SENTIMENT ANALYSIS FOR FINANCIAL NEWS AND ARTICLES

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Abstract : Mining financial text documents and understanding the sentiments of individual investors, institutions and markets is an important and challenging problem in the literature. Current approaches to mine sentiments from financial texts largely rely on domain specific dictionaries. However, dictionary based methods often fail to accurately predict the polarity of financial texts. This paper aims to improve the state-of-the-art and introduces a novel sentiment analysis approach that employs the concept of financial and non-financial performance indicators. It presents an association rule mining based hierarchical sentiment classifier model to predict the polarity of financial texts as positive, neutral or negative.

IndexTerms **- Sentiment analysis, Financial news, Performance indicators, Text mining, Machine learning, Classification.**

I. INTRODUCTION

Sentiment analysis and opinion mining have received a significant consideration in the literature due to its wide applicability in business, management and social science disciplines. It has been effectively applied in certain domains like movies, product reviews, travel reviews and finance. Financial sentiment analysis is considered as challenging problem or the finance sectors. Current approaches to financial sentiment analysis make use of generic dictionary [8, 16], domain specific dictionary [5, 9,10, 12,13] or statistical/machine learning methods [2, 6, 8, 13] to determine polarity in financial texts. Some of the common dictionaries used in the financial sentiment analysis literature include Harvard GI (HGI) , MPQA [18], Sentiwordnet SenticNet, SentiStrength2 [17], LM [12], and Financial Polarity Lexicon (FPL) [13]. LM & FPL are finance-specific dictionaries.

Let us consider the following financial text sentences extracted from financial phrase bank dataset[13].

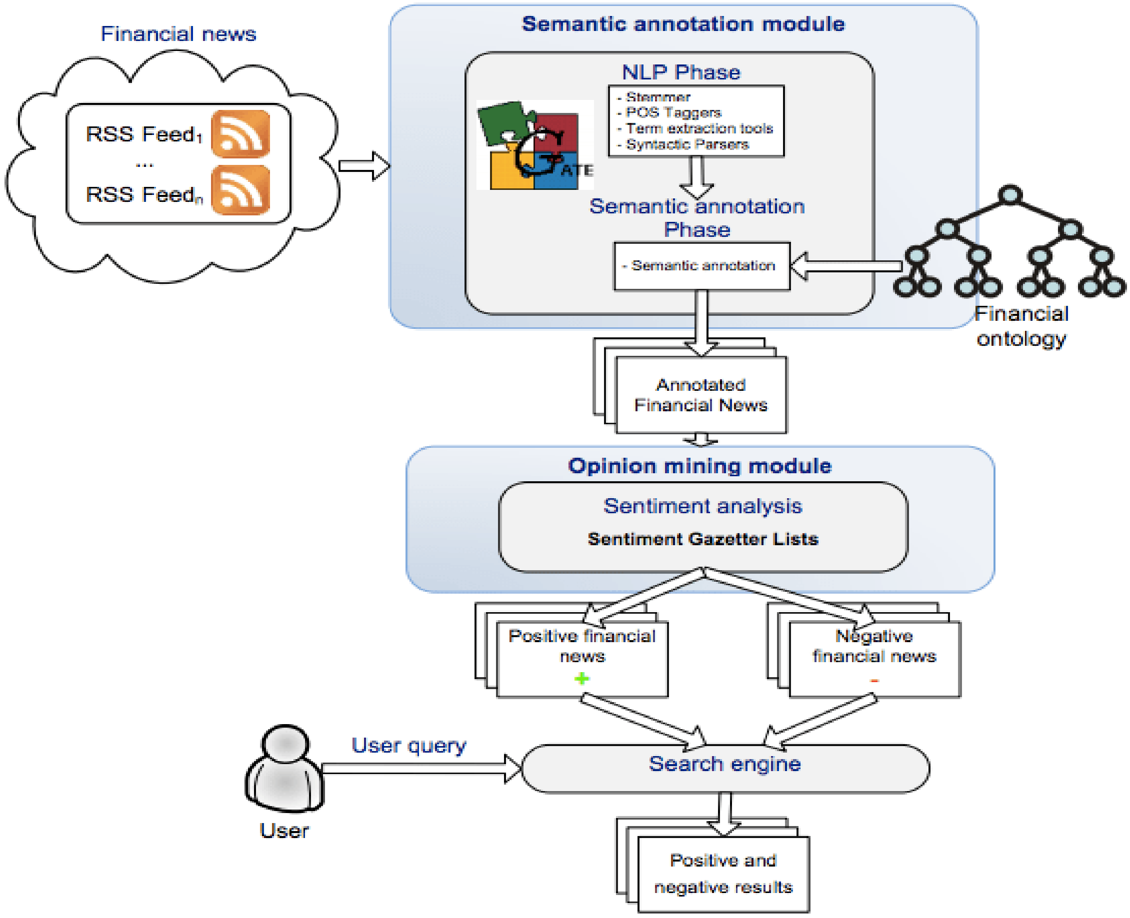
1. Halonen's office acknowledged receiving the letter but declined comment.
2. Financial details were not disclosed.
3. The serial bond is part of the plan to refinance the short-term credit facility.
4. Aspo's strong company brands ESL Shipping, Leipurin, Telko and Kauko markkinat aim to be the market leaders in their sectors.
5. DnB Nord of Norway is the most likely Nordic buyer for Citadele, while Nordea would be a good strategic fit according to published documents.
6. We are also pleased to welcome the new employees.

In the LM dictionary [12], declined, disclosed and refinance are negative words; similarly, strong, good and pleased are positive words. Therefore, each of the above sentences will be classified as positive or negative sentences by methods that use LM or other related domain dictionaries. However, it is quite clear that all of the above sentences are neutral statements from an investor or analyst perspective. A few research studies have attempted to go beyond just polarity based dictionaries and utilized financial entities (custom words [13] or noun phrases [17] or named entities [32]) to improve the quality of polarity detection. But, the use of financial entities often generates a lot of false positives and false negatives.

Let us consider the following sentences that contain at least one financial entity.

1. The company's board of directors has proposed a *dividend* of EUR 0.12 per share.
2. Amanda *Capital* has *investments* in 22 private *equity funds* and in over 200 unquoted companies mainly in Europe.
3. A corresponding increase of 85,432.50 euros in Ahlstrom's *share capital* has been entered in the Trade Register today.

All the above mentioned statements are neutral, though they contain financial terms or entities (*italized* words in text). Statement 3 indicates increase of a financial entity (share capital). Hence, the sentence is likely to be considered as positive with reference to the LM dictionary and financial entities (or noun phrases/named entities) [9,13].



This paper basically makes two important contributions to the literature. First, the paper introduces the use of performance indicators to predict polarity in financial texts found in news and articles. Second, the paper presents a hierarchical sentiment classifier model based on the concept of association rule mining [1].

I. RELATED LITERATURE

Financial sentiment analysis approaches in the literature can be broadly categorized as
(a) Generic dictionary based methods
(b) Domain specific dictionary based methods
(c) Statistical or machine learning based methods.

Generic dictionaries such as Harvard GI [33] are used in some of the previous works in financial sentiment analysis [34, 35]. The uses of generic dictionaries, moreover, lead to misunderstanding of common words in financial text and impact the performance of sentiment prediction [12] or stock price movements [9,10] Recent works in the literature [5, 9,10,13] predominantly use domain specific dictionary such as LM dictionary [12], and FPL [13].

Statistical or machine learning based methods [2, 11, 15, 25, 30, 38] use bag-of- words or n-grams as features and apply generative or discriminative classifier mod- els for predicting sentiments. Internet message postings were used by [2] to classify financial text as buy, hold or sell. The classifier results were then aggregated for a pre-defined time period and bullishness & agreement indices were computed. The authors also conducted a study on relationship between the computed indices and financial measures such as stock returns and market volatility. The experimental analysis show that stock messages help predict market volatility.

A naive baye's classifier model is used in [6] to classify sentences as positive, negative or neutral. The predicted sentence level opinions are aggregated to de- rive report level opinions. The authors show that their method outperforms both generic and domain specific dictionary methods. A naive baye's classifier model based on bag-of-words features is trained in [8] to predict the tone (as positive, neutral, negative or uncertain) of forward looking statements in corporate filings. The author presents evidence that dictionary based methods (both generic and domain specific) are unsuitable for analyzing tone of corporate filings.
Naïve baye's and support vector machine methods were used to predict sentiment of bloggers towards companies and their stocks [30]. The sentiment prediction was conducted using selected topic terms. Their work analyzes sentiment at the topic level and not at the sentence level as in [8, 13]. Other recent works in the literature that perform sentiment analysis include [9,10,14]. These analysis utilize sentiment dictionaries and extract sentiments from text and predict stock price movements or market returns. The proposed paper is distinct from such works as the focus of the current paper is primarily on predicting the polarity of news articles as positive, neutral or negative. A comparative analysis of the financial sentiment analysis works in the literature is presented in Table 1.

The polarity sequence model discussed in [13]. The authors propose an LPS model and utilize generic dictionary, MPQA [18] and domain specific LM dictionary [12]. The authors also enrich the finance lexicon by including (a) financial concept, (b) directional verbs such as increase, decrease, and (c) polarity for the interaction between financial concept and directional verb e.g. cost-increase is pre-labeled in the dictionary as negative; profit-increase is pre-labeled as positive. The authors also contribute to the literature by making an annotated financial sentiment corpus publicly available.
The LPS model discussed in [13] primarily works in three phases. In the first phase, entities are extracted along with their semantic orientations from the given

Literature	Nature	Dictionary		Method	Objective
Tetlock [15]	News	HGI	HGI words	Regression	Stock
Tetlock [16]	News 10-K	HGI	HGI words	Regression	Earnings,
Loughran[12]	Internet messages	LM	LM words	Regression	Returns
Antweiler[2]		-	BoW	NB	Volatility,
				Regression	Returns
Huang [6]	Analyst reports	LIWC		Regression	Earnings
		HGI,LM	BoW	NB	Polarity
Li [10]	News, Social Media news	HGI,LM	words Dictionary	SVM	Stock

Table 1 Comparison of financial sentiment analysis literature

1. HIERARCHICAL SENTIMENT CLASSIFIER

This section describes the proposed method for financial sentiment analysis. The method broadly consists of the following four key aspects.

1. **Domain specific lexicon** The proposed method uses a standard domain specific dictionary, LM dictionary [12]. In addition, the lexicon defines words related to performance indicators and directionality.

2. **Text tagging using lexicon** The given financial text is parsed and tagged by looking up words in the lexicon.

3. **Polarity classifier model** The tagged financial text is used to build a hierarchical classifier model. The classifier model utilizes the concept of association rule mining.

4. **Predict sentiment**

The polarity classifier model to make polarity predictions for new financial text sentences.

Category	Type of word (tags)	No. of words (% of all entries)
Performance	Lagging Indicator words (LagInd)	67 (2.29%)
Indicators	Leading indicator words (LeadInd)	70 (2.39%)
Directionality	Down (DOWN)	53 (1.81%)
	Up (UP)	51 (1.74%)
Finance-specific	Negative (NEG)	2337 (79.73%)
sentiment words	Positive (POS)	353 (12.04%)

Table 2 Distribution of words in the dictionary

II. STUDY OF THE EFFECT OF PERFORMANCE INDICATORS

In the next set of experiments, we study the influence of performance indicators and financial sentiment words on sentiment prediction. Three different scenarios were considered for the analysis: (1) using lagging indicators (along with directionality), (2) using both lagging and leading indicators (along with directionality), and (3) using all of the tags along with financial sentiment words (baseline case). The analysis results are presented in Table 6. The best F-measure and accuracy values are noticed in bold. In addition, the values that are tied are underlined.
The results present a few interesting insights, when it is analyzed in relation to the characteristics of the annotated datasets. First, the results for DS100 dataset using only the lagging indicators is relatively close to that of the baseline case. The performance difference between the two cases widens as we navigate down the table (DS75, DS66 and DS50). Second, the experimental performance results improve as the leading indicators are included in the model. Further performance improvements are observed when all of the tags are used. One can observe a correlation between inter-annotator agreement and the use of indicators. A model that uses only the lagging indicators works well when the inter-annotator agreement is 100%. The second model that use both lagging and leading indicators perform better, even when the inter-annotator agreement declines to 75%. Finally, the third model

works better, even when the inter-annotator agreement declines to a very low value of 50%. These results imply that human annotators, experienced in finance domain, have less agreement when a financial text uses leading indicators to describe company's performance. This is in line with our expectation, as the relationship amongst the leading indicators, investor sentiment and the firms future performance are often unclear. One can also find evidence from the finance and accounting literature on the lack of clear relationship between leading indicators and firm performance [12].

Let us consider the following two sentences:

1. VDW combined with LXE devices enhances productivity, enabling workers to use a single device to perform voice, scanning and keyboard functions.
2. Previous year, UPM cut production, closed mills in Finland and slashed 700 jobs.

The first sentence refers to worker productivity improvement (a leading indicator) and the second sentence refers to cut in production and jobs (leading indicators). Both of these sentences do not have 100% agreement and are annotated by 75% of the annotators as polarized i.e. the first and second sentences are marked respectively as positive and negative. The financial texts also contain general positive opinions.

For example, let us consider the following sentence:

"He believes that the soy-oats have a good chance of entering the UK market"

The above sentence contains neither lagging nor leading indicators but ex- presses a positive outlook. A high level of disagreement among annotators was observed and only 50% of the annotators have marked the above sentence as positive. Another sentence that has been evaluated as positive by 50% of the annotators was:"The companies strength is its Apetit brand".

From the foregoing discussions and the experimental results, it is clear that financial texts are interpreted differently based on the nature of the indicators and sentiment words. It is to be noticed that sentiment analysis in other domains (such as movies, music) utilizes general sentiment lexicon words to predict sentiments. In the financial sentiment analysis literature, similar approach has been borrowed with a refinement of dictionary words to finance domain. This paper presents a new perspective and suggests the use of multiple levels of analysis (lagging indicator, leading indicator, domain specific lexicon words) to improve the quality of financial sentiment analysis. The experimental analysis clearly demonstrates the utility of such a multi-level sentiment analysis.

The multi-level approach to financial sentiment analysis can be very useful in building models to suit specific application requirements. For example, an investor might prefer a model built using lagging (or lagging and leading) indicators over a more accurate baseline model. The former model is more likely to help the investor make the best investment decisions, even though it offers relatively lower accuracy.

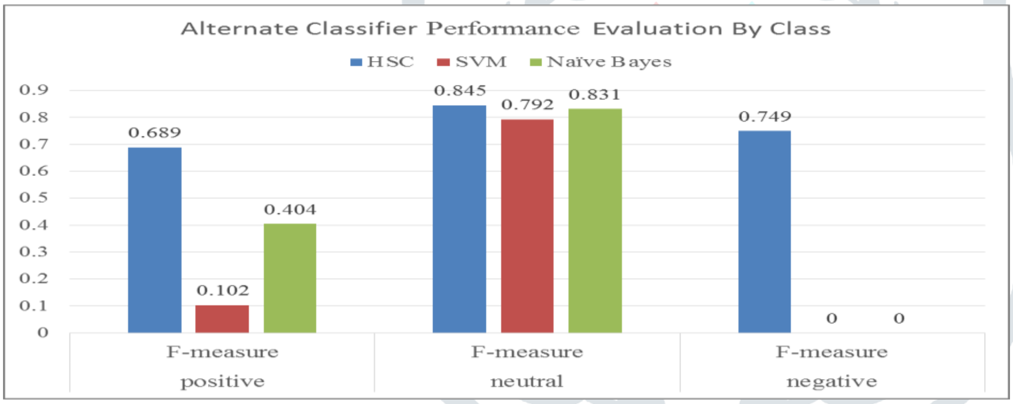


Fig. 2 Classifier Performance for DS50 dataset

CONCLUSION

This paper examined the use of performance indicators for predicting sentiments from financial texts. It presented a hierarchical classifier that uses the concept of association rules. The effectiveness of the classifier was demonstrated through rigorous experimental analysis on a benchmark financial dataset.

A study of the influence of performance indicators on sentiment prediction revealed interesting insights. The presence of varying levels of influence of lagging indicators, leading indicators and sentiment words on sentiment prediction were observed for different datasets. The results are clearly in alignment with the way humans interpret financial texts and make decisions.

As part of our future work, we plan to explore several interesting extensions. First, a more fine-grained analysis of performance indicators is likely to reveal interesting insights. For instance, a balanced scorecard approach [7] analyses company's performance from multiple dimensions, namely, financial, customers, internal business processes and learning & growth. Performance indicators can be categorized across each of these dimensions and the influence of each of the dimensions on financial sentiment can be explored. Second, advanced variable support rule mining methods can be studied to capture the directional dependencies in financial texts without using a lexicon. Third, the proposed method is not tuned to handle sentences that have mix of positive and negative orientations on performance indicators. One can investigate the use of utility mining [11] approaches to give different weights to different indicators. Such an approach allows one to capture varying influence of indicators and further improve sentiment prediction. The findings of this study are likely to be useful for financial institutions in building superior sentiment analysis models. The investors or financial analysts can make better investment decisions using qualitative financial texts.

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