

# Homework Assignment N°4

BML36

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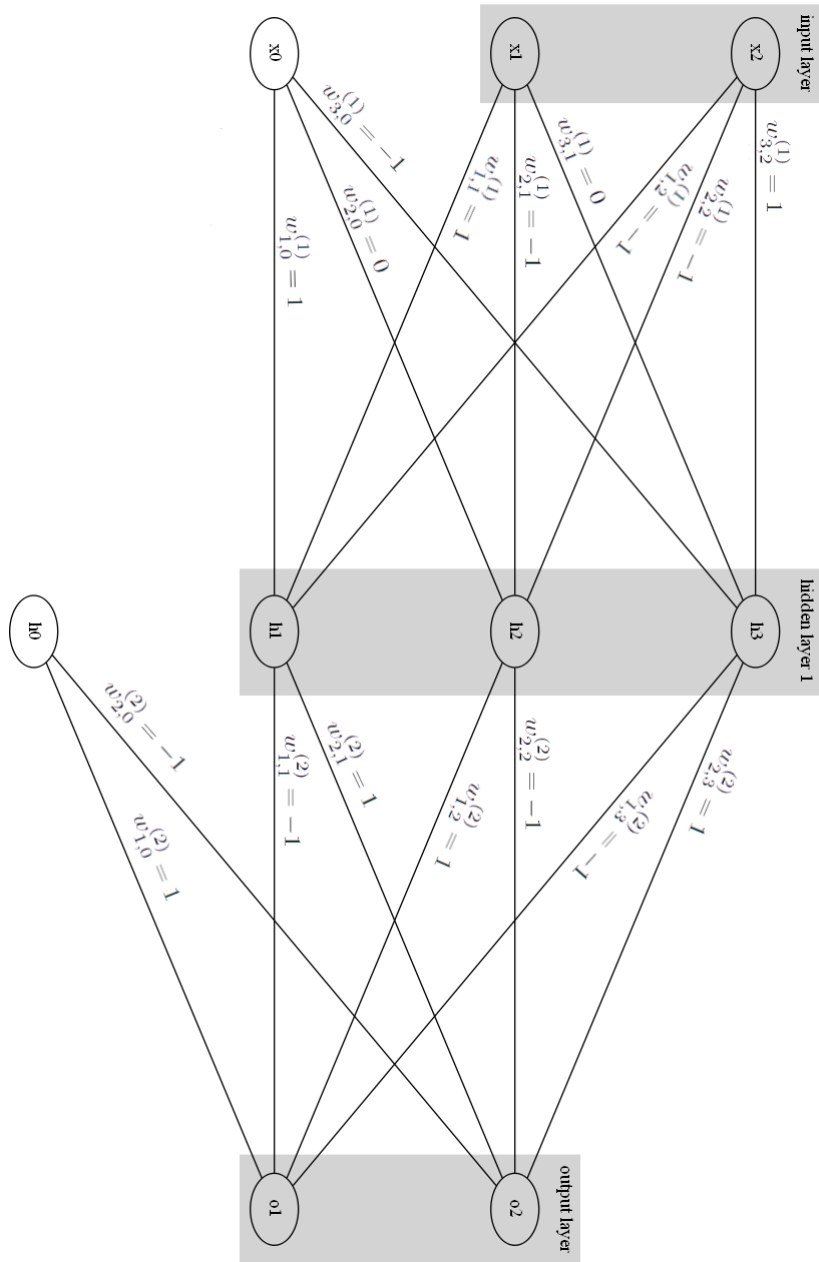
## 1 Exercise 1: NN 1-D output

### 1.1 Part a

## 2 Exercise 2: NN 2-D output

### 2.1 Part a

The neural network described in this exercise could be represented like this.



It is structured in 3 parts: the input layer first (denoted  $x1, x2$ ), then the hidden layer (denoted  $h1, h2$  and  $h3$ ) and then the output layer (denoted  $o1$  and  $o2$ ). Nodes with indice 0 represent the bias introduced into the model.

Each arc carries the value of the weight (denoted  $w_{k,j}^{(l)}$  where  $l$  is the layer,  $k$  is the destination node and  $j$  is the origin node which lies in the layer  $l - 1$ ).

To compute the output of the neural network, we need to propagate through the network the values of the input. Hidden layer applies a sigmoïd activation function and output neurons have a linear activation function (identity function).

Thus we can first compute every  $a_k^{(1)}$ , the signal recieved by each node in the hidden layer. It is easier to make this computation under matrix representation, let's introduce the input vector  $X$  and the weights of the first layer  $W^{(1)}$ :

$$X = [a_i^{(0)}] = [x_i] = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$W^{(1)} = [w_{j,i}^{(1)}] = \begin{bmatrix} 1 & 0 & -1 \\ 1 & -1 & 0 \\ -1 & -1 & 1 \end{bmatrix}$$

The signal recieved by the hidden layer is given by the following formula:

$$H_{j \neq 0} = [a_j^{(1)}]_{j \neq 0} = X^T W^{(1)} = \begin{bmatrix} 1 \\ -2 \\ 0 \end{bmatrix}$$

Before repeating the same procedure, we need to apply the activation function to each recieved signal and then concatenate the bias.

The hidden layer uses the sigmoïd function as activation:

$$\sigma(H_{j \neq 0}) = [\sigma(a_j(1))] = \begin{bmatrix} \sigma(1) \\ \sigma(-2) \\ \sigma(0) \end{bmatrix} \approx \begin{bmatrix} 0.731 \\ 0.119 \\ 0.5 \end{bmatrix}$$

Now we can concatenate the bias at the beginning with a fixed value of 1:

$$H_{out} \approx \begin{bmatrix} 1 \\ 0.731 \\ 0.119 \\ 0.5 \end{bmatrix}$$

The vector  $H_{out}$  is the signed emitted by the hidden layer.

We can now repeat the same procedure with the second layer with  $H_{out}$  as input

and use the weights of the output layer.  
The weights of the second layer are the following:

$$W^{(2)} = [w_{k,j}^{(2)}] = \begin{bmatrix} 1 & -1 \\ -1 & 1 \\ 1 & -1 \\ -1 & 1 \end{bmatrix}$$

And we can compute the signal recieved by the output layer:

$$O = [a_k^{(2)}] = H_{out}^\top W^{(2)} \approx \begin{bmatrix} -0.112 \\ 0.112 \end{bmatrix}$$

This is the output of our neural network as the activation function of the output neuron is the identity function.

## 2.2 Part b

The formula to compute  $\delta_i^{(l)}$  is the following:

$$\delta_i^{(l)} = \frac{\partial E_n}{\partial a_i^{(l)}}$$

Where  $l$  is the layer and  $i$  is the index of the neuron.

But to compute the value of this expression for different values of  $l$  and  $i$ , we need to know the expression of  $E_n$  first.  $E_n$  is the error of the network on the data sample number  $n$ . It is defined as follows:

$$E_n(w) = \frac{1}{2} \sum_{k=1}^D (y_k(x_n, w) - t_{n,k})^2$$

Where  $N$  is the number of output neurons (in our case 2),  $x_n$  the input data and  $t_n$  the target related to  $x_n$ ,  $w$  the current weights of the neural network and  $y_k$  the function that computes the  $k^{\text{th}}$  coordinate of the NN's prediction based on the input data.

In our case, we can rewrite this expression to this:

$$E_n(w) = \frac{1}{2} \sum_{k=1}^2 (y_k(x_n, w) - t_{n,k})^2$$

And because the activation function of the output layer is the identity function, we also have the following equation:

$$y_k(x_n, w) = h(a_k^{(2)}) = a_k^{(2)}$$

The analytical expressions of  $\delta_1^{(2)}$  and  $\delta_2^{(2)}$  directly follows:

$$\delta_i^{(2)} = \frac{\partial E_n}{\partial a_i^{(2)}} = \frac{1}{2} \frac{\partial \sum_{k=1}^2 (a_k^{(2)} - t_{n,k})^2}{\partial a_i^{(2)}} = a_i^{(2)} - t_{n,i}$$

We finally get the following numerical values:

$$\delta_1^{(2)} = a_1^{(2)} - t_{n,1} = -0.112 - 1 = -1.112$$

$$\delta_2^{(2)} = a_2^{(2)} - t_{n,2} = 0.112 - (-1) = 1.112$$

### **2.3 Part c**

The formula to update a weight is