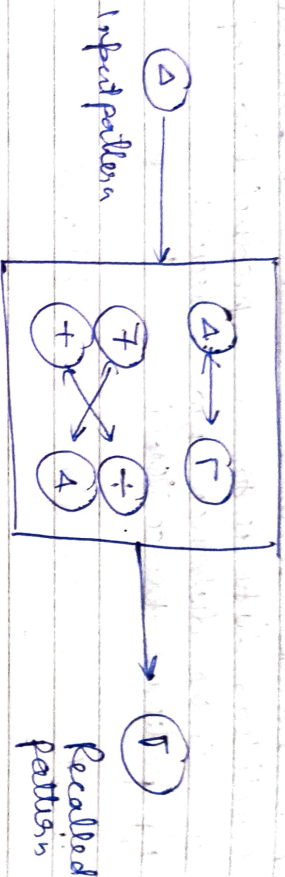


# ASSOCIATIVE MEMORY DATE: / /

An associative memory which belongs to the class of single layer feedforward or recurrent network architecture depending on its association capability, exhibits Hebbian learning.



$(4, 7)$ ,  $(7, 4)$  &  $(+, +)$  are associated patterns  
 $\leftrightarrow$  associations symbols

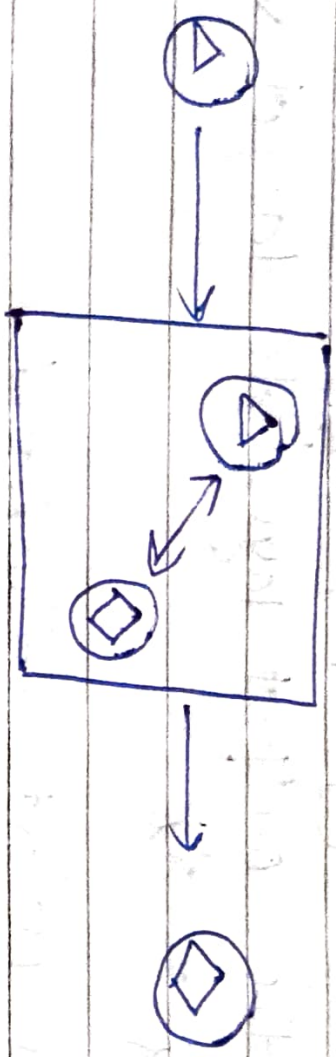
$\Rightarrow$  An associative memory is a storehouse of associated patterns which are encoded in some form. When the storehouse is triggered or initiated with pattern, the associated pattern pair is recalled or output.

$\Rightarrow$  If the associated pattern pairs  $(x, y)$  are different and if the word recalls a  $y$  given an  $x$  or vice versa, then it termed as heteroassociative memory, useful for identification of patterns.

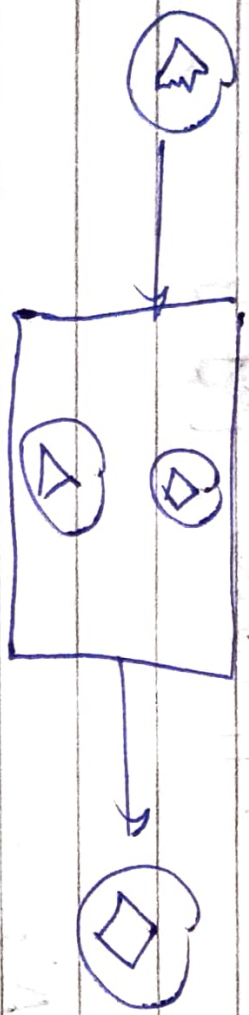
$\Rightarrow$  If  $x$  &  $y$  refers to the same patterns, then word is termed as autoassociative memory -  
character recognition.

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Autoassociative correlations memories are known as auto correlator & other hetero correlator.



Heteroassociative  
memory



Autoassociative  
memory

## ⇒ Autoassociative Memory

It uses Hebb's Rule.

These associative net has same no. of neurons in the input & output layers as the training and the target output vectors are same. The association b/w the patterns is stored by their weights

→ Training algo

① Set all the weights to zero

$$W_{ij} = 0 \quad (j = 1, 2, \dots, n \quad \& \quad i = 1, 2, 3, \dots, m)$$

② Repeat step ③ to ⑤ for all input-output vectors.

③ Activate the input layer to training input vector.

$$x_j = (j = 1 \dots n)$$

④ Activate the output layer to target vector

$$y_j = t_j$$

⑤ Perform weight adjustment.

$$W_{ij}(\text{new}) = W_{ij}(\text{old}) + \eta x_j y_j \quad \text{Hebb Rule}$$

→ Testing Algo -

The weight obtained from training algo is considered for testing.  
Set the activation function for the network.

$$\text{net } \cancel{y} = \cancel{w}^T x$$

The activation function can be binary or bipolar step function.

→ Outer Product Rule -

Outer product rule is an alternative for Hebb's rule for weight adjustment.

$$\text{Input vector } x = \left\{ \begin{array}{c} x_1 \\ x_2 \\ \vdots \\ x_n \end{array} \right\}, \quad t = \left\{ \begin{array}{c} t_1 \\ t_2 \\ \vdots \\ t_n \end{array} \right\}$$

The outer product is obtained by performing multiplication of input vector with transpose of target vector.

$$y = x t^T = \begin{bmatrix} x_1 \\ \vdots \\ x_i \\ \vdots \\ x_n \end{bmatrix}_{n \times 1} \cdot [t_1 \dots t_j \dots t_m]_{1 \times m}$$

$$W_{ij} = \begin{bmatrix} x_1 t_1 & \dots & x_1 t_j & \dots & x_1 t_m \\ \vdots & & \vdots & & \vdots \\ x_i t_1 & \dots & x_i t_j & \dots & x_i t_m \\ \vdots & & \vdots & & \vdots \\ x_n t_1 & \dots & x_n t_j & \dots & x_n t_m \end{bmatrix}_{n \times m}$$

So weight is

$$W_{ij} = \sum_{p=1}^P x_i(p) t_j(p) \quad \text{or}$$

$$W = \sum_{p=1}^P x(p) t^T(p)$$

Ex  $\rightarrow$   $x = \begin{bmatrix} 1 \\ -1 \\ 1 \\ 1 \end{bmatrix}$   $t = \begin{bmatrix} 1 \\ -1 \\ 1 \\ 1 \end{bmatrix}$

Output vector  $y = x t^T$

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$$W = \begin{bmatrix} 1 & -1 & 1 & 1 \\ -1 & 1 & -1 & -1 \\ 1 & -1 & 1 & 1 \\ 1 & -1 & 1 & 1 \end{bmatrix} 4 \times 4$$

(i) Test the network

$$\text{net} = W^T x = \begin{bmatrix} 1 & -1 & 1 & 1 \\ -1 & 1 & -1 & -1 \\ 1 & -1 & 1 & 1 \\ 1 & -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ 1 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 4 \\ -4 \\ 4 \\ 4 \end{bmatrix}$$

Activation function

$$y_i = f(\text{net}) = \begin{cases} 1 & \text{if } \text{net} > 0 \\ -1 & \text{if } \text{net} \leq 0 \end{cases}$$

$$= \begin{bmatrix} 1 \\ -1 \\ 1 \\ 1 \end{bmatrix}$$

(ii) Testing the network with one misclass

# ⇒ Hetero-associative Memory ⇒

It retrieves the pattern from memory where input and output (target) patterns are different.

The correlation b/w the input patterns & the output pattern is determined by the weights.

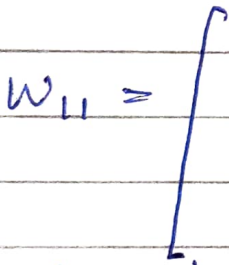
Training algo is similar.

Ex →

	$x_1$	$x_2$	$x_3$	$x_4$	$t_1$	$t_2$
Pattern 1	1	0	1	0	1	0
" 2	1	0	0	1	1	0
" 3	1	1	0	0	0	1
" 4	0	0	1	1	0	1

Outer product. 
$$W = \sum_{p=1}^P x(p) t(p)^T$$

for Pattern 1:  $w_{11}$       for 2:  $w_{22}$       for 3:  $w_{33}$       for 4:  $w_{44}$



final weights 
$$W = w_{11} + w_{22} + w_{33} + w_{44}$$