ANALYSING DISTRIBUTION WITH SELF-ORGANIZING MAPS

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Abstract

The purpose of the paper is to illustrate how a self-organizing map, a specific type of neural network, can be used in distribution analysis. A self-organizing map is a clustering, visualisation and abstraction method the idea of which is to show the data set in another, more usable, representation form. Therefore, it is a usable method for data analysis and we anticipate that it might also assist in distribution analysis. In this paper, we analyse the profitability of a company's shipments. As a result, we found that a self-organizing map can simplify the analysis, since we concentrate on groups instead of single shipments. Furthermore, it shows how the profitability factors vary by customers or deliveries.

INTRODUCTION

The distribution process is a substantial part of logistics. As Ploos van Amstel and D'hert (1996) emphasise, its effectiveness and efficiency are very important nowadays for two main reasons. First, distribution is a very significant factor in fulfilling customer service and, second, its share of total product costs has increased.

Both effectiveness and efficiency are usually related to the term performance. Therefore, reporting should assess, follow, and improve performance. Besides, it should provide insight into the functionality of organisational units (The NEVEM workgroup, 1989). Commonly, a logistics manager judges performance from regular reports and audits and many of them are generated in the normal course of business operations such as stock status reports, warehouse and truck fleet utilisation reports, as well as warehouse and transport cost reports (Ballou, 1992).

Reporting may have the following forms: *written*, *graphical*, *tabular*, or a *combination* of them. Written reports are based on quantitative data but strength is, however, lost when they are translated into written form. Besides, formulation can be a time-consuming job. The graphical report provides a fast analysis of the situation but it is limited in the simple determination of precise values (The NEVEM workgroup, 1989). Nevertheless, the popularity of visualisation is increasing because of its quick presentation of information in a usable format (Smith, 1995). Usually, visualisation of reports is based on the popular graphics of bars, pies, or lines. However, these figures are mostly shown in accordance with two variables and, thus, they concentrate on a specific aspect of a phenomenon. In the tabular presentation, we usually have several columns of variables simultaneously, but, the complex multi-column format does not facilitate an integration of the features of these variables. Therefore, instead of an overall assessment, it may provide an indication of separate aspects of the issue (Smith and Taffler, 1996).

Neural networks (NNs) are an information processing technique. They have been used already in many applications especially in engineering, data analysis and scientific computing for several tasks such as pattern recognition (Oja, 1992). Their capability to find novel patterns or statistical significant characteristics among data has also inspired logisticians. Halmari and Lundberg (1991) suggested that NNs might be knowledge organisers and refiners as well as a memory and an evaluator of interrelated judgements and decisions in logistics. Allen and Helferich (1990) considered that NNs may be feasible within logistics because they can recognise patterns in huge databases.

A Kohonen's *self-organizing map* (SOM) is a specific type of neural networks that uses so-called *competitive learning algorithm* and *unsupervised learning*. This means that we usually have a two-dimensional grid of units where the high-dimensional training data is mapped without a human's intervention. It is a clustering, visualisation and abstraction method the idea of which is to show the data set in another, more usable, representation form (Kohonen, 1997).

Hence, the main advantages of SOM are found in its capability to organise large numbers of unlabelled data quickly into a form that reveals the underlying structure within the data. Therefore, we discover easily important relationships among the data that otherwise might be unnoticed (Freeman and Skapura, 1991). The quickness itself may be a reason to use a method as Kohonen (1997) stresses.

Kaski and Kohonen (1996) presented the welfare states of the countries with SOM. They showed that SOM could illustrate the structures in an arbitrary data set and, thus, describe different aspects of a phenomenon. They summed up four reasons why SOM is good for exploratory data analysis. First, SOM visualises a data set in an ordered form. Second, the order inherent in the mapping enables its usage as a natural groundwork on which the individual statistical indicators can be visualised as grey levels. This groundwork is more easily comprehensible than bare statistical tables. Third, the structures can automatically be visualised on the map and the degree of clustering is presented by shades of grey. Last, SOM can deal with missing data. They also pointed out that SOM is a unique method compared to statistical analysis methods because it projects and clusters the data set at the same time.

Martín-del-Brío and Serrano-Cinca (1993) analysed and represented financial data with self-organizing maps. They as well as Kohonen and Kaski (1996) stress that this methodology is suitable to data processing in other fields. Besides those papers, some other promising studies of data analysis with self-organizing maps have been published in different business areas: predictions in financial markets (Binks and Allinson, 1991), recreating sites on coastal areas (Carlson, 1991), predicting bankruptcies (Back *et al*, 1995; Kiviluoto and Bergius, 1997; Shumsky and Yarovoy, 1997), structuring financial data for benchmarking (Back *et al*, 1995), discovering a typical consumer behaviour by profiling receipts (Sipilä, 1994), and finding out tourists' psychograph (Dolnicar, 1997).

In this paper, we use SOM to structure the shipments of a profit centre of a firm into groups based on so-called *weight maps*. We analyse cost and price data from about 3500 shipments. The data concerns about 100 customers during 15 months in the 1990's. Although we use these data items, other performance measures could have been used. The data set could also include a different number of customers or a different time period.

We anticipate that self-organizing maps might assist in distribution analysis because they can compress huge data sets and visualise them in an easily understandable way. SOM is a quick method to structure a data set in accordance with the variables selected. The visualisation is based on every variable used in a sense that it is based on the similarities and dissimilarities of all the variables. The analysis shows how the factors investigated vary by, e.g., customers or delivery ways. Therefore, the method may be applied to several purposes in distribution such as providing insight into the existing distribution, showing changes in the distribution manner for one customer, or being used for benchmarking purposes between various distribution manners.

The rest of the paper is organised as follows. Section 2 presents the used methodology including distribution and its performance measuring, self-organizing maps, and the choice of input variables. Section 3 describes the training procedure of self-organizing maps. Section 4 illustrates how self-organizing maps may be applied to analyse distribution information. Finally, the conclusions are presented in Section 5.

METHODOLOGY

Distribution and its performance

In this study, we focus on distribution. It concerns the material flow from a production facility to a customer including warehouses and transport. Basically, it helps in revenue generation by providing a desired customer service at the lowest total cost (Bowersox *et al*, 1986). Usually, firms have several alternatives to organise their distribution.

Performance can be understood in two ways: a process of carrying out something or a result of a process. We have both *financial* and *non-financial* measures in logistics. The former may evaluate, e.g., short-term profit or longer-term return on investments. However, these ratios tell us very little about the activities that caused the results. For that reason, we need different information about the central characteristics of the activities. They may focus on utilisation levels, delivery service, or lead-time (Aronsson *et al*, 1988).

Caplice and Sheffi (1994) present three primary forms of measurement, which together can capture the performance of business processes:

- *Utilisation* measures input usage.
- *Productivity* measures transformational efficiency of a process and it is typically reported as a ratio of actual outputs produced to actual inputs consumed.
- *Effectiveness* measures the quality of a process output and it is, typically, reported as a ratio of an actual output to a norm output.

A detailed list of possible measures for distribution is found in Ploos van Amstel's and D'hert's (1996) article. A firm does not need them all in its distribution analyses but usually one measure is not enough. The purpose determines which measures should be used. Anyhow, they should present a rich mixture that captures the critical elements of the examined process and possible deviations (the NEVEM workgroup, 1989).

Self-organizing maps

Neural networks are an information processing technique. They differ from the conventional data or information processing techniques in a way that we do not program them beforehand with instruction sequences. Instead, they learn from examples, which are formed as *input vectors*. The idea behind NNs is the physiological function of the human's brain and nervous system. They have various *architectures* and each of them have their own unique mix of, e.g., information processing capabilities, domains of applicability, techniques for use, required training data, and training method (Hecht-Nielsen, 1990).

Figure 1 shows an example of the structure of a self-organizing map neural network. It is a *single layered network* and, thus, it has only two layers: an *input layer* and an *output layer*. The layers consist of data processing units called input or output *neurons* depending on the layer they exist. Each input neuron is connected to all output neurons. The *connections* are presented with lines and they transmit signals from the input neurons to the output ones.

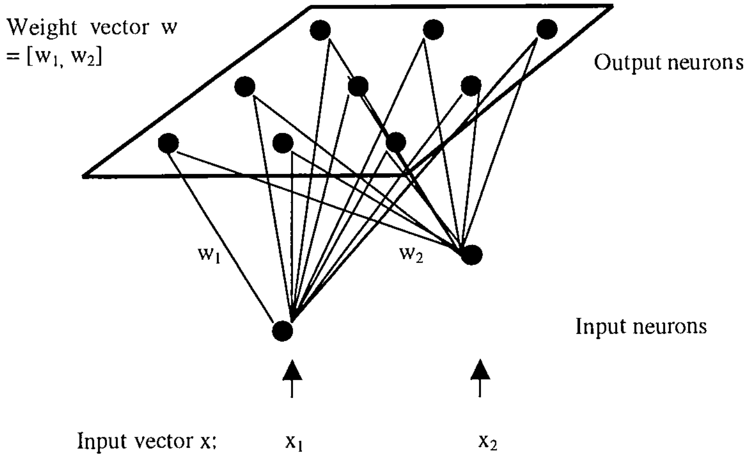

Figure 1 - The structure of self-organizing maps

The input layer has exactly as many neurons as an input vector has variables (Freeman and Skapura, 1991). The input neurons work as buffers that distribute the input data to the neurons on the second layer, without performing any computation (Martín-del-Brío and Serrano-Cinca, 1993). Thus, the input layer's neurons together present an input pattern for all output neurons.

The output layer consists of several neurons. Their number and order determine the network topology. It depends on the application and a user usually defines it. Commonly, the output neurons are arranged in a two-dimensional grid because it provides a better visualisation capability. This lattice type of array can be defined as *rectangular*, *hexagonal*, or even *irregular* (Kohonen, 1997). In a rectangular grid each neuron is connected to four neighbours, whereas each neuron is connected to six neighbours in a hexagonal grid. Only the neurons at the edge of the grid make an exception. Kohonen *et al* (1996) suggest using the hexagonal one because of its effective visual display. Such a form of output layer is shown in Figure 2.

Every output neuron stores a *weight vector* w. It is formed by the *scalar weights* w_i, where i = 1,2,3,... is the input connection. Therefore, each weight vector has the same dimensionality as the input vectors.

The maps learn by a self-organisation process. This means that training is done with input data alone without the presence of an external teacher. This is called unsupervised learning and the input data is called unlabelled data (Freeman and Skapura, 1991). In this case, we do not need a priori knowledge of the number of the clusters (Venugopal and Baets, 1994). Neither is a priori knowledge about the input's membership in a particular class required. Instead, the clusters are defined with gradually detected characteristics and a history of training (Fullér, 1995).

The training is an iterative process where the examples are presented as input vectors to the network one by one in random order. Learning happens in two phases each time the network receives a new input. In the *competition phase*, every output neuron receives the same input vector. Then, the input vector is compared to each weight vector in some metric in order to find out the weight vector that is closest to the input vector. In many practical applications, the smallest of the *Euclidean distances* can be used to define the best-matching weight vector. At the same time, the winner neuron is found. Next, the weight vectors of the winner and its neighbourhood neurons are adjusted in the direction of the input vector. This updating forms a globally ordered map in continued learning. (Kohonen, 1997)

We have two learning parameters, which control this learning process. The *learning rate* influences the size of adjusting the weights after every training step, whereas the *neighbourhood size* ($N_c(t)$ in Figure 2) determines to what extent the winner affects the neighbourhood neurons. Usually, the neighbourhood size shrinks and the learning rate decreases during the ordering process (Kohonen, 1997). The number of learning steps also affects the quality of the map because the performance of the network typically continues to improve monotonically as training progresses (Hecht-Nielsen, 1990).

As a result of training, the weight vectors have converged to practically stationary values and we have a topology-preserved map. This means that two input items, which are close in the input space, are mapped onto the same or neighbouring neurons on the map. Thus, each output neuron represents similar examples of the input space, whereas a set of similar neurons creates a group. Together the output neurons form a map of the input space.

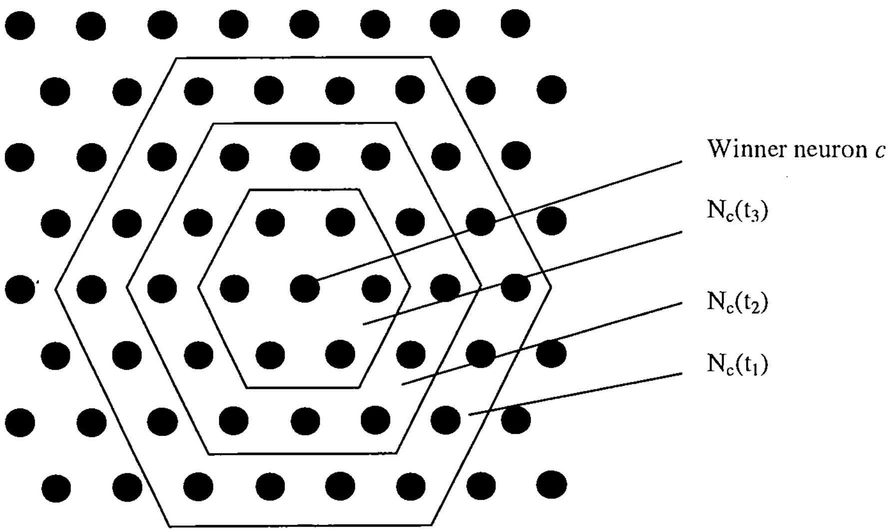

Figure 2 - An example of topological neighbourhood (t1 < t2 < t3) (source: adapted from Kohonen, 1997, 87)

Choice of input vector variables

Before we teach the network, we should collect enough sufficient training data and code it into n-dimensional input vectors. Every variable in the vector represents one specific feature of the example. In these vectors, we use continuous valued data. The number of the chosen variables determines the dimensionality for the input vector.

The logistics data used in this study is provided by a profit centre of a Finnish forest company. Its market areas are in Europe, Africa, Middle East, Far East and America. The company buys most of the distribution functions, such as ship transport, warehouse operations and land transport, from external organisations. The company has two clearly distinct distribution practices. Some shipments are delivered direct to the customer by containers. In the other, more common practice, products are shipped to a foreign harbour and then they are delivered from there with a land transport vehicle to a customer. Mostly, the firm follows a specific delivery route for each customer. However, the deliveries may vary because of changes in e.g. the storage times or delivery amounts.

Logistics costing mirrors the materials flow and it may be used for separate cost and revenue analyses by customer type, market segment, or distribution channel (Christopher, 1992). Gattorna and Walters (1996) point out that ideally every order should be profitable. They also note that within an existing product/market structure, profitability is largely determined by what happens after the product is manufactured. Additionally, they stress that it is significant to know how costs of servicing a customer vary by, e.g., customer, order size, or order type.

In this study, we focused on shipments' profitability, which is one possible success criterion for distribution. When calculating profitability, we need both revenues and costs. In our example, we took the selling price as revenue although it should cover many other things than only distribution costs. Besides, we took into account several costs caused by distribution. However, the capital bound with inventory was left out. Hence, the analysis mirrors each shipment and visualises how profitability varies by customers. Table 1 shows a summary of the seven chosen variables in this study.

Table 1 - The variables

Variable		**Including**	**Relation between costs *)**
Domestic costs	FIM / ton	payment of a shipment going abroad; domestic transport; costs of a domestic harbour	x
Sea freight	FIM / ton		20x
Foreign harbour costs	FIM / ton	costs of a foreign harbour, e.g. warehouse costs	3x
Foreign transport costs	FIM / ton	land transport from a harbour to a customer	5x
Direct transport costs	FIM / ton	costs of delivery by a container	40x
Other costs	FIM / ton	custom clearance; other administrative costs	1-2x
Price	FIM / kg		

*) Note. These expressions give only a rough understanding of the magnitudes. Actually, no linearity exists between the costs and the relations vary between the shipments.

TRAINING THE NETWORK

In this section, we illustrate the network building process. We used The Self-Organizing Map Program Package version 3.1 created by The SOM Programming Team of the Helsinki University of Technology in the network building.

The first step in the construction process was to create the input vectors. Thus, each shipment in the training data was formed as an input vector, which had seven components. Each of them represented one of the seven variables shown in Table 1. The training data included foreign European shipments during 15 months in the 1990's. The whole sample contained data from about 3500 shipments from about 100 European customers excluding trial shipments, which were dropped out from the training. They are small quantities of the product with minimal fee or no fee at all and, therefore, they differ strongly from the normal situation. Otherwise, the map would have been too rough for interpretations since the trial shipments were clearly separated on the map and the others were too similar to each other.

Before we started the training, we pre-processed the data. The pre-processing may be regarded as a fixed transformation of the variables. It may have also other meanings such as a reduction of the dimensionality of the input data (Bishop, 1995). Many pre-processing methods exist (see e.g. Kohonen, 1997; Martín-del-Brío and Serrano-Cinca, 1993) and the selection from them depends on the purpose of the network and the data.

Pre-processing of the input data affects both the self-organizing network building and the final appearance of the map (Martín-del-Brío and Serrano-Cinca, 1993). For instance, SOM finds two variables that have high variance and strongly affect the ordering (Kohonen, 1997). This might misrepresent the data for the aimed purpose and in many cases we need to eliminate that effect. In our data set, other costs had the biggest variance, whereas price had the smallest variance. Therefore, the other costs were too highly weighted in relation to their share in the total costs without pre-processing. Besides, the changes of price did not appear clearly on the map, as they should. For these reasons, we pre-processed the data items in a way that the variance of the columns, i.e. each variable, was normalised. Typically, this is done in a way that a variable will have zero mean and unit standard deviation (Refenes, 1995).

We chose the hexagonal layout with rectangular edges for our map. Another important issue for visualisation is the size of the map. It can not be too small or too big for the purpose. However, no specific rule exists for its determination. Thus, we constructed several maps of different sizes. We chose the one where the layer consisted of 320 neurons arranged in a 16 x 20 rectangular grid, because it was appropriate enough to this research problem.

Firstly, we initialised the weight vectors at random values and then we trained the network in two phases. The first one ordered the initialised weight vectors of the map to approximately right places, whereas the second one fine-tuned the map into final ordering. The number of learning steps in the final convergence phase should be reasonably long to reach a good statistical accuracy for the mapping. If the data set does not include enough examples, we can present the set more than once. Thus, we have many *epochs*, i.e. one presentation of the whole set of training patterns (Martín-del-Brío & Serrano-Cinca, 1993).

In both training phases, we have the learning parameters described in the previous section: the neighbourhood size and the learning rate factor. To reach the global ordering, the process starts with a wide neighbourhood size. The learning rate starts out just below 1.0 at the beginning of the training (Kohonen, 1997). In the SOM_PAK, the neighbourhood size shrinks to unit and the learning rate decreases towards zero very slowly during the ordering process. In the first phase, both learning parameters are bigger than in the second phase. The second phase should also have much more iterations than the first one. The values of the parameters used in this study are presented in Table 2.

We modified the learning process by changing the initial values. We selected the map with the minimum *average quantization error* to be the best as Kohonen *et al* (1996) suggest. It is an average of the Euclidean distances of each input vector and its best matching weight vector. Table 2 summarises the network building information.

Table 2 - Summary of the network building information

	First phase	Convergence phase
Learning rate	0.9	0.03
Neighbourhood size	12	2
Learning iterations	2500	197500
Total iterations	200000	
Quantisation error	0.2653	
Rectangular grid	16 x 20	
Shipments	about 3500	
Customers	about 100	

RESULTS

As a result of the above-described training process, we achieved the *shipment map* in Figure 3. The SOM_PAK program package provides this visualisation form called the *U-matrix method* (i.e. the Unified distance matrix). It is a grey-level illustration of the weight vectors and, therefore, it is also a profile of the input vectors, i.e. the shipments in this study, in accordance with the features that SOM has detected from the data.

Figure 3 illustrates a map with a 16 x 20 rectangular grid of neurons. The neurons are those hexagons that include a black spot in the middle. Every side by side neuron is separated from each other by another hexagon without any spot. It shows the difference between the weight vectors of these two neurons. When the hexagon is white, it means that the weight vectors are very similar, whereas the darker area shows bigger dissimilarity. Therefore, the light areas are clusters with similar input patterns and the darker areas may be seen as separators between them (Iivarinen *et al*, 1994).

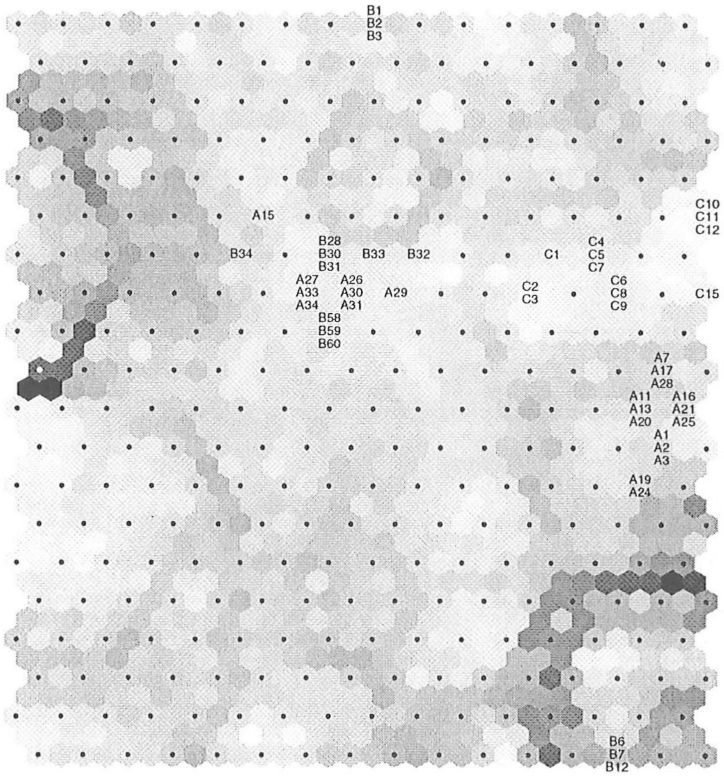

Figure 3 - The shipment map

For the purposes of analysis, we labelled the shipments of three customers in a way that the letter expresses the customer and the number after it shows how recent the shipment is. For instance, C1 is the oldest shipment of the customer C whereas C15 is the newest one. Customers A, B, and C are from different countries in Europe. Therefore, the delivery structures of their orders vary from each other and their shipments are located differently on the map.

Weight maps Figure 4 illustrates so-called weight maps. A weight map images the values of one variable with grey levels. We can create a weight map to each variable used in the input vector. These maps are of the same size as the shipment map. However, every circle presents now one neuron and their locations correspond to the locations of the neurons in the U-matrix form. The white colour of the neuron means the highest value of that variable in the data set, whereas the black neuron means the smallest value of that variable. The values between these two extremes are coloured with different levels of grey.

From the weight maps, we can observe, e.g., the following issues. Direct transport costs have an impact on the right bottom corner and nowhere else. On the other hand, foreign transport and harbour costs together with sea freight have an effect nearly all over the map but not in that corner. The reason is that in deliveries by containers, we have only direct transport costs, whereas three other above-mentioned costs are zero in the data set. In the other deliveries, the situation is the reverse.

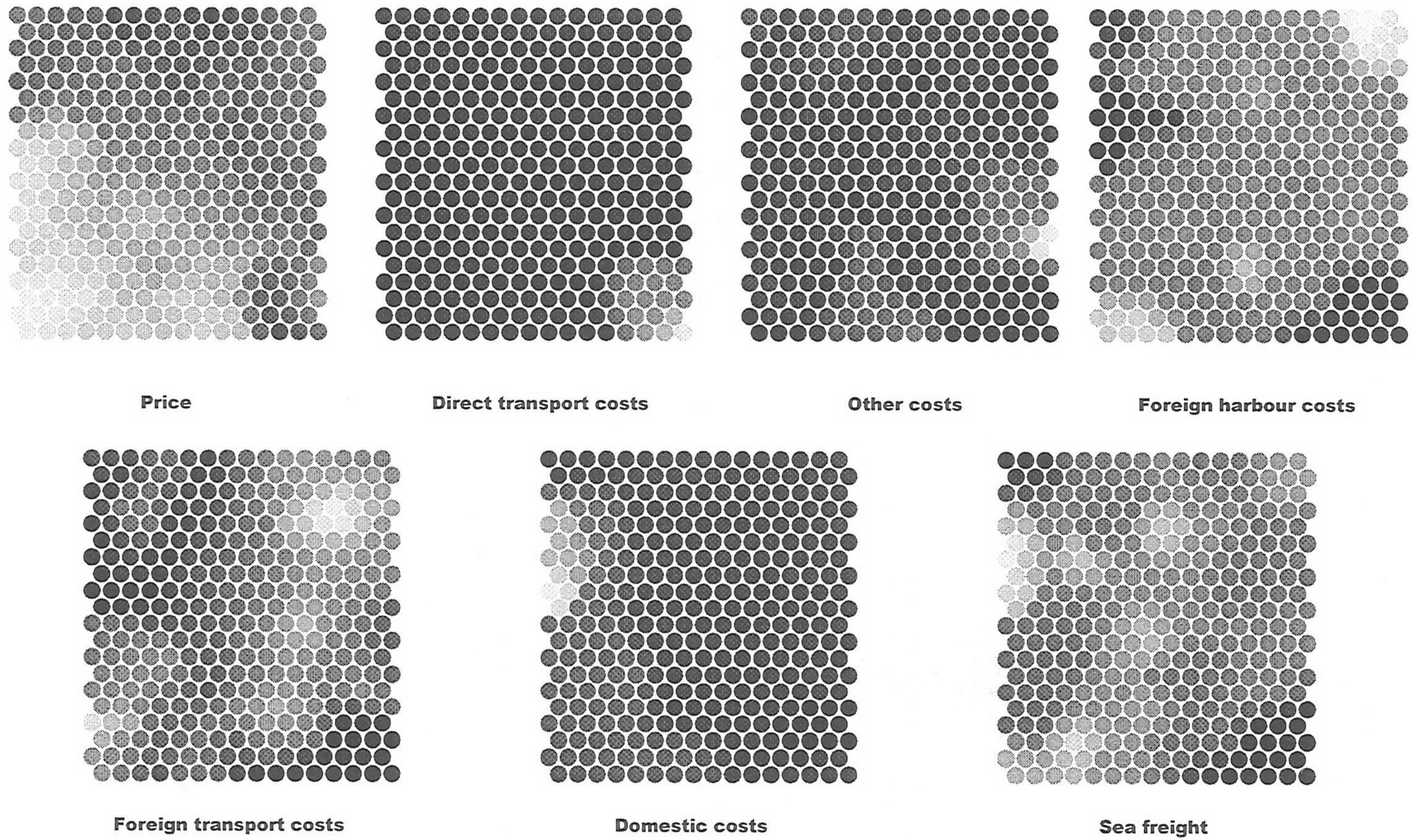

Figure 4 – The weight maps (light colour equals high value, dark colour equals low value)

This means that direct transport costs have a zero value in the data set and, therefore, these values are presented with black on the weight map. Hence, darker neurons clearly separate two different delivery practices on the 'shipment map' in Figure 3: shipments delivered by containers in the right bottom corner and the other shipments. The image of the latter group has less clear boundaries. The reason is that the data set is quite homogenous. But, although no explicit clusters exist, SOM discovers lighter areas with high clustering tendency and the darker grey neurons are separators for them (Kaski and Kohonen, 1996).

In the same manner, we can find for the other variables the areas where they have the biggest and smallest values. These areas are easily discovered for domestic and other costs as well as price. We also find those places for foreign transport and harbour costs, likewise for sea freight although they have some influence nearly everywhere. In this way, the weight maps assist to interpret typical features of the shipments on the various areas on the map.

Shipments within the groups As we can see from Figure 3, the shipments of each customer form groups which means that they are quite similar. Now, we can compare the weight maps to the shipment map to find out the typical features of the shipment groups in accordance with their costs and price.

Our interpretation for the shipment groups is the following (note that the expressions of the levels of the values are related to the values in the data set):
- *A1 - A25, except A15*: In this group, domestic costs have a low value. Both price and foreign transport costs are also quite low. The latter one has some changes in that group. Foreign harbour and other costs as well as sea freight are at medium level.
- *B1 - B3*: Here, price as well as domestic and other costs are low. Foreign transport costs are also quite low. Instead, both foreign harbour costs and sea freight are at medium level.
- *B6, B7, B12*: These shipments have been delivered by containers. Therefore, it has only direct transport costs, which are at medium level. The other variables have a low value in the time period investigated.
- *C1 - C10*: This group's foreign harbour and foreign transport costs are at medium level. Domestic and other costs have a low value and sea freight as well as price have also quite a low value.
- *The rest of the shipments labelled*: Here, domestic costs and other costs have a low value and price is also quite low. Foreign transport and foreign harbour costs as well as sea freight are at medium level. However, foreign transport costs change inside this group.

In the same manner, we can define the features of the other shipments on the other parts of the map.

Shipments over time On the shipment map, we have shipments from 15 months and the labels present the chronological order for the shipments of each customer. Therefore, we can analyse whether the customers' shipments have changed during that time.

The shipments of customer C belong to the same light area. The reason is that neither costs or price are changing in any radical way during that time. Only some very small movements exist and they are mostly caused by the changes in exchange rates. Thus, label C represents the shipments of a good customer in a sense that the customer's delivery time and delivery amounts are regular.

Customer A's shipments are included in two separate groups. The change of the delivery way has had an impact on the cost structure and, thus, caused this movement from one group into another. One explanation for this may be the decrease in the storage costs in the foreign harbour because the firm has moved from bigger delivery quantities to smaller ones. Hence, we may expect that the smaller quantities do not stay as long in the harbour warehouse as earlier.

The third customer is labelled with B. Its shipments do not seem to belong to any specific group. For instance, some shipments such as B6, B7, and B12 have been delivered by containers. The customer has had liquidity problems that may explain the big changes in the shipments' deliveries. It has affected the cost structure of these shipments and the movements between various locations express this situation.

Hence, the map can also show the changes from one time to another in addition to the characters of the shipments. However, it does not tell the absolute values of the variables or profit. Instead, it provides insight into the direction of the changes. For instance, when the price remains unchanged and one cost variable increases, the profitability of that shipment decreases.

CONCLUSIONS

The objective of this study was to investigate the capability of self-organizing maps to assist in distribution analysis. We analysed the shipments of three customers and how they had changed during 15 months. For that purpose, we constructed the shipment map of about 3500 shipments of about 100 customers.

SOM provided us a visualisation of a huge number of shipments, which is a projection of them on a two-dimensional map that includes clusters. Visualisation might assist in reporting since tabular reports with only tens of rows together with just a few columns may blur the users understanding of the situation. On the other hand, the aggregate sum reports do not assist in further analysis when detailed information is needed. Therefore, SOM assists in formation of a quick understanding about the situation. Furthermore, the map has been formed in accordance with all those variables that have been used in the input vectors. Therefore, the U-matrix can provide a quick overview of the shipments' similarities according to the used variables.

As a result, we found that self-organizing maps with their handling and visualisation capabilities may lead to better observations and overview of large data set of shipments. It simplifies the analysis since we concentrate on groups instead of single shipments. They also show how the profitability factors vary by customers or delivery ways.

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