A Machine-Learning Approach to Estimating the Referential Properties of Japanese Noun Phrases

Masaki Murata, Kiyotaka Uchimoto, Qing Ma, and Hitoshi Isahara

Communications Research Laboratory, MPT,
2-2-2 Hikaridai, Seika-cho, Soraku-gun, Kyoto, 619-0289, Japan,
{murata,uchimoto,qma,isahara}@crl.go.jp,
WWW home page: http://www-karc.crl.go.jp/ips/murata

Abstract. The referential properties of noun phrases in the Japanese language, which has no articles, are useful for article generation in Japanese-English machine translation and for anaphora resolution in Japanese noun phrases. They are generally classified as generic noun phrases, definite noun phrases, and indefinite noun phrases. In the previous work, referential properties were estimated by developing rules that used clue words. If two or more rules were in conflict with each other, the category having the maximum total score given by the rules was selected as the desired category. The score given by each rule was established by hand, so the manpower cost was high. In this work, we automatically adjusted these scores by using a machine-learning method and succeeded in reducing the amount of manpower needed to adjust these scores.

1 Introduction

To estimate the referential property of a noun phrase (NP) in the Japanese language, which does not have any articles, is one of the most difficult problems in natural language processing [5]. The referential property of a noun phrase represents how the noun phrase denotes the referent and is classified into the following three types:

- An indefinite NP — denotes an arbitrary member of the class of the noun phrase.
  (Ex.) There are three dogs.

- A definite NP — denotes a contextually non-ambiguous member of the class of the noun phrase.
  (Ex.) The dog went away.

- A generic NP — denotes all members of the class of the noun phrase or the class itself of the noun phrase.
  (Ex.) Dogs are useful.
  Note that “dogs” in this sentence denotes general dogs and are classified generic.
Estimating the referential properties of noun phrases in Japanese sentences is useful for (i) generating articles when translating Japanese nouns into English and (ii) estimating the referents of noun phrases.

(i) Article generation in machine translation
In the process of generating articles, when a noun phrase is estimated to be indefinite, it is given the indefinite article, “a/an”, when it is singular, but is given no article when it is plural. When a noun phrase is estimated to be definite, it is given the definite article, “the”. When a noun phrase is estimated to be generic, usage in terms of articles is generated by a method used for generic noun phrases (a generic noun phrase can be given a definite or an indefinite article or no article, and may also be in the plural form).

For example, *hon* (book) in the following sentence is a generic noun phrase.

\[
\text{hon-toiunowa ningen-no seichou-ni kakasemasen} \\
(\text{book}) \ (\text{human being}) \ (\text{growth}) \ (\text{be necessary})
\]

(1)

So it can be translated as “a book,” “books,” or “the book” in English. Note that in the following sentence, *hon* (book) is a definite noun phrase.

\[
\text{kinou boku-ga kashita hon-wa yomimashitaka} \\
(\text{yesterday}) \ (I) \ (\text{lend}) \ (\text{book}) \ (\text{read})
\]

(2)

It can thus be translated as “the book” in English.

(ii) Anaphora resolution
Only a definite noun phrase can refer to a previous noun phrase and this is very useful in anaphora resolution. For example, in the following example, *hon* (book) in the second sentence is a generic noun phrase, so it cannot be referring to *hon* (book) in the first sentence.

\[
\text{hon-wo omiyage-ni kaimashita.} \\
(\text{book}) \ (\text{as a present}) \ (\text{buy})
\]

(I bought books as a present.)

(3)

As in the above explanation, the referential properties of noun phrases, i.e., generic, definite, and indefinite, are useful for article generation and anaphora resolution, and estimating them is a serious problem in natural language processing.

\[\text{Bond et al. have actually used the referential properties of noun phrases in generating articles.}\]
In the conventional estimation of referential properties \[5\], heuristic rules (made by hand) using surface clue words are used for estimation. For example, in sentence \(1\) above the referential property is estimated to be generic by using a Japanese clue word \textit{toiu-nowa}; in sentence \(2\), the referential property of a noun phrase, \textit{hon} (book), is estimated to be definite since the noun phrase is modified by an embedded sentence, \textit{kinou boku ga kashita} (I lent you yesterday). In their work, 86 heuristic rules were created. When plural rules conflicted and the rule used in estimation was ambiguous, the conflict was solved by using the scores given in the rules. These scores needed to be adjusted by hand in order to properly resolve conflicts.

In the current work, to reduce human costs of previous research, we have used a machine-learning method to automatically adjust these rules. We selected the maximum entropy method (which is robust for sparse data problems) as the machine-learning method.

2 How to estimate referential property

2.1 Method used in previous research

The previous research gave each referential property two evaluation values, \textit{possibility} and \textit{value}, by using heuristic rules and estimated the referential property according to these values. Here, \textit{possibility} is logically conjuncted and \textit{value} is added. As a result, the referential property whose \textit{possibility} is 1 and whose \textit{value} is maximum is estimated to be the desired one.

Heuristic rules are given in the following forms:

\[
(\text{condition for rule application}) \\
\Rightarrow \{ \text{indefinite (possibility, value)} \\
\text{definite (possibility, value)} \\
\text{generic (possibility, value)} \} 
\]

A surface expression, which contains a clue word for estimating the referential property, is written in \textit{condition for rule application}. \textit{Possibility} has a value of 1 when the categories indefinite, definite and generic are possible in the context checked by the condition. Otherwise, the \textit{possibility} value is 0. \textit{Value} means that a relative possibility value between 1 and 10 (an integer) is given according to the plausibility of the condition that the \textit{possibility} is 1. A larger value means the plausibility is high.

Several rules can be applicable to a specific noun in a sentence. In this case, the possibility values for the individual categories are added, and the category for the noun is decided as the category with the highest sum of possibility values.

86 rules were created. Some of the rules are given below.
(1) When a noun is modified by a referential pronoun, *kono* (this), *sono* (its), etc., then \{indefinite (0, 0) definite (1, 2) generic (0, 0)\}

\*kono hon-wa omoshiroi.

(This book is interesting.)

(2) When a noun is accompanied by a particle, *wa*, and the predicate is in the past tense, then \{indefinite (1, 0) definite (1, 3) generic (1, 1)\}

\*inu-wa mukou-he itta.

(The dog went away.)

(3) When a noun is accompanied by a particle, *wa*, and the predicate is in the present tense, then \{indefinite (1, 0) definite (1, 2) generic (1, 3)\}

\*inu-wa yakunitatsu doubutsu desu.

(Dogs are useful animals.)

When there are no clues, “indefinite” is assigned as the default value.

Let us look at an example of a noun to which several rules apply, *kudamono* (fruit) as used in the following sentence.

\*wareware-ga kinou tsumitotta kudamono-wa aji-ga iidesu.

(The fruit that we picked yesterday tastes delicious.)

All the rules were applied and the condition only satisfied the following seven rules which were then used to determine the degree of the definiteness of the noun.

(a) When a noun is accompanied by *wa*, and the corresponding predicate is not in the past tense (*kudamono-wa aji-ga iidesu*), then \{indefinite (1, 0) definite (1, 2) generic (1, 3)\}

(b) When a noun is modified by an embedded sentence which is in the past tense (*tsumitotta*), then \{indefinite (1, 0) definite (1, 1) generic (1, 0)\}

(c) When a noun is modified by an embedded sentence which has a definite noun accompanied by *wa* or *ga* (*wareware-ga*), then \{indefinite (1, 0) definite (1, 1) generic (1, 0)\}

(d) When a noun is modified by an embedded sentence which has a definite noun accompanied by a particle (*wareware-ga*), then \{indefinite (1, 0) definite (1, 1) generic (1, 0)\}

(e) When a noun is modified by a phrase which has a pronoun (*wareware-ga*), then \{indefinite (1, 0) definite (1, 1) generic (1, 0)\}

\(^2\) (a, b) means *possibility* (a) and *value* (b).
When a noun has an adjective as its predicate (kudamono-wa azi-ga iidesu),
then
\{indefinite (1, 0) definite (1, 3) generic (1, 4)\}

When a noun is a common noun (kudamono),
then
\{indefinite (1, 1) definite (1, 0) generic (1, 0)\}

By using the scores from these rules, total possibilities and values were calculated. The overall possibilities for all three categories were 1 because all three categories carried possibilities of 1 for all of these rules. The total values for all three categories were 1, 9, and 7, respectively, because the results of aggregating the values of all of these rules were 1 (= 0 + 0 + 0 + 0 + 0 + 0 + 1), 9 (= 2 + 1 + 1 + 1 + 1 + 3 + 0), and 7 (= 3 + 0 + 0 + 0 + 0 + 4 + 0), for the respective categories. A final score of {indefinite (1, 1) definite (1, 9) generic (1, 7)} was obtained, and the system judged, correctly, that the noun here is “definite.”

Each noun, from left to right, in the sentence was estimated according to (a) - (g) above. This process allows the decision process to make use of referential properties that has already been determined (see (c) and (d), for example).

In the method used in the previous work possibility and value had to be adjusted in order to estimate referential properties properly, and this required much work by human. Although gathering the clue words by hand might be effective, possibility and value can be adjusted by a certain machine-learning method. In this paper, we report on our use of the machine-learning method described in the next section, to verify this possibility.

### 2.2 The machine-learning method

A machine-learning method was applied to the estimation of referential properties. We used the maximum entropy method as a machine-learning method, which is robust against data sparseness, because it is difficult to make a large corpus tagged with referential properties. By defining a set of features in advance, the maximum entropy method estimates the conditional probability of each category in a certain situation of the features, and it is called the maximum entropy method since it maximizes entropy when estimating a probability. The process of maximizing entropy can make the probabilistic model uniform, and this effect is the reason that the maximum entropy method is robust against data sparseness. We used Ristad’s system [8,9] as the maximum entropy method. The three probabilities, generic, definite, or indefinite, are calculated from the output of Ristad’s system. The category having the maximum probability is judged to be the desired one.

To use the maximum entropy method, we must choose the features used in learning. We used the conditions of the 86 rules that had been used in the previous work. 86 features are thus used in learning.

If we use, for example, rules 1, 2, and 3 as described in Sec. 2.1, only condition parts are detected and the following three features are obtained.
1. Whether or not a noun is modified by a referential pronoun, \textit{kono} (this), \textit{sono} (its), etc.

2. Whether or not a noun is accompanied by a particle \textit{wa}, and the predicate is in the past tense.

3. Whether or not a noun is accompanied by a particle \textit{wa}, and the predicate is in the present tense.

Now, we use the last example from the previous section to explain how the referential property is estimated by the maximum entropy method.

\begin{align*}
\text{wareware-ga} & \hspace{0.5em} \text{kinou} & \hspace{0.5em} \text{tsumitotta} & \hspace{0.5em} \text{kudamono-wa} & \hspace{0.5em} \text{aji-ga} & \hspace{0.5em} \text{iidesu}. \\
(\text{we}) & \hspace{0.5em} (\text{yesterday}) & \hspace{0.5em} (\text{picked}) & \hspace{0.5em} (\text{fruit}) & \hspace{0.5em} (\text{taste}) & \hspace{0.5em} (\text{be good}) \\
(\text{The fruit}) & \hspace{0.5em} (\text{that we picked yesterday}) & \hspace{0.5em} \text{tastes delicious.})
\end{align*}

We again look at \textit{kudamono} (fruit). The same seven rules are again applied. The value assigned to each of the referential properties for each rule indicates the conditional probability of that category being correct when only that rule is applied and they are calculated by the maximum entropy method. The values written here were obtained in our experiment of “Machine-Learning 2” described in Sec.\textbf{3}.

(a) When a noun is accompanied by \textit{wa} and the corresponding predicate is not in the past tense, \textit{(kudamono-wa aji-ga iidesu)}, then
\begin{align*}
\{\text{indefinite 0.31} & \hspace{0.5em} \text{definite 0.29} \hspace{0.5em} \text{generic 0.40}\}
\end{align*}

(b) When a noun is modified by an embedded sentence which is in the past tense \textit{(tsumitotta)}, then
\begin{align*}
\{\text{indefinite 0.31} & \hspace{0.5em} \text{definite 0.49} \hspace{0.5em} \text{generic 0.19}\}
\end{align*}

(c) When a noun is modified by an embedded sentence which has a definite noun accompanied by \textit{wa} or \textit{ga} (\textit{wareware-ga}), then
\begin{align*}
\{\text{indefinite 0.19} & \hspace{0.5em} \text{definite 0.61} \hspace{0.5em} \text{generic 0.19}\}
\end{align*}

(d) When a noun is modified by an embedded sentence which has a definite noun accompanied by a particle (\textit{wareware-ga}), then
\begin{align*}
\{\text{indefinite 0.01} & \hspace{0.5em} \text{definite 0.80} \hspace{0.5em} \text{generic 0.18}\}
\end{align*}

(e) When a noun is modified by a phrase which has a pronoun (\textit{wareware-ga}), then
\begin{align*}
\{\text{indefinite 0.20} & \hspace{0.5em} \text{definite 0.44} \hspace{0.5em} \text{generic 0.37}\}
\end{align*}

(f) When a noun has an adjective as its predicate (\textit{kudamono-wa azi-ga iidesu}), then
\begin{align*}
\{\text{indefinite 0.13} & \hspace{0.5em} \text{definite 0.80} \hspace{0.5em} \text{generic 0.07}\}
\end{align*}

(g) When a noun is a common noun (\textit{kudamono}), then
\begin{align*}
\{\text{indefinite 0.72} & \hspace{0.5em} \text{definite 0.15} \hspace{0.5em} \text{generic 0.14}\}
\end{align*}

In the maximum entropy method the values assigned by the above rules are multiplied, the values in each category are normalized, and the category with
the highest value is judged to be the desired one. In this case, we multiplied and normalized the values of all the rules and obtained the following results:

\{ indefinite 0.001, definite 0.996, generic 0.002 \}

“Definite” had the highest value and was thus judged to be the desired category.

3 Experiment and Discussion

Morphological and syntactic information are used as features in estimating referential properties. Before estimating the referential property, morphology and syntax were analyzed \(^3\). We used the same learning set and test set as had been used in previous work.\(^4\) The 86 rules had been made by examining the learning set by hand. In the previous work, the values written in the 86 rules had been adjusted by checking the accuracy rates in the learning set.

Firstly, we carried out the following two experiments.

– Manual Adjustment — The estimation was made by using the method described in Sec 2.1. (This result is identical to the result of the previous work.)

– Machine-Learning 1 — The estimation was made by using the method described in Sec 2.2.

The results are listed in Tables 1 to 4. “Other” in the tables indicates that the referential property is ambiguous; such cases can be neglected here since they were few.

The accuracy rate obtained by Manual Adjustment (Table 2) in the test set was 68.9% and that of Machine-Learning 1 (Table 4) was 72.1%. The machine-learning method was thus more accurate than Manual Adjustment method. But, as can be seen in Tables 2 and 4, all the categories of Manual Adjustment are about 70% and the method did not have a bad-accuracy category. However, the result from Machine-Learning 1 of the “generic” category was low (5.2%). We cannot therefore conclude that Machine-Learning 1 reliably gives good results.\(^4\)

We felt that the reason for this low accuracy in estimating the “generic” category is that the frequency of “generic” terms is low and machine learning is biased toward “definite” terms, which have higher frequency than “generic” terms. We therefore carried out the following further experiments.

– Machine-Learning 2 — When machine learning is performed by using the maximum entropy method, the number of events in each category of the

\(^3\) The learning set: “Usage of the English Articles”\(^5\), a folktale “The Old Man with a Wen”\(^6\), and an essay tensei jingo. The test set: a folktale turu no ongaeshi\(^7\), an essay tensei jingo, “Pacific Asia in the Post-Cold-War World” (A Quarterly Publication of The International House of Japan Vol. 12, No. 2 Spring 1992).

\(^4\) Here, we assume that not producing a bad-accuracy category was more important than having the highest total accuracy rate. We then constructed Method 2 as described in the following passages. However, if we assume that having the highest total accuracy rate is more important than not producing a bad-accuracy category, Method 1 is, in fact, better.
Table 1. Manual Adjustment (learning set)

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| correct| 96    | 184 | 58  | 1     | 339   |
| incorrect| 4   | 28  | 8   | 1     | 41    |
| % of correct| 96.0 | 86.8 | 87.9 | 50.0 | 89.2  |

The Old Man with a Wen (104 sentences, 267 nouns)

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| correct| 73    | 140 | 6   | 1     | 222   |
| incorrect| 14  | 27  | 4   | 0     | 45    |
| % of correct| 83.9 | 84.0 | 60.0 | 100.0 | 83.2  |

an essay tensei jingo (23 sentences, 98 nouns)

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| correct| 25    | 35  | 16  | 0     | 76    |
| incorrect| 5   | 14  | 3   | 0     | 22    |
| % of correct| 83.3 | 71.4 | 84.2 | —    | 77.6  |

average % of appearance

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| % of appearance| 29.1 | 57.7 | 42.8 | 0.4   | 100.0 |
| % of correct| 89.4 | 84.0 | 84.2 | 66.7  | 85.5  |

Table 2. Manual Adjustment (test set)

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| correct| 109   | 363 | 13  | 10    | 495   |
| incorrect| 38   | 160 | 6   | 0     | 204   |
| % of correct| 74.2 | 69.4 | 68.4 | 100.0 | 70.8  |

an essay tensei jingo (75 sentences, 283 nouns)

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| correct| 75    | 81  | 16  | 0     | 172   |
| incorrect| 41   | 60  | 10  | 0     | 111   |
| % of correct| 64.7 | 57.5 | 61.5 | —    | 60.8  |

Pacific Asia (22 sentences, 192 nouns)

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| correct| 21    | 108 | 11  | 2     | 142   |
| incorrect| 17   | 31  | 2   | 0     | 50    |
| % of correct| 55.3 | 77.7 | 84.6 | 100.0 | 74.0  |

average % of appearance

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| % of appearance| 25.6 | 68.4 | 4.9 | 1.0   | 100.0 |
| % of correct| 68.1 | 68.7 | 69.0 | 100.0 | 68.9  |
### Table 3. Machine Learning 1 (learning set)

|                | indef | def | gen | other | total |
|----------------|-------|-----|-----|-------|-------|
| **Usage of the Articles (140 sentences, 380 nouns)** |       |     |     |       |       |
| correct        | 95    | 199 | 32  | 0     | 326   |
| incorrect      | 5     | 13  | 34  | 2     | 54    |
| % of correct   | 95.0  | 93.9| 48.5| 0.0   | 85.8  |
| **The Old Man with a Wen (104 sentences, 267 nouns)** |       |     |     |       |       |
| correct        | 71    | 151 | 1   | 0     | 223   |
| incorrect      | 16    | 18  | 9   | 1     | 44    |
| % of correct   | 81.6  | 89.4| 10.0| 0.0   | 83.5  |
| **an essay tensei jingo (23 sentences, 98 nouns)** |       |     |     |       |       |
| correct        | 21    | 46  | 5   | 0     | 72    |
| incorrect      | 9     | 3   | 14  | 0     | 26    |
| % of correct   | 70.0  | 93.9| 26.3| —     | 73.5  |
| **average**    |       |     |     |       |       |
| % of appearance| 29.1  | 57.7| 12.8| 0.4   | 100.0 |
| % of correct   | 86.2  | 92.1| 40.0| 0.0   | 83.4  |

### Table 4. Machine Learning 1 (test set)

|                | indef | def | gen | other | total |
|----------------|-------|-----|-----|-------|-------|
| **a folktale Turu (263 sentences, 699 nouns)** |       |     |     |       |       |
| correct        | 104   | 408 | 0   | 0     | 512   |
| incorrect      | 43    | 115 | 19  | 10    | 187   |
| % of correct   | 70.8  | 78.0| 0.0 | 0.0   | 73.3  |
| **an essay tensei jingo (75 sentences, 283 nouns)** |       |     |     |       |       |
| correct        | 72    | 108 | 2   | 0     | 182   |
| incorrect      | 44    | 33  | 24  | 0     | 101   |
| % of correct   | 62.1  | 76.6| 7.7 | —     | 64.3  |
| **Pacific Asia (22 sentences, 192 nouns)** |       |     |     |       |       |
| correct        | 21    | 130 | 1   | 0     | 152   |
| incorrect      | 17    | 9   | 12  | 2     | 40    |
| % of correct   | 35.3  | 63.5| 7.7 | 0.0   | 79.2  |
| **average**    |       |     |     |       |       |
| % of appearance| 25.6  | 68.4| 4.9 | 1.0   | 100.0 |
| % of correct   | 65.5  | 80.5| 5.2 | 0.00  | 72.1  |
**Table 5. Machine Learning 2 (learning set)**

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| **Usage of the Articles (140 sentences, 380 nouns)** |       |     |     |       |       |
| correct | 97    | 188 | 37  | 0     | 342   |
| incorrect| 3     | 24  | 9   | 2     | 38    |
| % of correct | 97.0  | 88.7| 86.4| 0.0   | 90.0  |
| **The Old Man with a Wen (104 sentences, 267 nouns)** |       |     |     |       |       |
| correct | 80    | 137 | 6   | 0     | 223   |
| incorrect| 7     | 32  | 4   | 1     | 44    |
| % of correct | 92.0  | 81.1| 60.0| 0.0   | 83.5  |
| **an essay tensei jingo (23 sentences, 98 nouns)** |       |     |     |       |       |
| correct | 26    | 40  | 17  | 0     | 83    |
| incorrect| 4     | 9   | 2   | 0     | 15    |
| % of correct | 86.7  | 81.6| 89.5| —     | 84.7  |
| **average** |       |     |     |       |       |
| % of appearance | 29.1  | 57.7| 12.8| 0.4   | 100.0 |
| % of correct | 93.6  | 84.9| 84.2| 0.0   | 87.0  |

**Table 6. Machine Learning 2 (test set)**

|        | indef | def | gen | other | total |
|--------|-------|-----|-----|-------|-------|
| **a folktale turu (263 sentences, 699 nouns)** |       |     |     |       |       |
| correct | 112   | 360 | 13  | 0     | 485   |
| incorrect| 35    | 163 | 6   | 10    | 214   |
| % of correct | 76.2  | 68.8| 68.4| 0.0   | 69.4  |
| **an essay tensei jingo (75 sentences, 283 nouns)** |       |     |     |       |       |
| correct | 79    | 88  | 14  | 0     | 181   |
| incorrect| 37    | 53  | 12  | 0     | 102   |
| % of correct | 68.1  | 62.4| 53.9| —     | 64.0  |
| **Pacific Asia (22 sentences, 192 nouns)** |       |     |     |       |       |
| correct | 25    | 110 | 10  | 0     | 145   |
| incorrect| 13    | 29  | 3   | 2     | 47    |
| % of correct | 65.8  | 79.1| 76.9| 0.0   | 75.5  |
| **average** |       |     |     |       |       |
| % of appearance | 25.6  | 68.4| 4.9 | 1.0   | 100.0 |
| % of correct | 71.8  | 69.5| 63.8| 0.0   | 69.1  |
learning set is multiplied by the inverse of its occurrence. For example, in this paper, we multiplied 4, 2, and 9 by the frequencies of “indefinite,” “definite,” and “generic.”

In other words, since generic noun phrases only made up 2/9 of definite noun phrases, we changed the frequencies of data as if definite noun phrases had occurred twice as often as in the actual data and generic noun phrases had occurred nine times more often than in the actual data. We found that this change made the frequencies of the three referential properties uniform and did not bias the analysis towards definite noun phrases. The change produced the following result. Machine-Learning 1 applies a general method of learning and learns data in order to maximize the following equation.

$$\text{evaluation function} = \frac{\% \text{ of correct in overall the data}}{6}$$

(6)

On the other hand, Machine-Learning 2 uses the frequencies of the referential properties and learns data in order to maximize the following equation.

$$\text{evaluation function} = \text{the average of}$$

$$\frac{\% \text{ of correct in “indefinite”}}{7}$$

$$\frac{\% \text{ of correct in “definite”}}{7}$$

$$\frac{\% \text{ of correct in “generic”}}{7}$$

(7)

The results for Machine-Learning 2 are listed in Tables 5 and 6. The accuracy rate of Machine-Learning 2 on the test set was 69.1%. This is nearly equal to the 68.9% obtained by using the Manual Adjustment. It was found that the accuracy rates for all three referential properties were about 70%. Since even for the worst category, “generic,” 63.8% was achieved, it is clear that Machine-Learning 2 was able to quite precisely estimate the referential properties.

As the above results show, we found that manual adjustment for estimating referential properties was not necessary and therefore human costs were decreased.

We also examined the values of the rules as given by the maximum entropy method used in Machine-Learning 2. We examine some of the rules as listed below. In each of the rules in the list, (i) the condition parts, (ii) values assigned by hand, and (iii) values assigned by Machine learning 2 are included.

1. Rules for indefinite noun phrases
   (a) When a noun is accompanied by a particle, *ga* (new-topic marker), then
   \{indefinite 1, 2 definite 1, 1 generic 1, 0\}
   \{indefinite 0.62, definite 0.21, generic 0.17\}

   In general, a noun accompanied by a particle, *ga*, one function of which is to indicate a new topic, roughly tends to be indefinite. The highest value is thus assigned to “indefinite” when manual adjustment is used. The value of “indefinite” as determined by Machine-Learning 2 is also the highest.
manual adjustment, the possibilities of all categories are set to 1, so any of the three categories can be the answer. In Machine-Learning 2, since the value of “indefinite” is not terribly high, (not, e.g., 0.99), any of the three categories can also be the answer.

(b) When a noun is modified by an adjective *aru* (a certain ∼), then
\{indefinite (1, 2) definite (0, 0) generic (0, 0)\}
\{indefinite 0.99, definite 0.0001, generic 0.0001\}

Generally, a noun modified by *aru* (a certain ∼) is indefinite. The values for possibility of the other categories are thus set to 0 in manual adjustment. The values used in Machine-Learning 2 are 0.0001, which is also a very small value. The value of “indefinite” is extremely high in Machine-Learning 2. We find that Machine-Learning 2 can judge that the category of a noun modified by *aru* is almost certainly indefinite.

2. Rules for definite noun phrases

(a) When a noun is a pronoun, then
\{indefinite (0, 0) definite (1, 2) generic (0, 0)\}
\{indefinite 0.005, definite 0.99, generic 0.005\}

When a noun is a pronoun, it is always definite, so the values of possibility of the other categories are manually set to 0. The values assigned to the other categories by Machine-Learning 2 are also very small.

(b) When a noun is modified by an embedded sentence which has a definite noun accompanied by *wa* or *ga* (nominative-case particle), then
\{indefinite (1, 0) definite (1, 1) generic (1, 0)\}
\{indefinite 0.19, definite 0.61, generic 0.19\}

Although such a noun is not always definite, it is likely to be definite. The value of “definite” in Machine-Learning 2 is the highest of the three, but is not extremely high.

3. Rules for generic noun phrases

(a) When a noun is followed by a particle *wa*, which does not have a modifier, then
\{indefinite (1, 0) definite (1, 1) generic (1, 1)\}
\{indefinite 0.03, definite 0.26, generic 0.71\}

The particle *wa*, which is a topic marker, is an expression which is likely to accompany either a definite noun phrase or a generic noun phrase. The possibility values of the two categories are both set to 1 by Manual Adjustment. Machine-Learning 2 found that the values assigned to “definite” and “generic” are higher than that assigned to “indefinite,” but “generic” is assigned a higher value than “definite.” This is because there are many rules for estimating that a noun phrase is “definite,” so a word can be estimated as “generic” if no other clue words appear.

(b) When a noun is followed by a particle *wa* and it modifies an adjective, then
\{indefinite (1, 0) definite (1, 3) generic (1, 4)\}
\{indefinite 0.13, definite 0.80, generic 0.07\}
Although “generic” is assigned the highest value by Manual Adjustment, “definite” is assigned the highest value by Machine-Learning 2. This is because of (i) a wrong estimate by Machine-Learning 2 due to a small learning set, (ii) the influence of other rules, such as the previous rule, or (iii) incorrect manual adjustment in the earlier work. If the actual reason is (i), then making the learning set larger should improve the results.

As stated above, the values assigned by Machine-Learning 2 tended to be similar to those obtained by hand, and they demonstrated some degree of linguistic intuition.

4 Conclusions

We have succeeded in creating a system for automatically giving rules values for solving conflicts when estimating the referential properties of noun phrases. We have thus shown that the cost in terms of human time of manually adjusting values is not unavoidable. We also found that, in machine learning, making the frequencies of the categories uniform can help to make their accuracy rates more uniform. Finally, we examined the values produced for rules by applying the Machine-Learning method, and confirmed that they were consistent with linguistic intuition.

References

1. Francis Bond, Kentaro Ogura, and Satoru Ikehara. Countability and Number in Japanese to English Machine Translation. In COLING ’94, pages 32–38, 1994.
2. Akihisa Kumayama. Usage of the English Articles. Taishukan Publisher, 1985. (in Japanese).
3. Sadao Kurohashi and Makoto Nagao. A Method of Case Structure Analysis for Japanese Sentences based on Examples in Case Frame Dictionary. IEICE Transactions on Information and Systems, E77–D(2):227–239, 1994.
4. Sadao Kurohashi and Makoto Nagao. Japanese Morphological Analysis System JUMAN version 3.5. Department of Informatics, Kyoto University, 1998. (in Japanese).
5. Masaki Murata and Makoto Nagao. Determination of referential property and number of nouns in Japanese sentences for machine translation into English. In Proceedings of the 5th TMI, pages 218–225, 1993.
6. Masaki Murata and Makoto Nagao. An estimate of referent of noun phrases in Japanese sentences. In COLING ’98, pages 912–916, 1998.
7. Kiyoaki Nakao. The Old Man with a Wen, volume 7 of Eiyaku Nihon Mukashibanashi Series. Nihon Eigo Kyouiku Kyoukai, 1985.
8. Eric Sven Ristad. Maximum Entropy Modeling for Natural Language. ACL/EACL Tutorial Program, Madrid., 1997.
9. Eric Sven Ristad. Maximum Entropy Modeling Toolkit, Release 1.6 beta. http://www.mnemonic.com/ software/memt, 1998.