Extracting Temporal Event Relations Based on Event Networks

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Abstract. Temporal event relations specify how different events expressed within the context of a textual passage relate to each other in terms of time sequence. There have already been impactful work in the area of temporal event relation extraction; however, they are mostly supervised methods that rely on sentence-level textual, syntactic and grammatical structure patterns to identify temporal relations. In this paper, we present an *unsupervised* method that operates at the document level. More specifically, we benefit from existing Open IE systems to generate a set of triple relations that are then used to build an event network. The event network is bootstrapped by labeling the temporal disposition of events that are directly linked to each other. We then systematically traverse the event network to identify the temporal relations between indirectly connected events. We perform experiments based on the widely adopted TempEval-3 corpus and compare our work with several strong baselines. We show that our unsupervised method is able to show better performance in terms of precision and f-measure over it supervised counterparts.

1 Introduction

The extraction of temporal relationships between events that have been mentioned in a textual passage is an important task in information extraction as it enables tasks such as building event timelines and arranging plots of events. Temporal information about events can assist in understanding the evolution of news stories or the development of a narrative. There have already been many application areas such as question answering [2, 5], document summarization [5, 16] and textual entailment [12, 13] that benefit from temporal event relationships.

Several approaches to temporal relation classification use machine-learning-based classifiers [6, 7, 9, 10] that are trained based on a predefined, finite and fixed schema of relation types. The common strategy of these techniques is to generate linguistic features based on syntactic, dependency, or shallow semantic structures of the text. Based on these features, supervised learning methods are used to identify pairs of events that are related to each other, and classify them based on pre-defined relation types. However, the state-of-the-art approaches [7, 10] suffer from two key drawbacks. First, they are focused on a limited subset of features, which might not, in many cases, be present in every sentence or be sparsely available. Second, training on linguistic structures such as the output of syntactic and dependency parsers does not necessarily

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identify all possible types of event relations when they are presented in different sentences or different documents. For instance, consider the three sentences shown Fig. 1. In this figure, the events in both $<e_2 - e_3>$, $<e_5 - e_8>$ are related to each other by the "BEFORE" temporal relation type. Here, while e_2 and e_3 are presented in the same sentence, events e_5 and e_8 are in different sentences. As such, sentences that rely on features based on grammatical parsers can fail to identify correct relation types.

1. "... the President Bush has *approved*$_{e2}$ *duty-free treatment*$_{e3}$ for imports... "
2. "Timex had *requested*$_{e5}$ duty-free treatment... "
3. " the Philippines and Thailand would be the main *beneficiaries*$_{e8}$ of the president's *action*$_{e9}$..."

Fig. 1. Samples of direct relation events $<e_2 - e_3>$, $<e_8 - e_9>$ and indirect relation events $<e_5 - e_3>$, $<e_3 - e_9>$ in textual document.

In this paper, our objective is to address these two challenges by adopting an Open Information Extraction (Open IE) strategy [4, 8, 14, 15], which is able to extract relations and their arguments without the need to restrict the search to predefined relation types or grammatical structures. We propose a method to extract temporal event relations by using an Open IE graph-based event network, which is built based on the patterns identified and extracted by Open IE systems. Particularly, we consider and incorporate all identified Open IE patterns that consist of at least one event instance in the event network, which is then systematically traversed for identifying temporal relations. As an example in Fig. 1, both $<e_2 - e_3>$ and $<e_5 - e_3>$ relations can be extracted from two Open IE patterns, namely ("President Bush", "has approved", "duty-free treatment for imports") and ("Timex", "had requested", "duty-free treatment"), respectively. Based on the constructed event network, we employ a shortest path strategy to determine the event flow between two events.

2 The Proposed Approach

An Open IE system extracts triples in the form of (arg1, rel, arg2) representing basic propositions or assertions from text. In this context, propositions are defined as coherent and non-over-specified pieces of information. In this study, we exploit Open IE to build an event network in order to extract temporal event relations. We consider extracting temporal event relations based on both events that are directly related to each other and those that can be indirectly linked to each other through links in the network. To this end, we propose an algorithm to detect event flows in the network that will be used to identify temporal event relations. An overview of our proposed approach is illustrated in Fig. 2.

2.1 Graph-Based Event Network

Our proposed graph-based event network is built directly from triples generated by Open IE systems. Two events that are present in the same extracted pattern are considered as two event nodes in the event network that are directly connected to each other with an edge. The collection of all the extracted Open IE triple patterns are used to complete the event network. Moreover, we use reference mapping to expand all possible event relations of the event network. Reference mapping is based on the context similarity of terms in the triple patterns.

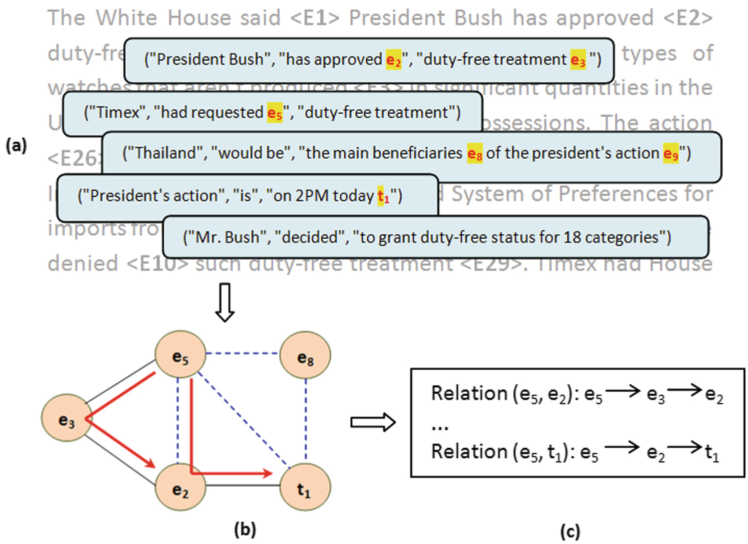

Fig. 2. An overview of the proposed approach with (a) Open IE extraction, (b) event network construction, and (c) event flow extraction.

2.2 Temporal Relation Identification

According to the TempEval-3 task description [10–12], two pairs of temporal events can be related to each other through one of four groups, namely Timex-Timex, Event-DCT, Event-Timex and Event-Event where DCT denotes *Document Creation Time* and Timex denotes *Temporal Expressions*. In this study, we present an algorithm to extract both direct and indirect temporal event relations in the event network based on event flow. Let us denote an event network as a graph $G(V, E)$ where each vertex denotes an event and each edge denotes a relation. Based on the event network, the objective is to determine the existence and type of temporal relation between two event nodes such as $\{X, Y\}$ expressed as $R\{X, Y\}$. Figure 3 presents the pseudo-code for our proposed algorithm for identifying temporal relations. The algorithm first proceeds to detect types of event relations. In case of a direct relation between two events, the *sieve* [17] implementation of the rules introduced in [3] are applied to identify relation types, and the corresponding edge in the network will be updated. In case of an indirect relation between two events, the relation will be determined based on its event flow. First, the algorithm will determine the shortest path between the two events resembling the potentially most likely temporal order of how events played out in reality.

Algorithm 1: Identifying temporal relations

```
Input:   Graph G = (V, E)
         Pair of events {X, Y}
Output:  Type of relation R(X, Y)
if Direct(X, Y) ∈ G then
    R(X, Y) ← Rules(E{X, Y}, G)
    Update(G)
else if Indirect(X, Y) ∈ G then
        R(X, Y) ← Time{X,Y}⊕Tense{X,Y}
        Update(G)
    if R(X, Y)=NULL then
            Event-flow{X,Y} ← Shortest-path({X, Y}, G))
            Rules(Event-flow{X,Y}, G)
            R(X, Y) ←Infer(Event-flow{X,Y})
            Update(G)
    end if
return R(X, Y)
```

Fig. 3. Algorithm for identifying temporal relations.

Once the shortest path between events is determined, it is possible to reason over the set of temporal relations observed on the shortest path to make a determination about the type of temporal relation between the two source and target events. Temporal relations of indirect relations are inferred through transitivity of temporal relations [1] on direct relations as shown in Fig. 4. For instance, consider events e_1 and e_4 in Fig. 4a, in this example, direct relations between events e_1 and e_2 as well as e_2 and e_4 have already been identified based on *sieve* and labeled as such. Now, given the shortest path between e_1 and e_4 passes through e_2, it is possible to infer that given e_1 happened before e_2 and e_2 was before e_4 that e_1 also happened before e_4.

3 Experimentation

3.1 Experimental Results

For benchmarking our approach, we conducted experiments on TempEval-3 on Task C [7, 10, 12]. The available dataset consists of news documents separated into testing and training sets. The testing set consists of 20 documents and the training set consists of 183 documents. We built the event network based on the generated Open IE triples extracted by the LS3RyIE system [15]. Note that, reference mapping was also applied to enhance node matching in the event network. We calculated the context from the

Open IE patterns using cosine similarity then merged those nodes with a score ≥ 0.5. As a result of this process, 968 and 2,537 triples were generated by the Open IE system that were then used to build the event network for the testing and training sets, respectively. Based on the TempEval-3 task, we evaluate the approach on four categories, namely Event-Event (E-E), Event-Timex (E-T), Event-DCT (E-D), and Timex-Timex (T-T). It should be noted that unlike the state of the art baselines that are supervised temporal relation extraction methods, our work is completely unsupervised and as such we do not require separate training and testing datasets. For this reason, we report the performance of our work on the data available in both sets.

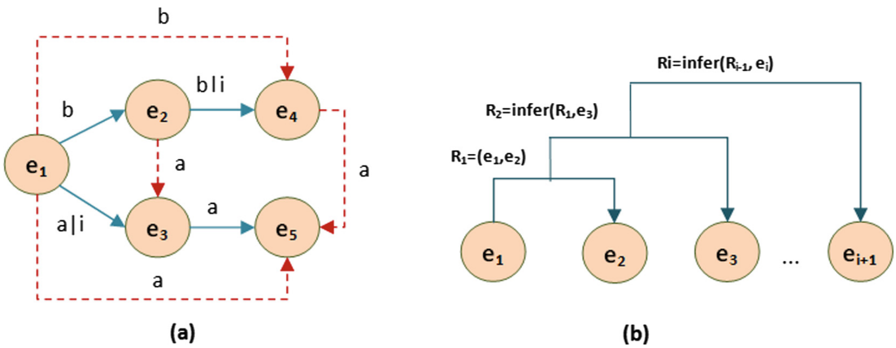

Fig. 4. Inferred relations; (a) Inferred sample relations in three nodes path ($e_1 - e_4$, $e_2 - e_3$, $e_1 - e_5$, $e_4 - e_5$) with b: before; i: includes; a: after; (b) Recursively inferred relations.

Table 1. Experimental results on four categories.

Categories	Testing set			Training set		
	Precision	Recall	F-measure	Precision	Recall	F-measure
E-E	60.63	41.81	49.49	60.51	47.21	53.04
E-T	84.82	73.21	78.58	82.37	60.06	69.47
E-D	88.24	87.50	87.86	70.63	68.75	69.68
T-T	62.50	62.50	62.50	77.77	68.62	72.91
Overall	72.92	57.54	64.32	69.58	57.18	62.77

The performance results obtained using our proposed approach on the testing and training sets are shown in Table 1. In the testing set, the system achieved F-measures of 49.49%, 78.58%, 87.86%, and 62.50% for Event-Event, Event-Time, E-DCT, and Time-Time, respectively. Regarding training set, the system obtained F-measures of 53.04%, 69.47%, 69.68% and 72.91% for Time-Time, Event-DCT, Event-Time and Event-Event, respectively. Overall, the system yielded F-measures of 64.32% and 62.77% on testing and training sets.

In Table 2, we compare our method with several strong baseline approaches designed for Task C of TempEval-3. UTTime [6] employs features based on syntactic parsing including phrase structures while Laokulrat et al. [7] extract event relations using time graphs and stacked learning. TRelPro [9] and CATENA [10] employ an SVM classifier based on event linguistic features such as POS tags, chunking, dependency paths, and others. The numbers reported in Table 2 are the results of 5-fold cross-validation evaluation strategy. The evaluation shows that our proposed method is the best performing system against the state-of-the-art baselines. It should be pointed out that our approach obtained improved performance over these baselines even though it is fully unsupervised while the baselines operate under a supervised context.

Table 2. Performance comparison.

	Precision	Recall	F-measure
UTTime [6]	55.60	57.40	56.50
TRelPro [9]	58.48	58.80	58.17
Laokulrat et al. [7]	57.60	57.90	57.80
CATENA [10]	62.60	61.30	61.90
Proposed method	70.82	57.31	63.35

3.2 Discussion

Our approach benefits from the relation patterns extracted by Open IE systems to build the initial event network and bootstraps the temporal event extraction process by determining the type of temporal relation between two directly linked events. The advantages of our proposed work are two folds: (1) it is completely unsupervised and hence does not require any hand-annotated samples by inferring indirect temporal relation types between events by systematically traversing the event network, and (2) it works at the document level and not sentence level and hence can identify temporal relations between events that have not been expressed in the same sentence. This is made possible due to the linking of different events in the network whose linking transcends individual sentences and forms a representation of events in the document.

However, our method also faces some limitations: (*i*) our proposed approach is dependent on the performance of the underlying Open IE system and hence in cases when the Open IE system cannot extract event mentions, the corresponding event nodes will not be created in the event network and hence temporal relations will be missed. The lower recall of our method, noted in Table 2, can be explained as such. (*ii*) Our method is dependent on reference mapping to identify similar event nodes in the event graph, which is currently performed through cosine similarity. However, more complex co-reference resolution methods and semantic matching of event types can improve the reference mapping process and lead to better overall performance.

4 Concluding Remarks

In this paper, we have presented an unsupervised method for extracting temporal relations between events by building an event network structure primarily based on information from Open IE systems. The event network is the basis for systematically exploring the possible temporal relations between events by considering how events can be reached from one another. We performed comparative benchmarking of our proposed method using the TempEval-3 dataset and compared our work against several strong baselines. Our experiments show that while our approach is unsupervised, it is able to outperform supervised baselines in terms of precision and f-measure. Our future work will consist of addressing the two limitations of our work, namely quantifying the impact of the performance of the Open IE systems on our work and also exploring more systematic ways for performing reference mapping.

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