Jointly Extracting Japanese Predicate-Argument Relation with Markov Logic

Katsumasa Yoshikawa,   Masayuki Asahara   and   Yuji Matsumoto

Graduate School of Information Science,

Nara Institute of Science and Technology

8916-5, Takayama-cho, Ikoma, Nara 630-0192, Japan

`{katsumasa-y,masayu-a,matsu}@is.naist.jp`

Abstract

This paper describes a new Markov Logic approach for Japanese Predicate-Argument (PA) relation extraction. Most previous work built separated classifiers corresponding to each case role and independently identified the PA relations, neglecting dependencies (constraints) between two or more PA relations. We propose a method which collectively extracts PA relations by optimizing all argument candidates in a sentence. Our method can jointly consider dependency between multiple PA relations and find the most probable combination of predicates and their arguments in a sentence. In addition, our model involves new constraints to avoid considering inappropriate candidates for arguments and identify correct PA relations effectively. Compared to the state-of-the-art, our method achieves competitive results without large-scale data.

1 Introduction

Predicate-argument (PA) relation extraction is one of the challenging problems in Natural Language Processing. The analysis extracts semantic information such as "who did what to whom", which is often useful to various applications like information extraction, document summarization, and machine translation.

Predicate-argument relation extraction is often called semantic role labeling. In English, it has been researched on large corpora such as FrameNet (Fillmore et al., 2001) and Prop-Bank (Palmer et al., 2005). CoNLL Shared Task 2008 (Surdeanu et al., 2008) is a representative work of semantic role labeling based on these corpora. Japanese PA relation extraction is a kind of semantic role labeling but an argument is often called *case*. A typical example of Japanese PA re-
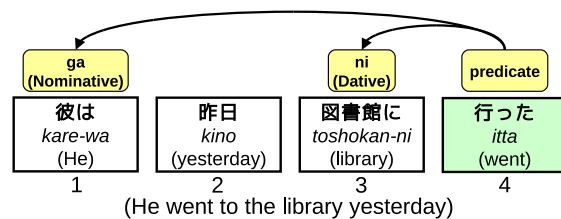

Figure 1: Example of Predicate-Argument Structure

lation is shown in Figure 1. In this example, "行った (went)" is a predicate and there are two arguments for the predicate, that is, a nominative case role (ga) is "彼 (He)" and a dative case role (ni) is "図書館 (library)".

In Japanese, Taira et al. (2008) and Imamura et al. (2009) tackled PA relation extraction on NAIST Text Corpus (Iida et al., 2007). They created three separated models corresponding to each of the case; ga (Nominative), wo (Accusative), and ni (Dative).

Even though some English semantic role labeler apply global models, most of them solve problems on a *per-predicate* basis (Toutanova et al., 2008; Watanabe et al., 2010). In this work, we propose an approach to Japanese PA relation extraction on a *per-sentence* basis and utilize important dependencies between one PA relation and another in the same sentence. In order to use such dependencies as global constraints, we apply a Markov Logic approach to Japanese PA relation extraction. In recent years, in English semantic role labeling, a Markov Logic model has achieved one of the state-of-the-art results (Meza-Ruiz and Riedel, 2009a). With global constraints between multiple PA relations, a Markov Logic model can avoid inconsistencies between several PA relations and improve performance of extraction.

In addition, we introduce new global constraints to effectively delete inappropriate argument candidates which are unrelated to PA relations. We consider that extraction of PA relations and dele-
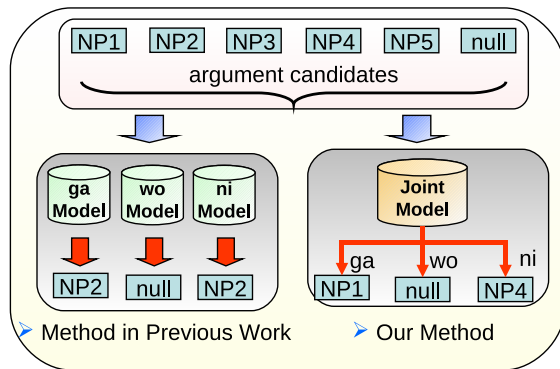
1125

Figure 2: Difference in Methods

tion of the other phrases are two sides of the same coin. We jointly perform such extraction and deletion with Markov Logic.

Through our experiments, we report the effectiveness of the Markov Logic approach to Japanese PA relation extraction in detail. We show that our model with global constraints outperforms the model without them. Comparison with previous work shows that our Markov Logic approach achieves competitive results without selectional preference features obtained from large-scale unlabelled data. In qualitative analysis, we find that our global model resolves some difficult cases such as PA relations in relative clauses.

The remainder of this paper is organized as follows: Section 2 describes related work; Section 3 introduces Markov Logic; Section 4 explains our proposed Markov Logic Network; Section 5 presents and discusses the experimental setting and the results; and in Section 6 we conclude and present ideas for future research.

2 Related Work

In Japanese, PA annotated corpora such as Kyoto Text Corpus (KTC) (Kawahara et al., 2002) and NAIST Text Corpus (NTC) (Iida et al., 2007) have been developed and utilized. [1] CoNLL Shared Task 2009 (Hajič et al., 2009) included Japanese PA relation extraction on the data from KTC.

The data we used in this work is from NTC. NTC is based on the same text as KTC, which contains 38,384 sentences from 2,929 news articles. [2] The annotation in NTC has the three case roles: "ga (Nominative)", "wo (Accusative)", and "ni (Dative)". The predicate-argument annotation in NTC is based on deep cases and is more difficult to ana-

lyze than the surface case annotations which KTC employs. Note that KTC includes morphological information, base phrase segmentation, and syntactic dependency structure. We can merge these annotation from KTC and deep case annotation from NTC.

There are two main previous work with NTC. First, Taira et al. (2008) researched extraction of PA relations by SVM classifiers and decision lists. Their approach focused on not only verbal predicates but also nominal predicates. Secondly, Imamura et al. (2009) combined a Maximum Entropy model with a language model learned from large-scale corpora and achieved the state-of-the-art results.

Both Taira et al. and Imamura et al. created an independent model for each of the cases *ga, wo*, and *ni* (the left box in Figure 2). So, their models neglect the dependencies between cases. For example, the method in previous work produces "NP2" for both ga and ni cases. Though it is unlikely that the same noun phrase occupies two argument positions of a predicate, it is possible with their models.

However, our Markov Logic approach creates a joint model for the three cases and finds the most probable assignments taking into consideration the dependency between them. As a result, our model can prevent such an unlikely result (See the right box in Figure 2).

Moreover, in contrast to Imamura's work, our method does not exploit large-scale corpora. They depended on their language model derived from large-scale corpora to decide the selectional preference between a predicate and an argument. On the other hand, we handle the problem by global optimization *per-sentence* without using large-scale corpora.

In the CoNLL Shared Task 2009 (Hajič et al., 2009), a competition of multilingual semantic role labeling was held and Japanese was one of the target languages. In the shared task, Meza-Ruiz and Riedel (2009b) proposed a joint approach with Markov Logic. They also reported their Markov Logic approach for English semantic role labeling in detail (Meza-Ruiz and Riedel, 2009a). Their method divided the problem into four subtasks: predicate identification, argument identification, sense disambiguation, and role labeling. The subtasks are solved jointly. [3] We adapt their model to

---

[1] KTC is annotated with surface cases and NTC is annotated with deep cases

[2] These articles are from a Japanese newspaper, "Mainichi Shinbun"

[3] Note, in the CoNLL *2009* Shared Task, predicate identification is not necessary. So, they used the CoNLL *2008* Shared Task data in their work.

Japanese PA relation extraction on NTC. In order to compare with Taira et al. (2008) and Imamura et al. (2009), we perform only argument identification and role labeling.

About joint models of semantic role labeling without using Markov Logic, there are various previous work on CoNLL Shared Task Data. For example, Toutanova et al. (2008) and Watanabe et al. (2010) proposed joint models on the data of CoNLL Shared Task 2005 and 2009, respectively. While their models solve the problem on a *per-predicate* basis, our Markov Logic model solves it on a *per-sentence* basis. An optimization on a per-sentence basis is necessary and desirable for PA relation extraction on NTC since NTC has deep case annotations without case-frame dictionaries corresponding to them.

3 Markov Logic

It has long been clear that local classification alone cannot adequately solve all prediction problems we encounter in practice. This observation motivated a field within machine learning, often referred to as Statistical Relational Learning (SRL), which focuses on the incorporation of global correlations that hold between statistical variables (Getoor and Taskar, 2007).

One particular SRL framework that has recently gained momentum as a platform for global learning and inference in AI is Markov Logic (Richardson and Domingos, 2006), a combination of first-order logic and Markov Networks. It can be understood as a formalism that extends first-order logic to allow formulae that can be violated with some penalty. From an alternative point of view, it is an expressive template language that uses first order logic formulae to instantiate Markov Networks of repetitive structure. In the field of NLP, the Markov Logic approach has been applied to various tasks such as entity resolution (Singla and Domingos, 2006), information extraction (Poon and Domingos, 2007), and coreference resolution (Poon and Domingos, 2008), among others.

From a wide range of SRL languages we chose Markov Logic because it supports discriminative training (as opposed to generative SRL languages such as PRM (Koller, 1999)). Moreover, several Markov Logic software libraries exist and are freely available (as opposed to other discriminative frameworks such as Relational Markov Networks (Taskar et al., 2002)).

A *Markov Logic Network* (MLN) M is a set of pairs (ϕ, w) where ϕ is a first order formula and w is a real number (the formula's weight). It defines a probability distribution over sets of ground atoms, or so-called *possible worlds*, as follows:

$$p(\mathbf{y}) = \frac{1}{Z} \exp\left(\sum_{(\phi,w)\in M} w \sum_{\mathbf{c}\in C^\phi} f_\mathbf{c}^\phi (\mathbf{y}) \right) \quad (1)$$

Here each $\mathbf{c}$ is a binding of free variables in ϕ to constants in our domain. Each $f_\mathbf{c}^\phi$ is a binary feature function that returns 1 if in the possible world $\mathbf{y}$ the *ground formula* we get by replacing the free variables in ϕ with the constants in $\mathbf{c}$ is true, and 0 otherwise. C^ϕ is the set of all bindings for the free variables in ϕ. Z is a normalization constant. Note that this distribution corresponds to a Markov Network (the so-called *Ground Markov Network*) where nodes represent ground atoms and factors represent ground formulae.

Designing formulae is only one part of the game. In practice, we also need to choose a training regime (in order to learn the weights of the formulae we added to the MLN) and a search/inference method that picks the most likely set of ground atoms (PA relations in our case) given our trained MLN and a set of observations. However, implementations of these methods are often already provided in existing Markov Logic interpreters such as *Alchemy* [4] and *Markov thebeast*. [5]

4 Proposed Markov Logic Network

This section describes our Markov Logic model for Japanese PA relation extraction. We will describe our proposed Markov Logic Network (MLN) in detail. First, let us define logical predicates for our MLN. The three *hidden* predicates are listed in Table 1.

predicate	definition
isArg(i)	Bunsetsu i is an argument
delete(i)	Bunsetsu i is deleted
role(i, j, r)	Bunsetsu i has an argument j with role r

Table 1: Hidden Predicates

Note that Japanese dependency parsing is based on *bunsetsu* units, which are similar in concept to English base phrases. In order to exploit information parsed in this way, we handle all logical predicates by bunsetsu phrases (not tokens).

The hidden predicates model the decisions we

---

[4] http://alchemy.cs.washington.edu/
[5] http://code.google.com/p/thebeast/

1127

logical predicate	description	example
word(i, w)	Bunsetsu *i* has word form *w*	行った (went), 彼 (he)
stem(i, s)	Bunsetsu *i* has stem *s*	行く (go)
pos(i, p)	Bunsetsu *i* has POS tag *p* (coarse-grained)	名詞 (noun)
dpos(i, p)	Bunsetsu *i* has POS tag *p* (fine-grained)	名詞-一般 (noun-general)
ne(i, n)	Bunsetsu *i* has named entity tag *n* (from NE tagger)	PERSON，LOCATION
kana(i, k)	Bunsetsu *i* has kana (Romanization) *k*	itta, kare
isPred(i)	Bunsetsu *i* is a predicate	True or False
numeric(i)	Bunsetsu *i* has a number character	True or False
definite(i)	Bunsetsu *i* contains the article corresponding to DEFINITE "the", such as "sore" or "sono"	True or False
demonstrative(i)	Bunsetsu *i* contains the article corresponding to DEMONSTRATIVE "this" or "that", such as "kono" or "ano"	True or False
particle(i)	Bunsetsu has a particle such as "wa","ga","wo", "ni"	True or False
goiCate(i, g)	Bunsetsu *i* has lexical category tag *g* in Nihongo Goi Taikei (Ikehara et al., 1997)	スポーツ (sport), 女性 (female)
goiMatch(i, j)	Bunsetsu phrases *i* and *j* satisfy the selectional restriction of Nihongo Goi Taikei	True or False
dep(i, j, d)	Dependency label between *i* and *j* is *d*	True or False
path(i, j, l)	Syntactic path between *i* and *j* is *l*	↑↓ (sibling), ↑↑ (ancestor)

Table 2: Observed Predicates

need to make: whether a bunsetsu phrase *i* is an argument of some predicate (argument identification); whether a bunsetsu phrase *i* is deleted (phrase deletion); whether a bunsetsu phrase *j* is an argument of the predicate *i* with semantic role *r* (role labeling).

Here the first two types of decision can be modeled through unary logical predicates *isArg(a)* and *delete(i)*, while the other type can be represented by a ternary logical predicate *role(p, a, r)*. Because we do not know their information at test time, we call them *hidden*.

Our Markov Logic approach is based on English semantic role labeling with Markov Logic as proposed by Meza-Ruiz and Riedel (2009a). As mentioned earlier, they divided the problem into four subtasks and defined five hidden predicates (*isPredicate, isArgument, hasRole, role*, and *sense*). In order to be comparable with the previous work in Japanese PA relation extraction (Taira et al., 2008; Imamura et al., 2009), we deal with only argument identification and role labeling in our research. Therefore, we define only the three hidden predicates in Table 1.

In addition to the hidden predicates, we define *observed* logical predicates representing informa-

tion at test time. For example, in our case we could introduce a predicate *word(i, w)* which indicates that a phrase *i* has the word form *w*. We list the all observed predicates in Table 2.

With our predicates defined, we can now go on to incorporate our intuition about the task using weighted first-order logic formulae. In the following we will explain the formulae of our proposed MLN. Sections 4.1 and 4.2 describe our local and global formulae for *isArg* and *role*, respectively. Section 4.3 mentions the formulae for deletion.

4.1 Local Formulae

We say that a formula is *local* if its groundings relate any number of observed ground predicates to exactly one hidden ground predicate. Local formulae are defined with some observed predicates from Table 2 and a hidden predicate from Table 1.

The local formulae for *isArg* and *delete* capture the relation of the bunsetsu phrases with their lexical and syntactic properties (simple phrase property). The formula describing a local property of word form is

$$word(a, +w) \Rightarrow isArg(a) \qquad (2)$$

which implies that a bunsetsu *a* is an argument with a weight that depends on the word form. Note, the + notation indicates that the MLN contains one in-

Type	Formula	Description
hard	$isArg(a) \Rightarrow \exists p.\exists r.role(p,a,r)$	Every argument must relate to at least one predicate
hard	$role(p,a,r) \Rightarrow isArg(a)$	If a plays the role r for p, then a has to be an argument
hard	$role(p,a,r_1) \wedge r_1 \neq r_2 \Rightarrow \neg role(p,a,r_2)$	There is exact one case role between a predicate and an argument

Table 3: Global Formulae for *isArg* and *role*

stance of the rule, with a separate weight, for each assignment of the variables with a plus sign.

The local formulae for *role* represent properties between two bunsetsu phrases (linked phrases property). For example, the following formula

$$ne(a,+n) \wedge dep(p,a,+d)$$
$$\Rightarrow role(p,a,+r) \qquad (3)$$

denotes a local property of named entity and syntactic dependency.

As in Formula (3), some observed predicates (*goiMatch, dep*, and *path*) in Table 2 construct formulae using other observed predicates in this table.

First-order logical formulae such as Formulae (2) and (3) become the feature templates of MLN. Each template produces several instantiations. An example of a template instantiation based on Figure 1 is

$$ne(1, PERSON) \wedge dep(4,1, "D")$$
$$\Rightarrow role(4,1,\text{ga}) \qquad (4)$$

which is a typical expansion from Formula (3).

4.2 Global Formulae

The intuition behind the previous formulae can also be captured using a local classifier. However, Markov Logic also allows us to say more:

$$isArg(a) \Rightarrow \exists p.\exists r.role(p,a,r) \qquad (5)$$

In this formula, we made a statement about more global properties of a PA relation extraction that cannot be captured with local classifiers. This formula ensures the consistency between predicate and argument, that is, arguments belong to at least one predicate. This type of rule forms the core idea of our global model.

Global formulae involve two or more atoms of hidden predicates and enable us to jointly deal with argument identification, phrase deletion, and role labeling. With global formulae, our MLN considers not only a single decision at a time but also handles several decisions, simultaneously. Our global formulae for argument identification and role labeling are shown in Table 3.

All the formulae in Table 3 are hard constraints which enforce consistency between the hidden predicates. In MLN, formulae of hard constraint are defined as special formulae with *infinite* weights. A possible world which violates hard constraints is never chosen as a correct answer. For example, Formula (5) is such a global formula. Another formula ensuring the consistency between *role* and *isArg* is

$$role(p,a,r) \Rightarrow isArg(a) \qquad (6)$$

which indicates "If a phrase a plays the role r for p, then a must be an argument".

The last global formula

$$role(p,a,r_1) \wedge r_1 \neq r_2 \Rightarrow \neg role(p,a,r_2) \qquad (7)$$

implies that there is only one case role between a predicate p and an argument a. Formula (7) enables us to prevent the contradiction shown in Figure 2.

4.3 Deletion Formulae

Let us explain formulae for deletion in this section, independently. The main idea of our deletion is to delete bunsetsu phrases which are unrelated to PA relations and to help extract correct arguments. Extraction of correct arguments and deletion of non-arguments are two sides of the same idea. An example is shown in Figure 3. We have a main verb "行った (went)" as a predicate and there are five argument candidates for it. We want to extract correct arguments, "彼は (He)" for ga-case and "図書館 (library)" for ni-case among the five candidates. Here, if we can remove an instrumental case, "母の新しい車で (by mother's new car)", extracting the correct arguments becomes much easier.

Notably, our significant contribution is doing this deletion processes with extraction of PA relations, simultaneously. Deleting too many bunsetsu phrases often hurts the recall because it often deletes correct arguments. We call this phenomena *over-deletion*. Performing extraction and deletion by one joint model prevents over-deletion and improves the performance of PA relation extraction.

Deletion formulae are also divided into local and global. However, local formulae implement the same properties for *isArg* we mentioned in Section 4.1. As an exception, a characteristic local formula
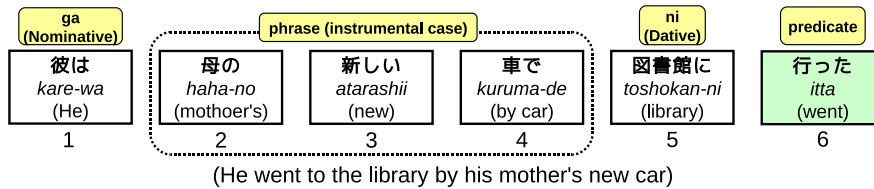
(He went to the library by his mother's new car)

Figure 3: Example of PA Relation with Instrumental Case

is

$$dep(i, j, +d) \wedge isPred(j) \Rightarrow \neg delete(i). \quad (8)$$

which implies the PA relations with syntactic dependencies are not deleted. It implements the fact that PA relations often have syntactic dependency relations. Actually, we can find that dependency relations are dominant in Table 5 and Formula (8) contributes to improve performance.

However, the local formulae address the deletion of a single bunsetsu phrase and we cannot expect a large improvement by adding *delete*. The main contributions of *delete* come from the global deletion formulae.

The global formulae for *delete* have three hard and one soft constraints. We show the global formulae in Table 4. The first three formulae in this table show the hard constraints which ensure the consistency between *delete* and the other two hidden predicates (*isArg* and *role*). The most important formula of them is

$$delete(i) \Rightarrow \neg isArg(i) \quad (9)$$

which implies that the deleted phrase does not become an argument.

The last formula in Table 4 is defined as a soft constraint:

$$word(h, +w) \wedge pos(h, +p) \wedge dep(h, m, +d)$$
$$\wedge delete(h) \Rightarrow delete(m) \quad (10)$$

which denotes "if a head phrase h is removed, then the child phrases m should be deleted". This formula does not always hold but the remaining uncertainty with regard to this formula is captured by a weight trained from corpora. This constraint implements the important deletion concept as we mentioned earlier.

Considering the example in Figure 3, Formula (10) is grounded as,

$$word(4, \text{"車で"}) \wedge pos(4, \text{NOUN+PARTICLE})$$
$$\wedge dep(4, 2, \text{"D"}) \wedge delete(4) \Rightarrow delete(2) \quad (11)$$

which implies that "if '車で (by car)' is removed, '母の (mother's)' should be also removed". Figure 4 shows the dependency parsed tree extracted from
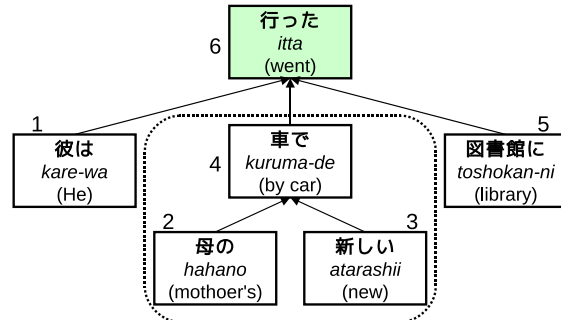

Figure 4: Deletion of Instrumental Case

the sentence in Figure 3. The subtree under "車で (by car)" should be deleted by Formula (11).

Note that Japanese dependency parsing usually targets only unlabeled parsing. Almost all labels are "D". [6] Therefore, we exploit the *word* and *pos* of head bunsetsu phrases as a substitution. In Japanese, word form and POS implicitly give us information similar to dependency labels. However, if we exploit our method in English, labeled information such as *probj* or *amod* should be helpful to train proper weights for Formula (10).

5 Experimental Results

5.1 Experimental Setup

Our experimental setting is based on previous work (Taira et al., 2008; Imamura et al., 2009) which was performed on NAIST Text Corpus.

Let us summarize our used data and tools. The data used, NAIST Text Corpus version 1.4β, has news articles and editorials. As training examples, we use articles published from January 1st to January 11th and editorials from January to August. As development data, we use articles published on January 12th and 13th and editorials in September. For evaluation, we use articles dated January 14th to 17th and editorials dated October to December. This way to split the data is same as Taira et al. (2008). We show the statistics of the evaluation data in Table 5.

As seen in this table, "ga-case" is dominant. PA relations which have syntactic dependency re-

---

[6]We sometimes have "P", "A", and "I" labels but it is not enough to model our deletion idea.

Type	Formula	Description
hard	$isArg(a) \Rightarrow \neg delete(a)$	If a is an argument then it is not deleted.
hard	$delete(i) \Rightarrow \neg isArg(i)$	If a bunsetsu i is deleted then it is not an argument.
hard	$role(p, a, r) \Rightarrow \neg delete(p) \wedge \neg delete(a)$	If a is an argument of p with the role r then neither p nor a is deleted.
soft	$word(h, +w) \wedge pos(h, +p) \wedge dep(h, m, +d) \wedge$ $delete(h) \Rightarrow delete(m)$	If a head phrase h is deleted with word w and POS p then a child phrase m is deleted.

Table 4: Global Deletion Formulae

	ga	wo	ni
Dep.	13,086	5,192	3,645
Zero-Intra	4,556	376	231
Total	17,642	5,568	3,876

Table 5: Statistics in Evaluation Data

	Local			Global		
	P	R	F	P	R	F
isArg	79.2	71.4	75.1	94.6	84.2	89.1
delete	86.6	90.4	88.4	94.3	97.9	96.1
role	86.3	72.5	78.8	85.5	**77.7**	81.4

Table 6: Local vs Global

lations (Dep.) are much more common than intra-sentential zero-anaphoric PA relations (Zero-Intra). However, in Japanese, we often find zero-anaphoric PA relations called *case ellipsis*. More detailed descriptions of PA relation types are shown in (Iida et al., 2006). Note that we target only PA relations which occur in a sentence (*intra-sentential* PA relations). The joint approach using Markov Logic is computationally hard even if it targets only *intra-sentential* PA relations. Therefore, extraction of *inter-sentential* PA relations which are crossing sentence boundaries is intractable. Moreover, our approach finds the most optimized PA assignments in a whole sentence. To keep consistency in a sentence, we delete the sentences which have inter-sentential PA relations.

For extracting features, we exploit the annotation of Kyoto Text Corpus as the POS and the syntactic dependency of bunsetsu phrases. We perform named entity tagging using CaboCha version 0.53. [7] Based on Taira's work, we introduce selectional restriction features from a Japanese Thesaurus, Nihongo Goi Taikei (Ikehara et al., 1997). Learning and inference algorithms for our joint model are provided by Markov thebeast, a Markov Logic engine tailored for NLP applications.

5.2 Results

First, let us show the comparison between the models with/without global constraints in Table 6. ***Global*** is the model with global constraints and ***Local*** is without them. Note that the local and global formulae of deletion are also included in ***Local*** and ***Global***, respectively. Table 6 shows Precision (P), Recall (R), and F1-value (F) of each hidden predicate. We can find that ***Global*** yielded clear im-

provements for all hidden predicates. These improvements are statistically significant. [8] These results suggest that the three target subtasks (argument identification, phrase deletion, and role labeling) can cooperate with each other. For PA relation extraction (*role*), the recall was mainly improved (the value in bold type).

We perform a simple analysis of hidden predicate removal. For each hidden predicate, a model was trained with that predicate removed and all other predicates retained. For PA relation extraction (*role*), Table 7 shows the model performance with removal of the *isArg* and *delete* predicates.

The removal of *delete* drops the model performance larger than that of *isArg*. While the removal of *isArg* drops the precision and saves the recall, the removal of *delete* is the other way around.

Next, we evaluate the results of PA relation extraction (*role*) by each case, "ga (Nominative)", "wo (Accusative)", and "ni (Dative)" in Table 8. All scores in the table are F1-value. Our ***Global*** model is more advantageous in "Zero-Intra" than ***Local*** model. Especially, in ga-case of Zero-Intra the score jumped from 42.1pt to 54.1pt (+12pt). Again, with global constraints, our global model finds the most probable state in the sentence. It is often difficult to extract Zero-Intra PA relations with only local features because syntactic dependencies between them are weak. Therefore, our global constraints contribute to find correct assignments of PA relations and we got a large improvement in Zero-Intra.

Let us compare our results with the state-of-the-art (Taira et al., 2008; Imamura et al., 2009). In Table 8, we show the best scores in bold types for

---

[7]http://code.google.com/p/cabocha/

[8]$\rho < 0.01$, McNemar's test 2-tailed

	Local			Global			[Taira, 2008]			[Imamura, 2009]		
	ga	wo	ni	ga	wo	ni	ga	wo	ni	ga	wo	ni
Dep.	85.7	91.2	79.5	**88.8**	91.3	79.7	75.6	88.2	**89.5**	87.0	**93.9**	80.8
Zero-Intra	42.1	7.3	0.0	**54.1**	10.3	0.0	30.2	11.4	**3.7**	50.0	**30.8**	0.0

Table 8: Comparison to the State-of-the-Art (F1)

Predicate Removed	P	R	F
No removal (**Global**)	85.5	77.7	81.4
-isArg	**84.8**	77.9	81.2
-delete	85.3	**76.8**	80.8
-isArg-delete (**Local**)	86.3	72.5	78.8

Table 7: Effect of Hidden Predicate Removal

each case. For ga-case, our model, **Global**, outperformed the others. On the other hand, for wo-case and ni-case, our results were relatively lower than them. Because our approach deals with the all three cases by one joint model and ga-case is dominant in the data, it extracts more numbers of ga-case than the others. However, ga-case is often the most important for PA relation extraction and sometimes called *indispensable case*. Our method can extract such important information better than previous work. Although our model did not exploit large-scale corpora, our results are competitive to the results of Imamura et al. (2009).

Error Analysis

(this) (reason) (Gray Wolf) (**revival in the US**)
この ため , 灰色狼の 米復活を
1 2 3 4
(plan) (**FWS**) (in Canada) (capture)
進める 魚類野生動物局が カナダで 捕獲した
5 6 7 8
(wild) (**twelve wolves**) (transport by air)
野性の 十二匹を 空輸 .
9 10 11
(Form this reason, FWS which plans to revive Gray Wolf in the US captured twelve wolves in Canada and transported them by air.)

In the above sentence, we have three predicates (gray boxed) and three arguments (underlined). The relations between predicates and arguments are complex with relative clause and often cause misunderstandings.

About this sentence, our **Local** model output:

$$\{role(5, 6, ga), role(5, 4, wo), role(8, 6, ga),$$
$$role(11, 2, ga), role(11, 10, wo)\}$$

It did not output wo-case of "捕獲した (capture)". Because we do not have case-frame dictionary in NTC, our models did not know that "捕獲した" usually requires wo-case (Accusative).

Another error is underlined that ga-case of "空輸

(transport by air)" is identified as "ため (reason)", because "ため" is only a phrase dependent on "空輸".

On the other hand, **Global** improved the errors as

$$\{role(5, 6, ga), role(5, 4, wo), role(8, 6, ga),$$
$$role(8, 10, wo), role(11, 6, ga), role(11, 10, wo)\}.$$

By global optimization in a sentence, our **Global** model overcame the lack of semantic features and successfully identified "十二匹を" as wo-case of "捕獲した". This PA relation is in a relative clause and often hard to identify. Though Abekawa and Okumura (2005) resolved Japanese PA relations in relative clauses by exploiting large-scale corpora, our Markov Logic approach handles this problem by global optimization. Moreover, in global model, $\{delete(1), delete(2), delete(7)\}$ are also output and "この" and "ため" did not become argument candidates. As a result, "魚類野性動物局が" was correctly selected as a ga-case of "空輸".

6 Conclusion

In this paper, we proposed a new Markov Logic approach for Japanese predicate-argument (PA) relation extraction. Our model exploited global constraints between multiple PA relations and introduced phrase deletion. Our global constraints successfully improved the performance of PA relation extraction. In comparison to the state-of-the-art, our approach achieved competitive results with no large-scale data.

As future work, we will introduce utilizing features derived from large-scale data following Imamura's work. Selectional preference features from large-scale corpora are expected to improve the performance for extracting wo-case and ni-case. We will also investigate the state-of-the-art technique of sentence compression in related to our deletion approach. It might be interesting to evaluate our approach in sentence compression tasks. Adding sentence compression might make the PA relation extractor more efficient and allow us to extract *inter-sentential* PA relations, too.

References

Takeshi Abekawa and Manabu Okumura. 2005. Corpus-based analysis of japanese relative clause constructions. In *Proceedings of 2nd International Joint Conference on Natural Language Processing (IJCNLP)*, pages 46–57, Jeju Island, Korea.

Charles J. Fillmore, Charles Wooters, and Collin F. Baker. 2001. Building a large lexical databank which provides deep semantics. In *Proceedings of the Pacific Asian Conference on Language, Information and Computation(PACLIC)*, Hong Kong.

Lise Getoor and Ben Taskar, 2007. *Introduction to Statistical Relational Learning*, chapter 12, pages 339–371. The MIT Press, Cambridge Massachusetts 02142.

Jan Hajič, Massimiliano Ciaramita, Richard Johansson, Daisuke Kawahara, Maria Antònia Martí, Lluís Màrquez, Adam Meyers, Joakim Nivre, Sebastian Padó, Jan Štěpánek, Pavel Straňák, Mihai Surdeanu, Nianwen Xue, and Yi Zhang. 2009. The conll-2009 shared task: Syntactic and semantic dependencies in multiple languages. In *Proceedings of the Thirteenth Conference on Computational Natural Language Learning (CoNLL 2009): Shared Task*, pages 1–18, Boulder, Colorado, June. Association for Computational Linguistics.

Ryu Iida, Kentaro Inui, and Yuji Matsumoto. 2006. Exploiting syntactic patterns as clues in zero-anaphora resolution. In *Proceedings of the 21st International Conference on Computational Linguistics and the 44th annual meeting of the Association for Computational Linguistics*, ACL-44, pages 625–632, Stroudsburg, PA, USA. Association for Computational Linguistics.

Ryu Iida, Mamoru Komachi, Kentaro Inui, and Yuji Matsumoto. 2007. Annotating a japanese text corpus with predicate-argument and coreference relations. In *Proceedings of the Linguistic Annotation Workshop*, LAW '07, pages 132–139, Stroudsburg, PA, USA. Association for Computational Linguistics.

Satoru Ikehara, Masahiro Miyazaki, Satoshi Shirai, Akio Yokoo, Hiromi Nakaiwa, Kentaro Ogura, Yoshifumi Ooyama, and Yoshihiko Hayashi. 1997. *Nihongo Goi Taikei, A Japanese Lexicon*. Iwanami Shoten, Tokyo.

Kenji Imamura, Kuniko Saito, and Tomoko Izumi. 2009. Discriminative approach to predicate-argument structure analysis with zero-anaphora resolution. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP (ACL-IJCNLP), Conference Short Papers*, pages 85–88, Suntec, Singapore, August. Association for Computational Linguistics.

Daisuke Kawahara, Sadao Kurohashi, and Koichi Hashida. 2002. Construction of japanese relevance-tagged corpus (in japanese). In *the 8th Annual Meeting of the Association for Natural Language Processing*, pages 495–498.

Daphne Koller, 1999. *Probabilistic Relational Models*, pages 3–13. Springer, Berlin/Heidelberg, Germany.

Ivan Meza-Ruiz and Sebastian Riedel. 2009a. Jointly identifying predicates, arguments and senses using markov logic. In *Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 155–163, Boulder, CO, USA, June. Association for Computational Linguistics.

Ivan Meza-Ruiz and Sebastian Riedel. 2009b. Multilingual semantic role labelling with markov logic. In *Proceedings of the Thirteenth Conference on Computational Natural Language Learning (CoNLL 2009): Shared Task*, pages 85–90, Boulder, Colorado, June. Association for Computational Linguistics.

Martha Palmer, Paul Kingsbury, and Daniel Gildea. 2005. The proposition bank: An annotated corpus of semantic roles. *Computational Linguistics*, 31.

Hoifung Poon and Pedro Domingos. 2007. Joint inference in information extraction. In *Proceedings of the Twenty-Second National Conference on Artificial Intelligence*, pages 913–918, Vancouver, Canada. AAAI Press.

Hoifung Poon and Pedro Domingos. 2008. Joint unsupervised coreference resolution with Markov Logic. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, pages 650–659, Honolulu, Hawaii, October. Association for Computational Linguistics.

Matthew Richardson and Pedro Domingos. 2006. Markov logic networks. *Machine Learning*, 62(1-2):107–136.

Parag Singla and Pedro Domingos. 2006. Entity resolution with markov logic. In *Proceedings of the Sixth International Conference on Data Mining (ICDM)*, pages 572–582, Washington, DC, USA. IEEE Computer Society.

Mihai Surdeanu, Richard Johansson, Adam Meyers, Lluís Màrquez, and Joakim Nivre. 2008. The conll 2008 shared task on joint parsing of syntactic and semantic dependencies. In *CoNLL 2008: Proceedings of the Twelfth Conference on Computational Natural Language Learning*, pages 159–177, Manchester, England, August. Coling 2008 Organizing Committee.

Hirotoshi Taira, Sanae Fujita, and Masaaki Nagata. 2008. A japanese predicate argument structure analysis using decision lists. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 523–532, Honolulu, HI, USA. Association for Computational Linguistics.

Ben Taskar, Abbeel Pieter, and Daphne Koller. 2002. Discriminative probabilistic models for relational data. In *Proceedings of the 18th Annual Conference on Uncertainty in Artificial Intelligence (UAI-02)*, pages 485–492, San Francisco, CA. Morgan Kaufmann.

Kristina Toutanova, Aria Haghighi, and Christopher D. Manning. 2008. A global joint model for semantic role labeling. *Computational Linguistics*, 34:161–191, June.

Yotaro Watanabe, Masayuki Asahara, and Yuji Matsumoto. 2010. A structured model for joint learning of argument roles and predicate senses. In *Proceedings of the ACL 2010 Conference Short Papers*, pages 98–102, Uppsala, Sweden, July. Association for Computational Linguistics.