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Multidimensional sentiment calculation method for Twitter based on emoticons

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Abstract

Purpose – The purpose of this paper is to propose a method of calculating the sentiment value of a tweet based on the emoticon role.

Design/methodology/approach – Classification of emoticon roles as four types showing “emphasis”, “assuagement”, “conversion” and “addition”, with roles determined based on the respective relations to sentiment of sentences and emoticons.

Findings – Clustering of users of four types based on emoticon sentiment.

Originality/value – Formalization, using regression analysis, of the relation of sentiment between sentences and emoticons in all roles.

Keywords Sentiment, Twitter, Emoticon, Microblog

Paper type Research paper

1. Introduction

Through the rapid progress of microblogging systems such as Twitter and Facebook, people can easily post their experiments and sentiments to the Internet. Microblogging systems have become popular for two reasons. One is that microblogging systems are convenient because they consist of short messages. The other is that they are real-time systems: users can post and obtain information easily in real time. Therefore, the speed of information communication increases. Users can easily post their experiments and sentiment anywhere and anytime in real time. For example, when a user watches news, movies or sports on TV, the user might post sentiments such as “This is very sad news. I was crying!!” to the microblogging system. When a user buys a new camera, the user might post “This camera is very cute. I’m so happy!!”. Sentiments, as represented by these sentences, are expected to be users’ candid assessments. After extracting their sentiments from the microblogging system, one can use the sentiments for recommendation and summarization systems, marketing of new products, and so on. Therefore, analyzing sentiments from microblogging systems is important, but it is difficult.

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Many recent studies have analyzed sentiments from Web-related information. Almost all target sentiments are treated as a positive/negative sentiment. Positive/negative sentiment is sufficient to ascertain the reputation of products in the marketing of products or is effective as information for recommendation systems. However, when using sentiments for recommendation and summarization systems targeting movies, television shows, books and sports, the mere assessment of positive/negative sentiment is insufficient. Because human sentiments are complex, one might feel sentiments of many kinds from movies, television shows, books, and so on. For "This is a very sad movie. I was crying!!", the words "sad" and "cry" signify negative sentiment. The sentence becomes a negative sentence based solely on an assessment of positive/negative sentiment. However, if a user likes a sad movie and the user wants to cry when watching the movie, the sentence is not negative for the user. In this way, a user feels complexity in sentiments related to movies, television shows, books and sports. They post complex sentiments to the microblogging system. We propose a method of analyzing multidimensional sentiments from a microblogging system. As described herein, our target microblogging system is Twitter. Multidimensional sentiments of many types have been reported. Nakamura (1993) describe ten sentiment dimensions. Plutchik (1960) describes eight basic sentiment dimensions. Kumamoto (2010) uses six sentiment dimensions to represent readers' impressions of news articles. Takaoka and Nadamoto (2011) describes another six dimensions of sentiments. As described herein, we use the ten sentiment dimensions of Nakamura *et al.*, 2003 (see Table I) to analyze the sentiments of tweets.

Twitter, as a text-based communication tool, cannot accommodate non-verbal communication such as gestures and eye contact. Users sometimes use emoticons to tweet delicate sentiments as an alternative to non-verbal communication tools. We gathered and investigated a large indefinite number of Japanese tweets (about 90,000 tweets). Results show that about 20 per cent of the tweets (17,647 tweets) had emoticons. In many cases, emoticons profoundly affect the tweet sentiments. For example, the tweet "Today was happy:)" is apparently happier than "Today was happy", while the tweet "I was angry:)" is not angrier than "I was angry". In these examples, the emoticons alter the tweet sentiment by enhancing or softening their original sentiment. We propose emoticon roles of four types, which are determined by comparing sentiments of sentences only and sentiments of sentences with emoticons. At this time, we consider that a user can feel different sentiments for same emoticon; we also propose user types

Sentiment categories English (Japanese)	Words
Joy (KI/yorokobi)	Fun, interesting, good
Anger (DO/ikari)	Crazy, irritating
Sorrow (AI/aware)	Dowdy, gammy, gaunt
Fear (FU/kowagari)	Terrible, worried
Shame (CHI/haji)	Disgraceful, squirmy
Liking (KOU/suki)	Lovely, honey, pleasantly
Dislike (KEN/kirai)	Hateful, gloomy
Excitement (KOH/takaburi)	Irritated, vexation
Relief (AN/yasuragi)	Relax, simple, sporty
Surprise (KYOU/odoroki)	Abstracted, amazement

Table I. Ten sentiment categories

for sentiment of emoticons. For example, in the case of Japanese emoticons "(T_T)", the meaning is the crying, but some users using no emoticons anytime feel that it signifies laughing. Therefore, we analyze clusters using the emoticon tweet.

The technical points of this paper are as follows:

- analysis of multidimensional sentiments of tweets;
- analysis of emoticon roles; and
- clustering of user based on sentiment of emoticon.

This paper is organized as follows: Section 2 discusses related work; Section 3 presents a sentiment lexicon compilation; Section 4 describes emoticon lexicon compilation; Section 5 proposes emoticon roles of four types; Section 6 proposes a method for calculating the sentiment values of emoticon tweets; Section 7 discusses experiment results; Section 8 presents the emoticon user type and Section 9 concludes the paper and describes future work.

2. Related work

2.1 Sentiment analysis

Recently, studies of sentiment analysis have been actively pursued. Especially, methods for analyzing positive and negative sentiments have been proposed by many researchers. Dave's (2003) method classifies Web site reviews into positive reviews and negative reviews. Kobayashi *et al.* (2001) propose a dictionary-based method for acquiring a P/N lexicon that specifies whether each entry means a positive or negative concept. Their method is based on a bootstrap method. Fujimura *et al.* (2005) classify Web pages into positive and negative classes and extract a reputation from the Web. They propose a scoring method to extract reputation. In contrast, we propose a method for analyzing multidimensional sentiments of tweets.

Multidimensional sentiment vectors have been proposed in various sentiment models. For example, the model by Plutchik (1960, 2001) is one of the most typical sentiment models. The Plutchik model includes clustering eight basic emotions into four-dimensional sentiment vectors: "Acceptance – Disgust", "Anticipation – Surprise", "Joy – Sadness" and "Anger – Fear". Tokuhisa *et al.* (2008) propose a method for inferring the emotion of a speaker conversing with a dialogue system from the semantic content of the speaker's utterance. For instance, from the sentence "I was disappointed because the shop was closed and I'd traveled a long way to get there." pulled from the Web, they learn that the clause "the shop was closed and I'd traveled a long way to get there." is an example of an event that provokes disappointment. As described in this paper, they refer to such an example as an emotion-provoking event and refer to a collection of event-provoking events as an emotion-provoking event corpus. Their sentiment model incorporates emotions of eleven kinds: happiness, pleasantness, relief, fear, sadness, disappointment, unpleasantness, loneliness, anger, anxiety and neutral. Takamura *et al.* (2005) propose a method that calculates semantic orientation of words. They regard semantic orientation of words as the spin of an electron. Then, they model the word network as a spin model. Kumamoto *et al.* (2011) specifically examine sentiments related to multidimensional impressions to extract from Web news. Their impression model comprises three-dimensional sentiment vector, "Sad – Happy" "Angry – Glad" and "Strained – Peaceful", and each component value of the vectors is a real number between 0 and 1. They also propose a method for determining the impressions which people feel from reading news articles. Their hypothesis is that "words in the news articles which include impression word *e* represent the impression". Their system was designed using co-occurrence between the word in the news article and emotion words. Kumamoto (2010) and Kumamoto *et al.* (2011) propose a method of extracting impressions from how people feel as they see or hear the content. Takaoka and Nadamoto (2011) propose a method for extracting the sentiment from words of wisdom using their proposed six-dimensional sentiment. Moreover, they propose a system that searches for words of wisdom based on user's sentiment. However, our method not only analyzes sentiment of emoticons but also takes the role of emoticons into consideration in analyzing sentiment of tweets.

2.2 Emoticon-based sentiment analysis

Numerous studies have conducted emoticon sentiment analysis. Table II presents a classification of emoticon sentiment analysis studies. As shown in Table II, studies of emoticon sentiment analysis are roughly classifiable into two categories: studies targeting only emoticons and studies targeting sentences with emoticons. Some earlier studies of the literature (Cho *et al.*, 2006; Ito *et al.*, 2008; Nakamura *et al.*, 2003; Kazama *et al.*, 2013; Zhao *et al.*, 2012) analyze sentiment of emoticons only. Our proposed method analyzes sentiment of sentences with emoticons, and differs from these studies. Other studies of the literature (Urabe *et al.*, 2013; Hogenboom *et al.*, 2013; Aoki *et al.*, 2011; Soranaka *et al.*, 2012; Dayalani and Patil, 2014; Pak *et al.*, 2010; Go *et al.*, 2009) analyzed sentiment of sentences with emoticons, as our study does. However, our method not only analyzes the sentiment of emoticons but also incorporates the role of emoticons in analyzing the sentiment of tweets.

Urabe *et al.* (2013) propose a system that recommends an emoticon based on a user's sentiment. Hogenboom *et al.* (2013) extracts sentiment by considering both the sentence sentiment and emoticons. Aoki *et al.* (2011) propose a method to create sentiment vectors of emoticons using the co-occurrence relation between sentiment words and emoticons derived from weblog articles. Soranaka *et al.* (2012) analyze a co-occurrence relation between emotional words and emoticons in a text. Their method also extracts sentiment from tweets based on their results. Dayalani and Patil (2014) are able to generate a training dataset automatically by referring to the sentiment present in tweets containing emoticons. Then, they classified them as positive, negative or neutral. Pak *et al.* (2010) use Twitter for

Literature no.	Only emoticons	Sentences + emoticons
(12)	×	
(13)	×	
(14)	×	
(15)	×	
(16)	×	
(17)		×
(18)		×
(19)		×
(20)		×
(21)		×
(22)		×
(23)		×

Table II. Classification of studies on emoticons

emoticons of two types (happy emoticons and sad emoticons) to denote positive and negative sentiment. Go *et al.* (2009) construct corpora using emoticons; then, they classify the tweets as positive or negative. In contrast, our proposed method analyzes the multidimensional sentiment of a tweet by considering the role of the emoticon included in the tweet.

3. Compiling a sentiment lexicon

A sentiment lexicon plays an important role in computing the sentiment of text data. The lexicon requires quantification of words based on their sentiment. We use Kumamoto's *et al.* (2011) sentiment lexicon compilation system to create our sentiment lexicon. In the system, input data are words featuring target sentiment dimensions, which constitute bipolar scales, and documents which have numerous words. The system creates a sentiment lexicon based on calculating co-occurrence frequency between sentiment words that are defined in advance and numerous words in documents. The lexicon consists of sentiment dimensions, words categorized by each dimension and a sentiment value of each word. Kumamoto has compiled his sentiment lexicon based on three bipolar scales suitable for representing sentiment of news articles, "Happy – Sad", "Glad – Angry", and "Peaceful – Strained" using numerous words extracted from news articles. However, it is difficult to use his lexicon in sentiment analysis of tweets because his lexicon created from news articles is not suitable for representing sentiment of tweets. Therefore, we use the following input data to compile a sentiment lexicon.

3.1 Sentiment dimension

Kumamoto's three bipolar scales are insufficient to calculate tweet sentiments because tweet sentiments are more complex. We use Nakamura's ten-dimensional sentiment (Nakamura, 1993) (see Table I). Their sentiment consists of ten monopolar scales, not of bipolar scales. Therefore, we use the Plutchik's wheel of emotions (Plutchik, 1960) to create five bipolar scales for representing the ten-dimensional sentiments from the ten monopolar scales. Our input bipolar scales are "Sorrow – Joy", "Dislike – Liking", "Shame – Relief", "Fear – Anger", and "Surprise – Excitement".

3.2 Documents which have numerous words

Almost all tweets are written colloquially. They differ from wording of news articles. It is necessary to compile a sentiment lexicon for Twitter, but Twitter includes numerous slang expressions and disorderly grammar. Moreover, it is difficult to calculate co-occurrence frequency with sentiment words. Therefore, we use movie review data to compile the sentiment lexicon because many colloquial styles are included in the data, without much slang or disorderly grammar. We use 74,000 sentences of Yahoo! movie review data[1] to compile the sentiment lexicon. We register about 5,600-7,500 words in each dimension in the sentiment lexicon. Table III shows examples of the sentiment lexicon.

4. Compiling an emoticon lexicon

Usually, English emoticons consist of 1-byte characters shown in a vertical presentation as: o). In contrast, Japanese emoticons consist of 1-byte or 2-byte characters presented horizontally as (^o^). Our proposed method targets Japanese emoticons as a first step of this study. Japanese tweets include many emoticons. Also, Japanese emoticon lexicons exist. However, they cannot be used for our ten-dimensional sentiments. They have no sentiment values. We must compile an emoticon lexicon that includes emoticons and their sentiment values based on the ten-dimensional sentiment. Compiling an emoticon

Sentiment	Entry word	Sentiment value	Entry word	Sentiment value	Entry word	Sentiment value
Joy	Fun	0.91	Important	0.54	Interesting	0.85
Liking	Miss	0.64	Love	0.71	Affection	0.62
Relief	Relief	0.45	Peace	0.81	Rest	0.82
Sorrow	Sad	0.45	Melancholy	0.82	Hurt	0.62
Dislike	Disagreeable	0.82	Hate	0.75	Ache	0.72
Fear	Afraid	0.45	Fear	0.64	Anxiety	0.55
Anger	Angry	0.87	Bellow	0.54	Revenge	0.72
Shame	Blush	0.72	Shame	0.87	Bashful	0.56
Excitement	Thrill	0.45	Amazing	0.57	Sensation	0.72
Surprise	Surprised	0.71	Consternation	0.54	Panic	0.52

Table III. Example of entries in our sentiment lexicon

lexicon based only on user experiments is difficult because emoticons consist of assemblage of characters. Moreover, emoticons of so many kinds exist. Users can create new emoticons freely. We consider that parts of the human face such as the mouth, nose, and eyes represent their sentiment. The parts of emoticons are parts of a human face. We particularly examine the parts of emoticons to compile the emoticon lexicon. Using our proposed method, we can add a new emoticon at any time. The following is an explanation of the emoticon lexicon compilation process.

4.1 Extract emoticons

We extracted emoticons that had a high frequency of appearance from Twitter. First, we extracted 17,647 tweets that had emoticons from Twitter. Then, we extracted 100 emoticons with highest frequency from all the tweets. Table IV shows a portion of the extracted emoticons as examples.

4.2 Determine the sentiment of the emoticons

We conducted an experiment to ascertain the sentiment of the emoticons extracted in Section 4.1. Ten subjects who use emoticons very often participated in our experiment. First, the subjects selected a maximum of three sentiments as the sentiments they felt strongly from watching an emoticon. At this time, the value of the sentiment which was

Sentiment	Emoticons
Joy	(^o^) (^^) (^−^)
Liking	(^o^) (´∇`) (≧∇≦)
Relief	(´∇`) (･ω･) (･_･)
Sorrow	(>_<) (´_`) (ToT)
Dislike	('･ ･`) ('･_･`) ('; ω ;`)
Fear	('; ω ;`) (;ﾟДﾟ) (; 'Д`)
Anger	(`Д´) (`･ω･´) (･`Д´･)
Shame	(>_<) (^_^;) (″ω″)
Excitement	(`Д´) (≧∇≦) (･`ω´･)
Surprise	(ﾟДﾟ) (¯д¯;) (ﾟ_ﾟ)

Table IV. Examples of gathered emoticons the most strongly felt is 3, the next is 2 and the third one is 1. As the results, values representing strength of sentiments were determined for all the 100 emoticons. We summed the values of respective sentiments. Then, we determined the emoticons whose sentiment values are greater than a threshold. We regard the threshold as 4.6 in this paper. At this time, an emoticon can have a maximum of four sentiments.

4.3 Determine the sentiment of emoticon parts

We separated emoticons into parts and determined the sentiment value of each part. The parts are "eyes", "mouth", "eyebrows" and "cheek". Almost Japanese emoticons have no nose as parts. We do not care about the nose as this moment. We counted the sentiment value of each part based on the results of Section 4.2. Table V shows examples of sentiments of emoticon parts.

4.4 Add other emoticons to the emoticon lexicon

We manually determined other emoticons' sentiment based on the results of Section 4.3. If all parts of a new emoticon represent "happy", then the sentiment of the emoticon becomes "happy". If parts of new emoticons represent different sentiments, we regard all sentiments that have a higher value than a threshold as the emoticon's sentiments. Eventually, we added 400 emoticons to the emoticon lexicon. Table VI shows examples from the emoticon lexicon.

Table V.
Examples of assigned sentiments of every part

Parts	Types of parts	Sentiment
(^^)	Eye	Joy, liking, relief
(> <)	Eye	Sorrow, dislike, surprise
(. .)	Eye	Sorrow, dislike, shame
(° °)	Eye	Surprise
(≧ ≦)	Eye	Joy, liking, excitement
(o)	Mouth	Fear
(ω)	Mouth	Relief
(´ `)	Eyebrow	Fear
(。。)	Cheek	Joy
(〃 〃)	Cheek	Joy, excitement

Table VI.
Example of emoticon lexicon

Sentiment	Emoticons
Joy	(^o^) (^^) (^−^)
Liking	(^o^) (´ ∇ `) (≧∇≦)
Relief	(´ ∇ `) (・ω・) (・∀・)
Sorrow	(>_<) (´・_・`) (ToT)
Dislike	(´・_・`) (´・ω・`) (´ ; _ ; `)
Fear	(´ ; _ ; `) ((((;°Д°))))))) (;°Д°)
Anger	(`Д´) (`・ω・´) (`Д´)
Shame	(>_<) (^_^;) (〃 ω 〃)
Excitement	(`Д´) (≧∇≦) (`・ω・´)
Surprise	(((°Д°;))) (￣д￣;) (° _°)

5. Determining a tweet sentiment based on the emoticon role

Our proposed method determines the sentiment of a tweet based on the sentiment of a sentence in the tweet and the role of an emoticon following the sentence.

5.1 Determining sentiment of a sentence in a tweet

Using a morphological analysis system, our proposed method extracts words from a tweet. Then, the method looks up the extracted words in the sentiment lexicon. As words in a tweets often have fluctuation of description, the method may not be able to match the words with any entry word in the sentiment lexicon. We use Juman as a morphological analysis system. Juman has a representative description like the ID of the basic vocabulary. Therefore, we considered making effective use of this representative description when the method looks up words in a tweet in the sentiment lexicon. However, the original Juman does not have a sufficient number of representative descriptions. Therefore, we manually added 32,326 new representative descriptions to a word dictionary for Juman. Our proposed method looks up words extracted from a tweet in the sentiment lexicon using their representative descriptions and obtains their sentiment values. Table VII shows how to calculate sentiment values of two sentences with no emoticons. In the case shown in Table VII, two words, "great" and "funny", are extracted from the first sentence. Each word has five sentiment values. Each sentiment value of the sentence is calculated by summing sentiment values of the constituent words in the corresponding sentiment dimension. As the results, the sentiment of the first sentence is represented as "Joy = 0.98", "Anger = 0.01", "Fear = 0.01", "Liking = 0.05", "Excitement = 0.73" and "Shame = 0.70".

5.2 Role of emoticons

5.2.1 User experiment. We define the role of emoticons based on the relations between sentiments of the sentences and emoticons constituting tweets. We conducted user experiments to investigate their relations. The experiment conditions are the following:

- *Subjects*: 100 people.

  From 10 to 50 s; ten men and ten women in each age group.

- *Datasets*: 200 tweets.

  First, we collected 100 tweets from Twitter, each including at least one emoticon, and defined these tweets as emoticon tweets. Next, we removed any emoticons from all the emoticon tweets, and defined the consequently obtained ones as sentence tweets.

Entry word	Joy	Sorrow	Anger	Fear	Liking	Dislike	Excitement	Surprise	Relief	Shame
Tweet: I feel absolutely good										
Great	0.13	0	0.01	0	0.01	0	0.7	0	0	0.38
Fun	0.85	0	0	0.01	0.04	0	0.03	0	0	0.32
Total	0.98	0	0.01	0.01	0.05	0	0.73	0	0	0.7
Tweet: I feel absolutely good										
Absolutely	0.52	0	0	0	0.23	0	0.2	0	0	0
Good	0.45	0	0	0	0.7	0	0	0	0.03	0
Total	0.97	0	0	0	0.93	0	0.2	0	0.03	0

Table VII. Example of extraction of the sentence sentiment value

First, the subjects read 100 sentence tweets, and judged their sentiment. Next, the subjects read 100 emoticon tweets, and judged their sentiment. When they judged the sentiment, they were asked to select up to three sentiments and assign a score between 1 and 10 for each selected sentiment. We calculated sentiment values of each tweet by summing the assigned scores in each sentiment dimension. We regard the largest one of the sentiment values as the sentiment value of the tweet, and ignore other values. If all sentiment values are less than a threshold, we regard the tweet as sentimentless. In our experiment, we regard the threshold as 48, which is average of sentiment values. Table VIII shows an example of the sentence tweet results. Table IX shows an example of the emoticon tweet results.

5.2.2 Determining the emoticon role. We ascertain the emoticon role from results of our experiment. In our experiment, we used a ten-dimensional sentiment, but when we determine the emoticon role, we use a one-dimensional sentiment consisting of three classes: “positive”, “negative” and “neutral”. This was performed to avoid combinatorial explosion between the ten-dimensional sentiments. Then, we change the 10-dimensional sentiment to the one-dimensional sentiment: we regard “Joy”, “Liking”, “Relief” and “Excitement” as positive, “Sorrow”, “Dislike”, “Shame”, “Fear”, “Surprise” and “Anger” as negative. Sentiment of the tweets which are not classified into positive or negative is dealt with as neutral. We compare sentiment of each sentence tweet (by our experiment), sentiment of an emoticon following the sentence tweet (by emoticon lexicon), and sentiment of the corresponding emoticon tweet (by our experiment). Table X shows the number of tweets in each dimension.

The results of the comparison showed four types of emoticon roles: “Emphasis”, “Assuagement”, “Conversion” and “Addition”. Table XI shows a classification of the emoticon roles. Our proposed method cannot deal with the cases that sentiment of emoticon tweets becomes neutral because our purpose of research is to mine the sentiments from emoticon tweets. Therefore, we do not classify the cases in Table XI. We also disregard the cases that the number of tweets is one in Table XI because we consider the cases as rare. Table XII shows each role of the sentiment and its characteristics. We explain each role in the following.

5.2.2.1 Emphasis: emoticons enhance the sentence sentiment in a tweet. When a positive emoticon is with a positive sentence, the emoticon enhances the positive sentence sentiment. When a negative emoticon is with a negative sentence, the emoticon enhances the negative sentence sentiment. That is, when both emoticons and sentences have the same sentiment, the emoticon role becomes “Emphasis”. When the role of an emoticon in an emoticon tweet is “Emphasis”, sentiment of sentences in the tweet is enhanced.

5.2.2.2 Assuagement: emoticons assuage the sentence sentiment in a tweet. As shown in Table XI, when a negative emoticon is used with a strong positive sentence in an emoticon tweet, sentiment of the emoticon tweet becomes weak positive. When a positive emoticon is used with a strong negative sentence in an emoticon tweet, the sentiment of the emoticon tweet becomes weak negative. That is, when a sentence with a weak sentiment is used with an emoticon with its opposite sentiment, the emoticon role becomes “Conversion”. When the role of an emoticon in an emoticon tweet is “Conversion”, sentiment of the sentences in the tweet is converted into its opposite sentiment.

5.2.2.3 Conversion: emoticons change the sentence sentiment in a tweet. When a negative emoticon is used with a weak positive sentence in an emoticon tweet, sentiment of the emoticon tweet becomes negative. When a positive emoticon is used with a weak

Table VIII. Example of experiment datasets without emoticons

Tweet	Joy	Sorrow	Anger	Fear	Liking	Dislike	Excitement	Surprise	Relief	Shame
I have lots of worries because I just left my parents	18	243	15	88	30	31	13	27	31	19
I feel hell of a disgusted	0	36	205	41	35	65	22	13	7	0
I bet I'll get mad if you flunk!	13	50	127	76	29	33	38	8	4	5
I love the view from the school	141	3	21	29	110	13	5	0	40	2
Maybe the biggest surprise for me most recently	16	19	4	34	32	27	19	210	22	7
I often get mad lately	1	73	136	28	21	50	26	28	19	16
To be honest I get sick of doing nothing but studying	15	102	31	32	33	144	16	5	3	3
I feel hell of a lonely because I rarely see you nowadays	26	191	28	8	36	28	12	6	5	13
Lots of cracking happy things happened today	244	21	13	29	64	2	24	5	26	7
It is not the main venue but I am glad to see it	198	15	1	8	63	4	40	16	17	8

Table IX.
Example of experiment datasets with emoticons

Tweet	Joy	Sorrow	Anger	Fear	Liking	Dislike	Excitement	Surprise	Relief	Shame
I have lots of worries because I just left my parents (´▽`)	72	87	49	57	66	56	25	256	37	24
I feel hell of a disgusted (`ω´)	9	42	225	55	19	49	27	10	1	2
I bet I'll get mad if you flunk! (`ω´#)	16	27	174	95	46	45	62	17	14	4
I love the view from the school (^^)	189	5	21	6	158	5	11	0	57	1
Maybe the biggest surprise for me most recently (￣ε￣#)	25	29	58	22	39	41	27	161	6	19
I often get mad lately (´・_・`)	8	96	105	36	36	42	14	18	24	13
To be honest I get sick of doing nothing but studying (^O^)	62	60	29	19	42	84	17	39	37	13
I feel hell of a lonely because I rarely see you nowadays (=^▽^=)	51	86	36	26	33	67	2	10	15	25
Lots of cracking happy things happened today (^O^)	325	17	10	8	81	33	37	8	38	1
It is not the main venue but I am glad to see it (´・ω・`)	129	46	19	1	51	40	26	15	22	2

negative sentence in an emoticon, sentiment of the emoticon tweet becomes positive. That is, when a sentence with a weak sentiment is used with an emoticon with its opposite sentiment, the emoticon role becomes "Conversion". When the role of an emoticon in an emoticon tweet is "Conversion", sentiment of the sentences in the tweet is converted into its opposite sentiment.

5.2.2.4 Addition: emoticons add sentiment to a neutral sentiment sentence. When a negative emoticon is used with a neutral sentence in an emoticon tweet, sentiment of the emoticon tweet becomes negative. When a positive emoticon is used with a neutral sentence in an emoticon, sentiment of the emoticon tweet becomes positive. Therefore, when a neutral sentence is followed by a positive or negative emoticon,

Combination of sentiment	Sentiment of tweet		
Sentence + emoticons	Positive	Negative	Neutral
positive + positive	14	0	0
positive + negative	12	5	3
positive + neutral	0	0	0
negative + positive	1	19	0
negative + negative	1	35	0
negative + neutral	0	0	0
neutral + positive	3	0	1
neutral + negative	0	3	1
neutral + neutral	0	0	0

Table X. Result analysis of every sentiment polarity of sentence, emoticon and tweet

Combination of sentiment	Sentiment of tweet		
Sentence + emoticons	Positive	Negative	Neutral
positive + positive	Emphasis	–	–
positive + negative	Assuagement	Conversion	–
positive + neutral	–	–	–
negative + positive	Conversion	Assuagement	–
negative + negative	–	Emphasis	–
negative + neutral	–	–	–
neutral + positive	Addition	–	–
neutral + negative	–	Addition	–
neutral + neutral	–	–	–

Table XI. Roles of emoticon

Role	Characteristics	Example
Emphasis	Sentiment of sentence = Sentiment of emoticon	I did it! ヽ(´▽`)/
Assuagement	Sentiment of sentence <-> Sentiment of emoticon	I'm fed up with this (^O^)
Conversion	Sentiment of sentence <-> Sentiment of emoticon and, Sentiment of sentiment is greater than the sentiment of sentence	I have a lot of cares (´∀`)
Addition	There is no sentiment of sentence but there is a sentiment of emoticons	I am in school (^O^)

Table XII. Features in emoticon roles the emoticon role becomes "Addition". When the role of an emoticon in an emoticon tweet is "Addition", sentiment of the sentence in the tweet becomes the same with sentiment of the emoticon.

6. Calculating sentiment values of a tweet based on the emoticon role

Figure 1 shows a scatter diagram exhibiting the relation of the sentiment values between the emoticon tweets (vertical axis) and the sentence tweets (horizontal axis) in the role of "Emphasis". A strong positive correlation is apparent between the data series in the Figure 1. Then, we hit an idea that we calculate a correlation between the emoticon sentiment and the sentence sentiment in all roles. As the results, we found that their coefficients of correlation are 0.95-0.98. It is possible to formalize the relation of sentiment values between emoticon tweets and sentence tweets in all roles using regression analysis. However, in the case of "Addition", regression analysis is not applied because sentiment of the sentences is neutral and the sentences have no sentiment value. Therefore, we formalize the relation in roles of "Emphasis", "Assuagement" and "Conversion".

Figure 2 shows comprehensive results of regression analysis. It is readily apparent that the roles of "Emphasis" and "Assuagement" have a strong positive correlation. The role of "Conversion" has a strong negative correlation. Table XIII shows results of regression expressions by calculation using simple linear regression analysis. Table XIV shows results of the coefficient of determination and the coefficient of correlation for each role. From Table XIV, we find that results of the simple linear regression analysis are all good: all coefficients of determination are greater than 0.5. In the case of "Addition", we infer that sentiment values of tweets are the same with those of emoticons in the tweets because sentiment of the sentences is neutral. We calculate the average of the sentiment values of the emoticons added to the tweets as a weight: the weight becomes 5.8.

The flow of calculating the sentiment values of an emoticon tweet includes the following five steps:

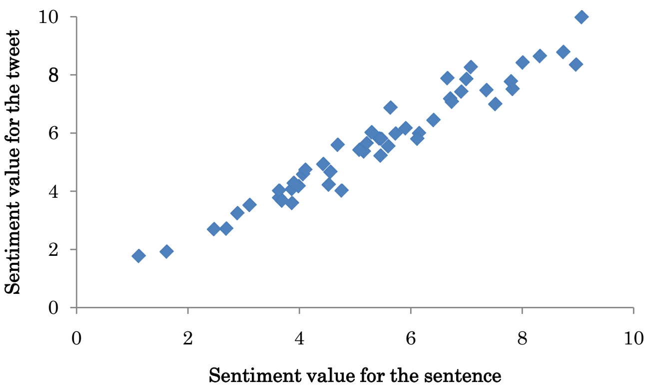

Figure 1.
Scatter diagram in case of "Emphasis"

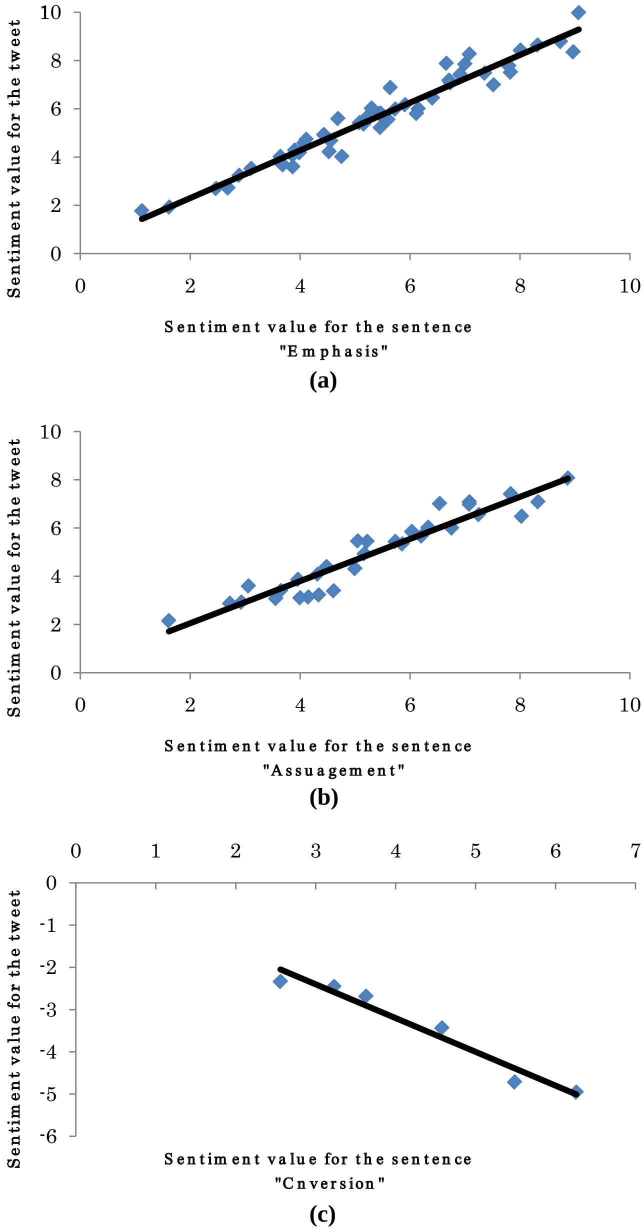

Figure 2. Regression analysis results

(1) Separating an emoticon tweet into a sentence tweet and an emoticon.
(2) Calculating sentiment values of the sentence tweet using the sentiment lexicon we created.
(3) Determining sentiment of the emoticon using the emoticon lexicon we created.
(4) Identifying the emoticon role based on results of (2) and (3).
(5) Calculating sentiment values of the emoticon tweet using a regression expression corresponding to the emoticon role.

7. Experiment

7.1 Method of experiment

We conducted an experiment using five-fold cross-validation to confirm the effectiveness of the proposed method. Following are the four experiment methods:

(1) We divided 100 arbitrary tweets into five, which were obtained from the datasets used in the user experiments in 5.2.1. We regard 20 tweets as one dataset; we have five datasets. We determined the role of emoticons in all tweets based on sentence sentiment and emoticons.
(2) We applied simple linear regression analysis to data consisting arbitrary four of the five datasets in each role of "Emphasis", "Assuagement" and "Conversion", and consequently we obtained a regression equation for each role. We also calculated the weight of "Addition".
(3) We calculated sentiment values of all tweets in the remaining dataset in each role of "Emphasis", "Assuagement" and "Conversion" using the regression expressions obtained in (2). We also calculated sentiment values of all tweets in the remaining dataset in the role "Addition" using the weight obtained in (2).
(4) We calculated root mean square errors (RMSEs) between the calculated sentiment values and the averages of the sentiment values manually scored in the user experiment in the remaining dataset. We calculated an average of the five RMSEs calculated from a total of five unlearned data sets in each role.

7.2 Results and discussion

Table XV presents results of the averages of the five RMSEs in each role for our proposed method and a baseline method, where the RMSEs for the baseline method were

Table XIII. Regression equations based on emoticon roles

Role	Regression equations
Emphasis	$y = 0.9886x + 0.3215$
Assuagement	$y = 0.8728x + 0.3083$
Conversion	$y = -0.8002x + 0.001$

Table XIV. Coefficients of determination and coefficients of correlation of emoticon roles

Role	Coefficient of determination	Coefficient of correlation
Emphasis	0.95	0.97
Assuagement	0.91	0.95
Conversion	0.95	0.98

calculated as differences between the sentiment values of emoticon tweets and those of sentence tweets in the remaining dataset.

The results of our proposed method are better than those of the baseline in the roles of "Emphasis", "Assuagement" and "Addition". However, in the case of "Conversion", our proposed method has almost as high accuracy as the baseline method. We consider that this results from the fact that few tweets were classified into the "Conversion" and there is a great variation in number among the results of datasets. We must increase tweets that are classified into "Conversion" to calculate their sentiment values more accurately. Table XVI presents examples of sentiment of a tweet based on the emoticon role. Results show that our proposed method is effective for calculating sentiments of tweets with emoticons.

8. The emoticon user type

8.1 Clustering and discussion

As described in this paper, we use Ward's method to clustering and create a dendrogram. Figure 3 shows a dendrogram produced by clustering for the user experiment in Section 5.2.1 using Ward's method. In the dendrogram, the horizontal axis shows the distance of each cluster; the vertical axis shows a subject's number. We discuss the number of clusters, which depends on the cluster distance as follows.

8.1.1 In a case of distance 4.50 (divided three clusters). The first cluster consists of subjects' numbers from 3 to 35. The answers of the subjects are the same as those of the experiment described in Section 5.2.1. They have a common sentiment to the emoticon. The second cluster consists of a subject's number from 2 to 74. The answers of the subjects differ from the result of the experiment in Section 5.2.1, meaning that they have a slightly strange impression to the emoticon. The third cluster consists of subjects' numbers from 9 to 93. Subjects did not really make a special effort in the experiment: their answers are the same impression for tweets.

8.1.2 In a case of distance 3.50 (divided four clusters). The first cluster is the same as in the case of distance 4.50. The second cluster consists of subject's numbers from 2 to 88. They are part of second cluster in the case of distance 4.50, meaning that they have a slightly strange sentiment to the emoticon. The third cluster consists of subject's numbers from 4 to 74, subjects did not respond in all experiments. The fourth cluster is the same as the case of distance 4.5. In this case, we can extract bad results, which are in Clusters 3 and 4. We designate these clusters as bad result clusters.

This case is better than distance 4.5, but we do not extract different sentiments in each user type.

8.1.3 In a case of distance 3.25 (divided five clusters). The first cluster is the same as the case of distance 4.50. The second cluster consists of subjects' numbers from 2 to 43: the subjects are influenced by emoticons because the accuracy of the results of tweets with emoticon is better than the result of tweets without emoticons. The third cluster consists of subjects' numbers from 23 to 88: subjects dislike emoticons because they judge negative sentiment such as "Shame", "Anger" and "Dislike" for tweets with emoticon. The fourth and fifth clusters are bad result clusters.

Table XV. Estimation of overall accuracy based on five-fold cross-validation

Method	Emphasis	Conversion	Assuagement	Addition
Proposed method	0.28	0.96	0.38	0.50
Baseline method	0.44	0.97	0.59	0.63

Table XVI.
Example of results

Tweet	Joy	Sorrow	Anger	Fear	Liking	Dislike	Excitement	Surprise	Relief	Shame
Study just get fed up (^O^)	0	0.2	0.03	0.12	0.3	0.31	0	0	0	0
I will anger After taking a point not good (` ・_・ ´)	0	0	0.81	0.52	0	0.02	0	0	0	0

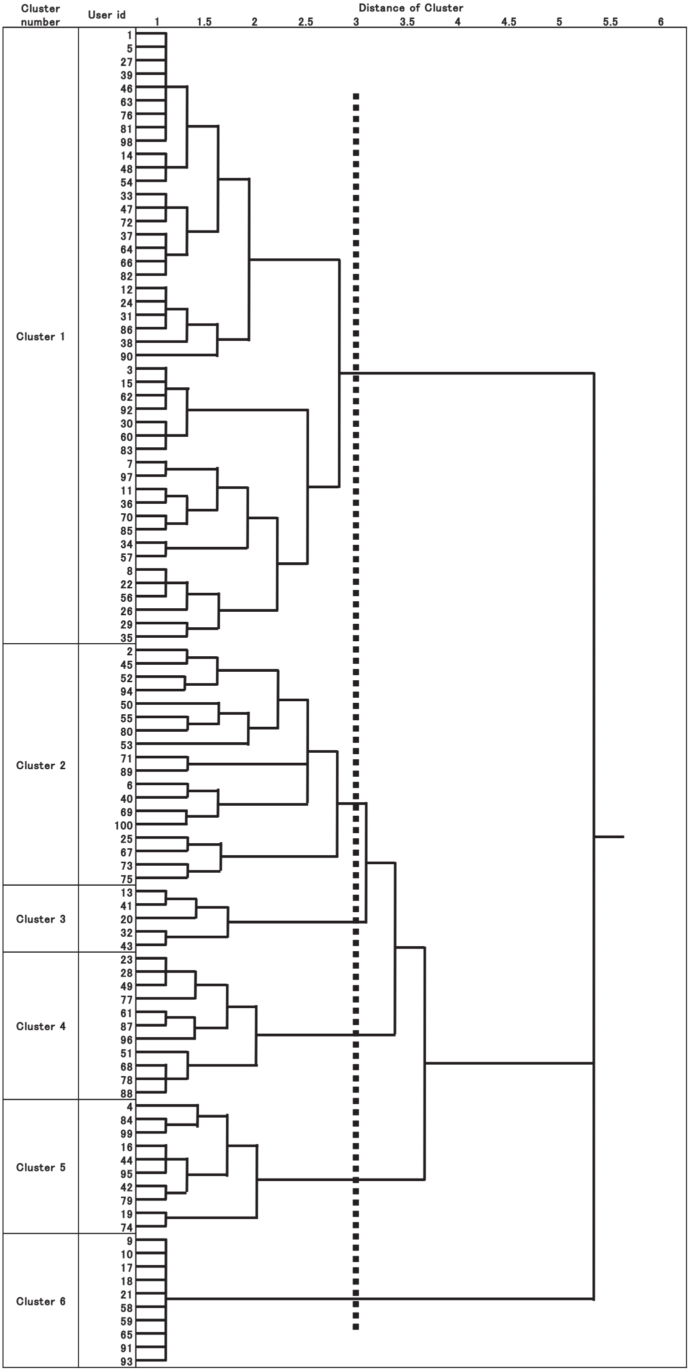

Figure 3.
Dendrogram that was created by the cluster analysis

In this case, the result is better than in the case of distance 3.5 because we can divide susceptible subjects and dislike subjects for emoticons. However, in the second cluster, there are mixed subjects which have different sentiments to the emoticon.

8.1.4 In a case of distance 3.00 (divided six clusters). The first cluster is the same as the case of distance 4.50. The second cluster consists of subjects' numbers from 2 to 75, subjects are influenced by emoticons, but they do not understand the meaning of emoticons well because the accuracies of the results of tweets with emoticon are low (Table XVII). The third cluster consists of subjects' numbers from 23 to 88: the subjects are influenced by emoticons. They also understand meaning of emoticons well because the accuracy of the result of tweets with and without emoticon are high (Table XVII). The fourth cluster is the same as that in the case of distance 3.25, which means that subjects do not like emoticons. The fifth and sixth clusters are bad result clusters.

This case is better than distance 3.25 because we can divide the influence of two types by emoticons.

8.1.5 In a case of distance 2.25 (divided eight clusters). In this case, the first cluster and second cluster are parts of the first cluster at a distance of 3.0. The first cluster consists of a subjects' numbers from 1 to 90: they have common sentiment to the emoticon. The second cluster consists of subjects' number from 3 to 35: they have the same sentiment to the first cluster but the value is lower than the first cluster. In this case, the third cluster and fourth cluster are a part of the second cluster in the case of distance 3.0. The third cluster consists of subjects' number from 2 to 100. The fourth cluster consists of subjects' numbers from 25 to 75. They also have similar sentiment, but the values differ. Fifth to eighth clusters are the same as the case of distance 3.0.

The purpose of our clustering is dividing user types based on the emoticon sentiment. Then, this case has overly small clusters.

8.2 Determining the emoticon user type

From the result of clustering, we can divide users of four types, of which cases are distance 3.0, except for two bad result clusters:

- *Case 1*: common sentiment user type.

  This type is first cluster in distance 3.0. Users have common sentiment for tweets and emoticons.

- *Case 2*: influence and not understanding emoticon types.

  This type is a second cluster in distance 3.0. Users are influenced by emoticons but they do not understand the meanings of emoticons well.

Table XVII. Precision of sentiment of each cluster of tweets

Each cluster	Precision of matches sentiment of Tweets in all users	Precision of matches sentiment of emoticons
The first cluster	0.86	0.18
The second cluster	0.16	0.27
The third cluster	0.56	0.36
The fourth cluster	0.25	0.17
The fifth cluster	0.06	0.6
The sixth cluster	0.01	0.00

- *Case 3*: influence and understanding emoticon type.

  This type is third cluster in distance 3.0, users are influenced by emoticons. They also understand roles of emoticons well.
- *Case 4*: dislike emoticon type.

  This type is a fourth cluster in distance 3.0. Users do not like emoticons.

9. Conclusion

As described in this paper, we proposed a method of calculating the sentiment values of tweets based on emoticon roles. Specifically, we accomplished the following:

- We compiled a sentiment lexicon and an emoticon lexicon.
- We proposed emoticons of four types: "Emphasis", "Assuagement", "Conversion" and "Addition". We also ascertained the emoticon roles based on relations of sentiment between the sentence and emoticons.
- We formalized the relation of sentiment between sentences and emoticons in all the roles using regression analysis.
- We clustered for types of users based on the emoticon sentiment.

Future studies will calculate the tweet sentiment based on emoticon frequency. We will also study personalized mining of the tweet sentiment based on the emoticon user type.

Note

1. Yahoo! movie review data are available at: http://movies.yahoo.co.jp/

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