

# Improving Multi-lingual Alignment Through Soft Contrastive Learning

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## Abstract

Making decent multi-lingual sentence representations is critical to achieve high performances in cross-lingual downstream tasks. In this work, we propose a novel method to align multi-lingual embeddings based on the similarity of sentences measured by a pre-trained mono-lingual embedding model. Given translation sentence pairs, we train a multi-lingual model in a way that the similarity between cross-lingual embeddings follows the similarity of sentences measured at the mono-lingual teacher model. Our method can be considered as contrastive learning with *soft* labels defined as the similarity between sentences. Our experimental results on five languages show that our contrastive loss with soft labels far outperforms conventional contrastive loss with hard labels in various benchmarks for bitext mining tasks and STS tasks. In addition, our method outperforms existing multi-lingual embeddings including LaBSE, for Tatoeba dataset. The code is available at <https://github.com/YAI12xLinq-B/IMASCL>

## 1 Introduction

Learning good representations (or embeddings) of sentences and passages is crucial for developing decent models adaptive to various downstream tasks in natural language processing. Compared with the high quality mono-lingual sentence embeddings developed in recent years (Wang et al., 2023; Song et al., 2020), multi-lingual sentence embeddings have a room for improvement, mostly due to the difficulty of gathering translation pair data compared to mono-lingual data. This motivated recent trials on improving the performance of multi-lingual embeddings.

One of the prominent approaches trains the multi-lingual embeddings using contrastive learning (Zhang et al., 2022; Gao et al., 2021). Given

a translation pair for different languages, this approach trains the model in a way that the embeddings for translation pairs are brought closer together, while embeddings for non-translation pairs are pushed further apart (Feng et al., 2020). Despite several benefits of this contrastive learning approach, Ham and Kim (2021) pointed out that current training method ruins the mono-lingual embedding space. To be specific, this issue arises from the fact that existing contrastive loss treats sentences that are not exact translation pairs identically (as negative pairs), irrespective of the semantic similarity of those sentences.

Another prominent approach is distilling mono-lingual teacher embedding space to a multi-lingual student model. The basic idea is, letting the multi-lingual embeddings of student models follow the mono-lingual embeddings of teacher model. This approach is motivated by the assumption that English embeddings are well constructed enough to guide immature multi-lingual embeddings. For example, Reimers and Gurevych (2020) proposed a distillation method using mean-squared-error (MSE) loss, which is shown to be effective in learning embeddings for low-resource languages. Also, Heffernan et al. (2022) used a distillation method where the teacher is the English embedding of a multi-lingual model. Unfortunately, existing distillation methods cannot fully utilize the translation pairs. Since conventional methods choose the most reliable English embeddings as the teacher model, translation pairs from non-English language parallel corpus are not fully leveraged.

In this paper, we propose a novel distillation method for improving multi-lingual embeddings, by using *soft* contrastive learning. See Figure 1. Given  $N$  translation pairs  $\{(s_i, t_i)\}_{i=1}^N$ , our method first computes the mono-lingual sentence similarity matrix from the teacher model. Each element of this similarity matrix is a continuous value. We distill such *soft* label to the cross-lingual sentence

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similarity matrix computed for the multi-lingual student model. In other words, the anchor similarity matrix computed from the teacher model is used as a pseudo-label for contrastive loss. Our main contributions are as follows:

- We propose a novel method of fine-tuning multi-lingual embeddings by distilling the sentence similarities measured by mono-lingual teacher models. Compared with the conventional contrastive learning which uses hard labels (either positive or negative for sentence pairs), our method chooses *soft* labels for measuring the sentence similarities.
- Compared with conventional contrastive learning and monolingual distillation method using MSE, our soft contrastive learning has much improved performance in bitext mining tasks, Tatoeba, BUCC and FLORES-200, for five different languages.
- For Tatoeba, our method outperforms existing baselines including LaBSE, LASER2 and MPNet-multi-lingual.

## 2 Related Works

Constructing multi-lingual embedding has been actively studied for recent years (Heffernan et al., 2022; Artetxe and Schwenk, 2019; Duquenne et al., 2023). For example, LaBSE (Feng et al., 2020) shows remarkable bitext retrieval performances, which is first pretrained with masked language modeling (MLM) (Devlin et al., 2018) and translation language modeling (TLM) (Conneau and Lample, 2019) tasks, and then fine-tuned with translation pairs using contrastive loss, i.e. translation ranking task. Also, mUSE (Yang et al., 2019) uses translation based bridge tasks from Chidambaram et al. (2018) to make a multilingual embedding space. In short, mUSE (Yang et al., 2019) is trained for translation ranking task with hard negatives.

Reimers and Gurevych (2020) introduced distilling the mono-lingual embedding of a teacher model (using sBERT (Reimers and Gurevych, 2019)) to the multi-lingual embedding of a student model (using XLM-R (Conneau et al., 2019)) with MSE loss, which enables a good bitext retrieval performance only with small amounts of parallel data. Several follow-up papers (Duquenne et al., 2023; Heffernan et al., 2022) achieved good performances by using this distillation approach. For example, Heffernan et al. (2022) successfully improved the per-

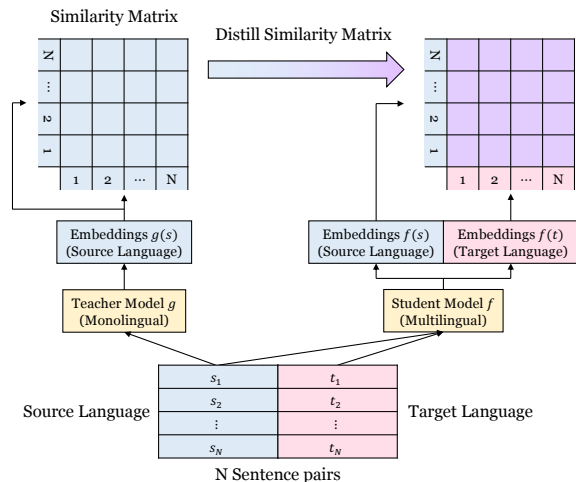


Figure 1: Overall framework of our method. Given  $N$  sentence pairs from source/target languages, we train a multi-lingual student model  $f$  by using the similarity between sentences measured by a mono-lingual teacher model  $g$ . Our contrastive loss function in Eq. 2 uses soft-label  $w(i, j)$  defined in Eq. 4 and 5.

formance on low-resource languages with the aid of the distillation approach. Compared with existing distillation methods, our work distills the similarities between sentences measured by mono-lingual embeddings, instead of directly distilling the mono-lingual embedding space of the teacher model.

## 3 Proposed Method

Suppose we are given  $N$  translation pairs, denoted by  $(s_1, t_1), (s_2, t_2), \dots, (s_N, t_N)$ , where  $s_i$  is the  $i$ -th sentence in the source language and  $t_i$  is the corresponding sentence in the target language. We train a multi-lingual student model  $f$  by using the similarities between mono-lingual sentences measured by a teacher model  $g$ . Here,  $g$  can be either a mono-lingual model or using only a single language from multi-lingual models. Specifically, we first use the teacher network  $g$  to measure the similarity of sentences  $\{s_i\}_{i=1}^N$  in the source language. The cosine similarity between sentences  $s_i$  and  $s_j$  measured by encoder  $g$  is denoted by

$$\text{sim}_g(s_i, s_j) = \frac{\cos(g(s_i), g(s_j))}{\tau},$$

where  $\tau$  is the temperature parameter. Then, we train multi-lingual encoder  $f$  in a way that

$$\text{sim}_g(s_i, s_j) \approx \text{sim}_f(s_i, t_j) \approx \text{sim}_f(t_i, s_j) \quad (1)$$

*i.e.*, the similarity of  $i$ -th sentence and  $j$ -th sentence is maintained across different language pairs. Such objective is reflected in our contrastive loss

$$L_{row} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N w(i, j) \log\left(\frac{e^{\text{sim}_f(s_i, t_j)}}{\sum_{n=1}^N e^{\text{sim}_f(s_i, t_n)}}\right) \quad (2)$$

where  $w(i, j)$  is the label using similarity between  $s_i$  and  $s_j$ . The standard contrastive loss used in LaBSE (Feng et al., 2020) and mE5 (Wang et al., 2024) has the form of Eq. 2 where

$$w(i, j) = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

*i.e.*, two sentences ( $s_i$  and  $s_j$ ) are considered as a positive pair only if  $i = j$ , and labeled as a negative pair otherwise.

Since the naïve labeling method above cannot fully capture the semantic relationship between different sentence pairs, we propose following  $w(i, j)$  by applying the softmax function on the similarity matrix measured at the teacher model.

$$w(i, j) = \frac{e^{\text{sim}_g(s_i, s_j)}}{\sum_{n=1}^N e^{\text{sim}_g(s_i, s_n)}} \quad (4)$$

$w(i, j)$ , namely Priority label, calculates label based on the similarity using the anchor language sentences. In Eq 4, we assume the source language as an anchor. Note that both the source and the target language are available as an anchor language, thus we need to choose one.

Thus, we consider a variant of  $w(i, j)$ , namely Average label, which mixes monolingual embedding spaces of source and target language by averaging similarity.

$$w(i, j) = \frac{e^{(\text{sim}_g(s_i, s_j) + \text{sim}_g(t_i, t_j))/2}}{\sum_{n=1}^N e^{(\text{sim}_g(s_i, s_n) + \text{sim}_g(t_i, t_n))/2}} \quad (5)$$

In fact, this only works when the teacher model is multi-lingual, and the student encoder  $f$  trains in a following way, which is different from the Eq. 1.

$$(\text{sim}_g(s_i, s_j) + \text{sim}_g(t_i, t_j))/2 \approx \text{sim}_f(s_i, t_j) \approx \text{sim}_f(t_i, s_j)$$

The contrastive loss discussed above is uni-directional. Following the common symmetric bi-directional contrastive loss, e.g., (Radford et al., 2021), the symmetric loss using our soft label is defined as

$$L_{cross} = L_{row} + L_{col} \quad (6)$$

where  $L_{row}$  is in Eq. 2 and

$$L_{col} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N w(i, j) \log\left(\frac{e^{\text{sim}_f(s_i, t_j)}}{\sum_{n=1}^N e^{\text{sim}_f(s_n, t_j)}}\right).$$

**Training Monolingual Space (TMS)** Note that our objective  $L_{cross}$  given in Eq. 6 is to learn only the cross-lingual similarity of the student model. In addition to that, we consider learning with additional mono-lingual loss  $L_{mono}$  in Eq. 7, the distillation loss measured by the similarity between each monolingual sentence pair. This approach of using  $L_{mono}$  on top of  $L_{cross}$  is dubbed as training monolingual space (TMS). The combined loss term is shown in Eq. 8, where the parameter  $\lambda$  controls the balance between the cross-lingual loss and the mono-lingual loss term. Note that using TMS is orthogonal to the choice of using the Priority label or the Average label.

$$L_{mono} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N w(i, j) \log\left(\frac{e^{\text{sim}_f(s_i, s_j)}}{\sum_{n=1}^N e^{\text{sim}_f(s_n, s_j)}}\right) + -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N w(i, j) \log\left(\frac{e^{\text{sim}_f(t_i, t_j)}}{\sum_{n=1}^N e^{\text{sim}_f(t_n, t_j)}}\right) \quad (7)$$

$$L = \lambda \cdot L_{cross} + L_{mono} \quad (8)$$

## 4 Experimental Settings

This section describes the details of our experimental setting, for both training and evaluation.

### 4.1 Training setup

The translation pairs used for training are downloaded from OPUS<sup>1</sup> (Tiedemann, 2012), where the volume of each language corpus is given in Appendix B. We focus on five languages: English (en), French (fr), Japanese (ja), Korean (ko), and Russian (ru). We train two types of models, cross-lingual and multi-lingual. For each cross-lingual model, we use en-ko, en-ja, en-ru, and en-fr pairs, respectively. For the multi-lingual model, we train with all translation pairs for five languages.

As discussed in Sec. 3, we consider two types of soft label  $w(i, j)$ : the Priority label in Eq. 4 defines the soft label by using the similarity measured at

<sup>1</sup><https://opus.nlpl.eu>

a mono-lingual embedding (for a pre-defined anchor language), while the Average label in Eq. 5 uses the similarity averaged out over mono-lingual embeddings of both source and target language. Note that we need to choose the anchor language (among the source and the target language), for the former one. By default, we set the priority of the languages based on the volume of each language corpus used in training, thus having the following order: en, ru, ja, fr, and ko. The anchor language is defined as the one with higher priority between language pair. We also apply TMS, which is shown in Eq. 8, using shared  $w(i, j)$  for the monolingual alignment and cross-lingual alignment.

Each model is trained for 30 epochs<sup>2</sup> on 2 RTX-3090 GPUs with global batch size 32. We use the cross-accelerator to expand negative samples, as described in Appendix C.2. The initial learning rate is set to  $\gamma = 5 \cdot 10^{-3}$ , and we linearly decay the learning rate. We use the AdamW optimizer. We tune the temperature parameter on en-ko bilingual dataset, and set it to  $\tau = 0.1$ . Also, we set the portion of cross-lingual loss in TMS as  $\lambda = 0.1$ . We apply the mixed precision training, to improve the training efficiency.

## 4.2 Evaluation tasks

**Bitext Mining** We evaluate our model on three bitext mining datasets, Tatoeba (Artetxe and Schwenk, 2019), BUCC (Zweigenbaum et al., 2017) and FLORES-200 (Costa-jussà et al., 2022). Tatoeba and BUCC are English-centric translation pair benchmark datasets that are included in MTEB (Muennighoff et al., 2022), and FLORES-200 is a  $N$ -way parallel benchmark dataset. Throughout the paper, we use the average accuracy measured from both directions (e.g., en $\rightarrow$ ko and ko $\rightarrow$ en) for BUCC and Tatoeba. We measure the average xSIM error rate from (Heffernan et al., 2022) for each languages in FLORES-200.

**Semantic Textual Similarity (STS)** We evaluate our model on STS datasets to examine how well mono-lingual and cross-lingual spaces are formed. We test on STS12-STS22 and the STS benchmark in MTEB (Muennighoff et al., 2022), and measure the average spearman correlation for each of the en, ko, fr, ru and en-fr.

<sup>2</sup>We early stopped with Tatoeba validation set. Most of the trains were stopped at between 10 and 20 epoch.

Lang	Student Model	Teacher Model	Tatoeba (en-xx)	BUCC (en-xx)	STS (en)	STS (xx)
en-ko	mE5 <sub>base</sub>	mE5 <sub>base</sub>	<b>0.917</b>	-	<b>0.777</b>	<b>0.762</b>
		E5 <sub>base</sub>	0.907	-	0.759	0.740
		MPNet	0.869	-	0.692	0.685
	XLM-R	mE5 <sub>base</sub>	0.896	-	0.704	0.707
		E5 <sub>base</sub>	0.897	-	0.702	0.702
		MPNet	0.864	-	0.648	0.650
en-fr	mE5 <sub>base</sub>	mE5 <sub>base</sub>	<b>0.963</b>	<b>0.982</b>	<b>0.783</b>	0.775
		E5 <sub>base</sub>	0.956	0.973	0.764	0.782
		MPNet	0.944	0.963	0.706	<b>0.785</b>
	XLM-R	mE5 <sub>base</sub>	0.951	0.973	0.699	0.744
		E5 <sub>base</sub>	0.949	0.961	0.692	0.747
		MPNet	0.942	0.956	0.637	0.761

Table 1: Comparison of various combinations of student and teacher models, in terms of the bitext mining (accuracy) and STS (spearman correlation score) performances. The best performance is achieved when both teacher and student use mE5<sub>base</sub> model.

## 5 Results

We first test the model trained with a single language pair, and then show the result when the model is trained with multiple language pairs.

### 5.1 Effect of the Student/Teacher Model

Table 1 shows the effect of the (student, teacher) model pair on the performance of our soft contrastive loss, using loss in Eq. 6, without TMS. We test two student model architectures, mE5<sub>base</sub> (Wang et al., 2024) and XLM-R (Conneau et al., 2019), and three teacher models, mE5<sub>base</sub> (Wang et al., 2024), E5<sub>base</sub> (Wang et al., 2022), and MPNet<sup>3</sup> (Song et al., 2020). The details of the student model selection are described in Appendix C.1. One can confirm that using mE5<sub>base</sub> for both teacher and student performs the best in both STS and bitext mining tasks. Thus, for the following experiments, we use mE5<sub>base</sub> for both teacher and student as a baseline.

### 5.2 Effectiveness of Our Loss

Recall that we propose training a student model using the contrastive loss with soft labels obtained from the teacher model. We denote our method as *soft contrastive loss*, and observe the effect of different loss functions in Table 2 and Table 3. Given a pre-trained student model, we fine-tune it with different losses. We compare two types of contrastive loss in Eq. 2, where one uses *soft* label  $w(i, j)$  (Priority label in Eq. 4) with TMS (Eq. 8) and the other uses *hard* label  $w(i, j)$  in Eq. 3. Note that mUSE (Yang et al., 2019) and LaBSE (Feng et al., 2020) use hard labels in contrastive loss where the translation pair is the only available positive pair,

<sup>3</sup><https://huggingface.co/sentence-transformers/all-mpnet-base-v2>

Lang	Loss	Tatoeba (en-xx)	BUCC	STS (en)	STS (xx)
en-ko	Soft Contrastive (Ours)	<b>0.916</b>	-	0.788	0.778
	Hard Contrastive	0.863	-	0.674	0.675
	MSE (Reimers and Gurevych, 2020)	0.911	-	<b>0.803</b>	<b>0.793</b>
	mUSE (Yang et al., 2019)	0.853	-	0.715	0.698
	Pretrained Model	0.873	-	<u>0.802</u>	0.777
en-fr	Soft Contrastive (Ours)	<b>0.960</b>	<b>0.987</b>	0.796	<b>0.791</b>
	Hard Contrastive	0.937	0.933	0.675	0.748
	MSE (Reimers and Gurevych, 2020)	0.959	0.980	<b>0.803</b>	0.704
	mUSE (Yang et al., 2019)	0.950	0.984	0.713	0.771
	Pretrained Model	0.951	<u>0.984</u>	<u>0.802</u>	<u>0.781</u>
en-ja	Soft Contrastive (Ours)	<b>0.956</b>	-	0.798	-
	Hard Contrastive	0.933	-	0.730	-
	MSE (Reimers and Gurevych, 2020)	0.949	-	<b>0.808</b>	-
	mUSE (Yang et al., 2019)	0.925	-	0.742	-
	Pretrained Model	0.931	-	<u>0.802</u>	-
en-ru	Soft Contrastive (Ours)	<b>0.951</b>	<b>0.979</b>	0.787	<b>0.616</b>
	Hard Contrastive	0.949	0.955	0.666	0.545
	MSE (Reimers and Gurevych, 2020)	0.945	0.978	<b>0.804</b>	0.601
	mUSE (Yang et al., 2019)	0.944	<u>0.978</u>	0.720	0.548
	Pretrained Model	0.936	<u>0.978</u>	<u>0.802</u>	<u>0.615</u>

Table 2: Comparison of different loss functions used for fine-tuning pre-trained student model, tested on bitext mining tasks and STS tasks. The gray shaded method is the baseline which uses the pre-trained student model as it is. The best performance is indicated in bold, second most performance is indicated with an underline, throughout this paper. For Tatoeba dataset, our *soft* contrastive loss outperforms all compared losses.

Pretrained model	Fine-tune loss	Tatoeba	BUCC	FLORES-200
mE5 <sub>base</sub>	Soft Contrastive (Ours)	<b>0.949</b>	<b>0.983</b>	<b>0.02</b>
mE5 <sub>base</sub>	MSE	0.942	0.975	0.05
mE5 <sub>base</sub>	-	0.923	0.981	0.16
MPNet-multilingual	-	0.945	0.970	0.28
LASER2	-	0.939	0.981	0.20
LaBSE	-	<b>0.948</b>	<b>0.985</b>	<b>0.01</b>

Table 3: Comparison between existing models and fine-tuning loss on multi-lingual data, tested on bitext mining. Measured accuracy for Tatoeba and BUCC, while measuring xSIM error rate for FLORES-200. Note that fine-tuned with MSE is the same approach as Reimers and Gurevych (2020). Ours show similar performance to current SoTA, LaBSE.

corresponds to Eq. 3. We also test using MSE loss for distilling the embeddings of the teacher model to the embeddings of the student model, as in (Reimers and Gurevych, 2020).

Table 2 provides the performances tested on bitext mining tasks and STS tasks trained with a single language pair, i.e. cross-lingual version of ours. We test on four different language pairs {en-xx} where xx is either ko, fr, ja, or ru.

We have three major observations. First, our *soft* contrastive loss outperforms conventional *hard* contrastive loss in all performance metrics in all language pairs. For example, in Tatoeba dataset, our method has up to 5.3% accuracy gain (e.g., from 86.3% to 91.6% for en-ko pair) compared with hard contrastive loss. Note that compared with the pre-trained model (shown in the gray shaded region in Table 2), additional training with hard

contrastive loss sometimes harms the performance, e.g., the accuracy degrades from 87.3% to 86.3% in Tatoeba dataset for the model trained with en-ko pair, and the STS performance degrades from 0.802 to 0.666 for the model trained with en-ru pair, which is critical.

Second, our *soft* contrastive loss provides the best performance in the bitext mining task, Tatoeba, and BUCC, for all language pairs. Compared with the pre-trained student model, additional training with soft contrastive loss improves the accuracy up to 4.3%.

Third, the STS performance for non-English languages is improved, after training with our soft contrastive loss. For example, after training with en-fr translation pair, the STS performance elevates by 0.01 when using soft contrastive loss, while 0.077 degradations (from 0.781 to 0.704) shown in MSE loss (Reimers and Gurevych, 2020).

Furthermore, we demonstrate the effectiveness of our loss through training with multiple language pairs, i.e. multi-lingual version of ours. Table 3 shows the bitext mining performances of multi-lingual models, tested on five languages, en, ko, ja, fr and ru. We also test the performance of pre-trained multi-lingual model checkpoints, namely, mE5<sub>base</sub> (Wang et al., 2024), LASER2 (Artetxe and Schwenk, 2019), LaBSE (Feng et al., 2020), and MPNet-multilingual<sup>4</sup> (Reimers and Gurevych, 2020). We trained with en-xx pairs (en-ko, en-ja, en-ru, and en-fr) for the fine-tuning. As a result, ours outperforms Reimers and Gurevych (2020) in every bitext mining task. Moreover, compared to other pretrained models, ours shows close results to current bitext mining State-of-the-Art, LaBSE.

### 5.3 Factor Analysis on Our Method

**Priority vs Average** We compare the two soft label methods we proposed in Eq. 4, 5 by varying the label functions, shown in Table 4, 5. *Priority* and *Average* stand for the loss described in Eq. 6 with  $w(i, j)$  from Eq. 4, 5, respectively. TMS stands for the loss with monolingual alignment shown in Eq. 8.

Table 4, 5 shows the performance of model trained with single language pair data and multiple language pairs data respectively (cross-lingual and multi-lingual). Both *Priority* and *Average* significantly improved the performance of most bitext mining compared to the pretrained model. While

<sup>4</sup><https://huggingface.co/sentence-transformers/paraphrase-multilingual-mpnet-base-v2>

Lang	Loss	Tatoeba (en-xx)	BUCC	STS (en)	STS (xx)
en-ko	<i>Average</i>	0.912	-	0.771	0.757
	<i>Priority</i>	<b>0.917</b>	-	0.777	0.762
	<i>Priority + TMS</i>	0.916	-	0.788	<b>0.778</b>
	Pretrained Model	0.873	-	<b>0.802</b>	0.777
en-fr	<i>Average</i>	0.959	0.981	0.767	<b>0.794</b>
	<i>Priority</i>	<b>0.963</b>	0.982	0.783	0.775
	<i>Priority + TMS</i>	0.960	<b>0.987</b>	0.796	0.791
	Pretrained Model	0.951	0.984	<b>0.802</b>	0.781
en-ja	<i>Average</i>	0.957	-	0.787	-
	<i>Priority</i>	<b>0.960</b>	-	0.787	-
	<i>Priority + TMS</i>	0.956	-	0.798	-
	Pretrained Model	0.931	-	<b>0.802</b>	-
en-ru	<i>Average</i>	<b>0.955</b>	<b>0.980</b>	0.775	0.612
	<i>Priority</i>	0.953	0.979	0.781	0.607
	<i>Priority + TMS</i>	0.951	0.979	0.787	<b>0.616</b>
	Pretrained Model	0.936	0.978	<b>0.802</b>	0.615

Table 4: Comparison of each variation trained with cross-lingual data, in terms of the bitext mining and STS performances. *Priority* shows slightly better performance than *Average* in bitext mining tasks, except for en-ru. Applying TMS enhances the STS performance, better than a pre-trained model for the non-English language.

Loss	Parallel Corpus	Tatoeba	BUCC	FLORES-200
<i>Average</i>	All pairs	0.950	0.979	0.04
<i>Priority</i>	All pairs	<b>0.952</b>	0.978	0.04
<i>Priority + TMS</i>	All pairs	0.948	0.983	0.04
<i>Average</i>	en-xx	0.948	0.979	0.04
<i>Priority</i>	en-xx	0.942	0.979	0.05
<i>Priority + TMS</i>	en-xx	0.949	<b>0.983</b>	<b>0.02</b>
Pretrained Model	-	0.923	0.981	0.16

Table 5: Comparison of different loss on multi-lingual data, in terms of the bitext mining task performances.

the performance gap between *Priority* and *Average* is trivial in Table 5, *Priority* shows slightly better performance than *Average* for bitext mining in Table 4. Yet, *Average* performs better on STS (xx) performances. For example, for models trained with en-fr, *Average* achieves 0.794, which 0.019 higher than the *Priority* (0.775)

**Effect of TMS** We validate the effectiveness of TMS by comparing *Priority* and *Priority + TMS* in Table 4, 5. Table 4 shows that using TMS improves the performance significantly on STS in all language pairs. For example, TMS increases STS performances with en-ko pairs from 0.011 higher on STS (en) and 0.016 higher on STS (xx). Though there was no performance gain in bitext mining after applying TMS, still *Priority + TMS* shows much better performance than the pre-trained model.

The impact of TMS is more dramatic in a multi-lingual experiment setting, shown in Table 5. Applying TMS shows the best STS performance shown in Appendix A, and even the best performance in bitext mining tasks shown in Table 5.

**Effect of Language Pair Selection** We expect there was an interference that arose from using mul-

Data	STS					Tatoeba	BUCC	FLORES-200
	en	ko	fr	ru	en-fr			
en-xx, fr-xx	<b>0.757</b>	0.694	<b>0.742</b>	<b>0.589</b>	<b>0.765</b>	<b>0.948</b>	<b>0.983</b>	<b>0.04</b>
en-xx, ru-xx	<b>0.757</b>	<b>0.696</b>	0.718	0.586	0.758	0.946	0.979	0.07

Table 6: Comparison of varying language pairs for train corpus, tested on bitext mining tasks) and STS tasks. The model trained on en-xx, fr-xx performs better than the model trained on en-xx, ru-xx for STS in all languages.

iple languages as a teacher, as there was less performance gain for BUCC and FLORES-200 when expanding a corpus size (from using only en-xx to all pairs). Thus, we made an additional experiment to analyze the effects of language selection on the performance.

Table 6 shows the results of training with our method on less language pairs. We test our method on language pairs containing en or fr (denoted by en-xx and fr-xx), and language pairs containing en or ru (denoted by en-xx and ru-xx). All tests in Table 6 are trained without TMS on the priority labels using our loss.

Using the pair en-xx, fr-xx performs better than using en-xx, ru-xx in most of the benchmarks. Not only bitext mining but also STS shows better performances for most languages. Even for ru STS, we can observe that en-xx, fr-xx performs better than en-xx, ru-xx. This can be seen as a synergy or interference between languages, which has a significant impact on performance. Thus, by selecting teacher languages that share similar monolingual embedding space, we believe we can achieve much better performance in multilingual tasks. We leave this as a future work.

## 6 Conclusion

In this paper, we proposed a method of improving multi-lingual embeddings, with the aid of the sentence similarity information measured at the mono-lingual teacher models. Our method can be considered as a variant of existing contrastive learning approach, where our method uses *soft* labels defined as the sentence similarity, while existing methods use *hard* labels. We tested our method on five different languages including en, ko, ja, fr, and ru. Our method shows the best performance in the Tatoeba dataset, and achieved high performance in other bitext mining tasks as well as STS tasks.

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