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Predictive Power of Public Emotions as Extracted from Daily News Articles on the Movements of Stock Market Indices

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***Abstract*—The emergence of computing power and the abundance of data have made it possible to assist human decisions, especially in the stock markets, in which the ability to predict future values would lower the risk of investing. In this paper, we present a new approach for identifying the predictive power of public emotions extracted from various sections of daily news articles on the movements of stock market indices. The approach utilizes the results of a lexicon emotion analysis conducted on crowd-annotated news to extract various types of public emotions from daily news articles. We also propose a model and an analysis method to score news articles regarding public emotions, and to identify which news sections and emotions cause movements in a stock market index. The results of an experiment conducted with 24,763 news articles show that some types of public emotions are significantly correlated with changes in the trading volume and the closing price of a stock market.**

Keywords—Emotion analysis; Sentiment analysis; Predictive power analysis

I. INTRODUCTION

Past studies show that stock market prices do not follow a random walk model and that they are indeed to some degree predictable. For instance, weather conditions have been found to have significant effects on stock prices [1]. People's emotions, which can be directly influenced by new information, also play a significant role in human decisions [2]. A number of studies have analyzed texts from social network services (SNS), blogs and news to try to determine correlations between social events and news, and stock prices. However, most of these works analyze only articles in specific categories (e.g., financial sections) rather than utilizing various types of articles [3]. Moreover, some of these studies classify public emotions as only positive and negative rather than classifying them into multiple types [4].

The main research question in this study can be stated as follows: 'Which types of public emotions extracted from which sections of news have predictive power on the movements of stock prices and trading volumes?' To answer this question, we develop a novel approach to determine public emotions as numerical values by applying emotion analysis to daily news articles. The proposed approach utilizes the results of a lexicon emotion analysis generated from crowd-annotated news to provide a novel emotion scoring model.

The rest of the paper is organized as follows. Section 2 summarizes the related work. In Section 3, we describe our approach of scoring public emotions from news articles. In Section 4, we verify the effectiveness of our approach, followed by the conclusion and a description of future work in Section 5.

II. RELATED WORKS

There have been several attempts to extract human emotions from SNS postings and personal blog pages, of which the contents usually reflect how people react to recent events and news [5][6]. However, there exists a time lag between the time when the incidents occur and the time when people's emotions are expressed in SNS postings and on blogs. In addition, messages posted on SNS and personal blogs are usually too brief and informal to classify them into certain categories, which would be essential when attempting to identify the types of incidents that may affect investors' decisions. Moreover, the majority of SNS and blog users are young people, which may lead to a biased analysis of public emotions.

Owing to these drawbacks, several studies have utilized news articles to identify people's emotions and analyze their effects on financial markets. However, most of these approaches focus on utilizing only news articles from the financial section, articles published by organizations with a link to the economy, or only news directly related to specific companies. It has been found that economic news alone cannot explain more than one third of stock returns [7].

Other approaches simply classify texts in news articles, SNS or blog posts into positive, negative and/or neutral categories in an effort to analyze people's emotions [4]. However, earlier studies found that people's emotions are represented as mixed types [8], implying that the classification of emotions into only a few categories cannot effectively represent human emotions, which may be affected by text when it is read.

In summary, there have been no prior studies which have attempted to identify the types of emotions and news sections that affect stock market indices and trading volumes through an analysis of daily news articles.

III. EXTRACTION OF PEOPLE'S EMOTIONS FROM DAILY NEWSPAPER ARTICLES

A. Source selection

We collected a total of 24,763 news articles from three major news sections: national, business and politics, from five major English news providers in Korea during the year 2015. Table I lists the names of the news article providers and the number of news articles used in the study.

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Algorithm 1. Emotion measurement of a given news article

```
1: Procedure SCORE_ARTICLE(Article)
2:     tokenize ← Tokenize(Article.toLower())
3:     pos_tag ← Pos_tag(tokenize)
4:     emotions ← vector(0)
5:     for each word ∈ pos_tag do
6:         if pos ∈ {noun, verb, adjective, adverb}
7:             lemma ← Lemmatize(word.getWord())
8:             emotions += Depechemood.get(lemma, pos)
9:     end for
10: return emotions
```

TABLE I. NEWS ARTICLES USED FOR THE ANALYSIS

News provider	Number of articles
Chosun	2,442
Joongang	4,943
Korea Times	9,243
Korea Herald	7,000
Hani	1,135

B. Preprocessing

We tokenize all sentences in each news article into words according to an English dictionary. For each word, we identify its part of speech (POS) and lemmatize words to obtain their lemma form. To perform these steps, we utilize NLTK[1], a popular natural language toolkit. In our analysis, we consider only four parts of speech: nouns, verbs, adjectives and adverbs. We do not consider other types, such as pronouns or articles, because they are usually used as connectors that connect important words within sentences. Duplicated words are retained because they may reflect the level of emotions that people may feel when reading the article.

C. Scoring

1) Emotion measurement from news articles

Because the goal of our study is to find the types of emotions that cause changes to a stock market index, we choose an emotion analysis tool that classifies text into multiple emotion types rather than simply annotating articles with a polarity value.

In our approach, we use DepecheMood [9] as our main tool for extracting emotion scores from news articles. Jacopo proposed DepecheMood, which is composed of 37,771 English terms as lexica represented in the lemma#PoS format. Each entry is annotated with eight different emotion scores corresponding to 'afraid', 'amused', 'angry', 'annoyed', 'don't care', 'happy', 'inspired', and 'sad'. These scores are generated using crowd-sourced annotations provided by the readers of news articles from rappler.com[2]. We consider their word-by-emotion matrix with word frequencies normalized such that the likelihood of the occurrence of each word is taken into account. In our analysis, we refer to a list that consists of eight emotions of word *w* as a vector score $\vec{e}(w)$. Each word is assigned a vector score of zero or a value defined in DepecheMood. A vector score of zero is assigned to a word which exists in a news article but not in DepecheMood. The majority of the terms with a vector score of zero are simple names. The following equation defines the *vector score of a word w*,

Algorithm 2. Emotion scoring on a given day and of a given news group

```
1: Procedure SCORE_DAY(day, group)
2:     emotions ← vector(0)
3:     articles ← GetArticles(day, group)
4:     for each article ∈ articles do
5:         emotions += SCORE_ARTICLE(articles)
6:     end for
7:     for each emotion ∈ emotions do
8:         total += emotions.get(emotion)
9:     end for
10: return emotions/total
```

$$\vec{e}(w) = \begin{cases} \vec{e_w} & \text{if } w \in D \\ \vec{0} & \text{if } w \notin D \end{cases}, \tag{1}$$

Where $\overrightarrow{e_w}$ refers to the vector score as defined in DepecheMood, and *D* refers to the set of words available in DepecheMood.

Line 8 in Algorithm 1 is about aggregating the vector scores of all preprocessed words in an article so as to produce the *vector score of an article A*, as follows:

$$\vec{e}(A) = \sum_{w \in A} \vec{e}(w) \tag{2}$$

Usually, news articles from the same source and the same section are displayed (arranged) close to each other. People usually read all of the news in their preferred news section at once.

Therefore, we group news articles from the same source and same section on a day together, after which we generate and assign a vector score to each news group. As explained earlier, each element of a vector score represents the score of the corresponding emotion. At lines 7-10 in Algorithm 2, the value of an emotion in a given article group is calculated as the ratio of the corresponding emotion over the summation of all elements in the vector score. The following equation defines the *vector score of a day d from news group G*,

$$\vec{e}(G_d) = \frac{\sum_{A \in G_d} \vec{e}(A)}{\sum_i \sum_{A \in G_d} \vec{e_i}(A)}, \tag{3}$$

where $\vec{e}_i$ refers to the *i*-th element of the vector score. In (3), we consider the significance of each news article, as news providers usually put more text for important articles and/or produce multiple news articles about the same issue. Each element of the vector score is a ratio value in which both the dividend and the devisor depend on the number of news articles. Thus, the effect of the number of news articles on a given day is eliminated.

Next, we define the *vector score of a day* by summing all vector scores of news group *G* on the day *d*, as follows.

$$\vec{e}(d) = \sum \vec{e}(G_d) \tag{4}$$

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[1] http://www.nltk.org/
[2] http://www.rappler.com/

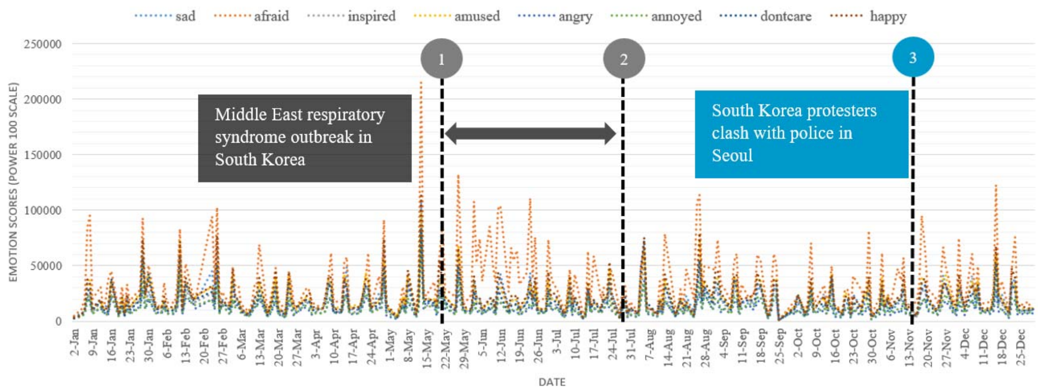

Fig. 1. Emotion scores of the year 2015 with marking on major events

IV. EVALUATION

A. Experimental settings

The market index data was retrieved from Google Finance[1]. The news articles were crawled from five news sources, as shown in Table I. The experiments were conducted on a computer that runs Ubuntu 14.04.3 LTS (64bit) with an Intel (R) Core(TM) i7-2600K CPU @ 3.40GHz with 8.00GB of RAM.

B. Results and analysis

We compare the scores against major events which occurred in Korea during the year 2015. We identify any significant emotion changes when major events occurred. Fig. 1 shows the emotion scores generated from all news sections with the time periods when the major events occurred marked.

As shown in Fig. 1, the overall emotion scores fluctuate as time passes. In addition, the scores of all emotions show similar trends. However, during the period when the Middle East respiratory syndrome occurred (the period between ① and ② in Fig. 1), the 'afraid' emotion score was much higher than the other emotion scores. This indicates the correctness of the categorization of our emotion scores. There were significant decreases in all emotion scores when there was a protester clash with police in Seoul (the period marked by ③). This may have a number of reasons. For instance, news providers may have been aware of the increasing tension and tried to avoid using emotional words in their news articles.

To validate whether the changes in emotion scores cause movements in the closing price and trading volume of the KOrea composite Stock Price Index (KOSPI), we measure the causality relationship using the Granger causality test. The Granger causality test is a statistical hypothesis test for determining whether a time-series is useful in forecasting another (Y). Our null hypothesis is that 'public emotions Granger-cause changes in KOSPI closing prices and/or trading volumes'. We apply the following two models for causality testing.

$$M_1 : Y_t = \alpha + \sum_{i=1}^{n} \beta_i Y_{t-i} + \epsilon_t \tag{5}$$

$$M_2 : Y_t = \alpha + \sum_{i=1}^{n} \beta_i Y_{t-i} + \sum_{i=1}^{n} \gamma_i X_{t-i} + \epsilon_t \tag{6}$$

The first model (5) uses only n previous stock prices/trading volumes (Y) to predict the current stock price/trading volume (Y_t). The second model (6) also includes n previous values of our emotion scores to predict the current stock price/trading volume (Y_t). The n value is termed a lagged value. We can say that public emotions (X) Granger-cause changes in the KOSPI closing prices and/or trading volumes (Y) if the prediction from the second model (6) is better than that from the first model (5).

To test the null hypothesis, we apply an F-test, as follows,

$$f = \frac{SSR_1 - SSR_2}{n} / \frac{SSR_2}{m - 2n - 1}, \tag{7}$$

where SSR_1 and SSR_2 are the sum of squares residuals of (5) and (6), respectively, and m is the number of observations. In (7), f has an F-distribution with parameters n and $m\text{-}2n\text{-}1$. Therefore, we check whether the time-series X Granger-causes the time-series Y by checking the p-value. The p-values of the Granger causality correlation between the emotion scores and the KOSPI closing prices with a lagged value of 1 are shown in Table II. The p-values which are less than 0.05 are shown in bold face. We cannot find any causality relationship when the lagged value is greater than 1.

As shown in Table II, the emotions 'happy' and 'amused' as extracted from the national news section of the previous day (t-1) provide predictive information on the movement of the KOSPI closing price of the current day (t). This result is consistent with the results of a study by Bollen, who found that the emotions, 'calm' and 'happy' as extracted from Twitter posts contain predictive information on Dow Jones Industrial Average (DJIA) closing prices [6].

Similarly, the p-values of the correlation between the emotion scores and KOSPI trading volumes with a lagged value

TABLE II. STATISTICAL SIGNIFICANCE OF THE GRANGER-CAUSALITY CORRELATION BETWEEN EMOTION SCORES AND KOSPI CLOSING PRICE

	All	**Finance**	**National**	**Politics**
Sad	0.328041	0.0581543	0.1980005	0.7453813
Afraid	0.196867	0.07170193	0.1561535	0.6770511
Inspired	0.8492785	0.1049162	0.1567212	0.7953541
Amused	0.1354825	0.1022722	**0.02145663**	0.5596599
Angry	0.2823989	0.05574286	0.2283474	0.8909498
Annoyed	0.2297359	0.0586311	0.1085093	0.6428736
Don't care	0.2989907	0.07795712	0.06843091	0.5905551
Happy	0.2201465	0.05260349	**0.04402209**	0.7918315

TABLE III. STATISTICAL SIGNIFICANCE OF THE GRANGER-CAUSALITY CORRELATION BETWEEN EMOTION SCORES AND KOSPI TRADING VOLUMES

	All	**Finance**	**National**	**Politics**
Sad	**0.01607**	**0.000583**	0.5563	0.5994
Afraid	0.05377	**0.001394**	0.5476	0.5161
Inspired	0.06137	**0.002239**	0.5438	0.466
Amused	0.05391	**0.001434**	0.6545	0.3905
Angry	0.06954	**0.00455**	0.423	0.4779
Annoyed	0.06632	**0.002659**	0.4596	0.367
Don't care	**0.0333**	**0.00146**	0.5883	0.4716
Happy	**0.03494**	**0.001082**	0.6956	0.3936

of 2 are shown in Table III. We found that the second model (6) outperforms the first model (5) when the lagged value is less than 2.

As shown in Table III, all types of emotions extracted from the financial news section of the previous day (*t-1*) and the day before the previous day (*t-2*) provide predictive information on the movement of the KOSPI trading volume of the current day (*t*). In addition, all types of emotions have nearly identical effects on the KOSPI trading volumes.

C. Threats to validity

Each news provider classifies their news articles into different categories. For example, some news sources classify news articles into categories such as 'people', and 'defense' rather than using more general categories, i.e., 'national'. Mapping between these different categorizations of articles may be subjective.

For the emotion analysis, we utilize a specific tool, DepecheMood. However, it is known to have relatively high precision levels and covers most of the language. It achieves 64% language coverage and a F1 score of 0.21~0.54 on regression tests.

In this analysis, we make use of news articles from five majors news providers in Korea for a year. We think that the dataset used here is large enough (it contains 24,763 news articles with an average length of 384 words) to generalize the results of our analysis.

V. CONCLUSION AND FUTURE WORKS

In this paper, we proposed a method of extracting public emotions from news articles and then determining the causality between emotions and market indices and trading volumes. The main contributions of our work are as follows. First, we utilized a crowd-sourced lexicon to analyze news articles and to identify public emotions. Secondly, we proposed an emotion scoring model to predict public emotions based on daily news articles.

We verified the emotion score results against the major events which occurred during the testing period. We also analyzed which types of emotions that are extracted from which news sections contain predictive power to predict the market index and trading volumes using the Granger causality test. We found that 1) all emotions extracted from financial news articles of the previous day and the day before the previous day provide predictive information about the current day's trading volume, and 2) the emotions 'amused' and 'happy' from the national news articles of the previous day provide predictive information for the current day's market closing price.

According to the result of this study, we conclude that public emotions affect people's behaviors of buying and selling stocks. In our future research, we will extend our approach to improve the emotion scoring model by considering a psychological model, such as how people perceive emotions. We will also conduct more analyses on the effect of other types of emotions.

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