

# **The Perceptron**

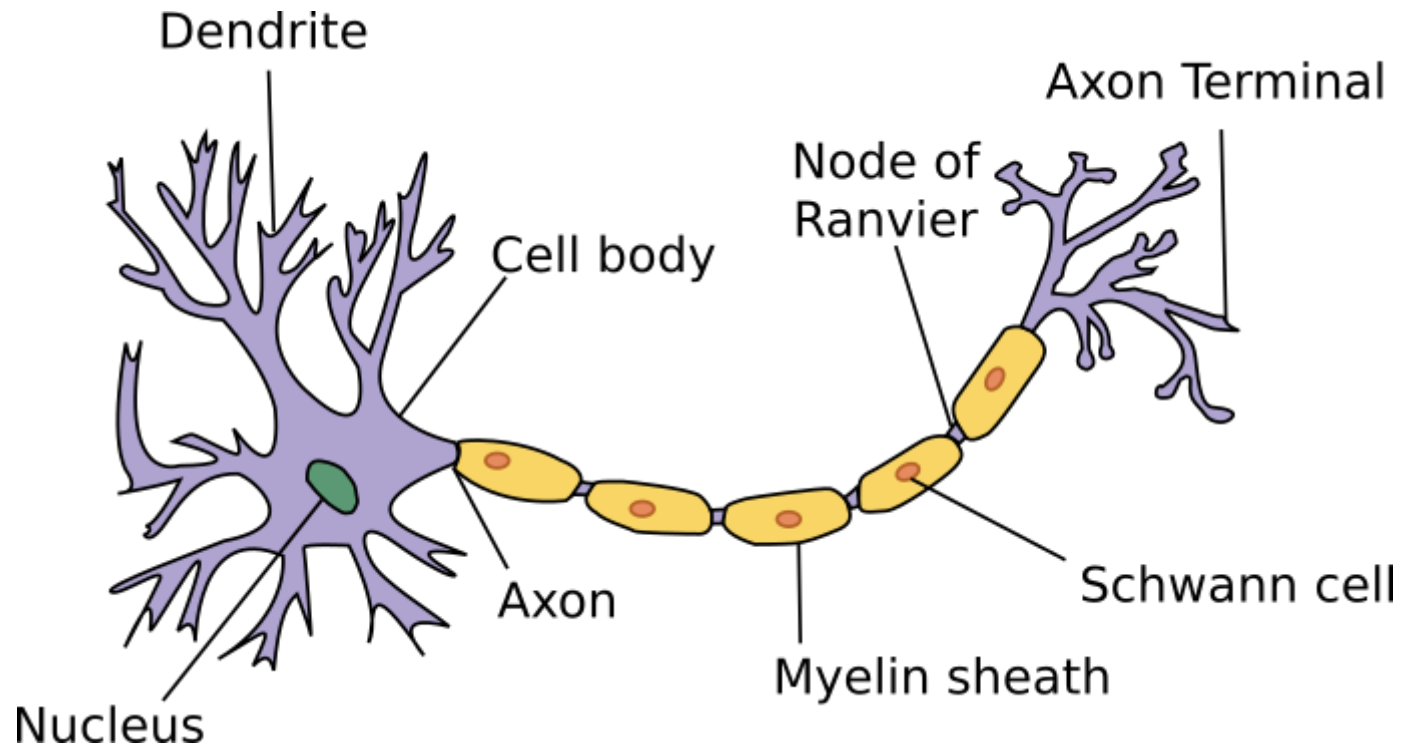
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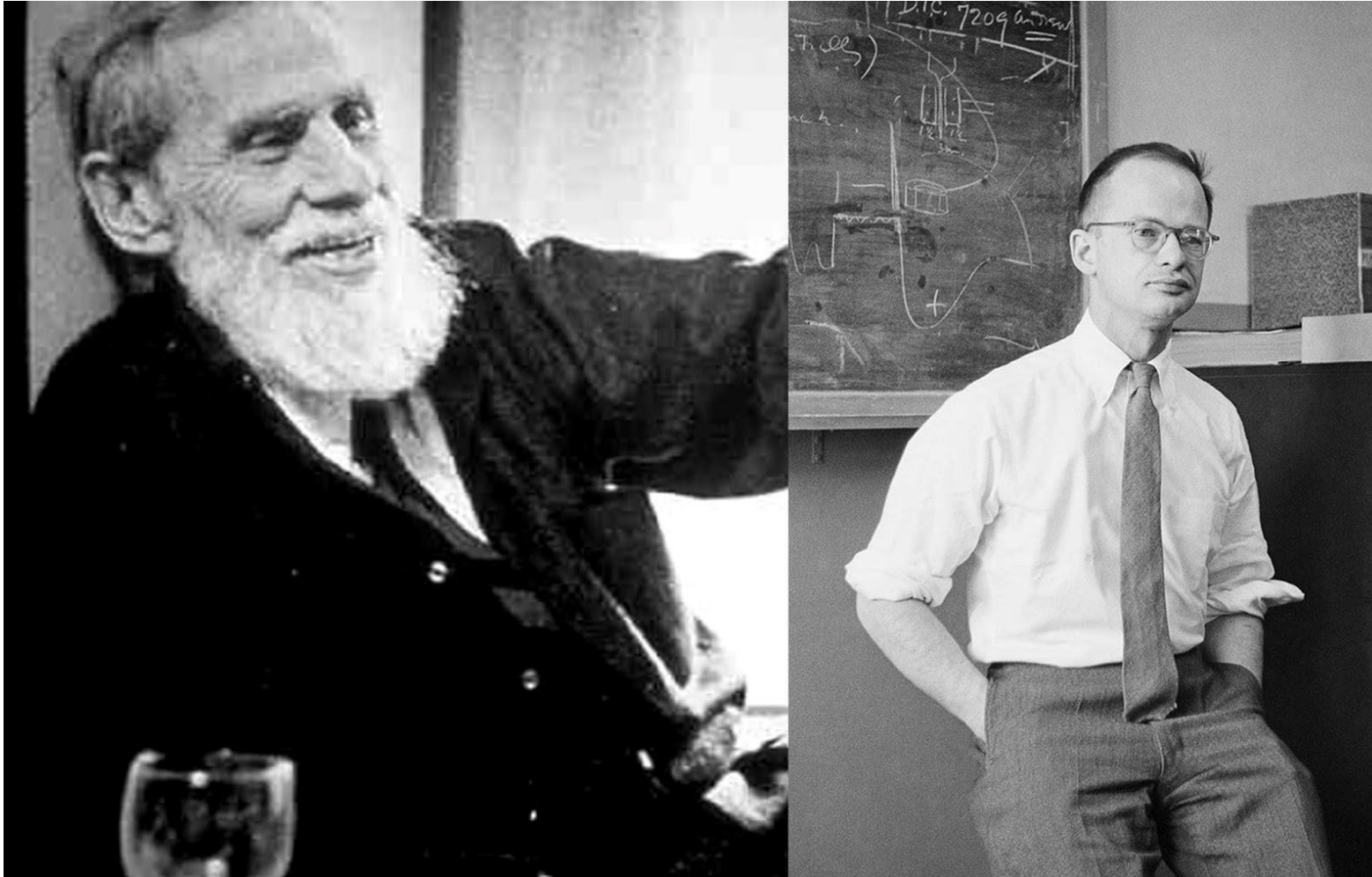
# This session:

- **Biological Neuron**
- **Some history**
- **Technical neuron**

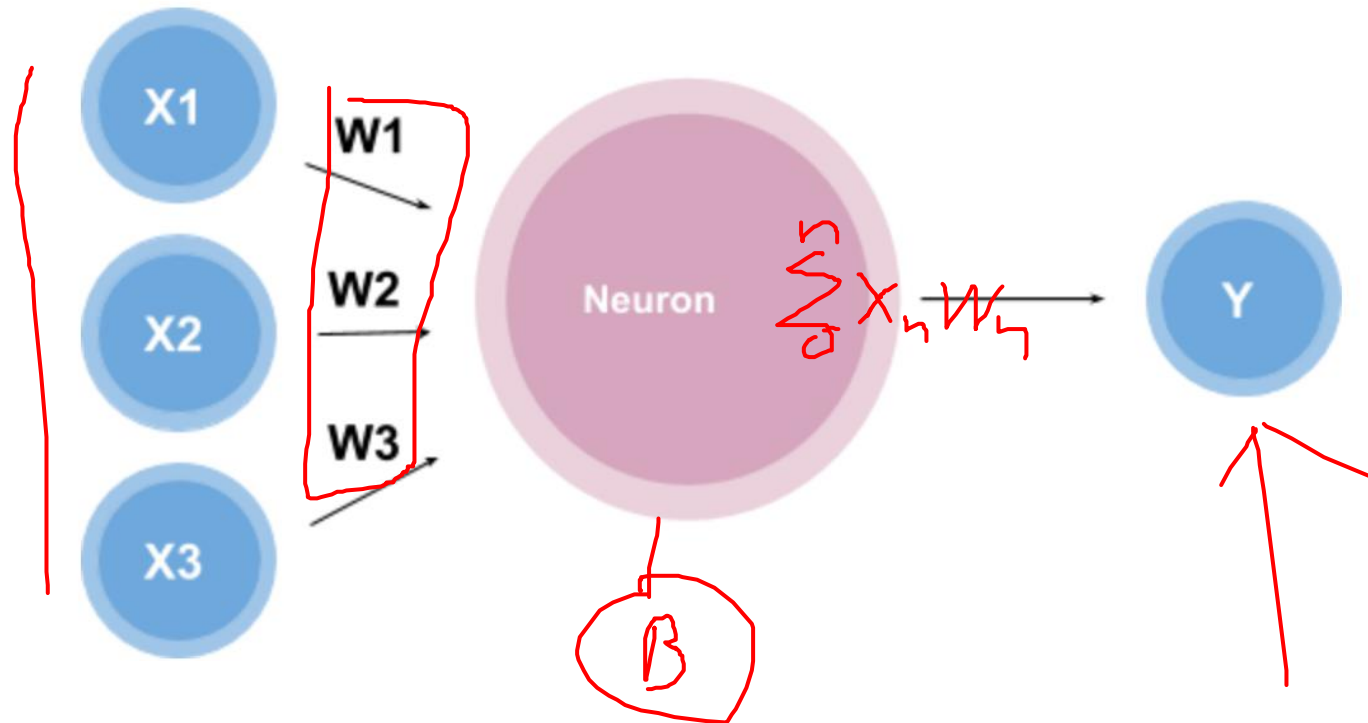
# Biological Neuron



# History

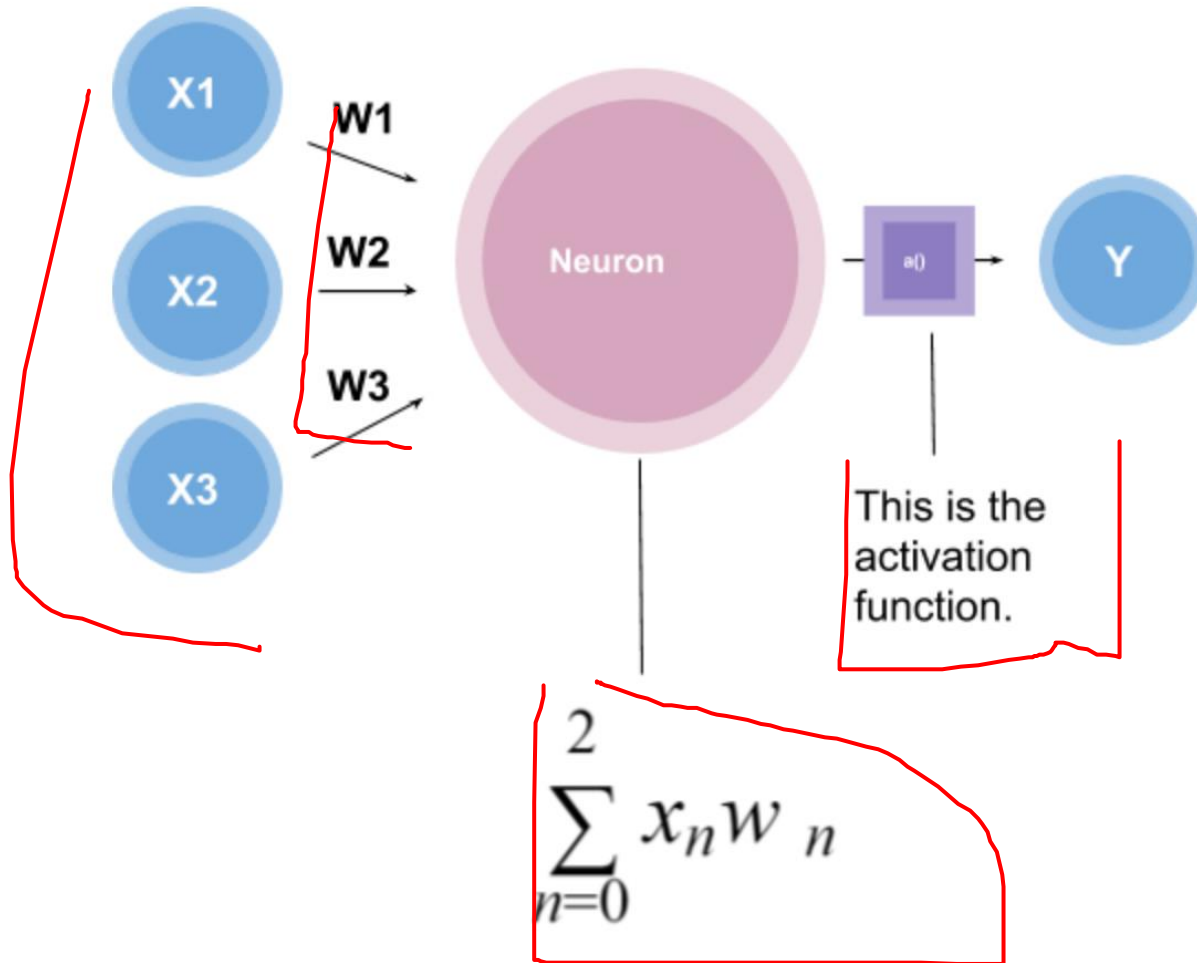






$$y = x_1 w_1 + x_2 w_2 + x_3 w_3$$

# Activation Function

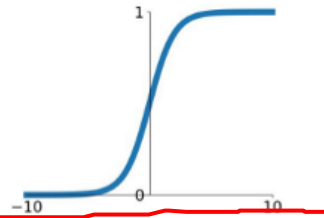




## Activation Functions

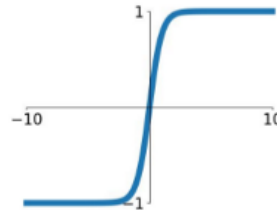
### Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



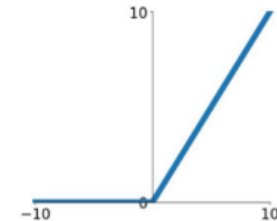
### tanh

$$\tanh(x)$$



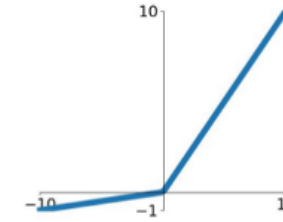
### ReLU

$$\max(0, x)$$



### Leaky ReLU

$$\max(0.1x, x)$$

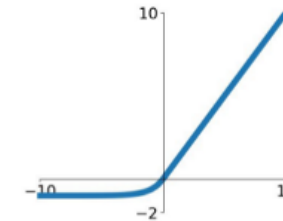


### Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

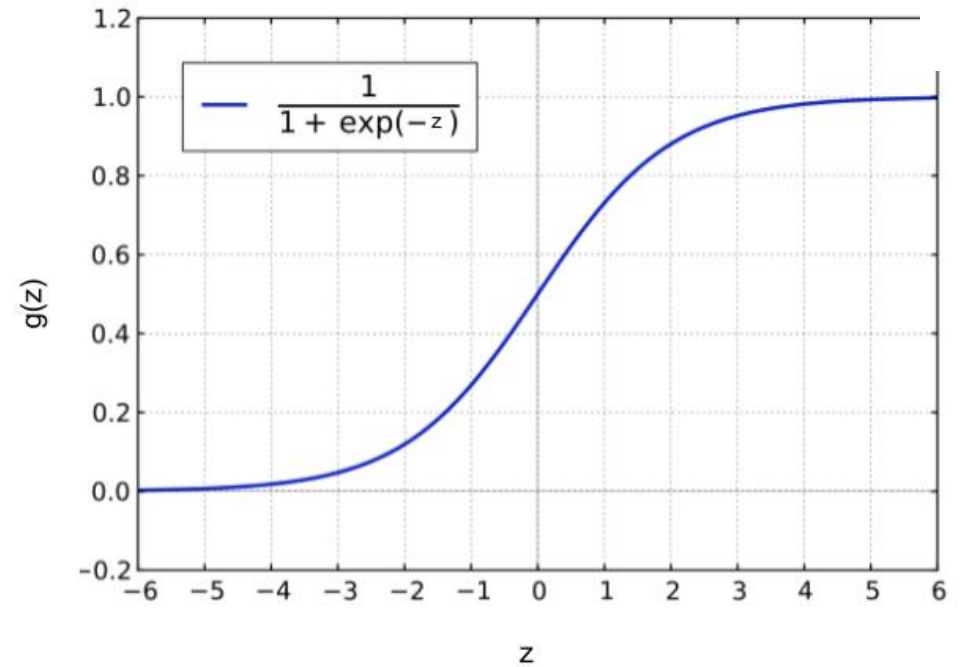
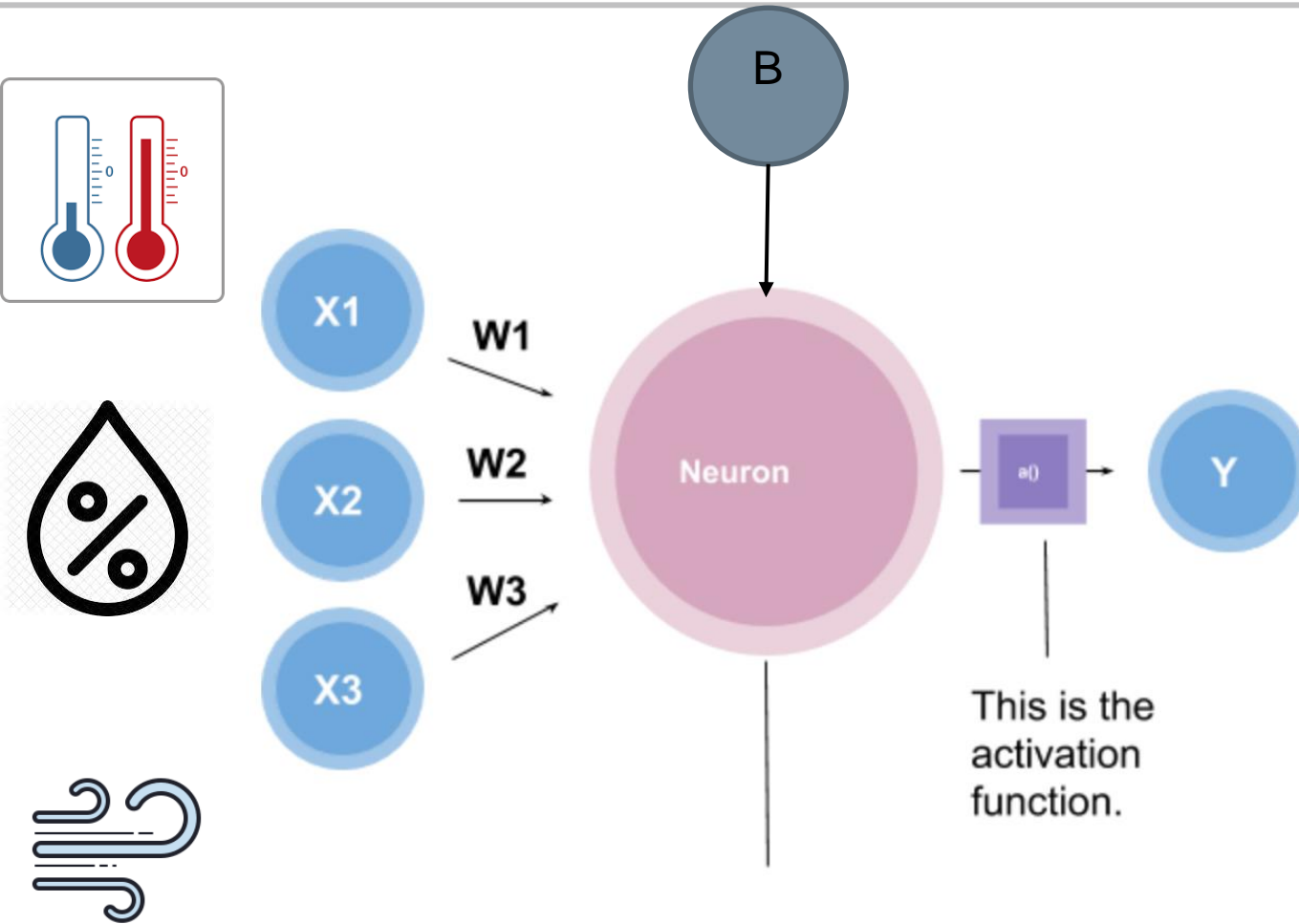
### ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

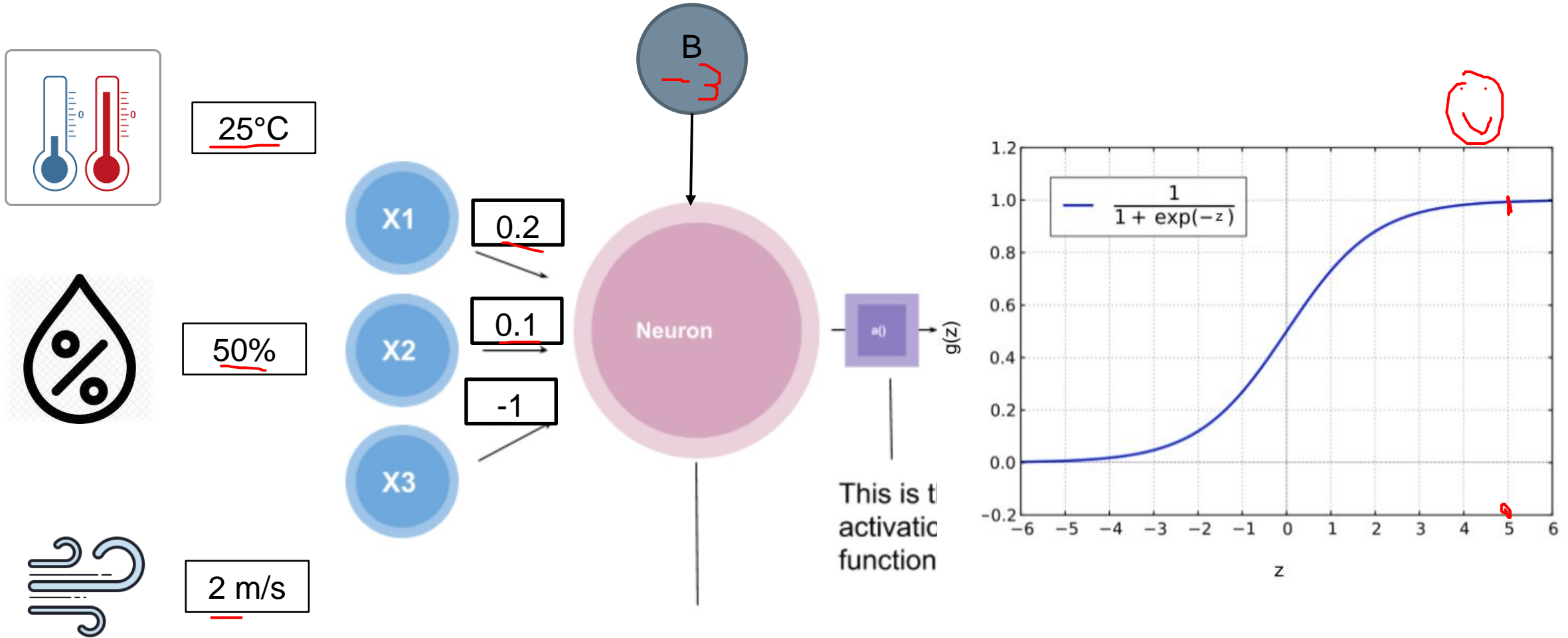




# Small example

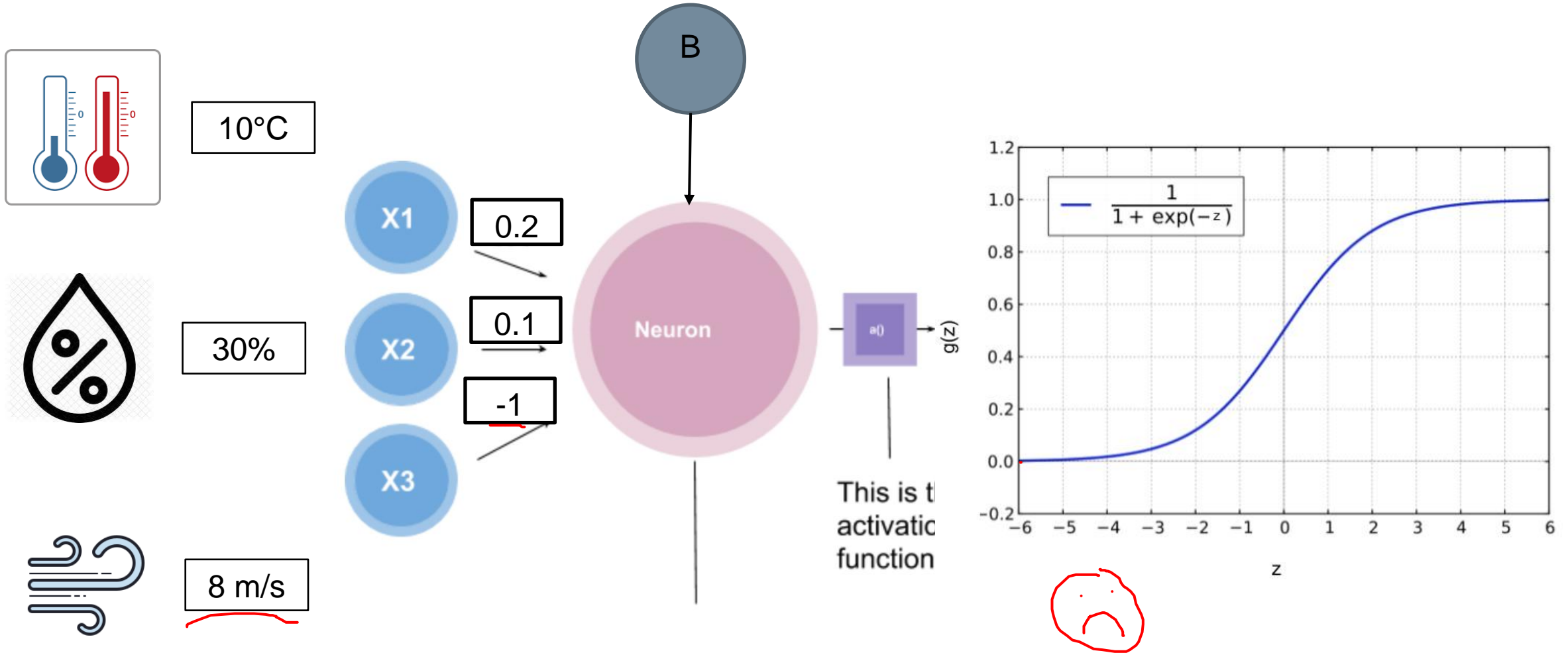


# Small example



$$z = \underline{25 \cdot 0.2} + \underline{50 \cdot 0.1} + \underline{2 \cdot (-1)} - 3 = \underline{5}$$

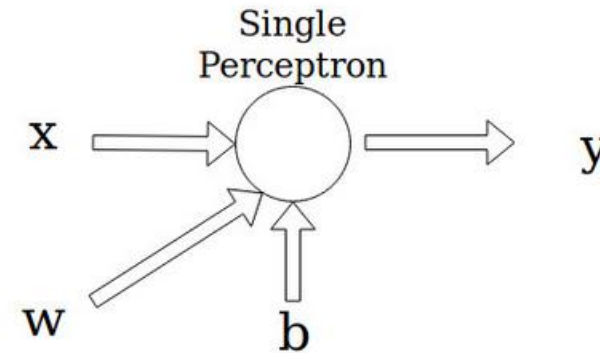
# Small example



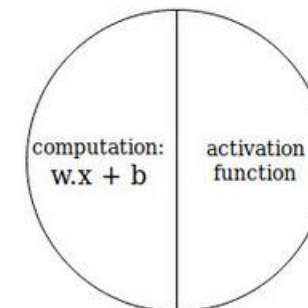
$$z = 10 \cdot 0.2 + 10 \cdot 0.1 + 8 \cdot (-1) - 3 = -6$$

# One example

$$\begin{aligned}x &= 0.2 \\w &= 0.5 \\b &= 1 \\y &= 1\end{aligned}$$



Inside a perceptron



$$\begin{aligned} comp &= w * x + b \\ comp &= 0.5 * 0.2 + 1 \\ \Rightarrow comp &= 1.1 \end{aligned}$$

$$\begin{aligned} y_{pred} &= \frac{1}{1 + e^{-comp}} \\ y_{pred} &= \frac{1}{1 + e^{-1.1}} \\ \Rightarrow y_{pred} &= 0.750260105 \end{aligned}$$

# Backpropagation

$$error = (y - y_{pred})^2$$

$$error = (1 - 0.750260105)^2$$

$$\Rightarrow error = \underline{0.062370014}$$

$$\frac{\delta error}{\delta w} = \frac{\delta error}{\delta y_{pred}} * \frac{\delta y_{pred}}{\delta comp} * \frac{\delta comp}{\delta w}$$

we need to calculate :

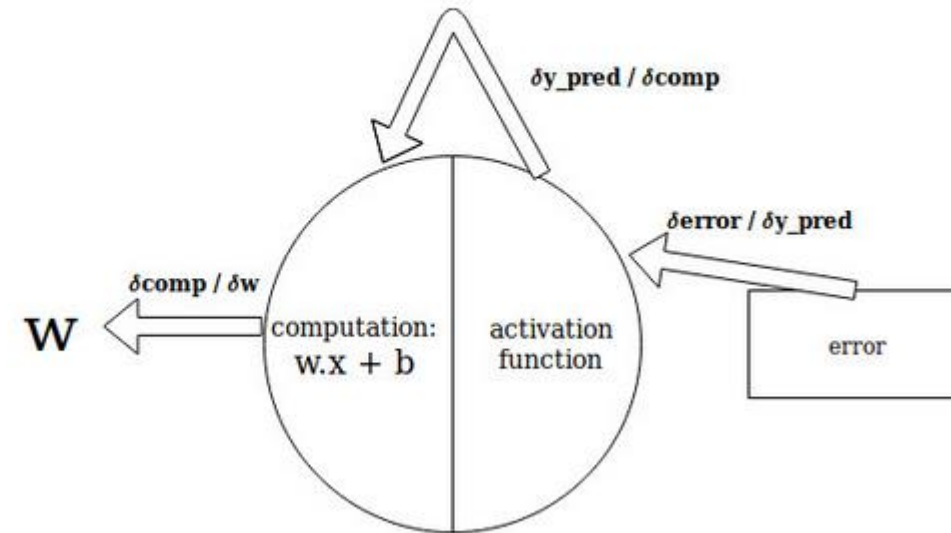
$\frac{\delta error}{\delta w}$  to get the deviation of  $w$ .

$$error = (y - y_{pred})^2$$

$$\frac{\delta error}{\delta y_{pred}} = 2 * (y - y_{pred}) * (0 - \underline{1})$$

$$\frac{\delta error}{\delta y_{pred}} = 2 * (1 - 0.750260105) * (-1)$$

$$\Rightarrow \frac{\delta error}{\delta y_{pred}} = \underline{-0.49947979}$$



Now,

$$y_{pred} = \frac{1}{1 + e^{-comp}}$$

$$\frac{\delta y_{pred}}{\delta comp} = y_{pred} * (1 - y_{pred})$$

$$\frac{\delta y_{pred}}{\delta comp} = 0.750260105 * (1 - 0.750260105)$$

$$\Rightarrow \frac{\delta y_{pred}}{\delta comp} = 0.18736987984$$

Lastly,

$$comp = w * x + b$$

$$\frac{\delta comp}{\delta w} = x$$

$$\Rightarrow \frac{\delta comp}{\delta w} = 0.2$$

Finally,

$$\frac{\delta error}{\delta w} = -0.49947979 * 0.18736987984 * 0.2$$

$$\Rightarrow \frac{\delta error}{\delta w} = -0.01871749364$$

$$w = w - \alpha \frac{\delta error}{\delta w}$$

0,5

$$comp = 0.50187174936 * 0.2 + 1$$

$$\Rightarrow comp = 1.10037434987$$

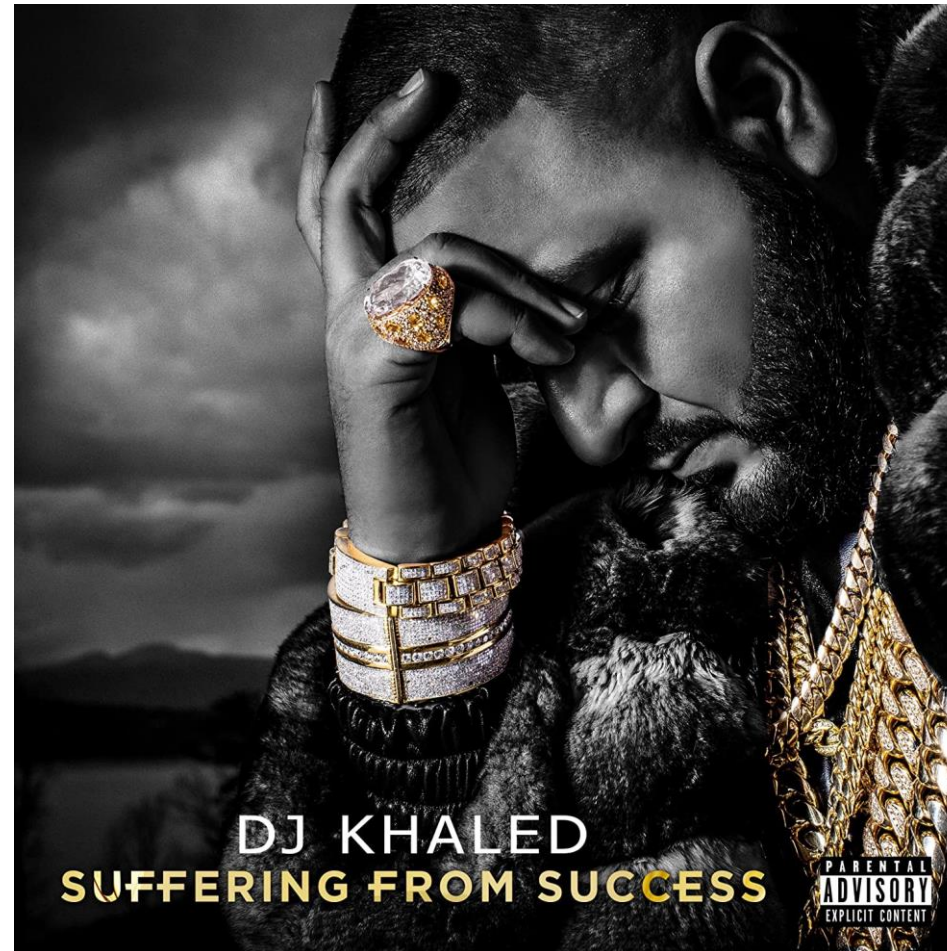
$$y_{pred} = \frac{1}{1 + e^{-1.10037434987}}$$

$$\Rightarrow y_{pred} = 0.75033024$$

$$error = 0.062334988$$

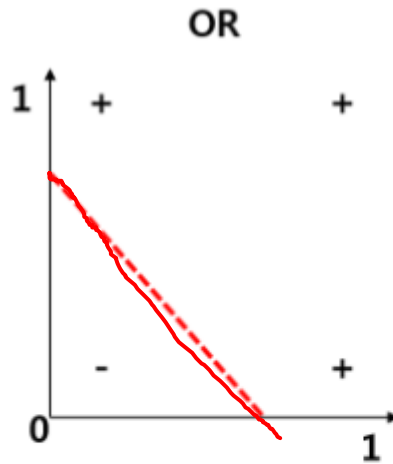


**As you can see, the error has decreased by 0.000035026**

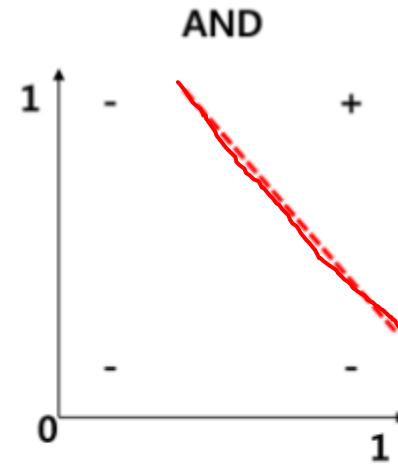




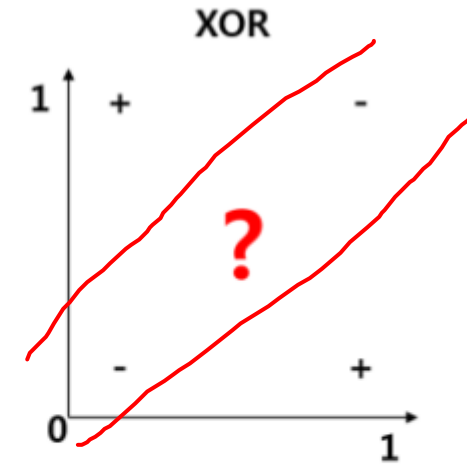
# Some problems to solve



$x_1$	$x_2$	$y$
0	0	0
0	1	1
1	0	1
1	1	1

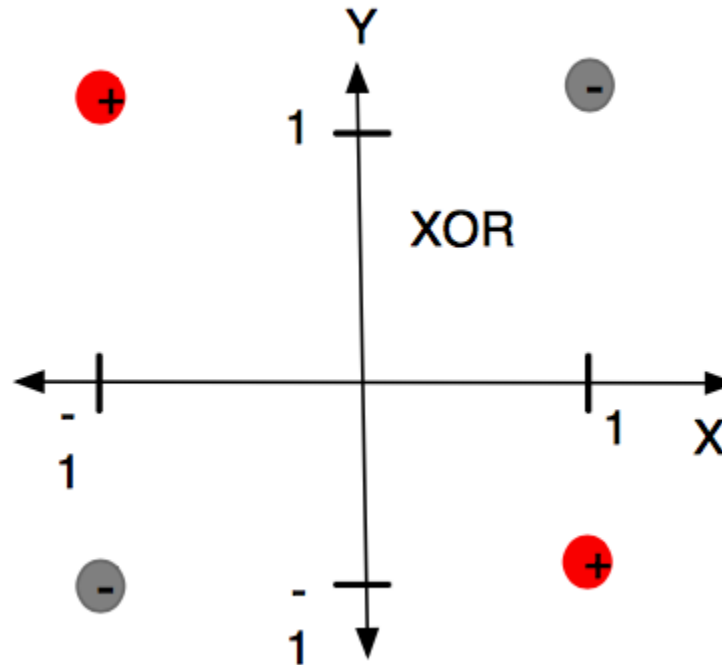


$x_1$	$x_2$	$y$
0	0	0
0	1	0
1	0	0
1	1	1

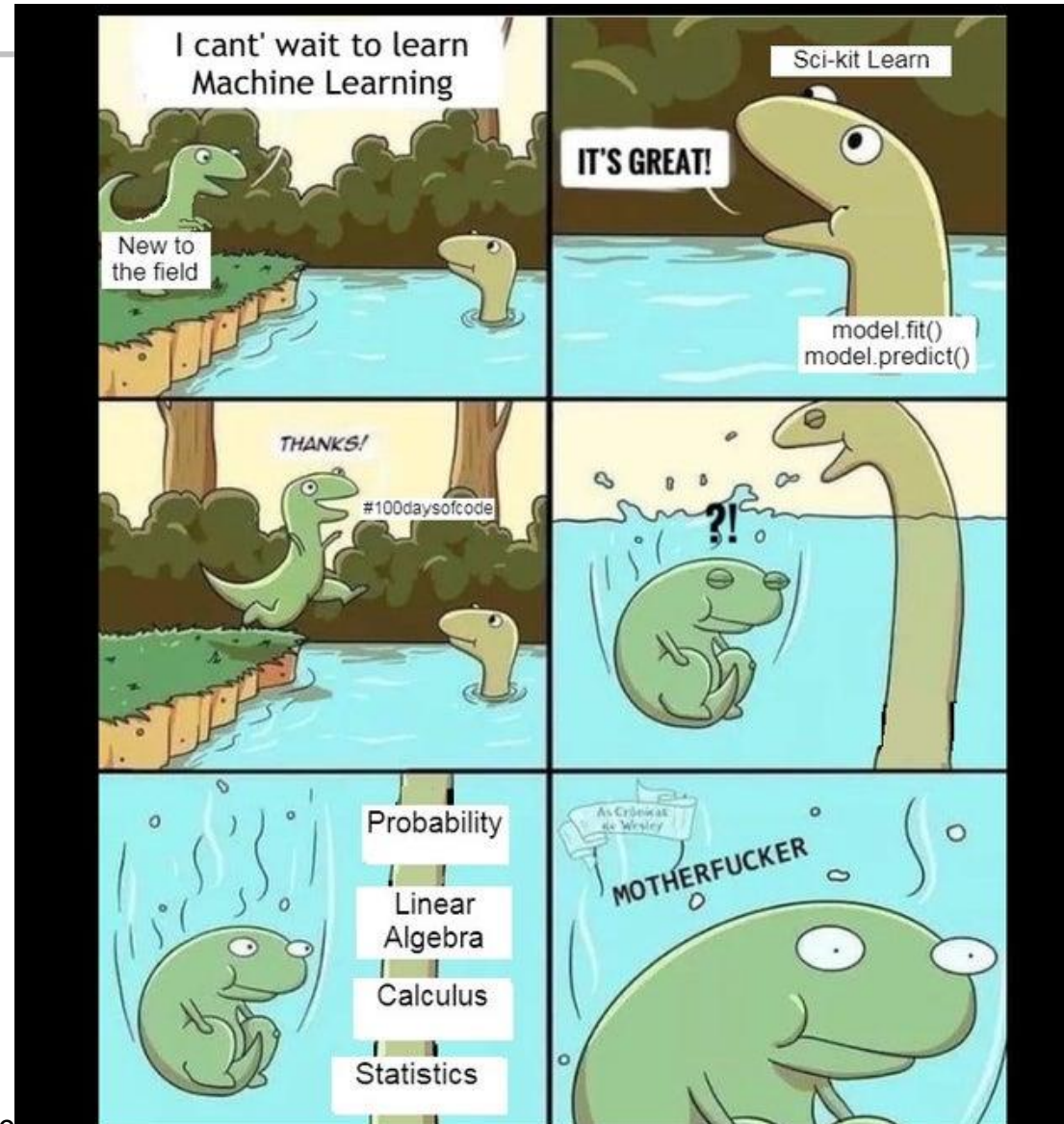


$x_1$	$x_2$	$y$
0	0	0
0	1	1
1	0	1
1	1	0

# But what is with XOR?



# Linear Algebra for Deep Learning





# Why Math?

Linear algebra, probability and calculus are the ‘languages’ in which machine learning is formulated. **Learning these topics will contribute a deeper understanding of the underlying algorithmic mechanics and allow development of new algorithms.**

Scalar   Vector   Matrix   Tensor

1

$$\begin{bmatrix} 1 \\ 2 \end{bmatrix}$$
$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$
$$\begin{bmatrix} \begin{bmatrix} 1 & 2 \end{bmatrix} & \begin{bmatrix} 3 & 2 \end{bmatrix} \\ \begin{bmatrix} 1 & 7 \end{bmatrix} & \begin{bmatrix} 5 & 4 \end{bmatrix} \end{bmatrix}$$



Scalars are **single numbers**

*0th*-order tensor

The notation:  $x \in \mathbb{R}$

E.g.

int, float, complex, bytes, Unicode

```
1  # In-Built Scalars
2  a = 5
3  b = 7.5
4  print(type(a))
5  print(type(b))
6  print(a + b)
7  print(a - b)
8  print(a * b)
9  print(a / b)
```

scalars.py hosted with ❤ by GitHub

[view raw](#)

```
<class 'int'>
<class 'float'>
12.5
-2.5
37.5
0.6666666666666666
```

# Vectors

Scalars are ordered arrays of single numbers

1<sup>th</sup>-order tensor

The notation:  $x \in \mathbb{R}^x$

E.g.

$x = [x_1 \ x_2 \ x_3 \ x_4 \ \dots \ x_n]$

```
1 import numpy as np
2
3 # Declaring Vectors
4
5 x = [1, 2, 3]
6 y = [4, 5, 6]
7
8 print(type(x))
9
10 # This doesn't give the vector addition.
11 print(x + y)
12
13 # Vector addition using Numpy
14
15 z = np.add(x, y)
16 print(z)
17 print(type(z))
18
19 # Vector Cross Product
20 mul = np.cross(x, y)
21 print(mul)
```

vectors.py hosted with ❤ by GitHub

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```
<class 'list'>
[1, 2, 3, 4, 5, 6]
[5 7 9]
<class 'numpy.ndarray'>
[-3  6 -3]
```

Scalars are rectangular arrays consisting of numbers

*2th*-order tensor

If  $m$  and  $n$  are positive integers, that is  $m, n \in \mathbb{N}$  then the  $m \times n$  matrix contains  $m \cdot n$  numbers, with  $m$  rows and  $n$  columns.

The full  $m \times n$  matrix can be written as:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix}$$

$$\mathbf{A} = [\mathbf{a}_{ij}]_{m \times n}$$

$$\begin{pmatrix} \underline{1} & 2 & \underline{3} \\ 4 & 5 & 6 \end{pmatrix} * \begin{pmatrix} 7 & \underline{8} \\ 9 & \underline{10} \\ 9 & \underline{12} \end{pmatrix} = \begin{pmatrix} 52 & \underline{64} \\ 127 & 154 \end{pmatrix}$$

Where,

$$\underline{[1, 2, 3] * [8, 10, 12] = \underline{1} * \underline{8} + \underline{2} * \underline{10} + \underline{3} * \underline{12} = 64}$$

# Transpose Matrix

$$A = \begin{pmatrix} 1 & 4 \\ -2 & 3 \end{pmatrix} \quad A^T = \begin{pmatrix} 1 & -2 \\ 4 & 3 \end{pmatrix}$$

$$A = \begin{pmatrix} 1 & 2 & 1 \\ 4 & 4 & 5 \\ 6 & 7 & 7 \end{pmatrix} \quad B = \begin{pmatrix} -7 & -7 & 6 \\ 2 & 1 & -1 \\ 4 & 5 & -4 \end{pmatrix}$$

$$A*B = \begin{pmatrix} -7 + 4 + 4 & -28 + 8 + 20 & -42 + 14 + 28 \\ -7 + 2 + 5 & -28 + 4 + 25 & -42 + 4 + 35 \\ 6 - 2 - 4 & 24 - 4 - 20 & 36 - 7 - 28 \end{pmatrix}$$

$$= \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

**What is a perceptron draw an example and name the parts**

**Which activation functions do you know?**

**What is Backpropagation used for?**



<https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53>

<https://towardsdatascience.com/what-is-a-perceptron-basics-of-neural-networks-c4cfea20c590>

German:

<https://www.youtube.com/watch?v=kLEhMF-GXYQ>