NEURAL NETWORKS

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GRADING

- MidTerm Exam 50%
- Final Exam 50%

The exams will include material covered in lecture.

Recommended Textbooks

(references for the content of the lecture)

- Jacek M. Zurada, **Introduction to Artificial Neural Systems**, PWS Publishing Company, 1995.
- Simon Haykin, **Neural Networks: A Comprehensive Foundation**, Macmillan College Publishing Company, 1994.
- Mohamad H. Hassoun, **Foundamentals of Artificial Neural Networks**, The MIT Press, 1995.
- Laurene Fausett, **Fundamentals of Neural Networks: Architectures, Algorithms, and Applications**, Prentice Hall International, Inc., 1994.

Potential Course Plan

- Introduction to Neural Networks
- Basic Concepts
- Mathematical Review for Neural Networks
- Learning in Neural Networks
- Multilayer Neural Networks
- Feedforward NNs, Feedback NNs.
- Associative Memories
- Hopfield Neural Networks
- Bidirectional Associative Memory Neural Networks
- Cellular Neural Networks
- Support Vector Machines

Introduction to Neural Networks

Lecture 1

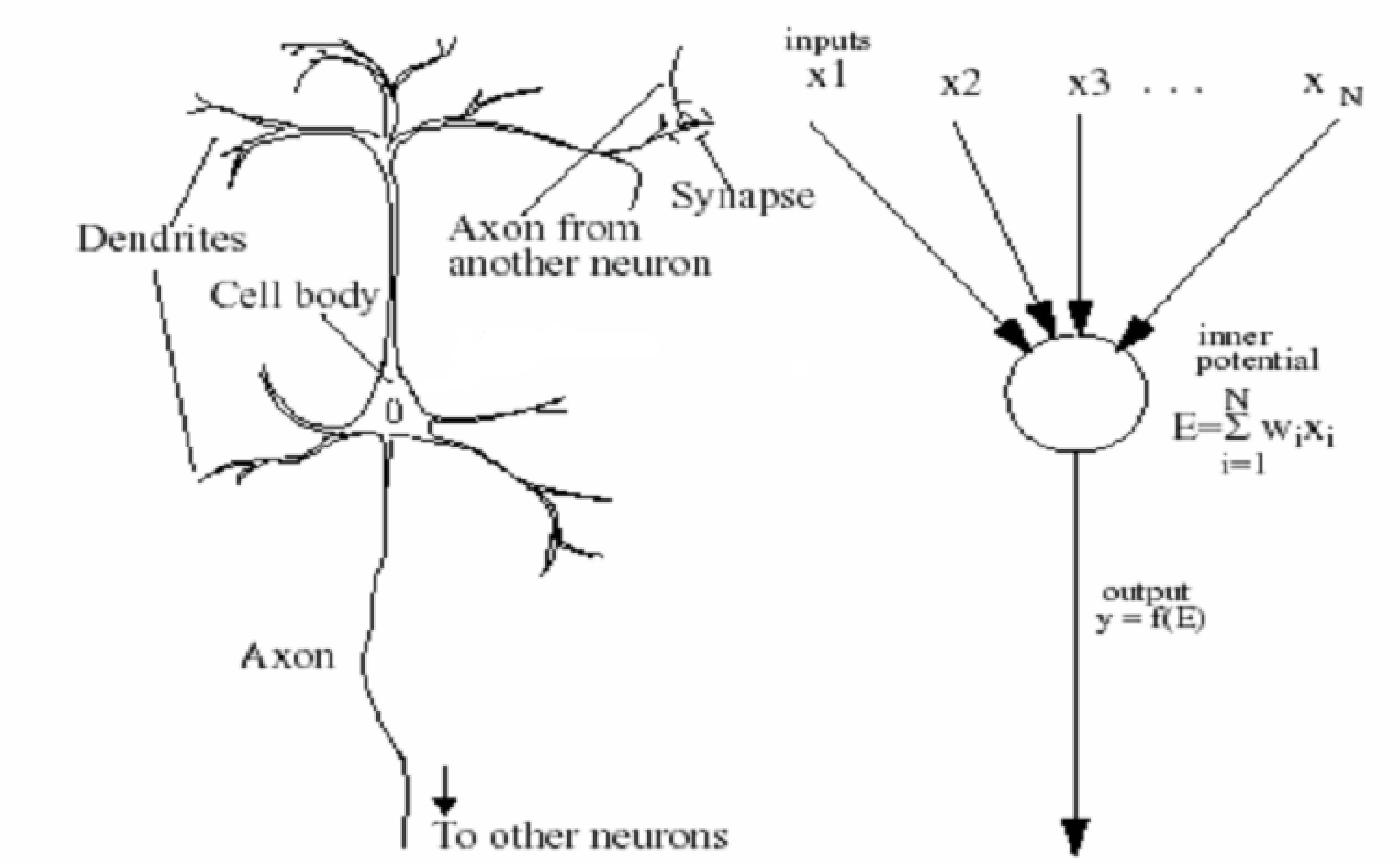
What is (Artificial) Neural Network?

- An **artificial neural network (ANN)**, usually called **neural network** **(NN)**, is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks.

What is (Artificial) Neural Network?

- In an artificial neural network, simple artificial nodes, variously called "**neurons**", are connected together to form a network of nodes mimicking the biological neural networks.

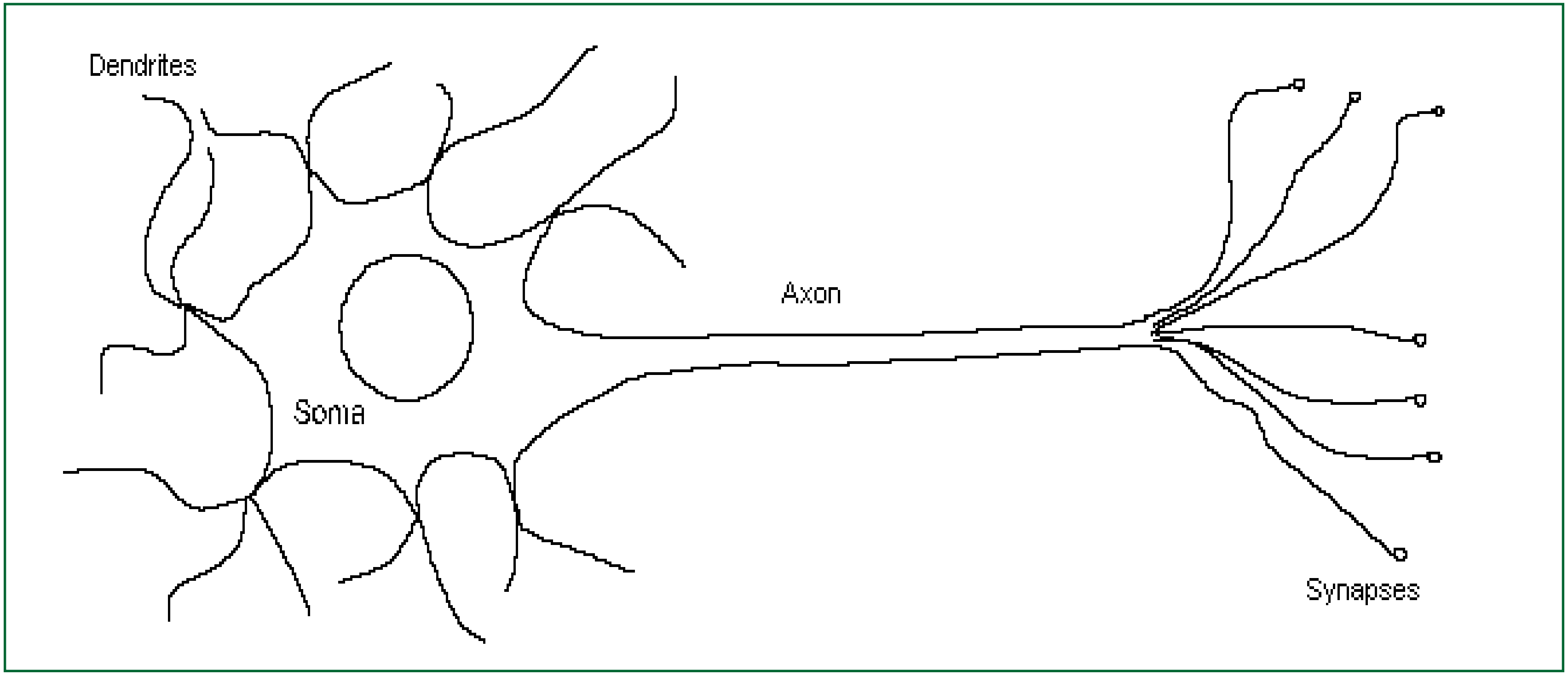
From Biological to Artificial Neural Networks



From Biological to Artificial Neural Networks

- **A biological cell :** consists of dendrites, a cell body(soma), and an axon.
- **The synapses (narrow gaps) :** transmit activations between the dendrites and axon.
- **The dendrites :** receive incoming signals from other nerve axons via synapse.
- **The axon :** is an output mechanism for a neuron

Biological Neuron



- **Dendrites** carry electrical signals in into the cell body(soma).
- **The soma(cell body)** integrates and thresholds the incoming signals.
- **The axon** is a single long nerve fiber that carries the signal from the soma to other neurons.
- **A synapse** is the connection between dendrites and axons of two neurons.

- **A neuron works as follows**

– Signals (impulses) come into the dendrites through the synapses.

– All signals from all dendrites are summed up in the cell body.

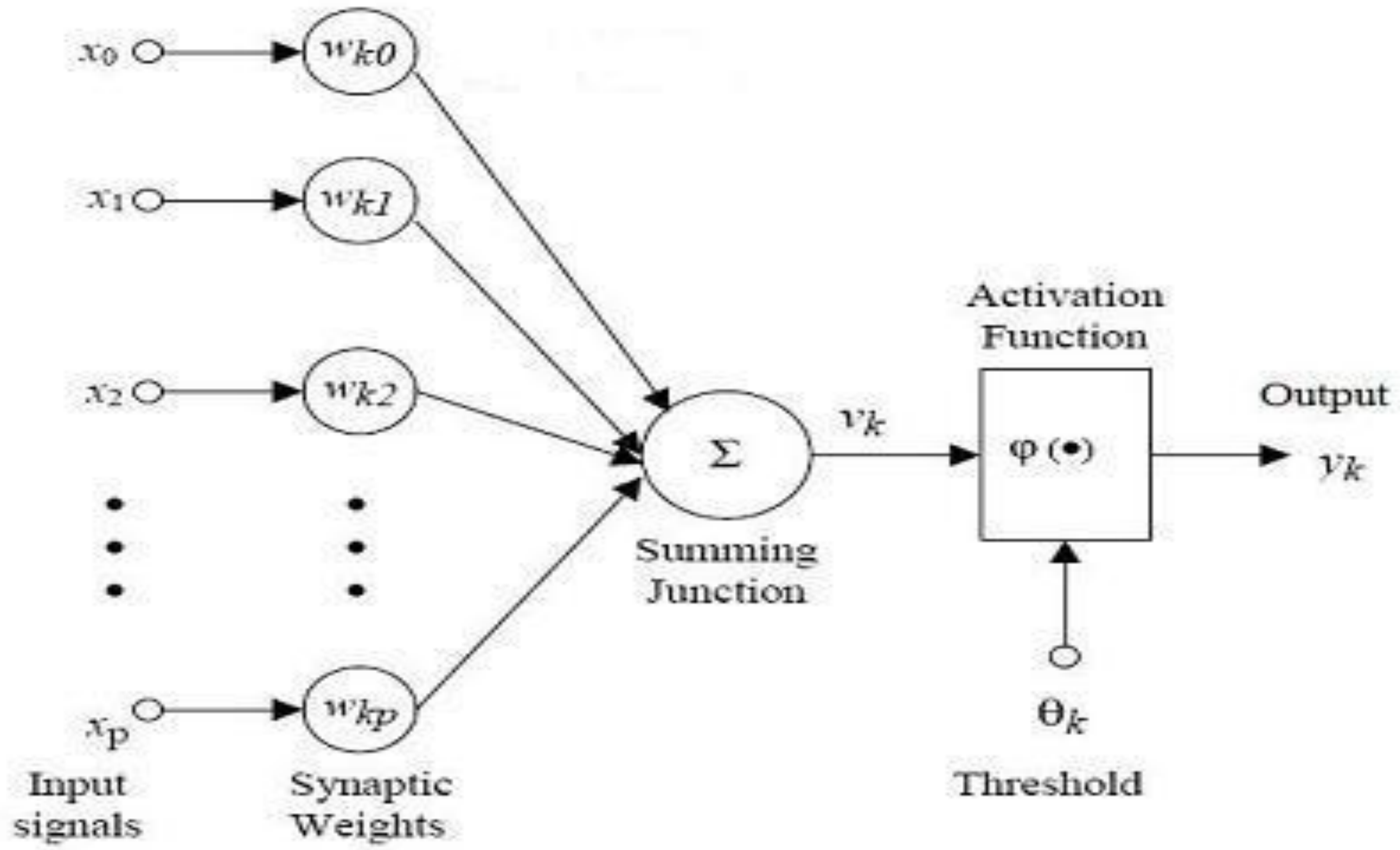
– When the sum is larger than a threshold, the neuron fires, and sends out an impulse signal to other neurons through the axon.

- Incoming signals to a dendrite may be inhibitory or excitatory.
- The strength of any input signal is determined by the strength of its synaptic connection.
- A neuron sends an impulse down its axon if excitation exceeds inhibition by a critical amount (threshold/offset/bias) within a time window.
- *Memories* are formed by the modification of the **synaptic strengths** which can change during the entire life of the neural systems.

What is Artificial Neuron?

- Artificial neurons are the constitutive units in an artificial neural network.
- The artificial neuron receives one or more inputs (representing the one or more dendrites)
- sums them to produce an output (representing a biological neuron's axon).
- Usually the sums of each node are weighted, and the sum is passed through a non-linear function known as an activation function or transfer function.
- The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions, piecewise linear functions, or step functions.

What is Artificial Neuron?



A Model of *k*th neuron in ANN

- w_{k1} : the effect of *1*st neuron to *k*th neuron

  w_{k2} : the effect of *2*nd neuron to *k*th neuron

  ....

  .....

  w_{kn} : the effect of *n*th neuron to *k*th neuron
- $\sum$ (Summing Function) : determines the total effect of input signals
- u_k : Net input of *k*. Neuron

$$u_k = \sum_{i=1}^{n} w_{ki} . x_i$$

- $f(.)$: Activation Function
- $y_k = f(u_k)$: Output

Types of Activation Function

tanh $$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

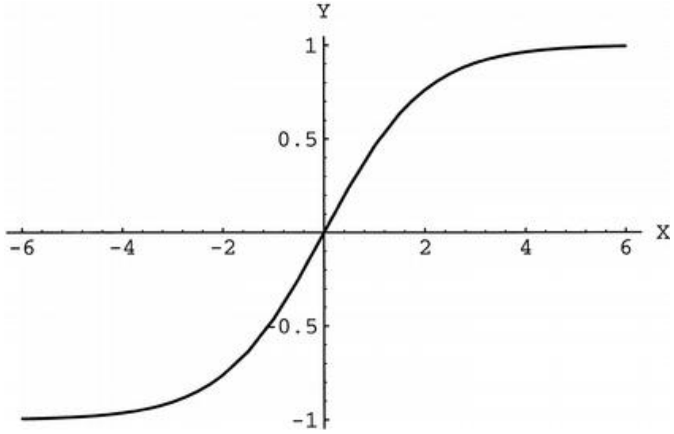
Sigmoid (bipolar) $$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}}$$

Sigmoid (unipolar) $$f(x) = \frac{1}{1 + e^{-x}}$$

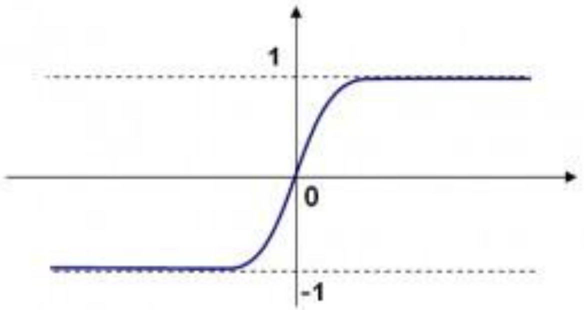
Sgn(.) $$f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$$

Step $$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

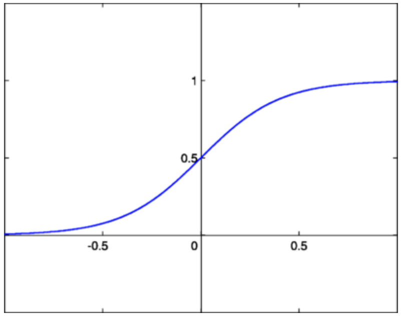
- ✓ Bounded
- ✓ Continuous



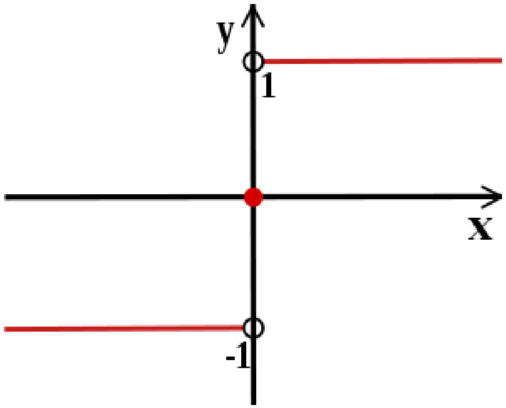
Tangent Hiperbolic



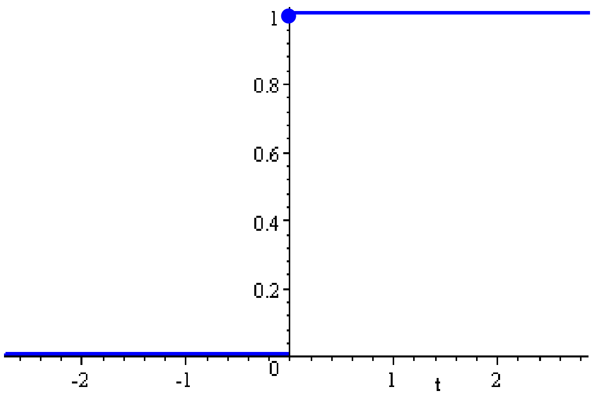
Sigmoid bipolar



Sigmoid unipolar



Signum

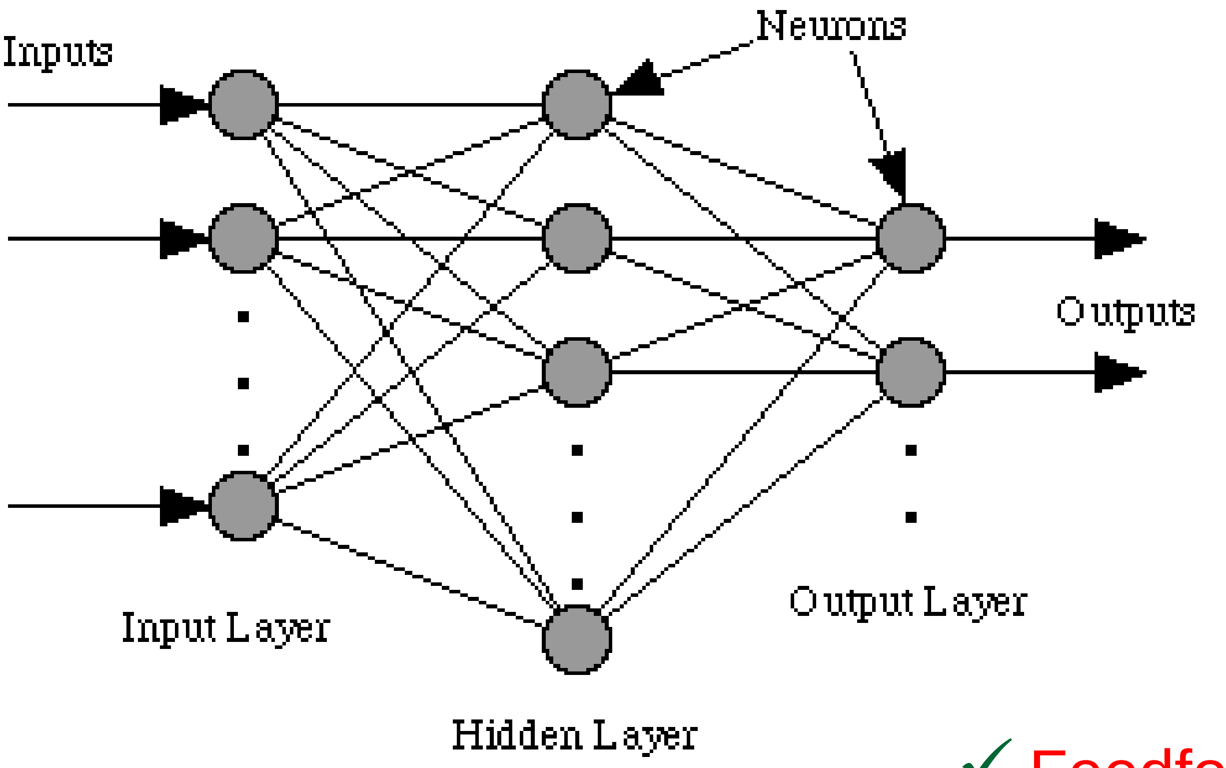


Step

❖ Main elements of Neuron :

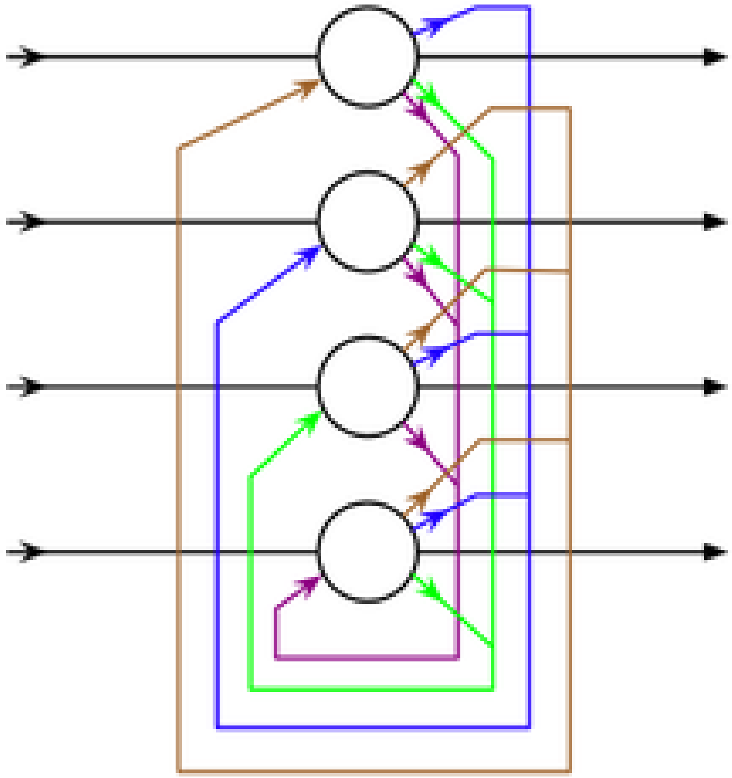
1. Synapses
   (determine the type and amount of energy)
2. Adder
   (determines the net input of neuron)
3. Activation Function
   (determines the behaviour of neuron)
   (implies nonlinearity to the system)

Artificial Neural Network



- ✓ Feedforward
- ✓ Multilayer

Artificial Neural Network



$$y_{n+1} = f(y_n, u)$$

✓ Recurrent
(at least one feedback loop)

✓ Single Layer

The Architecture of ANN

- Number of inputs and outputs of the network;
- Number of layers;
- How the layers are connected to each other;
- The activation function of each layer;
- Number of neurons in each layer.

Notations for *j*. Neuron in an ANN

n = Number of neurons in ANN

x_i = Input Signal → $x_i = [x_1 \; x_2 \; \ldots . \; x_n]^T$

w_{ji} = Weight coefficients (from *i*. neuron to *j*. neuron)

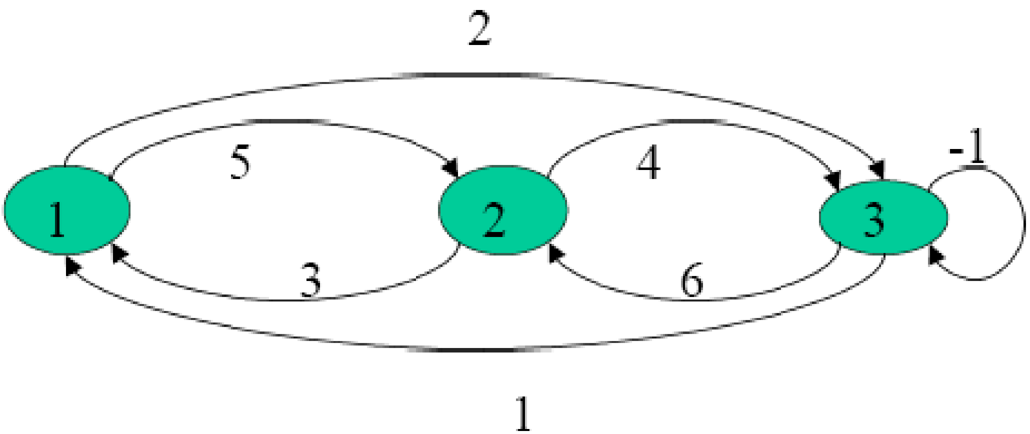
u_j = Net Input → $u_j = \sum_{i=1}^{n} w_{ji}.x_i$

y_j = Output → $y_j = f(u_j) = f\left(\sum_{i=1}^{n} w_{ji}.x_i \right)$

f = Activation Function

$W = \{w_{ji}\}$: Weight Matrix

$n = 3$



$$W = \begin{pmatrix} 0 & 3 & 1 \\ 5 & 0 & 6 \\ 2 & 4 & -1 \end{pmatrix}$$

$$u_j = \sum_{i=1}^{n} w_{ji}.x_i$$

For neuron (1) $\quad j = 1$

$u_1 = w_{11}x_1 + w_{12}x_2 + w_{13}x_3$

$w_{j1}\ w_{j2}\ w_{j3}$: weights come into neuron j

$w_{1i}\ w_{2i}\ w_{3i}$: weights go out of neuron i

For neuron (2) $\quad j = 2$

$u_2 = w_{21}x_1 + w_{22}x_2 + w_{23}x_3$

For neuron (1) $\quad j = 3$

$u_3 = w_{31}x_1 + w_{32}x_2 + w_{33}x_3$

Learning in Neural Networks

- By adjusting the weights of an artificial neuron we can obtain the output we want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. But we can find algorithms which can adjust the weights of the ANN in order to obtain the desired output from the network. This process of adjusting the weights is called ***learning*** or ***training***.

Various Neural Network Models

- Hopfield Neural Networks
- Cellular Neural Networks
- Cohen-Grossberg Neural Networks
- Neutral Neural Networks
- Bidirectional Associative Memory Neural Networks
- Etc.

Applications of Neural Networks

- Optimization Problems
- Associative Memory
- Pattern Recognition i.e. recognizing handwritten characters
- Image Processing
- Noise Removal
- Signal Processing
- Etc.

Potential Dynamical Behaviors of NNs

- Stability
- Chaos
- Oscillations
- Unstability
- Limit Cycles
- Periodic Solution

Benefits of Neural Networks

Neural Network derives its computing power through,

First,

- its massively parallel distributed structure

Second,

- its ability to learn and therefore generalize

Generalization, refers to the neural network producing reasonable outputs for inputs not encountered during training (learning).

Benefits of Neural Networks

- The use of neural networks offers the following useful properties and capabilities :

1. *Nonlinearity.* An artificial neuron can be linear or nonlinear. A neural network, made up of an interconnection of nonlinear neurons, is itself nonlinear. Moreover, the nonlinearity is of a special kind in the sense that it is *distributed* throughout the network. Nonlinearity is a highly important property, particularly if the underlying physical mechanism responsible for generation of the input signal is inherently nonlinear.

Benefits of Neural Networks

2. *Input-Output Mapping.* A popular paradigm of learning called *supervised learning* involves modification of the synaptic weights of a neural network by applying a set of labeled *training samples* or *task examples*. Each example consists of a unique *input signal* and a corresponding *desired response*. The network is presented with an example picked at random from the set, and the synaptic weights of the network are modified to minimize the difference between the desired response and the actual response of the network. The training of the network is repeated for many examples in the set until the network reaches a steady state where there are no further significant changes in the synaptic weights. Thus, the network learns from the examples by constructing an ***input-output mapping*** for the problem at hand.

Benefits of Neural Networks

3. *Adaptivity.* Neural networks have a built-in capability to *adapt* their synaptic weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily retrained to deal with minor changes in the operating environment conditions. Moreover, when it is operating in a nonstationary environment (i.e. one where statistics change with time) a neural network can be designed to change its synaptic weights in real time.

Benefits of Neural Networks

4. *Evidential Response.* In the context of pattern classification, a neural network can be designed to provide information not only about which particular pattern to select, but also about the confidence in the decision made. This latter information may be used to reject ambiguous patterns, and thereby improve the classification performance of the network.
5. *Fault Tolerance.* A neural network, implemented in hardware form, has the potential to be inherently *fault tolerant*, or capable of robust computation.

Benefits of Neural Networks

6. *VLSI Implementability.* The massively parallel nature of a neural network makes it potentially fast for the computation of certain tasks. This same feature makes a neural network well suited for implementation using *very-large-scale-integrated* (VLSI) technology. One particular beneficial virtue of VLSI is that it provides a means of capturing truly complex behavior in a highly hierarchical fashion.

Benefits of Neural Networks

7. *Uniformity of Analysis and Design.* Basically, neural networks enjoy universality as information processors. We say this in the sense that the same notation is used in all domains involving the application of neural networks. This feature manifests itself in different ways :

- Neurons, in one form or another, represent an ingredient common to all neural networks
- This commonality makes it possible to share theories and learning algorithms in different applications of neural networks
- Modular networks can be built through a seamless integration of modules

Benefits of Neural Networks

8. *Neurobiological Analogy .* The design of a neural network is motivated by analogy with the brain, which is a living proof that fault tolerant parallel processing is not only physically possible but also fast and powerful. Neurobiologists look to neural networks as a research tool for the interpretation of neurobiological phenomena. On the other hand, engineers look to neurobiology for new ideas to solve problems more complex than those based on conventional hard-wired design techniques.