Robust Cross-lingual Embeddings from Parallel Sentences

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Abstract
Recent advances in cross-lingual word embeddings have primarily relied on mapping-based methods, which project pre-trained word embeddings from different languages into a shared space through a linear transformation. However, these approaches assume word embedding spaces are isomorphic between different languages, which has been shown not to hold in practice (Søgaard et al., 2018), fundamentally limiting their performance. This motivates investigating joint learning methods which can overcome this impediment, by simultaneously learning embeddings across languages via a cross-lingual term in the training objective. We propose a bilingual extension of the CBOW method which leverages sentence-aligned corpora to obtain robust cross-lingual word and sentence representations. Our approach significantly improves cross-lingual sentence retrieval performance over all other approaches while maintaining parity with the current state-of-the-art methods on word-translation. It also achieves parity with a deep RNN method on a zero-shot cross-lingual document classification task, requiring far fewer computational resources for training and inference. As an additional advantage, our bilingual method leads to a much more pronounced improvement in the the quality of monolingual word vectors compared to other competing methods.

1 Introduction
Cross-lingual representations—such as embeddings of words and phrases into a single comparable feature space—have become a key technique in multilingual natural language processing. They offer strong promise towards the goal of a joint understanding of concepts across languages, as well as for enabling the transfer of knowledge and machine learning models between different languages. Therefore, cross-lingual embeddings can serve a variety of downstream tasks such as bilingual lexicon induction, cross-lingual information retrieval, machine translation and many applications of zero-shot transfer learning, which is particularly impactful from resource-rich to low-resource languages.

Existing methods can be broadly classified into two groups (Ruder et al., 2019): mapping methods leverage existing monolingual embeddings which are treated as independent, and apply a post-process step to map the embeddings of each language into a shared space, through a linear transformation (Mikolov et al., 2013b; Lample et al., 2018; Joulin et al., 2018). On the other hand, joint methods learn representations concurrently for multiple languages, by combining monolingual and cross-lingual training tasks (Luong et al., 2015; Coulmance et al., 2015; Gouws et al., 2015; Vulic and Moens, 2015; Chandar et al., 2014; Hermann and Blunsom, 2014).

While recent work on word embeddings has focused almost exclusively on mapping methods, which require little to no cross-lingual supervision, (Søgaard et al., 2018) establish that their performance is hindered by linguistic and domain divergences in general, and for distant language pairs in particular. Principally, their analysis shows that cross-lingual hubness, where a few words (hubs) in the source language are nearest cross-lingual neighbours of many words in the target language, and structural non-isometry between embeddings do impose a fundamental barrier to
the performance of linear mapping methods. Ormazabal et al. (2019) propose using joint learning as a means of mitigating these issues. Given parallel data, such as sentences, a joint model learns to predict either the word or context in both source and target languages. As we will demonstrate with results from our algorithm, joint methods yield compatible embeddings which are closer to isomorphic, less sensitive to hubness, and perform better on cross-lingual benchmarks.

Contributions. We propose the Bi-Sent2Vec algorithm, which extends the Sent2Vec algorithm (Pagliardini et al., 2018; Gupta et al., 2019) to the cross-lingual setting. We also revisit TransGram (Coulmance et al., 2015), another joint learning method, to assess the effectiveness of joint learning over mapping-based methods. Our contributions are

- On cross-lingual sentence-retrieval and monolingual word representation quality evaluations, Bi-Sent2Vec significantly outperforms competing methods, both jointly trained as well as mapping-based ones while preserving state-of-the-art performance on cross-lingual word retrieval tasks. For dis-similar language pairs with relatively smaller amount of parallel data, Bi-Sent2Vec outperform their competitors by an even larger margin on all the tasks hinting towards the robustness of our method.

- Faruqui and Dyer (2014) show that training on parallel data additionally enriches monolingual representation quality. Our experiments show that the gain in monolingual performance is significantly more pronounced in Bi-Sent2Vec as compared to other competing cross-lingual embedding methods.

- As an added advantage, Bi-Sent2Vec performs on par with a multilingual RNN based sentence encoder, LASER (Artetxe and Schwenk, 2018), on MLDoc (Schwenk and Li, 2018), a zero-shot cross-lingual transfer task on documents in multiple languages. Compared to LASER, our method improves computational efficiency by an order of magnitude for both training and inference, making it suitable for resource or latency-constrained on-device cross-lingual NLP applications.

2 Related Work

The literature on cross-lingual representation learning is extensive. Most recent advances in the field pursue unsupervised (Artetxe et al., 2017; Lample et al., 2018; Chen and Cardie, 2018; Hoshen and Wolf, 2018; Grave et al., 2018b) or supervised (Joulin et al., 2018; Lample et al., 2018) mapping or alignment-based algorithms. All these methods use existing monolingual word embeddings, followed by a cross-lingual alignment procedure as a post-processing step—that is to learn a simple (typically linear) mapping from the source language embedding space to the target language embedding space.

Supervised learning of a linear map from a source embedding space to another target embedding space (Mikolov et al., 2013b) based on a bilingual dictionary was one of the first approaches towards cross-lingual word embeddings. Additionally enforcing orthogonality constraints on the linear map results in rotations, and can be formulated as an orthogonal Procrustes problem (Smith et al., 2017). However, the authors found the translated embeddings to suffer from hubness, which they mitigate by introducing the inverted softmax as a corrective search metric at inference time. Artetxe et al. (2017) align embedding spaces starting from a parallel seed lexicon such as digits and iteratively build a larger bilingual dictionary during training.

In their seminal work, Lample et al. (2018) propose an adversarial training method to learn a linear orthogonal map, avoiding bilingual supervision altogether. They further refine the learnt mapping by applying the Procrustes procedure iteratively with a synthetic dictionary generated through adversarial training. They also introduce the ‘Cross-Domain Similarity Local Scaling’ (CSLS) retrieval criterion for translating between spaces, which further improves on the word translation accuracy over nearest-neighbour and inverted softmax metrics. They refer to their work as Multilingual Unsupervised and Supervised Embeddings (MUSE). In this paper, we will use MUSE to denote the unsupervised embeddings introduced by them, and “Procrustes + refine” to denote the supervised embeddings ob-

1https://github.com/epfml/Bi-Sent2Vec
...tained by them. Chen and Cardie (2018) similarly use “multilingual adversarial training” followed by “pseudo-supervised refinement” to obtain unsupervised multilingual word embeddings (UMWE), as opposed to bilingual word embeddings by Lample et al. (2018). Hoshen and Wolf (2018) describe an unsupervised approach where they align the second moment of the two word embedding distributions followed by a further refinement. Building on the success of CSLS in reducing retrieval sensitivity to hubness, Joulin et al. (2018) directly optimize a convex relaxation of the CSLS function (RCSLS) to align existing monolingual embeddings using a bilingual dictionary.

While none of the methods described above require parallel corpora, all assume structural isomorphism between existing embeddings for each language (Mikolov et al., 2013b), i.e. there exists a simple (typically linear) mapping function which aligns all existing embeddings. However, this is not always a realistic assumption (Søgaard et al., 2018)—even in small toy-examples it is clear that many geometric configurations of points can not be linearly mapped to their targets.

Joint learning algorithms such as TRANSGRAM (Coulmance et al., 2015) and Cr5 (Josifoski et al., 2019), circumvent this restriction by simultaneously learning embeddings as well as their alignment. TRANSGRAM, for example, extends the Skipgram (Mikolov et al., 2013a) method to jointly train bilingual embeddings in the same space, on a corpus composed of parallel sentences. In addition to the monolingual Skipgram loss for both languages, they introduce a similar cross-lingual loss where a word from a sentence in one language is trained to predict the word-contents of the sentence in the other. Cr5, on the other hand, uses document-aligned corpora to achieve state-of-the-art results for cross-lingual document retrieval while staying competitive at cross-lingual sentence and word retrieval. TRANSGRAM embeddings have been absent from discussion in most of the recent work. However, the growing abundance of sentence-aligned parallel data (Tiedemann, 2012) merits a reappraisal of their performance.

Ormazabal et al. (2019) use BiVEC (Luong et al., 2015), another bilingual extension of Skipgram, which uses a bilingual dictionary in addition to parallel sentences to obtain word-alignments and compare it with the unsupervised version of VECMAP (Artetxe et al., 2018b), another mapping-based method. Our experiments show this extra level of supervision in the case of BiVEC is redundant in obtaining state-of-the-art performance.

In a related line of work, representations from cross-lingual language models (Conneau and Lample, 2019; Schuster et al., 2019) have been used to obtain cross-lingual representations. However, these methods obtain contextual word representations as opposed to the stand-alone word representation models discussed here.

3 Model

We propose Bi-SENT2VEC, a cross-lingual extension of SENT2VEC proposed by Pagliardini et al. (2018), which in turn is an extension of the C-BOW embedding method (Mikolov et al., 2013a). SENT2VEC is trained on sentence contexts, with the word and higher-order word n-gram embeddings specifically optimized toward obtaining robust sentence embeddings using additive composition. Formally, SENT2VEC obtains representation \(v_s\) of a sentence \(S\) by averaging the word-n-gram embeddings (including unigrams) as \(v_s := 1/|R(S)| \sum_{w \in R(S)} v_w\) where \(R(S)\) is the set of word n-grams in the sentence \(S\).

The SENT2VEC training objective aims to predict a masked word token \(w_t\) in the sentence \(S\) using the rest of the sentence representation \(v_{S\setminus\{w_t\}}\). To formulate the training objective, we use logistic loss \(\ell : x \mapsto \log (1 + e^{-x})\) in conjunction with negative sampling. More precisely, for a raw text corpus \(C\), the monolingual training objective for SENT2VEC is given by

\[
\min_{U, V} \sum_{S \in C} \sum_{w_t \in S} \left( \ell\left( u_{w_t}^\top v_{S\setminus\{w_t\}}\right) + \sum_{w' \in N_{w_t}} \ell\left( -u_{w_t}^\top v_{S\setminus\{w_t\}}\right) \right)
\]

where \(w_t\) is the target word and, \(V\) and \(U\) are the source n-gram and target word embedding matrices respectively. Here, the set of negative words \(N_{w_t}\) is sampled from a multinomial distribution where the probability of picking a word is directly proportional to the square root of its frequency in the corpus. Each target word \(w_t\) is sampled with probability \(\min\{1, \sqrt{f_{w_t}}/f_{w_t} + t/f_{w_t}\}\) where \(f_{w_t}\) is the frequency of the word in the corpus.
We adapt the S2V model to bilingual corpora by introducing a cross-lingual loss in addition to the monolingual loss in equation (1). Given a sentence pair \( S = (S_{l_1}, S_{l_2}) \) where \( S_{l_1} \) and \( S_{l_2} \) are translations of each other in languages \( l_1 \) and \( l_2 \), the cross-lingual loss for a target word \( w_l \) in \( l_1 \) is given by

\[
\ell \left( u_w^T v_{S_{l_2}} \right) + \sum_{w' \in N_{w_l}} \ell \left( -u_w^T v_{S_{l_2}} \right)
\]

Thus, we use the sentence \( S_{l_1} \) to predict the constituent words of \( S_{l_2} \) and vice-versa in a similar fashion to the monolingual S2V, shown in Figure 1. This ensures that the word and n-gram embeddings of both languages lie in the same space.

![Figure 1: An illustration of the Bi-S2V training process](image)

Assuming \( C \) to be a sentence aligned bilingual corpus and combining equations (1) and (2), our Bi-S2V model objective function is formulated as

\[
\min_{U,V} \sum_{S \in C} \sum_{l \in S} \left( \ell \left( u_{w_l}^T v_{S_{l_2} \mid \mu_{l_2}} \right) + \sum_{w' \in N_{w_l}} \ell \left( -u_{w_l}^T v_{S_{l_2} \mid \mu_{l_2}} \right) + \right)
\]

\[
\ell \left( u_{w_l}^T v_{S_{l_1}} \right) + \sum_{w' \in N_{w_l}} \ell \left( -u_{w_l}^T v_{S_{l_1}} \right)
\]

**Implementation Details.** We build our C++ implementation on the top of the FASTTEXT library (Bojanowski et al., 2016; Joulin et al., 2016). Model parameters are updated by asynchronous SGD with a linearly decaying learning rate.

Our model is trained on the ParaCrawl (Esplà-Gomis, 2019) v4.0 datasets for the English-Italian, English-German, English-French, English-Spanish, English-Hungarian and English-Finnish language pairs. For the English-Russian language pair, we concatenate the OpenSubtitle corpus\(^2\) (Lison and Tiedemann, 2016) and the Tanzil project\(^3\) (Quran translations) corpus. The number of parallel sentence pairs in the corpora except for those of English-Finnish and English-Hungarian used by us range from 17-32 Million. Number of parallel sentence pairs for the dis-similar language pairs (English-Hungarian and English-Finnish) is approximately 2 million. Evaluation results for these two language pairs can be found in Subsection 4.4. Exact statistics regarding the different corpora can be found in the Table 7 in the Appendix. All the sentences were tokenized using Spacy tokenizers\(^4\) for their respective languages.

For each dataset, we trained two different Bi-S2V models: one with unigram embeddings only, and the other additionally augmented with bigrams. The earlier TransGram models (Coulmance et al., 2015) were trained on a small amount of data (Europarl Corpus (Koehn, 2005)). To facilitate a fair comparison, we train new TransGram embeddings on the same data used for Bi-S2V. Given that TransGram and Bi-S2V are a cross-lingual extension of Skipgram and S2V respectively, we use the same parameters as Bojanowski et al. (2016) and Gupta et al. (2019), except increasing the number of epochs for TransGram to 8, and decreasing the same for Bi-S2V to 5. Additionally, a preliminary hyperparameter search (except changing the number of epochs) on Bi-S2V and TransGram did not improve the results. All parameters for training the TransGram and Bi-S2V models will be made public.

In order to make the comparison more extensive, we also train VECMAP (mapping-based) (Artetxe et al., 2018b,a) and BiVEC (joint-training) (Luong et al., 2015) methods on the same corpora using the exact pipeline as Ormazabal et al. (2019).

\(^2\)http://www.opensubtitles.org/
\(^3\)http://tanzil.net/
\(^4\)https://spacy.io/
### 4 Evaluation

Glavas et al. (2019) show that Bilingual Dictionary Induction (Cross-lingual word retrieval) task is not sufficient enough for gauging the quality of cross-lingual embeddings. Moreover, Kementschedjieva et al. (2019) point out gaps in the MUSE dataset for Cross-lingual word retrieval. Consequently, we use a variety of tasks to assess the quality of the word and sentence embeddings. We compare our results using the following four benchmarks:

- Cross-lingual word retrieval
- Monolingual word representation quality
- Cross-lingual sentence retrieval
- Zero-shot cross-lingual transfer of document classifiers

where benchmarks are presented in order of increasing linguistic granularity, i.e. word, sentence, and document level. We also analyze the effect of training data by studying the relationship between representation quality and corpus size.

We use the code available in the MUSE library\(^5\) (Lample et al., 2018) for all evaluations except the zero-shot classifier transfer, which is tested on the MLDoc task (Schwenk and Li, 2018)\(^6\).

#### 4.1 Word Translation

The task involves retrieving correct translation(s) of a word in a source language from a target language. To evaluate translation accuracy, we use the bilingual dictionaries constructed by Lample et al. (2018). We consider 1500 source-test queries and 200k target words for each language pair and report P@1 scores for the supervised and unsupervised baselines as well as our models in Table 1.

**Table 1:** Word translation retrieval P@1 for various language pairs of MUSE evaluation dictionary (Lample et al., 2018). NN: nearest neighbours. CSLS: Cross-Domain Similarity Local Scaling. For methods where the retrieval method is not mentioned, one with the best average performance out of NN and CSLS was chosen. Double midrule separates mapping-based and jointly trained methods. (‘en’ is English, ‘fr’ is French, ‘de’ is German, ‘ru’ is Russian, ‘it’ is Italian) (‘uni.’ and ‘bi.’ denote unigrams and bigrams respectively)

| Method | en-es | en-fr | en-de | en-ru | en-it | avg. |
|--------|-------|-------|-------|-------|-------|------|
| MUSE   | 81.7  | 83.3  | 82.3  | 82.1  | 74.0  | 72.2 |
| UMWE   | 82.5  | 83.1  | 82.5  | 82.1  | 74.6  | 72.5 |
| Procrustes + refine | 82.4 | 83.9 | 82.3 | 83.2 | 75.3 | 73.2 |
| RCSLS  | 83.7  | 87.1  | 84.1  | 84.7  | 79.2  | 77.5 |
| MUSE (unsupervised) | 81.7 | 83.3 | 82.3 | 82.1 | 74.0 | 72.2 |
| UMWE (Chen and Cardie, 2018) | 82.5 | 83.1 | 82.5 | 82.1 | 74.6 | 72.5 |
| Procrustes + refine (Lample et al., 2018) | 82.4 | 83.9 | 82.3 | 83.2 | 75.3 | 73.2 |
| RCSLS (Joulin et al., 2018) | 83.7 | 87.1 | 84.1 | 84.7 | 79.2 | 77.5 |
| VECMAP (unsupervised) (Artetxe et al., 2018b) | 87.4 | 87.8 | 88.3 | 88.5 | 84.3 | 87.2 |
| VECMAP (supervised) (Artetxe et al., 2018a) | 87.2 | 90.2 | 87.6 | 90.4 | 83.7 | 86.8 |
| BiVEC NN (Luong et al., 2015) | 87.4 | 88.6 | 86.8 | 89.1 | 85.7 | 87.2 |
| BiVEC CSLS (Luong et al., 2015) | 87.6 | 89.1 | 88.8 | 90.3 | 86.4 | 87.2 |
| TRANSGRAM (Coulomance et al., 2015) | 91.6 | 88.6 | 89.1 | 90.1 | 87.5 | 87.2 |
| Bi-SEnt2VEC uni. NN | 86.9 | 91.6 | 86.9 | 91.0 | 86.0 | 88.7 |
| Bi-SEnt2VEC uni. + bi. NN | 89.4 | 92.9 | 89.3 | 92.8 | 86.7 | 89.3 |
| Bi-SEnt2VEC uni. CSLS | 86.0 | 91.7 | 86.4 | 91.4 | 84.6 | 88.8 |
| Bi-SEnt2VEC uni. + bi. CSLS | 89.0 | 92.1 | 88.9 | 92.4 | 86.5 | 89.0 |

#### 4.2 Monolingual Word Representation Quality

We assess the monolingual quality improvement of our proposed cross-lingual training by evaluating performance on monolingual word similar-
Table 3: Cross-lingual sentence retrieval. We report P@1 scores for 2000 source queries searching over 200 000 target sentences. For methods where the retrieval method is not mentioned, one with the best average performance out of NN and CSLS was chosen. Reduction in error is calculated with respect to B1-SENT2VEC uni. + bi. CSLS and the best non-B1-SENT2VEC method. Double midrule separates mapping-based and jointly trained methods.

| Method             | en-es | en-fr | en-de | en-it | avg. |
|--------------------|-------|-------|-------|-------|------|
| MUSE               | 71.5  | 72.7  | 68.8  | 69.2  | 53.4 |
| UMWE               | 70.4  | 73.2  | 66.1  | 68.8  | 51.0 |
| RCSLS              | 26.7  | 26.9  | 19.3  | 21.2  | 8.8  |
| VecMAP (unsupervised) | 81.7  | 82.1  | 79.8  | 80.4  | 62.8 |
| VecMAP (supervised) | 81.3  | 81.0  | 80.4  | 80.7  | 62.6 |
| BiVEC NN           | 69.8  | 77.1  | 54.7  | 75.5  | 56.1 |
| BiVEC CSLS         | 81.6  | 83.4  | 78.1  | 81.6  | 71.6 |
| TransGram          | 83.8  | 82.7  | 80.4  | 81.6  | 72.7 |
| Bi-SENT2VEC uni. NN | 86.4  | 87.8  | 83.4  | 85.2  | 80.2 |
| Bi-SENT2VEC uni. + bi. NN | 87.8  | 87.9  | 83.9  | 86.1  | 79.7 |
| Bi-SENT2VEC uni. CSLS | 88.5  | 89.5  | 86.4  | 87.1  | 83.0 |
| Bi-SENT2VEC uni. + bi. CSLS | 89.6  | 89.7  | 87.4  | 87.8  | 84.0 |
| Reduction in error | 36.8% | 37.6% | 35.7% | 33.7% | 41.4% |

Table 3: Cross-lingual sentence retrieval. We report P@1 scores for 2000 source queries searching over 200 000 target sentences. For methods where the retrieval method is not mentioned, one with the best average performance out of NN and CSLS was chosen. Reduction in error is calculated with respect to B1-SENT2VEC uni. + bi. CSLS and the best non-B1-SENT2VEC method. Double midrule separates mapping-based and jointly trained methods.

4.3 Cross-lingual Sentence Retrieval

The primary contribution of our work is to deliver improved cross-lingual sentence representations. We test sentence embeddings for each method obtained by bag-of-words composition for sentence retrieval across different languages on the Europarl corpus. In particular, the tf-idf weighted average is used to construct sentence embeddings from word embeddings. We consider 2000 sentences in the source language dataset and retrieve their translation among 200K sentences in the target language dataset. The other 300K sentences in the Europarl corpus are used to calculate tf-idf weights. Results for P@1 of unsupervised and supervised benchmarks vs our models are included in Table 3.

4.4 Performance on dis-similar language pairs

We report a substantial improvement on the performance of previous models on cross-lingual word and sentence retrieval tasks for the dis-similar language pairs (English-Finnish and English-Hungarian). We use the same evaluation scheme as in Subsections 4.1 and 4.3 Results for these pairs are included in Table 4.

4.5 Zero-shot Cross-lingual Transfer of Document Classifiers

The MLDoc multilingual document classification task (Schwenk and Li, 2018) consists of news documents given in 8 different languages, which
Table 4: Cross-lingual word and sentence retrieval for dis-similar language pairs (P@1 scores). ‘en’ is English, ‘fi’ is Finnish, ‘hu’ is Hungarian. B\(_{I-S\text{ENT}2\text{VEC}}\) denotes B\(_{I-S\text{ENT}2\text{VEC}}\). For methods where the retrieval method is not mentioned, one with the best average performance out of NN and CSLS was chosen. Reduction in error is calculated with respect to B\(_{I-S\text{ENT}2\text{VEC}}\) uni. CSLS and the best non-B\(_{I-S\text{ENT}2\text{VEC}}\) method. Double midrule separates mapping-based and jointly trained methods.

| Method          | word retrieval en-fi | en-hu | sentence retrieval en-fi | en-hu |
|-----------------|----------------------|-------|-------------------------|-------|
|                 | en-es                | en-fr | en-de                   | en-it |
| MUSE            | 48.1                 | 59.5  | 53.9                    | 64.9  |
| RCSLS           | 61.8                 | 69.9  | 67.0                    | 73.0  |
| VecMap (unsp.)  | 62.5                 | 66.8  | 61.6                    | 68.7  |
| VecMap (sup.)   | 62.6                 | 78.3  | 63.7                    | 76.6  |
| BiVec NN        | 62.1                 | 55.3  | 62.1                    | 53.7  |
| BiVec CSLS      | 69.6                 | 78.0  | 72.4                    | 78.4  |
| TransGram       | 69.7                 | 81.1  | 73.1                    | 80.8  |
| BiS2V uni. NN   | 71.2                 | 85.4  | 75.6                    | 83.9  |
| BiS2V uni. + bi. NN | 68.5 | 81.7  | 71.4                    | 79.4  |
| BiS2V uni. CSLS | 72.0                 | 86.5  | 76.3                    | 85.1  |
| BiS2V uni. + bi. CSLS | 70.1 | 84.4  | 73.7                    | 81.7  |
| Reduction in error | 7.6%   | 28.6% | 8.7%                    | 22.4% |

| Method          | en-es  | en-fr  | en-de  | en-it  |
|-----------------|--------|--------|--------|--------|
| LASER           | 79.3   | 69.6   | 78.0   | 80.1   |
| B\(_{I-S\text{ENT}2\text{VEC}}\) | 74.0   | 71.5   | 81.6   | 82.2   |

Table 5: MLDoc Benchmark results (Schwenk and Li, 2018). A document classifier was trained on one language and tested on another without additional training/fine-tuning. We report % accuracy.

need to be classified into 4 different categories. To demonstrate the ability to transfer trained classifiers in a robust fashion between languages, we use a zero-shot setting, i.e., we train a classifier on embeddings in the source language, and report the accuracy of the same classifier applied to the target language. As the classifier, we use a simple feed-forward neural network with two hidden layers of size 10 and 8 respectively, optimized using the Adam optimizer. Each document is represented using the sum of its sentence embeddings.

We compare the performance of B\(_{I-S\text{ENT}2\text{VEC}}\) with the LASER sentence embeddings (Artetxe and Schwenk, 2018) in Table 5. LASER sentence embedding model is a multi-lingual sentence embedding model which is composed of a biLSTM encoder and an LSTM decoder. It uses a shared byte pair encoding based vocabulary of 50k words. The LASER model which we compare to was trained on 223M sentences for 93 languages and requires 5 days to train on 16 V100 GPUs compared to our model which takes 1-2.5 hours for each language pair on 30 CPU threads.

4.6 Effect of Corpus Size on Representation Quality

We conduct an ablation study on how B\(_{I-S\text{ENT}2\text{VEC}}\) embeddings’ performance depends on the size of the training corpus. We uniformly sample smaller subsets of the En-Fr ParaCrawl dataset and train a B\(_{I-S\text{ENT}2\text{VEC}}\) model on them. We test word/sentence translation performance with the CSLS retrieval criterion, and monolingual embedding quality for En-Fr with increasing ParaCrawl corpus size. The results are illustrated in Figures 2 and 3.
In the following section, we discuss the results on monolingual and cross-lingual benchmarks, presented in Tables 1 - 5, and a data ablation study for how the model behaves with increasing parallel corpus size in Figure 2 - 3. The most impressive outcome of our experiments is improved cross-lingual sentence retrieval performance, which we elaborate on along with word translation in the next subsection.

Cross-lingual evaluations For cross-lingual tasks, we observe in Table 1 that jointly trained embeddings produce much better results on cross-lingual word and sentence retrieval tasks. B1-SENT2VEC’s performance on word-retrieval tasks is uniformly superior to mapping methods, achieving up to 11.5% more in P@1 than RCSLS for the English to German language pair, consistent with the results from Ormazabal et al. (2019). It is also on-par with, or better than competing joint methods except on translation from Russian to English, where TRANSGRAM and BiVEC receive a significantly better score. For word retrieval tasks, there is no discernible difference between CSLS/NN criteria for B1-SENT2VEC, suggesting the relative absence of the hubness phenomenon which significantly hinders the performance of cross-lingual word embedding methods.

Our principal contribution is in improving cross-lingual sentence retrieval. Table 3 shows B1-SENT2VEC decisively outperforms all other methods by a wide margin, reducing the relative P@1 error anywhere from 33.7% to 48.9%. Our model displays considerably less variance than others in quality across language pairs, with at most a ≈ 5% deficit between best and worst, and nearly symmetric accuracy within a language pair. TRANSGRAM and BiVEC also outperform the mapping-based methods, but still fall significantly short of B1-SENT2VEC’s. These results can be attributed to the fact that B1-SENT2VEC directly optimizes for obtaining robust sentence embeddings using additive composition of its word embeddings. Since B1-SENT2VEC’s learning objective is closest to a sentence retrieval task amongst current state-of-the-art methods, it can surpass them without sacrificing performance on other tasks.

Despite using an extra amount of supervision in the form of word-alignments, BiVEC fails to outperform TRANSGRAM models pointing towards a redundancy in this extra level of supervision.

Cross-lingual evaluations on dis-similar language pairs. Unlike other language pairs in the evaluation, English-Finnish and English-Hungarian pairs are composed of languages from two different language families (English being an Indo-European language and the other language being a Finno-Ugric language). In Table 4, we see that the performance boost achieved by B1-SENT2VEC on competing methods methods is
more pronounced in the case of dis-similar language pairs as compared to pairs of languages close to each other. This observation affirms the suitability of Bi-\textsc{Sent2Vec} for learning joint representations on languages from different families.

**Monolingual word quality.** For the monolingual word similarity tasks, we observe large gains over existing methods. \textsc{Sent2Vec} is trained on the same corpora as us, and \textsc{FastText} vectors are trained on the CommonCrawl corpora which are more than 100 times larger than ParaCrawl v4.0. In Table 2, we see that Bi-\textsc{Sent2Vec} outperforms them by a significant margin on SimLex-999 and WS-353, two important monolingual word similarity benchmarks. This observation is in accordance with the fact (Faruqui and Dyer, 2014) that bilingual contexts can be surprisingly effective for learning monolingual word representations. However, amongst the joint-training methods, Bi-\textsc{Sent2Vec} also outperforms \textsc{TransGram} and Bi\textsc{Vec} trained on the same corpora by a significant margin, again hinting at the superiority of the sentence level loss function over a fixed context window loss.

**Effect of n-grams.** Gupta et al. (2019) report improved results on monolingual word representation evaluation tasks for \textsc{Sent2Vec} and \textsc{FastText} word vectors by training them alongside word n-grams. Our method incorporates their results based on the observation that unigram vectors trained alongside with bigrams significantly outperform unigrams alone on the majority of the evaluation tasks. We can see from Tables 1 - 3 that this holds for the bilingual case as well. However, in case of dis-similar language pairs(Table 4), we observe that using n-grams degrades the cross-lingual performance of the embeddings. This observation suggests that use of higher order n-grams may not be helpful for language pairs with contrasting grammatical structures.

**Effect of corpus size.** Considering the cross-lingual performance curve exhibited by Bi-\textsc{Sent2Vec} in Figure 2, increasing corpus size for the English-French datasets up to 1-3.1M lines appears to saturate the performance of the model on cross-lingual word/sentence retrieval, after which it either plateaus or degrades slightly.

It should be noted from Figure 3 that the monolingual quality does keep improving with an increase in the size of the corpus. A potential way to overcome this issue of plateauing cross-lingual performance is to give different weights to the monolingual and cross-lingual component of the loss with the weights possibly being dependent on other factors such as training progress.

**Comparison with a cross-lingual sentence embedding model and performance on document level task.** On the MLDoc classifier transfer task (Schwenk and Li, 2018) where we evaluate a classifier learned on documents in one language on documents in another, Table 5 shows we achieve parity with the performance of the \textsc{Laser} model for language pairs involving English, where Bi-\textsc{Sent2Vec}’s average accuracy of 77.8% is slightly higher than \textsc{Laser}’s 77.3%. While the comparison is not completely justified as \textsc{Laser} is multilingual in nature and is trained on a different dataset, one must emphasize that Bi-\textsc{Sent2Vec} is a bag-of-words method as compared to \textsc{Laser} which uses a multi-layered bi-\textsc{STM} sentence encoder. Our method only requires to average a set of vectors to encode sentences reducing its computational footprint significantly. This makes Bi-\textsc{Sent2Vec} an ideal candidate for on-device computationally efficient cross-lingual NLP, unlike \textsc{Laser} which has a huge computational overhead and specialized hardware requirement for encoding sentences.

6 Conclusion and Future Work

We introduce a cross-lingual extension of an existing monolingual word and sentence embedding method. The proposed model is tested at three levels of linguistic granularity: words, sentences and documents. The model outperforms all other methods by a wide margin on the cross-lingual sentence retrieval task while maintaining parity with the best-performing methods on word translation tasks. The improvements are starker on dis-similar language pairs on both of the tasks illustrating the appropriateness of our method for such cases. Our method achieves parity with \textsc{Laser} on zero-shot document classification, despite being a much simpler model.

The success of our model on the bilingual level calls for its extension to the multilingual level especially for pairs which have little or no parallel corpora. While the amount of bilingual/multilingual parallel data has grown in abundance, the amount of monolingual data available
is practically limitless. Consequently, we would like to explore training cross-lingual embeddings with a large amount of raw text combined with a smaller amount of parallel data.

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References
Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2017. Learning bilingual word embeddings with (almost) no bilingual data. In ACL.
Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018a. Generalizing and improving bilingual word embedding mappings with a multi-step framework of linear transformations. In Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, pages 5012–5019.
Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018b. A robust self-learning method for fully unsupervised cross-lingual mappings of word embeddings. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 789–798.
Mikel Artetxe and Holger Schwenk. 2018. Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. Transactions of the Association for Computational Linguistics, 7:597–610.
Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2016. Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 5:135–146.
A. P. Sarath Chandar, Stanislas Lauly, Hugo Larochelle, Mitesh M. Khapra, Balaraman Ravindran, Vikas C. Raykar, and Amrita Saha. 2014. An autoencoder approach to learning bilingual word representations. In NIPS.
Xilun Chen and Claire Cardie. 2018. Unsupervised multilingual word embeddings. In EMNLP.
Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. In Advances in Neural Information Processing Systems 32, pages 7057–7067. Curran Associates, Inc.
Jocelyn Coulmance, Jean-Marc Marty, Guillaume Wenzek, and Amine Benh Alloum. 2015. Trans- gram, Fast Cross-lingual Word-embeddings. In EMNLP - Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1109–1113.
M. Esplà-Gomis. 2019. ParaCrawl: Web-scale parallel corpora for the languages of the EU.
Manaal Faruqui and Chris Dyer. 2014. Improving vector space word representations using multilingual correlation. In EACL.
Lev Finkelstein, Evgeniy Gabrilovich, Yossi Matias, Ehud Rivlin, Zach Solan, Gadi Wolfman, and Eytan Ruppin. 2001. Placing search in context: the concept revisited. In WWW.
Goran Glavas, Robert Litschko, Sebastian Ruder, and Ivan Vulic. 2019. How to (properly) evaluate cross-lingual word embeddings: On strong baselines, comparative analyses, and some misconceptions. In ACL.
Stephan Gouws, Yoshua Bengio, and Greg Corrado. 2015. Bilbowa: Fast bilingual distributed representations without word alignments.
Edouard Grave, Piotr Bojanowski, Prakhar Gupta, Armand Joulin, and Tomas Mikolov. 2018a. Learning Word Vectors for 157 Languages. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), Miyazaki, Japan. European Language Resources Association (ELRA).
Edouard Grave, Armand Joulin, and Quentin Berthet. 2018b. Unsupervised alignment of embeddings with wasserstein procrustes. In AISTATS.
Prakhar Gupta, Matteo Pagliardini, and Martin Jaggi. 2019. Better word embeddings by disentangling contextual n-gram information. In NAACL-HLT.
Karl Moritz Hermann and Phil Blunsom. 2014. Multilingual distributed representations without word alignment. In International Conference on Learning Representations.
Felix Hill, Roi Reichart, and Anna Korhonen. 2014. Simlex-999: Evaluating semantic models with (genuine) similarity estimation. *Computational Linguistics*, 41:665–695.

Yedid Hoshen and Lior Wolf. 2018. Non-adversarial unsupervised word translation. In *EMNLP*.

Martin Josifoski, Ivan S Paskov, Hristo S Paskov, Martin Jaggi, and Robert West. 2019. Cross-lingual document embedding as reduced-rank ridge regression. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*, pages 744–752. ACM.

Colette Joubarne and Diana Inkpen. 2011. Comparison of semantic similarity for different languages using the google n-gram corpus and second-order co-occurrence measures. In *Canadian Conference on AI*.

Armand Joulin, Piotr Bojanowski, Tomas Mikolov, Hervé Jégou, and Edouard Grave. 2018. Loss in translation: Learning bilingual word mapping with a retrieval criterion. In *EMNLP*.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016. Bag of tricks for efficient text classification. In *EACL*.

Yova Kementchedjhieva, Mareike Hartmann, and Anders Søgaard. 2019. Lost in evaluation: Misleading benchmarks for bilingual dictionary induction. In *EMNLP/IJCNLP*.

Philipp Koehn. 2005. Europarl: A parallel corpus for statistical machine translation.

Guillaume Lample, Alexis Conneau, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2018. Word translation without parallel data. In *International Conference on Learning Representations*.

Pierre Lison and Jörg Tiedemann. 2016. Opensubtitles2016: Extracting large parallel corpora from movie and tv subtitles. In *LREC*.

Thang Luong, Hieu Pham, and Christopher D Manning. 2015. Bilingual word representations with monolingual quality in mind. In *Proceedings of the 1st Workshop on Vector Space Modeling for Natural Language Processing*, pages 151–159.

Tomas Mikolov, Kai Chen, Gregory S. Corrado, and Jeffrey Dean. 2013a. Efficient estimation of word representations in vector space. In *International Conference on Learning Representations*.

Tomas Mikolov, Quoc V. Le, and Ilya Sutskever. 2013b. Exploiting similarities among languages for machine translation. *ArXiv*, abs/1309.4168v1.

Aitor Ormazabal, Mikel Artetxe, Gorka Labaka, Aitor Soroa, and Eneko Agirre. 2019. Analyzing the limitations of cross-lingual word embedding mappings. In *ACL*.

Matteo Pagliardini, Prakhar Gupta, and Martin Jaggi. 2018. Unsupervised learning of sentence embeddings using compositional n-gram features. In *NAACL-HLT*.

Sebastian Ruder, Ivan Vulic, and Anders Søgaard. 2019. A survey of cross-lingual word embedding models. *J. Artif. Intell. Res.*, 65:569–631.

Tal Schuster, Ori Ram, Regina Barzilay, and Amir Globerson. 2019. Cross-lingual alignment of contextual word embeddings, with applications to zero-shot dependency parsing. In *NAACL-HLT*.

Holger Schwenk and Xian Li. 2018. A Corpus for Multilingual Document Classification in Eight Languages. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, Miyazaki, Japan. European Language Resources Association (ELRA).

Samuel L. Smith, David H. P. Turban, Steven Hamblin, and Nils Y. Hammerla. 2017. Offline bilingual word vectors, orthogonal transformations and the inverted softmax. In *International Conference on Learning Representations*.

Anders Søgaard, Sebastian Ruder, and Ivan Vulic. 2018. On the limitations of unsupervised bilingual dictionary induction. In *ACL*.

Jörg Tiedemann. 2012. Parallel data, tools and interfaces in opus. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC-2012)*, pages 2214–2218.
Ivan Vulic and Marie-Francine Moens. 2015. Bilingual word embeddings from non-parallel document-aligned data applied to bilingual lexicon induction. In ACL.
Appendix

A Dataset Information and Statistics

| Code | Language |
|------|----------|
| de   | German   |
| en   | English  |
| es   | Spanish  |
| fi   | Finish   |
| fr   | French   |
| hu   | Hungarian|
| it   | Italian  |
| ru   | Russian  |

Table 6: Language codes.

| Dataset                  | # sentences | # tokens |
|--------------------------|-------------|----------|
| en-de ParaCrawl v4.0     | 17M         | 308M     |
| en-es ParaCrawl v4.0     | 22M         | 477M     |
| en-fi ParaCrawl v4.0     | 2.16M       | 42M      |
| en-fr ParaCrawl v4.0     | 32M         | 665M     |
| en-hu ParaCrawl v4.0     | 1.91M       | 31M      |
| en-it ParaCrawl v4.0     | 13M         | 261M     |
| en-ru OpenSubtitles + Tanzil | 27M       | 363M     |
| Wikipedia - en           | 70M         | 1792M    |
| Wikipedia - de           | –           | 1384M    |
| Wikipedia - fr           | –           | 1108M    |
| Wikipedia - es           | –           | 797M     |
| Wikipedia - it           | –           | 702M     |
| Wikipedia - ru           | –           | 824M     |
| Common Crawl - en        | –           | 600B     |
| Common Crawl - de        | –           | 66B      |
| Common Crawl - fr        | –           | 68B      |
| Common Crawl - it        | –           | 36B      |
| Common Crawl - es        | –           | 72B      |

Table 7: Dataset sizes. For bilingual datasets we report the number of English tokens. M and B stand for $10^6$ and $10^9$ respectively.

We used ParaCrawl v4.0 corpora for training Bi-Sent2Vec, Sent2Vec, BiVec, VecMap and TransGram embeddings except for En-Ru pair for which we used OpenSubtitles and Tanzil corpora combined. MUSE and RCSLS vectors were trained from FastText vectors obtained from Wikipedia dumps (Grave et al., 2018a).

B Additional Monolingual Word Representation Quality Tables

| Method | Dataset          | SimLex-999 en | WS-353 en | RG-65 fr |
|--------|------------------|---------------|-----------|----------|
| MUSE   | en               | 0.38          | 0.74      | 0.61     |
| RCSLS  | en               | 0.38          | 0.74      | 0.62     |
| FASTTEXT-Common Crawl | 0.49          | 0.75      | 0.54     |
| VecMap (unsupervised) | 0.41          | 0.72      | 0.58     |
| VecMap (supervised)   | 0.42          | 0.73      | 0.59     |
| BiVec   | en               | 0.40          | 0.72      | 0.57     |
| TransGram | en            | 0.42          | 0.74      | 0.59     |
| Sent2Vec uni.         | –               | 0.49          | 0.58      | 0.51     |
| Bi-Sent2Vec uni.      | –               | 0.57          | 0.78      | 0.60     |
| Bi-Sent2Vec uni. + bi.| 0.60          | 0.82      | 0.66     |

Table 8: Monolingual word similarity task performance of our methods when trained on en-es ParaCrawl data. We report Pearson correlation scores.

| Method | Dataset          | SimLex-999 en | WS-353 en | RG-65 fr |
|--------|------------------|---------------|-----------|----------|
| MUSE   | en               | 0.38          | 0.74      | 0.72     |
| RCSLS  | en               | 0.38          | 0.74      | 0.70     |
| FASTTEXT-Common Crawl | 0.49          | 0.75      | 0.76     |
| VecMap (unsupervised) | 0.39          | 0.72      | 0.76     |
| VecMap (supervised)   | 0.40          | 0.72      | 0.78     |
| BiVec   | en               | 0.40          | 0.70      | 0.74     |
| TransGram | en            | 0.39          | 0.72      | 0.74     |
| Sent2Vec uni.         | –               | 0.46          | 0.75      | 0.71     |
| Bi-Sent2Vec uni.      | –               | 0.55          | 0.78      | 0.74     |
| Bi-Sent2Vec uni. + bi.| 0.59          | 0.79      | 0.78     |

Table 9: Monolingual word similarity task performance of our methods when trained on en-fr ParaCrawl data. We report Pearson correlation scores.

| Method | Dataset          | SimLex-999 en | WS-353 en | RG-65 fr |
|--------|------------------|---------------|-----------|----------|
| MUSE   | en               | 0.38          | 0.41      | 0.74      | 0.68     |
| RCSLS  | de               | 0.38          | 0.43      | 0.74      | 0.70     |
| FASTTEXT-Common Crawl | 0.49          | 0.39      | 0.75      | 0.64     |
| VecMap (unsupervised) | 0.40          | 0.40      | 0.70      | 0.61     |
| VecMap (supervised)   | 0.41          | 0.42      | 0.71      | 0.63     |
| BiVec   | en               | 0.40          | 0.41      | 0.71      | 0.62     |
| TransGram | de            | 0.42          | 0.42      | 0.74      | 0.66     |
| Sent2Vec uni.         | –               | 0.48          | 0.38      | 0.70      | 0.63     |
| Bi-Sent2Vec uni.      | –               | 0.56          | 0.47      | 0.76      | 0.68     |
| Bi-Sent2Vec uni. + bi.| 0.59          | 0.53      | 0.75      | 0.70     |

Table 10: Monolingual word similarity task performance of our methods when trained on en-de ParaCrawl data. We report Pearson correlation scores.