Evaluation of Pattern Generalization Effect under Development of Pattern Dictionary for Machine Translation

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Abstract. Recently, the first version of a large-scale pattern dictionary was developed to realize pattern-based machine translations. To obtain the best possible coverage within a limited amount of funding, it is very important to consider the selection methods, such as how many new patterns should be added, or how to further generalize the current patterns. To do this, this paper proposes an evaluation parameter η called "an equivalent pattern quantity" which represents the equivalent effects of pattern generalization using the quantity in the current pattern dictionary, and then two evaluations were conducted. First, we evaluated generalizations using the "insertion" and "omission" marks. These generalizations are already in the current dictionary, so we just had to compare the coverage of the current dictionary with the coverage of the dictionary without these marks. Second, we evaluated generalizations using "tense" and "modality" functions, which has not been done yet. The correct realization of these generalizations is the task that should be consider to select, so that trial dictionaries must be automatically realized and used. The results are as follows. The number of equivalent patterns η for insertion and omission marks was 20 and 2.3 each. On the other hand, the number for tense and modality functions was 2.2 in total. Based these results, we believe that the generalization effect of "tense and modality" is not so high compared to "insertion marks" but a very close match to "omission mark." Thus, we could decide the way for the coverage improvement.

Keywords: pattern-based machine translation, sentence pattern generalization, coverage, equivalent pattern quantity η

1 Introduction

Machine translation paradigms are classified into rule-based, example-based, and statistical machine translations[1]. Pattern-based translation, which is a kind of example-based machine translation, was investigated to improve the quality of machine translations[2], [3], [4]. Because precise translations are necessary when patterns are matched to source language sentences, it is important to construct a sufficient number of reliable pattern pairs in which the source language and target language patterns are semantically equivalent. To solve this problem, Ikehara proposed a principle that defines the "linearity" and "non-linearity" of linguistic expression component, which was then used to semi-automatically construct the first version of a large-scale sentence pattern dictionary from sentence-pair corpus that includes 155,000 pairs of Japanese/English complex/compound sentences (1,582,761 Japanese words and 1,235,028 English words). This dictionary consists of three levels of sentence pattern sub-dictionaries: a word-level (122,619 pattern pairs), a phrase-level (94,382 pattern pairs), and a clause-level (12,200 pattern pairs) [5].

The next problem is to improve the coverage of the pattern dictionary to match more input sentences. Because funds are limited, it is very important to consider which tasks should be spent the funds on. This means we need to decide whether to add some new patterns to the current dictionary or to further generalize the existing patterns of the dictionary.

To accomplish this selection, we propose an evaluation parameter η called "an equivalent pattern quantity," which represents the equivalent effects of pattern generalization using the content of the existing pattern dictionary. Evaluations were conducted for the following two examples using the word-level sentence pattern dictionary. First, we evaluated the generalizations using the descriptions of "insertion" and "omission" marks. These generalizations have already been recorded in the current dictionary. Then, we eliminated the insertion and omission marks, and compared the coverage of the generalized (current) dictionary with the coverage of the not-generalized (eliminated) dictionary. Second, we evaluated the generalizations using "tense" and "modality" functions. This generalization has not been done yet. The correct realizations of these generalizations is the task that should be consider to select, so that trial dictionary must be automatically realized and used. If it is clear that the generalization of "tense" and "modality" is effective, we would choice the correct realization rather than the task to add some new patterns.

2 Sentence pattern

2.1 Basic descriptors

Ordinary translation patterns, or translation template consist of letters and variables. Partial expressions in Japanese/English where word/phrase/clause alignment succeeds are replaced with variables.

Our sentence pattern is a kind of translation pattern. However, there is another condition for replacing with variables. The condition is that some partial expressions which are translated simultaneously have to be replaced with one variable. Our replacing steps consists of three levels; word level, phrase level, and clause level. The level restricts the maximum range of the variables.

Following is an example of early sentence patterns. Because a word "日本一" corresponds to "the best ... in Japan," the letters remain in the word level. But in the phrase level, both "日本一のピアニスト" and "the best pianist in Japan" are phrases, so they are replaced with variables $NP3$.

Org. St.	彼は実は日本一のピアニストだ。 Actually, he is the best pianist in Japan.
Word Lv.	$N1$ は $ADV2$ 日本一の $N3$ だ。 $ADV2$, $N1$ is the best $N3$ in Japan.
Phr. Lv.	$N1$ は $ADV2NP3$ だ。 $ADV2$, $N1$ is $NP3$.
Cls. Lv.	$CL1$ だ。 $CL1$.

2.2 Extended descriptors

The above example shows early sentence patterns. In the first version of the sentence pattern dictionary contains "insertion" and "omission" marks and "functions."

2.2.1 Insertion mark

Since ordinary translation pattern includes syntactic structure as a condition for matching, such a partial expression "その男 (sono-otoko/the man)" matches a pattern component "$N1$." But sentence pattern does not match because the condition of variable is strict.

Therefore "insertion mark" is used in sentence pattern in order to accept redundant expressions. Insertion mark allows pattern matching even if an input sentence has redundant expressions that satisfy the part-of-speech constrained by the insertion mark. For example, an insertion mark "$/_k$" is put before $N1$ to accept adnominal words (i.e. $/_kN1$ は $ADV2$ 日本一の $N3$ だ。).

The first version of our sentence pattern dictionary contains five kinds of insertion marks, as shown in Table 1.

Table 1: List of insertion marks

Dsc.	Constraints	Mark location
$/_y$	Adverbial clause	At beginning of pattern, and between clauses
$/_t$	Adnominal clause	Before noun phrase having no adnominal clause
$/_c$	Case elements (noun + postpositional word)	Before/after case element
$/_f$	Adverbial words (adverb word/phrase, adverbial adjective)	At beginning of pattern, and before case element/predicate
$/_k$	Adnominal words (adjective, determiner, adnominal verb, noun phrase element(i.e. "Noun + の"))	Before noun phrase

Table 2: Frequently used omission marks (top 10)

Order	Description	Meaning	Frequency(patterns)
1	$[REN]$	Omit determiner	9,480
2	[N の]	Omit noun phrase element "N の"	7,022
3	$[ADV]$	Omit adverb	6,306
4	$[AJ]$	Omit adjective	1,512
5	$[AJV]$	Omit nominal adjectival	1,409
6	$[TIME]$	Omit noun meaning time	687
7	[その]	Omit determiner "その"	538
8	[$TIME$ の]	Omit noun phrase element "$TIME$ の"	371
9	[$TIME$ は]	Omit adverbial phrase "$TIME$ は"	347
10	[自分の]	Omit noun phrase element "自分の (one's)"	277

2.2.2 Omission mark

When translating Japanese to English by patterns, an English pattern is selected by a matched Japanese pattern. The descriptors of Japanese pattern have a great influence on the selection of English pattern. In other words, such descriptors that have little influence on the selection should not have strong condition.

Therefore "omission mark" is used. It allows pattern matching without matching bracketed descriptors. For example, in the above mentioned word-level pattern, if $ADV2$ is enclosed with a pair of omission mark "[ ]" (i.e. $/_k N1$ は $[ADV2]$ 日本一の $N3$ だ。), the pattern can match a sentence "彼は日本一のピアニストだ。"

Omission marks are applied to adverbial or adnominal (adjectival) words/phrases in the patterns. There are 38,489 patterns containing omission marks in the word-level sentence pattern dictionary(Table 2).

2.2.3 Tense and modality functions

Japanese auxiliary verbs and postpositional words are synonymic. For example, "だ (da)", "である (dearu)", and "です (desu)" represents *decesion* and "彼はピアニストだ。", "彼はピアニストである。", and "彼はピアニストです。" can be translated to the same English sentence, "He is a pianist." In order to absorb the difference of expressions, "functions" are used (i.e. $/_k N1$ は $[ADV2]$ 日本一の $N3$.<u>*dantei*</u>。).

Tense expressions in Japanese aren't clear. In many cases, an auxiliary verb/suffix "た/だ (ta/da)" indicates the past tense, while "だろう/でしょう (darou/deshou)" indicates future tense. These expressions are described by functions "*.kako*=(た/だ)," "*.darou*=(だろう/でしょう)" in the sentence patterns. If there isn't such an auxiliary verb/post-positional word, the tense is assumed to be present tense. Therefore, not-matching "*.kako*/*.darou*" means present-tense in the pattern matching method.

The word-level sentence pattern dictionary consists of 32,384 patterns that include the "*.kako*" function, 54 patterns that include "*.darou*", and 89,451 patterns that include neither "*.kako*" nor "*.darou*." Additionally, 37 kinds of modality function are defined and used in 55,310 patterns. In this paper, the "modality function" includes "aspect." Table 3 shows the frequency of the modality functions.

2.3 Example of sentence patterns

Our sentence patterns were made from Japanese complex/compound sentence and its English sentence. Figure 1 shows an example of sentence pattern pair and the original sentences, which contain the marks and the functions.

2.4 Sentence pattern matching

Sentence pattern matching is realized using ATN-method. Each sentence pattern is converted into a network. So, 122,619 networks are generated from the word-level pattern dictionary.

After a sentence is given, all networks are tried to be match with the sentence in a basic procedure. However as the letters in the pattern are strong condition for the matching, the number of the traversed networks is decreased by previously confirming the letters of the pattern and input letters.

Finally, the pattern matching routine outputs all the matched patterns and the expressions bound to variables. The average time for matching 122,619 patterns was about 0.4 seconds per sentence (average 23 letters) except the morphological analysis time.

Table 3: Frequently used modality functions (top 10)

Order	Description	Primary meaning and expression	Frequency(patterns)
1	*.teiru*	Continuative “ている/でいる (teiru/deiru)”	9,565
2	*.rareru*	Passive voice/mood/spontaneity/respect “れる/られる (reru/rareru)”	7,378
3	*.dantei*	Decision “だ/です/である (da/desu/dearu)”	7,166
4	*.hitei*	Negative “ない/ず (nai/zu)”	6,731
5	*.desumasu*	Polite “です/ます (desu/masu)”	4,302
6	*.meireigo*	Imperative “て下さい/で下さい/給え (tekudasai/dekudasai/tamae)”	2,804
7	*.you*	Intention “よう (you)”	2,734
8	*.suitei*	Presumption “ようだ (youda)”	1,779
9	*.sase*	Causative “せる/させる (seru/saseru)”	1,199
10	*.tekureru*	Giving and receiving of action “てくれる/でくれる (tekureru/dekureru)”	1,071

Japanese sentence:	私は自分が言いたかったことは既に言い尽くした。 (Watashi-wa Jibun-ga Ii-taka-tta Koto-wa Sudeni Ii-Tsukushi-ta) (I-topic I-sbj Say-Want-past Thing-sbj Already Say-All-past)
English sentence:	I have already said everything I wanted to say.
Japanese pattern:	$/_{ytcfk}N1$ は $/_{tcfk}N2$ が $/_{cf}V3.tai.kako$ ことは $/_{cf}[ADV4]/_{cf}$ 言い尽くした。
English pattern:	$N1$ have $[ADV4]$ said everything $N2$ wanted to $V3$.

Figure 1: An example of sentence pattern pair and the original sentences

3 Evaluation parameters

Ikehara proposed several evaluation parameters for pattern matching[6]. To decide whether “to add new patterns” or “to generalize the current patterns,” an evaluation parameter based on the number of patterns is more comparable than the coverage parameters, which is explained in Section 3.1. Next, Section 3.2 describes “an equivalent pattern quantity η” to improve the coverage parameters.

3.1 Coverage parameters: R_1 and N

3.1.1 Definition

The matched pattern ratio R_1 represents the ratio of the number of input sentences that have one or more matched patterns M to the number of all the input sentences I; that is $R_1 = M/I$. The average of the matched patterns N refers to the ratio of the number of matched patterns P to the number of all input sentences, that is $N = P/I$.

3.1.2 Coverage properties

The coverage parameters R_1 and N were measured during the pattern matching experiment, which used a large-scale input sentence set and a pattern dictionary. The parameters R_1 and N depend on the dictionary size. The relationship between the size and the parameters were estimated using some different-scale pattern dictionaries. Here, we refer to the relationship as “coverage property.”

Figure 2 shows two coverage properties of the dictionary size vs. R_1 and the dictionary size vs. N. The input sentence set used for measuring was comprised of sentences that were used to construct sentence patterns. But this experiment is like cross-validation because the pattern constructed from the input sentence was not counted as the pattern matched to the sentence.

The increasing rate of the coverage property of R_1 decreases with the dictionary size as seen in Figure 2(a). On the other hand, the coverage property of N is proportional. Therefore, the approximate equations for these properties are assumed as follows, where regression analysis gives $\lambda_1 = 0.005038$, $\lambda_2 = 0.47171$, and $\lambda_3 = 0.0001093$.

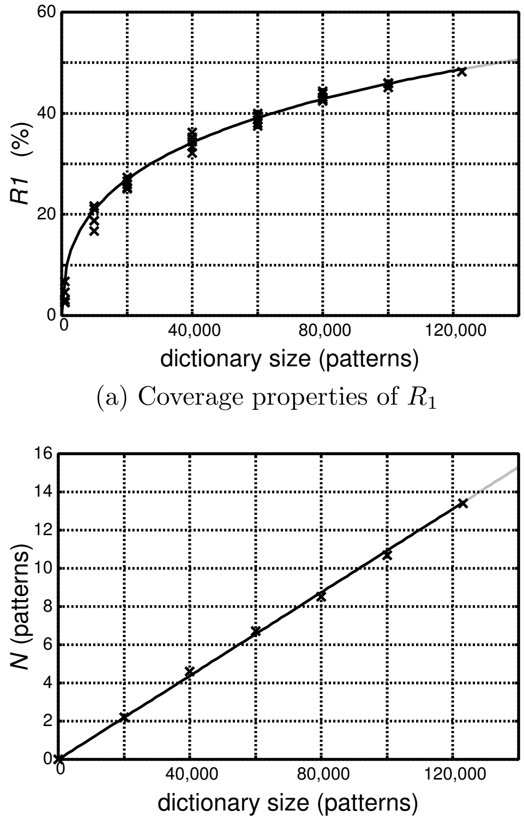
$$R_1 = (1 - exp(-\lambda_1 p^{\lambda_2})) \times 100 \qquad (\%)$$

$$N = \lambda_3 p \qquad (patterns)$$

3.2 Coverage improvement parameter: η

3.2.1 Definition

This paper describes “an equivalent pattern quantity η” as the coverage improvement parameter based on the number of patterns. η indicates the



(a) Coverage properties of R_1

(b) Coverage properties of N

Figure 2: Coverage properties of the word-level sentence pattern dictionary

results of the comparison between two pattern dictionaries called "a base pattern dictionary" and "a target pattern dictionary." η is defined by the following equation, where B is the quantity in a base dictionary, which is usually a not-generalized pattern dictionary, and X is the converted quantity in a base dictionary required to obtain the same coverage as the target dictionary, which is usually a generalized pattern dictionary.

$$\eta = X/B$$

3.2.2 Calculation of η using coverage properties

η can be calculated from the coverage properties; for instance, the converted quantity X is obtained by both an inverse function of the property and the measured coverage. The procedure is as follows:

1. Measure a coverage C_{base} and a coverage property $c(p)$ using pattern matching between a large-scale input set and a base pattern dictionary, where p is the size of the base dictionary.
2. Measure a coverage C_{target} using pattern matching between the same input set and a target pattern dictionary.
3. Calculate X using the inverse function of $c(p)$ and the coverage parameter C_{target}. Because the function $c(p)$ is an approximation function, B should be calculated in the same manner using $c(p)$ and C_{base}.
4. Thus, η via coverage property c or η_c is calculated using $c^{-1}(C_{target})/c^{-1}(C_{base})$.

4 Experimental generalization evaluation

This experimentation uses the word-level sentence pattern dictionary as the base dictionary. Section 4.1 describes how to make target dictionaries from the base dictionary and Section 4.2 shows the coverage improvement parameters η of each target dictionary.

4.1 Target dictionary construction

4.1.1 Construction by removing marks

The base dictionary is already generalized in terms of some kinds of descriptors using insertion/omission marks, as mentioned in section 2.2.1 and 2.2.2. In order to evaluate their effect, seven target dictionaries were constructed by removing five types of insertion marks, omission marks, and both insertion and omission marks. Note that the η of the simplified target dictionaries will be less than 1 if the base dictionary includes effective generalization. Figure 3 shows the simplification process.

4.1.2 Construction using generalized functions

In order to generalize tense in patterns, *tense-free functions* are set instead of past/future functions, or are set in the location available for inserting tense expressions. The *tense free function* matches past and future expressions or nothing for input words but matching doesn't fail, because there is no auxiliary verb that explicits present-tense in Japanese.

To generalize pattern modality, the modality functions are set as optional. Therefore, the generalized patterns are available for matching input

Japanese sentence:	こんなに客が少なくては商売上がったりだ。
Japanese base pattern:	$/_y$[こんなに]$/_{tk}$ 客が $/_{cf}AJ1$ ては $/_{tcfk}N2$ 上がったりだ。
Simplified pattern (removed $/_t$):	$/_y$[こんなに]$/_k$ 客が $/_{cf}AJ1$ ては $/_{cfk}N2$ 上がったりだ。
Simplified pattern (removed [ ]):	$/_y$ こんなに $/_k$ 客が $/_{cf}AJ1$ ては $/_{cfk}N2$ 上がったりだ。

Figure 3: Examples of the simplified patterns

Japanese base pattern1:	$/_yN1$ は $/_{cf}$ うなずきながら $/_{tcfk}N2$ の $/_{cfk}N3$ を $/_{cf}V4.kako$。
Generalized pattern1:	$/_yN1$ は $/_{cf}$ うなずきながら $/_{tcfk}N2$ の $/_{cfk}N3$ を $/_{cf}V4[.kako \vert .darou]$。
Japanse base pattern2:	$/_yN1$ は $/_{cf}$ 新しく $/_{cf}$ 買った $/_{cfk}N2$ を $/_{cf}V3.hitei$。
Generalized pattern2:	$/_yN1$ は $/_{cf}$ 新しく $/_{cf}$ 買った $/_{cfk}N2$ を $/_{cf}V3.hitei[.kako \vert .darou]$。

Figure 4: Examples of the patterns generalized for tense

sentences that do not have the same modal expression as the patterns.

There are 37 kinds of modality functions in the base dictionary. This experiment focused on only 10 of them, as showing in Table 3. Thus, 13 target dictionaries are constructed. For instance, as shown in Table 3, there are 10 dictionaries for each 10 modalities, one 10-modality-generalized dictionary, one tense-generalized dictionary, and one tense-and-10-modality-generalized dictionary.

These target dictionaries may include semantically incorrect generalizations, so they are called trial dictionaries. But because these generalizations are used to roughly estimate the coverage improvement effect using the tense-modality function generalization, inaccuracy is not a problem at this time.

4.2 Evaluation results

In this experiment, we used the same input sentence set as in Section 3.1 for pattern matching to each of the 20 target dictionaries described in Section 4.1. We used two types of coverage improvement parameters or η_{R1} and η_N, calculated using coverage properties $R1$ and N.

Table 4 shows the evaluation results. The target dictionaries (1), (1-i), (1-ii), (1-iii), (1-iv), (1-v) and (2) were constructed by removing marks. Because all η's are less than 1, the effect of removing the marks is quantitatively clarified. The inverse number indicated in Table 4 can be compared with the ratios η of the target dictionaries (3), (3a), (3b), and so on.

Dictionary(1) is the most effective for overall generalization, but individual insertion marks are not very effective. This indicates that combining the insertion marks is more effective. Dictionary(2) is the second most effective because the omission marks enable these omission of adverbial and adjectival expressions. But, contrary to our expectations, dictionary(3) was not as effective as dictionary(1) because of incomplete generalizations. For instance, the generalizing the functions only allowed matching to omit the modality expressions. It should have allowed matching to insert the modality expressions.

5 Discussion

5.1 Easier estimation

To estimate the generalization effect of the tense/modality functions, some target dictionaries were constructed automatically. But it will be more difficult to construct the target dictionary if the generalization conditions become more difficult. Here we show two ways to estimate more easily.

5.1.1 Estimation using logical pattern increase

The increase in the number of patterns by generalization can be counted logically in some case. For example, a non-generalized pattern "$V1.teiru$" can be generalized into "$V1[.teiru]$". The latter pattern means the following two patterns "$V1.teiru$" and "$V1$", allowing us to obtain one new pattern. With this in mind, we expect logically counted patterns to be available to estimate the coverage improvement parameter, represented by η_L.

In the base dictionary, there are 9,505 patterns containing "$.teiru$" and the quantity of the generalized patterns is 132,124. Thus, η_L is 132,124/122,619 = 1.08. The other η_L are also counted in the same manner(shown in Table 4). The η_{R1}, η_N, and η_L of the target dictionary(3b) are similar each other, but the ones from dictionary(3) and (3a) are not. This is because η_L is calculated without considering the tense expression frequencies in the input sentence set.

Japanese base pattern:	$/_y TIME1/_{cf}V2$ とすぐ $/_{tcfk}N3$ を $/_{cf}V4.teinei$。
Generalized pattern:	$/_y TIME1/_{cf}V2$ とすぐ $/_{tcfk}N3$ を $/_{cf}V4[.teinei]$。

Figure 5: Example of the pattern generalized for modality

Table 4: Evaluation results of pattern generalization effect

Target dictionary type	$\eta_{R1}(1/\eta_{R1})$	$\eta_N(1/\eta_N)$	η_L
(1) No insertion marks	0.05 (20.0)	0.14 (7.14)	-
(1-i) no $/_y$ mark	0.65 (1.54)	0.81 (1.23)	-
(1-ii) no $/_t$ mark	0.96 (1.04)	0.98 (1.02)	-
(1-iii) no $/_c$ mark	0.51 (1.96)	0.50 (2.00)	-
(1-iv) no $/_f$ mark	0.77 (1.30)	0.89 (1.12)	-
(1-v) no $/_k$ mark	0.83 (1.20)	0.83 (1.20)	-
(2) No omission marks	0.39 (2.56)	0.72 (1.39)	-
(3) Tense-modality generalizations	2.15	2.29	4.75
(3a) Tense generalizations	1.53	1.36	2.65
(3b) Modality generalizations	1.49	1.40	1.48
(3b-i) *.teiru* generalization	1.19	1.10	1.08
(3b-ii) *.rareru* generalization	1.06	1.08	1.06
(3b-iii) *.dantei* generalization	1.02	1.02	1.06
(3b-iv) *.hitei* generalization	1.05	1.02	1.05
(3b-v) *.teinei* generalization	1.03	1.03	1.04
(3b-vi) *.meireigo* generalization	1.05	1.02	1.02
(3b-vii) *.you* generalization	1.02	1.02	1.02
(3b-viii) *.suitei* generalization	1.07	1.01	1.01
(3b-ix) *.sase* generalization	1.01	1.05	1.01
(3b-x) *.tekureru* generalization	1.01	1.02	1.01

(see section 5 for η_L)

5.1.2 Estimation using dictionary subset

The second concept for making estimation easier is to use the subset of target dictionary. Table 5 shows the η_{R1} and η_N for each subset. η_N becomes consistent earlier than η_{R1}. After 5,000-pattern generalizations the estimation using η_N may be successful.

According to the analysts that concerned the pattern dictionary development, 2,000 patterns can be modified in a short term. Therefore a trial dictionary that is like this size can be modified by hand, and this estimation would be available under difficult generalization conditions.

Table 5: Size of target dictionary(3a) vs. η

Dictionary size	η_{R1}	η_N
100	0.01	0.15
500	0.13	0.15
1,000	4.07	1.12
5,000	1.64	1.30
10,000	1.83	1.40
20,000	2.05	1.34
40,000	1.72	1.47
80,000	1.69	1.39
122,619	1.53	1.36

5.2 Differences between η_{R1} and η_N

We used two kinds of coverage properties to calculate η. As Table 4 shows, the difference between η_{R1} and η_N is from 1 to 13 for dictionaries(1) and (2), but is less than 1 for dictionary(3). Which η should be referred? $R1$ is more important than N because we tried to evaluate the coverage of pattern matching by using $R1$. However $R1$'s property is exponential and may include more errors than N. In fact, the estimation method in section 5.1.2 shows η_N gets constant in smaller size. Therefore, linear N seems to be more advantageous for the estimation of the generalization effect.

6 Conclusions

We described an evaluation parameter η called "an equivalent pattern quantity" to find ways to develop a large-scale sentence pattern dictionary and then evaluated 4 types of generalization using insertion and omission marks, and tense and modality functions. The generalization results of the word-level sentence pattern dictionary (122,619 pattern pairs) are as follows. The η for the insertion and omission marks were 20 and 2.3 each, while that of the tense and modality functions was 2.2 in total. Based on these results, we believe that the effect of generalizing tense and modality is not as high as that of insertion marks but a very close match to omission marks. Since the effect of $\eta = 2.2$ corresponds to adding 147,142 patterns to the current word level pattern dictionary, we decided to further generalize the current patterns in order to improve the coverage.

We have already started to correctly generalize tense and modality functions. So in near future work, we will compare the coverage between the trial dictionary and the second version of the dictionary. Next, since the evaluation method for the generalization will help the decision making when developing example-based knowledge base, we will measure other generalization points.

Acknowledgments

This research was conducted by the Japan Science and Technology Agency (JST) as a Core Research for Evolutional Science and Technology (CREST) project.

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