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# Neural Machine Translation Model with a Large Vocabulary Selected by Branching Entropy

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## Abstract

Neural machine translation (NMT), a new approach to machine translation, has achieved promising results comparable to those of traditional approaches such as statistical machine translation (SMT). Despite its recent success, NMT cannot handle a larger vocabulary because the training complexity and decoding complexity proportionally increase with the number of target words. This problem becomes even more serious when translating patent documents, which contain many technical terms that are observed infrequently. In this paper, we propose to select phrases that contain out-of-vocabulary words using the statistical approach of branching entropy. This allows the proposed NMT system to be applied to a translation task of any language pair without any language-specific knowledge about technical term identification. The selected phrases are then replaced with tokens during training and post-translated by the phrase translation table of SMT. Evaluation on Japanese-to-Chinese, Chinese-to-Japanese, Japanese-to-English and English-to-Japanese patent sentence translation proved the effectiveness of phrases selected with branching entropy, where the proposed NMT model achieves a substantial improvement over a baseline NMT model without our proposed technique. Moreover, the number of translation errors of under-translation by the baseline NMT model without our proposed technique reduces to around half by the proposed NMT model.

## 1 Introduction

Neural machine translation (NMT), a new approach to solving machine translation, has achieved promising results (Bahdanau et al., 2015; Cho et al., 2014; Jean et al., 2014; Kalchbrenner and Blunsom, 2013; Luong et al., 2015a,b; Sutskever et al., 2014). An NMT system builds a simple large neural network that reads the entire input source sentence and generates an output translation. The entire neural network is jointly trained to maximize the conditional probability of the correct translation of a source sentence with a bilingual corpus. Although NMT offers many advantages over traditional phrase-based approaches, such as a small memory footprint and simple decoder implementation, conventional NMT is limited when it comes to larger vocabu-

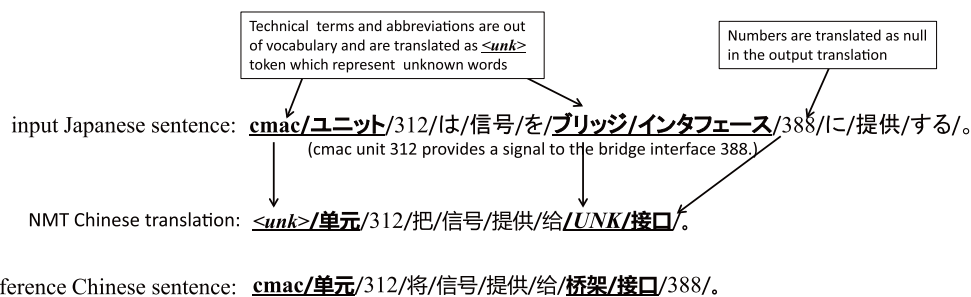


Figure 1: Example of translation errors when translating patent sentences with technical terms using NMT

larities. This is because the training complexity and decoding complexity proportionally increase with the number of target words. Words that are out of vocabulary are represented by a single “*unk*” token in translations, as illustrated in Figure 1. The problem becomes more serious when translating patent documents, which contain several newly introduced technical terms.

There have been a number of related studies that address the vocabulary limitation of NMT systems. Jean et al. (2014) provided an efficient approximation to the softmax function to accommodate a very large vocabulary in an NMT system. Luong et al. (2015b) proposed annotating the occurrences of the out-of-vocabulary token in the target sentence with positional information to track its alignments, after which they replace the tokens with their translations using simple word dictionary lookup or identity copy. Li et al. (2016) proposed replacing out-of-vocabulary words with similar in-vocabulary words based on a similarity model learnt from monolingual data. Sennrich et al. (2016) introduced an effective approach based on encoding rare and out-of-vocabulary words as sequences of subword units. Luong and Manning (2016) provided a character-level and word-level hybrid NMT model to achieve an open vocabulary, and Costa-Jussà and Fonollosa (2016) proposed an NMT system that uses character-based embeddings.

However, these previous approaches have limitations when translating patent sentences. This is because their methods only focus on addressing the problem of out-of-vocabulary words even though the words are parts of technical terms. It is obvious that a technical term should be considered as one word that comprises components that always have different meanings and translations when they are used alone. An example is shown in Figure 1, where the Japanese word “ブリッジ”(bridge) should be translated to Chinese word “桥架” when included in technical term “bridge interface”; however, it is always translated as “桥”.

To address this problem, Long et al. (2016) proposed extracting compound nouns as technical terms and replacing them with tokens. These compound nouns then are post-translated with the phrase translation table of the statistical machine translation (SMT) system. However, in their work on Japanese-to-Chinese patent translation, Japanese compound nouns are identified using several heuristic rules that use specific linguistic knowledge based on part-of-speech tags of morphological analysis of Japanese language, and thus, the NMT system has limited application to the translation task of other language pairs. In this paper, based on the approach of training an NMT model on a bilingual corpus wherein technical term pairs are replaced with tokens as in Long et al. (2016), we aim to select phrase pairs using the statistical approach of branching entropy; this allows the proposed technique to be applied to the translation task on any language pair without needing specific language knowledge to formulate the rules for technical term identification. Based on the results of our experiments on many pairs of languages: Japanese-to-Chinese, Chinese-to-Japanese, Japanese-to-English and English-to-Japanese, the

proposed NMT model achieves a substantial improvement over a baseline NMT model without our proposed technique. Our proposed NMT model achieves an improvement of 1.2 BLEU points over a baseline NMT model when translating Japanese sentences into Chinese, and an improvement of 1.7 BLEU points when translating Chinese sentences into Japanese. Our proposed NMT model achieves an improvement of 1.1 BLEU points over a baseline NMT model when translating Japanese sentences into English, and an improvement of 1.4 BLEU points when translating English sentences into Japanese. Moreover, the number of translation error of under-translations<sup>1</sup> by the the baseline NMT model without our proposed technique reduces to around half by the proposed NMT model.

## 2 Neural Machine Translation

NMT uses a single neural network trained jointly to maximize the translation performance (Bahdanau et al., 2015; Cho et al., 2014; Kalchbrenner and Blunsom, 2013; Luong et al., 2015a; Sutskever et al., 2014). Given a source sentence  $\mathbf{x} = (x_1, \dots, x_N)$  and target sentence  $\mathbf{y} = (y_1, \dots, y_M)$ , an NMT model uses a neural network to parameterize the conditional distributions

$$p(y_z | y_{<z}, \mathbf{x})$$

for  $1 \leq z \leq M$ . Consequently, it becomes possible to compute and maximize the log probability of the target sentence given the source sentence as

$$\log p(\mathbf{y} | \mathbf{x}) = \sum_{l=1}^M \log p(y_l | y_{<l}, \mathbf{x})$$

In this paper, we use an NMT model similar to that used by Bahdanau et al. (2015), which consists of an encoder of a bidirectional long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) and another LSTM as decoder. In the model of Bahdanau et al. (2015), the encoder consists of forward and backward LSTMs. The forward LSTM reads the source sentence as it is ordered (from  $x_1$  to  $x_N$ ) and calculates a sequence of forward hidden states, while the backward LSTM reads the source sentence in the reverse order (from  $x_N$  to  $x_1$ ), resulting in a sequence of backward hidden states. The decoder then predicts target words using not only a recurrent hidden state and the previously predicted word but also a context vector as followings:

$$p(y_z | y_{<z}, \mathbf{x}) = g(y_{z-1}, s_{z-1}, c_z)$$

where  $s_{z-1}$  is an LSTM hidden state of decoder, and  $c_z$  is a context vector computed from both of the forward hidden states and backward hidden states, for  $1 \leq z \leq M$ .

## 3 Phrase Pair Selection using Branching Entropy

Branching entropy has been applied to the procedure of text segmentation (e.g., (Jin and Tanaka-Ishii, 2006)) and key phrases extraction (e.g., (Chen et al., 2010)). In this work, we use the left/right branching entropy to detect the boundaries of phrases, and thus select phrase pairs automatically.

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<sup>1</sup>It is known that NMT models tend to have the problem of the under-translation. Tu et al. (2016) proposed coverage-based NMT which considers the problem of the under-translation.

### 3.1 Branching Entropy

The left branching entropy and right branching entropy of a phrase  $w$  are respectively defined as

$$H_l(w) = - \sum_{v \in V_l^w} p_l(v) \log_2 p_l(v)$$

$$H_r(w) = - \sum_{v \in V_r^w} p_r(v) \log_2 p_r(v)$$

where  $w$  is the phrase of interest (e.g., “ブリッジ/インターフェース” in the Japanese sentence shown in Figure 1, which means “bridge interface”),  $V_l^w$  is a set of words that are adjacent to the left of  $w$  (e.g., “を” in Figure 1, which is a Japanese particle) and  $V_r^w$  is a set of words that are adjacent to the right of  $w$  (e.g., “388” in Figure 1). The probabilities  $p_l(v)$  and  $p_r(v)$  are respectively computed as

$$p_l(v) = \frac{f_{v,w}}{f_w} \quad p_r(v) = \frac{f_{w,v}}{f_w}$$

where  $f_w$  is the frequency count of phrase  $w$ , and  $f_{v,w}$  and  $f_{w,v}$  are the frequency counts of sequence “ $v,w$ ” and sequence “ $w,v$ ” respectively. According to the definition of branching entropy, when a phrase  $w$  is a technical term that is always used as a compound word, both its left branching entropy  $H_l(w)$  and right branching entropy  $H_r(w)$  have high values because many different words, such as particles and numbers, can be adjacent to the phrase. However, the left/right branching entropy of substrings of  $w$  have low values because words contained in  $w$  are always adjacent to each other.

### 3.2 Selecting Phrase Pairs

Given a parallel sentence pair  $\langle S_s, S_t \rangle$ , all  $n$ -grams phrases of source sentence  $S_s$  and target sentence  $S_t$  are extracted and aligned using phrase translation table and word alignment of SMT according to the approaches described in Long et al. (2016). Next, phrase translation pair  $\langle t_s, t_t \rangle$  obtained from  $\langle S_s, S_t \rangle$  that satisfies all the following conditions is selected as a phrase pair and is extracted:

- (1) Either  $t_s$  or  $t_t$  contains at least one out-of-vocabulary word.<sup>2</sup>
- (2) Neither  $t_s$  nor  $t_t$  contains predetermined stop words.
- (3) Entropies  $H_l(t_s)$ ,  $H_l(t_t)$ ,  $H_r(t_s)$  and  $H_r(t_t)$  are larger than a lower bound, while the left/right branching entropy of the substrings of  $t_s$  and  $t_t$  are lower than or equal to the lower bound.

Here, the maximum length of a phrase as well as the lower bound of the branching entropy are tuned with the validation set.<sup>3</sup> All the selected source-target phrase pairs are then used in the

<sup>2</sup>One of the major focus of this paper is the comparison between the proposed method and Luong et al. (2015b). Since Luong et al. (2015b) proposed to pre-process and post-translate only out-of-vocabulary words, we focus only on compound terms which include at least one out-of-vocabulary words.

<sup>3</sup>Throughout the evaluations on patent translation of both language pairs of Japanese-Chinese and Japanese-English, the maximum length of the extracted phrases is tuned as 7. The lower bounds of the branching entropy are tuned as 5 for patent translation of the language pair of Japanese-Chinese, and 8 for patent translation of the language pair of Japanese-English. We also tune the number of stop words using the validation set, and use the 200 most-frequent Japanese morphemes and Chinese words as stop words for the language pair of Japanese-Chinese, use the 100 most-frequent Japanese morphemes and English words as stop words for the language pair of Japanese-English.

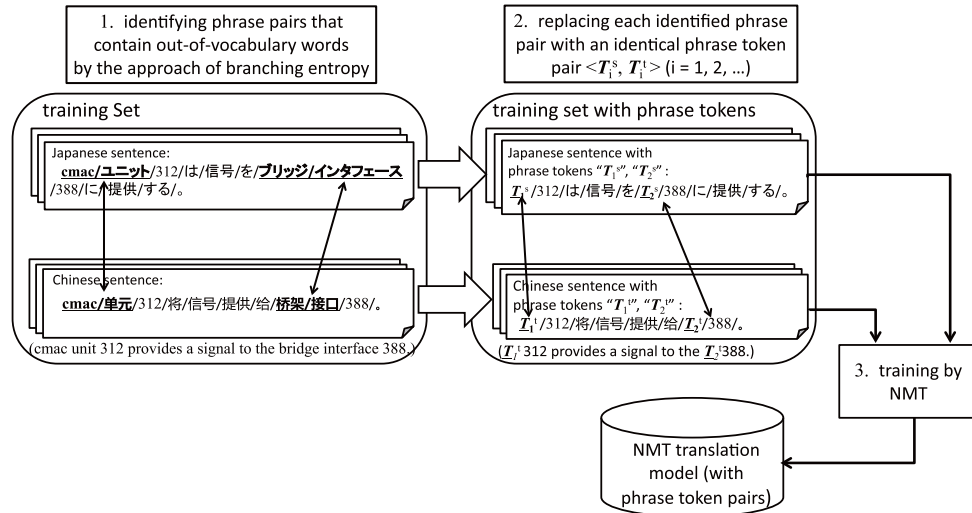


Figure 2: NMT training after replacing phrase pairs with token pairs  $\langle T_i^s, T_i^t \rangle$  ( $i = 1, 2, \dots$ )

next section as phrase pairs.<sup>4</sup>

## 4 NMT with a Large Phrase Vocabulary

In this work, the NMT model is trained on a bilingual corpus in which phrase pairs are replaced with tokens. The NMT system is then used as a decoder to translate the source sentences and replace the tokens with phrases translated using SMT.

### 4.1 NMT Training after Replacing Phrase Pairs with Tokens

Figure 2 illustrates the procedure for training the model with parallel patent sentence pairs in which phrase pairs are replaced with phrase token pairs  $\langle T_1^s, T_1^t \rangle$ ,  $\langle T_2^s, T_2^t \rangle$ , and so on.

In the step 1 of Figure 2, source-target phrase pairs that contain at least one out-of-vocabulary word are selected from the training set using the branching entropy approach described in Section 3.2. As shown in the step 2 of Figure 2, in each of the parallel patent sentence pairs, occurrences of phrase pairs  $\langle t_1^s, t_1^t \rangle$ ,  $\langle t_2^s, t_2^t \rangle$ ,  $\dots$ ,  $\langle t_k^s, t_k^t \rangle$  are then replaced with token pairs  $\langle T_1^s, T_1^t \rangle$ ,  $\langle T_2^s, T_2^t \rangle$ ,  $\dots$ ,  $\langle T_k^s, T_k^t \rangle$ . Phrase pairs  $\langle t_1^s, t_1^t \rangle$ ,  $\langle t_2^s, t_2^t \rangle$ ,  $\dots$ ,  $\langle t_k^s, t_k^t \rangle$  are numbered in the order of occurrence of the source phrases  $t_1^s$  ( $i = 1, 2, \dots, k$ ) in each source sentence  $S_s$ . Here note that in all the parallel sentence pairs  $\langle S_s, S_t \rangle$ , the tokens pairs  $\langle T_1^s, T_1^t \rangle$ ,  $\langle T_2^s, T_2^t \rangle$ ,  $\dots$  that are identical throughout all the parallel sentence pairs are used in this procedure. Therefore, for example, in all the source patent sentences  $S_s$ , the phrase  $t_1^s$  which appears earlier than other phrases in  $S_s$  is replaced with  $T_1^s$ . We then train the NMT model on a bilingual corpus, in which the phrase pairs are replaced by token pairs  $\langle T_i^s, T_i^t \rangle$  ( $i = 1, 2, \dots$ ), and obtain an NMT model in which the phrases are represented as tokens.<sup>5</sup>

<sup>4</sup>We sampled 200 Japanese-Chinese sentence pairs, manually annotated compounds and evaluated the approach of phrase extraction with the branching entropy. Based on the result, (a) 25% of them are correct, (b) 20% subsume correct compounds as their substrings, (c) 18% are substrings of correct compounds, (d) 22% subsume substrings of correct compounds but other than (b) nor (c), and (e) the remaining 15% are error strings such as functional compounds and fragmental strings consisting of numerical expressions.

<sup>5</sup>We treat the NMT system as a black box, and the strategy we present in this paper could be applied to any NMT system (Bahdanau et al., 2015; Cho et al., 2014; Kalchbrenner and Blunsom, 2013; Luong et al., 2015a; Sutskever et al.,

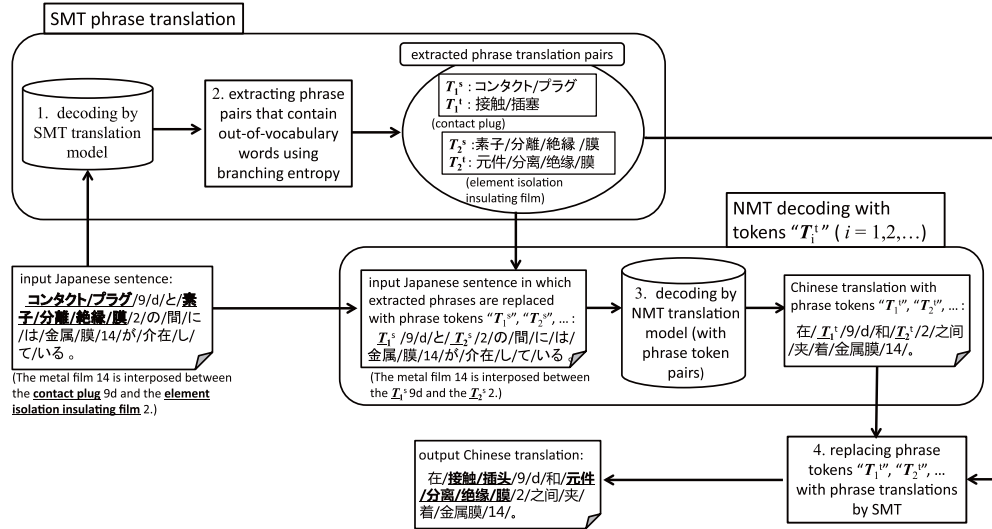


Figure 3: NMT decoding with tokens “ $T_i^s$ ” ( $i = 1, 2, \dots$ ) and the SMT phrase translation

## 4.2 NMT Decoding and SMT Phrase Translation

Figure 3 illustrates the procedure for producing target translations by decoding the input source sentence using the method proposed in this paper.

In the step 1 of Figure 3, when given an input source sentence, we first generate its translation by decoding of SMT translation model. Next, as shown in the step 2 of Figure 3, we automatically extract the phrase pairs by branching entropy according to the procedure of Section 3.2, where the input sentence and its SMT translation are considered as a pair of parallel sentence. Phrase pairs that contains at least one out-of-vocabulary word are extracted and are replaced with phrase token pairs  $\langle T_i^s, T_i^t \rangle$  ( $i = 1, 2, \dots$ ). Consequently, we have an input sentence in which the tokens “ $T_i^s$ ” ( $i = 1, 2, \dots$ ) represent the positions of the phrases and a list of SMT phrase translations of extracted Japanese phrases. Next, as shown in the step 3 of Figure 3, the source Japanese sentence with tokens is translated using the NMT model trained according to the procedure described in Section 4.1. Finally, in the step 4, we replace the tokens “ $T_i^t$ ” ( $i = 1, 2, \dots$ ) of the target sentence translation with the phrase translations of the SMT.

## 5 Evaluation

### 5.1 Patent Documents

Japanese-Chinese parallel patent documents were collected from the Japanese patent documents published by the Japanese Patent Office (JPO) during 2004-2012 and the Chinese patent documents published by the State Intellectual Property Office of the People’s Republic of China (SIPO) during 2005-2010. From the collected documents, we extracted 312,492 patent families, and the method of Utiyama and Isahara (2007) was applied<sup>6</sup> to the text of the extracted patent families to align the Japanese and Chinese sentences. The Japanese sentences were segmented into a sequence of morphemes using the Japanese morphological analyzer MeCab<sup>7</sup> with

2014).

<sup>6</sup>Herein, we used a Japanese-Chinese translation lexicon comprising around 170,000 Chinese entries.

<sup>7</sup><http://mecab.sourceforge.net/>

Table 1: Statistics of datasets

	training set	validation set	test set
Japanese-Chinese	2,877,178	1,000	1,000
Japanese-English	1,167,198	1,000	1,000

Table 2: Automatic evaluation results (BLEU)

System	ja → ch	ch → ja	ja → en	en → ja
Baseline SMT (Koehn et al., 2007)	52.5	57.1	32.3	32.1
Baseline NMT	56.5	62.5	39.9	41.5
NMT with PosUnk model (Luong et al., 2015b)	56.9	62.9	40.1	41.9
NMT with phrase translation by SMT (phrase pairs selected with branching entropy)	<b>57.7</b>	<b>64.2</b>	<b>40.3</b>	<b>42.9</b>

the morpheme lexicon IPAdic,<sup>8</sup> and the Chinese sentences were segmented into a sequence of words using the Chinese morphological analyzer Stanford Word Segment (Tseng et al., 2005) trained using the Chinese Penn Treebank. In this study, Japanese-Chinese parallel patent sentence pairs were ordered in descending order of sentence-alignment score and we used the topmost 2.8M pairs, whose Japanese sentences contain fewer than 40 morphemes and Chinese sentences contain fewer than 40 words.<sup>9</sup>

Japanese-English patent documents are provided in the NTCIR-7 workshop (Fujii et al., 2008), which are collected from the 10 years of unexamined Japanese patent applications published by the Japanese Patent Office (JPO) and the 10 years patent grant data published by the U.S. Patent & Trademark Office (USPTO) in 1993-2000. The numbers of documents are approximately 3,500,000 for Japanese and 1,300,000 for English. From these document sets, patent families are automatically extracted and the fields of “Background of the Invention” and “Detailed Description of the Preferred Embodiments” are selected. Then, the method of Utiyama and Isahara (2007) is applied to the text of those fields, and Japanese and English sentences are aligned. The Japanese sentences were segmented into a sequence of morphemes using the Japanese morphological analyzer MeCab with the morpheme lexicon IPAdic. Similar to the case of Japanese-Chinese patent documents, in this study, out of the provided 1.8M Japanese-English parallel sentences, 1.1M parallel sentences whose Japanese sentences contain fewer than 40 morphemes and English sentences contain fewer than 40 words are used.

## 5.2 Training and Test Sets

We evaluated the effectiveness of the proposed NMT model at translating parallel patent sentences described in Section 5.1. Among the selected parallel sentence pairs, we randomly extracted 1,000 sentence pairs for the test set and 1,000 sentence pairs for the validation set; the remaining sentence pairs were used for the training set. Table 1 shows statistics of the datasets.

According to the procedure of Section 3.2, from the Japanese-Chinese sentence pairs of the training set, we collected 426,551 occurrences of Japanese-Chinese phrase pairs, which

<sup>8</sup><http://sourceforge.jp/projects/ipadic/>

<sup>9</sup>It is expected that the proposed NMT model can improve the baseline NMT without the proposed technique when translating longer sentences that contain more than 40 morphemes / words. It is because the approach of replacing phrases with tokens also shortens the input sentences, expected to contribute to solving the weakness of NMT model when translating long sentences.

Table 3: Human evaluation results of pairwise evaluation (the score ranges from  $-100$  to  $100$ )

System	ja $\rightarrow$ ch	ch $\rightarrow$ ja	ja $\rightarrow$ en	en $\rightarrow$ ja
Baseline NMT	-	-	-	-
NMT with PosUnk model (Luong et al., 2015b)	9	10.5	8	6.5
NMT with phrase translation by SMT (phrase pairs selected with branching entropy)	<b>14.5</b>	<b>17</b>	<b>11.5</b>	<b>15.5</b>

are 254,794 types of phrase pairs with 171,757 unique types of Japanese phrases and 129,071 unique types of Chinese phrases. Within the total 1,000 Japanese patent sentences in the Japanese-Chinese test set, 121 occurrences of Japanese phrases were extracted, which correspond to 120 types. With the total 1,000 Chinese patent sentences in the Japanese-Chinese test set, 130 occurrences of Chinese phrases were extracted, which correspond to 130 types.

From the Japanese-English sentence pairs of the training set, we collected 70,943 occurrences of Japanese-English phrase pairs, which are 61,017 types of phrase pairs with unique 57,675 types of Japanese phrases and 58,549 unique types of English phrases. Within the total 1,000 Japanese patent sentences in the Japanese-English test set, 59 occurrences of Japanese phrases were extracted, which correspond to 59 types. With the total 1,000 English patent sentences in the Japanese-English test set, 61 occurrences of English phrases were extracted, which correspond to 61 types.

### 5.3 Training Details

For the training of the SMT model, including the word alignment and the phrase translation table, we used Moses (Koehn et al., 2007), a toolkit for phrase-based SMT models. We trained the SMT model on the training set and tuned it with the validation set.

For the training of the NMT model, our training procedure and hyperparameter choices were similar to those of Bahdanau et al. (2015). The encoder consists of forward and backward deep LSTM neural networks each consisting of three layers, with 512 cells in each layer. The decoder is a three-layer deep LSTM with 512 cells in each layer. Both the source vocabulary and the target vocabulary are limited to the 40K most-frequently used morphemes / words in the training set. The size of the word embedding was set to 512. We ensured that all sentences in a minibatch were roughly the same length. Further training details are given below: (1) We set the size of a minibatch to 128. (2) All of the LSTM’s parameter were initialized with a uniform distribution ranging between  $-0.06$  and  $0.06$ . (3) We used the stochastic gradient descent, beginning at a fixed learning rate of 1. We trained our model for a total of 10 epochs, and we began to halve the learning rate every epoch after the first seven epochs. (4) Similar to Sutskever et al. (2014), we rescaled the normalized gradient to ensure that its norm does not exceed 5. We trained the NMT model on the training set. The training time was around two days when using the described parameters on a 1-GPU machine.

We compute the branching entropy using the frequency statistics from the training set.

### 5.4 Evaluation Results

In this work, we calculated automatic evaluation scores for the translation results using a popular metrics called BLEU (Papineni et al., 2002). As shown in Table 2, we report the evaluation scores, using the translations by Moses (Koehn et al., 2007) as the baseline SMT and the scores using the translations produced by the baseline NMT system without our proposed approach as the baseline NMT. As shown in Table 2, the BLEU score obtained by the proposed NMT



Table 4: Human evaluation results of JPO adequacy evaluation (the score ranges from 1 to 5)

System	ja → ch	ch → ja	ja → en	en → ja
Baseline SMT (Koehn et al., 2007)	3.5	3.7	3.1	3.2
Baseline NMT	4.2	4.3	3.9	4.1
NMT with PosUnk model (Luong et al., 2015b)	4.3	4.3	4.0	4.2
NMT with phrase translation by SMT (phrase pairs selected with branching entropy)	<b>4.5</b>	<b>4.6</b>	<b>4.1</b>	<b>4.4</b>

Table 5: Numbers of untranslated morphemes / words of input sentences (for the test set)

System	ja → ch	ch → ja	ja → en	en → ja
Baseline NMT	89	92	415	226
NMT with phrase translation by SMT (phrase pairs selected with branching entropy)	43	45	246	134

model is clearly higher than those of the baselines. Here, as described in Section 3, the lower bounds of branching entropy for phrase pair selection are tuned as 5 throughout the evaluation of language pair of Japanese-Chinese, and tuned as 8 throughout the evaluation of language pair of Japanese-English, respectively. When compared with the baseline SMT, the performance gains of the proposed system are approximately 5.2 BLEU points when translating Japanese into Chinese and 7.1 BLEU when translating Chinese into Japanese. When compared with the baseline SMT, the performance gains of the proposed system are approximately 10.0 BLEU points when translating Japanese into English and 10.8 BLEU when translating English into Japanese. When compared with the result of the baseline NMT, the proposed NMT model achieved performance gains of 1.2 BLEU points on the task of translating Japanese into Chinese and 1.7 BLEU points on the task of translating Chinese into Japanese. When compared with the result of the baseline NMT, the proposed NMT model achieved performance gains of 0.4 BLEU points on the task of translating Japanese into English and 1.4 BLEU points on the task of translating English into Japanese.

Furthermore, we quantitatively compared our study with the work of Luong et al. (2015b). Table 2 compares the NMT model with the PosUnk model, which is the best model proposed by Luong et al. (2015b). The proposed NMT model achieves performance gains of 0.8 BLEU points when translating Japanese into Chinese, and performance gains of 1.3 BLEU points when translating Chinese into Japanese. The proposed NMT model achieves performance gains of 0.2 BLEU points when translating Japanese into English, and performance gains of 1.0 BLEU points when translating English into Japanese.

We also compared our study with the work of Long et al. (2016). As reported in Long et al. (2017), when translating Japanese into Chinese, the BLEU of the NMT system of Long et al. (2016) in which all the selected compound nouns are replaced with tokens is 58.6, the BLEU of the NMT system in which only compound nouns that contain out-of-vocabulary words are selected and replaced with tokens is 57.4, while the BLEU of the proposed NMT system of this paper is 57.7. Out of all the selected compound nouns of Long et al. (2016), around 22% contain out-of-vocabulary words, of which around 36% share substrings with the phrases selected by branching entropy. The remaining 78% compound nouns do not contain out-of-vocabulary words and are considered to contribute to the improvement of BLEU points compared with the proposed method. Based on this analysis, as one of our important future work, we revise the

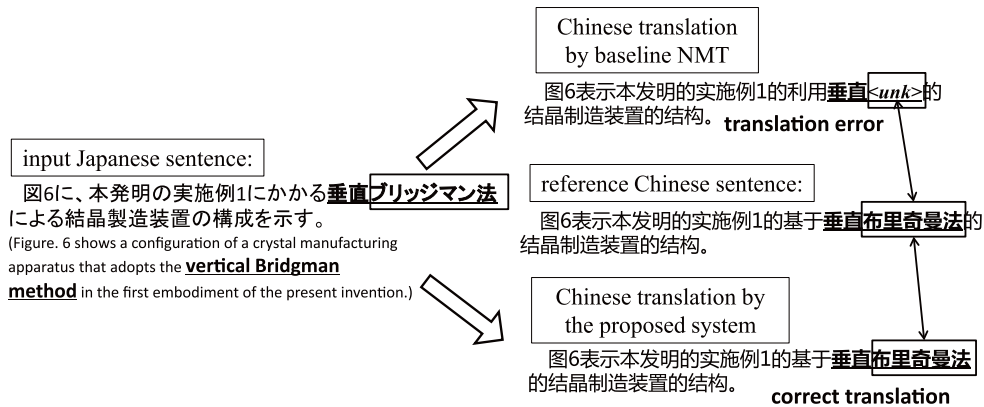


Figure 4: An example of correct translations produced by the proposed NMT model when addressing the problem of out-of-vocabulary words (Japanese-to-Chinese)

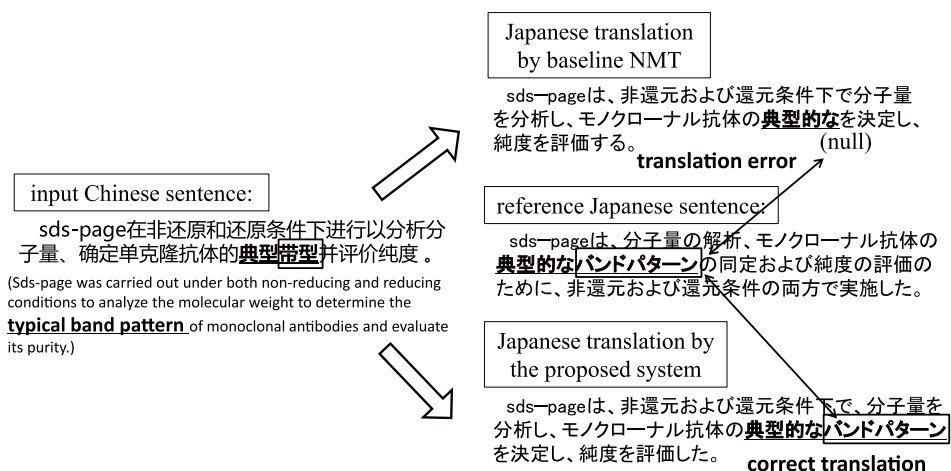


Figure 5: An example of correct translations produced by the proposed NMT model when addressing the problem of under-translation (Chinese-to-Japanese)

procedure in Section 3.2 of selecting phrases by branching entropy and then incorporate those in-vocabulary compound nouns into the set of the phrases selected by the branching entropy.

In this study, we also conducted two types of human evaluations according to the work of Nakazawa et al. (2015): pairwise evaluation and JPO adequacy evaluation. In the pairwise evaluation, we compared each translation produced by the baseline NMT with that produced by the proposed NMT model as well as the NMT model with PosUnk model, and judged which translation is better or whether they have comparable quality. The score of the pairwise evaluation is defined as below:

$$score = 100 \times \frac{W - L}{W + L + T}$$

where W, L, and T are the numbers of translations that are better than, worse than, and comparable to the baseline NMT, respectively. The score of pairwise evaluation ranges from -100 to 100. In the JPO adequacy evaluation, Chinese translations are evaluated according to the quality evaluation criterion for translated patent documents proposed by the Japanese Patent

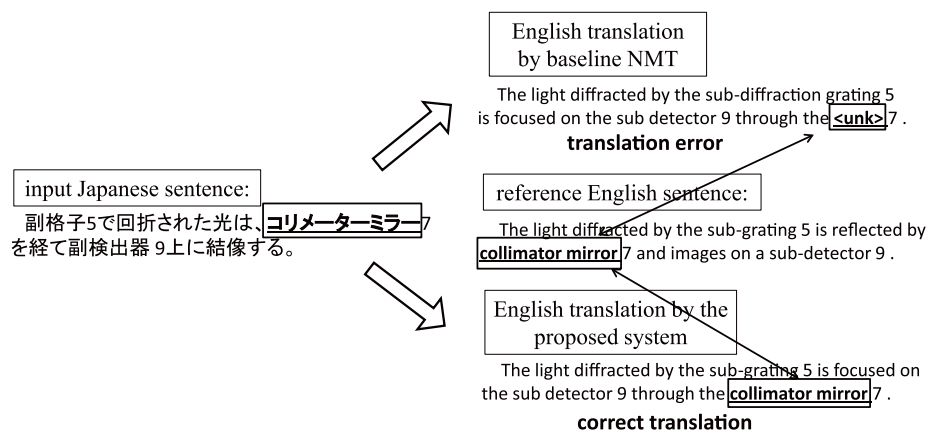


Figure 6: An example of correct translations produced by the proposed NMT model when addressing the problem of out-of-vocabulary words (Japanese-to-English)

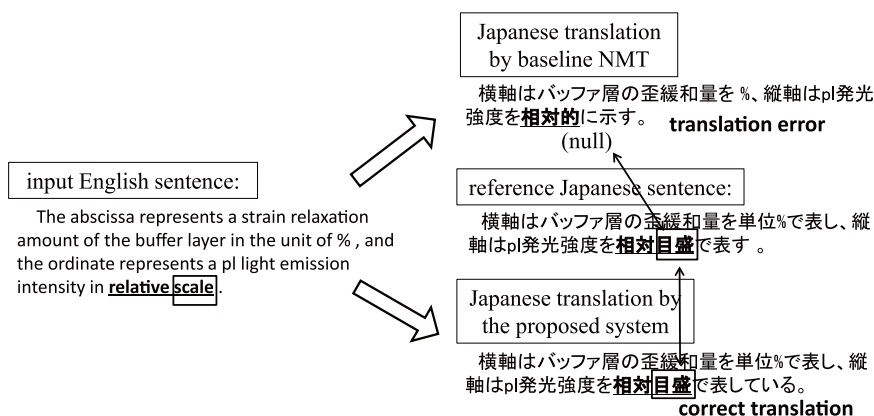


Figure 7: An example of correct translations produced by the proposed NMT model when addressing the problem of under-translation (English-to-Japanese)

Office (JPO).<sup>10</sup> The JPO adequacy criterion judges whether or not the technical factors and their relationships included in Japanese patent sentences are correctly translated into Chinese. The Chinese translations are then scored according to the percentage of correctly translated information, where a score of 5 means all of those information are translated correctly, while a score of 1 means that most of those information are not translated correctly. The score of the JPO adequacy evaluation is defined as the average over all the test sentences. In contrast to the study conducted by Nakazawa et al. (2015), we randomly selected 200 sentence pairs from the test set for human evaluation, and both human evaluations were conducted using only one judgement. Table 3 and Table 4 shows the results of the human evaluation for the baseline SMT, baseline NMT, NMT model with PosUnk model, and the proposed NMT model. We observe that the proposed model achieves the best performance for both the pairwise and JPO adequacy evaluations when we replace the tokens with SMT phrase translations after decoding the source sentence with the tokens.

<sup>10</sup>[https://www.jpo.go.jp/shiryoutoushin/chousa/pdf/tokkyohonyaku\\_hyouka/01.pdf](https://www.jpo.go.jp/shiryoutoushin/chousa/pdf/tokkyohonyaku_hyouka/01.pdf) (in Japanese)

For the test set, we also counted the numbers of the untranslated words of input sentences. As shown in Table 5, the number of untranslated words by the baseline NMT reduced to around 50% in the cases of ja → ch and ch → ja by the proposed NMT model, and reduced to around 60% in the cases of ja → en and en → ja.<sup>11 12</sup> This is mainly because part of untranslated source words are out-of-vocabulary, and thus are untranslated by the baseline NMT. The proposed system extracts those out-of-vocabulary words as a part of phrases and replaces those phrases with tokens before the decoding of NMT. Those phrases are then translated by SMT and inserted in the output translation, which ensures that those out-of-vocabulary words are translated.

Figure 4 compares an example of correct translation produced by the proposed system with one produced by the baseline NMT. In this example, the translation is a translation error because the Japanese word “ブリッジマン (Bridgman)” is an out-of-vocabulary word and is erroneously translated into the “*<unk>*” token. The proposed NMT model correctly translated the Japanese sentence into Chinese, where the out-of-vocabulary word “ブリッジマン” is correctly selected by the approach of branching entropy as a part of the Japanese phrase “垂直ブリッジマン法 (vertical Bridgman method)”. The selected Japanese phrase is then translated by the phrase translation table of SMT. Figure 5 shows another example of correct translation produced by the proposed system with one produced by the baseline NMT. As shown in Figure 5, the translation produced by baseline NMT is a translation error because the out-of-vocabulary Chinese word “帯型 (band pattern)” is an untranslated word and its translation is not contained in the output translation of the baseline NMT. The proposed NMT model correctly translated the Chinese word into Japanese because the Chinese word “帯型 (band pattern)” is selected as a part of Chinese phrase “典型帯型 (typical band pattern)” with branching entropy and then is translated by SMT. Moreover, Figure 6 and Figure 7 compare examples of correct translations produced by the proposed system with those produced by the baseline NMT when translating patent sentences in both directions of Japanese-to-English and English-to-Japanese.

## 6 Conclusion

This paper proposed selecting phrases that contain out-of-vocabulary words using the branching entropy. These selected phrases are then replaced with tokens and post-translated using an SMT phrase translation. Compared with the method of Long et al. (2016), the contribution of the proposed NMT model is that it can be used on any language pair without language-specific knowledge for technical terms selection. We observed that the proposed NMT model performed much better than the baseline NMT system in all of the language pairs: Japanese-to-Chinese/Chinese-to-Japanese and Japanese-to-English/English-to-Japanese. One of our important future tasks is to compare the translation performance of the proposed NMT model with that based on sub-word units (e.g. Sennrich et al. (2016)). Another future task is to improve the performance of the present study by incorporating the in-vocabulary non-compositional phrases, whose translations cannot be obtained by translating their constituent words. It is expected to achieve a better translation performance by translating those kinds of phrases using a phrase-based SMT instead of using NMT.

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<sup>11</sup>Although we omit the detail of the evaluation results of untranslated words of the NMT model with PosUnk model (Luong et al., 2015b) in Table 5, the number of the untranslated words of the NMT model with PosUnk model is almost the same as that of the baseline NMT, which is much more than that of the proposed NMT model.

<sup>12</sup>Following the result of an additional evaluation where having approximately similar size of the training parallel sentences between the language pairs of Japanese-to-Chinese/Chinese-to-Japanese and Japanese-to-English/English-to-Japanese, we concluded that the primary reason why the numbers of untranslated morphemes / words tend to be much larger in the case of the language pair of Japanese-to-English/English-to-Japanese than in the case of the language pair of Japanese-to-Chinese/Chinese-to-Japanese is simply the matter of a language specific issue.

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