Bitext Mining for Low-Resource Languages via Contrastive Learning

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Abstract

Mining high-quality bitexts for low-resource languages is challenging. This paper shows that sentence representation of language models fine-tuned with multiple negatives ranking loss, a contrastive objective, helps retrieve clean bitexts. Experiments show that parallel data mined from our approach substantially outperform the previous state-of-the-art method on low resource languages Khmer and Pashto.

1 Introduction

Modern neural machine translation (NMT) system’s success largely depends on the amount of high quality parallel training data. ParaCrawl1, One of the popular projects to mine bitexts, crawls webpages and retrieve sentence pairs for various languages. In this paper, we improve the quality of bitexts mined from ParaCrawl for two of the low resource languages (data size smaller than 10 million), Khmer (km) and Pashto (ps). ParaCrawl mines corpus with a pipeline of four major steps:

1. Website Crawling: crawl websites and collect contents of web pages.
2. Document Alignment: from collected web pages, find contents that align with each other in different languages. Since web page has blocks of contents, this step aligns content on document level
3. Sentence Alignment: from aligned documents, retrieve aligned sentences by finding matched sentences pairs of two languages.
4. Sentence Filtering: from aligned sentences, filter out noisy sentence pairs and use the rest as clean parallel data for downstream tasks such as training NMT systems.

While each step of the pipeline can be improved, we focus on sentence alignment and sentence filtering steps, both of which could benefit from an improved sentence scoring function. In this paper, we apply contrastive learning (Chen et al., 2020; Henderson et al., 2017) to fine-tune a sentence transformer model and use it to align and filter sentences for Pashto and Khmer. Our contrastively fine-tuned sentence transformer achieves better results than previous state-of-the-art sentence representation LASER (Artetxe and Schwenk, 2019b) as well as other top-performance filtering systems (Acarciçek et al., 2020; Lu et al., 2020) submitted to WMT 2020 Corpus Filtering Task (Koehn et al., 2020). We release a toolkit2 for replicating our experiments and it can be applied to other language pairs with document-aligned data.

2 Related Work

2.1 Sentence Alignment

Earlier sentence aligners use heuristics such as sentence length and word frequency to find matching sentence pairs in two documents. One such tool, Hunalign (Varga et al., 2007), is still used today to align sentences from document pairs in the ParaCrawl project. More recent aligners such as

1https://paracrawl.eu/
2Code available at: https://github.com/steventan0110/align-filter
Bleualign (Sennrich and Volk, 2010) use translation system to get both documents into the same language and find matching sentence pairs. Another recent aligner, Vecalign3 (Thompson and Koehn, 2019) uses time series warping (Salvador and Chan, 2007) to improve the algorithm run-time for alignment and can be used with any cross-lingual sentence embedding such as LASER to compute a similarity score.

2.2 Sentence Pair Filtering

Different filtering methods have been proposed in the past few years, for instance in the context of the shared tasks organized by WMT (Buck and Koehn, 2016; Koehn et al., 2018, 2019, 2020) and BUCC (Zweigenbaum et al., 2017, 2018). The cosine similarity score computed by LASER is widely used to filter sentences because (1) pre-trained LASER embedding models are publicly available and (2) computing cosine similarity based on embeddings is fast. Another high performance method is dual conditional cross-entropy (Junczys-Dowmunt, 2018), which uses translation system to find maximal symmetric agreement among sentence pairs. With recent advance on pre-trained language models such as BERT (Devlin et al., 2018), Roberta (Liu et al., 2019) and XLM- Roberta (Conneau et al., 2019), proxy learning (sentence filtering as a binary classification task) (Açarçiçek et al., 2020) also performs very well.

3 Methodology

3.1 Fine-tune Sentence Transformer

Açarçiçek et al. (2020) proposed proxy learning for the sentence filtering task. They used a pre-trained language model with a binary classification head to detect high quality sentence pairs. Inspired by proxy learning, sentence transformers (Reimers and Gurevych, 2019), and contrastive learning (Chen et al., 2020), we fine-tuned sentence transformers following figure 2 to learn a sentence embedding for source and target languages. To fine-tune sentence transformers (we use sentence-BERT, or SBERT), we construct positive and negative pairs to train models with Multiple Negative Ranking Loss (MNR; Henderson et al., 2017). Given N aligned sentence pairs \{(s_1, t_1), \cdots (s_N, t_N)\}, each aligned pair is a positive sample. To construct negative samples, for any given source sentence \(s_i\), we use window size \(W\) to take neighbors of \(t_i\) to form negative samples \{(\(s_i, t_{i-w}\), \(s_i, t_{i-w+1}\), \cdots, \(s_i, t_{i+w}\))\}. We also randomly sample R sentences from target side to form negative samples with \(s_i\). Following MNR Loss, the training objective is computed as

\[
J(s, t, \theta) = -\frac{1}{K} \sum_{i=1}^{K} \left[ d(s_i, t_i) - \log \sum_{j=1}^{2W+R} e^{d(s_i, t_j)} \right]
\]  

(1)

Where \(K\) is the batch size, \((s_i, t_i)\) is the aligned source-target sentence pair (positive sample) and \((s_i, t_j)\) is the negative sample. The distance or similarity score is measured by cosine similarity:

\[
d(s_i, t_i) = \cos(r_{s_i}, r_{t_i})
\]  

(2)

where \(r_{s_i}\) is the high dimensional sentence representation of \(s_i\) encoded by the pre-trained language model \(\theta\). By minimizing \(J(s, t, \theta)\), the model learns to maximize the difference between similarity scores of positive and negative pairs. Therefore, models fine-tuned with MNR not only recognize similar sentences but can also discard noisy sentences. The advantage of our fine-tuned models against other contrastively trained systems like Açarçiçek et al. (2020) is that our representation...
can be quickly computed for millions of sentences and then used for alignment or filtering tasks.

### 3.2 Sentence Alignment

The task of sentence alignment is to find matching sentence pairs in each aligned document pair \( \{D^{\text{src}}, D^{\text{tgt}}\} = \{(s_1, s_2, \cdots, s_n), (t_1, t_2, \cdots, t_n)\} \). We hope to retrieve \( k \) sentence pairs \( \{(s_{i_1}, t_{j_1}), \cdots, (s_{i_k}, t_{j_k})\} \), where each index \( i_k(j_k) \) correspond to a set of indexes in \( D^{\text{src}}(D^{\text{tgt}}) \). For example, \( i_1 = (1, 2, 3), j_1 = (1) \) stands for aligning \( \{s_1, s_2, s_3\} \) from source to \( \{t_1\} \) from target. We use Vecalign as the alignment algorithm because it is designed to work with any high dimensional sentence embedding and it uses approximate dynamic programming algorithm that run in \( O(NM) \) time \((N \text{ and } M \text{ are the number of sentences in source and target document})\). Therefore we use Vecalign to quickly align sentences in document-aligned corpus by feeding in LASER or our fine-tuned SBERT embedding. For details of Vecalign, we direct readers to the original paper\(^4\).

### 3.3 Sentence Filtering

We replicated the filtering system from HUAWEI (Açarçiçek et al., 2020) which rank 1\(^{st}\) on corpus filtering task for Pashto and 2\(^{nd}\) for Khmer in WMT 2020. HUAWEI’s system directly fine-tune language models with a binary classification head\(^5\) so we can filter the corpus by ranking scores predicted by the model. We also experimented with sentence representation (LASER and our fine-tuned SBERT) to filter corpus. Since we need to compute a similarity score based on two high dimensional vectors, we resort to margin score (Artetxe and Schwenk, 2019a), a similarity function that is shown to alleviate the "hubness" problem (Radovanović et al., 2010; Lazaridou et al., 2015). For each given sentence pair \((x, y)\) and the encoded representation \((r_x, r_y)\), the score is computed as

\[
d(r_x, r_y) = \text{margin}(\cos(r_x, r_y),
\sum_{z \in \text{NN}_k(x)} \frac{\cos(r_x, r_z)}{2k} + \sum_{z \in \text{NN}_k(y)} \frac{\cos(r_y, r_z)}{2k})
\]

(3)

where \(\text{NN}_k(x)\) is the \(k\)-nearest neighbor of \(x\) in the corpus\(^6\). In practice, we use ratio as the margin function, namely \(\text{margin}(a, b) = \frac{a}{b}\).

### 4 Experiments and Results

#### 4.1 Mined Datasets Description

We use the evaluation setup of the WMT 2020 shared task on parallel corpus filtering\(^7\) (Koehn et al., 2020). Alignment and filtering methods are evaluated by training MT systems on the resulting parallel corpora and assessing their quality with BLEU (Papineni et al., 2002). We start with the sentence-aligned corpus and the document-aligned corpus provided by WMT. We denote the sentence-aligned corpus as HUNALIGN since it is aligned by Hunalign\(^8\) tool. We use Vecalign with LASER embeddings and our fine-tuned SBERT embeddings on the released document-aligned corpus, producing two more versions of sentence-aligned corpora: LASER-ALIGN and SBERT-ALIGN.

For each of the three versions of parallel corpus (LASER-ALIGN, SBERT-ALIGN, and HUNALIGN), we de-noise it with three filtering methods: LASER-FILTER, SBERT-FILTER, HUAWEI-FILTER. Both LASER-FILTER and SBERT-FILTER rank sentences with margin score function, with the only difference being the sentence representation. HUAWEI-FILTER is our replication of the filtering system from HUAWEI as described in section 3.3.

#### 4.2 Results and Analysis

To evaluate performance of different methods, we rely on the BLEU score (Papineni et al., 2002) of the neural machine translation model trained following the Flores baseline setting\(^9\). Complete experimental results (Table 1 and 2) and detailed description of preprocessing and fine-tuning steps are included in appendix. In this section, Figures 3 and 4 are used to help visualize results. Figure 3 shows the best BLEU score achieved by each sentence-aligned corpus. For each corpus, we experimented with three filtering techniques and only the highest score of the three is plotted. For both languages (ps

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\(^4\)https://aclanthology.org/D19-1136.pdf  
\(^5\)We follow their practice to fine-tune XLM-Roberta model  
\(^6\)We use Faiss (Johnson et al., 2019) to compute the score and use its default value \(k=4\)  
\(^7\)https://www.statmt.org/wmt20/parallel-corpus-filtering.html  
\(^8\)http://mokk.bme.hu/en/resources/hunalign/  
\(^9\)https://github.com/facebookresearch/flores
and km), the best score is from **SBERT-ALIGN** (10.43 for Pashto and 11.83 for Khmer), which is about 1 BLEU point boost compared to the winning system in WMT20. The substantial difference between semantic-representation-based methods (LASER/SBERT-align) and heuristic-based method (Hunalign) can be easily found in the plot. Between **LASER-ALIGN** and **SBERT-ALIGN**, the advantage of the latter seems small but here we only plot the highest score out of three filtering methods. In fact, most time **HUAWEI-FILTER** works the best (and it is the most computational-intensive filtering method of the three). Therefore, we plot figure 4 to better compare LASER and fine-tuned SBERT. We uses LASER or SBERT for both sentence alignment and filtering steps. **SBERT**-based alignment and filtering works much better than the LASER-based method (about +2 BLEU), demonstrating SBERT’s effectiveness as alignment & filtering technique.

Combining results above, we show that SBERT is a better representation of low resource languages, a better quality-scoring mechanism for sentence alignment and filtering. We believe there is still room for further improvement, since SBERT is only fine-tuned on target language and English but WMT-released document-aligned corpus are noisy, with boilerplate and sentences in the wrong language. A natural next step is to fine-tune SBERT with our proposed technique on much larger amount of data, covering more languages.

## 5 Conclusion

We empirically show that SBERT, fine-tuned with Multiple Negative Ranking Loss, is a good sentence representation of low resource languages. Using our fine-tuned SBERT as a sentence-aligner (with Vecalign) or filter (with margin-based score) produces better training data for downstream neural machine translation models.
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6 Appendix

6.1 Evaluation Dataset Size

Our experiments’ results are shown in Table 1 and 2, where three types of alignment method and three types are filtering methods are experimented (in total 9 combinations). For each of the 9 possible alignment-filtering method, 4 versions are created based on how much data is sub-sampled. We use the threshold 2, 3, 5, 7 million (#tokens on English side) following the practice from WMT 2020 Corpus Filtering Task. Note that for Khmer, we see that the BLEU scores are still going up for some alignment-filtering methods (for example, for SBERT-ALIGN HUAWEI-FILTER, BLEU goes up from 11.13 to 11.83). Therefore we also experimented with sub-sampling 9-million datasets and verified that BLEU score did not increase anymore.

6.2 Preprocessing

For sentence alignment step, we did not employ any pre-processing techniques because most documents contain noisy sentences and removing those sentences would make it harder to align sentences. After retrieving sentence-aligned datasets (LASER-ALIGN, SBERT-ALIGN, HUNALIGN), we pre-process the datasets before sentence filtering step. First, we de-duplicate the datasets, which filters out about 90% data (since most aligned sentences are duplicate pairs). Second, we remove the sentence pair that has over 90% overlap between source and target side sentences. Lastly, We also use fasttext language id\textsuperscript{10} to check every aligned sentence pair and remove it if its English side is not predicted as en. Note that this is a very lenient filter given the noisy sentence-aligned dataset we retrieved. In fact, language id filtering plays an important role for LASER-FILTER for km-en task. The BLEU score under LASER-FILTER is significantly worse than the other two filtering methods, especially when sub-sample size is small (2 or 3 million tokens). This is because LASER would select many sentence pairs that is not Khmer as top-scoring pairs. When filtering out sentences based on language id for both English and Khmer, LASER-FILTER can achieve better performances (though still worse than our SBERT-FILTER and HUAWEI-FILTER results), similar to the scores reported in WMT 2020 Corpus Filtering Task.

\textsuperscript{10}https://fasttext.cc/docs/en/language-identification.html

6.3 Fine-tune Sentence-BERT

To build SBERT-ALIGN corpus, we fine-tune the SBERT model as described in section 3.1 and figure 2. To fine-tune SBERT, we need a parallel corpus to sample positive and negative pairs from. We experimented with both HUNALIGN and LASER-ALIGN corpus. It is unsurprising that LASER-ALIGN works better because it has more correctly aligned sentences. Thus, we fine-tuned SBERT based on the LASER-ALIGN corpus and then use it to align sentences from document-aligned data, producing the sentence-aligned corpus SBERT-ALIGN.
## Table 1: BLEU Score of Neural Machine Translation model trained on ps-en datasets that are mined with different sentence-alignment and sentence-filtering methods. Each row corresponds to one sentence-aligner and each column corresponds to one sentence-filter. Under each filter methods, four sub-columns indicate the number of millions of English tokens sub-sampled from the corpus following the practice from WMT20 Shared Task on Corpus Filtering (Açarçinek et al., 2020). The bold numbers are the highest scores for each alignment type, which are used to plot figure 3

| Alignment Type | LASER Filter | SBERT Filter | HUAWEI Filter |
|---------------|--------------|--------------|---------------|
|               | 2M | 3M | 5M | 7M | 2M | 3M | 5M | 7M | 2M | 3M | 5M | 7M |
| HUNALIGN      | 6.19 | 7.53 | 7.71 | 7.86 | 7.96 | 8.73 | 9.05 | 8.44 | 7.48 | 8.70 | 9.26 | 8.33 |
| LASER-ALIGN   | 6.04 | 7.73 | 7.03 | 7.99 | 8.41 | 9.17 | 9.82 | 8.76 | 9.35 | 10.18 | 10.38 | 8.70 |
| SBERT-ALIGN   | 6.13 | 7.72 | 8.66 | 8.44 | 8.13 | 9.08 | 10.07 | 9.00 | 9.19 | 10.02 | 10.43 | 9.61 |

## Table 2: BLEU Score of Neural Machine Translation model trained on km-en datasets that are mined with different sentence-alignment and sentence-filtering methods. The bold numbers are the highest scores for each alignment type, which are used to plot figure 3

| Alignment Type | LASER Filter | SBERT Filter | HUAWEI Filter |
|---------------|--------------|--------------|---------------|
|               | 2M | 3M | 5M | 7M | 2M | 3M | 5M | 7M | 2M | 3M | 5M | 7M |
| HUNALIGN      | 5.60 | 6.70 | 7.59 | 8.37 | 7.94 | 8.27 | 8.33 | 8.02 | 8.77 | 9.25 | 10.38 | 10.03 |
| LASER-ALIGN   | 5.29 | 6.91 | 9.05 | 9.33 | 9.03 | 9.44 | 10.13 | 10.79 | 8.96 | 9.86 | 11.11 | 11.68 |
| SBERT-ALIGN   | 4.96 | 7.02 | 8.65 | 9.14 | 9.22 | 9.45 | 10.18 | 10.12 | 8.85 | 10.15 | 11.13 | 11.83 |