A Practical Approach to Advanced Text Mining in Finance

Julia Klevak, Joshua Livnat, and Kate Suslava

Julia Klevak
is a director of systems development at QMA in Newark, NJ.
julia.klevak@qma.com

Joshua Livnat
is a professor emeritus of accounting in the Stern School of Business Administration at New York University in New York, NY and the head of research at QMA in Newark, NJ.
jlivnat@stern.nyu.edu

Kate Suslava
is an assistant professor of management in the Freeman College of Management at Bucknell University in Lewisburg, PA.
kate.suslava@bucknell.edu

The sheer volume of data available for analysis can be a daunting prospect for an investor. Some of these data are structured and normalized—for example, numeric information from financial statements or analysts' earnings forecasts. However, a large body of data is available in the form of text, such as Securities and Exchange Commission (SEC) filings, news, materials scraped from the web, and so on. The construction of an investment signal from text is a complex task because it requires the ability to identify positive and negative parts of the text, weight the different parts, and construct a final score. In this study, we briefly review the evolution of the analysis of text in finance and accounting and provide a concrete example through the analysis of earnings conference call transcripts.

The early literature in finance and accounting used a simplistic way to score a text: counting the number of positive and negative words in the text to determine the overall tone of the text. Researchers initially identified positive and negative words using general dictionaries developed in psychology, such as the *General Inquirer* (Tetlock 2007). It soon became clear that the business use of words is different from the general use, and some words that are generally considered negative may not be so in a business context. For example, *liability* has a negative connotation in general use; however, in the language of business it simply refers to the company's debts. The word *sinking* normally has a negative sentiment, but in business communication, using this word in the phrase *sinking fund* refers to a regular financing practice. On the other hand, although *reconciliation* is generally a positive word, in business a *bank reconciliation* is a regular accounting procedure that does not carry any sentiment.

Some authors reacted to this challenge by constructing their own dictionary of positive and negative words (Henry 2008). A more comprehensive effort was made by Loughran and McDonald 2011; they used Form 10-K SEC filings, the annual form publicly listed companies are required to file, to construct a comprehensive dictionary from words that were frequently used by firms. This list of words still needed to be classified into positive and negative categories, as well as uncertainty, litigious, modal, and constraining categories.[1] This became the golden standard in academic studies afterward, and many studies used it to analyze various channels of financial disclosures: the management discussion and analysis (MD&A) section of 10-Q and 10-K (Feldman et al. 2010), earnings conference calls (Brochet, Loumioti, and Serafeim 2015; Suslava 2016), loan agreements (Bozanic, Cheng, and Zach 2018),

[1] See: https://sraf.nd.edu/textual-analysis/resources/.

and initial public offering prospectuses (Fishe, North, and Smith 2014).

The most common approach in text mining has been to count the number of positive and negative words in a text and construct an overall score based on these quantities, which then defines the tone or sentiment of the text. For example, one can use the number of positive words minus the number of negative words, scaled by the total number of words (or the sum of positive and negative words) as a measure of tone. Some studies use only the proportion of negative words in a text to measure tone because text generated by a company, such as press releases, tend to have a positive bias. Using word lists to identify the tone of a document is essentially a blunt tool and may be used as a cursory and superficial instrument, similar to taking body temperature to diagnose an illness. Realizing this bluntness, some authors focused on comparisons across time for the same company, which can mitigate the positive bias inherent in self-reporting.

Another text mining approach is to use *classification*, which can be performed at the level of the entire document, the individual paragraph, or even the specific sentence. Typically, the classification process begins with training data (i.e., a preliminary set of annotated examples that provide the basis for classification of future documents). Of course, to obtain decent accuracy with future classification, the training set is crucially important. Using more annotated examples typically leads to a more accurate classification. Additionally, the training set should be annotated in a similar manner. Having several annotators, which is often the case in obtaining a large training set, leads to inconsistency across annotators, which will likely reduce the future accuracy of the classification. This approach is similar to the doctor who searches for symptoms that may indicate the types of illnesses the patient may be suffering.

As an example of the classification approach, Li (2010) used phrases that discuss future events in the MD&A sections of SEC filings to assess the quality of earnings and improve the predictability of future earnings. His approach was based on identifying words that denote the future (e.g., *expect*) and assessing whether the entire sentence was positive or negative, using a large sample of examples to classify future phrases. Using a large dataset of annotated sentences to classify future text is also the basis of some commercial work in text mining (e.g., the news sentiment approach used by RavenPack).

It should be noted that in addition to measuring the tone or sentiment of a text, one can use a classification technique to identify events that are present in the text. For example, using training data on acquisition announcements by companies, one can develop a classification tool that will seek to identify future occurrences of acquisitions in other documents. What reduces the accuracy of future identification of events is the similarity in reporting of events that involve more than one company. For example, language used to describe an acquisition may be similar to the language used to report merger and acquisition activity, joint ventures, alliances, and so on. Thus, the accuracy of event extraction from a text is dependent on the number of extracted events, the size of the training set, and the correct annotation of the training set.

A third and more sophisticated text mining approach is based on writing natural language processing (NLP) rules to extract specific events from text. These rules use the semantic structure of a sentence to report the event, and in some cases this approach involves writing numerous NLP rules for a single event. This approach usually yields more accurate identification of events in a text, but it requires expending significant effort for each event. However, NLP offers the rule creator an opportunity to continuously improve the rules when extracted events are wrong or when omitted events have not been extracted by the rules. This approach is more specific and targeted and is similar to various medical tests the doctor orders to better diagnose a patient's condition.

Other, more mechanical types of textual analyses include comparing texts from the same company across time to identify differences (Cohen, Malloy, and Nguyen 2015) or counting the number of words or numbers in a document (Zhou 2018). Similarly, several authors examined how text clarity and readability affect investors (Li 2008; Biddle, Hilary, and Verdi 2009; Lehavy, Li, and Merkley 2011; De Franco et al. 2015). Others use the business description in the 10-K to examine the similarity of firms' products and operations (Hoberg, Phillips, and Prabhala 2014). Such approaches, although worthwhile from the perspective of research topics, are less interesting as text mining endeavors because they are based on well-known mechanical tools for processing text.

The purpose of this study is to illustrate an advanced approach to text mining that is based on writing specific NLP rules to identify events without advanced knowledge of NLP theory. The approach uses software that allows a domain expert to easily write NLP rules that identify events of interest for the expert in that domain, quickly test the rules by searching for other examples within a small corpus of documents from that domain, and then decide whether to use that rule on the entire domain or to modify it. We show in the following the application of the approach to earnings conference call transcripts. We should emphasize that the approach we describe in this article is one efficient way of writing rules but not necessarily the only way.

AN EASY PROCESS TO RULE WRITING

The approach we describe is based on software developed by Amenity Analytics, Inc. (Amenity).[2] Amenity's software is used to process a text and to extract from it both the tone (sentiment) and events for which Amenity has developed specific rules. The extracted tone is based on expanded word lists that the founders have accumulated through their long experience working with financial literature. In addition to words, Amenity's software has cataloged phrases that are often used in financial texts and has carefully written rules to identify sentences and even complete paragraphs as positive or negative. Amenity has also written rules around events it considers important and assigned weights to the various events, reflecting its views on the significance of these events. Thus, a document is given a numeric score based on a combination of sentiment and events captured from the text.

For advanced users, the real benefit of the software is in the user's ability to write additional rules to identify events without having any NLP expertise. This is accomplished through a few steps that we will outline. The first step involves creating a small sample of documents from the corpus. These documents are then processed through the software and are available for viewing. The text of each document is annotated in color to reflect the words and phrases used for extracted sentiment and events; the user has the ability to indicate whether these annotations are correct or not. The second step in rule writing is to highlight a sentence or a phrase of interest, which is used by the program to parse the sentence and create a graph of the parsed sentence. The user can examine the graph and then easily modify it to make it more general, so the program can identify similar structures in other documents. For example, the user can omit company-specific identifications ("The agricultural products segment"), specific numerical values ("generated growth of 18%"), and auxiliary words ("*has* generated") and use synonyms for the key words ("generated" and "growth"). The software automatically creates an NLP equivalent of the modified parsed graph. The next step is to determine the efficacy of the rule for other documents. This is done by clicking on a "Find Matches" button, which retrieves other examples from the sample corpus. If only the original example is retrieved, it is likely that the rule is not general enough and additional parts may be omitted. If a sufficient number of other examples are correctly extracted and the user is satisfied with the rule, the user assigns a name to the event (e.g., Revenue Growth), determines its polarity (e.g., positive), and saves the rule. The user can also determine the weight that should be attached to the event, depending on its perceived importance in predicting future returns. On reprocessing the documents in the corpus, all identified Revenue Growth events should now be highlighted and color-coded for their polarity. For example, if the manager said, "Sales were affected negatively because our Florida stores did not generate the expected growth," the software will flag the event Revenue Growth as negative.

Note that the software does all the heavy lifting of writing NLP rules. The user is only required to home in on a sentence or a phrase that is of interest and then easily construct a rule that addresses what the user wanted and is sufficiently general to capture other examples in the corpus. The software allows people who are domain experts to write rules, thereby making the task of rule writing more efficient and streamlined and more efficiently utilizing the domain expert's perspective on events that typically affect security prices. However, it should be stressed that having people who are both domain experts and proficient in NLP is likely to yield even greater benefits.

AN APPLICATION TO EARNINGS CONFERENCE CALL TRANSCRIPTS

A few weeks after the fiscal quarter ends, most companies issue a press release that provides preliminary

[2] The software was licensed from the vendor through a paid subscription. There are no beneficial agreements between the authors and Amenity.

details about their performance in the prior quarter. Many companies will also host a conference call with analysts to provide additional color on the press release. The call typically consists of two parts: a scripted part during which management discusses the newly issued release, which then often opens the floor to a question and answer discussion with analysts. The transcripts of these conference calls are available for consumption through several vendors.

Earnings conference call transcripts are of particular interest to quantitative investors. First, these transcripts are available for a large proportion of the investable universe (typically over 80% of the 3,000 largest companies in the United States). Second, this source of data becomes available at regular quarterly intervals. Third, like earnings surprises and estimate revisions, which were shown to exhibit investors' underreaction and autocorrelations, conference call tone signals are also likely to be autocorrelated from quarter to quarter. Finally, quantitative portfolios are typically broad, with many positions and with small bets on those positions. This is ideal for a text-mining tool, which is likely to make errors in identifying the precise tone or tone change of a specific firm but is likely to be correct more often than not for a broad portfolio, if constructed appropriately. We should note, however, that the conference call occurs immediately after earnings are released. To the extent that investors react to the earnings and the information contained in the earnings press release, the stock price may have already incorporated the information discussed during the call. Thus, in all our tests we control for the earnings surprise and the abnormal return around the earnings announcement, which captures other information in the earnings press release.

Analysis

For this analysis, we obtained conference call transcripts from Thomson Reuters for the period 2002–2016. We restricted our sample to earnings conference calls of US companies that had preliminary earnings information in the Compustat Point-in-Time database and returns in the Center for Research in Security Prices (CRSP) database. For each conference call, we first calculated the earnings surprise (*SUE*) as the earnings per share (EPS) reported in the earnings release minus the EPS reported in the same quarter of the prior year, and minus the average same-quarter EPS differences in the prior eight quarters.[3] We scale this earnings surprise by the standard deviation of the same-quarter EPS differences during the prior eight quarters. We then rank all the earnings surprises during a calendar quarter into quintiles (0 through 4), divide by 4, and subtract 0.5. We use this transformed variable as an independent variable in quarterly regressions of the abnormal future return on various signals. Its coefficient is equivalent to the return on a hedge portfolio that has a long position in the top quintile (4, the largest positive earnings surprises) and a short position in the bottom quintile (0, the most negative earnings surprises).

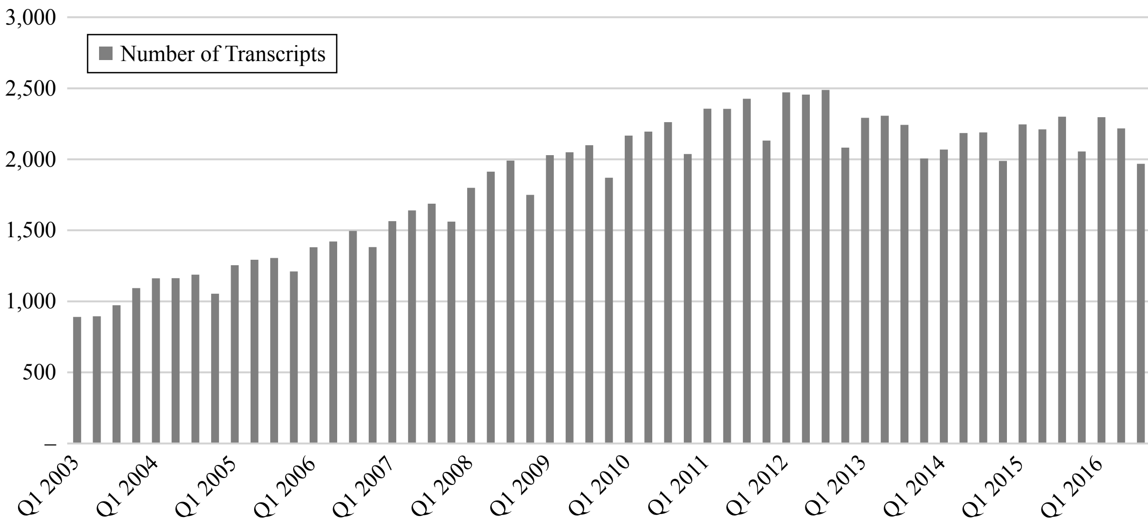
We use two abnormal return windows in this study. The first is a short window around the earnings release date [−1, +1], where day 0 is the earnings release date (*XRET_PRELIM*). The second begins on day +2 through one day after the earnings announcement date of the subsequent quarter (*XRET_DRIFT*). We use *XRET_PRELIM* to complement the earnings surprise in case additional information is released in the preliminary earnings announcement. As we did for *SUE*, we rank *XRET_PRELIM* within a calendar quarter into quintiles, divide the rank by 4, and subtract 0.5. The longer return window is a standard definition of the drift return. We calculate abnormal return as the buy-and-hold return on the stock minus the value-weighted buy-and-hold return on all stocks of the same size (three groups), book/market ratio (B/M; three groups), and 11-month momentum (three groups).

The initial analysis we performed on the conference call transcripts involved counting the number of positive words (POS) and negative words (NEG) according to Loughran and McDonald (2011). For each transcript, we calculated the word count tone as (POS − NEG)/(POS + NEG). We then calculated the word-count tone change variable as the transcript tone minus the average tone of all available transcripts for this company in the prior 370 days (*TONE_CH_L&M*). Thus, the tone change was a number in the range of [−2, +2]. In the following, we provide evidence about the incremental contribution of *TONE_CH_L&M* to the drift return beyond the earnings surprise and the short-window return around the earnings announcement.

To assess the contribution of using Amenity's software plus our rule writing, we began by writing

[3] The subtraction of the average differences adjusts for cases in which earnings grow (or decline) by a constant amount each period.

Exhibit 1
Quarterly Earnings Conference Call Transcripts



Source: Thomson Reuters conference call transcripts, Compustat Point-in-Time data, CRSP return data, and authors' analysis.

additional rules on six areas of interest to us. One of these areas included operational issues discussed by management or analysts. For example, we identified any problems in distributing products, sourcing raw materials, labor strikes, and so on and created specific rules to identify such events under the heading of *operational problems*. We added approximately 500 rules to the roughly 3,600 rules that Amenity already had already written to capture events. Using our own weights for these rules, we obtained a new tone score for each transcript based on a weighted combination of sentiment scores and event scores. In addition, we compiled a list of euphemisms that management or analysts used on the conference call, such as *headwinds*, *speedbumps, and hiccups,* (Suslava 2016), and created specific rules to identify those. We added the euphemisms score to the combined sentiment and events score and calculated a total tone score as (POS − NEG)/(POS + NEG). As before, we focused on the tone change variable by subtracting the average tone of all available earnings transcripts in the prior 370 days (*TONE_CH_AM*).

Results

Exhibit 1 shows the number of transcripts per quarter for the period of our analysis, where we have earnings surprise, returns, and tone change variables. We begin with about 890 transcripts in 2003, exceed 2,000 in 2009, and remain at that level through 2016, with slight variations. Thus, we have good representation of many firms in the investable universe.

Exhibit 2 reports summary statistics on our main variables. It shows that firms with conference calls tend to be larger, have comparable B/M ratios to the universe, have median abnormal returns that are negative, and have median earnings surprises and tone change variables that are positive.

Exhibit 3 provides the correlations among the variables used in the cross-sectional regressions in the following. Recall that *SUE* and *XRET_PRELIM* were transformed to variables between −0.5 and +0.5, so their coefficients in the regression will reflect the return on the hedge portfolio that is long the top (most positive) quintile minus the bottom (most negative quintile). We follow a similar procedure for the two tone change variables. As can be seen from the exhibit, the drift return is positively and significantly associated with all the independent variables, but its highest correlation is with *TONE_CH_AM*, followed by *TONE_CH_L&M*, *XRET_PRELIM*, and *SUE*. Note the high correlation (50%) between the *TONE_CH_AM* and *TONE_CH_L&M* variables. However, the *TONE_CH_AM* variables did not have high correlations with the earnings surprises or the short-window abnormal returns,

EXHIBIT 2
Descriptive Statistics

Variable	*N*	Mean	Median	Std. Dev.	Q1	Q3
TONE_CH_L&M	101,125	0.006	0.011	0.156	–0.092	0.109
TONE_CH_AM	101,125	0.000	0.007	0.196	–0.119	0.126
SUE	101,125	–9.102	–0.026	2,836.380	–0.717	0.637
MKT	101,125	6,756.79	1,211.860	23,759.85	393.02	3,829.41
BM	101,125	0.610	0.481	0.615	0.284	0.760
XRET_PRELIM	101,125	0.241	0.110	8.626	–3.760	4.189
XRET_DRIFT	101,125	0.611	–0.102	20.129	–9.235	9.142

Notes: Exhibit 2 reports summary statistics for variables used in subsequent tests. TONE_CH_L&M *is the difference between the L&M tone in a company's conference call and the mean L&M tone in the company's conference calls held within the preceding 370 calendar days. L&M tone is a sentiment signal based on the Loughran and McDonald dictionary and calculated as the difference between the positive sentiment score and the negative sentiment score, scaled by the sum of the positive and the negative sentiment score.* TONE_CH_AM *is calculated in the same manner as* TONE_CH_L&M *but is based on the Amenity score, which consists of Amenity sentiment and events score, including events identified by the authors.* SUE *is calculated as the EPS reported in the earnings release minus the EPS reported in the same quarter of the prior year and minus the average same-quarter EPS differences in the prior eight quarters, scaled by the standard deviation of the same-quarter EPS differences during the prior eight quarters.* MKT *is the market value of equity at the conference call date.* BM *is shareholders' equity divided by pre-earnings announcement market value.* XRET_PRELIM *is the buy-and-hold return on a stock minus the average return on a matched size–B/M–momentum portfolio in the interval [–1, +1], where day 0 is the preliminary earnings announcement date.* XRET_DRIFT *is the buy-and-hold return on a stock minus the average return on a matched size–B/M–momentum portfolio from two days after the preliminary earnings announcement date through one day after the subsequent quarter's preliminary earnings announcement.*

Source: Thomson Reuters conference call transcripts, authors' analysis using Amenity software, CRSP returns, and Compustat Point-in-Time earnings.

EXHIBIT 3
Pearson Correlations

	XRET_DRIFT	*SUE*	*XRET_PRELIM*	*TONE_CH_L&M*	*TONE_CH_AM*
XRET_DRIFT	1				
SUE	0.027***	1			
XRET_PRELIM	0.033***	0.160***	1		
TONE_CH_L&M	0.048***	0.212***	0.228***	1	
TONE_CH_AM	0.036***	0.157***	0.176***	0.503***	1

Notes: This exhibit reports Pearson correlations for our testing variables. All variables are defined in the footnotes to Exhibit 2.

***** denotes significance at the 1% level.*

Source: Thomson Reuters conference call transcripts, authors' analysis using Amenity software, CRSP returns, and Compustat Point-in-Time earnings.

indicating a sufficiently different potential source of information.

Exhibit 4 contains the results of quarterly cross-sectional regressions of the abnormal drift returns on various independent variables in the manner of Fama and MacBeth (1973). We report the average quarterly coefficient and its *t*-statistic over the 55 quarters used in the study.

The first specification shows the contribution of earnings surprises and the short-window abnormal returns around the earnings announcement to explain the drift return. Both are positive and statistically significant, as we expected based on prior studies. Together they yield about 3% of abnormal return per quarter, again in line with prior studies. In the second specification, we added the L&M tone change to the prior two explanatory variables. All three independent variables are still positive and significant, but now the word-count tone change contributes the most to the drift, with a quarterly hedge return of 1.66%, bringing the total drift return to 4.19%, a significant increase in return. Our third specification introduces the Amenity tone change

EXHIBIT 4

Fama–MacBeth Regressions of Excess Returns

Variables	*XRET_ PRELIM*	*XRET_ PRELIM*	*XRET_ DRIFT*
INTERCEPT	0.6631**	0.6626**	0.6622**
	(2.10)	(2.10)	(2.10)
TONE_CH_L&M		1.6567***	
		(7.65)	
TONE_CH_AM			2.2657***
			(10.18)
SUE	1.3282***	1.1039***	0.9071**
	(3.70)	(3.09)	(2.57)
XRET_PRELIM	1.6763***	1.4319***	1.2561***
	(5.67)	(4.87)	(4.31)
No. Obs.	101,125	101,125	101,125
No. Regressions	55	55	55
Quarter FE	YES	YES	YES
R^2	0.54%	0.71%	0.78%

*Notes: The exhibit presents the results of Fama–MacBeth style quarterly cross-sectional regressions of the excess drift buy-and-hold return (*XRET_DRIFT*) after the conference call dates. For regression analysis* SUE *and* XRET_PRELIM *are normalized between −0.5 and 0.5 by ranking them into the quintiles every fiscal quarter, dividing the rank by 4, and subtracting 0.5. All unscaled variables are defined in the footnotes to Exhibit 2. The t-statistics are reported in parentheses.*

**** denotes significance at the 1% level.*

*** denotes significance at the 5% level.*

Source: Thomson Reuters conference call transcripts, authors' analysis using Amenity software, CRSP returns, and Compustat Point-in-Time earnings.

variable (*TONE_CH_AM*), which shows a hedge return of 2.27% per quarter, bringing the total contribution of the three variables to 4.45% per quarter. Thus, our effort of using Amenity's software and writing additional rules to capture our own events and euphemisms added another 26 bps of abnormal return per quarter.[4]

CONCLUSIONS

This study proposes an advanced approach to analyzing text and converting it into a numerical score, which is easy to implement with the right software. This approach determines the sentiment in the document, but more importantly, it identifies additional events of importance to the user. The software allows the writing of NLP rules by individuals who are not data scientists or NLP experts but are experts in the particular domain from which the text originated. This reduces the cost of writing rules to capture relevant events and makes the text mining process more efficient. Another advantage of this approach is that each firm can create its own rules to capture specific events from the same text used by other firms, but each will have its own secret sauce. Furthermore, each firm that uses such software will have incentive to continuously engage in writing new rules to capture new events of interest and improve its future returns. This same process can also be used to generate rules that capture specific items of interest, such as newly imposed tariffs (see Klevak et al. 2018) or sensitivity to operations in a specific country.

[4]Controlling for size and B/M in the regressions did not change the relative order and the significance of the contributions.

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