

Perceptrons, Logical Functions, and the XOR problem

Deep Learning Pills #2



Francesco Cicala · Follow

Published in Towards Data Science

6 min read · Aug 31, 2018



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Today we will explore what a Perceptron can do, what are its limitations, and we will prepare the ground to overreach these limits! Everything supported by graphs and code.

Elements from Deep Learning Pills #1

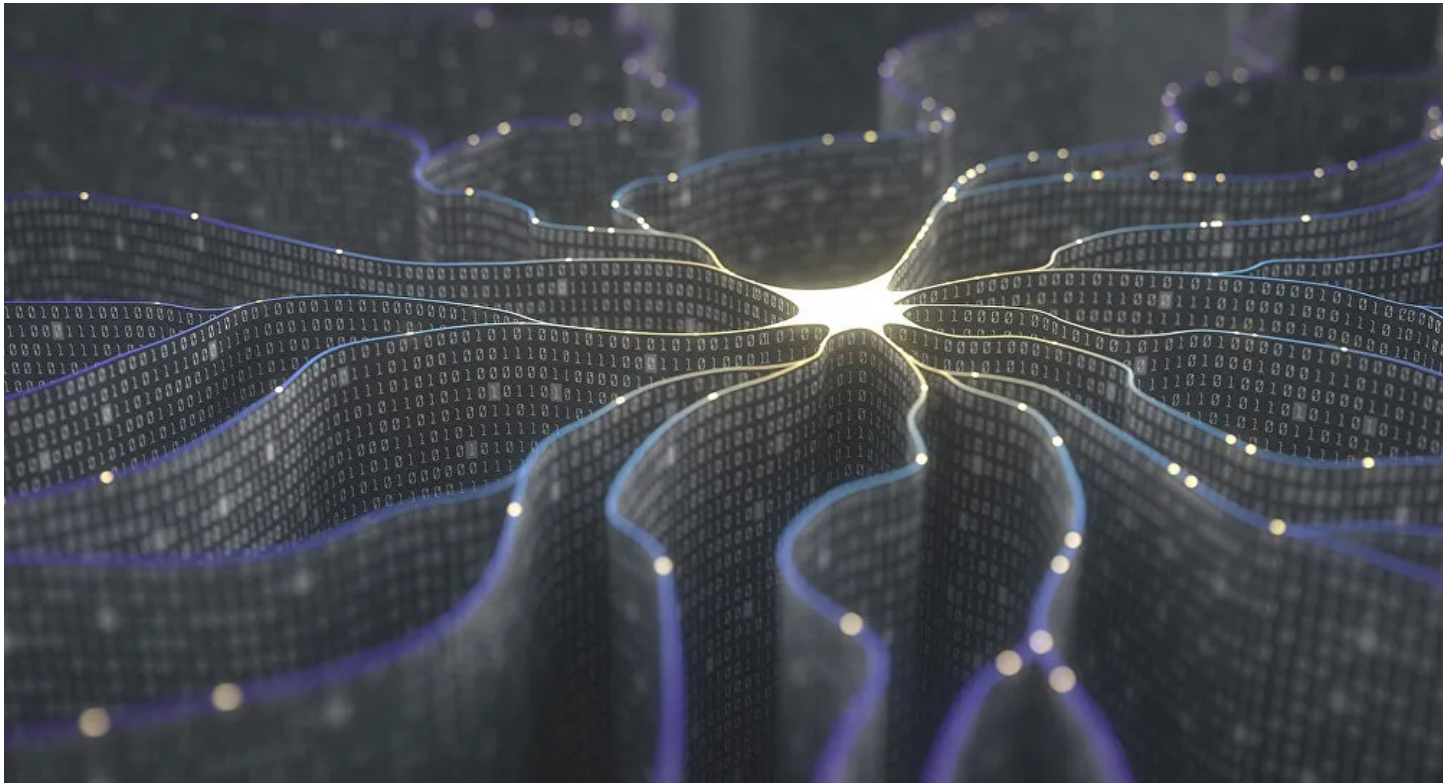
In Part 1 of this series, we introduced the Perceptron as a model that implements the following function:

$$\begin{aligned}\hat{y} &= \Theta(w_1x_1 + w_2x_2 + \dots + w_nx_n + b) \\ &= \Theta(\mathbf{w} \cdot \mathbf{x} + b)\end{aligned}$$

$$\text{where } \Theta(v) = \begin{cases} 1 & \text{if } v \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

For a particular choice of the parameters \mathbf{w} and b , the output \hat{y} only depends on the input vector \mathbf{x} . I'm using \hat{y} ("y hat") to indicate that this number has been

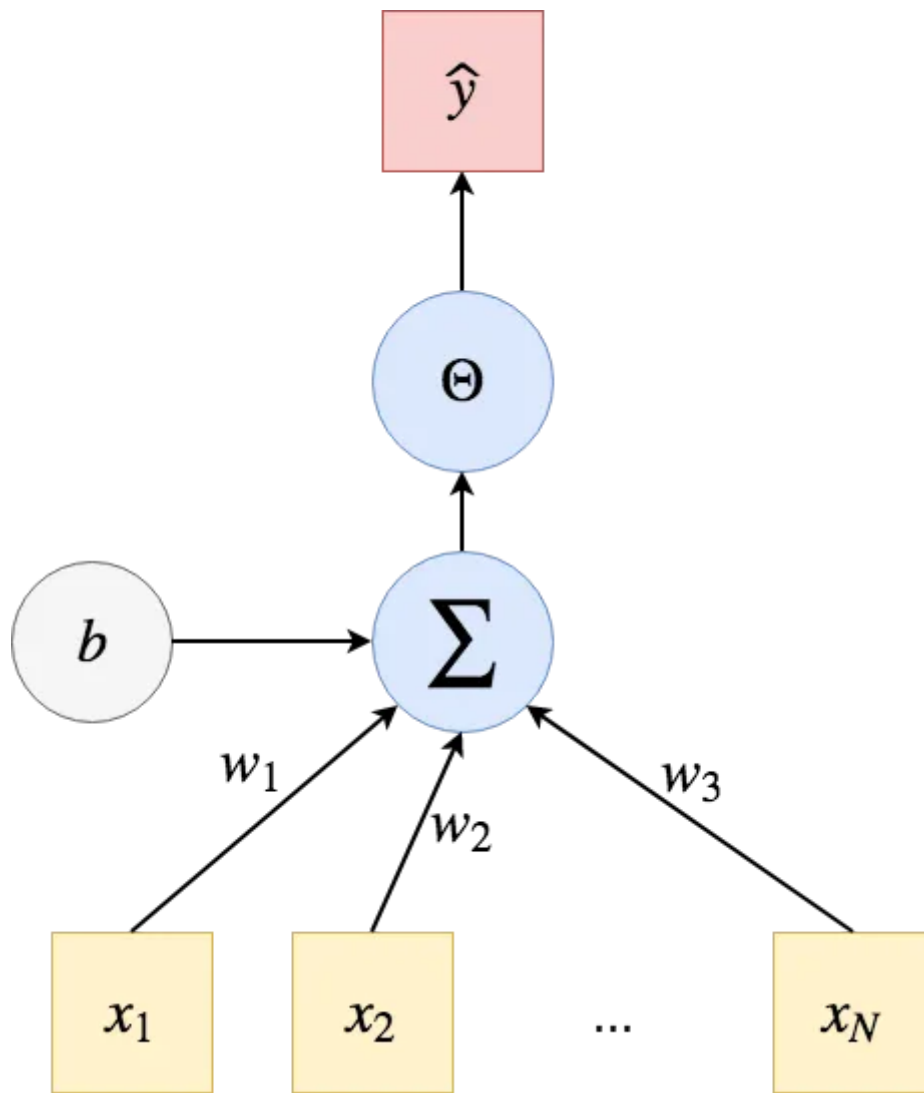
produced/predicted by the model. Soon, you will appreciate the ease of this notation.



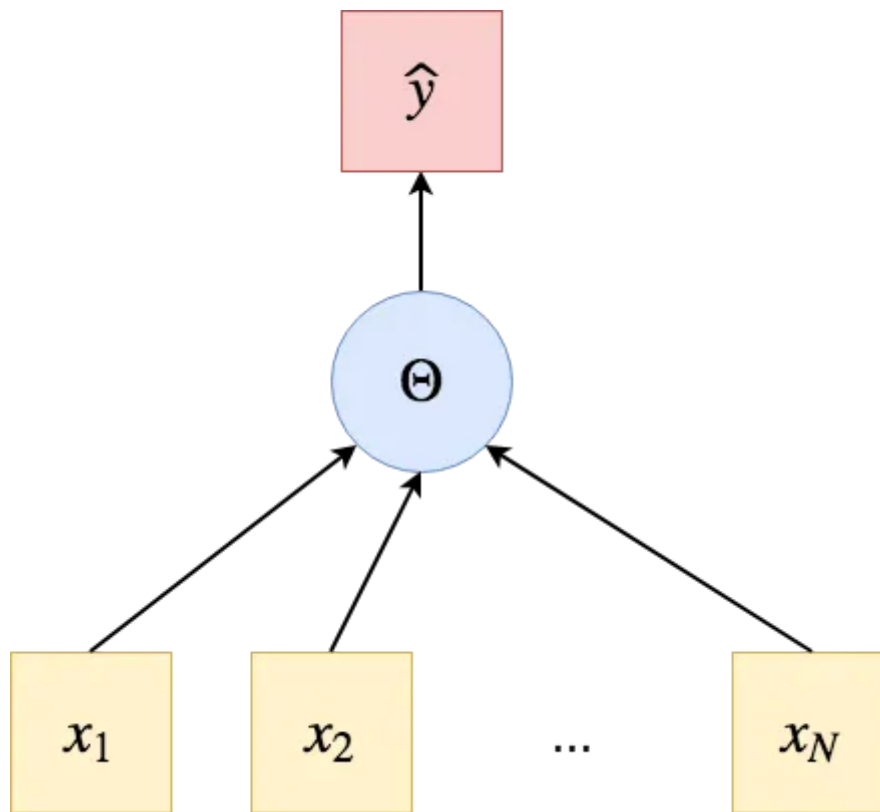
Computational Graph

To visualize the **architecture** of a model, we use what is called **computational graph**: a directed graph which is used to represent a math function. Both variables and operations are nodes; variables are fed into operations and operations produce variables.

The computational graph of our perceptron is:



The Σ symbol represents the linear combination of the inputs x by means of the weights w and the bias b . Since this notation is quite heavy, from now on I will simplify the computational graph in the following way:



What can a perceptron do?

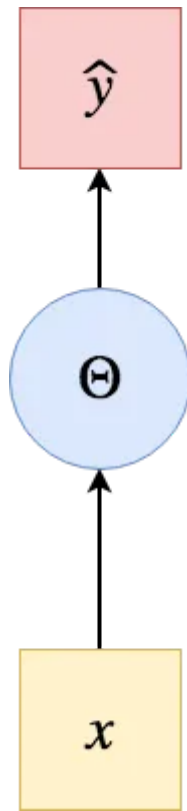
I am introducing some examples of what a perceptron can implement with its *capacity* (I will talk about this term in the following parts of this series!). Logical functions are a great starting point since they will bring us to a natural development of the theory behind the perceptron and, as a consequence, **neural networks**.

A	B	A AND B	A OR B	NOT A
False	False	False	False	True
False	True	False	True	True
True	False	False	True	False
True	True	True	True	False

NOT logical function

Let's start with a very simple problem:

Can a perceptron implement the NOT logical function?



NOT(x) is a 1-variable function, that means that we will have one input at a time: $N=1$. Also, it is a **logical function**, and so both the input and the output have only two possible states: 0 and 1 (i.e., False and True): the Heaviside step function seems to fit our case since it produces a binary output.

With these considerations in mind, we can tell that, if there exists a perceptron which can implement the NOT(x) function, it would be like the one shown at left. Given two parameters, w and b , it will perform the following computation:
$$\hat{y} = \Theta(wx + b)$$

The fundamental question is: do exist two values that, if picked as parameters, allow the perceptron to implement the NOT logical function? When I say that a *perceptron implements a function*, I mean that for each input in the function's domain the perceptron returns the same number (or vector) the function would return for the same input.

Back to our question: those values exist since we can easily find them: let's pick $w = -1$ and $b = 0.5$.

```

1  import numpy as np
2
3  def unit_step(v):
4      """ Heavyside Step function. v must be a scalar """
5      if v >= 0:
6          return 1
7      else:
8          return 0
9
10 def perceptron(x, w, b):
11     """ Function implemented by a perceptron with
12         weight vector w and bias b """
13     v = np.dot(w, x) + b
14     y = unit_step(v)
15     return y
16
17 def NOT_percep(x):
18     return perceptron(x, w=-1, b=0.5)
19
20 print("NOT(0) = {}".format(NOT_percep(0)))
21 print("NOT(1) = {}".format(NOT_percep(1)))

```

not.py hosted with ❤ by GitHub

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And we get:

```

NOT(0) = 1
NOT(1) = 0

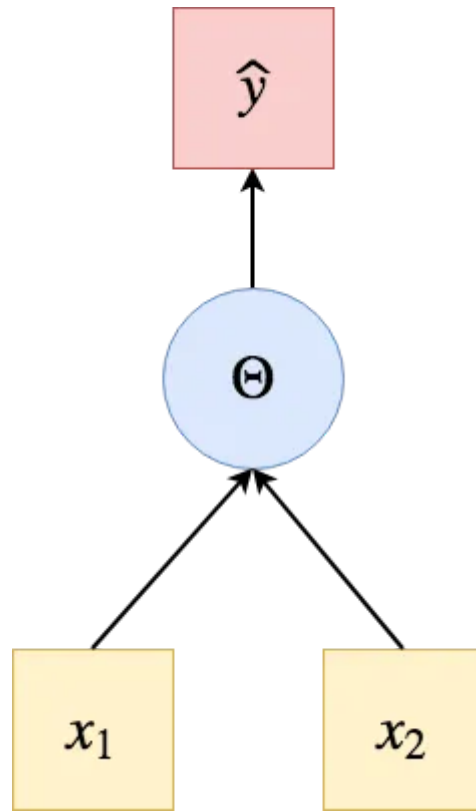
```

We conclude that the answer to the initial question is: yes, a perceptron can implement the NOT logical function; we just need to **properly set its parameters**. Notice that my solution isn't unique; in fact, solutions, intended as (w, b) points, are infinite for this particular problem! You can use your favorite one ;)

AND logical function

The next question is:

Can a perceptron implement the AND logical function?



The AND logical function is a 2-variables function, $AND(x_1, x_2)$, with binary inputs and output.

This graph is associated with the following computation:

$$\hat{y} = \Theta(w_1 * x_1 + w_2 * x_2 + b)$$

This time, we have three parameters: w_1 , w_2 , and b .

Can you guess which are three values for these parameters which would allow the perceptron to solve the **AND problem**?

SOLUTION:

$$w_1 = 1, w_2 = 1, b = -1.5$$

```

1  def AND_percep(x):
2      w = np.array([1, 1])
3      b = -1.5
4      return perceptron(x, w, b)
5
6  # Test
7  example1 = np.array([1, 1])
8  example2 = np.array([1, 0])
9  example3 = np.array([0, 1])
10 example4 = np.array([0, 0])
11
12 print("AND({}, {}) = {}".format(1, 1, AND_percep(example1)))
13 print("AND({}, {}) = {}".format(1, 0, AND_percep(example2)))
14 print("AND({}, {}) = {}".format(0, 1, AND_percep(example3)))
15 print("AND({}, {}) = {}".format(0, 0, AND_percep(example4)))

```

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And it prints:

```

AND(1, 1) = 1
AND(1, 0) = 0
AND(0, 1) = 0
AND(0, 0) = 0

```

OR logical function

$OR(x_1, x_2)$ is a 2-variables function too, and its output is 1-dimensional (i.e., one number) and has two possible states (0 or 1). Therefore, we will use a perceptron with the same architecture as the one before. Which are the three parameters which solve the OR problem?

SOLUTION:

$w_1 = 1, w_2 = 1, b = -0.5$


```

1  def OR_percep(x):
2      w = np.array([1, 1])
3      b = -0.5
4      return perceptron(x, w, b)
5
6  # Test
7  example1 = np.array([1, 1])
8  example2 = np.array([1, 0])
9  example3 = np.array([0, 1])
10 example4 = np.array([0, 0])
11
12 print("OR({}, {}) = {}".format(1, 1, OR_percep(example1)))
13 print("OR({}, {}) = {}".format(1, 0, OR_percep(example2)))
14 print("OR({}, {}) = {}".format(0, 1, OR_percep(example3)))
15 print("OR({}, {}) = {}".format(0, 0, OR_percep(example4)))

```

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```

OR(1, 1) = 1
OR(1, 0) = 1
OR(0, 1) = 1
OR(0, 0) = 0

```

XOR — ALL (perceptrons) FOR ONE (logical function)

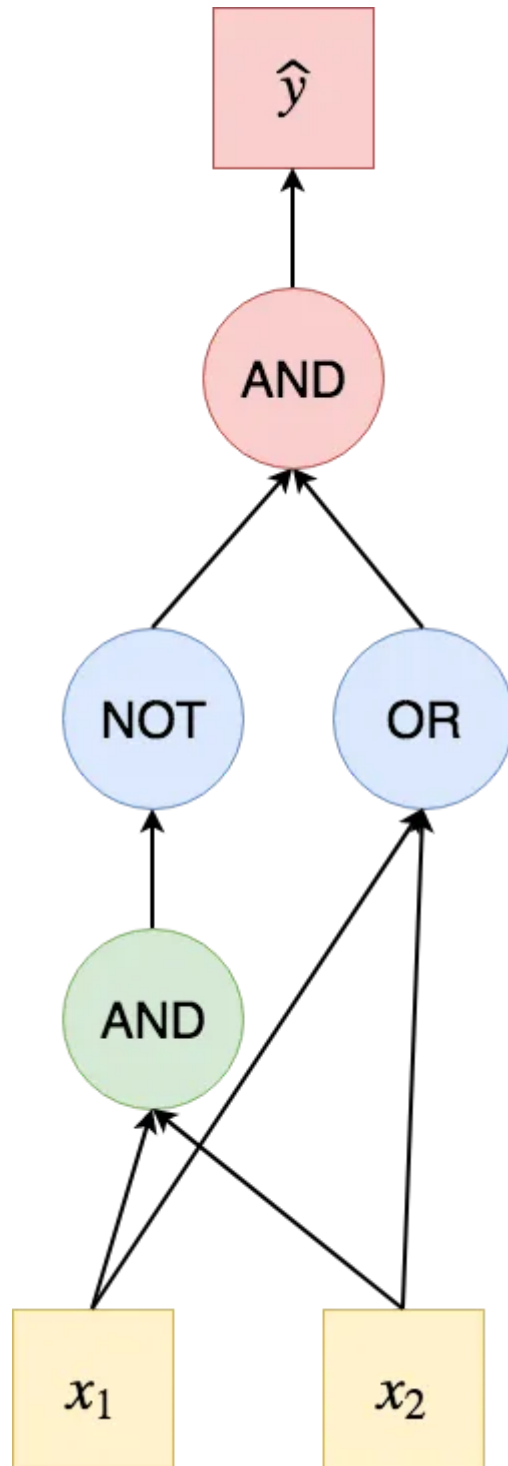
We conclude that a single perceptron with an Heaviside activation function can implement each one of the fundamental logical functions: NOT, AND and OR. They are called *fundamental* because any logical function, no matter how complex, can be obtained by a combination of those three. We can infer that, **if we appropriately connect the three perceptrons we just built, we can implement any logical function!** Let's see how:

How can we build a network of fundamental logical perceptrons so that it implements the XOR function?

A	B	XOR
0	0	0
0	1	1
1	0	1
1	1	0

SOLUTION:

$$XOR(x_1, x_2) = \textcolor{red}{AND}(\textcolor{blue}{NOT}(\textcolor{green}{AND}(x_1, x_2)), \textcolor{blue}{OR}(x_1, x_2))$$



```

1  def XOR_net(x):
2      gate_1 = AND_percep(x)
3      gate_2 = NOT_percep(gate_1)
4      gate_3 = OR_percep(x)
5      new_x = np.array([gate_2, gate_3])
6      output = AND_percep(new_x)
7      return output
8
9  print("XOR({}, {}) = {}".format(1, 1, XOR_net(example1)))
10 print("XOR({}, {}) = {}".format(1, 0, XOR_net(example2)))
11 print("XOR({}, {}) = {}".format(0, 1, XOR_net(example3)))
12 print("XOR({}, {}) = {}".format(0, 0, XOR_net(example4)))

```

xor_net.py hosted with ❤ by GitHub

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And the output is:

```

XOR(1, 1) = 0
XOR(1, 0) = 1
XOR(0, 1) = 1
XOR(0, 0) = 0

```

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Some of you may be wondering if, as we did for the previous functions, it is possible to find parameters' values for a single perceptron so that it solves the XOR problem all by itself.

I won't make you struggle too much looking for those three numbers, because it would be useless: the answer is that they do not exist. **Why?** The answer is that the XOR problem is not **linearly separable**, and we will discuss it in depth in the next chapter of this series!

I will publish it in a few days, and we will go through the linear separability property I just mentioned. I will reshape the topics I introduced today within a geometrical perspective. In this way, every result we obtained today will get its natural and intuitive explanation.

If you liked this article, I hope you'll consider to give it some claps! Every clap is a great encouragement to me :) Also, feel free to get in touch with me on [Linkedin](#)!