

# Textual Emotion Processing From Event Analysis

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## Abstract

Textual emotion recognition has gained a lot of attention recent years; it is however less developed due to the complexity nature of emotion. In this paper, we start with the discussion of a number of fundamental yet unresolved issues concerning emotion, which includes its definition, representation and technology. We then propose an alternative solution for emotion recognition taking into account of emotion causes. Two pilot experiments are done to justify our proposal. The first experiment explores the impact of emotion recognition. It shows that the context contains rich and crucial information that effectively help emotion recognition. The other experiment examines emotion cause events in the context. We find that most emotions are expressed with the presence of causes. The experiments prove that emotion cause serves as an important cue for emotion recognition. We suggest that the combination of both emotion study and event analysis would be a fruitful direction for deep emotion processing.

## 1 Introduction

The study of emotion attracts increasingly greater attention in the field of NLP due to its emerging wide applications, such as customer care (Gupta et al., 2010), and social information understanding (Lisa and Steyvers, 2010). In contrast to sentiment, which is the external subjective evaluation, emotion mainly concentrates on the internal mental state of human (Ortony et al., 1987). Emotion is indeed a highly complicated concept that raises a lot of controversies in the theories of emotion re-

garding the fundamental issues such as emotion definition, emotion structure and so on. The complexity nature of emotion concept makes automatic emotion processing rather challenging.

Most emotion studies put great effort on emotion recognition, identifying emotion classes, such as *happiness*, *sadness*, and *fear*. On top of this surface level information, deeper level information regarding emotions such as the experiencer, cause, and result of an emotion, needs to be extracted and analyzed for real world applications. In this paper, we discuss these two closely related emotion tasks, namely emotion recognition and emotion cause detection and how they contribute to emotion processing.

For emotion recognition, we construct an emotion corpus for explicit emotions with an unsupervised method. Explicit emotions are emotions represented by emotion keywords such as e.g., “*shocked*” in “*He was shocked after hearing the news*”. In the course of emotion recognition, the keyword in an explicit emotion expression is deleted and only contextual information remains. In our pilot experiments, the context-based emotion identification works fairly well. This implies that plenty of information is provided in the context for emotion recognition. Moreover, with an in-depth analysis of the data, we observe that it is often the case that emotions co-occur and interact in a sentence. In this paper, we deal with emotion recognition from a dependent view so as to capture complicated emotion expressions.

Emotion is often invoked by an event, which in turn is very likely to elicit an event (Descartes 1649, James 1884, Plutchik 1980, Wierzbicka

1999). Despite the fact that most researches recognize the important role of events in emotion theories, little work, if not none, attempts to make explicit link between events and emotion. In this paper, we examine emotion constructions based on contextual information which often contains considerable relevant eventive information. In particular, the correlations between emotion and cause events will be explored based on empirical data. Emotion causes refer to explicitly expressed propositions that evoke the corresponding emotions.

To enhance emotion recognition, we examine emotion causes occurring in the context of an emotion. First, we manually annotate causes for emotions in our explicit emotion corpus. Since an emotion cause can be a complicated event, we model emotion cause detection as a multi-label problem to detect a cross-clause emotion cause. Furthermore, an in-depth linguistic analysis is done to capture the different constructions in expressing emotion causes.

The paper is organized as follows. Section 2 discusses some related work regarding emotion recognition and emotion cause detection. In Section 3, we present our context-based emotion corpus and provide some data analysis. Section 4 describes our emotion recognition system, and discusses the experiments and results. In Section 5, we examine our emotion cause detection system, and discuss the performances. Finally, Section 6 concludes our main findings for emotion processing from the event perspective.

## 2 Related Work

Most current emotion studies focus on the task of emotion recognition, especially in affective lexicon construction. In comparison with emotion recognition, emotion cause detection is a rather new research area, which account for emotions based on the correlations between emotions and cause events. This section discusses the related research on emotion recognition and emotion cause detection.

### 2.1 Emotion Recognition

Although emotion recognition has been intensively studied, some issues concerning emotion remain unresolved, such as emotion definition,

emotion representation, and emotion classification technologies.

For the emotion definition, emotion has been well-known for its abstract and uncertain definition which hinders emotion processing as a whole. Ortony et al., (1987) conducted an empirical study for a structure of affective lexicon based on the ~500 words used in previous emotion studies. However, most of the emotion corpora in NLP try to avoid the emotion definition problem. Instead, they choose to rely on the intuition of annotators (Ren's Blog Emotion Corpus, RBEC, Quan and Ren, 2009) or authors (Mishne's blog emotion corpus, Mishne, 2005). Therefore, one of the crucial drawbacks of emotion corpora is the problem of poor quality. In this paper, we explore emotion annotation from a different perspective. We concentrate on explicit emotions, and utilize their contextual information for emotion recognition.

In terms of emotion representation, textual emotion corpora are basically annotated using either the enumerative representation or the compositional representation (Chen et al., 2009). The enumerative representation assigns an emotion a unique label, such as *pride* and *jealousy*. The compositional representation represents an emotion through a vector with a small set of fixed basic emotions with associated strength. For instance, *pride* is decomposed into "*happiness + fear*" according to Turner (2000).

With regard to emotion recognition technologies, there are two kinds of classification models. One is based on an independent view (Mishne, 2005; Mihalcea and Liu, 2006; Aman and Szpakowicz, 2007; Tokuhisa et al., 2008; Strapparava and Mihalcea, 2008), and the other is a dependent view (Abbasi et al, 2008; Keshtkar and Inkpen, 2009). The independent view treats emotions separately, and often chooses a single-label classification approach to identify emotions. In contrast, the dependent view takes into account complicated emotion expressions, such as emotion interaction and emotion co-occurrences, and thus requires more complicated models. Abbasi et al. (2008) adopt an ensemble classifier to detect the co-occurrences of different emotions; Keshtkar and Inkpen (2009) use iteratively single-label classifiers in the top-down order of a given emotion hierarchy. In this paper, we examine emotion recognition as a multi-label problem and investigate several multi-label classification approaches.

## 2.2 Emotion Cause Detection

Although most emotion theories recognize the important role of causes in emotion analysis (Descartes, 1649; James, 1884; Plutchik, 1962; Wierzbicka 1996), yet very few studies in NLP explore the event composition and causal relation of emotions. As a pilot study, the current study proposes an emotion cause detection system.

Emotion cause detection can be considered as a kind of causal relation detection between two events. In other words, emotion is envisioned as an event type which triggers another event, i.e. cause event. We attempt to examine emotion cause relations for open domains. However, not much work (Marcu and Echihabi, 2002; Girju, 2003; Chang and Choi, 2006) has been done on this kind of general causal relation for open domains.

Most existing causal relation detection systems contain two steps: 1) cause candidate identification; 2) causal relation detection. However, Step 1) is often oversimplified in real systems. For example, the cause-effect pairs are limited to two noun phrases (Chang and Choi, 2005; Girju, 2003), or two clauses connected with selected conjunction words (Marcu and Echihabi, 2002). Moreover, the task of Step 2) often is considered as a binary classification problem, i.e. “causal” vs. “non-causal”.

With regard to feature extraction, there are two kinds of information extracted to identify the causal relation in Step 2). One is constructions expressing a cause-effect relation (Chang and Choi, 2005; Girju, 2003), and the other is semantic information in a text (Marcu and Echihabi, 2002; Persing and Ng, 2009), such as word pair probability. Undoubtedly, the two kinds of information often interact with each other in a real cause detection system.

## 3 Emotion Annotated Sinica Corpus (EASC)

EASC is an emotion annotated corpus comprising two kinds of sentences: emotional-sentence corpus and neutral-sentence corpus. It involves two components: one for emotion recognition, which is created with an unsupervised method (Chen et al.

2009), and the other is for emotion cause detection, which is manually annotated (Chen et al. 2010).

### 3.1 The Corpus for Emotion Recognition

With the help of a set of rules and a collection of high quality emotion keywords, a pattern-based approach is used to extract emotional sentences and neutral sentences from the Academia Sinica Balanced Corpus of Mandarin Chinese (Sinica Corpus). If an emotion keyword occurring in a sentence satisfies the given patterns, its corresponding emotion type will be listed for that sentence. As for emotion recognition, each detected keyword in a sentence is removed, in other words, the sentence provides only the context of that emotion. Due to the overwhelming of neutral sentences, EASC only contains partial neutral sentences besides emotional sentences. For experiments, 995 sentences are randomly selected for human annotation, which serve as the test data. The remaining 17,243 sentences are used as the training data.

In addition, in the course of creating the emotion corpus, Chen et al. (2009) list the emotion labels in a sentence using the enumerative representation. Besides, an emotion taxonomy is provided to re-annotate an emotion with the compositional representation. With the taxonomy, an emotion is decomposed into a combination of primary emotions (i.e. *happiness*, *fear*, *anger*, *sadness*, and *surprise*).

From this corpus, we observe that ~54% emotional sentences contain two emotions, yet only ~2% sentences contain more than two emotions. This implies emotion recognition is a typical multi-label problem. Particularly, more effort should be put on the co-occurrences of two emotions.

### 3.2 The Corpus for Emotion Cause Detection

Most emotion theories agree that the five primary emotions (i.e. *happiness*, *sadness*, *fear*, *anger*, and *surprise*) are prototypical emotions. Therefore, for emotion cause detection, we only deal with the emotional sentences containing a keyword representing one of these primary emotions. Beyond a focus sentence, its context (the previous sentence and the following sentence) is also extracted, and those three sentences constitute an entry. After

filtering non-emotional and ambiguous sentences, 5,629 entries remain in the emotion cause corpus.

Each emotion keyword is annotated with its corresponding causes if existing. An emotion keyword can sometimes be associated with more than one cause, in such a case, both causes are marked. Moreover, the cause type is also identified, which is either a nominal event or a verbal event (a verb or a nominalization).

From the corpus, we notice that 72% of the extracted entries express emotions, and 80% of the emotional entries have a cause, which means that causal event is a strong indicator for emotion recognition.

Furthermore, since the actual cause can sometimes be so complicated that it involves several events, we investigate the span of a cause text as follows. For each emotion keyword, an entry is segmented into clauses with some punctuations, and thus an entry becomes a list of cause candidates. In terms of the cause distribution, we find ~90% causes occurring between ‘left\_2’ and ‘right\_1’. Therefore, our cause search is limited to the list of cause candidates which contains five text units, i.e. <left\_2, left\_1, left\_0, right\_0, right\_1>. If the clause where emotion keyword locates is assumed as a focus clause, ‘left\_2’ and ‘left\_1’ are the two previous clauses, and ‘right\_1’ is the following one. ‘left\_0’ and ‘right\_0’ are the partial texts of the focus clause, which locate in the left side of and the right side of the emotion keyword, respectively. Finally, we find that ~14% causes occur cross clauses.

## 4 Emotion Processing with multi-label models

### 4.1 Multi-label Classification for Emotion recognition

Based on our corpus, two critical issues for emotion recognition need to be dealt with: emotion interaction and emotion co-occurrences. Co-occurrence of multiple emotions in a sentence makes emotion recognition a multi-label problem. Furthermore, the interaction among different emotions in a sentence requires a multi-label model to have a dependent view. In this paper, we explore two simple multi-label models for emotion recognition.

**The Binary-based (BB) model:** decompose the task into multiple independent binary classifiers (i.e., “1” for the presence of one emotion; “0” for the absence of one emotion), where each emotion is allocated a classifier. For each test instance, all labels (emotions) from the classifiers compose a vector.

**The label powset (LP) model:** treat each possible combination of labels appearing in the training data as a unique label, and convert multi-label classification to single-label classification.

Both the BB model and the LP model need a multi-class classifier. For our experiment, we choose a Max Entropy package, Mallet<sup>1</sup>. In this paper, we use only words in the focus sentence as features.

### 4.2 Emotion Recognition Experiments

To demonstrate the impact of our context-based emotion corpus to emotion recognition, we compare EASC data to Ren’s Blog Emotion Corpus (RBEC). RBEC is a human-annotated emotion corpus for both explicit emotions and implicit emotions. It adopts the compositional representation with eight emotion dimensions (*anger, anxiety, expect, hate, joy, love, sorrow, and surprise*). For each dimension, a numerical value ranging in {0.0, 0.1, 0.2... 1.0} indicates the intensity of the emotion in question. There are totally 35,096 sentences in RBEC. To fairly compare with the EASC data, we convert a numerical value to a binary value. An emotion exists in a sentence only when its corresponding intensity value is greater than 0.

For RBEC data, we use 80% of the corpus as the training data, 10% as the development data, and 10% as the test data. For EASC, apart from the test data, we divide its training data into two sets: 90% for our training data, and 10% for our development data. For evaluation of a multi-label task, three measures are used: accuracy (extract match ratio), Micro F1, and Macro F1. Accuracy is the extract match ratio of the whole assignments in data, and Micro F1 and Macro F1 are the aver-

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<sup>1</sup> <http://mallet.cs.umass.edu/>

Table 1: The overall performances for the multi-label models

	EASC		RBEC	
	BB	LP	BB	LP
Accuracy	21.30	28.07	22.99	28.33
Micro F1	41.96	46.25	44.77	44.74
Macro F1	34.78	35.52	36.48	38.88

age scores of F scores of all possible values for all variables. Micro F1 takes the emotion distribution into account, while Macro F1 is just the average of all F scores. Note that due to the overwhelming percentage of value 0 in the multi-label task, during the calculating of Micro F1 and Macro F1, most previous multi-label systems take only value 1 (indicating the existence of the emotion) into account.

In Table 1, we notice that the emotion recognition system on our context-based corpus achieves similar performance as the one on human-annotated corpus. This implies that there is rich contextual information with respect to emotion identification.

## 5 Emotion Cause Detection

Most emotion theories agree that there is a strong relationship between emotions and events (Descartes 1649, James 1884, Plutchik 1980, Wierzbicka 1999). Among the rich information in the context of an emotion, cause event is the most crucial component of emotion. We therefore attempt to explore emotion causes, and extract causes for emotion automatically.

### 5.1 Emotion Cause Detection

Based on the cause distribution analysis in Section 3.2, in contrast to binary classification used in previous work, we formalize emotion cause detection as a multi-label problem as follows.

Given an emotion keyword and its context, its label is the locations of its causes, such as “left\_1, left\_0”. Then, we use the LP model to identify the cause for each sentence as well as an emotion keyword. With regard to emotion cause detection, the LP model is more suitable than the BB model because the LP model can easily capture the possible label combinations.

In terms of feature extraction, unlike emotion recognition, emotion cause detection relies more

on linguistic constructions, such as “*The BP oil spill makes the country angry*”, “*I am sad because of the oil spill problem*” and so on.

According to our linguistic analysis, we create 14 patterns to extraction some common emotion cause expressions. Some patterns are designed for general cause detection using linguistic cues such as conjunctions and prepositions. Others are designed for some specific emotion cause expressions, such as epistemic markers and reported verbs. Furthermore, to avoid the low coverage problem of the rule-based patterns, we create another set of features, which is a group of generalized patterns. For details, please refer to Chen et al. (2010).

### 5.2 Experiments

For EASC, we reserve 80% as the training data, 10% as the development data, and 10% as the test data. For evaluation, we first convert a multi-label tag outputted from our system into a binary tag (‘Y’ means the presence of a causal relation; ‘N’ means the absence of a causal relation) between the emotion keyword and each candidate in its corresponding cause candidates. We then adopt three common measures, i.e. precision, recall and F-score, to evaluate the result.

A naive baseline is designed as follows: The baseline searches for the cause candidates in the order of <left\_1, right\_0, left\_2, left\_0, right\_1>. If the candidate contains a noun or a verb, this clause is considered as a cause and the search stops.

Table 2 shows the overall performances of our emotion cause detection system. First, our system based on a multi-label approach as well as powerful linguistic features significantly outperforms the naive baseline. Moreover, the greatest improvement is attributed to the 14 linguistic patterns (LP). This implies the importance of linguistic cues for cause detection. Moreover, the general patterns (GP) achieve much better per-

formance on the recall and yet slightly hurt on the precision.

The performances (F-scores) for ‘Y’ and ‘N’ tags separately are shown in Table 3. First, we notice that the performances of the ‘N’ tag are much better than the ones of ‘Y’ tag. Second, it is surprising that incorporating the linguistic features significantly improves the ‘Y’ tag only (from 33% to 56%), but does not affect ‘N’ tag. This suggests that our linguistic features are effective to detect the presence of causal relation, and yet do not hurt the detections of ‘non\_causal’ relation. Furthermore, the general feature achieves ~8% improvements for the ‘Y’ tag.

Table 2: The overall performance with different feature sets of the multi-label system

	Precision	Recall	F-score
Baseline	56.64	57.70	56.96
LP	74.92	66.70	69.21
+ GP	73.90	72.70	73.26

Table 3: The separate performances for ‘Y’ and ‘N’ tags of the multi-label system

	‘Y’	‘N’
Baseline	33.06	80.85
LP	48.32	90.11
+ GP	56.84	89.68

## 6 Discussions

Many previous works on emotion recognition concentrated on emotion keyword detection. However, Ortony et al. (1987) pointed out the difficulty of emotion keyword annotation, be it manual or automatic annotation. Emotion keywords are rather ambiguous, and also contain other information besides affective information, such as behavior and cognition. Therefore, contextual information provides important cues for emotion recognition. Furthermore, we propose an alternative way to explore emotion recognition, which is based on emotion cause. Through two pilot experiments, we justify the importance of emotion contextual information for emotion recognition, particularly emotion cause.

We first examine emotion processing in terms of events. Context information is found to be very important for emotion recognition. Furthermore, most emotions are expressed with the presence of causes in context, which implies that emotion cause is the crucial information for emotion recognition. In addition, emotion cause detection also explores deep understanding of an emotion. Compared to emotion recognition, emotion cause detection requires more semantic and pragmatic information. In this paper, based on the in-depth linguistic analysis, we extract different kinds of constructs to identify cause events for an emotion.

To conclude, emotion processing is a complicated problem. In terms of emotion keywords, how to understand appropriately to enhance emotion recognition needs more exploration. With respect to emotion causes, first, event processing itself is a challenging topic, such as event extraction and co-reference. Second, how to combine event and emotion in NLP is still unclear, but it is a direction for further emotion studies.

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