Visualizing Emotions from Chinese Blogs by Textual Emotion Analysis and Recognition Techniques

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Published 19 August 2014

The research on blog emotion analysis and recognition has become increasingly important in recent years. In this study, based on the Chinese blog emotion corpus (Ren-CECps), we analyze and compare blog emotion visualization from different text levels: word, sentence, and paragraph. Then, a blog emotion visualization system is designed for practical applications. Machine learning methods are applied for the implementation of blog emotion recognition at different textual levels. Based on the emotion recognition engine, the blog emotion visualization interface is designed to provide a more intuitive display of emotions in blogs, which can detect emotion for bloggers, and capture emotional change rapidly. In addition, we evaluated the performance of sentence emotion recognition by comparing five classification algorithms under different schemes, which demonstrates the effectiveness of the Complement Naive Bayes model for sentence emotion recognition. The system can recognize multi-label emotions in blogs, which provides a richer and more detailed emotion expression.

Keywords: Natural language processing; affective computing; emotion recognition; emotion visualization.

1. Introduction

Given the rapidly growing popularity and size of the Internet, research on weblogs is also increasing. Weblogs are more like personal journals, consisting of a lot of day to day thoughts, emotions, and actions of an individual, which provide a platform and rich resource for human related research, for example, automatically identifying bloggers by age, gender, personality, sentiment (also called opinion), and affect (also called emotion).
The research on blog emotion analysis and recognition has become increasingly important in recent years. As response time of blogs is faster than traditional media, and bloggers are not constrained by formality, a blog emotion analysis and recognition system can detect emotion for bloggers, capture emotional change, and predict future emotion rapidly. It would be helpful for solving some social and psychological problems, and giving early warnings, such as for suicide or terrorism.

Blog emotion analysis and recognition are essentially a textual content-based information extraction and classification problem. Compared with other text styles, the main characteristics of emotional expressions in blogs mainly include:

1. The integrity and continuity of using language. As blogs are personal diaries, using a way of narrative writing to express feelings, compared with text messages and spoken dialogs, the emotional expression is more integrated and the content has time continuity. So blogs can be used as a kind of good material to analyze and track a writer’s emotion change.

2. Highly personal and subjective writing style. Identification of emotion holder and emotion target is very important in the task of textual emotion recognition. In blogs, in most cases bloggers are seen as emotion holders and all entities in blogs as emotion targets. Meanwhile, most of the expressions in blogs are subjective, so the main focus of blog emotion recognition is multiple emotion recognition, that is, classify a text according to a blogger’s emotions (e.g., happy, sorrow) instead of based on its polarity (i.e., positive or negative).

3. New words and expressions are constantly emerging in blogs. Current available emotion lexicons are not able to meet the need of blog emotion analysis and recognition, so automatically recognition of word emotion according to its certain context is vital for a robust blog emotion recognition system.

In this paper, we focus on visualizing emotions from Chinese blogs using textual emotion analysis and recognition techniques. As emotion is inherently abstract and nonvisual, visualizing emotions inferred from blogs allows a fast view on the emotion structure of a blog article. A Chinese blog emotion corpus (Ren-CECps) has been used as emotion resource for this study. Based on Ren-CECps, we analyze and compare blog emotion visualization from different text levels: word, sentence, and paragraph. Then, a blog emotion visualization system is designed for practical applications, which includes two main parts: a blog emotion recognition engine and an emotion visualization interface. The blog emotion recognition engine is composed of three modules: word emotion recognition, sentence emotion recognition, and document emotion recognition. Machine learning methods are applied for the implementation, which can provide multiple emotion recognition in blogs. The blog emotion visualization interface is designed to provide more intuitive display of emotions in blogs, which can detect emotion for bloggers, and capture emotional change rapidly.

The remainder of this paper is organized as follows. In Sec. 2, a literature review is conducted on the studies of textual affective computing and emotion
visualization. Section 3 first presents a brief introduction of the emotion knowl-
edgebase, Ren-CECps, then presents blog emotion visualization methods based on
Ren-CECps. Section 4 presents the principle of our blog emotion recognition engine
and the emotion visualization interface. Section 5 concludes this work with closing
remarks and future directions.

2. Literature Review

Within the psychosociological models of communication, language is no longer seen
as merely carrier of information, but also as ‘an essential dimension of the culture to
which are ascribed most of the social values and representations on which collective
exchanges and practices are based. Written text is rich in semantics, content
meaning as well as emotions. In more recent years, there is a strong growth of
research interest on affective computing from the view of improving human–com-
puter interfaces.

Classified by different classification targets, there are basically two highly-related
branches of textual-based affective computing, one is sentiment analysis (or opinion
mining), the other is emotion recognition.

Sentiment analysis aims to extract and mine opinions, views, and attitudes from
online reviews. It focuses on the valence of a text (i.e., positive or negative; bad or
good) rather than assigning the text to a particular emotion category (e.g., angry or
sad). Sentiment analysis dates back to the late 1990s, current-day sentiment
analysis is mainly classified into two classes: document-level, which focuses on
producing an overall opinion from one document; and feature-level which aims to
discover feature entities from sentences and then identifies opinions that are asso-
ciated with each entity.

Textual emotion recognition aims to classify the mood of a single text into a basic
emotion category, which has close relationship with the research of cognitive psy-
chology. Different from emotion information access from speech recognition, facial
expression detection, gesture expression recognition, and physiological
signal monitoring. Textual emotion recognition is linguistic-based affective com-
puting technique, mainly based on machine learning and semantic analysis techni-
cues, and as such it shares a number of characteristics with other tasks such as
information extraction and text mining.

Classifying the emotion of a single text is a hard task; state-of-the-art methods in
text classification achieve only modest performance in this domain. Classifying by
the cues for emotional expression, there are basically two ways for textual emotion
recognition: the emotion-invoking event-based method and the emotional word-
based method. Emotion-invoking event-based method focuses on detecting emotion
of an individual “event” embedded in a sentence. For example, Liu et al. proposed an
approach based on a large-scale common sense knowledgebase (ConceptNet) to
classify sentences into basic emotion categories. Wu et al. reported an approach of
using the semantic labels (SLs) and attributes (ATTs) of entities of a sentence for
sentence level emotion detection.\(^3\)\(^6\) Lu et al. recently reported an approach based on the probability distribution of common mutual actions histogram between entities for event-level textual emotion sensing.\(^3\)\(^7\) Emotion-invoking event-based method would be effective for those sentences with explicit emotion-invoking events. However, there are a lot of sentences that can evoke emotion without emotion-invoking events. In addition, emotion-invoking event-based method is hard to recognize the emotions for a compound sentence.

The emotion lexicon-based method can be seen as the most natural approach and also probably the most popular method. The weakness of this approach is the limitation of existing emotion lexicons. As new words are constantly emerging on the Internet, existing emotion lexicons are not able to feed the requirements of Internet emotion analysis and recognition.

Although textual emotion recognition provides a convenient way to grasp the emotions of a text, especially for the huge amounts of texts on the Internet, emotion is inherently abstract and nonvisual, visualizing emotions inferred from text allows a fast view on the emotions of a text. Some researches and projects on textual emotion visualization include “Synesketch: textual emotion recognition and visualization engine”,\(^3\)\(^8\) “We Feel Fine: visualizing human emotions”,\(^3\)\(^9\) and visualizing text affective structure.\(^4\)\(^0\) Synesketch uses the WordNet-based lexicon of words and their emotional weights together with NLP heuristics to “feel” basic emotions in the text: happiness, sadness, fear, anger, disgust, and surprise (categories defined by Ekman\(^4\)\(^1\)). Based on that, software generates appropriate visual patterns. “We Feel Fine”\(^3\)\(^8\) provides several visualizations of human emotions inferred from text that is posted on the Internet. The system searches the world’s newly posted blog entries for occurrences of the phrases “I feel” and “I am feeling”. When it finds such a phrase, it records the full sentence, up to the period, and identifies the “feeling” expressed in that sentence (e.g., sad, happy, depressed, etc.). Liu et al.\(^4\)\(^0\) affectively analyzed using a textual affect sensing engine, and sentences are annotated using six basic emotions proposed by Ekman. Then, colors used to represent each of these emotions are sequenced into a color bar.

3. Blog Emotion Visualization Based on Ren-CECps

3.1. The Chinese emotion corpus: Ren-CECps

Ren-CECps (a Chinese emotion corpus developed by Ren-lab)\(^a\) is constructed on the basis of a relative fine-grained annotation scheme, which annotates emotions in text at four levels: document, paragraph, sentence, and word. The dataset consists of 1487 blog articles published at sina blog, sciencenet blog, etc. The corpus contains 11,255 paragraphs, 35,096 sentences, and 878,164 Chinese words.\(^4\)\(^2\) Figure 1 shows an example of an annotation file (xml format) in Ren-CECps.

\(^a\)http://a1-www.is.tokushima-u.ac.jp/member/ren/Ren-CECps1.0/DocumentforRen-CECps1.0.html.
In Ren-CECps, the emotions of a document (paragraph, sentence, and word) are represented by a vector:

\[ \mathbf{d} = (e_1, e_2, \ldots, e_n). \]  

(3.1)

Here, \( e_i (1 \leq i \leq n) \) is a basic emotion class contained in document \( d \). The values of \( e_i \) range from 0.0 to 1.0 (discrete number), indicating the intensity of each basic emotion class. Ren-CECps selects eight basic emotions (expectation, joy, love, surprise, anxiety, sorrow, angry, and hate) for manual annotation. Accordingly, emotions of a document in Ren-CECps are represented as

\[ \mathbf{d} = (\text{expect}, \text{joy}, \text{love}, \text{surprise}, \text{anxiety}, \text{sorrow}, \text{angry}, \text{hate}). \]  

(3.2)
The example document in Fig. 1 contains three emotions, and the corresponding emotion vector is represented as
\[
d = (0.0, 0.6, 0.9, 0.0, 0.0, 0.7, 0.0, 0.0).
\]

During the process of annotating Ren-CECps, annotators were encouraged to follow their “first intuition,” that is, they were not forced to follow any criteria for selecting emotion categories and intensities. Additional details about the annotation agreement analysis of the Ren-CECps corpus can be found in Ref. 42.

### 3.2. Blog emotion visualization based on Ren-CECps

#### 3.2.1. Blog emotion visualization based on word emotions

Emotional words are most direct manifestation of textual emotion. Based on emotional words in an article, the following information is considered to be used for blog emotion visualization:

1. positions of emotional words in an article;
2. emotion categories of emotional words;
3. emotion intensities of emotional words.

Take the blog in Fig. 1 as an example, Table 1 lists the emotional words annotated in this blog.

Figure 2 shows the emotion distribution of the emotional words in this blog. We use different colors to represent the different emotions. The correspondence between colors and basic emotions is based on “Emotions Color Wheel”. Word emotion annotation is from Ren-CECps. For the emotional word that appears multiple times in this blog, like “ ($) (Cry)”, it showed only once in Fig. 2.

Figure 2 shows that most emotional words of this blog maintain the emotions of sorrow, followed by joy and love. Except for the information of emotion distribution that can be inferred from this figure, more information, for example, emotion intensity and emotion change of the blogger, is difficult to obtain. Then, based on Fig. 2, according to the order in which these emotional words are appearing in the text, the emotions of this blog are illustrated by Fig. 3. If a word maintains more than one emotion, its emotions are represented by multiple blended colors. Emotion intensities are distinguished by color depth.

From the view of the order in which these emotional words are appearing in the blog, this blog starts with surprise as emotion, ends with love as emotion, and anxiety as emotion is always found throughout the whole text. We can also find that the words with similar emotions tend to appear together.

Figure 3 demonstrates that the use of word emotions can reflect blog emotions generally. However, the negative words, degree words, conjunctions and

\(^{6}\text{http://www.do2learn.com/organizationtools/EmotionsColorWheel/index.htm.}\)
Table 1. The emotional words of the blog in Fig. 1.

<table>
<thead>
<tr>
<th>Chinese</th>
<th>English</th>
<th>Chinese</th>
<th>English</th>
</tr>
</thead>
<tbody>
<tr>
<td>震惊</td>
<td>Shock</td>
<td>信任</td>
<td>Trust</td>
</tr>
<tr>
<td>悲痛</td>
<td>Grieved</td>
<td>灾害</td>
<td>Disaster</td>
</tr>
<tr>
<td>开心</td>
<td>Happy</td>
<td>镇定</td>
<td>Calm</td>
</tr>
<tr>
<td>废墟</td>
<td>Ruins</td>
<td>乐观</td>
<td>Optimism</td>
</tr>
<tr>
<td>救援</td>
<td>Help</td>
<td>微笑</td>
<td>Smile</td>
</tr>
<tr>
<td>哭</td>
<td>Cry</td>
<td>感动</td>
<td>Moving</td>
</tr>
<tr>
<td>没事</td>
<td>Out of danger</td>
<td>团结</td>
<td>Unite</td>
</tr>
<tr>
<td>笑</td>
<td>Laugh</td>
<td>灾难</td>
<td>Disaster</td>
</tr>
<tr>
<td>笑声</td>
<td>Laughter</td>
<td>对抗</td>
<td>Confrontation</td>
</tr>
<tr>
<td>畏惧</td>
<td>Fear</td>
<td>胜利</td>
<td>Victory</td>
</tr>
<tr>
<td>坚强</td>
<td>Strong</td>
<td>泪水</td>
<td>Tear</td>
</tr>
<tr>
<td>顽强</td>
<td>Tenacious</td>
<td>平安</td>
<td>Safety</td>
</tr>
</tbody>
</table>

Fig. 2. (Color online) The emotion distribution of the emotional words of the blog in Fig. 1.

Fig. 3. (Color online) Blog emotion visualization based on the order of emotional words appearing in a blog.
punctuations that appear around emotional words may change their emotions, so the use of sentence emotions will reflect blog emotions more accurate.

### 3.2.2. Blog emotion visualization based on sentence and paragraph emotions

Sentence emotions are determined by the varieties of linguistic expressions that indicate emotion, such as emotional word/phrase, degree word, negative word, conjunction, and so on. The emotion sequence composed by each sentence emotion in a blog describes a blogger’s emotional experience and change. Therefore, it can be assumed that the emotion structure of a blog is consistent with the order of emotional sentences in this blog. Paragraph emotions are a summarization of sentence emotions, which provide a rough review of blog emotions. Table 2 lists the sentence and paragraph emotions annotated in the blog in Fig. 1. (The sentences and paragraphs without emotions are not included in Table 2.)

Based on the order of emotional sentences and paragraphs that appear in this blog, the emotions of this blog are illustrated in Fig. 4.

<table>
<thead>
<tr>
<th>Paragraph</th>
<th>Sentence</th>
<th>Paragraph</th>
<th>Sentence</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Expectation, joy, sorrow</td>
<td>1</td>
<td>Sorrow</td>
</tr>
<tr>
<td>2</td>
<td>Sorrow, love</td>
<td>2</td>
<td>Sorrow</td>
</tr>
<tr>
<td>3</td>
<td>Joy, love, sorrow</td>
<td>3</td>
<td>Sorrow</td>
</tr>
<tr>
<td>4</td>
<td>Expectation, love</td>
<td>4</td>
<td>Sorrow, love</td>
</tr>
</tbody>
</table>

Table 2. Sentence and paragraph emotions of the blog in Fig. 1.

![Emotion marks](#)

**Emotional sentences:**

![Emotional sentences](#)

**Emotional paragraphs:**

![Emotional paragraphs](#)

Fig. 4. (Color online) Blog emotion visualization based on the order of emotional sentences and paragraphs in a blog.
From the view of sentence emotions, Fig. 4 shows that sorrow and expectation are the main emotions of this blog, followed by love and joy. Compared with Fig. 3 that is based on word emotions, based on sentence emotions, Fig. 4 reflects the emotion of this blog more accurately. From Fig. 4, we can also easily track the blogger’s emotions change that starts from surprise, to joy and love, and then to expectation and anxiety, finally ends with love and expectation. The use of paragraph emotions summarizes the blog emotion in a simpler way. Figure 4 shows that love is the main emotion of this blog, followed by sorrow, expectation, and joy.

Through the above analysis, we can conclude that the uses of sentence and paragraph emotions are better than the use of word emotions for blog emotion visualization because they are more accurate. But in practical applications, sentence and paragraph emotions are derived from word emotions. So the acquirement of word emotions is prerequisite for emotion visualization. Then, word emotions should be used for further recognition of sentence and paragraph emotions.

4. Emotion Recognition for Blog Emotion Visualization

In practical applications, a blog emotion visualization system includes two main parts: a blog emotion recognition engine and an emotion visualization interface, as shown in Fig. 5.

The blog emotion recognition engine includes three modules: word emotion recognition, sentence emotion recognition, and document emotion recognition. Ren-CECps is used as the basic emotion resource to build the system.

4.1. Word emotion recognition module

Emotional words have been well used as the most obvious choice as feature in the task of textual emotion recognition. Different from previous work using existing

![Diagram of blog emotion recognition engine and emotion visualization interface](image-url)
emotion lexicons, the blog emotion recognition engine recognizes emotion in words based on the context. This module is based on our previous work, a Maximum entropy (MaxEnt) classification model has been built with nine contextual features for this task. Ren-CECps has been used for features extraction and MaxEnt model construction. Table 3 lists the features.

Table 3. Features for word emotion recognition in blogs.

<table>
<thead>
<tr>
<th>Features</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word Feature (F1)</td>
<td>Word itself to be recognized.</td>
</tr>
<tr>
<td>N-words Feature (F2)</td>
<td>The surrounding words of length 1 for the current word ((w_i)) to be recognized: ((w_{i-1}; w_i; w_{i+1})).</td>
</tr>
<tr>
<td>POS Feature (F3)</td>
<td>The part of speech of the current word to be recognized.</td>
</tr>
<tr>
<td>N-POS Feature (F4)</td>
<td>The part of speeches of the surrounding words of length 1 for the current word to be recognized: ((pos_{i-1}; pos_i; pos_{i+1})).</td>
</tr>
<tr>
<td>Pre-is-degree-word Feature (F5)</td>
<td>If the previous word of the current word to be recognized is a degree word, the value is true, otherwise the value is false.</td>
</tr>
<tr>
<td>Pre-is-negative-word Feature (F6)</td>
<td>If the previous word of the current word to be recognized is a negative word, the value is true, otherwise the value is false.</td>
</tr>
<tr>
<td>Pre-is-conjunction Feature (F7)</td>
<td>If the previous word of the current word to be recognized is a conjunction, the value is true, otherwise the value is false.</td>
</tr>
<tr>
<td>Pre-N-words Emotion Feature (F8)</td>
<td>The all emotions of the previous words of the current word to be recognized in a sentence: (pre_{e_0}; \ldots; pre_{e_{i-1}}). The value of this feature for a word ((w_i)) is obtained only after the computation of the emotions for its previous words.</td>
</tr>
<tr>
<td>Pre-N-words Emotion State Feature (F9)</td>
<td>The all emotion states of the previous words of the current word to be recognized in a sentence: (pre_{es_0}; \ldots; pre_{es_{i-1}}). The value of this feature for a word ((w_i)) is obtained only after the computation of the emotion states for its previous words.</td>
</tr>
</tbody>
</table>

As shown in Table 4, when we only use Word Feature (F1), the F-value of task (a) achieved a high value (96.3). However, the F-values of task (b) are relatively low, that means the problem of recognizing the eight basic emotions for emotion words is a lot more difficult than the problem of recognizing emotional and unemotional words, so we focus on task (b).

As can be seen from Table 4, when only contextual features are used, the highest F-value is \( (a = 97.1, b = 72.5) \) when Pre-is-degree-word Feature (F5),
Complement Naive Bayes (CNB) was proposed to deal with some of the problems. 4.2.1. The method

Complement Naive Bayes (CNB) was proposed to deal with some of the problems with Naive Bayes classifiers: (1) Naive Bayes selects poor weights for the decision

Pre-is-negative-word Feature (F6), Pre-is-conjunction Feature (F7) are added. We also find that Pre-N-words Emotion Feature (F8) increases the F-value. The best results are obtained when Pre-N-words Emotion State Feature (F9) is added.

<table>
<thead>
<tr>
<th>Feature type</th>
<th>Features</th>
<th>F1 (a)</th>
<th>F1 (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>$f_1 = w_i$</td>
<td>96.3</td>
<td>63.0</td>
</tr>
<tr>
<td>F2</td>
<td>$f_1 = w_{i-1} w_i w_{i+1}$</td>
<td>94.8</td>
<td>60.7</td>
</tr>
<tr>
<td>F1 + F2</td>
<td>$f_1 = w_i, f_2 = w_{i-1} w_i w_{i+1}$</td>
<td>96.5</td>
<td>69.0</td>
</tr>
<tr>
<td>F1 + F2 + F3</td>
<td>$f_1 = w_i, f_2 = w_{i-1} w_i w_{i+1}, f_3 = pos_i$</td>
<td>96.8</td>
<td>71.1</td>
</tr>
<tr>
<td>F1 + F2 + F3 + F4</td>
<td>$f_1 = w_i, f_2 = w_{i-1} w_i w_{i+1}, f_3 = pos_i, f_4 = pos_{i-1} pos_{i+1}$</td>
<td>97.1</td>
<td>72.0</td>
</tr>
<tr>
<td>F1 + F2 + F3 + F4 + F5 + F6 + F7</td>
<td>$f_1 = w_i, f_2 = w_{i-1} w_i w_{i+1}, f_3 = pos_i, f_4 = pos_{i-1} pos_{i+1}$</td>
<td>97.1</td>
<td>72.5</td>
</tr>
<tr>
<td>F1 + F2 + F3 + F4 + F5 + F6 + F7 + F8</td>
<td>$f_1 = w_i, f_2 = w_{i-1} w_i w_{i+1}, f_3 = pos_i, f_4 = pos_{i-1} pos_{i+1}$</td>
<td>97.3</td>
<td>72.7</td>
</tr>
<tr>
<td>F1 + F2 + F3 + F4 + F5 + F6 + F7 + F8 + F9</td>
<td>$f_1 = w_i, f_2 = w_{i-1} w_i w_{i+1}, f_3 = pos_i, f_4 = pos_{i-1} pos_{i+1}$</td>
<td>97.3</td>
<td>73.3</td>
</tr>
</tbody>
</table>

4.2.2. Sentence emotion recognition module

4.2.1. The method

Complement Naive Bayes (CNB) was proposed to deal with some of the problems with Naive Bayes classifiers: (1) Naive Bayes selects poor weights for the decision
boundary when one class has more training examples than another; (2) features are assumed to be independent; (3) multinomial Naive Bayes does not model text well. With practical advantages of CNB, it has been used for the task of sentence emotion recognition. The algorithm steps are listed as follows:

**Algorithm 1 CNB for sentence emotion recognition.**

Let $S = (s_1, \ldots, s_n)$ be a set of sentences;

1. Features extraction for $s$; (The features include recognized word emotion, and word emotion state).

   Let $s_{ij}$ be the count of feature $i$ in sentence $j$.

   Let $y = (y_1, \ldots, y_n)$ be the sentence emotion state labels.

2. $s_{ij} = \log (s_{ij} + 1)$ (TF transform).

3. $s_{ij} = s_{ij} \log \frac{\sum_k s_{ik}}{\sum_k \delta_{ik} ^{s_{ik}}}$ (IDF transform, where $\delta_{ik}$ is 1 if feature $i$ occurs in sentence $j$, 0 otherwise.)

4. $s_{ij} = \frac{s_{ij}}{\sqrt{\sum_k (s_{ik})^2}}$.

5. CNB’s estimate $\hat{\theta}_c = \frac{\sum_{j:y_j \neq c} s_{ij} \alpha_i}{\sum_{j:y_j \neq c} s_{ij} + \alpha_i}$ (CNB’s estimate weights using data from all classes except $c$, $\alpha$ and $\alpha_i$ are smoothing parameters).

6. $w_{ci} = \log \hat{\theta}_c$.

7. $w_{ci} = \frac{\sum_i w_{ci}}{\sum_i w_{ci}}$ (weight normalization).

8. Let $t = (t_1, \ldots, t_n)$ be a test sentence; features extraction for $t$.

   (The features include recognized word emotion, and word emotion state).

9. Let $t_i$ be the count of feature $I$. Label the sentence according to $l(t) = \arg\min_c \sum_i t_i w_{ci}$.

Based on the word emotion recognition module, the sentence emotion recognition module takes word emotions and word emotion states as features. In the training stage, the features are extracted from training sentences to build a CNB emotion classification model. In the testing stage, the features extracted from testing sentences are input to the CNB classification model. Then, emotions of a sentence are output from this classification model. In the stages of training and testing, sentence emotions are encoded into sentence emotion states. The emotion corpus (Ren-CECps) has been used for feature extraction and model construction.

4.2.2. Evaluation of sentence emotion recognition

To evaluate the performance of sentence emotion recognition, we have experimented other five classifier algorithms under different schemes for this task. Table 5 lists the machine learning algorithms and the empirical parameter settings.

The experiments are performed using 10-fold cross-validation over a set of 35,096 sentences from 1487 Ren-CECps articles. Table 6 shows the experimental
results measured by precision ($P$), recall ($R$), and F-score ($F = 2 \cdot P \cdot R / (P + R)$), respectively. The validation results are averaged over 10 rounds. The evaluation F-score results include:

(a) Recognize emotional and unemotional sentences;
(b) Recognize the eight basic emotions for emotional sentences (single emotion matching).

Using recognized word emotions, as shown in Table 6, CNB achieved better results (both tasks a and b) than other classification algorithms, which demonstrates the effectiveness of CNB model for this task. We also find that it is much harder to recognize the eight basic emotions for emotional sentences (task b) than to recognize emotional and unemotional sentences (task a). Statistics on Ren-CECPs showed that 38.5% sentences have more than one emotions. Multi-emotion sentences are indispensable for expressing complex feelings in use of language.

It can also be observed from Table 6 that SVM algorithm also showed promising results, especially for task (b). And then we further explore the performance of using

<table>
<thead>
<tr>
<th>Classifier algorithm</th>
<th>Scheme</th>
<th>Function</th>
<th>Parameter settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>DecisionStump</td>
<td>Trees</td>
<td>Build one-level decision trees</td>
<td>Classification is based on entropy</td>
</tr>
<tr>
<td>ConjunctiveRule</td>
<td>Rules</td>
<td>Conjunctive rule learner</td>
<td>(1) Number of folds for reduced Error Prunning (REP) = 3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2) The minimal weights of instances within a split = 2.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3) Number of antecedents for pre-pruning = 3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4) The seed of randomization = 1</td>
</tr>
<tr>
<td>SVM</td>
<td>Functions</td>
<td>Support vector classification</td>
<td>(1) Kernel function: Linear</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>Metalearning algorithm</td>
<td>Boost using the AdaBoostM1 method</td>
<td>(2) The complexity constant = 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3) Percentage of weight mass to base training on = 100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4) Use resampling for boosting</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(5) Number of iterations = 10</td>
</tr>
</tbody>
</table>

Table 6. The precision ($P$), recall ($R$), and F-score ($F$) of sentence emotion recognition by different classification algorithms.

<table>
<thead>
<tr>
<th>Classifier algorithm</th>
<th>(a)</th>
<th>(b)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P$</td>
<td>$R$</td>
</tr>
<tr>
<td>DecisionStump</td>
<td>80.3</td>
<td>92.3</td>
</tr>
<tr>
<td>ConjunctiveRule</td>
<td>77.1</td>
<td>84.2</td>
</tr>
<tr>
<td>SVM</td>
<td>85.8</td>
<td>89.7</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>82.1</td>
<td>97.2</td>
</tr>
<tr>
<td>CNB</td>
<td><strong>87.3</strong></td>
<td><strong>90.1</strong></td>
</tr>
<tr>
<td>Avg.</td>
<td>82.5</td>
<td>90.7</td>
</tr>
</tbody>
</table>
different kernel functions in SVM algorithm. Table 7 shows the best F-score ($F$) of sentence emotion recognition obtained by using different kernel functions in SVM with the corresponding parameter settings.

Table 7. The best F-score ($F$) of sentence emotion recognition obtained by using different kernel functions in SVM algorithm.

<table>
<thead>
<tr>
<th>Kernel function</th>
<th>Parameter settings</th>
<th>F-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear: $u' \times v$</td>
<td>$C$ 1 $\varepsilon$ -- $D$ -- $\gamma$ -- $\text{coef0}$ --</td>
<td>87.7 75.7</td>
</tr>
<tr>
<td>Polynomial: $(\gamma \times u' \times v + \text{coef0})^D$</td>
<td>1 0.1 3 0.1 0</td>
<td>92.0 74.8</td>
</tr>
<tr>
<td>RBF (Radial basis function): $\exp(-\gamma \times</td>
<td>u-v</td>
<td>)^2$</td>
</tr>
<tr>
<td>Sigmoid: $\tanh(\gamma \times u' \times v + \text{coef0})$</td>
<td>1 0.1 -- 0.1 10</td>
<td>92.0 74.8</td>
</tr>
</tbody>
</table>

*Note: Parameters description: $C$: complexity constant, $\varepsilon$: the epsilon for round-off error, $D$: degree in kernel function, $\gamma$: gamma in kernel function, $\text{coef0}$: coef0 in kernel function. "--" means the item is not included.*

Table 7 shows that the best F-score ($F$) of task (a) is 92.0%, which was obtained by using polynomial and sigmoid kernel functions, and it is equal to the result obtained by CNB algorithm; while the best F-score ($F$) of task (b) is 75.7%, which was obtained by using linear and RBF and kernel functions, it is slightly (0.9%) lower than the result obtained by CNB algorithm.

Figure 6 shows run time (ms/sentence) comparison of SVM algorithm with different kernel functions and CNB algorithm. Observing from Fig. 6, we can find that SVM algorithm with polynomial kernel is the most time-consuming algorithm (spent about 61.2 ms for recognizing a sentence). However, the CNB algorithm is the fastest algorithm.

Fig. 6. Run time (ms/sentence) comparison of SVM algorithm with different kernel functions and CNB algorithm.
algorithm (spend about 0.4 ms for recognizing a sentence). Therefore, CNB algorithm showed better performance than SVM algorithm for this task.

Table 8 compares the use of word emotion recognized by our word emotion recognition module (Sec. 4.1) and annotation by annotators for sentence emotion recognition.

From Table 8, we find that the F-score results obtained by using recognized word emotion for tasks (a) and (b) are close to the F-score results obtained by using annotated word emotion, which demonstrates the effectiveness of the word emotion recognition module.

The experiments on parameter setting show that, by normalizing the word weights for each class in CNB, the results for task (b) can be further improved to 77.1% (using recognized word emotions). But using a smoothing value is not helpful for the performance.

Conducting an error analysis, some errors occur due to the mistakes caused by word emotion recognition in sentence. As emotional words are used as the main feature for sentence emotion recognition, the mistakes caused in word emotion recognition lead to wrong results in sentence emotion recognition. The experiments also showed that the emotions of the sentences containing negative words, conjunctions, or question mark are more difficult to be recognized than the sentences without negative words, conjunctions, or question mark. For performance improvement, more features (such as negative words, degree words, conjunctions, and emotional punctuation) should be considered for sentence emotion recognition in the future work.

### 4.3. Documents emotion recognition module

Document emotion is obtained based on the results of sentence emotion recognition. The emotions appearing with higher frequency in all sentences are selected as candidates. By referring to the method of automatic abstracting important sentences proposed by Ref. 43, articles’ structural information as well as some heuristic rules have been used to remove obviously unimportant sentences. And by referring to the statistics of Ren-CECps, the average emotion number in document is 2.85. So, document emotion is selected for not more than three emotion classes.

<table>
<thead>
<tr>
<th>Classifier algorithm</th>
<th>(a) Recognized</th>
<th>(a) Annotated</th>
<th>(b) Recognized</th>
<th>(b) Annotated</th>
</tr>
</thead>
<tbody>
<tr>
<td>DecisionStump</td>
<td>85.9</td>
<td>85.3</td>
<td>73.2</td>
<td>74.1</td>
</tr>
<tr>
<td>ConjunctiveRule</td>
<td>80.5</td>
<td>82.1</td>
<td>70.0</td>
<td>71.5</td>
</tr>
<tr>
<td>SVM</td>
<td>87.7</td>
<td>96.2</td>
<td>75.7</td>
<td>85.4</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>85.9</td>
<td>85.3</td>
<td>73.2</td>
<td>74.1</td>
</tr>
<tr>
<td>CNB</td>
<td><strong>92.0</strong></td>
<td><strong>92.0</strong></td>
<td><strong>76.6</strong></td>
<td><strong>82.1</strong></td>
</tr>
<tr>
<td>Avg.</td>
<td>86.4</td>
<td>88.1</td>
<td>73.7</td>
<td>77.4</td>
</tr>
</tbody>
</table>
The emotion visualization interface is designed to illustrate emotions at different text scale. To more intuitively show emotions, we use eight different face marks instead of colors to represent the basic emotions (expectation, joy, love, surprise, anxiety, sorrow, angry, and hate) in blogs. The textual emotion recognition engine recognizes multiple-emotion in each word, each sentence, and the whole document for an input blog. Figure 7 illustrates the emotion visualization interface. The left part of this visualization interface is an input blog. The central part shows document structure and recognized document emotion of this blog. The right part shows a table containing sentence emotions of this blog.

The emotion visualization interface allows a fast view on the emotion structure of a blog article, and captures emotional change of the blog author. As shown in Fig. 7, the main content of this input blog article is: The blogger talked about the terrible Sichuan earthquake scenes, and called for donations to help the affected people. With the emotion recognition results, we can easily grasp the document emotion (expectation, anxiety, and sorrow) of this blog by looking at the face marks in the central part of this visualization interface. They deliver the topic emotion of this blog. By looking over sentence emotion in the right table, we may track emotion change of the blogger from expectation to anxiety and sorrow, and then from anxiety and sorrow to expectation, joy, and love.
5. Conclusion and Future Directions

Work on blogs has exploded in popularity in recent times. From the point of view of information access, the blogspace offers many natural opportunities beyond traditional search facilities, such as trend detection, topic tracking, link tracking, affect detection, etc. As response time of blogs is faster than traditional media, and bloggers are not constrained by formality, emotion analysis from blogs offers a convenient way to detect bloggers’ emotions, which is helpful for solving some social and psychological problems, and giving early warnings, such as in the case of suicide or terrorism. Blog emotion analysis is essentially a task of textual emotion analysis based on some characteristics of blogs. Written text sentences are rich in conveying emotional information in blogs. In this study, we proposed to visualize blog emotion from different text levels: word, sentence, paragraph, and document. As emotion is inherently abstract and nonvisual, visualizing emotions inferred from blogs allows a fast view on the emotion structure of a blog article.

In this paper, we analyzed and compared blog emotion visualization from different text levels. A blog emotion visualization system was designed for practical applications, which includes two main parts: a blog emotion recognition engine and an emotion visualization interface. Machine learning methods were applied for the implementation of blog emotion recognition at different textual levels. Based on the emotion recognition engine, the blog emotion visualization interface is designed to provide a more intuitive display of emotions in blogs, which can detect emotion for bloggers, and capture emotional change rapidly. The system can recognize multiple emotions in documents, sentences, and words, which provides a richer and more detailed emotion expression in blog.

The next work to be done in the future is to develop a real-time emotion recognition system for online blogs, twitter, and more social media. And such a system will be used for some applications, like detecting some social or psychological problems, such as sarcasm and false positives.

Acknowledgments

This research has been partially supported by the National High-Tech Research & Development Program of China 863 Program under Grant No. 2012AA011103, National Program on Key Basic Research Project of China 973 Program under Grant No. 2014CB347600, National Natural Science Foundation of China under Grant No. 61203312, the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry, and Key Science, Technology Program of Anhui Province under Grant No. 1206c0805039, and the Ministry of Education, Science, Sports and Culture, Japan, Grant-in-Aid for Scientific Research (A), 22240021.

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