

# Capturing Emotion Events from Web Posts Using Patterns for Emotion Recognition

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## Abstract

The system-provided tags for posters to record their current emotions on social websites have served as useful materials for emotion analysis on social media. LiveJournal<sup>1</sup>, which collects a large amount of user posts and their respective emotions from 132 options, is one of the system providing these tags and thus very often is utilized for developing emotion analysis techniques. Detecting emotions from web posts often has been treated as a text classification problem and various features extracted from posts have been tested for their usefulness in machine learning methods. This paper approaches this research problem from a different perspective by recognizing emotion events using learned patterns. With the sentence structure from the parsing tree, our method keeps as many verbs as possible and removes trivial information to put a whole emotion event in a nutshell. Starting with pattern extraction, our system not only can determine the emotion class of an input post but also can bring out major events of a specific emotion by important patterns. From the analysis of these major events, we also find that same events happening to different persons arouse different emotions. Experiments on 16,000 posts labeled with one of 40 major emotion tags from LiveJournal show that our method outperform the previous results. In addition to evaluate the performance by the traditional metrics accuracy and AUC (Area Under the Curve) for the classification problem, we propose a new evaluation metric MED (Mean Emotion Distance) which considers the strength and likelihood of emotions according to the emotion wheel. MED will give larger penalty to the comparably wrong answer among incorrect ones, and it has the potential to display the emotion of a post in a 3D chromatic visualization model for further applica-

tions. Overall, the proposed system and evaluation metric MED in this paper facilitate the process of improving the emotion classification techniques.

## 1 Introduction

Emotion analysis has attracted much attention in research communities due to the close relativeness to people and its large amount of applications. The emotions researchers tried to detect were usually defined by psychologists Ku et al. (2012) or social media websites where people can express their feelings by writing articles and labeled themselves a specific emotion tag. The number of major emotions defined by psychologists usually range from 5 to 10 including those like happy, angry, sad, surprise, disgust, etc. However, detecting emotions in the articles from the websites is usually more challenging. There are two reasons for this: there are usually more emotion categories which include minor emotions defined by psychologists, and there are also informal emotions like “empty”, “blah”, “sick” included. LiveJournal is one of such social media websites. It allows users to freely note their emotions or select the most appropriate one from 132 predefined tags when posting articles. Posts in LiveJournal are often selected as experimental materials for emotion classification in the research community because of availability of correct answers.

Detecting emotions from texts is often treated as a text classification problem. Therefore, traditional approaches and machine learning approaches for classification are widely used for solving this problem. However, Internet articles contain much noise due to the casual writing style. Therefore, the performance is difficult to improve. Mishne (2005) has done some thorough experiments to show that for articles in LiveJournal, even people can only classify them to the degree of 60% accuracy. Moreover, the traditional evaluation methods for classification, i.e., accuracy and AUC, view each class as of equal importance. This is not true for emotion classification as some

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<sup>1</sup> <http://www.livejournal.com/>

emotions do relate to each other more closely. This could be the reason that the performances of emotion classification on articles of LiveJournal reported in literature had little significance. Therefore, though using materials from LiveJournal for research are very handy and it can work as a benchmark, it is not easy to decide which system is more superior based on the experimental results.

In this paper, we also hope to utilize the LiveJournal materials to develop techniques for emotion classification. We try to solve the mentioned problem from two aspects. First, we propose a pattern-based approach to capture emotion events and avoid noise in web articles. Second, we propose a new evaluation metric Mean Emotion Distance (MED) which considers the relations between emotions and gives the less appropriate answer more penalty. In the process of designing methods and performing experiments, we will highlight the advantages of the proposed pattern-based approaches by showing example instances and evaluating using traditional metrics and MED.

## 2 Related Work

Emotion recognition has been an active research field. Numerous approaches have been proposed for detecting different emotions from textual data.

Mihalcea & Liu employed a corpus-based approach to extract salient keywords for seeking out *happy* and *sad* emotions in the blog posts. Tao adopted the keyword spotting method to build a lexicon from context. Each keyword in the lexicon contains six emotion tags and corresponding weights. Similarly, Yang et al. created emotion lexicons using Yahoo! Kimo Blog as corpora. In their studies, emoticons were introduced to identify emotions associated with textual keywords. Chaumartin developed a rule-based system, which utilized the linguistic information from knowledge bases to detect six specific emotions in news headlines. The results show that their approach is capable to achieve high accuracy on emotion and valence annotations with the help of several lexicon resources, including *WordNet*, *WordNet-Affect* and *SentiWordNet*. In addition to surface keywords or emoticons, Liu et al. presented a set of commonsense-based linguistic affect models, which employed a real-world knowledge base of commonsense to recognize six basic emotions at the sentence level.

Apart from using handcrafted models or rule-based approaches, a number of researches considered emotion recognition task as a classification problem. Mishne conducted preliminary experiments in classifying emotions of blog text at the document level. He used a variety of features for the classification process and utilized the *SVM* classifier to identify the intensity of the community mood. Tokuhisa et al. proposed a two-step method for the sentence-level emotion classification. Firstly, the sentences are grouped into two categories, emotion-involved and neutral using a *SVM* classifier; then the sentences tagged with emotion-

involved are further classified into ten emotion classes by a *k*-nearest-neighbor (*kNN*) classifier.

Each method has its advantage and shortage, for example, approaches utilizing human-craft lexicon and pre-defined rules often perform better than statistical machines learning model in small corpus. However, building lexicons could be painstaking, time-consuming and might not achieve high coverage of emotion keywords and events. Therefore, Yang et al. built a hybrid model that incorporates lexicon-based keyword spotting and several machine learning-based emotion classification models. The results generated by each modules are integrated using vote-based strategies and it demonstrates that the system is capable of recognizing 15 different emotion in the suicide notes.

Although several natural language processing techniques have been used in the hybrid model and they could well complement each other to achieve high accuracy, it is still challenging to recognize emotions in sentences containing implicit affective meaning. For example, in this sentence, “Recently, I really wish I have someone staying with me”, we can easily recognize the emotion *lonely* even there is no explicit emotion expression. To discover the implicit events, we introduced a *Scenario Identification* method utilizing grammatical relations as well as a set of pre-specified semantic structures. After that, we adopted a hybrid model to combine the *Scenario identification* with machine learning classifier aiming to effectively recognize emotions in blog posts.

## 3 Pattern

We focus on the issue of recognizing emotions in blog posts. It is still challenging for past approaches using shallow linguistic features such as *n*-grams, POS tags and word frequency to detect emotions when there is barely affective keyword existed in a sentence. Moreover, people often convey their mental states by describing a certain event rather than using direct or explicit emotion words in blog posts. For example, consider this post, *I got hit by a drunk driver.*, it’s never difficult for human to capture the negative (e.g., *angry* or *depressed*) emotion event without any affective keywords. Thus, it is important to incorporate deep linguistic information to help capture such events, which can precisely reflect the authors’ intended emotions.

### 3.1 Pattern extraction

Due to insufficient affect keyword in emotional expressions, previous research use fragments of sentences as features aiming at better capturing emotion events. The most widely used fragments are word sequences, i.e., *n*-grams, with varied window sizes. (2005 Mishne, 2008 Tokuhisa)

However, low-order *n*-grams such as unigrams, bigrams are often not very comprehensible by human. On the other hands, a higher order *n*-gram will have

the generated text repeat tremendous portions of the source text. It leads to the result that researches often limit the length of n-grams for computational efficiency.

Therefore, this study aims to extract more informative fragments or multiword expressions which are representative of certain event. In the mean time, researches in linguistic indicate that verbs play a central role in the syntactic and semantic interpretation of a sentence (Joanis 2003).

According to this results, we extract verbs and corresponding arguments by grammatical relations and semantic roles to construct verb argument frames. Consider this sentence, for example, *I have a pretty good chance of getting accepted!*, which is a post in LiveJournal labeled as the *excited* mood tag. We identify the verb *have* along with its subject *I* and direct object *chance* to form a verb argument frame:  $\langle I, have, chance \rangle$ .

Compare to previous approaches using n-grams (e.g., *I have a, have a pretty*), verb argument frames (e.g.,  $\langle I, have, chance \rangle$ ) may carry much closer meaning to the origin sentence. In addition, large amounts of n-gram generated as the window size increased to cover all arguments of a verb, in this case, the window size is 6, i.e., *I have a pretty good chance*.

In this paper, we preliminarily consider four major types of verb arguments, subject, object, negation and prepositional phrase, to construct patterns.

### 3.2 Pattern scoring

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### 3.3 Text Pre-processing

Given a full-text blog post, each sentence is processed to obtain word lemma, part-of-speech (POS) tags, and grammatical relations. For instance, four different grammatical relations are extracted, including *subject*, *auxiliary*, *negation*, and *object*, (see Table 1) in the sentence in Example 1. ~~The sets of lexical information are used in the further steps, i.e., machine learning models and scenario identification process.~~

### 3.4 Negation Detection

Similar to past researches on emotion recognition task, we also build a module to determine whether a word is associated with a negation signal. A traditional and common approach is to construct a lexicon containing negation modifiers, such as *no*, *not* or *never*, to detect negation in a sentence. However, it could lead to completely opposite results. Consider the sentence, “I am *not* you, I feel *anxious* sometime”. We can easily obtain the negation modifier *not* and the emotion keyword *anxious* by simply looking up the lexicon, and generate the emotion ex-

pression, “*not anxious*”. Obviously, this expression is inappropriate and not representative for the intended meaning.

For this, we utilize the syntactic information, i.e., grammatical relations, to identify the negation signal, which is truly associated with the target emotion word.

According to grammatical relation, “*neg(you, not)*”, we realize that the negation is associated with the pronoun *you* instead of the emotion keyword *anxious*.

## 3.5 Emotion Recognition

We divide the emotion recognition module into two parts: keyword spotting and the scenario identification process that target for emotion recognition from the explicit and implicit affective expression respectively.

### 3.5.1 Keyword Spotting

In this module, we construct a keyword lexicon from a pre-compiled list of emotion words based on the occurrence of each word in the corpus. This provides an explicit emotion information that can complement with the implicit scenario information provided by our pro-posed approach.

### 3.5.2 Scenario Identification

#### Pattern extraction

~~In the first stage of scenario identification process, we aim at extracting verb arguments to form patterns based on pre-specified syntactic structures. For this, we collect a set of grammatical relations, which are provided by a syntactic parser, from the given sentence in a blog post. In order to extract **representative** patterns for a sentence, we empirically defined a set of syntactic structures, e.g., *subject + verb + object*, listed in Table 2.~~

Consider the sentence “I couldn’t handle it” (Example 1.) According to the pre-specified syntactic structure, the subject *I*, and the object *it* for the verb *handle* can be extracted and combined to form a tuple of verb arguments,  $\langle I, handle, it \rangle$ . Table 1 shows the example sentences and their corresponding grammatical relations provided by a dependency parser as well as the extracted verb argument tuples.

In addition, we introduce the notation “ $\_$ ” to represent the negation, e.g., in Example 1, “handle” is annotated as “ $\_$ handle” according to the relation *neg(handle, n’t)*.

After that, we combine the verb argument tuples with the negation relation and substitute the verbs with corresponding lemma to form a set of lexical patterns from the given sentence. For instance, two sets of lexical patterns are extracted,  $\{I\_handle\}$ ,  $\{I\_hate\}$ , from Example 1 and 2 respectively.

### Scenario lexicon construction

In the second stage of scenario identification process, we utilize the sets of patterns extracted in the previous section to represent implicit emotion expression and to identify the corresponding underlying emotions.

For this, we introduce the *emotion tendency*, which represents the frequency distribution on all emotions, for each pattern.

Let  $P = \{p_1, p_2, \dots, p_n\}$  be the set of patterns extracted from the corpus. Each pattern  $p_i$  in  $P$  is associated with two vectors containing the frequency distributions of pattern frequencies  $PF$  as well as the document frequencies  $DF$  respectively, which are defined as:

$$PF_i = \langle pf_{i,1}, pf_{i,2}, \dots, pf_{i,m} \rangle \quad (1)$$

$$DF_i = \langle df_{i,1}, df_{i,2}, \dots, df_{i,m} \rangle \quad (2)$$

where  $m$  is the size of  $E$  (i.e., the set of predefined emotions). Each elements in both  $PF$  and  $DF$  are calculated using the equations below:

$$pf_{i,j} = \frac{\sum_{d \in D \wedge t(d)=e_j} f(p_i, d)}{\sum_{d \in D} f(p_i, d)} \quad (3)$$

$$df_{i,j} = \frac{|\{d \in D : p_i \in d \wedge t(d) = e_j\}|}{|\{d \in D : p_i \in d\}|} \quad (4)$$

where  $t: d \rightarrow e$  is a function that gives the pre-specified emotion  $e$  of a document  $d$ ;  $f$  takes two arguments and outputs the number of occurrence of a pattern  $p$  in a document  $d$ .

For example, consider the sentence, “I just want someone to love me”. For the verb want, a pattern “I want someone” can be extracted according to the predefined syntactic structure: *subject + verb + object*. Table 3 lists the number of occurrence of this pattern ( $op$ ), and the number of documents containing the pattern ( $dp$ ).

In this example, five emotion classes are considered, i.e.,  $E = \{happy, lonely, sad, creative, depressed\}$ . According to the equation (3) and (4), we obtain the two vectors for this pattern:  $PF = \langle 0, 0.43, 0.08, 0.14, 0.34 \rangle$  and  $DF = \langle 0, 0.48, 0.14, 0.05, 0.33 \rangle$ . These two vectors show that the pattern “I want someone” has the strongest *emotion tendency* to the emotion class *lonely*.

Once the vectors are calculated, we build a lexicon containing all the extracted patterns and their corresponding vectors representing emotion tendency.

### Subject person substitution

From the observations on the extracted patterns, we notice that the same event happening to different people may arouse different emotions. Thus, the subject in a pattern should be important. For example, the patterns *I made mistakes* and *she made mistakes* represent totally different situations. The difference is that the former one is in first person and the latter one

is in third person, which is an important information we should keep in these two pattern. However, we should also remove trivial information containing in the subject of a pattern. For example, the patterns *Alice made mistakes* and *she made mistakes* are both in third person and thus represent similar events. In this case, they should not be considered as different patterns. That is, the difference between *Alice* and *she* should not be kept.

Based on the above, we conclude that the person of a subject would affect the underlying emotions for the same events happening to different people. Thus, we substitute the subject in an extracted pattern by its person, no matter it was originally a noun, a pronoun or a name. For example, consider the three patterns *student is jealous*, *he is jealous* and *Maggie is jealous* extracted according to the syntactic structure *subject + verb-to-be + adjective*. Since their subjects are all in third person, these three different patterns actually represent similar scenarios. In this case, we then substitute their *subjects* with *SUBJ\_3* and their *be verbs* with *be*. Consequently, these three patterns would merge into one pattern *SUBJ\_3 be jealous*, and together represent the same implicit emotion expression.

| emotion   | pf | df |
|-----------|----|----|
| happy     | 0  | 0  |
| lonely    | 15 | 10 |
| sad       | 3  | 3  |
| creative  | 5  | 1  |
| depressed | 12 | 7  |
| sum       | 35 | 21 |

Table 3: # of occurrence of pattern “I want someone” in different emotion classes

### 3.6 System fusion

In the previous stage, each pattern lexicon is constructed based on a predefined syntactic structure. However, different patterns can be extracted from a single sentence based on different syntactic structure. We can consider them at the same time to comprehensively represent the implicit events in a sentence. In addition, the detected keywords can also be combined with the learned patterns to achieve better results. Thus, we simply apply linear combination with different weights to combine several modules.

|                  | Sentence                    | Grammatical relations   | Verb arguments                          | Patterns                                    |
|------------------|-----------------------------|---|---|---|
| <i>Example 1</i> | I couldn't handle it.       | nsubj(handle, I)<br>aux(handle, could)<br>neg(handle, n't)<br>doobj(handle, it)                 | <I, handle, it>.                        | <i>I _handle it</i>                         |
| <i>Example 2</i> | I hate the work and classes | nsubj(hated, I)<br>det(work, the)<br>doobj(hated, work)<br>cc(work, and)<br>conj(work, classes) | <I, hated, work><br><I, hated, classes> | <i>I hate work</i><br><i>I hate classes</i> |

Table 1: The grammatical relations, verb arguments and patterns for example sentences

|                  | Grammatical relations   | Verb arguments        | Person substitution   | Patterns                 |
|------------------|---|-----------------------|-----------------------|--------------------------|
| <i>Example 3</i> | poss(friend, my)<br>nsubj(jealous, friend)<br>cop(jealous, is)                              | <friend, is, jealous> | <SUBJ_3, BE, jealous> | <i>SUBJ_3 BE jealous</i> |
| <i>Example 4</i> | nsubj(jealous, they)<br>cop(jealous, are)   | <they, are, jealous>  | <SUBJ_3, BE, jealous> | <i>SUBJ_3 BE jealous</i> |
| <i>Example 5</i> | nsubj(jealous, Maggie)<br>cop(jealous, is)<br>advmod(jealous, so)<br>prep_of(jealous, them) | <Maggie, is, jealous> | <SUBJ_3, BE, jealous> | <i>SUBJ_3 BE jealous</i> |

Table 2: The person substitution on subjects for example sentences

|                  | SV     | VO     | SVO    | SVC    | Args   | KS     | FS     | YSVM   | MSVM   |
|------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Accuracy (Top-1) | 51.82% | 50.97% | 51.12% | 50.81% | 51.10% | 52.35% | 54.33% | 53.18% | 55.54% |
| MED (Top-1)      | 1.094  | 1.145  | 0.919  | 0.921  | 1.012  | 1.083  | 1.066  | 0.963  | -      |
| MED (All)        | 9.360  | 8.672  | 6.253  | 6.965  | 8.129  | 9.293  | 9.257  | 9.085  | -      |

Table 3: Accuracy and MED (MED 要改)

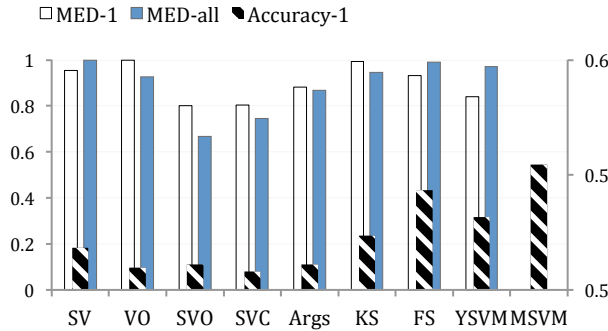


Figure 1: Accuracy and MED (MED 要改)

## 4 Experiment and results

In our method we build several lexicons containing the emotion tendency information of keywords and patterns to predict emotions for blog posts. Under this circumstance, effectively and precisely calculating the emotion tendency plays a significant role in lexicon-based approaches, and this relies on large amounts of data.

For this reason, we performed experiments on a corpus containing blog posts collected from *LiveJournal*, which is a free weblog service with millions of users. The most distinguished feature of *LiveJournal* is that users can attach a mood tag to their blog post. The mood tag is chosen from a predefined list with 132 tags or be entered as free-text. Similar to the experiment conducted in the previous works (Yang and Liu [2012], Mishne [2005]), we use the dataset, LJ40K<sup>2</sup>, which is a subset of the 21 million posts Leshed and Kaye (2006) collected. LJ40K contains 40,000 blog posts tagged in top 40 occurring moods in the entire corpus, i.e., 1,000 blog posts in each mood.

With 40K blog posts collected, we take three main steps to enrich our corpus with syntactic and semantic information.

Firstly, we use *Stanford Parser*, Klein and Manning (2003), to obtain the POS tags and the typed-dependency sentence structures. Next, we introduce a emotional list of words from *WordNetAffect*, Straparava and Valitutti, (2004), to discover affective text for keyword spotting. Finally, we recognize the per-

<sup>2</sup> Data set available at <http://mac.citi.sinica.edu.tw/LJ>



sons' names by identifying pronouns, looking up the lexical information in *WordNet*, Miller (1995), as well as a list of gendered English first names<sup>3</sup> compiled by Mark Kantrowitz and Bill Ross.

## 4.1 System used

One of the questions we wanted to answer in this research was what formation of patterns can precisely capture the scenarios, i.e., implicit emotion expression, from a blog post.

For this, we looked into the semantic role and extracted specific semantic arguments like *subjects*, *objects*, *adjective collocates* associated with a verb in a sentence.

| system | description  |
|--------|--|
| SV     | <i>subject + verb</i> patterns                     |
| VO     | <i>verb + object</i> patterns                      |
| SVO    | <i>subject + verb + object</i> patterns            |
| SVC    | <i>subject + linking verb + adjective</i> patterns |
| Args   | <i>all arguments of the verb</i> patterns          |
| KS     | emotional keywords                                 |
| FS     | Fusion system: <b>SV+KS+SVC</b>                    |
| YSVM   | features: words with TF-IDF scores                 |
| MSVM   | features: syntactic and semantic information       |

Table2: systems used and corresponding contents

## 4.2 Experiment metrics

In order to evaluate the performances of different systems, we carried out two metrics.

First, we use **Accuracy**, which is a traditional evaluation method for classification problem.

The second metric is the **Mean Emotion Distance** (MED), which considers the strength and likelihood of emotions according to the emotion wheel model proposed by Robert Plutchick in 1980.

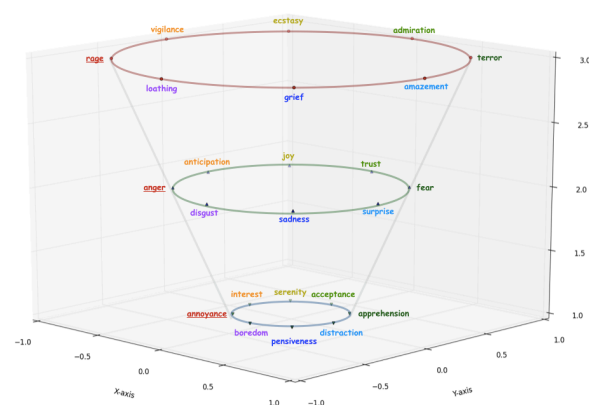


Figure X: Robert Plutchick's emotion wheel model.

## 4.3 Evaluation results

[results]

## 5 Conclusion

According to the experiments conducted by Mishne (2005), even the human classification on *LiveJournal* can only achieve 63% accuracy. This indicates that the emotion tags of blog posts in *LiveJournal* reflect the authors' subjective emotions, which makes this task much more challenging to machines. In this paper, we presented experiment results showing that our approach combining keyword spotting and learned patterns can achieve comparable accuracy with previous works (Yang and Liu [2012], Mishne [2005])

The task of emotion detection from web posts was usually treated as a classification problem, where the strength and likelihood of wrong answers were not considered. Using the proposed MED evaluation metric, the results show that our approach can rank the emotions based on their similarity to the users' emotions more precisely by capturing implicit events. However, in our approach, the learned patterns are extracted based on sets of predefined syntactic structures. However, the set of structures that is most representative of implicit emotional events needs to be further explored through experiments or linguistic analysis.

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<sup>3</sup> English Names Corpus (<http://nltk.googlecode.com/svn/trunk/nltk-old/data/names.readme>), which contains 5k female and 3k male first names.

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