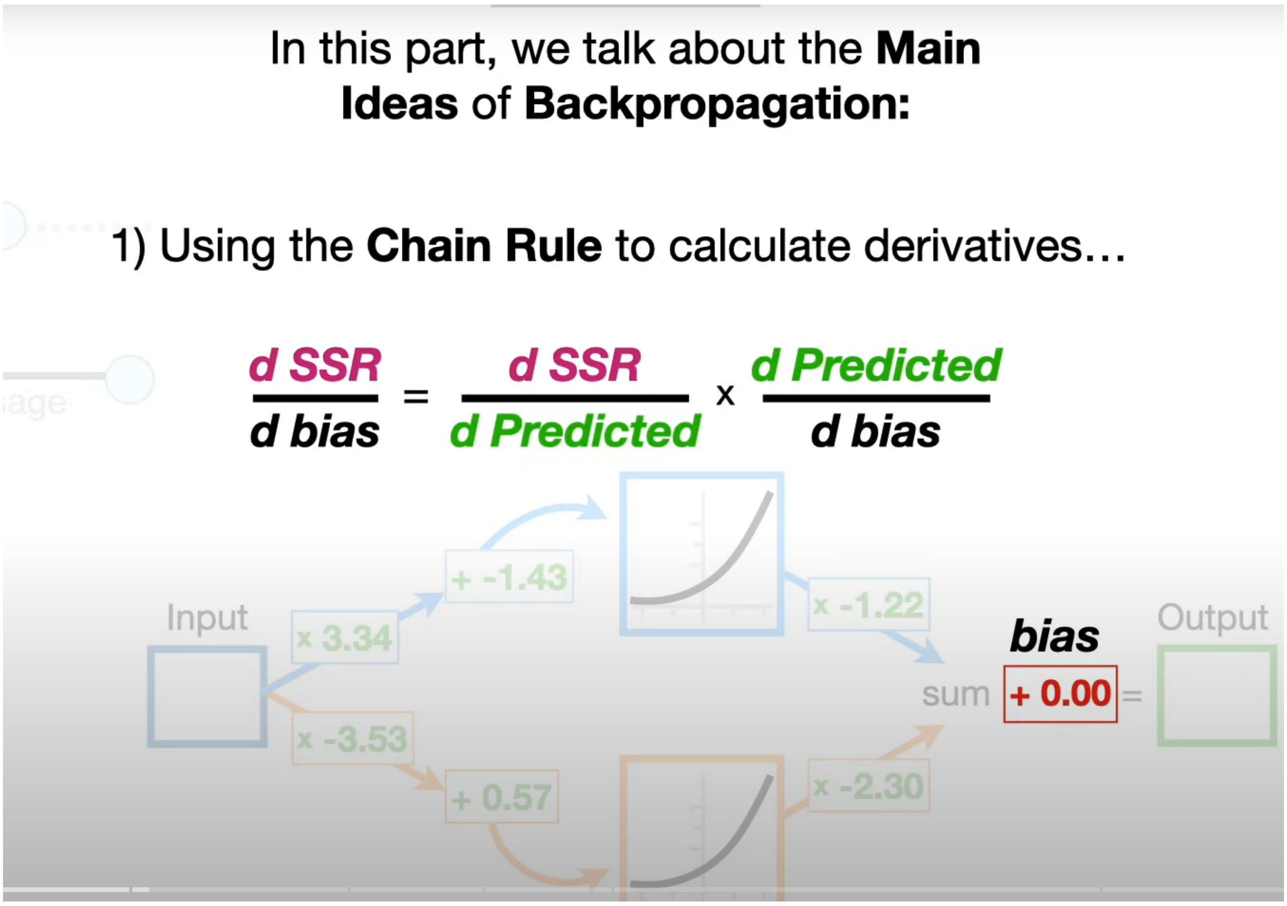
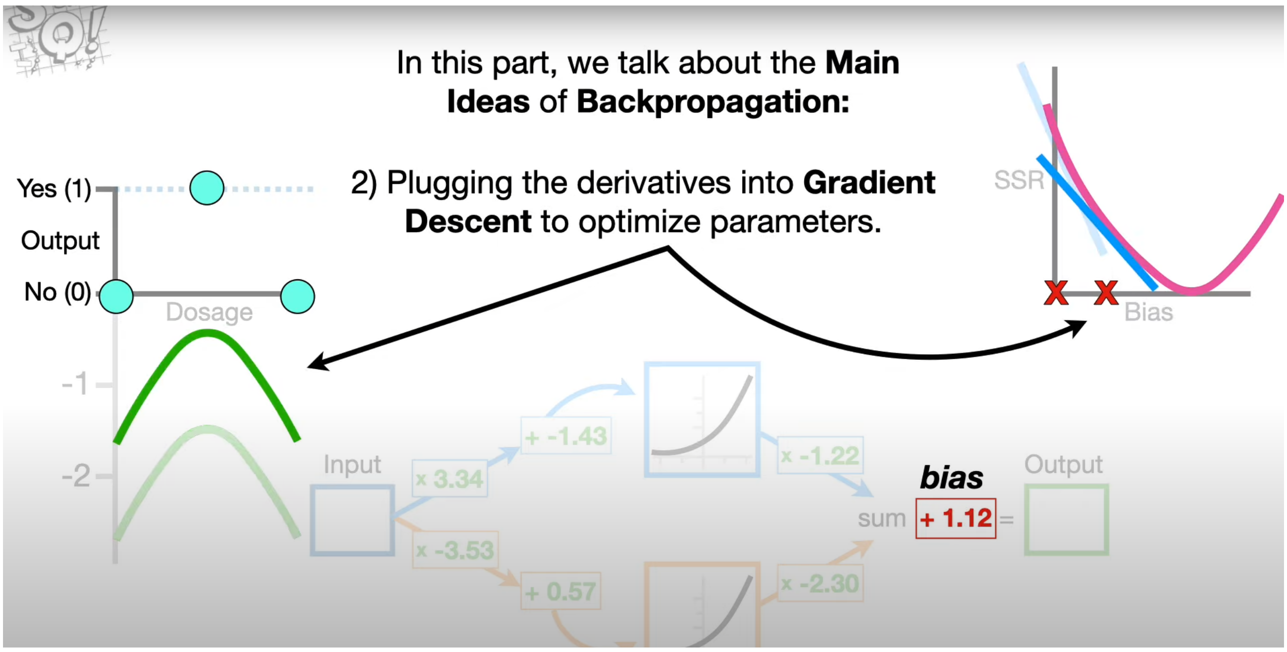
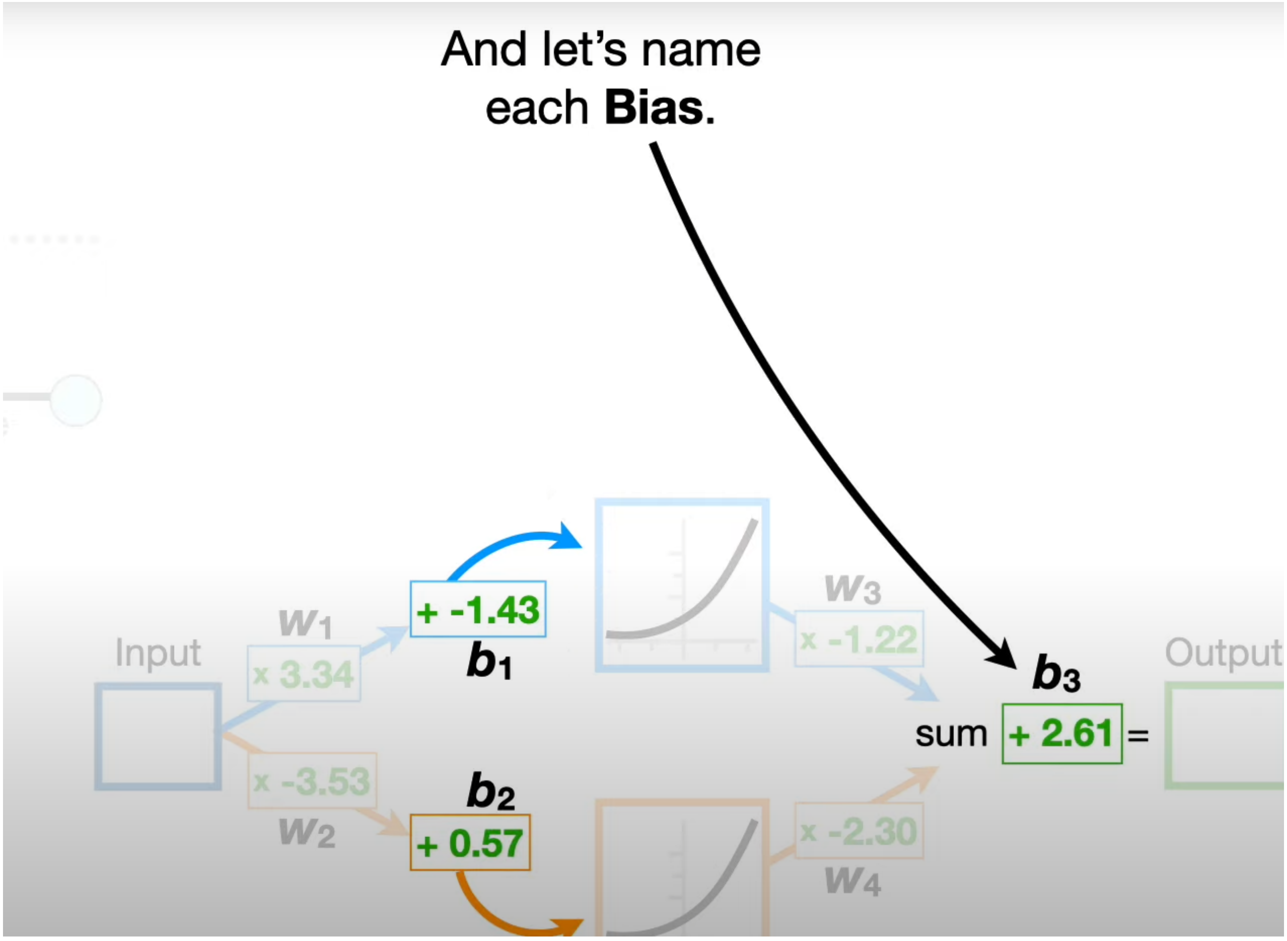
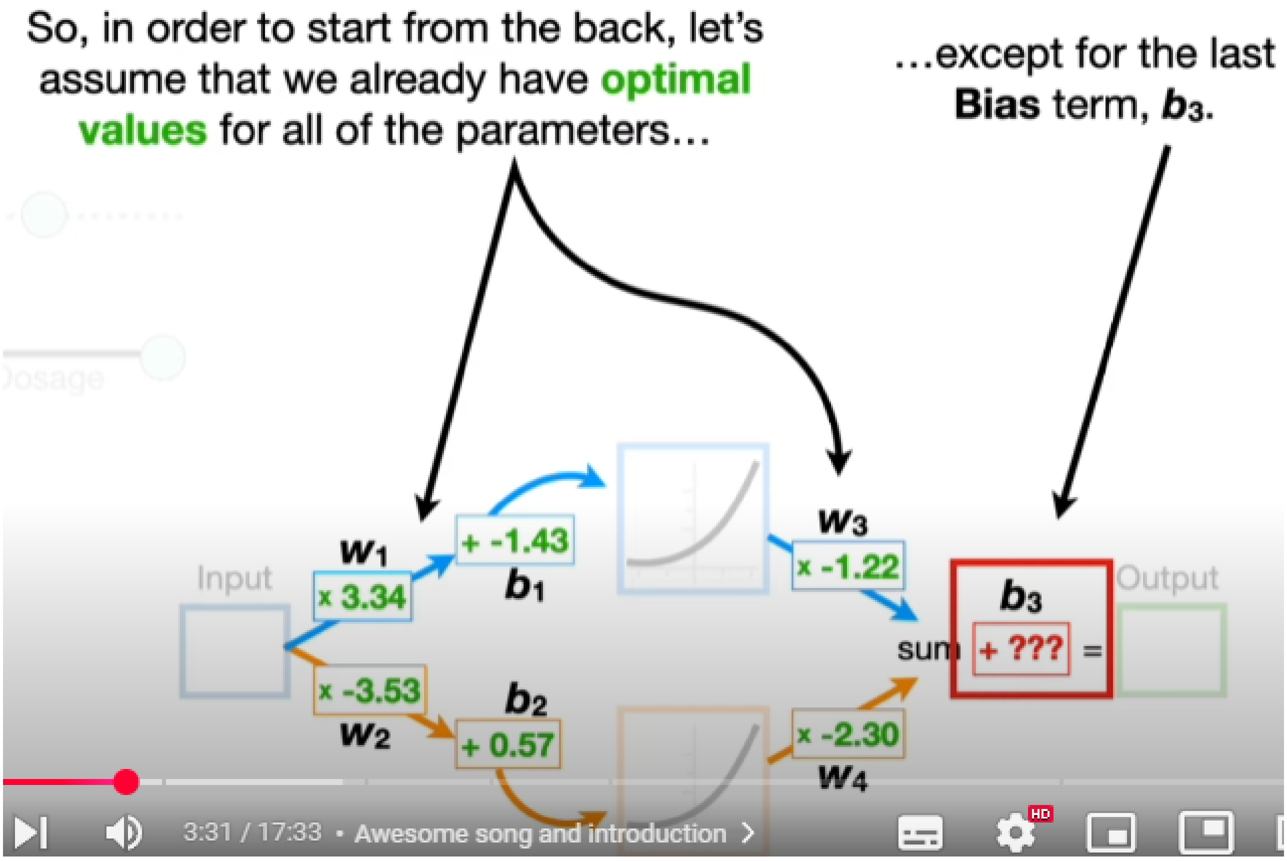
Backpropagation Main Ideas

- It optimizes the **Weights** and **Biases** in Neural Networks.
- 

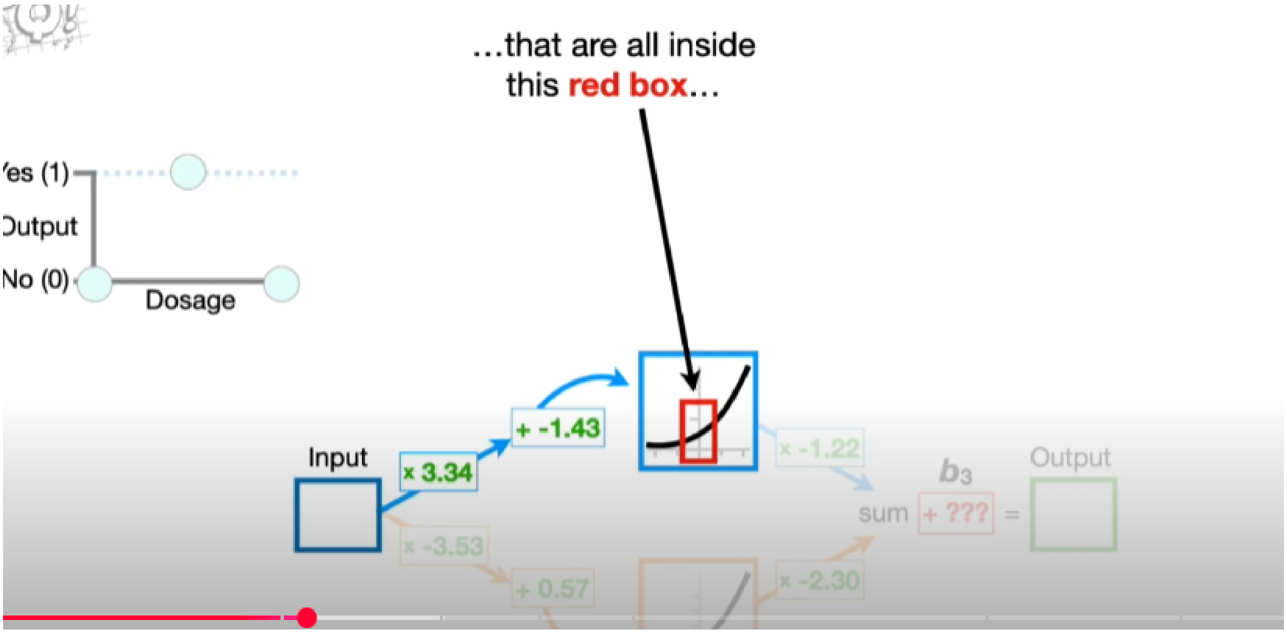
- 

- 

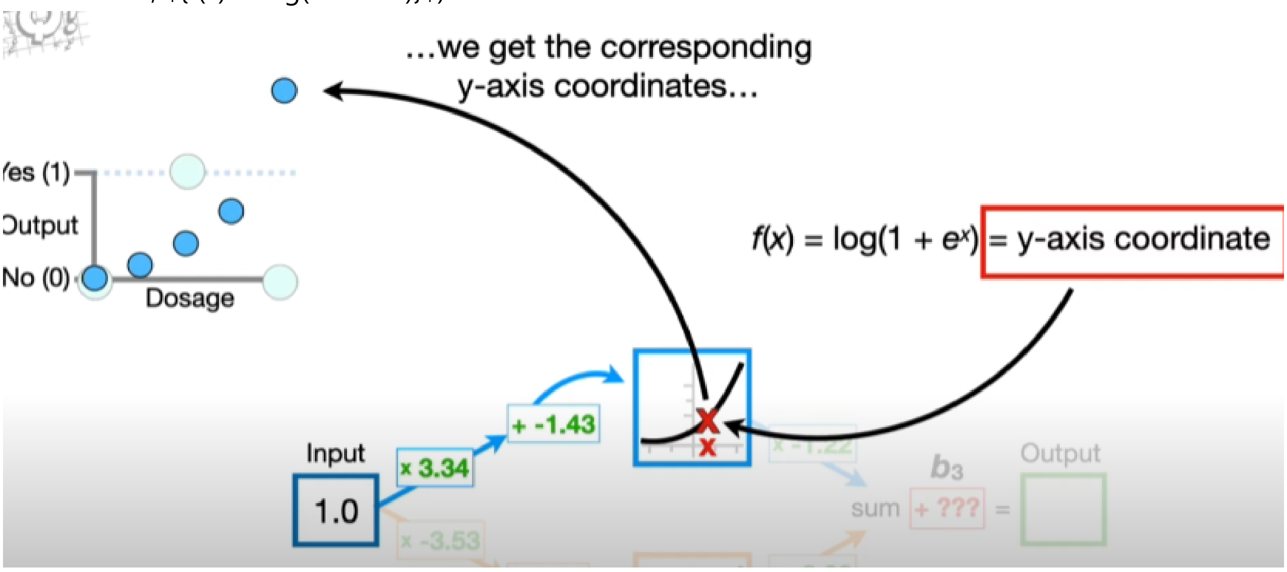
- Let's name weights (w_1, w_2, w_3 and w_4) and biases (b_1, b_2 and b_3).
- Backpropagation works with the last parameter and works its way backwards to estimate all of the other parameters.
- However, we can discuss main idea by estimating last parameter , bias b_3.
- 

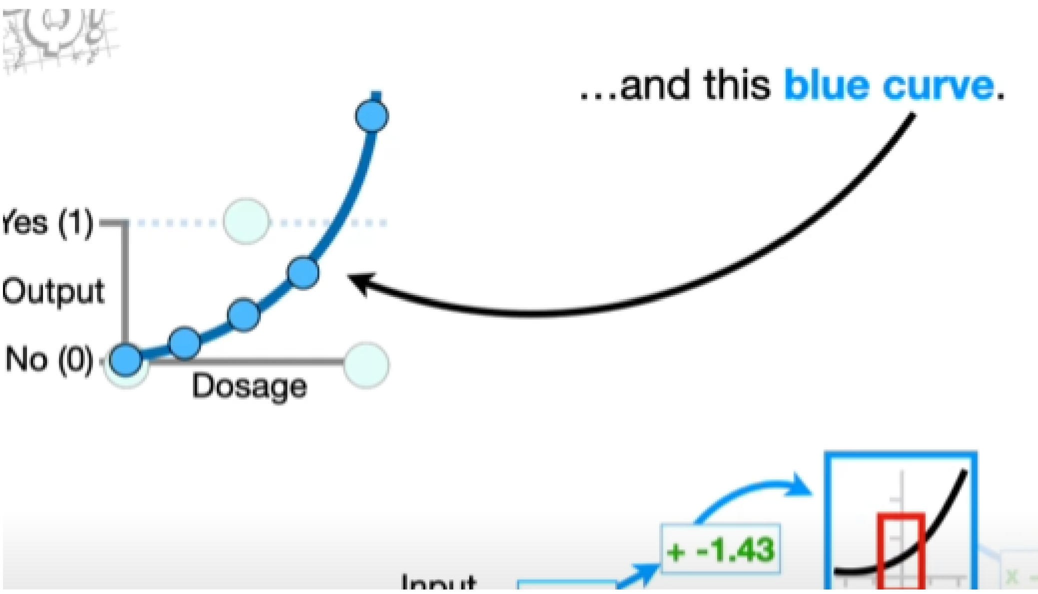
> Note : Unoptimized Doses and Optimized Doses

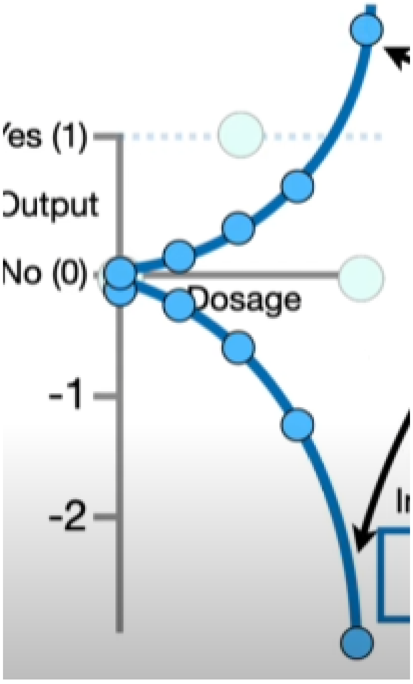
- Now if we run Dosages from 0 to 1 through the connection to the top Node in the Hidden Layer, then we get the x-axis coordinates for the Activation Function

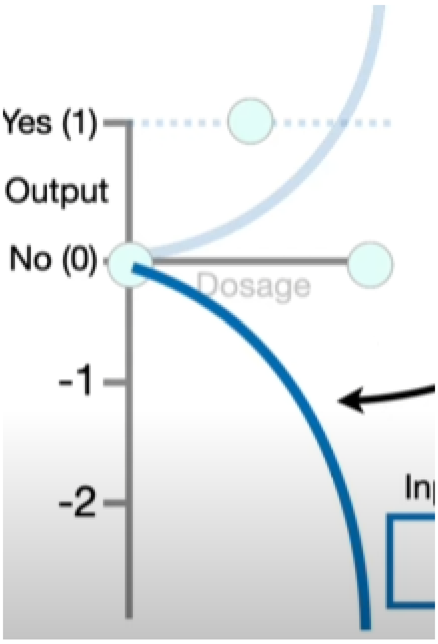


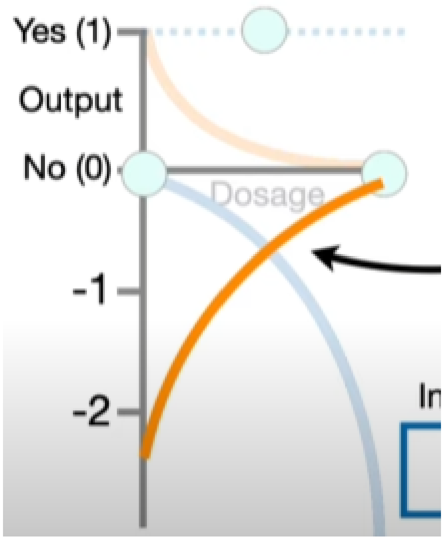
and when we plug the x-axis coordinates into the Activation Function (in this case is Softplus Activation Function i.e., $f(x) = \log(1 + e^x)$)



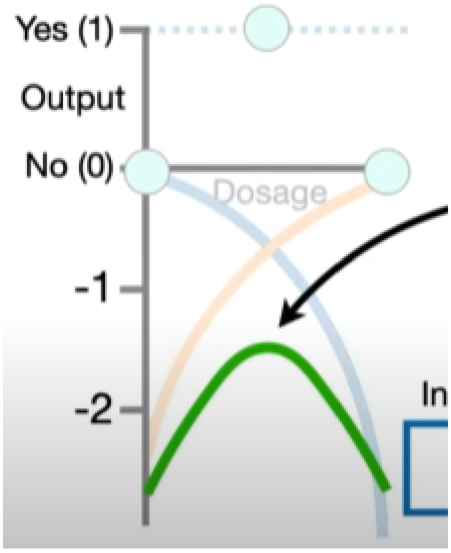


- Then we multiply the y-axis coordinates on the blue curve by -1.22 

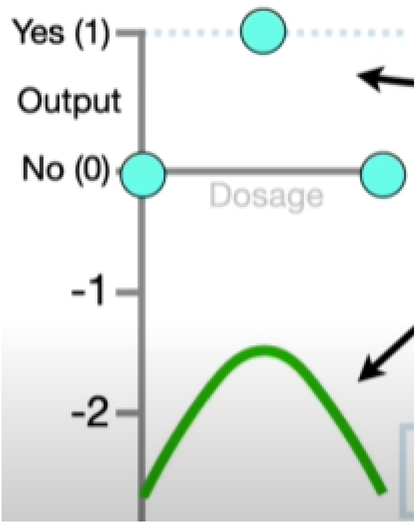


  and then we get the final blue curve.
- Now if we run Dosages from 0 to 1 through the connection to the bottom Node in the Hidden Layer, ...


  and then we get the final orange curve.



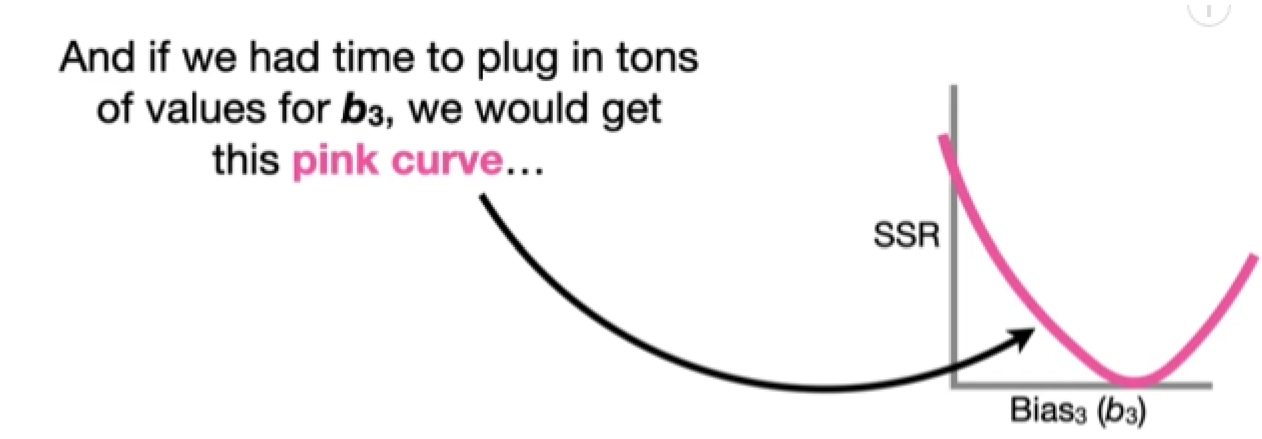
- Adding those blue and orange curves will get us a green squiggle
- Since we don't have optimal value of b_3, we gotta give it some initial value like 0.
- 0 means green squiggle doesn't move and it is far from observed values.

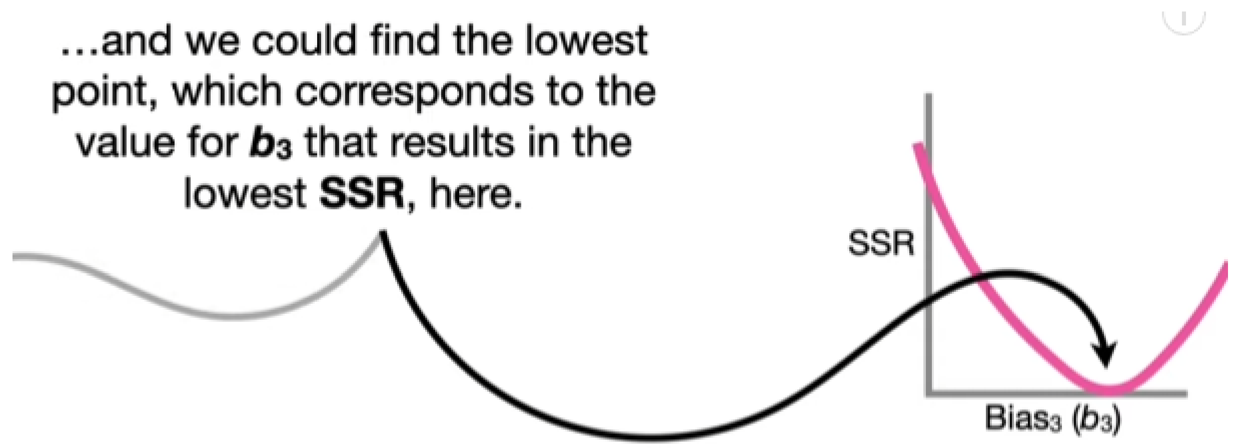


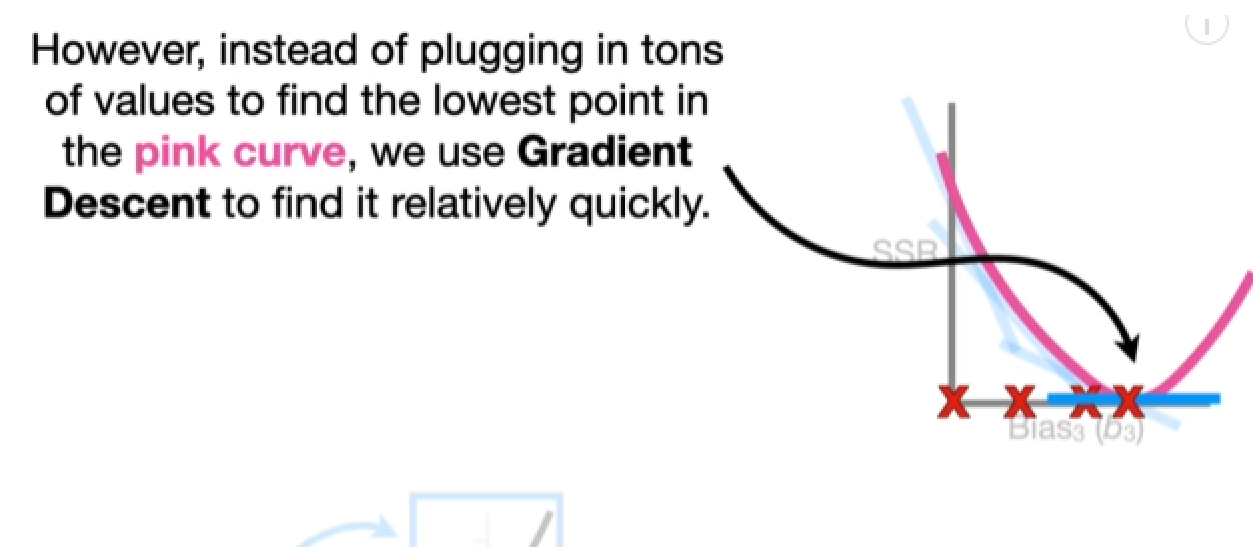
- It can be quantified how good it fits the data by calculating Sum of $Squared$ $Residuals$ $=$ $\sum_{i=1}^{n} {(Observed_i - Predicted_i)^2}$.

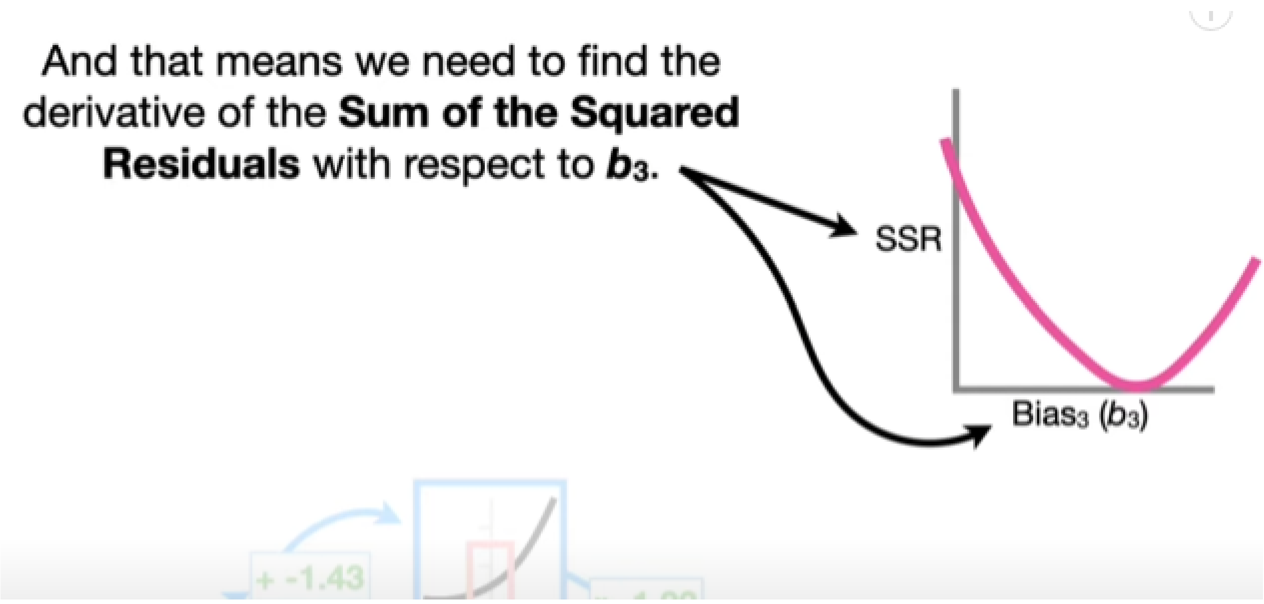
> Note : Changing Bias means Squiggle translates

Bias	Sum of Squared Residuals
0	20.4
1	7.8
2	1.11
3	0.46


And if we had time to plug in tons of values for b_3, we would get this pink curve…
SSR
Bias$_3$ (b_3)


…and we could find the lowest point, which corresponds to the value for b_3 that results in the lowest **SSR**, here.
SSR
Bias$_3$ (b_3)





- Now, since Sum of $Squared$ $Residuals$ $=$ $\sum_{i=1}^{n} {(Observed_i - Predicted_i)^2}$, and each $$Predicted$$ value comes from $green$ $squiggle_i$, which comes from last part of neural network.
- Therefore, $green$ $squiggle_i$ $=$ $blue$ $+$ $orange$ $+$ b_3 .
- For Gradient Descent to optimize b_3, we need to take SSR's derivative $w.r.t$ b_3.

$\frac{d , SSR}{d , b_3}$

- Therefore by **The Chain Rule**,

- ### $\frac{d , SSR}{d , b_3}$ $=$ $\frac{d , SSR}{d , Predicted}$ $\times$ $\frac{d , Predicted}{d , b_3}$

    1. ### $\frac{d , SSR}{d , Predicted} = -2 \times \sum_{i=1}^{n} {(Observed_i - Predicted_i)}$

2. ## $\frac{d , Predicted}{d , b_3} = 1$

3. ## $\frac{d , SSR}{d , b_3} = -2 \times \sum_{i=1}^{n} {(Observed_i - Predicted_i)}$

> > Note : Let Learning Rate be 0.1

Bias	$\frac{d , SSR}{d , b_3}$	Step Size = $\frac{d , SSR}{d , b_3} \times \text{Learning Rate}$	$ \text{New } b_3 = \text{Old } b_3 - \text{Step Size}$
0	-15.7	$-15.7 \times 0.1 = -1.57$	1.57
1.57	-6.26	$-6.26 \times 0.1 = -0.626$	2.19

Do it till Step Size close to 0.

- Most optimized $b_3 = 2.61.$