EMS: Efficient and Effective Massively Multilingual Sentence Representation Learning

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Abstract—Massively multilingual sentence representation models, e.g., LASER, SBERT-distill, and LaBSE, help significantly improve cross-lingual downstream tasks. However, multiple training procedures, the use of a large amount of data, or inefficient model architectures result in heavy computation to train a new model according to our preferred languages and domains. To resolve this issue, we introduce efficient and effective massively multilingual sentence representation learning (EMS), using cross-lingual sentence reconstruction (XTR) and sentence-level contrastive learning as training objectives. Compared with related studies, the proposed model can be efficiently trained using significantly fewer parallel sentences and GPU computation resources without depending on large-scale pre-trained models. Empirical results show that the proposed model significantly yields better or comparable results with regard to bi-text mining, zero-shot cross-lingual genre classification, and sentiment classification. Ablative analyses demonstrate the effectiveness of each component of the proposed model. We release the codes for model training and the EMS pre-trained model, which supports 62 languages (https://github.com/Mao-KU/EMS).

Index Terms—Efficient and Effective Language-Agnostic Sentence Representation, Cross-Lingual Token-Level Reconstruction, Contrastive Learning, Zero-Shot Cross-Lingual Transfer, Bi-text Mining, Cross-Lingual Sentence Classification.

1 INTRODUCTION

CROSS-LINGUAL sentence representation (CSR) models [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14] prove to be essential for NLP tasks like cross-lingual sentence retrieval and cross-lingual transfer on downstream tasks without the need for initial training and monolingual model. Thus, CSR models benefit low-resource languages without sufficient training data.

A majority of the CSR training methods can be ascribed to one of the following two categories: global fine-tuning or fixed representation. Global fine-tuning methods indicate that for a specific downstream task, we conduct fine-tuning by updating pre-trained language models e.g., mBERT [4], XLM [8], and XLM-R [13]. The fine-tuning efficiency of this method group is determined by the scale of the pre-trained model. Thus, the update of the large-scale parameters of the pre-trained model tends to be the computation bottleneck for fine-tuning. The computationally lite global fine-tuning methods have been explored sufficiently either by compressing the model [15] or training a student model by knowledge distillation [16], [17], [18]. On the other hand, fixed representation methods, e.g., LASER [6], aim to train the CSR that aligns the representation space across languages without further fine-tuning. As a result, this group of methods can be efficiently adapted to several cross-lingual downstream tasks by merely adding a multi-layer perceptron, without the need for tuning parameters within the pre-trained CSR model. However, existing fixed representation methods for learning CSR models, LASER [6], SBERT-distill [12], and LaBSE [11], require a considerable amount of data, complicated model architectures, or monolingual/multilingual pre-trained language models, for which the efficient model has not been explored.

In this study, we present Efficient and effective massively Multilingual Sentence representation learning (EMS), a computationally lite and effective architecture for training CSR without relying on any large-scale pre-trained language model, which makes it computational lite to train a CSR model according to our preferred domains or language groups and may have a promising future for deploying pre-trained CSR models on memory-limited devices. In particular, we propose cross-lingual token-level reconstruction (XTR) and sentence-level contrastive learning as training objectives. XTR captures the target token distribution information, whereas the contrastive objective serves to recognize translation pairs. We claim that these two objectives lead to effective language-agnostic sentence representation for the encoder-only model without language model pre-training, and the encoder-only model results in highly efficient model training. Compared with previous massively multilingual fixed representation methods, EMS can be trained using significantly fewer training data and less GPU consumption.

We extend our previous studies [14], lightweight bilingual sentence representation learning, to the massively multilingual scenario in this study. We explore how to train a model efficiently and effectively for a massively multilingual scenario. To address this, we tailor the model capacity for a large number of languages and introduce a language token embedding layer for the generative objective and a linear layer for the contrastive objective. Moreover, we observe that joint training with the XTR objective and alignment-based sentence-level contrastive objective proposed in our previous study benefit massively multilingual training. In addition, with regard to the model performance, we validate the effectiveness of our language-agnostic sentence representation with more evaluation benchmarks in...
this study, along with the contribution of each model component via the ablation study.

Despite the small amount of training data and low-cost training, experimental results demonstrate that the proposed EMS learned a robustly aligned multilingual sentence representation space. With regard to the Tatoeba [6] cross-lingual similarity benchmark, EMS significantly achieves better results than LASER and SBERT-distill and comparable results considering middle- and high-resource languages compared with LaBSE. Moreover, we evaluate the model performance for mining parallel sentences from larger comparable corpora, including the task of ParaCrawl [19] sentence retrieval and BUCC benchmark [20, 21]. The experimental results show that EMS performs better than SBERT-distill and comparably with LASER. Furthermore, we evaluate the language-agnostic representation based on three classification tasks in a zero-shot manner, document genre classification based on MLDoc [22], and sentiment classification based on two Amazon review datasets [23], [24]. Empirical results show that EMS outperforms LASER and SBERT-distill on MLDoc and one of the Amazon review datasets and yields comparable performance with SBERT-distill and LaBSE on the other Amazon review dataset.

2 RELATED WORK

We revisit generative and contrastive objectives, which are crucial for training CSR models.

Generative Objectives measure a generation probability of the token prediction, via training a language model, which primarily contributes to the performance of downstream tasks. BERT’s masked language model (MLM) [4] and its variants [8, 13, 25] focus on optimizing the encoder-side token generation probability. Sequence-to-sequence learning uses the encoder-decoder framework to train either a translation task [1, 2, 6] or a sentence reconstruction task [26, 27, 28] through optimizing the decoder-side token generation probability. Subsequently, sentence representation can be constructed using the encoder-side output for both groups of the generative objectives.

Contrastive Objectives aim to transform the representation space by adjusting the distance between the representations of tokens (or the sentences), which are used jointly with the generative objectives to improve sentence representation learning. Next sentence prediction (NSP) in BERT [4], token discrimination in ELECTRA [29], sentence discrimination in DeCLUTR [30], and hierarchical contrastive objective in HICTL [31] are the typical ones.

In this study, we analyze what generative objective is optimal for the efficient universal sentence representation learning and augment it with a proper contrastive objective by joint training based on our previous study [14].

3 PROPOSED METHODS

We conduct massive multilingual CSR learning by employing the dual transformer encoder as the backbone of the training framework. For the training objective, we propose a novel cross-lingual training method, which jointly optimizes generative and contrastive objectives. We introduce cross-lingual token-level reconstruction (XTR) as the generative objective and employ sentence-level self-supervised learning as the contrastive objective. The training framework and objectives that we propose are expected to learn a well-aligned representation space for multiple languages.

3.1 Architecture

We introduce the dual transformer sharing parameters to encode parallel sentences along with several linear layers to extract cross-lingual information and compute the generative and contrastive losses (Fig. 1). We use parallel corpora as the training data. First, we build monolingual sentence representations u and v on top of a transformer encoder. Two groups of the multi-lingual perceptrons (MLP) are employed to construct two training objectives. Unlike SBERT-distill [12] employing XLM-R [3] and LaBSE [11] employing MLM [4] and TLM [8] pre-trained encoders, the dual transformer architecture in this study is highly effective without any pre-trained models, which leads to an efficient training phase. After completing the model training, given a sentence in any language, we use the transformer encoder to infer the language-agnostic sentence representation. We can implement cross-lingual downstream tasks in a zero-shot manner using u or v, as they are representations independent of the specific language.

Specifically, as shown in Fig. 1, assume that we have a parallel corpus C that includes multiple languages \{l_1, l_2, ..., l_N\}, and each sentence pair \(S = (S_l, S_{l'})\) contains a sentence in language \(l\) and its translation in language \(l'\), where \(l, l' \in \{l_1, l_2, ..., l_N\}\), as shown in the blue dashed box in Fig. 1. We use the dual transformer encoder \(E\) sharing parameters to encode each sentence pair. Assume that the transformer encoder outputs of \(S_l\) are \((h_1^T, h_2^T, ..., h_{\|S_l\|}^T)\), where \(\|S_l\|\) indicates the length of \(S_l\). We use the mean-pooled hidden states as the language-agnostic sentence representation u:

\[
u = \frac{1}{\|S_l\|} \sum_i h_i
\]

Similarly, we can obtain v for \(S_{l'}\).

3.2 Generative Objective

Generative objective plays an essential role for CSR learning. SBERT-distill and LaBSE use the pre-trained models as the model initialization; therefore, the pre-trained language models for each language serve as generative objectives. LASER finished the model training in one run without using any pre-training models, and the translation objective serves as a cross-lingual generative objective. Inspired by LASER, we include the generative objective for the one-run model training. However, the presence of the transformer decoder in LASER increases the computational overhead. Instead, we propose a novel generative objective known as cross-lingual token-level reconstruction (XTR) to improve the training efficiency while retaining the quality of sentence representation, which circumvents using the transformer decoder.

1. languages for which we possess over 300k parallel sentences for training data.

2. SBERT-distill also possesses the mBERT version; however, the initialization by XLM-R achieves better performance.
As we expect the XTR objective to measure a cross-lingual reconstruction loss, it is necessary to notify the model what the target language is. Thus, we compute a target language representation for each sentence by employing a language embedding layer $L_{la}$ to encode the target language token (e.g., $<2en>$ if the target language is English). More precisely, for each sentence pair $S = (S_l, S_r)$,

$$u_{la} = W_{la} h_l$$

$$v_{la} = W_{la} h_l$$

where $W_{la} \in \mathbb{R}^{d_{la} \times d_{emb}}$ denotes the parameters of $L_{la}$. $h_l$ and $h_l'$ respectively denote the one-hot embedding of $<$2en$>$ and $<$2fr$>$, $d_{la}$ and $d_{emb}$ denote the dimension of the language embedding and the size of the vocabulary, respectively.

Subsequently, we concatenate the language representation with the sentence representation and use a fully connected layer $L_{fc}$ to transform the concatenated representation for extracting the cross-lingual information. Finally, we use another linear embedding layer $L_{emb}$ followed by Softmax to transform the representation to present two probability distributions, which are formulated as:

$$q_{Si} = \text{softmax}(W_{emb}\sigma_{xtr}(W_{fc}(u_{la} \oplus u)))$$

$$q_{Si'} = \text{softmax}(W_{emb}\sigma_{xtr}(W_{fc}(v_{la} \oplus v)))$$

where $W_{emb} \in \mathbb{R}^{d_{emb}}$, $W_{fc} \in \mathbb{R}^{(d_{la}+d) \times (d_{la}+d)}$, and $d$ indicates the dimension of $u$ (or $v$). $\sigma_{xtr}$ is the activation function in $L_{fc}$, for which we use swish [32]. $\oplus$ indicates the concatenation over the first dimension.

Assume that $B_i$ is a batch sampled from the training corpus $C$. Then, the training loss of the XTR objective for the $B_i$ is formulated as follows:

$$L_{XTR}^{(i)} = \sum_{S \in B_i} \left( D_{KL}(p_{S_l}(W) \parallel q_{S_l}) + D_{KL}(p_{S_l'}(W) \parallel q_{S_{l'}}) \right)$$

where $D_{KL}$ denotes KL-divergence and $W$ indicates the vocabulary set. As illustrated in the orange dashed box in Fig. 1, we use discrete uniform distribution for the tokens in $S_l$ to define $p_{S_l}$. Specifically, for each $w \in W$, $p_{S_l}(w)$ is defined as:

$$p_{S_l}(w) = \begin{cases} \frac{N_w}{\|S_l\|}, & w \in S_l \\ 0, & w \notin S_l \end{cases}$$

where $N_w$ is the number of times $w$ appears in the sentence $S_l$. This way, $p_{S_l}$ is a probability distribution over the vocabulary, which is used to define the generative objective. The part within the red dashed box indicates the pre-trained EMS model for downstream tasks.

As we expect the XTR objective to measure a cross-lingual reconstruction loss, it is necessary to notify the model what the target language is. Thus, we compute a target language representation for each sentence by employing a language embedding layer $L_{la}$ to encode the target language token (e.g., $<2en>$ if the target language is English). More precisely, for each sentence pair $S = (S_l, S_r)$,

$$u_{la} = W_{la} h_l$$

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where $W_{la} \in \mathbb{R}^{d_{la} \times d_{emb}}$ denotes the parameters of $L_{la}$. $h_l$ and $h_l'$ respectively denote the one-hot embedding of $<$2en$>$ and $<$2fr$>$, $d_{la}$ and $d_{emb}$ denote the dimension of the language embedding and the size of the vocabulary, respectively.

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$$q_{Si} = \text{softmax}(W_{emb}\sigma_{xtr}(W_{fc}(u_{la} \oplus u)))$$

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where $W_{emb} \in \mathbb{R}^{d_{emb}}$, $W_{fc} \in \mathbb{R}^{(d_{la}+d) \times (d_{la}+d)}$, and $d$ indicates the dimension of $u$ (or $v$). $\sigma_{xtr}$ is the activation function in $L_{fc}$, for which we use swish [32]. $\oplus$ indicates the concatenation over the first dimension.

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$$L_{XTR}^{(i)} = \sum_{S \in B_i} \left( D_{KL}(p_{S_l}(W) \parallel q_{S_l}) + D_{KL}(p_{S_l'}(W) \parallel q_{S_{l'}}) \right)$$

where $D_{KL}$ denotes KL-divergence and $W$ indicates the vocabulary set. As illustrated in the orange dashed box in Fig. 1, we use discrete uniform distribution for the tokens in $S_l$ to define $p_{S_l}$. Specifically, for each $w \in W$, $p_{S_l}(w)$ is defined as:

$$p_{S_l}(w) = \begin{cases} \frac{N_w}{\|S_l\|}, & w \in S_l \\ 0, & w \notin S_l \end{cases}$$

where $N_w$ is the number of times $w$ appears in the sentence $S_l$. This way, $p_{S_l}$ is a probability distribution over the vocabulary, which is used to define the generative objective. The part within the red dashed box indicates the pre-trained EMS model for downstream tasks.
where \( N_w \) indicates the number of words \( w \) in sentence \( S_i \), and \( N_w \) is 1 in most cases. \( \| S_i \| \) indicates the length of \( S_i \). In other words, \( p_{S_i}(W) \) is approximately an average of one-hot embeddings of \( S_i \)'s tokens. Similarly, we can obtain the definition of \( p_{S_{i'}}(W) \).

Herein, we use the KL-divergence to measure the similarity between the token distribution of the sentence in the target language and the model output of the sentence in the source language, which helps align the language-agnostic representation space. In our previous study [14], we introduced another generative objective known as unified generative task (UGT). We will provide empirical results and analyses to show that this objective is not relevant in the massive multilingual scenario and current model architecture (see Section 5.6).

### 3.3 Contrastive Objective

Based on our previous study [14], we employ a sentence-level contrastive objective as an assisting objective to force the model to grasp similar information of sentences across languages. We demonstrate that the sentence-level contrastive objective is a beneficial model component to jointly assist the generative objective. In Section 5.6, we provide empirical shreds of evidence that this objective plays a beneficial role in the generative objective introduced in Section 5.2.

Specifically, we employ in-batch sentence-level contrastive learning by discriminating between positive and negative samples for each sentence. Given a sentence, its translation (paired sentence in another language) is deemed as a positive sample, whereas other sentences within the batch are used as the negative samples. Unlike our previous study, we add two fully-connected layers to decrease the dimension of the sentence representation to compute the contrastive objective, following [33]. Assume that \( B_i \) is a batch sampled from the training corpus \( C_i \) and the \( j \)-th sentence pair of \( B_i \) is \( S_i^{(j)} = (S_i^{(j)}, S_i^{(j)}) \). Then the sentence-level contrastive objective for \( B_i \) is formulated as follows:

\[
L_{\text{contra}}^{(i)} = - \sum_{S_{i}^{(j)} \in B_i} \left( \log \frac{\exp(\text{sim}(S_i^{(j)}, S_i^{(j)}) / T)}{\sum_{S_{i}^{(k)} \in B_i} \exp(\text{sim}(S_i^{(j)}, S_i^{(k)}) / T)} + \log \frac{\exp(\text{sim}(S_i^{(j)}, S_i^{(j)}) / T)}{\sum_{S_{i}^{(k)} \in B_i} \exp(\text{sim}(S_i^{(k)}, S_i^{(j)}) / T)} \right) \tag{8}
\]

where \( T \) denotes a temperature hyperparameter to scale the cosine similarity. \( \text{sim}(S_i, S_{i'}) \) is defined as:

\[
\text{sim}(S_i, S_{i'}) = \cos(h(S_i), h(S_{i'})) \tag{9}
\]

\[
h(S_i) = W_1 S_{\text{contra}}(W_2 u) \tag{10}
\]

\[
h(S_{i'}) = W_1 S_{\text{contra}}(W_2 v) \tag{11}
\]

where \( W_1 \in \mathbb{R}^{d_{\text{contra}} \times d} \) and \( W_2 \in \mathbb{R}^{d \times d} \) mean the weights of two fully-connected layers, and \( d_{\text{contra}} < d \). According to [33], we use ReLU [34] for \( d_{\text{contra}} \).

In [14], moreover, we introduced a sentence similarity-based contrastive task. However, we discard that objective in this study because we found that it can hardly affect the multilingual model training and performs trivially after adding two fully-connected layers, thus decreasing the representation dimensions.

### 3.4 Joint Training

We train the model by jointly optimizing the losses of the proposed generative and contrastive objectives. Specifically, we simultaneously train each batch with Eqs. (6) and (8):

\[
L = \frac{1}{\| B_i \|} (L_{\text{XTR}}^{(i)} + L_{\text{contra}}^{(i)}) \tag{12}
\]

where \( \| B_i \| \) denotes the number of sentence pairs within batch \( B_i \), namely, the batch size. Both \( L_{\text{XTR}} \) and \( L_{\text{contra}} \) play a dominant role for massively multilingual CSR training (details are given in Section 5.6).

### 4 Model Training

In this section, we introduce the parallel corpora that we used to train language-agnostic sentence representations and specific preprocessing and training details.

#### 4.1 Training Data

We collected parallel corpora for 62 languages from OPUS [35] (See Table 1). The 62 languages that we selected cover all the languages in OPUS and the languages suggested by the cross-lingual generalization benchmark, XTREME [37]. While gathering each corpus, we used toolkit provided by [35] and [12]. Specifically, we used the following corpora for training:

**Europarl** is a parallel corpus extracted from the European Parliament website by Philipp Koehn [39]. We used the entire corpus for each language pair.

**GlobalVoices** is a parallel corpus of news stories from the website Global Voices compiled and provided by CASMACAT [7]. We used the entire corpus for each language pair.

**NewsCommentary** is a news commentary parallel corpus provided by WMT [8] for training statistical machine translation. We used the entire corpus for each language pair.

**OpenSubtitles** is a parallel corpus of movie subtitles collected from opensubtitles.org [40]. Considering that the lengths of most sentences are short, we used at most 2M sentence pairs for each language pair to control the training data size.

**Ted** is a parallel corpus comprising TED talks. We used the 2020 version crawled by [12], which includes 4000 TED talks for each language pair available.

**UNPC** United nations parallel corpus of six languages [41]. We used 5M sentence pairs for en–ru and 2M sentence pairs for other language pairs.

3. https://opus.nlpl.eu/
4. We do not distinguish between traditional and simplified Chinese.
5. https://github.com/Helsinki-NLP/OpusTools
6. https://github.com/UKPLab/sentence-transformers
7. http://casmacat.eu/corpus/global-voices.html
8. https://statmt.org/
9. As the number of en–ru sentence pairs from other parallel corpora is relatively small, we used more for data for en–ru to balance the size for different language pairs.
WikiMatrix is a parallel corpus crawled by [36]. We used the entire corpus for each language pair. Tatoeba is a parallel corpus gathered from Tatoeba’s website [10] the language learning supporting website. As training on the Tatoeba benchmark will probably improve the evaluation performance on the WikiMatrix benchmark [6], following [12], we excluded the training data of Tatoeba for most language pairs. Only for the language pairs that are not included in the aforementioned corpora, we used Tatoeba corpora.

The aforementioned training data leads to a 143M parallel corpus. As listed in Table 1, we used much less data for 43 languages than LASER. Moreover, we excluded the JW300 [42] corpus and pruned OpenSubtitles and UNPC corpora and included less training data than SBERT-distill [11].

In the next section, we will show that our model yields better or comparable sentence representation performance, compared with LASER and SBERT-distill. In addition, [11] used 6B parallel data to fine-tune the pre-trained mBERT, which leads to enormous computational resource consumption and is impractical to reproduce. However, the proposed model used a limited number of parallel sentences while retaining the sentence representation performance.

### 4.2 Preprocessing Details

For the parallel corpus containing 62 languages, we removed the sentences that appear in any evaluation dataset (see Section 5). We tokenized Chinese using jieba [12] and Japanese using Jumanpp [13, 14]. We used Moses tokenizer for other languages [14]. We converted all the sentences to lowercase. Subsequently, we applied SentencePiece [15] to convert words to subwords, which leads to a vocabulary with 60k tokens [16]. Finally, we add 62 language tokens (e.g., <2en>, <2fr>, ...) to the 60k vocabulary.

### 4.3 Training Details

We employed transformer encoder [46] as the basic unit of the training architecture (Fig. 1). We conducted a grid search for optimal hyperparameter combinations by observing the validation loss on the WikiMatrix validation datasets (Table 2).

As a result, the dual transformer encoder sharing parameters has 6 layers, 16 attention heads, a hidden size of 1024, and a feed-forward size of 4096. The transformer encoder can be substituted by encoders with other structures. $d_v$, $d_a$, and $d_{intra}$ are 1024, 60,000, 128, and 128, respectively. We set 0.1 for the temperature $T$ of the contrastive objective.

For the model training, we fed the parallel sentences into the dual transformer encoder and truncated the sentences up to 120 tokens [17]. We trained three epochs for the entire training corpus with the Adam optimizer [47], the learning rate, and weight decay.
rate of 0.0003 with the linear warm-up strategy of 10,000 steps, a weight decay of 0.0001, and a dropout rate of 0.1 for the transformer encoder. We used four V100 GPUs to conduct the model training with a batch size of 152 parallel sentences.

### 4.4 Comparison with Competing Models

As listed in Table 3, the proposed method includes 143M parallel sentences for model training, which is significantly less than those of other massively multilingual models. However, we employ the dual transformer architecture as the basic model unit, whereas LASER requires the encoder–decoder architecture to perform the translation task, where the presence of the decoder decreases training efficiency. Compared with SBERT-distill and LaBSE, which use the dual transformer architecture, our model can be trained without conducting language model pre-training using monolingual sentences or distilling from a robust multilingual pre-trained teacher encoder. More precisely, SBERT-distill is trained with the English-SBERT teacher and XLM-R [13] student encoders, where two large-scale pre-trained models lead to heavy computation overhead and XLM-R [13] student encoders, where two large-scale pre-trained models lead to heavy computation overhead and XLM-R [13] student encoders, where two large-scale pre-trained models lead to heavy computation overhead and XLM-R [13] student encoders, where two large-scale pre-trained models lead to heavy computation overhead. Moreover, it is critical to distinguish the positive translation from several hard negative samples. Although all these studies do not rely on a robust pre-trained model, the heavy computation load of hard negative samples for each sentence limits the feasibility of their methods to a small number of languages, i.e., fewer than 16.

### 5 Evaluation

In this section, we evaluate the performance of the language-agnostic sentence representation on two groups of the downstream tasks. On the one hand, without any further fine-tuning, we test the parallel sentence retrieval capability of the model using the cosine similarity between sentences. We evaluate this based on the following three tasks: Tatoeba benchmark [6], BUCC benchmark [20, 21], and cross-lingual sentence retrieval on the ParaCrawl corpus [19]. On the other hand, by fine-tuning a simple multi-layer perceptron, we evaluate the model performance based on three cross-lingual sentence classification tasks in a zero-shot manner. Three evaluation tasks include the MLDoc benchmark [22] and cross-lingual sentiment classification on two versions of the multilingual Amazon review corpora [23, 24]. The former group of the evaluation measures the alignment performance of the language-agnostic sentence representation space, whereas the latter group evaluates the fundamental natural language understanding (NLU) ability of the model. Complex NLU tasks, e.g., XNLI [50], are evaluated in LASER, and it has been proven that universal sentence representation models are not competent to address such tasks. Thus, we do not include the evaluation of XNLI in this study. Furthermore, we analyze the effectiveness of each component of the model structure based on an ablation study.
For all the evaluation tasks, we compare the following massively multilingual sentence representation models:

- **LASER** [8] employed the BiLSTM encoder–decoder to train the language-agnostic representations for 93 languages by optimizing the translation task. 223M parallel sentences are used for training.
- **SBERT-distill** [12] trained language-agnostic representations for 50 languages by distilling the monolingual pre-trained encoder. Our training data are a subset of their data (Section 5.1). “paraphrase-xlm-r-multilingual-v1” is used for evaluation.

**LaBSE** [11] trained language-agnostic sentence representation for 109 languages by fine-tuning the sentence-level contrastive task from mBERT. We italicize this model in the following tables (results) as the upper bound performance on downstream tasks because a large number of parallel sentences, 6B, are used for training.

**EMS** (ours) By extending our previous study [14], we trained a language-agnostic sentence representation model for 62 languages. We used significantly less training data, thus less computation overhead, than those used in the previous study. The proposed model can be easily trained from the beginning without relying on the pre-trained multilingual encoder.

### 5.1 Tatoeba Similarity Search

We use Tatoeba benchmark [6] to evaluate the cross-lingual alignment between English and other 58 languages. Specifically, given a sentence in language $l_1$, we retrieve its translation from several sentences in language $l_2$. We use cosine similarity for retrieving sentences and report the average P@1 of $l_1 \rightarrow l_2$ and $l_2 \rightarrow l_1$ because both directions show similar precision considering a language pair.

As the results are listed in Table 4 in most languages, EMS achieves better retrieval precision than LASER and SBERT-distill. By observing the average score, 89.8, significantly outperforms LASER’s 84.7 and is slightly higher than SBERT-distill’s 87.7. We further summarize the results of Table 4 in Table 6. First, with regard to 15 main languages that mUSE [10] supports, our model achieves the best retrieval precision, even better than LaBSE, which leverages 6B for training. Second, with regard to 38 languages that XTREME [37] supports, 48 languages that SBERT-distill supports, 43 languages for which all the models used more than or less than 300k parallel sentences for training. Refer to Table 1; “<300k” and “>300k” contain 42 and 11 languages, respectively.

### Table 5

| Model       | amh | ang | arq | arz | ast | awa | aze | bel | ber | bos | bre | cbk | ceb | cha |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| LASER       | 42.0| 37.7| 39.5| 68.9| 86.2| 36.1| 66.0| 69.6| 68.2| 96.5| 15.8| 77.0| 15.7| 29.2|
| SBERT-distill | 67.9| 25.0| 30.6| 63.7| 78.3| 46.5| 85.0| 86.9| 6.8 | 95.8| 10.1| 69.4| 11.7| 25.9|
| EMS (ours)  | 0.6 | 47.4| 48.7| 77.7| 82.2| 56.1| 62.1| 70.3| 7.6 | 96.6| 12.0| 80.6| 30.1| 46.4|

### Table 6

**Average P@1 results of different groups of the languages on Tatoeba benchmark.** Bold are the best precisions among LASER, SBERT-distill, and EMS (the proposed model). “mUSE,” “XTREME,” and “SBERT-distill” denote the 15, 38, and 48 languages, respectively, that the respective model or benchmark includes. “<LASER” denotes the 43 languages that use less training data than LASER. “>300k” and “<300k” indicate that the overall LASER, SBERT-distill, and EMS (the proposed model) include more than or less than 300k parallel sentences for training.

| Model       | mUSE (15) | XTREME (38) | SBERT-distill (48) | <LASER (43) | >300k (42) | <300k (11) |
|-------------|-----------|-------------|-------------------|-------------|-----------|-----------|
| mUSE        | 93.9      | -           | -                 | -           | -         | -         |
| LASER       | 95.1      | 84.2        | -                 | 89.6        | 94.4      | 58.3      |
| SBERT-distill | 94.9     | 85.5        | 94.8              | -           | 92.1      | 73.3      |
| EMS (ours)  | 96.6      | 88.2        | 95.0              | 91.8        | 95.4      | 72.0      |
| LaBSE       | 96.2      | 94.7        | -                 | -           | 95.8      | 93.9      |
sentences. This demonstrates the effectiveness of the proposed efficient model on middle- and high-resource languages. Finally, with regard to 11 low-resource languages for which less than 300k training data are used, EMS achieves better results than LASER by a significant margin, whereas it is comparable with SBERT-distill.

Furthermore, we evaluate the other 54 unnoticed languages of our model (Table 5). Few languages were trained in LASER and LaBSE. Although few languages are trained in LASER, we observe that EMS still yields results comparable with LASER for these 54 languages. This indicates that EMS has cross-lingual transferability for unnoticed languages to a certain extent.

### 5.2 BUCC: Bi-text Mining

Moreover, we evaluate the model’s cross-lingual retrieval performance on BUCC benchmark [20], [21] that contains the comparable corpora with the size of 150k~1.2M for four language pairs: English–German, English–French, English–Russian, and English–Chinese. This task measures the model’s ability to extract parallel sentences from the comparable corpora. Following LASER and SBERT-distill, we use the margin-based scoring function [51] for mining parallel sentences.

Results measured using F1 are listed in Table 8. We observe that EMS exhibits significantly higher results than mUSE [10] and SBERT-distill. However, compared with LASER and LaBSE, EMS exhibits slightly poor performance. Such performance deterioration is negligible because it can be attributed to incorrect gold labels within the BUCC dataset, which is also mentioned in [12]. For example, three extracted sentence pairs listed in Table 7 are translation pairs, whereas they are not contained in the official gold labels.

### 5.3 Cross-Lingual Sentence Retrieval

The Tatoeba benchmark supports the cross-lingual retrieval evaluation based on small-scale (1000 sentences for most language pairs) data, whereas the BUCC benchmark supports retrieval from large-scale data for four language pairs. Therefore, we conduct a cross-lingual sentence retrieval evaluation based on large-scale comparable data for 21 language pairs. Based on our previous study [14], given 2000 sentences in language 1, we conduct the translation retrieval from 200k candidate sentences in language 2. Unlike our previous study, we used parallel sentences from ParaCrawl v5.0 [19] for evaluation because the previously used Europarl corpus is included in the training data in this study. We calculate P@1 for each language pair using margin-based scoring [51].

As reported in Table 9, EMS performs significantly better than SBERT-distill and is comparable with LASER and LaBSE. The 21 languages evaluated herein are trained with more than 300k parallel sentences, for which we used approximately half of the LASER’s training data and a tiny fraction of the LaBSE’s training data. This suggests that our training architecture and objective are rather effective for languages where we used a certain number of parallel sentences.

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**Example 1**

en: The Declaration of Brussels (1874) stated that the “honours and rights of the family...should be respected.”

zh: 布鲁塞尔宣言（1874年）表示，“家庭荣誉和权利...应当受到尊重。”

**Example 2**

en: In 2004, the E.U. undertook a major eastward enlargement, admitting ten new member states (eight of which were former communist states).

zh: 2004年欧盟进行了一次大规模东扩，接纳10个新成员国（其中的8个是前共产主义国家）。

**Example 3**

en: In March 2013, Ban Ki-moon had also recommended to the Council that women raped in war have access to abortion services.

zh: 2013年3月，潘基文同样建议安理会保证在战争中被强奸的女性能享有堕胎服务。

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**TABLE 7**

Extracted parallel sentence examples from BUCC that are not included in the official gold labels.

| Example | Source Language | Target Language |
|---------|----------------|----------------|
| Example 1 | en | zh |
| Example 2 | en | zh |
| Example 3 | en | zh |

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**TABLE 8**

F1 Scores on the BUCC benchmark. Bold fonts denote the best precisions among LASER, SBERT-distill, and EMS (the proposed model).

| Model | en-de | en-fr | en-ru | en-zh | Avg. |
|-------|-------|-------|-------|-------|------|
| mUSE  | 88.5  | 86.3  | 89.1  | 86.9  | 87.7 |
| LASER | 95.4  | 92.4  | 92.3  | 91.2  | 92.8 |
| SBERT-distill | 90.8  | 87.1  | 88.6  | 87.8  | 88.6 |
| EMS (ours) | 93.3  | 90.2  | 91.3  | 92.1  | 91.7 |
| LaBSE  | 95.9  | 92.5  | 92.4  | 93.0  | 93.5 |

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**TABLE 9**

Cross-lingual sentence retrieval results on ParaCrawl. We report P@1 scores of 2,000 source queries while searching among 200k sentences in the target language. Best performance results among LASER, SBERT-distill, and EMS are in bold font.

| Model | bg | cs | da | de | el | es | et | fi |
|-------|----|----|----|----|----|----|----|----|
| LASER | 89.3 | 87.5 | 86.1 | 87.4 | 85.8 | 87.4 | 87.7 | 83.4 |
| SBERT-distill | 83.3 | 73.6 | 78.6 | 81.4 | 72.2 | 72.5 | 75.1 | 73.7 |
| EMS (ours) | 90.9 | 85.5 | 85.1 | 90.1 | 81.4 | 90.9 | 87.7 | 83.4 |
| LaBSE | 91.2 | 87.8 | 88.9 | 90.4 | 85.3 | 89.8 | 88.3 | 82.8 |

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**TABLE 8**

F1 Scores on the BUCC benchmark. Bold fonts denote the best precisions among LASER, SBERT-distill, and EMS (the proposed model).

| Model | en-de | en-fr | en-ru | en-zh | Avg. |
|-------|-------|-------|-------|-------|------|
| mUSE  | 88.5  | 86.3  | 89.1  | 86.9  | 87.7 |
| LASER | 95.4  | 92.4  | 92.3  | 91.2  | 92.8 |
| SBERT-distill | 90.8  | 87.1  | 88.6  | 87.8  | 88.6 |
| EMS (ours) | 93.3  | 90.2  | 91.3  | 92.1  | 91.7 |
| LaBSE  | 95.9  | 92.5  | 92.4  | 93.0  | 93.5 |

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22. We use the code from [https://github.com/UKPLab/sentence-transformers/blob/master/examples/applications/parallel-sentence-mining/bucc2018.py](https://github.com/UKPLab/sentence-transformers/blob/master/examples/applications/parallel-sentence-mining/bucc2018.py)
5.4 MLDoc: Multilingual Document Classification

Subsequently, we evaluate the model performance based on the MLDoc classification task. MLDoc is a benchmark to evaluate cross-lingual sentence representations, which contain datasets for eight languages [52]. Following [9], we conduct the evaluation in the zero-shot manner using 1000 sentences in language \( l_1 \) for training, 1000 sentences in language \( l_1 \) for validation, and 4000 sentences in language \( l_2 \) for test. Specifically, we train a multilayer perceptron classifier based on source language representations and test the classifier for the target language.

We list the average results of 5 runs for 7 language pairs and 14 directions in Table 10. We significantly observe higher accuracies of EMS in most directions than those of LASER and SBERT-distill. These results demonstrate the effectiveness of the proposed training method. Although LASER yields better performance for English→Japanese and English→Chinese, it performs much worse in the reverse directions. We further calculate the average accuracy discrepancy between two directions for each language pair. LASER shows 7.3, whereas SBERT-distill is 3.5 and EMS is 4.7. This indicates that LASER is highly sensitive to the specific cross-lingual transfer direction, whereas SBERT-distill and EMS are much more robust.

5.5 CLS: Cross-Lingual Sentiment Classification

Moreover, we gauge the quality of language-agnostic sentence representation based on the sentiment classification task. We use the two versions of the Amazon review datasets for evaluation to conduct the zero-shot cross-lingual classification. The version-1 dataset [23] includes the data for English–German, English–French, and English–Japanese on “books,” “dvd,” and “music” domains for each language pair. For each language pair and domain, we use 2000 sentences in language \( l_1 \) for training, 2000 sentences in language \( l_1 \) for validation, and 2000 sentences in language \( l_2 \) for test. However, the version-2 dataset [24] includes five language pairs, whereas different genres of the reviews are mixed. For each language pair, we use 2000 sentences for training, 4000 sentences for validation, and 4000 sentences for the test. Same as on MLDoc, we train a multi-layer perceptron using the language-agnostic sentence representations in language \( l_1 \) and test the classifier for another language.

As listed in Tables 11 and 12, EMS significantly outperforms LASER and performs comparably to LaBSE on the two versions of the datasets, which proves the effectiveness of EMS. SBERT-distill achieves comparable results on the version-2 dataset, whereas its performance negligibly deteriorates on the version-1 dataset. This can be attributed to SBERT-distill’s capability of clustering similar sentences (Section 4.1 in [12]). On the version-1 dataset, each genre of the reviews is evaluated; more similar sentences in each genre compared with version-2 lead to lower classification accuracy for version-1.
for cross-lingual sentence retrieval and classification tasks, respectively.

As listed in Table 13, we observe that the performance significantly decreases on Tatoeba and MLDoc benchmarks by removing the language token, sentence-level contrastive objective, XTR objective, or the linear layer within the contrastive objective. Moreover, sharing the transformer embedding layer parameters with the $L_{emb}$ in the XTR objective and replacing XTR with UGT degrade the model performance. Among all these ablations, we observe a significant decrease in low-resource languages for training data less than 300k, which indicates that the performance is more sensitive to model components on low-resource languages. This motivates future exploration to improve the model performance more for low-resource languages. By comparing $−langs$ tok with $−L_{cntrs}$, we observe superior performances of $−L_{cntrs}$ on MLDoc and $−L_{XTR}$ on Tatoeba, which demonstrates that the generative objective contributes more for the classification downstream tasks, whereas the contrastive objective is more beneficial for the detection of parallel sentences. Moreover, we observe a negligible decrease in $−langs$ tok on the Tatoeba benchmark. As the ground-truth label we designed for the XTR objective includes the information of tokens in specific languages, the effect of the language token gradually diminishes during the model training. In addition, by replacing V100 GPUs with A100 GPUs and a larger batch size of 200 parallel sentences, no significant fluctuation is observed, which suggests that EMS is robust to the computation resource.

6 Conclusion

This study presents EMS, an efficient and effective method for language-agnostic sentence representation learning. To improve training efficiency while retaining the quality of sentence representations, we propose a novel framework to jointly train “XTR” generative and sentence-level contrastive objectives. The empirical results based on three cross-lingual sentence retrieval tasks and three cross-lingual sentence classification tasks demonstrate the effectiveness of EMS. We plan to further shrink the model architecture based on knowledge distillation for faster inference experience in future studies.

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