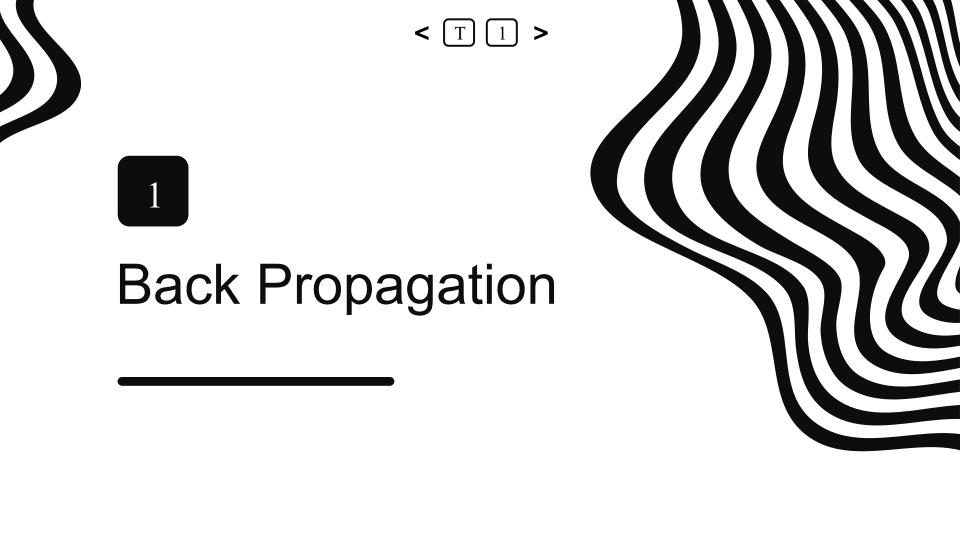
Lecture 11 Part 2

Back Propagation

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Back Propagation

Remember Gradient Descent?

Gradient descent is an optimization algorithm commonly used to train machine learning models and neural networks.

Chain Rule

$$\frac{dy}{dx} = \frac{dy}{dx} = \frac{da}{dx}$$

< T 1 >

Chain Rule

$$y = 5x + 3$$
$$x = t^2$$

Now we have to find $\frac{dy}{dt}$

What generally we do,

$$y = 5x + 3$$

= 5(t²)+3
= 5t²+3

$$\frac{dy}{dt} = \frac{d(5t^2+3)}{dt}$$
$$= 10t$$

y = 5x + 3 $x = t^{2}$ $\frac{dy}{dt} = ?$

• Y is function of X
• X is a function of T

Instead of doing this
$$\frac{dy}{dt} = \frac{d(5t^2+3)}{dt}$$

$$\frac{dy}{dt} = \frac{d(5t^2+3)}{dt}$$

$$\frac{dy}{dt} = \frac{dx}{dt}$$

y = 5x + 3

 $x = t^2$

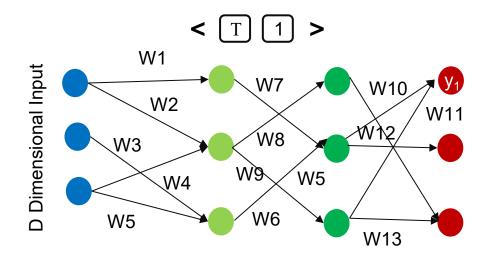
 $\frac{d}{dx}(5x+3) * \frac{d}{dt}(t^2)$

=5 *2t = 10t

Chain Rule

this

But in chain rule we see

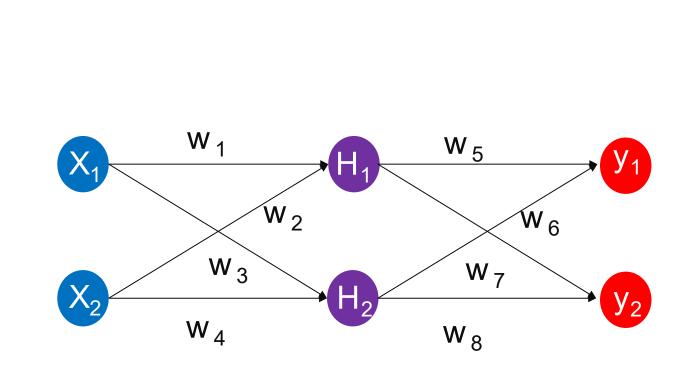


Total Error =
$$\frac{1}{2}$$
 (T₁-outy₁)² + $\frac{1}{2}$ (T₂-outy₂)²+ $\frac{1}{2}$ (T₃-outy₃)²

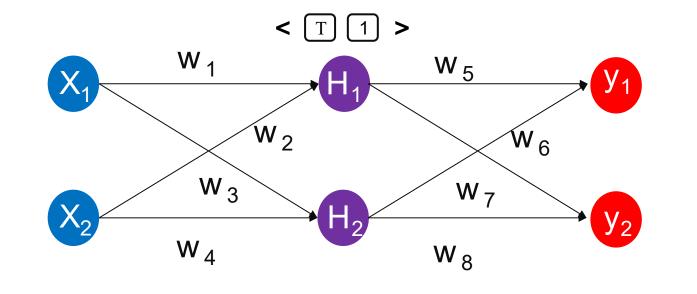
Outy₁= activation($w_{10}x_1 + w_{11}x_2$)

$$\frac{dError}{dW_{11}} = \frac{dError}{douty_1} * \frac{douty_1}{dy_1} * \frac{dy_1}{dw_{11}}$$

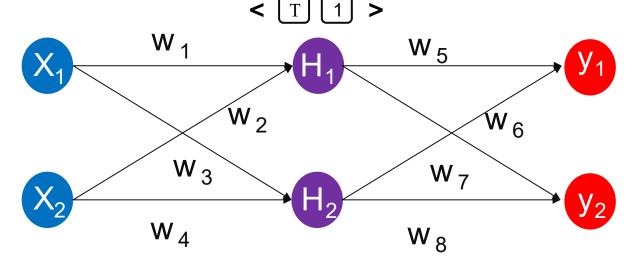
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$$H_1 = x_1^* w_1 + x_2^* w_2 + b_1$$
 $H_2 = x_1^* w_3 + x_2^* w_4 + b_2$
output_ $H_1 = \frac{1}{1 + e^{-H_1}}$ output_ $H_2 = \frac{1}{1 + e^{-H_2}}$



$$y_1 = out_H_1 * w_5 + out_H_2 * w_6 + b_3$$
 $y_1 = out_H_1 * w_7 + out_H_2 * w_8 + b_4$

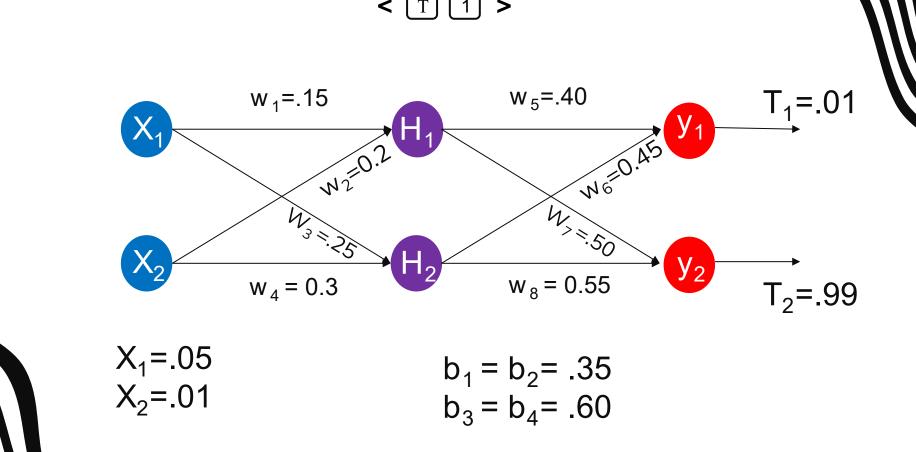
output_y _1 = $\frac{1}{1 + e^{-y_1}}$

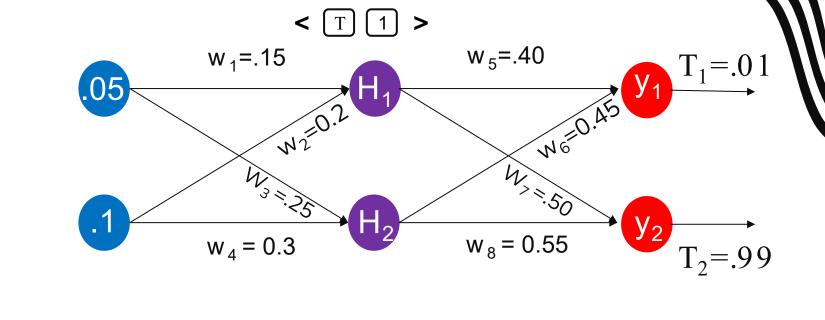
$$W_4$$
 W_8 W_8 $W_1 = outH_1 * W_7 + outH_1 * W_7 + outH_1 * W_1 + outH_2 * W_2 + outH_2 * W_3 + outH_4 * W_1 + outH_4 * W_1 + outH_4 * W_2 + outH_4 * W_3 + outH_4 * W_1 + outH_4 * W_2 + outH_4 * W_3 + outH_4 * W_1 + outH_4 * W_2 + outH_4 * W_3 + outH_5 * W$

output_ $y_1 = \frac{1}{1 + e^{-y_1}}$

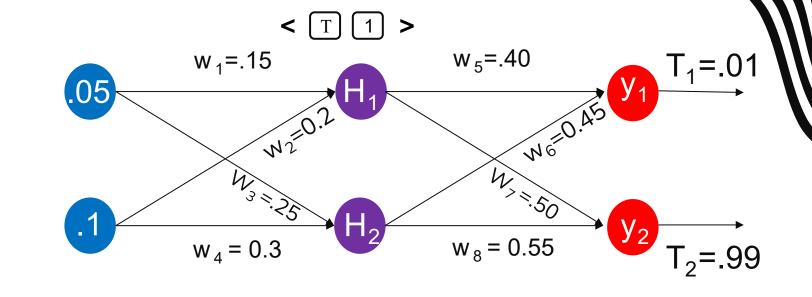
What we just learnt is called forward pass

Now Lets see a mathematical example

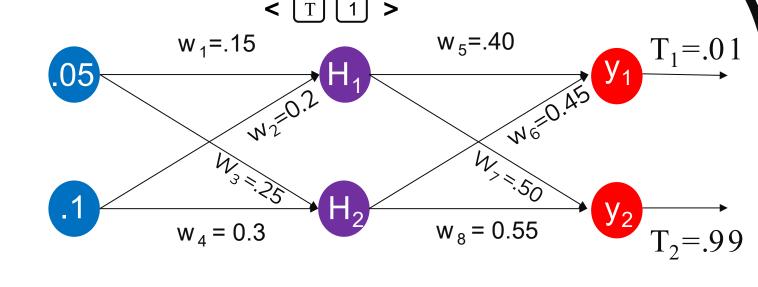




$$H_1 = x_1^* W_1 + x_2^* W_2 + b_1$$
 output_ $H_1 = \frac{1}{1 + e^{-H_1}}$
 $H_1 = .05 * .15 + .1 * .2 + .35$ = .5932



 H_2 = .3925 output_H $_2$ = .59688

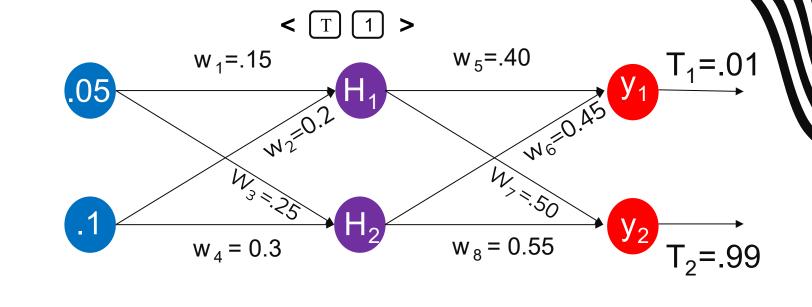


$$y_1 = out_H_1 * w_5 + out_H_2 * w_6 + b_3$$
 output_y $y_1 = \frac{1}{1 + e^{-y_1}}$

= .7513

= 1.1056

= .5932 *.4 + .59688 *.45 +.6



y2 = 1.22 output_y₁ = .77

Total Error =
$$\frac{1}{2} (T_1 - \text{outy}_1)^2 + \frac{1}{2} (T_2 - \text{outy}_2)^2$$

$$\frac{dError}{dW_5} = \frac{dError}{douty_1} * \frac{douty_1}{dy_1} * \frac{dy_1}{dw_5}$$

$$\frac{dError}{d\ outy_1} = \frac{d}{d\ outy_1} \left(\frac{1}{2} \left(T_1 - \text{outy}_1\right)^2 + \frac{1}{2} \left(T_2 - \text{outy}_2\right)^2\right)$$

$$= 2^* \frac{1}{2} * (T_1 - \text{outy}_1) * (0-1) + 0$$

 $= -(T_1 - \text{outy}_1)$

Total Error = $\frac{1}{2}(T_1 - \text{outy}_1)^2 + \frac{1}{2}(T_2 - \text{outy}_2)^2$

 $\frac{d \ outy_1}{dy_1} = Derivative of Sigmoid$

 $=_{outy_1} *(1 - outy_1)$

Derivative of Sigmoid

 $\frac{d\mathbf{O}(x)}{dy_1} = \mathbf{O}(x) * (1 - \mathbf{O}(x))$



$$\frac{dError}{dW_5} = \frac{dError}{douty_1} * \frac{douty_1}{dy_1} * \frac{dy_1}{dw_5}$$



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Total Error =
$$\frac{1}{2}(T_1-outy_1)^2 + \frac{1}{2}(T_2-outy_2)^2$$

$$\frac{dError}{dW_5} = \frac{dError}{douty_1} * \frac{douty_1}{dy_1} * \frac{dy_1}{dw_5}$$

$$\frac{dW_5}{dW_5} = \frac{douty_1}{douty_1} + \frac{dy_1}{dw_5}$$

$$\frac{dy_1}{dx_1} = \frac{d}{dx_2} (\text{out } H_1 * w_5 + \text{out } H_2 * w_6 + b_3)$$

$$\frac{dy_1}{dw_5} = \frac{d}{dw_5} (\text{out}_{-H_1} *_{W_5} + \text{out}_{-H_2} *_{W_6} + b_3)$$

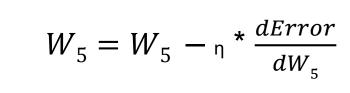
 $= out H_1 + 0 + 0$

= out H_1

$$\frac{dy_1}{dw_5} = \frac{d}{dw_5}$$

Total Error =
$$\frac{1}{2}$$
(T₁-outy₁)² + $\frac{1}{2}$ (T₂-outy₂)²

$$\frac{dError}{dW_5} = -(\frac{dError}{\frac{1}{d} \frac{-outy_1}{outy_1}}) * \frac{douty_1}{\frac{outy_1}{dy_1}} * \frac{dy_1}{\frac{outy_1}{dw_5}} H_1$$





Do the same for all weight

