Influence Analysis of Emotional Behaviors and User Relationships Based on Twitter Data

Kiichi Tago and Qun Jin*

Abstract: One of the main purposes for which people use Twitter is to share emotions with others. Users can easily post a message as a short text when they experience emotions such as pleasure or sadness. Such tweets serve to acquire empathy from followers, and can possibly influence others’ emotions. In this study, we analyze the influence of emotional behaviors to user relationships based on Twitter data using two dictionaries of emotional words. Emotion scores are calculated via keyword matching. Moreover, we design three experiments with different settings: calculate the average emotion score of a user with random sampling, calculate the average emotion score using all emotional tweets, and calculate the average emotion score using emotional tweets, excluding users of few emotional tweets. We evaluate the influence of emotional behaviors to user relationships through the Brunner–Munzel test. The result shows that a positive user is more active than a negative user in constructing user relationships in a specific condition.

Key words: Twitter; social data analysis; emotional behavior; user relationship; Brunner–Munzel test

1 Introduction

Social Network Services (SNSs) such as Twitter have become increasingly popular in the world. A user can post a short message within 140 characters and easily obtain others’ feedbacks. Twitter users can speedily post their feelings and share their emotions, which is easier than blog-style SNSs, such as Facebook. If one finds a favorite user, he/she can add that user to his/her favorite list without that user’s permission. This action is called “follow”, and the person being followed is called “followee”, which is the distinctive feature of Twitter.

Users follow and unfollow others with various motives or reasons such as topics, interests, personality, and impression. In this study, we assume emotional expression as one of these factors. Tweets are considered to affect the relationship between a user and others on Twitter where emotional expression is frequently performed. If a user frequently posts negative tweets, his or her follower will feel uncomfortable, which is likely to be a factor of a diminished follow relationship.

Consider human relations in the real world for example. An unpleasant expression will negatively influence human relationship because of harming others’ feelings. The same influence occurs to user relationships on Twitter.

On the contrary, a friendly and bright person in the real world has richer human relationships than a negative person. Such positive users on Twitter can be expected to construct a richer relationship. In this study, we assume that emotional behaviors will influence user relationships.

In this study, we analyze the influence of emotional behaviors and user relationships using a statistical method. The question we ask here is whether the user relation is constructed by different processes between positive and negative users. This study serves as a comparative study on the differences of user relations.
relationships between positive and negative users.

The rest of this paper is organized as follows: Section 2 presents an overview of the related work on Twitter and emotion; Section 3 introduces our approach to scoring emotional tweets and extracting features of positive/negative users; Section 4 provides and discusses the result of the statistical tests; and Section 5 concludes this study, and highlights future work.

2 Related Work

Many studies on extracting emotion from a natural language have been conducted in the past few years. The mainstream subject is to classify emotions and improve accuracy\(^1\)\(^-\)\(^4\). The classification method with positive and negative keyword matching has been used in many studies. Some of these studies also categorized multi-dimensional emotions\(^5\). The present study focuses on an approach using positive and negative keyword matching.

2.1 Emotion extraction by natural language processing

Fujita et al.\(^6\) adopted positive, negative, and neutral classification categories and analyzed whether any influences existed between an emotional tweet and its successive emotional tweets (feedbacks). As a result, they revealed three findings: first, positive words for emotion sharing with others are easy to spread; second, a neutral emotion posted by one user and his/her followers induces a successive neutral emotion; and third, even if negative words are posted, these words are difficult to spread.

Ruan et al.\(^7\) analyzed the features of pessimists and optimists. They calculated the average emotion score for each user using machine learning, and defined 25% of the users with a higher score as optimistic users and 25% with a lower score as pessimistic users. They also reported that optimistic users tend to have more social relationships, but tweet less than pessimistic users.

Taketomi and Hisano\(^8\) examined the trend of personal feelings from tweet frequency. Their study showed that heavy users post aggressive words more than light users and tend to have a larger number of followers than their own’s followees. Meanwhile, light users do not like to use aggressive words to express their emotions and supposedly express their personal feelings only for sharing.

2.2 User relationship on SNS

Many studies also discussed user relationships on Twitter.

Kwak et al.\(^9\) obtained a data set of 41.7 million user profiles and 1.47 billion social relations and compared three different measures of influence: number of followers, pagerank, and number of retweets. Using these measures, they found that the ranking of the most influential group of users differed depending on the measure.

Java et al.\(^10\) analyzed the community, in which the word “gaming” appeared frequently. They used the Clique Percolation Method to visualize the community and investigate which words often appear. They showed that users share not only topics related to games but also their emotions and daily experiences. However, they did not report what kind of emotional expressions these were.

Tanaka et al.\(^11\) proposed the classification of motives for a user to follow another into three types, namely user-oriented, content-oriented, and mutuality. Meanwhile, Koide et al.\(^12\) investigated the follow relationships using the graph theory and calculated the mutual coupling coefficient between each node. Consequently, they obtained a high co-link group and a low co-link group. The high co-link group became a larger group with closed relationships and no popular users, whereas the low co-link group was divided by different topics, and popular users became the center of each topic.

Human relations on Twitter are often a subject in the study of community detection\(^13\)\(^-\)\(^17\). Xu et al.\(^17\) defined two roles of SNS users: hub users and outliers. They proposed to detect them and the communities they belong to from the network using the structural clustering algorithm. As a result, they found that hub users are connected to multiple communities and have much influence on every community they belong to. In contrast, the outliers were connected to a single community with a single link and have little or no influence on other users.

2.3 Position of this study

Almost all of the abovementioned studies were conducted based on the user’s own characteristics, such as the behavior or community formation of positive/negative users. Only a few focused on the reaction and influence caused by emotional expressions. Although some studies analyzed the generative process
of emotional tweets, only a few investigated the user relationships influenced by emotions. Ruan et al.\cite{7} presented that optimistic users have strong social ties. Their claim was based on the existence of many optimists in politician followers. However, they as well as many other existing works did not analyze the relationship among ordinary users.

The present study focuses on analyzing whether some correlation exists between emotional behaviors and user relationships.

3 Our Approach

3.1 Overview of our approach

This section describes our approach and method. Figure 1 shows the outline of our approach.

First, we set conditions, collect users, and select sample users by random sampling. The tweets of these selected users become the Twitter corpus.

Next, we attach an emotion score for each tweet and define the tweet with a word scored by two dictionaries as the emotional tweet. Several methods can be used to provide emotion scores. We apply a simple method herein and make a keyword matching between an emotional word dictionary and the morphologically analyzed tweets. The emotional word dictionary has an emotion score for each word, and we calculate the sum as the emotion score of the tweet. We do not attach the emotion score to the tweet if the tweet has no emotional words.

We then calculate the average emotion score for each user. This score is calculated by averaging the emotion scores of randomly selected tweets or all emotional tweets per user. The average emotion score indicates the emotional trend of the user.

After that, we define two groups, namely the positive (P-Group) and negative (N-Group) groups. We then sort users in a descending order by their average emotion scores and define the top 25% of users as the P-Group and the lower 25% as the N-Group by referring to Ruan et al.’s method\cite{7}.

Finally, we apply the statistical test between the positive and negative groups, and investigate the influence of emotional behaviors on the user relationships on Twitter.

3.2 Data collection

We obtained 5000 user accounts using Twitter API under the following conditions to build the Twitter corpus:
- Language: Japanese;
- Number of followers: 20–40 persons;
- Number of updates: more than ten tweets per day;
- Search keyword: “Ha” (in Japanese);
- Not including “bot” in the username.

These conditions were set based on the research by Fujita et al.\cite{6} Taketomi and Hisano\cite{8} revealed that users with fewer followers use Twitter to share their emotion; hence, we set the limitation of followers to 20 to 40. In addition, we set the search keyword to obtain users. Searching for users by a keyword was necessary to acquire users. The word “Ha” is the
Japanese particle to be used regardless of generation, gender, or topic. Therefore, collecting tweets with almost no bias became possible.

We selected 600 users by random number sampling from the acquired 5000 users due to the Twitter API limitation. We set these users as the sample group. These 600 sample users included 26 non-public users. As a result, we finally obtained 574 sample users.

Data acquisition performed for one month from March 13 to April 13, 2017. The total number of tweets was 62,729. The acquired data included tweet timestamp, user name, user ID, profile, tweet content, tweet ID, tweet target user ID, ID list of followers, number of followees, ID list of followers, number of followers, and number of mutual followers.

### 3.3 Emotion score measurement

We used two emotion word dictionaries in Japanese and conducted the experiments with a different dictionary.

First, we measured the emotion score of tweets using the emotional word dictionaries, which had emotional words with a positive/negative score or label. Two emotional word dictionaries are mainly used in Japanese, namely the sentiment polarity correspondence table (thereafter, Dict A)\(^{[18]}\) and the Japanese sentiment polarity dictionary (thereafter, Dict B)\(^{[19,20]}\). The former dictionary scores positive words from 0 to +1 and negative words from 0 to −1. The latter dictionary labels word as positive, negative, and neutral. We regard the positive label as +1, the negative label as −1, and the neutral label as 0.

We then score tweets using Dict A, which contains 55,124 words (49,982 negative words, 20 neutral words, and 5122 positive words). We used this dictionary to perform a morphological analysis and keyword matching between a morpheme and keywords. We used a software called “Mecab” for the morphological analysis\(^{[21]}\). We attached a score from the dictionary to the word of the decomposed word that exists in the dictionary.

The emotion score of the word \( ESWA_i \) is attached if it exists in Dict A; otherwise, null is given:

\[
ESWA_i = \begin{cases} 
  s, & \text{if a word } W_i \text{ exists in Dict A} \\
  null, & \text{otherwise}
\end{cases}
\]

The emotion score of a tweet \( ESTA \) is the sum of all the emotional words in the tweet that exist in Dict A, which is defined as follows:

\[
ESTA = \sum_{i=1}^{[ESWA_i]} ESWA_i
\]

(If \( ESWA_i \) is null, it is regarded as 0.)

If no any emotional word exists, we do not include it in this calculation. We attach null as the score when the tweet does not have any emotional words. Table 1 shows the word coverage rate of this dictionary. In this table, the coverage rates of the positive and negative words were almost the same. The positive and negative words were extracted in a well-balanced manner, and almost no bias exists. Table 2 shows how many words matched the dictionary with all the morphemes.

We also used Dict B, which has 18,620 words (5497 positive words, 8164 negative words, and 4959 neutral words), and is of a relatively good balance. We scored tweets by the same method using this dictionary. We attach 1 to a positive word and −1 to a negative word.

The emotion score of the word \( ESWB_i \) is attached if it exists in Dict B; otherwise, null is given:

\[
ESWB_i = \begin{cases} 
  s, & \text{if a word } W_i \text{ exists in Dict B} \\
  null, & \text{otherwise}
\end{cases}
\]

The emotion score of the tweet \( ESTB \) is the sum of all the emotional words in the tweet that exist in Dict B:

\[
ESTB = \sum_{i=1}^{[ESWB_i]} ESWB_i
\]

(It is regarded as 0 if \( ESWB_i \) is null.)

Table 3 shows the word coverage rate of this dictionary. The coverage rates of the positive and negative words were almost the same. We use an emotional tweet only if it is attached with a score by both dictionaries.

| Table 1 | Coverage rate of Dict A. |
|---------|-------------------------|
| Number of words | Matched | Coverage rate (%) |
| Positive | 5122 | 1407 | 27.5 |
| Negative | 49982 | 13417 | 26.8 |
| Total | 55104 | 14824 | 26.9 |

| Table 2 | Coverage rate of morphemes using Dict A. |
|---------|-------------------------|
| All kinds of morphemes | Matched | Coverage rate (%) |
| 1840332 | 442316 | 24.0 |
### Table 3 Coverage rate of Dict B.

|          | Number of words | Matched | Coverage rate (%) |
|----------|-----------------|---------|-------------------|
| Positive | 5 497           | 1 626   | 29.6              |
| Negative | 8 164           | 2 029   | 24.9              |
| Total    | 13 661          | 3 655   | 27.4              |

Both the coverage rates of the positive and negative words were from 25% to 30%. We considered that this dictionary could also extract emotional words in a well-balanced manner. Table 4 shows how many words matched the dictionary with all morphemes, and the rate seemed very low. We considered that the reason for this is that the dictionary was big, while the tweets we used were quite limited in vocabulary.

### 4 Result and Analysis

#### 4.1 Statistical test settings

Firstly, we excluded 51 outlier users who posted ten or fewer tweets during the experiment period, because we assumed that they provide no or less influence on others. Therefore, we obtained a data set of 523 users. We designed three experiments with different conditions as follows:

- **Case 1**: calculate the average emotion score by randomly sampling 15 emotional tweets among a total of 523 user samples.
- **Case 2**: calculate the average score of all emotional tweets with the total sample being 523 users.
- **Case 3**: calculate the average score of all emotional tweets, excluding users, whose emotional tweets were equal to or fewer than 19, which was half of the average of the emotional tweet counts. The total sample becomes 311 users.

We analyzed the differences in the user relationships between the P-Group and the N-Group using Dict A and Dict B, respectively. We applied the Brunner-Munzel test\[22\], a statistical method, to confirm the differences between the two groups. This method ranked each group and the combined group of these two in a descending order by the sampled values. The basic statistic values, such as \(W\)-value and \(t\)-value, were also further calculated based on these ranks and sample size. This method conducted only a two-sided test, and the null hypothesis can be rejected when the \(p\)-value is lower than the significance level. The \(p\)-value decreases as the absolute value of the \(t\)-value increases and indicates the possibility supporting the null hypothesis that there is no significant difference between the two groups. If the \(p\)-value is lower than 0.05, a significance is assumed to be confirmed. In case the \(p\)-value is lower than 0.01, a difference is assumed to almost certainly exist. We used the Brunner-Munzel test because of the data characteristic. In statistics, the statistical method to be applied depends on the normality and/or equality of variance. Normality means the data follows the normal distribution. That is, the data is distributed with a top value in the center of the distribution curve. The equality of variance is the feature that the data distributions of two groups are nearly equal. The characteristic of this test was that guaranteeing the normality and equality of variance was not necessary, and can be applied to data of any distribution. As Natori\[23\] mentioned, the Mann-Whitney’s U-test and Student’s t-test can calculate a wrong \(p\)-value. He suggested that researchers should use Welch’s t-test or Brunner-Munzel test if they have an adequate sample size. The Welch’s t-test is a test that uses the average value, while the Brunner-Munzel test is a test using the median.

We conducted the tests on R\[24\], which is a famous open-source software for data analysis. The tested items were as follows:

- followee fluctuation;
- follower fluctuation;
- mutual follow fluctuation;
- count of emotional tweets;
- count of all tweets.

Table 5 shows the results while Tables 6 and 7 and Figs. 2 and 3 present the details for Case 3.

#### 4.2 Analysis and discussion

Cases 1 and 2 showed considerably different results for each dictionary. The results greatly depended on the exclusion method of the user and the calculation method of the average emotion score. In other words, researchers need to carefully consider how to exclude users and prepare data of emotional tweets.

In Case 3, the result of the Brunner–Munzel test at a significance level of 5% using Dict A confirmed a significant difference for the followee fluctuation, follower fluctuation, and mutual follow fluctuation. Table 6 shows the detailed data, while Figs. 2a–2c
illustrate the data distribution of each group. In these figures, the small circle means each datum. The horizontal width indicates the frequency of the data similar to a histogram.

In addition, as the result of a test with the same conditions using Dict B, a significant difference was confirmed for the followee fluctuation, follower fluctuation, and mutual follow fluctuation. Table 7 shows the data in detail, while Figs. 3a–3c depict the data distribution of each group with a significant difference. The positive group had a larger value for all the significant differences. The same experiment result as Dict A was confirmed. We assumed that both dictionaries were constructed in a well-balanced manner; hence, the result accuracy was improved by excluding the outlier users.

We investigated the details of the top seven users with emotional tweets of 200 or more to further verify our results. Figure 4 demonstrates the data distribution of the emotional tweet counts for all users. The top seven users were those few users with many tweets. Among the top seven users, we determined using Dict A that five users belonged to the P-Group; one was in the N-Group; and one did not belong to either group. Figure 5a shows the fluctuation of three items using Dict A (i.e., follow fluctuation, follower fluctuation, and mutual follow fluctuation). Using Dict B, we found five users in the P-Group and two users, who did not belong to either group. Figure 5b shows the fluctuation of three items using Dict B. The average of the follow fluctuation, follower fluctuation, and mutual follow fluctuation of these seven users were much larger than those of all users. Table 8 shows the results in detail. Therefore, we could expect that the effectiveness of these results was reliable.

As Xu et al. revealed, outliers exist in the SNS community. Similar to their results, our findings suggest that statistical processing of the raw data set may result in an ineffective significant value, and we need to exclude the outliers.
In summary, these results indicated that a positive user is more sociable than a negative user. They express their positive emotions, actively connect with others, and construct rich relationships. If others follow a positive user, he/she tends to follow them back and make mutual relationships. On the contrary, negative users are harder to follow than positive users because they frequently express their negative emotion and are less likely to follow others. Therefore, they have poorer relationships than positive users.

5 Conclusion

In this study, we used two dictionaries of emotional words and tested them against emotional tweets and human relations. The result using the sentiment polarity correspondence table showed that a positive user has a
higher motivation to follow other users than a negative user. The result using the Japanese sentiment polarity dictionary also showed the same feature. These results indicated that positive users have richer relationships and do not build unilateral human relationships. If a user follows a positive user, the positive user follows back and builds the mutual relationship.

A more detailed investigation on the top seven users with many emotional expressions verified this result, indicating that the reliability of the result was high. In addition, the findings of the two dictionaries were well matched as a result of the condition setting for the outliers. In other words, the condition for the outliers has an important meaning when using a statistical method.

The result and the insight obtained in this study indicated that we can extract the features of the positive and negative users. We expect this to be helpful in the creation of a rich human relationship on SNSs, such as Twitter. Recommending users with similar interests.
or topics is generally common. Moreover, we can recommend sociable and active users as well as similar users by applying this study result to improve the user’s quality of experience.

The present study used a simple method of matching words and morphemes of the emotional word dictionaries; thus, we could not provide a score to a word which is not listed in the dictionaries. In our future work, we plan to use machine learning for emotion classification, specifically Naive Bayes classification, which calculates the probability of belonging to a category for each word, to solve this problem. Therefore, positive and negative labels can be assigned to all words in the tweets, and the difference between the positive and negative users can be tested.

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Kiichi Tago received the bachelor degree of arts in 2013 from Waseda University, Japan. He is currently working toward his M.S. degree at the Graduate School of Human Sciences, Waseda University. His research interests include big data, social networking service, natural language processing, cognitive psychology, and behavioral analysis.

Qun Jin received the BS degree from Zhejiang University, China in 1982, the MS degree from Hangzhou Institute of Electronic Engineering and the Fifteenth Research Institute of Ministry of Electronic Industry, China in 1984, and the PhD degree from Nihon University, Japan in 1992. He worked in the Department of Computer Science, Hangzhou Institute of Electronic Engineering, China, from December 1984 to March 1989. In April 1992, he joined the Systems Research Center, INES Corporation, Japan. From April 1995 to March 1999, he worked as an associate professor in the Department of Information Science and Intelligent Systems, Faculty of Engineering, Tokushima University, Japan. From April 1999 to March 2003, he was an associate professor in the School of Computer Science and Engineering, the University of Aizu, Japan. Dr. Jin moved to Waseda University, Japan, in April 2003, where he holds a tenured full professor position at the Networked Information Systems Laboratory, Department of Human Informatics and Cognitive Sciences, Faculty of Human Sciences. He has been extensively engaged in research works in the fields of computer science, information systems, and social and human informatics. He seeks to exploit the rich interdependence between theory and practice in his work with interdisciplinary and integrated approaches. Dr. Jin has published more than 200 refereed papers in the world-renowned academic journals, such as ACM Transactions on Intelligent Systems and Technology, IEEE Transactions on Human–Machine Systems, IEEE Transactions on Learning Technologies, and Information Sciences (Elsevier), and international conference proceedings in the related research areas. He also served as a general chair, program chair, and a TPC member for numerous international conferences. Moreover, he served as editor-in-chief, associate editor, editorial board member, and guest editor for many scientific journals. His recent research interests cover human-centric ubiquitous computing, behavior and cognitive informatics, big data, personal analytics and individual modeling, cyber security, cyber-enabled applications in healthcare, and computing for well-being. He is a senior member of IEEE and IEEE CS (USA), and IPSJ (Japan), and a member of ACM (USA), IEICE and JSAI (Japan), and CCF (China).