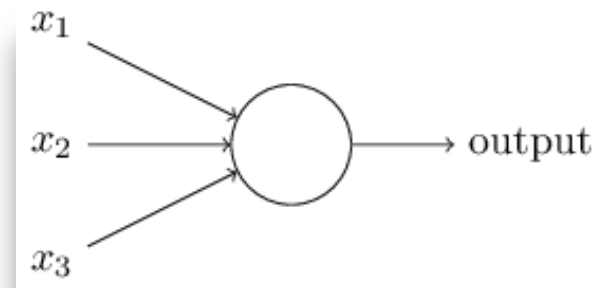


PERCEPTRON/NEURON

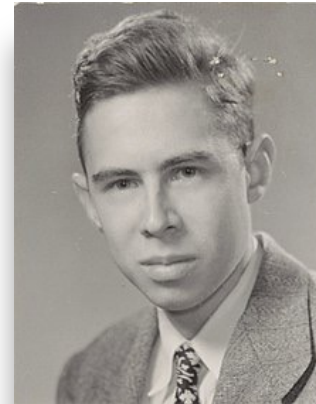
# PERCEPTRON

---

- The basic unit of a NN is a **perceptron**:



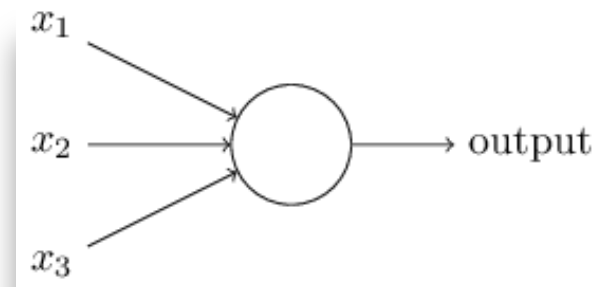
- Perceptron was introduced by **Frank Rosenblatt** in 1957.



# PERCEPTRON

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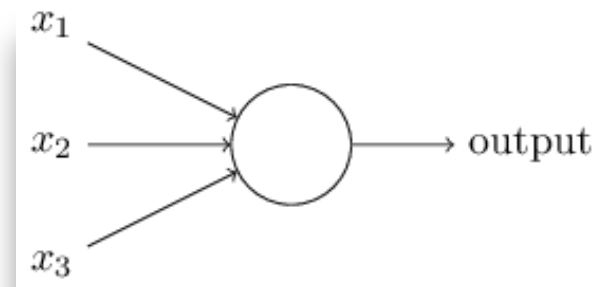
- How do we relate input with output?



# PERCEPTRON

---

- How do we relate input with output?

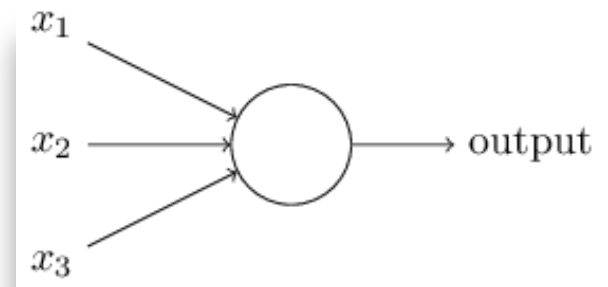


- H1: output depends on a **threshold TH**
  - Example: if  $x_1 + x_2 + x_3 > TH$  return 1; 0 otherwise

# PERCEPTRON

---

- How do we relate input with output?



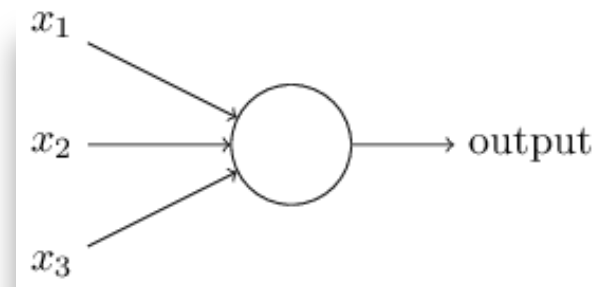
- H2: H1 + weighted input
  - Example: if  $x_1 * w_1 + x_2 * w_2 + x_3 * w_3 > TH$  return 1; 0 otherwise

But... this function will always be 0 in (0, 0, ...).

# PERCEPTRON

---

- How do we relate input with output?



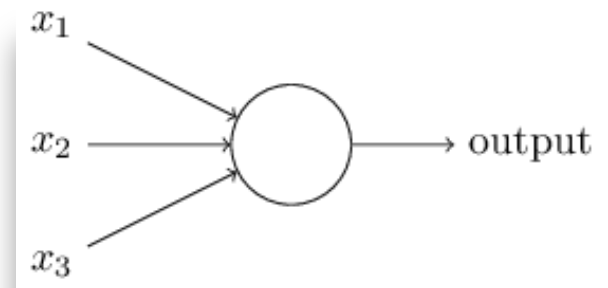
- H3: H2 + bias ( $b$ )
  - Example:  $x_1 * w_1 + x_2 * w_2 + x_3 * w_3 + 1 * b$

Without  $b \Rightarrow$  poorer fit. But, even with  $b \Rightarrow$  linear

# PERCEPTRON => NEURON

---

- How do we relate input with output?

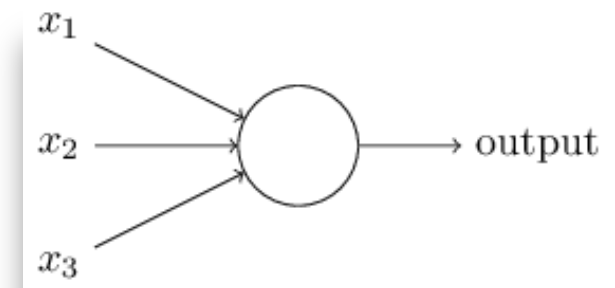


- H4: H3 + activation function

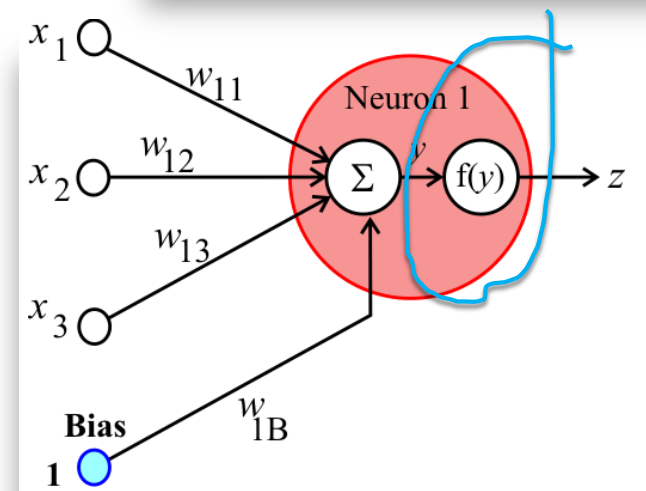
Mostly set to make a non-linear transformation which allows to fit nonlinear hypotheses

# NEURON

- How do we relate input with output?



- H4: H3 + activation function

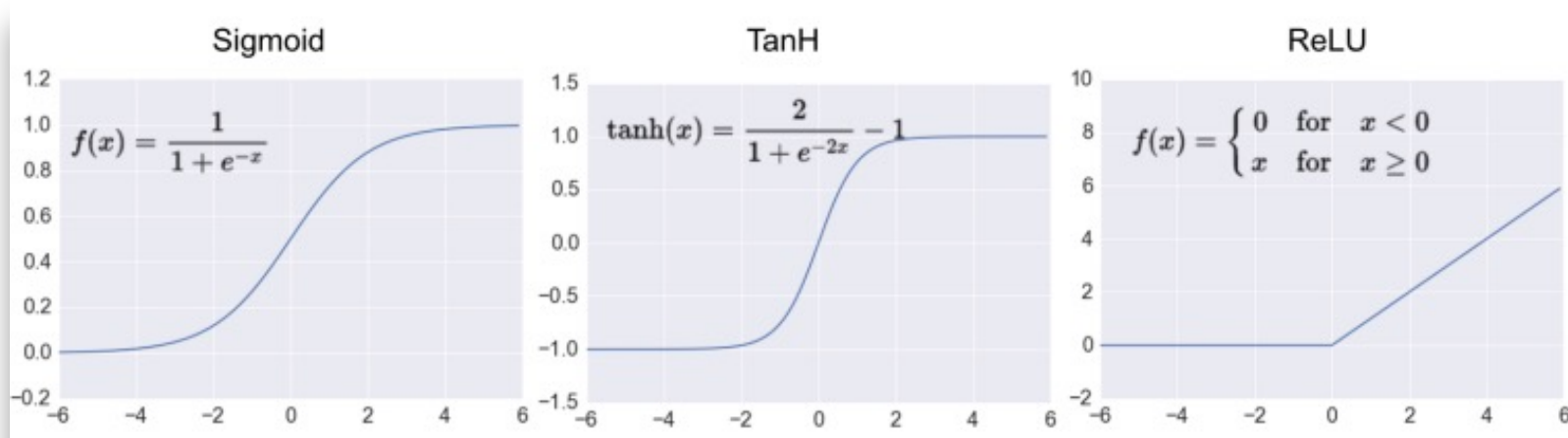




# NEURON

---

- Multiple activation functions are available.
- Some examples:



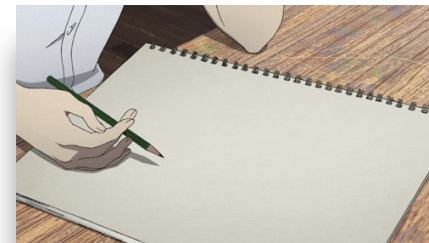
<https://www.kdnuggets.com/2017/09/neural-network-foundations-explained-activation-function.html>

## EXAMPLE (Jurafsky)

---

- Let
  - $W = [0.2, 0.3, 0.9]$
  - $x = [0.5, 0.6, 0.1]^T$
  - $b$  (bias) = 0.5
  - $y = \sigma(W \cdot x + b) = (\sigma \text{ (sigma = sigmoid function)}) = 1/(1+e^{-(W \cdot x + b)})$

What is the value of  $y$ ?



<https://giphy.com/gifs/writing-11ikeVaUfcXLWM>

## EXAMPLE (Jurafsky)

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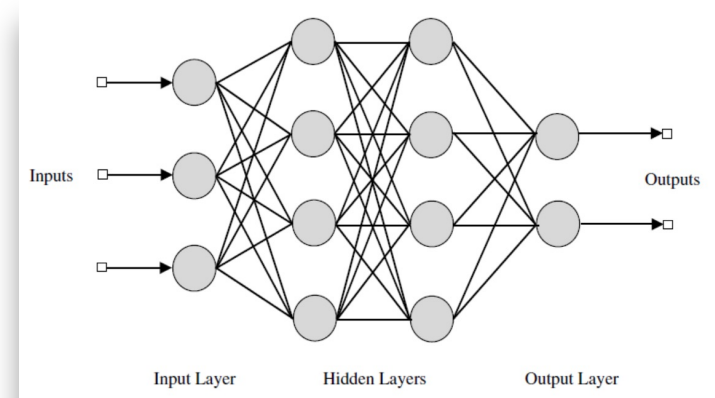
- Let
  - $W = [0.2, 0.3, 0.9]$
  - $x = [0.5, 0.6, 0.1]^T$
  - $b \text{ (bias)} = 0.5$
  - $y = \sigma(W \cdot x + b) = (\sigma \text{ (sigma = sigmoid function)}) = 1/(1+e^{-(W \cdot x + b)})$ 
    - $W \cdot x = [0.2, 0.3, 0.9] \cdot [0.5, 0.6, 0.1]^T = 0.2 \cdot 0.5 + 0.3 \cdot 0.6 + 0.9 \cdot 0.1 = 0.37$
    - $W \cdot x + b = 0.37 + 0.5 = 0.87$
    - $y = 1/(1 + e^{-0.87}) = 0.7$

# FEED-FORWARD NEURAL NETWORK (or MULTI-LAYER NEURAL NETWORK)

# FEED-FORWARD NEURAL NETWORK

---

- We increase the expressive power of the network by adding **intermediate layers** of neurons before the final output layer, yielding more complex, non-linear classifiers.
  - Note: In the standard architecture, each layer is **fully-connected** (Jurafsky)



<http://cse22-iiith.vlabs.ac.in/exp4/index.html>

# FEED-FORWARD NEURAL NETWORK

---



- How do we make the perfect cookies?
  - We make various tests, varying the recipe
    - First step: follow recipe, taste, if perfect we stop, otherwise:
      - Second step: we change the recipe (we change ingredients or some quantities of the ingredients), taste, if perfect we stop, otherwise:
        - Third step:...
- Neural Networks (NN) work in a similar manner

# FEED-FORWARD NEURAL NETWORK

---

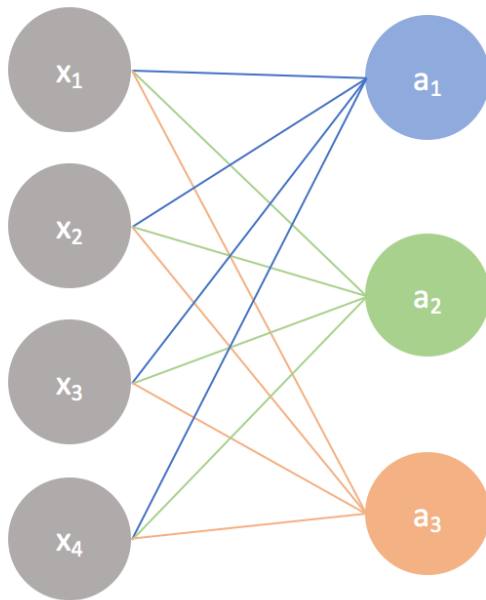
- Neural Networks:
  - Initialization
  - Take input and process it (forward propagation)
  - Result is compared with the desired output => the error is obtained
  - Try to minimize the error, by changing some elements in the network (backward propagation).
    - We update each weight, so that the actual output becomes closer to the target output (minimizing the error). A learning rate is used ( $\eta$ ).

# FEED-FORWARD NEURAL NETWORK

Input layer

Output layer

A simple neural network



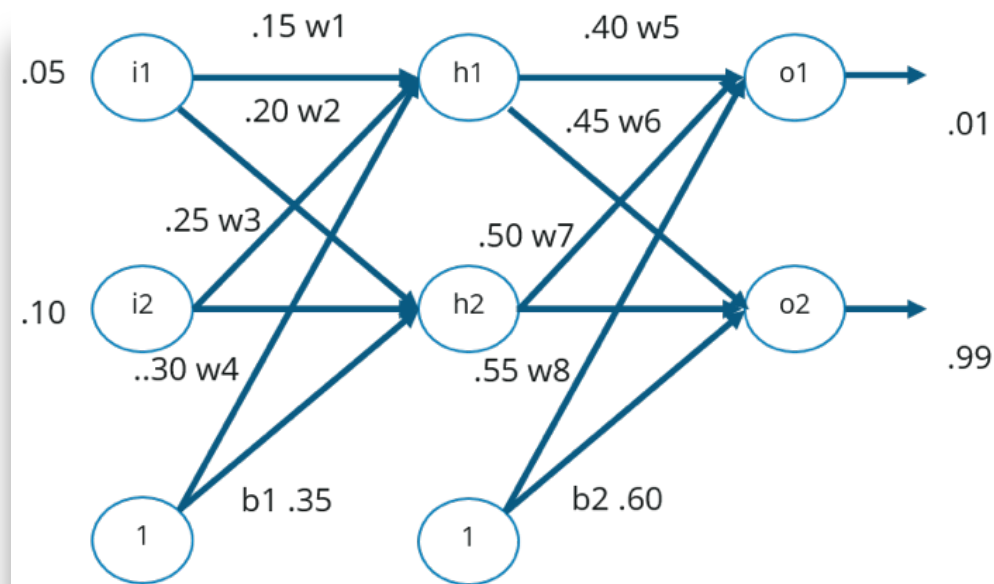
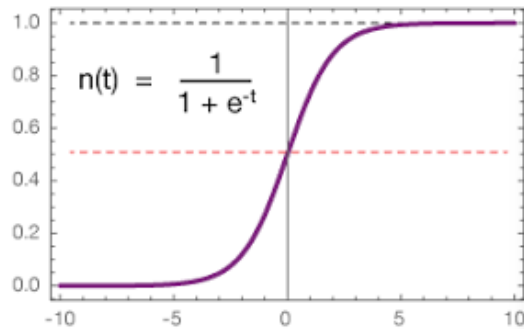
$$\begin{bmatrix} w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b \\ b \\ b \end{bmatrix} = \begin{bmatrix} w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \end{bmatrix} \xrightarrow{\text{activation}} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$$



# FEED-FORWARD NEURAL NETWORK

Input: 0.05, 0.1    Output: 0.01, 0.99

Initial weights and bias: random, Activation function: logistic function



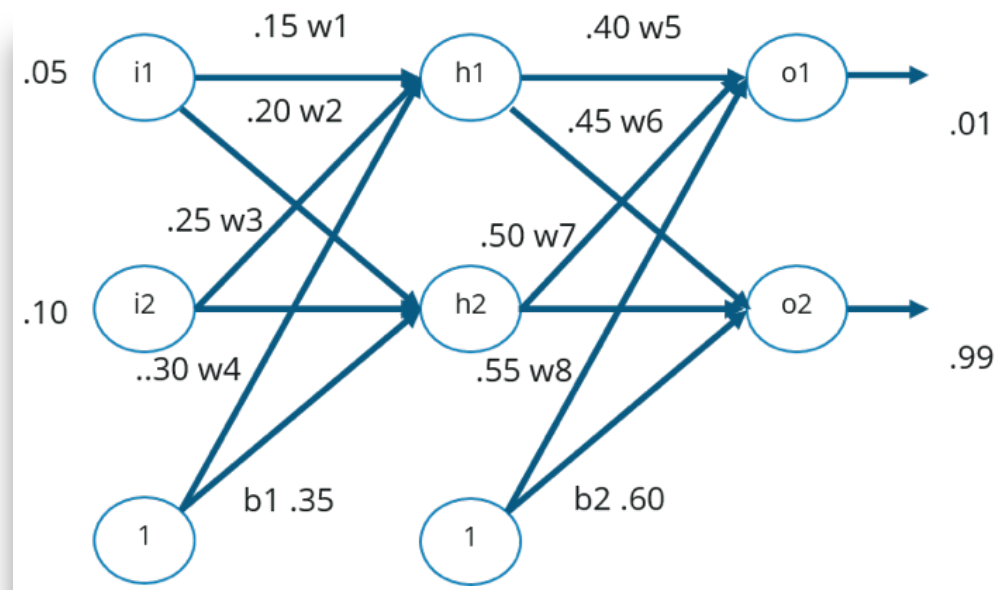
Example from:  
<https://www.edureka.co/blog/backpropagation/>

# FEED-FORWARD NEURAL NETWORK (FORWARD PROPAGATION)

$$\text{net}_{h1} = w_1 * i_1 + w_2 * i_2 + b_1 * 1 = 0.15 * 0.05 + 0.2 * 0.1 + 0.35 * 1 = 0.3775$$

Plus activation on  $\text{net}_{h1}$ :  $\text{out}_{h1} = 0.593269992$

By the same token, calculate:  $\text{net}_{h2}$ ,  $\text{out}_{h2}$ ,  $\text{net}_{o1}$ ,  $\text{out}_{o1}$ ,  $\text{net}_{o2}$ ,  $\text{out}_{o2}$

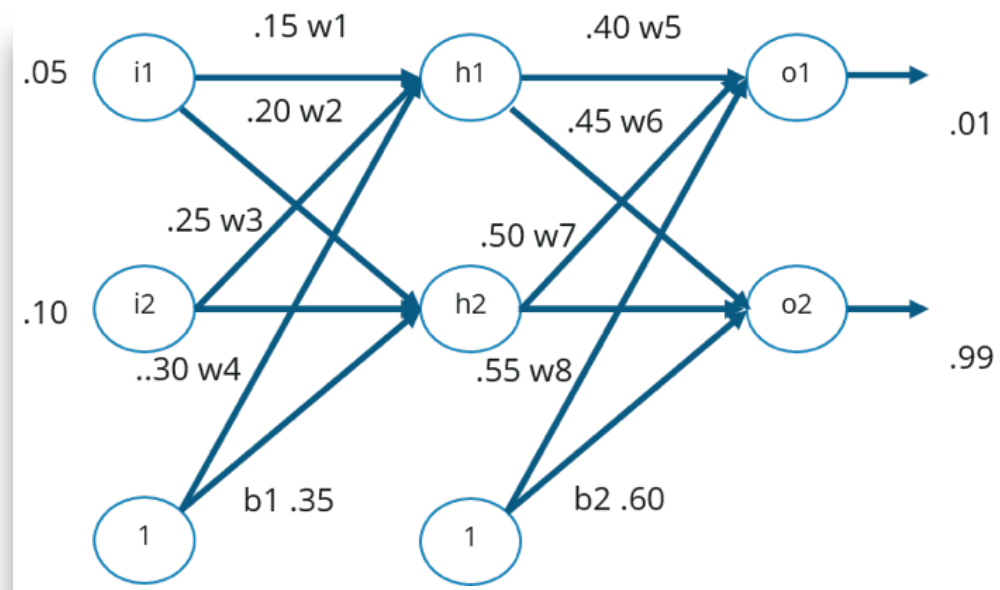


# FEED-FORWARD NEURAL NETWORK (ERROR)

---

$$E_{o1} = \frac{1}{2} (\text{target}_{o1} - \text{out}_{o1})^2 = 0.274811083, E_{o2} = 0.023560026$$

$$E_{\text{total}} = E_{o1} + E_{o2} = 0.298371109$$

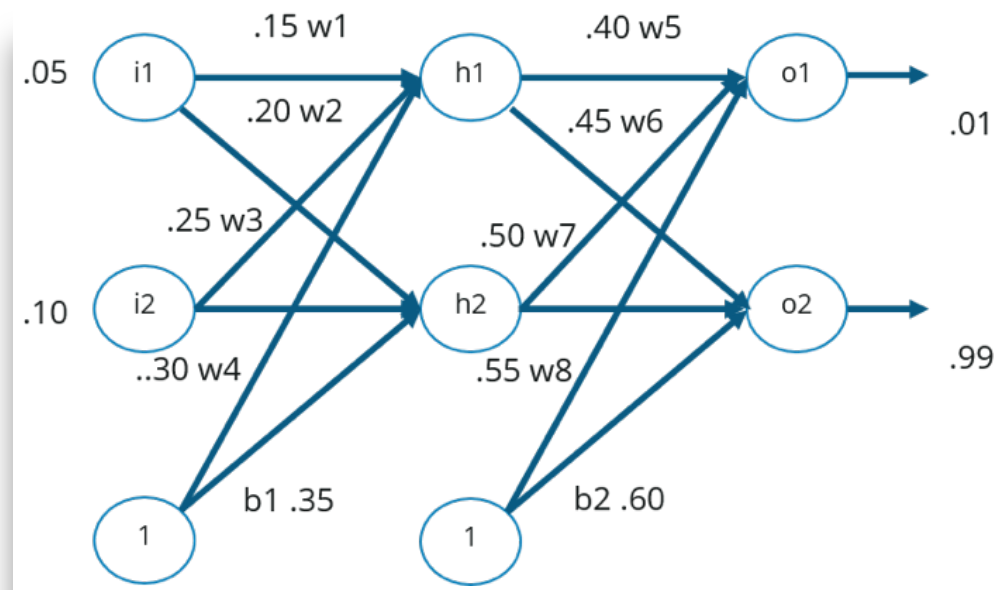


# FEED-FORWARD NEURAL NETWORK (BACKWARD PROPAGATION)

---

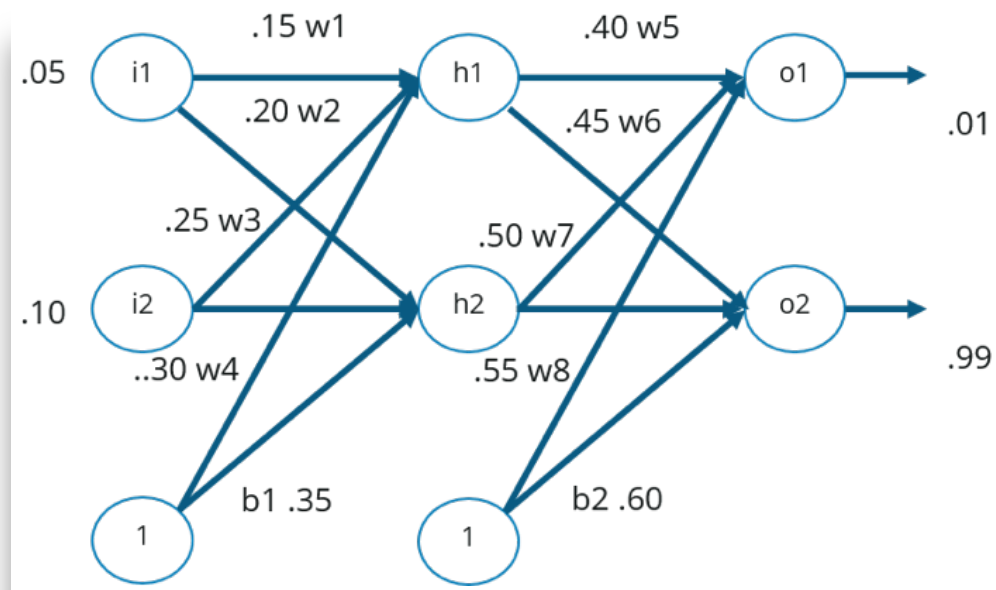
How much a change in  $w_5$  affects the total error?

=> partial derivative of  $E_{\text{total}}$  with respects to  $w_5$  = the gradient with respect to  $w_5$



# FEED-FORWARD NEURAL NETWORK (BACKWARD PROPAGATION)

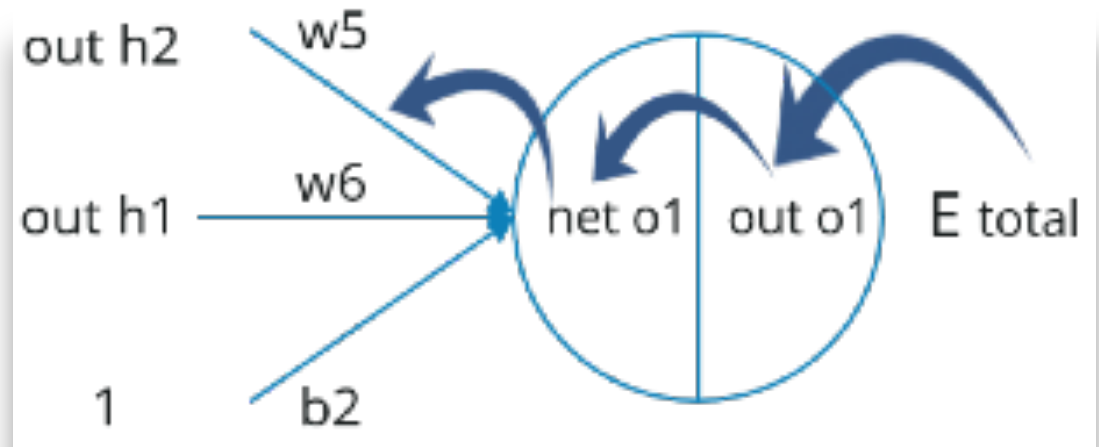
Need to calculate:  $\frac{\partial E_{total}}{\partial w_5}$



# FEED-FORWARD NEURAL NETWORK (BACKWARD PROPAGATION)

CHAIN RULE:

$$\frac{\delta E_{total}}{\delta w_5} = \frac{\delta E_{total}}{\delta out\ o1} * \frac{\delta out\ o1}{\delta net\ o1} * \frac{\delta net\ o1}{\delta w_5}$$



# FEED-FORWARD NEURAL NETWORK

## (BACKWARD PROPAGATION)

---

- As  $E_{\text{Total}} = \frac{1}{2} (\text{target}_{o1} - \text{out}_{o1})^2 + \frac{1}{2} (\text{target}_{o2} - \text{out}_{o2})^2$ :

$$\frac{dE_{\text{Total}}}{d\text{out}_{o1}} = -(\text{target}_{o1} - \text{out}_{o1}) = -(0.01 - 0.75136507) = 0.74136507$$

- As  $\text{out}_{o1} = 1/(1+e^{-\text{net}_{o1}})$ :

$$\frac{d\text{out}_{o1}}{d\text{net}_{o1}} = \text{out}_{o1} (1 - \text{out}_{o1}) = 0.186815602$$

- As  $\text{net}_{o1} = w_5 * \text{out}_{h1} + w_6 * \text{out}_{h2} + b_2 * 1$ :

$$\frac{d\text{net}_{o1}}{dw_5} = \text{out}_{h1} = 0.593269992$$

# FEED-FORWARD NEURAL NETWORK

## (BACKWARD PROPAGATION)

---

$$\frac{dE_{Total}}{dout_{o1}} = -(\text{target}_{o1} - \text{out}_{o1}) = -(0.01 - 0.75136507) = 0.74136507$$

$$\frac{dout_{o1}}{dnet_{o1}} = \text{out}_{o1} (1 - \text{out}_{o1}) = 0.186815602$$

$$\frac{dnet_{o1}}{dw_5} = \text{out}_{h1} = 0.593269992$$

$$\frac{\delta E_{total}}{\delta w_5} = \frac{\delta E_{total}}{\delta out\ o1} * \frac{\delta out\ o1}{\delta net\ o1} * \frac{\delta net\ o1}{\delta w_5}$$



# FEED-FORWARD NEURAL NETWORK

## (BACKWARD PROPAGATION)

---

$$\frac{dE_{Total}}{dw_5} = 0.74136507 * 0.186815602 * 0.593269992 = 0.082167041$$

$$\frac{\delta E_{total}}{\delta w_5} = \frac{\delta E_{total}}{\delta out\ o1} * \frac{\delta out\ o1}{\delta net\ o1} * \frac{\delta net\ o1}{\delta w_5}$$

# FEED-FORWARD NEURAL NETWORK (BACKWARD PROPAGATION)

Being  $\eta$  the Learning rate:

$$w_5 = w_5 - \eta * \frac{\partial E_{total}}{\partial w_5}$$

And we update  $w_5$

