## 

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## Supervised Learning in Neural Networks (Part 6)

## ANN as Heteroassociative Memory (Bidirectional associative memory)

- The Hopfield network represents an auto-associative type of memory; it can retrieve a corrupted or incomplete memory but cannot associate this memory with another different memory.
- Human memory is essentially associative. We use a chain of mental associations to recover a lost memory: We associate the faces with names, letters with sounds, etc.
- To associate one memory with another, we need a recurrent neural network capable of accepting an input pattern on one set of neurons and producing a related, but different, output pattern on another set of neurons.
- Bidirectional associative memory (BAM), first proposed by Bart Kosko.
- BAM is hetero-associative, meaning given a pattern it can return another pattern which is potentially of a different size.
- BAM is content-addressable memory.
- The Bidirectional associative memory maps bipolar binary vectors

$$
\begin{aligned}
& a=\left[\begin{array}{llll}
a_{1} & a_{2} & \ldots & a_{n}
\end{array}\right]^{t}, \quad a_{i}= \pm 1, \quad i=1,2, \ldots, n, \\
& \text { Input vectors } \\
& \mathrm{b}=\left[\begin{array}{llll}
\mathrm{b}_{1} & \mathrm{~b}_{2} & \ldots & \mathrm{~b}_{\mathrm{m}}
\end{array}\right]^{\mathrm{t}}, \quad \mathrm{~b}_{\mathrm{i}}= \pm 1, \quad \mathrm{i}=1,2, \ldots, \mathrm{~m}, \\
& \text { Output vectors Or vice versa. }
\end{aligned}
$$

- The BAM correlation encoding scheme is extended to a general Hebbian learning law.

- The basic idea behind the BAM is to store pattern pairs so that when ndimensional vector $\mathbf{X}$ from set $\mathbb{A}$ is presented as input, the BAM recalls mdimensional vector $\mathbf{Y}$ from set $\mathbf{B}$, but when $\mathbf{Y}$ is presented as input, the BAM recalls $\mathbf{X}$. A BAM network is one with two fully connected layers, in which the links are all bi-directional (The neurons in input layer are fully interconnected to the neurons in the output layer. There is no interconnection among neurons in the same layer. The weight from input layer to output layer is same as the weights from output layer to input layer). A BAM network may be trained, or its weights may be worked out in advance. It is used to map a set of vectors Xi (input layer) to a set of vectors Yi (output layer).
- To develop the BAM, we need to create a correlation matrix for each pattern pair we want to store. The correlation matrix is the matrix product of the input vector $\mathbf{X}$, and the transpose of the output vector $\mathbf{Y}^{\mathrm{T}}$. The BAM weight (memory) matrix is the sum of all correlation matrices, that is

$$
\begin{equation*}
W=\sum_{m=1}^{M} X_{m} Y_{m}^{T} \tag{1}
\end{equation*}
$$

Where $\mathbb{M}$ is the number of pattern pairs to be stored in the BAM. The weight matrix associates all $\mathbf{X}-\mathbf{Y}$ pairs.

- If a BAM network is used to implement an auto-associative memory then the input layer is the same as the output layer, i.e., there is just one layer. This network can be used to retrieve a pattern given a noisy or incomplete pattern.
- Stability of the BAM: The BAM is unconditionally stable. This means that any set of associations can be learned without risk of instability.
- The BAM is capable of error correction.
- The output is updated asynchronously (for a given time, only a single neuron is allowed to update its output).
- A content-addressable memory is a type of memory that allows for the recall of data based on the degree of similarity between the input pattern and the patterns stored in memory. It refers to a memory organization in which the memory is accessed by its content as opposed to an explicit address like in the traditional computer memory system. Therefore, this type of memory allows the recall of information based on partial knowledge of its contents.


## Bidirectional associative memory training algorithm:

1) Storage (learning): In the learning step for BAM we need to find weight matrix between, M pairs of patterns (fundamental memories) are stored in the synaptic weights of the network according to the equation 1

## Assume

Set $A: X_{1}=\left[\begin{array}{l}1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1\end{array}\right] \quad X_{2}=\left[\begin{array}{r}-1 \\ -1 \\ -1 \\ -1 \\ -1 \\ -1\end{array}\right] \quad X_{3}=\left[\begin{array}{r}1 \\ 1 \\ -1 \\ -1 \\ 1 \\ 1\end{array}\right] \quad X_{4}=\left[\begin{array}{r}-1 \\ -1 \\ 1 \\ 1 \\ -1 \\ -1\end{array}\right]$
Set B: $Y_{1}=\left[\begin{array}{l}1 \\ 1 \\ 1\end{array}\right] \quad Y_{2}=\left[\begin{array}{l}-1 \\ -1 \\ -1\end{array}\right] \quad Y_{3}=\left[\begin{array}{r}1 \\ -1 \\ 1\end{array}\right] \quad Y_{4}=\left[\begin{array}{r}-1 \\ 1 \\ -1\end{array}\right]$
The input layer $=6$ neurons and the output layer $=3$ neurons
The weight matrix W

$$
\begin{aligned}
& W=\left[\begin{array}{l}
1 \\
1 \\
1 \\
1 \\
1 \\
1
\end{array}\right]\left[\begin{array}{lll}
1 & 1 & 1
\end{array}\right]+\left[\begin{array}{l}
-1 \\
-1 \\
-1 \\
-1 \\
-1 \\
-1
\end{array}\right]\left[\begin{array}{lll}
-1 & -1 & -1
\end{array}\right]+\left[\begin{array}{r}
1 \\
1 \\
-1 \\
-1 \\
1 \\
1
\end{array}\right]\left[\begin{array}{lll}
1 & -1 & 1
\end{array}\right]+\left[\begin{array}{r}
-1 \\
-1 \\
1 \\
1 \\
-1 \\
-1
\end{array}\right]\left[\begin{array}{lll}
-1 & 1 & -1
\end{array}\right] \\
&=\left[\begin{array}{lll}
4 & 0 & 4 \\
4 & 0 & 4 \\
0 & 4 & 0 \\
0 & 4 & 0 \\
4 & 0 & 4 \\
4 & 0 & 4
\end{array}\right]
\end{aligned}
$$

2) Testing

- We need to confirm that the BAM is able to
$\circ$ recall $Y_{m}$ when presented $X_{m}$.
$\bigcirc$ recall $X_{m}$ when presented $Y_{m}$
Using

$$
Y_{m}=\operatorname{sign}\left(W^{T} X_{m}\right), \quad m=1.2, \ldots, M
$$

$$
Y_{1}=\operatorname{sign}\left(W^{T} X_{1}\right)=\operatorname{sign}\left\{\left[\begin{array}{llllll}
4 & 4 & 0 & 0 & 4 & 4 \\
0 & 0 & 4 & 4 & 0 & 0 \\
4 & 4 & 0 & 0 & 4 & 4
\end{array}\right]\left[\begin{array}{l}
1 \\
1 \\
1 \\
1 \\
1 \\
1
\end{array}\right]\right\}=\left[\begin{array}{l}
1 \\
1 \\
1
\end{array}\right]
$$

And using

$$
\begin{aligned}
& X_{m}=\operatorname{sign}\left(W Y_{m}\right), \quad m=1.2, \ldots, M \\
& X_{3}=\operatorname{sign}\left(W Y_{3}\right)=\operatorname{sign}\left\{\left[\begin{array}{lll}
4 & 0 & 4 \\
4 & 0 & 4 \\
0 & 4 & 0 \\
0 & 4 & 0 \\
4 & 0 & 4 \\
4 & 0 & 4
\end{array}\right]\left[\begin{array}{r}
1 \\
-1 \\
1
\end{array}\right]\right\}=\left[\begin{array}{r}
1 \\
1 \\
-1 \\
-1 \\
1 \\
1
\end{array}\right]
\end{aligned}
$$

All four pairs are recalled perfectly

## 3) Retrieval

- Present an unknown vector (probe) $X$ (corrupted or incomplete version of a pattern from set $\mathbf{A}$ or $\mathbf{B}$ ) to the BAM and retrieve a stored association:

$$
X \neq X_{m}, \quad m=1,2, \ldots, M
$$

- Initialize the BAM:

$$
X(\mathbf{0})=X, \quad p=\mathbf{0}
$$

$\circ$
Calculate the BAM output at iteration $\boldsymbol{p}$ :

$$
Y(p)=\operatorname{sign}\left[W^{T} X(p)\right]
$$

- Update the input vector $\boldsymbol{X}(\boldsymbol{p})$ :

$$
X(p+1)=\operatorname{sign}[W Y(p)]
$$

- Repeat the iteration until convergence, when input and output remain unchanged.
Example:
$X=\left(\begin{array}{llllll}-1 & 1 & 1 & 1 & 1 & 1\end{array}\right)$---single error pattern
This probe applied as the BAM input and produces $Y_{1}$, the $Y_{1}$ is then used as input and the BAM retrieves the vector $X_{1}$


## Problems of BAMM Network

- Storage capacity of the BAMM: The maximum number of associations to be stored in the BAM should not exceed the number of neurons in the smaller layer.
- Incorrect convergence. The BAM may not always produce the closest association.


## Example

Consider four 16-pixel bit maps of letter characters should be associated to 7-bit
binary vectors as below:

$\mathbf{a}^{(1)}=[111 \text {-11-1-1-11-1-1-1111-1] }]^{\text {( }}$
$\mathbf{b}^{(1)}=[1-1-1-1-111]^{\mathrm{T}}$;
$\mathrm{a}^{(2)}=[1-1 \text {-11111-111-1111-1-11] }]^{\mathrm{T}}$;
$\mathbf{b}^{(2)}=\left[\begin{array}{lll}1-1 & -1 & 1 \\ \text { (3)-1] }\end{array}\right.$;
$\mathrm{a}^{(3)}=[11111-1-11 \text {-1-11-1-11111] }]^{\mathrm{T}}$;
$b^{(3)}=[1-111-11-1]^{T}$;
$\mathrm{a}^{(4)}=\left[-1-1\right.$-1-1-1-1-111111-1-1-11] $\mathbf{c}^{\mathrm{T}}$;
$\mathbf{b}^{(4)}=\left[-1\right.$ 1 1-11-11] ${ }^{\mathrm{T}}$;

