



UNIVERSIDADE
CATÓLICA
PORTUGUESA

BRAGA

Machine Learning

Session 20 - T

Neural Networks

Ciência de Dados Aplicada

2023/2024

Perceptron

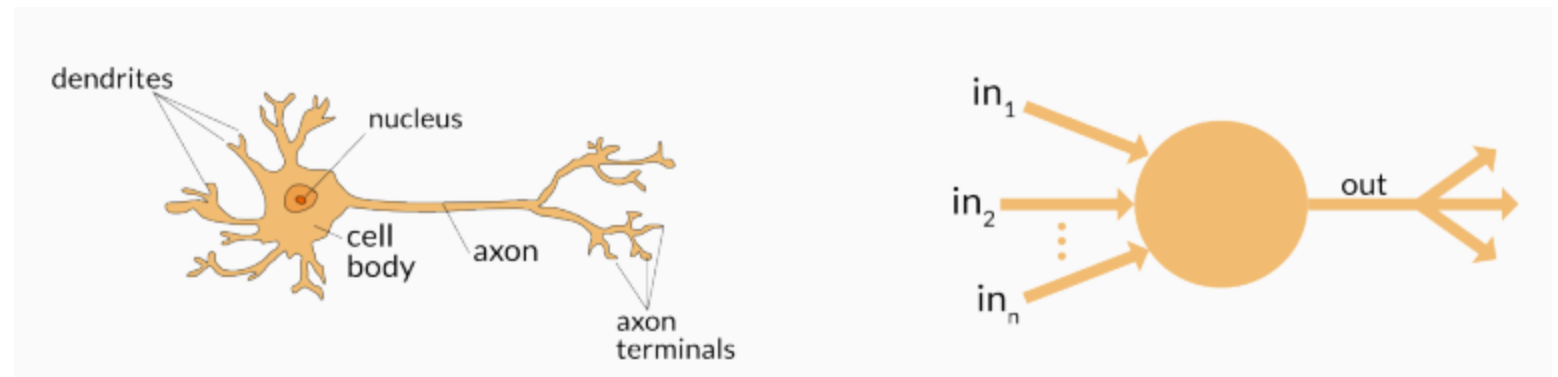
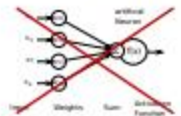


1958 Perceptron



1969
Perceptrons
book

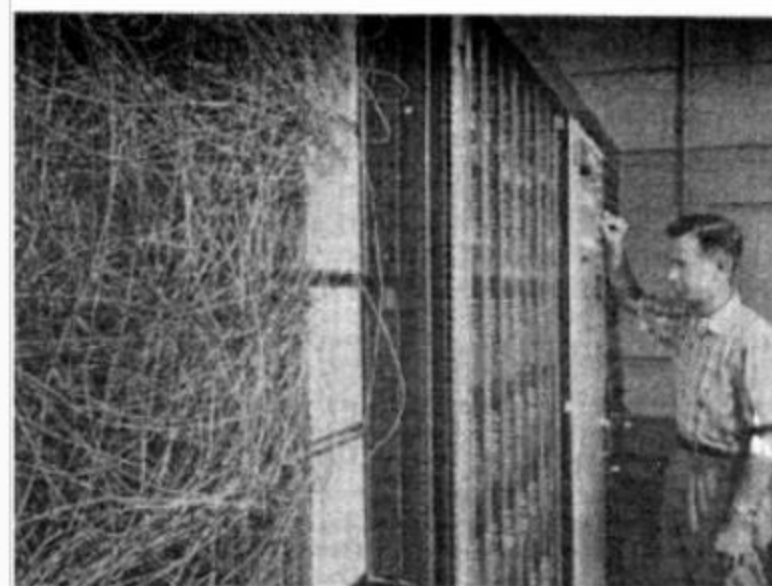
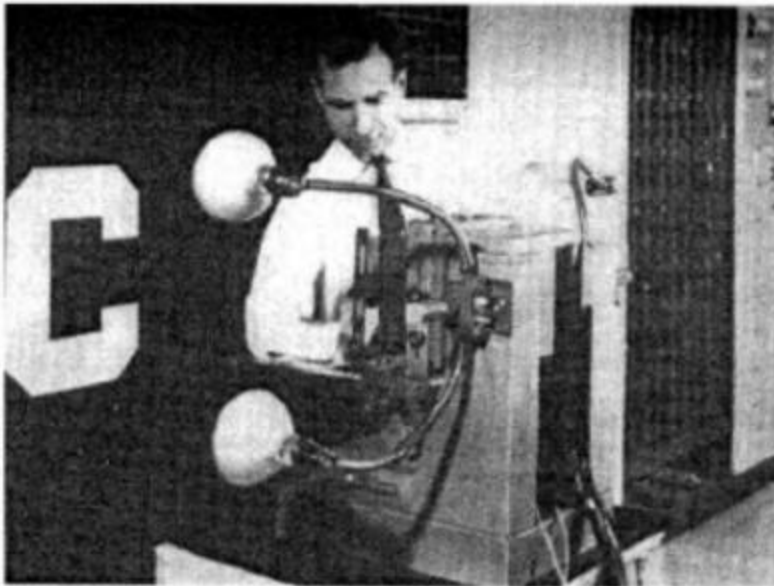
Perceptron criticized



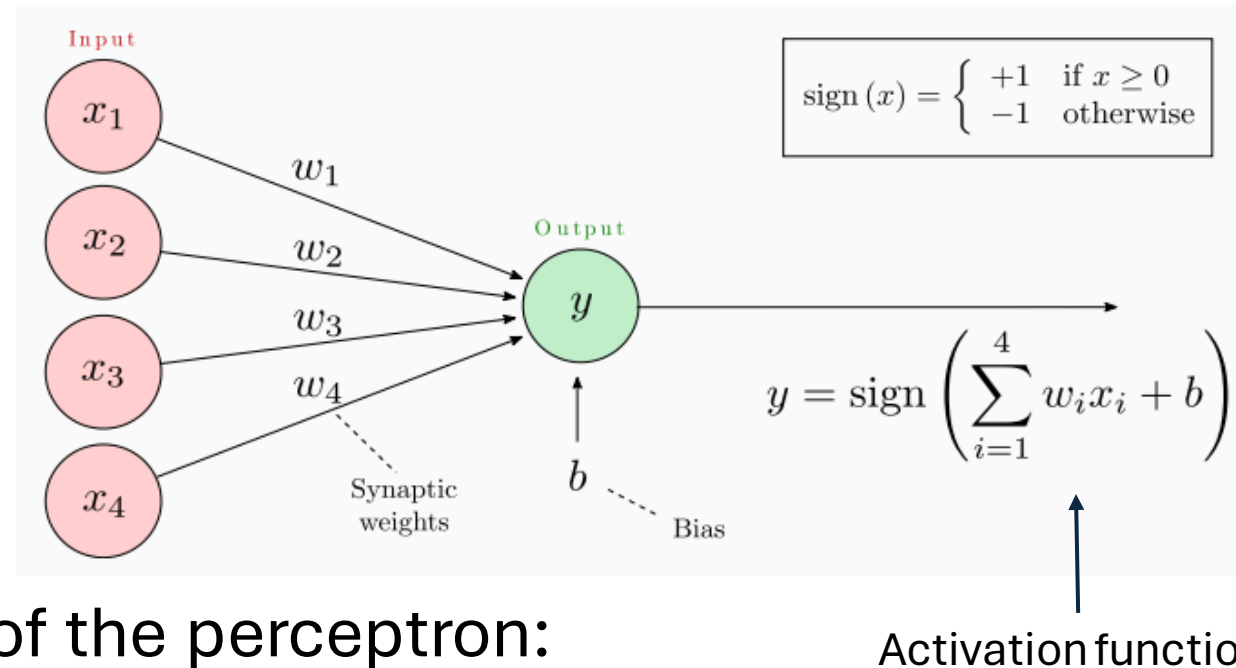
Perceptron

- First binary classifier based on supervised learning;
- Foundation of modern artificial neural networks;

Perceptron (Frank Rosenblatt, 1958)

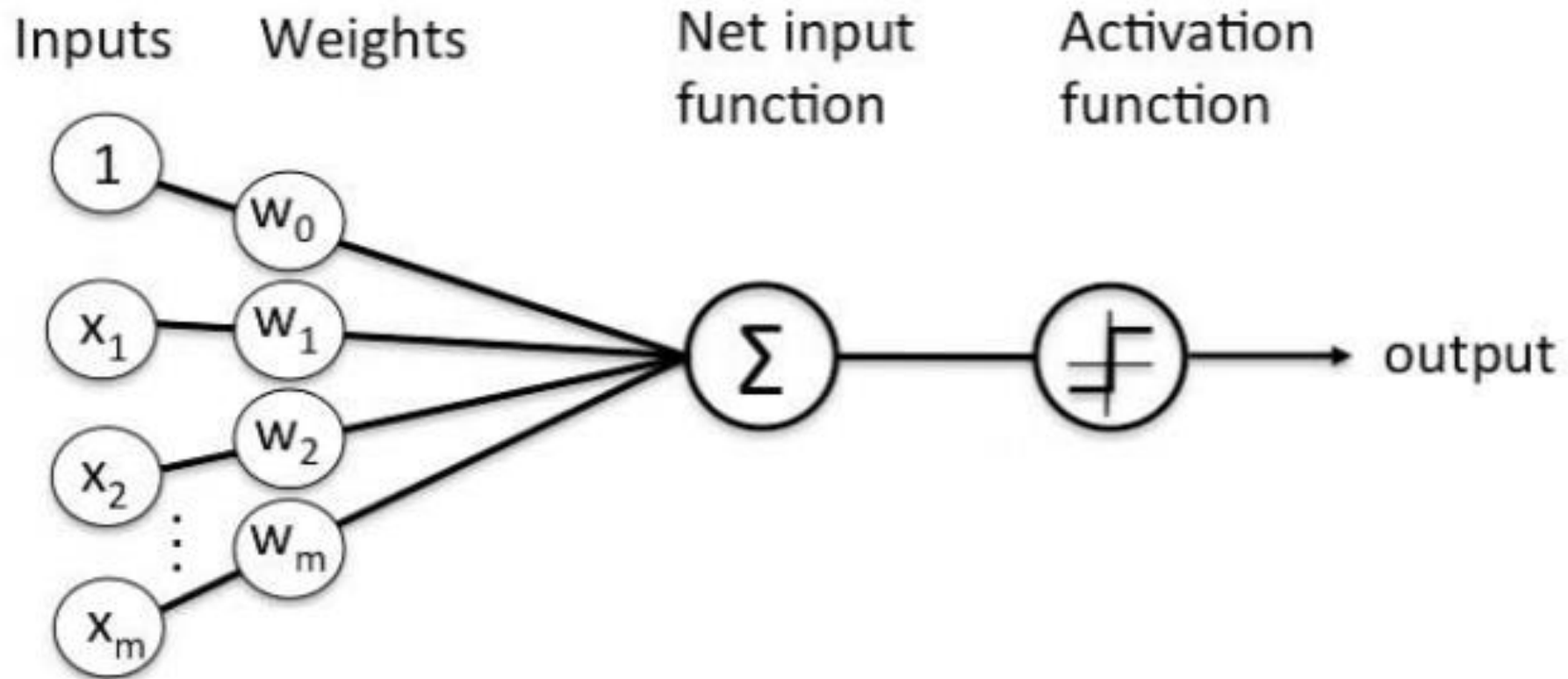


Representation of the Perceptron

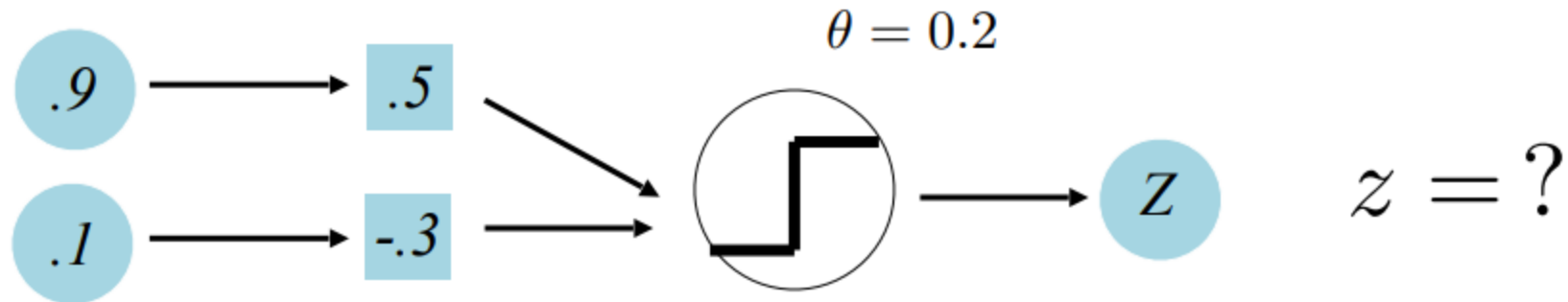


- Parameters of the perceptron:
 - w_k : weights
 - b : bias
- Training \rightarrow adjusting the weights and bias.

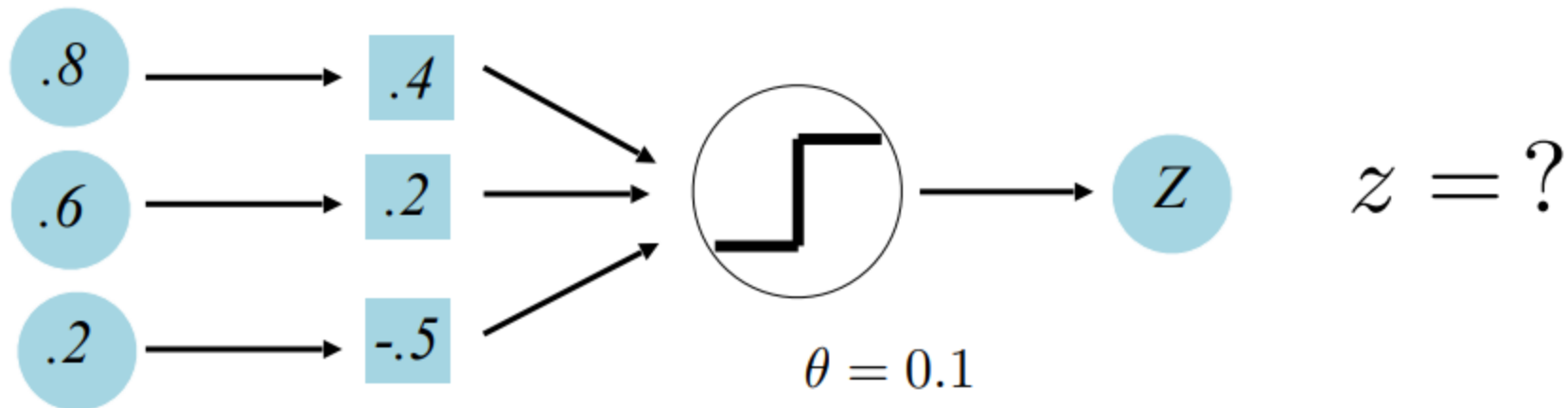
Alternative Representation of the Perceptron



Perceptron Examples

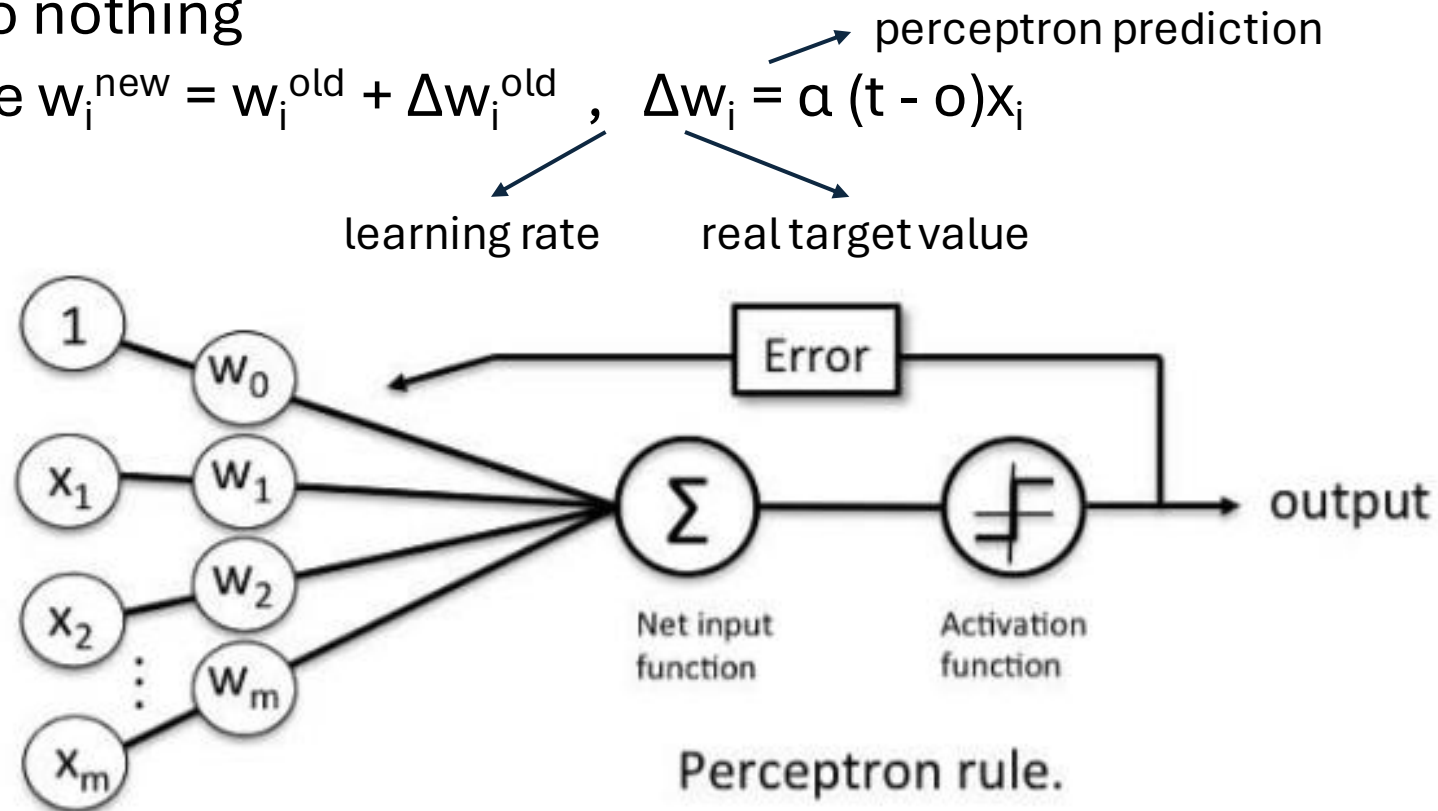


$$z = \begin{cases} 1, & \text{if } w \cdot x > \theta \\ 0, & \text{if } w \cdot x \leq \theta \end{cases}$$



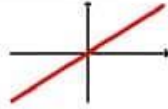
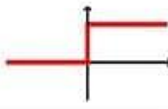
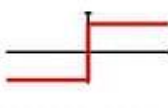

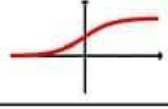
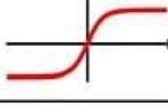

Perceptron Learning Rule

- Suppose that x is a feature vector, y is the correct class label, and y' is the predicted class label computed using the current weights.
 - If $y' = y$, do nothing
 - Otherwise $w_i^{\text{new}} = w_i^{\text{old}} + \Delta w_i^{\text{old}}$, $\Delta w_i = \alpha (t - o)x_i$



Activation Functions

- Outputs the label given an input or a set of inputs

Activation Function	Equation	Example	1D Graph
Linear	$\phi(z) = z$	Adaline, linear regression	
Unit Step (Heaviside Function)	$\phi(z) = \begin{cases} 0 & z < 0 \\ 0.5 & z = 0 \\ 1 & z > 0 \end{cases}$	Perceptron variant	
Sign (signum)	$\phi(z) = \begin{cases} -1 & z < 0 \\ 0 & z = 0 \\ 1 & z > 0 \end{cases}$	Perceptron variant	
Piece-wise Linear	$\phi(z) = \begin{cases} 0 & z \leq -1/2 \\ z + 1/2 & -1/2 \leq z \leq 1/2 \\ 1 & z \geq 1/2 \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multilayer NN	
Hyperbolic Tangent (tanh)	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multilayer NN, RNNs	
ReLU	$\phi(z) = \begin{cases} 0 & z < 0 \\ z & z > 0 \end{cases}$	Multilayer NN, CNNs	

A horizontal timeline illustrating the evolution of Artificial Neural Networks (ANNs) from 1958 to 1989. The timeline is represented by a horizontal line with vertical tick marks indicating specific years. Above the line, the year 1958 is marked, corresponding to the 'Perceptron' model. Below the line, the year 1969 is marked, corresponding to the 'Perceptrons book'. To the left of the 1969 mark, there is a small image of the book cover and the text 'Perceptron criticized'. Further along the timeline, the year ~1980 is marked, corresponding to the 'Multilayer network'. To the left of this mark, there is a diagram of a multilayer network with 'Input Patterns' at the bottom, 'Internal Representation Units' in the middle, and 'Output Patterns' at the top. Finally, the year 1989 is marked, corresponding to the 'Universal Approximation Theorem'.

1958 Perceptron

1969 Perceptrons book

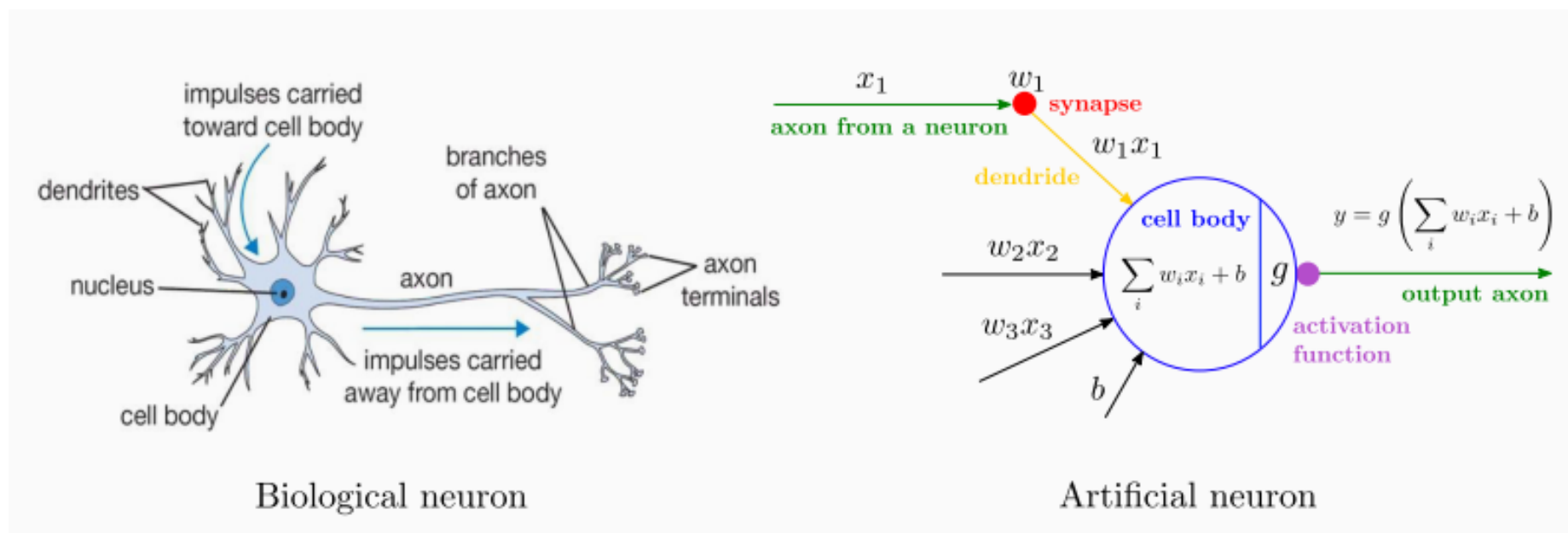
Perceptron criticized

~1980 Multilayer network

1989 Universal Approximation Theorem

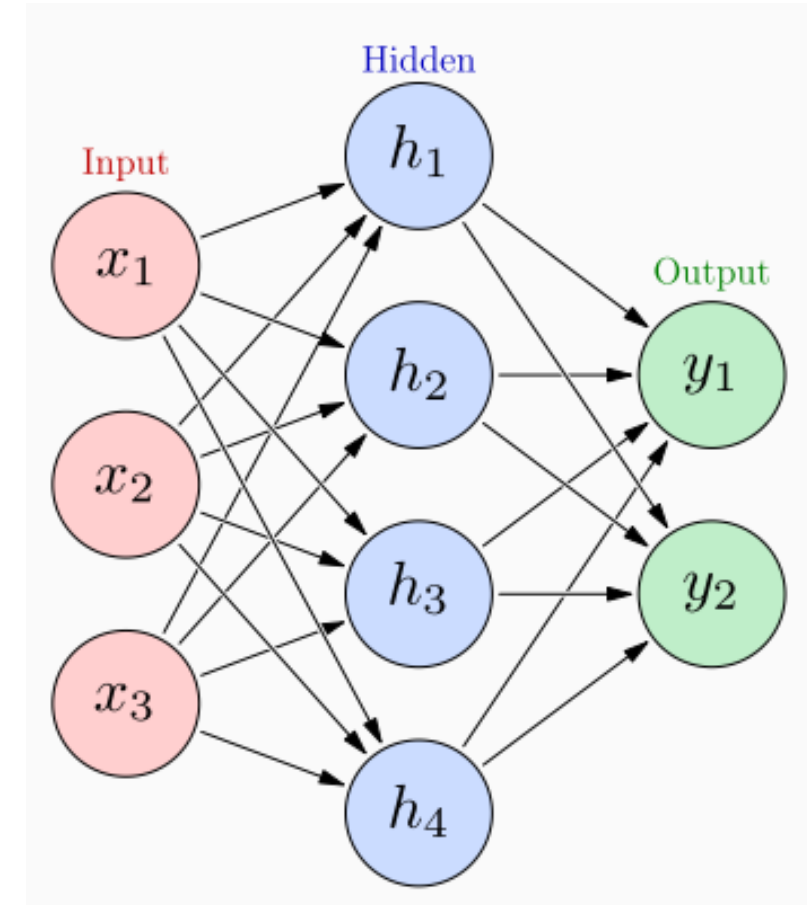
Mulilayer Perceptron

- AKA Artificial Neural Networks
- Artificial Neuron



Artificial Neural Networks

- Inter-connection of several artificial neurons (also called nodes or units);
- Each "level" in the graph is called a layer:
 - Input layer;
 - Hidden layer(s);
 - Output layer.
- Each neuron in the hidden layers acts as a classifier / feature detector;
- Feedforward neural network (no cycles):
 - First and simplest type of neural network;
 - Information moves in one direction.



Artificial Neural Networks

$$h_1 = g_1 (w_{11}^1 x_1 + w_{12}^1 x_2 + w_{13}^1 x_3 + b_1^1)$$

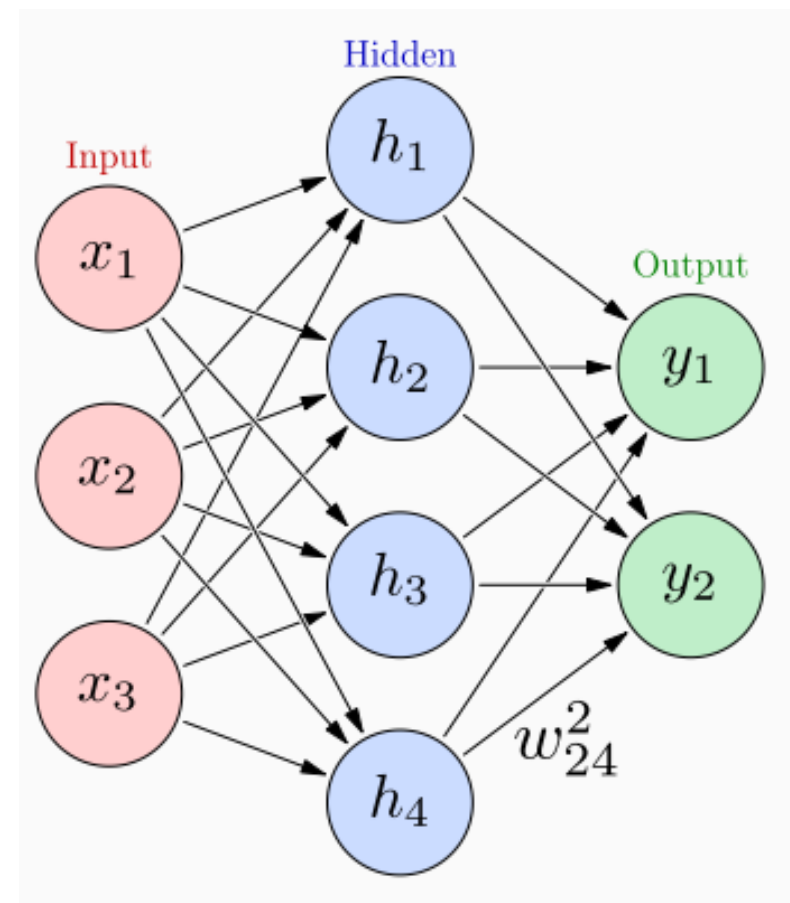
$$h_2 = g_1 (w_{21}^1 x_1 + w_{22}^1 x_2 + w_{23}^1 x_3 + b_2^1)$$

$$h_3 = g_1 (w_{31}^1 x_1 + w_{32}^1 x_2 + w_{33}^1 x_3 + b_3^1)$$

$$h_4 = g_1 (w_{41}^1 x_1 + w_{42}^1 x_2 + w_{43}^1 x_3 + b_4^1)$$

$$y_1 = g_2 (w_{11}^2 h_1 + w_{12}^2 h_2 + w_{13}^2 h_3 + w_{14}^2 h_4 + b_1^2)$$

$$y_2 = g_2 (w_{21}^2 h_1 + w_{22}^2 h_2 + w_{23}^2 h_3 + w_{24}^2 h_4 + b_2^2)$$



- w_{ij}^k weight between previous node j and next node i at layer k ;
- g_k is any activation function applied to each its input vector

Artificial Neural Networks

$$h_1 = g_1 (w_{11}^1 x_1 + w_{12}^1 x_2 + w_{13}^1 x_3 + b_1^1)$$

$$h_2 = g_1 (w_{21}^1 x_1 + w_{22}^1 x_2 + w_{23}^1 x_3 + b_2^1)$$

$$h_3 = g_1 (w_{31}^1 x_1 + w_{32}^1 x_2 + w_{33}^1 x_3 + b_3^1)$$

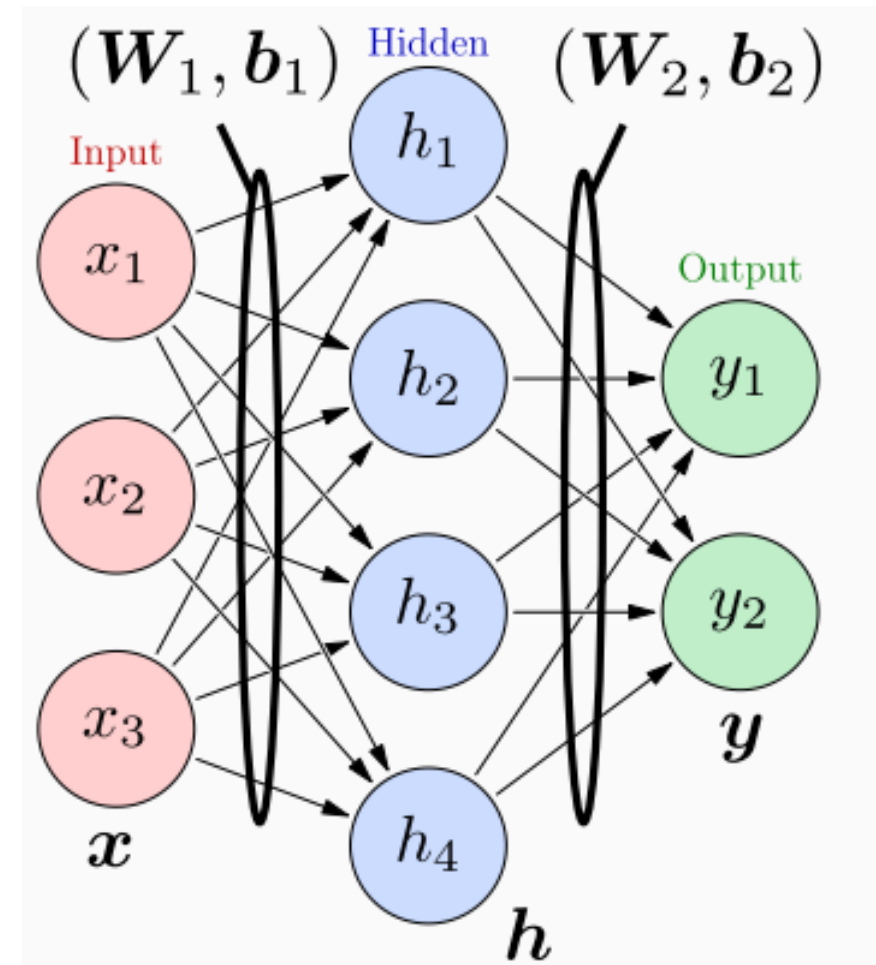
$$h_4 = g_1 (w_{41}^1 x_1 + w_{42}^1 x_2 + w_{43}^1 x_3 + b_4^1)$$

$$\mathbf{h} = g_1 (\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1)$$

$$y_1 = g_2 (w_{11}^2 h_1 + w_{12}^2 h_2 + w_{13}^2 h_3 + w_{14}^2 h_4 + b_1^2)$$

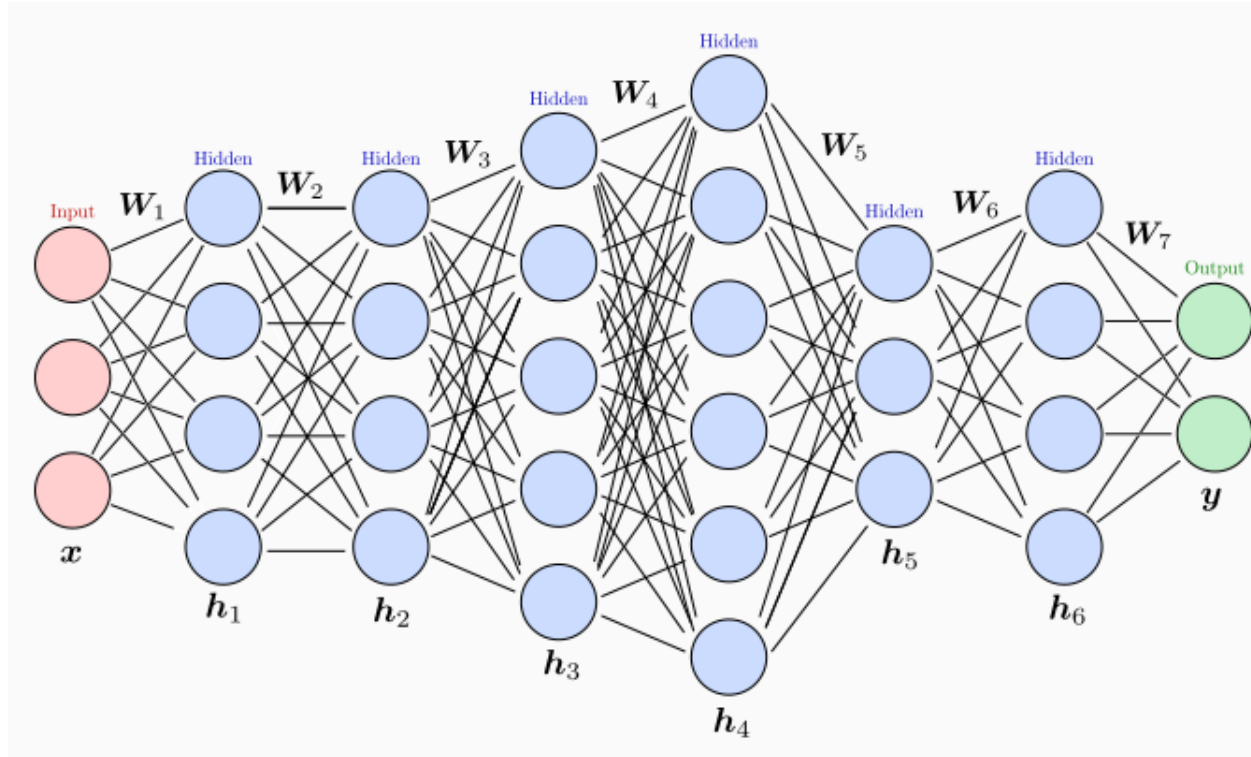
$$y_2 = g_2 (w_{21}^2 h_1 + w_{22}^2 h_2 + w_{23}^2 h_3 + w_{24}^2 h_4 + b_2^2)$$

$$\mathbf{y} = g_2 (\mathbf{W}_2 \mathbf{h} + \mathbf{b}_2)$$



- The matrices \mathbf{W}_k and biases \mathbf{b}_k are learned from labeled training data.

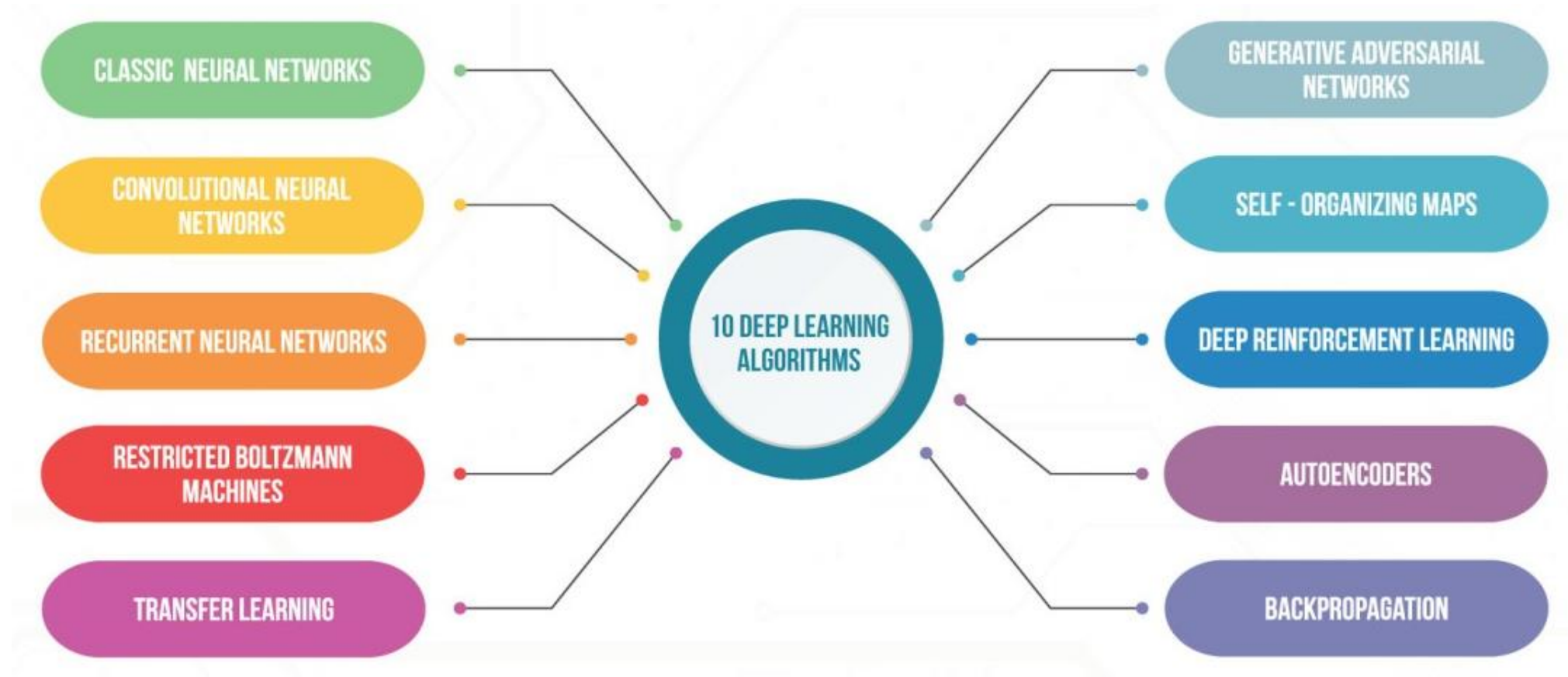
Artificial Neural Networks



- It can have 1 hidden layer only (shallow network);
- It can have more than 1 hidden layer (deep network);
- Each layer can have a different size, and hidden and output layers often have different activation functions.

Deep Learning

- Not covered in this curricular unit!



Resources

- Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. In Psychological Review (Vol. 65, Issue 6, pp. 386–408). American Psychological Association (APA). <https://doi.org/10.1037/h0042519>
- <https://simplilearn.com/tutorials/deep-learning-tutorial/perceptron>