Massively Multilingual Sentence Embeddings for Zero-Shot Cross-Lingual Transfer and Beyond

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Abstract

We introduce an architecture to learn joint multilingual sentence representations for 93 languages, belonging to more than 30 different language families and written in 28 different scripts. Our system uses a single BiLSTM encoder with a shared BPE vocabulary for all languages, which is coupled with an auxiliary decoder and trained on publicly available parallel corpora. This enables us to learn a classifier on top of the resulting sentence embeddings using English annotated data only, and transfer it to any of the 93 languages without any modification. Our approach sets a new state-of-the-art on zero-shot cross-lingual natural language inference for all the 14 languages in the XNLI dataset but one. We also achieve very competitive results in cross-lingual document classification (MLDoc dataset). Our sentence embeddings are also strong at parallel corpus mining, establishing a new state-of-the-art in the BUCC shared task for 3 of its 4 language pairs. Finally, we introduce a new test set of aligned sentences in 122 languages based on the Tatoeba corpus, and show that our sentence embeddings obtain strong results in multilingual similarity search even for low-resource languages. Our PyTorch implementation, pre-trained encoder and the multilingual test set will be freely available.

1 Introduction

While the recent advent of deep learning has led to impressive progress in Natural Language Processing (NLP), these techniques are known to be particularly data hungry, limiting their applicability in many practical scenarios. An increasingly popular approach to alleviate this issue is to first learn general language representations on unlabeled data, which are then integrated in task-specific down-

stream systems. This approach was first popularized by word embeddings (Mikolov et al., 2013b; Pennington et al., 2014), but has recently been superseded by sentence-level representations (Conneau et al., 2017; Peters et al., 2018; Devlin et al., 2018). Nevertheless, all these works learn a separate model for each language and are thus unable to leverage information across different languages, greatly limiting their potential performance for low-resource languages.

In this work, we are interested in **universal** language agnostic sentence embeddings, that is, vector representations of sentences that are general with respect to two dimensions: the input language and the NLP task. The motivations for such a representation are multiple: the hope that languages with limited resources benefit from joint training over many languages, the desire to perform zero-shot transfer of an NLP model from one language (e.g. English) to another, and the possibility to handle code-switching. We achieve this by using a single encoder that can handle multiple languages, so that semantically similar sentences in different languages are close in the resulting embedding space.

Most research in multilingual NLP focuses on high-resource languages like Chinese, Arabic or major European languages, and is usually limited to a few (most often only two) languages. In contrast, we learn joint sentence representations for 93 different languages, including under-resourced and minority languages (see Tables 1 and 2). Our system is trained on freely available parallel texts only. The contributions of this paper are as follows:

 We substantially improve on previous work to learn joint multilingual sentence representations. We learn one shared encoder that can handle 93 different languages. All languages

This work was performed during an internship at Facebook AI Research.

are jointly embedded in a shared space, in contrast to most other works which usually consider separate English/foreign alignments. We cover 34 language families and 28 different scripts.

- We outperform the state-of-the-art on zeroshot cross-lingual natural language inference (XNLI dataset) and classification (ML-Doc dataset), bitext mining (BUCC dataset) and multilingual similarity search (Tatoeba dataset), for almost all considered languages. These results were obtained with a single pretrained BiLSTM encoder for all 93 languages and tasks, without any fine-tuning.
- We define a new test set based on the freely available Tatoeba corpus and provide baseline results for 122 languages. We report accuracy for multilingual similarity search on this test set, but the corpus could also be used for MT evaluation.

The remaining of this paper is organized as follows. In the next section, we first summarize related work. Section 3 then describe our approach in detail. All experimental results are given in Sections 4 and 5, and the paper concludes with a discussion and directions for future research. Dataset details and additional result analysis can be found in the appendix.

2 Related work

Following the success of word embeddings (Mikolov et al., 2013b; Pennington et al., 2014), there has been an increasing interest in learning continuous vector representations of longer linguistic units like sentences. These sentence embeddings are commonly obtained using a Recurrent Neural Network (RNN) encoder, which is typically trained in an unsupervised way over large collections of unlabelled corpora. For instance, the skip-thought model of Kiros et al. (2015) couple the encoder with an auxiliary decoder, and train the entire system end-to-end to predict the surrounding sentences over a large collection of books. It was later shown that more competitive results could be obtained by training the encoder over labeled Natural Language Inference (NLI) data (Conneau et al., 2017). This was recently extended to multitask learning, combining different training objectives like that of skip-thought, NLI and machine translation (Cer et al., 2018; Subramanian et al., 2018).

While the previous methods consider a single language at a time, multilingual representations have attracted a large attention in recent times. Most of this research focuses on crosslingual word embeddings (Ruder et al., 2017), which are commonly learned jointly from parallel corpora (Gouws et al., 2015; Luong et al., 2015). An alternative approach that is becoming increasingly popular is to train word embeddings independently for each language over monolingual corpora, and then map them to a shared space based on a bilingual dictionary (Mikolov et al., 2013a; Artetxe et al., 2018a) or even in a fully unsupervised manner (Conneau et al., 2018a; Artetxe et al., 2018b). Cross-lingual word embeddings are often used to build bag-of-word representations of longer linguistic units by taking their respective centroid (Klementiev et al., 2012). While this approach has the advantage of requiring a weak (or even no) cross-lingual signal, it has been shown that the resulting sentence embeddings works rather poorly in practical crosslingual transfer settings (Conneau et al., 2018b).

A more competitive approach that we follow here is to use a sequence-to-sequence encoder-decoder architecture (Schwenk and Douze, 2017; Hassan et al., 2018). The full system is trained end-to-end on parallel corpora akin to neural machine translation: the encoder maps the source sequence into a fixed-length vector representation, which is used by the decoder to create the target sequence. This decoder is then discarded, and the encoder is kept to embed sentences in any of the training languages. While some proposals use a separate encoder for each language (Schwenk and Douze, 2017), sharing a single encoder for all languages also gives strong results (Schwenk, 2018a).

Nevertheless, most existing work is either limited to few, rather close languages (Schwenk and Douze, 2017) or, more commonly, consider pairwise joint embeddings with English and one foreign language only (España-Bonet et al., 2017; Guo et al., 2018). To the best of our knowledge, all existing work on learning multilingual representations for a large number of languages is limited to word embeddings (Ammar et al., 2016), ours being the first paper exploring massively multilingual sentence representations.

Finally, while all the previous approaches learn

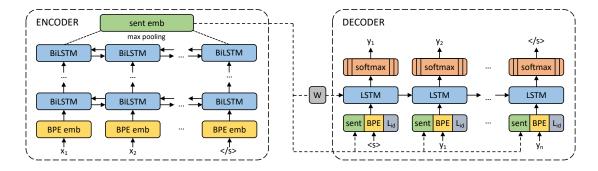


Figure 1: Architecture of our system to learn multilingual sentence embeddings.

a fixed-length representation for each sentence, a recent research line has obtained very strong results using variable-length representations instead, consisting of contextualized embeddings of the words in the sentence (Peters et al., 2018; Howard and Ruder, 2018; Devlin et al., 2018). For that purpose, these methods train either an RNN or selfattentional encoder over unnanotated corpora using some form of language modeling. A classifier can then be learned on top of the resulting encoder, which is commonly further fine-tuned during this supervised training. Despite the strong performance of these approaches in monolingual settings, we argue that fixed-length approaches provide a more generic, flexible and compatible representation form for our multilingual scenario, ¹ and our model indeed outperforms the multilingual BERT model (Devlin et al., 2018) in zeroshot transfer (see Section 4.1).

3 Proposed method

We use a single, language agnostic BiLSTM encoder to build our sentence embeddings, which is coupled with an auxiliary decoder and trained over parallel corpora. From Section 3.1 to 3.3, we describe its architecture, our training strategy to scale to up to 93 languages, and the training data used for that purpose.

3.1 Architecture

Figure 1 illustrates the architecture of the proposed system, which is based on Schwenk (2018a). As it can be seen, sentence embeddings are obtained by applying a max-pooling operation over the out-

put of a BiLSTM encoder. These sentence embeddings are used to initialize the decoder LSTM through a linear transformation, and are also concatenated to its input embeddings at every time step. Note that there is no other connection between the encoder and the decoder, as we want all relevant information of the input sequence to be captured by the sentence embedding.

We use a single encoder and decoder in our system, which are shared by all languages involved. For that purpose, we build a joint byte-pair encoding (BPE) vocabulary with 50k operations, which is learned on the concatenation of all training corpora. This way, the encoder has no explicit signal on what the input language is, encouraging it to learn language independent representations. In contrast, the decoder takes a language ID embedding that specifies the language to generate, which is concatenated to the input and sentence embeddings at every time step.

Scaling up to almost hundred languages, which use very different syntax, writing scripts and linguistic concepts, naturally calls for an encoder with sufficient capacity. In this paper, we limit our study to a stacked BiLSTM with 1 to 5 layers, each 512-dimensional. The resulting sentence representations (after concatenating both directions) are 1024 dimensional. The decoder has always one layer of dimension 2048. The input embedding size is set to 320, while the language ID embedding has 32 dimensions.

3.2 Training strategies

In preceding work (Schwenk and Douze, 2017; Schwenk, 2018a), each sentence at the input was jointly translated into all other languages. While this approach was shown to learn high-quality representations, it poses two obvious drawbacks when trying to scale to a large number of lan-

¹For instance, there is not always a one-to-one correspondence among words in different languages (e.g. a single word of a morphologically complex language might correspond to several words of a morphologically simple language), so having a separate vector for each word might not transfer as well across languages.

			Details	Training	Tatoeba l	Tatoeba test set		
SO3	ISO2	Name	Family	Script	corpus size	$en \to xx$	$xx \to en$	size
ıfr	af	Afrikaans	Germanic	Latin	67k	11.20	9.90	100
sqi	sq	Albanian	Albanian	Latin	3.2M	1.80	2.30	100
ımh	am	Amharic	Ethopian	Ge'ez	88k	60.71	55.36	16
ara aym	ar ay	Arabic Aymara	Arabic Aymaran	Arabic Latin	8.2M 14k	8.30 n/a	7.80 n/a	100
aze	az	Azerbaijani	Turkic	Latin; Cyrillic; Persian	254k	44.10	23.90	100
eus	eu	Basque	Isolate	Latin	1.2M	5.70	5.00	100
oen	bn	Bengali	Indo-Aryan	Eastern-Nagari	913k	10.80	10.00	100
oer	ber	Berber languages	Berber	Latin	62k	29.80	33.70	100
10b	nb	Bokmål Norwegian Bosnian	Germanic	Latin	4.1M 4.2M	1.30	1.10	100
oos ore	bs br	Breton	Slavic Celtic	Latin Latin	4.2M 29k	3.95 83.50	3.11 84.90	35 100
oul	bg	Bulgarian	Slavic	Cyrillic	4.9M	4.50	5.40	100
cat	ca	Catalan	Romance	Latin	813k	4.00	4.20	100
emn	zh	Chinese mandarin	Chinese	Chinese	8.3M	4.10	5.00	100
swh	sw	(Coastal) Swahili	Niger-Congo	Latin	173k	45.64	39.23	39
ırv	hr	Croatian	Slavic	Latin	4.0M	2.80	2.70	100
es lan	cs da	Czech Danish	Slavic Germanic	Latin Latin	5.5M 7.9M	3.10 3.90	3.80 4.00	100 100
ıld	nl	Dutch	Germanic	Latin	8.4M	3.10	4.30	100
eng	en	English	Germanic	Latin	2.6M	n/a	n/a	100
epo	eo	Esperanto	constructed	Latin	397k	2.70	2.80	100
est	et	Estonian	Uralic	Latin	5.3M	3.20	3.40	100
ìn	fi	Finnish	Uralic	Latin	7.9M	3.70	3.70	100
ra	fr	French	Romance	Latin	8.8M	4.40	4.30	100
lg	gl	Galician	Romance	Latin	349k	4.60	4.40	100
at leu	ka de	Georgian German	Kartvelian Germanic	Georgian Latin	296k 8.7M	60.32 0.90	67.83 1.00	74 100
11	el	Greek	Hellenic	Greek	6.5M	5.30	4.80	100
au	ha	Hausa	Afro-Asiatic	Latin: Arabic	127k	n/a	n/a	100
eb	he	Hebrew	Semitic	Hebrew	4.1M	8.10	7.60	100
in	hi	Hindi	Indo-Aryan	Devanagari	288k	5.80	4.80	100
un	hu	Hungarian	Uralic	Latin	5.3M	3.90	4.00	100
sl_	is	Icelandic	Germanic	Latin	2.0M	4.40	4.40	10
nd	id	Indonesian	Malayo-Polynesian	Latin	4.3M	5.20	5.80	100
es a	ps it	Iranian Persian (Farsi) Italian	Iranian Romance	Persian Latin	4.9M 8.3M	7.20 4.60	6.00 4.80	100 100
on	ja	Japanese	Japonic	Kanjii	3.2M	3.90	5.40	100
ab	Ju	Kabyle	Berber	Latin (modified)	15k	39.10	44.70	100
or	ko	Korean	Koreanic	Hangul	1.4M	10.60	11.50	100
ur	ku	Kurdish	Iranian	Latin; Persian	50k	80.24	85.37	4
VS	lv	Latavian	Baltic	Latin	2.0M	4.50	4.70	10
at	la	Latin	Romance	Latin	19k	41.60	41.50	100
t do	lt	Lithuanian Low German / Saxon	Baltic	Latin	3.2M	4.10	3.40	100
ds nkd	mk	Macedonian / Saxon	Germanic Slavic	Latin Cyrillic	12k 4.2M	18.60 5.20	15.60 5.40	100 100
ılg	mg	Malagasy	Malayo-Polynesian	Latin	355k	n/a	n/a	10
sm	ms	Malay	Malayo-Polynesian	Latin	2.9M	3.40	3.80	10
nal	ml	Malayalam	Dravidian	Malayalam	373k	3.35	2.91	6
iv	dv	Maldivian (Divehi)	Indo-Aryan	Thaana	90k	n/a	n/a	
ıar	mr	Marathi	Indo-Aryan	Devanagari	31k	9.00	8.00	10
ol	pl	Polish	Slavic	Latin	5.5M	2.00	2.40	10
or	pt	Portuguese	Romance	Latin	8.3M	4.70	4.90	10 10
on is	ro ru	Romanian; Moldavian Russian	Romance Slavic	Latin Cyrillic	4.9M 9.3M	2.50 4.90	2.70 5.90	10
rp	sr	Serbian	Slavic	Cyrillic; Latin	4.0M	4.30	5.00	10
nd	sd	Sindhi	Iranian	Persian; Devanagari	91k	n/a	n/a	10
in	si	Sinhala	Indo-Aryan	Sinhala	796k	n/a	n/a	
k	sk	Slovak	Slavic	Latin	5.2M	3.10	3.70	10
V	sl	Slovenian	Slavic	Latin	5.2M	4.50	3.77	8
om	so	Somali	Cushitic	Latin	85k	n/a	n/a	10
oa	es	Spanish	Romance	Latin	4.8M	1.90	2.10	10
we gl	sv tl	Swedish Tagalog	Germanic Malayo-Polynesian	Latin Latin	7.8M 36k	3.60 47.40	3.20 51.50	10 10
;ı ;k	tg	Tajik	Iranian	Cyrillic	124k	47.40 n/a	51.50 n/a	10
ım	ta	Tamil	Dravidian	Tamil	42k	31.60	29.64	3
ıt	tt	Tatar	Turkic	Cyrillic	119k	72.00	65.70	10
el	te	Telugu	Dravidian	Telugu	33k	18.38	22.22	2
na	th	Thai	Kra-Dai	Thai	4.1M	4.93	4.20	5
ır	tr	Turkish	Turkic	Latin	5.7M	2.30	2.60	10
ig	ug	Uighur	Turkic	Arabic	88k	59.90	49.60	10
kr	uk	Ukrainian	Slavic	Cyrillic	1.4M	5.80	5.10	100
rd zb	ur	Urdu	Indo-Aryan	Arabic	746k	20.00	16.20	100
	uz	Uzbek	Turkic	Latin; Cyrillic	118k	82.24	80.37	4

Table 1: List of the 75 out of 93 languages used to trained the proposed model with at least 10k training examples, along with their language family, writing system, the resulting similarity error rate on the Tatoeba test set, and the number of sentences in it. Dashes denote language pairs excluded for containing less than 100 test sentences.

			Details		Training	Tatoeba l	Error [%]	Tatoeba
ISO3	ISO2	Name	Family	Script	corpus size	$en \rightarrow xx$	$xx \to en$	test set size
hye	hy	Armenian	Armenian	Armenian	6k	59.97	67.79	742
bel	be	Belarusian	Slavic	Cyrillic	5k	31.20	36.50	1000
mya	my	Burmese	Sino-Tibetan	Burmese	2k	n/a	n/a	_
dtp		Central/Kadazan Dusun	Malayo-Polynesian	Latin	1k	92.10	93.50	1000
khm	km	Central Khmer	Khmer	Khmer	625	77.01	81.72	722
cbk		Chavacano	Creole, Romance	Latin	1k	24.20	21.70	1000
kzj		Coastal Kadazan	Malayo-Polynesian	Latin	560	91.60	94.10	1000
cor	kw	Cornish	Celtic	Latin	2k	91.90	93.20	1000
mhr		Eastern Mari	Uralic	Cyrillic	1k	87.70	91.50	1000
ido	io	Ido	constructed	Latin	3k	17.40	15.20	1000
ina	ia	Interlingua	constructed	Latin	9k	5.40	4.10	1000
ile	ie	Interlingue	constructed	Latin	3k	14.70	12.80	1000
gle	ga	Irish	Irish	Latin	732	93.80	95.80	1000
kaz	kk	Kazakh	Turkic	Cyrillic	4k	80.17	82.61	575
lfn		Lingua Franca Nova	constructed	Latin	2k	35.90	35.10	1000
oci	oc	Occitan (post 1500)	Romance	Latin	3k	39.20	38.40	1000
wuu		Wu Chinese	Chinese	Chinese	2k	25.80	25.20	1000
yue		Yue Chinese	Chinese	Chinese	4k	37.00	38.90	1000

Table 2: List of the 18 very low-resource languages included during training of the proposed model, along with their language family, writing system, the resulting similarity error rate on the Tatoeba test set, and the number of sentences in it. Dashes denote language pairs excluded for containing less than 100 test sentences.

guages. First, it requires an N-way parallel corpus, which is difficult to obtain for all languages. Second, it has a quadratic cost with respect to the number of languages, making training prohibitively slow as the number of languages is increased. In our preliminary experiments, we observed that similar results can be obtained by using less target languages – two seem to be enough.² At the same time, we relax the requirement for N-way parallel corpora by considering independent alignments with the two target languages, e.g. we do not require each source sentence to be translated into the two target languages.

Training minimizes the cross-entropy loss on the training corpus, alternating over all combinations of the languages involved. For that purpose, we use Adam with a constant learning rate of 0.001 and dropout set to 0.1, and train for a fixed number of epochs. Our implementation is based on fairseq,³ and we make use of its multi-GPU support to train on 16 NVIDIA V100 GPUs with a total batch size of 128,000 tokens. Unless otherwise specified, we train our model for 17 epochs, which takes about 5 days. Stopping training early decreases the overall performance only slightly.

3.3 Training data and pre-processing

As described in Section 3.2, training requires bitexts aligned with two target languages. We choose English and Spanish for that purpose, as most of the data is aligned with these languages.⁴ We collect training corpora for 93 input languages by combining the Europarl, United Nations, Open-Subtitles2018, Global Voices, Tanzil and Tatoeba corpus, which are all publicly available on the OPUS website⁵ (Tiedemann, 2012). Appendix A provides a more detailed description of this training data, while Tables 1 and 2 summarize the list of all languages used for training, their language family, writing script and the size of the bitexts. Our training data comprises a total of 223 million parallel sentences.

In preliminary experiments, we observed that the domain of the training data played a key role in the performance of our sentence embeddings in different tasks. Some tasks (BUCC, MLDoc) tend to perform better when the encoder is trained on long and formal sentences, whereas other tasks (XNLI, Tatoeba) benefit from training on shorter and more informal sentences. In an attempt to achieve a general purpose sentence encoder that

²Note that, if we had a single target language, the only way to train the encoder for that language would be autoencoding, which we observe to work poorly. Having two target languages avoids this problem.

³https://github.com/pytorch/fairseq

⁴Note that it is not necessary that all input languages are systematically aligned with both target languages. Once we have several languages with both alignments, the joint embedding is well conditioned, and we can add more languages with one alignment only, usually English.

⁵http://opus.nlpl.eu

performs well on all tasks, we aimed at balancing the size of training corpora with long and short sentences. For that purpose, we used at most two million sentences from OpenSubtitles, although more data is available for some languages.

All pre-processing is done with Moses tools:⁶ punctuation normalization, removing non-printing characters and tokenization. As the only exception, Chinese and Japanese texts were segmented with Jieba⁷ and Mecab,⁸ respectively. All the languages are kept in their original script with the exception of Greek, which we romanize into the Latin alphabet.

4 Experimental evaluation

In contrast with the well-established evaluation frameworks for English sentence representations (Conneau et al., 2017; Wang et al., 2018), there is not yet a commonly accepted standard to evaluate multilingual sentence embeddings. The most notable effort in this regard is probably the XNLI corpus (Conneau et al., 2018b), an NLI test set similar to MultiNLI (Williams et al., 2017) for which the premises and hypotheses were translated into 14 languages by professional translators. We train an NLI classifier on top of our multilingual sentence embedding using English training data, and evaluate its zero-shot transfer performance in the remaining languages (Section 4.1). So as to obtain a more complete picture of the behavior of our multilingual sentence representations, we also evaluate them in cross-lingual document classification (MLDoc, Section 4.2), and bitext mining (BUCC, Section 4.3). However, all these datasets only cover a subset of our 93 languages, so we also introduce a new test set for multilingual similarity search in 122 languages, including several languages for which we have no training data but whose language family is covered (Section 4.4). We remark that we use the same pre-trained BiLSTM encoder for all tasks and languages without any fine-tuning.

4.1 XNLI: cross-lingual NLI

NLI has become a widely used task to evaluate sentence representations (Bowman et al., 2015; Williams et al., 2017). Given two sentences, a premise and a hypothesis, the task consists in de-

ciding whether there is an *entailment*, *contradiction* or *neutral* relationship between them. XNLI is a recent effort to create a dataset similar to the English MultiNLI for several languages (Conneau et al., 2018b). 2,500 development and 5,000 test sentences have been translated from English into 14 languages by professional translators, making results across different languages directly comparable. Note that no human translated training data is provided; instead, different systems are to use English training data from MultiNLI, and their transfer performance is evaluated on the rest of languages.

We train a classifier on top of our multilingual encoder using the usual combination of the two sentence embeddings: $(p, h, p \cdot h, |p-h|)$, where p and h are the premise and hypothesis. For that purpose, we use a feed-forward neural network with two hidden layers of size 512 and 384, trained with Adam. All hyperparameters were optimized on the English XNLI development corpus, and then, the same classifier was applied to all languages of the XNLI test set. As such, we did not use any training or development data in any of the foreign languages. Note, moreover, that the multilingual sentence embeddings are fixed and not fine-tuned on the task or the language.

We report our results in Table 3, along with several baselines from Conneau et al. (2018b) and the recently released multilingual BERT model (Devlin et al., 2018). As it can be seen, our proposed method establishes a new state-of-the-art in zeroshot cross-lingual transfer (i.e. training a classifier on English data and applying it to all other languages) for all languages but Spanish. Our transfer results are strong and homogeneous across all languages: for 11 of them, the zero-short performance is (at most) 5% lower than the one on English, including distant languages like Arabic, Chinese and Vietnamese, and we also achieve remarkable good results on low-resource languages like Swahili. In contrast, BERT achieves excellent results on English, outperforming our system by 7.5 points, but its zero-shot cross-lingual transfer performance is much weaker. For instance, the loss in accuracy for both Arabic and Chinese is

 $^{^6}$ http://www.statmt.org/moses

https://github.com/fxsjy/jieba

⁸https://github.com/taku910/mecab

⁹Note that the multilingual variant of BERT is not discussed in its paper (Devlin et al., 2018). Instead, the reported results were extracted from the README of the official GitHub project at https://github.com/google-research/bert/blob/master/multilingual.md on 12/19/2018.

		EN							EN -	→ XX						
		21,	fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur
Zero-Shot Transfer, o	ne NLI syster	n for a	ll lang	guage	s:											
Conneau et al. (2018c) BERT uncased*	X-BiLSTM X-CBOW Transformer	73.7 64.5 <u>81.4</u>	67.7 60.3	68.7 60.7 <u>74.3</u>		60.5	67.9 60.4 –				66.4 58.8 –	64.1 56.9			55.7 50.4	
Proposed method	BiLSTM	73.9	71.9	72.9	<u>72.6</u>	73.1	74.2	71.5	69.7	71.4	72.0	69.2	71.4	65.5	62.2	61.0
Translate test, one En	glish NLI sys	tem:														
Conneau et al. (2018c) BERT uncased*	BiLSTM Transformer		<u>70.4</u>		68.7 74.4		<u>70.4</u>	<u>67.8</u> –	<u>66.3</u>	66.8 70.4	<u>66.5</u> –	64.4	68.3 70.1	<u>64.2</u> -	<u>61.8</u> -	59.3 62.1
Translate train, separ	ate NLI syste	ms for	each	langu	age:											
Conneau et al. (2018c) BERT cased*	BiLSTM Transformer	73.7 81.9			66.5 75.9	66.4 -	67.4 -	66.5 -		65.8 <u>70.7</u>		62.8 <u>68.9</u> †	67.0 76.6			56.6 61.6

Table 3: Accuracies on the test set of the XNLI cross-lingual natural language inference task. All results from Conneau et al. (2018c) correspond to max-pooling, which outperforms the last-state variant in all cases. Results which imply the use of MT do not use a multilingual model and are not directly comparable with zero-shot transfer. Overall best results are in bold, the best ones in each group are underlined.

2.5 points for our system, compared to 19.3 and 17.6 points for BERT. Finally, we also outperform all baselines of Conneau et al. (2018b) by a substantial margin, with the additional advantage that we use a single pre-trained encoder, whereas X-BiLSTM learns a separate encoder for each language by aligning it to the English one.

For completeness, we also provide results that include the use of Machine Translation (MT). This can be done in two ways: 1) translate the test data into English and apply the English NLI classifier, or 2) translate the English training data and train a language specific NLI classifier for each language. It should be stressed that we are not evaluating multilingual sentence embeddings anymore, but rather the quality of the MT system and a monolingual model. Moreover, the use of MT incurs in an important overhead with either strategy: translating test makes inference substantially more expensive, whereas translating train results in a separate model for each language. As shown in Table 3, our approach outperforms all translation baselines of Conneau et al. (2018b) with the exception of Urdu. We also outperform MT BERT for Arabic and Thai, and are very close for Urdu.

Finally, it is worth mentioning that, thanks to its multilingual nature, our system can also handle premises and hypothesis in different languages. As reported in Appendix B, the proposed method obtains very strong results in these settings, even

for distant language combinations like French-Chinese.

4.2 MLDoc: cross-lingual classification

Cross-lingual document classification is a typical application of multilingual representations. In order to evaluate our sentence embeddings in this task, we use the MLDoc dataset of Schwenk and Li (2018b), which is an improved version of the Reuters benchmark (Lewis et al., 2004; Klementiev et al., 2012) with uniform class priors and a wider language coverage. There are 1,000 training and development documents and 4,000 test documents for each language, divided in 4 different genders. Just as with the XNLI evaluation, we consider the zero-shot transfer scenario: we train a classifier on top of our multilingual encoder using the English training data, optimizing hyperparameters on the English development set, and evaluating the resulting system in the remaining languages. We use a feed-forward neural network with one hidden layer of 10 units.

As shown in Table 4, our system obtains the best published results for 5 of the 7 transfer languages. We believe that our weaker performance on Japanese can be attributed to the domain and sentence length mismatch between MLDoc and the parallel corpus we use for this language (Open-Subtitles).

^{*} Results for BERT (Devlin et al., 2018) are extracted from its GitHub README⁹

[†] Monolingual BERT model for Thai from https://github.com/ThAIKeras/bert

		EN			Е	$N \to X$	X		
			de	es	fr	it	ja	ru	zh
Schwenk	MultiCCA + CNN	92.20	81.20	72.50	72.38	69.38	67.63	60.80	74.73
and Li	BiLSTM (Europarl)	88.40	71.83	66.65	72.83	60.73	-	-	-
(2018a)	BiLSTM (UN)	88.83	-	69.50	74.52	-	-	61.42	71.97
Proposed	Proposed method		84.78	77.33	77.95	69.43	60.30	67.78	71.93

Table 4: Accuracies on the MLDoc zero-shot cross-lingual document classification task (test set).

		TR	AIN		TEST				
	de-en	fr-en	ru-en	zh-en	de-en	fr-en	ru-en	zh-en	
Azpeitia et al. (2017)	83.33	78.83	-	-	83.74	79.46	-	_	
Grégoire and Langlais (2017)	-	20.67	-	-	-	20	-	-	
Zhang and Zweigenbaum (2017)	-	-	-	43.48	-	-	-	45.13	
Azpeitia et al. (2018)	84.27	80.63	80.89	76.45	85.52	81.47	81.30	77.45	
Bouamor and Sajjad (2018)	-	75.2	-	-	-	76.0	-	-	
Chongman Leong and Chao (2018)	-	-	-	58.54	-	-	-	56	
Schwenk (2018b)	76.1	74.9	73.3	71.6	76.9	75.8	73.8	71.6	
Artetxe and Schwenk (2018)	94.84	91.85	90.92	91.04	95.58	92.89	92.03	92.57	
Proposed method	95.43	92.40	92.29	91.20	96.19	93.91	93.30	92.27	

Table 5: F1 scores on the BUCC mining task.

4.3 BUCC: bitext mining

Bitext mining is another natural application for multilingual sentence embeddings. Given two comparable corpora in different languages, the task consists in identifying sentence pairs that are translations of each other. For that purpose, one would commonly score sentence pairs by taking the cosine similarity of their respective embeddings, so parallel sentences can be extracted through nearest neighbor retrieval and filtered by setting a fixed threshold over this cosine score (Schwenk, 2018a). However, it was recently shown that this approach suffers from scale inconsistency issues (Guo et al., 2018), and Artetxe and Schwenk (2018) proposed the following alternative score addressing it:

$$\begin{aligned} & \operatorname{score}(x,y) = \operatorname{margin}(\cos(x,y), \\ & \sum_{z \in \operatorname{NN}_k(x)} \frac{\cos(x,z)}{2k} + \sum_{z \in \operatorname{NN}_k(y)} \frac{\cos(y,z)}{2k}) \end{aligned}$$

where x and y are the source and target sentences, and $\mathrm{NN}_k(x)$ denotes the k nearest neighbors of x in the other language. The paper explores different margin functions, with ratio (margin $(a,b)=\frac{a}{b}$) yielding the best results. This notion of margin is related to CSLS as proposed in Conneau et al. (2018a). The reader is referred to Artetxe and Schwenk (2018) for a detailed discussion.

We use this method to evaluate our sentence embeddings on the BUCC mining task (Zweigenbaum et al., 2017, 2018), using exact same hyperparameters as Artetxe and Schwenk (2018). The goal is to extract parallel sentences from a comparable corpus between English and four foreign languages: German, French, Russian and Chinese. The dataset consists of 150K to 1.2M sentences for each language, split into a sample, training and test set, with about 2–3% of the sentences being parallel.

As shown in our results in Table 5, our sentence embeddings establish a new state-of-theart for all language pairs with the exception of English-Chinese test. Quite remarkably, we also outperform Artetxe and Schwenk (2018) themselves, who use two separate models covering 4 languages each (English/French/Spanish/German and English/French/Russian/Chinese). The average performance over the four languages increased from 93.27 to 93.92. Not only are our results better, but our model also covers many more languages, so it can potentially be used to mine bitext for any combination of the 93 languages supported.

4.4 Tatoeba: similarity search

While XNLI, MLDoc and BUCC are well established benchmarks with comparative results available, they only cover a small subset of our 93 lan-

guages. So as to better assess the performance of our model in all these different languages, we introduce a new test set of similarity search for 122 languages based on the Tatoeba corpus. The dataset consists of up to 1,000 English-aligned sentence pairs for each language. Appendix C describes how the dataset was constructed in more details. Evaluation is done by finding the nearest neighbor for each sentence in the other language according to cosine similarity and computing the error rate.

We report our results in Tables 1 and 2. Contrasting these results with those of XNLI, one would assume that similarity error rates below 5% are indicative of strong downstream performance. This is the case for 37 languages, while there are 48 languages with an error rate below 10% and 55 with less than 20%, covering 22 different families and 15 different scripts. There are only 15 languages with error rates above 50%.

We believe that our competitive results for many low-resource languages are indicative of the benefits of joint training, which is also supported by our ablation results in Section 5.3. In relation to that, Appendix E reports similarity search results for 29 additional languages without any training data, showing that our encoder can also generalize to unseen languages to some extent as long as it was trained in related languages.

5 Ablation experiments

In this section, we explore different variants of our approach and study the impact on the performance for all our evaluation tasks. We report average results across all languages. For XNLI, we also report the accuracy on English.

5.1 Encoder depth

Table 6 reports the performance on the different tasks for encoders with one, three or five layers. We were not able to achieve good convergence with deeper models. It can be seen that all tasks benefit from deeper models, in particular XNLI and Tatoeba, suggesting that a single layer BiL-STM has not enough capacity to encode so many languages.

5.2 Multitask learning

Multitask learning has been shown to be helpful to learn English sentence embeddings (Subrama-

Depth	Tatoeba Err [%]	BUCC F1	MLDoc Acc [%]	XNLI-en Acc [%]	XNLI-xx Acc [%]
1	37.96	89.95	69.42	70.94	64.54
3	28.95	92.28	71.64	72.83	68.43
5	26.31	92.83	72.79	73.67	69.92

Table 6: Impact of the depth of the BiLSTM encoder.

nian et al., 2018; Cer et al., 2018). The most important task in this approach is arguably NLI, so we explored adding an additional NLI objective to our system with different weighting schemes. As shown in Table 7, the NLI objective leads to a better performance on the English NLI test set, but this comes at the cost of a worse cross-lingual transfer performance in XNLI and Tatoeba. The effect in BUCC is negligible.

				XNLI-en Acc [%]	
×1 ×2	26.31 26.89 28.52	92.83 93.01 93.06	72.79 74.51 71.90	73.67 73.71 74.65	69.92 69.10 67.75
$\times 3$	27.83	92.98	73.11	75.23	61.86

Table 7: Multitask training with an NLI objective and different weightings.

5.3 Number of training languages

So as to better understand how our architecture scales to a large amount of languages, we train a separate model on a subset of 18 evaluation languages, and compare it to our main model trained on 93 languages. We replaced the Tatoeba corpus with the WMT 2014 test set to evaluate the multilingual similarity error rate. This covers English, Czech, French, German and Spanish, so results between both models are directly comparable. As shown in Table 8, the full model equals or outperforms the one covering the evaluation languages only for all tasks but MLDoc. This suggests that the joint training also yields to overall better representations.

#langs			XNLI-en Acc [%]	
All (93) Eval (18)		72.79 75.63	73.67 72.99	69.92 68.84

Table 8: Comparison between training on 93 languages and training on the 18 evaluation languages only.

 $^{^{10}}$ We consider the average of en \rightarrow xx and xx \rightarrow en

6 Conclusions

In this paper, we propose an architecture to learn multilingual sentence embeddings for 93 languages. We use a single language-agnostic BiLSTM encoder for all languages, which is trained on publicly available parallel corpora and applied to different downstream tasks without any fine-tuning. Our model sets a new state-of-theart for most languages in zero-shot cross-lingual natural language inference (XNLI), cross-lingual document classification (MLDoc), and bitext mining (BUCC). We also introduce a new test set of cross-lingual similarity search in 122 languages, and show that our approach is competitive even for low-resource languages. To the best of our knowledge, this is the first successful exploration of massively multilingual sentence representations.

In the future, we would like to explore alternative architectures for the encoder. In particular, we plan to replace our BiLSTM with the Transformer, which has been shown to work better in different settings (Vaswani et al., 2017; Devlin et al., 2018). Moreover, we would like to explore possible strategies to exploit monolingual training data in addition to parallel corpora, such as using pre-trained word embeddings, backtranslation (Sennrich et al., 2016; Edunov et al., 2018), or other ideas from unsupervised machine translation (Artetxe et al., 2018c; Lample et al., 2018). Finally, we would like to replace our languagespecific tokenization and BPE segmentation with a language agnostic approach similar to Sentence-Piece.¹¹

The model and code used in this paper will be freely available in the framework of the LASER toolkit. 12

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¹¹https://github.com/google/
sentencepiece

¹²https://github.com/facebookresearch/ LASER

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Pierre Zweigenbaum, Serge Sharoff, and Reinhard Rapp. 2018. Overview of the Third BUCC Shared Task: Spotting Parallel Sentences in Comparable Corpora. In *BUCC*.

A Training data

Our training data consists of the combination of the following publicly available parallel corpora:

- Europarl provides high-quality translations for 21 European languages (Koehn, 2005). The size varies from 400k to 2M sentence pairs, in function of the date the respective country joined the European Union.
- United Nations: More than 11 million sentences in the six official languages of the United Nations (Ziemski et al., 2016). We only use the first two million sentences in Arabic, Russian and Chinese.
- OpenSubtitles2018: A collection of translations of movie subtitles in 57 languages (Lison and Tiedemann, 2016). The corpus size varies from few thousand sentences (e.g. Armenian or Kazakh) to more than 50 million (e.g. Spanish or Romanian). We keep at most 2 million entries for each language pair.
- Global Voices: A parallel corpus of news stories from the Global Voices website (38 languages). This is a rather small corpus with less than 100k sentence in most of the languages.
- Tanzil: A collection of Quran translations in 42 languages. The style and vocabulary is very different from news texts. The average size is 135k sentences.
- **Tatoeba:** A community supported collection of English sentences and translations into more than 300 languages. We use this corpus to extract a separate test set of up to 1,000 sentences for many languages (see Section 4.4 and C). For languages with more than 1,000 entries, we use the remaining ones for training.

Using all these corpora would provide parallel data for more than hundred languages. However, we finally only kept 93 different languages to train the multilingual sentence embeddings. In particular, we discarded several constructed languages with little practical use (Klingon, Kotava, Lojban, Toki Pona and Volapük).

B XNLI results for all language combinations

Table 9 reports the accuracies of our system on the XNLI test set when the premises and hypothesis are in a different language (e.g. premise in Russian and hypothesis in Thai). The numbers in the diagonal correspond to the main results reported in Table 3.

We observe that our approach seems to handle the combination of different languages very well. We do not have evidence that very distant languages perform considerably worse. It rather seems that the combined performance is mostly bounded by the accuracy of the language which performs worst when used alone. As an example, Greek-Russian achieves very similar results than Bulgarian-Russian, two Slavic languages. Combing French with Chinese, two totally different languages, is only 1.5 points worse than French/Spanish, two very close languages.

C Tatoeba dataset

Tatoeba¹³ is an open collection of English sentences and high quality translations into more than three hundred languages. The number of available translations is updated every Saturday. We downloaded the snapshot on November 19th 2018 and performed the following processing:

- Removal of sentences that contain "@" or "http". This is motivated by the fact that emails and web addresses are not language specific.
- Removal of sentences with less than three words (before tokenization). These are usually sentences with limited semantic information.
- Removal of sentences that appear multiple times, either in the source or the target.

After filtering, we created test sets of up to 1,000 aligned sentences with English. This amount of texts is available for 78 languages. Limiting the number of sentences to 500, we increase the coverage to 101 languages, and even 141 languages with 100 parallel sentences. It should be stressed that, in general, the English sentences are not the same for the different languages. This implies that the error rates are not necessarily comparable between the languages.

¹³https://tatoeba.org/eng/

D Tatoeba: result analysis

We provide here some analysis on the results given in Tables 1 and 2. We have 48 languages with an error rate below 10% and 55 with less than 20%, respectively (English included). The languages with less than 20% error belong to 20 different families and use 12 different scripts. It is nice to find six languages in this list for which we have only small amounts of bitexts (less than 400k), namely Esperanto, Galician, Hindi, Interlingua, Malayam and Marathi. The two constructed languages probably benefit from their inspiration by other European languages.

Overall, we observe low similarity error rates on the Indo-Aryan languages, namely Hindi, Bengali, Marathi and Urdu. The performance on Berber languages ("ber" and "kab") is remarkable, although we have less than 100 thousand sentences to train them. This is a typical example of languages which are spoken by several millions of people, but for which the amount of written resources is very limited. It is quite unlikely that we would be able to train a good sentence embedding with language specific corpora only. This clearly shows the benefit of joint training on many languages.

Fifteen languages have similarity error rates of more than 50%. Four of them are low-resource languages with their own script and which are alone in their family: Amharic, Armenian, Khmer and Georgian. This makes it difficult to benefit from joint training. On the other hand, one can also argue that is surprising that a language like Khmer performs much better than random (99.9% error rate) with only 625 training examples. Khmer probably benefits of the fact that he have trained our model on other languages of the region which have influenced Khmer, namely Thai and Vietnamese. There are also several Turkic languages (Kazakh, Tatar, Uighur and Uzbek) and Celtic languages (Breton and Cornish) with high error rates. We hope to improve their performance in the future.

E Tatoeba: results for unseen languages

We extend our Tatoeba experiments to 29 languages without any training data (see Table 10). Many of them are recognized minority languages spoken in specific regions, e.g. Asturian, Faroese, Frisian, Kashubian, North Moluccan Malay, Piemontese, Swabian or Sorbian. All

share some similarities, at various degrees, with other major languages, but also differ by their own grammar or specific vocabulary. This enables our encoder to perform reasonably well. We can probably assume that these are mainly spoken languages with limited resources in written form. The six languages which perform worst are Mongolian, Welsh, Xhosa Pampangan, Yiddish and Gaelic. We include these results here as baseline for future research.

_								Н	ypothe	esis							
		en	ar	bg	de	el	es	fr	hi	ru	sw	th	tr	ur	vi	zh	avg
	en	73.8	70.0	71.9	72.8	72.2	72.1	72.2	65.9	71.3	61.4	67.5	69.6	61.0	70.6	70.3	69.5
	ar	70.5	71.3	71.0	70.0	70.5	70.5	69.9	64.8	69.9	60.0	67.1	68.2	60.6	69.4	70.0	68.3
	bg	72.6	71.1	74.2	72.3	72.6	72.0	72.6	65.5	71.7	60.8	69.0	69.8	61.2	70.5	70.5	69.7
	de	71.9	69.6	71.8	72.5	71.4	71.6	71.5	65.2	70.8	60.4	68.1	69.1	60.5	70.0	70.6	69.0
	el	72.8	70.0	71.7	72.1	73.0	71.4	71.5	65.1	71.7	60.9	68.1	69.4	60.9	69.8	70.3	69.2
	es	73.2	70.3	72.4	72.6	72.3	72.9	72.2	65.0	71.1	61.4	68.0	69.8	60.5	70.4	70.3	69.5
ise	fr	73.2	70.3	72.2	72.5	71.5	72.1	71.8	65.8	71.2	61.4	68.1	70.0	60.9	70.9	70.4	69.5
Premise	hi	66.6	65.9	66.6	67.2	66.0	66.1	65.5	65.4	66.4	58.9	63.7	65.8	59.5	65.5	66.0	65.0
Pre	ru	71.3	69.9	72.2	71.4	71.3	71.1	71.2	64.4	72.0	60.8	67.9	68.7	60.5	69.9	70.0	68.8
	sw	65.7	64.4	65.6	64.9	65.3	65.1	64.5	61.4	64.8	62.2	63.3	64.5	58.2	65.0	65.1	64.0
	th	70.5	69.2	71.3	70.1	70.3	70.1	69.6	65.1	70.1	62.0	69.1	67.7	60.9	69.9	69.6	68.4
	tr	70.6	69.1	70.3	70.3	70.1	70.6	69.8	64.0	69.1	61.3	67.3	69.7	60.6	69.7	68.9	68.1
	ur	65.5	64.7	65.3	65.9	66.0	65.6	64.8	62.0	65.2	58.2	63.2	64.1	61.0	64.3	65.0	64.1
	vi	71.6	69.7	72.1	71.0	71.1	71.2	70.5	65.4	70.9	61.2	68.9	69.2	60.5	71.9	70.3	69.0
	zh	71.5	69.9	71.7	71.1	70.9	71.2	70.7	64.0	70.8	60.4	68.6	68.9	60.2	69.7	71.4	68.7
	avg	70.8	69.0	70.7	70.4	70.3	70.2	69.9	64.6	69.8	60.8	67.2	68.3	60.5	69.2	69.2	68.1

Table 9: Accuracies on the XNLI test set of our approach when the premise and hypothesis are in different language. The results in the diagonal correspond to the accuracies reported in Table 3.

			Details		Training	Tatoeba l	Error [%]	Tatoeba
ISO3	ISO2	Name	Family	Script	corpus size	$en \rightarrow xx$	$xx \to en$	test set size
arq		Algerian Arabic	Arabic	Arabic	none	58.62	62.46	911
ast		Asturian	Romance Ibero	Latin	none	12.60	14.96	127
awa		Awadhi	Indo-Aryan	Devanagari	none	63.20	64.50	231
ceb		Cebuano	Malayo-Polynesian	Latin	none	81.67	87.00	600
cha	ch	Chamorro	Malayo-Polynesian (branch)	Latin	none	64.23	77.37	137
arz		Egyptian Arabic	Arabic	Arabic	none	31.24	31.03	477
fao	fo	Faroese	Germanic	Latin	none	28.24	28.63	262
gla	gd	Gaelic; Scottish Gaelic	Celtic	Latin	none	95.66	96.98	829
jav	jv	Javanese	Malayo-Polynesian	Latin	none	73.66	80.49	205
csb		Kashubian	Slavic	Latin	none	54.55	58.89	253
mon	mn	Mongolian	Mongolic	Cyrillic	none	89.55	94.09	440
max		North Moluccan Malay	Malay Creole	Latin	none	48.24	50.00	284
nov		Novial	constructed	Latin	none	33.07	35.02	257
nno	nn	Nynorsk Norwegian	Germanic	Latin	none	13.40	10.00	1000
ang		Old English	Germanic	Latin	none	58.96	65.67	134
pam		Pampangan; Kapampangan	Philippine	Latin	none	93.10	95.00	1000
pms		Piemontese	Romance	Latin	none	50.86	49.90	525
orv		Russian old	Slavic	Cyrillic	none	68.26	75.45	835
dsb		Sorbian Lower	Slavic	Latin	none	48.64	55.32	479
hsb		Sorbian Upper	Slavic	Latin	none	42.44	48.65	483
swg		Swabian	Germanic	Latin	none	50.00	58.04	112
gsw		Swiss German	Germanic	Latin	none	52.99	58.12	117
tzl		Talossan	constructed	Latin	none	54.81	55.77	104
tuk	tk	Turkmen	Turkic	Latin	none	75.37	83.25	203
war		Waray	Malayo-Polynesian	Latin	none	84.20	88.60	1000
cym	cy	Welsh	Celtic	Latin-Welsch	none	89.74	93.04	575
fry	fy	Western Frisian	Germanic	Latin	none	46.24	50.29	173
xho	xh	Xhosa	Niger-Congo	Latin	none	90.85	92.25	142
yid	yi	Yiddish	Germanic	Hebrew	none	93.28	95.40	848

Table 10: Performance on the Tatoeba test set for languages and variants for which we have no training data.