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Evolving connectionist systems for adaptive learning and knowledge discovery: Trends and directions

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ABSTRACT

This paper follows the 25 years of development of methods and systems for knowledge-based neural network systems and more specifically the recent evolving connectionist systems (ECOS). ECOS combine the adaptive/evolving learning ability of neural networks and the approximate reasoning and linguistically meaningful explanation features of symbolic representation, such as fuzzy rules. This review paper presents the classical now hybrid expert systems and evolving neuro-fuzzy systems, along with new developments in spiking neural networks, neurogenetic systems, and quantum inspired systems, all discussed from the point of few of their adaptability, model interpretability and knowledge discovery. The paper discusses new directions for the integration of principles from neural networks, fuzzy systems, bio- and neuroinformatics, and nature in general.

1. Hybrid connectionist systems

The human brain uniquely combines low level neuronal learning in the neurons and the connections between them and higher level rule abstraction leading to adaptive learning and abstract concept formation. This is the ultimate inspiration for the development of hybrid connectionist systems where specially constructed artificial neural networks (NN) are trained on data so that after training abstract knowledge representation can be derived that explains the data and can be further interpreted as a knowledge-based system. Examples of such hybrid connectionist systems are connectionist-based expert systems [15], neuro-fuzzy systems [39], evolving connectionist systems [20], evolving fuzzy systems [3].

In the past 50 years several seminal works in the areas of neural networks [1,2,11], fuzzy systems [40,41] and rule-based expert systems [7] opened a new field of information science – the creation of new types of hybrid systems that combine the learning ability of neural networks, at a lower level of information processing, and the reasoning and explanation ability of rule-based systems, at the higher level. The first hybrid connectionist expert systems combined NN and propositional type of rules – either production rules, implemented in CLIPS [14–18], 94–96; or first order logic rules implemented in PROLOG [19].

Combining NN and fuzzy rule based systems is illustrated on a simple example in Fig. 1. A NN module is trained to predict the value of a stock index based on the current day and the day before prices. At a higher level a fuzzy reasoning module combines the predicted value by the NN module with a macro-economic variable (Good or Bad state of the economy) and a variable representing the political situation in the country (stable or unstable) using the following types of fuzzy rules [19]:

$$\begin{aligned}&IF < \textit{the predicted by the NN module stock value is high}\\&\quad > AND < \textit{the economic situation is good} > AND\\&\quad < \textit{the political situation is Stable})THEN < \textit{buy stock} > \qquad (1)\end{aligned}$$

A traditional Multi-Layer Perceptron (MLP) NN is used to implement the NN module in Fig. 1 and a fuzzy inference system is used to implement the Fuzzy rule-based decision module. In addition to these two module, a specifically constructed fuzzy neural network module is used to be trained on data and to extract fuzzy trading rules. Fuzzy neural networks and their further development as evolving connectionist systems are presented next in the paper.

2. Fuzzy neurons and fuzzy neural networks. Evolving connectionist systems

A low-level integration of fuzzy rules into a single neuron model and larger neural network structures, tightly coupling learning and fuzzy reasoning rules into connectionists structures, was

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initiated by Professor Takeshi Yamakawa and other Japanese scientists and promoted at a series of IIZUKA conferences in Japan [39]. Since then, many models of fuzzy neural networks were developed based on these principles [8,19,23].

The evolving neuro-fuzzy systems developed these ideas further, where instead of training a fixed connectionist structure, the structure and its functionality were evolving from incoming data, often in an on-line, one-pass learning mode. This is the case with the evolving connectionist systems, ECOS [20–24].

ECOS are modular connectionist based systems that evolve their structure and functionality in a continuous, self-organised, on-line, adaptive, interactive way from incoming data [20]. They can process both data and knowledge in a supervised and/or unsupervised way. ECOS learn local models from data through clustering of the data and associating a local output function for each cluster represented in a connectionist structure. They can learn incrementally single data records or chunks of data and also incrementally change their input features. ECOS further develops some connectionist information processing principles already introduced in classical NN models, such as: SOM, RBF, FuzzyARTMap, Growing neural gas, neuro-fuzzy systems, RAN.

ECOS perform *adaptive local learning* – neurons are allocated as centres of data clusters and the system creates local models in these clusters. The clustering used in ECOS is on-line, one-pass, evolving clustering, which is in contrast to the traditional fuzzy clustering methods that use pre-defined number of clusters and many iterations [5,38].

The following are the main principles of ECOS as stated in [20]:

(1) Fast learning from large amount of data, e.g. using 'one-pass' training, starting with little prior knowledge.
(2) Adaptation in a real time and in an on-line mode where new data is accommodated as it comes based on local learning.
(3) 'Open', evolving structure, where new input variables (relevant to the task), new outputs (e.g. classes), new connections and neurons are added/evolved 'on the fly'.
(4) Both data learning and knowledge representation is facilitated in a comprehensive and flexible way, e.g. supervised learning, unsupervised learning, evolving clustering, 'sleep' learning, forgetting/pruning, fuzzy rule insertion and extraction.
(5) Active interaction with other ECOSs and with the environment in a multi-modal fashion.
(6) Representing both space and time in their different scales, e.g.: clusters of data, short- and long-term memory, age of data, forgetting, etc.
(7) System's self-evaluation in terms of behaviour, global error and success and related knowledge representation.

In 1998 Walter Freeman, who attended the ICONIP conference then, commented on the proposed ECOS concepts: "...Through the 'chemicals' and let the system grow ...".

The development of ECOS, as a trend in neural networks and computational intelligence that started in 1998 [20] continued as many improved or new computational *methods* that use the ECOS principles have been developed along many *applications.*

Here the concepts of ECOS are illustrated on two implementations: Evolving Fuzzy Neural Network, EFuNN [21] and Dynamic Evolving Neuro-Fuzzy Inference Systems, DENFIS [24]. Examples of EFuNN and DENFIS are shown in Figs. 2 and 3 respectively. In ECOS, clusters of data are created based on similarity between data samples either in the input space (this is the case in some of the ECOS models, *e.g.* the dynamic neuro-fuzzy inference system DENFIS), or in both the input and output space (this is the case in the EFuNN models). Samples (examples) that have a distance to an existing neuronal node (cluster centre, rule node) less than a certain threshold are allocated to the same cluster. Samples that do not fit into existing clusters form new clusters. Cluster centres are continuously adjusted according to new data samples, and new clusters are created incrementally. ECOS learn from data and automatically create or update a local fuzzy model/function, e.g.:

$$IF < data\ is\ in\ a\ fuzzy\ cluster\ Ci > THEN < the\ model\ is\ Fi >, \quad (2)$$

where Fi can be a fuzzy membership function (EFuNN, [21], a linear or regression function (Fig. 4) or a NN model [22,24].

Fig. 2 shows an example of EFuNN model that consists of 5 layers: input neurons accept real-value inputs; fuzzy input layer produces fuzzy membership values between 0 and 1 according to the membership degree of a corresponding input value to one of several (in this case just two) fuzzy membership functions (e.g. Small and Large values); evolving rule (case) neuronal nodes that represent evolving clusters of data with their connection weights representing the coordinates of these clusters; fuzzy output neurons, calculating the membership degrees of the output value that corresponds to the input vector, to output membership functions (in this case only 3 are shown); output neuron that represents the real output value that correspond to the input vector.

Adaptive (evolving) learning in EFuNN is performed through supervised clustering of the input data vectors so that input vectors that are similar and have similar output values are clustered in one cluster represented by the same rule node.

Fig. 3 shows an example of DENFIS for a real problem application [22]. Five input variables are used that represent data and a real value output is associated with each example (sample, vector). The DENFIS learning consist of unsupervised clustering (clusters are created based only on the similarity of the input

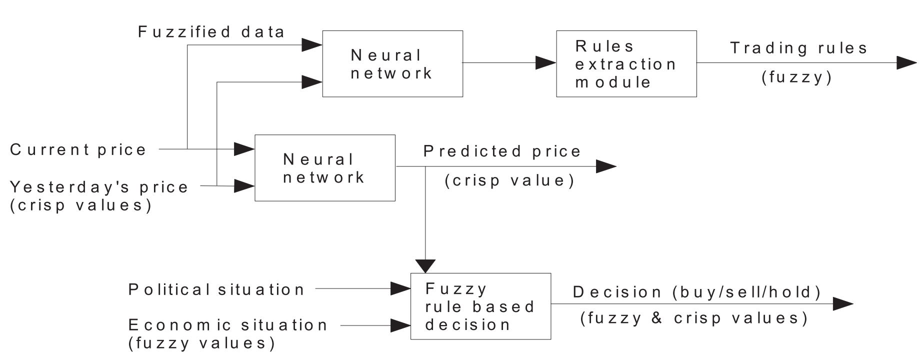

Fig. 1. A hybrid NN-fuzzy rule-based expert system for financial decision support (from [19]).