Adversarial Subword Regularization for Robust Neural Machine Translation

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Abstract
Exposing diverse subword segmentations to neural machine translation (NMT) models often improves the robustness of machine translation. As NMT models experience various subword candidates, they become more robust to segmentation errors. However, the distribution of subword segmentations heavily relies on the subword language models from which erroneous segmentations of unseen words are less likely to be sampled. In this paper, we present adversarial subword regularization (ADVSR) to study whether gradient signals during training can be a substitute criterion for choosing segmentation among candidates. We experimentally show that our model-based adversarial samples effectively encourage NMT models to be less sensitive to segmentation errors and improve the robustness of NMT models in low-resource datasets.

1 Introduction
Subword segmentation is a method of segmenting an input sentence into a sequence of subword units (Sennrich et al., 2016; Wu et al., 2016; Kudo, 2018). Segmenting a word to the composition of subwords alleviates the out-of-vocabulary problem while retaining encoded sequence length compactly. Due to its effectiveness in the open vocabulary set, the method has been applied to many NLP tasks including NMT (Gehring et al., 2017; Vaswani et al., 2017; Devlin et al., 2019; Yang et al., 2019).

Recently, Byte-Pair-Encoding (BPE) (Sennrich et al., 2016) has become one of the de facto subword segmentation methods. However, as BPE segments each word into subword units deterministically, NMT models with BPE always observe the same segmentation result for each word and often fail to learn diverse morphological features. In this regard, Kudo (2018) proposed subword regularization, a training method that exposes multiple segmentations using a unigram language model. As a result, other applications including NMT adopted subword regularization for the robustness of their models (Kim, 2019; Drexler and Glass, 2019; Müller et al., 2019).

However, subword regularization relies on the subword unigram language model to sample segmentation candidates. This causes NMT models to experience only limited sets of subword segmentations which are mostly observed in training sets. Thus, NMT models trained with the subword regularization can also fail to inference the meaning of unseen or noisy words having unseen segmentations. Figure 1 shows an example of a segmentation error from typos and the translation result from each model. This issue can be particularly problem-
atic for low resource languages where many morphological variations are not present in the training data.

In this work, we explore a different sampling strategy for the subword segmentations using gradient signals. We introduce a simple training method called adversarial subword regularization (ADVSR) to raise resilience against unseen segmentations or segmentation errors. We adopt the adversarial training framework (Goodfellow et al., 2014; Miyato et al., 2016; Ebrahimi et al., 2017; Cheng et al., 2019) to search for a subword segmentation. Our proposed method greedily searches for an adversarial subword segmentation which will likely incur the highest loss for each training sample. Our experiment shows that the NMT models trained with ADVSR consistently outperform the stochastic subword regularization at a maximum of 2.2 BLEU scores in standard benchmark datasets including IWSLT and MTNT. We also show that our model is highly robust to input typos.\(^1\)

2 Background

Subword Regularization Subword regularization (Kudo, 2018) exposes multiple subword candidates during training via on-the-fly data sampling. Proposed training method optimizes the parameter set \(\theta\) with marginal log-likelihood:

\[
\mathcal{L}(\theta) = \sum_{n=1}^{N} \mathbb{E}_{x \sim P_{\text{seg}}(x|X^{(n)})} \log P(y|x; \theta)
\]  

where \(x\) and \(y\) are sampled segmentations from the sentence \(X\) and \(Y\) through the unigram language model \(P_{\text{seg}}(\cdot)\). However as the exact optimization of Eqn. 1 is intractable, a finite number of samples\(^2\) are used during training.

The probability of a tokenized output is obtained by the product of each subword’s occurrence probability, where subword occurrence probabilities are attained through the Bayesian EM algorithm (Dempster et al., 1977; Liang et al., 2007; Liang and Klein, 2009). Segmentation output with maximal probability is acquired by using Viterbi algorithm (Viterbi, 1967).

Adversarial Regularization in NLP Adversarial samples are constructed by corrupting the original input with a small perturbation which distorts the model output. Miyato et al. (2016) adopted the adversarial training framework to the task of text classification, where input embeddings were perturbed with adversarial noise \(\hat{r}\):

\[
c_i^r = Ex_i + \hat{r}_i
\]  

where, \(\hat{r}_i = \arg\min_{\|r\| \leq \epsilon} \ell(X, r; Y; \theta)\) \(\epsilon\) is an embedding matrix, \(c_i^r\) is a perturbed embedding vector, and \(\ell(\cdot)\) is log-likelihood obtained with the input embeddings perturbed with noise \(r\). As it is computationally expensive to exactly estimate \(\hat{r}\) in Eqn. 3, Miyato et al. (2016) resorts to the linear approximation method (Goodfellow et al., 2014), where \(\hat{r}_i\) is approximated as follows:

\[
\hat{r}_i = \epsilon \frac{g_i}{\|g\|_2}, \quad g_i = \nabla_{e_i} \ell(X, Y; \theta)
\]  

where \(\epsilon\) indicates the degree of perturbation and \(g_i\) denotes a gradient of the loss function with respect to a word vector. Moreover, Ebrahimi et al. (2017) extended adversarial training framework to directly perturb discrete input space, i.e. character, through the first-order approximation by the use of gradient signals.

3 Approach

Our motivation is that relying on the likelihood criterion obtained from the training data exposes limited sets of subword candidates, hence hinders the NMT model in the consistent understanding for diverse segmentations from the word. We conjecture that this may harm the translation quality of the NMT models when morphological variations occur.

Therefore, we propose a simple training method that exposes diverse, but adversarial segmentation candidates through the use of gradient signals that can effectively regularize the NMT model. Our method seeks adversarial segmentations on-the-fly, thus the model chooses the subword candidates that are vulnerable to itself according to the state of the model at each training step.

3.1 Problem Definition

Our method generates a sequence of subwords by greedily replacing the word’s original segmentation to that of adversarial ones estimated by gradients. Given a source sentence \(X\) and a target sentence\(^3\)
As it is intractable to select the most adversarial word changes, the corresponding embedding and wise average operation for the aggregation for \( f \) where, \( e \) denotes the embedding lookup operation, \( d \) denotes the hidden dimension of embeddings and \( j \) as one of \( k \). We simply use the element-wise average operation for the aggregation for \( f \) in Eqn. 6, 7. Therefore if the segmentation of the word changes, the corresponding embedding and gradient vector will change accordingly.

### 3.2 Adversarial Subword Regularization

As it is intractable to select the most adversarial sequence of subwords, we greedily search for word-wise adversarial segmentation candidates. We approximately seek for the adversarial segmented result of a \( i \)-th word from the sentence \( X \) by following criteria which was originally proposed by Ebrahimi et al. (2017) and was used in other applications (Cheng et al., 2019; Wallace et al., 2019)

\[
\hat{x}_i = \arg\min_{x_i \in \Omega(x_i)} g_{\hat{x}_i}^T \cdot [e(\hat{x}_i) - e(x_i)]
\]

where Eqn. 9 approximately seeks the word’s segmented output \( \hat{x}_i \) which maximizes the loss. \( x_i \) represents one of the tokenized output among the possible candidates given raw text \( X_i \), and \( \hat{x}_i \) denotes an original segmentation of \( i \)-th word with maximal probability.

We uniformly select words in the sentence at a certain probability and replace them into adversarial subwords’ composition respectively. The ratio of words to replace into adversarial subwords is dependent on its sentence length, where we perturbed in-between quarter to third depending on the dataset. For generating the segmentation candidates per word, we use sentencepiece tokenizer (Kudo, 2018) and set the maximal number as 8. We seek the adversarial subword sequence for both the source sentence and the target sentence. Note that we only need a single gradient calculation for generating the sentence of adversarial subwords for both the source and the target sentence.

The existing adversarial training methods in the NLP domain generally trains the model with both the original samples and the adversarial samples (Miyato et al., 2016; Ebrahimi et al., 2017; Cheng et al., 2019; Motoki Sato, 2019). However, we trained the model with only the adversarial samples for the sake of fair comparison with the baselines.

### 4 Experimental Setup

#### 4.1 Datasets and Implementation Details

We conduct experiments on a low-resource multilingual dataset, IWSLT\(^3\), where unseen morphological variations outside the training dataset can occur frequently. We also test NMT models on MTNT (Michel and Neubig, 2018) which is a testbed for evaluating the NMT systems on noisy text scrapped from Reddit. We use the English-French language pair dataset. Table 1 summarizes the statistics of the datasets. Furthermore, for evaluating the robustness of the trained NMT models to the typos, we generate synthetic test data with typos that people often make. We utilize the NMT models trained on a clean benchmark dataset for evaluation of the MTNT (Michel and Neubig, 2018) and the synthetic dataset.

For all experiments, we use Transformer-Base (Vaswani et al., 2017) as a backbone model and follow the same regularization and optimization procedures by Vaswani et al. (2017) where we trained with joined dictionary of the size 16k. Our implementation is based on Fairseq.\(^4\)

\(^3\)https://iwslt.org/
\(^4\)https://github.com/pytorch/fairseq
### Table 1: Data statistics. The number in the parentheses denotes the number of sentences in the MTNT2019 test set which was provided by the WMT Robustness Shared Task (Li et al., 2019)

| Dataset | Lang Pair     | Number of sentences (train/valid/test) |
|---------|---------------|----------------------------------------|
| IWSLT17 | FR ↔ EN       | 232k / 890 / 1210                      |
|         | AR ↔ EN       | 231k / 888 / 1205                      |
| IWSLT15 | CS ↔ EN       | 105k / 1553 / 1327                     |
|         | VI ↔ EN       | 133k / 1553 / 1268                     |
| IWSLT13 | TR ↔ EN       | 132k / 887 / 1568                      |
|         | PL ↔ EN       | 144k / 767 / 1564                      |
| MTNT1.1 | FR → EN      | 19k / 886 / 1022 (1233)                |
|         | EN → FR      | 35k / 852 / 1020 (1401)                |

### Table 2: BLEU scores on the main results. Bold indicates the best score and all scores whose difference from the best is not statistically significant (with p-value of 0.05). (Statistical significance is computed via bootstrapping (Koehn, 2004))

| Lang Pair     | BASE | SR | ADVSR |
|---------------|------|----|-------|
| IWSLT17       |      |    |       |
| FR → EN       | 39.9 | 39.1| 40.0 |
| EN → FR       | 39.3 | 39.4| 40.0 |
| AR → EN       | 31.7 | 32.3| 33.3 |
| EN → AR       | 14.4 | 14.3| 14.7 |

| Lang Pair     | BASE | SR | ADVSR |
|---------------|------|----|-------|
| IWSLT15       |      |    |       |
| CS → EN       | 26.9 | 27.0| 27.8 |
| EN → CS       | 20.4 | 21.7| 23.6 |
| VI → EN       | 28.1 | 28.4| 29.2 |
| EN → VI       | 30.9 | 31.7| 32.5 |

| Lang Pair     | BASE | SR | ADVSR |
|---------------|------|----|-------|
| MTNT2018      |      |    |       |
| FR → EN       | 25.7 | 27.6| 27.9 |
| EN → FR       | 26.6 | 27.9| 29.2 |
| MTNT2018 + FT |      |    |       |
| FR → EN       | 36.5 | 37.9| 38.8 |
| EN → FR       | 33.2 | 34.4| 35.3 |

| Lang Pair     | BASE | SR | ADVSR |
|---------------|------|----|-------|
| MTNT2019      |      |    |       |
| FR → EN       | 27.6 | 29.3| 30.2 |
| EN → FR       | 22.8 | 23.8| 24.1 |
| MTNT2019 + FT |      |    |       |
| FR → EN       | 36.2 | 38.1| 38.6 |
| EN → FR       | 27.6 | 28.2| 28.9 |

**4.2 Evaluation**

For inference, we use a beam search with a beam size of 4. For evaluation, we used the best checkpoint which performed best in the validation dataset. We evaluated translation quality through BLEU (Papineni et al., 2002) computed by SacreBLEU (Post, 2018). Our baselines are the NMT models trained with deterministic segmentations having maximum probability, and the subword regularization method (Kudo, 2018). We set the hyperparameters of subword regularization equivalent to that of Kudo (2018). Byte Pair Encoding (Sennrich et al., 2016) is not used as the baseline model since the performance is almost the same as that of BASE according to Kudo (2018).

### 5 Experiments

#### 5.1 Main Results

Table 2 shows the main results on standard benchmark datasets. Our method improves over the BASE and the SR consistently. This shows that diversely exposing various segmentations is more effective than making the NMT models observe limited sets of segmentation candidates in the low-resource setting. Specifically, ADVSR maximally improves 2.2 BLEU over SR and 3.5 BLEU over BASE in the English to Czech dataset. We assume that the large gains are due to the linguistic characteristic of Czech, which is morphologically rich.

Generally, our method shows its effectiveness when the source languages are morphologically complex. The performance improvement over the baselines in in-domain datasets can be explained by the robustness to unseen lexical variations, i.e. compound words, where shortage of training data can evoke the problem. Our method effectively exposes vulnerable and diverse subword candidates to the NMT model by not relying on subword unigram language model trained on the train dataset.

#### 5.2 Results on Out Domain Datasets

For evaluating robustness to the out-of-domain distribution, we evaluate the NMT models trained with clean benchmark datasets on the out domain benchmark dataset, MTNT (Michel and Neubig, 2018). We use the training and validation datasets.
Table 4: BLEU scores on the synthetic dataset of typos. The column lists results for different noise fractions.

| Method | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|--------|-----|-----|-----|-----|-----|
|        | FR  | EN  |     |     |     |
| BASE   | 30.7| 25.6| 20.3| 16.2| 11.4|
| SR     | 33.2| 28.5| 23.3| 18.7| 14.7|
| ADVSR  | 34.8| 32.0| 29.2| 25.7| 22.2|

5.3 Results on Synthetic Dataset

Additionally, we conduct an experiment to see the change of translation quality according to various noise levels. We synthetically generated 3 types of noise, 1. character drop, 2. character swap, 3. character insert and perturbed each word with the given noise probability.

Table 4 shows the result. As the noise fraction increases, our method shows its high robustness compared to the baseline models maximally improving 10.8 BLEU scores over BASE, and 7.5 over SR. This verifies that our method effectively improves the robustness of the NMT models against segmentation errors from typos.

6 Related Work

Subword segmentation has been widely used since Byte-Pair-Encoding (Sennrich et al., 2016) was proposed. Kudo (2018) introduced subword regularization and other segmentation methods have been propose as well (Creutz and Lagus, 2005; Schuster and Nakajima, 2012; Chitnis and DeNero, 2015). Recently, the BPE-dropout (Provilkov et al., 2019) was introduced, which enables the stochastic segmentation of the BPE. Also, there is another line of research that utilizes character-level segmentation (Luong and Manning, 2016; Lee et al., 2017; Cherry et al., 2018).

Other works explored generating synthetic or natural noise for regularizing NMT models (Belinkov and Bisk, 2018; Sperber et al., 2018; Karpukhin et al., 2019). Michel and Neubig (2018) introduced a dataset scrapped from Reddit for testing the NMT systems on the noisy text. Recently, a shared task on building the robust NMT models was held (Li et al., 2019; Bérard et al., 2019).

Our method extends the adversarial training framework, which was initially developed in the vision domain (Goodfellow et al., 2014) and has begun to be adopted in the NLP domain recently (Miyato et al., 2016; Samanta and Mehta, 2017; Motoki Sato, 2019; Wang et al., 2019; Cheng et al., 2019). Miyato et al. (2016) first adopted the adversarial training framework on text classification by perturbing embedding space with continuous adversarial noise. Wang et al. (2019) and Motoki Sato (2019) extended the corresponding method to regularize the language models and the NMT models respectively. Their methods regularize neural models by perturbing embedding space, whereas our model perturbs the discrete input space. Cheng et al. (2019) introduced adversarial training framework by discrete word replacements where candidates were generated from the the language model. However, our method does not replace the word but replaces its subword composition. Therefore distortion is not perceived in the context of adversarial attack.

7 Conclusion

In this study, we propose adversarial subword regularization which virtually augments training data by exposing diverse segmentations using gradient signals. As shown in our experiments, sampling segmentations from subword unigram language might bias NMT models to frequent segmentations in the training set and make them vulnerable to unseen lexical variations. Our method effectively improves the robustness of the NMT models to unseen segmentations, especially in low-resource settings.

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