

ARTIFICIAL INTELLIGENCE 2

The Perceptron

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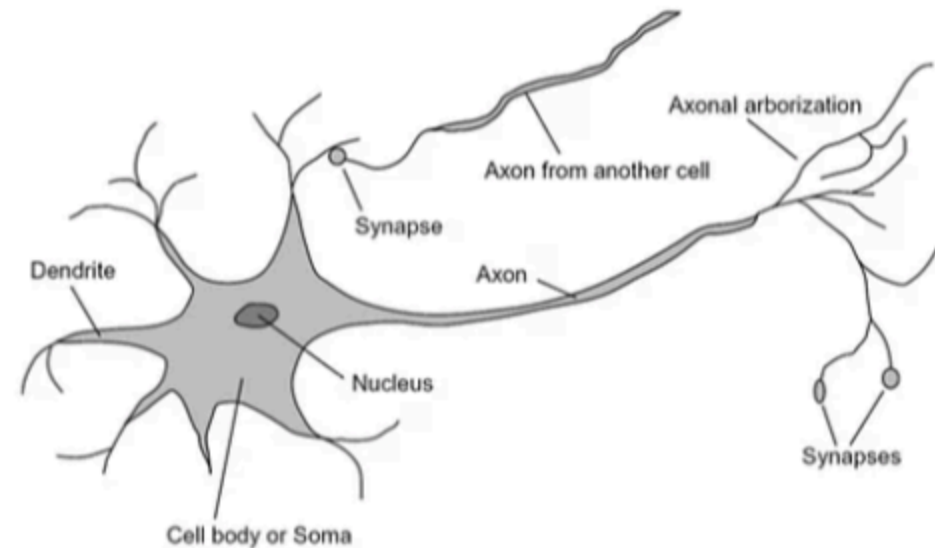
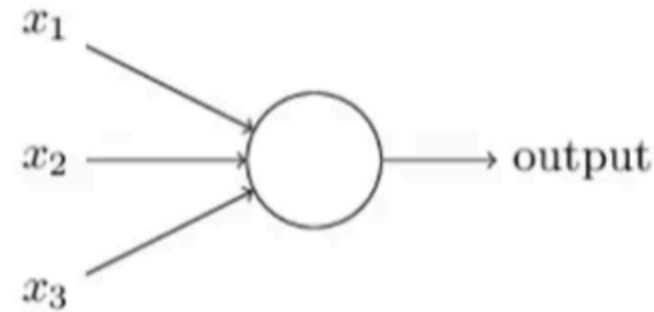


A Biological Inspiration

Artificial neural networks are loosely inspired by the **human brain**.

Each **biological neuron** in the brain operates through electrochemical signals and consists of:

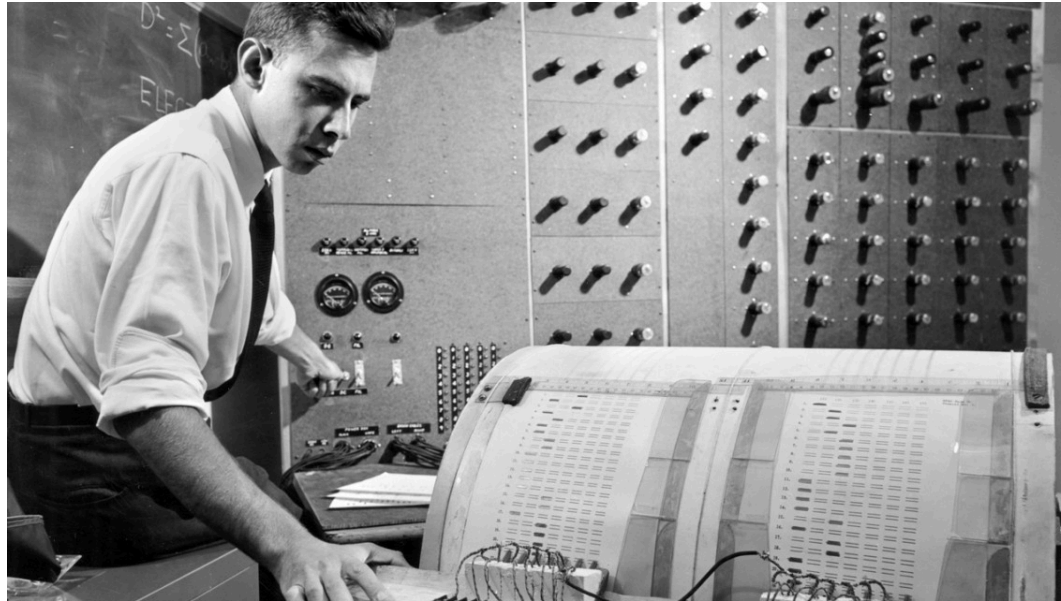
- a **cell body** with **dendrites** receiving inputs;
- an **axon** sending outputs.



Computational Model of a Biological Neuron

The **artificial neuron network** was invented in 1943 by Warren McCulloch and Walter Pitts in "A logical calculus of the ideas immanent in nervous activity."

The **perceptron** was first simulated by Frank Rosenblatt in 1957 on an IBM 704.



From Linear Regression to the Perceptron

We have a dataset with M features and N rows, and a target column.

	1	2	3	...	M	y
[1]	$x_1^{[1]}$	$x_2^{[1]}$	$x_3^{[1]}$	...	$x_M^{[1]}$	$y^{[1]}$
[2]	$x_1^{[2]}$	$x_2^{[2]}$	$x_3^{[2]}$	...	$x_M^{[2]}$	$y^{[2]}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
[N]	$x_1^{[N]}$	$x_2^{[N]}$	$x_3^{[N]}$	...	$x_M^{[N]}$	$y^{[N]}$

The multiple linear regression model can be written as:

$$\hat{y}^{[i]} = w_1 x_1^{[i]} + w_2 x_2^{[i]} + \cdots + w_M x_M^{[i]} + b$$

From Linear Regression to the Perceptron

Let's just focus on a single row i

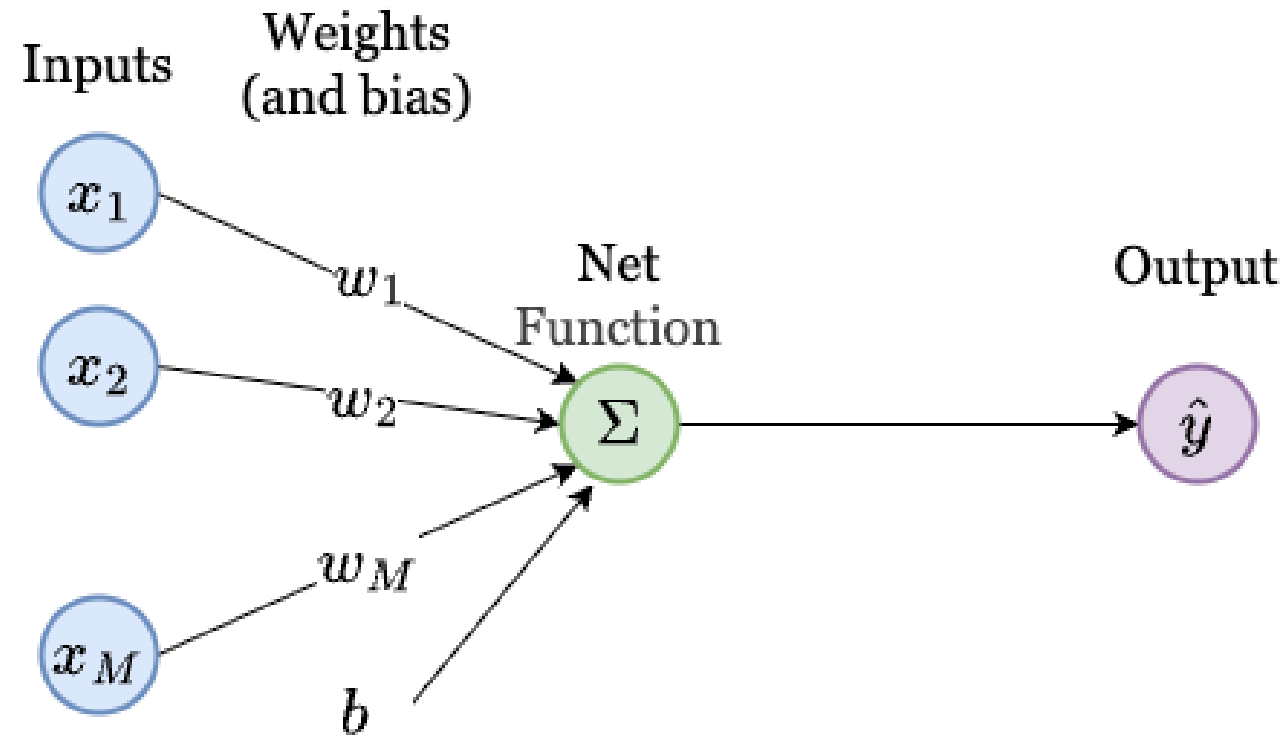
	1	2	3	...	M	y
$[i]$	$x_1^{[i]}$	$x_2^{[i]}$	$x_3^{[i]}$	...	$x_M^{[i]}$	$y^{[i]}$

And drop the instance index i for easier notation:

$$\hat{y} = w_1x_1 + w_2x_2 + \cdots + w_Mx_M + b$$

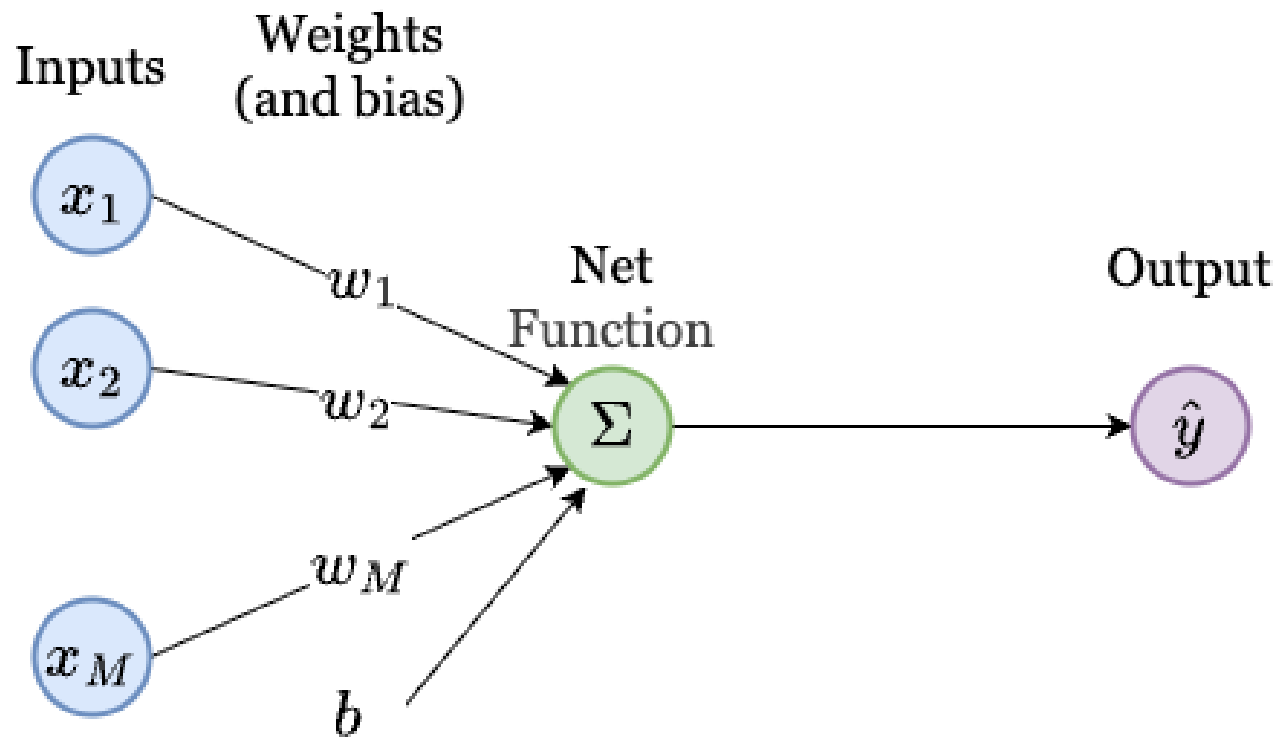
From Linear Regression to the Perceptron

$$\hat{y} = w_1x_1 + w_2x_2 + \cdots + w_Mx_M + b$$



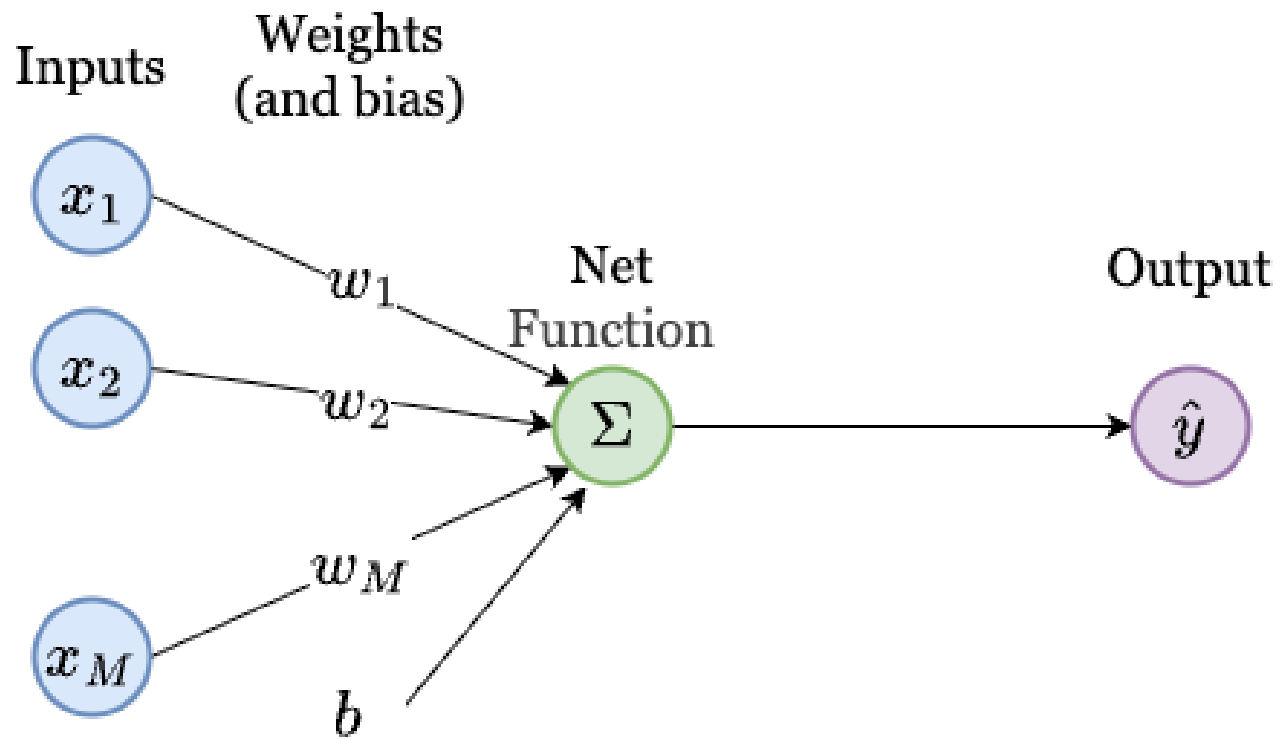
From Linear Regression to the Perceptron

$$\hat{y} = \sum_{j=1}^M w_j x_j + b$$



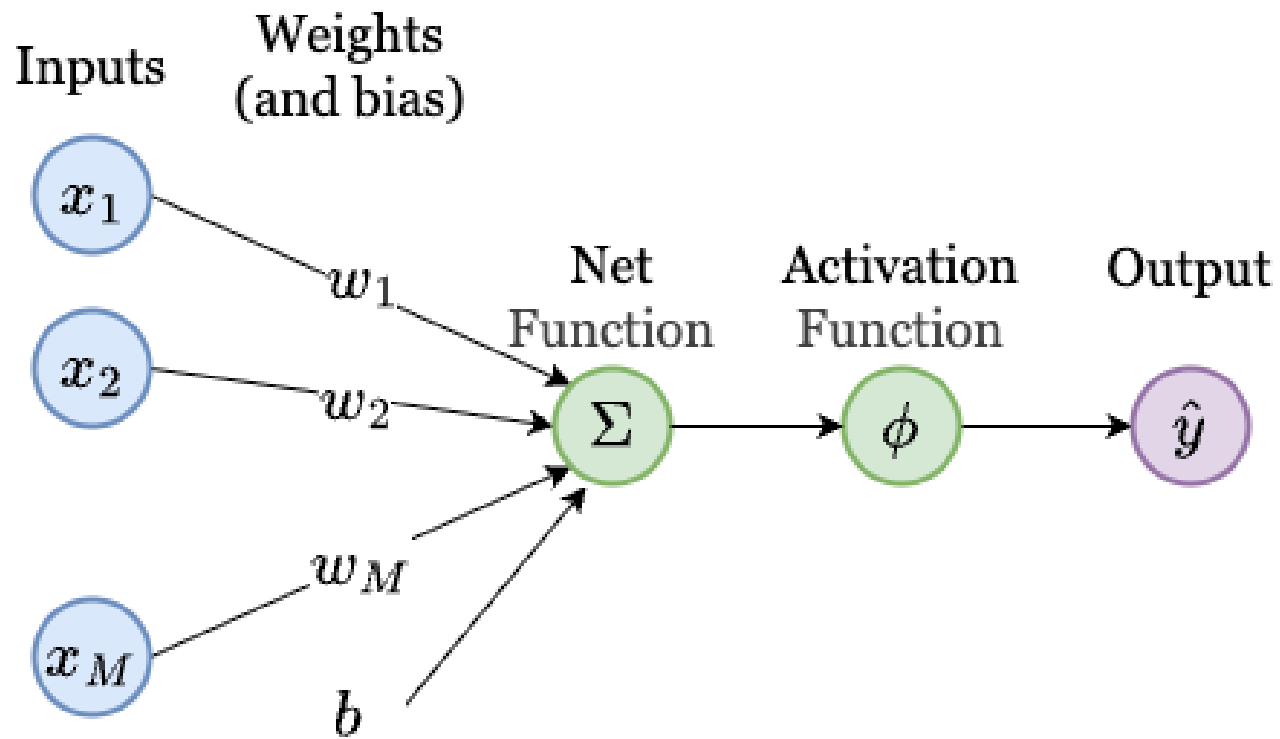
From Linear Regression to the Perceptron

$$\hat{y} = \sum_{j=1}^M w_j x_j + b$$

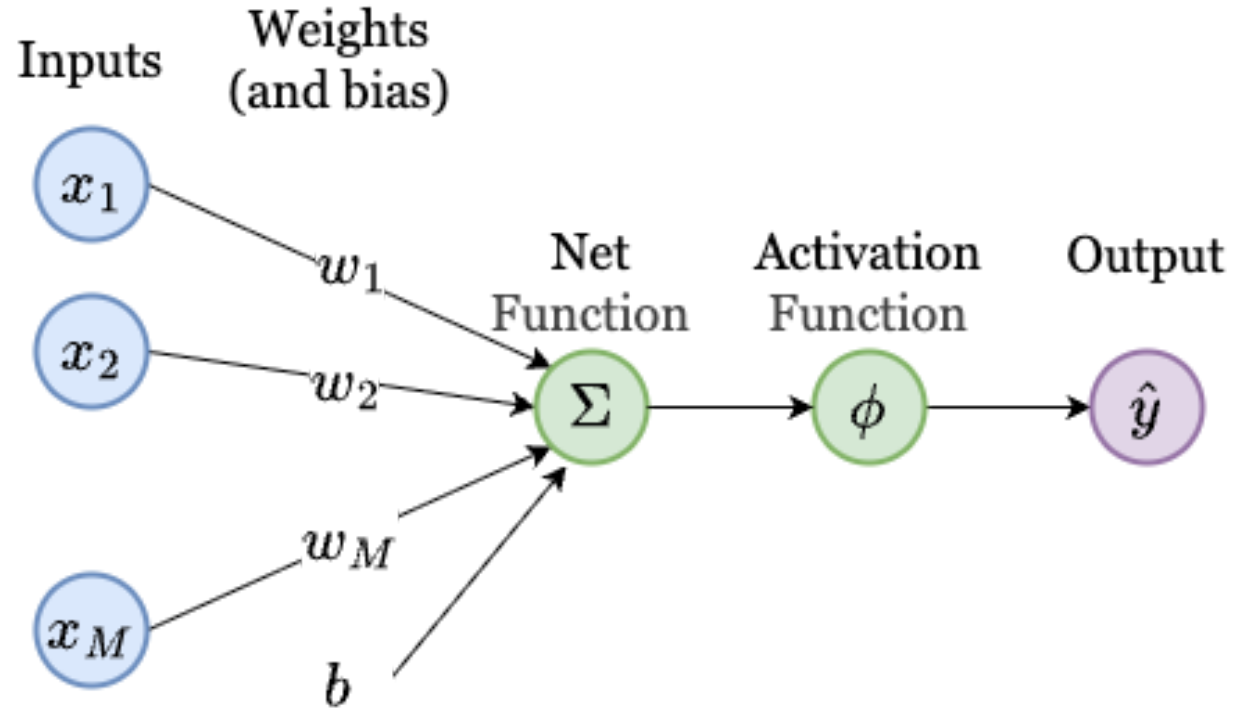


The Perceptron

$$\hat{y} = \phi \left(\sum_{j=1}^M w_j x_j + b \right) = \phi(z)$$



The Perceptron



ϕ is called the **activation function** and in the classical perceptron it is the **sign** function:

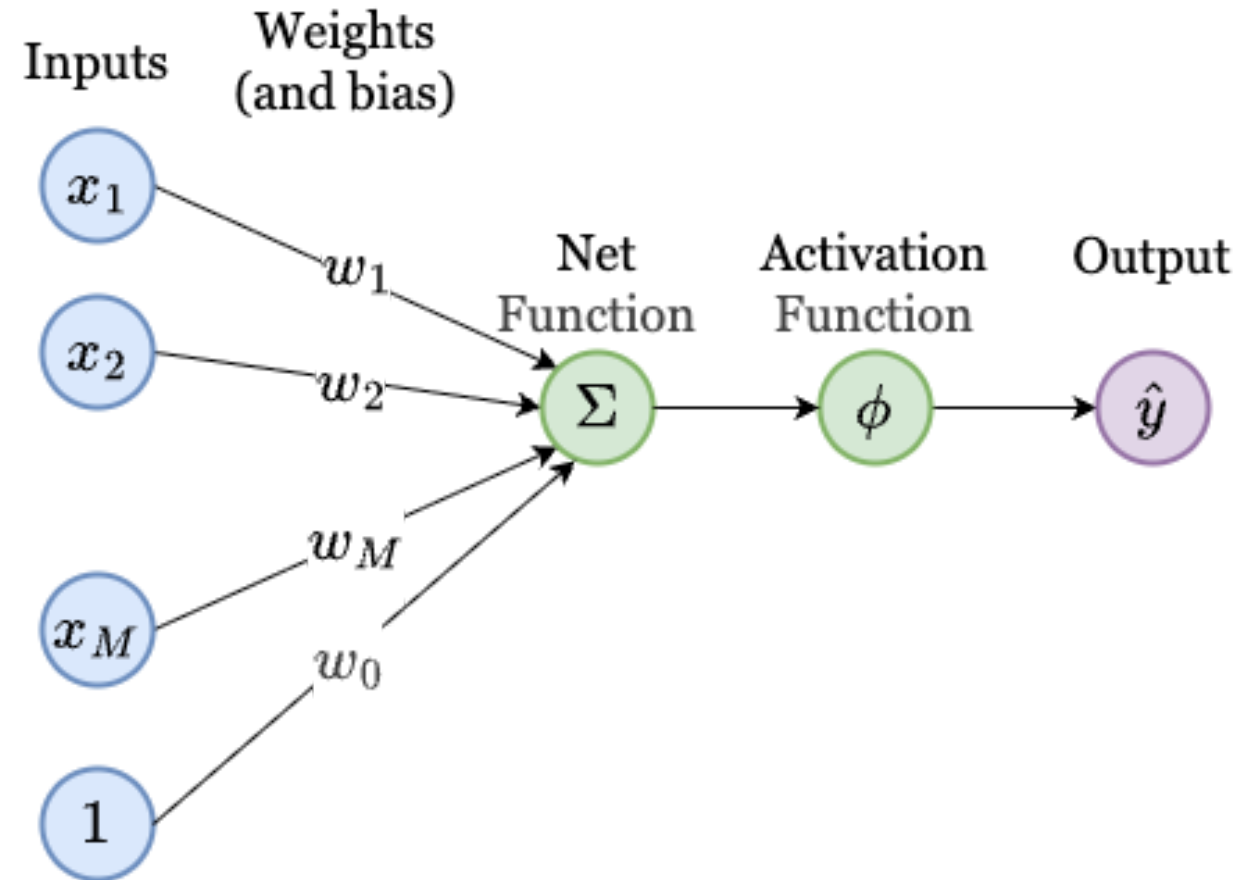
$$\hat{y} = \text{sign}(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ -1 & \text{if } z < 0 \end{cases}$$

$$\hat{y} = \text{sign} \left(\sum_{j=1}^M w_j x_j + b \right) = \text{sign}(z)$$

The Perceptron (alternative formulation)

For ease of notation sometimes the bias is replaced by an additional input neuron $x_0 = 1$, multiplied by a weight w_0 .

$$\hat{y} = \text{sign} \left(\sum_{j=0}^M w_j x_j \right) = \text{sign}(z)$$



Perceptron Inference Example

x_1	x_2	y
3	1	-1

Let the perceptron parameters be:

$$w_1 = 1, \quad w_2 = -2, \quad b = 0.5$$

For the input $(x_1, x_2) = (3, 1)$:

$$z = w_1 x_1 + w_2 x_2 + b = 1 \cdot 3 + (-2) \cdot 1 + 0.5 = 1.5$$

$$\hat{y} = \text{sign}(z) = 1 \quad \text{wrong prediction!}$$

The Perceptron Learning Algorithm

Note that the, contrary to linear regression, the output of a classical perceptron is a **label**, either positive 1, or negative -1 .

So the perceptron is a (binary) **classification** model!

We want to find the best weights to solve the classification task so we need to train (modify) the weights when the model is wrong.

To train a perceptron we use an **online** procedure, i.e., we update the weights one example at a time, immediately after each misclassified sample.

The Perceptron Learning Algorithm

1. Initialize the weights $[w_0, \dots, w_M]$ (usually at $\mathbf{0}$);

Repeat: for each training example $\mathbf{x}^{[i]} = [x_1^{[i]}, \dots, x_M^{[i]}]$, with label $y^{[i]}$:

2. Inference: compute

$$\hat{y}^{[i]} = f(\mathbf{x}^{[i]}) = \text{sign} \left(\sum_{j=0}^M w_j x_j^{[i]} \right);$$

3. Update the weights with (only if $\hat{y}^{[i]} \neq y^{[i]}$):

$$\mathbf{w}_{\text{new}} = \mathbf{w}_{\text{old}} + \underbrace{\lambda}_{\text{learning rate}} \underbrace{(y^{[i]} - \hat{y}^{[i]})}_{\text{error}} \mathbf{x}^{[i]}$$

until one full pass over the data (epoch) produces no change in the weights.

The Perceptron Learning Algorithm

$$\mathbf{w}_{\text{new}} = \mathbf{w}_{\text{old}} + \underbrace{\lambda}_{\text{learning rate}} \underbrace{(y^{[i]} - \hat{y}^{[i]})}_{\text{error}} \mathbf{x}^{[i]}$$

$e = (y^{[i]} - \hat{y}^{[i]})$ is the error, i.e., the difference between the real label and the predicted one. It can be:

- 0 when $y^{[i]} = \hat{y}^{[i]}$ so no update is needed
- 2 if $y^{[i]} = 1$ and $\hat{y}^{[i]} = -1$: weight must be increased so that $f(\mathbf{x})$ will increase
- -2 if $y^{[i]} = -1$ and $\hat{y}^{[i]} = 1$: weight must be decreased so that $f(\mathbf{x})$ will decrease

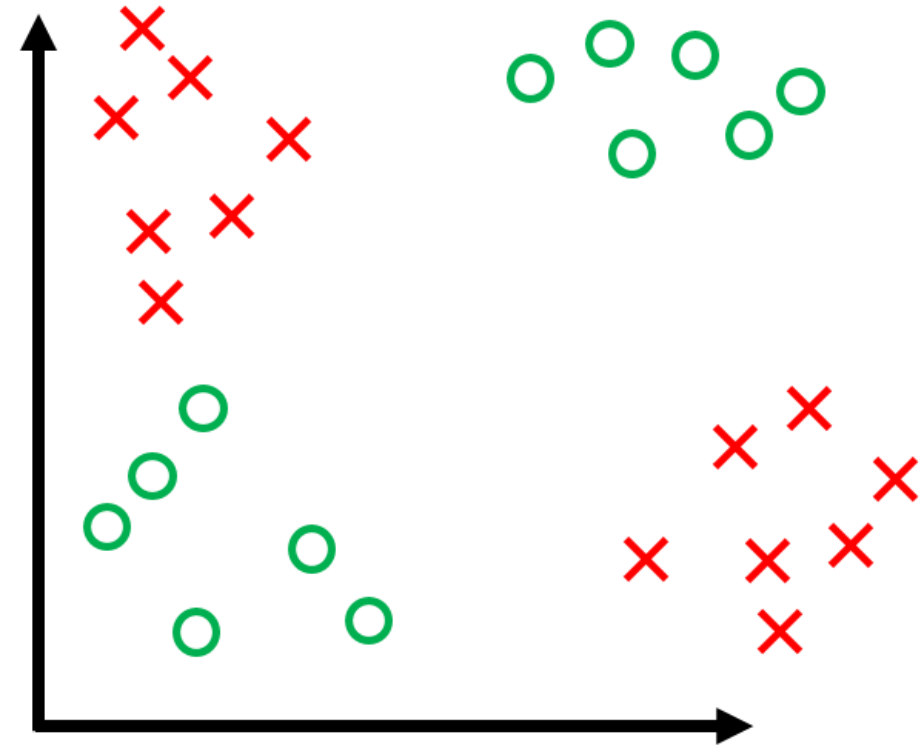
$\lambda \in (0, 1]$ is the learning rate used to control the amount of adjustment made in each iteration.

An equivalent formulation of the perceptron update is often presented using only the true label in the adjustment step. With labels encoded as -1 and +1, both forms are identical up to a constant factor, which can be absorbed into the learning rate.

Perceptron Convergence

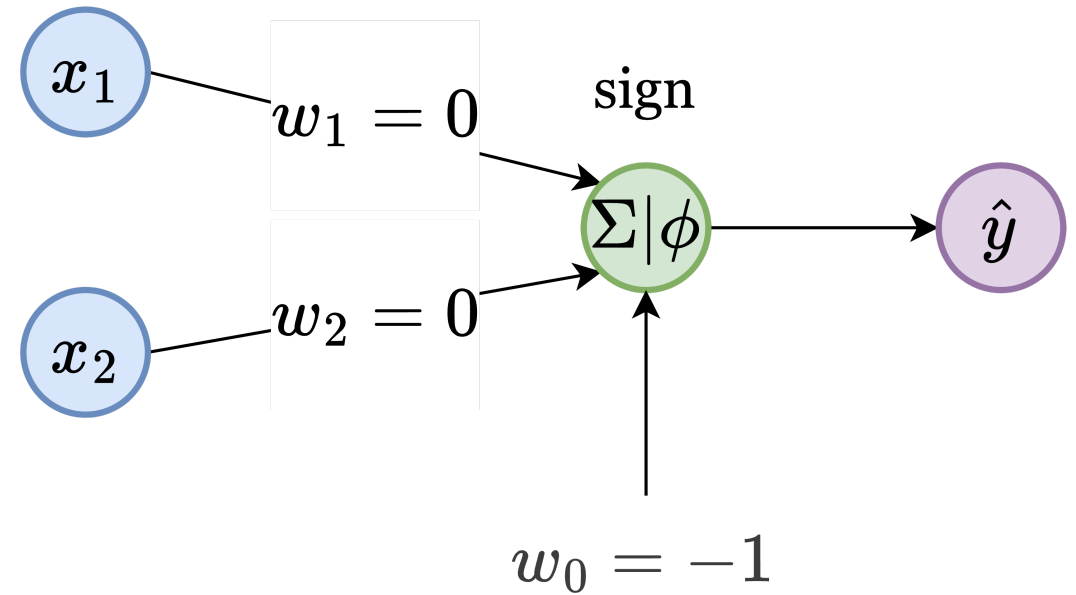
The Perceptron was arguably one of the first algorithm with a strong formal guarantee.

- If a dataset is **linearly separable**, the Perceptron will find a separating hyperplane in a finite number of updates.
- If the data is **not linearly separable**, it will loop forever.



Example

	x_1	x_2	y
[1]	0	1	-1
[2]	0	0	1
[3]	1	2	-1



$$\lambda = 0.3$$

$$\phi = \text{sign}$$

Example - Iteration 1.

$$\mathbf{x}^{[1]} = [0, 1], \quad y^{[1]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}\left(\underbrace{w_1}_0 \cdot \underbrace{x_1}_0 + \underbrace{w_2}_0 \cdot \underbrace{x_2}_1 + \underbrace{w_0}_{-1}\right) \\ &= \text{sign}(-1) = -1\end{aligned}$$

$$e = \underbrace{y}_{-1} - \underbrace{\hat{y}}_{-1} = 0 \quad \text{OK}$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0

Example - Iteration 2.

$$\mathbf{x}^{[2]} = [0, 0], \quad y^{[2]} = 1$$

$$\begin{aligned}\hat{y} &= \text{sign}(0 \cdot 0 + 0 \cdot 0 - 1) \\ &= \text{sign}(-1) = -1\end{aligned}$$

$$e = 1 - (-1) = 2 \quad \text{UPDATE}$$

$$w_1 \leftarrow \underbrace{w_1}_0 + \underbrace{\lambda}_{0.3} \cdot \underbrace{e}_2 \cdot \underbrace{x_1}_0 = 0$$

$$w_2 \leftarrow 0 + 0.3 \cdot 2 \cdot 0 = 0$$

$$w_0 \leftarrow -1 + 0.3 \cdot 2 \cdot \underbrace{1}_{x_0=1} = -0.4$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2

Example - Iteration 3.

$$\mathbf{x}^{[3]} = [1, 2], \quad y^{[3]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}(0 \cdot 1 + 0 \cdot 2 - 0.4) \\ &= \text{sign}(-0.4) = -1\end{aligned}$$

$$e = -1 - (-1) = 0 \quad \text{OK}$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0

Example - Iteration 4.

$$\mathbf{x}^{[1]} = [0, 1], \quad y^{[1]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}(0 \cdot 0 + 0 \cdot 1 - 0.4) \\ &= \text{sign}(-0.4) = -1\end{aligned}$$

$$e = -1 - (-1) = 0 \quad \text{OK}$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0

Example - Iteration 5.

$$\mathbf{x}^{[2]} = [0, 0], \quad y^{[2]} = 1$$

$$\begin{aligned}\hat{y} &= \text{sign}(0 \cdot 0 + 0 \cdot 0 - 0.4) \\ &= \text{sign}(-0.4) = -1\end{aligned}$$

$$e = 1 - (-1) = 2 \quad \text{UPDATE}$$

$$w_1 \leftarrow 0 + 0.3 \cdot 2 \cdot 0 = 0$$

$$w_2 \leftarrow 0 + 0.3 \cdot 2 \cdot 0 = 0$$

$$w_0 \leftarrow -0.4 + 0.3 \cdot 2 \cdot 1 = 0.2$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2

Example - Iteration 6.

$$\mathbf{x}^{[3]} = [1, 2], \quad y^{[3]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}(0 \cdot 1 + 0 \cdot 2 + 0.2) \\ &= \text{sign}(0.2) = 1\end{aligned}$$

$$e = -1 - 1 = -2 \quad \text{UPDATE}$$

$$w_1 \leftarrow 0 + 0.3 \cdot (-2) \cdot 1 = -0.6$$

$$w_2 \leftarrow 0 + 0.3 \cdot (-2) \cdot 2 = -1.2$$

$$w_0 \leftarrow 0.2 + 0.3 \cdot (-2) \cdot 1 = -0.4$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2
[3]	0.2	0	0	-2

Example - Iteration 7.

$$\mathbf{x}^{[1]} = [0, 1], \quad y^{[1]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}((-0.6) \cdot 0 + (-1.2) \cdot 1 - 0.4) \\ &= \text{sign}(-1.6) = -1\end{aligned}$$

$$e = -1 - (-1) = 0 \quad \text{OK}$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2
[3]	0.2	0	0	-2
[1]	-0.4	-0.6	-1.2	0

Example - Iteration 8.

$$\mathbf{x}^{[2]} = [0, 0], \quad y^{[2]} = 1$$

$$\begin{aligned}\hat{y} &= \text{sign}(0 + 0 - 0.4) \\ &= \text{sign}(-0.4) = -1\end{aligned}$$

$$e = 1 - (-1) = 2 \quad \text{UPDATE}$$

$$w_1 \leftarrow -0.6 + 0.3 \cdot 2 \cdot 0 = -0.6$$

$$w_2 \leftarrow -1.2 + 0.3 \cdot 2 \cdot 0 = -1.2$$

$$w_0 \leftarrow -0.4 + 0.3 \cdot 2 \cdot 1 = 0.2$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2
[3]	0.2	0	0	-2
[1]	-0.4	-0.6	-1.2	0
[2]	-0.4	-0.6	-1.2	2

Example - Iteration 9.

$$\mathbf{x}^{[3]} = [1, 2], \quad y^{[3]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}((-0.6) \cdot 1 + (-1.2) \cdot 2 + 0.2) \\ &= \text{sign}(-2.8) = -1\end{aligned}$$

$$e = -1 - (-1) = 0 \quad \text{OK}$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2
[3]	0.2	0	0	-2
[1]	-0.4	-0.6	-1.2	0
[2]	-0.4	-0.6	-1.2	2
[3]	0.2	-0.6	-1.2	0

Example - Iteration 10.

$$\mathbf{x}^{[1]} = [0, 1], \quad y^{[1]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}((-0.6) \cdot 0 + (-1.2) \cdot 1 + 0.2) \\ &= \text{sign}(-1.0) = -1\end{aligned}$$

$$e = -1 - (-1) = 0 \quad \text{OK}$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2
[3]	0.2	0	0	-2
[1]	-0.4	-0.6	-1.2	0
[2]	-0.4	-0.6	-1.2	2
[3]	0.2	-0.6	-1.2	0
[1]	0.2	-0.6	-1.2	0

Example - Iteration 11.

$$\mathbf{x}^{[2]} = [0, 0], \quad y^{[2]} = 1$$

$$\begin{aligned} \hat{y} &= \text{sign}(0 + 0 + 0.2) \\ &= \text{sign}(0.2) = 1 \end{aligned}$$

$$e = 1 - 1 = 0 \quad \text{OK}$$

	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2
[3]	0.2	0	0	-2
[1]	-0.4	-0.6	-1.2	0
[2]	-0.4	-0.6	-1.2	2
[3]	0.2	-0.6	-1.2	0
[1]	0.2	-0.6	-1.2	0
[2]	0.2	-0.6	-1.2	0

Example - Iteration 12.

$$\mathbf{x}^{[3]} = [1, 2], \quad y^{[3]} = -1$$

$$\begin{aligned}\hat{y} &= \text{sign}((-0.6) \cdot 1 + (-1.2) \cdot 2 + 0.2) \\ &= \text{sign}(-2.8) = -1\end{aligned}$$

$$e = -1 - (-1) = 0 \quad \text{OK}$$

A full epoch without updates so we can stop, the algorithm converged!

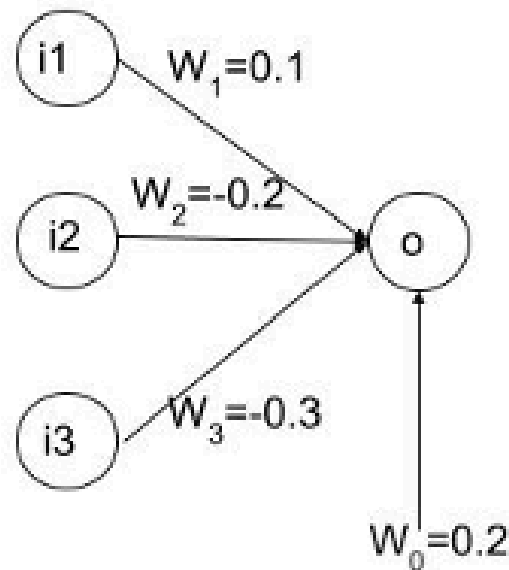
	w_0	w_1	w_2	e
[1]	-1	0	0	0
[2]	-1	0	0	2
[3]	-0.4	0	0	0
[1]	-0.4	0	0	0
[2]	-0.4	0	0	2
[3]	0.2	0	0	-2
[1]	-0.4	-0.6	-1.2	0
[2]	-0.4	-0.6	-1.2	2
[3]	0.2	-0.6	-1.2	0
[1]	0.2	-0.6	-1.2	0
[2]	0.2	-0.6	-1.2	0
[3]	0.2	-0.6	-1.2	0

Exercise 1

Exercise 2 (6 points)

Train the following neural network until the method converges. The activation function is the function: $f(x) = \text{sign}(x)$ and $\lambda=0.2$.

Reminder: at the end of each step write the updated weights. The update formula is: $W_{new} = W_{old} + \lambda \cdot (real_{label} - pred_{label}) \cdot input$

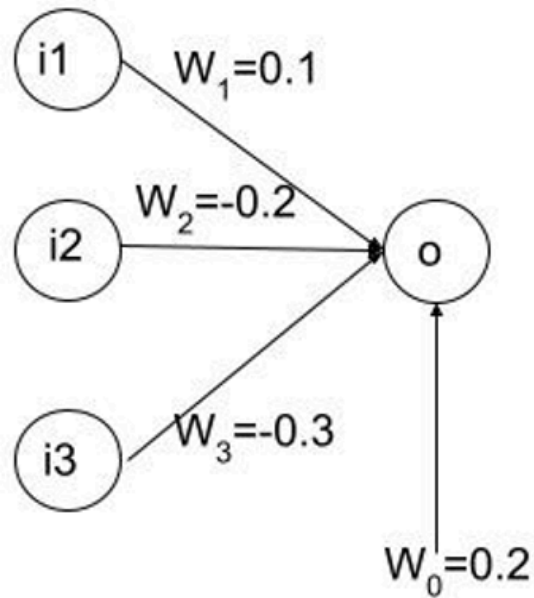


i1	i2	i3	Real label
1	0	-1	1
1	1	0	-1
-1	0	1	-1

Exercise 2

Exercise 2 (6 points)

Train the following neural network until the method converges. The activation function is the function: $f(x) = \text{sign}(x+0.1)$ (where $\text{sign}(x)$ is equal to +1 when $x \geq 0$, is equal to -1 otherwise) and $\lambda=0.2$. Reminder: the update formula is: $W_{new} = W_{old} + \lambda \cdot (real_{label} - pred_{label}) \cdot input$



i1	i2	i3	Real label
1	0	-1	1
0	1	0	1
0	0	1	-1