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Cover
Calligraphy by Professor Ching-Chun Hsieh, founding president of ACLCLP
Text excerpted and compiled from ancient Chinese classics, dating back to 700 B.C.
This calligraphy honors the interaction and influence between text and language
Contents

Papers

BCCWJ-TimeBank: Temporal and Event Information Annotation on Japanese Text................................................................. 1
Masayuki ASAHARA, Sachi KATO, Hikari KONISHI, Mizuho IMADA, and Kikuo MAEKAWA

Transliteration Extraction from Classical Chinese Buddhist Literature Using Conditional Random Fields with Language Models........................................................................................................ 25
Yu-Chun Wang, Karol Chia-Tien Chang, Richard Tzong-Han Tsai, and Jieh Hsiang

Modeling Human Inference Process for Textual Entailment Recognition................................................................................ 39
Hen-Hsen Huang, Kai-Chun Chang, and Hsin-Hsi Chen
BCCWJ-TimeBank: Temporal and Event Information Annotation on Japanese Text

Masayuki ASAHARA*, Sachi KATO*, Hikari KONISHI*, Mizuho IMADA*, and Kikuo MAEKAWA*

Abstract

Temporal information extraction can be divided into the following tasks: temporal expression extraction, time normalisation, and temporal ordering relation resolution. The first task is a subtask of a named entity and numeral expression extraction. The second task is often performed by rewriting systems. The third task consists of event anchoring. This paper proposes a Japanese temporal ordering annotation scheme that is used to annotate expressions by referring to ‘the ‘Balanced Corpus of Contemporary Written Japanese’ (BCCWJ). We extracted verbal and adjective event expressions as <EVENT> in a subset of BCCWJ and annotated a temporal ordering relation <TLINK> on the pairs of these event expressions and time expressions obtained from a previous study. The recognition of temporal ordering by language recipients tends to disagree with the normalisation of time expressions. Nevertheless, we should not strive for unique gold annotation data in such a situation. Rather, we should evaluate the degree of inter-annotator discrepancies among subjects in an experiment. This study analysed inter-annotator discrepancies across three annotators performing temporal ordering annotation. The results show that the annotators exhibit little agreement for time segment boundaries, whereas a high level of agreement is exhibited for the annotation of temporal relative ordering tendencies.

Keywords: Temporal Information Processing, Event Semantics, Corpus Annotation.

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1. Introduction

Temporal information processing in natural language texts has received increasing scholarly attention in recent years. Since the temporal orders of events often have implications for causal relations (cause and effect), identifying them is an essential task for deep understanding of language. Several types of resources for English temporal information processing have been developed, including an annotation specification TimeML (Pustejovsky et al., 2003a) and annotated corpora, such as TimeBank (Pustejovsky et al., 2003b) and Aquaint TimeML Corpus.

The English annotation specification has been extended as an International Standard Organization (ISO) standard of a temporal information mark-up language, namely ISO TimeML (Pustejovsky, Lee, Bunt, & Romary, 2010), which covers Italian, Spanish, Chinese, and other languages. Temporal information-annotated corpora in various languages have been developed and been shared by natural language processing researchers. TempEval-2 (Verhagen, Sauri, Caselli, & Pustejovsky, 2010), a task for the SemEval-2010, and TempEval-3 (UzZaman et al., 2013), a task for the SemEval-2013, have been proposed as shared temporal-relation reasoning tasks. In these shared tasks, datasets for English, Italian, Spanish, Chinese, and Korean are provided.

Nevertheless, there is no such resource for the Japanese language. In this paper, we present a means of porting a subset of ISO-TimeML into the Japanese language and describe the basic specifications of ‘BCCWJ-TimeBank,’ which is a realisation of the temporal information annotation of the ‘Balanced Corpus of Contemporary Written Japanese,’ or BCCWJ (Maekawa, 2008).

The purposes of temporal information annotation differ in accordance with the research goal. For natural language processing, users may need to develop and evaluate analysers for the annotation. Hence, for linguistic purposes, some users may want to formalise semantic expressions for temporal and event information expressions. Other users may want to evaluate human cognitive processes related to the expressions. The former purpose requires unique and consistent annotations. The latter purpose does not require consistent annotation; instead, it may require ways to evaluate variation among annotations. In this study, we conduct ‘pair annotation’ to formalise semantic expressions for temporal expressions. We also perform evaluation of the cognitive process of the expressions for temporal ordering annotation.

Porting TimeML into other languages can be challenging because of differences between languages. Even if we made a standardisation of ISO-TimeML, there would still be slight differences among the resources in terms of annotation targets, styles, formalism, philosophy, objectives, and focuses. Our research target is ‘temporal ordering’ in Japanese documents. We want to establish a machine learning-based temporal ordering analyser of the event and time
expressions in Japanese. Before we develop the temporal ordering analyser, however, we have to analyse how well human annotators detect the temporal ordering. Therefore, our main research question in this article is to evaluate human annotators’ skills in Japanese temporal ordering annotation. We permit inconsistency in semantic-level annotation among the annotators and quantitatively evaluate this inconsistency for the type of temporal ordering. Under the main research question, we did not perform sound and complete localization of ISO-TimeML to Japanese, as previous research has done.

The contributions of this work are as follows. First, to the best of our knowledge, this is the first corpus-based study on Japanese temporal information annotation. Second, we introduce two annotation paradigms for linguistic research. One paradigm is ‘pair programming’-like annotation for consistent annotation. The other paradigm is annotation as a subjective experiment. Third, we evaluate cognitive processes in human temporal information processing.

The rest of this paper is organised as follows. Section 2 discusses previous studies related to this work. Section 3 briefly presents our annotation specification. Section 4 outlines the annotation processes of our work. Section 5 presents the corpus statistics and evaluations. Finally, Section 6 concludes this paper.

2. Previous Studies

This section discusses previous studies on BCCWJ-TimeBank. Section 2.1 presents English temporal information processing. Section 2.2 presents ISO-TimeML, which is a standardisation of the annotation schema. Section 2.3 presents Asian language resources related to temporal information processing. Section 2.4 explains the target corpus of Japanese.

2.1 English Temporal Information Processing

MUC-6 (Grishman & Sundheim, 1996) was a workshop on information extraction, which included temporal expression extraction as a subtask. TimeML <TIMEX3> tags used to be the de facto standard of normalization of temporal expressions; however, temporal information processing was then extended to event semantics. TimeML provides an annotation schema for event expressions and temporal relation extraction. Following this, TimeBank and some other corpora were developed. Using this corpus, machine learning-based temporal relation extraction methods have been developed (Boguraev & Ando, 2005; Mani, 2006). In addition, shared task workshops, including TempEval (Verhagen et al., 2007), TempEval-2 (Verhagen et al., 2010), and TempEval-3 (UzZaman et al., 2013), have been held in more formalized evaluation settings.
2.2 ISO-TimeML: Standardisation of the Annotation Schema

The ISO Technical Committee (TC 37) has proposed several standards for language resources under the collective category ‘Terminology and other language and content resources’. The committee (SC) is divided into four areas. TC 37/SC 4 is charged with looking at annotation standards for all areas of natural language resources. This area includes six working groups (WG) to design language annotation specification mark-up languages, such as stand-off mark-up and XML. TC 37/SC 4/WG 2, the semantic annotation WG, discusses semantic annotation standards. The original TimeML developers and TC 37/SC 4/WG 2 defined ISO-TimeML as a Semantic Annotation Framework (SemAF)-Time, that is ISO-24617-1:2012, within the context of TC 37/SC 4.

TimeML and ISO-TimeML define four types of entities: <TIMEX3>, <EVENT>, <MAKEINSTANCE>, and <SIGNAL>. The <TIMEX3> tag specifies various attributes of time expressions, such as tid, type, quant, freq, mod, and value. The time expressions are categorized into four types: DATE, TIME, DURATION, and SET. The attribute @value includes the normalised values of the time expressions in a machine-readable format. The <EVENT> tag specifies various attributes of event expressions, including the class of the event, tense, grammatical aspect, polarity, and modal information. The <MAKEINSTANCE> tag presents the event instances expressed by <EVENT>-tagged expressions. Finally, the <SIGNAL> tag annotates elements to indicate how temporal objects are related amongst themselves.

TimeML and ISO-TimeML also define several types of links. Among these, <TLINK> expresses temporal order among instances of time expressions, event expressions, or both.

2.3 Time Information Annotation in Asian Languages

Japanese temporal information processing is still being developed. We have developed temporal expression extraction resources only as a subtask of named entity extraction. The IREX NE Task (Sekine & Isahara, 2000) includes time expressions as the target. Sekine, Sudo, and Nobata (2002) maintained an extended named entity hierarchy for Japanese and other languages, which includes five subcategories of time expressions and six subcategories of period expressions.

In the case of Chinese, Cheng developed a Time-ML compatible Chinese Temporal Annotation Corpus (Cheng et al., 2008a) and proposed some models for the data (Cheng et al., 2008b). This was the first localization work with TimeML for Chinese and was before ISO-TimeML. Cheng performed temporal ordering information annotation on 151 articles from the Penn Chinese Treebank (Xue et al., 2005). In their work, syntactic dependency relations derived from the Penn Chinese Treebank were utilized for the annotation and temporal ordering estimation. There are two representative temporal information annotated
corpora in addition to the abovementioned works: the Chinese part of the ACE 2005 multilingual training corpus (Walker et al., 2006) and the TempEval-2 Chinese data sets (Xue & Zhou, 2010). The former is only for temporal expression extraction and normalization. The latter focuses on the temporal ordering of four relations, similar to this work, and it will be presented in Section 3.4. The TempEval-2 Chinese data sets are also based on 60 articles from the Penn Chinese Treebank that were analysed by a two-phase double blind and adjudication process. Nevertheless, sound and complete annotation cannot be achieved. Recently, the temporal expression annotation of TempEval-2 Chinese data was fixed by Li et al. (2014), and a Chinese temporal tagger based on the new annotation is publicly available.

In the case of Korean, KTimeML is a temporal information annotation guideline for Korean (Im et al., 2009). Im and his colleagues utilized morpheme-based stand-off annotation and surface-based annotation.

A contrastive evaluation among Asian temporal information language resources is difficult. The research objectives vary among the previous articles. In addition, some detailed annotation guidelines are not in the previous articles but are written in manuals in their own language. Nevertheless, we emphasize that the temporal information processing of Asian languages is still an ongoing process. There are no sound and complete language resources on temporal information processing. One reason might be that the localization of all ISO-TimeML tags and attributes does not always help the temporal information processing. In addition, there are still language-independent issues for each language. Another reason might be that the human recognition system of temporal information is not stable among people. This article attempts to evaluate the human recognition system of temporal ordering in cognitive experiments.

2.4 BCCWJ and its Annotations

BCCWJ was publicly released in 2011 by the National Institute for Japanese Language and Linguistics (NINJAL) in Japan. It consists of three sub-corpora: ‘Publication,’ ‘Library,’ and ‘Special purpose’. ‘Publication’ consists of samples extracted randomly from books, magazines, and newspapers published during 2001-2005. ‘Library’ consists of randomly extracted samples from texts in circulation at libraries during the period 1986-2005. Finally, the ‘Special purpose’ sub-corpus consists of several mini-corpora without a statistical sampling method being used. It includes text from Yahoo! Answers, Yahoo! Blogs, white papers, and school textbooks. The total size of BCCWJ is about 100 million words.

The part of BCCWJ called ‘CORE’ manually annotates word boundaries, base phrase boundaries, and morphological information. CORE consists of six registers found in ‘Publication’ and ‘Special purpose’: books (PB), magazines (PM), and newspapers (PN) from ‘Publication,’ along with Yahoo! Answers (OC), Yahoo! Blogs (OY), and white papers
(OW) from ‘Special purpose’. The size of CORE is about 1.3 million words.

The BCCWJ data include several annotations, such as metadata, document structure, sentence boundaries, word boundaries, and phrase (bunsetsu) boundaries. NINJAL suggests two sorts of word delimitation definitions: one is a short word unit and the other is a long word unit. Each of these word delimitations is coded with the UniDic part-of-speech tag (Den et al., 2008).

Several research institutes have developed further linguistic annotations for CORE, such as syntactic dependency structures, developed by Nara Institute of Science and Technology (NAIST) and NINJAL; predicate-argument relations, developed by NAIST; named entities, developed by Tokyo Institute of Technology (TITECH); modality, developed by Tohoku and Yamanashi Universities; and Japanese framenet, developed by Keio University. The multi-word functional expressions are maintained by Tsukuba University. The CORE samples are split into annotation priority sets from A to E to allow the annotations to overlap as much as possible. Some of these annotations can be used as presupposed information for our annotation. In this way, BCCWJ is the most promising resource making linguistic annotations for both NLP and linguistic researchers.

Table 1 shows the basic statistics and priority sets of BCCWJ CORE. The word unit is based on the short word unit, UniDic standard (Den, Nakamura, Ogiso, & Ogura, 2008); UniDic is a lexicon for Japanese morphological analysis.

### Table 1. BCCWJ CORE: Registers and priority sets.

<table>
<thead>
<tr>
<th>Register</th>
<th>(Abbr.)</th>
<th>Priority Set</th>
<th># of Samples</th>
<th># of Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>White Paper</td>
<td>OW</td>
<td>A to D</td>
<td>62</td>
<td>197,011</td>
</tr>
<tr>
<td>Books</td>
<td>PB</td>
<td>A to D</td>
<td>83</td>
<td>204,050</td>
</tr>
<tr>
<td>Newspapers</td>
<td>PN</td>
<td>A to E</td>
<td>340</td>
<td>308,504</td>
</tr>
<tr>
<td>Yahoo! Answers</td>
<td>OC</td>
<td>A to B</td>
<td>938</td>
<td>93,932</td>
</tr>
<tr>
<td>Magazines</td>
<td>PM</td>
<td>A to D</td>
<td>86</td>
<td>202,268</td>
</tr>
<tr>
<td>Yahoo! Blog</td>
<td>OY</td>
<td>A to B</td>
<td>471</td>
<td>92,746</td>
</tr>
</tbody>
</table>

3. Temporal Information Annotation Specification

This section presents a specification for Japanese temporal information annotation. The annotation is realised as BCCWJ-TimeBank. The specification is based on TimeML (Pustejovsky et al., 2003a) and is adapted for the Japanese language. Figure 1 shows an example of the annotation. Below, we present an overview of the specification of TimeML tags: <TIMEX3> for temporal expressions, <EVENT> and <MAKEINSTANCE> for event expressions, and <TLINK> for temporal ordering. We mention other tags that we exclude
BCCWJ-TimeBank: Temporal and Event Information Annotation on Japanese Text

3.1 Overview of Japanese Temporal Information Annotation

This section presents an overview of the Japanese temporal information annotation.

We introduce three types of tags for the annotation: i) the time expression tag <TIMEX3>, ii) the event expression and event instance tags <EVENT> and <MAKEINSTANCE>, iii) the temporal relation tag <TLINK>. We explain the specifications of each tag in the following subsections.
Note that our research objective is not the localization of ISO-TimeML for Japanese but is to investigate the ability of the human recognition process of temporal ordering. We omitted detailed localization of ISO-TimeML tags and attributes. In the original TimeML, <SIGNAL>, <SLINK>, and <ALINK> are defined. <SIGNAL> is used with some temporal prepositions and conjunctions in English, <SLINK> is used for subordination relations, and <ALINK> is used for non-constituent aspectual relations. Currently, we are not using these with the BCCWJ-TimeBank. We leave these directions for our future work for the following reason. According to the specification <SIGNAL> in TimeML, ISO-TimeML, and (Setzer, 2001), we have to annotate nearly all of the functional words (auxiliary verbs and postpositions) that should be tagged <SIGNAL>. If we do not introduce any subcategories for each functional word, annotating all of the functional words is the same as annotating none of the functional words. <SLINK> should be annotated after the annotation of the subordinate clause boundaries with the clause functions. Although <ALINK> should be annotated as an aspectual compound main verb structure in Japanese, verbs other than the main verb in a compound verb are defined as auxiliary verbs, according to the definition of the UniDic POS tagset. As presented in Section 2.3, the previous work on Chinese also focuses on <TLINK>.

3.2 <TIMEX3>: Temporal Expression Annotation
The target temporal expressions for <TIMEX3> are DATE, TIME, DURATION, and SET by @type. We do not permit any nests of <TIMEX3>. We clip the expressions according to characters because Japanese does not have word delimitation spaces.

The attributes of @tid, @type, @value, @freq, @quant, and @mod have been inherited from the original TimeML. There is an issue regarding which calendar to use in porting TimeML to Japanese. In Japan, we use not only the Western calendar but also a native Japanese calendar that is based on the year of the Emperor’s reign. We introduce a new attribute @valueFromSurface to address this issue. @valueFromSurface includes a @value-like string to indicate a machine-readable date/time value. @value includes the normalised version of value, whereas @valueFromSurface includes the non-normalised version of the value, which can be generated on rewrite rules. @valueFromSurface can encode Japanese calendars. For example, ‘平成 26 年’ (the 26th year of the Heisei era) is encoded in the @valueFromSurface as ‘H26’ and normalised as the @value of ‘2014’ in the ISO-8601-like format.

The difference between @value and @valueFromSurface shows the use of the normalisation procedure. Nevertheless, we cannot judge whether the <TIMEX3> is fully normalized (fully specified) or underspecified. We introduce another new attribute, @definite, to indicate whether the <TIMEX3> is fully specified ‘true’ or underspecified ‘false’.
3.3 <EVENT>, <MAKEINSTANCE>: Event Expression Annotation

Next, we need to annotate the event expressions and instances to link the temporal ordering to <TIMEX3>. The event expression candidates are automatically extracted from the BCCWJ of morphological information. We define long word units with verbs and adjectives, resulting in a total of 4,953 event expression candidates. First, the candidates are judged by two annotators as to whether the target expression is an event expression. If the expression boundaries are not valid, a longer expression covering the candidate is redefined by the annotators. Second, the annotators judge whether there are any instances of the target expression on the timeline. If an instance is recognised, the annotators define a <MAKEINSTANCE> in the corpus. The <MAKEINSTANCE> is a stand-off from the event expression, but is linked to the <EVENT> tag by the @eid attribute. Third, the annotators annotate the @class attribute on the <EVENT>. There are nine @class attributes: seven for event instances (OCCURRENCE, REPORTING, PERCEPTION, ASPECTUAL, I_ACTION, I_STATE, STATE) and two for non-instances (NULL and NONE). The difference between NULL and NONE is that the former is applied by <EVENT> annotators and the latter by <TLINK> annotators. The instances are double-checked by both <EVENT> and <TLINK> annotators. These attributes are described in more detail below.

- OCCURRENCE: These are event expressions without event arguments describing something that happens or occurs in the world (the argument event). Most event expressions belong to this class.
- REPORTING: These are event expressions with an event argument describing the action of an animate actor declaring, narrating, or informing about the argument event.
- PERCEPTION: These are event expressions with an event argument describing the physical perception of the argument event.
- ASPECTUAL: These are event expressions with an event argument describing some aspectual feature of the argument event.
- I_ACTION: These are intentional action expressions with an event argument describing an action or situation to introduce the argument event, from which we can infer something, given its relation with the I_ACTION.
- I_STATE: These are intentional state expressions with an event argument referring to an alternative or possible world.
- STATE: These are state expressions in the timeline. We only annotate these when an instance is introduced and becomes an argument of other event expressions.
- NULL, NONE: These are non-instance expressions

The annotator discriminates whether the target is an event or a state (STATE). Then, he or she judges whether the target has an event argument (OCCURRENCE). Finally, he or she
categorises any target with an event argument into one of the five categories of REPORTING, PERCEPTION, ASPECTUAL, I_ACTION, and I_STATE.

The two annotators and two supervisors defined a detailed linguistic annotation specification employing some Japanese language tests that are based on linguistic research (Kudo, 1995, 2004; Nakamura, 2001). The two annotators were trained on the specification until the agreement rate reached 75%.

<MAKEINSTANCE> attributes such as @tense, @aspect, and @modality are not well-maintained in the current status. Japanese tense and aspect from the surface forms cannot be matched to ISO-TimeML. Japanese ‘surface tense’ is marked by -u and -ta and ‘surface aspect’ is marked by -u and -teiru.

In the case of tense, the surface tense only expresses the difference between past and non-past. Furthermore, the event marked by the surface tense may have discrepancies with the temporal ordering on the timeline. Nevertheless, the temporal ordering relation <TLINK> between DCT and the target event expresses ‘deep tense’ information. The deep tense information is a translingual feature. When we want to investigate the discrepancy between surface tense and deep tense, it can be done by comparing tense morphemes from the short word unit and <TLINK> with DCT.

In the case of aspect, Japanese has some alternative surface aspectual expressions such as -tearu and -teoru. These aspectual expressions, excluding -ru and -teiru, are called ‘semi-aspectual expressions’ in Kudo (1995). These rich surface aspectual systems cannot be mapped on the ISO-TimeML original labels. Furthermore, the aspectual systems in Japanese vary among regions or dialects (Kudo, 2004). We believe this issue is beyond the scope of our current work, and we will treat this issue in our future work.

In the case of modality, Yamanashi University and Tohoku University developed annotation of modality information in BCCWJ. The researchers focused on whether the target event happened or did not happen in the real world in their annotation schema. Their research objective is different from ours. Nevertheless, they provide rich information on tense aspect and modality structure in their research. Layering their annotation on BCCWJ-TimeBank makes the corpus more informative.

3.4 <TLINK>: Temporal Ordering Annotation

<TLINK> defines the temporal ordering of temporal information expressions and event expressions. We used a variant of Allen’s interval algebra as <TLINK> labels; there are 13 labels for temporal ordering and three for event-subevent relations.

We also have one label ‘vague’ for underspecified relations. Figure 3 shows the thirteen labels for temporal ordering and the three for event-subevent relations. The three underlined
labels, namely ‘is_included,’ ‘identity,’ and ‘includes,’ are event-subevent versions of ‘during,’ ‘equal,’ and ‘contains,’ respectively. Strictly speaking, we can also define event-subevent versions of ‘finishes,’ ‘started-by,’ ‘starts,’ and ‘finished-by’. We did not define these, however, because they are rare and TimeML did not define them.

Note that Japanese is a strictly head-final language.
The matrix verb phrases tend to be put near the end of sentence.

Figure 2. <TLINK>: The four types of relations.
<TLINK> annotators are different from <EVENT> and <MAKEINSTANCE> annotators. Three annotators annotate the <TLINK> labels on some of the pairs among <TIMEX3> and <MAKEINSTANCE>. The number of <TLINK> candidates is equal to the combination number of <TIMEX3> and <MAKEINSTANCE>. It is difficult to check all possible pairs in the documents; therefore, we limited the target pairs to the following four types of relations:

- ‘DCT’: relations between a <TIMEX3> of document creation time (DCT) and an event instance;
- ‘T2E’: relations between a <TIMEX3> (non DCT) and an event instance within one sentence;
- ‘E2E’: relations between two consecutive event instances; and
- ‘MAT’: relations between two consecutive matrix verbs of event instances.

Figure 2 presents the four types of relations.

If the relation is between two different possible worlds, we use the label ‘vague’. When we regard the ‘vague’ relations as disjointed links, the connected subgraph indicates the different possible worlds. The value of <TIMEX3> is regarded not as a time point but as a time interval. The event instance of a punctual verb is regarded as a time point occurrence, whereas the other event instances are regarded as time interval occurrences. Figure 3 presents an overview of the <TLINK> labels.

![Figure 3. <TLINK> labels.](image_url)
3.5 Other Tags in TimeML and ISO-TimeML

We will annotate <SIGNAL>, <SLINK>, and <ALINK> in the original TimeML tag in the future. In terms of the BCCWJ annotation background, several institutes are working together to take responsibility for layers of annotations. Some tags in TimeML originals presuppose other layers’ annotation. To reduce annotation cost and to keep consistency among the professionals in other institutes, we postpone <SIGNAL>, <SLINK>, and <ALINK> until the presupposed annotation is finished. For example, <SIGNAL> tags are highly related to the multi-word functional words. <SLINK> tags are related to the subordinate clause structures in the treebank annotation. <ALINK> tags are related to the compound verb construction annotation.

3.6 Comparison with other Temporal Information Annotated Corpora in Asian Languages

This section presents a contrastive comparison with the previous research on Asian language resources.

First, the IREX NE Task data in Japanese (Sekine & Isahara, 2000) and the Chinese part of the ACE 2005 multilingual training corpus (Walker et al., 2006) focused only on time expression extraction and normalization.

Second, both of Cheng’s works (Cheng et al., 2008a) and the TempEval-2 Chinese data sets focus on automatic <TLINK> annotation. <SLINK> and <ALINK> are not annotated on these resources. <TLINK> in Cheng’s work is an annotated subset of the event and time expression pairs, and it expands the relation among the transition rules of temporal logic. On the other hand, <TLINK> in the TempEval-2 Chinese data sets targets limited pairs of the event and time expressions, which is almost the same as our approach, described in Section 3.4.

Third, KTimeML (Im et al., 2009) is a TimeML compatible annotation schema. Nevertheless, the researchers introduce several changes to the original TimeML markup philosophy, including a change from word-based in-line annotation to morpheme-based stand-off annotation. In the annotation definition, we inherit some <TIMEX3> standards from KTimeML, such as introduction of the week of the month.

Fourth, we discuss the word segmentation issue in Asian languages. CJK languages are written without word boundaries. The two Chinese resources are based on the Penn Chinese Treebank, and they use the word unit from the original Penn Chinese Treebank. KTimeML uses a morpheme unit from Korean. Nevertheless, they introduce the stand-off style annotation over the morpheme. BCCWJ-TimeBank uses the short word unit of the original BCCWJ.
There are still differences in several layers of the annotation among the Asian temporal information annotated language resources. Space limitations do not permit a full discussion of these differences.

4. Annotation Processes

This section presents the annotation processes. First, we present the MAMA-cycle and MATTER-cycle. Then, we introduce two additional paradigms for the annotation processes: MAMA-cycle with a pair-programming type of method for <TIMEX3> and annotation as a cognitive science experiment for <TLINK>. Note that we cannot introduce new annotation methods for <EVENT> and <MAKEINSTANCE>. We performed these two annotations by a simple MAMA-cycle.

4.1 MAMA-cycle and MATTER-cycle

O’Reilly’s book, Natural Language Annotation for Machine Learning (Pustejovsky & Stubs, 2012), presents two types of annotation cycles. The MAMA-cycle, whose initials represent Model-Annote-Model-Annote, stresses the importance of creating a guideline or specification. The MATTER-cycle, whose initials represent Model-Annote-Train-Test-Evaluate-Revise, stresses the importance of creating the language analysers. Train and Test are the phases of machine learning in creating language analysers. Figure 4 presents the two types of cycles.

**Figure 4. MAMA-cycle and MATTER-cycle.**

The two cycles are aimed at producing effective guidelines, good language analysers, or both. Nevertheless, our research objective is different. The BCCWJ-TimeBank guidelines inherit most of the original TimeML/TimeBank schema. Our contribution to these guidelines is limited to the localization of the schema. We may produce language analysers in future work; however, we did not aim at the development of a temporal ordering relation analyser in the current stage. Our research objective is somewhat related to cognitive science because we would like to evaluate the human annotators’ cognitive process of temporal ordering. Thus, in this work, we propose two additional annotation paradigms: MAMA-cycles with pair annotation and Annotation as a cognitive science experiment.
4.2 MAMA-cycle with Pair Annotation for <TIMEX3>
We used XML Editor oXygen 3 for <TIMEX3> annotation, and we defined DTD for BCCWJ-TimeBank. The DTD enables us to use the machine-aided (such as XML validation and a completion mechanism) environment of oXygen. An annotator performs in-line annotation on the original text corpus. We introduce a pair-programming type of method in which a display is shared by an annotator and supervisor. Although the method is stressful for both the annotator and supervisor, the data become more consistent and annotation errors are reduced. Figure 5 illustrates the proposed annotation process.

4.3 Annotation as a Cognitive Science Experiments for <TLINK>
Next, we performed a cognitive science experiment for <TLINK> annotations. In this paradigm, we evaluated the human cognitive process for perceiving the timeline. Here, we explain the process in detail. First, the supervisor gives annotation guidelines to three annotators. Second, the three annotators individually annotate <TLINK> information on the same dataset. Finally, the researchers evaluate the variance and differences among the three annotations. During this process, the annotators perform individual, not inter-annotator, revision. Figure 6 illustrates the proposed annotation process.
5. Corpus Statistics and Evaluations

This section presents basic statistics on BCCWJ-TimeBank, the Japanese corpus annotated for temporal information. We also consider the annotation environment of BCCWJ-TimeBank.

5.1 <TIMEX3>

Table 2 shows annotation target samples for <TIMEX3>. The column ‘W/TIMEX’ shows the number of samples or sentences that include at least one temporal information expression. Some samples in the registers OW (white paper), OC (Yahoo! Answers), and OY (Yahoo! Blogs) do not include any temporal information expressions.

Table 2. <TIMEX3>: Annotation target samples.

<table>
<thead>
<tr>
<th>Register (Priority set)</th>
<th># of Samples</th>
<th># of Sentences</th>
<th># of Words</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL</td>
<td>w/TIMEX</td>
<td>(Rate)</td>
</tr>
<tr>
<td>OW (A)</td>
<td>17</td>
<td>16</td>
<td>(94%)</td>
</tr>
<tr>
<td>PB (A)</td>
<td>25</td>
<td>25</td>
<td>(100%)</td>
</tr>
<tr>
<td>PN (A, B)</td>
<td>110</td>
<td>110</td>
<td>(100%)</td>
</tr>
<tr>
<td>OC (A)</td>
<td>518</td>
<td>250</td>
<td>(48%)</td>
</tr>
<tr>
<td>PM (A)</td>
<td>23</td>
<td>23</td>
<td>(100%)</td>
</tr>
<tr>
<td>OY (A)</td>
<td>257</td>
<td>198</td>
<td>(77%)</td>
</tr>
</tbody>
</table>

Table 3 shows the basic statistics of <TIMEX3> annotations. The table shows the number of <TIMEX3> by @type and @definite and shows the relation of {@value and @valueFromSurface}. @type has four labels: DATE, TIME, DURATION, and SET. We exclude document creation time (DCT), which is given in corpus metadata, from the statistics. Then, we analyse the statistics on the basis of two perspectives. The first is whether @definite is ‘true’ or ‘false,’ in other words, whether the temporal information expression is fully specified or underspecified. The fully specified expression can be mapped on the timeline, while the underspecified expression cannot. The second perspective is whether @value and @valueFromSurface are identical (‘=’) or not (‘≠’). The former have undergone some normalisation procedure from the annotators, while the latter have not.

A total of 5,297 temporal information expressions were annotated in the corpus. Of those, 1,639 (30%) are fully specified expressions without any normalisation procedures applied. Further, 2,023 (37%) of the total can be normalised by contextual information, and 1,875 (34%) cannot. The third group needs more external information to be able to be normalised.
Table 3. <TIMEX3>: @type×@definite×{@value, @valueFromSurface}.

<table>
<thead>
<tr>
<th>@definite</th>
<th>True (fully specified)</th>
<th>False (underspecified)</th>
</tr>
</thead>
<tbody>
<tr>
<td>@value and @valueFromSurface</td>
<td>All</td>
<td>=</td>
</tr>
<tr>
<td>DATE</td>
<td>2214 (61%)</td>
<td>381 (10%)</td>
</tr>
<tr>
<td>TIME</td>
<td>188 (37%)</td>
<td>1 (0%)</td>
</tr>
<tr>
<td>DURATION</td>
<td>1129 (92%)</td>
<td>1128 (92%)</td>
</tr>
<tr>
<td>SET</td>
<td>131 (85%)</td>
<td>129 (84%)</td>
</tr>
<tr>
<td>ALL</td>
<td>3662 (66%)</td>
<td>1639 (30%)</td>
</tr>
</tbody>
</table>

In the ‘DATE’ expressions, most of the fully specified expressions (@definite ‘true’; 61%) have had manual normalisation performed (@value ≠ @valueFromSurface; 50%). This fact shows that the normalisation procedure is important for temporal information processing. The normalisation includes conversion from the Japanese to the Western calendar, including, conversion from a 2-digit to a 4-digit calendar, and completion year (taken from the document creation time).

In the ‘TIME’ expressions, most fully specified expressions have had manual normalisation performed. The normalisation includes completion date (from the document creation time) and resolution of a.m./p.m. ambiguity.

In the ‘DURATION’ and ‘SET’ expressions, @definite ‘true’ means that the length of the temporal region on the timeline can be uniquely determined. When we map this on the timeline, we need <TLINK> information with ‘DATE’ or ‘TIME’ expressions or event expressions.

Note that we reduce the annotation target samples of <EVENT>, <MAKEINSTANCE>, and <TLINK> PN register (A), which total 54 samples. The reason is that only the PN (newspaper) sample has date-level document creation time information as metadata. Table 4 shows the statistics of <TIMEX3> in the PN (A) samples.

Table 4. <TIMEX3>: Statistics in PN (A).

<table>
<thead>
<tr>
<th>DCT or class</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCT(DATE)</td>
<td>54</td>
</tr>
<tr>
<td>DATE</td>
<td>727</td>
</tr>
<tr>
<td>TIME</td>
<td>107</td>
</tr>
<tr>
<td>DURATION</td>
<td>291</td>
</tr>
<tr>
<td>SET</td>
<td>19</td>
</tr>
<tr>
<td>ALL</td>
<td>1198</td>
</tr>
</tbody>
</table>
5.2 <EVENT> and <MAKEINSTANCE>

We annotate <EVENT> and <MAKEINSTANCE> tags only on the PN register (A). Table 5 shows the statistics of <EVENT> tags by @class. Event instances by <MAKEINSTANCE> are defined on the last seven @class in the tables. The number of <MAKEINSTANCE> is 3,839.

Table 5. <EVENT>: Statistics in PN (A).

<table>
<thead>
<tr>
<th>&lt;EVENT&gt;@class</th>
<th>count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-instance</td>
<td>(1129)</td>
</tr>
<tr>
<td>NULL</td>
<td>1114</td>
</tr>
<tr>
<td>NONE</td>
<td>15</td>
</tr>
<tr>
<td>Event instance w/o event arg</td>
<td>(2352)</td>
</tr>
<tr>
<td>OCCURRENCE</td>
<td>2352</td>
</tr>
<tr>
<td>Event instance w/ event arg</td>
<td>(1291)</td>
</tr>
<tr>
<td>REPORTING</td>
<td>126</td>
</tr>
<tr>
<td>PERCEPTION</td>
<td>27</td>
</tr>
<tr>
<td>ASPECTUAL</td>
<td>63</td>
</tr>
<tr>
<td>I_ACTION</td>
<td>880</td>
</tr>
<tr>
<td>I_STATE</td>
<td>195</td>
</tr>
<tr>
<td>State instance</td>
<td>(181)</td>
</tr>
<tr>
<td>STATE</td>
<td>181</td>
</tr>
</tbody>
</table>

5.3 <TLINK>

The three annotators were independently trained for <TLINK> annotation. The annotation was performed on four types of relations: ‘DCT,’ ‘T2E,’ ‘E2E,’ and ‘MATRIX’.

Table 6 shows annotation agreement among the 13+3+1 labels by the three annotations and relation types. The three $\cap$-connected numbers are the label counts by each of the three annotators. The right number after ‘=’ is the agreed count.

The agreed counts for ‘after,’ ‘during,’ ‘contains,’ and ‘before’ are higher than the others. These relations do not exhibit boundary matching between the two time intervals. The relation ‘equal’ is the most frequent of those that do include interval boundary matching. Other relations are infrequent and show low agreement counts across the three annotators. These findings reveal that a judgment of interval boundary matching is rare and is difficult for human annotators. The relation ‘vague’ was agreed on 314 times by the three annotators. This fact shows that the discrimination of possible worlds might
be possible by annotation.

Table 6. \(<\text{TLINK}>\): Annotation agreement by Annotators × Labels × Relation types.

<table>
<thead>
<tr>
<th>Relation types</th>
<th>DCT</th>
<th>T2E</th>
<th>E2E</th>
<th>MATRIX</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count</td>
<td>3839</td>
<td>2188</td>
<td>2972</td>
<td>1245</td>
<td>10244</td>
</tr>
<tr>
<td>after</td>
<td>2352</td>
<td>2326</td>
<td>2133</td>
<td>1961</td>
<td>3667</td>
</tr>
<tr>
<td>met-by</td>
<td>0</td>
<td>5</td>
<td>10</td>
<td>2</td>
<td>30</td>
</tr>
<tr>
<td>overlapped-by</td>
<td>11</td>
<td>15</td>
<td>4</td>
<td>2</td>
<td>73</td>
</tr>
<tr>
<td>finishes</td>
<td>2</td>
<td>10</td>
<td>11</td>
<td>1</td>
<td>18</td>
</tr>
<tr>
<td>during</td>
<td>449</td>
<td>424</td>
<td>650</td>
<td>217</td>
<td>872</td>
</tr>
<tr>
<td>started-by</td>
<td>1</td>
<td>9</td>
<td>10</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>equal</td>
<td>1</td>
<td>37</td>
<td>70</td>
<td>1</td>
<td>363</td>
</tr>
<tr>
<td>starts</td>
<td>2</td>
<td>30</td>
<td>91</td>
<td>14</td>
<td>38</td>
</tr>
<tr>
<td>contains</td>
<td>164</td>
<td>85</td>
<td>144</td>
<td>63</td>
<td>1441</td>
</tr>
<tr>
<td>finished-by</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>overlaps</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>1</td>
<td>84</td>
</tr>
<tr>
<td>meets</td>
<td>1</td>
<td>25</td>
<td>26</td>
<td>2</td>
<td>123</td>
</tr>
<tr>
<td>before</td>
<td>739</td>
<td>767</td>
<td>746</td>
<td>572</td>
<td>2604</td>
</tr>
<tr>
<td>is_included</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>identity</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>includes</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>vague</td>
<td>115</td>
<td>191</td>
<td>157</td>
<td>38</td>
<td>808</td>
</tr>
</tbody>
</table>

Annotator A ∩ Annotator B ∩ Annotator C = Agreed count

Table 7 shows agreement rates by relation type across the three evaluation schemata. We define the schemata as follows. ‘Label 13+3+1’ is the most fine-grained evaluation schema; in it, all 13+3+1 relations are discriminated. ‘Label 13+1’ is a schema without event-subevent discrimination, in which ‘is_included,’ ‘identity,’ and ‘includes’ are regarded in the same way as ‘during,’ ‘equals,’ and ‘contains,’ respectively. ‘Label 5+1’ is a TempEval-like schema, in which 13+3+1 relations are generalised into 5+1 relations: ‘BEFORE,’ ‘BEFORE-OR-OVERLAP,’ ‘OVERLAP,’ ‘OVERLAP-OR-AFTER,’ ‘AFTER,’ and ‘VAGUE’.

The agreement rate across all relations is 65.3% (Cohen’s kappa 0.733) using the most fine-grained evaluation schema (Label 13+3+1). We perform \(<\text{TLINK}>\) annotations on fixed
relation pairs for four types. TimeBank 1.2 jointly performs <TLINK> annotations without fixing the relation pairs. In this method, the <TLINK> relation agreement rate is 77% and the relation pair agreement 55%. We believe that the BCCWJ-TimeBank <TLINK> relation agreement rate is in no way inferior to that of TimeBank 1.2. Among the four relation types, the agreement rate of ‘DCT’ is the highest and that of ‘T2E’ is the second highest. The relation between a temporal information expression and an event instance is easier to determine than the relation between two event instances. This is because the interval of the temporal information expression is more easily defined on the timeline than the interval of the event instance is. Under the relaxed relation evaluation schema, the agreement rates of ‘E2E’ and ‘MATRIX’ increase. This means that, while interval boundary matching in these event instances is hard for the annotators to agree upon, interval anteroposterior relations can be agreed upon.

Table 7. <TLINK>: Annotation agreement by relation type across three evaluation schemata.

<table>
<thead>
<tr>
<th>Relation types</th>
<th>DCT</th>
<th>T2E</th>
<th>E2E</th>
<th>MATRIX</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Count</td>
<td>3839</td>
<td>2188</td>
<td>2972</td>
<td>1245</td>
<td>10244</td>
</tr>
<tr>
<td>Label 13+3+1</td>
<td>0.743(2854)</td>
<td>0.691(1513)</td>
<td>0.552(1642)</td>
<td>0.545(679)</td>
<td>0.653(6688)</td>
</tr>
<tr>
<td>Label 13+1</td>
<td>0.743(2854)</td>
<td>0.691(1513)</td>
<td>0.561(1667)</td>
<td>0.560(697)</td>
<td>0.657(6731)</td>
</tr>
<tr>
<td>Label 5+1</td>
<td>0.747(2873)</td>
<td>0.734(1605)</td>
<td>0.627(1862)</td>
<td>0.623(776)</td>
<td>0.695(7116)</td>
</tr>
</tbody>
</table>

Agreement rate(Agreed count)

Finally, Table 8 shows agreement by two entity types: DCT and TIMEX of <EVENT>@class. Relations with STATE tend to show low agreement rates, and relations between DCT/TIMEX and STATE are lower than relations between DCT/TIMEX and other event instances. This is because recognition of the time interval boundaries of state expressions is difficult for the annotators. In event instances with event arguments, relations with REPORTING and I_ACTION tend to show higher than average agreement rates.
Table 8. <TLINK>: Annotation agreement by {DCT, <TIMEX3>, <EVENT>@class} × <EVENT>@class.

<table>
<thead>
<tr>
<th></th>
<th>DCT</th>
<th>TIMEX</th>
<th>OCC</th>
<th>REP</th>
<th>PER</th>
<th>ASP</th>
<th>I_A</th>
<th>I_S</th>
<th>STA</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>OCCURRENCE</td>
<td>0.739</td>
<td>0.702</td>
<td>0.551</td>
<td>0.625</td>
<td>0.286</td>
<td>0.718</td>
<td>0.559</td>
<td>0.592</td>
<td>0.422</td>
<td>0.656</td>
</tr>
<tr>
<td>Abbr. OCC</td>
<td>(2352)</td>
<td>(1320)</td>
<td>(1602)</td>
<td>(104)</td>
<td>(7)</td>
<td>(39)</td>
<td>(494)</td>
<td>(130)</td>
<td>(102)</td>
<td>(6159)</td>
</tr>
<tr>
<td>REPORTING</td>
<td>0.881</td>
<td>0.697</td>
<td>0.663</td>
<td>0.222</td>
<td>1.000</td>
<td>0.667</td>
<td>0.519</td>
<td>0.368</td>
<td>0.500</td>
<td>0.694</td>
</tr>
<tr>
<td>Abbr. REP</td>
<td>(126)</td>
<td>(66)</td>
<td>(95)</td>
<td>(9)</td>
<td>(2)</td>
<td>(3)</td>
<td>(52)</td>
<td>(19)</td>
<td>(12)</td>
<td>(385)</td>
</tr>
<tr>
<td>PERCEPTION</td>
<td>0.815</td>
<td>0.700</td>
<td>0.444</td>
<td>NaN</td>
<td>0.000</td>
<td>NaN</td>
<td>0.500</td>
<td>1.000</td>
<td>0.000</td>
<td>0.646</td>
</tr>
<tr>
<td>Abbr. PER</td>
<td>(27)</td>
<td>(10)</td>
<td>(18)</td>
<td>(0)</td>
<td>(1)</td>
<td>(0)</td>
<td>(6)</td>
<td>(1)</td>
<td>(1)</td>
<td>(65)</td>
</tr>
<tr>
<td>ASPECTUAL</td>
<td>0.714</td>
<td>0.615</td>
<td>0.545</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.643</td>
<td>0.000</td>
<td>0.000</td>
<td>0.627</td>
</tr>
<tr>
<td>Abbr. ASP</td>
<td>(63)</td>
<td>(52)</td>
<td>(44)</td>
<td>(6)</td>
<td>(2)</td>
<td>(2)</td>
<td>(14)</td>
<td>(1)</td>
<td>(1)</td>
<td>(185)</td>
</tr>
<tr>
<td>I_ACTION</td>
<td>0.808</td>
<td>0.720</td>
<td>0.576</td>
<td>0.690</td>
<td>0.667</td>
<td>0.765</td>
<td>0.631</td>
<td>0.527</td>
<td>0.333</td>
<td>0.698</td>
</tr>
<tr>
<td>I_STATE</td>
<td>0.651</td>
<td>0.686</td>
<td>0.490</td>
<td>0.250</td>
<td>0.750</td>
<td>0.429</td>
<td>0.545</td>
<td>0.875</td>
<td>0.333</td>
<td>0.594</td>
</tr>
<tr>
<td>STATE</td>
<td>0.492</td>
<td>0.398</td>
<td>0.356</td>
<td>0.600</td>
<td>1.000</td>
<td>0.444</td>
<td>0.431</td>
<td>0.333</td>
<td>0.238</td>
<td>0.424</td>
</tr>
<tr>
<td>Abbr. STA</td>
<td>(181)</td>
<td>(83)</td>
<td>(118)</td>
<td>(5)</td>
<td>(3)</td>
<td>(9)</td>
<td>(51)</td>
<td>(9)</td>
<td>(21)</td>
<td>(481)</td>
</tr>
<tr>
<td>ALL</td>
<td>0.743</td>
<td>0.691</td>
<td>0.548</td>
<td>0.618</td>
<td>0.560</td>
<td>0.649</td>
<td>0.573</td>
<td>0.562</td>
<td>0.374</td>
<td>0.653</td>
</tr>
<tr>
<td></td>
<td>(3839)</td>
<td>(2188)</td>
<td>(2524)</td>
<td>(157)</td>
<td>(25)</td>
<td>(77)</td>
<td>(984)</td>
<td>(233)</td>
<td>(203)</td>
<td>(10244)</td>
</tr>
</tbody>
</table>

Agreement rate
(Agreed count)

6. Conclusion

This paper has presented temporal information annotation on BCCWJ. This is the first corpus-based study on Japanese temporal information annotation with the ISO-TimeML standard. We adapted the temporal information annotation specification of the original TimeML and ISO-TimeML to the Japanese language in several layers: <TIMEX3>, <EVENT>, <MAKEINSTANCE>, and <TLINK>. In addition, we introduced two annotation paradigms for linguistic research on Japanese temporal information: the MAMA-cycle annotation with a pair-programming method on <TIMEX3> and the annotation as a cognitive experiment on <TLINK>. Finally, we evaluated the cognitive process in human temporal information processing. The achieved temporal ordering agreement rates were 65.3%.

In future research, we will continue to investigate machine-learning-based temporal ordering estimation. In English temporal ordering, the tense and aspect information in <MAKEINSTANCE> are important features. In Japanese temporal ordering, however, the
morphologically overt information is ‘る(-ru)’ vs. ‘た(-ta)’ for non-past and past tense, and ‘る(-ru)’ vs. ‘ている(-teiru)’ for limited aspect. We will report the results of this temporal ordering estimation in future publications.

We also intend to take advantage of BCCWJ’s status as the first balanced large-scale shared corpus of Japanese by analysing our annotation in comparison to the syntactic and semantic annotations conducted on BCCWJ by several Japanese research institutes, as mentioned in Section 2.2. Since Japanese is a modality-rich language, the modality annotations by these other institutes will be important for temporal ordering.

Furthermore, we will continue to evaluate the cognitive process in human temporal information processing. In this study, the annotators were professionally trained. In our next study, we will use crowdsourcing with 200 experimental subjects for the temporal ordering annotation. We will compare the annotation results between trained annotators and crowdsourcing subjects and will evaluate any differences between the specialists and non-specialists to further our understanding of human temporal information processing.

Reference


Transliteration Extraction from Classical Chinese Buddhist Literature Using Conditional Random Fields with Language Models

Yu-Chun Wang*, Karol Chia-Tien Chang*, Richard Tzong-Han Tsai#, and Jieh Hsiang*

Abstract

Extracting plausible transliterations from historical literature is a key issue in historical linguistics and other research fields. In Chinese historical literature, the characters used to transliterate the same loanword may vary because of different translation eras or different Chinese language preferences among translators. To assist historical linguists and digital humanities researchers, this paper proposes a transliteration extraction method based on the conditional random field method with features based on the language models and the characteristics of the Chinese characters used in transliterations. To evaluate our method, we compiled an evaluation set from two Buddhist texts, the Samyuktagama and the Lotus Sutra. We also constructed a baseline approach with a suffix array based extraction method and phonetic similarity measurement. Our method significantly outperforms the baseline approach, and the method achieves recall of 0.9561 and precision of 0.9444. The results show our method is very effective for extracting transliterations in classical Chinese texts.

Keywords: Transliteration Extraction, Classical Chinese, Buddhist Literature, Language Model, Conditional Random Fields, CRF.

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1. Introduction

Cognates and loanwords play important roles in the research of language origins and cultural interchange. Therefore, extracting plausible cognates or loanwords from historical literature is a key issue in historical linguistics. The adoption of loanwords from other languages is usually through transliteration. In Chinese historical literature, the characters used to transliterate the same loanword may vary because of different translation eras or different Chinese language/dialect preferences among translators. For example, in classical Chinese Buddhist scriptures, the translation process of Buddhist scriptures from Sanskrit to classical Chinese occurred mainly from the 1st century to 10th century. In these works, the same Sanskrit words may be transliterated into different Chinese loanword forms. For instance, the surname of the Buddha, Gautama, is transliterated into several different forms, such as “瞿曇” (qü-tan) or “喬答摩” (qiao-da-mo), and the name “Culapanthaka” has several different Chinese transliterations, such as “朱利槃特” (zhu-li-pan-te) and “周利槃陀伽” (zhou-li-pan-tuo-qie). In order to assist researchers in historical linguistics and other digital humanities research fields, an approach to extract transliterations in classical Chinese texts is necessary.

Many transliteration extraction methods require a bilingual parallel corpus or text documents containing two languages. For example, Sherif & Kondrak (2007) proposed a method for learning the string distance measurement function from a sentence-aligned English-Arabic parallel corpus to extract transliteration pairs. Kuo et al. (2007) proposed a transliteration pair extraction method using a phonetic similarity model. Their approach is based on the general rule that, when a new English term is transliterated into Chinese (in modern Chinese texts, e.g. newswire), the English source term usually appears alongside the transliteration. To exploit this pattern, they identify all of the English terms in a Chinese text and measure the phonetic similarity between those English terms and their surrounding Chinese terms, treating the pairs with the highest similarity as the true transliteration pairs. Despite its high accuracy, this approach cannot be applied to transliteration extraction in classical Chinese literature since the prerequisite (of the source terms alongside the transliteration) does not apply.

Some researchers have tried to extract transliterations from a single language corpus. Oh & Choi (2003) proposed a Korean transliteration identification method using a Hidden Markov Model (HMM) (Rabiner, 1989). They transformed the transliteration identification problem into a sequential tagging problem in which each Korean syllable block in a Korean sentence is tagged as either belonging to a transliteration or not. They compiled a human-tagged Korean corpus to train a hidden Markov model with predefined phonetic features to extract transliteration terms from sentences by sequential tagging. Goldberg & Elhadad (2008) proposed an unsupervised Hebrew transliteration extraction method. They
adopted an English-Hebrew phoneme mapping table to convert the English terms in a named entity lexicon into all of the possible Hebrew transliteration forms. The Hebrew transliterations then were used to train a Hebrew transliteration identification model. Nevertheless, Korean and Hebrew use an alphabetical writing system, while Chinese is ideographic. These identification methods heavily depend on the phonetic characteristics of the writing system. Since Chinese characters do not necessarily reflect actual pronunciation, these methods are difficult to apply to the transliteration extraction problem in classical Chinese.

This paper proposes an approach to extract transliterations automatically in classical Chinese texts, especially Buddhist scriptures, with supervised learning models based on the probability of the characters used in transliterations and the language model features of Chinese characters.

2. Method

To extract the transliterations from the classical Chinese Buddhist scriptures, we adopted a supervised learning method, the conditional random fields (CRF) model. The features we used in the CRF model are described in the following subsections.

2.1 Probability of each Chinese Character in Transliterations

According to our observation, in the classical Chinese Buddhist texts, the Chinese characters used in transliteration show some characteristics. Translators were inclined to choose characters without obstructing the comprehension of the sentences. Although the number of Chinese characters is large, the number of possible syllables in Chinese is limited. Therefore, one Chinese character may share the same pronunciation with several other characters, and a translator may choose rarely used characters for transliteration.

Thus, the probability of a Chinese character being used in transliteration is an important feature to identify transliteration in the classical Buddhist texts. In order to measure the probability of every character used in transliterations, we collected the frequency of all the Chinese characters in the Chinese Buddhist Canon. Then, we applied the suffix array method (Manzini & Ferragina, 2004) to extract the terms with their counts from all the texts of the Chinese Buddhist Canon. The extracted terms then were filtered through a list of selected transliteration terms from the Buddhist Translation Lexicon and Ding Fubao’s Dictionary of Buddhist Studies. The extracted terms in the list were retained, and the frequency of each Chinese character was calculated. Thus, the probability of a given Chinese character \( c \) in transliteration can be defined as:
\[
\text{Prob}(c) = \log \frac{\text{freq}_{\text{trans}}(c)}{\text{freq}_{\text{all}}(c)}
\]

where \( \text{freq}_{\text{trans}}(c) \) is \( c \)'s frequency used in transliterations, and \( \text{freq}_{\text{all}}(c) \) is \( c \)'s frequency appearing in the entire Chinese Buddhist Canon. The logarithm in the formula is designed for CRF discrete feature values.

### 2.2 Character-based Language Model of the Transliteration

Transliterations may appear many times in one Buddhist sutra. The preceding character and the following character of the transliteration may be different. For example, for the phrase “於憍薩羅國” (yu-jiao-sa-luo-guo, “in Kosala state”), if we want to identify the actual transliteration, “憍薩羅” (jiao-sa-luo, Kosala), from the extra characters “於” (yu, in) and “國” (guo, state), we must first use an effective feature to identify the boundaries of the transliteration.

In order to do that, we propose a language-model-based feature. A language model assigns a probability to a sequence of \( m \) words \( P(w_1, w_2, \ldots, w_m) \) by means of a probability distribution. The probability of a sequence of \( m \) words can be transformed into a conditional probability:

\[
P(w_1, w_2, \ldots, w_m) = P(w_1)P(w_2 | w_1)P(w_3 | w_1, w_2) \cdots P(w_m | w_1, w_2, \ldots, w_{m-1})
\]

\[
= \prod_{i=1}^{m} P(w_i | w_{1:i-1})
\]

In practice, we can assume that the probability of a word only depends on its previous word (bi-gram assumption). Therefore, the probability of a sequence can be approximated as:

\[
P(w_1, w_2, \ldots, w_m) \approx \prod_{i=1}^{m} P(w_i | w_{i-1})
\]

We collected person and location names from the Buddhist Authority Database and the known Buddhist transliteration terms from The Buddhist Translation Lexicon (翻譯名義集)\(^1\) to create a dataset with 4,301 transliterations for our bi-gram language model. We used these transliterations to train the bi-gram language model. Such a language model may suffer from the sparse data problem. Nevertheless, since we adopted the language models as a feature for a supervised learning model, the sparse data problem is not serious in our approach.

After building the bi-gram language model, we applied it as a feature for the supervised model. Following the previous example, “於憍薩羅國” (yu-jiao-sa-luo-guo, “in Kosala state”), for each character in the sentence, we first computed the probability of the current

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\(^1\) [http://www.cbeta.org/result/T54/T54n2131.htm](http://www.cbeta.org/result/T54/T54n2131.htm)
character and its previous character. For the first character “於”, since there is no previous word, the probability is \( P(於) \). For the second character “橋”, the probability of the two characters is \( P(於橋) = P(於)P(橋|於) \). We then computed the probability of the second and third characters: \( P(橋薩) = P(橋)P(薩|橋) \), and so on. If the probability changes sharply from that of the previous bi-gram, the previous bi-gram may be the boundary of the transliteration. Since the character “於” rarely appears in transliterations, \( P(於橋) \) is much lower than \( P(橋薩) \). We may conclude that the left boundary is between the first two characters “於橋”.

### 2.3 Pronunciation-based Language Model of the Transliteration

In addition to the character-based language model mentioned in the previous section, we also constructed a language model based on the pronunciations instead of characters. Since many Chinese characters may have the same pronunciation, different Chinese characters might be chosen to translate the same Sanskrit term. For example, the Sanskrit term, Arhat, has different Chinese transliteration forms, such as “阿羅訶” (a-luo-he) and “阿羅呵” (a-luo-he). The last Chinese characters (“訶” and “呵”) are different, but the Chinese pronunciations are the same. Therefore, a language model based on the pronunciation instead of Chinese character may overcome this kind of character variation problem. In order to construct a pronunciation based language model, the Chinese characters have to be converted into phoneme forms.

The pronunciation of Chinese characters, however, varies diachronically and synchronically. The same Chinese characters may have been pronounced differently in different regions and eras of ancient China. Therefore, we cannot base our language model on modern Chinese pronunciation. Furthermore, Chinese characters are ideographic and the pronunciations may not be reflected by the ideogram. Thus, it is difficult to find out how a character was pronounced in the past. In the seventh century (in the Sui dynasty), a new kind of pronunciation dictionary, *Qieyun*, was published by Lu Fayan, based on five earlier rhyming dictionaries that no longer exist. As a guide to the recitation of literary texts and an aid in the composition of verse, *Qieyun* quickly became popular and became the national standard of pronunciation during the ensuing Tang dynasty (618 - 907 C.E.). Unfortunately, the actual content of the *Qieyun* did not last into the modern era. In 1008, during the Northern Song Dynasty (960 - 1127 C.E.), a group of scholars commissioned by the emperor produced an expanded revision of *Qieyun* called *Guangyun*. Until the mid-20th century, the oldest complete rhyming book known was *Guangyun*, although existing copies are marred by numerous transcription errors. Thus, all studies of the rhyming book tradition were actually based on *Guangyun*. Since the period of the Buddhist literature translation from Sanskrit to classical Chinese is mainly from Tang dynasty to Song dynasty, which all belong to middle
Chinese era, we use Guangyun as an approximation to the pronunciation of Chinese characters in middle Chinese.

Since there were no phonological symbols or alphabetical writing systems in middle Chinese, rhyming books like Guangyun record contemporary character pronunciations with fanqie “反切” analyses. Fanqie represents a character’s pronunciation with another two characters, combining the former’s “initial” and the latter’s “rhyme” and tone. An English equivalent would be to combine the initial of ‘peek’ /pʰiːk/ and the rhyme of ‘cat’ /kæt/ to get ‘pat’ /pʰæt/. Take the character “東” [tuŋ] for example. The fanqie of the character is “德紅” ([tok] and [huŋ]), so that we can get its pronunciation if we know the actual pronunciation of these two fanqie characters. Although fanqie is an effective method to represent the pronunciation of a Chinese character, it is still hard to analyze because the usage of two characters for the initial and rhyme is arbitrary. Fortunately, a revision of Guangyun included additional annotations by some scholars. They analyzed all the characters used in fanqie and categorized the homophones into groups and chose an identical Chinese character standing for the group. After the analysis, there are 36 initials and 106 rhymes in Guangyun. In addition to the initial and rhyme, there are other features added into the revision of Guangyun, such as fanqie, initial, rhyme, openness (round or unround), level (different medial vowels), and tone.

To employ the data from Guangyun in our analyses, we must first convert the Chinese characters it uses to represent pronunciation into International Phonetic Alphabet (IPA) notation. There are many researchers who have tried to reconstruct the actual pronunciations of the characters in middle Chinese. We use the reconstruction of middle Chinese pronunciation proposed by Wang Li for this task. Take the character “洪” for example. Its initial “匣” is converted to IPA [ɣ] and its rhyme “東” is converted to [uŋ], giving us a final reconstructed IPA phonemic form of [ɣuŋ].

All of the Chinese characters used to construct the language model are converted into middle Chinese IPA representations by Guangyun. Nevertheless, one Chinese character might have several pronunciations. The homographs create difficulty in converting the Chinese characters into their actual pronunciations. Nevertheless, there are few tools and resources for classical Chinese and middle Chinese to deal with this problem. Therefore, we use a heuristic method to determine the most used pronunciation for each Chinese character. We found that the Kangxi Dictionary (康熙字典) often gives the most used pronunciation first for each Chinese character. Therefore, if one Chinese character has several different fanqie pronunciations, we check the description of the character in the Kangxi Dictionary and find the first matched fanqie as the final pronunciation of the character. Take the character “解” for example. In Guangyun, the character “解” has two fanqie pronunciations: “佳買” and “胡買”. The description of the character “解” in Kangxi Dictionary is “【唐韻】
Transliteration Extraction from Classical Chinese Buddhist Literature Using Conditional Random Fields with Language Models

【正韻】佳買切【集韻】【韻會】舉解切，𢧵皆上聲。【說文】判也。从刀判牛角。【莊子·養生主】庖丁解牛。【左傳·宣四年】宰夫解黿。【前漢·陳湯傳】支解人民。【註】謂解截其四支也。⋯”

We can find the first fanqie is “佳買”. Therefore, we can determine the most used pronunciation of the character “解” is “佳買”, then convert it into IPA representation form [kai].

The feature value of the pronunciation-based language model is similar to the character-based language model described in Section 2.2. Following the previous example, “於僧行國” (in Kosala state), we first convert the characters in the sentence into IPA representation, such as [ʔ o kiu sat la kuok]. We then compute the probability of the current character and its previous character. For the first character “於” [ʔ o], since there is no previous word, the probability is \( P(ʔ o) \). For the second character “僧行” [kiu], the probability of the two characters is \( P(ʔ o \ kiu) = P(ʔ o)P(\text{kiu}|\ ʔ o) \). We then compute the probability of the second and third characters: \( P(\text{kiu sat}) = P(\text{kiu})P(\text{sat}|\text{kiu}) \), and so on.

2.4 Functional Words

We take classical Chinese functional words into consideration. These characters have special grammatical functions in classical Chinese and are seldom used to transliterate foreign names. This is a binary feature that records the character as a functional word or not. The functional words are listed as follows: 之 (zhi), 乎 (hu), 且 (qie), 兀 (yi), 邪 (ye), 於 (yu), 哉 (zai), 相 (xiang), 遂 (sui), 嗟 (jie), 與 (yu), and 唸 (yi).

2.5 Appellation and Quantifier Words

After observing the transliterations appearing in classical Chinese literature, we note that there are some specific patterns in the characters following the transliteration terms. Most of the characters following the transliteration are appellation or quantifier words, such as 山 (san, mountain), 海 (hai, sea), 國 (guo, state), 洲 (zhou, continent). Examples are 贊闍崛山 (qi-du-jui-san, Vulture mountain), 江薩羅國 (jü-sa-luo-guo, Kosala state), and 瞻部洲 (zhan-bu-zhou, Jambu continent). Therefore, we collect the Chinese characters that usually are used as appellation or quantifiers following transliterations and design this feature. This is a binary feature that records whether a character is used as an appellation or quantifier word or not.

2.6 CRF Model Training

We adopted the supervised learning models, conditional random field (CRF) (Lafferty et al., 2011), to extract the transliterations in classical Buddhist texts. For the CRF model, we formulated the transliteration extraction problem as a sequential tagging problem.
2.6.1 Conditional Random Fields

Conditional random fields (CRFs) are undirected graphical models trained to maximize a conditional probability (Lafferty et al., 2011). A linear-chain CRF with parameters $\Lambda = \lambda_1, \lambda_2, \ldots$ defines a conditional probability for a state sequence $y = y_1 \ldots y_T$, given that an input sequence $x = x_1 \ldots x_T$ is

$$P_{\Lambda}(y | x) = \frac{1}{Z_x} \exp \left( \sum_{t=1}^{T} \sum_{k} \lambda_k f_k(y_{t-1}, y_t, x_t) \right)$$

where $Z_x$ is the normalization factor that makes the probability of all state sequences sum to one, $f_k(y_{t-1}, y_t, x_t)$ is often a binary-valued feature function, and $\lambda_k$ is its weight. The feature functions can measure any aspect of a state transition, $y_{t-1} \rightarrow y_t$, and the entire observation sequence, $x$, centered at the current time step, $t$. For example, one feature function might have the value 1 when $y_{t-1}$ is the state B, $y_t$ is the state I, and $x_t$ is the character “國” (guo). Large positive values for $\lambda_k$ indicate a preference for such an event; large negative values make the event unlikely.

The most probable label sequence for $x$,

$$y^* = \arg \max_y P_{\Lambda}(y | x)$$

(5)

can be efficiently determined using the Viterbi algorithm.

2.6.2 Sequential Tagging and Feature Template

The classical Buddhist texts were separated into sentences by the Chinese punctuation. Then, each character in the sentences was taken as a data row for CRF model. We adopted the tagging approach motivated by the Chinese segmentation (Tsai et al., 2006) which treats Chinese segmentation as a tagging problem. The characters in a sentence are tagged in B class if it is the first character of a transliteration word or in I class if it is in a transliteration word but not the first character. The characters that do not belong to a transliteration word are tagged in O class. We adopted the CRF++ open source toolkit\(^2\). We trained our CRF models with the unigram and bigram features over the input Chinese character sequences. The features are shown as follows.

Unigram: $s_{-2}, s_{-1}, s_{0}, s_{1}, s_{2}$

Bigram: $s_{-1} s_{0}, s_{0} s_{1}$

\(^2\) http://crfpp.googlecode.com
where the current substring is $s_0$ and $s_i$ is other characters relative to the position of the current character.

3. Evaluation

3.1 Data Set

We chose Samyuktagama (雜阿含經), a Buddhist scripture from the Chinese Buddhist Canon maintained by Chinese Buddhist Electronic Text Association (CBETA), as our data set for evaluation. The Samyuktagama is one of the most important scriptures in Early Buddhism and contains a lot of transliterations because it records in detail the teachings and the lives of the Buddha and many of his disciples.

The Samyuktagama is an early Buddhist scripture collected shortly after the Buddha’s death. The term agama in Buddhism refers to a collection of discourses, and the name Samyuktagama means “connected discourses”. It is among the most important sutras in Early Buddhism. The authorship of the Samyuktagama is traditionally attributed to Mahakssyapa, Buddha’s disciple, and five hundred Arhats three months after the Buddha’s death. An Indian monk, Gunabhadra, translated this sutra into classical Chinese in the Liu Song dynasty around 443 C.E. The classical Chinese Samyuktagama has 50 volumes containing about 660,000 characters. As the amount of text in the Samyuktagama is immense, we took the first 20 volumes as the training set, and the last 10 volumes as the test set.

We also wanted to see whether the supervised learning model trained by one Buddhist scripture can be applied to another Buddhist scripture translated in a different era. Therefore, we chose another scripture, the Lotus Sutra (妙法蓮華經), to create another test set. The Lotus sutra is a famous Mahayana Buddhist scripture probably written down between 100 BC and 100 C.E. The earliest known Sanskrit title for the sutra is the Saddharma Pundarika Sutra, which translates to “the Good Dharma Lotus Flower Sutra”. In English, the shortened form Lotus Sutra is common. The Lotus Sutra has been regarded highly in a number of Asian countries where Mahayana Buddhism traditionally has been practiced, such as China, Japan, and Korea. The Lotus Sutra has several classical Chinese translation versions. The most widely used version was translated by Kumarajiva (鳩摩羅什 in Chinese) in 406 C.E. It has eight volumes and 28 chapters containing more than 25,000 characters. We selected the first 5 chapters as a different test set to evaluate our method.

3.2 Baseline Method

There are a few research projects focused on transliteration extraction from classical Chinese literature. Nevertheless, in order to compare and show the effectiveness of our method, we constructed a baseline system with widely used information extraction methods. Since many
previous research projects on transliteration extraction are based on phonetic similarity or phoneme mapping approaches, we also used these methods to construct the baseline system. First, the baseline system used the suffix array method to extract all the possible terms for the classical Chinese Buddhist scriptures. Then, the extracted terms were converted into Pinyin sequences by a modern Chinese pronunciation dictionary. We also adopted the collected transliteration list used in Section 2.1 and converted the transliterations into Pinyin sequences. Next, for each extracted term, the baseline system measured the Levenshtein distance between the Pinyin sequences of the extracted terms and all the transliterations as the phonetic similarity. If the extracted term had a Levenshtein distance less than the threshold (distance $\leq 3$ in our baseline) from one of the transliterations we collected, the extracted term would be regarded as a transliteration; otherwise, the term would be dropped.

### 3.3 Evaluation Metrics

We used two evaluation metrics, recall and precision, to estimate the performance of our system. Recall and precision are widely used measurements in many research fields, such as information retrieval and information extraction (Manning et al., 2008). In digital humanities, a key issue is the coverage of the extraction method. To maximize usefulness to researchers, a method should be able to extract as many potential transliterations from literature as possible. Therefore, in our evaluation, we used recall, defined as follows:

$$\text{Recall} = \frac{|\text{Correctly extracted transliterations}|}{|\text{Transliterations in the data set}|}$$  \hspace{1cm} (6)

In addition, the correctness of the extracted transliterations is also important. To avoid wasting time on useless information, a method should be able to extract correct transliterations from literature as much as possible. Thus, we also used precision, defined as follows:

$$\text{Precision} = \frac{|\text{Correctly extracted transliterations}|}{|\text{All extracted transliterations}|}$$  \hspace{1cm} (7)

With precision and recall, the F-score measurement also was adopted as a weighted average of the precision and recall. The F1-score is defined as follows:

$$F_{1}\text{-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$  \hspace{1cm} (8)

### 3.4 Evaluation Results

Table 1 shows the results of our method with two different language models and the baseline system on different test sets. The gold standards of these two test sets were compiled by human experts who examined all of the sentences in the test sets and recognized each
transliteration for evaluation. The results show that our method with the character-based language model could extract 95.61% of the transliterations in the Sumyuktagama and 94.74% in the Lotus Sutra. On the precision measurement, our method also achieved pretty good results, which show that most of the terms our method extract are actual transliterations. The pronunciation-based language model does not perform well as the character-based one in both recall and precision metrics.

Table 1. Evaluation results of transliteration extraction.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Precision</th>
<th>Recall</th>
<th>(F_1)-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our Approach</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(character-based LM)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samyuktagama</td>
<td>0.8810</td>
<td>0.9561</td>
<td>0.9170</td>
</tr>
<tr>
<td>Lotus Sutra</td>
<td>0.9444</td>
<td>0.9474</td>
<td>0.9459</td>
</tr>
<tr>
<td>Our Approach</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(pronunciation-based LM)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samyuktagama</td>
<td>0.8477</td>
<td>0.7530</td>
<td>0.7975</td>
</tr>
<tr>
<td>Lotus Sutra</td>
<td>0.2081</td>
<td>0.6447</td>
<td>0.3146</td>
</tr>
<tr>
<td>Our Approach</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(character &amp; pronunciation based LM)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samyuktagama</td>
<td>0.8224</td>
<td>0.7349</td>
<td>0.7762</td>
</tr>
<tr>
<td>Lotus Sutra</td>
<td>0.4581</td>
<td>0.7763</td>
<td>0.5762</td>
</tr>
<tr>
<td>Baseline</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samyuktagama</td>
<td>0.0399</td>
<td>0.7771</td>
<td>0.0759</td>
</tr>
<tr>
<td>Lotus Sutra</td>
<td>0.0146</td>
<td>0.5789</td>
<td>0.2848</td>
</tr>
</tbody>
</table>

Our method outperforms the baseline system. The baseline system cannot extract most transliterations due to the limit of the suffix array method since the suffix array method only extracts the terms that appear twice or more often in the context. Furthermore, phonetic similarity is not effective to filter the transliterations, which causes the low precision performance of the baseline method. These results demonstrate that our method can save humanities researchers a lot of labor-intensive work in examining the transliteration.

4. Discussion

4.1 Effectiveness of Transliteration Extraction

Our method can extract many transliterations from the Samyuktagama, such as “迦毘羅衛” (jia-pi-luo-wei, Kapilavastu, the name of an ancient kingdom where the Buddha was born and raised), “尼拘律” (ni-jü-lü, Nyagro, the forest name in the Kapilavastu kingdom), and “摩伽陀” (muo-qie-tuo, Magadha, the name of an ancient Indian kingdom). These transliterations do not appear in the training set, but our method can still identify them. In addition, our method also discovered many transliterations in the Lotus Sutra that do not appear in the Samyuktagama, such as “娑伽羅” (suo-qie-luo, Sagara, the name of the king of the sea world in ancient Indian mythology), “鳩槃茶 / 鳩槃茶”
Kumbhanda, one of a group of dwarfish, misshapen spirits among the lesser deities of Buddhist mythology), and “阿鞞跋致” (a-pi-ba-zhi, Avaivart, “not turn back” in Sanskrit). Since the characteristics of the Lotus Sutra are different from the Samyuktagama in many aspects, it shows that the supervised learning model trained by one Buddhist scripture may apply to other Buddhist scriptures translated in different eras and translators.

We have also discovered that transliterations may vary even in the same scripture. In the Samyuktagama, the Sanskrit term “Chandala” (someone who deals with the disposal of corpses and is a Hindu lower caste, formerly considered untouchable) has two different transliterations: “旃陀羅” (zhan-tuo-luo) and “栴陀羅” (zhan-tuo-luo).

The Sanskrit term “Magadha” (the name of an ancient Indian kingdom) has three different transliterations: “摩竭陀” (muo-jie-tuo), “摩竭提” (muo-jie-ti), and “摩伽陀” (muo-qie-tuo). The variations of the transliterations of the same word give clues of who the translators were and the progress of the translations. These variations may help the study of historical Chinese phonology and philology.

4.2 Comparison between Character-based and Pronunciation-based Language Models

From the evaluation results, we find that the pronunciation-based language model approach does not perform as well as the character-based one. Especially for the Lotus Sutra data set, the precision of the pronunciation-based approach drops sharply. Many non-transliteration candidates are extracted by the approach with the pronunciation-based language model, such as “逮得”, “何因”, “悅可”, “後必憂”, and “但離”. Since the pronunciation-based language model only considers the pronunciations instead of the actual characters and semantics, some terms that are not transliterations but have similar pronunciation patterns to those used in transliterations are extracted as false positives. The results also show that the supervised learning model with the pronunciation-based language model trained by the Samyuktagama does not predict well on other Buddhist literature, such as the Lotus Sutra. Since these two Buddhist works have many differences in content, the model that is only based on pronunciation cannot deal with the differences to get better results.

4.3 Error Cases

Although our method can extract and identify most transliteration pairs, some transliteration pairs cannot be identified. The error cases can be divided into several categories. The first one is that a few terms cannot be extracted, such as “闍維” (she-wei, Jhapita, cremation, a monk’s funeral pyre). This transliteration is seldom used and only appears three times in the final part of the Samyuktagama. The widely used transliteration of the term “Jhapita” is “荼
The other case is incorrect boundaries of the transliterations. Sometimes, our method may extract shorter terms, such as “韋提” (wei-ti, correct transliteration is “韋提希”, wei-ti-xi, Vaidehi, a female person name), “波羅” (po-luo, correct transliteration is “波羅柰”, po-luo-nai, Varanasi, a location name in Northern India), “瞿利摩羅” (qü-li-muo-luo, correct transliteration is “央瞿利摩羅”, yang-qü-li-muo-luo, Angulimala, one of the Buddha’s disciples). This problem is due to the probability generated by the language model. For example, the probability of the first two characters of the transliteration “央瞿利摩羅”, P央瞿, is very low. This causes the CRF model to predict that the first character “央” (yang) does not belong to the transliteration. If more transliterations can be collected to build a better language model, this problem can be overcome.

In some cases, our method extracts longer terms, such as “阿那律陀夜” (a-na-lü-tuo-ye) while the correct transliteration is “阿那律陀”, (a-na-lü-tuo, Aniruddha, one of the Buddha’s closest disciples); and “兒富那婆藪” (er-fu-na-po-sou), while the correct transliteration is “富那婆藪” (fu-na-po-sou, Punabbasu, a kind of ghost in Buddhist mythology). In these cases, the preceding or following characters are often used in transliterations. There are cases where a transliteration is immediately followed by another transliteration. For example, our method extracts the term “闡陀舍利” (chan-tuo-she-li), which actually comprises two transliteration terms “闡陀” (chan-tuo, Chanda, one of the Buddhist’s disciples) and “舍利” (she-li, Sarira, Buddhist relics). It is difficult to separate them without any additional semantic clues. Although our method sometimes might extract incomplete transliterations with incorrect boundary, checking the boundary of a transliteration is not difficult for a human expert. Therefore, the extracted incorrect transliterations also have the benefit of helping humanities researchers quickly find and check plausible transliterations.

5. Conclusion

The transliteration extraction of foreign loanwords is an important task in research fields, such as historical linguistics and digital humanities. We propose an approach that can extract transliteration automatically from classical Chinese Buddhist scriptures. Our approach comprises the conditional random fields method with designed features that are suitable to identify transliteration characters based on language models and textual characteristics. The first feature is the probability of each Chinese character used in transliterations. The second feature is probability of the sequential bigram characters or phonemic representations measured by the language model method. In addition, functional words, appellation, and
quantifier words are regarded as binary features. The transliteration extraction problem is formulated as a sequential tagging problem, and the CRF method is used to train a model to extract the transliterations from the input classical Chinese sentences. To evaluate our method, we constructed an evaluation set from the two Buddhist texts, the Samyuktagama and the Lotus Sutra, which were translated into Chinese in different eras. We also constructed a baseline system with a suffix array based extraction method and phonetic similarity measurement for comparison. The recall of our method achieved 0.9561 and the precision was 0.9444. The results show our method outperforms the baseline system and is effective for extracting transliterations from classical Chinese texts. Our method can find the transliterations among the immense classical literature to help many research fields, such as historical linguistics and philology.

Reference


Modeling Human Inference Process for Textual Entailment Recognition

Hen-Hsen Huang*, Kai-Chun Chang* and Hsin-Hsi Chen*

Abstract
To prepare an evaluation dataset for textual entailment (TE) recognition, human annotators label rich linguistic phenomena on text and hypothesis expressions. These phenomena illustrate implicit human inference process to determine the relations of given text-hypothesis pairs. This paper aims at understanding what human think in TE recognition process and modeling their thinking process to deal with this problem. At first, we analyze a labelled RTE-5 test set which has been annotated with 39 linguistic phenomena of 5 aspects by Mark Sammons et al., and find that the negative entailment phenomena are very effective features for TE recognition. Then, a rule-based method and a machine learning method are proposed to extract this kind of phenomena from text-hypothesis pairs automatically. Though the systems with the machine-extracted knowledge cannot be comparable to the systems with human-labelled knowledge, they provide a new direction to think TE problems. We further annotate the negative entailment phenomena on Chinese text-hypothesis pairs in NTCIR-9 RITE-1 task, and conclude the same findings as that on the English RTE-5 datasets.

Keywords: Textual Entailment Recognition, Chinese Processing, Semantic.

1. Introduction
Textual Entailment (TE) is a directional relationship between pairs of text expressions, text ($T$) and hypothesis ($H$). Given a text pair $T$ and $H$, if human would consider that the meaning of $H$ is right by using the information of $T$, then we can infer $H$ from $T$ and say that $T$ entails $H$ (Dagan, Glickman, & Magnini, 2006). (S1) shows an example where $T$ entails $H$.

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(S1) **T:** Norway’s most famous painting, ‘The Scream’ by Edvard Munch, was recovered Saturday, almost three months after it was stolen from an Oslo museum.  
**H:** Edvard Munch painted ‘The Scream’.

Because such an inference is important in many applications (Androutsopoulos & Malakasiotis, 2010), the researches on textual entailment have attracted much attention in recent years. Recognizing Textual Entailment (RTE) (Bentivogli et al., 2011), a series of evaluations on the developments of English TE recognition technologies, have been held seven times up to 2011. In the meanwhile, TE recognition technologies in other languages are also underway. The 9th NTCIR Workshop Meeting first introduced a TE task in Chinese and in Japanese called Recognizing Inference in Text (RITE-1) into the IR series evaluation (Shima et al., 2011).

The overall accuracy is used as the only evaluation metric in most TE recognition tasks (Androutsopoulos & Malakasiotis, 2010). However, it is hard to examine the characteristics of a system when only considering its performance by accuracy. Sammons et al., (2010) proposed an evaluation metric to examine the characteristics of a TE recognition system. They annotated text-hypothesis pairs selected from the RTE-5 test set with a series of linguistic phenomena required in the human inference process. When annotators assume that some linguistic phenomena appear in their inference process to determine whether T entails H, they would label the T-H pair with these phenomena. The RTE systems are evaluated by the new indicators, such as how many T-H pairs annotated with a particular phenomenon can be correctly recognized. The indicators can tell developers which systems are better to deal with T-H pairs with the appearance of which phenomenon. On the other hand, that would give developers a direction to enhance RTE systems.

For example, (S2) is an instance that matches the linguistic phenomena Exclusive Relation, and this phenomenon suggests T does not entail H. More than one argument of H, i.e., Venus Williams, Marion Bartoli, 2007, and Wimbledon Championships, appear in T, but the relation defeated in H contracts the relation triumphed in T.

(S2) **T:** Venus Williams triumphed over Marion Bartoli of France 6-4, 6-1 yesterday to win the Women's Singles event at the 2007 Wimbledon Championships. For the first time, an American and Frenchwoman were matched up to compete for the British women's singles title. A Wimbledon champion in 2000, 2001 and 2005, Williams was not the favorite to win the title again this year. Currently ranked 23rd in the world, she entered the tournament in the shadow of her sister, Serena Williams.
**H**: Venus Williams was defeated by Marion Bartoli at the 2007 Wimbledon Championships.

Such linguistic phenomena are thought as crucial in the human inference process by annotators. In the RITE-2 in the 10th NTCIR Workshop Meeting, some linguistic phenomena for TE in Japanese are reported in the unit task subtask (Watanabe et al., 2013). In a similar manner, types of some linguistic phenomena in Chinese are consulted in the RITE-VAL task in the 11th NTCIR Workshop Meeting. In this paper, we use this valuable resource from a different aspect. Instead of using the labelled linguistic phenomena in the evaluation of TE recognition, we aim at knowing the ultimate performance of TE recognition systems which embody human knowledge in the inference process. The experiments show five negative entailment phenomena may be strong features for TE recognition, and this finding confirms the previous study of Vanderwende et al (2006). Moreover, we propose a method to acquire the linguistic phenomena automatically and use them in TE recognition. Our method is evaluated on both the English RTE-5 dataset and the Chinese NTCIR-9 RITE-1 dataset. Experimental results show that our method achieves decent performances near the average performances of RTE-5 and NTCIR-9 RITE-1. Compared to the other methods incorporating a lot of features, only a tiny number of binary features are required by our methods.

This paper is organized as follows. In Section 2 we introduce the linguistic phenomena used by annotators in the inference process, do a series of analyses on the human annotated dataset released by Mark Sammons et al., and point out five significant negative entailment phenomena. Section 3 specifies the five negative entailment phenomena in detail, proposes a rule-based method and a machine learning method to extract them from T-H pairs automatically, and discuss their effects on TE recognition. In Section 4, we extend the methodology to the BC (binary class subtask) dataset distributed by NTCIR-9 RITE-1 task (Shima et al., 2011), annotate the dataset similar to the schema of Sammons et al. (2010), discuss if the negative entailment phenomena also appear in Chinese T-H pairs, and show their effects on TE in Chinese. Section 5 concludes the remarks.

### 2. Analyses of Human Inference Process in Textual Entailment

We regard the human annotated phenomena as features in recognizing the binary entailment relation between the given T-H pairs, i.e., ENTAILMENT and NO ENTAILMENT. Total 210 T-H pairs were chosen from the RTE-5 test set by Sammons et al. (2010), and total 39 linguistic phenomena divided into the following 5 aspects as follows, including knowledge domains, hypothesis structures, inference phenomena, negative entailment phenomena, and

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1. https://sites.google.com/site/ntcir11riteval/home-ct/task-guideline
knowledge resources, are annotated on the selected dataset. Table 1 summarizes the phenomena in the five aspects.

(a) **Knowledge Domains (Hypothesis Types)**: Each phenomenon in this aspect denotes whether the information in H belongs to the corresponding knowledge domain.

(b) **Hypothesis Structures**: Each phenomenon in this aspect denotes whether the H contains elements of the corresponding type.

(c) **Inference Phenomena**: Each phenomenon in this aspect indicates the corresponding linguistic phenomenon which is used to infer H from T.

(d) **Negative Entailment Phenomena**: Each phenomenon in this aspect is a pattern which may appear in negative entailment instances.

(e) **Knowledge Resources**: Each phenomenon in this aspect is a kind of knowledge or common senses which are required in the inference process in textual entailment.

<p>| Table 1. Five aspects of linguistic phenomena relating to textual entailment. |</p>
<table>
<thead>
<tr>
<th>Aspect</th>
<th>Phenomena Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Domains</td>
<td>“be in”, “cause”, “come from”, “create”, “die/injure/kill”, “group”, “kinship”, “name”, “win/compete”, “work”</td>
</tr>
<tr>
<td>Hypothesis Structures</td>
<td>“has Named Entity”, “has Numerical Quantity”, “has implicit relation”, “has locative argument”, “has nominalization relation”, “has temporal argument”</td>
</tr>
<tr>
<td>Knowledge Resources</td>
<td>“event chain”, “factoid”, “parent-sibling”, “simple rewrite rule”, “spatial reasoning”, “numeric reasoning”</td>
</tr>
</tbody>
</table>

2.1 Five Aspects as Features

We train SVM classifiers to evaluate the performances of the five aspects of phenomena as features for TE recognition. The implementation LIBSVM with the RBF kernel (Chang & Lin, 2011) is adopted to develop classifiers with the parameters tuned by grid search. The experiments are done with 10-fold cross validation.
For the dataset of Sammons et al. (2010), two annotators are involved in labeling the above 39 linguistic phenomena on the T-H pairs. They may agree or disagree in the annotation. In the experiments, we consider the effects of their agreement. Table 2 shows the results. Five aspects are first regarded as individual features, and then merged together. The two schemes, Annotator 1 and Annotator 2, mean the phenomena labelled by annotator 1 and annotator 2 are used as features, respectively. The scheme “1 AND 2”, a strict criterion, denotes a phenomenon exists in a T-H pair only if both annotators agree with its appearance. In contrast, the scheme “1 OR 2”, a looser criterion, denotes a phenomenon exists in a T-H pair if at least one annotator marks its appearance.

We can see that the aspect of negative entailment phenomena is the most significant features of the five aspects. With only 9 phenomena in this aspect, the SVM classifier achieves accuracy above 90% no matter which labeling schemes are adopted. Comparatively, the best accuracy in RTE-5 task is 73.5% (Iftene & Moruz, 2009). In negative entailment phenomena aspect, the “1 OR 2” scheme achieves the best accuracy whereas the performances of Annotator 1 and “1 OR 2” are the same in the setting with all the five aspects as features. In the following experiments, we adopt this labeling scheme.

Table 2. The accuracy of recognizing binary TE relation with the five aspects as features.

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Annotator 1</th>
<th>Annotator 2</th>
<th>1 AND 2</th>
<th>1 OR 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Domains</td>
<td>50.95%</td>
<td>52.38%</td>
<td>52.38%</td>
<td>50.95%</td>
</tr>
<tr>
<td>Hypothesis Structures</td>
<td>50.95%</td>
<td>51.90%</td>
<td>50.95%</td>
<td>51.90%</td>
</tr>
<tr>
<td>Inference Phenomena</td>
<td>74.29%</td>
<td>72.38%</td>
<td>72.86%</td>
<td>74.76%</td>
</tr>
<tr>
<td>Negative Entailment Phenomena</td>
<td>97.14%</td>
<td>95.71%</td>
<td>92.38%</td>
<td>97.62%</td>
</tr>
<tr>
<td>Knowledge Resources</td>
<td>69.05%</td>
<td>69.52%</td>
<td>67.62%</td>
<td>69.52%</td>
</tr>
<tr>
<td>ALL</td>
<td>97.14%</td>
<td>92.20%</td>
<td>90.48%</td>
<td>97.14%</td>
</tr>
</tbody>
</table>

2.2 Negative Entailment Phenomena

There is a large gap between negative entailment phenomena aspect and the second effective aspect (i.e., inference phenomena). Moreover, using the negative entailment phenomena aspect as features only is even better than using all the 39 linguistic phenomena as features. We further analyze which negative entailment phenomena are more significant.

There are nine linguistic phenomena in the aspect of negative entailment phenomena. We take each phenomenon as a single feature to do the task of two-way textual entailment recognition. Table 3 shows the experimental results. The first column is the phenomenon ID, the second column is the phenomenon, and the third column is the accuracy of using the
phenomenon in the binary classification. Comparing with the best accuracy 97.62% shown in Table 2, the highest accuracy in Table 3 is 69.52%, when missing argument is adopted. Each phenomenon may be suitable for some T-H pairs, and consequently all negative entailment phenomena together achieve the best performance.

Table 3. Accuracy of recognizing TE relation with individual negative entailment phenomena.

<table>
<thead>
<tr>
<th>Phenomenon ID</th>
<th>Negative entailment Phenomenon</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Name Entity mismatch</td>
<td>60.95%</td>
</tr>
<tr>
<td>1</td>
<td>Numeric Quantity mismatch</td>
<td>54.76%</td>
</tr>
<tr>
<td>2</td>
<td>Disconnected argument</td>
<td>55.24%</td>
</tr>
<tr>
<td>3</td>
<td>Disconnected relation</td>
<td>57.62%</td>
</tr>
<tr>
<td>4</td>
<td>Exclusive argument</td>
<td>61.90%</td>
</tr>
<tr>
<td>5</td>
<td>Exclusive relation</td>
<td>56.67%</td>
</tr>
<tr>
<td>6</td>
<td>Missing modifier</td>
<td>56.19%</td>
</tr>
<tr>
<td>7</td>
<td>Missing argument</td>
<td>69.52%</td>
</tr>
<tr>
<td>8</td>
<td>Missing relation</td>
<td>68.57%</td>
</tr>
</tbody>
</table>

We consider all possible combinations of these 9 negative entailment phenomena, i.e., \( C_1^9 + \ldots + C_9^9 \) = 511 feature settings, and use each feature setting to do the task of two-way entailment relation recognition by SVM classifiers. The notation \( C_n^m \) denotes a set of \( m!/(m-n)! \times n! \) feature settings, each with \( n \) features. For the sake of paper space, we only list the best 4 results in each combination set \( C_n^m \) shown in Table 4. Each feature setting is denoted by a set of phenomenon IDs enclosed parentheses. The notations between combination sets \( C_1^9 \sim C_4^9 \) and \( C_5^9 \sim C_8^9 \) are a slight difference because of the table space. For clarification, we list the phenomena not involved in the combination sets \( C_5^9 \sim C_8^9 \). For example, the notation “\( -(0,1,2,6) \)” equals to the notation “\( (3,4,5,7,8) \)”, which means the feature setting is composed of disconnected relation (ID: 3), exclusive argument (ID: 4), exclusive relation (ID: 5), missing argument (ID: 7) and missing relation (ID: 8).

The model using all nine phenomena achieves the best accuracy of 97.62%. Examining the combination sets, we find phenomena IDs 3, 4, 5, 7 and 8 appear quite often in the top 4 feature settings of each combination set. In fact, this setting achieves an accuracy of 95.24%, which is the best performance in \( C_5^9 \) combination set. On the one hand, adding more phenomena into \( (3, 4, 5, 7, 8) \) setting does not have much performance difference. On the other hand, removing some phenomena from \( (3, 4, 5, 7, 8) \) setting or adopting features rather than these phenomena decreases the performance. The best performance of using the feature
setting (-0.6), i.e., only 7 phenomena, is the same as that of using all 9 phenomena shown in Table 2.

**Table 4. Accuracy of combination of negative entailment phenomena.**

<table>
<thead>
<tr>
<th>$C_0^0$</th>
<th>$C_0^1$</th>
<th>$C_0^2$</th>
<th>$C_0^3$</th>
<th>$C_0^4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>-(-0)</td>
<td>97.62%</td>
<td>97.62%</td>
<td>96.67%</td>
<td>-(-0,1,2,6)</td>
</tr>
<tr>
<td>-(-1)</td>
<td>97.62%</td>
<td>97.14%</td>
<td>96.19%</td>
<td>-(-0,1,3,6)</td>
</tr>
<tr>
<td>-(-2)</td>
<td>97.14%</td>
<td>96.67%</td>
<td>96.19%</td>
<td>-(-1,2,3,6)</td>
</tr>
</tbody>
</table>

We follow Sammons et al.’s definitions (2010) and describe the five significant negative entailment phenomena (3, 4, 5, 7, 8) as follows.

(a) **Disconnected Relation**: The arguments and the relations in H are all matched by counterparts in T. None of the arguments in T is connected to the matching relation.

(b) **Exclusive Argument**: There is a relation common to both H and T, but one argument is matched in a way that makes H contradict T.

(c) **Exclusive Relation**: There are two or more arguments in H that are also related in T, but by a relation that means H contradicting T.

(d) **Missing Argument**: Entailment fails because an argument in H is not present in T, either explicitly or implicitly.

(e) **Missing Relation**: Entailment fails because a relation in H is not present in T, either explicitly or implicitly.

The correlations between these five phenomena are shown in Table 5. Each row presents the T-H pairs which are labelled with the corresponding negative entailment phenomenon by the scheme “1 OR 2”. Each column in each row denotes the percentage of the T-H pairs which are also labelled with another negative entailment phenomenon. For example, the number of the T-H pairs which are labelled with “Disconnected Relation” is 14, and 2 of the 14 T-H pairs are also labelled with “Missing Argument”. Therefore, the column “Missing Argument” in the
row “Disconnected Relation” shows the number 2/14 = 14.29%. Table 5 shows the low correlations between most significant negative entailment phenomena. In other words, these phenomena are complementary.

Table 5. Correlations between the five significant negative entailment phenomena.

<table>
<thead>
<tr>
<th></th>
<th>Disconnected Relation</th>
<th>Exclusive Argument</th>
<th>Exclusive Relation</th>
<th>Missing Argument</th>
<th>Missing Relation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disconnected Relation</td>
<td>100.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>14.29%</td>
<td>42.86%</td>
</tr>
<tr>
<td>Exclusive Argument</td>
<td>0.00%</td>
<td>100.00%</td>
<td>8.70%</td>
<td>8.70%</td>
<td>8.70%</td>
</tr>
<tr>
<td>Exclusive Relation</td>
<td>0.00%</td>
<td>16.67%</td>
<td>100.00%</td>
<td>0.00%</td>
<td>16.67%</td>
</tr>
<tr>
<td>Missing Argument</td>
<td>4.88%</td>
<td>4.88%</td>
<td>0.00%</td>
<td>100.00%</td>
<td>41.46%</td>
</tr>
<tr>
<td>Missing Relation</td>
<td>15.38%</td>
<td>5.13%</td>
<td>5.13%</td>
<td>43.59%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Number of Occurrences</td>
<td>14</td>
<td>23</td>
<td>12</td>
<td>41</td>
<td>39</td>
</tr>
</tbody>
</table>

In the above experiments, we do all the analyses on the corpus annotated with linguistic phenomena by human. In some sense, we aim at knowing the ultimate performance of TE recognition systems embodying human knowledge in the inference. Of course, the human knowledge in the inference cannot be captured by TE recognition systems fully correctly. In the later experiments, we explore the five critical features, (3,4,5,7,8), and examine how the performance is achieved if they are extracted automatically.

3. Negative Entailment Phenomena Extraction

The experimental results in Section 2.2 show that disconnected relation, exclusive argument, exclusive relation, missing argument, and missing relation are significant. Our experiments show the combination of these five phenomena is even more powerful. Vanderwende et al. (2006) suggested some phenomena that are the clue to false entailments. To model the annotator’s inference process, we must first determine the arguments and the relations existing in T and H, and then align the arguments and relations in H to the related ones in T. It is easy for human to find the important parts in a text description in the inference process, but it is challenging for a machine to determine what words are important and what are not, and to detect the boundary of arguments and relations. Moreover, two arguments (relations) of strong semantic relatedness is not always literal identical.
In the following, two methods are proposed to extract the phenomena from T-H pairs automatically in Section 3.2 and Section 3.3. The pre-processing of the pairs is described in Section 3.1.

### 3.1 Preprocessing

Before extraction, the English T-H pairs are pre-processed according to following considerations.

(a) **Numerical Character Transformation**: All the numerical values are normalized to a single format. The fractional numbers and percentages are converted to real numbers.

(b) **Stemming**: The stemming is performed to each word in the T-H pair with NLTK (Bird, 2002).

(c) **Part-of-Speech Tagging**: Stanford Parser is performed to tagging each word in the T-H pair (Levy & Manning, 2003).

(d) **Dependency Parsing**: Stanford Parser also generates the dependency pairs from T and H (de Marneffe et al., 2006). The results of dependency parsing contain crucial information for capturing negative entailment phenomena.

### 3.2 A Rule-Based Method

Noun phrases are the fundamental elements for comparing the existences of entailment. Given a T-H pair, we first extract 4 sets of noun phrases based on their POS tags: \{noun in H\}, \{named entity (nnp) in H\}, \{compound noun (cnn) in T\}, and \{compound noun (cnn) in H\}. Then, we extract 2 sets of relations: \{relation in H\} and \{relation in T\}, where each relation in the sets is in a form of \textit{Predicate(Argument1, Argument2)}. Some typical examples of relations are \textit{verb(subject, object)} for verb phrases, \textit{neg(A, B)} for negations, \textit{num(Noun, number)} for numeric modifier, and \textit{tmod(C, temporal argument)} for temporal modifier. A predicate has only 2 arguments in this representation. Thus, a di-transitive verb is in terms of two relations.

Instead of measuring the relatedness of T-H pairs by comparing T and H on the predicate-argument structure (Wang & Zhang, 2009), our method tries to find the five negative entailment phenomena based on the similar representation. Each of the five negative entailment phenomena is extracted as follows according to their definitions. To reduce the error propagation which may be arisen from the parsing errors, we directly match those nouns and named entities appearing in H to the text in T. Furthermore, we introduce WordNet to align synonyms in H and T.
(a) **Disconnected Relation**: If (1) for each \( a \in \{ \text{noun in H} \} \cup \{ \text{nnp in H} \} \cup \{ \text{cnn in H} \} \), we can find \( a \in T \) too, and (2) for each \( r_1 = h(a_1, a_2) \in \{ \text{relation in H} \} \), we can find a relation \( r_2 = h(a_3, a_4) \in \{ \text{relation in T} \} \) with the same header, but with different arguments, i.e., \( a_3 \neq a_1 \) and \( a_4 \neq a_2 \), then we say the T-H pair has the “Disconnected Relation” phenomenon.

(b) **Exclusive Argument**: If there exist a relation \( r_1 = h(a_1, a_2) \in \{ \text{relation in H} \} \), and a relation \( r_2 = h(a_3, a_4) \in \{ \text{relation in T} \} \) where both relations have the same header, but either the pair \((a_1, a_3)\) or the pair \((a_2, a_4)\) is an antonym by looking up WordNet, then we say the T-H pair has the “Exclusive Argument” phenomenon.

(c) **Exclusive Relation**: If there exist a relation \( r_1 = h_1(a_1, a_2) \in \{ \text{relation in T} \} \), and a relation \( r_2 = h_2(a_3, a_4) \in \{ \text{relation in H} \} \) where both relations have the same arguments, but \( h_1 \) and \( h_2 \) have the opposite meanings by consulting WordNet, then we say that the T-H pair has the “Exclusive Relation” phenomenon.

(d) **Missing Argument**: For each argument \( a_1 \in \{ \text{noun in H} \} \cup \{ \text{nnp in H} \} \cup \{ \text{cnn in H} \} \), if there does not exist an argument \( a_2 \in T \) such that \( a_1 = a_2 \), then we say that the T-H pair has “Missing Argument” phenomenon.

(e) **Missing Relation**: For each relation \( r_1 = h_1(a_1, a_2) \in \{ \text{relation in H} \} \), if there does not exist a relation \( r_2 = h_2(a_3, a_4) \in \{ \text{relation in T} \} \) such that \( h_1 = h_2 \), then we say that the T-H pair has “Missing Relation” phenomenon.

### 3.3 A Machine Learning Method

We aim at finding meta-features to describe the characteristic of negative entailment phenomena, and use them for classification. We analyse the dependencies in a T-H pair with Stanford dependency parser (de Marneffe et al., 2006) and derive two dependency sets DT and DH for T and H, respectively, where a dependency \( gr(g, d) \) is in terms of a binary grammatical relation \( gr \) between a governor \( g \) and a dependent \( d \). We further define the following three multisets to capture the relationships between T and H:

(a) \{H only\} = \{gr|gr(g, d) \in DT \cap DH\}

(b) \{Partially identical in governor\} = \{gr|gr(g_1, d_1) \in DT, gr(g_2, d_2) \in DH, d_1 \neq d_2\}

(c) \{Partially identical in dependent\} = \{gr|gr(g_1, d) \in DT, gr(g_2, d) \in DH, g_1 \neq g_2\}

A T-H pair is represented as a feature vector \((V(a), V(b), V(c))\), where the dimensions of the three vectors \(V(a), V(b), \) and \(V(c)\) are the number of grammatical relations in the
dependency parser. The weights of each grammatical relation $gr$ in $V(a)$, $V(b)$, and $V(c)$ are the number of $gr$ appearing in the multisets \{H only\}, \{Identical in governor only\} and \{Identical in dependent only\}, respectively. The SVM classifier with the RBF kernel is adopted to develop classifiers with the parameters (cost and gamma) tuned by grid search and evaluated with 10-fold cross validation.

### 3.4 Experiments and Discussion

The following two datasets are used in English TE recognition experiments.

(a) 210 pairs from part of RTE-5 test set: The 210 T-H pairs are annotated with the linguistic phenomena by human annotators in the work of Mark Sammons et al (2010). They are selected from the 600 pairs in RTE-5 test set, including 51% ENTAILMENT and 49% NO ENTAILMENT.

(b) 600 pairs of RTE-5 test set: The original RTE-5 test set, including 50% ENTAILMENT and 50% NO ENTAILMENT.

Table 6 shows the performances of the negative entailment phenomena detection by rule-based and machine-learning methods. The performances of rule-based model are especially poor. The major challenge is to identify the arguments in T-H pairs. (S3) shows an instance. The correct arguments of H in (S3) are “Fifth Amendment right” and “driving license”, but the arguments captured by our method are “Fifth Amendment” and “license”. The issue can be improved with a better dependency parser.

(S3) T: “There is a rational basis to distinguish between people driving cars and semi trucks,” Jambois said. “All I would say is I think he has an uphill battle.” The lawsuit says the truckers’ Fifth and Fourteenth amendment rights are being violated because there is no way for them to apply for an occupational license. Mutschler said the state is taking away the truckers’ right to drive a truck for a living. He said he will argue that while driving is a privilege, once a person has a license for work, it becomes a right.

H: Fifth Amendment right is about driving license.
Table 6. Performance of negative entailment phenomena detection. Reported in Precision (P), Recall (R), and F-Score (F).

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Rule-based</th>
<th>Learning-based</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P(%)</td>
<td>R(%)</td>
</tr>
<tr>
<td>Disconnected Relation</td>
<td>9.52</td>
<td>28.57</td>
</tr>
<tr>
<td>Exclusive Argument</td>
<td>12.94</td>
<td>47.83</td>
</tr>
<tr>
<td>Exclusive Relation</td>
<td>5.71</td>
<td>33.33</td>
</tr>
<tr>
<td>Missing Argument</td>
<td>32.11</td>
<td>37.81</td>
</tr>
<tr>
<td>Missing Relation</td>
<td>23.08</td>
<td>61.54</td>
</tr>
<tr>
<td>Average</td>
<td>16.67</td>
<td>41.82</td>
</tr>
</tbody>
</table>

Although the rule-based method is poorly-performed, and the machined learning method is not so good at precision and F-Score, the resulting models for TE recognition achieve decent performances. These interesting results are depicted in Table 7. The “Human-annotated” column shows the performance achieved by using the phenomena annotated by human. Using “Human-annotated” phenomena can be seen as the upper-bound of the experiments. In data set (a), the performance of using all the 5 phenomena as features by the machine learning method (M2) is better than that of using the rule-based method (M1). However, the results are reverse in data set (b). This may be because data set (b) contains some cases that cannot be recognized by the model trained from the T-H pairs annotated by human. On the other hand, the rule-based method is implemented directly from the definitions, which is more robust.

Though the performance of using the phenomena extracted automatically by machine is not comparable to that of using the human annotated ones, the accuracy achieved by using only 5 features (59.17%) is just a little lower than the average accuracy of all runs in RTE-5 formal runs (60.36%) (Bentivogli et al., 2009). It shows that the significant phenomena are really effective in dealing entailment recognition even though the phenomena detector is extremely simple. If we can improve the performance of the automatic phenomena detection algorithm, it may make a great progress on the textual entailment.

So far the experiments are two-stage classification. In the first stage, we perform the rule-based or the learning-based model to extract the five negative entailment phenomena. And then, the presences of the five phenomena are used as binary features to recognize the TE in the second stage. In this perspective, the features used for phenomena extraction in Section 3.3 are the meta-features of M2. In order to understand the impact of error-propagation, we train a one-stage TE recognizer, M3, by using the meta-features of M2 as features directly. Table 8 compares M1, M2, and M3. The models M2 and M3 do the TE recognition according to the same information, but the two-stage classifier M2 slightly outperforms M3. This result
suggests that the concept of negative entailment phenomena is useful for TE recognition.

**Table 7. Accuracy of textual entailment recognition using the extracted phenomena as features.**

<table>
<thead>
<tr>
<th></th>
<th>Dataset (a): 210 pairs</th>
<th>Dataset (b): 600 pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rule-based (M1)</td>
<td>Learning-based (M2)</td>
</tr>
<tr>
<td>Disconnected Relation</td>
<td>50.95%</td>
<td>54.76%</td>
</tr>
<tr>
<td>Exclusive Argument</td>
<td>50.95%</td>
<td>50.95%</td>
</tr>
<tr>
<td>Exclusive Relation</td>
<td>50.95%</td>
<td>52.38%</td>
</tr>
<tr>
<td>Missing Argument</td>
<td>53.81%</td>
<td>57.62%</td>
</tr>
<tr>
<td>Missing Relation</td>
<td>50.95%</td>
<td>50.95%</td>
</tr>
<tr>
<td>All</td>
<td>52.38%</td>
<td>60.00%</td>
</tr>
</tbody>
</table>

**Table 8. Accuracies of two-stage and one-stage classification.**

<table>
<thead>
<tr>
<th>Stages of Classification</th>
<th>Model</th>
<th>Feature Source</th>
<th>Dataset (a): 210 pairs</th>
<th>Dataset (b): 600 pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-Stage</td>
<td>M1</td>
<td>Rule-based</td>
<td>52.38%</td>
<td>59.17%</td>
</tr>
<tr>
<td></td>
<td>M2</td>
<td>Machine learning</td>
<td>60.00%</td>
<td>57.83%</td>
</tr>
<tr>
<td>One-Stage</td>
<td>M3</td>
<td>Meta-features of M2</td>
<td>56.19%</td>
<td>57.00%</td>
</tr>
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</table>

4. Negative Entailment Phenomena in Chinese RITE Dataset

To make sure if negative entailment phenomena exist in other languages, we apply the methodologies in Sections 2 and 3 to the dataset of RITE-1 BC-CT task in NTCIR-9. This dataset contains total 900 traditional Chinese T-H pairs, including 50% ENTAILMENT and 50% NO ENTAILMENT. We annotate all the nine negative entailment phenomena on Chinese T-H pairs according to the definitions by Sammons *et al.* (2010) and analyze the effects of various combinations of the phenomena on the new annotated Chinese data. To avoid the influence from the actual entailment label (ENTAILMENT/NO ENTAILMENT), annotators can only see the part of T and H.

Table 9 shows the performances of TE recognition in Chinese with the human knowledge. The interpretation of this table is the same as that of Table 4. The accuracy of using all the nine phenomena as features (i.e., $C_9^0$ setting) is 91.11%. It shows the same tendency as the analyses on English data. The significant negative entailment phenomena on Chinese data, i.e.,
(3,4,5,7,8), are the same as those on English data. Besides, we can use only six phenomena to achieve the same performance as using all nine phenomena as features. Furthermore, we also classify the entailment relation by the phenomena extracted automatically by the rule-based method. The process is similar to those of English text described in Section 3.1 and Section 3.2, while Additional effort of processing is required for Chinese text. We segmented Chinese words with Stanford word segmenter (Chang et al., 2008) and performed Chinese dependency parsing using Stanford parser and the CNP parser (Chen et al., 2009). We extract two sets of negative entailment phenomena according to the parsing results of Stanford parser and CNP parser separately. Both sets are used as independent features to achieve a better performance.

Table 9. Accuracy of combination of negative entailment phenomena on Chinese data.

<table>
<thead>
<tr>
<th>C^9_8</th>
<th>C^9_7</th>
<th>C^9_6</th>
<th>C^9_5</th>
<th>C^9_4</th>
</tr>
</thead>
<tbody>
<tr>
<td>-(1)</td>
<td>91.11%</td>
<td>-(1,6)</td>
<td>91.11%</td>
<td>-(0,2,6)</td>
</tr>
<tr>
<td>-(2)</td>
<td>91.11%</td>
<td>-(2,6)</td>
<td>91.11%</td>
<td>-(0,1,6)</td>
</tr>
<tr>
<td>-(6)</td>
<td>91.11%</td>
<td>-(2,6)</td>
<td>91.11%</td>
<td>-(0,1,6)</td>
</tr>
<tr>
<td>-(0)</td>
<td>90.78%</td>
<td>-(0,1)</td>
<td>90.78%</td>
<td>-(0,2,6)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C^9_3</th>
<th>C^9_2</th>
<th>C^9_1</th>
</tr>
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<tr>
<td>(3,4,5,7)</td>
<td>89.00%</td>
<td>(3,5,7)</td>
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<tr>
<td>(3,5,7,8)</td>
<td>87.89%</td>
<td>(4,5,7)</td>
</tr>
<tr>
<td>(0,4,5,7)</td>
<td>87.89%</td>
<td>(0,5,7)</td>
</tr>
<tr>
<td>(1,3,5,7)</td>
<td>87.44%</td>
<td>(2,5,7)</td>
</tr>
</tbody>
</table>

The rule-based method obtains a similar result of TE recognition in Chinese. The accuracy achieved by using the five automatically extracted phenomena as features is 57.11%, and the average accuracy of all runs in NTCIR-9 RITE task is 59.36% (Shima et al., 2011). Compared to other methods using a lot of features, only 12 binary features are used in our method.

5. Conclusion

In this paper we conclude that the negative entailment phenomena have a great effect in dealing with TE recognition. The systems with human annotated knowledge achieve very good performance. Experimental results show that not only can it be applied to the English TE problem, but also has the similar effect on the Chinese TE recognition. To automatically capture the negative entailment phenomena in the text, we propose the phenomenon extraction algorithms with the rule-based and the learning-based approaches. Though the automatic extraction of the negative entailment phenomena still needs a lot of efforts, it gives us a new
direction to deal with the TE problem. The fundamental issues such as determining the boundary of the arguments and the relations, finding the implicit arguments and relations, verifying the antonyms of argument and relations, and determining their alignments need to be further examined to extract correct negative entailment phenomena. Besides, multi-class TE recognition will be explored in the future.

Reference


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| 學生會員  | 500.-   | 50.-    （限國內學生）
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<table>
<thead>
<tr>
<th>No.</th>
<th>Title</th>
<th>Surface</th>
<th>US$ &amp; EURP</th>
<th>ASIA</th>
<th>VOLUME</th>
<th>AMOUNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Structure for Parsing Mandarin -- Its Frame and General Applications--</td>
<td></td>
<td>ASIA 15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>V-N 複合名詞討論篇</td>
<td>12</td>
<td>21</td>
<td>17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>新聞語料庫字頻統計表</td>
<td>8</td>
<td>13</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>新聞語料庫詞頻統計表</td>
<td>18</td>
<td>30</td>
<td>24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>新聞常用動詞詞頻與分類</td>
<td>10</td>
<td>15</td>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>中文詞類分析</td>
<td>10</td>
<td>15</td>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>現代漢語中的法相詞</td>
<td>5</td>
<td>10</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>中文書面語頻率詞典（新聞語料詞頻統計）</td>
<td>18</td>
<td>30</td>
<td>24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.</td>
<td>古漢語字頻表</td>
<td>11</td>
<td>16</td>
<td>14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10.</td>
<td>注意檢索現代漢語字頻表</td>
<td>8</td>
<td>13</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11.</td>
<td>中央研究院平衡語料庫的內容與說明</td>
<td>3</td>
<td>8</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12.</td>
<td>訊息為本的格位語法與其剖析方法</td>
<td>3</td>
<td>8</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13.</td>
<td>「搜」文解字－中文詞類研究與資訊用分詞標準</td>
<td>8</td>
<td>13</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14.</td>
<td>古漢語詞頻表（甲）</td>
<td>19</td>
<td>31</td>
<td>25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15.</td>
<td>論語詞頻表</td>
<td>9</td>
<td>14</td>
<td>12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16.</td>
<td>詞類詞典</td>
<td>18</td>
<td>30</td>
<td>26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17.</td>
<td>Accumulated Word Frequency in CKIP Corpus</td>
<td>15</td>
<td>25</td>
<td>21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18.</td>
<td>自然語言處理及計算語言學相關術語中英對譯表</td>
<td>4</td>
<td>9</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>19.</td>
<td>現代漢語口語對話語料庫標註系統說明</td>
<td>8</td>
<td>13</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20.</td>
<td>Computational Linguistics &amp; Chinese Languages Processing (One year)</td>
<td>---</td>
<td>100</td>
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<td></td>
<td></td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>編號</th>
<th>書目</th>
<th>會員</th>
<th>非會員</th>
<th>冊數</th>
<th>金額</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>no.92-01, no. 92-04 (合訂本) ICG 中的論旨角色與 A conceptual Structure for Parsing Mandarin--its Frame and General Applications--</td>
<td>NT$ 80</td>
<td>NT$ 100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>no.92-02, no. 92-03 (合訂本) V-N 複合成詞討論篇 與 V-R 複合動詞討論篇</td>
<td>120</td>
<td>150</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>no.93-01 新聞語料庫字頻統計表</td>
<td>120</td>
<td>130</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>no.93-02 新聞語料庫詞頻統計表</td>
<td>360</td>
<td>400</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>no.93-03 新聞常用動詞詞頻與分類</td>
<td>180</td>
<td>200</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>no.93-05 中文詞類分析</td>
<td>185</td>
<td>205</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>no.93-06 現代漢語中的法相詞</td>
<td>40</td>
<td>50</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>no.94-01 中文書面語頻率詞典（新聞語料詞頻統計）</td>
<td>380</td>
<td>450</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.</td>
<td>no.94-02 古漢語字頻表</td>
<td>180</td>
<td>200</td>
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<td></td>
</tr>
<tr>
<td>10.</td>
<td>no.95-01 拼音檢索現代漢語字頻表</td>
<td>75</td>
<td>85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11.</td>
<td>no.95-02/98-04 中央研究院平衡語料庫的內容與說明</td>
<td>75</td>
<td>85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12.</td>
<td>no.95-03 訊息為主的格位語法與其解析方法</td>
<td>75</td>
<td>80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13.</td>
<td>no.96-01 「搜」文解字－中文詞彙研究與書籍用分詞標準</td>
<td>110</td>
<td>120</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14.</td>
<td>no.97-01 古漢語詞頻表（甲）</td>
<td>400</td>
<td>450</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15.</td>
<td>no.97-02 論語頻率表</td>
<td>90</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16.</td>
<td>no.98-01 詞頻詞典</td>
<td>395</td>
<td>440</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17.</td>
<td>no.98-02 Accumulated Word Frequency in CKIP Corpus</td>
<td>340</td>
<td>380</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18.</td>
<td>no.98-03 自然語言處理及計算語言學相關術語中英對譯表</td>
<td>90</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>19.</td>
<td>no.02-01 現代漢語口語話語料庫標註系統說明</td>
<td>75</td>
<td>85</td>
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<tr>
<td>20.</td>
<td>論文集 COLING 2002 紙本</td>
<td>100</td>
<td>200</td>
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</tr>
<tr>
<td>21.</td>
<td>論文集 COLING 2002 光碟片</td>
<td>300</td>
<td>400</td>
<td></td>
<td></td>
</tr>
<tr>
<td>22.</td>
<td>論文集 COLING 2002 Workshop 光碟片</td>
<td>300</td>
<td>400</td>
<td></td>
<td></td>
</tr>
<tr>
<td>23.</td>
<td>論文集 ISCSLP 2002 光碟片</td>
<td>300</td>
<td>400</td>
<td></td>
<td></td>
</tr>
<tr>
<td>24.</td>
<td>交談系統暨語境分析研討會講義 （中華民國計算語言學學會1997第四季學術活動）</td>
<td>130</td>
<td>150</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25.</td>
<td>中文計算語言學期刊（一年四期）年份：</td>
<td>--</td>
<td>2,500</td>
<td></td>
<td></td>
</tr>
<tr>
<td>26.</td>
<td>Readings of Chinese Language Processing</td>
<td>675</td>
<td>675</td>
<td></td>
<td></td>
</tr>
<tr>
<td>27.</td>
<td>討論策略與機器翻譯 1990</td>
<td>150</td>
<td>165</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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Contents

Papers

BCCWJ-TimeBank: Temporal and Event Information Annotation on Japanese Text................................................................. 1
Masayuki ASAHIKA, Sachie KATO, Hikari KONISHI, Mizuho IMADA, and Kikuo MAEKAWA

Transliteration Extraction from Classical Chinese Buddhist Literature Using Conditional Random Fields with Language Models........................................................................................................... 25
Yu-Chun Wang, Karol Chia-Tien Chang, Richard Tzong-Han Tsai, and Jieh Hsiang

Modeling Human Inference Process for Textual Entailment Recognition.................................................................................. 39
Hen-Hsen Huang, Kai-Chun Chang, and Hsin-Hsi Chen

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