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:

$$CI = \frac{2(1 - P(I_2|I_1))}{\sqrt{N}},$$

where N stands for the number of training inputs. The value of P(I$_2$|I$_1$) - CI is then compared against a threshold $\tau$. If larger, we can say that I$_1$ can be implied from I$_2$. Likewise, P(I$_1$|I$_2$) decides whether I$_1$ can be implied from I$_2$. 