Overview of NTCIR-13 ECA Task

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ABSTRACT
This paper presents the overview of NTCIR-13 emotion cause analysis (ECA) task. This task is designed to evaluate the emotion cause analysis techniques which automatically determine whether a clause contain the cause of emotion expression. Unlike the regular evaluation tasks on sentiment analysis or emotion classification, this evaluation task focus on exploring the cause stimulate the emotion. To support this evaluation, the text are manually labelled emotion category and emotion cause to construct an emotion cause corpus which follows the scheme of W3C Emotion Markup Language. We designed two subtasks: The emotion cause detection subtask for identifying the clause containing the emotion cause corresponding to an emotion expression. The emotion cause extraction subtask is designed to evaluate the techniques for detecting the exact boundary of the emotion cause. Eleven teams participated this task and eventually, three valid results for emotion cause detection subtask on Chinese side are submitted. Evaluations shows that the top system achieved 66.5% F-score.

Keywords
Evaluation; Emotion Cause Analysis; Dataset

1. INTRODUCTION
With the rapidly growth of subjective text, the studies on sentiment analysis or emotion analysis has attract much research interests. In recent years, there has been a large body of research work on emotion classification from text. Most existing work only focused on the classification of emotions into one of the pre-defined emotion categories, for example, Ekman's six basic emotion categories [1] as well as the emotion components extraction [2-7]. Some corresponding bakeoffs or evaluations were organized in the past three years, such as the Emotion Analysis in Chinese Weibo text task on NLP&CC 2013 [8] and NLP&CC 2014 [9]. However, in many cases, persons care more about the stimuli, or the cause of emotions. For instance, business organizations are more interested in finding out why people like or dislike products or services offered by them from users' comments or reviews rather than a simple categorization of sentiments. Similarly, instead of gauging public opinions towards policies or political issues using frequency counts, governments would like to know the triggering factors of negative attitudes expressed online. As such, there has been an increasing interest in the research on emotion cause analysis more recently [11]. Unfortunately, the lack of annotated corpora and standard metrics for this task has limited the research on this topic. Thus, we propose to organize a new task, emotion cause analysis (ECA), in NTCIR 13.

In this task, we focus on evaluating the techniques for analyzing and extracting the emotion cause from text. Here, emotion cause is defined as the things stimulus the occurrence or change of an emotion. The emotion cause analysis task aims to identify the reason behind an expression of an emotion. Normally, it is regarded as a more difficult task, compared to emotion classification, since it normally requires a deep understanding of the text that conveys emotions.

For the example given below:

Example 1:

当日，跟中新社记着谈起建言献策的初衷，白金跃陷入回忆，并略显激动。

On that day, talking about the original intention of giving advice with the reporter of China News Service, Yuejin Bai lost in memories, and seemed to be a little excited.

Here, the key emotion expression is "激动/*excited*" while the cause of emotion is "陷入回忆/*lost in memories*". The task we proposed aims to detect the cause of emotion in the text. The metric is on the clause level. It means that we need to identify which clause contains the cause of the emotion. In this example, the emotion cause is in the third clause "白金跃陷入回忆/*Yuejin Bai lost in memories*".

To support the ECA evaluation, we manually constructed a corpus with emotion category and emotion cause labels on both Chinese and English. In Chinese part, considering that the text in the city news contains more emotion expressions, the city news text on sina.com was selected as the raw text. As for the English part, the English novel text was selected. The emotion category corresponding to the emotional sentences and emotion keywords are then manually annotated. Next, for each identified emotional sentence, the text corresponding to direct cause which stimuli the emotion are annotated. The annotations follows the scheme of W3C Emotion Markup Language. In this way, we construct a corpus with emotion cause annotation for the evaluation as the training and testing data. Meanwhile, more text with only emotion category labels are annotated. They are used to support the development of semi-supervised emotion cause detection algorithms.

We designed two subtasks including emotion cause detection at the clause level and emotion cause extraction. The first subtask aims to evaluate the techniques for detecting the clause which contains emotion cause. It can be treated as a clause-level binary text classification problem. The second subtask is designed to evaluate the techniques for detecting the boundary of the emotion cause. It can be regarded as an information extraction task.

Eleven teams participated the ECA task. Three teams submitted their results for the first subtask on Chinese dataset. The achieved highest F-score is 66.5%. No valid result on the English is submitted. The evaluation shows that the emotion cause detection is a challenge subtask while the emotion cause extraction subtask is more difficult. The performance on both subtasks have a lot of room for improvement.

The rest of this paper is organized as follows. Section 2 briefly reviews the related works on emotion cause analysis. Section 3 presents the construction of the annotated emotion cause corpus. Section 4 presents the design of the evaluation. Section 5 presents the evaluation results and discussions. Finally, Section 6 concludes this paper.

2. RELATED WORK

Some scholars have done some work in the field of emotion cause detection. At present, the method used in emotion cause analysis is divided into two categories. These two categories are rule-based method and statistic-based method.

Lee et al. first raised the concept of emotion cause from the perspective of linguistics [11]. They annotated a small scale news text emotional corpus from Academia Sinica Balanced Chinese Corpus. They identified seven linguistic cues and two sets of linguistic rules to detect emotion cause. On the basis of this study, Lee et al. presented a rule based method to detect emotion cause automatically [12]. On the basis of this data set, Chen et al. proposed a template matching based method to detection emotion cause [13]. Neviarouskaya et al. constructed an emotion cause corpus containing 532 sentences specific for 22 emotions [14]. They then proposed a method to estimate the linguistic relation between the emotion and its cause candidates. Gui et al. extended the rule based method to informal text in Weibo text (Chinese tweets) [15].

In addition to the rule based method, statistical based emotion cause detection techniques were proposed. By means of crowd-sourcing, Russo et al. [16] summarized some possible emotion cause phrases which were combined together randomly to obtain potential emotion causes based on co-occurrence frequency. Ghazi et al. applied conditional random fields (CRFs) to detect emotion cause [17]. However, there was a limitation that the emotion word and its causes must be in the same sentence. Gui et al. modeled an emotion as event. They proposed an event-driven multi-kernel Support Vector Machine based method to extract emotion cause [18]. Using the same dataset, Gui et al. proposed to treat emotion cause identification as a reading comprehension task in QA [19]. They proposed a convolutional multiple-slot deep Memory Network based method to identify the emotion cause.

3. CORPUS CONSTRUCTION

3.1 Raw Text Collection

We take 3-year (2013–2015) Chinese city news from NEWS SINA of 20,000 articles as the raw corpus. Based on a list of emotion keywords, we extract instances by keywords matching from the raw text. For each matched keyword, we extract three preceding clauses and three following clauses as the context of an instance. If a sentence has more than 3 clauses in each direction, the context will include the rest of the sentence to provide the complete context. For simplicity, we omit the cross-paragraph contexts.

Note here that the presence of keywords does not necessarily convey emotional information due to different possible reasons, such as negative polarity and sense ambiguity. Meanwhile, the presence of emotion keywords does not necessarily guarantee the existence of emotional cause either.

As for the English side, we chose English novel text, which contains many emotion key words and emotion causes. The instances are extracted following the similar procedure with an English emotion keyword list.

3.2 Corpus Annotation

The emotion cause corpus construction is done in three steps. The first step is to identify the emotional instances through keyword matching and human verification. For each identified emotion expression, their corresponding context are extracted. In the second step, the emotion cause is identified and annotated in the extracted context. In the last step, the corpus is constructed through formatting the annotations by following the W3C Emotion Markup Language format.

In first step, the annotation of emotional words and corresponding emotion causes is listed in detail below:

- To improve the efficiency, we applied emotion word lexicon (in Chinese and English, respectively) to roughly match the emotional words in the text.
- Manually correct the emotion word matching errors. Meanwhile, we add the correct emotion words to the dictionaries to improve the accuracy of the next operation of match. Noted here that some emotional words have no corresponding emotional causes.
- For each matched emotion word, we extract three preceding clauses and three following clauses as the context of an instance. In this process, we keep that one instance has one emotion key word.

In second step, the emotion cause is identified and annotated. Generally speaking, we annotated the following information:

- The emotion category,
- the clause id
- whether the clause belongs to cause
- cause id
- cause segment
- whether the clause contains emotion word

In the final step, we format the annotations by following the W3C Emotion Markup Language which is a xml file with predefined emotion related elements.

To ensure the annotation quality, the annotators are firstly trained through duplicate annotation and discussion. In the formal annotation period, each emotion expression instance is duplicate annotated by two annotators. Their disagreements are discussed with the third annotator. Majority voting is applied to generate the annotation results.

Two annotated example instances, on Chinese and English, respectively, are given below.

```
<emotion id="10">
   <category name="happiness" value="3"/>
   <clause cause="N" id="1" keywords="N">
      <text>他们来到了巴思</text>
   </clause>
   <clause cause="N" id="2" keywords="Y">
      <text>凯瑟琳心里不觉急煎煎</text>
      <keywords keywords-begin="21" keywords-lenth="9">急煎煎
</keywords>
   </clause>
   <clause cause="N" id="3" keywords="N">
      <text>乐滋滋的</text>
   </clause>
   <clause cause="Y" id="4" keywords="N">
      <text>车子驶近景致优美、引人入胜的城郊</text>
      <cause begin="0" id="1" lenth="48">车子驶近景致优美、引
人入胜的城郊</cause>
   </clause>
   <clause cause="N" id="5" keywords="N">
      <text>以及后来驶过通往旅馆的几条街道时</text>
   </clause>
   <clause cause="N" id="6" keywords="N">
      <text>只见她两眼左顾右盼</text>
   </clause>
   <clause cause="N" id="7" keywords="N">
      <text>东张西望</text>
   </clause>
   <clause cause="N" id="8" keywords="N">
      <text>她来这里是想玩个痛快</text>
   </clause>
   <clause cause="N" id="9" keywords="N">
      <text>她已经感到很痛快了</text>
   </clause>
</emotion>
```

Figure 1. An Annotated Chinese Instance.

```
<emotion id="1632">
   <category name="fear" value="2"/>
   <clause cause="N" id="1" keywords="N">
      <text>The Trojans heard that shout</text>
   </clause>
   <clause cause="N" id="2" keywords="N">
      <text> and saw that host</text>
   </clause>
   <clause cause="N" id="3" keywords="N">
      <text> And marvelled</text>
   </clause>
   <clause cause="N" id="4" keywords="Y">
      <text>ushed with fear were all their hearts Foreboding doom</text>
      <keywords keywords-begin="11" keywords-lenth="4">fear</keywords>
   </clause>
   <clause cause="Y" id="5" keywords="N">
      <text> for like a huge cloud seemed That throng of foes: with clashing
arms they came: Volumed and vast the dust rose 'neath their feet.</text>
      <cause begin="4" id="1" lenth="45"> like a huge cloud seemed That throng
of foes</cause>
   </clause>
</emotion>
```

Figure 2. An Annotated English Instance.

3.3 Statistic of the Dataset

After removing some irrelevant instances, we labeled 2619 instances for Chinese and 2403 instances for English. Besides, we labeled extra 10,000 documents with emotion key words only for building semi-supervised systems for each language.

In this dataset, we limited each instance to only contain one emotion word. Normally, an emotion instance has only one cause while in many cases, more causes are identified. Table 1 gives the statistics of emotion causes.

Table 1. Statistic of Emotion Causes

Item	Number (Chinese)	Number (English)
Instance	2619	2403
Clause	31110	34382
Emotion causes	4054	4858
Doc with 1 cause	1728	410
Doc with 2 cause	554	1817
Doc with 3 cause	211	2
Doc with 4 cause	76	140
Doc with 5 cause	33	0
Doc with 6 cause	9	24
Doc with 7 cause	4	0
Doc with 8 cause	3	9
Doc with 10 cause	1	2
Doc with 12 cause	0	1

It is observed that, corresponding to 2,619 Chinese and 2,403 English instances, 4,054 and 4,858 emotion causes are annotated, respectively. It means that, on the average, 1.55 and 2.02 causes are identified for each Chinese and English emotion expression, respectively. It is also shown that about 65% instances contain one cause (65.98%), 21.15% instances have two causes, 8.06% instances contain 3 causes and only 7.83% instances contain more than 3 causes.

The emotion category distribution statistics are listed in Table 2 (Chinese) and Table 3, respectively.

Table 2. Distribution of Emotion Categories (Chinese).

Emotion	Number	Percentage (%)
Fear	493	18.82
Surprise	398	15.20
Disgust	196	7.48
Sadness	723	27.61
Anger	300	11.45
Happiness	509	19.43

From Table 2 and Table 3, an interesting phenomenon is observed that that most of emotions in Chinese and English data are both *Sadness* and *Happiness*.

Table 3. Distribution of Emotion Categories (English)

Emotion	Number	Percentage
Fear	496	20.64
Surprise	323	13.44
Disgust	184	7.66
Sadness	527	21.93
Anger	227	9.45
Happiness	641	26.67

Table 4 and Table 5 shows the position distribution of emotion causes on Chinese and English dataset, respectively. Here, the centroid is the clause where the emotion keyword occurs.

It is observed that about 53.47% emotion causes are adjacent to emotion key words in Chinese and 76.16% in English. Thus, the position information is shown as an effective feature.

Table 4. Position Distribution of Emotion Causes (Chinese)

Position	Number	Percentage
Previous 3 clauses	280	6.85
Previous 2 clauses	572	13.99
Previous 1 clause	1135	33.03
In the same clause	632	15.45
Next 1 clause	420	10.27
Next 2 clauses	250	6.11
Next 3 clauses	123	3.01
Other	678	11.29

Table 5. Position Distribution of Emotion Causes (English)

Position	Number	Percentage
Previous 3 clauses	136	2.78
Previous 2 clauses	288	5.88
Previous 1 clause	653	13.33
In the same clause	2501	51.15
Next 1 clause	577	8.29
Next 2 clauses	216	11.80
Next 3 clauses	102	2.09
Other	426	8.71

4. EVALUATION SETTING AND EVALUATION METIRCS

The emotion cause detection (ECA) task aims to evaluate the systems which extract the emotion cause for each emotion keyword. The evaluation is designed to perform on both Chinese and English text.

4.1 Subtasks

The evaluation designed two subtasks. The first subtask is emotion cause detection at the clause level. This subtask aims to evaluate the techniques for identifying the clause which contains emotion cause. It may be regarded as a clause-level binary text classification problem. Each clause should be classified into two classes:

YES: The clause is the cause of the specific emotion keyword.

NO: The clause is not the cause of the specific emotion keyword.

Example 2:

伊拉克细菌武器的曝光，使联合国大为震惊。

The exposure of Iraq's bacteriological weapons shocked the United Nations.

There are two clauses in this instance in Chinese. Corresponding the keyword "震惊/*shocked*", it is observed that the direct cause is "伊拉克细菌武器的曝光/ *The exposure of Iraq's bacteriological weapons*". Thus, the expected output label for the first clause is "YES", and for the second one "NO".

The second subtask is emotion cause extraction. This subtask is designed to evaluate the techniques for detecting the exact boundary of the emotion cause. It can be regarded as an information extraction task.

Example 3:

然而在水边发现了育萍的物品，这让大伙更加担心。

However, the discovery of Yuping's belongings near the river, which makes everyone more worried.

For this instance, the cause of the emotion "担心/*worry*" occurred in the first clause. The output of this subtask should be the emotion cause text "在水边发现了育萍的物品/ *the discovery of Yuping's belongings near the river*". Actually, this subtask is designed to find boundary of the cause fragment in the cause clause.

4.2 Evaluation Metrics

For the first subtask, emotion cause detection at the clause level, the evaluation metrics are designed based on the typical text classification metrics:

$$Precision_{clause} = \frac{\#correct\ cause\ relevant\ clauses}{\#detected\ cause\ relevant\ clause} \quad (1)$$

$$Recall_{clause} = \frac{\#correct\ cause\ relevant\ clauses}{\#annotated\ cause\ relevant\ clause} \quad (2)$$

$$F-measure_{clause} = \frac{2 \times Precision_{clause} \times Recall_{clause}}{Precision_{clause} \times Recall_{clause}} \quad (3)$$

For the second subtask, emotion cause extraction, the evaluation metrics are designed based on the overlapping between the detected emotion cause and the annotation at the phrase level:

$$Precision_{phrase} = \frac{1}{\#d} \sum_{i \in d} \frac{length\ of\ overlapping\ in\ document_i}{length\ of\ detected\ cause\ in\ document_i} \quad (4)$$

$\boldsymbol{Recall_{phrase}} = =$

$$\frac{\mathbf{1}}{\#\boldsymbol{d}} \sum_{i \in d} \frac{\boldsymbol{length\ of\ overlapping\ in\ document_i}}{\boldsymbol{length\ of\ detected\ cause\ in\ document_i}} \quad \textbf{(5)}$$

$\boldsymbol{F - measure_{phrase}} =$

$$\frac{\mathbf{2} \times \boldsymbol{Precision_{phrase}} \times \boldsymbol{Recall_{phrase}}}{\boldsymbol{Precision_{phrase}} \times \boldsymbol{Recall_{phrase}}} \quad \textbf{(6)}$$

Where, *d* in equation 4 and equation 5 represent the number of documents.

4.3 Data Delivery

For each language, 3,000 documents are annotated with emotion causes, in which, 2,500 documents are released as the training data and 500 documents are used as the testing data. Furthermore, 10,000 documents with emotion category labels are released for building semi-supervised systems.

5. EVALUATION RESULTS AND DISCUSSIONS

Eleven teams participate ECA task. Three participants submitted valid results for the emotion cause detection subtask on Chinese side.

5.1 Submission Systems

The neuL team applied the decision tree algorithm to classify each clause into two categories. The GDUFS team and NLP@WUST team both treat emotion cause detection as a sequence tagging problem. The team GDUFS uses structural Support Vector Machine as a sequence labeling model. The NLP@WUST team uses the conditional random field as the classier.

The NLP@WUST and GDUFS team both used the features of noun, verb and the number of nouns and verbs in the text. Thee three teams all use the distance information related features. The major employed features are listed in the Table 6.

Table 6. Major Features Adopted by The Participators

Features	Description
Nouns	The nouns in the present sentence, if not, fill "NULL".
Verbs	The verbs in the present sentence, if not, fill "NULL".
Numbers of Nouns	The number of nouns contained in the present sentence.
Numbers of Nouns	The number of nouns contained in the present sentence.
Distance	Distance between present sentence and emotional keyword. The values represented to Left2, Left1, Keyword, Right1 and Right2 clauses are -2, -1, 0, 1 and 2, respectively.

5.2 Evaluation Results

GDUFS team applied the structural support vector machine (SSVM) to label the sequence. The structural support vector machine model is formalized as follows:

$$min_{\omega,\xi} ||w||^2 + C \sum_{n=1}^{\ell} \xi_n \quad \textbf{(7)}$$

$$\text{s.t.} < \omega, \psi(x_n, y_n) > - < \omega, \psi(x_n, y) > + \xi_n \geq \Delta(y_n, y)$$

$$\text{n} = 1,2, \dots, \ell, \qquad \forall \text{y} \in \mathcal{Y}$$

This team used lexical, distance and contextual features. Their adopted lexical features are similar to the features of NLP@WUST with small difference.

For the emotion cause detection subtask, the evaluation results are listed in Table 7.

Table 7. Evaluation Results for Emotion Cause Detection Subtask (Chinese)

Team	Model	Precision	Recall	F-measure
neuL	Decision Tree	0.4462	0.6983	0.5545
GDUFS	SSVM	0.6711	0.6416	0.6561
NLP@WUST	CRF	0.6930	0.6398	0.6654

The neuL team utilized the category of emotion keyword as one feature which was not used in other teams. Actually, there should be a critical relation between emotion categories and emotion causes. The performance of GDUFS team and NLP@WUST team may also benefit from the use of emotion category feature.

5.3 Discussions

The evaluation results show that there are much room to improve the emotion cause analysis performance. Meanwhile, the evaluation results show the difficulties in emotion cause detection and emotion cause extraction.

We take emotion cause detection problem as a kind of classification problem. Since the limited scale of annotated dataset, the supervised-based approach is difficult to achieve a good performance. Unfortunately, no participator provided the algorithm which considering the semi-supervised learning. Meanwhile, the annotated dataset show obviously unbalanced in six emotion categories. The participant should consider this problem.

The emotion cause extraction looks more difficult. No participator provided the results for this subtask. Furthermore, no results on English side is submitted. It partially attribute to the difficulty that segment clauses from sentences in English. More efforts must be made in this field.

6. CONCLUSION

In this paper, we present the overview of the NTCIR-13 shared task on emotion cause analysis (ECA). It is designed to evaluate the techniques for identifying the cause of emotion in text. The evaluation are performed on both Chinese and English side. This evaluation designed two subtasks including emotion cause detection subtask which identifies the clauses containing emotion cause, and emotion cause extraction subtask which determines the boundary of emotion cause in the clause. Three participant teams submitted their results for the first subtask on Chinese side. The highest achieved F-score is 66.5%. It shows that there still are much room to improve in this emotion cause analysis problem, especially emotion cause extraction problem.

In this evaluation, we constructed the largest emotion cause annotated corpus on both Chinese and English, based on our knowledge. This resource is expected to promote the research on emotion cause analysis worldwide.

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