Segment-based Fine-grained Emotion Detection for Chinese Text

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Abstract

Emotion detection has been extensively studied in recent years. Current baseline methods often use token-based features which cannot properly capture more complex linguistic phenomena and emotional composition in fine grained emotion detection. A novel supervised learning approach—segment-based fine-grained emotion detection model for Chinese text has been proposed in this paper. Different from most existing methods, the proposed model applies the hierarchical structure of sentence (e.g., dependency relationship) and exploits segment-based features. Furthermore, the emotional composition in short text is addressed by using the log linear model. We perform emotion detection on our dataset: news contents, fairly tales, and blog dataset, and compare our proposed method to representative existing approaches. The experimental results demonstrate the effectiveness of the proposed segment-based model.

1 Introduction

Emotion detection aims to identify fine-grained emotion categories (e.g., happy, angry, disgust, fear, sadness and surprise) of a given text, and it is a challenging and difficult problem with applications throughout natural language processing.

Currently, the most widely used probability models for emotion classification are supervised based machine learning algorithms, such as Naive Bayes (NB) and Support Vector Machine (SVM) etc,. Researchers have trained the classifier depends on corpus-based features, mainly unigrams, combined with lexical features (Alm et al, 2005; Aman and Szpakowicz, 2007; Katz, et al, 2007). Nevertheless, these methods used in the emotion classification system concentrate on token based features and do not include any linguistic or contextual information, which often yields poor performance. Therefore, recent studies have investigated the approach using contextual information around emotional words to identify fine grained emotion classes. (Das and Bandyopadhyay, 2010) observe that the emotion word, POS, intensifier and direct dependency features play an important role in extracting emotional expressions as well as tagging sentences with emotions and intensities. (Diman Ghazi et al., 2012) propose an approach which takes the contextual emotion of a word and the syntactic structure of the sentence into account to classify sentences by emotion classes. However, these works still use token-based features, which cannot address the problem of the emotional composition, especially those that are the expression-level representations.

There has been previous work using composition rules and statistical methods to handle sentiment composition. (Moilanen and Pulman, 2007) propose a theoretical composition model, and evaluate a lexical dependency parsing post-process implementation, which treat both negation and intensifier via three models: sentiment propagation, polarity conflict resolution and polarity reversal. (Choi and Cardie, 2008) incorporate structural inference motivated by compositional semantics into the learning procedure for subsentential sentiment analysis. (Socher et al., 2011, 2012) present matrix-vector representations with a recursive neural network. The model is built on a parse tree where the nodes are associated to a vector. The matrix captures how each constituent modifies its neighbor. (Baptiste Chardon et al,. 2013) propose a computational model that accounts for the effects of negation and modality on opinion expressions. However, it is not as clear how to use a compositional treatment to classify fine grained emotion classes. Sentiment composition combines

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individual positive and negative words or phrases, and the final polarity of a sentence is positive or negative. Nevertheless, it is more challenging and difficult to make categorization into distinct emotion classes for the higher level of classification in emotion recognition task. In order to facilitate our discussion, consider the following examples:

1.不过在教堂里,站在讲台上的牧师却是大叫大嚷,非常生气. (But inside the church the pastor stood in the pulpit, and spoke very loudly and angrily.)[anger]

2.迷信使她的血一会儿变冷,一会儿变热.(Superstition made her alternately shudder with cold or burn with the heat of fever.)[fear]

3.骑在桦木条上的那个蜡人忽然变得又高又大了.他像一阵旋风似地扑向纸花那儿去,说:"居然把这样的怪想头灌进一个孩子的脑子里去!全是些没有道理的幻想!"这蜡人跟那位戴宽帽子的枢密顾问官一模一样,而且他的那副面孔也是跟顾问官一样发黄和生气.可是那些纸花在他的瘦腿上打了一下,于是他缩做一团,又变成了一个渺小的蜡人.(All at once the wax doll which rode on the carnival rod seemed to grow larger and taller, and it turned round and said to the paper flowers, "How can you put such things in a child's head? they are all foolish fancies;" and then the doll was exactly like the lawyer with the broad brimmed hat, and looked as yellow and as cross as he did; but the paper dolls struck him on his thin legs, and he shrunk up again and became quite a little wax doll.)[anger]

In the first example, we can use the key words "大叫","大嚷"(spoke very loudly), and "生气"(anger), to easily identify the emotion classes of the sentence. However, in the second example, we cannot use the words "血"(blood), "变冷"(make cold), "变热"(make burn) or the phrase "血变冷" and "血变热" to easily detect the final emotion category of the sentence. "血" and "变冷" carry "fear" category, and the words "血" and "变热" can be classified as "joy", but the final emotion label of the sentence is "fear". In the last example, there are four types of emotion classes for sub-sentential segments, for example, "蜡人变得又高又大"(the wax doll seemed to grow larger and taller)[joy], "怪想头"(such things) [surprise], "没有道理的幻想!"(foolish fancies)[anger], "生气"(anger) [anger], and "一个渺小的蜡人"(a little wax doll)[sad], but the overall emotion of the short text is "anger".

These examples demonstrate that a sentence or short text exists several expression-level emotion labels, and the words or constituents interact with each other to yield the overall emotion label, which cannot be easily resolved by token-based methods. To solve this problem, we present segment-based supervised learning approach to investigate how to recognize the overall emotion tag of a sentence or short text. Closer to our current purposes is the work of (Nakagawa et al, 2010). It employs a conditional random field (CRF) for sentiment classification of Japanese and English subjective sentences using dependency tree-based method. In their method, the sentiment polarity of each dependency subtree, which is not observable in training data, is represented by a hidden variable. The polarity of the whole sentence is calculated in consideration of interactions between the hidden variables. However, this research doesn't work on the fine grained emotion recognition and it is unable to deal with multiple consecutive tokens (e.g., a phrase).

In this paper, we employ semi-Markov conditional random fields (semi-CRFs) for segment-based emotion detection. Semi-CRFs (Sarawagi and Cohen, 2004) are more powerful than CRFs in that they can assign labels to segments instead of tokens; hence, features can be defined at the segment level. To our knowledge, segment-based fine-grained emotion recognition for Chinese text has not been attempted. Our learning framework can be determined in a three-step process: (1) segment the input sentence or short text into some dependency subtrees and then (2) employ the semi-CRFs with various context informed features to assess the emotion classes of the constituents of the segment, and (3) exploit a composition learning model to combine the segment level emotion labels. We evaluate the proposed model on our construction dataset, which consists of news content, fairy tales and blog dataset, and the experimental results show that segment-based learning algorithm works well in our experimental data.

2 Related Work

Supervised learning method has been well studied and used in fine-grained emotion detection with promising results. (Alm et al., 2005) explores the text-based emotion prediction problem empirically, using supervised machine learning. (Das and Bandyopadhyay, 2010) deals with the extraction of emotional expressions and tagging of English blog sentences with Ekman's six basic emotion tags and any of the three intensities: low, medium and high. Baseline system is developed based on WordNet Affect lists and dependency relations. SVM based supervised framework is employed by incorporating different word and context level features. (Chaffar and Inkpen, 2011) adopts a supervised machine learning approach to recognize six basic emotions (anger, disgust, fear, happiness, sadness and surprise) using a heterogeneous emotion-annotated dataset which combines news headlines, fairy tales and blogs. (Saif Mohammad, 2012) uses word-level affect lexicons to provide significant improvements in sentence-level emotion classification. (Purver and Battersby, 2012) describe a set of experiments using automatically labeled data to train supervised classifiers for multi-class emotion detection in Twitter messages with no manual intervention. (Diman Ghazi et al., 2012) present a method which enables us to take the contextual emotion of a word and the syntactic structure of the sentence into account to classify sentences by emotion classes.

Other related studies on this task are emotion resource construction. (Xu et al., 2010) adopts a graph-based algorithm to build Chinese emotion lexicons for public use. (Patra et al., 2013) uses the Potts model for constructing emotion lexicon annotated with Ekman's six basic emotion classes. There are also studies that analyzed the deeper level information, such as color-concept-emotion associations (Volkova et al., 2012); emotion causes detection (Chen et al., 2010); and learning hashtags to improve emotion classification performance (Qadir and Riloff, 2013). In sentiment composition, the presence of modalities is generally used to combine the individual positive and negative word (Moilanen and Pulman, 2007; Choi and Cardie, 2008; Nakagawa, 2010; Socher et al., 2011, 2012; Chardon et al,.2013). There is a few works on the higher level of composition in emotion recognition task.

Different from above approaches, we use a segment-based method for the fine-grained emotion detection. To use the strengths of segment-based features, we propose to employ the semi-Markov Conditional Random Field, which was previously used in information extraction to tag continuous segments of input sequences and outperformed conventional CRFs in the task of named entity recognition and opinion extraction (Sarawagi and Cohen, 2004; Okanohara et al., 2006; Andrew, 2006; Yang and Cardie, 2012). We describe this model in the following section.

3 Segment-based Emotion Detection using semi-CRF

In this section, we first introduce the semi-Markov conditional random field and then elaborate the proposed segment-based emotion detection model.

3.1 Semi-CRF

In this subsection we briefly review the semi-Markov conditional random field. We follow the definitions in (Sarawagi and Cohen, 2004). Let $s = s_1^m =< s_1, \cdots, s_m >$ denote a segmentation of an observed sequence x. To represent all the information associated with each segmentation, we define s_i as $s_i =< t_i, u_i, y_i >$, which consisting of three components: a start position t_i, an end position u_i, and a label y_i. We assume that segments have a positive length bounded above by the pre-defined upper bound L ($1 \leq u_i - t_i + 1 \leq |x|$) and completely cover the sequence x without overlapping, that is, s satisfies $t_1 = 1$, $u_m = |x|$, and $t_i + 1 = u_i + 1$ for i = 1, ..., m-1. For emotion detection, a valid segmentation of the sentence "善良的姑娘细心地照顾这只弱小的猫" might be $s =< (1, 3, happy), (4, 6, happy), (7, 11, sad) >$, corresponding to the label sequence $y =< happy, happy, sad >$.

Then, Semi-CRF defines a conditional probability of a state sequence y given an observed sequence x by:

$$p(y, s|x) = \frac{1}{Z(x)} exp(\sum_{i=1}^{m} \sum_{t=1}^{|s|} \lambda_i f_i(x, s, y)) \quad (1)$$

where $f_i(x, s, y) = f_i(y_{j-1}, y_j, x, s_j)$ is a feature function and Z(x) is the normalization factor as defined for CRF. The model parameters are a set of real-valued weights $\lambda = \{\lambda_j\}$, each of which represents the weight of a feature.

$$Z(x) = \sum_{s'} exp(\sum_{i=1}^{m} \sum_{t=1}^{|s|} \lambda_i f_i(x, s', y)) \quad (2)$$

The inference problem for semi-CRF can be solved by using a semi-Markov analog of the usual Viterbi algorithm. An implementation of semi-CRF is available at http://crf.sourceforge.net.

3.2 Segment-based Emotion Detection Model

In this subsection, we will describe our segment-based emotion detection model (see Figure 1).

Assume that we are given a sequence of observations $x = x_1^J =< x_1, \cdots, x_J >$ and we would like to infer a corresponding label y^t, where $y^t \in y$ is one of the Ekman’s six basic emotion types such as happiness, sadness, fear, surprise, anger and disgust. Every emotion class is regarded as a possible emotion tag for the input sentence or short text with a posterior probability $p(y|x)$.

Our proposed segment-based approach can be determined in a three-step process: at first, a sentence or short text is divided into non-fixed length segments. We construct segment units from the dependency parse tree of each sentence, and then build up possible segment candidates based on those units. More specifically, the dependency subtrees that contain the path from the root node (e.g., core verb 照顾(take care of)) to leaf node are selected for the candidate segmentation. For instance, let us consider the subjective sentence "善良的姑娘细心地照顾这只弱小的猫"(Good girl carefully take care of the small cat). The dependency parse tree of this sentence is illustrated in Figure 2. We can select four dependency subtrees (善良的姑娘,照顾) (good girl, take care of), (细心地,照顾) (carefully, take care of), (照顾,这只,猫) (take care of, the cat), and (照顾,弱小的猫) (take care of, the small cat) as the candidate segmentations. The reason that the dependency representations are chosen as the segment unit is, compared with phrase-structure tree, it can describe more complicated structure information of a sentence (such as the long distance dependency relation). Then, we use the segmentation strings as observations and supply various context-informed features as inputs to the semi-CRF to assess the emotion classes of the segment. That is, instead of determining y directly from x, we introduce hidden variables $z = (z_1, \cdots, z_m)$ as intermediate decision variables, where $z_i = (s_i, y_i)$ and $y_i \in \{$ happiness, sadness, fear, surprise, anger, disgust, none $\}$, so that y_i represents whether s_i is a phrase with happiness, sadness, fear, surprise, anger, or disgust, or none of the above. In the above example, we can obtain the emotion label of each segment $y =< happy, happy, happy, sad >$. At last, once we determine the intermediate decision variables, we use a probabilistic model based on log linear model to combine expression-level emotion categories. For simplicity, we decompose the probability by introducing two probability distribution models: expression-level emotion detection model and emotion tag distribution model. Specifically, for the segment-based emotion detection problem, the discriminate function can be defined as follows:

$$
\begin{aligned}
p(y^t|x) &= \sum_{s,y} p(s_1^K|x) \cdot p(y_1^K|s_1^K, x) \cdot p(y^t|y_1^K, s_1^K, x) \\
&= \sum_{s,y} \prod_{k=1}^{K} p(y_1^K, s_1^K|x) \cdot p(y^t|y_1^K)
\end{aligned}
\tag{3}
$$

There are two probability distributions:

- Expression-level emotion detection model: $p(y, s|x)$. This model describes the distribution of the sequence of segmentation $s_i(1:k)$ and its corresponding emotion tag $y_i(1:k)$. This distribution can be calculated directly by the semi-CRF model.

- Emotion tag distribution model: $p(y^t|y_1^K)$. This model describes the probability distribution of the emotion classes. Where y_1^K is expression-level emotion tag and y^t indicates the overall emotion tag. This distribution can be calculated by similar n-gram model.

In this study, we use the maximum a posteriori estimation with Gaussian priors for parameter estimation. The inference problem can be solved by the Viterbi algorithm.

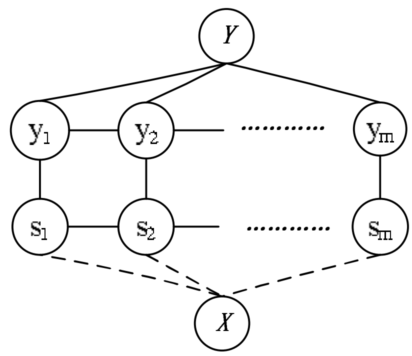

Figure 1: Graphical presentation for semi-CRF segment based model

3.3 Feature Design

We reused features in the original token-based model based on unigram, POS tags, emotion word lists and context-informed dependency relations.

Bag-of-words: Surface forms of word unigrams and bigrams in the sentence are used as features.

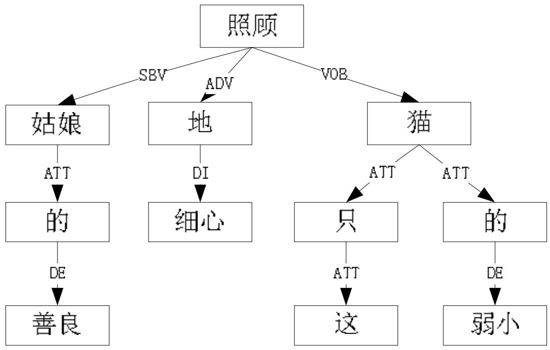

Figure 2: A dependency parse tree example. There are four segment units in the sentence

Part-of-speech: The part-of-speech (POS) of the current word and the surrounding words are used as a feature for emotion classification.

Content bag-of-words: N (noun), V (verb), JJ (adjective) words by POS is used as features.

Emotion word lists: This set of features is based on the emotion-word itself. The emotion class of a word can be assigned as the word's prior emotion tag according to the Chinese emotion lexicon, which is a translation and extension version of WordNet-Affect lexicon and its construction details described as section 4.1.

Dependency relations: This set of features is binary indicators of whether the leaf phrase in the dependency parse tree belongs to one of the emotion classes. The dependencies are all binary relations: a grammatical relation holds between a governor (head) and a dependent (modifier). Dependency arcs are stored as 3-tuples of the form $< w_1, r, w_2 >$, denoting occurrences of words w_1 and word w_2 related by the syntactic dependency r.

After parsing the sentence and getting the dependencies, we count the following dependency-tree boolean features for the emotional word, if this sentence have the emotional words:

- Whether the word is in a "neg" dependency (negation modifier): true when there is a negation word which modifies the emotional word.

- Whether the word is in an "amod" dependency (adjectival modifier): true if the emotional word is (i) a noun modified by an adjective or (ii) an adjective modifying a noun.

- Whether the word is in an "advmod" dependency (adverbial modifier): true if the emotional word (i) is a non-clausal adverb or adverbial phrase which serves to modify the meaning of a word, or (ii) has been modified by an adverb.

If the sentence has not any emotional word, we will consider the adjective words and its around words.

4 Experiments and results

4.1 Data Construction

In this subsection, we explain the dataset and lexicon used in our experiments. Table 1 shows the details of the construction dataset, and Figure 3 displays the distribution of the six emotion classes (happy, fear, sad, surprised, angry, and disgust) in the corpora. The various corpora and lexicon have the following origins:

(1) Chinese emotion lexicon. Currently, there is not any open and free existing Chinese emotion lexicon with fine-grained emotion classes. Therefore, the first resource we need to construct is an emotional lexicon of Chinese with various emotion categories. The English WordNet Affect lists (Strapparava et al., 2004) based on Ekman's six basic emotion types have adequate number of emotion word entries. These English words lists can be used to convert to Chinese words using English to Chinese bilingual dictionary or thesaurus. Our final lexicon contains 1810 entries.

(2) News dataset. This news domain corpus is created manually by two annotators. The annotation process proceeds as follows: they have been trained separately and work independently in order to avoid any annotation bias and get a true understanding of the task difficulty. Each annotator marks the sentence level or short text with one of six primary emotions (Ekman, 1992), and then calculate the kappa value to assess such reliability regarding emotion categories with a value of 0.7 or above it indicating complete agreement. Disagreements can be annotated by the third one, then calculate the kappa value.

(3) Alm's translation dataset. This data set is based on Alm's dataset (Alm et al., 2005), which include annotated sentences from fairy tales, and five emotion tags (happy, fearful, sad, surprised and angry-disgusted) from the Ekman's list of basic emotions were used for sentences or short text annotations. The construction process of this dataset proceeds as follows: firstly, we collect English-Chinese parallel corpora of fairy tales, and split the text into individual sentences. Secondly, select Chinese sentences which corresponding translation appeared in Alm's Dataset accord-

Table 1: The dataset entries used in our experiment

Chinese emotion lexicon	Alm's translation dataset	News dataset	Blog dataset	unlabeled corpora
1810	1223	1135	1000	115M

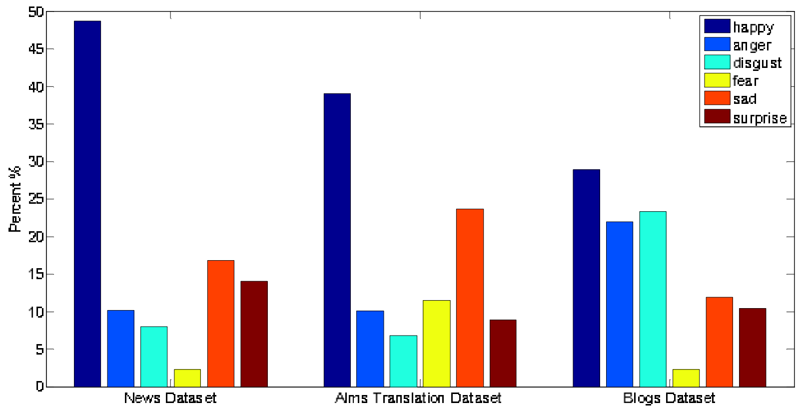

Figure 3: The distribution of the six emotions (happy, fear, sad, surprised, angry, and disgust)in the corpora

ing to sentence alignment strategy. Lastly, annotate angry and disgusted sentences by manually. Since Alm's dataset doesn't separate the angry and disgusted categories.

(4) Blog dataset. This dataset consists of emotion-rich sentences or short text collected from blogs. These sentences or short text are labeled with six emotion tags by two annotators. The annotation process is the same as that of news dataset.

(5) Unlabeled corpora. We downloaded additional 15M Chinese version of children's story from Andersen's and Green's fairy tales and 100M Chinese news dataset to use as the unlabeled set. We haven't select blog corpora, because it is noisy. This allows us to check the performance of each system on the same kinds of data, and the unlabeled set and the test set are in the same domain and have similar underlying feature distributions.

4.2 Preprocessing

Given a labeled or an unlabeled data, we first carry out segmentation and part-of-speech (POS) tagging on each sentence or short text using the Stanford toolkit, and then apply a simple word filter based on POS tags to select content words (nouns, verbs, and adjectives). In next step, we create dependency parse tree produced by the Stanford dependency parser, and construct dependency subtrees. As we all know, the performance of Chinese dependency parser is not very satisfactory. Hence, we modify several wrong results manually. We just want to testify our idea of that the fragments based on dependency grammar are better than tokens.

4.3 Experimental Results

In this subsection, we report experimental results on our dataset which contains news dataset, Alm's translation dataset and blogs dataset. The entries of our dataset are short text or sentence. The news dataset consists of 1135 entries and its average length is 27.09. The Alm's translation dataset consist of 1223 entries and its average length 34.76. The blog dataset contains 1000 entries and its average length is 30.73. The tasks on the Alm's translation dataset may be difficult because the syntactic structures of the sentences are less restricted and highly variable.

Table 2, Table 3 and Table 4 respectively shows the accuracy result of our segment-based method compared to two token-based approach using SVM and MaxEnt, and a segment-based method using CRF models (similar to the work of (Nakagawa et al., 2010)), which employ five kinds of feature sets (BOW, contentBOW, part-of-speech, emotion words and dependency relations) and their combination features, setting 10-fold cross validation as a testing option.

As shown in Table 2-4, we can obtain below conclusions:

(1) We can see that our approach based on the

Table 2: Experimental results on news dataset %

Feature	SVM	MaxEnt	CRF	Our approach
BOW	46.84	46.1	53.29	53.33
contentBOW	48.59	47.8	55	55.74
contentBOW+POS	48.64	47.67	56.78	56.69
contentBOW+Emotion	51.46	50.7	57.41	58.55
contentBOW+Emotion+POS	50.2	47.1	58.53	61.53
contentBOW+Emotion+POS+Dependency	54.45	54.32	59.06	65.12

Table 3: Experimental results on Alm's translation dataset %

Feature	SVM	MaxEnt	CRF	Our approach
BOW	39.59	40.30	35.79	40.09
contentBOW	39.98	40.59	35.87	42.11
contentBOW+POS	40.19	38.82	36.05	43.95
contentBOW+Emotion	45.86	42.26	39.44	46.49
contentBOW+Emotion+POS	46.15	40.98	41.89	48.95
contentBOW+Emotion+POS+Dependency	48.23	45.05	45.68	50.81

Table 4: Experimental results on blog dataset %

Feature	SVM	MaxEnt	CRF	Our approach
BOW	46.09	45.81	44.24	45.62
contentBOW	46.34	46.06	46.33	46.19
contentBOW+POS	46.56	45.93	46.92	47.01
contentBOW+Emotion	47.92	46.03	47.23	47.63
contentBOW+Emotion+POS	48.38	45.77	47.98	48.63
contentBOW+Emotion+POS+Dependency	50.05	48.12	49.61	53.23

segment-based semi-CRF model has the highest accuracy rate for each dataset using the combination features of contentBOW + Emotion + POS + Dependency. Segment-based approach performed better than token-based approach for the news dataset, but without expected results for the Alm's translation and blogs dataset. This result, on the one hand, demonstrates that Semi-CRF is more powerful than CRF, and on the other hand, our emotion tag distribution model gives effective results. For token-based method, SVM gives a better result than MaxEnt for all three of our Chinese corpora.

(2) The accuracy rate of SVM has slightly less than our model, but the results of MaxEnt and CRF is unbalanced. As we notice from table 2 to table 4, CRF gives better results on the news dataset than on the Alm's translation dataset, but the results of MaxEnt on all dataset is worst. The reasons for this result may be due to the bias problem of MaxEnt.

(3) We can observe that using the combination features of contentBOW + Emotion + POS + Dependency has the highest accuracy rate for each dataset and each classifier. There are two types of features achieve significantly improvements: emotion words and the dependency relations, for example, on news dataset, SVM with contentBOW has the accuracy rate of 48.59% and adding emotion words has the accuracy rate of 51.46%, showing the improvements of 2.87%. This is not surprising result since emotion words has key influence to detection of the emotion category of a sentence. However, the words or constituents interact with each other to yield the overall emotion label, there exists expression level emotion. Dependency relationship features can solve this problem and improve the performance of the system,like in the example above,adding Dependency relationship features has the accuracy rate of

54.45%, showing the improvements of 5.86%.

When the baseline system use the content-BOW features, the POS, Emotion and Dependency representation improve the accuracy rates of the SVM, CRF and our classifier for each dataset, but the use of POS representation for the MaxEnt classifier decreased the accuracy rate compared to the Emotion and Dependency representations. One reason lead to this problem might be the quality of the data we use in this experiment.

(4) Overall performances on the news dataset are better than on the Alm's translation dataset and blogs dataset. The reason perhaps is that the syntactic structures of the sentences from Alm's translation dataset are less restricted and highly variable, and the sentences from blogs dataset are noisy, and there exist some linguistic or spelling error.

5 Conclusion

In this paper, we present a segment-based learning approach for fine-grained emotion detection. In this method, the emotion label of each dependency subtree of a subjective sentence or short text is represented by a hidden variable. The values of the hidden variables are calculated in consideration of interactions between variables whose nodes have head-modifier relation in the dependency tree. Differ from the existing token-based approach, the segment-based emotion detection model can simultaneously exploit both the linguistic structure and the expression-level emotion relation embedded in sentences or short text. Three different dataset, which contains news content, fairly tales, and blogs data, is constructed to test our proposed model, and the experimental results show that our approach performed the best on three emotion corpora and make a statistically significant improvement over other classification algorithms, reflecting its potential usage in the emotion detection task.

References

P. Ekman. 1992. *An argument for basic emotions Cognition and Emotion*, 6(3):169–200.

C. Alm, D. Roth, and R. Sproat. 2005. *Emotions from text: Machine learning for text-based emotion prediction, In Proceedings of HLT – EMNLP*, 579–586.

Saima Aman and Stan Szpakowicz. 2007. *Identifying Expressions of Emotion in Text, TSD 2007*, 196–205.

Phil Katz, Matthew Singleton, Richard Wicentowski. 2007. *SWAT-MP: The SemEval-2007 Systems for Task 5 and Task 14, Proceedings of the 4th International Workshop on Semantic Evaluations (SemEval-2007). Prague*,308–313

Karo Moilanen and Stephen Pulman. 2007. *Sentiment Composition, In Proceedings of Recent Advances in Natural Language Processing*.

Yejin Choi and Claire Cardie. 2008. *Learning with Compositional Semantics as Structural Inference for Subsentential Sentiment Analysis, EMNLP 2008*,793–801.

Richard Socher, Jeffrey Pennington, Eric H. Huang, Andrew Y. Ng, Christopher D. Manning. 2011. *Semi-Supervised Recursive Autoencoders for Predicting Sentiment Distributions, EMNLP 2011*,151–161.

Richard Socher, Brody Huval, Christopher D. Manning, Andrew Y. Ng. 2012. *Semantic Compositionality through Recursive Matrix-Vector Spaces, EMNLP-CoNLL 2012*,1201–1211.

Baptiste Chardon, Farah Benamara, Yannick Mathieu,Vladimir Popescu, Nicholas Asher. 2013. *Sentiment Composition Using a Parabolic Model, Proceedings of the 10th International Conference on Computational Semantics (IWCS 2013)* .

Tetsuji Nakagawa, Kentaro Inui, Sadao Kurohashi. 2010. *Dependency Tree-based Sentiment Classification using CRFs with Hidden Variables, HLT-NAACL 2010*,786–794.

S. Chaffar and D. Inkpen. 2011. *Using a heterogeneous dataset for emotion analysis in text, In Canadian Conference on AI*,62–67.

S. M. Mohammad. 2012. *Portable Features for Classifying Emotional Text, 2012 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*,587–591.

Matthew Purver and Stuart Battersby. 2012. *Experimenting with Distant Supervision for Emotion Classification, Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*,482–491.

Ge Xu, Xinfan Meng, Houfeng Wang. 2010. *Build Chinese Emotion Lexicons Using A Graph-based Algorithm and Multiple Resources, In Proceeding of COLING-10*,1209–1217.

Braja Gopal Patra, Hiroya Takamura, Dipankar Das, Manabu Okumura and Sivaji Bandyopadhyay. 2013. *Construction of Emotional Lexicon Using Potts Model, International Joint Conference on Natural Language Processing*,674–679.

Svitlana Volkova, William B. Dolan, Theresa Wilson. 2012. *CLex: A Lexicon for Exploring Color, Concept and Emotion Associations in Language, Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*,306–314.

Ying Chen, Sophia Yat Mei Lee, Shoushan Li, Chu-Ren Huang. 2010. *Emotion Cause Detection with Linguistic Constructions, Proceedings of the 23rd International Conference on Computational Linguistics (Coling 2010)*,179–187.

Ashequl Qadir, Ellen Riloff. 2013. *Bootstrapped Learning of Emotion Hashtags hashtags4you, Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*,2–11.

Dipankar Das and Sivaji Bandyopadhyay. 2010. *Identifying Emotional Expressions, Intensities and Sentence level Emotion Tags using a Supervised Framework, PACLIC 2010*,95–104.

Diman Ghazi, Diana Inkpen, Stan Szpakowicz. 2012. *Prior versus Contextual Emotion of a Word in a Sentence, Proceedings of the 3rd Workshop on Computational Approaches to Subjectivity and Sentiment Analysis*,70–78.

Sunita Sarawagi, William W. Cohen. 2004. *Semi-Markov Conditional Random Fields for Information Extraction, NIPS 2004*.

Daisuke Okanohara, Yusuke Miyao, Yoshimasa Tsuruoka, Jun'ichi Tsujii. 2006. *Improving the Scalability of Semi-Markov Conditional Random Fields for Named Entity Recognition, ACL 2006*,465–472.

Galen Andrew. 2006. *A Hybrid Markov/Semi-Markov Conditional Random Field for Sequence Segmentation, EMNLP 2006*,465–472.

Bishan Yang, Claire Cardie. 2012. *Extracting Opinion Expressions with semi-Markov Conditional Random Fields, EMNLP-CoNLL 2012*,1335–1345.

C Strapparava, A Valitutti. 2004. *WordNet-Affect: an Affective Extension of WordNet, LREC 2004*,1083–1086.