IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 13, 2020, accepted March 28, 2020, date of publication April 6, 2020, date of current version April 23, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2985726

An Emotion Expression Extraction Method for Chinese Microblog Sentences

FUJI REN, (Senior Member, IEEE), AND QIAN ZHANG
Faculty of Engineering, Tokushima University, Tokushima 7700814, Japan
Corresponding author: Fuji Ren (ren@is.tokushima-u.ac.jp)

ABSTRACT With the rapid spread of Chinese microblog, a large number of microblog topics are being generated in real-time. More and more users pay attention to emotion expressions of these opinionated sentences in different topics. It is challenging to label the emotion expressions of opinionated sentences manually. For this endeavor, an emotion expression extraction method is proposed to process millions of user-generated opinionated sentences automatically in this paper. Specifically, the proposed method mainly contains two tasks: emotion classification and opinion target extraction. We first use a lexicon-based emotion classification method to compute different emotion values in emotion label vectors of opinionated sentences. Then emotion label vectors of opinionated sentences are revised by an unsupervised emotion label propagation algorithm. After extracting candidate opinion targets of opinionated sentences, the opinion target extraction task is performed on a random walk-based ranking algorithm, which considers the connection between candidate opinion targets and the textual similarity between opinionated sentences, ranks candidate opinion targets of opinionated sentences. Experimental results demonstrate the effectiveness of algorithms in the proposed method.

INDEX TERMS Emotion classification, unsupervised emotion label propagation, emotion expression extraction, random walk.

I. INTRODUCTION

With the increasing popularity of microblog services, more and more users read microblog messages, express their views, or record their minds via these services. A lot of hot topics, which contain events that happen in real-time, appear in the microblogging site every day, and attract users to read and discuss emotion expressions in them. Emotion expressions refer to opinion targets of opinionated sentences, along with emotions. Emotion expressions of opinionated sentences in a topic can help readers understand more related events and other users' attitudes on this topic.

Researches on Chinese microblog messages usually focus on emotion analysis at a sentence level. For opinionated sentences in different topics, not only emotions but also opinion targets, provide a wealth of messages. It will consume so much time and workforce to label emotions and opinion targets of a large number of opinionated sentences manually. Thus, an automatic approach is needed to analyze opinion targets of opinionated microblog sentences along with emotions.

The associate editor coordinating the review of this manuscript and approving it for publication was Xiang Zhao.

Emotion lexicons are widely used in textual emotion analysis [1], [2], especially for word-level and sentence-level emotion classification tasks. Some potential emotional network words in microblog sentences, which are not in emotion lexicons, influence the performance of lexicon-based emotion classification methods. Opinion target extraction has already been studies based on supervised learning methods [3], [4], or dependency parsing methods [5], [6]. Rule-based opinion target extraction methods are not suitable for microblog sentences because the microblog sentence structure is irregular. Existing some opinionated microblog sentences contain any words, which can be chosen as opinion targets. It is more challenging to find opinion targets for these sentences.

According to the above situation, we study the emotion expression extraction method for Chinese microblog sentences in this paper. The proposed method mainly contains two tasks: emotion classification and opinion target extraction. For the emotion classification task, we use a lexicon-based emotion classification algorithm to compute emotion values in emotion label vectors of opinionated sentences based on emotional words in sentences. Considering the issue above, we adopt an existing algorithm to find more emotional words automatically. We assume that similar opinionated sentences in a topic focus on the same emotion labels. Based on this assumption, an unsupervised emotion label propagation algorithm is proposed to revise the emotion label vectors of opinionated sentences. The emotion of each opinionated sentence is determined by the highest emotion value in its emotion label vector.

After analyzing the emotions of opinionated sentences, we want to extract the opinion targets of these sentences. Nouns and nouns phrases in sentences are chosen as candidate opinion targets. Then, we propose a random walk-based ranking algorithm, which considers the connection between candidate opinion targets and the textual similarity between opinionated sentences, ranks candidate opinion targets of opinionated sentences.

The main contributions in this research are summarized as below:

- We develop an emotion expression extraction method for microblog sentences, which consists of subjective recognition, emotion classification, and opinion target extraction.
- We classify opinionated sentences into different emotions by a lexicon-based emotion classification algorithm and an unsupervised emotion label propagation algorithm.
- We propose a random walk-based ranking algorithm, which is used to rank candidate opinion targets for opinionated sentences, to address the opinion target extraction task. This algorithm does not need any labeled data.

The remainder of this paper is organized as follows: Section II discusses related works. Section III shows an overview of the proposed emotion expression extraction method. Section IV and Section V describe the emotion classification task and the opinion target extraction task in the proposed method separately. Section VI provides experimental results of Section IV, and Section V. Section VII presents our conclusions and future work.

II. RELATED WORKS

The emotion expression extraction method for Chinese microblog sentences mainly contains two tasks: emotion classification and opinion target extraction. In this section, we discuss some related works of the above two tasks.

A. CHINESE MICROBLOG EMOTION CLASSIFICATION

Textual emotion classification methods, like emotion recognition methods of reviews [7], [8], articles [9], and so on, have been investigated by researchers in recent years. With the development of Weibo 2.0, microblog posts and comments are created every day, in which, the update information provides a wealth of resources of publicly available text messages, many researchers analyzed the emotion of Chinese textual based on the microblogging platform [10]–[12].

The current emotion classification methods contain lexicon-based methods and machine learning methods. Lexicon-based emotion classification methods rely on the open-source emotion lexicons [13], the emotion values of textual were computed based on some formulated rules. Zhang *et al.* [14] presented a lexicon-based emotion analysis method for Chinese microblog messages. They conducted an emotion value calculation based on the emotion weights of emotional words in the microblog text. They aimed to support network regulators' work better. Cui *et al.* [15] introduced a lexicon-based sentiment analysis method. They constructed a microblog lexicon that contains representative topic words and out-of-vocabulary (OOV) words. These words are typically irregular and are not existing regular lexicons. Li *et al.* [16] proposed a lexicon-based multi-class semantic orientation analysis method for microblog messages on public events. This emotion classification method contains five categories: Joy, Blue, Concern, Anger, and Fear.

Many existing textual emotion classification methods for microblog messages are based on machine learning, like Naïve Bayes (NB)-based method [17], Support Vector Machine (SVM)-based method [18], and conditional random fields (CRF)-based method [19]. Wu *et al.* [20] proposed a framework called SMSC (Structured Microblog Sentiment Classification), which combine social context information with textual content information, in order to classify the emotions of microblog messages more accurately. Tang *et al.* [21] investigated the propagation-based emotion analysis method for microblogging textual. They provided a propagating process to incorporate various types of emotional signals in the microblogging textual into a coherent model. They proposed a novel sentiment analysis framework that learns from both labeled and unlabeled data by iteratively alternating a propagating process and a fitting process.

The emotion classification task in our proposed method is also based on emotion lexicons. We adopt an existing algorithm to discover emotional words and then compute different emotion values in emotion label vectors of opinionated sentences by a lexicon-based algorithm. All emotion label vectors are revised by an unsupervised emotion label propagation algorithm in order to make results more accurately. Only emotion lexicons are required in this emotion analysis process, which obtains easier than labeled microblog sentences.

B. OPINION TARGET EXTRACTION

The concept of opinion mining was first proposed by Hatzivassiloglou and McKeown [22] in 1997. With the rapid development of the Internet and the increasing popularity of Internet commentary information, opinion mining has gradually become one of the major research fields of data mining. Opinion target extraction is one task of opinion mining.

When studying the opinion targets of customers' comments, the opinion target extraction task is also called the aspect extraction task. Aspect refers to the most fine-grained comment object in the comment. For example: in a customer's feedback, "The performance of this phone is very good.", "this phone" is the aspect of this sentence.

Many researchers studied opinion target extraction methods based on dependency parsing. Liu *et al.* [6] analyzed comments based on the dependency parsing model after textual preprocessing. They chose frequent aspects by rules and revised some wrong aspects by the Alpha-Beta algorithm. Chinsha and Joseph [5] focused on aspect-level opinion mining. They proposed a new syntactic based approach for it, which uses syntactic dependency, the aggregate score of opinion words, SentiWordNet, and the aspect table together for opinion mining.

Blei *et al.* [23] proposed a topic model called Latent Dirichlet Allocation (LDA). It is a probabilistic graphical model [24], which can be used for textual classification, regression analysis, and other tasks of textual analysis. The topic is hidden information in the model, which makes results in more detail. Many researchers proposed opinion target extraction methods based on the topic model. They modeled aspects and other words in opinionated sentences as topics [4], [25], [26]. Mukherjee and Liu [27] proposed two novel semi-supervised models: seeded aspect and sentiment model (SAS) and maximum entropy-SAS model (ME-SAS). Aspects and words are extracted by the SAS model, respectively, and then aspects and aspect-based words are extracted simultaneously by the ME-SAS model. Experimental results demonstrated that the performance of the model is better than the Dirichlet Forest-LDA (DF-LDA) model, which was proposed by Andrzejewski *et al.* [28]. Wang *et al.* [29] proposed two semi-supervised models to extract seed words from the description of e-commerce products and classified these seed words into different categories.

The study of the opinion target extraction task in our proposed method for Chinese microblog sentences is different from the aspect extraction methods above. Compared with other opinionated sentences from product comments, opinionated microblog sentences are irregular, and many network words exist in them. These factors have a great impact on the opinion target extraction results based on dependency parsing methods. In addition, opinion targets in opinionated microblog sentences are nouns and noun phrases, which are more than two characters. It is not suitable to model these opinion targets by topic models.

We extract opinion targets of opinionated sentences based on a random walk-based ranking algorithm. The random walk-based algorithm is usually applied in recommending systems [30]–[32]. The opinion target extraction task can be considered as recommending the most suitable candidate opinion target for each opinionated sentence as the opinion target.

III. METHOD OVERVIEW

The emotion expression extraction method for Chinese microblog sentences contains three tasks, and Fig. 1 shows the overview of this process. We first find opinionated sentences for further study from all microblog sentences in a topic. Then, we analyze the emotions of opinionated sentences and extract opinion targets from them.

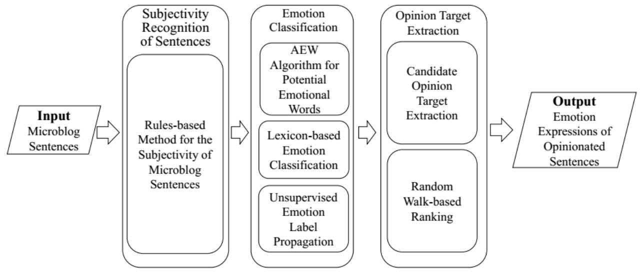


FIGURE 1. Flow chart of the emotion expression extraction method for Chinese microblog sentences.

In this paper, we use a rule-based method to recognize opinionated microblog sentences. After that, we use a lexicon-based emotion classification algorithm to compute different emotion values in emotion label vectors of opinionated sentences based on emotional words in which many emotional words are discovered via an automatic emotion weight (AEW) algorithm. Finally, an unsupervised emotion label propagation algorithm is used to revise emotion label vectors.

For the opinion target extraction task, we first extract candidate opinion targets of opinionated sentences. Then, a random walk-based ranking algorithm is proposed to rank candidate opinion targets for each opinionated sentence. More details about the above three tasks are presented in the following sections.

IV. EMOTION CLASSIFICATION

A. RULES-BASED SUBJECTIVE RECOGNITION OF SENTENCES

The emotion expression extraction method is aimed to find emotion expressions of opinionated sentences, so we first need to recognize opinionated sentences from all microblog sentences. Opinionated sentences refer to sentences with subjective expression. The subjective expression contains evaluation expression and speculation expression; the former includes personal emotions, comments, judgments, and opinions, and the latter is an expression of non-actual events or mental state.

The study of subjective recognition of sentences has attracted many researchers' attention [33], [34]. Solutions are commonly studied based on machine learning methods [35], [36]. For microblog sentences, the subjective recognition methods based on some specific expressions [37] have difficulty in realizing because many microblog sentences are full of noise, wrong Chinese characters, and contain numerous abbreviations and network words.

Researchers, who study subjective recognition and emotions for sentences simultaneously, consider that sentences without emotional words are non-opinionated sentences. Non-opinionated sentences have a high probability of being recognized as opinionated sentences in these researches.

In this paper, we aim to achieve a high recall for opinionated sentences of each topic. We use a rule-based method to find non-opinionated sentences. Rules are shown as follows.

Algorithm 1 Lexicon-based Emotion Classification

Input: Polarity of potential emotional words, emotion lexicons, opinionated sentences.

Output: Emotion label vectors $\boldsymbol{S}_{\boldsymbol{e}_v}(v \in V)$ of opinionated sentences.

1. Construct the emotion label vector $\boldsymbol{S}_{\boldsymbol{e}_v}(v \in V)$ for each microblog sentence and all values in the vector are equal to zero;
2. Set the emotion value of the verbs and adjectives as 1.0 if the verbs and adjectives exist in emotion lexicons;
3. Set the emotion value of the potential emotional word, which is discovered by the AEW algorithm, as e, $e \in [0, 1]$;
4. The emotion values of words are doubled when degree adverbs are before these words, the emotion values of words are the opposite when negative adverbs are before these words. Each value in an emotion label vector $\boldsymbol{S}_{\boldsymbol{e}_v}(v \in V)$ is determined by the sum of corresponding emotion values of words in the opinionated sentence.

Rule1: The number of Chinese characters in the sentence is equal to zero; stop words do not take into consideration.

Rule2: The number of infrequent punctuations in the sentence is more than six.

Rule3: The sentence contains the URL and no useful information.

Rule4: Only emoticons exist in the sentence.

Rule5: The pronoun “我” (I) exists in the sentence, and the sentence does not have any nouns or other personal pronouns.

Rule6: Some specific words, which usually appear in non-opinionated sentences, like “召开” (convene), “举行” (hold), “发布” (publish), exist in the sentences.

We find non-opinionated sentences according to the six rules above, and additional sentences are considered as opinionated sentences for further emotion expression extraction.

B. LEXICON-BASED EMOTION CLASSIFICATION ALGORITHM

Potential emotions of network words have a significant influence on the emotion classification result. Therefore, a method is needed to find emotional words automatically to meet the requirement of recognizing a lot of potential emotional words in microblog sentences.

Zhang [38] proposed an automatic emotion weight (AEW) algorithm based on Bayesian theory. This algorithm uses a particular type of co-occurrence to compute the emotion weights of potential emotional words. The polarity of potential emotional words is determined by their emotion weights. AEW algorithm has domain independence and excellent scalability.

We use the AEW algorithm to compute emotion values of words and recognize the polarity of words via their emotion values. A lexicon-based emotion classification algorithm is summarized in Algorithm 1.

TABLE 1. Motivation examples.

No.	Emotion labels	Opinionated microblog sentences
1	POS	和朋友打篮球很有趣！(It is funny to play basketball with friends)
2	POS	和男朋友弹钢琴很有趣！(It is funny to play the piano with my boyfriend)
3	POS	和同学们一起打篮球很开心！ (I feel glad to play basketball with my classmates)

C. UNSUPERVISED EMOTION LABEL PROPAGATION ALGORITHM

Some issues exist in the output of Algorithm 1. Emotion values in emotion label vectors of some opinionated sentences are all equal to zero. In addition, some potential emotional words in opinionated sentences cannot be found, and emotions of some emotional words are not correctly recognized.

For this endeavor, we revise emotion label vectors of opinionated sentences that are computed by Algorithm 1. We observe that similar sentences may have the same emotions; examples are shown in TABLE 1. Sentence 1 and sentence 2 have the same adjective, sentence 1 and sentence 3 have the same noun. Emotion labels of three sentences are all “POS”. Inspired by this, we propose an unsupervised emotion label propagation algorithm to revise the emotion label vectors of opinionated sentences to make them more accurately.

Label propagation [39], [40], is a graph-based semi-supervised learning method. It aims to predict the label information of unlabeled nodes by the connection between nodes. We treat each opinionated sentence as a node, and each node has its emotion label vector that includes the “POS” value and the “NEG” value. In each iteration, the emotion label vector of each node propagates to its adjacent nodes according to the textual similarity between opinionated sentences. The emotions of opinionated sentences are determined by the highest values in emotion label vectors. The steps are summarized in Algorithm 2.

An undirected graph $\mathrm{G_{emotion}} = < \mathrm{V}, \mathrm{E}, \tilde{M}_{\mathrm{emotion}} >$ is built for each topic. A node $v \in V$ represents an opinionated sentence, and an edge $e \in E$ represents the linking between two opinionated sentences. The matrix $\tilde{M}_{emotion}$ is used to measure the weights of linking between sentences, which is determined by cosine similarity between opinionated sentences.

$$M_{emotion_{s_m,s_n}} = \cos(\boldsymbol{N_m}, \boldsymbol{N_n}) = \frac{\boldsymbol{N_m} \cdot \boldsymbol{N_n}}{\|\boldsymbol{N_m}\| \cdot \|\boldsymbol{N_n}\|} \quad (1)$$

$\boldsymbol{N_m}$ and $\boldsymbol{N_n}$ are term vectors of opinionated sentences S_m and S_n, their weights are determined by their term frequencies. $\tilde{M}_{emotion}$ can be obtained by normalizing each row of M_{emotion} $(\sum_{s_n} M_{emotion_{s_m,s_n}} = 1)$.

The initial emotion label vector of each opinionated sentence is provided by the output of Algorithm 1, so we do not need any labeled data in Algorithm 2. Emotion label vectors of those opinionated sentences, the emotion values in which are all zeros, are assigned as the sum of emotion label vectors of their preceding and following sentences.

Algorithm 2 Unsupervised Emotion Label Propagation

Input: Similarity matrix of opinionated sentence $\tilde{M}_{emotion}$, emotion label vectors $\boldsymbol{S}_{\boldsymbol{e}_v}$ $(v \in V)$, the acceptance probability p^{accept} of the initial emotion label vectors.
Output: New emotion label vectors $\hat{S}_{\boldsymbol{e}_v}$ $(v \in V)$.
for all $v \in V$ **do**
$\hat{S}_{\boldsymbol{e}_v} \leftarrow \boldsymbol{S}_{\boldsymbol{e}_v}$
end for
repeat
for all $v \in V$ **do**
$\boldsymbol{E}_v \leftarrow \sum_{w \in V, v \neq w} \tilde{M}_{emotion_{wv}} \hat{S}_{\boldsymbol{e}_w}$
$\hat{S}_{\boldsymbol{e}_v} \leftarrow p^{accept} \boldsymbol{S}_{\boldsymbol{e}_v} + (1 - p^{accept}) \boldsymbol{E}_v$
end for
until convergence

In each iteration, the emotion label vector of a node v is influenced by its adjacent nodes, which is recorded by the matri $\boldsymbol{E}_v$.

$$\boldsymbol{E}_v = \sum_{w \in V, v \neq w} \tilde{M}_{emotion_{wv}} \hat{S}_{\boldsymbol{e}_w} \tag{2}$$

$\tilde{M}_{emotion_{wv}}$ weights the propagation of the node $w(w \in V$ and $w \neq v)$ to the node v.

Each emotion label vector is updated by the following equation in each iteration.

$$\hat{S}_{\boldsymbol{e}_v} = p^{accept} \boldsymbol{S}_{\boldsymbol{e}_v} + (1 - p^{accept}) \boldsymbol{E}_v \tag{3}$$

p^{accept} is the acceptance probability of initial emotion label vector $\boldsymbol{S}_{\boldsymbol{e}_v}$. Unsupervised emotion label propagation algorithm converges when the change of the emotion label vector is less than 10^{-4} in ten iterations. The emotion label of each opinionated sentence is determined by its highest emotion value in the new emotion label vector $\hat{S}_{\boldsymbol{e}_v}$. The emotion labels of opinionated sentences that emotion values in the new emotion label vectors are the same are "OTHER".

V. OPINION TARGET EXTRACTION

A. MOTIVATION

In this section, we describe the opinion target extraction task in the proposed emotion expression extraction method.

Opinion targets are important and fine-grained information in opinionated sentences. Existing some opinionated sentences, like the opinionated sentence "奇迹、、、" (wonder...) in the topic "90后当教授" (the woman born in the 90s becomes a professor) do not contain any words which can be chosen as opinion targets. It is easy to recognize that the topic is the opinion target of the above-opinionated sentence manually. Therefore, the topic should be taken into consideration when extracting candidate opinion targets for opinionated sentences. We consider candidate opinion targets that are extracted from opinionated sentences are explicit candidate opinion targets, and others are implicit candidate opinion targets. Both explicit candidate opinion targets and implicit candidate opinion targets are taken into account in studying opinion targets of microblog sentences for the better opinion target extraction result.

TABLE 2. Motivation examples.

Topics	Opinion targets	Opinionated sentences
#90后暴打老人# #a man born in the 90s beat an older man#	90后 (a man born in the 90s)	1.打老人你就火了，你丫的还暴打老人！(You will be "famous" when you hit an older man. It is unbelievable that you beat him!)
	90后 (a man born in the 90s)	2.就算老人有千错万错，也不应动武 (Whatever an older man did, you should not beat him)
	90后暴打老人(a man born in the 90s beat an older man)	3. 就是因为这样的败类，玷污我们90后…………(People born in the 90s like us are looked down on because of these misbehaving people……)
#菲军舰恶意撞击# #Philippine navy vessel hits Chinese fishing boat#	政府 (The government)	4.政府还是不够强硬 (The government is still not strong enough)
	政府 (The government)	5.政府为何不能强硬一些? (Why can not the government be stronger?)

We observe three points can be helpful to the opinion target extraction task:

- We observe that the candidate opinion target O_j may be the opinion target of the opinionated sentence S_m when the candidate opinion target O_j has a co-occurrence relation with candidate opinion targets of the opinionated sentence S_m in a topic. In TABLE 2, "90后" (a man born in the 90s) and "老人" (an older man) coexist in many sentences in the topic "90后暴打老人#" (a man born in the 90s beats an older man), "90后" is the opinion target of sentences (sentence 1 and sentence 2) which contain the candidate opinion target "老人".
- We observe that the candidate opinion target O_j may be the opinion target of the opinionated sentence S_m when some characters in the candidate opinion target O_j are the same with some characters in candidate opinion targets of the opinionated sentence S_m in a topic. "#90后暴打老人#" is the opinion target of sentence 3, which has the same characters with the candidate opinion target "90 90后" of sentence 3.
- Two similar opinionated sentences in a topic may have the same opinion target. In TABLE 2, the textual of sentence 4 and sentence 5 is similar, and they have the same opinion target "政府" (the government).

B. CANDIDATE OPINION TARGET EXTRACTION

Nouns, personal pronouns, and noun phrases in opinionated sentences are extracted as candidate opinion targets. Each candidate opinion target contains at least two characters. TABLE 3 shows regular expressions of noun phrases. For those opinionated sentences without explicit candidate opinion targets, we add their preceding opinionated sentences'

TABLE 3. Regular expressions of noun phrases.

Regular expressions	Regular expressions	Regular expressions
noun+noun	noun+noun+noun	noun+"的" (of) + noun
pronoun +noun	pronoun + noun+noun	time word+"的" (of) + noun
time word+ pronoun + noun		

TABLE 4. Statistics of the user dictionary.

All words	Nouns	Adjectives	Verbs
Number of words	8	24	6

explicit candidate opinion targets to their implicit candidate opinion targets.

In the microblogging site, every topic is represented in the form of "#...#" and the textual information is between two symbols "#", like "#彭宇承认撞了南京老太太#" (#Peng Yu admitted to knocking over the Nanjing Granny#). The topic and nouns/noun phrases in it are extracted as implicit candidate opinion targets for opinionated sentences in this topic.

Existing Chinese word segmentation tools cannot segment irregular microblog sentences well. The word segmentation result has a significant influence on opinion target extraction results. For example, the word "90后" (persons born after 1990) is a vital candidate opinion target of opinionated sentences in the topic "90后当教授" (a woman born in the 90s becomes a professor). However, this word is segmented into character "90" and character "后"(later), which cannot be considered as a candidate opinion target. Therefore, we use the following steps to find vital words from the topic:

Step1: we use the Chinese word segmentation tool to segment the textual of the topic into words.

Step2: we combine the two adjacent words as a new word. We admit this new word when it appears in more than five opinionated sentences.

Step3: we increase the number of consecutive words to get the new word and admit the new word when it appears in more than five opinionated sentences. We repeat this process until the new word is the same as the topic.

We add new words to the user dictionary to improve the word segmentation result, which is obtained by the Chinese word segmentation tool. We also revise the part of speech of some words, which play an essential role in the opinion target extraction task but cannot be correctly recognized by the tool. For example, a topic contains an anti-virus software called "360". Here, the part of speech of "360" is a noun rather than a numeral which is determined by the Chinese word segmentation tool. We add the word "360" and its part of speech to the user dictionary. Statistics of revised words are shown in TABLE 4. Adjectives in the user dictionary are classified into different emotions manually.

C. RANDOM WALK-BASED RANKING ALGORITHM

We describe the random walk-based ranking algorithm in detail. Considering that most opinionated sentences have only one opinion target, so we assume each opinionated sentence has only one opinion target in this study.

A two-layer undirected graph $G_{so} =< S\cup O, E_{so}, \tilde{M}_{so} >$ is constructed to find opinion targets of opinionated sentences. The graph G_{so} contains two subgraphs $G_{opinion} =< O, E_o >$ and $G_{sentence} =< O, E_s >$. The node $z \in S \cup O$ represents a candidate opinion target in $G_{opinion}$ or an opinionated sentence in $G_{sentence}$. An edge $e \in E_{so}$ represents the linking between the candidate opinion target and the opinionated sentence. The cross-domain matrix $\tilde{M}_{so}$, which needs to be computed by the algorithm, is used to measure the weights of linking between candidate opinion targets and opinionated sentences. The purpose of the random walk-based ranking algorithm is to rank the weights of linking between candidate opinion targets and opinionated sentences.

In the subgraph $G_{opinion}$, a node $o \in O$ represents a candidate opinion target, and an edge $e{\in}E_o$ represents the linking between two candidate opinion targets. The transition matrix $\tilde{M}_{oo}$ for candidate opinion targets is defined by the connection between candidate opinion targets. The connection between candidate opinion targets is measured by their character similarity, which is represented by the matrix M_{oo}^{char}, and their co-occurrence relation in opinionated sentences, which is represented by the matrix M_{oo}^{co}.

We use the Jaccard index to compute the character similarity between candidate opinion targets. It is determined by the same characters in two candidate opinion targets. In (4), $A(\cdot)$ represents a set of characters in the word. We use (5) to measure the weight of the co-occurrence relation between two candidate opinion targets. Considering a situation, "90后" and "老人" coexist in many opinionated sentences in a topic, the candidate opinion target "90后暴打老人" may be the opinion target of sentences which have the candidate opinion target "老人". The matrix M_{oo} is defined as (6) considering the above case. M'_{oo} is the matrix that all values in the matrix M_{oo} are divided by the maximum value in the matrix M_{oo}.

$$M_{oo}^{char}(O_i, O_j) = \left|\frac{A(O_i)\cap A(O_j)}{A(O_i)\cup A(O_j)}\right| \tag{4}$$

$$M_{oo}^{co}(O_i, O_j) = \frac{the\ number\ of\ sentences\ which\ contain\ O_i\ and\ O_j}{the\ number\ of\ sentences\ which\ contain\ O_i or O_j} \tag{5}$$

$$M_{oo} = M_{oo}^{co} \times M_{oo}^{char} \tag{6}$$

In the subgraph $G_{sentence}$, a node $s \in S$ represents an opinionated sentence, and an edge $e \in E_s$ represents the linking between two opinionated sentences. The transition matrix M_{ss} for opinionated sentences is defined as

$$M_{ss}(S_i, S_j) = \frac{\cos(N_i, N_j)}{\sum_{k\in S}\cos(N_i, N_k)} \tag{7}$$

where the cosine similarity between two opinionated sentences is the same as (1).

Consider a random walk on $G_{opinion}$ or $G_{sentence}$, at each step, we perform on candidate opinion target domain or

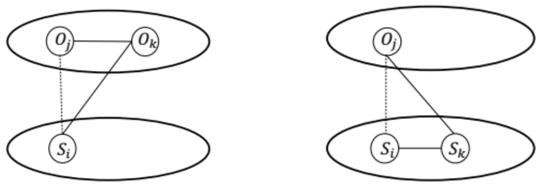


FIGURE 2. Two routes we consider when updating the cross-domain probability matrix.

opinionated sentence domain is not as a usual random walk, but jump to any node with the probability α [41]. The new transition matrices $\tilde{M}_{oo}$ and $\tilde{M}_{ss}$ are shown as follows:

$$\tilde{M}_{oo} = (1-\alpha)\, M_{oo}^{'} + \frac{1}{|W_o|} M_{ones} \quad (8)$$

$$\tilde{M}_{ss} = (1-\alpha)\, M_{ss} + \frac{1}{|W_s|} M_{ones} \quad (9)$$

$|W_o|$ in (8) is the total number of candidate opinion targets, $|W_s|$ in (9) is the total number of opinionated sentences, $M_{ones} \in R^{|W_o|\times|W_o|}$ in (8) and $M_{ones} \in R^{|W_s|\times|W_s|}$ in (9) are matrices with all values in them are one.

We set initial weights of linking between candidate opinion targets and opinionated sentences and use the matrix M_{so} to record them. Candidate opinion targets contain explicit candidate opinion targets and implicit candidate opinion targets. The initial weight of the corresponding position in the matrix set as 1.0 if the candidate opinion target is the explicit candidate opinion target of the opinionated sentence, and the weight set as w for implicit candidate opinion targets of opinionated sentences. We consider that the textual of the topic is more important than candidate opinion targets, which are extracted from it. The weights of implicit candidate opinion targets which are extracted from the topic should be lower than the weights of other implicit candidate opinion targets in order to improve the performance of the opinion target extraction. This assumption is proved in the experiment. Other values in M_{so} are equal to 0.0.

Algorithm 3 Random Walk-Based Ranking

Input: The initial cross-domain matrix M_{so}, the transition matrix of candidate opinion targets $\tilde{M}_{oo}$, the transition matrix of opinionated sentences $\tilde{M}_{ss}$, the indicator matrix label_M, the acceptance probability $p^{initial}$ of the initial matrix M_{so}.
Output: the cross-domain matrix $\tilde{M}_{so}$.
1. $\tilde{M}_{so}(0) \leftarrow M_{so}$
2. **repeat**
3. $D_{so}(t+1) \leftarrow 0.5\tilde{M}_{ss} \times \tilde{M}_{so}(t) + 0.5\tilde{M}_{so}(t)\times\tilde{M}_{oo}$
4. $\tilde{M}_{so}(t+1) \leftarrow p^{inital} M_{so} + (1-p^{inital}) D_{so}(t+1)$
5. $\tilde{M}_{so}(t+1) \leftarrow \tilde{M}_{so}(t+1)$label_M
6. **until convergence**

The weights are updated based on the connection between candidate opinion targets, and the textual similarity between opinionated sentences. We consider two types of routes can change the weights of linking between candidate opinion targets and opinionated sentences. The matrix D_{so} is used to record the influence for the weight of linking between each candidate opinion target and each opinionated sentence. Two routes are illustrated in Fig. 2. We update the matrix D_{so} and the cross-domain matrix $\tilde{M}_{so}$ during the random walk process over G_{so}. The random walk-based ranking algorithm is summarized in Algorithm 3, which has the random walk in candidate opinion target domain or opinionated sentence domain.

The matrix D_{so} at time $t+1$ is calculated as follows.

$$D_{so}(t+1) = 0.5\tilde{M}_{ss} \times \tilde{M}_{so}(t) + 0.5\tilde{M}_{so}(t)\times\tilde{M}_{oo} \quad (10)$$

The matrix $\tilde{M}_{so}$ is updated as follows.

$$\tilde{M}_{so}\,(t+1) = p^{inital} M_{so} + (1-p^{inital}) D_{so}(t+1) \quad (11)$$

p^{inital} is the acceptance probability of the initial matrix M_{so}. We use an indicator matrix label_M to clear the weights of linking between opinionated sentences and candidate opinion targets that do not belong to opinionated sentences.

The algorithm converges when the change of the values in the same position of each row of the matrix $\tilde{M}_{so}$ is less than 10^{-4} in ten iterations.

TABLE 5. Statistics of the CMSAE data.

All annotated sentences	3416
Opinionated sentences with emotion labels	2207
Opinionated sentences with their opinion targets	2152
All annotated opinion targets	2361

TABLE 6. Statistics of the emotion lexicons.

All words	Positive words	Negative words	Degree adverbs	Negative words
Number of words	7384	12660	220	44

VI. EXPERIMENTS

A. EXPERIMENT DATA

Our experimental data is from the 2012 Chinese Microblog Sentiment Analysis Evaluation (CMSAE) held by the China Computer Federation (CCF). It contains three tasks that are subjective recognition of microblog sentences, emotion classification, and emotion expression extraction.

There are 20 topics in the data. Emotions and emotion expressions of opinionated sentences were labeled manually. More detailed are given in TABLE 5.

Our emotion lexicons consist of Taiwan University emotion lexicons NTUSD [42] and HowNet [43] for the study of our emotion classification task. The statistics of emotion lexicons are shown in TABLE 6.

B. EVALUATION METHODS

1) SUBJECTIVE RECOGNITION OF SENTENCES

The evaluation methods, precision, recall, and F-measure we adopt for the subjective recognition task are identical with CMASE. Evaluation equations are defined as the following:

$$\text{Precision} = \frac{\#system\_correct(opinion = Y)}{\#system\_proposed(opinion = Y)} \quad (12)$$

$$\text{Recall} = \frac{\#system\_correct(opinion = Y)}{\#gold(opinion = Y)} \tag{13}$$

$$\text{F}-\text{measure} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{14}$$

where *#system_correct(opinion=Y)* is the number of correct opinionated sentences in the experimental result. *#gold(opinion=Y)* is the number of opinionated sentences which are labeled manually. *#system_proposed(opinion=Y)* is the number of opinionated sentences in the experimental result.

2) EMOTION CLASSIFICATION

Accuracy is adopted for evaluating our emotion classification method. It is defined as

$$\text{Accuracy} = \frac{\#system\_correct(polarity = POS, NEG, OTHER)}{\#gold(polarity = POS, NEG, OTHER)} \tag{15}$$

where, *#system_correct(polarity=POS, NEG, OTHER)* is the number of sentences that emotion analysis results are correct. *#gold(polarity=POS, NEG, OTHER)* is the number of sentences in the experimental result.

3) OPINION TARGET EXTRACTION

Precision, recall, and F-measure, which are identical with CMASE, are adopted as opinion target extraction evaluation methods. Opinion target extraction evaluation methods consist of the strict evaluation method and the soft evaluation method. The precision, recall, and F-measure of the strict evaluation method are defined as follows:

$$\text{Precision} = \frac{\#system\_correct}{\#system\_proposed} \tag{16}$$

$$\text{Recall} = \frac{\#system\_correct}{\#gold} \tag{17}$$

$$\text{F}-\text{measure} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{18}$$

#system_correct is the number of correct opinion targets in the experimental result. *#gold* is the number of opinion targets which are labeled manually. *#system_proposed* is the number of opinion targets in the experimental result.

For the soft evaluation method, the span coverage c between the proposed opinion target and the gold opinion target is defined as:

$$c(s, s') = \frac{|s \cap s'|}{|s'|} \tag{19}$$

$|*|$ in (19) is used to count characters, and $s \cap s'$ represents the same characters in two opinion targets.

The span coverage C between the proposed opinion target set S' and the gold opinion target set S is defined as (20).

$$C(S, S') = \sum_{s \in S} \sum_{s' \in S'} c(s, s') \tag{20}$$

Precision, recall, and F-measure of the soft evaluation method are as follows:

$$\text{Precision} = \frac{C(S, S')}{|S'|} \tag{21}$$

$$\text{Recall} = \frac{C(S', S)}{|S|} \tag{22}$$

$$\text{F}-\text{measure} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{23}$$

$|*|$ in (21) and (22) means the number of opinion targets in the set.

C. EXPERIMENTAL RESULTS

1) OPINIONATED SENTENCE IDENTIFICATION RESULTS

We use six rules to find opinionated sentences. Four rules (Rule 1-Rule 4) are common rules for the study of the subjective recognition of sentences. Rule 5 and Rule 6 are made by our experience. Our experiments also examine the performance of Rule 5 and Rule 6. The experimental results are given in TABLE 7.

TABLE 7 shows that all experimental results have good recall and low precision. The addition of Rule 5 and Rule 6 hardly improve the experimental result. We analyze the reasons which are summarized as follows:

- Non-opinionated microblog sentences, which contain the personal pronoun "I", usually exist other nouns or noun phrases. Rule 5 may be suitable for the subjective recognition of microblog posts, like "我今天很开心." ("I feel very happy today.").
- Irregular microblog sentences rarely contain words that usually appear in non-opinionated sentences; the words we use in Rule 6 are unsuitable for the subjective recognition of microblog sentences.

2) EMOTION CLASSIFICATION RESULTS

We demonstrate the emotion recognition performance of our proposed method for opinionated microblog sentences in this section.

We first compare our proposed method with supervised machine learning methods. We select 70% labeled opinionated sentences randomly as training data and the rest as test data. All opinionated sentences are represented by the normalized word frequency vector, and their text features are determined by the term frequency-inverse document frequency algorithm. We use the Multinomial Naïve Bayes (NB) classifier, the Decision Tree classifier, the Linear Support Vector Machine (SVM) classifier, and the Multilayer Perceptron (MLP) classifier, which are provided by the machine learning library Sklearn, to classify sentences into different emotions. We then use a recurrent convolutional network, which is provided by the deep learning library Keras documentation for comparison. We randomly sample 70% labeled opinionated sentences as training data and the rest as test data. The experimental results are shown in TABLE 8.

In TABLE 8, AEW refers to the automatic emotion weight algorithm we use to discover potential emotional words.

TABLE 7. Results of subjective recognition of microblog sentences.

Rules	Precision	Recall	F-measure
Rule 1+ Rule 2+ Rule 3+ Rule 4+ Rule 5	0.668	0.976	0.793
Rule 1+ Rule 2+ Rule 3+ Rule 4+ Rule 6	0.664	0.981	0.792
Rule 1+ Rule 2+ Rule 3+ Rule 4+ Rule 5+ Rule 6	0.668	0.975	0.793

TABLE 8. Results of emotion classification.

No.	Emotion classification methods	Accuracy
1	Normalized word frequency vector + Term frequency-inverse document frequency+ Multinomial NB classifier	0.813
2	Normalized word frequency vector + Term frequency-inverse document frequency+ Decision Tree classifier	0.811
3	Normalized word frequency vector + Term frequency-inverse document frequency+ Linear SVM classifier	**0.878**
4	Normalized word frequency vector + Term frequency-inverse document frequency+ MLP classifier	0.789
5	One-hot encoding+ Long short-term memory+Conv1D+MaxPooling1D	0.816
6	Lexicon-based emotion classification + Unsupervised Emotion Label Propagation (II)	0.775
7	AEW + Lexicon-based emotion classification	0.713
8	AEW + Lexicon-based emotion classification + Unsupervised Emotion Label Propagation (I)	0.790
9	AEW + Lexicon-based emotion classification + Unsupervised Emotion Label Propagation (II)	0.844

Unsupervised Emotion Label Propagation (I) in TABLE 8 means Algorithm 2 is performed on opinionated sentences that all emotion values in their emotion label vectors are the same. Unsupervised Emotion Label Propagation (II) means Algorithm 2 is performed on all opinionated sentences. We set the acceptance probability $p^{accpet}= 0.5$, and the emotion value $e= 0.5$.

Several observations are made from TABLE 8:

- Emotion classification accuracy of our proposed method is higher than the results based on the Multinomial NB classifier, the Decision Tree classifier, and the MLP classifier but lower than the result based on the Linear SVM classifier. Despite the fact that our result is not better than the result of the SVM-based method, this gap is acceptable considering that supervised learning methods need a lot of labeled experimental data, which is more challenging to get than emotion lexicons.
- The experimental result of the deep learning method gets to 0.816 after 20 epochs. It is obvious in TABLE 8 that the result of the deep learning method is lower than our result and has a big gap with the result of the SVM-based method. The reason may be that the performance of the deep learning method is influenced by the lack of enough labeled data. Machine learning methods are more suitable for analyzing the small amount of data.
- The AEW algorithm improves the emotion classification performance of the proposed method significantly.
- The unsupervised emotion label propagation algorithm improves the experimental result effectively. The result of No. 9 is higher than No. 8 proves that the unsupervised emotion label propagation algorithm also can revise emotion label vectors of opinionated sentences that have different emotion values in them.
- The result of No. 6 is the lowest in TABLE 8. Both rule quality in the lexicon-based algorithm and emotional words influence the experimental result.

3) OPINION TARGET EXTRACTION RESULTS

We compare our proposed method with an unsupervised method based on [41]. Experimental data and candidate opinion targets for the comparison method Cminer are the same as ours. For Cminer, the similarity between opinionated sentences is measured by (1), and the similarity between candidate opinion targets is measured by (4). Afterward, an unsupervised label propagation algorithm is proposed to rank candidate opinion targets for opinionated sentences in a topic.

Cminer has two essential parameters: the weight w for implicit candidates and the injection probability p^{inj}. We set two experiments for Cminer: the same weights of all implicit candidates (Cminer-1) and the different weights of implicit candidates (Cminer-2). Experiments for our proposed method are also performed on the same weights (Ours-1) and the different weights (Ours-2) of implicit candidate opinion targets. The weights of implicit candidate opinion targets are fixed as 0.7 for experiments that have the same weights. For experiments that have different weights, the weights of implicit candidate opinion targets which are extracted from the topic are equal to 0.5, and other weights are fixed as 0.7. The injection probability p^{inj} in Cminer and the acceptance probability $p^{initial}$ in our proposed method are all set as 0.5.

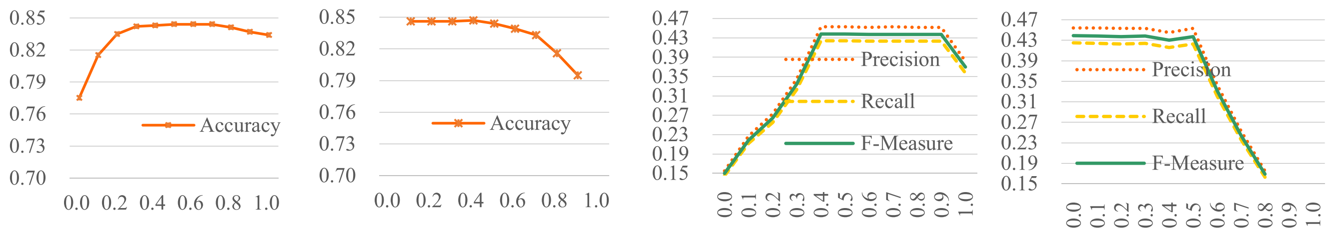
Experimental results are shown in TABLE 9. Ours-2 meets the best result among all results. The results of Cminer-2 and Ours-2 are higher than Cminer-1 and Ours-1, in both strict evaluation method and soft evaluation method, demonstrate the effectiveness of different weight values for implicit candidate opinion targets.

4) EMOTION EXPRESSION EXTRACTION RESULTS

We perform the opinion target extraction task based on the result of the subjective recognition task and the emotion classification task to obtain emotion expressions of opinionated sentences. Evaluation methods for emotion expression extraction are the strict evaluation method and the soft evaluation method, which are similar to evaluation methods of opinion target extraction. The difference is the result of emotion expression extraction requires the correctness of opinion targets along with their emotions. In this paper, we consider

TABLE 9. Comparison of results of different methods.

Extraction objects	Method	Strict			Soft		
		Precision	Recall	F-measure	Precision	Recall	F-measure
Opinion target extraction	Cminer-1	0.370	0.346	0.358	0.562	0.535	0.548
	Cminer-2	0.409	0.382	0.395	0.576	0.552	0.564
	Ours-1	0.409	0.382	0.395	0.606	0.514	0.556
	Ours-2	0.453	0.423	0.437	0.606	0.573	0.589
Emotion expression extraction	Team1	0.303	0.275	0.288	0.387	0.356	0.371
	Team2	0.311	0.177	0.225	0.404	0.223	0.287
	Team3	0.260	0.164	0.201	0.398	0.249	0.307
	Ours	0.338	0.333	0.335	0.467	0.460	0.463



(a) Influence of the emotion value of the potential emotional word
(b) Influence of the acceptance probability of initial vector
(c) Influence of the acceptance probability of the initial matrix
(d) Influence of the weight of implicit candidate opinion target

FIGURE 3. Influence of the parameters in our proposed method.

that the emotion of each opinion target is the same as the emotion of the opinionated sentence.

We compare emotion expression extraction results with three teams [41], which participated in the 2012 Chinese Microblog Sentiment Analysis Evaluation (CMSAE). The results are shown in TABLE 9. We set the acceptance probability $p^{accpet} = 0.5$, the emotion value $e = 0.5$, and the acceptance probability $p^{initial} = 0.5$. The weights of implicit candidate opinion targets which are extracted from the topic are equal to 0.5, and other weights of implicit candidate opinion targets are fixed as 0.7.

It is evident that the result of our proposed method is better than the other three teams. It increases by 16% and 25% in the F-measure of the strict evaluation method and the soft evaluation method compared to Team1.

D. IMPACT OF THE PARAMETERS

We examine the influence of four essential parameters of the emotion expression extraction method in this section.

There are two important parameters in the emotion classification task. One is the emotion value e of the potential emotional word in Algorithm 1. Another is the acceptance probability p^{accpet} of the initial emotion label vector in Algorithm 2. The random walk-based ranking algorithm has two essential parameters: the weight w of the implicit candidate opinion target and the acceptance probability $p^{initial}$ of the initial matrix in Algorithm 3.

We fix the acceptance probability p^{accpet} of the initial emotion label vector as 0.5 to study the influence of the emotion value e of the potential emotional word. The experimental result is shown in Fig. 3. (a). The potential emotional words are not taken into consideration in Algorithm 1 when the emotion value $e = 0.0$. It is evident that the accuracy increases when the emotion value of the potential emotional word varies from 0.1 to 0.3 and then remains stable when the emotion value varied from 0.3 to 0.9. Emotion classification accuracy slightly reduces when the emotion value $e = 1.0$.

We study the impact of the acceptance probability p^{accpet} of the initial emotion label vector, so we fix the emotion value e of the potential emotional word as 0.5. In Fig. 3. (b), we can see that accuracy keeps steady when the acceptance probability of the initial emotion label vector is less than 0.6. Accuracy begins to decrease with increasing the acceptance probability. Emotion classification accuracy is lower than 0.8 when the acceptance probability is fixed as 0.9.

There are two parameters in the random walk-based ranking algorithm: the acceptance probability $p^{initial}$ of the initial matrix and the weight w of the implicit candidate opinion target.

We study the impact of the acceptance probability $p^{initial}$ of the initial matrix, so the weight w is fixed as 0.5 for implicit candidate opinion targets, which are extracted from the topic and 0.7 for other implicit candidate opinion targets. The experimental result is shown in Fig. 3. (c). We can observe that precision, recall, and F-measure of the strict evaluation method increase when the acceptance probability varies from 0.0 to 0.4, and then keep steady when $p^{initial}$ changes from 0.4 to 0.9. Then, the results start to decrease with increasing the acceptance probability $p^{initial}$.

We fix the acceptance probability $p^{initial}$ of the initial matrix as 0.5 to study the influence of the weight w of the implicit candidate opinion target. In Fig. 3. (d), values on the abscissa represent the weights for implicit candidate opinion targets which are extracted from the topic, and the weights for other implicit candidate opinion targets are 0.2 higher than values on the abscissa. Precision, recall, and F-measure of the strict evaluation method keep steady when the weight w varies from 0.0 to 0.5. The results decrease when the weight w is bigger than 0.5.

E. ERROR ANALYSIS

The performance of our proposed emotion expression extraction method is far below expectations. We analyze the causes of error.

Microblog sentences contain noisy and misspelling, which cause the low-performance of subjective recognition of these sentences based on rule-based methods. In the future, we will consider the method to solve the above problem from a different perspective, like we revise irregular microblog sentences to common sentences and then perform subjective recognition of them via more suitable rules.

For the opinion target extraction task, we extract noun phrases as candidate opinion targets according to the specific expressions in TABLE 3. Some opinion targets cannot be found in this process. For example, an opinion target "如此的一代" (persons in the 90s generation) is segmented into "如此/pronoun+ 的 /particle+ 一 /numeral+ 代 /classifier" by the Chinese word segmentation tool, its expression does not match any expressions in TABLE 3, so it is impossible to extract the correct opinion target as the candidate opinion target of this opinionated sentence. In addition, the performance of the random walk-based ranking algorithm will be influenced by a large number of candidate opinion targets when we consider more unusual expressions for noun phrase extraction. It is still a problem to achieve a balance between the quality of candidate opinion targets and the performance of the random walk-based ranking algorithm.

VII. CONCLUSION AND FUTURE WORK

In this paper, we develop an emotion expression extraction method for Chinese microblog sentences, which mainly contains emotion classification and opinion target extraction. Emotion expressions of opinionated sentences in different topics can help understand related events and users' attitudes on these topics. For the emotion classification task, we propose a lexicon-based emotion classification algorithm to compute emotion values in emotion label vectors of opinionated sentences. An unsupervised emotion label propagation algorithm is used to revise the emotion label vectors of opinionated sentences to make final results closer to their real condition. For the opinion target extraction task, a random walk-based ranking algorithm is proposed to rank candidate opinion targets of opinionated sentences. Experimental results demonstrate the effectiveness of the proposed method.

In the future, we plan to study subjective recognition rules for opinionated microblog sentences. Moreover, we will consider a method to discover new words in opinionated microblog sentences automatically in order to improve the segmentation result of the Chinese word segment tool.

REFERENCES

[1] M. A. Ayyoub, S. B. Essa, and I. Alsmadi, "Lexicon-based sentiment analysis of arabic tweets," *Int. J. Social Netw. Mining*, vol. 2, no. 2, pp. 101–114, 2015.
[2] C. S. Khoo and S. B. Johnkhan, "Lexicon-based sentiment analysis: Comparative evaluation of six sentiment lexicons," *J. Inf. Sci.*, vol. 44, no. 4, pp. 491–511, Aug. 2018.
[3] B. Xu, T. Zhao, S. Wang, and D. Zheng, "Extraction of opinion targets based on shallow parsing features," *Acta Automat. Sinica*, vol. 37, no. 10, pp. 1241–1247, 2011.
[4] J. Kessler and N. Nicolov, "Targeting sentiment expressions through supervised ranking of linguistic configurations," in *Proc. 3th Int. AAAI Conf. Weblogs Social Media*, 2009, pp. 1–8.
[5] C. T. C and S. Joseph, "A syntactic approach for aspect based opinion mining," in *Proc. IEEE 9th Int. Conf. Semantic Comput.*, Feb. 2015, pp. 24–31.
[6] H. Liu, Y. Zhao, B. Qin, and T. Liu, "Comment target extraction and sentiment classification," *J. Chin. Inf. Process.*, vol. 24, no. 1, pp. 84–88, 2010.
[7] S. Aloufi and A. E. Saddik, "Sentiment identification in football-specific tweets," *IEEE Access*, vol. 6, pp. 78609–78621, 2018.
[8] H. Han, J. Liu, and G. Liu, "Attention-based memory network for text sentiment classification," *IEEE Access*, vol. 6, pp. 68302–68310, 2018.
[9] A. Balahur, R. Steinberger, M. Kabadjov, V. Zavarella, E. Goot, M. Halkia, B. Pouliquen, and J. Belyaeva, "Sentiment analysis in the news," in *Proc. 7th Int. Conf. Lang. Resour. Eval.*, 2010, pp. 17–23.
[10] C. Quan and F. Ren, "A blog emotion corpus for emotional expression analysis in Chinese," *Comput. Speech Lang.*, vol. 24, no. 4, pp. 726–749, Oct. 2010.
[11] L. Wang, M. Wang, X. Guo, and X. Qin, "Microblog sentiment orientation detection using user interactive relationship," *J. Electr. Comput. Eng.*, vol. 2016, pp. 1–6, May 2016.
[12] J. Li and F. Ren, "Emotion recognition of weblog sentences based on an ensemble algorithm of multi-label classification and word emotions," *IEEJ Trans. Electron., Inf. Syst.*, vol. 132, no. 8, pp. 1362–1375, 2012.
[13] G. Xu, Z. Yu, H. Yao, F. Li, Y. Meng, and X. Wu, "Chinese text sentiment analysis based on extended sentiment dictionary," *IEEE Access*, vol. 7, pp. 43749–43762, 2019.
[14] S. Zhang, Z. Wei, Y. Wang, and T. Liao, "Sentiment analysis of chinese micro-blog text based on extended sentiment dictionary," *Future Gener. Comput. Syst.*, vol. 81, pp. 395–403, Apr. 2018.
[15] A. Cui, H. Zhang, Y. Liu, M. Zhang, and S. Ma, "Lexicon-based sentiment analysis on topical chinese microblog messages," in *Semantic Web and Web Science*. New York, NY, USA: Springer, 2013, pp. 333–344.
[16] Y. Li, X. Li, F. Li, and X. Zhang, "A lexicon-based multi-class semantic orientation analysis for microblogs," in *Proc. Asia–Pacific Web Conf.* Cham, Switzerland: Springer, 2014, pp. 81–92.
[17] J. K. Rout, K.-K.-R. Choo, A. K. Dash, S. Bakshi, S. K. Jena, and K. L. Williams, "A model for sentiment and emotion analysis of unstructured social media text," *Electron. Commerce Res.*, vol. 18, no. 1, pp. 181–199, Mar. 2018.
[18] B. Yan, Z. Yang, Y. Ren, X. Tan, and E. Liu, "Microblog sentiment classification using parallel SVM in apache spark," in *Proc. IEEE Int. Congr. Big Data*, Jun. 2017, pp. 282–288.
[19] H. Xia, Y. Yang, X. Pan, Z. Zhang, and W. An, "Sentiment analysis for online reviews using conditional random fields and support vector machines," *Electron. Commerce Res.*, pp. 1–18, May 2019, doi: 10.1007/s10660-019-09354-7.
[20] F. Wu, Y. Huang, and Y. Song, "Structured microblog sentiment classification via social context regularization," *Neurocomputing*, vol. 175, pp. 599–609, Jan. 2016.
[21] J. Tang, C. Nobata, A. Dong, Y. Chang, and H. Liu, "Propagation-based sentiment analysis for microblogging data," in *Proc. SIAM Int. Conf. Data Mining*, 2015, pp. 577–585.
[22] V. Hatzivassiloglou and K. McKeown, "Predicting the semantic orientation of adjectives," in *Proc. 35th Annu. Meeting Assoc. Comput. Linguistics, 8th Conf. Eur. Chapter Assoc. Comput. Linguistics*, 1997, pp. 174–181.
[23] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, no. 1, pp. 993–1022, Mar. 2003.

[24] C. Bishop, "Pattern recognition and machine learning errata," *IEEE Trans. Inf. Theory*, vol. 9, no. 4, pp. 257–261, Jan. 2006.

[25] Y. Hu, J. Boyd-Graber, B. Satinoff, and A. Smith, "Interactive topic modeling," *Mach. Learn.*, vol. 95, no. 3, pp. 423–469, Jun. 2014.

[26] Q. Zhang, S. Zhang, F. Ren, and X. Zhang, "Aspect-based and affective meaning in microblogging comments via topic model," *J. Chin. Inf. Process.*, vol. 33, no. 6, pp. 116–123 and 140, 2019.

[27] A. Mukherjee and B. Liu, "Aspect extraction through semi-supervised modeling," in *Proc. 50th Annu. Meeting Assoc. Comput. Linguistics*, 2012, pp. 339–348.

[28] D. Andrzejewski, X. Zhu, and M. Craven, "Incorporating domain knowledge into topic modeling via Dirichlet forest priors," in *Proc. 26th Annu. Int. Conf. Mach. Learn. (ICML)*, 2009, pp. 25–32.

[29] T. Wang, Y. Cai, H.-F. Leung, R. Y. K. Lau, Q. Li, and H. Min, "Product aspect extraction supervised with online domain knowledge," *Knowl.-Based Syst.*, vol. 71, pp. 86–100, Nov. 2014.

[30] M. Jiang, P. Cui, X. Chen, F. Wang, W. Zhu, and S. Yang, "Social recommendation with cross-domain transferable knowledge," *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 11, pp. 3084–3097, Nov. 2015.

[31] T.-A.-N. Pham, X. Li, G. Cong, and Z. Zhang, "A general recommendation model for heterogeneous networks," *IEEE Trans. Knowl. Data Eng.*, vol. 28, no. 12, pp. 3140–3153, Dec. 2016.

[32] Z. Jiang, H. Liu, B. Fu, Z. Wu, and T. Zhang, "Recommendation in heterogeneous information networks based on generalized random walk model and Bayesian personalized ranking," in *Proc. 11th ACM Int. Conf. Web Search Data Mining (WSDM)*, 2018, pp. 288–296.

[33] R. Liu, X. Hao, and Y. Li, "Research on Chinese perspective sentences identification based on semantic pattern with semi-supervised machine learning," *J. Nanjing Univ. Natural Sci.*, vol. 54, no. 5, pp. 967–973, Oct. 2018.

[34] U. Yaqub, N. Sharma, R. Pabreja, S. A. Chun, V. Atluri, and J. Vaidya, "Analysis and visualization of subjectivity and polarity of Twitter location data," in *Proc. 19th Annu. Int. Conf. Digit. Government Res. Governance Data Age*, 2018, p. 67.

[35] S. Ding, J. Wu, and H. Li, "Chinese microblogging opinion recognition based on SVM model," *J. China Soc. Sci. Tech. Inf.*, vol. 35, no. 12, pp. 1235–1243, 2016.

[36] S. M. W. Moraes, A. L. L. Santos, M. Redecker, R. M. Machado, and F. R. Meneguzzi, "Comparing approaches to subjectivity classification: A study on portuguese tweets," in *Proc. Int. Conf. Comput. Process. Portuguese Lang.*, 2016, pp. 86–94.

[37] Y. Li, X. Zhou, Y. Sun, and H. Zhang, "Research and implementation of Chinese microblog sentiment classification," *J. Softw.*, vol. 28, no. 12, pp. 3183–3205, 2017.

[38] H. Zhang, H. Li, and Q. Li, "Research on automatic emotional word detection and polarity weighting algorithm," *J. Chin. Inf. Process.*, vol. 31, no. 3, pp. 48–54, 2017.

[39] U. N. Raghavan, R. Albert, and S. Kumara, "Near linear time algorithm to detect community structures in large-scale networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 76, no. 3, Sep. 2007, Art. no. 036106.

[40] R. Zhang and Z. Ren, "An improved algorithm for community discovery in social networks based on label propagation," in *Proc. 12th Int. Conf. Fuzzy Syst. Knowl. Discovery (FSKD)*, Aug. 2015, pp. 1493–1497.

[41] X. Zhou, X. Wan, and J. Xiao, "CMiner: Opinion extraction and summarization for chinese microblogs," *IEEE Trans. Knowl. Data Eng.*, vol. 28, no. 7, pp. 1650–1663, Jul. 2016.

[42] A. Li, P. Di, and G. Duan, "Document sentiment orientation analysis based on sentence weighted algorithm," *J. Chin. Comput. Syst*, vol. 36, no. 10, pp. 2252–2256, 2015.

[43] Z. Dong and Q. Dong. (1999). *Introduction to HowNet*. [Online]. Available: http://www.keenage.com

FUJI REN (Senior Member, IEEE) received the Ph.D. degree from the Faculty of Engineering, Hokkaido University, Japan, in 1991. From 1991 to1994, he was a Chief Researcher with CSK. In 1994, he joined the Faculty of Information Sciences, Hiroshima City University, as an Associate Professor. Since 2001, he has been a Professor with the Faculty of Engineering, Tokushima University. His current research interests include natural language processing, artificial intelligence, affective computing, emotional robot. He is a Fellow of the Japan Federation of Engineering Societies, IEICE, and CAAI. He is the Academician of the Engineering Academy of Japan and EU Academy of Sciences. He is the Editor-in-Chief of the *International Journal of Advanced Intelligence* and the Vice President of CAAI. He is the President of International Advanced Information Institute, Japan.

QIAN ZHANG received the master's degrees from Nantong University, in 2018, and the Tokushima University, in 2019. She is currently pursuing the Ph.D. degree with Tokushima University. Her research interests include natural language processing, affective computing, and data mining.