December 2007

# Mining Quarterly Reports for Intraday Stock Price Trends

Anna Mironenko
*Taganarog Institute of Technology*

Antonina Durfee
*Appalachian State University*

# Mining Quarterly Reports for
# Intraday Stock Price Trends

**Antonina Durfee**
**Appalachian State University, NC, USA**
durfeea@appstate.edu

**Anna Mironenko**
**Taganrog Institute of Technology, Southern Federal University, Russia**
akloptch@mail.ru

## Abstract

*This paper proposes a methodology for predicting a change in stock prices trends for the time immediately following the publishing of quarterly reports. The methodology consists of three components. The first component benchmarks companies from the same line of business based on their financial ratios. The second component retrieves quarterly reports that share common patterns. The third component determines the direction of a stock price trend. The results indicate that mining of quarterly reports allows capturing important patterns which influence the traders' expectation and result in stock price change.*

*Keywords: data mining, stock prediction*

## Introduction

Business forecast is a crucial process for planning and decision making, and thus, prediction of stock price trends for publicly traded companies is a popular and far–reaching goal. Most of the studies for stock price prediction are based on analysis of the numeric indices, such as company financial ratios, S&P index, current stock prices, monthly growth, changes of macroeconomic factor, and changes in market volatility (Cao, Leggio et al. 2005; Pai, Chang et al. 2005). Conversely, some traders' expectations are built on disclosed textual materials, such as, top-expert opinions, CEO's interviews, press releases, and market analysis, news, quarterly and annual reports. Processing and analyzing the huge amount of finance-related textual and numeric information looking for the hints of companies' future financial performance and strategic development is becoming time prohibitive.

Bad earnings reports, negative press releases, roundabout message and indefinite style of annual reports normally cause traders to sell stocks at the lower price. Similarly, optimistic and straight forward style of financial reports, good earning numbers and positive news contribute to increasing buying pressure that drives stock prices up. By law, annual and quarterly reports contain information on past financial performance of a company. The style and managerial priorities used in the descriptive part of the reports disclose important information on the future of a company. Unlike numbers that simply state facts, textual descriptions provide explanations why those had occurred (Kloptchenko, Eklund et al. 2002).

There are a number of computer-based methods for analyzing quantitative accounting and finance data ranging from spreadsheets to neural networks. However, there are not as many computer-based methods for analyzing qualitative data, and there are even fewer methods that combine quantitative and qualitative data to do forecasts. Data and text mining methods offer the opportunity to discover hidden patterns that can be useful for particular purposes from huge amounts of data (Fayyad, 1996). The combination of data and text mining (TM) methods allows discovery of more complex patterns in business-related data and brings additional understanding of real-world business situations to the decision makers.

In this paper we assume that the probabilities of the paths in the random walk model change immediately after quarterly report announcement and that this skewness can be derived from the style and content of a report without consideration for other related information. Based on the assumption we propose a methodology to predict a direction of stock price trend every time a quarterly report is released. The methodology is based on the discovery of common patterns in texts of quarterly reports and historic financial performance of companies from the same line of business. Firstly, we cluster the quantitative data from quarterly reports in the form of financial ratios using the Self-Organizing Map (SOM). Secondly, we perform content-based clustering of qualitative data from textual parts of quarterly reports using a proprietary prototype-matching methodology. Thirdly, we classify the results from quantitative and qualitative clustering using a multilayered feed-forward neural network (MFNN). Our conceptual framework is tested on recent quarterly performance of Nokia, Ericsson, and Motorola and continues on the study by (Karlsson, Back et al. 2001) where a SOM on historic financial ratios of 99 telecommunication companies was built. The quantitative data consists of a number of calculated financial ratios, and the qualitative part consists of textual parts of reports.

# Background

Modern corporate communication includes things such as fact books or fact sheets, news releases, Web sites, financial reports and meetings or conference calls with analysts or investors. New communication and information technologies have simultaneously increased the types of media and decreased the companies' costs of direct communication with all elements of the investment community. Consequently, companies' choices of communications with the investment community involve not only matters of disclosure content but also delivery media. Nonetheless, the annual report remains a centerpiece of corporate communication. Its historical and symbolic value, along with the breadth of its distribution makes it able to convey the company's facts and message.

While annual reports have a long history, it was not until 1933 that U.S. securities regulation established a set of disclosure requirements for publicly traded firms (Bricker, 2000). Annual Reports are published for the benefit of shareholders and are not required by law. Any particular content also is not required for annual reports, though they typically include extensive financial information. Annual reports have evolved since that time, to contain several key elements, including a set of financial statements with related notes and auditor's letter, a CEO's letter, and Management's Discussion and Analysis. Publicly traded companies publish annual reports and submit filings to the Securities Exchange Commission in the USA (MIT-Libraries 2001). Regulations have also specified that certain types of disclosures and discussions be included in a company's financial report to prevent companies from providing false or incomplete information to mislead investors and disturb the market. Research indicates that annual reports have multiple audiences, including stockholders and the financial community, and varying objects, ranging from questions of stewardship to outright promotions of the company (Hawkins and Hawkins, 1986). Annual reports while being important documents to stockholders and financial communities and firmly regulated are still the controversial ones. They generate disagreement regarding audience, objectives and credibility.

In short-term perspective quarterly reports are the important means for companies in appraising past performance and projecting future opportunities to their readers, who primarily consist of investors and analysts. In order to assess the comparability of financial numeric and textual information from annual or quarterly reports, the large quantity of reports must be read and analyzed. Industrial analysts have individual intuitive methods to uncover indications and hints about companies' future financial performance by reading their financial reports and making "professional guesses". Manual detection of important hints is a time-consuming process that requires a lot of training, background knowledge, and experience. The availability of computerized TM solutions for detecting companies' future financial intentions can be used in two ways: it can lighten the work load of analysts, or it can conceivably help companies' officials to sway the public opinion by manipulating and faking positive writing style. Since the language of quarterly reports has not been studied to any larger extent, our literature review is based on a broad body of literature written on the language of annual reports, conducted within linguistics, business communication, finance, and decision making studies.

There have been a number of studies attempting to resolve the controversial nature of company annual reports as a medium of corporate communication with investors during the last decades. Thomas (1997) concentrated on transitivity, thematic structure, context, cohesion and condensation in the language used in the reports by studying the annual reports of a machine tool manufacturer during a period, which began with prosperity and ended with severe losses. During the time of analysis, the structure of the language used in the reports had changed. The researcher saw an increase in the use of passive constructions, which present the actor (i.e. the company) as "being" rather than as "doing" as the profits decrease. This indicates that management is trying to present itself as a victim of unfortunate circumstances to create an impression of objectivity for the reader. Nonetheless, when the company was making more profit, it presented itself as aggressive and forward moving through the use of active voice and verbs with both an actor and a goal. A close look at the language structure in the letters to stockholders made by Thomas (1997) showed that the structure of the financial reports indirectly reveals some strategic things that the company may not wish to announce directly to its outside audience. A similar

opposition between the actions of the company and circumstances created by nonhuman agents has been noted by (Kendal, 1993). Kendal (1993) introduced the concept of drama and classified the words and phrases describing actors and objects in the drama into two groups, god terms and devil terms. Some examples of god terms such as *growth*, *increased sales* and *competitive position* are the words representing unquestionably good concepts in the eyes of the company. Devil terms are terms like *losses*, *decline in sales* and *regulations*. In the annual reports analysed by Kendal, the company clearly plays the part of the hero, and the U.S government is presented as the villain of the drama, trying to obstruct the actions of the hero in the American economy setting. Similar terminology is used in the quarterly reports that constitute the material for my study. According to (Kohut and Segars, 1992) communication strategies hidden in annual reports differ in terms of the subjects emphasized when the company's performance worsens.

The annual and quarterly reports have a similar structure, conventions and communicative purposes. (Grant, Fogarty et al. 2000) examined the annual reports of sixteen Fortune 500 companies from eight different industries. The analysis showed that the content of annual reports is contingent upon company culture, management, performance, regulatory requirements, and a variety of other factors. The study found that changes in the composition of the company had an impact on the content of the annual report, but not in easily predictable ways. The profitability of companies did not systematically affect the amount of their disclosures for the current year, but affected the composition of disclosures. While studying the relationship between readability of annual reports and financial performance of the companies, Subramanian, Isley, et al. (1993) had shown that the annual reports of the well-performed companies were easier to read than those of poorly performed companies. The annual reports are not only the best possible description of a company, but are also a description of a company's managerial priorities. Osborne, Stubbart, et al. (2001) explored the strategic goals of the companies described in the presidents' letters to stakeholders. After performing computer-aided content analysis of more than four hundred president's letter to shareholders, and examining the empirical linkages between mentioned themes and companies' performances, they concluded that the text in annual reports reflects the strategic thinking and alignment with goal of company's management.

The first attempts to semi-automatically analyze and compare the information from quantitative and qualitative parts of annual reports were made by (Back, Toivonen et al. 2001), (Back, Vanharanta et al. 1999). Their results indicated that there are differences in clustering results of qualitative and quantitative data due to a slight tendency to exaggerate the real financial performance in the text. Kloptchenko, Eklund et al. (2002) discovered that quarterly reports tend to contain information on both future and past performance, so that the tables with financial numbers indicate what a company has done and linguistic structure and written style in textual part indicate what a company will do. They suggest using these indications for forecasting purposes.

Numeric data analysis with regard to predicting stock market direction or stock prices trends was undertaken by (Cao, Leggio et al. 2005; Pai, Chang et al. 2005). Text analysis with correspondence to stock market dynamics was undertaken by Wuthrich et al (1998). A dictionary consisting of 392 keywords was composed from news articles from five popular financial websites available before the opening of the Hong Kong stock market provided a ground for running k-nearest neighbor and neural network algorithms. An average obtained accuracy for a model was 46%, which is significantly better than 33% of random prediction assuming bullish, bearish or neutral output. The authors provided evidences to Market hypothesis which states that new information affects the stock price within very short time. Lavrenko, Schmill et al. (2000) focused on analysis of intraday stock prices for financial time series and their correlation with content of news articles. The authors evaluated their method by performing market simulation that led to an average profit per trade of 0.23%. Mittermayer (2004) analyzed and categorized press releases and derived stock trading recommendations from them using supervised learning algorithm. The average profit per trade using the proposed system was 0.11% and 0% for a random trader, respectively.

# Methodology

Our framework consists of three components: mining quantitative and qualitative data from quarterly reports and classifying retrieved findings to determine stock trend direction (bullish, bearish or neutral).

The SOM clustering ability was utilized for financial benchmarking of quantitative data (Back et al., 2001). SOMs are useful tools for exploratory data analysis that create a two-dimensional map from highly-dimensional input data (Kohonen, 1997). A map resembles a landscape with identifiable borders to differentiate different clusters that are made up of input variables with similar characteristics (Honkela, Kaski et al. 1997). In order to make the quantitative data comparable, seven financial ratios were calculated following the recommendation of international benchmarking of (Lehtinen, 1996). Seven financial ratios: *Operating Margin*, *Return on Total Assets* (ROTA) and *Return on Equity* (ROE), one liquidity ratio, *Current Ratio*, two solvency ratios *Equity to Capital* and *Interest Coverage,* and only one efficiency ratio *Receivables Turnover* fulfilled the criteria of good validity and reliability. The formulas for the ratios and data standardization can be found in (Kloptchenko, Eklund et al. 2002).

The prototype-matching text clustering methodology proposed by Visa et al. (2002) was used for qualitative data analysis. A prototype is a document or a part of it, which is of specific interest to a particular user. The chosen prototype is matched with an existing document collection to find the most similar documents in a collection. Constructing the histograms of the documents' word and sentence code numbers according to the corresponding value of quantization allowed us to compare documents to each other simply by calculating the Euclidian distances between their histograms. The smallest Euclidian distance between word histograms indicates a commonality in vocabulary of the reports. The smallest Euclidian distance between sentence histograms indicates similarities in written style and/or content of the reports (Visa, Toivonen et al. 2002).

A supervised neural network was trained by backpropagation algorithm to classify clustering results (Rumelhart, Widrow et al. 1994). The feedforward artificial neural networks used for nonlinear transformations of a multidimensional input variable into another multidimensional output variable (Safer and Wilamowski, 1999). A measure of performance indicates how well a neural network has learned the relationships in the data. In prediction problems this measure is an error between the predicted outputs and the actual desired outputs. In the study we followed the recommendations given by Walczak and Cerpa (1999) to choose the size of test and train data set, appropriate learning algorithm, network architecture, number of hidden nodes and type of activation function to avoid overfitting the network.

# Results

## *Quantitative data analysis*

By carefully analyzing an output map, six major clusters of companies were identified using both the U-matrix map and the individual feature planes. By analyzing the shades of the borders between the hexagons, we found similarities as well as differences among them. The identified clusters are presented in Figure 1 in the form of a U-matrix map. Groups $A_1$ and $A_2$ represent the class of the best-performing companies. For the companies situated in subgroup $A_1$, profitability is very good, with very high values in Operating Margin, ROTA, and ROE ratios. Group B represents the companies with slightly lower performance. These companies are distinguished by good profitability. ROE values are excellent. These companies have lower liquidity and solvency ratios than the companies in Groups A. Companies from groups $C_1$ and $C_2$ have moderate performance. In the $C_1$ group, companies possess decent values in profitability, liquidity, and Equity to Capital ratios. Companies from the $C_2$ subgroup have decent values of profitability, but low liquidity, Interest Coverage and Receivables Turnover ratios. The values of Equity to Capital ratio, on the other hand, are good. Group D contains companies with poor performance, distinguished by low values of profitability and solvency ratios. At the same time, values of liquidity are average, and Receivables Turnover varies from very good to bad.
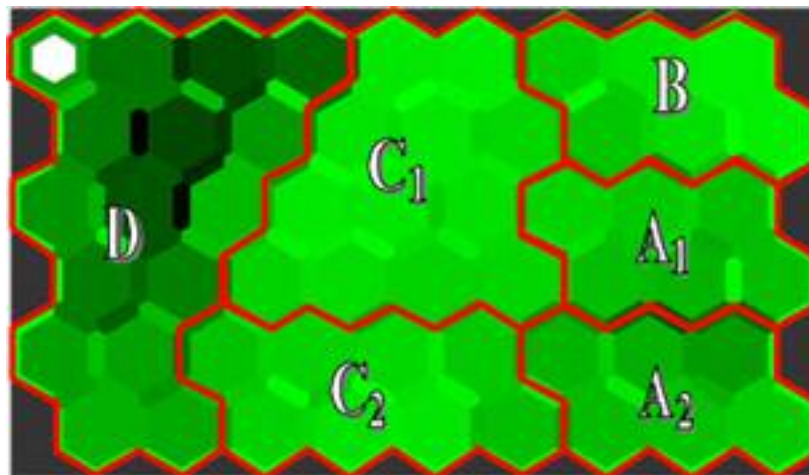


**Figure 1. The U-matrix with six identified clusters.**

The historic performance of companies positioned on U-matrix is presented in Figure 2. For instance, the map reads that **Ericsson**, is facing severe financial difficulties during 2001-2002. Previously it have been situated close to or inside the above average groups, but during the last two years it shows much poorer results, and is situated in the worst group. Nokia,

on another hand, migrated from the best performing group to a mediocre back to the best performing group during a time of analysis.
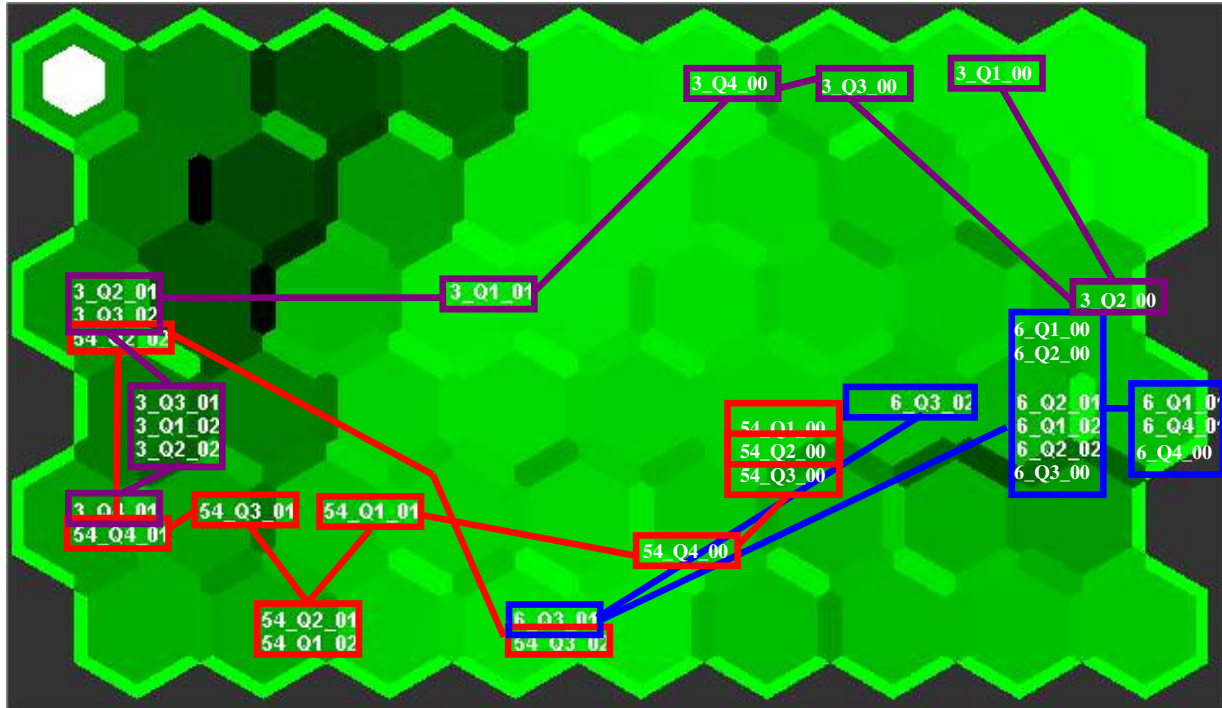


**Figure 2. The identified clusters and the quarterly movements of Ericsson(3), Motorola(54), and Nokia(6).**

## *Qualitative data analysis*

After running the prototype-matching algorithm on an entire collection of sample reports, the closest matches to every report were obtained. The example of text mining results from qualitative data clustering for Ericsson is presented in Table 1. The column contains a report-prototype in the gray-shaded header and the four closest matches to it in the consequent rows. The bold letters by the report codes denote the cluster from which a particular report belongs to from the quantitative clustering.

It reads, for example, that the report from Ericsson year 2000, quarter 1 positioned by data mining step among companies from group B, on a sentence level is similar to a report from Nokia, year 2000, quarter 1. Nokia at that time was among the best performing companies from group $A_1$. The second closest by content report to the Ericsson report is the report from Motorola 2001, quarter 3 which performed poorly and was clustered in group D, and so on. This means that the reports from Nokia 2000, quarter 1, Motorola 2001, quarter 3 and the Ericsson 2000, quarter 1 have similarities in sentence construction and word choice, contributing to similarities in structure and written style. Word choice has less impact on determining the closest matches than the sentence construction. As evidence of that, quarter names and proper names, e.g. Nokia, Motorola or Ericsson, do not determine the clusters.

As a general observation, the reports from the companies with good and steady financial performance have the reports from the well-performed companies among their closest matches, i.e. appearance of the Nokia report from 2001, quarter 4 among the closest matches. If a company's performance worsens in the future, then the reports from average or badly performed companies fire among the closest matches, i.e. the Ericsson report from 2000, quarter 4. The report from Motorola year 2000 quarter 3 has linguistics peculiarities and can be disregarded from the quantitative analysis.

*Forecasting from a combination of quantitative and qualitative data mining*

An individual multilayered feed forward neural network for every analyzed company because every company has its own trend, cycle of development and speed of applying changes to affect its performance was constructed. Additionally, every company has a unique style to describe its evolution during the reported period in every quarterly report. Training one network for all the reports from three companies did not give any robust results due to the individual trends that the companies follow. Because of the limitation of our data set and the nature of our research, where we want to find out whether the company worsens or improves its performance, we merge clusters $A_1$ and $A_2$ into cluster A (best performers), and clusters $C_1$ and $C_2$ into cluster C (moderate performers) resulting into a four level performance scale. Stock prices were collected from www.money.cnn.com, on days after reports were released. We decoded the inputs on the scale from 1 to 4, so that cluster A corresponds to 1, B to 2, C to 3, and D to 4; bullish (increase in price) trend was decoded as 1 and bearish (decrease in price) trend was decoded as 2.

| decoded data | 1st match | 2nd match | 3rd match | 4th match | Target Output | Output |
|---|---|---|---|---|---|---|
| Nokia2000RQ1 | 2 | 3 | 3 | 1 | 2 | 2 |
| Nokia2000RQ2 | 1 | 4 | 1 | 4 | 2 | 2 |
| Nokia2000RQ3 | 1 | 4 | 3 | 3 | 1 | 1 |
| Nokia2000RQ4 | 1 | 3 | 4 | 1 | 2 | 2 |
| Nokia2001RQ1 | 1 | 1 | 4 | 3 | 2 | 2 |
| Nokia2001RQ2 | 1 | 3 | 1 | 3 | 2 | 2 |
| Nokia2001RQ3 | 4 | 1 | 4 | 1 | 1 | 1 |
| Nokia2001RQ4 | 1 | 1 | 4 | 1 | 2 | 2 |
| Nokia2002RQ1 | 1 | 3 | 1 | 1 | 2 | 2 |

**Table 2. Sample of training and testing data and architecture of the MFNN for Nokia**

| Ericsson2000RQ1 **B** |
|---|
| Nokia2000RQ1 $A_1$ |
| Motorola2001RQ3 **D** |
| Motorola2000RQ2 |

| Ericsson2000RQ2 $A_1$ |
|---|
| Ericsson2000RQ3 **B** |
| Nokia2001RQ4 $A_1$ |
| Nokia2000RQ3 $A_1$ |
| Ericsson2000RQ1 **B** |

| Ericsson2000RQ3 **B** |
|---|
| Ericsson2000RQ2 $A_1$ |
| Ericsson2000RQ4 $C_1$ |
| Ericsson2000RQ1 $A_1$ |
| Nokia2001RQ4 $A_1$ |

| Ericsson2000RQ4 $C_1$ |
|---|
| Ericsson2000RQ3 **B** |
| Motorola2001RQ2 **D** |
| Ericsson2000RQ1 **B** |
| Motorola2001RQ3 **D** |

| Ericsson2001RQ1 $C_1$ |
|---|
| Ericsson2001RQ3 **D** |
| Ericsson2001RQ2 **D** |
| Nokia2001RQ4 $A_1$ |
| Nokia2001RQ3 $C_2$ |

| Ericsson2001RQ2 **D** |
|---|
| Nokia2001RQ3 $C_2$ |
| Motorola2001RQ4 **D** |
| Nokia2001RQ4 $A_1$ |
| Ericsson2001RQ1 $C_1$ |

**Table 1. The sample of the closest matches to Ericsson reports**

We use grouping of company obtained from SOM clustering (from 4.1), and the closest matches obtained from qualitative clustering (from 4.2) as input variables for MFNNs. For every company data we train three-layered MFNN with one node in a hidden layer. Table 2 presents the sample of Ericsson data set that was fed into training the MFNN for predicting Ericsson performance in 2002, quarter 1.

Similar data sets for Motorola and Nokia were used to create separate MFNNs. The activation functions used in the hidden and final layers were sigmoidal. We have tried to reduce the dimensionality of the MFNN by decreasing the number of input variables, but according to the domain knowledge, four first matches capture the tendency of future financial performance the optimal way. Therefore, despite the overfitting problem, we trained 5-1-1 MFNN for the analyzed companies. Although we did not use any validation sets in our exploratory study, the fact that financial performance for all three companies could be predicted by MFNN with similar architecture intuitively proves the initial idea. We use Neural Works Predict software to train MFNN.

## Limitations, conclusions and future work

The proposed methodology was designed for performing competitor or industry analysis, as well as determining the direction of stock price trend of the companies within the same line of business. We clustered the financial ratios of the companies using SOM and visualized this classification. Then, we analyzed the textual parts of quarterly reports for the same period of time, in order to reveal the heuristic relationship between the written style and facts stated by the numbers (ratios).

This research extended the work of (Kloptchenko, Eklund et al. 2002) by predicting the future financial performance of the companies based on the hidden stylistic indications in textual parts of the reports by means of MFNN. Before a dramatic change occurs in company financial performance, we see a change in the written style of a financial report. The tone tends to be closer to the next company performance and result in fluctuation of stock prices. If the company's position is worse during the next quarter, the report of the current quarter gets more pessimistic, even though the actual financial

performance remains the same. Although Nokia is the best performer from a financial ratios standpoint for the analyzed years, its stock prices fluctuate every time the quarterly report is announced. When values of Nokia's financial ratios had declined in the third quarter of 2001, its stock price had increased. This example illustrates that the successful style and optimistic message used in a report to explain the decrease in the financial figures impact on traders' expectations and influence stock prices.

As the strongest limitation of our exploratory study we consider the small size of data collection in text clustering that created danger of MFNN overfitting and restricted the validation. Our sample dataset is too limited to draw a general accurate conclusion on predicting power of MFNN over the future financial performance, because they are the best tools to work with "big" data. However, in the dynamic business environment there is a place to the forecasting situation when the data set grows as time passes by. Moreover, sometimes the accuracy of prediction results can even be reduced by large historic data, if the business cycle and outside market condition change multiple times during analysis. The limited vocabulary (terms related to finance and the telecommunications sector), extensive use of proprietary names (such as 3G, bluetooth), and indications of time period (quarter, year, annual), slightly influenced the clustering ability in our qualitative analysis. We plan to expand the study to a larger collection of quarterly/annual reports and try to train another predictive model with a different learning algorithm, such as radial basis neural network.

Our future work is directed toward trying out the methodology with a more extensive data set, and for companies from different lines of business. The desired ultimate output on the research is to come up with a user-friendly prototype-system with automatic data gathering, choosing parameters for SOM and MFNN, and automatic cluster detection in SOM. The quantitative data mining using SOM, qualitative data mining using prototype-matching methodology and classifying the clustering results using MFNN provide a sound framework for future extension and experimentation.

# References

Back, B., J. Toivonen, Viza A., Vanharanta, H , (2001), "Comparing numerical data and text information from annual reports using self-organizing maps." International Journal of Accounting Information Systems **2**(4): 249-269.

Back, B., H. Vanharanta, J. Toivonen, Viza A (1999), Knowledge Discovery in Analyzing Texts in Annual Reports. IFORS SPC-9, Intelligent Systems and Active DSS, Turku, Finland.

Bricker, R. (2000). Corporate Communications: NonFinancial Performance Indicators and Operating Measures An Introduction to the Literature**:** 1-10.

Cao, Q., K. Leggio, Schniederjans M. (2005), "A comparison between Fama and French's model and artificial neural networks in predicting the Chinese stock market " Computers & Operations Research **32**(10): 2499

Fayyad, U. (1996). "Data Mining and Knowledge Discovery: Making Sense Out of Data." IEEE Expert: 20-25.

Grant, J., T. Fogarty, et al. (2000), Corporate Reporting of Nonfinancial Performance Indicators. Morristown, NJ, Financial Executives Research Foundation.

Hawkins, D. F. and B. A. Hawkins (1986), The effectiveness of the annual reports as a communication vehicle. Morristown, NJ, Executive Research Foundation.

Honkela, T., S. Kaski, et al. (1997), WEBSOM - Self-Organizing Maps of Document Collections. WSOM'97: Workshop on Self-Organizing Maps, Espoo, Helsinki University of Technology.

Karlsson, J., B. Back, et al. (2001), Financial Benchmarking of Telecommunications Companies. Turku, Turku Centre for Computer Science.

Kendal, J. (1993), "Good and evil in chairmen's "boiler plate": an analysis." Organization Studies **14**: 571-592.

Kloptchenko, A., T. Eklund, Back, B., Viza, A., Vanharanta, H. (2002), Combining Data and Text Mining Techniques for Analyzing Financial Reports. The 8th Americas Conference on Information Systems, Dallas, USA.

Kohut, G. and A. Segars (1992). "The president's letter to stockholders: An examination of corporate communication strategy." Journal of Business Communication **29**(1): 7-21.

Lavrenko, V., D. Schmill, Lawrie, D., Ogilvie, R., Jemsem D., Allan, J., (2000), Language Models for Financial News Recommendation. The 9th International Conference on Information and Knowledge Management, New York, ACM press.

MIT-Libraries (2001). Corporate Reports.Cambridge, MA, USA

Mittermayer, M. (2004). Forecasting Intraday Stock Price Trends with text Mining Techniques. The 37th Hawaiian International Conference on System Sciences, Big Island, USA, IEEE press.

Osborne, J. D., C. I. Stubbart, A. Ramaprasad (2001). "Strategic Groups and Competitive Enactment: A Study of Dynamic Relationships between Mental Models and Performance." Strategic Management Journal **22**: 435-454.

Pai, P., P. Chang, Z. Xiong (2005).,"Hybrid learning fuzzy neural models in stock price forecasting " Journal of Information & Optimization Sciences **26**(3): 495.

Rumelhart, D., B. Widrow, M. Lehr, (1994). "The Basic Ideas in Neural Networks." Communications of the ACM **37**(3): 87-92.

Safer, A. and B. M. Wilamowski (1999). <u>Using neural networks to predict abnormal returns of quarterly earnings</u>. International Joint Conference on Neural Networks - IJCNN'99, Washington, DC.

Subramanian, R., R. Isley, R. Blackwell (1993), "Performance and readability: A comparison of annual reports of profitable and unprofitable corporations." <u>Journal of Business Communication</u> **30**: 50-61.

Visa, A., J. Toivonen, B. Back, H. Vanharanta, (2002). <u>Example Based Text Matching Methodology for Routing Tasks</u>. The Eleventh Text Retrieval Conference (TREC 2002), Gaithersburg, Maryland, NIST.

Walczak, S. and N. Cerpa (1999). "Heuristics principles for the design of Artificial Neural Networks." <u>Information and Software Technology</u> **41**(2): 109-119.