Constructing a Temporal Relation Identification System of Chinese based on Dependency Structure Analysis

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Abstract: We propose a machine learning-based temporal relation identification method for Chinese. Our research is the first work of the temporal relation identification between verbal events in Chinese texts. The procedure of the temporal relation identification is based on the use of syntactic dependency relations. We focus on the adjacent event pairs, head-modifier event pairs and sibling event pairs in dependency relation. Then, the extracted relations are used to extend the long distance relations by the inference rules. We survey the coverage of our system with a small corpus. The result shows that our proposed system covers about 52% of temporal relations of all possible event pairs (the top line coverage is 65%).

1 Introduction

Extracting temporal information in documents is a useful technique for many NLP applications such as question answering, text summarization, machine translation, and so on. The temporal information is coded in three types of expressions: 1. temporal expressions, which describe time or period in the actual or hypothetical world; 2. expressions of action or state that occur at a time point or for a period of time; 3. temporal relations, which describe the ordering relation between an event expression and a temporal expression, or between two event expressions.

There are many researches dealing with temporal expressions and event expressions (Han et al., 2006; Ahn et al., 2007). Extracting temporal expressions is a subtask of named Entity Recognition (IREX committee, 1999) and is widely studied in many languages. Normalization of temporal expressions is investigated in evaluation workshops (Chinchor, 1997). Event semantics is investigated in linguistics and AI fields (Bach, 1986). However, researches at temporal relation extraction are still limited. Temporal relation extraction includes the following issues: identifying events, anchoring events on the timeline, ordering events, and reasoning with contextually underspecified temporal expressions. Several knowledge resources for identifying tense and aspect of verbs, temporal adverbs, and other world knowledge are necessary for temporal relation extraction (Mani, et al., 2006).

We propose a machine learning method for event-to-event temporal relation identification for Chinese. In Chinese, tense and aspect information is not morphologically encoded in event verbs because of lack of inflectional form change. The issue should be addressed in machine translation systems between Chinese and the other language. However, the issue is pushed aside in many researches.

Still, a few researches focus on the issue. In English, Mani (2006) proposed a machine learning method for event-to-event and event-to-time relation identification, but their method deal with limited types of temporal relations. There is no system that can both deals both of the following two tasks of temporal relation identification: first, to identify the temporal element pairs; second, to assign a label to the pairs that are identified. In Chinese, Li's research (2004) proposed a machine learning method for temporal relation identification. However, they only considered the relation between adjacent verbs in a small scale corpus. They did not deal with long distance temporal relations.

In English, TimeBank (Pustejovsky, et al., 2006), a temporal information annotated corpus, is available to machine learning approaches for automatically extracting temporal relation. Whereas, Chinese resource for temporal information processing is still limited. In our previous research

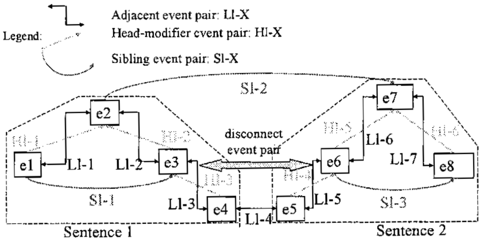


Figure 1. The example of annotating the temporal relations between events.

(Cheng, 2007), we proposed a dependency structure based method to annotate temporal relations manually on a limited set of event pairs and extended the relations using inference rules. The dependency structure helps to detect subordinate and coordinate structures in sentences.

We construct a temporal relation identification system for Chinese based on our corpus. The identifying procedure of the system uses dependency structure analysis. The method covers long distance temporal relations with limited computational cost. This system can identify the temporal relations between events where they are assumed to be described by verbs. We focus on not event-to-time relation, but event-to-event relation, because the number of event-to-event relations is larger than the number of event-to-time relations. Furthermore, the issue on event-to-event relations is more difficult than the issue on event-to-time relations.

In the next section, we describe the procedure of identifying the temporal relations between events that are proposed in the previous research (Cheng, 2007). In section 3, we describe the construction of our temporal relation identification system. In section 4, we introduce our temporal relation tagged corpus and then we perform an experiment for investigating the performance of our temporal relation identifier. Finally, we discuss the results of experiments and our future direction.

2 Temporal relation annotation based on dependency structure

We propose a machine learning based temporal relation identifying system for Chinese. The procedure of the temporal relation identification is enhanced with the use of syntactic dependency structure. The idea is introduced from the data analysis of TimeBank in our previous work (Cheng, 2007). TimeBank annotated according to TimeML

Cheng (2007)	TimeML (2005)	Allen (1983)
AFTER	AFTER	after
	IAFTER	met-by
OVERLAPPED−BY		overlapped-by
	ENDS	finishes
DURING	DURING/IS_INCLUDED	during
BEGUN_BY	BEGUN_BY	started-by
SIMULTANEOUS	SIMULTANEOUS/IDENTITY	equal
INCLUDES	INCLUDES/DURING_INV	contains
ENDED_BY	ENDED_BY	finished-by
OVERLAPS		overlaps
	BEGINS	starts
BEFORE	IBEFORE	meets
	BEFORE	before

Table 1. The temporal relation classes

guideline includes all understandable temporal relations between two entities[1]. However, to annotate or identify full temporal information on a newswire text requires large human effort and computational cost. To reduce the human effort and computational cost, they introduce several simplifications on the original TimeML. First, they handle events expressed only by verbs. Second, they focus on three types of event pairs in a complete graph according to dependency structure and use inference rules to extend relations. By identifying the three types of temporal relation and using the inference rules to extend the temporal relations, they do not need to consider all possible event pairs but they can identify a number of useful temporal relations.

2.1 The definition of the events

According to the TimeML guideline for English, verbs, nominalized verbs, adjectives, predicative and prepositional phrases can represent events. However, to recognize an instance of nominalized verb represents an event or not is difficult in Chinese articles. Chunking phrases and clauses is another difficult process in Chinese. To simplify the process of recognizing events, they only regard single word verbs as events.

2.2 Three types of event pairs

They focus on three types of event pairs in the following occurrences in sentences. The first is the adjacent event pairs. The second and third types are the head-modifier and the sibling event pairs in dependency structure tree representation of a sentence. The first type (adjacent event pairs) and the

[1] TimeBank includes the relations between two temporal expressions, two events and a event-expression pair

	The relation between event "B" and "C"				
The relation between event "A" and "C"	after	before	during	include	simultaneous
after	after			after	after
before		before		before	before
during	after	before	during		during
include				include	include
simultaneous	after	before	during	include	simultaneous
	The relation between event "A" and "C"				

Table 2. Some inference rules.

other two types (head-modifier or sibling event pairs) are not exclusive. Following our investigation (Cheng, 2007) of TimeBank, 85% temporal relations between events are adjacent or head-modifier event pairs. Therefore we can acquire most of the important temporal relations by considering adjacent events and dependency structures.

Our guideline defines three types of temporal relation of an event to another as following definition:

- RLP (Relation to Linear Preceding event): Relation between the focus event and the adjacent event at the immediately proceeding position. (Relation of adjacent event pair).
- RTA (Relation to Tree Ancestor event): Relation between the focus event and the ancestor event connected by a dependency relation (Relation of Head-modifier event pair).
- RTP (Relation to Tree Preceding event): Relation between the focus event and its sibling event in a dependency structure (Relation of Sibling event pair).

Figure 1 illustrates the relation of three types of event pairs in an article. There are two sentences with eight events (from e1 to e8) which are dependency structure analyzed and the polygons with dashed-lines show the boundary of sentences. The angle-line links show adjacent event pairs (from Ll-1 to Ll-7). The dotted-line links show head-modifier event pairs (from Hl-1 to Hl-6) and the curve links show sibling event pairs (from Sl-1 to Sl-3). An event pair can be an adjacent event pair and a head-modifier event pair at the same time.

Most of subordinate event pairs are in head-modifier relations, and most of coordinate event pairs are in sibling relations. Dependency structure can help to extract those relations. Some of the adjacent event pairs and the sibling event pairs represent temporal relations between sentences. In this example, the links Sl-4 (sibling) and Ll-7

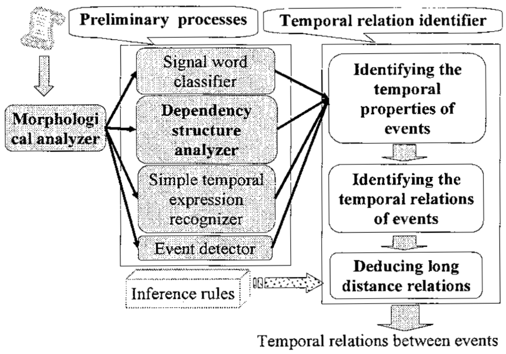


Figure 2. Our proposed system.

(adjacent) span two sentences. Intuitionally, although the event pair "e4" and "e5" are in different sentences, they should be given a temporal relation in the annotation strategy. Events "e2" and "e7" are the matrix event (the root events) of these sentences. They are also considered in the strategy.

Table 1 lists the temporal relation classes for each temporal relation types compared to related researches (TimeML and Allen's definitions (Allen, 1983)). We use this definition to specify the temporal relation classes.

2.3 Use of inference rules

After annotating relation tags, they use inference rules (Table 2) to extend the temporal relations.

We only consider strictly logical relations to define these inference rules. For example, if an event A occurs before an event B, and the event B occurs before an event C, then the event A occurs before the event C. The blank spaces in Table 2 are ambiguous cases.

In the Mani's work (2006), their inference rules adopt some syntactic or semantic features[2] to disambiguate the relation between events. These features need more linguistic knowledge of Chinese. Therefore, we use the inference rules that only adopt unambiguous relations without syntactic / semantic features.

3 Proposed System

This section describes our proposed system. Figure 2 illustrates the structure of our temporal relation identification system. It consists of three parts – "morphological analyzer (word segmenter and

[2] Such as the "POS" tag and the "TENSE" tag are used for creating inference rules in (Mani, et al., 2006).

POS tagger)", "preliminary processes" and "temporal relation identification". The first part is a Hidden Markov Model based morphological analyzer (GOH, 2006), which segments the input text into words and gives POS-tags to each word. The POS-tags of this analyzer correspond to the POS-tags in Penn Chinese Treebank (Xia, 2000). Then the second part of our system, "preliminary processes", adds the syntactic and some information to the text for processing the next part. The third part is "temporal relation identification". It identifies the temporal properties and temporal relation of events, and then deduces long distance relations by inference rules. The system finally outputs the temporal relation set. Below, we begin with the description of "the preliminary processes", since the morphological analyzer is not our main contribution.

3.1 Preliminary processes

The input of the preliminary processes is morphologically analyzed text. In the experimental evaluation, we use a word segmented, POS tagged corpus-- Penn Chinese Treebank. For general purpose, we use Goh's (2006) morphological analyzer to make the input. The input is used in the four preliminary processors: event detector, dependency structure analyzer, signal word classifier, and simple temporal expression recognizer.

Event detector:

Event detector identifies events in the input. Our identification system considers verbs in articles as the event candidates. Event detector selects words with verb POS-tags corresponding to the Penn Chinese Treebank tags: "VA", "VE", "VC" and "VV", which are attributive adjective, existential verb, copula verb and normal verb, respectively.

Dependency structure analyzer:

The dependency structure analyzer is an important part of our system, because our proposed identifier adopts dependency structures. We developed a dependency structure analyzer (Cheng, 2005) which is trained by Penn Chinese Treebank. The performance of the analyzer is 86% word dependency accuracy and 63% sentence accuracy.

Signal word classifier:

"SIGNAL" tagged entity in TimeML is a textual element that makes explicit the relation holding between two events. It can be conjunctions, prepositions and localizer words. We collect the SIGNAL candidates in Chinese following the guideline of the POS-tags in CKIP Treebank (CKIP, 1993). The words in SIGNAL candidates can describe a temporal relation between two events or a location relation between two objects in different context. The signal word classifier recognizes the signal entity candidate by dictionary look-up, and then classify by SVM whether the entity expresses a temporal relation or a location relation. We newly annotate Chinese SIGNAL words on our corpus. The accuracy of SIGNAL word classification in the preliminary experiment is 91%.

Simple temporal expression recognizer:

In our research, we only focus on the temporal relations between events and do not consider the relations of temporal expressions. However, recognizing the temporal expression is still important component for our task. We consider simple numerical temporal expressions, which include the year and date with Chinese numerical expressions (ex: 一九九四年五月 (May, 1994)). This preliminary process uses simple rules to detect the numerical temporal expressions and to order these expressions. The temporal expression recognizer output is also used our temporal relation identifier.

3.2 Temporal relation identifier

After finishing the preliminary processes, the temporal relation identifier acquires basic information for identifying the temporal relations of events. However, several properties which include temporal information of events are not considered. We define four temporal properties of events for analyzing the relations. The system identifies the temporal properties of events and adds the results into features for temporal relation identification. Next, the temporal relation identifier identifies the relation between the limited verb pairs. Finally, the system extends the identified local relations to the long distance relations by inference rules.

Identifying the temporal properties of events:

Properties of an event are the temporal characteristics of the focus event. These properties roughly correspond to the classification of verbs in (Dorr

Temporal property	value	definition
Actuality	actual	Future schedule of fact and circumstance, or the decision which exist.
	hypothetical	The temporal relation between events cannot be defined in the flow of composition time.
Dynamic characteristic	state	The event describes a truth, a static result of an action and a mental situation.
	dynamic	The event describes an action and the process of an occurrence.
Period	durative	The event occurs in a boundary or non-boundary time period.
	instantaneous	The event occurs in a short time period that the period is close to zero.
	repeat	A durative or a instantaneous event repeats by a time interval.
Telicity	telic	The occurrence time period of an event has a predicable ending point.
	non-telic	The occurrence time period of an event does not have a predicable ending point.
	continue-state	An event describes a result statement of its occurrence.

Table 3. The definition of temporal properties.

and Olsen, 1997) but our previous work (Cheng, 2008) add a property-"actuality" to describe if an event occurs in actual world or not. Other temporal properties include the telicity, the dynamic characteristic and the occurrence period of an event. The values of properties with their definitions are shown Table 3.

The last three properties can also describe the verb classification by Vendler (1967) or other verb classification (Li et al., 2005) by the combination of the attribute values.

The property "actuality" is the actuality of the event, that is, the event is real a happened event or not, or annotators should consider the temporal relation of the event or not. This event class depends on the usage of verbs in different situations.

These temporal properties of events are important features for machine learner to analyze the temporal relations. For example, if the focus event is an instantaneous event, it cannot have a temporal relation "include" to another event. Therefore the system identifies these properties before the temporal relation identification. SVM-based temporal property identifiers are trained based on the our corpus. The temporal property identifier outputs are used in the following temporal relation identifier.

Identifying the temporal relations of events:

After identifying the temporal properties of events, the system identifies the temporal relations of each type of events. The temporal relation types are described in section 2.2. We add a subordinate relation tag –"subordinate" for an event, which corresponds to the "SLINK" in TimeML. Subordination relation is used for contexts introducing relations between two events. Following our investigation (Cheng, 2007), the subordinate relations almost correspond to head-modifier relation pairs in the dependency structure. Therefore, we define the relation tag –"subordinate" as the subordinate relation between the focus event and its head event in the dependency structure. It includes the following values: "none", "hypothetical", "descriptive", "reporting", "introducing", "passive" and "conditional".

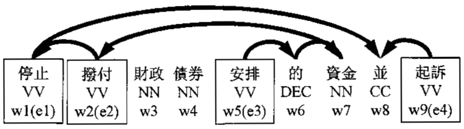
The system analyzes the three temporal relation types and the subordinate relation tag by a machine learner (SVM). The machine learner trains the models of each relation tag by one-vs.-others strategy. Therefore, the models use different features for machine learning.

Deducing long distance relations:

Finally, the system deduces the long distance relations between sentences (ex: "e3" and "e6" in Figure 1) and the missing relations in local sentence (ex: "e5" and "e7" in Figure 1) by the inference rules (Table 2). Therefore, the system does not need to consider all combination of events but can identify most of the temporal relations between events by this procedure.

4 Further annotation on the our corpus

For training the machine learning models of the temporal relation identification system, we need a dependency parsed corpus for using the information of the dependency structure and need a temporal relation annotated corpus. We proposed the annotation (Cheng, 2007) on the Penn Chinese Treebank. Since the Penn Chinese Treebank does not include the head-modifier relations; we transformed phrase structures into dependency structures using head rules (Cheng, 2005). The head rules decide the head word of each phrase in the phrase structure. Our annotation (Cheng, 2007) includes temporal relations without fine-grained information. We added the temporal property of



(To stop providing funds that was prepared by financial bond, and to prosecute ...)

	停止	撥付	安排	起訴
actuality	actual	actual	actual	actual
dynamic	dynamic	dynamic	dynamic	dynamic
period	instantaneous	durative	instantaneous	instantaneous
telicity	telic	telic	telic	telic
RLP	none	END_BY	BEFORE	AFTER
RTA	none	none	none	simultaneous
RTP	none	END_BY	BEFORE	first
SUB	none	explanation	explanation	none

All temporal relations between events	{安排,拨付,before}, {安排,停止,before}, {安排,起诉,before}, {拨付,停止,before}, {拨付,起诉,before}, {停止,起诉,simultaneous}

Figure 3. The example of the event annotation.

the event in (Cheng, 2008). We annotated the subcategories ("hypothetical", etc.) temporal relations of events on the corpus. This annotated corpus is used as the training corpus for temporal relation identifier (section 3.2) and it contains 151 Chinese news articles with 7239 events, 1945 sentences and 49691 tokens.

For investigating the performance of our identification system, we need a small corpus in which all possible verb pairs are annotated as a testing data. We want to observe the temporal relation coverage of our system. However, we cannot observe in a large corpus. Because annotating all event pair manually is time-consume. Therefore, we select 50 articles the annotated data that are not included in training data, and pick up the first two paragraphs of each article. This small test corpus includes 732 events (verbs) and 5010 tokens.

Figure 3 illustrates an example of temporal relation annotation in training / testing data (not all possible verb pair annotation, but limited pair annotation based on dependency structure). The annotators infill appropriate values into the blank space in the table. These blocks include the temporal properties (actuality, dynamic, period and telicity) and the temporal relations (RLP, RTA, RTP and SUB). For creating a golden standard data, we annotate all understandable relation in testing articles. These relations are shown in the row "All temporal relations between events". We also compare the consistency between two annotators in annotating the testing data. The result is shown in the column "consistency" of Table 5. The annotator discusses many instances to make the data consistent. Even so, the consistency does not achieve 100%. This result shows the difficulty of the temporal relation annotation.

Considering the dependency structure in this example, the events "停止 (to stop)" and "起诉 (to prosecute)" are coordinate events. The annotator regards that the suitable value of the attribute RTP of the event "起诉" is "simultaneous". The attributes "RTP" of the other events are "none" because each of these events is an only child. The ancestor event of the events "拨付 (to provide)" and "安排 (to prepare)" are the same as their linear adjacent events, therefore the value of the tag "RLP" is the same as the tag "RTA". Because the event "停止" is the first event and is the root event of the dependency tree, it has neither its linear adjacent events nor its ancestor event. Therefore the values of the attributes "RLP" and "RTA" are "none". In annotating the subordinate relation ("SUB"), the event "安排" is a subordinate event of its head event "拨付". And the event "拨付" is the subordinate event of the event "停止".

The procedure to annotate limited temporal relation does not need to consider all combinations of events. Therefore it can reduce manual efforts. In the annotating work from a dependency tagged text (not annotated any temporal information), the average working time for annotation on the dependency parsed article is twenty-five minutes. This is shorter than the working time of TimeML annotating (several hours per article).

5 System performance investigation

In this section, we perform evaluation experiment of our system. For the system performance investigation, we start from word-segmented and POS tagged text which comes from Penn Chinese Treebank. We evaluate the overall system performance which includes the preliminary processes (signal word classifier, dependency structure analyzer, simple temporal expression recognizer, and event detector) and temporal relation identifier (temporal property identifier, local temporal relation identifier, and long distance temporal relation identifier based on inference rules.

We apply the temporal relation annotated corpus (section 4) to train the machine learner and evaluate the performance and coverage of the system.

Attributes	accuracy	consistency
Temporal properties		
actuality	0.86	0.90
dynamic	0.85	0.87
period	0.78	0.84
telicity	0.79	0.81
Temporal relations		
Adjacent event pair (RLP)	0.68	0.82
Sibling event pair (RTP)	0.67	0.95
Head-modifier event pair (RTA)	0.70	0.86
Subordinate	0.67	0.87

Table 5. The accuracy of the temporal relation identification system and the consistency in manual effort.

First, we examine the accuracy of identifying temporal properties/relations of events. For estimating the accuracy and coverage simple, we use the POS-tagged testing data, i.e. the POS tags and word segmentation are correct. Then input the POS-tagged token sequence into the system.

The accuracy of automatic identification is shown in Table 5. Following the process flow in Figure 2, the system uses the result of the preliminary processes and then identifies the temporal properties and temporal relation tags. Therefore, the result of temporal relation identification includes the error in the preliminary processes. Because the temporal relation identification is latter than the temporal properties identification, the result also includes the error of the temporal property identification. The results of temporal properties identification cause the results of temporal relation identification worse. However, in our preliminary experiments (not in table 5), if we do not use the results of temporal property identification, the accuracy of temporal relation identification decreased 1~2% in each relation type. Therefore, identifying the temporal properties before the temporal relations identification is necessary and to improve the accuracy of temporal properties can improves the accuracy of temporal relation identification.

Next, we investigate the coverage of the temporal relations that are identified by our proposed system. That is, we compare the output of our system with the result of the manual identification that considers all combinations of events.

Table 6 describes the results. The column "Identifying by automatic system" is the result of our system. The column "manual effort" is the annotator's work with our proposed criteria. This column

	Identifying by automatic system	Manual effort
Adjacent event pair (RLP)	732	718
Sibling event pair (RTP)	561	563
Head-modifier event pair (RTA)	198	215
Total extracted event relations	1276	1089
After using inference rules to extend relation (Consistent with correct data)	5359 (3451)	5008 (4339)
All event combinations (Correct data)	6646	6646
Precision	0.64	1
Recall	0.52	0.653

Table 6. The coverage of the temporal relation identification system.

can be considered to the maximum coverage of our system. We focus on the three types of temporal relation (RTA, RLP and RTP) and then use inference rules (the row "After using inference rules to extend relation"). The row "All event combinations (Correct data)" is the golden data that manually consider all event combinations. Then we estimate the recall and precision of our system and the manual effort.

The results show that our system achieves 52% recall for the top line recall 65% (the coverage of the manual annotation based on the limited verb pairs). The main error is that our inference rules are not perfect. In the deducing process, many long distance event pairs cannot be deduced because the deducing chain includes ambiguous event pairs then the chain broken. Therefore, to infill the inference rules in Table 1 are a future work and can improving the coverage of the system.

There is no research based on same data set and corpus guideline, therefore we can not compare the result to other research. However, in the shared task—TempEval (Verhagen, 2007), the task "temporal relations between matrix verbs" resembles the goal of our research. The F-measure in TempEval shared task distribute in 40%~50%. The result of the shared task also shows the difficulty of automatic temporal relation analysis.

6 Conclusion and future direction

Temporal information is an important dimension of natural language processing. Researches on temporal relation identification are still limited. We propose a machine learning-based temporal relation identification method from plain text. Our research is the first work of the automatic temporal relation identification between verbs in Chinese texts.

The process of temporal relation identification includes following steps: morphological analysis, preliminary processes (include dependency analysis), temporal relation identification (includes the temporal property identification) and to extend the long distance temporal relations using the inference rules. We survey the coverage of our system with a small corpus. SVM is used as the machine learner in our experiments. The accuracies of identifying the temporal relation types of events are 68%~70%. The result shows that our proposed system covers about 52% of temporal relations of all possible event pairs for the top line coverage is 65%. The average working time required for one article (with 80 events) is about 30 minutes in our annotation work. It is shorter than the annotating work of TimeBank (needs more than one hour for one article).

For improving the performance of our temporal relation annotating system, there are two directions that we can focus on: First, we need to add more information for the machine learner. For example, we only use the simple numerical expression as a feature. However, many useful temporal expressions cannot be analyzed such as the expression of time intervals. Adding the inference rules is another future direction for our research. We do not use the syntactic / semantic information to define the rules. Adding inference rules can supply more long distance relation.

Another future research is that we would like to introduce the causal relation knowledge of verbs (this is similar to VerbOcean (Chklovski, 2004)). Now, we are constructing Chinese causal relation knowledge of verbs. We forecast that this causal verb pairs is useful information for our system.

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