Self-Organizing Learning Array and Its Application to Economic and Financial Problems

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ABSTRACT
A new Self-Organizing Learning Array (SOLAR) system has been realized in software. SOLAR is capable of handling a wide variety of classification problems. It has a regular array structure with sparsely interconnected computing elements and local learning rules. Unlike artificial neural networks, this structure scales well to large systems capable of solving complex pattern recognition and classification tasks. This paper shows its application in economic and financial fields. Several prediction and classification cases are studied. The results have been compared with the existing methods.
Keywords: Self-Organizing Learning Array, economics and financial statements, banking, default prediction

1. INTRODUCTION
Over the last decade, computational intelligence has been widely used to solve various economic and financial problems, including modeling, prediction, recognition and analysis. Tsitsiklis [1] introduced and analyzed a simulation-based approximate dynamic programming method for pricing complex American-style options, with a possibly high-dimensional underlying state space. This research involves the evaluation of value functions at a finite set, consisting of “representative” elements of the state space. Magdon-Ismail [2] gave a self-contained introduction to the risk neutral or martingale approach to the pricing of financial derivatives. This approach provides a rich source of problems ideally suited to the application of Monte Carlo methods.. Finally, Atiya [3] gave a survey of bankruptcy prediction methods. He introduced financial ratio and equity-based indicators for neural network based bankruptcy prediction with improved performance. His conclusion was that neural networks were superior to other techniques in bankruptcy prediction.

A lot of effort has been made to form a bridge between the computational finance and some technical tools developed by engineers and scientists A re-configurable neural network design Self Organizing Learning Arrays (SOLAR) has been proposed recently [4]. It proved to be a useful tool applicable to different real world problems. The hardware structure of SOLAR is similar to programmable arrays such as Field Programmable Gate Arrays (FPGAs). SOLAR neurons learn from outside inputs and inputs from other neurons to form their outputs. They are trained to react to inputs and participate in classification. Information from each neuron is collected to form the final decision. During training, SOLAR’s structure organizes itself and each neuron is self re-configured. In our previous work, SOLAR was simulated on standard benchmarks and proved to be advantageous [5] over many existing neural networks and machine learning algorithms.

In this paper, SOLAR is introduced to solve economic and financial problems. Since its structure resembles organization of neural networks, we pay particular attention to compare their performance with SOLAR. The rest of this paper is organized as follows. Section 2 briefly describes the architecture of SOLAR. Section 3 discusses SOLAR software simulation and data processing. In Section 4, SOLAR is applied to a bankruptcy prediction problem and two financial status recognition targets. SOLAR’s performance is compared with the existing methods. Finally, a summary is given in Section 5.

2. SOLAR ARCHITECTURE
SOLAR architecture has self-organizing learning and hardware-reconfiguration ability. SOLAR differs from classical artificial neural networks (ANNs) in the way it is organized and how it learns. Its most important advantage over ANNs is hardware efficiency. While classical ANNs are wire dominated (wiring area grows as a cube of the number of neurons), SOLAR’s interconnection area grows almost linearly with the number of neurons. This linear relationship benefits hardware implementation of SOLAR.

Comparing to neural networks SOLAR has deep multilayer structure. This gives better utilization of hardware components. In spite of only sparse connections it can attain or exceed performance of equivalent neural networks. It learns in a robust way – no over-fitting is observed – as the learning mechanism is governed by data entropy in the learning subspaces. Learning stops as the amount of entropy in subsequent subspaces is reduced, so the required number of neurons to solve a given problem is automatically determined. Each computing element (neuron) works on data from its selected subspace and confidence of its classification result depends on the number of training data in this subspace. Simple problems will use only a small number of neurons in the SOLAR array. Other neurons can be utilized to solve other problems. Therefore, SOLAR has capability of multiple-task learning, representing the knowledge acquired during training in various subsets of its network structure.

In SOLAR, we adopt feed forward network structure for its stability and fast learning. SOLAR architecuture, as shown in Fig. 1, is implemented by an array of sparsely connected identical processing units (neurons). The initial connections are randomly generated and will be refined though training. The modular nature of the array is emphasized by full integration of its routing and processing resources. Fig 2 shows a more detailed view of SOLAR basic cell. It contains a neuron, a configurable switching unit (CSU), and a bidirectional routing unit (BRU). Each neuron receives its data inputs (NI) either from primary inputs or other neurons and sends its outputs (NO) to other neurons via its routing resources.

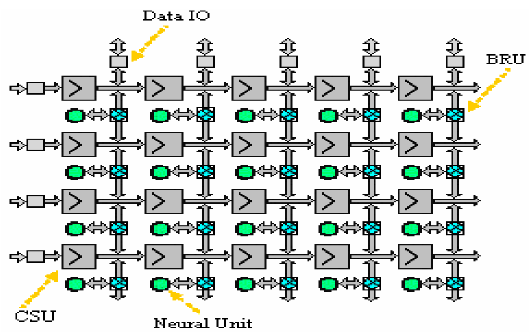

Figure1. SOLAR architecture

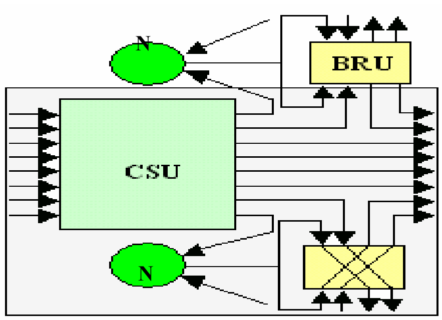

Figure2. Basic cell of SOLAR

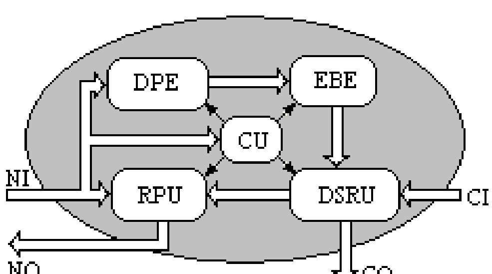

Figure3. Neuron

Neuron contains several building blocks: reconfigurable processing unit (RPU) which performs most of its arithmetic and logic operations, control unit (CU) which organizes data flow and operations of the neuron, dynamic probability estimator (DPE), an optional entropy based evaluator(EBE) and dynamic self-reconfiguration memory.

Since neurons are data driven, they respond to activities on their input terminals. If several neurons are activated as a group, they can share the same control unit. EBE uses the estimated probabilities to estimate class entropy, information index and selects optimum operation of each neuron as described in SOLAR algorithm [5]. It is respossible for setting the neuron's configuration bits which are stored in DSRU. EBE can be shared by neurons which are not activated at the same time (for instance, if learning proceeds from a neuron on one level to the next one). By connectiong CO of one neuron to CI of another one, a configuration data path can be obtained to scan the configuration information of the entire neural network in or out.

3. SOLAR SIMULATION AND DATA PROCESSES

SOLAR has been simulated in MATLAB. The simulation was carried out with self-organizing hardware design considerations, for instance, hardware computation realization and neural array construction. An application input data is presented to SOLAR with n input features. These n features form the dimensions of the input space. So jth individual input appears as an n-dimensional vector: $X^j = [X_1^j X_2^j \ldots X_n^j]^T$. Therefore the whole input data set, which consists of s individuals, could be organized in an input matrix,

$$\overline{X} = \{X^1, \ldots X^s\} = \begin{bmatrix} X_1^1 X_1^2 \ldots X_1^s \\ \ldots \\ X_n^1 X_n^2 \ldots X_n^s \end{bmatrix}$$

Generally, not all the features are continuous numerical values. Some of them may be in form of discrete symbolic values. Since SOLAR operations accept only numerical inputs, the symbolic features need to be transformed into real numbers [6]. Practically there may be a few unavailable elements in the input space. A default value for each of these missing elements needs to be assigned to make the input space complete. The default values are desired to minimize the Mahalanobis distance to the cluster data from a given class, as discussed in detail in [5]. Since all the features X_1 through X_n are obtained from different measurements, their scale may vary greatly. Obviously all the input features have to be rescaled to equalize their significance.

As the result, the pre processing of SOLAR's input matrix will be carried out in 3 steps:

1. Make all the features numerical, set values for symbols of the discrete features.
2. Determine default values for each features, fill up all the blank items.
3. Rescale all the features to a unified range.

After SOLAR's input data matrix has been properly processed, it will be separated into a training set and a testing set. SOLAR neurons perform local learning. They have larger possibility to inherit data from nearby neighbors. The input data to each neuron forms the individual input space of this neuron. All the neurons are designed to operate on the full range of data. Therefore, they need to rescale their own input space. Each neuron collects the scaling information during the training procedure and applies it to testing data.

SOLAR's neural operations have been designed based on simple elemental operations, for example, identity, exponent or logarithm functions. Combination of the elemental operations generates complicated expressions, which separate different classes in the input space. Based on this separation, each neuron obtains statistical information on classification. Those neurons that are well trained will contribute their information in the final voting.

As mentioned above, the initial structure of SOLAR is randomly generated. The diversity of individual systems may result in different classification results on the same testing set. In order to obtain more stable and statistically robust output, SOLAR ensemble is used. Several SOLAR systems with random differences in their initial structures are generated in parallel. They are trained separately and vote together on the same testing set. An example of SOLAR ensemble is shown in Figure 4, n individual SOLARs are combined to perform classification.

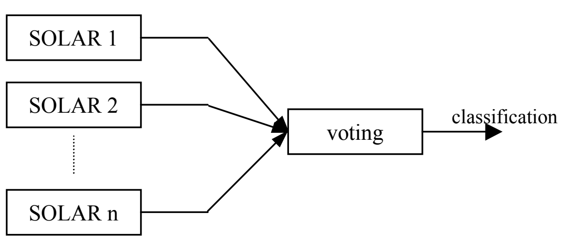

Figure 4. SOLAR Ensemble

4. SOLAR APPLICATION TO ECONOMIC AND FINANCIAL PROBLEMS

SOLAR has been tested with three economic and financial problems. Case one is bankruptcy prediction, where SOLAR is used to predict companies that will file for chapter 11 in 3 years. Case two is credit card approval decision. SOLAR made decisions on whether or not to approve credit card based on personal information. Case three is adult income classification. With this classification, banks are able to make proper decisions on loans.

Case one: Bankruptcy Prediction

Bankruptcy prediction has been a very important topic in the past decades. A lot of effort has been made to model the prediction of bankruptcy. Atiya gave a review of existing bankruptcy prediction methods as well as his new results in [3]. He used traditional neural networks in his prediction. He collected data for 716 solvent US corporations and 195 defaulted ones (defaulted within 1 to 36 months). Taking different instances before the default, he expanded the data set into 1160 input points. These points are grouped as an in-sample set and a out-of-sample set, used for training and testing respectively. There are two systems of indicators discussed in that paper. One is based on financial ratios alone and the other is based on financial ratios and price-based indicators, named financial ratio and equity-based system. The financial ratio and equity-based system provides a significant improvement on the prediction correct rate compared with traditional methods.

We also used the data set he provided with slightly different total number of samples. We used SOLAR to perform bankruptcy prediction based on the input space of the financial ratio and equity-based system. The correct rates are compared with the results from [3] on the out-of-sample set in Table 1. In this case SOLAR gives slightly better results than the methods in [3].

Table 1. Correct Prediction Rate of Bankruptcy

Time to default	correct rate % of [3]	correct rate % of SOLAR	correct rate % using all
6 month or less	86.15	85.11	87.23
6 to 12 months	81.48	84.09	86.36
12 to 18 months	74.60	76.19	90.24
18 to 24 months	78.13	55.17	72.24
more than 24 months	66.67	64.29	75.00
total defaulted	78.13	75.13	83.96
solvent	90.07	92.74	93.42
total	85.50	85.80	**90.04**

Since SOLAR is able handle complicated problems, we also carried out this prediction with all available indicators (63 in our database) instead of using the systems introduced in [3]. A single SOLAR network can provide significant improvement in correct prediction rate (90.04% vs. 85.5%), as shown in the third column of Table 1. In addition, SOLAR is a general-purpose identifier and predictor. It was never designed and optimized for any particular types of problems. However, this experiment shows that SOLAR is good at prediction problems based on large sized databases.

Case two: Australian Credit Card Approval Problem

Credit card approval is a common problem that most machine learning algorithms can be applied to. To compare SOLAR with other existing methods, a credit card database [7] was used as a benchmark. This database is available from ftp at cs.uci.edu (128.195.1.1) in directory/pub/machine-learning databases.

Several traditional classification algorithms have been tested on this benchmark [7], including learning machines, neural networks and statistical methods. Their mis-classification rates were reported in the literature and are listed in Table 2 together with results for SOLAR networks. As we can see from Table 2, SOLAR shows better classification rate than all the listed methods except for CAL5. However, SOLAR acts better than all the neural network methods listed in this table. In addition, decision tree methods, such as CAL5 and C4.5 are believed to have better performance on credit card problems [7] while SOLAR was not specifically design for this case.

Table 2. Mis-probability Comparison on Credit Card Approval

Algorithm	Mis-prob.	Algorithm	Mis-prob.
CAL5	0.131	C4.5	0.155
SOLAR	**0.135**	SMART	0.158
Itule	0.137	Baytree	0.171
DIPOL92	0.141	AC2	0.181
Logdisc	0.141	k-NN	0.181
Discrim	0.141	NewID	0.181
CART	0.145	ALLOC80	0.201
RBF	0.145	CN2	0.204
CASTLE	0.148	LVQ	0.197
Naivebay	0.151	Quadisc	0.207
IndCART	0.152	Default	0.440
Bprop	0.154	Kohenen	-

Case three: Loan Decision-Adult Income Classification [6] [7]

Besides credit card approval, potential customer analysis is an example of another real world application to which banks or financial companies can apply computational intelligence. Again performance of SOLAR is compared with existing methods. Although SOLAR does not perform as well as the best algorithms, it is the only artificial neural network on the list.

Table 3. Adult Income Classification

Algorithm	Mis-prob.	Algorithm	Mis-prob.
FSS Naive Bayers	0.1405	CN2	0.1600
NBTrees	0.1410	Naive-Bayers	0.1612
C4.5-auto	0.1446	Voted ID3 (0.8)	0.1647
IDTM(Decision table)	0.1446	T2	0.1687
HOODG/SOLAR	**0.1482**	1R	0.1954
C4.5 rules	0.1494	Nearest-Neighbor (3)	0.2035
OC1	0.1504	Nearest-Neighbor (1)	0.2142
C4.5	0.1554	Pebls	Crashed
Voted ID3 (0.6)	0.1564		

5. SUMMARY

A new computational intelligence algorithm self-organizing learning array (SOLAR) and its applications in economic and financial fields are introduced in this paper. SOLAR can be widely used in this field, on prediction, classification and recognition problems. Both the concept and the implementation of SOLAR are being developed. Since SOLAR performs its pattern recognition tasks in subsets of its neurons, an associative learning is one of its potential features. This is a topic for further study. With associative learning in place, SOLAR will be able to solve problems which relate to each other in a meaningful and innovative way.

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