北京理工大学

本科生毕业设计（论文）外文翻译

外文原文题目： A rule-based approach to emotion cause detection for Chinese micro-blogs

中文翻译题目： 对中文微博基于规则的情绪原因检测

毕业设计（论文）题目： 基于神经网络的文本情绪原因识别研究

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Expert Systems with Applications 42 (2015) 4517–4528

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A rule-based approach to emotion cause detection for Chinese micro-blogs

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ARTICLE INFO

Article history:
Available online 7 February 2015

Keywords:
Text mining
Emotion causes
Micro-blog
Cause component proportion

ABSTRACT

Emotion analysis and emotion cause extraction are key research tasks in natural language processing and public opinion mining. This paper presents a rule-based approach to emotion cause component detection for Chinese micro-blogs. Our research has important scientific values on social network knowledge discovery and data mining. It also has a great potential in analyzing the psychological processes of consumers. Firstly, this paper proposes a rule-based system underlying the conditions that trigger emotions based on an emotional model. Secondly, this paper extracts the corresponding cause events in fine-grained emotions from the results of events, actions of agents and aspects of objects. Meanwhile, it is reasonable to get the proportions of different cause components under different emotions by constructing the emotional lexicon and identifying different linguistic features, and the proposed approach is based on Bayesian probability. Finally, this paper presents the experiments on an emotion corpus of Chinese micro-blogs. The experimental results validate the feasibility of the approach. The existing problems and the further works are also present at the end.

1. Introduction

In the era of information explosion, the social network applications present a platform for people to share various news and information sources. As for the micro-blog in China, it has gradually become more popular, and millions of people present and share their opinions every day. The micro-blogs can convey almost all aspects of public opinions, including the description of emergencies, incidents, disasters and some other hot events. Perhaps some of them are full of emotions and sentiments. As a result, many researchers in the field of natural language processing pay more attention to Chinese micro-blog textual emotion processing (Liu, 2012), especially the emotion classification (Desmet & Hoste, 2013; Huang, Peng, Li, & Lee, 2013; Kontopoulos, Berberidis, Dergiades, & Bassiliades, 2013; Yang & Yu, 2013), and the corresponding social relations (Hu, Tang, Tang, & Liu, 2013). Generally, individual emotion generation, expression and perception are influenced by many factors. The emotion cause is considered to be the event or condition that can trigger the corresponding emotion, so emotion cause analysis is essential to mine the public opinion and knowledge discovery. In previous related work, the cause events can be composed of verbs, nominalizations and nouns, and these can evoke the presence of the corresponding emotions by some linguistic cues (Lee, Chen, Huang, & Li, 2013a). For example, as for the sentence (1), the causative verb is *"rang4"* (make), and the emotional keyword is *"Kai1 Xin1"* (happy). With the help of the linguistic rules, we can infer that the emotion cause event is *"Zhe4 Ci4 Chun1 You2"* (this spring outing). Meanwhile, Li and Xu (2014) applied the technology of emotion cause extraction to the micro-blog textual emotion classification.

(1) *Zhe4 Ci4 Chun1 You2 Rang4 Wo3 Hen3 Kai1 Xin1.*[2] (This spring outing makes me very happy.)

In this paper, we combine the relevant knowledge in the field of computer science, emotion psychology and the technology of natural language processing together to explore the emotion causes effectively. Firstly, this paper proposes an emotion model with cause events, and the model describes the conditions that trigger

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[1] Indicates equal contributions from these authors.

[2] It is the original Chinese sentence, and the corresponding literal English translation is shown below.

http://dx.doi.org/10.1016/j.eswa.2015.01.064
0957-4174/

bloggers' emotions in the progress of cognitive evaluation. Meanwhile, all of the sub-events are extracted from micro-blogs. Then this paper detects the corresponding cause events with the help of the proposed rule-based algorithm. Finally, the proportions of different cause components under different emotions are calculated by constructing the emotional lexicon from the corpus and combining different linguistic features.

This paper is organized as follows: Section 2 discusses the related work on various aspects of emotion processing. Section 3 focuses on the method of emotion cause component analysis. Section 4 presents the performance evaluation and the experimental results. In the end, we discuss the remaining challenges and possibilities for the future works.

2. Related work

2.1. Emotion psychological model

As for the cognitive psychology, it focuses on the senior psychological process of human, such as the OCC model which was first proposed by Ortony, Clore and Collins in their book "The Cognitive Structure of Emotions" (Andrew, Clore, & Allan, 1988). The OCC model provided a psychological model of the eliciting conditions of emotions. But it fell short of capturing the logical structure. And Steunebrink, Dastani, and Meyer (2009) proposed a new inheritance-based view of the logical structure of emotions of the OCC model by identifying and clarifying several of the ambiguities. Latter, Steunebrink, Dastani, and Meyer (2012) proposed a formal model of emotion trigger. First, it captured the conditions which triggered emotions in a semiformal way and the main psychological notions used in the emotion model. After that, they proposed a BDI-based framework (belief–desire–intention) to mine the corresponding emotion.

2.2. Emotion classification

In the traditional algorithm on emotion classification, some researchers mainly focus on the following aspects: text processing (e.g., segmentation, part-of-speech tagging, named entity recognition, dependency parsing, etc.), feature extraction and the classification algorithm (e.g., rule-based and machine learning-based methods, etc.). In He (2013), the performances of the three methods (i.e., naive Bayesian, SVM, and SMO) were compared in micro-blog emotion classification. Moraes, Valiati, and Neto (2013) presented an empirical comparison between SVM and ANN for document-level sentiment analysis. Liu, Ren, Sun, and Quan (2013) analyzed the emotion of micro-blog hot events by making use of kernel and SVM method. Wen and Wan (2014) proposed an approach based on class sequential rules to classify the given micro-blog texts into seven emotion types. Li, Li, Li, and Zhang (2014) proposed an approach to generate a multi-class sentiment lexicon by using HowNet, NTUSD and Sina Micro-blog posts. The posts were represented as the lexical vectors based on the lexicon. Then the Semi-GMM and KNN by using symmetric KL-divergence were proposed to classify the lexical vectors for sentiment classification. Liu and Chen (2015) proposed a multi-label classification based approach for emotion analysis, including text segmentation, feature extraction and multi-label classification.

2.3. Construction of the emotional lexicon and multi-language features extraction

As for the emotional lexicon, it can be used to process and identify the emotional words. It usually can be constructed by manual process and acquiring automatically from the corpus (Xu, Liu, Pan, Ren, & Chen, 2008). In the process of emotion analysis, identifying the multi-language features in micro-blog posts is necessary to compute the emotion intensity scores. As for the related work, Zhai, Xu, Kang, and Jia (2011) exploited effective features for Chinese sentiment classification, such as sentiment words, substrings,substring-groups, and key-substring-groups features. Li, Pan, Jin, Yang, and Zhu (2012) expanded a few high-confidence sentiment and topic seeds in target domain by the given RAP algorithm. Ren and Quan (2012) made an analysis on emotion expressions, including the following factors for emotion change: negative words, conjunctions, punctuation marks and contextual emotions. Quan, Wei, and Ren (2013) combined sentiment lexicon and dependency parsing for sentiment classification, and they extracted the evaluation objects based on the dependency and calculated the similarity between the words based on HowNet. Zhang, Xu, and Xu (2015) focused on the semantic features between words by clustering the similar features on the basis of word2vec.

Unlike the related methods, this paper incorporates the method of Chi-squared test, PMI and word2vec into the construction of the emotional lexicon based on Chinese micro-blog corpus.

2.4. Emotion cause analysis

In the aspect of emotion cause analysis, emotions can be invoked by the cause events. Lee, Zhang, and Huang (2013b) presented an event-based emotion corpus to analyze the interaction between event structures and emotions in the text. Lee et al. (2013a) constructed a Chinese emotion cause annotated corpus and presented seven groups of linguistic cues and two sets of generalized linguistic rules for the detection of emotion causes. Li and Xu (2014) proposed and implemented a novel method for identifying emotions of micro-blog posts, and tried to infer and extract the emotion causes by using knowledge and theories from other fields such as sociology. Nguyen, Phung, Adams, and Venkatesh (2013) extracted events using behaviors of sentiment signals and burst structure in social media, and these events often caused the behavioral convergence of the expression of shared emotion. Rao, Li, Mao, and Liu (2014) proposed two sentiment topic models (i.e., Multi-label Supervised Topic Model (MSTM) and Sentiment Latent Topic Model (SLTM)) to extract the latent topics that evoked emotions of readers, then the topics were seen as the causes of emotions as well.

Unlike the above works, this paper presents a novel emotion cause component analysis method for Chinese micro-blog posts. The innovation of this paper lies in mining the micro-blog data by analyzing the corresponding emotion on the basis of an emotion model. And then this paper also presents the subsystem for detecting and extracting the cause events by the designing rules in fine-grained emotions. Thirdly, constructing the emotional lexicon and identifying the multi-language features in micro-blog posts are used to analyze the emotion intensity scores. Finally, this paper presents the proportions of different cause components.

3. Emotion cause component analysis

The main flow on emotion cause component analysis is shown in Fig. 1. On the basis of the corresponding processing, the proportions of different cause components under different emotions will be obtained.

3.1. ECOCC model construction

Based on the cognitive theory, this paper improves the structure about the eliciting conditions of emotions in accordance with the OCC model referred in Andrew et al. (1988) and presents an

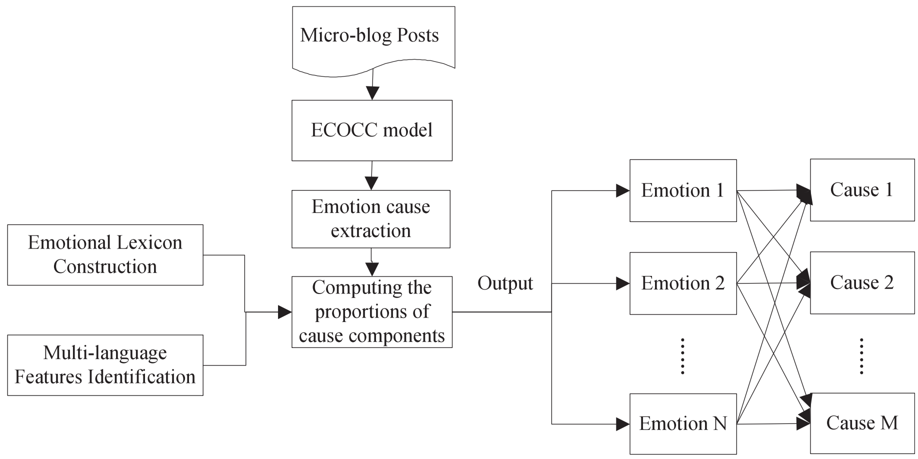

Fig. 1. The framework of the emotion cause component analysis.

emotion model named as ECOCC (Emotion-Cause-OCC) model for micro-blog posts. The ECOCC model combines emotion psychology with computer science to analyze the corresponding emotion cause events. It describes a hierarchy that classifies 22 fine-grained emotions. This hierarchy contains three main branches (i.e., results of events, actions of agents and aspects of objects), and some branches are combined to form a group of the compound and extended emotions. Here, the 22 fine-grained emotions can be divided into the following five groups:

- The emotions in a branch of "results of events": "Hope", "Fear", "Joy" and "Distress".
- The emotions in a branch of "actions of agents": "Pride", "Shame", "Admiration" and "Reproach".
- The emotions in a branch of "aspects of objects": "Liking" and "Disliking".
- The compound emotions in the branches of "results of events" and "actions of agents": "Gratification", "Remorse", "Gratitude"and "Anger".
- The extended emotions: "Satisfaction", "Fears-confirmed", "Relief", "Disappointment", "Happy-for", "Resentment", "Gloating" and "Pity".

On the basis of these main branches, the components of the model matching the emotional rules are divided into six sub-classes (i.e., event_state, event_norm, action_agent, action_norm, object_entity and object_norm). Within the components, the evaluation-schemes can be defined from event_state (i.e., the state that something will happen, the state that something has happened, the state that something did not happen), action_agent (i.e., the emotional agent or others) and object_entity (i.e., the elements of objects). They can be defined as six types (i.e., prospective, confirmation, disconfirmation, main-agent, other-agent and entity). Meanwhile, the corresponding evaluation-standards are defined from the aspects of event_norm (i.e., being satisfactory or unsatisfactory for the event), action_norm (i.e.,being approval or disapproval for the agent) and object_norm (i.e., being attractive or unattractive to the entity). And they can be defined as another six types (i.e., desirable, undesirable, praiseworthy, blameworthy, positive, negative, etc.). In addition, this paper collects the emotional words by using the HowNet,[3] and the National Taiwan University Sentiment Dictionary[4] (where 3505 terms belong to "desirable, praiseworthy, positive" domain, while 9427 terms belong to "undesirable, blameworthy, negative" domain) as the evaluation-standard library for evaluating the relevant events, actions and objects respectively. Finally, we can get the degree of satisfaction of events, approval of agents, and attraction of objects.

The rules (see Table 1) are used to describe the production processes of the 22 types of emotions according to the components in the ECOCC model. Here, "s" means the micro-blog post, "C" represents the cause components that trigger emotions, "→" represents the state that changes from one to the other, "∩" has the same meaning as "and" and "∪" has the same meaning as "or". The particular introduction will be shown in the next subsections.

3.1.1. Production rules of the base emotions on "results of events"

In the "results of events", when the evaluation-scheme of event_state is prospective, and if the evaluation-standard of event_goal is desirable, the corresponding emotion is "Hope". Otherwise, its emotion is "Fear". On the other hand, the corresponding emotions are "Joy" and "Distress", according to the different evaluation-standards of event_state (i.e., confirmation and disconfirmation). For example, in the given Chinese micro-blog post (2), it contains some future characteristics (i.e., *"Ming2 Tian1"* (<u>tomorrow</u>)). As it is a prospective event and the evaluation-standard of event_goal is desirable (*"Wo3 Men Neng2 You3 Yi1 Ge4 Kuai4 Le4 De Ye3 Chui1"* (<u>we can have a happy picnic</u>)), so the emotion is "Hope", and its corresponding emotion cause event is *"Wo3 Men Neng2 You3 Yi1 Ge4 Kuai4 Le4 De Ye3 Chui1"* (<u>we can have a happy picnic</u>).

(2) *Tian1 Qi4 Yu4 Bao4 Shuo1 Ming2 Tian1 Shi4 Ge4 Qing2 Tian1, Wo3 Xi1 Wang4 Wo3 Men Neng2 You3 Yi1 Ge4 Kuai4 Le4 De Ye3 Chui1*. (The weather forecast says tomorrow is sunny, and I hope we can have a happy picnic.)

3.1.2. Production rules of the base emotions on "actions of agents"

Within the "actions of agents", we can analyze the emotion from the perspective of main-agent (e.g., author or blogger) and other-agent. If the evaluation-scheme of action_agent is main-agent and the evaluation-standard of action_norm is praiseworthy (or blameworthy), then its corresponding emotion is "Pride" (or"Shame"). If other-agent has a praiseworthy (or blameworthy) behavior, then its corresponding emotion is "Admiration" (or "Reproach"). For example, in the given Chinese micro-blog post (3), the main-agent is *"Wo3 Men"* (<u>we</u>) and the other-agent is "Alan", and the text shows the "Admiration" emotion and the corresponding emotion cause event is *"Alan Jiu4 Qi3 Le Yi1 Ming2 Luo4 Shui3 Nv3 Hai2"* (<u>Alan rescued a drowning girl</u>).

[3] http://www.keenage.com/.
[4] http://nlg18.csie.ntu.edu.tw:8080/opinion/index.html.

Table 1
The emotional rules.

Classes	The 22 emotional rules
The emotions in the branch of "results of events"	Hope(C)$\stackrel{def}{=}$Prospective(s)∩ Desirable(s) Fear(C)$\stackrel{def}{=}$Prospective(s)∩ Undesirable(s) Joy(C)$\stackrel{def}{=}$[Confirmation(s)∪Disconfirmation(s)]∩ Desirable(s) Distress(C)$\stackrel{def}{=}$[Confirmation(s)∪Disconfirmation(s)]∩Undesirable(s)
The emotions in the branch of "actions of agents"	Pride(C)$\stackrel{def}{=}$main-agent∩Praiseworthy(s) Shame(C)$\stackrel{def}{=}$main-agent∩Blameworthy(s) Admiration(C)$\stackrel{def}{=}$other-agent∩Praiseworthy(s) Reproach(C)$\stackrel{def}{=}$other-agent∩Blameworthy(s)
The emotions in the branch of "aspects of objects"	Liking (C)$\stackrel{def}{=}$ entity ∩Positive(s) Disliking(C)$\stackrel{def}{=}$entity∩Negative(s)
Compound emotions	Gratification(C)$\stackrel{def}{=}$Pride(C)∩Joy(C) Remorse(C)$\stackrel{def}{=}$Shame(C)∩Distress(C) Gratitude(C)$\stackrel{def}{=}$ Admiration (C)∩Joy (C) Anger(C)$\stackrel{def}{=}$Reproach(C)∩Distress(C)
Extended emotions	Satisfaction(C)$\stackrel{def}{=}$Joy(C)∩[Prospective(s)→Confirmation(s)]∩ Hope(C) Fears-confirmed(C)$\stackrel{def}{=}$Distress(C)∩[Prospective(s)→Confirmation(s)] ∩ Fear(C) Relief(C)$\stackrel{def}{=}$Joy(C)∩[Prospective(s)→Disconfirmation(s)] ∩ Fear(C) Disappointment(C)$\stackrel{def}{=}$Distress(C)∩[Prospective(s)→Disconfirmation(s)] ∩ Hope(C) Happy-for(C)$\stackrel{def}{=}$Joy(C)∩[other-agent∩Praiseworthy(s)∩Desirable(s)] Resentment(C)$\stackrel{def}{=}$Distress(C)∩[other-agent ∩ Blameworthy(s) ∩ Desirable(s)] Gloating(C)$\stackrel{def}{=}$Joy(C)∩[other-agent∩ Blameworthy(s)∩Undesirable(s)] Pity(C)$\stackrel{def}{=}$Distress(C)∩[other-agent∩Praiseworthy(s)∩Undesirable(s)]

(3) *Wo3 Men Wei4 Alan Jiu4 Qi3 Le Yi1 Ming2 Luo4 Shui3 Nv3 Hai2 Gan3 Dao4 Zi4 Hao2.* (We are proud of Alan for rescuing a drowning girl.)

3.1.3. Production rules of the base emotions on "aspects of objects"

As for the "aspects of objects", it is reasonable to classify the given emotions into "Liking" and "Disliking" according to the corresponding evaluation-standard (i.e., positive or negative). For example, in the given Chinese micro-blog post (4), the entity is *"Xiao3 Gou3"* (<u>puppy</u>). According to its characters, the evaluation-standard of the object_norm is positive, so the corresponding emotion is "Liking", and the corresponding emotion cause event is *"Xiao3 Gou3 Tai4 Ke3 Ai4 Le"* (<u>lovely puppy</u>).

(4) *Wo3 Jia1 De Xiao3 Gou3 Tai4 Ke3 Ai4 Le!*. (So lovely of my puppy!).

3.1.4. Production rules of the "compound emotions": Gratification, Gratitude, Remorse and Anger

Some Base emotions can be combined into the compound emotions. In detail, the combination of "Joy" and "Pride" will generate the "Gratification" emotion, while the combination of "Joy" and "Admiration" will generate the "Gratitude" emotion. The combination of "Distress" and "Shame" will generate the "Remorse" emotion, and the combination of "Distress" and "Reproach" will generate the "Anger" emotion. For example, in the given Chinese micro-blog post (5), it presents a blameworthy behavior (*"Ta1 Ba3 Wei2 Yi1 De Shui3 Bei1 Da3 Sui4 Le"* (<u>he broke the only glass</u>)) and an undesirable result (*"Wo3 Men Mei2 Fa3 He1 Shui3 Le"* (<u>we could not drink water</u>)). The event leads main-agent to generate the "Anger" emotion, and its cause event is *"Ta1 Ba3 Wei2 Yi1 De Shui3 Bei1 Da3 Sui4 Le"* (<u>he broke the only glass</u>).

(5) *Ta1 Ba3 Wei2 Yi1 De Shui3 Bei1 Da3 Sui4 Le, Wo3 Men Mei2 Fa3 He1 Shui3 Le.* (He broke the only glass so we could not drink water).

3.1.5. Production rules of the "extended emotions": Satisfaction, Fears-confirmed, Relief, Disappointment, Happy-for, Resentment, Gloating, Pity

"Satisfaction", "Fears-confirmed", "Relief" and "Disappointment" emotions within the ECOCC model are the extended emotions. In detail, while the evaluation-scheme of the event has changed from prospective to confirmation, and the evaluation-standard of the event is desirable (or undesirable), then the corresponding emotion is "Satisfaction" (or "Fears-confirmed"). On the other hand, if the evaluation-scheme of the event has changed from prospective to disconfirmation, and the evaluation-standard of the event is undesirable (or desirable), then the emotion is "Relief" (or "Disappointment"). Similarly, "Happy-for", "Resentment", "Gloating", "Pity" emotions within the ECOCC model are also the extended emotions, which are described by combining results of events and actions of agents. In detail, as for other-agent, when the evaluation-standard of event_goal is desirable, if its base emotion is "Joy" (or "Distress") and the evaluation-standard of action_norm is praiseworthy (or blameworthy), then the emotion is "Happy-for" (or "Resentment"). In addition, when the evaluation-standard of event_goal is undesirable, if its base emotion is "Joy" (or "Distress") and the evaluation-standard of action_norm is blameworthy (or praiseworthy), the emotion is "Gloating" (or "Pity").

3.2. Emotion cause component detection and extraction

The related work has shown that the emotion cause event is consisted of a list of sub-events, which can be formalized as a triple

$U = (nouns, verbs, nouns)$. In this paper, the external events and the internal events are taken into consideration. As for the former, they are considered as the indirect reasons that can trigger emotions and they are also inferred and extracted according to the characters of the micro-blogs. For the latter, this paper proposes the model of extracting sub-events from the results of events, actions of agents and aspects of objects based on the ECOCC model. The Algorithm 1 describes the main process of cause event extraction.

Algorithm 1. The algorithm of the external and internal cause events extraction

```
ECO ← The external events
ECI ← The internal events
M ← The method of emotion cause extraction
for each clause in the micro-blog post do
    topic ← The feature set of #Topic#
    E ← The results of events
    A ← The actions of agents
    O ← The aspects of objects
    if topic is in clause then
        ECO ← Reprocess topic according to Regular Expression
    end if
    if E is in clause then
        ECI ← Extract E according to M
    end if
    if A is in clause then
        ECI ← Extract A according to M
    end if
    if O is in clause then
        ECI ← extract O according to M
    end if
end for
```

3.2.1. Analyzing the external event

Through analyzing the Chinese micro-blog posts, these sentences with the style of "#Topic#" usually contain some social or hot news, which perhaps influence on the corresponding emotion transition tendency. So it is necessary to extract the external event and make it as the emotion cause event. It can be obtained by using the regular expression rule. For example, in the example post (6), by using the regular expression to match the external event, this paper can obtain the external event: *"Li3 Na4 Ao4 Wang3 Du2 Guan4"* (Li Na won the Australian Open).

(6) *#Li3 Na4 Ao4 Wang3 Du2 Guan4# Hen3 Zan4!* (#Li Na won the Australian Open # Great!).

3.2.2. Analyzing the "results of events"

The internal event is usually the direct reason for triggering the change of individual emotion and it can be extracted from the domain of results of events, actions of agents and aspects of objects based on the ECOCC model. As for the domain of results of events, the LTP[5] (Language Technology Platform) is used to set up the model of extracting sub-events based on the named entity recognition, dependency parsing, semantic role labeling, and so on Che, Li, and Liu (2010). The main steps are as follows:

- Labeling the parts of speech of Chinese (e.g., nouns, verbs, adjectives) within the micro-blog posts by using our Chinese segmentation algorithm.
- Identifying the person names, place names and institutions by using Chinese named entity recognition.
- Identifying the core relation of subject–verbs and verb–objects by using dependency parsing.
- Identifying the phrases labeled with the semantic role (i.e., A0) for the actions of the agent, the semantic role (i.e., A1) for actions of the receiver, or four other different core semantic roles (i.e., A2–A5) for different predicates by using the semantic role labeling, respectively.

For example, as for the micro-blog post: *"Wo3 Bang1 Wu2 Bao3 Chun1 Xian1 Sheng1 Pai1 She4 Le Zhe4 Ben3 Shu1 De1 Feng1 Mian4 She4 Ying3, Zhen1 De3 Hao3 Ji1 Dong4 A1!"* (I help Mr. Wu Baochun to take the cover of the book, and it is really very exciting!), the result of semantic parsing is as follows (see Fig. 2):

In detail, this paper first selects the phrases which are labeled as A0, A1, A2–A5 (if it exists) and then combines the above components as the basis of event recognition. Otherwise, the triple $U = (nouns, verbs, nouns)$ will be used as another basis of event recognition. In addition, in the process of the internal event recognition, there are some prospective-events, which stand for the desire for the future events of individual. The processing steps are as follows:

- Determining the feature-words, e.g., *"Jiang1 Lai2"* (in the future), *"Ming2 Tian1"* (tomorrow), *"Ming2 Nian2"* (next year), if they exist.
- Analyzing the lexical features, syntactic features, the characteristics of words, and then generating the feature sets.
- Exploring the relationship between the feature sets and the events by dependency parsing and then confirming the prospective content.

By describing the results of events, it is easy to decide the corresponding emotion and its causes according to the evaluation-schemes and the evaluation-standards.

3.2.3. Analyzing the "actions of agents"

As for the domain of actions of agents, this paper extracts the class of ACT in HowNet which contains a large number of words describing different kinds of actions. If the predicate verb belongs to the class of ACT and there exists an initiative relationship between itself and the agent, then this structure can be used as a kind of agent's action. On the other hand, as for the main-agent, it contains the explicit-agent and the implicit-agent. The former is highlighted in the text and has the subject–predicate relationship with the predicate verb. The latter does not appear in the text, but it is usually expressed by the context and the act of the verb. Finally, on the basis of the description of the actions of agents, it is easy to decide the corresponding emotion and its causes according to the evaluation-schemes and the evaluation-standards.

3.2.4. Analyzing the "aspects of objects"

Meanwhile, the corresponding emotions "Liking" and "Disliking" can describe the reactions of the agent to the corresponding object respectively. For recognizing the characteristic information of aspects of objects, it needs to extract the entities on the basis of the HowNet corpus so as to find the subject–predicate relationship by using dependency parsing. The features of objects are extracted by using the semantic role labeling to confirm the evaluation-standards of object_norm. And then we can get the final emotion and its corresponding cause components.

[5] http://www.ltp-cloud.com/demo/.

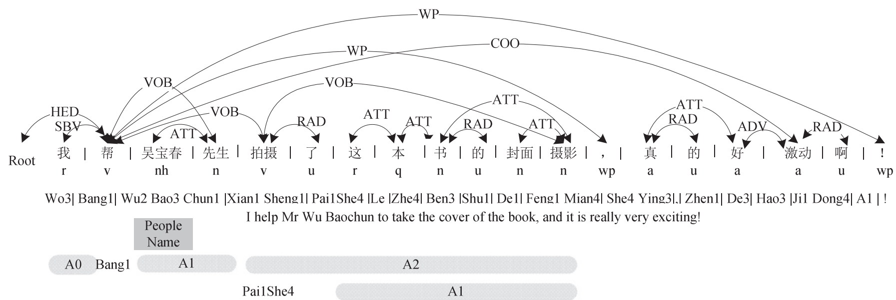

Fig. 2. The result of semantic parsing.

3.2.5. Algorithm on emotion cause extraction

To show the process of the proposed algorithm better, this paper presents the corresponding pseudo-code on cause event extraction. P_i is one of the generation rules of 22 emotions and *E_cause* is the set of emotion causes. *ECI* and *ECO* stand for the internal events and the external events, respectively (see Algorithm 2).

Algorithm 2. The algorithm of emotion cause extraction

```
d ← 1 ... 22
Pi ← Generate rule sets of emotion
Extract cause events by rules in Pi
for each sentence in the micro-blog post do
  ECI ← Extract the internal events according to Pi
  ECO ← Extract the external events
  if ECI == 0   &&   ECO == 0 then
    break
  else
    E_cause ← ECI or ECO
  end if
end for
```

3.3. Emotion cause component analysis

It is clear that several cause events may trigger only one emotion, while one cause event may trigger several emotions. Different cause events have different influences on the production of emotions. The proportion of one cause event in all cause events will also be different. The bigger the proportion is, the greater the probability of triggering emotion is. To achieve the proportion, we commence from the emotion intensities of cause events by constructing the emotional lexicon and identifying the multi-language features in micro-blogs, such as emoticons, negation words, punctuations, conjunctions and degree adverbs, and so on. Finally, the proportion will be calculated based on Bayesian probability.

3.3.1. Emotional lexicon construction

Generally, the emotional lexicon can be constructed manually and automatically from the corpus. Firstly, the standard lexicon can be constructed manually, including the following three steps:

- The choice of emotion types: In our previous work, the ECOCC model describes 22 fine-grained emotions. Each emotion is obtained by analyzing the complex emotions of humanity and the cognitive theory. So it is reasonable to choose the 22 types of emotions as the base emotions.
- The setting of the emotion intensity: As different emotional words have different emotion intensity scores, so the scores can be divided into five level ranges (i.e., 0–1.0, 1.0–2.0, 2.0–3.0, 3.0–4.0 and 4.0–5.0). Among them, 0–1.0 represents the word with the weakest emotion intensity; and 4.0–5.0 represents the corresponding word with the strongest emotion intensity. For example, "Kai1 Xin1 (happy)" belongs to the emotion of "Joy", and its emotion intensity score is 5.0, i.e., the fifth level.
- The choice of standard emotional words: The standard emotional words which belong to 22 different types of emotions are selected manually. And those words are from HowNet, National Taiwan University Sentiment Dictionary, and the Affective Lexicon Ontology (Xu et al., 2008). We give them the corresponding emotion intensities by the setting of the emotion intensity. This work will be completed by three different annotators in order to get a better result.

As for getting the larger capacity and more comprehensive lexicon, it needs to be expanded three times by acquiring automatically from the corpus. The first expansion is completed by chi-square test which can extract the high-frequency and high-class relevance keywords perfectly. This paper chooses the micro-blog posts containing 22 types of emotions as the training data (about 20,000 posts). The emotional keywords will be extracted from the training data by chi-square test, and the emotion intensity of each keyword is marked according to the relevance. The greater the relevance is, the stronger the intensity is. After that, the second expansion is completed by the method based on PMI (i.e., Pointwise Mutual Information). During this processing, the undetermined words are chosen from the corpus, and then the emotion intensities can be determined by the mutual information between the undetermined words and the standard emotional words in the corpus (Xu et al., 2008). The formula (1) of PMI is list as follows. And the parameter k stands for the number of emotion types ($1 \leqslant k \leqslant 22$), WD_k represents the word belonging to the kth emotion in the corpus, ST_{kj} represents the jth word belonging to the kth emotion in the standard lexicon. Finally, the words with the maximum mutual information will be added into the lexicon, and the emotion intensities of the standard words will be as their emotion intensities.

$$PMI(WD_k, ST_{kj}) = \log \frac{P(WD_k ST_{kj})}{P(WD_k)P(ST_{kj})} \tag{1}$$

The third expansion is completed by the word2vec[6] which provides an efficient implementation for computing vector representation of words by using the continuous bag-of-words and skip-gram architectures (Mikolov, Chen, Corrado, & Dean, 2013). Taking full advantage of the tool, we can complete the word clustering and choose the synonyms. Firstly, a large number of posts are collected randomly from Sina Micro-blog website (weibo.com) to constitute a 1.5 G micro-blog dataset. They are transformed to vector

[6] http://word2vec.googlecode.com/svn/trunk/.

representation of words. Then the synonyms of the standard emotional words are chosen as the candidate words. Secondly, it needs to compute the similarity between the candidate word and the standard word. The candidate word with the maximum similarity will be added into the lexicon. Meanwhile, the emotion intensities of the selected words can be defined as the formula (2) below. WD_i represents the ith word in the candidate word list, ST_j represents the jth word in the standard word list, $SIM(WD_i, ST_j)$ represents the maximum similarity between the candidate word and the standard word, and $I(ST_j)$ represents the emotion intensity of the standard word.

$$E_i = SIM(WD_i, ST_j) * I(ST_j) \tag{2}$$

Finally, the emotional lexicon based on 22 types of emotions is shown as follows (see Table 2):

3.3.2. Emoticons analysis

Emoticons can express far more complex emotions. As for the social network domain, according to Twitter statistics, the emoticon "" accounts for 10% in the top 100 emoticons. Meanwhile, in previous research works, people tend to classify emoticons into three types: positive, negative and neutral. Some more specific emoticons should be taken into consideration, such as "Happy", "Sadness", "Fear", "Anger", "Disgust" and "Surprise" (Yuan & Purver, 2012). Unlike the related works, this paper will combine the emoticon with the emotion intensity to calculate the proportion of the corresponding cause component.

Table 2
Details of the emotional lexicon.

The 22 types of emotions	The number of words	The number of five level ranges (0–1):(1–2):(2–3):(3–4):(4–5)
Distress	2890	208:704:1262:564:152
Disappointment	1719	628:329:553:177:32
Pity	3670	3268:130:155:70:47
Remorse	3259	2935:139:93:63:29
Fears-confirmed	2200	276:543:808:429:144
Fear	595	155:150:158:96:36
Resentment	276	3:23:113:112:25
Anger	1050	43:283:416:212:96
Disliking	3794	218:1019:1632:724:201
Reproach	13576	1001:3669:5563:2702:641
Shame	555	186:126:154:65:24
Hope	1009	40:284:474:154:57
Admiration	18302	2299:4454:7290:3235:1024
Liking	3134	213:1214:1156:444:107
Gratification	483	39:267:43:96:38
Gratitude	3781	3375:169:159:54:24
Joy	3942	302:1426:1634:482:98
Pride	3426	3070:124:73:116:43
Gloating	952	76:365:472:25:14
Relief	3681	28:1523:2001:82:47
Happy-for	5805	1911:1502:1774:519:99
Satisfaction	2526	54:1078:1270:88:36

Definition 1. The micro-blogs can be formulated as a triple $U = (C, R, T)$, where C means the emoticon list, R is the emotional keyword list, and T represents the micro-blog post list. As for one post, it can be regarded as a triple $u_x = (CV_i, RV_{kj}, t_n)$, where CV_i means the ith emoticon in C, RV_{kj} is the jth emotional keyword in R of the kth ($1 \leqslant k \leqslant 22$) emotion, t_n represents the nth post in T. If CV_i and RV_{kj} appear within t_n at the same time, the corresponding co-occurrence frequency is defined as $|CO(CV_i, RV_{kj})|$.

Definition 2. As for the co-occurrence intensity between the corresponding emoticon and the emotional keyword, it can be represented as $\delta_{ij}(CV_i, RV_{kj})$, see the formula (3), where $|CV_i|$ is the number of CV_i appearing in t_n, and $|RV_{kj}|$ is the number of RV_{kj} appearing in t_n.

$$\delta_{ij}(CV_i, RV_{kj}) = \frac{|CO(CV_i, RV_{kj})|}{(|CV_i| + |RV_{kj}|) - |CO(CV_i, RV_{kj})|} \tag{3}$$

According to the above definitions, it is easy to construct the co-occurrence graph (see Fig. 3). For example, E is the set of center nodes containing emoticons (e.g., CV_1, CV_2, CV_3, etc.), and D is the set of leaf nodes containing emotional keywords (e.g., RV_{11}, RV_{12}, RV_{13}, etc.). P is the set of the edge between E and D, and P represents the degree of closeness between the emotion intensities of CV_i and RV_{kj}. If the edge is longer, then the emotion intensities of both are closer (Cui, Zhang, Liu, & Ma, 2011).

As for the weight of the edge in the co-occurrence graph (which is defined as $W_{ij}(CV_i, RV_{kj})$), it can be set to a value which is equal to the co-occurrence intensity, see the formula (4):

$$W_{ij}(CV_i, RV_{kj}) = \delta_{ij}(CV_i, RV_{kj}) \tag{4}$$

According to the above equations and definitions, the emotion intensity of the ith emoticon (which is called as I_{ICON_i}) can be inferred as follows, see the formula (5), and E_j is the emotion intensity of the jth emotional keyword.

$$I_{ICON_i} = E_j * \max_{1 \leqslant k \leqslant 22} W_{ij}(CV_i, RV_{kj}) \tag{5}$$

3.3.3. Degree adverbs analysis

Besides emoticons, the modification of degree adverbs is also considered in computing the emotion intensities of cause events. In this paper, we use the intensifier lexicon including 219 degree adverbs, which are divided into five levels: "Ji2 Qi2 | extreme"; "Hen3 | very"; "Jiao4 | more"; "Shao1 | -ish" and "Qian4 | insufficiently" (Zhang & He, 2013). Then the influence coefficient is set to x, and the value of x is +0.5, +0.3, −0.1, −0.3 and −0.5, respectively. The "−" has the function of weakening the emotion intensities of the corresponding words while the "+" has the function of strengthening the emotion intensities of the corresponding words. The exponential function e^x is applied to adjust the emotion intensity. Finally, the emotion intensity of the ith emotional keyword (called I_{DA_i}) which is influenced by degree adverbs can be calculated by the following formula (6). Here, E_i is the emotion

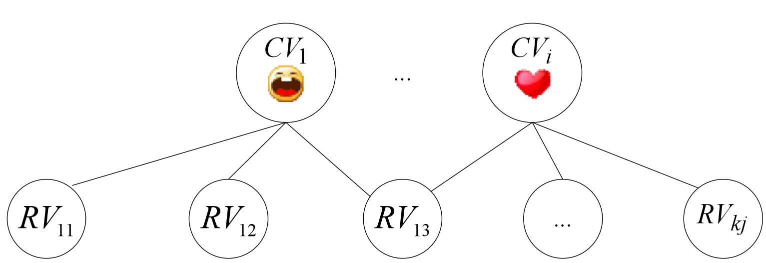

Fig. 3. The co-occurrence graph.

intensity of the ith emotional keyword, and γ is the adjustable parameter.

$$I_{DA_i} = \gamma e^x E_i (\gamma \geqslant 1) \tag{6}$$

3.3.4. Negation words recognition and analysis

As negation words can impact the negative transformation of emotions or impact the emotion intensity scores, it is reasonable to analyze this from the following aspects which are common phenomena especially in Chinese micro-blogs.

- Double negation: Double negation has many fixed patterns, such as two negative adverbs appearing in succession or the combination of one negative adverb with one rhetorical question, and so on. Most of them express an affirmative meaning and there exists no transformation of emotion. Meanwhile their emotion intensities become more stronger. For example, "*How could I don't like you?*". This sentence expresses the strong emotion ("Liking"). Here, I_{NEGA_i} is used to express the modified result of the emotion intensity of the ith emotional keyword, see the following formula (7), and the parameter η is the adjustable parameter, E_i is the emotion intensity of the ith emotional keyword.

$$I_{NEGA_i} = \eta E_i (\eta > 1) \tag{7}$$

- The location of the negation word impacts the emotion intensity: If the location of the negation word changes, the emotion and the corresponding emotion intensity will also be changed. For example, the difference between "*not very like*" and "*not like*" is that the former is affirmative and the latter is negative. Table 3 describes the influence of the locations of negation words in three patterns. "NE" means the negation words, "DA" means the degree adverbs, "EW" means the emotional keywords. The parameter α and β stand for the adjustable parameters respectively, and "$-$" is the sign of the transformation of emotion.

Table 3
Details of the location of negation words.

Patterns	Description	Formalization
NE + DA + EW	Having the same type of emotion with the emotional keyword, but it is weaker than the original emotion intensity	$I_{(NEGA_i)} = \beta E_i (0 < \beta < 1)$
NE + EW	Having the reversed type of emotion with the emotional keyword, but it is same with the original emotion intensity, or it is neutral	$I_{(NEGA_i)} = -E_i$ or $I_{(NEGA_i)} = 0$
DA + NE + EW	Having the reversed type of emotion with the emotional keyword, and the emotion intensity is modified by the degree adverbs	$I_{(NEGA_i)} = -\alpha e^x E_i (\alpha \geqslant 1)$

3.3.5. Punctuations processing

As for Chinese micro-blogs, there usually exist a large number of emotional punctuation marks such as the exclamation mark, the interrogation mark and so on. They usually strengthen or promote the emotion intensities of sentences in some manners. On the other hand, the repetitive punctuations can strengthen or promote the emotion intensities more obviously than the single punctuation. The formula (8) is used to compute the emotion intensity which is influenced by punctuations (called I_{PUNC_i}). E_i is the emotion intensity of the ith emotional keyword, and ε is the adjustable parameter that can be confirmed by the degree of repeatability which has a direct relationship with the number of punctuations.

$$I_{PUNC_i} = \varepsilon * E_i (\varepsilon \geqslant 1) \tag{8}$$

Furthermore, with regard to the interrogative sentences, they cannot be analyzed from the above aspects. The reason is that within the Chinese micro-blogs, the frequencies of interrogative sentences under 22 different types of emotions are diverse, and the description of interrogative sentences is shown in Table 4. It is clear that the interrogative sentences mainly appear in the emotions of "Reproach" and "Resentment". This shows that people usually use the interrogation mark to express the two emotions. It also provides an evidence to analyze emotions. Moreover, the interrogation mark has different means in different circumstances, even changes the emotion. For example, as for the sentence: "*This book is very well?*", it is an interrogative sentence which describes a positive attitude to this book literally, but its actual mean is that this book is not good. In another case, "*Who can help me to repair the broken bike?*", which is an interrogative sentence describing a negative attitude, and here, the interrogation mark strengthens this emotion.

3.3.6. Conjunctions processing

There are different kinds of conjunctions such as coordinating conjunctions, adversative conjunctions, causal conjunctions and so on. In some cases, conjunctions may play an emphatic role on the emotional expression. For example, the conjunction *"Dan4 Shi4"* (but) mainly emphasizes the event with a strong emotion behind it. And the influencing parameters are divided into two classes. One is that the conjunction impacts on the emotion intensity of its front event, and the influencing parameter is set to F_{before}. The other is the conjunction impacts on the emotion intensity of its back event, and the influencing parameter is set to F_{after}. If $(F_{before} = F_{after})$, it means that the conjunction has the same effect both on the front event and the back event, so the values of the two parameters are set to 1. If $(F_{before} < F_{after})$, it means that the conjunction has no effect on the front event but strengthens the emotion intensity of the back event, so this paper sets $(F_{before}=1)$ and $(F_{after} > 1)$. If $(F_{before} > F_{after})$, it presents the opposite case with $(F_{before} < F_{after})$, so this paper sets $(F_{before} > 1)$ and $(F_{after} = 1)$. The following Table 5 describes different situations of conjunctions.

Table 4
Distribution of interrogative sentences in 22 types of emotions.

Emotion	Proportion	Emotion	Proportion	Emotion	Proportion
Admiration	0.16	Gratification	0.08	Relief	0.08
Anger	0.18	Gratitude	0.05	Remorse	0.11
Disappointment	0.13	Happy-for	0.09	Reproach	0.34
Disliking	0.09	Hope	0.05	Resentment	0.27
Distress	0.12	Joy	0.10	Satisfaction	0.06
Fear	0.09	Liking	0.08	Shame	0.13
Fear-confirmed	0.13	Pity	0.17	–	–
Gloating	0.09	Pride	0.06	–	–

Table 5
Different situations of conjunctions.

Conjunctions	Examples	The effect of the influencing parameters
Coordinating conjunctions	He2 | and, Yu3 | with, Kuang4 Qie3 | in addition, etc	$F_{before} = F_{after}$
Continuing conjunctions	Ze2 | then, Nai3 | thus, Yu2 Shi4 | hence, etc	$F_{before} < F_{after}$
Adversative conjunctions	Que4 | however, Dan4 Shi4 | but, Ran2 Er3 | nevertheless, etc.	$F_{before} < F_{after}$
Causal conjunctions	Yin1 Wei4 | because, You2 Yu4 | due to, Yin1 Ci3 | hence, Suo3 Yi3 | so, etc	$F_{before} < F_{after}$
Alternative conjunctions	Huo4 | or, Bu4 Shi4…Jiu4 Shi4 | either…or…, etc	$F_{before} = F_{after}$
Comparative conjunctions	Ru2 Tong2 | as, Si4 Hu1 | as if, Bu4 Ru2 | no as, etc	$F_{before} < F_{after}$
Concessive conjunctions	Sui1 Ran2 | although, Jin3 Guan3 | though, Ji2 Shi3 | even though, etc	If the main clause belongs to the front event, $F_{before} > F_{after}$; If the main clause belongs to the back event, $F_{before} < F_{after}$
Progressive conjunctions	Bu4 Dan4…Hai2 | not only…but also, Shen4 Zhi4 | even, etc	$F_{before} < F_{after}$

Therefore, this paper proposes the following formula (9) to express the modified result of the emotion intensity of the ith emotional keyword (called I_{CONJ_i}).

$$I_{CONJ_i} = \begin{cases} F_{before} * E_i & F_{before} > F_{after} \\ E_i & F_{before} = F_{after} \\ F_{after} * E_i & F_{before} < F_{after} \end{cases} \tag{9}$$

3.3.7. The calculation of cause component proportion based on Bayesian probability

The Bayesian algorithm is widely used to many fields such as text classification, word segmentation, information extraction and so on. This paper describes the proportions of cause components under different emotions from the perspective of the prior probability and the conditional probability by combining the characteristics of Bayesian probability model.

Firstly, this paper constructs an emotion cause component matrix $\rho(s)$ for the micro-blog posts, see the formula (10). $E(C_m)$ represents the emotion vector with cause components, m is the serial number of 22 types of emotions, E_{nm} represents the nth emotion cause intensity score of the mth emotion.

$$\rho(s) = (E(C_1), E(C_2), \ldots, E(C_m))^T = \begin{pmatrix} E_{11} & \ldots & E_{1m} \\ \vdots & \ddots & \vdots \\ E_{n1} & \ldots & E_{nm} \end{pmatrix} \tag{10}$$

The proportion of the nth cause component under the mth emotion (which is defined as $P(Emo_m|Cau_n)$) can be computed based on the Bayesian probability, see the formula (11).

$$P(Emo_m|Cau_n) = \frac{P(Cau_n|Emo_m)P(Emo_m)}{\sum_{m=1}^{22} P(Emo_m)P(Cau_n|Emo_m)} \tag{11}$$

Within the above formula (11), the parameter Emo_m is the mth emotion and Cau_n is the nth cause component under Emo_m. The prior probability $P(Emo_m)$ is the probability distribution of Emo_m. It can be calculated by the formula (12) and (13), where the parameter $SCORE(Emo_m)$ is the mth emotion intensity score which can be modified by the multi-language features in micro-blogs. The parameter I_{ICON_i} is the result modified by emoticons in micro-blogs. The parameter I_{DA_i} is the result modified by degree adverbs. The parameter I_{NEGA_i} is the result modified by negation words. The parameter I_{PUNC_i} is the result modified by punctuations. The parameter I_{CONJ_i} is the result modified by conjunctions. All of them are described in the above sections. If there is no any linguistic feature, the modified result will be ignored and set to 0.

$$P(Emo_m) = \frac{SCORE(Emo_m)}{\sum_{m=1}^{22} SCORE(Emo_m)} \tag{12}$$

$$SCORE(Emo_m) = \sum_{i=1} (E_i + I_{DA_i} + I_{NEGA_i} + I_{ICON_i} + I_{PUNC_i} + I_{CONJ_i}) \tag{13}$$

Within the above formula (11), $P(Cau_n|Emo_m)$ is the probability density function of the nth cause component in a known condition of emotion. It can be calculated by the formula (14) and (15), where $SCORE(Cau_n)$ is the emotion intensity score of the nth cause component under the mth emotion. It is also influenced by the multi-language features.

$$P(Cau_n|Emo_m) = \frac{SCORE(Cau_n)}{\sum_{n=1} SCORE(Cau_n)} \tag{14}$$

$$SCORE(Cau_n) = \sum_{i=1} (E_{im} + I_{DA_{im}} + I_{NEGA_{im}} + I_{ICON_{im}} + I_{PUNC_{im}} + I_{CONJ_{im}}) \tag{15}$$

3.3.8. Demonstration

In this section, for better understanding the whole operation of our work, we present a demonstration. The details are shown as follows:

For example, when a sentence is inputted into our system, we suppose that you can get two types of emotions by the method of emotion cause extraction referred in Sections 3.1 and 3.2, namely "*emotion1*" and "*emotion2*". Meanwhile, you can also obtain the two cause events under "*emotion1*" (i.e., "*cause1*" and "*cause2*") and one cause event under "*emotion2*" (i.e., "*cause3*"). Then, by using the calculation method of cause components proportions in Section 3.3, you can get the proportions of different cause components. We suppose that the proportion of "*cause1*" in all cause events under "*emotion1*" is "*p1*", the proportion of "*cause2*" in all cause events under "*emotion1*" is "*p2*", and the proportion of "*cause3*" is "*p3*" under "*emotion2*". The three proportions meet the following condition:

$$p1 + p2 + p3 = 1. \tag{16}$$

4. Experimental results and analysis

In this section, we present some experiments. First, it needs to construct the emotion cause annotated corpus from Chinese Sina Micro-blog (weibo.com). The dataset is crawled by our related work based on simulating browsers behaviors (Gao, Zhou, & Grover, 2014). Then, it needs to do cause extraction experiment based on the above corpus.

4.1. Dataset and metrics

4.1.1. The experimental dataset

In order to obtain the micro-blog dataset, some strategies based on simulating browsers' behaviors are used to obtain more than 18,000 posts from Chinese Sina Micro-blog (weibo.com). Within the dataset, the micro-blog posts are short, and most of them are less than 140 characters. Users can use the "#" hashtag which marks the hot topics, the emoticons, web links, or pictures in their posts. After the pre-processing (i.e., removing duplicates, filtering irrelevant results and doing some conversions), 16,371 posts are remained in our dataset. Meanwhile, every data needs to be labeled the emotion type and the corresponding cause by some markers manually. As each post may contain different types of emotions, we cannot label it with one kind of emotions, so the proposed 22 kinds of emotions are summed up as five categories (i.e., "*Happiness*", "*Anger*", "*Disgust*", "*Fear*" and "*Sadness*"). In the process of annotating, in order to avoid the ambiguity and simplify the problem, only the micro-blog posts that express explicitly emotion will be labeled with a tag of the corresponding emotion. The labeling task will be completed by three markers in the field of emotion processing. We label the posts according to the following rules:

- If there are more emotions within a post, only the predominant emotion will be labeled then.
- If the post contains the emotion type and the corresponding cause component at the same time, both will be labeled then.
- If the post does not have any cause component, only the type of emotion will be labeled.
- If two of the markers cannot decide which component is the cause, the third marker will label it then.
- If all of the markers do not distinguish which emotion the post belongs to, the post will be marked neutrally.
- After completing the marking tasks, the author must check the results in order to ensure the accuracy of the tag.

The marked results of the experimental dataset are shown in Table 6.

4.1.2. Evaluation metrics

To evaluate the performance, this paper uses the following three metrics: precision (U_P), recall (U_R) and F-score (U_F), see the formula (17)–(19), respectively. S is the set of all posts in the collection. NEC is the number of posts with cause components which are identified through our algorithm. NEM is the total number of posts with cause components.

$$U_P = \frac{s_i \in S|Proportion(s_i) \text{ is correct}}{NEC} \tag{17}$$

$$U_R = \frac{s_i \in S|Proportion(s_i) \text{ is correct}}{NEM} \tag{18}$$

$$U_F = \frac{2 * U_P * U_R}{U_P + U_R} \tag{19}$$

As for the correctness of the cause components proportions under different emotions, the following method is used to analyze. Firstly, the proportional range of each cause component is divided into ten levels, and each level is expressed as $\tau_i(1 \leqslant i \leqslant 10) : \tau_1 \in (0\%-10\%)$, $\tau_2 \in (10\%-20\%)$, $\tau_3 \in (20\%-30\%)$, $\tau_4 \in (30\%-40\%)$, $\tau_5 \in (40\%-50\%)$, $\tau_6 \in (50\%-60\%)$, $\tau_7 \in (60\%-70\%)$, $\tau_8 \in (70\%-80\%)$, $\tau_9 \in (80\%-90\%)$ and $\tau_{10} \in (90\%-100\%)$, respectively. The sampled posts with cause components are labeled manually according to the above proportional levels. Secondly, the proportion of the cause component is obtained according to our algorithm, and then it is set to x. If the absolute error between x and τ_i is less than φ (φ is a calibration parameter), the result is correct; otherwise, it is incorrect. The formula is shown as follows.

$$|x - \tau_i| < \varphi. \tag{20}$$

Table 6
Details of the micro-blog data.

Coarse-emotions	Number of posts	Number of posts with causes
Happiness	504	354
Anger	472	452
Disgust	150	137
Fear	140	131
Sadness	304	255
Neutral	14801	N
Total	16371	1329

4.2. Experimental analysis on emotion causes

The goal of our work is to examine the effects of emotion cause extraction. In order to achieve this goal, this paper groups the experiment into two aspects: one is to verify the feasibility of our algorithm in the aspect of emotion cause component detection, the other is to verify whether using the multi-language features effectively can improve the accuracy of calculation of cause component proportion.

As the first point, this paper compares our method with other two methods, and both are discussed in the literature review. In Method I, Lee et al. (2013a) detected emotion causes with a linguistic rule-based approach. And Method II is designed on the rule-based subsystem from the micro-blog posts based on the common social network characteristics and other carefully-generalized linguistic patterns (Li & Xu, 2014). The difference between ours and others is the approach on extracting emotion causes. This paper uses an emotion model to extract emotion causes, and Method I and Method II rely on the linguistic cues to extract emotion causes. This paper uses the same metric as Li's (Li & Xu, 2014) to evaluate the performance.

Although the three experiments use the micro-blog dataset and make the F-score as the evaluation metric, the performance of our method is superior to others compared to Method I and Method II. The results are shown in Table 7. Table 7 shows the performance of our method and the other two methods. The F-score of our proposed approach is improved by 12.95% and 4.21%, respectively. The result shows the feasibility of this approach and lays a foundation for the calculation of cause component proportion.

Latter, the seven groups are organized in the following Table 8 on the same micro-blog dataset. And the corresponding results of the experiment are shown in Table 9.

Table 7
Comparison among the methods.

Our method (%)	Method I (%)	Method II (%)
65.51	52.56	61.30

Table 8
Experiments of the seven groups.

Experiments	Descriptions
Baseline	Calculating the proportions only from the emotion intensities of keywords (which is called "EW").
EW + DA	Calculating the proportions combining EW with degree adverbs.
EW + ICON	Calculating the proportions combining EW with emoticons in Chinese micro-blogs.
EW + NEGA	Calculating the proportions combining EW with negation words.
EW + PUNC	Calculating the proportions combining EW with punctuations.
EW + CONJ	Calculating the proportions combining EW with conjunctions.
EW + ALL	Calculating the proportions combining EW with the five features (DA + ICON + NEGA + PUNC + CONJ).

Table 9
Results of the experiment.

Experiments	Precision (%)	Recall (%)	F-score (%)
Baseline	76.52	64.48	69.99
EW + DA	77.05	64.94	70.48
EW + ICON	79.91	67.34	73.09
EW + NEGA	79.55	67.04	72.76
EW + PUNC	77.50	65.31	70.89
EW + CONJ	77.32	65.16	70.72
EW + ALL	82.50	69.53	75.46

Table 9 shows the results of emotion cause component analysis in different aspects. The precision of the overall experiment is 82.50% which is higher than the other experiments. And the baseline without any linguistic feature has the lowest F-score which is 69.99%. If the experiment is conducted by combining with emoticons, then the F-score increases to 73.09%. Similarly, if we add the other features, the F-score also increases.

Meanwhile, the recall metric is lower in the experiment. There are three reasons leading to this phenomenon. First, the length of micro-blog post is shorter and flexible. If the post only contains an emoticon, it is difficult to extract the emotion cause event. So this will lead to lower recall ratio. Second, from the perspective of micro-blog users, some people tend to express emotions, but perhaps they do not say what triggers their emotions. In this case, we cannot detect the corresponding cause event. Third, there may exist some deviations in the proportional ranges which are labeled and the calculative proportions although the experiment effectively detects the cause components, and as a result, this may also reduce the recall ratio. In the near future, enhancing the recall ratio is necessary. As our current dataset is not very big, increasing the micro-blog dataset is necessary. According to the characteristics of micro-blog, some new features of micro-blog should be taken into consideration.

Fig. 4 presents the comparison among the corresponding baseline experiment and the proposed algorithm with multi-language features in terms of F-score metrics. Obviously, recognizing the linguistic features of emoticons, negation words, punctuations, conjunctions and degree adverbs can be helpful in extracting emotion causes and calculating the proportions of the cause components. We also find that the emoticons and the negation words have a greater influence on calculating the proportion. And the precisions of the two experiments are 79.91% and 79.55%, respectively. That is, people tend to use the two features to express strong emotions in micro-blogs.

On the other hand, even though the performance of the precision and the recall is not extremely high, our method can extract the cause events that trigger different emotions effectively and find the main cause component by the proportions of causes under public emotions. For example, if most people are in "Anger" emotion, we can quickly find out what triggers the generation of the emotion.

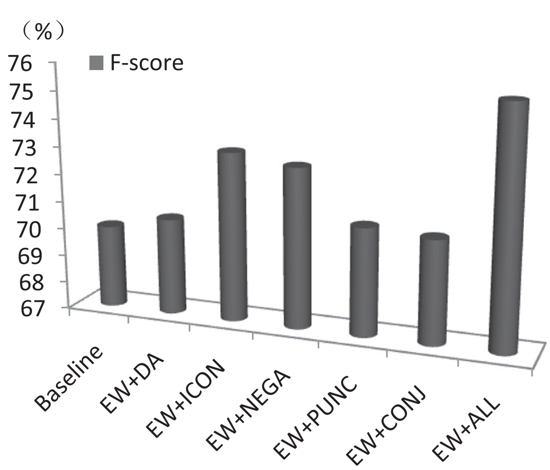

Fig. 4. Comparison of F-score of the seven different experiments.

Our research has significant values. First, as for the application area of crisis management, our work can be useful for dealing with public emergencies. By analyzing the causes of public emotions in social media, it is easy to explore the existing problems of the society. Second, our research is an important branch of emotion mining. It has a profound influence on identifying the implied emotions. Meanwhile, we try to combine the theories of cognitive psychology, emotion psychology and linguistics in our research together. This has important scientific values both on social network knowledge discovery and data mining. Third, mining the relations between the emotions and the corresponding causes is important for product design, and it can also help users to comprehensively analyze the psychological processes of consumers and the psychological mechanisms of implanting advertising.

5. Conclusions and future works

By using the Chinese micro-blog as the experimental dataset, this paper presents a rule-based approach to emotion cause component detection for Chinese micro-blogs. Firstly, this paper presents the ECOCC emotion model and extracts the corresponding cause components in fine-grained emotions. The emotional lexicon can be constructed manually and automatically from the corpus. Meanwhile, the proportions of cause components can be calculated in the influence of the multi-language features based on Bayesian probability. The experiment results show the feasibility of the approach.

Even though some achievements have been made, inadequacies are also existed in the research. There are five significant future directions and they can be meaningful for mining much deeper information for emotion analysis and emotion cause detection in social media.

From the level of research methods, there are two aspects. First, Table 9 obviously presents that different linguistic features play an important role in calculating the proportions of different cause components. Hence, more new features, such as different semantic structures and complicated linguistic patterns, should be explored. Second, we try to use the method based on statistical learning to mine the emotion causes. Meanwhile, exploring the relationship between the time and the cause event will be another meaningful future direction. These research results can help people find the changing rules of the cause event in different periods of time.

From the level of applied research, there are three aspects. First, our research could be applied to precision marketing for product recommendation. For example, we can recommend some cosmetic products to some special customers at the right time. Second, our research result should be used as an approach or method on social management. Through analyzing the causes of public emotions in social media, the government, for example, can find some existing problems. Third, our research can also be used to develop a system of opinion analysis system. It can help people find valuable information and make the right decision. We believe that these research directions are valuable future directions for the research community of expert systems with application.

Acknowledgments

This work is sponsored by National Natural Science Foundation of China (Grant Nos.: 61175110, 61272362) and National Basic Research Program of China (973 Program, Grant No.: 2012CB316301). It is also sponsored by National Science Foundation of Hebei Province (Grant No.: F2013208105), Key Research Project for University of Hebei Province (Grant No.: ZD2014029).

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通过使用情绪原因提取方法的基于文本的情感分类

摘要

近年来，社交网络在人们形成观点和做出决定上所起到的日益增长的巨大作用已经引起了各界的关注。微博作为时下最流行的社交网络应用之一，允许所有人对不同的话题分享自己的观点并且参与讨论，因此它也被看做获取人们的观点和情感数据的丰富来源。在这篇论文里，我们提出并且实现了一种新的用于识别微博帖子中包含的情感的方法。不同于传统的主要基于统计学的方法，我们尝试通过引入像社会学等其他领域的知识和理论，来推测和抽取产生情感的原因。根据一个理论：相应的触发事件是产生情绪的必不可少的一部分，情绪原因提取技术被看做是提高选择特征的质量的关键性一步。首先，在经过对样本数据的全面的分析之后，我们构建了一个基于规则的自动化系统用于检测和提取每一个情绪化的帖子的情绪触发事件。我们同时建立了一个通过人工标注的中文微博帖子情绪语料库。之后，我们根据已经提取出来的触发事件训练处一个分类器用于对微博帖子进行情感分类。我们所构建的系统的整体表现使我们相信其具有很好的应用价值和未来。实验结果表明我们的方法在选择有用且包含充足语义信息的特征方面非常有效。我们的系统在大多数方面都大大超越了基本要求，这也表明了它的巨大潜力。这一探索将会对情感分类的研究任务提供一种新的方法并且为未来的文本情感处理打下坚实的基础。

1. 简介

微博是博客的一种形式，它运行用户发表简短的文本贴（通常对长度做了严格限制，不得超过 200 个字符）。微博博主可以发表对很多话题的看法，这其中包括了日常生活、对电影或书的评论以及对社会事件的观点。因为微博的简单和随意的特点，微博用户的数量近年来增长的非常迅速。微博用户可以很快的更新他们的内容，这使得微博服务也扮演着实时新闻发布的中心的角色。一些机构比如公司、慈善团体和政府部门把微博作为市场营销和处理公共关系的工具。微博正在逐渐变成一个信息、想法和观点汇聚的平台。如今，许多人做决定的时候都

会受到他们在微博中关注的博主的影响。微博中的帖子被看做是挖掘情感和观点数据的丰富资源。挖掘微博社区中的用户情感在实现公共观点追踪、信息过滤和顾客关系管理等问题上引起了广泛的关注。

文本中的情感分析时现在自然语言处理领域中一个很热的研究方向。文本情感的探测或分类是许多学者和研究人员关注的任务。尽管细节部分可能存在差异，但通常而言，情感分析的目标是相同的——检测并且识别出给定文本中所传达的情感类型，比如高兴、生气和惊讶。由于基于统计学的分类方法的固有性质，通常研究人员所采用的最常用的方法都是基于统计的模型。特征选择算法例如 InfoGain 和 χ^2 测试，分类算法例如支持向量机（SVM）和 K-最近邻算法（K-NN），是一些传统的用于文本分类任务的方法。然而，这些方法在下面两个问题上表现的并不好。第一个是对于带有否定或反问的问题的复杂语句，这些方法并不能很好的处理。第二个是对于像为什么会有这样的情绪或者这样的情绪是如何产生的这样的更深层次的信息，在这些方法中通常是被忽略的。但是，这些更深层次的信息是非常有趣的并且有时候可以更好地反映句子中的隐含的情感。如果我们想像一下一个普通人是怎样感受和理解一篇文章中所隐含的情感，我们就会注意到经常是那些在统计学上并不十分明显的因素比如事件、人物的反应，才真正决定了我们对文章所表达情感的理解。在对人们发布到网络上的帖子中所包含的情感进行分类的时候我们通常出于直觉就会把这些因素考虑进去。

在很多被他人提出并且接受的与情感如何产生问题有关的因素中，触发事件经常都被看做是最关键的因素之一。许多不同学科的学者一直在研究情感和触发事件之间的关系和相互作用。从心理学的角度来看，有理论相信触发事件本身应该是情感经历中不可缺少的一部分。在社会学领域，Kleres 提出了“叙事分析”这一方法论，它通过找到发生了什么来系统的分析情感。Lee，Chen，和 Huang 设计了一个基于规则的系统用于检测产生情感的原因。尽管这些研究人员并没有专注于完成自动化情感分类的任务，但它们为我们的工作打下了坚实的基础。

在这篇论文中，我们采用了一种全新的方法对文本所隐含的情感进行分类。我们提出了一种利用情感原因抽取技术实现的情感分类技术，这种技术是整合了跨学科的知识和对微博数据的研究分析而得出的。我们把它看做一种新的方法是因为我们并不知道以前有任何的情感分类工作用到过这种技术。我们专注于识别从微博这一最受欢迎同时影响力最大的中文博客社区中抽取出的帖子中所隐含的情感。我们将情感触发事件作为切入点以克服传统方法中的一些缺陷。由相同的事件所触发的情感和反应被假定是相似的，因此由反问句导致的问题可以被减少。另外，我们也将深层次的语义信息考虑了进去。实验结果表明我们的系统可以以一个很好的精确度从微博帖子中提取出情感触发事件。基于有效的触发事件提取技术，我们的系统在情感分类上的效果有了巨大的提升。

本文的其余部分结构如下。第 2 节讨论了情感分析的相关工作，包括传统方法和新探索。第三部分简要介绍了中文微博平台微博，并介绍了利用情感原因提取技术提出的方法。在第 4 节中，我们的方法的两个阶段的实验结果被报告和讨论。第 5 节介绍了结论和我们今后的工作。

2. 相关工作

在这一部分，我们将展示并简要介绍情感分析任务的相关工作。

2.1 情感等级

分类主要有两种方式：二元分类（情感极性的粗粒度分类）和多级分类（细粒度多级分类）。

大多数先前的研究工作都集中在二元分类，即正面和负面。但是，能显示更详细信息的多级分类系统通常有更多实际的意义。例如，如果用户确切的情感状态是已知的，商业广告就可以实现更精确地推送并且不那么烦人。更多地了解用户的当前感受也会帮助社交网站创造一种更温暖和友好的氛围。尽管当前众多的理论中对情感多级分类问题并没有达成统一的共识，但一般有几种假定的基本的情感类型。一些主要的情绪类型，比如高兴和愤怒在类似的研究中是直观且常见的。在我们的研究中，为了实现性能与类别的丰富性之间的平衡我们采用了 Ekman 和 Friesen（1971）的六个基本情绪类别（快乐，愤怒，厌恶，恐惧，悲伤，惊喜）。应该指出的是，没有分隔正确与错误的分界线。情感类别的设置应该根据不同的情况进行适当的设置。

2.2 文本情感分类

一般来说，对于文本中的情感处理的研究和应用仍然处于一个非常初级的阶段。自然语言固有的的二义性和微妙性是许多使这项任务非常具有挑战性的因素中的一部分，尤其是在社交网络环境中，句子往往不完整、语无伦次。有很多的研究都专注于在不同类型的文本中识别和划分情绪类别，如新闻、报告、儿童童话故事、产品评论和客户反馈。通常有两种常见的方法来解决这个问题，即基于规则的和基于机器学习的方法。Chaumartin（2007）提出并实现了一种基于规则的用于标记新闻头条中的情绪的系统。它根据语言知识和预定义规则来计算单词的情绪极性。尽管这个系统达到了高精度，但召回率很低。当涉及到基于机器学习的方法时，Tan 和 Zhang（2008）探讨了四种特征选择方法（MI，IG，CHI 和 DF）和五种学习方法（质心分类器，K 近邻，winnow 分类器，朴素贝叶斯和支持向量机）。实验结果表明 IG 和 SVM 表现最好。他们还指出分类器严重依赖于域和主题。 Tokuhisa，Inui 和 Matsumoto（2008）采用 k-最近邻（k-NN）方法和两步分类模型。基于从网络提取的非常大量的数据，这个系统的表现明显要由于基准线。方法和数据集上也会存在差异。Ghazi，Inkpen 和 Szpakowicz（2010）对分层和平坦的分类方法进行了比较。唐和陈（2011）从作者角度，读者视角以及使用 Plurk 数据集的组合视角对情感挖掘进行建模。Ye，Zhang 和 Law（2009）采用了情感分类技术进行评估挖掘并在一个大型的训练数据集上达到超过 80％的准确率。 Kontopoulos，Berberidis，Dergiades 和 Bassiliades（2013）提出了利用基于本体技术对 Twitter 帖子进行的更有效的情绪分析

我们的工作与其他人不同。 我们首先引入一些来自其他领域，比如社会学的人类情感知识，并调查研究了微博上的帖子，以揭示原因事件和某些特定类型的情绪之间的一些联系。基于由 Lee 等人提出的框架 （2010a），我们还开发了一个适用于对微博数据进行情感原因提取的子系统。另外，我们不只是检测情绪原因。这一能有效的挖掘深层次信息的情感原因提取子系统，将被整合为我们的情绪分类系统的一部分，这会使得我们的分类结果变得更好。我们的探索将为情绪处理问题提供一种全新的方式。

3. 利用情绪原因检测技术进行的情感分类

我们的方法背后的基本思想是寻找对情绪是“有意义”的特征，而不是简单地选择具有较高的共现度的单词。图 1 描述了我们的情感分类方法的总体框架。在以下小节中，我们将扩展系统的重要部分，解释我们如何利用情绪原因对微博上的帖子进行情绪分类。

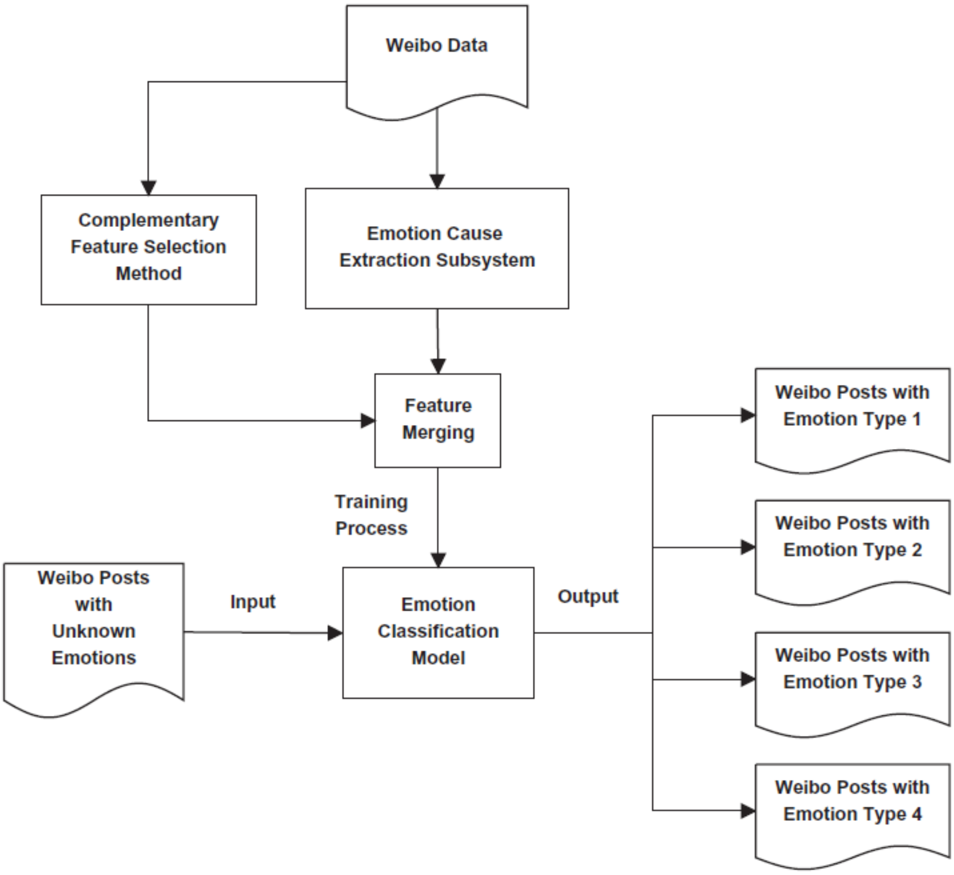

图 1. 利用情绪原因检测技术的情绪分类的一般工作流程图

3.1. 微博社交社区

微博，中文名称为“微博”，是中国的一个基于互联网的社交网络服务。 微博上的内容在格式是与Twitter类似的。每个帖子的长度都限制为140个字符。用户可以使用“@ UserName”格式来提及或与他人交谈，使用“＃TagName＃”主题标签格式来标记主题或关键点。此外，微博还提供了一些先进的功能。用户可以在他们的帖子中插入各种图形表情和网页链接或附加视频或图片。 帖子可以被评论并使用''// @ UserName''格式'重新发布'。它也作为即时通讯服务用来在用户之间交换实时消息。在2009年推出的微博迅速吸引了巨大的用户数量，现在已经成为中国是最流行的网站之一，超过 30％的互联网用户正在使用它。如图2显示了的微博的搜索热度。

图 2. 微博的谷歌搜索度趋势

典型的微博帖子是由用户所提交的简短的非正式文本。微博被选为我们的研究中的测试数据的目标来源是出于以下原因。 首先，它是最受欢迎的中国互联网用户在线发表意见的平台。因此假设包含情绪和情绪触发事件的帖子的数量是很巨大是没有任何问题的。其次，研究现代社交网络的环境中的情感分类有很多实际效益。第三，以前的研究很少关注来自网络的中文帖子。

在自动从微博上获得随机数目的帖子后，我们需要执行一些必要的预处理步骤。像网络链接和地理标记这样会造成干扰的内容会被删除。然后我们使用ICTCLAS工具包可以用适当的词性（POS）标签来解析，分割和标记中文帖子。

3.2.利用情绪原因实现的特征选择子系统

从社会学的角度来看，叙事是不可分割且带有自身情感的结构。叙事分析可以作为一个研究和检测情绪的方法（Kleres，2011）。人类的情感经历具有关键性的的叙述层面。这种技术背后的关键思想是如果已知“谁的行为如何，谁发生了什么”（Sarbin，1989）那么我们就能够对情感进行推断并分析。除此之外，

外部事件通常被视为某些情绪的触发器（Wierzbicka，1999）。Kleres（2011）也词汇和句法层面列举了一些语言表现形式，这可以让我们更好的理解情绪是如何被表达和理解的。例如，就整个句子的层面来讲，在一个带有感情色彩的含有中立的成分和对情感和双重命题的直接引用是很常见的

除了心理学家和社会学家所阐述的的意义之外，这个方法论方法也描述了一个分析框架，这个框架使得我们能够以一种不同的方式来看待情绪处理问题。由于情绪和事件之间有很强的联系，我们很自然地想到找出引发情绪的事件可能有助于挖掘情绪。所以在我们的工作中我们尝试通过找出为什么会产生情绪以及他们如何被人类读者感受到来检测情绪。首先，我们采用情绪事件的概念。 如 Talmy（2000）所述，’触发事件’应该是情感产生的原因。应该指出原因事件并不总是我们通常理解上的实际触发事件。它也可能是导致某人产生某种情绪或者某种看法的事件。这里有些例子，在这些例子中，原因事件部分被着重强调了。

1. *Shi3 Zai4 Tai4 Gao1 Xing4 Le, Wo3 De Fen3 Si1 Chao1 Guo4 Bai3 Wan3 Le!*
   (I am so thrilled that I have more than one million followers now!)
2. *Zu3 Qiu3 Zhi3 Shi4 Yi1 Xiang4 You3 Xi4. Yan3 Bian4 Cheng2 Ru2 Ci3 Xue4 Xing1 De4 Si1 Sha1, Bei1 Ai1 A4!*
   (Soccer is just a game. How could it turn into such a violent fight. What a tragedy!)
3. *Zui4 Ai4 Zhou1 Mo1 De4 Hao3 Shi2 Guang1 Le. He2 Qin1 You3 Yi4 Qi3 Chi1 Fan4, He1 Cha2. Zhen1 Shi4 Tai4 Qie4 Yi4 La.*
   (Love the good time of weekend most. It is such a pleasure to have dinner and drink some tea with family and friend.)

Lee 等人 （2010a）证明了挖掘像情绪原因事件这类深度信息的的可行性，这恰好情感叙事性的社会学理论相符。他们介绍一个精心设计的多才多艺的框架用于情绪原因事件检测。 该框架由以下关键部分组成：

1. 标记列表：标记情感原因事件出现的的关键字列表。
2. 情感关键字列表：通常用于表达情绪或感受的单词和短语的列表。
3. 语言模式集：描述的情绪如何表达以及元素如何组织的语言模式表。

由于和在文本中检测和抽取情绪原因事件具有相似的目标，我们决定引入基于规则的方法的一般结构。然而，Lee 等人（2010a）的工作是基于“中国科学院现代汉语平衡语料库”的，简称“科学语料库”（Chen，Huang，Chang，＆Hsu，1996 年）。这个语料库收集的文本包括新闻报道、小说和诗，这些文本通常很长且规范。而我们的工作正好相反，我们的重点是在微博上发布的简短（有时甚至不完整）并且不正式的帖子。在文本类型上存在的明显的区别意味着算法的原始设置不在适用于我们的任务。

为了克服这个问题，我们进行了彻底的调查研究以重新设计系统。首先，我们基于微博研究了一个单独的包含超过 1000 个随机情绪实体的开发数据集。我们测试了整个语言暗示词列表（Lee，Ying，＆Huang，2010b）中的词汇，以研究每个单词在识别情绪原因事件的出现上的效果。一些形式词和短语在微博中极为罕见，一些日常的随意性表达更有可能被互联网用户使用。基于手动检查，我们从标记列表中删除了并不经常与原因事件搭配出现的词，并添加一些新的词汇。表 1 是适应微博帖子后的标记列表。

表 1.语言标记词列表

Group No.	Cue Words
I	'let/make': Rang4, Ling4, Shi3, Gao3De2, Nong3De2, Shi3De2
II	'to think about': Xiang3, Xiang3Dao4, Xiang3Qi3, Yi1Xiang3
	'to talk about': Shuo1Dao4, Jiang3Dao4
III	'to feel': Gan3Dao4, Jue2De2, Gan3Jue2
IV	'to see': Kan4Dao4, Kan4Jian4, Jian4Dao4
	'to hear': Ting1Dao4, Ting1Shuo1
	'to know': Zhi1Dao4, De2Zhi1, Fa1Xian4
V	'for': Wei4Le, Dui4Yu2
VI	'because': Yin1, Yin1Wei4, You2Yu2
VII	'is': Shi4, De4Shi4
	'can': Neng2, Neng2Gou4, Ke3Yi3

出于同样的原因，传统的情感词汇列表比如由知网提供的并不适用于微博数据。相反，我们使用在经过长期工作后建立的情感词汇列表。它总共包含 1845 个通常用来表达感受，意见和情绪的单词和短语。该清单涵盖了许多中文流行的网络词汇和短语像''Niu2''（超棒）和''Gei3Li4''（真棒）。它还包括大部分的同义词和常见关键字变体。

然后，在将 Kleres（2011）描述的互联网用户典型的表达习惯和的结构模式考虑在内之后，我们独立地归纳出了一组语言模式，用于精确定位情感原因。由于长度限制，每个帖子通常都只专注于一个主题。简洁而富有表现力的特征通常暗示着它很可能成为情感原因事件如果事件是从帖子中提取的话。另外，我们删除了子句约束使模式匹配过程更加灵活。

我们的最终目标是对情感类型进行分类。情绪原因提取是为了改进传统特征选择过程而进行的尝试。很明显，如果选定的特征中有太多的噪声，分类器难以实现良好性能。所以在我们设计规则集时，精度比召回率有更高的优先级。
。表 2 列出了我们总结出的用于描述中文微博帖子中的元素之间的联系的语言模式，包括情绪化表达式、关键词和情绪原因。

表 2. 情绪原因检测的语言模式

No.	Linguistic pattern
1	C + I + E + K E: the nearest Noun after I C: the nearest (Noun, Verb, Noun) before I
2	E + K + II/III/IV + C E: the nearest Noun before II/III/IV C: the nearest (Noun, Verb, Noun) after II/III/IV
3	V/VI + C + E + K E: the nearest Noun before K C: the nearest (Noun, Verb, Noun) after V/VI
4	E + "yue4Cyue4K" E: the nearest Noun before "yue4Cyue4K" C: the nearest (Noun, Verb, Noun) in "yue4Cyue4K"
5	E + K + V/VI + C E: the nearest Noun before K C: the nearest (Noun, Verb, Noun) after V/VI
6	IV + C + [E] + K C: the nearest (Noun, Verb, Noun) after IV
7	E + V/VI + C + K E: the nearest Noun before V/VI C: the (Noun, Verb, Noun) between V/VI and K
8	C + E + IV + K E: the nearest Noun before IV C: the nearest (Noun, Verb, Noun) before E
9	[E + K] + VII + C + [E + K] one of the two 'E + K' must present C: the nearest (Noun, Verb, Noun) after VII

在表 2 中出现的缩写和符号的解释如下所示：

- C: Cause event
- I/II/III/IV/V/VI/VII: Linguistic markers in the corresponding group
- E: Experiencer
- K: Emotion Keyword
- "[]": Optional linguistic components.

在自然语言中，动词和名词都可以用来叙述事件。 Lee 等人（2010a）利用（名词，动词，名词）结构来表示事件，但是由于一些现实的困难不得不使用分句来代替。但是，因为微博很简短，有时由不完整的句子组成或者在很多情况下一个分句就可能包括了帖子中大半的内容。为了更准确地指出帖子中的情绪原因，我们设计的表达方案如下。首先，系统寻找（名词，动词，名词）的结构作为基本框架。因为情绪原因可以表示为命题或名义（Lee 等，2010a）同时由于微博具有的非正式性特点，没有必要同时用两个名词和一个动词来表示情绪原因。在实践中，如果三者中至少有一个是被认为是匹配的，那么原因（C）就会被看做是模式的一部分。在定位为这个框架之后，该框架之外的文本将被丢弃。换句话说，只有这个框架内的子串被保留并作为情感原因返回，而不是保留包含结构的整个子句。以下给出两个例子。

1. **Original Post:** *"Zhong1 Guo2 Hao3 Sheng1 Yin1" Rang4 Wo3 Jing1 Tan4, Zhe4 Shou3 Ge1 Ba3 Wo3 Ye3 Chang4 De2 high Qi3 Lai Le, Shui4 Bu4 Zhao2 Jiao4.*
   ("The Voice" surprised me. This song really made me excited and unable to sleep.)
   Linguistic Pattern: [C (Noun):(*"Zhong1 Guo2 Hao3 Sheng1 Yin1"*)]+[I:*Rang4*]+[E: *Wo3*] + [K: *Jing1 Tan4*]
   ([C (Noun): ("The Voice")] [K:surprised] [E:me])
   Emotion Cause Event: *"Zhong1 Guo2 Hao3 Sheng1 Yin1"*
   ("The Voice")
2. **Original Post:** *Zai4 Jia1 Li3 Dou1 You3 Ming2 Xian3 Zhen4 Gan3, Ke3 Shi1 Di4 Zhen4 Ju2 Que4 Mei2 Neng1 Fa1 Bu4 Yu4 Gao4, Nong4 De2 Ren2 Men2 Hen3 Shi4 Fen4 Nu4.*
   (We can even felt the shake in our apartments, but the Seismological Bureau failed to send any warning, which made people very angry.)
   Linguistic Pattern: [C (Noun,Verb,Noun):*(Di4 Zhen4 Ju2, Mei2 Neng1 Fa1 Bu4, Yu4 Gao4)*] + [I: *Nong4 De2*] + [E: *Ren Men2*] + [K: *Fen4 Nu4*]
   ([C (Noun, Verb, Noun): (Seismological Bureau, failed to send, warning)] [I: made] [E:people] [K: angry])
   Emotion Cause Event: *Di4 Zhen4 Ju2 Que4 Mei2 Neng1 Fa1 Bu4 Yu4 Gao4*
   (Seismological Bureau failed to send any warning)

对于这两个示例，都会应用语言模式 1 来提取原因。在例 1 中，只有一 个名词被找到，所以它被保存为情绪原因。在例 2 中，整个（名词，动词，名词），三元组被找到，所以这个结构中的子字符串被保存为情绪原因。

在已经抽取出了用于训练的帖子中的情绪原因之后，所有表示原因事件的字符串被保留。然后我们从情绪原因的集合中删除所有的停止词。我们之所以将“去除停用词”从预处理步骤移到到这里是因为我们的情绪原因抽取子系统部分依赖于停用词（语言标记）。然后我们组合所有剩余的单词和情感关键字（K），这些情绪关键字被用于在抽取阶段组成情绪原因事件集合。情绪原因集合是（C）s 和（K）s 的聚集。

对于帖子中是否包含明确的情绪和相应的原因，有三种情况：

1. 中性帖子（包括情绪类型过于模糊以至于无法判断情绪类型的帖子）；
2. 带有情绪和情绪的帖子。
3. 有情感，但没有明确表达情感的帖子。

显然，如果我们只使用情绪原因提取子系统的输出作为选定的特征，情况 1 和 3 将是难以区分，因为它们都不含可提取的情绪原因。为了将那些包含情绪却没有明确的情绪原因的句子和中性句区分开来，我们必须找出一种特征选择方法可以应用于情况 3。我们选择 χ^2（卡方）测试。χ^2 测试是依赖性的经典测试方法。它将观察得到的数据与根据具体假设预期得到的数据进行对比。卡方是观测

值与预期值平方差的总和与预期值的做除法得到的值。χ^2 测试的定义式为：

$$\chi^2=\sum\frac{(O-E)^2}{E}$$

在表达式中，χ^2 是卡方，O 是在每个类别上的观测频率，E 是期望的频率。

以 χ^2 测试为补充，我们的特征选择策略可以直接生成。由情绪原因提取和 χ^2 测试产生的两组特征被混合以最终的特征集。算法 1 描述了合并过程，其中的 emocause_set 是情绪原因的集合，Chi_list 是按 χ^2 测试分数降序排列的单词列表，final_set 为最终的特征集。

Algorithm 1. Feature set merging

1: $d \leftarrow$ predefined dimension of final feature set
2: $d\_cause \leftarrow$ sizeof ($emocause\_set$)
3: $r \leftarrow d - d\_cause$
4: $final\_set \leftarrow emocause\_set$
5: **for** each w in Chi_list **do**
6:   **if** r == 0 **then**
7:     break
8:   **else**
9:     **if** w is not in $final\_set$ **then**
10:       add w to $final\_set$
11:       $r \leftarrow r - 1$
12:     **else**
13:       *continue*
14:     **end if**
15:   **end if**
16: **end for**

3.3 用于情绪分类的 SVM 和 SVR

支持向量机（SVM）已经被证明是可以被用于文本驱动的情绪分类的有效模型。基于风险最小化原则，SVM 根据从训练数据中选择的元素做出决定。它寻求一个超平面来将训练数据分为正面和负面两个类别。图 3 描绘 SVM 的基本机制。

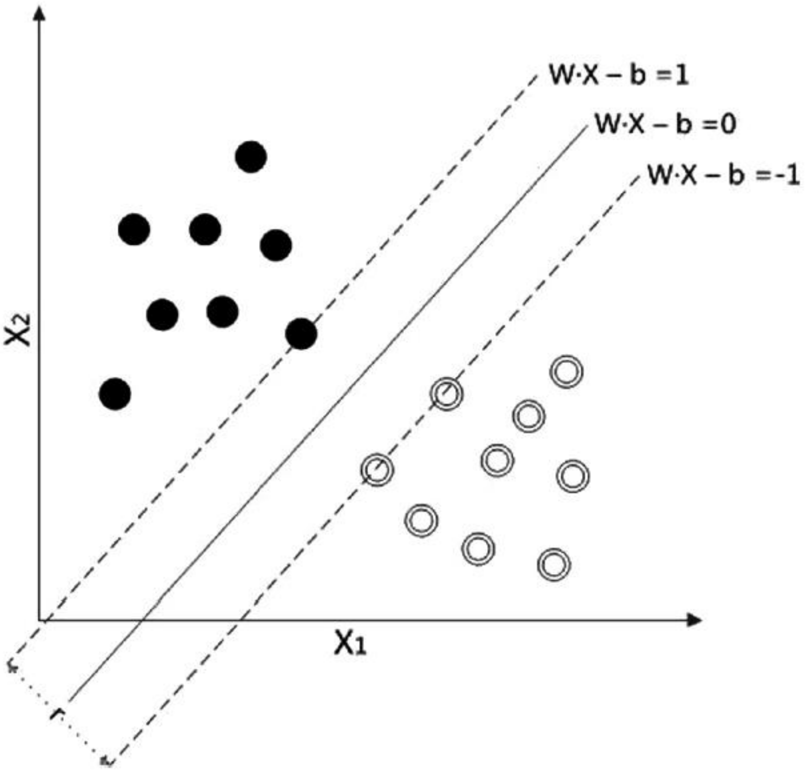

图 3. 具有余量的 SVM 最大超平面

就选定的核心函数 K（x，y）而言，SVM 有几种不同的变体。在我们的工作中，我们将讨论限定在线性内核函数上，因为其具有相对较高的性能。此外，因为我们的工作集中在从微博网站随机抓取的简短和不规范的文本上，因此我们支持向量回归（SVR）用于分类任务。 SVR 是由 Drucker，Burges，Kaufman，Smola 和 Vapnik（1997）提出的 SVM 的一种版本。它使用与 SVM 相同的原理，但 SVR 的输出是一个实数。对于处理一个不平衡的数据集而言，这是一个更好的选择。
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4.实验和讨论

我们的实验分两步完成：

1. 抽取情绪原因事件；
2. 训练并且测试分类器

在这一节，首先介绍我们构建的基于微博的数据集。之后我们将说明实验的两个步骤以及分别用到的对应的评估方法。

4.1 微博情绪数据集

首先，我们从微博上随机爬取下 20000 多个帖子。删除重复的帖子之后，16485 个帖子被留在了我们的数据库中。两个人工标记员对语料库中的所有语料进行人工标注，标注出它们的情绪类型并且如果情绪原因存在也需要标注出情绪原因。为了避免歧义并简化问题，只有明确表达某种类型的情绪的语料会被标记为“具有情绪“，并且被标记上相应的情绪标签。当多中情绪存在于同一个词条中，只有主导词被选中并贴上标签。如果情绪类型不清楚或难以确定，这些条目将被视为中立。帖子注释不一致被转发给第三个注释者作最后决定。此外，所有帖子在注释后均由作者确认。

情绪原因事件由目标文件的一个子串表示。例如，在句子“Zhen1 Gao Xing4，Jin1 Tian1 Dao4 Gong1 Si1 Hou4 Ling3 Dao3 Gei3 Wo3 MenMei3 Ge4 Ren2 Dou1 Fa1 Le4 Hong2 Bao1。”（“今天真高兴在我们到公司后，我们的老板给了每个人一些奖金”），字符串“Ling3 Dao3 Gei3 Wo3 MenMei3 Ge4 Ren2 Dou1 Fa1 Le4 Hong2 Bao1。”（“老板给大家一些奖励”）被复制并标记为情绪原因事件。标注者被指示遵循最小长度的规则，这意味着只有标记足够覆盖原因的最短长度。我们假设在微博上没有超过 140 个字符的帖子，这意味具有多个情绪原因事件的情形是非常罕见的，可以被忽略，因此这种假设是合理的。。表 3 列出了在我们的语料库中每种情绪分类对应的的实例的实际数量。我们保持数据集处于不平衡状态，因为我们认为这反映了实际情况。一个重要的原因在于很大比例的帖子是没有评论的重新发布或者是由第三方应用程序自动生成。此外，通常不包含情绪的新闻标题占了中性帖子的很大一部分。

表 3. 语料库摘要

Emotion	Number of posts	Number of posts with causes
Happiness	513	354 (69.0%)
Anger	478	452 (94.6%)
Disgust	153	137 (89.5%)
Fear	125	61 (48.8%)
Sadness	313	255 (81.5%)
Surprise	102	46 (45.1%)
Neutral	14801	N/A
Total	16485	1305

4.2 情绪原因抽取

4.2.1 评估标准

与其他的自然语言处理任务类似，我们用三个关键变量来评估我们的实验结果：精确度、召回率和 f-分数。在我们对情绪原因抽取子系统的评估中，精确度和召回率的定义如下所示：

$$Precision(G,S) = \frac{\sum_{P_i \in G} \sum_{k_j \in P_i} ListP(SList_j, GList_j)}{\sum_{P_i \in S} \sum_{k_j \in P_i}} \quad (1)$$

$$Recall(G,S) = \frac{\sum_{P_i \in G} \sum_{k_j \in P_i} ListR(SList_j, GList_j)}{\sum_{P_i \in G} \sum_{k_j \in P_i}} \quad (2)$$

$$ListP(SList, GList) = \frac{\sum_{SStr_j \in SList} \max_{GStr_i \in GList} StrP(GStr_i, SStr_j)}{|SList|} \quad (3)$$

$$ListR(SList, GList) = \frac{\sum_{GStr_j \in GList} \max_{SStr_i \in SList} StrR(GStr_i, SStr_j)}{|GList|} \quad (4)$$

其中 G 是人类注释的黄金标准原因集合，S 是我们的系统产生的原因集合，P_i是在数据集中的一个微博帖子，k_j是这篇文章中的情绪关键词，$SList_j$和 $GList_j$是对应在 P_i中的关键字 k_j的系统输出和黄金标准的情感原因列表，$SStr_i$和 $GStr_i$是表示情绪原因的字符串。

有两种方法可以计算 StrP 和 StrR：松弛匹配 1 和松弛匹配 2（Lee 等人，2010a)。松弛匹配 1 只考虑系统输出字符串和我们的黄金标准字符串之间是否有任何重叠。松弛匹配 2 需要考虑重叠长度。因为我们打算对原因提取系统的改进进行简要评估，因此我们简化了这部分并采用了松弛匹配 1 的方案。

$$StrP(GStr, SStr) = \begin{cases} 1 & if\ GStr\ and\ SStr\ overlaps \\ 0 & else \end{cases} \quad (5)$$

$$StrR(GStr, SStr) = \begin{cases} 1 & if\ GStr\ and\ SStr\ overlaps \\ 0 & else \end{cases} \quad (6)$$

计算出来的 F-分数通常作为精确度和召回率的谐波平均值。

4.2.2 原因抽取的结果

为了评估我们针对微博环境重新设计的基于规则的系统的，我们根据李等人（2010a）提出的相同的规则和语言线索在相同的微博数据集上进行原因抽取实验。

因为文本类型之间的差异，我们决定采用相同的基线以实现更好的比较。这个简单的基准线可以用一条规则来描述：C（V）+ K，表示在情绪关键字左边包含第一个动词的子句就是情绪原因子句。

表 4 显示了基线和初始规则集的性能。最初的规则集在精确度方面明显优于基准线。但是，其召回率远低于基线。造成这个结果的一个主要原因是初始的规则集不是基于微博帖子设计的，这也是证明了我们调整工作的必要性。

表 4. 原始原因抽取规则集的性能

	Precision	Recall	F-score
Baseline	45.06	51.24	47.95
The original rule-set	71.63	41.51	52.56

表 5 显示了我们系统的整体性能。因为语言标记列表和专为微博帖子设计的规则集的存在，系统的精确度和召回率都大大提高。

表 5. 重新设计算法的性能

	Precision	Recall	F-score
Redesigned algorithm	75.70	51.59	61.30

表 6 显示了基准线和我们的整合了情绪原因的系统在情绪分类上的性能。符号“with EC”意味着情绪分类的结果是利用情绪原因提取技术得到的。对于大多数情绪类别（高兴，愤怒，恐惧和惊奇），我们的系统具有更高的精度同时保持同一级别的召回。对于情绪类别讨厌，虽然我们的系统精度较低，但召回率更高。就可以同时评价评估精确度和召回率的 F 评分而言，我们的系统在大多数情况下明显优于基线。具体而言，高兴的 f 分数提高了 1.6%愤怒 2.0%，厌恶提高了 9.2%，惊奇提高了 0.8%。这表明情绪原因提取技术在选择更有效，含有更丰富信息的特征方面非常有效。对于悲伤这种情绪分类，我们的系统无法超越基准。我们的假设是不开心的时候人们不愿意陈述原因。人们在像高兴或惊奇这样的积极或强烈的情绪之下更热衷于描述当下的情况。所以从表达悲伤情绪的帖子中抽取情绪原因的效果并没有从表达其他感情的帖子中抽取情绪原因的效果好。

尽管通常精度和召回率还不是很高，改善的结果确实证明了我们提出的方法的巨大潜力。此外，随着训练数据集的规模变得越来越大，像 χ^2 测试这样的经典特征选择方法计算复杂度呈指数增长，而基于规则的系统只有线性增长趋势。

5. 结论和未来工作

情绪分类具有广泛的应用空间。一个准确和高效的分类系统是非常有趣的。在研究中，我们引入了关于从社会学中引入的关于情绪和叙事的关系，同时利用情绪原因提取技术研究了文本情绪分类的任务。我们对一个中文微博平台进行了实验。首先，自动收集了 16485 可能存在情绪的帖子。之后我们的工作分两子步骤完成：利用情绪原因提取技术的特征选择和利用 SVR 技术的情绪分类。我们基于通用的社交网络特征和其他经过详细总结的语言模式设计了一个基于规则的

子系统用来从原始文本中检测和提取原因事件。这个子系统的输出用于生成用于训练分类器的特征集。我们也说明了基准线的情况。实验结果表明，利用情绪原因提取技术，我们的系统大多数情况下明显跑赢了基准系统。具有前景的结果表明利用来自其他学科的知识和方法的模型改善传统情绪分类模型的潜力。

尽管利用情绪原因提取技术，我们成功的获得了非常好的结果，我们工作还不够全面的。仍然有很多等待着我们去研究的对人类情绪会产生巨大影响的因素存在。处理具有复杂的语言模式的文本仍然具有很大的挑战。除此之外，总结和设计语言模式的工作仍然经过良好训练的人类专家耗费大量的人力和时间。

在未来的工作上，我们首先需要测试其他的元素以发现它们在我们的任务中的优缺点。我们也计划设计一个更复杂的原因提取系统，以更好的解决具有挑战性的情况同时减少错误。更多的语言模式也需要继续探索。最后，我们需要找到一种方法可以自动产生和修改模式集合，这样的话人类需要付出的劳动就可以最小化。