Available online at www.sciencedirect.com

ScienceDirect

Fuzzy Sets and Systems 253 (2014) 1–27

FUZZY sets and systems

www.elsevier.com/locate/fss

Fuzzy Boolean Nets – a nature inspired model for learning and reasoning

José Alberto Tomé, Joao Paulo Carvalho *

INESC-ID, Instituto Superior Técnico, Universidade de Lisboa, Rua Alves Redol, n° 9, 1000-029, Lisboa, Portugal

Received 21 July 2012; received in revised form 22 April 2014; accepted 23 April 2014

Available online 1 May 2014

Abstract

This paper presents Fuzzy Boolean Nets (FBN), a nature inspired Boolean neural model, in the sense that it exhibits topologic similarities with natural systems, as well as learning dynamic activity at low level and high immunity to individual errors or deletions of neurons or synaptic connections. It is shown that one can interpret reasoning in FBN as a particular case of fuzzy qualitative reasoning. It is proven that the model is a Universal Approximator since it can be interpreted as a Parzen Window probability density estimator. Also, conditions for learning a discrete set of rules without cross influence are investigated, being proven that this goal can be achieved with an appropriate net parameters relationship. Moreover, adequate parameter choices for learning continuous functions with interpolation capabilities are deduced.

Keywords: Learning; Qualitative reasoning; Fuzzy; Weightless Boolean Neural Nets

1. Introduction and related work

Reasoning and learning in nature are supported on extremely complex neural structures. Various artificial neural models have been inspired on such structures, the most famous being the well-known artificial neural nets (ANN), which are based on neurons with weighted inputs from other neurons. When associated with the backpropagation learning algorithm [38,40], which progressively reduces the error with the teaching experiments, ANN provide an effective and efficient learning and reasoning mechanism. A different model uses coherent Neuron Activity from Chaotic Neural Networks [44] on a novel approach where learning pretends to reduce the amount of modification needed to keep errors small rather than to reduce the error itself. Even though these models are proven and efficient, they do not take into consideration the fact that, in nature, the activity on neural areas is the only visible (or at least measurable) effect representing the "value" or intensity of the variables associated with those areas. ANN, CNN and most other artificial neural network models, do not have mechanisms to represent such areas: each neuron represents by itself an output variable. Therefore these approaches suffer from the problem of low immunity to individual neuron

* Corresponding author.
E-mail address: joao.carvalho@inesc-id.pt (J.P. Carvalho).

http://dx.doi.org/10.1016/j.fss.2014.04.020

or synaptic errors, since a single error may compromise the entire process. In this paper we present a type of neural nets that are organized into neural areas, the Fuzzy Boolean Nets (FBN), and where variable values are associated with activity of entire neural areas.

Other neural nets approaches are based on weightless connections between neurons. Weightless neural Networks have been studied for a long time [1] and they precede the above-mentioned weighted Neural Nets. They can implement the same kind of applications; in particular learning and applying that knowledge on a number of tasks, e.g., pattern recognition, logical synthesis, knowledge-Based Inference Systems, text categorization, [32,42,51]. These Nets are known also as Boolean Nets, since elementary neurons have only two possible states: "0" and "1". The neurons of these weightless nets are basically look up tables that memorize sub-sets of presented n binary inputs and generalization is obtained in networks of these neurons by intersection of the answers of the neurons. FBN differ from these in many ways; neurons are organized into neural areas with specific meaning, the values of variables are given by activation ratios of these areas, sets of qualitative rules are established on learning, and reasoning on these rules can be implemented.

A different category of Boolean Networks are the Kauffman Boolean Nets [26] that were first presented as a model of genetic regulatory systems based on biochemically grounds (genes can affect other genes by inhibiting or activating their expression). The main characteristic of these nets is that both their Boolean nodes and their connections are random. They are interpreted as a discrete dynamical system, that is, each node logical function works dynamically to compute the node state at the next time step depending on the input values coming from other nodes (synchronously or asynchronously in a way that resembles cellular automata). It is the statistical behavior of the state space that is of interest. The Boolean nets presented in this paper are of a different nature – the randomness is applicable only to topology (and only to the set of connections coming from each area, i.e., there is a macro organization), and the node Boolean functions are established during a learning process. It is not the dynamics of the state space which is a matter of interest but the degree of output activations for a given input activation.

The capabilities of artificial neural networks to apprehend, through experimental learning, the relations between systemic variables, may benefit from the flexibility and explanation capabilities of Fuzzy Systems using both paradigms on a synergetic cooperation. A different perspective from that of looking for synergies between Fuzzy Systems and Neural Networks is presented in the work of Benitez et al. [3], where the authors have proven an equality between a certain class of Neural Networks and Fuzzy Rule-Based Systems. This provides a way for seeing Neural Nets as Rule-Based Systems and a method for knowledge acquisition.

One possible approach to use the above mentioned synergy is through the fuzzification of the neural net components, such as the development of fuzzy neurons [18,19,37,52], of fuzzy perceptrons [27] and the introduction of fuzziness on back Propagation networks for pattern classification [35]. Special attention deserve ART models. Fuzzy ART [4] performs unsupervised learning of recognition classes of analog or binary vectors of features. It is based on previous ART neural model but uses fuzzy operators on the algorithm (the MIN operator). Each class corresponds to a category node, and learning is performed by updating a vector of weights in an incremental but converging way. The creation of categories can be tuned and their proliferation avoided. Fuzzy ARTMAP [5] incorporates two Fuzzy ART modules linked by an associative learning net and a controller to create hidden units that correspond to the classes. It performs incremental supervised learning of categories and multidimensional maps minimizing predictive error and maximizing predictive generalization. This kind of synergetic cooperation between neural nets and fuzzy systems may also appear under the form of Neural Fuzzy Systems where the fuzzy inference system is improved with learning capabilities through the use of neural nets as system components. This approach has been used for implementing components of fuzzy inference systems and for developing Neural Fuzzy Controllers. Models for fuzzy inference using neural nets have been presented by many authors, among them Keller [28], Takagi and Hayashi [45] and Horikawa et al. [22]. A comprehensive presentation of neural fuzzy controllers integrating elements of fuzzy logic control and connectionist structure is presented by Lin and Lee in [31]. In this context it is worth to point out the ANFIS [24] inference system, also a Neural Fuzzy Controller, implemented in the framework of adaptive systems that integrates features of Neural Nets and Fuzzy Systems and uses a hybrid learning using both rules and I/O data.

Another type of learning fuzzy neural networks is the Evolving Fuzzy Neural Net, mEFuNNs [25], which uses a hybrid supervised and unsupervised incremental learning. mEFuNNs use a set of neuron layers, of which one is composed of rule nodes that evolve and represent prototypes of input output data associations. These nodes can be inserted, pruned and adjusted in an on-line process. At each moment the output vector of a mEFuNN is calculated