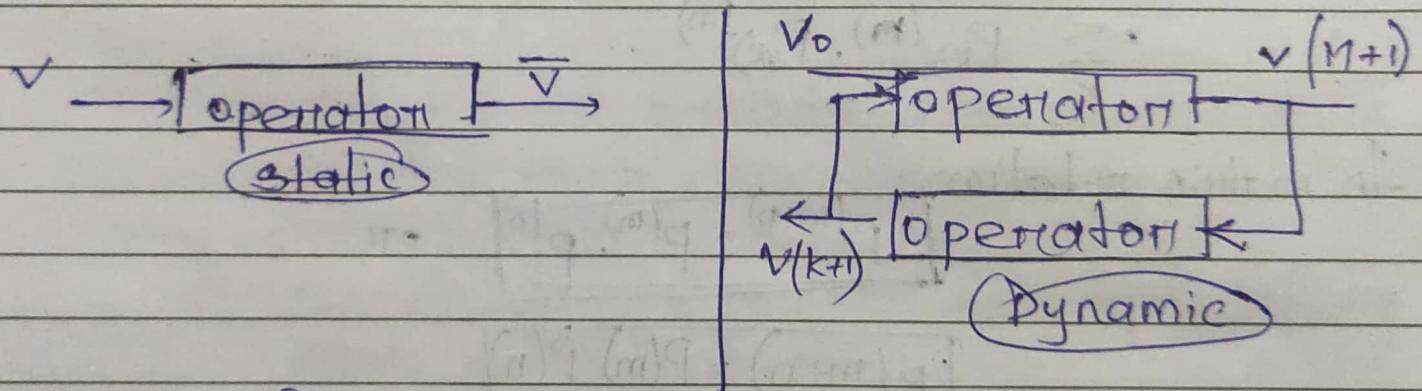


Associative memory: Associative memory networks can be seen as simplified model of human brain which can associate similar patterns.

- ⇒ It exhibits hebbian learning.
- ⇒ An associative memory is a store of associated patterns which are encoded in some form.
- ⇒ When storehouse is triggered with a pattern, the associated pair is recalled.
- ⇒ Associated memory is divided into two:
 - i) Static ⇒ recall output in one single feed forward pass.
 - ii) Dynamic ⇒ recalls through recurrent pass

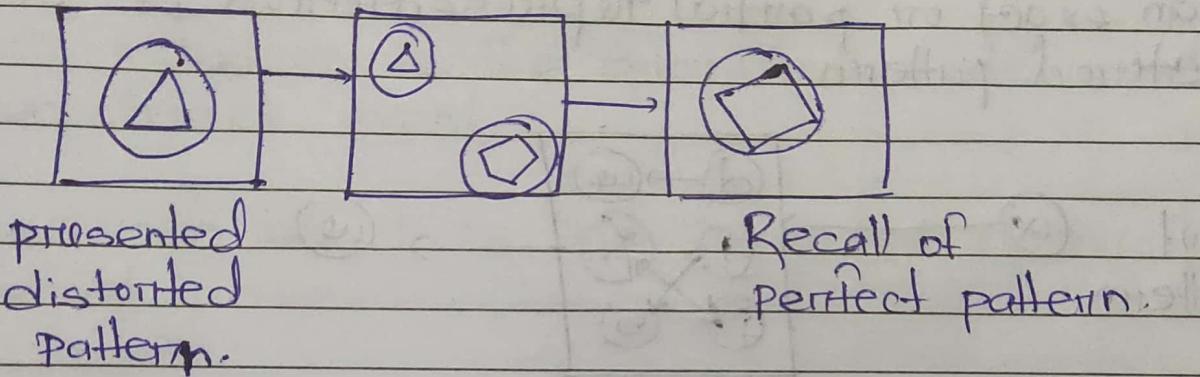


⇒ Types of associative memory:

- i) Auto Associative: same input and output pair.
- ii) Hetero Associative: associative patterns are different.

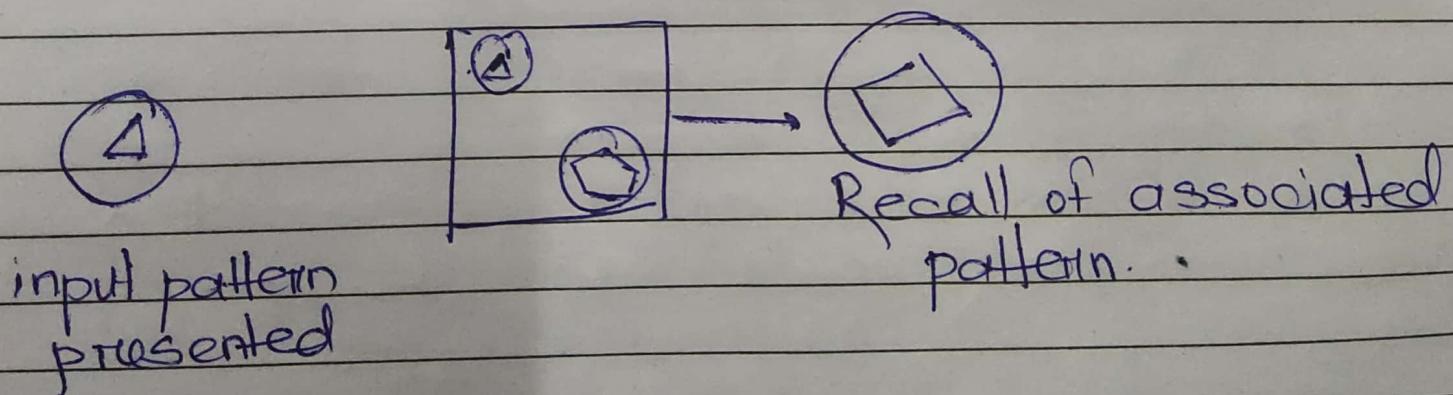
An associative memory is a content-addressable structure that maps a set of input patterns to a set of output patterns.

- Auto-associative memory: It recovers a previously stored pattern that most closely relates to the current pattern auto associative correlation:



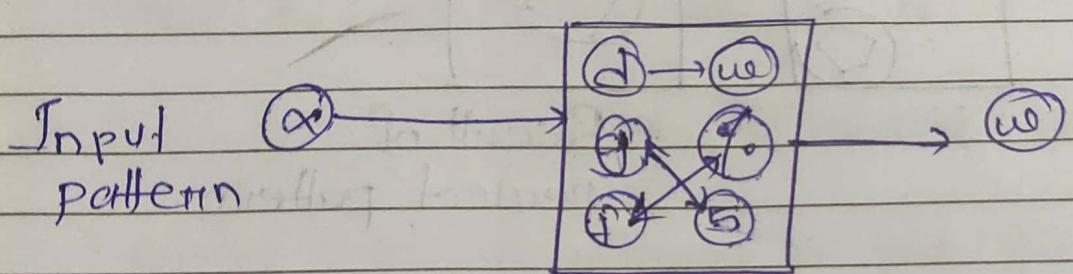
- Hetero-associative memory: The recovered pattern is generally different from the input pattern not only in type and format but also in content.

Also known as hetero-associative correlation.



■ Working of Associative Memory:

Associative memory is a depository of associated pattern which in some form. If the depository is triggered with a pattern the associated pattern pair appear at the associated output. The input could be an exact or partial representation of a stored pattern.



If the memory is produced with an input pattern, may say \oplus , the associated pattern w is recovered automatically.

- ⇒ encoding or memorization
- ⇒ errors and noise
- ⇒ performance measure.

■ Mathematical Pattern:

Pattern term is used in context of neural networks to mean a set of activations across a pool of units (neurons).

ANN combines biological principles with advanced statistics to solve problems in domains such as pattern recognition.

Pattern → Pattern is the quantitative description of an object, event.

Patterns can be classified as spatial or temporal pattern.

- i) Spatial: Example are picture, weather, map, video, games.
- ii) Temporal: Example are speech signal, ECG, etc. These pattern involves the ordered sequence of data appeared in time.

■ Pattern classification:

The main goal of pattern classification is to assign a physical object, event or phenomenon to one of the pre-specified.

For example:

We classify various objects into different categories like living, non-living thing etc.

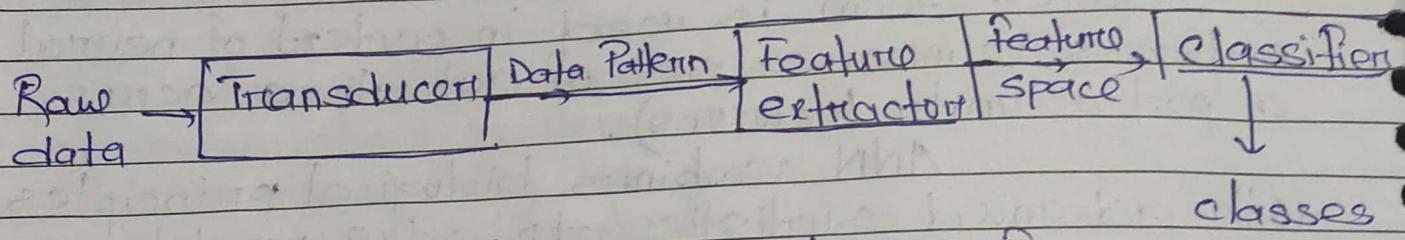


fig: Block diagram of classification

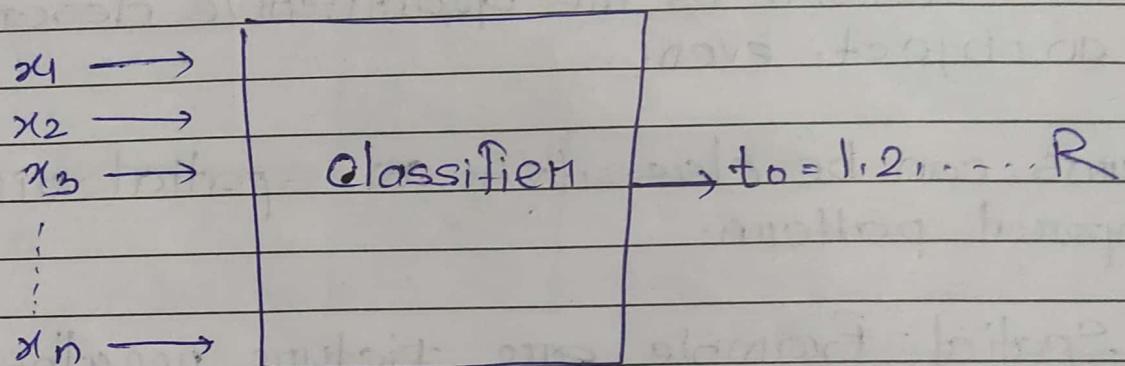


fig: General diagram of pattern classifier

→ Transducer generally converts one form of energy to another form of energy.

Here, the input is Raw data space $\mathbf{x} = [x_1, x_2, \dots, x_n]$ and output is transducer is data in pattern space that belong to certain category that is $t_0 = 1, 2, \dots, R$.

Converted data is at the output can be compressed. Compressed data is called feature.

Hebbian learning: It was proposed by Donald D Hebb. It is one of the first and also easiest learning rule in the neural network used for pattern classification. It's a single layer NN having one input layer with n units and one output layer with one unit.

The rule works by updating the weights between neurons in the neural network for each training sample.

■ Hebbian learning Rule Algo:

1. Set all weights to zero, $w_i = 0$ for $i = 1$ to n and bias to 0.
2. For each input vector s (input vector) : t (target output pair), do step 3 to 5.
3. Set activation for input units with the input vector $x_i = s_i$ for $i = 1$ to n .
4. Set the corresponding output value to the output neuron, i.e. $y = t$.
5. Update weight and bias by applying Hebb rule for all $i = 1$ to n .

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

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

Bidirectional Associative Memory:

BAM is a hetero-associative, content-addressable memory consist of 2 layers. It is similar to linear associator but connections are bidirectional that is,

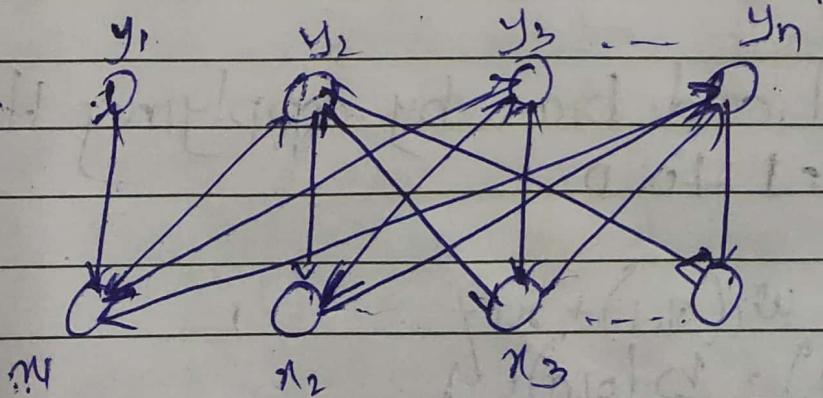
$$w_{ij} = w_{ji} \quad \text{for } \begin{cases} i = 1, 2, \dots, m \\ j = 1, 2, \dots, n \end{cases}$$

- BAM allows forward and backward flow of information.

- ⇒ In BAM, the units in both layers serve as both input and output units depending on the direction of propagation.

- ⇒ Propagating the signals from X layer to Y layer makes the units in X layer act as input units while units in Y layer act as output unit. Same is true for other direction because memory is bidirectional.

- ⇒ BAM model can perform both auto and hetero associative to call of stored info.



→ Like in linear association and hopfield networks encoding in BAM can be carried out by using

$W_{LK} = \alpha K^T Y_K$ (to store a single associated pattern pair).

$W = \alpha \sum_{K=1}^P W_{LK}$ (to store simultaneously several associated pattern pairs)

This process is generally called ~~storage~~ encoding storage or encoding

After encoding network can be used for decoding. The decoding process is as follows:

- 1) Input layer can be applied either on x layer or on the y layer depending on direction of propagation.
- 2) When input pattern is applied, network will propagate the input pattern to other layers allowing the units in other layers to compute their output value.
- 3) Pattern that was produced by other layers is propagated back to original layer and in original layer compute the output value.
- 4) This process is repeated until further propagation and computation do not result in a change in the associations of units.

in both layers where final pattern pair is one of the stored associated pattern pair.

- 5) Final pattern pair that will be produced by the networks depend on initial pattern pair and connection weight matrix.

Addition and Deletion of Pattern Pairs:

Given a set of pattern pairs (x_i, y_i) for

$i = 1, 2, \dots, n$ and set of correlation Matrix M.

- ⇒ a new pair (x', y') can be added.
- ⇒ an existing pair (x_j, y_j) can be deleted from memory model.

Addition:

Addition: Add new pair (x', y') to existing correlations Matrix M, then new matrix M_{new} is given by,

$$M_{\text{new}} = X_1^T Y_1 + X_2^T Y_2 + \dots + X_n^T Y_n + x'^T y'$$

Deletion: Subtract the matrix corresponding to an existing pair (x_j, y_j) from matrix M, then correlation matrix is given by,

$$M_{\text{new}} = M - (X_j^T Y_j)$$

■ Discrete BAM: Network propagate an input pattern x to layer Y and X layers compute the net input using:

Input is calculated. $y_i = \sum_{j=1}^m x_j w_{ij}$

O/P is calculated. $y_i(t+1) = \begin{cases} +1 & \text{if } y_i > 0 \\ y_i(t) & \text{if } y_i = 0 \\ -1 & \text{if } y_i < 0 \end{cases}$

Pattern y produced on Y layer is then propagated back to X layer and X layer compute value.

Input, $x_j = \sum_{i=1}^n y_i w_{ij}$

O/P, $x_j(t+1) = \begin{cases} +1 & \text{if } x_j > 0 \\ x_j(t) & \text{if } x_j = 0 \\ -1 & \text{if } x_j < 0 \end{cases}$

■ Continuous BAM: In this, the units use hyperbolic tangent o/p function. The units in X -layer's have an external input I_i while unit in Y -layer's have an extra external input J_i .
For $i=1, 2, \dots, m$ and $j=1, 2, \dots, n$.

These extra input lead to a modification in the computation of net inputs.

$$x_i = \sum_{j=1}^n y_j w_{ij} + I_i$$

$$y_j = \sum_{i=1}^m x_i w_{ij} + J_j$$

■ Storage and Retrieval Algorithm:

Storage algorithm is called encoding and retrieval algorithm is called decoding process.

Given,

P bipolar binary vector $\{s^{(1)}, s^{(2)}, \dots, s^{(P)}\}$

where, s^m is $n \times 1$ for $m = 1, 2, \dots, P$

Initializing vector v^0 is $n \times 1$.

Storage Algorithm \Rightarrow

Step 1: Weight matrix w is $(n \times m)$: $w \leftarrow 0$,
 $m \leftarrow 1$.

Step 2: Vector s^m is stored. So, the storage algo. for calculating the weight matrix is,

$$w \leftarrow s^m s^{m \top} \\ \text{OR, } w_{ij} = (1 - S_{ij}) \sum_{m=1}^P s_i^{(m)} s_j^{(m)}$$

Step 3: If $m < P$, then $m \leftarrow m+1$ and go to Step 2. Otherwise go to step 4.

Step 4: Storage is complete, output vector w .

Good Write

Retrival Algorithm:

Step 1: Cycle counter K is initialized $K \leftarrow 1$.
Within the cycle counter i is initialized
 $i \leftarrow 1$ and initialized as $v \leftarrow v^0$.

Step 2: Integrands $1, 2, \dots, n$ are arranged in
an ordered random sequence of
updation is not used them $\alpha_1 = 1, \alpha_2 = 2, \dots$
 $\alpha_m = n$ or $\alpha_i = i$ at each update cycle.

Step 3: Neutron i is updated by computing
new α_i

$$\text{new } \alpha_i = \sum_{j=1}^n w_{ij} \alpha_j V_j$$

Step 4: If $i < n$ then $i \leftarrow i+1$ and go to
Step 3, otherwise go to step 5.

Step 5: If $\text{new } \alpha_i = V \alpha_i$ for $i = 1, 2, \dots, n$.

Hopfield network: (Unsupervised learning)

- ⇒ It is a form of Recurrent artificial neural network invented by John Hopfield.
- ⇒ It is a type of ANN. (feedback)
- ⇒ Secure as content-addressable memory system with binary threshold units.
- ⇒ Types
 - Discrete
 - Continuous.
- ⇒ Hopfield networks have a scalar value associated with each state of the network referred to as the "energy"

■ Discrete Hopfield network:

Discrete

Bipolar
 $a_i \leftarrow \begin{cases} 1 & \text{if } \sum w_{ij} s_j > \theta_i \\ -1 & \text{otherwise} \end{cases}$
Binary.
 $a_i \leftarrow \begin{cases} 1 & \text{if } \sum w_{ij} s_j > \theta_i \\ 0 & \text{otherwise} \end{cases}$

w_{ij} = strength of connection weight

s_j = state of unit j

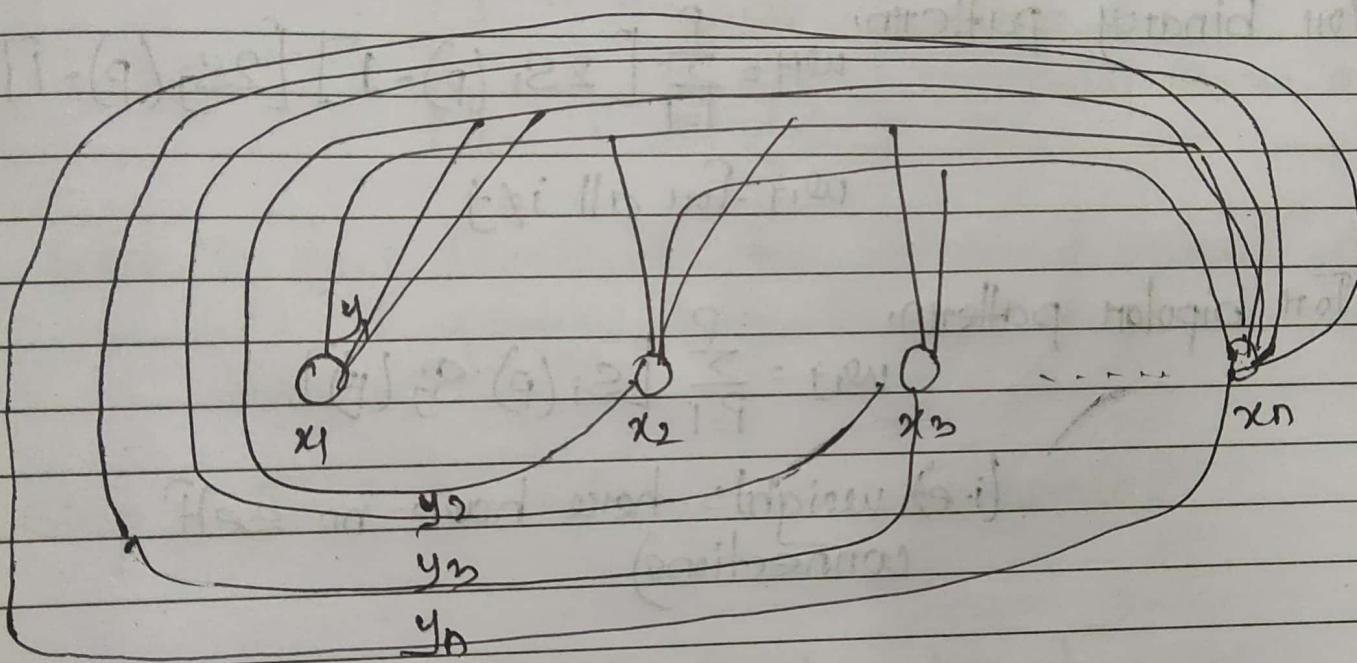
θ_i = threshold of unit i

$$E = -\frac{1}{2} \sum_j w_{ij} s_i s_j + \sum_i \theta_i s_i$$

Good Write

Structure and Architecture:

- Each neuron has an inverting and non-inverting output.
- Being fully connected the output of each neuron is an input to all the neurons but not self.



Here, $x_1, x_2, \dots, x_n \rightarrow$ Input to the n given neuron.

$y_1, y_2, y_3, \dots, y_n \rightarrow$ Output obtained from the n given neurons.

$w_{ij} \rightarrow$ weight associated with connection between the i^{th}

④ Training Algorithm:

For storing a set of input pattern $s(p)$ [$p=1$ to P] whence,

$s(p) = s_1(p) \dots s_l(p)$
 $\dots s_n(p)$, the weight matrix given by

① For binary pattern,

$$w_{ij} = \sum_{p=1}^P [2s_i(p)-1] [2s_j(p)-1]$$

w_{ij} for all $i \neq j$

② For bipolar pattern,

$$w_{ij} = \sum_{p=1}^P [s_i(p)s_j(p)]$$

(i.e.) weights here have no self connections)

⑤ Training Algorithm

Step 1 = Initialize weights (w_{ij}) to store patterns (using training algo)

Step 2 = For each input vector y_i , perform steps 3-8.

Step 3 = Make initial activations of the network equal to the external input vector.

$$y_i = x_i \quad (\text{for } i=1 \text{ to } n)$$

Step 4 = For each vector y_i , perform step 5-8

Step 5. Calculate the total input y_i of the network y_{in} using the equation,

$$y_{in} = x_i + \sum_j [y_j w_{ji}]$$

Step 6. Apply activation over the total input to calculate the output as per the equation

$$y_i = \begin{cases} 1 & \text{if } y_{in} > \theta_i \\ y_i & \text{if } y_{in} = \theta_i \\ 0 & \text{if } y_{in} < \theta_i \end{cases} \quad \text{where } \theta_i \text{ is normally taken as 0.}$$

Step 7: Now, feedback the obtained output y_i to all other units. Thus, activation vectors are updated.

Step 8: Test the network convergence.

⇒ Continuous Hopfield network ⇒

Here, the time parameter is treated as a continuous variable. So, instead of getting binary/bipolar outputs, we can obtain values that lie between 0 and 1.

It can be used to solve constrained optimization and associative memory problems.

$$v_i = g(u_i) \quad \begin{array}{l} \text{where, } v_i = \text{output from the} \\ \text{continuous hopfield} \\ u_i = \text{internal activity} \\ \text{of a node in continuous} \end{array}$$

Good Write