Contradiction Resolution for Foreign Exchange Rates Estimation

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Keywords: Self-evaluation, Outer-evaluation, Contradiction Resolution, Information-theoretic Learning, Free Energy, SOM.

Abstract: In this paper, we propose a new type of information-theoretic method called "contradiction resolution." In this method, we suppose that a neuron should be evaluated for itself (self-evaluation) and by all the other neurons (outer-evaluation). If some difference or contradiction between two types of evaluation can be found, the contradiction should be decreased as much as possible. We applied the method to the self-organizing maps with an output layer, which is a kind of combination of the self-organizing maps with the RBF networks. When the method was applied to the dollar-yen exchange rates, prediction and visualization performance could be improved simultaneously.

1 INTRODUCTION

In this paper, we propose a new information-theoretic method called "contradiction resolution," aiming to improve prediction and visualization performance. In the method, a neuron is evaluated differently. If contradiction between different types of evaluation can be observed, this contradiction is decreased as much as possible. We here consider only two types of evaluation, namely, self and outer-evaluation. In the self-evaluation, a neuron's output is evaluated for itself, meaning that the output is determined by considering the neuron itself. On the other hand, in the outer-evaluation, a neuron's output is evaluated by considering all possible neighboring neurons. Then, if the outputs from the self and outer-evaluation are different from each other, this difference or contradiction should be minimized.

In neural networks, no attempts have been made to consider different types of evaluation. Some methods have been exclusively concerned with self-evaluation. More concretely, neurons have been forced to be as independent as possible (Comon, 1994). On the other hand, neurons have been forced to cooperate with each other as much as possible in the self-organizing maps (Kohonen, 1995), (Kohonen, 1990), (Kohonen, 1982). In the self-organizing maps, much attention has been paid to the outer-evaluation for cooperation. In our method, we can separate self and outer-evaluation, meaning that we can examine the influence of the other neurons on a neuron. Then, we can control this influence depending upon given objectives. In this paper, we aim to improve prediction as well as visualization performance. This improvement is expected to be realized only when we can flexibly control self and outer-evaluation.

2 THEORY AND COMPUTATIONAL METHODS

2.1 Self and Outer Evaluation

We distinguish between self- and outer-evaluation for neurons. Figure 1(a) shows an example of self-evaluation, where a neuron in the center produces its output, independently of its neighbors. This is called "self-evaluation," because the output can be obtained only by evaluating its own activity. In other words, neurons respond to input patterns individually. A self-evaluated neuron responds to input patterns without considering the outputs of the neighboring neurons. On the other hand, a neuron's output is determined by considering all neighboring neurons except the neuron itself, as shown in Figure 1(b). Thus, the neuron's output is determined by evaluating all neighboring neurons' outputs except the output from the neuron itself. This situation is called "outer-evaluation."

Kamimura R..
Contradiction Resolution for Foreign Exchange Rates Estimation.
DOI: 10.5220/0004152905290535
In *Proceedings of the 4th International Joint Conference on Computational Intelligence* (NCTA-2012), pages 529-535
ISBN: 978-989-8565-33-4

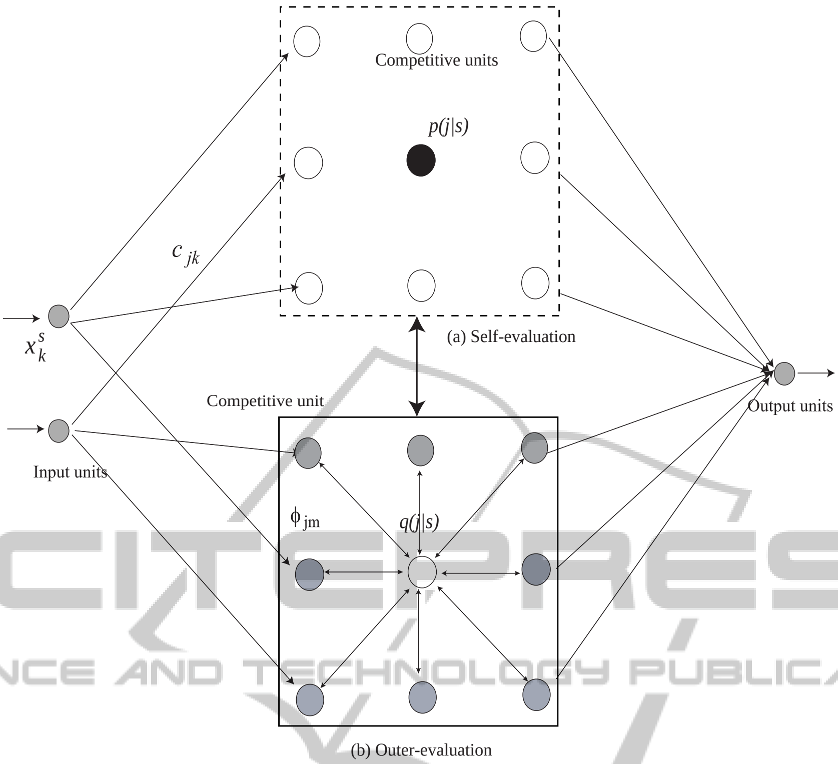


Figure 1: Two types of evaluation, namely, self (a) and outer (b) evaluation.

2.2 Self and Outer-evaluated Outputs

Let us explain how to compute outputs by self and outer-evaluation shown in Figure 1. The jth competitive unit output can be computed by

$$v_j^s = \exp\left\{-\frac{1}{2}(\mathbf{x}^s - \mathbf{c}_j)^T \blacksquare (\mathbf{x}^s - \mathbf{c}_j)\right\}, \quad (1)$$

where $\mathbf{x}^s$ and $\mathbf{c}_j$ are supposed to represent L-dimensional input and weight column vectors, where L denotes the number of input units. The $L \times L$ matrix $\blacksquare$ is called a "scaling matrix," and the klth element of the matrix denoted by $(\blacksquare)_{kl}$ is defined by

$$(\blacksquare)_{kl} = \delta_{kl} \frac{1}{\sigma_\beta^2}, \quad k, l = 1, 2, \cdots, L. \quad (2)$$

where σ_β is a spread parameter. In our experiments, the spread parameter is computed by

$$\sigma_\beta = \frac{1}{\beta}, \quad (3)$$

where β is larger than zero. The output is increased when connection weights become closer to input patterns. Now, suppose that the jth neuron is related to the mth neuron by ϕ_{jm}. In order to demonstrate how our method of contradiction resolution can be used, we applied them to self-organizing maps. For this application, all we have to do is to replace the relation function ϕ_{jm} by the SOM's neighborhood function. The neighborhood function is defined by

$$\phi_{jc} \propto \exp\left(\frac{\|\mathbf{r}_j - \mathbf{r}_c\|^2}{2\sigma_\gamma^2}\right), \quad (4)$$

where $\mathbf{r}_j$ and $\mathbf{r}_c$ denote the position of the jth and the cth unit on the output space, and σ_γ is a spread parameter.

Then, the output from the jth neuron by the self-evaluation is defined by

$$y_j^s = \sum_{m=1}^{M} \delta_{jm} \phi_{jm} v_m^s, \quad (5)$$

where M is the number of competitive units and δ_{jm} is one only if $j = m$, and zero for all the other cases. Thus, the output y_j^s is equivalent to the output v_j^s. The normalized output can be defined

$$p(j \mid s) = \frac{v_j^s}{\sum_{m=1}^{M} v_m^s}. \quad (6)$$

Then, we consider outer-evaluation, which is defined by

$$z_j^s = \sum_{m=1}^{M} (1 - \delta_{jm}) \phi_{jm} v_m^s. \quad (7)$$

The output by the outer-evaluation is the sum of all neighboring neurons' outputs except the jth neuron. The normalized output is defined by

$$q(j \mid s) = \frac{y_j^s}{\sum_{m=1}^{M} y_m^s}. \tag{8}$$

2.3 Contradiction Resolution

Our objective is to minimize contradiction between the self- and outer-evaluation. To represent the contradiction, we introduce the Kullback-Leibler divergence between two types of neurons

$$KL = \sum_{s=1}^{S} p(s) \sum_{j=1}^{M} p(j \mid s) \log \frac{p(j \mid s)}{q(j \mid s)}, \tag{9}$$

where S is the number of input patterns. When the KL divergence is minimized, supposing that errors between patterns and weights are fixed, we have

$$p^*(j \mid s) = \frac{q(j \mid s) v_j^s}{\sum_{m=1}^{M} q(m \mid s) v_m^s}. \tag{10}$$

By puting this optimal firing probability into the KL divergence, we have the free energy function:

$$\begin{aligned} F &= -2\sigma^2 \sum_{s=1}^{S} p(s) \\ &\quad \times \log \sum_{j=1}^{M} \exp\left\{ -\frac{1}{2} (\mathbf{x}^s - \mathbf{c}_j)^T \blacksquare (\mathbf{x}^s - \mathbf{c}_j) \right\}. \end{aligned} \tag{11}$$

This equation can be expanded as

$$\begin{aligned} F &= \sum_{s=1}^{S} p(s) \sum_{j=1}^{M} p(j \mid s) \|\mathbf{x}^s - \mathbf{w}_j\|^2 \\ &\quad + 2\sigma_\beta^2 \sum_{s=1}^{S} p(s) \sum_{j=1}^{M} p(j \mid s) \log \frac{p(j \mid s)}{q(j \mid s)}. \end{aligned} \tag{12}$$

Thus, the free energy can be used to decrease KL divergence as well as quantization errors. By differentiating the free energy, we can realize the re-estimation formula

$$\mathbf{w}_j = \frac{\sum_{s=1}^{S} p^*(j \mid s) \mathbf{x}^s}{\sum_{s=1}^{S} p^*(j \mid s)}. \tag{13}$$

3 RESULTS AND DISCUSSION

In computing the experimental results, attention was paid to the easy reproduction and evaluation of the final results. For easy reproduction, we used the well-known SOM toolbox of Vesanto et al. (Vesanto et al., 2000) because the final results of the SOM have been very different, given the small changes in implementation such as initial conditions. We have confirmed the reproduction of stable final results by using this package. In addition, we used the RBF network learning to obtain connection weight from competitive units to output units without any regularization terms, because we did not obtain favorable results by using the regularization. For comparison, we used the results by the conventional RBF networks in which regularization parameters were controlled to produce the best possible results.

3.1 Dollar-Yen Exchange Rates

We used the dollar-yen exchange rate fluctuation of 2011 for the purpose of visualization and prediction. The two-thirds of the data were used for training and the remaining data was for testing. We tried to examine how the prediction and visualization performance could be improved. For example, in terms of visual performance, we tried to extract features we could intuitively infer from the exchange rates. Figure 2 shows the exchange rates during 2011. The period was divided into three main periods, with an additional one showing the highest and lowest peaks. In the first period, relatively high rates are observed. Between the first and the second period, the rates fluctuated greatly, reaching the highest and lowest points. In the second period, the rates gradually decreased. Finally, in the third period, the rates became lower and more stable. We must examine how our intuition for the exchange rates can be realized by the conventional self-organizing maps and contradiction resolution.

3.1.1 Prediction Performance

First, we examined how our method could improve prediction performance for the testing and training data. Table 1 shows the summary of errors and information when the map size is 10 by 5. The mean squared errors between outputs and targets for the testing data were 0.240 when the parameter β was one. Then the errors decreased gradually and reached their lowest point of 0.054 when the parameter β was ten. On the other hand, by the conventional SOM and the RBF with the Ridge regression, the errors were 0.056 and 0.062, respectively. Thus, the contradiction resolution showed the lowest errors for the MSE. Correlation coefficient between targets and outputs increased gradually from 0.736 ($\beta = 1$) to the lowest of 0.933 ($\beta = 10$). On other hand, the SOM and RBF produced 0.929 and 0.919, respectively. The correla-

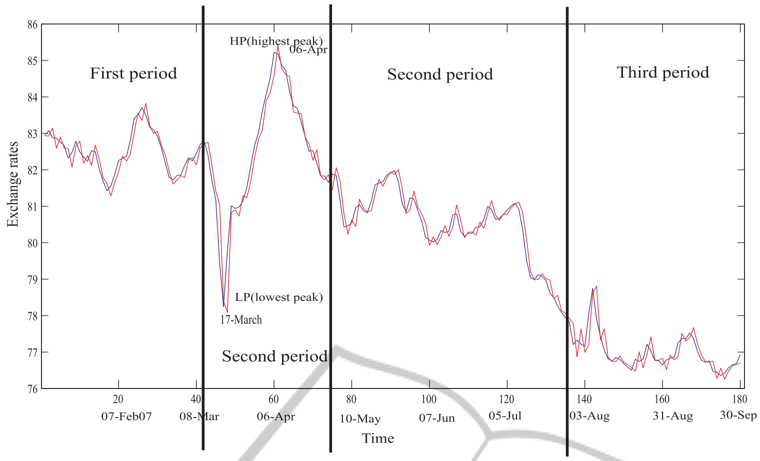


Figure 2: Training data of dollar-yen exchange rates during 2011.

tion coefficient by the contradiction was higher than that by the conventional two methods.

Then, we computed quantization and topographic errors for the training data. The quantization errors decreased gradually and reached the final point of 0.437 when the spread parameter β was increased from one to 20. By the conventional SOM, the quantizatoin error was 0.505. The topographic error increased from zero (($\beta = 1$) to the maximum value of 0.206 ($\beta = 10$). Then, the topographic error decreased gradually and reached the lowest point of 0.039. The topographic error by the SOM was 0.211. Finally, mutual information between input patterns and competitive units increased gradually when the parameter β was increased. We could see that the correlation coefficient between information and MSE was -0.947. When information increased, the MSE between outputs and targets for the testing data decreased. The correlation coefficient between information and the coefficient coefficient between outputs and targets was 0.874. When mutual information between input patterns and competitive units increased, the correlation coefficient between outputs and targets increased. We could also see that the correlation coefficient between information and quantization errors was -0.992, meaning that quantization errors decease when mutual information or organization increased. This means that mutual information increase or increase in organization in networks is closely related to prediction and visualization performance except topographic errors.

3.1.2 Visual Performance

Figure 3 shows the U-matrices by SOM and our method. Figure 3 (a) shows the U-matrix by the conventional SOM where we could not see clear class boundaries. On the other hand, when the parameter β was three in Figure 3(b), one straight boundary in brown could be detected in the middle of the U-matrix. When the parameter was increased to five in Figure 3(c), the straight boundary deteriorated slightly on the right hand side of the line. When the parameter was further increase from 10 in Figure 3(d) to 20 in Figure 3(f), class boundaries in warmer colors became more complicated. Figures 4(a) and (b) show the U-matrices and the corresponding labels by the conventional SOM (b) and by the contradiction resolution (a) when the network size was 10 by 5 and the parameter β was ten. We can infer from these figures that the entire period was divided into three periods, namely, first, second and third period. In addition, the highest and lowest peaks were separately treated as shown in Figure 2(a). On the other hand, by the conventional SOM in Figure 2(b), class boundaries on the U-matrix and the labels were weaker.

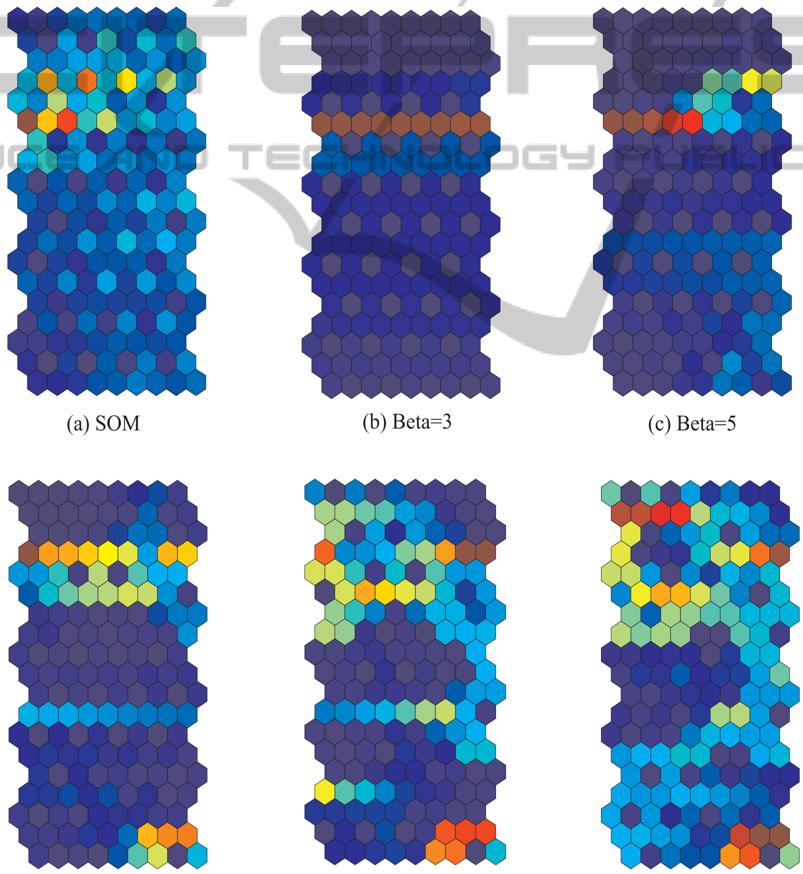
3.2 Discussion

We here discuss visual and prediction performance with some remarks on the possibility of our method.

First, our method could be applied to the self-organizing maps to improve visualization performance. In self-organizing maps, neurons are treated equally, having no individual characteristics. The main objective is to make neurons as similar as possible to each other. The self-organizing maps' property of cooperation has the effect to weaken class boundaries. Thus, many methods on the visualization of SOM knowledge have been accumulated (Sammon, 1969), (Ultsch and Siemon, 1990), (Ultsch, 2003), (Vesanto, 1999), (Kaski et al., 1998), (Yin, 2002), (Su and Chang, 2001), (Xu et al., 2010), to cite a few. Our contradiction resolution, as shown in the experimen-

Table 1: MSE between outputs and targets, correlation coefficient (CC) between outputs and targets, quantization errors (QE), topographic errors (TE) and mutual information by our method and SOM for 10 by 5 map. The symbol CC* represents correlation coefficients between information (INF) and the other measures. The symbol RR represents the RBF networks with Ridge regression.

β	MSE	CC	QE	TE	INF
1	0.240	0.736	3.960	0.000	0.000
3	0.068	0.914	0.999	0.100	0.117
5	0.072	0.908	0.670	0.200	0.129
10	0.054	0.933	0.581	0.206	0.130
15	0.055	0.932	0.504	0.072	0.132
20	0.055	0.932	0.437	0.039	0.135
SOM	0.056	0.929	0.505	0.211	0.134
CC*	-0.947	0.874	-0.992	0.255	
RR	0.062	0.919			



(a) SOM (b) Beta=3 (c) Beta=5

(d) Beta=10 (e) Beta=15 (f) Beta=20

Figure 3: U-matrices by the conventional SOM (a) and our method with 10 by 5 map whose parameter β ranged between 3 an 20 for the dollar-yen exchange rate.

tal results, can control cooperation so as to minimize contradiction between individual and collective characteristics of neurons. Experimental results showed that this control of cooperation was effective in producing produce clearer class boundaries.

Second, our method could improve prediction performance. Compared with the results by the RBF with the Ridge regression, our method showed better per-

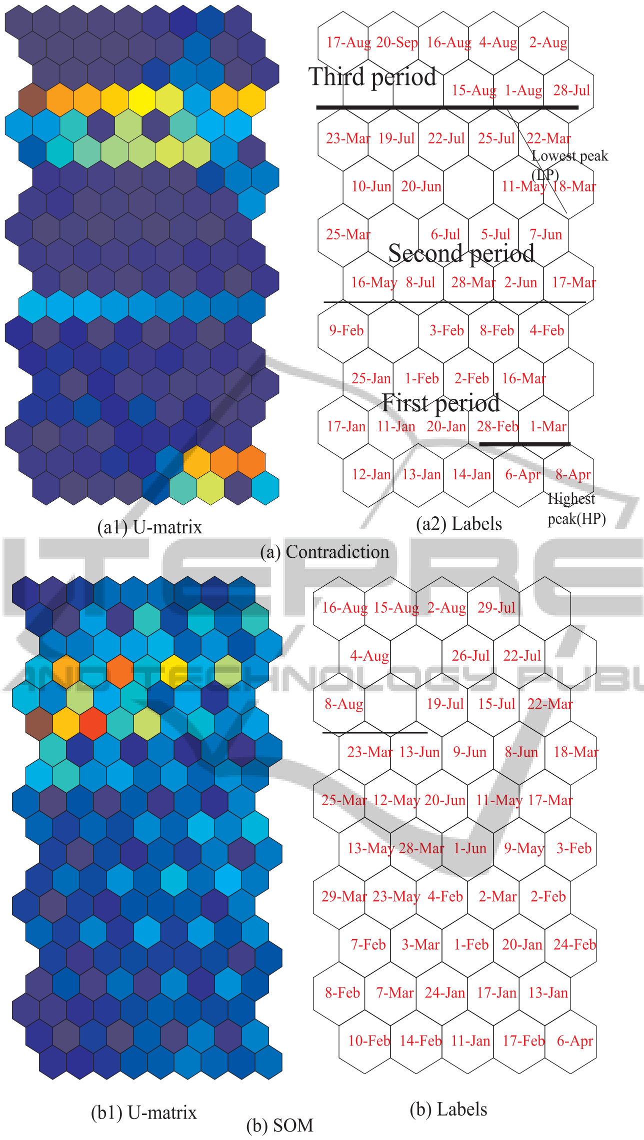


Figure 4: U-matrix and labels for 10 by 5 map by contradiction resolution (a) and SOM (b) for the dollar-yen exchange rate.

formance in terms of MSE and correlation coefficient between outputs and targets for the testing data as in Table 1. When visual performance, for example, in terms of the U-matrix, was improved, prediction performance seemed to be improved as in Table 1. In neural learning, one of the most serious problems is that we cannot interpret and explain why and how neural networks can produce outputs. Internal representations obtained by learning is so complex that it is impossible to interpret them. In addition, we can say that interpretation is not necessarily related to the improved prediction performance. We must improve the prediction performance, scarifying interpretation performance. The present results suggest that prediction and interpretation performance are closely related and both types of performance can be improved simultaneously.

Finally, contradiction resolution can be extended to a variety of relations between neurons. Because we used self-organizing maps, relations between neurons were estimated by distance between neurons on the map. However, we can imagine a variety of relations between neurons. One possibility is that even if two neurons are far from each other in terms of distance on the map, they can be considered to be close to each other if they respond quite similarly to input patterns. By incorporating different types of relations between neurons, we can create different types of neural network for different objectives.

4 CONCLUSIONS

In this paper, we have proposed a new type of information-theoretic method called ”contradiction resolution.” In this method, a neuron is evaluated for itself (self-evaluation) and by all the other neurons (outer-evaluation). If some difference or contradiction between two types of evaluation can be found, it should be decreased as much as possible. We applied the method to the dollar-yen exchange rate fluctuation. Our method showed better performance in terms of visualization and prediction performance. For example, the prediction performance for the testing data was better than that by the conventional SOM and the RBF with ridge regression. The U-matrices obtained by our method showed much clearer class boundaries by which we could classify the dollar-yen exchange rates into three periods. In addition, quantization and topographic errors could be decreased to a level lower than that by the conventional SOM. This means that the prediction performance could be improved, keeping fidelity to input patterns. Thus, our method shows a possibility that prediction performance and visualization performance can be improved simultaneously.

REFERENCES

Comon, P. (1994). Independent component analysis: a new concept. *Signal Processing*, 36:287–314.

Kaski, S., Nikkila, J., and Kohonen, T. (1998). Methods for interpreting a self-organized map in data analysis. In *Proceedings of European Symposium on Artificial Neural Networks*, Bruges, Belgium.

Kohonen, T. (1982). Self-organized formation of topological correct feature maps. *Biological Cybernetics*, 43:59–69.

Kohonen, T. (1990). The self-organization map. *Proceedings of the IEEE*, 78(9):1464–1480.

Kohonen, T. (1995). *Self-Organizing Maps*. Springer-Verlag.

Sammon, J. W. (1969). A nonlinear mapping for data structure analysis. *IEEE Transactions on Computers*, C-18(5):401–409.

Su, M.-C. and Chang, H.-T. (2001). A new model of self-organizing neural networks and its application in data projection. *IEEE Transactions on Neural Networks*, 123(1):153–158.

Ultsch, A. (2003). U*-matrix: a tool to visualize clusters in high dimensional data. Technical Report 36, Department of Computer Science, University of Marburg.

Ultsch, A. and Siemon, H. P. (1990). Kohonen self-organization feature maps for exploratory data analysis. In *Proceedings of International Neural Network Conference*, pages 305–308, Dordrecht. Kulwer Academic Publisher.

Vesanto, J. (1999). SOM-based data visualization methods. *Intelligent Data Analysis*, 3:111–126.

Vesanto, J., Himberg, J., Alhoniemi, E., and Parhankangas, J. (2000). SOM toolbox for Matlab. Technical report, Laboratory of Computer and Information Science, Helsinki University of Technology.

Xu, L., Xu, Y., and Chow, T. W. (2010). PolSOM-a new method for multidimentional data visualization. *Pattern Recognition*, 43:1668–1675.

Yin, H. (2002). ViSOM-a novel method for multivariate data projection and structure visualization. *IEEE Transactions on Neural Networks*, 13(1):237–243.