

Lesson 4: Associative Memory

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4.1 Introduction

From natural intelligence, associative memory refers to the ability to remember relationships between concepts, and not just the individual concepts themselves.

Associative memory in computing is a special type of memory that is optimized for performing searches through data, as opposed to providing a simple direct access to the data based on the address. It is also known as content addressable memory (CAM) or associative storage or associative array.

4.2 Types of associative memories

There are the two types of associative memories namely Auto Associative Memory and Hetero Associative memory.

4.3 Auto Associative Memory

This is a single layer neural network in which the input training vector and the output target vectors are the same. The weights are determined so that the network stores a set of patterns.

4.3.1 Architecture

As shown in the following figure below, the architecture of Auto Associative memory network has 'n' number of input training vectors and similar 'n' number of output target vectors.

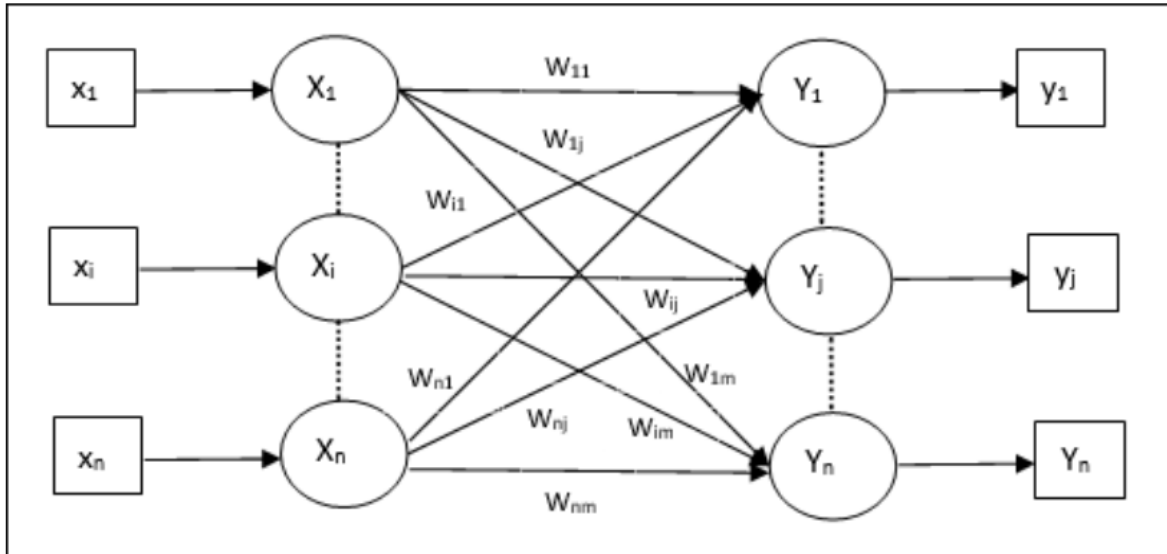


Figure 4. 1: The architecture of an associative memory network

4.3.2 Auto Associative Memory Training Algorithm

For training, this network uses the Hebb or Delta learning rule.

Step 1 – Initialize all the weights to zero as $w_{ij} = 0 \quad i = 1_{ton}, j = 1_{ton}$

Step 2 – Perform steps 3-4 for each input vector.

Step 3 – Activate each input unit as follows: $x_i = s_i (i = 1_{ton})$

Step 4 – Activate each output unit as follows: $y_j = s_j (j = 1_{ton})$

Step 5 – Adjust the weights as follows: $w_{ij}(new) = w_{ij}(old) + x_i y_j$

4.3.3 Auto Associative Memory Testing Algorithm

Step 1 – Set the weights obtained during training for Hebb's rule.

Step 2 – Perform steps 3-5 for each input vector.

Step 3 – Set the activation of the input units equal to that of the input vector.

Step 4 – Calculate the net input to each output unit $j = 1$ to n $y_{inj} = \sum_{i=1}^n x_i w_{ij}$

Step 5 – Apply the following activation function to calculate the output:

$$y_j = f(y_{inj}) = \begin{cases} +1 & \text{if } y_{inj} > 0 \\ -1 & \text{if } y_{inj} \leq 0 \end{cases}$$

4.4 Hetero Associative memory

Similar to Auto Associative Memory network, this is also a single layer neural network. However, in this network the input training vector and the output target vectors are not the same. The weights are determined so that the network stores a set of patterns. Hetero associative network is static in nature, hence, there would be no non-linear and delay operations.

4.4.1 Hetero Associative memory Architecture

As shown in the following figure, the architecture of Hetero Associative Memory network has 'n' number of input training vectors and 'm' number of output target vectors.

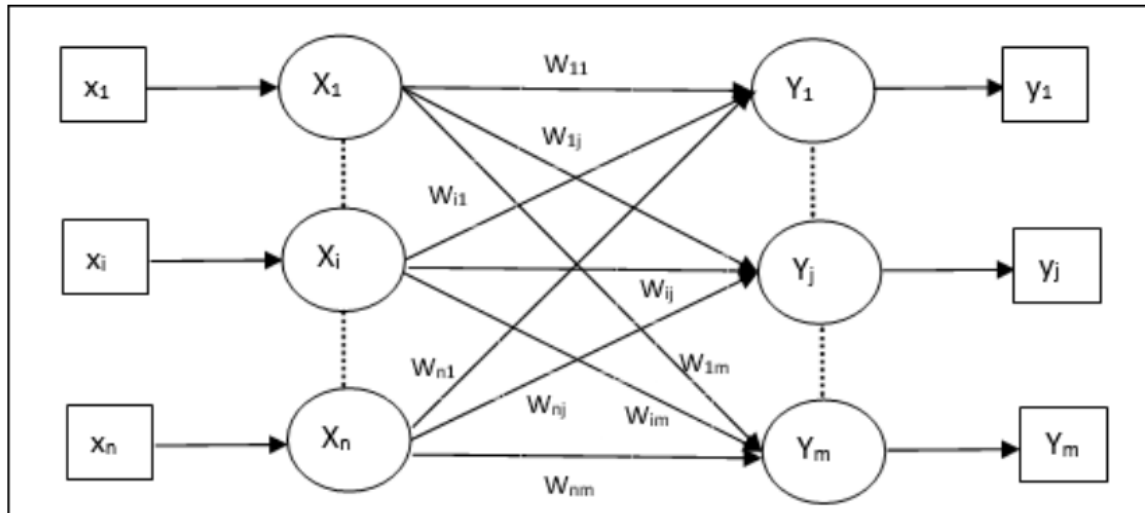


Figure 4. 2: Architecture of Hetero Associative Memory Network

4.4.2 Hetero Associative memory Training Algorithm

For training, this network is using the Hebb or Delta learning rule.

Step 1 – Initialize all the weights to zero as $w_{ij} = 0 \quad i = 1_{ton}, j = 1_{tom}$

Step 2 – Perform steps 3-4 for each input vector.

Step 3 – Activate each input unit as follows: $x_i = s_i (i = 1_{ton})$

Step 4 – Activate each output unit as follows: $y_j = s_j (j = 1_{tom})$

Step 5 – Adjust the weights as follows: $w_{ij}(new) = w_{ij}(old) + x_i y_j$

4.4.2 Hetero Associative memory Testing Algorithm

Step 1 – Set the weights obtained during training for Hebb's rule.

Step 2 – Perform steps 3-5 for each input vector.

Step 3 – Set the activation of the input units equal to that of the input vector.

Step 4 – Calculate the net input to each output unit $j = 1$ to m ;

$$y_{inj} = \sum_{i=1}^n x_i w_{ij}$$

Step 5 – Apply the following activation function to calculate the output

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

4.5 Correlation matrix as an associative memory

Correlation matrix memories (CMMs) are neural associative memories which are able to store a large number of associations between binary patterns, and can store and recall these patterns at great speed. Associative memory is also known as content addressable memory (CAM) or associative storage or associative array. It is a special type of memory that is optimized for performing searches through data, as opposed to providing a simple direct access to the data based on the address.

4.6 Error correction learning

Error-Correction Learning, used with supervised learning, is the technique of comparing the system output to the desired output value, and using that error to direct the training. Notably, error correction learning is based on the difference between actual output & desired output.

4.7 Pseudoinverse matrix as an associative memory

In psychology, associative memory is defined as the ability to learn and remember the relationship between unrelated items. This would include, for example, remembering the name of someone or the aroma of a particular perfume. Hence, associative memory is a depository of associated patterns which in some form, if the depository is triggered with a pattern, the associated pattern pair appears at the output. The input could be an exact or partial representation of a stored pattern.

4.8 Lesson 4 Questions

1. Discuss the nature of the information stored in visual short-term memory. What evidence is there for visual short-term memory being distinct from iconic memory and from memory for other modalities?