

Chapter 1

Perceptrons

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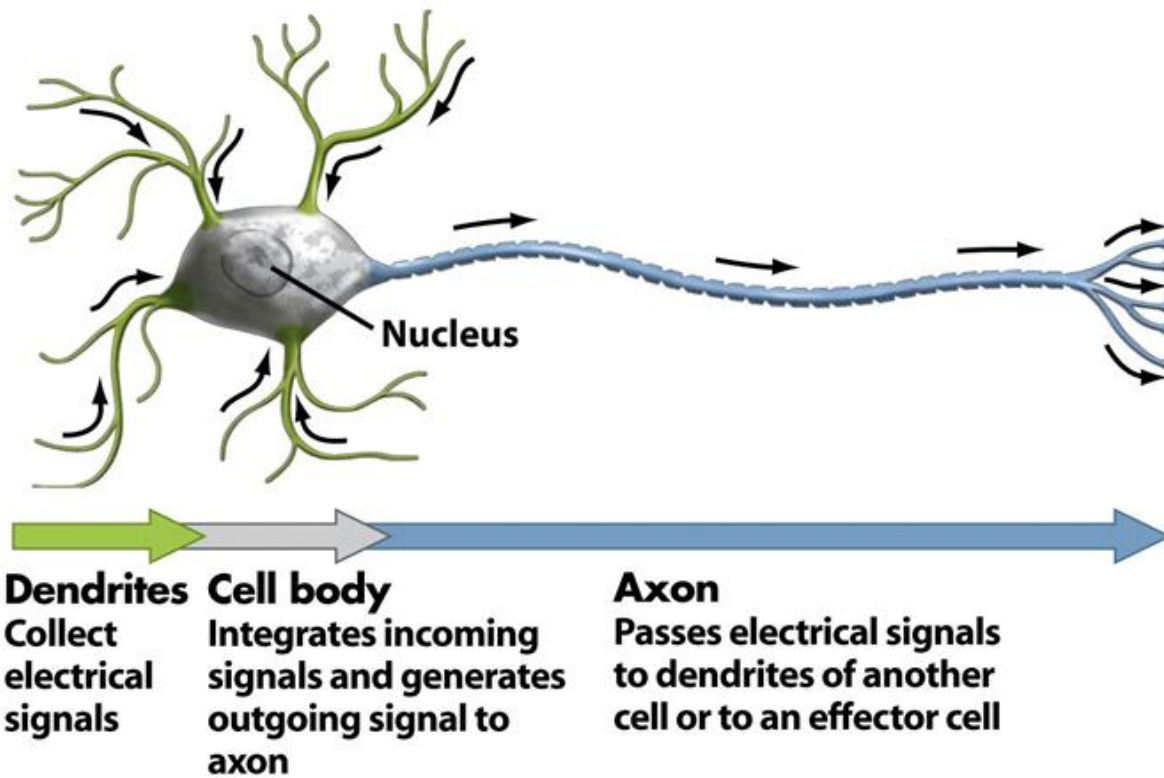


Figure 45-2b Biological Science, 2/e
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Introduction

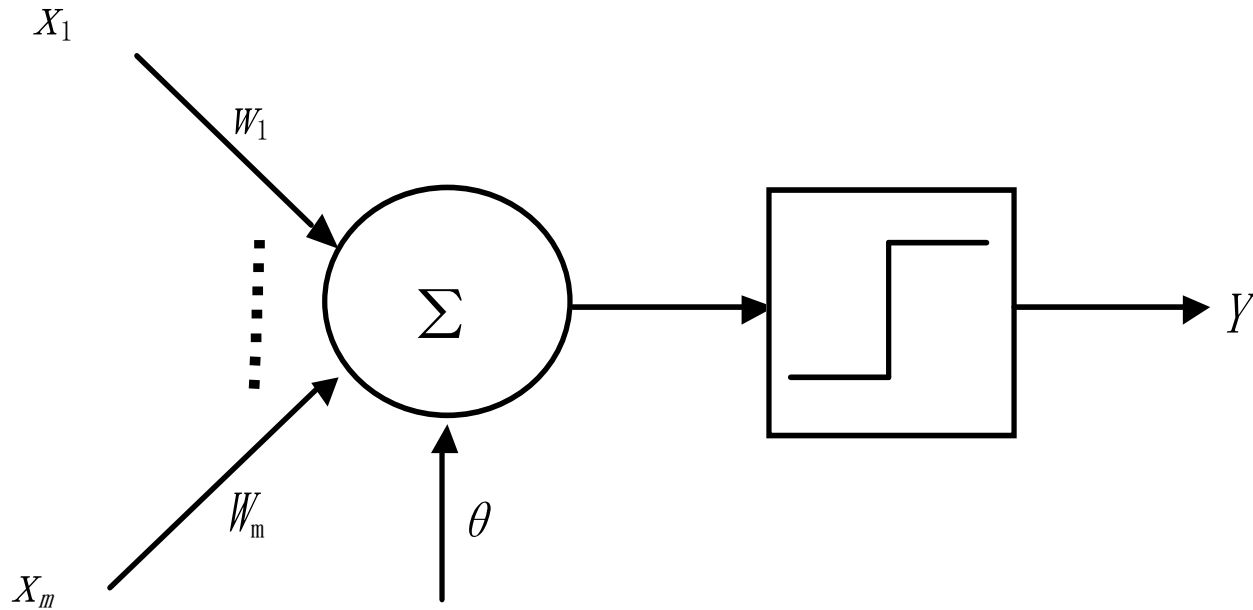
- Proposed by McCulloch and Pitts, and Hebb, Rosenblatt in 1957
- The simplest form of a neural network used for **linearly separable problems**
- ***Perceptron convergence theorem***
- One neuron for two-class problems, multiple neurons for multi-class problems (multi-layer perceptron)
- **Theoretically, multilayer perceptron can be used to solve any classification and regression problem with BP learning algorithm**

Overview

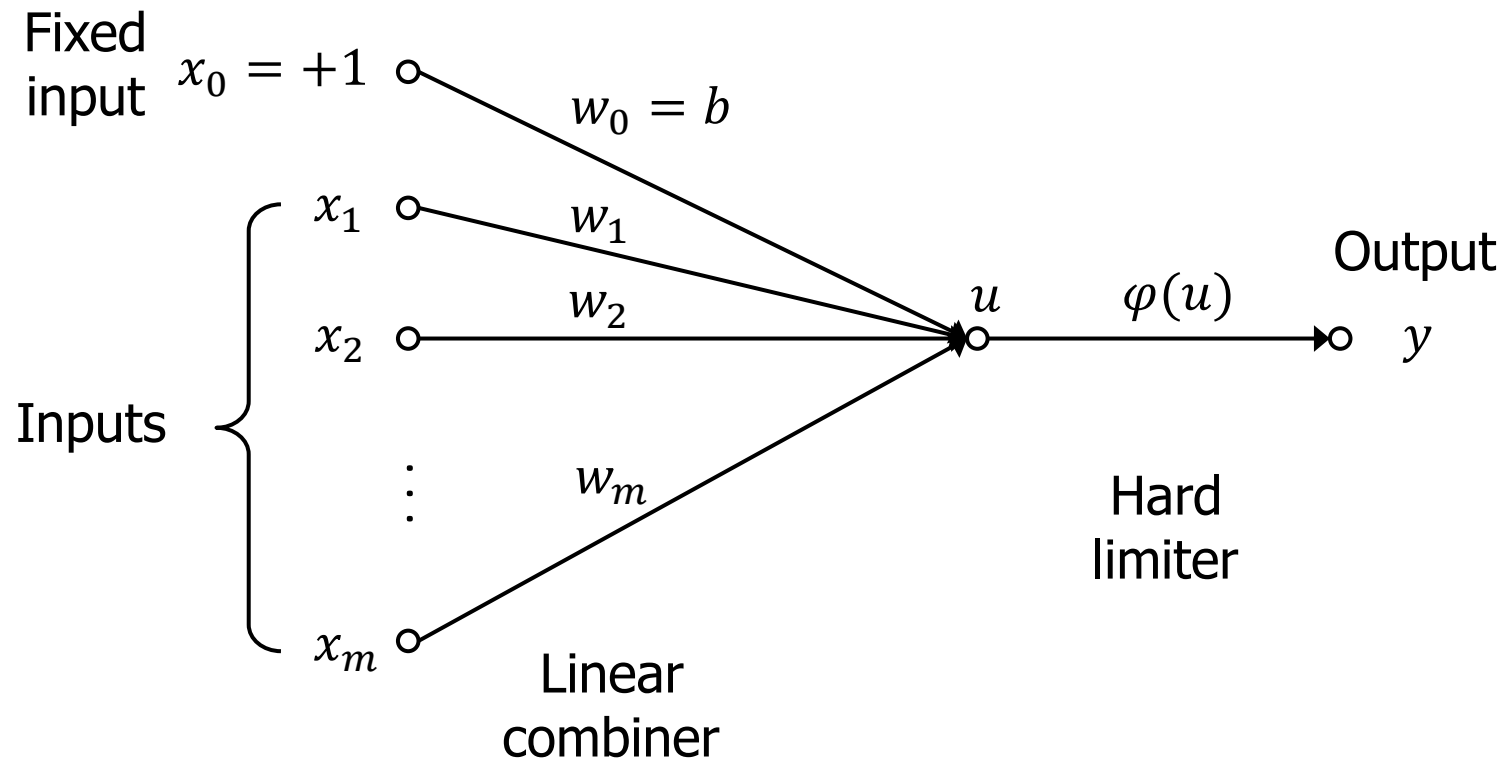
- Single layer Perceptron
- Multilayer Perceptron
 - BP Learning algorithm
 - Others

Simple layer Perceptron

Perceptron Unit



Single Layer



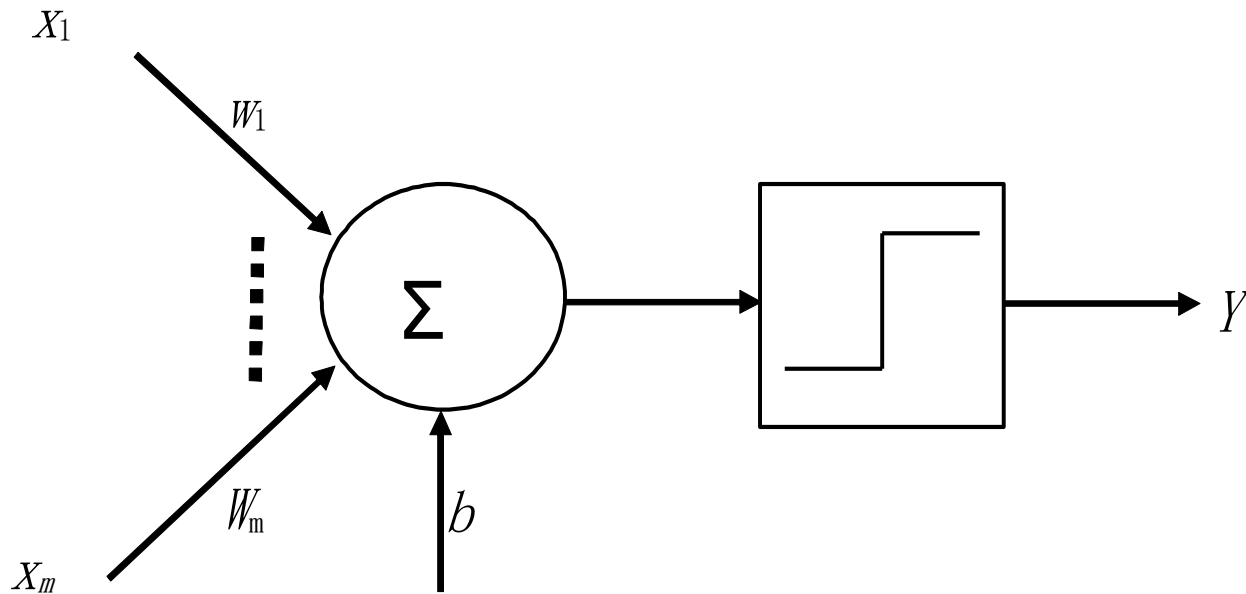
A model of neuron

- Inputs x_i , the m elements of $x(i)$ originate at different points in input space.
- Synaptic weights w_i ,
- Weighted sum on inputs

$$u = w_0x_0 + w_2x_2 + \dots + w_mx_m = \langle w, x \rangle$$

- The problem is how to design a multiple input — single output model of the unknown dynamical system by building it around a single linear or nonlinear neuron — control the adjustment of the weights.

Classifier



$$y_i = f(\sum w_{ij}x_j + b)$$

$$f(u_j) = \begin{cases} 1 & u_j \geq 0 \\ -1 & u_j < 0 \end{cases}$$

Supervised learning

- Teacher gives samples of inputs $x(n)$ and corresponding desired outputs $t(n)$
- Goal is to find weights which imitate the behavior of the teacher

Learning Rule

$$w_i(n+1) = w_i(n) + \eta(t(n) - y(n))x_i(n)$$

$$i = 1, 2, \dots, m$$

- If the n -th input $x(n)$ is correctly classified, i.e., $t(n)=y(n)$
 - Nothing happens
- Otherwise, $t(n) \neq y(n)$
 - Update weights (two cases)

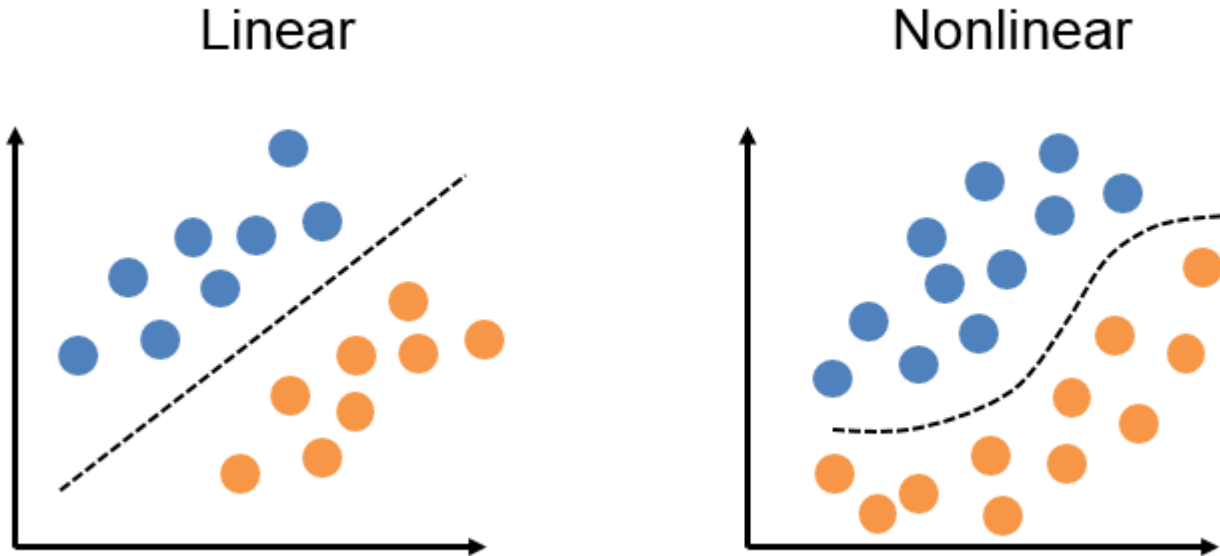
Adjust the Weights

- Adjust the weights
 - Start from randomly initialized weights
 - Update weights according to the rule
 - Stops when convergence or other condition is met

Perceptron convergence theorem

- For linearly separable problems, the algorithm **converges at finite steps**
- See proof (another pdf)

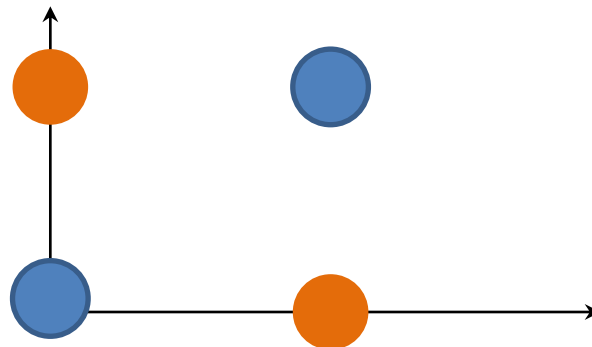
Linear and nonlinear data



Linear function can separate the data without any error

XOR Problem

- Some classifications are impossible
- A famous example: XOR problem
 - Class 1: $(0, 0)$ and $(1, 1)$
 - Class 2: $(1, 0)$ and $(0, 1)$
 - The classes are not linearly separable, i.e. there is no hyperplane (line in this case) separating the classes.



To be continued