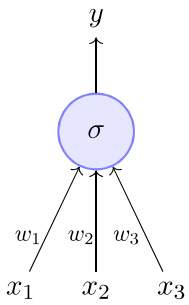
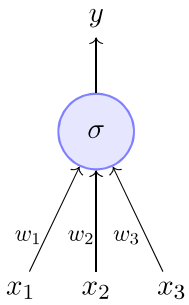
Module 2.1: Biological Neurons



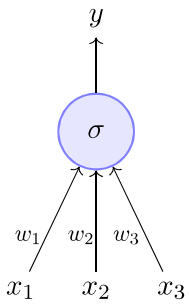
Artificial Neuron

- The most fundamental unit of a deep neural network is called an *artificial neuron*



Artificial Neuron

- The most fundamental unit of a deep neural network is called an *artificial neuron*
- Why is it called a neuron ? Where does the inspiration come from ?



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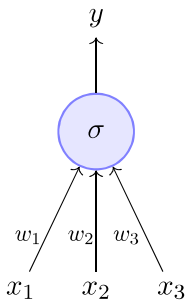

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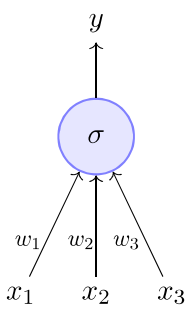

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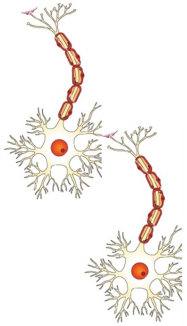
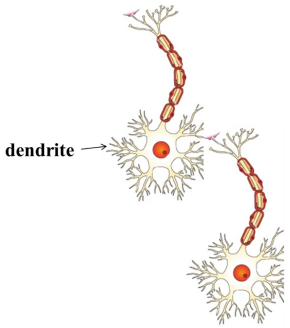
- *biological neurons = neural cells = neural processing units*
- We will first see what a biological neuron looks like ...



Biological Neurons*

*Image adapted from
https://cdn.vectorstock.com/i/composite/12,25/neuron-cell-vector-81225.jpg



Biological Neurons*

- **dendrite:** receives signals from other neurons

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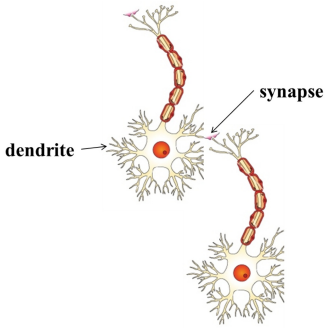

Biological Neurons*

- **dendrite:** receives signals from other neurons
- **synapse:** point of connection to other neurons

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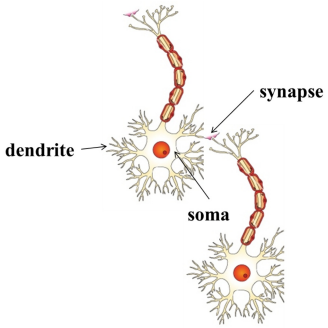

Biological Neurons*

- **dendrite:** receives signals from other neurons
- **synapse:** point of connection to other neurons
- **soma:** processes the information

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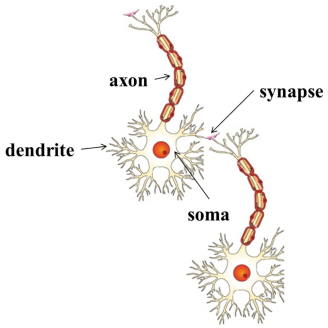

Biological Neurons*

- **dendrite:** receives signals from other neurons
- **synapse:** point of connection to other neurons
- **soma:** processes the information
- **axon:** transmits the output of this neuron

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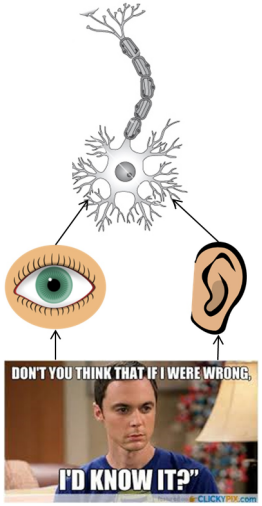

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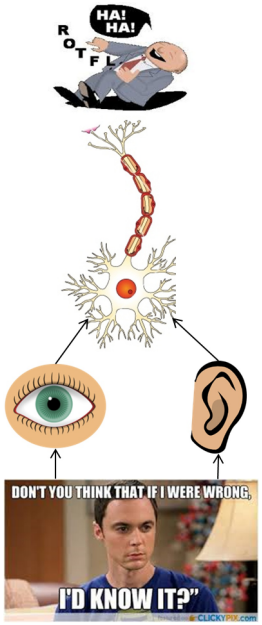
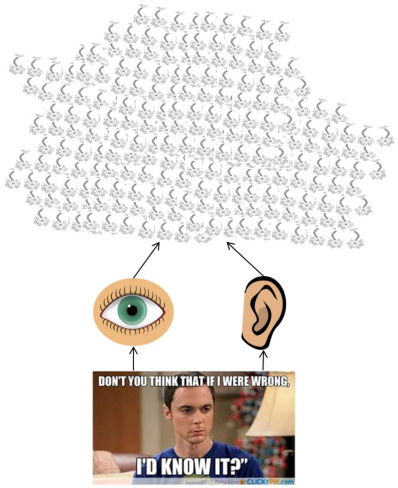
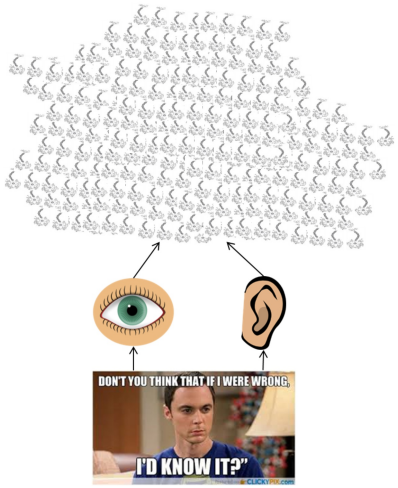


- Let us see a very cartoonish illustration of how a neuron works
- Our sense organs interact with the outside world
- They relay information to the neurons
- The neurons (may) get activated and produces a response (laughter in this case)



- Of course, in reality, it is not just a single neuron which does all this



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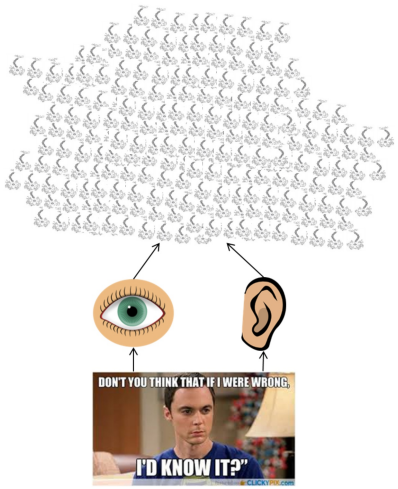
- There is a massively parallel interconnected network of neurons



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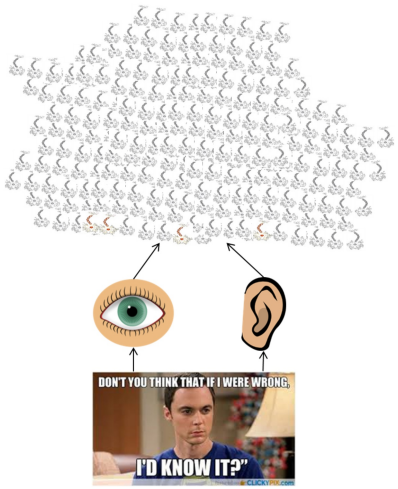

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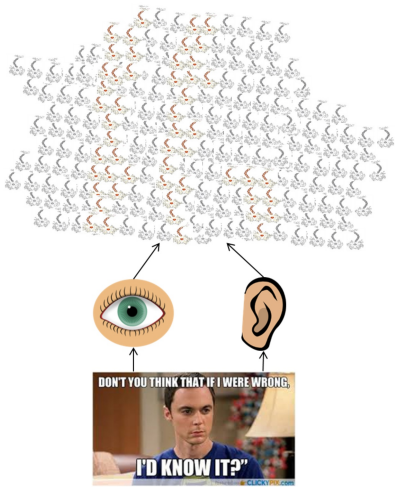
- The sense organs relay information to the lowest layer of neurons
- Some of these neurons may fire (in red) in response to this information and in turn relay information to other neurons they are connected to



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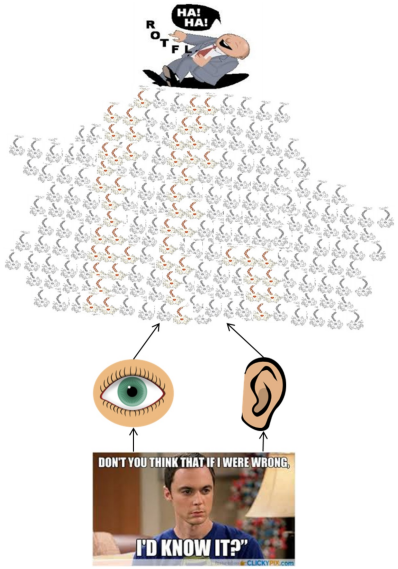

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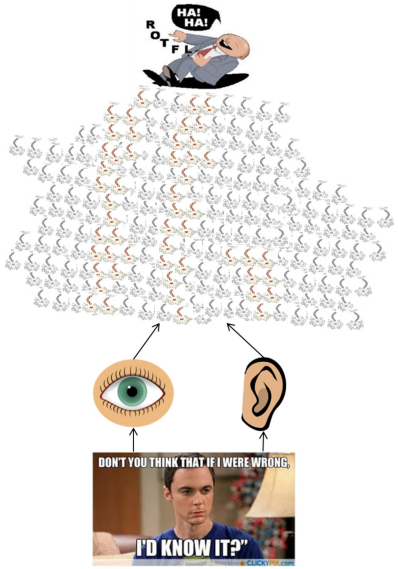

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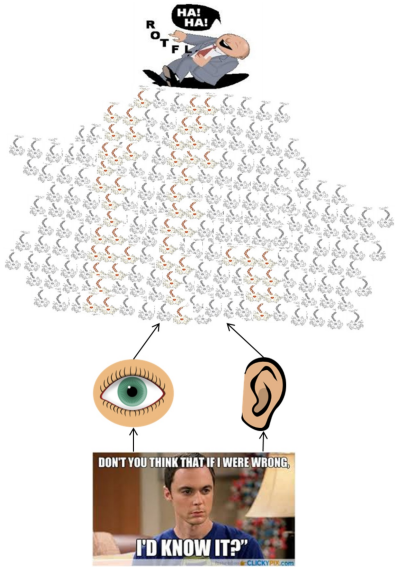
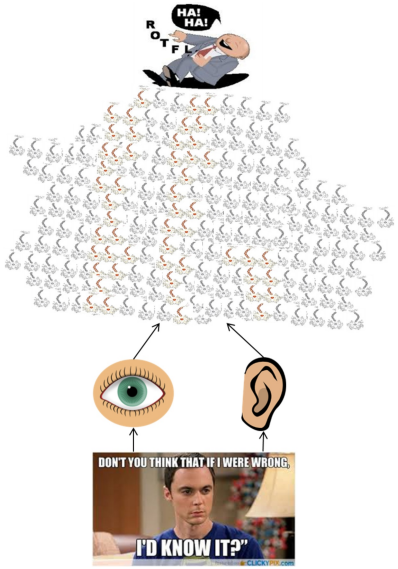
- An average human brain has around 10^{11} (100 billion) neurons!



- This massively parallel network also ensures that there is division of work



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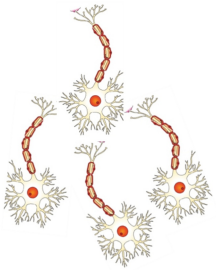

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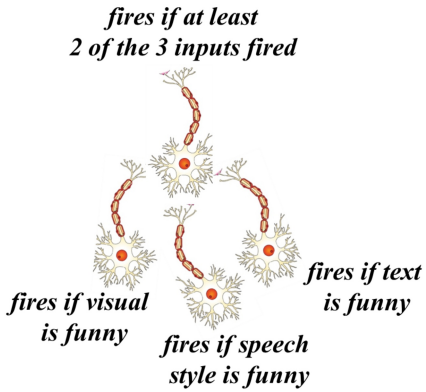

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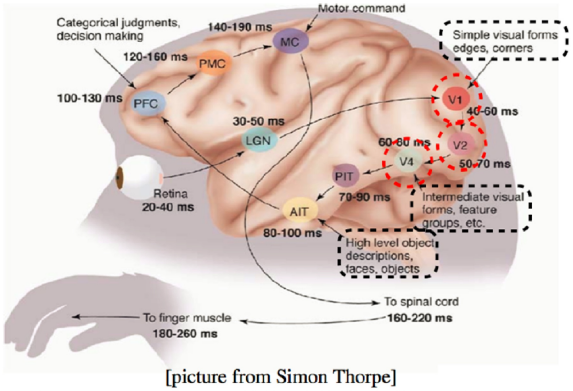
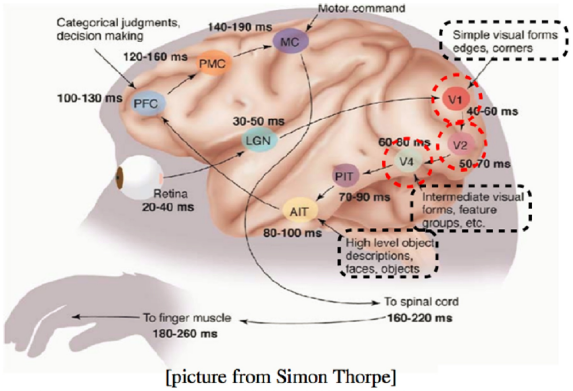
- The neurons in the brain are arranged in a hierarchy



[picture from Simon Thorpe]

- The neurons in the brain are arranged in a hierarchy
- We illustrate this with the help of visual cortex (part of the brain) which deals with processing visual information



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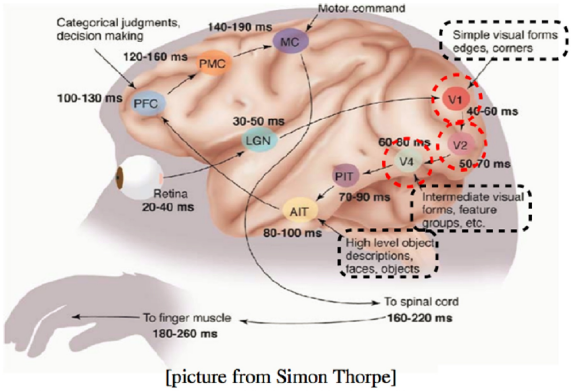
- Starting from the retina, the information is relayed to several layers (follow the arrows)



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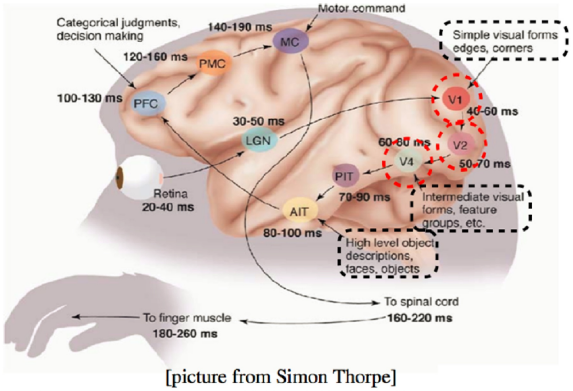
- The neurons in the brain are arranged in a hierarchy
- We illustrate this with the help of visual cortex (part of the brain) which deals with processing visual information
- Starting from the retina, the information is relayed to several layers (follow the arrows)
- We observe that the layers $V1$, $V2$ to AIT form a hierarchy (from identifying simple visual forms to high level objects)

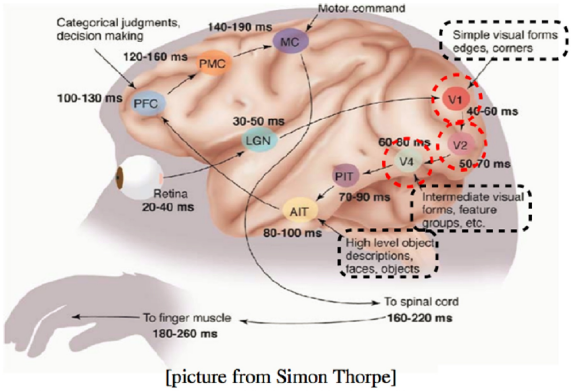


[picture from Simon Thorpe]

Layer 1: detect edges & corners

Sample illustration of hierarchical processing*

*Idea borrowed from Hugo Larochelle's lecture slides



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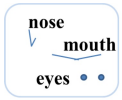

Layer 2: form feature groups

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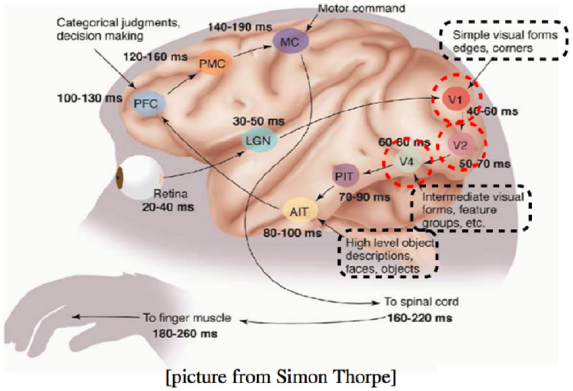

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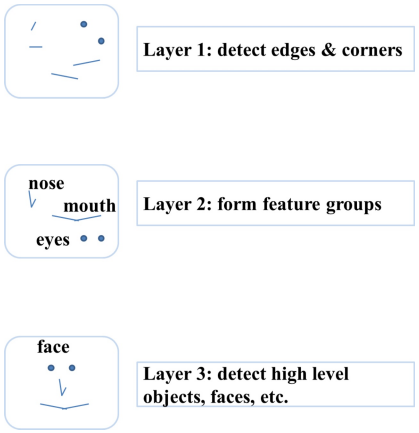

Sample illustration of hierarchical processing*

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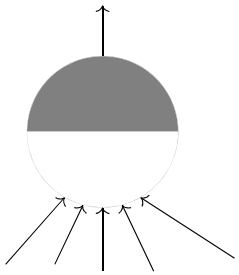
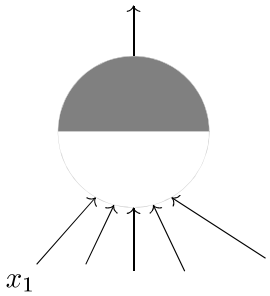
Disclaimer

- I understand very little about how the brain works!
- What you saw so far is an overly simplified explanation of how the brain works!
- But this explanation suffices for the purpose of this course!

Module 2.2: McCulloch Pitts Neuron



- McCulloch (neuroscientist) and Pitts (logician) proposed a highly simplified computational model of the neuron (1943)



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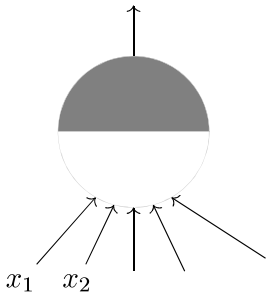

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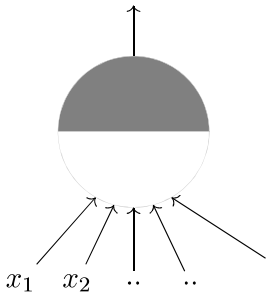

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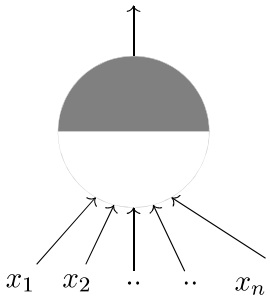

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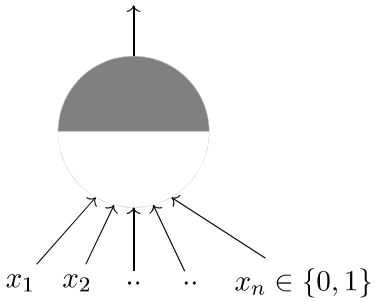

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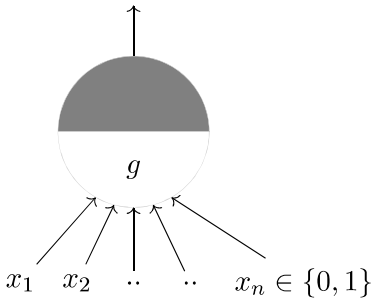

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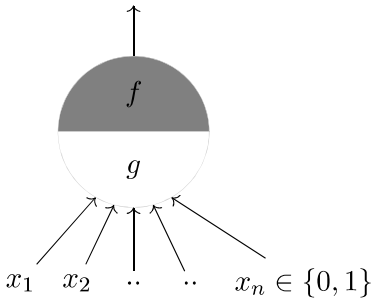

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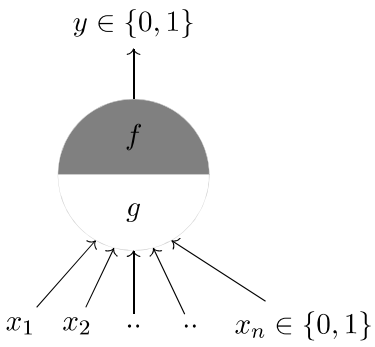
- g aggregates the inputs and the function f takes a decision based on this aggregation



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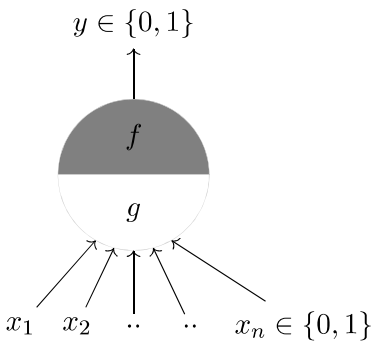

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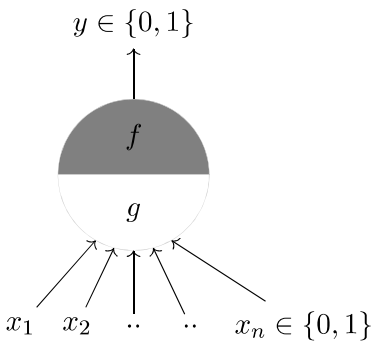

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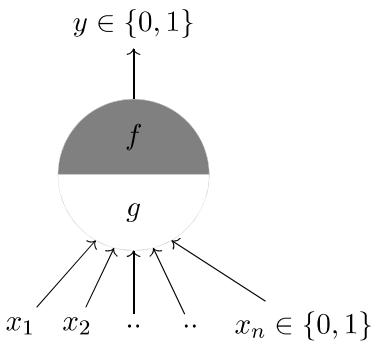

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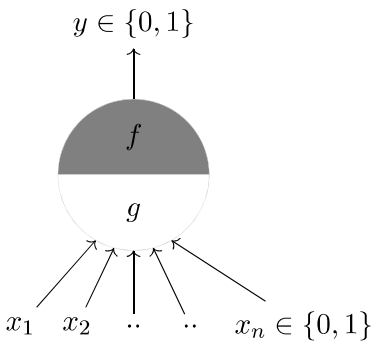

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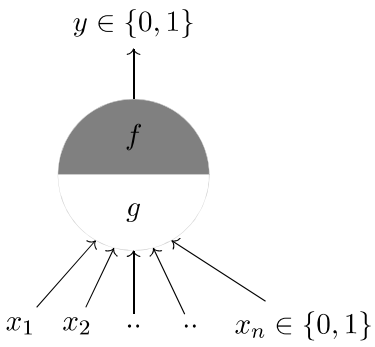

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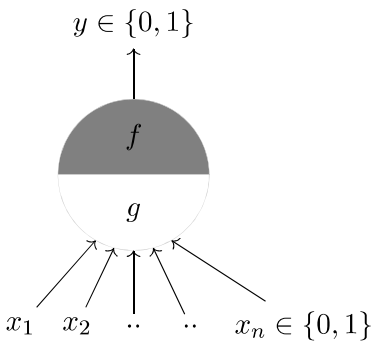

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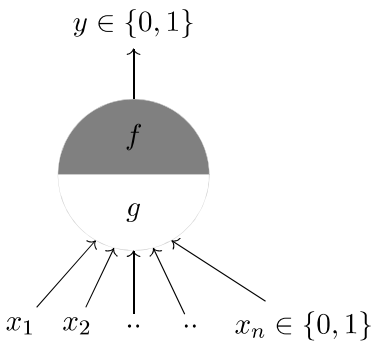

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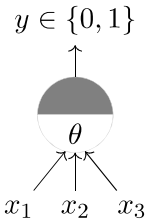
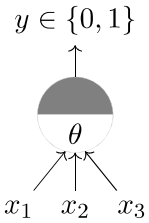
- This is called Thresholding Logic

Let us implement some boolean functions using this McCulloch Pitts (MP) neuron ...



A McCulloch Pitts unit



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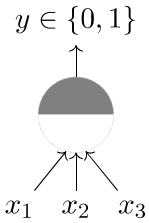
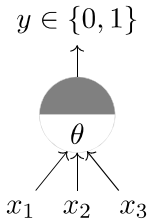


AND function



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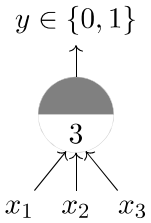

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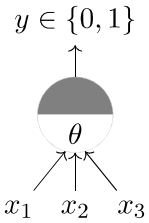

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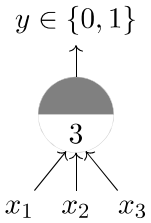

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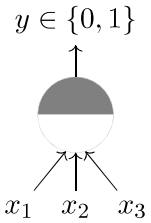

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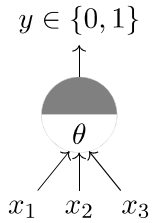

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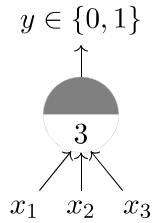

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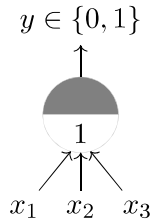

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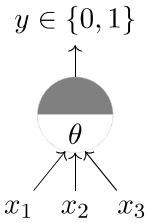

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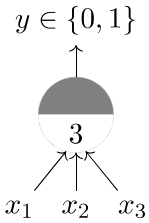

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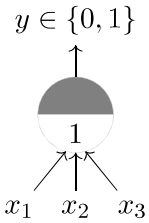

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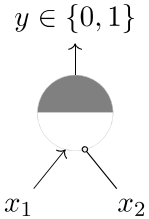

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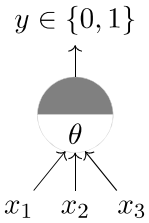

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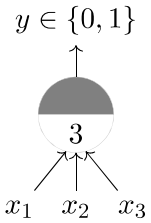

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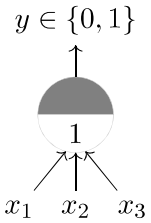

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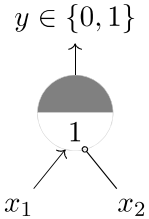

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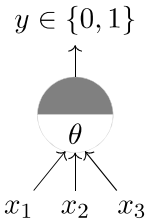

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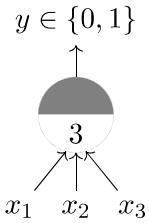

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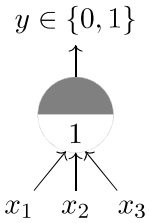

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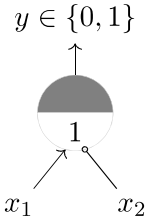

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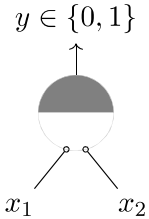

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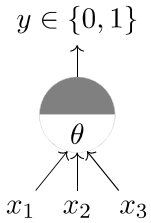

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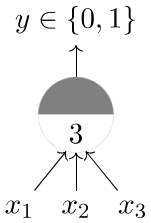

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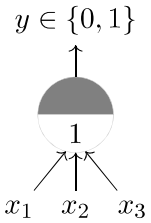

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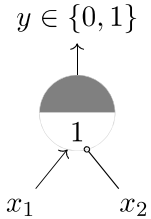

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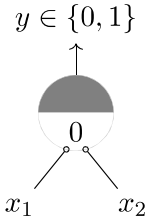

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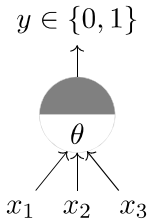

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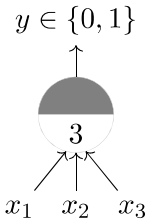

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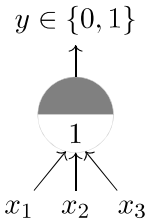

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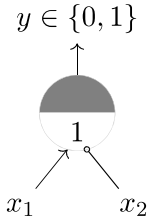

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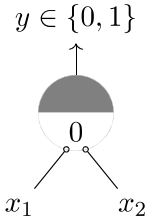

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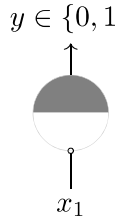

NOT function

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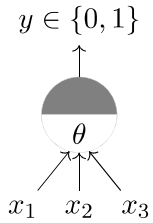

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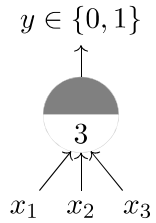

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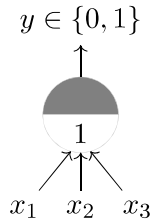

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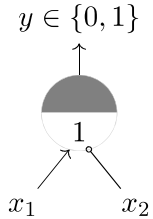

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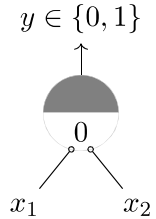

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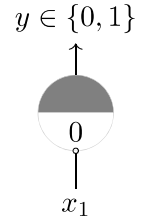

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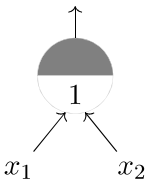
- Can any boolean function be represented using a McCulloch Pitts unit ?

- Can any boolean function be represented using a McCulloch Pitts unit ?
- Before answering this question let us first see the geometric interpretation of a MP unit ...

$y \in \{0, 1\}$



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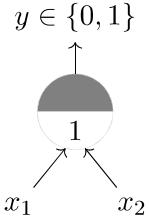

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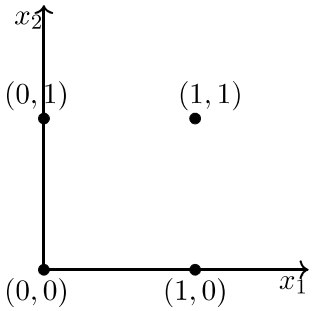

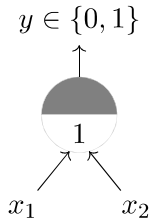

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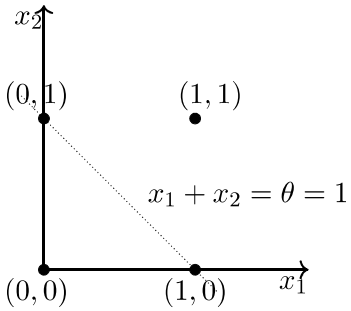

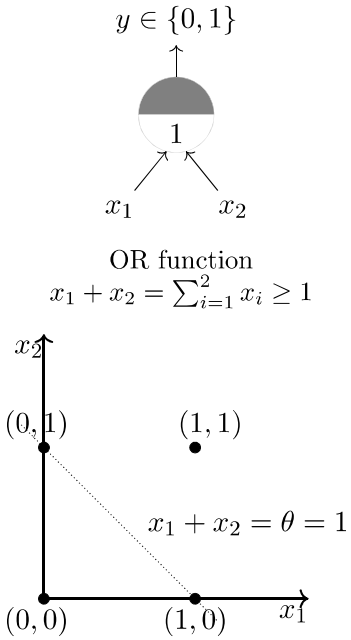

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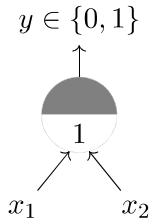

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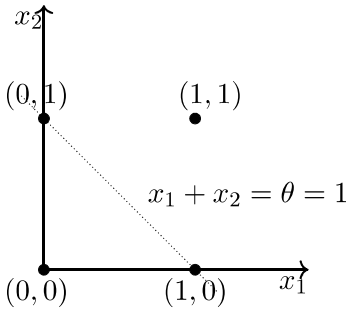

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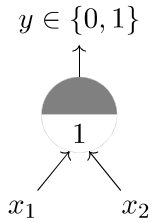

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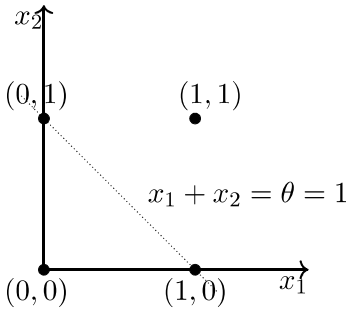

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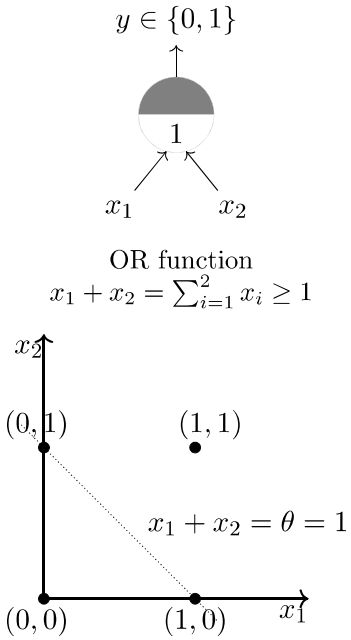

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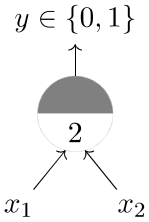
- Let us convince ourselves about this with a few more examples (if it is not already clear from the math)



AND function
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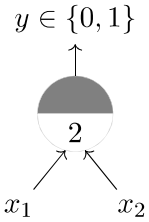

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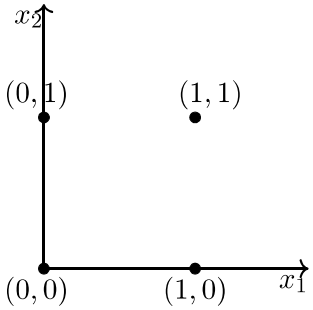

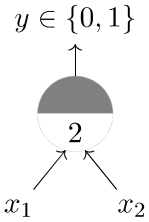

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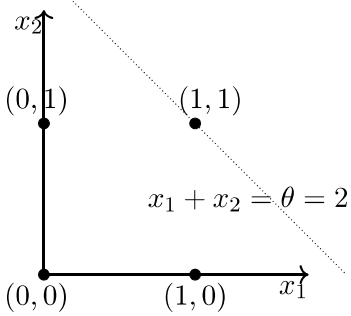

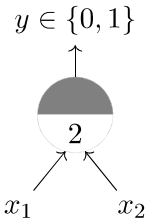

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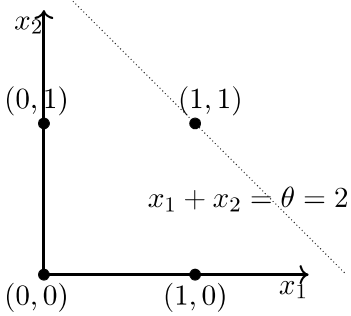
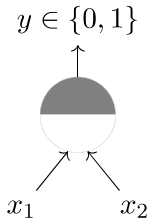
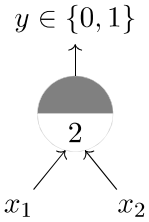




Tautology (always ON)



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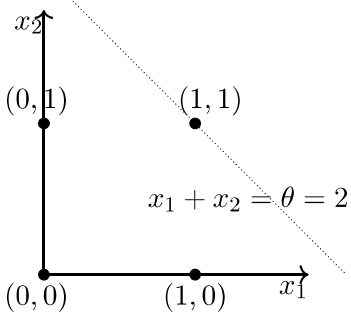

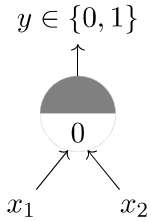

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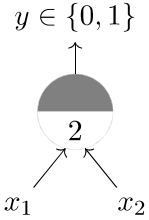

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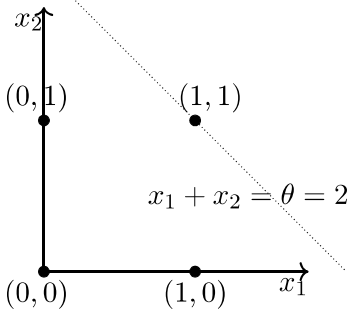

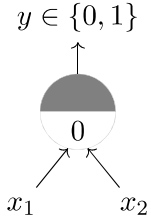

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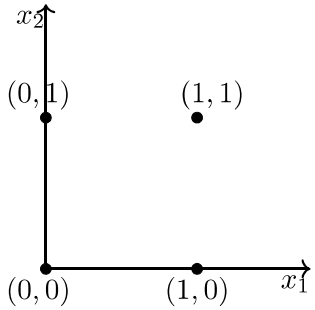

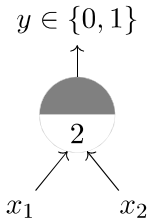

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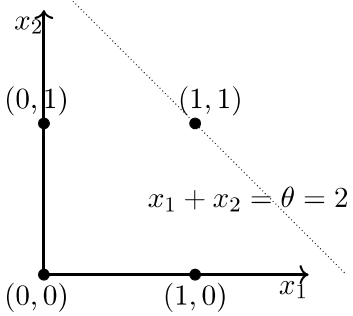

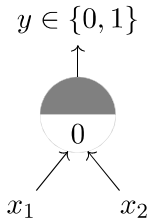

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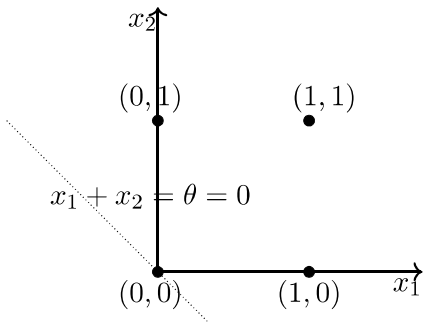
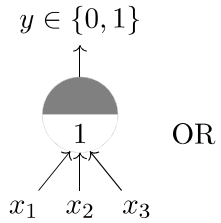
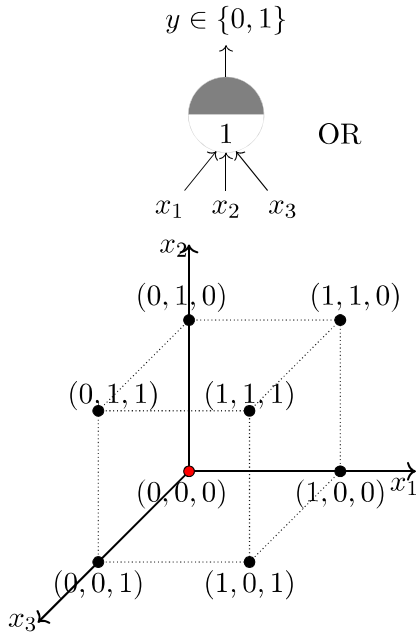




OR

- What if we have more than 2 inputs?



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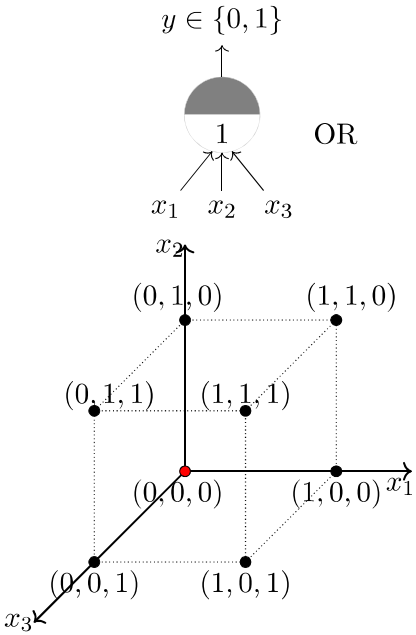

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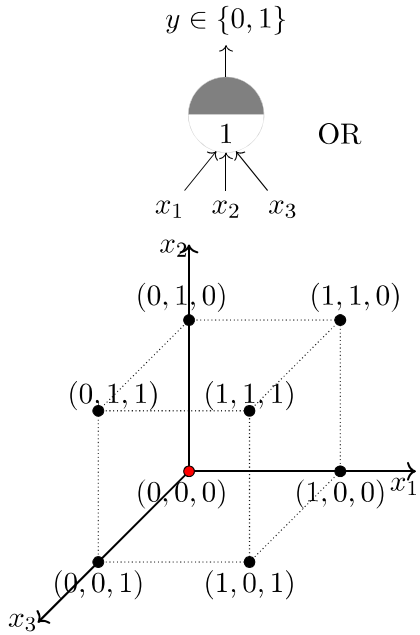

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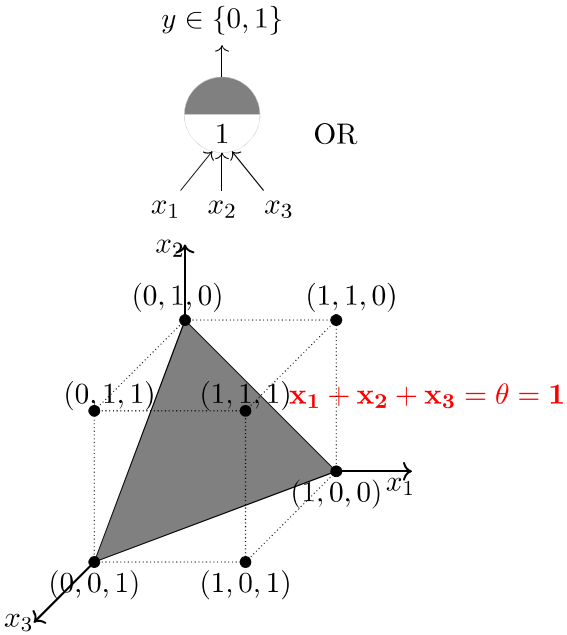

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- Linear separability (for boolean functions) : There exists a line (plane) such that all inputs which produce a 1 lie on one side of the line (plane) and all inputs which produce a 0 lie on other side of the line (plane)