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Emotion Analysis on Social Big Data

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Abstract

In this paper, we describe a method of emotion analysis on social big data. Social big data means text data that is emerging on Internet social networking services.We collect multilingual web corpora and annotated emotion tags to these corpora for the purpose of emotion analysis. Because these data are constructed by manual annotation, their quality is high but their quantity is low. If we create an emotion analysis model based on this corpus with high quality and use the model for the analysis of social big data, we might be able to statistically analyze emotional sensesand behavior of the people in Internet communications, which we could not know before. In this paper, we create an emotion analysis model that integrate the high-quality emotion corpus and the automatic-constructed corpus that we created in our past studies, and then analyze a large-scale corpus consisting of Twitter tweets based on the model. As the result of time-series analysis on the large-scale corpus and the result of model evaluation, we show the effectiveness of our proposed method.

Keywords

emotion analysis; social big data analysis; affective computing

1 Introduction

In the past 10 years, information and communication techniques increased their speed and became more stabilized. Especially in business scenes, communications and information exchanges by the Internet are essential. The text data generated among people communicating on the Internet have been referred to and reused in various scenes, and they have become more and more important. One of the merits of text data is their sizes. Their sizes are smaller than those of image data or audio data; moreover, their sizes can be further reduced by compression without decreasing the amount of information. On the other hand, it is still a difficult task for computers (artificial intelligence) to accurately analyze writers' intentions from text information, although computers continue to increase their speed and accuracy of data processing. Without reading between the lines or understanding contextual information or background knowledge, it would be difficult to understand semantic or affective information precisely. Thus, a text mining technique has been developed to reshape and analyze (calculate) data so that people can interpret the data easily. By using the text mining technique, we can study trends in certain topics from large-scale text data on the Web.

Comments on SNS or Internet articles on hot news are often distributed rapidly. They tend to be stored in our consciousness as implicit knowledge. Such implicit knowledge is essential for human communications. Therefore, we thought that dialogue agents or dialogue robots would be able to generate a greater variety of responses by using implicit knowledge. Recently, a technique of the Internet of Things has been developed, and velocity of information communication from human to SNS as well as from SNS to things such as robots has increased. All intelligent systems connected to the Internet have been required to process a huge amount of data.

A humanoid robot constructed by Ref Lab has a human appearance [1]–[3]. This robot has emotions by itself. By controlling the emotions, it can communicate with humans not only with language but also with gestures, voices and facial expressions. What is more necessary for robots to make natural conversations with humans is not an information processing mechanism higher than humans, but a sensitivity and an ability to feel sympathy for others that affect their next behavior. Social big data usually includes information related to opinions or sensibilities of many people. To apply this information to conversation with humans, robots must make responses by referring to the information that is suitable for the personal attributes of the conversation partner, such as knowledge level, gender, age, job and hobby. The emotion analysis of social big data would be necessary for further advancement of robots that can talk with humans.

In this paper, we will survey text mining techniques for emotion analysis of social big data on social media, and propose an

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emotion analysis approach for social big data by using existing techniques.

2 Emotion Analysis of Text Data

In this section, we introduce related research projects on emotion analysis, the linguistic resources and text mining methods that have been constructed and proposed by our research groups.

2.1 Ren-CECps

Quan and Ren [4] constructed a weblog corpus, "Ren-CECps," for emotion analysis. They made the corpus by annotatingemotion tags on weblog articles written in Chinese by word, sentence, paragraph and article units. Quan et al. [5] studied emotion analysis based on this corpus.

In addition to this study, several other studies have applied this corpus to Chinese emotion analysis [6]–[8]. However, because this corpus was made by collecting Chinese weblog articles, we cannot directly use the corpus for application to other languages without translation.

2.2 Japanese-English Parallel Emotion Corpus

There are several studies that applied emotion analysis to other languages, such as [9] and [10]. Some of the studies tried approaches used for English or other languages, adjusted parameters to become more suitable for other languages, or changed how to construct a corpus. On the other hand, regarding languages with large differences, Matsumoto and Ren [11] studied Japanese-English emotion estimation. It is said that automatic translation between the Japanese and English languages is comparatively difficult. Although neural machine translation (NMT) methods [12] have been developed in recent years, it is still difficult to obtain their perfect parallel translation relations.

Matsumoto et al. [13] considered that a small number of corpora with annotation of emotion labels was available. They proposed a method to automatically construct an emotion corpus in different languages based on one language. They used a Japanese-English parallel corpus and Japanese-English translation dictionary to refine translation candidates by word unit based on the correspondence relations between emotion polarities of the word and the sentence. Then they added similar sentences to the training data and realized accuracy improvement.

Because our research aimed to analyze emotion in Japanese tweets, it was a problem that there were few Japanese emotion-labeled corpora. Shortage of annotated data is also seen in other languages. Therefore, a semi-automatic corpus construction method was proposed to reduce the cost of manual labeling [14].

2.3 Weblog Depression Corpus

Matsumoto et al. [15] constructed a corpus that collected weblogs with annotation of the writers' emotions for the purpose of early detection of depressive tendency in the writers. The target weblog articles were written by those who were depressive or had depressive tendency and those who did not have depressive tendency. This corpus annotated emotion tags by sentence and article units and articles written in about one month were chronologically listed for each writer.

They also constructed a depression key phrase dictionary that registered key phrases often used by depressed patients. A system to detect depression tendency was constructed using this dictionary and its efficiency was evaluated [15].

Ren et al. [16] proposed a new paradigm called "Enriching Mental Engineering" to deal with mental health mechanically and constructed corpora and dictionaries. Based on these corpora and dictionaries, they analyzed the blogs written by those with depression tendencies and described the results. In this study, they considered a method to classify bloggers into those with depressive or non-depressive tendency. Their method was based on a scale called "emotional density," changes of a blogger's emotional states, and frequencies of expressed emotions.

2.4 Japanese Youth Slang Emotion Corpus

Ren and Matsumoto [14] proposed a method to semi-automatically construct a weblog emotion corpus including Japanese slangs. The source corpus was constructed manually and consisted of utterance sentences collected on the Web. These utterances included one or more slangs. To study the relevance of these slangs and emotions, they compared the results of emotion estimations when slangs were used as feature or not.

This method is based on an assumption that unknown expressions such as slang expressions are expressing emotions of the utterances in the training data. With this assumption, they constructed a slang emotion corpus and used the corpus for semi-automatic construction of slang emotion corpora. However, as the number of unknown slangs continues to increase, the corpus must be updated constantly. Therefore, semi-automatic construction still requires a lot of manual tasks.

In this study, we proposed a method to annotate emotion labels based on reliable and less ambiguous information such as emotional expressions, pictogram (emoji) or emoticon (facemark). By this method, we attempted to avoid excessive personal costs.

As for many slangs and expressions whose meanings and surfaces are not related to each other, it is difficult to judge whether they are used as slang or not; therefore, we did not treat slangs as special expressions in this study.

2.5 Personality Analysis

Matsumoto et al. [17] proposed a method to analyze a user's personality based on his/her SNS posts. Personality analysis has been attracting a lot of attention recently and is realized in IBM Watson [18]. The method proposed by Matsumoto et al. acquires distributed representations from a set of chronologically sorted tweets and correlates those tweets and egogram assessment results.

This correlated data is trained by ego-state unit using machine learning method, and the ego-state level classifier is constructed. In this way, they have succeeded in analyzing Twitter users' personalities chronologically. Twitter is being updated every day and the number of its active users is now 328,000,000 (June 2016–April 2017), which is the largest number of users among microblog SNS (mainly using short texts). We thought that Twitter would be suitable as a social big data repository to analyze tendencies of people's personalities.

In this paper, we try to apply distributed semantic representations, which were used for personality analysis, to emotion analysis. By converting text data into distributed semantic representations, we use them as features. This makes a classifier more robust to unknown expressions that are not included in training data and reduce dimensions of feature space. As a result, we think it will be possible for largely reducing calculation time.

3 Hybrid Emotion Estimation Model

In this paper, we acquire semantic distribution representations of words based on a machine learning method by using Twitter data, and estimate emotions by using the obtained distribution representations. Moreover, we integrate a manually annotated emotion corpus and an automatically annotated emotion corpus, and use them as a training data set for a Hybrid Emotion Estimation Model (HEEM). We try to use this model for large-scale data that is thought to include a lot of unknown information.

3.1 Construction of a Hybrid Emotion Estimation Model

Many of the previous training data for machine learning were manually annotated by reliable workers. However, generally, complex machine learning such as deep learning requires a certain amountof data. Small-sized data is not enough to learn a model with sufficient accuracy. Therefore, recently, data augmentation method and transferring learning have been studied a lot to increase training data automatically.

As a method to easily increase training data, "distant supervision" has been attracting attention recently.This method increases training data by automatically generating labeled data from unlabeled data in information extraction tasks. Different from a semi-supervised learning, the method does not use labeled data directly for training, but uses them as clues to extract labeled data automatically from unlabeled data.

We focus on "emojis" that explicitly express emotions, and use the approach to automatically increase the training data for use of machine learning, by annotating emotion labels to utterances that include emojis. Our proposed method uses a trained model by Emoji2Vec [19] and calculates similarities between pictographs. As for emotion labels, we use seven emotions (joy, love, surprise, anger, sorrow, anxiety, and neutral). One of the seven emotion labels is annotated on faces created with combinations of 67 characters (Facemark, including cats' facial expressions). As for emotions without any annotation of labels, we look at the labeled pictographs with similar vectors. Emotions of the most similar five pictographs are annotated as emotion labels of the unlabeled emoticon. Equation (1) shows annotation of an emotion vector onan emoticon.

EE(top5) indicates a set of the most similar five emotion-labeled pictographs with a target emoticon e_i. $sim\left(e_i, ee_j\right)$ indicates similarity between emoticon e_i and emotion labeled emoticon ee_j. If similarity is low, the emoticon might be a noise. In this study, we decide a threshold of similarity as 0.3. When emoticon similarity falls below 0.3, the emoticon is excluded from $EE\,(top5)$.

$$evec_{e_i} = \frac{1}{\left|EE\left(top5\right)\right|} \sum_{ee_j \in EE\left(top5\right)} s\left(e_i, ee_j\right) \times evec_{ee_j}. \quad (1)$$

There are over 2,000 kinds of pictographs available in Twitter. The number of pictographs to which we could annotate emoticon emotion vectors by using the above method was 955. We call the dictionary that registers pictographs with annotation of emotion vectors as "Emoji Emotion Vector Dictionary (EEVD)". We annotated emotion vectors on tweets including pictographs by using the EEVD. If one tweet included more than one emoticon, we annotated the average value of the emoji emotion vectors on the tweet. We used the set of tweets with annotated emotion vectors as a training data set.

We tried to analyze emotion accurately by combining the emotion analysis model derived from the manually annotated emotion corpus and the emotion analysis model derived from the automatically labeled emotion corpus. In the case of the manually labeled corpus, because the corpus size is small, the model based on that corpus is thought to be weak to unknown expressions. Therefore, we tried to construct an emotion analysis model robust to unknown expressions by considering word distribution representations and subword information.

On the other hand, the automatically labeled corpus includes various expressions. However, there might be included many tweets that have no features in tweet texts except for the pictographs, because the corpus was automatically labeled based on pictographs. The emotion analysis model derived from pictographs might have advantages in estimation from tweets with fewer features; however, the model might be weak to direct expressions.

Therefore, in this study, we attempted hybrid emotion analysis by the following two types of methods.

1) Model Switching Method (MSM)

This method switches the model for emotion analysis by judging whether the model is suitable for the input tweet. For judgment of the model, we used the content rates of unknown word (CR_{unk}), emoji (CR_{emoji}), emoticon (CR_{face}), and emotional expression (CR_{em}) as features. The model switching classifier was trained by support vector machine (SVM) using 10,000 sentences from each corpus used for each model training.

2) Mixed Model Method (MMM)

Because the corpus size affects training, we constructed the emotion analysis model by using both the automatic annotation corpus and the manual corpus. **Fig. 1** shows the making flow of HEEM.

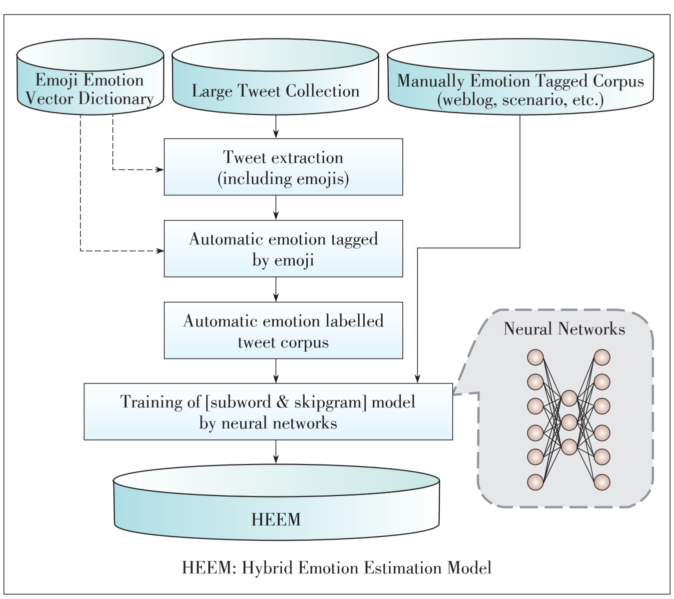
The emotion estimation model based on pictographs uses tweets with annotation of emotion vectors as training data. Our method clusters emotion vectors, tries to make a model to estimate emotion vector clusters, and finally constructs a fine-grained emotion analysis model.

Many of the existing studies sought to estimate emotion categories; therefore, they made training data by considering that one sentence corresponded to one emotion.However, there are tweets including more than one pictograph, so we thought that it would be possible to assume that these tweets express more than one emotion.

Our method estimated the emotion vector cluster to which the tweet is thought to belong based on skip-gram model. Then, we calculateda tweet emotion vector by multiplying the probability value of the estimated cluster and a centroid vector. In this process, we improved general versatility of emotion analysis by using the top K clusters with highest probability values for calculation.

3.2 Emotion Analysis by Time Series for Each User Attribute

The profiles of twitter users are attribute information of the users and written by themselves. However, in the default setting of Twitter, the profile must be written in free format; therefore, the quality of attribute information for each user differs.



▲Figure 1. Making flow of hybrid emotion estimation model.

Twifile [20] is a website where Twitter users can register detailed profile information such as self-introduction, annotations of "personal tag," "favorite tag," "unfavorite tag," etc. **Table 1** summarizes frequently appearing tag information.

In our study, we regarded such tag information as features indicating attributes and clustered the users. For each set of three kinds of tags ("personal tag," "favorite tag," and "unfavorite tag"), we converted those tag sets into 300-dimension-word-distributed representation-averaged vectors and created 900-dimension real-valued vectors. We employed these as user vectors and divided them into k clusters by using the unsupervised clustering method (k-means method).

For each user cluster, we chronologically sorted out the tweet sets by 7-day units, calculated the emotion expression tweets' emotions by HEEM, and visualized the result. **Fig. 2** shows the number of users of each cluster. From this figure, we can find uneven numbers of users according to clusters. We thought it natural that hobbies or attributes would vary among the registered users. The clusters with a small number of users might include other accounts of the same users. Therefore, user clustering was thought to be effective for removing noise for detecting tendency.

Figs. 3, **4**, and **5** show the time-series analysis results when the number of clusters was divided as 5, 10, and 15. The colors of lines show the kinds of emotions.

The results showed that we could grasp the tendency by focusing on users' attributes. However, analysis with larger datasets for longer periods would be necessary because the dataset used in this experiment was small. It has already been provedin the existing studies that there are differences in accuracy of emotion analysis depending on the difference of emotion expressions for each user's attribute [21]. Therefore, it would be necessary to create an emotion analysis model adjusted for each user's attribute.

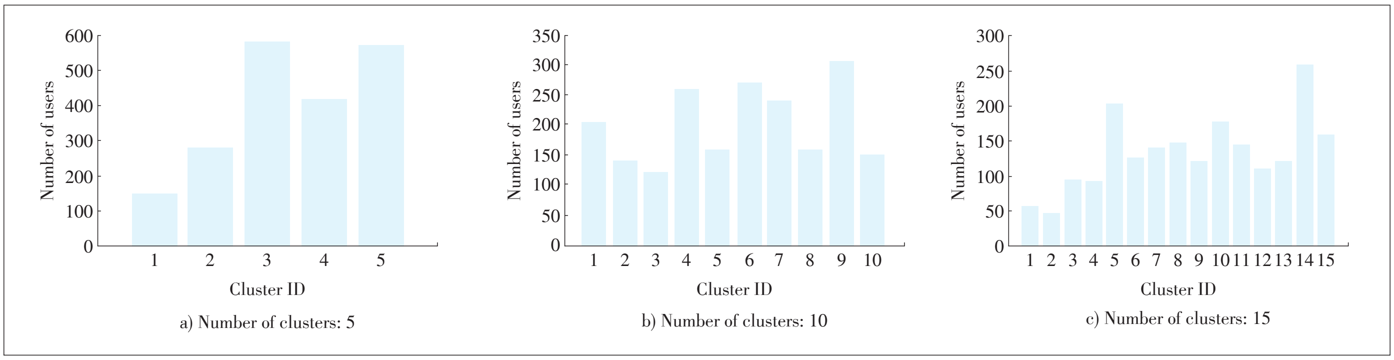
4 Experiment

4.1 Model Evaluation of HEEM

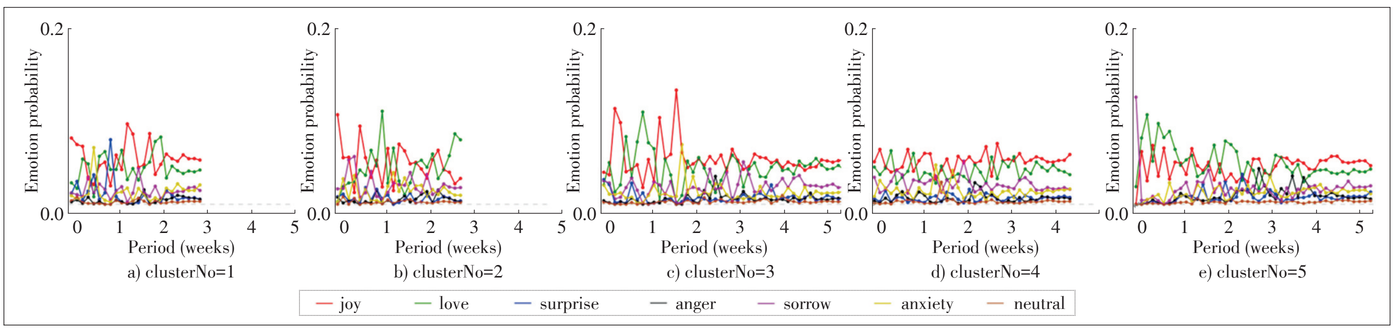
We conducted an experiment to validate the effectiveness of the proposed method. As an evaluation test set, we used the

▼Table 1. Examples of frequently appearing tags

Favorite tag		Unfavorite tag		Personal tag	
Anime	746	Insect	688	Female	1258
Game	575	Horror	220	Male	891
Music	575	Cockroach	194	Blood type A	584
Cat	425	Male	157	Blood type O	473
VOCALOID	340	Female	155	Blood type B	409
Comic	333	Cat	153	High-school student	381
Voice Actor	309	Anime	151	Student	296



▲**Figure 2. Number of users in each cluster.**



▲**Figure 3. Results of time-series analysis of emotion when the number of clusters was 5.**

tweet sentences of 15 male and 15 female users. **Table 2** shows details of the test set and the training data. We used fastText [22]–[24] as a machine learning tool for training word-distributed representations and an emotion classifier. The learning parameter was set for a skip-gram model as window=5, dimension: 300. Other parameters were used as default settings.

We conducted the experiments under the following four by the emotion estimation model created by training on the automatically labeled corpus:

1) The emotion estimation model created by training on the automaticallylabeled corpus

2) The emotion estimation model created by training on the manuallylabeled corpus

3) Model Switching Method (MSM)

4) Mixed Model Method (MMM)

The following subsections describe the experimental results and discussions.

4.2 Experimental Results

The experimental results for male and female users under Condition 1) are shown in **Figs. 6** and **7**. The lower numbers of the horizontal axis indicate cluster numbers, and the upper numbers of the horizontal axis indicate the parameter K, which means the number of examples used for emotion estimation. When the number of clusters is over 16, big differences are not found between their accuracies. When the value of K is 3, F_1-Scores are very high.

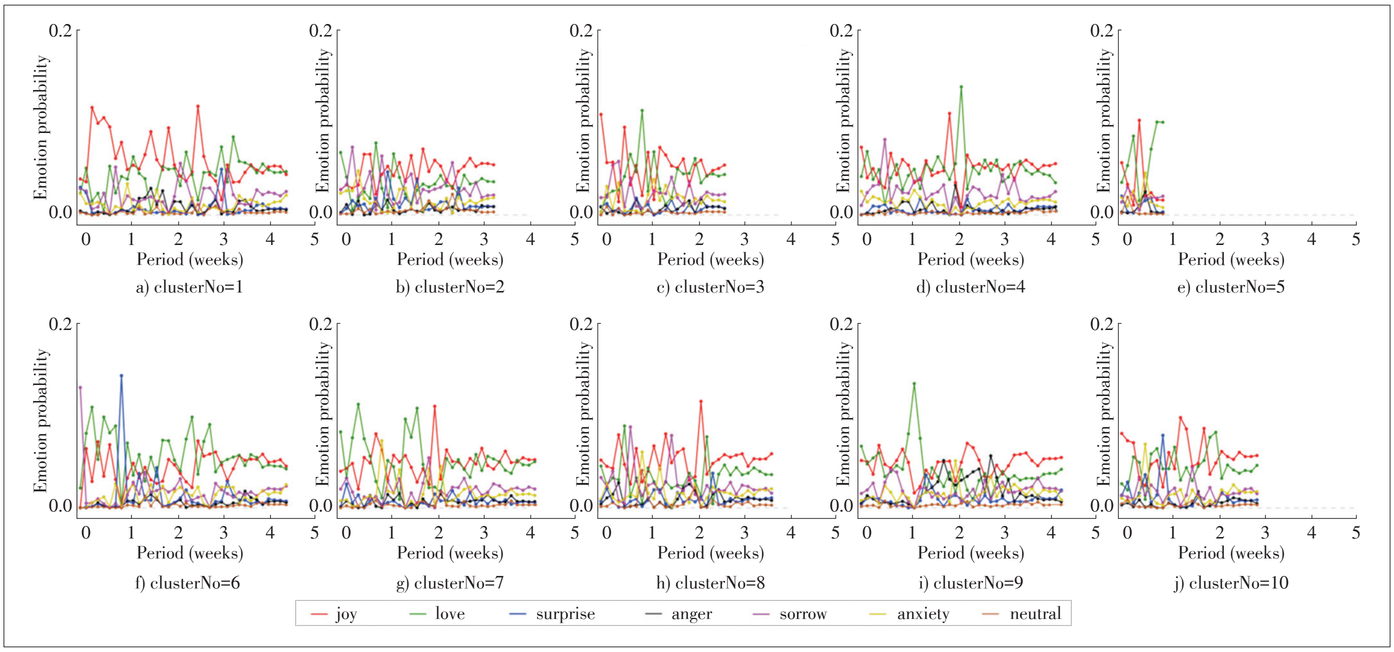
It was found that the precisions in females became higher than those in males when the cluster number was 32. The previous survey already proved that female users more often use pictographs than male uses. This means that the emotion estimation model based on emoticons is suitable for emotion estimation of female users' tweets. **Table 3** shows the experimental results under Condition 2).

As seen in the results, the averaged F1-Scores did not show distinctive differences between male and female users. Overall, these results under Condition 2) showed higher accuracy than the results under Condition 1).

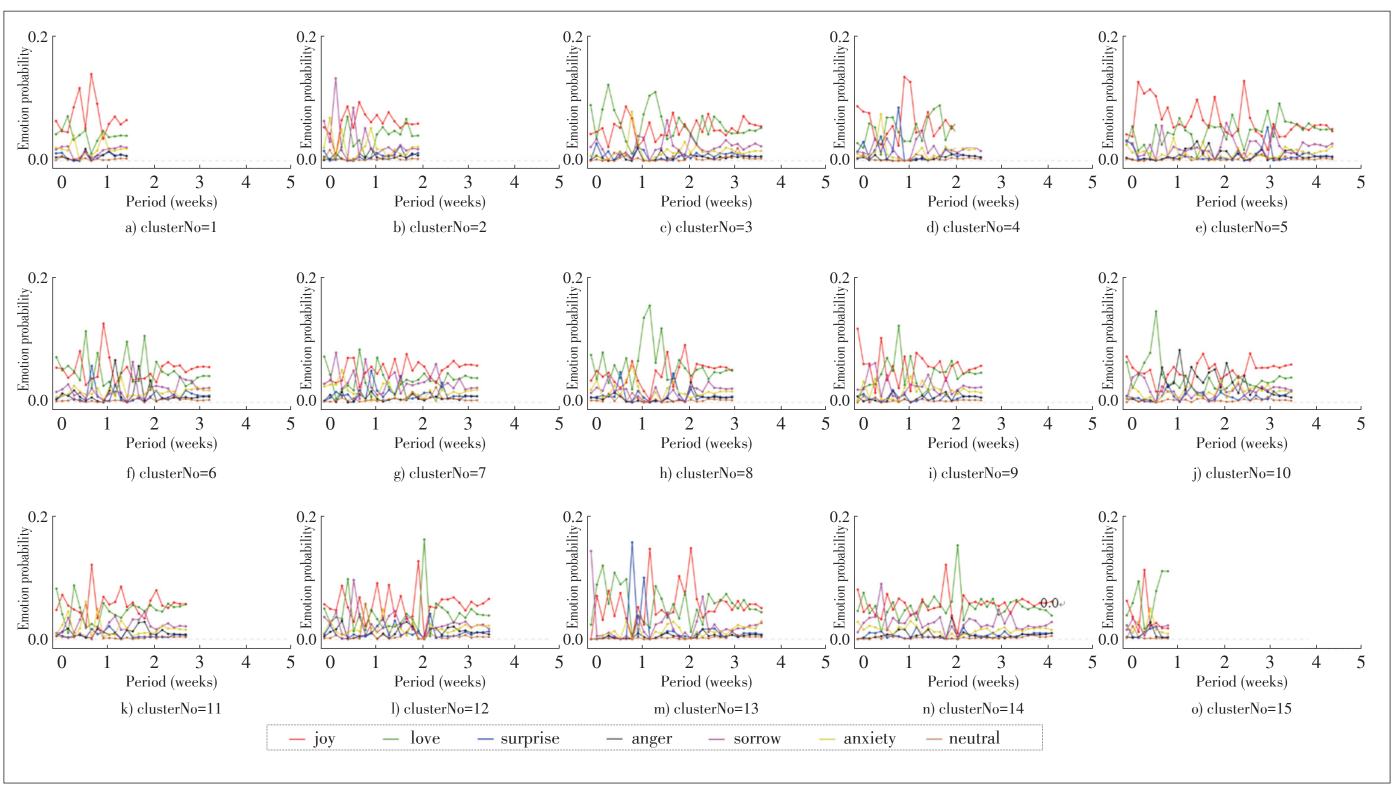
Next, we evaluated the accuracy under Condition 3) and Condition 4) that combined two models. **Tables 4** and **5** show the results. The results showed that the mixed model had the highest F1-Score. Simply, as for F_1-Score, if we use automatically an annotated corpus based on emoticons to create a model, the general versatility may increase; however, the accuracy would decrease compared to the model based on the manually annotated corpus.

4.3 Discussions

In the evaluation experiment, the highest accuracy was observed in MMM. That proves the effectiveness of the model that trains on both the high quality manual corpus and the automatically labeled emotion corpus. On the other hand, the corpus was added under the limited condition that the tweets included pictographs. We should further consider a method of adding under other conditions such as that the tweets include emoticons or emotion expressions.We did not find big differ-



▲Figure 4. Results of time-series analysis of emotion analysis when the number of clusters was 10.



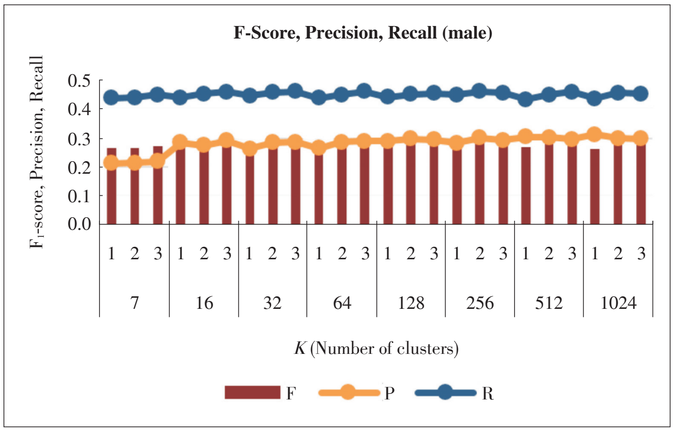
▲Figure 5. Results of time-series analysis of emotion when the number of clusters was 15.

▼Table 2. Evaluation test set and training data

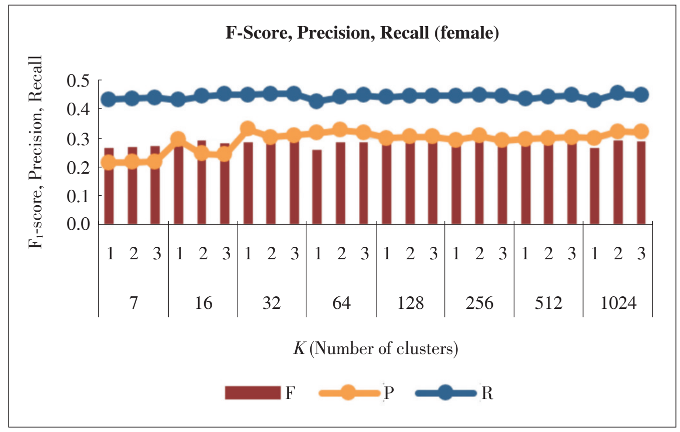
Test data (labeled)		Training data (labeled)		Pretraining data (unlabeled)
4483 tweets (Male: 15 users)	4479 tweets (Female: 15 users)	MAC: 46,979 sentences	AAC: 198,968 sentences	1,100,000 tweets

ences between the analysis accuracies of male and female users. The results might suggest that creating different emotion estimation models for males and females is important.

We trained with the word-distributed representations based on skip-gram as features to increase versatility. However, the



▲Figure 6. Experimental results of the emotion estimation model by automatically annotated corpus (male).



▲Figure 7. Experimental results of the emotion estimation model by automatically annotated corpus (female).

▼Table 3. Experimental results under Condition 2)

Label	Male			Female		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Anxiety	0.292	0.480	0.363	0.261	0.657	0.373
Love	0.220	0.791	0.344	0.251	0.775	0.379
Joy	0.931	0.905	0.918	0.940	0.950	0.945
Sorrow	0.226	0.599	0.328	0.194	0.570	0.289
Neutral	0.397	0.386	0.391	0.372	0.297	0.331
Anger	0.141	0.755	0.238	0.168	0.663	0.268
Surprise	0.251	0.110	0.153	0.314	0.116	0.169
Average	0.351	0.575	0.391	0.357	0.575	0.394

▼Table 4. Experimental results with Condition 3) (MSM)

Label	Male			Female		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Anxiety	0.288	0.478	0.360	0.244	0.629	0.351
Love	0.219	0.797	0.343	0.251	0.777	0.380
Joy	0.931	0.905	0.918	0.940	0.950	0.945
Sorrow	0.228	0.598	0.331	0.196	0.576	0.292
Neutral	0.395	0.386	0.390	0.369	0.280	0.318
Anger	0.141	0.752	0.238	0.164	0.620	0.260
Surprise	0.249	0.103	0.146	0.247	0.120	0.161
Average	0.350	0.574	0.389	0.344	0.564	0.387

differences according to gender might be absorbed by using the word-distributed representation model based on the corpus collected,regardless of gender. Therefore, we could not consider frequently appearing emotional expressions or usage of these emotional expressions according to gender.

The MMM achieved higher accuracy than the MSM. For this reason, we believe that the feature used for switching the models had problems. We used the content rates of unknown word (CR_{unk}), emoji (CR_{emoji}), emoticon (CR_{face}), and emotional expression (CR_{em}) of tweets as features; however, there were few tweets including emoji in the test data used for the experiment. **Table 6** summarizes the accuracy using AAC model for each gender, and the CR_{unk}, CR_{emoji}, CR_{face}, and CR_{em} of failure and success tweets.

This table showed that the number of female users selecting the AAC model was 8 times larger than the number of male users, and the accuracy was also higher. There were almost no differences in CR_{unk} or CR_{em} according to gender; however, CR_{emoji} for females was higher than that of males, and CR_{face} of males was a little higher than that of females. However, this result does not prove that the more emojis are included, the more successful emotion estimation becomes. Considering that the MSM sometimes can but sometimes cannot select the appropri-

▼Table 5. Experimental results with Condition 4) (MMM)

Label	Male			Female		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Anxiety	0.271	0.442	0.336	0.224	0.554	0.319
Love	0.213	0.769	0.333	0.247	0.774	0.375
Joy	0.898	0.968	0.932	0.918	0.958	0.938
Sorrow	0.262	0.584	0.362	0.226	0.692	0.341
Neutral	0.446	0.296	0.356	0.431	0.321	0.368
Anger	0.134	0.706	0.225	0.217	0.337	0.264
Surprise	0.178	0.251	0.208	0.158	0.225	0.186
Average	0.343	0.574	0.393	0.346	0.552	0.399

▼Table 6. Accuracy using AAC model for each gender and CR_{unk}, CR_{emoji}, CR_{face}, and CR_{em}

	Male				Female			
Accuracy	0.573 (43/75)				0.688 (353/513)			
	CR_{unk}	CR_{emoji}	CR_{face}	CR_{em}	CR_{unk}	CR_{emoji}	CR_{face}	CR_{em}
Failure	0.616	0.038	0.001	0.005	0.676	0.065	0.005	0.007
Success	0.653	0.055	0.002	0.006	0.675	0.059	0.227	0.009

ate model, we thought that the accuracy was not improved compared to when another model was used.

The evaluation test corpus collected the tweets written by the famous twitter users, so the corpus had bias. However, we might observe the tendency of difference from the general other users by analyzing emotions of those who make utterances publicly according to their attributes.

5 Conclusions

In this paper, we proposed a versatile method to analyze social big data on SNS. The proposed method creates the HEEM, which improves general versatility and does not decrease accuracy by machine learning based on the MAC, which is created manually, and the AAC, which includes tweets automatically labeled by emoji vector.

We clustered the users whose profiles could be acquired from the profile publishing site. Then, we analyzed each tweet's emotion for each user cluster. As a result, we found the emotional change tendency between the user clusters. However, because it is clear that there are differences between emotional expressions for each attribute, we would like to consider the creation of the emotion analysis model for each attribute and adaptation of emotion estimation model for users.

In this paper, we also proposed an emotion analysis method by using the word-distributed representation vector considering both skip-gram and sub-word as features. We believe that those features are suited for the analysis of social big data.

We expect that the proposed methods can be used for emotion analysis of huge social big data, and can develop it to a higher level of analysis. In future work, we would like to detect users who display suicidal tendency or post inappropriate remarks by combining the depressive analysis, personality analysis and topic modeling method.

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