Do Two Negatives Make Good News or Worse News? Extending Textual Analysis of Corporate Disclosures beyond Counting Words

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Advances in textual analysis techniques and computation power have enabled financial researchers to incorporate qualitative data into empirical studies at a scale previously infeasible. Investors and money managers now can purchase news services with textual/sentiment analysis as an add-on service. Li (2011b) provided an extensive review of existing literature on textual analysis of corporate disclosures. He classified the central research questions into three groups. The first examined the tone/sentiment of corporate disclosures. The second group looked at transparency/readability. The last group (designated as other by Li) included measuring the amount of text and non-textual measures, such as body language and voice affects. In this paper, our primary interest is in assessing the tone/sentiment of corporate disclosures using a more powerful textual analysis technique than those used in existing literature.

Prior studies employed one of two general approaches to textual analysis. The first is a dictionary based approach. Often the tone of a document is estimated using a normalized frequency of positive and negative word count. Tetlock (2007) was one of the first studies using this approach. Both Tetlock (2007) and Tetlock, saar-Tsechansky and Macskassy (2008) used the General Inquirer, which incorporated the Harvard-IV-4 classification dictionary to distinguish positive versus negative words. Longhran and McDonald (2010) examined over 50,000 annual reports and created a finance dictionary that mitigated many short-comings in the Harvard-IV-4 dictionary. Rogers, Van Buskirk and Zechman (2010) used a combination of Diction[1], the finance dictionary created by Longhran and McDonald (2010) and the dictionary by Henry (2008). Feldman, Govindaraj, Livnat, Segal (2010) also used the Longhran and McDonald (2010) finance dictionary but they examined the change in tone from period to period. Documents examined in these studies included 10-K, 10-Q reports, especially the Management Discussion and Analysis (MDA) section, Wall Street Journal columns and news wires, such as earnings announcements. Findings from these studies were not unanimous. For example, Tetlock, et al (2008) found that negative words in news wires predicted lower unexpected future earnings. On the other hand, Longhran and McDonald (2010) found that negative words in 10-K/10-Q reports predicted positive earnings surprise. Feldman et al (2010) found that change in tone in the MDA was significantly related to stock price changes immediately following the filing dates.

In addition to simply classifying words as positive or negative, several studies expanded the categories of words in the dictionary. Muslu, Radhakrishnan, Subramanyam, Lim (2010) estimated a forward looking intensity measure using a dictionary they constructed. They identified 69 forward-looking words and phrases and specified 11 word-categories such as “operations”, “employees”, “macroeconomy”. Longhran and McDonald extended their

[1]Diction is a commercially available software that reports the tone of a text message.

dictionary classification beyond “positive” and “negative”. As of April 2011, (www.nd.edu/~mcdonald/Word_Lists.html accessed 4/16/2011) they included categories for “uncertainty”, “litigious”, “modal strong” and “modal weak”. Engelberg (2008) created a dictionary with five categories: “positive fundamentals”, “negative fundamentals”, “future outlook”, “environment” and “operations”. Muslu et al (2010) found that stock price changes were larger on filing date for firms with a higher forward looking measure. Engelberg (2008) demonstrated statistically and economically significant abnormal trading profits from a long-short strategy using textual information. Results from these studies suggested that more comprehensive textual analysis may yield additional information not incorporated in conventional quantitative factors such as firm size, accruals, etc..

Another approach to textual analysis is statistical based. Li (2011a) and Huang, Zang and Zheng (2010) both used a Naive Bayesian machine learning approach to estimate the tone of a document.[2] Li (2011a) defined four tone levels: “positive”, “negative”, “neutral”, “uncertain” and twelve content categories: “revenue”, “cost”, etc. He concluded that the Naive Bayesian approach performed better than the dictionary-based approach in analyzing 10K and 10Q reports. He found that the tone of the forward looking statement in MDA was positively correlated with future firm performance and provided additional information controlling for other fundamental variables. Huang et al (2010) examined the sentiments of analyst reports. They compared the Naive Bayesian approach against three dictionary based approaches: Diction, General Inquirer and Linguistic Inquiry and Word Count, and also concluded that the Naive Bayesian approach outperformed the others. They found that cumulative abnormal return (CAR) was significantly related to analyst opinion, controlling for contemporaneous quantitative variables and adjusted R^2 increased from 0.52% before including the opinion variables to over 3.01%.

The exception to using a single approach in estimating sentiments was Das and Chen (2007). They used 5 different classifiers: Naive Classifier, Vector Distance Classifier, Discriminant-based Classifier, Adjective-Adverb Phrase Classifier and Bayesian Classifier to analyze the sentiments of discussions on stock message boards. The final sentiment classification was based on majority vote and messages were designated as either “buy”, “sell” or “hold”. If the classifiers did not reach a majority vote, a message was not classified. They concluded that the combined approach, referred as the Voting Classifier, was similar in accuracy as the Bayesian classifier but had fewer false positives.

In this study, we utilize a Semantic Relationship (SR) Classifier to evaluate sentiment in publicly available financial documents. Existing studies use text processing systems that analyze texts at a word or phrase level without considering the sentence structure and the roles of the words in

[2]Brown and Tucker (2011) used a Vector Space Model, which was independent of dictionaries, to create a MDA modification score that measured the degree of changes in the MDA content from year to year. However, they did not measure the tone or change of tone in the MDA.

the sentence. In contrast, this study uses a language processing system that applies linguistic theories to model how humans process language. The core of the system is an adaptive parsing technology that is an implementation of Meta-S calculus, an adaptive grammar[3] formalism, and the corresponding Adaptive(k) parsing algorithm, referred to as the Meta-S Adaptive Parser (Jackson, 2000a, 2000b). These algorithms utilize X-bar theory (Chomsky, 1995) to identify syntactic features and express basic semantic relations within a sentence as theta-roles (Parsons, 1990). The end result is a Meta-S Language Processing System (MSLPS) that can recognize entities, syntactic structure and semantic meaning. Another feature of MSLPS is that it incorporates multiple ontologies, from general linguistic to domain-specific resources, including user-defined terms. The system will choose the most appropriate resources to use in the analysis. For example, Longhran and McDonald (2011) argued that non-finance ontologies, such as the Harvard-IV-4, misclassify some terms as negative (e.g. liability, cost) because these are accounting terms and do not convey sentiment by themselves. MSLPS will recognize whether the word "cost" in a sentence should be treated as an accounting term, thereby eliminating the ambiguity. However, since "cost" is inversely related to profit, if cost is increasing, then it is a negative event. Therefore, the sentiment of a sentence depends on the relationship between the words, not just the words themselves. The last and perhaps most powerful feature of MSLPS is its ability to automatically learn and extend ontological resources.

The following examples illustrate how MSLPS processes text using linguistic theories and how it differs from other word-based methodologies. Consider the sentence:

Higher same-store sales growth fueled strong consolidated earnings.

MSLPS will identify "Higher" as an adjective which modifies the noun phrase "same-store sales growth". Semantically "higher" is an increasing term. "Same-store sales growth" is an accounting term reflecting "revenue" and when modified by the increasing term "higher", the entire phrase describes a positive event. The remaining sentence is processed in a similar manner. Therefore, the overall sentiment of this sentence is strongly positive. Now consider another sentence:

Higher employee health insurance costs undermined consolidated earnings.

"Higher" is an adjective that modifies the noun phrase "employee health insurance costs". Semantically "higher" is an increasing term. But "employee health insurance costs" is an accounting term reflecting "cost" and when modified by the increasing term "higher", the entire phrase describes a negative event and the overall sentiment of this sentence is negative.

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[3] http://en.wikipedia.org/wiki/Adaptive_grammar provides a good overview on adaptive grammar. (Accessed 5/1/2011)

The output of word-based methodologies is highly dependent on the dictionary used. For example, none of the words in the first sample sentence and only one word (undermined) in the second sentence appeared in Longhran and McDonald (2011). So based on their dictionary, the first sentence will be considered neutral and the second sentence will be negative. Engelberg (2008) classified "sales" as a positive fundamental, earnings as a positive fundamental and cost as a negative fundamental. A simple word count ratio will give the first sentence a positive fraction of 2/8 or 0.25. The second sentence will have a positive fraction of ⅛ and a negative fraction of ⅛. The General Inquirer[4] classifies the words "growth" and "consolidated" as positive words in the first sentence. However, since the word "growth" is part of the noun phrase "same-store sales growth" and the word "consolidated" is part of the noun "consolidated earnings", they are accounting terms and do not convey sentiment without additional modifiers. For the second sentence, the General Inquirer classifies "health" and "consolidated" as positive words and "undermined" as a negative word. A simple word count would conclude the second sentence as slightly positive when in fact, its overall sentiment is negative. In this example, none of the existing methods correctly identify the sentiment of both sentences.

The next step in this project is to develop a sentiment calculation algorithm for the Semantic Relationship (SR) Classifier. The last part of the project will compare the performance of the SR Classifier against existing classifiers.

[4] http://www.webuse.umd.edu:9090/

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