Morphological and Language-Agnostic Word Segmentation for NMT*

Dominik Macháček, Jonáš Vidra, and Ondřej Bojar

Charles University, Faculty of Mathematics and Physics,
Institute of Formal and Applied Linguistics,
Malostranské náměstí 25,
118 00 Prague, Czech Republic
{machacek,vidra,bojar}@ufal.mff.cuni.cz
http://ufal.mff.cuni.cz

Abstract. The state of the art of handling rich morphology in neural machine translation (NMT) is to break word forms into subword units, so that the overall vocabulary size of these units fits the practical limits given by the NMT model and GPU memory capacity. In this paper, we compare two common but linguistically uninformed methods of subword construction (BPE and STE, the method implemented in Tensor2Tensor toolkit) and two linguistically-motivated methods: Morfessor and one novel method, based on a derivational dictionary. Our experiments with German-to-Czech translation, both morphologically rich, document that so far, the non-motivated methods perform better. Furthermore, we identify a critical difference between BPE and STE and show a simple pre-processing step for BPE that considerably increases translation quality as evaluated by automatic measures.

1 Introduction

One of the key steps that allowed to apply neural machine translation (NMT) in unrestricted setting was the move to subword units. While the natural (target) vocabulary size in a realistic parallel corpus exceeds the limits imposed by model size and GPU RAM, the vocabulary size of custom subwords can be kept small.

The current most common technique of subword construction is called byte-pair encoding (BPE) by Sennrich et al. [6]. Its counterpart originating in the

* This work has been supported by the grants 18-24210S of the Czech Science Foundation, SVV 260 453 and “Progress” Q18-Q48 of Charles University, H2020-ICT-2014-1-645452 (QT21) of the EU, and using language resources distributed by the LINDAT/CLARIN project of the Ministry of Education, Youth and Sports of the Czech Republic (projects LM2015071 and OP VVV VI CZ.02.1.01/0.0/0.0/16 013/0001781). We thank Jaroslava Hlaváčová for digitizing excerpts of [7] used as gold-standard data for evaluating the segmentation methods.

1 http://github.com/rsennrich/subword-nmt/
commercial field is wordpieces \cite{10}. Yet another variant of the technique is implemented in Google’s open-sourced toolkit Tensor2Tensor,\footnote{http://github.com/tensorflow/tensor2tensor} namely the SubwordTextEncoder class (abbreviated as STE below).

The common property of these approaches is that they are trained in an unsupervised fashion, relying on the distribution of character sequences, but disregarding any morphological properties of the languages in question.

On the positive side, BPE and STE (when trained jointly for both the source and target languages) allow to identify and benefit from words that share the spelling in some of their part, e.g. the root of the English “legalization” and Czech “legalizace” (noun) or “legalizační” (adj). On the downside, the root of different word forms of one lemma can be split in several different ways and the neural network will not explicitly know about their relatedness. A morphologically motivated segmentation method could solve this issue by splitting words into their constituent semantics- and syntax-bearing parts.

In this paper, we experiment with two methods aimed at morphologically adequate splitting of words in a setting involving two morphologically rich languages: Czech and German. We also compare the performance of several variations of BPE and STE. Performance is analysed both by intrinsic evaluation of morphological adequateness, and extrinsically by evaluating the systems on a German-to-Czech translation task.

2 Morphological Segmentation

Huck et al. \cite{2} benefit from linguistically aware separation of suffixes prior to BPE on the target side of medium-size English to German translation task (overall improvement about 0.8 BLEU). Pinnis et al. \cite{5} show similar improvements with analogical prefix and suffix splitting on English to Latvian.

Since there are no publicly available morphological segmentation tools for Czech, we experimented with an unsupervised morpheme induction tool, Morfessor 2.0 \cite{9}, and we developed a simple supervised method based on derivational morphology.

2.1 Morfessor

Morfessor \cite{9} is an unsupervised segmentation tool that utilizes a probabilistic model of word formation. The segmentation obtained often resembles a linguistic morpheme segmentation, especially in compounding languages, where Morfessor benefits from the uniqueness of the textual representation of morphs. It can be used to split compounds, but it is not designed to handle phonological and orthographical changes as in Czech words “ženě”, “žné” (“harvest” in singular and plural). In Czech orthography, adding plural suffix “e” after “ně” results in “ně”. This suffix also causes phonological change in this word, the first “e” is dropped. Thus, “ženě” and “žné” are two variants of the same morpheme, but Morfessor can’t handle them appropriately.
2.2 DeriNet

Our novel segmentation method works by exploiting word-to-word relations extracted from DeriNet [11], a network of Czech lexical derivations, and MorfFlex [1], a Czech inflectional dictionary. DeriNet is a collection of directed trees of derivationally connected lemmas. MorfFlex is a list of lemmas with word forms and morphological tags. We unify the two resources by taking the trees from DeriNet as the basis and adding all word forms from MorfFlex as new nodes (leaves) connected with their lemmas.

The segmentation algorithm works in two steps: Stemming of words based on their neighbours and morph boundary propagation.

We approximate stemming by detecting the longest common substring of each pair of connected words. This segments both words connected by an edge into a (potentially empty) prefix, the common substring and a (potentially empty) suffix, using exactly two splits. For example, the edge “mávat” (to be waving) → “mávout” (to wave) has the longest common substring of “máv”, introducing the splits “máv-at” and “máv-nout” into the two connected words.

Each word may get multiple such segmentations, because it may have more than one word connected to it by an edge. Therefore, the stemming phase itself can segment the word into its constituent morphs; but in the usual case, a multi-morph stem is left unsegmented. For example, the edge “mávat” (to be waving) → “mávající” (waving) has the longest common substring of “máv”, introducing the splits “máv-a-t” and “máv-a-jící”. The segmentation of “mávat” is therefore “máv-a-t”, the union of its splits based on all linked words.

To further split the stem, we propagate morph boundaries from connected words. If one word of a connected pair contains a split in their common substring the other word does not, the split is copied over. This way, boundaries are propagated through the entire tree. For example, we can split “máva-jící” further using the other split in “máv-a-t” thanks to it lying in the longest common substring “máva”. The segmentation of “mávající” is therefore “máv-a-jící”.

These examples also show the limitations of this method: the words are often split too eagerly, resulting in many single-character splits. The boundaries between morphemes are fuzzy in Czech because connecting phonemes are often inserted and phonological changes occur. These cause spurious or misplaced splits. For example, the single-letter morph a in máv-a-t and máv-a-jící does not carry any information useful in machine translation and it would be better if we could detect it as a phonological detail and leave it connected to one of the neighboring morphs.

3 Data-Driven Segmentation

We experimentally compare BPE with STE. As we can see in the left side of Figure 1, a distinct feature of STE seems to be an underscore as a zero suffix mark appended to every word before the subword splits are determined. This small trick allows to learn more adequate units compared to BPE. For example,
the Czech word form “tramvaj” (“a tram”) can serve as a subword unit that, combined with zero suffix (“.”) corresponds to the nominative case or, combined with the suffix “e” to the genitive case “tramvaje”. In BPE, there can be either “tramvaj” as a standalone word or two subwords “tramvaj@@” and “e” (or possibly split further) with no vocabulary entry sharing possible.

To measure the benefit of this zero suffix feature, we modified BPE by appending an underscore prior to BPE training in two flavours: (1) to every word (“BPE und”), and (2) to every word except of the last word in the sentence (“BPE und non-final”).

Another typical feature of STE is to share the vocabulary of the source and target sides. While there are almost no common words in Czech and German apart from digits, punctuation and some proper names, it turns out that around 30% of the STE shared German-Czech vocabulary still appears in both languages. This contrasts to only 7% of accidental overlap of separate BPE vocabularies.

### 4 Morphological Evaluation

#### 4.1 Supervised Morphological Splits

We evaluate the segmentation quality in two ways: by looking at the data and finding typical errors and by comparing the outputs of individual systems with gold standard data from a printed dictionary of Czech morpheme segmentations [7]. We work with a sample of the book [7] containing 14581 segmented verbs transliterated into modern Czech, measuring precision and recall on morphs and morph boundaries and accuracy of totally-correctly segmented words.

#### 4.2 Results

Figure 1 shows example output on two Czech sentences. The biggest difference between our DeriNet-based approach and Morfessor is that Morfessor does not segment most stems at all, but in contrast to our system, it reliably segments...
inflectional endings and the most common affixes. The quality of our system depends on the quality of the underlying data. Unfortunately, trees in DeriNet are not always complete, some derivational links are missing. If a word belongs to such an incomplete tree, our system will not propose many splits. None of the methods handles phonological and orthographical changes, which also severely limits their performance on Czech.

The results against golden Czech morpheme segmentations are in Table 1.

The scores on boundary detection seem roughly comparable, with different systems making slightly different tradeoffs between precision and recall. Especially the DeriNet-enhanced STE (“DeriNet+STE”) system sacrifices some precision for higher recall. The evaluation of morph detection varies more, with the best system being the standard BPE, followed by BPE with shared German and Czech vocab. This suggests that adding the German side to BPE decreases segmentation quality of Czech from the morphological point of view.

The scores on boundary detection are necessarily higher than on morph detection, because a correctly identified morph requires two correctly identified boundaries — one on each side.

Overall, the scores show that none of the methods presented here is linguistically adequate. Even the best setup reaches only 62% F1 in boundary detection which translates to meagre 0.77% of all words in our test set without a flaw.

### 5 Evaluation in Machine Translation

#### 5.1 Data

Our training data consist of Europarl v7 [3] and OpenSubtitles2016 [8], after some further cleanup. Our final training corpus, processed with the Moses tokenizer [4], consists of 8.8M parallel sentences, 89M tokens on the source side, 78M on the target side. The vocabulary size is 807k and 953k on the source and target, respectively.

We use WMT[^3] newstest2011 as the development set and newstest2013 as the test set, 3k sentence pairs each.

All experiments were carried out in Tensor2Tensor (abbreviated as T2T), version 1.2.9[^4], using the model `transformer_big_single_gpu`, batch size of 1500 and `learning_rate_warmup_steps` set to 30k or 60k if the learning diverged.

[^3]: http://www.statmt.org/wmt13
[^4]: http://github.com/tensorflow/tensor2tensor

### Table 1. Morph segmentation quality on Czech as measured on gold standard data.

| Segmentation       | Morph Detection Precision | Recall | F1 | Boundary Detection Precision | Recall | F1 | Word Accuracy |
|--------------------|---------------------------|--------|----|--------------------------------|--------|----|---------------|
| BPE                | 21.24                     | 12.74  | 15.93 | 77.38                         | 52.44  | 62.52 | 0.77          |
| BPE shared vocab   | 19.99                     | 11.75  | 14.80 | 77.04                         | 51.49  | 61.72 | 0.69          |
| STE                | 13.03                     | 7.79   | 9.75 | 77.08                         | 51.77  | 61.93 | 0.23          |
| STE+Morfessor      | 11.71                     | 7.59   | 9.21 | 74.49                         | 52.85  | 61.83 | 0.23          |
| STE+DeriNet        | 13.89                     | 10.44  | 11.92 | 70.76                         | 55.00  | 61.89 | 0.35          |
Table 2. Data characteristics and automatic metrics after 300k steps of training.

| STE          | Morfessor+STE | DeriNet+STE | Google Translate | STE DeriNet+STE | BPE shrd voc |
|--------------|---------------|-------------|------------------|----------------|--------------|
| de           | de            | de          | de               | de             | de           |
| tokens       | types         | %           | BLEU             | CharactER      | chrF3        | BEER         |
| 97M          | 87M           | 54k 74k 29k | 18.78           | 61.27          | 47.82        | 50.34        |
| 95M          | 98M           | 63k 63k 26k | 18.22           | 62.27          | 47.30        | 50.00        |
| 138M         | 308M          | 63k 69k 36k | 16.99           | 64.26          | 45.64        | 49.04        |
| 94M          | 138M          | 80k 56k 35k | 15.31           | 69.44          | 44.77        | 47.91        |
| 139M         | 86M           | 41k 84k 26k | 14.51           | 68.81          | 43.51        | 47.56        |
| 95M          | 85M           | 56k 71k 26k | 13.79           | 97.94          | 46.44        | 42.40        |

The desired vocabulary size of subword units is set to 100k when shared for both source and target and to 50k each with separate vocabularies.

Since T2T SubwordTextEncoder constructs the subword model only from a sample of the training data, we had to manually set the file_byte_budget variable in the code to 100M, otherwise not enough distinct wordforms were observed to fill up the intended 100k vocabulary size.

For data preprocessed by BPE, we used T2T TokenTextEncoder which allows to use a user-supplied vocabulary. Final scores (BLEU, CharactER, chrF3 and BEER) are measured after removing any subword splits and detokenizing with Moses detokenizer. Each of the metric implementation handles tokenization on its own.

Machine translation for German-to-Czech language pair is currently underexplored. We included Google Translate (as of May 2018, neural) into our evaluation and conclude the latest Transformer model has easily outperformed it on the given test dataset.

Due to a limited number of GPU cards, we cannot afford multiple training runs for estimating statistical significance. We at least report the average score of the test set as translated by several model checkpoints around the same number of training steps where the BLEU score has already flattened. This happens to be approximately after 40 hours of training around 300k training steps.

5.2 Experiment 1: Motivated vs. Agnostic Splits

Table 2 presents several combinations of linguistically motivated and data-driven segmentation methods. Since the vocabulary size after Morfessor or DeriNet splitting alone often remains too high, we further split the corpus with BPE or STE. Unfortunately, none of the setups performs better than the STE baseline.

5.3 Experiment 2: Allowing Zero Ending

Table 3 empirically compares STE and variants of BPE. It turns out that STE performs almost 5(!) BLEU point better than the default BPE. The underscore feature allowing to model zero suffix almost closes the gap and shared vocabulary also helps a little.

As Figure 2 indicates, the difference in performance is not a straightforward consequence of the number of splits generated. There is basically no difference
Table 3. BPE vs STE with/without underscore after every (non-final) token of a sentence and/or shared vocabulary. Reported scores are avg±stddev of T2T checkpoints between 275k and 325k training steps. CharacTER, chrF3 and BEER are multiplied by 100.

| split                      | underscore | shared vocab | BLEU | CharacTER | chrF3 | BEER |
|---------------------------|------------|--------------|------|-----------|-------|------|
| STE after every token     | ✓          | ✓            | 18.58±0.06 | 61.43±0.68 | 44.80±0.29 | 50.23±0.16 |
| BPE after non-final tokens| ✓          | ✓            | 18.24±0.08 | 63.80±0.88 | 44.37±0.24 | 49.84±0.15 |
| BPE after non-final tokens| ✓          | ✓            | 18.07±0.08 | 63.24±1.98 | 44.21±0.20 | 49.72±0.11 |
| BPE after every token     | ✓          | ✓            | 13.88±0.18 | 81.84±3.33 | 36.74±0.51 | 42.46±0.51 |
| BPE                       | ✓          | ✓            | 13.69±0.66 | 76.72±4.03 | 36.60±0.63 | 42.33±0.60 |
| BPE                       | ✓          | ✓            | 13.66±0.38 | 82.66±3.54 | 36.73±0.53 | 42.41±0.56 |

Fig. 2. Histogram of number of splits of words based on their frequency rank. The most common words (left) remain unsplit by all methods, rare words (esp. beyond the 50k vocabulary limit) are split to more and more subwords.

between BPE with and without underscore but shared vocabulary leads to a lower number of splits on the Czech target side. We can see that STE in both languages splits words to more parts than BPE but still performs better. We conclude that the STE splits allow to exploit morphological behaviour better.

6 Discussion

All our experiments show that our linguistically motivated techniques do not perform better in machine translation than current state-of-the-art agnostic methods. Actually, they do not even lead to linguistically adequate splits when evaluated against a dictionary of word segmentations. This can be caused by the fact that our new methods are not accurate enough in splitting words to morphs, maybe because of the limited size of DeriNet and small amount of training data for Morfessor, maybe because they don’t handle the phonological and orthographical changes, so the amount of resulting morphs is still very high and most of them are rare in the data.
One new linguistically adequate feature, the zero suffix mark after all but final tokens in the sentence showed a big improvement, while adding the mark after every token did not. This suggests that the Tensor2Tensor NMT model benefits from explicit sentence ends perhaps more than from a better segmentation, but further investigation is needed.

7 Conclusion

We experimented with common linguistically non-informed word segmentation methods BPE and SubwordTextEncoder, and with two linguistically-motivated ones. Neither Morfessor nor our novel technique relying on DeriNet, a derivational dictionary for Czech, help. The uninformed methods thus remain the best choice.

Our analysis however shows an important difference in STE and BPE, which leads to considerably better performance. The same feature (support for zero suffix) can be utilized in BPE, giving similar gains.

References

1. Hajič, J., Hlaváčová, J.: MorfFlex CZ (2013), http://hdl.handle.net/11858/00-097C-0000-0015-A780-9, LINDAT/CLARIN dig. library, Charles University
2. Huck, M., Riess, S., Fraser, A.: Target-side word segmentation strategies for neural machine translation. In: WMT. pp. 56–67. ACL (2017)
3. Koehn, P.: Europarl: A Parallel Corpus for Statistical Machine Translation. In: MT Summit. pp. 79–86. AAMT, AAMT, Phuket, Thailand (2005)
4. Koehn, P., et al.: Moses: Open source toolkit for statistical machine translation. In: ACL Poster and Demonstration Sessions. pp. 177–180 (2007)
5. Pinnis, M., Krišlauks, R., Deksne, D., Miks, T.: Neural Machine Translation for Morphologically Rich Languages with Improved Sub-word Units and Synthetic Data, pp. 237–245. Springer International Publishing, Cham (2017)
6. Sennrich, R., Haddow, B., Birch, A.: Neural machine translation of rare words with subword units. In: ACL. pp. 1715–1725 (2016)
7. Slavíčková, E.: Retrográdní morfematický slovník češtiny. Academia (1975)
8. Tiedemann, J.: News from OPUS - A collection of multilingual parallel corpora with tools and interfaces. In: RANLP, vol. V, pp. 237–248 (2009)
9. Virpioja, S., Smit, P., Grönnroos, S.A., Kurimo, M.: Morfessor 2.0: Python implementation and extensions for Morfessor baseline. Tech. rep. (2013), Aalto University publication series SCIENCE + TECHNOLOGY; 25/2013
10. Wu, Y., et al.: Google’s neural machine translation system: Bridging the gap between human and machine translation. CoRR abs/1609.08144 (2016)
11. Zabokrtský, Z., Ševčíková, M., Straka, M., Vidra, J., Limburská, A.: Merging data resources for inflectional and derivational morphology in Czech. In: LREC (2016)