Senior Lecturer Adrian COSTEA, PhD
Department of Statistics and Econometrics
The Bucharest Academy of Economic Studies
Tomas EKLUND, PhD
Department of Information Technologies
Åbo Akademi University, Turku, Finland
Jonas KARLSSON, PhD
Statistics and Research Åland, Mariehamn, Finland
Professor Vergil VOINEAGU, PhD
Department of Statistics and Econometrics
The Bucharest Academy of Economic Studies

FINANCIAL PERFORMANCE ANALYSIS OF SCANDINAVIAN TELECOMMUNICATION COMPANIES USING STATISTICAL AND NEURAL NETWORK TECHNIQUES

Abstract. *In this paper we apply a new methodology presented in our previous work to classify telecom companies in respect to their financial performance. We have two goals: to validate our methodology and, using it, to gain insights in a turbulent period in the telecommunications sector. We have obtained higher accuracy rates for the classification models than in our previous studies, and smaller differences between training and test dataset accuracy rates. The two classification techniques have performed similarly in terms of accuracy rates (decision tree, slightly better) and class predictions (multinomial logistic regression, slightly more optimistic). We have analyzed the movements of Scandinavian telecommunications companies. The results are similar to previous findings and show a strong connectivity with what had really happened to Scandinavian telecommunication companies during the second part of the last decade.*

Keywords: *self-organizing-map, logistic regression, decision trees, financial performance, telecom companies.*

JEL Classification: C45, C49, C81, D83

1 Introduction

The growth of the service sector in national economies has brought telecommunications into the spotlight. The quality of traditional forms of telecommunications has improved substantially in the last decade. Also, the rapid development of mobile telephone networks and video and Internet technologies, has had an unprecedented impact on the lives of individuals, as well as on the way people do business. In the last decade a dramatic change in the ownership structure of telecommunications companies has taken place, from public (state-owned) monopolies to private companies. As new competitors arise, companies need intelligent tools to gain a competitive advantage. Also, investors and financial analysts need tested tools to gain information about how companies perform financially compared to their competitors, what they are good at, who the major competitors are, etc. (Karlsson et al., 2001). In this paper we apply a new methodology proposed in Costea and Eklund (2003) to classify telecommunications companies in respect to their financial performance. First we use the SOM (Self-Organizing Map) algorithm to cluster the companies, constructing a two-dimensional U-matrix map. We then attach the class labels to each data row from the dataset and apply two classification methods to develop class prediction models. As we have presented in Costea and Eklund (2003) the two classification methods (multinomial logistic regression and decision tree algorithm) performed similarly on a financial dataset on pulp and paper companies, in terms of their accuracy rates. As a conclusion of this research, we now want to be able to validate our methodology against a dataset consisting of financial data on telecommunications companies. Here we focus more on understanding how different financial factors can and do contribute to the companies' movements from one group/cluster to another. We base our research on one previous study (Karlsson et al., 2001), in which the authors use SOM to evaluate the financial performance of telecommunications companies. The problem with this approach is that we basically have to train new maps, or standardize the new data according to the variance of the old dataset, in order to add new labels to the maps. Inserting new data into an existing SOM model becomes a problem when the data have been standardized, for example, within an interval like [0,1]. Also, the retraining of maps requires considerable time and expertise. In this paper we go one step further and build a model that enables us to predict how the companies would be classified by a particular SOM model. We propose that our methodology solves these problems associated with adding new data to an existing SOM cluster model.

The rest of the paper is organized as follows. Section 2 relates our study with its research area: data mining for knowledge discovery. In section 3 we briefly present the related research concerning the application in this study: financial performance benchmarking. Section 4 presents our new methodology to model the relationship between some financial variables of telecommunications companies and their financial performance classifications. In the following section we present the results of clustering phase, and then in section 6, the two classification models are applied and compared. In section 7 we analyze the results using the data for some companies in 2000, and finally, we present our conclusions.

2 Knowledge Discovery Process

Managers are more and more often confronted with complex economic problems and with the limitations associated with using traditional techniques to analyze their data.

The large amounts of data within organizations and the limited possibilities for finding patterns in the row data have lead managers and researchers to rethink the process of analyzing the data. With increasing frequency, managers are turning to *Knowledge Discovering in Databases* (KDD) for help in analyzing the large amounts of financial data available today. The actual data mining is only one part of the entire KDD process, as is illustrated in Figure 1. The KDD process is as follows (Adriaans & Zantinge, 1996).

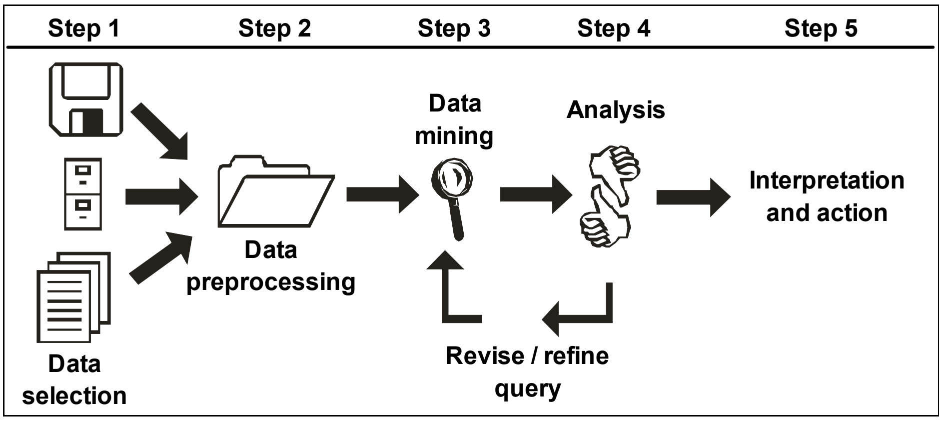

Figure 1. The KDD process. (Adapted from Adriaans & Zantinge, 1996)

In the first step, data selection, the data to be used are selected, and their sources are identified. The data can be from several sources, for example, databases, data warehouses, flat files, etc. In the second step, preprocessing, the selected data are preprocessed, i.e., cleaned and coded. Firstly, the data have to be cleaned in order to correct errors, account for missing data, remove duplicate data, etc. External sources can also be used to enrich the data. Finally, the data are coded. In the third step, data mining, the actual data-mining tool is used. In the fourth step the output is reviewed by an expert, and the query is refined if necessary. If the expert is content with the results, they are interpreted and actions are taken based on the output (Adriaans & Zantinge, 1996).

In this paper, the data consist of financial statements from a number of international telecommunications companies. A number of financial ratios, chosen from a study on the reliability and validity of financial ratios in international comparisons (Lehtinen, 1996), are calculated. The SOM (self-organizing map) algorithm is used for data mining. Analysis of the final map revealed a number of clusters, representing different classes of financial performance.

This cluster analysis forms the base upon which we built our class predictive models.

3 Related Research in Companies' Financial Performance Benchmarking

Financial benchmarking and performance analysis have been often studied in the research literature. Many different approaches have been proposed, ranging from statistical approaches to artificial intelligence and visual data mining techniques. Applications include credit/bond rating, failure/bankruptcy prediction and competitor analysis.

The SOM has been extensively applied for tasks related to medicine and engineering, and to a lesser extent, for tasks related to financial performance analysis (Oja et al., 2003). In an important financial performance task, bankruptcy prediction, the SOM has been widely tested (e.g., Martín-del-Brío and Serrano Cinca, 1993; Back et al. 1995; Serrano-Cinca, 1996:1998a:1998b; Kiviluoto, 1998). Several papers have also been written on using the SOM for macro level financial performance analysis (e.g., Arciniegas et al., 2001; Costea et al., 2001; Kasabov et al., 2000; Kaski and Kohonen, 1996; Länsiluoto et al. 2004).

In a strongly related SOM application, Back *et al.* (1998) perform a financial benchmarking of more than 120 international pulp-and-paper companies between 1985 and 1989, based on their annual financial statements. The authors used nine financial ratios to study the performance of the companies over time, and conclude that there are benefits in using the SOM to manage large and complex financial data. Eklund *et al*. (2003) further investigate the suitability of the SOM for financial benchmarking of international pulp and paper companies. The dataset consisted of seven financial ratios calculated for 77 companies for six years (1995-2000), and the model is used to e.g., benchmark the Top 5 companies in terms of size, identify the best and poorest performers, and to study mergers and acquisitions. In Eklund et al. (200x), the model is validated through an expert survey, lending further support for using the SOM for financial benchmarking. In a similar study, Karlsson *et al*. (2001) used the SOM to benchmark companies in the international telecommunications sector.

Ohlson (1980) is one of the first studies to apply *logistic regression* (LR) to predicting the likelihood of companies' bankruptcy. Since it is less restrictive than other statistical techniques (e.g., discriminant analysis) LR has been used intensively in financial analysis. De Andres (2001, p. 163) provides a comprehensive list of papers that used LR for models of companies' financial distress.

Induction techniques such as Quinlan's C4.5/C5.0 decision-tree algorithm were also used in assessing companies' financial performance. Shirata (2001) used a C4.5 decision-tree algorithm together with other techniques to tackle two problems concerning Japanese firms: prediction of bankruptcy and prediction of going concern status.

Examples of other techniques used to perform different clustering and classification tasks can also be found in the current related literature. For example, Ştefănescu et al. (2008) proposed two algorithms for hierarchical classification: CLAS.1, based on an ultrametric distance, and CLAS.2, based on a scatter function to classify the shares from Bucharest Stock Exchange which had profit during the last two years. Jaba et al. (2008) analyzed the dynamics of the unemployment rate in Romania using Principal Component Analysis and Discriminant Analysis. Ruxanda (2009) illustrated how potential functions method can be used to perform supervised pattern recognition, and Trandafil et al. (2009) applied Black and Scholes structural approach on credit risk in the case of the companies listed on Romanian Stock Exchange

4 Short description of the methodology

The methodology presented in Costea and Eklund (2003) consists of two phases: a clustering phase, in which we obtain several clusters that contain similar data-vectors in terms of Euclidean distances, and a classification phase, in which we construct a class predictive model in order to place the new row data within the clusters obtained in the first phase as they become available.

There are several clustering methods available, and they can be divided into two categories: *hierarchical* and *non-hierarchical*. Hierarchical clustering can be further divided into *splitting* and *merging techniques*. In the case of merging hierarchical clustering, each input data-vector is first associated with a cluster. Then, a measure is used to calculate the distance between all clusters. The two clusters that are closest to each other are then merged. These steps are repeated until one single cluster is obtained. For further information on different clustering techniques and how they work, read Han and Kamber (2006). Non-hierarchical (partitive) clustering techniques directly divide the data into clusters so that the intra-cluster distance is minimized and inter-cluster distance is maximized (Tan et al., 2002). Among clustering techniques, the SOM (a non-hierarchical clustering technique) has the advantages of good visualization and low computational cost.

In the classification phase we want to build a model that describes one categorical variable (our performance class) against a vector of dependent variables (in our case: the financial ratios). In the literature (Hand et al., 2001) three approaches to build real classifiers are presented: the *discriminative approach*, the *regression approach* and the *class-conditional approach*. The two classification techniques used in this paper and in Costea and Eklund (2003) belong to the regression approach. The decision tree algorithm can be included in both discriminative or regression approaches, depending upon how it is set up: if the tree provides the posterior class probability distribution at each leaf (regression approach) or the tree provides only the predicted class at each leaf (discriminative approach). The decision tree software tool that we use (See5 software) supports the regression approach in the sense that it calculates these posterior probabilities for each new data row.

The different steps included in our methodology are presented below.

- Steps for the clustering phase:
- preprocessing of initial data,
- training using the SOM algorithm,
- choosing the best map, and
- identifying the clusters and attaching outcome values to each data row.

Steps for the classification phase using multinomial logistic regression:
- developing the analysis plan, estimation of logistic regression,
- assessing model fit (accuracy),
- interpreting the results, and
- validating the model.

Steps for the classification phase using the decision tree algorithm:
- constructing a decision tree using a classifier,
- assessing model accuracy,
- interpreting the results, and
- validating the model.

This methodology was applied on Karlsson et al.'s (2001) financial dataset that consists of 462 data rows for 88 companies from five different regions: Asia, Canada, Continental Europe, Northen Europe, and USA. The time span is 1995-1999. We use the data for the year 2000 to test our classification models.

5 Applying SOM

The SOM algorithm is a well-known unsupervised-learning algorithm developed by Kohonen in the early 80's. A comprehensive explanation of this algorithm and its software implementation can be found in Kohonen (1997) and Kohonen et al. (1996).

When training the maps with SOM we followed the same procedure as in Karlsson et al. (2001). First of all, in order to avoid the algorithm placing too much emphasis on extreme values, we have limited the range of the all variables to –50, 50. Then, the data were standardized using several standardization methods: the standard deviation of the entire dataset, the standard deviation of each individual variable, the variance of the entire dataset, and the variance of each individual variable. Different values for SOM parameters were tested on the four obtained datasets. Finally, we chose the variance of the entire dataset as the standardization method due to better maps in terms of their readability. The final map average quantization error was: 0.039245. The chosen U-matrix map and its clearly identifiable clusters are presented below (Figure 2):

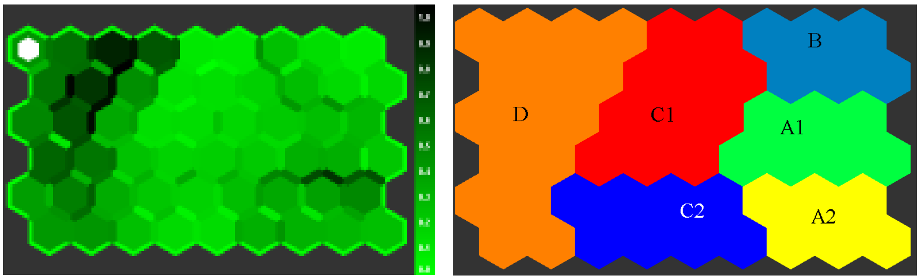

Figure 2. (a) The final 9x6 U-matrix map and (b) the identified clusters on the map.

The financial ratios used were the same as in Karlsson et al. (2001):

Table 1. The financial ratios used

Profitability ratios	1. Operating Margin 2. ROTA 3. ROE
Liquidity ratios	4. Current Ratio
Solvency ratios	5. Equity to Capital 6. Interest Coverage
Efficiency Ratios	7. Receivables Turnover

In order to define the different clusters features planes were analyzed as well as the row data. By analyzing the feature planes one can easily discover how well the companies have been performing according to each financial ratio. Dark colors of neurons on a feature plane correspond to low values for that particular variable, while light colors correspond to higher values. In our particular case, all of the variables are positively correlated with company performance (higher values for variables imply good performance by the company and vice versa). The class variable that we add to the dataset for each data row is in this case measured on an ordinal scale, rather then on an interval one. This means that the classes (A_1, A_2, B, C_1, C_2, D) are in ascending order in terms of companies' financial performance, but they are not equally distributed (the distances among different classes are different). A short explanation of the characteristics of each group/ cluster is presented below:

Group A_1 – corresponds to the best performing companies (profitability very good, solvency decent, liquidity slightly worse). Sample companies: British Telecom (97-99), Nokia (97-99), Samsung (95, 99), etc.

Group A_2 – the second best performing group (slightly lower profitability than Group A_1, strong liquidity and solvency). Sample companies: Benefon (95-97), Motorola (95), Sonera (98), etc.

Group B – includes companies with slightly poorer financial performance than the A groups (good profitability, especially ROE ratio, poorer liquidity and solvency than the A companies). Sample companies: Alcatel (97-98), Nokia (95-96), etc.

Group C_1 – decent profitability, good liquidity, poorer solvency and efficiency (Interest Coverage and Receivables Turnover). Sample companies: DoCoMo (95-99), Sonera (95), etc.

Group C_2 – is slightly poorer than the C_1 group. It contains companies with decent profitability, poor liquidity, and poor solvency and efficiency ratios. Examples: British Telecom (95-96), Motorola (96-99), Telia (95-99), etc.

Group D – the poorest group: poor profitability and solvency, average liquidity. It mainly contains service providers from Europe and USA, and Japanese companies in 98-99 (due to the Asian financial crisis that peaked in 1997-98).

After we chose the final map, and identified the clusters, we attached class values to each data row as follows: 1 – A_1, 2 – A_2, 3 – B, 4 – C_1, 5 – C_2, 6 – D. In the next section we will construct two different classification models to classify the data for the year 2000 into already existing clusters. We will compare the two models in terms of their accuracy rates and class prediction performances.

When constructing the maps (.cod files) we have used a built-in Windows software program, developed by one of the authors, which is based on SOM_PAK C source files that are available at http://www.cis.hut.fi/research/som_pak/. Nenet v1.1a, available for free-demo download at http://koti.mbnet.fi/~phodju/nenet/Nenet/Download.html, was used to visualize the ".cod" files.

6 Applying the two classification techniques

A more detailed presentation of each classification technique (multinomial logistic regression – MLR and decision tree induction – DTI) can be found in Costea and Eklund (2003). Here, we will apply our methodology and try to validate it.

Firstly, **multinomial logistic regression** was applied on the dataset (updated with values for the class variable, i.e., the associated cluster from the SOM). Our research problem was to find a relationship between a categorical variable (financial performance class) and a financial data-vector. We had no problems regarding requirements about size and missing data in our dataset. As in Costea and Eklund (2003), the SPSS software package was used to perform the logistic regression. To see how well the model fits the data we look at the "Model Fitting information" and "Pseudo R-Square" output tables of SPSS (chi-square value has a significance of < 0.0001 and Nagelkerke $R^2 = 0.978$). This means that there is a strong relationship between the class variables and the financial ratios (97.8% of the class variation is explained by variations in input variables). To evaluate the accuracy rate of 92.4%, we used two criteria (to calculate two new accuracy rates): the proportional by chance and maximum by chance accuracy rates (Table 2).

Table 2. Evaluate the model accuracy

	Model	Proportional by chance criterion	Maximum by chance criterion
Telecom	92.4%	17.83%	24.5%

The model accuracy rate is validated against both criteria (it exceeds both standards: 1.25 * 17.83% = 22.3% and 1.25 * 24.5% = 30.62%). To interpret the results of our analysis, we study the "Likelihood Ratio Test" and "Parameter Estimates" output tables of SPSS. All variables are significant ($p < 0.01$), except "Current Ratio" ($p = 0.16$), which means that this variable doesn't have a strong contribution to explaining class predictions. However, keeping this variable will not harm our model. Not all coefficients for all regression equations are statistically significant. By looking at columns "B" and "exp(B)" from the "Parameter Estimates" output table, we can determine the direction of the relationship and the contribution to performance classification of each independent variable. The findings are as expected e.g.: the likelihood that one data row will be classified into group A_1 is positively correlated with profitability and solvency ratios and, slightly, negatively correlated with liquidity and efficiency ratios. This corresponds with the characteristics of group A_1 (findings of Karlsson et al. (2001)).

We validate our MLR model by splitting the data into two parts of the same size (231 data-rows). When we have used first part ("split" = 0) as training sample, we have used the second one as test sample, and vice versa. The results are presented below (Table 3):

Table 3. Datasets' accuracy rates and accuracy rates estimators when applying multinomial logistic regression

		Main dataset	Part1 (split=0)	Part2 (split=1)
Telecom	Model Chi-Square ($p < 0.0001$)	1374.786	680.809	793.776
	Nagelkerke R^2	0.978	0.976	0.997
	Learning Sample	92.4%	90.5%	99.6%[2]
	Test Sample	no test sample	83.9%	85.5%
	Significant coefficients ($p<0.02$)	ALL except: Current Ratio[3]	ALL except: ROTA[4]	ALL except: RT[5]

Comparing the results with what we obtained when applying MLR in Costea and Eklund (2003), we can say that here we have higher accuracy rates, and smaller differences between training and test dataset accuracy rates (90.5% - 83.9% against 89% - 76.1%). The accuracy rate of the "Part1" dataset (90.5%) validates the main dataset's accuracy rate (92.4%). We have obtained a large accuracy rate for "Part2" dataset (99.6%), most probably, due to multicollinearity among variables, the small dimension of training dataset (231 data-rows), and/or the problem of variables selection and outliers. Consequently, in this case, we obtained pseudo-R^2 coefficients (Nagelkerke R^2 = 0.997). However, when validating, we take into consideration the results of "Part1" training dataset with "Part2" being the test dataset.

Secondly, Quinlan's **C4.5/C5.0 decision tree algorithm** (Quinlan, 1993) was applied on our "Telecom" dataset. We use the See5.0 free-demo software that implements a higher-level version of the algorithm. We performed three runs of the See5 software, exactly like we did when applying logistic regression: one for the whole dataset, another using the first split dataset ("split=0"), and the other using the second half of the data ("split=1"). Due to the number-of-rows restriction (max 400 rows) of See5.0 demo-software, we have used 75% (346) of the data rows to build the initial tree. The remaining 25% was used to calculate a test accuracy rate. To validate the model we split the dataset into two parts (50% of data rows each), and exactly like in the MLR case, we used one as the training dataset and the other as the test dataset. The results are presented in the next table (Table 4).

[2] This high accuracy rate is due to quasi-complete separation of the data (probably, too small sample size).

[3] This coefficient is significant for $p < 0.160$.

[4] This coefficient is significant for $p < 0.122$.

[5] Unexpected singularities in the Hessian matrix are encountered. Possible multicolinearity problems.

Table 4. Dataset accuracy rates and accuracy rates estimators when applying decision tree algorithm

		Main dataset	Part1 (split=0)	Part2 (split=1)
Telecom	Learning Sample	95.1%	91.8%	93.5%
	Test Sample	87.9%	89.6%	85.7%
	cross-validation	86.4%	no cross-validation	no cross-validation

When constructing the trees we have used fuzzy thresholds to avoid the problem of small changes in the values of the attribute possibly changing the branch taken to test the next attribute. Using fuzzy thresholds both branches of the tree are explored and the results combined to give a predicted class. For comparability reasons, we kept the two most important parameters constant: $m = 5$, which measures the minimum number of cases each leaf-node should have, and $c = 25\%$ (default value) that is a confidence factor used in pruning the tree.

By looking at Tables 3 and 4 we can compare the two classification models: the accuracy rates for the main dataset were close to each other (92.4% and 95.1%), with slightly better classification for the decision tree. The classification models were validated against split datasets for both models: (90.5% and 99.6% for MLR) and (89.6% and 85.7% for DT).

If we compare the results of this study with what we have obtained in Costea and Eklund (2003), we can state that here the accuracy rates are higher (the models fit the data better) for both classification techniques. We can also verify our findings (which correspond to findings in Rudolfer et al. (1999)) that the two classification techniques perform similarly in terms of models' accuracy rates.

In the next section we will validate our models against their class predictions using data from the year 2000 for Scandinavian companies. We will also show how these companies have moved on the map and how this relates to reality.

7 Benchmarking and Prediction Analyses of Companies

In this section we benchmark and predict different performance classes (year 2000) for Scandinavian telecommunications companies. While this can be a further research problem, it is not our intention to benchmark/classify the financial performance of all 88 companies in this study, but rather, to test our methodology on this important and more (for us) familiar telecommunications industry.

In the following, each company's performance will be illustrated on the map in Figure 3.

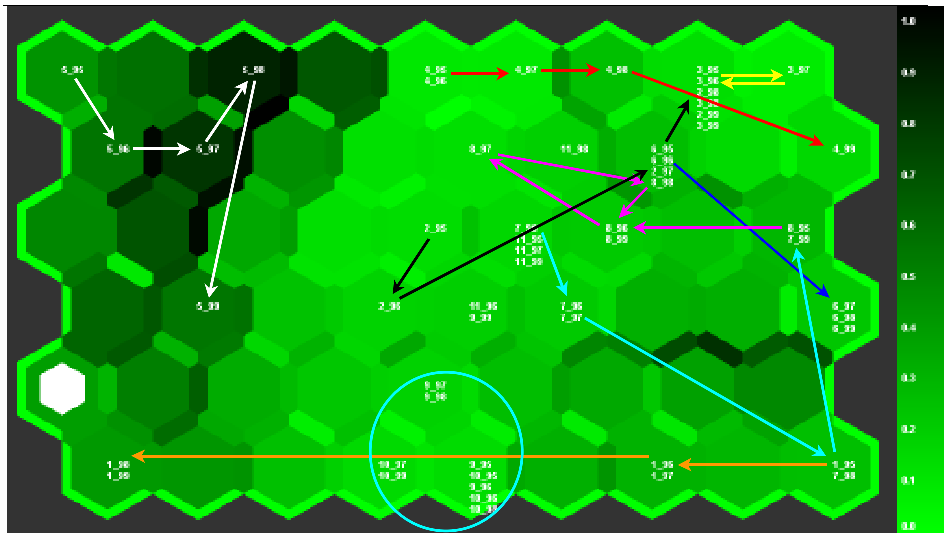

Figure 3. The financial performance of Scandinavian telecommunications companies during 1995-99

Benefon (No. 1, orange arrows), a small Finnish mobile phone manufacturer, shows excellent performance during the years 1995-97, remaining in Group A_1. However, the effects of the Russian and Asian financial crises were heavy on the company, and Benefon slipped into the poorest group, group D. Profitability dropped considerably during 1998-99, but solvency remained high. In 2000, profitability was still heavily negative, but less so than during 1999. However, solvency was much lower.

Doro (No. 2, black arrows) is a Swedish manufacturer of telecom equipment showing steady improvements in its financial performance. In 1995-96 the company is in Group C1, but increasing profitability (especially in ROE) places the company in Group B, quite near Ericsson, for the rest of the period. In 2000, Doro's profitability was negative, especially in ROE.

Ericsson (No. 3, yellow arrows), a Swedish major manufacturer of mobile phones and network technology, shows very good performance during 1995-99, remaining in Group B. Profitability, solvency, and liquidity are very good, although not quite as good as for Group A_1. Ericsson also has very high values in receivables turnover. In 2000, Ericsson's performance continued to be strong, with slight increases in nearly all ratios.

Helsingin Puhelin Yhtiöt (No. 4, red arrows, now Elisa) is the second largest Finnish service provider, and like Sonera, is showing good performance. In 1995-97 the company is in Group C1, but steadily improving financial performance brings the company into Group B in 1998. The year 2000 brought problems for HPY, and the values in nearly all ratios dropped.

NetCom (No. 5, white arrows) is a Swedish service provider that operates in a number of Scandinavian countries. Heavy startup costs have kept the company in Group D for the entire period. The results for 1998 and 1999 were actually positive, but poor values in ROE have kept the company in Group D. In 2000, NetCom's equity problems were finally solved, resulting in a considerable improvement in ROE and Equity to Capital.

Nokia (No. 6, blue arrows), the leading mobile phone manufacturer, is consistently the best performing Scandinavian telecommunication company. The company is located in Group B during 1995-96, but increased values in all financial ratios pushed the company into Group A_1. Nokia's performance continued to be strong in 2000, with slight improvements in nearly all ratios.

Sonera (No. 7, turquoise arrows, now Telia Sonera), the largest Finnish service provider, performs well rising from Group C_1 in 1995 to Group A_1 in 1996-97. In 1998, a drop in profitability forces Sonera into Group A_2. In 1999, profitability increased again, and Sonera moved back into Group A_1. In 2000, Sonera's profitability improves but solvency decreases, indicating increasing indebtedness. In fact, Sonera's Equity to Capital has been falling steadily, from 36.22 in 1996 to 18.47 in 2000.

Tele Denmark (No. 8, purple arrows) remains in the same area of the map, starting out in Group A_1, but dropping into Group C_1 due to decreasing profitability in 1997. However, in 1998 increasing profitability brings the company into Group B, and then in 1999, to Group A_1. In 2000, Tele Denmark's performance continues to improve.

Telia (No. 10, Sweden) and TeleNor (No. 9, Norway) are interestingly similar in performance, and the companies actually discussed a merger during the course of 1999-2000. However, the deal never materialized due to ownership disagreements. The performance of the two companies is very similar, although Telia shows slightly better profitability and liquidity, while TeleNor shows slightly higher solvency. In 2000 TeleNor's profitability drops, while Telia's profitability increases. Both companies' solvency decreases somewhat, more for TeleNor.

In Table 5, the class predictions based on financial data for the year 2000 are illustrated.

Table 5. Class predictions using two classification models

Company	OM	ROTA	ROE	Current	EC	IC	RT	label	Predicted Cluster	
									MLR	**DT**
Benefon	-17.03	-30.02	-74.63	1.21	25.10	-12.05	5.93	1_00	D	D
Doro	-2.11	-3.90	-63.69	2.23	13.87	-1.26	6.85	2_00	D	D
Ericsson	11.39	14.63	67.26	1.88	16.80	7.52	3.94	3_00	B	B
HPY	11.98	7.70	10.87	0.53	15.70	3.84	5.81	4_00	C_1	C_1
NetCom	18.77	14.77	66.37	2.75	16.02	4.14	10.10	5_00	B	B

Nokia	19.01	34.98	52.49	1.57	52.22	50.75	5.09	6_00	A_2	A_2
Sonera	84.97	30.11	140.15	0.80	18.47	12.76	1.07	7_00	A_1	B
TeleDenmark	29.07	22.26	49.46	1.18	36.96	6.86	2.64	8_00	A_1	A_1
TeleNor	9.91	5.57	6.76	1.01	24.52	1.99	4.41	9_00	C_1	C_1
Telia	22.20	12.08	22.39	2.37	51.02	41.57	2.52	10_00	A_2	A_2
Average	18.81	10.82	27.74	1.55	27.07	11.61	4.84	11_00	A_1	C_1

Comparing the two classification techniques in terms of their financial class predictions, we can state that while MLR is more optimistic than DT, the two methods results are very similar. There are 2 cases out of 11 that are classified differently: Sonera (7_00) and Average (11_00). This is due to the fact that our MLR and DT models emphasize different variables: the DT model relies heavily on ROE, Interest Coverage, Equity to Capital, while the first MLR equation (that calculates the probability that class = A_1) has a higher coefficient (greater weight) for Operating Margin, and a lower coefficient for ROE than the third MLR equation (class = B). Also, the value 140 for ROE can be considered an outlier compared to the other ROE values, and consequently, can negatively affect the DT classification model.

8 Conclusions

In this study, we were interested in two different goals, which are inter-correlated: to benchmark/classify worldwide telecommunications companies and to test our new clustering/classification methodology (presented in Costea and Eklund (2003)) on this important and sensitive sector. The two goals are inter-correlated in the sense that we use the methodology to achieve the classification of telecommunications companies as accurately as our methodology allows.

When benchmarking, we have analyzed the movements of Scandinavian telecommunications companies. The results show a strong connectivity with what had actually happened to these companies during 1995-1999, which was verified using existing domain knowledge from the textual parts of the annual reports and Karlsson et al. (2001). Then, we have used new financial data (for the year 2000) to place the companies on the map. We have to underline the fact that our methodology does not allow us to predict the different values for financial variables, but rather to make CLASS predictions based on already known financial data. We are not doing time-series analysis, looking for trends for each particular variable.

While our approach, in this study, is more to validate the methodology presented in Costea and Eklund (2003), in the future we will focus on more practical problems. Once we have validated the class prediction models, we can focus on different telecommunications actors/characteristics separately, by answering questions like: “How do the largest manufacturers perform and how will they perform compared to each other?” or “To what extent has the Asian financial crisis affected the Japanese telecommunications sector?" or focusing on one single company: "What lead Ericsson to experience the huge losses in 2001-2002? How it will perform in the future, financially?"

To validate the methodology we have used different tests: ease-of-readability and the average quantization error for the clustering phase, accuracy rates and performance of class prediction (how it corresponds to the reality) for the classification phase. We have obtained a good (in terms of the above two criteria) final U-matrix map, and clearly identified the six financial performance clusters. The methodology pasted the classification phase's test, as well: we have obtained higher accuracy rates than in the previous study, and smaller differences between training and test dataset accuracy rates. The results emphasize our findings presented in Costea and Eklund (2003): the two classification techniques have performed similarly in terms of accuracy rates (DT, slightly better) and class predictions (MLR, slightly more optimistic). We, therefore, propose that our methodology greatly extends the feasibility of using self-organizing maps for financial analysis.

REFERENCES

[1]**Adriaans, P. and Zantinge D. (1996),** ***Data Mining***. Addison-Wesley Longman: USA;

[2]**Arciniegas, I., Daniel, B. and Embrechts, M.J. (2001),** ***Exploring Financial Crises Data with Self-Organizing Maps (SOM)*** in Allinson, N. Yin, H., Allinson, L. and Slack, J. (Eds.), *Advances in Self-Organizing Maps*, Springer-Verlag, London, pp. 39-46;

[3]**Back, B., Oosterom, G., Sere, K. and van Wezel, M. (1995),** ***Intelligent Information Systems within Business: Bankruptcy Predictions Using Neural Networks***. The *3rd European Conference on Information Systems (ECIS'95)*, Athens, Greece, June 1–3;

[4]**Back, B., Sere, K., and Vanharanta, H. (1998),** ***Managing Complexity in Large Databases Using Self-Organizing Maps***. *Accounting Management and Information Technologies* **8**(4):191-210;

[5]**Costea, A., Kloptchenko, A., Back, B. (2001),** ***Analyzing Economical Performance of Central-East-European Countries Using Neural Networks and Cluster Analysis***. *Proceedings of the Fifth International Symposium on Economic Informatics*, I. Ivan. and I. Rosca (eds), Academy of Economic Studies Publishing House, Bucharest, Romania, pp. 1006-1011;

[6]**Costea, A. and Eklund, T. (2003),** ***A Two-level Approach to Classifying Countries/Companies Economic/Financial Performance***. Intelligent Systems and Soft Computing, in proceedings of the *Thirty-sixth Annual Hawaii International Conference on System Sciences (HICSS 36)*, Hawaii, USA, January 6-9;

[7]**De Andres, J. (2001),** ***Statistical Techniques vs. SEE5 Algorithm. An Application to a Small Business Environment***. *The International Journal of Digital Accounting Research* **1**(2): 153-178;
[8]**Eklund, T., Back, B., Vanharanta, H., Visa, A. (2003),** ***Financial Benchmarking Using Self-Organizing Maps – Studying the International Pulp and Paper Industry***. *Data Mining - Opportunities and Challenges* (Chapter 14 – pp. 323-349). J. Wang, Ed. Hershey, PA, Idea Group Publishing;
[9]**Han, J., and Kamber, M. (2006),** ***Data Mining – Concepts and Techniques*****.** Morgan Kaufmann Publishers;
[10]**Hand, D., Mannila, H., and Smyth, P. (2001),** ***Principles of Data Mining***. The MIT Press. Cambridge;
[11]**Jaba, E., Bălan, C., Roman, M., Viorica, D., and Roman M.D. (2008),** ***Employment Rate Prognosis on the Basis of the Development Environment Trend Displayed by Years-Clusters***, Economic Computation and Economic Cybernetics Studies and Research, Vol. 3-4, pp. 123-136;
[12]**Karlsson, J., Back, B., Vanharanta, H., and Visa, A. (2001*), Financial Benchmarking of Telecommunication Companies***. *TUCS Technical Report* No. 395. Turku Centre for Computer Science: Turku;
[13]**Kasabov, N., Erzegovezi, L., Fedrizzi, M., Beber, A., and Deng, D. (2000),** ***Hybrid Intelligent Decision Support Systems and Applications for Risk Analysis and Prediction of Evolving Economic Clusters in Europe***. *Future Directions for Intelligent Information Systems and Information Sciences*. N. Kasabov (ed.). Springer Verlag, pp. 347-372;
[14]**Kaski, S. and Kohonen, T. (1996),** ***Exploratory Data Analysis by the Self-Organizing Map: Structures of Welfare and Poverty in the World*** . In Apostolos, P.N.R., Abu-Mostafa, Y., Moody, J. and Weigend, A. (Eds), *Neural Networks in Financial Engineering*, World Scientific, Singapore, pp. 498-507;
[15]**Kiviluoto, K. (1998),** ***Predicting Bankruptcies with the Self-organizing Map***. *Neurocomputing*, Vol 21, No 1-3, pp. 191-201;
[16]**Kohonen, T., Hynninen, J., Kangas, J., and Laaksonen, J. (1996),** ***SOM_PAK: The Self-Organizing Map Program Package***. Helsinki University of Technology;
[17]**Kohonen, T. (1997),** ***Self-Organizing Maps***. 2nd edition. Springer-Verlag. Heidelberg;
[18]**Lehtinen, J. (1996),** ***Financial Ratios in an International Comparison***. Acta Wasaensia. 49. Vasa;
[19]**Länsiluoto, A., Eklund, T., Back, B., Vanharanta, H. and Visa, V. (2004),** ***Industry Specific Cycles and Companies' Financial Performance - Comparison with Self-Organizing Maps***. *Benchmarking: An International Journal*, Vol 11, No 4, pp. 267-286;
[20]**Martín-del-Brío, B. and Serrano-Cinca, C. (1993),** ***Self Organizing Neural Networks for the Analysis and Representation of Data: some Financial Cases*****.** *Neural Computing & Applications*. Springer Verlag (ed.) **1**(2): 193-206.
[21]**Ohlson, J.A. (1980),** ***Financial Ratios and the Probabilistic Prediction of Bankruptcy***. *Journal of Accounting Research* **18**(1):109-131;

[22]**Oja, M., Kaski, S., and Kohonen, T. (2003),** ***Bibliography of Self-Organizing Map (SOM) Papers:*** *1998-2001;* Addendum. *Neural Computing Surveys* **3**: 1-156;
[23]**Quinlan, J.R. (1993),** ***C4.5 Programs for Machine Learning***. Morgan Kaufmann Series in Machine Learning. Morgan Kaufmann Publishers. San Mateo;
[24]**Rudolfer, S., Paliouras, G., and Peers, I. (1999),** ***A Comparison of Logistic Regression to Decision Tree Induction in the Diagnosis of Carpal Tunnel Syndrome***. *Computers and Biomedical Research* 32 (1999), 391-414;
[25]**Ruxanda, G. (2009),** ***Supervised Pattern Recognition with Potential Functions Method***. Economic Computation and Economic Cybernetics Studies and Research, ASE Publishing House, Bucharest,; Vol. 2, pp. 43-60;
[26]**Serrano-Cinca, C. (1996),** ***Self Organizing Neural Networks for Financial Diagnosis***. *Decision Support Systems*. Elsevier Science **17**: 227-238;
[27]**Serrano-Cinca, C. (1998a),** ***Self-organizing Maps for Initial Data Analysis: Let Financial Data Speak for Themselves. Visual Intelligence in Finance using Self-organizing Maps***. Guido Deboeck and Teuvo Kohonen (eds.). Springer Verlag, July 1998;
[28]**Serrano-Cinca, C. (1998b),** ***From Financial Information to Strategic Groups - a Self Organizing Neural Network Approach***. *Journal of Forecasting*. John Wiley and Sons (ed.), September, **17**: 415-428;
[29]**Shirata, C.Y. (2001),** ***The Relationship between Business Failure and Decision Making by Manager: Empirical Analysis.*** Proceedings of *13^{th} Asian-Pacific Conference on International Accounting Issues*, October 28, 2001, pp. 20-23.
[30]**Ştefănescu, V., Ferrara, M., and Dedu, S. (2008),** ***Algorithms for Hierarchical Classification with Applications in Portfolio Management***; Journal of Economic Computation and Economic Cybernetics Studies and Research, ASE Publishing House, Bucharest; Vol. 3-4, pp. 109-122;
[31]**Tan, R.P.G.H., van den Berg, J., and van den Bergh, W.-M. (2002),** ***Credit Rating Classification using Self Organizing Maps***. In: eds. Smith, K., Gupta, J., *Neural Networks in Business: Techniques and Applications*, IDEA Group Publishing, pp. 140-153, 2002;
[32]**Trandafil, C., Brezeanu, P., and Huidumac, C. (2009),** ***Empirical Perspective on Corporate Default Risk at Industry Level. Case-Study on Companies Listed on Romanian Stock Exchange,*** *E*conomic Computation and Economic Cybernetics Studies and Research; ASE Publishing House, Bucharest Vol. 1, pp. 203-218.