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# Toward Automatic Analysis of Financial Reports: Readability of Quarterly Reports and Companies' Financial Performance

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#### ABSTRACT

Reading manually annual and quarterly reports helps financial analysts and decision makers to judge companies' financial performance. Professionals infer from a report not only the current financial performance and strategic outlook of a company but also its prospective financial performance. They have insightful methods to find some intuitive indications of the future financial performance of a company from analyzing numbers from a report, reading its textual part and making professional guesses. The manual analysis of financial reports requires a lot of time, and time is a costly asset in a financial community. Automatically detected patterns by text mining methods characterize the writing style of the reports and can potentially provide analysts with the ground for professional guesses. One of the most attractive features of the successful report is its readability. Theoretically the readability of the reports is bond with company financial performance. This paper investigates the relationship between readability of financial reports and companies' financial performance. We study the contribution of the readability toward the tone of a report. The patterns detected by one specific text mining method are characterized the tone of reports.

#### Keywords

Annual and quarterly reports, text mining, readability.

#### INTRODUCTION

Information technologies have simultaneously increased the types of media and decreased the companies' costs of direct communication with all elements of the investment community. However, the annual and quarterly reports remain a centerpiece of corporate communication. Annual reports contain several key elements, among which is a set of financial statements with related notes and auditor's letter, a CEO's or president's letter to stakeholders, and Management's Discussion and Analysis. Regulations have specified that certain types of disclosures and discussions have to be included in a company's financial report. Disclosing certain discussions to the public aim at preventing 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).

Financial analysts, decision makers and industrial experts read the entire collection of financial reports in order to assess the numeric and textual information from them and to compare to companies' financial performance. Professionals intuitively infer from the reports not only the current financial performance and strategic outlook of a company but also its future financial performance. They have individual methods to discover indications of the future financial performance of a company by intuitively identifying key concepts and overall tone of analyzed reports. Those indications consist of word choice and order, the order of concepts and facts introduced, and the subjects emphasized in reports. Although investment decisions are often based on analyzing numeric financial measures from the reports, the textual parts of the reports are widely read and used to validate, support and explain numeric measures.

Reading the reports and detecting indications of future performance are time-consuming manual processes that require training, extensive background knowledge, and analytical experience. Text mining methods aim at detecting distinctive patterns in textual documents automatically. The patterns characterize the peculiarities of a writing style<sup>1</sup> and a tone of an

<sup>&</sup>lt;sup>1</sup> The term, "style," in this study refers to the shape, tone, and force of sentences used in the reports.

analyzed report. They form the indications that can relate to companies' financial performance. Automatic discovery of those patterns can save time of financial analysts by lighten up the burden of reading all the financial reports.

The readability of the reports is bond with company financial performance. Theoretically the companies that perform well should produce easy to read financial reports by using active voice verbs, be straightforward and concise in introduction of the new concepts. Often companies compromise the readability ease and accuracy of the reports by trying to promote positive corporate image in annual or quarterly report. In our research we address three issues: readability of the reports, companies' financial performance and reports' tone. We use the prototype matching method suggested by Visa et al. (2000), compute the Bull Composed Index (BCI) and Reading Ease (Flesch) scores suggested by Bullfighter TM by Deloitte Consulting in the research. The prototype matching method aims at detecting automatically some shared patterns in the reports that correspond to their tone. It enables the comparison of textual parts of the financial reports by determining differences and similarity in their writing styles, word choices and introduction of new concepts and subjects. Bullfighter <sup>TM</sup> works more like the spelling and grammar checker. It focuses on jargon terms ("bulls") and readability of the reports. As a sample data set, we have chosen quarterly reports from the leaders in the telecommunications sector: Ericsson, Motorola, and Nokia, from the years 2000-2003.

We begin our explanation by providing a short overview of studies related to analysis of textual parts of financial reports. Then, we describe the methodology. We use the prototype matching method for text mining of the financial reports. We explain a method of computing the readability of reports based on determination of jargon terms used in text. We then relate financial performance of the companies with readability of their financial reports by reviewing an example of using both, the prototype matching method and BCI for analysis of telecommunications companies' reports. Next, we review the results and limitation. Finally, we highlight a number of issues for further investigation.

#### BACKGROUND

Although annual reports are firmly regulated and important documents to stockholders and financial communities, they are still controversial documents. They generate divergence regarding audience, objectives and credibility. According to (Fugere, 2003), "reading" Enron documents through "Bullfighter" showed that the communication strategies in them were getting more and more obscure in the three years prior to all Enron trouble. During the last decade there have been a number of studies attempting to resolve the divergent nature of companies' annual reports as their medium of corporate communication with investors.

The annual reports are not only the best possible description of a company, but are also a description of a company's managerial priorities. Thus, the communication strategies hidden in annual reports differ in terms of the subjects emphasized when the company's performance worsens (Kohut and Segars, 1992). Thomas (1997) concentrated on transitivity, thematic structure, context, cohesion, and condensation in the language used in the reports. The researcher studied the annual reports of a machine tool manufacturer during a period that 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 use of passive constructions has increased as profits decrease. This indicated management's attempts to present itself as a victim of unfortunate circumstances to create an impression of objectivity to the reader. Nonetheless, when the company's profit increased, a company presented itself as aggressive and forward moving through the use of the active voice and verbs with both an actor and a goal. A similar opposition between the actions of the company and circumstances created by nonhuman agents (i.e. market, competition, etc.) has been noted by (Kendal, 1993). The researcher classified the words and phrases describing actors and objects into two groups: words *growth, increased sales* and *competitive position* represent unquestionably good concepts; words *losses, decline in sales,* and *regulations* represent bad concepts in the eye of the company. An important conclusion of the study by (Thomas, 1997) was the confirmation of the Pollyanna Hypothesis that states that regardless of the financial state of the company, the language in the annual letters is predominantly positive.

Several studies have been made with a focus on the relationship between the readability of the annual reports and the financial performance of a company (Subramanian et al., 1993). Readability measures are primarily based on factors such as the number of words in the sentences and the number of letters or syllables per word (i.e., as a reflection of word frequency) (Graesser et al., 2003). Flesch Reading Ease formula is one of the most commonly used measurements of readability. As linguistic research has shown, the annual reports of the companies that performed well were easier to read than those of companies that did not perform well. (Kohut and Segars, 1992) examined the content of annual reports in the best and poorest performing companies in the Fortune 500. They concluded that such technical characteristics as word count and number of

sentences may serve as predictors of the future performance of a company. The body of research suggests that annual reports are valuable to investors because they contain rudimentary information that is relevant to forecasting the future performance of a company.

The language of quarterly reports has not been studied as extensively as annual reports, both within linguistics and business communication studies. However, for the subsequent study, we used quarterly reports since they contain more up-to-date information that influence decision-making in the short-term. The reports have similar structures, genre, conventions, communicative purpose and audience, but the time spans are different. From a short-term perspective, quarterly reports are important means for companies to appraise past performance and project future opportunities to the readers, who primarily consist of investors and analysts.

Traditionally the analyzing the numeric financial measures are used to benchmark companies' financial performance (Bendell et al., 1998). Disclosure and readability studies suggest that financial reports do not accurately portray a company and its performance. The accurate portrayals are influenced by additional elements such as shift in the subject emphasized, word choice and order used to introduce positive or negative concepts in the financial reports. An arsenal of subjective communication tools allows reports' writers to tell many stories to cover up companies financial performance (Stanton and Stanton, 2001). The first attempts to objectively analyze a company's performance, by examining and comparing stories presented in numeric and textual parts of annual reports, were made in the studies by (Back et al., 1999), (Back et al., 2001). Their results indicated inequalities in numeric and textual data clustering due to a slight tendency to exaggerate the performance in the text. It was proposed that text might correspond better to the next year's numerical data. (Kloptchenko et al., 2002) continued the research in this field, using an improved text mining method, a different hypothesis and data set. They 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 has done and linguistic structure and written style in textual part indicate what a company has done and linguistic structure and written style in textual part indicate what a company has done and linguistic structure and written style in textual part indicate what a company has done and linguistic structure and written style in textual part indicate what a company will do. However, the readability issues in conjunction with the companies' financial performance were neglected.

#### METHODOLOGY

Our methodology section builds on several steps: one step of detecting jargon terms, computing Flesch score and BCI index using Bullfighter<sup>TM</sup>, another step of detecting similarities among reports using the prototype matching method and the essential step of comparing the performance of the companies with the results of the first two steps. The performance of the companies were determined by clustering financial ratios presented in the numeric part of the quarterly reports using the Self-Organizing Map (SOM) by (Karlsson, 2002).

#### Readability of Quarterly Reports

The BCI is 10-point scale index. The values of BCI decreases when a writer of the report runs into trouble with either of its components, the Bull Index (BI) and Flesch Reading Ease score. The BI shows how many and how frequent jargon and overused terms, such as *global, synergize, envisioneer*, appear in the report on a 100-point scale. A skillful writer aims for score in the 90 to 100 range. Rudolf's Flesch Readability formula is widely used and accepted (Flesch, 1979) for characterization of understandability and clarity of writing. Flesch formula for reading ease was adopted by Bullfighter with adjustment to account for a readership of an above-average education level (Deloitte\_Consulting, 2003). The output of the Flesch Reading Ease formula is a number from 0 to 100, with a higher score indicating easier reading so that even children will understand it. The average document has a Flesch Reading Ease score in range of [6, 70}, so that 0 corresponds to extremely difficult to read text with average sentence length of 15-20 words and 2-syllable words, 100 corresponds to very easy to read text with average sentence length of 15-20 words and 2-syllable words. The components of Flesch reading ease formula is explained in (Graesser et al., 2003). It is influenced by average of sentence length (the number of words divided by the number of sentences) and average number of syllables per word (the number of syllables divided by the number of sentences) and average number of syllables per word (the number of syllables divided by the number of BI and lower values of Flesch score.

#### Mining Textual Parts of Quarterly Reports with the Prototype Matching Method

The prototype matching method proposed by Visa et al. 2001 was used for finding similarities among textual parts of the reports. The 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 reports in a collection. The method is based on textual collection preprocessing, i.e. word and sentence level processing. We transform every word into a number, taking into account word length in ASCII symbols, and the ASCII value of every character in a word. We create a common word

histogram for the entire text collection and choose a suitable Weibull cumulative distribution. Each word after quantization is presented as a bin number and the values of the best-fitted Weibull distribution. We create a common word histogram for the entire text collection. The most common words in the text gain a dense resolution in the histogram bins.

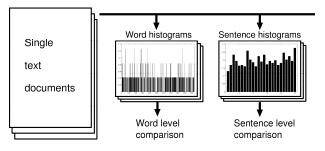


Figure 1. The process of comparing documents based on extracted histograms on word and sentence levels

We perform similar procedures for converting every word into a bin number on the sentence level, in order to present the whole sentence as a vector. Hereafter, we consider the Fourier transformed encoded sentences as input vectors and choose a cumulative distribution the same way as on the word level. We divide the distribution into logarithmically equal bins, the number of which is equal to the number of all sentences in the text collection. The best-fitted Weibull distribution is found based on the cumulative distribution of the coded sentences and their scalar quantization to equally distributed bins. Constructing the histograms of the documents' word and sentence code numbers according to the corresponding value of quantization (Toivonen et al., 2001) 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 common vocabulary of the reports. The smallest Euclidian distance between sentence histograms indicates similarities in written style and/or content of the reports (Visa et al., 2001). Figure 1 schematically depicts the process of comparing documents from a collection of documents. It consists of collecting various text documents into a single repository, creating word histograms based on the distribution of word frequencies in a collection, and creating sentence histograms based on the distribution of sentence level clustering shows the semantic similarities between documents.

#### Determining Financial Position from the Numeric Parts of Quarterly Reports

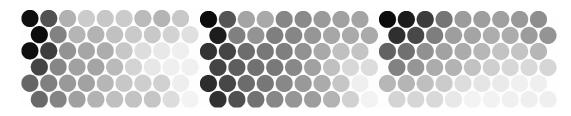
The SOM clustering ability (Kohonen, 1997) was used for financial benchmarking of numeric financial data and determining companies' financial performance. SOMs are useful tools for exploratory data analysis that create a two-dimensional map from highly-dimensional input data. This map resembles a landscape in which it is possible to identify borders to differentiate different clusters that consist of input variables with similar characteristics (Honkela et al., 1997). In order to make the quantitative data comparable, seven selected financial ratios were calculated (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 (Eklund, 2002).

To visualize the final self-organizing map we use the unified distance matrix method (U-matrix). The 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. Feature planes, representing the values in a single vector column, are used to identify the characteristics of these clusters. (Karlsson, 2002) had specified the data preprocessing and standardization methods and parameters for training SOM for our data set.

#### RESULTS

#### **Financial Performance**

By carefully analyzing the output map, six major clusters of companies were identified. To identify the clusters we used both the U-matrix map and the individual feature planes. Figure 2 shows examples of the feature plane maps, in this case for the ratios Operating Margin, ROTA and Equity to Capital. High values are indicated by lighter shades, and lower values by darker shades. By analyzing the shades of the borders between the hexagons on the U-matrix map, it is possible to find



similarities as well as differences. Furthermore, the values of the neurons have been evaluated in order to determine that the clusters are correct. The identified clusters are presented in Figure 2, in the form of a U-matrix map.

Figure 2. The Feature Planes for the Ratios Operating Margin, Return on Total Assets, and Equity to Capital

As a result analyzed companies were clustered into six groups according to their financial performance. Group  $A_1$  and Group  $A_2$  represent the class of the best-performed 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  $C_1$  group, companies possess decent values in profitability, liquidity, and Equity to Capital ratios. Companies from  $C_s$  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 the class of the companies with bad performances. Their distinguishing features are 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 (Kloptchenko et al., 2002). Table 1 presents the sample of evolution of financial performance of Ericsson, Motorola and Nokia determined by clustering their financial ratios by SOM.

Ericsson2000Q2 A <sub>1</sub>	Ericsson2000Q3 B	Ericsson2000Q4 C1	Ericsson2001Q1 C1	Ericsson2001Q2 D
Motorola2000Q2 C1	Motorola2000Q3 C <sub>1</sub>	Motorola2000Q4 C <sub>2</sub>	Motorola2001Q1 C <sub>2</sub>	Motorola2001Q2 D
Nokia2000Q2 A <sub>1</sub>	Nokia2000Q3 A <sub>1</sub>	Nokia2000Q4 A <sub>1</sub>	Nokia2001Q1 A <sub>1</sub>	Nokia2001Q2 A <sub>1</sub>

Table1. The sample of companies' performance determined by SOM clustering of their financial ratios

#### **Readability of Quarterly Reports**

The data set consists of 48 quarterly reports from Ericsson, Motorola and Nokia for years 200-2003 obtained from their home pages. We have calculated the BI, Flesch scores and BCI for all the reports using the Bullfighter and rely on build-in dictionary of financial jargon which was based on extensive practice in business communication and financial analysis of Deloitte Consulting. Table 2 presents the sample of statistics and BCI computation for Ericsson quarterly reports for years 2000-2003.

	Number of	Sentence Length	Word Length		Flesch		Financial
Year/Quarter	words	Average	Average	BI	score	BCI	performance
2000Q1	2528	18.7	1.8	96	33	5.6	В
2000Q2	3470	16.6	1.9	94	31	5.4	$A_1$
2000Q3	3511	16.5	1.9	97	33	5.7	В
2000Q4	3313	16.3	1.9	96	32	5.5	$C_1$
2001Q1	2581	19.5	1.8	99	33	5.8	C <sub>1</sub>
2001Q2	3239	19.7	1.8	95	33	5.6	D
2001Q3	2591	20.2	1.9	98	29	5.2	D
2001Q4	3094	19.6	1.9	98	29	5.2	D
2002Q1	3498	17.8	1.9	95	30	5.2	D
2002Q2	3822	23.5	1.9	99	26	4.9	D
2002Q3	3127	21.1	1.8	99	30	5.3	D
2002Q4	3390	22.5	1.9	99	27	5	D
2003Q1	3547	19.6	1.9	97	30	5.2	$C_2$
2003Q2	3066	20.3	1.9	99	28	5.1	D
2003Q3	2725	20.1	1.9	96	24	4.6	D
2003Q4	2966	21.5	1.9	94	26	4.7	D

Table 2. BI, Flesch score and BCI for quarterly reports of Ericsson

Ericsson2000RQ1 B Nokia2000RQ1 A<sub>1</sub>

Motorola2001RQ3 **D** Motorola2000RO2 **C**<sub>1</sub>

Ericsson2000RQ3 B

Ericsson2000RQ2 A1

Ericsson2000RQ3 **B** Nokia2001RQ4 **A**<sub>1</sub>

Nokia2000RQ3 A1

Ericsson2000RO1 B

Ericsson2000RQ3 B

Ericsson2000RQ2 A1

Ericsson2000RQ4 C1

Ericsson2000RQ1 A<sub>1</sub> Nokia2001RQ4 A<sub>1</sub>

Ericsson2000RQ4 C1

Ericsson2000RQ3 B

Motorola2001RQ2 **D** Ericsson2000RQ1 **B** 

Motorola2001RQ3 D

Ericsson2001RQ1 C1

Ericsson2001RQ3 D Ericsson2001RQ2 D

Nokia2001RQ4 A1

Nokia2001RQ3 C2

Ericsson2001RQ2 D

Motorola2001RQ4 **D** Nokia2001RQ4 **A**<sub>1</sub>

Ericsson2001RQ1 C1

Nokia2001RQ3 C2

As a result, the values of BI index were quite high for all analyzed reports, in ranges [94, 99] for Ericsson, [88, 98] for Motorola and [72, 99] for Nokia. At the same time the Flesch scores were rather low, in ranges [24, 33] for Ericsson, [12, 19] for Motorola and [15, 26] for Nokia. Motorola had tendency to use the in average longest sentences and words trying to explain fact in the reports. Moreover, it overused bull terms that contributed to its low Flesch score. In average Ericsson used the shortest words and sentences that contributed to the better BCI. This resulted in low values of BCI. It ranged in narrow interval from [4.6, 5.8] for Ericsson, [3.4, 4.1] for Motorola and [3.4, 4.6] for Nokia.

There is no linear relationship between Ericsson financial performance and readability of its' financial report according to the calculated readability indexes. For instance, the easiest to read Ericsson report from the first quarter of 2001 (BCI=5.8)

conveys the below average financial performance ( $C_1$ ). The rest of the analyzed reports revealed the following. Motorola reports stating generally poor financial performance were almost as easy to read as reports from best performing Nokia.

#### **Mining Quarterly Reports**

The example of the obtaining results from mining Ericsson reports using the prototype matching method is presented in Table 2. 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 the quantitative clustering to which a particular report belongs.

It reads, for example, that the Ericsson report from 2000, quarter 1 belonging to group B - well performing companies. At the sentence level it has the closest report by content from Nokia, 2000, quarter 1 belonging to best performing companies from group  $A_1$ . The second closest match is the report from Motorola 2001, quarter 3 from the group D and so one. This means that the reports from Nokia 2000, quarter 1, Motorola 2001, quarter 3 and the Ericsson report from 2000, quarter 1 have similarities in sentence construction and word choice, which constitutes the language structure and written style. Word choice has a small impact on determining the closest matches that form clusters than the sentence construction. As an evidence of that, quarter names and proper names, e.g. Nokia, Motorola or Ericsson, did not determine the clusters. At the same time, the following word phrases with positive connotation were similar among all of them *sales grow, sales increase, incomeoperating, margin up, capital gains, cash-flow increased, progress, volume exceed, positive experience, largest market.* 

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 Nokia report from 2001, quarter 4 among the closest matches to Ericsson report from the first quarter of 2000. If a company's performance worsens in the future, than the reports from average or badly performed companies fire among the closest matches. For Ericsson report from the forth quarter of 2000 the closest matches reported about poor performance of Motorola in the second and third quarters of 2001. The prototype matching method is able to detect some peculiarities of writing style that are not related to the readability of the reports but relate to the financial performance of the companies. The closest-matches share some patterns with report-prototype which are not explicitly detectable by professionals. Those patterns contribute to a tone of a report that can be described by them.

Table 2. The sample of the closest matches to Ericsson reports (Sentence level)

#### DISCUSSION

The results of the current research did not support the conclusion of (Subramanian et al., 1993). The postulate that "the better company perform, the easier to read its financial report" was not proved to be true by calculated BCIs. The narrow ranges of BCI show that all reports from every company contains some peculiarities of writing style that are equally difficult to comprehend by the readers, so that despite of company performance the writing style of the report does not become more or less clear. The values of AWLs for reports from the same company are almost constant. Each company maintains its own unique writing style and word choice despite of how good or bad things for a company within particular time period were. Reading ease and use of jargon terms does not reveal any indications of how company performed or will perform and does not determine the tone of the report. At the same time, the prototype matching method detects some similarities among quarterly reports that comprise the tone of the report and refer to companies' future financial performance. It happens because the prototype matching method detects similarities in word choice, word order, sentence construction (i.e. using passive voice instead of active voice), new concept introduction and subject shift (i.e. talking about political risks in Ericsson report 2000, quarter 3 and SARs in Asia in Ericsson reports in 2000 to shift the audience attention from its poor performance). BI and

Flesch readability ease score consider word choice and length of the sentence but did not consider the semantic of words built into sentence construction that are essential determinants for the text mining method.

#### LIMITATION

There are, of course, a number of problems associated with constructing a methodology for automatic analysis of quarterly reports based on data that are freely presented on the Internet. We can divide methodology limitations in, at least, two categories: limitations that are specific for each individual method and limitations regarding their integration and data set. For example, with all its advantages over standard clustering techniques, the SOM has one major drawback: verification of the achieved clustering results. This issue is addressed in (Wang, 2001). The author proposes a number of techniques for verifying clustering results. Maybe human classification of companies' financial performance would be more accurate but more costly and slower.

Text mining techniques have a number of disadvantages due to the highly dimensional structure of text. Two textual pieces can often be nearest neighbors in terms of using similar vocabulary, without actually belonging to the same semantic class. Prototype-matching clustering is an exploratory technique that possesses some difficulties with determination of the clusters, and with their comparison with quantitative clustering. Although, theoretically, text implies richer information about an event than a numerical snapshot of the fact does, this is difficult to verify. Even having excellent text mining techniques on hand that could mine the indications of future financial performances of the company, those indications can be easily concealed by smart word choice and sentence construction.

Also, as was illustrated by the Enron and WorldCom scandals, the financial information presented in annual reports is not always reliable. Of course, if this incorrect information is inserted into our system, the results will also be incorrect. Moreover, there might be unintentional mistakes in the data. Therefore, some kind of error detection and handling capabilities should be built into the system. This is also required by the actual definition of KDD, which includes data cleaning and error detection (Fayyad et al., 1996).

Another strongest limitation is the size of the financial report collection. The restricted vocabulary (terms related to finance and the telecommunications sector), extensive use of proprietary names (such as Motorola, Nokia, and Ericsson), indications of time period (quarter, year, annual), and predefined "bull"-dictionary of financial jargon and overused terms (strategic, enterprise, leverage, global, cutting edge, synergy, scalable) impact the results.

To measure readability, coherence and comprehensiveness of a text, more than surface features need to be taken in consideration than jargon term usage and sentence and word lengths such as considered by Bullfighter <sup>TM</sup>. Quantitative and qualitative factors like the number of anaphora, number of overlapping text segment, vocabulary difficulty, sentence and text structure, concreteness and abstractness, are equally needed.

#### CONCLUSIONS

The annual and quarterly reports remain a centerpiece of corporate communication. Annual report readers want more company information; they want it dished up in a clear, brief and useful manner to be laid out for quick and easy access. Reading the reports and detecting important indications is a time-and-expertise-consuming manual process. The reports convey the company's facts and message through its historical and symbolic values. Every company has distinctive peculiarities of its business writing style, ways of explaining things and justifying its financial performance that the readers of the reports intuitively detect. While the numeric part of a report tells the reader what had happened with a company, textual part explains why it had happened. However, important managerial priorities that potentially affect company future financial performance are presented in textual part of the reports. Readers want the president's letter to shareholders to be relevant, understandable and easy to read. This research investigates the relationship between readability of financial reports and companies' financial performance, and contribution of the readability toward tone of the reports. We compare the readability of the quarterly reports with the patterns detected by the prototype matching method. Those patterns characterize tone of the reports that is linked to companies' financial performance. In this research we calculated the readability and jargon usage indexes. The readability ease and severity of jargon were related to the companies' financial performance. As linguistic research suggested, the better performance of the company is – the easier to read its report was not proved to be true by the current study. However, the number of minor finding was made. First, every company despite of its performance is bound with peculiarities of its writing style. Writing style depends on word choice to describe the facts, the nature of the facts (whether it has positive or negative impact on company financial performance) and the way of explaining those facts. Second, the prototype matching method is able to detect mentioned above peculiarities and tone of the report that correspond directly the company future financial performance. Detected by text mining method peculiarities or patterns provide to the analysts the ground for professional guesses in a timely manner.

#### REFERENCES

- 1. Back, B., J. Toivonen, et al. (2001). "Comparing numerical data and text information from annual reports using selforganizing maps." International Journal of Accounting Information Systems **2**(4): 249-269.
- 2. Back, B., H. Vanharanta, et al. (1999). Knowledge Discovery in Analyzing Texts in Annual Reports. IFORS SPC-9, Intelligent Systems and Active DSS, Turku, Finland.
- 3. Bendell, T., L. Boulter, et al. (1998). Benchmarking for Competitive Advantage. London, Pitman Publishing.
- 4. Deloitte\_Consulting (2003). Meet Bull Fighter: How software will change your life (but not really). New York, Deloitte\_Consulting, Inc.
- 5. Eklund, T. (2002). Financial Benchmarking Using Self-Organizing Maps A Study of the International Forest Products Industry. Department of Information Systems. Turku, Åbo Akademi University.
- 6. Fayyad, U., Piatetsky-Shapiro, G. and Smyth, P. (1996) Knowledge Discovery and Data Mining: Towards a Unifying Framework. In *The Second International Conference on Knowledge Discovery and Data Mining (KDD-96)*(Eds, Simoudis, E., Han, J. and Fayyad, U.) AAAI Press, Portland, Oregon, pp. 82-88.
- 7. Flesch, R. (1979). Let's Start With the Formula. HOW TO WRITE PLAIN ENGLISH, Harpercollins (P).
- 8. Fugere, B. (2003). Bull Fighter: Stripping the Bull out of Business. Fox News. New York, Deloitte Consulting, Inc.
- 9. Graesser, A. C., D. S. McNamara, et al. (2003). Coh-Metrics Research: Readability formulas, Institute for Intelligent Systems, Department of Psychology, The University of Memphis.
- 10. Hawkins, D. F. and B. A. Hawkins (1986). The effectiveness of the annual reports as a communication vehicle. Morristown, NJ, Executive Research Foundation.
- 11. 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.
- 12. Karlsson, J. (2002). Data-Mining, Benchmarking and Analysing Telecommunications Companies. Licentiate Thesis at the Department of Information Systems. Turku, Abo Akademi University.
- 13. Kendal, J. (1993). "Good and evil in chairmen's "boiler plate": an analysis." Organization Studies 14: 571-592.
- 14. Kloptchenko, A., T. Eklund, et al. (2002). Combining Data and Text Mining Techniques for Analyzing Financial Reports. The 8th Americas Conference on Information Systems, Dallas, USA.
- 15. Kohonen, T. (1997). Self-Organizing Maps. Leipzig, Germany, Springer-Verlag.
- 16. 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.
- 17. Stanton, P. a. and J. Stanton (2001). Researching Corporate Annual reports: An Analysis of Perspectives Used. The Third Asia Pacific Interdisciplinary Research in Accounting Conference (APIRA), Adelaide, South Australia.
- 18. Subramanian, R., R. Isley, et al. (1993). "Performance and readability: A comparison of annual reports of profitable and unprofitable corporations." Journal of Business Communication **30**: 50-61.
- 19. Thomas, J. (1997). "Discourse in the Marketplace: The Making Meaning of Annual Reports." Journal of Business Communication **34**: 47-66.
- 20. Toivonen, J., A. Visa, et al. (2001). Validation of Text Clustering Based on Document Contents. Machine Learning and Data Mining in Pattern Recognition (MLDM 2001), Leipzig, Germany, Springer-Verlag.
- 21. Visa, A., J. Toivonen, et al. (2001). Prototype-matching Finding Meaning in the Books of the Bible. Hawaii International Conference on System Science, HICSS-34, Maui, Hawaii, USA.
- 22. Wang, S. (2001). Cluster Analysis Using a Validated Self-Organizing Method: Cases of Problem Identification. *International Journal of Intelligent Systems in Accounting, Finance and Management*, **10**, 127-138