

# Artificial Intelligence

(Intro. Planning and ANN)

**Dr. Priyadarshan S. Dhabe,**

Ph.D, IIT Bombay,  
Assistant Professor in Information Technology

## Syllabus-

- **Planning-** Blocks world, STRIPS, Implementation using goal stack.
- **Introduction to Neural networks:-** basic, comparison of human brain and machine, biological neuron, general neuron model, activation functions, Perceptron learning rule, applications and advantages of neural networks.
- **Brief introduction to single layer and multiplayer networks.**

## What is planning?

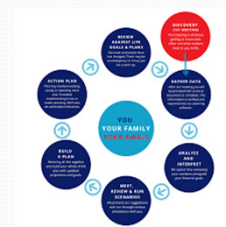


- Ref:- Wikipedia
- **Automated planning and scheduling**, sometimes denoted as simply **AI planning**, is a branch of artificial intelligence that concerns the realization of strategies or action sequences, typically for execution by intelligent agents, autonomous robots and unmanned vehicles.
- Planning is one of the aspect of human intelligence, we want to put in to machines.

## What is planning?



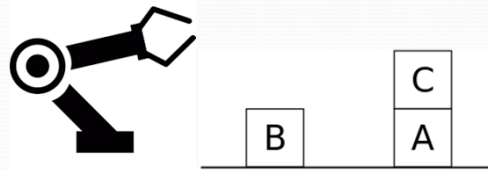
- **Planning definition-**
- Can be broadly defined as the process of computing several steps of a problem solving procedure before executing any of them.
- Planning decompose the problem into sub-problems/parts
- These sub-parts
  - interacts with each other
  - Are Ordered to solve big problem



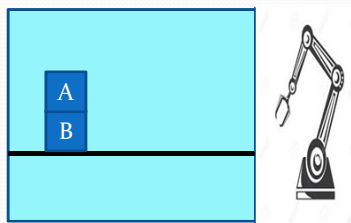
## The Blocks world domain

- The domain considered for planning systems
  - There is a flat surface on which blocks can be placed.
  - Each block has exactly same size and is identified with an alphabet. There are many such blocks.
  - At most one block can be stacked on the another block, since they are of same size.
  - There is a robot arm that can manipulate the blocks
  - Predicates are used to represent facts in the blocks world

$$ON(A,B) \wedge ONTABLE(B)$$



## The Blocks world domain



4. **PUTDOWN(A)**- Put block A down on the table. The arm must be holding block A.

Robot arm can perform following actions

1. **UNSTACK(A,B)**- Pick up the block A from its current position on block B. The arm must be empty and no block should be on the top of A
2. **STACK(A,B)**- Place block A on block B. The arm must already be holding block A and the surface of B must be clear
3. **PICKUP(A)**- Pick up block A from the table and hold it. Precondition- arm must be empty and there must be nothing on the top of A

## The Blocks world domain

- Following predicates describe the block world

$ON(A, B)$  – block A is on block B

$ONTABLE(B)$ - block B is on Table

$CLEAR(A)$ - There is nothing on the top of block A

$HOLDING(A)$ - Robot arm is currently holding block A

$ARMEMPTY$ - The arm is holding nothing

- Various logical statements are true in the blocks world

$[\exists x : HOLDING(x)] \rightarrow \neg ARMEMPTY$

$\forall x : ONTABLE(x) \rightarrow \neg \exists y : ON(x, y)$

$\forall x : [\neg \exists y : ON(y, x)] \rightarrow CLEAR(x)$

## Components of a planning system

- Planning can also be viewed as **searching** of various operators that can be applied at current state to obtain new state .
- There must be a **component** to perform following functions
  1. **Choose the best rule** to apply next based on the best available heuristic information
  2. **Apply the chosen rule** to compute the new problem state that arises from its application
  3. **Detect when a solution has been found**
  4. **Detect dead ends** so that they can be abandoned and the system's effort directed in more fruitful directions.
  5. **Detect when an almost correct solution has been found** and employ special techniques to make it totally correct.



## Components of a planning system

- **Choosing a rule to apply-**
  - if several rules are available, then find the best rule by exploiting the heuristic information. The chosen rule must allow to reduce the difference between current state and the goal state, in planning procedure.
- **Applying rules-**
  - Each rule has a precondition and consequent
  - Frame axioms – are axioms that describes the situation after application of the rule, are used.
  - STRIPS- a robot problem solving system uses frame axioms

## STRIPS-Stanford Research Institute Problem Solver

- STRIPS is developed in 1971, by Fikes and Nilsson
- Each robotic arm operation is described by list of new predicates that the operator causes to become true and a list of old predicates that it causes to become false.
- These two list are called as ADD and DELETE lists, respectively.
- A third list must also be specified for each operator called PRECONDITION. It lists predicates that must be true for the operator to be applied.
- Any predicate not included in either ADD or DELETE is assumed to be unaffected by it. Thus, unrelated things need not be considered.

## STRIPS- Style operators for blocks world domain

*STACK*( $x, y$ )

P:  $\text{CLEAR}(y) \wedge \text{HOLDING}(x)$

D:  $\text{CLEAR}(y) \wedge \text{HOLDING}(x)$

A:  $\text{ARMEMPTY} \wedge \text{ON}(x, y)$

*UNSTACK*( $x, y$ )

P:  $\text{ON}(x, y) \wedge \text{CLEAR}(x) \wedge \text{ARMEMPTY}$

D:  $\text{ON}(x, y) \wedge \text{ARMEMPTY}$

A:  $\text{HOLDING}(x) \wedge \text{CLEAR}(y)$

*PICKUP*( $x$ )

P:  $\text{CLEAR}(x) \wedge \text{ONTABLE}(x) \wedge \text{ARMEMPTY}$

D:  $\text{ONTABLE}(x) \wedge \text{ARMEMPTY}$

A:  $\text{HOLDING}(x)$



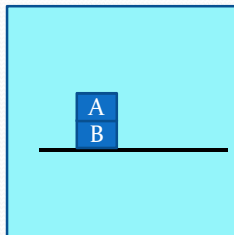
## STRIPS- Style operators for blocks world domain

*PUTDOWN*( $x$ )

P:  $\text{HOLDING}(x)$

D:  $\text{HOLDING}(x)$

A:  $\text{ONTABLE}(x) \wedge \text{ARMEMPTY}$



The situation in blocks world can be described as  
 $\text{ON}(A, B) \wedge \text{ONTABLE}(B) \wedge \text{CLEAR}(A)$

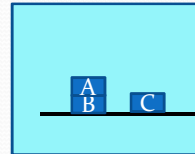
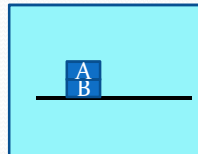


After applying operator *UNSTACK*(A,B), the description of the world would be

$\text{ONTABLE}(B) \wedge \text{CLEAR}(B) \wedge \text{HOLDING}(A)$

## Components of a planning system

- **Detecting a solution-**
  - Planning procedures transforms a given state into another by application of operators. **How will it know it has done?**
  - If the states are described with the help of **properties**, the matter becomes difficult
  - Using **predicate  $P(x)$** , the goal state is described and it is tested for **termination** of planning procedures.
  - There can be multiple goal states e.g. **ON(A,B)**



## Components of a planning system

- **Detecting dead ends-**
  - Planning procedures **searches** for **sequence of operators** to solve a problem.
  - It must be able to detect, when **exploring** a path that **never lead to a solution** (or at least **unlikely to lead to one**). This fact must be true in **reasoning forward** or **backward**

## Components of a planning system

- **Repairing an almost correct solution-**
  - A bigger problem is decomposed into several sub-problems. But combining solutions of several sub-solutions **may not yield** the solution to original problem. Thus, following **alternates** are used.
    - 1. Throw that solution- wasted efforts
    - 2. If the difference between two sub-solutions A and B is greater than zero, then call problem solving system to eliminate this difference.
    - 3. Try more appropriate operators
    - 4. Keep the problems as it is till the **last moment**. Then when as much info as possible is available, then complete the solution (eliminate the difference). This approach is called **least commitment strategy**.

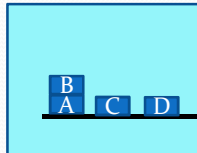
## Goal stack planning

- This approach is used in **STRIPS**
- The **problem solver** makes use of a **single stack** that contains both **goals** and **operators**, that has been proposed to satisfy those **goals**.
- The problem solver relies on a **KB** that describes the current situation and a set of operators described as **PRECONDITION, ADD, DELETE** lists



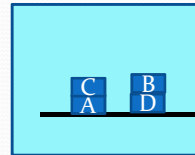
## Goal stack planning-working

Start



$ON(B,A) \wedge$   
 $ONTABLE(A) \wedge$   
 $ONTABLE(C) \wedge$   
 $ONTABLE(D) \wedge$   
 $ARMEMPTY$

Goal



$ON(C,A) \wedge$   
 $ON(B,D) \wedge$   
 $ONTABLE(A) \wedge$   
 $ONTABLE(D)$

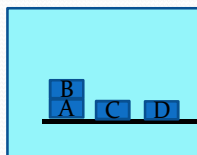
When we start solving this problem, the goal stack is simply

$ON(C,A) \wedge ON(B,D) \wedge ONTABLE(A) \wedge ONTABLE(D)$

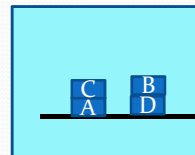
We want to separate this problem into 4 sub problems, one for each component of the original goal

## Goal stack planning-working

Start



Goal



$ON(C,A) \wedge ON(B,D) \wedge ONTABLE(A) \wedge ONTABLE(D)$

Two of the sub-problems  $ONTABLE(A)$  and  $ONTABLE(D)$  are already true in the initial state. Thus, we will work for remaining two

Depending on the order in which we want to solve sub-problems two goal stacks are possible.

Let  $OTAD = ONTABLE(A) \wedge ONTABLE(D)$

$ON(C,A)$   
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

**Stack 1**

$ON(B,D)$   
 $ON(C,A)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

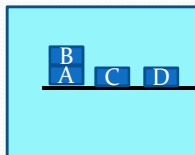
**Stack 2**

## Goal stack planning-working

- At each step of the problem solving process, the **top of the stack** will be pursued.
- When a **sequence of operators** that satisfies it is found, that sequence is applied to the **state description**, yielding **new description**.
- The process continues till the **goal stack is empty**.
- The **last check** is the **original goal** is compared with the **final state derived** from the application of chosen operators.

## Goal stack planning-working

On the stack we have  $ON(C,A)$  which is **not true**. Thus, will find operators that could make it true. Out of 4 operators we are considering (stack, unstack, pickup, putdown) only  $STACK(C,A)$  can make it possible and thus replace  $ON(C,A)$  by  $STACK(C,A)$



$ON(C,A)$   
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

Our new stack will be

$STACK(C,A)$   
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

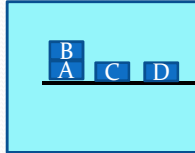
But, in order to apply operator  $STACK(C,A)$ , its precondition must hold so we must establish them as sub goals

$CLEAR(A)$   
 $HOLDING(C)$   
 $CLEAR(A) \wedge HOLDING(C)$   
 $STACK(C,A)$   
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

Thus, our new goal stack will be

## Goal stack planning-working

CLEAR(A)  
HOLDING(C)  
 $CLEAR(A) \wedge HOLDING(C)$   
STACK(C,A)  
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$



$ON(B,A)$   
CLEAR(B)  
ARMEMPTY  
HOLDING(C)  
 $CLEAR(A) \wedge HOLDING(C)$   
STACK(C,A)  
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

Next we check that CLEAR(A) is not true and only operator that can make it true is UNSTACK(B,A) and thus, our new goal stack will be

UNSTACK(B,A)  
HOLDING(C)  
 $CLEAR(A) \wedge HOLDING(C)$   
STACK(C,A)  
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

Apply preconditions of UNSTACK(B,A) which are  $ON(B,A)$ , CLEAR(B) and ARMEMPTY. Thus our goal stack will be

Now we will compare top of stack  $ON(B,A)$  with our model and learn that it is satisfied so we will pop the stack till ARMEMPTY.

## Goal stack planning-working

Our goal stack at this point will be

We now try to solve the goal HOLDING(C), but it is not true. It can be made true by operator PICKUP(C) and thus add preconditions of PICKUP(C) on stack, which are  $CLEAR(C) \wedge ONTABLE(C) \wedge ARMEMPTY$

Our goal stack at this point will be

ONTABLE(C)  
CLEAR(C)  
ARMEMPTY  
 $CLEAR(A) \wedge HOLDING(C)$   
STACK(C,A)  
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

ONTABLE(C) and CLEAR(C) are true, thus pop them. But ARMEMPTY is not satisfied since HOLDING(B) is true (due to UNSTACK(B,A)). TO make ARMEMPTY as true we will use STACK(B,D), since it is in the goal. Apply all the preconditions of STACK(B,D) to the stack

HOLDING(C)  
 $CLEAR(A) \wedge HOLDING(C)$   
STACK(C,A)  
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$

CLEAR(D)  
HOLDING(B)  
 $CLEAR(D) \wedge HOLDING(B)$   
STACK(B,D)  
 $CLEAR(A) \wedge HOLDING(C)$   
STACK(C,A)  
 $ON(B,D)$   
 $ON(C,A) \wedge ON(B,D) \wedge OTAD$



## Goal stack planning-working

- At some stage our stack will look like

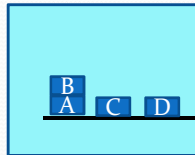
At this point **problem solver** will halt and produce **a plan** with following actions in the specified order

1. UNSTACK(B,A)
2. STACK(B,D)
3. PICKUP(C)
4. STACK(C,A)

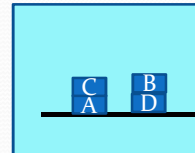
```

CLEAR(D)
UNSTACK(B,A)
CLEAR(D) ^ HOLDING(B)
STACK(B,D)
ONTABLE(C) ^ CLEAR(C) ^ ARMEMPTY
PICKUP(C)
CLEAR(A) ^ HOLDING(C)
STACK(C,A)
ON(B,D)
ON(C,A) ^ ON(B,D) ^ OTAD
  
```

**Start**



**Goal**



## Introduction to Artificial Neural networks

Human Brain



Human brain is massively parallel processor

-Basic computing unit  
"Neuron"

- A neuron is connected to several other neurons
- The connection is called "synapse" and its property is "synaptic weight"
- Neurons communicates with electrical impulses of short duration with milli-electron-volt
- **Statistics**
  - Neurons= $10^{11}$
  - Synapse= Trillions= $10^{18}$
  - 1 volt= $10^{-18}$  ev



## Why to study ANN?



- Consider **intelligence** exhibited by some animals.
- Consider a problem of identifying a photo of a familiar person from a group photo requires **considerable time or hours** for a **supercomputer** (using **fastest H/W** and **fastest algorithm**). But the **Dogs** can recognize their masters in **10 m sec** from a crowd.
- Who is intelligent?

## Why to study ANN?

- **Echo locating bat.**

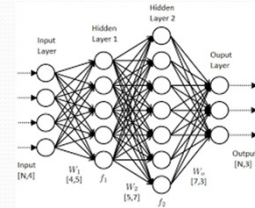


- It is a bird, who don't have "eyes" instead **echo sensors**.
- Mostly active in night.
- Eats insects near by the trees.
- How they catch their target?.
- They capture reflection of an emitted rays from target to detect it.

Echo locating bats are **several times intelligent** than the well designed **radar systems** in terms of **HIT ratios**.

## Why ANN?

- **Visual** and **audible** pattern recognition is found most difficult with the machines.
- **Animals** are intelligent than the **computers**, which are **inspired** from **human brain**.
- This fact motivated scientists to study the brain.
- ANN is outcome of such a sincere study.
- ANN is a new way of computation called **neuro-computing** as opposed to **digital computing**.
- ANN system works like **human brain** that has capability to **learn** and **reason**.



## Human brain and Machine



- | <b>Human Brain</b>   | <b>Machine</b>                             |
|--|--|
| 1. Outperform in cognitive tasks.                          | 1. Outperform in precise calculatory task. |
| 2. Basic computation unit ( <b>neuron</b> ) is non-linear. | 2. Basic computational unit is linear.     |
| 3. Switching speed is order of $10^{-3}$ (msec)            | 3. Switching speed is $10^{-9}$ (pico sec) |
| 4. Massively parallel processor ( $10^{11}$ )              | 4. Few processor                           |
| 5. Consumes less power                                     | 5. Consumes more power.                    |

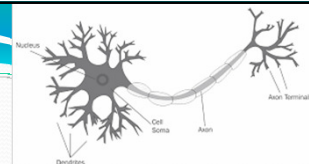


## Structure Of Human brain

- Human brain consists of  $10^{11}$  computational units called “*neurons*”. (which is approx. the number of stars in Milky Way!!) Each neuron is connected to at least  $10^4$  other neuron with “*synaptic link*”.
- Neurons communicate with each other in terms of *electrical impulses* generated by a biochemical process. Thus brain can be considered as densely connected network conditioned by bio-chemical process.



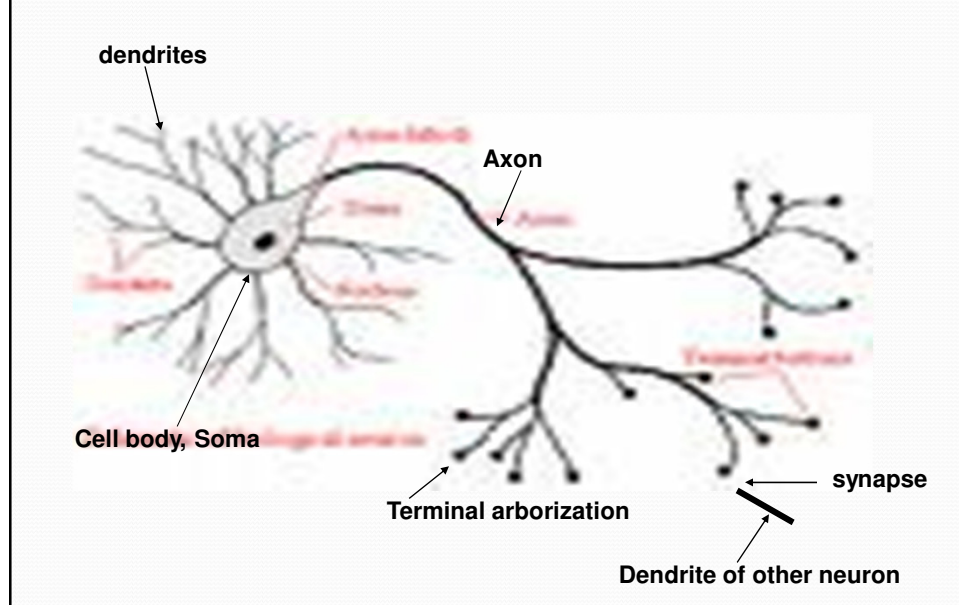
## Biological neuron



- The elementary nerve cell is called a neuron, which is the fundamental building block of the biological neural network.
- A neuron has three major regions 1) Dendrites 2) Axon and 3) Cell body
- Dendrites forms a dendritic tree, which is fine bush of thin fibers around neuron body (see and draw fig.).
- Dendrites receives information to the neuron and thus are acting as input channels.

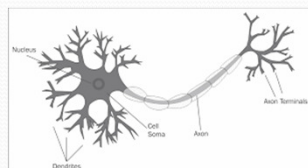


## Schematic of biological neuron model.



## Biological neuron

- Neuron throws its output on **Axon**, which can be treated as **output channel** of neuron.
- **Dendrites** of a neuron are connected to **axons** of another neighboring neurons.
- End part of Axon splits into fine **arborization** (**arbo**-means tree in Latin)
- The **axon-dendrite** contact organ is called a **synapse**. The **synapse** is where the neuron introduces its signal to another neuron.





## Biological neuron

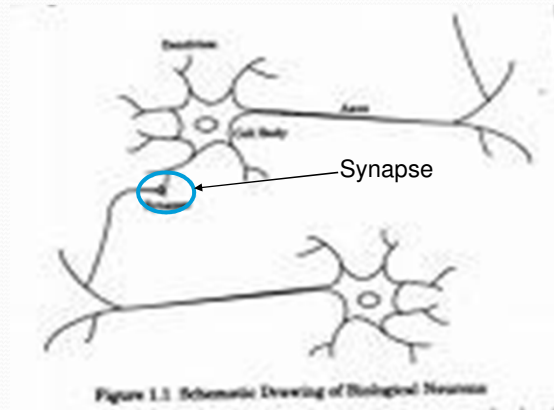


Figure 1.1 Schematic Drawing of Biological Neurons



Connected neurons

## General neuron model

In 1943 Warren S. McCulloch, a neuroscientist, and Walter Pitts, a logician, published "A logical calculus of the ideas immanent in nervous activity" in the Bulletin of Mathematical Biophysics 5: 115-133. In this paper McCulloch and Pitts tried to understand how the brain could produce highly complex patterns by using many basic cells that are connected together. These basic brain cells are called neurons, and McCulloch and Pitts gave a **highly simplified model** of a neuron in their paper.



<http://www.mind.ilstu.edu/curriculum/modOverview.php?modGUI=212>

## General neuron Model

- In, general neuron model input is given as vector **x**, weights are represented with vector **w** and output **o** is function of net.
- The **net input**, **net** or **internal activity level** of neuron is calculated as

$$net = \sum_{i=1}^n w_i x_i$$

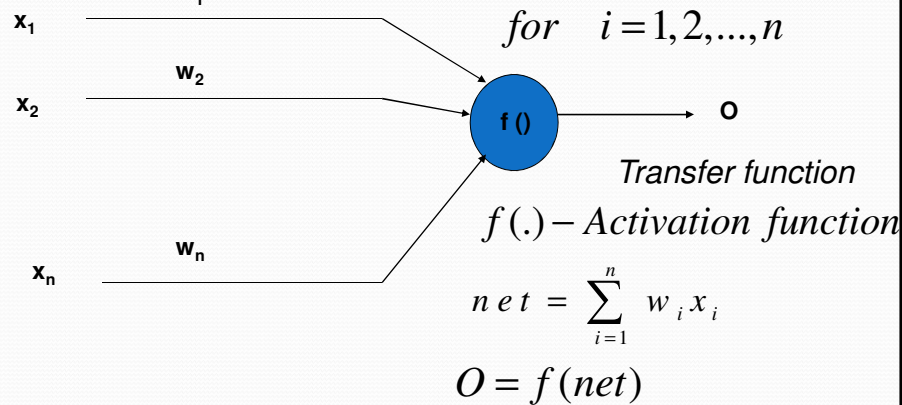
## General neuron Model

$w = [w_1, w_2, \dots, w_n]$  weight vector

$x = [x_1, x_2, \dots, x_n]$  Input vector

$w_i = \text{any value}$

for  $i = 1, 2, \dots, n$



## Activation functions

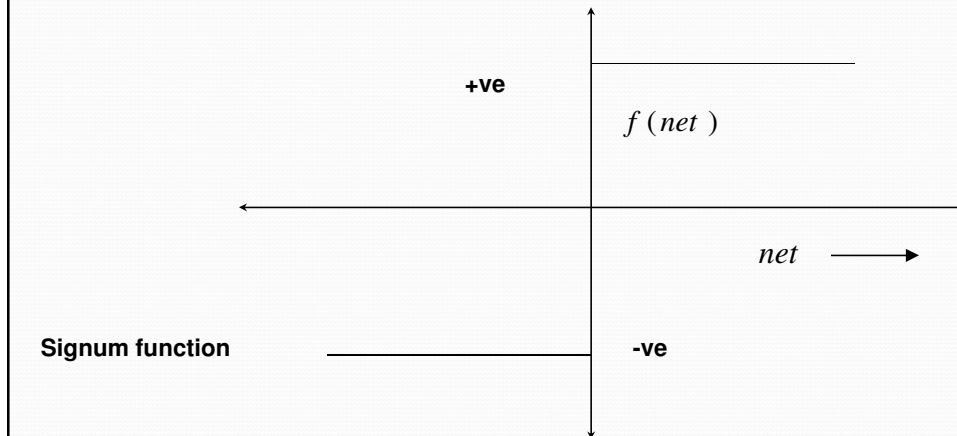
- Based on sign of output they are of two type
  - **Unipolar** (either positive or negative)
  - **Bi-polar** (both positive and negative)
- Based on nature of function they are of two type
  - **Continuous**
  - **Discrete**
- Thus **unipolar continuous, bipolar continuous, unipolar discrete and bipolar discrete** are possible types.

## Activation functions

- **General neuron model** is commonly used in ANN literature but can use **different** activation functions.
- Some of the activation functions are shown below.

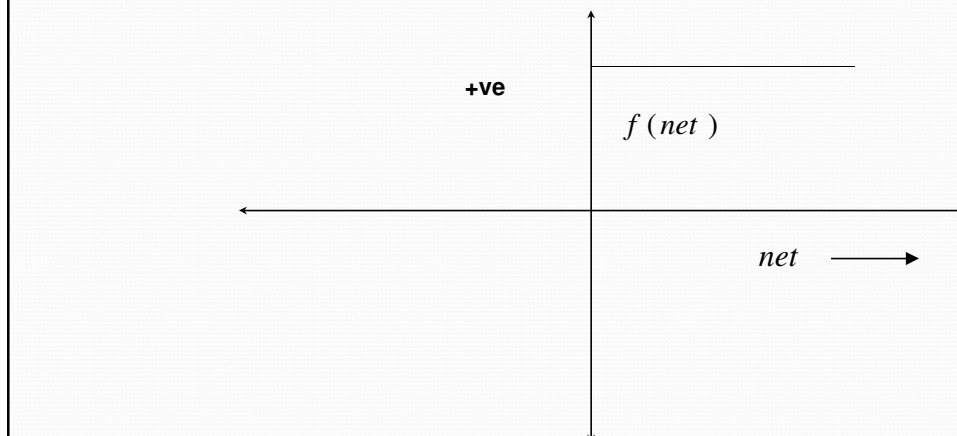
## Bipolar Binary-Activation function

$$f(net) = \text{sgn}(net) = \begin{cases} +1 & \text{if } net > 0 \\ -1 & \text{if } net < 0 \end{cases} \quad \text{Undefined for } net=0$$



## Unipolar Binary-Activation function

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

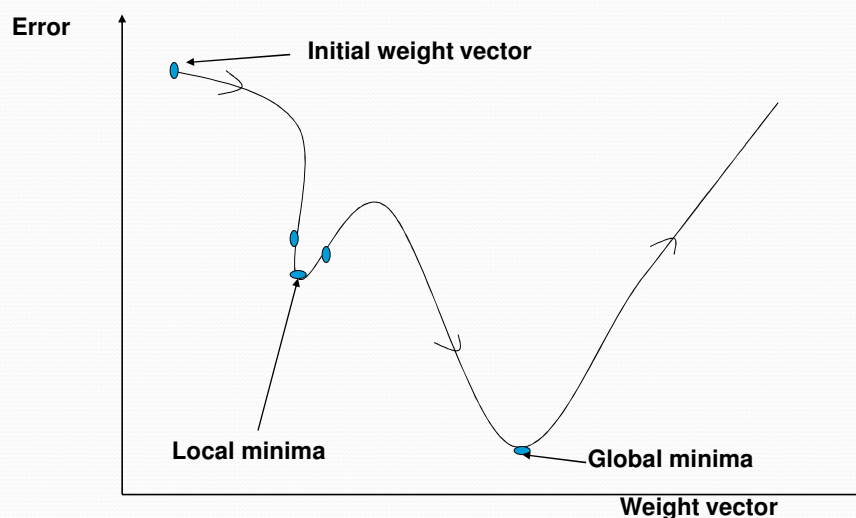


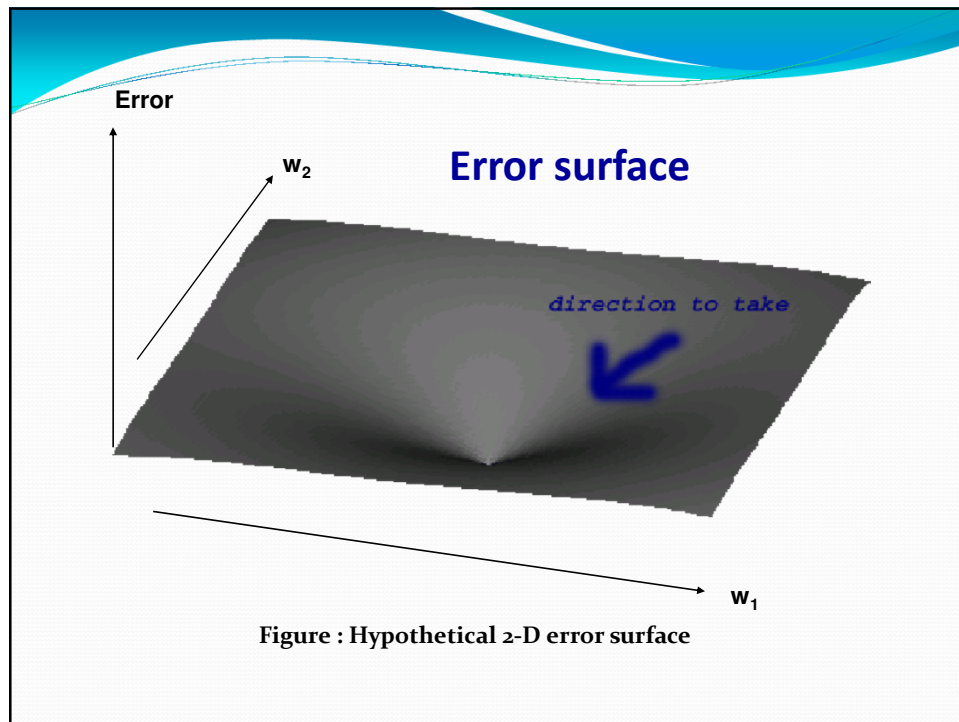


## How neuron learns?

- It learns by adjustment of its weights. Weights are adjusted to **reduce the error** in desired output and actual output of a neuron.
- Various learning rules are used to update the weights based on mode of learning i.e supervised or unsupervised learning

## Philosophy of Learning





## Perceptron Learning Rule

- Invented by **Rosenblatt** (A psychologist) in 1958. It is the first neural network.
- It is **supervised**.
- Learning signal ( $r$ ) is the difference between desired output and actual output.  $r=(d_k-o_k)$
- This rule can be stated as

$$W^{k+1} = W^k + \Delta W$$

$$W^{k+1} = W^k + c * r * x^k$$

$$W^{k+1} = W^k + c * (d_k - o_k) * x^k$$

## Perceptron Learning Rule

$$W^{k+1} = W^k + \Delta W$$

$$W^{k+1} = W^k + c * r * x^k$$

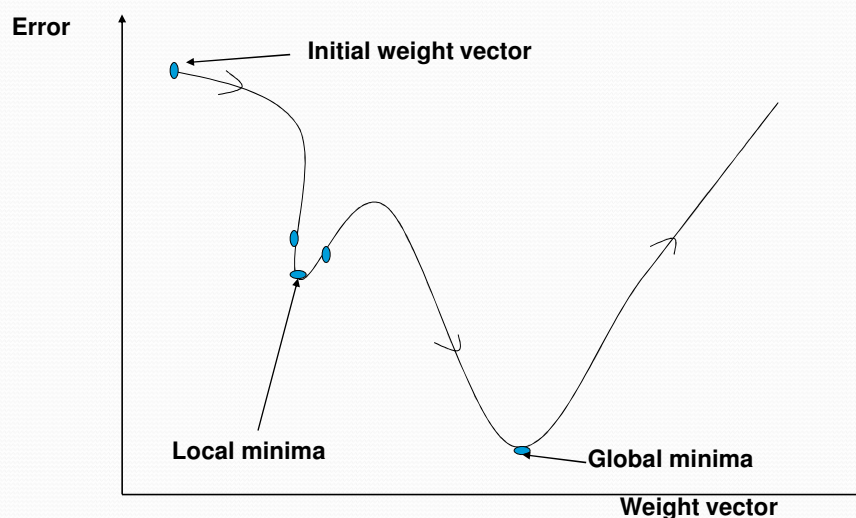
$$W^{k+1} = W^k + c * (d_k - o_k) * x^k$$

**C- learning rate >0, user defined parameter**

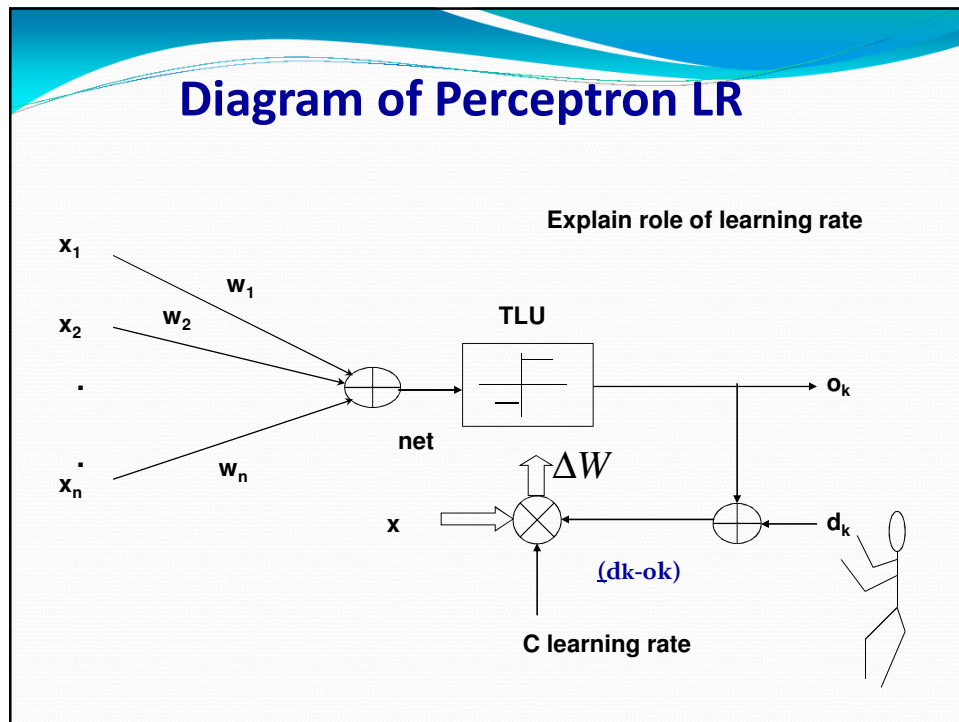
### Extreme cases of C

1. C too large- we will not get the optimal weight vector
2. C too less- We will require more training time

## Extreme values of C and learning



## Diagram of Perceptron LR



## Features of Perceptron LR

- **Learning:-Supervised.**
- **Weight initialized:- ANY**
- **Neuron type:- Binary (uni and bipolar )**
- **Used:- Classification and recognition**



## Single Perceptron Learning problem

Initial weight vector  $W^0 = [1, -1, 0, 0.5]$

Use Perceptron Learning rule to update weights for following three inputs use  $c=1$  and *signum* function if the desired outputs are 1, -1 and 1, respectively

$$f(net) = \text{sgn}(net) = \begin{cases} +1 & \text{if } net > 0 \\ -1 & \text{if } net < 0 \end{cases}$$

$$net = \sum_{i=1}^n w_i x_i$$

$$O = f(net)$$

$$X_1 = [1, -2, 1.5, 0]$$

$$X_2 = [1, -0.5, -2, -1.5]$$

$$X_3 = [0, 1, -1, 1.5]$$

$$W^{k+1} = W^k + c * (d_k - o_k) * x^k$$

Answer

$$1. W1 = [1, -1, 0, 0.5]$$

$$2. W2 = [-1, 0, 4.0, 3.5]$$

$$3. W3 = [-1.0, 0, 4.0, 3.5]$$

## Applications of neural network

- Pattern classification/ Recognition/clustering
- Prediction and forecasting
- Fault diagnosis.
- Correlation.

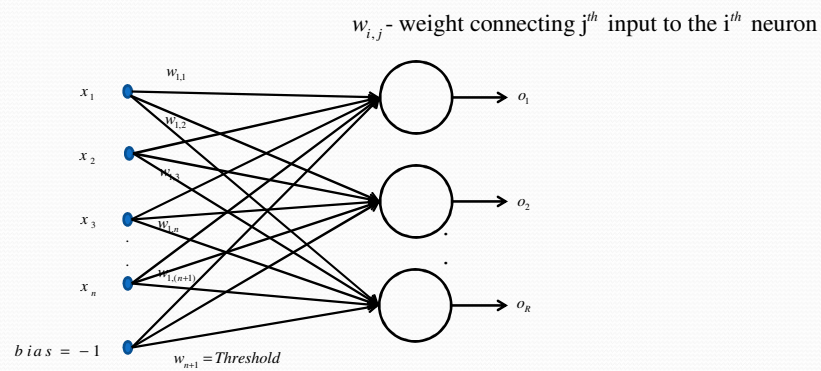
## Advantages of neural networks

1. Capability to learn and learn on fly.
2. Superior for cognitive task.
3. Fault tolerant ability.

### Reference Book:-

Title:- *“An introduction to Artificial neural systems”*  
– By Jacek M. Zurada, Jaico Publication

## Single layer Perceptron Classifiers



### Representation of pattern classes

1. Local :- each neuron represents a class
2. Global:- a specific output of all the neurons represents a class

Weight matrix  $W$  is of size  $R \times (n+1)$

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \dots & w_{1,(n+1)} \\ w_{2,1} & w_{2,2} & \dots & w_{2,(n+1)} \\ \dots & \dots & \dots & \dots \\ w_{R,1} & w_{R,2} & \dots & w_{R,(n+1)} \end{bmatrix}$$

Desired output  $d_i$  is of size  $(R \times 1)$

$$d_i = \begin{bmatrix} d_{i,1} \\ d_{i,2} \\ \dots \\ d_{i,R} \end{bmatrix}$$

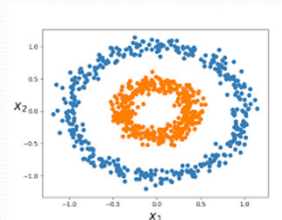
## R- class Single layer discrete Perceptron training algorithm

- ▶ Given  $P$  training pairs  $\{x_1, d_1, x_2, d_2, \dots, x_p, d_p\}$  where  $x_i$  is  $(n \times 1)$ ,  $d_i$  is  $(R \times 1)$ ,  $i = 1, \dots, P$
- ▶ The augmented input vectors are  $y_i = \begin{bmatrix} x_i \\ -1 \end{bmatrix}$ , for  $i = 1, \dots, P$
- ▶ In the following,  $k$  is training step and  $p$  is step counter within training cycle.
  1. Choose  $c > 0$
  2. Initialize weights at small random values,  $W = [w_{ij}]$  is  $R \times (n + 1)$
  3. Initialize counters and error:  $k \leftarrow 1$ ,  $p \leftarrow 1$ ,  $E \leftarrow 0$
  4. Training cycle begins here. Set  $y \leftarrow y_p$ ,  $d \leftarrow d_p$ ,  $o_i = \text{sgn}(w_i^T y)$  for  $i = 1, \dots, R$  (sgn is sign function)
  5. Update weights  $w_i \leftarrow w_i + \frac{1}{2}c(d_i - o_i)y$  for  $i = 1, \dots, R$
  6. Find error:  $E \leftarrow \frac{1}{2}(d_i - o_i)^2 + E$  for  $i = 1, \dots, R$
  7. If  $p < P$  then  $p \leftarrow p + 1$ ,  $k \leftarrow k + 1$ , go to step 4, otherwise, go to step 8.
  8. If  $E = 0$  the training is terminated, otherwise  $E \leftarrow 0$ ,  $p \leftarrow 1$  go to step 4 for new training cycle.

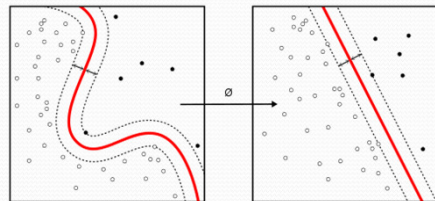
Alshai, Farzaneh Abdollahi Neural Networks Lecture 2 46

## R- class Single layer discrete Perceptron training algorithm

- Pattern classes must be pairwise linearly separable



Non-linearly separable

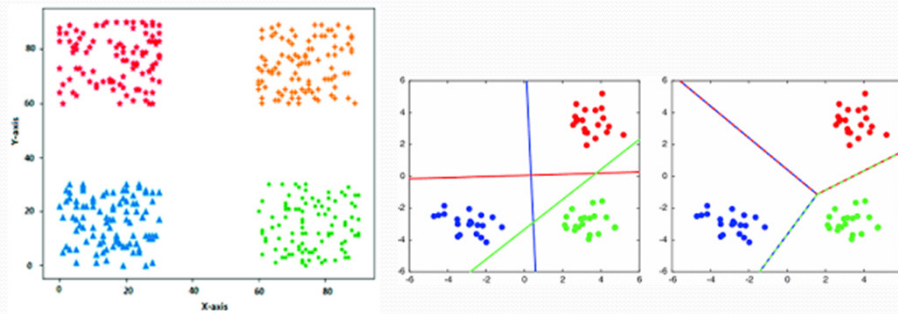


Linearly separable

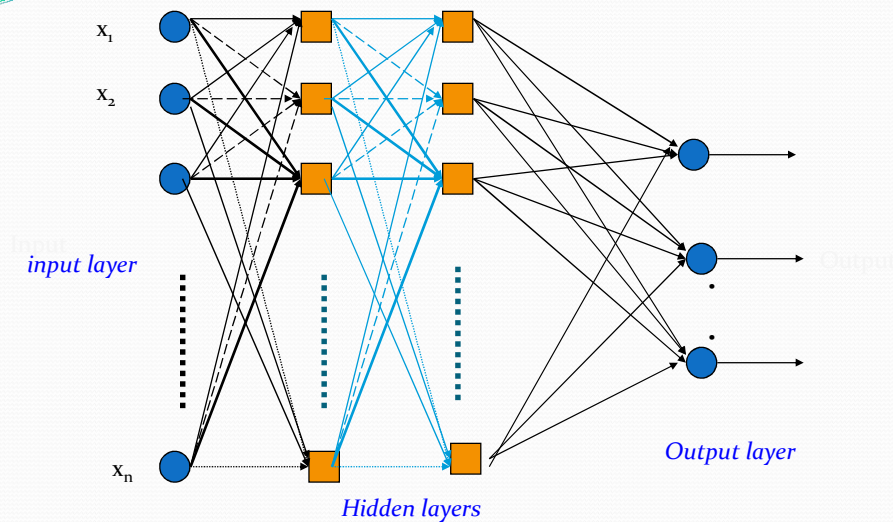
- For non-linearly separable patterns we need multi-layer neural networks



## Example scatterplots of pairwise linearly separable classes



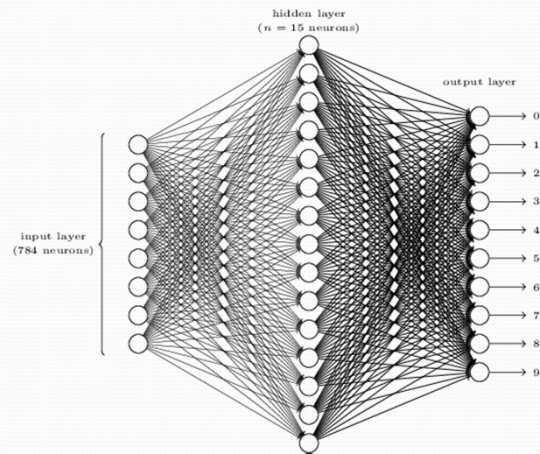
## Architecture of Multi-layer perceptron



Reference- <http://neuralnetworksanddeeplearning.com/chap2.html>

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### A sample 3 –layer neural network architecture for handwritten digit recognition



Reference:- <http://neuralnetworksanddeeplearning.com/chap1.html>

### Deep Learning Neural networks

- Neural networks/Architectures with thousands of hidden layers are called “**deep architectures**” and their learning is called “**deep Learning**” (proposed in 1967)
- They need considerable **computing power** and thus generally implemented on **high performance computing platform (>1 TFLOPS)** with many CPUs and GPUs
- Human brain is itself a deep architecture which is motivation behind deep learning.
- Deep learning machines exhibited **super human** capabilities for a specific **cognitive tasks**. (NVIDIA DIGITS)
- **Tensor Processing Unit (TPU)** is designed specifically for deep learning architectures with library “**Tensor Flow**”. TPU is highly optimized for tensor operations.
- Some new NVIDIA GPUs also provide “**Tensor Cores**” for accelerating tensor operations on GPU (e.g **Tesla V100**, has 640 tensor cores and provides 100 TFLOPS)