

Tracing Trending Topics by Analyzing the Sentiment Status of Tweets

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Abstract. Information spreads much faster through social networking services (SNSs) than through traditional news media because users can upload data anytime, anywhere. SNSs users are likely to express their emotional status to let their friends or other users know how they feel about certain events. This is the main reason why many studies have employed social media data to uncover hidden facts or issues by analyzing social relationships and reciprocated messages between users. The main goal of this study is to discover who is isolated, why, and how the issue of social bullying can be addressed through an in-depth analysis of negative Tweets. For this, our study takes the basic approach by tracking events considered to be exciting by users and then analyzing the sentiment status of their Tweets collected between November and December 2009 by Stanford University. The results suggest that users tend to be happier during evenings than during afternoons. The results also identify the precise date of breaking news.

Keywords: Sentiment analysis, Social Networking Services, Twitter.

1. Introduction

Twitter and Facebook are two of the most popular Social Networking Services (SNSs) in the world. SNSs represent an online platform that facilitates social networks or relations between users for sharing interests, activities, and information among others. Because of the rapid development of the wireless internet infrastructure and smartphones, users can find and share information anytime, anywhere. This represents a dramatic transformation of the online lifestyle. Users no longer have to go back home or to an internet cafe to search for information or upload photos. They can simply find and share information by using their smartphones.

One particular event solidified Twitter's position as a major SNS. On January 15, 2009, a U.S. Airways jet crashed into the Hudson River, and the first photograph of the accident appeared on Twitter before even a local news outlet arrived at the scene [16,7]. In addition, there was another well-known event in Iran that many people on the street tweeted about what was happening on the ground when no major news outlet in Iran was covering the event. This event suggests that Twitter is not just a social community but a form of social media. Because of the wide popularity of Twitter, users disseminate a

diverse range of information reflecting their emotional state in trending events such as earthquakes, acts of terrorism, weather disturbances, and celebrity actions. This has led to an increasing number of diverse Twitter data sets. There were approximately 29 billion total Tweets on November 6, 2010¹.

Many studies have suggested that SNSs are crude coal that has to be turned into diamonds [15,11,8]. This study focuses on discovering who is isolated, why, and how the issue of social bullying can be addressed by analyzing the sentiments reflected in reciprocated messages between Twitter users. A number of studies have examined Twitter to determine who affects others and what issues excite users by using small data sets in limited domains. On the other hands, this study employs a full set of Tweets collected between November and December 2009 by Stanford University [24] to determine the breaking events by focusing on how the flow of sentiments and the frequency of Tweets change. We analyzed more than 110 million Tweets on a daily/hourly basis by using the LIWC (Linguistic Inquiry Word Count)², a program designed by Pennebaker et al. to calculate the degree of more than 80 sentiment categories, including positive and negative emotions. The results indicate no meaningful statistic and emotional flow on a daily basis. However, the hourly results indicate that users were happier during evening than during afternoons (during work), providing support for the findings of previous research in psychology. In addition, the results reveal the precise date of trending events.

The rest of this paper is organized as follows: Section 2 provides a literature review and describes the LIWC method. Section 3 explains the flow of sentiments and the frequency of Tweets based on the LIWC method and the experiment. Section 4 provides an example for tracking breaking news by using Twitter, and Section 5 concludes by suggesting some interesting avenues for future research.

2. Motivations and Related Works

Sentiment analysis and opinion mining are subfields of natural-language processing and text analytics for determining the attitudes of speakers or writers to reveal what others think [17,1,9]. These techniques have been applied to online review systems, personal blogs, and surveys to automatically analyze huge amounts of data. Researchers have started to consider Twitter data because of their potential to provide a better understanding of sentiments [2,10]. Twitter users are likely to express their personal feelings without being constrained, and therefore there may be sentiment related to various topics on Twitter. In particular, previous research has examined whether Twitter can be considered a form of news media by analyzing all Tweets (about 106 million) collected between June and September 2009 [16] and found clear evidence that Twitter is a form of news media because retweets spread widely regardless of the number of users following the original Tweet. A Yahoo research teams examined long-term, structure-rich events such as football games instead of one-shot events or breaking news such as earthquakes [3]. However, detecting and tracking headline events on Twitter still receive considerable research attention.

To detect breaking news on Twitter, many researchers have considered word frequency and the degree of sentiment in Tweets [22,18,12]. [22] focused on the frequency of proper

¹ <http://gigatweeter.com>

² <http://www.liwc.net>

nouns instead of conducting a sentiment analysis using the LIWC, which was employed by the research [18,13]. The LIWC is a powerful program for calculating the degree of more than 80 sentiment categories, including positive and negative emotions, in given sentences [20,14]. Table 1 presents an example of psychological categories for affective processes.

Table 1. Psychological categories for text processing based on the LIWC

Psychological Process	Grand Mean
Affective Process	4.41
Positive Emotion	2.74
Negative Emotion	1.63
Anxiety	0.33
Anger	0.47
Sadness	0.37
...	...

There are four main categories available for determining the degree of sentiments in given blocks of text by using the LIWC. The first category is a linguistic process that includes word counts, total pronouns, auxiliary verbs, and the past tense, among others. This process is a step for calculating the linguistic structure of some given text based on a predefined dictionary. The second category is a psychological process and is the most important category in the LIWC. This process can estimate the social ratio, positive/negative emotions, insights, causation, discrepancies, and tentative, among others, by using a dictionary of psychological words. For example, if the given text includes positive words such as “love,” “nice,” and “happy” instead of negative ones such as “gloomy,” “nasty,” and “fool” then the degree of positive emotions for the text goes exceeds 2.74, which is the grand mean for positive emotions. The other processes are personal concerns and spoken categories referring to “the development and psychometric properties of LIWC 2007 [21].”

As each target work is processed, the dictionary file is searched, looking for a dictionary match with the current target word. If the target word matches the dictionary word, the appropriate word category scale for that word is incremented. As the target text file is being processed, counts for various structural composition elements [6].

Because the LIWC can easily calculate positive or negative emotions in the given text, it has been applied to capture real-time moods of Twitter users to identify those who are depressed [19]. In addition, it has been used to analyze public opinion and moods in elections [4]. The effectiveness of the LIWC has been verified by many researches [23,5], but it still has a limitation in that it cannot calculate the degree of sentiments for the given text because of technological issues. That is, it returns zero for all degrees. In addition, the degree of positive or negative emotions is excessively high for short sentences. Therefore, we introduce a simple method to overcome this issue for analyzing sentiment degree if LIWC is failed.

In this study, we conduct an experiment to analyze the flow of sentiments between November and December 2009 by using the LIWC. In the analysis of Tweets on an hourly

basis, we ignore any hourly interval with fewer than 100 Tweets in order to avoid the problem that the degree of positive/negative emotions is excessively high.

3. Sentiment Analysis

We conducted a sentiment analysis using Tweets between November and December 2009 based on the LIWC. The data were collected by Stanford University and consisted of more than 110 million Tweets covering a diverse range of topics. We first calculated the number of Tweets and their positive/negative degrees by date in order to find hidden information under Tweets shown in the Figure 1. Here we focused only on the affective processes described in Table 1. The results for the sentiment flow clearly indicate no meaningful events. Unexpectedly, however, the positive and negative emotions just followed the frequency of Tweets. In other words, the emotional degree of given texts messages using LIWC was somehow influenced by the number of test sentences. This suggests that the longer the test sentence, the more likely the positive word is in the sentence. As we can see in the Figure 1, the degrees of positive and negative emotion were suddenly dropped on a certain day. This is the curious issue that we have to study for finding a reason why those degrees were decreased. It may be the problem of LIWC or because of the some events. This will be explained in the next Section. We hereby, focused on analyzing Tweets on an hourly basis in order to find other unknown issues. We separated all the collected Tweets by hour and calculated their positive/negative emotions as shown in Figure 2.

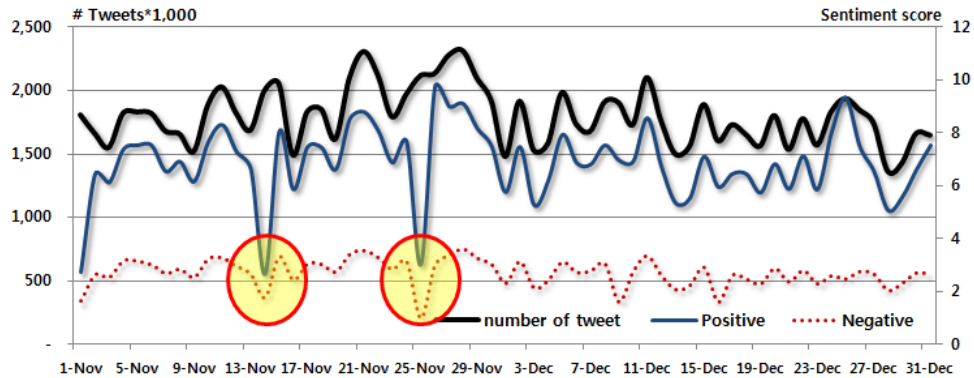
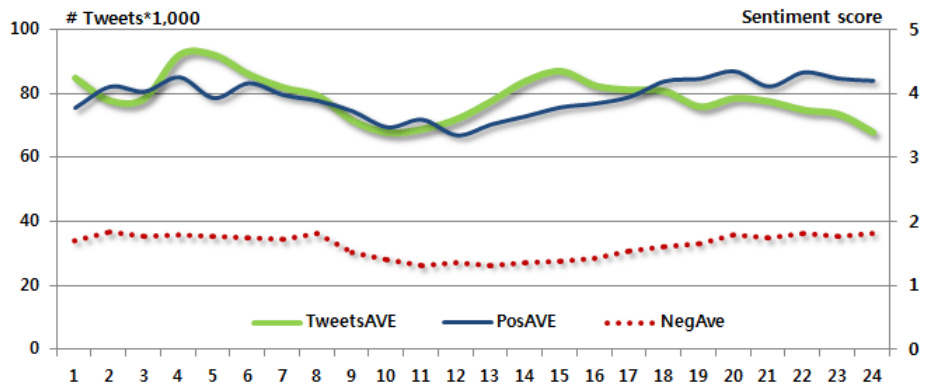
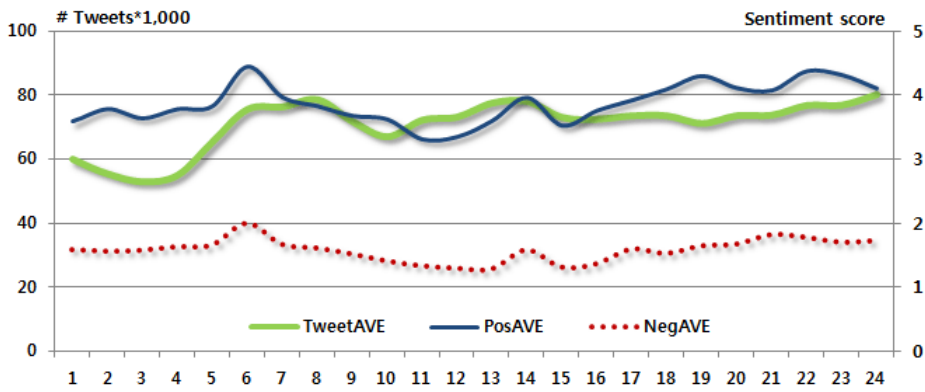


Fig. 1. Tweets and their daily sentiment flow from November to December 2009

Figure 2 show the results by hour for the analysis period. The analysis results for sentiments in Tweets by date were correlated with the number of Tweets as represented in Figure 1. However, we determined the hidden hourly pattern: Happy Tweets were more likely during mornings and evening than during afternoons (during work). The means for positive and negative categories were 2.74 and 1.63, respectively, indicating that users were more likely to express positive emotions than negative ones. This result may be due to users sending Tweets with the phrases “good morning” and “good night” during mornings and evenings, respectively.



(a) Average Tweets and their hourly sentiment flow in November 2009



(b) Average Tweets and their hourly sentiment flow in December 2009

Fig. 2. Average Tweets and their hourly sentiment flow in November and December 2009

3.1. Sentiment Analysis for Tracking Trending Events

We examined the applicability of Twitter data to the analysis of breaking events by using the LIWC followed by the proposed process shown in Figure 3. We first collected trending topics based on Google trends in November 2009 which were “Black Friday,” “Tiger Woods,” “modern warface 2,” “watch-moves.net,” “2012,” “new moon,” “toys r us,” “twilight,” and “best buy,” in that order and those in December 2009 which were “Brittany Murphy,” “Tiger Woods,” “avatar,” “Christmas,” “meteo,” “farmville,” “weather,” “weather forecast,” and “wii,” in that order. And then, we classified Tweets by those keywords in order to simplify our experiment.

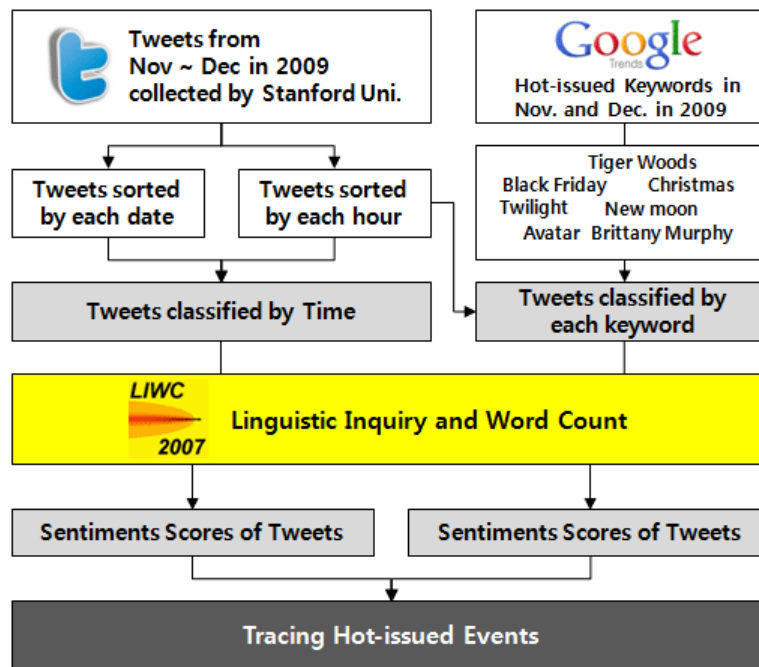


Fig. 3. The sentiment analysis process for Tweets

We explored the meaning of these keywords first for a better understanding of our research. “Black Friday” referred to Thanksgiving Day, particularly to the beginning of the Christmas shopping season. Because of large discounts offered on this day, the keyword “Black Friday” ranked first on November 2009 in Google trends. There were other shopping-related keywords in November related to Black Friday: “toys r us” and “best buy.” Users searched Google to find and share information with others on which products to buy on Black Friday. The following Figure 4 indicates the fact that the number of Tweets for these correlated keywords was increased on the same day.

The keyword “Tiger Woods” followed and referred to the most successful professional golfer in the world. The reason why his name ranked high was because he had a car accident on November 27. The movie-related keywords “2012” and “New moon” also

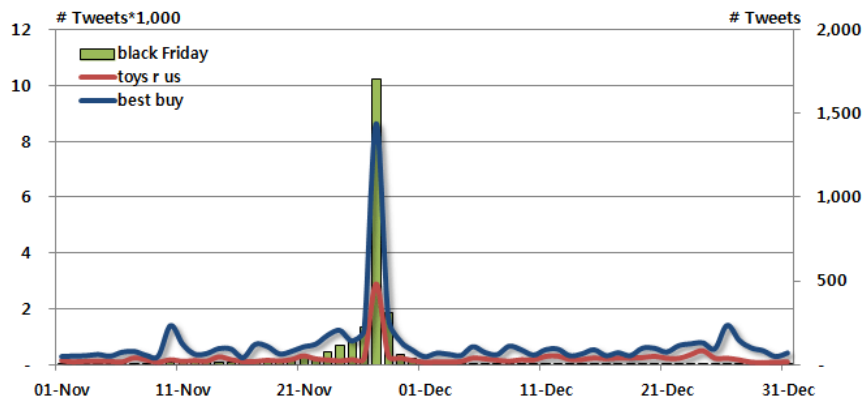


Fig. 4. Tweets flows of “Black Friday,” “toys r us,” and “best buy” between November and December 2009

appeared in November because those movies were released in that month. Another important keyword was “Brittany Murphy,” an American actress/singer who died on December 20. In addition, the keywords “Christmas” and “wii” were similar “Black Friday,” “toys r us,” and “best buy.” The keyword “wii” referred to a home video game console released by Nintendo and ranked first in a survey of children on that the most wanted Christmas presents.

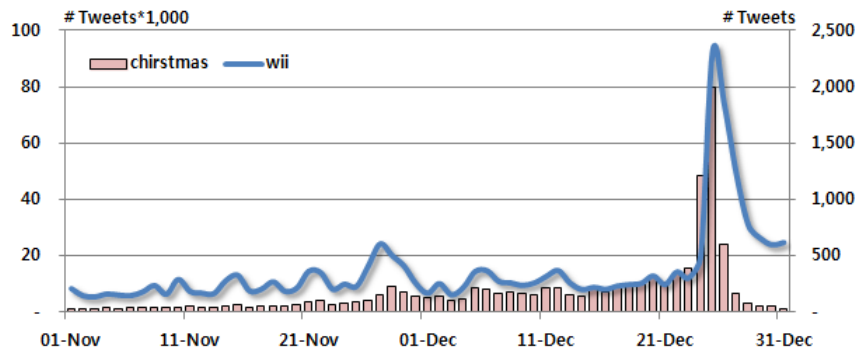


Fig. 5. Tweets flows of “Christmas” and “wii” between November and December 2009

We conducted a sentiment analysis to track these keywords by classifying 110 million Tweets into their corresponding keywords for November and December based on the simple text-matching method. Figure 6 shows noteworthy results for the frequency of Tweets. The frequency of Tweets about Black Friday increased suddenly on November 27, 2009, the date of Black Friday. However, the number of Tweets about Black Friday dropped sharply after only a day. This was a one-shot event, and therefore it attracted

attention for only a few days. The frequency of Tweets with the keywords “2012,” “new moon,” and “twilight” increased rapidly on some days, namely when these movies were released in the U.S. on November 12 and 20, respectively.

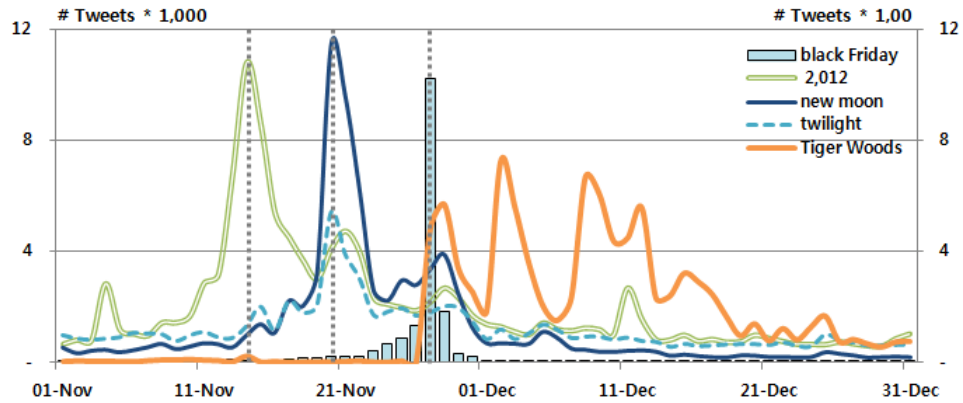


Fig. 6. Tweets flows of five keywords between November and December 2009

However, the keyword “Tiger Woods” had more than three peaks, making it difficult to determine the precise date of the event. Therefore, we conducted a sentiment analysis of Tweets with the keyword “Tiger Woods” to trace the type of event associated with the golfer and the precise date of the event.

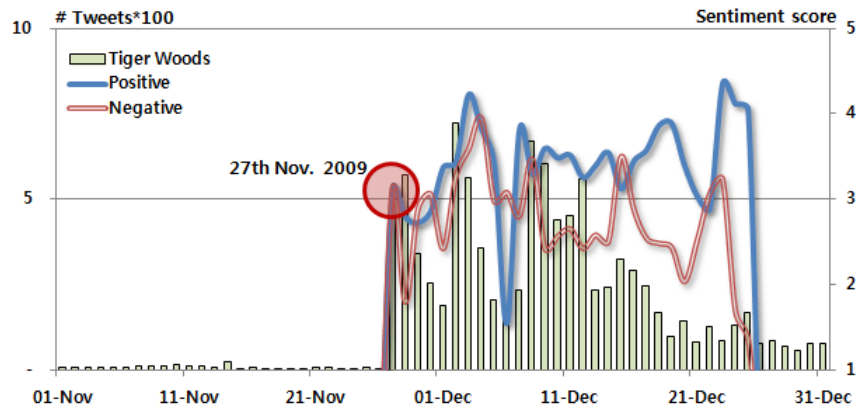


Fig. 7. Tweets and their daily sentiment flow for “Tiger Woods” from November to December 2009

Although, the Tweets and positive/negative flows have several peaks shown in Figure 7, it is clear to see that the number of tweets was suddenly increased on November 27, 2009. The positive and negative emotions for “Tiger Woods” exceeded their grand means for the specific dates. This was because Tiger Woods had a car accident on November 27. And publics were being worried about him for a while. There is an interesting flows related to another celebrity “Brittany Murphy.” As we mentioned before, she died on December 20 but her graphs is different than Tiger Woods.

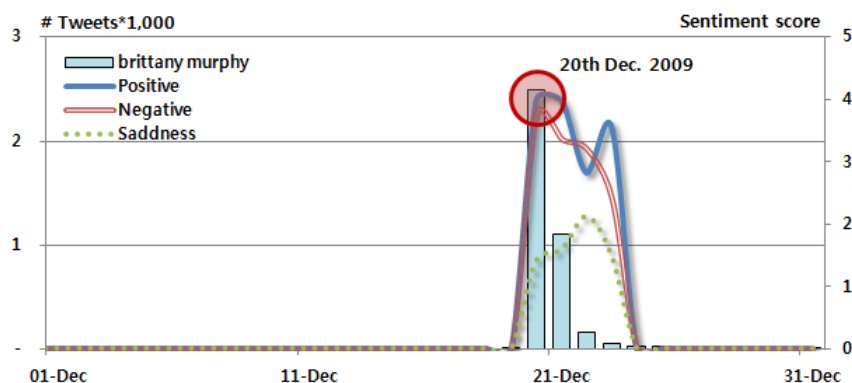
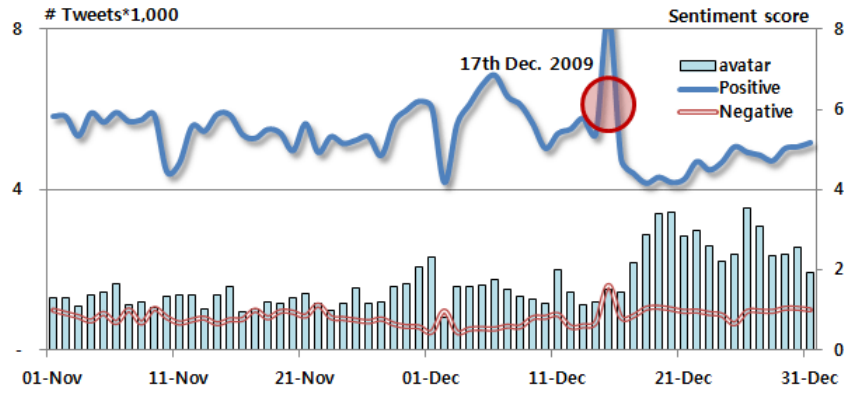


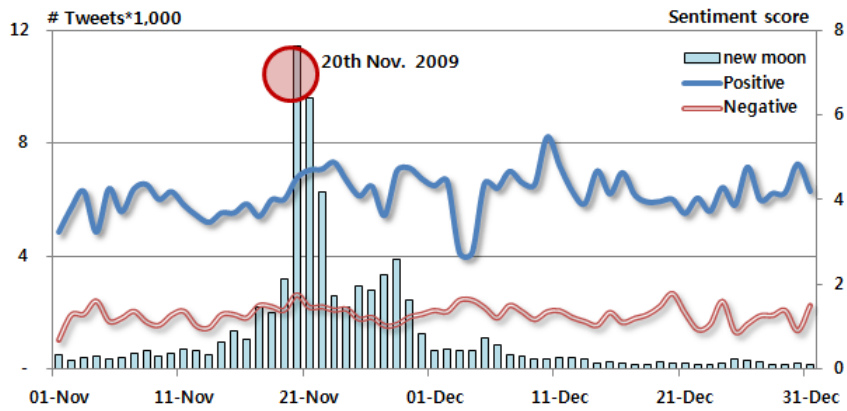
Fig. 8. Tweets and their daily sentiment flow for “Brittany Murphy” in December 2009

We can also trace the precise day when the events were happened using our proposed method. The interesting is that Brittany Murphy had been tweeted for only few days compared with Tiger Woods had been tweeted consistently. We can assume that she was less famous than Tiger Woods. This suggests that we can also trace or predict the popularity of celebrities. The results reveal another example related to movies. Users tweeted about movies to share information. Figure 9 shows the results for “new moon” and “avatar,” which were released on November 17 and December 20, respectively. As shown in Figure 9, the movie “avatar” showed higher positive degree than “new moon.” The movie “new moon” was interesting to users for a few days based on Figure 9(b).

Before the movie was released, the number of Tweets was less than 1,000. After November 20, however, it exceed 10,000, decreasing after 10 days to less than 500. The positive degree during this period was not low, but there was no noteworthy peak in the flow. By contrast, the movie “avatar” was tweeted more than 1,000 times before it was released. The degree of positive emotions was higher than that for “new moon.” In addition, the number of Tweets after December 17 remained above 2,000, indicating that users were more satisfied with “avatar.” This suggests that an analysis of the flow of sentiments and the frequency of Tweets for a given movie can shed some light on whether the movie satisfies Twitter users. Given that Twitter was not nearly as popular in 2009 as it is now, an analysis of sentiment scores for recent Tweets about the movies is likely to reveal more robust results. Here the problem is that the huge number of Tweets would make such an analysis a costly effort.



(a) Sentiment analysis graph for the movie "avatar"



(b) Sentiment analysis graph for the movie "new moon"

Fig. 9. The frequency of Tweets and the flow of sentiments by day in November and December 2009

4. Conclusion and Future Research

This study provides a sentiment analysis of Tweets by using the LIWC method to verify whether Twitter data can be used to track the occurrence of breaking events and determine whether users are satisfied by such events. We employed a set of 110 million Tweets collected by Stanford University between November and December 2009. We found no noteworthy results for sentiments in Tweets by date, but the results by hour indicate that users were more likely show positive emotions during mornings and evenings than during afternoons. This may be explained by the fact that users sent greetings such as “good morning” and “good evening.” We focused only on Tweets about trending topics during the analysis period based on data from Google instead of the 110 million Tweets and found that it was possible to trace the precise date of an event by analyzing the number of Tweets and their sentiment scores. Users expressed both positive and negative emotions in celebrity tragedies. In addition, it was possible to trace how users evaluated specific movies. This study offers clear evidence that Twitter provides valuable opportunities for tracking breaking news worldwide. However, it is difficult to take advantage of these opportunities because of the sheer number of Tweets, which explains the limited domains considered in many studies of Twitter.

Future research should provide an in-depth analysis of negative Tweets to determine who is isolated, why, and how this problem can be addressed. Many researchers have focused on determining who influences whom and who are more influential than others. However, there are many unknown users who are isolated and have various psychological problems. These users are more likely to express negative emotions than positive ones. In this regard, future research should identify isolated groups of SNS users to help them better relate to normal users.

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