MODULE 1

Artificial intelligence can be loosely interpreted to mean incorporating human intelligence to machines.

Whenever a machine completes tasks based on a set of stipulated rules that solve problems (algorithms), such an “intelligent” behavior is what is called artificial intelligence.

For example, such machines can move and manipulate objects, recognize whether someone has raised the hands, or solve other problems

Machine learning can be loosely interpreted to mean empowering computer systems with the ability to “learn”. The intention of ML is to enable machines to learn by themselves using the provided data and make accurate predictions.

ML is a subset of artificial intelligence; in fact, it’s simply a technique for realizing AI.It is a method of training algorithms such that they can learn how to make decisions.

Training in machine learning entails giving a lot of data to the algorithm and allowing it to learn more about the processed information

Deep learning is a subfield of ML, concerned with algorithms inspired by the structure and function of Brain called Artificial Neural Networks

In other words, DL is the next evolution of machine learning.

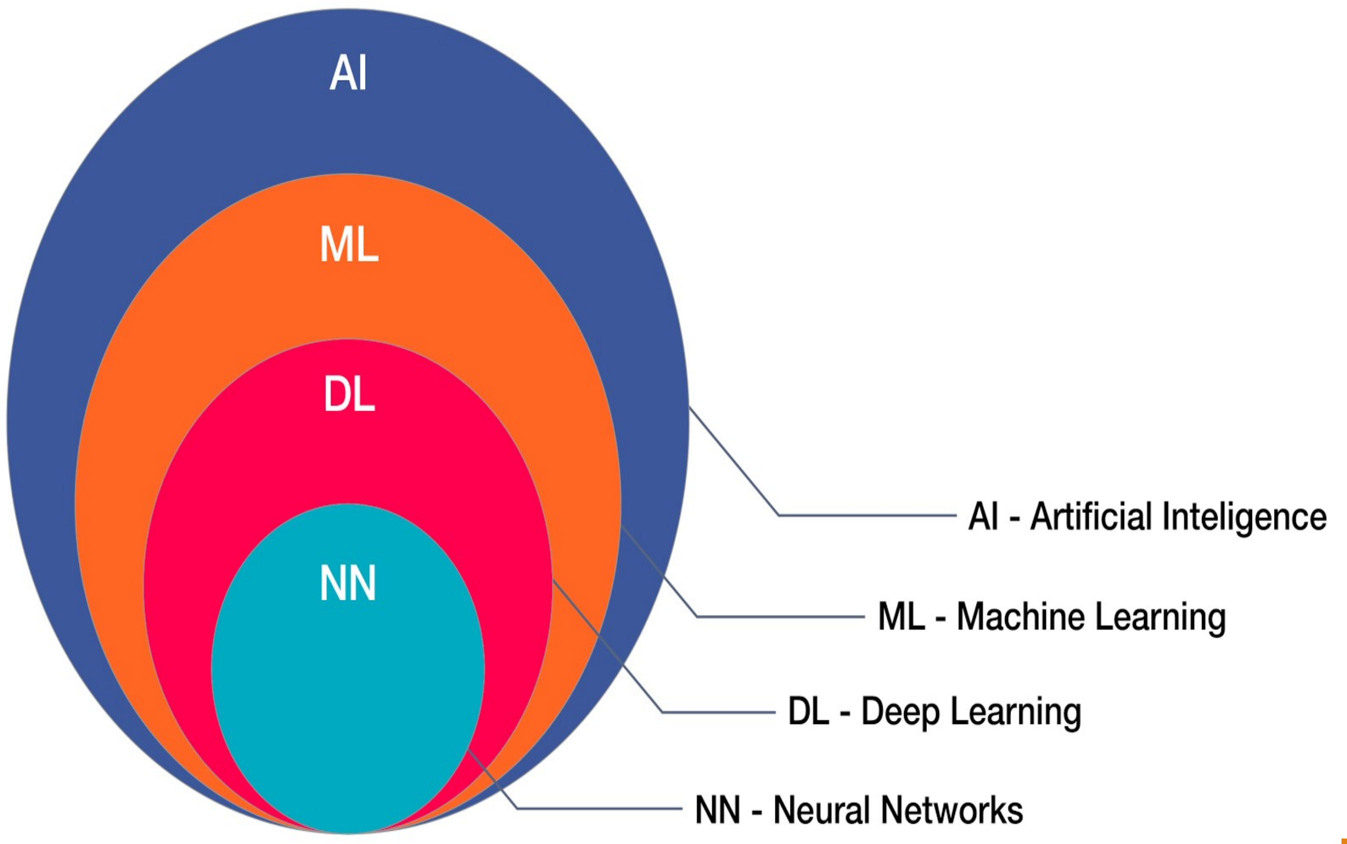
DL algorithms are roughly inspired by the information processing patterns found in the human brain.

Just like we use our brains to identify patterns and classify various types of information, deep learning algorithms can be taught to accomplish the same tasks for machines.

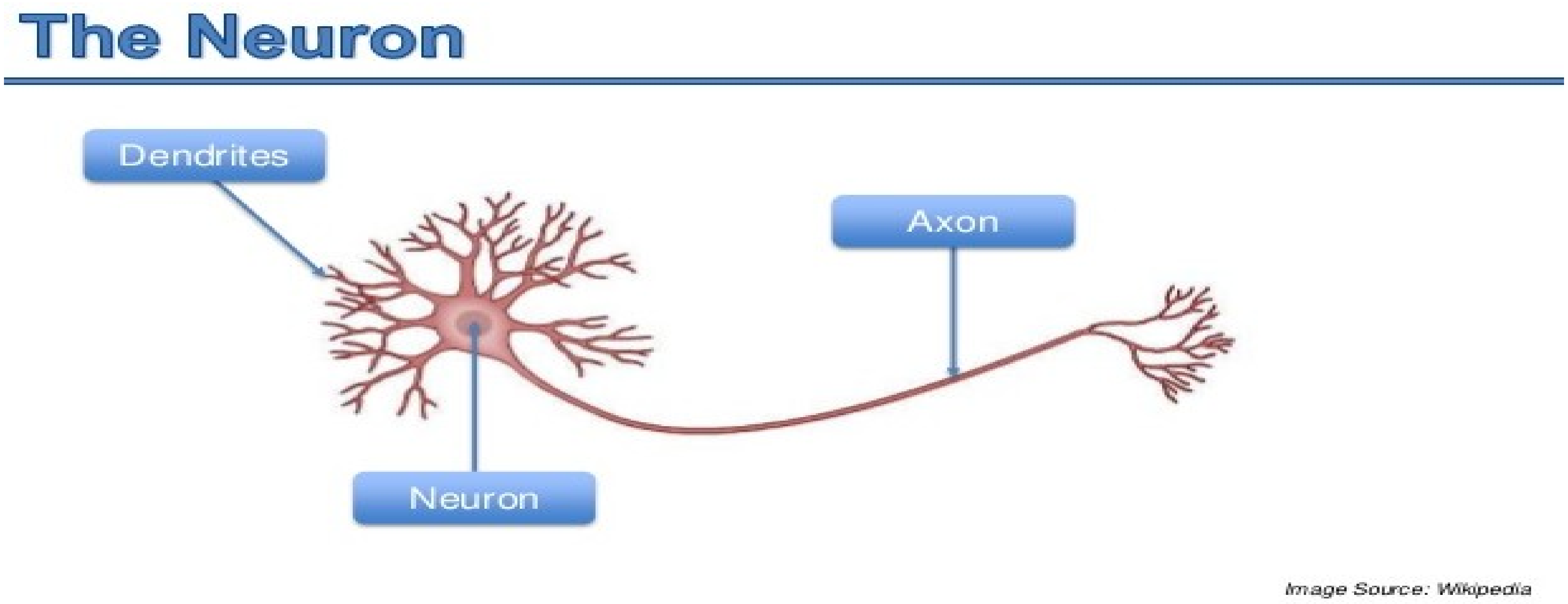
Whenever we receive a new information, the brain tries to compare it to a known item before making sense of it — which is the same concept deep learning algorithms employ.

For example, artificial neural networks (ANNs) are a type of algorithms that aim to imitate the way our brains make decisions.

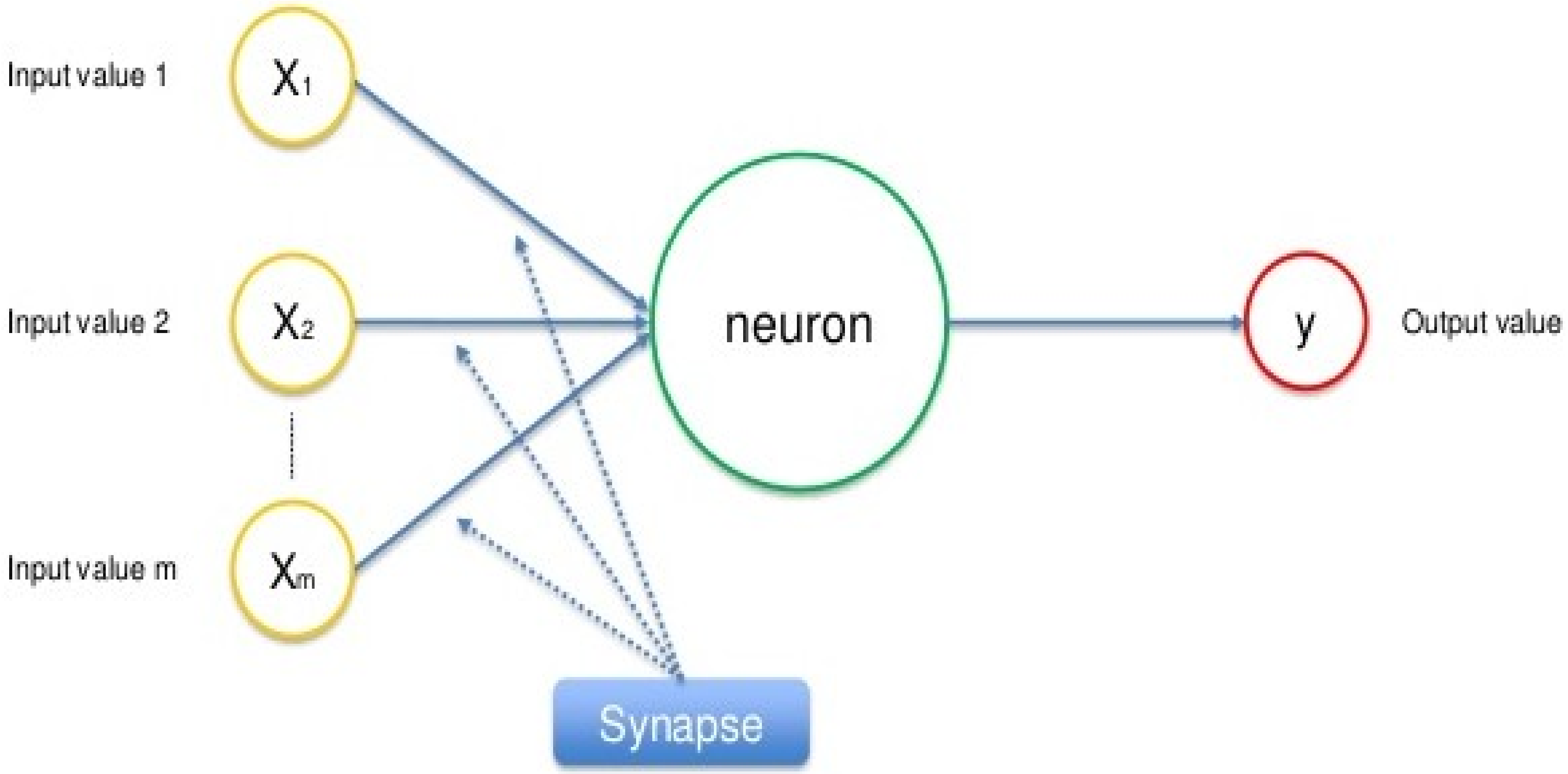
A **Neural Network** is a biological representation of neurons in the brain it deals with all the connections and chemical reactions in the brain and tries to imitate the same type of operations. **Artificial Neural Networks** are the computational models inspired by the human brain



Neural networks were inspired by the *neural architecture of a human brain*, and like in a human brain the basic building block is called a *Neuron*. Its functionality is similar to a human neuron, i.e. it takes in some inputs and fires an output.



The Neuron

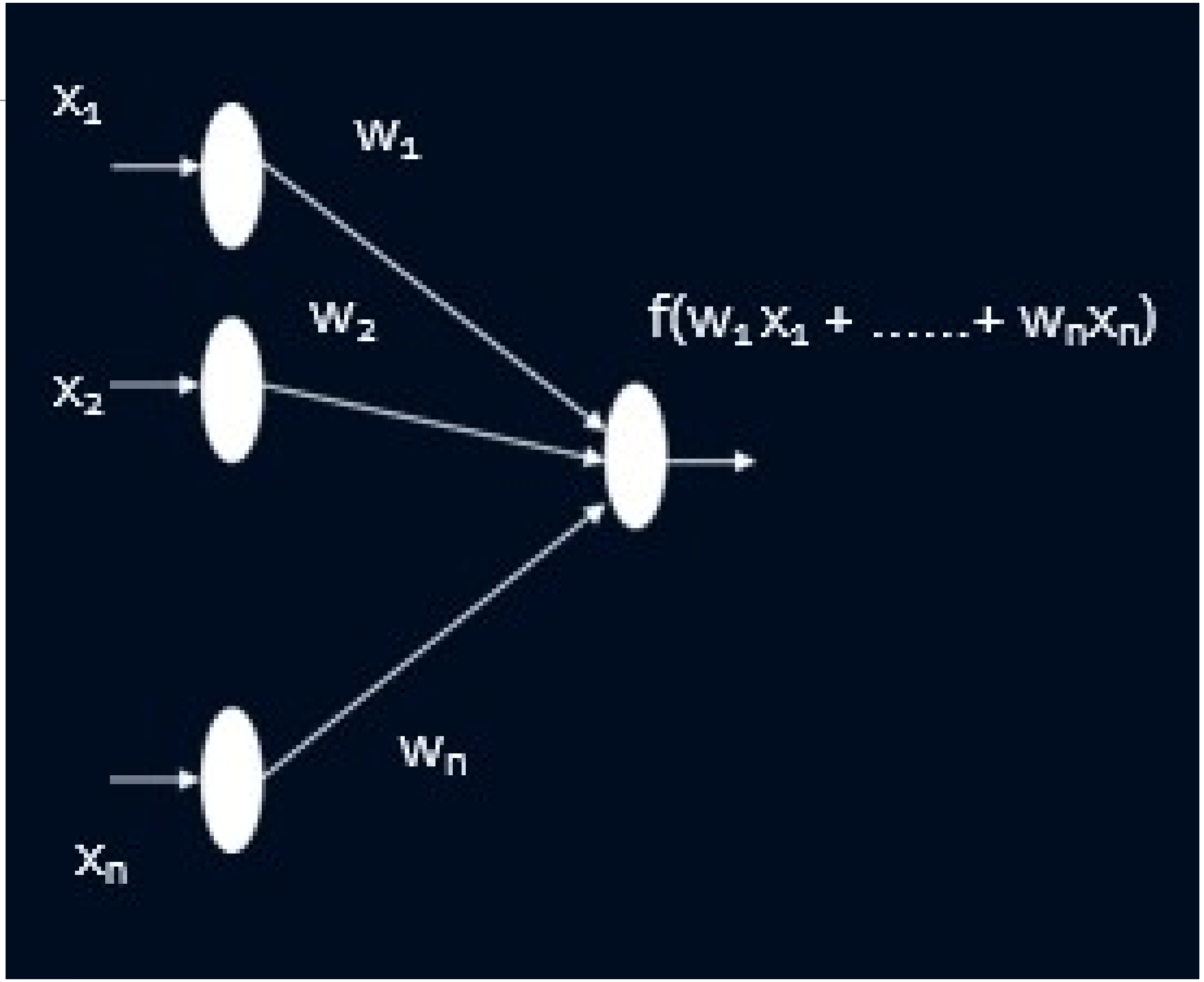

Input value 1
X1
Input value 2
X2
Input value m
Xm
neuron
y
Output value
Synapse

ARTIFICIAL NEURON MODEL

- Inputs to the network are represented by the mathematical symbol, x_n
- Each of these inputs are multiplied by a connection weight , w_n

$$sum = w_1 x_1 + \ldots\ldots + w_n x_n$$

These products are simply summed , fed through the transfer function, f( ) to generate a result and then output.

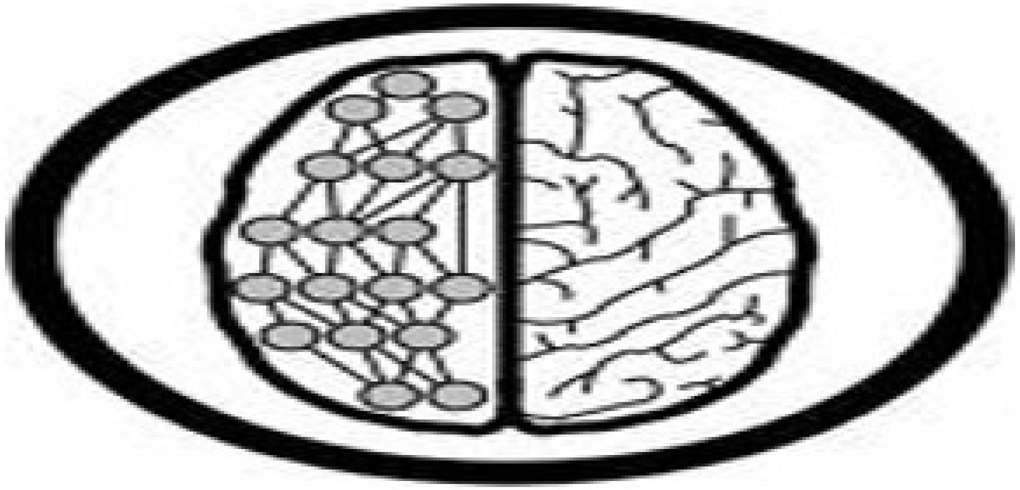


TERMINOLOGY

Biological Terminology	**Artificial Neural Network Terminology**
Neuron	Node/Unit/Cell/Neurode
Synapse	Connection/Edge/Link
Synaptic Efficiency	Connection Strength/Weight
Firing frequency	Node output

How do ANNs work?

- An artificial neural network (ANN) is either a hardware implementation or a computer program which strives to simulate the information processing capabilities of its biological exemplar. ANNs are typically composed of a great number of interconnected artificial neurons. The artificial neurons are simplified models of their biological counterparts.
- ANN is a technique for solving problems by constructing software that works like our brains.

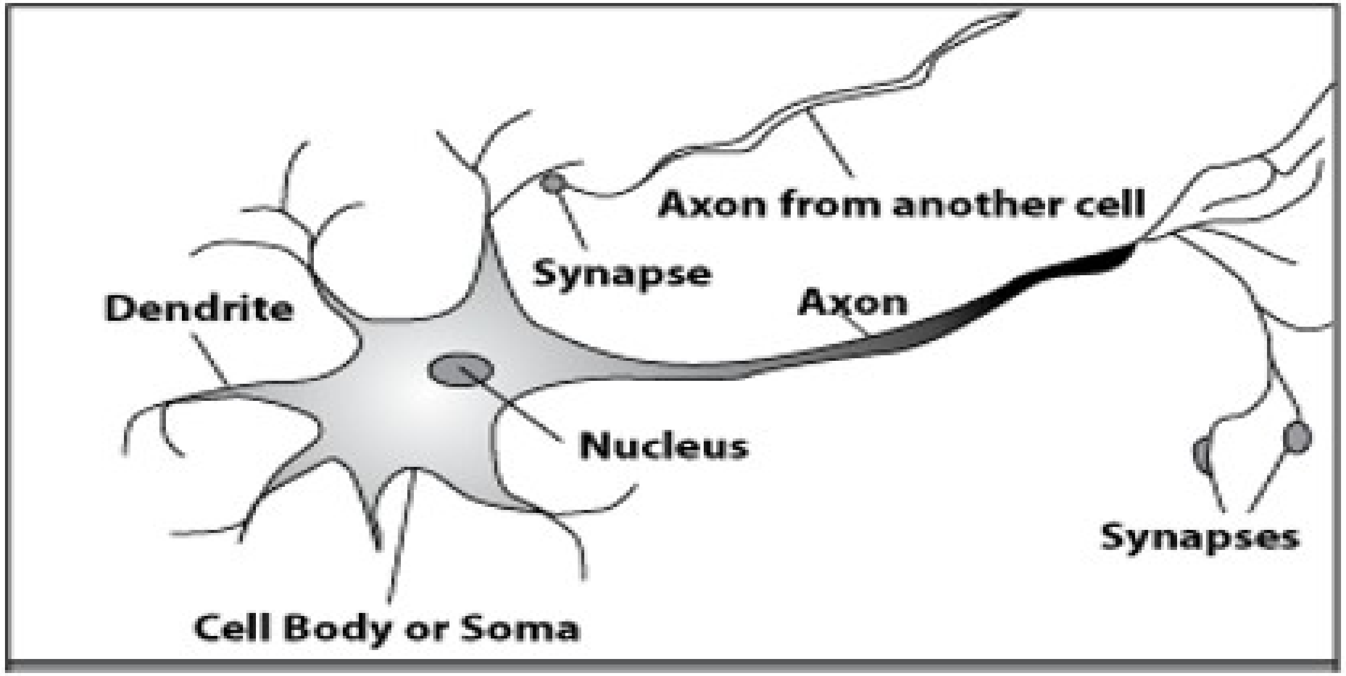


How do our brains work?

- The Brain is a massively parallel information processing system.
- Our brains are a huge network of processing elements. A typical brain contains a network of 10 billion neurons.

How do our brains work?

- A processing element



Dendrites: Input
Cell body: Processor
Synaptic: Link
Axon: Output

A neuron is connected to other neurons through about *10,000 synapses*

A neuron receives input from other neurons. Inputs are combined

Once input exceeds a critical level, the neuron discharges a spike - an electrical pulse that travels from the body, down the axon, to the next neuron(s)

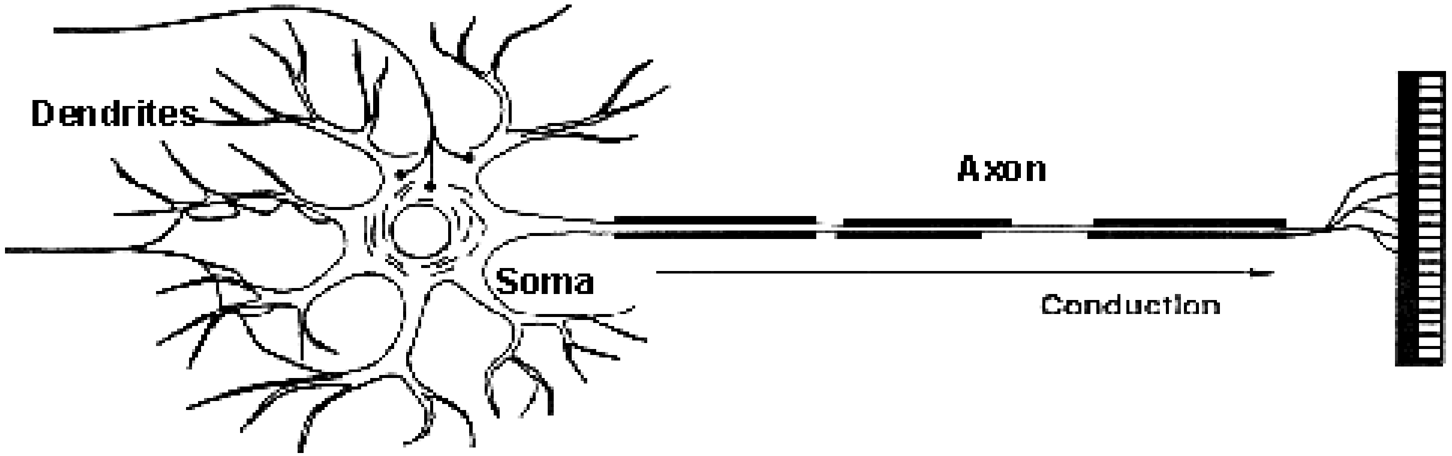
The axon endings almost touch the dendrites or cell body of the next neuron.

Transmission of an electrical signal from one neuron to the next is effected by neurotransmitters.

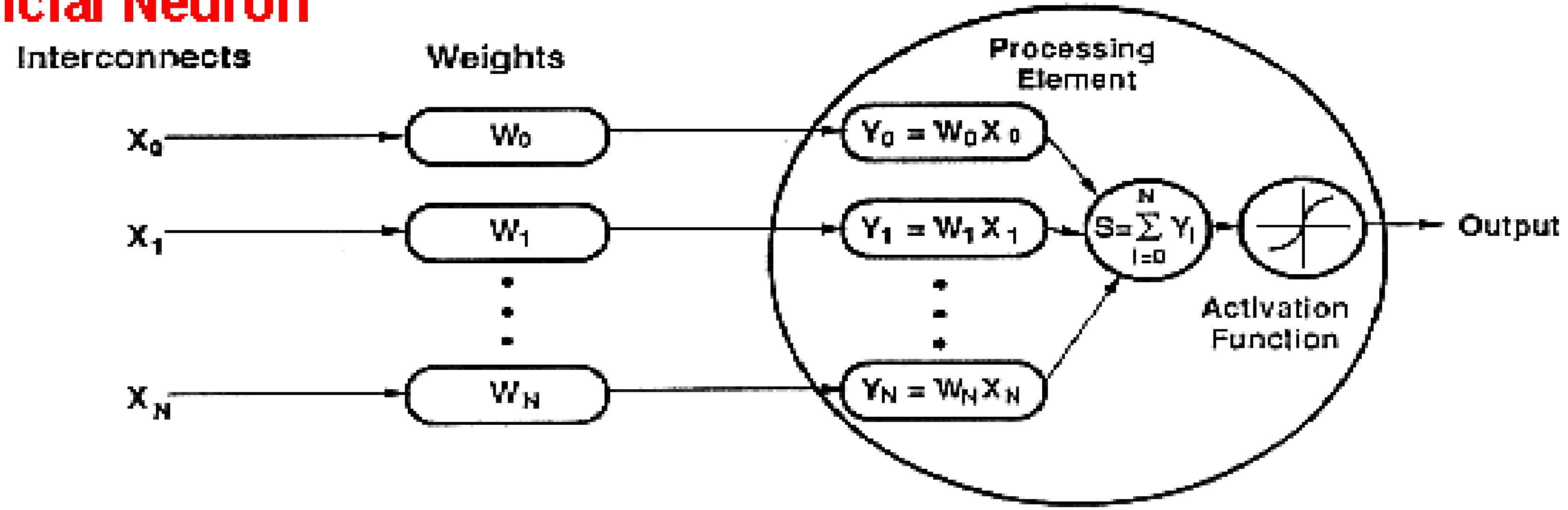
Neurotransmitters are chemicals which are released from the first neuron and which bind to the Second.

This link is called a synapse. The strength of the signal that reaches the next neuron depends on factors such as the amount of neurotransmitter available.

Biological Neuron

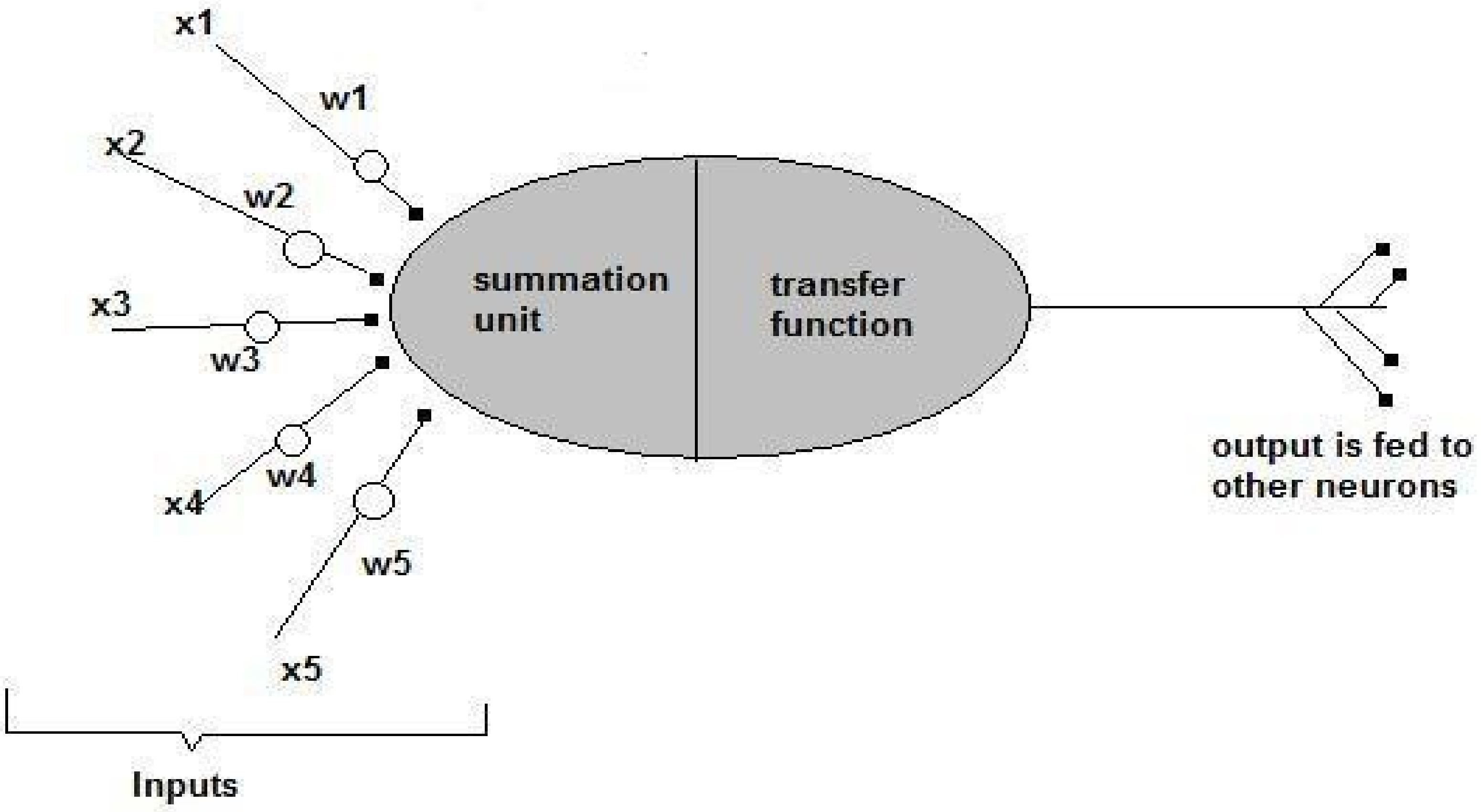


Artificial Neuron



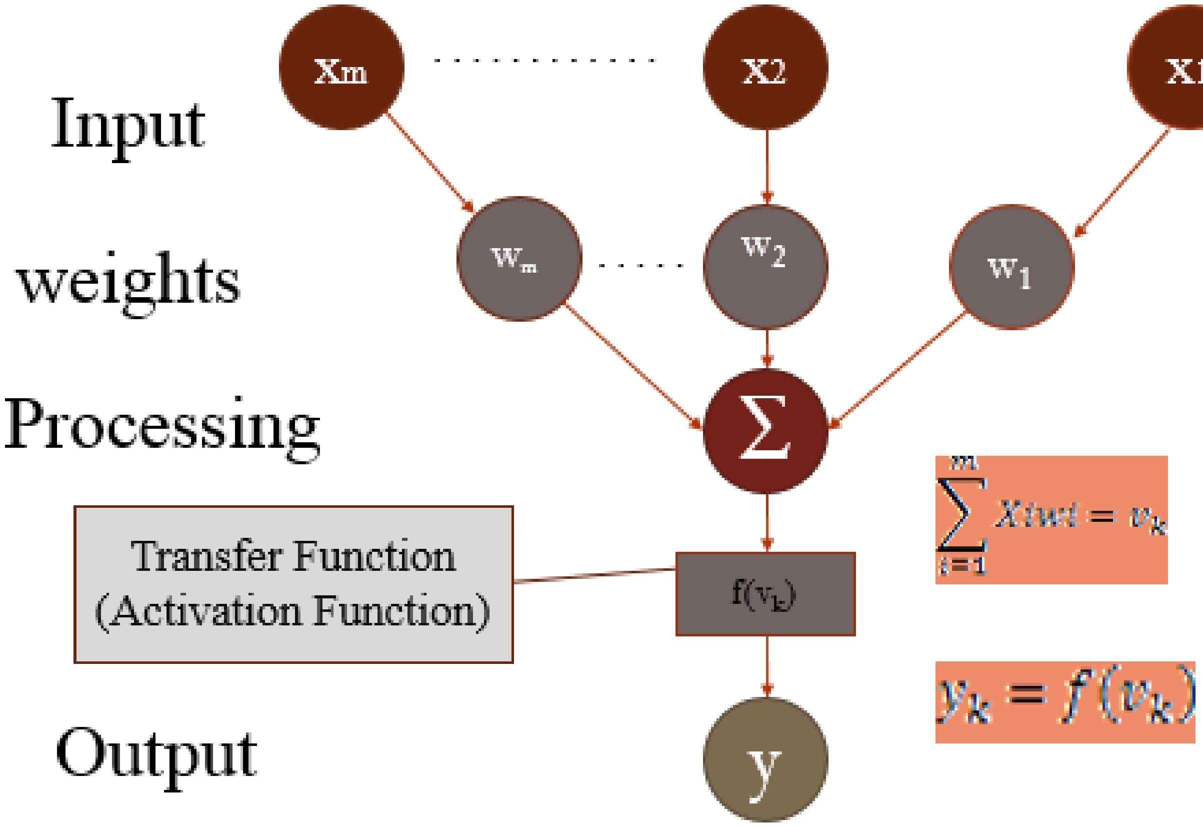
An artificial neuron is an imitation of a human neuron

A Single Neuron



How do ANNs work?

The signal is not passed down to the next neuron verbatim



Computers vs. Neural Networks

“Standard” Computers	Neural Networks
• one CPU	highly parallel processing
• fast processing units	slow processing units
• reliable units	unreliable units
• static infrastructure	dynamic infrastructure

History

1943: McCulloch and Pitts proposed a model of a neuron --> Perceptron

1960s: Widrow and Hoff explored Perceptron networks (which they called "Adalines") and the delta rule.

1962: Rosenblatt proved the convergence of the perceptron training rule.

1969: Minsky and Papert showed that the Perceptron cannot deal with nonlinearly-separable data sets---even those that represent simple function such as X-OR.

1970-1985: Very little research on Neural Nets

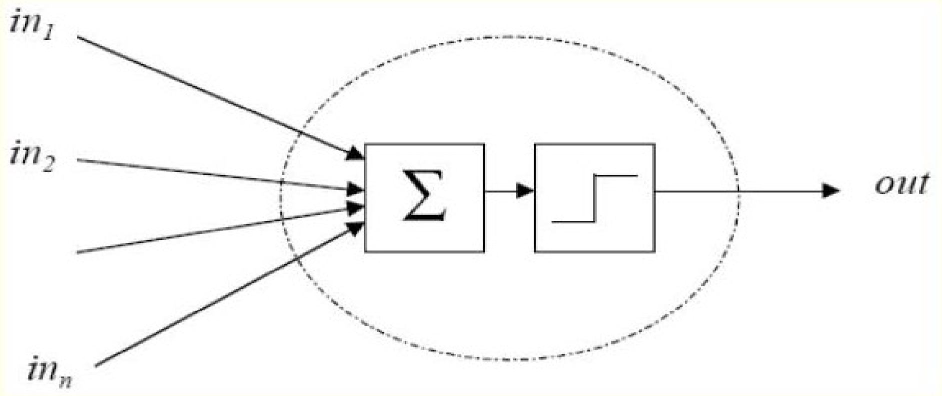
1986: Invention of Backpropagation [Rumelhart and McClelland, but also Parker and earlier on: Werbos] which can learn from nonlinearly-separable data sets.

Since 1985: A lot of research in Neural Nets

MODELS OF NEURON

The McCulloch-Pitts Neuron

- This vastly simplified model of real neurons is also known as a ***Threshold Logic Unit*** :
  - A set of synapses (i.e. connections) brings in activations from other neurons.
  - A processing unit sums the inputs, and then applies a non-linear activation function (i.e. squashing/transfer/threshold function).
  - An output line transmits the result to other neurons.



In **McCulloch-Pitts** (MP) model (Figure 1.2) the activation (x) is give
by a weighted sum of its M input values (a_i) and a bias **term** (θ). Th

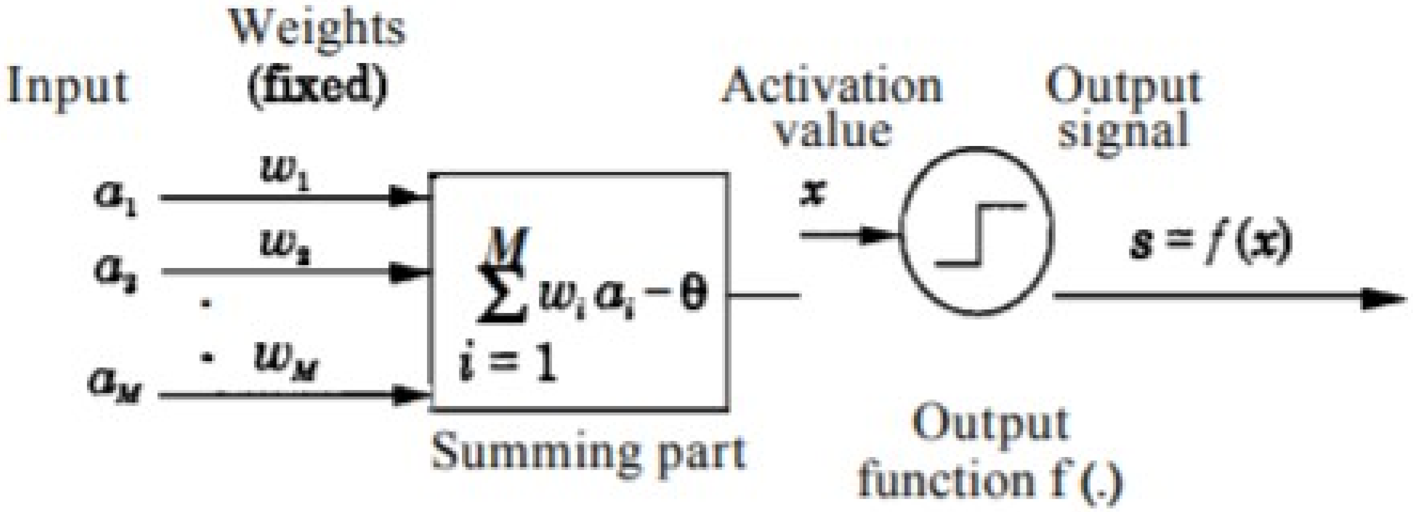


Figure 1.2 **McCulloch-Pitts** model of a neuron.

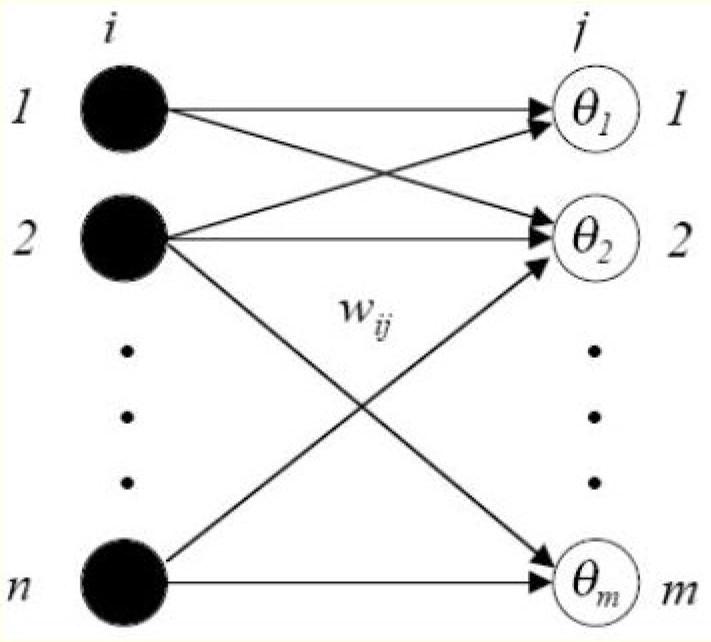
output signal (s) is typically a nonlinear function $f(x)$ of the activatio
value x. The following equations describe the operation of an MP mode

Activation: $$x = \sum_{i=1}^{M} w_i a_i - \theta$$

Output signal: $$s = f(x)$$

The Perceptron

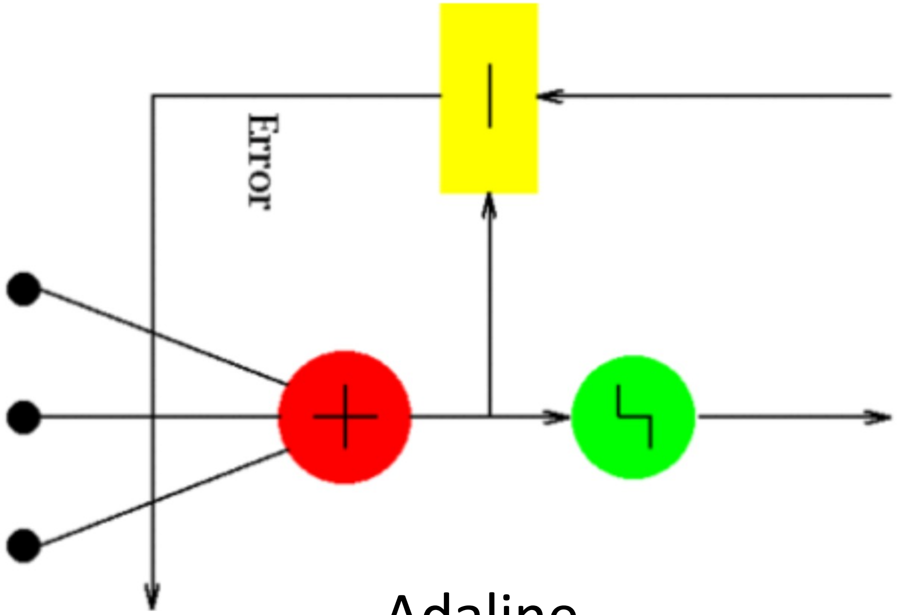
- We can connect any number of McCulloch-Pitts neurons together in any way we like.
- An arrangement of one input layer of McCulloch-Pitts neurons feeding forward to one output layer of McCulloch-Pitts neurons is known as a ***Perceptron***.



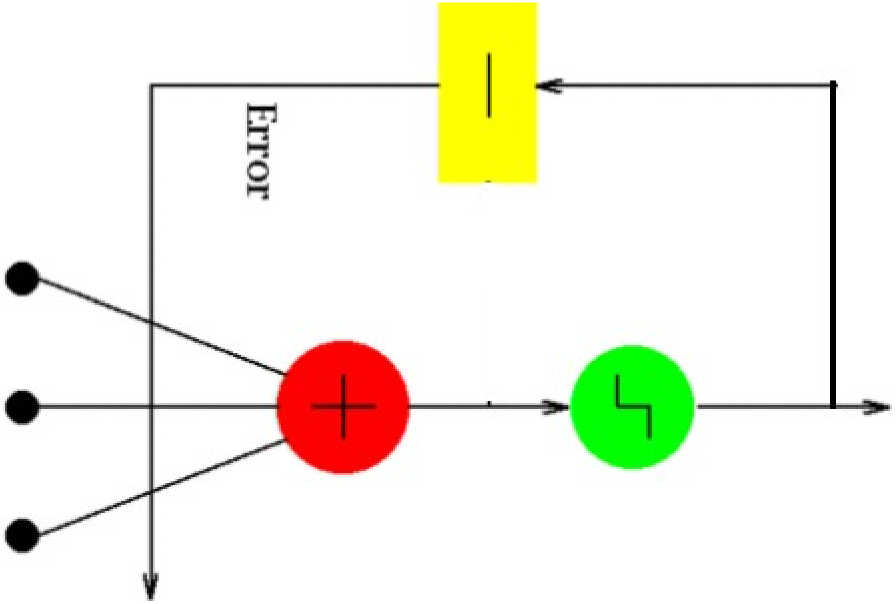
$$out_j = \mathrm{sgn}\left(\sum_{i=1}^{n} out_i w_{ij} - \theta_j\right)$$

Adaline and perceptron

The difference between Adaline and the standard (McCulloch–Pitts) perceptron is that in the learning phase, the weights are adjusted according to the weighted sum of the inputs (the net). In the standard perceptron, the net is passed to the activation (transfer) function and the function's output is used for adjusting the weights.



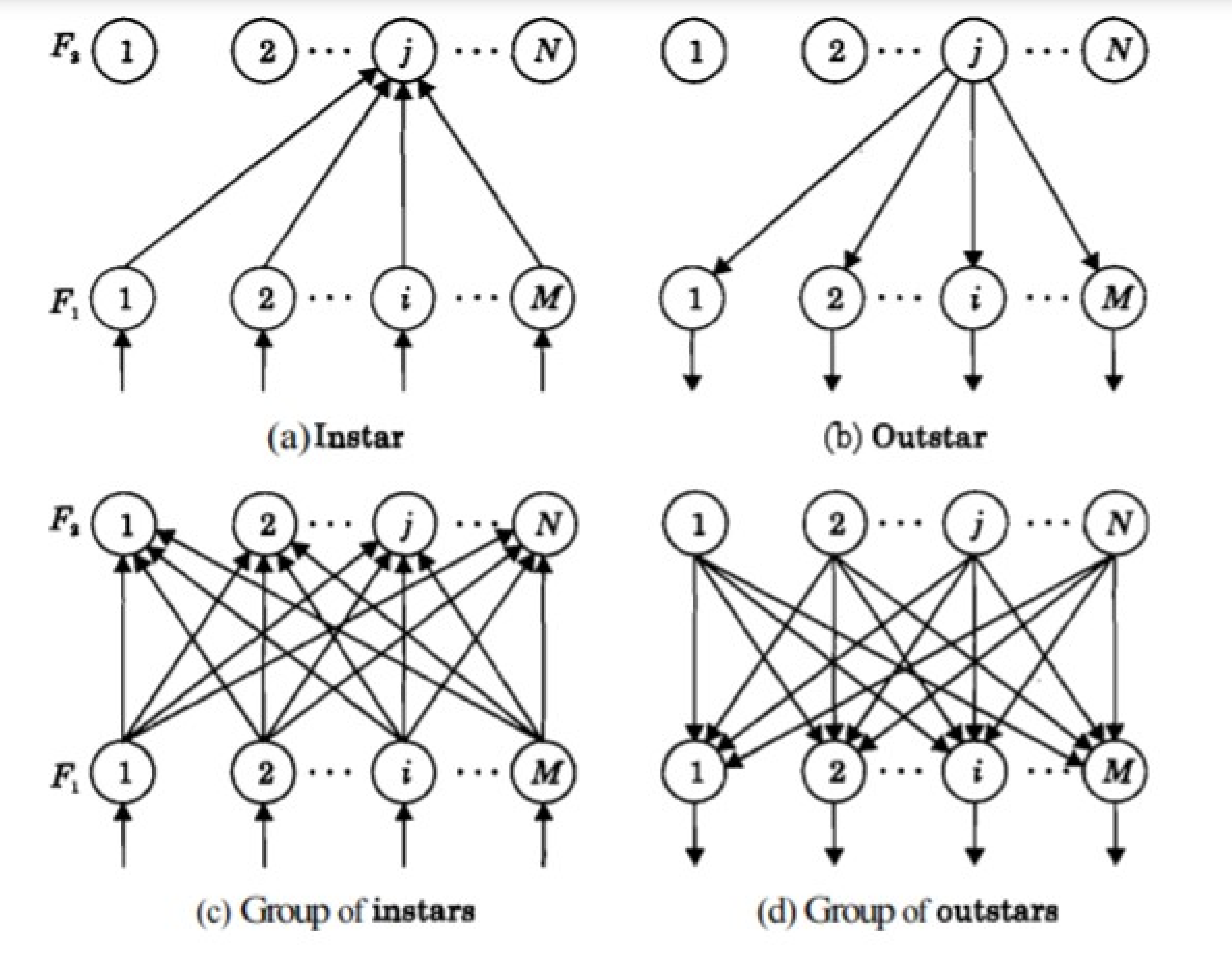
Adaline



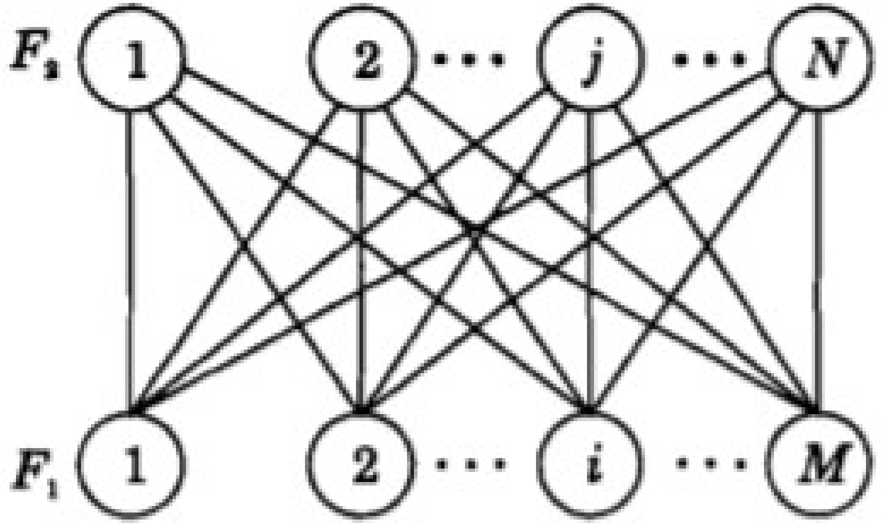
Perceptron

TOPOLOGY

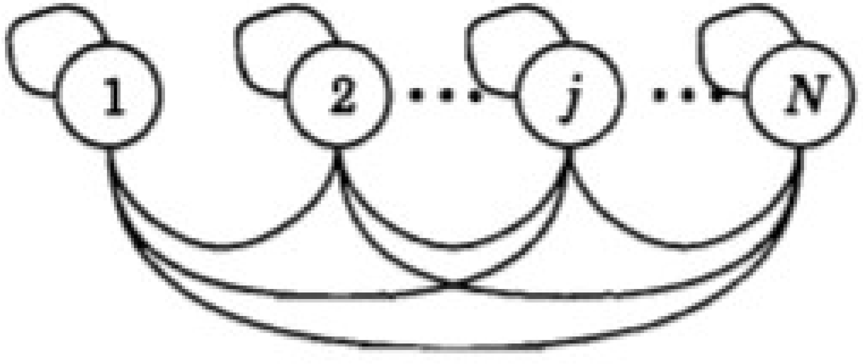
Artificial neural networks are useful only when the processing units are organised in a suitable manner to accomplish a given pattern recognition task. This section presents a few basic structures which will assist in evolving new architectures. The arrangement of the processing units, connections, and pattern input OR output is referred to as topology



(a) Instar
(b) Outstar
(c) Group of instars
(d) Group of outstars



(e) Bidirectional associative memory



(f) Autoassociative memory

Let us consider two layers F1 and F2 with M and N processing units, respectively. By providing connections to the Jth unit in the F2 layer from all the units in the F1 layer, we get two network structures a) **instar and b) outstar**

When all the connections from the units in F1 to F2 are made as in Figure , we obtain a heteroassociation network. This network can be viewed as a c) **group of instars**, if the flow is from Fl to F2. On the other hand, if the flow is from F2 to F1, then the network can be viewed as a

d) **group of outstars**

When the flow is bidirectional, we get a **e) bidirectional associative memory** where either of the layers can be used as input'output.

If the two layers Fl and F2 coincide and the weights are symmetric, then we obtain an

f) autoassociative memory in which each unit is connected to every other unit and to itself