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Construction of Predicate Argument Structure Annotator Based on Event Type Thesaurus

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In this research we construct a predicate argument structure annotator that can disambiguate predicate's semantic concept and semantic role types of its arguments in a running texts. The semantic concepts are manually constructed and systematically organized by event type of predicates according to linguistically-motivated lexical semantic structure. For example the following predicates "get", "take", "buy", "obtain", "take", "rob" and "rent" must contain a shared meaning of 'Getting from something'; and the difference of "get" and "rent" must be with/without ownership of the obtained object. We describe this semantic shared/different meaning with abstracted LCS-base structure in our Thesaurus, e.g., The semantic structure of "get" might be ([Agent] CAUSE BECOME [Theme] BE AT [Goal=person]), and "rent" might be more detailed structure as [Agent] CAUSE (BY MEANS OF [Agent] renting [Theme]) BECOME [Theme] BE AT Goal=person]). This thesaurus is continuously constructed taking into account what are the base semantic structure among all Japanese predicates. Thus by making predicate argument structure annotator (we call ASA) based on thesaurus, we can see how the thesaurus's concepts can catch the same expressions of natural language. For this purpose, ASA can recognized idiom and equivalent expressions of predicates e.g., "X ga Y ni hone-wo oru (X gives oneself trouble about Y)" and "X ga Y ni kurou-suru (X has difficulty with Y)" with disambiguating verb senses "hone-wo oru (gives oneself trouble about/break one's back)". By constructing predicate argument structure with systematic thesaurus, we try to convert running texts into more semantically controllable descriptions.

1. Introduction

After Turing machine is proposed as a model of calculation, the theory has been realized as computers, and then computers lead to the invention of not only automated machines such as controller units and mobile phones but also the Web that is a social system for people all over the world. On the Web quite a lot of for human activities are recorded and then now we have big data of partial copy of human's cognition, i.e., thinking, making decisions, like/dislike, solving problems, or understanding situations. Turing machine is an answer for what calculation is, however, what human's cognition is has not been solved yet; thus we believe that natural language understanding must be an issue to be solved utilizing large documents on the Web.

Our research described here is a challenge of constructing a language understanding model on the basis of crossing three research domains: linguistics, natural language processing, and artificial intelligence. Currently we focus on how we can describe predicate meaning because predicates play key role in deciding sentence meaning with syntactic structure. In linguistics, WordNet and FrameNet are proposed according to deep insights of how we recognize words in sentences. In natural language processing domain, The Q&A system IBM WATSON*1 consisting of statistical learning system with Wiki pedia-based text data has showed high performance on factoid Q&A task. In AI domain, mathematical and practical models

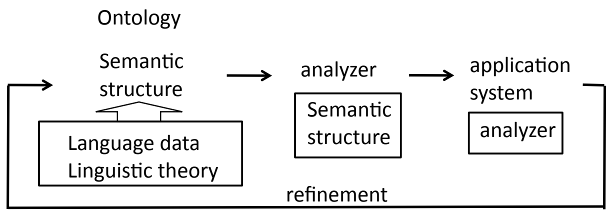

Figure 1: Framework of our research project to refine semantic description

dealing with semantics are proposed; for example, Montague grammar[Montague 73] showed the possibility of direct translation from natural language to mathematical logics. Dowty[Dowty 79] applied a lexical decomposition approach to verb meaning in Montague grammar. Various kinds of modal logic are proposed to express meaning of sentences in AI and intensional logic and temporal logic are applied in Montague grammar.

In each research domain various models and methods are proposed, however, they are not directly connected: that is, linguistic frame work does not show how the defined concepts e.g., Frames in FrameNet can be applied to reasoning on documents; the specialized Q&A system in NLP does not show what the appropriate framework of semantic description to deal with sentence meaning is; mathematical logic does not show how the proposed logical system can solve the practical Q&A task.

Thus we take an approach to refine semantic description crossing three research domains. Firstly we define semantic structure of predicates on the basis of language expression

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*1 http://www-03.ibm.com/press/us/en/presskit/27297.wss data and regard the semantic structure as temporal ontology of predicate semantics; we make an analyzer that identifies semantic structure from plain texts and construct an application system to practical NLP tasks using the analyzer as a middleware for finding semantic relations; we refine the semantic structure according to performance of the application systems to the NLP tasks. By doing this, we believe that we can find the common ground of semantic structure and its application framework to deal with predicates.

The current status of our research project is that we have organized the first version of abstracted semantic structure (i.e., types) of Japanese verbs according to example sentences, and construct a rule-based predicate-argument structure annotator called ASA that can disambiguate verb meanings and semantic role types of its arguments. Then in the following sections, firstly we show proposed verb thesaurus and its design, and then describe how ASA deals with verb semantics, and finally we show the experimental results of ASA's disambiguation performance on several running texts.

2. Background: how to describe predicate meaning for NLP

In linguistics various kinds of semantic descriptions are proposed e.g., Lexical Conceptual Structure [Jackendoff 90] [Kageyama 96a], Generative Lexicon [Pustejovsky 95] from the view of morphosyntactic research, and WordNet [Fellbaum 98], FrameNet[Baker 98], VerbNet [Kipper-Schuler 05] and PropBank [Palmer 05] Levin's English Verb Classes and Alternations (EVCA) [Levin 93] Dorr's LCS [Dorr 97] from the view of language resource. Various kinds of semantic descriptions are proposed, however, only a few descriptions of verb meanings are applied to text understanding system in formal approach.

For example, Dowty [Dowty 79] applied semantic primitives proposed in LCS such CAUSE and BECOME into Montague Grammar to translate natural sentences to enrich parser's performance to filter out ungrammatical expressions. In Conceptual Dependency [Schank 72] Schank defined several essential verb concepts such as Physical (hit, eat), Emotional (love), Transfer (trans), Communication, Direction (move), Reflexive (go), Intransitive (sleep, be), State (want, believe), CAUSE, and POSSESSION to extract concepts of English sentences. CD is a challenging framework of complementing unexpressed meaning to simulate understanding conversations. For instance, in the following conversation:

- "Do you want a piece of chocolate?"
- "I just had an ice cream cone."

We can understand that the answer indicates negative (Schank 72:618), but there is no obvious negative expression in the words. The CD proposes a method to estimate that "eat" may satisfy the person, and then the person will not need chocolate using verb concepts; thus the answer will be regarded as negative. Since limited expressions are only taken into account in CD, we need to clarify what kinds of semantic primitives can solve what kinds of practical problems such as text mining, Q&A system, and knowledge extraction from Web in NLP. Thus we need a research project to build a predicate ontology based on both linguistic theory and practical task.

3. Thesaurus of Predicate Argument Structure

The proposed verb thesaurus of predicate argument structure is a framework of describing verb classes (i.e., concepts) taking into account shared meaning of verbs and verbs arguments using decomposed meaning like LCS. Lexical decomposition approach has been applied in LCS, however, our decomposition approach is different from LCS; that is we do not limit the semantic primitives such as CAUSE, BECOME, BE and etc., but we permit to use more complex meanings as primitives; for example RENTING for the verbs "hire" and "rent", and BUYING for "buy", "purchase" (see Figure 2). The reasons we incorporate the primitives that have complex meaning are below.

(1) Limited primitives are too coarse to express word meanings; for example it must be hard to describe the different meaning between "recapture" and "rent".

(2) Meaning of a verb must be depend on the other words: Imagine that the situation we can say "buy", we "get" something by "paying" money to the seller. So the meaning of "buy" may related to "get" and "pay".

Thus we do not concentrate on describing an independent verb meaning deeply, but we concentrate on describing differences/shared meaning between verbs; for example, the shared meaning between "buy" and "get" is getting something from someone and the differentiate meaning of them is payment. Thus in our decompositional semantic description, we keep the same structure for shared meaning, and use different primitives such as BUYING and for different meaning between verb concepts in their semantic descriptions (Figure 2).

In the following sections, we describe how we define the top level nodes of thesaurus, and how we describe the relations between semantic role labels and example sentences.

3.1 Thesaurus of verb classes

In our analyses of verb expressions, we found that general meaning of verbs such as "get" and "obtain", while verbs that have detailed meaning of them e.g., "purchase", "rent", and "recapture". Thus we assume hierarchy of verb classes with granularity of assuming concepts: a parent verb class includes all meanings of verb concepts in children verb classes; for example, a verb class *Moving_One's_Possession_From* subordinates *Buying*, *Repossessing* and *Renting* in Figure 2.

Instances of verb classes are verbs in the designated verb meanings: note that verbs are polysemous then instances are verbs in the meaning; for example, the mean-

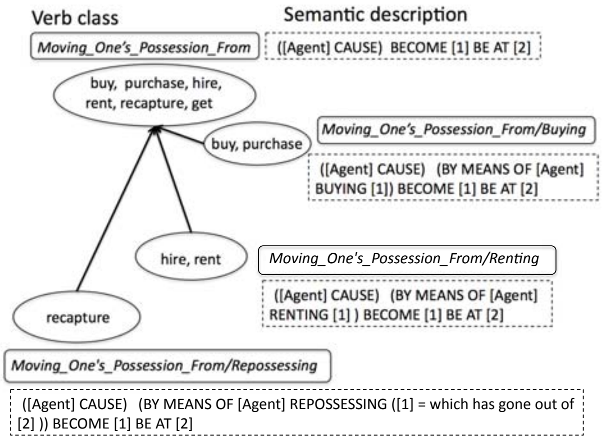

Figure 2: Example of verb class and semantic description in thesaurus of predicate argument structure

ing of "get" as "get oranges" is an instance of *Moving_One's_Possession_From*; but "get the idea" must be an instance of *Understanding*. Idioms are categorized as the same manner. Thus in a parent verb class, all of the verb meanings existing in subordinate verb classes that are detailed meaning of the parent verb class. In Figure 2, the verb class *Moving_One's_Possession_From* contains "buy", "purchase", "hire" "rent", "recapture", and "get"; "buy" and "purchase" belong to *Buying* subclass, "hire" and "rent" to *Renting*, "recapture" to *Repossessing*. Where the verb meaning "get" does not belong to any subclass, this indicates that "get" is an abstracted meaning then "get" must be upper level of the words "buy", "purchase" and the others. This hierarchy of verb class must correspond to troponymy in WordNet [Fellbaum 98].

The hierarchy of verb classes correspond to LCS [Kageyama 96b] and Vendler's aspectual analysis of verbs categories: that is, state (know, believe, have), achievement (recognize, spot, find), activity or process (work, run, push a cart), accomplishment (write a book, push a cart to the corner). Vendler proposed these 4 categories, but we merge achievement and accomplishment into it Change_of_state since the difference between achievement and accomplishment is only the existence of causer. Thus the top level nodes of our verb thesaurus are *Activity*, *State*, and *Change_of_state* (see Figure 3).

By doing this organization, our verb classes can correspond to LCS that describes internal meaning of verb classes. Since LCS can deal with final state, previous state and action by cause, our thesaurus can recognize an entailment relation between action, process and stative meaning; for example, "Ken put the book on the shelf" can indicate "the book moved to the shelf" and "the book is on the shelf". Since these structures are realized in semantic description described at each verb node as expressing what the verb class indicates, this ontology can grasp several aspects of verb meaning crossing thesaurus via substructure in semantic descriptions.

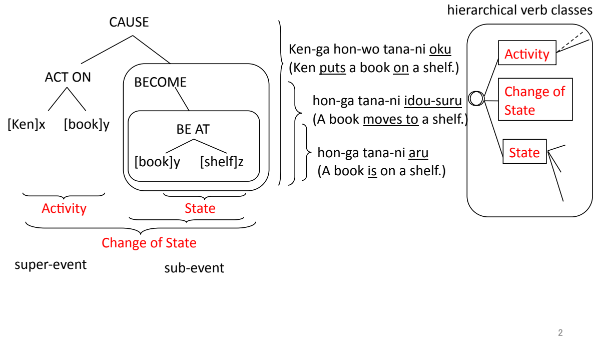

Figure 3: Example of verb class and semantic description in thesaurus of predicate argument structure

3.2 Semantic description and linking to example sentences

Each verb class has a semantic description expressing (1) shared meaning of parent semantic skeleton like LCS, (2) differentiate meaning from sister verb classes, and (3) semantic relations between arguments. In Figure 4 shows an example of semantic description for *Buying* verb class.

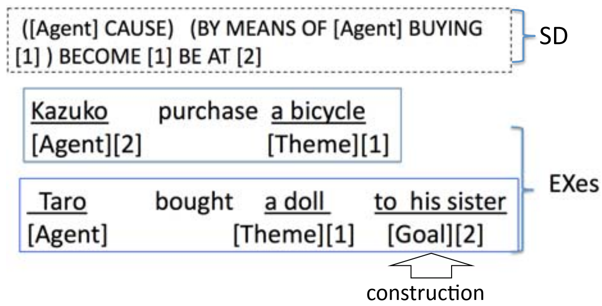

Figure 4: Example of semantic description and linking to example sentences

In semantic description Agent indicates a special argument type that means a causer of the verb's event. The number [1] and [2] in the semantic description indicates linking numbers to arguments in each example sentence. This semantic description expresses "[2] obtains [1] by the action of Agent buying [1] caused by Agent". In example sentences, we annotate (1) linkings between arguments in a sentence and arguments in the semantic description, and (2) semantic role types to the arguments.

The reason why we define semantic role label not on semantic description but on example sentences is (1) semantic role labels are depend on sentences, (2) label must be help of understanding what the meaning of arguments and summarize their function in the future work. As show in Figure 4, in the first example sentence, Kazuko will obtain the bicycle, however, in the second sentence, Taro's sister will obtain the bicycle. This is caused by the function of "to" prepositional phrase called in construction [Goldberg 95]. Besides we do not know how many types of these construction in previously, our thesaurus will show more clear linking types between semantic description and example sentences by accumulating example sentences.

Our thesaurus contains about 700 verb classes with 5 hierarchy, 80 semantic role labels on 4400 Japanese verbs (7400 verb meanings) and 7400 example sentences. The thesaurus is freely browsable and downloadable[*2]

4. Predicate Argument Structure Annotator (ASA)

A semantic structure annotator, ASA, was constructed on the basis of our thesaurus of predicate-argument structure. The modules and resources of ASA are described at Figure 5.

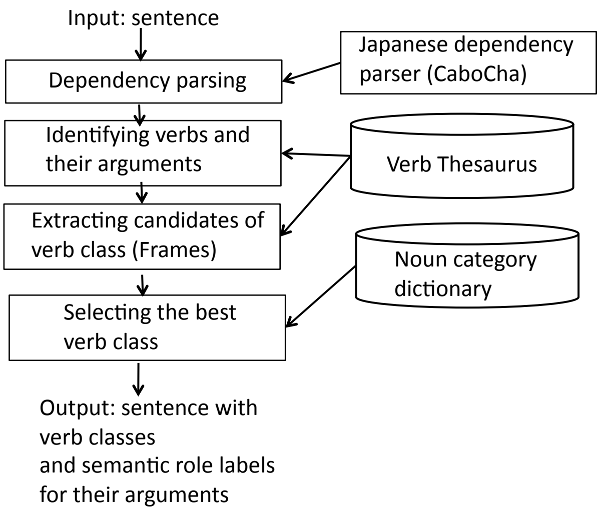

Figure 5: System of predicate argument structure annotator ASA.

The ASA detects target verbs and their arguments in a sentence by using a Japanese dependency parser CaboCha[*3] and then the ASA identifies the verb classes and semantic role labels of their arguments on the matching module on the basis of the thesaurus. Since our thesaurus has verbs of multiword expressions, ASA detect all candidates of verb idioms such as "hone-ga-oreru" (have difficulty in). In this section, we focus on the identification of verb classes and describe the details of the matching algorithm below.

In our thesaurus, for polysemous verbs, each verb sense categorized to a verb class has a few example sentences that are parsed, and noun categories[*4] are tagged to their arguments as Figure 6.

Figure 6 shows example sentences of "employ"[*5] belonging to two verb classes, i.e., *Take_up_post* and *Use*. The curly brackets in the sentences denote noun categories that are automatically annotated by a dictionary-based noun classifier proposed at [Takeuchi 09].

Verb class: ***Take_up_post***
Verb: employ
Example sentence:

- The company {ORG} employs Mr. Smith {HUM} as an accountant {ABS}.
- They {HUM} employs him {HUM} to their company {ORG}.

Verb class: ***Use***
Verb: employ
Example sentence:

- He {HUM} employs the new approach {ABS}.

Figure 6: Analyzed example sentences for the verb "employ" for each verb class in the thesaurus

Since each verb sense in a verb class only has a few example sentences, statistical learning methods do not work well in the preliminary tests. Thus, as the basic strategy for detecting the word class (i.e., word sense) of an input sentence, we take a nearest neighbor approach: find the most similar example sentence compared to the input sentence, and take the verb class of the example sentence as the word sense. The similarity between an input sentence and an example sentence is evaluated on the similarity of the arguments between them; the similarity of the arguments is evaluated on three features: shallow syntactic position, noun categories, and surface words. Since there exist one or two key arguments to disambiguate the verb classes, our similarity evaluation approach will detect and give high scores to the key pairs of the arguments. For example, in Figure 6 the noun category of the direct object position of "employ" i.e., Human (of "Smith" and "him") or Abstract (of "approach") is a good clue to disambiguate the verb classes between *Take_up_post* and *Use*.

Thus to disambiguate verb sense for an input sentence X is to detect the verb class $\hat{C}$ giving the highest score of $SimSnt$ among the example sentences Y_C in a verb class C.

$$\hat{C} = \underset{C}{\operatorname{argmax}}\, SimSnt(X, Y_C). \tag{1}$$

To evaluate the $SimSnt$ function, a matching arguments operation MA is performed on an input sentence X and an example sentence Y_C, and MA produces matched argument pairs such as x_i and yc_i.[*6]

$$SimSnt(X, Y_C) = \sum_{i \in MA(X, Y_C)} SimArg(x_i, yc_i), \tag{2}$$

where the $SimArg$ function is evaluated on matching scores

*2 http://cl.cs.okayama-u.ac.jp/rsc/data/.
*3 http://code.google.com/p/cabocha/.
*4 We use 10 noun categories such as human, non-human, bodypart, organization, object, place, time, abstract, number and event based on a Japanese dictionary [NINJAL 04].
*5 Our target verbs and sentences are Japanese, but to provide simple explanations, we describe the examples in English. The issues and approaches in English are the same as in Japanese.
*6 MA finds corresponding arguments on the basis of $MatchScr$.

and weights between paired arguments;

$$SimArg(x_i, yc_i) = MatchScr(x_i, yc_i) \times Weight_C(yc_i). \tag{3}$$

The function $MatchScr$ gives a matching score evaluating the above three features for an argument pair of a and b as

$$MatchScr(a,b) = \begin{cases} 2(\text{ syntactic position, noun} \\ \quad \text{category and surface word} \\ \quad \text{are the same)} \\ 1(\text{syntactic position and noun} \\ \quad \text{category are the same)} \\ 0(\text{other}). \end{cases} \tag{4}$$

The function $Weight_C$ gives scores of the contribution of arguments to a verb class based on their syntactic position with the noun category of the example sentences. $Weight_C$ for an argument c consists of two functions:

$$TheWeight_C(b) = WforC(b) \times WamgCs(b) \tag{5}$$

The first function $WforC$ evaluates the contribution of an argument b to the target verb class C among the example sentences as

$$WforC(b) = 1/\left(\log\frac{|S_C|}{|\{s_C : s_C \ni SN(b)\}|} + 1\right) \tag{6}$$

which is an inverted tf-idf assuming that tf is '1.' In the equation, S_C denotes the example sentences for the verb class C, and s_C denotes the example sentences that contain a pattern of syntactic position with a noun category SN of the argument b. Equation (6) indicates that an argument must be important if the argument whose syntactic position with a noun category constantly occurs with all the example sentences for a verb class. $WforC$ then gives a high score to the argument b. For example in Figure 6, $WforC$("Smith") $= 1/(\log\frac{2}{2} + 1) = 1$ in the verb class *Take_up_post*.

The second function $WamgCs$ is used to evaluate the contribution of an argument b to a verb class C among the verb classes of the target verb as

$$WamgCs = \log\frac{|VC|}{|\{vc_C : vc_C \ni SN(b)\}|} + 1 \tag{7}$$

which is an tf-idf assuming that tf is '1'. In the equation, VC denotes verb classes of the target verb, and vc_C denotes verb classes in which at least one example sentence contains a pattern of SN of the argument b. Equation (7) indicates that an argument for a verb class must be important if the argument's SN occurs with a specific verb class VC. $WamgCs$ then gives a high score to the argument b. For example, $WamgCs$("Smith") in the verb class *Take_up_post* is $\log\frac{2}{1} + 1$.

Since all of the parameters are calculated on the basis of the example sentences in the thesaurus, the performance of the ASA's verb class disambiguation depends on the quality and quantity of the thesaurus.

5. Experiments of Indentifying Verb Classes and Semantic Role Labels

We evaluate the performance of ASA on several data comparing with statistical learning based model. In previous work, we applied ASA and CRF-based verb sense disambiguator on SemEval-2010 Japanese verb sense disambiguation task and we found that ASA's outperformed the CRF-based model in recall rates [Takeuchi 11]. In the previous work, we have not evaluated the performance of annotating semantic role labels. Thus we construct an annotate corpus of semantic role labels and verb classes on Mainichi news articles and then evaluate the performance of ASA comparing with CRF-based model. In the following sections, we describe CRF-based annotation model as competitor, experimental set up: annotated corpus and evaluation methods, and then experimental results. ,

5.1 CRF-based verb class and SRL annotator

We apply a statistical learning model, Conditional Random Fields [Lafferty 01] to verb class and SRL annotator as a competitive alternative to the ASA. CRFs is a probabilistic model for labeling sequence data, and we defined labels are verb classes and SRLs in the annotated corpus (see Section 5.2).

CRFs selects the best output sequence that is a sequence of defined labels i.e., $\mathbf{Y} = (\mathbf{Y}_1, \mathbf{Y}_2, ..., \mathbf{Y}_n)$ given input word sequence $\mathbf{X} = (\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_n)$ by the following equations:

$$P(\mathbf{Y}|\mathbf{X}) = \frac{\exp(\Lambda \cdot \mathbf{F}(\mathbf{Y}, \mathbf{X}))}{\mathbf{Z_X}}, \tag{8}$$

$$\mathbf{Z_X} = \sum_{\mathbf{Y}_h} \exp(\Lambda \cdot \mathbf{F}(\mathbf{Y}_h, \mathbf{X})), \tag{9}$$

where $\mathbf{Y}_h$ denotes possible label candidates, and $\sum_{\mathbf{Y}_h}$ denotes the sum of all possible verb class and SRL sequences from an input word sequence $\mathbf{X}$.

$$\Lambda \cdot \mathbf{F}(\mathbf{Y}, \mathbf{X}) = \sum_i \sum_k \lambda_k f_k(< x_{i-1}, y_{i-1} >< x_i, y_i >), \tag{10}$$

where λ_k is a weight for the feature vector f_k, which denotes possible partial combinations between input x_i and output label y_i. The position $i-1$ denotes the previous position, and $(< x_{i-1}, y_{i-1} >< x_i, y_i >)$ indicates a combination between an input word sequence x_{i-1}, x_i and output labels y_{i-1}, y_i. Since f_k is a Boolean function, then

$$f_k(< x_{i-1}, y_{i-1} >< x_i, y_i >) = \begin{cases} 1(\text{the combination} \\ < x_{i-1}, y_{i-1} >< x_i, y_i > \\ \text{occurs in partial} \\ \text{analyses)} \\ 0(\text{otherwise}). \end{cases} \tag{11}$$

CRFs needs training corpus, that is, correctly verb class and SRL annotated corpus that is described in the next section.

5.2 Experimantal set up

We constructed an annotated corpus of verb class and SRL annotated corpus on Kyoto Text Corpus version 4.0 *7 Annotation of verb class is done not for each article, but for each verb senses, that is, 10 example sentences would be annotated for each verb sense*8. In annotated corpus, sentences are about 1480, target verbs are 93, annotated verb sense is 1377, SRLs are 2130. The type of SRLs are expanded to adjunctions such as Time-point, Time-Repeat, Limit, Premise, Reason, Boundary Instrument, Purpose, Time-Line, Manner, Location and Causer that are not defined in Verb Thesaurus. Thus we modified the ASA to deal with SRLs that are independent from verb classes.

We divided this annotated corpus into 780 sentences as training data and 700 sentences as test data. The training data is only used for the CRFs-based model; both CRFs and ASA are evaluated on test data. The performance of disambiguation of verb class and SRL is evaluated using recall rate as bellow:

$$\text{Recall of verb class} = \frac{\#\text{Verbclasses correctly identified by system}}{\#\text{All tagged verbs in test corpus}}$$

$$\text{Recall of SRL} = \frac{\#\text{Arguments correctly identified by system}}{\#\text{All tagged arguments in test corpus.}}$$

The both systems output only the best label sequence of verb classes and SRLs, then recall and precision rates are the same for the target verbs. From the different view, in the experiments we do not evaluate the performance for the all verbs in the test corpus because only selected verbs are annotated in the test corpus.

5.3 Experimental results and discussions

Table 1 shows the recall rates of verb class and SRL disambiguation in the test corpus. The ASA outperformed CRFs in verb class annotation, but CRFs performed higher accuracy than ASA in SRL annotation. This experimental

Table 1: Recall of verb class and SRL disambiguation in Kyoto Text Corpus

	Verb class	SRL
CRFs	0.70	0.61
ASA	0.72	0.54

results seem to be straightforward; i.e., the performance of CRFs depends on the amount of training corpus. The target verb classes are defined more than 700 types in thesaurus (i.e., in ASA), but verb types in this corpus are totally 93 types then verb classes are 148 types; the instances of verb classes in the corpus are 1377, thus 9.3 (1377/148) examples for a verb class exist. In contrast, SRLs are defined about 100 types but 60 types, 2130 instances in this corpus, then 35.5 (2130/60) examples for a SRL. Thus SRLs examples are much higher than verb class then CRFs would succeeded in SRLs annotation.

From this results we can estimate the maximum verb class annotation accuracy must be 70% even if we construct large annotated corpus of verb classes that contains 10 example sentences for each verb class. In contrast, SRLs annotation must be more difficult task because the both systems does not work well in SRLs annotation comparing with verb class annotation though more SRL examples would be in the corpus. This indicates that it is not the problem of amount of examples, but we need to find better feature set for discriminating SRLs.

Looking at the errors by ASA. The following two major reasons are found:

(1) mismatching noun categories between test sentence and example sentence in the thesaurus, and

(2) insufficient arguments in example sentence.

As for (1), we found that nouns in arguments of the test sentences are not registered in noun dictionary then ASA missed the selection of verb class. For instance, “akarusa” is not registered in

```
keizai-mo    akarusa-wo  torimodosu
economy-NOM  bright-ACC  be restored
(Business has recovered)
```

noun dictionary; this may be because “akarusa” is a deadjectival noun from the adjective “akarui” (bright). Thus we have to make an algorithm to cover these modified words.

As for (2), we found that the key arguments in verb class do not appear in the test sentences.

```
Test sentence:
yaku  ikkagetu  nyuuin-sita   miyamoto-shi
about one-month hospitalized Miyamoto Mr.
(Mr. Miyamoto, hospitalized about one-month)
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In the verb thesaurus the example sentences for the verb “nyuuin-suru” are illustrated in Figure 7. The verb class

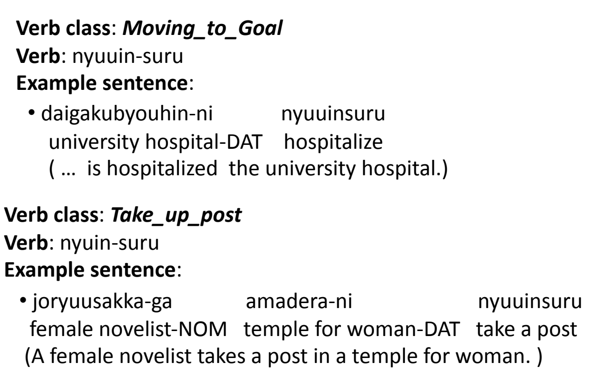

Figure 7: Example sentences of “nyuuin-suru” in the verb thesaurus

*7 http://nlp.ist.i.kyoto-u.ac.jp/.
*8 Since Kyoto Text Corpus is news articles, there is a limitation of distribution of verb sense occurrence. For example, a Japanese verb “nyuuin-suru” has at least two verb senses “go to hospital” and “become a priest”, but only the former verb sense occurs in news articles.

Moving_to_Goal is the correct answer for the above test sentence, however, the subject in the example sentence is omitted then ASA could not matching the subject "miyamoto" (Miyamoto) to that of the example sentence in *Moving_to_Goal*. Thus we add more example sentences, not only CRFs-model but also ASA will increase the performance of verb class and SRL annotation.

6. Conclusion

In this paper we proposed a research framework that covers three research domain, i.e., linguistics, natural language processing, artificial intelligence to clarify how to describe predicate meaning to deal with practical texts. We also show the current results of this research, that is, construction of predicate-argument thesaurus for verbs motivating NLP, and an annotator of predicate-argument structure called ASA for input texts. The experimental results of ASA and CRFs based annotation system of verb classes and semantic role labels show that the accuracy is about 70% in verb class annotation and SRLs is about from 54 to 61%. This shows that we need large scale annotation example sentences.

In this paper we only show verb classes in the thesaurus, however, we internally expanded the number and kinds of registered lexicon, i.e., adding other verbs, adjectives and adjectival verbs for Japanese. By adding adjectives, currently we found that the total system how we can describe the relation between verb concept and stative expressions by adjectives. In the future work we will show how these semantic descriptions help a system to understand natural language in practical problems.

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