

# ML

## LECTURE-23

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# Backpropagation

- ❖ The backpropagation algorithm was **discovered in 1985-86.**
- ❖ Here is an outline of the algorithm.
- ❖ 1. **Initially the weights are assigned at random.**
- ❖ 2. Then the algorithm **iterates through many cycles of two processes until a stopping criterion is reached. Each cycle is known as an epoch.** Each epoch includes:
  - ❖ (a) A **forward phase** in which the **neurons are activated in sequence from the input layer to the output layer, applying each neuron's weights and activation function along the way.** Upon reaching the final layer, an output signal is produced.
  - ❖ (b) A **backward phase** in which the network's output signal resulting from the forward phase is compared to the true target value in the training data. **The difference between the network's output signal and the true value results in an error that is propagated backwards in the network to modify the connection weights** between neurons and reduce future errors.
- ❖ 3. The technique used to determine how much a weight should be changed is known as **gradient descent method.** At every stage of the computation, the error is a function of the weights. **If we plot the error against the weights, we get a higher dimensional analog of something like a curve or surface. At any point on this surface, the gradient suggests how steeply the error will be reduced or increased for a change in the weight. The algorithm will attempt to change the weights that result in the greatest reduction in error.**

# Backpropagation Example

## ❖ Input values

❖  $X_1=0.05$

❖  $X_2=0.10$

## ❖ Initial weight

❖  $W_1=0.15$      $w_5=0.40$

❖  $W_2=0.20$      $w_6=0.45$

❖  $W_3=0.25$      $w_7=0.50$

❖  $W_4=0.30$      $w_8=0.55$

## ❖ Bias Values

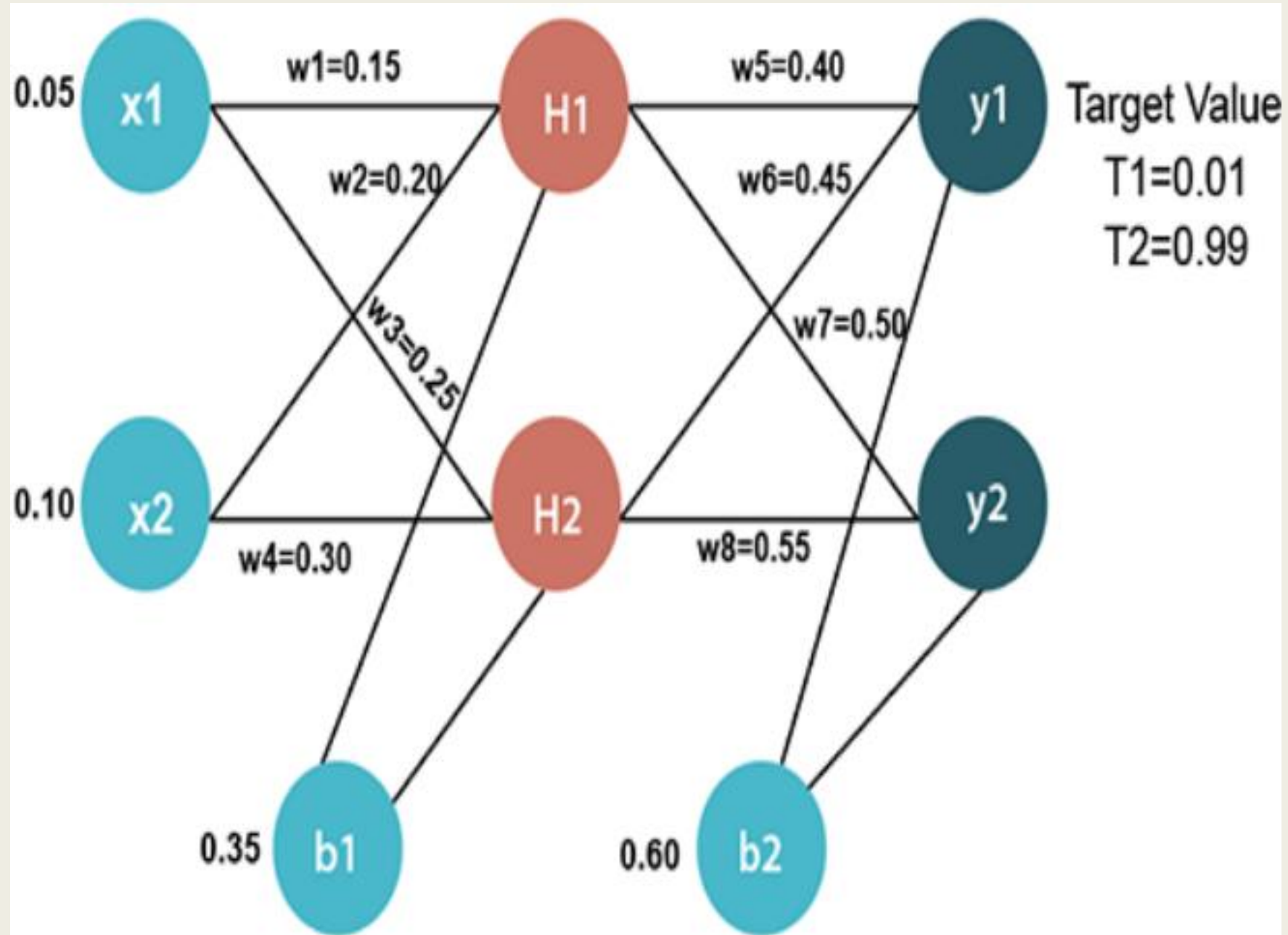
❖  $b_1=0.35$

❖  $b_2=0.60$

## ❖ Target Values

❖  $T_1=0.01$

❖  $T_2=0.99$



# Backpropagation Example Solution

## ❖ Forward Pass

❖ To find the value of H1 we first multiply the input value from the weights as

❖  $H1 = x1 \times w1 + x2 \times w2 + b1 = 0.05 \times 0.15 + 0.10 \times 0.20 + 0.35 = 0.3775$

❖ To calculate the final result of H1, we performed the sigmoid function as

$$H1_{final} = \frac{1}{1 + \frac{1}{e^{H1}}}$$
$$H1_{final} = \frac{1}{1 + \frac{1}{e^{0.3775}}}$$
$$H1_{final} = 0.593269992$$

❖ We will calculate the value of H2 in the same way as H1

❖  $H2 = x1 \times w3 + x2 \times w4 + b1 = 0.05 \times 0.25 + 0.10 \times 0.30 + 0.35 = 0.3925$

❖ To calculate the final result of H1, we performed the sigmoid function as

$$H2_{final} = \frac{1}{1 + \frac{1}{e^{H2}}}$$
$$H2_{final} = \frac{1}{1 + \frac{1}{e^{0.3925}}}$$
$$H2_{final} = 0.596884378$$

# Backpropagation Example Solution

- ❖ Now, we calculate the values of y1 and y2 in the same way as we calculate the H1 and H2.
- ❖ To find value of y1, we first multiply the input value i.e., the outcome of H1 and H2 from the weights as
- ❖  $y1 = H1 \times w5 + H2 \times w6 + b2 = 0.593269992 \times 0.40 + 0.596884378 \times 0.45 + 0.60 = 1.10590597$
- ❖ To calculate the final result of y1 we performed the sigmoid function as

$$y1_{\text{final}} = \frac{1}{1 + \frac{1}{e^{y1}}}$$
$$y1_{\text{final}} = \frac{1}{1 + \frac{1}{e^{1.10590597}}}$$
$$y1_{\text{final}} = 0.75136507$$

- ❖ We will calculate the value of y2 in the same way as y1
- ❖  $y2 = H1 \times w7 + H2 \times w8 + b2 = 0.593269992 \times 0.50 + 0.596884378 \times 0.55 + 0.60 = 1.2249214$
- ❖ To calculate the final result of y2, we performed the sigmoid function as

$$y2_{\text{final}} = \frac{1}{1 + \frac{1}{e^{y2}}}$$
$$y2_{\text{final}} = \frac{1}{1 + \frac{1}{e^{1.2249214}}}$$
$$y2_{\text{final}} = 0.772928465$$

# Backpropagation Example Solution

- ❖ Our target values are 0.01 and 0.99. Our  $y_1$  and  $y_2$  value is not matched with our target values  $T_1$  and  $T_2$ .
- ❖ Now, we will find the total error, which is simply the difference between the outputs from the target outputs. The total error is calculated as

$$E_{\text{total}} = \sum \frac{1}{2} (\text{target} - \text{output})^2$$

- ❖ So, the total error is

$$\begin{aligned} &= \frac{1}{2} (t_1 - y_{1_{\text{final}}})^2 + \frac{1}{2} (T_2 - y_{2_{\text{final}}})^2 \\ &= \frac{1}{2} (0.01 - 0.75136507)^2 + \frac{1}{2} (0.99 - 0.772928465)^2 \\ &= 0.274811084 + 0.0235600257 \\ &\mathbf{E_{\text{total}} = 0.29837111} \end{aligned}$$

- ❖ Now, we will backpropagate this error to update the weights using a backward pass.

# Backpropagation Example Solution

## ❖ Backward pass at the output layer

- ❖ To update the weight, we calculate the error correspond to each weight with the help of a total error. The error on weight  $w$  is calculated by differentiating total error with respect to  $w$ .

$$\text{Error}_w = \frac{\partial E_{\text{total}}}{\partial w}$$

- ❖ We perform backward process so first consider the last weight  $w_5$  as

$$\text{Error}_{w_5} = \frac{\partial E_{\text{total}}}{\partial w_5} \dots \dots \dots (1)$$

$$E_{\text{total}} = \frac{1}{2} (T1 - y1_{\text{final}})^2 + \frac{1}{2} (T2 - y2_{\text{final}})^2 \dots \dots \dots (2)$$

- ❖ From equation two, it is clear that we cannot partially differentiate it with respect to  $w_5$  because there is no any  $w_5$ . We split equation one into multiple terms so that we can easily differentiate it with respect to  $w_5$  as

$$\frac{\partial E_{\text{total}}}{\partial w_5} = \frac{\partial E_{\text{total}}}{\partial y1_{\text{final}}} \times \frac{\partial y1_{\text{final}}}{\partial y1} \times \frac{\partial y1}{\partial w_5} \dots \dots \dots (3)$$



# Backpropagation Example Solution

❖ Now, we calculate each term one by one to differentiate  $E_{\text{total}}$  with respect to  $w_5$  as

$$\frac{\partial E_{\text{total}}}{\partial y_{1\text{final}}} = \frac{\partial \left( \frac{1}{2} (T_1 - y_{1\text{final}})^2 + \frac{1}{2} (T_2 - y_{2\text{final}})^2 \right)}{\partial y_{1\text{final}}}$$

$$= 2 \times \frac{1}{2} \times (T_1 - y_{1\text{final}})^{2-1} \times (-1) + 0$$

$$= -(T_1 - y_{1\text{final}})$$

$$= -(0.01 - 0.75136507)$$

$$\frac{\partial E_{\text{total}}}{\partial y_{1\text{final}}} = \mathbf{0.74136507 \dots \dots \dots (4)}$$

$$y_{1\text{final}} = \frac{1}{1 + e^{-y_1}} \dots \dots \dots (5)$$

$$\frac{\partial y_{1\text{final}}}{\partial y_1} = \frac{\partial \left( \frac{1}{1 + e^{-y_1}} \right)}{\partial y_1}$$

$$= \frac{e^{-y_1}}{(1 + e^{-y_1})^2}$$

$$= e^{-y_1} \times (y_{1\text{final}})^2 \dots \dots \dots (6)$$

$$y_{1\text{final}} = \frac{1}{1 + e^{-y_1}}$$

$$e^{-y_1} = \frac{1 - y_{1\text{final}}}{y_{1\text{final}}} \dots \dots \dots (7)$$



# Backpropagation Example Solution

- ❖ Putting the value of  $e^{-y}$  in equation (5)

$$\begin{aligned} &= \frac{1 - y1_{final}}{y1_{final}} \times (y1_{final})^2 \\ &= y1_{final} \times (1 - y1_{final}) \\ &= 0.75136507 \times (1 - 0.75136507) \\ &\frac{\partial y1_{final}}{\partial y1} = 0.186815602 \dots \dots \dots (8) \\ y1 &= H1_{final} \times w5 + H2_{final} \times w6 + b2 \dots \dots \dots (9) \\ \frac{\partial y1}{\partial w5} &= \frac{\partial (H1_{final} \times w5 + H2_{final} \times w6 + b2)}{\partial w5} \\ &= H1_{final} \\ \frac{\partial y1}{\partial w5} &= 0.596884378 \dots \dots \dots (10) \end{aligned}$$

- ❖ So, we put the values of  $\frac{\partial E_{total}}{\partial y1_{final}}$ ,  $\frac{\partial y1_{final}}{\partial y1}$ , and  $\frac{\partial y1}{\partial w5}$  in equation no (3) to find the final result.

$$\begin{aligned} \frac{\partial E_{total}}{\partial w5} &= \frac{\partial E_{total}}{\partial y1_{final}} \times \frac{\partial y1_{final}}{\partial y1} \times \frac{\partial y1}{\partial w5} \\ &= 0.74136507 \times 0.186815602 \times 0.593269992 \\ \text{Error}_{w5} = \frac{\partial E_{total}}{\partial w5} &= 0.0821670407 \dots \dots \dots (11) \end{aligned}$$

# Backpropagation Example Solution

- ❖ Now, we will calculate the updated weight  $w5_{new}$  with the help of the following formula

$$\begin{aligned}w5_{new} &= w5 - \eta \times \frac{\partial E_{total}}{\partial w5} \text{ Here, } \eta = \text{learning rate} = 0.5 \\&= 0.4 - 0.5 \times 0.0821670407 \\w5_{new} &= 0.35891648 \dots \dots \dots (12)\end{aligned}$$

- ❖ In the same way, we calculate  $w6_{new}$ ,  $w7_{new}$ , and  $w8_{new}$  and this will give us the following values
- ❖  $w5_{new} = 0.35891648$
- ❖  $w6_{new} = 408666186$
- ❖  $w7_{new} = 0.511301270$
- ❖  $w8_{new} = 0.561370121$

# Backpropagation Example Solution

## ❖ Backward pass at Hidden layer

- ❖ Now, we will backpropagate to our hidden layer and update the weight  $w_1$ ,  $w_2$ ,  $w_3$ , and  $w_4$  as we have done with  $w_5$ ,  $w_6$ ,  $w_7$ , and  $w_8$  weights.
- ❖ We will calculate the error at  $w_1$  as

$$\text{Error}_{w_1} = \frac{\partial E_{\text{total}}}{\partial w_1}$$
$$E_{\text{total}} = \frac{1}{2} (T_1 - y_{1\text{final}})^2 + \frac{1}{2} (T_2 - y_{2\text{final}})^2$$

- ❖ From eqn (2), it is clear that we cannot partially differentiate it with respect to  $w_1$  because there is no any  $w_1$ . We split equation (1) into multiple terms so that we can easily differentiate it with respect to  $w_1$  as

$$\frac{\partial E_{\text{total}}}{\partial w_1} = \frac{\partial E_{\text{total}}}{\partial H_{1\text{final}}} \times \frac{\partial H_{1\text{final}}}{\partial H_1} \times \frac{\partial H_1}{\partial w_1} \dots \dots \dots (13)$$

- ❖ Now, we calculate each term one by one to differentiate  $E_{\text{total}}$  with respect to  $w_1$  as

$$\frac{\partial E_{\text{total}}}{\partial H_{1\text{final}}} = \frac{\partial (\frac{1}{2} (T_1 - y_{1\text{final}})^2 + \frac{1}{2} (T_2 - y_{2\text{final}})^2)}{\partial H_1} \dots \dots \dots (14)$$

- ❖ We again split this because there is no any  $H_{1\text{final}}$  term in  $E_{\text{total}}$  as

$$\frac{\partial E_{\text{total}}}{\partial H_{1\text{final}}} = \frac{\partial E_1}{\partial H_{1\text{final}}} + \frac{\partial E_2}{\partial H_{1\text{final}}} \dots \dots \dots (15)$$

# Backpropagation Example Solution

- ❖  $\frac{\partial E_1}{\partial H1_{final}}$  and  $\frac{\partial E_2}{\partial H1_{final}}$  will again split because in E1 and E2 there is no H1 term. Splitting is done as

$$\frac{\partial E_1}{\partial H1_{final}} = \frac{\partial E_1}{\partial y1} \times \frac{\partial y1}{\partial H1_{final}} \dots \dots \dots (16)$$

$$\frac{\partial E_2}{\partial H1_{final}} = \frac{\partial E_2}{\partial y2} \times \frac{\partial y2}{\partial H1_{final}} \dots \dots \dots (17)$$

- ❖ We again Split both  $\frac{\partial E_1}{\partial y1}$  and  $\frac{\partial E_2}{\partial y2}$  because there is no any y1 and y2 term in E1 and E2. We split it as

$$\frac{\partial E_1}{\partial y1} = \frac{\partial E_1}{\partial y1_{final}} \times \frac{\partial y1_{final}}{\partial y1} \dots \dots \dots (18)$$

$$\frac{\partial E_2}{\partial y2} = \frac{\partial E_2}{\partial y2_{final}} \times \frac{\partial y2_{final}}{\partial y2} \dots \dots \dots (19)$$

- ❖ Now, we find the value of  $\frac{\partial E_1}{\partial y1}$  and  $\frac{\partial E_2}{\partial y2}$  by putting values in equation (18) and (19) as

- ❖ From equation (18)

$$\begin{aligned} \frac{\partial E_1}{\partial y1} &= \frac{\partial E_1}{\partial y1_{final}} \times \frac{\partial y1_{final}}{\partial y1} \\ &= \frac{\partial(\frac{1}{2}(T1 - y1_{final})^2)}{\partial y1_{final}} \times \frac{\partial y1_{final}}{\partial y1} \\ &= 2 \times \frac{1}{2}(T1 - y1_{final}) \times (-1) \times \frac{\partial y1_{final}}{\partial y1} \end{aligned}$$

# Backpropagation Example Solution

❖ From equation (8)

$$= 2 \times \frac{1}{2} (0.01 - 0.75136507) \times (-1) \times 0.186815602$$
$$\frac{\partial E_1}{\partial y_1} = 0.138498562 \dots \dots \dots (20)$$

❖ From equation (19)

$$\frac{\partial E_2}{\partial y_2} = \frac{\partial E_2}{\partial y_{2\_final}} \times \frac{\partial y_{2\_final}}{\partial y_2}$$
$$= \frac{\partial (\frac{1}{2} (T_2 - y_{2\_final})^2)}{\partial y_{2\_final}} \times \frac{\partial y_{2\_final}}{\partial y_2}$$
$$= 2 \times \frac{1}{2} (T_2 - y_{2\_final}) \times (-1) \times \frac{\partial y_{2\_final}}{\partial y_2} \dots \dots \dots (21)$$

$$y_{2\_final} = \frac{1}{1 + e^{-y_2}} \dots \dots \dots (22)$$

$$\frac{\partial y_{2\_final}}{\partial y_2} = \frac{\partial (\frac{1}{1 + e^{-y_2}})}{\partial y_2}$$
$$= \frac{e^{-y_2}}{(1 + e^{-y_2})^2}$$
$$= e^{-y_2} \times (y_{2\_final})^2 \dots \dots \dots (23)$$

$$y_{2\_final} = \frac{1}{1 + e^{-y_2}}$$

$$e^{-y_2} = \frac{1 - y_{2\_final}}{y_{2\_final}} \dots \dots \dots (24)$$

# Backpropagation Example Solution

Putting the value of  $e^{-y_2}$  in equation (23)

$$\begin{aligned} &= \frac{1 - y_{2_{\text{final}}}}{y_{2_{\text{final}}}} \times (y_{2_{\text{final}}})^2 \\ &= y_{2_{\text{final}}} \times (1 - y_{2_{\text{final}}}) \\ &= 0.772928465 \times (1 - 0.772928465) \\ \frac{\partial y_{2_{\text{final}}}}{\partial y_2} &= \mathbf{0.175510053 \dots \dots \dots (25)} \end{aligned}$$

From equation (21)

$$\begin{aligned} &= 2 \times \frac{1}{2} (0.99 - 0.772928465) \times (-1) \times 0.175510053 \\ \frac{\partial E_1}{\partial y_1} &= \mathbf{-0.0380982366126414 \dots \dots \dots (26)} \end{aligned}$$

# Backpropagation Example Solution

❖ Now from equation (16) and (17)

$$\begin{aligned}\frac{\partial E_1}{\partial H1_{final}} &= \frac{\partial E_1}{\partial y1} \times \frac{\partial y1}{\partial H1_{final}} \\ &= 0.138498562 \times \frac{\partial(H1_{final} \times w_5 + H2_{final} \times w_6 + b2)}{\partial H1_{final}} \\ &= 0.138498562 \times \frac{\partial(H1_{final} \times w_5 + H2_{final} \times w_6 + b2)}{\partial H1_{final}} \\ &= 0.138498562 \times w_5 \\ &= 0.138498562 \times 0.40\end{aligned}$$

$$\frac{\partial E_1}{\partial H1_{final}} = \mathbf{0.0553994248 \dots \dots \dots (27)}$$

$$\begin{aligned}\frac{\partial E_2}{\partial H1_{final}} &= \frac{\partial E_2}{\partial y2} \times \frac{\partial y2}{\partial H1_{final}} \\ &= -0.0380982366126414 \times \frac{\partial(H1_{final} \times w_7 + H2_{final} \times w_8 + b2)}{\partial H1_{final}} \\ &= -0.0380982366126414 \times w_7 \\ &= -0.0380982366126414 \times 0.50\end{aligned}$$

$$\frac{\partial E_2}{\partial H1_{final}} = \mathbf{-0.0190491183063207 \dots \dots \dots (28)}$$



# Backpropagation Example Solution

Put the value of  $\frac{\partial E_1}{\partial H1_{final}}$  and  $\frac{\partial E_2}{\partial H1_{final}}$  in equation (15) as

$$\begin{aligned}\frac{\partial E_{total}}{\partial H1_{final}} &= \frac{\partial E_1}{\partial H1_{final}} + \frac{\partial E_2}{\partial H1_{final}} \\ &= 0.05539994248 + (-0.0190491183063207) \\ \frac{\partial E_{total}}{\partial H1_{final}} &= \mathbf{0.0364908241736793 \dots \dots \dots (29)}\end{aligned}$$

We have  $\frac{\partial E_{total}}{\partial H1_{final}}$ ; we need to figure out  $\frac{\partial H1_{final}}{\partial H1}$ ,  $\frac{\partial H1}{\partial w1}$  as

$$\begin{aligned}\frac{\partial H1_{final}}{\partial H1} &= \frac{\partial \left( \frac{1}{1 + e^{-H1}} \right)}{\partial H1} \\ &= \frac{e^{-H1}}{(1 + e^{-H1})^2} \\ e^{-H1} \times (H1_{final})^2 \dots \dots \dots (30)\end{aligned}$$

$$H1_{final} = \frac{1}{1 + e^{-H1}}$$

$$e^{-H1} = \frac{1 - H1_{final}}{H1_{final}} \dots \dots \dots (31)$$

# Backpropagation Example Solution

Putting the value of  $e^{-H1}$  in equation (30)

$$\begin{aligned} &= \frac{1 - H1_{\text{final}}}{H1_{\text{final}}} \times (H1_{\text{final}})^2 \\ &= H1_{\text{final}} \times (1 - H1_{\text{final}}) \\ &= 0.593269992 \times (1 - 0.593269992) \\ \frac{\partial H1_{\text{final}}}{\partial H1} &= \mathbf{0.2413007085923199} \end{aligned}$$

We calculate the partial derivative of the total net input to H1 with respect to  $w1$  the same as we did for the output neuron:

$$H1 = H1_{\text{final}} \times w5 + H2_{\text{final}} \times w6 + b2 \dots \dots \dots (32)$$

$$\begin{aligned} \frac{\partial y1}{\partial w1} &= \frac{\partial (x1 \times w1 + x2 \times w3 + b1 \times 1)}{\partial w1} \\ &= x1 \end{aligned}$$

$$\frac{\partial H1}{\partial w1} = \mathbf{0.05 \dots \dots \dots (33)}$$

# Backpropagation Example Solution

So, we put the values of  $\frac{\partial E_{\text{total}}}{\partial H1_{\text{final}}}$ ,  $\frac{\partial H1_{\text{final}}}{\partial H1}$ , and  $\frac{\partial H1}{\partial w1}$  in equation (13) to find the final result.

$$\begin{aligned}\frac{\partial E_{\text{total}}}{\partial w1} &= \frac{\partial E_{\text{total}}}{\partial H1_{\text{final}}} \times \frac{\partial H1_{\text{final}}}{\partial H1} \times \frac{\partial H1}{\partial w1} \\ &= 0.0364908241736793 \times 0.2413007085923199 \times 0.05 \\ \text{Error}_{w1} &= \frac{\partial E_{\text{total}}}{\partial w1} = \mathbf{0.000438568 \dots \dots \dots (34)}\end{aligned}$$

Now, we will calculate the updated weight  $w1_{\text{new}}$  with the help of the following formula

$$\begin{aligned}w1_{\text{new}} &= w1 - \eta \times \frac{\partial E_{\text{total}}}{\partial w1} \text{ Here } \eta = \text{learning rate} = 0.5 \\ &= 0.15 - 0.5 \times 0.000438568 \\ w1_{\text{new}} &= \mathbf{0.149780716 \dots \dots \dots (35)}\end{aligned}$$

In the same way, we calculate  $w2_{\text{new}}$ ,  $w3_{\text{new}}$ , and  $w4$  and this will give us the following values

$$\mathbf{w1_{\text{new}}=0.149780716}$$

$$\mathbf{w2_{\text{new}}=0.19956143}$$

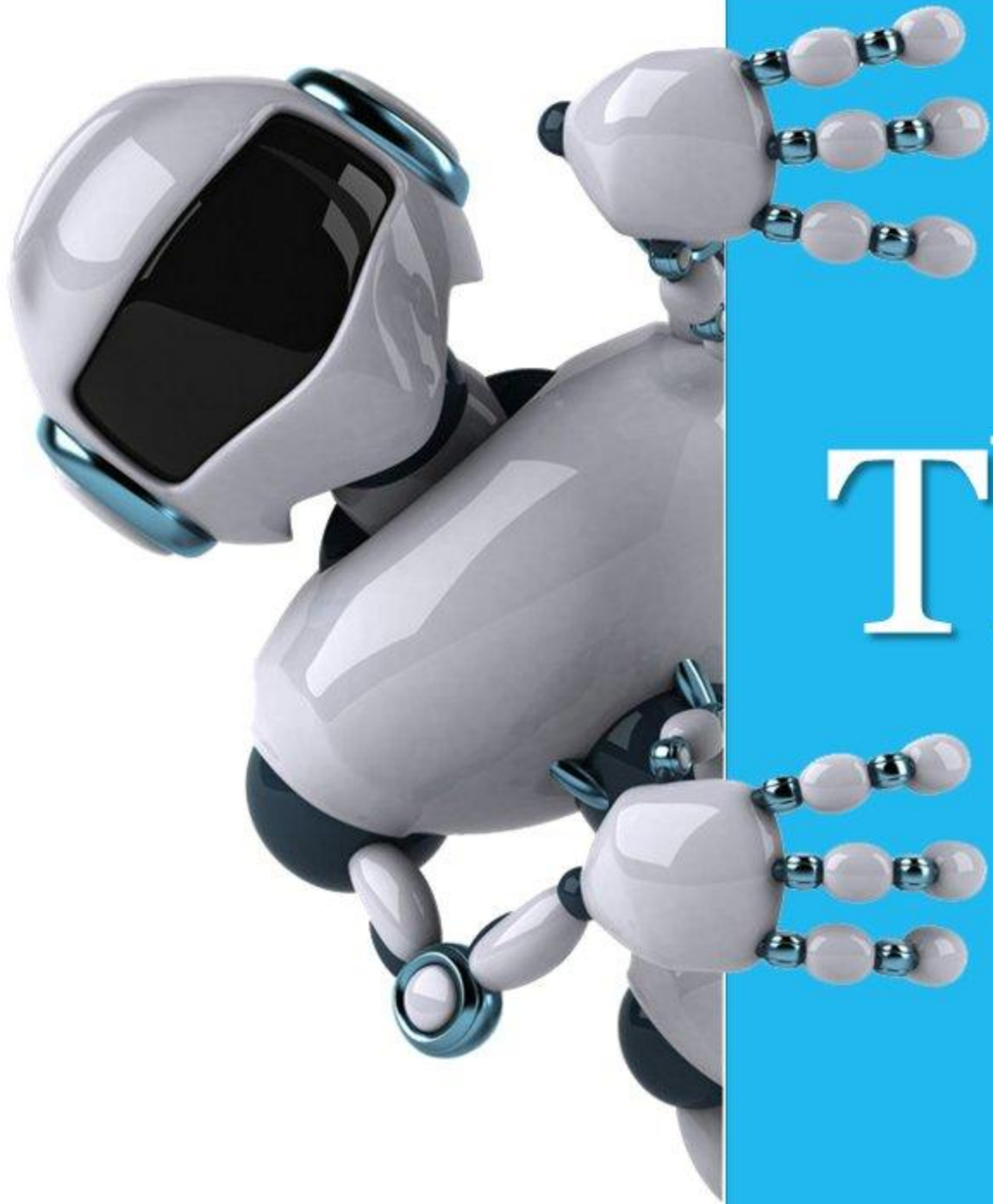
$$\mathbf{w3_{\text{new}}=0.24975114}$$

$$\mathbf{w4_{\text{new}}=0.29950229}$$

# Backpropagation Example Solution

- ❖ We have updated all the weights.
- ❖ We found the error 0.298371109 on the network when we fed forward the 0.05 and 0.1 inputs.
- ❖ In the first round of Backpropagation, the total error is down to 0.291027924.
- ❖ **After repeating this process 10,000, the total error is down to 0.0000351085.**
- ❖ At this point, the outputs neurons generate 0.159121960 and 0.984065734 i.e., nearby our target value when we feed forward the 0.05 and 0.1.





Thank you