ARTIFICIAL NEURAL NETWORKS
UNIT 1

INTRODUCTION AND ANN STRUCTURE

What is a neural network?

Work on artificial neural networks, commonly referred to as "'neural networks," has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, nonlinear, and parallel computer (information-processing system). It has the capability to organize its structural constituents known as neurons. so as to perform certain computations many times faster than the fastest digital computer in existence today.

Consider, for example, human vision, which is an information-processing task. It is the function of the visual system to provide a representation of the environment around us and, more important, to supply the information we need to interact with the environment.

For another example, consider the sonar of a bat. Sonar is an active echo-location system. In addition to providing information about how far away a target (e.g., a flying insect) is, a bat sonar conveys information about the relative velocity of the target, the size of the target, the size of various features of the target.

At birth, a brain has great structure and the ability to build up its own rules through what we usually refer to as "experience." Indeed, experience is built up over time, with the most dramatic development of the human brain taking place during the first two years from birth; but the development continues well beyond that stage.

A "developing" neuron is synonymous with a plastic brain: Plasticity permits the developing nervous system to adapt to its surrounding environment. Just as plasticity appears to be essential to the functioning of neurons as information-processing units in the human brain, so it is with neural networks made up of artificial neurons.

A neural network is a machine that is designed to model the way in which the brain performs a particular task & network is usually implemented by using electronic components or is simulated in software on a digital computer.

To achieve good performance, neural networks employ a massive interconnection of simple computing cells referred to as "neurons" or "processing units."

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective. Neural networks are also referred to in literature as neurocomputers, connectionist networks, parallel distributed processors, etc.

Benefits of Neural Networks

It is apparent that a neural network derives its computing power through,

1. Its massively parallel distributed structure.
2. Its ability to learn and therefore generalize.

Generalization refers to the neural network producing reasonable outputs for inputs not encountered during training (learning). These two information-processing capabilities make it possible for neural networks to solve complex (large-scale) problems by decomposing into a number of relatively simple tasks, and neural networks are assigned a subset of the tasks that match their inherent capabilities.

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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. Nonlinearity is a highly important property if the underlying physical mechanism responsible for generation of the input signal is inherently nonlinear.

2. Input-Output Mapping A popular paradigm of learning called learning with a teacher or 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 produced by the input signal in accordance with an appropriate statistical criterion. 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.

3. Adaptivity Neural networks have a built-in capability to adapt their synaptic weights to changes in the surrounding environment. Moreover, when it is operating in a nonstationary environment, a neural network can be designed to change its synaptic weights in real time. The natural architecture of a neural network for pattern classification, signal processing, and control applications, coupled with the adaptive capability of the network, make it a useful tool in adaptive pattern classification, adaptive signal processing, and adaptive control.

For example, an adaptive system with short time constants may change rapidly and therefore tend to respond to spurious disturbances, causing a drastic degradation in system performance. To realize the full benefits of adaptivity, the principal time constants of the system should be long enough for the system to ignore spurious disturbances and yet short enough to respond to meaningful changes in the environment.

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.

5. Contextual Information Knowledge is represented by the very structure and activation state of a neural network. Every neuron in the network is potentially affected by the global activity of all other neurons in the network. Consequently, contextual information is dealt with naturally by a neural network.

6. Fault Tolerance. A neural network, implemented in hardware form, has the potential to be inherently fault tolerant, or capable of robust computation, in the sense that its performance degrades gracefully under adverse operating conditions.

For example, if a neuron or its connecting links are damaged, due to the distributed nature of information stored in the network, the damage has to be extensive before the overall response of the network is degraded seriously. Thus, in principle, a neural network exhibits a graceful degradation in performance rather than catastrophic failure.

7. VLSI Implementability The massively parallel nature of a neural network makes it potentially fast for the computation of certain tasks. This 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.

8. 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.

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9. 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 (arlificial) 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.

HUMAN BRAIN

The human nervous system may be viewed as a three-stage system, as depicted in the block diagram.

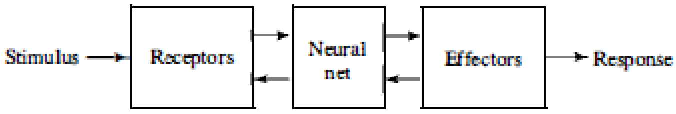

FIGURE 1.1 Block diagram representation of nervous system.

Central to the system is the brain, represented by the neural (nerve) net, which continually receives information, perceives it, and makes appropriate decisions. Two sets of arrows are shown in the figure. Those pointing from left to right indicate the forward transmission of information-bearing signals through the system. The arrows pointing from right to left signify the presence of feedback in the system. The receptors convert stimuli from the human body or the external environment into electrical impulses that convey information to the neural net (brain). The effectors convert electrical impulses generated by the neural net into discernible responses as system outputs.

Ramon y Cajal (1911), introduced the idea of neurons as structural constituents of the brain. Typically, neurons are five to six orders of magnitude slower than silicon logic gates; events in a silicon chip happen in the nanosecond (10-9 s) range, whereas neural events happen in the millisecond (10-3 s) range. However, the brain makes up for the relatively slow rate of operation of a neuron by having a truly staggering number of neurons (nerve cells) with massive interconnections between them.

It is estimated that there are approximately 10 billion neurons in the human cortex, and 60 trillion synapses or connection. The net result is that the brain is an enormously efficient structure. Specifically, the energetic efficiency of the brain is approximately 10-16 joules (1) per operation per second, whereas the corresponding value for the best computers in use today is about 10-6 joules per operation per second.

Synapses are elementary structural and functional units that mediate the interactions between neurons. The most common kind of synapse is a chemical synapse, which operates as follows. A synapse converts a presynaptic electrical signal into a chemical signal and then back into a postsynaptic electrical signal. In electrical terminology, such an element is said to be a nonreciprocal two-port device.

→A synapse is a simple connection that can impose excitation or inhibition, but not both ou the receptive neuron. In an adult brain, plasticity may be accounted for by two mechanisms: the creation of new synaptic connections between neurons, and the modification of existing synapses. Axons, the transmission lines, and dendrites, the receptive zones, constitute two types of cell filaments that are distinguished on morphological grounds; an axon has a smoother surface, fewer branches, and greater length, whereas a dendrite has an irregular surface and more branches. Neurons come in a wide variety of shapes and sizes in different parts of the brain.

Following figure illustrates the shape of a pyramidal cell, which is one of the most common types of cortical neurons. Like many other types of neurons, it receives most of its inputs through dendritic spines; The pyramidal cell can receive 10,000 or more synaptic contacts and it can project onto thousands of target cells.

The majority of neurons encode their outputs as a series of brief voltage pulses. These pulses, commonly known as action potentials or spikes, originate at or close to the cell body of neurons and then propagate across the individual neurons at constant velocity and amplitude.

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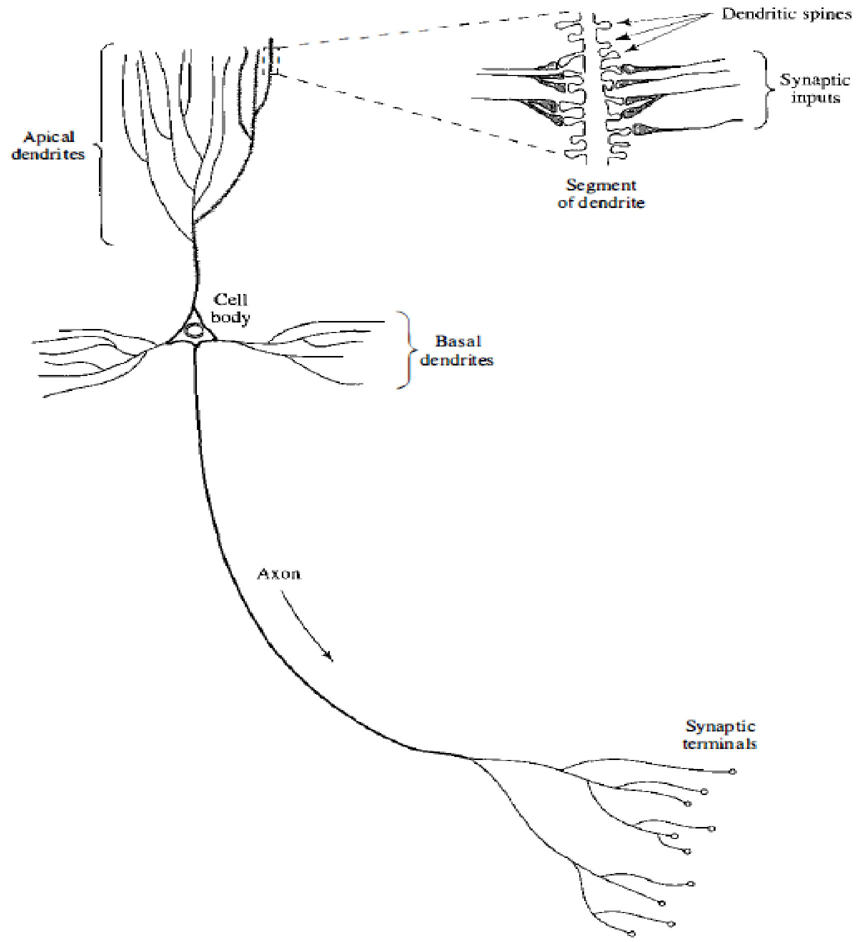

FIGURE 1.2 The pyramidal cell.

In the brain there are both small-scale and large-scale anatomical organizations, and different functions take place at lower and higher levels. Figure 1.3 shows a hierarchy of interwoven levels of organization that has emerged from the extensive work done on the analysis of local regions in the brain.

The synapses represent the most fundamental level, depending on molecules and ions for their action. At the next levels we have neural microcircuits, dendritic trees, and then neurons.

A neural microcircuit refers to an assembly of synapses organized into patterns of connectivity to produce a functional operation of interest. A neural microcircuit may be likened to a silicon chip made up of an assembly of transistors. The smallest size of microcircuits is measured in micrometers (fLm), and their fastest speed of operation is measured in milliseconds.

The neural microcircuits are grouped to form dendritic subunits within the dendritic trees of individual neurons. The whole neuron, about 100um in size, contains several dendritic subunits.

At the next level of complexity we have local circuits made up of neurons with similar or different properties; these neural assemblies perform operations characteristic of a localized region in the brain.

This is followed by interregional circuits made up of pathways, columns. and topographic maps. which involve multiple regions located in different parts of the brain.

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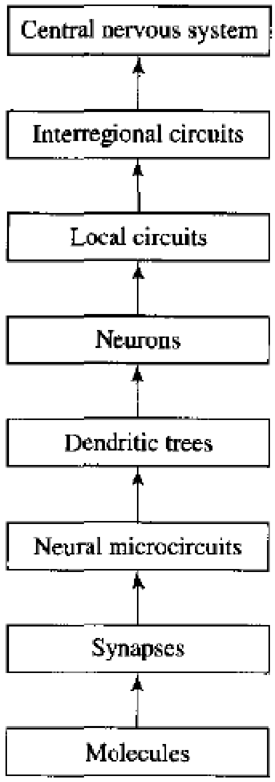
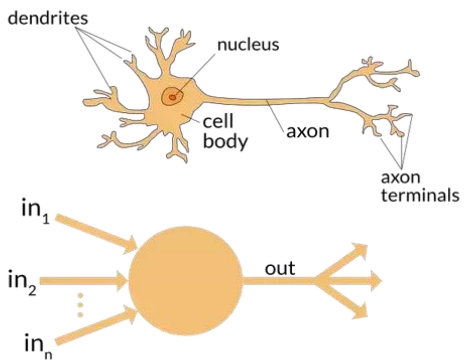


FIGURE 1.3 Structural organization of levels in the brain.

Biological neurons and Artificial neurons

Biological neuron consists of a cell nucleus which receives input from other neurons through a web of input terminals, or branches called dendrites. The combination of dendrites is often referred to as a dendritic tree, which receives excitatory or inhibitory signals from other neurons via an electrochemical exchange of neurotransmitters. Depending on this signal aggregated from all synapses from the dendritic tree, the neuron is either activated or inhibited, or in other words, switched on or switched off respectively, after a process called neural summation. The neuron has an electrochemical threshold, analogous to an activation function in artificial neural networks, which governs whether the accumulated information is enough to activate the neuron. The final result is then fed into other neurons and the process begins again. When humans meet new people or see new things every day, they learn what they look like and how they evolve with time. This is achieved by making minor alterations to the neural networks residing in their brains as they evolve. The same phenomenon applies to other tasks as well.



Artificial Neural Network (ANN) tries to approximate the structure of human brain and are fed with massive amount of data to learn, all at once. Neural network architecture is arranged into layers, where each layer consists of many simple processing units called nodes, further connected to several nodes in the layers above and below it. The data is fed into the lowest layer which is then relayed to the next layer. However, ANNs can also learn based on a pre-existing representation.

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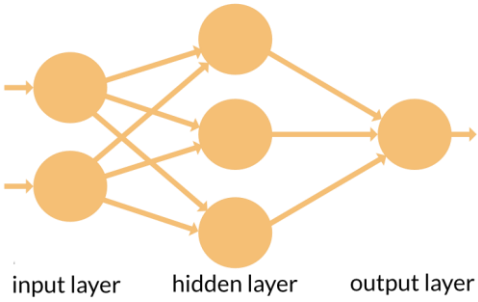
This process is called fine-tuning and consists of adjusting the weights from a pre-trained network topology at a relatively slow learning rate to perform well on newly supplied input training data. While artificial neural nets were initially designed to function like biological neural networks, the neural activity and capability in our brains is far more complex than suggested by artificial neurons. Unlike Human Neural Networks, ANN cannot yet be trained to work well for many heterogeneous tasks simultaneously.



Major Differences between these two are -

- **Field of application:** ANNs are specialized**.** They can perform one task. They might be perfect at playing chess, but they fail at playing go (or vice versa). Biological neural networks can learn completely new tasks.
- **Signal transport and processing**: The human brain works asynchronously, ANNs work synchronously.
- **Parameter count**: Humans have many billions of adjustable parameters. Even the most complicated ANNs only have several million learnable parameters.
- **Training algorithm**: ANNs use Gradient Descent for learning. Human brains use something different (but we don't know what)
- **Processing speed**: Single biological neurons are slow, while standard neurons in ANNs are fast.
- **Topology**: Biological neural networks have complicated topologies, while ANNs are often in a tree structure
- **Power consumption**: Biological neural networks use very little power compared to artificial networks.
- **Training time**: Biological networks usually don't stop / start learning. ANNs have different fitting (train) and prediction (evaluate) phases.

The Functionalities that describe Biological and Artificial neurons are as follows.

1. **Size**: our brain contains about 10 billion neurons and more than a 60 trillion synapses (connections). The number of "neurons" in artificial networks is much less than that but comparing their numbers this way is misleading. Deep Neural Networks usually consist of input neurons, output neurons and neurons in the hidden layers, in-between. All the layers are usually fully connected to the next layer, meaning that artificial neurons usually have as many connections as there are artificial neurons in the preceding and following layers combined. The limitation in size isn't just computational: simply increasing the number of layers and artificial neurons does not always yield better results in machine learning tasks.
2. **Topology:** all artificial layers compute one by one, instead of being part of a network that has nodes computing asynchronously. Feedforward networks compute the state of one layer of artificial neurons and their weights, then use the results to compute the following layer the same way. During backpropagation, the algorithm computes some change in the weights the opposing way, to reduce the difference of the feedforward computational results in the output layer from the expected values of the output layer. **Layers aren't connected to non-neighboring layers,** but it's possible to somewhat mimic loops with recurrent and LSTM networks. In biological networks, neurons can fire asynchronously in parallel, have small-

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world nature with a small portion of highly connected neurons (hubs) and a large amount of lesser connected ones. Since artificial neuron layers are usually fully connected, this small-world nature of biological neurons can only be simulated by introducing weights that are 0 to mimic the lack of connections between two neurons.

3. **Speed:** certain biological neurons can fire around 200 times a second on average. Signals travel at different speeds depending on the type of the nerve impulse, ranging from 0.61 m/s up to 119 m/s. Signal travel speeds also vary from person to person depending on their gender, age, height, temperature, medical condition, lack of sleep etc. Information in artificial neurons is instead carried over by the continuous, floating point number values of synaptic weights. How quickly feedforward or backpropagation algorithms are calculated carries no information, other than making the execution and training of the model faster.
4. **Fault-tolerance:** biological neuron networks due to their topology are also fault-tolerant. Information is stored redundantly so minor failures will not result in memory loss. They don't have one "central" part. The brain can also recover and heal to an extent. Artificial neural networks are not modeled for fault tolerance or self regeneration, though recovery is possible by saving the current state (weight values) of the model and continuing the training from that save state. Training artificial neural networks for longer periods of time will not affect the efficiency of the artificial neurons.
5. **Power consumption**: the brain consumes about 20% of all the human body's energy — despite it's large cut, an adult brain operates on about 20 watts (barely enough to dimly light a bulb) being extremely efficient. Taking into account how humans can still operate for a while, when only given some c-vitamin rich lemon juice and beef tallow, this is quite remarkable. Our machines are way less efficient than biological systems. Computers also generate a lot of heat when used, with consumer GPUs operating safely between 50–80 degrees Celsius instead of 36.5–37.5 °C.
6. **Signals**: an action potential is either triggered or not — biological synapses either carry a signal or they don't. Artificial neurons accept continuous values as inputs and apply a simple non-linear, easily differentiable function (an activation function) on the sum of its weighted inputs to restrict the outputs' range of values.
7. **Learning:** we still do not understand how brains learn, or how redundant connections store and recall information. Brain fibers grow and reach out to connect to other neurons, neuroplasticity allows new connections to be created or areas to move and change function, and synapses may strengthen or weaken based on their importance**.** Artificial neural networks in the other hand have a predefined model, where no further neurons or connections can be added or removed. Only the weights of the connections can change during training. Learning can be understood as the process of finding optimal weights to minimize the differences between the network's expected and generated output

<u>Model of an ANN</u>

A neuron is an information-processing unit that is fundamental to the operation of a neural network. The following diagram shows the model of a neuron, which forms the basis for designing (artificial) neural networks.

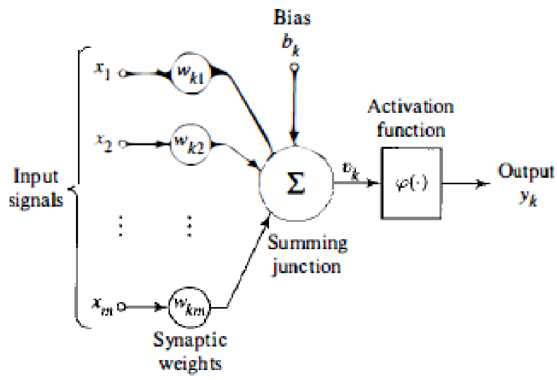

FIGURE 1.5 Nonlinear model of a neuron.

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Here we identify three basic elements of the neuronal model:
1. A set of synapses or connecting links, each of which is characterized by a weight or strength of its own. Specifically, a signal xj a t the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj}"
It is important to make a note of the manner in which the subscripts of the synaptic weight w_{kj} are written. The first subscript refers to the neuron in question and the second subscript refers to the input end of the synapse to which the weight refers. Unlike a synapse in the brain, the synaptic weight of an artificial neuron may lie in a range that includes negative as well as positive values.
2. An adder for summing the input signals, weighted by the respective synapses of the neuron; the operations described here constitute a linear combiner.
3. An activation function for limiting the amplitude of the output of a neuron. The activation function is also referred to as a squashing function in that it squashes (limits) the permissible amplitude range of the output signal to some finite value. Typically, the normalized amplitude range of the output of a neuron is written as the closed unit interval [0,1] or alternatively [- 1,1].
The neuronal model also includes an externally applied bias, denoted by b_k. The bias b_k has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively.
In mathematical terms, we may describe a neuron k by writing the following pair of equations:

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \qquad (1)$$

and

$$y_k = \varphi(u_k + b_k) \qquad (2)$$

Where x1,x2,….xm are the input signals; Wk1, Wk2, ….. wkm are the synaptic weights of neuron k; U_k is the linear combiner output due to the input signals; b_k is the bias; $\varphi(\cdot)$ is the activation function; and Y_k is the output signal of the neuron.
The use of bias b_k has the effect of applying an affine transformation to the output Uk of the linear combiner in the model of Figure, as shown by

$$v_k = u_k + b_k \qquad (3)$$

In particular, depending on whether the bias b_k is positive or negative, the relationship between the induced local field or activation potential v_k of neuron k and the linear combiner output U_k is modified in the manner illustrated in following figure; hereafter the term "induced local field" is used.

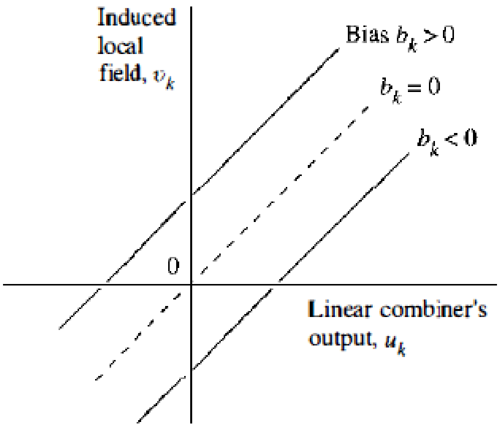

FIGURE Affine transformation produced by the presence of a bias; note that $v_k = b_k$ at $u_k = 0$.

The bias b_k is an external parameter of artificial neuron k. We may account for its presence as in Eq. (2). Equivalently, we may formulate the combination of Eqs. (1) to (1) as follows:

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$$v_k = \sum_{j=0}^{m} w_{kj} x_j \qquad (4)$$

and

$$y_k = \varphi(v_k) \qquad (5)$$

In Eq. (4) we have added a new synapse. Its input is $x_0 = +1$ (6)
and its weight is $w_{k0} = b_k$ (7)

We may therefore reformulate the model of neruon k as in Following Figure. In this figure the effect of the bias is accounted for by doing two things: (1) adding a new input signal fixed at + 1. and (2) adding a new synaptic weight equal tD the bias b_k. Although the models of Fig. 1.5 and 1.7 are different in appearance, they are mathematically equivalent.

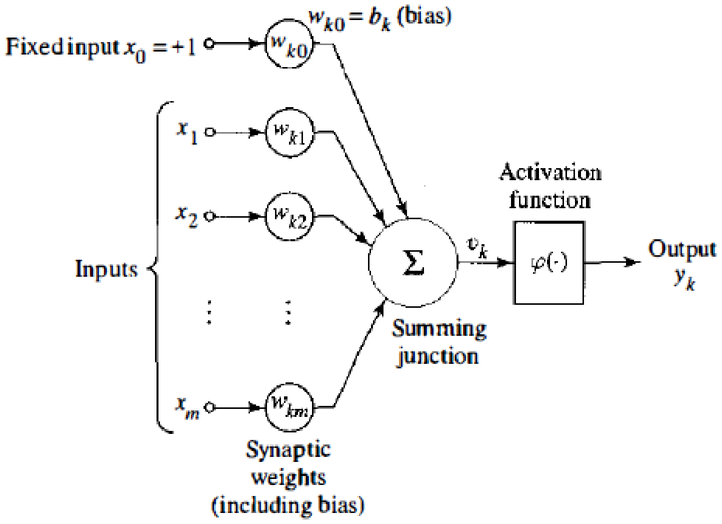


FIGURE 1.7 Another nonlinear model of a neuron.

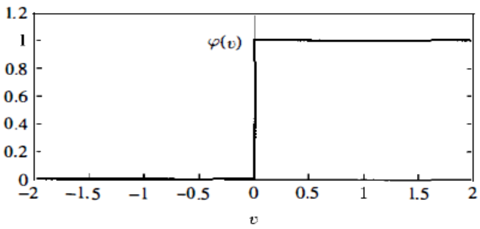
Activation functions used in ANNs

The activation function denoted by $\varphi(v)$ defines the output of a neuron in terms of the induced local field v. Here we identify three basic types of activation functions:

1. Threshold Function
2. Piecewise-Linear Function
3. Sigmoid Function

Threshold Function For this type of activation function described in following figure , we have

$$\varphi(v) = \begin{cases} 1 & \text{if } v \geq 0 \\ 0 & \text{if } v < 0 \end{cases} \qquad (8)$$



In engineering literature, this form of a threshold function is commonly referred to as a Heaviside function. Correspondingly, the output of neuron k employing such a threshold function is expressed as

$$y_k = \begin{cases} 1 & \text{if } v_k \geq 0 \\ 0 & \text{if } v_k < 0 \end{cases} \qquad (9)$$

where v_k is the induced local field of the neuron; that is

$$v_k = \sum_{j=1}^{m} w_{kj} x_j + b_k \qquad (10)$$

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Such a neuron is referred to in the literature as the McCulloch-Pitts model, in recognition of the pioneering work done by McCulloch and Pitt. In this model, the output of a neuron takes on the value of 1 if the induced local field of that neuron is nonnegative and 0 otherwise. This statement describes the all-or-none property of the McCulloch-Pitts model.

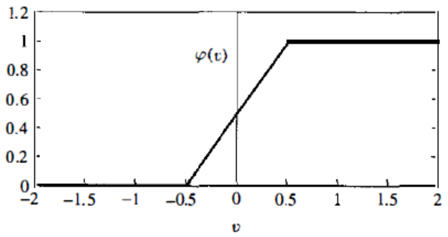
Piecewise - Linear Function For the piecewise-linear function described in following figure, we have

$$\varphi(v) = \begin{cases} 1, & v \geq +\frac{1}{2} \\ v, & +\frac{1}{2} > v > -\frac{1}{2} \\ 0, & v \leq -\frac{1}{2} \end{cases} \qquad (11)$$

where the amplification factor inside the linear region of operation is assumed to be unity. This form of an activation function may be viewed as an approximation to a nonlinear amplifier. The following two situations may be viewed as special forms of the piecewise-linear function:

• A linear combiner arises if the linear region of operation is maintained without running into saturation.

• The piecewise-linear function reduces to a threshold function if the amplification factor of the linear region is made infinitely large.

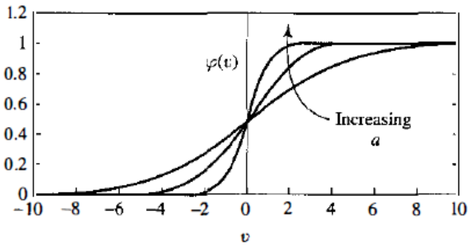


Sigmoid Function The sigmoid function, whose graph is s-shaped, is the most common form of activation function used in the construction of artifical neural networks. It is defined as a strictly increasing function that exhibits a graceful balance between linear and nonlinear behavior.

An example of the sigmoid function is the logistic function defined by

$$\varphi(v) = \frac{1}{1 + \exp(-av)} \qquad (12)$$

where a is the slope parameter of the sigmoid function. By varying the parameter a, we obtain sigmoid functions of different slopes, as illustrated in following figure.



In fact, the slope at the origin equals a/4. In the limit, as the slope parameter approaches infinity, the sigmoid function becomes simply a threshold function. Whereas a threshold function assumes the value of 0 or 1, a sigmoid function assumes a continuous range of values from 0 to 1 .

The activation functions defined in Eqs. (8), (11), and (12) range from 0 to + 1. It is sometimes desirable to have the activation function range from -1 to + 1, in which case the activation function assumes an antisymmetric form with respect to the origin; that is, the activation function is an odd function of the induced local field. Specifically, the threshold function of Eq. (8) is now defined as

$$\varphi(v) = \begin{cases} 1 & \text{if } v > 0 \\ 0 & \text{if } v = 0 \\ -1 & \text{if } v < 0 \end{cases} \qquad (13)$$

which is commonly referred to as the signum function. For the corresponding form of a sigmoid function we may use the hyperbolic tangent function defined by $\varphi(v) = \tanh(v)$ (14).

Allowing an activation function of the sigmoid type to assume negative values as prescribed by Eq. (14) has analytic benefits.

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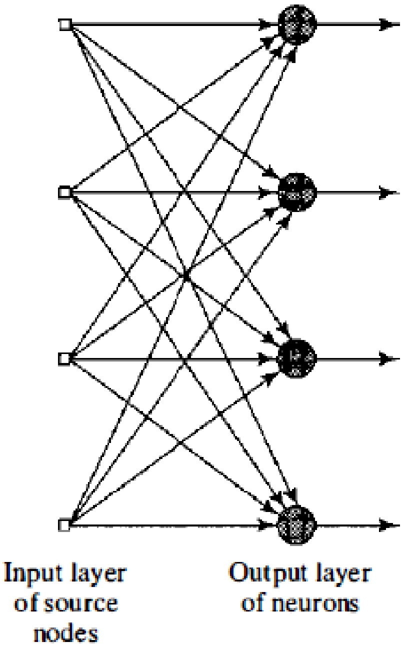
<u>Typical classes of network architectures</u>

The manner in which the neurons of a neural network are structured is intimately linked with the learning algorithm used to train the network. In this section we focus our attention on network architectures (structures). In general, we may identify three fundamentally different classes of network architectures:

1. Single-Layer Feedforward Networks
2. Multilayer Feedforward Networks
3. Recurrent Networks

Single-Layer Feedforward Networks

In a layered neural network the neurons are organized in the form of layers. In the simplest form of a layered network, we have an input layer of source nodes that projects onto an output layer of neurons (computation nodes), but not vice versa, In other words, this network is strictly a feedforward or acyclic type, It is illustrated in following figure for the case of four nodes in both the input and output layers. Such a network is called a single- layer network, with the designation "single-layer" referring to the output layer of computation nodes (neurons).



Feedforward or acyclic network with a single layer of neurons.

Multilayer Feedforward Networks

The second class of a feedforward neural network distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons or hidden units, The function of hidden neurons is to intervene between the external input and the network output in some useful manner, By adding one or more hidden layers, the network is enabled to extract higher-order statistics. The ability of hidden neurons to extract higher-order statistics is particularly valuable when the size of the input layer is large.

The source nodes in the input layer of the network supply respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e., the first hidden layer). The output signals of the second layer are used as inputs to the third layer, and so on for the rest of the network. Typically the neurons in each layer of the network have as their inputs the output signals of the preceding layer only. The set of output signals of the neurons in the output (final) layer of the network

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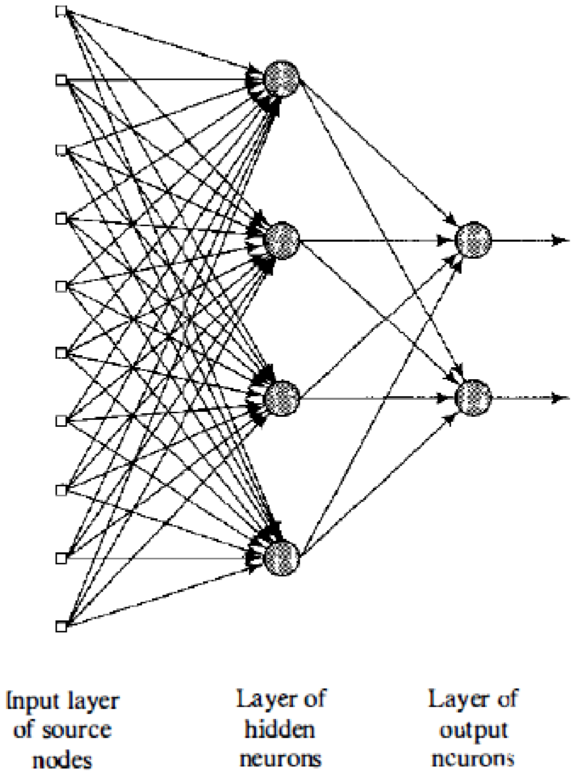
constitutes the overall response of the network to the activation pattern supplied by the source nodes in the input (first) layer. The architectural graph in following Figure illustrates the layout of a multilayer feedforward neural network for the case of a single hidden layer. For brevity the network in Figure is referred to as a 10-4-2 network because it has 10 source nodes, 4 hidden neurons, and 2 output neurons. As another example, a feedforward network with m source nodes, h_1 neurons in the first hidden layer, h_2 neurons in the second hidden layer, and q neurons in the output layer is referred to as an m-h_1-h_2-q network.



Fully connected feedforward or acyclic network with one hidden layer and one output layer.

The neural network in above Figure is said to be fully connected in the sense that every node in each layer of the network is connected to every other node in the adjacent forward layer. If some of the communication links (synaptic connections) are missing from the network, we say that the network is partially connected.

Recurrent Networks

A recurrent neural network distinguishes itself from a feedforward neural network in that it has at least one feedback loop. For example, a recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons, as illustrated in the architectural graph in following Figure. In the structure depicted in this figure there are no self-feedback loops in the network; self feedback refers to a situation where the output of a neuron is fed back into its own input. The recurrent network illustrated in following Figure also has no hidden neurons.

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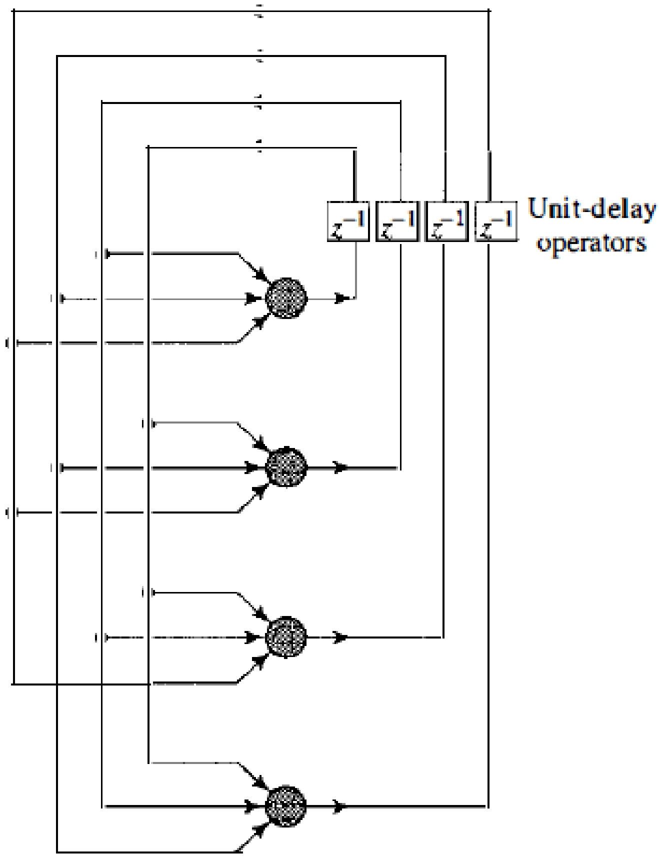
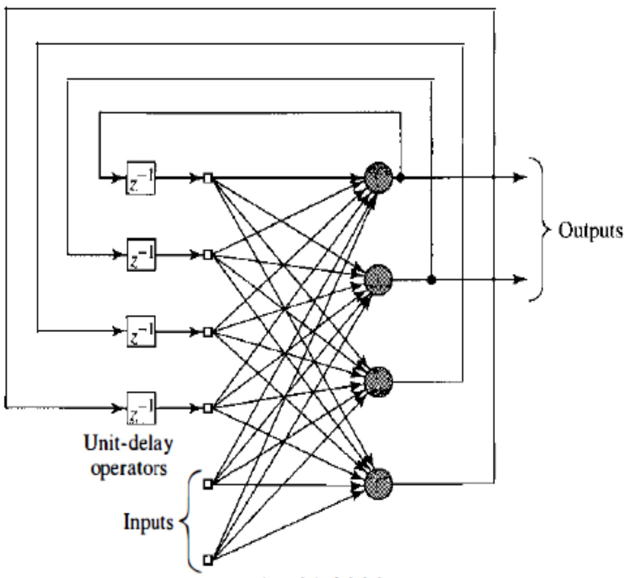


Recurrent network with no self-feedback loops and no hidden neurons.

In following fig. we illustrate another class of recurrent networks with hidden neurons. The feedback connections shown in Fig originate from the hidden neurons as well as from the output neurons. The presence of feedback loops, whether in the recurrent structure of above Figure or that of following Figure has a profound impact on the learning capability of the network and on its performance. Moreover, the feedback loops involve the use of particular branches composed of unit-delay elements (denoted by Z^{-1}), which result in a nonlinear dynamical behavior, assuming that the neural network contains nonlinear units.



Recurrent network with hidden neurons.

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