A Method of Event Ontology Mapping

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Abstract Ontology mapping is an important solution to ensure interoperability while integrating heterogeneous and distributed data sources. This paper proposes an approach for ontology mapping based on event, which enable the mapping between event-based information with more abundant semantics. Firstly, this paper gives the definition of event ontology mapping, and then proposes an comprehensive semantic similarity calculation model based on the similarity of events and event structures. Experiments show that the proposed model can effectively find the semantic relations of event in two event ontologies.

Keywords Event ontology mapping · Semantic similarity · Semantic neighbor

1 Introduction

Ontology is the core of semantic web, and it is widely used in the areas such as data integration, metadata management and data exchange. However, due to various cultural backgrounds and comprehensions of ontology, different usage habits of terms leads to an ocean of ontologies with different structures, which causes the limited integration and limited sharing of data. In order to accomplish interoperability of semantics ontology, it is necessary to establish mapping relations among heterogeneous ontologies. Whereas most current ontology matching methods are based on calculation of concepts correspondence [1], it will result in semantic information loss while processing event-based data because of “Tennis Problem” [2]. In recent years, research on the use of events as a key concept for representing knowledge, organizing and structuring media on the web is surging, especially in

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semantic web community. Event ontology is a shared, formal and explicit specification of an event class system model that exists objectively, which has become new paradigm for describing and reasoning event-based knowledge in web. Event-based ontology matching is necessary for integrating heterogeneous data sources in event-centered domain application, such as emergency response, public opinion monitoring, history and cultural heritage, etc.

Aims at the event ontology mapping in semantic web application, this paper firstly gives the definition of event ontology mapping, and then proposes a semantic similarity calculation model based on the similarity of event classes and event class structure. The similarity of event classes is calculated by the similarity of common elements in different event. The similarity of event class structure is obtained by calculating the similarity of semantic neighbor sets. The semantic neighbors of event class could be found in a certain semantic radius in event ontology network structure.

The paper is organized as follows. Section 2 reviews the related work. Section 3 introduces concepts about event ontology. Section 4 proposes the mapping approach of event ontology. We present experimental results and analysis in Sect. 5. Finally, Sect. 6 concludes the paper.

2 Related Work

The ontology mapping problem has been researched extensively in the past decade, yet, despite this research, it is still considered an "unsolved" problem [3]. Currently, basic matcher is a similarity function of a pair of entities, $\sigma : o \times o \rightarrow R$ where R is [0,1]. In point-to-point approach, matching uses lexical or structural similarity of labels or instances. Current ontology mapping methods can be categorized as: terminological mapping [4], structural mapping [5] and semantic technique [6]. Ontology mapping have gained a large amount of attention and regarded as an important solution that enables interoperability across heterogeneous systems and semantic web applications. A single mapping method maybe not afford all mapping tasks, consequently, different methods sometimes are combined to realize concept mapping in ontologies.

According to [4], currently methods of ontology mapping face several difficulties, such as difficulty in processing word variations in the same ontology or across ontologies while terminological mapping, difficulty in processing many kinds of variations that occur in ontologies while structural mapping. At the same time, ontology requires inductive inputs but semantics technique is deductive in nature, currently, there is a lack of interoperability between inductive technique and deductive semantic techniques.

From our perspective, event-based concept mapping is arduous to be accomplished by using traditional conceptualized mapping technologies. Event-based information involves objects, action, time, location and so on, the traditional concept mapping usually results in loss of semantics. In additional, relations between events contains more semantic information than the hierarchical relationships between concepts. How to use these semantic relations to enhance the mapping between the event ontologies is worthy of study. This is also the motivation of this paper.

3 Concepts About Event Ontology

Definition 1 (*Event*) We defined event as a thing happening in a certain time and place, which is involved in some actors, objectives and action features with statuses changing. Event e is defined as a 6-tuple formally:

$$Event ::= \langle A, O, T, P, S, L \rangle$$

where, A means an action happen in an event, O means actors and objects involved in an event, T means instant and interval time of an event, P means the place that an event happens in, S means statuses of object O before and after an event, L indicates linguistic expressions of text-based event, it includes the language expression of events and event elements. L is also the key parameter to calculate the similarity between event classes [7].

Definition 2 (*Event Class*) Event class is an abstract event that represents a set of events with some common characteristics, denoted as EC:

$$EC = (E, C_A, C_O, C_T, C_P, C_S, C_L)$$

$C_i = \{c_{i1}, c_{i2}, \ldots, c_{im}, \ldots\}$ ($i \in \{A, O, T, P, S, L\}$, m ≥ 0) where E means an event set, called extension of the event class, C_i denotes the common characteristics set of certain event element (element i), called intension of the event class and event element class, c_{im} denotes one of the common characteristics of event factor i.

Definition 3 (*Event Ontology*) An Event ontology EO is a shared, formal and explicit specification of an event class system model that exists objectively. Event ontology EO can be defined as a 4-tuple formally:

$$EO = \langle UECs, ECs, R, Rules \rangle,$$

where:

1. $UECs$ is a set of upper event classes in the event ontology, each UEC represents a category, all of the UEC constitute a tree category structure of an event ontology;
2. $ECs = \{EC_1, EC_2, \ldots, EC_n\}$ is a set of event classes;
3. $R = \{r \mid r$ is the relation of $\langle EC_i, EC_j \rangle\}$, $r \in \{R_{is\_a}, R_{compOf}, R_{cause}, R_{follow}, R_{concur}\}$. R_{is_a} means subsumption relations, R_{compOf} means composition relations, R_{cause} means causality relations, R_{follow} means follow relations, R_{concur} means concurrency relations.

4. *Rules* is set of rules be expressed in logic languages, including rules for inference of upper level event categories and rules for relations inference among events.

4 Event Ontology Mapping

4.1 Definitions About Event Ontology

Event ontology mapping is to specify how the event classes in various event ontologies map to each other. In this section, we defined two concepts about event ontology.

Definition 4 (*Event Class Mapping Consistency*) Event ontologies EO_1, EO_2, we use C to denote the consistency of the two event classes EC_1 and EC_2 in EO_1 and EO_2, defined as a 4-tuple:

$$C ::=\ _{def} < id, EC_1, EC_2, S >$$

where *id* means the unique identification of the consistency, EC_1 and EC_2 represent event classes, S represents semantic similarity between event class EC_1 and EC_2, matching $S \in [0, 1]$. User can set the threshold value of S according to the requirement of application. It means EC_1 is consistence with EC_2 while the similarity is above the value of S.

Definition 5 (*Event Ontology Mapping*) Event ontology EO_1, EO_2, event ontology mapping M is represented by a set of consistency of mapping.

$$M ::=\ _{def}(c_1, c_2, \ldots\ldots, c_n)\ (0 < n \leq |EO_1 \leftrightarrow EO_2|)$$

where $|EO_1 \leftrightarrow EO_2|$ is the pairs count of mapping between EO_1 and EO_2.

4.2 Event Ontology Comprehensive Semantic Similarity Calculation Model

According to the event class definition above, an event class is composed of six elements. So, the similarity between two event classes basically results from the similarities between their common elements (such as action, participants and places). As well, the relationships among event classes provide context semantics for event classes, and it is rather easy to notice that two event classes with high similarity always have similar relation structure with their neighbors in event ontology. In this section, we present an event ontology comprehensive semantic similarity calculation model based on features of event inner structure and event

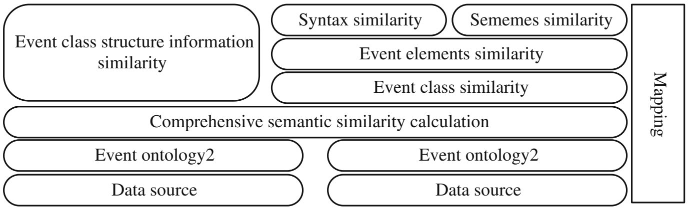

Fig. 1 A simple high level view of a mapping process

relationship network structure. As shown in Fig. 1, the calculation process of event class similarity includes two parts. First is the calculation of the event class similarity, which can be calculated through the elements similarity of event classes. Second is the calculation of event class structures similarity. As mentioned above, the relations between the events are divided into two categories: taxonomic relations and non-taxonomic relations. We can use semantic neighbors of event classes to express the semantic relationships among event classes. According to the event class network structure in event ontology, taking the event class as the center and setting a semantic radius *r*. In this range, the value of *r* reflects the close or distant relation between event classes. While the calculation of event classes similarities in the first step, we got a similarity distribution table. Some of the similarity value might be very small or even zero, which means sparse relation between event classes, but in fact, some implicit semantic relations between them can be extracted in the semantic neighbor sets. We take the biggest similarity of event classes in the semantic neighbor sets as the similarity of semantic neighbor sets. It would eventually get a similarity distribution table. Furthermore, two similarity distribution tables are integrated together. Finally the biggest similarity value corresponding to the event class is taken as the final similarity value.

4.2.1 Event Class Similarity Calculation

Event class is an abstract event that represents a set of events with common characteristics. The event class EC_1 is denoted as $EC_1 = \{e_{11}, e_{12}, \ldots, e_{1n}\}$, while the event class EC_2 is denoted as $EC_2 = \{e_{21}, e_{22}, \ldots, e_{2m}\}$. The similarity between EC_1 and EC_2 can be calculated as follows:

$$\mathrm{sim}(EC_1, EC_2) = \frac{1}{m * n} \sum_{i=1\ldots n, j=1\ldots m} sim\left(arg_{1i}, arg_{2j}\right)\left(arg \in \{a, o, t, p, s\}\right) \tag{1}$$

where $sim(arg_{1i}, arg_{2j})$ means the similarity of event elements. The calculation of elements similarity will be introduced in detail below.

While modeling an event class with 6-tuple event model, event elements described with natural language (*objects, action and place*) or assertion expressions (*time and status*), which may be a simple word, a phrase or a sentence. So, the calculation of elements similarity include the syntax similarity and semantics similarity. We utilize the method in [8] to calculate the syntax similarity of elements.

Definition 6 (*Syntax Similarity Calculation*)

$$\mathrm{sim}_{syntax}(con_1, con_2) = \frac{2\sum_j length\big(\max SameSubString_j(con_1, con_2)\big)}{length(con_1) + length(con_2)} \tag{2}$$

where max $SameSubString_j(con_1, con_2)$ means that the jth longest common substring of the two elements: con_1 and con_2. Finding the longest common substring of these elements and remove it from the original string. Then continue to find the longest common substring from the rest string, until there is no longest common substring.

While calculating semantics similarity, we query the concept from HowNet [9], which has rich semantics information about concepts and inter-conceptual. Similarity between simple words is related to the calculation of the sememe similarity and concept similarity. We utilize the method in [10] to calculate the sememe similarity of words.

Definition 7 (*Similarity Calculation of Sememes*)

$$\mathrm{sim}(p_1, p_2) = \frac{comLevel}{height_{tree} + dis_{p1,p2}} \tag{3}$$

where the "*comLevel*" is the minimum common parent node level, the $height_{tree}$ is the depth of sememes-tree, $dis\_\{\{p_1, p_2\}\}$ is the path distance of the sememes. The "notional word" in HowNet described as follows:

$$\text{semantic item: } \left(\begin{array}{l} \text{The first basic semene Description} = \text{basic semene} \\ \text{The other basicsemene} = \{\text{basic semene}_\text{b}, \text{basic semene}_\text{c}, \ \ldots\} \\ \text{Relation semene description} = \left(\begin{array}{l} \text{Relation semene}_1 = \text{basic semene}_\text{x}|\text{word}_\text{x} \\ \text{Relation semene}_2 = \text{basic semene}_\text{y}|\text{word}_\text{y} \\ \ldots \end{array} \right) \\ \text{Relation symbol description} = \left(\begin{array}{l} \text{Relation symbol}_1 = \text{semene}_\text{u}|\text{word}_\text{u}, \text{semene}_\text{v}|\text{word}_\text{v}, \\ \text{Relation symbol}_2 = \text{semene}_\text{s}|\text{word}_\text{s}, \text{semene}_\text{t}|\text{word}_\text{t}, \\ \ldots \end{array} \right) \end{array} \right)$$

Each part of the description is a set of sememes. It is necessary to calculate the sets of sememes' similarity before calculating the similarity between two concepts. The similarity of sememes' similarity can be expressed as follows.

Definition 8 ***(Similarity Calculation of Sememe Sets)***

$$\mathrm{sim}(set_1, set_2) = \frac{|sem_{set_1 \leftrightarrow set_2}|}{|set_1| + |set_2|} \left(\frac{\sum_{i=1}^{|pair_{set_1 \leftrightarrow set_2}|} sim(p_{1i}, p_{2i})}{|pair_{set_1 \leftrightarrow set_2}|} \right) \tag{4}$$

where set_1 and set_2 denote the set of sememes, $|set_1|$ is the count of sememes in sets, $|sem_{set_1 \leftrightarrow set_2}|$ is the total count of sememes in two sets which have semantic relations, $|pair_{set_1 \leftrightarrow set_2}|$ is the count of pairs which have semantic relations in two sets. The semantic similarity between two concepts is composed of the four portions in notional word described above in HowNet. The similarity calculation is as follows.

Definition 9 (*Concept Similarity Calculation*)

$$\mathrm{sim}(con_1, con_2) = \sum_{i=1}^{4} \beta_i \prod_{j=1}^{i} sim_j(set_1, set_2) \tag{5}$$

where β_i is the degree of each part's influence in the notional word's concept, the values of the degree decrease gradually, and $\beta_1 + \beta_2 + \beta_3 + \beta_4 = 1$. We can get the empirical value of β_i: $\beta_1 = 0.5$, $\beta_2 = 0.2$, $\beta_3 = 0.17$, $\beta_4 = 0.13$.

There are several semantic descriptions for $SimpleWord_1$ and $SimpleWord_2$ in HowNet. If $SimpleWord_i = \{con_{i1}, con_{i2}, \ldots, con_{im}\}(i = 1, 2)$, we can get the words' similarity as follows:

$$sim(simpleWord_1, simpleWord_2) = \max_{i=1\ldots n, j=1..m} sim\left(con_{1i}, con_{2j}\right) \tag{6}$$

The result will be the maximum value of semantic concepts' similarity. Or a set of sequences, $sequence_i = \{simpleWord_{i1}, simpleWord_{i2}, \ldots, simpleWord_{im}\}$ $(i = 1, 2)$, then the formula of word sequences' similarity calculation as follows:

Definition 10 (*Word Sequence Similarity Calculation*)

$$sim(seq_1, seq_2) = \frac{|sem_{set_1 \leftrightarrow set_2}|}{|seq_1| + |seq_2|} \left(\frac{\sum_{i=1}^{|pair_{set_1 \leftrightarrow set_2}|} sim(simpleWord_{1i}, simpleWord_{2i})}{|pair_{set_1 \leftrightarrow set_2}|} \right) \tag{7}$$

where $|seq_1|$ is the count of simple words in set, $|sem_{seq_1 \leftrightarrow seq_2}|$ is the total count of words which have semantic relationships in set_1 and set_2. $|pair_{seq_1 \leftrightarrow seq_2}|$ is the pairs count of sets which has semantic relations in two sets. If there is only a simple word in both of the sequences set, it is equivalent to the formula (6).

Definition 11 (*Elements Similarity Calculation*)

$$\begin{aligned} sim(arg_1, arg_2) = {} & wgt_{\arg\_syn} {}^{*}\, sim_{syntax}(arg_1, arg_2) + wgt_{\arg\_sem} \\ & {}^{*}\, sim_{semantic}(arg_1, arg_2)\ (arg \in \{a, o, t, p, s\}) \end{aligned} \tag{8}$$

where $wgt_{\arg\_syn}$ and $wgt_{\arg\_sem}$ are weights of syntax similarity and semantic similarity, $wgt_{\arg\_syn} + wgt_{\arg\_sem} = 1$, we take sigmoid to calculate the values of $wgt_{\arg\_syn}$ and $wgt_{\arg\_sem}$. The calculation of event similarity could be obtained as follows:

$$sim(event_1, event_2) = \sum\nolimits_{i=1}^{5} w_{arg} {}^{*}\, sim(arg_1, arg_2)\ (arg \in \{a, o, t, p, s\}) \tag{9}$$

$w_a + w_o + w_t + w_p + w_s = 1$, the weight assignment is based on sigmoid function. In the formula above, each element is assigned a weight which means its importance in the event. $\sum\nolimits_{i=1}^{5} weight = 1, arg_{i(i=1,2,\ldots5)}$ means elements of an event.

4.2.2 Calculation of Event Class Structure Information Similarity

Event ontology is a network that composed of event classes and relations. The similarity of event classes structure information defined as $sim_S(ECS_1, ECS_2)$. ECS_1 denotes an event class structure with a set of semantic nodes, it taking EC_1 as the center and a set of neighbor nodes with a semantic radius *r* (each element in ECS_1 has a distance *p* with EC_1, and *p* <= *r*). The node in ECS_1 representation as a triple, ⟨*pre_eventClass, relation, eventClass*⟩, where *pre_eventClass* denotes its preceding node, *relation* means event relation between these two nodes, *eventClass* denotes event class in this node. ECS_2 has the same structure.

The algorithm of calculation for event class structure information similarity is given as below:

```
    path = 1; r = 5; ThresholdValue tv; sim(ECS1,ECS2) = 0; Node preA = EC1; preB = EC2;
    ECS1 = {EC1, neighbor node set}; ECS2 = {EC2, neighbor node set};
  while(path <= r){//5
    List nodesA = preA.directNeighborNodes; List nodesB = preB.directNeighborNodes;
    for(i = 0; I < nodesA.length; i++){//4
      Node A = nodesA[i];
      maxSimilarityValue = 0;
      for(j = 0; j < nodesB.length; j++){//3
        B = nodesB[j] ;
        if(sim(A.eventClass, B.eventClass) >= tv&&sim(A.eventClass, B.eventClass) >
  maxSimilarityValue){ //2
          similarity = sim(A.eventClass, B.eventClass)/path;
          if(A.relation == B.relation){//1
            similarity = similarity * (1 + ( path / r * 10));
          }//1
          maxSimilarityValue = sim(A.eventClass, B.eventClass);
        }//2
      }//3
      simecs(ECS1, ECS2) = Simecs(ECS1,ECS2) + similarity;
    }//4
    path = path + 1; preA = A; preB = B;
  }//5
```

In the algorithm, the directNeighborNodes means a function to obtain all neighbor nodes with path is 1. Eventually, the comprehensive semantic similarity formula is *max{sim(*ECS_1*,*ECS_2*), sim(*EC_1*,*EC_2*)}*, and the similarity between EC_1 and EC_2 can be obtained by using the formula (1).

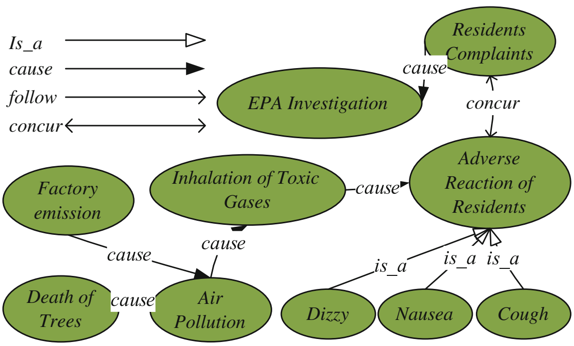

Fig. 2 Event ontology of air pollution caused by factory gas emissions

5 Experiment and Analysis

In this section, we present the process of the similarity calculation between two sample event ontology, and try to find semantics relation mapping between them.

Before the similarity calculation of event classes, by analyzing and event-oriented annotating more than 60 articles about air pollution and water pollution from internet, and under the instruction of environmental experts, we create two ontology models as shown in Figs. 2 and 3. The air pollution event ontology describes factory gas emission would result in air pollution; and air pollution would result in inhalation of toxic gas and death of trees; inhalation of toxic gas would cause health hazard and complaints from residents; health hazard includes adverse reaction of residents, such as dizzy, nausea and cough, and severely health injury, such as poisoning and death; complaints would result in investigation from environmental protect administration (EPA). The water pollution ontology describes a series of event classes caused chemical leakage of vehicle, as shown in Fig. 3.

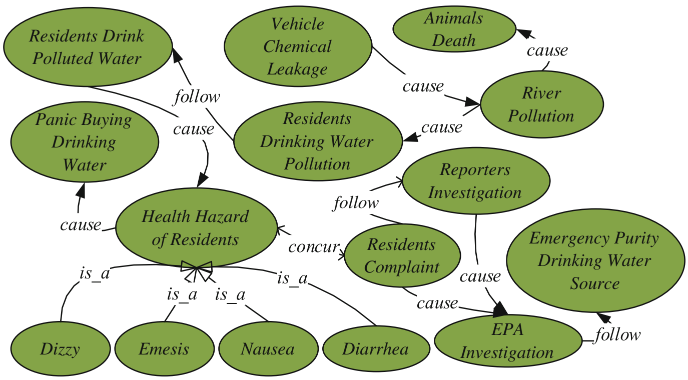

Fig. 3 Event ontology of water pollution caused by vehicle chemical leakage

5.1 Event Class Similarity and Event Class Structure Information Similarity

The events are from the news report on the internet, and the elements of event are annotated manually. Event ontology A represents "*air pollution incident caused by factory gas emissions*"; event ontology B represents "*water pollution incident caused by vehicle chemical leakage*", the number of events are listed in Table 1 as follows.

According to the calculation methods of the event class similarity, the results of similarity among event classes are shown in Table 2.

For the calculation of event class structure similarity, we need to get the semantic neighbor sets of each event class, calculating the semantic similarity between them by using the given formula given in Sect. 4.2.1. From the event ontology figures above, the semantic neighbor sets of each event class can be found out, such as "*air pollution*" semantic neighbor sets are {*factory emission, inhalation of toxic gases, death of trees*}. The similarity of structure information is calculated by using the algorithm given in Sect. 4.2.2 (Table 3).

When the results of two calculations are tabulated, choosing the largest value as the semantic similarity between event classes, then get the comprehensive semantic similarity calculation results as shown in Table 4.

Table 1 Events number of event ontology A and event ontology B

Name of event classes in event ontology A	Event num	Name of event classes in event ontology B	Event num
Factory emission EC_{A1}	20	Vehicle chemical leakage EC_{B1}	15
Air pollution EC_{A2}	20	River pollution EC_{B2}	20
Inhalation of toxic gases EC_{A3}	15	Residents drinking water pollution EC_{B3}	15
Death of trees EC_{A4}	15	Residents drink polluted water EC_{B4}	20
Adverse reaction of residents EC_{A5}	15	Animals death EC_{B5}	20
Residents' complaints EC_{A6}	20	Panic buying drinking water EC_{B6}	20
EPA investigation EC_{A7}	25	Health hazard of residents EC_{B7}	40
Dizzy EC_{A8}	10	Residents complaint EC_{B8}	20
Nausea EC_{A9}	10	Reporters investigation EC_{B9}	15
Cough EC_{A10}	10	EPA investigation EC_{B10}	25
		Emergency purity drinking water source EC_{B11}	20
		Dizzy EC_{B12}	10
		Emesis EC_{B13}	10
		Nausea EC_{B14}	10
		Diarrhea EC_{B15}	10

Table 2 Similarity results of event class

	EC_{A1}	EC_{A2}	EC_{A3}	EC_{A4}	EC_{A5}	EC_{A6}	EC_{A7}	EC_{A8}	EC_{A9}	EC_{A10}
EC_{B1}	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
EC_{B2}	0.000	0.342	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
EC_{B3}	0.000	0.101	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000
EC_{B4}	0.000	0.000	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001
EC_{B5}	0.000	0.000	0.000	0.303	0.000	0.000	0.000	0.000	0.000	0.000
EC_{B6}	0.000	0.000	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.001
EC_{B7}	0.000	0.000	0.001	0.000	0.734	0.001	0.000	0.001	0.001	0.001
EC_{B8}	0.000	0.001	0.001	0.000	0.001	0.802	0.000	0.001	0.001	0.001
EC_{B9}	0.001	0.000	0.000	0.000	0.000	0.001	0.341	0.000	0.000	0.000
EC_{B10}	0.001	0.002	0.000	0.000	0.000	0.001	0.872	0.000	0.000	0.000
EC_{B11}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EC_{B12}	0.000	0.000	0.001	0.000	0.201	0.001	0.000	0.803	0.324	0.121
EC_{B13}	0.000	0.000	0.001	0.000	0.114	0.001	0.000	0.213	0.847	0.092
EC_{B14}	0.000	0.000	0.001	0.000	0.201	0.001	0.000	0.191	0.207	0.108
EC_{B15}	0.000	0.000	0.001	0.000	0.215	0.001	0.000	0.102	0.133	0.103

Table 3 Distribution of event class structure similarity

	EC_{A1}	EC_{A2}	EC_{A3}	EC_{A4}	EC_{A5}	EC_{A6}	EC_{A7}	EC_{A8}	EC_{A9}	EC_{A10}
EC_{B1}	0.342	0.000	0.342	0.342	0.000	0.001	0.000	0.000	0.000	0.000
EC_{B2}	0.101	0.303	0.101	0.303	0.000	0.001	0.001	0.000	0.000	0.000
EC_{B3}	0.342	0.001	0.342	0.342	0.001	0.001	0.000	0.001	0.001	0.001
EC_{B4}	0.101	0.001	0.734	0.101	0.001	0.734	0.001	0.734	0.734	0.734
EC_{B5}	0.342	0.000	0.342	0.342	0.000	0.001	0.000	0.000	0.000	0.000
EC_{B6}	0.000	0.001	0.734	0.000	0.001	0.734	0.000	0.734	0.734	0.734
EC_{B7}	0.001	0.001	0.215	0.001	0.803	0.847	0.802	0.215	0.215	0.215
EC_{B8}	0.002	0.001	0.734	0.002	0.001	0.734	0.001	0.734	0.734	0.734
EC_{B9}	0.002	0.002	0.002	0.002	0.802	0.872	0.802	0.001	0.001	0.001
EC_{B10}	0.001	0.001	0.001	0.001	0.802	0.001	0.802	0.001	0.001	0.001
EC_{B11}	0.002	0.000	0.002	0.001	0.001	0.872	0.001	0.000	0.000	0.000
EC_{B12}	0.000	0.001	0.734	0.000	0.001	0.734	0.001	0.734	0.734	0.734
EC_{B13}	0.000	0.001	0.734	0.000	0.001	0.734	0.001	0.734	0.734	0.734
EC_{B14}	0.000	0.001	0.734	0.000	0.001	0.734	0.001	0.734	0.734	0.734
EC_{B15}	0.000	0.001	0.734	0.000	0.001	0.734	0.001	0.734	0.734	0.734

Table 4 Comprehensive semantic similarity value

	EC_{A1}	EC_{A2}	EC_{A3}	EC_{A4}	EC_{A5}	EC_{A6}	EC_{A7}	EC_{A8}	EC_{A9}	EC_{A10}
EC_{B1}	0.342	0.000	0.342	0.342	0.000	0.001	0.001	0.000	0.000	0.000
EC_{B2}	0.101	0.342	0.101	0.303	0.000	0.001	0.001	0.000	0.000	0.000
EC_{B3}	0.342	0.101	0.342	0.342	0.001	0.001	0.001	0.001	0.001	0.001
EC_{B4}	0.101	0.001	0.734	0.101	0.001	0.734	0.001	0.734	0.734	0.734
EC_{B5}	0.342	0.000	0.342	0.342	0.000	0.001	0.000	0.000	0.000	0.000
EC_{B6}	0.000	0.001	0.734	0.000	0.001	0.734	0.000	0.734	0.734	0.734
EC_{B7}	0.001	0.001	0.215	0.001	0.803	0.847	0.802	0.215	0.215	0.215
EC_{B8}	0.002	0.001	0.734	0.002	0.001	0.802	0.001	0.734	0.734	0.734
EC_{B9}	0.002	0.002	0.002	0.002	0.802	0.872	0.802	0.001	0.001	0.001
EC_{B10}	0.001	0.001	0.001	0.001	0.802	0.001	0.872	0.001	0.001	0.001
EC_{B11}	0.002	0.000	0.002	0.001	0.001	0.872	0.001	0.000	0.000	0.000
EC_{B12}	0.000	0.001	0.734	0.000	0.201	0.734	0.001	0.803	0.734	0.734
EC_{B13}	0.000	0.001	0.734	0.000	0.114	0.734	0.001	0.734	0.734	0.734
EC_{B14}	0.000	0.001	0.734	0.000	0.201	0.734	0.001	0.734	0.734	0.734
EC_{B15}	0.000	0.001	0.734	0.000	0.215	0.734	0.001	0.734	0.734	0.734

6 Conclusion

In this paper, we defined the concept of event ontology mapping, and proposed a comprehensive semantic similarity calculation model based on the event classes and event class structure information to accomplish the mapping between event ontologies. The experimental results show that the proposed calculation model can be used to find semantic mapping between event classes from different ontologies effectively. Because of the complexity of event ontology, there are still some problems need to be solved in the future. Firstly, the limitation of vocabulary coverage in HowNet affected the precision of semantic similarity calculation. Secondly, the semantic neighbors of event classes are not always be selected accurately.

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