Extending the Subwording Model of Multilingual Pretrained Models for New Languages

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Abstract

Multilingual pretrained models are effective for machine translation and cross-lingual processing because they contain multiple languages in one model. However, they are pretrained after their tokenizers are fixed; therefore it is difficult to change the vocabulary after pretraining. When we extend the pretrained models to new languages, we must modify the tokenizers simultaneously.

In this paper, we add new subwords to the SentencePiece tokenizer to apply a multilingual pretrained model to new languages (Inuktitut in this paper). In our experiments, we segmented Inuktitut sentences into subwords without changing the segmentation of already pretrained languages, and applied the mBART-50 pretrained model to English-Inuktitut translation.

1 Introduction

Various pretrained models have been released in recent years. Among them, multilingual pretrained models, for example, multilingual BERT (mBERT) (Devlin et al., 2019), XLM-RoBERTa (Conneau et al., 2020), mBART (Liu et al., 2020; Lewis et al., 2020), and mT5 (Xue et al., 2021), are effective for cross-lingual processing and machine translation because they contain multiple languages in one model. However, the vocabulary sets of multilingual pretrained models are fixed before pretraining, and it is difficult to change the vocabulary after pretraining. This restriction becomes a problem when we enhance the multilingual pretrained models for new languages.

The vocabulary set can be added to the pretrained models by extending word embedding tables (Wang et al., 2020). However, these models are pretrained after the tokenizers (and their models) are fixed. When we change the vocabulary set in the pretrained models, we must simultaneously modify the tokenizers.

If a new language uses known letters, an existing multilingual tokenizer can segment input sentences into known subwords, which are included in the vocabulary of the multilingual pretrained models. Therefore, tokenization is not a crucial problem in this case (even though it is not optimal). For instance, mBART-50 (Tang et al., 2020), which is a multilingual encoder-decoder pretrained model, supports 52 languages and uses SentencePiece (Kudo and Richardson, 2018; Kudo, 2018)\(^1\) as the tokenizer. The model of SentencePiece for mBART-50 was learned using a corpus that consisted of 100 languages, which included all languages of the pretrained model. When we add a new language to mBART-50, we can divert the tokenizing model without modification if the letters of the language are already included in the tokenizer.

If the letters of new languages are not supported by the tokenizer, one solution is to transliterate unseen letters into Latin letters (Muller et al., 2021). This approach is appropriate for encoder models such as mBERT. However, it is not suitable for decoders because we should generate the unique letters of the languages.

Another solution is to separate the tokenizer of the new language from the others. However, we want to enhance the tokenizer model while maintaining the vocabulary set of the original languages because sentences in the new language often contain words in the original languages (e.g., numbers, named entities, and code switching).

In this paper, we focus on the tokenizers of multilingual pretrained models. Specifically, we add new subwords to the SentencePiece tokenizer to apply an mBART-50 model to new languages. The task in this paper is English-Inuktitut translation, which was a shared task at the WMT-20 conference (Barrault et al., 2020). Because the Inuktitut language is not supported in either the mBART-

\(^1\)https://github.com/google/sentencepiece
the 50 model or its SentencePiece tokenizer, we add Inuktitut subwords to the models. To add new subwords to the SentencePiece model, we must not only add new entries but also estimate their costs. In this paper, we estimate the costs of new subwords and tokenize Inuktitut text into subwords without changing the original languages.

The remainder of this paper is organized as follows: In Section 2, we explain related work, which includes studies on the adaptation of multilingual pretrained models to new languages (Section 2.1) and an overview of the SentencePiece tokenizer (Section 2.2). In Section 3, we describe our proposal, that is, the addition of subwords to the SentencePiece model. In Section 4, we evaluate the tokenization and translation results of English-Inuktitut translation, and we conclude the paper in Section 5.

2 Related Work

2.1 Adaptation of Multilingual Pretrained Models to New Languages

In this section, we mainly discuss the tokenizers required to add new languages to multilingual pretrained models.

Ebrahimi and Kann (2021) enhanced the multilingual pretrained model XLM-R to 1,600 languages. They trained a new SentencePiece model from scratch using the multilingual corpora of all languages (i.e., original and new languages) and did not use the tokenizing model of XLM-R. Therefore, the training corpora of the original languages are necessary.

Muller et al. (2021) added new languages to the mBERT models. If the new language consisted of unseen letters, they transliterated them to Latin characters and applied the WordPiece tokenizer (Schuster and Nakajima, 2012). Therefore, the original corpora of the original languages are necessary.

Wang et al. (2020) added new languages to mBERT models by extending their word embedding tables. Although the authors did not describe the details of the tokenizers, we assume that unknown letters were segmented into letters because mBERT uses the WordPiece tokenizer.

Artetxe et al. (2020) trained a tokenizer independently for new languages. However, the vocabulary of the new tokenizer was mismatched with the subwords of the original languages because new languages often contain words in the original languages (e.g., numbers, named entities, and code switching). Similarly, Pfeiffer et al. (2020) enhanced mBERT and XLM-R using tokenizers trained separately for each language.

Our objective is to provide subword tokenization to a new language while maintaining the tokenization of the original languages, and apply multilingual pretrained models to the new language. By maintaining the tokenization of the original languages, we leverage the effects of the pretrained models.

2.2 SentencePiece Tokenizer

SentencePiece is a tokenizer that directly tokenizes input text into subwords (called lossless encoding). It is used as the tokenizer for multilingual pretrained models because it can process languages in which word boundaries are explicitly indicated by a space character (e.g., English) and those without a word boundary (e.g., Chinese and Japanese) in the same manner.

Although SentencePiece supports byte-pair encoding (Sennrich et al., 2016), we discuss the unigram model, which is the default model of SentencePiece that is used for mBART-50.

2.2.1 Subword Tokenization of SentencePiece

To achieve lossless encoding, SentencePiece converts input text into text without space characters by substituting the spaces for a special letter (Unicode letter U+2581 by default). Then it tokenizes converted text into subwords as follows (Figure 1) (Manning and Schütze, 1999). Note that this is identical to the morphological analysis method for unsegmented languages (e.g., MeCab (Kudo et al., 2004)).

1. The input text is matched with the unigram model (corresponding to a morphological analysis dictionary) of the tokenizer, and all subword candidates obtained from the model are structured into a lattice.

2. The Viterbi search is applied to the lattice to search for the best path (i.e., the path of highest likelihood). A subword sequence is output on the Viterbi path.

2.2.2 Learning the Unigram Model

The unsupervised learning algorithm of hidden Markov models (Manning and Schütze, 1999) is
applied to the learning of the unigram model. The procedure is as follows. The algorithm simply eliminates subwords in the initial model, where the vocabulary of the final model becomes a subset of that of the initial model.

1. Build the initial model from the training corpora.
   (a) Obtain subword candidates by acquiring substrings in the corpora using a suffix array.
   (b) Supply each subword candidate with a likelihood computed from the relative frequency in the corpora.

2. Iterate the following procedure until the vocabulary size of the model becomes predefined.
   (a) Update the likelihood of the subwords (twice) using the EM algorithm.
      i. E Step:
         Analyze sentences in the corpora using the current model, and compute the likelihood of each subword in the sentence by applying the forward-backward algorithm.
      ii. M Step:
         Collect the likelihoods of all subwords in the corpora and update the model.
   (b) Eliminate the low-likelihood subwords from the model (e.g., 20 percent of all subwords).

To balance speed and quality, the step 2.(a) is performed only twice because we do not need fully accurate likelihoods in early iterations (it is enough to specify subword candidates for elimination). By iterating the step 2., we can obtain accurate likelihoods close to convergence.

3 Adding Subwords to the Unigram Model

If the new language uses known letters, an original multilingual tokenizer can segment input sentences into known subwords, which are included in the vocabulary of the multilingual pretrained models. Therefore, tokenization is not a crucial problem in this case even though it is not optimal.

By contrast, when the new language uses unknown letters, we cannot determine the vocabulary of the pretrained model because the string of an entire sentence becomes unknown words in lossless encoding. A way to solve this problem is to segment the string into letters and recognize them as tokens. However, this method is disadvantageous to downstream tasks such as machine translation because token sequences become very long. Our method segments sentences in the new language into subwords while restricting both the lengths of token sequences and vocabulary size.

In this paper, we add only subwords that include unknown letters to the tokenizer to segment the new language into subwords without changing the results of existing corpora.

Algorithm 1 shows the learning algorithm of the additional subword model. This algorithm learns the additional model \( M \) that includes subwords that do not exist in the original model \( M_{\text{org}} \).

- The GENERATEINITMODEL function (Lines 8 to 15) generates the initial model. The initial model includes substrings that appear in corpus \( C \) as subword candidates.
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- Lines 2 to 6 are the main loop. We update the likelihoods in model \( M \) twice using the EM algorithm (the UPDATELIKELIHOOD function). When analyzing the training corpora (Lines 16 to 18), we use a mixture of the original model
and additional model, but only update the additional model (Line 19). Then, we eliminate 20 percent of the low-likelihood subwords in one loop.

4 Inuktitut Translation Experiments

In this paper, we evaluate our method for translation between English (En) and Inuktitut (Iu), which was the shared task at the WMT-20 conference (Barrault et al., 2020). Table 1 shows an example of En-Iu translation. Inuktitut is written using the letters of the “Unified Canadian Aboriginal Syllabics (U+1400 - U+167F)” of the Unicode Standard.

Although the SentencePiece model of mBART-50 was trained on a corpus that consisted of 100 languages and included 250K subwords, it does not contain Unified Canadian Aboriginal Syllabics. Therefore, if we analyzed Inuktitut sentences using this model, subword segmentation would fail, and most tokens would become out-of-vocabulary (OOV).2

In the shared task at WMT-20, the training corpora were provided by the organizers. All participants trained their tokenizer from scratch, and no teams used published multilingual pretrained models (Zhang et al., 2020; Chen et al., 2020; Kocmi, 2020; Roest et al., 2020; Knowles et al., 2020; Bawden et al., 2020).

4.1 Experimental Settings

Corpora The size of the parallel corpus used in the shared task at WMT-20 is shown in Table 2.

Table 2: English-Inuktitut parallel corpus size.

| Set         | #Sentences |
|-------------|------------|
| Training    | 1,308,277  |
| Development | 5,173      |
| Test        | 2,971      |

Tokenizer Setting We learned {2K, 4K, 8K} additional subwords from the Inuktitut side of the parallel corpus.

We converted the unigram model provided from mBART-50 into a text model using the spm_export_vocab command of SentencePiece. We implemented the extension described in Sections 2.2.1, 2.2.2, and 3 using Python. Note that we normalized the input sentences (including space conversion) using the spm_normalize command.

Baselines In our experiments, we set three baselines for tokenization.

- mBART-50 Tokenization Model: We used the SentencePiece model provided from mBART-50 with no change.
- Inuktitut Letters: After segmentation using the mBART-50 tokenization model, we further divided the Inuktitut subwords into letters.
- Shared Vocabulary 32K Model: From the English-Inuktitut parallel corpus, we learned a shared model using SentencePiece. The vocabulary size was 32K.3

3When we tokenize the Inuktitut language using the original tokenizer, sentences are segmented by spaces because SentencePiece bundles continuous unknown letters as a token.

3We tested the vocabulary sizes of 16K, 32K, and 64K.
Translation System and Model  We used the Fairseq translator (Ott et al., 2019).

The mBART-50 model\(^4\) that we used is an encoder-decoder model. It can be used as a multilingual translation model if we fine-tune it using parallel corpora. In this paper, we used the bidirectional model between English and Inuktitut fine-tuned using the parallel corpus.

We used Wang et al. (2020)'s approach to adapt mBART-50 to a new language. Specifically, we extended the word embedding tables of the encoder and decoder as follows to achieve Inuktitut translation using mBART-50:

- mBART-50 learns and translates sentences while appending language tags in the source and target sequences. To accept the new tags, we added the Inuktitut language tag (iu_CA) to the word embedding tables.
- We also added the new subwords, which we had added to the tokenizer, to the word embedding tables.

Wang et al. (2020) applied continued pretraining to the extension of the word embedding tables using monolingual corpora. By contrast, we randomly initialized the extension and learned it during fine-tuning together with the other parameters.

As the baseline translator, we used a Transformer big model (Vaswani et al., 2017), which we trained from scratch using only the parallel corpus tokenized by the shared vocabulary 32K model.

Hyperparameters  Table 3 shows the list of hyperparameters during the fine-tuning of the mBART-50 model and testing. Because the total number of training tokens changes depending on the tokenizer, we unified the warmup time to one epoch.

Note that we used the same hyperparameters for training the Transformer big model and fine-tuning the mBART-50 model, except for the learning rate and warmup time (LR=0.0004, warmup=5 epochs).

4.2 Results of Tokenization

Table 4 shows the results of the tokenization of Inuktitut sentences in the test set. It shows the number of tokens for a sentence and the OOV rate, which we measured using the vocabulary of the translation model. Although all tokenizers had high OOV rates, we could reduce them by adding new words (embeddings) to the vocabulary of mBART-50. The “additional words for no OOVs” in Table 4 indicate the number of words to add to the vocabulary.

In neural machine translation, it is advantageous if the number of tokens for a sentence is small. In our experiment, the least number of tokens was obtained by the tokenization using the mBART-50 tokenization model. This was because SentencePiece tokenized the sentences using space characters, and over 40% of tokens became OOV. It is quite difficult to train a translation model using this tokenizer because we must add over 1.5 million words into the vocabulary of mBART-50.\(^5\)

The shared vocabulary 32K model achieved the next smallest number of tokens. However, we would have to add 27K out of 32K subwords because the vocabulary of this model is different from that of mBART-50.

In the case of the Inuktitut letters, although we would have to add only 141 subwords to the vocabulary to achieve no OOVs, the length of input/output sequences became long, that is, 80 tokens per sentence.

By contrast, the numbers of tokens obtained by our method were less than half that of the “Inuktitut letters” case, even though they were larger than those of the mBART-50 tokenization model and shared vocabulary 32K model.\(^6\) Our tokenizer can eliminate OOVs while controlling the number of additional subwords.

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\(^4\)https://dl.fbaipublicfiles.com/fairseq/models/mbart50/mbart50.pretrained.tar.gz

\(^5\)The vocabulary size of the Inuktitut language tends to be large because it has inflection and agglutination.

\(^6\)The number of additional words required to maintain no OOVs and that for the tokenizer did not match. This is because the tokenizer was trained using the monolingual corpus, and the vocabulary contained subwords that did not appear in the parallel corpus.

Table 3: Hyperparameters for training and test.
| Type                     | Tokenizer                        | #Tokens/Sent. in Test Set | OOV Rate in Test Set | Additional Words for No OOVs in Training Set |
|-------------------------|----------------------------------|---------------------------|----------------------|---------------------------------------------|
| Baselines               | mBART-50 Tokenization Model      | 20.9                      | 43.1%                | 1,553,466                                   |
|                         | Inuktitut Letters                | 80.0                      | 85.1%                | 141                                         |
|                         | Shared Vocabulary 32K Model      | 22.0                      | 82.7%                | 26,657                                      |
| Our Method              | 2K Additional Subwords           | 37.9                      | 68.7%                | 2,001                                       |
|                         | 4K Additional Subwords           | 34.6                      | 65.7%                | 4,001                                       |
|                         | 8K Additional Subwords           | 31.8                      | 62.8%                | 8,001                                       |

Table 4: Number of tokens for a sentence in the Inuktitut test set, OOV rate viewed from the original vocabulary of mBART-50, and number of additional words to eliminate OOVs.

| Translation Model       | Tokenizer                         | #Added Emb. | OOV Rate | BLEU En → Iu | BLEU Iu → En |
|-------------------------|-----------------------------------|-------------|----------|--------------|--------------|
| Transformer Big Model   | Shared Vocabulary 32K Model       | —           | 0.0%     | 8.3          | 21.5         |
| mBART-50 Model          | mBART-50 Tokenization Model       | 0           | 43.1%    | 1.7 (-)      | 7.0 (-)      |
|                         |                                   | 1,553,466   | 12.1%    | N/A          | N/A          |
|                         | Inuktitut Letters                | 140         | 0.0%     | 9.8 (+)      | 23.5 (+)     |
|                         | Shared Vocabulary 32K Model       | 26,657      | 0.0%     | 9.6 (+)      | 22.8 (+)     |
|                         | 2K Additional Subwords           | 2,000       | 0.0%     | **10.2 (+†)  | **23.5 (+)   |
|                         | 4K Additional Subwords           | 4,000       | 0.0%     | 9.7 (+)      | 23.3 (+)     |
|                         | 8K Additional Subwords           | 8,000       | 0.0%     | 9.8 (+)      | 23.2 (+)     |

Table 5: BLEU scores for English and Inuktitut translation. Bold values indicate the highest BLEU scores in each direction. (+) and (-) marks indicate that the score was significantly better and worse than that of the Transformer big model (with shared vocabulary 32K tokenization), respectively. (+†) indicates that the score was significantly better than that of the mBART-50 model (Inuktitut letter tokenization).

When we tokenized the English sentences in the test set using our tokenizers, we obtained two sentences with different tokenizations. The differences were that continuous periods ‘....’ were segmented into ‘...’ or ‘...’ or ‘...', which rarely affected the translation.

### 4.3 Translation Results

The translation results are shown in Table 5. We used a Transformer big model (Vaswani et al., 2017) as the baseline. We fine-tuned the mBART-50 translation models after we extended the word embeddings of “#Added Emb.” “OOV Rate” indicates the OOV rate in the test set after we extended the word embeddings. For the evaluation, we used sacreBLEU (Post, 2018) and performed a significance test using bootstrap resampling, implemented in sacreBLEU, with 5% of the significance rate ($p < 0.05$).

First, comparing the translation models, the BLEU scores of the mBART-50 pretrained model improved from that of the Transformer big model in both the En-Iu and Iu-En directions, regardless of the tokenizer (except for the mBART-50 tokenization model). Even though the mBART-50 model does not include Inuktitut, pretraining was effective in improving the BLEU scores.

Focusing on the tokenizers in the mBART-50 translation model, we could not obtain a meaningful translation using the original mBART-50 tokenization model because of the high OOV rate. To reduce the OOV rate, we added over 1.5 million words, but we could not fine-tune the mBART-50 pretrained model because of the memory limitation. Among the baseline tokenizers, Inuktitut letter tokenization had the highest BLEU score. The BLEU score of the shared vocabulary 32K model was lower than that of the Inuktitut letters.

Compared with Inuktitut letter tokenization, the BLEU score of the “2K Additional Subwords” of En-Iu translation was significantly higher, but significant differences were not observed in the other tokenizers of ours. The small number of the additional subwords tend to be high BLEU score. We suppose these results indicate that fine-tuning alleviated the difference between the tokenizers.

To summarize, we could apply the multilingual pretrained model mBART-50 to Inuktitut translation by segmenting Inuktitut sentences into subwords, and consequently improved the BLEU
In this paper, we added new subwords to the SentencePiece tokenizer to apply a multilingual pre-trained model to new languages. The proposed method added new subwords with unknown letters and their likelihood to the original model without changing previous tokenization results.

In our experiments, we segmented Inuktitut sentences into subwords, while controlling the number of additional subwords. We applied our tokenizer to the mBART-50 pretrained model for Inuktitut translation. As a result, the BLEU scores improved for the new language.

Although we estimated only additional subwords in this study, our method can re-estimate the likelihood of existing subwords. In future work, we will evaluate the effectiveness of adding arbitrary subwords to the original models because some researchers have reported that optimized tokenization improves the accuracy of downstream tasks (He et al., 2020; Hiraoka et al., 2021).

We release our implementation for learning additional subword models via GitHub.\(^7\)

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