Extraction of Event Elements Based on Event Ontology Reasoning

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Abstract. This paper proposes an event elements extraction method based on event ontology reasoning by constructing an upper event ontology and event elements reasoning rules based on event non-taxonomic relations. Event elements extraction includes three steps: data preprocessing; complementing event elements initially; event elements reasoning. The experimental results show that this method can improve the accuracy of event elements extraction.

Keywords: Event ontology reasoning · Event elements · Event elements extraction

1 Introduction

In the field of NLP, event is a structured knowledge unit with bigger granularity than concept, which is in line with human cognition. Therefore, in the field of AI, researchers hope that event-related (including action, time, place and people) information can be automatically identified from text by machine, thus to achieve some automatic text processing tasks, such as text classification, topic detection and tracking and so on. Therefore, identification of event elements has become an important sub-task of event information extraction.

The machine learning method considers event extraction as a classification problem and has good robustness, but it requires large-scale corpus labeled as model training base, which results in very laborious manual annotation. For shortcomings of machine learning method, this paper proposes an event elements extraction method based on event ontology. This method enables machine to mimic users' reading habits, utilize event ontology to associate event information and reasons about event elements including place, time, subject and object.

2 Related Work

Machine learning method is more objective and does not require much human intervention and domain knowledge, which includes two key steps, classifier construction and feature selection. In [1], machine learning methods were utilized to identify

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relevant semantic role of verb in Persian. In [2], machine learning methods were used to identify key events of Chinese news stories and extract event 5W1H elements. In [3] event elements identification was divided into two steps: identify named entities, time phrases and event elements words; use maximum entropy classifier to classify elements. A method was proposed in [4] to identify event type argument by combining event trigger expansion and a binary classifier and multi-class classification based on maximum entropy. A method was proposed in [5] to identify event elements based on semi-supervised clustering and feature weighting.

In addition to machine learning methods, pattern matching methods in event elements identification are also frequently used. The key idea of these methods is to create a series of models and match sentences with template to achieve a purpose of event identification and extraction. These methods are only suitable for specific areas and lack of versatility. In [6], a method of Web news-oriented event multi-elements retrieval is studied. In [7], multi-pattern matching method was utilized to identify event elements on the ACE Chinese corpus, but the rules adopted are limited and results are not satisfactory. In [8] and [9], a new task of cross-document event extraction method and a biomedical event extraction system were proposed respectively.

3 Construction of Event Ontology

In the field of information extraction, event is defined as “a refined retrieval-used theme”. Topic Detection and Tracking (TDT) sponsored by DARPA defined event as “a thing happens in a certain time and place”. The main definitions about event of this paper are from our previous work [10]. In this section, we review these concepts briefly.

3.1 Event Related Concepts

Definition 1 ***(Event).*** We define event as a thing happens in a certain time and environment, which some actors participate in and shows some action features. Event e can be defined as a 6-tuple formally: $e = (A, O, T, V, P, L)$, where A means an action set happened in an event; O means objects involved in the event; T means time; V means place; P denotes assertions; L means language expressions.

Definition 2 ***(Event Class).*** Event Class denotes a set of events with common features, defined as: $EC = (E, C_1, C_2, \dots, C_6)$, $C_i = \{c_{i1}, c_{i2} \dots, c_{im}, \dots\}(1 \le i \le 6, m \ge 0)$. Where E is event set, called extension of event class. C_i is called intension of event class. It denotes common features set of certain event element (element i). c_{im} denotes one of common features of event element i.

Definition 3 ***(Taxonomic Relations).*** There exists subsumption relation between event class $EC_1 = (E_1, C_{11}, C_{12}, \dots, C_{16})$ and event class $EC_2 = (E_2, C_{21}, C_{22}, \dots, C_{26})$ if and only if $E_2 \subset E_1$, or $C_{2i} \subseteq C_{1i} (i = 1,2, \dots ,6)$. We call EC_1 hypernym event class and EC_2 hyponym event class, denoted as $EC_2 \subset EC_1$.

Definition 4 ***(Non-taxonomic Relations).*** ① Causal Relation: it is denoted as $(\lambda \mathrm{EC}_1 \to \mathrm{EC}_2)$. λdenotes the probability that events of event class EC_2 happen caused by events of event class EC_1. ②Follow Relation: Another event of EC_2 the subject participates in happens after an event of EC_1 specified subject participates in happens, denoted as$(EC_1 \rhd EC_2)$. ③Concurrence Relation: If EC_1 concur with EC_2 in a certain length of time, and the occurrence probability is above a specified threshold, there is a concurrence relation between EC_1 and EC_2, denoted as$(EC_1 \parallel EC_2)$. ④Composition Relation: If each event instance of event class EC_1 is composed of one event instance of event class EC_2 and other event classes, EC_2 *is part of* EC_1, denoted as$(EC_1 \nless EC_2)$.

Definition 5 ***(Event Ontology).*** Event ontology EO is defined as a 4-tuple ly: $EO = (UECS, ECS, R, Rules)$. *UECS* is a set of upper event classes; *ECS* is a set of event classes; *R* means the relations between event classes; *Rules* is set of rules be expressed in logic languages.

3.2 Upper Event Ontology

In support of event elements reasoning, this paper constructs an upper event ontology based on event ontology of reference [10]. Upper event ontology defines event taxonomic hierarchy model, as shown in Table 1.

Table 1. Upper event ontology structure

1 *Class :HumanEvent*	2 *Class :NatureEvent*
1.1 *Class :SinglePersonEvent*	2.1 *Class :NonNatureForceEvent*
1.1.1 *Class :PersonObject_SinglePersonEvent*	2.1.1 *Class :PersonObject_ NonNatureForceEvent*
1.1.1.1 *Class :Continue_PO_SinglePersonEvent*	2.1.1.1 *Class :Continue_PO_NonNatureForceEvent*
1.1.1.2 *Class :Instant_PO_SinglePersonEvent*	2.1.1.2 *Class :Instant_PO_NonNatureForceEvent*
1.1.2 *Class :NonObject_SinglePersonEvent*	2.1.2 *Class : NonPersonObject _NonNatureForceEvent*
1.1.2.1 *Class :Continue_NO_SinglePersonEvent*	2.1.2.1 *Class :Continue_NPO_NonNatureForceEvent*
1.1.2.2 *Class :Instant_NO_SinglePersonEvent*	2.1.2.2 *Class :Instant_NPO_NonNatureForceEvent*
1.1.3 *Class :NonPersonObject_SinglePersonEvent*	2.1.3 *Class :NonObject_NonNatureForceEvent*
1.1.3.1 *Class :Continue_NPO_SinglePersonEvent*	2.1.3.1 *Class :Continue_NO_NonNatureForceEvent*
1.1.3.2 *Class :Instant_NPO_SinglePersonEvent*	2.1.3.2 *Class :Instant_NO_NonNatureForceEvent*
1.2 *Class :PublicEvent*	2.2 *Class :NatureForceEvent*
1.2.1 *Class :NonPersonObject_PublicEvent*	2.2.1 *Class :PersonObject_ NatureForceEvent*
1.2.1.1 *Class :Instant_NPO_PublicEvent*	2.2.1.1 *Class :Continue_NatureForceEvent*
1.2.1.2 *Class :Continue_NPO_PublicEvent*	2.2.1.2 *Class :Instant_NatureForceEvent*
1.2.2 *Class :PersonObject_PublicEvent*	2.2.2 *Class : NonPersonObject _ NatureForceEvent*
1.2.2.1 *Class :Continue_PO_PublicEvent*	2.2.2.1 *Class :Continue_NPO_NatureForceEvent*
1.2.2.2 *Class :Instant_PO_PublicEvent*	2.2.2.2 *Class :Instant_NPO_NatureForceEvent*
1.2.3 *Class :NonObject_PublicEvent*	2.2.3 *Class :NonObject_ NatureForceEvent*
1.2.3.1 *Class :Continue_NO_PublicEvent*	2.2.3.1 *Class :Continue_NO_NatureForceEvent*
1.2.3.2 *Class :Instant_NO_PublicEvent*	2.2.3.2 *Class :Instant_NO_NatureForceEvent*

The first level of upper event ontology is divided into two categories: human event class and natural event Class, according to subject category of event class.

The second level is further sorted according subjects of event class. Human event class is divided into single person event class and public event class. Natural event class is divided into natural force events and non-natural force events.

The third level of upper event ontology is sorted according to objects of event class. Human event class is divided into person object event class, non-person object event class and non-object event class. Nature force event class is divided into person object nature force event class, non-person object nature force event class and non-object nature force event class while non-nature force event class can be divided in the same way.

The fourth level is sorted based on the third level according to time element. Time elements tend to be divided into time points and the time periods, and accordingly, events can be divided into transient events and continuous events.

4 Reasoning Rules and Reasoning Procedure of Event Elements

4.1 Reasoning Rules of Event Elements

Taxonomic relations and non-taxonomic relations have different effects on elements reasoning. In taxonomic relations, when the abstract event class an event belongs to is queried in upper event ontology, restrictions of the event elements can be obtained. For example, if an event class (such as thunderstorm) belongs to instant nature force event class, its start time and end time are same, and its object is empty.

Table 2. Event elements reasoning rules for event relations of $CPOPE \times CPOPE$

a. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \nless EC_1) \Rightarrow (ST(e_1) \geq ST(e_2)) \cap (ET(e_1) \leq ET(e_2))$
b. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \nless EC_1) \Rightarrow P(e_1) = P(e_2)$
c. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \nless EC_1) \Rightarrow Sub(e_1) = Sub(e_2)$
d. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \nless EC_1) \Rightarrow Obj(e_1) \subseteq Obj(e_2)$
e. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \rightarrow EC_1) \Rightarrow ST(e_1) < ST(e_2)$
f. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \rightarrow EC_1) \Rightarrow P(e_1) = P(e_2)$
g. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \rightarrow EC_1) \Rightarrow Obj(e_1) = Sub(e_2)$
h. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \rhd EC_1) \Rightarrow ET(e_1) < ST(e_2)$
i. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \rhd EC_1) \Rightarrow P(e_1) = P(e_2)$
j. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \rhd EC_1) \Rightarrow Sub(e_1) = Sub(e_2)$
k. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \parallel EC_1) \Rightarrow P(e_1) = P(e_2)$
l. $(e_1 \in EC_1) \cap (e_2 \in EC_2) \cap (EC_1 \parallel EC_1) \Rightarrow (ST(e_1) \leq ST(e_2)) \cap (ET(e_1) \geq ET(e_2))$

Non-taxonomic relations are main content of event elements reasoning in this paper, which can contact context. After studying features of all event types in the fourth level of upper event ontology and a large number of cases, a set of event elements reasoning rules are proposed for combination of every two event types according to relations between events. Table 2 shows twelve event elements reasoning rules for event relations of the two *Continue_PO_PublicEvent* event types(referred to as *CPOPE* type, namely two events existing relations belong to public continue events many people take part in, such as "*assistance*" and "*on-site rescue*"). Similarly, other combinations also have reasoning rules. In these rules, the $P(e_i)$ represents place, and $ST(e_i)$ represents start time, and $ET(e_i)$ represents end time, $Sub(e_i)$ represent subject, $Obj(e_i)$ represents object.

4.2 Process of Event Elements Identification

This paper mainly identify event elements appear in news reports, focusing on identifying and complementing four elements (time, place, subject and object). Segment for an article using segmentation tool, and get a set of events from texts using language performance of event classes in event ontology, and then extract all named entities from this sample, and create a two-dimensional matrix. In this matrix, columns are events; rows are event elements; *0* denotes it is not element of the event; *1* denotes place element; *2* denotes start time; *3* denotes end time; *4* denotes subject; *5* denotes object. Complementing event elements actually update the matrix. A_{ij} denotes a matrix consisting of all the events of an article.

$$A_{ij} = \begin{array}{cc} & \begin{array}{cccccccccc} w_1 & w_2 & w_3 & w_4 & w_5 & w_6 & w_7 & w_8 & w_9 & w_{10} \end{array} \\ \begin{array}{c} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \\ e_6 \\ e_7 \\ e_8 \end{array} & \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 3 & 4 & 5 & 0 & 0 & 2 & 0 & 0 \\ 0 & 2 & 3 & 0 & 0 & 0 & 1 & 0 & 4 & 5 \\ 0 & 0 & 3 & 4 & 5 & 2 & 1 & 0 & 0 & 0 \\ 1 & 0 & 3 & 4 & 5 & 2 & 0 & 0 & 0 & 0 \\ 0 & 2 & 3 & 5 & 0 & 0 & 1 & 0 & 4 & 0 \\ 0 & 2 & 3 & 5 & 0 & 0 & 1 & 0 & 4 & 0 \\ 1 & 2 & 3 & 4 & 0 & 0 & 0 & 0 & 0 & 5 \end{bmatrix} \end{array}$$

Identification process of event elements are following three steps: data preprocessing, complementing event elements initially according to words position, event elements reasoning.

In data preprocessing stage, first, segment for an article and revise manually; then identify event triggers and corresponding event elements using event ontology. In order to calculate positional relations between words in subsequent steps, tag number of words in sentences using sentence as a unit.

In initial complementing stage, the distance between event triggers and elements can be calculated using paragraph number, sentence number and word number tagged in data processing. The nearest words are selected as initial complementing results. For an event *a* of the text, steps of initial complementing event elements are as follows:

Step 1: Get element word *argul* from elements words list; *confident (e, i)* is confidence of the *i-th* element of the event, which is initialized to 0, then go to step 2;

Step 2: Calculate confidence of the element: *if* (*e* and *argu1* locate in the same sentence) *confidence*= α/|word number of *e* - word number of *augu1*|; else if (e and *argu1* locate in the same paragraph) *confidence* = β/| word number of *e* - word number of *augu1*|; else *confidence* = γ/| word number of *e* - word number of *augu1*|; then go to step 3;

Step 3: If the *confidence*(*e*, *i*) is higher than the previous, it is updated to *the confidence*; or keep previous *confidence* and element unchanged, then go to step 4;

Step 4: Go to step 1, continue to remove event elements from the list until all event elements are taken from the list.

Here α, β, and γ are used to calculate weight of confidence. Their values ensure that value of confidence decreases with increasing distance (in general, the confidence which elements and triggers are in a same sentence is larger than one in a different sentence). Therefore, values of α, β, γ can be respectively *100*, *10* and *1*.

In event elements reasoning stage, initial complementing results in the second stage are used to reason elements. First, get elements restrictions of the event through querying the upper event class the event belongs to. If an element of some events is default, it is not complemented. If subjects of some events are only people, they are complemented by named entities. Then use one of two associated events to reason related elements of another event through above reasoning rules. The event of the largest confidence is selected as a seed event. Input Seed events, and query events existing non-taxonomic relation with seed events from event ontology, and then query event types of two events associated with every relation, and then determine elements reasoning rules base according to event types of the two events and reason related information.

4.3 Case Study

The following is a semi-automated tagged news report: e_i denotes an event trigger, and l_i denotes place, and t_i denotes time, and p_i denotes participants (including subject and object).

新快报讯，8月20日早上6点(**t_1**)，阿尔及利亚以东150公里的卜伊拉(**l_1**)发生汽车炸弹(**p_1**)**爆炸**(**e_1**)事件，造成11人(**p_2**)**死亡**(**e_2**)。*(According to Xinkuai Express, at 6:00 am on August 20th, car bomb was exploded 150 kilometers east of Algeria , killing 11 people dead.)*

当地媒体报道称，包括4名军事人员在内的31人(**p_3**)**受伤**(**e_3**)。目前(**t_2**)，当地(**l_2**)正对伤者(**p_4**)进行**救治**(**e_4**)。*(Local media said that 31 people including 4 military officers were injured. So far, the wounded has been on treatment in the local.)*

Step 1, complemented elements are shown in table 3 according to words location distance, and *conf* is confidence:

Step 2, reason related information according to restrictions of event classes in event ontology:

e_1 *is_a Instant_NonNatureForceEvent=>*e_1*.ST=*e_1*.ET=*t_1*,* e_1*.OBJECT=null*

The above formula shows that event type of e_1 mapped to upper event ontology is *Instant_NonNatureForceEvent*. Conclusions can be drawn from above: e_1 is an *InstantEvent*, so start time and end time are same; the event describes subject's own changes, so there is no object. In step 1, element word p_1 is complemented as object of e_1, which does not meet the restriction *Instant_NonNatureForceEvent* doesn't have object. So in step 2, object of e_1 is revised as empty.

Table 3. Event elements complementation through words location distance

Event	LOC	ST	ET	SUBJECT	OBJECT	conf
e_1	l_1	t_1	t_1	p_1	p_1	291.7
e_2	l_1	t_1	t_1	p_2	p_2	247.6
e_3	l_1	t_2	t_2	p_3	p_3	221

e_4	l_2	t_2	t_2	p_4	p_4	165

Similarly, we can draw:

e_2 *is_a Instant_NonObject_SinglePersonEvent=>* $e_2.ST=e_1.ET=t_1$, $e_2.OBJECT=null$

e_3 *is_a Continue_NonObject_SinglePersonEvent=>* $e_3.OBJECT =null$, $e_3.ET>e_3.ST=t_1$

e_4 *is_a Continue_PersonObject_PublicEvent=>* $e_4.OBJECT =$ 伤者, $e_4.ET>e_4.ST=t_2$

And $e_4.SUBJECT=$医疗人员, which is obtained through specific *treatment* event class.

Step 3, following relations are obtained from querying event ontology: e_1 *cause* e_2, e_1 *cause* e_3, e_2 *concur* e_3, e_3 *cause* e_4.

e_1 is used as seed event. According to event types of e_1 and e_2, corresponding reasoning rules are found from rules base, and then other event elements are reasoned:

e_1 *cause* e_2 $=>e_1.ST< e_2.ST=> e_2.ST = e_2.ET = t1+$; e_2 *concur* e_3 $=>e_2.ST=e_3.ST=> e_3.ST = e_3.ET = t_1+$

e_3 *cause* e_4 $=> e_3.ST< e_4.ST=> e_4.ST=t_1{+}{+}(t_2=t_1{+}{+})$; e_3 *cause* e_4 $=> e_3.LOC= e_4.LOC(l_2=l_1) => e_4.LOC = l_1$

Finally, results are shown in table 4.

Table 4. Results of elements reasoning

Event	LOC	ST	ET	SUBJECT	OBJECT
e_1	l_1	t_1	t_1	p_1	*null*
e_2	l_1	t_1+	t_1	p_2	*null*
e_3	l_1	t_1+	$t_1{+}{+}$	p_3	*null*
e_4	l_1	$t_1{+}{+}$	$t_1{+}{+}{+}$	医务人员	p_4

So if an event itself doesn't have object element, its object value is null; the happen time of event is updated; some default elements are complemented according to event ontology; absolute time and place are reasoned from some relative time and place (such as "*current*", "*local*"). To a certain extent, event elements are complemented.

5 Experiment and Analysis

5.1 Experiment

The experimental data set is Chinese Emergency Corpus (CEC) [11], which contains earthquakes, fires, accidents and terrorist attacks five types, a total of 205. Place, subject, object and time elements are complemented for events of CEC. Experiment is divided into two parts.

Experiment 1: Elements are complemented according to positional relations between triggers and any other event elements.

Experiment 2: Reasoning results are used to complement event elements according to reasoning rules proposed in this paper. Based on experiment 1, Experiment 2 is divided into two parts: (1) event with the highest confidence and occurring in the first paragraph is used as a seed event; (2) event with the highest confidence and occurring in other paragraph is used as a seed event.

5.2 Analysis of Experiment Results

In experiment 1, statistic results of random selected 195 events from CEC are shown in table 5:

Table 5. Complemented results of neighboring position elements for different relations

Element	Precision	Recall	F1 measure
Place	65.8%	62.5%	64.1%
Time	60.3%	66.6%	63.3%
Subject	48.5%	72.3%	58.1%
Object	54.3%	52.7%	53.5%

Just as shown in table 5: recall, precision and F1 values of place and time elements have reached more than 60%, which indicates that extraction of the two elements can achieve a preliminary desired results using positional relation between triggers and elements, but subjects and objects are not. First, because number of subjects and objects words in the article appears much more than subject and object themselves, which easily interferes with each other in sentences; second, because annotations of subjects and objects are not as clear as time and place. Some subjects may be objects of other events and vice versa; third, because some events may have many subjects and objects, but this method can only complement one of them.

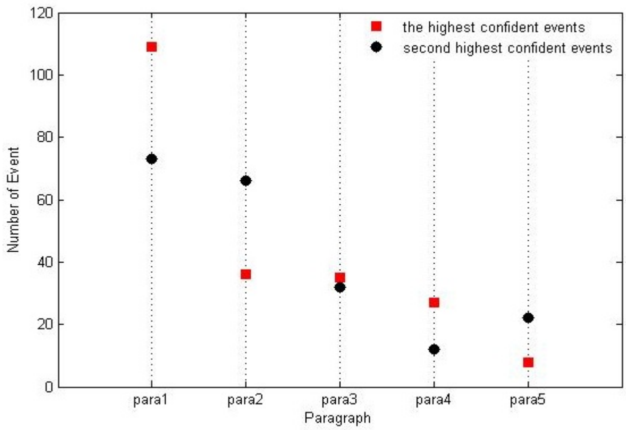

Fig. 1. Events distribution with the highest and second highest confidence

Experiment 1 only uses positional relations between words, but some factors like types of events and relations of context are not taken into account. So experiment 2 updates results of experiment 1 through reasoning rules. Event distributions with the highest confidence are shown in figure 1.

As shown in figure 1, events of the highest and second highest confidence generally appear in the first paragraph, or in the second paragraph, and some evenly distribute in other paragraphs. These events in the first paragraph are basically core events, but events

Table 6. Complement results based on element reasoning for different seed events

Element	FirstPara_Event			OtherPara_Event		
	P	R	F1	P	R	F1
Place	78.3%	82.3%	80.3%	73.5%	80.7%	76.9%
Time	80.9%	76.2%	78.5%	75.7%	73.6%	74.6%
Subject	69.3%	73.7%	71.4%	68.0%	66.9%	67.4%
Object	70.5%	68.6%	69.5%	65.6%	65.3%	64.5%

in other paragraph are almost not. So events with the highest confidence in the first paragraph and ones in other paragraph with the highest confidence are selected as seed events. Reasoning results of experiment 2 are shown in table 6.

Just as shown in table 6: P, R and F1 values are improved much more than experiment 1. In complementation of event elements, the interference of positional relations between words can be excluded. Identification of subject and object also avoid problems arising from experimental 1, especially for subject of many events. In addition, in the second experiment, events are mapped to event classes of event ontology, which can get restrictions of elements and take full account of categories and the default of event elements. For example, for some natural disaster events, their subject is nature through querying upper event ontology. In general, subject like nature is default, which causes that the real subject can't be obtained by complemented method of word distance in experiment 1. Event restrictions obtained from event ontology revise the results of experiment 1. For non-default elements, more suitable elements can be selected through element restrictions of event classes, which improves experimental effect. In selecting seed events, experimental results of the first part (with the highest confidence and in the first paragraph) are slightly better than the second part. The experiment results above show that event elements can be better identified by using event class relations and seed events in the first paragraph can achieve better experimental effect.

6 Conclusion

By construction of upper event ontology and event elements reasoning rules set, this paper proposed an event elements extraction method. This method reduces the dependence on scale of rules and corpus; Experimental results show that this proposed method can effectively improve identification performance of event elements. But there still need some improvements: the current accuracy of automatic identification of event indicators and event elements can't reach a more desired degree; the structure of event ontology affects the effect of identification; the reasoning rules need to be further improved. In our future research, event ontology will be enriched, including enriching and optimizing event types, restriction of event classes and reasoning rules of event elements. The event information identified can be used in text representation based on events, such as construction of text event networks.

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