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Emotion Classification in Microblog Texts Using Class Sequential Rules

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Abstract

This paper studies the problem of emotion classification in microblog texts. Given a microblog text which consists of several sentences, we classify its emotion as *anger*, *disgust*, *fear*, *happiness*, *like*, *sadness* or *surprise* if available. Existing methods can be categorized as lexicon based methods or machine learning based methods. However, due to some intrinsic characteristics of the microblog texts, previous studies using these methods always get unsatisfactory results. This paper introduces a novel approach based on class sequential rules for emotion classification of microblog texts. The approach first obtains two potential emotion labels for each sentence in a microblog text by using an emotion lexicon and a machine learning approach respectively, and regards each microblog text as a data sequence. It then mines class sequential rules from the dataset and finally derives new features from the mined rules for emotion classification of microblog texts. Experimental results on a Chinese benchmark dataset show the superior performance of the proposed approach.

Introduction

Sentiment analysis and opinion mining is one of the most active research areas in the natural language processing field (Liu 2012). In recent years, a large number of studies have focused on sentiment analysis and opinion mining on social media. Due to some intrinsic characteristics of the texts produced on social media sites, such as the limited length and casual expression, sentiment analysis on them is a challenging task. Previous studies mainly focus on lexicon-based (Hu and Liu. 2004) and machine learning based methods (Pang et al., 2002). The performance of lexicon-based methods relies heavily on the quality of emotion lexicon, and the performance of machine learning methods such as SVM and Naïve Bayes relies heavily on the features we design and the most widely-used features are ngram-based and lexicon-based features.

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In this study, we focus on emotion classification of Chinese microblog texts (e.g. Sina Weibo), which aims to classify a Chinese microblog text into one of multiple emotion categories (i.e. "*anger*", "*disgust*", "*fear*", "*happiness*", "*like*", "*sadness*", "*surprise*" and "*none*"). Note that the task we address is a document-level sentiment analysis task, which is usually more challenging than sentence-level tasks. Unfortunately, existing lexicon-based or machine learning based methods usually cannot achieve satisfactory performance because these methods usually treat a microblog text as a bag of words or a bag of sentences and they do not consider information about text order and discourse structure in a microblog text. A Chinese microblog text usually contains several sentences because a microblog text of 140 Chinese characters is not short at all, and the emotion category of a microblog text is usually determined by the sequence of the emotion categories of the sentences in the text and the discourse relations between the sentences. Table 1 gives an example microblog text with three sentences and their emotion labels. The emotion label of sentence 1 is *none*, the emotion label of sentence 2 is *sadness*, and the emotion label of sentence 3 is *happiness*. The last two sentences are connected by a adversative conjunction "但是" (but). Based on the emotion sequence and the conjunction, we can determine the emotion label of the whole microblog text as *happiness*.

	Sentence	Emotion
1	今天下雨。 (Today is rainy.)	*none*
2	我有点郁闷 [流泪]！ (I am a little depressed [tears]!)	*sadness*
3	但是在家里看书也不错 [嘻嘻]。 (But staying at home to read some books is also not so bad [hee hee].)	*happiness*

Table 1: An example microblog text with three sentences.

In order to make better use of the text order and the discourse structure information for emotion classification of microblog texts, we propose to leverage class sequential rules to derive new effective features for supervised emotion classification. We first obtain two potential emotion labels of each sentence in a microblog text by using traditional lexicon-based and machine learning based methods, and also extract the conjunctions between two adjacent sentences in the microblog text. We then convert the microblog text into a sequence of emotion labels and conjunctions. Based on the sequence dataset, we can mine class sequential rules by using pattern mining techniques and new features are then derived from the mined class sequential rules and used for supervised classification.

There are at least two advantages for our approach:

1) Our approach can consider the order of sentences and the discourse relationships between sentences in a microblog text.

2) Though our approach is dependent on the sentence-level emotion classification results, it can tolerate faults caused by a single method, because we obtain two emotion labels for each sentence with two different methods, and we can make use of both two emotion labels of each sentence in our approach.

Experiments are conducted on a benchmark CMSAE dataset for emotion classification of Chinese microblog texts and the results demonstrate that our proposed approach is very competitive and it can significantly outperform a few relevant baselines.

Related Work

Since early 2000, sentiment analysis has grown to be one of the most active research areas in the natural language processing field (Liu 2012). Previous studies mainly focused on reviews (Liu and Seneff 2009), forum discussions (Shi et al. 2009) and blogs (Chesley et al. 2006).

Sentiment Classification aims to classify a document into three polarity classes, i.e. "positive", "negative" or "neutral". Pang et al. (2002) firstly applied machine learning techniques to determine whether a review is positive or negative. Apart from classifying a text simply as positive or negative, some studies aim to identify the emotion of a text, such as anger, happiness, etc. Mishne (2005) utilized SVM to train an emotion classifier with 132 moods in blog posts. Yang (2007) investigated the emotion classification of web blog corpora using SVM and CRF based machine learning techniques.

As the development of social media, a large number of studies have investigated the problem of sentiment analysis on Twitter and Chinese microblogs. Go et al. (2009) used three machine learning algorithms for classifying the sentiment of Twitter texts using distant supervision, and they reported SVM outperforms other classifiers. Read (2005) further used emoticons to collect training corpus. Davidov et al. (2010) utilized Twitter hashtags and smileys as sentiment labels to acquire data. Barbosa and Feng (2010) leveraged three sources with noisy labels as training data and used SVM to train a classifier. Liu et al. (2012) trained a language model based on the manually labeled data and then used the noisy emoticon data for smoothing in a different perspective. Liu et al. (2012) constructed a graph using the input Chinese microblog collection based on forwarding, commenting and sharing relation features to determine the sentiment of each microblog text.

In this paper, we propose to leverage class sequential rule in machine learning methods to classify the emotion at document level. Class sequential rule (Liu 2007) has been used for identifying comparative sentences in text documents (Jindal and Liu 2006) and opinion feature extraction (Hu and Liu 2006).

Basic Approaches

In this section, we introduce the basic lexicon-based and learning-based methods for both document-level and sentence-level emotion classification. On the one hand, the two methods will be used as baselines for emotion classification of the whole microblog texts. On the other hand, we will use the two methods to obtain emotion labels of each sentence in a microblog text, and leverage the sentence-level emotion labels in our proposed approach.

Lexicon-Based Approach

Lexicon-based approaches rely heavily on an emotion lexicon. In our experiments, we construct a Chinese emotion lexicon from three resources: 1) We use the emotion lexicon from DUTIR[1] which consists of seven emotion types used in this study. In our experiments, we abandon some emotion words that are not suitable for our corpus. 2) We collect and use a few slang words which will be helpful for emotion classification. 3) We collect a list of emoticons from the microblog web site[2] to enhance the lexicon. Table 2 shows the total number of words for each emotion type in our lexicon.

Emotion Type	*anger*	*disgust*	*fear*	*happiness*	*like*	*sadness*	*surprise*
Number	431	9624	1096	1859	10237	2227	218

Table 2. Number of emotion lexicons in our experiments.

We use a Chinese segmentation tool - ICTCLAS[3] to segment a Chinese microblog text into words. Based on the constructed emotion lexicon, we count the number of emotion words occurring in a text for each emotion type, and then the emotion label of the text is simply determined as the emotion type with the largest number of emotion words appearing in the text. If a text does not contain emotion words, the text is labeled as "*none*".

The above process can also be applied on a sentence to get the sentence-level emotion label.

[1] http://ir.dlut.edu.cn/
[2] http://www.weibo.com
[3] http://www.ictclas.org

SVM-Based Approach

Since SVM has demonstrated its superiority for sentiment classification in previous studies, we adopt SVM as the learning model in learning-based approaches. In particular, we use the LIBSVM toolkit [4] for multiclass emotion classification. For both document-level and sentence-level emotion classification, we make use of the following three kinds of text-based features in our experiments.

1) **Word Features**: All the Chinese words appearing in a microblog text or sentence are used as features.

2) **Punctuation Features**: Some punctuation sequences can reflect special kinds of emotions, and we collect a list of such punctuation sequences as features. For example, "???" may reflect an "*anger*" emotion and "!!!" may reflect a "*surprise*" emotion.

3) **Emotion Lexicon Features**: We take the number of words of each emotion type occurring in a text or sentence as feature. For instance, there are only three words occurring in the "*happy*" category of the constructed lexicon and one word occurring in the "*like*" category of the lexicon in a text, and thus, the corresponding feature values are: 0(*anger*), 0(*disgust*), 0(*fear*), 3(*happiness*), 1(*like*), 0(*sadness*), 0(*surprise*).

Proposed Approach

We now present our proposed approach to classifying a microblog text into multiple emotion types. Our proposed approach originally makes use of sentence-level class sequential rules for the sentiment/emotion classification task. Firstly, our approach uses lexicon-based and SVM-based methods to obtain two emotion labels for each sentence in a microblog text. Secondly, we transform microblog texts to sequences of sentence-level emotion labels and conjunctions involved. Thirdly, we mine *class sequential rules* (CSR) from the sequences. Finally, we derive features from CSRs and use them for SVM-based emotion classification of the whole text. In our approach, CSRs embody information about the order of sentences and the discourse relations between sentences, and they are implicit and useful patterns for emotion classification.

We will first describe class sequential rules and the CSR mining algorithm, and then describe each major step in our approach.

Class Sequential Rules Mining

Following the descriptions in (Liu 2007), let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of items. A *sequence* is an ordered list of itemsets. An *itemset* is a non-empty set of items. We denote a sequence s by $<a_1,\ldots, a_i,\ldots, a_r>$, where a_i is an itemset, also called an *element* of s, and a_i is denoted by $\{x_1, \ldots, x_j, \ldots, x_k\}$, where $x_j \in I$ is an item. An item can only occur once in an element of a sequence, but can occur multiple times in different elements. A sequence $s_1 = a_1a_2\ldots a_r$ is a *subsequence* of another sequence $s_2 = b_1b_2\ldots b_m$, if there exist integers $1 \le j_1 < j_2 < \ldots < j_{r-1} \le j_r \le m$ such that $a_1 \subseteq b_{j1}$, $a_2 \subseteq b_{j2}$, …, $a_r \subseteq b_{jr}$. We also say that s_2 contains s_1.

Let us see an example. We have $I = \{1, 2, 3, 4, 5, 6, 7\}$. The sequence $<\{3\}\{4, 5\}>$ is contained in $<\{6\}\{3, 7\}\{4, 5, 6\}>$ because $\{3\} \subseteq \{3, 7\}$, $\{4, 5\} \subseteq \{4, 5, 6\}$. However, $<\{3, 8\}>$ is not contained in $<\{3\}\{8\}>$ and vice versa.

The input sequence data D for mining is a set of pairs, i.e., $D = \{(s_1, y_1), (s_2, y_2), \ldots, (s_n, y_n)\}$, where s_i is a sequence and $y_i \in Y$ is a class label. Y is the set of all classes. In our context, Y = {*anger*, *disgust*, *fear*, *happiness*, *like*, *sadness*, *surprise*, *none*}, A *class sequential rule* (CSR) is an implication of the form:

$$X \to y \text{ , where } X \text{ is a sequence, and } y \in Y$$

A data instance (s_i, y_i) is said to *cover* the CSR if X is a subsequence of s_i. A data instance (s_i, y_i) is said to *satisfy* the CSR if X is a subsequence of s_i and $y_i = y$. The *support* (sup) of the rule is the fraction of total instances in D that satisfy the rule. The *confidence* (conf) of the rule is the proportion of instances that cover the rule also satisfy the rule.

Table 3 gives an example sequence database with five sequences and two classes, c_1 and c_2. Using the minimum support of 20% and minimum confidence of 40%, one of the discovered CSRs is:

$$<\{1\}\{3\}\{7,8\}> \to c_1 \text{ [support = 2/5 and confidence = 2/3]}$$

Data sequences 1 and 2 satisfy the rule, and data sequence 1, 2 and 5 cover the rule.

	Data Sequence	Class
1	$<\{1\}\{3\}\{5\}\{7, 8, 9\}>$	c_1
2	$<\{1\}\{3\}\{6\}\{7, 8\}>$	c_1
3	$<\{1, 6\}\{9\}>$	c_2
4	$<\{3, 5\}\{6\}>$	c_2
5	$<\{1\}\{3\}\{4\}\{7, 8\}>$	c_2

Table 3. An example sequence database for mining CSRs

Given a labeled sequence data set D, a minimum support (*minsup*) and a minimum confidence (*minconf*) threshold, The CSR mining algorithm described in (Liu 2007) is used for mining CSRs that meet the requirements of *minsup* and *minconf* and the details of the algorithm are omitted here due to page limit.

Mining CSRs from Microblog Texts

In this subsection, we aim to transform each microblog text in both the training dataset and the test dataset into a sequence. In our context, I includes all emotion labels and conjunction words. Each sentence in a microblog text is represented as an itemset of one or two emotion labels, and each conjunction word is also represented as an itemset.

[4] http://www.csie.ntu.edu.tw/~cjlin/libsvm/

Therefore, a microblog text is represented by a sequence of itemsets.

In previous sections we have introduced how to use lexicon-based method and learning-based method to obtain two emotion labels for each sentence. The advantage we have two emotion labels for each sentence is that we can use both two emotion labels to match the sequential pattern features and thus improve the performance.

For instance, considering the example in Table 1, the microblog text consists of three sentences. Firstly, we use lexicon-based method to obtain the emotions of the sentences as *none-sadness-happiness* respectively, then we use the SVM-based method to obtain the emotions as *sadness-sadness-happiness* respectively. Note that "但是" (but) at the beginning of the third sentence is a conjunction. Finally we can transform this microblog text into a sequence as follows:

<{*none*, *sadness*} {*sadness*} {但是 (*but*)} {*happiness*}>

The reason why we add conjunctions into the sequence is that conjunction words are usually reflecting discourse relationships between sentences (e.g. coordinative relation, adversative relation, causal relation, etc.), and the discourse relationships between sentences have great impact on the emotion of the whole microblog text. We found the conjunctions usually appear at the beginning of a sentence, and a conjunction can indicate the relation between the sentences before and after it. Therefore, it will be useful if we add the conjunctions to the sequence. We collect and use 54 conjunctions. For instance, "但是" (but) and "尽管" (although) indicate a adversative relation, and "所以" (as a result) indicates a causal relation.

More specifically, we construct the sequence database from the microblog texts with the following steps:

1) For each sentence in a microblog text in the test set, we use both the lexicon-based method and the SVM-based method to identify the emotion of the sentence. If these two emotions are the same, the sentence will get one emotion label; otherwise, the sentence will get two emotion labels. For each sentence in a microblog text in the training set, we directly use the emotion label of the sentence which has already been provided by human annotators. Note that in the training dataset, a primary emotion and a possible secondary emotion are manually annotated for each sentence, and we use the primary emotion as the label of the sentence.

2) We combine the emotion labels of each sentence with the conjunctions at the beginning of the sentences to transform a microblog text into a sequence.

3) In the training set, the emotion label of a microblog text is attached to the corresponding sequence as a class.

For example, we can obtain the following data instance from the example in Table 1 if we know the emotion label of the whole microblog text as *happiness*.

(<{*none*, *sadness*} {*sadness*} {但是(*but*)} {*happiness*}>, *happiness*)

Based on the database of data instances constructed from the training set, we can use the CSRs mining algorithm to mine CSRs that meet the requirements of *minsup* and *minconf*. The CSRs represent indicative patterns specific to different emotions types.

Note that some conjunctions and emotions appear very frequently, while some others appear rarely, therefore only a single minimum support to control the CSRs generation procedure is not sufficient, because in order to mine the patterns that involve infrequent conjunctions and emotions, we need to set the minimum support value very low, which will cause the frequent conjunctions and emotions to generate a large amount of superfluous patterns which will cause overfitting. So we adopt a multiple minimum supports strategy which has been studied in (Jindal and Liu 2006). In this strategy, the minimum support of a rule is determined by multiplying the minimum frequency in the training dataset of the items in the rule and a parameter τ. Thus, *minsup* changes according to the actual frequencies of the items in the data, and for a rule with frequent items the *minsup* will be high and for a rule with rare items the *minsup* will be low.

Emotion Classification of Microblog Texts

After we mine a number of CSRs from the training set, we use the sequential pattern X in each CSR $X \rightarrow y$ as a feature. If the corresponding pattern (sequence) of a microblog text contain X, then the corresponding feature value of the text is set to 1, and is set to 0 otherwise. In addition, we also use word, punctuation and emotion lexicon features. Finally, we use the LIBSVM toolkit for model training and testing.

Experiments

Dataset

We use the benchmark dataset from the 2013 Chinese Microblog Sentiment Analysis Evaluation (CMSAE)[5]. The task is to recognize the fine-grained emotion type of a Chinese microblog text. There are seven emotion types: *anger*, *disgust*, *fear*, *happiness*, *like*, *sadness* and *surprise*. If a text has no emotion, it is labeled as *none*. The training set contains 4000 microblog texts and 13252 sentences. Each text has been annotated with a primary emotion label and each sentence has been annotated with a primary emotion label and a possible secondary emotion label. The test dataset contains 10000 microblog texts and 32185 sentences. The primary emotion type for each microblog text has been annotated. All the texts were collected from Sina Weibo, a very popular Chinese microblogging

[5] http://tcci.ccf.org.cn/conference/2013/pages/page04_eva.html

website. Table 4 shows the number distribution of each emotion type at the document level.

emotion type	train dataset	test dataset
anger	235	436
disgust	425	935
fear	49	102
happiness	371	1116
like	597	1558
sadness	388	744
surprise	112	236
none	1823	4873
total	4000	10000

Table 4. Number distribution of each emotion type at document level in training and test datasets

Performance Measure

Usually precision, recall and F-measure are used for performance measurement. When dealing with multiple classes we use macro average and micro average for evaluation. The macro average and micro average on precision, recall and F-measure are computed as follows:

$$Macro\_Precision = \frac{1}{7}\sum_i \frac{\#system\_correct(emotion = i)}{\#system\_proposed(emotion = i)}$$

$$Macro\_Recall = \frac{1}{7}\sum_i \frac{\#system\_correct(emotion = i)}{\#gold(emotion = i)}$$

$$Macro\_F-measure = \frac{2 \times Macro\_Precision \times Macro\_Recall}{Macro\_Precision + Macro\_Recall}$$

$$Micro\_Precision = \frac{\sum_i \#system\_correct(emotion = i)}{\sum_i \#system\_proposed(emotion = i)}$$

$$Micro\_Recall = \frac{\sum_i \#system\_correct(emotion = i)}{\sum_i \#gold(emotion = i)}$$

$$Micro\_F-measure = \frac{2 \times Micro\_Precision \times Micro\_Recall}{Micro\_Precision + Micro\_Recall}$$

#system_proposed is the number of microblog texts classified in the dataset. *#system_correct* is the number of microblog texts correctly classified in the dataset. *#gold* is the number of microblog texts manually annotated. *i* is one of the seven emotion types including *anger*, *disgust*, *fear*, *happiness*, *like*, *sadness* and *surprise*. Note that the type of *none* is not considered for meaningful comparison.

Comparison Methods

In the experiments, two versions of our proposed approach are used for comparison:

Our Method (CSRs only): It uses the SVM-based approach to classify the emotion of a microblog text, and only the features derived from CSRs are used.

Our Method (All Features): It uses the SVM-based approach to classify the emotion of a microblog text, and both CSRs-based features and text-based features are used.

Our proposed methods are compared with the best CMSAE team and a few baselines:

1) **Best CMSAE Team**: Nine teams participated in the emotion classification task of CMSAE and seventeen results were submitted for the open test (allowed to use any resources) finally. The method of the best team is used as baseline here. In addition to an emotion lexicon, the best team manually constructs a large number of emotion expression rules to match a text and determine its emotion.

2) **Lexicon**: It uses the lexicon-based approach mentioned earlier to classify emotions of microblog texts directly.

3) **SVM**: It uses the SVM-based approach mentioned earlier to classify emotions of microblog texts directly

4) **Lexicon vote**: It first uses the lexicon-based approach to classify emotions of the sentences in a microblog text, and then uses simple majority vote to determine the emotion of the microblog text.

5) **SVM vote**: It first uses the SVM-based approach to classify emotions of the sentences in a microblog text, and then uses simple majority vote to determine the emotion of the microblog text.

6) **FirstSen(Lexicon)**: It uses the lexicon-based approach to classify the emotion of the first sentence in a microblog text, and then uses it as the emotion label of the microblog text. The assumption is that the first sentence is sometimes the summary of the microblog text.

7) **FirstSen(SVM)**: It uses the SVM-based approach to classify the emotion of the first sentence in a microblog text, and then uses it as the emotion label of the microblog text.

8) **LastSen(Lexicon)**: It uses the lexicon-based approach to classify the emotion of the last sentence in a microblog text, and then uses it as the emotion label of the microblog text. The assumption is that the last sentence is sometimes the summary of the microblog text.

9) **LastSen(SVM)**: It uses the SVM-based approach to classify the emotion of the last sentence in a microblog text, and then uses it as the emotion label of the microblog text.

In the experiments, the parameter values are set by a five-fold cross-validation process on the training set. The parameters in our method are set as *minconf* = 0.01 and τ = 0.05.

Comparison Results

Table 5 shows the comparison results of our methods and baseline methods. Our methods outperform all baseline methods over both macro average F-measure and micro average F-measure, and our method with all features achieves the best performance. The results demonstrate the efficacy of the CSRs-based features. Comparing our method with all features and our method with CSRs-based features only, the former method gets a slightly increased performance, which also shows the usefulness of the text-based features. Both lexicon-based and SVM-based approaches outperform the best CMSAE team due to high quality of the emotion lexicon constructed in our experiments. The simple majority vote methods do not

Method	macro average			micro average		
	precision	recall	F-measure	precision	recall	F-measure
Best CMSAE Team	0.2842	0.348	0.3129	0.3232	0.3868	0.3521
Lexicon*#	0.4150	0.3648	0.3883	0.4131	0.4142	0.4137
SVM*#	0.3671	0.3289	0.3469	0.4252	0.4085	0.4167
Lexicon vote*#	0.4202	0.349	0.3813	0.414	0.3919	0.4026
SVM vote*#	0.3505	0.2482	0.2906	0.4225	0.3415	0.3777
FirstSen(Lexicon) *#	0.4235	0.2104	0.2811	0.3962	0.2302	0.2912
FirstSen(SVM) *#	0.3745	0.1515	0.2157	0.4326	0.2009	0.2744
LastSen(Lexicon) *#	0.4264	0.2407	0.3077	0.4164	0.277	0.3327
LastSen(SVM) *#	0.369	0.1737	0.2362	0.4479	0.2383	0.3111
Our Method (CSRs only)	0.4064	0.4267	0.4163	0.3924	0.4882	0.4351
Our Method (All features)	0.4133	0.4283	**0.4207**	0.3991	0.495	**0.4419**

Table 5. Comparison results with other methods. (/ # indicates that the p-value for sign test between this method and Our Method (All features)/Our Method (CSRs only) is smaller than 0.05. The detailed results for Best CMSAE Team are not available and thus sign test is not performed for it.)*

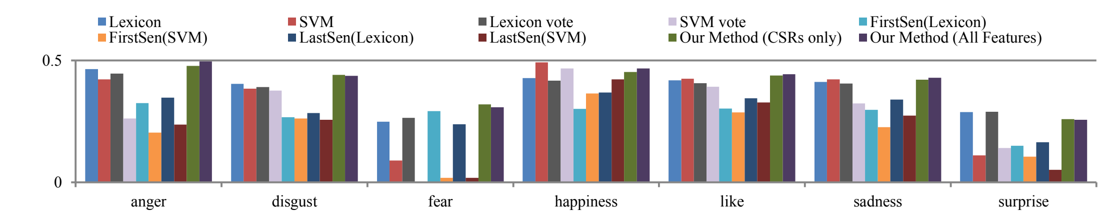


Figure 1: F-measure on seven emotion types for different approaches.

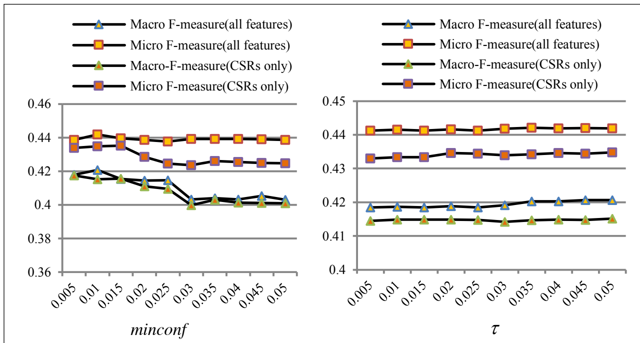
perform very well because they simply consider a microblog text as a bag of sentences and ignore the text order and discourse relationships between sentences. The methods based on first sentence or last sentence do not perform well because the first or last sentence of a microblog text is not often the summary of the text.

Figure 1 demonstrates the F-measure values on seven emotion types for our methods and baseline methods. We can see that our methods can achieve better performances on "*anger*", "*disgust*", "*fear*", "*like*", "*sadness*" than all baseline methods apparently. However, due to heavy reliance on the quality of emotion lexicon, the baseline methods perform extremely unstably on different emotions. Overall, our methods outperform the baseline methods on average.

Parameter Sensitivity Study

In order to investigate how the minimum confidence threshold influences the emotion classification performance. We conduct experiments with different values of *minconf*. Figure 2(a) shows the performance changes for our methods. In this figure, *minconf* ranges from 0.005 to 0.05. We can see the micro F-measure scores are almost steady over a wide range of values of *minconf*, and the macro F-measure scores decline slightly when *minconf* is set to a larger value due to the amount of the mined CSRs reduces quickly for some emotion types. Overall, the performances of our methods are not significantly influenced by the value of *minconf*.

In order to investigate how the multiple minimum support parameter τ influences the emotion classification performance. We conduct experiments of different values of the parameter τ. In Figure 2(b), τ also ranges from 0.005 to 0.05. We can see from the figure that the both the macro F-measure and micro F-measure of our methods are stable on the wide range of the value of parameter τ.



(a) minimum confidence threshold *(b) multiple minimum support parameter*

Figure 2: Influence of the parameters

Conclusion and Future Work

In this paper, we study the problem of emotion classification in microblog texts. We propose an approach based on class sequential rules and experimental results on a Chinese benchmark dataset demonstrate the efficacy and robustness of our method.

In our future work, we will improve the performance of our approach by making use of more discourse information and social network information.

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