Associative Learning in Hierarchical Self Organizing Learning Arrays

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Abstract. In this paper we introduce feedback based associative learning in self-organized learning arrays (SOLAR). SOLAR structures are hierarchically organized and have the ability to classify patterns in a network of sparsely connected neurons. These neurons may define their own functions and select their interconnections locally, thus satisfying some of the requirements for biologically plausible intelligent structures. Feed-forward processing is used to make necessary correlations and learn the input patterns. Associations between neuron inputs are used to generate feedback signals. These feedback signals, when propagated to the associated inputs, can establish the expected input values. This can be used for hetero and auto associative learning and pattern recognition.

1. Introduction

Associative learning has been long recognized as one of the necessary elements of intelligence, thus it is desirable that an artificial system that mimics biological intelligence be able to perform both spatial and temporal associations. Associative networks were developed as a special class of artificial neural networks to handle associative learning and retrieval of information. There are two types of associative networks, hetero-associative (HA) and auto-associative (AA). Hetero-associative networks are capable of making associations between two or more different types of input signals. Auto-associative networks learn associations between elements of the same input vector. Such networks can learn various patterns, and then recall the pattern based on a fractional part of a pattern. Examples of HA networks include multilayer perceptron [1], the counter-propagation network [2], the bidirectional associative memory [3] and multi-associative spatio-temporal network [4], while the Hopfield network [5] and the Vogel associative memories [6,7] are AA. In this paper we present a model of the self-organizing learning array that implements both the hetero and the auto-associative learning.

Spatio-temporal associations are particularly important in both biological and electro-mechanical systems. For instance, a spatio-temporal association may trigger a reactive response in an animal or guide the robot to its target. Time delays have been used in Hopfield networks [5] to generate spatio-temporal sequences which are time dependent sequences of spatial patterns. Storage and retrieval of spatio-temporal sequences was studied in many papers ([8 - 10]). While the proposed approaches achieved reasonable storage and retrieval of input sequences, they have some serious drawbacks if one wants to implement them in biologically plausible structures. In this paper we take on a different approach to pattern storage and associations. A hierarchical, multilayer structure based on our self-organizing learning architecture [11] is used, and we demonstrate that such structure can make the necessary associations between patterns using sparsely connected neurons.

SOLAR (Self-Organized Learning Array) is a regular, two or three-dimensional array of identical processing cells, connected to programmable routing channels. Each cell in the array has ability to self-organize by adapting its functionality in response to information contained in its input signals. Cells choose their input signals from the adjacent routing channels and send their output signals to the routing channels. Like artificial neural networks (ANNs), SOLAR is inspired by the structure of biological neural networks and shares their robust, distributed and parallel signal processing, yet it differs from existing realizations of ANNs. It has a deep multi-layer hierarchical structure, which helps to handle complexity of target problems, it uses online learning with dynamically set neuron functions and dynamically learned sparse connections, efficient in hardware realization. Prior study of SOLAR structures reported in [11] concentrated on demonstrating its pattern recognition and classification abilities. In this paper we introduce a feedback mechanism with inhibitory connections and associative learning to SOLAR.

This paper has been organized in 4 sections. The second section discusses the structure and behavior of the proposed network. Section 3 presents testing results on several bench-mark machine learning problems. Section 4 contains conclusions.

2. Network Structure and Operations

In this work, the network has been formed as a two-dimensional structure, which is pseudorandomly constructed with interconnection structure of small world networks [12]. For a recognition task, it is trained with the input features that represent the patterns, and the corresponding codes that represent the classification. The input span, defined by the number of rows, is set equal to or greater than the dimensionality of inputs. The depth of the network (the number of hierarchical levels) is set according to the input span. In a hierarchical structure, each neuron connects only to the neurons of the previous layer. Once the learning is completed, a network is capable to make necessary associations, such that when presented with the pattern only, it drives feedback to the associated inputs to assert the unknown code values. Similar to pattern recognition, missing data can be found from feedback traced to the unknown portion of the input.

The outside input should be presented to the network in a binary form ranging from 0 to 1. The signal strength is measured as the distance between the signal level and 0.5. A signal is determinate if it is 0 or 1. It is a low (or high) if it is below (or above) 0.5, and is unknown or inactive if it is 0.5. The probabilities of I_1 and I_2 being low or high and their joint probabilities can be recorded in each neuron. The conditional probabilities $P(I_2 | I_1)$ and $P(I_1 | I_2)$ can then be computed.

A simplified confidence interval measure is used for each of the probabilities: $\mathrm{CI} = \frac{2(1 - P(\mathrm{I}_2 \mid \mathrm{I}_1))}{\sqrt{\mathrm{N}}}$, where N stands for the number of training inputs. The value of $P(\mathrm{I}_2 \mid \mathrm{I}_1)$ - CI is then compared against a threshold τ. If larger, we can say that I_1 can be **implied** from I_2. Likewise, $P(\mathrm{I}_1 \mid \mathrm{I}_2)$ decides whether I_1 can be **implied** from I_2.

Definition: Inputs I_1 and I_2 of a neuron are **associated** if and only if I_2 can be implied from I_1 and I_1 can be implied from I_2 simultaneously. Such a neuron is then an **associative neuron**. Otherwise it is a **transmitting neuron**.

Fig. 1 illustrates six different situations of I_1 and I_2 inputs that an associative neuron may receive in training.

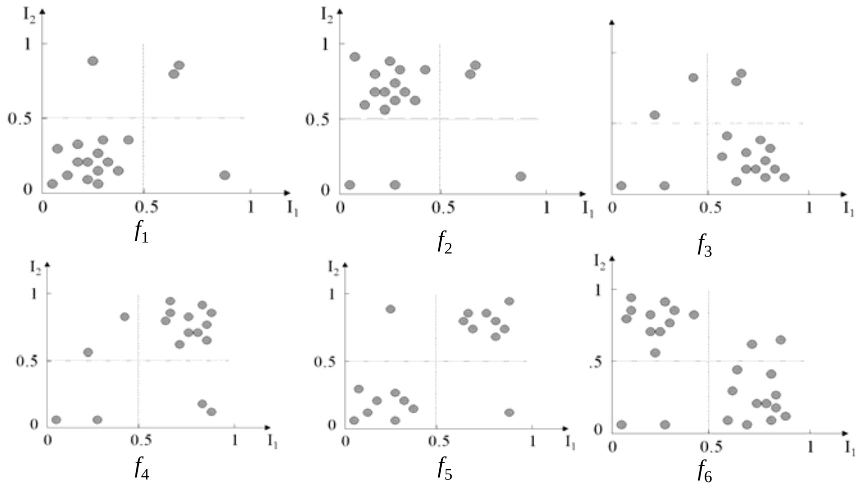


Fig. 1. Input Distribution to an Associative Neuron

2.1 Feed Forward Scheme

For the simplicity of discussion, we assume a fixed interconnection structure where each neuron has two inputs I_1 and I_2 and a single output O. The task of a neuron during training is to discover the potential relationship between the two inputs and to remember it. The neuron needs to select a proper transfer function f from a predefined set F that can best describe the relationship between I_1 and I_2. It can then generate output O using f. Six functions, f_1 to f_6, are designed to include all the logic relationships between I_1 and I_2 in an associative neuron, as shown in Fig. 1. In an associative neuron, the majority of the training data is either distributed in one **dominant quadrant**, or two diagonal quadrants. f_1 to f_4 are designed for the four possible locations of the dominant quadrant. Their output is always 1 for the dominant quadrant, and 0 for all the others. When data points are mostly distributed in two diagonal quadrants, f_5 and f_6 are used as shown in Fig. 1. To accommodate noise f_5 and f_6 are defined only based on I_1 to include all the data points. For example,

$$f_5(\mathrm{I}_1, \mathrm{I}_2) = \begin{cases} 0, & \text{if} \quad \mathrm{I}_1 \text{ is low} \\ 1, & \text{if} \quad \mathrm{I}_1 \text{ is high} \end{cases} \tag{1}$$

The neuron output is set “inactive” or 0.5, whenever either one of the inputs is 0.5.

$$O = \begin{cases} 0.5, & \text{if} \quad I_1 = 0.5 \text{ or } I_2 = 0.5 \\ f(I_1, I_2), & \text{otherwise} \end{cases} \tag{2}$$

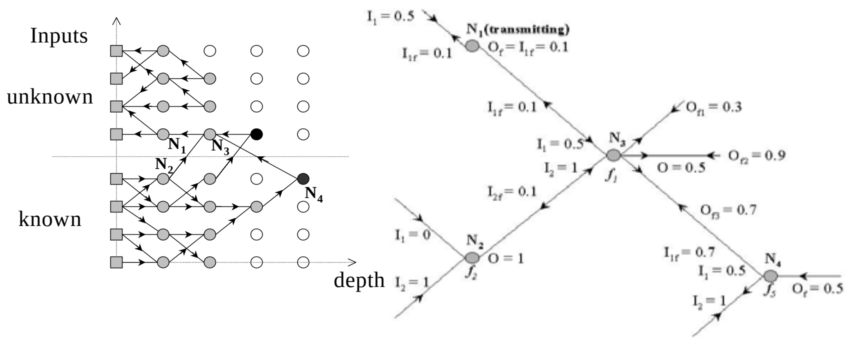
If a neuron observes any distribution other than what is included in Fig. 1, it is a transmitting neuron. It simply transmits the input with higher entropy, called the **dominant input,** to O, with the other ignored. An input I_1 is the dominant input if

$$\text{abs}(P(I_1 \text{ is low}) - P(I_1 \text{ is high})) < \text{abs}(P(I_2 \text{ is low}) - P(I_2 \text{ is high})) \tag{3}$$

2.2 Feedback Scheme

During testing, missing parts of the data need to be recovered from existing data through association. For example, in a pattern recognition problem, the neurons that are physically connected to the unknown code inputs are responsible for providing feedback from the associative neurons and define the values of the code. This, in turn, can be used either to classify the input pattern or to recover the uncertain inputs.

The feedback scheme is an important part of associative learning. Fig. 3(a) shows a conceptual view of the network with separated known and unknown inputs. The white circles are the neurons that do not participate in signal processing. The black circles are **actively associating neurons** defined below. The gray circles are the remaining neurons involved in signal processing. The neurons on the known side generalize the information that activates associative neurons, which generate feedback to the unknown side. In order to explain the working mechanism in single neurons, Fig. 2(b) shows a snapshot of the communication among four interconnected neurons.



a b

Fig. 2. Neuron Feedback Scheme

When a neuron receives at least one active output feedback, the strongest feedback O_f triggers the feedback to the neuron's inputs. The input/output relationship in the feedback scheme for each neuron can be described by one of the following types.

1. Transmitting neurons. A transmitting neuron (e.g. N_1 in Fig. 2,) simply passes O_f back into its dominant input. When the feedback I_{1f} is stronger than the dominant input I_1, I_1 will be overwritten by I_{1f}.

2. Associative neurons with determined inputs. If I_1 and I_2 of an associative neuron (e.g. N_2 in Fig. 2,) are either 0 or 1, O will consequently be at full strength. O_f won't be able to change O. Feedback takes no effect and information passes forward.

3. Associative neurons with active feedbacks and inactive input(s). For an associative neuron that doesn't have determinate signals on both inputs (e.g. N_3 in Fig. 2,) O_f creates feedbacks I_{1f} and I_{2f} through the function *f*. If the feedback signals are stronger than the original inputs, these inputs will be overwritten. Consequently, overwritten inputs become feedback signals to the neurons N_1 and N_2, to which N_3 inputs are linked. These neurons pass information backwards and they are not allowed to propagate forward to higher hierarchical layers.

4. Associative neurons with inactive feedbacks. Some neurons located deeply in the network may not receive active feedback at all, (e.g. N_4 in Fig. 2). If one of their inputs is inactive, it will be overwritten based on its association with the other input and the neuron function *f*. These type of neurons are called **actively associating** and are the backbone of the associative processing in SOLAR. For instance, since I_1 is 0.5 for N_4, the feedback to I_1 is determined based on the known input I_2 and the function f_5. For neurons that fit scenarios 3 and 4, the input feedback is calculated differently for each function, based on the strength of O_f and the quality of each neuron's learning, which is not described in full details in this paper.

3. Simulation Results

Several benchmark classification and missing data recovery tasks have been used to test the performance of the proposed network.

Teaching Assistant Evaluation database [13] consists of 151 instances, 5 features and 3 equally sized classes. After a 15-cross validation, the overall correct classification rate of SOLAR is 68.33% compared to 67% in [13].

SOLAR was also tested with the Iris database [14], which has 3 classes, 4 numeric attributes and 150 instances. The hierarchical SOLAR network gets an average classification rate of 75.33% from a 15-cross validation. An optimal input arrangement (using straight sliding bars and merging features and class id code) could further improve the performance to 86%. For comparison, results reported in literature [15] give correct classification rate for the Iris database between 91.33% and 97.33%.

The Glass Identification Database [16] was used to study the impact of the target problem's complexity on the depth of the network. The network was first trained and tested with the whole database, which contains 6 classes and 9 features, and then with half of the database that only has 3 classes. It was found that the more classes were used, the more layers SOLAR needs in its hierarchical structure.

In addition, the network has successfully accomplished binary image recovery tasks. Although the current setup uses a two dimensional architecture, it is believed that a three dimensional network would handle image related problems better.

4. Conclusions

This paper presents an associative learning network based on a hierarchical SOLAR structure. SOLAR is a biologically inspired machine-learning concept. It is a sparsely connected network organized as a fixed lattice of distributed, parallel processing units (neurons). The associative learning SOLAR network described in this paper is constructed as a fixed connection network with feedback and inhibitory links. Similar to Vogel's distributed auto-associative memories [7], SOLAR discovers the correlation between inputs and establishes associations inside the neurons, without a need to differentiate between the associated classification code and data patterns. It is capable of handling a wide variety of machine learning tasks including classification and data recovery, and is suitable for online learning. The SOLAR organization will be further modified towards an advanced machine intelligence system capable of associative learning, adaptations, and value driven interaction with environment.

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