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Using Twitter trust network for stock market analysis

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ABSTRACT

Online social networks are now attracting a lot of attention not only from their users but also from researchers in various fields. Many researchers believe that the public mood or sentiment expressed in social media is related to financial markets. We propose to use trust among users as a filtering and amplifying mechanism for the social media to increase its correlation with financial data in the stock market. Therefore, we used the real stock market data as ground truth for our trust management system. We collected stock-related data (tweets) from Twitter, which is a very popular Micro-blogging forum, to see the correlation between the Twitter sentiment valence and abnormal stock returns for eight firms in the S&P 500. We developed a trust management framework to build a user-to-user trust network for Twitter users. Compared with existing works, in addition to analyzing and accumulating tweets' sentiment, we take into account the source of tweets – their authors. Authors are differentiated by their power or reputation in the whole community, where power is determined by the user-to-user trust network. To validate our trust management system, we did the Pearson correlation test for an eight months period (the trading days from 01/01/2015 through 08/31/2015). Compared with treating all the authors equally important, or weighting them by their number of followers, our trust network based reputation mechanism can amplify the correlation between a specific firm's Twitter sentiment valence and the firm's stock abnormal returns. To further consider the possible auto-correlation property of abnormal stock returns, we constructed a linear regression model, which includes historical stock abnormal returns, to test the relation between the Twitter sentiment valence and abnormal stock returns. Again, our results showed that by using our trust network power based method to weight tweets, Twitter sentiment valence reflect abnormal stock returns better than treating all the authors equally important or weighting them by their number of followers.

1. Introduction

Online social media (e.g. Twitter) is becoming more popular, as it is easier for users to post and spread information than with traditiona l media. With more users joining in online social networks, more data is available. Therefore, many data-driven applications, such as disaster detection [1], election predictions [2,3], information filtering [4], opinion mining [5–7] and so on benefit from this trend. Among them, financial market analysis is one of the most attractive fields and has attracted a lot of attention [8–12].

The stock market is a very hot topic in the field of finance and economics. Many researchers try to analyze and predict stock returns based on various types of theories [13,14]. For example, Chartist theory [15] assumes that the stock market's past behavior patterns will recur in the future. Thus we can predict future stock returns by using historical data. In contrast to Chartist theory, Random Walk theory [16,17] considers stock returns as identical independent variables. Although these theories' assumptions are different, many existing works use historical stock market data, such as open price, close price, daily trade volume and so on, to predict future stock returns.

Besides historical stock market performance, investors' decisions can be affected by news [18] and media [8,10,19–21]. Also, public mood or sentiment which is reflected in media plays an important role in investors' decision making processes [22,23]. Investors' decisions in turn can affect stock market. Therefore, stock market is related with public mood in news or media.

With the popularity of Twitter and its easy-to-use open Application Programming Interfaces (APIs), there exist many works that use Twitter as a platform to analyze and predict stock market activities, including both indicator-level and firm-level analysis [9,11,12,24,25]. In addition to academic researchers, firms are also paying attention to Twitter for their commercial purposes. Many firms use Twitter to interact with their investors and customers

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[26]. Compared with traditional media, Twitter is efficient. To use Twitter to analyze stock market, typically Twitter feeds (tweets) are first analyzed by sentiment analysis tools to extract their sentiment, then tweet sentiments are aggregated together. Aggregated Twitter sentiment valence is then used for financial market analysis. Most widely used sentiment analysis tools generate binary results (positive or bullish vs. negative or bearish), although some sentiment analysis can generate multi-level sentiment results.

The main hypothesis of this work is that the users reputation, built by the inter trust among them, using our trust management system, helps in making better predictions of the stock market. To verify this hypothesis and to validate our trust management system, we collected stock-related data from Twitter to see the correlation between Twitter sentiment valence and abnormal stock returns. Therefore, the correlation between Twitter sentiment valence, filtered by our trust management system, and abnormal stock returns served as ground truth for our trust management system. We selected eight firms which are the top eight mentioned firms (which have the largest number of tweets) in our data set. The reason we selected these eight firms is that, for other firms, the average number of daily tweets is low. Based on only a small number of tweets, we think that the analysis is not reliable. For the selected eight firms we collected their stock data correspondingly from Yahoo! Finance. As indicated in [27], the source (users) of tweets is also an important factor. Therefore, unlike many existing works which treat all the authors equally important or ignore authors' identities, in addition to analyzing tweets' sentiment, we also take into account tweets' authors. We adapted our trust management framework [28] and constructed a user-to-user trust network for Twitter users based on their tweeting behaviors. Then, users were differentiated by their reputation or power in the whole community, where reputation or power is determined by the user-to-user trust network. Furthermore, to aggregate tweets together for Twitter sentiment valence, each tweet is weighted by its author's power.

To compare our approach to other ones, we used the Pearson correlation tests among results for eight months time (the trading days from 01/01/2015 through 08/31/2015). Compared to treating all the authors equally important or weighting them by their number of followers, our trust network based reputation mechanism amplifies the correlation between a specific firm's Twitter sentiment valence and the firm's stock abnormal returns. To further consider the possible auto-correlation property of abnormal stock returns and to test the relation between Twitter sentiment valence and abnormal stock returns, we constructed a linear regression model, which includes historical stock abnormal returns. Again, our results show that by using our trust network power based method to weight tweets, Twitter sentiment valence reflect abnormal stock returns better than other two methods, that is treating all the authors equally important or weighting them by their number of followers.

The remaining portion of this paper is organized as follows: in Section 2, we introduce some background knowledge and literature works in this field. In Section 3, we introduce our trust management framework and adapt it to Twitter. Also, we propose a simple method to calculate for users' power or reputation. In Section 4, we illustrate how we aggregate Twitter sentiment valence for the firms. And we propose our trust network power based method as well as other two baseline methods. In Section 5, we give detailed information about the data sets we used in this work. Also, we compare our trust network power based method with other two baseline methods regarding Pearson correlation coefficients and a linear regression model. In Section 6, we conclude our work and list several limitations of applicability of this work as well as some potential future work.

2. Background and related works

Twitter, as one of the most popular online social media platforms, provides its users the ability to share and spread their opinions. It also enables users who have the same interests to form groups. The stock market is among one of the hottest topics among Twitter users. There are many stock market-related groups or gurus on Twitter, such as StockTwits, FinancialTimes, MarketWatch, and so on. Recent research has shown that investors are likely to post financial news or articles and share their opinions on Twitter [29]. Compared with traditional media, Twitter feeds can be incorporated instantly into stock prices. Therefore, Twitter has become a widely used platform for researchers to analyze and predict stock returns.

As Refs. [8,19,20] pointed out, investors' emotions or sentiments can be reflected by the stock market. Negative sentiment or pessimism on social media might induce a stock price to drop. Positive sentiment is more likely to induce stock prices to increase than neutral or pessimism sentiment. Therefore, given users' text (tweets), natural language processing methods are needed to analyze investors' emotions. There exist many sentiment analysis tools. Roughly, they can be divided into two categories: word count analysis strategy and machine learning strategy. Word count analysis strategy uses dictionaries to determine sentiment for each word and then aggregate words' sentiment together. Most commonly used dictionaries in this field include Harvard-IV dictionary [30] and Loughran and McDonald's financial dictionary [31]. Among machine learning methods, most of them are classifiers, such as Naive Bayes classifier, SVM classifier, and so on. One of the problems of the machine learning strategy is that it requires a set of labeled training data, which might need a huge load of manual work. In this work, we use an existing sentiment analysis tool – SentiStrength [32], which is designed for short informal text.

Twitter sentiment valence is then measured based on the detected positive and negative tweets. Various Twitter sentiment valence measurements are used in literature [8,11,29,33]. In principle, Twitter sentiment valence measures the ratio of positive tweets to negative tweets. To investigate the linear relation between Twitter sentiment valence and stock prices or stock returns, Pearson correlation coefficients [12,29,34] and beta coefficients of linear regression models [9,11,33] are widely used in literature.

Existing works in this field can be divided into two categories based on their focus. Indicator-level works mainly focus on indicators, such as Dow Jones Industrial Average Index, NASDAQ, S&P 500 index, and so on. This type of work focuses on the whole industry. Indicator-level works include [8,9,35,36]. More recently, researchers are also paying much attention to firm-level works; as the name itself indicates, instead of investigating the whole industry, this type of work focuses on specific firms. Refs. [11,29,33,34,37,38] belong to firm-level works. In this paper, we focus on specific firms.

Bollen et al., [9] used OpinionFinder and Google-Profile of Mood States (GPOMS) to measure sentiment for tweets. Rather than outputting binary sentiment results (OpinionFinder), GPOMS measures sentiment in six dimensions, which includes calm, alert, sure, vital, kind, and happy. And it showed that only calm is related to Dow Jones Industrial Average Index. Tetlock [8] did experiments with Wall Street Journal, and mainly focused on the pessimism score of the media. It showed that high media pessimism scores caused the drop in stock market prices. Zhang et al., [36] classified tweets into fear, worry, and hope based on the corresponding words. It showed that Twitter sentiment (fear, worry, and hope) is negatively correlated with Dow Jones Industrial Average Index, NASDAQ and S&P 500 index. Similarly, Gilbert and Karahalios [35] measured anxiety, worry, and fear in LiveJournal,