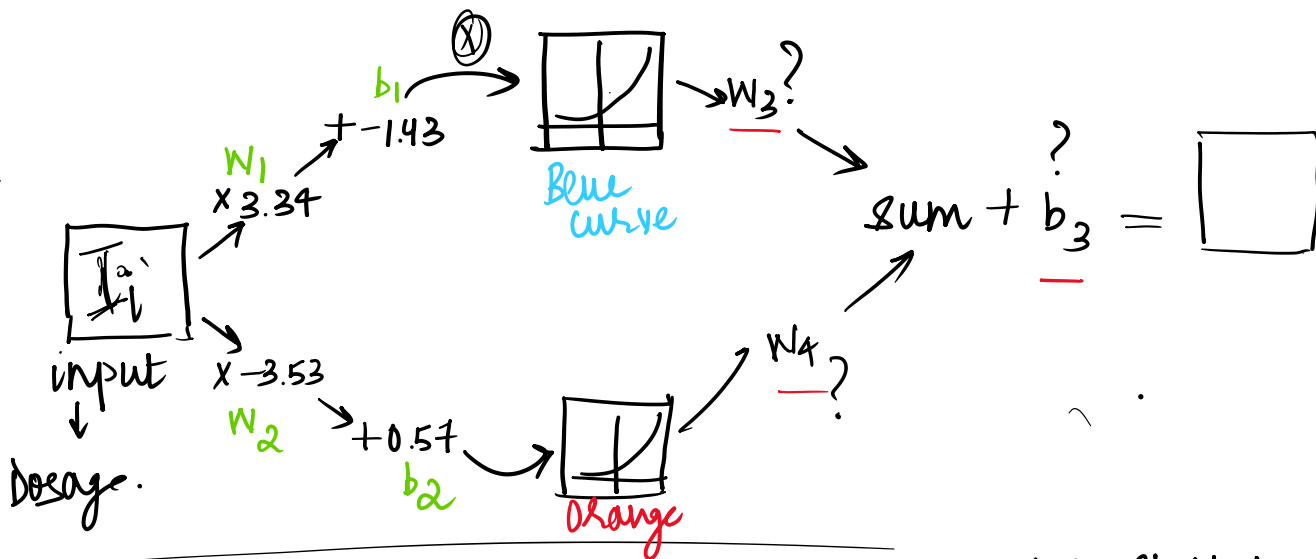


REVISION

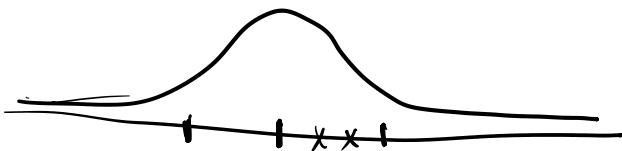


We use the chain rule to find derivative of SSR.  
Gradient Descent →  
 optimal value of  $b_3$

★ OPTIMIZE 3 PARAMETERS SIMULTANEOUSLY



\* Standard Normal Distribution



Mean = 0  
Std. Dev = 1

We start by assuming

$$b_3 = 0$$

$$w_3 = 0.36$$

$$w_4 = 0.63$$

1. We run Dosage from [0 to 1]
2. Get corresponding y-axis coordinates by using obtained x values in  $f(x) = \log(1 + e^x) = y\text{-axis coordinates}$ .

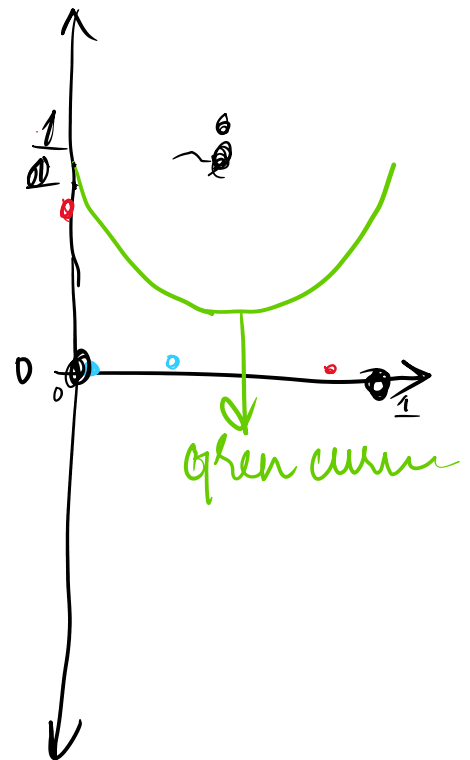
Activation fun.

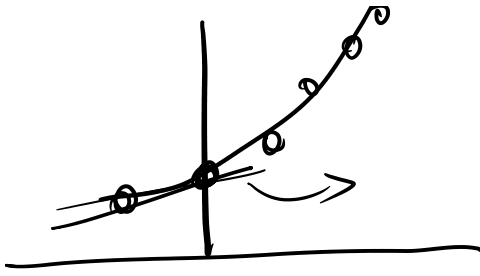
3. Find out how well the green curve fits on the data.

→ SSR

$$SSR = \frac{\sum (Obs. - pred)^2}{SSR}$$

$$= (0 - 0.72)^2 + (1 - 0.46)^2 + (0 - 0.71)^2$$

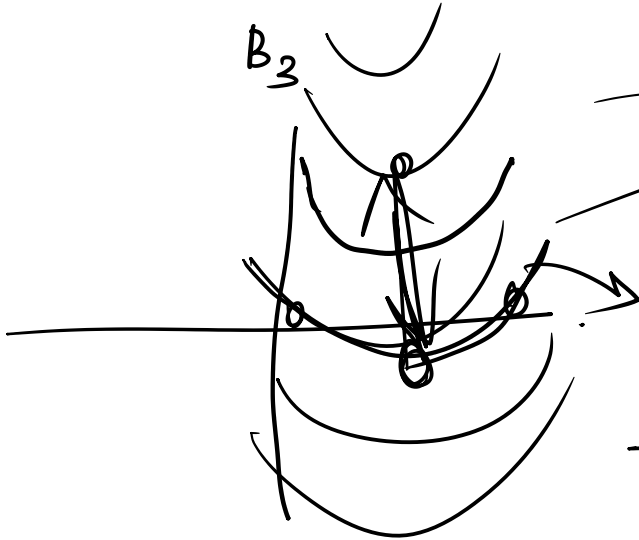




1.4

$$b_3 = -0.5$$

5)  $\rightarrow$  this is the optimal value of  $b_3$  when  $w_3$  &  $w_4$  are ass. ---



$$\frac{dSSR}{db_3} = \frac{dSSR}{dP_{predicted}} \times \left( \frac{dP_{pred}}{db_3} \right)$$

Predict  $d_i = \text{green} - \text{blue} + \text{orange}$   
 $b_3$

Q How to optimize (how to find derivative of SSR)  
w.r.t  $w_3$  &  $w_4$ .

$$SSR = \sum_{i=1}^{n=3} (\text{Observed}_i - \text{Pred}_i)^2$$

$$\underline{x_{1,i}} = \underline{I_i} \times 3.34 + -1.43$$

$$x_{1,1} = 0 \quad x_{3,34} = -$$

$$\underline{y_{1,i}} = f(x_{1,i}) = \log(1 + e^x)$$

$$\begin{aligned} * \text{Predicted}_i &= \text{green curr}_i \\ &= \underbrace{y_{1,i} \times w_3}_{\text{blue}} + \underbrace{y_{2,i} \times w_4}_{\text{orange}} + b_3 * \end{aligned}$$

$$\frac{dSSR}{dw_3} = \frac{dSSR}{d(\text{Pred})} \times \frac{d\text{Pred}}{dw_3} = \sum_{i=1}^{n=3} -2(o_i - p_i) \times y_{1,i}$$

$$\frac{dSSR}{dw_4} = \frac{dSSR}{d(\text{Pred})} \times \frac{d\text{Pred}}{dw_4} = \sum_{i=1}^{n=3} -2(o_i - p_i) \times y_{2,i}$$

$$\frac{dSSR}{db_3} = \frac{dSSR}{d(\text{Pred})} \times \frac{d\text{Pred}}{db_3} = \sum_{i=1}^{n=3} -2 \times (o_i - p_i) \times 1$$

$$\begin{aligned} \frac{dSSR}{d\text{Pred}} &= \frac{d}{d\text{Pred}} \sum_{i=1}^{n=3} (o_i - \text{Pred}_i)^2 \\ &= \sum_{i=1}^{n=3} 2(o_i - \text{Pred}_i) = 2 \end{aligned}$$

$$\begin{aligned} \frac{d\text{Pred}}{dw_3} &= \frac{d}{dw_3} [y_{1,i} w_3 + y_{2,i} w_4 + b_3] \\ &= y_{1,i} + 0 + 0 = y_{1,i} \end{aligned}$$

$$\frac{dPred}{dw_4} = y_{2,i}$$

$$\frac{dSSR}{dw_3} = \sum_{i=1}^3 -2 (b_i - p_i) \times y_{1,i}$$

$$= -2 \times (0 - pred_1) \times y_{1,1} - 2 \times (1 - pred_2) \times y_{1,2} \\ - 2 \times (0 - pred_3) \times y_{1,3} \\ = 2.58.$$

$$\frac{dSSR}{dw_4} = 1.26, \quad \frac{dSSR}{db_3} = 1.90$$

$$\text{Step Size} = \text{derivative of } w_3 \times LR \stackrel{0.1}{=} 0.258.$$

$$new w_3 = old w_3 - \text{step size}.$$

$$= [0, 10], \quad new w_4, \quad new b_4$$

\* We repeat this process until the predictions no longer improve very much.

→ Max no of step size.