# Analyzing Financial Performance with Self-Organizing Maps


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**Abstract**

Self-organizing maps have shown their suitability for analyzing financial data in a number of studies. They overcome the assumption on normality in the underlying distribution encountered when using multivariate statistical methods as well as difficulties in finding an appropriate functional form for the distributions. Moreover, the results are rather easy to visualize when there are several explanatory variables. Our aim in this study is to get further evidence of this method's suitability to analyze financial data. We show that it can be used to analyze financial performance both between companies in one period and in several periods. We anticipate that self-organizing maps can be used in future for comparing financial performance between different companies and between the same company over time.


## 1 Introduction

Self-organizing maps (SOM) lend themselves very well for analyzing financial data [5, 1, 2]. They overcome the assumption on normality in the underlying distribution encountered when using multivariate statistical methods as well as difficulties in finding an appropriate functional form for the distributions. Moreover, the results are rather easy to visualize when there are several explanatory variables. Our aim in this study is to get further evidence of this method's suitability to analyze financial data. We use it to analyze financial performance between different forest companies world wide over a time period of four years. We anticipate that self-organizing maps can be used in future as an analyzing tool when comparing financial performance between different companies and between the same company over time.

## 2 Self -organizing maps

In this study we want to classify companies according to their financial performance. We want to identify clusters of companies according to their financial performance. Moreover, we are interested in the movements of companies from one cluster to another over time. The self-organizing map has turned out to be a good tool for problems of this type.

A self-organizing map is trained using unsupervised learning. During the training process the network has no knowledge of the desired outputs and hence, the clusters. The training process is characterized by a competition between the output nodes. The input patterns are presented to the network one by one, in random order. The output nodes compete for each and every pattern. The output node with a reference vector that is closest to the input vector is called the winner. The reference vector of the winner is adjusted in the direction of the input vector, and so are the reference vectors of the surrounding nodes in the output array. The size of adjustment in the reference vectors of the neighboring nodes is dependent on the distance of that node from the winner in the output array. In this way the output nodes start to represent certain features in the input vectors and form the clusters.

We use two learning parameters: the learning rate and the neighborhood width parameter. Our criterion for the quality of a good map was the average quantization error, which is an average of the Euclidean distances of each input vector and its best matching reference vector in the map. For more information on self-organizing maps we refer to [4].

## 3 Database and selection of companies

A database developed by a Finnish consulting firm embedded in a large benchmarking system further developed from [9] is used as the experimental financial knowledge base for the neural network tests. This database consists of standardized income statements, balance sheets and cash flow statements of more than 50 companies in the international pulp and paper industry. The database also consists of specific financial ratios, calculated using information from the standardized reports as well as general company information concerning products and production volumes. There are about 30 different key ratios for each company. The companies are all based in one of three regions: North America, Northern Europe or Central Europe. The financial data covers four years from 1988 to 1991, i.e., a newer period than in our previous studies which was based on [6, 7, 8]. In our previous studies the whole period was on the average economically successful for forest companies during the whole time period. In this study we have two years of good economic time and two years of recession.

For our experiment we selected 50 North-American, Central European and Northern-European pulp and paper companies from the database. The companies are listed in Table 1.

## 4 Choice of ratios

Text-books on accounting provide plenty of financial ratios. However, the large variety of different ratios does not make it easy to find a set of them which would present a company's overall performance. Since there is no unambiguous theory according to which one could define the most informative financial figures, it is obvious that different people consider different ratios as the best. The selection depends usually on empirical results from previous studies on the analysts own preferences and, of course, on the purpose of intended use of the ratios. The set of ratios will be different according to whether the intended use is strategic management, bankruptcy predictions or forecasting on the stock market.

In our case the population of ratios is given. It is the 30 ratios in the benchmarking system. These ratios are already organized in the benchmarking system into six groups under the headings:

| | |
|---|---|
| 1) Profitability | 4) Liquidity |
| 2) Indebtedness | 5) Working capital |
| 3) Capital Structure | 6) Cash flow ratios |

Our next step was to choose a set of ratios from this population. We decided to use the same ratios as in our previous studies when possible [1, 2]. The choices in our previous study was based on an empirical study conducted using ten financial analysts from a large Finnish bank who participated in a validation test of the benchmarking system [10]. In the validation test the financial analysts had to deal with issues in the realm of strategic decision-making. If a ratio in that study was used by at least five analysts it was selected as a variable for the network in our study.

| Country | # | Company | # | Company |
|---|---|---|---|---|
| Sweden | 4 | AB Statens Skogsindustrier | 14 | Svenska Cellulosa AB (SCA) |
| | 6 | Korsnäs AB | 15 | Stora Kopparbergs Bergslags AB |
| | 7 | Mo och Domsjö AB | 16 | Södra Skogsägarna AB |
| | 10 | Norrlands Skogsägarens Cellulosa AB | | |
| Finland | 18 | Enso-Gutzeit Oy | 28 | Oy Veitsiluoto Ab |
| | 21 | Kymmene Oy | 29 | Yhtyneet Paperitehtaat Oy |
| | 23 | Metsä-Serla Oy | 137 | Metsä-Botnia |
| | 26 | Sunila Oy | 138 | Myllykoski |
| Norway | 31 | Norske Skogindustrier A.S. | | |
| USA | 37 | Boise Cascade Corporation | 60 | Sonoco Products Company |
| | 40 | Chesapeake Corporation | 61 | Stone Container Corporation |
| | 41 | Consolidated Papers Inc. | 63 | Temple-Inland Inc. |
| | 44 | Federal Paper Board Company | 65 | Union Camp Corporation |
| | 46 | Georgia-Pacific Corporation | 66 | Wausau Paper Mills Company |
| | 49 | International Paper Company | 67 | Westvaco Corporation |
| | 51 | Kimberly-Clark Corporation | 68 | Weyerhaeuser Company |
| | 52 | Longview Fibre Company | 139 | Bowatex Inc. |
| | 53 | Louisiana-Pacific Corporation | 140 | Pope & Talbot Inc. |
| | 56 | Pentair Inc. | 141 | Willamette Industries |
| | 57 | Potlatch Corporation | | |
| Canada | 72 | Canfor Corporation | 79 | Donohue Inc.&Donohue Inc. |
| | 75 | Canadian Pacific Forest Products Ltd. | 82 | MacMillan Bloedel Ltd. |
| | 78 | Domtar Inc. | 86 | Repap Enterprises Corporation Inc. |
| Germany | 96 | Haindl Papier | 135 | Steibeis Holding GmbH |
| Holland | 107 | Koninlijke Nederlandse Papierfabrieken N. V. (KNP) | | |
| Portugal | 127 | Soporcel | | |
| UK | 136 | Arjo Wiggins Appleton | | |
| Switzerland | 130 | Attisholz | 131 | Biber Holding |

Table 1: The selected companies

This rule resulted in the following eight ratios. The numbers in parentheses indicate the appropriate ratio group number shown above.

1. Operating margin (% of sales) (1)
2. Net income (% of sales) (1)
3. Current ratio (4)
4. Net Indebtness (% of sales) (2)
5. Equity/Total Assets (3)
6. Return on equity (ROE) (1)
7. Cash Flow (% of sales) (6)
8. Fixed investments (% of sales) (6)

We note that there are three profitability measures, one indebtedness measure, one capital structure measure, one liquidity measure, no working capital measures and two cash flow measures. It seems reasonable that the emphasis is on profitability in a benchmarking situation.

## 5 Training the networks

The actual construction work was performed using The Self-Organizing Map Program Package (SOM_PAK) version 3.1 prepared by the SOM Programming Team of the Helsinki University of Technology.

We started by standardizing the ratios in the database using histogram equalization [3] in order to ease the SOMs learning process and to improve its performance.

All the maps were trained in two phases. The purpose of the first training phase was to order the randomly initialized reference vectors of the maps to "approximately correct" values. During the second phase the maps were "fine-tuned", i.e., final ordering of the reference vectors took place.

We constructed one map for the whole period 1988-1991 contrary to our previous studies where we constructed maps separately for each of the years 1985, 1986, 1987 and 1989. The network topology chosen was the same as before, i.e., hexagonal with 15 x 10 nodes in each map. The parameters of the three best maps with respect to the average quantization error are given in Table 2.

| Random seed | Phase | Training length | Learning rate | Neighbourhood width | Quantization error |
|---|---|---|---|---|---|
| 6 | 1 | 10000 | 0.07 | 10 | |
| | 2 | 75000 | 0.04 | 3 | 0.262128 |
| 4 | 1 | 7000 | 0.05 | 10 | |
| | 2 | 90000 | 0.04 | 3 | 0.262572 |
| 38 | 1 | 3000 | 0.07 | 10 | |
| | 2 | 85000 | 0.03 | 3 | 0.262953 |

Table 2: Network parameters

## 6 Results

In the construction process a large number of maps were initialized and trained. The best map was more carefully inspected, i.e., the locations of the companies (Figure 1) and the values of the reference vector components (corresponding to financial ratios) for the period were analyzed using the visualization capabilities of the program (Figure 2). In Figure 1, 26.1 means that this is the location of firm 26 in analysis period 1, i.e., 1988 and 26.2 is the location of firm 26 in analysis period 2, i.e., 1989 etc. The value of each reference vector component in each node is visualized by grey-level imaging, light shades representing high values and dark shades representing low values (Figure 2).

We have chosen to interpret the results for the Finnish companies and the US companies. The interpretation could be similarly done for any companies from any countries. The Finnish companies are numbered between 18 and 29 and 137 and 138 the US companies are numbered between 37 and 68 and 139, 140 and 141.

Typically a successful company would be profitable, solvent and growing. A profitable company would typically have a high operating margin, a high net income, a high return on equity. A solvent company would typically have a high equity to total assets, low net indebtedness with high current ratio and high cash flow. A growing company would typically have medium to high investments.

Figure 1 shows that most of the Finnish companies are located in the left uppermost corner while most of the the US companies are in the middle and lower left side in periods 1 and 2. Analyzing the vector component maps in Figure 2 tells us that companies in the left upper most corner have the following characteristics: high operating margin, high net income, high return on equity, high net indebtedness, low equity to total assets, low current ratio, high cash flow and fixed investments. The companies in the middle and lower left have also high values for operating income, net income,

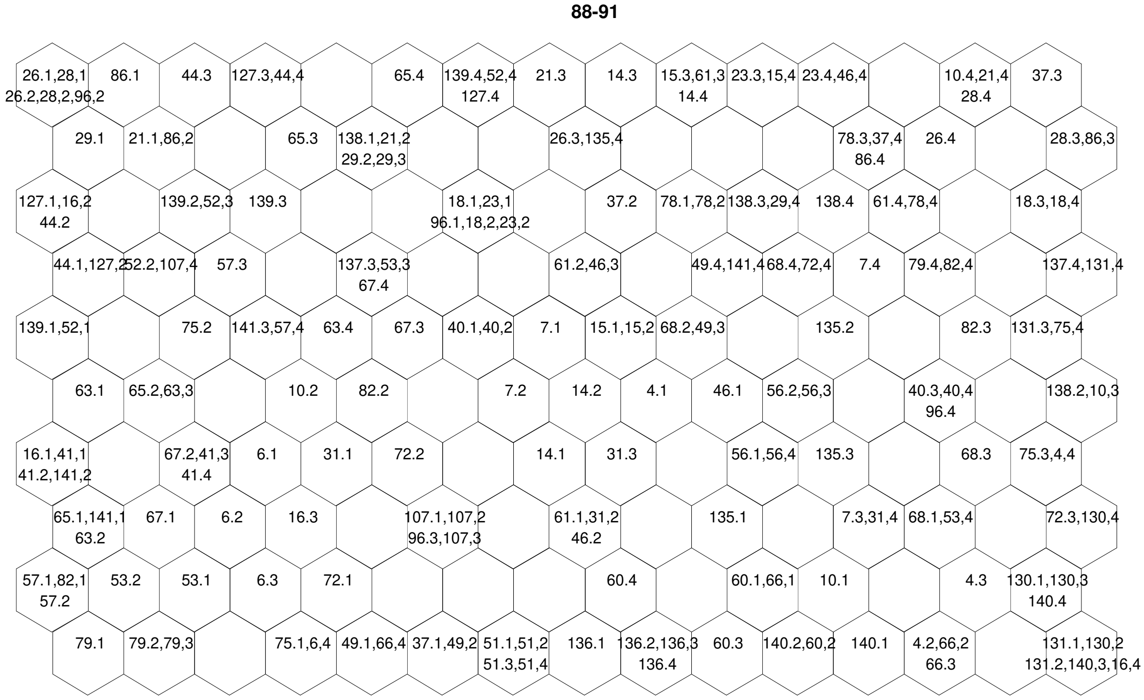


Figure 1: Map for the years 1988-1991

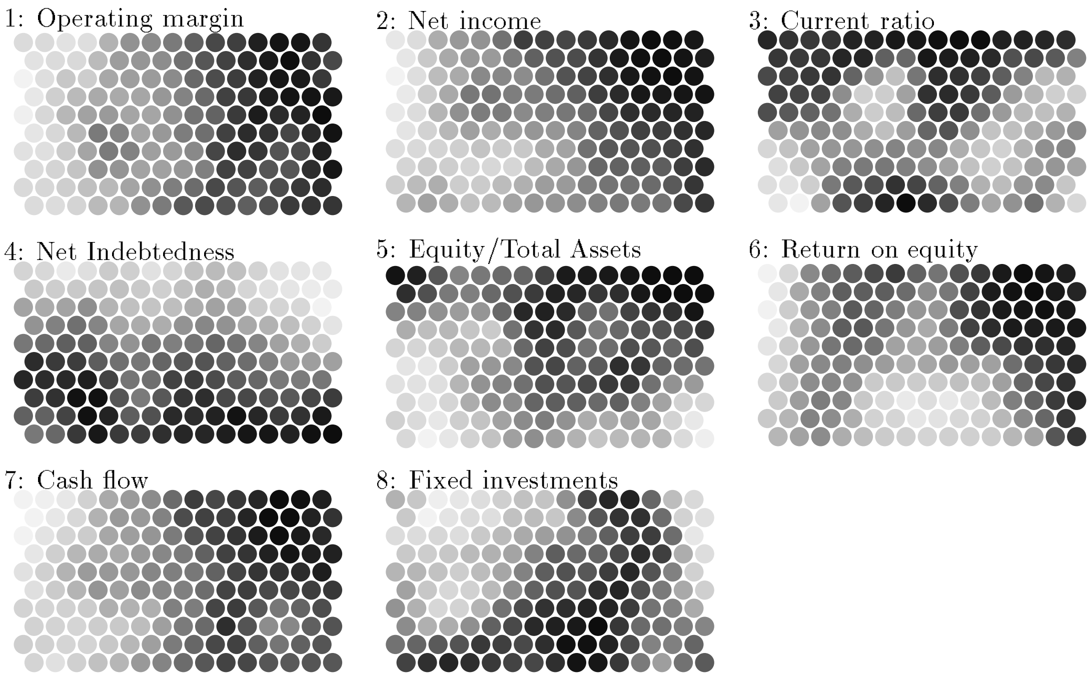


Figure 2: Reference vector component plane maps for years 1988-1991

investments and cash flow, but they have higher current ratio, lower indebtedness rate and higher equity to total assets, i.e., in periods 1 and 2 the Finnish and US companies are profitable and growing, but the US companies have clearly a better capital structure.

In periods 3 and 4 most of the Finnish companies have moved to the uppermost right corner and part of the US companies are there too, but part are in the middle of Figure 1. Analyzing the vector component maps tells us that companies in the right uppermost corner have the following characteristics: low operating margin, low net income medium current ratio, high net indebtedness, low equity to total assets, low return on equity, low cash flow and medium to high investments. Companies in the middle of the map have medium operating profit, medium net income, high to medium current ratio, medium to low indebtedness, medium equity to total assets, high return on equity, high cash flow, and low investment rate, i.e., the US companies are still profitable, have a better capital structure and have a lower investment rate.

The self-organizing maps provide a good tool for analyzing the financial performance between different companies in one period and between periods and differences between the same company over time.

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