## PREFERRING OLD AGE HOME: A FUZZY APPROACH USING EXTENDED BIDIRECTIONAL ASSOCIATIVE MEMORY

## DR.A.PRAVEENPRAKASH, KANIMOZHIRAMAN, R.SUMATHI, J.JAYALAKSMI

**Abstract:** The number of persons above the age of 60 years is fast growing, especially in India. India is the second most populous country in the world. India, like many traditional societies, today faces a unique situation in providing care for its elderly as the existing old-age support structures in the form of family, kith and kin, are fast eroding and the elderly are ill-equipped to cope alone with their lives in the face of infirmity and disability. The onus of caring for the elderly is therefore now much more on the state than the family and will necessitate the creation of adequate institutional support. The BAM modal was introduced by Bart Kosko in 1988 and modified in the year 2001[14]. The extended by directional Associate memories was introduced by S.R.Kannan(2005)[15]. In this paper we find the reason for preferring old age home by the old age people using Extended Bidirectional Associative Memories.

**Keywords:** Bidirectional Associative Memory, Extended Bidirectional Associative Memory, Old age, Old age Home ,Neural Networks.

**Introduction:** This paper takes survival data directly from old age people and compares it with different neurons of EBAM, predicting the most influential inputs in each data as to the reasons for preferring old age home. The focus of this research is on real data collected in India. The survival data has been obtained directly from people in the old age home in Chennai, Tamilnadu, India. This paper has determined the feelings of types of reason by the scale from -10 to 10. The feeling has been taken from each old age home about types of reason and it quantized by the scale.

This paper selects the following types of reason for leaving home with the help of experts

A1 - Daughter In Law

- A2 No male child
- A3 Finance Problem
- A4 No Children
- A5 Attitude Problem (ego)
- A6 Health problem

To analyze or get feelings of types of reason from the old people, this paper selects many

stages of family

- (B1) poor family staging.
- (B2) low middle family staging.
- (B3) middle family staging.
- (B4) high middle family staging.

(B5) rich family staging.

**Ebam For Preffering Old Age Home:** A discrete twolayers EBAM with threshold signal functions, arbitrary thresholds and inputs, an arbitrary but a constant synaptic connection [4,5] matrix V and discrete time-steps k are defined by the following equations

$$X_{i}^{k+1} = \sum_{j=1}^{p} S_{j}(y_{j}^{k}) V_{ij} + I_{i}$$
(1)  
$$Y_{j}^{k+1} = \sum_{i=1}^{n} S_{i}(x_{i}^{k}) V_{ij} + j_{j}$$
(2)

Where  $V_{ij} \in V$ , ( $S_i$  and  $S_j$  are signal functions).  $S_i$  and  $S_j$  are representing extended binary or bipolar threshold

functions.  $I_i$  and  $J_j$  represents the directly experienced sensory information or directly applied control information. Here in this two layers BAM, these  $I_i$  and  $J_j$ are considered as zero. The thresholds for extended binary and bipolar signal functions are defined in the recall process of the EBAM. The extended binary and bipolar single functions are given in equations (3), (4).

$$S_{i}(X_{i}^{k}) = \begin{cases} 1, & \text{if } x_{i}^{k} > 0, \\ \text{statunchange if } x_{i}^{k} = 0, \\ -1, & \text{if } x_{i}^{k} < 0. \end{cases}$$
(3)  
$$S_{j}(Y_{j}^{k}) = \begin{cases} 1, & \text{if } y_{j}^{k} > 0, \\ \text{statunchange if } y_{j}^{k} = 0, \\ -1, & \text{if } y_{j}^{k} < 0. \end{cases}$$

At any moment different neurons can "decide" whether to compare their activation to their threshold. At each moment any of the  $3^n$  subsets of  $F_x$  neurons, or the  $3^p$ subsets of the  $F_y$  neurons, can decide to change state. Each neuron may randomly decide whether to check the threshold conditions in equations (3),(4). At each moment each neuron defines a random variable that can assume the value ON(+1) or state unchanged (0) or ON (-1). The network is often assumed to be deterministic and state changes are synchronous, that is, an entire field of neurons is updated at a time. In case of a simple asynchrony, only one neuron makes a state change decision at a time. When the subsets represent that entire fields Fx and Fy, synchronous state change results. In a real life problem, the entries of the constant synaptic matrix of memory matrix V [6] depends upon the investigators feelings. The memory matrix is given a weight according to their feelings.

3. Working Procedure: The basic structure of the EBAM with two layers is explained. EBAM will be used in finding the reason for preferring old age homes . Consider, the n neurons in layer one correspond to vector  $F_x$  and p neurons in layer two correspond to vector  $F_y$ . The two layers are bidirectional related. The vector F<sub>y</sub> is recalled from activation  $F_x$  by the memory matrix (or weight matrix) V [7]. The memory matrix (weight matrix) transpose  $V^{T}$  allows activation  $F_{v}$  to recall Fx, [8,9]. When an arbitrary vector is an input into a network, the network activates to a stable state via an interactive process. In the EBAM, if an arbitrary input is presented, the activation process is explained as following. Consider two layers EBAM with n neurons in F<sub>x</sub> and p neurons in F<sub>v</sub>. An n by p, matrix V represents the forward synaptic projections from  $F_x$  to  $F_y$  [10,11]. The p by n matrix transpose  $V^T$ , represents the backward projection  $F_v$  to  $F_{\boldsymbol{x}}.$  Let the matrix  $\boldsymbol{V}$  and  $\boldsymbol{V}^{T}$  corresponds to

$$\mathbf{V} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \cdots & \vdots \\ a_{p1} & \cdots & a_{pn} \end{pmatrix} \quad \mathbf{V}^{\mathrm{T}} = \begin{pmatrix} a_{11} & \cdots & a_{pn} \\ \vdots & \cdots & \vdots \\ a_{1n} & \cdots & a_{pn} \end{pmatrix}$$

Suppose at initial time k, all the neurons in Fy are ON. So, the signal state vector S (Y<sub>K</sub>) at time k corresponds to S (Y<sub>K</sub>) = (n signal vectors). Suppose also, that the joint effects of feedback from F<sub>x</sub> and prior initial input produce the activation-state vector X<sub>K</sub> at F<sub>x</sub>, Where  $X_k = (x_1^2 + x_2^2 + ... + x_n^2)$ 

Now, consider how the EBAM network behaves if all neuronal state-change decisions are synchronous. First, at time k + 1 the  $F_x$  neurons transduce their real valued activations into a binary signal state vector S (X<sub>K</sub>,).

Synchronous operation means that each Fx neuron thresholds its activation in parallel, according to equations (3),(4) and with zero thresholds. The result gives the binary signal vector  $S = (X_k) = [1, 1 \dots -1, 0, 1]$  (Since 'zero' neuron is considered as zero and all other neurons are in the ON (+ or - direction) state). The index notation in  $S(X_k)$  implicitly assumes that neurons instantaneously transduce activations to signals. If this is unrealistic, we can introduce an extra time-step to model the time lag. For simplicity, we shall assume instantaneous activation transduction.

Next, at time k + 1, these Fx signals pass forward through the filter V to affect the activations of the Fv neurons. The p of Fy neurons computes p dot products or correlations. The signal state vector  $S = (X_k)$  multiplies each of the p columns of V. Since  $S(X_k)$  denotes a row vector, we can write this parallel dot product computation as the vector matrix multiplication,

$$S(X_{k})V = \left(\sum_{i=1}^{n} S_{i}(x_{i}^{k})V_{i1}, \sum_{i=1}^{n} S_{i}(x_{i}^{k})V_{i2}, \dots, \sum_{i=1}^{n} S_{i}(x_{i}^{k})V_{in}\right)$$
$$= y_{1}^{k+1}, y_{2}^{k+1}, \dots, y_{p}^{k+1}$$
(5)

We synchronously compute the new signal state vector  $S(Y_{k+l})$  by applying in parallel the threshold law (3),(4) with zero threshold to each  $F_y$  neuron. The result gives the new  $F_y$  signal state vector.  $S = (Y_{k+1}) = [0, l, \dots -l, 0, 1]$ , where  $l \in [-1,0, 1]$ . The first neuron of  $Y_{k+l}$  is negative, all other neurons are in the ON (+ and - direction) state. The signal vector  $S(Y_{k+l})$  then passes backward through the synaptic filter  $V^T$  at time k + 2.  $S(Y_k)$   $V^T = x_1^{k+2}, x_2^{k+2}, \dots, x_n^{k+2} = x_{k+2}$ .

Synchronous thresholding at  $F_x$  at time k + 2, now reveals a EBAM fixed-point equilibrium.

 $S(X_{k+1}) = [l_1, l_2, ..., l_{n-2}, 0, l_n] = S(X_k)$ . Since  $S(X_{k+2}) = S(X_k)$  passing  $S(X_{k+2})$  forward through V will produce  $S(Y_{k+1})$  at Fy at time k + 3. Passing  $S(Y_{k+3}) = S(Y_{k+1})$  backward through V<sup>T</sup> will produce  $S(X_{k+2})$  again at Fx. These three signal-state vectors will pass back and forth in extended bidirectional equilibrium forever or until new inputs perturb the system out of equilibrium. Suppose we keep the first Fy neuron ON, this may be called asynchronous state-change policy. At time k, all the  $F_Y$  neurons are ON. The k + 1 vectors of Fx signals  $S(X_k)$  is the same as before, and so leads to the same Fy activation vector  $F_{y+1}$ .  $S(Y_{k+1}) = S(X_k)V$ .

The equilibrium state may set at  $S(Y_{k+3}) = S(Y_{k+1})$ . Similarly, the equilibrium state for  $S = (X_{k+4}) = S =$   $(\overline{X}_{k+2})$ S. The binary pair  $([l_1, l_2, ..., l_n], [l_1, l_2, ..., l_p])$  represents a fixed point of the EBAM dynamical system. The following three-quantization levels are taken for signal vectors. They are [-1, 0, 1] extended binary and bipolar codings.

**3.1. EBAM with Survival Data:** In this section, this paper proposes EBAM with several neurons, to do most influential input selection for survival data(s). As described in the previous section, EBAM with neurons that capture the semantic flexibility inherent in the survival data.

Now, consider the EBAM with six neurons in the first layer Fy and five neurons in the second layer Fx. The six neurons of the first layer are representing the types of reason, the five neurons of the second layer are representing the family stagings. The Table 1, lists the types of reason from family stagings.

Table 1.Survival data					
	$B_1$	<b>B</b> <sub>2</sub>	<b>B</b> <sub>3</sub>	$B_4$	<b>B</b> <sub>5</sub>
A <sub>1</sub>	5	6	0	6	2
A <sub>2</sub>	8	8	6	-5	4
A <sub>3</sub>	6	9	10	9	5
$A_4$	10	6	8	5	-4
A <sub>5</sub>	-5	-4	6	7	8
Δ.	-3	0	5	8	9

$$\mathbf{V} = \begin{pmatrix} 5 & 6 & 0 & 6 & 2 \\ 8 & 8 & 6 & -5 & 4 \\ 6 & 9 & 10 & 9 & 5 \\ 10 & 6 & 8 & 5 & -4 \\ -5 & -4 & 6 & 7 & 8 \\ -3 & 0 & 5 & 8 & 9 \end{pmatrix}$$
$$\mathbf{V}^{\mathrm{T}} = \begin{pmatrix} 5 & 8 & 6 & 10 & -5 & 3 \\ 6 & 8 & 9 & 6 & -4 & 0 \\ 0 & 6 & 10 & 8 & 6 & 5 \\ 6 & -5 & 9 & 5 & 7 & 8 \\ 2 & 4 & 5 & -4 & 8 & 9 \end{pmatrix}$$

## **References:**

- 1. B. Kosko, Adaptive bidirectional associative memories, Applied Optics 26, 4947-4960, (1987).
- H. Shi, Y. Zhao and X. Zhuang, A general model for bidirectional associative memories, IEEE Trans. Syst., Man, Cybern. B 28, 1558-1564, (Aug. 1988).
- 3. T.-D. Eom, C, Choi and J.-J. Lee, Generalized asymmetrical bidirectional associative memory, Machine Intelligence and Robotic Control 1 (1), 43-45, (1999). Extended Bidirectional Associative
- 4. J.J. Hopfield, Neural networks and physical systems with emergent collective computational abilities, Proc. Nat. Acad. Sci. 79 (5), 2554-2558, (1982).
- 5. R.J. McEliece, E.C. Posner, E.R. Rodemich and S.S. Venkatesh, The capacity of the Hopfield Associative

$$\begin{split} S(X_k) &= \begin{bmatrix} 1 & -1 & 0 & 1 & 1 & 1 \end{bmatrix} V = \begin{bmatrix} -1 & 0 & 1 & 1 & 1 \end{bmatrix} = Y_{k+l}, \\ S(Y_{k+1}) &= \begin{bmatrix} -1 & 0 & 1 & 1 & 1 \end{bmatrix} V^{T} = \begin{bmatrix} 1 & -1 & 1 & -1 & 1 & 1 \end{bmatrix} = X_{k+2}, \\ S(X_{k+2}) &= \begin{bmatrix} 1 & -1 & 1 & -1 & 1 & 1 \end{bmatrix} V = \begin{bmatrix} -1 & -1 & 1 & 1 & 1 \end{bmatrix} = Y_{k+3}, \\ S(Y_{k+3}) &= \begin{bmatrix} -1 & -1 & 1 & 1 & 1 \end{bmatrix} V^{T} = \begin{bmatrix} -1 & -1 & 1 & -1 & 1 & 1 \end{bmatrix} = X_{k+4}, \\ S(X_{k+4}) &= \begin{bmatrix} -1 & -1 & 1 & -1 & 1 & 1 \end{bmatrix} V = \begin{bmatrix} -1 & -1 & 1 & 1 & 1 \end{bmatrix} = Y_{k+5}, \\ S(Y_{k+5}) &= \begin{bmatrix} -1 & -1 & 1 & 1 & 1 \end{bmatrix} V^{T} = \begin{bmatrix} -1 & -1 & 1 & -1 & 1 & 1 \end{bmatrix} = X_{k+6}, \\ S(X_{k+6}) &= \begin{bmatrix} -1 & -1 & 1 & -1 & 1 & 1 \end{bmatrix} V = \begin{bmatrix} -1 & -1 & 1 & 1 & 1 \end{bmatrix} = Y_{k+7}, \\ S(Y_{k+5}) &= S(Y_{k+7}) \end{split}$$

The pair  $[-1 - 1 \ 1 - 1 \ 1 \ ]$ ,  $[-1 - 1 \ 1 \ 1 \ 1 \ ]$  represents a fixed point of the EBAM dynamical system. Equilibrium for the system occurs at the time k+6, when the starting time was k. The fixed point suggest that Daughter In Law is the major cause for preferring old age home by the old age people. Attitude Problem (ego), Health problem are not a reasons for preferring old age home. It also shows that No Children is also a major cause for preferring old age home.

**Conclusion:** The EBAM introduced 60 training set of neurons for survival data , and the survival data analyzed with neurons. The fixed point of the EBAM dynamical system is obtained for each training set of neurons, this way, the neurons capture the semantic flexibility inherent in complex feelings or opinion from survival data. This paper has only given the result from the analysis. Result for survival data from neurons of EBAM. Regarding EBAM for survival data , Daughter In Law plays an important role . The other factors also contribute to preferring old age home. The fixed point for the input vectors are reached at different times (that is at k + 6 or at k + 7).

**Suggetions**: The Daughter-in-Law are suggested to treat their parent-in-laws and their parent equally. Some more suggestion to daughter-in-laws: Treat your parent-in-law with respect. Consider their older and wiser. They may have been through a lot of hardships in their life. In fact, talk to your parent-in-law and ask them about their childhood, growing up, raising kids, and life experiences. When they shares their life with you they will develop a liking for you and that can lead to a strong bond between the two of you.

Memory, IEEE Trans. Inform. Theory 1T-33, 1-33, (July 1987).

- K. Nakano, Association--A Model of assocative memory,, IEEE Trans. Syst. Man. Cybern. SMC--2, 380-388, (1972).
- 7. T. Kohonen, Correlation matrix memories, IEEE Trans. Comput. 21, 353-359, (1972).
- B. Kosko, Bidirectional associative memories, IEEE Transactions on Systems, Man and Cybernetics 18, 49-60, (1988).
- 9. W.W. Tryon, A bidirectional associative memory explanation of post traumatic stress disorder, Clinical Psychology Review 19 (7), 789-81, (1990).
- 10. H. Kang, Multilayer associative neural network

(MANN): Storage capacity versus perfect recall, IEEE Trans. Neural Networks 5, 812-822, (Sep. 1994).

- Y.F. Wang, J.B. Cruz, Jr. and J.H. Mulligan Jr., Two coding strategies for bidirectional associative memory, IEEE Trans. Neural Networks 1, 81-92, (1990).
- 12. D.-L. Lee, W.-J. Wang, A multivalued bidirectional associative memory operating on a complex domain, Neural Network 19 (11), 1623-1635, (1998).
- 13. P.K. Simpson, Higher-ordered and interconnected bidirectional associative memories, IEEE Transactions on System, Man and Cybernetics 20, 637-653.
- 14. Kosko, B.,(1997) "Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence", Prentice Hall of India.
- 15. S.R.Kannan,(2005),Extended Bidirectional Associative Memories: A Study On Poor Education, Mathematical and Computer Modelling 42(2005) 389-395.
- 16. A.Praveen Prakash, Kanimozhiraman and N.Vanathi (2012), "A Fuzzy tool to study the problem of children of working mother", Engineering sciences International Research Journal(113-116).

\* \* \*

Dr.A.Praveen Prakash/Department of Mathematics /Hindustan University/Chennai/India.

Mrs.Kanimozhiraman/Research Scholar/ Department of Mathematics/ Hindustan University/

Chennai/ India/ kanimozhiraman@yahoo.co.in

R.Sumathi/Department of Mathematics/Kcg College of Technology,Chennai/India

J.Jayalaksmi /Department of Mathematics /Kcg College of Technology/Chennai/ India