The GDUFS System in NTCIR-13 ECA Task

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ABSTRACT
Our system participates the evaluation task of emotion cause detection, which is a subtask of emotion cause analysis evaluation in NTCIR-13. The aim of the subtask is to find the clause that contain emotion cause, which is treated as a sequence labeling problem in our system. We employ a structural SVM tool, and build four types of features, including lexical information, distance, contexts and linguistic rule features, to build the sequence labeling model. Official results show that the system achieves an averaged performance in all participating systems.

CCS Concepts
• Information systems→Information retrieval→Retrieval tasks and goals→Sentiment analysis.

Keywords
Emotion Cause Analysis; Sentiment Analysis; Structural SVM;

Team Name

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Subtasks

Emotion Cause Detection(Chinese)

1. INTRODUCTION
Current research on sentiment analysis focuses on fine-grained information extraction and knowledge mining, such as aspect extraction[3], opinion holder identification[18] and emotion cause detection[7]. In comparison with traditional tasks such as polarity classification, fine-grained sentiment analysis concerns much about finding out aspects or attributes that a product review refers to, extracting opinion holders and their stances for public policies, or detecting reasons of an emotional expression. Apparently, exploring such issues contributes to better understanding sentiment in texts.

Among the fine-grained sentiment analysis tasks, emotion cause analysis is a high challenging one, which aims at finding out the stimuli, or the cause of an emotion. For example, an auto manufacturer want to know the reasons that people like or dislike its automotive products, while a government may prefer to obtain the causes that a public policy is supported or objected to. To explore empirical methods as well as evaluate systems for detecting emotion causes in texts, the NTCIR-13 conference holds an evaluation task named Emotion Cause Analysis(ECA)[6], the aim of which is to find the cause of an emotion in texts. In such task, there are two subtasks, that is, Emotion Cause Detection and Emotion Cause Extraction. The former one is to evaluate the techniques for detecting the clause which contains emotion cause, while the latter one is evaluate the techniques for detecting the boundary of the emotion cause. Such subtasks are designed to evaluate the performances of the participating systems with coarse- and fine-grained emotion cause analysis, respectively.

Our team participates in the former subtask. Intuitively, such subtask can be cast as a binary classification problem, i.e., each clause is determined whether it contains an emotion cause or not. However, in such case, each clause or sentence will be classified independently, without considering relations between them, which may achieve low performance. To leverage on such relations, our system implements a Structural SVM(SSVM) based sequence labeling model to detect emotion cause in texts. Sequence labeling models consider the impact of labeled units to those unlabeled ones, which may fit emotion cause detection more than classification models. Our system also build a feature space, including lexical, distance and contextual features for the SSVM model. Official results show the performance of our emotion cause detection system.

The rest of this paper is organized as follows. Section 2 shows related work of emotion cause detection. Section 3 describes the sequence labeling model as well as the features employed in our system. Section 4 shows the official experimental results and some discussions about error cases. Finally, some conclusions are drawn in Section 5.

2. RELATED WORK
Emotion classification, which is one of the main topics in textual emotion analysis, has been well studied for years. Related work on emotion classification is mainly categorized as knowledge-based and feature-based approaches. Knowledge-based approaches employ emotion lexicons[17], domain lexicons[1] or emotional patterns[16] to detect emotions in texts, while feature-based approaches classify emotional texts by leveraging on sophisticated classification models as well as rich features[14, 15]. Although the result of such analysis is a coarse one in comparison with rich affective information in texts, e.g., stance of emotion holder and the cause of emotion, it is still useful in simple application scenes, such as box office forecasting and product recommendation[4].

For better understanding emotions in texts, fine-grained emotion analysis topics, including emotion cause analysis, are continuously explored in recent years. In the view of emotion cause analysis, emotions can be invoked by cause events, thus emotion cause corpora are built to analyze the interaction between emotions and their causes[10, 11]. Based on these resources, research on emotion cause detection has also been done to explore fine-grained semantic relations in emotional texts. Rule-based approaches detect emotion cause by linguistic rules, which are essentially the description of cue words, their sequence ordering and linguistic constraints[5, 10]. Statistical approaches treats emotion cause detection as a machine learning problem, and employ various learning models, such as SVM[7], MaxEntropy[2] and Conditional Random Field(CRF)[12] to identify emotion cause in emotional texts. For a better performance, linguistic rules are also adopted in those learning approaches.

3. THE APPROACH

3.1 Emotion Cause Detection as Sequence Labeling

Emotion cause detection can be cast as a classification problem, where each clause is judged whether it contains the cause of an emotion or not. Classification models, such as decision trees, support vector machines or maximum entropy models can be employed for this task. Among those classification models, Support Vector Machine(SVM) based approaches are practically proved to be efficient for sentiment analysis tasks[8, 9]. However, it may achieve low performance when dealing with emotion cause detection. The reason lies in that, such approaches classify each clause or sentence independently, without considering relations between them. In fact, such relations may play an important role in emotion cause detection. Take the following sentence as an example[1]:

> My aunts enjoy inviting me to their romance book club, and I always feel trapped because I don't want to hurt their feelings by saying no.

The emotion holder *I* in this sentence have the emotion *disgust*, and the clause *I don't want to hurt their feelings by saying no* indicates the cause of such emotion. Apparently, the connective *because* indicates the emotion cause, thus it is a high probability that the first clause is not the emotion cause. In other words, class labels of relative clauses help to judge class label of an assigned clause.

Based on it, we treat emotion cause detection as a sequence labeling problem. In sequence labeling models, labels of relative units are considered, e.g., labels of left or right units, which may contributes to judge class label of an assigned unit.

3.2 Structural SVM

Sophisticated models, such as Conditional Random Field(CRF), Hidden Markov Model(HMM), Perceptron and SSVM, are employed for sequence labeling. Nguyen et al.[13] made an experiment to compare seven sequence labeling models in POS tagging task, in which SSVM achieved the best performance among all the models. Based on it, we employ SSVM as the sequence labeling model. The standard SSVM is formalized as follows:

$$\begin{gathered}\min_{w,\xi}\ ||w||^2 + C\sum_i \xi_i \\ \text{s.t. } \langle w, \Psi(x_i, y_i)\rangle - \langle w, \Psi(x_i, y)\rangle + \xi_i \geqslant \Delta(y_i, y) \\ \forall i, y_i \in \mathcal{Y}_i\end{gathered} \tag{1}$$

where $\Psi(x, y)$ denotes the feature vector extracted from the input x and the output y, ξ_i is the slack variable and C is the regularization parameter that controls the trade-off between training error minimization and margin maximization. Apparently, the function $\Psi(\cdot)$ greatly impact the performance of SSVM.

3.3 Features

In our approach, lexical information, distance, contexts and linguistic rules are considered for building feature space. As to lexical information, nouns and verbs are considered, since an emotion always evokes by an object or an action. For example, the sentence *The world community is infuriated by this destruction* contains the emotion *anger*, and the cause is *this destruction*, which is a nominal phrase. Another example is the sentence *Known the things happened in the last 10 minutes of his life, a lot of people left the sad tears*, where the emotion is *sadness*, and the cause is the first clause, which represents an action. The lexical features are listed as follows:

Noun It is a boolean value, which is true if the syntactic head word of current clause is a noun, and false if not.

Verb It is a boolean value, which is true if the syntactic head word of current clause is a verb, and false if not.

Noun Count It is a numeric value, which is the total count of nouns in current clause.

Verb Count It is a numeric value, which is the total count of verbs in current clause.

Keyword If a clause contains a keyword of emotion, the feature is the keyword itself; otherwise, it is valued as NULL.

Indicator It is a boolean value, which is true if a verbal, conjunctional or prepositional indicator(shown in Table 1) appears in current clause, and false if not.

The distance feature computes the distance between a clause and the clause containing an emotional keyword. Here the distance means how many clauses are between such clause and the clause containing an emotion keyword. Since all emotional keywords have already been given in the training and test dataset, the feature values are easily computed. The feature is described as follows:

Distance It is a numeric value, representing the distance between current clause and the clause containing an emotional keyword. For example, if a current clause is the first one on the left of the clause containing an emotional keyword, the value is -1; for the first one on the right, the value is +1.

Contextual information also plays an important role in indicating relationship between two clauses. Contextual features are similar with the keyword and indicator feature in lexical features, except that contextual features focus on left and right clauses but not current clause.

Heuristics are also helpful for emotion cause detection. For example[2],

> 对于 人们 购买 板蓝根 防病 的 积极 态度 ， 医学 专家 均 给予 了 肯定 ， 称赞 市民 的 自我 保健 意识 的确 比 几年 前 提高 了 。

> for people purchase radix isatidis disease prevention de positive attitude , medical expert all give le affirmation , acclaim citizen de self healthcare awareness indeed than several years ago improve le .

[1] The example comes from the English training data with id 501.

[2] The example comes from the Chinese training data with id 1026.

All medical experts affirmed the positive attitude of disease prevention by purchasing radix isatidis and acclaimed for the improvement of citizens' self-care awareness.

Although the keyword 称赞 acclaim indicates the emotion happiness, it is still difficult to find the cause of the emotion because there is not any explicit causal indicators such as 因为 because or 由于 due to. Alternatively, such cause can be targeted in clause level if we use heuristics like 对于 for + cause + emotion/keyword. Apparently, linguistic rules contributes to judging emotions as well as causes that result in such emotions in texts with complex semantic relations.

Lee et al.[10] defined linguistic rules to recognize clauses that probably contain emotion cause. Following this idea, our system also define a linguistic rule set for emotion cause detection, shown in Table 1.

Table 1. Linguistic rule set

ID	Rule
1	EC(B/F)+CV+EM
2	CC(B/F)+EC(B/F)+EM
3	EM+CC(F/A)+EC(F/A)
4	CC(B/F)+EC(B/F)+EM
5	PP(B/F)+EC(B/F)+EM
6	SV(B/F)+EC(B/F)+EM
7	EM+CT+EC(F/A)

In Table 1, EC denotes emotion cause; CV denotes causative verbs, which includes 使 make, 令 make, 让 make, and their synonyms; EM denotes emotional words, which contains those words such as 高兴 happy, 伤心 sad, 吃惊 surprise, and their synonyms as well; EM also denotes those emotional keywords, which come from the training data, that probably indicate an emotion, for example, 称赞 praise indicates the emotion happiness; CC denotes causal conjunctions, such as 因为 because, 由于 due to, 因此 therefore as well as their synonyms in the causal conjunction set; PP denotes preposition, which includes those words such as 为了 for, 对于 for and 以 by; SV denotes sensory verbs, which contains those verbs such as 想到 think, 听到 hear and 看到 see; CT denotes connectives, such as 的是 that, 的说 to say, 地是 that. F, B and A denotes the position of a word related to current clause; B denotes such word or phrase is in the current clause, F denotes such word or phrase is in the clause that is on the left of current clause and A on the right.

4. EXPERIMENT

4.1 Official Results

Official evaluation results are reported in this section. We participated in Chinese emotion cause detection subtask, in which 2,200 paragraphs with emotion cause annotation of training data and 2,000 paragraphs of test data were given. Each clause in a paragraph is labeled with an emotion, the cause of the emotion and the keyword that probably indicates the emotion, if have. Precision, recall and F-1 score are adopted as the metrics.

Table 2. Official results of emotion cause detection

Precision	Recall	F-score
0.6711	0.6417	0.6561

SVM Struct is employed in our experiment is an implementation of SSVM for predicting structural outputs. It provides various kinds of kernel functions, such as linear, polynomial, radial basis and sigmoid function. Since Radial basis function(RBF) is a sophisticated kernel which performs good in multiple scenes, especially the one that features is much less than training samples, it is appropriate in the experiment as the kennel function. The parameter γ in RBF is tuned with 10-fold cross validation. Other parameters in the experiment are default values in SVM Struct. Table 2 shows the official results.

4.2 Error Analysis

In this subsection, errors of main types as well as their reasons in emotion cause detection are discussed. Since the test data has not been released yet, we pick out the errors from the results of emotion cause detection in the development data and classify them into four types: false causal indicator, implicit causative relation, unrecognized long distance discourse relation and multiple cause clauses. We then give an example for each type of error and some discussions as well.

False causal indicator leads to wrong judgment of incorrect cause to an emotion. Such indicator can be a causative verb, a causal conjunction, a preposition or a sensory verb. Take the text with id 75 as an example:

对于 李世铭 一家 来说 ， 那 天 是 一个 大喜 的 日子 . 被 拐骗 45 天 的 儿子 在 那 天 终于 回家 了

to Li Shimin family to say , that day is one big de day . bei abduct 45 day de son at that day finally go home le

That day was a big day to Li Shimin's family. His son who had been abducted 45 days finally came home at that day.

The emotional keyword in this example is 大喜 big, which results from the following sentence. But the cause is misjudged as the first clause, which is probably due to the preposition 对于 to, and the reason is obvious, since the first clause is recognized as the cause according to the fifth linguist rule. To solve the problem, more constraints can be appended to that rule, but it will lead to a decreasing precision because of the rigid restriction.

The second type of errors is implicit causative relation, that is, both an emotion and its cause appear at a text, which does not contain an indicator to that cause, e.g., a causative verb, a causal conjunction or a sensory verb. For example,

走投无路 的 贺先生 只好 回到 老家 宁波 ，尝试 联系 自已 的 子女 . 多年 未 见 ，子女 心中 难免 有所 怨恨 ，态度 极为 冷淡 ，都 不 愿 见面

in desperation de Mr. He only come back hometown Ningbo , attempt contact self de children . many years not meet , children in mind hardly have some resent , attitude very frigid , even not willing meet

In desperation, Mr. He had to return to his hometown Ningbo, trying to contact his children. Since they had not seen him for many years, everyone of them hardly kept the mind out of resentment, had a very frigid attitude and even were not willing to meet with him.

The example comes from the text with id 183. The keyword 怨恨 resentment indicates the emotion disgust, and the reason is in the left clause, that is, not seen him for many years. The system makes a wrong judgment that it is not the cause of the emotion, probably because there is not any indicator in the clause. Although a cause clause without explicit cause indicator is often the left or right one of the clause with an emotion, the system is still difficult to judge which one is the cause clause to the emotion. Actually, it needs fine-grained semantic analysis, for example, implicit discourse relation analysis, which needs more discourse knowledge as well as discourse analysis technologies rather than linguistic rules.

The third type of errors is unrecognized long distance discourse relation. In such case, an emotion has a long distance with its cause in texts. Take the text with id 103 as an example:

男子 不远千里 会 网友，发现 女子 长相 与 照片 判若两人 体形 也 相差 甚远 。 女子 辩称 ，自己 就 是 照片 中 的 人，不过 是 化了妆，用 了 美图 工具 . 大失所望 之余 ，男子 认为 受到 欺骗 ，怒火之下 大打出手

man without regarding a long way meet cyber friend find woman appearance with photo much unlike physique also difference much . woman argue , self exactly is photo in de guy , only is make up , use le photo editing tool . great disappointment with , man think is fool , with angry beat up

The man traveled a long way to meet his cyber friend, but he found that what she looked like was much different with her photos, so was her shape. She argued that she was exactly the one in the photos, whom only wear make-up, and the photos was just edited by photo editing tools. The man was very disappointed and thought he was fooled by her. He was very angry and beat her up.

The keyword in this text is 大失所望 disappoint, indicating the emotion sadness, which is in the seventh clause. However, the cause of such emotion is what she looked like was much different with her photos, so was her shape, which is located in the second clause. Such long distance raises the probability of misjudgment of emotion cause detection.

The fourth type of errors is the incomplete detection of multiple cause clauses, that is, the system does detect all the causes for an emotion. For example:

得到 公司 的 鼓励 后，两人 在 同事 面前 可以 大大方方 牵手 了，不仅如此，还 会 得到 同事 的 祝福，他们 觉得 很 开心

getting company de encouragement after , two people at colleague in front of can get straight down holding hands le , not only that , also will get colleague de best wishes , they feel very happy

After getting encouragement by the company, the two can get straight down to hold hands in the presence of their colleagues, and not only that, they will receive best wishes from their colleagues. These make them very happy.

The example comes from the text with id 96. In this case, the emotion 开心 happiness has two causes, that is, hold hands in the presence of their colleagues and receive best wishes from their colleagues. However, only one cause that is closer to the emotion is detected by the system. To solve it, rules to recognize coordinating constituents can be appended into the linguistic rule set.

5. CONCLUSION

This paper reports our system that participates in the evaluation task of Emotion Cause Analysis in NTCIR-13. In the system, a structural SVM model is employed, and four types of features, namely lexical information, distance, contexts and linguistic rules, are built for training and prediction. Official results show that the system achieves an averaged performance in all participating systems. We also analyze four main types of errors, including false causal indicator, implicit causative relation, unrecognized long distance discourse relation and multiple cause clauses, and give some discussions on how to improve the system in the future.

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