Linear Associative Memory: A New Perspective
Anoop Singh Rajput, Nitesh Yadav, Govind Saini
Student, CSE, Dronacharya College of Engineering, Haryana, India

ABSTRACT
The theoretical, practical and technical description of linear associative memory which has developed in last 40 years. There is detail description of linear associative memory of neural network. What it is, how it works and how it is helping in neural network.

KEYWORDS: linear associative memory, capacity, robustness challenges

1. INTRODUCTION
Learning can be considered as a process of forming associations between related patterns. For example visual image may be associated with another visual image, or the fragrance of fresh-mown grass may be associated with a visual image of feeling. Memorization of a pattern could be associating the pattern with itself. Therefore, in such networks the input pattern cause an output pattern which may be similar to the input pattern or related to that. An important characteristic of the association is that an input stimulus which is similar to the stimulus for the association will invoke the associated response pattern. For example, if we learn to read music, so that we associate with fingering on a stringed instrument, we do not need to see the same form of musical note we originally learned if the note is larger, or handwritten, we still can recognize and play. So after learning it is expected to make a good guess and provide appropriate response. Another example, ability to recognize a person either in person or from a photo even his/her appearance has been changed. This is relatively difficult to program by a traditional computer algorithms. Associative memories belong to class of NN that learn according to a certain recording algorithms. They require information a priori and their connectivity matrices (weights) must often need to be formed in advance. Writing into memory produces changes in the neural interconnections Reading of the stored info from memory named recall, is a transformation of input signals by the network. Associative memory which uses NN concepts may resemble digital computer memory.

• Let us compare their difference:
  ➢ Digital memory is address-addressable memory:
    ▪ data have input and output lines
    ▪ A word line access the entire row of binary cells containing word data bits.
    ▪ Activation takes place when the binary address is decoded by an address decoder.

Associative memories can be implemented either by using feed forward or recurrent neural networks. Such associative neural networks are used to associate one set of vectors with another set of vectors, say input and output patterns. The aim of an associative memory is, to produce the associated output pattern whenever one of the input pattern is applied to the neural network. The input pattern may be applied to the network either as input or as initial state, and the output pattern is observed at the outputs of some neurons constituting the network. According to the way that the network handles errors at the input pattern, they are classified as interpolative and accretive memory. In the interpolative memory it is allowed to have some deviation from the desired output pattern when added some noise to the related input pattern.
However, in accretive memory, it is desired the output to be exactly the same as the associated output pattern, even if the input pattern is noisy. Another classification of associative memory is such that while the memory in which the associated input and output patterns differ are called heteroassociative memory, it is called autoassociative memory if they are the same.

- Associative memory is content addressable memory
  - The words are accessed based on the content of the key vector
  - When the network is excited by a portion of the stored date, the efficient response of autoassociative memory is the completed x(i) vector
  - In heteroassociative memory the content of x(i) provides the stored vector v(i)
  - There is no storage for prototype x(i) or v(i) at any location of network
  - The entire mapping is distributed in the network.
  - The mapping is implemented through dense connections, feedback or/and a nonlinear thresholding operation.

II. ASSOCIATIVE NETWORK MEMORY CAN BE

- Static: networks recall an output response after an input has been applied in one feed forward pass, and, theoretically, without delay. They were termed instantaneous
- Dynamic: memory networks produce recall as a result of output/input feedback interaction, which requires time.

III. STATIC MEMORY

- Implement a feed forward operation of mapping without a feedback, or recursive update, operation.
- They are sometimes called non-recurrent
- The mapping can be expressed as
  \[ v^k = M_1[x^k] \]
  Where k: index of recursion, M1 operator symbol

IV. DYNAMIC MEMORY

- exhibit dynamic evolution in the sense that they converge to an equilibrium state according to the recursive formula
  \[ v^{k+1} = M_2[x^k, v^k] \]
- This is a nonlinear difference equation.
- Hopfield model is an example of a recurrent network for which the input x^0 is used to initialize v^0, i.e., x^0 = v^0, and the input is then removed.
- So the formula will be simplified to \[ v^{k+1} = M_2[v^k] \]
V. MOTIVATION

- Human ability to retrieve information from applied associated stimuli
  - Ex. Recalling one’s relationship with another after not seeing them for several years despite the other’s physical changes (aging, facial hair, etc.)
  - Enhances human awareness and deduction skills and efficiently organizes vast amounts of information
- Why not replicate this ability with computers?
  - Ability would be a crucial addition to the Artificial Intelligence Community in developing rational, goal oriented, problem solving agents

VI. CAPACITY VS. ROBUSTNESS CHALLENGES

- In early memory models, capacity was limited to the length of the memory and allowed for negligible input distortion
  - Ex. Linear Associative Memory
- Recent years have increased the memory’s robustness, but sacrificed capacity
  - J. J. Hopfield’s proposed Hopfield Network
VII. INFORMATION CAPACITY AND CRITICAL CAPACITY

In order to demonstrate the importance of sparseness in associative memory patterns and to prove the efficiency of sparse NAMs it was necessary to develop a clean definition of the information capacity of NAMs. Such a definition is best given in terms of information theory, considering the total amount of information that can effectively be stored in and retrieved from an associative memory matrix of a given size (Palm, 1980, 1992; Palm & Sommer, 1992, 1995). Using proper definitions it was possible to show that an asymptotical (large memory matrices) optimal capacity of ln 2 ≈ 0.69 bit per matrix entry can be achieved for sparse memory patterns with the binary storage version (Palm, 1980), and 1/(2 ln 2) ≈ 0.72 bit per matrix entry can be achieved with the additive storage version (Palm, 1988, 1990). The difference between these two values is quite small; in the binary version, however, one clearly needs just one hardware bit for one matrix entry, whereas one needs somewhat more hardware.

The main reason for the large difference in performance is the sparseness of the memory patterns used with the Hebb rule in the so-called Willshaw model (Willshaw et al., 1969). This parameter range has not been well-treated in the early physics literature, probably due to the misleading symmetry assumption (symmetry with respect to sign change) that was imported from spin-glass physics. This prevented the use of binary {0, 1} activity values and the corresponding Hebb rule and the discovery of sparseness. It also led to unrealistic neural models, both concerning neural activity (an active neuron carries more information than a passive one) and connectivity (a synaptic weight cannot cross the boundary between excitatory, positive and inhibitory, negative). Only in 1988, it was the contribution of Mischa Tsodyks that brought {0, 1} activity modeling, the Hebb rule for synaptic plasticity and sparseness to a broader recognition in the theoretical physics community (Tsodyks & Feigelman, 1988). He showed that for sparse Hebbian associative memories $\alpha = 1/(2 \ln 2) \approx 0.72$, corresponding to an information capacity (for auto-associative pattern completion) of about 0.18 (Palm, 1988, 1991; see also Schwenker, Sommer, & Palm, 1996). The corresponding older result for the sparse binary Willshaw model is $\alpha = \ln 2$ resulting in an information capacity of 14ln 2 ≈ 0.17 (Palm, 1991; see also Palm & Sommer, 1992; Schwenker et al., 1996).

REFERENCE


