Evolving Self-organizing Map and its Application in Generation of A World Macroeconomic Map

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Abstract

A new algorithm of evolving self-organizing map (ESOM) is described as a dynamic extension of the Self-organizing map (SOM), where network structure is evolved in an online adaptive mode. Integrated as parts of the New Zealand Repository for Connectionist-Based Intelligent Information Systems, SOM, ESOM and related modules are applied in a case study on evolving a world macroeconomic map for evaluation on dynamic movements in macroeconomic performance of individual countries as well as country clusters.

1 Introduction

In real world information systems, there are always large amount of data flows that are updated daily, hourly or even every minute. These heavy data flows contain information which, once extracted, can be significant for future decision-making.

There is a growing interest in the exploration of intelligent solutions for data analysis and processing, especially in financial and economic information systems. It is expected that these solutions can overcome difficulties in dealing with complex dynamics of multivariate data, noise or distortion which occurs during data collection, or lack of domain knowledge [11].

One major objective of the Connectionist-Based Intelligent Information Systems (CBIIS) project carried out in the Department of Information Science, University of Otago, is to construct a repository of intelligent connectist-based information systems (RICBIS) and apply it to solve real world problems in a variety of application fields, including financial and economic data analysis and prediction, image and video processing, speech recognition and robot navigation etc. RICBIS implements a number of intelligent connectionist-based modules under the ECOS principles such as fast incremental learning ability and evolvable network structure as proposed in [9], and some other neural network modules. Further information about RICBIS can be found at [19].

Experiments and implementation have been made for analysis of the European Monetary Union (EMU) macroeconomics and financial index prediction using RICBIS. In this paper, we will focus on the problem on global macroeconomic analysis and the generation of a map that displays the clusters and developing trends in the world macroeconomy.

This paper is organised as follows. In Section 2, we first give a brief introduction on our computational models. In section 3, a case study on international macroeconomic data is presented in an effort to generate a world macroeconomic map. Finally our conclusion and future plan are given in Section 4.

2 ESOM and Other RICBIS Computational Models

Here some RICBIS modules related to this study are discussed, including self-organizing map (SOM), evolving fuzzy neural networks (EFuNN) and evolving self-organizing map (ESOM).

2.1 SOM

The SOM algorithm is proposed by Kohonen [13] to transform incoming data of high dimensionality into one- or two-dimensional discrete maps of topology order. With good ability of dimension reduction, clustering and multi-variate data visualisation, SOM is closely related to statistical methods like PCA and MDS [7][15][18]. Applications of SOM in financial area can be found in [3][11][12][18].

Given a set of data, the algorithm will try to generate a map consisting of nodes connected in lattice. Such a map is usually on a two-dimensional plane for visualisation purposes. Once the map is set out, given a new pattern of data, or a *feature code* as input, the map will search among its grid nodes, each of which corresponds to a prototype feature code. The new pattern will be categorised onto the best-matching node. The algorithm is also referred as Self-Organizing Feature Map, or Kohonen Map.

The topology preserving property of SOM is acquired in the sense that similar input patterns match to the same map node or nodes in neighbourhood.

The feature map can be interpreted and used in a number of ways as found in the large SOM bibliography, including:

- Categorisation. For a given feature code, find the best matching node and the feature code is taken as belonging to the category, with a crisp or fuzzy membership. Each category node can take labels from the best matched data entries and this is a very useful practice for data visualisation.

- Clustering. Once the feature map is formed, one can partition the nodes into a few groups according to their distances between each other. This can be done by either further forcing the node vectors to self-organise into several groups [18], or to use Sammon's algorithm [16] to project high dimensional feature vectors onto two-dimensional space, keeping the order of distance between nodes and then visualise the clusters on the two-dimensional plane. Other methods to obtain clustering visually on the feature map have been given in [12][15].

It should be noted that although the SOM serves to reduce dimension and produce a map of topology preservation, little clue for data structure is available in the low-dimensional mapping space. Even its topology preservation ability is weakened by the fact that nearby mapping nodes may prototype data entries which are not close to each other. Therefore SOM is not an ideal tool for data clustering and visualisation.

There are alternative SOM algorithms (semantic, fuzzy, and hierarchical etc.)[14]. Some of them are commented in [1][17].

2.2 EFuNN

This is an ECOS extension of Fuzzy Neural Networks (FuNN) [8]. EFuNN can learn in an incremental, adaptive way through one-pass propagation of data samples. It features good generalisation ability, an evolving network structure, fast online learning, automatic node pruning and aggregation, and the ability to explain the learned networks via extraction of fuzzy rules.

More details of EFuNN algorithms are available in [9][10]. Experiments going on indicate that EFuNN is very competitive in tasks such as online data prediction and classification [10].

2.3 ESOM

ESOM is an alternative of SOM algorithm we derived from the ECOS principles, borrowing ideas from the SOM and EFuNN algorithms. Unlike SOM which is typically initialised with a two-dimensional lattice, ESOM starts from an empty network and evolves a compact linked representation from incoming data entries.

2.3.1 Algorithm

We denote the ESOM network at time t as a triplet of a node set $\Omega \subset E^d$, an interconnection set $\mathcal{C}$, and a parameter set $\mathcal{P}$:

$$\mathcal{E}^t = (\Omega^t, \mathcal{C}^t, \mathcal{P}) \tag{1}$$

with each node $\mathbf{w}_i \in \Omega^t$ as a vector of dimension d, $i = 1...N$, and N is the number of nodes in Ω^t.

The learning process can be summarised as follows:

1. Input a new data entry $\mathbf{x}$;

2. If none of the nodes matches the data vector with a small error, i.e., for all $i = 1...N$,

   $$\|\mathbf{w}_i - \mathbf{x}\| > \epsilon$$

   (ϵ is an error threshold), create a new node in the network which represents exactly vector $\mathbf{x}$:

   $$\Omega^{t+1} = \Omega^t \cup \mathbf{x} \tag{2}$$

   Connect the new node with its first two nearest neighbours $\mathbf{w}_{n1}$ and $\mathbf{w}_{n2}$:

   $$\mathcal{C}^{t+1} = \mathcal{C}^t \cup c(\mathbf{x}, \mathbf{w}_{n1}) \cup c(\mathbf{x}, \mathbf{w}_{n2}) \tag{3}$$

   Here $c(\cdot, \cdot)$ denotes a connection between two vectors.

3. Otherwise update the matching node and each of its neighbours, denoted as $\mathbf{w}$, according to their distances to data vector $\mathbf{x}$, a relation represented by a function f:

$$\Omega^{t+1} = f(\Omega^t, \mathbf{x}) \tag{4}$$

with each node being modified as

$$\Delta\mathbf{w} = \gamma\ e^{-\|\mathbf{w}-\mathbf{x}\|/\sigma^2}(\mathbf{x} - \mathbf{w}) \tag{5}$$

where γ is a small learning rate and σ controls the effective neighbourhood spread.

4. Gradually prune weak connections and inactive nodes;

5. Repeat all steps above.

ESOM is aimed at life-long learning so convergence is ruled out. With a relatively small learning rate and a data sequence which is long enough, however, it can be expected that an optimum set of prototypes representing the original data can be learned.

2.3.2 Network structure

The network structure of ESOM is different from that of SOM, since that no topology is provided for the feature map a priori and prototype nodes can not be organised onto one- or two-dimensional lattices. This causes difficulty in visualisation of the feature map, as the prototype space is usually of high dimensionality. This problem can be solved, however, using Sammon's algorithm which projects high dimensional data into low dimensional space while keeping the distance ordering as best as possible.

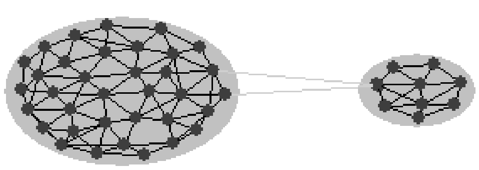

Fig. 1: *The connections in gray between two clusters will be clipped in ESOM.*

The connections between map nodes are used to maintain the neighbourhood relationships between close nodes. The strength of the neighbourhood relation is determined by the distance between connected nodes. If the distance is too big, giving a weak strength under a threshold, the connection can be clipped. In this way the feature map can be split apart and data structures such as clusters and outliers can emerge. This is illustrated in Fig.1. We use this technique in our experiment for the macroeconomic case study given in Section 3.

2.3.3 Comparison with other algorithms

The weight vector update rule in Eq.(5) is very similar to that of SOM, except that for the neighbourhood function the vector distance between nodes is used, rather than the grid distance in SOM [13].

There have been a few SOM variations which support incremental learning with dynamic network structures, e.g., Blackmore's incremental grid growing algorithm (IGG) [2], and Fritzke's Growing Network Grid (GNG) [6]. In IGG nodes and connections can be added to or deleted from the feature map, which is on a limited two-dimensional space. Unlike GNG, ESOM prototypes are assigned directly using data sample instead of applying an empirical midpoint interpolation. This suggests that learning starts with a memory on novelty, and continues by adapting existed memory to the changing environment. Generally speaking, compared with SOM and its variations, ESOM sacrifices geometry constraint on feature maps for more accuracy and efficiency.

2.3.4 Simulation results

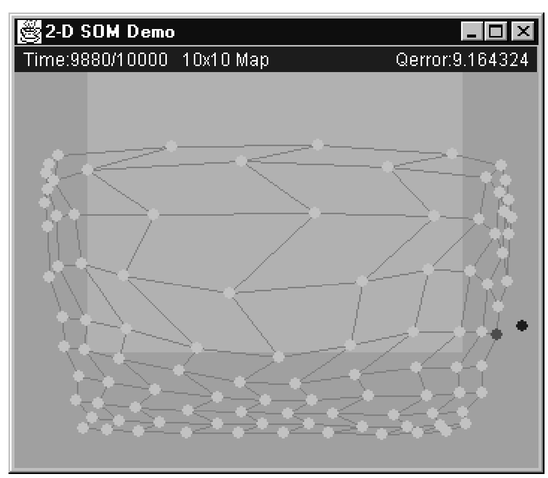

Fig. 2: *SOM of signals generated from a U-shape. Quantisation error is 9.16 with 100 nodes. Border effect is observed.*

Simulations are carried out using random signals generated uniformly from some two-dimensional shapes, one of which as the U-shape

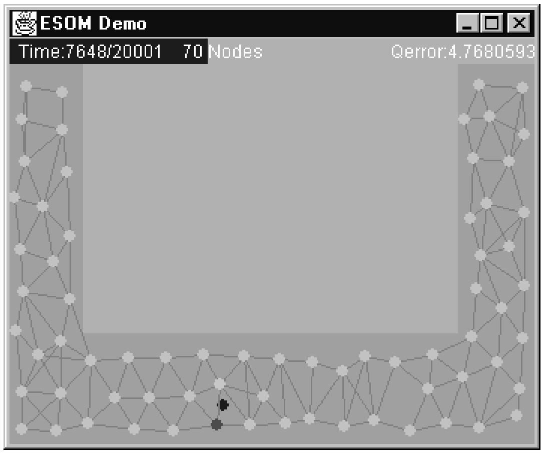

Fig. 3: *ESOM of the U-shape signals. Quantisation error is 4.76 with 70 nodes. No border effect.*

shown in Fig.2 and Fig.3. These simulations results can be summarised into the following phenomena:

- ESOM does not have the *border effect* which frustrates SOM [17], i.e., prototypes staying always close to the centre of input data space.
- Without fixed topology in the feature map ESOM does not need to unfold maps of ill initialisation. SOM, however, needs to start with a large neighbourhood to cope with this problem.
- Less redundant nodes are produced in ESOM while overall quantisation error is reduced.
- It takes less time for ESOM to form a good feature map for the random signals.

3 A Case Study: Mapping the Global Macroeconomy

3.1 Background and data sets

This study is initiated from our case study system for risk analysis of European Monetary Union economy [11], which employs a number of economic and financial indicators to predict possible shocks from which EMU market is unfortunately not immune, and develop a computational system for analyzing and anticipating signals of abrupt changes of volatility in financial markets. Here we focus on the problem of generating a world macroeconomic map to evaluate movements in national and regional macroeconomy.

Macroeconomic data in the period from 1994 to 1998 are collected for fifteen EMU countries, UK, US, and Asian countries such as Japan (JP) and Thailand(TH). The data is taken from [5]. The data set has four attributes, namely annual change percentage of stock market (PCH), debt over GDP (DBT/GDP), deficit over GDP (DEF/GDP), and inflation rate. Each data entry carries a label composed by country code and time numbers, which will be used later for the generation of a labelled map. Data are also collected on quarterly basis to enable quarterly analysis.

3.2 Implementation and experimental results

This case study is implemented with the RICBIS Java Interface, which integrates a number of intelligent computational modules inside a user interface running as a Java applet, hosted in the RICBIS home page at URL http://divcom.otago.ac.nz/infosci/kel/ricbis/. SOM and ESOM modules used for this study are coded in Java and included in the RICBIS applet.

Hereafter results from our experiments on annual macroeconomic data are presented.

A 12×12 two-dimensional map is first trained using SOM. The size of the map is selected empirically so as to obtain a well-expanded mapping space. The map learned from the annual macroeconomic data is shown in Fig.4, where map nodes are displayed with hexagons labelled with best-matching data entries and tinted according to the PCH component value of the corresponding feature vector. An EMU cluster is formed in the central part of the map, including the following countries: OE(Austria), NL(Netherland), DK(Denmark), IR(Ireland), SD(Sweden), BD(Germany) and FR(France). Non-EMU countries UK and US also fall into this cluster. Four EMU countries fall out apparently: IT(Italy), BG(Belgium), GR(Greece) in area of high inflation rate on the right, and SW(Switzerland) on the left side.

In Fig.5 the annual movements made by Italy and Ireland from 1994 to 1998 is compared. IR moves gradually towards the upper part, which corresponds to high PCH and low DBT/GDP. IT, on the other hand, stays outside of the EMU cluster. In 1998, however, it retained such a position close to IR94 and SD94, giving a suggestion that it may finally fall within the EMU cluster within a couple of years.

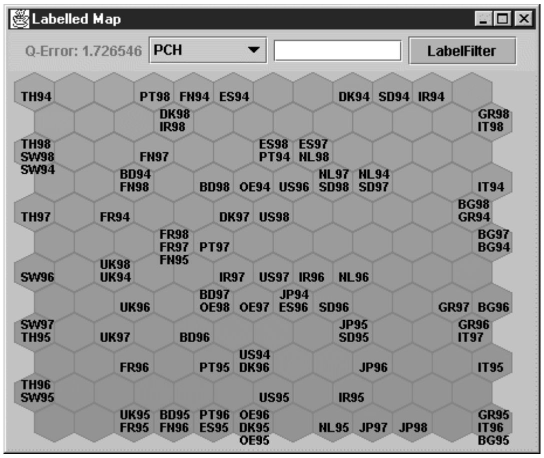

Fig. 4: *The Map for annual macroeconomic data using SOM.*

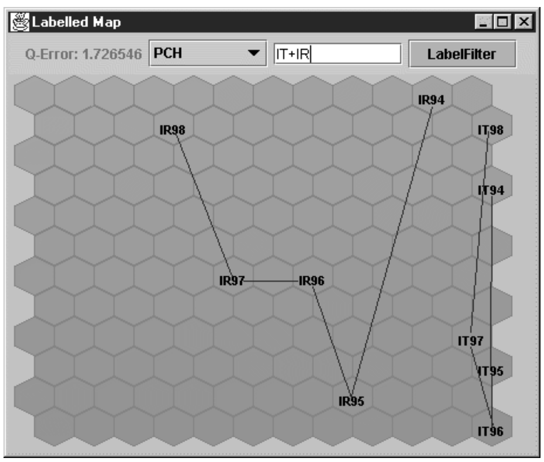

Fig. 5: *Directions of annual development of IT and IR macroeconomy.*

The SOM experiment given above is interesting because of the visualisation ability, especially when a colour palette is used that matches the scale of corresponding vector components. But the distance between map nodes can not be easily displayed and this makes it difficult to find clusters visually.

Another annual map is next evolved with the same data set and shown in Fig.6. The map is first clustered using ESOM algorithm, and then projected onto a two-dimensional plane for visualisation using Sammon's algorithm. Hence both clustering and data structure are available within the map. The layout of labelled nodes is quite similar to that of Fig.4, but the ESOM map gives more explicit information on the node distances.

Using a clipping threshold of 0.3, as shown in Fig.6, clusters in the annual macroeconomic performance data are revealed. Here we find two major clusters, the EMU cluster with countries like FR, BD, FN, IR etc. plus UK and US, the fall-out cluster with GR, IT, BG, and some outliers such as SW(Switzerland) and TH(Thailand).

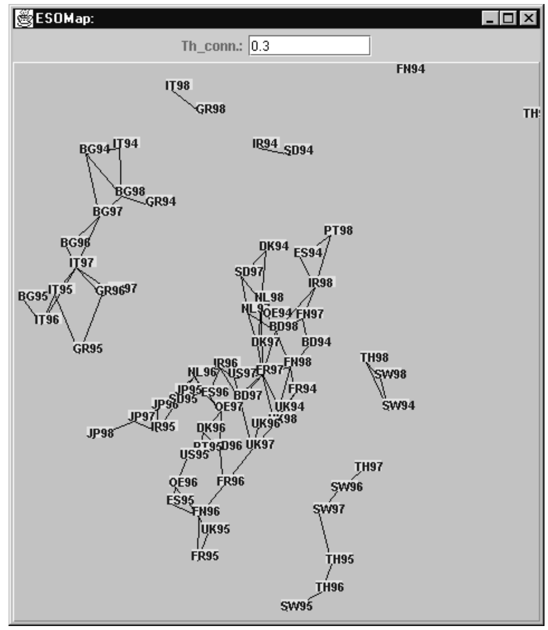

Fig. 6: *The ESOM visualised with Sammon projection shows the data structure.*

4 Conclusion

This paper introduces an evolving self-organizing map (ESOM) as an evolving variation of the Kohonen SOM, featuring its quick online learning ability and a feature map of more compactness, more quantisation accuracy, and less geometric constraint.

From the case study of world macroeconomic analysis, it is clear that the SOM and ESOM modules are useful tools for data clustering, dynamics analysis, and visualisation. With further improvement on the computational models and experiments on a larger data collection, we hope that more interesting patterns can be found in the world macroeconomic development and therefore provide useful reference to risk analysis and investment.

Acknowledgements
The work is fully supported by Grant UOO-808, funded by the Foundation for Research, Science and Technology (FRST), New Zealand.

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