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 PropBank (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 relation 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-
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 analyze 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 sub-tasks are solved jointly. 3 We adapt their model to

1KTC is annotated with surface cases and NTC is annotated with deep cases
2These articles are from a Japanese newspaper, “Mainichi Shinbun”
3Note, 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 \((\phi, w)\) where \( \phi \) 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:

\[
p(y) = \frac{1}{Z} \exp \left \{ \sum_{(\phi, w) \in M} w \sum_{c \in C^\phi} f_c^\phi(y) \right \}
\]

Here each \( c \) is a binding of free variables in \( \phi \) to constants in our domain. Each \( f_c^\phi \) is a binary feature function that returns 1 if in the possible world \( y \) the ground formula we get by replacing the free variables in \( \phi \) with the constants in \( c \) is true, and 0 otherwise. \( C^\phi \) is the set of all bindings for the free variables in \( \phi \). \( Z \) 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 \( r \) |

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/
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 $\text{isArg}(a)$ and $\text{delete}(i)$, while the other type can be represented by a ternary logical predicate $\text{role}(p,a,r)$. 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 ($\text{isPredicate}$, $\text{isArgument}$, $\text{hasRole}$, $\text{role}$, and $\text{sense}$). 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 information at test time. For example, in our case we could introduce a predicate $\text{word}(i,w)$ 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 $\text{isArg}$ and $\text{role}$, 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 $\text{isArg}$ and $\text{delete}$ 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

$$\text{word}(a, +w) \Rightarrow \text{isArg}(a) \quad (2)$$

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-
The local formulae for \textit{role} represent properties between two bunsetsu phrases (linked phrases property). For example, the following formula

\[
\neg \text{Arg}(a) \Rightarrow \exists \text{p}. \exists \text{r}. \text{role}(p, a, r)
\]

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

\[
\neg \text{Arg}(1, \text{PERSON}) \land \text{dep}(4, 1, \text{“D”}) \Rightarrow \text{role}(4, 1, \text{ga})
\]

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 allows us to say more:

\[
\text{isArg}(a) \Rightarrow \exists \text{p}. \exists \text{r}. \text{role}(p, a, r)
\]

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 \textit{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 \textit{role} and \textit{isArg} is

\[
\text{role}(p, a, r) \Rightarrow \text{isArg}(a)
\]

which indicates “If a phrase \textit{a} plays the role \textit{r} for \textit{p}, then \textit{a} must be an argument”.

The last global formula

\[
\text{role}(p, a, r_1) \land r_1 \neq r_2 \Rightarrow \neg \text{role}(p, a, r_2)
\]

implies that there is only one case role between a predicate \textit{p} and an argument \textit{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 \textit{isArg} we mentioned in Section 4.1. As an exception, a characteristic local formula...
is
\[
\text{dep}(i, j, +d) \wedge \text{isPred}(j) \Rightarrow \neg \text{delete}(i).
\] (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
\[
\text{delete}(i) \Rightarrow \neg \text{isArg}(i)
\] (9)

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

The last formula in Table 4 is defined as a soft constraint:
\[
\text{word}(h, +w) \wedge \text{pos}(h, +p) \wedge \text{dep}(h, m, +d)
\]
\[
\wedge \text{delete}(h) \Rightarrow \text{delete}(m)
\] (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,
\[
\text{word}(4, \text{“車で”}) \wedge \text{pos}(4, \text{NOUN+PARTICLE})
\]
\[
\wedge \text{dep}(4, 2, \text{“D”}) \wedge \text{delete}(4) \Rightarrow \text{delete}(2)
\] (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 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.
Table 4: Global Deletion Formulae

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

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

Table 5: Statistics in Evaluation Data

Table 6: Local vs Global

|        | 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 8, we show the best scores in bold types for art (Taira et al., 2008; Imamura et al., 2009). In


ections of PA relations and we got a large improvement (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), the recall was mainly improved 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 art (Taira et al., 2008; Imamura et al., 2009). In

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 improvements for all hidden predicates. These improvements are statistically significant. 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).

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. Based on Taira’s work, we introduce selection 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.

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Local  Global  [Taira, 2008]  [Imamura, 2009]

|       | Local | Global | [Taira, 2008] | [Imamura, 2009] |
|-------|-------|--------|--------------|-----------------|
|       | 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)

Error Analysis

| 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).

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 Abe 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, “魚類野生動物局が” 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.
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