

Learning-Based Argument Structure Analysis of Event-Nouns in Japanese

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Abstract

Previous work on predicate-argument structure analysis has focused largely on verbs and adjectives. However, to extract richer information from such a sentence as “His decision was right,” not only the predicate “was right” but also the noun “decision” need to be identified as an event denoting expression. Here, we call event denoting nouns *event-nouns*, which refer to events like “he decided something.” We define a task of argument structure analysis of event-nouns in Japanese. Some event-nouns, such as *ryouri* “cook/cuisine”, do not always refer to an event, and word sense disambiguation of event-nouns has to be done depending on their context. In this paper, we present an unsupervised machine learning method to extract patterns of event-nouns for event-hood determination. We also investigate verb-noun co-occurrences and support verb constructions for argument identification of event-nouns.

1 Introduction

The beginning of predicate-argument structure analysis using machine learning methods goes back to Gildea and Jurafsky (2002). They defined the semantic role labeling(SRL) task as finding core and adjunct arguments of predicates or verbs in the FrameNet’s (Fillmore and Baker, 2000) semantics. The PropBank (Palmer et al., 2005) is one of the corpora annotated with semantic roles, which adds semantic analysis to the parsed syntactic tree of the Penn Treebank (Marcus et al., 1993) based on the VerbNet (Kipper et al., 2000). Using the PropBank, evaluation campaigns were carried

out at the CoNLL 2004 and 2005 shared tasks ¹, and there have been a number of improvements in machine learning methods with respect to SRL.

In addition to the predicate-argument structure, there have been several projects annotating the sets of arguments that co-occur with nouns. NomBank (Meyers et al., 2004b) is one of the projects that annotate nouns and their arguments. It focuses on nominalization of verbs in English, and thus it follows the PropBank scheme to add a semantic information layer to the Penn Treebank. For example, in a sentence like “His decision was to leave.” one can assume that the noun “decision” refers to an event [REL=*decision*, A0=*his*, A1=*to leave*]. We call such a kind of nouns *event-nouns* and semantic roles like X and Y *arguments*. Despite the fact that the predicate-argument structure analysis is actively studied, there are only a few analysis models developed for nominalized predicates (Jiang and Ng, 2006; Xue, 2006).

In this paper, we discuss several issues in the argument structure analysis of event-nouns in Japanese. The main contributions of this work are (1) the task definition and corpus annotation of event-nouns, (2) using unsupervised method to extract syntactic contexts from large corpora, and (3) building a co-occurrence model and a resource of support verb constructions for the argument structure analysis of event-nouns. The remaining sections of this paper are organized as follows: we first describe the argument structure analysis of event-nouns in section 2. We divide argument structure analysis of event-nouns into two sub-tasks: event-hood determination and argument identification, and propose an unsupervised method to learn contextual clues for determination in section 3. We then propose a supervised method using verb-noun co-occurrence statistics

¹<http://www.lsi.upc.edu/~srlconll/>

and syntactic clues for argument identification in section 4. Finally, we conclude our work and present future directions in section 5.

2 Argument Structure Analysis of Event-Nouns in Japanese

Argument identification of event-nouns is similar to the semantic role labeling (SRL) task for predicates. However, compared to argument structure analysis of predicates, there is a major difference between the argument structure analysis of predicates and event-nouns.

The problem is that some event-nouns have several meanings including an event-reading and other readings. This is especially important in Japanese because verbal nouns, which refer to the same type of events as the base verbs denote, have the same surface form as their base verbs. For example, given a sentence

- (1) *watashi-wa saikin koushu-denwa_i-kara*
 I-NOM recently public phone-ABL²
kanojo-ni denwa_j-o shi-naku-na-tta
 her-DAT call-ACC do-NEG-become-PAST
 Recently, I stopped using public phones to call my girl friend.

The common noun *denwa_i* refers to a phone as a physical object while the verbal noun *denwa_j* refers to an event of someone’s calling somebody else. Note that both nouns *denwa_i* and *denwa_j* have the same surface form, and the verbal noun *denwa_j* has the base verb *denwa-suru* “make a call”. Thus, word sense disambiguation has to be done if a noun can denote both an object and an event. For that purpose, we define *event-hood*³ as whether a given verbal noun refers to an event or an object. If there is a noun that refers to an event, these nouns are said to have event-hood.

To address this issue, we divide the argument structure analysis of event-nouns into two major tasks. The first task is *event-hood determination* and the second task is *argument identification*. Event-hood determination is the task of determining whether event-nouns refer to events or not given in a context. Argument identification is the task of identifying the arguments of event-nouns which refer to events.

The concept of event-nouns is a superset of result nominals, *simple* event nominals, and *complex*

²The instrumental case is not obligatory for *denwa_j*

³Event-hood here does not discriminate between a specific instance and the generic sense of an event, and we do not differentiate them.

event nominals described in Grimshaw (1990). The difference between *simple* and *complex* event nominals is that *complex* event nominals have an associated event structure and argument structure. Since verbal nouns are a subset of *complex* event nominals, we can exploit semantically rich lexicons of verbs for the argument identification task.⁴ There are a number of simple event nominals like ‘congress’, which do not have a direct correspondence to verbs, but they are beyond the scope of this paper.

2.1 Description of Annotation

One interesting issue in the annotation of the argument structure of event nouns is how we abstract the argument structure. The PropBank and NomBank use semantic roles as a label to the arguments structure. However, it is still disputable whether or not to use semantic roles to label arguments at least in Japanese. We chose cases instead of semantic roles to annotate Japanese texts for the following reasons:

1. there is still only limited consensus on the semantic granularity and the set of semantic relations we need in Japanese,
2. the mapping rule from cases to semantic roles in Japanese seems straightforward if one has access to semantically rich resources like the VerbNet, and
3. manual annotations of semantic roles tend to be more expensive than those of cases, such as nominative, accusative and dative.

Therefore, we annotate the argument structure of event-nouns in terms of cases. We use surface cases for each event as if it were expressed in a single sentence using the active voice. For instance, in the sentence (1), we annotate [REL=*denwa_j*, NOM=*watashi*, DAT=*kanojo*].

Also, when annotating Japanese texts, zero-anaphora (intra- and inter-sentential zero pronouns) and exophoric relations must be taken care of. We annotate all inter-sentential, intra-sentential and exophoric relations for each event-noun. Obligatory cases vary from event-noun to event-noun, and we chose nominative, accusative and dative for a starting point. We do not annotate other cases at the moment because they are less reliable to annotate than these three cases.

⁴The method described in this paper would also apply to the languages other than Japanese which have nominalization.

We asked two annotators to annotate the same portion of the Kyoto Text Corpus, and calculated inter-annotator agreement of the corpus for 30 randomly selected sentences. The annotation results are evaluated by calculating recall and precision in which one annotation result is regarded as target instances and the other as selected instances. Note that arguments of event-nouns are considered for calculation of recall and precision only when event-hood are annotated by both annotators. The results are shown in Table 1.

Table 1: Inter-annotator agreement of event-nouns

	precision		recall	
event-hood	0.905	(1281/1415)	0.810	(1281/1582)
nominative	0.798	(1038/1300)	0.804	(1038/1291)
accusative	0.893	(469/525)	0.765	(469/613)
dative	0.717	(66/92)	0.606	(66/109)

With regard to inter-annotator agreement, event-hood annotation and nominative/accusative case annotation achieve high results, although the annotation of the dative case shows relatively poor inter-annotator agreement. The reason seems to be that the dative case is less obligatory than the other two cases and the two annotators do not agree on the annotation criteria. We plan to build and use a case frame dictionary based on verbs to minimize mis-classification of case frames.

The distribution of each case (nominative/accusative/dative) in our corpus is shown in Table 2. Exophora is a reference in a text or utterance to something external to it, which is only fully intelligible in terms of information about the extralinguistic situation.

From Table 2, we can see that nominative cases distribute widely, whereas a large number of accusative and dative cases exist in the same chunk or in dependency relations.

Our event-tagged corpus (Iida et al., 2007) is available online ⁵ for research purposes and has been downloaded by a wide variety of affiliations.

2.2 Related work

For the task of argument structure analysis of event-nouns for Japanese, the Kyoto Text Corpus Version 4.0 (Kurohashi and Nagao, 1997) has been annotated with the argument structure of event-nouns. However, they do not explicitly discuss the

task of event-hood determination and there is no discussion on agreement ratio of the corpus. We annotated the whole of the Kyoto Text Corpus Version 3.0, whereas only 12% of the Kyoto Text Corpus Version 4.0 was annotated with cases.

For the analysis model, Jiang and Ng (2006) proposed a maximum entropy approach to the argument identification of event-nouns. They explored several features specific to event-nouns. For example, they added features indicating whether the argument depends on the event-noun, whether the event-noun depends on a predicate, and so forth to let a machine learning classifier capture support verb constructions. However, they neither investigated features such as co-occurrence for identifying global arguments which are syntactically distant from the event-nouns, nor used a lexicon to identify support verb constructions.

3 Event-hood Determination of Nouns

3.1 Unsupervised Learning of Syntactic Contextual Clues

According to the Distributional Hypothesis (Harris, 1954), it can be expected that the distribution of the contexts where verbal nouns with an event-reading occur tends to be different from that of verbal nouns with an object-reading. Furthermore, the former distribution is expected to be close to the context distribution of verbal nouns that have unambiguously event-readings while the latter distribution should be close to that of common nouns with only object-readings. Based on this intuition, we propose to learn syntactic context clues useful for event-hood determination in an unsupervised fashion as follows.

To learn the patterns of noun phrases, we encoded sequences of parts of speech of morphemes (window size 3) and the sequence of morphemes in dependency relations into a tree structure, and then extract a pattern as a sub-tree of the encoded tree. POS tagging and dependency parsing were performed by ChaSen ⁶ and CaboCha ⁷.

Positive instances are unambiguous event-nouns which only have event-reading like *shim-pai* “concern”. We used nouns which are members of the category “Noun-Abstract-Event-hood-{Action,Event}” in Japanese Lexicon (Ikehara et al., 1997). Also, negative instances are unambiguous nouns which only have object-readings. We then defined them as proper nouns and com-

⁵<http://cl.naist.jp/nldata/corpus/>

⁶<http://chasen-legacy.sourceforge.jp/>

⁷<http://chasen.org/~taku/software/cabochoa/>

Table 2: The distribution of nominative, accusative and dative cases of event-nouns and predicates (predicates are shown in parenthesis)

	same chunk	intra-sentential dependency rel.	other	inter-sentential	exophoric
nominative	2024; 7%(0%)	6428; 23%(42%)	7131; 25%(31%)	5185; 18%(12%)	7501; 27%(15%)
accusative	5519; 50%(0%)	3424; 31%(84%)	1102; 10%(13%)	854; 8%(3%)	41; 0%(0%)
dative	841; 43%(3%)	418; 22%(88%)	470; 24%(7%)	201; 10%(3%)	10; 0%(0%)

mon nouns like *isu* “chair” in the category “Noun-Object” in the thesaurus. We used articles from one month of Mainichi Newspapers (positive instances:117,581, negative instances:282,419).

In order to capture the patterns of nouns, we used a tree classifier called BACT⁸ (Kudo and Matsumoto, 2004). BACT iteratively selects weighted sub-trees effective for classifying training data by learning tree structure using the Boosting algorithm (Freund and Schapire, 1996). If it is given sentences parsed in word dependency structure, it learns syntactic patterns as rules for classifying them.

If the weighted sum of all the tree patterns occurring in a test sentence is positive BACT classifies it as positive, while the weighted sum is negative BACT classifies the instance as negative. Therefore, acquired sub-tree patterns with high positive weight are strong indication of having event-hood and those with high negative weight are strong indication of not having event-hood. Acquired sub-trees with high weights are shown in Table 3.

3.2 Experiments

For the event-hood determination task, we used Support Vector Machines⁹ (Vapnik, 1998) to learn the contexts of event-nouns, and ran 10-fold cross validation to evaluate the performance of our system.

The baseline system chooses a predominant sense in our event-tagged corpus. Our proposed model takes into account the patterns of event-nouns obtained by BACT in addition to some heuristic features. Extracted patterns and the features used in the experiment are summarized in Table 5. Evaluation was performed on 80 articles (800 sentences) from newspapers. The evaluation set contains 1,659 event-nouns (575 instances have event-hood).

Table 4: Results of event-hood determination

	precision	recall	f-measure
Predominant(baseline)	60.4	88.2	71.7
Unsupervised(proposed)	73.3	80.2	76.6

Table 5: Features used for event-hood determination

Baseline features
WordForm
HeadWordFrom
HeadPOS
SemanticCategory ¹⁰
SelectionPreference ¹¹
AnoB (if head word of noun A in the expression of “A no B”)
SemanticCategoriesInChunk
POSeSOfPreviousChunk
POSeSOfNextChunk
POSeSOfCurrentChunk
Features obtained by BACT
FollowsVerbalNoun
FollowsGeneralNoun+GeneralNoun
PrecedesVerbalNoun
PrecedesVerbalNoun+Particle
PrecedesVerbalNoun+GeneralNoun
NumOfVerbalNouns

⁸<http://chasen.org/~taku/software/bact/>

⁹<http://www.chasen.org/~taku/Software/TinySVM/>

Table 3: Examples of sub-trees effective for event-hood determination

Sub-trees with positive weights for event-hood determination	weight
(chunk-pos (verbal-noun verbal-noun))	1.13
(follows (particle verbal-noun))	1.01
(follows (noun-suffix))	0.61
Sub-trees with negative weights for event-hood determination	weight
(precedes (verbal-noun))	-0.92
(follows (verbal-noun))	-0.54
((follows (particle)) (precedes (verbal-noun)))	-0.50

3.3 Discussions

As shown in Table 4, sub-tree patterns improve performance of event-hood determination. Using local information to extract sub-tree patterns outperforms the baseline in precision. We would like to emphasize that our proposed method achieves at least as good result as the baseline system with only a small fraction of the data using unsupervised pattern mining method from an untagged corpus, while the baseline system needs a fair amount of sense-tagged corpus. From this point of view, we intend to make further investigation on integrating compound noun and word composition information into sub-trees.

One possible way to improve event-hood determination is to use more contextual clues. For example, consider the following sentence:

- (2) *tsuma-ga genchi-to denwa-no*
 wife-NOM on site-DAT phone
yaritori-o tsuduke-ta
 exchange-ACC continue-PAST
 My wife continued calling the person on site.

In sentence (2), the event-noun *denwa* “phone-call” has event-hood with its nominative *tsuma* “wife”. For event-hood determination, the appearance of such a noun that well satisfies the selectional preference of an argument of a verbal noun may be a good indication that the verbal noun has event-hood.

4 Argument Identification

4.1 Background

The second task of argument structure analysis of event-nouns is argument identification. Argument

¹⁰We used Bunrui Goi Hyou (National Language Research Institute, 1964) for finding semantic category of given nouns.

¹¹We used the verb lexicon from EDR (National Institute of Communication Technology, 2002) to obtain selection preferences between event-nouns and their arguments.

identification is the task of finding the arguments of an event denoted by an event-noun.

As shown in Table 2, while 84% of the accusative cases and 88% of the dative cases of predicates appear at the position which has a direct dependency relation with the corresponding predicate, only 31% of the accusative cases and 22% of the dative cases of event-nouns are in a direct dependency relation. Even when there are dependency relations between event-nouns and arguments, the arguments are not marked by case markers such as accusative case marker ‘*o*’ and dative case marker ‘*ni*’, while predicates usually have arguments marked by case markers.

From our corpus study, about half of the accusative and dative cases occur in the same chunk as event-nouns and form compound nouns. To deal with this issue, we tried to utilize verb-noun co-occurrences for the argument identification task of event-nouns.

The remaining 21.7% of the event-nouns are in support verb constructions. We build a case-aligned dictionary between event-nouns and predicates for identifying support verb constructions.

4.2 Using Verb-noun Co-occurrence

To confirm that we can use the verb-noun co-occurrence model for the argument identification task, we explored the verb-noun co-occurrence model using only verbal nouns which have verbs of the same surface form. An advantage of using the verb-noun co-occurrence is that we can use an automatic parser on a large amount of unlabeled data and obtain verb-noun co-occurrences marked with cases. We assume that the verb-noun co-occurrence is similar to that of event-nouns and their argument nouns.

To resolve the data-sparseness, we used a PLSI (Hoffman, 1999)-based model to smooth the verb-noun co-occurrence distribution. Fujita et al. (2004) interpret the document *d* in PLSI as a pair

of $\langle v, c \rangle$ and the word w in PLSI as an n , where v, c, n stand for verb, case, and noun, respectively. The probability of verb-noun co-occurrence can be defined as follows using a latent semantic variable z :

$$P(\langle v, c, n \rangle) = \sum_{z \in Z} P(\langle v, c \rangle | z) P(n | z) P(z)$$

Z is a set of random variables denoting latent semantic classes, and PLSI reduces the dimension of the word matrix into $|Z|$ using the probability distribution. $P(\langle v, c \rangle | z)$, $P(n | z)$, and $P(z)$ can be estimated by EM algorithm. With the help of PLSI, one can calculate the probability of $P(\langle v, c, n \rangle)$, $P(n | z)$, and $P(z)$.

We used point-wise mutual information (Hindle, 1990) for co-occurrence measurement.

$$PMI(\langle v, c \rangle, n) = \log \frac{P(\langle v, c, n \rangle)}{P(\langle v, c \rangle)P(n)}$$

4.3 Building a Case Alignment Dictionary

Meyers et al. (2004a) indicate that a large number of nominalized verbs are in the support verb construction¹² and share arguments with main verbs. Jiang and Ng (2006) also address this problem, and they invented several features for a machine learning-based classifier to capture support verb construction. In contrast to their approach, since the support verb construction is a closed set and a list of support verbs can be compiled manually, we deal with this issue by developing a dictionary containing alignments from arguments of event-nouns to arguments of predicates that share arguments with event-nouns. For example, given a sentence

- (3) *kare-ga kanojo-ni benkyo-wo oshie-ta*
 he-NOM her-DAT study-ACC teach-PAST
 He taught a lesson to her.

the predicate-argument structure is [REL=*oshie*, NOM=*kare*, DAT=*kanojo*, ACC=*benkyo*] and the argument structure of the event-noun is [REL=*benkyo*, NOM=*kanojo*]. In this case, the predicate *oshie* “teach” and the event-noun *benkyo* “study” share the argument *kanojo* “her” for dative and nominative, respectively.

The event-tagged corpus contains 2,173 types and 8,190 tokens of support verb constructions. Top ten frequent support verb constructions are shown in Table 6.

¹²We followed their definition of a support verb as a verb which takes at least two arguments NP₁ and XP₂ such that XP₂ is an argument of the head of NP₁.

Figure 1: Number of types and tokens of support verb constructions.

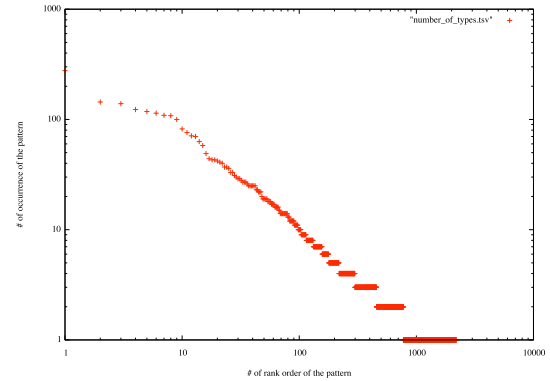


Table 6: Top ten frequent support verb constructions. S, N and E stand for a shared argument, non-shared noun phrase and event-noun, respectively.

pattern of support verb constructions	frequency
S-ga E-o suru “do”	1181(14.4%)
S-ga E-o okona-u “perform”	277(3.4%)
S-ga N-o suru	144(1.9%)
S-ga E-ni suru	139(1.7%)
S-ga suru	123(1.5%)
S-ga E-o N-ni suru	118(1.4%)
S-ga E-o uke-ru “get”	114(1.4%)
S-ga E-o tsuduk-eru “continue”	109(1.3%)
S-ga E-o susum-eru “promote”	108(1.3%)
S-ga E-o meza-su “aim to”	100(1.2%)

We extracted from a web corpus (Kawahara and Kurohashi, 2006) two million patterns of predicates on which event-nouns depend directly.¹³ We then looked the top two thousands frequent pairs (it covers 80% of the entire patterns by token). We asked two annotators to test for each case given a predicate pattern whether event-nouns share any arguments with the predicate, provided by the example phrases taken from the web corpus.

Sample entry looks like [(ACC_{event}, *oshie-ru* “teach”) = DAT_{pred} → NOM_{event}].

Although the coverage of the dictionary of our entire event-tagged corpus (different from the web corpus) is still 49%, using the created dictionary alone for argument identification task achieves 72% in precision and 35% in recall, where precision = correct/(correct + found in the dictionary but incorrect) and recall = correct/all pred. in SVCs.

¹³Automatic dependency parsing was performed by KNP (<http://nlp.kuee.kyoto-u.ac.jp/nl-resource/KNP.html>).

4.4 Argument Identification using Co-occurrence Statistics and Syntactic Clues

We used our event-tagged corpus for evaluation. Training and test sets were taken from two days of newspapers annotated by two annotators. We discarded tags on which two annotators did not agree. The training set consists of a day of newspapers (137 articles) and the test set consists of another day of newspapers (150 articles). We used instances that have arguments in a sentence only. The system should perform argument identification given an event-noun and its correct case frame.¹⁴

We used Support Vector Machines for the classifier. The implementation we used was TinySVM. We used polynomial kernel function with second degree ($d = 2$). Other parameters were set to the default values.

For the baseline model, we used features proposed by the Japanese zero-anaphora resolution model in Iida et al. (2006), because the task of argument identification of event-nouns is analogous to the zero-anaphora resolution task in such a way that both tasks include determination of semantic appropriateness (anaphoricity and event-hood) and identification of the best candidate. Features which were not applicable to event-nouns were eliminated.¹⁵ Since argument identification is performed on morphological units, we added positional features within a chunk and grammatical features of POS of morphemes in a chunk.

To model the support verb construction explicitly, we added a binary feature to test whether event-nouns depend on support verbs listed in Muraki (1990).¹⁶ Also, we added a binary feature whether the pattern of event-nouns and predicates are in the case aligned dictionary. All the novel features for argument structure analysis of event-nouns are indicated by the asterisk mark ‘*’.

¹⁴In a real application the system should also determine case frames, but we are not solving this issue for the time being.

¹⁵Because event-nouns syntactically differ from verbs we cannot set voice and adverb features. Also, we did not use heuristic features based on centering theory.

¹⁶128 expressions are taken from Muraki (1990)

Table 7: Features used for the argument identification task

Lexical features
WordForm
Grammatical features
POS
POSeInChunk*
HasDefiniteExp
HasDemonstrativeExp
Particle
Semantic features
CoocScoreOfNewsModel
CoocScoreOfWebModel
DifferenceOfCoocScoresOfNewsModel
DifferenceOfCoocScoresOfWebModel
SelectionPreference (Ikehara et al., 1997)
PronounType
NamedEntityType
Positional features
DistanceBetweenNPAndPred
IsBeginningChunkOfSentence
IsEndingChunkOfSentence
IsBeginningMorphemeOfChunk*
IsEndingMorphemeOfChunk*
PredPrecedesNP
NPPrecedesPred
NPDirectlyDependsOnPred
NPDependsOnPred*
PredDirectlyDependsonNP
PredDependsOnNP*
PredDependsOnSupportVerb*
NPDependsOnSupportVerb*
PredSharesArguments*
InQuotation

We trained the tournament model (Iida et al., 2005) on a tuple of the event-noun, correct argument, and a candidate of an argument. For each pair, it learns features and preference which candidate wins. In decoding, it picks a candidate from a set of noun phrases one by one, and identifies as an argument the one that wins the knock-out tournament.

We compared three models with the baseline. +COOC model uses the scores of co-occurrence models as features of SVM, and +SVC model uses the binary features of the support verb constructions. We calculated accuracies for each case and model.

The accuracies of three models are shown in Table 8.

4.5 Discussions

Incorporating co-occurrence model outperforms accuracies over baseline in every case. Furthermore, using the case alignment dictionary and a

Table 8: Results of the argument identification task

Feature	NOM	ACC	DAT
Baseline	60.5	79.7	73.0
+SVC	64.2	78.0	71.4
+COOC	67.1	80.1	74.6
+SVC+COOC	68.3	80.1	74.6

list of support verbs slightly improves accuracies of nominative and dative. One of the reasons why the dictionary does not have any effect is that 90% of the accusative cases are already either in the same chunk as the event-nouns or in dependency relations. 92% of the shared arguments are nominative cases, and it is not surprising that the information of support verb construction improves the accuracy of nominative case more than other two cases.

A typical error in the deterministic argument identification is failure in capturing local arguments.

- (4) *Tom-ga John-no*
Tom-NOM John-no
rensho-wo tome-ta
consecutive victories-ACC stop-PAST
Tom stopped John’s consecutive victories.

In this example, correct argument structure is [REL=*rensho*, NOM=*John*], but the system outputs [REL=*rensho*, NOM=*Tom*] because it matches the entry *X-wo tome-ru* “stop X” and does not consider other arguments in the same noun phrase. We will develop a hierarchical model which looks for local arguments before expanding its search for distant arguments.

5 Conclusion

In this paper we explained the argument structure analysis of event-nouns in Japanese. We described our annotation scheme for event-nouns and defined two tasks for argument structure analysis.

First, we proposed an unsupervised method to collect noun phrase patterns for identifying the event-hood. From our experiments, the precision and recall of determination of event-hood were 73.3% and 80.2%.

Second, we built a machine learning based analysis model of the argument identification task of event-nouns using verb-noun co-occurrences from large corpora. We showed that the co-occurrence information is effective for the argument identification task. Using a case alignment dictionary

improves accuracy of nominative and accusative cases.

It is still an open question how we can incorporate a co-occurrence model into the argument structure analyser of event-nouns. In this paper, we combined co-occurrence models and syntactic patterns as features of machine learning methods. However, they could be used in other ways. For example, we could use co-occurrence scores to filter noun candidates for argument identification, and also we could filter arguments with highly accurate syntactic patterns. We plan to further investigate the model of argument structure analysis and extends the model to identify inter-sentential and exophoric arguments of event-nouns.

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