Classifying the influence of negative affect expressed by the financial media on investor behavior

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Abstract. Prior text mining studies have documented a causal link between human emotions and stock market patterns, yet relatively little research exists into what triggers these emotions. This paper aims to bridge the gap by empirically testing a social psychology theory of human behavior. Underlying our approach lies Attribution Theory, which addresses how observers form causal inferences and moral judgments to explain human behavior, particularly those with negative outcomes. The system presented here works in three stages. The first phase computes a measure of media pessimism by counting negative terms from the General Inquirer dictionary to detect acts of corporate irresponsible behavior. The second phase extends the term-counting approach to capture contextual information. Emotion topic priors are incorporated in a Latent Dirichlet Allocation (LDA) model to infer the financial media's expression of negative emotions. The proposed system combines the two components in an ensemble tree to classify the impact of financial media allegations on a company's stock market patterns. The paper underlines the potential benefit of text mining technology for the support of investor strategies, and more generally demonstrates the power of combining multiple methods for applications in specific domains.

1 Introduction

There is a large body of work on affective text mining (e.g. product reputation mining, customer opinion extraction, and sentiment classification) [8], yet relatively little research has explored the social psychological mechanism that links affective terms expressed by the media to human behavior [1,2,3]. The stock market provides an interesting setting to evaluate text-based emotion cause detection. Given limited time and cognitive processing abilities, investors often turn to the financial media to determine the salience of news when forming their investment decisions [4,5]. Prior studies document a link between emotions such as investor fear and happiness to stock market patterns[8][5][34]. Such emotions are known as attribution-independent emotions [6,7] because they lack clear attribution to particular events. The examination of investors' attribution-dependent emotions (e.g. anger, contempt and disgust) presents a gap in the affective text mining literature. Such emotions are linked to specific triggering events and, in the context of the stock market, may be invoked when a publically-listed corporation is accused of acts of irresponsible behavior. From an applications perspective, our results may be of interest to investors seeking to interpret attributions and emotions expressed by the financial media as part of their investment analysis [5]. It can therefore be seen as an illustration of the cross-over potential of text mining.

The rest of this paper is structured as follows. Section 2 draws on literature from the fields of social psychology, organizational studies and emotion-based textual analysis and discusses the influence of media attributions and emotions on public perceptions with regard to investors' behavior. Section 3 describes the components of the proposed joint emotion-topic model that combines a measure of media pessimism and a probabilistic topic model in an ensemble tree. We outline our financial media corpus, present the experiments and discuss the results. Finally, we conclude and suggest avenues for future research.

2 Related Literature

2.1 Background: crisis emotions

In this study we examine the role of negative affect [22], defined as the human experience of negative emotions (e.g. anger, fear, disgust, guilt, and nervousness), on investor behavior. Prior research in the fields of social psychology [9] and finance [5] suggest that, due to cognitive limitations, negative information has a greater impact on investor behavior than positive information. Underlying our approach lies Attribution Theory, the dominant theory developed in the field of social psychology [10], which addresses how observers form causal inferences and moral judgments to explain irresponsible behavior. The theory holds that people make judgments about the causes of events, especially unexpected events with negative outcomes.

The financial media play a critical role in influencing the reputation of companies [4] by expressing views that are often written to provoke a public reaction [11]. Consider, for example, a news report of a factory fire that causes employee fatalities. If the news coverage emphasizes the firm's intentional negligence [3], anger might dominate the public's response; the public may consider the firm an object of blame for not controlling the crisis or preventing it from happening. If the news story focuses on the victims' personal lives or their families' suffering, a feeling of sadness may be invoked [3]. Alternatively, if the media emphasize that the accident may occur again, fear may dominate the public's emotions [6], which may result in a boycott of the firm's products [28]. Consequently, how the media perceive, feel about, and evaluate corporate behavior can influence investors' behavior [4]. To our knowledge, there is no empirical evidence that provides a large-scale test of this proposition. Our study aims to demonstrate how the field of text mining can contribute to the generation of an empirical foundation for this claim, and provide a deeper insight into the kind of individual and collective human behavior exhibited in response to corporate allegations. This is assessed by inferring media attributions of responsibility during corporate crises and evaluating the impact on investors' behavior.

2.2 Affective text mining

While early text-based emotion processing studies [13][11] regarded emotion analysis as a classification task to detect basic emotion states such as "happy" and "sad", subsequent studies have considered a deeper understanding of emotions [1][13] by assuming that emotions are invoked by the perception of external events that in turn trigger reactions [14,15,16]. Our proposed approach employs a joint emotion-topic model to mine affective content [17,18] and is motivated by research in the field of social psychology which suggests that emotions are formed as mixtures from a limited number of primary emotions [16]. The mixture distributions, known as 'dyads', include outrage, a combination of primary emotions surprise and anger, contempt a blend of disgust and anger, and remorse, an amalgam of sadness and disgust. We employ an implementation of Latent Dirichlet Allocation (LDA) [19] to model this insight.

3 JOINT EMOTION–TOPIC MODEL

In this section we describe the components of the system, provide an evaluation and a discussion of the results. The first phase computes a measure of media pessimism expressed in documents. The second phase implements a topic model to discover contextual information, by inferring negative affect associated with media attributions of corporate culpability. The final stage combines the two components in an ensemble tree

3.1 Media pessimism

Following prior text mining studies in the field of finance [28][30], we define a document as a financial media allegation of irresponsible corporate behavior and compute a measure of media pessimism by counting terms using the General Inquirer dictionary [20][21]. The dictionary contains 1,915 positive words and 2,291 negative words. Negative terms include: 'accident', 'error', 'negligence' and 'disaster'. We perform a pre-processing step that consists of Snowball stemming and stop word removal and measure the standardized fraction of negative terms in a document [21]. We include the media pessimism measure as a component within the ensemble tree.

3.2 Emotion-Topic Model

The media pessimism component treats negative terms individually and cannot discover the contextual information within the document to associate attributions of blame. The second phase therefore extends the approach and employs a LDA model [19] to infer negative affect [17][18]. We label this the emotion-topic model. A traditional topic is a list of words sorted by the probability that each word can be generated from the topic. In the emotion-topic model, a topic is related to the distribution of word emotions. We seed negative affect topics, obtained from the General Inquirer dictionary [20], as priors in the LDA model. Our intention is to capture 'global' topics of emotions expressed within the documents [23]. We implement standard settings for LDA hyper-parameters with $\alpha = 50/K$ and $\beta=.01$ where K is the number of topics [25], and adopt a heuristic approach to set the number of topics equal to four. This choice is based on prior studies that identify that four negative emotions (anger, fright, anxiety, and sadness) dominate the public's emotions during times of crisis [2]. Table 1 identifies the top terms associated with the topic clusters. As noted in [25], the task of annotating labels to topic clusters is challenging because the English language 'does not contain emotion words for certain combinations' of dyads (Section 2.2). We therefore manually annotate labels associated with the inferred topic clusters.

Table 1. Representative document terms

fear	anger	remorse	contempt
nervous	touchy	sorrow	outcry
twitch	concern	bereavement	sufferer
misunderstand	overflow	lone	loveless
helpless	concern	estranged	rot
hysterical	angry	mortify	rage

We include the resulting document topic probabilities as components within the ensemble tree.

4 JOINT EMOTION–TOPIC MODEL

In this section we discuss our corpus of financial media. We then outline the evaluation of the ensemble classification tree, present the results and provide a discussion.

4.1 Data

Our news source is a corpus created from Dow Jones Newswires (DJNW); a source considered to influence investor sentiment [5]. News articles are retrieved from financial blogs, (e.g. MarketWatch.com), on-line newspapers (e.g. The Wall Street Journal) and financial magazines (e.g. Barron.com). We include the 'Editorial Commentary' and the 'Letters to the Editor' sections on the assumption that these articles contain more opinionated views than fact based articles [31]. We conduct keyword searches on the headline and the first sentence of news stories that contain the terms 'accusation' or 'allegation' in lemmatized form. These terms are chosen because they convey negative connotations of corporate behavior, though they are insufficient in their own right to determine the nature, severity and cause of an allegation for an investor to determine the potential impact on a firm's stock market patterns [4]. Drawing on prior organizational studies, we search for news related to companies in Fortune magazine's list of the 'World's Most Admired Companies' [32]. This group of firms is considered to be 'newsworthy' of journalists' attention [4], and more likely to be negatively impacted by allegations [31]. Our corpus consists of 35,678 daily news stories for 598 global companies for the period 1 January 2009 to 31 December 2013.

4.2 Experimental setup

The goal of ensemble methods is to combine the prediction of several models built with a given learning algorithm in order to improve the generalizability and robustness over a single model. The goal of ensemble methods is to combine the prediction of several models built with a given learning algorithm in order to improve the generalizability and robustness over a single model. We use the Random Forest algorithm [26] to combine the system components and to introduce randomness into the classifier construction.

To classify the likelihood that a given media allegation associated with an act of irresponsible corporate behavior will negatively impact investors' behavior, we compute a measure of investor sentiment obtained from stock market patterns [27][33]. A fall in share price on the day of the announcement implies that investors assess that the allegation news is detrimental to the company's reputation [28]. We define a binary variable that equals one if the change in a company's stock market pattern is negative on the day of the allegation announcement, and zero otherwise. To control for exogenous events that may be announced on the same day as the media allegation we impose a second condition such that the magnitude of the fall in a company's share price must exceed any observed fall in the overall stock market (MSCI All Country World) index [30][33]. This constraint implies that the fall in a company's share price can be attributed to the allegation news rather than exogenous stock market conditions [27].

Experiments were validated using 10-fold cross validation. The dataset is divided into 10 equal sized sets; the classifier is trained on 9 datasets and tested on the remaining dataset. The process is repeated 10 times and we calculate the average across folds. For evaluation, we select precision and recall measures and for completeness include the F1-measure. The metrics are defined below:

$$Precision = \frac{\#\ of\ correct\ classifications\ of\ companies'\ stock\ market\ patterns}{total\ \#\ of\ classifications}$$

$$Recall = \frac{\#\ of\ correct\ classifications\ of\ companies'\ stock\ market\ patterns}{total\ \#\ of\ media\ allegations}$$

$$F1\ score = \frac{2\ x\ \ precision\ x\ recall}{precision + recall}$$

Table 2 displays the evaluation metrics for each of model components and the system.

Table 2. Model evaluation

				Change vs. the baseline		
Model	**Precision**	**Recall**	**F1-measure**	**Precision**	**Recall**	**F1-measure**
Media pessimism (baseline)	0.469	0.482	0.475			
Emotion-topic model	0.509	0.429	0.465	8.4%	-11.0%	-2.1%
Joint emotion-topic model	0.541	0.479	0.508	15.2%	-0.6%	6.8%

4.3 Discussion

Our findings indicate that the term counting and topic modeling approaches capture distinct, yet complementary dimensions of media sentiment. Precision for the joint emotion-topic model improves by 15% versus the baseline. To aid our understanding of the system, Figure 1 displays the decision tree results for one of the folds. The numbers in the grey boxes provide the associated probability values associated with the likelihood of a negative stock market pattern. A value of 1 indicates a 100% likelihood of a negative stock market pattern for a company on the day of the media allegation.

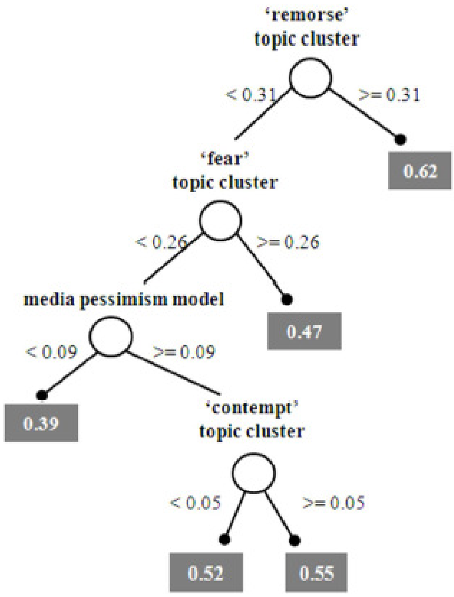

Fig 1. Example classification tree from one fold

Our findings suggest the presence of a hierarchical relationship between negative affect expressed in the financial media and a company's stock market patterns. The dominance of the emotions of remorse and fear is consistent with prior studies that document investors' risk-averse behavior during crises [3][7][34]. Our results provide a new insight into negative affect and investor behavior. In particular, the 'contempt' topic cluster appears to be a more important predictor of negative stock market patterns, when related to acts of irresponsible corporate behavior, than the emotion of fear.

5 CONCLUSION

In this study, we examine the relationship between acts of irresponsible corporate behavior, the associated negative affect expressed by the financial media and the impact on investors' behavior. Prior studies identify a statistical relationship between investors' emotions and stock market patterns but do not provide a theory to explain this link. Our study aims to demonstrate how the field of text mining can contribute to the generation of an empirical foundation to test theories developed in the fields of social psychological and organizational studies. The results of our research may be of interest to investors seeking to incorporate text-based emotion processing into their investment analysis. In future research we intend to integrate the impact of allegations expressed via social media and other online sources.

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