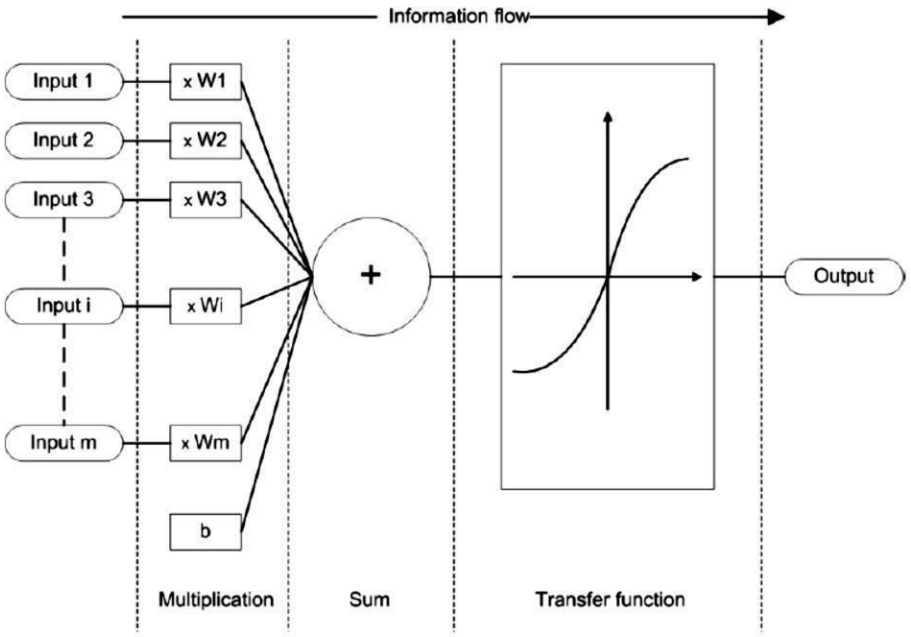
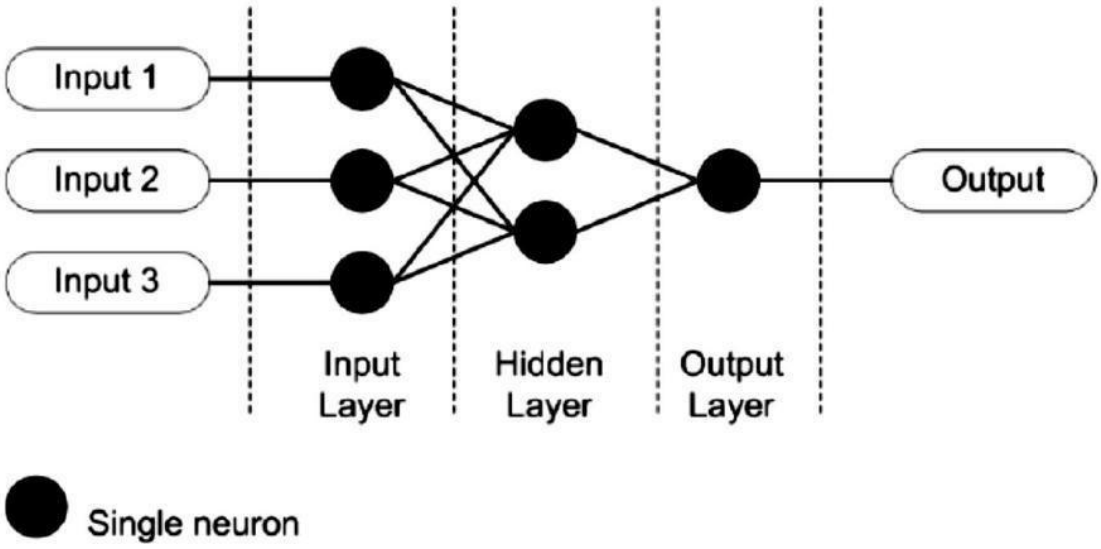
UNIT-4
NEURAL NETWORKS

WHAT IS ARTIFICIAL NEURAL NETWORK?

An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. Basic building block of every artificial neural network is artificial neuron, that is, a simple mathematical model (function). Such a model has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron the inputs are weighted what means that every input value is multiplied with individual weight. In the middle section of artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron the sum of previously weighted inputs and bias is passing through activation function that is also called transfer function.





BIOLOGICAL NEURON STRUCTURE AND FUNCTIONS.

A neuron, or nerve cell, is an electrically excitable cell that communicates with other cells via specialized connections called synapses. It is the main component of nervous tissue. Neurons are typically classified into three types based on their function. Sensory neurons respond to stimuli such as touch, sound, or light that affect the cells of the sensory organs, and they send signals to the spinal cord or brain. Motor neurons receive signals from the brain and spinal cord to control everything from muscle contractions to glandular output. Interneurons connect neurons to other neurons within the same region of the brain or spinal cord. A group of connected neurons is called a neural circuit.

A typical neuron consists of a cell body (soma), dendrites, and a single axon. The soma is usually compact. The axon and dendrites are filaments that extrude from it. Dendrites typically branch profusely and extend a few hundred micrometers from the soma. The axon leaves the soma at a swelling called the axon hillock, and travels for as far as 1 meter in humans or more in other species. It branches but usually maintains a constant diameter. At the farthest tip of the axon's branches are axon terminals, where the neuron can transmit a signal across the synapse to another cell. Neurons may lack dendrites or have no axon. The term neurite is used to describe either a dendrite or an axon, particularly when the cell is undifferentiated.

The soma is the body of the neuron. As it contains the nucleus, most protein synthesis occurs here. The nucleus can range from 3 to 18 micrometers in diameter.

The dendrites of a neuron are cellular extensions with many branches. This overall shape and structure is referred to metaphorically as a dendritic tree. This is where the majority of input to the neuron occurs via the dendritic spine.

The axon is a finer, cable-like projection that can extend tens, hundreds, or even tens of thousands of times the diameter of the soma in length. The axon primarily carries nerve signals away from the soma, and carries some types of information back to it. Many neurons have only one axon, but this axon may—and usually will—undergo extensive branching, enabling communication with many target cells. The part of the axon where it emerges from the soma is called the axon hillock. Besides being an anatomical structure, the axon hillock also has the greatest density of voltage-dependent sodium channels. This makes it the most easily excited part of the neuron and the spike initiation zone for the axon. In electrophysiological terms, it has the most negative threshold potential.

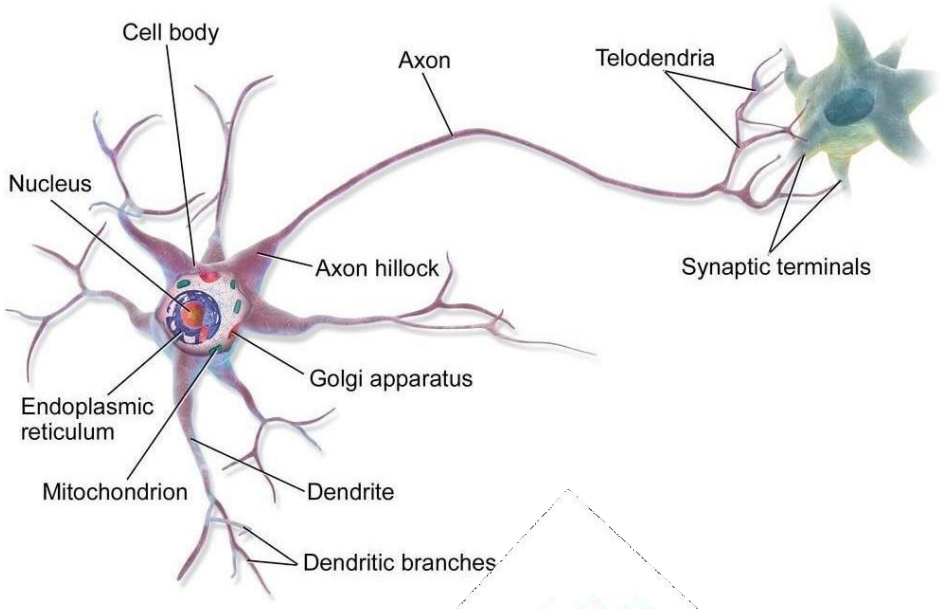
While the axon and axon hillock are generally involved in information outflow, this region can also receive input from other neurons.

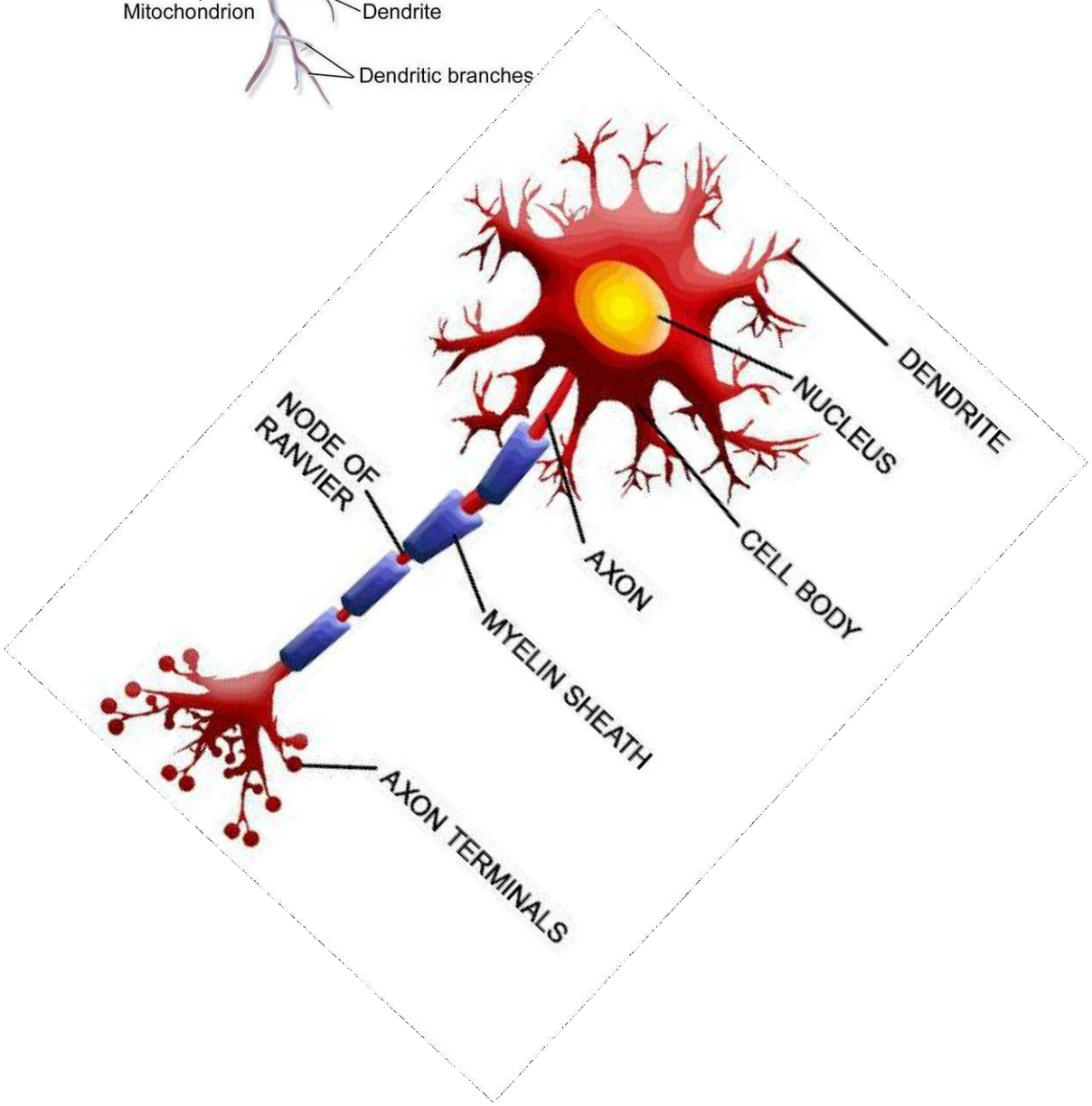
The axon terminal is found at the end of the axon farthest from the soma and contains synapses. Synaptic boutons are specialized structures where neurotransmitter chemicals are released to communicate with target neurons. In addition to synaptic boutons at the axon terminal, a neuron may have en passant boutons, which are located along the length of the axon.

Most neurons receive signals via the dendrites and soma and send out signals down the axon. At the majority of synapses, signals cross from the axon of one neuron to a dendrite of another. However, synapses can connect an axon to another axon or a dendrite to another dendrite. The signaling process is partly electrical and partly chemical. Neurons are electrically excitable, due to maintenance of voltage gradients across their membranes. If the voltage changes by a large amount over a short interval, the neuron generates an all-or-nothing electrochemical pulse called an action potential. This potential travels

rapidly along the axon, and activates synaptic connections as it reaches them. Synaptic signals may be excitatory or inhibitory, increasing or reducing the net voltage that reaches the soma.

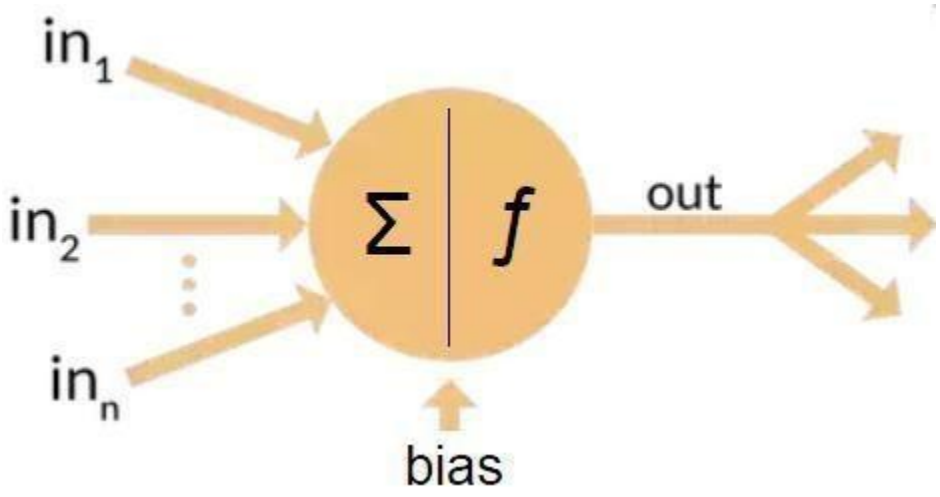
In most cases, neurons are generated by neural stem cells during brain development and childhood. Neurogenesis largely ceases during adulthood in most areas of the brain. However, strong evidence supports generation of substantial numbers of new neurons in the hippocampus and olfactory bulb.

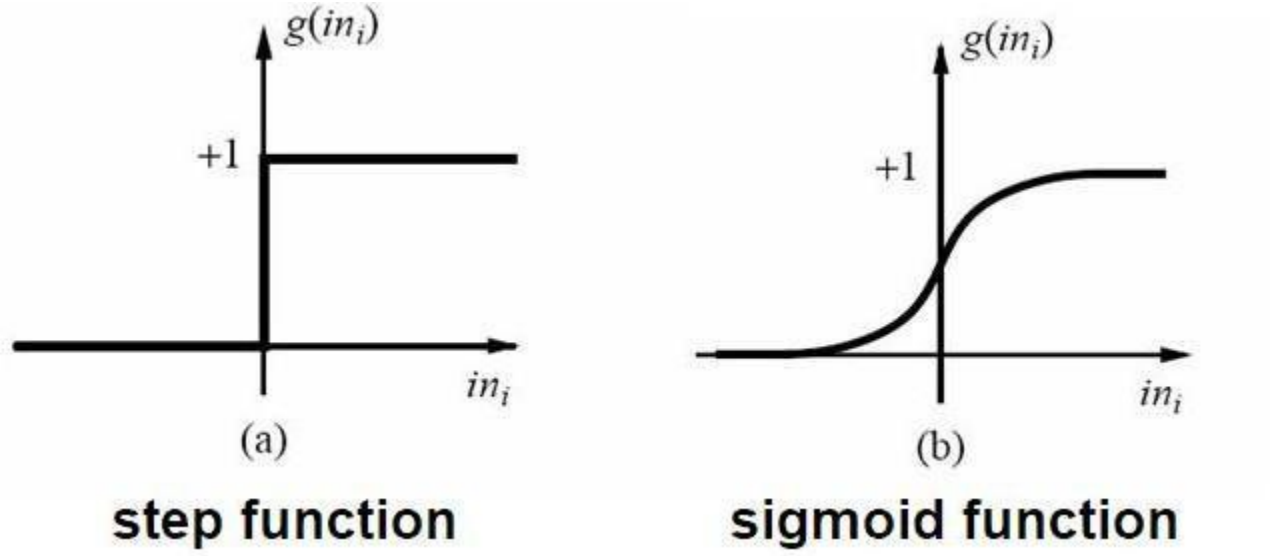




STRUCTURE AND FUNCTIONS OF ARTIFICIAL NEURON.

An artificial neuron is a mathematical function conceived as a model of biological neurons, a neural network. Artificial neurons are elementary units in an artificial neural network. The artificial neuron receives one or more inputs (representing excitatory postsynaptic potentials and inhibitory postsynaptic potentials at neural dendrites) and sums them to produce an output (or activation, representing a neuron's action potential which is transmitted along its axon). Usually each input is separately 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. They are also often monotonically increasing, continuous, differentiable and bounded. The thresholding function has inspired building logic gates referred to as threshold logic; applicable to building logic circuits resembling brain processing. For example, new devices such as memristors have been extensively used to develop such logic in recent times.





STATE THE MAJOR DIFFERENCES BETWEEN BIOLOGICAL AND ARTIFICIANEURAL NETWORKS

1. Size: Our brain contains about 86 billion neurons and more than a 100 synapses (connections). The number of "neurons" in artificial networks is much less than that.

2. Signal transport and processing: The human brain works asynchronously, ANNs work synchronously.

3. Processing speed: Single biological neurons are slow, while standard neurons in ANNs are fast.

4. Topology: Biological neural networks have complicated topologies, while ANNs are often in a tree structure.

5. 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 sex, age, height, temperature, medical condition, lack of sleep etc. Information in artificial neurons is carried over by the continuous, floating point number values of synaptic weights. There are no refractory periods for artificial neural networks (periods while it is impossible to send another action potential, due to the sodium channels being lock shut) and artificial neurons do not experience "fatigue": they are functions that can be calculated as many times and as fast as the computer architecture would allow.

6. Fault-tolerance: biological neuron networks due to their topology are also fault-tolerant. Artificial neural networks are not modeled for fault tolerance or self regeneration (similarly to fatigue, these ideas are not applicable to matrix operations), though recovery is possible by saving the current state (weight values) of the model and continuing the training from that save state.

7. 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. For benchmark: a single Nvidia GeForce Titan X GPU runs on 250 watts alone, and requires a power supply. 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°Celsius instead of 36.5–37.5 °C.

8. Learning: we still do not understand how brains learn, or how redundant connections store and recall information. By learning, we are building on information that is already stored in the brain. Our knowledge deepens by repetition and during sleep, and tasks that once required a focus can be executed automatically once mastered. 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 (and biases representing thresholds) can change during training. The networks start with random weight values and will slowly try to reach a point where further changes in the weights would no longer improve performance. Biological networks usually don't stop / start learning. ANNs have different fitting (train) and prediction (evaluate) phases.

9. 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.

10. Training algorithm: ANNs use Gradient Descent for learning. Human brains use something different (but we don't know what).

BRIEFLY EXPLAIN THE BASIC BUILDING BLOCKS OF ARTIFICIAL NEURAL NETWORKS.

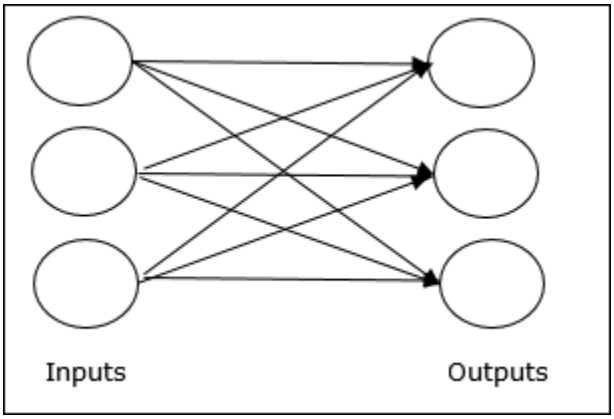
Processing of ANN depends upon the following three building blocks:

1. Network Topology
2. Adjustments of Weights or Learning
3. Activation Functions

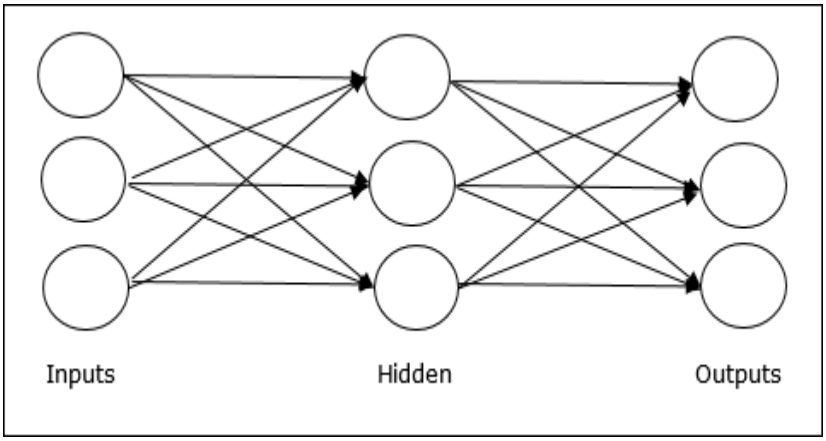
1. Network Topology: A network topology is the arrangement of a network along with its nodes and connecting lines. According to the topology, ANN can be classified as the following kinds:

A. Feed forward Network: It is a non-recurrent network having processing units/nodes in layers and all the nodes in a layer are connected with the nodes of the previous layers. The connection has different weights upon them. There is no feedback loop means the signal can only flow in one direction, from input to output. It may be divided into the following two types:

- **Single layer feed forward network:** The concept is of feed forward ANN having only one weighted layer. In other words, we can say the input layer is fully connected to the output layer.

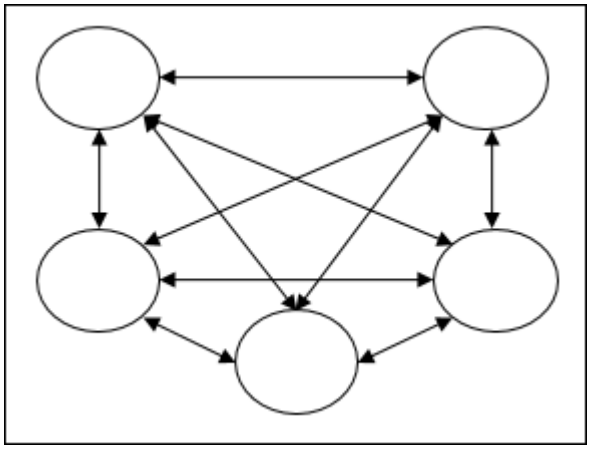


- **Multilayer feed forward network:** The concept is of feed forward ANN having more than one weighted layer. As this network has one or more layers between the input and the output layer, it is called hidden layers.

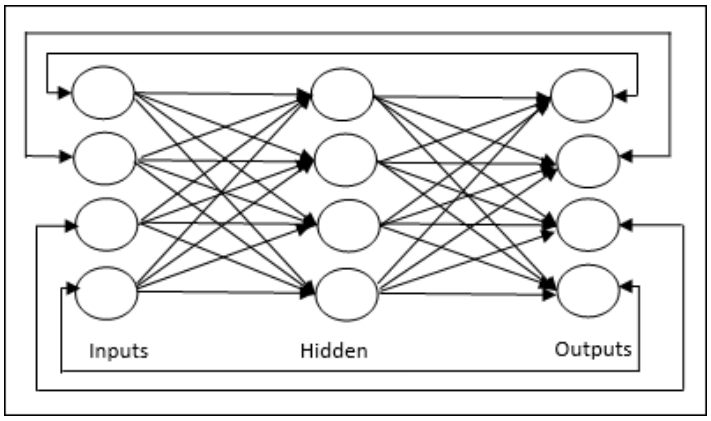


B. Feedback Network: As the name suggests, a feedback network has feedback paths, which means the signal can flow in both directions using loops. This makes it a non-linear dynamic system, which changes continuously until it reaches a state of equilibrium. It may be divided into the following types:

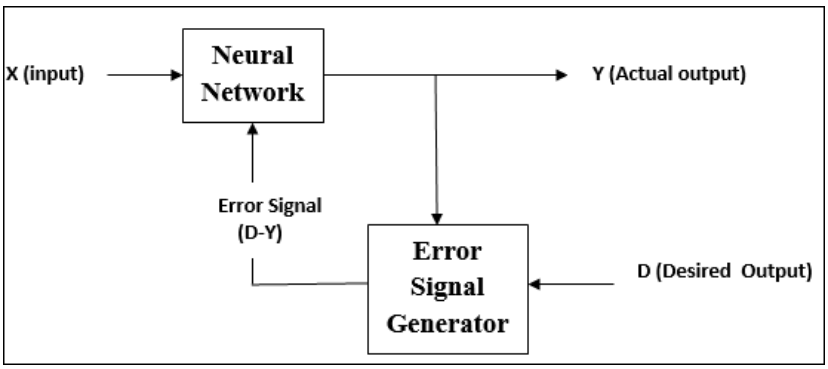
- **Recurrent networks:** They are feedback networks with closed loops. Following are the two types of recurrent networks.
- **Fully recurrent network:** It is the simplest neural network architecture because all nodes are connected to all other nodes and each node works as both input and output.



- **Jordan network** – It is a closed loop network in which the output will go to the input again as feedback as shown in the following diagram.

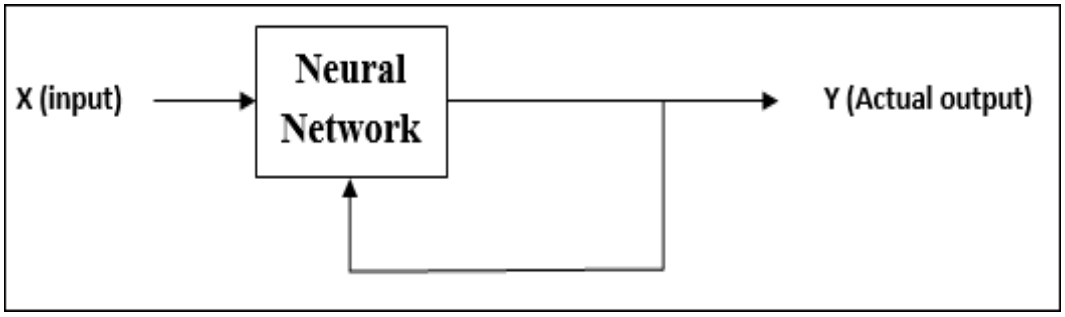


2. Adjustments of Weights or Learning: Learning, in artificial neural network, is the method of modifying the weights of connections between the neurons of a specified network. Learning in ANN can be classified into three categories namely supervised learning, unsupervised learning, and reinforcement learning.

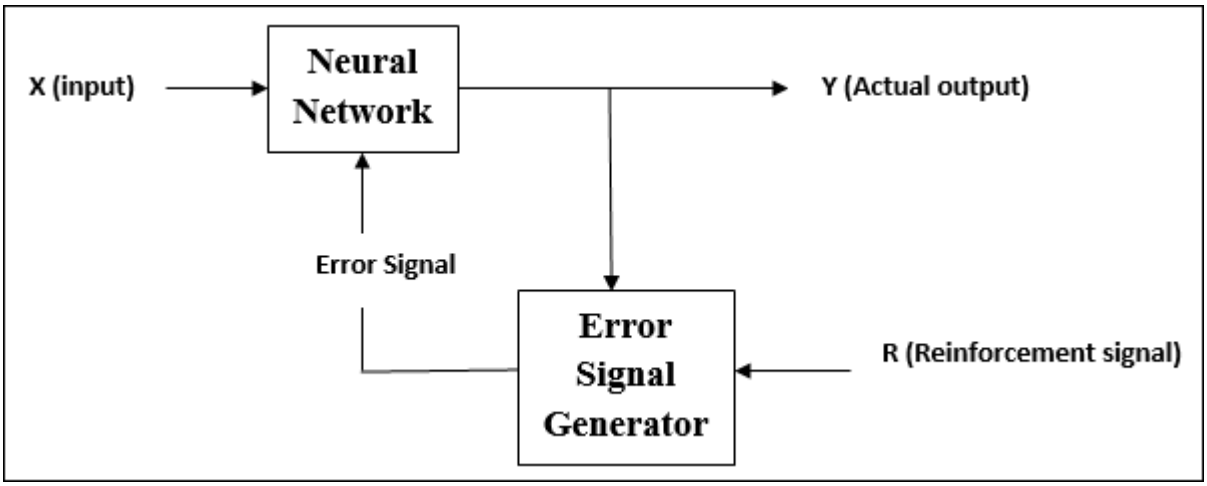


Supervised Learning: As the name suggests, this type of learning is done under the supervision of a teacher. This learning process is dependent. During the training of ANN under supervised learning, the input vector is presented to the network, which will give an output vector. This output vector is compared with the desired output vector. An error signal is generated, if there is a difference between the actual output and the desired output vector. On the basis of this error signal, the weights are adjusted until the actual output is matched with the desired output.

Unsupervised Learning: As the name suggests, this type of learning is done without the supervision of a teacher. This learning process is independent. During the training of ANN under unsupervised learning, the input vectors of similar type are combined to form clusters. When a new input pattern is applied, then the neural network gives an output response indicating the class to which the input pattern belongs. There is no feedback from the environment as to what should be the desired output and if it is correct or incorrect. Hence, in this type of learning, the network itself must discover the patterns and features from the input data, and the relation for the input data over the output.



Reinforcement Learning: As the name suggests, this type of learning is used to reinforce or strengthen the network over some critic information. This learning process is similar to supervised learning, however we might have very less information. During the training of network under reinforcement learning, the network receives some feedback from the environment. This makes it somewhat similar to supervised learning. However, the feedback obtained here is evaluative not instructive, which means there is no teacher as in supervised learning. After receiving the feedback, the network performs adjustments of the weights to get better critic information in future.



3. **Activation Functions:** An activation function is a mathematical equation that determines the output of each element (perceptron or neuron) in the neural network. It takes in the input from each neuron and transforms it into an output, usually between one and zero or between -1 and one. It may be defined as the extra force or effort applied over the input to obtain an exact output. In ANN, we can also apply activation functions over the input to get the exact output. Followings are some activation functions of interest:

i) Linear Activation Function: It is also called the identity function as it performs no input editing. It can be defined as: $F(x) = x$

ii) Sigmoid Activation Function: It is of two type as follows –

- **Binary sigmoidal function:** This activation function performs input editing between 0 and 1. It is positive in nature. It is always bounded, which means its output cannot be less than 0 and more than 1. It is also strictly increasing in nature, which means more the input higher would be the output. It can be defined as

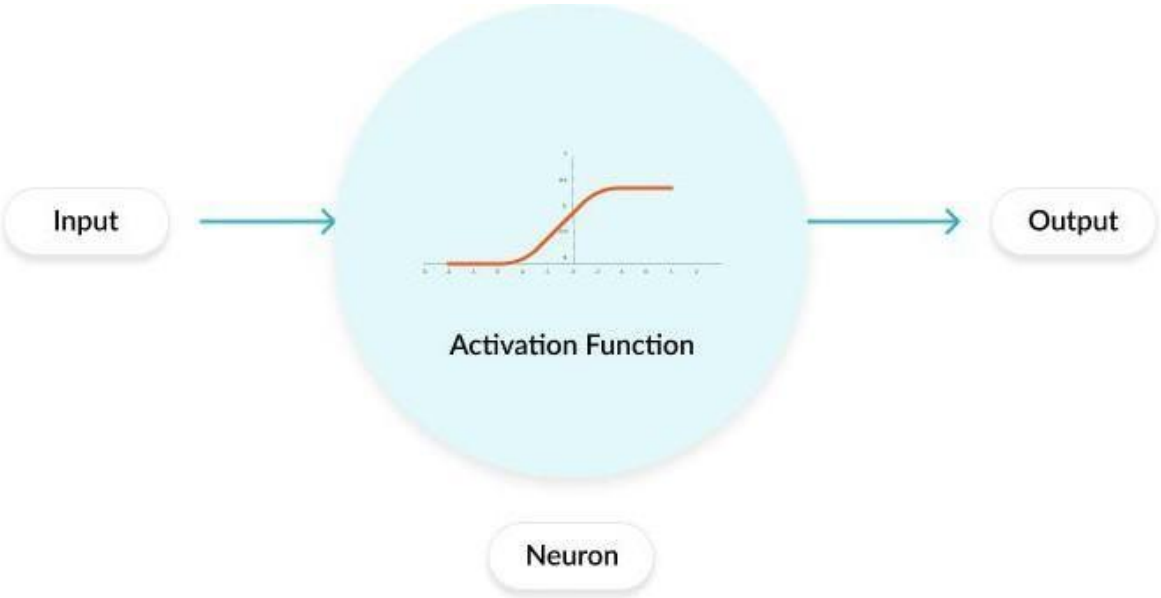
$$F(x)=sigm(x)=11+exp(−x)F(x)=sigm(x)=11+exp(−x)$$

- **Bipolar sigmoidal function:** This activation function performs input editing between -1 and 1. It can be positive or negative in nature. It is always bounded, which means its output cannot be less than -1 and more than 1. It is also strictly increasing in nature like sigmoid function. It can be defined as

$$F(x)=sigm(x)=21+exp(−x)−1=1−exp(x)1+exp(x)$$

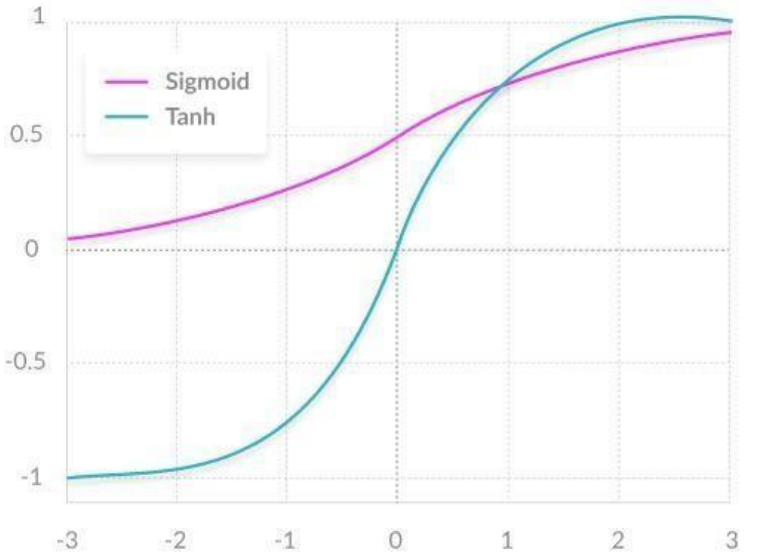
WHAT IS A NEURAL NETWORK ACTIVATION FUNCTION?

In a neural network, inputs, which are typically real values, are fed into the neurons in the network. Each neuron has a weight, and the inputs are multiplied by the weight and fed into the activation function. Each neuron's output is the input of the neurons in the next layer of the network, and so the inputs cascade through multiple activation functions until eventually, the output layer generates a prediction. Neural networks rely on nonlinear activation functions—the derivative of the activation function helps the network learn through the backpropagation process.



SOME COMMON ACTIVATION FUNCTIONS INCLUDE THE FOLLOWING:

1. **The sigmoid function** has a smooth gradient and outputs values between zero and one. For very high or low values of the input parameters, the network can be very slow to reach a prediction, called the *vanishing gradient* problem.
2. **The TanH function** is zero-centered making it easier to model inputs that are strongly negative strongly positive or neutral.
3. **The ReLu function** is highly computationally efficient but is not able to process inputs that approach zero or negative.
4. **The Leaky ReLu** function has a small positive slope in its negative area, enabling it to process zero or negative values.
5. **The Parametric ReLu** function allows the negative slope to be learned, performing backpropagation to learn the most effective slope for zero and negative input values.
6. **Softmax** is a special activation function use for output neurons. It normalizes outputs for each class between 0 and 1, and returns the probability that the input belongs to a specific class.
7. **Swish** is a new activation function discovered by Google researchers. It performs better than ReLu with a similar level of computational efficiency.



Two common neural network activation functions - Sigmoid and Tanh

APPLICATIONS OF ANN

1. Data Mining: Discovery of meaningful patterns (knowledge) from large volumes of data.
2. Expert Systems: A computer program for decision making that simulates thought process of a human expert.
3. Fuzzy Logic: Theory of approximate reasoning.
4. Artificial Life: Evolutionary Computation, Swarm Intelligence.
5. Artificial Immune System: A computer program based on the biological immune system.
6. Medical: At the moment, the research is mostly on modelling parts of the human body and recognizing diseases from various scans (e.g. cardiograms, CAT scans, ultrasonic scans, etc.).Neural networks are ideal in recognizing diseases using scans since there is no need to provide a specific algorithm on how to identify the disease. Neural networks learn by example so the details of how to recognize the disease are not needed. What is needed is a set of examples that are representative of all the variations of the disease. The quantity of examples is not as important as the 'quantity'. The examples need to be selected very carefully if the system is to perform reliably and efficiently.

7. Computer Science: Researchers in quest of artificial intelligence have created spin offs like dynamic programming, object oriented programming, symbolic programming, intelligent storage management systems and many more such tools. The primary goal of creating an artificial intelligence still remains a distant dream but people are getting an idea of the ultimate path, which could lead to it.
8. Aviation: Airlines use expert systems in planes to monitor atmospheric conditions and system status. The plane can be put on autopilot once a course is set for the destination.
9. Weather Forecast: Neural networks are used for predicting weather conditions. Previous data is fed to a neural network, which learns the pattern and uses that knowledge to predict weather patterns.
10. Neural Networks in business: Business is a diverted field with several general areas of specialization such as accounting or financial analysis. Almost any neural network application would fit into one business area or financial analysis.
11. There is some potential for using neural networks for business purposes, including resource allocation and scheduling.
12. There is also a strong potential for using neural networks for database mining, which is, searching for patterns implicit within the explicitly stored information in databases. Most of the funded work in this area is classified as proprietary. Thus, it is not possible to report on the full extent of the work going on. Most work is applying neural networks, such as the Hopfield-Tank network for optimization and scheduling.
13. Marketing: There is a marketing application which has been integrated with a neural network system. The Airline Marketing Tactician (a trademark abbreviated as AMT) is a computer system made of various intelligent technologies including expert systems. A feed forward neural network is integrated with the AMT and was trained using back-propagation to assist the marketing control of airline seat allocations. The adaptive neural approach was amenable to rule expression. Additionally, the application's environment changed rapidly and constantly, which required a continuously adaptive solution.
14. Credit Evaluation: The HNC company, founded by Robert Hecht-Nielsen, has developed several neural network applications. One of them is the Credit Scoring system which increases the profitability of the existing model up to 27%. The HNC neural systems were also applied to mortgage screening. A neural network automated mortgage insurance under writing system was developed by the Nestor Company. This system was trained with 5048 applications of which 2597 were certified. The data related to property and borrower qualifications. In a conservative mode the system agreed on the under writers on 97% of the cases. In the liberal model the system agreed 84% of the cases. This is system run on an Apollo DN3000 and used 250K memory while processing a case file in approximately 1 sec.

ADVANTAGES OF ANN

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organisation: An ANN can create its own organisation or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Pattern recognition: is a powerful technique for harnessing the information in the data and generalizing about it. Neural nets learn to recognize the patterns which exist in the data set.
5. The system is developed through learning rather than programming.. Neural nets teach themselves the patterns in the data freeing the analyst for more interesting work.

6. Neural networks are flexible in a changing environment. Although neural networks may take some time to learn a sudden drastic change they are excellent at adapting to constantly changing information.
7. Neural networks can build informative models whenever conventional approaches fail. Because neural networks can handle very complex interactions they can easily model data which is too difficult to model with traditional approaches such as inferential statistics or programming logic.
8. Performance of neural networks is at least as good as classical statistical modelling, and better on most problems. The neural networks build models that are more reflective of the structure of the data in significantly less time.

LIMITATIONS OF ANN

In this technological era everything has Merits and some Demerits in others words there is a Limitation with every system which makes this ANN technology weak in some points. The various Limitations of ANN are:-

1) ANN is not a daily life general purpose problem solver.
2) There is no structured methodology available in ANN.
3) There is no single standardized paradigm for ANN development.
4) The Output Quality of an ANN may be unpredictable.
5) Many ANN Systems does not describe how they solve problems.
6) Black box Nature
7) Greater computational burden.
8) Proneness to over fitting.
9) Empirical nature of model development.

ARTIFICIAL NEURAL NETWORK CONCEPTS/TERMINOLOGY

Here is a glossary of basic terms you should be familiar with before learning the details of neural networks.

Inputs: Source data fed into the neural network, with the goal of making a decision or prediction about the data. Inputs to a neural network are typically a set of real values; each value is fed into one of the neurons in the input layer.

Training Set: A set of inputs for which the correct outputs are known, used to train the neural network.

Outputs : Neural networks generate their predictions in the form of a set of real values or boolean decisions. Each output value is generated by one of the neurons in the output layer.

Neuron/perceptron: The basic unit of the neural network. Accepts an input and generates a prediction.

Each neuron accepts part of the input and passes it through the activation function. Common activation functions are sigmoid, TanH and ReLu. Activation functions help generate output values within an acceptable range, and their non-linear form is crucial for training the network.

Weight Space: Each neuron is given a numeric weight. The weights, together with the activation function, define each neuron's output. Neural networks are trained by fine-tuning weights, to discover the optimal set of weights that generates the most accurate prediction.

Forward Pass: The forward pass takes the inputs, passes them through the network and allows each neuron to react to a fraction of the input. Neurons generate their outputs and pass them on to the next layer, until eventually the network generates an output.

Error Function: Defines how far the actual output of the current model is from the correct output. When training the model, the objective is to minimize the error function and bring output as close as possible to the correct value.

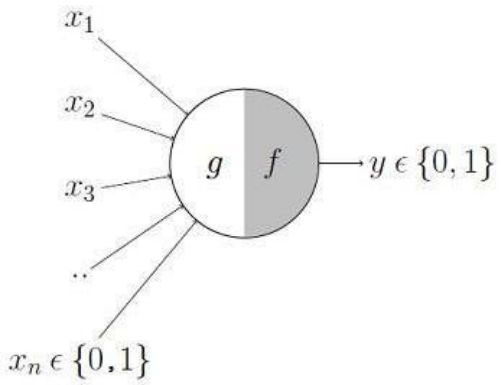
Backpropagation: In order to discover the optimal weights for the neurons, we perform a backward pass, moving back from the network's prediction to the neurons that generated that prediction. This is called backpropagation. Backpropagation tracks the derivatives of the activation functions in each successive neuron, to find weights that bring the loss function to a minimum, which will generate the best prediction. This is a mathematical process called *gradient descent*.

Bias and Variance: When training neural networks, like in other machine learning techniques, we try to balance between bias and variance. Bias measures how well the model fits the training set—able to correctly predict the known outputs of the training examples. Variance measures how well the model works with unknown inputs that were not available during training. Another meaning of bias is a "bias neuron" which is used in every layer of the neural network. The bias neuron holds the number 1, and makes it possible to move the activation function up, down, left and right on the number graph.

Hyperparameters: A hyper parameter is a setting that affects the structure or operation of the neural network. In real deep learning projects, tuning hyper parameters is the primary way to build a network that provides accurate predictions for a certain problem. Common hyper parameters include the number of hidden layers, the activation function, and how many times (epochs) training should be repeated.

McCULLOGH-PITTS MODEL

In 1943 two electrical engineers, Warren McCullogh and Walter Pitts, published the first paper describing what we would call a neural network.



It may be divided into 2 parts. The first part, g takes an input, performs an aggregation and based on the aggregated value the second part, f makes a decision. Let us suppose that I want to predict my own decision, whether to watch a random football game or not on TV. The inputs are all boolean i.e., {0,1} and my output variable is also boolean {0: Will watch it, 1: Won't watch it}.

So, x_1 could be 'is Indian Premier League On' (I like Premier League more)

x_2 could be 'is it a knockout game (I tend to care less about the league level matches)

x_3 could be 'is Not Home' (Can't watch it when I'm in College. Can I?)

x_4 could be 'is my favorite team playing' and so on.

These inputs can either be excitatory or inhibitory. Inhibitory inputs are those that have maximum effect on the decision making irrespective of other inputs i.e., if x_3 is 1 (not home) then my output will always be 0 i.e., the neuron will never fire, so x_3 is an inhibitory input. Excitatory inputs are NOT the ones that will make the neuron fire on their own but they might fire it when combined together. Formally, this is what is going on:

$$g(x_1, x_2, x_3, ..., x_n) = g(\mathbf{x}) = \sum_{i=1}^{n} x_i$$

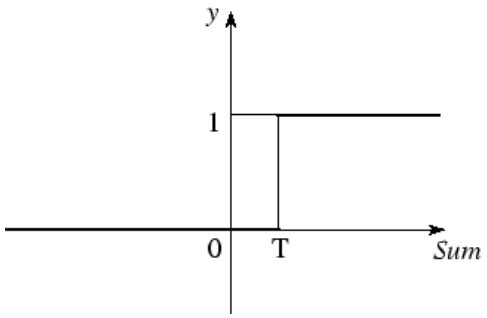
$$\begin{aligned} y = f(g(\mathbf{x})) &= 1 \quad if \quad g(\mathbf{x}) \geq \theta \\ &= 0 \quad if \quad g(\mathbf{x}) < \theta \end{aligned}$$

We can see that g(x) is just doing a sum of the inputs — a simple aggregation. And theta here is called thresholding parameter. For example, if I always watch the game when the sum turns out to be 2 or more, the theta is 2 here. This is called the Thresholding Logic.

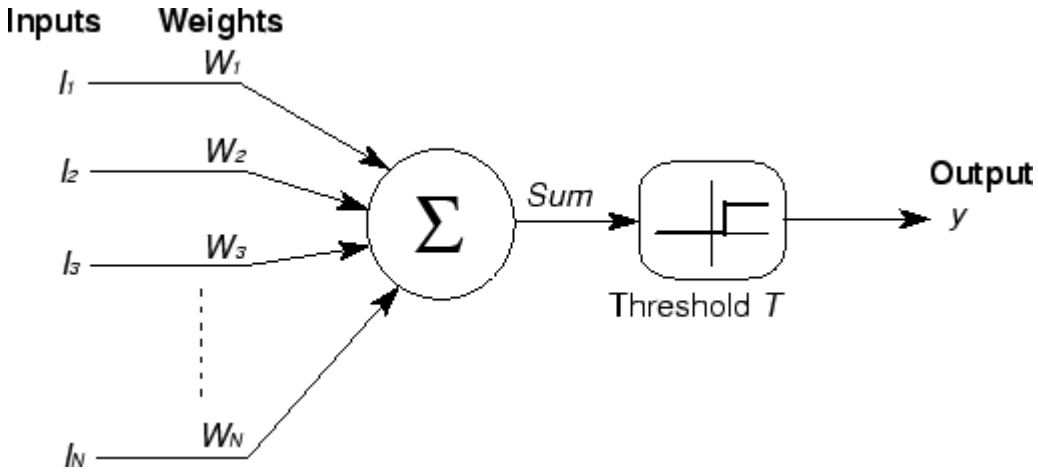
The McCulloch-Pitts neural model is also known as linear threshold gate. It is a neuron of a set of inputs I_1, I_2,I_3,...I_m and one output 'y' . The linear threshold gate simply classifies the set of inputs into two different classes. Thus the output y is binary. Such a function can be described mathematically using these equations:

$$Sum = \sum_{i=1}^{N} I_i W_i, \qquad y = f(Sum).$$

Where, $W_1, W_2, W_3, ..., W_m$ are weight values normalized in the range of either $(0,1)$ or $(-1,1)$ and associated with each input line, Sum is the weighted sum, and T is a threshold constant. The function f is a linear step function at threshold T as shown in figure 2.3. The symbolic representation of the linear threshold gate is shown in figure below.



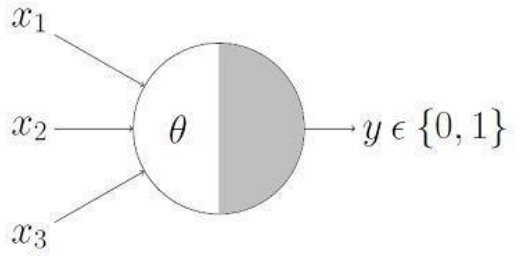
Linear Threshold Function



Symbolic Illustration of Linear Threshold Gate

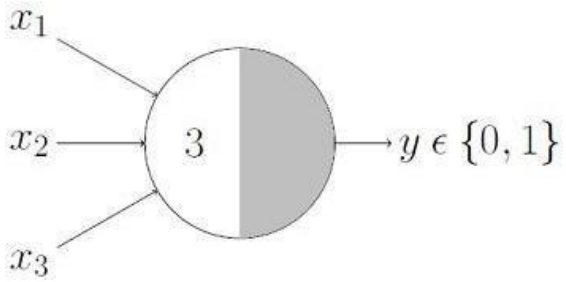
BOOLEAN FUNCTIONS USING McCULLOGH-PITTS NEURON

In any Boolean function, all inputs are Boolean and the output is also Boolean. So essentially, the neuron is just trying to learn a Boolean function.



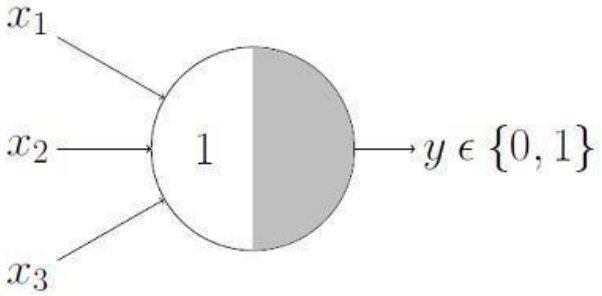
This representation just denotes that, for the boolean inputs x_1, x_2 and x_3 if the g(x) i.e., sum ≥ theta, the neuron will fire otherwise, it won't.

AND Function



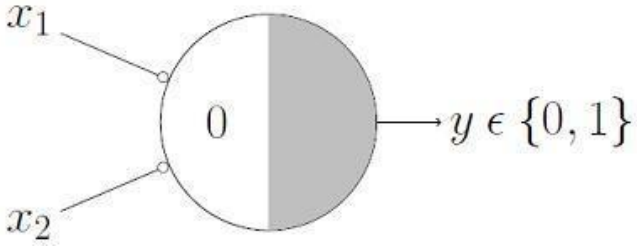
An AND function neuron would only fire when ALL the inputs are ON i.e., g(x) ≥ 3 here.

OR Function



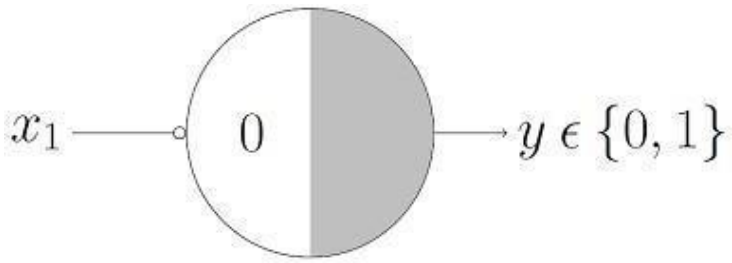
For an OR function neuron would fire if ANY of the inputs is ON i.e., g(x) ≥ 1 here.

NOR Function



For a NOR neuron to fire, we want ALL the inputs to be 0 so the thresholding parameter should also be 0 and we take them all as inhibitory input.

NOT Function



For a NOT neuron, 1 outputs 0 and 0 outputs 1. So we take the input as an inhibitory input and set the thresholding parameter to 0.

We can summarize these rules with the McCullough-Pitts output rule as:

The McCulloch-Pitts model of a neuron is simple yet has substantial computing potential. It also has a precise mathematical definition. However, this model is so simplistic that it only generates a binary output and also the weight and threshold values are fixed. The neural computing algorithm has diverse features for various applications. Thus, we need to obtain the neural model with more flexible computational features.

WHAT ARE THE LEARNING RULES IN ANN?

Learning rule is a method or a mathematical logic. It helps a Neural Network to learn from the existing conditions and improve its performance. Thus learning rules updates the weights and bias levels of a network when a network simulates in a specific data environment. Applying learning rule is an iterative process. It helps a neural network to learn from the existing conditions and improve its performance.

The different learning rules in the Neural network are:

1. Hebbian learning rule – It identifies, how to modify the weights of nodes of a network.
2. Perceptron learning rule – Network starts its learning by assigning a random value to each weight.
3. Delta learning rule – Modification in sympatric weight of a node is equal to the multiplication of error and the input.
4. Correlation learning rule – The correlation rule is the supervised learning.
5. Outstar learning rule – We can use it when it assumes that nodes or neurons in a network arranged in a layer.

1. **Hebbian Learning Rule:** The Hebbian rule was the first learning rule. In 1949 Donald Hebb developed it as learning algorithm of the unsupervised neural network. We can use it to identify how to improve the weights of nodes of a network. The Hebb learning rule assumes that – If two neighbor neurons activated and deactivated at the same time, then the weight connecting these neurons should increase. At the start, values of all weights are set to zero. This learning rule can be used for both soft- and hard-activation functions. Since desired responses of neurons are not used in the learning procedure, this is the unsupervised learning rule. The absolute values of the weights are usually proportional to the learning time, which is undesired.

$$W_{ij} = x_i * x_j$$

Mathematical Formula of Hebb Learning Rule.

2. **Perceptron Learning Rule:** Each connection in a neural network has an associated weight, which changes in the course of learning. According to it, an example of supervised learning, the network starts its learning by assigning a random value to each weight. Calculate the output value on the basis of a set of records for which we can know the expected output value. This is the learning sample that indicates the entire definition. As a result, it is called a learning sample. The network then compares the calculated output value with the expected value. Next calculates an error function ∈, which can be the sum of squares of the errors occurring for each individual in the learning sample which can be computed as:

$$\sum_i \sum_j \left(E_{ij} - O_{ij} \right)^2$$

Mathematical Formula of Perceptron Learning Rule

Perform the first summation on the individuals of the learning set, and perform the second summation on the output units. E_{ij} and O_{ij} are the expected and obtained values of the j^{th} unit for the i^{th} individual. The network then adjusts the weights of the different units, checking each time to see if the error function has increased or decreased. As in a conventional regression, this is a matter of solving a problem of least squares. Since assigning the weights of nodes according to users, it is an example of supervised learning.

3. **Delta Learning Rule:** Developed by Widrow and Hoff, the delta rule, is one of the most common learning rules. It depends on supervised learning. This rule states that the modification in sympatric weight of a node is equal to the multiplication of error and the input. In Mathematical form the delta rule is as follows:

$$\Delta w = \eta \, (t - y) \, x_i$$

Mathematical Formula of Delta Learning Rule

For a given input vector, compare the output vector is the correct answer. If the difference is zero, no learning takes place; otherwise, adjusts its weights to reduce this difference. The change in weight from ui to uj is: dwij = r* ai * ej. where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form an independent set then learn arbitrary associations using the delta rule.

It has seen that for networks with linear activation functions and with no hidden units. The error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has the least value. The vertex of this paraboloid represents the point where it reduces the error. The weight vector corresponding to this point is then the ideal weight vector. We can use the delta learning rule with both single output unit and several output units. While applying the delta rule assume that the error can be directly measured. The aim of applying the delta rule is to reduce the difference between the actual and expected output that is the error.

4. **Correlation Learning Rule:** The correlation learning rule based on a similar principle as the Hebbian learning rule. It assumes that weights between responding neurons should be more positive, and weights between neurons with opposite reaction should be more negative. Contrary to the Hebbian rule, the correlation rule is the supervised learning, instead of an actual. The response, oj, the desired response, dj, uses for the weight-change calculation. In Mathematical form the correlation learning rule is as follows:

$$\Delta w_{ij} = \eta x_i d_j$$

Mathematical Formula of Correlation Learning Rule

Where d_j is the desired value of output signal. This training algorithm usually starts with the initialization of weights to zero. Since assigning the desired weight by users, the correlation learning rule is an example of supervised learning.

5. Out Star Learning Rule: We use the Out Star Learning Rule when we assume that nodes or neurons in a network arranged in a layer. Here the weights connected to a certain node should be equal to the desired outputs for the neurons connected through those weights. The out start rule produces the desired response t for the layer of n nodes. Apply this type of learning for all nodes in a particular layer. Update the weights for nodes are as in Kohonen neural networks. In Mathematical form, express the out star learning as follows:

$$w_{jk} = \begin{cases} \eta(y_k - w_{jk}) & \text{if node j wins the competition} \\ 0 & \text{if node j losses the competition} \end{cases}$$

Mathematical Formula of Out Star Learning Rule

This is a supervised training procedure because desired outputs must be known.

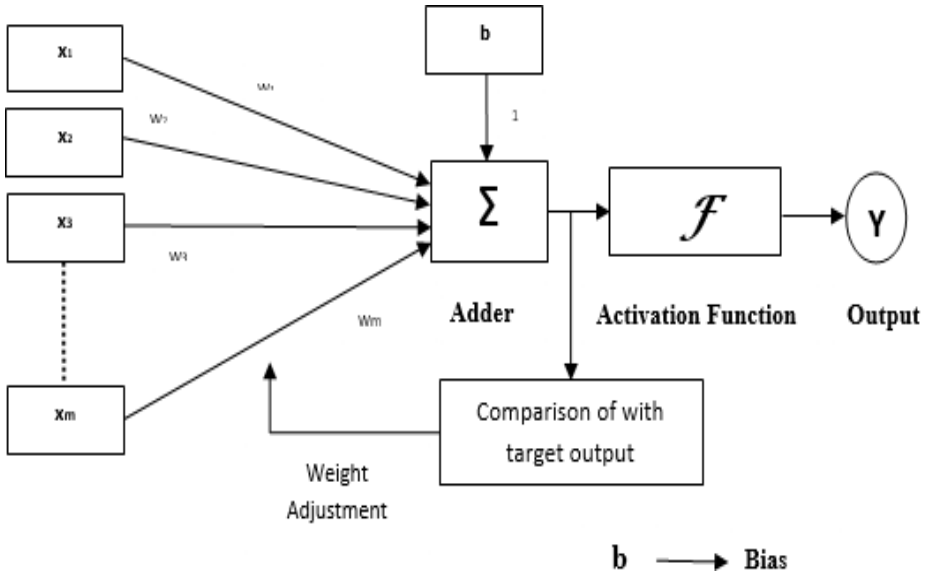
BRIEFLY EXPLAIN THE ADALINE MODEL OF ANN.

ADALINE (Adaptive Linear Neuron or later Adaptive Linear Element) is an early single-layer artificial neural network and the name of the physical device that implemented this network. The network uses memistors. It was developed by Professor Bernard Widrow and his graduate student Ted Hoff at Stanford University in 1960. It is based on the McCulloch–Pitts neuron. It consists of a weight, a bias and a summation function. 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. Some important points about Adaline are as follows:

- It uses bipolar activation function.
- It uses delta rule for training to minimize the Mean-Squared Error (MSE) between the actual output and the desired/target output.
- The weights and the bias are adjustable.

Architecture of ADALINE network: The basic structure of Adaline is similar to perceptron having an extra feedback loop with the help of which the actual output is compared with the desired/target output. After comparison on the basis of training algorithm, the weights and bias will be updated.

Architecture of ADALINE: The basic structure of Adaline is similar to perceptron having an extra feedback loop with the help of which the actual output is compared with the desired/target output. After comparison on the basis of training algorithm, the weights and bias will be updated.



Training Algorithm of ADALINE:

Step 1 – Initialize the following to start the training:

- Weights
- Bias
- Learning rate α

For easy calculation and simplicity, weights and bias must be set equal to 0 and the learning rate must be set equal to 1.

Step 2 – Continue step 3-8 when the stopping condition is not true.

Step 3 – Continue step 4-6 for every bipolar training pair s : t.

Step 4 – Activate each input unit as follows:

$$x_i = s_i \ (i=1 \text{ to } n)$$

Step 5 – Obtain the net input with the following relation:

$$y_i = b + \sum_i^n x_i \ w_i$$

Here 'b' is bias and 'n' is the total number of input neurons.

Step 6 – Apply the following activation function to obtain the final output:

$$f(y_{in}) = \begin{cases} 1, \text{if } y_{in} \geq 0 \\ -1, \text{if } y_{in} < 0 \end{cases}$$

Step 7 – Adjust the weight and bias as follows :

Case 1 – if $y \neq t$ then, $w_i(new) = w_i(old) + \alpha(t - y_{in})x_i$

$$b(new) = b(old) + \alpha(t - y_{in})$$

Case 2 – if $y = t$ then, $w_i(new) = w_i(old)$

$$b(new) = b(old)$$

Here 'y' is the actual output and 't' is the desired/target output. $(t - y_{in})$ is the computed error.

Step 8 – Test for the stopping condition, which will happen when there is no change in weight or the highest weight change occurred during training is smaller than the specified tolerance.

EXPLAIN MULTIPLE ADAPTIVE LINEAR NEURONS (MADALINE).

Madaline which stands for Multiple Adaptive Linear Neuron, is a network which consists of many Adalines in parallel. It will have a single output unit. Three different training algorithms for MADALINE networks called Rule I, Rule II and Rule III have been suggested, which cannot be learned using backpropagation. The first of these dates back to 1962 and cannot adapt the weights of the hidden-output connection.[10] The second training algorithm improved on Rule I and was described in 1988.[8] The third "Rule" applied to a modified network with sigmoid activations instead of signum; it was later found to be equivalent to backpropagation. The Rule II training algorithm is based on a principle called "minimal disturbance". It proceeds by looping over training examples, then for each example, it:

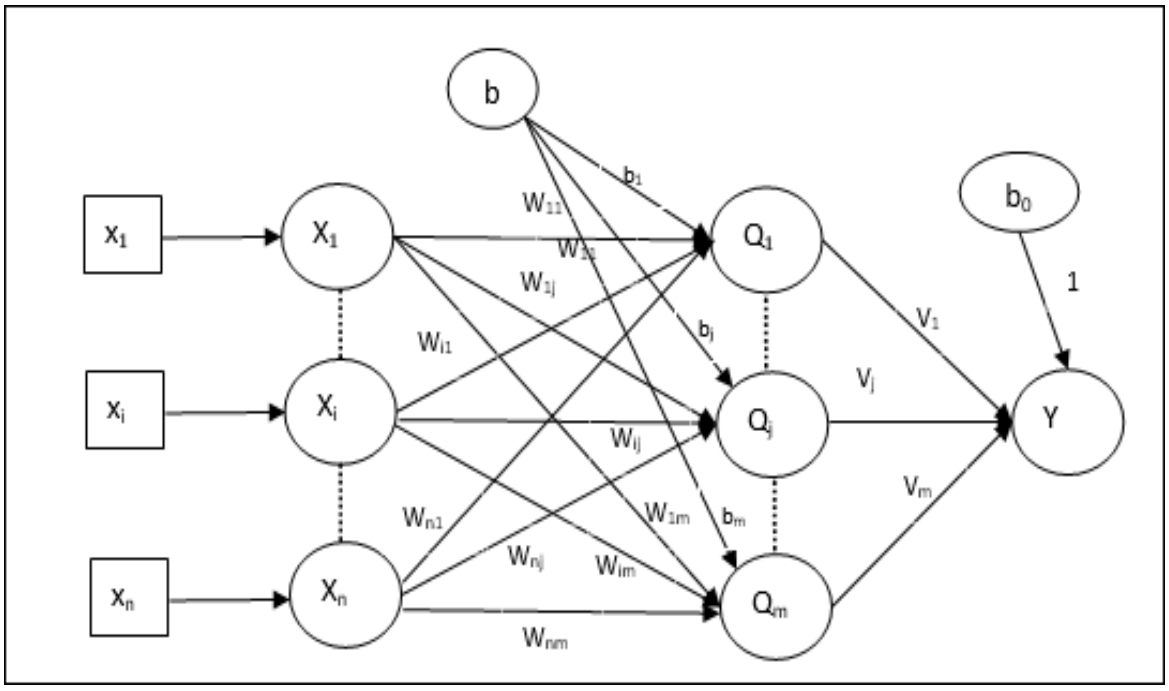
- finds the hidden layer unit (ADALINE classifier) with the lowest confidence in its prediction, tentatively flips the sign of the unit,
- accepts or rejects the change based on whether the network's error is reduced,
- stops when the error is zero.

Some important points about Madaline are as follows:

- It is just like a multilayer perceptron, where Adaline will act as a hidden unit between the input and the Madaline layer.
- The weights and the bias between the input and Adaline layers, as in we see in the Adaline architecture, are adjustable.
- The Adaline and Madaline layers have fixed weights and bias of 1.
- Training can be done with the help of Delta rule.

BRIEFLY EXPLAIN THE ARCHITECTURE OF MADALINE

MADALINE (Many ADALINE) is a three-layer (input, hidden, output), fully connected, feed-forward artificial neural network architecture for classification that uses ADALINE units in its hidden and output layers, i.e. its activation function is the sign function. The three-layer network uses memistors. The architecture of Madaline consists of "n" neurons of the input layer, "m" neurons of the Adaline layer, and 1 neuron of the Madaline layer. The Adaline layer can be considered as the hidden layer as it is between the input layer and the output layer, i.e. the Madaline layer.



Training Algorithm of MADALINE

By now we know that only the weights and bias between the input and the Adaline layer are to be adjusted, and the weights and bias between the Adaline and the Madaline layer are fixed.

Step 1 – Initialize the following to start the training:

- Weights
- Bias
- Learning rate α

For easy calculation and simplicity, weights and bias must be set equal to 0 and the learning rate must be set equal to 1.

Step 2 – Continue step 3-8 when the stopping condition is not true.
Step 3 – Continue step 4-6 for every bipolar training pair s:t.
Step 4 – Activate each input unit as follows:

$$x_i = s_i (I = 1 \text{ to } n)$$

Step 5 – Obtain the net input at each hidden layer, i.e. the Adaline layer with the following relation:

$$O_{inj} = b_j + \sum_{i}^{n} x_i \; w_{ij} \; j = 1 \; to \; m$$

Here 'b' is bias and 'n' is the total number of input neurons.

Step 6 – Apply the following activation function to obtain the final output at the Adaline and the Madaline Layer:

$$(y_{in}) = \begin{cases} 1, if \; x \geq 0 \\ -1, if \; x < 0 \end{cases}$$

Output at the hidden Adaline unit $Q_j = f(Q_{inj})$
Final output of the network $y = f(y_{in})$
i.e.

$$y_{inj} = b_0 + \sum_{j=1}^{m} Q_j \; v_j$$

Step 7 – Calculate the error and adjust the weights as follows –

Case 1 – if y ≠ t and t = 1 then,

$$w_{ij}(new) = w_{ij}(old) + \alpha(1 - Q_{inj})x_i$$
$$b_j(new) = b_j(old) + \alpha(1 - Q_{inj})$$

In this case, the weights would be updated on Qj where the net input is close to 0 because t = 1.

Case 2 – if y ≠ t and t = -1 then,

$$w_{ik}(new) = w_{ik}(old) + \alpha(-1 - Q_{ink})x_i$$
$$b_k(new) = b_k(old) + \alpha(-1 - Q_{ink})$$

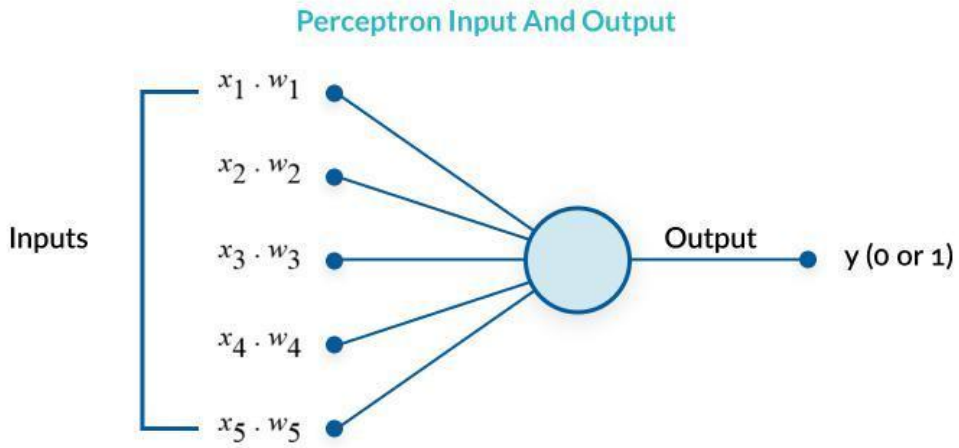
In this case, the weights would be updated on Qk where the net input is positive because t = -1. Here 'y' is the actual output and 't' is the desired/target output.

Case 3 – if y = t, then there would be no change in weights.

Step 8 – Test for the stopping condition, which will happen when there is no change in weight or the highest weight change occurred during training is smaller than the specified tolerance.

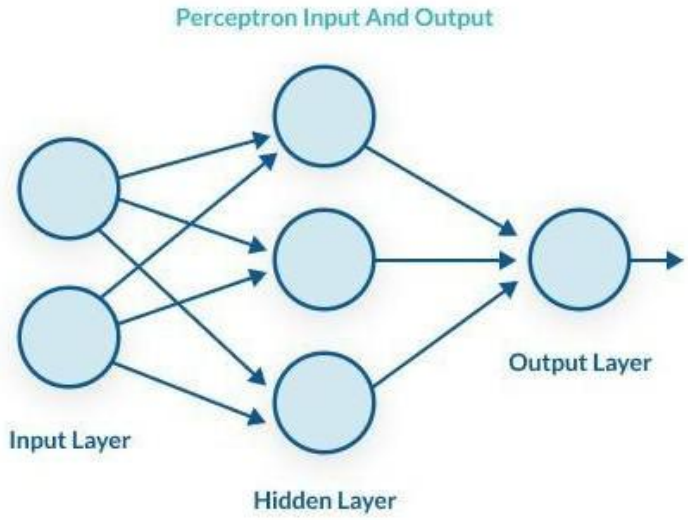
WHAT IS A PERCEPTRON?

A perceptron is a binary classification algorithm modeled after the functioning of the human brain—it was intended to emulate the neuron. The perceptron, while it has a simple structure, has the ability to learn a



What is Multilayer Perceptron?

A multilayer perceptron (MLP) is a group of perceptrons, organized in multiple layers, that can accurately answer complex questions. Each perceptron in the first layer (on the left) sends signals to all the perceptrons in the second layer, and so on. An MLP contains an input layer, at least one hidden layer, and an output layer.



The perceptron learns as follows:

1. Takes the inputs which are fed into the perceptrons in the input layer, multiplies them by their weights, and computes the sum.
2. Adds the number one, multiplied by a "bias weight". This is a technical step that makes it possible to move the output function of each perceptron (the activation function) up, down, left and right on the number graph.
3. Feeds the sum through the activation function—in a simple perceptron system, the activation function is a step function.
4. The result of the step function is the output.

A multilayer perceptron is quite similar to a modern neural network. By adding a few ingredients, the perceptron architecture becomes a full-fledged deep learning system:

- **Activation functions and other** hyperparameters**:** a full neural network uses a variety of activation functions which output real values, not boolean values like in the classic perceptron. It is more flexible in terms of other details of the learning process, such as the number of training iterations (iterations and epochs), weight initialization schemes, regularization, and so on. All these can be tuned as hyperparameters.
- **Backpropagation**: a full neural network uses the backpropagation algorithm, to perform iterative backward passes which try to find the optimal values of perceptron weights, to generate the most accurate prediction.
- **Advanced architectures**: full neural networks can have a variety of architectures that can help solve specific problems. A few examples are Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Generative Adversarial Networks (GAN).

Pattern recognition problems

Pattern recognition problems in neural networks refer to tasks that involve identifying and classifying patterns within data. These problems typically require the network to learn and understand the underlying structure or features in the input data in order to make accurate predictions or classifications.

In pattern recognition problems, the neural network is trained on a labeled dataset, where each data instance is associated with a corresponding class or category. The network learns to extract relevant features or patterns from the input data and maps them to the appropriate output class.

Examples of pattern recognition problems include:

1. Image Classification: The network is trained to recognize and classify images into different categories, such as identifying whether an image contains a cat or a dog.

2. Speech Recognition: The network is trained to convert spoken words or phrases into written text, allowing it to recognize and transcribe spoken language.

3. Handwriting Recognition: The network is trained to recognize handwritten characters or words and convert them into digital text.

4. Object Detection: The network is trained to identify and locate specific objects within an image, such as detecting and localizing cars or pedestrians in a self-driving car application.

5. Facial Recognition: The network is trained to identify and verify individuals based on their facial features, enabling applications like biometric authentication or surveillance systems.

In all these examples, the neural network learns to recognize patterns or distinctive features in the data by adjusting its internal weights and biases through the training process. This enables it to generalize and make accurate predictions or classifications on new, unseen data.

3.1 Pattern Recognition Problem

In any pattern recognition task we have a set of input patterns and the corresponding output patterns. Depending on the nature of the output patterns and the nature of the task environment, the problem could be identified as one of association or classification or mapping. The given set of input-output pattern pairs form only a few samples of an **unknown** system. From these samples the pattern recognition model should capture the characteristics of the system. Without looking into the details of the system, let us assume that the input-output patterns are available or given to us. Without loss of generality, let us also assume that the patterns could be represented as vectors in multidimensional spaces. We first state the most straightforward pattern recognition problem, namely, the pattern association problem, and discuss its characteristics.

Pattern Association Problem: Given a set of input-output pattern pairs $(a,, \mathbf{b}_1), (\mathbf{a}_2, \mathbf{b}_2), \ldots, (\mathbf{a}_l, \mathbf{b}_l), \ldots, (\mathbf{a}_L, \mathbf{b}_L)$ where $\mathbf{a}_l = (a_{l1}, a_{l2}, \ldots, a_{lM})$ and $\mathbf{b}_l = (b_{l1}, b_{l2}, \ldots, b_{lN})$ are M and N dimensional vectors, respectively, design a neural network to associate each input pattern with the corresponding output pattern.

If $\mathbf{a}_l$ and $\mathbf{b}_l$ are distinct, then the problem is called **heteroassociation.** On the other hand, if $\mathbf{b}_l = \mathbf{a}_l$, then the problem is called autoassociation. In the latter case the input and the corresponding output patterns refer to the same point in an N-dimensional space, since $M = N$ and $a_{li} = b_{li}$, i = 1, 2, ..., N, l = 1, 2, ..., L.

The problem of storing the association of the input-output pattern pairs $(\mathbf{a}_l, \mathbf{b}_l)$, I = 1, 2, ..., L, involves determining the weights of a network to accomplish the task. This is the training part. Once stored, the problem of recall involves determining the output pattern for a given input pattern by applying the operations of the network on the input pattern.

The recalled output pattern depends on the nature of the input and the design of the network. If the input pattern is the same as one of those used in the training, then the recalled output pattern is the same as the associated pattern in the training. If the input pattern is a noisy version of the trained input pattern, then the pattern may not be identical to any of the patterns used in training the network. Let the input pattern is $\hat{\mathbf{a}} = \mathbf{a}_l + \varepsilon$, where ε is a (small amplitude) noise vector. Let us assume that $\hat{\mathbf{a}}$ is closer (according to some distance measure) to $\mathbf{a}_l$ than any other $\mathbf{a}_k$, $k \neq$ I. If the output of the network for this input $\hat{\mathbf{a}}$ is still $\mathbf{b}_l$, then the network is designed to exhibit an accretive behaviour. On the other hand, if the network produces an output $\hat{\mathbf{b}} = \mathbf{b}_l + 6$, such that $|6| \to 0$ as $|\varepsilon| \to 0$, then the network is designed to exhibit an interpolative behaviour.

Depending on the interpretation of the problem, several pattern

recognition tasks can be viewed as variants of the pattern association problem. We will describe these tasks in Section 3.3. First we will consider three basic functional units of neural networks which perform the pattern association and related pattern recognition tasks.

3.2 Basic Functional Units

There are three types of artificial neural networks. They are: (i) feedforward, (ii) feedback and (iii) a combination of both. The simplest networks of each of these types form the basic functional units. They are ***functional*** because they can perform by themselves some simple pattern recognition tasks. They are ***basic*** because they form building blocks for developing neural network architectures for complex pattern recognition tasks to be described later in Chapter 7.

The simplest feedforward network (Figure 3.1) is a two layer network with M input units and N output units. Each input unit is

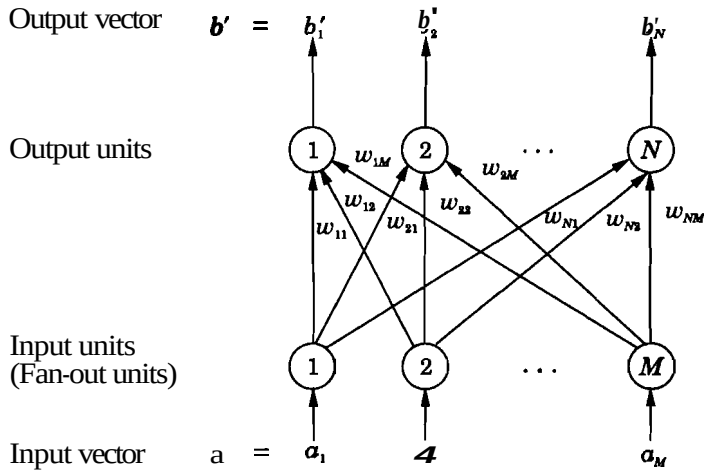


Figure 3.1 Basic feedforward neural network.

connected to each of the output units, and each connection is associated with a weight or strength of the connection. The input units are all linear, and they merely perform the task of fan-out, i.e, each unit is providing N outputs, one to each output unit. The output units are either linear or nonlinear depending on the task that the network should perform. Typically, feedforward networks are used for pattern association or pattern classification or pattern mapping.

The simplest feedback network, shown in Figure 3.2, consists of a set of N processing units, each connected to all other units. The connection strengths or weights are assumed to be symmetric, i.e., $w_{ij} = w_{ji}$, for $i \neq j$. Depending on the task, the units of the network could be linear or nonlinear. Typically feedback networks are used for autoassociation or pattern storage.

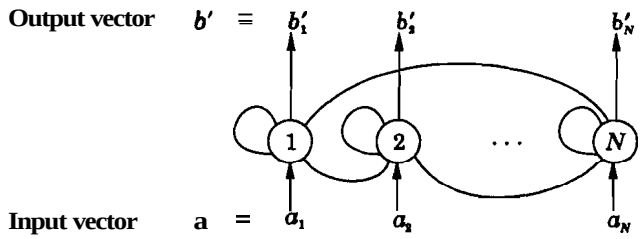


Figure 3.2 Basic feedback neural network.

The simplest combination network is called a competitive learning network, shown in Figure 3.3. It consists of an input layer of units

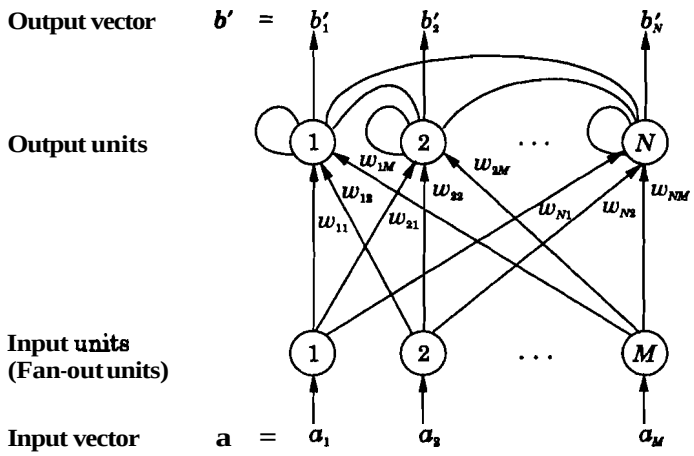


Figure 3.3 Basic competitive learning network.

feeding to the units in the output layer in a feedforward manner, and a feedback connection among the units in the output layer, including self-feedback. Usually the connection strengths or weights of the feedforward path are adjustable by training the network for a given pattern recognition task. The feedback connection strengths or weights in the output layer are usually fixed to specific values depending on the problem. The input units are all linear, and they merely perform the task of fan-out, i.e., each unit providing N outputs, one to each output unit. The output units are either linear or nonlinear depending on the task the network should perform. Typically the competitive learning network is used for pattern grouping/clustering.

3.3 Pattern Recognition Tasks by the Functional Units

Table 3.1 gives a summary of the pattern recognition tasks that can be performed by the three functional units described in the previous

section. All the pattern recognition tasks listed are simple, and can be viewed as variants of the pattern association problem. Each of these tasks can be described in terms of mapping of points from one multidimensional space onto another multidimensional space. In this section the geometrical interpretations of the pattern recognition tasks are given to obtain a clear understanding of the problems.

The input pattern space $\mathcal{R}^M$ is an M-dimensional space, and the input patterns are points in this space. Likewise the output pattern space $\mathcal{R}^N$ is an N-dimensional space, and the output patterns are points in this space. The pattern spaces are shown as circles in the figures used to illustrate the pattern recognition tasks.

3.3.1 Pattern Recognition Tasks by Feedforward Neural Networks

In this section we will discuss three pattern recognition tasks that can be performed by the basic feedforward neural network.

Pattern association problem: The pattern association problem is illustrated in Figure 3.4. The input patterns are shown as a,, $\mathbf{a}_2$, $\mathbf{a}_3$

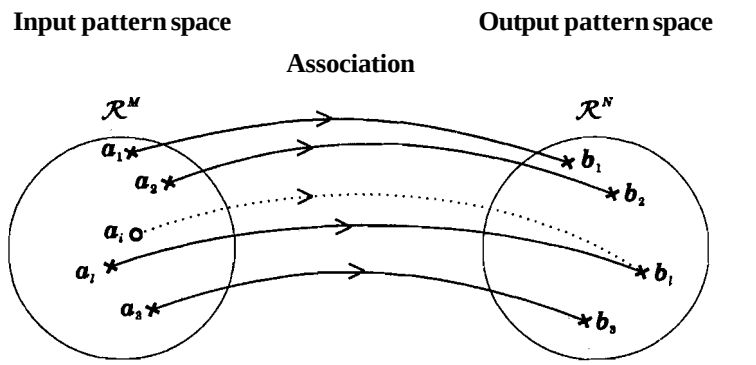


Figure 3.4 Illustration of pattern association task.

and the corresponding output patterns as $\mathbf{b}_1$, b,, $\mathbf{b}_3$. The objective of designing a neural network is to capture the association between input-output pattern pairs in the given set of training data, so that when any of the inputs $\mathbf{a}_l$ is given, the corresponding output $\mathbf{b}_l$ is retrieved. Suppose an input pattern $\mathbf{a}_i$ not used in the training set is given. If the training input pattern $\mathbf{a}_l$ is the closest to $\mathbf{a}_i$, then the pattern association network should retrieve the output pattern $\mathbf{b}_l$ for the input pattern $\mathbf{a}_i$. Thus the network should display accretive behaviour. The pattern $\mathbf{a}_i$ can be viewed as a noisy version of the pattern a,. That is $\mathbf{a}_i$ = a, + ε, where ε is a noise vector.' If the amplitude of the noise added to $\mathbf{a}_l$ is so large that the noisy input pattern is closer to some pattern (say $\mathbf{a}_k$) other than the correct one (a,), then the network produces an incorrect output pattern

$\mathbf{b}_k$, $k \neq l$. Thus an incorrect output pattern would be retrieved for the given noisy input.

An example of a pattern association problem is associating a unique binary code to a printed alphabet character, say $[00000]^T$ for A, $[00001]^T$ for B, etc. (See Figure 3.5). The input patterns A, B, etc.,

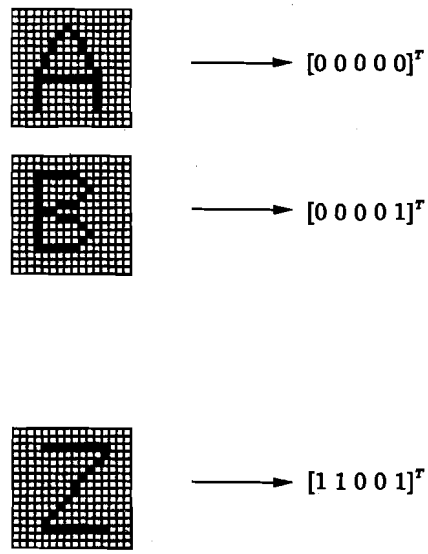


Figure 3.6 An example of pattern association problem.

could be represented as black and white pixels in a grid of size, say 16 x 16 points. Then the input pattern space is a binary 256-dimensional space, and the output pattern space is a binary 5-dimensional space. Noisy versions of the input patterns are obtained when some of the pixels in the grid containing a character are transformed from black to white or vice versa.

Note that the performance of a network for the pattern association problem is mainly dictated by the distribution of the training patterns in the input space. This point will be discussed in detail in Chapter 4.

Pattern classification problem: In the pattern association problem if a group of input patterns correspond to the same output pattern, then typically there will be far fewer output patterns compared to the number of input patterns. In other words, if some of the output patterns in the pattern association problem are identical, then the number of distinct output patterns can be viewed as class labels, and the input patterns corresponding to each class can be viewed as samples of that class. The problem then becomes a pattern classification problem as illustrated in Figure 3.6.

In this case whenever a pattern belonging to a class is given as input, the network identifies the class label. During training, only a

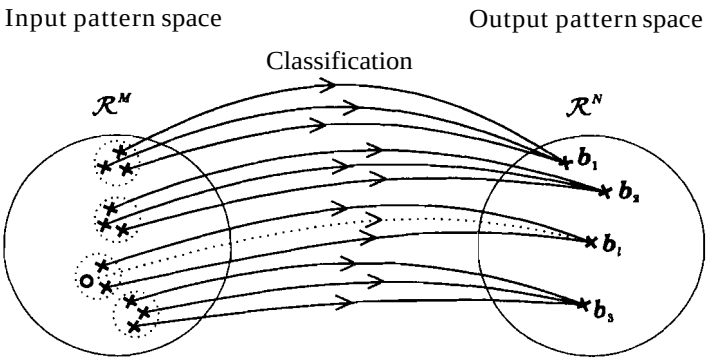


Figure 3.6 Illustration of pattern classification task.

few samples of patterns for each class are given. In testing, the input pattern is usually different from the patterns used in the training set for the class. The network displays an accretive behaviour in this case.

An example of pattern classification problem could be labelling hand printed characters within a specified grid into the corresponding printed character. Note that the printed character patterns are unique and fixed in number, and serve as class labels. These labels could be a unique 5-bit code as shown in Figure 3.7. For a given

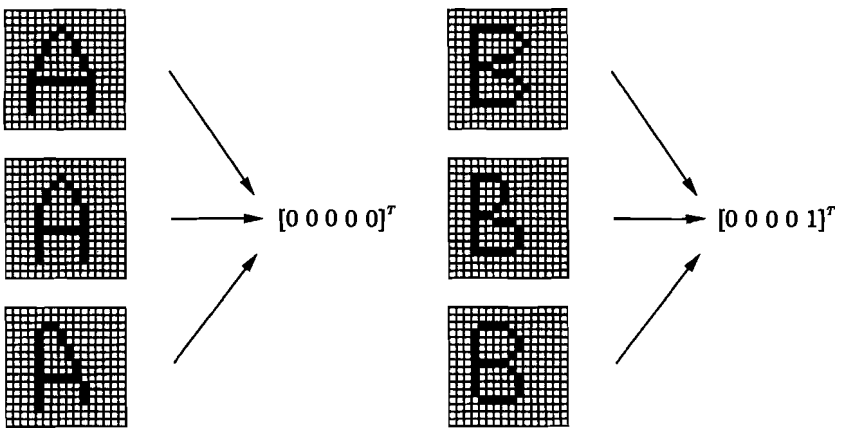


Figure 3.7 An example of pattern classification problem.

character, the samples of hand-printed versions of the character are not identical. In fact the dimensionality of the input pattern space will have to be very large in order to represent the hand-printed characters accurately. An input pattern not belonging to any class may be forced into one of the predetermined class labels by the network.

Note that the performance of a network for the pattern classification problem depends on the characteristics of the samples associated with each class. Thus grouping of the input patterns by

the class label dictates the performance. This point will be discussed in detail in Chapters 4 and 7.

Pattern mapping: Given a set of input-output pattern pairs as in the pattern association problem, if the objective is to capture the implied mapping, instead of association, then the problem becomes a pattern mapping problem (Figure 3.8). In a pattern mapping problem

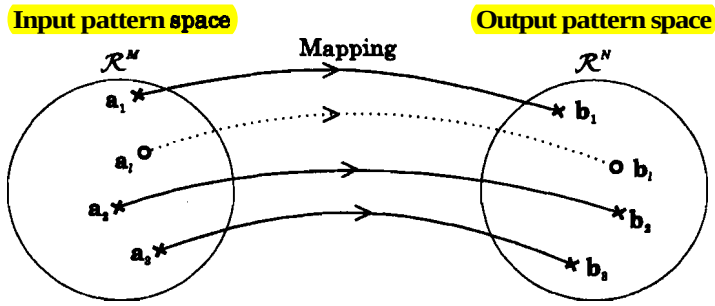


Figure 3.8 Illustration of pattern mapping task.

both the input and the output patterns are only samples from the mapping system. Once the system behaviour is captured by the network, the network would produce a possible output pattern for a new input pattern, not used in the training set. The possible output pattern would be approximately an interpolated version of the output patterns corresponding to the input training patterns close to the given test input pattern. Thus the network displays an interpolative behaviour. Typically the input and output pattern spaces are continuous in this case, and the mapping function must be smooth for the interpolation to work satisfactorily.

An example of the data for a pattern mapping problem could be the input data given to a complex physical system and the corresponding output data from the system for a number of trials. The objective is to capture the unknown system behaviour from the samples of the input-output pair data.

A pattern mapping problem is the most general case, from which the pattern classification and pattern association problems can be derived as special cases. The network for pattern mapping is expected to perform generalization. The details of how well a given network can do generalization will be discussed in Chapter 7.

3.3.2 Pattern Recognition Tasks by Feedback Neural Networks

In this section we will discuss three pattern recognition tasks that can be performed by the basic feedback neural networks.

Autoassociation problem: If each of the output patterns $\mathbf{b}_l$ in a

pattern association problem is identical to the corresponding input patterns $\mathbf{a}_l$, then the output pattern space is identical to the input pattern space (Figure 3.9). In such a case the problem becomes an

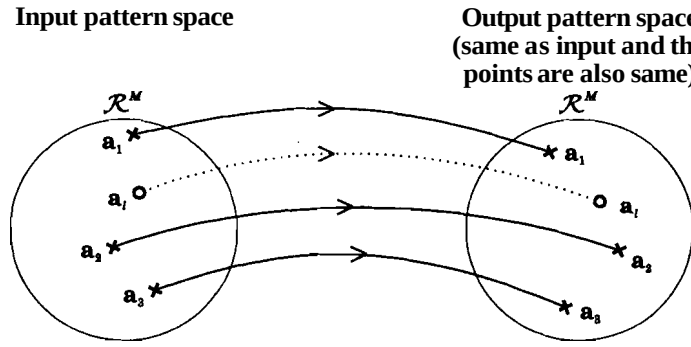


Figure 3.9 Illustration of autoassociation task.

autoassociation problem. This is a trivial case where the network merely stores the given set of input patterns. When a noisy input pattern is given, the network retrieves the same noisy pattern. Thus there is an absence of accretive behaviour.

A detailed analysis of the autoassociation problem is given in Chapter 5. Note that the special case of $\mathbf{b}_l = \mathbf{a}_l$, $l = 1, 2, \ldots, L$ in the pattern association task is considered as a problem of heteroassociation task to be addressed by a feedforward network The term autoassociation task is thus used exclusively in the context of feedback networks.

Pattern storage problem: In the autoassociation problem, if a given input pattern is stored in a network for later recall by an approximate input pattern, then the problem becomes a pattern storage problem (Figure 3.10). Any input vector close to a stored input pattern will

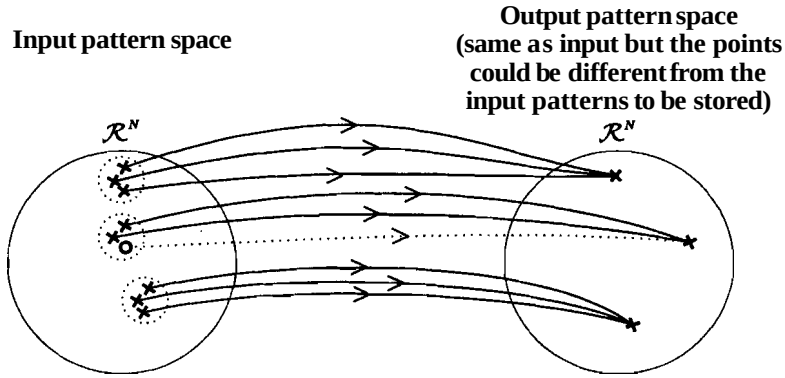


Figure 3.10 Illustration of pattern storage task.

recall that input pattern exactly from the network, and thus the network displays accretive behaviour. The stored patterns could be

the same as the input patterns given during training. In such a case the input pattern space is a continuous one, and the output space consists of a fixed finite set of (stored) patterns corresponding to some of the points in the input pattern space. The stored patterns could also be some transformed versions of the input patterns, but of the same dimension as the input space. In such a case the stored patterns may correspond to different points in the input space.

Due to its accretive behaviour, the pattern storage network is very useful in practice. A detailed analysis of this network is given in Chapter 5.

Pattern environment storage probiem: If a set of patterns together with their probabilities of occurrence are specified, then the resulting specification is called pattern environment. The design of a network to store a given pattern environment aims at recall of the stored patterns with the lowest probability of error. This is called a pattern environment storage problem. A detailed analysis of this problem together with the network design is given in Chapter 5.

3.3.3 Pattern Recognition Tasks by Competitive Learning Neural Networks

In this section we will discuss three pattern recognition tasks that can be performed by a combination neural network consisting of feedforward and feedback parts. The network is also called the competitive learning network.

Temporary pattern storage: If a given input pattern is stored in a network, even in a transformed form, in such a way that the pattern remains only until a new pattern input is given, then the problem becomes that of a short term memory or temporary storage problem. This is only of academic interest. However, a detailed analysis of this problem is given in Chapter 6.

Pattern clustering problem: Given a set of patterns, if they are grouped according to similarity of the patterns, then the resulting problem is called pattern clustering. It is illustrated in Figure 3.11. There are two types of problems here. In one case the network displays an accretive behaviour (Figure 3.11a). That is, if an input pattern not belonging to any group is presented, then the network will force it into one of the groups. The input pattern space is typically a continuous space. The test input patterns could be the same as the ones used in the training or could be different. The output pattern space consists of a set of cluster centres or labels.

The second type of problem displays interpolative behaviour as shown in Figure 3.11b. In this case, a test input pattern not belonging

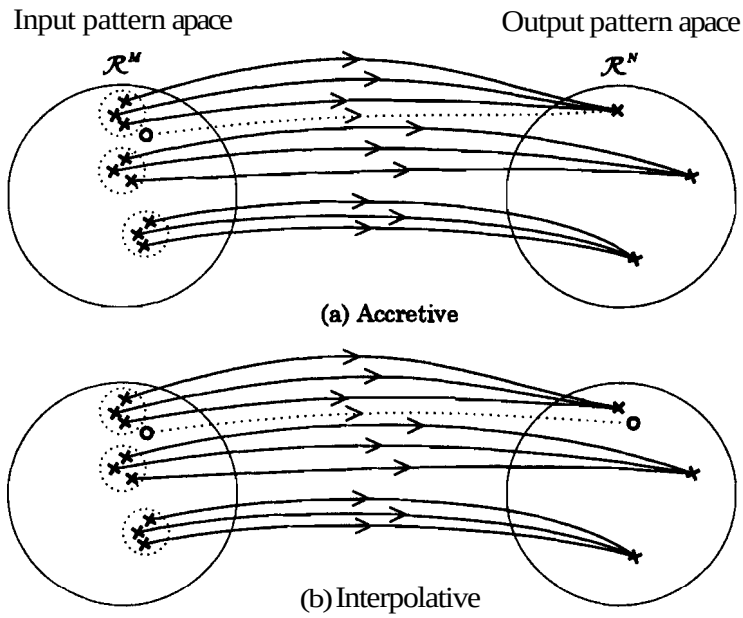


Figure 3.11 Illustration of two types of pattern clustering tasks.

to any group produces an output which is some form of interpolation of the output patterns or cluster centers, depending on the proximity of the test input pattern to the input pattern groups formed during training.

Pattern clustering also leads to the problem of vector quantization. A detailed analysis of these problems is given in Chapter 6.

Feature mappIng problem: In the pattern clustering problem a group of approximately similar input patterns are identified with a fixed output pattern or a group label. On the other hand, if similarities of the features of the input patterns have to be retained in the output, the problem becomes one of feature mapping. In this, a given set of input patterns are mapped onto output patterns in such a way that the proximity of the output patterns reflect the similarity of the features of the corresponding input patterns. When a test input pattern is given, it will generate an output which is in the neighbourhood of the outputs for similar patterns. Note that typically the number of output patterns are fixed, but they are much larger than in the pattern clustering case, and they are organized physically in the network in such a way that the neighbourhood pattern labels reflect closeness of features. A detailed analysis of the feature mapping problem is given in Chapter 6.

In summary, this chapter dealt with some basic functional units of neural networks and a description of the pattern recognition tasks that these units can perform. In particular, we have identified three

basic networks: feedforward, feedback and competitive learning networks. We have defined the pattern association problem as a basic problem, and we have seen how several other pattern recognition tasks could be interpreted as variants of this problem. We have discussed each of the pattern recognition tasks in the form of a mapping problem. What we have not discussed is how the basic functional units perform the corresponding pattern recognition tasks mentioned in this chapter. The next three chapters deal with a detailed analysis of these tasks by the networks.

Revlew Questions

1. What are the three functional units? Why are they called functional units?
2. Explain the meaning of (a) accretive behaviour and (b) interpolative behaviour.
3. Distinguish between pattern association, pattern classification and pattern mapping tasks.
4. Give a real life example of a pattern mapping problem.
5. Explain the difference between autoassociation problem and heteroassociation problem.
6. What is meant by a pattern environment storage problem? Give a real life example to illustrate the problem.
7. Explain the difference between the accretive and interpolative type of clustering problems.
8. Explain what is meant by feature mapping? Explain the problem with a real life example from speech production.
9. Explain how recognition of handwritten digits is closer to a classification type problem, whereas recognition of vowel sounds in continuous speech is closer to a feature mapping type of problem.