DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

CST444 – SOFT COMPUTING

CST444	SOFT COMPUTING	CATEGORY	L	T	P	CREDIT	YEAR OF INTRODUCTION
		PEC	2	1	0	3	2019

Syllabus

Module – 1 (Introduction to Soft Computing & Artificial Neural Network)

Introduction to Soft Computing. Difference between Hard Computing & Soft Computing. Applications of Soft Computing. Artificial Neurons Vs Biological Neurons. Basic models of artificial neural networks – Connections, Learning, Activation Functions. McCulloch and Pitts Neuron. Hebb network.

Module – 2 (Supervised Learning Network)

Perceptron Networks– Learning rule, Training and testing algorithm. Adaptive Linear Neuron– Architecture, Training and testing algorithm. Back propagation Network – Architecture, Training and testing algorithm.

Module - 3 (Fuzzy Logic & Defuzzification)

Fuzzy sets – properties, operations on fuzzy set. Fuzzy membership functions, Methods of membership value assignments – intuition, inference, Rank Ordering. Fuzzy relations– operations on fuzzy relation. Fuzzy Propositions. Fuzzy implications. Defuzzification– Lamda cuts, Defuzzification methods.

Syllabus

Module - 4 (Fuzzy Inference System & Genetic Algorithm)

Fuzzy Inference Systems - Mamdani and Sugeno types. Fuzzy Logic Controller. Concepts of genetic algorithm. Operators in genetic algorithm - coding, selection, cross over, mutation. Stopping condition for genetic algorithm.

Module - 5 (Multi Objective Optimization & Hybrid Systems)

Multi objective optimization problem. Principles of Multi- objective optimization, Dominance and pareto-optimality. Optimality conditions. Neuro-fuzzy hybrid systems. Genetic – neuro hybrid systems.

What is Computing?

Concept of Computing

- Given the sides of triangle, calculate the area.
- Given an array of numbers, sort the numbers in ascending order.

Concept of Computing

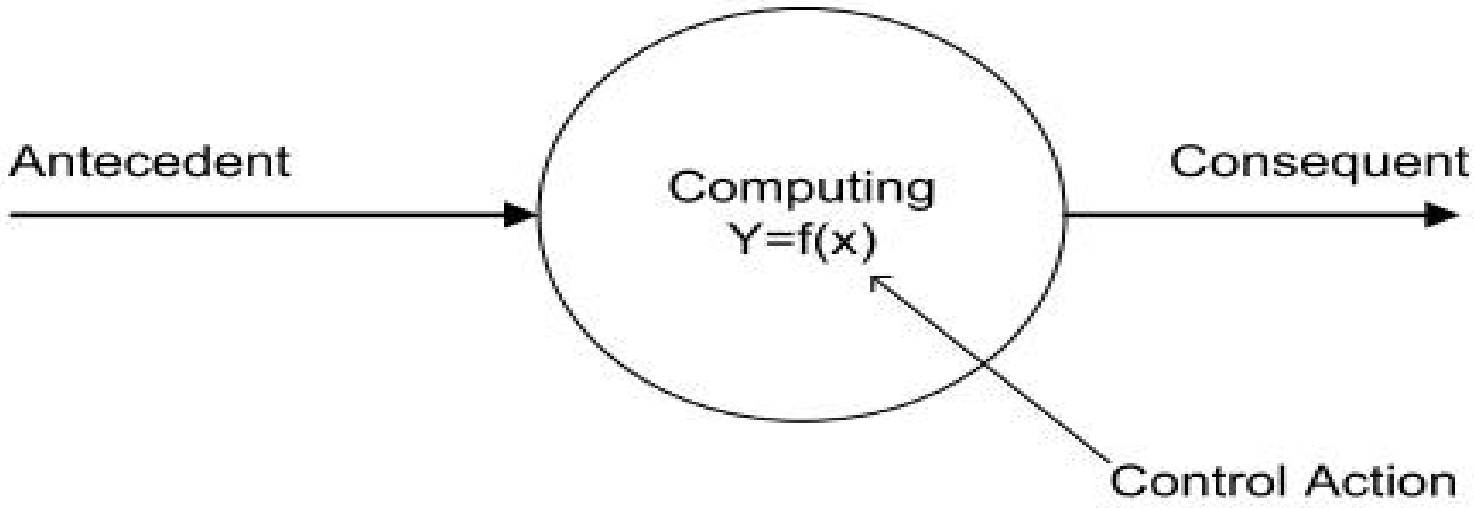


Figure : Basic of computing

$y = f(x)$, f is a mapping function
f is also called a formal method or an algorithm to solve a problem.

Examples of hard computing

1. Solving numerical problems for example finding root of polynomials or finding integration or derivation we usually follow some mathematical models.
2. Searching and sorting techniques are frequently used in many softwares. So these are basically followed by some unambiguous steps and it always gives the precise result and it is basically defined correctly by means of an algorithm.
3. Solving computational geometry problems. For example finding the shortest tour in a graph.

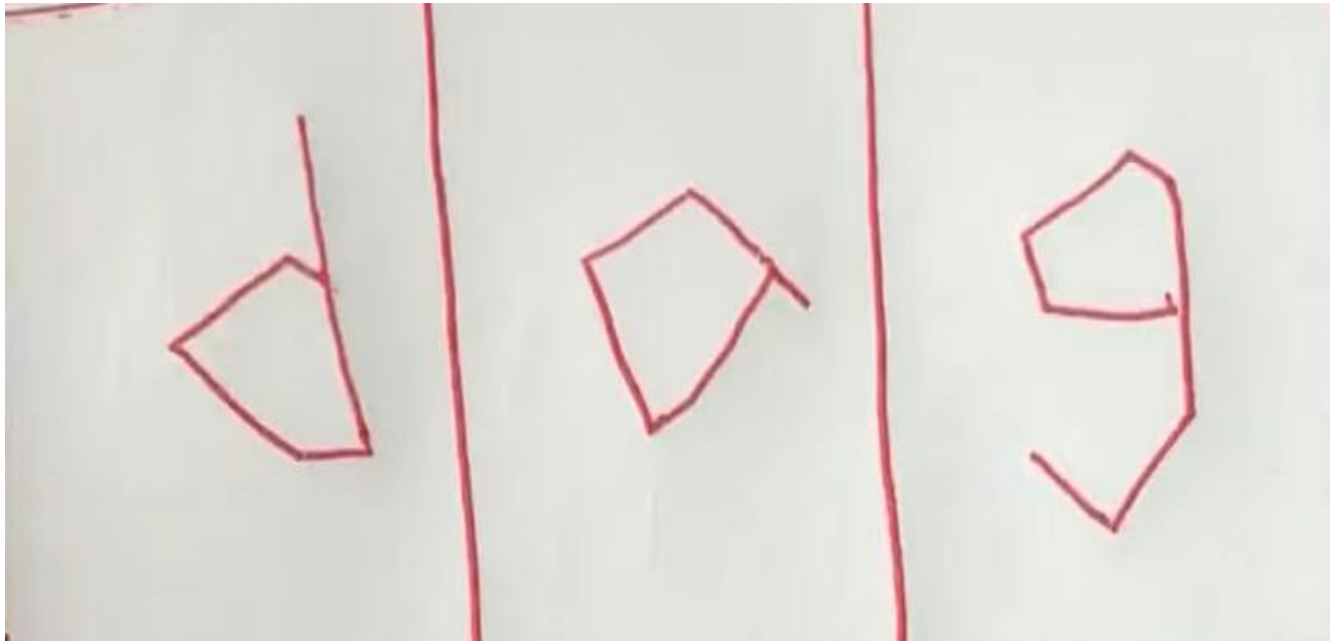
Hard Computing

In 1996, LA Zade (LAZ) introduced the term hard computing.

According to LAZ: We term a computing as "Hard" computing, if

- **Precise result is guaranteed**
- **Control action is unambiguous**
- **Control action is formally defined (i.e. with mathematical model**

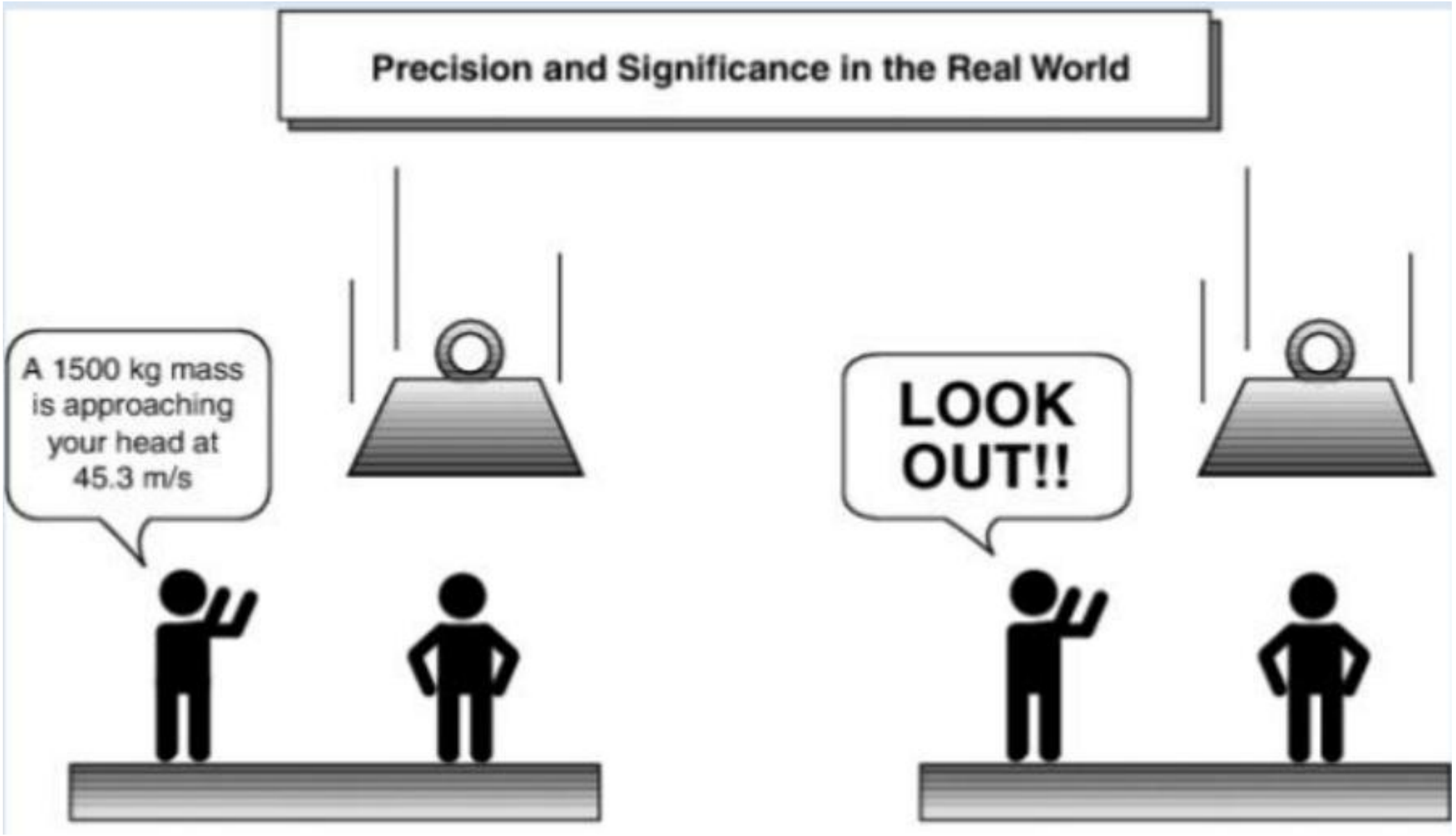
Identify the word



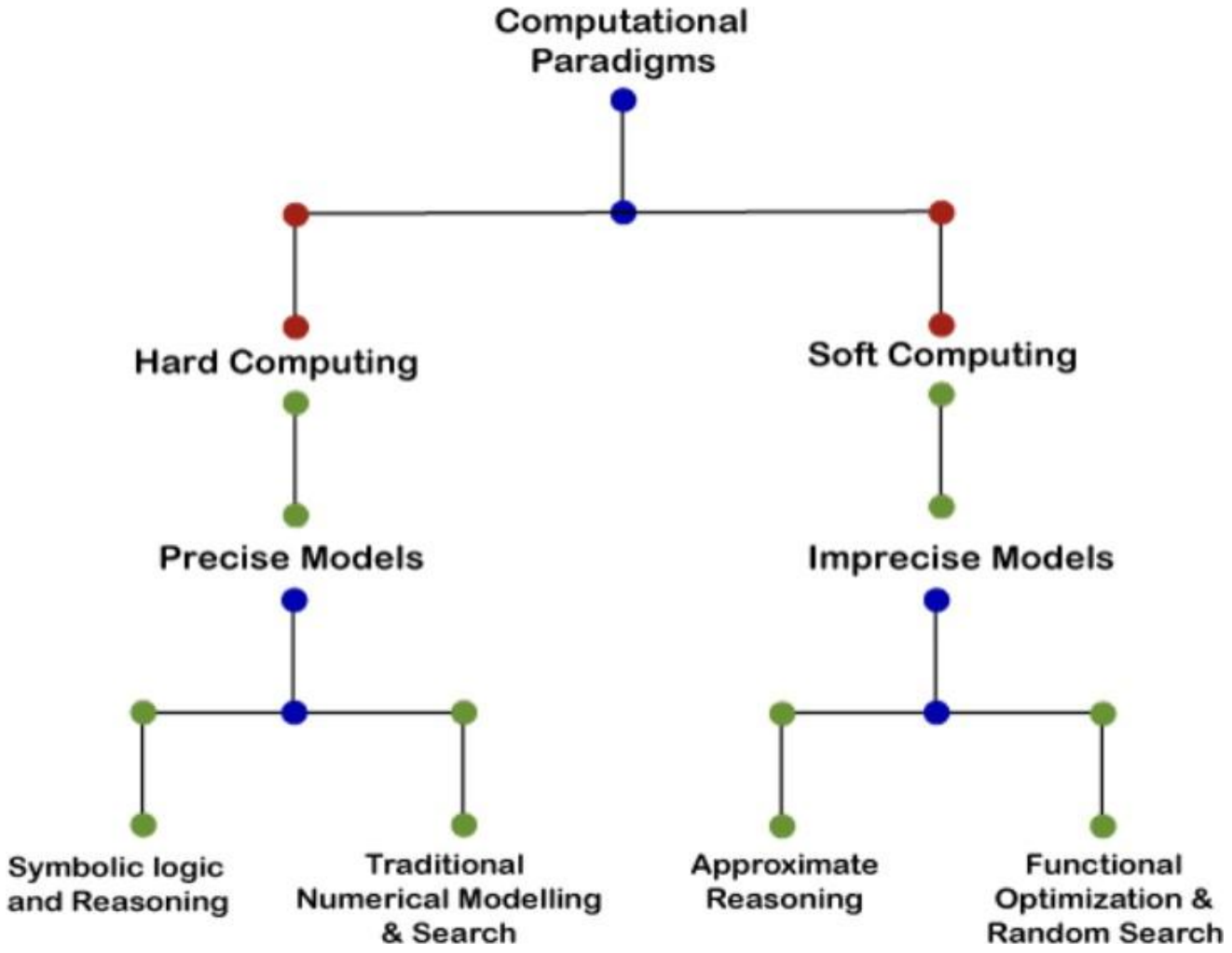
Identify the word

- dag or dog?
- If we are given a hint that it is an animal. Then we can say it is a dog.
- How we are able to find that?
- How a newborn understands fire is dangerous?
- What is the algorithm behind that ?
- We identified through experience and learning.
- This type of complex computation is called Soft Computing

Significance of precision in real world ?


Precision and Significance in the Real World
A 1500 kg mass is approaching your head at 45.3 m/s
LOOK OUT!!

Problem Solving Methodologies



Soft computing

- The term soft computing was proposed by the inventor of fuzzy logic, **Lotfi A. Zadeh**
  - Soft computing is a collection of methodologies that aim to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost.
  - The role model for soft computing is the human mind
- **Characteristics of soft computing**
  - It does not require any mathematical modeling of problem solving.
  - It may not yield the precise solution.
  - Adaptive (i.e., it can adjust to the change of dynamic environment).
  - Use some biological inspired methodologies such as genetics, evolution, Ant's behaviors, particles swarming, human nervous system, etc.).

Problem Solving Methodologies

- Symbolic logic & reasoning - deals with how symbols relate to each other. It assigns symbols to verbal reasoning in order to be able to check the veracity of the statements through a mathematical process. Used calculus
- Traditional numerical modelling and search - Numerical methods
- Approximate reasoning - x is small; x and y are approximately equal; therefore y is more or less small
- Functional optimization and random search

The difference between hard computing and soft computing are as follows

Hard Computing	Soft Computing
• The analytical model required by hard computing must be precisely represented	• It is based on uncertainty, partial truth tolerant of imprecision and approximation.
• Computation time is more	• Computation time is less
• It depends on binary logic, numerical systems, crisp software.	• Based on approximation and dispositional.
• Sequential computation	• Parallel computation
• Gives exact output	• Gives appropriate output
• Examples: Traditional methods of computing using our personal computer.	• Example: Neural networks like Adaline, Madaline, ART networks, etc.

Advantages of Soft Computing

It made for solving non−linear problems in which mathematical models are not available.

It introduced the human knowledge (*recognition, understanding, learning and others*) into the field of computing.

Why Soft Computing

- Human can:
  1. take decisions
  2. inferences from previous situation experienced
  3. expertise in an area
  4. adapt to changing environment
  5. learn to do better
  6. social behavior of collective intelligence

Fuzzy Logic

Neural Networks

Evolutionary algorithms

Soft computing

- There are three types of soft computing techniques
  - Artificial Neural Network
  - Fuzzy Logic
  - Genetic algorithm

Soft computing

- **Artificial Neural Network**

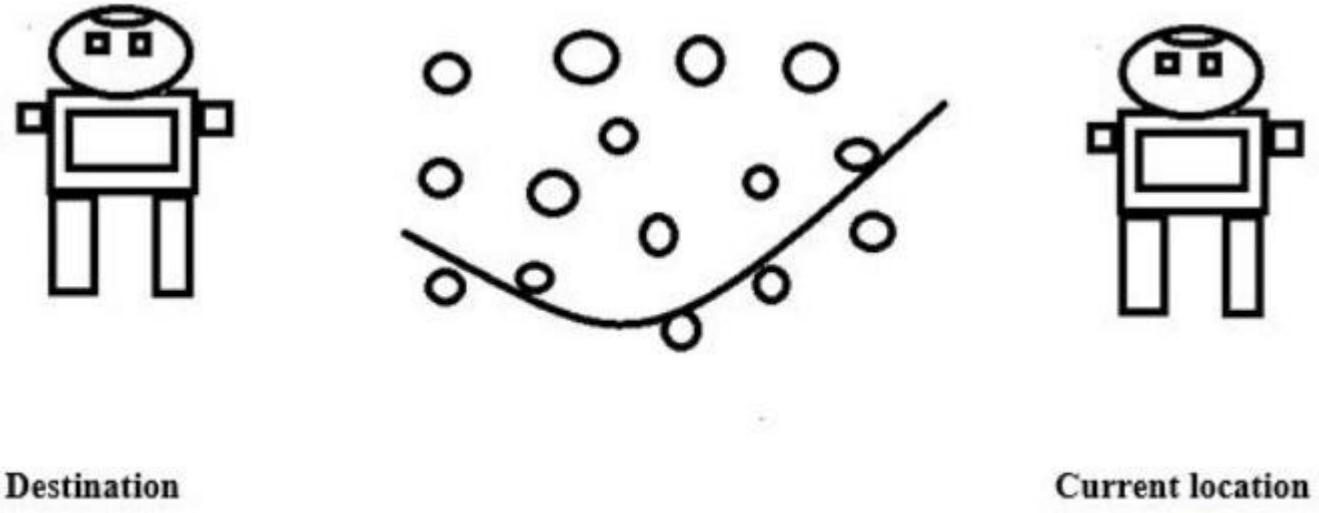
  - **Hand written character recognition (Artificial Neural Networks)**

How Soft Computing?

- **How a student learns from his teacher?**
- Teacher asks questions and tell the answers then.
- Teacher puts questions and hints answers and asks whether the answers are correct or not.
- Student thus learn a topic and store in his memory.
- Based on the knowledge he solves new problems.
- This is the way how human brain works.
- Based on this concept Artificial Neural Network is used to solve problems.

Soft computing

- Examples of soft computing-fuzzy logic



fuzzy – logic

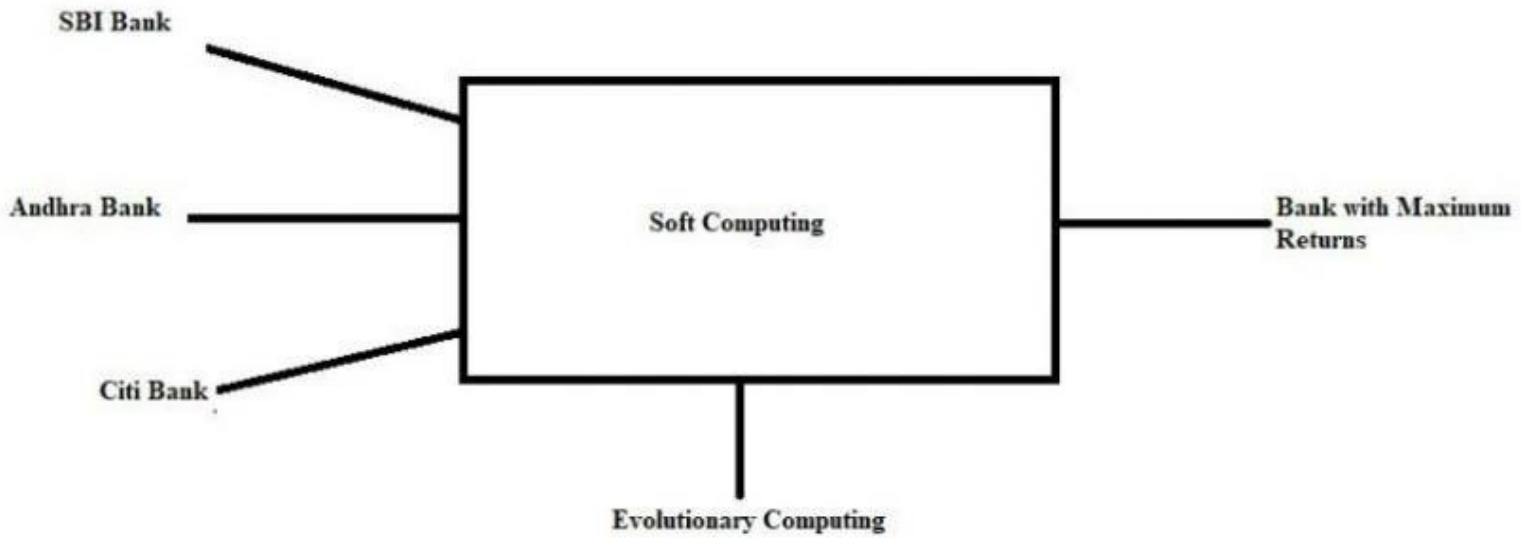
- An example of a robot that wants to move from one place to another within a short time where there are many obstacles on the way. Now the question arises is that how the robot can calculate its movement to reach the destination point, without colliding to any obstacle. These types of problems have uncertainty problem which can be solved using fuzzy logic

How Soft Computing?

- **How a doctor treats his patient?**
- Doctor asks the patient about suffering.
- Doctor find the symptoms of diseases.
- Doctor prescribed tests and medicines.
- This is exactly the way Fuzzy Logic works.
- Symptoms are correlated with diseases with uncertainty
- Doctor prescribes tests/medicines fuzzily

Soft computing

- Examples of soft computing-Genetic Algorithm



- A person who wants to invest some money in the bank, we know there are different banks available with different schemes and policies. Its individual interest how much amount to be invested in the bank, so that he can get maximum profit. There are certain criteria for the person that is, how he can invest and how can he get profited by investing in the bank. These criteria can be overcome by the “Evolutional Computing” algorithm like genetic computing.

How Soft Computing?

- **How world selects the best?**
- It starts with a population (random).
- Reproduces another population (next generation).
- Rank the population and selects the superior individuals.
- Genetic algorithm is based on this natural phenomena.
- Population is synonymous to solutions.
- Selection of superior solution is synonymous to exploring the optimal solution

Applications of Soft Computing

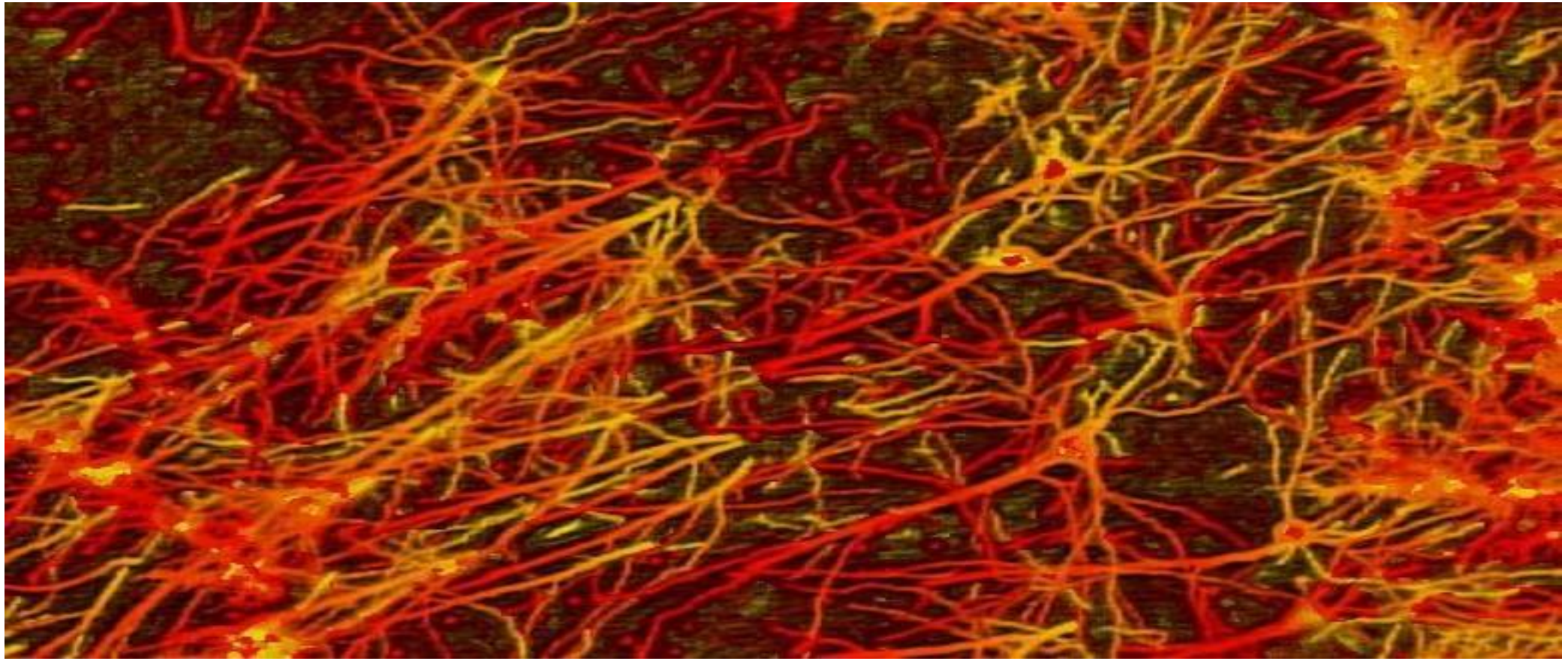
- Handwriting Recognition
- Image Processing and Data Compression
- Automotive Systems and Manufacturing
- Soft Computing to Architecture
- Decision-support Systems
- Soft Computing to Power Systems
- Soft computing in investment and trading
- Soft computing in bioinformatics

Biological Neural Network

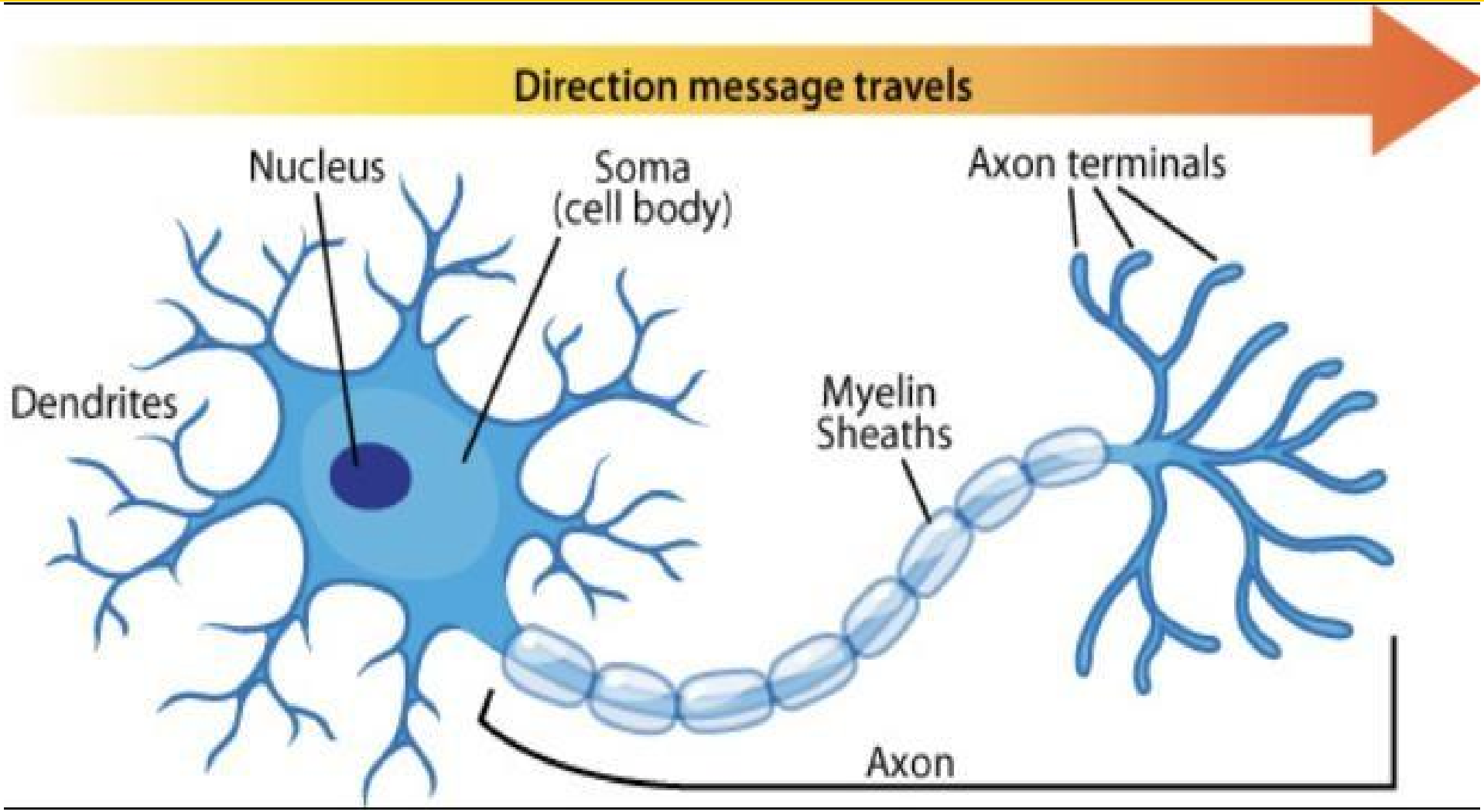
About Human Brain

- Cells within the nervous system, called neurons, communicate with each other in unique ways.
- The neuron is the basic working unit of the brain, a specialized cell designed to transmit information to other nerve cells, muscle, or gland cells.
- The human brain contains around 100 billion neurons(interconnected neurons)and each neuron can connect up to 2,00,000 other neurons.(10^{11} neurons approximately)
- Each neuron consists of a cell body, dendrites, and an axon.
- The approximate size of neuron body(in micrometer) is 10-80. The gap of Biological neuron at synapses is 200nm.

Interconnection in brain



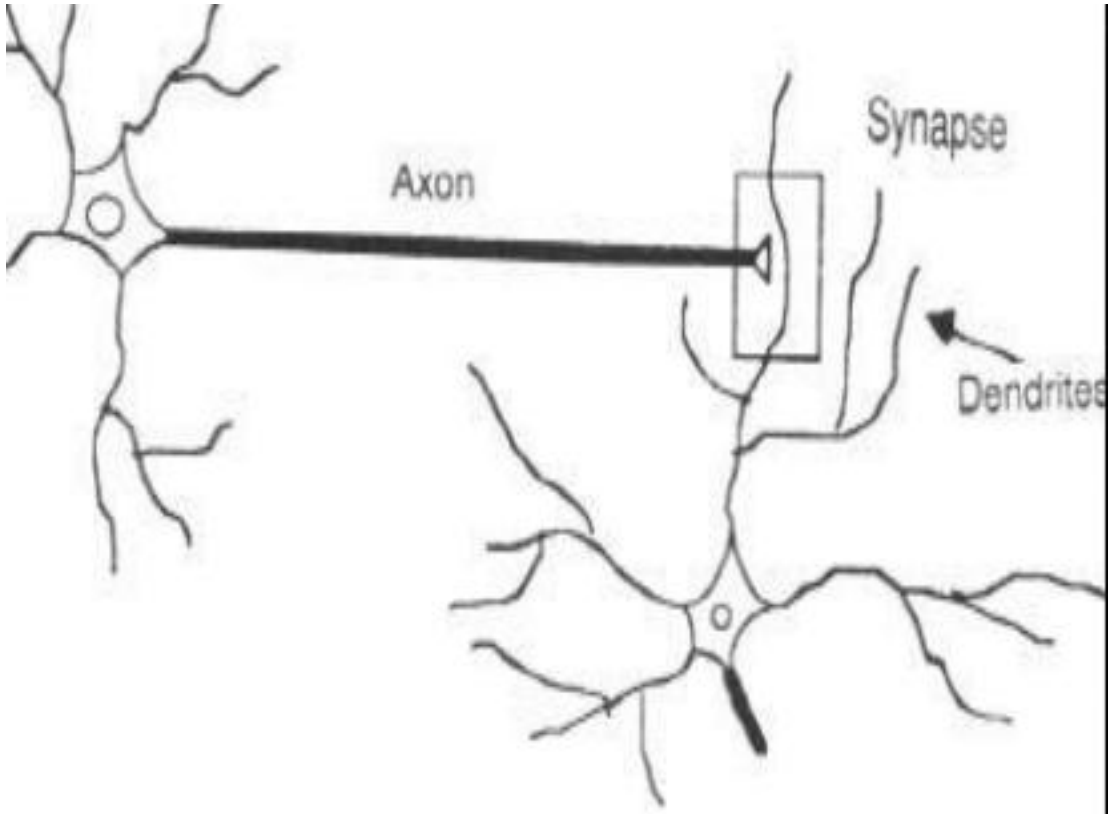
Biological Neurons



Biological Neurons

- It consists of
  - **Soma or cell body** where cell nucleus is situated
  - **Dendrites** –Tree like network made of nerve fibre connected to cell body which receives signals
  - **Axon**-Single long connection extending from the cell body which carries impulses of the neuron and transmit signals
  - **Synapse** –The end of the axon splits into fine strands, each strand terminates into a small bulb like organ called Synapse.
  - There are approximately 10^4 synapses/neurons in human brain.There are 10^{15} synaptic connection are there in human brain

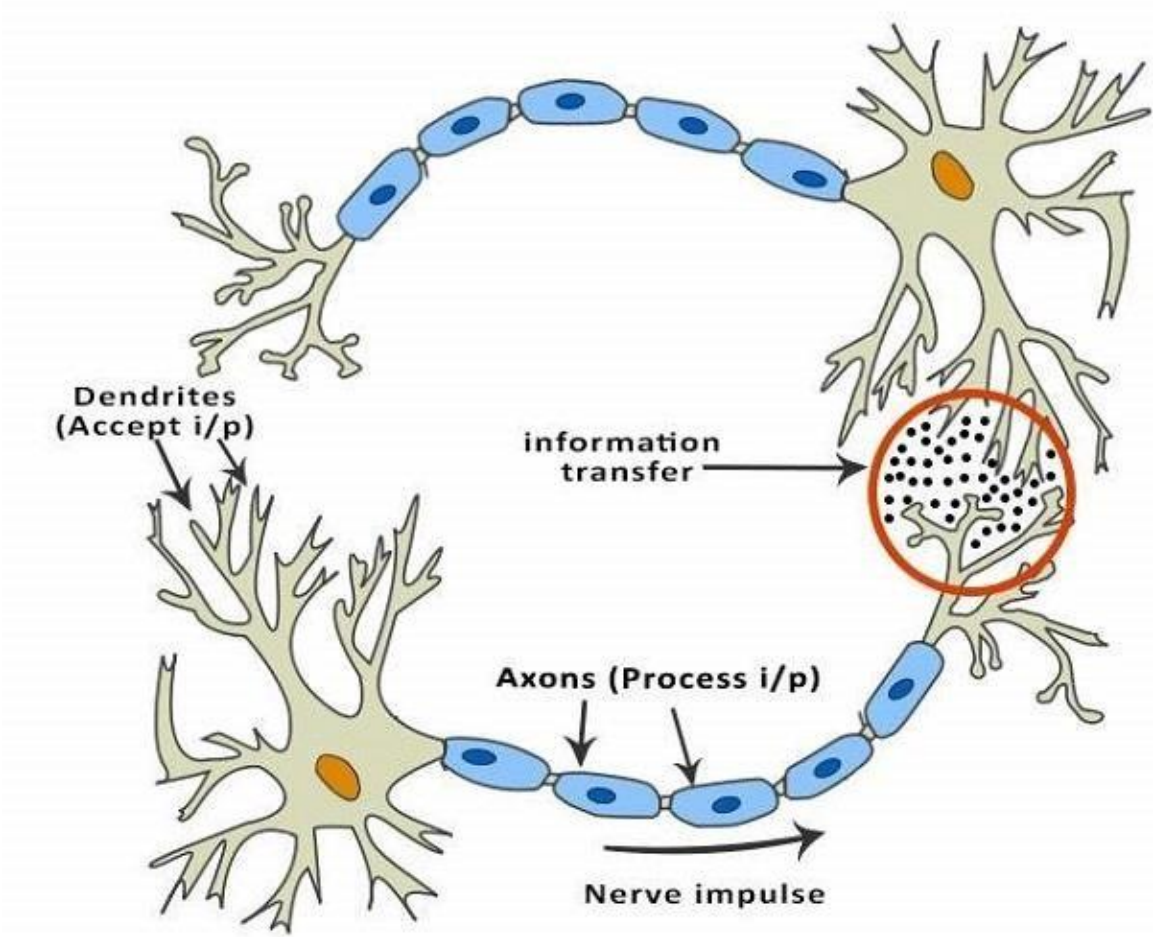
Biological Neurons



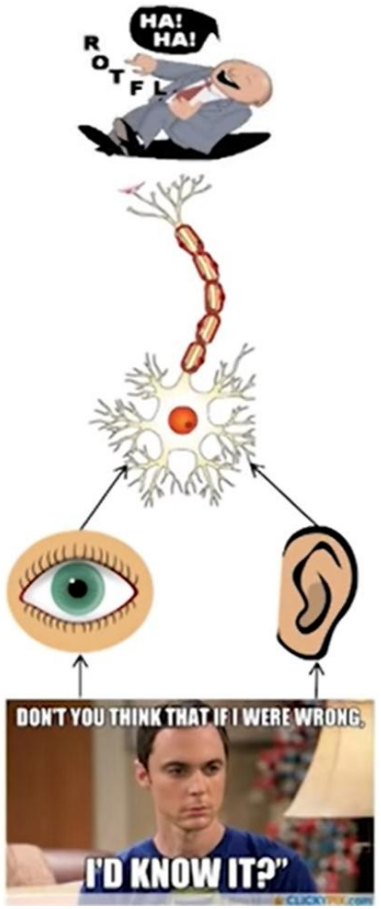
- ✓ In the human brain, a typical neuron collects signals from others through a host of fine structures called *dendrites*.
- ✓ The neuron sends out spikes of electrical activity through a long, thin stand known as an *axon*, which splits into thousands of branches.
- ✓ At the end of each branch, a structure called a *synapse* converts the activity from the axon into electrical effects that ***inhibit*** or **excite** activity in the connected neurons.

- Electric impulse is passed between synapse and dendrites.
- ***Synapse***- Axon split into strands and strands terminates into small bulb like organs called as synapse.
- It is a chemical process which results in increase /decrease in the electric potential inside the body of the receiving cell.
- If the electric potential reaches a threshold value, receiving cell fires & pulse / action potential of fixed strength and duration is send out through the axon to synaptic junction of the cell.
- After that, cell has to wait for a period called ***refractory period.***
- Synapses are said to be
  - ***Inhibitory*** **if the parsing impulses prevent the firing of receiving cell**
  - ***Excitatory*** **If the parsing impulses cause the firing of cells**

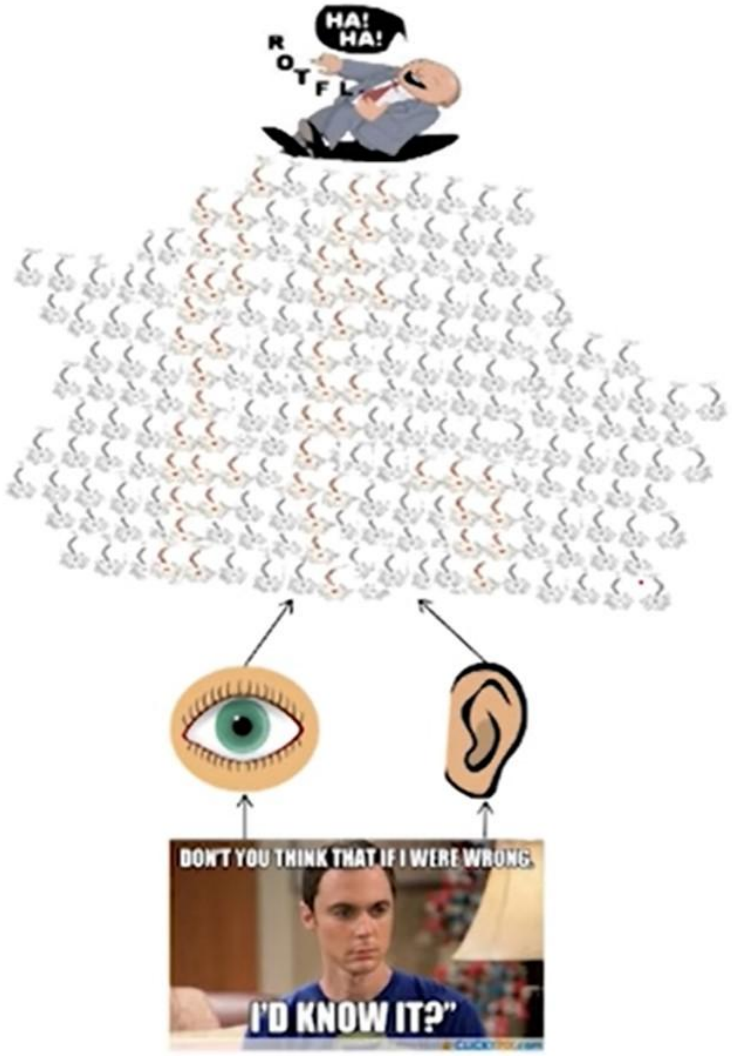
Biological Neurons



Working of neuron

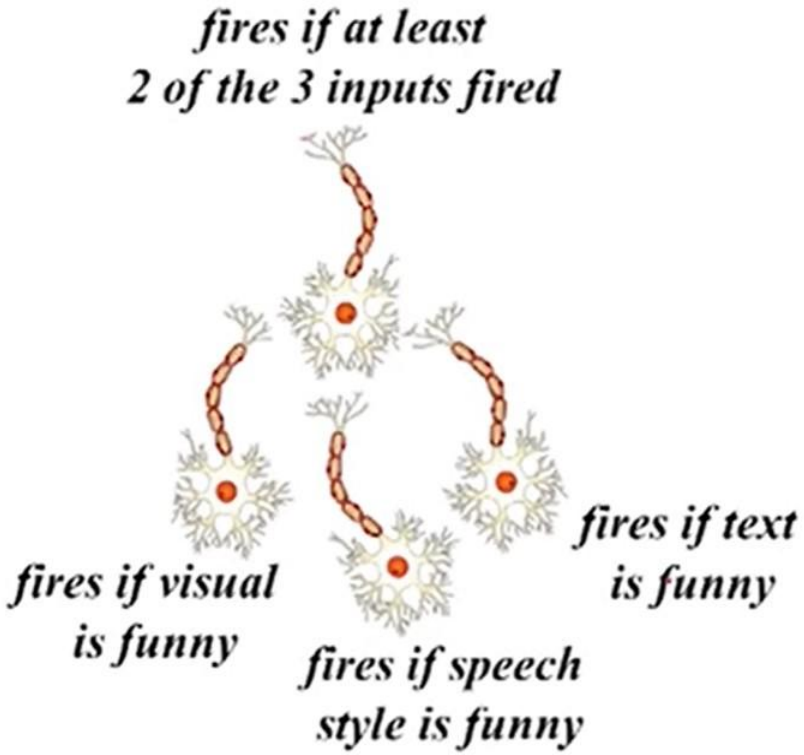


- Let us see a very cartoonish illustration of how a neuron works
- Our sense organs interact with the outside world
- They relay information to the neurons
- The neurons (may) get activated and produces a response (laughter in this case)



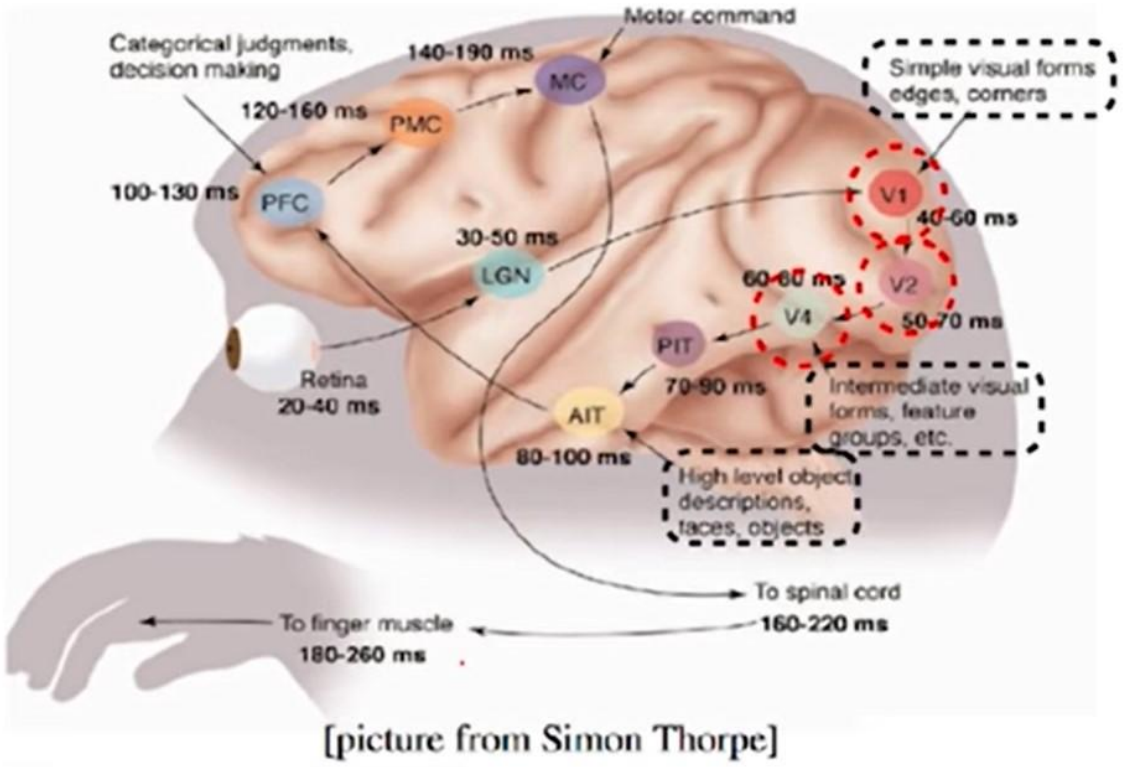
- Of course, in reality, it is not just a single neuron which does all this
- There is a massively parallel interconnected network of neurons
- The sense organs relay information to the lowest layer of neurons
- Some of these neurons may fire (in red) in response to this information and in turn relay information to other neurons they are connected to
- These neurons may also fire (again, in red) and the process continues eventually resulting in a response (laughter in this case)
- An average human brain has around 10^{11} (100 billion) neurons!

Working of neuron



- This massively parallel network also ensures that there is division of work
- Each neuron may perform a certain role or respond to a certain stimulus

Hierarchical Processing of Brain



[picture from Simon Thorpe]

Layer 1: detect edges & corners

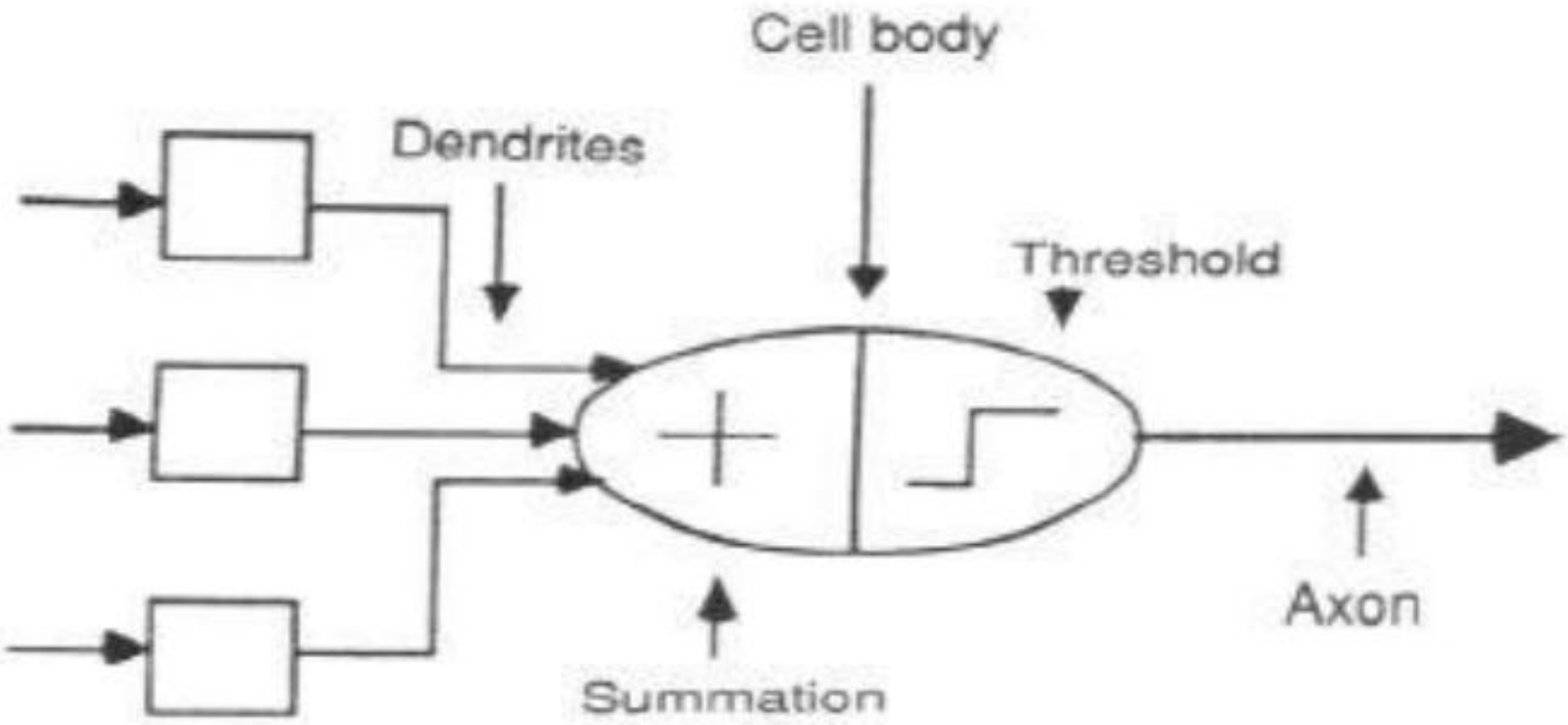
Layer 2: form feature groups

Layer 3: detect high level objects, faces, etc.

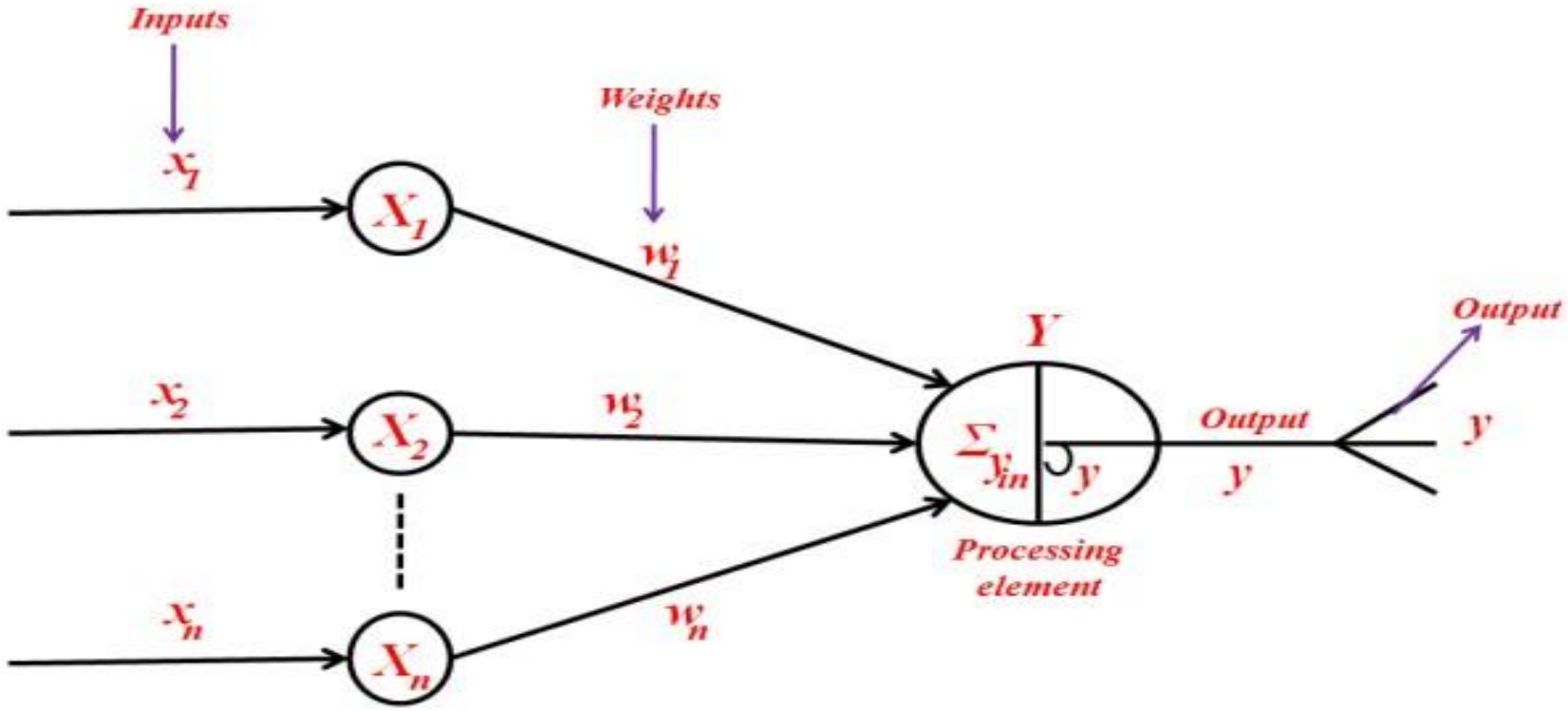
Sample illustration of hierarchical processing*

Artificial Neural Network

ASSOCIATION OF BIOLOGICAL NET WITH ARTIFICIAL NET



Mathematical model



The net input is calculayed as

$$y_{in} = x_1 w_1 + x_2 w_2 + \ldots + x_n w_n = \sum_{i=1}^{n} x_i w_i$$

Mathematical model

- The weight represent the strength of the synapse connecting input and the output neuron
- A positive weight corresponds to the excitatory synapses
- A negative weight corresponds to the inhibitory synapses

Biological neuron vs Artificial neuron

Biological neuron	Artificial neuron
Cell	Neuron
Dendrites	Weights or interconnections
Soma	Net input
Axon	Output

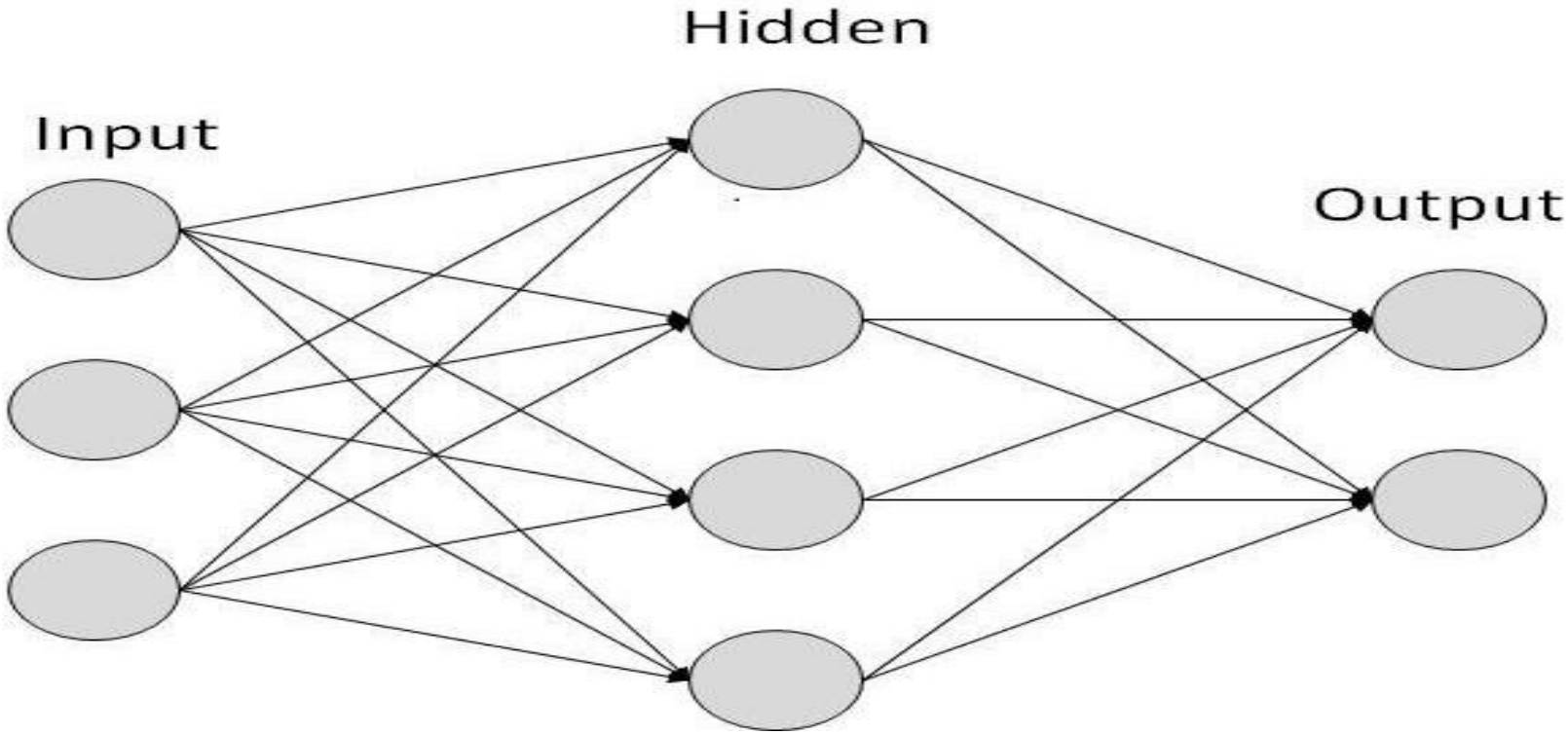
What are neural network?

- ***Neural Networks*** (NNs) are networks of neurons, for example, as found in real (i.e. biological) brains.
- ***Artificial Neurons*** are crude approximations of the neurons found in brains. They may be physical devices, or purely mathematical constructs.
- ***Artificial Neural Networks*** (ANNs) are networks of Artificial Neurons, and hence constitute crude approximations to parts of real brains. They may be physical devices, or simulated on conventional computers.
- From a practical point of view, an ANN is just a parallel computational system consisting of many simple processing elements connected together in a specific way in order to perform a particular task.

Artificial Neural Network

- ANN is an efficient Information processing paradigm which resembles the characteristics of a biological neural network.
- ANN is composed of **large number of interconnected processing elements called neurons or nodes**
- Each neuron is connected with the other by a connection link.
- Each connection link is associated with weights which contain information about the input signal.
- This information is used by the neurons net to solve a particular problem

Artificial Neural Network

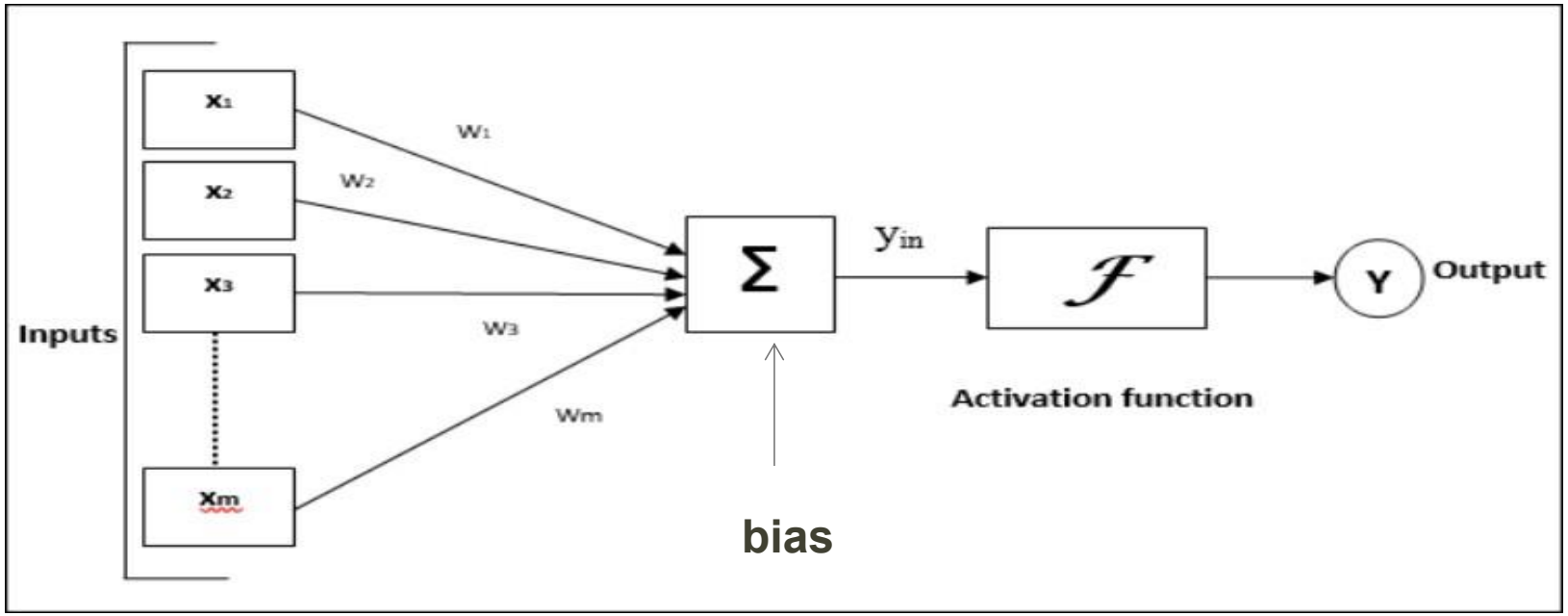


Types of layers

- The input layer.
  - Introduces input values into the network.
  - No activation function or other processing.
- The hidden layer(s).
  - Perform classification of features
  - Two hidden layers are sufficient to solve any problem
  - Features imply more layers may be better
- The output layer.
  - Functionally just like the hidden layers
  - Outputs are passed on to the world outside the neural network.

Artificial Neuron Model

- ANN is a model that simulates the human brain created artificially to solve complex problems
- To depict the basic operation of neuron net ,consider a set of neurons, say x_1, x_2.---x_m are the input signals and Y_{in} is the Net input and 'y' is the output neuron which receives the signal.
- Each neuron is connected to other neuron by means of directed communication links and associated with weights w_1, w_2,.....w_m



Artificial Neuron Model

For the above general model of artificial neural network, the net input can be calculated as follows −

$$y_{in} = x_1.w_1 + x_2.w_2 + x_3.w_3 \ldots x_m.w_m$$

i.e., Net input $y_{in} = \sum_i^m x_i.w_i$

The output can be calculated by applying the activation function over the net input.

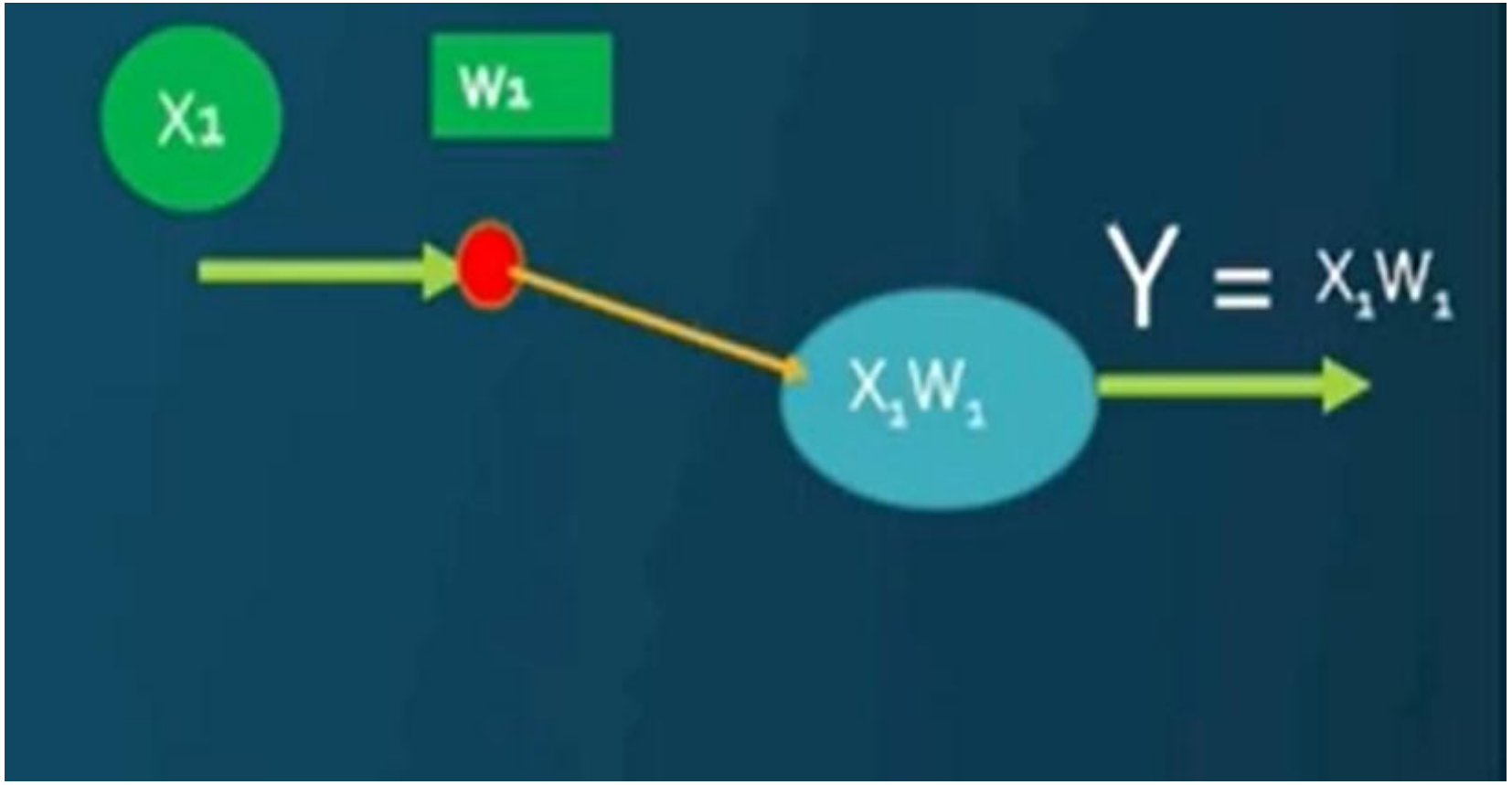
$$Y = F(y_{in})$$

Output = function $netinputcalculated$

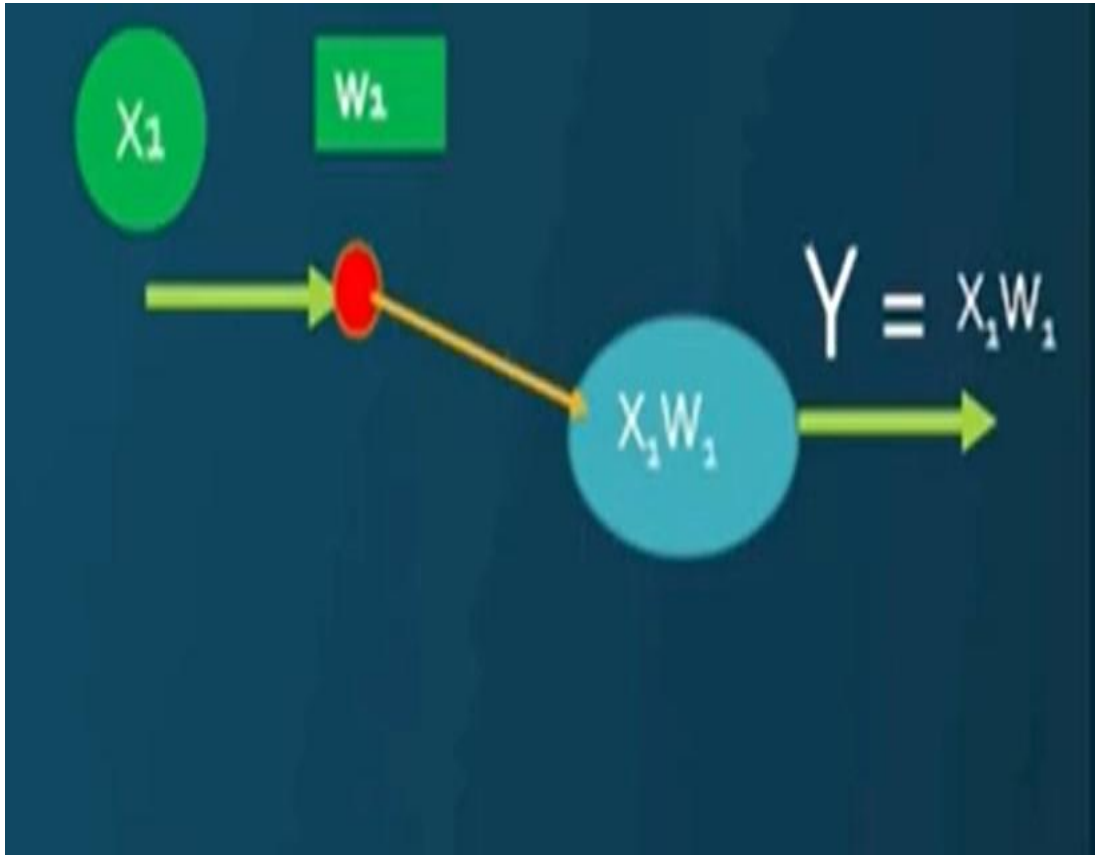
Artificial Neuron Model- additional points

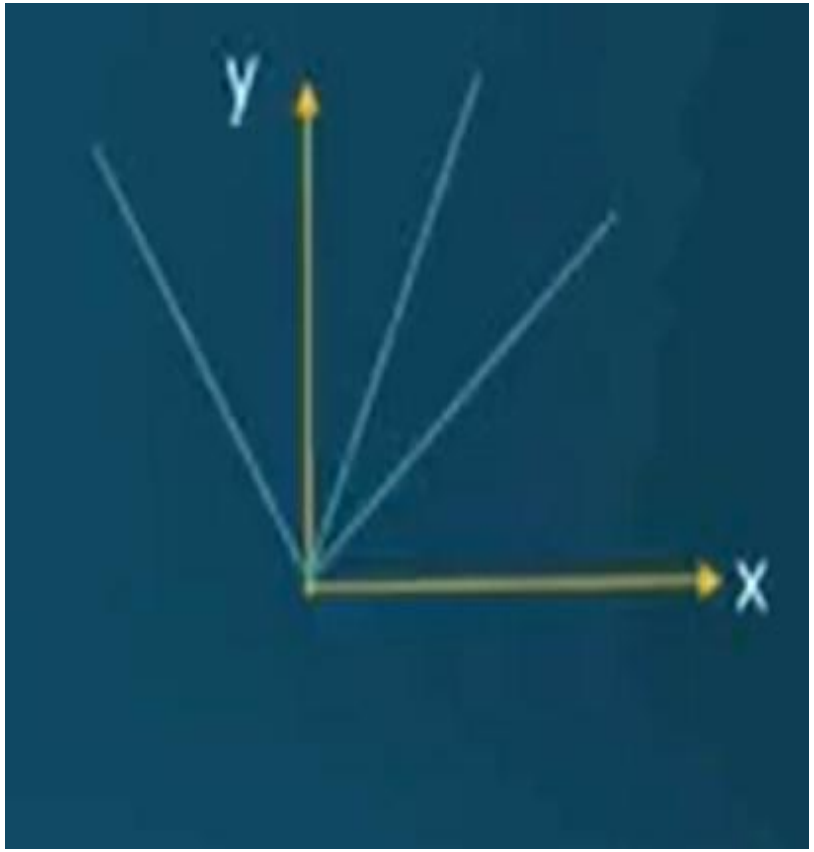
- The function to be applied over the net input is called the activation functions
- i represent the ith processing element
- w weight represents the strength of synapse connecting the input and output neurons
- Excitatory Synapse –Positive Weights
- Inhibitory Synapse –Negative Weights
- Bias Bias included in the network has its impact in calculating the net input
- Bias is included by adding $x_0=1$ to the input vector x.so the input signal value can be 1 and denoted by b and can be considered like another weight with weight 1.
- Negative bias helps in decreasing the net input of the network
- Positive bias helps in increasing the net input of the network
- As a result of the bias effect ,output of the network can be varied

Why Bias?

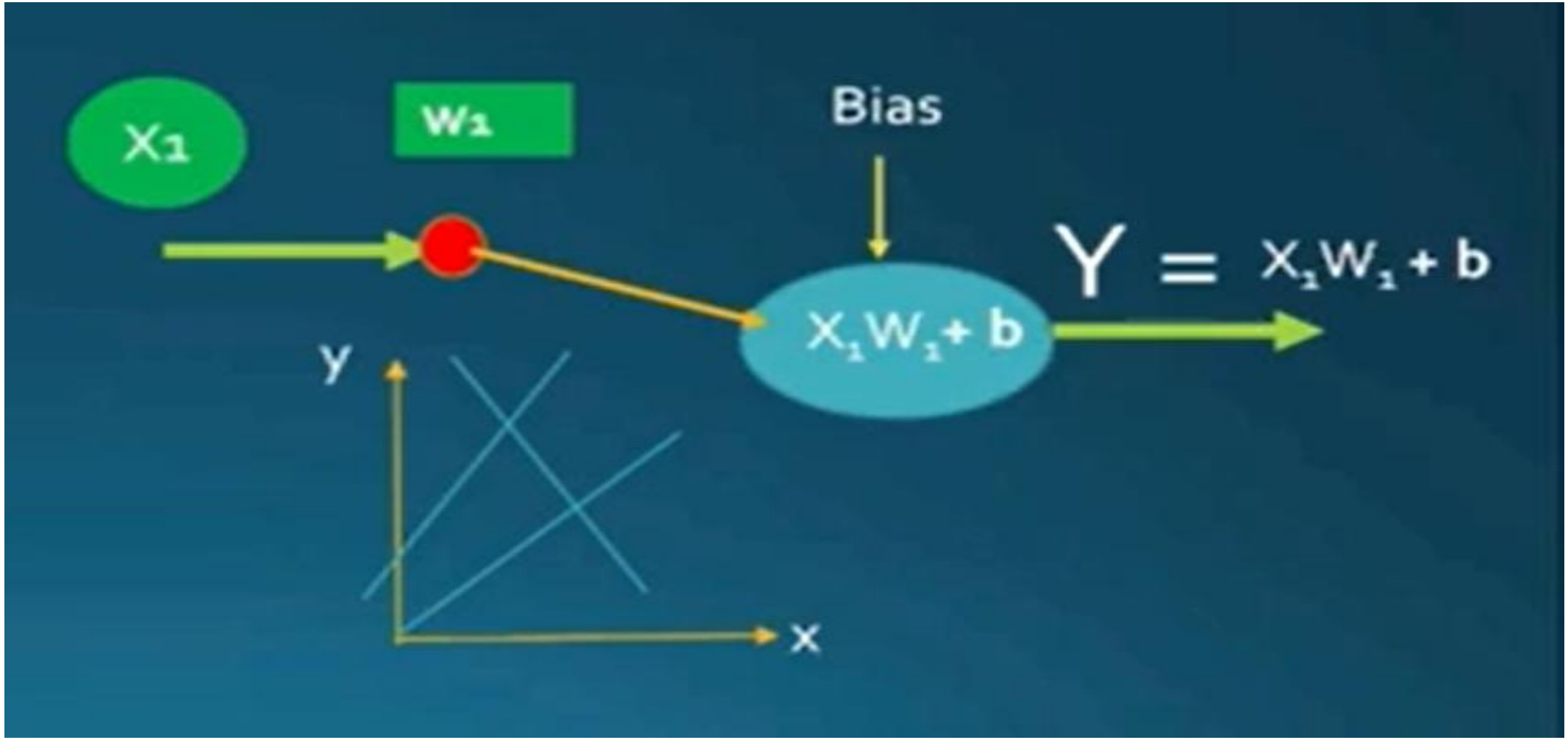


Why Bias?

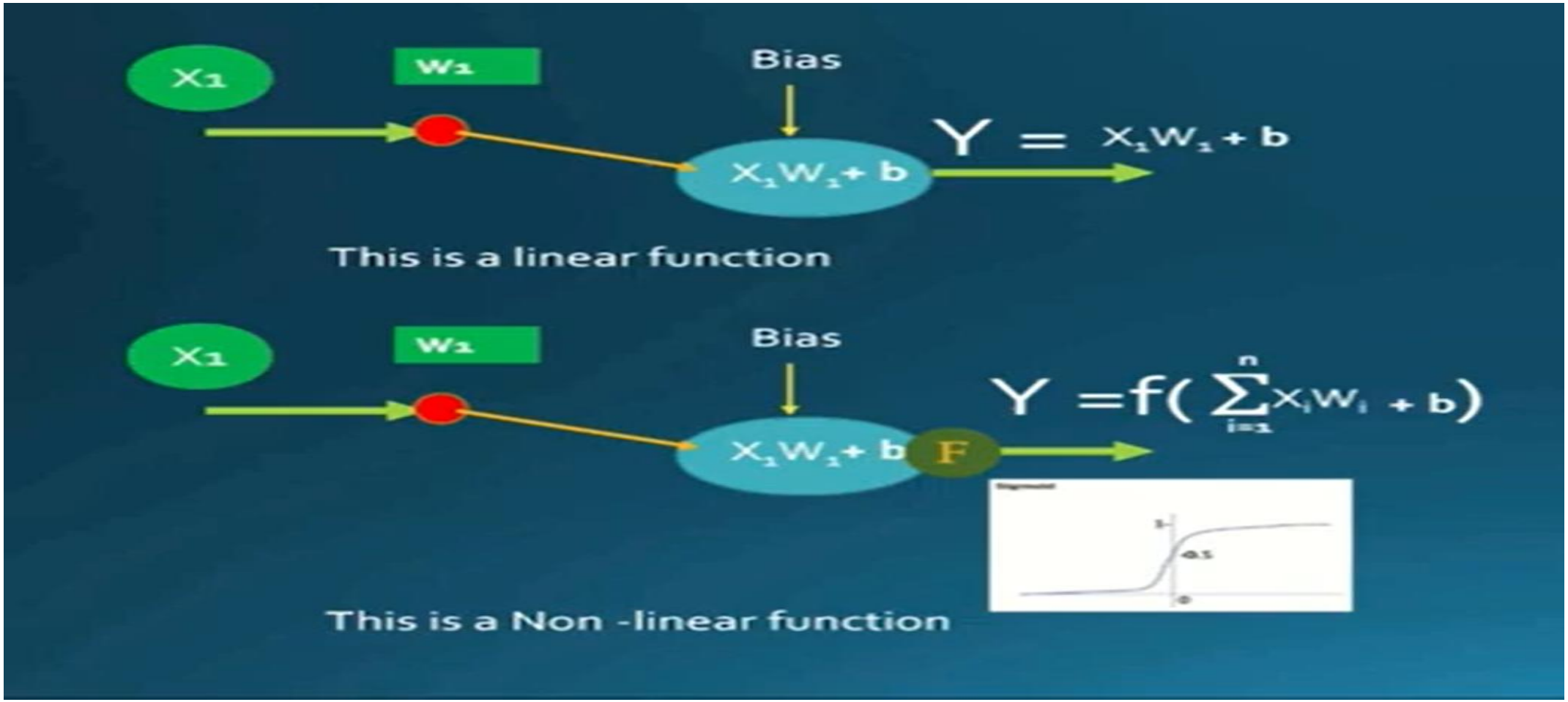




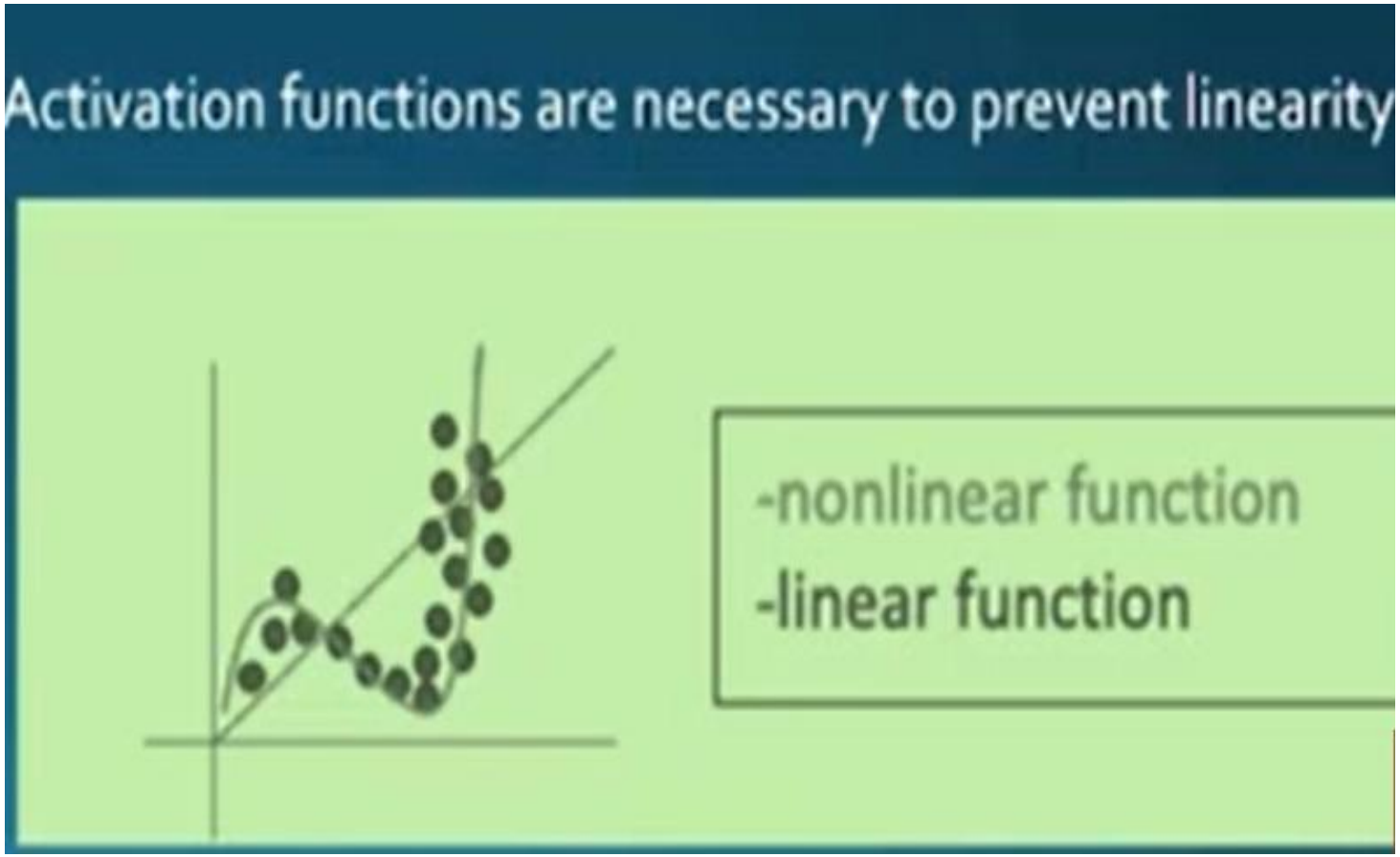
Why Bias?



Why Activation function?



Why Activation function?



Comparison between ANN and BNN

	BNN	ANN
Processing	Massively parallel, slow but superior than ANN	Massively parallel, fast but inferior than BNN
Size	10^{11} neurons and 10^{15} interconnections	10^{2} to 10^{4} nodes
Learning	They can tolerate ambiguity	Very precise, structured and formatted data is required to tolerate ambiguity
Fault tolerance	Performance degrades with even partial damage	It is capable of robust performance, hence has the potential to be fault tolerant
Storage capacity	Stores the information in the synapse	Stores the information in continuous memory locations

Advantages of ANN

- Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
- Self-Organisation: An ANN can create its own organisation or representation of the information it receives during learning time.
- 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.

Features of ANN

- Parallel Distributed information processing
- High degree of connectivity between basic units
- Connections are modifiable based on experience
- Learning is a continuous unsupervised process
- Learns based on local information
- Performance degrades with less units

Evolution of neural network

Year	Neural network	Designer	Description
1943	McCulloch and Pitts neuron	McCulloch and Pitts	Arrangement of neurons is combination of logic gate. Unique feature is threshold
1949	Hebb network	Hebb	If two neurons are active, then their connection strengths should be increased.
1958,1959, 1962,1988, 1960	Perceptron Adaline	Frank Rosenblatt, Block, Minsky and Papert Widrow and Hoff	Weights are adjusted to reduce the difference between the net input to the output unit and the desired output

Evolution of neural network

Year	Neural network	Designer	Description
1972	Kohonen self-organizing feature map	Kohonen	Inputs are clustered to obtain a fired output neuron.
1982,1984, 1985,1986, 1987	Hopfield network	John Hopfield and Tank	Based on fixed weights. Can act as associative memory nets
1986	Back propagation network	Rumelhart, Hinton and Williams	i) Multilayered ii) Error propagated backward from output to the hidden units

Evolution of neural network

Year	Neural network	Designer	Description
1988	Counter propagation network	Grossberg	Similar to kohonen network
1987-1990	Adaptive resonance Theory(ART)	Carpenter and Grossberg	Designed for binary and analog inputs.
1988	Radial basis function network	Broomhead and Lowe	Resemble back propagation network , but activation function used is Gaussian function
1988	Neo cognitron	Fukushima	For character recogniton.

Problems

Problem

Q1:Calculate the net input of the following network

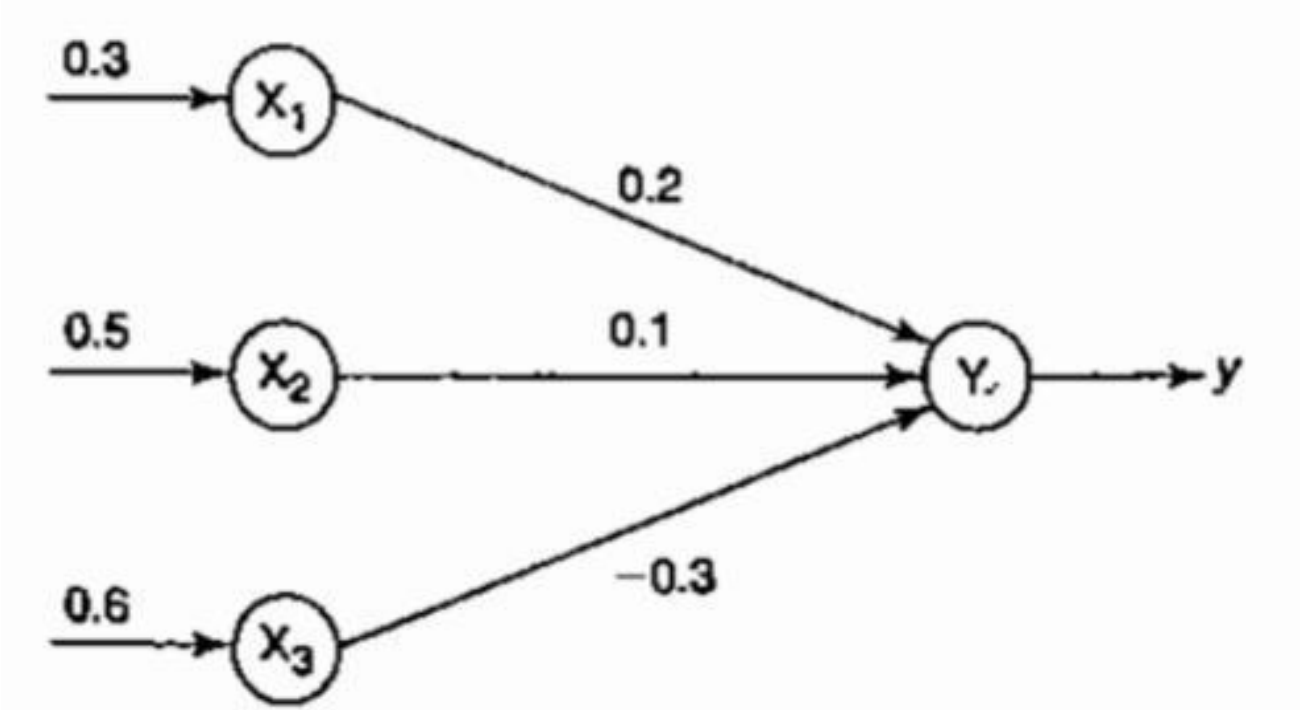


Figure 1 Neural net.

Problem

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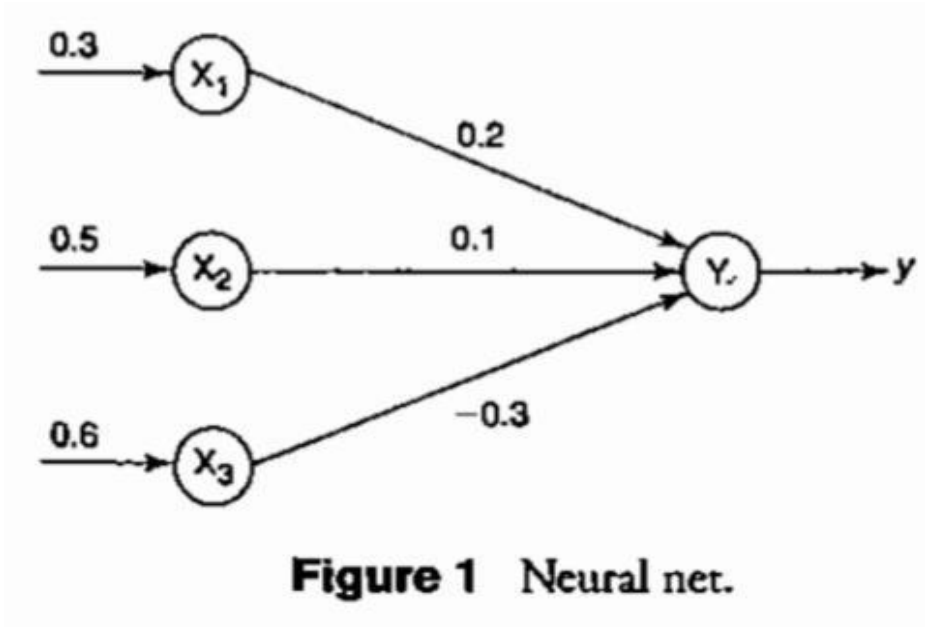


Figure 1 Neural net.

The given neural n/w has 3 i/p neurons and one o/p neuron.

Inputs, $X = [x_1, x_2, x_3] = [0.3, 0.5, 0.6]$

weights, $W = [w_1, w_2, w_3] = [0.2, 0.1, -0.3]$

The net i/p can be calculated as

$$y_{in} = x_1 w_1 + x_2 w_2 + x_3 w_3$$

$$= 0.3 \times 0.2 + 0.5 \times 0.1 + 0.6 \times -0.3$$

$$= -0.07$$

Problem

Q2:Calculate the net input of the following network

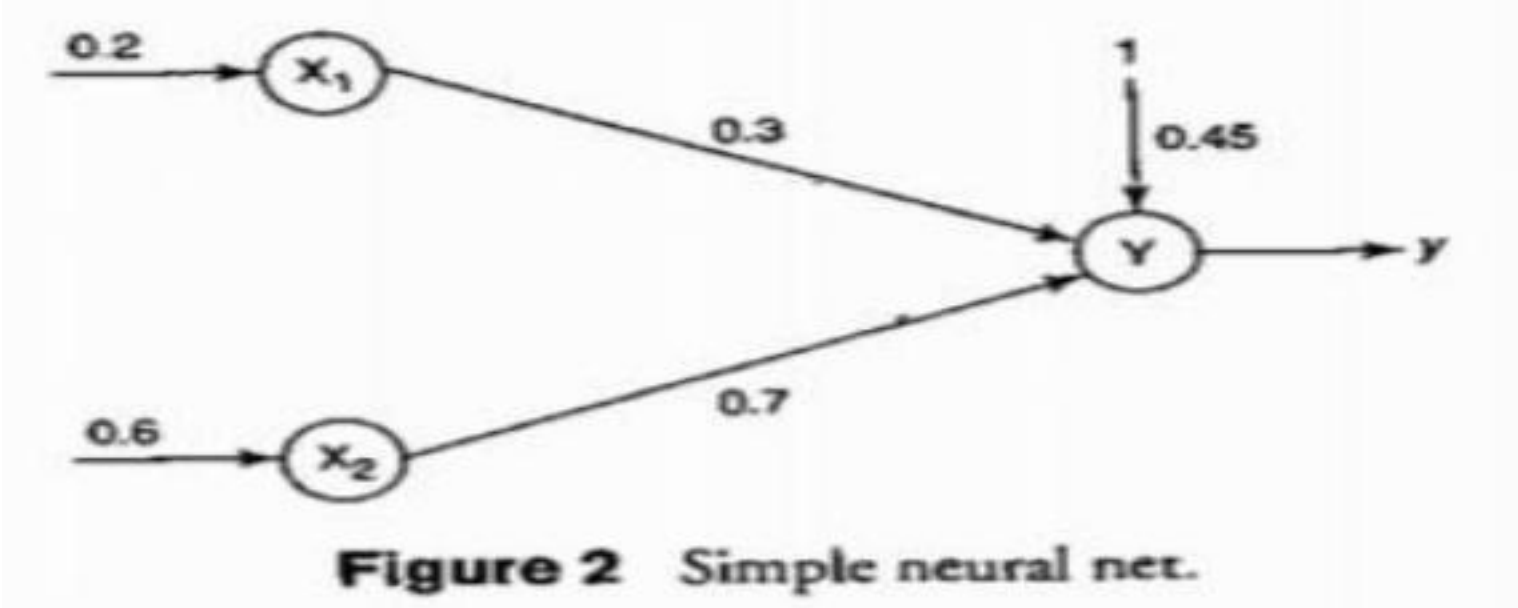


Figure 2 Simple neural net.

The net input to the output neuron is

$$y_{in} = b + \sum_{i=1}^{n} x_i w_i$$

Problem

Q2:Calculate the net input of the following network

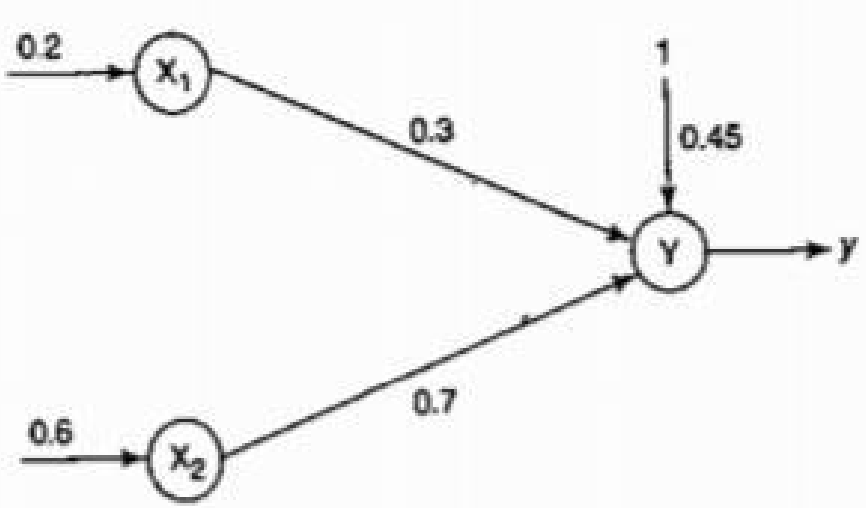


Figure 2 Simple neural net.

The net input to the output neuron is

$$y_{in} = b + \sum_{i=1}^{n} x_i w_i$$

Input, $x = [x_1, x_2] = [0.2, 0.6]$

Weight, $w = [w_1, w_2] = [0.3, 0.7]$

The net i/p calculated with bias included,

$$y_{in} = x_0 w_0 + x_1 w_1 + x_2 w_2$$

where x_0 is the bias i/p and w_0 (b) is the bias weight

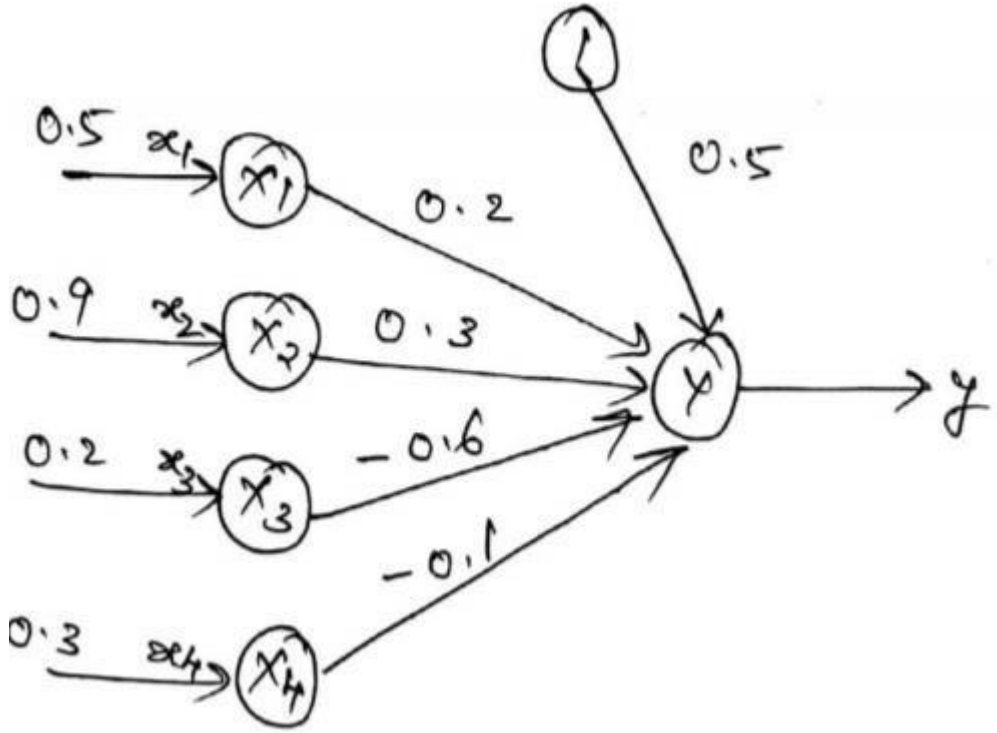
i.e, $x_0 = 1$ and w_0 or $b = 0.45$

$$\therefore y_{in} = 1 \times 0.45 + 0.2 \times 0.3 + 0.6 \times 0.7$$

$$= \underline{0.93}$$

Problems

Q3:Calculate the net input of the following network



The net input to the output neuron is

$$y_{in} = b + \sum_{i=1}^{n} x_i w_i$$

Problems

The given neural n/w has 4 i/p neurons, and one o/p neuron.

Input, $x = [x_1, x_2, x_3, x_4] = [0.5, 0.9, 0.2, 0.3]$

weight, $w = [w_1, w_2, w_3, w_4] = [0.2, 0.3, -0.6, -0.1]$

The net i/p calculated with bias included

$$y_{in} = x_0 w_0 + x_1 w_1 + x_2 w_2 + x_3 w_3 + x_4 w_4$$

where x_0 is the bias i/p and

w_0 is the Bias weight.

i.e, $x_0 = 1$ and $w_0 = 0.5$

$$\therefore y_{in} = 1 \times 0.5 + 0.5 \times 0.2 + 0.9 \times 0.3 + 0.2 \times -0.6 + 0.3 \times -0.1$$

$$= \underline{0.72}$$

Basic models of Artificial Neural Networks

Basic models of artificial neural networks

- The models of Artificial neural network is characterized by three basic entities namely

    1. *Connections* between the neurons called its *architecture*
    2. Training or *learning rules* *adopted for updating and adjusting weights* on the connections
    3. *Activation function*.

Connections

Connections

- The *arrangement of neurons to form layers* and the *connection pattern formed within and between layers* is called the ***network architecture***

Connections

- Generally there are two categories of neural network connections

1. Feed forward network / Feedback network
2. Single layer / Multi layer network

- A neural net in which the signals flow from the input units to the output units in a forward direction is called feed-forward network
- If outputs are directed back as input to the processing elements in the same layer/proceeding layer –feedback network.

Feedback network

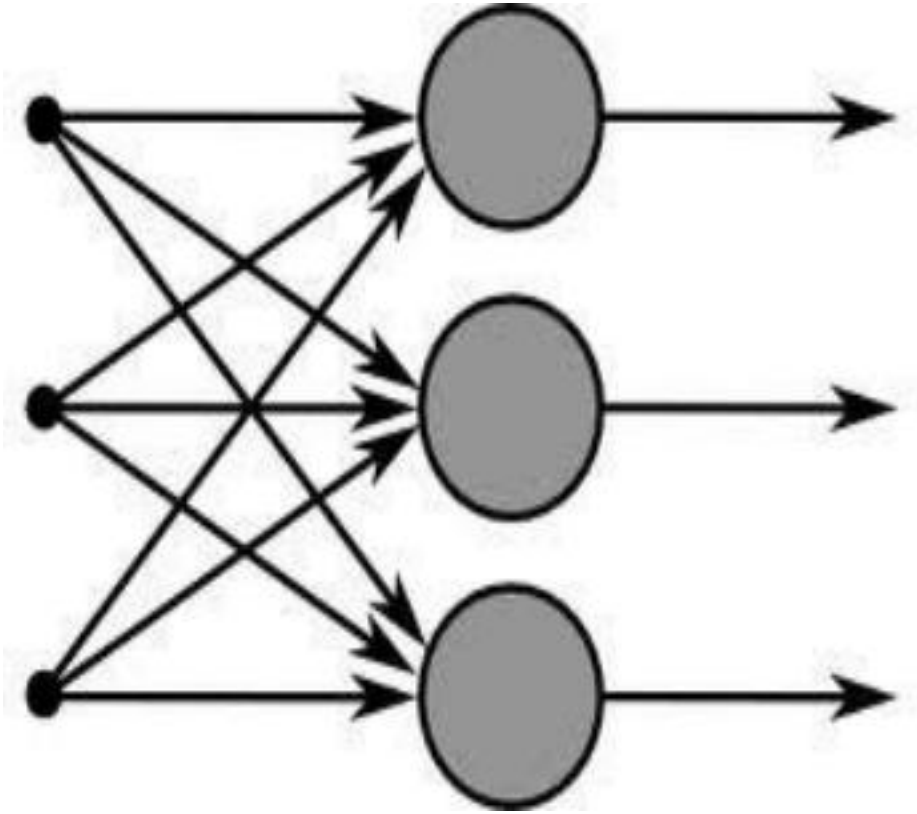
- If the output are directed back to the input of the same layer then it is ***lateral feedback.***
- ***Recurrent networks*** are networks with feedback networks with closed loop.

Connections

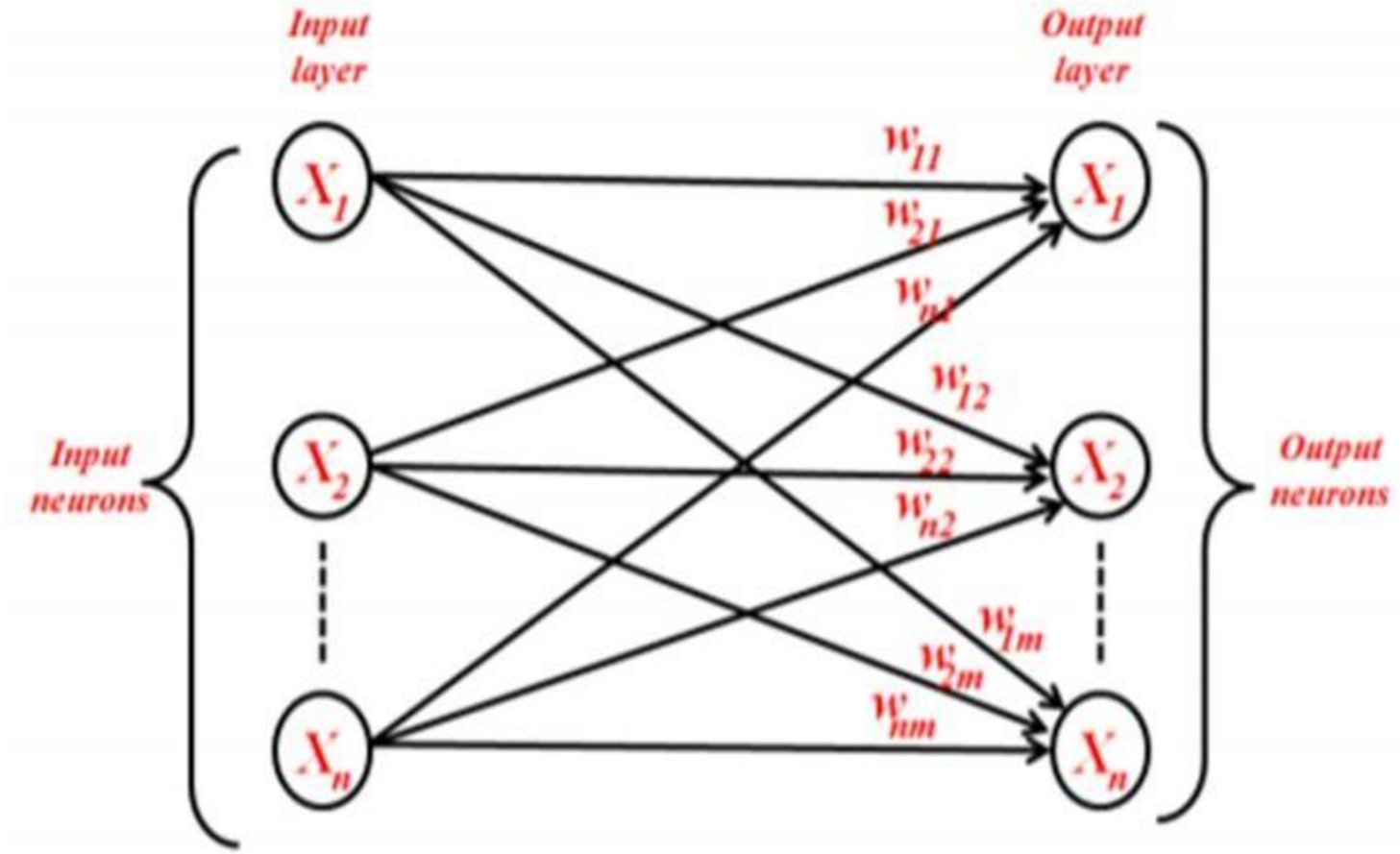
- Five types:
  - ***Single layer feed forward network***
  - ***Multilayer feed-forward network***
  - ***Single node with its own feedback***
  - ***Single-layer recurrent network***
  - ***Multilayer recurrent network***

Single layer Feed- Forward Network

- Layer is formed by taking processing elements and combining it with other processing elements.
- Input and output are linked with each other
- Inputs are connected to the processing nodes with various weights, resulting in series of outputs one per node.

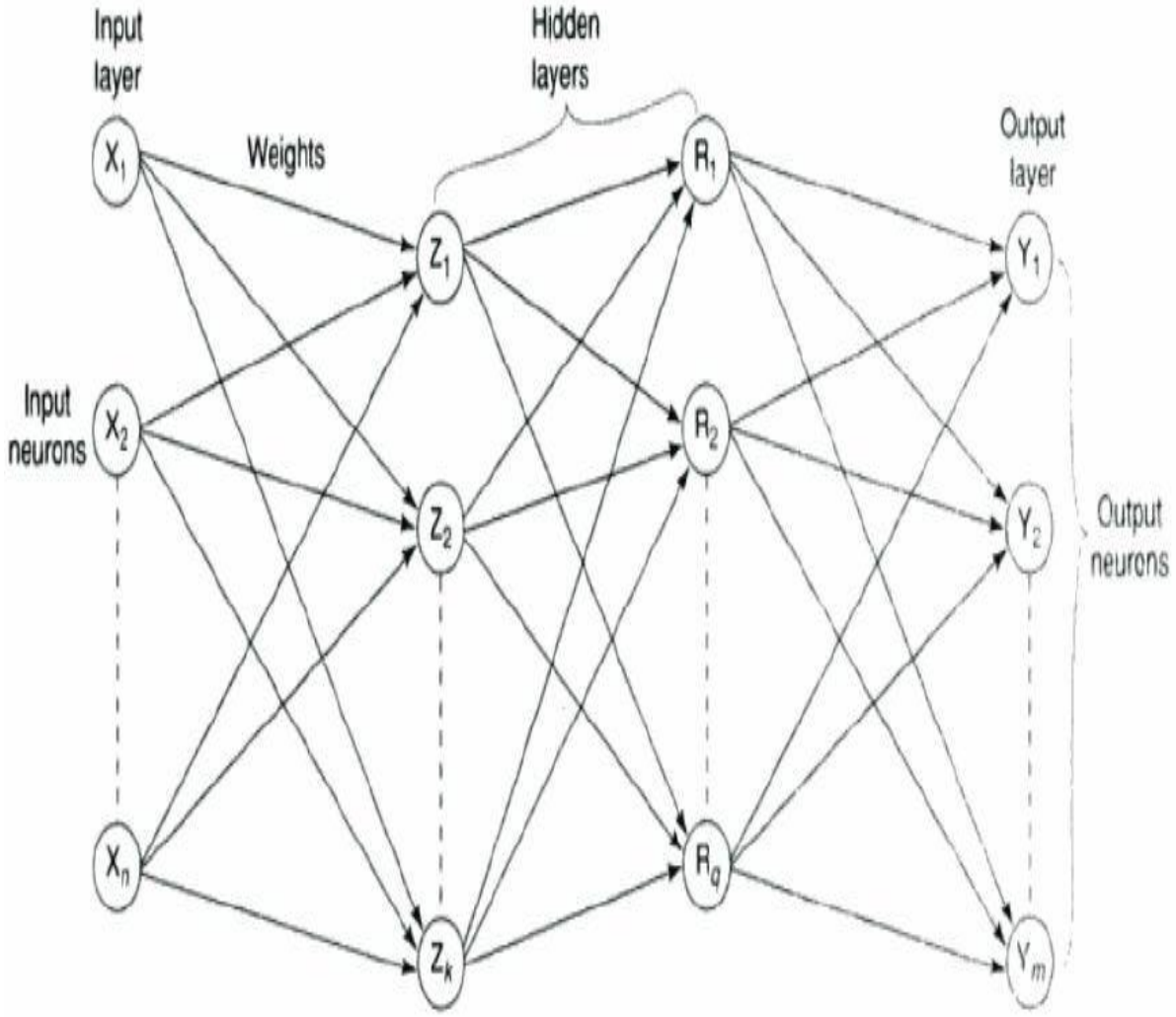


Single layer feed forward network



Multilayer feed-forward network

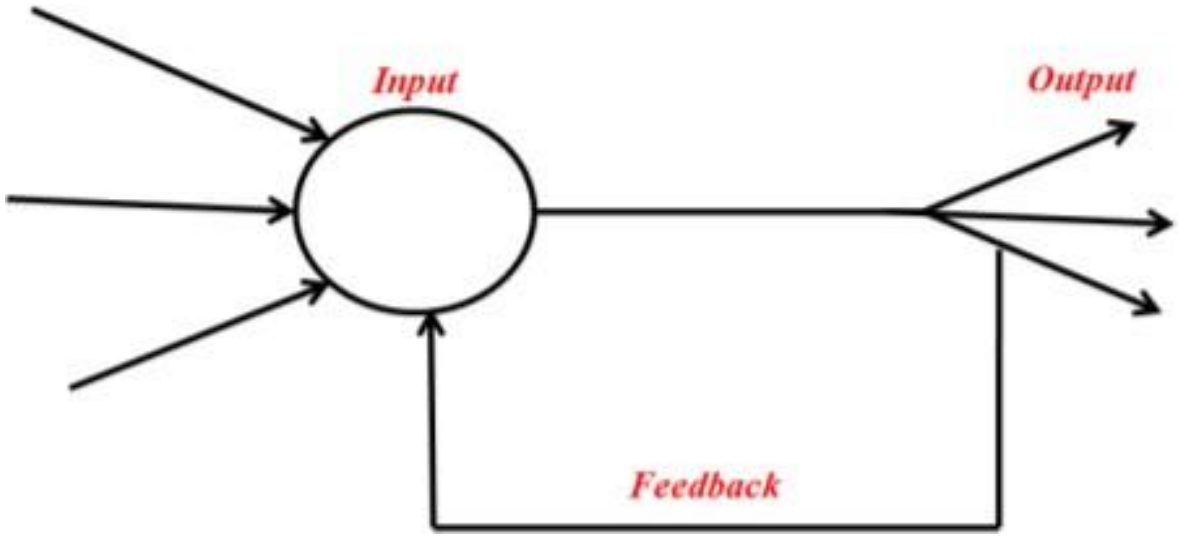
- Formed by the interconnection of several layers.
- Input layer receives input and buffers input signal.
- Output layer generated output.
- Layer between input and output is called ***hidden layer.***
- Hidden layer is internal to the network.
- More the hidden layer, more is the complexity of network, but efficient output is produced.



Connections

Single node with its own feed back

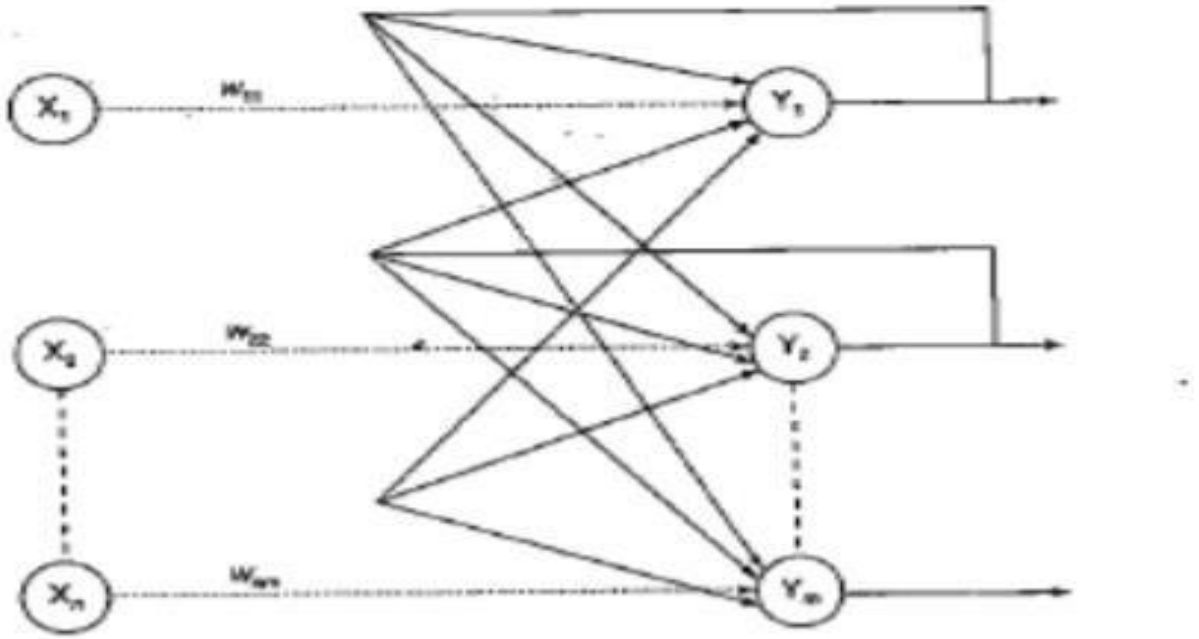
- This shows a simple recurrent neural network model having a single neuron with Feedback to itself



Connections

Single layer recurrent network

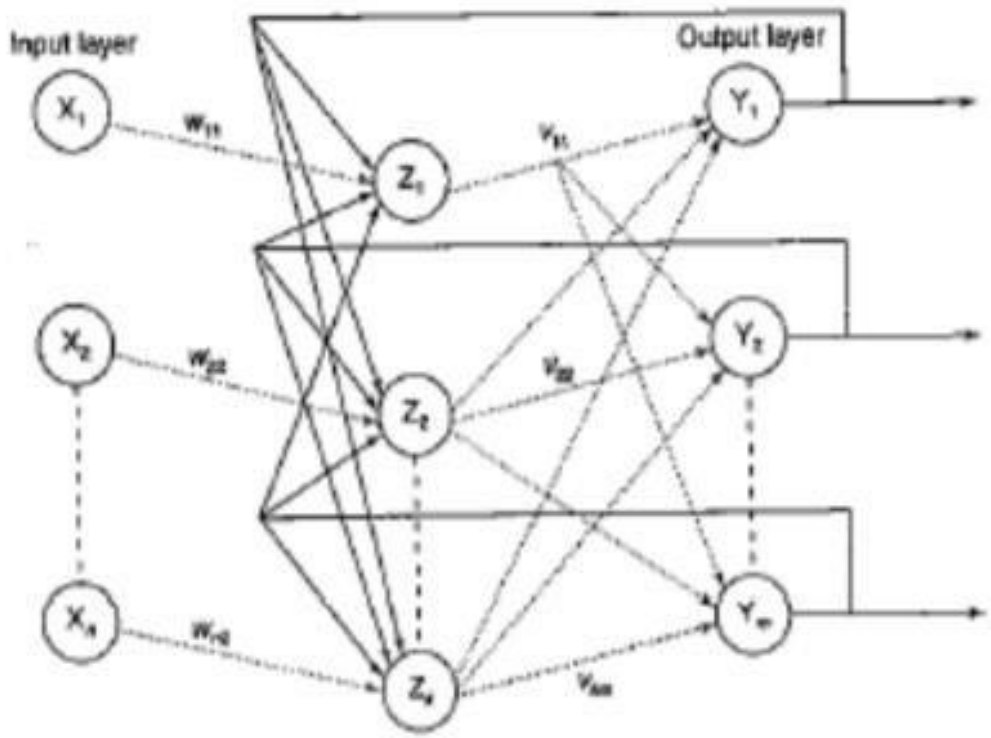
- Single layer network with a feedback connection in which a Processing elements output can be directed back to PE itself or to the other PE or to both



Connections

Multi layer recurrent network

- A PE's output can be directed back to the nodes in a preceding layer forming a multilayer recurrent network
- A PE's o/p can be directed back to the PE's itself and·to PE in the same layer or preceding layer



Training /Learning

2.Learning

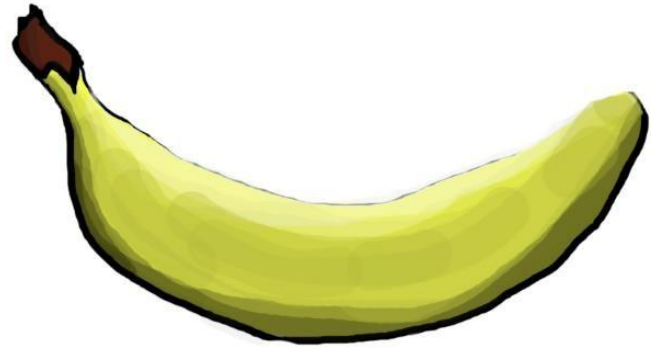
- Learning, in artificial neural network, is the method of modifying the weights of connections between the neurons of a specified network.
- The main property of ANN is its ability to learn
- Generating the output in response to the input after processing is called Learning.
- The method of setting the values of the weights called *training* is an important characteristic of neural nets.
- Based on the training methodology used neural nets can be distinguished into
  - Supervised Learning
  - Unsupervised Learning
  - Reinforcement Learning

2.Learning

- **supervised learning** takes place under the supervision of a teacher. This learning process is dependent.
- Basically supervised learning is when we teach or train the machine using data that is well labelled. Which means some data is already tagged with the correct answer.
- After that, the machine is provided with a new set of examples(data) so that the supervised learning algorithm analyses the training data(set of training examples) and produces a correct outcome from labelled data

2.Learning-supervised learning example

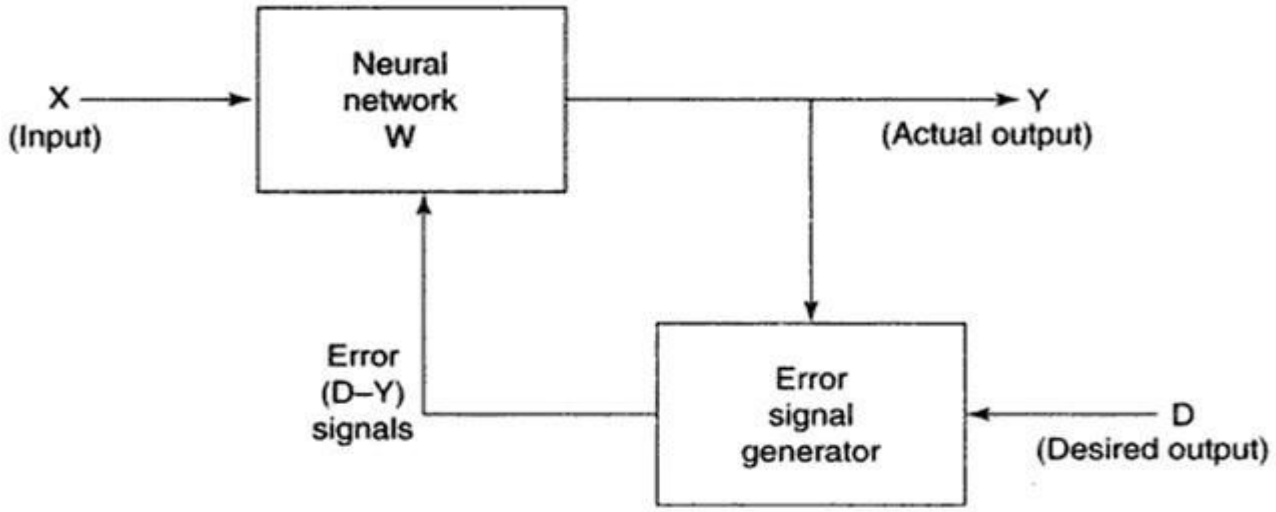
- suppose you are given a basket filled with different kinds of fruits.
- The first step is to train the machine with all the different fruits one by one like this
- If the shape of the object is rounded and has a depression at the top, is red in color or green, then it will be labeled as –**Apple**.
- If the shape of the object is a long curving cylinder having Green-Yellow color, then it will be labeled as –**Banana**.
- Now suppose after training the data, you have given a new separate fruit, say Banana from the basket, and asked to identify it.



2.Learning- Supervised Learning

- During the training of ANN under supervised learning, the input vector is presented to the network, which will produce an output vector. This output vector is compared with the desired/target output vector.
- An error signal is generated if there is a difference between the actual output and the desired/target output vector. On the basis of this error signal, the weights would be adjusted until the actual output is matched with the desired output.
- In ANN each input vector requires a corresponding target vector ,which represents the desired output.The i/p vector along with target vector is called Training Pair.
- In this type a supervisor is required for error minimization.

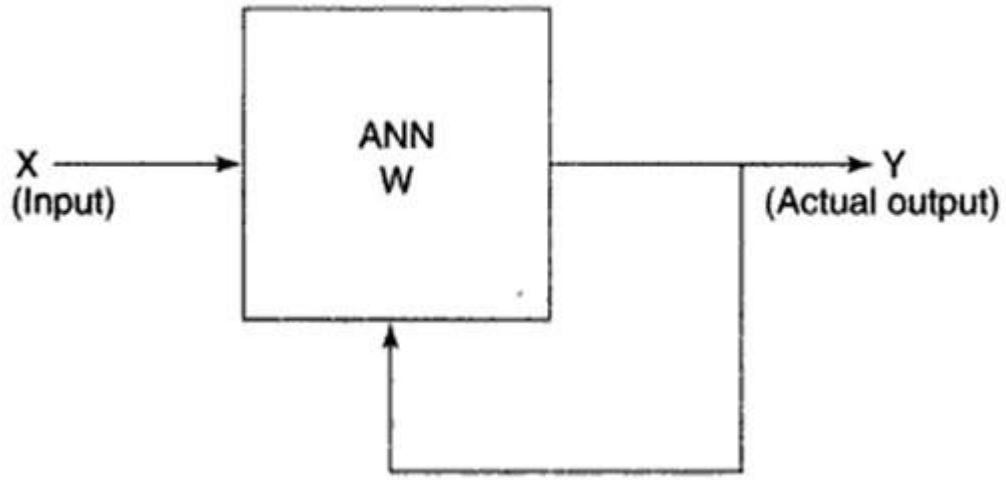
2.Learning- Supervised Learning



- Supervised learning is classified into two categories of algorithms:
- **Classification**: A classification problem is when the output variable is a category,
- **Regression**: A regression problem is when the output variable is a real value,
- Supervised learning deals with or learns with “labeled” data.
- This implies that some data is already tagged with the correct answer.

2.Learning Unsupervised Learning

- In unsupervised learning no teacher is available.
- Learning process is independent.
- The learner only discovers persistent patterns in the data consisting of a collection of perceptions. This is also called exploratory learning.



2.Learning

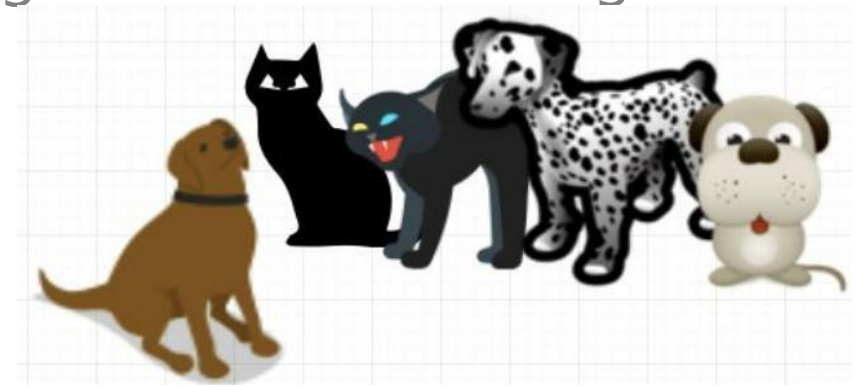
Unsupervised Learning

- The i/p vectors of similar types are grouped without the use of training data.
- In the training process ,the network receives the i/p patterns and organizes these patterns to form clusters.
- When a new input pattern is applied the neural network gives the output response indicating the class to which the i/p pattern belongs .
- If for an i/p ,a pattern class cannot be found ,then a new class can be generated.
- By self organizing process exact clusters will be formed by discovering similarities and dissimilarities among the objects
- Finding out malicious network attacks from a sequence of anomalous data packets is an example of unsupervised learning.

2.Learning

Unsupervised Learning

- Unlike supervised learning, no teacher is provided that means no training will be given to the machine.
- Therefore the machine is restricted to find the hidden structure in unlabeled data by itself.
- Here the task of the machine is to group unsorted information according to similarities, patterns, and differences without any prior training of data.
- Ex: the machine has no idea about the features of dogs and cats so we can't categorize it as 'dogs and cats '. But it can categorize them according to their similarities, patterns, and differences,
- It mainly deals with unlabelled data.



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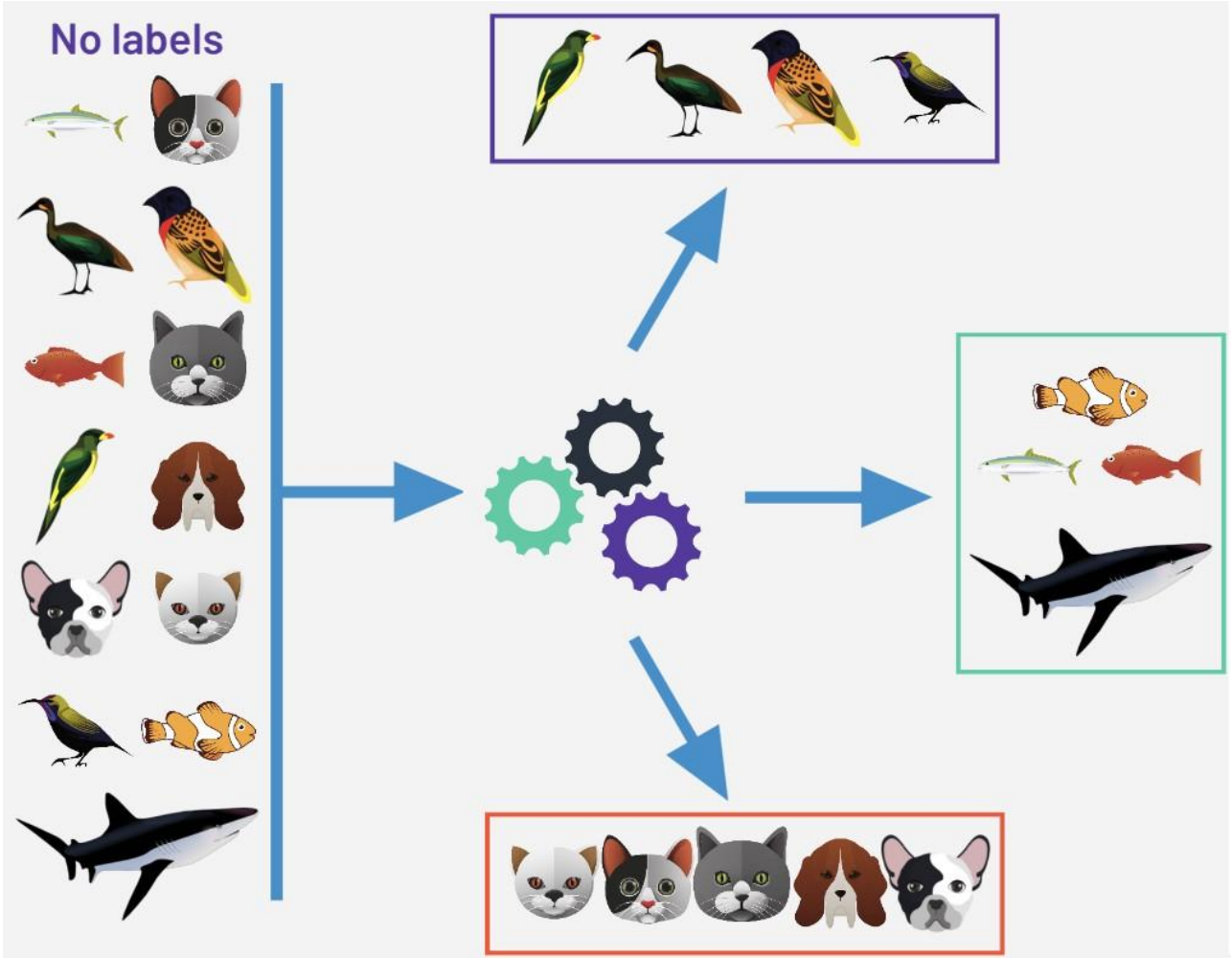
2.Learning

Unsupervised Learning

- Unsupervised learning is classified into two categories of algorithms:

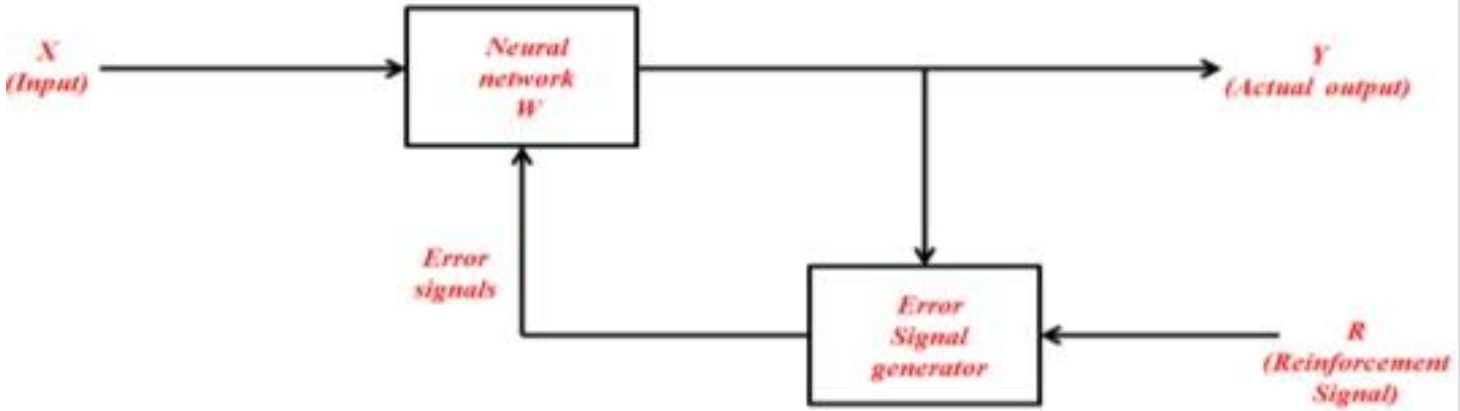
- **Clustering**: A clustering problem is where you want to discover the inherent groupings in the data, such as grouping customers by purchasing behavior.
- **Association**: An association rule learning problem is where you want to discover rules that describe large portions of your data, such as people that buy X also tend to buy Y.



2.Learning

Reinforcement Learning

- Similar to supervised learning. But only critic information available.
- In reinforcement learning the learning is based on critic information and the feedback sent is known as Reinforcement signal.
- The network receives some feedback from the environment.

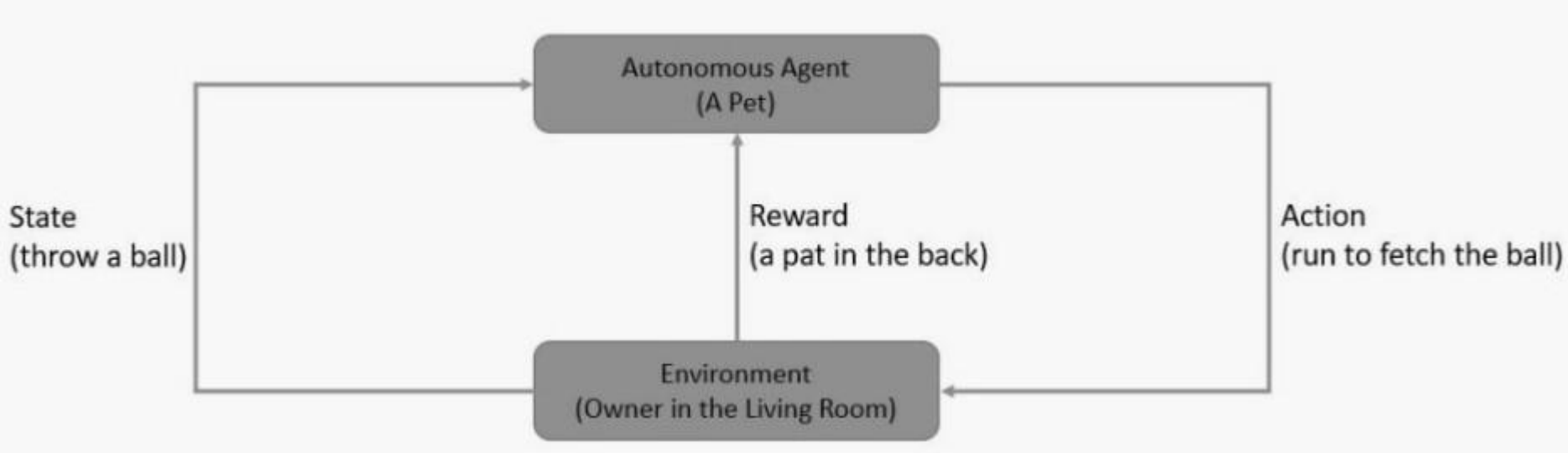


2.Learning

Reinforcement Learning

- The ANN makes a decision by observing its environment.
- If the observation is negative, the network adjusts its weights to be able to make a different required decision the next time..
- Examples include a robot in a unknown terrain where its get a punishment when its hits an obstacle and reward when it moves smoothly.
- It is a trial and error method.
- Reinforcement learning is about an autonomous agent taking suitable actions to maximize rewards in a particular environment. Over time, **the agent learns from its experiences and tries to adopt the best possible behavior**.
- In the case of reinforcement learning, we limit human interaction to changing the environment states, and the system of rewards and penalties. This **setup is known as the Markov Decision Process**

2.Learning Reinforcement Learning



- example of training a pet.
- **consider the pet as an autonomous agent**. If you're trying to train the pet in our living room, that can be considered as the environment:
- you can throw a ball and expect the pet to run and fetch it. Here, throwing the ball represents a state that the environment presents, and running to fetch it represents an **action** that the pet may take.
- **issue rewards immediately or delay them to some point in the future.**

Activation Function

3.Activation Function

- In ANN activation function may be defined as the extra force or effort applied over the net input to obtain an exact output.Activation function is applied over the net input to calculate the o/p of the ANN
- **An Activation Function** decides whether a neuron should be activated or not by calculating weighted sum and further adding bias with it..
- This means that it will decide whether the neuron's input to the network is important or not in the process of prediction using simpler mathematical operations.
- Linear and Non linear activation functions can be used to generate the neurons response.
- Linear
  - Identity functions
  - Binary Step Function
  - Bipolar step functions
- Non Linear
  - Sigmoid Function
  - Ramp Function

3.Activation Function

- linear activation function
  - It is simply a linear regression model.
  - It has limited power and ability to handle complexity varying parameters of input data.
  - with linear activation functions, no matter how many layers in the neural network, the last layer will be a linear function of the first layer (because a linear combination of linear functions is still a linear function).
  - So a linear activation function turns the neural network into just one layer.
- Non-Linear Activation Functions
  - Modern neural network models use non-linear activation functions.
  - They allow the model to create complex mappings between the network's inputs and outputs, which are essential for learning and modeling complex data, such as images, video, audio, and data sets which are non-linear or have high dimensionality.

3.Activation Function

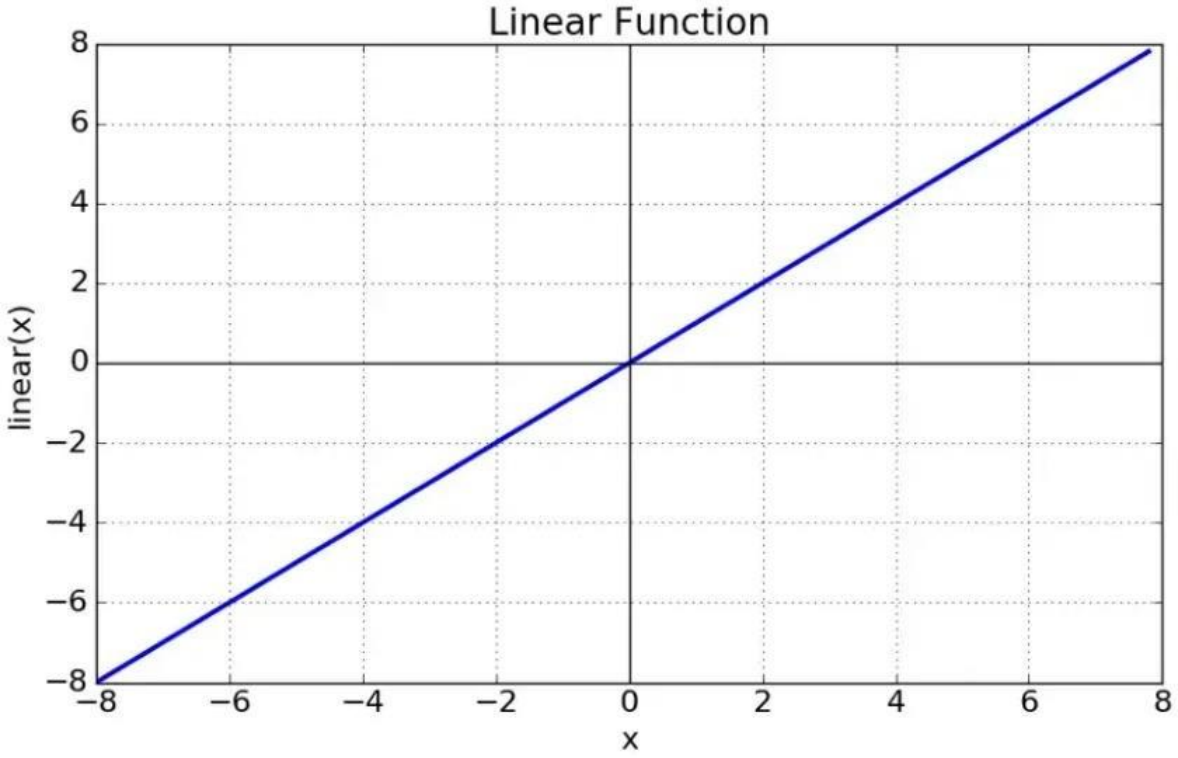


Fig: Linear Activation Function

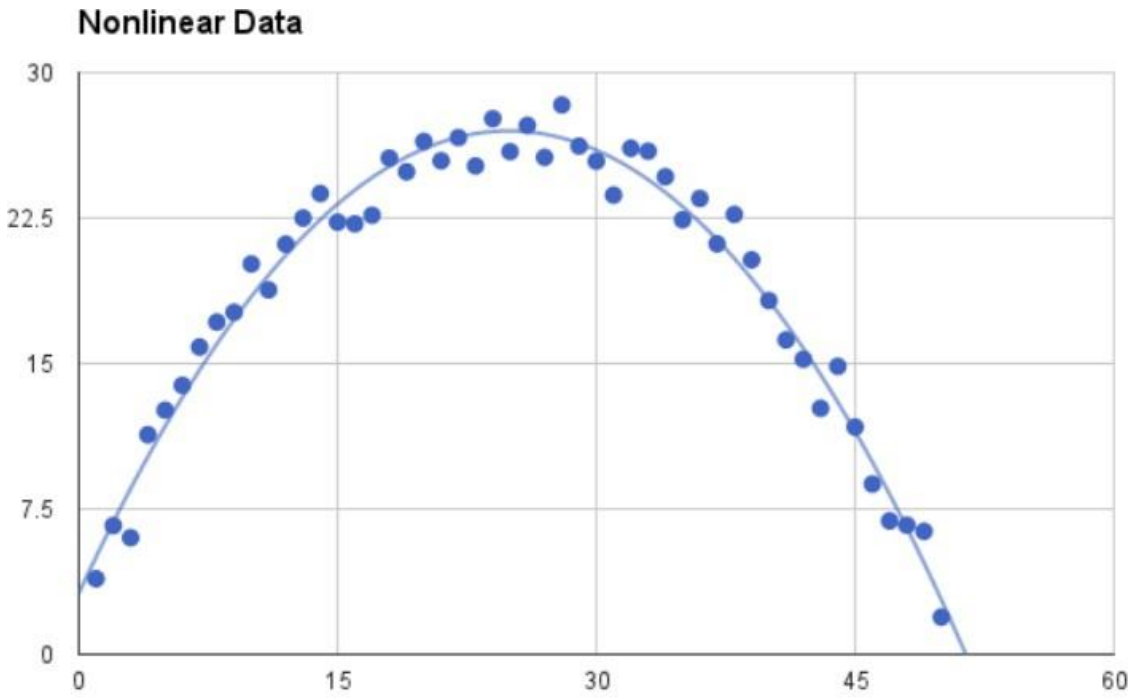


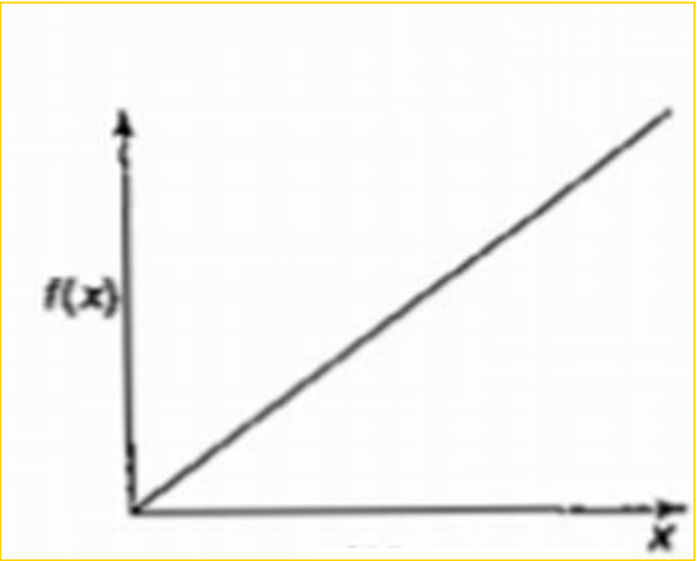
Fig: Non-linear Activation Function

3.Activation Function

1. *Identity function*: It is a linear function and can be defined as

$$f(x) = x \quad \text{for all } x$$

The output here remains the same as input.
The input layer uses the identity activation function.



- Two major problems:
- Back-propagation is not possible — The derivative of the function is a constant, and has no relation to the input, X. So it's not possible to go back and understand which weights in the input neurons can provide a better prediction.
- All layers of the neural network collapse into one — with linear activation functions, no matter how many layers in the neural network, the last layer will be a linear function of the first layer

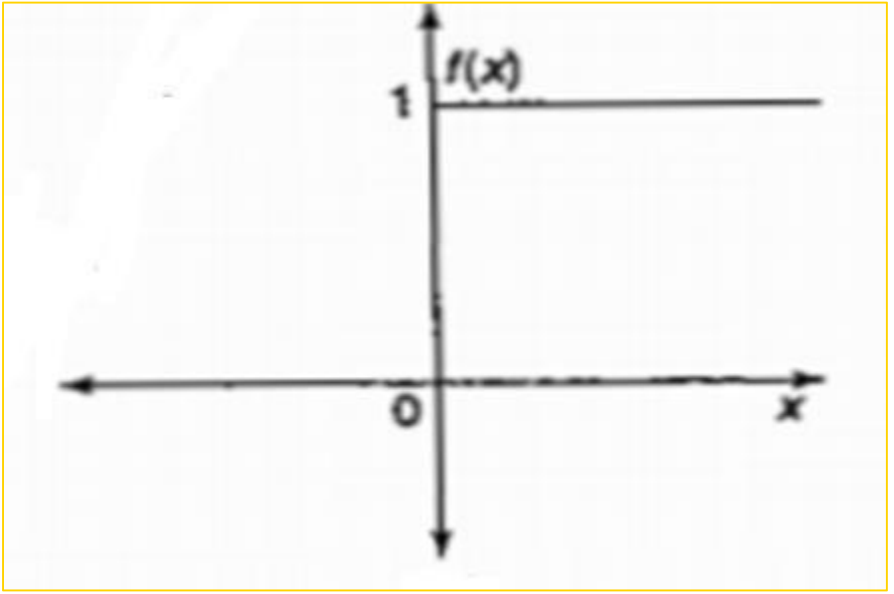
3.Activation Function

2. *Binary step function*: This function can be defined as

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

where θ represents the threshold value.

This function is most widely used in single-layer nets to convert the net input to an output that is a binary (1 or 0).



limitations of binary step function:

- It cannot provide multi-value outputs so, it cannot be used for multi-class classification problems.
- The gradient of the step function is zero, which causes a hindrance in the backpropagation process.

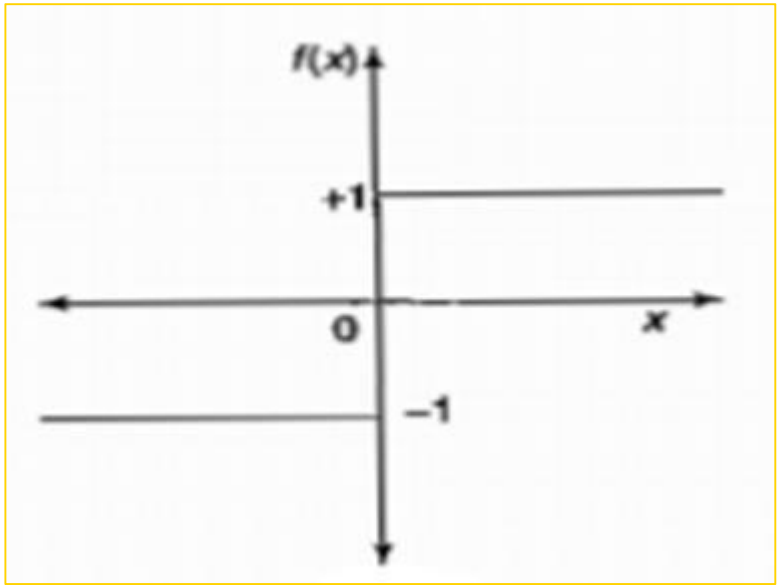
3.Activation Function

3. *Bipolar step function*: This function can be defined as

$$f(x) = \begin{cases} 1 & \text{if } x \geqslant \theta \\ -1 & \text{if } x < \theta \end{cases}$$

where θ represents the threshold value.

This function is also used in single-layer nets to convert the net input to an output that is bipolar (+1 or −1).



- In the **Bipolar Step Function**, if the value of Y is above a certain value known as the threshold, the output is +1and if it's less than the threshold then the output is -1.
- It has bipolar outputs (+1 to -1). It can be utilized in single-layer networks.

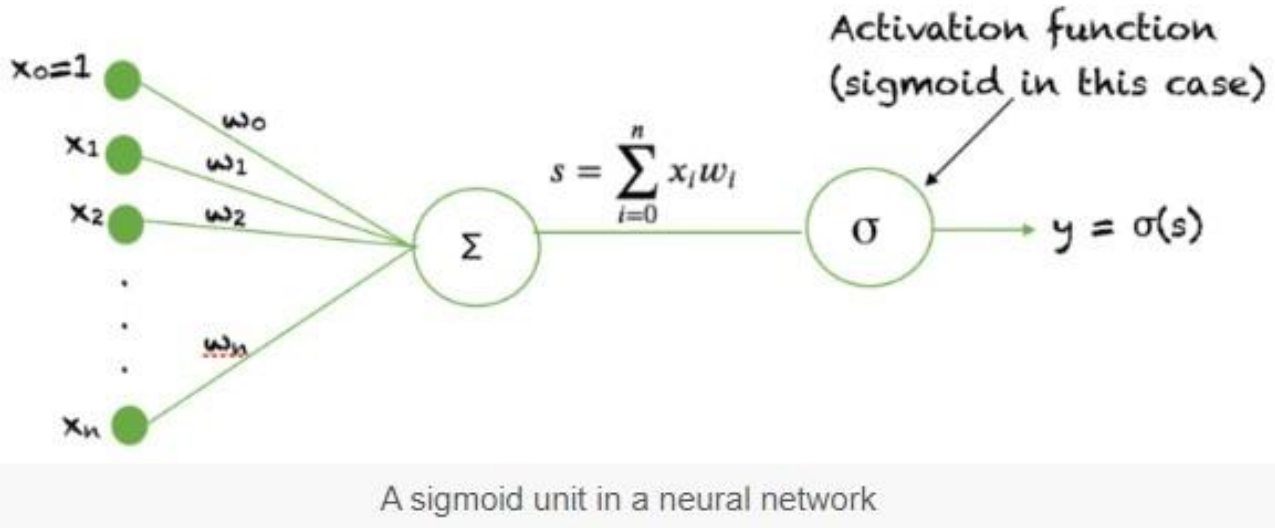
3.Activation function

4.Sigmoidal Functions

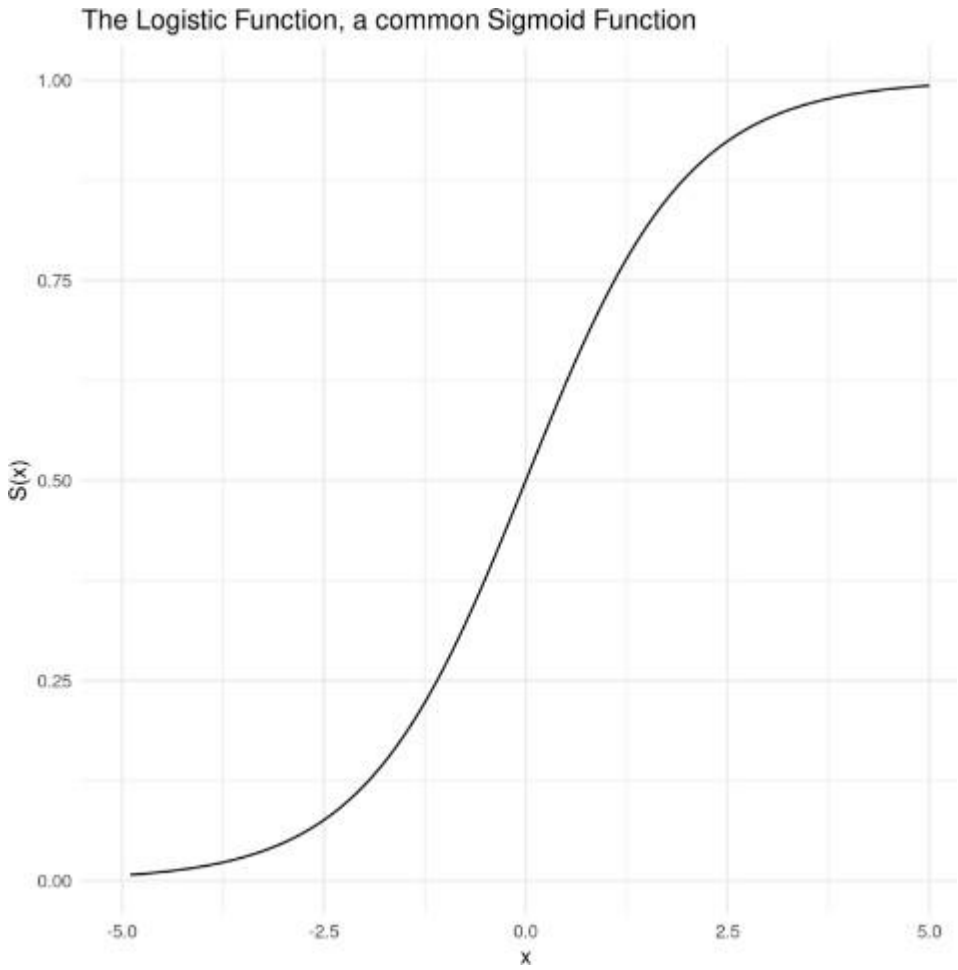
- A sigmoidal function is a mathematical function having a characteristic "S"-shaped curve or sigmoid curve.
- When the activation function for a neuron is a sigmoid function it is a guarantee that the output of this unit will always be between 0 and 1.
- Also, as the sigmoid is a non-linear function, the output of this unit would be a non-linear function of the weighted sum of inputs.
- This function takes any real value as input and outputs values in the range of 0 to 1.
- The larger the input (more positive), the closer the output value will be to 1.0, whereas the smaller the input (more negative), the closer the output will be to 0.0
- They are widely used in backpropagation networks because of the relationship between the value of the functions at a point and the value of the derivative at that point which reduces the computational burden during training.
- Sigmoidal functions are of two types
  - Binary Sigmoidal Function
  - Bipolar Sigmoidal function

3.Activation function

Sigmoidal Functions



A sigmoid unit in a neural network



3.Activation Function

Binary sigmoid function:

It is also termed as logistic sigmoid function or unipolar sigmoid function.

It can be defined as

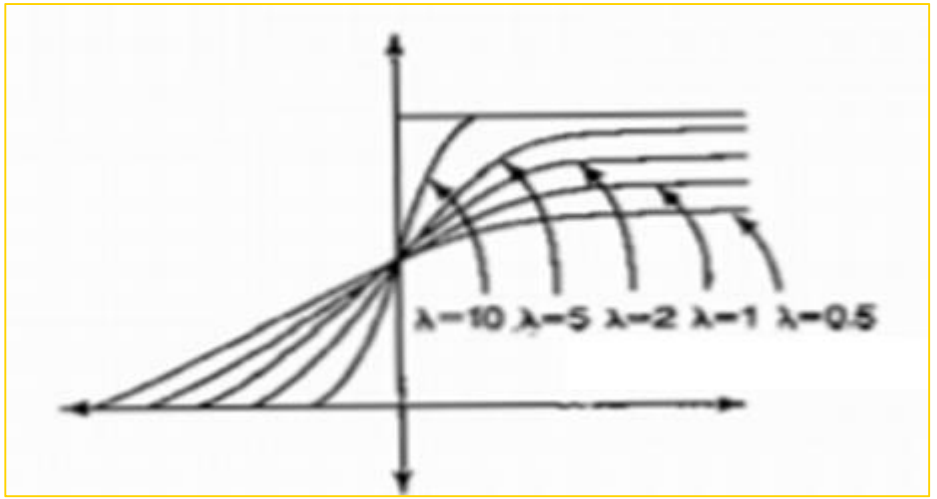
$$f(x) = \frac{1}{1 + e^{-\lambda x}}$$

where λ is the steepness parameter.

The derivative of this function is

$$f'(x) = \lambda f(x)[1 - f(x)]$$

Here the range of the sigmoid function is from 0 to 1.



- Binary Sigmoid Function or **Sigmoid function** is a logistic function where the output values are either binary or vary from 0 to 1.
- It is differentiable, non-linear, and produces non-binary activations
- sigmoid activation is not a zero-centric function.

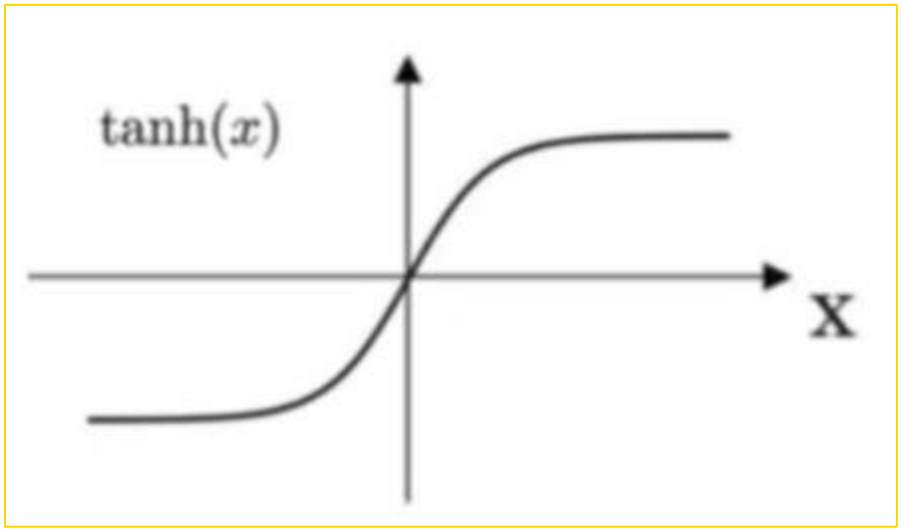
3.Activation Function

Bipolar sigmoid function:

This function is defined as

$$f(x) = \frac{2}{1 + e^{-\lambda x}} - 1$$

$$= \frac{1 - e^{-\lambda x}}{1 + e^{-\lambda x}}$$



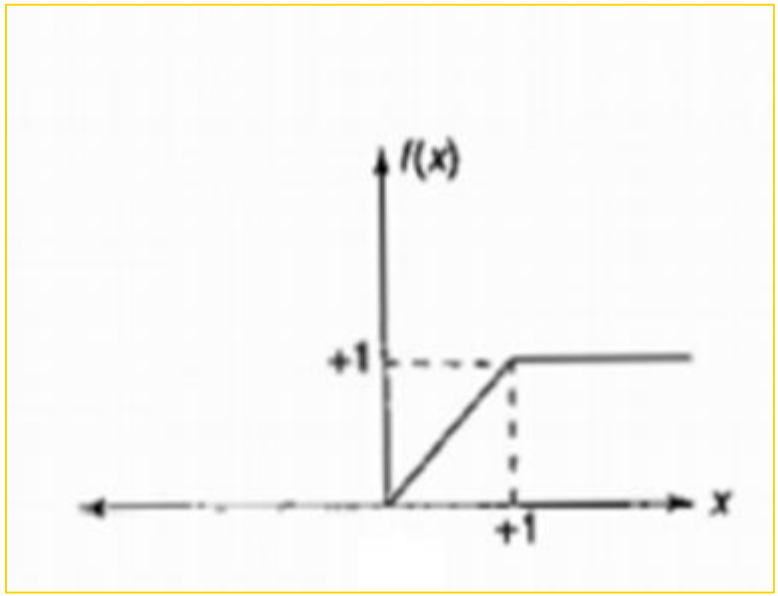
- Hyperbolic Tangent Function or Tanh is a logistic function where the output value varies from -1 to 1. Also known as **Bipolar Sigmoid Function**.
- The output of Tanh centers around 0 and sigmoid's around 0.5. Tanh Convergence is usually faster if the average of each input variable over the training set is close to zero

3.Activation Function

5. *Ramp function:*

The ramp function is defined as

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

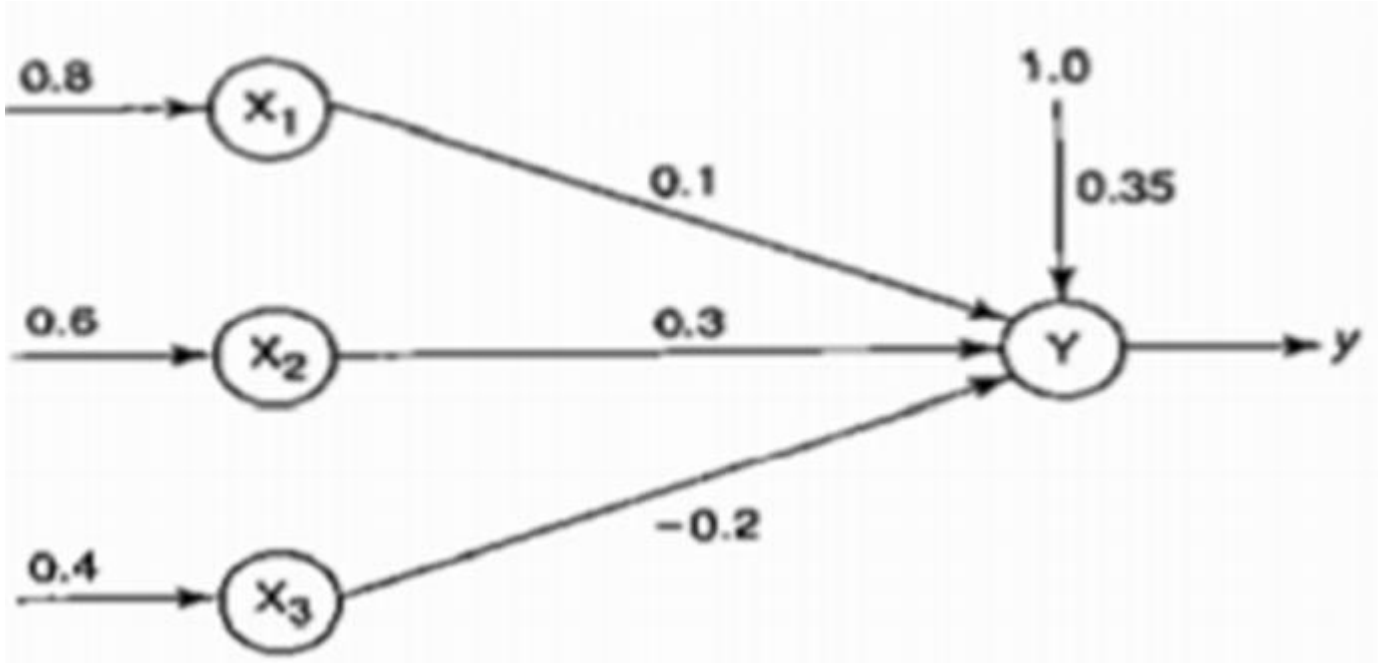


- ReLu stands for the rectified linear unit (ReLU). It is the most used activation function in the world. It output 0 for negative values of x. This is also known as a ramp function..
- The name of the **ramp function** is derived from the appearance of its graph.
- ReLu(Rectified Linear Unit) is like a linearity switch. If you don't need it, you "switch" it off. If you need it, you "switch" it on.
- ReLu also provides the benefit of sparsity and sigmoids result in dense representations. Sparse representations are more useful than dense representations.

Problems

Q1 :Activation Function

- Obtain the output of the neuron Y for the network shown in Figure using the following activation functions
-



The net input to the output neuron is

$$y_{in} = b + \sum_{i=1}^{n} x_i w_i$$

Q1 :Activation Function

The given network has 3 i/p neurons and one o/p neuron.

Input, $X = [x_1, x_2, x_3] = [0.8, 0.6, 0.4]$

Weight, $W = [w_1, w_2, w_3] = [0.1, 0.3, -0.2]$

Where x_0 is the bias i/p and w_0 is the bias weight.

i.e, $x_0 = 1$ and $w_0 = 0.35$

$$\therefore \boxed{Y_{in} = x_0 w_0 + x_1 w_1 + x_2 w_2 + x_3 w_3}$$

$$= 1 \times 0.35 + 0.8 \times 0.1 + 0.6 \times 0.3 + 0.4 \times -0.2$$

$$= \underline{\underline{0.53}}$$

Q1 :Activation Function

(i) For binary sigmoidal activation function,

$$y = f(y_{in}) = \frac{1}{1 + e^{-y_{in}}}$$

$$= \frac{1}{1 + e^{-0.53}}$$

$$= 0.625$$

Q1 :Activation Function

(2) For bipolar sigmoidal activation function

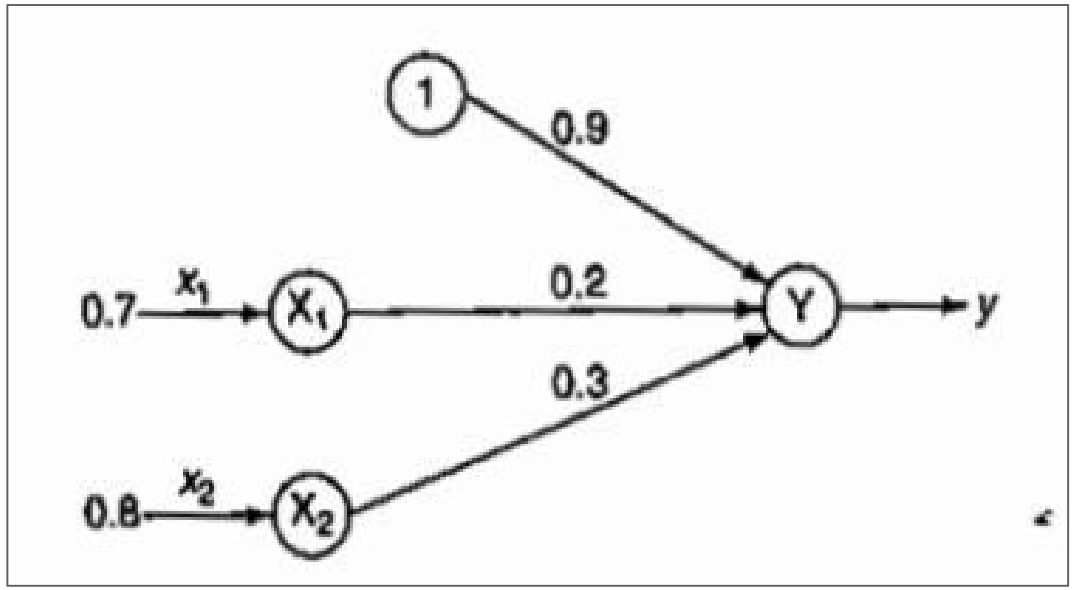
$$y = f(y_{in}) = \frac{2}{1 + e^{-y_{in}}} - 1$$

$$= \frac{2}{1 + e^{-0.53}} - 1$$

$$= \underline{0.259}$$

Q2 :Activation Function

- Calculate the net o/p of the NN using the bipolar and binary sigmoidal activation function



The net input to the output neuron is

$$y_{in} = b + \sum_{i=1}^{n} x_i w_i$$

Q1 :Activation Function

The given n/w has 2 i/p neurons and one o/p neuron.

Input, $x = [x_1, x_2] = [0.7, 0.8]$

weight, $w = [w_1, w_2] = [0.2, 0.3]$

The net i/p calculated with bias included,

$$y_{in} = x_0 w_0 + x_1 w_1 + x_2 w_2$$

where x_0 is the bias i/p and w_0 is the bias weight

i.e, $x_0 = 1$, $w_0 = 0.9$

$$\therefore y_{in} = 1 \times 0.9 + 0.7 \times 0.2 + 0.8 \times 0.3$$

$$= 1.28$$

Q1 :Activation Function

(1) For binary sigmoidal activation function

$$y = f(y_{in}) = \frac{1}{1 + e^{-y_{in}}}$$

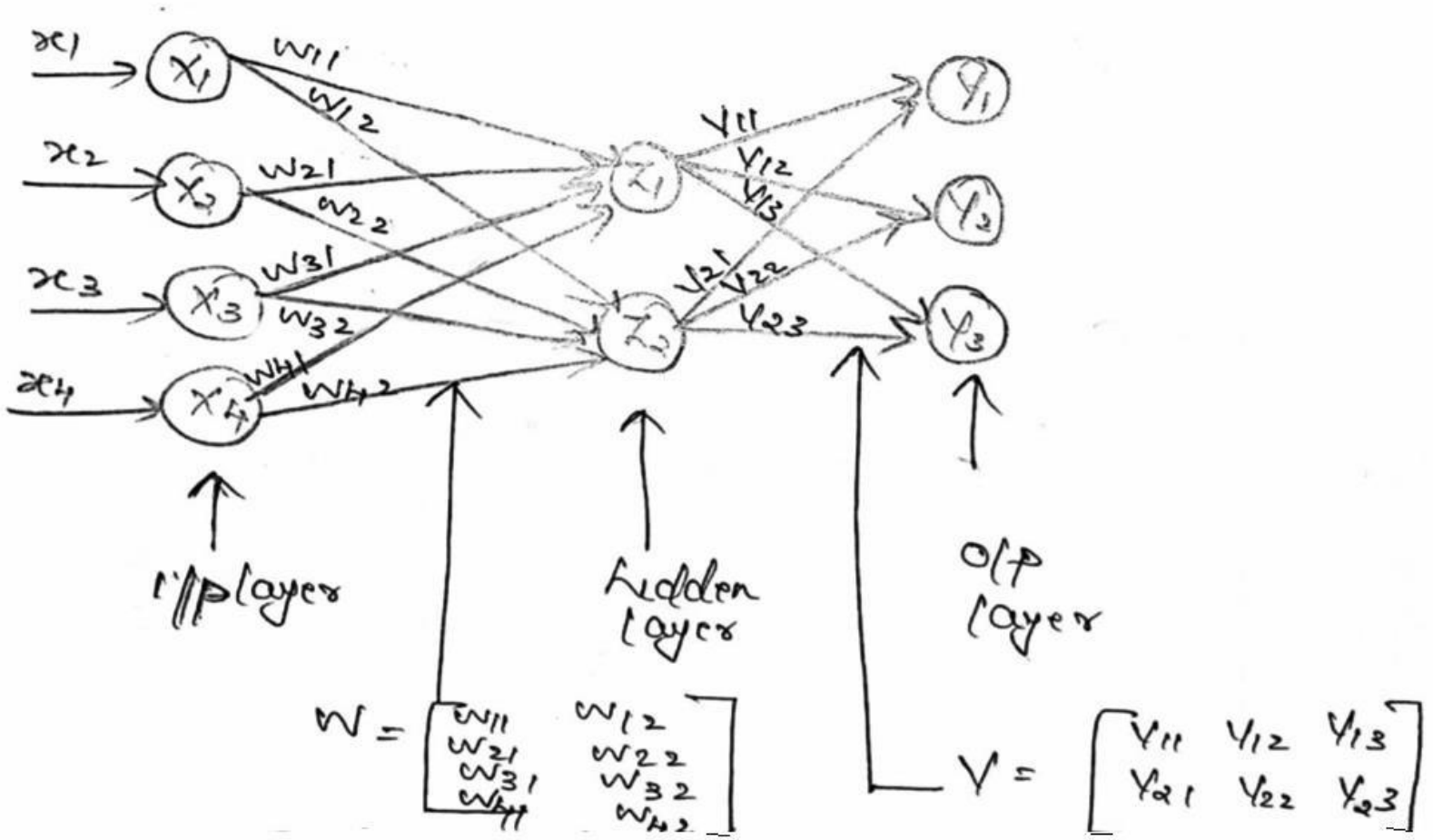
$$= \frac{1}{1 + e^{-1.28}} = 0.78$$

(2) For bipolar sigmoidal activation function

$$y = f(y_{in}) = \frac{2}{1 + e^{-y_{in}}} - 1 = \frac{2}{1 + e^{-1.28}} - 1 = 0.56$$

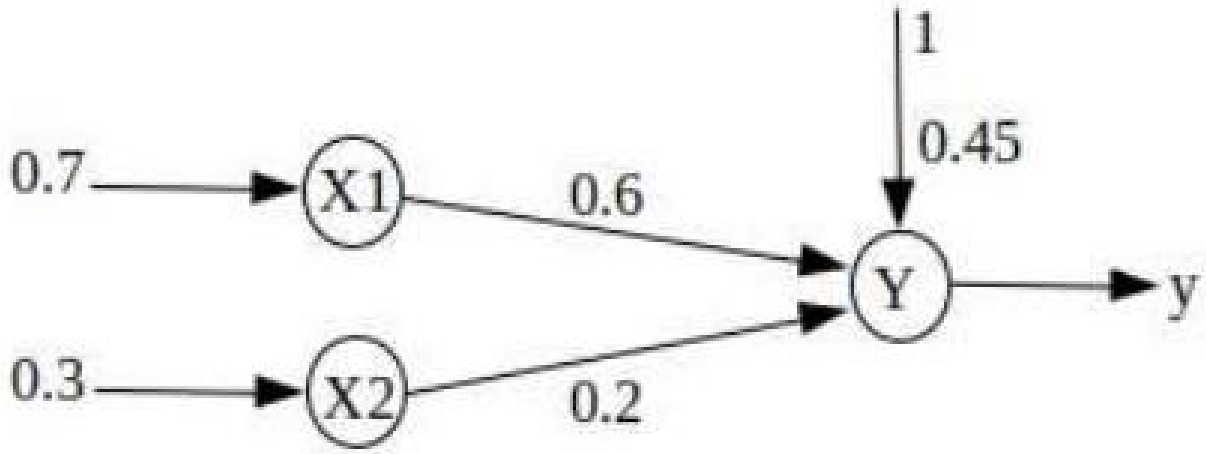
Q3 :Activation Function

- Construct a feed forward network with 4 input nodes,2 hidden nodes and 3 o/p nodes



Q4 :Activation Function [Univ ques January 2022]

- Calculate the net input to the neuron Y for the network shown in figure. Compute output of the neuron Y using binary sigmoidal activation function.



The net input to the output neuron is

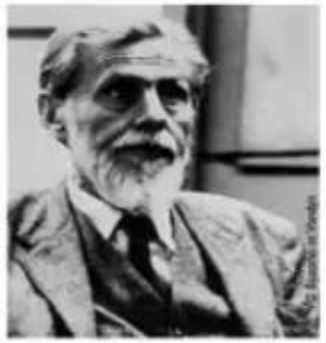
$$y_{in} = b + \sum_{i=1}^{n} x_i w_i$$

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

- Net input to the neuron Y =0.93
- Output of the neuron Y using binary sigmoidal activation function=0 .72

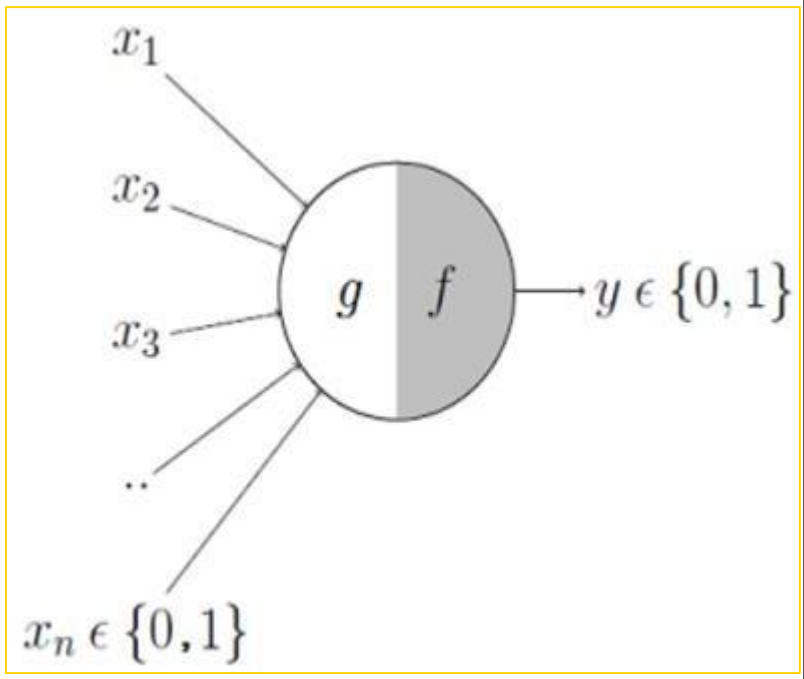
McCulloch and Pitts Neuron

McCulloch and Pitts Neuron



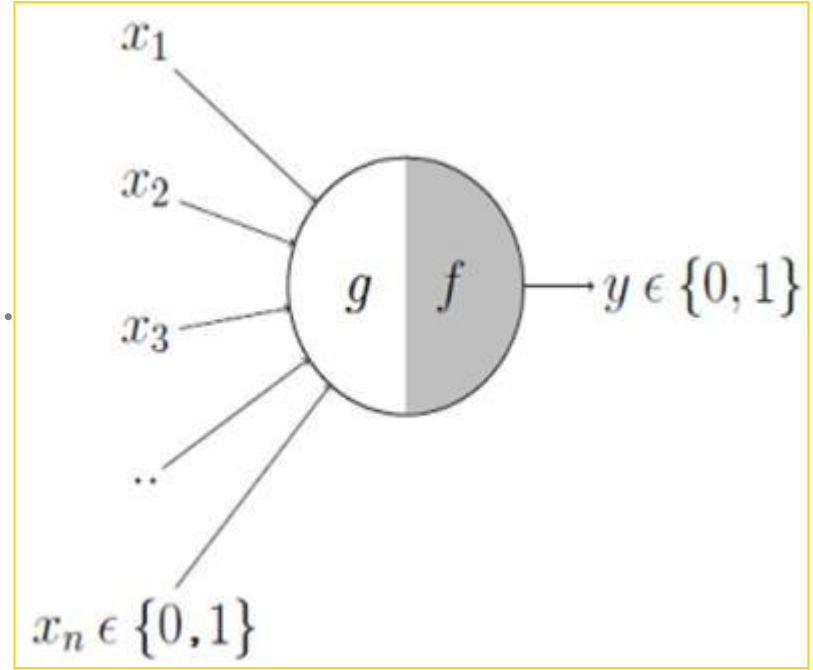
Warren McCulloch was a neuroscientist who created computational models based on threshold logic which split the inquiry into two distinct approaches, focused on biological processes in the brain and application of neural networks to artificial intelligence.

Walter Pitts was a logician who proposed the first mathematical model of a neural network. The unit of this model, a simple formalized neuron, is still the standard of reference in the field of neural networks. It is often called a McCulloch–Pitts neuron.

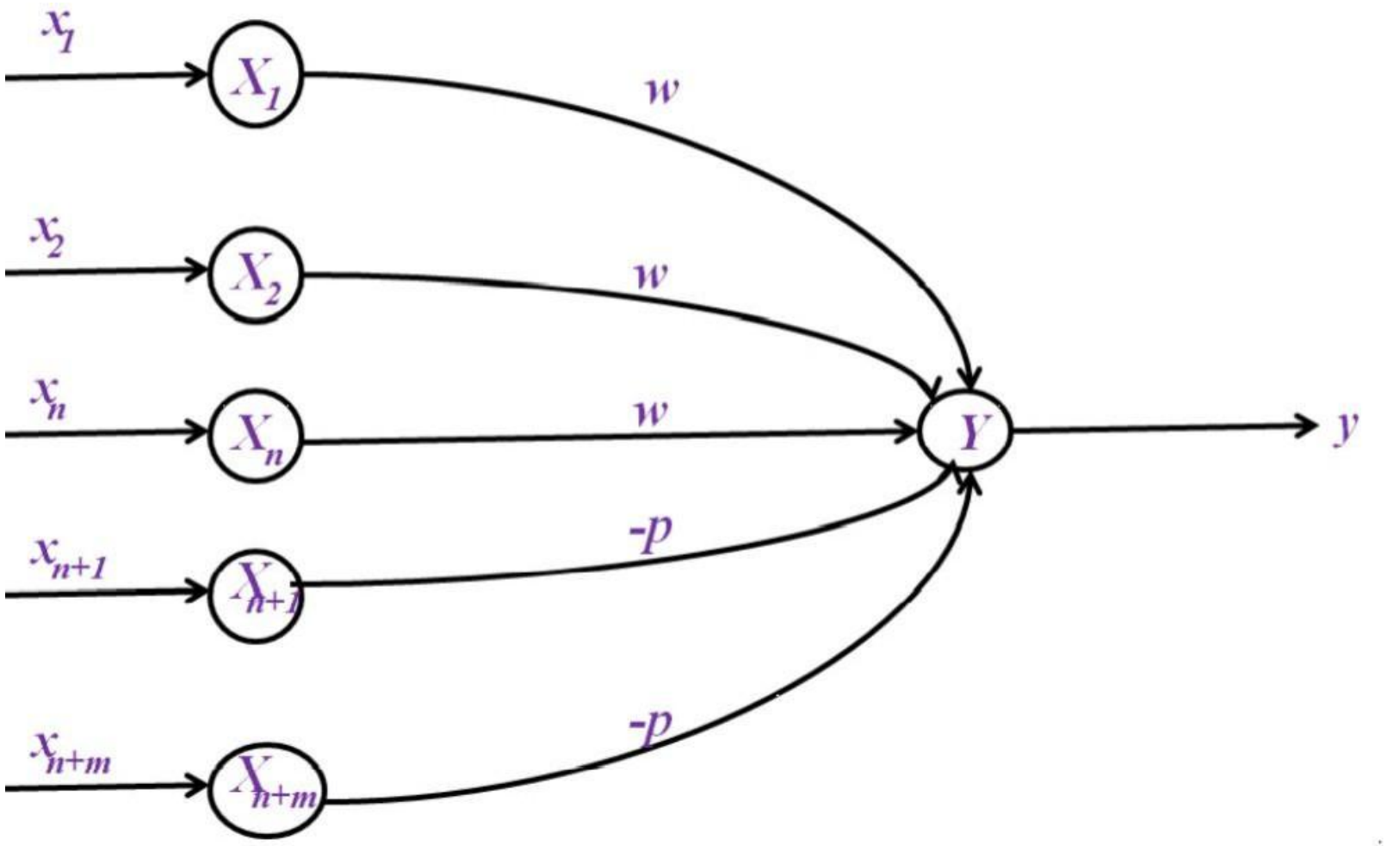


McCulloch and Pitts Neuron

- The first Mathematical /computational model of a Biological Neuron was proposed by Warren MuCulloch (neuroscientist) and Walter Pitts (logician) in 1943.
- It is considered as the earliest Neural Network and is also called M-P Neuron.
- M P Neurons are connected by directed weighted paths.
- It's main purpose is to process the binary data.i-e the activation of a M-P neuron is binary(at any time neuron may fire/may not fire).
- Logic gates /functions can be used in application
- 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.



Architecture of McCulloch and Pitts Neuron



Architecture of McCulloch and Pitts Neuron

- Weights associated with the communication links excitatory(+ve weights) or inhibitory(-ve)
- M-P Neuron has either excitatory or inhibitory connections
- i/p's from $\mathbf{x_1}$ **to** $\mathbf{x_n}$ are excitatory weighted connections and will have same weights (w>0) and i/p's from x_{n+1} to x_{n+m} are inhibitory weighted connections with weight -p(p<0)
- There is a fixed threshold for each neuron.
- Firing of Neuron is based upon a Threshold.

$$y = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} \geq \theta \\ 0 & \text{if } y_{in} < \theta \end{cases}$$

- For inhibition to be absolute ,the threshold with the activation function should satisfy the following condition.

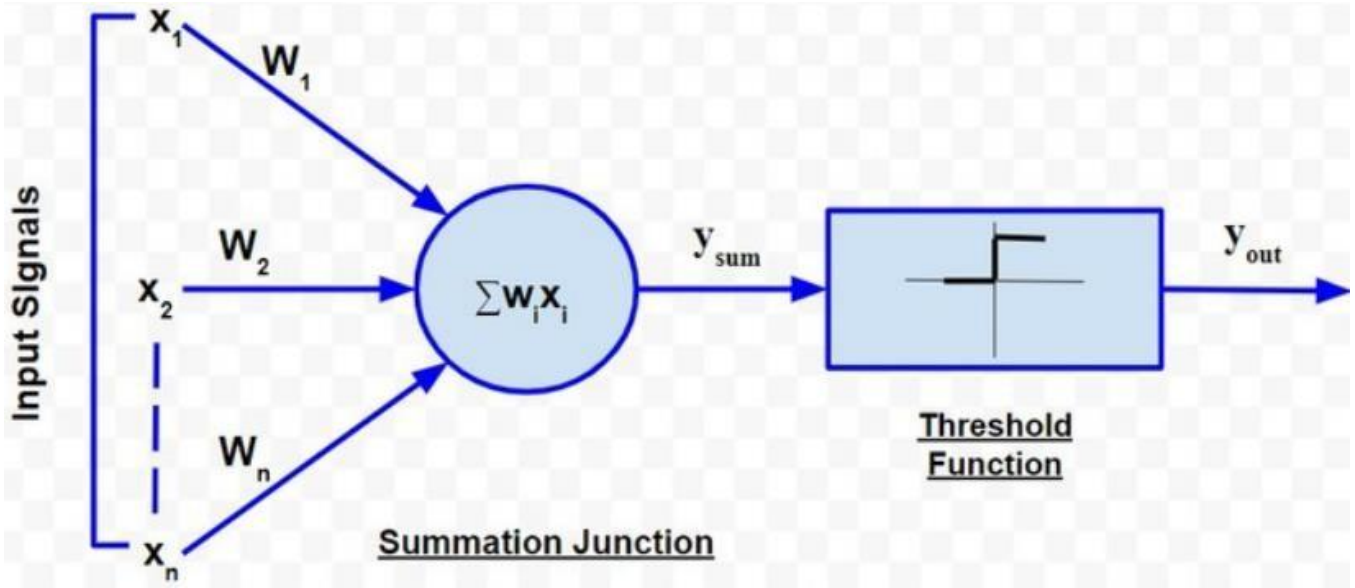
$$\theta > nw - p$$

- Where n→no of neurons , w→ weight of excitatory connections , p→ weight of inhibitory connections
- The o/p will fire if it contains 'k' or more excitatory inputs but no inhibitory inputs where

$$kw \geq \theta > (k-1)w$$

Architecture of McCulloch and Pitts Neuron

- Simple McCulloch-Pitts neurons can be used to design logical operations.
- For that purpose, the connection weights need to be correctly decided along with the threshold function
- The inputs of the McCulloch-Pitts neuron could be either 0 or 1. It has a threshold function as an activation function. So, the output signal y_{out} is 1 if the input y_{sum} is greater than or equal to a given threshold value, else 0



Example of McCulloch and Pitts Neuron

- **Person X carries an umbrella if it is sunny or if it is raining. We need to decide when Person X will carry the umbrella**
- There are four given situations. The situations are as follows:
  - First scenario: It is not raining, nor it is sunny
  - Second scenario: It is not raining, but it is sunny
  - Third scenario: It is raining, and it is not sunny
  - Fourth scenario: It is raining as well as it is sunny
- To analyze the situations using the McCulloch-Pitts neural model, consider the input signals as follows:
  - X_1: Is it raining? [0/1]
  - X_2 : Is it sunny? [0/1]
- So, the value of both scenarios can be either 0 or 1..

Example of McCulloch and Pitts Neuron

- **Person X carries an umbrella if it is sunny or if it is raining. We need to decide when Person X will carry the umbrella**
  - 1: not raining, not sunny
  - 2: not raining , sunny
  - 3: raining, and not sunny
  - 4: raining as well as sunny
  - From the truth table, we can conclude that in the situations where the value of y_{out} is 1 Person X needs to carry an umbrella.
  - We can use the value of both weights X_1 and X_2 as 1 and a threshold function as 1
  - Hence, he will need to carry an umbrella in scenarios 2, 3 and 4.

Situation	x1	x2	ysum	yout
1	0	0	0	0
2	0	1	1	1
3	1	0	1	1
4	1	1	2	1

$$y_{out} = f(y_{sum}) = \begin{cases} 1, x \geq 1 \\ 0, x < 1 \end{cases}$$

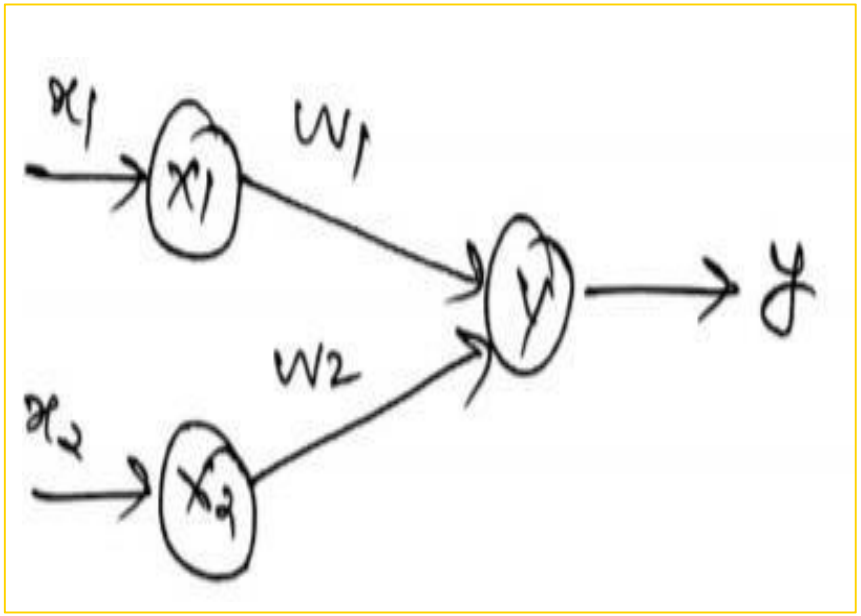
Problems McCulloch and Pitts Neuron

Implement AND function using M-P Neuron Model(Use Binary Data)

Implement AND function using M-P Neuron Model(Use Binary Data)

Truth table of AND

x_1	x_2	y
0	0	0
0	1	0
1	0	0
1	1	1



From the truth table, it is clear that for AND function the o/p neuron will fire only if $x_1 = 1$ and $x_2 = 1$.

Implement AND function using M-P Neuron Model(Use Binary Data)

Case 1:- Assume that all the weights are excitatory, i.e., $w_1 = w_2 = 1$

The net i/p calculated for four i/p

$(0,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 0 \times 1 = 0$

$(0,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 1 \times 1 = 1$

$(1,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 0 \times 1 = 1$

$(1,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 1 \times 1 = 2$

$\theta > nw - p$

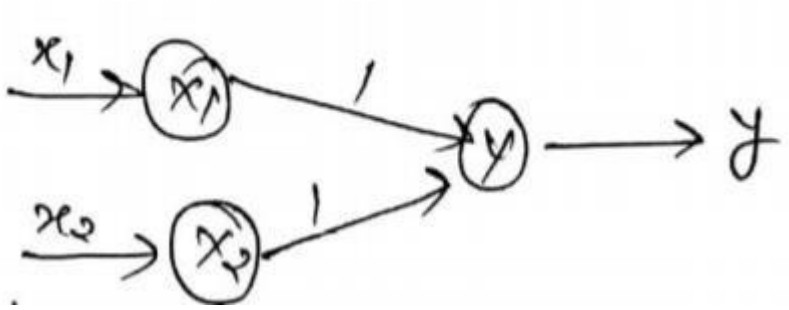
n=2
w=1
p=0
so nw-p=2*1-0
=2

Implement AND function using M-P Neuron Model(Use Binary Data)

$x_1 = 1$ and $x_2 = 1$ (whose $Y_{in} = 2$), we need to compare its Y_{in} with others to set threshold value.

From the Y_{in} calculated, it is clear that if we set threshold, $\theta \geq 2$, then truth table is satisfied, with $w_1 = 1$ and $w_2 = 1$

Thus the final nlw is



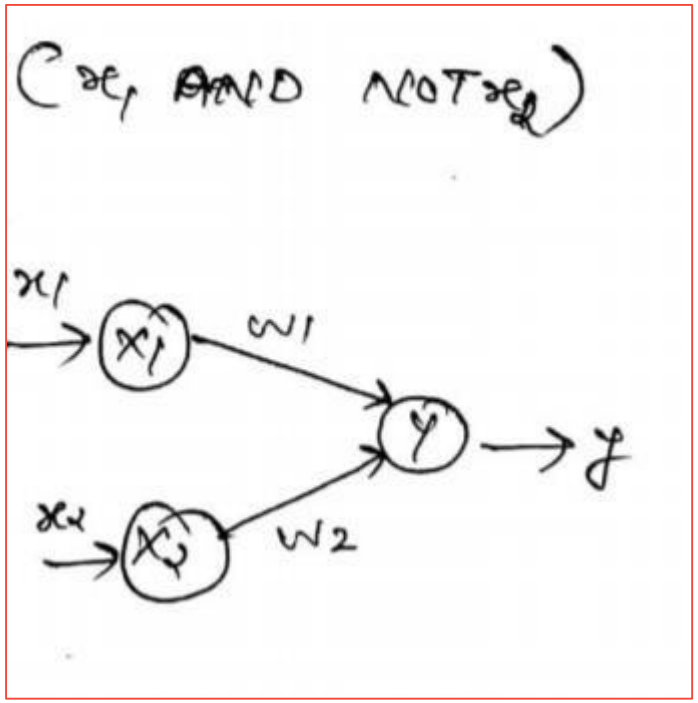
net o/p, $y = f(Y_{in})$

$$= \begin{cases} 1 & \text{if } Y_{in} \geq 2 \\ 0 & \text{if } Y_{in} < 2 \end{cases}$$

$$y = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} \geqslant \theta \\ 0 & \text{if } y_{in} < \theta \end{cases}$$

Implement ANDNOT function using M-P Neuron Model(Use Binary Data)

Implement AND NOT function using M-P Neuron Model(Use Binary Data)



Truth table of ANDNOT

x_1	x_2	NOT x_2	y
0	0	1	0
0	1	0	0
1	0	1	1
1	1	0	0

From the truth table, it is clear that for ANDNOT function the o/p neuron will fire only if $x_1 = 1$ and $x_2 = 0$.

Implement AND NOT function using M-P Neuron Model(Use Binary Data)

Case1 :- Assume that all the weights are excitatory i.e, $w_1 = w_2 = 1$.

The net i/p calculated for four i/p pairs are :-

(0,0) $\Rightarrow$ $y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 0 \times 1 = 0$

(0,1) $\Rightarrow$ $y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 1 \times 1 = 1$

(1,0) $\Rightarrow$ $y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 0 \times 1 = 1$

(1,1) $\Rightarrow$ $y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 1 \times 1 = 2$

From the calculated net i/ps, it is not possible to differentiate y_{in} for $x_1 = 1$ and $x_2 = 0$ (for which the neuron fires).

Hence these weights are not suitable.

$$y = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} \geq \theta \\ 0 & \text{if } y_{in} < \theta \end{cases}$$

Implement AND NOT function using M-P Neuron Model(Use Binary Data)

Case 2:- Assume one weight as excitatory and the other as inhibitory i.e,

$w_1 = 1, w_2 = -1$

The net i/p calculated for four i/p pairs are:-

$(0,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 0 \times -1 = 0$

$(0,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 1 \times -1 = -1$

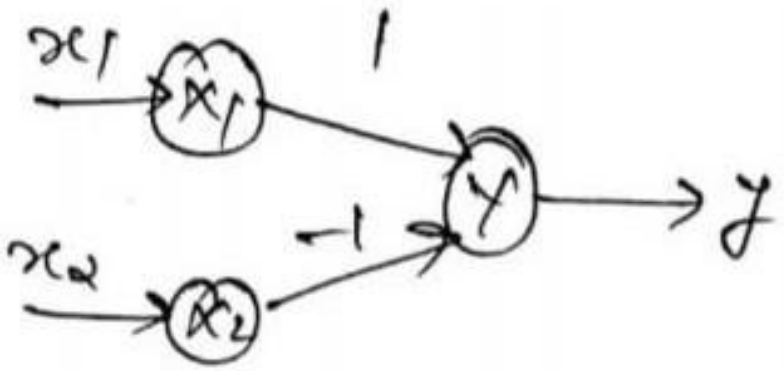
$(1,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 0 \times -1 = 1$

$(1,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 1 \times -1 = 0$

from the calculated net inputs, it is possible to differentiate y_{in} for $x_1 = 1$ and $x_2 = 0$.

Thus if we set $\theta \geq 1$ as threshold only y_{in} with $x_1 = 1$ and $x_2 = 0$ will produce o/p as 1. $\therefore w_1 = 1, w_2 = -1$ with $\theta \geq 1$

Implement AND NOT function using M-P Neuron Model(Use Binary Data)



and the net o/p, $y = f(y_{in})$

$$= \begin{cases} 1 & \text{if } y_{in} \geq 1 \\ 0 & \text{if } y_{in} < 1 \end{cases}$$

$\theta > nw - p$

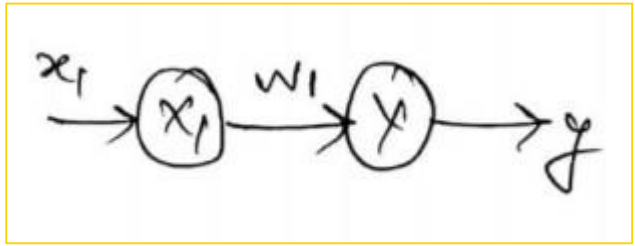
n=2
w=1
p=1
so nw-p=2*1-1
=1

Implement NOT function using M-P Neuron Model(with one input)

Implement NOT gate function using M-P Neuron Model (with one input x1)

Truth table

x_1	y
0	1
1	0



From the truth table, it is clear that for NOT function the o/p neuron will fire only if $x_1 = 0$

Case 1:- Assume that w_1 is excitatory

i.e., $w_1 = 1$

The net i/p calculated for four i/p pairs are:-

(0) $\Rightarrow y_{in} = x_1 w_1 = 0 \times 1 = 0$

(1) $\Rightarrow y_{in} = x_1 w_1 = 1 \times 1 = 1$

$$y = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} \geq \theta \\ 0 & \text{if } y_{in} < \theta \end{cases}$$

Implement NOT gate function using M-P Neuron Model (with one input x1)

from the calculated net i/ps, it is not possible to set a threshold value for $x_1 = 0$. (for which the neuron fires).

Hence these weights are not suitable.

Case 2:- Assume that w_1 is inhibitory i.e., $w_1 = -1$

The net i/p calculated for four i/p pairs are:-

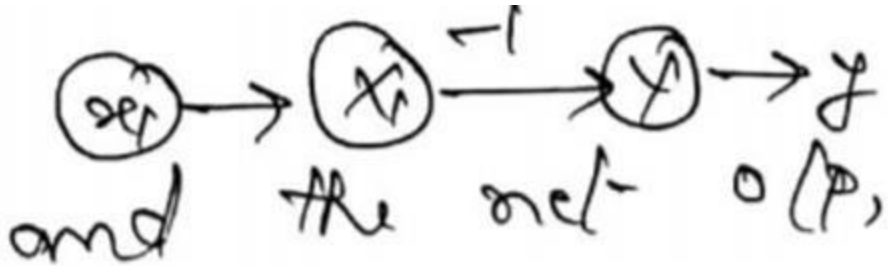
$(0) \Rightarrow y_{in} = x_1 w_1 = 0 \times -1 = 0$

$(1) \Rightarrow y_{in} = x_1 w_1 = 1 \times -1 = -1$

From the calculated net i/ps, it is possible to set y_{in}

and for $x_1 = 0$ thus the threshold value, $\theta \geq 0$. $\therefore w_1 = -1$ with $\theta \geq 0$

Implement NOT gate function using M-P Neuron Model (with one input x1)



$$y = f(y_{in})$$

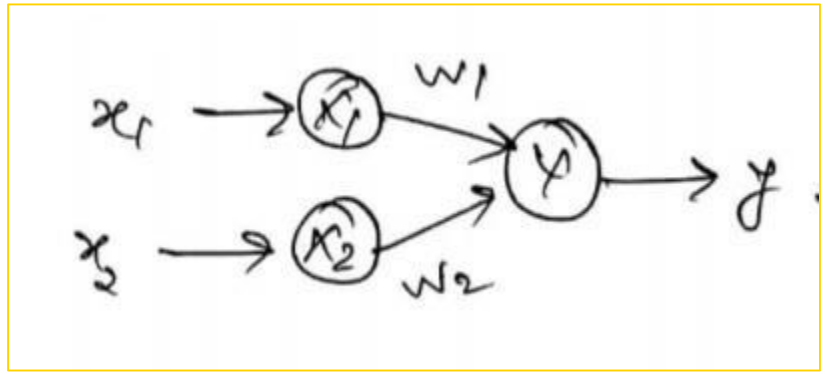
$$= \begin{cases} 1 & \text{if } y_{in} \geq 0 \\ 0 & \text{if } y_{in} < 0 \end{cases}$$

Implement OR function using M-P Neuron Model(Use Binary Data)

Implement OR gate function using M-P Neuron Model(with binary data)

Truth table

x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	1



From the truth table, it is clear that for OR function the O/P neuron will not fire if $x_1 = 0$ and $x_2 = 0$ and will fire for the remaining cases.

Implement OR gate function using M-P Neuron Model(with binary data)

case 1:- Assume that all the weights are excitatory, i.e, $w_1 = w_2 = 1$.

The net i/p calculated for four i/p pairs

$(0,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 0 \times 1 = 0$

$(0,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 1 \times 1 = 1$

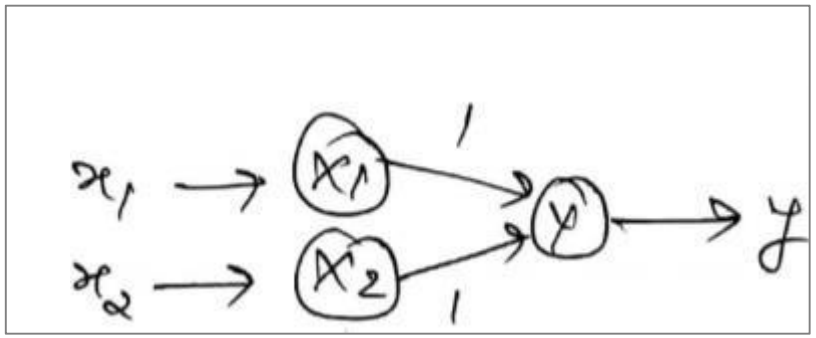
$(1,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 0 \times 1 = 1$

$(1,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 1 \times 1 = 2$

From, the y_{in} calculated it is clear that if we set threshold $\theta \geq 1$ then the truthtable is satisfied. i.e, The neuron will fire if $y_{in} \geq 1$, otherwise will not fire $\therefore w_1 = w_2 = 1$ with $\theta \geq 1$

$$y = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} \geqslant \theta \\ 0 & \text{if } y_{in} < \theta \end{cases}$$

Implement OR gate function using M-P Neuron Model(with binary data)



$$kw \geq \theta > (k-1)w$$

$$\theta > nw - p$$

the net o/p, $y = f(y_{in})$

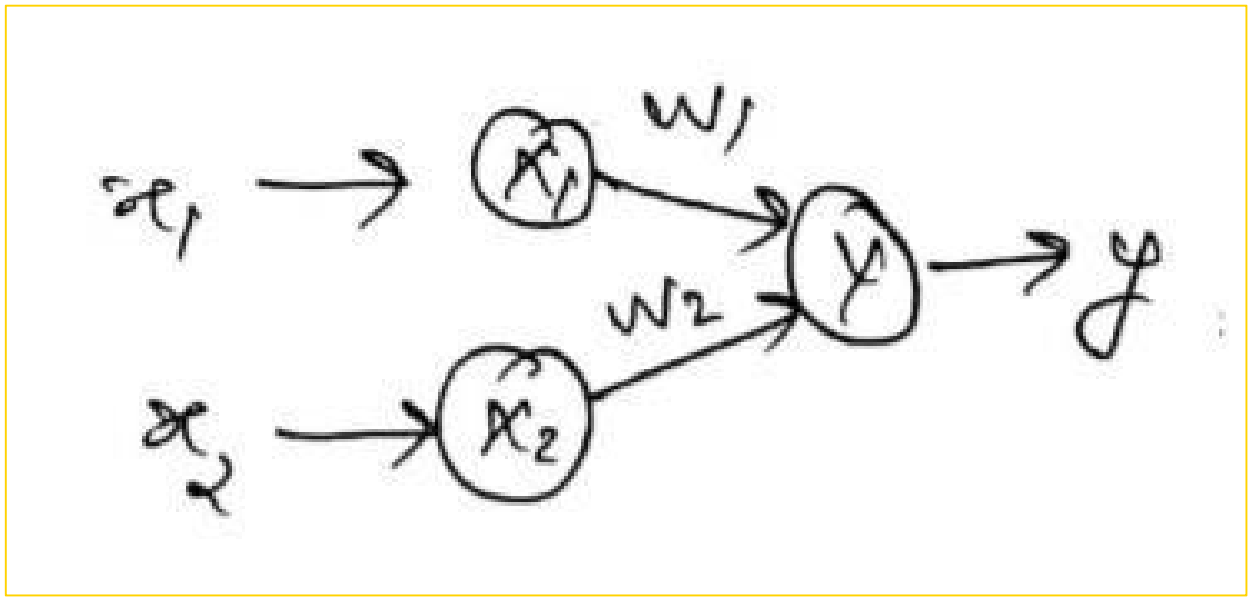
$$= \begin{cases} 1 & \text{if } y_{in} \geq 1 \\ 0 & \text{if } y_{in} < 1 \end{cases}$$

Implement NAND function using M-P Neuron Model(Use Binary Data)

Implement NAND(NOT-AND) gate function using M-P Neuron Model(with binary input

Truth table

x_1	x_2	y
0	0	1
0	1	1
1	0	1
1	1	0



from the truth table, it is clear that for NAND function the o/p neuron will not fire only if $x_1 = 1$ and $x_2 = 1$ and will fire for the remaining cases.

Implement NAND(NOT-AND) gate function using M-P Neuron Model(with binary input

Case 1:- Assume that all the weights are excitatory, i.e, $w_1 = w_2 = 1$. The net i/p calculated for the four i/p pairs are:-

$(0,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 0 \times 1 = 0$

$(0,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 1 \times 1 = 1$

$(1,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 0 \times 1 = 1$

$(1,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 1 \times 1 = 2$

From the calculated net i/ps, it is not possible to set a threshold value for $(x_1, x_2) = (0,0), (0,1)$ and $(1,0)$

Truth table

x_1	x_2	y	Yin
0	0	1	0
0	1	1	1
1	0	1	1
1	1	0	2

$$y = f(y_{in}) = \begin{cases} 1 & \text{if } y_{in} \geq \theta \\ 0 & \text{if } y_{in} < \theta \end{cases}$$

Implement NAND(NOT-AND) gate function using M-P Neuron Model(with binary input

Case 2:- Assume that the weights are $w_1 = 1$ and $w_2 = -1$

The net i/p calculated for four i/p pairs

$(0,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 0 \times -1 = 0$

$(0,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times 1 + 1 \times -1 = -1$

$(1,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 0 \times -1 = 1$

$(1,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times 1 + 1 \times -1 = 0$

Truth table

x_1	x_2	y	Yin
0	0	1	0
0	1	1	-1
1	0	1	1
1	1	0	0

From the calculated net i/ps, it is not possible to set a threshold value

Implement NAND(NOT-AND) gate function using M-P Neuron Model(with binary input

Case 3:- Assume that $w_1 = -1$ and $w_2 = 1$.

The net i/p calculated for four i/p pairs are

$(0,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times -1 + 0 \times 1 = 0$

$(0,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times -1 + 1 \times 1 = 1$

$(1,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times -1 + 0 \times 1 = -1$

$(1,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times -1 + 1 \times 1 = 0$

Truth table

x_1	x_2	y	Yin
0	0	1	0
0	1	1	1
1	0	1	-1
1	1	0	0

From the calculated net i/ps, it is not possible to set a threshold value

Implement NAND(NOT-AND) gate function using M-P Neuron Model(with binary input

Case 4 :-

Assume that both the weights are inhibitatory i.e, $w_1 = w_2 = -1$

The net i/p calculated for four i/p pairs are :-

$(0,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times -1 + 0 \times -1 = 0$

$(0,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 0 \times -1 + 1 \times -1 = -1$

$(1,0) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times -1 + 0 \times -1 = -1$

$(1,1) \Rightarrow y_{in} = x_1 w_1 + x_2 w_2 = 1 \times -1 + 1 \times -1 = -2$

Truth table

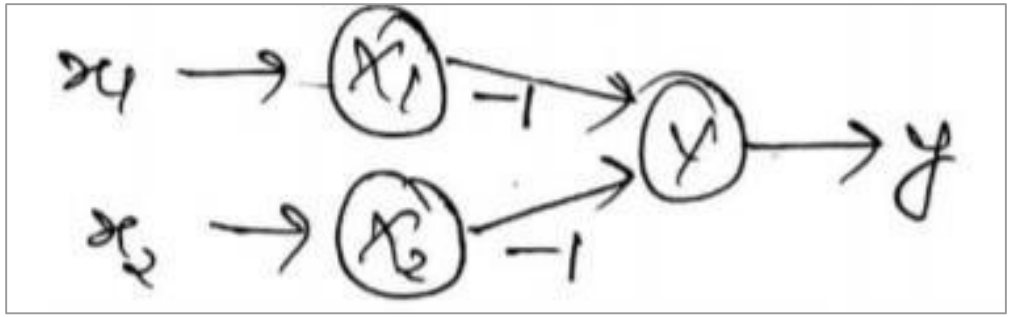
x_1	x_2	y	Yin
0	0	1	0
0	1	1	-1
1	0	1	-1
1	1	0	-2

Implement NAND(NOT-AND) gate function using M-P Neuron Model (with binary input)

From the calculated net i/ps, we can set the threshold value, θ as $\theta \geq -1$ with $w_1 = w_2 = -1$

The net o/p calculated as

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



$$\theta > nw - p$$

- =2*0-1
- =-1

Implement XOR function using M-P Neuron Model(Use Binary Data)

Implement XOR gate function using M-P Neuron Model (with binary input)

Solution:

The truth table for XOR function is given

x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	0

In this case, the output is "ON" for only odd number of 1's.

For the rest it is "OFF."

XOR function cannot be represented by simple and single logic function;

it is represented as

$$y = x_1\overline{x_2} + \overline{x_1}\,x_2$$

$$y = z_1 + z_2$$

where

$z_1 = x_1\overline{x_2}$ (function 1)

$z_2 = \overline{x_1}x_2$ (function 2)

$y = z_1\,(\mathrm{OR})\,z_2$ (function 3)

Implement XOR gate function using M-P Neuron Model (with binary input)

First function ($z_1 = x_1\overline{x_2}$):

The truth table for function z_1

x_1	x_2	z_1
0	0	0
0	1	0
1	0	1
1	1	0

The net representation is given as

Case 1: Assume both weights as excitatory, i.e.,

$$w_{11} = w_{21} = 1$$

Calculate the net inputs. For inputs,

$$(0, 0),\ z_{1in} = 0 \times 1 + 0 \times 1 = 0$$
$$(0, 1),\ z_{1in} = 0 \times 1 + 1 \times 1 = 1$$
$$(1, 0),\ z_{1in} = 1 \times 1 + 0 \times 1 = 1$$
$$(1, 1),\ z_{1in} = 1 \times 1 + 1 \times 1 = 2$$

Hence, it is not possible to obtain function z_1 using these weights.

Implement XOR gate function using M-P Neuron Model (with binary input)

First function ($z_1 = x_1\overline{x_2}$):

The truth table for function z_1

x_1	x_2	z_1
0	0	0
0	1	0
1	0	1
1	1	0

The net representation is given as

Case 2: Assume one weight as excitatory and the other as inhibitory, i.e.,

$$w_{11} = 1; \quad w_{21} = -1$$

Calculate the net inputs. For inputs

$$(0,0),\ z_{1in} = 0 \times 1 + 0 \times -1 = 0$$
$$(0,1),\ z_{1in} = 0 \times 1 + 1 \times -1 = -1$$
$$(1,0),\ z_{1in} = 1 \times 1 + 0 \times -1 = 1$$
$$(1,1),\ z_{1in} = 1 \times 1 + 1 \times -1 = 0$$

On the basis of this calculated net input, it is possible to get the required output.

Hence, $w_{11} = 1$

$w_{21} = -1$

$\theta \geq 1$ for the Z_1 neuron

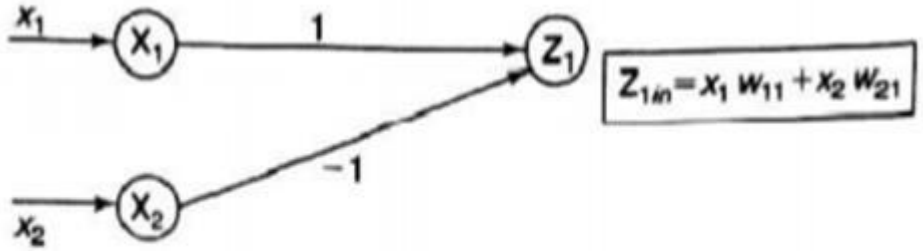


Figure Neural net for Z_1

Implement XOR gate function using M-P Neuron Model (with binary input)

Second function ($z_2 = \overline{x_1} x_2$):

The truth table for function z_2

x_1	x_2	z_2
0	0	0
0	1	1
1	0	0
1	1	0

The net representation is given as follows:
Case 1: Assume both weights as excitatory, i.e.,

$$w_{12} = w_{22} = 1$$

calculate the net inputs. For the inputs

$$(0, 0),\ z_{2in} = 0 \times 1 + 0 \times 1 = 0$$
$$(0, 1),\ z_{2in} = 0 \times 1 + 1 \times 1 = 1$$
$$(1, 0),\ z_{2in} = 1 \times 1 + 0 \times 1 = 1$$
$$(1, 1),\ z_{2in} = 1 \times 1 + 1 \times 1 = 2$$

Hence, it is not possible to obtain function z_2 using these weights.

Implement XOR gate function using M-P Neuron Model (with binary input)

Case 2: Assume one weight as excitatory and the other as inhibitory, i.e.,

$$w_{12} = -1; \quad w_{22} = 1$$

calculate the net inputs. For the inputs

$(0, 0)$, $z_{2in} = 0 \times -1 + 0 \times 1 = 0$

$(0, 1)$, $z_{2in} = 0 \times -1 + 1 \times 1 = 1$

$(1, 0)$, $z_{2in} = 1 \times -1 + 0 \times 1 = -1$

$(1, 1)$, $z_{2in} = 1 \times -1 + 1 \times 1 = 0$

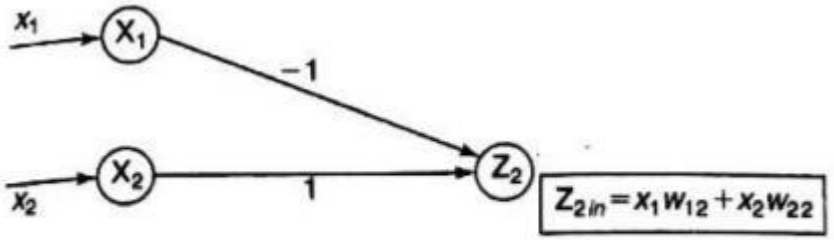


Figure Neural net for Z_2.

Thus, based on this calculated net input, it is possible to get the required output, i.e.,

$w_{12} = -1$

$w_{22} = 1$

$\theta \geqslant 1$ for the Z_2 neuron

Implement XOR gate function using M-P Neuron Model (with binary input)

Third function ($y = z_1$ OR z_2):

The truth table for this function

x_1	x_2	y	z_1	z_2
0	0	0	0	0
0	1	1	0	1
1	0	1	1	0
1	1	0	0	0

Here the net input is calculated using

$$y_{in} = z_1 v_1 + z_2 v_2$$

Case 1: Assume both weights as excitatory, i.e.,

$$v_1 = v_2 = 1$$

Now calculate the net input. For inputs

$$(0, 0),\ y_{in} = 0 \times 1 + 0 \times 1 = 0$$
$$(0, 1),\ y_{in} = 0 \times 1 + 1 \times 1 = 1$$
$$(1, 0),\ y_{in} = 1 \times 1 + 0 \times 1 = 1$$
$$(1, 1),\ y_{in} = 0 \times 1 + 0 \times 1 = 0$$

(because for $x_1 = 1$ and $x_2 = 1, z_1 = 0$ and $z_2 = 0$)

Implement XOR gate function using M-P Neuron Model (with binary input)

Setting a threshold of $\theta \geq 1$, $v_1 = v_2 = 1$, which implies that the net is recognized. Therefore, the analysis is made for XOR function using M–P neurons.

Thus for XOR function, the weights are obtained as

$w_{11} = w_{22} = 1$ (excitatory)
$w_{12} = w_{21} = -1$ (inhibitory)
$v_1 = v_2 = 1$ (excitatory)

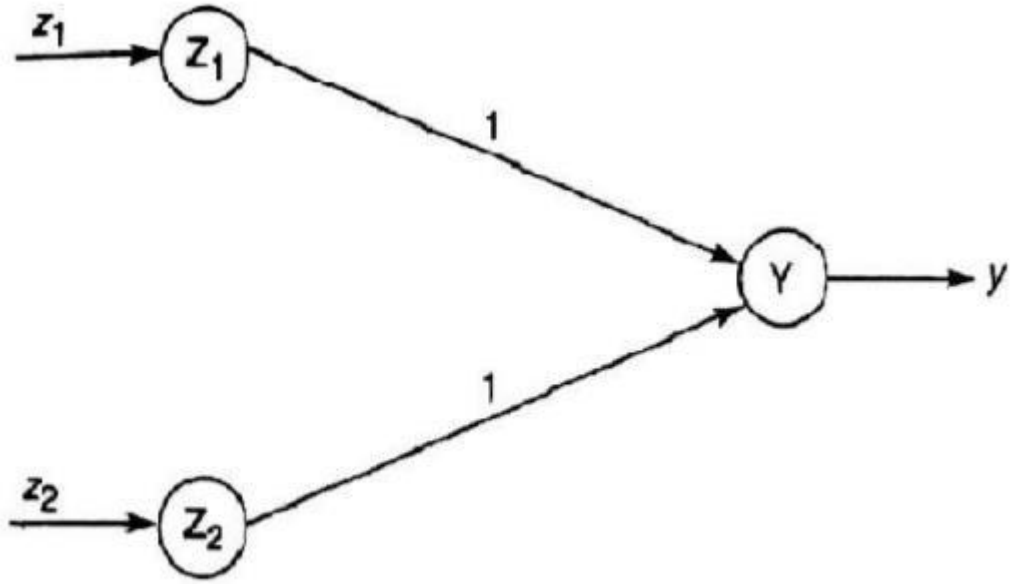
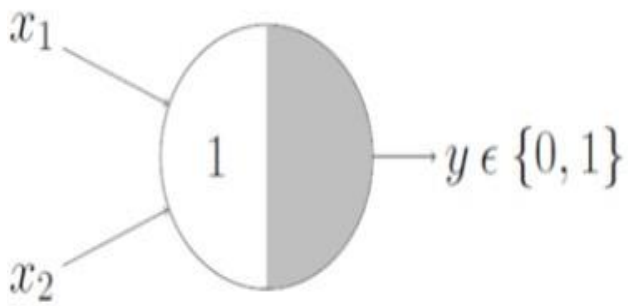


Figure Neural net for $Y(Z_1$ OR $Z_2)$.

McCulloch and Pitts Neuron Conclusion

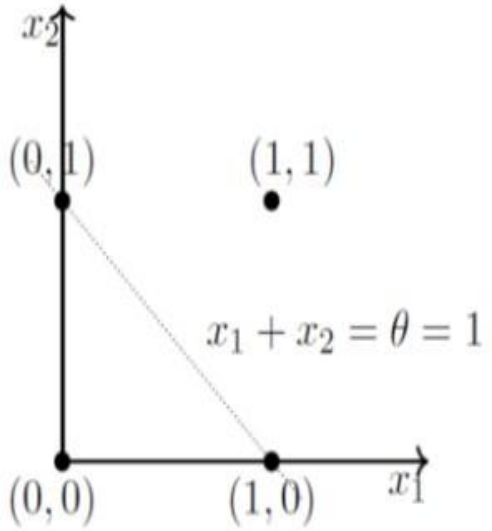
- McCulloch-pitts model doesn't have the ability of learning,because of fixed weight.
- Cannot handle non-boolean (say, real) inputs
- Need to hand code the threshold always
- inputs can either be *excitatory* or *inhibitory*.
- Inhibitory inputs are those that have maximum effect on the decision making irrespective of other inputs
- Excitatory inputs are NOT the ones that will make the neuron fire on their own but they might fire it when combined together

Geometric Interpretation Of M-P Neuron



OR function

$$x_1 + x_2 = \sum_{i=1}^{2} x_i \geq 1$$

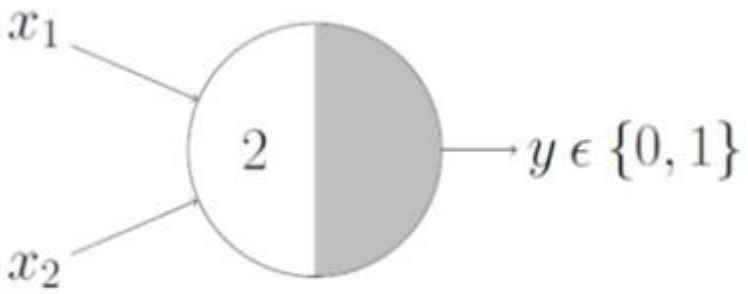


OR

A	B	Output
0	0	0
0	1	1
1	0	1
1	1	1

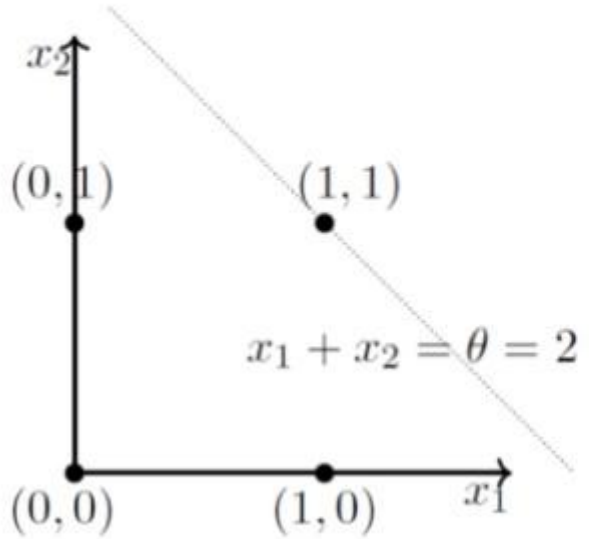
Geometric Interpretation Of M-P Neuron

AND Function



AND function

$$x_1 + x_2 = \sum_{i=1}^{2} x_i \geq 2$$



AND

A	B	Output
0	0	0
0	1	0
1	0	0
1	1	1

Hebb Network

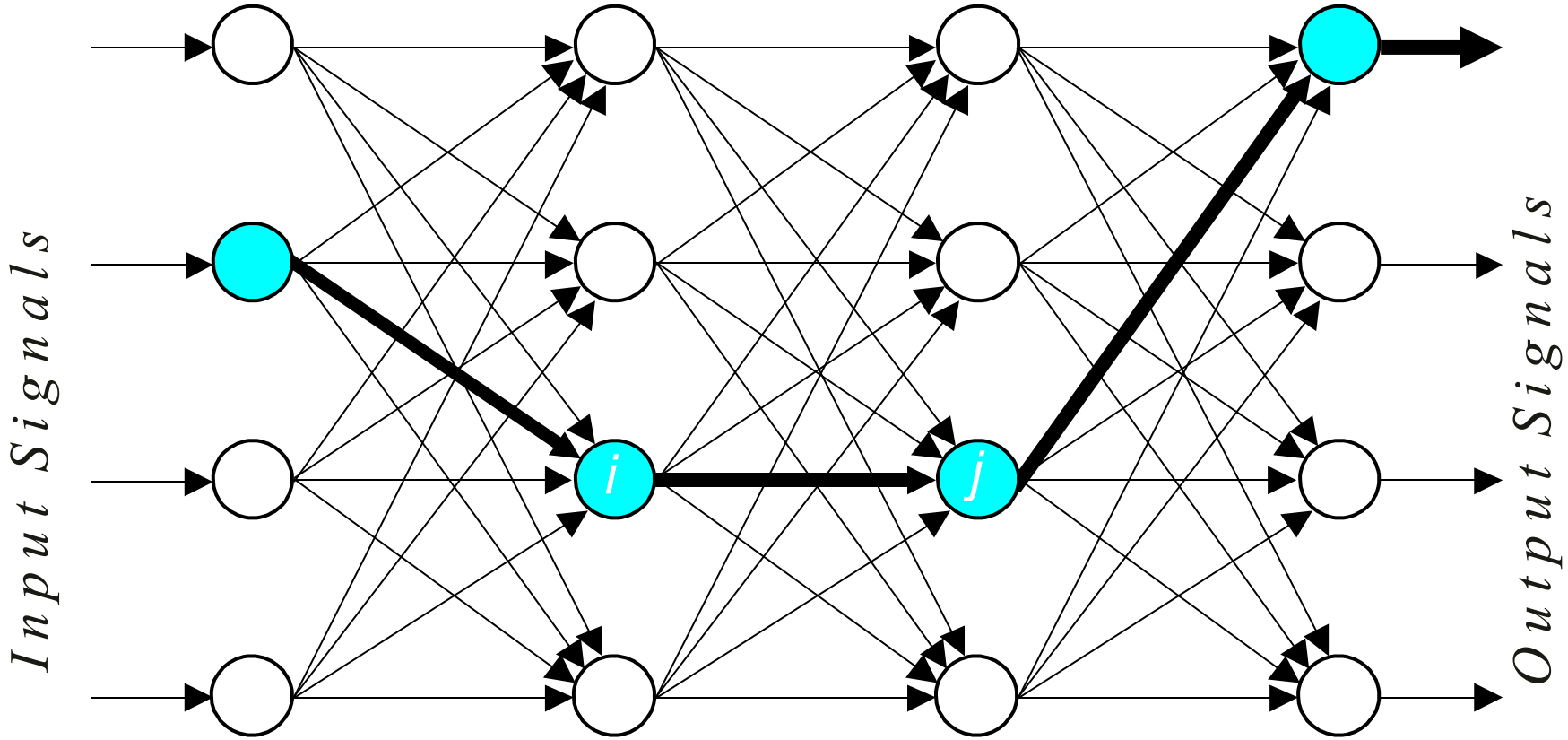
Hebb Network

- In 1949, Donald Hebb proposed one of the key ideas in biological learning, commonly known as Hebb's Law.
- Hebb introduced a neurophysiological ***postulate*** :
  - **"...When an axon of cell A is near enough to excite a cell B and repeatedly and persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells, such that A's efficiency as one of the cells firing B, is increased."**
- Hebb's Law states that if neuron i is near enough to excite neuron j and repeatedly participates in its activation, the synaptic connection between these two neurons is strengthened and neuron j becomes more sensitive to stimuli from neuron i.

Hebb Network

- In this, if 2 interconnected neurons are ON simultaneously then the weight associated with these neurons can be increased by the modification made in their synaptic gaps(strength).
- Hebb's Law can be represented in the form of two rules:
  1. If two neurons on either side of a connection are activated synchronously, then the weight of that connection is increased.
  2. If two neurons on either side of a connection are activated asynchronously, then the weight of that connection is decreased.
- Hebb's Law provides the basis for learning without a teacher.
- Learning here is a local phenomenon occurring without feedback from the environment.
- It is a kind of feed-forward, unsupervised learning.

Hebbian learning in a neural network



Hebb Network

- Hebb learning rule,is the oldest and simplest ANN rules, was introduced by Donald Hebb in his book *The Organization of Behavior* in 1949.
- It is more suited for bipolar data than binary data
- From the postulate , we may conclude that the connections between two neurons might be strengthened if the neurons fire at the same time and might weaken if they fire at different times.
- Hebb Rule states that "the weight vector is found to increase proportionately to the product of the input signal and the learning signal(o/p signal)"
- ANN learning rule defines how to adjust the weights of connections to get desirable output
- The process of adjusting the weight is known as **Learning.**
- The procedure to incrementally update each of weights in neural is based **on Training algorithm & Learning law**

Hebb Network

In Hebb learning, if the two interconnected neurons are *on* simultaneously, then the weight associated with these neurons can be increased by the modification made in their weight.

The weight update is given by,

$$w_i(new) = w_i(old) + x_i y$$

$$b(new) = b(old) + y$$

Hebb Network

In Hebb learning, if the two interconnected neurons are *on* simultaneously, then the weight associated with these neurons can be increased by the modification made in their weight.

The weight update is given by,

$$w_i(new) = w_i(old) + x_i y$$

$$b(new) = b(old) + y$$

Hebb Network Flowchart& Algorithm

Hebb Network-Training Algorithm

Step 0: Initialize the weights.

$$w_i = 0 \text{ for } i = 1 \text{ to } n$$

Step 1: Steps 2–4 have to be performed for each input training vector and target output pair, $s : t$.

Step 2: Input units activations are set.

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

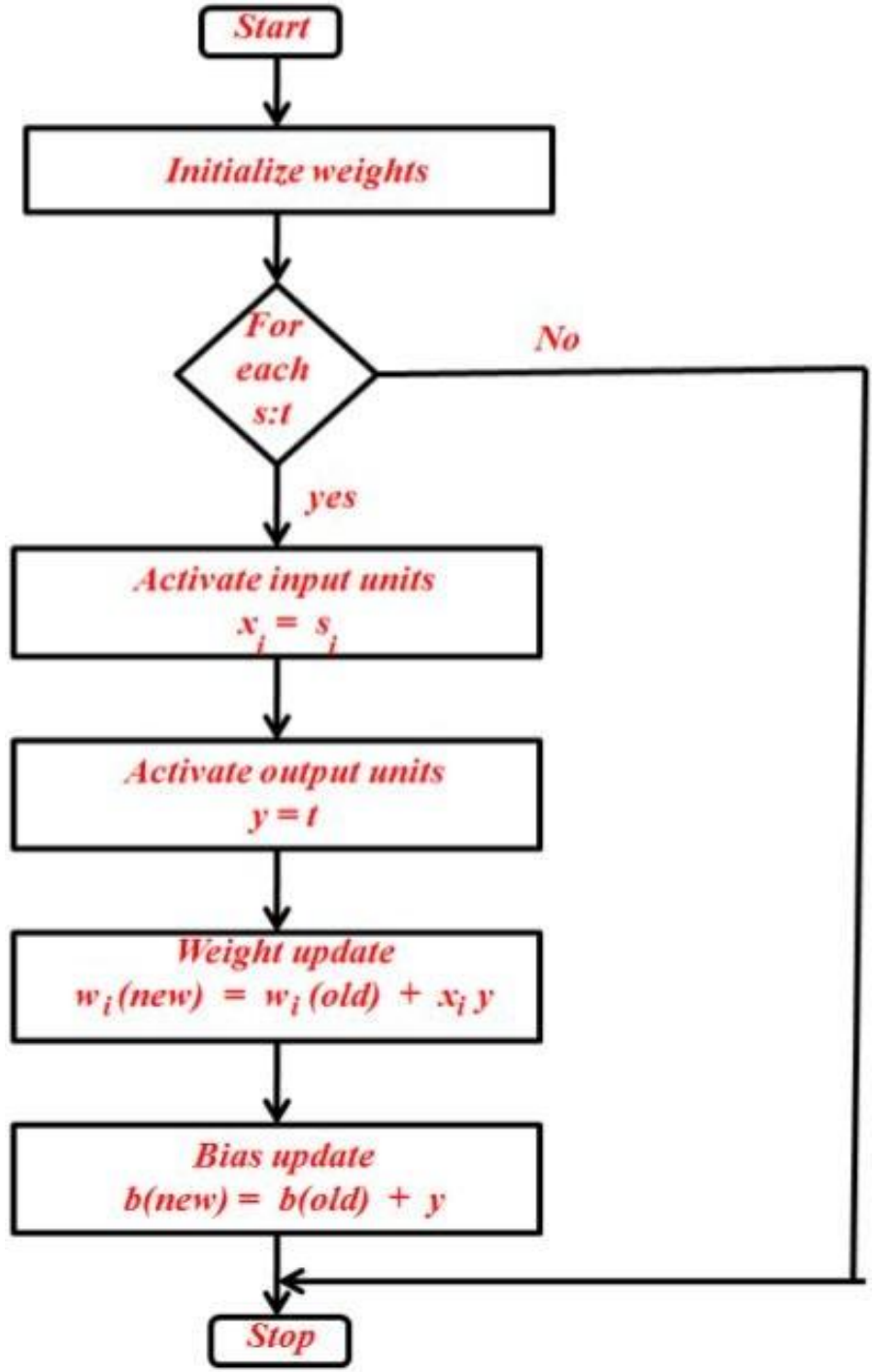
Step 3: Output units activations are set. $y = t$

Step 4: Weight adjustments and bias adjustments are performed.

$$w_i(new) = w_i(old) + x_i y$$

$$b(new) = b(old) + y$$

Change in weight, $\Delta w = xy$ $\Delta b = y$


Start
Initialize weights
For each s:t
No
yes
Activate input units
$x_i = s_i$
Activate output units
$y = t$
Weight update
$w_i(new) = w_i(old) + x_i y$
Bias update
$b(new) = b(old) + y$
Stop

Hebb Network Problem

Hebb Network -logical AND function

Design a Hebb Network to implement logical AND function .Use bipolar i/p and targets

2 Input AND Gate

TRUTH TABLE

INPUTS		OUTPUT
X	Y	Z
0	0	0
0	1	0
1	0	0
1	1	1

Training data table

Inputs			Target
x1	x2	b	y
1	1	1	1
1	-1	1	-1
-1	1	1	-1
-1	-1	1	-1

- AND function is very simple and mostly known to everyone where the output is **1/SET/ON** if both the inputs are **1/SET/ON.**
- But in this example, we have used **'-1'** instead of **'0'** this is because the Hebb network uses bipolar data and not binary data because the product item in the above equations would give the output as **0** which leads to a wrong calculation.

Design a Hebb Network to implement logical AND function .Use bipolar i/p and targets

- Step 1: Initially the weight and bias as set as Zero. w1=w2=b=0
- Step2 :First input[x1 x2 b]=[1 1 1] target y=1.

Setting the initial weight as old weight and applying the Hebb Rule.

((w1(old)=0, w2(old)=0, b(old)=0))

$$w_i(\text{new}) = w_i(\text{old}) + x_i y$$

$$w_1(\text{new}) = w_1(\text{old}) + x_1 y = 0 + 1 \times 1 = 1$$

$$w_2(\text{new}) = w_2(\text{old}) + x_2 y = 0 + 1 \times 1 = 1$$

$$b(\text{new}) = b(\text{old}) + y = 0 + 1 = 1$$

Training data table

Inputs			Target
x1	x2	b	y
1	1	1	1
1	-1	1	-1
-1	1	1	-1
-1	-1	1	-1

Design a Hebb Network to implement logical AND function .Use bipolar i/p and targets

$$w_1(\text{new}) = w_1(\text{old}) + x_1 y = 0 + 1 \times 1 = 1$$
$$w_2(\text{new}) = w_2(\text{old}) + x_2 y = 0 + 1 \times 1 = 1$$
$$b(\text{new}) = b(\text{old}) + y = 0 + 1 = 1$$

- The above calculated weights are used as the initial weight when second pattern is considered.
- Weight change here is $\Delta w_i = x_i y$

$$\Delta w_1 = x_1 y = 1 \times 1 = 1$$
$$\Delta w_2 = x_2 y = 1 \times 1 = 1$$
$$\Delta b = y = 1$$

Inputs				Weight changes			Weights		
x_1	x_2	b	y	Δw_1	Δw_2	Δb	w_1	w_2	b
							(0	0	0)
1	1	1	1	1	1	1	1	1	1
1	−1	1	−1						
−1	1	1	−1						
−1	−1	1	−1						

Design a Hebb Network to implement logical AND function .Use bipolar i/p and targets

- Second input[x1 x2 b]=[1 -1 1] target y=-1.

  Setting the initial weight as old weight and applying the Hebb Rule.

  ((w1(old)=1, w2(old)=1, b(old)=1))

- The weight changes here are:

Training data table

Inputs x1	Inputs x2	Inputs b	Target y
1	1	1	1
1	-1	1	-1
-1	1	1	-1
-1	-1	1	-1

$$w_i(\text{new}) = w_i(\text{old}) + x_i y$$

$$\Delta w_1 = x_1 y = 1 \times -1 = -1$$
$$\Delta w_2 = x_2 y = -1 \times -1 = 1$$
$$\Delta b = y = -1$$

$$w_1(\text{new}) = w_1(\text{old}) + \Delta w_1 = 1 - 1 = 0$$
$$w_2(\text{new}) = w_2(\text{old}) + \Delta w_2 = 1 + 1 = 2$$
$$b(\text{new}) = b(\text{old}) + \Delta b = 1 - 1 = 0$$

Inputs x_1	Inputs x_2	Inputs b	y	Weight changes Δw_1	Weight changes Δw_2	Weight changes Δb	Weights w_1	Weights w_2	Weights b
							(0	0	0)
1	1	1	1	1	1	1	1	1	1
1	−1	1	−1	−1	1	−1	0	2	0
−1	1	1	−1						
−1	−1	1	−1						

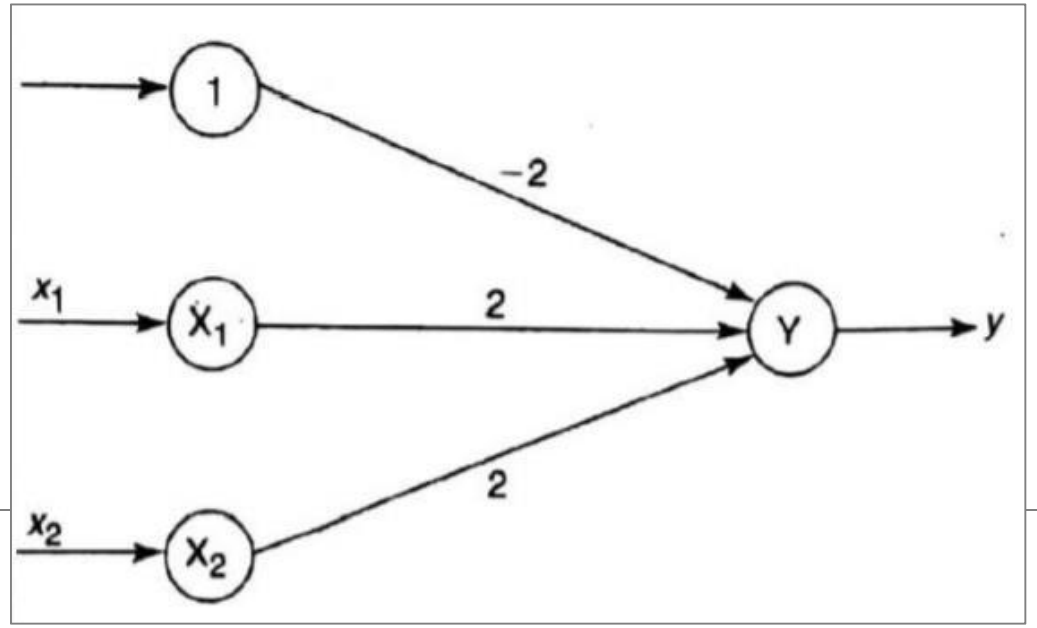
Design a Hebb Network to implement logical AND function .Use bipolar i/p and targets

Inputs				Weight changes			Weights		
x_1	x_2	b	y	Δw_1	Δw_2	Δb	w_1	w_2	b
							(0	0	0)
1	1	1	1	1	1	1	1	1	1
1	−1	1	−1	−1	1	−1	0	2	0
−1	1	1	−1	1	−1	−1	1	1	−1
−1	−1	1	−1						

Inputs				Weight changes			Weights		
x_1	x_2	b	y	Δw_1	Δw_2	Δb	w_1	w_2	b
							(0	0	0)
1	1	1	1	1	1	1	1	1	1
1	−1	1	−1	−1	1	−1	0	2	0
−1	1	1	−1	1	−1	−1	1	1	−1
−1	−1	1	−1	1	1	−1	2	2	−2

$$w_1 = 2; \quad w_2 = 2; \quad b = -2$$

The network can be represented as shown in Figure



Hebb Network -logical OR function

Design a Hebb Network to implement logical OR function Use bipolar i/p and targets

Truth Table		
A	B	Q
0	0	0
0	1	1
1	0	1
1	1	1

INPUTS		TARGETS
x1	x2	t
-1	-1	-1
-1	1	1
1	-1	1
1	1	1

INPUTS		bias	TARGETS
x1	x2	b	t
-1	-1	1	-1
-1	1	1	1
1	-1	1	1
1	1	1	1

Step 1: Initially the weight and bias as set as Zero. w1=w2=b=0

Step2 :First input[x1 x2 b]=[-1 -1 1] target y=-1.

Design a Hebb Network to implement logical OR function Use bipolar i/p and targets

Setting the initial weight as old weight and applying the Hebb Rule.

((w1(old)=0, w2(old)=0, b(old)=0))

$$w_i(\text{new}) = w_i(\text{old}) + x_i y$$

INPUTS		bias	TARGETS
x1	x2	b	t
-1	-1	1	-1
-1	1	1	1
1	-1	1	1
1	1	1	1

$w_1(\text{new}) = w_1(\text{old}) + x_1 y$ =0+-1X-1=1

$w_2(\text{new}) = w_2(\text{old}) + x_2 y$ =0+-1X-1=1

$b(\text{new}) = b(\text{old}) + y$ =0+-1=-1

The above calculated weights are used as the initial weight when second pattern is considered.Weight change here is $\Delta w_i = x_i y$

$\Delta w_1 = x_1 y = 1 \quad \Delta w_2 = x_2 y = 1 \quad \Delta b = y = -1$

Design a Hebb Network to implement logical OR function Use bipolar i/p and targets

INPUTS		bias	TARGETS	weight		b_{new}
x1	x2	b	t	w1	w2	b
-1	-1	1	-1	1	1	-1
-1	1	1	1			
1	-1	1	1			
1	1	1	1			

Second input[x1 x2 b]=[-1 1 1] target y=1.

Setting the initial weight as old weight and applying the Hebb Rule.

((w1(old)=1, w2(old)=1, b(old)=-1))

Design a Hebb Network to implement logical OR function Use bipolar i/p and targets

The weight changes here are:

$$\Delta w_1 = x_1 y = 1 \times -1 = -1$$

$$\Delta w_2 = x_2 y = 1 \times 1 = 1$$

$$\Delta b = y = 1$$

$$w_1(\text{new}) = w_1(\text{old}) + \Delta w_1 = 1 - 1 = 0$$

$$w_2(\text{new}) = w_2(\text{old}) + \Delta w_2 = 1 + 1 = 2$$

$$b(\text{new}) = b(\text{old}) + \Delta b = -1 + 1 = 0$$

INPUTS		bias	TARGETS	weight		b_{new}
x1	x2	b	t	w1	w2	b
-1	-1	1	-1	1	1	-1
-1	1	1	1	0	2	0
1	-1	1	1			
1	1	1	1			

Design a Hebb Network to implement logical OR function Use bipolar i/p and targets

- For third input

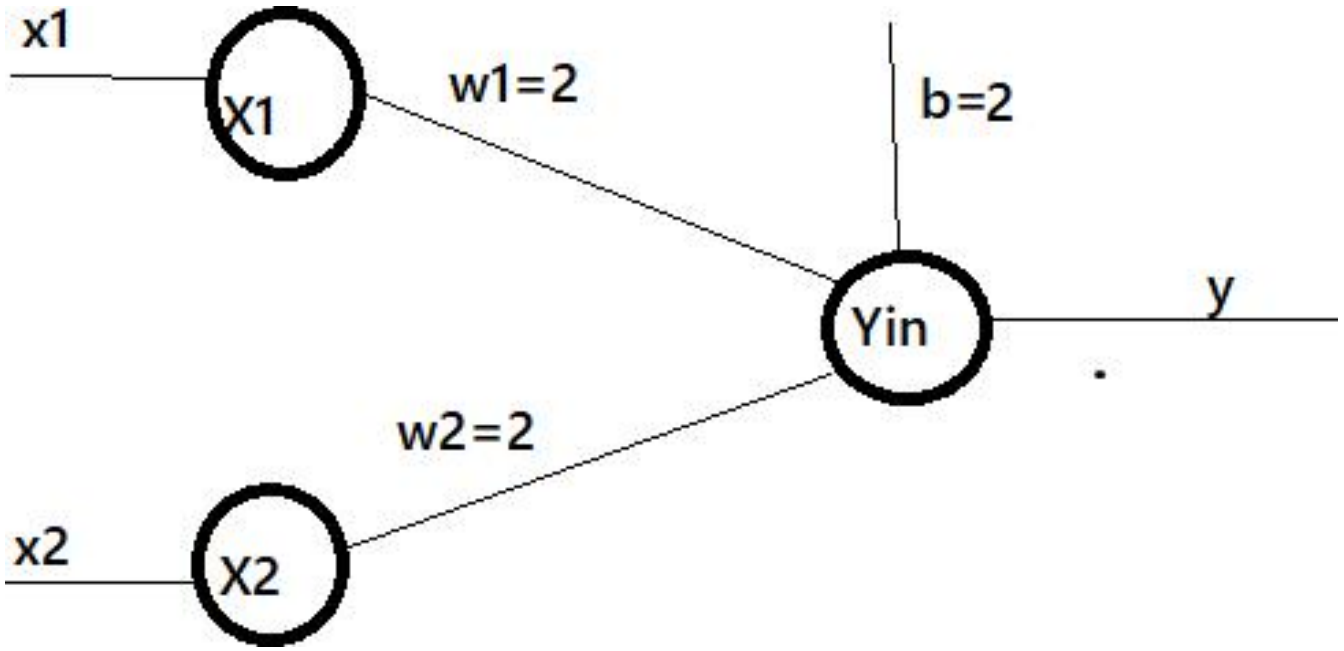
INPUTS		bias	TARGETS	weight		b_{new}
x1	x2	b	t	w1	w2	b
-1	-1	1	-1	1	1	-1
-1	1	1	1	0	2	0
1	-1	1	1	1	1	1
1	1	1	1			

Design a Hebb Network to implement logical OR function Use bipolar i/p and targets

- For fourth input

INPUTS		bias	TARGETS	weight		b_{new}
x1	x2	b	t	w1	w2	b
-1	-1	1	-1	1	1	-1
-1	1	1	1	0	2	0
1	-1	1	1	1	1	1
1	1	1	1	2	2	2

Design a Hebb Network to implement logical OR function Use bipolar i/p and targets



Hebb Network -logical XOR function

Design a Hebb Network to implement XOR function .Use bipolar i/p and targets

Truth Table		
B	A	Q
0	0	0
0	1	1
1	0	1
1	1	0
$Q = A\bar{B} + \bar{A}B$		

INPUTS		TARGETS
x1	x2	t
-1	-1	-1
-1	1	1
1	-1	1
1	1	1

INPUTS		bias	TARGETS
x1	x2	b	t
-1	-1	1	-1
-1	1	1	1
1	-1	1	1
1	1	1	1

Design a Hebb Network to implement XOR function .Use bipolar i/p and targets

Step 1: Initially the weight and bias as set as Zero. w1=w2=b=0

Step2 :First input[x1 x2 b]=[-1 -1 1] target y=-1.

Setting the initial weight as old weight and applying the Hebb Rule.
((w1(old)=0, w2(old)=0, b(old)=0))

$$w_i(\text{new}) = w_i(\text{old}) + x_i y$$

$w_1(\text{new}) = w_1(\text{old}) + x_1 y$ =0+-1X-1=1

$w_2(\text{new}) = w_2(\text{old}) + x_2 y$ =0+-1X-1=1

$b(\text{new}) = b(\text{old}) + y$ =0+-1=-1

Design a Hebb Network to implement XOR function .Use bipolar i/p and targets

The above calculated weights are used as the initial weight when second pattern is considered.Weight change here is $\Delta w_i = x_i y$

$$\Delta w_1 = x_1 y = 1$$

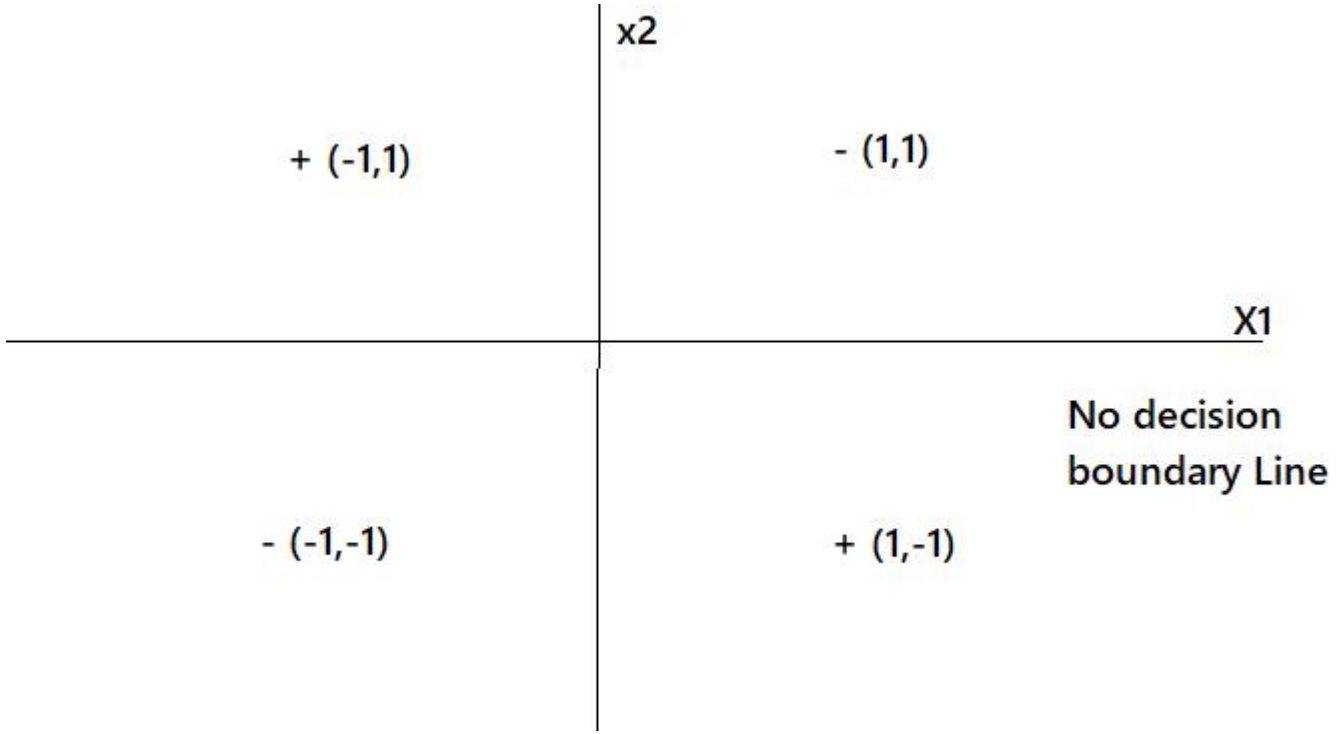
$$\Delta w_2 = x_2 y = 1$$

$$\Delta b = y = -1$$

Design a Hebb Network to implement XOR function .Use bipolar i/p and targets

INPUTS		bias	TARGETS	weight		b_{new}
x1	x2	b	t	w1	w2	b
-1	-1	1	-1	1	1	-1
-1	1	1	1	0	2	0
1	-1	1	1	1	1	1
1	1	1	1	0	0	0

Design a Hebb Network to implement XOR function .Use bipolar i/p and targets



Design a Hebb Network to implement XOR function .Use bipolar i/p and targets

- The final weights obtained after presenting all i/p functions do not give the correct o/p for all patterns
- Thus **XOR function is a special case of Pattern classification problem which is not linearly separable.**
- It can be made linear separable by separating +ve regions and –ve Regions

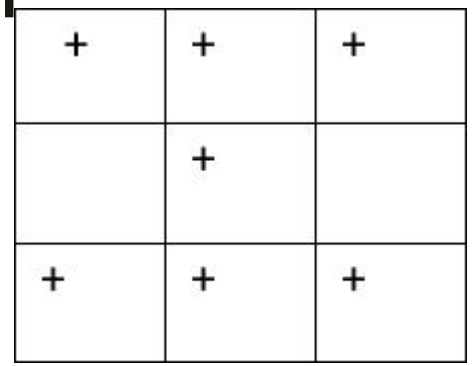
$$y = x1\overline{x2} + \overline{x1}x2$$

$$Y=z1+z2$$

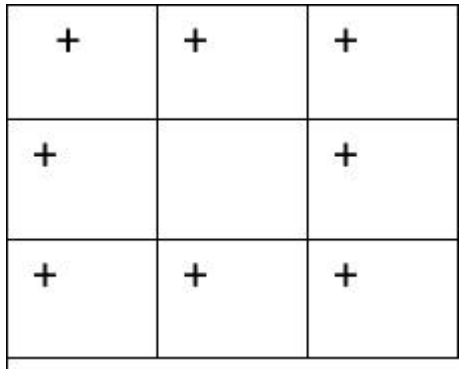
$$\text{Where } z1=x1\overline{x2} \ \& \ z2=\overline{x1}x2$$

Hebb Network -problem

Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern



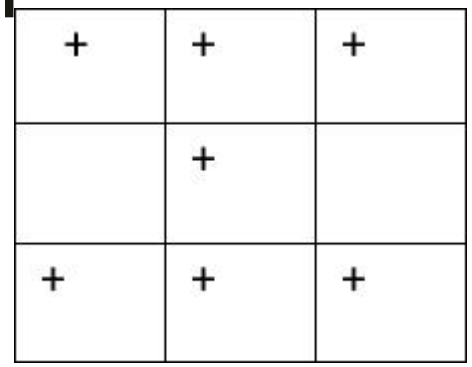
I



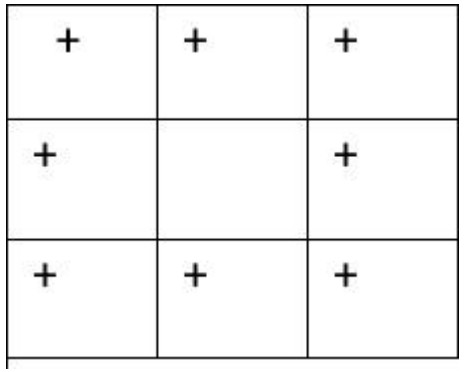
O

- The pattern shown is a 3X3 matrix formed in squares.
- The '+' symbol represent 1 and empty squares represent '-1'.
- I →belongs to the members of the class→target value 1
- 0→does not belongs to members of class→target value -1

Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern



I



O

Pattern	Inputs									Target	
	x1	x2	X3	X4	X5	X6	X7	X8	X9	y	
I	1	1	1	-1	1	-1	1	1	1	1	
O	1	1	1	1	-1	1	1	1	1	-1	

Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

- Here a single-layer network with nine input neurons, one bias and one output neuron is formed.
- Set the initial weights and bias to zero, i.e.,

  w1=w2=w3=w4=w5=w6=w7=w8=w9= 0
- Case 1: Presenting first input pattern (I), we calculate change in weights:

$$\Delta w_i = x_i y, \quad i = 1 \text{ to } 9$$

$$\Delta w_1 = x_1 y = 1 \times 1 = 1$$

$$\Delta w_2 = x_2 y = 1 \times 1 = 1$$

$$\Delta w_3 = x_3 y = 1 \times 1 = 1$$

$$\Delta w_4 = x_4 y = -1 \times 1 = -1$$

$$\Delta w_5 = x_5 y = 1 \times 1 = 1$$

$$\Delta w_6 = x_6 y = -1 \times 1 = -1$$

$$\Delta w_7 = x_7 y = 1 \times 1 = 1$$

$$\Delta w_8 = x_8 y = 1 \times 1 = 1$$

$$\Delta w_9 = x_9 y = 1 \times 1 = 1$$

$$\Delta b = y = 1$$

calculate the new weights

$$w_i(\text{new}) = w_i(\text{old}) + \Delta w_i$$

Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

Setting the old weights as the initial weights

$$w_1(\text{new}) = w_1(\text{old}) + \Delta w_1 = 0 + 1 = 1$$

$$w_2(\text{new}) = w_2(\text{old}) + \Delta w_2 = 0 + 1 = 1$$

$$w_3(\text{new}) = w_3(\text{old}) + \Delta w_3 = 0 + 1 = 1$$

Similarly, calculating for other weights

$$w_4(\text{new}) = -1, \quad w_5(\text{new}) = 1, \quad w_6(\text{new}) = -1,$$

$$w_7(\text{new}) = 1, \quad w_8(\text{new}) = 1, \quad w_9(\text{new}) = 1, \quad b(\text{new}) = 1$$

weights after presenting first input pattern

$$W_{(\text{new})} = [1\ 1\ 1\ -1\ 1\ -1\ 1\ 1\ 1\ 1]$$

weights									Bias
w1	w2	w3	w4	w5	w6	w7	w8	w9	b
1	1	1	-1	1	-1	1	1	1	1

Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

Pattern	Inputs									Target
	x1	x2	X3	X4	X5	X6	X7	X8	X9	y
I	1	1	1	-1	1	-1	1	1	1	1
O	1	1	1	1	-1	1	1	1	1	-1

weights									Bias
w1	w2	w3	w4	w5	w6	w7	w8	w9	b
1	1	1	-1	1	-1	1	1	1	1

Case 2: Now present the second input pattern (O).

The initial weights used here are the final weights obtained after presenting the first input pattern.

the weights are calculated as shown below ($y = -1$ with the initial weights being [1 1 1 −1 1 −1 1 1 1 1]).

$w_i(\text{new}) = w_i(\text{old}) + \Delta x_i \qquad [\Delta w_i = x_i y]$

$w_1(\text{new}) = w_1(\text{old}) + x_1 y = 1 + 1 \times -1 = 0$

$w_2(\text{new}) = w_2(\text{old}) + x_2 y = 1 + 1 \times -1 = 0$

$w_3(\text{new}) = w_3(\text{old}) + x_3 y = 1 + 1 \times -1 = 0$

$w_4(\text{new}) = w_4(\text{old}) + x_4 y = -1 + 1 \times -1 = -2$

$w_5(\text{new}) = w_5(\text{old}) + x_5 y = 1 + -1 \times -1 = 2$

Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

Pattern	Inputs									Target
	x1	x2	X3	X4	X5	X6	X7	X8	X9	y
I	1	1	1	-1	1	-1	1	1	1	1
O	1	1	1	1	-1	1	1	1	1	-1

weights									Bias
w1	w2	w3	w4	w5	w6	w7	w8	w9	b
1	1	1	-1	1	-1	1	1	1	1

$$w_6(\text{new}) = w_6(\text{old}) + x_6 y = -1 + 1 \times -1 = -2$$

$$w_7(\text{new}) = w_7(\text{old}) + x_7 y = 1 + 1 \times -1 = 0$$

$$w_8(\text{new}) = w_8(\text{old}) + x_8 y = 1 + 1 \times -1 = 0$$

$$w_9(\text{new}) = w_9(\text{old}) + x_9 y = 1 + 1 \times -1 = 0$$

$$b(\text{new}) = b(\text{old}) + y = 1 + 1 \times -1 = 0$$

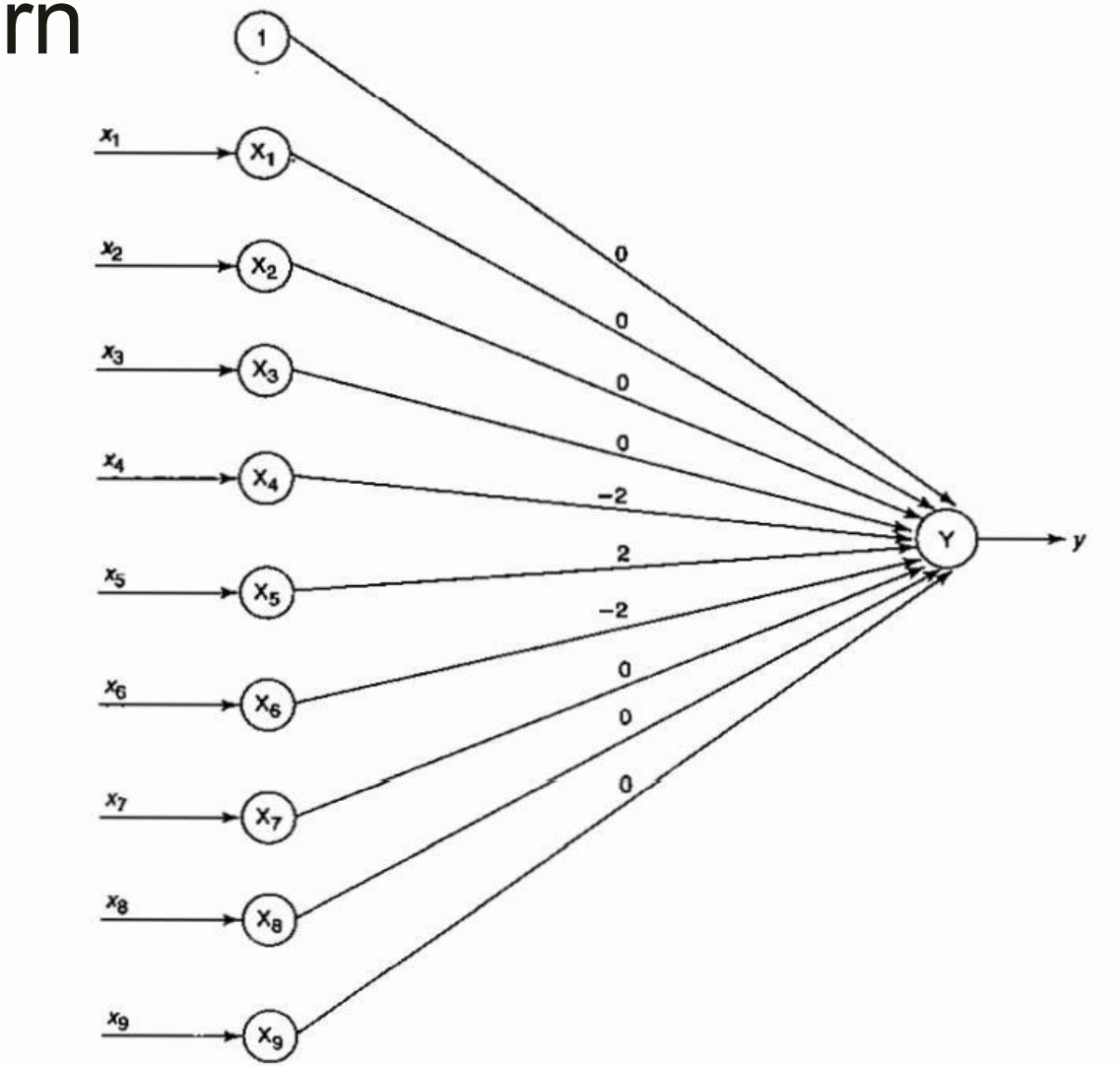
Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

The final weights after presenting the second input pattern are given as

$$W_{(new)} = [0\ 0\ 0\ -2\ 2\ -2\ 0\ 0\ 0\ 0]$$

weights									Bias
w1	w2	w3	w4	w5	w6	w7	w8	w9	b
1	1	1	-1	1	-1	1	1	1	1
0	0	0	-2	2	-2	0	0	0	0

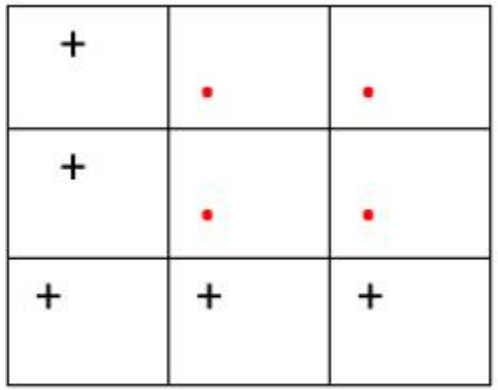
Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern



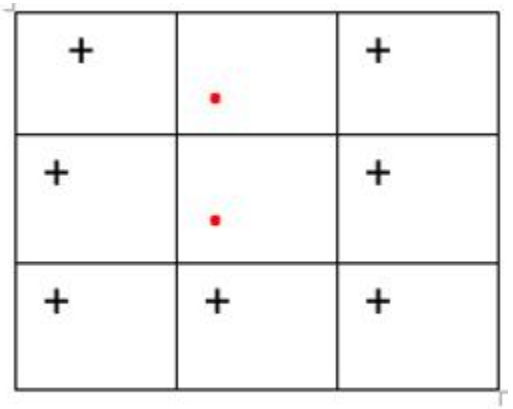
Hebb Network –tutorial questions

1.Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

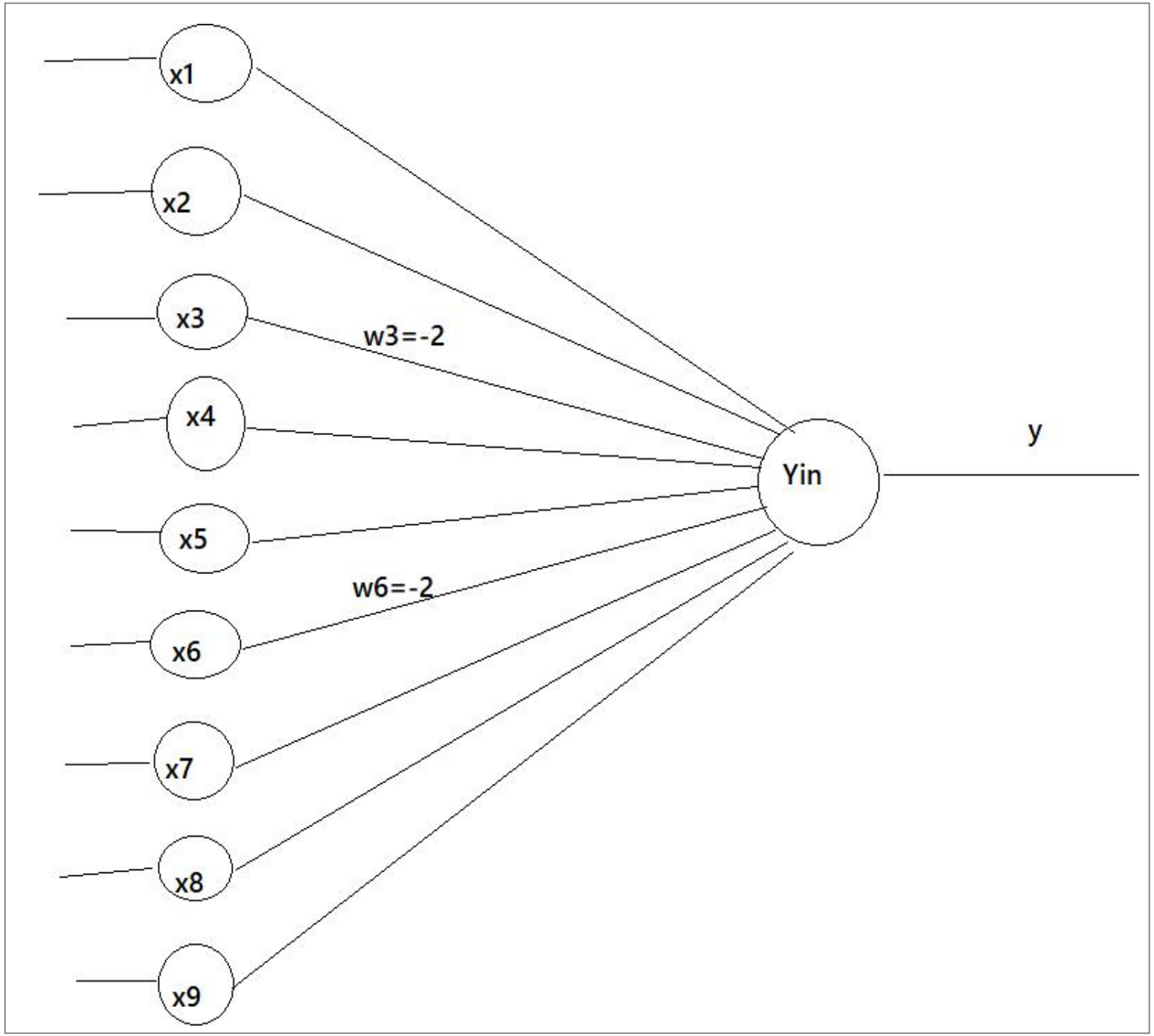
- Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern.
- L →belongs to the members of the class(+)→target value 1
- U→does not belongs to members of class(.)→target value -1



L



U


x1
x2
x3
w3=-2
x4
x5
w6=-2
x6
x7
x8
x9
Yin
y

2.Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

Using Hebb rule, Find the weight required toperform the following classification of the given input patterns shown below

The pattern is shown as 3X3 matrix form in the squares.

The "+" symbol represents the value 1 and dot indicate -1.

Consider "A" belongs to the member of the class so the target value is 1

and "E" does not belongs to the member of the class so the target value is -1

+	+	+
+	.	+
+	+	+
+	.	+
+	.	+

"A"

+	+	+
+	.	.
+	+	+
+	.	.
+	+	+

"E"

3.Using Hebb Network calculate the weight required to perform the following classification of given i/p pattern

- Using Hebb rule find weights required to perform following classifications. The vectors(1 -1 1 -1) and (1 1 1 -1) belongs to class (target value +1);
  vectors (-1 -1 1 1) and(1 1 -1 -1) do not belongs to class(target value -1).
  Also using each of training x vectors as input, test the response of the net

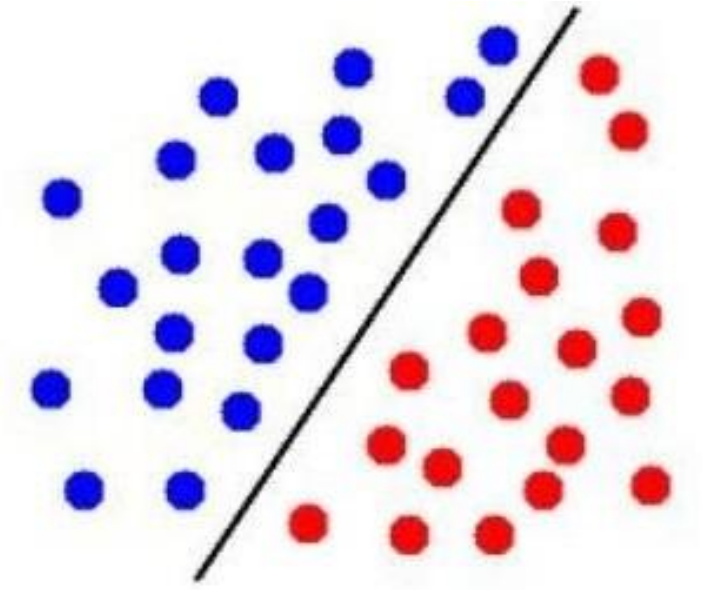
Linear Separability

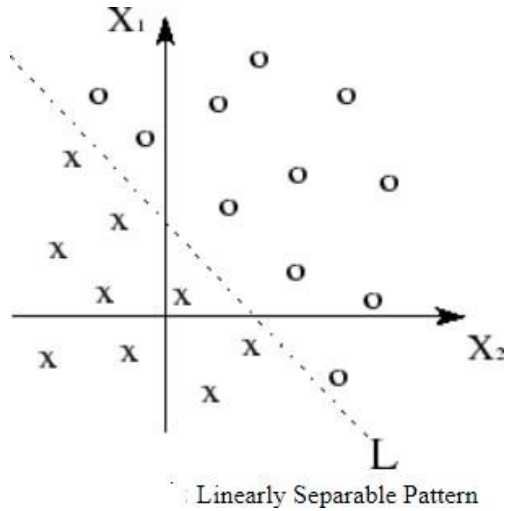
Linear separability

- **ANN does not give exact solution for a nonlinear problem.**
- **Linear separability is the concept wherein** , the separation of **input space into regions is based on whether the network response is positive or negative**.
- Linear separable means ,in the plane if we can splits the input data into two half-spaces such that all points of the first class should be in one half-space and other points of the second class should be in the other half-space.
- **In two dimensional space,** it means that there is a line, which separates points of one class from points of the other class.
- The idea of linearly separable is easiest to visualize and understand in 2 dimensions

Linear separability

- A dataset is said to be linearly separable if it is possible to draw a line that can separate the red and green points from each other.
- **For example**: In the following image, Let the two classes be represented by colors red and green. if blue circles represent points from one class and red circles represent points from the other class, then these points are linearly separable.

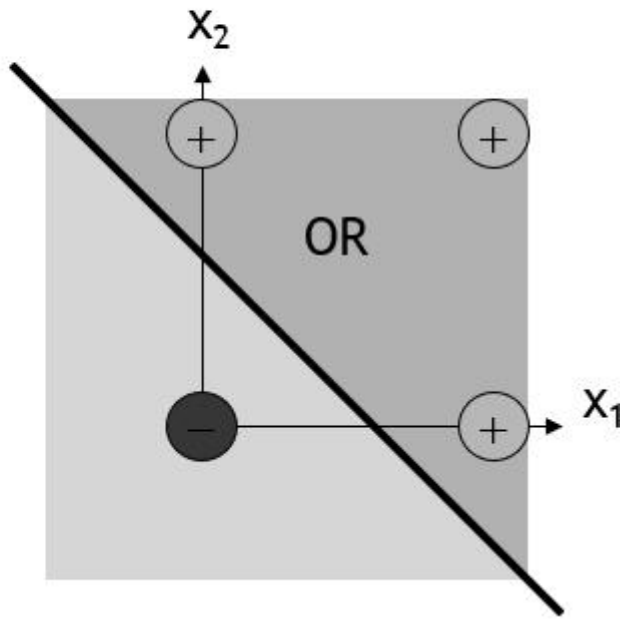




Linearly Separable Pattern

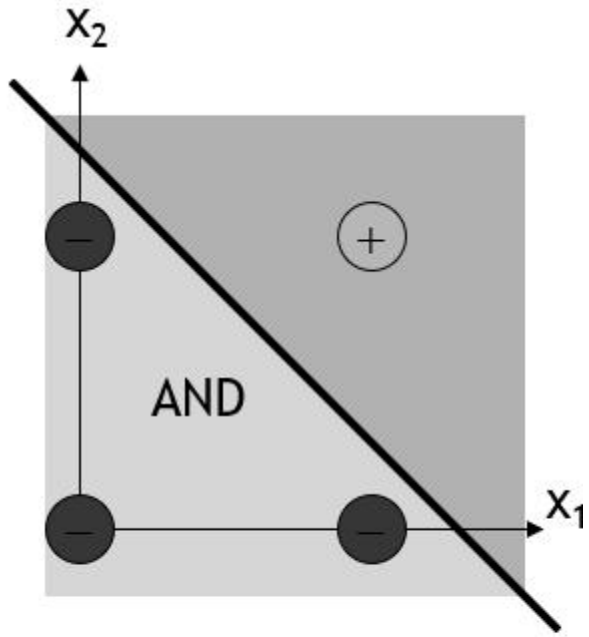
Linear separability

Truth Table		
A	B	Q
0	0	0
0	1	1
1	0	1
1	1	1
Read as A OR B gives Q		



Linear separability

Truth Table		
A	B	Q
0	0	0
0	1	0
1	0	0
1	1	1
Read as A AND B gives Q		

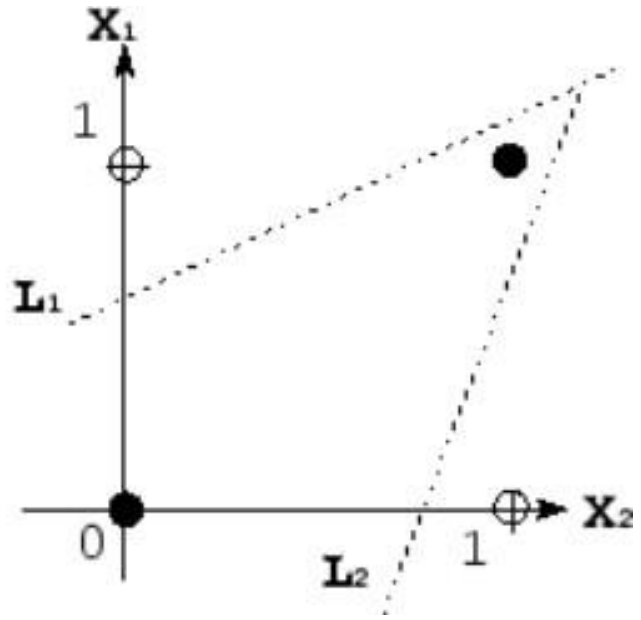


Linear separability

- The most classic example of linearly inseparable pattern is a logical exclusive-OR (XOR) function.
- The illustration of XOR function that two classes,
- 0 for black dot and 1 for white dot, cannot be separated with a single line.

X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0

$Y = X_1 \oplus X_2$



Thank You