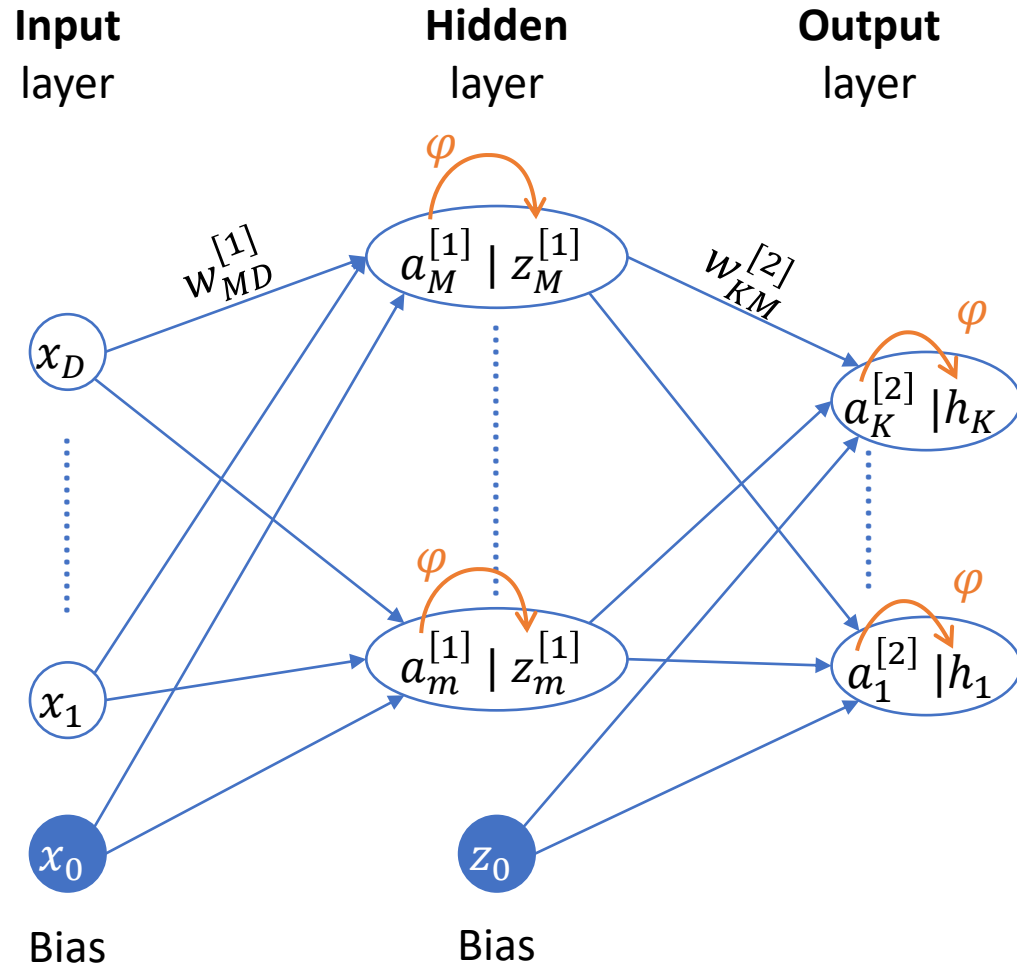


# NEURAL NETWORKS REVIEW



- $h_k = \varphi(a_k^{[2]})$ , where  $\varphi(\cdot)$  is an **activation function**
  - $\varphi(a) = \sigma(a) = \frac{1}{1 + \exp(-a)}$  logistic function
  - $\varphi(a) = \tanh(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}$  hyperbolic tangent
  - $\varphi(a) = \max\{0, a\}$  Rectified Linear Unit (ReLU)
- $a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m$
- $z_m = \varphi(a_m^{[1]})$
- $a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$

# EXERCICE 1

We have a fully connected network with the following characteristics:

- It takes 2D vectors as input.
- It has a hidden layer with two neurons.
- The output layer has one neuron.

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$
$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

(a) Draw the network from left (input) to right (output). Put also the units that represent the bias.

**Input**  
layer

**Hidden**  
layer

**Output**  
layer

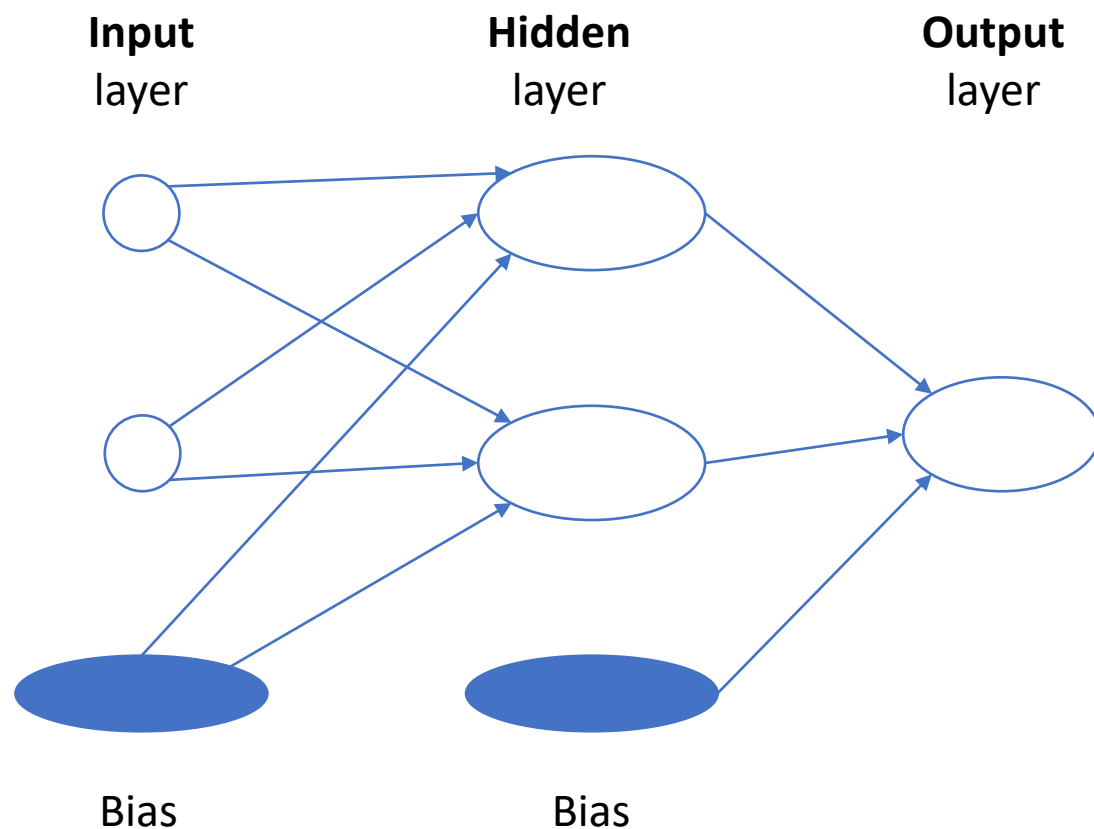
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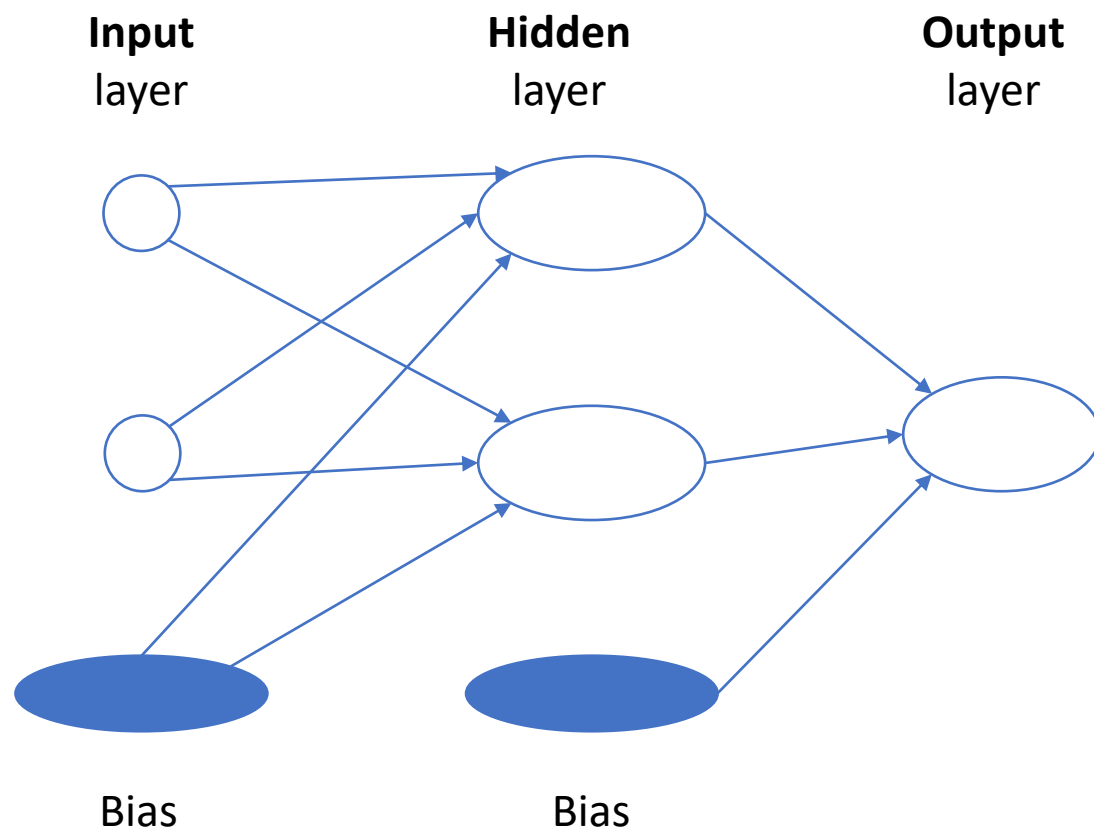
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(b) Put the name at each element of the graph and write, as a closed formula, the output in function of all the elements of the network.



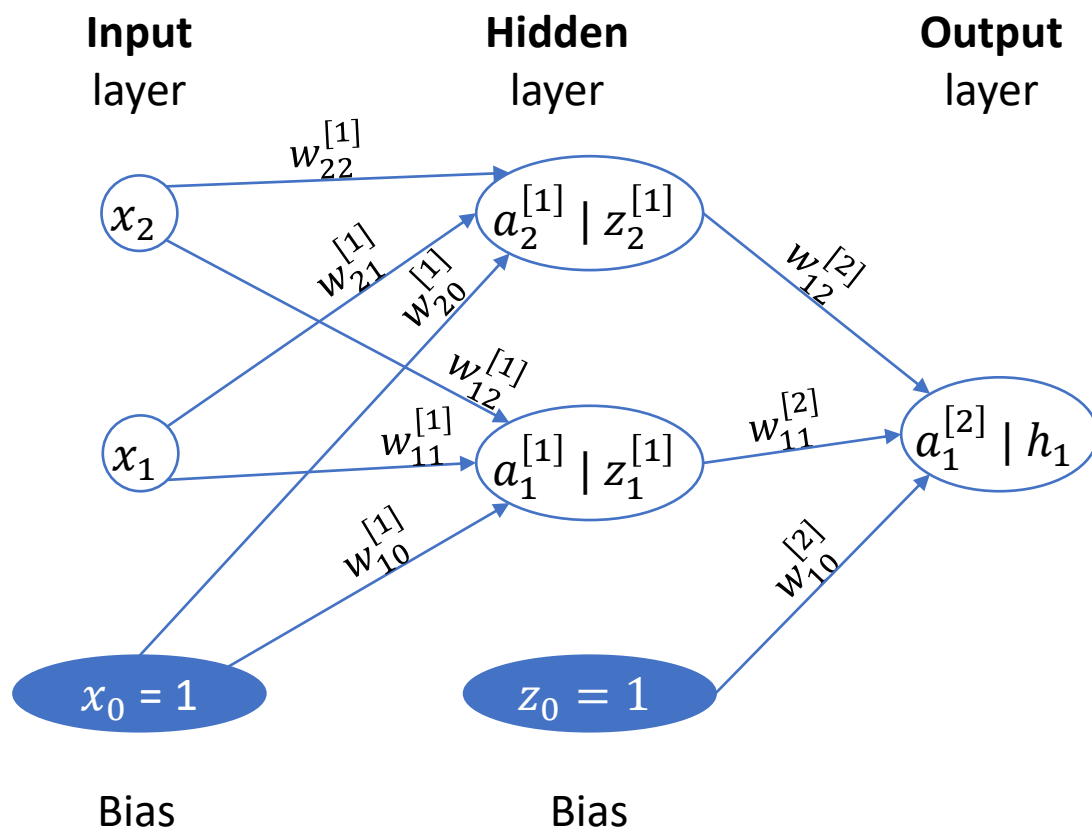
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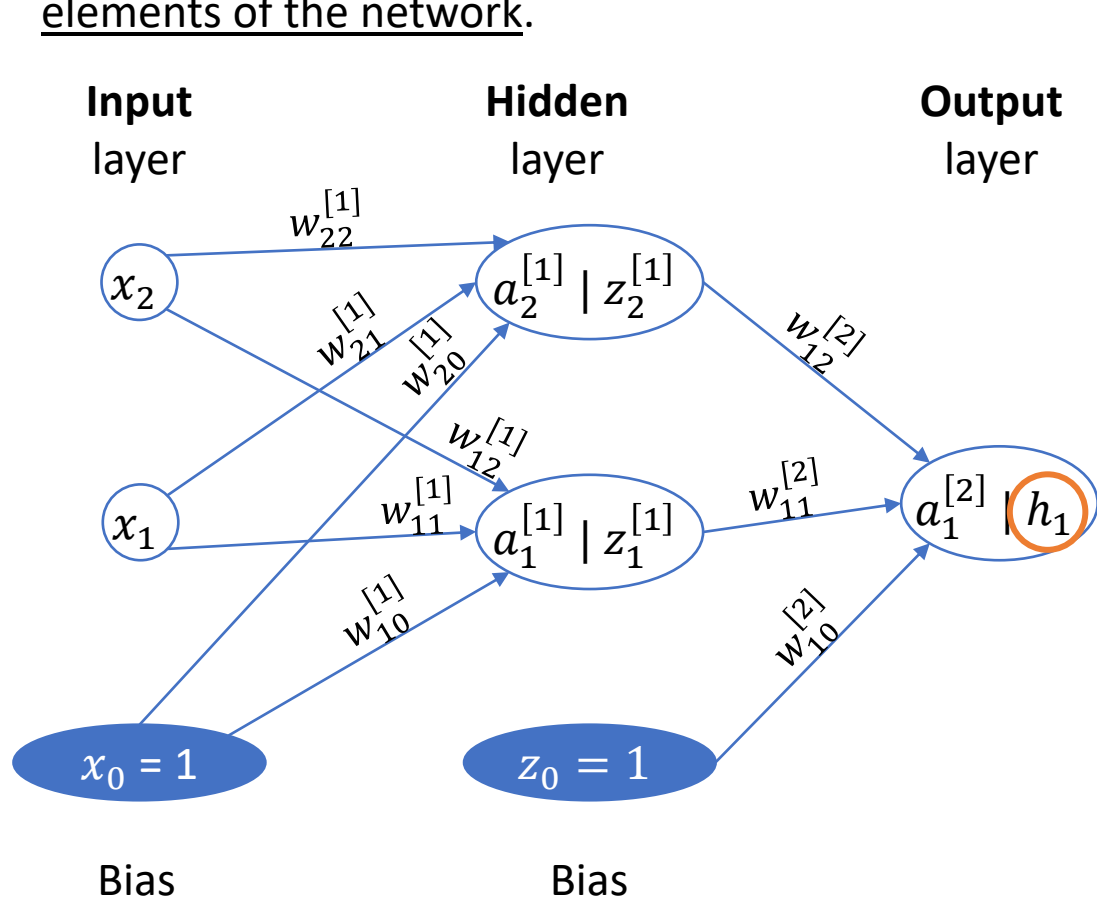
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$$h_1 = \boxed{?}$$

# EXERCISE 1

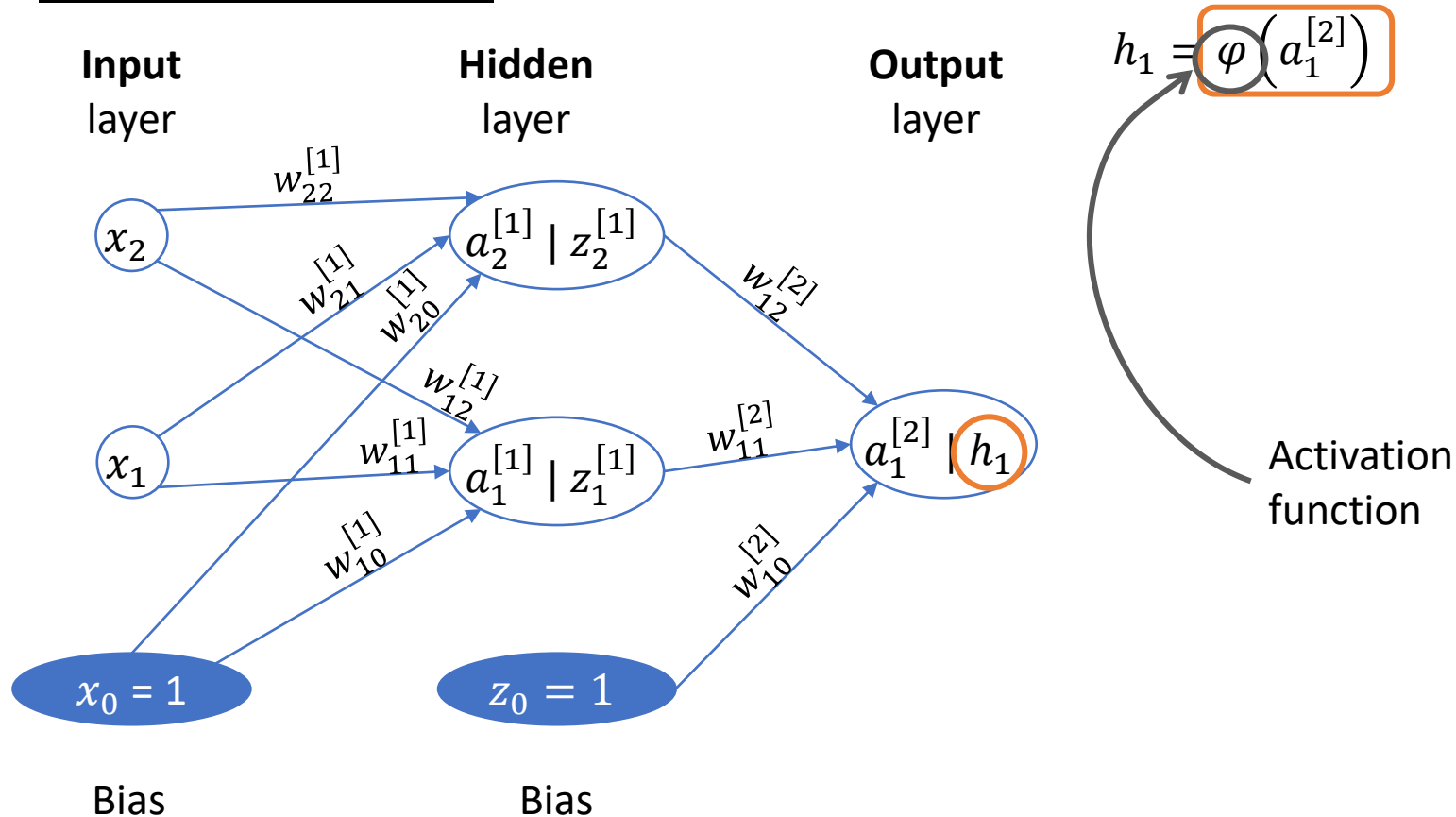
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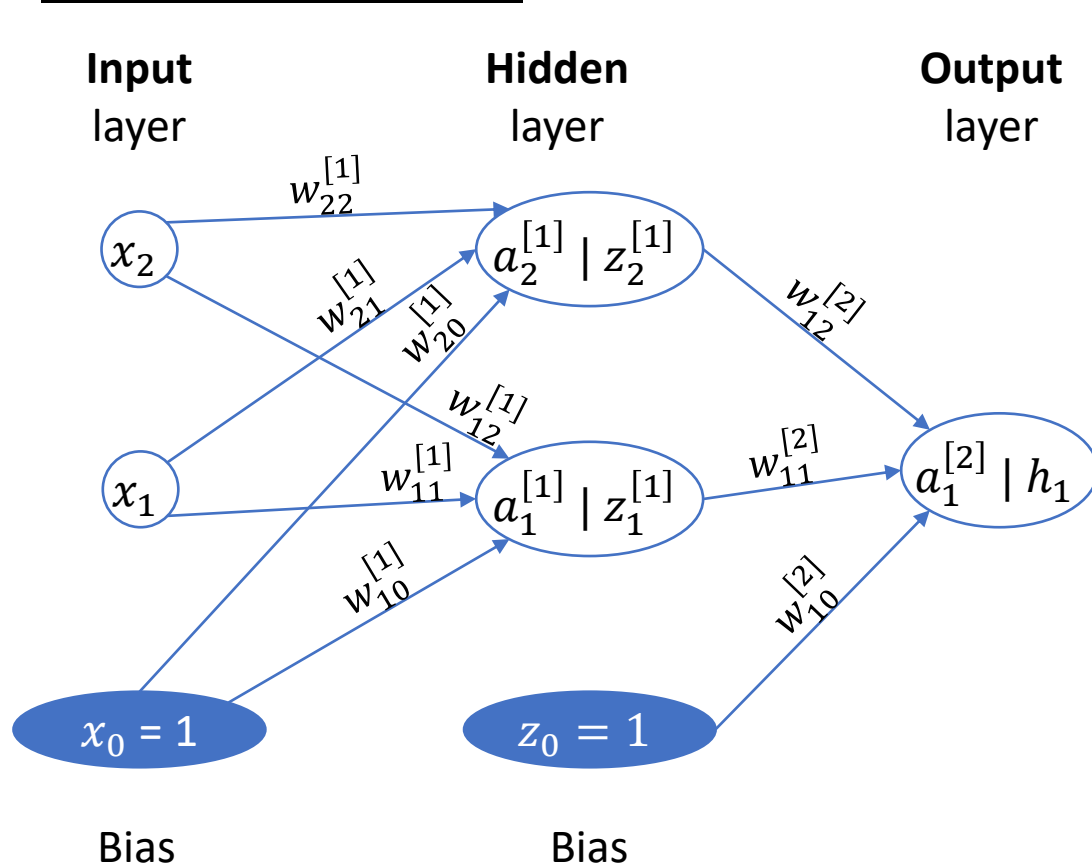
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(b) Put the name at each element of the graph and write, as a closed formula, the output in function of all the elements of the network.



$$h_1 = \varphi(a_1^{[2]})$$

||  
?



# EXERCICE 1

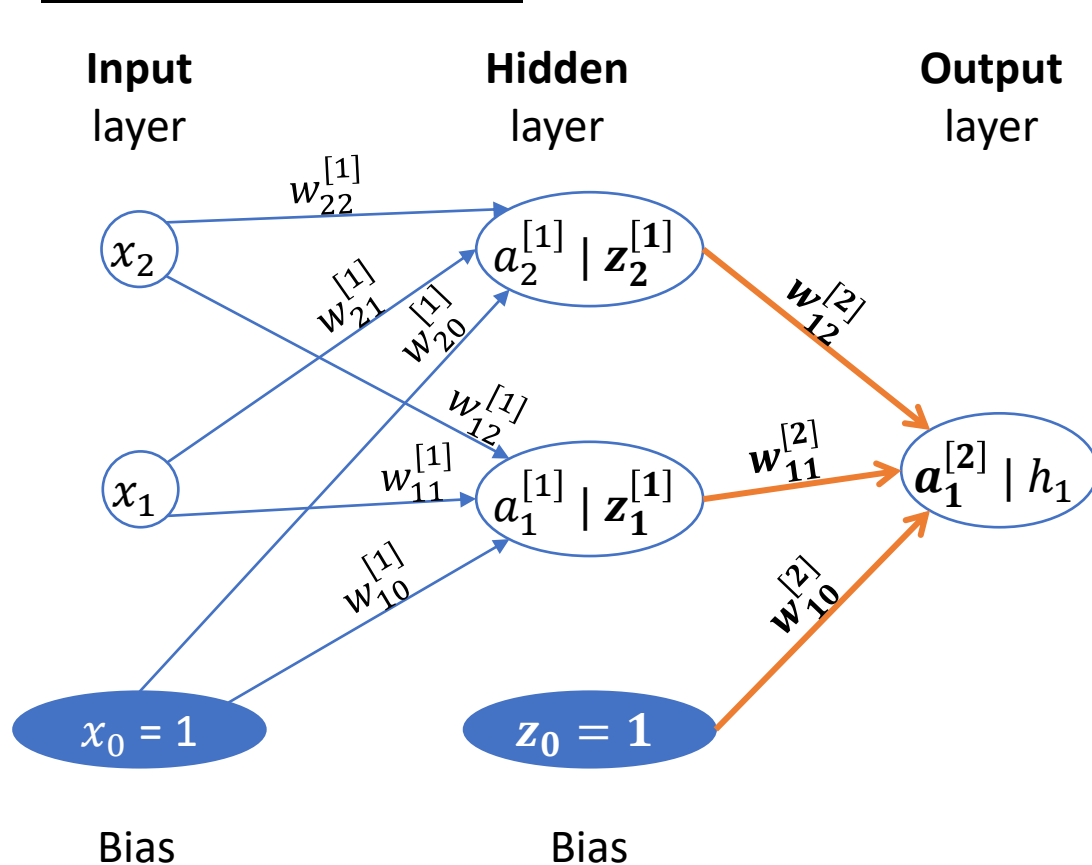
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(b) Put the name at each element of the graph and write, as a closed formula, the output in function of all the elements of the network.



$$h_1 = \varphi(a_1^{[2]})$$

$$\parallel$$

$$\sum_{m=0}^2 w_{1m}^{[2]} z_m^{[1]} = w_{10}^{[2]} z_0^{[1]} + w_{11}^{[2]} z_1^{[1]} + w_{12}^{[2]} z_2^{[1]}$$

# EXERCICE 1

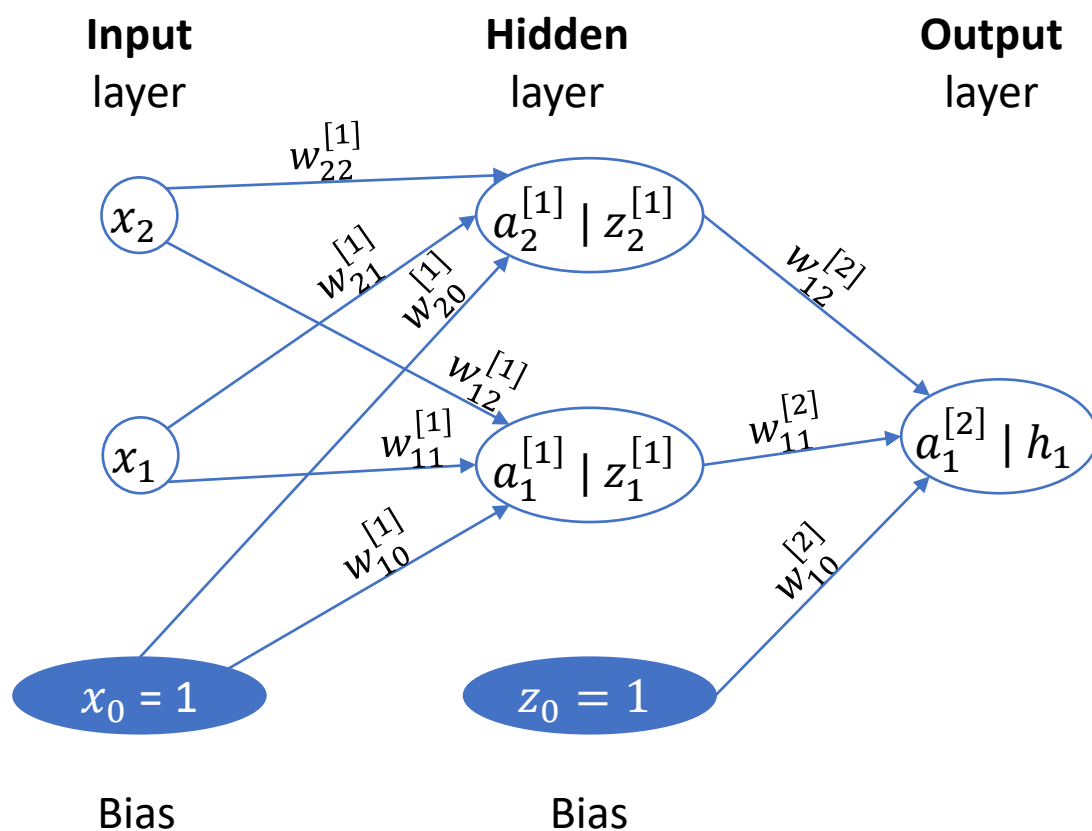
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(b) Put the name at each element of the graph and write, as a closed formula, the output in function of all the elements of the network.



$$h_1 = \varphi(a_1^{[2]})$$

$$= \varphi(w_{10}^{[2]} \underset{?}{\parallel} z_0^{[1]} + w_{11}^{[2]} \underset{?}{\parallel} z_1^{[1]} + w_{12}^{[2]} \underset{?}{\parallel} z_2^{[1]})$$

# EXERCICE 1

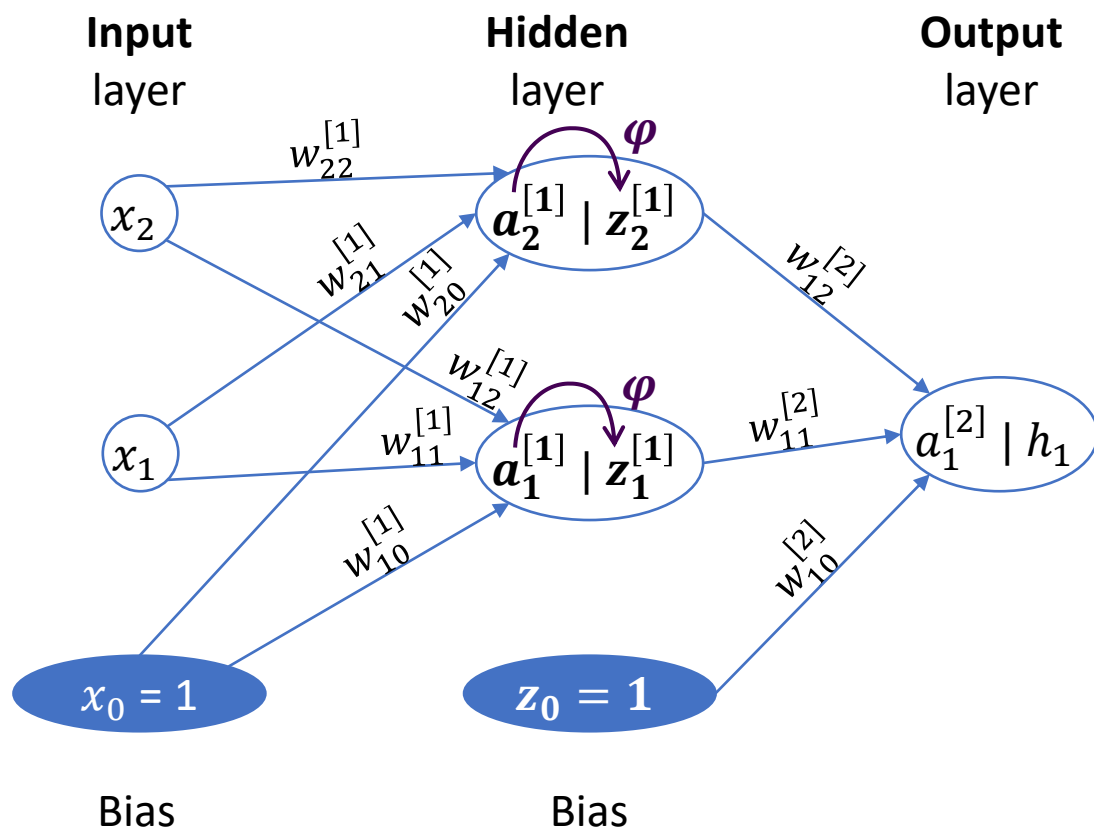
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$$h_1 = \varphi(a_1^{[2]})$$

$$= \varphi\left(w_{10}^{[2]} \underbrace{z_0^{[1]}}_{=1} + w_{11}^{[2]} \underbrace{z_1^{[1]}}_{=\varphi(a_1^{[1]})} + w_{12}^{[2]} \underbrace{z_2^{[1]}}_{=\varphi(a_2^{[1]})}\right)$$

# EXERCICE 1

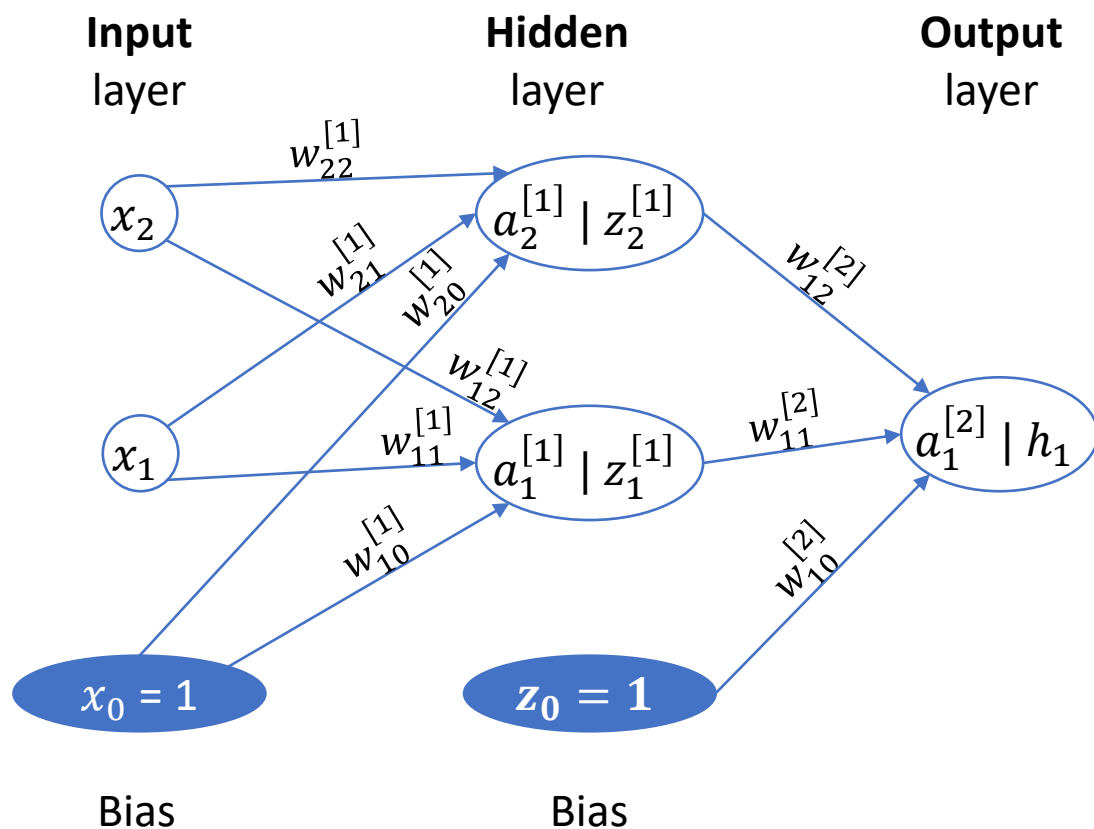
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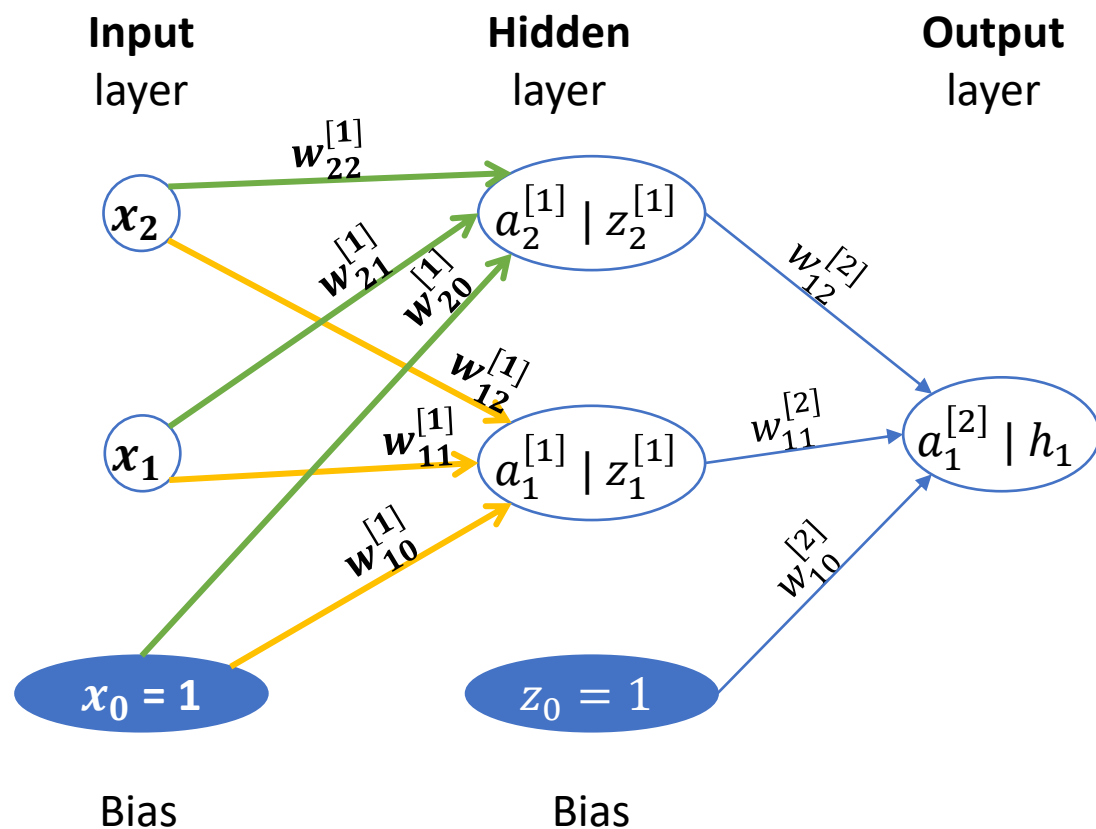
$\parallel$                        $\parallel$   
 $?$                        $?$

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$$= \varphi(w_{10}^{[2]} z_0^{[1]} + w_{11}^{[2]} z_1^{[1]} + w_{12}^{[2]} z_2^{[1]})$$

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$$\sum_{d=0}^D w_{1d}^{[1]} x_d$$

$$\sum_{d=0}^D w_{2d}^{[1]} x_d$$

$$w_{10}^{[1]} x_0 + w_{11}^{[1]} x_1 + w_{12}^{[1]} x_2$$

$$w_{20}^{[1]} x_0 + w_{21}^{[1]} x_1 + w_{22}^{[1]} x_2$$

# EXERCICE 1

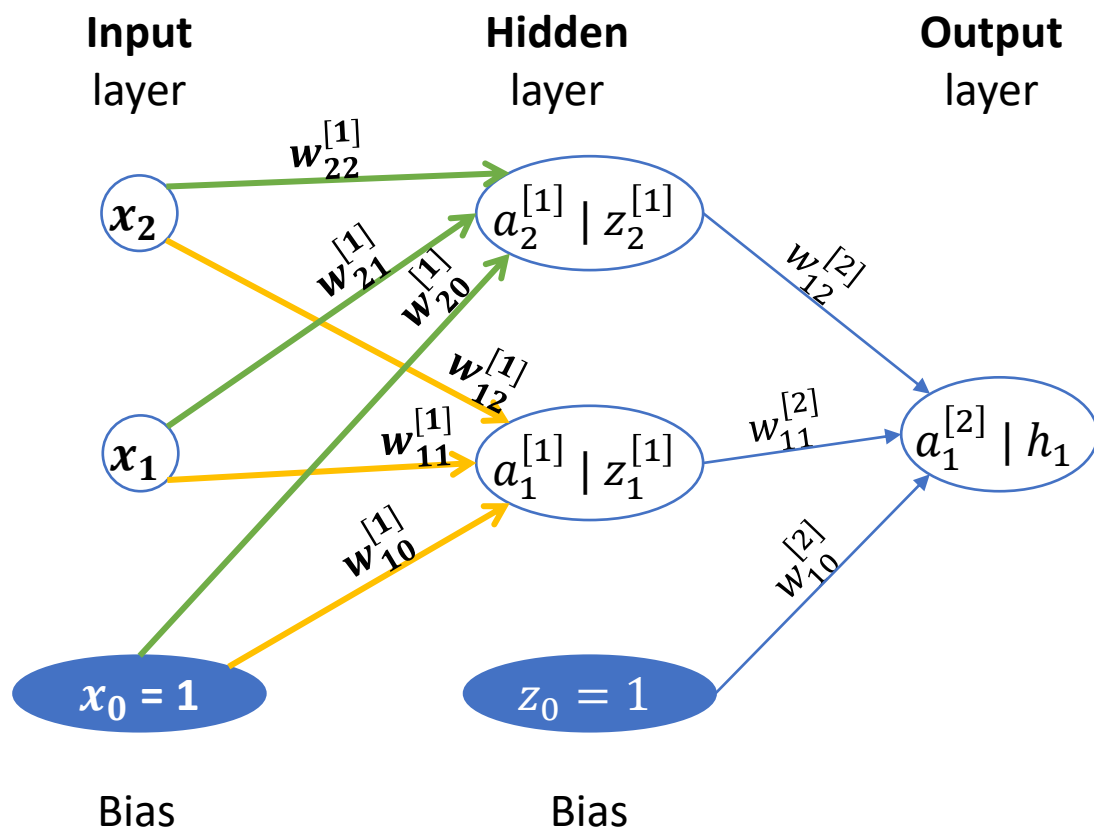
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$$h_1 = \varphi(a_1^{[2]})$$

$$= \varphi(w_{10}^{[2]} z_0^{[1]} + w_{11}^{[2]} z_1^{[1]} + w_{12}^{[2]} z_2^{[1]})$$

$$= \varphi(w_{10}^{[2]} 1 + w_{11}^{[2]} \varphi(a_1^{[1]}) + w_{12}^{[2]} \varphi(a_2^{[1]}))$$

$$= \varphi\left(w_{10}^{[2]} + w_{11}^{[2]} \varphi(w_{10}^{[1]} x_0 + w_{11}^{[1]} x_1 + w_{12}^{[1]} x_2) + w_{12}^{[2]} \varphi(w_{20}^{[1]} x_0 + w_{21}^{[1]} x_1 + w_{22}^{[1]} x_2)\right)$$

||  
**1**

# EXERCISE 1

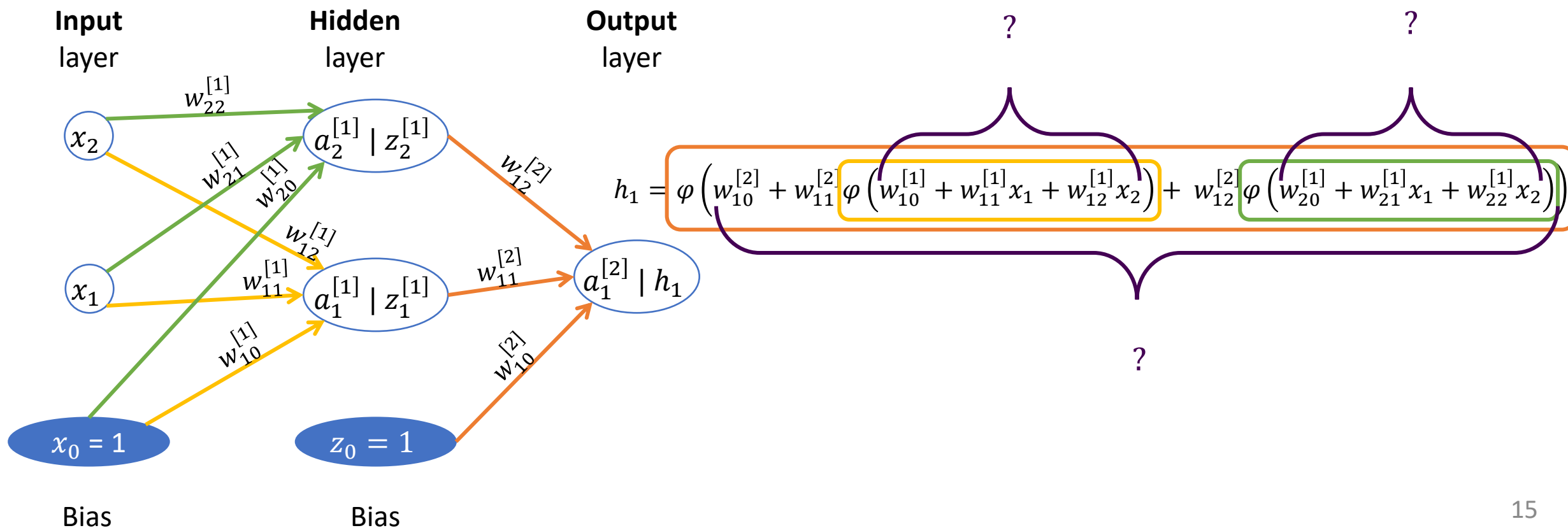
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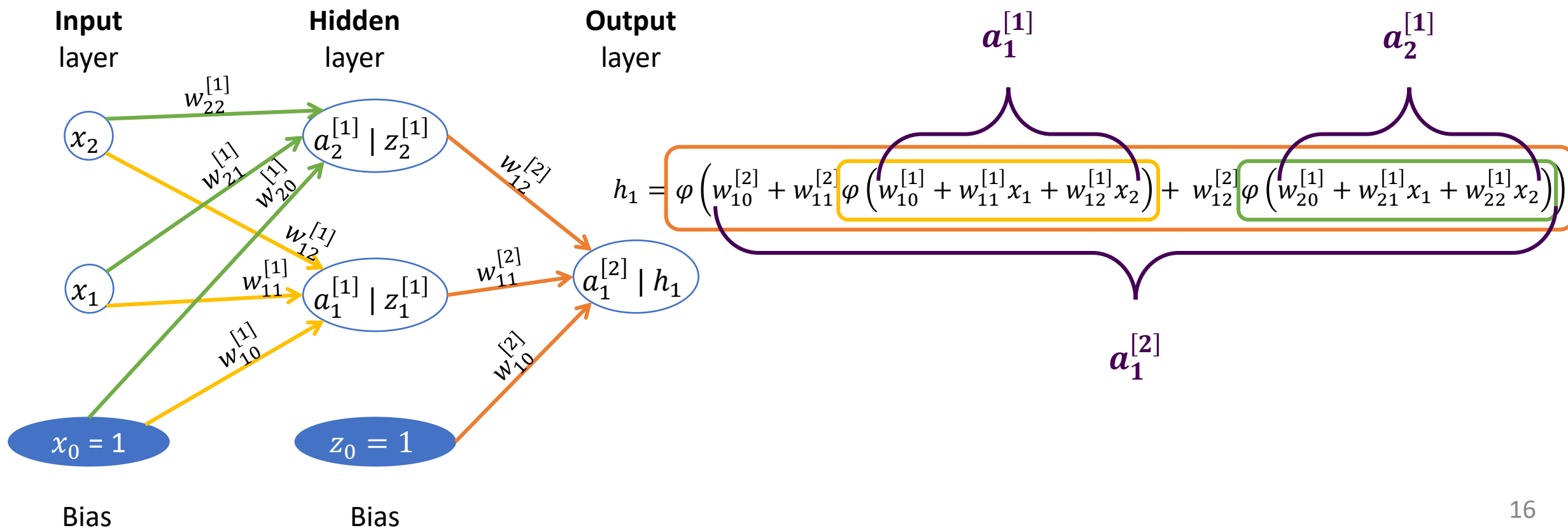
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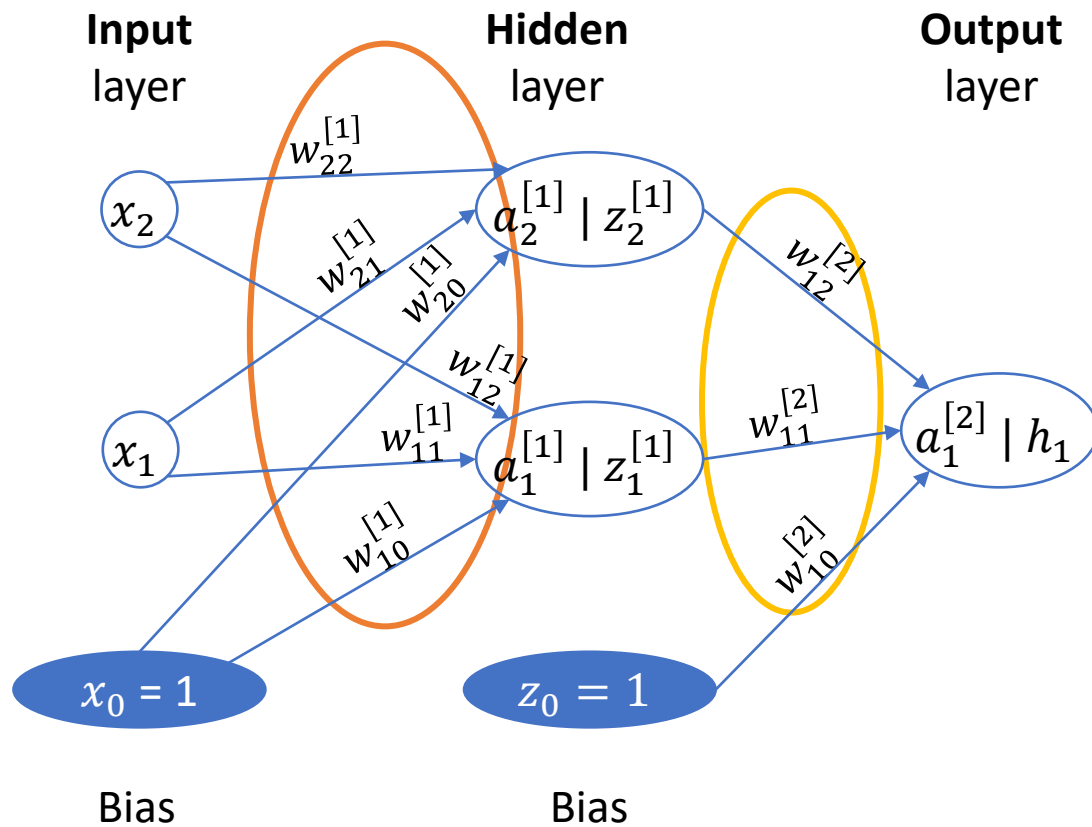
(b) Put the name at each element of the graph and write, as a closed formula, the output in function of all the elements of the network.





# EXERCISE 1

(c) Initialize the weights of the 1<sup>st</sup> layer to 0.1 and of the 2<sup>nd</sup> layer to 0.2. Take the point  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1$ . Calculate  $h(\mathbf{x}^{(1)})$  when all the activation function are sigmoids except in the output layer, where  $h(a) = a$ .



## NEW INFORMATION

$$w_{md}^{[1]} = 0.1 \quad \forall m, d$$

$$w_{1m}^{[2]} = 0.2 \quad \forall m$$

$$h_1 = \varphi(a_1^{[2]}) = a_1^{[2]}$$

$$z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]}) = \frac{1}{1 + \exp(-a_m^{[1]})}$$

$$\text{with } \sigma'(a) = \sigma(a)(1 - \sigma(a))$$

# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = ?$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

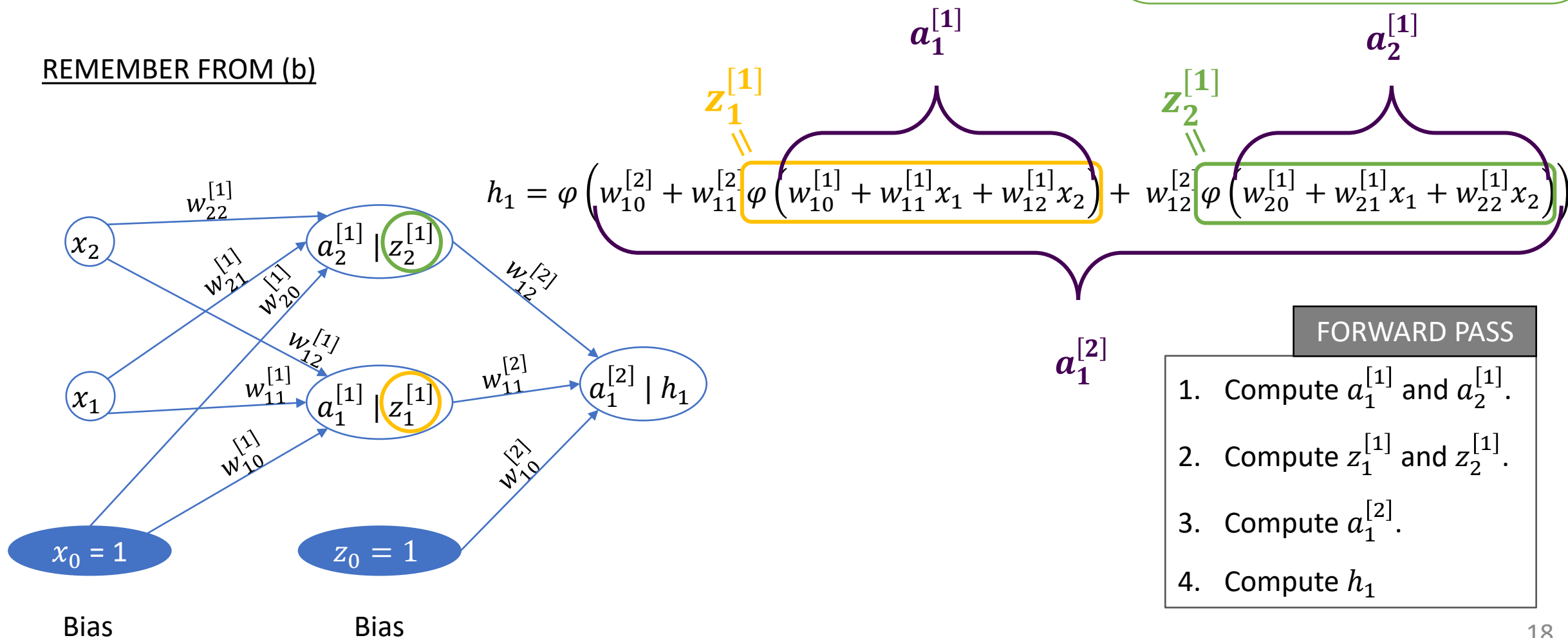
$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

REMEMBER FROM (b)



# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = ?$

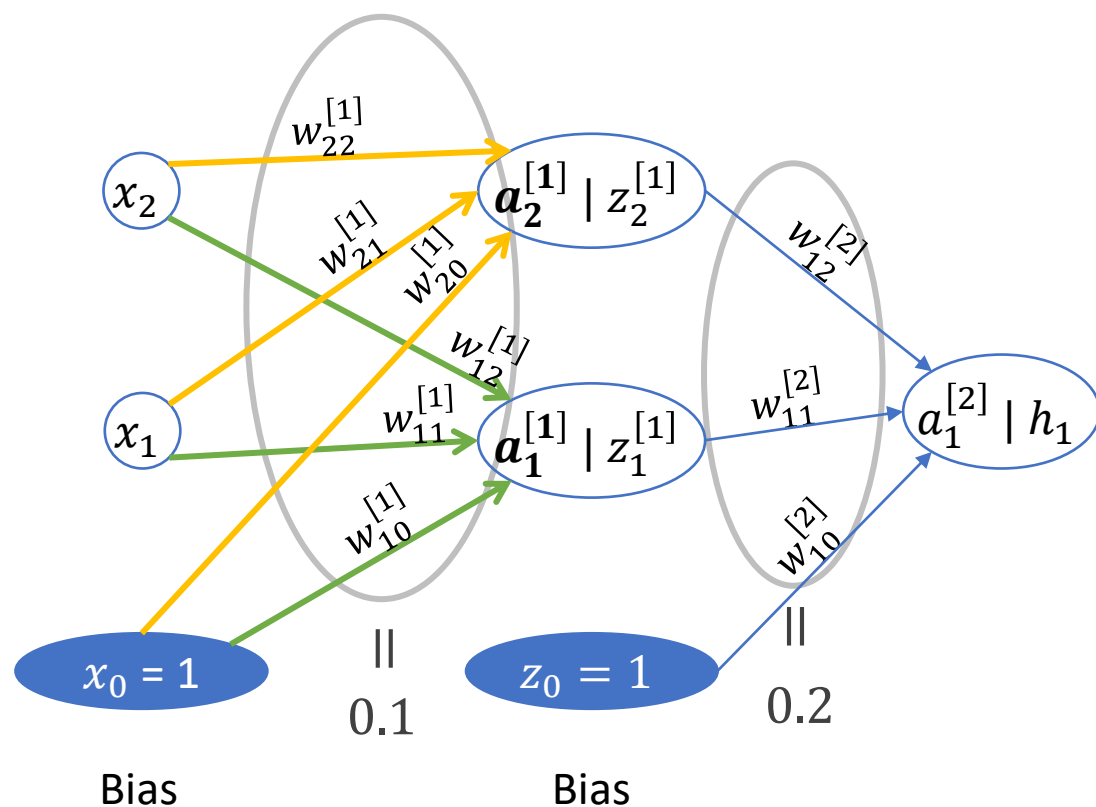
with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



1. Compute  $a_1^{[1]}$  and  $a_2^{[1]}$ .
2. Compute  $z_1^{[1]}$  and  $z_2^{[1]}$ .
3. Compute  $a_1^{[2]}$ .
4. Compute  $h_1$ .

$$a_1^{[1]} = \sum_{d=0}^2 w_{1d}^{[1]} x_d = w_{10}^{[1]} x_0 + w_{11}^{[1]} x_1 + w_{12}^{[1]} x_2 = ?$$

$$a_2^{[1]} = \sum_{d=0}^2 w_{2d}^{[1]} x_d = w_{20}^{[1]} x_0 + w_{21}^{[1]} x_1 + w_{22}^{[1]} x_2 = ?$$

# EXERCICE 1

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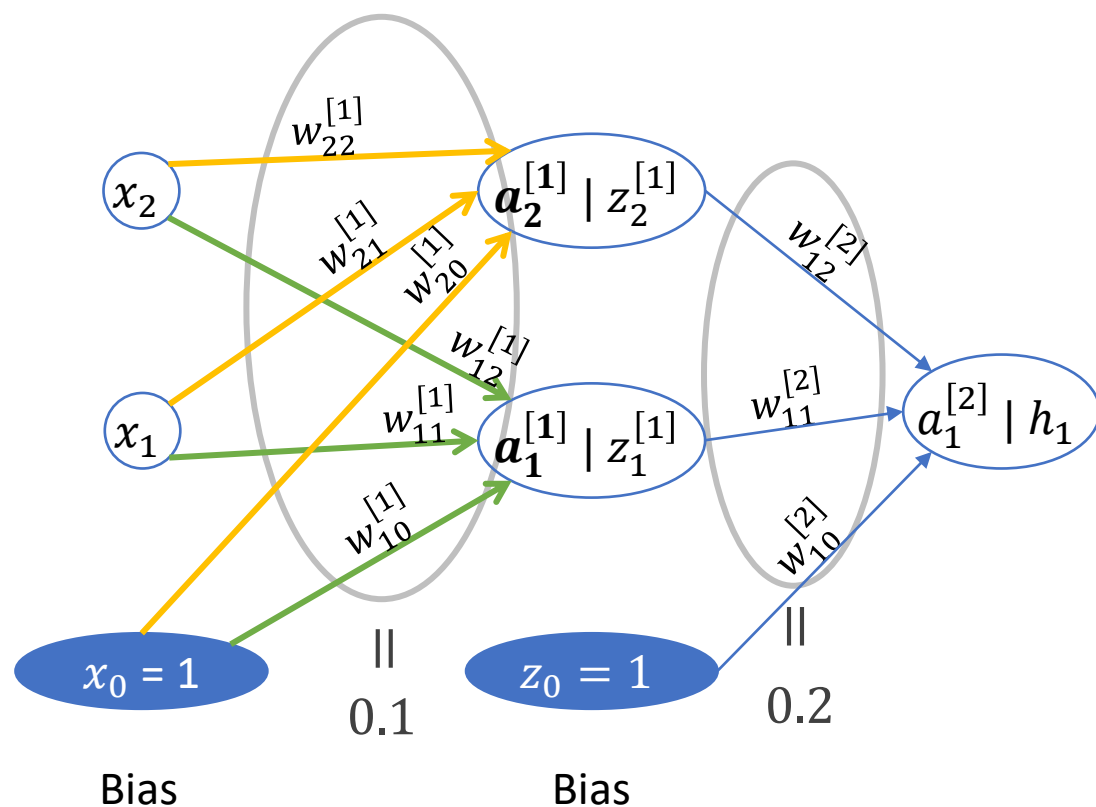
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$$a_1^{[1]} = \sum_{d=0}^2 w_{1d}^{[1]} x_d = w_{10}^{[1]} x_0 + w_{11}^{[1]} x_1 + w_{12}^{[1]} x_2$$

$$= 0.1 \cdot 1 + 0.1 \cdot 0.3 + 0.1 \cdot 0.5 = 0.18$$

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# EXERCICE 1

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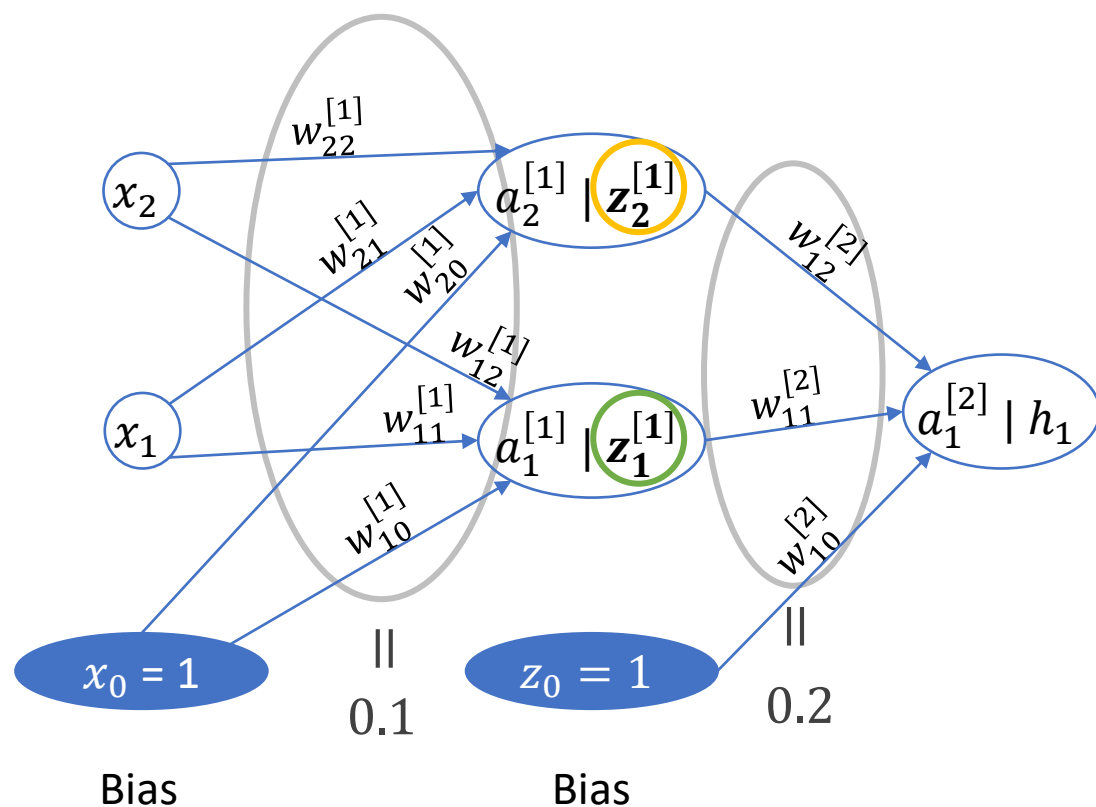
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$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



$$1. \quad a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$$

1. Compute  $a_1^{[1]}$  and  $a_2^{[1]}$ .
2. **Compute  $z_1^{[1]}$  and  $z_2^{[1]}$ .**
3. Compute  $a_1^{[2]}$ .
4. Compute  $h_1$ .

$$\mathbf{z}_1^{[1]} = \varphi(a_1^{[1]}) = \sigma(a_1^{[1]}) = ?$$

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# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = ?$

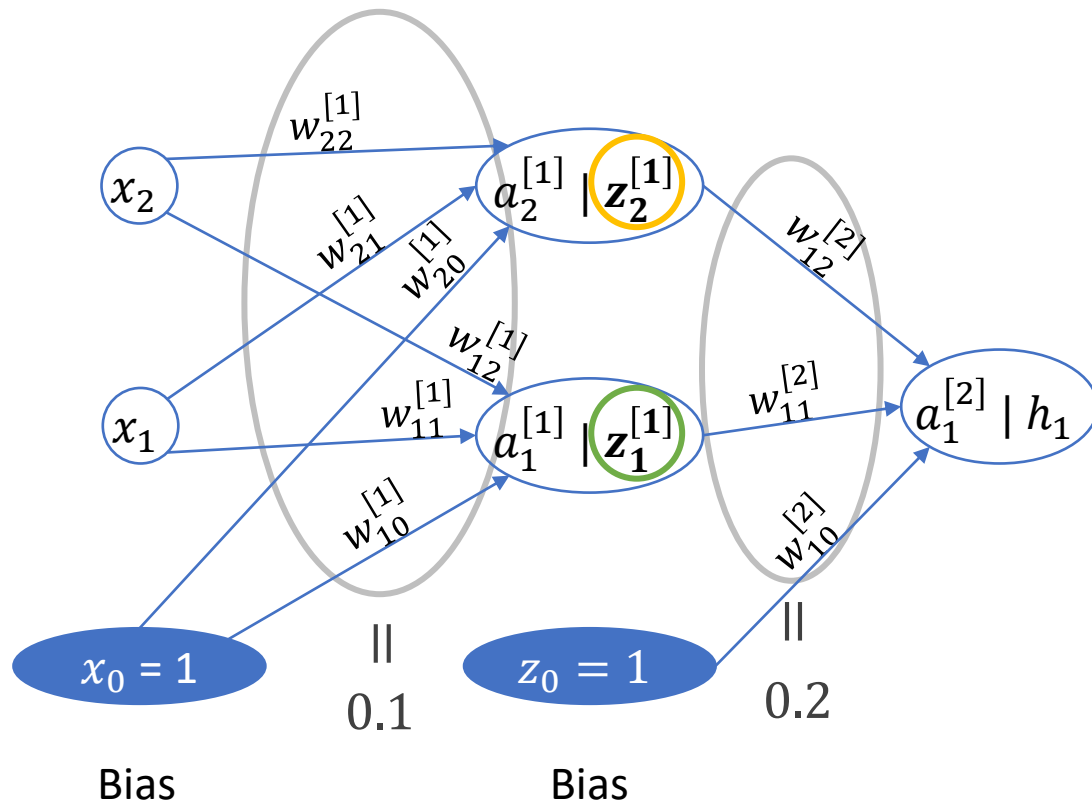
with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



1.  $a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$

1. Compute  $a_1^{[1]}$  and  $a_2^{[1]}$ .
2. **Compute  $z_1^{[1]}$  and  $z_2^{[1]}$ .**
3. Compute  $a_1^{[2]}$ .
4. Compute  $h_1$

$$\boxed{z_1^{[1]}} = \varphi(a_1^{[1]}) = \sigma(a_1^{[1]})$$

$$= \sigma(0.18) = \frac{1}{1 + \exp(-0.18)} = 0.54$$

$$\boxed{z_2^{[1]}} = \varphi(a_2^{[1]}) = \sigma(a_2^{[1]})$$

$$= \sigma(0.18) = \frac{1}{1 + \exp(-0.18)} = 0.54$$

# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = ?$

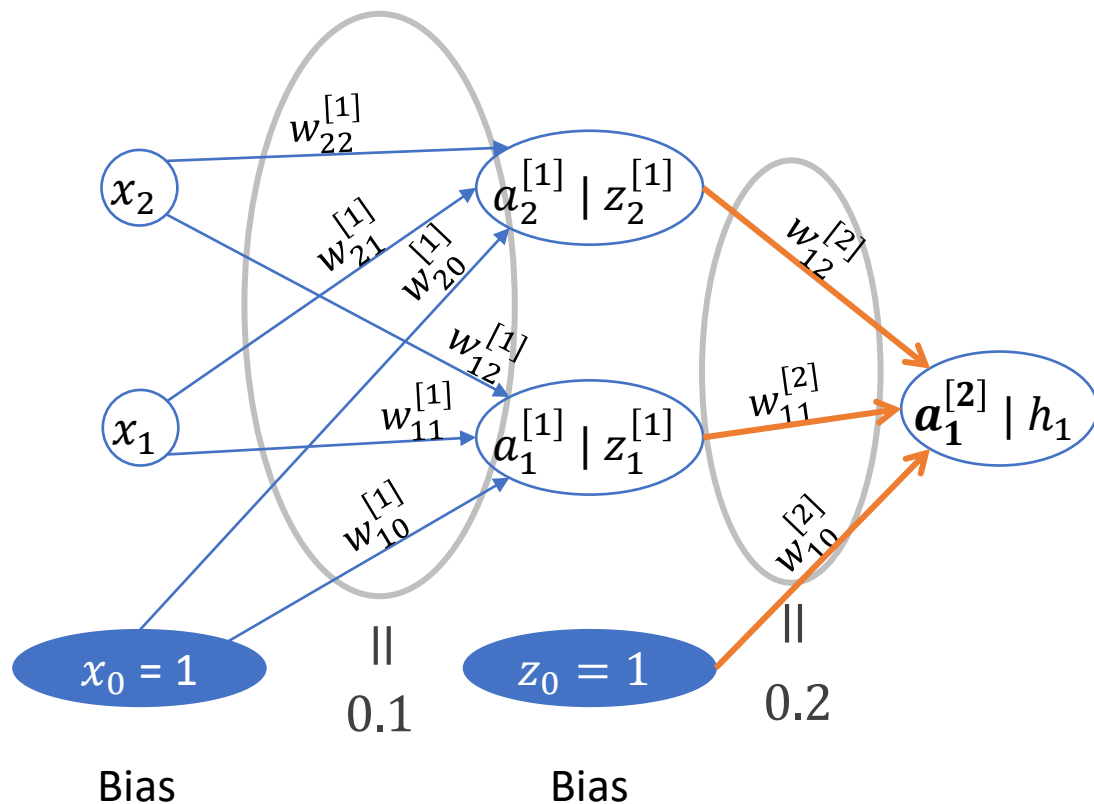
with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



$$1. \quad a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$$

$$2. \quad z_1^{[1]} = 0.54, z_2^{[1]} = 0.54$$

$$1. \quad \text{Compute } a_1^{[1]} \text{ and } a_2^{[1]}.$$

$$2. \quad \text{Compute } z_1^{[1]} \text{ and } z_2^{[1]}.$$

$$3. \quad \text{Compute } a_1^{[2]}.$$

$$4. \quad \text{Compute } h_1$$

$$a_1^{[2]} = \sum_{m=0}^2 w_{1m}^{[2]} z_m^{[1]} = w_{10}^{[2]} z_0^{[1]} + w_{11}^{[2]} z_1^{[1]} + w_{12}^{[2]} z_2^{[1]} = ?$$

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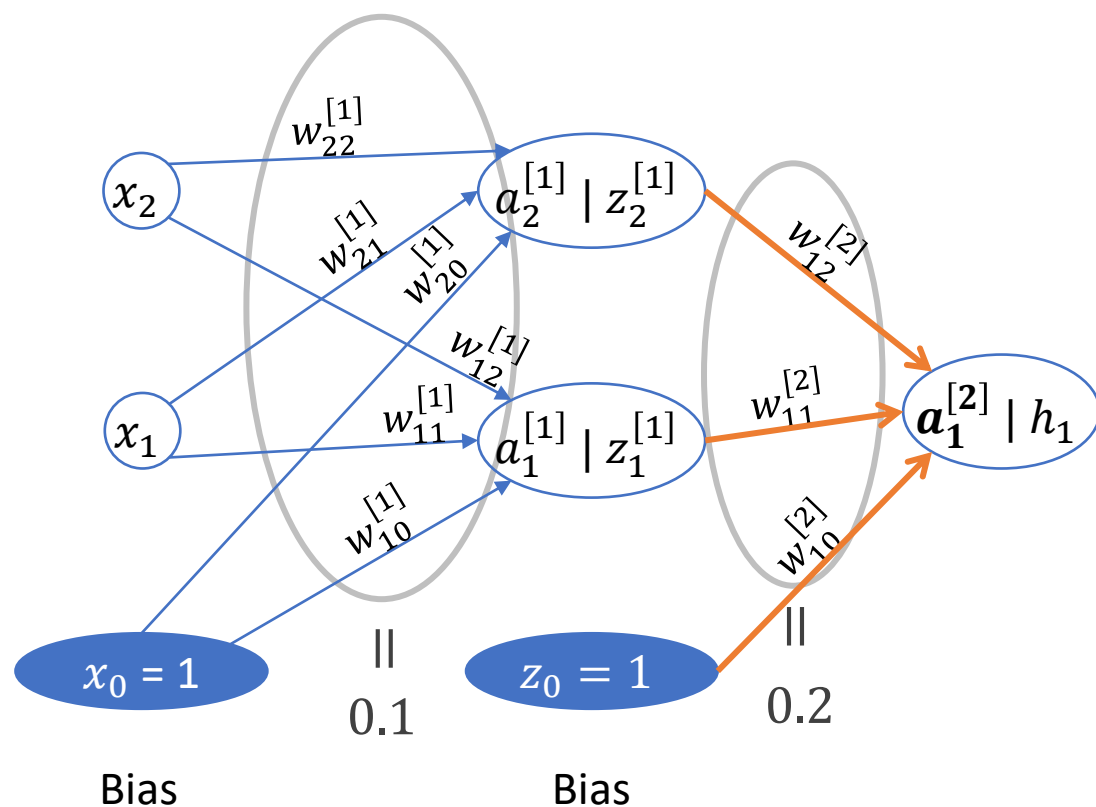
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$$= 0.2 \cdot 1 + 0.2 \cdot 0.54 + 0.2 \cdot 0.54 = 0.42$$



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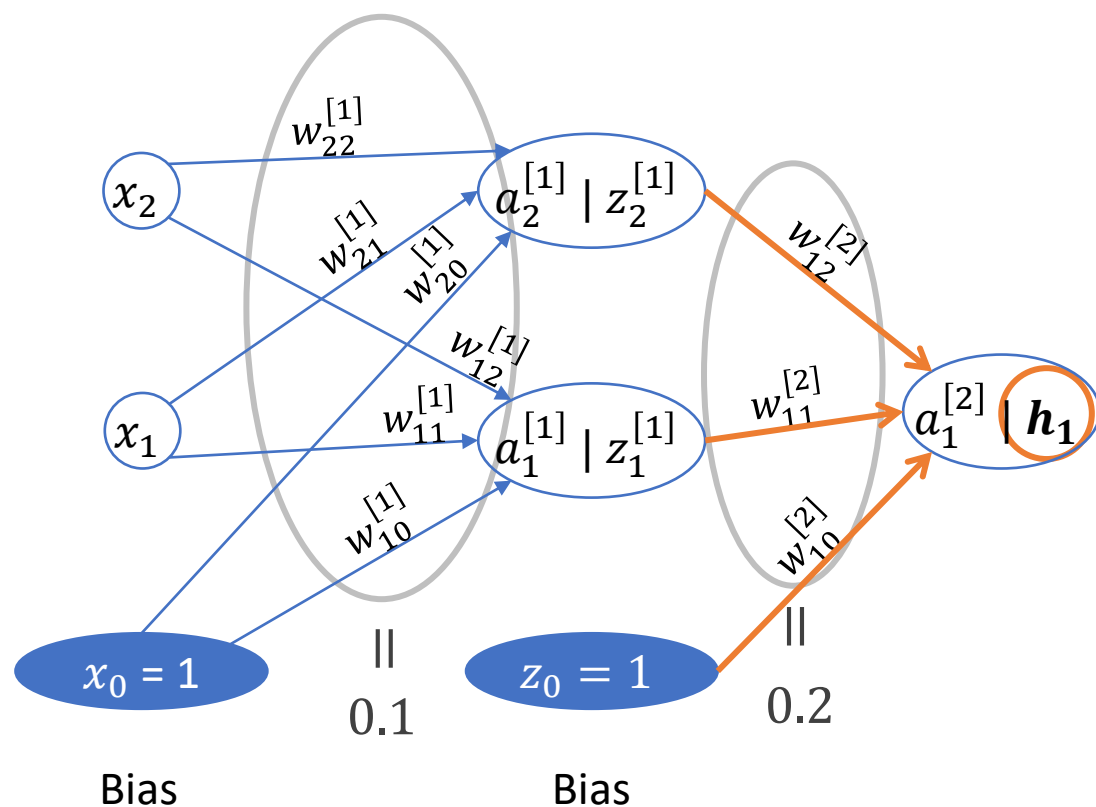
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3.  $a_1^{[2]} = 0.42$

1. Compute  $a_1^{[1]}$  and  $a_2^{[1]}$ .
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3. Compute  $a_1^{[2]}$ .
4. Compute  $h_1$

$$\boxed{h_1} = \varphi(a_1^{[2]}) = h_1(a_1^{[2]}) = ?$$

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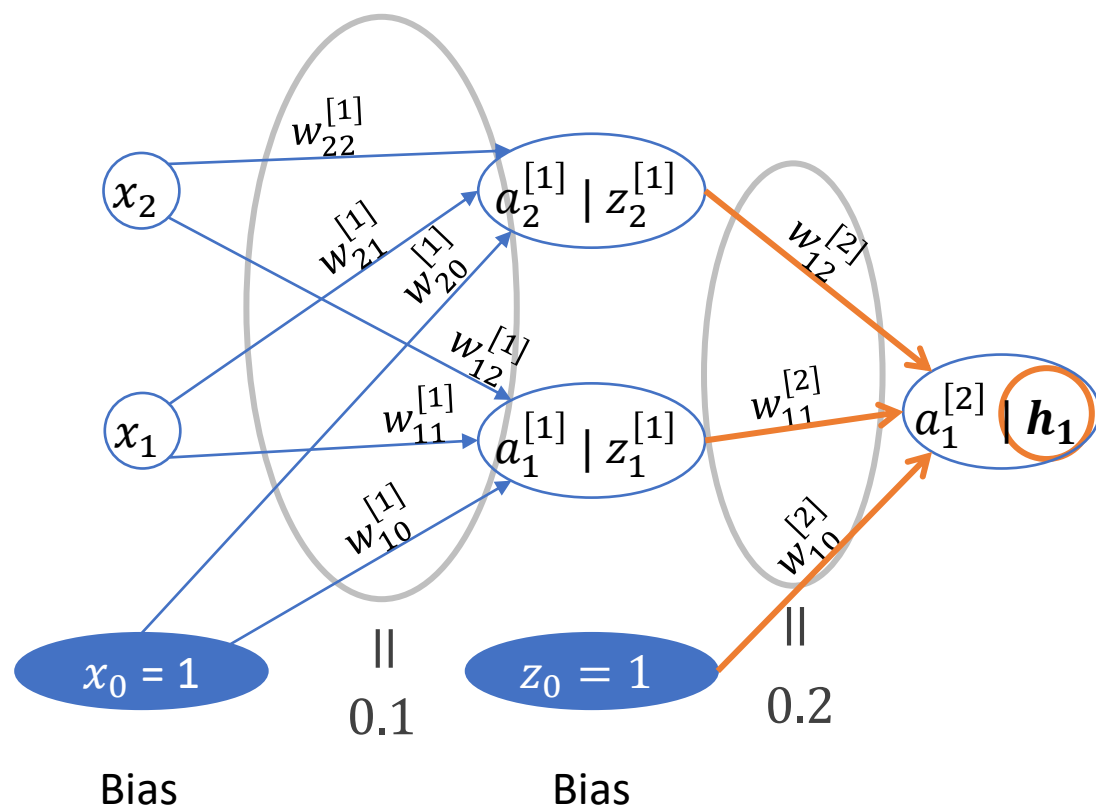
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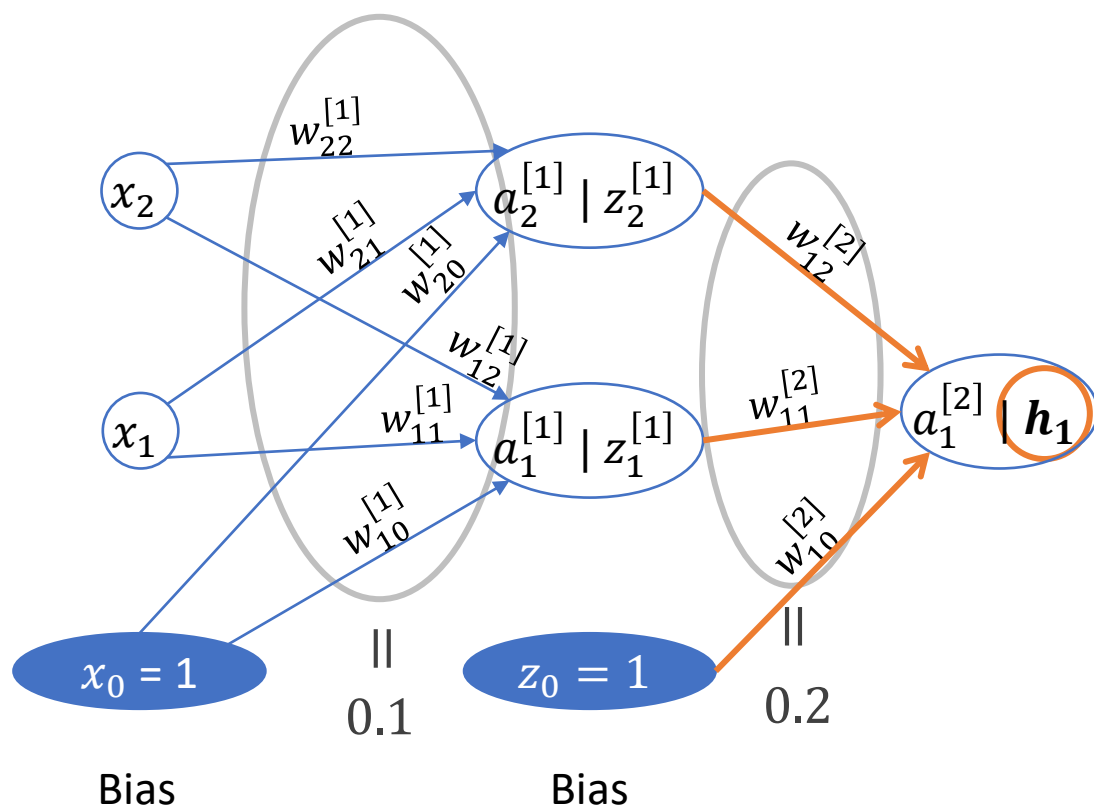
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$$\boxed{h_1} = \varphi(a_1^{[2]}) = h_1(a_1^{[2]}) = a_1^{[2]} = 0.42$$

$$\Rightarrow h(\mathbf{x}^{(1)}) = 0.42$$

# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

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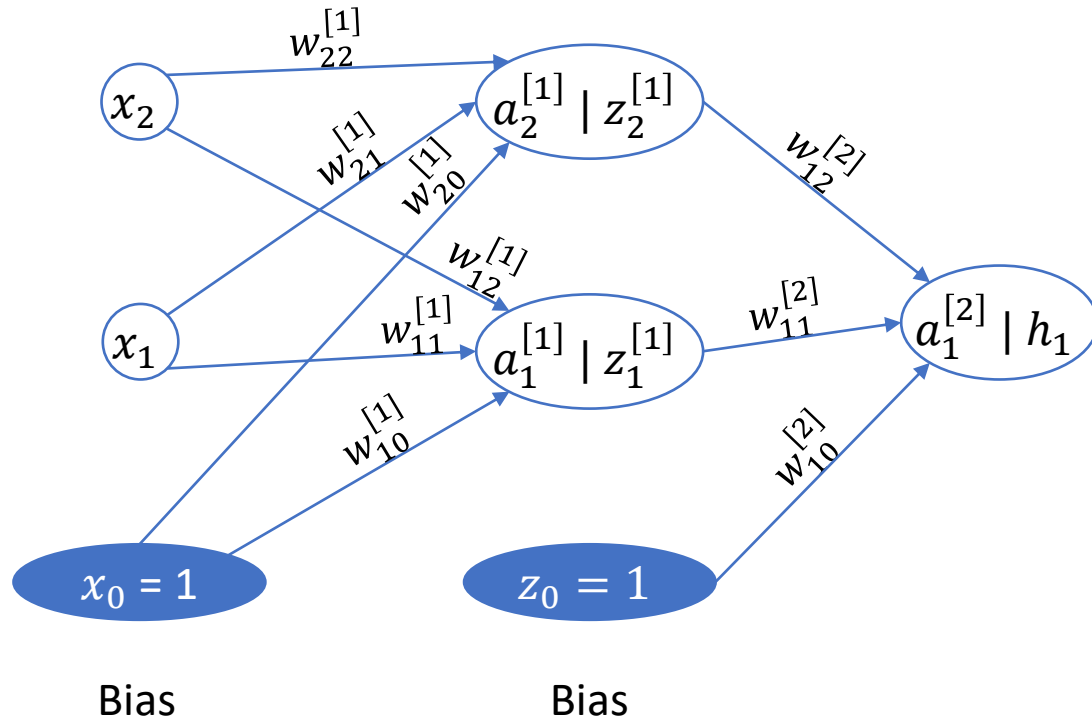
(i) Calculate the error using LS Error.

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## LEAST SQUARES ERROR

$$\mathbb{E}(\mathbf{x}^{(1)}) = ?$$

# EXERCICE 1

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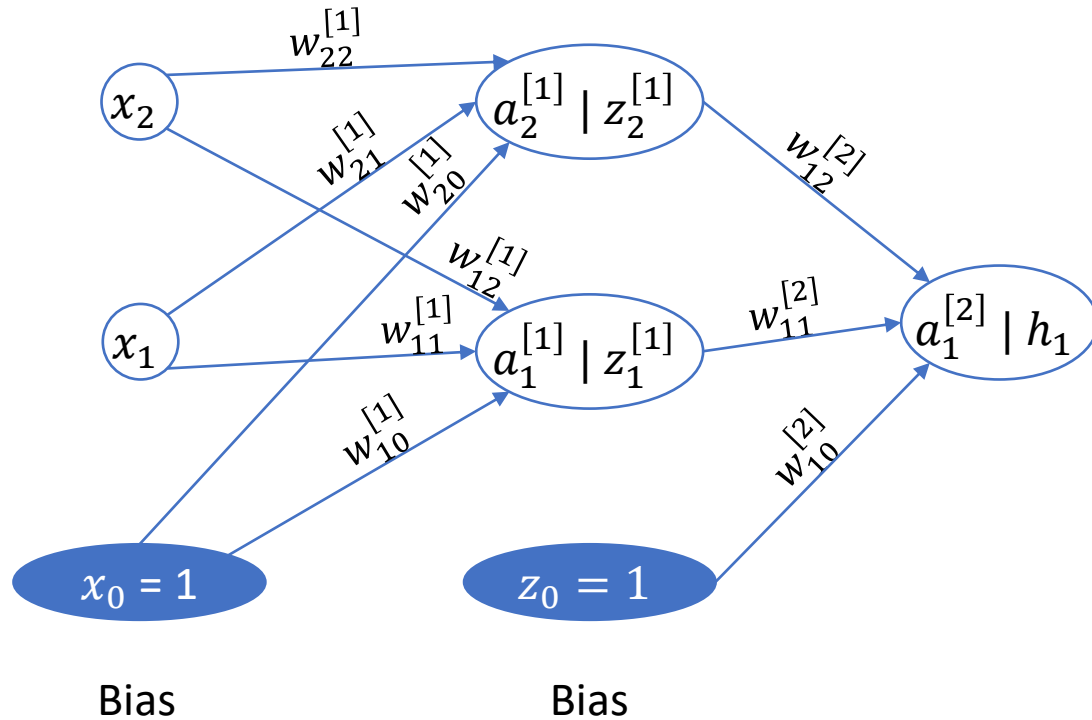
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## LEAST SQUARES ERROR

$$\mathbb{E}(\mathbf{x}^{(1)}) = \frac{1}{2} \sum_{n=1}^N (h(\mathbf{x}^{(n)}) - y^{(n)})^2$$

$$= \frac{1}{2} (h(\mathbf{x}^{(1)}) - y^{(1)})^2 = \frac{1}{2} (0.42 - 1)^2 = 0.17$$

# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

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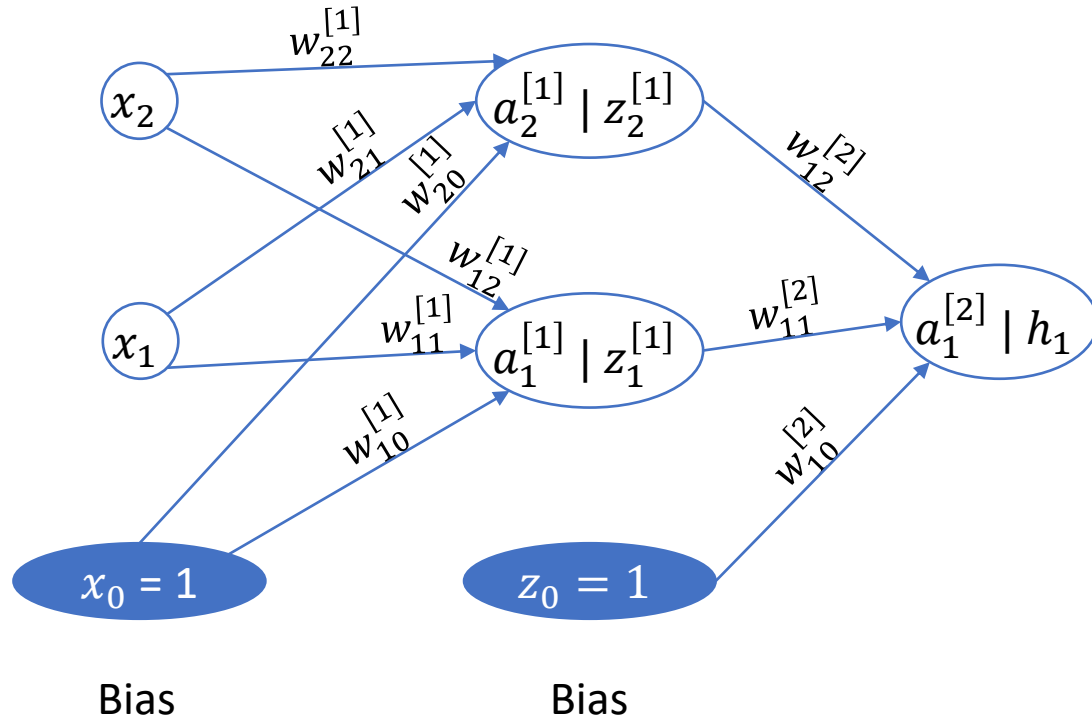
(ii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ . Draw only the part of the graph and the relations involved. What is the local error? How could the local error be used to calculate the derivatives of the error with respect to the weights of the output layer?

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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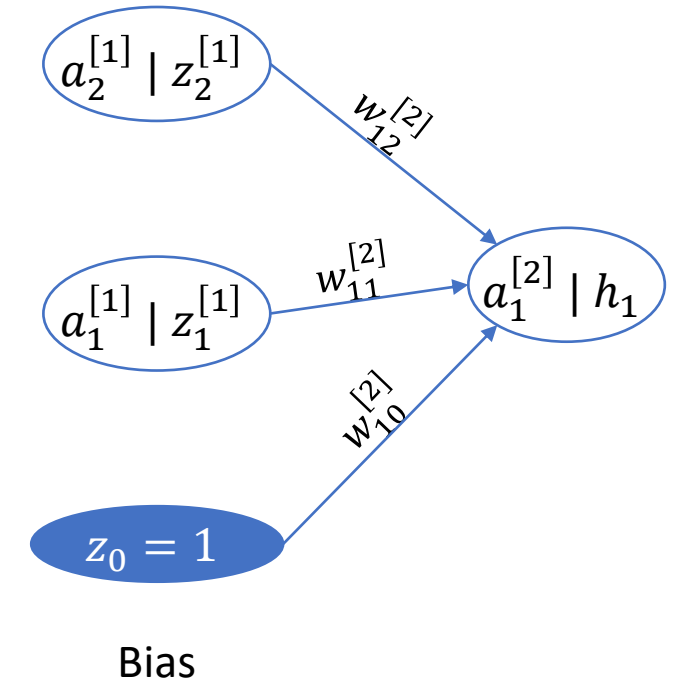
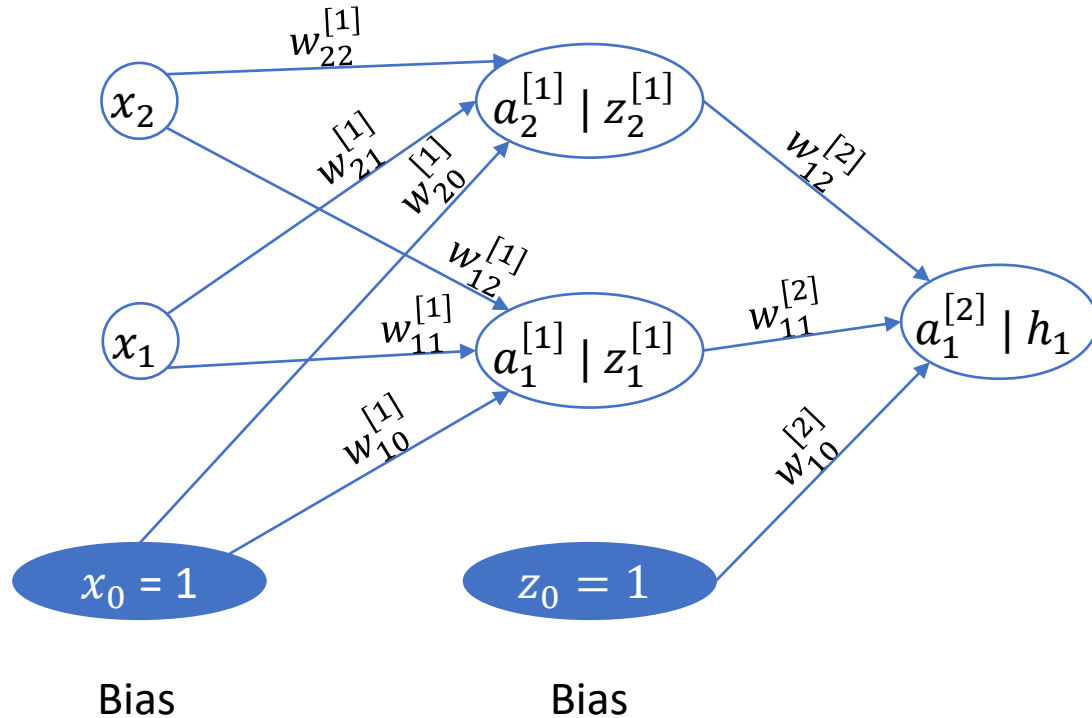
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(ii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

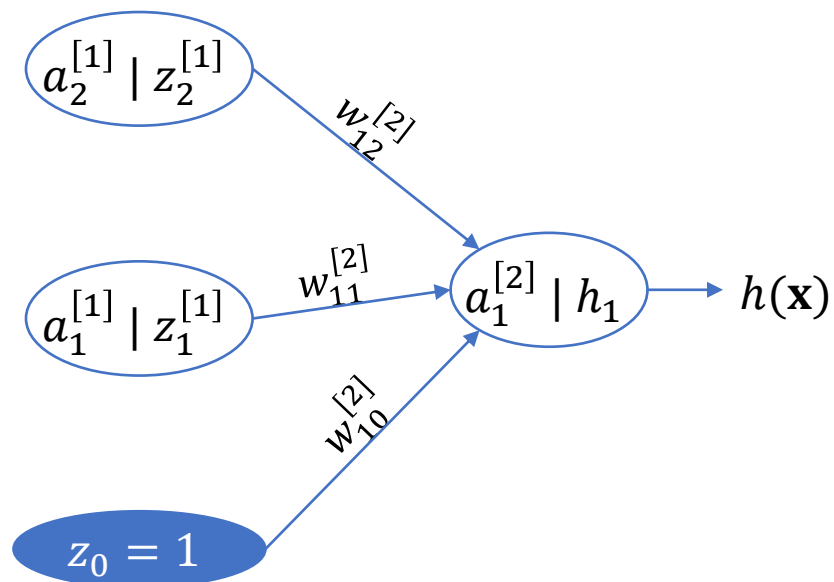
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BACK-PROPAGATION



$\mathbb{E}_1 = ?$

Error for input point  $\mathbf{x}^{(1)}$ .

Bias



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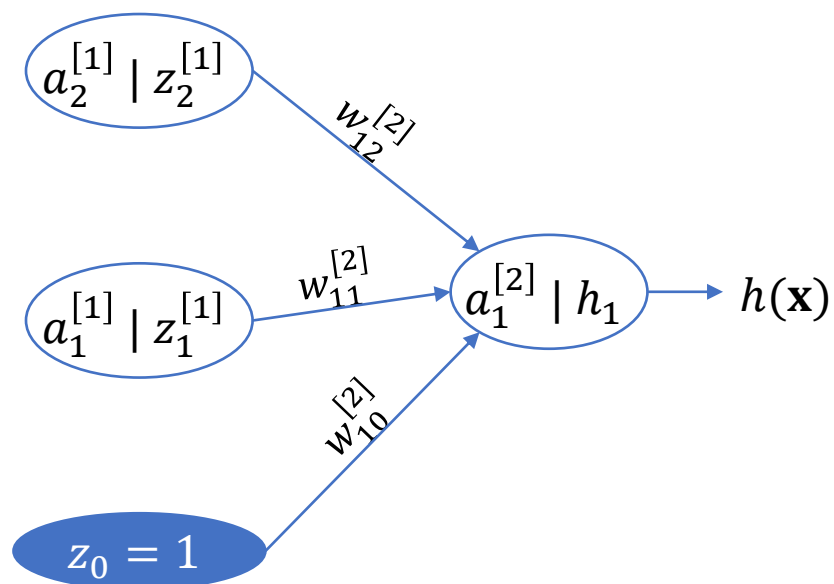
Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

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Bias

The **output of the network** for input point  $\mathbf{x}^{(1)}$ .

$$\mathbb{E}_1 = \frac{1}{2} (h(\mathbf{x}^{(1)}) - y^{(1)})^2 = \frac{1}{2} (h_1(a_1^{[2]}) - y^{(1)})^2$$

$h(\mathbf{x}^{(1)})$  is a function of  $a_1^{[2]}$ . Which in turn is a function of  $w_{1m}^{[2]}$  and  $z_m^{[1]}$ , for  $m = 1, 2$ .

$$h(\mathbf{x}^{(1)}) = h_1(a_1^{[2]}) = h_1\left(\sum_{m=0}^2 w_{1m}^{[2]} z_m^{[1]}\right)$$

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(ii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}}$$

CHAIN RULE

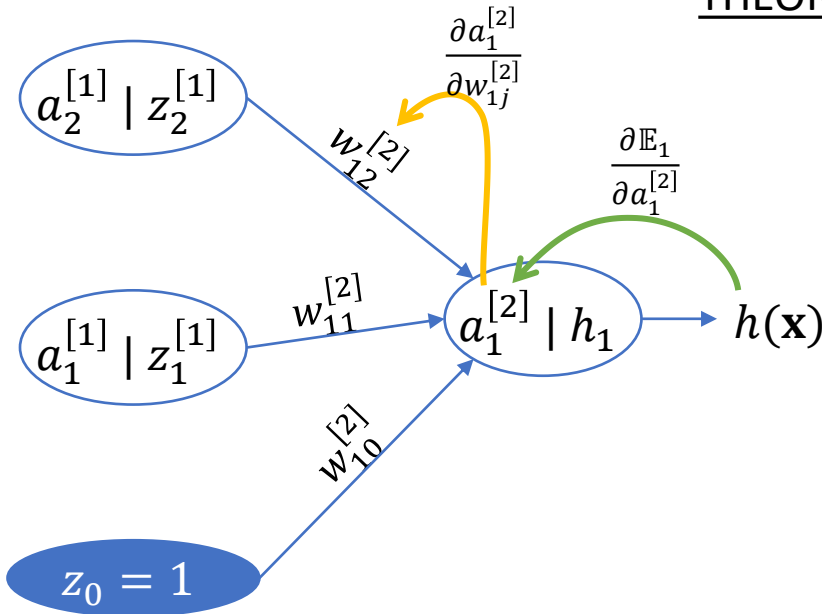
LOCAL ERROR

$$\partial_1^{[2]}$$

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = ?$$

$$\frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = ?$$

$$\mathbb{E}_1 = \frac{1}{2} (h(\mathbf{x}^{(1)}) - y^{(1)})^2 = \frac{1}{2} (h_1(a_1^{[2]}) - y^{(1)})^2$$



Bias

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

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Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} \quad \text{CHAIN RULE}$$

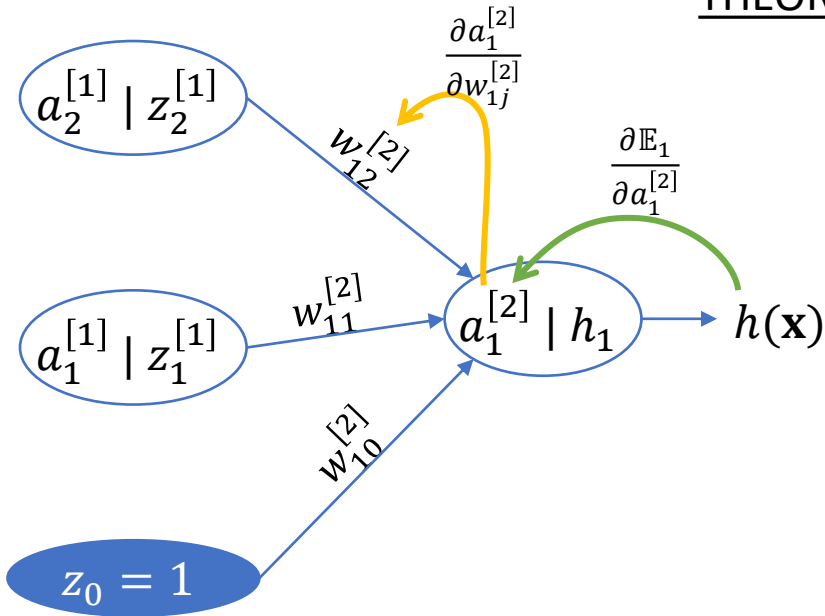
$$\mathbb{E}_1 = \frac{1}{2} (h(\mathbf{x}^{(1)}) - y^{(1)})^2 = \frac{1}{2} (h_1(a_1^{[2]}) - y^{(1)})^2$$

$$\text{LOCAL ERROR } \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = (h_1(a_1^{[2]}) - y^{(1)}) \cdot h'_1(a_1^{[2]}) = h_1(a_1^{[2]}) - y^{(1)}$$

$h_1(a) = a$

$$\frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = \frac{\partial}{\partial w_{1j}^{[2]}} \{ w_{10}^{[2]} + w_{11}^{[2]} z_1^{[1]} + w_{12}^{[2]} z_2^{[1]} \} = z_j^{[1]}$$

$a_1^{[2]}$



Bias

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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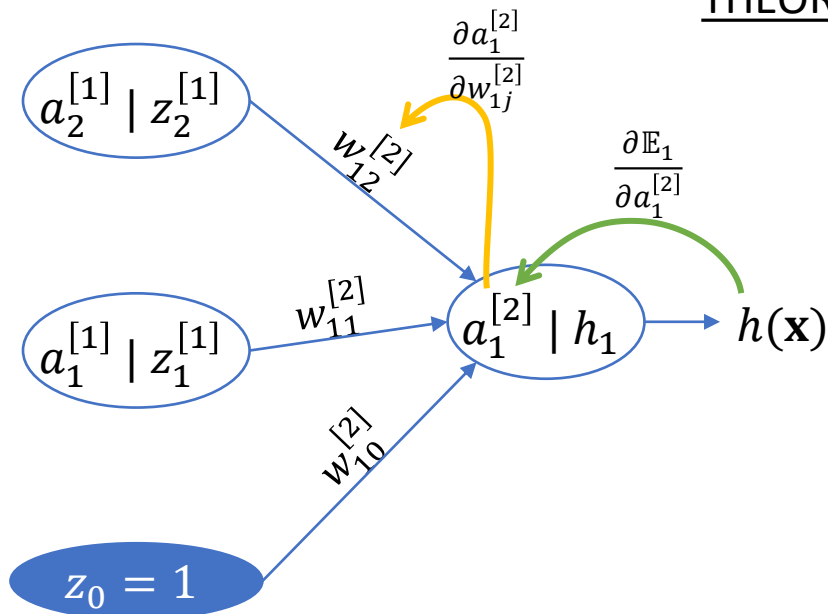
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THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = \underbrace{\left( h_1(a_1^{[2]}) - y^{(1)} \right)}_{\text{LOCAL ERROR}} \underbrace{z_j^{[1]}}_{\partial_1^{[2]}}$$



Bias

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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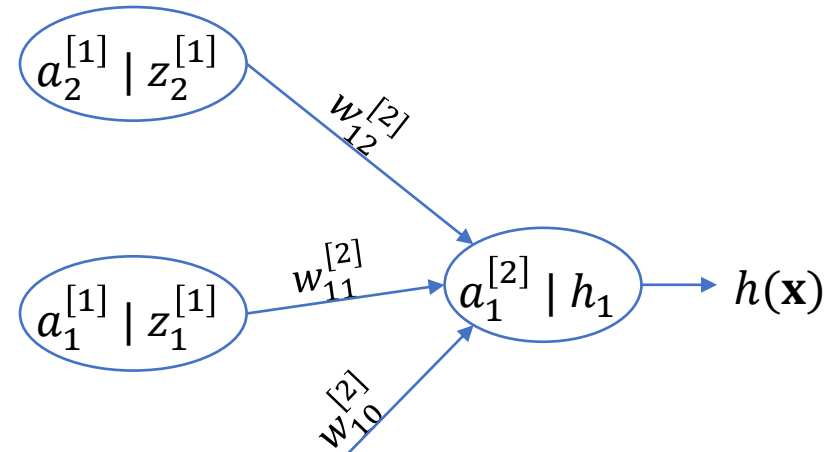
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THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = \left( h_1(a_1^{[2]}) - y^{(1)} \right) \cdot z_j^{[1]}$$

LOCAL ERROR  $\partial_1^{[2]} = \left( h_1(a_1^{[2]}) - y^{(1)} \right) = ?$



Bias

1.  $a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$
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# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

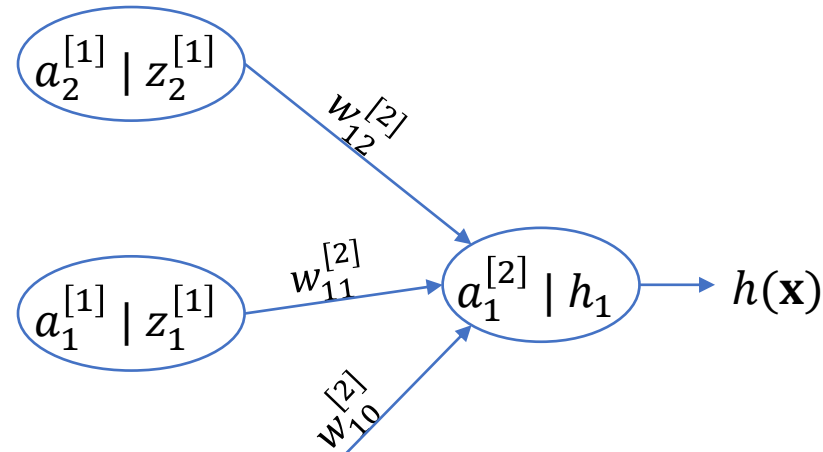
with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(ii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\delta_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = \left( h_1(a_1^{[2]}) - y^{(1)} \right) \cdot z_j^{[1]}$$



**LOCAL ERROR**

$$\begin{aligned} \delta_1^{[2]} &= \left( h_1(a_1^{[2]}) - y^{(1)} \right) \\ &= a_1^{[2]} - y^{(1)} = 0.42 - 1 = -0.58 \end{aligned}$$

1.  $a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$
2.  $z_1^{[1]} = 0.54, z_2^{[1]} = 0.54$
3.  $a_1^{[2]} = 0.42$

Bias

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

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(ii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = \left( h_1(a_1^{[2]}) - y^{(1)} \right) \cdot z_j^{[1]}$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{10}^{[2]}} = ?$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{11}^{[2]}} = ?$$

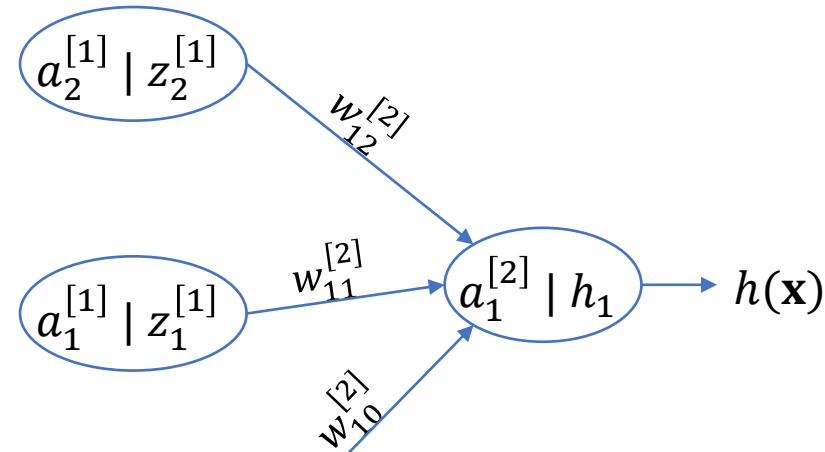
$$\frac{\partial \mathbb{E}_1}{\partial w_{12}^{[2]}} = ?$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

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Bias

1.  $a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$
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3.  $a_1^{[2]} = 0.42$

$$\partial_1^{[2]} = -0.58$$

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Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

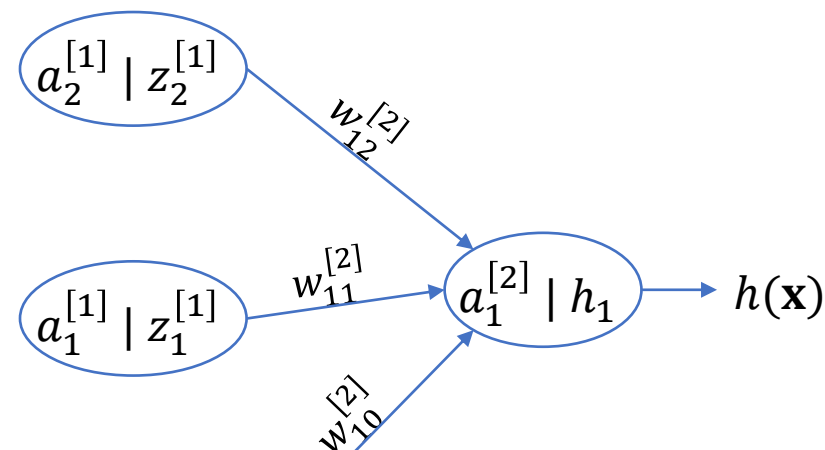
THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = \overbrace{\left( h_1(a_1^{[2]}) - y^{(1)} \right)}^{-0.58} \cdot z_j^{[1]}$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{10}^{[2]}} = -0.58 \cdot z_0^{[1]} = -0.58 \cdot 1 = -0.58$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{11}^{[2]}} = -0.58 \cdot z_1^{[1]} = -0.58 \cdot 0.54 = -0.31$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{12}^{[2]}} = -0.58 \cdot z_2^{[1]} = -0.58 \cdot 0.54 = -0.31$$



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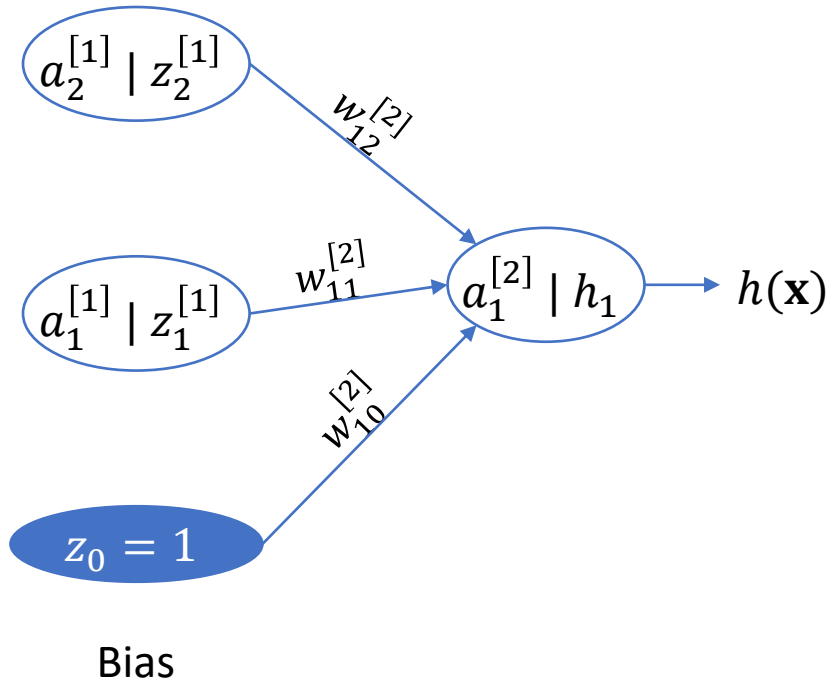
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$$\frac{\partial \mathbb{E}_1}{\partial w_{10}^{[2]}} = -0.58$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{11}^{[2]}} = -0.31$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{12}^{[2]}} = -0.31$$

**Gradient descent** for the weights of the output layer, with  $\alpha = 0.5$ ?

$$w_{10}^{[2]t+1} = w_{10}^{[2]t} - 0.5 \cdot (-0.58) = 0.2 + 0.29 = 0.49$$

$$w_{11}^{[2]t+1} = w_{11}^{[2]t} - 0.5 \cdot (-0.31) = 0.2 + 0.15 = 0.35$$

$$w_{12}^{[2]t+1} = w_{12}^{[2]t} - 0.5 \cdot (-0.31) = 0.2 + 0.15 = 0.35$$

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$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

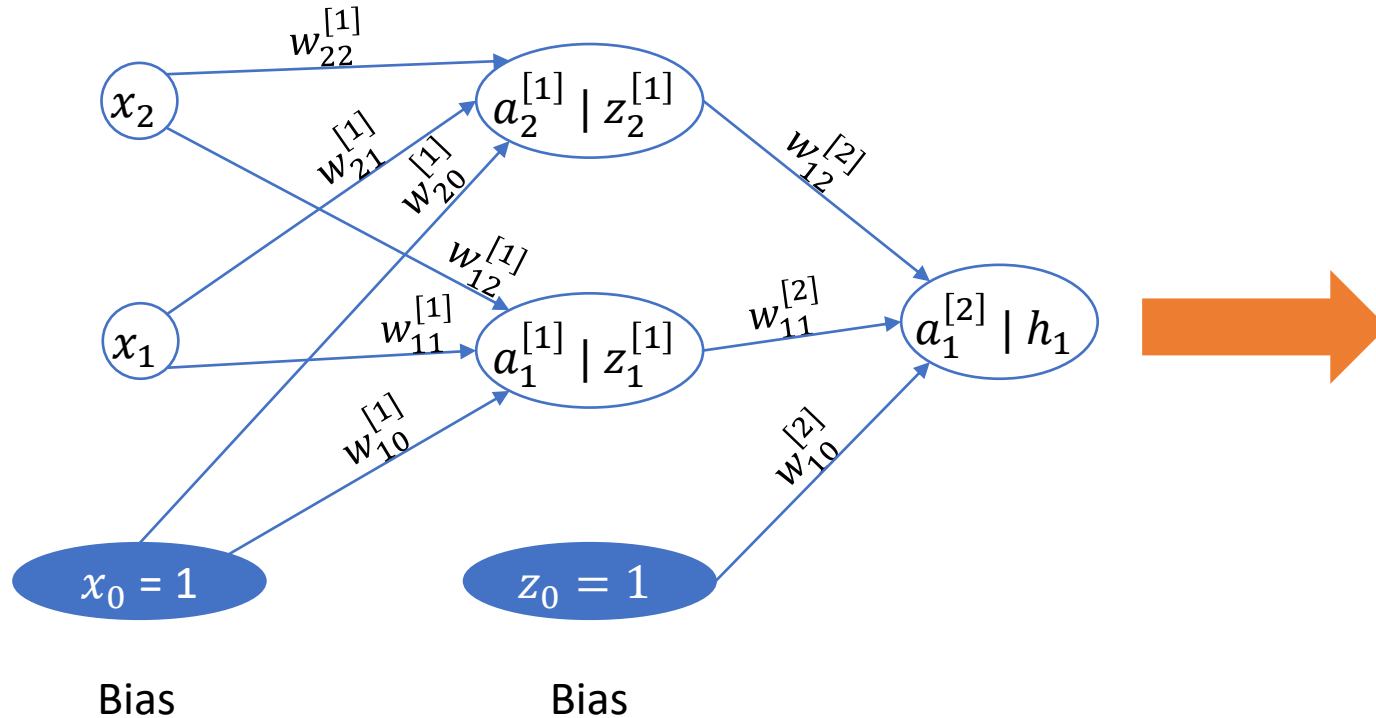
$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

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(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$ . Draw only the part of the graph and the relations involved.

Compute  $\partial_1^{[1]}$ ,  $\partial_2^{[1]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.



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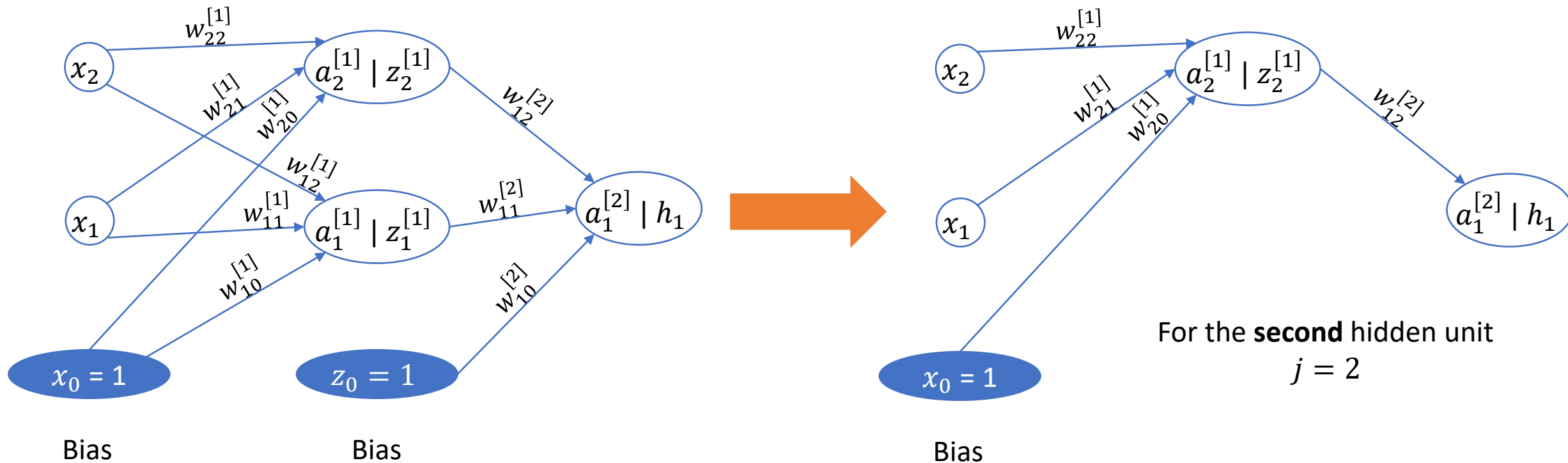
$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

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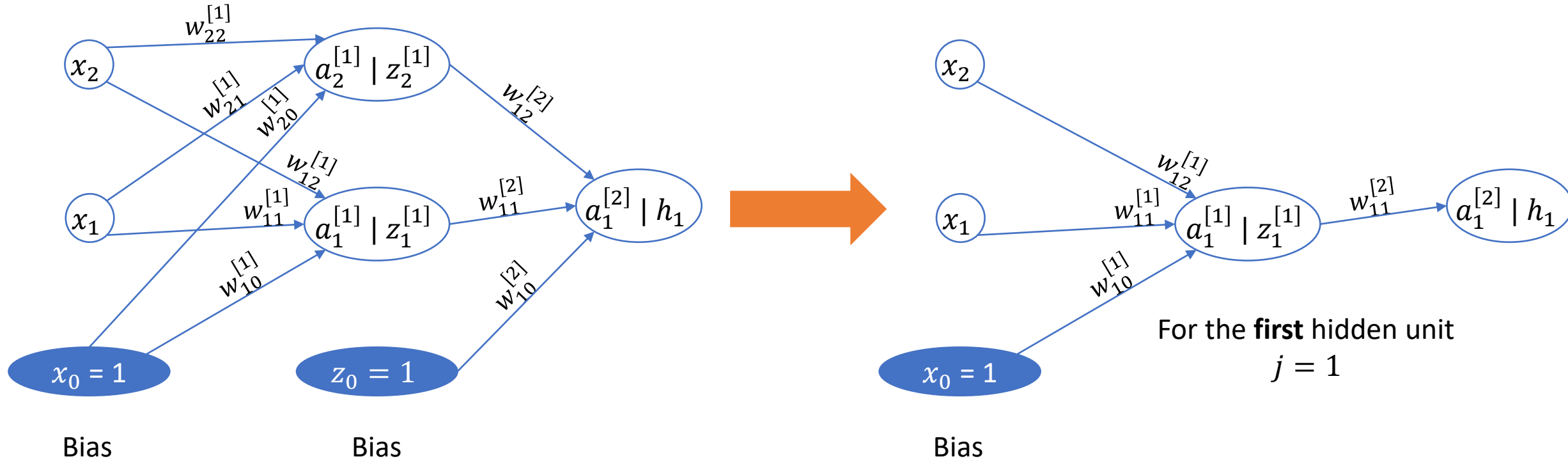
$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

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Compute  $\partial_1^{[1]}$ ,  $\partial_2^{[1]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.



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(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$ . Draw only the part of the graph and the relations involved.

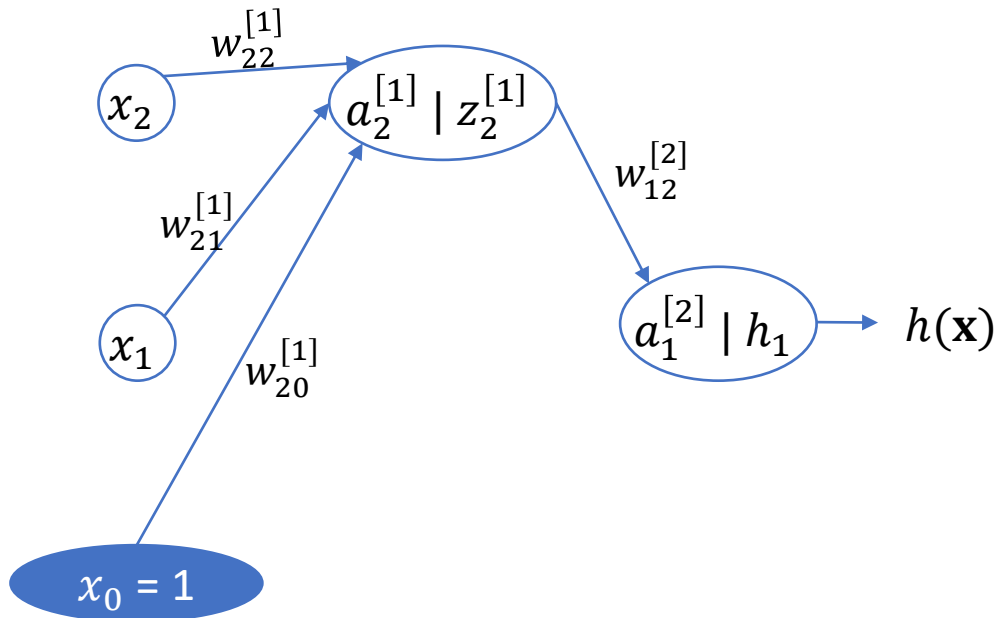
Compute  $\partial_1^{[1]}$ ,  $\partial_2^{[1]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

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We will proceed for the **second** hidden unit.

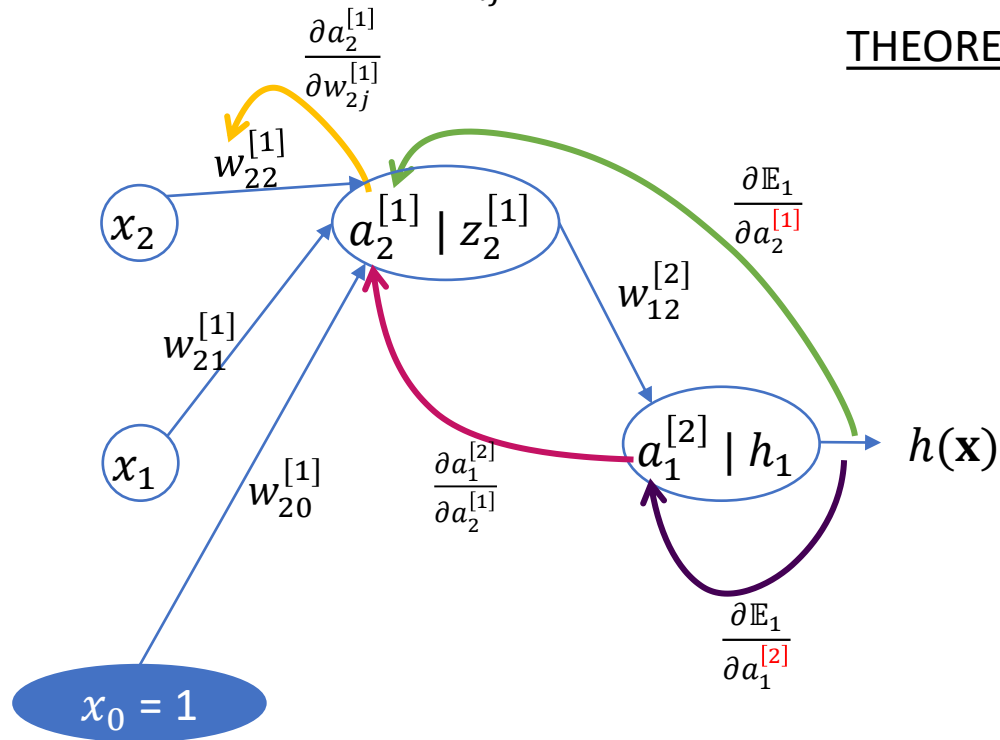
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(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$ .

Compute  $\partial_2^{[1]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.



THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}}$$

CHAIN RULE

LOCAL ERROR  $\partial_2^{[1]}$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}}$$

||  
 $\partial_1^{[2]}$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

$$a_1^{[2]} = \sum_{m=0}^2 w_{1m}^{[2]} z_m^{[1]} = \sum_{m=0}^2 w_{1m}^{[2]} \varphi(a_m^{[1]})$$

$$\mathbb{E}_1 = \frac{1}{2} (h(\mathbf{x}^{(1)}) - y^{(1)})^2 = \frac{1}{2} (h_1(a_1^{[2]}) - y^{(1)})^2$$

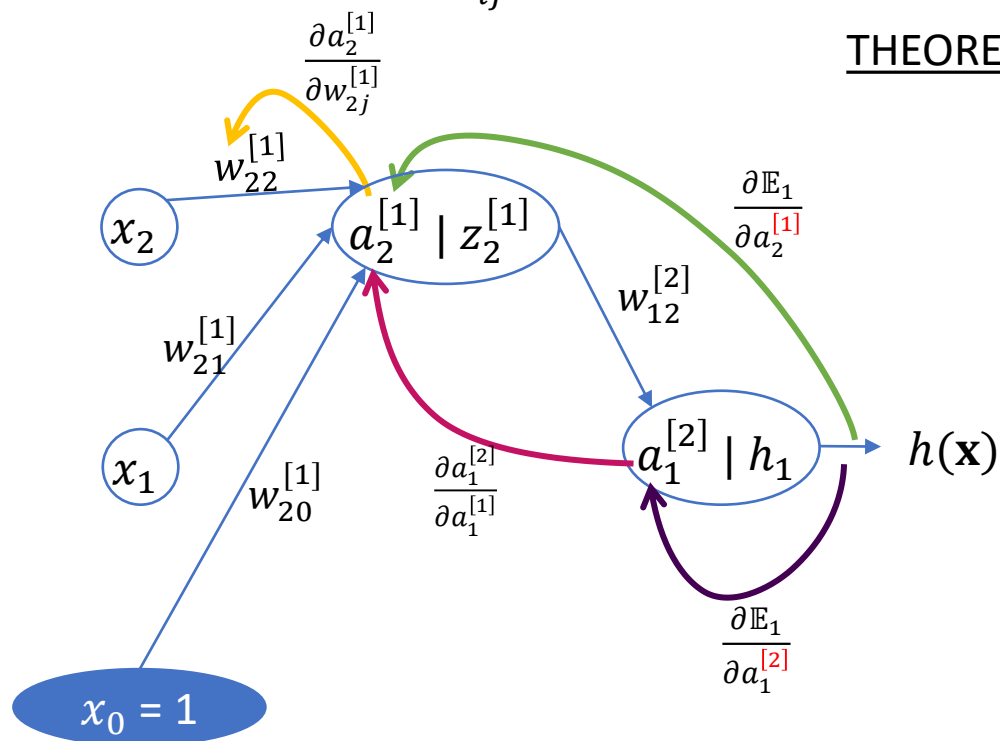
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(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$ .

Compute  $\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.



THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}}$$

$$= \begin{bmatrix} \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} & \frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} \end{bmatrix} \begin{bmatrix} \frac{\partial a_1^{[2]}}{\partial w_{2j}^{[1]}} \\ \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} \end{bmatrix}$$

CHAIN RULE

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = ?$$

$$\frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} = ?$$

$$\mathbb{E}_1 = \frac{1}{2} (h(\mathbf{x}^{(1)}) - y^{(1)})^2 = \frac{1}{2} (h_1(a_1^{[2]}) - y^{(1)})^2$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \delta_2^{[1]} \text{ LOCAL ERROR}$$

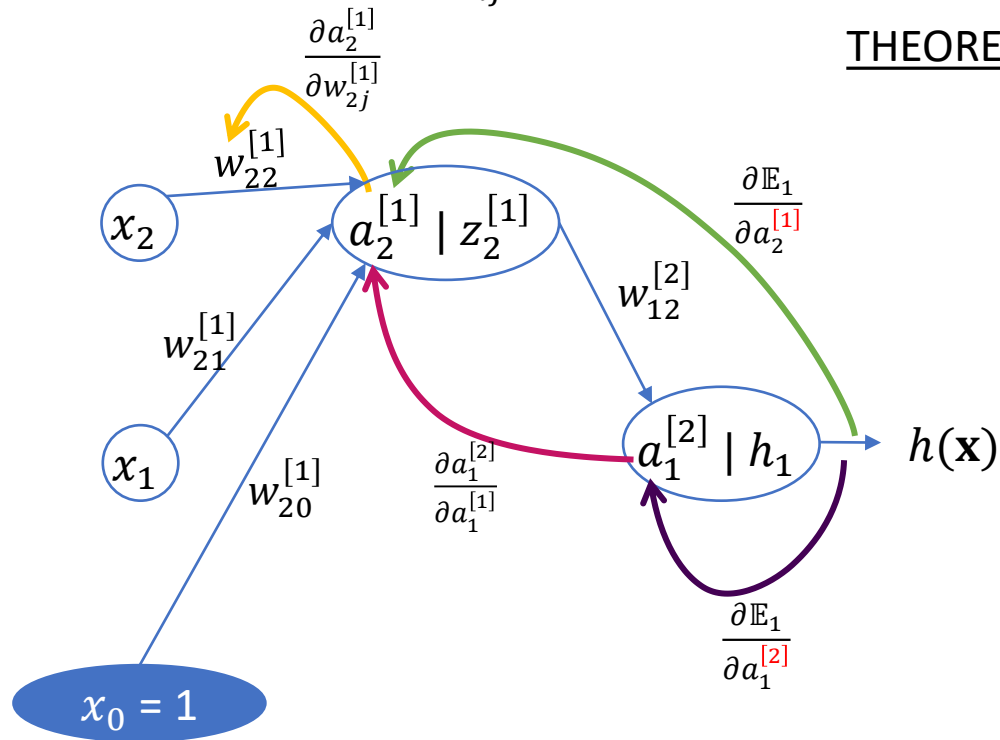
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$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \delta_2^{[1]} \text{ LOCAL ERROR}$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \left( \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \right) \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}}$$

CHAIN RULE

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = (h_1(a_1^{[2]}) - y^{(1)}) \cdot h'_1(a_1^{[2]}) = h_1(a_1^{[2]}) - y^{(1)}$$

$$\mathbb{E}_1 = \frac{1}{2} (h(\mathbf{x}^{(1)}) - y^{(1)})^2 = \frac{1}{2} (h_1(a_1^{[2]}) - y^{(1)})^2$$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}}$$

$$\frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} = ?$$



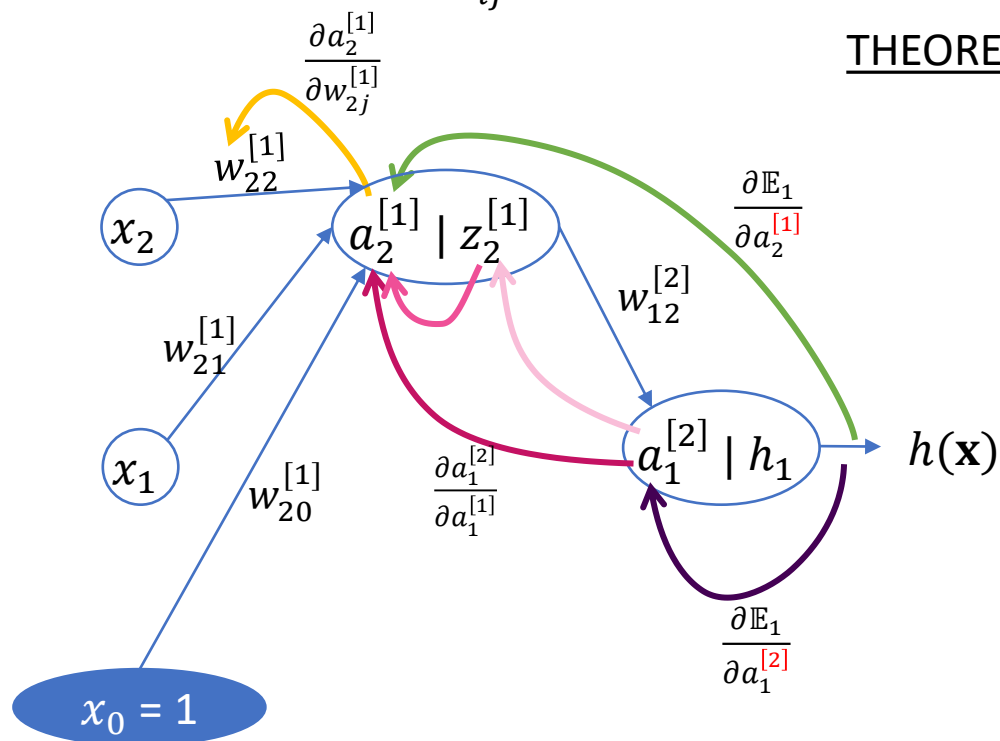
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$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \partial_2^{[1]} \quad \text{LOCAL ERROR}$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}}$$

CHAIN RULE

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = h_1(a_1^{[2]}) - y^{(1)} = \partial_1^{[2]}$$

$$a_1^{[2]} = \sum_{m=0}^2 w_{1m}^{[2]} z_m^{[1]} = \sum_{m=0}^2 w_{1m}^{[2]} \varphi(a_m^{[1]})$$

$$\frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} = \frac{\partial a_1^{[2]}}{\partial z_2^{[1]}} \frac{\partial z_2^{[1]}}{\partial a_2^{[1]}} = ?$$

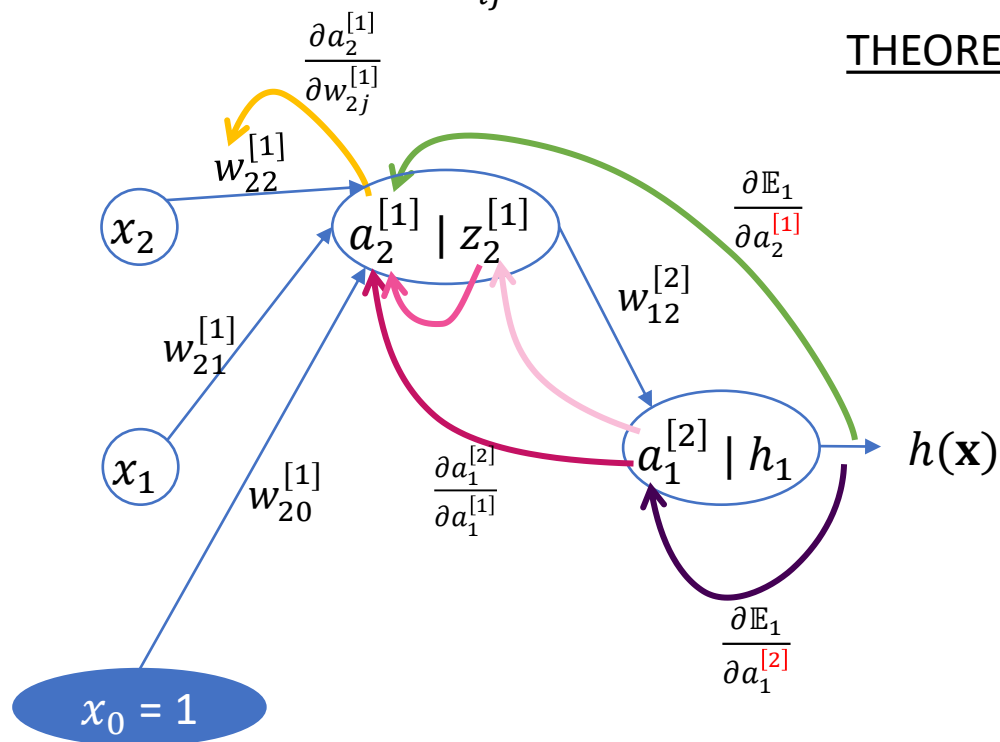
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$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \delta_2^{[1]} \text{ LOCAL ERROR}$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \left[ \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \right] \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}}$$

CHAIN RULE

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = h_1(a_1^{[2]}) - y^{(1)} = \delta_1^{[2]}$$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}}$$

$$\frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} = \frac{\partial a_1^{[2]}}{\partial z_2^{[1]}} \frac{\partial z_2^{[1]}}{\partial a_2^{[1]}}$$

$$= \frac{\partial}{\partial z_2^{[1]}} \{ w_{10}^{[2]} z_0^{[1]} + w_{11}^{[2]} z_1^{[1]} + w_{12}^{[2]} z_2^{[1]} \} \frac{\partial}{\partial a_2^{[1]}} \varphi(a_2^{[1]})$$

Activation function

$\sigma$

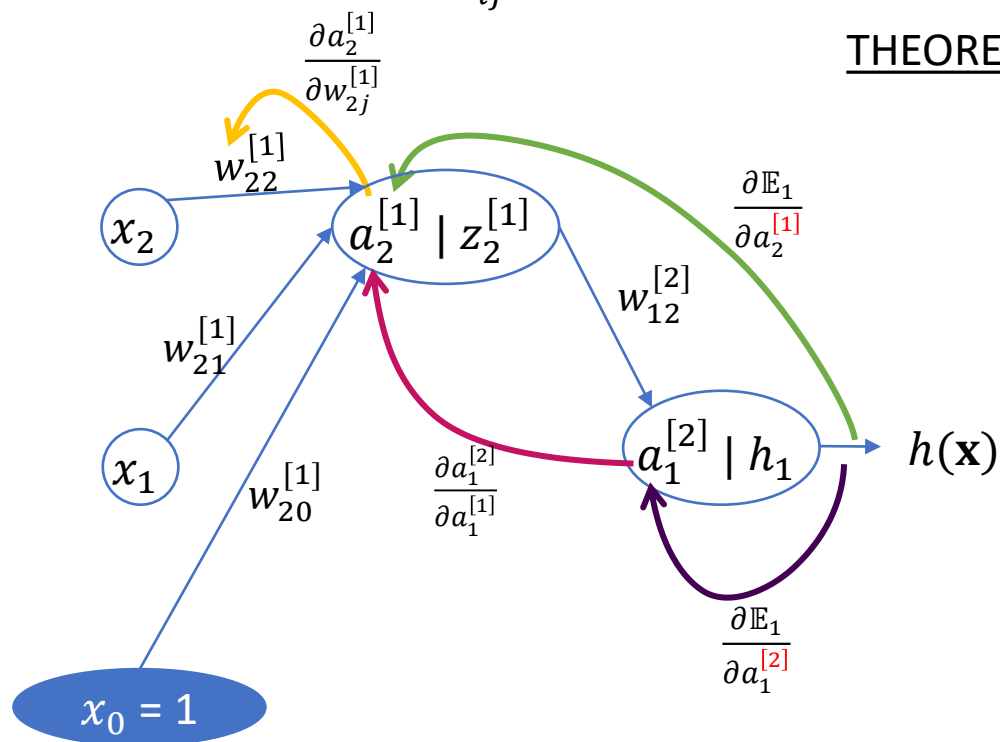
# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$ .

Compute  $\partial_2^{[1]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.



THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}}$$

$$= \begin{pmatrix} \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} & \frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} \end{pmatrix} \begin{pmatrix} \frac{\partial a_1^{[2]}}{\partial w_{2j}^{[1]}} \\ \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} \end{pmatrix}$$

CHAIN RULE

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = h_1(a_1^{[2]}) - y^{(1)} = \partial_1^{[2]}$$

$$\begin{aligned} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} &= \frac{\partial a_1^{[2]}}{\partial z_2^{[1]}} \frac{\partial z_2^{[1]}}{\partial a_2^{[1]}} \\ &= w_{12}^{[2]} \sigma'(a_2^{[1]}) \end{aligned}$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \partial_2^{[1]} \text{ LOCAL ERROR}$$

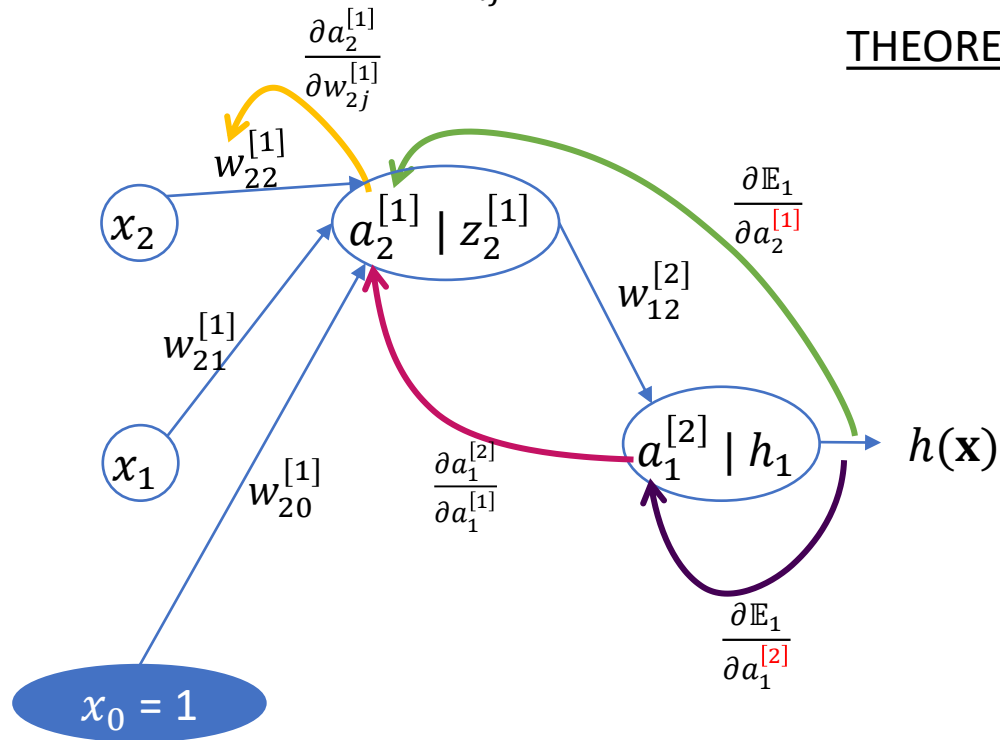
# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$ .

Compute  $\partial_2^{[1]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.



THEORETICALLY:

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \partial_2^{[1]} \text{ LOCAL ERROR}$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \begin{bmatrix} \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} & \frac{\partial \mathbb{E}_1}{\partial a_2^{[2]}} \end{bmatrix} \begin{bmatrix} \frac{\partial a_1^{[2]}}{\partial w_{2j}^{[1]}} \\ \frac{\partial a_2^{[2]}}{\partial w_{2j}^{[1]}} \end{bmatrix}$$

CHAIN RULE

$$\text{LOCAL ERROR } \partial_2^{[1]} \quad \frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \begin{bmatrix} \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} & \frac{\partial \mathbb{E}_1}{\partial a_2^{[2]}} \end{bmatrix} = \partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]})$$

$$\frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} = ?$$

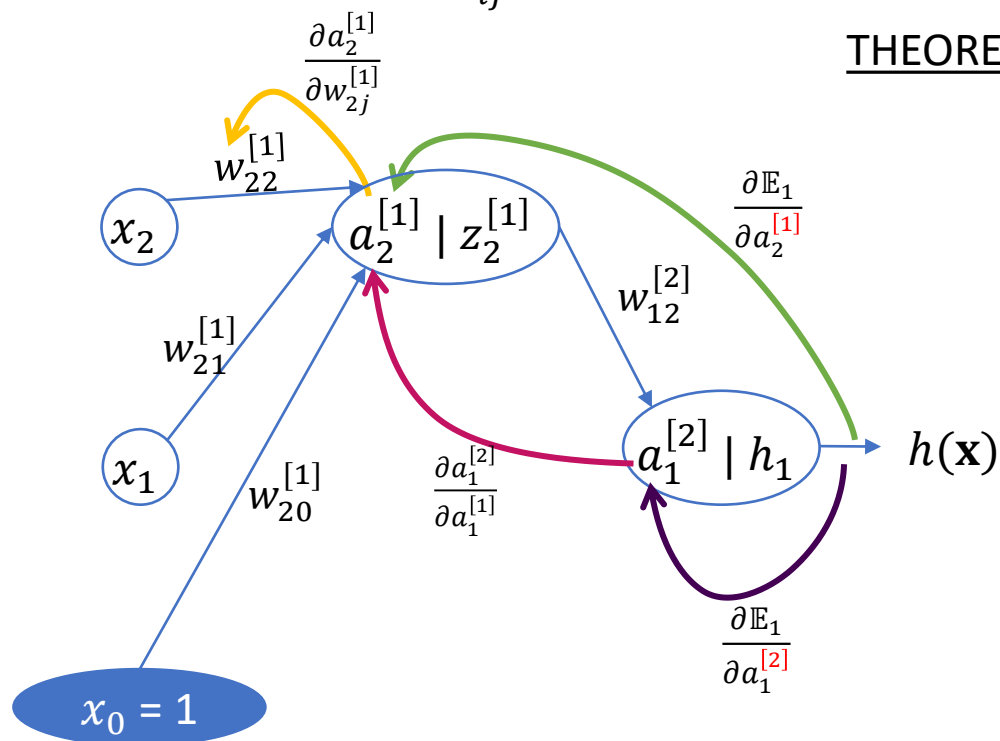
# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$ .

Compute  $\partial_2^{[1]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}}$  for all the parameters involved.



THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}}$$

$$= \begin{bmatrix} \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} & \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \end{bmatrix} \begin{bmatrix} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} \end{bmatrix}$$

CHAIN RULE

LOCAL ERROR  
 $\partial_2^{[1]}$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \begin{bmatrix} \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} & \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \end{bmatrix} = \partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]})$$

$$\frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} = \frac{\partial}{\partial w_{2j}^{[1]}} \{w_{10}^{[1]} x_0 + w_{11}^{[1]} x_1 + w_{12}^{[1]} x_2\} = x_j$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \partial_2^{[1]} \text{ LOCAL ERROR}$$

# EXERCICE 1

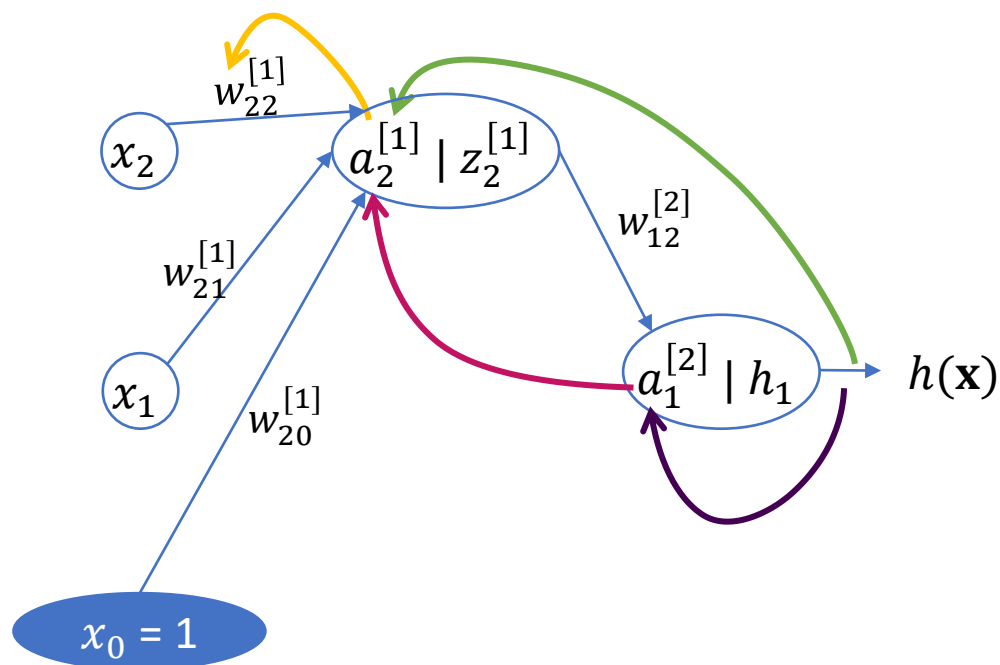
(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

THEORETICALLY:



$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

$$\frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \partial_2^{[1]} \text{ LOCAL ERROR}$$

$$\begin{aligned} \frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} &= \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} = \\ &= \partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]}) x_j \end{aligned}$$

# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

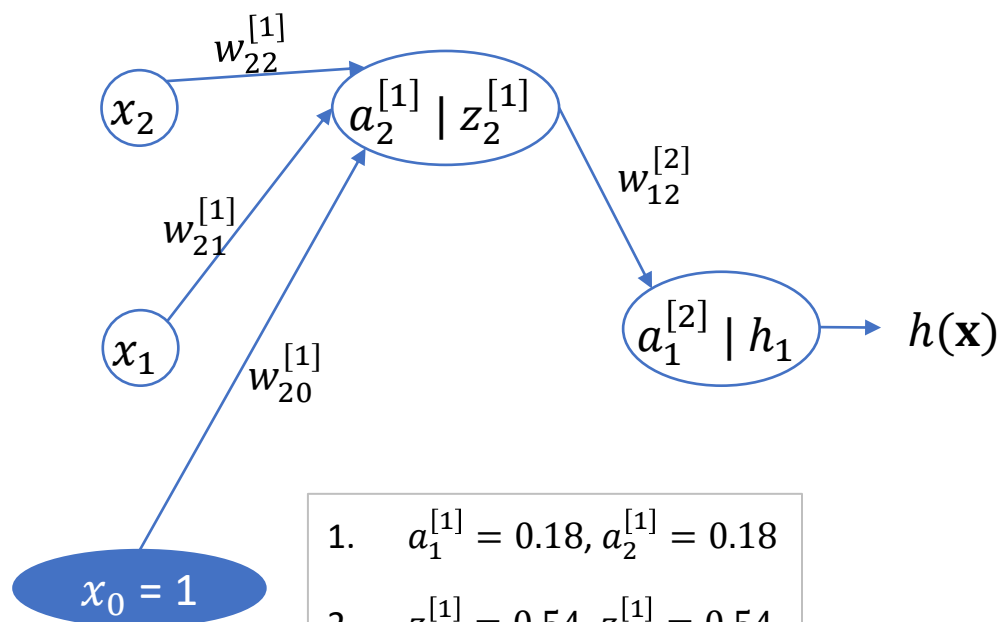
(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

THEORETICALLY:

$$\begin{aligned} \frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} &= \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} = \\ &= \partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]}) x_j \end{aligned}$$

$$\partial_2^{[1]} = ?$$



1.  $a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$
2.  $z_1^{[1]} = 0.54, z_2^{[1]} = 0.54$
3.  $a_1^{[2]} = 0.42$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$\begin{aligned} h_k &= \varphi(a_k^{[2]}) & a_k^{[2]} &= \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]} \\ z_m^{[1]} &= \varphi(a_m^{[1]}) & a_m^{[1]} &= \sum_{d=0}^D w_{md}^{[1]} x_d \end{aligned}$$

LOCAL ERROR

# EXERCICE 1

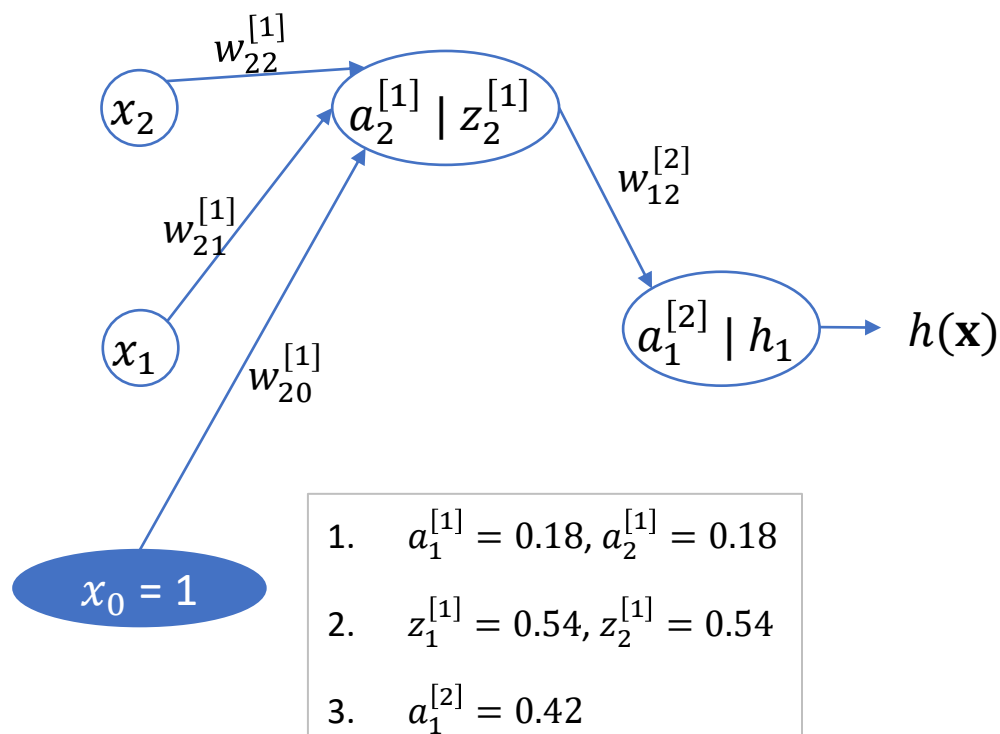
(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

THEORETICALLY:



$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

LOCAL ERROR

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} =$$

$$= \partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]}) x_j$$

$$\partial_2^{[1]} = \frac{\partial \mathbb{E}_1}{\partial a_2^{[1]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} = \partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]})$$

$$= (h_1(a_1^{[2]}) - y^{(1)}) w_{12}^{[2]} \sigma(a_2^{[1]}) (1 - \sigma(a_2^{[1]}))^2$$

$$= (0.42 - 1) 0.2 \sigma(0.18) (1 - \sigma(0.18)) = -0.03$$



# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

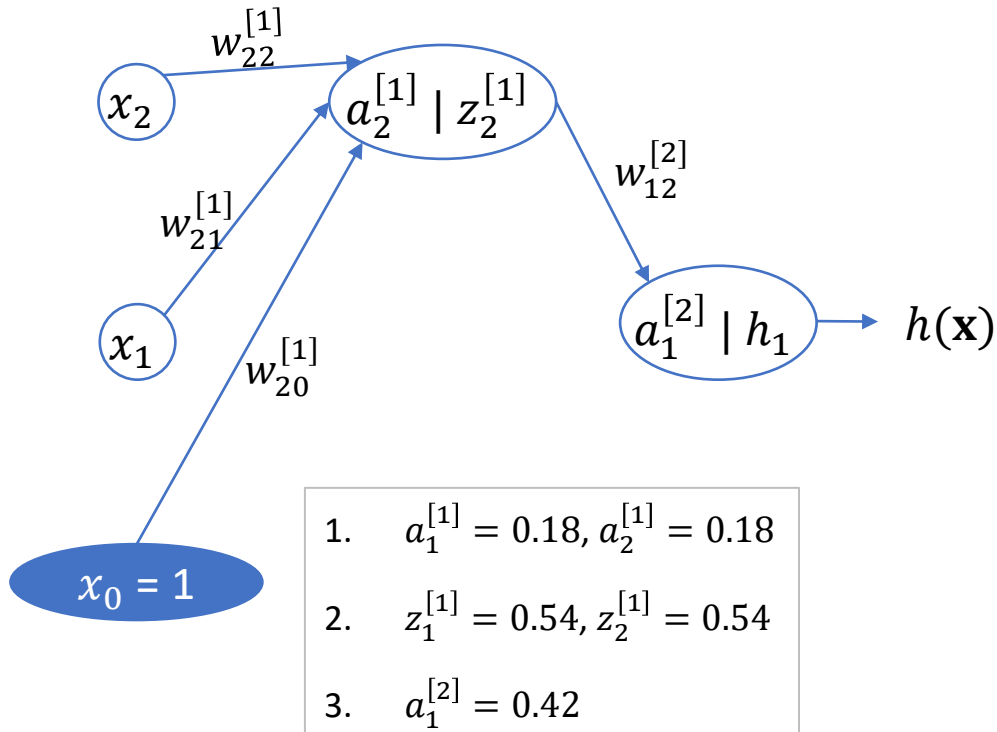
THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} = \overbrace{\partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]})}^{\partial_2^{[1]} = -0.03} x_j$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{20}^{[1]}} = ?$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{21}^{[1]}} = ?$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{22}^{[1]}} = ?$$



1.  $a_1^{[1]} = 0.18, a_2^{[1]} = 0.18$
2.  $z_1^{[1]} = 0.54, z_2^{[1]} = 0.54$
3.  $a_1^{[2]} = 0.42$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

# EXERCICE 1

(c)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.42$

with  $h_1(a_1^{[2]}) = a_1^{[2]}$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

(iii) We want to calculate the  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$ .

Compute  $\partial_1^{[2]}$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}}$  for all the parameters involved.

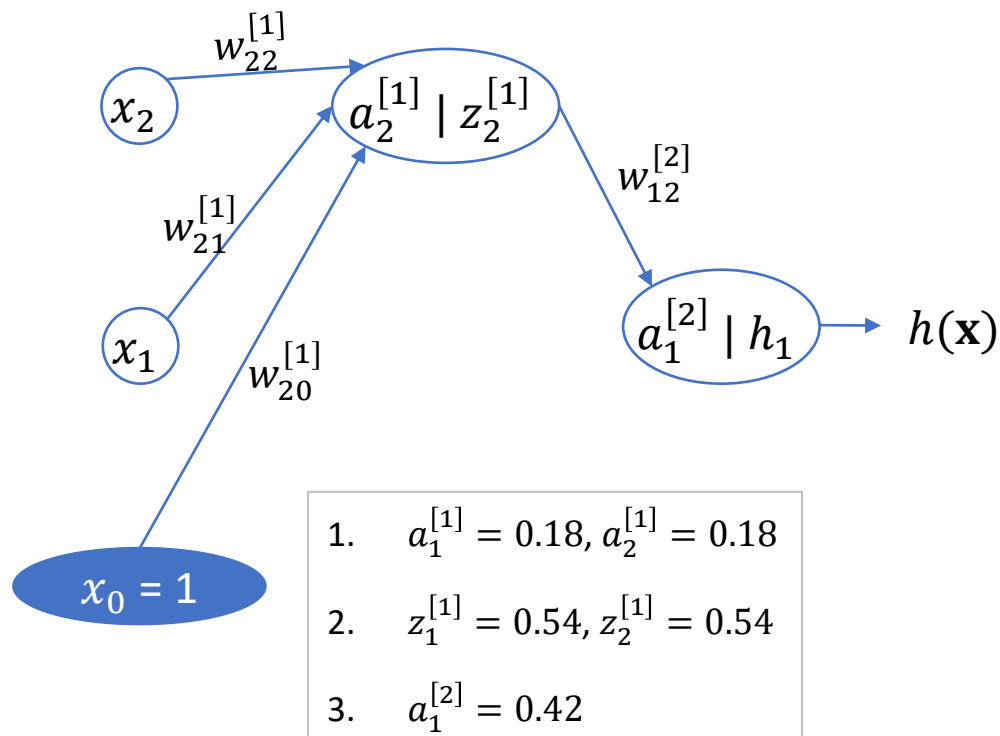
THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{2j}^{[1]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial a_2^{[1]}} \frac{\partial a_2^{[1]}}{\partial w_{2j}^{[1]}} = \overbrace{\partial_1^{[2]} w_{12}^{[2]} \sigma'(a_2^{[1]})}^{\partial_2^{[1]} = -0.03} x_j$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{20}^{[1]}} = -0.03 \cdot 1 = -0.03$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{21}^{[1]}} = -0.03 \cdot 0.3 = -0.009$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{22}^{[1]}} = -0.03 \cdot 0.5 = -0.015$$



$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

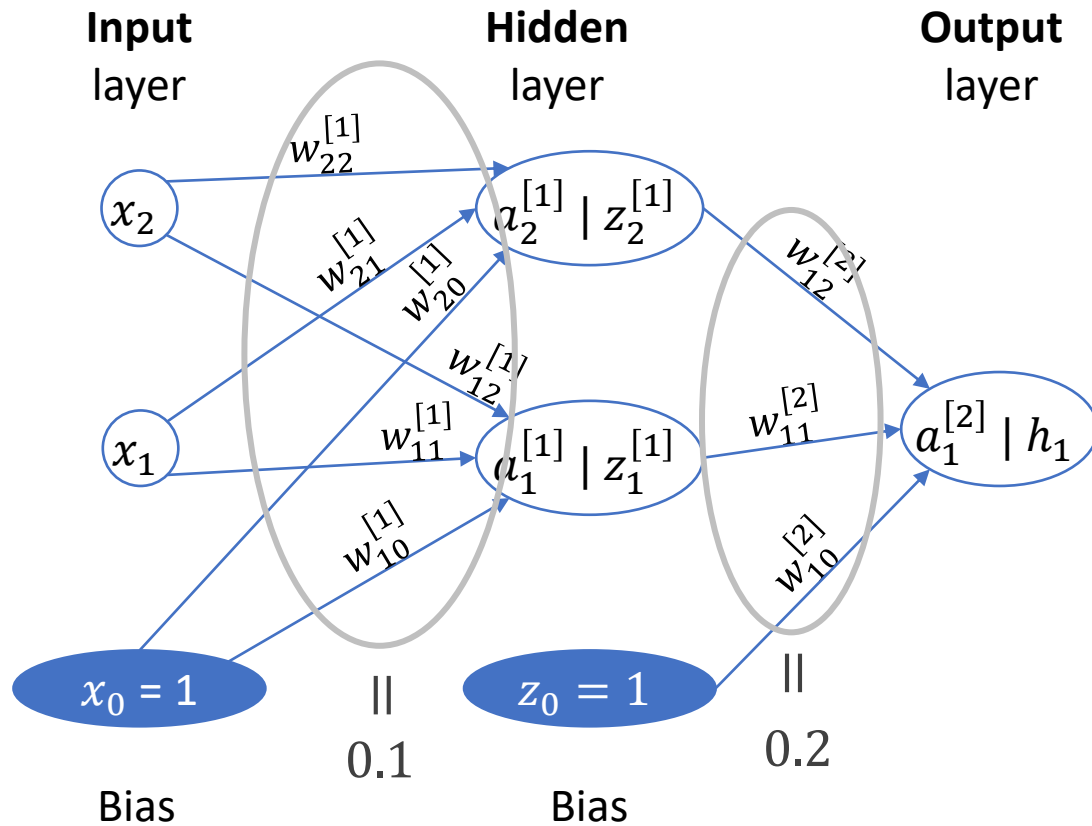
$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

# EXERCICE 1

(d) Same exercise as (c) but with the **sigmoid** for the activation function in the output layer and the **cross-entropy error**.



## NEW INFORMATION

$$h_1 = \varphi(a_1^{[2]}) = \sigma(a_1^{[2]})$$

$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

## TODO

$$h(\mathbf{x}^{(1)}) = ?$$

$$(i) \mathbb{E}_1 = ?$$

$$(ii) \partial_1^{[2]} = ? \text{ and } \frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}} = ?$$

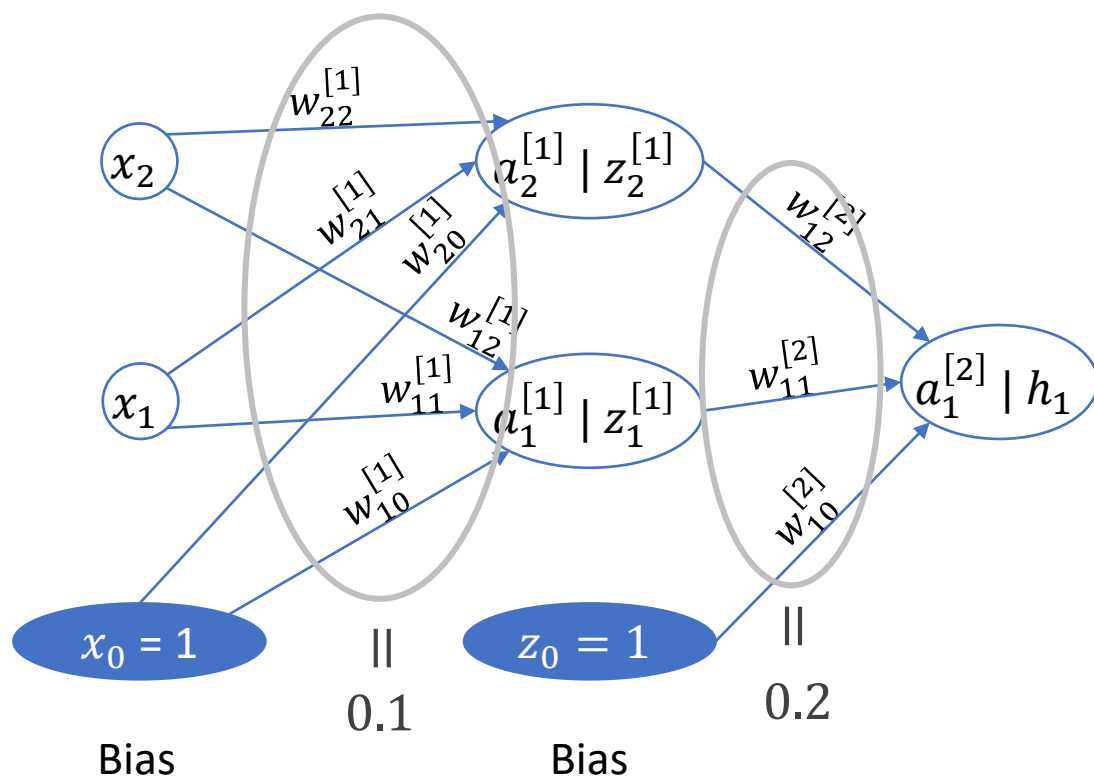
$$(iii) \partial_1^{[1]} = ?, \partial_2^{[1]} = ? \text{ and } \frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}} = ?$$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = ?$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$



$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

1. Compute  $a_1^{[1]}$  and  $a_2^{[1]}$ .
2. Compute  $z_1^{[1]}$  and  $z_2^{[1]}$ .
3. Compute  $a_1^{[2]}$ .
4. Compute  $h_1$ .

$$a_1^{[1]} = ?$$

$$a_2^{[1]} = ?$$

$$z_1^{[1]} = ?$$

$$z_2^{[1]} = ?$$

$$a_1^{[2]} = ?$$

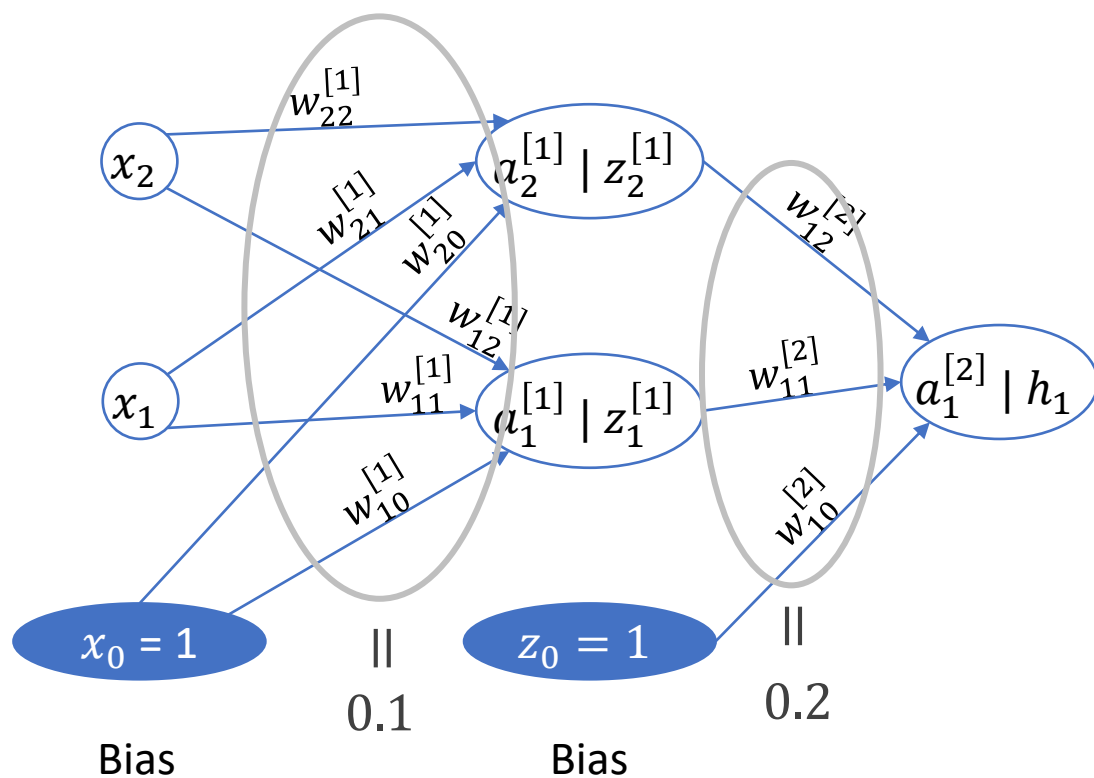
$$h_1 = ?$$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = ?$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$



$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

$$a_1^{[1]} = 0.18$$

$$a_2^{[1]} = 0.18$$

$$z_1^{[1]} = \sigma(0.18) = 0.54$$

$$z_2^{[1]} = \sigma(0.18) = 0.54$$

$$a_1^{[2]} = 0.42$$

$$h_1 = \sigma(0.42) = 0.60$$

$$\Rightarrow h(\mathbf{x}^{(1)}) = 0.60$$

1. Compute  $a_1^{[1]}$  and  $a_2^{[1]}$ .
2. Compute  $z_1^{[1]}$  and  $z_2^{[1]}$ .
3. Compute  $a_1^{[2]}$ .
4. Compute  $h_1$ .

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

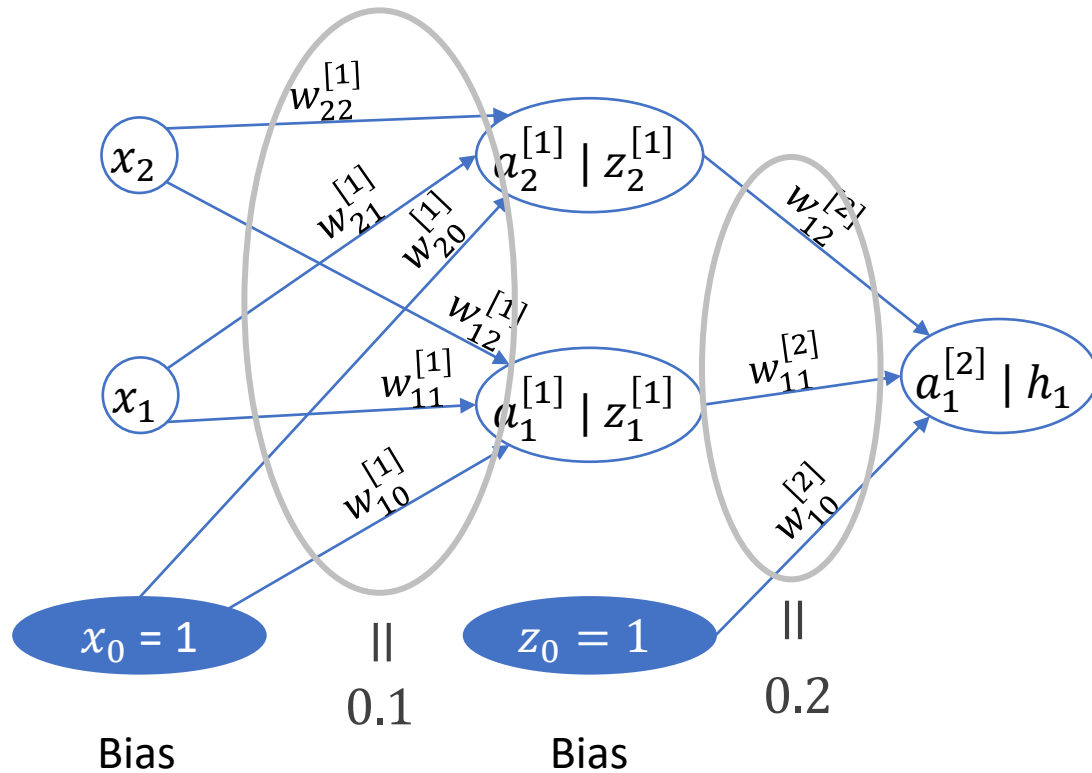
$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



(i)  $\mathbb{E}_1 = ?$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

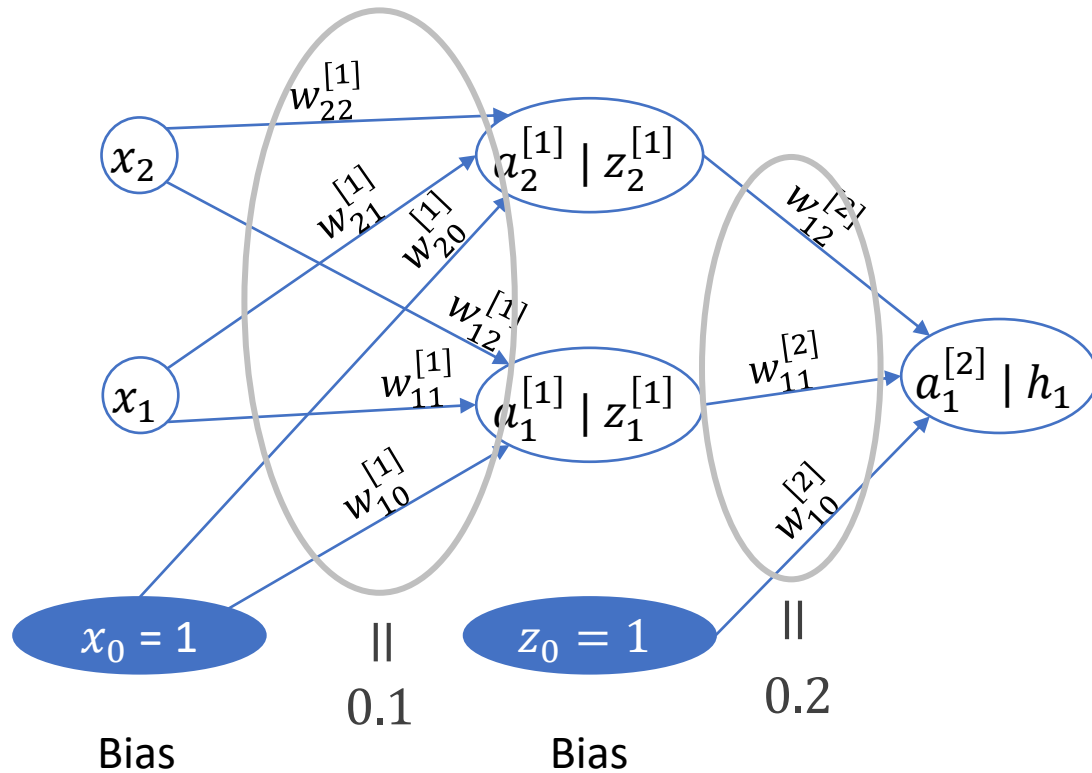
$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



(i)  $\mathbb{E}_1 = -1 \ln 0.60 - (1 - 1) \ln(1 - 0.60) = 0.51$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

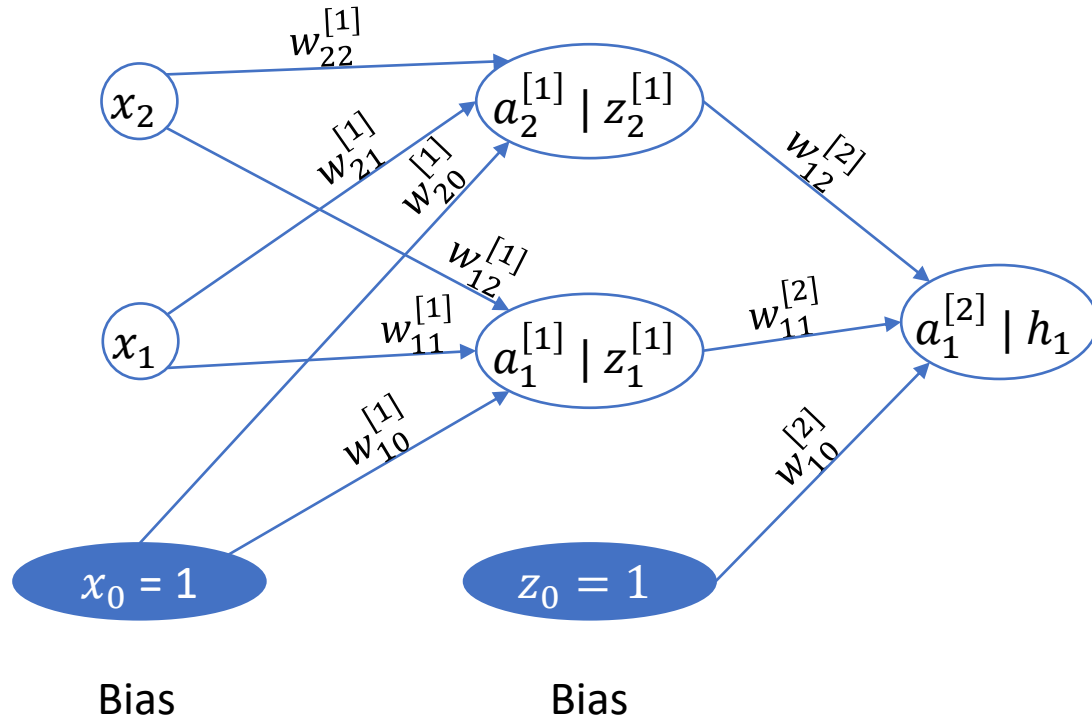
$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



(ii)  $\partial_1^{[2]} = ?$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[2]}} = ?$



# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

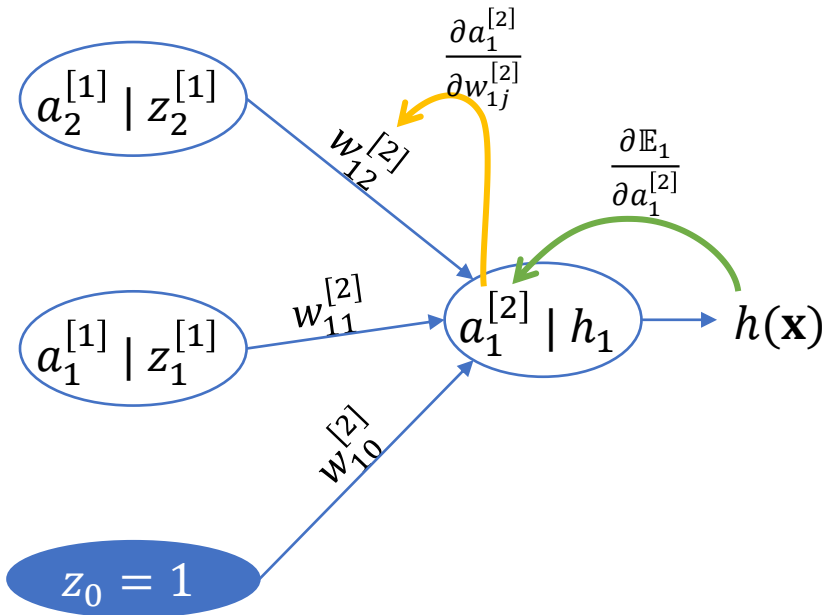
$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}}$$

CHAIN RULE



Bias

LOCAL ERROR

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}}$$

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = ?$$

$$\frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = ?$$

$$\mathbb{E}_1 = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$= -y^{(n)} \ln h_1(a_1^{[2]}) - (1 - y^{(n)}) \ln(1 - h_1(a_1^{[2]}))$$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

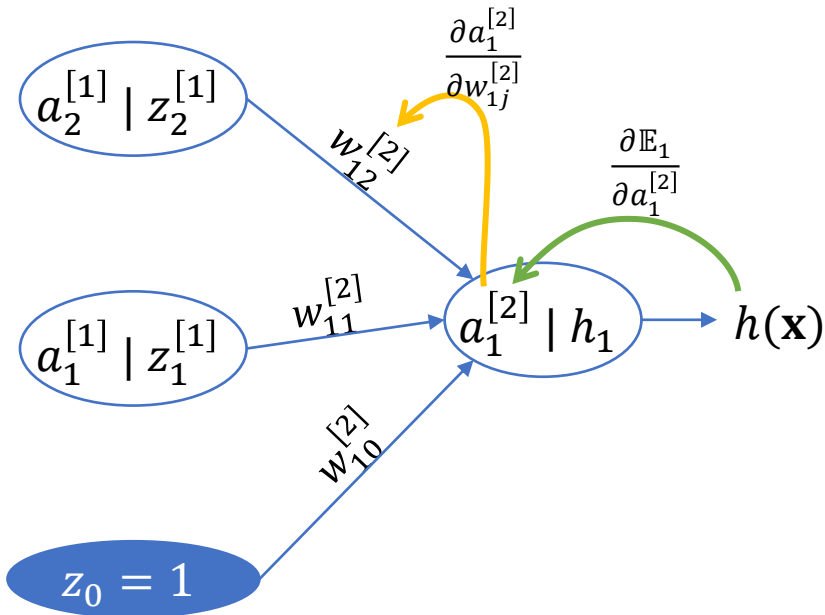
$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} \quad \text{CHAIN RULE}$$



Bias

LOCAL ERROR

$$\frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} = -\frac{y^{(n)}}{h_1(a_1^{[2]})} h_1'(a_1^{[2]}) + \frac{1 - y^{(n)}}{1 - h_1(a_1^{[2]})} h_1'(a_1^{[2]})$$

$$= -y^{(n)} (1 - h_1(a_1^{[2]})) + (1 - y^{(n)}) h_1(a_1^{[2]})$$

$$= -y^{(n)} + h_1(a_1^{[2]})$$

$$\frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = z_j^{[1]}$$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

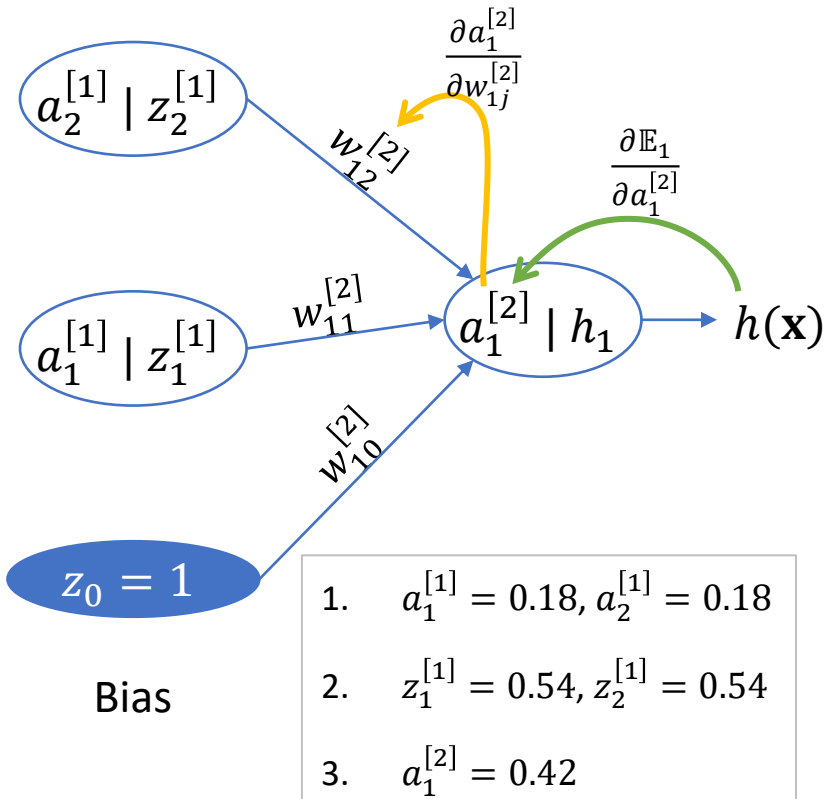
$$\sigma'(a) = \sigma(a)(1 - \sigma(a))$$

$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$

THEORETICALLY:

$$\frac{\partial \mathbb{E}_1}{\partial w_{1j}^{[2]}} = \frac{\partial \mathbb{E}_1}{\partial a_1^{[2]}} \frac{\partial a_1^{[2]}}{\partial w_{1j}^{[2]}} = (h_1(a_1^{[2]}) - y^{(n)}) z_j^{[1]}$$



**LOCAL ERROR**  $\delta_1^{[2]} = h_1(a_1^{[2]}) - y^{(n)} = \sigma(0.42) - 1 = -0.4$

$$\frac{\partial \mathbb{E}_1}{\partial w_{10}^{[2]}} = -0.4 \cdot 1 = -0.4$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{11}^{[2]}} = -0.21$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{12}^{[2]}} = -0.21$$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

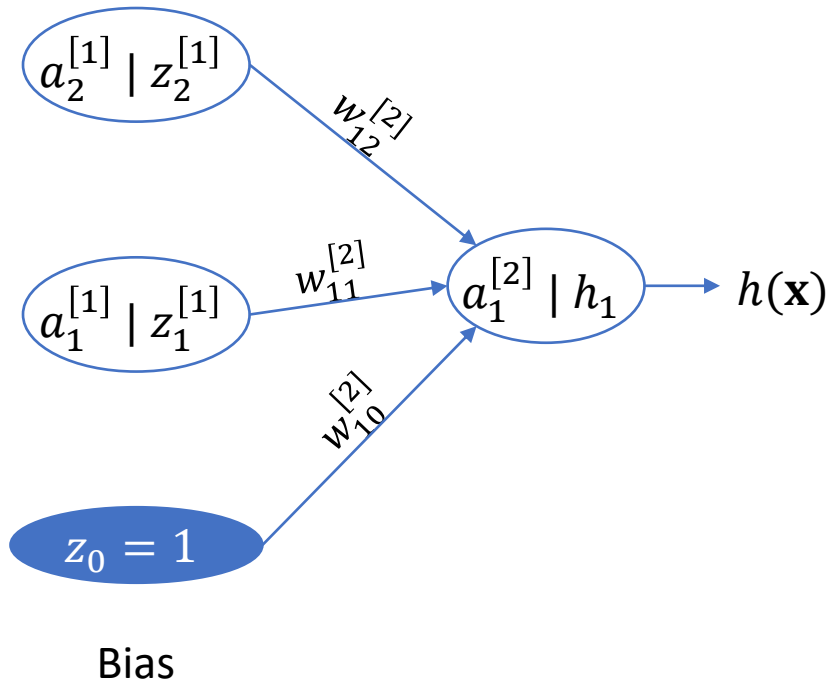
$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

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$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



$$\frac{\partial \mathbb{E}_1}{\partial w_{10}^{[2]}} = -0.4$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{11}^{[2]}} = -0.2$$

$$\frac{\partial \mathbb{E}_1}{\partial w_{12}^{[2]}} = -0.2$$

**Gradient descent** for the weights of the output layer, with  $\alpha = 0.5$ ?

$$w_{10}^{[2]t+1} = w_{10}^{[2]t} - 0.5 \cdot (-0.4) = 0.2 + 0.2 = 0.4$$

$$w_{11}^{[2]t+1} = w_{11}^{[2]t} - 0.5 \cdot (-0.2) = 0.2 + 0.1 = 0.3$$

$$w_{12}^{[2]t+1} = w_{12}^{[2]t} - 0.5 \cdot (-0.2) = 0.2 + 0.1 = 0.3$$

# EXERCICE 1

(d)  $\mathbf{x}^{(1)} = \begin{pmatrix} 0.3 \\ 0.5 \end{pmatrix}$  with  $y^{(1)} = 1 \longrightarrow h(\mathbf{x}^{(1)}) = 0.60$

with  $h_1(a_1^{[2]}) = \sigma(a_1^{[2]})$  and  $z_m = \varphi(a_m^{[1]}) = \sigma(a_m^{[1]})$

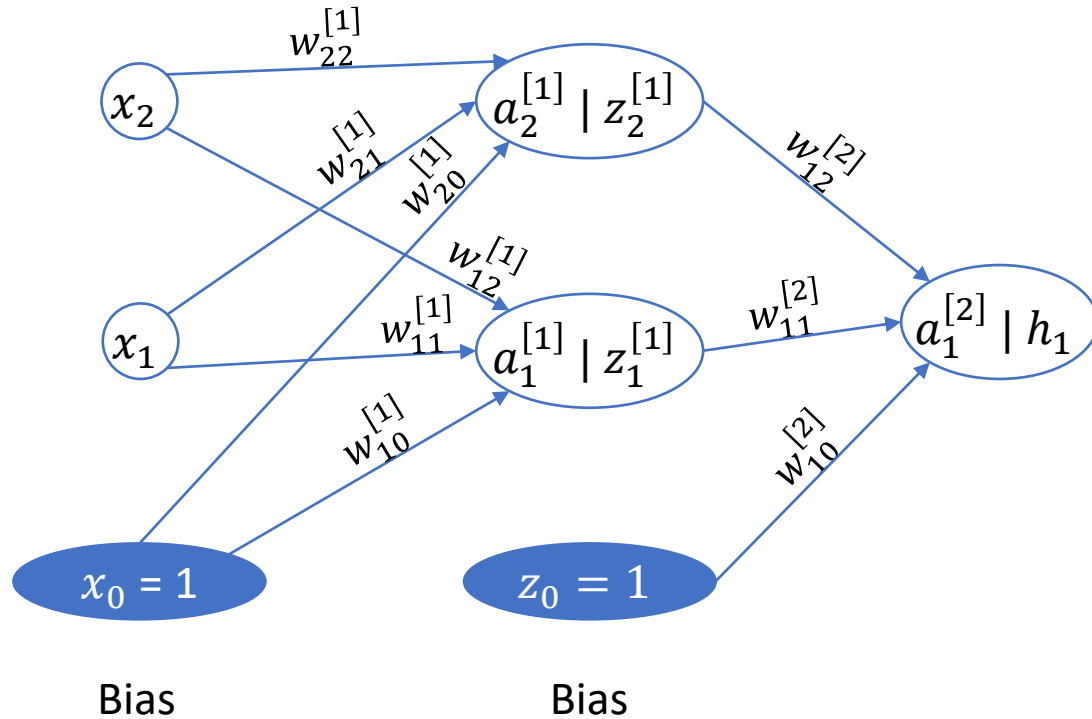
$$\mathbb{E}_n = -y^{(n)} \ln h(\mathbf{x}^{(n)}) - (1 - y^{(n)}) \ln(1 - h(\mathbf{x}^{(n)}))$$

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

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$$h_k = \varphi(a_k^{[2]}) \quad a_k^{[2]} = \sum_{m=0}^M w_{km}^{[2]} z_m^{[1]}$$

$$z_m^{[1]} = \varphi(a_m^{[1]}) \quad a_m^{[1]} = \sum_{d=0}^D w_{md}^{[1]} x_d$$



(iii)  $\partial_1^{[1]} = ?$ ,  $\partial_2^{[1]} = ?$  and  $\frac{\partial \mathbb{E}_1}{\partial w_{ij}^{[1]}} = ?$

SAME AS BEFORE