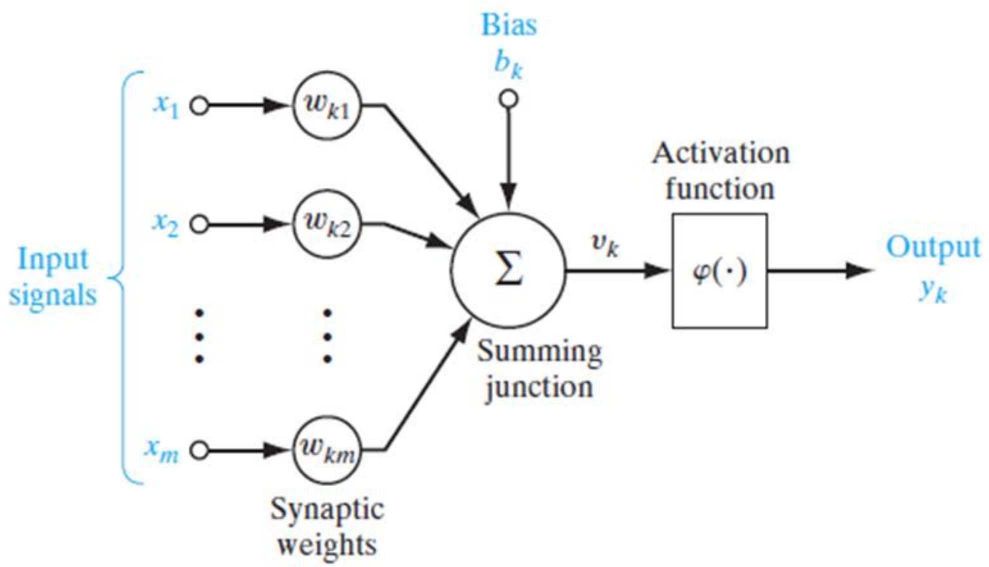
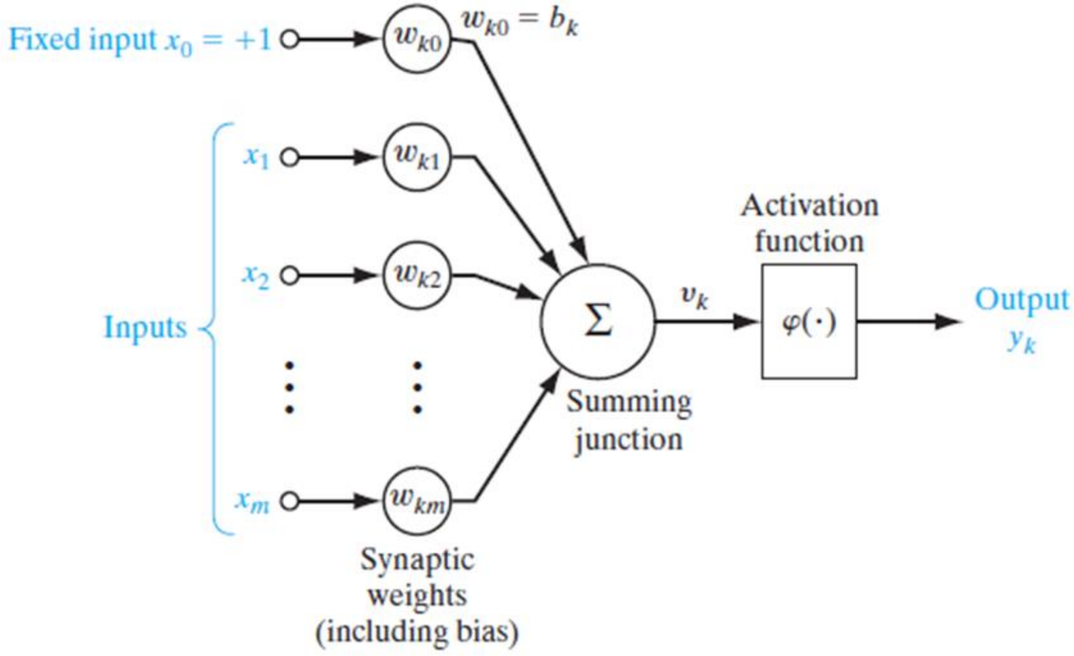
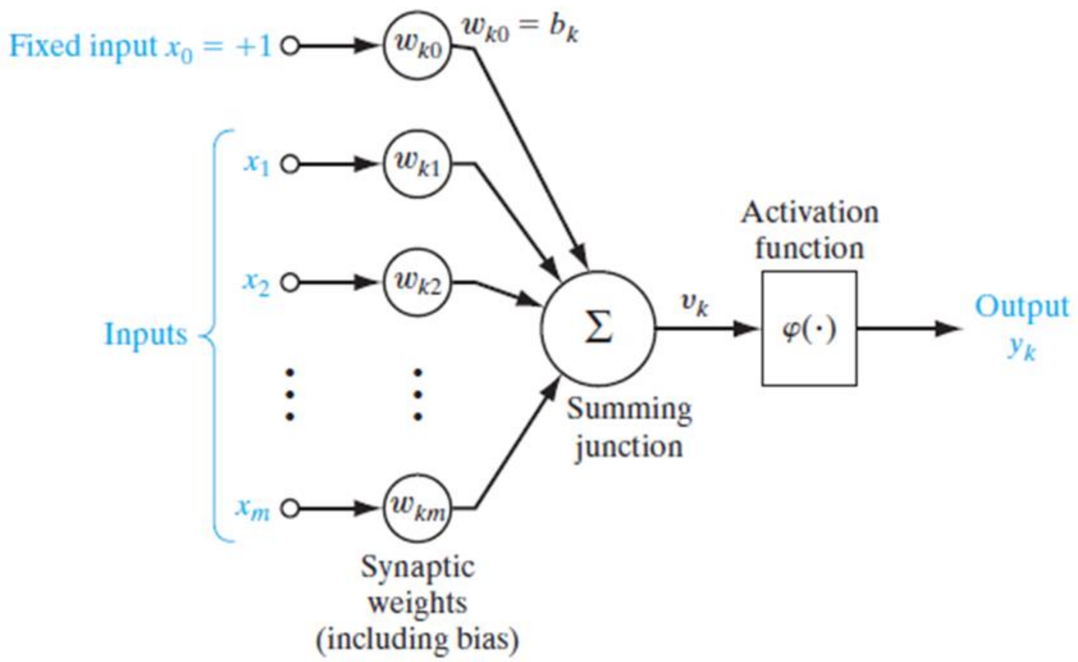
Artificial neural networks

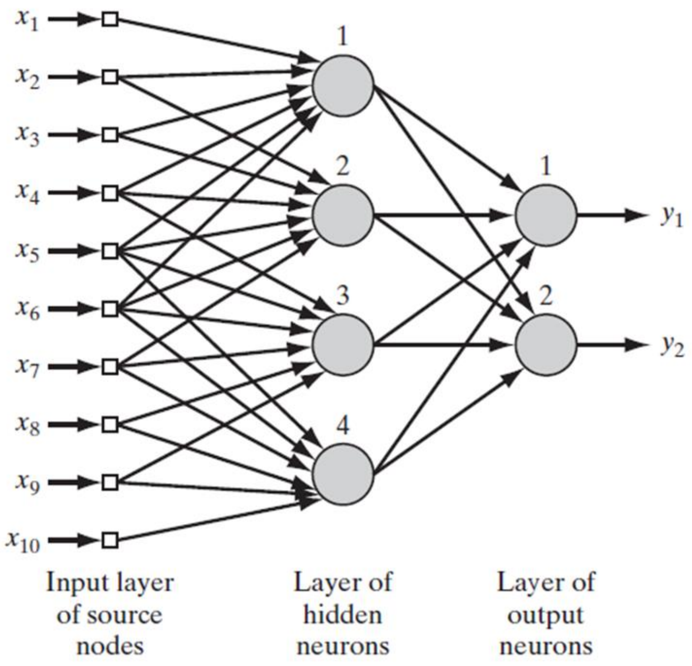
- Artificial neural networks (ANNs) are computing systems inspired by the biological neural networks . Such systems learn to do tasks by considering examples.
- An ANN is based on a collection of connected units called artificial neuron.







- $\mathrm{v}_k = \sum_{j=o}^{m} \omega_{kj} x_j$
- $y_k = \varphi(v_k)$ --output



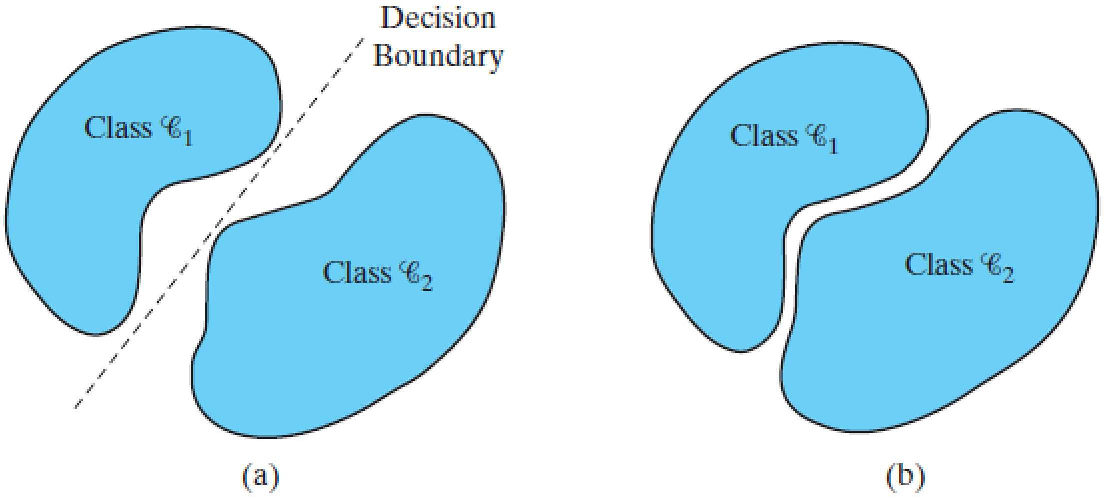
- Many neurons work together and become an artificial neural networks
- We can use some examples to train the neural networks and adjust the variables (synaptic weights) in it so it can be used in other cases.

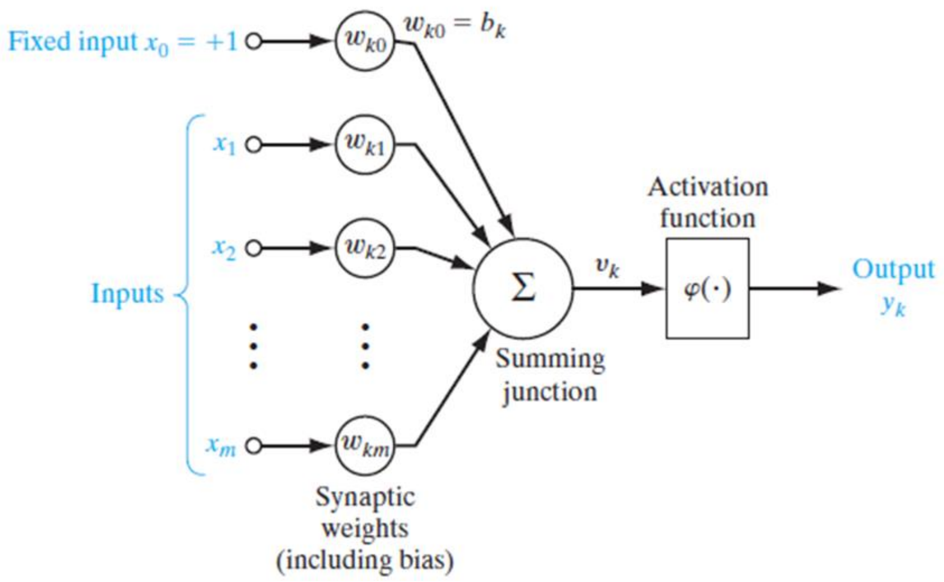
An example --Rosenblatt’s perceptron

- Rosenblatt’s perceptron is a linear classifier, it can decide whether an input, represented by a vector of numbers, belongs to some specific class or not.

- It can be proved that if we have two classes and they are linearly separable, then they can be separated through a limited number of steps.

- If two classes can be separated through a plane, then the two classes are called linearly separable.
- We define the plane as $\sum_{i=1}^{m} w_i x_i + b = 0$





- We define the input vector: $\mathbf{x}(n) = [+1, x_1(n), x_2(n), ..., x_m(n)]^T$
- Synaptic weights vector: $\mathbf{w}(n) = [b, w_1(n), w_2(n), ..., w_m(n)]^T$
- Output vector: $$v(n) = \sum_{i=0}^{m} w_i(n)x_i(n) = \mathbf{w}^T(n)\mathbf{x}(n)$$

n is the number of iterations

图片来源：Simon Haykin -- Neural Networks and Learning Machines

$$\mathbf{w}^T\mathbf{x} > 0 \text{ for every input vector } \mathbf{x} \text{ belonging to class } \mathscr{C}_1$$
$$\mathbf{w}^T\mathbf{x} \le 0 \text{ for every input vector } \mathbf{x} \text{ belonging to class } \mathscr{C}_2$$

if

$$\mathbf{w}(n+1) = \mathbf{w}(n) \quad \text{if } \mathbf{w}^T(n)\mathbf{x}(n) > 0 \text{ and } \mathbf{x}(n) \text{ belongs to class } \mathscr{C}_1$$
$$\mathbf{w}(n+1) = \mathbf{w}(n) \quad \text{if } \mathbf{w}^T(n)\mathbf{x}(n) \le 0 \text{ and } \mathbf{x}(n) \text{ belongs to class } \mathscr{C}_2$$

Else if

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \eta(n)\mathbf{x}(n) \quad \text{if } \mathbf{w}^T(n)\mathbf{x}(n) > 0 \text{ and } \mathbf{x}(n) \text{ belongs to class } \mathscr{C}_2$$
$$\mathbf{w}(n+1) = \mathbf{w}(n) + \eta(n)\mathbf{x}(n) \quad \text{if } \mathbf{w}^T(n)\mathbf{x}(n) \le 0 \text{ and } \mathbf{x}(n) \text{ belongs to class } \mathscr{C}_1$$

- 若 η为定值，设η=1
- 若 $\mathbf{w}^T(n)\mathbf{x}(n) < 0 \text{ for } n = 1, 2, \ldots,$ 且输入向量属于子集 $\mathscr{C}_1$
- 则令 $\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{x}(n)$ 进行迭代
- 可证明，在经过最多 $n_{\max} = \frac{\beta\|\mathbf{w}_o\|^2}{\alpha^2}$ 次迭代后，感知器权值ω(n)可以正确分类 $\mathscr{C}_1$ 与 $\mathscr{C}_2$ 。

- 若η(n)变化，设η(n)为满足 $\eta(n)\mathbf{x}^T(n)\mathbf{x}(n) > |\mathbf{w}^T(n)\mathbf{x}(n)|$ 最小整数
- 可见若第n次迭代 $\mathbf{w}^T(n)\mathbf{x}(n)$符号错误则 $\mathbf{w}^T(n+1)\mathbf{x}(n)$号正确。
- 即若第n次迭代错误，令x(n+1)=x(n)再进行迭代即可。

- The neural network we are using now usually has a variation of multilayer perceptrons.
- For example, convolutional Neural Network (CNN) has been applied to analyzing visual imagery.
- In high energy physics, we can use neural network in particle identification. There has been considerable recent activity applying deep convolutional neural nets (CNNs) to data from particle physics experiments. And it improved sensitivity than physics-variable based selections

Thanks