LCP-DROPOUT: Compression-based Multiple Subword Segmentation for Neural Machine Translation

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ABSTRACT

In this study, we propose a simple and effective preprocessing method for subword segmentation based on a data compression algorithm. Compression-based subword segmentation has recently attracted significant attention as a preprocessing method for training data in Neural Machine Translation. Among them, BPE/BPE-dropout is one of the fastest and most effective method compared to conventional approaches. However, compression-based approach has a drawback in that generating multiple segmentations is difficult due to the determinism. To overcome this difficulty, we focus on a probabilistic string algorithm, called locally-consistent parsing (LCP), that has been applied to achieve optimum compression. Employing the probabilistic mechanism of LCP, we propose LCP-dropout for multiple subword segmentation that improves BPE/BPE-dropout, and show that it outperforms various baselines in learning from especially small training data.

1 Introduction

Subword segmentation has been established as a standard preprocessing in neural machine translation (NMT) [1,2]. In particular, byte-pair-encoding (BPE)/BPE-dropout [3,4] is the most successful compression-based subword segmentation. We propose another compression-based algorithm (LCP-dropout) that generates multiple subword segmentations for the same input; thus, enabling data augmentation especially for small training data.

In NMT, a set of training data \((s, t) \in S \times T\) is given to the learning algorithm, where \(s\) is a sentence from the source language \(S\), and \(t\) is the corresponding sentence from the target \(T\). The learning algorithm first transforms the given input into a sequence of tokens. In many cases, the tokens correspond to words in the unigram language model. For example, the input \(s = w_1 w_2 \cdots w_n\) with the blank symbol _ is interpreted as \((w_1 - w_2 - \cdots - w_n)\) with the meta symbol _ representing potential bigram.

The extracted words are projected from a high-dimensional space consisting of all words to a low-dimensional vector space by word embedding [5], which enables us to easily handle distances and relationships between words and phrases. The word embedding have been shown to boost the performance of various tasks [6,7] in natural language processing. The space of word embedding is defined by a dictionary constructed from the training data, and the components of the dictionary are called the vocabularies. Embedding a word means representing the word by a set of vocabularies.

How to construct a dictionary is one of the most important tasks. Here, consider a simplest strategy that uses the words themselves in the training data as the vocabularies. If a word does not exist in the current dictionary, it is called an unknown word, and the algorithm decides whether or not to register it in the dictionary. Using a sufficiently large dictionary can reduce the number of unknown words as much as desired; however, as a trade-off, overtraining is likely
to occur, so the vocabulary size is usually limited to 10k and 32k. Therefore, the subword segmentation has been widely used to construct a small dictionary with high generalization performance [8,12].

Subword segmentation is a recursive decomposition of a word into substrings. For example, let the word ‘study’ be registered as a current vocabulary. By embedding ‘stud’ and ‘ying’ as new words, we can learn that these three words are similar. However, each time a new word appears, the number of vocabularies grows monotonically.

On the other hand, when we focus on the common substrings of these words, we can obtain a decomposition, such as ‘st-d’, ‘std-ied’, and ‘st-y’. Therefore, the idea of subword segmentation is not to register the word itself as a vocabulary but to register its substrings. In this case, ‘st’ and ‘std’ are known words because they can be represented by combining the registered subwords. These subwords can also be reused as parts of other words (e.g., student and studied), which can suppress the growth of vocabularies.

Various approaches have been proposed along this line. SentencePiece [13] is the pioneering study based on maximum likelihood estimation over unigram language model, having high performance. Since maximum likelihood estimation requires $O(nm)$ time for the size $n$ of training data and the maximum length $m$ of subwords, a simpler subword segmentation [3] based on BPE [14,15], which is known as one of the fastest data compression algorithms, and therefore has many applications, especially in information retrieval [16,17] has been proposed.

In the BPE-based segmentation, we start from the state where a sentence is regarded as a sequence of symbols, e.g., 'abracadabra' would be ‘a-b-r-a-c-a-d-a-b-r-a-a’. BPE calculates the frequency of occurrences of bigrams, merges the occurrences of the most frequent bigram, and registers it as a new vocabulary. In this example, ‘a-b’ is one of the most frequent bigrams; therefore, the sequence is transformed into ‘ab-r-a-c-a-d-a-b-r-a-a’ and ‘ab’ becomes a new vocabulary. If ‘ab-r’ is chosen as the next most frequent bigram, then ‘abr’ will be the next new one and the sequence will be ‘abr-a-c-a-d-a-b-r-a-a’. This process is repeated until the number of vocabularies reaches the limit. BPE can reduce the time complexity to $O(n)$.

However, frequency-based approach may generates inconsistent subwords for same substring occurrences. For example, ‘impossible’ and its substring ‘possible’ are possibly decomposed into undesirable subwords, such as ‘po-ass-ib-le’ and ‘i-mp-os-si-bl-e’, depending on the frequency of bigrams. Such merging disagreement can also be caused by misspellings of words or grammatical errors. BPE-dropout [4] proposed a robust subword segmentation for this problem by ignoring each merging with a certain probability. It has been confirmed that BPE-dropout can be trained with higher accuracy than the original BPE and SentencePiece on various languages.

In this work, we propose LCP-dropout: a novel compression-based subword segmentation employing the probabilistic near-optimum compression algorithm, called locally-consistent parsing (LCP) [18,19], for improving the shortcomings of BPE. Here, we describe an outline of original LCP. Suppose we are given a string $T = t_1t_2 \cdots t_n$ of length $n$ and a set of vocabularies, $V$, where $V$ is initially the set of all symbols appearing in $T$. LCP randomly assigns a label to each symbol in $V$ such that $L : V \to \{0, 1\}$. Then, $L$ yields a label sequence $L(T) = L(t_1) \cdots L(t_n)$. When LCP finds a ‘10’ in $L(T)$, it merges the corresponding bigram $t_it_{i+1}$ for $L(t_it_{i+1}) = 10$ and adds the new vocabulary $t_it_{i+1}$ to $V$. The above process is repeated until $|V|$ reaches the limit.

By this random assignment, if $t_i = t_j$, then $L(t_i) = L(t_j)$, and for a sufficiently small $k$, we can expect that $L[i, i+k]$ at any position $i$ contains ‘10’ with a high probability. Therefore, since an occurrence of ‘10’ plays the role of a landmark, LCP can merge bigrams without disagreement. Thus, LCP has been theoretically shown to be almost optimal compression [19]. It has also been applied to mainly information retrieval [18,20,21].

A notable feature of this probabilistic algorithm is that LCP assigns a new label to each vocabulary for each execution. Owing to this randomness, the LCP-based subword segmentation is expected to generate different subword sequences representing a same input; thus, it is more robust than BPE/BPE-dropout. Moreover, these multiple subword sequences can be considered as data augmentation for small training data in NMT.

LCP-dropout consists of two strategies: landmark by random labeling for all vocabularies and dropout of merging bigrams depending on the rank in the frequency table. Our algorithm requires no segmentation training in addition to counting by BPE and labeling by LCP and uses standard BPE/LCP in test time; therefore is simple. With various language corpora consisting of small datasets, we show that LCP-dropout outperforms the baseline algorithms: BPE/BPE-dropout/SentencePiece.

2 Background

We use the following notations throughout this paper. $\Sigma$ is the set of alphabet symbols, including the blank symbol. A sequence $S$ formed by symbols is called string. $S[i]$ and $S[i, j]$ are $i$-th symbol and substring from $S[i]$ to $S[j]$ of $S$, respectively. We assume the meta symbol ‘−’ not in $\Sigma$ to explicitly represent each subwords in $S$. For a string $S$ from
\(\Sigma \cup \{-\}\), a maximal substring of \(S\) including no \(-\) is called a subword. For example, \(S = a - b - a - a - b / a - b - a - a b\) contains the subwords in \(\{a, b\}/\{a, b, ab\}\), respectively.

In subword segmentation, the algorithm decomposes all the symbols in \(S\) by the meta symbol. When a trigram \(a - b\) is merged, the meta symbol is erased and the new subword \(ab\) is added to the vocabulary, i.e., \(ab\) is treated as a single vocabulary.

In the following, we describe previously proposed subword segmentation algorithms, called SentencePiece (Kudo [13]), BPE (Sennrich et al. [3]), and BPE-dropout (Provilkov et al. [4]), respectively. We assume that our task in NMT is to predict a target sentence \(T\) given a source sentence \(S\), where these methods (including our approach) are not task-specific.

### 2.1 SentencePiece

SentencePiece [13] can generate different decompositions for each execution. Here, we outline SentencePiece in the unigram language model. Given a set of vocabularies, \(V\), a sentence \(T\), and the probability \(p(x)\) of occurrence of \(x \in V\), the probability of the partition \(x = (x_1, \ldots, x_n)\) for \(T = x_1 \cdots x_n\) is represented as \(P(x) = \Pi_{i=1}^{n} p(x_i), x_i \in V\), where \(\Sigma_{x \in V} p(x) = 1\). The optimum partition \(x^*\) for \(T\) is obtained by searching for the \(x\) that maximizes \(P(x)\) from all candidate partitions \(x \in S(T)\).

Given a set of sentences, \(D\), as training data for a language, the subword segmentation for \(D\) can be obtained through the maximum likelihood estimation of the following \(L\) with \(P(x)\) as a hidden variable by using EM algorithm, where \(X^{(s)}\) is the \(s\)-th sentence in \(D\).

\[
L = \sum_{s=1}^{D} \log P(X^{(s)}) = \sum_{s=1}^{D} \log \left( \sum_{x \in S(X^{(s)})} P(x) \right)
\]

SentencePiece was shown to achieve significant improvements over the method based on subword sequences. However, this method is rather complicated because it requires a unigram language model to predict the probability of subword occurrence, EM algorithm to optimize the lexicon, and Viterbi algorithm to create segmentation samples.

### 2.2 BPE and BPE-dropout

BPE [14] is one of practical implementations of Re-pair [15], which is known as the algorithm with the highest compression ratio. Re-pair counts the frequency of occurrence of all bigrams \(xy\) in the input string \(T\). For the most frequent \(xy\), it replaces all occurrences of \(xy\) in \(T\) such that \(T[i, i + 1] = xy\), with some unused character \(z\). This process is repeated until there are no more frequent bigrams in \(T\). The compressed \(T\) can be recursively decoded by the stored substitution rules \(z \rightarrow xy\).

Since the naive implementation of Re-pair requires \(O(|T|^2)\) time, we use a complex data structure to achieve linear-time. However, it is not practical for large-scale data because it consumes \(\Omega(|T|)\) of space. Therefore, we usually split \(T = t_1 t_2 \cdots t_m\) into substrings of constant length and process each \(t_i\) by the naive Re-pair without special data structure, called BPE. Naturally, there is a trade-off between the size of the split and the compression ratio. BPE-based subword segmentation [3] (called BPE simply) determines the priority of bigrams according to their frequency and adds the merged bigrams as the vocabularies.

Since BPE is a deterministic algorithm, it splits a given \(T\) in one way. Thus, it is not easy to generate multiple partitions like stochastic approach (e.g., [13]). Therefore, BPE-dropout [4], ignoring the merging process with a certain probability, has been proposed. In BPE-dropout, for the current \(T\) and the most frequent \(xy\), for each occurrence \(i\) satisfying \(T[i, i + 1] = xy\), merging \(xy\) is dropped with a certain small probability \(p\) (e.g., \(p = 0.1\)). This mechanism makes BPE-dropout probabilistic and generates a variety of splits. BPE-dropout has been recorded to outperform SentencePiece in various languages. Additionally, BPE-based methods are faster and easier to implement than likelihood-based approaches.

### 2.3 LCP

Frequency-based compression algorithms (e.g. [14][15]) are known to be not optimum in theoretical point of view. Optimum compression here means a polynomial-time algorithm that satisfies \(|A(T)| = O(|A^*(T)| + \log |T|)\) with the output \(A(T)\) of the algorithm for the input \(T\) and the optimum solution \(A^*(T)\). Note that computing the optimum compression is NP-hard [22].
For example, consider a string $T = \cdots abcddef \cdots bcdef \cdots$. Assuming the rank of these frequencies: $\text{freq}(ab) > \text{freq}(bc) > \text{freq}(cd) > \cdots$, merging for $T$ is possibly $T = \cdots (ab)(cd)(ef) \cdots (bc)(de)(fg) \cdots$. However, the desirable merging would be $T = \cdots a(b)(c)(d)(ef) \cdots (bc)(de)(fg) \cdots$ considering the similarity of these substrings.

Since such pathological merging cannot be prevented by frequency information alone, frequency-based algorithms cannot obtain asymptotically optimum compression [23]. Various linear-time and optimal compressions have been proposed to improve this drawback. LCP is one of the simplest optimum compression algorithms. The original LCP, like Re-pair, is a deterministic algorithm. Recently, the introduction of probability into LCP [19] has been proposed, and in this study, we focus on the probabilistic variant. The following is a brief description of the probabilistic LCP.

We are given an input string $T = a_1a_2 \cdots a_n$ of length $n$ and a set of vocabularies, $V$. Here, $V$ is initialized as the set of all characters appearing in $T$.

1. Randomly assign a label $L(a) \in \{0, 1\}$ to each $a \in V$.
2. According to $L(a)$, compute the sequence $L(T) = L(a_1)L(a_2) \cdots L(a_n) \in \{0, 1\}^n$.
3. Merge all bigram $a_ia_{i+1}$ provided $L(T)[i, i + 1] = 10$.
4. Set $V = V \cup \{a_ia_{i+1}\}$ and repeat the above process.

The difference between LCP and BPE is that BPE merges bigrams with respect to frequencies, whereas LCP pays no attention to them. Instead, LCP merges based on the binary labels assigned randomly. The most important point is that any two occurrences of ‘10’ never overlap. For example, when $T$ contains a trigram $abc$, there is no possible assignment allowing $(ab)c$ and $a(bc)$ simultaneously. By this property, LCP can avoid the problem that frequently occurs in BPE. Although LCP theoretically guarantees almost optimum compression, as far as the authors know, this study is the first result of applying LCP to machine translation.

3 Our Approach: LCP-dropout

BPE-dropout allows diverse subword segmentation for BPE by ignoring bigram merging with a certain probability. However, since BPE is a deterministic algorithm, it is not trivial to generate various candidates of bigram. In this study, we propose an algorithm that enables multiple subword segmentation for the same input by combining the theory of LCP with the original strategy of BPE.

3.1 Algorithm description

We define the notations in our algorithm. Let $\Sigma$ be a set of finite symbols, called the alphabet. A string $w$ formed from $\Sigma$ is called word, denoted by $w \in \Sigma^*$. Let $\_\_\_\_$ be the explicit blank symbol not in $\Sigma$. Then, a string $s \in (\Sigma \cup \{\_\_\_\_\_\_\_\})^*$ is called a sentence.

We also assume a meta symbol '−' not in $\Sigma \cup \{\_\_\_\_\_\_\_\}$. By this, a sentence $x$ is extended to have all possible merges: Let $\hat{x}$ be the string of all symbols in $x$ separated by '−', e.g., $\hat{x} = a - b - a - b - b$ for $x = ababb$. For strings $x$ and $y$, if $y$ is obtained by removing some occurrences of $−$ in $x$, then we express the relation $y \preceq x$ and $y$ is said to be a subword segmentation of $x$.

After merging $a - b$ (i.e., $a - b$ is replaced by $ab$), the substring $ab$ is treated as a single symbol. Thus, we extend the notion of bigram to vocabularies of length more than two. For a string of the form $s = \alpha_1 - \alpha_2 - \cdots - \alpha_n$ such that each $\alpha_i$ contains no $−$, each $\alpha_i - \alpha_{i+1}$ is defined to be a bigram consisting of the vocabularies $\alpha_i$ and $\alpha_{i+1}$.

3.2 Example run

Table [?] presents an example of subword segmentation using LCP-dropout. Here, the input $X$ consists of a single sentence $ababacaacb$. The hyperparameters are $(v, \ell, k) = (6, 5, 0.5)$. First, the set of vocabularies is initialized to $V = \{a, b, c\}$; for each $a \in V$, a label $L(a) \in \{0, 1\}$ is randomly assigned (depth 0). Next, find all occurrences of 10 in $L$, and the corresponding bigrams are merged depending on their frequencies. Here, $L(ab) = L(ac) = 10$ but only $a - b$ is top-k bigram assigned 10, and then $a - b$ is merged to $ab$. The resulting string is shown in the depth 1 over the new vocabularies $V_1 = \{a, b, c, ab\}$. This process is repeated while $|V_m| < \ell$ for the next $m$. The condition $|V_2| = 5$ terminates the inner-loop of LCP-dropout, and then the subword $Y_1 = ab - abc - a - a - c - abc - b$ is generated. Since $|V(Y_1)| < v$, the algorithm generates the next subword segmentations $Y_2$ for the same input. Finally, we obtain the multiple subword segmentation $Y_1 = ab - abc - a - a - c - abc - b$ and $Y_2 = ab - ab - ca - a - ca - b - c - b$ for the same input string.
4 Experimental Setup

4.1 Baseline algorithms

Baseline algorithms are SentencePiece [13] with the unigram language model and BPE/BPE-dropout [3,4]. SentencePiece takes the hyperparameters $\ell$ and $\alpha$, where $\ell$ specifies how many best segmentations for each word are produced before sampling and $\alpha$ controls the smoothness of the sampling distribution. In our experiment, we use $(\ell = 64, \alpha = 0.1)$ that performed best on different data in the previous studies.

BPE-dropout takes the hyperparameter $p$, where during segmentation, at each step, some merges are randomly dropped with the probability $p$. If $p = 0$, the segmentation is equal to the original BPE and $p = 1$, the algorithm outputs the input string itself. Then, the value of $p$ can be used to control the granularity of segmentation. In our experiment, we use $p = 0$ for the original BPE and $p = 0.1$ for the BPE-dropout with the best performance.

4.2 Data sets, preprocessing, and vocabulary size

We verify the performance of the proposed algorithm for a wide range of datasets with different sizes and languages. Table 2 summarizes the details of the datasets and hyperparameters. These data are used to compare the performance of LCP-dropout and baselines (SentencePiece/BPE/BPE-dropout) with appropriate hyperparameters and vocabulary sizes shown in [4].

Before subword segmentation, we preprocess all datasets with the standard Moses toolkit[1] where for Japanese and Chinese, subword segmentations are trained almost from raw sentences because these languages have no explicit word boundaries; and thus, Moses tokenizer does not work correctly.

Based on a recent research on the effect of vocabulary size on translation quality, the vocabulary size is modified according to the dataset size in our experiments (Table 2).

To verify the performance of the proposed algorithm for small training data, we use News Commentary v16 [2] a subset of WMT14 [4] as well as KFTT[4]. In addition, we use a large training data in WMT14. The training step is set to 200,000 steps, while for Japanese and Chinese, the number of training steps is 3,000 and 5,000, respectively.

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1. https://github.com/moses-smt/mosesdecoder
2. https://data.statmt.org/news-commentary/v16
3. https://www.statmt.org/wmt14/translation-task.html
4. http://www.phontron.com/kftt
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Table 1: Example of multiple subword segmentation using LCP-dropout for the single sentence \( 'x = ababacaacabcb' \) with the hyperparameters \((v, \ell, k) = (6, 5, 0.5)\), where the meta symbol \(-\) is omitted, and \(L\) is the label of each vocabulary assigned by LCP. The resulting subword segmentation is \(Y = \{Y_1, Y_2\}\).

### 1-st trial

| input \(x\): depth 0 | a | b | a | b | c | a | a | c | a | b | c | b |
|----------------------|---|---|---|---|---|---|---|---|---|---|---|---|
| \(L\)               | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| depth 1              | ab | ab | c | a | c | ab | c | b |
| \(L\)               | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| \(Y_1\): depth 2    | ab | abc | a | a | c | abc | b |

### 2-nd trial

| same \(x\): depth 0 | a | b | a | b | c | a | a | c | a | b | c | b |
|----------------------|---|---|---|---|---|---|---|---|---|---|---|---|
| \(L\)               | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| depth 1              | a | b | a | b | ca | a | ca | b | c | b |
| \(L\)               | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| \(Y_2\): depth 2    | ab | abc | ca | a | ca | c | abc | b |

for all data. In training, pairs of sentences of source and target languages were batched together by approximate length. As shown in Table 2, the batch size was standardized to approximately 3k for all datasets.

Table 2: Overview of the datasets and hyperparameters. The hyperparameter \(v\) (vocabulary size) is common to all algorithms (baselines and ours) and others \((\ell \text{ and } k)\) are specific to LCP-dropout only.

| corpus     | language \((L_1 - L_2)\) | \#sentences \((\text{train/dev/test})\) | batch size | hyperparameters \((v, \ell, k)\) |
|------------|---------------------------|--------------------------------|-------------|----------------------------------|
| News       | En – De                   | 380k/2808/2906                  | 3072        | 16k, 16k/8k, 0.01/0.05/0.1       |
| Commentary | En – Fr                   | 357k/3020/3133                  | 3072        | 16k, 8k, 0.01                    |
| v16        | En – Zh                   | 305k/2968/2936                  | 3072        | 16k, 8k, 0.01                    |
| KFTT       | En – Ja                   | 440k/1166/1160                  | 3072        | 16k, 8k, 0.01                    |
| WMT14      | En – De                   | 4.5M/2737/3004                  | 3072        | 32k, 32k/16k, 0.01               |

4.3 Model, optimizer, and evaluation

NMT was realized by the seq2seq model, which takes a sentence in the source language as input and outputs a corresponding sentence in the target language [24]. A transformer is an improvement of seq2seq model, that is the most successful NMT. [25]

In our experiments, we used OpenNMT-tf [26], a transformer-based NMT, to compare LCP-dropout and other baselines algorithms. The parameters of OpenNMT-tf were set as in the experiment of BPE-dropout [4]. The batch size was set to 3072 for training and 32 for testing. We also use regularization and optimization procedure as described in BPE-dropout [4].

The quality of machine translation is quantitatively evaluated by BLEU score, i.e., the similarity between the result and the reference of translation. It is calculated using the following formula based on the number of matches in their \(n\)-grams. Let \(t_i\) and \(r_i\) \((1 \leq i \leq m)\) be the \(i\)-th translation and reference sentences, respectively.

\[
\text{BLEU} = BP_{\text{BLEU}} \cdot \exp \left( \sum_{n=1}^{N} w_n \log p_n \right), \quad p_n = \frac{\sum_{i=1}^{m} \#n\text{-gram that match in } t_i \text{ and } r_i}{\sum_{i=1}^{m} \#n\text{-gram in } t_i},
\]

where \(N\) is a small constant (e.g., \(N = 4\)), and \(BP_{\text{BLEU}}\) is the brevity penalty when \(|t_i| < |r_i|\), where \(BP_{\text{BLEU}} = 1\) otherwise. In this study, we use SacreBLEU [27]. For Chinese, we add option \(--\text{tok zh} \) to SacreBLEU. Meanwhile, we use character-based BLEU for Japanese.
Considering subword segmentation as a parsing tree, LCP produces a balanced parsing tree, whereas the tree produced by BPE tends to be longer for a certain path. For example, for a substring abcd, LCP tends to generate subwords like

Table 3: Experimental results of LCP-dropout for News Commentary v16 (Table 2) w.r.t the specified hyperparameters, where the translation task is $\text{De} \rightarrow \text{En}$. Bold indicates the best score.

| $k$ threshold $(k \in (0, 1])$ | #subword | BLEU $\ell = v$ | BLEU $\ell = v/2$ |
|-------------------------------|----------|----------------|-----------------|
| 0.01                          | 21.3     | 7.7            | 39.0            |
|                               | 39.7     |                |                 |
| 0.05                          | 4.7      | 3.7            | 39.0            |
|                               | 39.4     |                |                 |
| 0.1                           | 3.3      | 2.0            | 38.8            |
|                               | 39.4     |                |                 |

Table 4: Depth of label assignment in LCP-dropout.

| $k$ threshold $(k \in (0, 1])$ | $\ell = v$ | $\ell = v/2$ |
|-------------------------------|------------|--------------|
| 0.01                          | 83.7       | 54.9         |
|                               | 35.4       |              |
| 0.05                          | 18.7       | 13.0         |
|                               | 9.0        |              |
| 0.1                           | 10.3       | 7.5          |
|                               | 6.0        |              |

5 Experiments and Analysis

Table 3 summarizes the effect of hyperparameters $(v, \ell, k)$ on the proposed LCP-dropout. This table shows the details of multiple subword segmentation using LCP-dropout and BLEU scores for the language pair of English ($\text{En}$) and German ($\text{De}$) from News Commentary v16 (Table 2). For each threshold $k \in \{0.01, 0.05, 0.1\}$, $\text{En}$ and $\text{De}$ indicate the number of multiple subword sequences generated for the corresponding language, respectively. The last two values are the BLEU scores for $\text{De} \rightarrow \text{En}$ with $\ell = v$ and $\ell = v/2$ for $v = 16k$, respectively.

The threshold $k$ controls the dropout rate, and $\ell$ contributes to the multiplicity of the subword segmentation. The results show that $k$ and $\ell$ affect the learning accuracy (BLEU). The best result is obtained when $(k, \ell) = (0.01, \ell = v/2)$. This can be explained by the results in Table 4 which shows the depth of executed inner-loop of LCP-dropout for randomly assigning $\{0, 1\}$ to vocabularies, where when $\ell = v/2$, it means the average before the outer-loop terminates. Therefore, the larger this value is, the more likely it is that longer subwords will be generated. However, unlike BPE-dropout, the value of $k$ alone is not enough to generate multiple subwords. The proposed LCP-dropout guarantees the diversity by initializing the subword segmentation by $\ell (\ell < v)$. Using this result, we will fix $(k, \ell) = (0.01, v/2)$ as the hyperparameter of LCP-dropout.

Table 5 summarizes the main results. We show BLEU scores for News Commentary v16 and KFTT: $\text{En}$ and $\text{De}$ are the same in Table 3. In addition to these languages, we set French (Fr), Japanese (Ja), and Chinese (Zh). For each language, we show the average of the number of multiple subword sequences generated by LCP-dropout. For almost datasets, LCP-dropout outperforms the baselines algorithms. Meanwhile, we use the best ones reported in the previous study for the hyperparameters of BPE-dropout and SentencePiece.

Table 5 extracts the effect of alphabet size on subword segmentation. In general, Japanese $\text{Jn}$ and Chinese $\text{Zh}$ alphabets are very large, containing at least 2k alphabet symbols even if we limit them in common use. Therefore, the average length of words is small and subword semantics is difficult. For these cases, we confirmed that LCP-dropout has higher BLEU scores than other methods for these languages.

Table 6 also presents the BLEU scores for a large corpus (WMT14) for the translation $\text{De} \rightarrow \text{En}$. This experiment shows that LCP-dropout cannot outperform baselines with the hyperparameter we set. This is because the ratio of the vocabulary size $(v, \ell)$ to dropout rate $k$ is not appropriate. As data to support this conjecture, it can be confirmed that the multiplicity in the large datasets is much smaller than that of small corpus (Table 5). This is caused by the reduced repetitions of label assignments, as shown in Table 4 compared to Table 3. The results show that the depth of inner-loop is significantly reduced, which is why enough subwords sequences cannot be generated.

Table 7 presents several translation results. The ‘Reference’ represents the correct translation for each case, and the BLEU score is obtained from the pair of the reference and each translation result. We also show the average length for each reference sentence indicate by ‘ave./word’. These results show the characteristics of successful and unsuccessful translations by the two algorithms related to the length of words.

Considering subword segmentation as a parsing tree, LCP produces a balanced parsing tree, whereas the tree produced by BPE tends to be longer for a certain path. For example, for a substring $abcd$, LCP tends to generate subwords like
Table 5: Experimental results of LCP-dropout (denoted by LCP), BPE-dropout (denoted by BPE), and SentencePiece (denoted by SP) on various languages in Table 2 (small corpus: News Commentary v16 and KFTT, and large corpus: WMT14), where ‘multiplicity’ denotes the average number of sequences generated per input string. Bold indicates the best score.

| Corpus       | Language (multiplicity) | Translation Direction | LCP \((k = 0.01)\) | BPE \((p = 1, 0.1)\) | SP |
|--------------|-------------------------|-----------------------|---------------------|----------------------|----|
| News v16     | En → De                 | De → En              | 39.7                | 35.7                 | 39.1 | 38.9 |
| Commentary (21.3-7.7) | En → De             | 28.4                | 27.4                | 27.4                 | 27.5 |
| v16 (small)  | En → Fr                 | Fr → En              | 35.1                | 34.9                 | 34.9 | 34.2 |
|              | (23.0-19.3)             |                      |                    |                      |      |
|              | En → Zh                 | Zh → En              | 29.5                | 15.2                 | 28.2 | 28.3 |
|              | (26.0-8.7)              |                      |                    |                      |      |
| KFTT (small) | En → Ja                 | Ja → En              | 20.0                | 19.6                 | 19.6 | 19.2 |
|              | (17.7-10.0)             |                      |                    |                      |      |
| WMT14 (large)| En → De                 | De → En              | 28.7                | 28.9                 | 32.2 | 32.2 |
|              | (9.3-5.3)               |                      |                    |                      |      |

Table 6: Depth of label assignment for large corpus.

| top-k threshold \((k ∈ (0, 1))\) | \(t = v\) | \(t = v/2\) |
|----------------------------------|----------|-----------|
| 0.01                             | 24.0     | 18.0     |
| 1.0                              | 17.1     | 14.2     |

\(((ab)(cd))\), while BPE generates them like \(((ab)c)d\). In this example, the average length of the former is shorter than that of the latter. This trend is supported by the experimental results in Table 7 showing the average length of all subwords generated by LCP/BPE-dropout for real datasets. Due to this property, when the vocabulary size is fixed, LCP tends not to generate subwords of approximate length because it decomposes a longer word into excessively short subwords.

Therefore, LCP-dropout is considered to be superior in subword segmentation for languages consisting of short words. Table 5 including the translation results for Japanese and Chinese also supports this characteristic.

6 Conclusion

In this study, proposed LCP-dropout as an extension of BPE-dropout \[4\] for multiple subword segmentation by applying a near-optimum compression algorithm. The proposed LCP-dropout can properly decompose strings without background knowledge of the source/target language by randomly assigning binary labels to vocabularies. This randomness allows generating consistent multiple segmentations for the same string. As a result, LCP-dropout enables data augmentation on minor languages or limited fields, where sufficient training data are unavailable.

Multiple segmentation can also be achieved by likelihood-based methods. After SentencePiece \[13\], various extensions have been proposed \[28, 29\]. In contrast to these studies, our approach focuses on a simple linear-time compression algorithm.

Our algorithm does not require any background knowledge of the language compared to word replacement-based data augmentation, \[30, 31\] where some words in the source/target sentence are swapped with other words preserving grammatical/semantic correctness.

The effectiveness of LCP-dropout was confirmed for almost small corpora. Unfortunately, the optimal hyperparameter obtained in this study did not work well for a large corpus. Besides, the learning accuracy was found to be affected by the alphabet size of the language. Future research directions include an adaptive mechanism for determining the hyperparameters depending on training data and alphabet size.
Table 7: Examples of translated sentences by LCP-dropout ($k = 0.01$) and BPE-dropout ($p = 0.1$) with the reference translation for News Commentary v16. We show the average word length (ave./word) for each reference sentence as well as the average subword length (ave./subword) generated by respective algorithms for the entire corpus.

| Reference: | ‘Even if his victory remains unlikely, Bayrou must now be taken seriously.’ | BLEU = 5.00 |
|------------|--------------------------------------------------------------------------|----------|
| LCP-dropout: | ‘While his victory remains unlikely, Bayrou must now be taken seriously.’ | 84.5 |
| BPE-dropout: | ‘Although his victory remains unlikely, he needs to take Bayrou seriously now.’ | 30.8 |

| Reference: | ‘In addition, companies will be forced to restructure in order to cut costs and increase competitiveness.’ | BLEU |
|------------|--------------------------------------------------------------------------|--------|
| LCP-dropout: | ‘In addition, restructuring will force rms to save costs and boost competitiveness.’ | 12.4 |
| BPE-dropout: | ‘In addition, businesses will be forced to restructure in order to save costs and increase competitiveness.’ | 66.8 |

ave./subword 4.01 (LCP-dropout) : 4.31 (BPE-dropout)

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