

Written Assignment 3

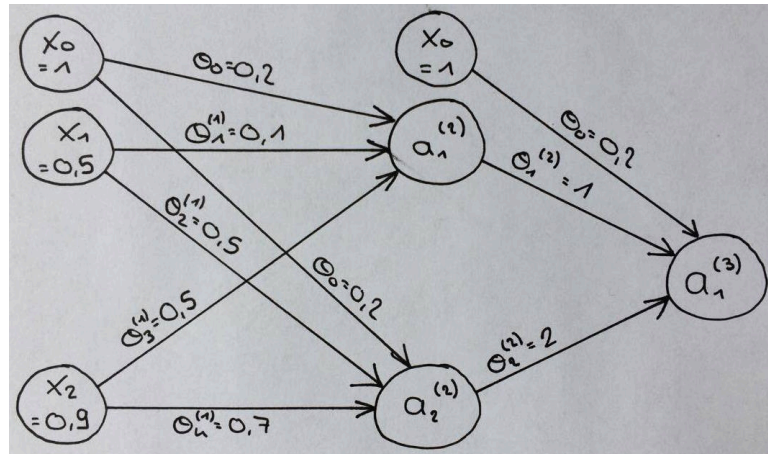
Machine Learning

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3. Neural Network figure:



1. Let $a_j^{(i)}$ denote the activation of node j in layer i .

$$a_1^{(2)} = g(\theta_0^{(1)}x_0 + \theta_1^{(1)}x_1 + \theta_3^{(1)}x_2) \quad || \text{ where: Sigmoid function } g(z) = \frac{1}{1+e^{-z}}$$

$$= g(0,2 \cdot 1 + 0,1 \cdot 0,5 + 0,5 \cdot 0,9)$$

$$= g(0,7)$$

$$= \frac{1}{1+e^{-0,7}}$$

$$\approx 0,6682$$

$$a_2^{(2)} = g(\theta_0^{(1)}x_0 + \theta_2^{(1)}x_1 + \theta_4^{(1)}x_2)$$

$$= g(0,2 \cdot 1 + 0,5 \cdot 0,5 + 0,7 \cdot 0,9)$$

$$= g(1,08)$$

$$= \frac{1}{1+e^{-1,08}}$$

$$\approx 0,7466$$

$$a_1^{(3)} = g(\theta_0^{(1)}x_0 + \theta_1^{(2)}a_1^{(2)} + \theta_2^{(2)}a_2^{(2)})$$

$$= g(0,2 \cdot 1 + 1 \cdot 0,6682 + 2 \cdot 0,7466)$$

$$= g(2,3814)$$

$$= \frac{1}{1+e^{-2,3814}}$$

$$\approx 0,9154$$

$$\approx 1$$

Choice of theta values:

Question 3.2. states that the correct output should be 1, so I chose the theta values such that $\frac{1}{1+e^{-z}}$ is closest to 1, i.e. such that z is as large as possible.

For example, multiplying the largest x value, x_2 , with the largest theta value, $\theta_4^{(1)}=0,7$, gives a larger ' z ' and thus an output closer to 1.

2. Let $\delta_j^{(i)}$ denote the error of node j in layer i .

$$\begin{aligned} \text{Then for the final node: } \delta_1^{(3)} &= a_1^{(3)} - y_1 & || \text{ from } \delta_j^{(i)} &= a_j^{(i)} - y_j \\ &= 0,9154 - 1 \\ &= -0,0846 \end{aligned}$$

For the previous nodes, we use: $\delta^{(i)} = \theta^{(i)} \delta^{(i+1)} \cdot g'(z^{(i)})$

So for the 2nd layer:

$$\begin{aligned} \delta_1^{(2)} &= \theta_1^{(2)} \delta_1^{(3)} \cdot g'(z_1^{(2)}) \\ &= \theta_1^{(2)} \delta_1^{(3)} \cdot [a_1^{(2)} \cdot (1-a_1^{(2)})] \\ &= 1 \cdot \delta_1^{(3)} \cdot 0,6682 \cdot (1-0,6682) \\ &= -0,0846 \cdot 0,6682 \cdot 0,3318 \\ &\approx -0,01876 \\ \delta_2^{(2)} &= \theta_2^{(2)} \delta_2^{(3)} \cdot g'(z_2^{(2)}) \\ &= \theta_2^{(2)} \delta_2^{(3)} \cdot [a_2^{(2)} \cdot (1-a_2^{(2)})] \\ &= 2 \cdot \delta_1^{(3)} \cdot 0,7466 \cdot (1-0,7466) \\ &= 2 \cdot -0,0846 \cdot 0,7466 \cdot 0,2534 \\ &\approx -0,03201 \end{aligned}$$

With updating the weights $\theta_1^{(2)} \rightarrow \theta_1^{(2)} + \delta_1^{(2)}$, we have:

$$\begin{aligned} a_1^{(3)} &= g[\theta_0^{(1)} x_0 + (\theta_1^{(2)} + \delta_1^{(2)}) a_1^{(2)} + (\theta_2^{(2)} + \delta_2^{(2)}) a_2^{(2)}] \\ &= g(0,2 \cdot 1 + (1-0,01876) \cdot 0,6682 + (2-0,03201) \cdot 0,7466) \\ &= g(2,3978) \\ &= \frac{1}{1+e^{-2,3978}} \\ &\approx 0,9167 \quad (\text{which is a little closer to one than before}) \end{aligned}$$

4.

1. For the perceptron, we have:

$$p(x_1, \dots, x_n) = \begin{cases} 1 & \text{if } w_0 + w_1 x_1 + \dots + w_n x_n > 0 \\ -1 & \text{if } w_0 + w_1 x_1 + \dots + w_n x_n \leq 0 \end{cases}$$

Since the line in figure a) is 2-dimensional, we can use $w_0 + w_1 x_1 + w_2 x_2$:

$$\begin{aligned} w_0 + w_1 x_1 + w_2 x_2 &= 0 \\ \Leftrightarrow x_2 &= \frac{-w_1}{w_2} x_1 - \frac{w_0}{w_2} \end{aligned} \quad (1)$$

Two points that lie on this line are A(-1,0) and B(0,2), so the slope of the line is given by:

$$\frac{\Delta y}{\Delta x} = \frac{0-2}{-1-0} = \frac{-2}{-1} = 2.$$

Thus

$$\frac{-w_1}{w_2} = 2 \Leftrightarrow w_1 = -2w_2 \quad (2)$$

Now, the coordinates of A and (2) are plugged into (1):

$$\begin{aligned} 0 &= \frac{2w_2}{w_2} (-1) - \frac{w_0}{w_2} \\ \Leftrightarrow \frac{w_0}{w_2} &= -2 \\ \Leftrightarrow w_0 &= -2w_2 \end{aligned}$$

Hence we have the system of equations:
$$\begin{cases} w_0 = -2w_2 \\ w_1 = -2w_2 \\ w_2 = w_2 \end{cases}$$

So one possibility (setting $w_2=1$) for the values of the weights is:

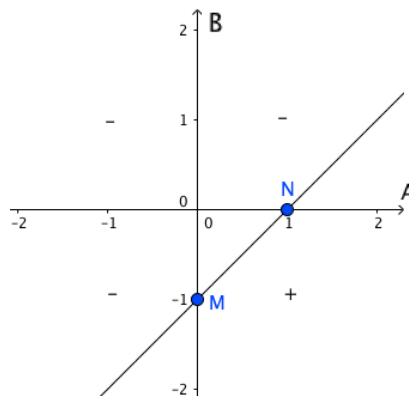
$$\begin{cases} w_0 = -2 \\ w_1 = -2 \\ w_2 = 1 \end{cases}$$

2.

a) All possible perceptron $p(x)$ outputs:

A	B	$p(A \text{ AND (NOT B)})$
1	1	-1
1	-1	1
-1	1	-1
-1	-1	-1

The graph of the perceptron is:



where the line of eq. $B = \frac{\Delta y}{\Delta x} A + k$ goes through $N(1,0)$ and $M(0,-1)$.

The slope of the line is $\frac{\Delta y}{\Delta x} = \frac{0 - (-1)}{1 - 0} = 1$.

So (filling in x_N, y_N) the line intersects the B-axis at $0 = 1 \cdot 1 + k \Leftrightarrow k = -1$

Hence, the equation of the line is:

$$B = A - 1$$

$$\Leftrightarrow -1 + A - B = 0$$

Comparing this to 3.2., a possibility for the values of the weights would be

$$\begin{cases} w_0 = -1 \\ w_1 = 1 \\ w_2 = -1 \end{cases}$$

b) All possible perceptron $p(x)$ outputs:

A	B	$p(A \text{ XOR } B)$
1	1	-1
1	-1	1
-1	1	-1
-1	-1	-1

$A \text{ XOR } B$ is the same thing as $[A \cap (\text{NOT } B)] \cup [(\text{NOT } A) \cap B]$.

Let's define one perceptron for each: P_1 gives $A \cap (\text{NOT } B)$

P_2 gives $(\text{NOT } A) \cap B$

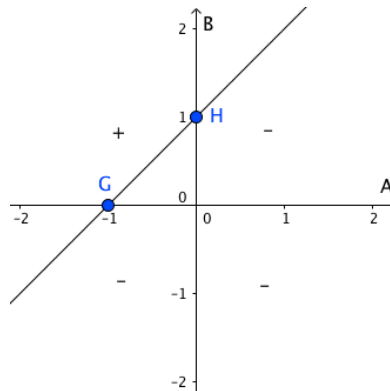
P_3 gives $A \text{ XOR } B$

P_1 is described in exercise 4.2.a).

P_2 has the following possible outputs:

A	B	$p((\text{NOT } A) \text{ AND } B)$
1	1	-1
1	-1	-1
-1	1	1
-1	-1	-1

with graph:

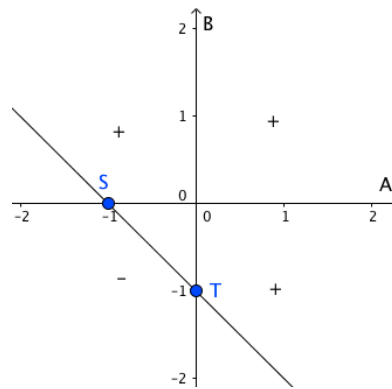


and with weights $\begin{cases} w_0 = 1 \\ w_1 = 1 \\ w_2 = -1 \end{cases}$ (found in the same way as in 4.2.a)

P_3 has the following possible outputs:

A	B	$p(P_1 \cup P_2)$
1	1	1
1	-1	1
-1	1	1
-1	-1	-1

with graph:



and with weights $\begin{cases} w_0 = 1 \\ w_1 = 1 \\ w_2 = 1 \end{cases}$ (found in the same way as in 4.2.a))

Figure of the network in the case $A = B = 1$:

