

# Pattern-Based English-Japanese Machine Translation with Statistical Method

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**Abstract**—Pattern-based machine translation needs translation patterns. Such translation patterns are usually made manually. A high-quality translation can be obtained if the input sentence matches the translation pattern and this translation pattern is correct. But it costs a lot to make translation patterns. We propose to make translation patterns automatically in order to decrease the cost. And we select translations by using word tri-gram scores. Finally, we demonstrated the effectiveness of the proposed method in English-Japanese machine translation experiments.

**Keywords**—component; Pattern-Based Machine Translation; Statistical Machine Translation; GIZA++;

## I. INTRODUCTION

### A. Pattern-Based Machine Translation

Pattern-based machine translation [6] was proposed in the 1960s. This form of machine translation uses the source language and target language translation patterns made manually. It has certain advantages. In particular, if the input sentence matches a translation pattern, the translated sentence will be of high quality. However, it has disadvantages as well. It cannot translate input sentences that do not match any of the prepared translation patterns. This means that to match many sentences, we either have to make many patterns or relaxed these patterns. Consequently, problem becomes either too high a translation cost or poor translation accuracy. This tradeoff has thus far been difficult to surmount, and hence, the amount of research on pattern-based machine translation has declined.

### B. Statistical Machine Translation

Statistical machine translation (SMT) was proposed in the 1990s. This translation method uses the source and target sentence pairs and has a translation model and a language model. A decoder uses these models to output a target sentence with the maximum probability. The following is an example of English-Japanese SMT [12].

$$J = \operatorname{argmax}_j P(j|e) \quad (1)$$

$$\simeq \operatorname{argmax}_e P(e|j)P(j) \quad (2)$$

Here,  $P(e|j)$  means the English-Japanese translation model, and  $P(j)$  means the Japanese language model. The translation model has probabilities of Japanese words

translated into English words. These probabilities are calculated from the English and Japanese sentence pairs. On the other hand, the language model has probabilities of Japanese word strings. The decoder selects the Japanese sentence by referring to the translation model and language model. Statistical machine translation was initially word-based. Recently, though, it has become phrase-based because of the translation performance.

### C. Proposed Method

Conventional pattern-based machine translation is costly because the translation patterns are made manually. In return, the output is grammatical and tends to be a good translation. On the other hand, statistical machine translation is low cost because it uses only source and target sentence pairs that do not have to be manually related. However, statistical machine translation often outputs ungrammatical translation sentences. To overcome these problems, we focused on that the corresponding word pairs between the source language and the target language can be automatically obtained from SMT [5]. GIZA++[3] can get the source and target word pairs automatically from the source and target sentence pairs. Thus, we can make the source and target translation patterns using the automatically obtained source and target word pairs.

We implemented the program for automatically create English-Japanese statistical pattern-based machine translation. This program makes the English-Japanese translation patterns and the English-Japanese word pairs as well. We investigated the proposed English-Japanese statistical pattern-based machine translation and surveyed the standard SMT to make a comparison with the proposed method.

## II. ENGLISH-JAPANESE PATTERN-BASED MACHINE TRANSLATION

The conventional English-Japanese pattern-based translation method is as follows [4].

Step 1 Prepare English-Japanese translation patterns and English-Japanese word pairs.

Step 2 Input an English sentence.

Step 3 Search for an English translation pattern that matches the input of Step 2.

Step 4 Output a Japanese translation pattern corresponding to the English translation pattern made in Step 3.

Step 5 Generate a Japanese translation sentence using the English-Japanese word pairs and a Japanese translation pattern in step 4.

Table I shows an example of English-Japanese pattern translation, and Table II shows examples of English-Japanese word pairs.

Input English sentence	The fire started in the kitchen .
English translation pattern	The X1 started in the X2 .
Japanese translation pattern	X1 は X2 から 出た 。
Output Japanese sentence	火 は 台所 から 出た 。

Table I  
EXAMPLE OF ENGLISH-JAPANESE PATTERN TRANSLATION

fire	火
kitchen	台所

Table II  
EXAMPLE OF ENGLISH-JAPANESE WORD PAIRS

### III. GIZA++

GIZA++[3] gets the source language and the target language word pairs by using the maximum likelihood correspondence from the source sentence and target sentence pairs. It also assigns a translation probability. GIZA++ is implemented with IBM model 1-5[2]. In this experiment, we used GIZA++ to obtain the English-Japanese word pairs and the Japanese-English word pairs.

### IV. PROPOSED METHOD

Conventional pattern-based machine translation costs a lot because its translation patterns are made by manually. In return, the output of pattern-based machine translation is grammatical and tends to be a good translation. On the other hand, statistical machine translation is low cost because it uses only source and target sentence pairs. However, statistical machine translation often outputs ungrammatical translations.

To overcome the above mentioned problems, we focused on the corresponding word pairs between the source language and the target language that can be automatically found with GIZA++. GIZA++ gets the source and target word pairs automatically from the source and target sentence pairs. The English-Japanese translation patterns can then be made from these English-Japanese word pairs.

The steps of the proposed method are described below.

#### A. Make the English-Japanese Word Dictionary

Translating only one way from English to Japanese will result in an unreliable the English-Japanese word dictionary. So, in order to increase reliability, we used both English-Japanese word pairs and Japanese-English word pairs to make the English-Japanese word dictionary.

The English-Japanese word dictionary was made as follows.

Step 1 Make English-Japanese word pairs and Japanese-English word pairs using GIZA++.

Step 2 Multiply the translation probabilities of the English-Japanese word pairs and the Japanese-English word pairs. Select the word pairs with probabilities higher than a threshold ( $\alpha$ ) and put them in the English-Japanese word dictionary.

Table III shows an example of the English-Japanese word dictionary and Table IV shows an example of the Japanese-English word dictionary.

fire	火	0.37
kitchen	台所	0.49

Table III  
EXAMPLE OF ENGLISH-JAPANESE WORD DICTIONARY

火	fire	0.22
台所	kitchen	0.71

Table IV  
EXAMPLE OF JAPANESE-ENGLISH WORD DICTIONARY

#### B. Make the English-Japanese Translation Patterns

We made the English-Japanese translation patterns by using the English-Japanese word dictionary and the English-Japanese sentence pairs.

The English-Japanese translation patterns are created with the following steps.

Step 1 Compare each English word of a English-Japanese sentence pair with every English word of the English-Japanese word dictionary.

Step 2 Compare every Japanese word of the English-Japanese word dictionary with each Japanese word of a English-Japanese sentence pair. (This "a English-Japanese sentence pair" is same as "a English-Japanese sentence pair" in step1.)

Step 3 Match up the English-Japanese word pairs and replace each pair with a variable, X1, X2, X3, etc.

Step 4 Repeat steps 1 to 3 for all sentence pairs.

Figure 1 shows an example of making an English-Japanese translation pattern.

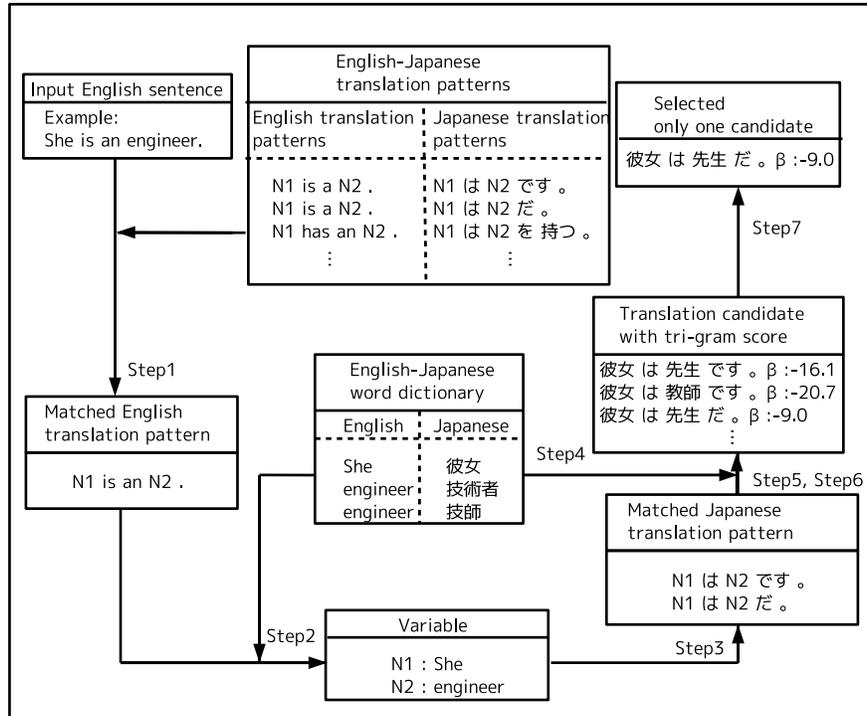


Figure 2. Generating a Japanese Translation Sentence

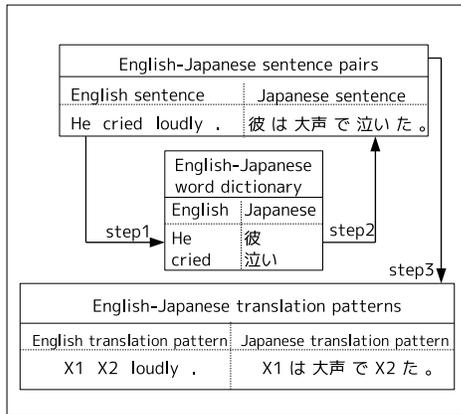


Figure 1. Making an English-Japanese Translation Pattern

### C. Generate the Japanese Translation Sentence

We generate Japanese translation sentences by using the English-Japanese word dictionary and the English-Japanese translation patterns.

The Japanese translation sentences are made as follows.

- Step 1 Select English translation patterns corresponding to the input English sentence.
- Step 2 Find the variables in the English translation pat-

terns and obtain the English words corresponding to the variables.

- Step 3 Obtain the Japanese translation patterns corresponding to the English translation patterns.
- Step 4 Find the variables in Japanese translation patterns and search for the Japanese words corresponding to the variables.
- Step 5 Replace variables in Japanese translation patterns with the Japanese word in Step 4.
- Step 6 Japanese translation sentence calculates the likelihood( $\beta$ ) by using Japanese word tri-gram. The likelihood( $\beta$ ) means the sum of Japanese word tri-gram scores with based 10 logarithm. Japanese word tri-gram are calculated from the English-Japanese sentence pairs.
- Step 7 If the result of step 5 generates multiple Japanese translation sentences, select only one sentence with the highest likelihood( $\beta$ ).

Figure 2 shows an example of generating a Japanese translation sentence.

### D. Notes

- If the probability of the word tri-gram data is 0.0, we set -1000.0 as a penalty.(It means that the word tri-gram data was not appeared in English-Japanese sentence pairs.)

Moreover, the following cases are not outputted as Japanese translation sentences.

- The input English sentence does not match any of the English translation patterns.
- For Step 2 or Step 4 of Section IV-C, the English word or the Japanese word couldn't be found in the English-Japanese word dictionary.

### E. Database

We used simple sentence pairs and complex/compound sentence pairs extracted from the EPWING electronic dictionaries [8]. We used 100,000 English-Japanese simple sentence pairs for the training and 10,000 English sentences for the test. The average of simple sentence is 9.0 word/sentence for the training in English. And the average of simple sentence is 10.5 word/sentence for the training in Japanese. Similarly, we used 100,000 translation pairs from compound/complex sentence pairs for the training and 10,000 English sentences for the test. The average of compound/complex sentence is 11.2 word/sentence for the training in English. And the average of compound/complex sentence is 13.9 word/sentence for the training in Japanese. We used Mecab [7] as the morphological analyzer and the standing tokenizer of Moses [5].

Table V shows example English-Japanese sentence pairs.

Simple Sentence	
English	The stars are twinkling .
Japanese	星が光っている。
Complex/Compound Sentence	
English	In order to move a car, first you have to start the engine .
Japanese	自動車を動かすにはまずエンジンをかけなければなりません。

Table V  
EXAMPLE SENTENCES

## V. EXPERIMENT

### A. Simple Sentences

- Making English-Japanese patterns

We used a word dictionary with  $\alpha=0.05$  to make the English-Japanese translation patterns. ( $\alpha$  is used in Step 2 of Section IV-A.) As a result, we obtained 17,128 English-Japanese word pairs (word dictionary) and 86,204 English-Japanese translation patterns.

- Generating Japanese translation sentences

We used a word dictionary with  $\alpha=0.005$  to generate the Japanese translation sentences. As a result, we obtained 76,202 English-Japanese word pairs (word dictionary).

### B. Compound/Complex Sentences

- Making English-Japanese patterns

We used a word dictionary with  $\alpha=0.05$  to make the English-Japanese translation patterns. ( $\alpha$  is used in Step 2 of Section IV-A.) As a result, we obtained 16,110 English-Japanese word pairs (word dictionary) and 87,674 English-Japanese translation patterns.

- Generating Japanese translation sentences

We used a word dictionary with  $\alpha=0.01$  to generate the Japanese translation sentences and obtained 49,704 English-Japanese word pairs (word dictionary).

### C. Tri-gram Data

We used 100,000 English-Japanese sentence pairs to calculate the Japanese word tri-gram.

### D. Baseline System (Moses)

We used Moses as the baseline system for comparison, and we didn't do parameter tuning [11] on Moses[5].

## VI. EXPERIMENTAL RESULTS

We classified the output Japanese translation sentences into four types (The A-rank ~ The D-rank). We used the likelihood( $\beta$ ) as a classifier. The four types are shown .

A-rank	$-1000.0 < \beta \leq 0.0$
B-rank	$-2000.0 < \beta \leq -1000.0$
C-rank	$-3000.0 < \beta \leq -2000.0$
D-rank	$-3000.0 \leq \beta$

$\beta$  : Sum of Japanese word tri-gram scores with based 10 logarithm.

Table VI  
FOUR TYPES FOR THE SUM OF JAPANESE WORD TRI-GRAM SCORES

### A. Example of Translation Sentences

#### 1) Simple Sentences:

Here, we show the simple sentence translation results. In Table VII ~ X, "Input" means the input English sentence. "English translation pattern" means the English translation pattern matching the input. "Japanese translation pattern" means Japanese translation patterns corresponding to an English pattern. "Proposed" means the translation sentence obtained by the proposed method. "Reference" means a correct sentence. "Baseline" is the output of Moses. " $\beta$ " means the sum of Japanese word tri-gram scores with based 10 logarithm.

#### [1] Example of the A-rank

We obtained 379 sentences in the A-rank. The results of the A-rank was attractive and was better than the baseline(Moses).

#### [a] Example of the A-rank

Input	A pendulum swings back and forth .
English translation pattern	A X1 swings back and forth .
Japanese translation pattern	X1 は 左右 に 振動 する。
Proposed	振り子は 左右 に 振動 する。 $\beta$ : -38.90
Reference	振り子は 左右 に 振動 する。
Baseline(Moses)	振り子は 左右 に している。

Table VII  
EXAMPLE OF A-RANK

An example of the A-rank is shown in Table VII. The result of the proposed method was the same as the reference sentence. This shows the effectiveness of the proposed method in this case.

#### [2] Example of the B-rank

We obtained 247 sentences in the B-rank. The results of the B-rank has both superior and inferior. And the B-rank had better results and worse results than the baseline(Moses).

##### [a] Better example of the B-rank

A better example of the B-rank is shown in Table VIII. The results of the proposed method resembles the reference

Input	She called him all the bad names .
English translation pattern	X1 called X2 all the bad names .
Japanese translation pattern	X1 は X2 を くそみそに 言った。
Proposed	彼女は 彼 を くそみそに 言った。 $\beta$ : -1036.215
Reference	彼女は ざんざん 彼の 悪口 を 言った。
Baseline(Moses)	彼女は 彼 を を けなした。

Table VIII  
BETTER EXAMPLE OF B-RANK

sentence.

##### [b] Worse Example of the B-rank

A worse example of the B-rank is shown in Table IX. The

Input	The telephone is out of order .
English translation pattern	X1 X2 X3 out of order .
Japanese translation pattern	X1 X2 は 狂い が きて X3 .
Proposed	その 電話 は 狂い が きて いる。 $\beta$ : -1034.338
Reference	電話 が こわれて いる。
Baseline(Moses)	その 電話 は 故障 して いる。

Table IX  
WORSE EXAMPLE OF B-RANK

results of the proposed method is unidiomatic despite its

meaning being more or less correct. On the other hand, the baseline(Moses) resembles the reference sentence.

#### [3] Example of the C-rank

We obtained 292 sentences in the C-rank. Some of the C-rank were better and some were worse. And the results of the C-rank were worse than the B-rank. However, they resembled the B-rank, we shall omit the example of the C-rank.

#### [4] Example of the D-rank

We obtained 2,334 sentences in the D-rank. The results of the D-rank was inferior. And the D-rank were worse than the baseline(Moses).

##### [a] Example of the D-rank

Below is an example of the D-rank translation. In Table X,

Input	Tell me the exact time .
English translation pattern	X1 X2 the X3 X4 .
Japanese translation pattern	X1 が X3 X4 を X2 た。
Proposed	話し が 掴め 時間 を くれた。 $\beta$ : -4017.981
Reference	正確 な 時刻 を 教えて ください。
Baseline(Moses)	正確 な 時刻 を 教えて ください。

Table X  
EXAMPLE OF D-RANK

the results of the proposed method is unsuitable, but the baseline(Moses) resembles the reference sentence.

#### 2) Compound/Complex Sentences:

##### [1] Example of the A-rank

We obtained 408 sentences in the A-rank. The results of the A-rank was attractive and was better than the baseline(Moses).

##### [a] Example of the A-rank

The following is an example of the A-rank.

In Table XI, the results of the proposed method is the same as the reference. This means the effectiveness of the proposed method in this case.

##### [2] Example of the B-rank

We obtained 31 sentences in the B-rank. The results of the B-rank was superior. This shows the effectiveness of the proposed method. However, they resembled the A-rank, we shall omit the B-rank example.

##### [3] Example of the C-rank

Input	It is foolish to take a hit-or-miss attitude toward exams .
English translation pattern	It X1 foolish to take a hit-or-miss attitude toward exams .
Japanese translation pattern	試験で一か八かやるのX1ばかっている。
Proposed	試験で一か八かやるのはばかっている。 $\beta$ : -63.413
Reference	試験で山をかけるのはばかっている。
Baseline(Moses)	で一か八かやるのはばかっている。

Table XI  
EXAMPLE OF A-RANK

We obtained 16 sentences in the C-rank. The results of the C-rank has both superior and inferior. The C-rank had better results and worse results than the baseline(Moses).

[a] Better example of the C-rank

A better example of the C-rank is shown below.

Input	He demonstrated that the world is round .
English translation pattern	X1 demonstrated that X2 X3 X4 round .
Japanese translation pattern	X1 X4 X3 が丸いということ X2 証明した。
Proposed	彼は世界が丸いということ を証明した。 $\beta$ : -2037.680
Reference	彼は地球は丸いということ を実証した。
Baseline(Moses)	世界はであることがわかったのではないかと心配している。

Table XII  
BETTER EXAMPLE OF C-RANK

In Table XII, the results of the proposed method resembles the reference sentence. On the other hand, the baseline is ungrammatical sentence.

[b] Worse Example of the C-rank

A worse example of the C-rank is as follows.

In Table XIII, the results of the proposed method is ungrammatical sentence. On the other hand, the baseline(Moses) is grammatical and correct sentence.

[4] Example of the D-rank

We obtained 368 sentences in the D-rank. The results of the D-rank was inferior. And the D-rank translations were worse than the Baseline(Moses).

[a] Example of the D-rank

Input	He was doomed to failure .
English translation pattern	He X1 X2 X3 X4 .
Japanese translation pattern	X4 X3 X2 て X1 た。
Proposed	失敗する運命ていた。 $\beta$ : -2018.231
Reference	彼は命数が尽きて失敗したのだ。
Baseline(Moses)	彼は結局失敗する運命に遭った。

Table XIII  
WORSE EXAMPLE OF THE C-RANK

Input	He was found dead .
English translation pattern	X1 X2 X3 X4 .
Japanese translation pattern	X1 X2 X4 では X3 。
Proposed	彼が死んを見つけたのもた。 $\beta$ : -4021.862
Reference	彼は死んで発見された。
Baseline(Moses)	彼が死んでいた。

Table XIV  
EXAMPLE OF D-RANK

An example of the D-rank is shown below.

In Table XIV, the results of the proposed method is ungrammatical sentence. On the other hand, the baseline(Moses) is grammatical and correct sentence.

## B. Automatic Evaluation Results

We evaluated the translations using automatic evaluation tools. We used the BLEU [1] and NIST [10] evaluation tools.

### 1) Simple Sentences:

We input 10,000 English sentences and obtained 3,252 sentences matching the English-Japanese translation patterns. We obtained 379 sentences in the A-rank, 247 in the B-rank, 292 in the C-rank, and 2,334 in the D-rank. And we compared our method with the baseline(Moses) for each rank. The automatic evaluation results are listed in Table XV. From the results in Table XV, we can see the

	Proposed		Baseline(Moses)	
	BLEU	NIST	BLEU	NIST
A-rank(379)	0.5664	6.9185	0.5434	6.7248
B-rank(247)	0.2993	4.4478	0.3097	4.2523
C-rank(292)	0.2228	3.9444	0.2466	3.9138
D-rank(2,334)	0.0686	3.0176	0.1614	3.8581
All rank(3,252)	0.1683	3.8956	0.2258	4.4613

Table XV  
AUTOMATIC EVALUATION RESULTS

BLEU and NIST values were higher for the A-rank. This means the proposed method was more effective than the

baseline(Moses) for the A-rank. However, the same cannot be said for the other ranks.

### 2) Compound/Complex Sentences:

We used 10,000 English sentences in this experiment. We obtained 823 sentences matching the English-Japanese translation patterns. We obtained 408 sentences in the A-rank, 31 in the B-rank, 16 in the C-rank, and 368 in the D-rank. And we compared the proposed method and the baseline(Moses) for each rank. The automatic evaluation results are listed in Table XVI. Table XVI shows that the BLEU and NIST

	Proposed		Baseline(Moses)	
	BLEU	NIST	BLEU	NIST
A-rank(408)	0.5662	7.7735	0.5348	7.4597
B-rank(31)	0.4717	4.8247	0.3573	3.9476
C-rank(16)	0.3517	3.6805	0.3225	2.8721
D-rank(368)	0.0710	2.3499	0.1451	3.0121
All rank(823)	0.3630	5.6752	0.3563	5.6218

Table XVI  
AUTOMATIC EVALUATION RESULTS

values were higher for the A-rank, B-rank, and the C-rank. That is, the proposed method was better than the baseline(Moses) for the A-rank, the B-rank, and the C-rank but not the D-rank.

### C. Human Evaluation Results

We carried out the ABX test [13] on the proposed method and the baseline(Moses) for each of the Japanese translation sentences. The ABX test is a human evaluation. And this evaluation was carried out only one person. It involves a count of the sentences using the following criteria.

- Proposed ○: The proposed method’s translation was better than the baseline (Moses).
- Proposed ×: The proposed method’s translation was worse than the baseline (Moses).
- No difference: There was no difference in translation quality between the proposed method and the baseline(Moses).
- Same: Both outputs were completely the same.

#### 1) Simple Sentences:

We selected 50 sentences at random for each rank. The results of the evaluation for simple sentences are listed in Table XVII. From Table XVII, we see that the proposed method was superior to the baseline(Moses) for the A-rank. On the other hand, the proposed method was inferior to the baseline(Moses) for the other ranks. This shows the effectiveness of the proposed method for the A-rank.

#### 2) Compound/Complex Sentences:

We selected 10 sentences at random for each rank. The results of the human evaluation for compound/complex sentences are listed in Table XVIII. Table XVIII indicates

rank	Proposed ○	Proposed ×	No difference	Same
A-rank	9	0	19	22
B-rank	6	11	24	9
C-rank	7	9	33	1
D-rank	1	10	39	0

Table XVII  
RESULTS OF HUMAN EVALUATION(SIMPLE SENTENCES)

Table XVIII  
RESULTS OF HUMAN EVALUATION(COMPOUND/COMPLEX SENTENCES)

rank	Proposed ○	Proposed ×	No difference	Same
A-rank	3	0	0	7
B-rank	4	0	5	1
C-rank	2	2	5	1
D-rank	0	2	8	0

the proposed method is superior to the baseline(Moses) for the A-rank and the B-rank. On the other hand, its results were split for the C-rank, and it was inferior to the baseline(Moses) for the D-rank. This shows the effectiveness of the proposed method for the A-rank and the B-rank.

## VII. DISCUSSION

### A. Automatic Evaluation of All Test Sentences

#### 1) Simple Sentences:

We made 10,000 test sentences that combined 379 sentences for the A-rank and 9621 sentences for the baseline(Moses). We called this data "Proposed+Baseline". Next, we evaluated "Proposed+Baseline" and the baseline(Moses). The results for all test sentences are shown below.

Table XIX  
COMPARISON OF ALL TEST SENTENCES

	BLEU	NIST
Proposed+Baseline	0.1381	3.7798
Baseline(Moses)	0.1375	3.7743

In Table XIX, the BLEU score of the "Proposed+Baseline" was higher than the baseline(Moses) by 0.006. This means the "Proposed+Baseline" was more effective than the baseline(Moses).

#### 2) Compound/Complex Sentences:

We made 10,000 test sentences that combined 408 sentences for the A-rank and 9,592 sentences for the baseline(Moses).

	BLEU	NIST
Proposed+Baseline	0.0999	3.1267
Baseline(Moses)	0.0987	3.1100

Table XX  
COMPARISON OF PROPOSED METHOD AND BASELINE(MOSES)

In Table XX, the BLEU score of the "Proposed+Baseline" was higher than the baseline(Moses) by 0.0012. This proves the effectiveness of the "Proposed+Baseline".

### B. Translation Accuracy of Proposed Method

English-Japanese translation experiments showed the effectiveness of the proposed method in the A-rank. The human evaluation especially favored the proposed method. In simple sentences of the A-rank in the ABX test, the proposed method was judged that 9 sentences well and no sentences poorly. The ABX test on compound/complex sentences of the A-rank showed that our method could translate 3 sentences were well and none of the translations were rated poorly.

### C. Comparison of Automatic Evaluation and Human Evaluation

The human evaluation showed that the proposed method worked for the simple sentences and the compound/complex sentences of the A-rank. On the other hand, the BLEU scores of the proposed method and the baseline(Moses) were not so good. We thought that they are the problem of automatic evaluation.

### D. Discussion of Compound/Complex Sentences of the B-rank

Although the B-rank compound/complex sentences were good translations, the simple sentences of the B-rank were worse. We thought that this was because there were fewer English-Japanese word pairs in the simple sentences for making the translation patterns. Thus, there were fewer variables and many characters were left in the compound/complex translation patterns. Therefore, when the input sentence matched an English translation pattern, we obtained a high-quality translation even though the number of matched sentences decreased.

### E. Examination of Word-based Statistical Machine Translation Decoder

The first generation of the statistical machine translation was word-based, and its performance was low. More recently, phrase-based statistical machine translation has gotten better results.

In the proposed method, we thought the English-Japanese word dictionary and English-Japanese translation patterns were equivalent to the translation model of SMT. And we thought the word tri-gram was equivalent to the language model of SMT. Consequently, we thought the proposed method was equivalent to a word-based SMT decoder.

### F. Increasing the number of matching the English-Japanese translation patterns

In this experiment, we matched 3252 sentences from the 10000 English simple sentences. Similarly, we matched 823 sentences from the 10000 English Compound/Complex sentences. We think that it is less number of matching the English-Japanese translation patterns. In future works, we must increase the number of matching the English-Japanese

translation patterns. So, we will do following two things to increase the number of matching the English-Japanese translation patterns.

#### 1) Translation Patterns:

We implemented the program to automatically create the English-Japanese translation patterns. However this program generate only one English-Japanese translation patterns by one English-Japanese sentence pairs. If a word has multiple meaning, we must generate multiple English-Japanese translation patterns. So, we will improve this program to increase the English-Japanese translation patterns.

#### 2) Extend the phrase-based pattern machine translation:

We implemented the program to generate the Japanese translation sentence. But this program is word-based pattern machine translation. For example, the variable "X1" accepts only one word. So, we can't translate phrase. (It is constructing two or more words.) In future works, we will make the program using phrase-based pattern machine translation.

### G. Other works

In section V-D, we didn't do parameter tuning. So, we must do re-experiment. Also, the number of the English-Japanese sentence pairs used for this experiment is small. It means that reliability of tri-gram data is small. So we will use the google- $N$ -gram [14] in this experiment.

## VIII. CONCLUSION

In this paper, we described pattern-based English-Japanese machine translation with statistical method. And we showed how to automatically create English-Japanese statistical pattern-based machine translation. Ordinarily, translation patterns are made by hand in pattern-based machine translation. Instead, we made them automatically using an SMT tool. In the experiments, we obtained high-quality translation sentences under certain conditions. The proposed method was especially effective in the human evaluation in the A-rank classification. For example, for the simple sentences, it obtained 9 correct sentences and 0 incorrect sentences than the baseline(Moses).

In the future, we will make a program using phrase-based pattern machine translation in order to increase the number of translations in the A-rank.

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## REFERENCES

- [1] Papineni Kishore, Salim Roukos, Todd Ward, Wei-Jing Zhu, "BLEU: a method for automatic evaluation of machine translation", 40th Annual meeting of the Association for Computational Linguistics, pp.311-318, 2002.
- [2] Peter F. Brown, Stephen Della Pietra, Vincent J. Della Pietra and Robert L. Mercer, "The Mathematics of Statistical Machine Translation: Parameter Estimation", Computational Linguistics, 19(2), pp.263-311, 1993.
- [3] Franz Josef Och, Hermann Ney, "A Systematic Comparison of Various Statistical Alignment Models", Computational Linguistics, pp.19-51, 2003.
- [4] Satoru Ikehara and Masashi Saraki and Masahiro Miyazaki and Naosi Ikeda and Yoshihiko Nitta and Satoshi Shirai and Katsumasa Shibata, "Analogical Mapping Method for MT based on Semantic Typology", EiC, pp.7-12, 2002.
- [5] Philipp Koehn, Marcello Federico, Brooke Cowan, Richard Zens, Chris Dyer, Ondřej Bojar, Alexandra Constantin, Evan Herbst, "Moses: Open Source Toolkit for Statistical Machine Translation", Proceedings of the ACL 2007 Demo and Poster Sessions, pp.177-180, 2007.
- [6] Hiroshi Maruyama, "Pattern-Based Translation: Context-Free Transducer and Its Applications to Practical NLP", in Proc. of Natural Language Pacific Rim Symposium, pp.232-237, 1993.
- [7] Taku Kudo, Kaoru Yamamoto, Yuji Matsumoto, "Applying Conditional Random Fields to Japanese Morphological Analysis", Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing (EMNLP-2004), pp.230-237, 2004.
- [8] Jin'ichi Murakami and Masato Tokuhisa and Satoru Ikehara, "Statistical Machine Translation using Long Phrase Tables", International Workshop on Spoken Language Translation, pp.151-155, 2007.
- [9] Takuya Nishimura and Jin'ichi Murakami and Masato Tokuhisa and Satoru Ikehara, "Statistical Machine Translation using translation patterns", The Association for Natural Language Processing, pp.676-679, 2010.
- [10] NIST, "Automatic Evaluation of Machine Translation Quality Using n-gram Co-Occurrence Statistics", <http://www.itl.nist.gov/iad/mig/test/mt/>, 2003.
- [11] Franz Josef Och, "Minimum error rate training for statistical machine translation", Proceedings of the ACL, 2003.
- [12] Richard Zens and Franz Josef Och and Hermann Ney, "Phrase-based Statistical Machine Translation", KI, pp.35-56, 2002.
- [13] YU-TING HUANG and HARRY T. LAWLESS, "Sensitivity of the ABX discrimination test", Journal of Sensory Studies-J SENS STUD, vol.13, no.2, pp.229-239, 1998.
- [14] Web 日本語 N グラム第 1 版 by Google, GSK カタログ GSK2007-C.