

Fundamentals of Neural Networks : AI Course

**lecture 37 & 38, notes, slides**

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Fundamentals of Neural Networks

Artificial Intelligence

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Neural network, topics : Introduction, biological  
neuron model,

artificial neuron model, notations,

functions; Model of artificial

neuron - McCulloch-Pitts neuron equa

**tion; Artificial neuron & basic**

elements, activation functions, threshold

function, piecewise linear

function, sigmoidal function; Neural network architectures - single layer feed-forward network, multi layer feed-forward network, recurrent networks; Learning Methods in Neural Networks - classification of learning algorithms, supervised learning, unsupervised learning, reinforced learning, Hebbian learning, gradient descent learning, competitive learning, stochastic

learning. Single-Layer NN System - single layer perceptron , learning algorithm for training, linearly separable task, XOR

Problem, learning algorithm, ADALINE  
Active Linear Element (ADALINE)  
architecture and training mechanism; Ap

plications of neural  
networks - clustering, classificati  
on, pattern recognition, function  
approximation, prediction systems.

## Fundamentals of Neural Networks

### Artificial Intelligence

#### Topics

(Lectures 37, 38 2 hours)

#### Slides

1.

#### Introduction

Why neural network ?, Research history, Biological  
neuron model,

Artificial neuron model,

Notations, Functions.

03-12

2.

#### Model of Artificial Neuron

McCulloch-Pitts Neuron Equation, Ar

Artificial neuron & basic elements,  
Activation functions & threshold function,  
piecewise linear function,  
sigmoidal function.

13-19

3.

Neural Network Architectures

Single layer feed-forward network, Multi layer  
feed-forward network,  
Recurrent networks.

20-23

4 Learning Methods in Neural Networks

Classification of learning algorithms  
, Supervised learning, Unsupervised  
learning, Reinforced learning, Hebbian Learning,  
Gradient descent

learning, Competitive learning, Stochastic  
learning.

24-29

5.

### Single-Layer NN System

Single layer perceptron : learning algorithm for training, linearly separable task, XOR Problem, learning algorithm; ADALINE

Element (ADALINE) : architecture, training mechanism

30-36

### 6. Applications of Neural Networks

Clustering, Classification / pattern recognition, Function approximation, Prediction systems.

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### 7. References :

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02

## Neural Networks

What is Neural Net ?

### ↳ A neural net

is an artificial representation of the human brain that

tries to simulate its learning process. An artificial neural network

(ANN) is often called a "

Neural Network

" or simply Neural Net (NN).

### ↳ Traditionally, the word neural network is

referred to a network of

biological neurons

in the nervous system that process and transmit

information.

### ↳ Artificial neural network is an

interconnected group of

artificial neurons

that uses a mathematical model or computational

model for information

processing based on a connectionist approach to computation.

↳ **The artificial neural networks** are made of interconnecting artificial neurons

which may share some properties of biological neural networks.

↳ **Artificial Neural network** is a network of simple processing elements (neurons) which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters.

↳ **Artificial neural network** is an adaptive system that changes its structure based on external or internal information that flows

through the network.

03

## **AI-Neural Network Æ Introduction**

### 1. Introduction

Neural Computers mimic certain processing capabilities of the human brain.

- Neural Computing is an information processing paradigm , inspired by biological system, composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems.

- Artificial Neural Networks (ANNs), like people, learn by example

- . - An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

- Learning in biological systems involves



adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

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## **AI-Neural Network Æ Introduction**

### 1.1 Why Neural Network

The conventional computers are good for

-

fast arithmetic and does

what programmer programs, ask them to do.

The conventional computers are

not so good for - interacting with

noisy data or data from the enviro

nment, massive parallelism, fault

tolerance, and adapting to circumstances.

The neural network systems help where we

can not formulate an

algorithmic solution or where we can get lots of

examples of the

behavior we require.

Neural Networks follow different paradigm for computing.

The von Neumann machines are based on the processing/memory abstraction of human information processing.

The neural networks are based on the parallel architecture of

biological brains.

Neural networks are a form of multiprocessor computer system, with

- simple processing elements ,
- a high degree of interconnection,
- simple scalar messages, and
- adaptive interaction between elements.

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## **AI-Neural Network ☒ Introduction**

1.2

## Research History

The history is relevant because for nearly two decades the future of Neural network remained uncertain. McCulloch and Pitts (1943) are generally recognized as the designers of the

first neural network

. They combined many simple processing units together

that could lead to an overall increase in computational power. They

suggested many ideas like : a neuron has a threshold level and once that

level is reached the neuron fires. It

is still the fundamental way in which

ANNs operate. The McCulloch and Pitts's

network had a fixed set of weights.

Hebb (1949) developed the

first learning rule

, that is if two neurons are active at the same time then the strength between them should be increased.

In the 1950 and 60's, many researchers (Block, Minsky, Papert, and Rosenblatt worked on perceptron. The neural network model could be proved to converge to the correct weights, that will solve the problem. The weight adjustment

(learning algorithm) used in the perceptron was found

more powerful than the learning rules used by Hebb. The perceptron caused great excitement. It was thought to produce programs that could think.

Minsky & Papert (1969) showed that perceptron

could not learn those  
functions which are not linearly separable.

The neural networks  
research declined  
throughout the 1970 and until mid  
80's because the perceptron could not learn  
certain important functions.

Neural network  
regained importance  
in 1985-86. The researchers, Parker  
and LeCun discovered a learning algorithm for  
multi-layer networks called  
back propagation  
that could solve problems that were not linearly  
separable.

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## **AI-Neural Network ☒ Introduction**

### 1.3

Biological Neuron Model

The human brain consists of a large number, more than a billion of neural cells that process information. Each cell works like a simple processor. The massive interaction between all cells and their parallel processing only makes the brain's abilities possible.

Fig. Structure of Neuron

Dendrites

are branching fibers that extend from the cell body or soma.

Soma or cell body

of a neuron contains the nucleus and other structures, support

chemical processing and production of

neurotransmitters.

Axon is a singular fiber carries information away from the soma to the

synaptic sites of other neurons (dendrites and somas), muscles, or glands.

Axon hillock

is the site of summation

for incoming

information. At any

moment, the collective influence of all

neurons that conduct impulses to a

given neuron will determine whether or not an

action potential will be initiated at the

axon hillock and propagated along the axon.

Myelin Sheath

consists of fat-containing

g cells that insulate the axon from electrical activity. This insulation acts to increase the rate of transmission of signals. A gap exists between each myelin sheath cell

along the axon. Since fat inhibits the propagation of electricity, the signals jump from one gap to the next.

Nodes of Ranvier

are the gaps (about 1  $\mu\text{m}$ ) between myelin sheath cells along axons

are Since fat serves as a good insulator, the myelin sheaths speed the rate of transmission of an electrical impulse along the axon.

Synapse

is the point of connection between two neurons



or a neuron and a muscle or a gland. Electrochemical communication between neurons takes place at these junctions. Terminal Buttons of a neuron are the small knobs at the end of an axon that release chemicals called neurotransmitters.

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## **AI-Neural Network ☞ Introduction**

### **↳ Information flow in a Neural Cell**

The input /output and the propagation of information are shown below.

### **Structure of a Neural Cell in the Human Brain**

Dendrites receive activation from other neurons.

Soma processes the incoming activations and converts them into

output activations.

Axons act as transmission lines to send activation to other neurons.

Synapses the junctions allow signal transmission between the axons and dendrites.

The process of transmission is by diffusion of chemicals called neuro-transmitters.

McCulloch-Pitts introduced a simplified model of this real neurons.

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## AI-Neural Network Introduction

### 1.4

#### Artificial Neuron Model

An artificial neuron is a mathematical function conceived as a simple model of a real (biological) neuron.

## ↳ The McCulloch-Pitts Neuron

This is a simplified model of real neurons, known as a Threshold Logic Unit.

Input

1 Input 2 Input  
n

A set of input connections brings in activations from other neurons. A processing unit sums the inputs, and then applies a non-linear activation function (i.e. squashing / transfer / threshold function).

An output line transmits the result to other neurons.

In other words ,

- The input to a neuron arrives in the form of signals.
- The signals build up in the cell.
- Finally the cell discharges (cell fires) through

the output .

- The cell can start building up signals again.

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Output

## AI-Neural Network ⌘ Introduction

### 1.5 Notations

Recaps : Scalar, Vectors, Matrices and Functions

⌘ **Scalar** : The number

$x_i$  can be added up to give a scalar number.

$$s = x_1 + x$$

$$_2 + x_3 + \dots + x$$

$$n = \quad x$$

i ⌘ **Vectors** : An ordered sets of related

numbers. Row Vectors

$$(1 \times n) \quad X = (x$$

$$_1, x_2, x_3, \dots, x$$

$$n), \quad Y = (y$$

1 , y2 , y

3 , . . . , y

n )      Add :

Two vectors of same length added to give another vector.

$$Z = X + Y = (x$$

1 + y1 , x

2 + y2 , . . . . , x

n + y

n)      Multiply:

Two vectors of same length multiplied to give a scalar.

$$p = X \cdot Y = x$$

1 y1 + x2 y2 + . . . . + x

nyn = x

i yi 10

i=1

ni=1n

## AI-Neural Network ➤ Introduction

↳ **Matrices :**  $m \times n$  matrix ,      row no =  $m$  ,  
column no =  $n$

$w_{11} \quad w_{12} \quad \dots \quad w_{1n}$

$w_{21} \quad w_{22} \quad \dots \quad w_{2n}$

$w_{31} \quad w_{32} \quad \dots \quad w_{3n}$

$\vdots$

$w_{m1} \quad w_{m2} \quad \dots \quad w_{mn}$

$\vdots$

$\vdots$

$w_{m1} \quad w_{m2} \quad \dots \quad w_{mn}$

$\vdots$

Add or Subtract

: Matrices of the same size are added or subtracted component by component.

$$A + B = C,$$

$$c_{ij} = a_{ij} + b_{ij}$$

$$c_{11} = a_{11} + b_{11}$$

$$c_{12} = a_{12} + b_{12}$$

$$c_{21} = a_{21} + b_{21}$$

$$c_{22} = a_{22} + b_{22}$$

Multiply :

matrix

A

multiplied by matrix

B gives matrix

C.

(m x n)

(n x p)

(m

x p)

elements

$$c_{ij} =$$

$$a_{ik} + b_{kj} \quad a_{11} \quad a_{12} \quad b_{11} \quad b_{12}$$

$c_{11} = a_{11}b_{11} + a_{12}b_{21}$

$c_{12} = a_{11}b_{12} + a_{12}b_{22}$

$c_{21} = a_{21}b_{11} + a_{22}b_{21}$

$c_{22} = a_{21}b_{12} + a_{22}b_{22}$

$c_{11} = a_{11}b_{11} + a_{12}b_{21}$

$c_{12} = a_{11}b_{12} + a_{12}b_{22}$

$c_{21} = a_{21}b_{11} + a_{22}b_{21}$

$c_{22} = a_{21}b_{12} + a_{22}b_{22}$

$c_{11} = a_{11}b_{11} + a_{12}b_{21}$

$c_{12} = a_{11}b_{12} + a_{12}b_{22}$

$c_{21} = a_{21}b_{11} + a_{22}b_{21}$

$c_{22} = a_{21}b_{12} + a_{22}b_{22}$

$c_{11} = a_{11}b_{11} + a_{12}b_{21}$

## AI-Neural Network ¶ Introduction

1.6 Functions The

Function  $y = f(x)$

describes a relationship, an input-output mapping,

from  $x$  to  $y$ . Threshold or Sign function



:  $\text{sgn}(x)$

defined as

1

if  $x \geq 0$   $\text{sgn}(x)$

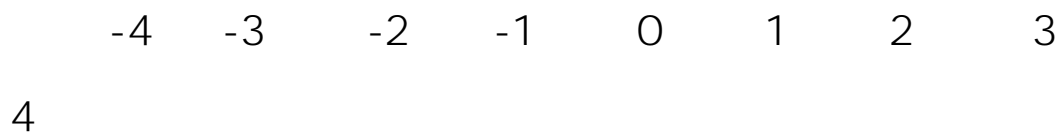
=

0 if  $x$

$< 0$

$\text{Sign}(x)$

O/P



I/P

Threshold or Sign function

: sigmoid(x)

defined as a smoothed  
(differentiable) form of the threshold function

1

sigmoid (x)

=

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

-x Sign(x)

O/P

-4 -3 -2 -1 0 1 2 3

4

I/P

## AI-Neural Network $\Leftrightarrow$ Model of Neuron

### 2. Model of Artificial Neuron

A very simplified model of real neurons is known as a Threshold Logic

Unit (TLU). The model is said to have :

- A set of synapses (connections) brings in activations from other neurons.
- A processing unit sums the inputs, and then applies a non-linear activation function (i.e. squashing / transfer / threshold function).
- An output line transmits the result to other neurons.

#### 2.1 McCulloch-Pitts (M-P) Neuron Equation

McCulloch-Pitts neuron is a simplified model of real biological neuron.

Input 1   Input 2   Input n

Simplified Model of Real Neuron

(Threshold Logic

Unit)

The equation for the output of a McCulloch-Pitts neuron as a function of 1 to n inputs is written as

Output

=

sgn

(

Input

i -

)

where    is the neuron<sup>TM</sup>'s activation threshold.

If

Input i

then Output

$= 1$

If

Input  $i <$

then Output

$= 0$  In this McCulloch-Pitts neuron model, the

missing features are :

- Non-binary input and output,
- Non-linear summation,
- Smooth thresholding,
- Stochastic, and
- Temporal information processing.

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Output

$i=1 \dots n$

## AI-Neural Network & Model Neuron

### 2.2 Artificial Neuron - Basic Elements

Neuron consists of three basic components - weights, thresholds, and a

single activation function

.

Fig Basic Elements of an Artificial Linear Neuron

Weighting Factors

$w$  The values  $w_1, w_2, \dots, w_n$

are weights to determine the strength of

input vector

$X = [x_1, x_2, \dots, x_n]^T$ . Each input is multiplied by the

associated weight of the neuron connection

$X^T W$ . The +ve weight

excites and the -ve weight inhibits the node

output.

$$I = X^T W = x_1 w_1 + x_2 w_2 + \dots + x_n w_n$$

$$I = x_1 w_1 + x_2 w_2 + \dots + x_n w_n$$

$$w_1 x_1 + w_2 x_2 + \dots + w_n x_n$$

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

**Threshold** The node's internal threshold

is the magnitude offset. It affects the activation of the node output

y as:

$$Y = f(I)$$

$$= f\left\{\sum_{i=1}^n w_i x_i - k\right\}$$

To generate the final output

Y, the sum is passed on to a non-linear filter f called Activation Function or Transfer function or Squash function

which releases the output

Y. 14

W1 W2Wnx1 x2 xn Activation

Function

i=1

SynapticWeights

Threshold



$$y = \sum_{i=1}^n n_i$$

n

## AI-Neural Network $\bowtie$ Model of Neuron

Threshold for a Neuron

In practice, neurons generally do not fire (produce an output) unless their total input goes above a threshold value.

The total input for each neuron is the sum of the weighted inputs to the neuron minus its threshold value. This is then passed through the sigmoid function. The equation for the transition in a neuron is :

$$a = 1/(1 + \exp(-x))$$

where  $x = \sum a_i w_i - Q$  a is the activation for the neuron

$a_i$  is the activation for neuron

$w_i$  is the weight

$Q$  is the threshold subtracted

## Activation Function

An activation function

$f$  performs a mathematical operation on the signal output. The most common activation functions are:

- Linear Function,
- Piecewise Linear Function,
- Tangent hyperbolic function
- Threshold Function,
- Sigmoidal (S shaped) function,

The activation functions are chosen depending upon the type of

problem to be solved by the network.

## AI-Neural Network & Model of Neuron

### 2.2 Activation Functions

$f$  -

Types

Over the years, researches tried several functions to convert the input into an output. The most commonly used functions are described below.

- I/P Horizontal axis shows sum of inputs.
- O/P Vertical axis shows the value the function produces i.e. output.
- All functions  $f$  are designed to produce values between 0 and 1.

#### 1. $\Sigma$ Threshold Function

A threshold (hard-limiter) activation function is either a binary type or a bipolar type as shown below.

binary threshold

O/p

I/P

Output of a binary threshold function produces

:

1 if the weighted sum of the inputs is +ve,

0 if the weighted sum of the inputs is -ve.

1 if  $I$

0  $Y = f(I) =$

0 if  $I$

$< 0$

bipolar threshold

O/p

I/P Output of a bipolar threshold function

produces :

1 if the weighted sum of the inputs is +ve,

-1 if the weighted sum of the inputs is -ve.

1

if  $I \geq 0$

$$Y = f(I) =$$

-1 if  $I$

$< 0$  Neuron with hard limiter activation function is called McCulloch-Pitts model.

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1

1

-1

**AI-Neural Network & Model of Neuron**

**& Piecewise Linear Function**

This activation function  
is also called saturating

linear function and can have either a binary or bipolar range for the saturation limits of the output.

The mathematical model for a symmetric saturation function is described below.

Piecewise Linear

O/p

I/P This is a sloping function that produces :

-1 for a -ve weighted sum of inputs,

1 for a +ve weighted sum of inputs.

I proportional to input for values between

+1 and

-1 weighted sum,

$$Y = f(I) = \begin{cases} 1 & \text{if } I \geq 1 \\ I & \text{if } -1 < I < 1 \\ -1 & \text{if } I \leq -1 \end{cases}$$

-1 if  $x < 0$

0 if  $x = 0$

1 if  $x > 0$

+1 if  $x > 0$

## AI-Neural Network & Model of Neuron

### 1 Sigmoidal Function

(S-shape function)

The nonlinear curved S-shape function is called the sigmoid function.

This is most common type of activation used to construct the neural

networks. It is mathematically well behaved, differentiable and strictly

increasing function.

Sigmoidal function

A sigmoidal transfer function can be written in the form:

$$Y = f(I) = \frac{f(I)}{1 + e^{-I}}, \quad 0 \leq f(I) \leq 1$$

This is explained as

0 for large -ve input values,



1 for large +ve values, with a smooth transition between the two.

is slope parameter also called shape parameter;

symbol the

is also used to represented this parameter.

The sigmoidal function is achieved using exponential equation.

By varying

different shapes of the function can be obtained which

adjusts the abruptness of the function as it changes between the two asymptotic values.

1

O/P

0.5

I/P

-4

-2

0

1

2

= 1.0

= 0.5

= 2.0

AI-Neural Network  $\bowtie$  Model of Neuron

↳ Example :

The neuron shown consists of four inputs with the weights.

Fig Neuron Structure of Example

The output

I of the network, prior to the activation function stage, is

+1

+1 I = X

T. W =

1 2 5 8

= 14

-1

+2

= (1 × 1) + (2 × 1) + (5 × -1) + (8 × 2) = 14

With a binary activation function  
the outputs of the neuron is:

$y$  (threshold

) = 1;

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+1+1+2 -1x1=1 x2=2 xn=8 Activation

Function

Summing

Junction

Synaptic

Weights

= 0 Threshold

$y \times 3 = 5$  |

## AI-Neural Network Architecture

### 3. Neural Network Architectures

An Artificial Neural Network (ANN) is  
a data processing system, consisting  
large number of simple

highly interconnected processing elements

as

artificial neuron in a network structure that can

be represented using a

directed graph

$G$ , an ordered 2-tuple

$(V, E)$ , consisting a set

$V$  of vertices

and a set

$E$  of edges.

- The vertices may represent neurons

(input/output) and

- The edges may represent synaptic links

labeled by the weights attached.

Example :

Fig. Directed Graph

Vertices  $V = \{$   
 $v_1, v_2, v_3,$   
 $v_4,$   
 $v_5 \}$  Edges  $E = \{$   
 $e_1, e_2,$   
 $e_3, e_4, e_5 \}$  20  
 $V_1 V_3 V_2 V_4 V_5 e_3 e_2 e_5 e_4 e_5$

## AI-Neural Network Architecture

### 3.1 Single Layer Feed-forward Network

The Single Layer Feed-forward Network consists of a single layer of weights, where the inputs are directly connected to the outputs, via a series of weights.

The synaptic links carrying weights connect every input to every output, but not other way.

This way it is considered a network of feed-forward type. The sum of the products of the weights and the inputs is calculated in each neuron node, and if the value is above some threshold (typically 0) the neuron fires and takes the activated value (typically 1); otherwise it takes the deactivated value (typically -1).

Fig. Single Layer Feed-forward Network

$w_{21}w_{11}w_{12}w_{n2}w_{n1}w_1mw_2mwnmw_{22}y_1 y_2 y_m x_1$   
 $x_2 x_n$  out  
 put  $y_j$  input  $x_i$  weights  $w_{ij}$  Single layer  
 Neurons

## AI-Neural Network $\bowtie$ Architecture

### 3.2 Multi Layer Feed-forward Network

The name suggests, it consists of multiple layers.  
 The architecture of  
 this class of network, besides having the input  
 and the output layers,  
 also have one or more intermediary layers called  
 hidden layers  
 . The  
 computational units of the hidden layer are  
 known as  
 hidden neurons  
 .



Fig. Multilayer feed-forward network in  
 $(m \times n)$   
configuration

- . - The hidden layer does intermediate computation before directing the input to output layer.
- The input layer neurons are linked to the hidden layer neurons; the weights on these links are referred to as input-hidden layer weights
- . - The hidden layer neurons and the corresponding weights are referred to as output-hidden layer weights
- . - A multi-layer feed-forward network with input neurons,  $m_1$  neurons in the first hidden layers,  $m_2$  neurons in the second hidden layers, and  $n$  output neurons in the output layers is written as  $(m_1 - m_2 \times n)$ .

- Fig. above illustrates a multilayer feed-forward network with a configuration  $(m \times n)$ .

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$w_{11} w_{12} v_{21} v_{11} w_{1m} v_{1m} v_{2m} V_m w_{11} x_1 x_2 x_3$

$y_3 y_1 y_2 y_n y_1 y_m$  Hidden Layer

neurons

$y_j$  Output Layer

neurons

$z_k$  Input Layer

neurons

$x_i$  Input

hidden layer

weights

$v_{ij}$  Output

hidden layer

$w_{ei}$

ghts

wjk

## AI-Neural Network Architecture

### 3.3

#### Recurrent Networks

The Recurrent Networks differ from feed-forward architecture.

A Recurrent network has at least one feed back loop.

Example :

Fig. Recurrent neural network

There could be neurons with self-feedback links; that is the output of a neuron is feedback into itself as input.

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$x_1, x_2, \dots, x_n$  Hidden Layer

neurons

$y_1, y_2, \dots, y_m$  Output Layer

neurons

$z_1, z_2, \dots, z_k$  Input Layer

neurons

$x_i$  Feedback

links

## AI-Neural Network & Learning methods

### 4. Learning methods in Neural Networks

The learning methods in neural networks are classified into three basic types :

- Supervised Learning,
- Unsupervised Learning
- Reinforced Learning

These three types are classified based on :

- presence or absence of

teacher

and

- the information provided for the system to learn.

These are further categorized, based on the rules

used, as

- Hebbian, - Gradient descent,
- Competitive
- Stochastic learning.

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## AI-Neural Network **Learning methods**

### Classification of Learning Algorithms

Fig. below indicate the hierarchical representation of the algorithms mentioned in the previous slide. These algorithms are explained in subsequent slides.

Fig. Classification of learning algorithms

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Neural Network

Learning algorithms

Unsupervised Learning

Supervised Learning

(Error based)

Reinforced Learning

(Output based)

Error Correction

Gradient descent

Stochastic

BackPropagationLeast Mean

Square

Hebbian

Competitive

## AI-Neural Network Learning methods

### ↳ Supervised Learning

- A teacher is present during learning process and presents expected output.
- Every input pattern is used to train the network.
- Learning process is based on comparison, between network's computed output and the correct expected output, generating "error".
- The "error" generated is used to change network parameters that result improved performance.

### ↳ Unsupervised Learning

- No teacher is present.
- The expected or desired output is not presented to the network.

- The system learns of its own by discovering and adapting to the structural features in the input patterns.

### **↳ Reinforced Learning**

- A teacher is present but does not present the expected or desired output but only indicates if the computed output is correct or incorrect.

- The information provided helps the network in its learning process.

- A reward is given for correct answer computed and a penalty for a wrong answer.    Note :

The Supervised and Unsupervised learning methods are most popular forms of learning compared to Reinforced learning.



## AI-Neural Network Learning methods

### ↳ Hebbian Learning

Hebb proposed a rule based on correlative weight adjustment.

In this rule, the input-output pattern pairs  $(X_i, Y_i)$

are associated by the weight matrix

$W$ , known as correlation matrix computed as

$$W = \sum_i X_i Y_i^T$$

where

$Y_i^T$  is the transpose of the associated output vector

$Y_i$  There are many variations of this rule proposed by the other researchers (Kosko, Anderson, Lippman)

$i=1$

$n$

## AI-Neural Network Learning methods

### 1 Gradient Descent Learning

This is based on the minimization of errors

$E$  defined in terms of weights

and the activation function of the network.

- Here, the activation function of the network is required to be

differentiable, because the updates of weight is dependent on

the gradient of the error

E. - If  $W_{ij}$  is the weight update of the link connecting the

$i$ th and the

$j$ th neuron of the two neighboring layers, then

$W_{ij}$  is defined as

$W_{ij}$

$$= ( \eta / W_{ij} )$$

where

$\eta$  is the learning rate parameters and

$( \eta / W_{ij} )$  is error

gradient with reference to the weight

$W_{ij}$

. Note :

The Hoffs Delta rule and Back-propagation learning rule are the examples of Gradient descent learning.

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## **AI-Neural Network Learning methods**

### **↳ Competitive Learning**

- In this method, those neurons which respond strongly to the input stimuli have their weights updated.
- When an input pattern is presented, all neurons in the layer compete,

and the winning neuron undergoes weight adjustment .

- This strategy is called "winner-takes-all"

.

### **4 Stochastic learning**

- In this method the weights are adjusted in a probabilistic fashion.
- Example : Simulated annealing which is a learning mechanism employed by Boltzmann and Cauchy machines.

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## **AI-Neural Network 5 Single Layer learning**

### **5. Single-Layer NN Systems**

Here, a simple Perceptron Model and an ADALINE Network Model is presented.

#### **5.1 Single Layer Perceptron**

Definition : An arrangement of one input layer of neurons feed forward

to one output layer of neurons is known as Single Layer Perceptron.

Fig. Simple Perceptron Model

$$y_j = \begin{cases} 1 & \text{if } \text{net } j \geq 0 \\ 0 & \text{if } \text{net } j < 0 \end{cases}$$

where  $\text{net } j = \sum_{i=1}^n x_i w_{ij} - \theta_j$

$x_1, x_2, \dots, x_n$  input  
 $w_{11}, w_{12}, \dots, w_{1n}$  weights  
 $\theta_j$  bias  
 $y_j$  output

wijSingle layer

Perceptron

## AI-Neural Network ÆSingle Layer learning

### ↳ Learning Algorithm for Training Perceptron

The training of Perceptron is a supervised learning algorithm where weights are adjusted to minimize error when ever the output does not match the desired output.

- If the output is correct then no adjustment of weights is done.

i.e.

=

- If the output is 1 but should have been 0 then the weights are decreased on the active input link

i.e.

=

–  $\eta \cdot x$

$i$  – If the output is

0 but should have been

1 then the weights are

increased on the active input link

i.e.

=

+  $\eta \cdot x_i$  Where  $w_{ij}$  is the new

adjusted weight,  $w_{ij}$  is the old weight

$x$

$i$  is the input and

$\eta$  is the learning rate parameter.

small leads to slow and

large leads to fast learning.

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$w_{ij}$

$K+1$

$W_{ij}$

$K+1 \times W_{ij} \times K \times W_{ij}$

$K+1 \times W_{ij} \times K \times W_{ij} \times K+1 \times W_{ij} \times K \times W_{ij} \times K$

## AI-Neural Network Æ Single Layer learning

### ↳ Perceptron and Linearly Separable Task

Perceptron can not handle tasks which are not separable.

- Definition : Sets of points in 2-D space are linearly separable if the

sets can be separated by a straight line.

- Generalizing, a set of points in n-dimensional space are linearly

separable if there is a hyper plane of (n-1)

dimensions separates

the sets.

Example

S1

S2



S1

S2

- (a) Linearly separable patterns
- (b) Not Linearly separable patterns

Note :

Perceptron cannot find weights for classification problems that are not linearly separable.

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## **AI-Neural Network Æ Single Layer learning**

### **↳ XOR Problem :**

Exclusive OR

operation

Input	x1	Input	x2	Output
-------	----	-------	----	--------

0	0	0
---	---	---

1 1 0

0 1 1

1 0 1

XOR

truth table

Even parity means even number of 1 bits in the input

Odd parity means odd number of 1 bits in the input

X2

(0, 1)

(1, 1)

(0, 0)

X1

(0, 1)

Output of XOR

in  $X_1, x_2$  plane

- There is no way to draw a single straight line so that the circles are on one side of the line and the dots on the other side.

- Perceptron is unable to find a line separating even parity input patterns from odd parity input patterns.

**33 • • • Even**

parit

**y • Odd parit**

y •

**AI-Neural Network • Single Layer learning**

**↳ Perceptron Learning Algorithm**

The algorithm is illustrated step-by-step.

Step 1 :

Create a peceptron with

(n+1)

input neurons

$x_0, x_1, \dots, x_n$

where

$x_0$

$x_0 = 1$  is the bias input

. Let

$O$  be the output neuron

. Step 2 :

Initialize weight

$W = (w_0,$

$w_1,$

$\dots, w_n)$

to random weights

. Step 3 :

Iterate through the input patterns

$X_j$  of the training set using the weight set;

ie compute the weighted sum of inputs

$net_j = \sum_i x_i w_{ij}$

for each input pattern

$j$ . Step 4 :

Compute the output

$y_j$  using the step function

1

if  $\text{net}_j$

0  $y_j$

$y_j = f(\text{net}_j)$

$y_j =$

where

$\text{net}_j$

$y_j =$

$x_i w_{ij}$

0

if  $\text{net}_j$

$y_j$

$< 0$

Step 5 :

Compare the computed output

$y_j$  with the target output

$y_j$

for each input pattern

$j$ .

If all the input patterns have been

classified correctly, then output

(read) the weights and exit.

Step 6 :

Otherwise, update the weights as given below :

If the computed outputs

$y_j$  is 1 but should have been

0,

Then  $w_i = w_i -$

$x_i$ ,  $i = 0, 1, 2, \dots, n$

If the computed outputs

$y_j$  is 0 but should have been

1,

Then  $w_i = w_i +$

$x_i, \quad i = 0, 1, 2, \dots, n$

where

$\eta$  is the learning parameter and is constant.

Step 7 :

goto step 3

END

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$i=1$

$n \ i=1$

$n$

## AI-Neural Network $\oplus$ ADALINE

### 5.2 ADaptive LINEar Element (ADALINE)

An ADALINE consists of a single neuron of the McCulloch-Pitts type, where its weights are determined by the normalized least mean square (LMS) training law. The LMS learning

ning rule is also referred to as

delta rule

. It is a well-established

supervised training

method that

has been used over a wide range of diverse

applications.

### **↳ Architecture of a simple**

ADALINE

The basic structure of an ADALINE is

similar to a neuron with a

linear activation function and a feedback loop.

During the training

phase of ADALINE, the input vector as well as

the desired output

are presented to the network.



[The complete training mechanism has been explained in the next slide.

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$W_1 W_2 \dots W_n \times 1 \times 2 \times n$  Neuron

ErrorDesiredOutput

Output

$\mathcal{E} +$

**AI-Neural Network  $\mathcal{E}$ ADALINE**

**$\mathcal{L}$  ADALINE**

Training Mechanism

(Ref. Fig. in the previous slide - Architecture of a simple ADALINE)

The basic structure of an ADALINE is similar to a linear neuron

with an extra feedback loop

. During the training phase of ADALINE, the input vector

$X = [x$

$1, x$

$2, \dots, x$

$n]^T$

as well as desired output are presented to the network.

The weights are adaptively adjusted based on delta rule.

After the ADALINE is trained, an input vector presented to the network with fixed weights will result in a scalar output.

Thus, the network performs an  $n$ -dimensional mapping to a scalar value.

The activation function is not used during the training phase.

Once the weights are properly adjusted, the response of the

trained unit can be tested by applying various

inputs, which are

not in the training set. If the network produces consistent

responses to a high degree with the test inputs, it is said

that the network could generalize. The process of training and

generalization are two important attributes of this network.

Usage of ADLINE : In practice, an ADALINE is used to

- Make binary decisions; the output is sent through a binary threshold.
- Realizations of logic gates such as AND, NOT and OR .
- Realize only those logic functions

that are linearly separable.

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## **AI-Neural Network Applications**

### 6. Applications of Neural Network

Neural Network Applications can be grouped in following categories:

Clustering:

A clustering algorithm explores the similarity between patterns and places similar patterns in a cluster. Best known applications include data compression and data mining.

Classification/Pattern recognition:

The task of pattern recognition is to assign an input pattern (like handwritten symbol) to one of many classes. This category

includes algorithmic implementations such as

associative memory.

Function approximation :

The tasks of function approximation is to find an estimate of the unknown function subject to noise.

Various engineering and scientific disciplines require function approximation.

Prediction Systems:

The task is to forecast some future values of a time-sequenced data. Prediction has a significant impact on decision support systems.

Prediction differs from function approximation by considering time factor.

System may be dynamic and may produce different results for the same input data based on system state (time).

## AI-Neural Network References

### 7. References : Textbooks

1.

"Neural Networks: A Comprehensive Foundation", by Simon S. Haykin, (1999),  
Prentice Hall, Chapter 1-15, page 1-889.

2.

"Elements of Artificial Neural Networks",  
by Kishan Mehrotra, Chilukuri K. Mohan  
and Sanjay Ranka, (1996), MIT Press, Chapter 1-7,  
page 1-339.

3.

"Fundamentals of Neural Networks: Architecture, Algorithms and Applications", by  
Laurene V. Fausett, (1993), Prentice Hall,  
Chapter 1-7, page 1-449.

4.

"Neural Network Design", by Martin T. Hagan,  
Howard B. Demuth and Mark  
Hudson Beale, ( 1996) , PWS Publ. Company,  
Chapter 1-19, page 1-1 to 19-14.

5.

"An Introduction to Neural Networks", by James  
A. Anderson, (1997), MIT Press,

Chapter 1- 17, page 1-585.

6.

"AI: A New Synthesis", by Nils J. Nilsson, (1998),  
Morgan Kaufmann Inc.,  
Chapter 3, Page 37-48.

7. Related documents from open  
source, mainly internet. An exhaustive list is  
being prepared for inclusion at a later date.