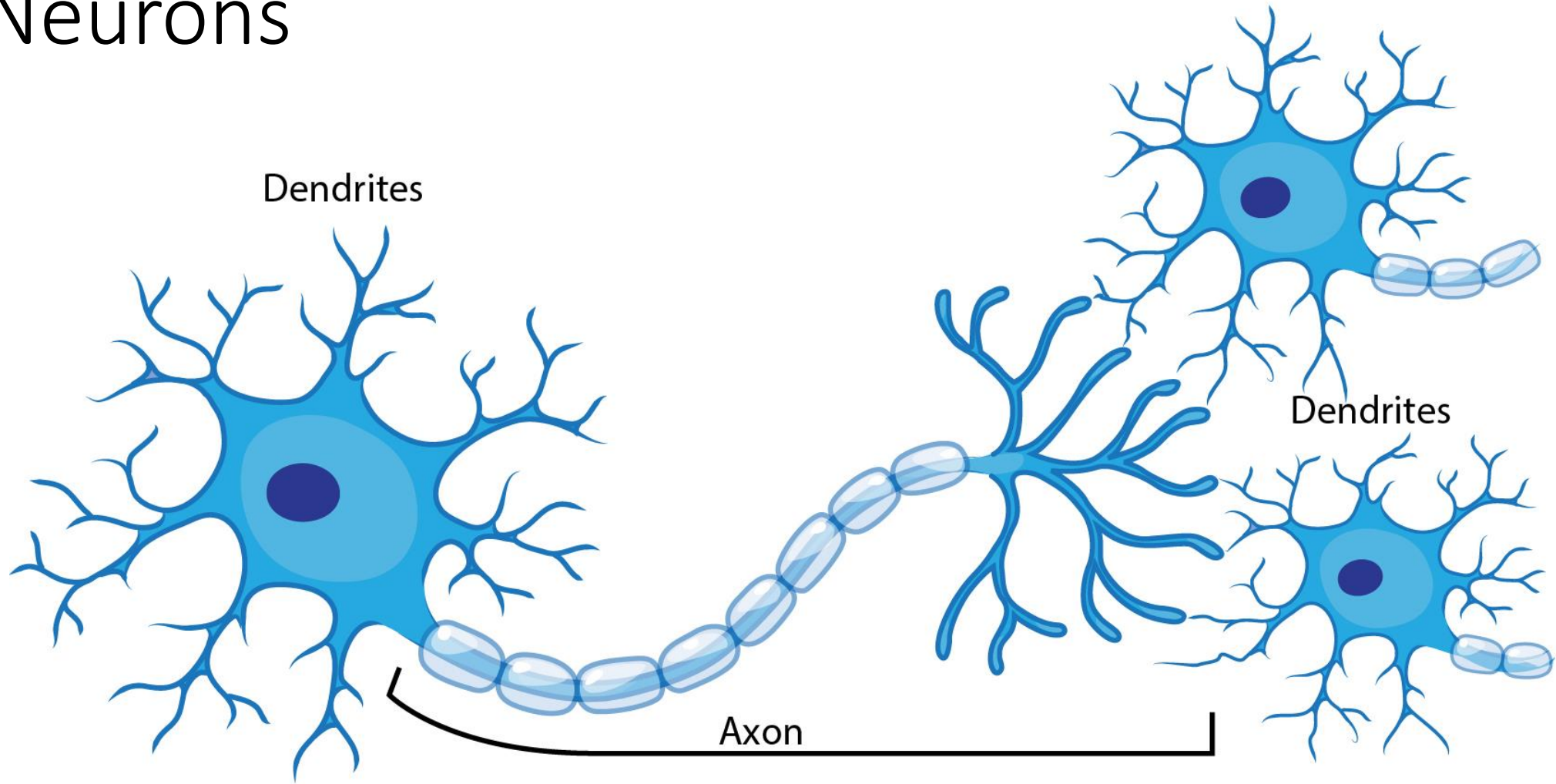


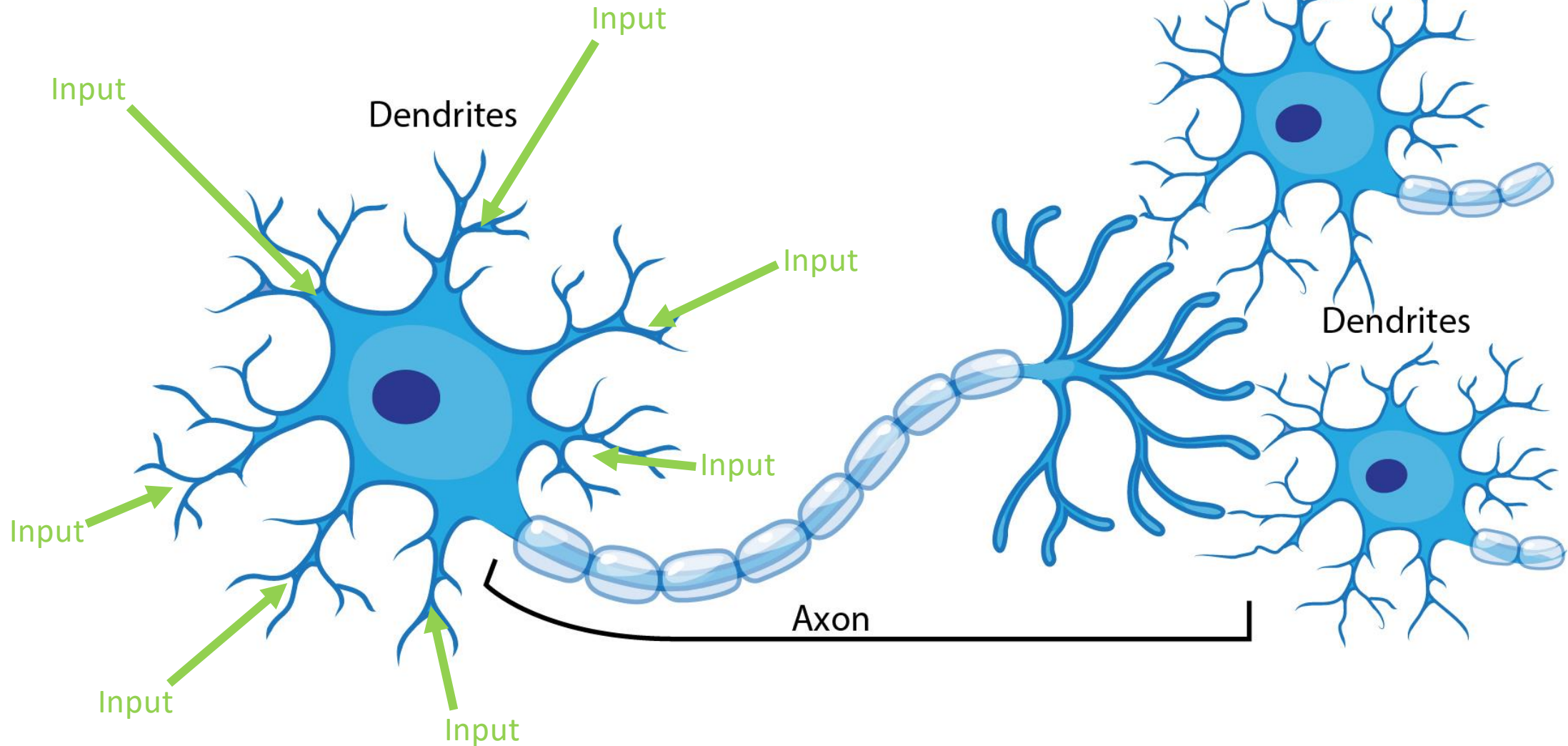
# Neural Computation

The Perceptron

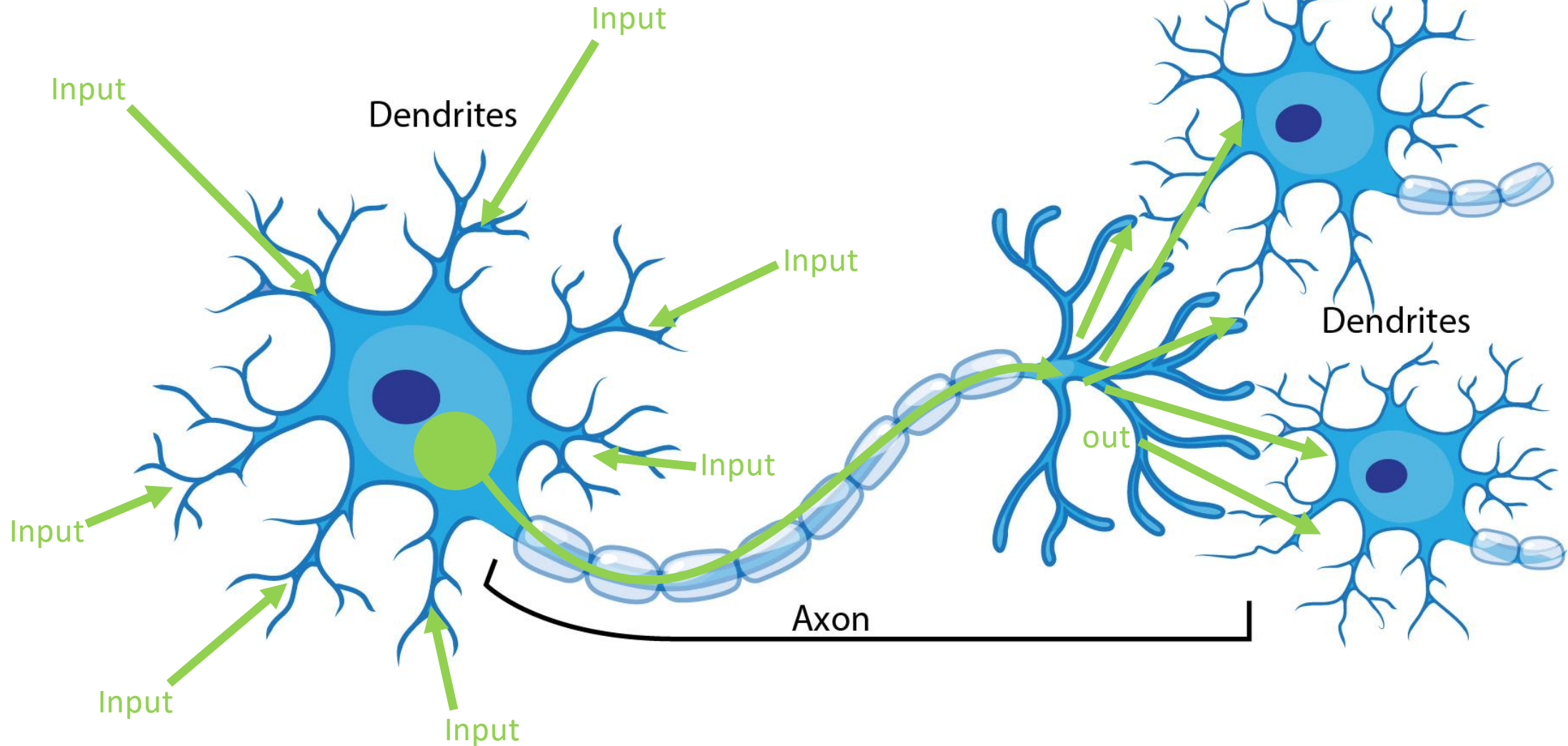
# Neurons



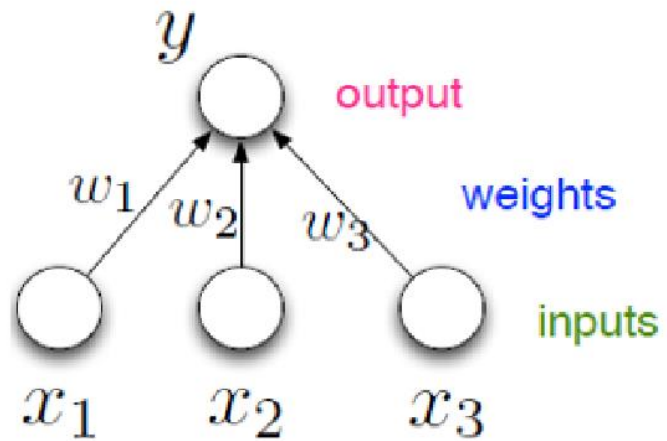
# Neurons



# Neurons

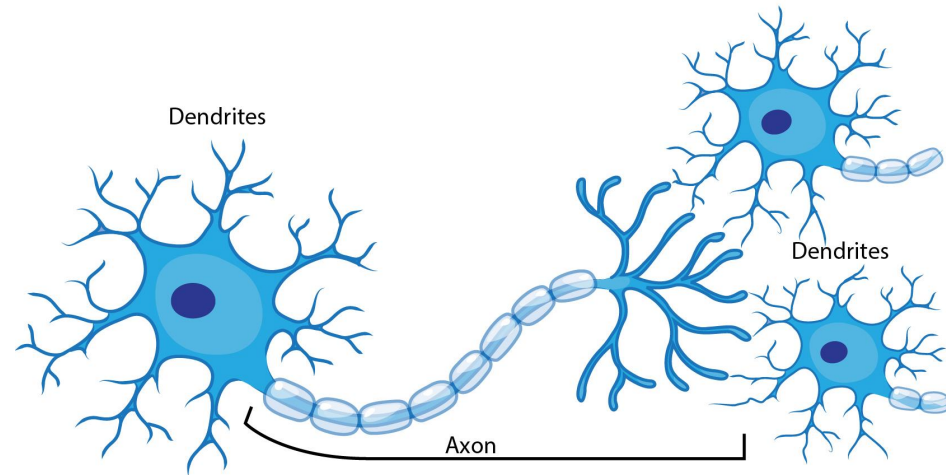


# Perceptron aka McCulloch-Pitts Neuron

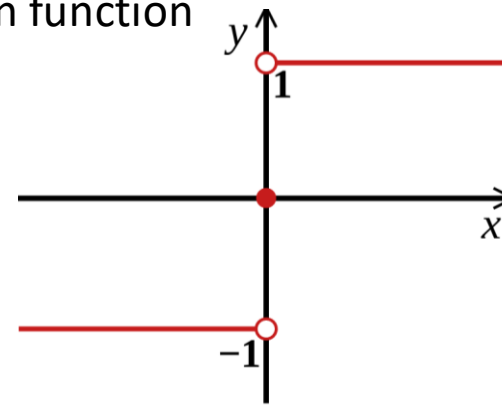


$$y = \text{sgn} \left( b + \sum_i x_i w_i \right)$$

Diagram illustrating the perceptron equation with color-coded labels: "output" (pink arrow pointing to  $y$ ), "bias" (blue arrow pointing to  $b$ ), "i'th weight" (blue arrow pointing to  $w_i$ ), and "i'th input" (green arrow pointing to  $x_i$ ).

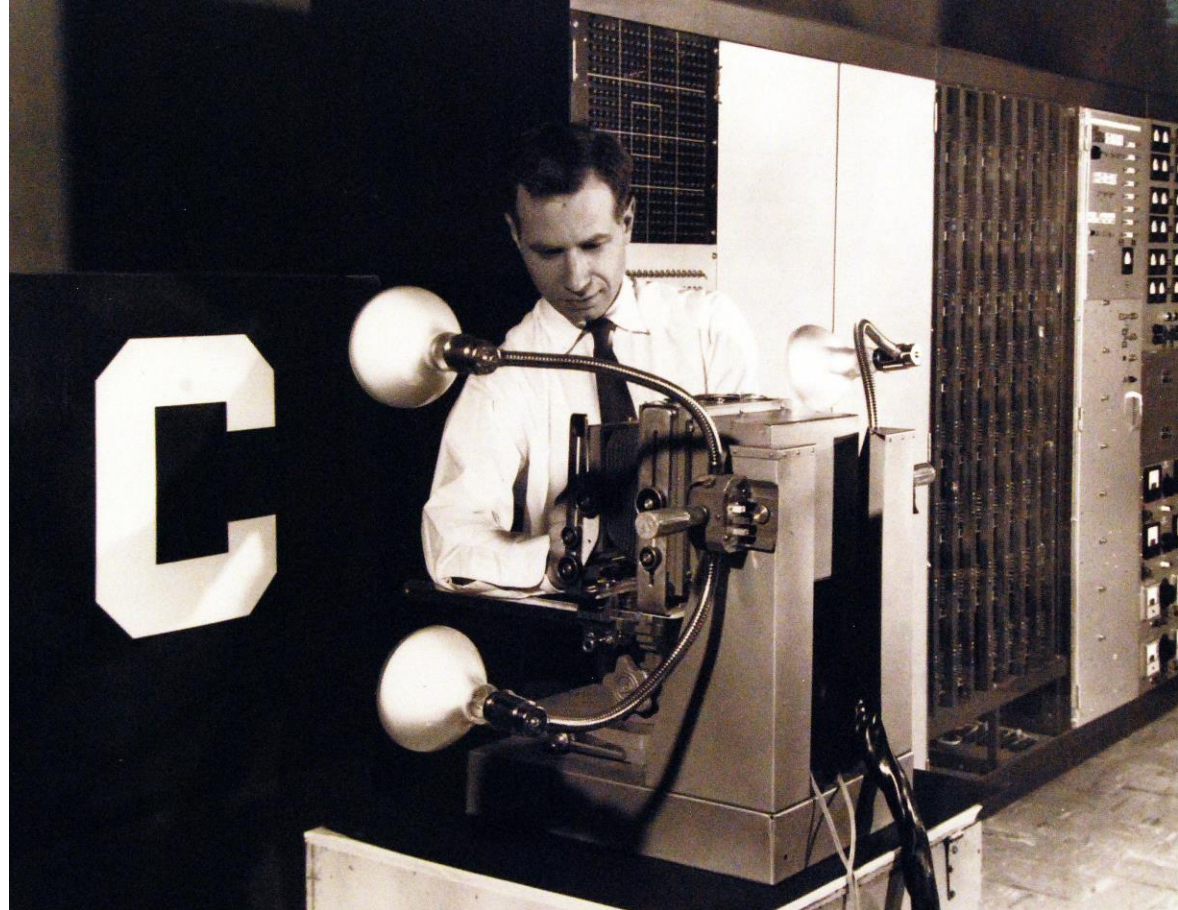
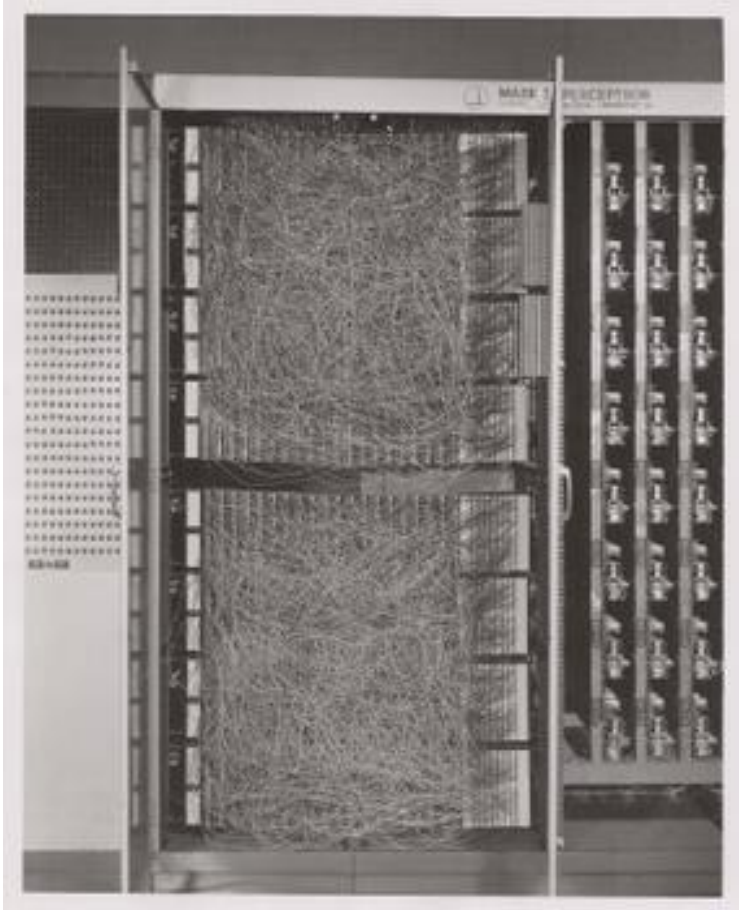


Sign function



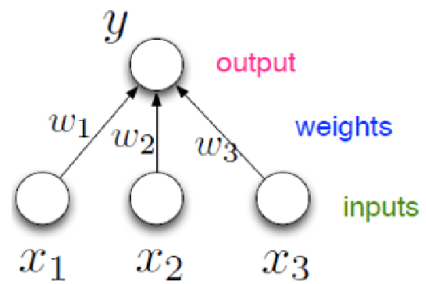


# Frank Rosenblatt's Perceptron



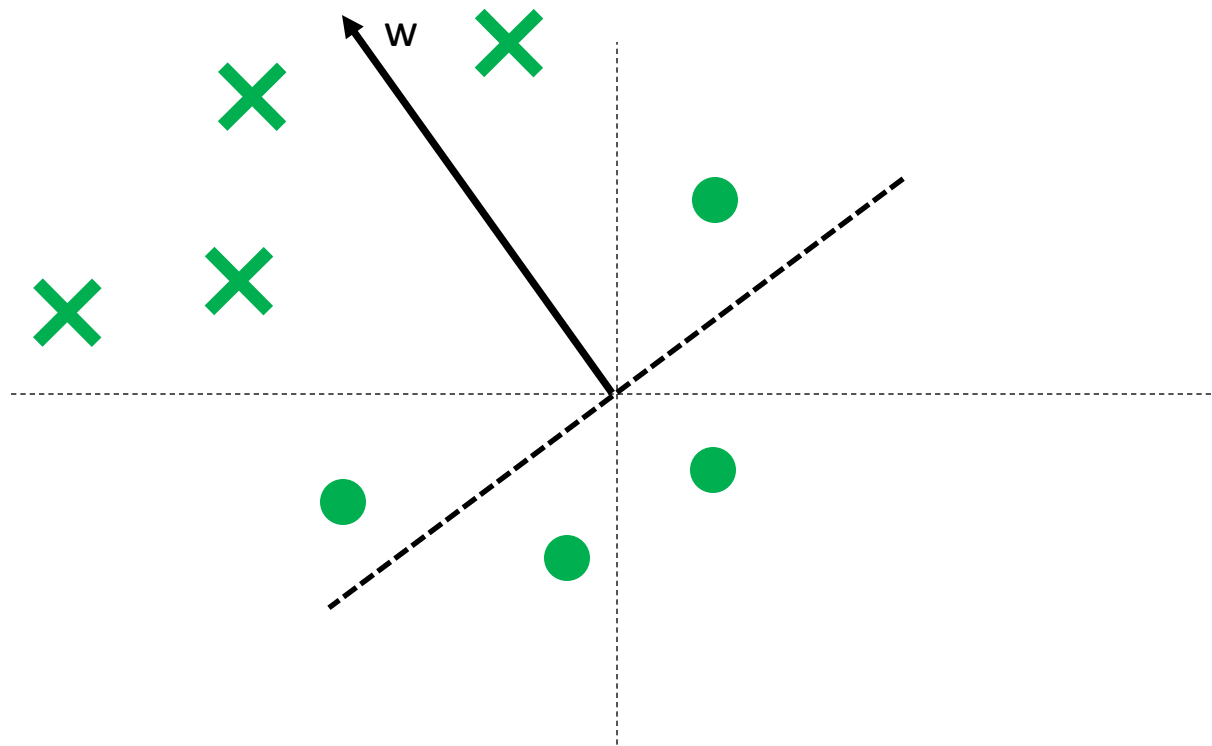
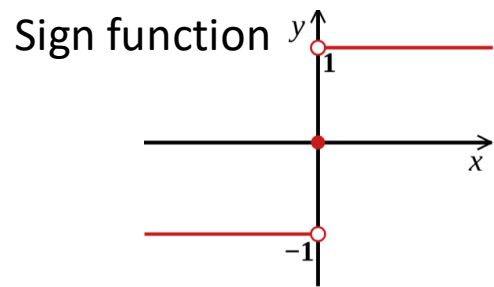
"the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence." - NY times 1958

# Perceptron Classifier

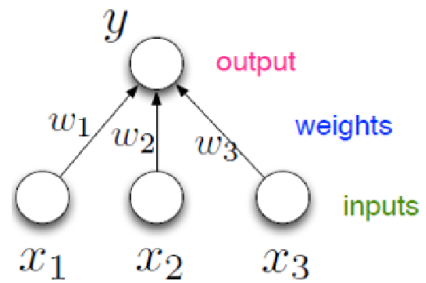


$$y = \text{sgn} \left( \underset{\text{bias}}{b} + \sum_i \underset{\substack{\text{i'th input} \\ \text{i'th weight}}}{x_i w_i} \right)$$

The equation shows the output  $y$  (labeled "output" in pink) is the sign of the sum of a bias  $b$  (labeled "bias" in blue) and the weighted sum of inputs  $x_i w_i$ . The  $x_i$  is labeled "i'th input" in green and  $w_i$  is labeled "i'th weight" in blue.

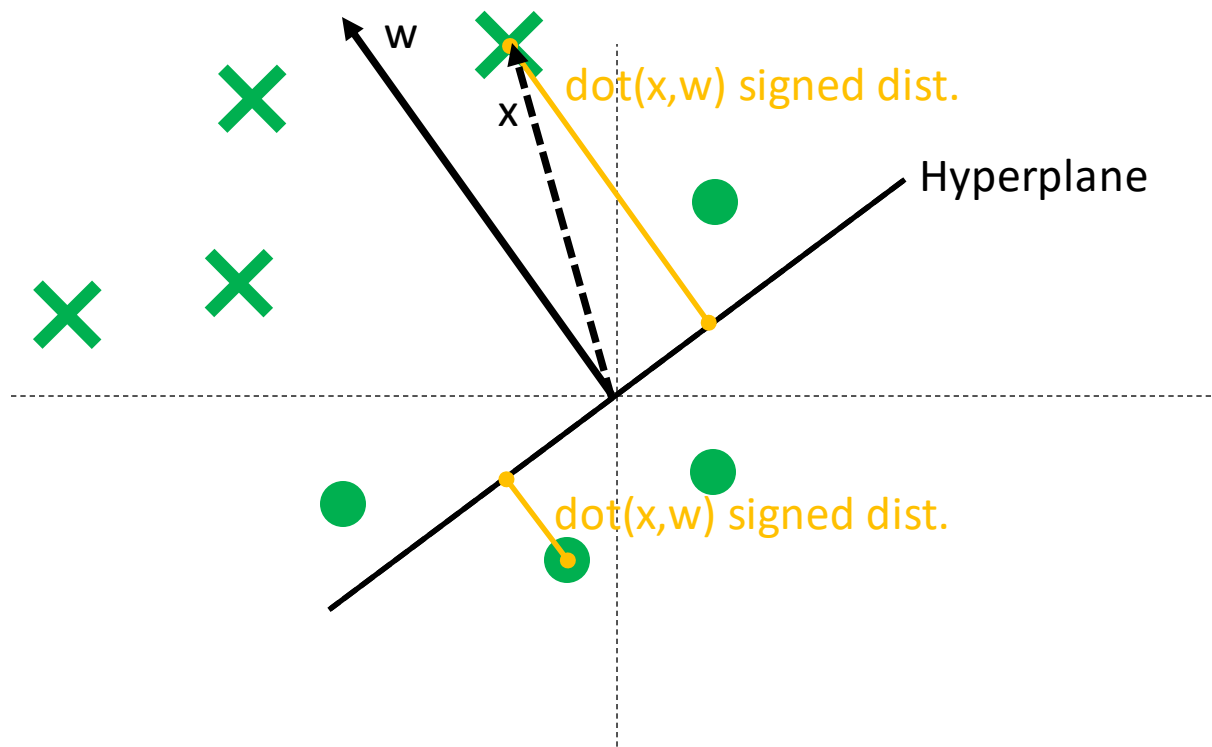
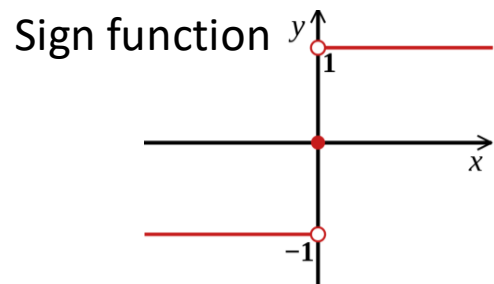


# Perceptron Classifier



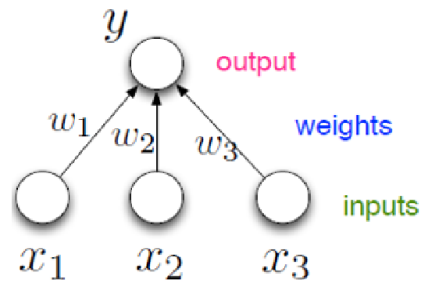
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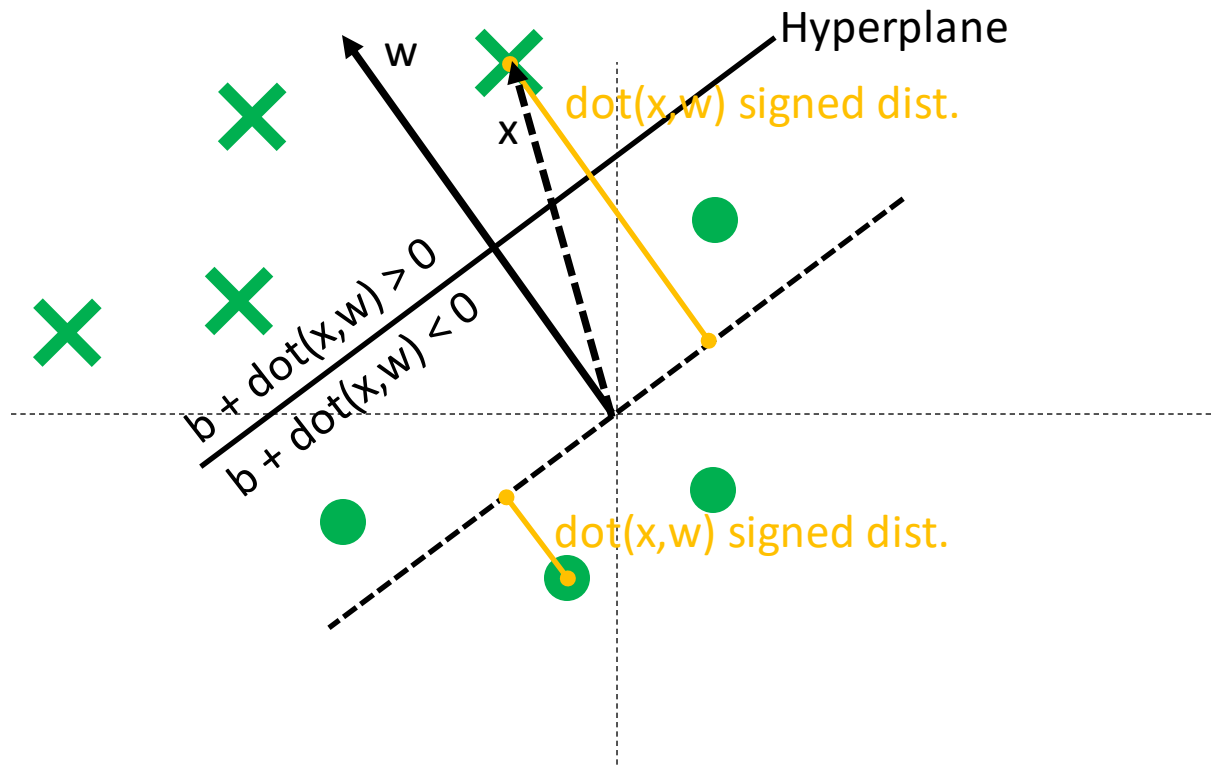
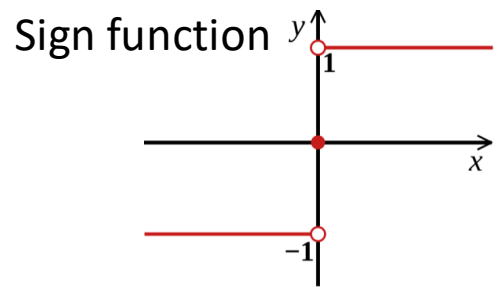


# Perceptron Classifier



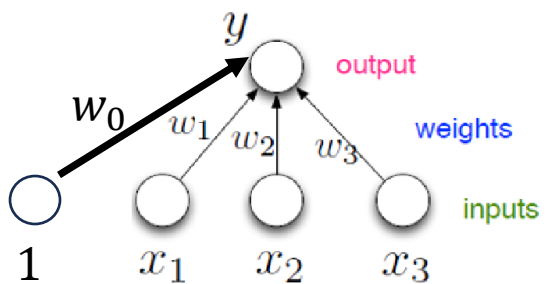
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# Perceptron Classifier (without bias)

| One   | Dist (km) | Day   | Commute time (min) |
|-------|-----------|-------|--------------------|
| $x_0$ | $x_1$     | $x_2$ | $y$                |
| 1     | 2.7       | 1     | 25                 |
| 1     | 4.1       | 1     | 33                 |
| 1     | 1.0       | 0     | 15                 |
| 1     | 5.2       | 1     | 45                 |
| 1     | 2.8       | 0     | 22                 |



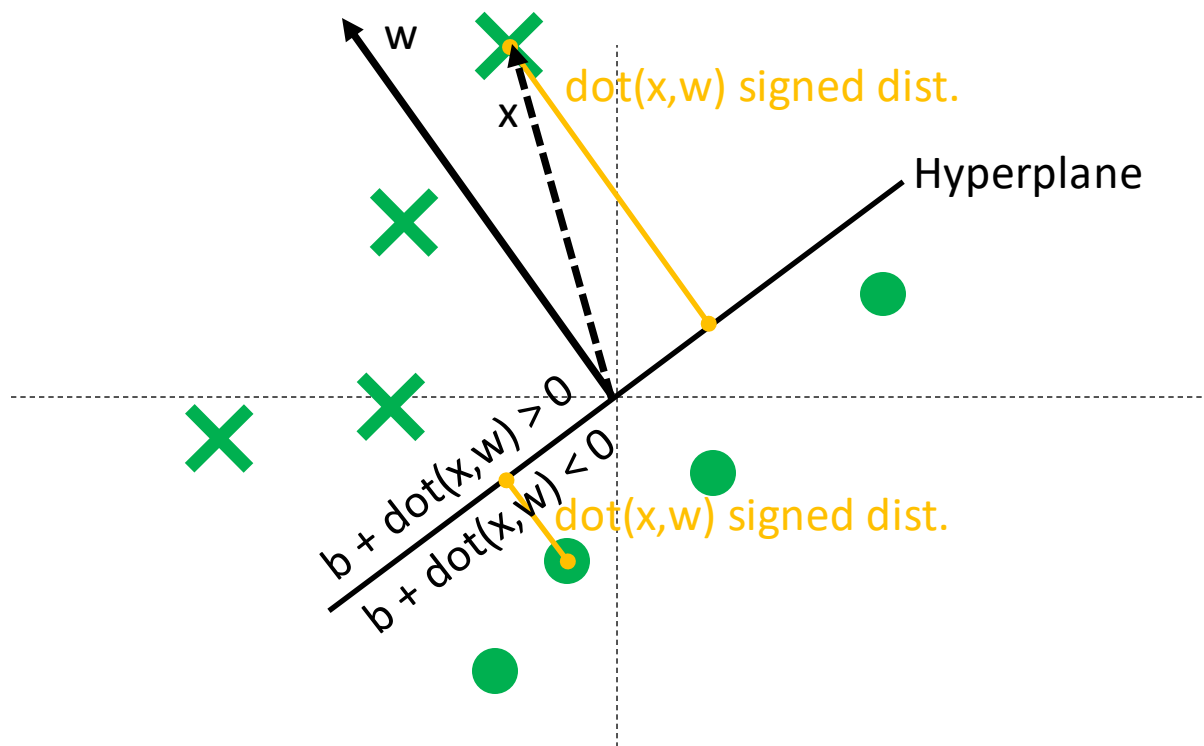
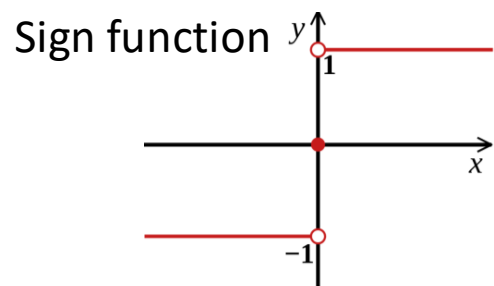
$$y = \text{sgn} \left( \cancel{b} + \sum_i x_i w_i \right)$$

output

bias

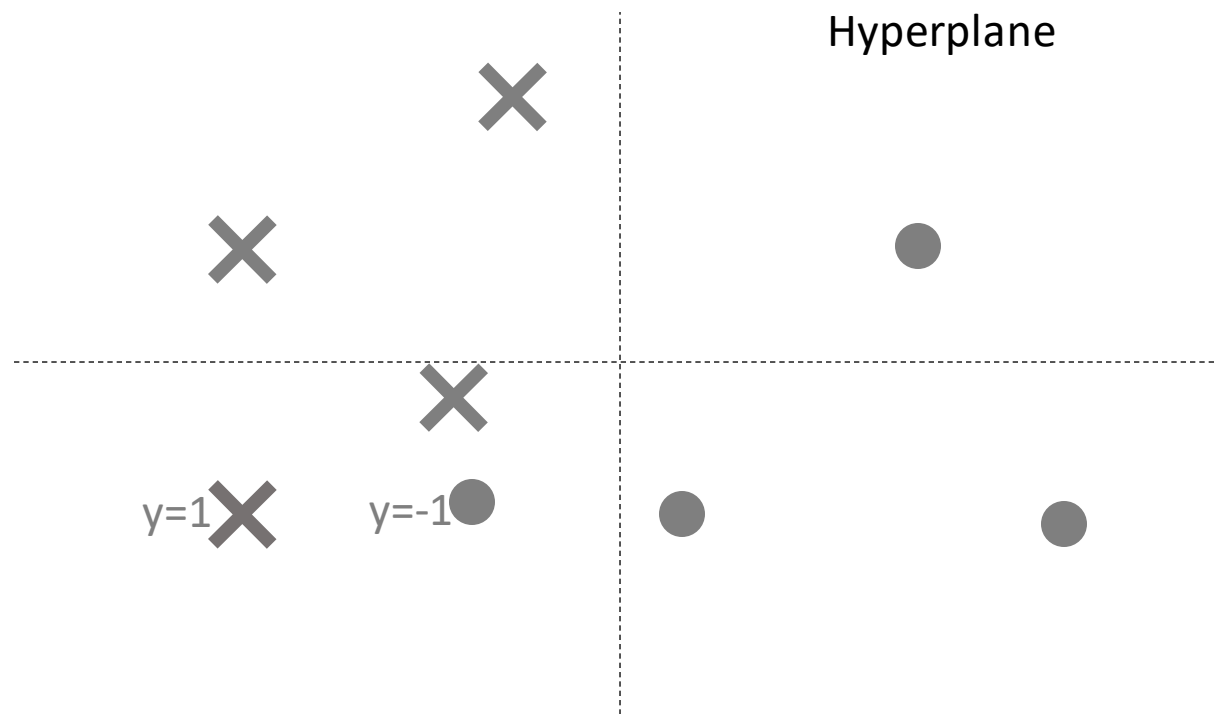
i'th weight

i'th input



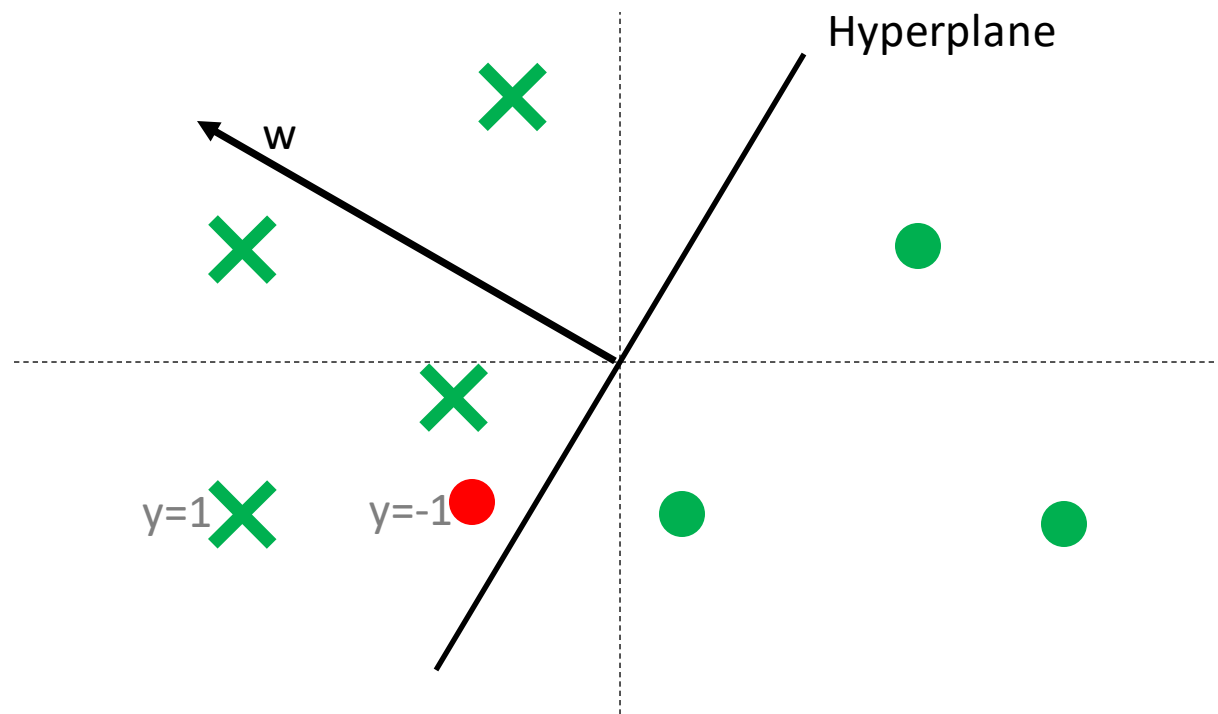
# Perceptron Algorithm

- 1: Initialize  $\mathbf{w} = 0$  ▷ we assume no bias for simplicity
- 2: **while** All training examples are **not** correctly classified **do**
- 3:     **for**  $(\mathbf{x}, y) \in S$  **do** ▷ Loop over each (feature, label) pair in the dataset
- 4:         **if**  $y \cdot \mathbf{w}^\top \mathbf{x} \leq 0$  **then** ▷ If the pair  $(\mathbf{x}, y)$  is misclassified
- 5:              $\mathbf{w} \leftarrow \mathbf{w} + y\mathbf{x}$  ▷ Update the weight vector  $\mathbf{w}$



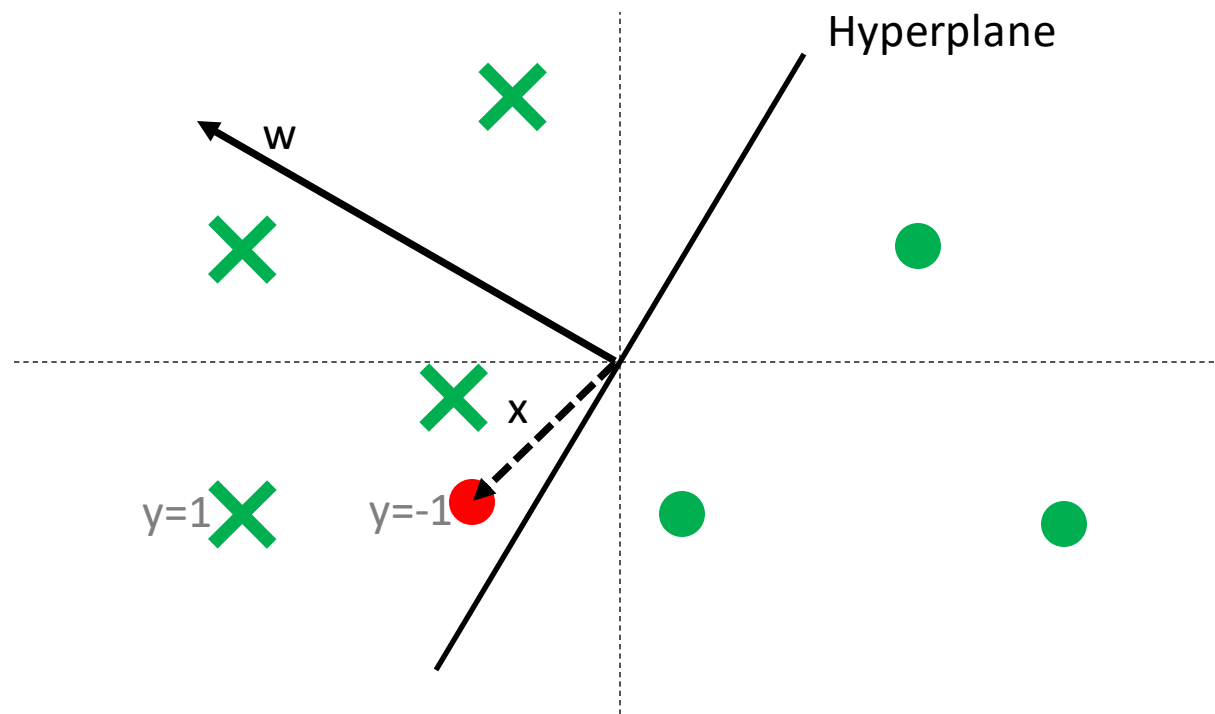
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# Perceptron Algorithm

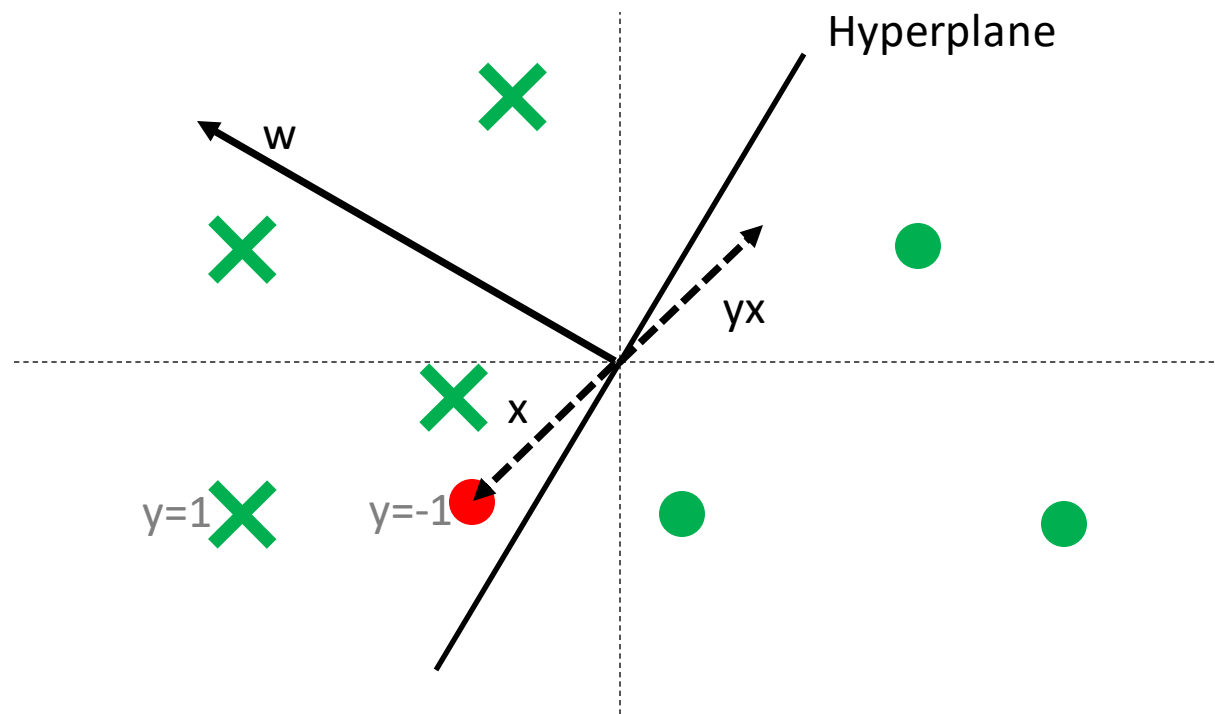
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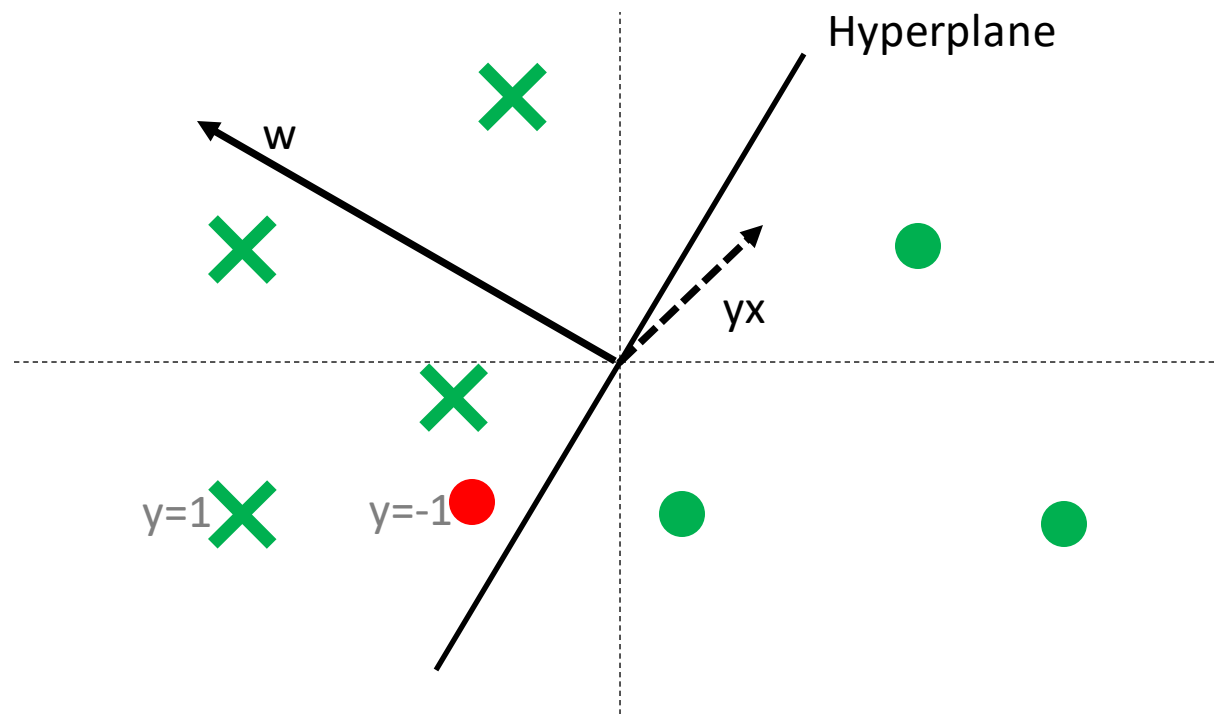
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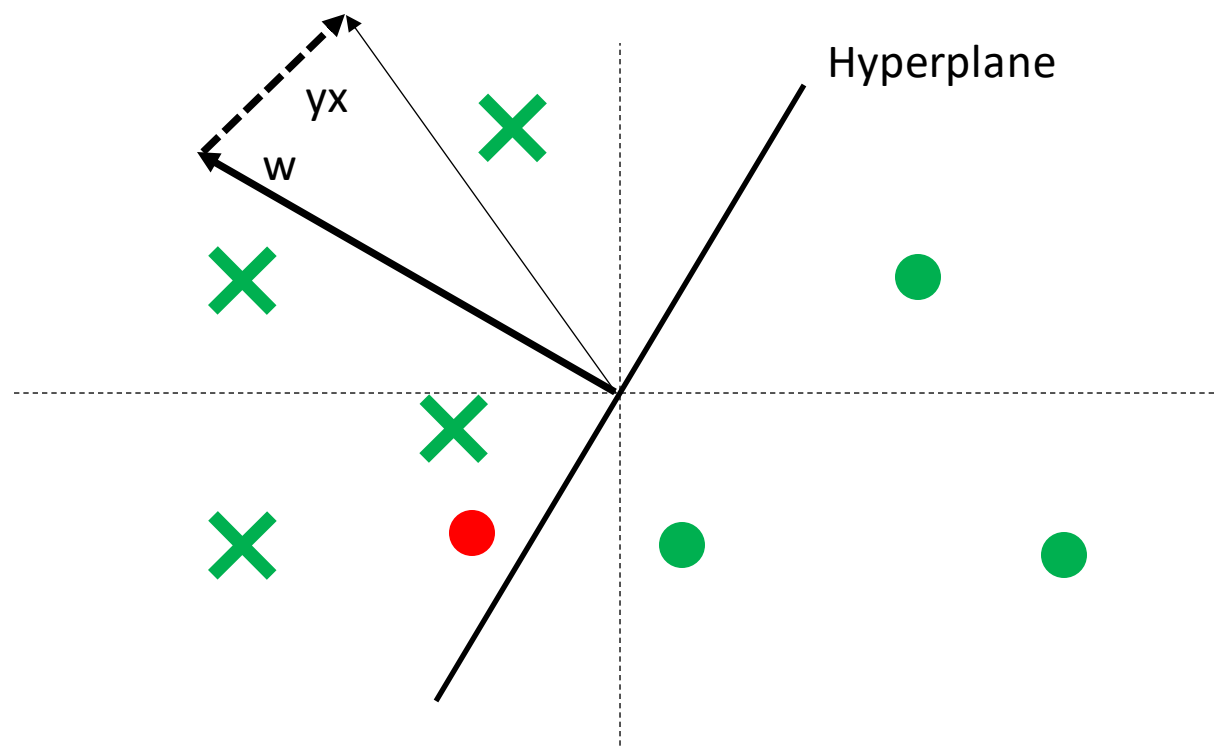
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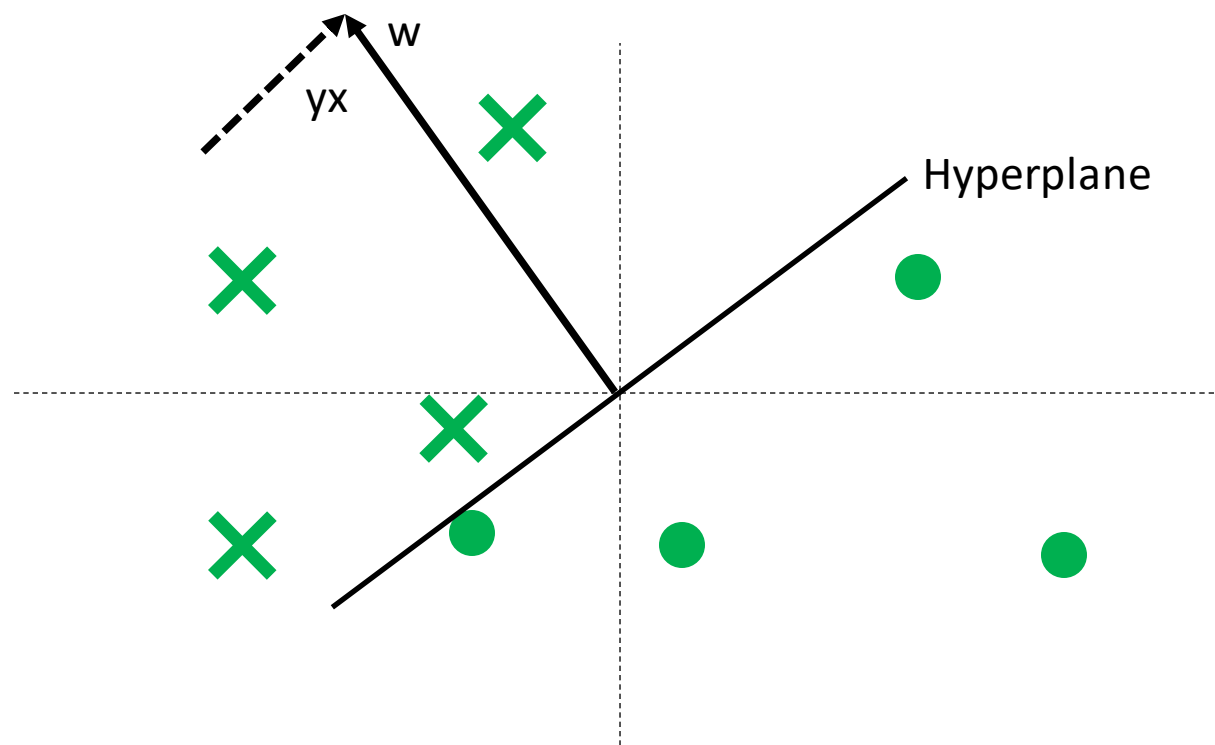
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# Perceptron Algorithm

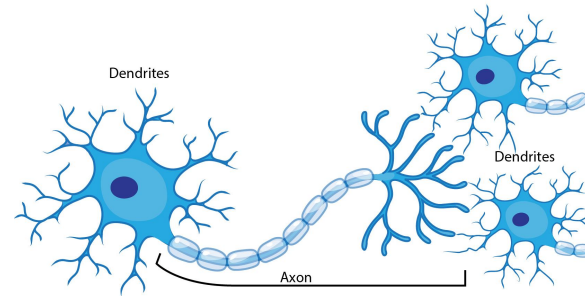
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# Summary

## Perceptron ...

- is (very) simple model of biological neuron



- implements linear classifier

$$y = \text{sgn} \left( b + \sum_i x_i w_i \right)$$

Diagram illustrating the perceptron equation:

- $y$ : output (pink arrow)
- $b$ : bias (blue arrow)
- $x_i$ :  $i$ 'th input (green arrow)
- $w_i$ :  $i$ 'th weight (blue arrow)

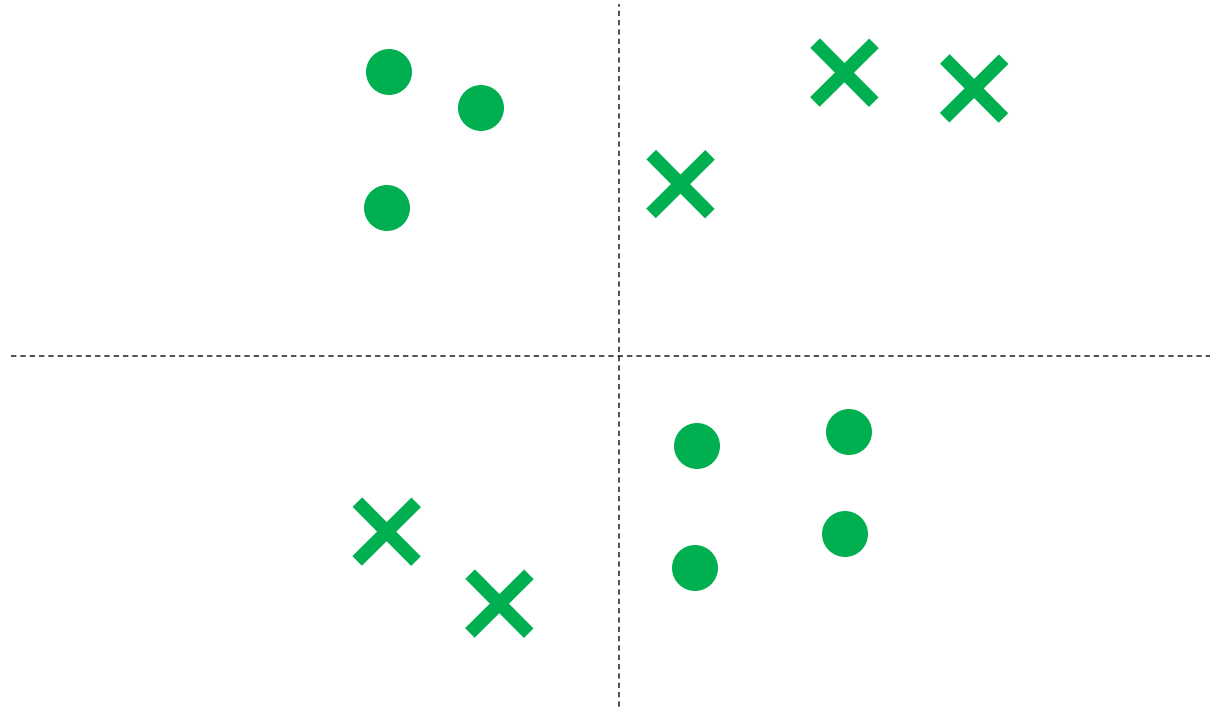
- Algorithm finds weights and biases
  - Guaranteed to stop if linearly separable

### Perceptron Algorithm

```
1: Initialize  $\mathbf{w} = 0$  ▷ we assume no bias for simplicity
2: while All training examples are not correctly classified do
3:   for  $(\mathbf{x}, y) \in S$  do ▷ Loop over each (feature, label) pair in the dataset
4:     if  $y \cdot \mathbf{w}^T \mathbf{x} \leq 0$  then ▷ If the pair  $(\mathbf{x}, y)$  is misclassified
5:        $\mathbf{w} \leftarrow \mathbf{w} + y\mathbf{x}$  ▷ Update the weight vector  $\mathbf{w}$ 
```

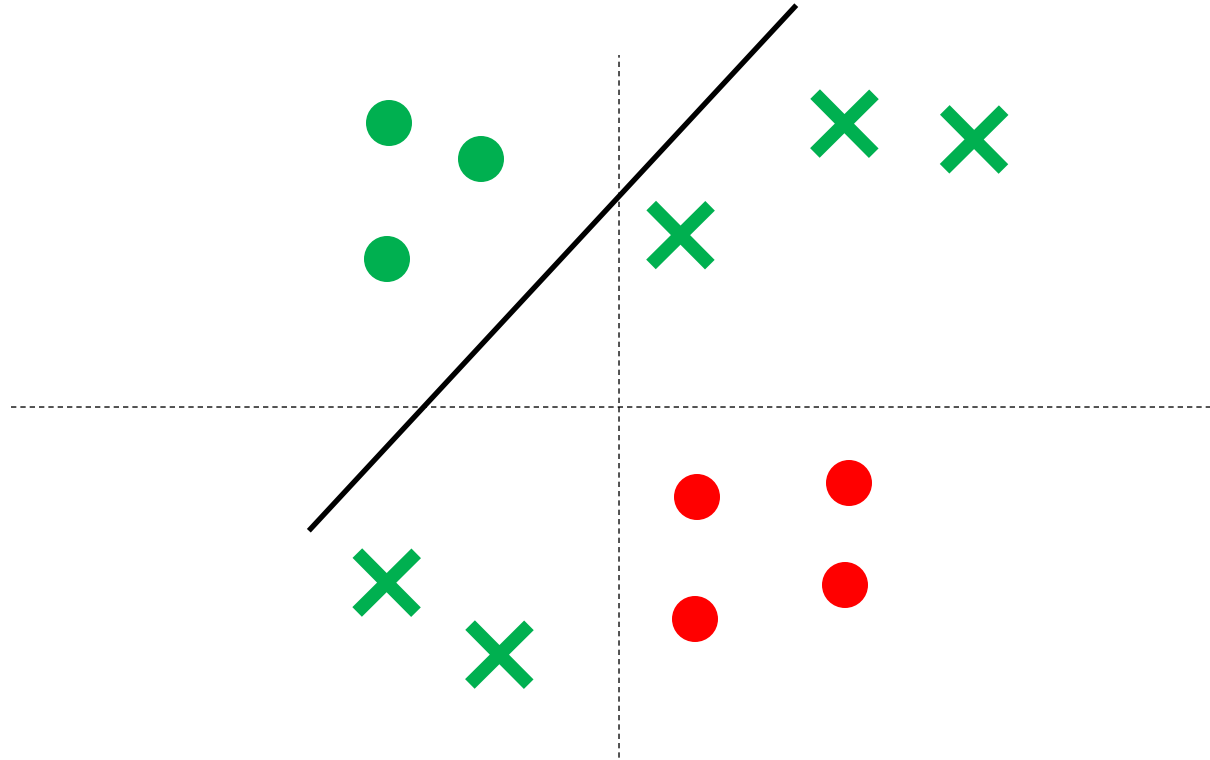


# Limitations



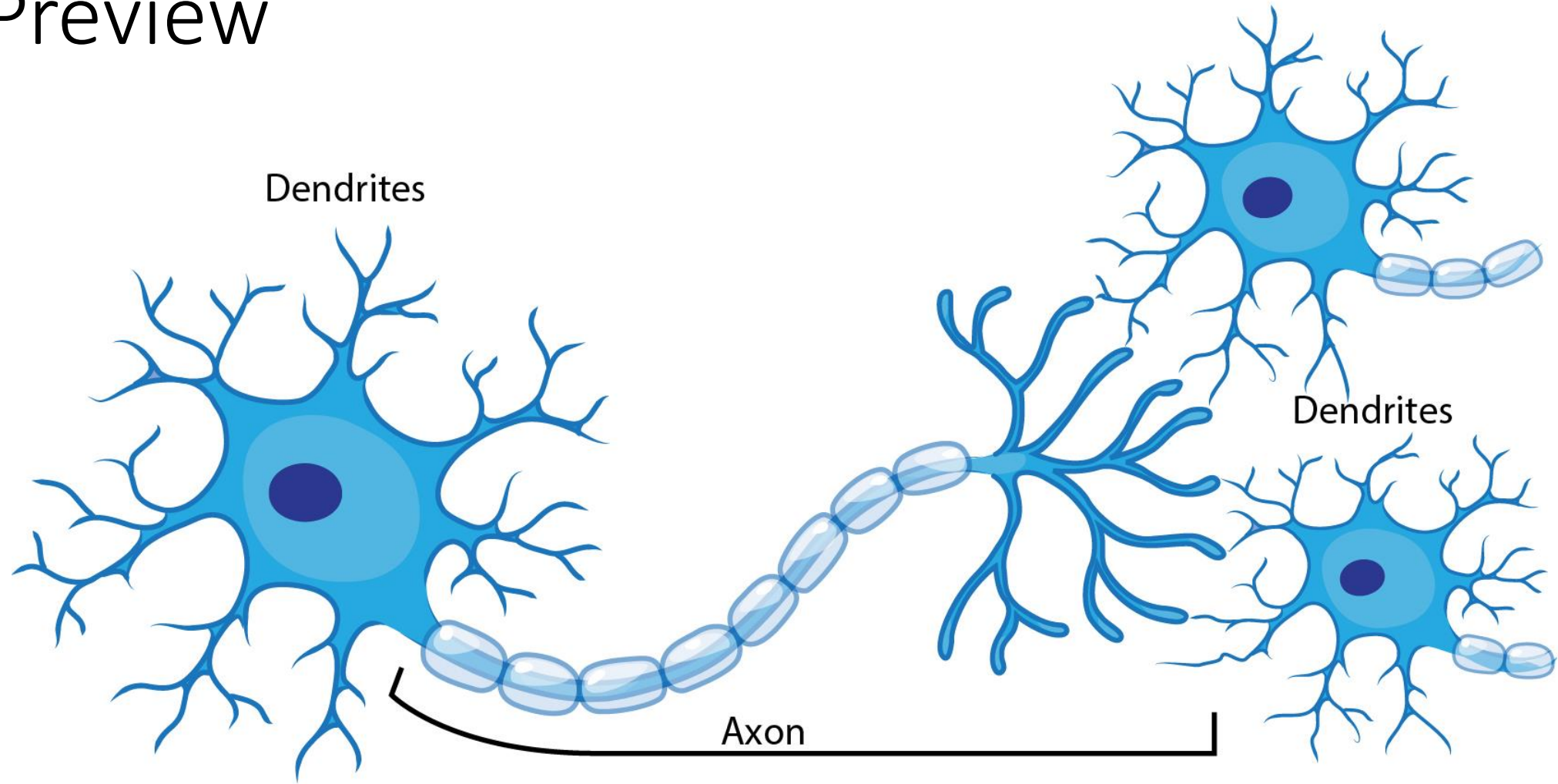
Some data is not linearly separable

# Limitations



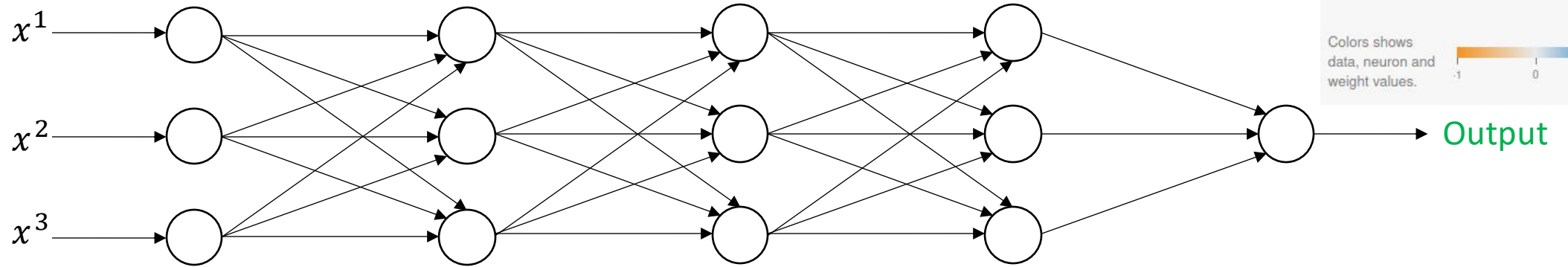
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# Preview

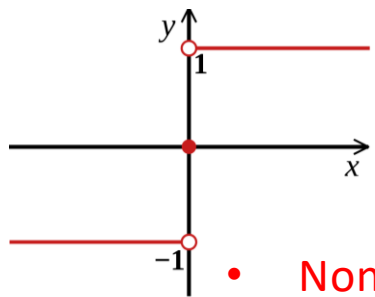


# Preview

Input



This is a perceptron



- Non-differentiable
- Problem Build soft perceptron

$$y = \text{sgn} \left( b + \sum_i x_i w_i \right)$$

output

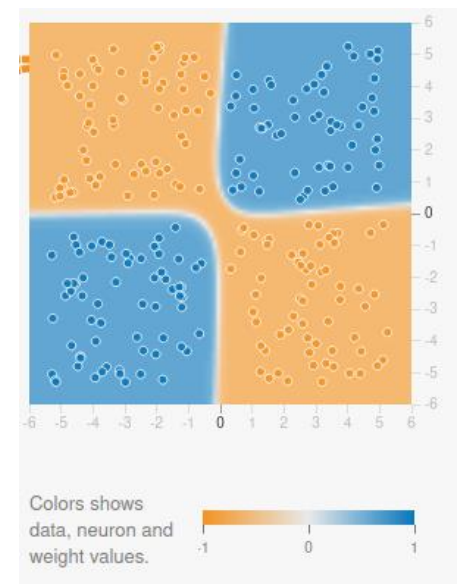
bias

i'th weight

i'th input

How can we train this?

- Perceptron algorithm no longer works
- Use gradient descent



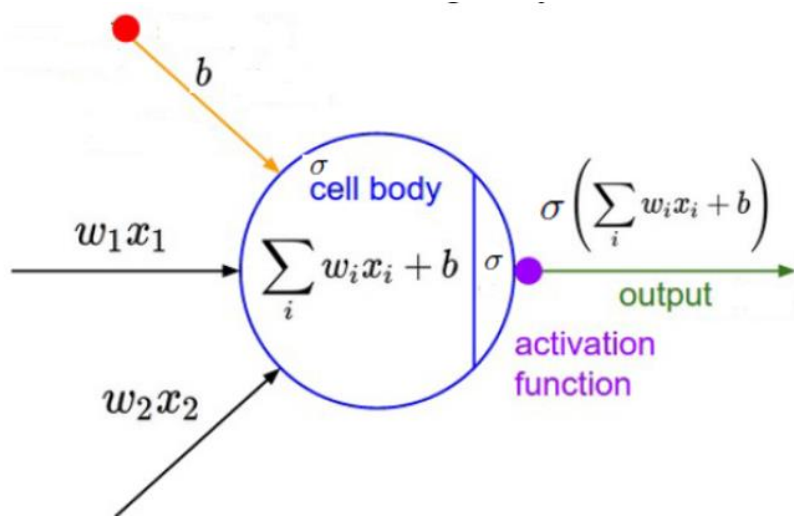
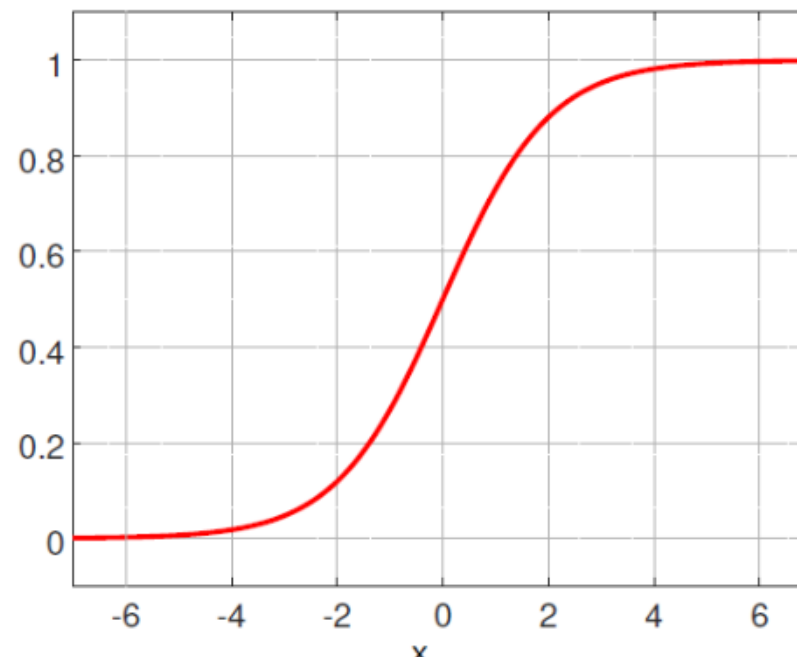
The idea is to replace the **sgn** function with a differentiable non-linear function

e.g., **sigmoid** function

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

Mapping:  $(-\infty, +\infty) \mapsto (0, 1)$

$\sigma'(x) = \sigma(x)(1 - \sigma(x))$  (exercise)



$$f(\mathbf{x}) = \sigma\left(\sum_i w_i x_i + b\right)$$

Interpret as probability



# Training

Dataset:  $n$  input/output pairs  $S = \{(\mathbf{x}^{(1)}, y^{(1)}), \dots, (\mathbf{x}^{(n)}, y^{(n)})\}$

Mean-Square Error

$$C(\mathbf{w}) = \frac{1}{2n} \sum_{i=1}^n \left( \underbrace{\sigma(\mathbf{w}^\top \mathbf{x}^{(i)} + b)}_{\text{predicted output}} - \underbrace{y^{(i)}}_{\text{output}} \right)^2.$$

How to compute?

$$\frac{\partial (\sigma(\mathbf{w}^\top \mathbf{x} + b) - y)^2}{\partial w_i}$$

In the next video

No closed form solution for the minimizer of  $C(\mathbf{w})$

Use **Gradient Descent** to train a  $\mathbf{w} \in \mathbb{R}^d$  with a small  $C(\mathbf{w})$

$$\mathbf{w}^{\text{new}} = \mathbf{w} - \eta \nabla C(\mathbf{w}) \quad \Longleftrightarrow \quad w_i^{\text{new}} = w_i - \eta \frac{\partial C(\mathbf{w})}{\partial w_i}.$$