

Table 2: The statistics of constructed NCFs.

Frequency ranking	Proportion of nouns with NCF	# of NCFs per noun with NCF	# of CSs per NCF	Coverage
-100	56.0%	1.34	1.07	17.3%
-1000	68.8%	1.17	1.16	25.6%
-10000	51.7%	1.11	1.17	27.0%
-100000	14.8%	1.05	1.13	17.6%
100001-	13.7%	1.0009	1.0053	12.5%
all	13.9%	1.0031	1.0101	100%

Table 3: Evaluation of constructed NCFs.

Precision	Recall	F-measure
62/70 (0.89)	62/84 (0.74)	0.81

sult. As for the 10,000 most frequently appeared nouns, which occupied about 70% of all noun appearances, the average number of case frames for a noun was 1.11, and the average number of case slots for a case frame was 1.17.

For evaluating the resultant case frames, we randomly selected 100 nouns from the 10,000 most frequent nouns, and created gold standard case frames for these nouns by hand. For each noun, case frames were given if the noun was considered to have any indispensable entity, and for each case frame, obligatory case slots were given manually: 70 case frames were created that had 84 case slots; 56 case frames had only one case slot, the other 14 case frames had two case slots. 30 nouns had no case frames.

We then evaluated the automatically constructed case slots for these selected nouns. The evaluation result is shown in Table 3: the system output 70 case slots, and out of them, 62 case frames were judged as correct. The F-measure was 0.81. Since the boundary between indispensable cases and optional cases of a noun is not always obvious, this score is considered to be reasonable.

2.3 Generalization of Examples

By using nominal case frames constructed from the Web, sparseness problem was alleviated to some extent, but still remained. For instance, there were thousands of named entities (NEs), which could not be covered intrinsically. To deal with this sparseness problem, we generalized the examples of case slots.

First, we used the categories that Japanese mor-

phological analyzer JUMAN³ adds to common nouns. In JUMAN, about twenty categories are defined and tagged to common nouns. For example, “*kuruma* (car),” “*niwatori* (chicken),” and “*tatemono* (building)” are tagged as “VEHICLE,” “ANIMAL” and “FACILITY,” respectively. For each category, we calculated the rate of categorized examples among all case slot examples, and added it to the case slot as “[CT:VEHICLE]:0.13.”

We also generalized NEs. We used a common standard NE definition for Japanese provided by IREX workshop (1999). We first recognized NEs in the source corpus by using an NE recognizer (Sasano and Kurohashi, 2008), and then constructed NCFs from the NE-recognized corpus. As well as categories, for each NE class, we calculated the NE rate among all case slot examples, and added it to the case slot as “[NE:PERSON]:0.22.” The generalized examples are also included in Table 1.

3 Probabilistic Model

In this study, we apply a lexicalized probabilistic model for zero anaphora resolution proposed in (Sasano et al., 2008) to associative anaphora resolution.

3.1 A Lexicalized Probabilistic Model for Zero Anaphora Resolution

In English, overt pronouns such as “she” and definite noun phrases such as “the company” are anaphors that refer to preceding entities (antecedents). On the other hand, in Japanese, anaphors are often omitted, which are called *zero pronouns*, and zero anaphora resolution is one of the most important techniques for semantic analysis in Japanese.

Here, we introduce our model for zero anaphora resolution (Sasano et al., 2008). This model first resolves coreference and identifies discourse entities; then from the end of each sentence, analyzes each predicate by the following steps:

1. Select a case frame temporarily.
2. Consider all possible correspondences between each input argument and a case slot of the selected case frame.
3. Regard case slots that have no correspondence as zero pronoun candidates.

³<http://nlp.kuee.kyoto-u.ac.jp/nl-resource/juman-e.html>