Improving Multilingual Sentence Embedding using Bi-directional Dual Encoder with Additive Margin Softmax

Yinfei Yang, Gustavo Hernandez Abrego, Steve Yuan, Mandy Guo, Qinlan Shen, Daniel Cer, Yun-hsuan Sung, Brian Strope, Ray Kurzweil

Google AI Language
{yinfeiy, gustavoha}@google.com

Abstract

In this paper, we present an approach to learn multilingual sentence embeddings using a bi-directional dual-encoder with additive margin softmax. The embeddings are able to achieve state-of-the-art results on the United Nations (UN) parallel corpus retrieval task. In all the languages tested, the system achieves P@1 of 86% or higher. We use pairs retrieved by our approach to train NMT models that achieve similar performance to models trained on gold pairs. We explore simple document-level embeddings constructed by averaging our sentence embeddings. On the UN document-level retrieval task, document embeddings achieve around 97% on P@1 for all experimented language pairs. Lastly, we evaluate the proposed model on the BUCC mining task. The learned embeddings with raw cosine similarity scores achieve competitive results compared to current state-of-the-art models, and with a second-stage scorer we achieve a new state-of-the-art level on this task.

1 Introduction

Neural machine translation (NMT) systems are highly sensitive to the volume and quality of the parallel data, known as bitext, used for model training. This motivates increased interest in collecting large amounts of parallel data corpora where filtering is used to guarantee quality. [Uszkoreit et al., 2010; Antonova and Misurjev, 2011] have shown that it is possible to mine parallel documents from the internet using large distributed systems, with computationally intensive and heavily engineered subsystems. Recently, lightweight end-to-end word and sentence embedding-based approaches have gained popularity and are showing some success for this purpose [Grégoire and Langlais, 2017; Bouamor and Sajjad, 2018; Schwenk, 2018; Guo et al., 2018; Artetxe and Schwenk, 2018]. These systems are usually easier to train as they require very little feature engineering.

One popular type of approach is based on cross-lingual embeddings, where two sentences in a translation pair are set to be close to each other in an embedding space. In this approach, given a source sentence, nearest-neighbor search can be used in the cross-lingual embedding space to find potential translation candidates. The nearest neighbors can be chosen in terms of cosine distance. However, current approaches produce noisy matches that require a re-scoring step in order to obtain a clean parallel corpus for training an NMT system [Guo et al., 2018; Artetxe and Schwenk, 2018].

We explore using a bi-directional dual encoder with additive margin softmax [Wang et al., 2018a]. The intuition is that we want to maximally separate sentences that are true translations of each other from similar sentences with overlapping but not identical meanings. Introducing a margin into the softmax attempts to achieve a fixed distance between class members and their respective decision boundaries. As shown in Figure 1, the margin around the decision boundaries tends to structure the embedding space such that examples from the same class have a more compact organization.

Extensive experiments demonstrate the learned multilingual sentence embeddings achieve state-of-the-art parallel sentence retrieval results. On the United Nations (UN) Parallel Corpus [Ziemski et al., 2016], the system achieves P@1 of 86% or higher (from 11.3 million candidates) in all the languages tested. NMT models trained on the mined parallel data are found to not only match or exceed the performance of both models trained on more complex filtering strategies but are also competitive with models trained on gold data. When the approach is extended to document-level embeddings by simply averaging all sentence embeddings, we achieve around 97% on P@1 (from 86k candidates) on
the UN document-level retrieval task.

On the BUCC bitext mining task [Zweigenbaum et al., 2018], using our sentence embeddings achieves competitive results compared to state-of-the-art models, with F-scores ranging from 84.6 to 89.2. These results significantly outperform the baseline models by around 10 points. With a second stage scorer we achieve a new state-of-the-art level, with F-scores ranging from 93.38 (ru-en) to 97.24 (de-en).

We summarize our contributions as follows:

i We introduce a novel bidirectional and additive margin softmax into the dual encoder framework for the bitext retrieval task;

ii Empirical results show that the proposed approach greatly stabilizes cosine similarity in the multilingual embedding space, which also leads to state-of-the-art results on the UN sentence-level bitext retrieval task;

iii We also introduce an approach to embed documents by simply averaging all sentence embeddings, which achieves nearly state-of-the-art results on the UN document-level bitext retrieval task;

iv We apply sentence level retrieval together with final ranking scoring to improve the state of the art on the BUCC mining task.

2 Related Work

Obtaining high-quality parallel corpora is one of the most critical problems in machine translation. One longstanding approach for extracting parallel corpora is to mine documents from the web [Resnik, 1999]. Early approaches leveraged metadata such as document publication dates, titles or document structure [Yang and Li, 2002; Munteanu and Marcu, 2005; Munteanu and Marcu, 2006; Chen and Nie, 2000; Resnik and Smith, 2003; Shi et al., 2006]. However, these approaches suffered from the fact that metadata associated with documents can be sparse or unreliable [Uszkoreit et al., 2010].

Another line of work consists of trying to identify bitexts using only textual information. Some text-based approaches for this task rely on methods such as n-gram scoring [Uszkoreit et al., 2010], named entity matching [Do et al., 2009], and cross-language information retrieval [Utiyama and Isahara, 2003; Munteanu and Marcu, 2005]. One common characteristic of these approaches is that they require very heavy feature and system engineering.

Recent work on using embedding-based approaches has shown promising results. Texts are mapped to an embedding space in order to determine whether they are bitexts. [Grégoire and Langlais, 2017] use a Siamese network [Yin et al., 2015] to map source and target language sentences into a shared embedding space. Then, a classifier is built to decide whether the sentences are parallel. [Hassan et al., 2018; Schwenk, 2018; Artetxe and Schwenk, 2018] formulate multilingual sentence embeddings in a shared space using the encoder states from a shared-encoder NMT system. The cosine similarity between these sentence embeddings is used as a measure of cross-lingual similarity.

[Guo et al., 2018] proposed a new approach using a dual-encoder architecture instead of a encoder-decoder one. The dual-encoder architecture optimizes the cosine similarity between the source and target sentences directly. Here, we extend this approach by using a bidirectional dual-encoder with additive margin softmax, which significantly improves the model performance.

3 Model

This section introduces our bidirectional dual-encoder model for bitext mining trained with additive margin softmax.

3.1 Dual Encoder Model

Figure 2 illustrates a dual-encoder model, consisting of paired encoders feeding a combination function. Such models are well suited for ranking problems such as conversation response prediction and translation candidate prediction [Yang et al., 2018; Guo et al., 2018]. Following [Guo et al., 2018], translation retrieval can be modeled as a ranking problem to place \( y_i \), the true translation of \( x_i \), over all other sentences in \( Y \). \( P(y_i \mid x_i) \) can be expressed as the following log-linear model, with \( \phi \) scoring the compatibility between the encoded representations of \( x_i \) and \( y_i \):

\[
P(y_i \mid x_i) = \frac{e^{\phi(x_i, y_i)}}{\sum_{\hat{y} \in Y} e^{\phi(x_i, \hat{y})}} \quad (1)
\]

\( P(y_i \mid x_i) \) is approximated during training by sampling negatives, \( y_n \), among translation pairs in the same batch:

\[
P_{\text{approx}}(y_i \mid x_i) = \frac{e^{\phi(x_i, y_i)}}{e^{\phi(x_i, y_i)} + \sum_{n=1,n \neq i}^{N} e^{\phi(x_i, y_n)}} \quad (2)
\]

When using dot-product as the scoring function, \( \phi \), a single matrix multiplication can be used to efficiently compute scores for all examples in the same batch. For source and target pairs, \( x_i \) and \( y_i \), the model can be optimized using the log-likelihood objective:

\[
\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{\phi(x_i, y_i)}}{e^{\phi(x_i, y_i)} + \sum_{n=1,n \neq i}^{N} e^{\phi(x_i, y_n)}} \quad (3)
\]

3.2 Bidirectional Dual Encoder

\( \mathcal{L} \) attempts to identify the correct \( y_i \) for each \( x_i \). Good embedding space representations of \( y_i \) and \( x_i \) should in principle
allow retrieval in both directions, i.e. from both \(x_i\) to \(y_j\) and \(y_j\) to \(x_i\). We introduce a bidirectional learning objective, \(\bar{L}_s\) that explicitly optimizes both forward and backward ranking:

\[
\bar{L}_s = L_s + L'_s
\]

### 3.3 Dual Encoder with Additive Margin Softmax

Additive margin softmax extends the scoring function \(\phi\) by introducing a large margin, \(m\), around positive pairs [Wang et al., 2018a].

\[
\phi'(x_i, y_j) = \begin{cases} 
\phi(x_i, y_j) - m & \text{if } i = j \\
\phi(x_i, y_j) & \text{if } i \neq j 
\end{cases}
\]

The margin, \(m\), improves the separation between translations and nearby non-translations. Using \(\phi'(x_i, y_j)\) with the bidirectional loss \(\bar{L}_s\), we obtain the additive margin bidirectional loss, \(\bar{L}_{ams}\).

\[
\bar{L}_{ams} = \frac{1}{N} \sum_{i=1}^{N} \frac{e^{\phi(x_i, y_j)} - m}{\sum_{i=1}^{N} e^{\phi(x_i, y_j)} + \sum_{n=1, n \neq i}^{N} e^{\phi(y_i, x_n)}}
\]

\[
\bar{L}_{ams} = L_{ams} + L'_{ams}
\]

### 4 Experimental Setup

In this section, we describe the training data and provide details about the training process.

#### 4.1 Training Data

The training corpus is extracted from the internet using a bitext mining system similar to the approach described in [Uszkoreit et al., 2010]. The extracted sentence pairs are filtered by a pre-trained data-selection scoring model [Wang et al., 2018b]. Human annotators manually evaluate sentence pairs from a small subset of the harvested pairs and mark the pairs as either GOOD or BAD translations. The data-selection scoring model threshold is chosen such that 80% of the retrained pairs from the manual evaluation are rated as GOOD. We select around 400 million sentences pairs for en-fr, en-es, en-de, en-ru and en-zh.\(^1\) For each language pair, we use 90% of the sentence pairs for training and 10% as development set for parameter tuning. We evaluate the trained models on the United Nations Parallel Corpus reconstruction task, and the BUCC bitext mining task.

\(^1\)We started with a large dataset. However, preliminary results showed that we could use only 10% of the data without downgrading the model performance in the hold-out dev set.

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\[N=[1, 4]\] for en-zh and \(N=[3, 6]\) for other language pairs. We use different settings of \(N\) for the en-zh pair because collocations of more than 3 character tokens are rare in Chinese.

\[\]During training, a vector length penalty is applied to the sentence embeddings. The length penalty is realized as the \(\ell_2\) norm of an embedding and is weighted within the loss by the constant 11.
Table 1: Precision at N (P@N) (%) of target sentence retrieval on the UN corpus. Models attempt to select the true translation target for a source sentence from the entire corpus (11.3 million aligned sentence pairs). [Guo et al., 2018] is a dual encoder (DE) model trained with deep averaging network (DAN) instead of transformer. In the last row, AM stands for “Additive Margin softmax”.

| Models               | en-fr   | en-es   | en-ru   | en-zh   |
|----------------------|---------|---------|---------|---------|
|                      | P@1     | P@3     | P@10    | P@1     | P@3     | P@10    | P@1     | P@3     | P@10    |
| [Guo et al., 2018]   | 48.9    | 62.3    | 73.0    | -       | -       | -       | -       | -       | -       |
| [Artetxe and Schwenk, 2018] | 83.3    | -       | -       | 85.8    | -       | -       | -       | -       | -       |
| DE                   | 80.7    | 87.9    | 91.2    | 85.6    | 92.7    | 95.1    | 83.9    | 89.7    | 92.0    |
| BiDE                 | 82.3    | 90.7    | 94.2    | 86.3    | 93.0    | 95.6    | 85.7    | 92.3    | 95.1    |
| BiDE+AM              | 86.1    | 93.5    | 96.1    | 89.0    | 95.2    | 97.2    | 89.2    | 94.8    | 96.9    |

Table 2: P@1 (%) on the UN corpus from forward search and backward search. Forward search treats English as source and the other language as target. Backward is vice versa.

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Table 3: BLEU scores on WMT testing sets of the NMT models trained on original UN pairs (Oracle) and on two versions of mined UN corpora at sentence level. (*) indicates $p < 0.001$ compared to the model trained on oracle pairs.

4 About 9.5 million unique translations remain for each language pair after de-duping.
mined sentence pairs. The first two rows show baseline models trained with the original UN pairs (Oracle) and from [Guo et al., 2018] respectively. All models perform very similarly, scoring within 2 BLEU points of each other. The one trained with pairs mined from the backward search achieves the highest performance in both language pairs. It is surprising to see that the model trained on mined data is even better than the model trained on original data. To investigate why, we examined some “false positive” examples returned by the nearest neighbor search. We found that many of them actually are quite good translations, with only a few words different from the actual translation pairs, some of them are even better aligned with the original translation. Our model is apparently filtering out some noise in the original data. While our results show that raw cosine similarity can perform as well on the UN corpus as a classifier based on methods from prior work [Guo et al., 2018], we are not claiming that filtering with a more sophisticated classifier is not useful. Section 5 explores filtering using a BERT-based model [Devlin et al., 2018].

5.3 Document-Level Retrieval

We experiment with the proposed model at document-level. For each document, we first compute the embeddings of all its sentences using the sentence-level model, e.g. BiDE+AM. Then, we average of all the sentence embeddings to obtain a document-level embedding. The document embeddings are used to perform approximate nearest neighbor search to identify document translations within the UN corpus.

Table 4 shows the P@1 results at document-level. The results of two baseline models are shown in rows 1 and 2. The baseline models require either a post-document matching step after the sentence-level retrieval [Guo et al., 2018] or a complex engineered system [Uszkoreit et al., 2010]. Rows 3 and 4 provide the results for both forward and backward retrieval using document embeddings obtained by averaging BiDE+AM sentence embeddings. Both en-fr and en-es models establish new state-of-the-art performance at 97% P@1. We also list the results of the averaging models for en-ru and en-zh. It is worth noticing that the performance is consistent across all language pairs.

5.4 Margin Value

Figure 4 shows the F1 scores for the en-fr model with different margin values, from 0 to 0.5. The model improved even with a small margin value, and it kept improving as the margin reached a value of 0.3. The figure also shows the mean cosine similarity scores for both positive and negative pairs. We leveraged our retrieval system to generate negative pairs by using as target in the pair the sentence that was retrieved in second place when the correct target was retrieved in first place. This makes the negative pairs especially challenging to be distinguished from the positive ones. The mean scores of positive pairs kept increasing with the margin value, while the mean of the negative pairs kept decreasing, showing the effectiveness of the additive margin softmax.

6 Evaluation on the BUCC Mining Task

In this section, we evaluate the proposed models on the BUCC mining task [Zweigenbaum et al., 2018]. The BUCC mining task is a shared task on parallel sentence extraction from monolingual corpora with a subset of them assumed to be parallel, and that has been available since 2016. We make use of the data from the 2018 shared task, which consists of corpora for four language pairs: fr-en, de-en, ru-en and zh-en. For each language pair, the shared task provides a monolingual corpus for each language and a gold mapping list containing true translation pairs. These pairs are the ground truth. The task is to construct a list of translation pairs from the monolingual corpora. The constructed list is compared to the ground truth, and evaluated in terms of the F1 measure. For more details on this task refer to [Zweigenbaum et al., 2018].

For each language pair, we iteratively retrieve the nearest neighbors for each source sentence. We then filter the retrieved nearest-neighbor pairs using the cosine similarity scores. Table 5 reports the precision, recall and F-score on the training set for both the forward and backward search. The BUCC forward search identifies English translations of source sentences from another language.5 The cosine score threshold is optimized by itself for comparison with [Arte et al. and Schwenk, 2018], which is listed in rows 1 and 2. Rows 3 and 4 show the performance of our model. Both the forward and backward search achieve very good performance on all metrics, with F-score ranges from 84.6 to 89.2. Both results perform better than the baseline models for fr-en and de-en. We obtain a large F-score performance gain of around 10 points. Once again, the search from non-English to En-

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5 The BUCC forward task contrasts with the UN forward task that identifies non-English translations of English sentences.
The positive/negative ratio is 1:10. 80% of them are used for training and the rest as negatives. We sample the negative pairs so that training and 20% are used for development. On the test set, we first retrieve the nearest neighbors and remove those pairs that are not nearest neighbor of each other. Then, the fine-tuned BERT classifier is applied to select the positive pairs.

The final results on the BUCC task are shown in table 6. Margin-based rescoring still helps to improve the F1 scores by 2 to 3 points on average, even using the simplified one-directional version from Eq. 10. The BERT rescoring model significantly outperforms the current state-of-the-art models, with F-scores ranging from 93.38 (ru-en) to 97.24 (de-en).

### 6.3 Analysis

Figure 5 shows the precision-recall curve on the training set of the BUCC shared task using a forward search with cosine similarly scoring. The curves show that the similarity scores are quite stable and a strong translation quality signal for all language pairs. The figure also lists the average precision for each language pair, ranging from 88% for fr-en to 94% for de-en, which are also very promising.

To better understand the learned embedding space and what could be improved by a second-stage scorer, we list typical failure cases drawn from the training set using a raw cosine similarity model for the zh-en task in table 7. The first “false positive” is actually not really a failure. It is a good translation but that happens to be missing in the gold pairs. [Zweigenbaum et al., 2018] mentioned that there are some true translations that are missing, but that they were not known to have affected the evaluation. However, our models do seem to be identifying some true translations that are not.

### 6.1 Margin Rescoring

We experiment with using a margin-based second-stage scorer similar to the one proposed by [Artetxe and Schwenk, 2018]. Pairs are rescored using the formula: $s(x, y) = \frac{\phi(x, y)}{\text{margin}(x, y)} + \phi(x, y)$, where $\phi$ is the cosine similarity function and

$$\text{margin}(x, y) = \sum_{z \in NN_k(x)} \frac{\phi(x, z)}{2k} + \sum_{z \in NN_k(y)} \frac{\phi(z, y)}{2k}$$

The formula is slightly modified from [Artetxe and Schwenk, 2018] by adding the cosine similarity $\phi$ as part of the final score.\(^6\) We also experiment with a simplified margin only considering one direction, which greatly reduces computation time and simplifies the system:

$$\text{margin}(x, y) = \sum_{y=1}^{k} \frac{\phi(x, y)}{k}$$

### 6.2 BERT Rescoring

We explore using a rescoring classifier based on fine-tuning a multilingual BERT model [Devlin et al., 2018]. For training, we use the nearest neighbor pairs mined from the BUCC training set. Pairs in the gold map list are treated as positives, and the rest as negatives. We sample the negative pairs so that the positive/negative ratio is 1:10. 80% of them are used for training and 20% are used for development. On the test set, we first retrieve the nearest neighbors and remove those pairs that are not nearest neighbor of each other. Then, the fine-tuned BERT classifier is applied to select the positive pairs.

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\(^6\)During early experiments, we found the new formulation consistently performed better than the original.
accounted for by the BUCC data. The second false positive is a typical error of the proposed model. The model has trouble differentiating sentences that are semantically similar but that include different numbers or entities, especially numbers with long digit sequences. Part of the error may originate from the tokenization and normalization steps. Interestingly, often several sentences are very close and with only differences in the numbers, e.g. (en-000065918) Males had a median income of $59,738 versus $39,692 for females; (en-000069337) Males had a median income of $31,106 versus $21,985 for females, etc. As the pattern is very clear, they can be simply removed by a second-stage scorer.

We also list two typical false negatives from the gold pairs. They are both “partial translation” pairs with cosine similarity close to the threshold. These cases are especially challenging, as it is even hard for humans to make a consistent judgment on them. We found that some partial translations are present in the gold set, but others are not in the BUCC training task. In practice, the threshold could be changed and fine-tuned based on the application use case. This type of error seems hard to be captured by a margin-based scorer. The BERT scorer, however, is likely capturing the human preference on the partial translations from the training data.

7 Conclusion

We present an approach to learn multilingual sentence embeddings using a bi-directional dual-encoder with additive margin softmax. The resulting embedding space leads to better retrieval performance on the United Nations (UN) parallel corpus and on the BUCC task. NMT systems trained on mined UN data retrieved using our models perform as well as NMT systems trained on the original UN bitext. Document-level embeddings obtained by simply averaging the sentence level embeddings from our model achieve a new state-of-the-art on UN document-level mining. Our model achieves performance competitive with the current state-of-the-art on BUCC. When combined with a BERT rescoring model, our performance on BUCC achieves a new state-of-the-art.

Acknowledgments

The authors are especially grateful to Wei Wang and Keith Stevens of the Google Translate Team for their valuable discussion and help running the data extraction and selection pipeline.

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Table 7: Failure cases drawn from the BUCC zh-en training set using cosine similarity scoring with a threshold of 0.78 tuned to maximize training set f-score. False positives are mined pairs that are not in the gold pairs. False negatives are gold pairs missed by the retrieval system or with scores lower than the threshold. The text in parentheses is the zh text translated using Google Translate. English glosses are provided for the Chinese sentences. We note that a number of errors are due to noisy pairs in the BUCC data.
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