Abstract

We propose a novel technique of combining multiple subword tokenizations of a single source-target language pair for use with multilingual neural translation training methods. These alternate segmentations function like related languages in multilingual translation, improving translation accuracy for low-resource languages and producing translations that are lexically diverse and morphologically rich. We also introduce a cross-teaching technique which yields further improvements in translation accuracy and cross-lingual transfer between high- and low-resource language pairs. Compared to other strong multilingual baselines, our approach yields average gains of +1.7 BLEU across the four low-resource datasets from the multilingual TED-talks dataset. Our technique does not require additional training data and is a drop-in improvement for any existing neural translation system.

1 Introduction

Multilingual neural machine translation (NMT, Dong et al. 2015; Johnson et al. 2017) models are capable of translating from multiple source and target languages. Besides allowing efficient parameter sharing (Aharoni et al., 2019) these models facilitate inherent transfer learning (Zoph et al., 2016; Firat et al., 2016) that can especially benefit low resource languages (Nguyen and Chiang, 2017; Gu et al., 2018; Neubig and Hu, 2018; Tan et al., 2019). A common technique to address lexical sharing and complex morphology in multilingual NMT is to decompose longer words into shorter subword units (Sennrich et al., 2016). Since subword units are produced using heuristic methods, not all subwords are created equally. This can put low- and extremely low-resource languages at a disadvantage, even when these languages are paired with a suitable high resource language. To diminish the impact of rare subwords in NMT, Kambhatla et al. (2022) leverage ciphertexts to augment the training data by constructing multiple-views of the source text. “Soft” decomposition methods based on transfer learning (Wang et al., 2018) address the problem of sub-optimal word segmentation with shared character-level lexical and sentence representations across multiple source languages (Gu et al., 2018). Wang et al. (2021) addressed this problem with a multiview-subword regularization technique that also improves the effectiveness of cross-lingual transfer in pretrained multilingual representations by simultaneously finetuning on different input segmentations from a heuristic and a probabilistic tokenizer. While subword-regularization methods (Kudo, 2018; Provilkov et al., 2020) have been widely explored in NMT, this work is the first to study them together with multilingual training methods.

Concretely, we construct pairs of “related languages” by segmenting an input corpus twice, each time with a different vocabulary size and algorithm for finding subwords: we use these “languages” (really, views of the same language) for multilingual training of an NMT model. We propose Multi-Sub training, a method that combines multilingual NMT training methods with a diverse set of auxiliary subword segmentations which func-
tion like related languages in a multilingual setting since they have distinct but partially-overlapping vocabularies and share the same underlying lexical and grammatical features. Our model is able to transfer information between segmentations analogous to the way information is transferred between typologically similar languages.

We also introduce a cross-teaching technique in which a model is trained to translate source sentences from one subword tokenization into target sentences from a different subword tokenization. By using Multi-Sub training together with cross-teaching, we obtain strong results on four low-resource languages in the multilingual TED talks dataset outperforming strong multilingual baselines, with the most significant improvements in the lowest-resource languages. In addition to improving the BLEU scores, our technique captures word compositionality better leading to improved lexical diversity and morphological richness in the target language. Multi-Sub with cross-teaching is better at clustering different languages in the sentence embedding space than previous methods including Multi-Sub without cross-teaching.

2 Auxiliary Segmentation as a Related Language

Pairing related languages is common in multilingual NMT\(^1\): Nguyen and Chiang (2017) combine Uzbek/Turkish and Uzbek/Uyghur; Johnson et al. (2017) study multilingual translation to and from English with pairs such as Spanish/Portuguese or Japanese/Korean. Neubig and Hu (2018) pair low resource languages like Azerbaijani with a related “helper” language like Turkish.

We take these techniques as motivation for the present work. Our principal contribution is to rethink what it means to use “related” languages in a multilingual translation model. Beyond simply employing other languages from the same family, or those with high lexical overlap, we show that a model trained on different segmentations of the same language can produce improvements in translation quality.

Rather than segmenting a corpus with a single tokenizer prior to training a translation model, we produce multiple segmentations using different tokenizers. Consider the example sentences in Figure 1. On both the source and target sides, the same sentence is represented using both Byte-pair Encodings (BPEs, Sennrich et al. 2016, with a “@” separator) and in parallel as sentencepieces (SP, Kudo 2018, with a “.” separator). Each segmentation uses a different vocabulary size, which guarantees that their subword sequences are to some extent distinct. The two tokenizations still resemble one other in many ways: (i) they have a non-trivial degree of lexical overlap (mostly between subwords which do not fall along word boundaries); (ii) they share the same grammatical structure, as both represent the same underlying language; and (iii) both sequences have the same semantic interpretation. We thus refer to the two segmentations as a pair of “related languages”.

Applying two segmentations to a parallel corpus yields a total of four “languages”: the source and target represented as BPE subwords, and the same represented using SP subwords. We obtain two source “languages” (each containing data from both high and low resource languages) and two target “languages”. Using this four way configuration, we train a model following a common multi-

\(^1\)Here we do not distinguish between languages which are related in the linguistic sense (having some genetic affiliation) and those which are related in a more pragmatic sense of having high lexical overlap.
lingual training method (Johnson et al., 2017): depending on the segmentation we want to translate into, we prepend a target token [2bpe] or [2sp] to the source side. We explore two different multilingual training configurations:

[BPE+SP]: In this setting, a source sentence in a particular segmentation is translated into the target with the same segmentation. Specifically, this model is trained multilingually on the pairs

\[ \text{BPE [src]} \rightarrow \text{BPE [tgt]} \]
\[ \text{SP [src]} \rightarrow \text{SP [tgt]} \]

Cross-teaching: In addition to BPE+SP, in this setting, each source sentence with a particular segmentation is translated into the target with alternate segmentation. This multilingual model is therefore trained on the following pairs:

\[ \text{BPE [src]} \rightarrow \text{SP [tgt]} \]
\[ \text{SP [src]} \rightarrow \text{BPE [tgt]} \]

Using multilingual training, our model is able to transfer information between BPE and SP segmentations in much the same way that conventional multilingual models transfer information between languages with a shared linguistic affiliation. Unlike data augmentation techniques which generate synthetic training data, Multi-Sub training uses only the content of the original training corpus. Furthermore, contrary to other works which employ multiple segmentations (Wang et al., 2018; Wu et al., 2020), Multi-Sub training and cross-teaching do not affect model architecture and do not require specialised training. Thus Multi-Sub training can be used as a simple, drop-in improvement to an existing neural translation model.

3 Experiments

3.1 Experimental Setup

Data Following prior work on low-resource and multilingual NMT (Neubig and Hu, 2018; Wang et al., 2018) we use the multilingual Ted talks dataset (Qi et al., 2018). We use four low resource languages (LRL): Azerbaijani (az), Belarusian (be), Galician (gl) and Slovak (sk), and four high resource languages (HRL): Turkish (tr), Russian (ru), Brazilian-Portuguese (pt), and Czech (cs). In all experiments and baselines, each LRL is paired with the related HRL and English is the target language.

Table 1 shows general statistics for each dataset. Based on the size of the training data, we consider az, be and gl as extremely low-resource while sk is a slightly higher-resource dataset.

| LRL | #train | #dev | #test | HRL | #train |
|-----|--------|------|-------|-----|--------|
| az  | 5.9k   | 671  | 903   | tr  | 182k   |
| be  | 4.5k   | 248  | 664   | ru  | 208k   |
| gl  | 10.0k  | 682  | 1007  | pt  | 185k   |
| sk  | 61.5k  | 2271 | 2445  | cs  | 103k   |

Table 1: Statistics from our low resource language (LRL) and high resource language (HRL) datasets.

Model Details Our model comprises a single bi-directional LSTM as encoder and decoder, with 128-dimensional word embeddings and 512-dimensional hidden states. We are careful to keep this configuration consistent with our baseline model (Neubig and Hu, 2018) to ensure a fair comparison. We use fairseq$^2$ to implement the baseline as well as our proposed models. We set dropout probability to 0.3, and use an adam optimizer with a learning rate of 0.001. In practice, we train a Multi-Sub model until convergence, and then use this model to continue training on cross-teaching data until convergence. For inference, we use beam size 5 with length penalty. We use sacrebleu$^3$ (Post, 2018) to report BLEU (Papineni et al., 2002) scores on the detokenized translations. We perform statistical significance tests for our results based on bootstrap resampling (Koehn, 2004) using compare-mt toolkit.$^4$

For fair comparison with prior work, we use BPE (Subword-nmt, Sennrich et al. 2016) as our primary segmentation toolkit and sentencepiece (SP, Kudo 2018) as our auxiliary tokenizer. We only use the BPE segmentations to tune our model via validation. In other words, while we train on both BPE and SP, we save model checkpoints that are optimized for BPE tokenized inputs.$^5$

Following Neubig and Hu (2018), we separately learn 8k BPE subwords on each of the source and target languages. When combining an LRL and a HRL, we take the union of the vocabulary on the source side and the target side separately. We use the same procedure with the SP tokenizer using a subword vocabulary size of 4k. To train BPE and SP together, we take the union of the vocabularies

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$^2$https://github.com/pytorch/fairseq

$^3$SacreBLEU signature: BLEU+CASE,MIXED+NUMREFS.1+SMOOTH.EXP+TOK.13A+VERSION.1.4.14

$^4$https://github.com/neulab/compare-mt

$^5$Our model can handle sentencepiece inputs as well. For a model that performs equally well on BPE and SP, construct a validation set with equal number of source sentences with both segmentations and save the checkpoints optimized for the validation metric. We chose BPE segments for validation to be comparable with previous work.
of the source and target sides separately, resulting in a vocabulary which is union of the BPE and SP subword vocabularies of each side.

3.2 Main results

We compare the results of our Multi-Sub models against various baselines in Table 2. Sub-sep models use a union of subword vocabularies learned separately for each of the source and target languages; the union is performed separately for the source and target sides yielding two separate vocabularies. Sub-joint refers to subword vocabularies learned jointly on the concatenation of all of the source and target languages. Such models consistently perform worse than their sub-sep counterparts for all datasets, as the HRL tends to occupy a larger share of the vocabulary and leaves the LRL with a smaller vocabulary as well as smaller subwords. Our reimplementation of the sub-sep model (Neubig and Hu, 2018) mitigates this by (separately) learning the same number of subwords for the HRL and LRL. Using words instead of subwords performs on par with the sub-sep model for $g_1 \rightarrow \text{en}$ but worse for other languages.

We see that our model, Multi-Sub, handily outperforms all of these baselines. Compared to the de-facto sub-sep model (highlighted in grey, and used as the baseline in the rest of the paper), Multi-Sub without cross-teaching gains +1.2 BLEU points on az and be, and +0.9 on gl. The improvement on cs is not large, but is significant at +0.4 BLEU.

We also compare our approach against more sophisticated models, such as soft decoupled encoding (SDE, Wang et al. 2018) which shares lexical and latent semantic representations across multiple source languages. Our modest Multi-Sub model with cross-teaching outperforms SDE (with words as lexical units) on three out of four languages, with the largest gain being +0.9 BLEU on az $\rightarrow \text{en}$. Multi-Sub consistently and significantly outperforms subword-level SDE on all language pairs with gains ranging from +0.4 BLEU to +2.5 BLEU. Note that although Multi-Sub is -0.7 BLEU behind word-level SDE on gl, it outperforms sub-sep by +2.6 BLEU and subword-level SDE by +2.5 BLEU.

Overall, our models are consistently better than the sub-sep baseline. For most languages, substantial improvements over the baseline come when the Multi-Sub model is combined with cross-teaching.

3.3 Comparison with Subword Regularization

Table 3 contrasts Multi-Sub against BPE-dropout (Provilkov et al., 2020), a subword regularization technique.\(^7\) For comparison we report results from the baseline sub-sep model with and without subword regularization. Our implementation applies BPE-dropout to the training data with probability $p = 0.1$, and the model and training are otherwise identical to sub-sep.

Although subword regularization improves upon the baseline model, the difference is small, likely because of the small amount of data avail-

\(^6\)The numbers are from our reimplementation of Neubig and Hu (2018). Original BLEU scores on this dataset were az: 10.9, be: 15.8, gl: 27.3, sk: 25.5 while a reimplementation by Wang et al. (2018) yields az: 10.9, be: 16.17, gl: 28.1, sk: 28.5. Our implementation matches the performance on all test sets except for gl where we lag by 0.5 points.

\(^7\)Using only one tokenizer (either BPE or SP) with different subword sizes closely resembles subword regularization. Using SP and BPE, on the other hand, results in different word-boundary markers that makes our technique distinct.

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| Lex Unit | Model | tr/az | ru/be | pt/gl | cs/sk |
|---------|-------|-------|-------|-------|-------|
| Word    | Lookup| 7.66  | 13.03 | 28.65 | 25.24 |
| Sub-joint| Lookup| 9.40  | 11.72 | 22.67 | 24.97 |
| Sub-sep  | UniEnc (Gu et al., 2018) | 4.80  | 8.13  | 14.58 | 12.09 |
| Sub-sep  | Lookup (Neubig and Hu, 2018) | 10.8  | 16.2  | 27.7  | 28.4 |
| Sub-sep  | Adaptation (All $\rightarrow$ Bi) (ibid.) | 11.7  | 18.3  | 28.8  | 28.2 |
| Word    | SDE (Wang et al., 2018) | 11.82 | 18.71 | 30.30 | 28.77 |
| Sub-sep  | SDE (ibid.) | 12.35 | 16.30 | 28.94 | 28.35 |
| Multi-Sub (BPE 8k + SP 4k) | Lookup [BPE + SP] (Ours) | 12.0** | 18.5** | 28.6** | 28.8** |
|         | Lookup + Cross-teaching (Ours) | 12.7** | 18.8** | 29.6** | 28.6** |

Table 2: All models are trained on a LRL and a related HRL with English as the target language with LSTMcs. BLEU scores are reported on the test set of the LRL. The sub-sep lookup model (Neubig and Hu, 2018) is our primary baseline (shaded in grey). Our best results compared to the baseline are underlined. Bolding indicates best overall results on the datasets. We indicate statistical significance w.r.t primary baseline with $\dagger$ ($p < 0.05$), $\ast$ ($p < 0.001$) and $\ast\ast$ ($p < 0.0001$).
Table 3: Comparing subword regularization (SR) with our best results. We use BPE-dropout (Provilkov et al., 2020) at $p = 0.1$.

| Sub-sep | + SR | Multi-sub |
|---------|------|-----------|
| tr/az   | 10.8 | 12.7      |
| ru/be   | 16.2 | 18.8      |
| pt/gl   | 27.7 | 29.6      |
| cs/sk   | 28.4 | 28.8      |
Table 5: Lexical diversity of the reference human translations vs. model outputs in different settings for each LRL.

| LRL | Model | BLEU | TTR | RTTR | LTTR | MTTR ↓ | HD-D | MTLD | MTLD-A | MTLD-Bi | Yule’s K ↓ |
|-----|-------|------|-----|------|------|--------|------|------|--------|---------|-------------|
| Az → En | Reference | - | 0.1845 | 22.98 | 0.8248 | 0.0367 | 0.8738 | 106.60 | 108.47 | 108.17 | 80.68 |
| 1 Base | | 10.8 | 0.0855 | 10.9615 | 0.7466 | 0.0600 | 0.7750 | 33.9342 | 38.3466 | 38.1259 | 170.4321 |
| 2 BPE 8k + SP 4k | | 12.0 | 0.0971 | 12.2866 | 0.7591 | 0.0752 | 0.7936 | 40.0937 | 44.7958 | 44.8005 | 152.0778 |
| 3 2 × Cross-teach | | 12.7 | 0.0993 | 12.4746 | 0.7610 | 0.0650 | 0.7961 | 41.3529 | 45.4622 | 45.3590 | 149.4563 |
| Be → En | Reference | - | 0.1863 | 20.83 | 0.8219 | 0.0366 | 0.8687 | 102.95 | 104.44 | 104.36 | 85.73 |
| 1 Base | | 16.2 | 0.1149 | 13.0503 | 0.7714 | 0.0556 | 0.8045 | 51.1452 | 52.4293 | 52.5771 | 139.7345 |
| 2 BPE 8k + SP 4k | | 18.5 | 0.1225 | 13.7806 | 0.7777 | 0.0542 | 0.8017 | 52.9199 | 53.0382 | 53.0415 | 147.5613 |
| 3 2 × Cross-teach | | 18.8 | 0.1249 | 14.0746 | 0.7799 | 0.0536 | 0.8071 | 54.8368 | 55.6391 | 55.7884 | 142.6042 |
| Gl → En | Reference | - | 0.1484 | 19.45 | 0.8043 | 0.0462 | 0.8643 | 91.22 | 94.81 | 94.67 | 87.92 |
| 1 Base | | 27.7 | 0.1329 | 17.1629 | 0.7924 | 0.0492 | 0.8312 | 72.9798 | 73.9316 | 73.8523 | 120.5782 |
| 2 BPE 8k + SP 4k | | 28.6 | 0.1365 | 17.6551 | 0.7952 | 0.0485 | 0.8328 | 76.0790 | 75.5915 | 75.5872 | 147.5613 |
| 3 2 × Cross-teach | | 29.6 | 0.1366 | 17.7624 | 0.7955 | 0.0484 | 0.8307 | 74.6902 | 73.7315 | 73.7201 | 112.5075 |
| Sk → En | Reference | - | 0.1253 | 25.5328 | 0.8047 | 0.0423 | 0.8689 | 95.38 | 102.52 | 102.24 | 86.20 |
| 1 Base | | 28.4 | 0.0935 | 18.9185 | 0.7769 | 0.0484 | 0.8383 | 72.5259 | 74.8386 | 74.9117 | 112.8484 |
| 2 BPE 8k + SP 4k | | 28.8 | 0.0954 | 19.3010 | 0.7787 | 0.0480 | 0.8411 | 74.5821 | 75.6236 | 75.6301 | 110.8807 |
| 3 2 × Cross-teach | | 28.6 | 0.0947 | 19.3118 | 0.7784 | 0.0480 | 0.8379 | 72.8657 | 74.7803 | 74.8770 | 112.6107 |

The ratio \( v_{LRL} / v_{HRL} \) is directly proportional to the number of training samples in the LRLs. This ratio has a generally negative correlation to the BLEU gains in our models—the more training data is available, the smaller the improvements. This strongly suggests that using auxiliary subwords as a foreign language is a technique best suited to low resource languages.

4.2 Linguistic Complexity

While estimating linguistic complexity is a multifarious task, lexical and morphological diversity are two of its major components. In this section we perform an exhaustive assessment of our models’ translations using lexical diversity metrics (Section 4.2.1) and morphological inflectional diversity metrics (Section 4.2.2).

4.2.1 Lexical Richness

We use several metrics to quantify lexical diversity across translations from different models. The metrics include type-token ratio (TTR) and its variants—Root TTR (RTTR, Guiraud 1960), Log TTR (LTTR), and (MATTR, Covington and McFall 2010)—hypergeometric distribution D (HDD, McCarthy and Jarvis 2007), measure of textual, lexical diversity (MTLD, McCarthy 2005) and Yule’s K (Yule, 2014). The scores for these measures are presented in Table 5 for our model outputs and for the reference human translations.

On average, Multi-Sub training with cross-teaching significantly improves the lexical diversity of the generated translations. Improvements in lexical diversity correlate with BLEU scores in all languages (which need not be the case, cf. Vanmassenhove et al. 2021), implying that our methods produce translations which are not only more accurate, but also richer and more varied in terms of vocabulary. These effects are most pronounced in the lowest-resource languages, az and be, where cross-teaching yields improvements in every metric relative to both the baseline and Multi-Sub training without cross-teaching. In gl, cross-teaching yields improvements in all metrics except MTLD and its variants, which are optimized by Multi-Sub training without cross-teaching. Sk is unique in that the greatest improvements for most metrics come from Multi-Sub training without cross-teaching. This parallels the pattern observed in the BLEU scores (Table 4), and confirms our earlier claim that cross-teaching is most effective in cases of extreme data scarcity, while Multi-Sub training without cross-teaching works better for high resource languages.

4.2.2 Morphological Richness

To examine the morphological complexity of the translations produced by our models, we averaged the inflectional diversity of the lemmas. Following Vanmassenhove et al. (2021), we used the Spacy-udpipe lemmatizer to retrieve all lemmas. Shannon Entropy (H, Shannon 1948) is used to measure the variety of inflected forms associated with a given lemma (higher entropy means more variation). Entropy is averaged across each lemma.

\[^8\text{The intent of this section is not to claim that LD metrics are potential indicators of proficiency, quality or sophistication; they simply represent qualities which may be desirable for certain applications, cf. Vanmassenhove et al. (2021).}\]

\[^9\text{https://github.com/TakeLab/spacy-udpipe}\]
in the model outputs.

**Simpson’s Diversity Index (D, Simpson 1949)** measures the probability that two randomly-sampled items have the same label; large values imply homogeneity (most items belong to the same category). We measure morphological diversity by computing the probability that two instances of a given lemma represent the same inflected form.

The results in Table 6 parallel the lexical diversity evaluation: in the extremely low-resource languages az and be, cross-teaching yields a clear improvement in both the entropy and diversity index of the output translations. The model thus employs a greater variety of inflectional forms, which provides more choices to the decoder (Vanmassenhove et al., 2021) (c.f. Fig. 8). In slightly higher-resource languages like sk, the impact of cross-teaching is less pronounced: the best diversity index is in gl, but Multi-Sub training without cross-teaching yields the best entropy. Multi-Sub training without cross-teaching also yields the greatest degree of morphological diversity in sk.

| Model          | gl   | sk   |
|----------------|------|------|
| Base           | 0.39 | 0.11 |
| Multi-Sub/Cross-teaching | **0.51** | **0.12** |

Table 7: F1 scores on zero-shot NER in sk and gl. † means the best result comes from cross-teaching; * means the best result comes without cross-teaching.

**4.3 Improved Cross-lingual Transfer**

**Downstream Task: NER** Multi-Sub training improves the usefulness of subword embeddings for downstream tasks. We train NER models on pt and cs using the pre-trained embeddings from our translation models; then, following Sharoff 2017, we evaluate each of these models on the corresponding LRL. Since the NER models are never trained on LRL data, this is a zero-shot evaluation where model performance should reflect the degree of multilinguality in the pre-trained embeddings. Table 7 reports F1 scores for this task. We observe that Multi-Sub training on its own can yield significant performance improvements (as in gl), but cross-teaching is sometimes required to obtain optimal results (as in sk).

**Visualizations of Sentence Embeddings** We find that cross-teaching significantly reduces the separation between different tokenizations in the sentence representations of certain languages. Figure 3 shows the distribution of sentence representations produced by our two tokenizers. In the baseline, BPE-tokenized sentences are clearly separated from (parallel) SP-tokenized sentences; in the Multi-Sub setting we observe less separation, although distinct clusters of BPE and SP inputs are still clearly visible. By contrast, in the cross-teaching setting, there is significant overlap between training data taken from Sevcikova et al. 2007, sk; test data from Piskorski et al. 2017, and pt/gl training and test data from Garcia and Gamallo 2014.
If you want to know about climate, you ask a climatologist.

This suggests that cross-teaching serves to eliminate “monolingual” subspaces (that is, subspaces representing a single tokenization) in favor of representing all input languages in the same joint space. On the basis of this result, we argue that cross-teaching is an effective technique for increasing the degree of multilinguality in a translation model.\textsuperscript{11}

### 5 Qualitative Analysis

We list translations for the baseline sub-sep and SDE models along with our Multi-Sub model in Table 8. While sub-sep results in an entirely unrelated translation of the gl word climatólogo, SDE produces a related word weather. Multi-Sub, however, produces an accurate translation of the word which is climatologist.

### 6 Related Work

Several techniques have been proposed to improve lexical representations for multilingual machine translation. Zoph et al. (2016) propose to first train a HRL parent model, then transfer some of the learned parameters to the LRL child model to initialize and constrain training. Similarly, Nguyen and Chiang (2017) pair related languages together and transfer source word embeddings from parent-HRL words to their child-LRL equivalents. Johnson et al. (2017); Neubig and Hu (2018), on the other hand, learn a joint vocabulary over several languages and train a single NMT model on the concatenated data. Gu et al. (2018) introduce a latent embedding space shared by all languages to enhance parameter sharing in lexical representation. Wang et al. (2018); Gao et al. (2020) use a similar idea but use character n-gram encodings (SDE) instead of the conventional subword/word embeddings. By contrast Multi-Sub does not involve any architectural changes and improves the representation of low-resource languages by training on multiple segmentations of the same corpus.

Subword-regularization methods (Kudo, 2018; Provilkov et al., 2020) share the motivation of alleviating sub-optimal subwords by exposing a model to multiple segmentations of the same word. However, our method is substantially different in that (i) we use two completely different subword algorithms with different vocabulary sizes (contra Wang et al. 2021), and (ii) we do not rely on expensive sampling procedures (contra Kudo 2018) or additional data to learn an LM. Especially for low-resource languages, our method not only improves translation quality but also enhances a model’s cross-lingual transfer capabilities. Finally, this simple architecture-agnostic technique can act as drop-in improvement for existing methods.

### 7 Conclusion

This work introduces Multi-Sub training with cross-teaching—a novel technique that combines multiple alternative subword tokenizations of a source-target language pair—to improve the representation of low-resource languages. Our proposed methods obtain significant gains on low-resource datasets from multilingual TED-talks. We performed exhaustive analysis to show that our methods also increase the lexical and morphological diversity of the output translations, and produce better multilingual representations which we demonstrate by performing zero-shot NER by exploiting representations from a high resource language. Multi-Sub training and cross-teaching are simple architecture-agnostic steps which can be easily applied to existing single or multilingual neural machine translation models and do not require any external data.

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\textsuperscript{11}In this respect, cross-teaching has a similar effect to BPE-dropout (Provilkov et al., 2020), which serves to eliminate monolingual subspaces at the level of subword embeddings (but recall our prior comments on the distinction between BPE-dropout and Multi-Sub in Section 3.3).
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References

Aharoni, Roee, Melvin Johnson, and Orhan Firat. 2019. Massively multilingual neural machine translation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies.

Covington, Michael A, and Joe D McFall. 2010. Cutting the gordian knot: The moving-average type–token ratio (mattr). Journal of quantitative linguistics, 17(2):94–100.

Dong, Daxiang, Hua Wu, Wei He, Dianhai Yu, and Haifeng Wang. 2015. Multi-task learning for multiple language translation. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, Beijing, China.

Firat, Orhan, Kyunghyun Cho, and Yoshua Bengio. 2016. Multi-way, multilingual neural machine translation with a shared attention mechanism. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies.

Gao, Luyu, Xinyi Wang, and Graham Neubig. 2020. Improving target-side lexical transfer in multilingual neural machine translation. In Findings of the Association for Computational Linguistics: EMNLP 2020.

Garcia, Marcos, and Pablo Gamallo. 2014. Multilingual corpora with coreferential annotation of person entities. In Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14), Reykjavik, Iceland. European Language Resources Association (ELRA).

Gu, Jiatao, Hany Hassan, Jacob Devlin, and Victor OK Li. 2018. Universal neural machine translation for extremely low resource languages. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies.

Guiraud, P. 1960. Problèmes et Méthodes de la Statistique Linguistique. Presses universitaires de France.

Johnson, Melvin, Mike Schuster, Quoc V Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, et al. 2017. Google’s multilingual neural machine translation system: Enabling zero-shot translation. Transactions of the Association for Computational Linguistics, 5:339–351.

Kambhatla, Nishant, Logan Born, and Anoop Sarkar. 2022. CipherDAug: Ciphertext Based Data Augmentation for Neural Machine Translation. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers).

Koehn, Philipp. 2004. Statistical significance tests for machine translation evaluation. In Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing, Barcelona, Spain.

Kudo, Taku. 2018. Subword regularization: Improving neural network translation models with multiple subword candidates. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics.

McCarthy, Philip M. 2005. An assessment of the range and usefulness of lexical diversity measures and the potential of the measure of textual, lexical diversity (MTLD). Ph.D. thesis, The University of Memphis.

McCarthy, Philip M. and Scott Jarvis. 2007. vocd: A theoretical and empirical evaluation. Language Testing, 24(4):459–488.

Neubig, Graham, and Junjie Hu. 2018. Rapid adaptation of neural machine translation to new languages. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing.

Nguyen, Toan Q, and David Chiang. 2017. Transfer learning across low-resource, related languages for neural machine translation. In Proceedings of the Eighth International Joint Conference on Natural Language Processing.

Papineni, Kishore, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting of the As-
Piskorski, Jakub, Lidia Pivovarova, Jan Šnajder, Josef Steinberger, and Roman Yangarber. 2017. The first cross-lingual challenge on recognition, normalization, and matching of named entities in slavic languages. In Proceedings of the 6th Workshop on Balto-Slavic Natural Language Processing, Valencia, Spain.

Post, Matt. 2018. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, Belgium, Brussels. Association for Computational Linguistics.

Provilkov, Ivan, Dmitrii Emelianenko, and Elena Voita. 2020. Bpe-dropout: Simple and effective subword regularization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1882–1892.

Qi, Ye, Devendra Sachan, Matthieu Felix, Sarguna Padmanabhan, and Graham Neubig. 2018. When and why are pre-trained word embeddings useful for neural machine translation? In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 529–535.

Sennrich, Rico, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, pages 1715–1725.

Sevcíková, Magda, Zdenek Zabokrtský, and Oldrich Kruza. 2007. Named entities in czech: Annotating data and developing NE tagger. In Text, Speech and Dialogue, 10th International Conference, TSD 2007, Pilsen, Czech Republic, September 3-7, 2007, Proceedings, volume 4629 of Lecture Notes in Computer Science, pages 188–195. Springer.

Shannon, Claude E. 1948. A mathematical theory of communication. Bell Syst. Tech. J., 27(3):379–423.

Sharoff, Serge. 2017. Toward pan-Slavic NLP: Some experiments with language adaptation. In Proceedings of the 6th Workshop on Balto-Slavic Natural Language Processing, Valencia, Spain. Association for Computational Linguistics.

Simpson, Edward H. 1949. Measurement of diversity. nature, 163(4148):688.

Tan, Xu, Jiale Chen, Di He, Yingce Xia, Tao Qin, and Tie-Yan Liu. 2019. Multilingual neural machine translation with language clustering. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 963–973.

Tweedie, Fiona J, and R Harald Baayen. 1998. How variable may a constant be? measures of lexical richness in perspective. Computers and the Humanities, 32(5):323–352.

Vanmassenhove, Eva, Dimitar Shterionov, and Matthew Gwilliam. 2021. Machine translationese: Effects of algorithmic bias on linguistic complexity in machine translation. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 2203–2213, Online.

Wang, Xinyi, Hieu Pham, Philip Arthur, and Graham Neubig. 2018. Multilingual neural machine translation with soft decoupled encoding. In International Conference on Learning Representations.

Wang, Xinyi, Sebastian Ruder, and Graham Neubig. 2021. Multi-view subword regularization. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 473–482, Online.

Wu, Lijun, Shufang Xie, Yingce Xia, Yang Fan, Jian-Huang Lai, Tao Qin, and Tieyan Liu. 2020. Sequence generation with mixed representations. In Proceedings of the 37th International Conference on Machine Learning, volume 119 of Proceedings of Machine Learning Research, pages 10388–10398. PMLR.

Yule, C Udny. 2014. The statistical study of literary vocabulary. Cambridge University Press.