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Visualisation of Complex Business Data: A Neural Network Approach

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Abstract

Reliable and well-audited financial statements attract the capital that finances business. Analytical auditing plays an important role in assisting the auditor in determining the nature, timing and extent of his or her substantive testing and in forming an overall opinion as to the reasonableness of recorded account values. It is used to improve the efficiency of auditing. Basically, in an analytical auditing one compares expected relationships among data items to actual observed relationships. This paper shows how neural networks, especially Kohonen's self-organising map (SOM) can be used in analytical auditing when auditing monthly account values. The SOM is used for clustering monthly data sets. Neural network systems are based on computational intelligence. The purpose is to show how the data sets of various accounts and various years form their own groups. We found that the SOM can add value to auditors in the analytical process: it is a tool for classifying and clustering data sets that reveals if some cluster contains data that a priory should not be in it. Therefore, it can be used for signalling unexpected fluctuations in data. Furthermore, the SOM is a possible technique embedded in the continuous auditing tool.

1. Introduction

Many parties, like investors, creditors, and managers, are interested in the accuracy of organisations' financial account values. Auditors are in a key position to monitor and control operations in organisations. They also need to take the necessary steps to restore public confidence in the capital market system and accounting profession that might have been shaken by the collapse of Enron etc. Also, the increasing use of information technology and computers in organisations requires auditors to obtain and evaluate evidence electronically. Companies are reporting their financial outcome quarterly and more and more companies present their financial information on a public network. Sometimes the speed at which these reports are made makes one wonder whether all the relevant information is audited and reliable. Therefore continuous monitoring and controlling are given more attention (Vasarhelyi *et al.* 1991). *Continuous auditing* is a type of auditing which produces audit results simultaneously with, or a short period of time after, the occurrence of relevant events (Vasarhelyi 2002).

The use of analytical auditing procedures is one way of becoming convinced of the reliability of the financial account values. The use of analytical auditing procedures means that the accuracy of account balances can be examined without considering the details of the individual transactions, which make up the account balance. They play an important role in assisting the auditor in determining the nature, timing and extent of his or her substantive testing and in forming an overall opinion as to the reasonableness of recorded account values (Weber *et al.* 1999). For example, in the US the use of analytical auditing procedures in the planning and overall review phases of an audit is required under Generally Accepted Auditing Principles (GAAP). Auditors could also use analytical auditing procedures in the fieldwork.

Auditing researchers have developed a variety of models to help the analytical auditing procedure. Blocher and Patterson (1996) have identified three types of analytical auditing techniques, including *trend analysis, ratio analysis* and *model-based procedures.* These procedures differ significantly in their ability to identify potential misstatement. Trend analysis relies on data for only a single account. Ratio analysis incorporates directly the expected relationships between two or more accounts. For example, turnover ratios are useful because there is typically a stable relationship between sales and other financial statement accounts, especially receivables and inventory. Although ratios are easy to compute, which in part explains their wide appeal, their interpretation is problematic, especially when two or more ratios provide conflicting signals. Indeed, ratio analysis is often criticised on the grounds of subjectivity, i.e. the auditor must pick and choose ratios in order to assess the overall performance of a client. Model-based procedures use operating and external data in addition to financial data to develop the expectation. We argue that an artificial neural network (ANN) is a useful technique for model-based procedures.

ANN systems are based on computational intelligence. Information technology development and processing capacities of PCs have made it possible to model ANN-based information systems for monitoring and controlling operations. ANNs have already been applied in many different business areas (Vellido *et al*. 1999; Zhang *et al*. 1998). ANNs are data driven techniques that can be used for prediction, classifying, and clustering tasks. They can learn, remember, and compare complex patterns (Medsker *et al*. 1994). They are claimed to be able to recognise patterns in data even when the data are noisy, ambiguous, distorted, or variable (Dutta 1993). They are capable of discovering data relationships. These features make ANNs suitable for many tasks within auditing. The computational intelligence that the ANN provides for an accounting information system may support users with such business intelligent information they need to make tactical and strategic decisions.

The major ANN-application areas in the auditing literature are detecting material errors (Coakley *et al.* 1991a; Coakley *et al.* 1991b; Coakley *et al.* 1993; Wu 1994; Coakley 1995; Busta *et al.* 1998; Koskivaara 2000) detecting management fraud (Green *et al.* 1997; Fanning *et al.* 1998; Feroz *et al.* 2000), and support for going concern decision (Hansen *et al.* 1992; Lenard *et al.* 1995; Koh *et al.* 1999; Anandarajan *et al.* 1999; Etheridge *et al.* 2000). ANNs have also been applied to internal control risk assessment (Davis *et al.* 1997; Ramamoorti *et al.* 1999), audit fee determination (Curry *et al.* 1998), and financial distress problems (Fanning *et al.* 1994). Going concern and financial distress are very close to or can even be included in bankruptcy studies, which is a very vast and rich ANN research area. Material error applications direct users' attention to those financial account values where the actual relationships are not consistent with the expected relationships. An auditor has to decide whether and what kind of further audit investigation is required to explain the unexpected results. Material error ANN-models either predict future values or classify data. The results of material error ANN-models seem promising at least as a supplement to traditional analytical auditing procedures and offer improved performance in recognising material misstatements within the financial accounts.

In this paper we show the feasibility of an ANN, especially Kohonen's self-organising map (SOM), in an analytical auditing process when auditing monthly account values. We study whether the SOM is capable of revealing monthly variations and clusters in the data sets in the meaningful matter. The SOM has proven to be suitable for data analysis tasks (Kohonen 1997). Although many papers on self-organising maps, since its invention in 1981, have been published, very few studies have dealt with the use of self-organisation maps for financial analysis. The studies by Martín-del-Brío *et al.* (1993) and Back *et al.* (1998) are examples of the application of the SOM for financial analysis. Martín-del-Brío *et al.* (1993) studied the financial statements of Spanish companies, and attempted to predict bankruptcies among Spanish banks during the 1977-85 banking crisis. Back *et al.* (1998) compared 120 companies in the international pulp and paper industry. Our aim is to receive evidence of this method's suitability to analyse monthly account data. We anticipate that the SOM recognises the relationships between different account values and reveals the time variation of the data sets. According to our information the SOM has not been applied earlier to analysing monthly account data sets.

The rest of the paper is organised as follows: Section 2 describes the methodology and the choice of the financial account values. Section 3 presents the construction of the self-organising maps and Section 4 presents a detailed analysis of the maps. The conclusions of this paper are presented in Section 5.

2. Methodology

In this section we provide a description of the self-organising map and describe the choice of the financial account values.

Self-Organising Maps

The SOM is a clustering and visualisation method and the purpose is to show the data set in another representation form (Kohonen 1997). It creates a two-dimensional map from n-dimensional input data. This map resembles a landscape in which it is possible to identify borders that define different clusters. These clusters consist of the input variables with similar characteristics, i.e. in this report, of account values' monthly variation.

The self-organising training trials continue until two input items, which are close in the input space, are mapped into the same or neighbouring neurons on the map. Output neurons create groups, which together form a map of the input neurons. The SOM has six learning parameters, *topology, neighbourhood type, X- and Y-dimensions, training rate*, *training length*, and *network radius*. The network topology refers to the form of lattice. There are two commonly used lattices, rectangular and hexagonal. In a rectangular lattice each neuron is connected to four neighbours, expect for the ones at the edge of the lattice. In the entire network we used, the output neurons are arranged in a hexagonal lattice structure. This means that every neuron is connected to exactly six neighbours, expect for the ones at the edge of the lattice. This choice was made following the guidelines of Kohonen (1997), since we expected the SOM to provide some benefit for the monitoring due to its visualisation capability. Neighbourhood type refers to the neighbourhood function used and the options are Gaussian and bubble. X- and Y-dimensions refer to the size of the map. In too small maps differences between clusters are hard to identify and in too large maps clusters will appear to be flat. The training rate factor refers to how much the neuron in the neighbourhood of the winning neuron learns from the input data vector. The training length measures the processing time, i.e. the number of iterations through the training data. The network radius refers to how many nodes around the "winning" neuron are affected during the learning process. The training process of the network is split into two parts. In part one, the map is "roughly" trained. In the second part, the network is fine-tuned.

Data

We used actual data comprising ten years' monthly income statements of a manufacturing company. The company was a medium-sized firm in Finland and its net sales amounted to approximately EUR 11 million per year. The accounts were chosen with the help of a CPA-auditor in the way that the accounts represented the major and the most interesting monthly income statement categories. The accounts and their monthly averages in thousand euros are presented in Table 1.

Table 1: *Financial Accounts (in EUR 1000)*

	90-99	1998	1999
Net sales	916	1325	1250
Materials + Change in inventory	215	297	259
Personnel costs	125	165	161
Gross margin	571	864	830
Administration	58	57	58
Total indirect	340	360	383
Operating profit	215	462	396
Receivables	1450	1630	1591
Trade debt	1468	2563	1965

The reasons for selecting the above accounts for our models are as follows.

Net sales (NS) are a significant value to audit. In this particular case variation between July and the other months is big because the company is closed in July. From the management's point of view it is better if the actual value is bigger than the budgeted value because then there are fewer disappointments. From the auditor's point of view this might raise doubts about whether all sales are recorded if the actual value is much below the prediction value.

Materials (Mat) + *Change in inventory* (CinIn) together should tell the total use of material during a certain period. The value should be in alignment with net sales as this is a manufacturing company.

Personnel costs (PC) should be in alignment with production and the total use of material.

Gross margin (CM) is an important value at least from the prediction point of view as well as to see how much money is left to cover indirect costs and profit.

Administration (Adm) is a good value to see the overall trend of the costs in the company and in the line of business.

Total indirect (TotInd) indicates all fixed costs. This value should be predicted in all cases because these costs do not depend on sales.

Operating profit (OP) is an interesting value at least from the prediction point of view. Furthermore, it is important to see that the operation is profitable in the long run.

Receivables (Rec) are an interesting and important value to follow in order to know how much of the company's money is "outside".

Trade debt (TD) tells how much the company has to pay "outside". Receivables and trade debts should be in alignment with the net sales.

3. Training the Networks

For the clustering purpose we used The Self-Organising Map Program Package version 3.1 created by The SOM Programming Team of the Helsinki University of Technology in the network building (Kohonen *et al.* 1995). For the visualisation of the results of the SOM we used Nenet -Demo version 1.1a created by The Nenet Team (Elomaa *et al.* 1999). Nenet is a user-friendly program designed to illustrate the use of SOMs, and it also provides individual parameter level maps, feature planes. This property suits our purposes perfectly, because we want to compare different accounts and months with each other.

We constructed two different kinds of maps with different input vectors. Firstly, we constructed a map so that in a vector there were the monthly data of the account per year as vector items. With this A-map we wanted to see how different accounts are situated in comparison to each other and to the previous years' values. Secondly, we constructed a map with the values of a certain month's data as vector values and presented them in a chronological order for the neural network. With this B-map we wanted to see whether there are any yearly tendencies in the data sets. These map approaches resemble analytical auditing procedures such as a comparison of current information with similar information for prior periods, and a study of relationships among the elements of information (Gauntt *et al.* 1997).

There are some rules of thumb when creating maps. The map ought to be rectangular, rather than square, in order to achieve a stable orientation in the data space. Normally, the x-axis should be about 30 per cent greater than the y-axis, thus forming a rectangular output map. Another recommendation is that the training length of the second part should be at least 500 times the number of the network units, in order to reach statistical accuracy (Kohonen 1997). We chose one where the layer consisted of 35 neurons arranged in a 5*7 hexagonal grid. As mentioned earlier hexagonal lattices are good for visualisation purposes. The neighbourhood function was the bubble. The training length and training rate in the first phase were 1750 and 0.5 and in the second phase 17500 and 0.05. The neighbourhood radius in the first phase was 9 and in the second phase 1.

To visualise the final self-organising map we used the *unified distance matrix (U-matrix).* This U-matrix method can be used to discover otherwise invisible relationships in a high-dimensional data space. It also makes it possible to classify data sets into clusters of similar values. The simplest U-matrix method is to calculate the distances between neighbouring neurons, and store them in the matrix, i.e. the output map, which can then be interpreted. If there are "walls" between neurons, the neighbouring ones are distant, i.e. the values differ significantly. The distance values are also displayed in colours when the U-matrix is visualised. On the maps we define the clusters by looking at the colour shades of the borders between the hexagons. The dark colours in the walls represent great distances while brighter colours indicate similarities amongst the neurons. The coloured borders between the hexagons are of great value when trying to determine and interpret clusters.

By viewing the individual feature planes it is possible to visualise the values of a single vector column, i.e. in this study, the maps for one month (A-maps) or for one account (B-maps). These feature planes can be visualised in order to discover how the company has been doing according to different months or different accounts. Because we selected accounts that depend on each other the feature planes of the months should be more or less similar.

4. Analytical Auditing with Maps

Next we show how the outputs of the SOM can be used in analytical auditing procedures. This analysing and testing situation resembles the final overall review stages in a real auditing situation. The auditor analyses the clusters of accounts and variations of the monthly feature planes in order to find whether the clusters are close enough to each other or whether there are any significant differences between the monthly feature planes (A-map). An auditor may also analyse whether the account values are close enough to the previous year's values (B-map). If the difference is significant an auditor has to decide how much and what kind of further work is needed.

Defining the Account Clusters

Studying the underlying monthly feature planes of the A-map (Figure 1), and the final A-map (Figure 2a) a number of clusters of accounts, and the characteristics of these clusters were identified (Figure 2b).

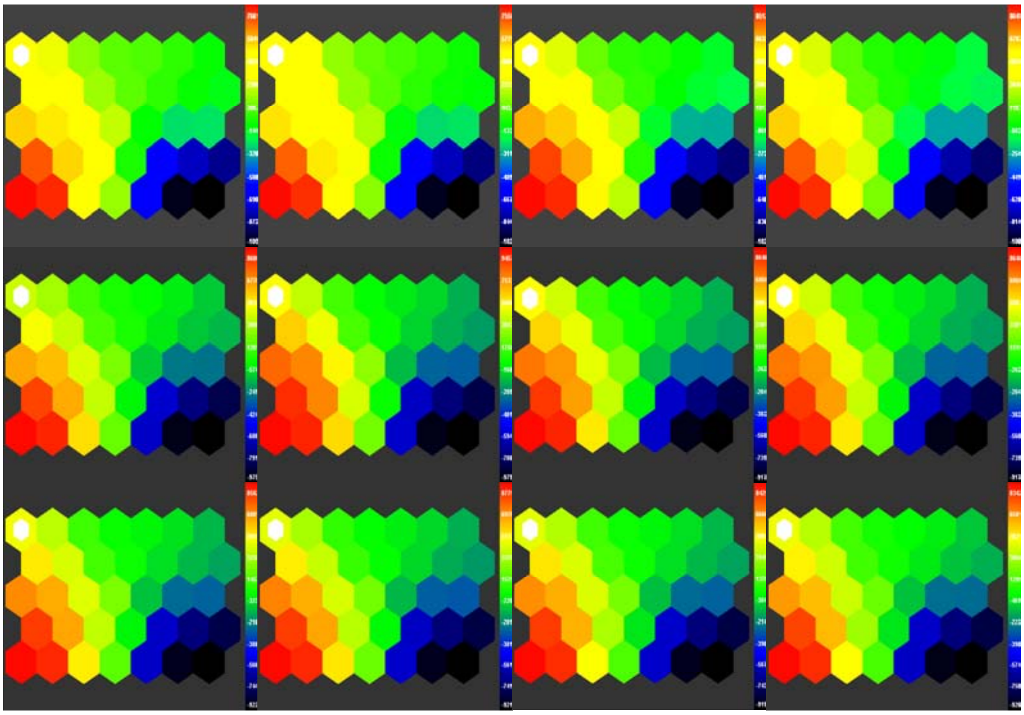

***Figure 1:** The feature planes maps for the months: January, February, March, and April at the top, May, June, July, and August in the middle, and September, October, November, and December at the bottom*

The feature planes in Figure 1 show a map for each month in this study where the red colour in the bottom left corners represents high values, which in our case implies revenue accounts. Dark colours in the bottom right corners show negative values, which in our case implies a trade debt account. From these feature planes we see that there is only a little variation between the months. For example, in the feature planes of June and July there are lighter neurons in the middle than in the other months' planes. However, the feature planes of the months are so similar that none of them gives any reason for auditing implications. This means that the relationships between the accounts included in this study are quite stable during the year. If the feature plane of the month differs much from the other feature planes it is a hint for an auditor to make more tests.

In Figure 2b we have named identified clusters according to the accounts these clusters contain. We labelled the last two years accounts to see whether the accounts are close to each other and to name the clusters. We identified four main clusters: *revenues, margins, costs, and trade debts.* Revenue and trade debt clusters were easy to identify based on the feature planes of the different months. Although the trade debts of the last two years are in the same neuron, the cluster itself is much bigger because the earlier years' trade debt values were more spread out on the map. The revenue cluster could be bigger based on the feature planes on March, June, July, and August, however, the labelling of gross margin and operating profit reveals that these neurons belong to the margins cluster. All the cost accounts in our study are situated in the upper right corner and therefore we named it the cost cluster. Receivables (Rec), net sales (NS), operating profit (OP), personnel costs (PC), change in inventory (CinIn), administration (Adm), and materials (Mat) of two last years are in the same neuron. The Gross margin (GM) and total indirect (TotInd) of 1998 and 1999 are in different neurons. This indicates that the relative monthly account value's variation of gross margin and total indirect is bigger than that of the other accounts in these years.

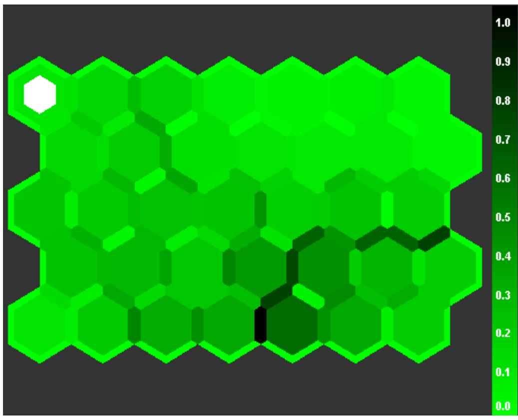

Figure 2a: The final A-map

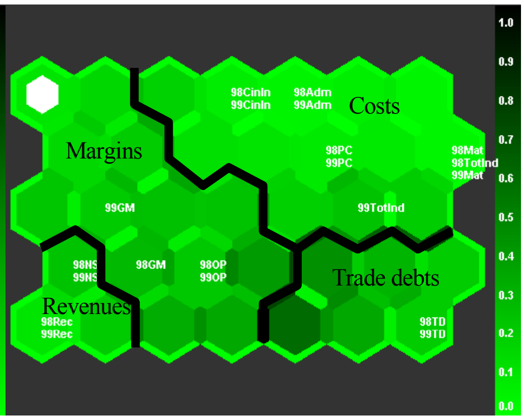

Figure 2b: *Identified clusters on the A-map*

Defining the Yearly Clusters

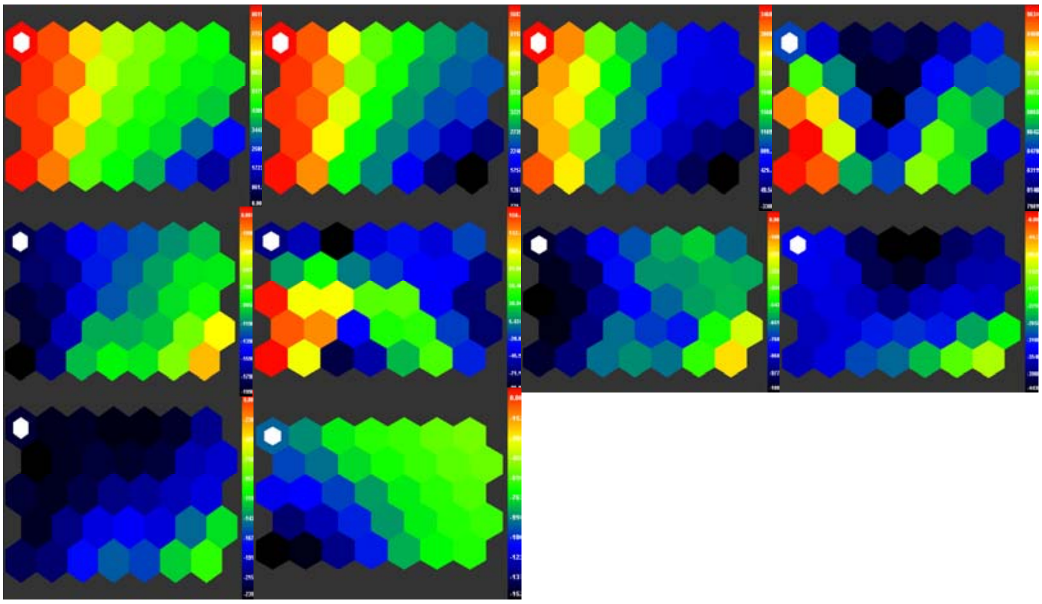

Figure 3: *Feature planes of accounts: Net sales, gross margin, operating profit, and receivables at the top, Materials, change in inventories, personnel costs, and administration in the middle, and Total indirect and trade debts at the bottom*

We also let the SOM cluster the account based on the month. With this B-map we want to see whether the months are close to each other and whether the different years are close to each other. We analysed the B-map with account feature planes (Figure 3) and by labelling all the months on the map. This way we found six clusters in a map. The feature planes of net sales, gross margin, operating profit, and receivables are at the top of the Figure 3. These accounts present in our sample the income accounts where the red colour illustrates high values, which are situated on the left side of the feature planes. The overall outlook of the net sales, gross margin and operating profit seems very similar. The feature planes of materials, change in inventories, personnel costs, and administration are in the middle. Materials and personnel costs have the same general outlook as net sales although the colours are opposite. Its is good because they should be in alignment. The feature planes of total indirect and trade debts are on the bottom line. In these feature planes the darker the colour gets the bigger the cost is.

In Figure 4a we have counted how many monthly data of the year belong to one cluster in the B-map. In Figure 4a we see that there is a tendency starting from the bottom right corner, where the early nineties data is situated, up towards the top of the map and then to the bottom left corner and once again up towards the top of the map. It seems that the best performance is in the bottom left corner where the monthly data from the year 1998 is located. All the July data are in the bottom line neurons. The first seven years' July data are in the ultimate bottom right corner of the map. The July data of 1997-1999 are also at the bottom right neurons of these years' clusters.

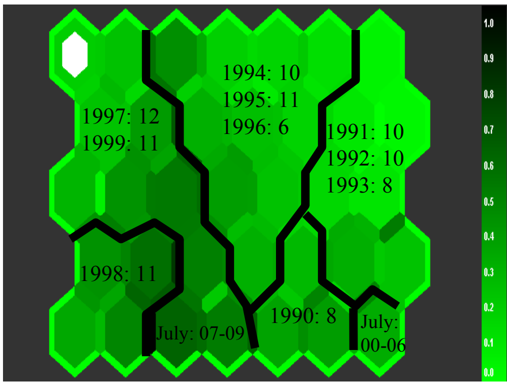

Figure 4a: *Yearly clusters of B-map*

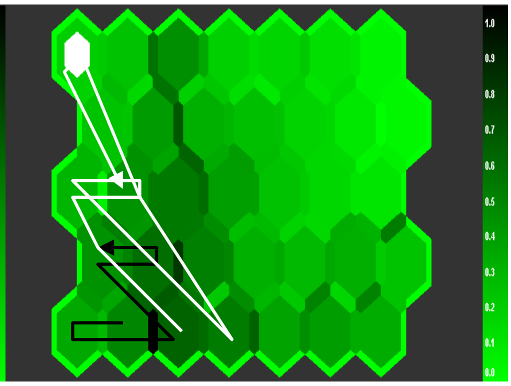

Figure 4b: *Movements of the 1998 (black) and 1999 (white) months*

We also illustrate with a black arrow the monthly movement in 1998 and with a white arrow the monthly movement in 1999 (Figure 4b). From these arrows we see that the movement of the 1999 monthly data on the B-map is much broader. The reason for the more compact movement of the 1998 data might be that the account values of that year are the biggest in the whole data set and therefore they have concentrated in one corner. The same but opposite reason applies to the July data, especially with the years 1990-1996. These account values are the smallest in the whole data set and therefore have concentrated in the bottom right corner. We also see from Figure 4b that both arrows start from and end at adjacent neurons.

Account Values

To ease the ANN's learning process and improve the quality of the map, the data is very often somehow pre-processed. We did not use any pre-processing method because we wanted to calculate the 1999 average account values based on the vector values in the output maps. In Table 2 we compare the actual average monthly account values to values calculated from the vector values of the A-map and B-map. On average it seems that the vector order we have in the B-map is better than the vector order in the A-map if we compare the output vector values.

Table 2: *Account Values*

	1999	A-map	B-map	A/1999	B/1999
Net sales	1250	1238	1239	-1 %	-1 %
Materials + Change in inventory	259	273	269	5 %	4 %
Personnel costs	161	123	161	-24 %	0 %
Gross margin	830	873	807	5 %	-3 %
Administration	58	59	56	2 %	-2 %
Total indirect	383	471	361	23 %	-6 %
Operating profit	396	467	394	18 %	0 %
Receivables	1591	1408	1532	-12 %	-4 %
Trade debts	1965	1626	1978	-17 %	1 %

Seeded Error

We seeded an extra use of material in the data in order to see whether the SOM recognises any difference. We manipulated the data by doubling the use of material in December 1999 in order to see its effects on maps and feature planes. This is a very tiny effect considering that in one map we have all the data from the ten years visible at the same time. In Figure 5 we show how the feature planes of the maps change because of this manipulation. On the left side of the figure we have the feature planes of the original data, and on the right side we have the feature planes of the manipulated data. The feature planes at the top of the figure are based on months (A-map) and the feature planes at the bottom of the figure are based on accounts (B-map). The white neurons on the left show the right place for the vector. The white neurons on the right show where the manipulated data vectors are. We have also circled the effects the manipulation has on the whole map. The monthly use of material is situated in the same neuron in both cases (see Figure 5 upper feature planes). However, the colour of the adjacent neuron has changed dramatically. On the account feature planes the change is more radical. The whole feature plane looks very different. The manipulation has turned the whole feature plane inside out. The neuron has changed its place and the colours of the adjacent neurons have changed.

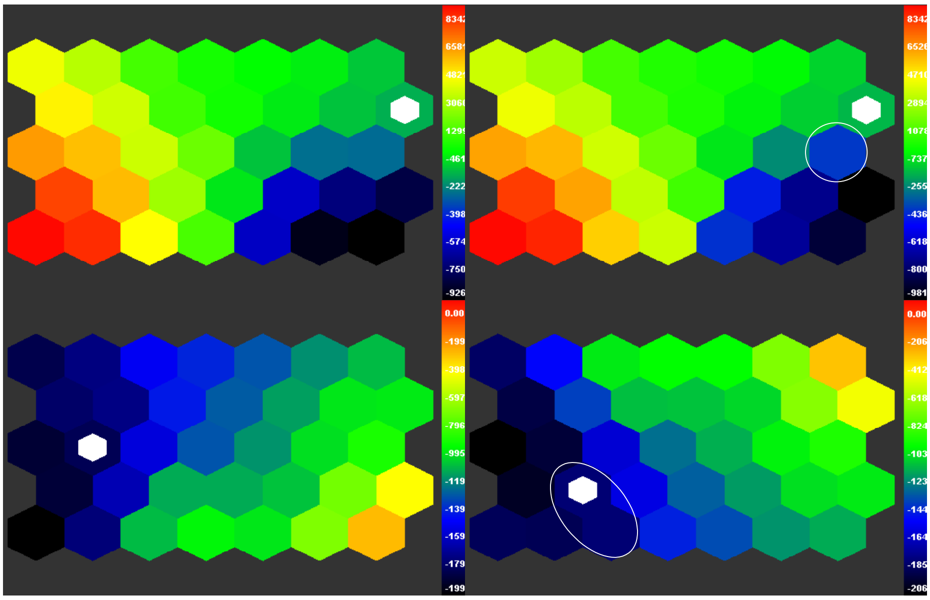

Figure 5: *Seeded Use of Material in December 1999*

5. Conclusions

In this paper we showed how the SOM could be used in the analytical auditing procedures when auditing monthly income statements. The SOM was used for the clustering and visualisation of the data sets and the purpose was to show account values in another representation form. We let the SOM cluster a manufacturing company's monthly account data from ten years. We found that the SOM is a tool for classifying these data sets, and that similar accounts form their clusters close to each other. We argue that the SOM can assist auditors in the analytical auditing process either in the planning or final overall review stages by visualising irregularities in the data and guiding the user to the heart of the problem. This study was carried out with audited data. Therefore an interesting supplement to the SOM's clustering power of monthly account values data is to apply it to unaudited data in praxis. Another way to proceed is to apply the SOM to analysing all the transactions of certain accounts. The development and assessment of advanced analysis methods like ANNs in an auditing context and for continuous auditing is important in order to support users with more efficient and effective means of monitoring account values. This is one way of restoring public confidence in the capital market system and accounting profession that might have been shaken by the Enron collapse.

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