A Probabilistic Model for Japanese Zero Pronoun Resolution Integrating Syntactic and Semantic Features

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Abstract

This paper proposes a method to resolve Japanese zero pronouns by identifying their antecedents. Our method uses a probabilistic model, which is decomposed into syntactic and semantic properties. A syntactic model is trained based on corpora annotated with anaphoric relations. However, a semantic model is trained based on a large-scale unannotated corpus, so as to counter the data sparseness problem. We also propose the notion of certainty to improve the accuracy of zero pronoun resolution. We show the effectiveness of our proposed method by way of experiments.

1 Introduction

In human languages, anaphoric expressions, such as pronouns, pro-verbs, and definite noun phrases, are often used to avoid redundant expressions and repetitions. To identify appropriate entities referred by anaphoric expressions is crucial in natural language processing, specifically, discourse analysis.

In the case of discourse analysis for English, motivated partially by Message Understanding Conferences (MUCs) (Grishman and Sundheim, 1996), a number of coreference resolution methods, in which coreference relations among noun phrases are identified, have been proposed.

However, in cases of other languages such as Japanese, Chinese, and Spanish, anaphoric expressions are often omitted. Specifically, omitted obligatory cases are usually termed zero pronouns. Since zero pronouns are not explicitly expressed (or written) in discourse, the process of identifying and resolving zero pronouns is different from general coreference resolution methods targeted in MUCs.

Identifying and resolving zero pronouns in a specific context are crucial for discourse analysis, and are also expected to enhance a number of natural language processing applications. For example, in machine translation from a language in which obligatory cases are often omitted (e.g., Japanese) to another language in which cases have to be expressed (e.g., English), omitted cases in the source language have to be identified and associated with appropriate antecedents, prior to generating a translation in the target language (Nakaiwa and Shirai, 1996).

A number of methods proposed to resolve anaphoric expressions including zero pronouns are classified into the two fundamental approaches: rule-based and statistical approaches.

In rule-based approaches (Brennan et al., 1987; Ferrández and Peral, 2000; Grosz et al., 1995; Hobbs, 1978; Kameyama, 1986; Mitkov et al., 1998; Okumura and Tamura, 1996; Walker et al., 1994), anaphoric relations between anaphors and their antecedents are identified by hand-crafted rules, which typically rely on syntactic structures, gender/number agreement, and selectional restrictions. However, rules that are developed for a specific language are not necessarily effective for other languages. For example, gender/number agreement in English cannot be applied to Japanese zero pronouns.

On the other hand, statistical approaches (Aone and Bennett, 1995; Ge et al., 1998; Kim and Ehara, 1995; Soon et al., 1999) use models produced based on corpora annotated with anaphoric relations. A number of corpus-based methods have recently been proposed and made great progress in much NLP research (e.g., parsing). However, only a few attempts have been made in the context of corpus-based statistical anaphora resolution for Japanese zero pronouns.

Motivated by the above background, we propose a probabilistic model for identifying antecedents of Japanese zero pronouns. In brief, our model is decomposed into two models related to syntactic and semantic properties, so as to improve the efficiency of probability estimation. In addition, our model can be trained based on both corpora annotated with anaphoric relations and those without annotations, to counter the data sparseness problem.

In this paper, we focus solely on zero pronouns whose antecedents exist in preceding sentences to zero pronouns (i.e., anaphora) since they are major reference in Japanese discourse.

Section 2 explains our zero pronoun resolution system focusing mainly on a proposing probabilistic model. Section 3 performs experiments related to zero pronoun resolution in Japanese texts and shows results, and Section 4 discusses related research.

2 A System for Japanese Zero Pronoun Resolution

2.1 Overview

Figure 1 depicts the overall design of our zero pronoun resolution system. In the following, we explain the entire process based on this figure.

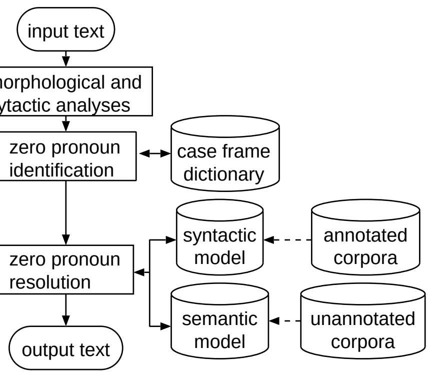

Figure 1: The overall design of our Japanese zero pronoun resolution system (dashed arrows denote the off-line process).

First, given an input Japanese text, our system performs morphological and syntactic analyses. In the case of Japanese, morphological analysis involves word segmentation and part-of-speech tagging because Japanese sentences lack lexical segmentation, for which we use the JUMAN morphological analyzer (Kurohashi and Nagao, 1998b). On the other hand, we use the KNP parser (Kurohashi, 1998) to identify syntactic relations between segmented words.

Second, in a zero pronoun identification phase, the system identifies all the possible zero pronouns in the input text by way of syntactic relations, for which we consult a case frame dictionary and regard omitted obligatory cases as zero pronouns. To put it more precisely, we use the IPAL basic verb dictionary (Information-technology Promotion Agency, 1987), which contains 861 Japanese verbs and 3,379 subcategorized case frames (the average number of case frames per verb is 3.9). Figure 2 shows a fragment of case frames for Japanese verb *nozomu*, where capitalized symbols denote semantic markers defined in the IPAL dictionary. For example, HUM and LOC denote human and location, respectively.

nominative	dative	verb (English gloss)
HUM/ORG-*ga*	ACT-*ni*	*nozomu* (to attend)
HUM/ORG-*ga*	ABS-*ni*	*nozomu* (to face)
LOC-*ga*	LOC-*ni*	*nozomu* (to face)

Figure 2: An example case frame for Japanese verb *nozomu*.

In the case where a verb in question is associated with more than one case frame, the most plausible case frame is selected by way of its governing verb complements. Let us take the following short sentence as an example for identifying zero pronouns:

kaidan-ni	*nozomu.*
(conference-dative)	(?)

In this example, the target verb (i.e., *nozomu*) is associated with three case frames in Figure 2. To select the most appropriate case frame, the verb complement "*kaidan-ni* (conference-dative)" is compared to the dative semantic marker related to each case frame.

However, we do not have a dictionary which associates nouns with IPAL semantic markers. Thus, we first consult the Japanese *Bunruigoihyou* thesaurus (National Language Research Institute, 1964) to obtain semantic classes associated with verb complements. In this thesaurus, each entry is assigned a five digit class code. In other words, this thesaurus can be considered as a tree, five levels in depth, with each leaf as a set of words.

Then, we correspond associated semantic classes with IPAL semantic markers by way of hand-crafted rules (Murata et al., 1999). Table 1 shows a fragment of the rules, where IPAL semantic markers (e.g., HUM and ORG) correspond to top three digit classes in the *Bunruigoihyou* thesaurus.

As a result, since word "*kaidan* (13351)" is categorized into ACT, and thus the first case frame (i.e., "to attend") is selected, we conclude that the nominative case is omitted, and thus is a zero pronoun. However, in the case where a verb in question is not defined in the IPAL dictionary, we

Table 1: A fragment of rules that associate IPAL semantic markers and semantic classes in the *Bunruigoihyou* thesaurus.

semantic markers	semantic classes
HUM (human)	120,121,122,123,124
ORG (organization)	125,126,127,128
ACT (act)	133,134,135,136,137,138

assume that only the nominative case, which is obligatory for many Japanese verbs, is associated with the target verb.

Third, in a zero pronoun resolution phase, antecedent candidates for each zero pronoun are extracted from the text. Although a possible search scope in extracting antecedent candidates includes all the sentences preceding to a zero pronoun, zero pronouns usually refer to entities within a limited proximity. Thus, our search scope ranges from a zero pronoun to the beginning of the previous paragraph.

All nouns and noun phrases in this range are extracted as antecedent candidates, which are ordered according to the extent to which they can be the antecedent for the target zero pronoun. From the viewpoint of probability theory, our task here is to compute a probability that zero pronoun ϕ refers to antecedent a_i, $P(a_i|\phi)$, and to select the antecedent candidate that maximizes the probability score.

In Section 2.2, we model zero pronouns and antecedents for this computation.

2.2 Modeling Zero Pronouns and Antecedents

According to existing methods for zero pronoun resolution and our preliminary study, we use the following six features to model zero pronouns and antecedents.

- Features for zero pronouns
  - Surface cases related to zero pronouns (c) :

    Their possible values are Japanese case marker suffixes, such as *ga* (nominative), *wo* (accusative), and *ni* (dative). Each of them indicates as to which case is omitted.
  - Semantic markers for which zero pronouns are categorized (s) :

    19 markers (e.g., ACT and HUM in Figure 2) defined in the IPAL verb dictionary (Information-technology Promotion Agency, 1987).
- Features for antecedents
  - Post-positional particles (p) :

    Post-positional particles play crucial roles in resolving Japanese zero pronouns (Kameyama, 1986; Walker et al., 1994).
  - Proximity (d) :

    This feature denotes the proximity (or distance) between a zero pronoun and antecedent candidate in an input text. In the case where they occur in the same sentence, the proximity takes the maximum value. In the case where an antecedent occurs in n sentences previous to the sentence including the target zero pronoun, the proximity decreases in reverse proportion to the value of n.
  - Constraints related to relative clauses (r) :

    This feature denotes whether an antecedent is included in a relative clause or not. In the case where it is included, the value of r takes *true* (1), otherwise takes *false* (0). The rational behind this feature is a fact that a Japanese zero pronoun tends *not* to refer to noun phrases in relative clauses.
  - Semantic classes (n) :

    This feature represents semantic classes associated with antecedents. We use 544 semantic classes defined in the Japanese *Bunruigoihyou* thesaurus (National Language Research Institute, 1964), which contains 55,443 Japanese nouns.

2.3 Our Probabilistic Model

Given the formal representation for zero pronouns and antecedents described in Section 2.2, the probability that zero pronoun ϕ refers to antecedent candidate a_i, $P(a_i|\phi)$, is expressed as in Equation (1).

$$P(a_i|\phi) = P(p_i, d_i, r_i, n_i|c, s) \qquad (1)$$

However, to improve the efficiency of probability estimation, we decompose the right side of Equation (1).

Since a preliminary investigation showed that d_i and r_i are relatively independent of other features, we approximate Equation (1) as in Equation (2).

$$P(a_i|\phi) \approx P(p_i, n_i|c, s) \cdot P(d_i) \cdot P(r_i) \qquad (2)$$

Here, p_i and c denote syntactic properties for candidate a_i and zero pronoun ϕ, respectively. On the other hand, n_i and s denote semantic properties for a_i and ϕ, respectively. Thus, we further approximate Equation (2) to derive Equation (3).

$$P(a_i|\phi) \approx P(p_i|c) \cdot P(d_i) \cdot P(r_i) \cdot P(n_i|s) \quad (3)$$

Here, we shall call the combination of the first three factors, $P(p_i|c) \cdot P(d_i) \cdot P(r_i)$, and the remaining factor, $P(n_i|s)$, syntactic and semantic models, respectively.

Each parameter in Equation (3) is computed as in Equations (4), where $F(x)$ denotes the frequency of x obtained from corpora annotated with anaphoric relations.

$$\begin{aligned} P(p_i|c) &= \frac{F(p_i, c)}{\sum_j F(p_j, c)} \\ P(n_i|s) &= \frac{F(n_i, s)}{\sum_j F(n_j, s)} \\ P(d_i) &= \frac{F(d_i)}{\sum_j F(d_j)} \\ P(r_i) &= \frac{F(r_i)}{\sum_j F(r_j)} \end{aligned} \quad (4)$$

2.4 Semantic Model Estimation

Since we need large-scale training corpora where semantic markers and classes are associated to estimate the semantic model, $P(n_i|s)$, the data sparseness problem becomes crucial. Therefore, we explore use of corpora without annotations of anaphoric relations in estimating the semantic model, instead of Equation (4).

We assume that semantic markers for verb complements are identified based on combinations of their governing verbs and case markers. For example, given verb *nozomu* and case marker *ga* (see Figure 2), one can easily predict what semantic marker is appropriate for that verb complement (i.e., HUM). Thus, we represent a semantic marker by verb v and case marker c, as in Equation (5).

$$\begin{aligned} P(n_i|s) &\approx P(n_i|v, c) \\ &= \frac{F(n_i, v, c)}{\sum_j F(n_j, v, c)} \end{aligned} \quad (5)$$

Since v and c are features for a zero pronoun, and n_i is a feature for an antecedent (see Section 2.2), annotated corpora are still needed to estimate $P(n_i|v, c)$. However, we can regard v, c, and n_i as features for a verb and its case element because a zero pronoun is an omitted case element. Thus, it is possible to estimate the probability $P(n_i|v, c)$ based on co-occurrences of verbs and their case elements, which can be extracted automatically from large-scale corpora analyzed by morph/syntax parsers.

2.5 Certainty for Zero Pronoun Resolution

Since our resolution system is not stand-alone, our system has to be contextualized as a module in practical NLP applications, such as machine translation systems. In those applications, it is desirable that our resolution module selectively outputs antecedents that are resolved with a higher certainty degree, so as to improve the accuracy of the system (consequently, the system coverage potentially decreases).

In view of this problem, we introduce the notion of certainty in our probabilistic model. We assume that in the following two cases, system outputs (i.e., antecedents with the greatest probability score computed by Equation (3)) are more likely to be correct:

- the probability score for the first antecedent is sufficiently great,
- the probability score for the first antecedent is significantly greater than that for the second antecedent candidate.

Therefore, we compute a certainty score for each zero pronoun, $C(\phi)$, as in Equation (6).

$$C(\phi) = t \cdot P_1(\phi) + (1 - t)(P_1(\phi) - P_2(\phi)) \quad (6)$$

Here, $P_1(\phi)$ and $P_2(\phi)$ denote scores for the first and second candidates, respectively, and t is a parametric constant ranging from 0 to 1.

3 Evaluation

3.1 Methodology

For the purpose of our evaluation, we used the *Kyotodaigaku* Text Corpus version 2.0 (Kurohashi and Nagao, 1998a), in which 20,000 articles included in *Mainichi Shimbun* newspaper articles published in 1995 are analyzed by JUMAN and KNP (i.e., the morph/syntax analyzers our system uses) and manually revised. From this corpus, we randomly sampled 30 editorials and 30 general articles (e.g., politics and sports). Editorials were distinguished from other articles because, a) they are mainly subjective opinions while general articles are relatively objective and, b) this difference potentially affects zero pronoun resolution.

We annotated the sample articles with anaphoric relations. Table 2 shows statistics associated with the sample articles, where "#correct antecedents in scope" denotes the the number of cases where correct antecedents are contained in a list of antecedent candidates extracted from the search scope and "included ratio" denotes the ratio between the number of correct antecedents included in the search scope and the total number of zero pronouns, which is calculated by dividing "#correct antecedent in scope" by "#zero pronouns." We focused solely on cases where zero pronouns are associated with antecedents in the search scope.

Table 2: Statistics associated with the sample articles.

	editorial	general
#articles	30	30
#sentences	867	423
#sentences per article	28.9	14.1
#zero pronouns	536	382
#correct antecedents in scope	498	355
included ratio (%)	92.9	92.9

We performed a leave-one-out cross-validation, where one article was used as a system input and the remaining 29 articles were used to produce a syntactic model. We also used six years worth of *Mainichi Shimbun* newspaper articles (Mainichi Shimbunsha, 1994–1999) to produce a semantic model as in Equation (5).

To extract a verb and its case element pairs from newspaper articles, we performed a morphological analysis by JUMAN and determined dependency relations using a relatively simple rule: we assumed that each noun modifies the most proximate verb. As a result, we obtained 12 million co-occurrence relations including 6,194 verbs.

3.2 Evaluation Metrics

We used accuracy and coverage as evaluation metrics, which are calculated as in Equation (7).

$$\begin{aligned} accuracy &= \frac{\#correct}{\#attempted} \\ coverage &= \frac{\#attempted}{\#identified} \end{aligned} \tag{7}$$

Here, $\#correct$ denotes the number of cases where zero pronouns contained in the system output were correctly resolved, and $\#attempted$ denotes the number of zero pronouns attempted to be resolved. In addition, $\#identified$ denotes the total number of zero pronouns in the input text.

3.3 Results of Comparative Experiments

We compared the performance of the following models in terms of zero pronoun resolution, where "*both*2" denotes our complete model.

- a semantic model as in Equation (4) ($sem1$)
- a semantic model produced based on co-occurrences of verbs and their complements as in Equation (5) ($sem2$)
- a syntactic model (syn)
- a combination of syntactic and semantic ($sem1$) models ($both1$)
- a combination of syntactic and semantic ($sem2$) models ($both2$)
- a rule-based model ($rule$)

As a control (baseline) model, we took approximately two man-months to develop a rule-based model ($rule$) through an analysis on ten articles in *Kyotodaigaku* Text Corpus. This model adopts the following rules typically used in other rule-based approaches: 1) semantic consistency between a zero pronoun and its antecedent candidate, 2) proximity between a zero pronoun and its antecedent candidate, 3) a post-positional particle that follows an antecedent candidate.

Table 3 shows the results of our comparative experiments.

Table 3: Results of zero pronoun resolution.

model	ranking	#correct (accuracy) editorial	#correct (accuracy) general
	1	124 (24.9%)	93 (26.2%)
*sem*1	2	195 (39.2%)	145 (40.8%)
	3	248 (49.8%)	186 (52.4%)
	1	145 (29.1%)	114 (32.1%)
*sem*2	2	214 (43.0%)	186 (52.4%)
	3	250 (50.2%)	221 (62.3%)
	1	173 (34.7%)	187 (52.7%)
syn	2	247 (49.6%)	222 (62.5%)
	3	300 (60.2%)	248 (69.9%)
	1	186 (37.3%)	173 (48.7%)
*both*1	2	260 (52.2%)	226 (63.7%)
	3	307 (61.6%)	252 (71.0%)
	1	**198 (39.8%)**	**192 (54.0%)**
*both*2	2	**274 (55.2%)**	**235 (66.2%)**
	3	**311 (62.4%)**	**268 (75.5%)**
	1	180 (36.1%)	131 (36.9%)
rule	2	259 (52.0%)	185 (52.1%)
	3	295 (59.2%)	222 (62.5%)

Here, the column "ranking" denotes a threshold for the ranking generated as the system output. In the case where the correct answer is ranked within the threshold, we judged the output correct. Bold figures denote the highest performance in each ranking across different models.

For each of models compared, the accuracy related to editorials was lower than one for general articles. This result implies that the domain of an input text affects the accuracy of Japanese zero pronoun resolution.

By comparing two different semantic models (i.e., $sem1$ and $sem2$), $sem2$ generally outperformed $sem1$. Possible explanations for this result would include:

- a large-scale corpus was available for modeling $sem2$,
- the semantic model in Equation (5), $P(n_i|v, c)$, could be produced for verbs unlisted in the IPAL dictionary,
- $sem2$ overcame the data sparseness problem due to a limited number of semantic markers in the IPAL dictionary.

Let us discuss the relation between syntactic and semantic models. The syntactic model outperformed both semantic models, irrespective of the article type. This result indicates that syntactic features are more effective than semantic features in resolving zero pronouns.

However, in the case where both syntactic and semantic models are used, the accuracy was generally improved. By comparing the cases of $both2$ and $rule$, the former generally outperformed the latter. Thus, we conclude that our final model integrating syntactic and semantic models was effective for zero pronoun resolution in Japanese.

At the same time, statistical methods generally require corpora annotated with anaphoric relations for modeling. Thus, we performed two additional experiments to investigate the relation between the corpus size used and accuracy.

For the first experiment, we varied the number of articles used for producing a syntactic model of $both2$. For the second experiment, we varied amount of newspaper articles used for producing a semantic model of $both2$, in which a syntactic model was trained based on 29 annotated articles. Figure 3 and Figure 4 show the results for above experiments, respectively.

In Figure 3, the accuracy for both editorial and general articles was improved as the number of training data increased. In Figure 4, the accuracy was marginally improved as the corpus size increased. However, it should be noted that in the latter case we did not need human supervision in producing corpora for modeling.

Finally, we evaluated the effectiveness of the certainty score, in which we set t in Equation (6) 0.5, and varied a threshold for the certainty score, so as to plot the coverage and accuracy. Figure 5 shows the result, where the accuracy was improved by decreasing the coverage, disregarding the article types.

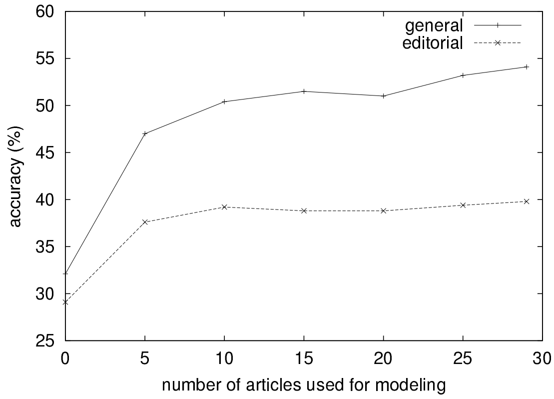

Figure 3: The relation between the size of training data and accuracy for a combination of syntactic and semantic models ($both2$).

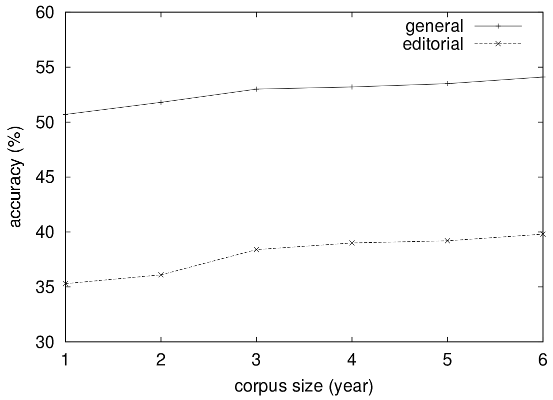

Figure 4: The relation between the corpus size and accuracy for a combination of syntactic and semantic models ($both2$).

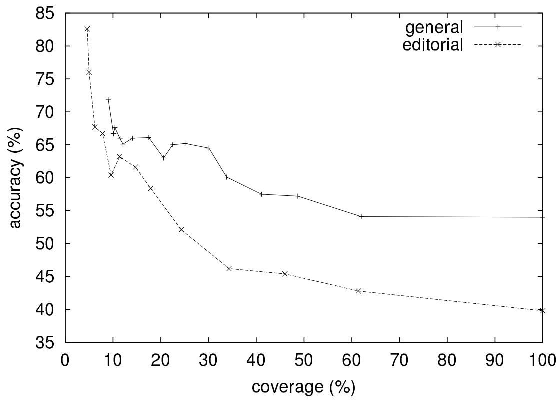

Figure 5: The trade-off between accuracy and coverage.

4 Related Work

A number of methods have been proposed to resolve anaphoric relations. However, to the best of our knowledge, Aone and Bennett (1995) and Kim and Ehara (1995) independently proposed corpus-based methods for Japanese zero pronoun resolution.

Aone and Bennett (1995) used a decision tree to determine appropriate antecedents for zero pronouns. They focused on proper and definite nouns used in anaphoric expressions as well as zero pronouns. However, their method resolves only anaphors that refer to organizations (e.g., private companies), which are relatively simpler when compared with our cases.

Kim and Ehara (1995) proposed a probabilistic model to resolve zero subjects (or quasi-zero pronoun (Aone and Bennett, 1995)) for the purpose of Japanese/English machine translation. In their model, the search scope for possible antecedents was limited to the sentence that contains zero pronouns (i.e., intra-sentential anaphora). On the other hand, we resolve zero pronouns in both intra/inter-sentential anaphora.

In addition, both above methods need annotated corpora for statistical modeling, while we used corpora without annotations related to anaphoric relations. As a result, unlike their cases, we can easily obtain large-scale corpora to avoid the data sparseness problem.

5 Conclusion

This paper proposed a method for Japanese zero pronoun resolution based on a probabilistic model, which is decomposed into syntactic and semantic models. We used large-scale corpora without annotations of anaphoric relations in producing semantic model. We also proposed the notion of certainty to improve the accuracy of our method. Through experiments, we showed that use of large-scale unannotated corpora improved the accuracy, and that a combination of syntactic and semantic models further improved the accuracy.

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