Global Inference to Chinese Temporal Relation Extraction

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Abstract

Previous studies on temporal relation extraction focus on mining sentence-level information or enforcing coherence on different temporal relation types among various event mentions in the same sentence or neighboring sentences, largely ignoring those discourse-level temporal relations in nonadjacent sentences. In this paper, we propose a discourse-level global inference model to mine those temporal relations between event mentions in document-level, especially in nonadjacent sentences. Moreover, we provide various kinds of discourse-level constraints, which derived from event semantics, to further improve our global inference model. Evaluation on a Chinese corpus justifies the effectiveness of our discourse-level global inference model over two strong baselines.

1 Introduction

Temporal relation extraction is to determine the temporal relationship (e.g., Before and After) holding among events. It has been drawing more and more attention due to the crucial importance of temporal information to various natural language processing (NLP) applications, such as language generation, information extraction, summarization, and question answering. The difficulty with this task is that temporal information about event mentions is sometimes not stated explicitly and one can only infer from their context. Currently, temporal relation extraction still remains a challenge in corpus construction and inference mechanism.

On one hand, although the TimeBank corpus (Pustejovsky et al., 2003), the commonly used corpus in previous studies, has largely promoted the development of temporal relation extraction, it only annotates a small subset of easily-identified event mention pairs. Moreover, it largely ignores almost all temporal relations between event mentions in nonadjacent sentences. These lead to fragmented relations and limit its applications to other NLP tasks, such as information extraction, and summarization. Finally, while constructing a fully-annotated corpus is expensive and time-consuming, many NLP tasks are normally interested in specific types of events. For example, a summarization or information extraction system on terrorism attacks may only concern with a few event types (e.g., Attack, Die, and Injure). Therefore, annotating an event-driven fully-annotated temporal relation corpus becomes a crucial issue to the success of real-life applications.

On the other hand, previous studies on temporal relation extraction focus on mining sentence-level information or enforcing coherence on different temporal relation types among various mentions in the same sentence or neighboring sentences, largely ignoring those discourse-level temporal relations in nonadjacent sentences. Specifically, only a few studies apply global inference models to exploit temporal relations in discourse level. Therefore, how to acquire discourse-level temporal information from those long-distance event mention pairs in nonadjacent sentences becomes another crucial issue to temporal relation extraction, especially for Chinese, as a discourse-driven language with a broad range of ellipsis and flexible sentence structures.

In this paper, we first annotate an event-driven fully-annotated Chinese temporal relation corpus, on the top of the ACE (Automatic Content Extraction) 2005 Chinese corpus. Then, we propose a discourse-
level global inference model to mine those temporal relations between event mentions in document-
level (especially in nonadjacent sentences) with various kinds of discourse-level constraints, which de-
ferred from event semantics, to further improve the global inference model. Evaluation indicates the
appropriateness of our event-driven fully-annotated Chinese corpus and justifies the effectiveness of our
discourse-level global inference model over two strong baselines.

2 Related Work

In this section, we give a brief overview of temporal relation extraction from two aspects: corpus con-
struction and inference mechanism.

2.1 Corpus Construction

Most of existing corpora for temporal relation extraction focus on English. As the commonly used cor-
pus in temporal relation extraction, the TimeBank corpus (Pustejovsky et al., 2003) has been adopted in
a series of TempEval competitions (Verhagen et al., 2007; Verhagen et al., 2010; Uz-Zaman et al., 2013),
facilitating the development and evaluation of temporal relation extraction systems. The problems with
the TimeBank corpus are that it only annotates a small subset of easily-identified event mention pairs
and that it largely ignores those temporal relations between event mentions in nonadjacent sentences.
These lead to fragmented relations and much limit its applications.

To overcome above problems, Do et al. (2012) produced an event-driven corpus on the ACE 2005
English corpus. However, “the annotator was not required to annotate all pairs of event mentions, but
as many as possible”, as stated in their paper. This makes the annotation inconsistent and difficult to
follow. Recently, Cassidy et al. (2014) enriched the TimeBank-Dense corpus, on the top of TimeBank.
Specifically, they approximated the completeness by labeling locally complete graphs over neighboring
sentences.

In comparison, there are few corpora for Chinese temporal relation extraction. Li et al. (2004) anno-
tated a Chinese corpus including 700 sentences. The TempEval-2 competition (Verhagen et al., 2010)
provided 780 instances of Chinese temporal event relations. Obviously, both corpora are rather small
and largely impede the research in Chinese temporal relation extraction. For example, no team partici-
pated in the TempEval-2 competition on Chinese temporal relation extraction.

2.2 Inference Mechanism

Due to the corpus limitation, previous studies on temporal relation extraction focus on inferring temporal
relations between event mentions in the same sentence or neighboring sentences from English text, 
dominated by feature-based approaches. Mani et al. (2006) applied the temporal transitivity rule to
greatly expand the corpus. Lapata and Lascarides (2006) introduced various kinds of syntactic and
clause-ordering features to classify the temporal relationship. Chambers et al. (2007) used previously
learned event attributes to classify the temporal relationship. Laokulrat et al. (2013), the best performing
one in the TempEval-3 competition, applied various predicate-argument structure features from a deep
syntactic parser to enhance their classifier. Mirza and Tonelli (2014) illustrated that simple features
resulted in a better performance than sophisticated features. Chambers et al. (2014) proposed a sieve-
based architecture to joint those different tasks of temporal relation extraction.

In comparison, few studies concern temporal relation extraction from Chinese text. Chen et al. (2008)
used verbal attributes to identify temporal relations of verbs. Li et al. (2004) presented a classifier-based
collaborative bootstrapping approach to analyze temporal relations in a small Chinese corpus.

While above studies focus on local information, a few studies sort to global inference, with focus on
exploiting global information via various kinds of temporal logic reflexivity and transitivity constraints,
using frameworks like Integer Linear Programming and Markov Logic Networks (Bramsen et al., 2006;
Chambers and Jurafsky, 2008; Yoshikawa et al., 2009). However, their gains are rather small, largely
due to the common disconnectedness in the sparsely annotated corpora (Chambers et al., 2014). To
overcome this problem, Denis and Muller (2011) decomposed temporal entities into sub-graphs and
enforced the coherence only within these substructures, while Do et al. (2012) proposed a joint event-
event and event-time classification model to enforce various coreference constraints.

Different from previous studies, we build an event-driven fully-annotated Chinese corpus and propose
a discourse-level global inference model to extract temporal relations between event mentions in document level, especially in nonadjacent sentences. To our knowledge, this is the first attempt in discourse-level global inference for temporal relation extraction from an event-driven fully-annotated corpus.

3 Data Construction and Baseline

In this section, we present the construction of our Chinese temporal relation corpus and the learning-based baseline.

3.1 Data Construction

To address various problems in existing corpora, as described above, we build an event-driven fully-annotated Chinese temporal relation corpus, on the top of the ACE 2005 Chinese corpus with 8 predefined event types and 33 predefined event subtypes (e.g., Die, Attack, and Transport). That is, all other event mentions of non-predefined event types are ignored in our corpus.

Different from previous corpora, each document in our corpus is annotated with the temporal relations between the mentions of all the events relevant to concerned events in the document, with the constraint of event-relevant completeness. Besides, we focus on four temporal relations, i.e., Before, After, Overlap and Unknown (without relationship or with vague relationship). This is a simplification of the TimeBank corpus, which defines 14 temporal relations. Since differentiating 14 temporal relation types is too hard, even for a well-educated person, much work has been done to simplify the temporal relation types, e.g., 6 types (Mani et al., 2006; Chambers et al., 2007; Cassidy et al., 2014) and 4 types (Do et al., 2012; UzZaman et al., 2013 (Chinese subtask)). Our work is a typical practice of such tendency.

Specifically, 163 documents from the ACE 2005 Chinese corpus are selected as our experimental data, which contains 1166 event mentions. These documents are from three different data sources (i.e., Broadcast News, Newswire and WebLog), very different in various aspects, such as quality, length and style. Two postgraduates in computer science are involved in corpus annotation and the Kappa value between the two annotators is 0.70, similar to TimeBank’s 0.71.

Table 1 shows 4 temporal relations and their occurrence frequencies in our event-driven fully-annotated corpus. The total number of event pairs in our corpus is three times larger than that of TimeBank. Since the ACE 2005 corpus is licensed, we cannot upload our annotated data. If anyone obtain the license of the ACE 2005 corpus, our corpus is free available for research purpose on request.

| Type       | Before | After | Overlap | Unknown | Total |
|------------|--------|-------|---------|---------|-------|
| #Number    | 7402   | 7402  | 4834    | 1494    | 21132 |

Table 1. The 4 temporal relations and their occurrence frequencies

We have implemented a tool to help the annotators to tag event relations easily and enforce the coherence in document level. Due to the reflexive property of event-event relationship, the annotators only need annotate half of the relations shown in Table 1. Besides, 7.1% of annotated event relations are Unknown, and this figure is much lower than that in TimeBank. The reason is that the relations between two ACE events of the predefined event types are relatively easy to be identified and this also verifies the relatively high Kappa value between the two annotators. In our corpus, the maximal size of the relations in a document is 625 (25 event mentions), while the minimal size is 2 (only 2 event mentions). If we ignore those Unknown relations, 32% of documents are not graph, but forest.

3.2 Baseline

Similar to the state-of-the-art system in temporal relation extraction, we employ a learning-based system as one of our baselines. As an event-event (E-E) classifier, this baseline predicts one of the four temporal relations, i.e. Before(B), After(A), Overlap(O), and Unknown(U), between two event mentions $e_i$ and $e_j$ as follows:

$$C_{E-E}(e_i, e_j) \rightarrow \{B, A, O, U\}$$

(1)

Besides those features adopted in English temporal relation extraction (e.g., D’Souza and Ng, 2014; Mirza and Tonelli, 2014), we also apply various kinds of Chinese-specific features to further boost the
performance of this baseline. Specifically, for each event mention pair \(<e_1, e_2>\) in a document, with
trigger mentions \(t_1\) and \(t_2\) respectively, its feature set can be divided into 5 categories:
1) **Lexical features** (14): the tokens of \(t_1\) and \(t_2\) (2); their POS tags (2); their preceding and
succeeding words (4); the POS tags of their preceding and succeeding words (4); the hedge or negative word
before \(t_1\) or \(t_2\) (2);
2) **Syntactic features** (4): the dependency path between \(t_1\) and \(t_2\) (1); the governors of \(t_1\) and \(t_2\) (2); the
constituent path between \(t_1\) and \(t_2\) (1);
3) **Event features** (18): the tense, polarity, genericity, modality and event type of \(e_1\) and \(e_2\) (10); the
agents (2), the patients (2), the times (2), and the places of \(e_1\) and \(e_2\) (2);
4) **Pairwise features** (9): the conjunction between \(e_1\) and \(e_2\) (1); whether \(e_1\) and \(e_2\) are in the same
sentence (1); whether \(e_1\) and \(e_2\) have the same tense (1), the same polarity (1), the same genericity
(1), the same modality (1), the same event type (1), and the same Time argument (1); whether \(e_1\) is
before \(e_2\) in the document (1);
5) **Semantic features** (7): whether \(t_1\) and \(t_2\) are synonym (1); whether the agent of \(e_1\) is the patient of \(e_2\)
(1); whether the agent of \(e_2\) is the patient of \(e_1\) (1); whether \(e_1\) and \(e_2\) have the same time (1), place
(1), agent (1) or patient (1).

All the sentences in the corpus are divided into words using the word segmentation tool ICTCLAS.
Besides, we use Berkley Parser and Stanford Parser to create the constituent and dependency parse
trees respectively. The event features (e.g., trigger, event tense, event type, event arguments) are derived
from the annotated data in the ACE 2005 Chinese corpus. After creating the training instances, we train
four one-vs-rest classifiers using the Maximum Entropy tool MaxEnt.

### 4 Global Inference on Event Semantics

While existing approaches, as the baseline described above, focus on limited event mention pairs in the
same sentence or neighboring sentences, our global inference model attempts to address those in non-
adjacent sentences. In this section, we first present the discourse-level global inference model to tem-
poral relation extraction and then introduce various kinds of discourse-level constraints to achieve global
optimization on the temporal relations of event mention pairs in both nonadjacent and adjacent sentences.

#### 4.1 Global Inference Model

To mine the interaction among events in a document, we optimize the predicted temporal graph, formed
by prediction from \(C_E\), with various kinds of discourse-level constraints derived from event semantics.

Let \(E=\{e_1, e_2, ..., e_n\}\) denote the set of event mentions in a document, \(e=\{(e_i, e_j) \in E \times E | [e_i, e_j] \in E, \neq \}\) the
set of event mention pairs, and \(R=\{B, A, O, U\}\) the set of temporal relations. Besides, let \(P_{<i,j,r>}\) denote
the prediction probability of \((e_i, e_j)\) with relation \(r (r \in R)\), given by the event-event classifier \(C_E\), and
\(x_{<i,j,r>}\) the binary indicator on the existence of relation \(r\) for \((e_i, e_j)\). Following Roth and Yih (2004) and
Li et al. (2013) in information extraction, we define the following log costs:

\[
c_{<i,j,r>} = -\log(P_{<i,j,r>})
\]

\[
\tilde{c}_{<i,j,r>} = -\log(1 - P_{<i,j,r>})
\]

Specifically, ILP (Integer Logical Programming), a global inference is employed to achieve global
optimization with the following objective function to maximize over a document as follows:

\[
\arg \min_x \sum_{(e_i, e_j) \in E} \sum_{r \in R} (c_{<i,j,r>} \times x_{<i,j,r>} + (1 - x_{<i,j,r>}) \times \tilde{c}_{<i,j,r>})
\]

s.t.

\[
x_{<i,j,r>} \in \{0,1\}
\]

\[
\sum_{r \in R} x_{<i,j,r>} = 1
\]

while binary constraint (5) ensures that \(x_{<i,j,r>}\) is binary value and equality constraint (6) ensures that
exactly only one temporal relation can be assigned to each event mention pair.

In addition, the reflexivity and transitivity constraints, as deployed in previous inference models

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(Bramsen et al., 2006; Chambers and Jurafsky, 2008; Do et al., 2012), are also applied to our model as follows:
\[
x_{i,j,r} - x_{j,i,r} = 0 \quad \forall r, \bar{r} \in R
\]
\[
x_{i,j,r} + x_{j,k,r} - x_{i,j,k,r} \leq 1 \quad \forall r \in \{B,A,O\}
\]

Here, reflexivity constraint (7) enforces the reflexive property of the event-event relationship, where relation \( \bar{r} \) denotes inverse relation \( r \) with possible \((r, \bar{r})\) pairs \{(A,B), (B,A), (U,U)\}, and transitivity constraint (8) states that if both event mention pairs \((e_i,e_j)\) and \((e_j,e_k)\) have the same temporal relation \( r \), temporal relation \( r \) must hold between \( e_i \) and \( e_k \), with event mention \( e_j \) as a bridge to link \( e_i \) and \( e_k \).

### 4.2 Discourse-level Constraints

Different from the TimeBank corpus which only annotates the temporal relations in the same sentence or neighboring sentences, our corpus is event-driven fully-annotated. That is, besides the temporal relations in the same sentence or neighboring sentences, our corpus also contains those in nonadjacent sentences, which occupy 56.3%. This poses the great necessity to address those temporal relations in non-adjacent sentences. Besides, although all the event types in the ACE corpus have a Time role, the statistics on our corpus shows that only 35.9% of event mentions have explicit Time arguments. This poses the great challenge to address those temporal relations in nonadjacent sentences due to the frequent lack of explicit Time arguments.

Motivated by the intuition that the intrinsic semantics of event mentions is helpful to reveal their temporal relations due to the semantic nature in the event definition, we propose various kinds of discourse-level constraints on time arguments, event relevance, event tense, discourse connective, and coreference to mine the temporal relations in both nonadjacent and adjacent sentences.

**Argument Time constraint**

Generally, an event can be expressed as “5W1H” (Who, What, Whom, Where, When and How). When, one of “5W”, indicates the time an event happens. Naturally, this argument is the solid evidence to identify the temporal relation between two event mentions. For example, if the Time argument of one event mention \( e_1 \) is “今日” (today) and that of the other mention \( e_2 \) is “昨日” (yesterday), it is obvious that the relation between \( e_1 \) and \( e_2 \) is After.

For time arguments, we can obviously have the following constraint, stating that if Time argument \( at_i \) of event mention \( e_i \) is before Time argument \( at_j \) of event mention \( e_j \), the temporal relation between \( e_i \) and \( e_j \) is \( B \), and if \( at_i \) is equal to \( at_j \), or they have overlap part, the temporal relation between \( e_i \) and \( e_j \) is \( Q \).
\[
x_{i,j,r} = 1 \quad \forall r \in \{B,Q\} \land r = \text{rel}(at_i,at_j)
\]

where function \( \text{rel}(at_i,at_j) \) returns one of the four temporal relations between \( at_i \) and \( at_j \). Due to the reflexivity constraint, it is unnecessary to enforce the constraint on after relation.

Since the ACE corpus uses Timex2 to annotate all temporal expressions, the Time arguments need to be normalized. In this study, we first divide all time tags into two categories: time point and time duration. Then, we implement a simple rule-based tool based on the DCT (Document Create Time) to normalize all time points as “year:month:day: hour:minute” and all time durations as (begintime, endtime) where begintime and endtime are normalized as the style of time point. As a result, 92.7% of Time arguments are normalized correctly.

**Event relevance constraint**

In a discourse, most of event mentions are normally structured around a specific topic, which acts as a bone to link all the relevant event mentions together into a narration, via various kinds of event relations. Those semantics-based event relations, i.e. event relevance, are thus helpful to infer the temporal relations among event mentions. For example, if there is a causal relation between an Attack and a Die event mention, it is obvious to infer they have the Before temporal relation. That is, a Die event is always the result of an Attack event.

Specifically, we learn event relevance from the training set by counting the occurrence frequency \( f_{<i,j,r>} \) for each event type pair \((evt_i, evt_j)\) (e.g., (Attack, Die)) with relation \( r \) in the training set. To eliminate
the accidental factor in statistics, we modify the occurrence frequency of an event type pair to 0 when it only appears once in the training set.

Accordingly, we have the following constraint on event relevance, stating that if an event type pair \((\text{evt}_i, \text{evt}_j)\) only has one occurrence frequency \(f_{\text{ci},j,r}>0\), the temporal relations of all event mention pairs in the test set with event type pairs \((\text{evt}_i, \text{evt}_j)\), are assigned with the temporal relation \(r\) according to constraint (10), and that if an event type pair \((\text{evt}_i, \text{evt}_j)\) has two or three occurrence frequencies (i.e., larger than 0), the relations of all event mention pairs with event type pair \((\text{evt}_i, \text{evt}_j)\), are enforced according to constraint (11).

\[
x_{\text{ci},j,r} = 1 \quad \forall f_{\text{ci},j,r} > 0 \land \sum_{r \in \text{SR}_1} f_{\text{ci},j,r} = 0 \quad (10)
\]

\[
\sum_{r \in \text{SR}_2} x_{\text{ci},j,r} = 1 \quad \forall f_{\text{ci},j,r} > 0 \quad (11)
\]

where \(\text{SR}_1\) refers to the set of all the temporal relations except \(r\) and \(\text{SR}_2\) refers to the set of all temporal relations whose occurrence frequencies are larger than 0.

**Tense constraint**

Event tense is also a helpful evidence to infer temporal relations. In the ACE 2005 corpus, each event mention has an annotated tense attribute, whose values are Past(P), Present(R) and Future(F) and have been used in the baseline. For example, it is normal to infer the Before relation between two event mentions whose tense are Past and Future respectively. Accordingly, we can have the following constraint, stating that if the tense \(t_{e_i}\) of \(e_i\) is Past and that of \(e_j\) is Present or Future, the temporal relation of \((e_i, e_j)\) is \(\text{B}\); and that if \(t_e\) is Present and \(t_e\) is Future, the temporal relation of \((e_i, e_j)\) is \(F\).

\[
x_{\text{ci},j,B} = 1 \quad \forall t_{e_i} = P \land t_{e_j} \in \{R, F\} \lor t_{e_i} = R \land t_{e_j} = F \quad (12)
\]

**Connective constraint**

In a discourse, the connective between two adjacent sentences or clauses can largely reveal their discourse relations. For example, the connective “because” illustrates the Cause relation. Likewise, the connective between two adjacent event mentions also explicitly unveils their temporal relation. For example, if the preceding event mention is the cause of the succeeding event mention, their temporal relation is Before. Besides, we find out that some verbs which represent the meaning of causality can indicate the temporal relation of an event mention pair. Take the following sentence as an example:

**E1**: 这起炸弹攻击(EV1: Attack) 事件 造成了 2 个人死亡 (EV2: Die). (This bomb terror (EV1) caused two persons to death (EV2).) -From CBS20001120.1000.0823

In sentence E1, the verb 造成 (cause) indicates that the temporal relation between the event mentions EV1 and EV2 is Before. Hence, we enumerate a set of Chinese verbs (e.g., 导致, 造成, 引起) whose meaning are “cause” and add them into our connective set \(\text{CS}\). Besides, we find out that only causal and temporal connectives are helpful to infer temporal relations. Therefore, respective connectives are selected from Appendix B of the PDTB 2.0 annotation manual, which provides a list of classified explicit connectives. Finally, we divided all words in \(\text{CS}\) into two subsets \(\text{CS}_1\) and \(\text{CS}_2\), according to the statistics from the training set, where all words in \(\text{CS}_1\) indicate that the preceding event mention occurs earlier than the succeeding one and all words in \(\text{CS}_2\) indicate that the preceding event mention occurs later than the succeeding one.

Accordingly, we have the following constraint on discourse connective, stating that if there is a connective \(\text{con} (\text{con} \in \text{CS})\) between two adjacent event mentions \(e_i\) and \(e_j\) in the same sentence or neighboring sentences, the temporal relation between \(e_i\) and \(e_j\) depends on whether \(\text{con}\) belongs to \(\text{CS}_1\) or \(\text{CS}_2\) as follows.

\[
x_{\text{ci},j,B} = 1 \quad \forall \text{con} \in \text{CS}_1
\]

\[
x_{\text{ci},j,F} = 1 \quad \forall \text{con} \in \text{CS}_2
\]
Coreference constraint

An event may have more than one mention in a document and these mentions refer to the same event, called coreference events. Take the following two sentences as examples:

**E2:** 埃塞俄比亚与厄立特里亚 23日在这里举行谈判(EV3: Meet)。(The talk (EV3) between Ethiopia and Eritrea will be held on 23rd.)

**E3:** 这次谈判(EV4: Meet)的目的是... (The goal of this talk (EV4) is ...) -From XIN20001024.2000.0141

It is obvious that two coreference event mentions EV3 and EV4 must have the same occurrence time and their relation is Overlap. Following Do et al. (2012), we also apply this constraint to our model and enforce the following constraint on event coreference, stating that if mentions $e_i$ and $e_j$ are coreferential event mentions, their temporal relation is Overlap.

$$x_{i,j,D_{op}} = 1 \quad \forall cr(e_i, e_j) = \text{true}$$  \hspace{1cm} (14)

where function $cr()$ return true when $e_i$ and $e_j$ are coreferential. Besides, we use the tool described in Teng et. al. (2015) to construct those coreference event chains.

5 Experimentation

In this section, we first evaluate our model for Chinese temporal relation extraction and then report the experimental results on our event-driven fully-annotated Chinese temporal relation corpus.

5.1 Experimental Settings

All the experiments are done on the event-driven fully-annotated Chinese temporal relation corpus, annotated on the top of the ACE 2005 Chinese corpus, as described in Subsection 3.1. We conduct all evaluations with 5-fold cross-validation at document level and each fold contains about 4000 event mention pairs. Following previous studies on temporal relation extraction, we employ Accuracy as evaluation metric, which measures the percentage of correctly classified test instances. This metric is the same as micro F-score since each temporal relation of each event mention pair must belong to one of the four relations.

In this study, we use *lp_solve* as the ILP solver which implements the Branch-and-Bound algorithm. It takes less than 3 seconds on average to decode a document on a PC with 3.4Ghz Intel i7 CPU and 16GB memory.

5.2 Experimental Results

Performance comparison

To evaluate the performance of our discourse-level global inference model (DGIM), we compare it with two strong baselines. The first is a classifier-based system, mentioned in Subsection 3.2, originated from the top performing English systems (D’Souza and Ng, 2014; Mirza and Tonelli, 2014). The second (GIM) is a global inference model with the reflexivity and transitivity constraints following Bramsen et al. (2006), Chambers and Jurafsky (2007), and Do et al. (2012). It is worth to note that all annotated data in DGIM are also used in the first classifier-based system. Table 2 compares the performance of two baselines and our inference model DGIM.

| Model      | Accuracy (%) (Gold events) | Accuracy (%) (Auto events) |
|------------|----------------------------|----------------------------|
| Baseline 1 (CE-E) | 62.17                      | 36.21                      |
| Baseline 2 (GIM)   | 64.12                      | 37.85                      |
| DGIM      | 68.36                      | 40.92                      |

Table 2. Performance comparison of different models

Table 2 shows that when all event mentions are known, i.e. with gold event mentions, DGIM significantly outperform the two baselines by 6.19% and 4.71% in accuracy respectively. All improvements from two baselines to DGIM are statistically significant ($p<0.000001$, McNemar’s test, 2-tailed). Besides, GIM outperforms the classifier-based model by 2.05% in accuracy, indicating the limitation of
the conventional reflexivity and transitivity constraints in previous studies. In comparison, DGIM out-
performs GIM by 4.24% in accuracy, indicating the effectiveness of our various discourse-level global constraints.

Table 2 also shows the performance comparison consistency when all the event mentions are auto-
matically extracted, as described in (Li et al., 2013) with the F1-score of 68.2% and 53.7% in event trigger extraction and event argument extraction respectively.

**Contributions of discourse-level constraints**

Table 3 illustrates the contributions of different discourse-level constraints to our DGIM model with gold event mentions.

| System                          | Accuracy (%) |
|--------------------------------|--------------|
| Baseline 1                      | 62.17        |
| +Reflexivity (7)                | +0.29        |
| +Before/After Transitivity (8)  | +0.54        |
| +Argument Time (9)              | +2.23        |
| +Event relevance (10,11)        | +1.26        |
| +Tense (12)                    | +0.48        |
| +Connective (13)                | +0.74        |
| +Coreference (Learned) (14)     | +0.69        |
| +Coreference (Gold) (14)        | +0.86        |

Table 3. Contributions of different discourse-level constraints to temporal relation extraction

1) The conventional reflexivity and before/after transitivity constraints slightly improve the accuracy. This is not as effective as that on TimeBank, due to that those wrong probabilities produced by the event-event classifier will be incorrectly propagated to more temporal relations of event mention pairs since each document in our corpus is fully-annotated. Although the improvements of above two constraints are limited, they can interact with others to either improve the performance or reduce the time complexity. For example, the reflexivity constraint can simplify our discourse-level constraints, since if we have applied a constraint to an event pair, it is unnecessary to apply the opposite constraint to their inverses.

2) The argument Time constraint gains most with 2.23% in accuracy, while the tense constraint gains least among all constraints. Different from TimeBank, an event always has a Time role in the ACE 2005 corpus. If both event mentions have the Time arguments, we have a high confidence to determine their temporal relation. The error of the argument Time constraint mainly comes from those event mentions with a vague time (e.g., 最近 (recently), 日前 (a few days ago)).

3) Intuitively, tense can clearly identify the temporal relation of two event mentions if they have different tenses. However, our preliminary experiment shows that this constraint harms the accuracy if we apply it to the whole document. The reason is that the tenses annotated in the ACE 2005 corpus are relative ones based on the statement of a sentence itself. For example, although two Transport event mentions “他要来美国” (He will come to U.S.) and “他来到了美国” (He arrived U.S.) have the Future and Past tenses respectively, they are coreferential events with different statement times. In this study, we only enforce this constraint on the sentence level.

4) The event relevance constraint gains an improvement of 1.26% in accuracy. This verifies that relevant events always occur in a regular order. In our experiments, we extract total 65 event type pairs to construct this constraint. For example, an Arrest-Jail event often occurs after an Attack event. Although this constraint contributes third, this is far from our expectation. Our error analysis shows that this constraint introduces lots of wrong predictions due to the lack of deep semantics, which is worth exploring in our future work.

5) Although the improvement of the connective constraint is not significant enough with a gain of 0.74% in accuracy, it achieves a high precision in predicting almost all event mention pairs enforced by this constraint, through discourse connective like “因为” (because), “后” (after) and “造成” (cause).

6) The conference constraint gains an improvement of 0.69% and 0.86% in accuracy with automatically learned (with F1-score of 61.7% using the tool described in Teng et. al. (2015) ) and gold conference respectively. These figures are much smaller than those in Do et al. (2012) (2.33% for
learned 9.91% for gold). This is largely due to that although 40% of event mentions in our corpus are coreferential, the accuracy of the temporal relation among two coreferential event mentions, produced by the baseline classifier-based model, is already very high (86.2%). In comparison, the baseline in Do et al. (2012) only achieves ~40% in accuracy. Besides, Do et al. (2012) employed a much smaller corpus of only 20 documents, in comparison with 163 documents in our study.

**Performance of different temporal relations**

Table 4 shows the accuracy on four temporal relations with gold event mentions. From Table 4, the performance of temporal relations Before, After and Overlap is higher than that of Unknown, much due to the low recall of the Unknown relation, caused by its low percentage (7.1%). Compared to the two baselines, our DGIM improves the F1-scores for all temporal relations, with the highest improvement on the Before and After relations and the lowest improvement on the Unknown relation, much due to the fact that almost all discourse-level constraints focus on relations Before, After and Overlap.

| Relation   | Baseline 1 | Baseline 2 | DGIM  |
|------------|------------|------------|-------|
| Before     | 63.43      | 65.30      | 72.21 |
| After      | 63.44      | 65.30      | 72.21 |
| Overlap    | 64.50      | 66.40      | 69.17 |
| Unknown    | 45.60      | 47.20      | 47.44 |

Table 4 Accuracies (%) of four temporal relations

**Analysis on adjacent or nonadjacent sentences**

Table 5 shows the percentages and performance of event mention pairs in same sentence, adjacent sentences and nonadjacent sentences with gold event mentions. We can find out that 56.3% of event mention pairs are in nonadjacent sentences. Those event mention pairs in the same sentence achieve the highest accuracy while those in nonadjacent sentences gains least among all three types. Table 5 also proves that our DGIM outperforms two baselines in all three sentence levels significantly.

| Distance      | Rate(%) | Baseline 1 | Baseline 2 | DGIM  |
|---------------|---------|------------|------------|-------|
| Same          | 18.6    | 68.13      | 69.13      | 72.25 |
| Adjacent      | 25.1    | 64.54      | 65.47      | 69.09 |
| Nonadjacent   | 56.3    | 59.15      | 61.87      | 66.75 |

Table 5. Accuracies (%) of event mention pairs in same sentence (Same), adjacent sentences (Adjacent) and nonadjacent sentences (Nonadjacent)

6 Conclusion

This paper first annotates an event-driven fully-annotated Chinese temporal relation corpus and then presents a novel discourse-level global inference model, enforced by various kinds of discourse-level constraints derived from event semantics, to recognize temporal relations of Chinese events in document-level, especially in nonadjacent sentences. Evaluation on an event-driven fully-annotated Chinese temporal relation corpus justifies the effectiveness of our discourse-level global inference model over two strong baselines.

Although our model focuses on Chinese, it can be naturally applied to other languages (e.g., English). Our future work will focus on how to introduce more linguistics-driven knowledge to boost our model and construct a joint modelling of temporal event relation extraction and event extraction on both Chinese and English.

Acknowledgements

The authors would like to thank three anonymous reviewers for their comments on this paper. This research was supported by the National Natural Science Foundation of China under Grant No. 61472265, No. 61402314 and No. 61331011, and partially supported by Collaborative Innovation Center of Novel Software Technology and Industrialization.
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