Improving Japanese-to-English Neural Machine Translation by Paraphrasing the Target Language

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Abstract

Neural machine translation (NMT) produces sentences that are more fluent than those produced by statistical machine translation (SMT). However, NMT has a very high computational cost because of the high dimensionality of the output layer. Generally, NMT restricts the size of the vocabulary, which results in infrequent words being treated as out-of-vocabulary (OOV) and degrades the performance of the translation. In order to improve the translation quality regarding words that are OOV in the target language, we propose a preprocessing method that paraphrases infrequent words or phrases expressed as OOV with frequent synonyms from the target side of the training corpus. In an evaluation using Japanese to English translation, we achieved a statistically significant BLEU score improvement of 0.55–0.77 over baselines that included the state-of-the-art method.

1 Introduction

Recently, neural-network-based methods have gained considerable popularity in many natural language processing tasks. In the field of machine translation, neural machine translation (NMT) is actively being researched because of the advantage that it can output sentences that are more fluent compared with statistical machine translation (SMT). However, NMT has a problem of high computational cost because it addresses the output generation task by solving a classification problem in vocabulary dimension. Typically, NMT has to restrict the size of the vocabulary to reduce the computational cost. Therefore, the target language vocabulary includes only high-frequency words (e.g., 30,000 high-frequency words) in training; other words are treated as out-of-vocabulary (OOV) and substituted with a special symbol such as “<unk>” in the output. The symbol has no meaning, so the output has reduced quality.

As a previous work attempting to reduce the OOV rate in NMT, Li et al. (2016), replaced OOV words with a translation table using word similarity in the training and test data. In particular, they replaced each OOV word with an in-vocabulary word using word similarity in a parallel training corpus; they reduced the OOV rate in the output and improved the translation quality. However, they sometimes substituted OOV words with a similar word such as a proper noun. In addition, they deleted OOV words that aligned to null, which can result in a loss of sentence content and reduced translation adequacy.

In this work, we present a preprocessing method for improving translation related to OOV words. We paraphrase low-frequency words treated as OOV in the target corpus with high-frequency words while retaining the meaning.

Our main contributions are as follows.

- We propose a paraphrasing-based preprocessing method for Japanese-to-English NMT to improve translation accuracy with regard to OOV words. Our method can be combined with any NMT system.

- We show that our method achieved a statistically significant BLEU (Kishore et al., 2002) score improvement of 0.58 and a METEOR (Lavie and Agarwal, 2007) score improvement of 0.52 over the previous method (Li et al., 2016) and reduced the OOV rate in output sentences by approximately 0.20.
2 Related Work

There have been studies on improving translation accuracy by reducing the OOV rate using pre- and post-processing for machine translation. Luong et al. (2015) proposed a post-processing method that translates OOV words with a corresponding word in the source sentence using a translation dictionary. This method needs to align training sentence pairs before training to learn correspondences between OOV words and their translations. In the method described in this paper, we need no word alignment, and we retain the meaning of the original word by paraphrasing the target side of the training corpus. Jean et al. (2015) proposed another post-processing method that translates each OOV word with the word that has the largest attention weight in the source sentence using a translation dictionary. Their method does not need word alignment, but it still does not necessarily consider the meaning in the target language, unlike our paraphrasing approach. Sennrich et al. (2016) applied byte pair encoding (BPE) to source and target corpora to split OOV words into units of frequent substrings to reduce the OOV rate. Their method splits words greedily without considering their meaning. Since we use lexical paraphrasing in the training data, we hope to reduce the OOV rate in the translation output while retaining the meaning. Additionally, since ours is a preprocessing method, it can be combined with a post-processing method.

On the other hand, there are methods similar to ours that paraphrase corpora as a preprocessing step of machine translation to reduce the complexity of source and/or target sentences. Sanja and Maja (2016) paraphrased source sentence vocabulary with a simple grammar as a preprocessing step for machine translation. They attempt to improve translation quality by reducing the OOV rate in the target language using paraphrasing without simplifying the source input sentences. Li et al. (2016) substituted OOV words in training corpora with a similar in-vocabulary word as pre- and post-processing steps. They replaced OOV words with frequent words using cosine similarity and a language model. They obtained word alignment between an OOV word and its counterpart in training corpora. In addition, they deleted OOV words from the training corpus if they aligned to null. However, this leads to a loss of sentence meaning and degrades the adequacy of the translation. They also might replace OOV words with similar but non-synonymous words since they used distributional similarity. For instance, they replaced “surfing” with “snowboard”, which leads to rewriting “internet surfing” as “internet snowboard”, resulting in a change of meaning. We use a paraphrase score calculated from bilingual pivoting instead of distributional similarity; therefore, we are not likely to paraphrase OOV words with inappropriate expressions. In the aforementioned example, we paraphrase “surfing” as “browser”, which preserves the original meaning to some extent.

3 Proposed Method

In this paper, we propose a preprocessing method that paraphrases infrequent words or phrases with frequent ones on the target side of the training sentences in order to train a better NMT model by reducing the number of OOV words while keeping their original meaning. We paraphrase infrequent words using a paraphrase dictionary that has paraphrase pairs annotated with a paraphrase score. We employ three scores: (1) paraphrase score, (2) language model (LM) score, and (3) a combination of these scores. The paraphrase score is meant to reflect translation adequacy, and the language model score is sensitive to fluency. We combined the paraphrase score and the language model score by linear interpolation\(^1\) as follows:

\[
\text{paraphrase\_score} = \lambda (\text{PPDBscore}) + (1 - \lambda) (\text{LMscore})
\]

Figure 1 shows an example of paraphrasing with a paraphrase lattice and the Viterbi algorithm. Suppose “defending” is OOV. We can paraphrase the OOV word “defending” with a frequent word, original: the pedagogues had quarrels.

paraphrase, first round: the educators had discussions.

paraphrase, second round: the teachers had discussions.

\(^1\)In a preliminary experiment, normalization of these scores was not found to yield any improvements.
Table 1: Japanese-to-English translation result of each method. † and ∗ indicate that the proposed method significantly outperformed the other methods at p<0.01 and p<0.05, respectively, using bootstrap resampling.

| method                  | BLEU | METEOR | OOV |
|-------------------------|------|--------|-----|
| baseline                | 25.70†| 31.06  | 1,123|
| Luong et al.            | 25.87†| 31.04  | 567 |
| Sennrich et al.         | 25.92∗| 31.50  | 0   |
| Li et al.               | 25.89∗| 31.10  | 832 |
| proposed (multi. word + phrase) | 26.47 | 31.62  | 668 |

“guaranteeing”, or we can paraphrase the OOV phrase “defending the rights” with another phrase, “the protection of the rights”, which has no OOV words. In addition to calculating the paraphrase score, our paraphrase algorithm calculates the 2-gram language model score in “assert guaranteeing the rights”, “assert the”, and “rights.” and chooses the highest scoring paraphrase, thus generating “they assert the protection of the rights.”. We do not calculate the 2-gram language model score in phrases.

In addition, our method can paraphrase OOV words iteratively until a paraphrase with frequent words is reached. In the lower example in Figure 1, suppose that “pedagogues” and “quarrels” are OOV. The latter word in the original sentence is paraphrased with a frequent word, “discussions”, whereas the former is paraphrased with an infrequent word, “educators”, in the first round. We can then paraphrase the infrequent word “educators” again, this time with a frequent word, “teachers”, in the second round. If we allow only the first round of paraphrasing, the infrequent word “pedagogues” will not be paraphrased with the frequent word “teachers” because the paraphrase dictionary does not have this entry, and the infrequent word “pedagogues” will not be paraphrased with the frequent word “educators”. In this paper, we express one-pass paraphrasing as “single”, and iterative paraphrasing as “multi.”. In addition, we use “word” when we paraphrase words, and “word + phrase” when paraphrasing words and phrases.

4 Experiment
4.1 Settings
In this study, we used the Japanese–English portion of the Asian Scientific Paper Excerpt Corpus (ASPEC) (Nakazawa et al., 2016). For training, we used one million sentence pairs ranked by alignment accuracy. We deleted sentence pairs longer than 41 words. The final training corpus contained 827,503 sentence pairs. We followed the official development/test split: 1,790 sentence pairs for development, and 1,812 sentence pairs for testing. We used the development dataset to select the best model and used the test dataset to evaluate BLEU scores.

We used the Moses script as an English tokenizer and MeCab3 (using IPAdic) as a Japanese tokenizer. We employed KenLM4 to build a 2-gram language model trained with all sentences from ASPEC. We utilized the XXXL-size PPDB 2.0 (Pavlick et al., 2015) as the English paraphrase dictionary and PPDB:Japanese (Mizukami et al., 2014) as the Japanese paraphrase dictionary. Neither of these dictionaries contains the ASPEC corpus. We paraphrased either the target side of the training corpus only or both the source and target sides of the training corpus to conduct a fair comparison. We experimented with \( \lambda = 0.0, 0.25, 0.50, 0.75, \text{ and } 1.0 \).

We used OpenNMT-py5 as the NMT system, which is a Python implementation of OpenNMT (Klein et al., 2017). We built a model with settings as described below. We used bi-recurrent-neural-network, batch size 64, epoch 20, embedding size 500, vocabulary size of source and target 30,000, dropout rate 0.3, optimizer SGD with learning rate 1.0, and number of RNN layers 2 with an RNN size of 500. Our baseline was trained with these settings without any paraphrasing. We re-implemented previous methods described in this paper (Luong et al., 2015; Li et al., 2016; Sennrich et al., 2016) using the underlying NMT with the abovementioned settings. We

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3https://github.com/taku910/mecab
4http://kheafield.com/code/kenlm/
5https://github.com/OpenNMT/OpenNMT-py
used BLEU (Kishore et al., 2002) and METEOR (Lavie and Agarwal, 2007) for extrinsic evaluation. We also analyzed the number of OOV words in the translated sentences as an intrinsic evaluation.

English PPDB 2.0 achieved higher quality than PPDB 1.0 by using a supervised regression model to estimate paraphrase scores. However, because there are no training data to build a supervised regression model for PPDBs other than in English, the quality of PPDBs in other languages may affect the quality of the proposed method. To investigate whether PPDB quality relates to translation quality, we performed English to Japanese translation by the proposed method using PPDB:Japanese (Mizukami et al., 2014).

Table 2 shows the BLEU score of the proposed method on English to Japanese translation. The best model improved the BLEU score by 0.18 over the baseline, and the number of OOV words in the output decreased slightly.

In the last experiment, we paraphrased the

| method                  | BLEU | OOV |
|-------------------------|------|-----|
| baseline                | 33.91| 1,003|
| single (word)           | 33.97| 915 |
| multi. (word)           | **34.09** | 966 |
| single (word + phrase)  | 33.65| 938 |
| multi. (word + phrase)  | 33.86| **902** |

Table 2: English-to-Japanese translation results with variations in the number of paraphrasings and the unit used.

4.2 Results

Table 1 shows the experimental results compared with those in previous work. The proposed method is multi. word + phrase paraphrasing. In the BLEU evaluation, our method significantly outperformed not only the baseline and Luong et al. (p<0.01) but also Sennrich et al. and Li et al. (p<0.05). We improved the BLEU score by 0.77 and the METEOR score by 0.56 as well as reducing the number of OOV words in the output by approximately 40% compared with the baseline.

Figure 2 reports the BLEU score of our method under variations in the linear interpolation coefficient and the number of paraphrasings. Figure 3 shows the number of OOV words in the output. The best BLEU score was achieved by multi-round paraphrasing and $\lambda = 0.50$, which means that the paraphrase score is balanced by the PPDB score and the LM score.

Figure 4: BLEU score in Japanese-to-English translation using source and target paraphrasing.
we can paraphrase domain-specific words and that these paraphrases can improve the translation. The paraphrases shown in the upper half of the table preserve meaning, whereas those in the lower half lose a little of the original meaning.

6 Conclusion

This paper has proposed a preprocessing method that paraphrases infrequent words with frequent words in a target corpus during training to train a better NMT model by reducing the OOV rate. An evaluation using the Japanese-to-English part of the ASPEC corpus showed a decrease in the OOV rate in the translation result and a significant improvement in the BLEU score over state-of-the-art methods. We expect that our method can be effective not only in NMT but also in other text generation tasks using neural networks, such as abstractive summarization, which solves the classification problem of vocabulary dimension.

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