Emotion Cause Detection with Linguistic Constructions

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Abstract

This paper proposes a multi-label approach to detect emotion causes. The multi-label model not only detects multi-clause causes, but also captures the long-distance information to facilitate emotion cause detection. In addition, based on the linguistic analysis, we create two sets of linguistic patterns during feature extraction. Both manually generalized patterns and automatically generalized patterns are designed to extract general cause expressions or specific constructions for emotion causes. Experiments show that our system achieves a performance much higher than a baseline model.

1 Introduction

Text-based emotion processing has been a center of attention in the NLP field in the past few years. Most previous researches have focused on detecting the surface information of emotions, especially emotion classes, e.g., "happiness" and "anger" (Mihalcea and Liu 2006, Strapparava and Mihalcea 2008, Abbasi et al, 2008, Tokuhisa et al. 2008). Although most emotion theories recognize the important role of causes in emotion analysis (Descartes, 1649; James, 1884; Plutchik 1980, Wierzbicka 1999), very few studies explore the interactions between emotion and causes. Emotion-cause interaction is the eventive relation which potentially yields the most crucial information in terms of information extraction. For instance, knowing the existence of an emotion is often insufficient to predict future events or decide on the best reaction. However, if the emotion cause is known in addition to the type of emotion, prediction of future events or assessment of potential implications can be done more reliably. In other words, when emotion is treated as an event, causal relation is the pivotal relation to discover. In this paper, we explore one of the crucial deep level types of information of emotion, i.e. cause events.

Our study focuses on explicit emotions in which emotions are often presented by emotion keywords such as "*shocked*" in "*He was shocked after hearing the news*". Emotion causes are the explicitly expressed propositions that evoke the presence of the corresponding emotions. They can be expressed by verbs, nominalizations, and nominals. Lee et al. (2010a) explore the causes of explicit emotions by constructing a Chinese emotion cause corpus. Based on this corpus, we formalize the emotion cause detection problem through extensive data analysis. We find that ~14% emotion causes are complicated events containing multi-clauses, to which previous cause detection systems can hardly be applied directly. Most previous cause detection systems focus on the causal relation between a pair of small-size text units, such as clauses or phrases. They are thus not able to detect emotion causes that are multi-clauses. In this paper, we formalize emotion cause detection as a multi-label classification task (i.e. each instance may contain more than one label), which allows us to capture long-distance information for emotion cause detection.

In term of feature extraction, as emotion cause detection is a case of cause detection, some typical patterns used in existing cause detection systems, e.g., "*because*" and "*thus*", can be adopted. In addition, various linguistic cues are examined which potentially indicate emotion causes, such as causative verbs and epistemic markers (Lee at al. 2010a). Then some linguistic patterns of emotion causes are manu-

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ally generalized by examining the linguistic context of the empirical data (Lee et al., 2010b). It is expected that these manually generalized patterns often yield a low-coverage problem. Thus, we extracted features which enable us to automatically capture more emotion-specific constructions. Experiments show that such an integrated system with various linguistic features performs promisingly well. We believe that the present study should provide the foundation for future research on emotion analysis, such as the detection of implicit emotion or cause.

The paper is organized as follows. Section 2 discusses the related work on cause-effect detection. Section 3 briefly describes the emotion cause corpus, and then presents our data analysis. Section 4 introduces the multi-label classification system for emotion cause detection. Section 5 describes the two kinds of features for our system, one is based on hand-coded patterns and the other is the generalized features. Section 6 presents the evaluation and performance of our system. Section 7 highlights our main contributions and the possible future work.

2 Related Work

Most previous studies on textual emotion processing focus on emotion recognition or classification given a known emotion context (Mihalcea and Liu 2006, Strapparava and Mihalcea 2008, Abbasi et al, 2008, Tokuhisa et al. 2008). However, the performance is far from satisfactory. One crucial problem in these works is that they limit the emotion analysis to a simple classification and do not explore the underlying information regarding emotions. Most theories conclude that emotions are often invoked by the perception of external events. An effective emotion recognition model should thus take this into account.

To the best of our knowledge, little research has been done with respect to emotion cause detection. Lee et al. (2010a) first investigate the interactions between emotions and the corresponding causes from a linguistic perspective. They annotate a small-scale emotion cause corpus, and identify six groups of linguistic cues facilitating emotion cause detection. Based on these findings, they develop a rule-based system for automatic emotion cause detection (Lee et al., 2010b).

Emotion cause detection can be considered as a kind of causal relation detection, which has been intensively studied for years. Most previous cause detection studies focus on a specific domain, such as aviation (Persing and Ng, 2009) and finance (Low, et al., 2001). Few works (Marcu and Echihabi, 2002; Girju, 2003; Chang and Choi, 2005) examine causal relation for open domains.

In recognizing causal relations, most existing systems involve two steps: 1) cause candidate identification; 2) causal relation detection. To simplify the task, most systems omit the step of identifying cause candidates. Instead, they often predefine or filter out possible causes based on domain knowledge, e.g., 14 kinds of cause types are identified for aviation incidents (Persing and Ng, 2009). For events without specific domain information, open-domain systems choose to limit their cause candidate. For example, the cause-effect pairs are limited to two noun phrases (Chang and Choi, 2005; Girju, 2003), or two clauses connected with fixed conjunction words (Marcu and Echihabi, 2002).

Given pairs of cause-effect candidates, causal relation detection is considered as a binary classification problem, i.e. "causal" vs. "non-causal". In general, there are two kinds of information extracted to identify the causal relation. One is patterns or constructions expressing a cause-effect relation (Chang and Choi, 2005; Girju, 2003), and the other is semantic information underlying in a text (Marcu and Echihabi, 2002; Persing and Ng, 2009), such as word pair probability. Undoubtedly, the two kinds of information usually interact with each other in a real cause detection system.

In the literature, the three common classification methods, i.e. unsupervised, semi-supervised, and supervised, have all been used for cause detection systems. Marcu and Echihabi (2002) first collected a cause corpus using an unsupervised approach with the help of several conjunction words, such as "*because*" and "*thus*", and determined the causal relation for a clause pair using the word pair probability. Chang and Choi (2005) used a semi-supervised method to recursively learn lexical patterns for cause recognition based on syntactic trees. Bethard and Martin (2008) put various causal information in a supervised classifier, such as the temporal information and syntactic information.

For our emotion cause detection, several practical issues need to be investigated and resolved. First, for the identification of cause candidates, we need to define a reasonable span of a cause. Based on our data analysis, we find that emotion causes often appear across phrases or even clauses. Second, although in emotion cause detection the effect is fixed, the cause is open-domain. We also notice that besides the common patterns, emotion causes have their own expression patterns. An effective emotion cause detection system should take them into account.

3 Corpus Analysis

In this section, we briefly introduce the Chinese emotion cause corpus (Lee et al., 2010a), and discuss emotion cause distribution.

3.1 Emotion Cause corpus

Lee at al. (2010a) made the first attempt to explore the correlation between emotions and causes, and annotate a Chinese emotion cause corpus. The emotion cause corpus focuses on five primary emotions, namely "happiness", "sadness", "fear", "anger", and "surprise". The emotions are explicitly expressed by emotion keywords, e.g., *gao1xing4* "happy", *shang1xin1* "sad", etc. The corpus is created as follows.

1. 6,058 entries of Chinese sentences are extracted from the Academia Sinica Balanced Corpus of Mandarin Chinese (Sinica Corpus) with the pattern-match method as well as the list of 91 Chinese primary emotion keywords (Chen et al., 2009). Each entry contains the focus sentence with the emotion keyword "<FocusSentence>" plus the sentence before "<PrefixSentence>" and after "<SuffixSentence>" it. For each entry, the emotion keywords are indexed since more than one emotion may be presented in an entry;
2. Some preprocessing, such as balancing the number of entry among emotions, is done to remove some entries. Finally, 5,629 entries remain;
3. 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).

Lee at al. (2010a) notice that 72% of the extracted entries express emotions, and 80% of the emotional entries have a cause.

3.2 The Analysis of Emotion Causes

To have a deeper understanding of emotion cause detection, we take a closer look at the emotion cause distribution, including the distribution of emotion cause occurrence and the distribution of emotion cause text.

The occurrence of emotion causes: According to most emotion theories, an emotion is generally invoked by an external event. The corpus shows that, however, 20% of the emotional entries have no cause. Entries without causes explicitly expressed are mainly due to the following reasons:

i) There is not enough contextual information, for instance the previous or the suffix sentence is interjections, e.g., *en heng* "aha";

ii) When the focus sentence is the beginning or the ending of a paragraph, no prefix sentence or suffix sentence can be extracted as the context. In this case, the cause may be beyond the context;

iii) The cause is obscure, which can be very abstract or even unknown reasons.

The emotion cause text: A cause is considered as a proposition. It is generally assumed that a proposition has a verb which optionally takes a noun occurring before it as the subject and a noun after it as the object. However, a cause can also be expressed as a nominal. In other words, both the predicate and the two arguments are optional provided that at least one of them is present. Thus, the fundamental issue in designing a cause detection system is the definition of the span of a cause text. As mentioned, most previous studies on causal relations choose to ignore the identification of cause candidates. In this paper, we first analyze the distribution of cause text and then determine the cause candidates for an emotion.

Based on the emotion cause corpus, we find that emotion causes are more likely to be expressed by verbal events than nominal events (85% vs. 15%). Although a nominalization (a kind of verbal events) is usually a noun phrase, a proposition containing a verb plays a salient role in the expressions of emotion causes, and thus a cause candidate are more likely to be a clause-based unit.

In addition, the actual cause can sometimes be too long and complicated, which involves several events. In order to explore the span of a cause text, we do the following analysis.

Table 1: The clause distribution of cause texts

Position	Cause (%)	Position	Cause (%)
Left_0	12.90	Right _0	15.54
Left_1	31.37	Right _1	9.55
Left_2	13.31	Right_n (n>1)	9.18
Left_n (n>2)	10.15		
Total	67.73		32.27

Table 2: The multi-clause distribution of cause text

Same clause	%	Cross-clauses	%
Left_0	16.80	Left_2_1_0	0.25
Left_1	31.82	Left_2_1	10.84
Left_2	7.33	Left_1_0	0.62
Right _0	18.97	Right_0_1	2.55
Right _1	10.59		
Total	85.75		14.25

Firstly, for each emotion keyword, an entry is segmented into clauses with four punctuations (i.e. commas, periods, question marks and exclamation marks), and thus an entry becomes a list of cause candidates. For example, when an entry has four clauses, its corresponding list of cause candidates contains five text units, i.e. <left_2, left_1, left_0, right_0, right_1>. If we assume the clause where emotion keyword locates is a focus clause, 'left_2' and 'left_1' are previous two 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. Moreover, a cause candidate must contain either a noun or a verb because a cause is either a verbal event or a nominal event; otherwise, it will be removed from the list.

Secondly, we calculate whether a cause candidate overlaps with the real cause, as shown in Table 1. We find that emotion causes are more likely to occur in the left of emotion keyword. This observation is consistent with the fact that an emotion is often trigged by an external happened event. Thirdly, for all causes occurring between 'left_2' and 'right_1', we calculate whether a cause occurs across clauses, as in Table 2. We observe that most causes locate within the same clause of the representation of the emotion (85.57%). This suggests that a clause may be the most appropriate unit to detect a cause.

4 Emotion Cause Detection Based on Multi-label Classification

A cause detection system is to identify the causal relation between a pair of two text units. For emotion cause detection, one of the two text units is fixed (i.e. the emotion keyword), and therefore the remaining two unresolved issues are the identification of the other text unit and the causal relation.

From the above data analysis, there are two observations. First, most emotion causes are verbal events, which are often expressed by a proposition (or a clause). Thus, we define another text unit as a clause, namely a cause candidate. Second, as most emotion causes occur between 'left_2' and 'right_1' (~80%), we define the cause candidates for an emotion as <left_2, left_1, left_0, right_0, right_1>.

Differing from the existing cause systems, we formalize emotion cause detection as a multi-label problem. In other words, given an emotion keyword and its context, its label is the locations of its causes, such as "left_1, left_0". This multi-label-based formalization of the cause detection task has two advantages. First, it is an integrated system detecting causes for an emotion from the contextual information. In most previous cause detection systems, a causal relation is identified based on the information between two small text units, i.e. a pair of clauses or noun phrases, and therefore it is often the case that long-distance information is missed. Second, the multi-label-based tagging is able to capture the relationship between two cause candidates. For example, "left_2" and "left_1" are often combined as a complicated event as a cause.

As a multi-label classification task, every multi-label classifier is applicable. In this study, we use a simple strategy: we treat each possible combination of labels appearing in the training data as a unique label. Note that an emotion without causes is labeled as "None". This converts multi-label classification to single-label classification, which is suitable for any multi-class classification technologies. In particular, we choose a Max Entropy tool, Mallet[1], to perform the classification.

5 Linguistic Features

As explained, there are basically two kinds of features for cause detection, namely pattern-based features and semantic-based features. In this study, we develop two sets of patterns based on linguistic analysis: one is a set of manually generalized patterns, and the other contains automatically generalized patterns. All of these patterns explore causal constructions either for general causal relations or for specific emotion cause relations.

5.1 Linguistic Cues

Based on the linguistic analysis, Lee et al. (2010a) identify six groups of linguistic cue words that are highly collocated with emotion causes, as shown in Table 3. Each group of the linguistic cues serves as an indicator marking the causes in different emotional constructions. In this paper, these groups of linguistic cues are reinterpreted from the computational perspective, and are used to develop pattern-based features for the emotion cause detection system.

Table 3: Linguistic cue words for emotion cause detection (Lee et al. 2010a)

Group	Cue Words
I: Prepositions	'for' as in 'I will do this for you': *wei4*, *wei4le* 'for' as in 'He is too old for the job': *dui4*, *dui4yu2* 'as': *yi3*
II: Conjunctions	'because': *yin1*, *yin1wei4*, *you2yu2* 'so': *yu1shi4*, *suo3yi3*, *yin1er2* 'but': *ke3shi4*
III: Light Verbs	"to make": *rang4*, *ling4*, *shi3*
IV: Reported Verbs	'to think about': *xiang3dao4*, *xiang3qi3*, *yi1xiang3*, *xiang3 lai2* 'to talk about': *shuo1dao4*, *shuo1qi3*, *yi1shuo1*, *jiang3dao4*, *jiang3qi3*, *yi1jiang3*, *tan2dao4*, *tan2qi3*, *yi1tan2*, *ti2dao4*, *ti2qi3*, *yi1ti2*
V: Epistemic Markers	'to hear': *ting1*, *ting1dao4*, *ting1shuo1* 'to see': *kan4*, *kan4dao4*, *kan4jian4*, *jian4dao4*, *jian4*, *yan3kan4*, *qiao2jian4* 'to know': *zhi1dao4*, *de2zhi1*, *de2xi1*, *huo4zhi1*, *huo4xi1*, *fa1xian4*, *fa1jue2* 'to exist': *you3*
VI: Others	'is': *deshi4* 'say': *deshuo1* 'at': *yu2* 'can': *neng2*

For emotion cause processing, Group I and II contain cues which are for general cause detection, and while Group III, IV and V include cues specifically for emotion cause detection. Group VI includes other linguistic cues that do not fall into any of the five groups.

Group I covers some prepositions which all roughly mean 'for', and Group II contains the conjunctions that explicitly mark the emotion cause. Group I is expected to capture the prepositions constructions in the focus clause where the emotion keyword locates. Group II tends to capture the rhetorical relation expressed by conjunction words so as to infer causal relation among multi-clauses. These two groups are typical features for general cause detection.

Group III includes three common light verbs which correspond to the English equivalents "to make" or "to cause". Although these light verbs themselves do not convey any concrete meaning, they are often associated with several constructions to express emotions and at the same time indicate the position of emotion causes. For example, "*The birthday party made her happy*".

One apparent difference between emotion causes and general causes is that emotions are often triggered by human activities or the perception of such activities, e.g., "*glad to say*" or "*glad to hear*". Those human activities are often strong indicators for the location of emotion

[1] http://mallet.cs.umass.edu/

causes. Group IV and V are used to capture this kind of information. Group IV is a list of verbs of thinking and talking, and Group V includes four types of epistemic markers which are usually verbs marking the cognitive awareness of emotions in the complement position. The epistemic markers include verbs of seeing, hearing, knowing, and existing.

5.2 Linguistic Patterns

With the six groups of linguistic cues, we generalize 14 rules used in Lee et al. (2010b) to locate the clause positions of an emotion cause, as shown in Table 4. The abbreviations used in the rules are given as follows:

C = Cause
K = Emotion keyword
B = Clauses before the focus clause
F = Focus clause/the clause containing the emotion verb
A = Clauses after the focus clause

Table 4: Linguistic rules for emotion cause detection (Lee et al. 2010b)

No.	Rules
1	i) C(B/F) + III(F) + K(F) ii) C = the nearest N/V before I in F/B
2	i) IV/V/I/II(B/F) + C(B/F) + K(F) ii) C = the nearest N/V before K in F
3	i) I/II/IV/V (B) + C(B) + K(F) ii) C = the nearest N/V after I/II/IV/V in B
4	i) K(F) + V/VI(F) + C(F/A) ii) C = the nearest N/V after V/VI in F/A
5	i) K(F)+II(A)+C(A) ii) C = the nearest N/V after II in A
6	i) III(F) + K(F) + C(F/A) ii) C = the nearest N/V after K in F or A
7	i) *yue4* C *yue4* K "the more C the more K" (F) ii) C = the V in between the two *yue4*'s in F
8	i) K(F) + C(F) ii) C = the nearest N/V after K in F
9	i) V(F) + K(F) ii) C = V+(an aspectual marker) in F
10	i) K(F) + *de* "possession"(F) + C(F) ii) C = the nearest N/V +的+N after *de* in F
12	i) K(B) + IV (B) + C(F) ii) C = the nearest N/V after IV in F
13	i) IV(B) + C(B) + K(F) ii) C = the nearest N/V after IV in B
14	i) C(B) + K(F) ii) C = the nearest N/V before K in B

For illustration, an example of the rule description is given in Rule 1.

Rule 1:
i) C(B/F) + III(F) + K(F)
ii) C = the nearest N/V before III in F/B

Rule 1 indicates that the cause (C) comes before Group III cue words. Theoretically, in identifying C, we look for the nearest verb/noun occurring before Group III cue words in the focus clause (F) or the clauses before the focus clause (B), and consider the clause containing this verb/noun as a cause. Practically, for each cause candidate, i.e. 'left_1', if it contains this verb/noun, we create a feature with "left_1_rule_1=1".

5.3 Generalized Patterns

Rule-based patterns usually achieve a rather high accuracy, but suffer from low coverage. To avoid this shortcoming, we extract a generalized feature automatically according to the rules in Table 4. The features are able to detect two kinds of constructions, namely functional constructions, i.e. rhetorical constructions, and specific constructions for emotion causes.

Local functional constructions: a cause occurring in the focus clause is often expressed with certain functional words, such as "*because of*", "*due to*". In order to capture the various expressions of these functional constructions, we identify all functional words around the given emotion keyword. For an emotion keyword, we search 'left_0' from the right until a noun or a verb is found. Next, all unigrams and bigrams between the noun or the verb and the emotion keyword are extracted. The same applies to 'right_0'.

Long-distance conjunction constructions: Group II enumerates only some typical conjunction words. To capture more general rhetorical relations, according to the given POS tags, the conjunction word is extracted for each cause candidate, if it occurs at the beginning of the candidate.

Generalized action and epistemic verbs: Group IV and V cover only partial action and epistemic verbs. To capture possible related expressions, we take the advantage of Chinese characters. In Chinese, each character itself usually has a meaning and some characters have a strong capability to create words with extended meaning. For example, the character "*ting1*-listen" combines with other characters to create words expressing "listening", such as *ting1jian4*, *ting1wen5*. With the selected characters regarding reported verbs and epistemic markers, each cause candidate is checked to see whether it contains the predefined characters.

6 Experiments

For the emotion cause corpus, we reserve 80% as the training data, 10% as the development data, and 10% as the test data. During evaluation, we first convert the multi-label tag outputted from our system into a binary tag ('Y' means the presence of a causal relation; 'N' indicates the absence of a causal relation) between the emotion keyword and each candidate in its corresponding cause candidates. Thus, the evaluation scores for binary classification based on three common measures, i.e. precision, recall and F-score, are chosen.

6.1 Linguistic Feature Analysis

According to the distribution in Table 1, we design a naive baseline to allow feature analysis. 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 verb, consider this clause as a cause and stop.

We run the multi-label system with different groups of features and the performances are shown in Table 5. The feature set begins with linguistic patterns (LP), and is then incorporated with local functional constructions (LFC), long-distance conjunction constructions (LCC), and generalized action and epistemic verbs (GAE), one by one. Since the 'N' tag is overwhelming, we report only the Mac average scores for both 'Y' and 'N' tags.

In Table 5, we first notice that the performances achieve significant improvement from the baseline to the final system (~17%). This indicates that our linguistic features are effective for emotion cause detection. In addition, we observe that LP and LFC are the best two effective features, whereas LCC and GAE have slight contributions. This shows that our feature extraction has a strong capability to detect local causal constructions, and is yet unable to detect the long-distance or semantic causal information. Here, 'local' refers to the information in the focus clause. We also find that incorporating LFC, which is a pure local feature, generally improves the performances of all cause candidates, i.e. ~5% improvement for 'left_1'. This indicates that our multi-label integrated system is able to convey information among cause candidates.

Table 5: 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
+ LFC	72.80	71.94	72.35
+ LCC	73.60	72.50	73.02
+ GAE	73.90	72.70	73.26

Table 6: 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
+ LFC	55.45	89.24
+ LCC	56.48	89.57
+ GPE	56.84	89.68

Table 6 shows the performances (F-scores) for 'Y' and 'N' tags separately. 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 only the 'Y' tag (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 detection of 'non_causal' relation. For the 'Y' tag, the features LP and LFC achieve ~15% and ~7% improvements respectively. LCC and GPE, on the other hand, show slight improvements only.

Finally, Table 7 shows the detailed performances of our multi-label system with all features. The last row shows the overall performances of 'Y' and 'N' tags. For the 'Y' tag, the closer the cause candidates are to the emotion keyword, the better performances the system achieves. This proves that the features we propose effectively detect local emotion causes, more effort,

Table 7: The detailed performance for the multi-label system including all features

'Y' tag	Precision	Recall	F-score	'N' tag	Precision	Recall	F-score
Left_0	68.92	68.92	68.92	Left_0	93.72	93.72	93.72
Left_1	57.63	63.35	60.36	Left_1	82.90	79.22	81.02
Left_2	29.27	20.69	24.24	Left_2	89.23	92.93	91.04
Right_0	67.78	64.89	66.30	Right_0	82.63	84.41	83.51
Right_1	54.84	30.91	39.54	Right_1	92.00	96.90	94.38
Total	58.84	54.98	56.84	Total	88.96	90.42	89.68

Table 8: The detailed performance for the single-label system including all features

'Y' tag	Precision	Recall	F-score	'N' tag	Precision	Recall	F-score
Left_0	65.39	68.92	67.11	Left_0	93.65	92.62	93.13
Left_1	61.19	50.93	55.59	Left_1	79.64	85.60	82.51
Left_2	28.57	20.69	24.00	Left_2	89.20	92.68	90.91
Right_0	70.13	57.45	63.16	Right_0	80.30	87.63	83.81
Right_1	33.33	40.00	36.36	Right_1	92.50	90.24	91.36
Total	55.67	50.00	52.68	Total	87.85	90.08	88.95

however, should be put on the detection of long-distance causes. In addition, we find that the detection of long-distance causes usually relies on two kinds of information for inference: rhetorical relation and deep semantic information.

6.2 Modeling Analysis

To compare our multi-label model with single-label models, we create a single-label system as follows. The single-label model is a binary classification for a pair comprising the emotion keyword and a candidate in its corresponding cause candidates. For each pair, all linguistic features are extracted only from the focus clause and its corresponding cause candidate. Note that we only use the features in the focus clause for "left_0" and "right_0". The performances are shown in Table 8.

Comparing Tables 7 and 8, all F-scores of the 'Y' tag increase and the performances of the 'N' tag remain almost the same for both the single-label model and our multi-label model. We also find that the multi-label model takes more advantage of local information, and improves the performances, particularly for "left_1".

To take an in-depth analysis of the cause detection capability of the multi-label model, an evaluation is designed that the label is treated as a tag from the multi-label classifier. Due to the tag sparseness problem (as in Table 2), only the "left_2, left_1" tag is detected in the test data, and its performance is 21% precision, 26% recall and 23% F-score. Furthermore, we notice that ~18% of the "left_1" tags are detected through this combination tag. This shows that some causes need to take into account the mutual information between clauses. Although the scores are low, it still shows that our multi-label model provides an effective way of detecting some of the multi-clauses causes.

7 Conclusion

We treat emotion cause detection as a multi-label task, and develop two sets of linguistic features for emotion cause detection based on linguistic cues. The experiments on the small-scale corpus show that both the multi-label model and the linguistic features are able to effectively detect emotion causes. The automatic detection of emotion cause will in turn allow us to extract directly relevant information for public opinion mining and event prediction. It can also be used to improve emotion detection and classification. In the future, we will attempt to improve our system from two aspects. On the one hand, we will explore more powerful multi-label classification models for our system. On the other hand, we will investigate more linguistic patterns or semantic information to further help emotion cause detection.

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