BERTSeg: BERT Based Unsupervised Subword Segmentation for Neural Machine Translation

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Abstract

Existing subword segmenters are either 1) frequency-based without semantics information or 2) neural-based but trained on parallel corpora. To address this, we present BERTSeg, an unsupervised neural subword segmenter for neural machine translation, which utilizes the contextualized semantic embeddings of words from characterBERT and maximizes the generation probability of subword segmentations. Furthermore, we propose a generation probability-based regularization method that enables BERTSeg to produce multiple segmentations for one word to improve the robustness of neural machine translation. Experimental results show that BERTSeg with regularization achieves up to 8 BLEU points improvement in 9 translation directions on ALT, IWSLT15 Vi→En, WMT16 Ro→En, and WMT15 Fi→En datasets compared with BPE. In addition, BERTSeg is efficient, needing up to 5 minutes for training.

1 Introduction

Subword segmentation is the task of splitting a word into smaller n-gram character units called subwords (Schuster and Nakajima, 2012). It alleviates the out-of-vocabulary (OOV) problem in neural machine translation (NMT) (Sutskever et al., 2014; Bahdanau et al., 2014; Vaswani et al., 2017) by enabling an NMT system to have a fixed-size vocabulary while being able to handle all possible words regardless of their frequencies.

Studies in subword segmentation fall into two categories: frequency-based approaches and neural network-based approaches. Frequency-based approaches (Sennrich et al., 2016; Kudo and Richardson, 2018; Kudo, 2018; Provilkov et al., 2020) adopt a greedy algorithm that generates the vocabulary with frequent subword fragments in the corpus during training and merges adjacent high-frequency fragments starting from characters recursively during inference. Among these methods, BPE-dropout (Provilkov et al., 2020) and SentencePiece with regularization (Kudo, 2018) generate multiple segmentations by random sampling. Frequency-based approaches do not consider semantic information of the subwords, therefore the generated segmentation is not linguistically motivated. For example, the word “fellowships” is segmented into “fell/ows/hip/s” by BPE whereas “fellow/ships” is a more linguistically motivated segmentation. Neural approaches such as DPE (He et al., 2020) implicitly considers the contextual semantic information of subwords by maximizing the generation probabilities of the target language sentences conditioned on the source language sentences. However, it trains on parallel sentences, which poses a problem for low-resource languages. DPE is slow because it calculates the probabilities of all possible sentence segmentations, therefore, not practical in high-resource scenarios.

We propose BERTSeg, an unsupervised neural subword segmenter that leverages contextualized word representations from the pre-trained model, characterBERT (El Boukkouri et al., 2020). It combines the advantages of frequency-based and neural

| BERTSeg Segmentation | watch/ing | un/break/able |
|----------------------|-----------|-------------|
| leak/ed              | wave/length/s |
| stress/ful          | share/holding/s |
| employ/er/s         | ab/normal/ly |

Table 1: BERTSeg produces linguistically intuitive subword segmentations.

| BERTSeg-Regularization Segmentation | represent/ed | represented |
|------------------------------------|--------------|-------------|
| re/presented                       | re/present/e/d |

Table 2: BERTSeg-Regularization samples multiple segmentations from one word.
Figure 1: **BERTSeg architecture.** The encoder is a characterBERT that generates average embeddings for one word in different contexts. The transformer decoder takes characters as input and generates probabilities of the next subword. During training, the objective is to maximize the probabilities of all possible segmentations. During inference, the model retraces the optimal segmentation.

![BERTSeg diagram](image)

2.1 Background: Word Modeling

We define a word as a single distinct meaningful element of writing. Technically, we split words in sentences with tools for different languages as described in Section 3. Let $x_{1:T}$ denote a word containing $T$ characters. $a_{1:T}$ is one segmentation of $x$ that comprises $c_{0}$ subwords $a_{i}$. $S(x)$ is the set of all possible segmentations of $x$. The generation probability $x$ can be defined as the sum of the probabilities of all segmentations shown in Eq. (1).

$$p(x_{1:T}) = \sum_{a_{1:c_{0}} \in S(x)} p(a_{1:c_{0}})$$

$$= \sum_{a_{1:c_{0}} \in S(x)} \prod_{i=1}^{c_{0}} p(a_{i}|a_{1},...,a_{i-1})$$

(1)

2.2 Proposed Method: BERTSeg

As shown in Figure 1, the proposed BERTSeg contains a characterBERT encoder (El Boukouri et al., 2020) and a mixed character-subword transformer decoder (He et al., 2020). The mixed character-subword transformer takes characters as input and generates sub-words as output. The model represents the history information by prefix characters $x_{1},...,x_{j}$ instead of previous subwords $a_{1},...,a_{j-1}$, where $j$ is the index of the last character in $a_{j-1}$.

Let $e_{x}$ denote the average-pooled contextualized word embeddings by characterBERT from all sentences containing word $x$. The generation probability can be calculated by Eq. (2).

$$\log p(x_{1:T}|e_{x}) = \log \sum_{a_{1:c_{0}} \in S(x)} \prod_{i=1}^{c_{0}} p(a_{i}|e_{x};x_{1},...,x_{j})$$

(2)

During training, we calculate the log $p(x_{1:T}|e_{x})$ in polynomial time by dynamic programming (DP) (He et al., 2020) and use $-\log p(x_{1:T}|e_{x})$ as the loss. During inference, we retrace the optimal segmentation $a$ through Eq. (3).

$$a = \arg \max_{a_{1:c_{0}} \in S(x)} \prod_{i=1}^{c_{0}} p(a_{i}|e_{x};x_{1},...,x_{j})$$

(3)
### 2.3 Probability Based Regularization

We propose BERTSeg-Regularization which performs subword regularization based on the probability distribution during inference. For segmentation $a_i$ with $p(a_i)$, the sampling probability $p_{\text{sample}}(a_i)$ is shown in Eq. (4), where $t$ is a temperature hyperparameter.

$$p_{\text{sample}}(a_i) = \frac{e^{\log p(a_i)/t}}{\sum_{a_i \in S(x)} e^{\log p(a_i)/t}} \quad (4)$$

The time complexity for generating the best $N$ segmentations is $O(N \log NT^2)$ through DP.

### 3 Experimental Settings

#### Datasets

Table 5 summarizes MT datasets from low- to high-resource. We use the English words of each dataset to train BERTSeg. We applied Juman++ (Tolmachev et al., 2018) to Japanese sentences, Stanford-segmenter (Manning et al., 2014) to Chinese sentences, and Moses tokenizer (Koehn et al., 2007) to sentences in other languages. We removed diacritics in Romanian sentences. We set the subword vocabulary size to 8k for all segmentation methods and NMT models.

#### Segmenter Settings

For BERTSeg, we used the characterBERT model (El Boukkouri et al., 2020) trained on English Wikipedia data as encoder, and pre-processed the English data of each dataset to obtain word embeddings. Our transformer decoder was 4-layer with 1 attention head. All hidden sizes in the model were 768. The vocabulary of possible subwords used a BPE vocabulary obtained from the English part of each dataset. To prevent overfitting, we set the gradient clip to 1.0 and trained the model until the loss of 7k high-frequency words was stable. BERTSeg-Regularization generated 10 segmentations with the highest probability for each word and $t$ was set to 5. We generated data of each epoch dynamically. Our method was applied to the English sentences, whereas sentences in the other languages used BPE or BPE-dropout.

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**Table 3:** Low-resource Asian languages → English MT BLEU score results. BERTSeg-Regularization consistently improves over all baselines. Statistical significance $p < 0.001$ is indicated by * against BPE and by ◦ against DPE. Subscript values denote the BLEU score differences from BPE.

| Dataset          | Fil→En | Id→En | Ja→En | Ms→En | Vi→En | Zh→En | Avg  |
|------------------|--------|-------|-------|-------|-------|-------|------|
| BPE (Sennrich et al., 2016) | 23.09 | 25.70 | 9.42  | 28.19 | 19.94 | 12.21 | 19.76 |
| VOLT (Xu et al., 2021) | 22.99 | 25.05 | 10.56 | 27.91 | 21.64 | 11.31 | 19.91 |
| DPE (He et al., 2020) | 24.04 | 26.66 | 9.93  | 27.89 | 20.06 | 10.72 | 19.88 |
| BERTSeg           | 24.84 +1.8 | 25.84 -0.1 | 10.97 +1.6 | 29.52 +1.3 | 20.86 -0.9 | 12.20 -0.0 | 20.71 -1.0 |
| With Regularization |        |       |       |       |       |       |      |
| BPE-dropout (Provilkov et al., 2020) | 28.18 | 28.02 | 12.84 | 31.59 | 23.67 | 13.91 | 23.04 |
| BERTSeg-Regularization | 31.09 *-8.6 | 28.86 *+1.2 | 15.56 *-6.1 | 32.97 *+4.8 | 24.58 *-4.6 | 15.03 *+2.8 | 24.68 *+4.9 |

**Table 4:** Low-resource Asian languages → English MT METEOR score results. BERTSeg-Regularization consistently improves over all baselines. Subscript values denote the BLEU score differences from BPE.

| Dataset          | Fil→En | Id→En | Ja→En | Ms→En | Vi→En | Zh→En | Avg  |
|------------------|--------|-------|-------|-------|-------|-------|------|
| BPE (Sennrich et al., 2016) | 29.05 | 31.05 | 20.12 | 32.74 | 27.64 | 22.85 | 27.24 |
| VOLT (Xu et al., 2021) | 29.16 | 30.98 | 21.24 | 32.50 | 28.37 | 22.22 | 27.41 |
| DPE (He et al., 2020) | 29.72 | 31.79 | 21.13 | 32.50 | 26.94 | 21.46 | 27.26 |
| BERTSeg           | 30.28 +1.2 | 31.25 +0.2 | 21.04 +0.9 | 33.34 +0.6 | 27.38 -0.3 | 22.57 -0.3 | 27.64 -0.4 |
| With Regularization |        |       |       |       |       |       |      |
| BPE-dropout (Provilkov et al., 2020) | 31.96 | 32.99 | 22.83 | 34.81 | 29.05 | 23.56 | 29.20 |
| BERTSeg-Regularization | 34.35 *+3.3 | 33.38 *+1.3 | 25.14 *+1.6 | 36.13 *+3.4 | 30.40 *+2.8 | 24.57 *+1.7 | 30.66 *+4.4 |

**Table 5:** Statistics of the corpora (# sentences).

| Dataset          | Train | Valid | Test  |
|------------------|-------|-------|-------|
| ALT Asian Langs-En | 18k   | 1,000 | 1,018 |
| IWSLT15 Vi-En     | 133k  | 1,553 | 1,268 |
| WMT16 Ro-En       | 612k  | 1,999 | 1,999 |
| WMT15 Fi-En       | 1.8M  | 1,500 | 1,370 |
Baseline methods are BPE (Sennrich et al., 2016),1 VOLT (Xu et al., 2021),2 DPE (He et al., 2020)3 and BPE-dropout (Provilkov et al., 2020).4 We used the official implementations with default settings of each method for sentences in both source and target languages.

NMT Settings We used the transformerbase architecture (Vaswani et al., 2017) and the fairseq framework (Ott et al., 2019). We trained the model until no BLEU score improvement for 10 epochs on the validation set. During inference, beam size was 12 and length penalty was 1.4. We report sacrec BLEU (Post, 2018) and METEOR (Banerjee and Lavie, 2005) on detokenized outputs.

4 Results and Analysis

MT Results Tables 3, 4, 6, and 7 compare the proposed methods with baseline methods. First, BERTSeg-Regularization achieves the best performance in all directions, significantly boosting BLEU scores up to 8 points and METEOR scores up to 5 points over BPE. Second, regularization is effective: methods with regularization show higher BLEU scores. Among methods w/o regularization, BERTSeg yields the highest BLEU and METEOR scores in most directions. Finally, we found the proposed method especially effective in low-resource scenarios with the help of the pre-trained model trained on large-scale data. As the train set grows, BPE and DPE gradually learn good segmentations, making the gap between BERTSeg smaller.

Table 6: High-resource MT BLEU score results. Statistical significance $p < 0.001$ is indicated by * against BPE and by ° against DPE. Subscript values denote the BLEU score differences from BPE.

|                | IWSLT15 Vi→En | WMT16 Ro→En | WMT15 Fi→En |
|----------------|----------------|-------------|-------------|
| **w/o Regularization** |
| BPE (Sennrich et al., 2016) | 27.09 | 32.54 | 17.45 |
| VOLT (Xu et al., 2021) | 27.16 | 31.89 | 17.25 |
| DPE (He et al., 2020) | 27.40 | 29.95 | 16.14 |
| BERTSeg | 27.80* | 32.33° | 17.54° |
| **With Regularization** |
| BPE-dropout (Provilkov et al., 2020) | 28.76 | 33.59 | 18.50 |
| BERTSeg-Regularization | 30.09* | 33.82° | 18.46° |

Table 7: High-resource MT METEOR score results. Subscript values denote the BLEU score differences from BPE.

|                | IWSLT15 Vi→En | WMT16 Ro→En | WMT15 Fi→En |
|----------------|----------------|-------------|-------------|
| **w/o Regularization** |
| BPE (Sennrich et al., 2016) | 31.16 | 35.18 | 27.06 |
| VOLT (Xu et al., 2021) | 30.90 | 34.90 | 26.73 |
| DPE (He et al., 2020) | 31.07 | 30.15 | 26.00 |
| BERTSeg | 31.36* | 35.16 ° | 27.32 ° |
| **With Regularization** |
| BPE-dropout (Provilkov et al., 2020) | 32.09 | 35.73 | 28.39 |
| BERTSeg-Regularization | 32.37* | 36.29° | 28.61° |

Training Speeds As presented in Table 8, the training speed of BERTSeg is substantially faster than the previous neural method DPE because it trains on word-level data. According to Zipf’s law, the number of distinct words in a document increases much slower than the increment of the total number of words. The speed is comparable to non-neural approaches, BPE, and faster than VOLT.

|                | ALT WMT16 Ro→En |
|----------------|-----------------|
| BPE (Sennrich et al., 2016) | 4 | 13 |
| VOLT (Xu et al., 2021) | 960 | 1,747 |
| DPE (He et al., 2020) | 3,477 | 68,334 |
| BERTSeg | 58 | 391 |

Table 8: Training speeds (seconds). 1: trained on CPU, ©: on 8 32GB GPUs, ♦: on 1 12GB GPU.

Size of Training Data With the pre-trained encoder, we can train a high-quality segmenter with a tiny train set. We train BERTSeg on words from 500k English sentences in the news commentary dataset and apply it to the ALT English words. The averaged BLEU score for MT is 24.45 whereas using only 18k ALT English data to train BERTSeg achieved 24.68 points, which are almost the same.

Subword Frequency Distribution Figure 2 shows the distribution of subword frequency in the decoded ALT train set of different methods with the same BPE vocabulary. Compared with BPE, BERTSeg generates more high-frequency (> 1000) subwords such as ed and ing. At the same time, more subwords in the vocabulary are not used during inference (with frequency 0). This phenomenon is also present in the comparison of BERTSeg-Regularization and BPE-dropout. Based on this
observation, it is possible to use a smaller vocabulary for BERTSeg. Additionally, we found the total subwords frequency of BERTSeg is higher because sometimes it also segments high-frequency words into subwords such as `years` into `year/s` whereas BPE keeps it as `years`.

![Subword frequency distributions of BPE, BPE-dropout, BERTSeg, and BERTSeg-Regularization.](image)

Figure 2: Subword frequency distributions of BPE, BPE-dropout, BERTSeg, and BERTSeg-Regularization.

**Zero-shot Word Segmentations**  Table 9 demonstrates the strong generalization ability on unseen words in the test set. Different from BPE which prefers high frequency pieces such as `fell` and `hip` in the word `fellowships`, BERTSeg identifies meaningful fragments `fellow` and `ships`.

| BERTSeg | BPE (Sennrich et al., 2016) |
|---------|-----------------------------|
| fellow/ships | fell/ows/hip/s |
| re/creation/al | rec/re/ational |
| dis/claim/er/s | disc/laim/ers |
| post/season | pos/se/e/ason |
| re/fresh/ed | ref/res/ed |
| worse/n/s | wor/s/ens |

Table 9: BERTSeg and BPE tested on unseen words.

**5 Related Work**

Early NMT studies apply word-level vocabulary to represent only frequent words, which causes the out-of-vocabulary (OOV) problem (Sutskever et al., 2014). To address this, character-based (Kim et al., 2016; Costa-jussà and Fonollosa, 2016; Ling et al., 2015), hybrid word-character based (Luong and Manning, 2016), or UTF-8 based (Shaham and Levy, 2021) NMT models were proposed. However, the resultant long input/output sequences increase the model and computational complexity.

Subword segmentation methods address the OOV problem by segmenting words into subwords that are in a fixed vocabulary of character n-grams. BPE (Sennrich et al., 2016; Gage, 1994) generates the subword vocabulary by first splitting all the sentences into characters, then iteratively saving the most frequent adjacent pairs into the vocabulary and merging them, until reaching the desired size. Each test sentence is segmented similarly. WordPiece (Schuster and Nakajima, 2012) and SentencePiece (Kudo and Richardson, 2018) are another two widely-used subword methods.

Among the subword methods, BPE (Sennrich et al., 2016) does not model the input sequence whereas SentencePiece (Kudo and Richardson, 2018) applies a unigram model to output probabilities of each segmentation. Based on sequence modeling via segmentations theory (Wang et al., 2017), the generation probability of a target sentence can be calculated by the sum of probabilities of all its possible segmentations. DPE (He et al., 2020) models the whole target sentence conditioned on the source sentence. However, we show that modeling words conditioned on their semantic embedding is a more efficient way.

Regularization as data augmentation can boost performance. BPE-dropout (Provilkov et al., 2020) randomly drops subword merge operation. SPM-regularization (Kudo, 2018) generates multiple segmentations with their probabilities. Leveraging the dynamic programming algorithm, we retrace the global best-$n$ segmentations with the highest probabilities in polynomial time.

**6 Conclusion and Future Work**

We proposed BERTSeg, an unsupervised neural subword segmenter for NMT, together with a regularization algorithm. MT results showed significant improvement over frequency-based and neural network-based methods. The training is efficient even compared with non-neural methods. To address the limitations shown in Appendix A, future works include eliminating the dependency on the BPE vocabulary, extending to a multilingual segmenter with mBERT (Devlin et al., 2019) embeddings, and applying it to other generation tasks.
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address this, a dual segmenter model is needed to optimize both the target segmentations and source segmentations.

**English Subword Segmenter Only** Currently we only train the subword segmenter for English due to there is only an English characterBERT model. However, we believe using embeddings from BERT or mBERT will not affect the performance, although it adds a dependency on the BERT tokenizer. To extend BERTSeg to mBERTSeg, a multilingual characterBERT is needed.

**Definition of Good Segmentation** The definition of good subword segmentation is beyond the scope of this paper, and we use the BLEU score as the metric to measure downstream tasks performance. However, measuring the segmentation quality is a more direct way. To achieve this, crowd-sourcing is a promising way to obtain a supervised subword segmentation dataset, at least for frequent words.

### B Example: Training and Inference

The training and inference are given by Equations 2 and 3, respectively. They are based on the sequence modeling theory that is first introduced in Wang et al. (2017) and there are multiple applications (Kawakami et al., 2019; Sun and Deng, 2018; Downey et al., 2021; Grave et al., 2019; Kreutzer and Sokolov, 2018; Wang et al., 2017). To understand the unsupervised training and inference processes more intuitively, we provide an example as illustrated in Figure 3.

In the training phase, the probability of the word “watching” is calculated by summing all possible segmentations. In the inference phase, we retrace the segmentation with the maximum probability for BERTSeg and retrace the best $N$ segmentations for BERTSeg-Regularization.

We also attached the code and will make the code public for better understanding and reproduction.

### C Example: Segmentations

We provide examples comparing the proposed method with BPE including high-frequency words, rare words and unseen words as shown in Table 10. We have the following observations:

- **For frequent words**, BERTSeg sometimes segment them into subwords even the word is in the vocabulary such as *official/s* and *use/d*. Additionally, the model can discriminate the

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**Figure 3:** An example of the training and inference phases.

**A Limitations**

Despite the effectiveness and efficiency, the proposed method has the following methodological and experimental limitations ranked in order of importance. We also provide directions to solve them as future works.

**Dependency on BPE Vocabulary** BERTSeg is a model to learn optimal segmentations for words but not paired with a vocabulary generation algorithm. Currently, the vocabulary is generated by BPE, therefore, many subwords in the vocabulary are not used, as shown in Figure 2. It is possible to address this by first generating a large vocabulary and then shrinking it iteratively, saving the commonly used subwords only, motivated by the SentencePiece work (Kudo and Richardson, 2018).

**Target Side Only** The goal of BERTSeg is to maximize the generation probability as shown in Eq. (2), therefore, can only apply to the target side data in generation tasks. Applying BERTSeg to the source side data will not improve the MT performance in our preliminary experiments, which is also reported in the DPE work (He et al., 2020). To
some observations from the experiments.

D Implementation Details of Baselines

This section aims to help to reproduce the results in the paper more easily. In the meantime, we provide

### Table 10: BERTSeg and BPE segmentations on frequent words, rare words and unseen words.

| BERTSeg         | BPE              |
|-----------------|------------------|
| **Frequent words** |                  |
| official/s      | officials        |
| edit/ion        | edition          |
| use/d           | used             |
| farm/er/s       | farmers          |
| contribute/d    | contributed      |
| normal/ty       | normal/ally      |
| seven/th        | seventh          |
| challenge/d     | challenge/ed     |
| over/night      | o/vernight       |
| language/s      | languages        |
| **Rare words**  |                  |
| inter/face/s    | inter/faces      |
| sea/ide         | sea/ide          |
| ab/normal/ly    | ab/normal/ally   |
| by/stand/er     | by/stand/er      |
| dis/comfort     | dis/comfort      |
| un/warrant/ed   | un/warranted     |
| in/definitely   | in/definitely    |
| **Unseen words**|                  |
| stable/d        | st/abled         |
| save/ls         | sa/vers          |
| M/li/ons        | Mill/ions        |
| Free/way        | Free/way         |
| M/i/s/behavior  | M/is/be/hav/ior  |
| m/o/u/n/ed      | m/our/ed         |
| M/a/d/a/m/e     | Mad/ame          |

Table 10: BERTSeg and BPE segmentations on frequent words, rare words and unseen words.

ambiguous situations very well. For example, the model can extract the prototype `challenge` from the word `challenged`.

- **For rare words** with frequency < 5 in the training set, BERTSeg gives much better segmentations than BPE, because BPE is a frequency-based method and thus handles rare words poorly.

- **For unseen words**, although the BERTSeg model gives better segmentations than BPE, we found that sometimes it oversegments words such as `M/a/d/a/m/e`. We guess it’s due to the low-quality word embedding from characterBERT, and we do not know the impact of this on the MT results.

D.1 BPE

**Vocabulary Size** Vocabulary size is a very important hyperparameter for the NMT experiments. For the ALT dataset, we did hyperparameter searching and 8,000 gave the highest BLEU scores averaged in all directions. For the IWSLT15 Vi-En, WMT16 Ro-En and WMT15 Fi-En datasets, we have tried two settings: 8,000 and 32,000, where using 8,000 gave a higher performance.

**The Size of Monolingual Data** In low-resource scenarios, using a larger monolingual dataset in the same domain to generate the BPE vocabulary gives better performance. We have used 500k English monolingual data from the news commentary dataset, and it gives 0.4 BLEU score improvements over using 18k ALT data to generate the BPE vocabulary.

**Comparison with SentencePiece** We used BPE as the baseline method because it gave higher performance (about 0.2 BLEU scores) than SentencePiece in low-resource scenarios. We assume that in the situation where the sentence is tokenized into words, the performance of BPE will be higher because the subwords in the BPE vocabulary do not contain spaces.

D.2 VOLT

| Dataset | Language | Size |
|---------|----------|------|
| ALT     | En/Id/Ja | 8k   |
| ALT     | Ms       | 6k   |
| ALT     | Vi       | 7k   |
| ALT     | Fil/Zh   | 9k   |
| IWSLT15 Vi-En | En/Vi | 7k   |
| WMT16 Ro-En | En    | 10k  |
| WMT16 Ro-En | Ro    | 11k  |
| WMT15 Fi-En | En    | 10k  |
| WMT15 Fi-En | Fi    | 8k   |

Table 11: Optimal BPE vocabulary sizes of languages in each dataset.
the results we got from hyperparameter searching, showing the effectiveness of the VOLT algorithm.

D.3 BPE-dropout
We have tried BPE-dropout rates of 0.05 and 0.1, where 0.1 gave higher BLEU scores. Note that statical BPE-dropout is not helpful, it is necessary to segment the train set for each epoch.

D.4 DPE
We basically followed the official implementations. The training requires 8 32GB GPUs to train for about one week for large datasets.