Representational Isomorphism and Alignment of Multilingual Large Language Models

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Abstract

In this paper, we investigate the capability of Large Language Models (LLMs) to represent texts in multilingual contexts. Our findings show that sentence representations derived from LLMs exhibit a high degree of isomorphism across languages. This existing isomorphism can facilitate representational alignments in zero-shot and few-shot settings. Specifically, by applying a contrastive objective at the representation level with only a few translation pairs (e.g., 100), we substantially improve models' performance on Semantic Textual Similarity (STS) tasks across languages. This representation-level approach proves to be more efficient and effective for semantic alignment than continued pretraining or instruction tuning. Interestingly, we also observe substantial STS improvements within individual languages, even without a monolingual objective specifically designed for this purpose.[1]

1 Introduction

Large Language Models (LLMs) demonstrate significant potential in solving multilingual tasks, such as machine translation (Kocmi et al., 2023) and multilingual QA (Agrawal et al., 2023). Notably, they exhibit strong few-show capabilities (Xu et al., 2023; Lai et al., 2024), where a small number of samples can lead to substantial performance improvements.

Representational isomorphism has been identified as one key source of few-shot capabilities in the context of word translation (Lample et al., 2017; Søgaard et al., 2018). In this paper, we analyze the multilingual sentence representation of LLMs from the perspective of isomorphism. We start by examining the geometric properties of representations derived from pairs of translation sentences. Using several widely used methods to extract embeddings from LLMs, we show that although the resulting embeddings are not well clustered in a common space for different languages, they exhibit high isomorphism — projecting them through an orthogonal matrix allows the sentence representations to be effectively aligned across languages. Moreover, it also explains the previous success of combining non-English inputs with English prompts (Etxaniz et al., 2024; Huang et al., 2023) for LLMs in multilingual tasks, where we argue that this spatial transformation occurs when using English prompts.

Building on this observation, we further investigate the potential of multilingual semantic alignment upon LLMs. We show that using a small number of English-centric translation samples (e.g., 100) with a contrastive loss (Gao et al., 2021) across language pairs effectively aligns the representation spaces. This alignment consistently improves performance on cross-lingual Semantic Textual Similarity (STS, Cer et al., 2017) tasks, proving to be more efficient and effective than continued language model training with multilingual samples. Interestingly, such progress also yields clear STS gains within each language, even in the absence of a monolingual objective specifically designed for this purpose. Given its high efficiency and effectiveness, we advocate for exploring representation-level alignment in future research.

2 Representational Analysis

2.1 Representation Extraction

Using prompts to extract sentence embeddings has been shown by Jiang et al. (2022a) to yield strong performance on masked language models like BERT (Devlin et al., 2019). PromptEOL (Jiang et al., 2023) extends this method to causal language models, e.g., OPT (Zhang et al., 2023) or LLaMA (Touvron et al., 2023), by employing a prompting template as follows:

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[1] https://github.com/moore3930/Representational_Isomorphism_and_Alignment.

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Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.33 / 0.67	0.61 / 0.97	0.03 / 0.82	0.36 / 0.96	0.82 / 0.96	0.76 / 0.99	0.49 / 0.90
AR	0.12 / 0.23	- / -	0.18 / 0.44	0.01 / 0.37	0.07 / 0.45	0.08 / 0.34	0.14 / 0.53	0.10 / 0.39
ZH	0.22 / 0.73	0.08 / 0.55	- / -	0.14 / 0.71	0.31 / 0.88	0.18 / 0.74	0.40 / 0.93	0.22 / 0.76
JA	0.04 / 0.33	0.02 / 0.34	0.21 / 0.59	- / -	0.17 / 0.56	0.03 / 0.56	0.06 / 0.62	0.09 / 0.50
RU	0.20 / 0.73	0.19 / 0.61	0.56 / 0.86	0.05 / 0.71	- / -	0.24 / 0.85	0.60 / 0.95	0.31 / 0.79
DE	0.67 / 0.88	0.09 / 0.62	0.37 / 0.89	0.01 / 0.80	0.36 / 0.92	- / -	0.83 / 0.96	0.39 / 0.85
ES	0.12 / 0.75	0.08 / 0.60	0.18 / 0.87	0.00 / 0.67	0.20 / 0.92	0.48 / 0.85	- / -	0.18 / 0.78
From X	0.23 / 0.61	0.13 / 0.57	0.35 / 0.77	0.04 / 0.68	0.24 / 0.78	0.30 / 0.72	0.47 / 0.83	0.25 / 0.71

Table 1: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection on high-resource languages. The embeddings in each language are derived from the LLaMA2-7B model using the prompting method as described in §2.1. “From X” and “Into X” denote the average results for each column and row, respectively. The Procurstes projection W for each translation direction is trained on NTREX, while the Precision@5 is tested based on the translation sentences from Flores. We report results derived from LLaMA2-13B, LLaMA3-8B, and BLOOM-7.1B in Appendix A.4.

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.78 / 0.73	0.93 / 0.94	0.95 / 0.93	0.76 / 0.94	0.96 / 0.96	0.97 / 0.97	0.89 / 0.91
AR	0.67 / 0.67	- / -	0.83 / 0.76	0.84 / 0.74	0.59 / 0.76	0.82 / 0.78	0.83 / 0.79	0.76 / 0.75
ZH	0.85 / 0.93	0.86 / 0.79	- / -	0.99 / 0.98	0.84 / 0.95	0.97 / 0.95	0.96 / 0.96	0.91 / 0.93
JA	0.88 / 0.92	0.86 / 0.78	1.00 / 0.97	- / -	0.83 / 0.95	0.96 / 0.95	0.95 / 0.95	0.91 / 0.92
RU	0.75 / 0.96	0.83 / 0.81	0.97 / 0.96	0.97 / 0.96	- / -	0.97 / 0.97	0.96 / 0.97	0.91 / 0.94
DE	0.90 / 0.96	0.68 / 0.79	0.91 / 0.94	0.89 / 0.94	0.75 / 0.96	- / -	0.99 / 0.97	0.85 / 0.93
ES	0.89 / 0.96	0.65 / 0.77	0.87 / 0.94	0.85 / 0.94	0.65 / 0.95	0.98 / 0.96	- / -	0.82 / 0.92
From X	0.82 / 0.90	0.78 / 0.78	0.92 / 0.92	0.91 / 0.92	0.74 / 0.92	0.94 / 0.93	0.94 / 0.93	0.86 / 0.90

Table 2: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection on high-resource languages. Note that all embeddings are derived from the prompting template in English, instead of the same language with input sentences. We report results derived from LLaMA2-13B, LLaMA3-8B, and BLOOM-7.1B in Appendix A.4.

This sentence : “[TEXT]” means in one word:“

where *[TEXT]* is the placeholder for the sentence to be investigated and the last layer's hidden vector for the last token ““” is extracted as the sentence representation. This method performs competently on semantic representation tasks (Agirre et al., 2015, 2016). Moreover, it provides an effective way to investigate the representations of LLMs.

Although some studies (Springer et al., 2024; Lei et al., 2024) have achieved more advanced performance using prompting, we adopt PromptEOL in this paper for its simplicity and generalizability. To adapt PromptEOL to a multilingual setting, we translate the English template mentioned above into other corresponding languages, e.g., a template,

Dieser Satz: “ [TEXT] ” bedeutet in einem Wort:“

is used for German. In the following sections, we derive representations of LLMs across languages by applying this method.

2.2 Cross-lingual Structural Analysis

We leverage *Procrustes* analysis (Schönemann, 1966) to measure the structural similarity of representations across languages. This method finds the optimal rotation and/or reflection (i.e., orthogonal linear transformation) to match points in a set of shapes, which ensures that the shape remains unchanged. Therefore, the precision in matching reflects the degree of isomorphism across spaces.

Formally, let's assume there are two sets of embeddings, A and B, derived from LLMs using sentence pairs in two different languages. Procrustes analysis learns an orthogonal linear projection W to map A into a shared space with B, by solving $min \, \|WA - B\|_F$ subject to $W^TW = I$. A closed-form solution $W = UV^T$ can be easily obtained from the singular value decomposition (SVD) of BA^T.

In this paper, we mainly conduct experiments on seven high-resource languages, namely English (EN), Arabic (AR), Chinese (ZH), Japanese (JA), Russian (RU), German (DE), and Spanish (ES), which encompass both similar and different language families and writing scripts. We investigate the structural similarity across all possible translation directions by training W on the corresponding translation samples built from NTREX (Federmann et al., 2022) and then testing on Flores (Goyal et al., 2022)[2]. Note that NTREX mainly focuses on the News domain while Flores is built from Wikipedia. Such out-of-domain testing (Wu and Monz, 2023; Wu et al., 2024) helps to assess the robustness and generalization capabilities, which provides a more realistic measure of how LLMs can handle diverse and unexpected inputs.

Specifically, we calculate Precision@k by using embeddings in WA to retrieve those in B and determine whether their counterparts are within the k-nearest neighbors based on cosine similarity. We use the precision after rotation to indicate the structural similarity within each translation direction.

2.3 Representation Discrepancy and Isomorphism

We begin our investigation by using sentence embeddings derived from prompting methods as mentioned in §2.1. Table 1 shows the success rate of the resulting embeddings in cross-lingual retrieval before/after applying Procrustes projection (§2.2). It is clear that 1) the initial representation discrepancies are generally substantial across languages, such as EN→JA (0.03), except for a few language pairs that are closer or use the same scripts, e.g., EN→DE (0.82). 2) However, after properly rotating (applying W), representations in most of the directions are well aligned, leading to clear gains from an average of 0.25 to 0.71. The results obtained from LLaMA2-13B, LLaMA3-8B, and BLOOM-7.1B models are provided in Appendix A.4, where a similar phenomenon can be observed.

In addition to these high-resource languages, we also conduct experiments on English (EN) and four low-resource languages: Lao (LAO), Czech (CES), Maltese (MLT), and Catalan (CAT). Table 16 shows the results. It is easy to see that although a relatively low success rate for cross-lingual retrieval in this setting, which is natural due to a lack of representation capability for low-resource languages, clear gains can still be observed after applying Procrustes projection.

To demonstrate the generalizability of our findings, we also apply another representation extraction method that takes the last token's output embedding without prompting as representations (last token pooling). The results shown in Appendix A.3 demonstrate that although it performs worse than the prompting method, the phenomenon still holds.

Overall, we argue that although representations from LLMs vary significantly across languages, they exhibit a high degree of isomorphism — properly rotating and/or reflecting the representation space can effectively align them.

2.4 Multilingual Representation via English Prompts

Previous studies show decent improvements can be achieved by simply adjusting or filling non-English instructions into English-centric prompting templates in the inference stage (Etxaniz et al., 2024; Huang et al., 2023). To explain this technique's success, we investigate how the representations of LLMs change with prompt language. For instance, using English, which is the predominant language during training, versus using the same languages §2.1 is written in.

Table 2 shows the success rate within the same data setting as §2.3 when using English prompts. Notably, the initial representations' degree of alignment is much higher than that in Table 1 (0.86 v.s., 0.25), resulting in similar alignment levels with the latter after rotation. Also, the gain from applying Procrustes projection is marginal in this setting. We interpret the degeneration of the rotation gain when using English prompts. Here, we argue that the corresponding spatial transformation, i.e., mapping representations into a shared English space has already taken place due to the use of an English prompt. In Table 17, we also show the results for low-resource languages, where the conclusions are also aligned.

In the following sections, we refer to using these English prompts (en-prompts) with non-English sentences as zero-shot representation alignment and conduct experiments based on this setting.

3 Semantic Analysis

Isomorphism is considered the foundation of few- or zero-shot capabilities in the context of word translation (Lample et al., 2017; Søgaard et al., 2018), where word-level semantics can be easily aligned across languages using a few word pairs. We hypothesize the existing isomorphism can also facilitate semantic alignments for LLMs across languages in a few-shot setting. Inspired by Mikolov et al. (2013), who applied a contrastive loss with a small dictionary to enable word-level semantic transfer, we explore the cross-lingual semantic

[2] NTREX and Flores are both multi-parallel. So it is easy to build translation data in each involved direction. Here, we merge all bitext in *dev* and *test* set for NTREX and Flores, resulting in 1,997 and 2,009 samples, respectively.

Model	Settings	EN	AR	ES	AR-EN	ES-EN	TR-EN	Avg
LLaMA2-7B	$self$-prompts	0.72	0.50	0.70	0.26	0.24	0.11	0.42
LLaMA2-7B	en-prompts	0.72	0.46	0.69	0.36	0.28	0.12	0.44
LLaMA2-7B	en-prompts (+100)	0.76	0.62	0.73	0.52	0.64	0.42	0.62
LLaMA2-7B	en-prompts (+1000)	0.82	0.62	0.80	0.54	0.75	0.55	0.68
Tower-7B	$self$-prompts	0.69	0.43	0.60	0.09	0.16	-0.07	0.32
Tower-7B	en-prompts	0.69	0.45	0.70	0.26	0.35	0.11	0.43
Tower-7B	en-prompts (+100)	0.73	0.57	0.67	0.50	0.60	0.41	0.58
Tower-7B	en-prompts (+1000)	0.76	0.60	0.65	0.54	0.62	0.47	0.61

Table 3: The multilingual and cross-lingual STS results in different settings. $self$-prompts and en-prompts denote using prompting methods in §2.1 and §2.4, respectively. Tower continues to pre-train LLaMA2 with large amounts of multilingual data but fails to align semantics. However, aligning LLaMA2 at the representation level using a few translation samples from NTREX (e.g., 100), results in clear improvements from 0.40 to 0.68. We provide results derived from other sizes of LLMs in Appendix A.5.

alignment of LLMs at the sentence level through contrastive learning in this section.

In Section 3.1, we describe the setting of evaluating cross-lingual semantic alignment, i.e., Semantic Textual Similarity (STS) tasks. In Section 3.2, we describe using contrastive learning with a few sentence pairs to align cross-lingual semantics.

3.1 Semantic Textual Similarity

In this section, we examine the multilingualism of LLM representations through the lens of Semantic Textual Similarity (STS) (Agirre et al., 2015, 2016). Each sentence pair in STS datasets is annotated from 0 to 5 indicating the pairwise semantic similarity. The Pearson correlation between the model-predicted and human-annotated similarity scores is used as the metric. The STS-17 shared task (Camacho-Collados et al., 2017) extends English-centric STS evaluation to multilingual settings. In this paper, we conduct experiments based on STS-17, which encompasses 3 monolingual STS (EN, AR, and ES) and 3 cross-lingual STS (AR-EN, ES-EN, and TR-EN) tasks.

Given the structure similarity of representations across languages, we test the few-shot capacity of aligning cross-lingual semantics within LLMs in the following sections.

3.2 Cross-lingual Contrastive Learning

Contrastive learning (Hadsell et al., 2006) learns effective representation by pulling semantically close neighbors together and pushing apart non-neighbors. Formally, given a set of paired examples $D = \{(x_i, x_i^+)\}_{i=1}^m$, where x_i and x_i^+ are semantically related, following Chen et al. (2020), a cross-entropy loss ℓ_i with in-batch negatives can be defined as follows:

$$\ell_i = -\log \frac{e^{sim(h_i,h_i^+)/\tau}}{\sum_{j=1}^{N} e^{sim(h_i,h_j^+)/\tau}}, \tag{1}$$

where h_i is the representation of x_i, τ is a temperature hyperparameter, and $sim(h_i, h_j)$ is the cosine similarity. In this paper, we directly extend the objective (Eq. 1) into a cross-lingual setting, where x_i and x_i^+ refer to the i-th possible translation pair.

Training Setting. We select 1,000 multi-parallel samples from NTREX as the training set and construct pair-wise samples covering EN→AR, AR→EN, EN→ES, and ES→EN[3]. Meanwhile, we leave TR-involved data empty to investigate the potential impact on unseen languages. We apply the in-batch cross-entropy loss as the objective and fine-tune LLMs with LoRA (Hu et al., 2021). Detailed hyperparameters are in Appendix A.1.

We compare cross-lingual STS under varying settings, including 1) Zero-shot prompting using self-language for the template, see §2.1, 2) Zero-shot prompting using English templates, see §2.4, 3) Using Tower (Alves et al., 2024) as the backbone, a multilingual LLM extensively trained on multilingual data based on LLaMA2, and 4) Applying cross-lingual contrastive objective. The summarized results can be found in Table 3.

3.3 Results and Discussion

Semantic Alignment across Languages. In Table 3, we show that the initial semantic representation ($self$-prompts) performs poorly in cross-lingual settings while applying en-prompts leads to relatively higher performance, which is in line with

[3] We cover both directions for each language pair to ensure all involved languages have a chance to be treated as negative samples in a batch.

the representational analysis in §2.4. Applying contrastive objectives at the representation level, even with just 100 samples, results in strong overall STS improvements from 0.44 to 0.62. Further gain can be achieved by extending the training size from 100 to 1,000 samples.

Interestingly, although the training objective is designed from a cross-lingual perspective (§3.2) — aligning representations from other languages to English — the monolingual STS performance (EN, AR, ES) also shows clear improvements. Notably, even the performance of English, the dominant language, improves significantly, rising from 0.72 to 0.82. We preliminarily interpret this phenomenon as indicating that representation alignment leads to better grounding across languages; however, we leave in-depth exploration for the future.

Sample- and Representation-Level Alignments. We observe that current studies (Xu et al., 2023; Alves et al., 2024; Lai et al., 2024; Gao et al., 2024) about the multilingualism of LLMs are mainly focusing on sample-level alignments, i.e., extending training or fine-tuning samples beyond English. For example, Tower (Alves et al., 2024) was further pretrained on a multilingual dataset encompassing 20 billion tokens based on LLaMA2. In Table 2, we clearly show that despite extensive sample-level alignments, Tower's semantic representation still fails to generalize effectively across languages, yielding only marginal gains over the base model, LLaMA2. Also, Gao et al. (2024) demonstrate that neither multilingual pretraining nor instruction tuning can substantially improve cross-lingual knowledge conductivity. To this end, we advocate for exploring representation-level alignment in the future given its high efficiency and effectiveness in semantic alignments for LLMs.

4 Related Work

4.1 Text Representation Using Large Language Models

Recent research has focused on extracting text representations directly from LLMs. Jiang et al. (2022b) use a meaning compression prompt, *This sentence : "[TEXT]" means in one word:"*, and utilize the output hidden state of the last token as the sentence embedding. Additionally, they leverage in-context learning (Dong et al., 2023) as an efficient way to enhance the performance of the extracted representations. Although effective, this approach highlights that the resulting embeddings tend to be task-specific, showing limited generalization across different downstream tasks, and are highly sensitive to the selection of demonstrations. To mitigate the absence of backward dependencies in LLMs, other studies explore enhancing LLMs by either duplicating the input texts (Springer et al., 2024) or incorporating bidirectional attention (BehnamGhader et al., 2024). Alternatively, Lei et al. (2024) generate broad embeddings that capture semantics from multiple distinct perspectives through the use of meta-task prompting for a single sentence.

However, these studies are limited to monolingual (English) scenarios. In this paper, we focus on the underexplored area of text representation in multilingual settings using LLMs.

4.2 Representational Analysis of LLMs

Pires et al. (2019) analyze the multilinguality of mBERT (Devlin, 2018) from both representational and downstream-tasks perspectives. They conclude that mBERT does create multilingual representations, but these representations exhibit systematic deficiencies affecting certain language pairs. In the context of decoder-only language models, Yuan et al. (2024) endeavors to examine the multilingual capability of LLaMA (Touvron et al., 2023) from the vocabulary sharing perspective by analyzing 101 languages. However, the multilingual representational analysis of LLMs remains underexplored. To the best of our knowledge, this paper is the first study investigating the representation of LLMs across languages and their relationship with downstream tasks.

5 Conclusion

In this paper, we investigate LLMs' representations from both geometric and semantic similarity perspectives. Our findings demonstrate that LLMs' representations exhibit a high degree of isomorphism across languages, which facilitates their cross-lingual zero-shot or few-shot capabilities in a multilingual context. For example, we show that the semantics representation of LLMs can easily be enhanced across languages by alignment at the representation level using as few as 100 translation samples, which is much more efficient and effective than sample-level pretraining or instruction tuning.

Limitations

We conduct experiments exclusively on four families of LLMs, namely LLaMA2, LLaMA3, Tower, and BLOOM. Therefore, the generalizability of our findings to other LLMs remains uncertain. Additionally, due to the limited language coverage in the STS17 task, our semantic analysis is restricted to a few languages.

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A Appendix

A.1 Fine-tuning Hyperparameters

We set the same hyperparameters for all experiments. The LoRA is applied to all *q_proj* and *v_proj* modules. The LoRA rank is 64, alpha is 16, and dropout is 0.05. The batch size is set to 32 and the gradient is accumulated for 4 steps, resulting in an actual batch size of 128. The learning rate is set to 5e-4. For experiments of fine-tuning with 100 and 1,000 samples, we trained with 10 and 3 epochs.

A.2 Representation Isomorphism with Additional Metrics

We present the results of Precision@1 and Precision@10 on representation isomorphism with LLaMA-7B in Table 4, 5, 6, and 7.

A.3 Representation Isomorphism with Last Token Pooling-Derived Representations

Table 8 shows the results on representation isomorphism with last token pooling-derived representations of the LLaMA2-7B model.

A.4 Representation Isomorphism with Other LLMs

Table 9 and 10 show the results on representation isomorphism with the LLaMA2-13B model. The results of LLaMA3-8B and BLOOM-7.1B are shown in Table 11, 12, 13, and 14.

A.5 Semantic Alignment across Languages

Table 15 shows the multilingual cross-lingual STS results in different settings upon 13B LLMs.

Precision@1	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.20 / 0.47	0.44 / 0.88	0.01 / 0.63	0.19 / 0.87	0.65 / 0.88	0.54 / 0.93	0.34 / 0.78
AR	0.06 / 0.09	- / -	0.10 / 0.26	0.00 / 0.2	0.03 / 0.26	0.02 / 0.21	0.06 / 0.33	0.05 / 0.23
ZH	0.07 / 0.52	0.02 / 0.36	- / -	0.07 / 0.50	0.12 / 0.71	0.07 / 0.57	0.11 / 0.79	0.08 / 0.57
JA	0.01 / 0.15	0.00 / 0.19	0.10 / 0.38	- / -	0.08 / 0.35	0.01 / 0.38	0.02 / 0.40	0.04 / 0.31
RU	0.01 / 0.52	0.01 / 0.43	0.38 / 0.72	0.02 / 0.54	- / -	0.09 / 0.73	0.36 / 0.86	0.14 / 0.63
DE	0.40 / 0.72	0.01 / 0.42	0.02 / 0.73	0.00 / 0.63	0.21 / 0.83	- / -	0.62 / 0.88	0.21 / 0.70
ES	0.02 / 0.55	0.04 / 0.41	0.09 / 0.72	0.00 / 0.49	0.11 / 0.80	0.26 / 0.73	- / -	0.09 / 0.62
From X	0.10 / 0.42	0.05 / 0.38	0.19 / 0.62	0.02 / 0.50	0.12 / 0.64	0.18 / 0.58	0.28 / 0.70	0.14 / 0.55

Table 4: The success rate (Precision@1) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA2-7B** model. The embeddings in each language are derived from the LLaMA2-7B model using the prompting method as described in §2.1.

Precision@10	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.40 / 0.73	0.67 / 0.98	0.05 / 0.88	0.44 / 0.98	0.86 / 0.97	0.82 / 0.99	0.54 / 0.92
AR	0.16 / 0.31	- / -	0.24 / 0.51	0.02 / 0.45	0.12 / 0.54	0.12 / 0.41	0.19 / 0.62	0.14 / 0.47
ZH	0.30 / 0.80	0.16 / 0.62	- / -	0.20 / 0.77	0.40 / 0.91	0.28 / 0.80	0.53 / 0.95	0.31 / 0.81
JA	0.06 / 0.41	0.06 / 0.42	0.28 / 0.69	- / -	0.23 / 0.64	0.06 / 0.65	0.13 / 0.70	0.14 / 0.58
RU	0.27 / 0.80	0.27 / 0.68	0.63 / 0.90	0.08 / 0.76	- / -	0.34 / 0.89	0.69 / 0.97	0.38 / 0.83
DE	0.78 / 0.92	0.16 / 0.69	0.46 / 0.92	0.04 / 0.84	0.43 / 0.95	- / -	0.88 / 0.97	0.46 / 0.88
ES	0.24 / 0.82	0.10 / 0.67	0.24 / 0.90	0.02 / 0.73	0.27 / 0.94	0.56 / 0.89	- / -	0.24 / 0.83
From X	0.30 / 0.68	0.19 / 0.64	0.42 / 0.82	0.07 / 0.74	0.32 / 0.83	0.37 / 0.77	0.54 / 0.87	0.32 / 0.76

Table 5: The success rate (Precision@10) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA2-7B** model. The embeddings in each language are derived from the LLaMA2-7B model using the prompting method as described in §2.1.

Precision@1	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.59 / 0.52	0.83 / 0.81	0.83 / 0.80	0.57 / 0.82	0.87 / 0.88	0.87 / 0.90	0.76 / 0.79
AR	0.50 / 0.44	- / -	0.68 / 0.56	0.69 / 0.56	0.41 / 0.58	0.63 / 0.61	0.65 / 0.63	0.59 / 0.56
ZH	0.70 / 0.79	0.67 / 0.60	- / -	0.96 / 0.92	0.68 / 0.86	0.89 / 0.87	0.80 / 0.88	0.78 / 0.82
JA	0.74 / 0.77	0.69 / 0.59	0.97 / 0.91	- / -	0.67 / 0.85	0.87 / 0.85	0.81 / 0.86	0.79 / 0.81
RU	0.51 / 0.84	0.63 / 0.64	0.91 / 0.88	0.88 / 0.87	- / -	0.88 / 0.93	0.86 / 0.91	0.78 / 0.85
DE	0.80 / 0.87	0.51 / 0.61	0.80 / 0.85	0.78 / 0.85	0.57 / 0.89	- / -	0.95 / 0.92	0.73 / 0.83
ES	0.76 / 0.87	0.45 / 0.58	0.73 / 0.83	0.69 / 0.82	0.46 / 0.87	0.94 / 0.91	- / -	0.67 / 0.81
From X	0.67 / 0.76	0.59 / 0.59	0.82 / 0.81	0.81 / 0.80	0.56 / 0.81	0.85 / 0.84	0.82 / 0.85	0.73 / 0.78

Table 6: The success rate (Precision@1) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA2-7B** model. Note that all embeddings are derived from the prompting template in English as described in §2.4, instead of the same language with input sentences.

Precision@10	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.83 / 0.80	0.95 / 0.96	0.97 / 0.95	0.80 / 0.96	0.98 / 0.97	0.98 / 0.98	0.92 / 0.94
AR	0.73 / 0.75	- / -	0.88 / 0.81	0.89 / 0.80	0.66 / 0.82	0.87 / 0.84	0.87 / 0.84	0.82 / 0.81
ZH	0.89 / 0.95	0.90 / 0.84	- / -	1.00 / 0.98	0.89 / 0.97	0.98 / 0.97	0.98 / 0.97	0.94 / 0.95
JA	0.91 / 0.94	0.90 / 0.83	1.00 / 0.98	- / -	0.88 / 0.97	0.98 / 0.97	0.98 / 0.97	0.94 / 0.94
RU	0.80 / 0.97	0.88 / 0.86	0.98 / 0.97	0.98 / 0.97	- / -	0.98 / 0.98	0.98 / 0.98	0.93 / 0.96
DE	0.93 / 0.97	0.74 / 0.84	0.94 / 0.96	0.92 / 0.96	0.79 / 0.97	- / -	0.99 / 0.98	0.89 / 0.95
ES	0.92 / 0.97	0.71 / 0.82	0.90 / 0.96	0.88 / 0.96	0.72 / 0.96	0.99 / 0.97	- / -	0.85 / 0.94
From X	0.86 / 0.92	0.83 / 0.83	0.94 / 0.94	0.94 / 0.94	0.79 / 0.94	0.96 / 0.95	0.96 / 0.95	0.90 / 0.93

Table 7: The success rate (Precision@10) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA2-7B** model. Note that all embeddings are derived from the prompting template in English as described in §2.4, instead of the same language with input sentences.

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.05 / 0.23	0.04 / 0.51	0.08 / 0.41	0.13 / 0.54	0.09 / 0.57	0.08 / 0.70	0.08 / 0.49
AR	0.03 / 0.07	- / -	0.02 / 0.13	0.02 / 0.08	0.03 / 0.13	0.01 / 0.12	0.02 / 0.16	0.02 / 0.12
ZH	0.19 / 0.24	0.08 / 0.18	- / -	0.46 / 0.34	0.15 / 0.37	0.19 / 0.40	0.11 / 0.44	0.20 / 0.33
JA	0.11 / 0.12	0.06 / 0.09	0.35 / 0.25	- / -	0.05 / 0.17	0.08 / 0.13	0.06 / 0.17	0.12 / 0.15
RU	0.15 / 0.23	0.05 / 0.12	0.08 / 0.30	0.06 / 0.15	- / -	0.19 / 0.36	0.18 / 0.45	0.12 / 0.27
DE	0.06 / 0.20	0.02 / 0.10	0.03 / 0.28	0.04 / 0.11	0.09 / 0.38	- / -	0.18 / 0.45	0.07 / 0.25
ES	0.07 / 0.28	0.02 / 0.14	0.02 / 0.33	0.02 / 0.15	0.08 / 0.45	0.13 / 0.43	- / -	0.06 / 0.30
From X	0.10 / 0.19	0.05 / 0.14	0.09 / 0.30	0.11 / 0.21	0.09 / 0.34	0.12 / 0.33	0.10 / 0.40	0.10 / 0.27

Table 8: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA2-7B** model. The embeddings are derived by taking the output hidden vector of the last token without prompting (**last token pooling**).

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.26 / 0.72	0.66 / 0.90	0.66 / 0.88	0.22 / 0.96	0.56 / 0.85	0.30 / 0.83	0.44 / 0.86
AR	0.02 / 0.37	- / -	0.09 / 0.28	0.11 / 0.34	0.10 / 0.64	0.03 / 0.33	0.03 / 0.41	0.06 / 0.40
ZH	0.02 / 0.68	0.04 / 0.29	- / -	0.42 / 0.50	0.02 / 0.68	0.00 / 0.32	0.00 / 0.38	0.08 / 0.47
JA	0.02 / 0.62	0.05 / 0.40	0.74 / 0.54	- / -	0.05 / 0.86	0.01 / 0.57	0.01 / 0.53	0.15 / 0.59
RU	0.01 / 0.43	0.07 / 0.30	0.07 / 0.28	0.12 / 0.43	- / -	0.02 / 0.47	0.02 / 0.48	0.05 / 0.40
DE	0.47 / 0.84	0.24 / 0.61	0.19 / 0.57	0.52 / 0.79	0.20 / 0.95	- / -	0.41 / 0.80	0.34 / 0.76
ES	0.25 / 0.71	0.29 / 0.52	0.09 / 0.46	0.46 / 0.57	0.14 / 0.83	0.52 / 0.70	- / -	0.29 / 0.63
From X	0.13 / 0.61	0.16 / 0.47	0.31 / 0.51	0.38 / 0.58	0.12 / 0.82	0.19 / 0.54	0.13 / 0.57	0.20 / 0.59

Table 9: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA2-13B** model. The embeddings in each language are derived from the LLaMA2-13B model using the prompting method as described in §2.1.

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.89 / 0.82	0.90 / 0.94	0.89 / 0.93	0.77 / 0.94	0.99 / 0.98	0.98 / 0.98	0.90 / 0.93
AR	0.81 / 0.80	- / -	0.82 / 0.86	0.86 / 0.85	0.78 / 0.85	0.94 / 0.88	0.94 / 0.88	0.86 / 0.85
ZH	0.59 / 0.95	0.89 / 0.88	- / -	1.00 / 0.98	0.88 / 0.97	0.97 / 0.97	0.99 / 0.98	0.89 / 0.96
JA	0.69 / 0.94	0.91 / 0.87	1.00 / 0.99	- / -	0.91 / 0.96	0.98 / 0.98	0.99 / 0.97	0.91 / 0.95
RU	0.44 / 0.95	0.94 / 0.89	0.94 / 0.98	0.95 / 0.97	- / -	0.98 / 0.99	0.98 / 0.98	0.87 / 0.96
DE	0.98 / 0.98	0.94 / 0.90	0.94 / 0.98	0.94 / 0.97	0.91 / 0.98	- / -	1.00 / 1.00	0.95 / 0.97
ES	0.95 / 0.97	0.93 / 0.88	0.90 / 0.97	0.91 / 0.96	0.86 / 0.97	0.99 / 0.98	- / -	0.92 / 0.96
From X	0.74 / 0.93	0.92 / 0.87	0.92 / 0.95	0.93 / 0.94	0.85 / 0.94	0.97 / 0.96	0.98 / 0.96	0.90 / 0.94

Table 10: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA2-13B** model. Note that all embeddings are derived from the prompting template in English as described in §2.4, instead of the same language with input sentences.

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
EN	- / -	0.87 / 0.97	0.98 / 0.99	0.89 / 0.98	0.93 / 0.99	0.97 / 0.98	0.99 / 1.00	0.94 / 0.98
AR	0.02 / 0.80	- / -	0.87 / 0.81	0.93 / 0.78	0.89 / 0.87	0.16 / 0.78	0.65 / 0.88	0.59 / 0.82
ZH	0.57 / 0.97	0.83 / 0.91	- / -	0.87 / 0.93	0.77 / 0.97	0.07 / 0.92	0.10 / 0.94	0.54 / 0.94
JA	0.13 / 0.90	0.85 / 0.89	0.93 / 0.92	- / -	0.60 / 0.94	0.06 / 0.94	0.20 / 0.97	0.46 / 0.93
RU	0.80 / 0.96	0.91 / 0.93	0.96 / 0.95	0.96 / 0.93	- / -	0.76 / 0.92	0.80 / 0.97	0.86 / 0.94
DE	0.98 / 0.98	0.84 / 0.94	0.93 / 0.96	0.92 / 0.98	0.85 / 0.98	- / -	0.98 / 0.98	0.92 / 0.97
ES	0.76 / 0.96	0.80 / 0.94	0.80 / 0.92	0.88 / 0.96	0.71 / 0.96	0.95 / 0.95	- / -	0.82 / 0.95
From X	0.54 / 0.93	0.85 / 0.93	0.91 / 0.92	0.91 / 0.93	0.79 / 0.95	0.49 / 0.92	0.62 / 0.96	0.73 / 0.93

Table 11: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA3-8B** model. The embeddings in each language are derived from the LLaMA3-8B model using the prompting method as described in §2.1.

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
en	- / -	0.83 / 0.95	0.96 / 0.98	0.94 / 0.96	0.97 / 0.98	0.99 / 0.98	0.99 / 0.98	0.95 / 0.97
ar	0.71 / 0.96	- / -	0.99 / 0.98	0.99 / 0.98	1.00 / 0.99	0.99 / 0.98	0.99 / 0.98	0.94 / 0.98
zh	0.79 / 0.98	0.98 / 0.98	- / -	1.00 / 0.99	1.00 / 0.99	0.99 / 0.99	0.99 / 0.99	0.96 / 0.99
ja	0.70 / 0.97	0.98 / 0.97	1.00 / 0.99	- / -	1.00 / 0.99	0.99 / 0.99	0.98 / 0.98	0.94 / 0.98
ru	0.91 / 0.98	0.98 / 0.99	0.99 / 0.99	0.99 / 0.99	- / -	1.00 / 0.99	0.99 / 0.99	0.98 / 0.99
de	0.98 / 0.98	0.93 / 0.98	0.99 / 0.99	0.98 / 0.99	1.00 / 0.99	- / -	1.00 / 0.99	0.98 / 0.99
es	0.97 / 0.98	0.90 / 0.97	0.96 / 0.98	0.95 / 0.97	0.98 / 0.98	0.99 / 0.98	- / -	0.96 / 0.98
From X	0.84 / 0.97	0.93 / 0.97	0.98 / 0.98	0.98 / 0.98	0.99 / 0.99	0.99 / 0.98	0.99 / 0.98	0.96 / 0.98

Table 12: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection with the **LLaMA3-8B** model. Note that all embeddings are derived from the prompting template in English as described in §2.4, instead of the same language with input sentences.

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
en	- / -	0.02 / 0.90	0.01 / 0.81	0.01 / 0.66	0.02 / 0.55	0.09 / 0.71	0.07 / 0.92	0.04 / 0.76
ar	0.01 / 0.37	- / -	0.01 / 0.50	0.01 / 0.29	0.01 / 0.17	0.01 / 0.19	0.02 / 0.48	0.01 / 0.33
zh	0.00 / 0.36	0.02 / 0.66	- / -	0.01 / 0.29	0.00 / 0.09	0.00 / 0.13	0.00 / 0.39	0.01 / 0.32
ja	0.00 / 0.23	0.01 / 0.40	0.01 / 0.30	- / -	0.01 / 0.18	0.00 / 0.23	0.00 / 0.24	0.01 / 0.26
ru	0.07 / 0.24	0.01 / 0.38	0.00 / 0.15	0.01 / 0.29	- / -	0.05 / 0.53	0.02 / 0.27	0.03 / 0.31
de	0.06 / 0.41	0.01 / 0.45	0.01 / 0.21	0.01 / 0.36	0.02 / 0.53	- / -	0.02 / 0.38	0.02 / 0.39
es	0.01 / 0.79	0.02 / 0.86	0.01 / 0.67	0.01 / 0.46	0.01 / 0.34	0.01 / 0.49	- / -	0.01 / 0.60
From X	0.03 / 0.40	0.02 / 0.61	0.01 / 0.44	0.01 / 0.39	0.01 / 0.31	0.03 / 0.38	0.02 / 0.45	0.02 / 0.43

Table 13: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection with the **BLOOM-7.1B** model. The embeddings in each language are derived from the BLOOM-7.1B model using the prompting method as described in §2.1.

Precision@5	EN	AR	ZH	JA	RU	DE	ES	Into X
en	- / -	0.01 / 0.91	0.01 / 0.87	0.03 / 0.64	0.35 / 0.63	0.69 / 0.83	0.26 / 0.97	0.22 / 0.81
ar	0.16 / 0.83	- / -	0.02 / 0.68	0.06 / 0.43	0.13 / 0.44	0.17 / 0.54	0.14 / 0.78	0.11 / 0.62
zh	0.01 / 0.91	0.02 / 0.81	- / -	0.18 / 0.62	0.04 / 0.47	0.04 / 0.63	0.02 / 0.82	0.05 / 0.71
ja	0.05 / 0.73	0.02 / 0.66	0.25 / 0.70	- / -	0.11 / 0.58	0.12 / 0.68	0.06 / 0.66	0.10 / 0.67
ru	0.57 / 0.61	0.01 / 0.60	0.01 / 0.51	0.04 / 0.51	- / -	0.73 / 0.70	0.10 / 0.65	0.24 / 0.60
de	0.63 / 0.82	0.01 / 0.68	0.01 / 0.62	0.04 / 0.58	0.42 / 0.70	- / -	0.12 / 0.78	0.20 / 0.70
es	0.11 / 0.96	0.01 / 0.85	0.01 / 0.80	0.04 / 0.56	0.24 / 0.62	0.22 / 0.77	- / -	0.10 / 0.76
From X	0.26 / 0.81	0.01 / 0.75	0.05 / 0.70	0.06 / 0.56	0.21 / 0.57	0.33 / 0.69	0.12 / 0.78	0.15 / 0.69

Table 14: The success rate (Precision@5) for cross-lingual retrieval **before/after** applying Procrustes projection with the **BLOOM-7.1B** model. Note that all embeddings are derived from the prompting template in English as described in §2.4, instead of the same language with input sentences.

Model	Settings	EN	AR	ES	AR-EN	ES-EN	TR-EN	Avg
LLaMA2-13B	en-prompts	0.72	0.55	0.60	0.45	0.31	0.28	0.49
LLaMA2-13B	en-prompts (+100)	0.74	0.57	0.63	0.57	0.66	0.52	0.62
LLaMA2-13B	en-prompts (+1000)	0.77	0.62	0.71	0.61	0.63	0.55	0.65
Tower-13B	en-prompts	0.73	0.59	0.64	0.37	0.42	0.49	0.54
Tower-13B	en-prompts (+100)	0.66	0.60	0.67	0.51	0.53	0.45	0.57
Tower-13B	en-prompts (+1000)	0.69	0.63	0.68	0.57	0.61	0.51	0.62

Table 15: The multilingual and cross-lingual STS results derived from **LLaMA2-13B** and **Tower-13B** in different settings. $self$-prompts and en-prompts denote using prompting methods in §2.1 and §2.4, respectively.

Precision@10	EN	LAO	CES	MLT	CAT	Into X
EN	- / -	0.04 / 0.16	0.45 / 0.93	0.05 / 0.50	0.64 / 0.93	0.30 / 0.63
LAO	0.02 / 0.04	- / -	0.02 / 0.06	0.03 / 0.11	0.03 / 0.06	0.03 / 0.07
CES	0.35 / 0.72	0.02 / 0.17	- / -	0.04 / 0.54	0.68 / 0.90	0.27 / 0.58
MLT	0.06 / 0.08	0.02 / 0.12	0.05 / 0.15	- / -	0.06 / 0.19	0.05 / 0.14
CAT	0.24 / 0.61	0.02 / 0.14	0.40 / 0.87	0.03 / 0.52	- / -	0.17 / 0.54
FROM X	0.17 / 0.36	0.03 / 0.15	0.23 / 0.50	0.04 / 0.42	0.35 / 0.52	0.16 / 0.39

Table 16: The success rate (Precision@10) for cross-lingual retrieval **before/after** applying Procrustes projection on low-resource languages. The embeddings in each language are derived from the LLaMA2-7B model using the prompting method as described in §2.1. “From X” and “Into X” denote the average results for each column and row, respectively. The Procurstes projection W for each translation direction is trained on NTREX, while the Precision@10 is tested based on the translation sentences from Flores.

Precision@10	EN	LAO	CES	MLT	CAT	Into X
EN	- / -	0.22 / 0.17	0.96 / 0.92	0.63 / 0.56	0.98 / 0.97	0.70 / 0.66
LAO	0.14 / 0.12	- / -	0.16 / 0.14	0.16 / 0.19	0.16 / 0.15	0.16 / 0.15
CES	0.91 / 0.96	0.17 / 0.20	- / -	0.72 / 0.68	0.99 / 0.98	0.70 / 0.70
MLT	0.50 / 0.46	0.19 / 0.25	0.61 / 0.57	- / -	0.68 / 0.61	0.49 / 0.47
CAT	0.92 / 0.97	0.14 / 0.17	0.97 / 0.95	0.69 / 0.65	- / -	0.68 / 0.68
From X	0.62 / 0.63	0.18 / 0.20	0.68 / 0.65	0.55 / 0.52	0.70 / 0.68	0.55 / 0.53

Table 17: The success rate (Precision@10) for cross-lingual retrieval **before/after** applying Procrustes projection on low-resource languages. Note that all embeddings are derived from the prompting template in English, instead of the same language with input sentences.