BPEmb: Tokenization-free Pre-trained Subword Embeddings in 275 Languages

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Abstract
We present BPEmb, a collection of pre-trained subword unit embeddings in 275 languages, based on Byte-Pair Encoding (BPE). In an evaluation using fine-grained entity typing as testbed, BPEmb performs competitively, and for some languages better than alternative subword approaches, while requiring vastly fewer resources and no tokenization. BPEmb is available at https://github.com/bheinzerling/bpemb.

Keywords: subword embeddings, byte-pair encoding, multilingual

1. Introduction
Learning good representations of rare words or words not seen during training at all is a difficult challenge in natural language processing. As a makeshift solution, systems have typically replaced such words with a generic UNK token. Recently, based on the assumption that a word’s meaning can be reconstructed from its parts, several subword-based methods have been proposed to deal with the unknown word problem: character-based recurrent neural networks (RNN) (Luong and Manning, 2016), character-based convolutional neural networks (CNN) (Chiu and Nichols, 2016), word embeddings enriched with subword information (FastText) (Bojanowski et al., 2017), and byte-pair encoding (BPE) (Sennrich et al., 2016), among others.

While pre-trained FastText embeddings are publicly available, embeddings for BPE units are commonly trained on a per-task basis (e.g. a specific language pair for machine-translation) and not published for general use.

In this work we present BPEmb, a collection of pre-trained subword embeddings in 275 languages, and make the following contributions:

• We publish BPEmb, a collection of pre-trained byte-pair embeddings in 275 languages;

• We show the utility of BPEmb in a fine-grained entity typing task; and

• We show that BPEmb performs as well as, and for some languages better than, alternative approaches while being more compact and requiring no tokenization.

2. BPEmb: Byte-pair Embeddings
Byte Pair Encoding is a variable-length encoding that views text as a sequence of symbols and iteratively merges the most frequent symbol pair into a new symbol. E.g., encoding an English text might consist of first merging the most frequent symbol pair t h into a new symbol th, then merging the pair th e into the in the next iteration, and so on. The number of merge operations o determines if the resulting encoding mostly creates short character sequences (e.g. o = 1000) or if it includes symbols for many frequently occurring words, e.g. o = 30,000 (cf. Table 1). Since the BPE algorithm works with any sequence of symbols, it requires no preprocessing and can be applied to untokenized text.

We apply BPE to all Wikipedias of sufficient size with various o and pre-train embeddings for the resulting BPE symbol using GloVe (Pennington et al., 2014), resulting in byte-pair embeddings for 275 languages. To allow studying the effect the number of BPE merge operations and of the embedding dimensionality, we provide embeddings for 1000, 3000, 5000, 10000, 25000, 50000, 100000 and 200000 merge operations, with dimensions 25, 50, 100, 200, and 300.

3. Evaluation: Comparison to FastText and Character Embeddings
To evaluate the quality of BPEmb we compare to FastText, a state-of-the-art approach that combines embeddings of tokens and subword units, as well as to character embeddings.

FastText enriches word embeddings with subword information by additionally learning embeddings for character n-grams. A word is then represented as the sum of its associated character n-gram embeddings including. In practice, representations of unknown word are obtained by adding the embeddings of their constituting character 3- to 6-grams. We use the pre-trained embeddings provided by the authors.

Character embeddings. In this setting, mentions are represented as sequence of the character unigrams they consist of. During training, character embeddings are learned for the k most frequent characters.
Fine-grained entity typing. Following Schütze (2017), we use fine-grained entity typing as test bed for comparing subword approaches. This is an interesting task for subword evaluation, since many rare, long-tail entities do not have good representations in common token-based pre-trained embeddings such as word2vec or GloVe. Subword-based models are a promising approach to this task, since morphology often reveals the semantic category of unknown words: The suffix -shire in Melfordshire indicates a location or city, and the suffix -osis in Myxomatosis a sickness. Subword methods aim to allow this kind of inference by learning representations of subword units (henceforth: SUs) such as character ngrams, morphemes, or byte pairs.

Method. Given an entity mention \( m \) such as Melfordshire, our task is to assign one or more of the 89 fine-grained entity types proposed by Gillick et al. (2014), in this case /location and /location/city. To do so, we first obtain a subword representation

\[
s = SU(m) \in R^{l \times d}
\]

by applying one of the above SU transformations resulting in a SU sequence of length \( l \) and then looking up the corresponding SU embeddings with dimensionality \( d \). Next, \( s \) is encoded into a one-dimensional vector representation

\[
v = A(s) \in R^d
\]

by an encoder \( A \). In this work the encoder architecture is either averaging across the SU sequence, an LSTM, or a CNN. Finally, the prediction \( y \) is:

\[
y = \frac{1}{1 + exp(-v)}
\]

(Shimaoka et al., 2017).

Data. We obtain entity mentions from Wikidata (Vrandečić and Krötzsch, 2014) and their entity types by mapping to Freebase (Bollacker et al., 2008), resulting in 3.4 million English instances like (Melfordshire: /location, /location/city). Train and test set are random subsamples of size 80,000 and 20,000 or a proportionally smaller split for smaller Wikipedias. In addition to English, we report results for a) the five languages having the largest Wikipedias as measured by textual content; b) Chinese and Japanese, i.e. two high-resource languages without tokenization markers; and c) eight medium- to low-resource Asian languages.

Experimental Setup. We evaluate entity typing performance with the average of strict, loose macro, and loose macro precision (Ling and Weld, 2012). For each combination of SU and encoding architecture, we perform a tree-structured Parzen Estimator hyper-parameter search (Bergstra et al., 2011) with at least 1000 hyper-parameter search trials (English, at least 50 trials for other languages) and report score distributions (Reimers and Gurevych, 2017). See Table 5 for hyper-parameter ranges.

4. Results and Discussion

4.1. Subwords vs. Characters vs. Tokens

Figure 1 shows our main result for English: score distributions of 1000+ trials for each SU and architecture. Token-based results using two sets of pre-trained embeddings (Mikolov et al., 2013; Pennington et al., 2014) are included for comparison.

Subword units. BPEmb outperforms all other subword units across all architectures (BPE-RNN mean score 0.624 ± 0.029, max. 0.65). FastText performs slightly
worse (FastText-RNN mean 0.617 ± 0.007, max. 0.63) even though the FastText vocabulary is much larger than the set of BPE symbols.

BPEmb performs well with low embedding dimensionality (Figure 2, right) and can match FastText with a fraction of its memory footprint (6 GB for FastText’s 3 million embeddings with dimension 300 vs 11 MB for 100k BPE embeddings (Figure 2, left) with dimension 25.). As both FastText and BPEmb were trained on the same corpus (namely, Wikipedia), these results suggest that, for English, the compact BPE representation strikes a better balance between learning embeddings for more frequent words and relying on compositionality of subwords for less frequent ones.

FastText performance shows the lowest variance, i.e., it robustly yields good results across many different hyperparameter settings. In contrast, BPEmb and character-based models show higher variance, i.e., they require more careful hyper-parameter tuning to achieve good results.

**Architectures.** Averaging a mention’s associated embeddings is the worst architecture choice. This is expected for character-based models, but somewhat surprising for token-based models, given the fact that averaging is a common method for representing mentions in tasks such as entity typing (Shimaoka et al., 2017) or coreference resolution (Clark and Manning, 2016). RNNs perform slightly better than CNNs, at the cost of much longer training time.

**4.2. Multilingual Analysis**

Table 2 compares FastText and BPEmb across various languages. For high-resource languages (top) both approaches

| Language    | FastText | BPEmb | \(\Delta\) |
|-------------|----------|-------|------------|
| English     | 62.9     | 65.4  | 2.5        |
| German      | 65.5     | 66.2  | 0.7        |
| Russian     | 71.2     | 70.7  | -0.5       |
| French      | 64.5     | 63.9  | -0.6       |
| Spanish     | 66.6     | 66.5  | -0.1       |
| Chinese     | 71.0     | 72.0  | 1.0        |
| Japanese    | 62.3     | 61.4  | -0.9       |
| Tibetan     | 37.9     | 41.4  | 3.5        |
| Burmese     | 65.0     | 64.6  | -0.4       |
| Vietnamese  | 81.0     | 81.0  | 0.0        |
| Khmer       | 61.5     | 52.6  | -8.9       |
| Thai        | 63.5     | 63.8  | 0.3        |
| Lao         | 44.9     | 47.0  | 2.1        |
| Malay       | 75.9     | 76.3  | 0.4        |
| Tagalog     | 63.4     | 62.6  | -1.2       |

Table 2: Entity typing scores for five high-resource languages (top), two high-resource languages without explicit tokenization, and eight medium- to low-resource Asian languages (bottom).
perform equally, with the exception of BPEmb giving a significant improvement for English. For high resources languages without explicit tokenization (middle), byte-pair encoding appears to yield a subword segmentation which gives performance comparable to the results obtained when using FastText with pre-tokenized text. Results are more varied for mid- to low-resource Asian languages (bottom), with small BPEmb gains for Tibetan and Lao. The large performance degradation for Khmer appears to be due to inconsistencies in the handling of unicode control characters between different software libraries used in our experiments and have a disproportionate effect due to the small size of the Khmer Wikipedia.

5. Limitations
Due to limited computational resources, our evaluation was performed only for a few of the 275 languages provided by BPEmb. While our experimental setup allows a fair comparison between FastText and BPEmb through extensive hyper-parameter search, it is somewhat artificial, since it disregards context. For example, Myxomatosis in the phrase Radiohead played Myxomatosis has the entity type /other/music, which can be inferred from the contextual music group and the predicate plays, but this ignored in our specific setting. How our results transfer to other tasks requires further study.

6. Replicability
All data used in this work is freely and publicly available. Code to replicate our experiments will be released upon publication at https://github.com/bheinzerling/bpemb.

7. Conclusions
We presented BPEmb, a collection of subword embeddings trained on Wikipedias in 275 languages. Our evaluation showed that BPEmb performs as well as, and for some languages, better than other subword-based approaches. BPEmb requires no tokenization and is orders of magnitudes smaller than alternative embeddings, enabling potential use under resource constraints, e.g. on mobile devices.

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| Unit      | Hyper-parameter | Space        |
|-----------|-----------------|--------------|
| Token     | vocabulary type | GloVe, word2vec |
| Character | embedding size   | 50, 100, 200, 500, 1000 |
| FastText  | -               | -            |
| BPEmb     | merge operations| 1k, 3k, 5k, 10k, 25k |
|           | embedding size  | 25, 50, 100, 200, 300 |

| Architecture | Hyper-parameter | Space |
|--------------|-----------------|-------|
| RNN          | hidden units    | 100, 300, 500, 700, 1000, 1500, 2000 |
|              | layers          | 1, 2, 3 |
|              | RNN dropout     | 0.0, 0.1, 0.2, 0.3, 0.4, 0.5 |
|              | output dropout  | 0.0, 0.1, 0.2, 0.3, 0.4, 0.5 |
| CNN          | filter sizes    | (2), (2, 3), (2, 3, 4, 5, 6), (3), (3, 4), (3, 4, 5, 6), (4, 4, 5, 6, 10), (5, 5, 6, 10, 15, 20) |
|              | number of filters| 25, 50, 100, 200, 300, 400, 500, 600, 700 |
|              | output dropout  | 0.0, 0.1, 0.2, 0.3, 0.4, 0.5 |

Table 3: Subword unit (top) and architecture (bottom) hyper-parameter space searched.
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