

Paper

Correlations and fluctuations in the word sets of collective emotions

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Received November 9, 2017; Revised February 2, 2018; Published July 1, 2018

Abstract: In recent times, research on extracting collective emotion from social media has been actively pursued. When constructing collective emotions from social media, a bag-of-words, which is made of an aggregation of related words' frequencies, is often used. However, correlations between targeted words, as well as fluctuations under the word aggregation process, have attracted little attention. In this research, we examine the correlations and fluctuations of words contained within the collective emotion in Japanese blogs. From our result, we found that correlations between words belonging to the same emotion tend to be higher than correlations between different emotions, and the fluctuation is reduced by the aggregation process. We believe that our conclusion is applicable not only to the frequency of occurrence of words but also to systems consisting of small components in various contexts.

Key Words: correlation, fluctuation, social media, text analysis

1. Introduction

Owing to the increasing user of social media platforms such as blogs and Twitter, the extraction of “collective emotion” from the social media has been receiving an enormous amount attention [1–3]. A pioneer work of collective emotion is “Hedonometrics” which measures happiness on a country level. They defined happiness based on keywords and measured various texts such as Twitter, blogs, songs, and United States address [4, 5]. Another pioneer study is measuring positive and negative polarity of emotion at world level [6]. They found circadian and seasonal rhythm across the globe using millions of public Tweets. There could be various ways to defining emotions like happiness, positive, and negative affects. Therefore, defining collective emotion is not straightforward. Unlike the thermometer in physics, there is no equipment to directly measure collective emotion directly. Therefore, researchers examine the words contained in the text written on the social media platforms and define collective emotion uniquely.

To study collective emotions, “bag-of-words”, which is the one of the vector expressions used in natural language processing methods, is usually used. In bag-of-words, words are separated and stored in a set, i.e., a bag. In a set, appearance order and dependency are ignored; however, only the frequency matters in most cases. Despite its simplicity, bag-of-words is known to be effective and has been widely used in natural language processing [7]. Furthermore, it is confirmed recently that

this bag-of words and dictionary-based methods are robust in their classification accuracy for longer text [8].

In many cases, the bag-of-words and pre-built dictionaries (words sets) are used for constructing collective emotions. Thus, collective emotion is constructed from the frequency of each word included in the pre-built dictionary as a small component. In pre-built dictionaries, words are carefully defined based on traditional psychology. For example, the Affective Norms for English Words (ANEW) is an English emotion dictionary that containing, approximately, a thousand words [9]. The Positive and Negative Affect Schedule (PANAS) is also a well-established English psychometric scale consisting of two 10-item mood scales [10]. Unlike ANEW, PANAS has been officially translated into a number of languages, including Russian and German. However, the Japanese version of PANAS has only been validated within a limited scope. In this study, we use the Japanese version of Profile of Mood States (POMS) [11], which we describe in detail in the next section.

In most cases, the final output behavior of a collective emotion is regarded as emphasized, and it is often compared to real social phenomena such as market indexes for application purposes. For instance, it was pointed that the emotion of *anxiety* in blogs and Standard & Poor's 500 Stock Index are correlated [12]. The emotion of *calm* in Twitter increased the prediction accuracy of the Dow Jones Industrial Average [13]. The emotion of *confusion* was approximately three months ahead of increases in the unemployment rate in Ireland [14]. Moreover, recently, collective emotion was said to have greater power to affect ideology [15].

On the other hand, little attention has been paid to the construction process of collective emotion. Thus, correlations among small components (words) and their distribution, and fluctuations during the aggregation process, have not been carefully considered. Since collective emotion depends on each word frequency, what we are expecting for collective emotion is not a dramatic change in each word frequency, but a vague shift in emotion formed from various words. Therefore, when we define collective emotion, we are expecting that each word frequency in the same emotion cancels small up and down spikes during the aggregation process. To maintain the transparency of our method, it is crucial to confirm whether such process is realized during the constructing a collective emotion from a word level.

In this study, we discuss these correlations and fluctuations from Japanese blogs through the process of constructing a collective emotion. In Section 2, we describe our data and our method to extract collective emotion. In Section 3, our results on correlations and their distribution of small components, as well as the change in fluctuation during the aggregation process, are shown. We discuss our results in the final section.

2. Data and method

2.1 Data

We employed data from Japanese blogs from November 1 in 2006, to February 28 in 2011, using a fee-charging service called 'Kuchikomi@kakaricho¹'. This service provides the daily number of Japanese blog articles that include any given target word more than once with a built-in spam filter. Here we used the strong level of the spam filter. As of October 2016, the full database contained more than 3.6 billion blog articles from 43 million independent accounts. Based on the fact that the frequency of Japanese blogs fluctuated extraordinarily during the Great East Japan Earthquake in 2011 [16], we decided to target the period up to that time.

2.2 Method: POMS

The Profile of Mood States (POMS) is the one of the psychological rating scales which has been widely used since 1970s [11]. It was originally developed to measure the effectiveness of pharmacological therapy for veterans in the U.S. POMS can measure temporal mood states based on answers to 65 short question items, which are also based on the following six extracted emotions:

- *Tension-Anxiety (Tension)* : 9 items

¹<http://kakaricho.jp> : Accessed December 6, 2016

- *Depression-Dejection (Depression)* : 15 items
- *Anger-Hostility (Anger)* : 12 items
- *Vigor* : 8 items
- *Fatigue* : 7 items
- *Confusion* : 7 items

In the following, the names of the POMS scales are shown in parentheses. Note that there are two opposite answering questions in *Tension* and *Confusion*, and seven dummy questions that were excluded in our procedure. The participants answered the question items with scores from zero (totally disagree) to four (totally agree).

POMS was officially translated into Japanese by a Japanese psychologist [17]. Since then, it has been used for various purposes, such as measuring conditions for athletes and conducting mental health checks in firms; therefore, POMS is considered reliable, even for Japanese.

Owing to the original usage, five emotions are negative and only *Vigor* is positive. Bollen et al. used POMS to extract collective emotions from Twitter over approximately a 1-year period [18]. They found that the POMS mood reflected some social/economic phenomena such as Thanksgiving Day and elections.

We developed our emotion dictionary based on Japanese POMS. The following procedures were conducted to develop our emotion dictionary.

1. Parse one word that best expresses the emotion from each POMS question item using a Japanese morphological analyzer, MeCab².
2. Confirm whether the parsed word expresses emotion by three independent people.
3. Add orthographical variants for words with the same pronunciation and meaning, but different spellings using UniDic³.
4. Exclude very low-frequency words. To keep adequate numbers of words in the emotion dictionary, we excluded the words that appeared fewer than five times per month as of October 2015, when no big events occurred.
5. Modify very high-frequency words that appear more than 1,000 times per day as of October 2015. If a word appears more than 1,000 times, add one or two new words immediately before or after the original word using original question sentences.
6. Adjust 20 to 25 words per emotion. If one emotion has more than 25 words, exclude from low-frequency words. If it still has fewer than 20 words per emotion, add synonyms using Japanese WordNet⁴. Note that there are 35 words in *Confusion* since there are many low-frequency words as a whole.
7. Check whether only one word is dominant in each emotion. If one word occupies more than 20% in an emotion, modify the word by procedure 5.
8. Choose 20 weblog articles randomly per listed word and have three independent people check whether the words are consistent with each emotion. If more than half the weblog articles are not consistent with the emotion, exclude the words from the dictionary.

As a result, the number and frequency of words were comparable for each emotion (Fig. 1). Eventually, our emotion dictionary has 21 words for *Tension*, 25 words for *Depression*, 25 words for *Anger*, 20 words for *Vigor*, 22 words for *Fatigue*, and 35 words for *Confusion*. Note that while we conducted

²<http://taku910.github.io/mecab/> : Accessed December 6, 2016

³<https://ja.osdn.net/projects/unidic/> : Accessed December 6, 2016

⁴<http://nlpwww.nict.go.jp/wn-ja/> : Accessed December 6, 2016

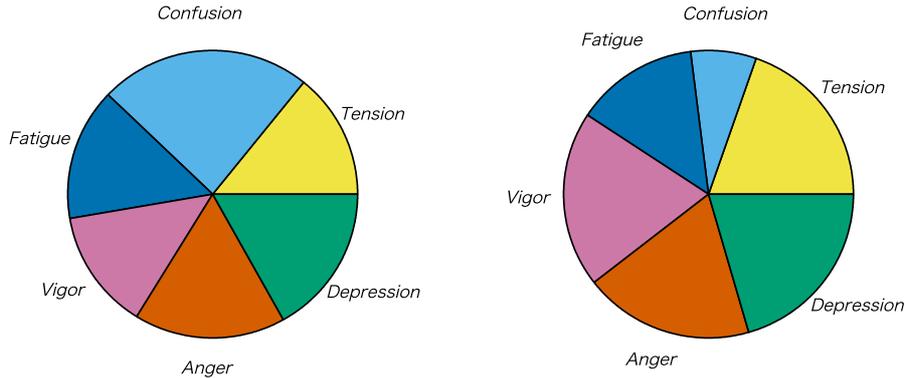


Fig. 1. Fraction of each emotion in our dictionary by number and mean frequency $\langle x_i^k \rangle$.

Table I. Breakdown of our collective emotion dictionary (word set).

Emotion	# words	Mean	SD	$\langle x_i^k \rangle$	Examples of words
<i>Tension</i>	21	186	205	8.8	worry, nervous
<i>Depression</i>	25	194	221	7.8	lonely, unhappy
<i>Anger</i>	25	179	167	7.2	annoying, hassle
<i>Vigor</i>	20	187	209	9.4	cheerful, active
<i>Fatigue</i>	22	130	112	5.9	tired, limp
<i>Confusion</i>	35	69	75	2.0	disarray, crowded

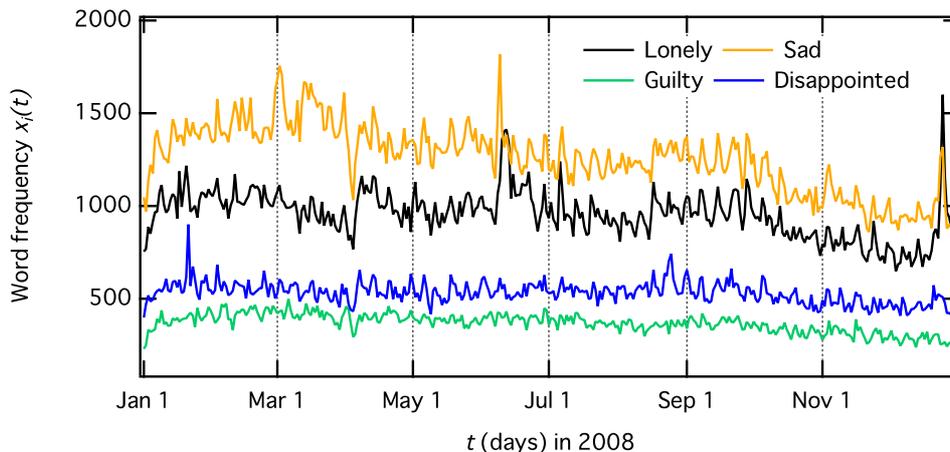


Fig. 2. Examples of daily words frequency $x_i^k(t)$ in emotion of *Depression*.

mentioned systematic method, number of words in our emotion dictionary is slightly different for each emotion. The summary of our emotion dictionary is shown in Table I.

Here, we used the time series for word i belonging to emotion k at day t , $x_i^k(t)$ to make the POMS emotion time series. Because of the system specification of ‘Kuchikomi@kakaricho’, if one blog article contained the same word i multiple times, we counted it as one. However, if one blog article contained different words i and j , we counted each word twice. Figure 2 shows some examples of word frequency $x_i^k(t)$.

3. Results

3.1 Correlations

Firstly, to check the stationarity, we applied the unit root test of Argumented Dickey-Fuller [19] for the daily difference of each time series $\Delta x_i^k(t) = x_i^k(t) - x_i^k(t-1)$. We confirmed that all word frequencies $\Delta x_i^k(t)$ passed the test with a significant level $p < 0.01$. We then examined the correlations between each word frequency $\Delta x_i^k(t)$ by Pearson’s correlation coefficient C_{ij} between word i and j as follows:

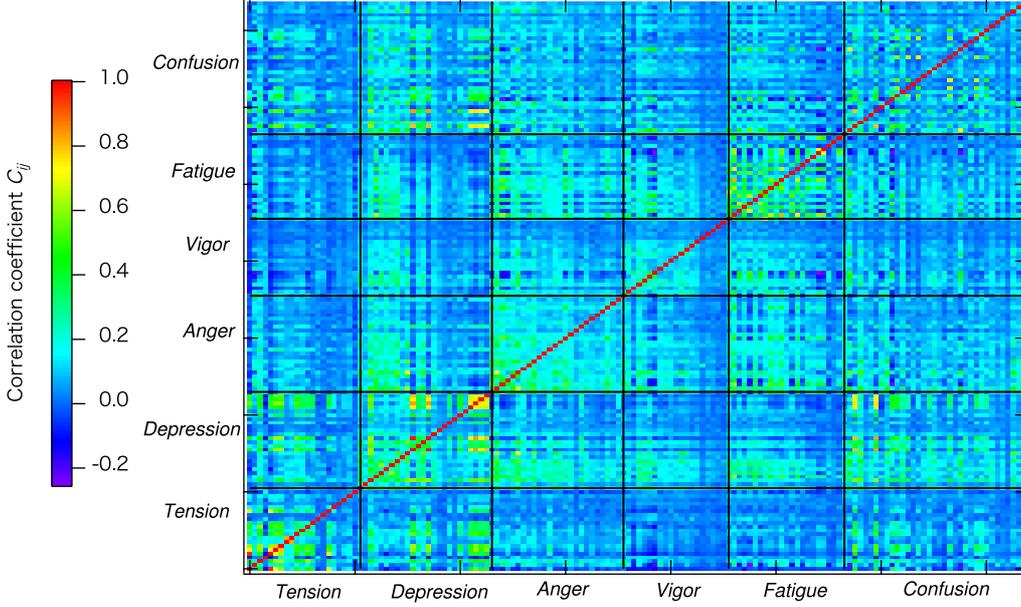


Fig. 3. Correlation matrix for all 148 words categorized by emotions.

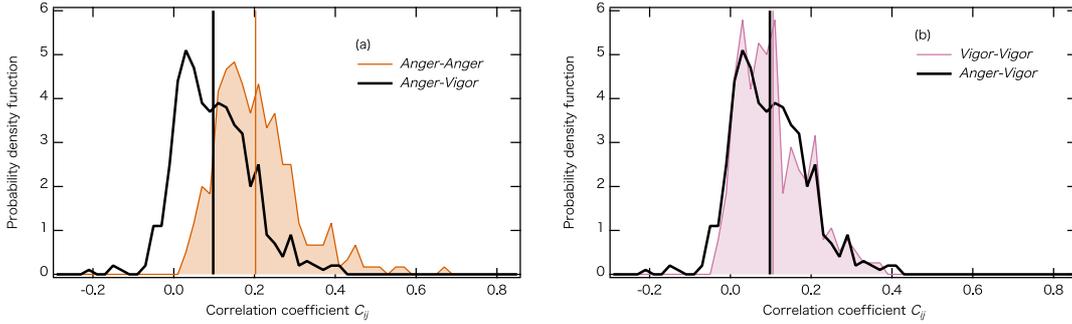


Fig. 4. Examples of correlation distributions. (a) An example in which the mean value of the correlation coefficient is significantly high. (*Anger-Anger*). (b) An example in which the mean value of the correlation coefficient is not significantly high (*Vigor-Vigor*).

$$C_{ij} = \frac{\langle \Delta x_i(t) \Delta x_j(t) \rangle - \langle \Delta x_i(t) \rangle \langle \Delta x_j(t) \rangle}{\sigma_i \sigma_j}, \quad (1)$$

where σ_i and σ_j are standard deviations of $\Delta x_i(t)$ and $\Delta x_j(t)$, respectively.

Figure 3 shows the correlation matrix of the whole word set, 148×148 . From the diagonal components, we can see that the correlation between words belonging to the same emotion tends to be higher than words belonging to the different emotions. The correlation coefficients C_{ij} were distributed normally as shown in Fig. 4. Table II shows the mean and the standard deviation (SD) of correlations between the emotions. In Fig. 4(a), we provide an example of a correlation between words belonging to the same emotion that is significantly higher than correlations among words belonging to the different emotions.

Table III summarizes significant difference among different emotions which is calculated by Welch's two-sample t -test that have different variances. For example, the mean correlation between *Anger* and *Vigor* is 0.10 as shown in the 3rd row and the 4th column of Table II. For *Anger*, 0.10 is significantly lower than 0.20 (*Anger-Anger* correlation) as shown in Fig. 4(a). On the other hand, for *Vigor*, 0.10 is not significantly lower than 0.11 (*Vigor-Vigor* correlation) as shown in Fig. 4(b). In this way, ** sign is added to the Table III of the 4th row and the 3rd column for *Anger*, but the 3rd row and the 4th column for *Vigor*. Thus, *Depression-Depression* correlation, *Anger-Anger* correlation, and *Fatigue-Fatigue* correlation are significantly higher than other emotions.

Most emotions showed the highest correlation among same emotions, *Confusion* did not show

Table II. Means and standard deviations of correlation coefficient between the emotions.

	<i>Tension</i>	<i>Depression</i>	<i>Anger</i>	<i>Vigor</i>	<i>Fatigue</i>	<i>Confusion</i>
<i>Tension</i>	0.11 ± 0.13	0.10 ± 0.08	0.11 ± 0.09	0.06 ± 0.07	0.08 ± 0.08	0.07 ± 0.07
<i>Depression</i>		0.19 ± 0.12	0.17 ± 0.11	0.12 ± 0.07	0.13 ± 0.10	0.14 ± 0.09
<i>Anger</i>			0.20 ± 0.10	0.10 ± 0.09	0.15 ± 0.12	0.12 ± 0.09
<i>Vigor</i>				0.11 ± 0.08	0.10 ± 0.11	0.09 ± 0.08
<i>Fatigue</i>					0.21 ± 0.21	0.11 ± 0.10
<i>Confusion</i>						0.11 ± 0.08

Table III. Summary of significant difference among different emotions. ** and * represent correlation coefficients between different emotions are lower with a significance level $p < 0.001$ and $p < 0.01$ respectively, than that of same emotion which is located in the same columns.

	<i>Tension</i>	<i>Depression</i>	<i>Anger</i>	<i>Vigor</i>	<i>Fatigue</i>	<i>Confusion</i>
<i>Tension</i>	-	**	**	**	**	**
<i>Depression</i>		-	*		**	
<i>Anger</i>		*	-		**	
<i>Vigor</i>	**	**	**	-	**	*
<i>Fatigue</i>	**	**	**		-	
<i>Confusion</i>	**	**	**		**	-

the highest correlation with itself more than other emotions. For example, the mean correlation *Confusion-Confusion* (0.11) did not exhibit a higher value than that of *Confusion-Depression* (0.14). Because the mean word frequency $\langle x_i^k \rangle$ in *Confusion* was smaller than the word frequencies of other emotions, we had 35 words in *Confusion* while other emotions were approximately 22 words (Table I). Furthermore, the correlation between *Depression* tended to be higher for all emotions, and it might be the cause for the different result from the other emotions.

3.2 Fluctuations

Because the appearance of a single word in the emotion dictionary can easily fluctuate owing to external factors, aggregating several words can reduce the fluctuation in general. Here, we aggregated the time series for word i belonging to emotion k at day t , $x_i^k(t)$, and defined the time series of emotion k as follows:

$$X_n^k(t) = \sum_{i=1}^{n^k} x_i^k(t), \quad (2)$$

where n^k is the aggregated number of words belonging to emotion k . The final numbers of n^k are 21, 25, 25, 20, 22, and 35 for *Tension*, *Depression*, *Anger*, *Vigor*, *Fatigue*, and *Confusion*, respectively.

We aggregated each time series of $x_i^k(t)$ in ascending order of mean frequency. Because fluctuation (standard deviation) of a blog time series increases with its mean [20], we could not compare it directly. Therefore, we then standardized the time series such that the mean was 0 and the variance was 1 for the comparison. In Fig. 5, we provide an example of *Anger*. Here, $Z_n^k(t)$ denotes the standardized series with aggregated n words in emotion k .

While all the time series in Fig. 5 had same values of variance 1, but they exhibited different characteristics. Thus, fluctuations of the time series seemed to decrease by the aggregating process. To quantify the fluctuation and aggregated word number n , we determined the difference between the maximum and minimum values in the standardized time series $D_n^k = \max\{Z_n^k(t)\} - \min\{Z_n^k(t)\}$.

The number D_n^k of aggregated words n is shown in Fig. 6(a). Because some words had sharp peaks in $x_i^k(t)$, the aggregated time series could easily fluctuate under the aggregation process. However, D_n^k converges to a finite number, approximately $n \sim 20$, for all emotions. This result suggests that aggregating 20 words could reduce the fluctuation and be appropriate for measuring the collective emotion.

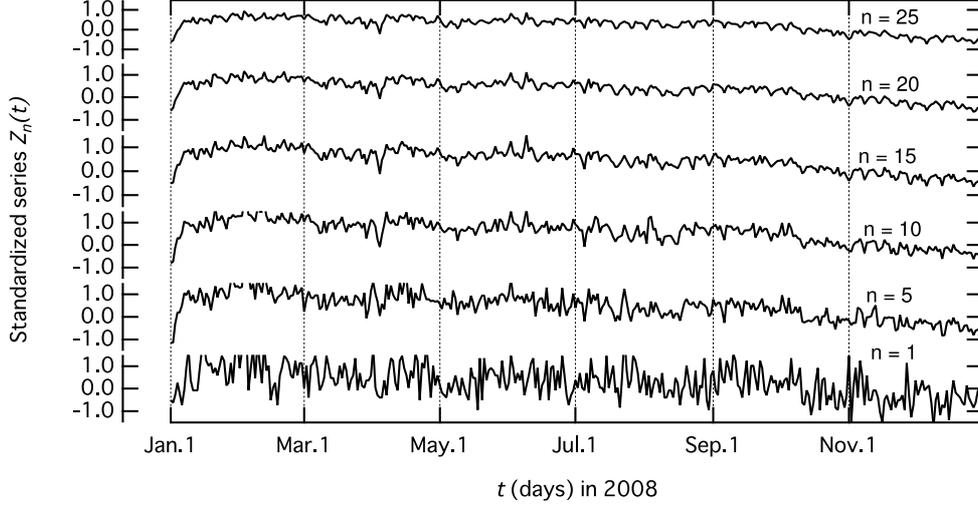


Fig. 5. Standardized time series $Z_n^k(t)$ of *Anger* in aggregation process. The number of aggregated words are 25, 20, 15, 10, 5, and 1 from the top.

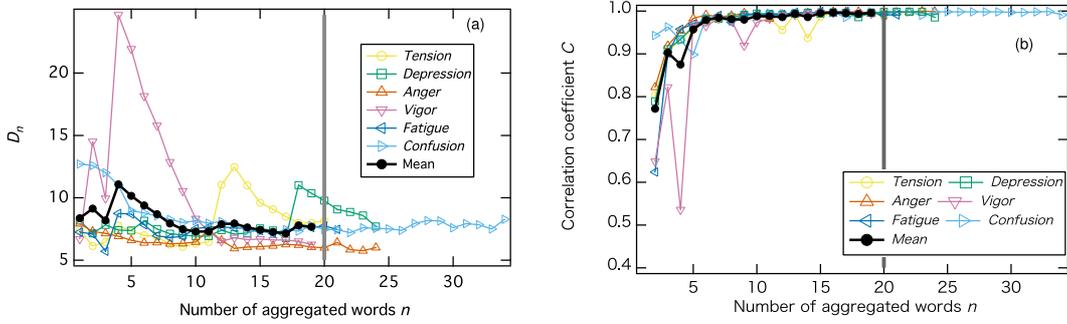


Fig. 6. (a) Difference in maximum and minimum values for standardized time series D_n and (b) correlation coefficient between $X_{n-1}^k(t)$ and $X_n^k(t)$ for the number of aggregated words n .

We also confirmed Pearson's correlation coefficient (Eq. (1)) between time series of $X_{n-1}^k(t)$ and $X_n^k(t)$ where $n = 2 \cdots n_k$ with aggregating each time series of $x_i^k(t)$ in ascending order of mean frequency. Correlation coefficient converged 1.0 when $n \sim 20$ in Fig. 6(b). It means that aggregating more than 20 words do not change the final result of collective emotion series.

4. Discussion

In this study, we examined correlations and fluctuations during the process of constructing collective emotion series in a Japanese blog space. Here we used POMS to define collective emotions in six dimensions because it is the well-established and has been in use for more than 20 years in various Japanese literature. Our defined collective emotion's word set is carefully confirmed and contains approximately 20 words in each of the six POMS emotions.

Here, we determined the correlations among each of word appearance. Because the correlations were distributed normally, we defined mean and standard deviation of correlations in each of six POMS emotions pairs. For three of POMS six emotions (*Depression*, *Anger*, and *Fatigue*), we confirmed that the mean correlation in the same emotion was significantly higher than the mean correlations for different emotions. For the remaining three emotions (*Tension*, *Vigor*, and *Confusion*), the mean correlation in the same emotion was not significantly high, which can be attributed to the occurrence of small spikes due to the external factors such as typhoons in these remaining three emotions [21].

We also checked the change in the fluctuations throughout the aggregation process of each word appearances. Because the mean word appearance allows for an increase in fluctuations, we standardized each of the aggregated time series to compare. We newly defined D_n of absolute difference of minimum and maximum of $Z_n^k(t)$, and found that around $n = 20$ words of aggregation saturated D_n

and can remove the spikes in the series.

The final result of our constructed collective emotion aligns moderately with periodic cycles [21], but we do not discuss the details in this study. Here, we mainly focused on constructing process of collective emotion. Since POMS has five negative emotions and only one positive emotion in the scale, it is essential to add new positive emotions for the analysis. For a possible candidate, POMS2 [22] that is the second edition of POMS with new positive emotion *Friendliness* has released and translated into Japanese recently. Furthermore, there are numerous other psychological measures. Extracting multidimensional emotions is a still challenging task that should be attempted in the future.

Our result is not limited to the social media data because aggregation of small components is very common in developing various economic indexes. For example, the world-famous stock market index of Dow Jones Industrial Average is a kind of aggregated value of major stocks. Calculated by a similar procedure, Nikkei 225 is also popular stock market index in Japan. Therefore, we believe that our results have important meanings in a wide range of fields.

Acknowledgments

The author would like to thank Hottolink Inc. for providing the data. The author gives special thanks to Dr. Takashi Sakaki and Mr. Sakae Mizuki from Hottolink Inc. for carefully checking the words during the construction of the dictionary. The author also would like to thank Dr. Hideki Takayasu and Dr. Misako Takayasu for fruitful discussions. This work is partially supported by Research grant “Support for restoring research from life events” provided by the Office of Diversity at the University of Tsukuba. This work was supported by JSPS KAKENHI Grand Number 17K12783.

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