

# Improving Emotion Recognition from Text with Fractionation Training

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## Abstract:

Previous approaches of emotion recognition from text were mostly implemented under keyword-based or learning-based frameworks. However, keyword-based systems are unable to recognize emotion from text with no emotional keywords, and constructing an emotion lexicon is a tough work because of ambiguity in defining all emotional keywords. Completely prior-knowledge-free supervised machine learning methods for emotion recognition also do not perform as well as on some traditional tasks. In this paper, a fractionation training approach is proposed, utilizing the emotion lexicon extracted from an annotated blog emotion corpus to train SVM classifiers. Experimental results show the effectiveness of the proposed approach, and the use of some other experimental design also improves the classification accuracy.

## Keywords:

Emotion recognition; SVM; fractionation training

## 1. Introduction

Since Picard proposed the concept of "affective computing" [1], it soon attracts researchers in the Natural Language Processing (NLP) community to place more emphasis on emotion recognition from texts. The motivation of this research is that text is the most popular medium, and especially it is the main communication tool on the Internet. With the growing available textual resources online, the domain of emotion recognition from text is opened up to arise new opportunities and challenges, and it also benefits human-computer interactions with other modalities like speech or facial expressions sensing [2][3]. A handful of approaches have been proposed for text-based emotion recognition.

Keyword-based approaches are the most intuitive ways when considering emotion recognition. Related work include Elliott's Affective Reasoner [4] and Ortony's Affective Lexicon [5]. However, the most

intuitive approaches always have the inevitable weaknesses. Recognizing emotion from text with no emotional keywords is a main problem, and some other like negation involved in text also results in poor recognition.

Because the original problem of emotion recognition from text can be seen as how to classify the input texts into different categories, it is very similar to text categorization. As a result, various machine learning models such as Naïve Bayes, Maximum Entropy, Support Vector Machines [6] and Conditional Random Fields [7] are applied and give encouraging experimental results.

This paper proposes a fractionation training approach to improve the accuracy of emotion recognition on a collection of blog sentences. To begin an experiment to recognize the state of emotion represented in text, all related research should firstly select suitable classes of emotions. We describe taxonomy of emotional states based on the Two-Factor Structure of Affect [8] in this study, considering the blog emotion corpus that we utilize is annotated with multiple emotional labels in sentence-level. The Support Vector Machines (SVM), which has proved successful in many other areas of text classification tasks, is selected as our basic classifier. Experimental results show that the fractionation training approach can outperform both the baseline informed by prior knowledge of the distribution of classifications, and the other one, which did the best performance in the sentiment classification experiments carried out by Pang *et al.* [6], using SVM classifier with boolean-valued unigram features. Linguistic processing and normalized tf-idf term weights also improve the classification accuracy, although not significantly.

The remaining parts of this paper are organized as follows. Section 2 describes the details of the blog emotion corpus we used, and proposes our emotion taxonomy to solve the multiple emotional labels problem in experimental data. Section 3 follows with the framework of the fractionation training approach. Experimental studies improving emotion recognition from text is described in Section 4, and the results also are analyzed in this section. We make a discussion about

the influences of feature selection in Section 5, and conclude this paper in Section 6.

## 2. Conclusion and Future Work

This section describes a Chinese blog emotion corpus, and proposes taxonomy of emotions to evaluate our approach.

### 2.1. A Blog Emotion Corpus

In recent years, the amount of blog posts has risen dramatically. It is no doubt that they are huge sources of emotion, and these sources for modeling are recognized as more private, honest, and polemic than opinions voiced in other style [9]. The blog emotion corpus Ren-CECps (The Ren-CECps corpus is described in details in [10]) and available at <http://a1-www.is.tokushima-u.ac.jp/member/ren/Ren-CECps1.0/Ren-CECps1.0.html>) based on a collection of blog posts from various Chinese blog communities, and it includes both the source blog posts and manual annotations on these blog posts. The annotations of this corpus are agreed by eleven annotators through a testing annotation period. It finally consists of 1487 blog documents, with 11,255 paragraphs, 35,096 sentences, and 878,164 Chinese words. The annotation frame includes 3 levels: document, paragraph, and sentence. All the annotated blog texts are organized into xml files. Based on previous affect models, Ren-CECps select *expect*, *joy*, *love*, *surprise*, *anxiety*, *sorrow*, *angry* and *hate* as the eight basic emotion classes for manual annotation.

In this paper, we work on the basic level - sentences, the annotation of which including intensities of the emotion classes, emotion holder/target, emotional words/phrases, rhetoric, emotional punctuations, emotion objective/subjective and emotion polarity [10]. Sentence-level classification is useful because most documents contain a mix of sentences with different categories of opinion or emotion, and more detailed emotional information are marked in annotations of Ren-CECps. One subset of 12,516 sentences coming from 500 blog posts in Ren-CECps are selected as the training set of our experiments. We don't only use this training set for supervised training, but also extract emotional keywords, privatives, and adversative conjunctions from its annotation to construct lexicons. And we collect 2,323 sentences from another 100 source blog posts in Ren-CECps as the test set.

### 2.2. Taxonomy of Emotions to Solve the Multiple Labels Problem

Some places in the annotation scheme of Ren-CECps are worth noting: Because of confusion on

boundaries between emotional categories, each sentence in the corpus could be labeled with one or more of the eight basic emotion classes when manually annotated. This scheme brings a problem when we apply statistical classifier to recognize emotional states from those sentences with multiple labels. Let's see a sentence coming from the corpus as below:

随着昔日"体操王子"飞翔着点燃北京奥运会主火炬, 1 3 亿中国人民和 6 0 亿世界人民共同期待的体育盛会终于拉开了序幕。

(With former "gymnastics prince" soaring to light up the main torch of Beijing Olympic Games, the sport with anticipation from 1,300,000,000 Chinese people together with 6,000,000,000 people of the world has begun the prologue finally.)

This sentence is assigned two labels of **joy** and **love** by annotator, and even the given intensities of two emotions are the same (They are both 0.7.). How to classify this kind of sentences by using a machine learning classifier now? In [11] attempted to utilize multi-label classification approach to solve this problem; however, the result wasn't satisfying. A less-complex Two-Factor Structure of Affect model was proposed by Watson and Tellegen in 1985 [8]. This model describes emotions in only two dimensions: that of Positive Affect and Negative Affect, both of which scale between High and Low [12]. They also define two further dimensions derived from a combination of Positive Affect and Negative Affect, as depicted in Figure 1.

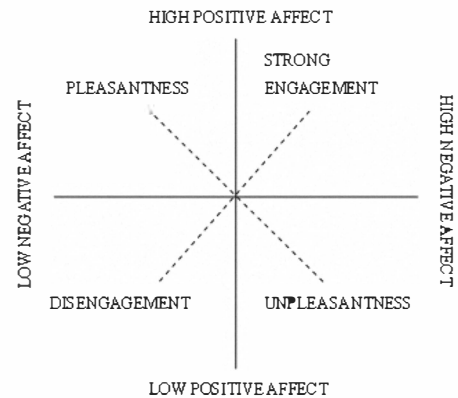


Figure 1. The Two-Factor Structure of Affect [8]

According to the Two-Factor Structure of Affect model, we propose our taxonomy of the Two-Factor Mapping Emotions illustrated in Figure 2. Contraposing the axes in Figure 1, emotional states "joy" and "love" are mapped to High Positive Affect pole (Hp); emotional states "anger" and "hate" are mapped to High Negative affect pole (Hn); emotional states "expect" and "surprise" are mapped to Low Positive Affect pole (Lp); emotional states "anxiety" and "sorrow" are mapped to Low Negative Affect pole (Ln). There are also four

quadrants marked as High Positive & High Negative Affect (HpHn), Low Positive & Low Negative Affect (LpLn), High Positive & Low Negative Affect (HpLn), and Low Positive & High Negative Affect (LpHn), because the combinations of different types of emotion could be found in our corpus. For example, the following sentence:

感受着小手的温度，享受着这份她对我的依恋，生怕动一下会让她的离我而去。

(Feeling the temperature of my baby daughter's hand, enjoying her attaching to me this moment, I'm afraid that her hand will move away if I even take a shake.)

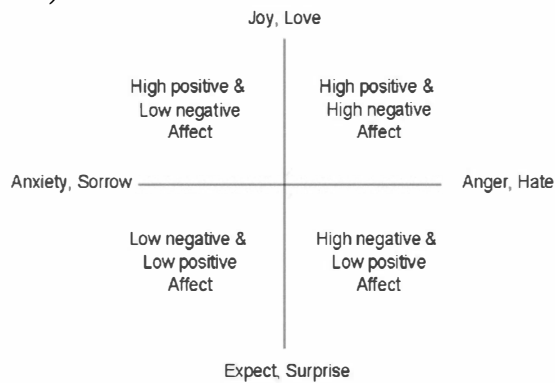


Figure 2. The Two-Factor Mapping Emotions

This sentence is annotated as both **joy** and **anxiety** by annotators (Their intensity are 0.7 and 0.4 respectively.), so we classify it to High Positive & Low Negative Affect. If a sentence has more than one manually annotated emotional label, the most intensive two or three of them would determine which category of Two-Factor Mapping Emotion it belongs to. The classification rules are illuminated as follows:

1. If the two emotional labels with the highest intensity of a sentence both come from one of the four pole classes (High Negative Affect, High Negative Affect, Low Positive Affect, Low Negative Affect), this sentence then would be classified as this pole classes;
2. Else if the two emotional labels with the highest intensity of a sentence come from different pole classes, it would be classified as one of the four compound classes (High Positive & High Negative Affect, High Positive & Low Negative Affect, Low Positive & Low Negative Affect, Low Positive & High Negative Affect) accordingly;
3. Else if a sentence has three or more emotional labels, and the two labels with the highest intensity of the sentence both come from one of the four pole classes, and the third most intensive label comes from a different pole class, it also would be classified as one of the four compound classes accordingly.

After reclassification, recognizing emotion of a sentence can be cast as a multi-class classification problem. Tagging sentences without any emotional label as Unemotional (Ue), the emotion classes chosen for our experiments are defined as the following:

$$C_{\text{emotion}} = \{Ue, Hp, Hn, Lp, Ln, HpHn, LpLn, HpLn, LpHn\}$$

### 3. Framework of the Fractionation Training Approach

The framework of a classical text classification system consists of text representation of the given training data, feature extraction and the processing of classification training. Some evaluation measures would be finally taken to estimate the results generated on test data. The framework of fractionation training approach in this paper is somewhere different from the classical framework, as shown in Figure 3.

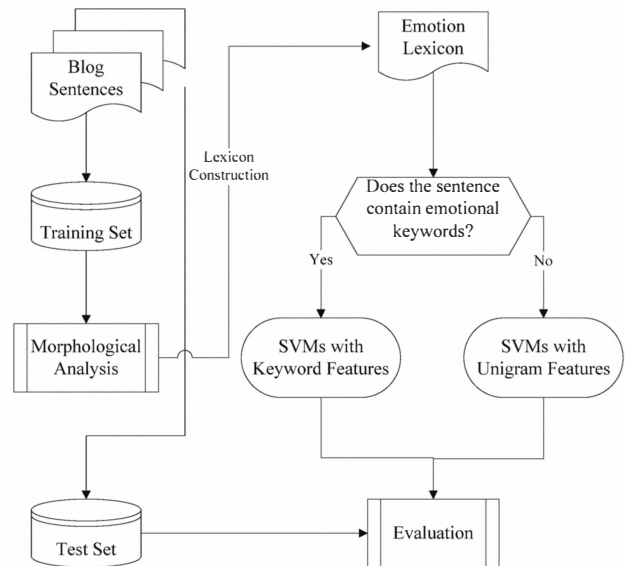


Figure 3. Framework of the fractionation training approach

#### 3.1. Different Feature Sets for Training

Because Chinese text is written without natural delimiters, Chinese Word Segmentation and POS Tagging Tools [13] is chosen to do morphological analysis for Chinese sentences at first. As we have mentioned in Subsection 2.1, the annotators of Ren-CECPs marked the emotional keywords/phrases that could evoke their emotions in the sentences. We extract all these emotional keywords/phrases from those annotated xml files of the training set, and finally construct an emotion lexicon including 14,207 emotional keywords/phrases.

After emotion lexicon extraction, we implement the

fractionation training, which means to train the sentences whether or not contain emotional keywords/phrases respectively. We propose this approach to try to recognize emotional state from sentences with no emotional keywords as well as those with emotional keywords, as recognizing emotional state from sentences with no emotion keywords are seen as the most important problem in related work [14]. We would get two training models and divide the sentences that need to be classified into two fractions, and the feature sets these two fractions utilize for training are different: for the sentences including emotional keywords/phrases which can be found in the emotion lexicon we constructed, we take such keywords/phrases as features; while for the sentences not including any emotional keywords/phrases, we use unigram features. The unigram features are all the individual words segmented by the segmentation tool, which are widely used in statistical NLP tasks.

### 3.2. Multi-class SVM Model

Whereas our goal is to predict emotion of a sentence in blog posts, which can be described as a multi-class classification problem, we choose Support Vector Machine (SVM) as our machine learning model in this paper. After Joachims's study [15], SVM is widely applied in text classification tasks, since they scale to the larger amount of features often incurred in this domain [16]. Yang also reports SVMs significantly outperform other classifiers for this type of tasks [17]. For our experiments, we use LIBSVM (<http://www.csie.ntu.edu.tw/~cjlin/libsvm/index.html>), a publicly available SVM package.

To our multi-class classification task of emotion recognition, LIBSVM uses the one-against-one approach [18], in which  $k(k-1)/2$  classifiers are constructed and each one trains data from two different classes [19]. One-against-one method has been proved more suitable for practical use than some other multi-class SVM methods [20].

## 4. Experimental Studies

### 4.1. Result of Fractionation Training Approach

**Experimental Setup:** The experiments are carried out on a training set including 12,516 sentences from 500 blog posts in Ren-CECPs, and a test set including 2,323 sentences from 100 blog posts in the same corpus, which we have introduced in Subsection 2.1. Taxonomy of Emotions proposed in Subsection 2.2 is used for evaluation. We apply SVM algorithm for classification with the help of the LIBSVM tool. Almost all parameters are set to their default values except the kernel function which is changed from a polynomial kernel function to a linear one, because the linear one usually performs better

for text classification tasks. And we choose *presence* term weighting scheme to value features we extracted first, which generates boolean-valued feature vectors.

**Baseline1:** When there are no previous experiments to compare against, prior knowledge of the distribution of classes are always used. The class that accounts for the highest proportion of sentences are assumed as the most useful in terms of evaluating an emotion recognition algorithm [12]. The accuracy using Baseline1 is 46.23%.

**Baseline2:** The *thumbs up or thumbs down? sentiment classification experiment* using SVM and unigram with the presence feature make the best performance in [6]. To compare with prior-knowledge-free supervised training method, we train SVM classifiers using unigram with the presence feature as Baseline2.

The results of fractionation training approach and baselines are shown in Table 1 (highest accuracies are bold while the lowest are italic in tables 1 through 3).

Table 1. Emotion recognition accuracies of the fractionation training approach and Baselines

	Accuracy
Baseline1	46.23%
Baseline2	46.97%
Fractionation	<b>55.75%</b>
2,323 test sentences; 12,516 training sentences	

Comparing Baseline1 and Baseline2, we see from Table1 that performance of the fractionation training approach improves significantly.

### 4.2. Additional Experiments

To see if the experimental design factors we add to our proposed approach could improve performance, we conduct the following additional experiments. We mainly investigate the use of simple linguistic processing to address the problems of negation and adversative conjunction, and utilize normalized tf-idf term weights for emotion recognition from text.

**Negation:** Negation is a big drawback lying in keyword-based approach for emotion classification. The sentence “我今天高兴。(I'm happy today.)”, can be easily classified as being happy, but it will likely fail on another sentence “我今天不高兴。(I'm not happy today.)”. We construct a privative lexicon as similar as we constructed the emotion lexicon. After automatic privative extraction from the training set, we manually select the most common 418 privatives for the privative

lexicon. Our negation processing uses the simple pattern “<Privative> - <Emotional Keyword/Phrase>” to detect if a privative occurs before an emotional keyword/phrase in a sentence, if true, this privative and its adjacent keyword/phrase would be combined to generate a new composite phrase, and then this composite phrase would be added into the emotion lexicon as a new phrase feature.

**Adversative conjunction:** Adversative conjunction could be seen as a form of latent negation to a certain extent, and it is more difficult to recognize than privative. As in the following sentence, “这件裙子价格很便宜, 但是样式设计太差。(This dress is cheap, **but** it is a terrible design.)”, it is not a bad thing if the price of the dress is cheap, however, because of the clause after the word “但是(but)”, we can know that the cheap dress is a terrible design, which indicates the writer of the sentence has a negative semantic orientation about it. We also extract adversative conjunctions from the training set, and manually select the most common 12 adversative conjunctions in Chinese, all of which mean “but” in English. If one of these twelve adversative conjunctions can be found in a sentence, we will only consider the clause after the adversative conjunction, and the part of sentence before the adversative conjunction would be disregarded. For instance, in the sentence “这件裙子价格很便宜, 但是样式设计太差。(This dress is cheap, but it is a terrible design.)”, we only analyze the later clause “但是样式设计太差 (but it is a terrible design)” and then classify this sentence as a negative emotion.

**Normalized tf-idf term weight:** Although presence term weighting scheme performs better than frequency in some previous work, some IR models employ heuristics and formal modeling approaches to evaluate the relevance of a term to a document more effectively [21][22]. Kim *et al.* test various combinations of normalized tf and idf features to verify the effectiveness of their term weighting schemes when using machine learning classifiers [21]. We utilize their best combination *BM25.TF·VS.IDF* as the other term weighting scheme in our experiments.

Table 2. Fractionation training results

	Presence	BM25.TF·VS.IDF
Fractionation	55.75%	56.74%
Fractionation+Negation	56.22%	56.69%
Fractionation+Adversative Conjunction	55.66%	56.91%
Fractionation+Negation+Adversative Conjunction	55.06%	<b>57.17%</b>

As observed in Table 2, the normalized tf-idf term weighting scheme of *BM25.TF·VS.IDF* performs better than presence. Negation processing results in slight

improvements with presence term weight, but drops the accuracy when using *BM25.TF·VS.IDF* term weight. The results of adversative conjunction processing are just the opposite. Note that the fractionation training combined with both negation processing and adversative conjunction processing performs the best when we use *BM25.TF·VS.IDF* term weight for features, but the same combination using presence features produces the worst accuracy result in the experiments. Though the simple rule-based recognition of negation/adversative conjunction may induce errors, it cannot explain the conflicting results. We analyze the results of different fractions and find that presence term weights combined with either adversative conjunction processing or both of negation processing and adversative conjunction processing decrease the number of correct classification in keywords/phrases feature fractions. These misclassifications reflect that presence term weights are not enough to evaluate the relevance of emotional keywords/phrases in short sentences.

## 5. Discussion about Influences of Feature Selection

In text classification, feature selection (FS) is a strategy that aims at making text classifiers more efficient and accurate. In this part, we design experiments to discuss how feature selection for unigrams influences the results of emotion recognition using our proposed approach.

Weighted Log Likelihood Ratio (WLLR) method [23] is proportional to the frequency measurement and the logarithm of the ratio measurement, which are regarded as the two basic measurements to estimate feature selection methods [24]. So we choose it to try our experiments in this research. The formula of it is defined as below [23]:

$$WLLR(t, c_i) = P(t | c_i) \log \frac{P(t | c_i)}{P(t | \bar{c}_i)} \quad (1)$$

Here  $P(t | c_i)$  stands for the probability that a sentence contains term  $t$ , under the condition that it belongs to category  $c_i$ , and  $P(t | \bar{c}_i)$  stands for the probability that a sentence contains term  $t$ , under the condition that it doesn't belong to category  $c_i$ . And it is estimated as in [24]:

$$WLLR = \frac{A_i}{N_i} \log \frac{A_i \cdot (N_{all} - N_i)}{B_i \cdot N_i} \quad (2)$$

$A_i$  is defined as the number of the sentences that contain the term  $t$  and also belong to category  $c_i$ , and  $B_i$  as the number of the sentences that contain the term  $t$  but do not belong to category  $c_i$ .  $N_i$  is the total number of the documents that belong to category  $c_i$ , and  $N_{all}$  is the total number of all documents from



the training data. We choose the maximum score for this FS method in our experiments since maximum score performs better than the average score [7].

In this study, we only carry out feature selection experiments on unigram feature set. At first, we test WLLR FS method with Baseline2, which trains unigram features for recognition. From Table 3, we can find that FS does help the classification of Baseline2. Using only 5,000 unigram features is even better than using all 24,174 unigram features.

Table 3. Influence on the approach of Baseline2

# of features	Accuracy
5,000	47.31%
1,0000	47.44%
1,5000	46.32%
2,0000	48.04%
2,4174	46.97%

Defining the fraction training unigram features of the approach in row 1 of Table 2 as “Fraction1”, the fraction training unigram features of the approach in row 2 of Table 2 as “Fraction2”, the fraction training unigram features of the approach in row 3 of Table 2 as “Fraction3”, and the fraction training unigram features of the approach in row 4 of Table 2 as “Fraction4” respectively, Figure 4 shows the accuracies of SVM classifiers choosing the top 5,000, 10,000, 15,000, 20,000 and all of the 24,174 unigram features, with presence term weight. However, in this case, SVM classifiers using all the unigram features perform better than those using the features after feature selection.

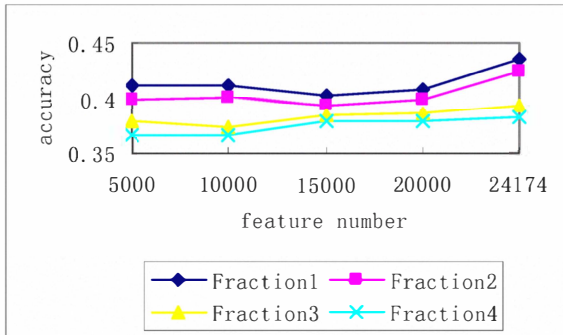


Figure 4. The classification accuracies of the four fractions while increasing the number of selected features

Two possible reasons for the low accuracy in this experiment are: First, we deal with imbalanced data in the experiment. Emotion annotation distributions in the training set and the test set are shown in Figure 5, from which we can observe that the emotion distribution of the test set is not as similar as the emotion distribution of the training set. Obviously, learning from imbalanced

data set is more difficult. Second, the sentences without obvious emotional keywords/phrases but can make annotators feel emotion delivered by the writer are essentially more complex and therefore need more features to identify the emotion classification. In addition, some of them are too short to be classified accurately.

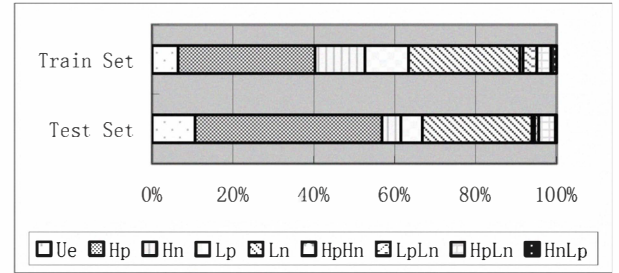


Figure 5. Emotion annotation distributions in the training set and the test set

## 6. Conclusion and Future Work

We have proposed a fractionation training approach to recognize emotion from text. Our experiments perform sentence-level emotion classification. A data set including 12,516 sentences and their annotations in Ren-CECs corpus is utilized for fractionation training, and we test the proposed approach on another 2,323 sentences from the same corpus. Our key idea is to distinguish if the sentences contain emotional keywords/phrases extracted from the training set or not, and then divide them into two fractions, and train these two fractions with different feature sets to gain SVM models. The fractionation training approach outperforms the experiment baselines significantly; we can observe about 10% improvement in accuracy resulting from the best combination of our experimental design from Table 2. In this paper, we further conduct experiments to investigate the influences of feature selection techniques on the classification results, using WLLR as our FS method. We can see from Figure 4 that feature selection for the unigram fraction has very slight influences on the classification accuracy of the proposed approach.

Our future work should include refining the emotion lexicon on the basis of manual annotation, since only selecting features for the unigram fraction could hardly help to improve the performance. In addition, we would attempt algorithms to process the imbalance data set. To identify the negation and adversative conjunction in sentences more precisely is another goal, as there still are many irregular forms of them influencing the emotional information in text.

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