Disambiguation with Verb-predictability: Evidence from Japanese Garden-path Phenomena

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Abstract

This paper proposes a new model for human sentence processing which makes use of *predictability* of verbs from nouns for ambiguity resolution. The main claim is that verb distribution given a subject noun and an object noun varies depending on the animacy of the object noun, and that this variance influences the GP effect in Japanese. First, we report experimental results showing the asymmetry for the object-animacy in the GP effect, which cannot be explained in terms of semantic fitness, that is essential in constraint-based models. Then, we show, on the basis of a corpus analysis, that the difference of the object-animacy is related not to semantic fitness between nouns and verbs but to predictability of verbs from nouns. Finally, we propose our model of disambiguation using verb-predictability, and, based on this model, explain the asymmetry for the object-animacy observed in our experiment.

Introduction

Language comprehension is one of the central issues in cognitive science. A number of models for human sentence processing have been proposed in psycholinguistics and computational linguistics. Earlier models in psycholinguistics were motivated by observations of human preferences in syntactic structure determination (Kimball, 1973; Frazier & Fodor, 1978; Frazier & Rayner, 1982). In recent studies, much attention has been paid to interactive models, or *constraint-based* models, which make use of various sorts of information from syntax, semantics, and discourse for ambiguity resolution (McClelland, St. John, & Taraban, 1989; MacDonald, 1994; Trueswell, Tanenhaus, & Kello, 1993; Trueswell, Tanenhaus, & Garnsey, 1994).

In a variant of constraint-based models, semantic fitness between nouns and verbs plays an important role in disambiguating alternative interpretations of a sentence. Consider the following example (Trueswell et al., 1994):

(1) The defendant examined by the lawyer turned out to be unreliable.

(2) The evidence examined by the lawyer turned out to be unreliable.

Sentences with reduced relative clauses such as (1) and (2) are temporarily ambiguous at the moment of the verb "examined" being read, since it can be interpreted as the past tense form or as the passive participial form. This ambiguity may cause strong processing difficulty, or *garden-path* (GP) effect, when an item inconsistent with favored interpretation will be read. In the above example, the prepositional phrase "by the lawyer" is inconsistent with the past tense/main verb interpretation of "examined." Trueswell et al. (1994) showed that people revealed GP effects at "by the lawyer" in (1) but not in (2). They explained this difference in the following way. In (1), the NP "the defendant," that is Animate, is a typical Agent of the verb "examine." Thus, people prefer the past tense/main verb interpretation, which allows "the defendant" to be the Agent of the verb. This results in a GP when the contradiction is found at "by the lawyer." On the other hand, in (2), the NP "the evidence," that is Inanimate, is not a typical Agent but a typical Theme of the verb "examine." Thus, people prefer the passive participial/reduced relative interpretation, which allows "the evidence" to be the Theme of the verb. This does not conflict with "by the lawyer." Trueswell et al. (1994) also found that semantic fitness between nouns and verbs was correlated with the reading times of the sentences.

The above results show that people utilize semantic fitness between nouns and verbs in disambiguation. Such a model, however, is difficult to apply to processing of head-final languages like Japanese. In Japanese, verbs are usually located at the ends of clauses. If we assume those models that use lexical-semantic information of verbs for disambiguation, it is concluded that people do not decide any preference among competing interpretations until they encounter the clause-ends. This is unrealistic from the viewpoint of the limited memory capacity of humans. For this reason, researchers on Japanese sentence processing also assume that ambiguity is resolved on the spot while reading a sentence (Inoue & Fodor, 1995; Mazuka & Itoh, 1995). It is, however, still unclear what kinds of information are essential for resolving ambiguity in Japanese.

In this paper, we propose a new model for human sentence processing which makes use of *predictability* of verbs from nouns for ambiguity resolution. The main claim is that verb distribution given a subject noun and an object noun varies depending on the animacy of the object noun, and that this variance influences the GP effect in Japanese. First, we report experimental results showing that, in Japanese, the Animate/Inanimate asymmetry in the GP effect is not observed for subject nouns but observed for object nouns. These results can not be explained in terms of semantic fitness, which is essential in constraint-based models. Second, we show, on the basis of analysis of a corpus, that Animate- and Inanimate-object sentences are different not in semantic fitness between nouns and verbs but in predictability of verbs from nouns. Third, we propose our model of disambiguation using verb-predictability, and, based on this model, we account for the asymmetry for the object-animacy observed in our experiment. The application of the model is, of course, not limited to Japanese.

Experiment

In Japanese, it is usual that more than one NPs precede a verb, which results in a sentence like "N_1-ga N_2-o V ..." When the verb is followed by another NP, indicating the presence of a relative clause, it is ambiguous whether "N_1-ga" and "N_2-o" belong to a single clause or two separate clauses, i.e., "N_1-ga" to the main clause and "N_2-o" to the relative clause. For instance, in (3), there are two interpretations at the moment of the verb "sagasita" being read, one that the NP "syoozyo-ga" and the NP "hahaoya-o" are incorporated into the single clause, and the other that the NP "hahaoya-o" is incorporated into the relative clause headed by the verb "sagasita" but the NP "syoozyo-ga" is located in the external clause.

(3) Syoozyo-ga hahaoya-o sagasita syoonen-o
girl-Nom-Ani mother-Acc-Ani looked for boy-Acc
mituketa
found
'The girl found the boy who looked for his mother.'

(4) Hukoo-ga hahaoya-o sagasita
something bad-Nom-Inani mother-Acc-Ani looked for
syoonen-ni otozureta
boy-Dat happened
'Something bad happened to the boy who looked for his mother.'

The prediction of constraint-based models is as follows. (3) causes a strong GP effect at the relativized NP "syoonen-o," since the Animate noun "syoozyo" is a typical subject (Agent) of the verb "sagasita" and, thus, people prefer the single-clause interpretation, which conflicts with the presence of the relative clause. In contrast, (4) causes no GP effect, since the Inanimate noun "hukoo" hardly appears as a subject (Agent) of the verb "sagasita" and, thus, people prefer the separate-clauses interpretation. The model also predicts that the GP effect is correlated with semantic fitness among the subject noun, the object noun, and the verb.

In this experiment, we examined how semantic fitness, controlled by the animacy of nouns, influences the GP effect in reading ambiguous Japanese sentences such as (3) and (4) by means of a self-paced-reading technique.

Method

Semantic-fit Rating. We carried out the semantic-fit rating in advance of the experiment, asking the typicallity of the subject relation for each nouns+verb pair. Our questions were concerned with subject, instead of Agent, relation, since the subject of a verb like "sagasita" is always Agent.

Sixteen transitive verbs which take Animate subjects were selected, one half of them being paired with Animate objects (e.g. "hahaoya-o sagasita (looked for one's mother)"), and the other half with Inanimate objects (e.g. "tabako-o sutta (smoked tobacco)"). For each of those object+verb pairs, a pair with Animate-subject, which satisfies the requirement of the verb, and a pair with Inanimate-subject, which does not, were constructed.[1] A total of 45 subjects rated the probability of co-occurrence for these subject+object+verb pairs on a 7 point-scale (1 = very uncommon, 7= very common). The mean ratings were significantly higher in the Animate-subject pairs than in the Inanimate-subject pairs, as is shown in Table 1. One should note that the animacy of the object nouns did not affect any rating scores.

Table 1: Mean co-occurrence ratings between nouns and verbs

		Ani-Subj	Inani-Subj
Obj+Verb	$(N = 16)$	6.49	1.69
- Ani-Obj	$(N = 8)$	6.53	1.79
Inani-Obj	$(N = 8)$	6.45	1.59

Subjects. Sixteen students from Osaka University, all native speakers of Japanese.

Target Sentences and Design. For each of the 32 subject+object+verb pairs used in the rating, an ambiguous sentence was generated. As mentioned above, half of the ambiguous sentences included Animate objects, like (3) or (4), and the other half included Inanimate objects, like (5) or (6).

(5) Gakusei-ga tabako-o sutta yuuzin-o
student-Nom-Ani tobacco-Acc-Inani smoked friend-Acc
tyuuisita
warned
'The student warned his friend who smoked tobacco.'

(6) Genbatu-ga tabako-o
severe punishment-Nom-Inani tobacco-Acc-Inani
sutta yuuzin-ni kudasareta
smoked friend-Dat was inflicted
'A severe punishment was inflicted on the friend who smoked tobacco.'

Also, 32 unambiguous control sentences were constructed, each of which was produced by reversing the order of the subject and the object of the main clause in the corresponding ambiguous sentence, as "Hahaoya-o sagasita syoonen-o syoozyo-ga mituketa." These 64 sentences were used for the target sentences. The factors of the experiment were the subject-animacy (Animate vs. Inanimate) and the sentence type (Ambiguous vs. Unambiguous). 16 test sentences for each subject were chosen from the target sentences in such a way that the same verb did not appear in more than one of the four conditions. A total of the 16 test sentences, four per condition, with 28 distractor sentences were presented to the subject on a CRT.

Procedure. In this experiment, a moving-window self-paced-reading technique was used. After a prompt was displayed, the first NP in the sentence appeared. With each press of a key, the next phrase was displayed at the right position of

[1] Note that the object noun was always selected so as to satisfy the requirement of the verb.

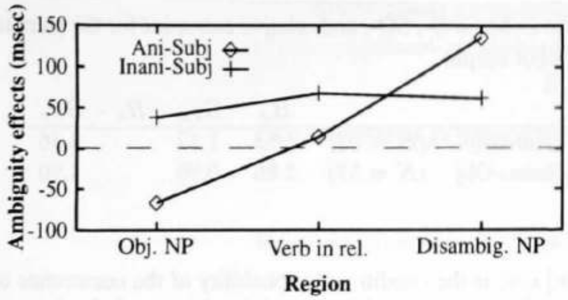

Figure 1: Mean ambiguity effects for subject condition

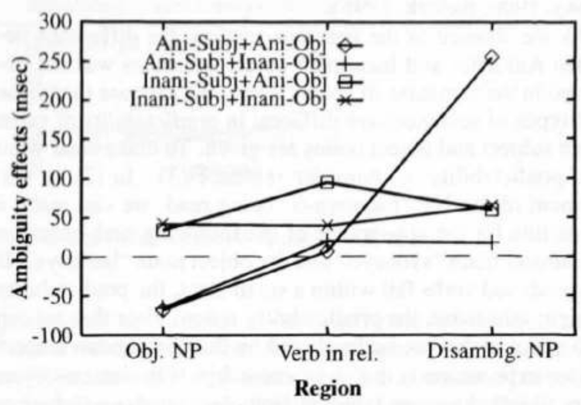

Figure 2: Mean ambiguity effects for subject × object conditions

the previous phrase. After reading each sentence, the subjects were instructed to answer a yes/no question in order to induce the subjects to pay attention to the experimental sentences. The reading times for all individual phrases were collected.

Results and Discussion

Scoring Region. A target sentence was divided into three scoring regions: (i) the object NP ("hahaoya-o"), (ii) the verb in the relative clause ("sagasita"), and (iii) the disambiguating NP ("syoonen-o"). Since there were no significant differences in reading times between the Animate- and the Inanimate-subject sentences for the Unambiguous condition, we used the ambiguity effects (the reading times for the Ambiguous sentences minus those for the Unambiguous ones) for the following analysis. Figure 1 shows the mean ambiguity effects for the three scoring regions. This data was used in the separate ANOVAs presented below.

The Object NP. At the object NP, there was a significant difference of the ambiguity effects between the Animate- and the Inanimate-subject sentences in both of the subject analysis and the item analysis ($F1(1, 15) = 5.68$, $p < .05$; $F2(1, 30) = 5.67, p < .05$).

The Verb in the Relative Clause. No significant difference was found for this region.

The Disambiguating NP. Unexpectedly, there was no significant difference of the ambiguity effects between the Animate- and the Inanimate-subject sentences ($F1(1, 15) = 1.70, p = .21$; $F2(1, 30) = 0.92, p = .35$). The mean reading times for the Ambiguous Animate-subject sentences were longer than the Unambiguous controls, but this difference was not significantly greater than that observed for the Inanimate-subject sentences, showing no clear GP effects. Moreover, the ambiguity effects did not correlate with the rating scores for the subject+object+verb pairs against the prediction of constraint-based models (Animate: $r = 0.28, p = .29$; Inanimate: $r = -0.17$, $p = .53$). These results suggest that semantic fitness between nouns and verbs did not necessarily determine the degree of the GP effect in Japanese.

Post-hoc Analysis

In considering the reason why clear GP effects were not found for the Animate-subject sentences, we next examined the effects of the animacy of the object nouns. When the target sentences were grouped in terms of the object-animacy, instead of the subject-animacy, a marginal correlation between the rating scores and the ambiguity effects was found for the Animate-object sentences ($r = 0.43, p < .1$). This suggested that the GP effect could be observed only in the Animate-object sentences.

To see if our prediction was correct, we conducted a post-hoc analysis for the reading times data with the object-animacy as a new factor. Figure 2 shows the mean ambiguity effects for the three scoring regions. Separate ANOVAs with two factors (the subject-animacy and the object-animacy) were performed on this data.

The Object NP and the Verb in the Relative Clause. No significant differences were found for these regions.

The Disambiguating NP. There was a significant interaction between the subject-animacy and the object-animacy in the subject analysis but not in the item analysis ($F1(1, 15) = 11.44$, $p < .01$; $F2(1, 14) = 2.12$, $p = .17$). In the subject analysis, the main effect of the object-animacy was also significant ($F(1, 15) = 4.59$, $p < .05$). The effect of the object animacy was carried by the Animate-subject sentences, in which the difference between the Animate- and the Inanimate-object sentences was significant ($F(1, 15) = 17.48$, $p < .01$). In contrast, the Inanimate-subject sentences showed no difference between the Animate- and the Inanimate-object conditions.

These results revealed that the processing difficulty appeared in the Animate-subject+Animate-object sentences like (3), but not in the Animate-subject+Inanimate-object sentences like (5). In other words, there was Animate/Inanimate asymmetry for object nouns despite of their irrelevance to the semantic-fit scores (6.53 vs. 6.45, see Table 1). This asymmetry for the object-animacy can not be explained by constraint-based models, which have proposed a strong effect of semantic fitness. We now turn to investigating what accounts for this asymmetry.

A Corpus Analysis

In order to examine differences between Animate- and Inanimate-object sentences, we conducted a computational-linguistic analysis using a corpus. Such corpus-based analysis has been widely used in recent computational studies on human sentence processing (Gibson & Pearlmutter, 1994; Jurafsky, 1996; Resnik, 1996).

As we showed in the previous section, the difference between Animate- and Inanimate-object sentences was not observed in the semantic-fit scores. Here, we suppose that those two types of sentences are different in *predictability* of verbs when subject and object nouns are given. To make clear what the 'predictability' is, consider sentence (3). In (3), at the moment of the NP "hahaoya-o" being read, we can make a prediction for the appearance of the following verb based on the subject noun "syoozyo" and the object noun "hahaoya." If the predicted verbs fall within a small class, the predictability is high; otherwise, the predictability is low. Note that we can also make such a prediction based on the object noun alone.[2]

Our expectation is that Animate-subject+Inanimate-object pairs like "gakusei-ga (student-Nom-Ani) tabako-o (tobacco-Acc-Inani)," with which (5) begins, show higher predictability than Animate-subject+Animate-object pairs like "syoozyo-ga (girl-Nom-Ani) hahaoya-o (mother-Acc-Ani)," with which (3) begins. More precisely, we predict that the difference between the SO-predictability and the O-predictability is greater in Animate-object pairs than in Inanimate-object pairs, and think that this explains the asymmetry for the object-animacy in the GP effect.

In this analysis, we examined whether such a difference in verb-predictability is, in fact, observed among sentences from a Japanese corpus.

Data

A total of 936 sentences matching with the following conditions were extracted from the EDR co-occurrence dictionary (Japan Electronic Dictionary Research Institute, 1996):[3] (i) the sentence is of the form "N-ga/o N-o/ga V," (ii) the verb has the active or stative form, (iii) the thematic-role of the object is Patient or Theme, and (iv) the semantic class of the object is Human or Goods.

All the nouns and the verbs were associated with semantic classes using the Bunrui-Goi-Hyo thesaurus (The National Language Research Institute, 1996). For those that have no entries in the thesaurus, the classes for the synonyms were used, and for those that have multiple entries, the most appropriate classes were selected by the first author's judgment. Any sentence containing at least one word whose semantic class was not uniquely determined by the above procedure was excluded from the data.

Method

In order to numerically express the predictability, we used the *entropy*, an information-theoretic concept. The SO-entropy $H_{s,o}$ of the verbs co-occurring with subject s and object o is defined as follows:

$$H_{s,o} = -\sum_{v} P(v \mid s, o) \log_2 P(v \mid s, o). \qquad \text{(I)}$$

[2] The predictability from both the subject and the object nouns is referred to as the SO-predictability, whereas the predictability from the object noun alone is referred to as the O-predictability.

[3] The EDR corpus is not a so-called *balanced* corpus such as the Brown corpus. Nevertheless, we used it, since it is the only publicly available Japanese corpus with rich annotations, which are required for our current purpose.

Table 2: Mean O-, SO-, and relative entropies for the pairs in the EDR corpus

		H_o	$H_{s,o}$	$H_o - H_{s,o}$
Ani-Obj	$(N = 52)$	3.53	1.17	2.36
Inani-Obj	$(N = 57)$	2.86	0.96	1.90

$P(v \mid s, o)$ is the conditional probability of the occurrence of the verb v given the subject s and the object o, defined as

$$P(v \mid s, o) = \frac{f(s, o, v)}{\sum_v f(s, o, v)}, \qquad \text{(II)}$$

where $f(s, o, v)$ is the frequency of the co-occurrence data "s-ga o-o v" in the corpus.

The SO-entropy $H_{s,o}$, given by (I), is small when the distribution of the verbs co-occurring with s and o is biased. Hence, the smaller the SO-entropy is, the higher the SO-predictability is. The O-entropy H_o of the verbs co-occurring with object o, which corresponds to the O-predictability, can be defined in a similar way.

In our corpus, the frequency $f(s, o, v)$ of the co-occurrence data "s-ga o-o v" was generally very small. The small number of co-occurrence data yielded very limited verb distributions and, hence, the obtained entropies were within a very small range. To avoid this problem, we constructed co-occurrence data not by using lexical items but by using semantic classes. That is, two lexical items associated with the same semantic class (e.g., "wife" and "husband") were treated as the same word.

Analysis I: Sentences in the EDR Corpus

For each of the Animate-subject+object pairs in the corpus, the following three entropies were calculated; (i) the O-entropy H_o of the verbs co-occurring with object o, (ii) the SO-entropy $H_{s,o}$ of the verbs co-occurring with subject s and object o, and (iii) the difference between H_o and $H_{s,o}$, the 'relative' entropy. Table 2 shows the means of the three entropies for the Animate- and the Inanimate-object pairs. (Those pairs that have only one co-occurrence data in the corpus were excluded from the analysis.)

There were significant differences of H_o and $H_o - H_{s,o}$ between the Animate- and the Inanimate-object pairs (H_o: $t = 4.67, p < .001$; $H_o - H_{s,o}$: $t = 2.98, p < .01$). The entropies for the Inanimate-object pairs were smaller than those for the Animate-object pairs. However, the difference of $H_{s,o}$ was marginal ($t = 1.75, p < .1$).

We also examined the co-occurrence probability $P(s, o \mid v)$ of subject s and object o given verb v, which is thought to express the semantic fitness among s, o, and v. However, no significant difference was found between the Animate- and the Inanimate-object pairs (0.1329 vs. 0.1328, $p = .99$).

These results showed that the difference between the Animate- and the Inanimate-object sentences appeared not in the co-occurrence probability but in the entropy, which represents the predictability of verbs from nouns.

	Single-clause interpretation		Separate-clauses interpretation
(5)	[gakusei-ga tabako-o v]		[gakusei-ga [tabako-o v] ...]
	$H_{s,o}$	$<$	H_o
(3)	[syoozyo-ga hahaoya-o v]		[syoo~~zyo-ga [hahaoya-o v~~] ...]
	$H_{s,o}$	$\ll$	H_o ***pruned***

Figure 3: Asymmetry between Animate- and Inanimate-object sentences

Table 3: Mean O-, SO-, and relative entropies for the pairs used in the experiment

		H_o	$H_{s,o}$	$H_o - H_{s,o}$
Ani-Obj	$(N = 7)$	3.09	2.64	0.45
Inani-Obj	$(N = 4)$	2.66	2.29	0.38

Analysis II: Target Sentences of the Experiment

The above results only indicated a qualitative difference between Animate- and Inanimate-object sentences. We now focus on the entropies for the 16 Animate-subject+object pairs used in our experiment.

Among the 8 pairs with Inanimate-objects, only four had the object nouns classified as Goods in our thesaurus. For these 4 Inanimate-object pairs and 7 out of the 8 Animate-object pairs, the co-occurrence data were found in the EDR corpus. (We used rude semantic classes for this analysis.) Table 3 shows the means of the three entropies for the 7 Animate- and the 4 Inanimate-object pairs.

Although the amount of data was too small to statistically show the difference between the Animate- and the Inanimate-object pairs, numerically, the tendency observed in the analysis I was replicated. That is, the O- and relative entropies for the Inanimate-object pairs were smaller than those for the Animate-object pairs.

Disambiguation with Verb-Predictability

Following the results presented in the previous section, we propose our model of disambiguation using verb-predictability, and, based on this model, we explain the asymmetry for the object-animacy observed in our experiment.

The Model

The proposed model is based on *bounded-ranked parallel* models (Gibson, 1991), though it does not imply any objection to other parsing architectures. The point here is not what architecture, parallel or serial, is adequate for human parsing models, but what kind of information is used for ambiguity resolution in human sentence processing.

In a bounded-ranked-parallel model, all possible interpretations are computed in parallel. At any moment while reading the sentence, those hypothesized interpretations are ranked according to certain metrics brought from some resources. Due to the memory limitation of humans, only those hypotheses having relatively high ranking scores are retained for the future process, the others being pruned. The criterion for the pruning is similar to one used in the *beam search* technique developed in the artificial intelligence field; that is, every hypothesis falling within a certain percentage of the most highly-ranked hypothesis is retained (Jurafsky, 1996).

In our model, predictability of verbs from nouns is used for ranking hypotheses. Hypotheses with high predictability are preferred. Moreover, a hypothesis with low predictability is abandoned, when the lowness of the predictability exceeds a threshold. If the correct interpretation of the sentence is pruned in the midst of the sentence, the GP effect appears.

Asymmetry between Animate- and Inanimate-Object Sentences

The Animate/Inanimate asymmetry in sentences like (3) and (5) are explained by this model in the following way (see Figure 3).

In either case, there are two hypotheses at the moment of the second NP ("hahaoya/tabako-o") being read, one that the first NP ("syoozyo/gakusei-ga") and the second NP are incorporated into the single clause (the left column in Figure 3), and the other that the second NP is incorporated into the relative clause headed by the (unseen) following verb but the first NP is located in the external clause (the right column). For each hypothesis, the ranking score in terms of verb-predictability, or entropy, is calculated. Note that, in our model, ranking of the hypotheses is done before the verb ("sagasita/sutta") is read. The difference between the entropies of the two hypotheses, which is expressed by the relative entropy defined in the previous section, would be small in an Inanimate-object sentence like (5), but large in an Animate-object sentence like (3).[4] (The actual values for (5) and (3) estimated from the EDR corpus are 0.45 and 0.87, respectively.) In the latter case, then, the low-ranked, separate-clauses hypothesis would be pruned due to the memory limitation, leading the sentence processor to a GP since only the abandoned hypothesis is compatible with the rest of the sentence.

In general, Animate-object sentences reveal higher relative entropies than Inanimate-object sentences, as shown in the previous section. This implies that the possibility of being led to GPs would also be higher in Animate-object sentences than in Inanimate-object sentences. This is the reason why the asymmetry for the object-animacy exists.

[4] We assume that the entropy relevant to a certain interpretation is determined on the basis of all the nouns that are hypothesized to co-occur with the following verb. Hence, the ranking score for the first hypothesis is determined by the SO-entropy, whereas that for the second hypothesis is determined by the O-entropy. Therefore, their difference is expressed by the relative entropy.

Comparison with Other Models

The constraint-based models (MacDonald, 1994; Trueswell et al., 1994) proposed that semantic fitness between nouns and verbs is essential for disambiguation. However, we have so far shown that semantic fitness is not adequate for explaining our experimental results. Structural preferences such as the Minimal Attachment Principle (Frazier & Fodor, 1978) are also inadequate, since our target sentences did not involve any structural differences between the Animate- and the Inanimate-object conditions.

In a computational model of lexical access proposed by Jurafsky (1996), the accessibility of a word to be read next is thought to be influenced by the prediction for the appearance of that word given the structure constructed so far. Although this model seems to resemble ours, an important difference exists. Jurafsky (1996) stated that, in disambiguation, the ranking is determined according to the 'probability of the structure constructed so far.' Our model clearly differs in the point that the 'prediction for the appearance of the next word' is also used in disambiguation.

Concluding Remarks

The empirical evidences provided in this paper would not be sufficient for defending our claims. For instance, since the EDR corpus is not made up of carefully chosen sentences, the results of our corpus analysis should be seen as only suggestive. Supplemental analysis using more natural data will be needed. Also, precisely designed experiments to examine the correlations between predictability and the reading times will be indispensable. Leaving these things for the future studies, we conclude this paper with adding another psycholinguistic finding brought by other authors as indirect, but convincing, evidence for the proposed model.

Yamashita-Butler (1994) showed that, in reading Japanese sentences, people temporarily decide the favored structure when a sequence of arguments is given, and predict the type of the following verb. She showed it by means of a lexical decision task, in which people revealed longer reaction times for transitive verbs after subject+direct-object+indirect-object sequences than for dative verbs after the same sequences. (Miyamoto (personal communication) obtained similar results by an online, self-paced reading task.) This result suggests that, before reading the verb, people abandon interpretations other than the single-clause interpretation. This also cannot be explained by the semantic fitness. If similar results are found by using the animacy of nouns as conditions, they will form a stronger evidence for our model.

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