# **Inducing Language-Agnostic Multilingual Representations**

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# Abstract

Cross-lingual representations have the potential to make NLP techniques available to the vast majority of languages in the world. However, they currently require large pretraining corpora, or assume access to typologically similar languages. In this work, we address these obstacles by removing language identity signals from multilingual embeddings. We examine three approaches for this: (i) re-aligning the vector spaces of target languages (all together) to a pivot source language; (ii) removing languages-specific means and variances, which yields better discriminativeness of embeddings as a by-product; and (iii) normalizing input texts by removing morphological contractions and sentence reordering, thus yielding language-agnostic representations. We evaluate on the tasks of XNLI and reference-free MT evaluation across 19 selected languages. Our experiments demonstrate the language agnostic behavior of our multilingual representations, allowing better zero-shot cross-lingual transfer to distant and low-resource languages, and decrease the performance gap by 8.9 points (M-BERT) and 18.2 points (XLM-R) on average across all tasks and languages. We particularly show that vector normalization can lead to more consistent gains and is complementary to input normalization and recently popular vector space re-alignment. We make our codes and models available <sup>1</sup>.

## 1 Introduction

Cross-lingual text representations (Devlin et al., 2019; Conneau et al., 2019) ideally allow for transfer between *any* language pair, and thus hold the promise to alleviate the data sparsity problem for low-resource languages. However, up to now, cross-lingual systems trained on English appear

to transfer poorly to target languages dissimilar to English (Wu and Dredze, 2019; Pires et al., 2019) and for which only small monolingual corpora are available (Conneau et al., 2019; Hu et al., 2020; Lauscher et al., 2020), as illustrated in Fig. 1.<sup>2</sup>

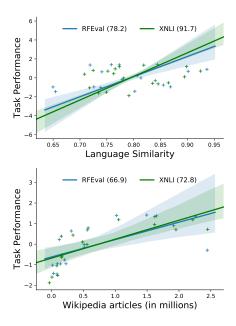


Figure 1: XNLI and RFEval performance for different language similarities to English (above) as well as data sizes in Wikipedia (below). Each point is a language, brackets give the Pearson correlation of points on the x-and y-axis. All results are normalized via z-score and produced by the last layer of m-BERT.

As a remedy, recent work has suggested to train representations on larger multilingual corpora (Conneau et al., 2019) and, more importantly, to realign them post-hoc so as to address the deficits of state-of-the-art contextualized encoders which have not seen any parallel data during training (Schuster et al., 2019; Wu and Dredze, 2019; Cao et al., 2020). However, re-mapping (i) can be costly, (ii) requires

Inttps://github.com/AIPHES/
Language-Agnostic-Contextualized-Encoders

<sup>&</sup>lt;sup>2</sup>We consider language similarity as the cosine similarity between the average representations of two languages over monolingual corpora from Wikipedia.

parallel data on word or sentence level, which may not be available abundantly in low-resource settings, and (iii) its positive effect has not yet been studied systematically.

In this work, we explore normalization as an alternative to re-mapping. In order to decrease the distance between languages and thus allow for better cross-lingual transfer, we normalize (i) the text inputs to encoders before vectorization, e.g., removing word contractions and reordering sentences and (ii) the representations themselves by removing means and standard deviations, a common operation in machine and deep learning (LeCun et al., 1998; Rücklé et al., 2018). We comparatively evaluate all three techniques—input normalization, vector normalization, post-hoc re-mapping—across a typologically diverse set of 19 languages from five language families with diverse sizes of monolingual corpora, two NLP tasks, and two stateof-the-art contextualized cross-lingual encoders multilingual BERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019).

We evaluate on two cross-lingual tasks of varying difficulty: (1) zero-shot cross-lingual text classification evaluates how well cross-lingual systems perform classification transfer from source to target languages; and (2) reference-free machine translation evaluation measures the ability of multilingual embeddings to assign adequate cross-lingual semantic similarity scores to text from two languages, where one of them is an oftentimes corrupt automatic machine translation.

Our contributions: (i) We show that input normalization can be beneficial and lead to solid performance gains of (up to) 4.7 points across our two challenging tasks. (ii) We show that normalizing vector spaces is surprisingly effective and rivals much more resource-intensive techniques such as re-mapping, and leads to more consistent gains. (iii) We show that all three techniques input normalization, vector space normalization, and re-mapping—are orthogonal and their gains oftentimes add up. This is a very important finding as it allows for improvements on a much larger scale, especially for highly distant and low-resource languages. (iv) We provide a thorough analysis, which includes investigation of the effects of normalization and post-hoc re-mapping across layers.

## 2 Related Work

Our work connects cross-lingual representations with linguistic typology.

Cross-lingual Transfer Static cross-lingual representations have long been used for effective crosslingual transfer and can even be induced without parallel data (Artetxe et al., 2017; Lample et al., 2018). As for the monolingual case, static crosslingual embeddings have recently been succeeded by contextualized ones, since these yield (often considerably) better results. The capabilities and limitations of the contextualized representation multilingual BERT (m-BERT) is a topic of vivid discourse. Pires et al. (2019) show surprisingly good transfer performance for m-BERT despite it being trained without any parallel data, and that transfer is better for typologically similar languages. Wu et al. (2019) show that language representations are not correctly aligned in m-BERT, but can be linearly re-mapped. Extending this, Cao et al. (2020) find that jointly aligning language representations to be more useful than language-independent rotations. However, we show that the discriminativeness of the resulting embeddings is still poor, i.e., random word pairs are often assigned very high cosine similarity scores by the upper layers of original encoders—not only m-BERT but especially its extension XLM-R.

Libovický et al. (2019) further observe that m-BERT representations of related languages are seemingly close to one another in the cross-lingual embedding space. They show that removing language-specific means from m-BERT can eliminate language identity signals. In contrast, we remove both language-specific means and variances. Despite this seemingly minor difference, we extend upon this work along several dimensions: 1) our analysis is much broader, covering more languages, encoders, and tasks, 2) we show that vector space normalization is as effective as other recently proposed fixes for m-BERT's limitations (especially re-mapping), but much cheaper and it is orthogonal to other solutions in that gains are almost additive.

Linguistic Typology in NLP. Structural properties of most of the world's languages can be queried via databases such as WALS (Dryer and Haspelmath, 2013). Bjerva et al. (2019a) show that such properties can be predicted with high accuracy for held-out languages, suggesting it might be possible to automatically obtain typologi-

cal information for languages without annotations. O'Horan et al. (2016); Ponti et al. (2019) suggest to inject typological information into models to bridge the performance gap between high- and low-resource languages. Cotterell et al. (2018) find that higher amounts of inflectional morphology in languages yield worse performance on bits per English character (BPEC). Bjerva and Augenstein (2018); de Lhoneux et al. (2018) show that cross-lingual transfer can be more successful between languages which share, e.g., morphological properties.

We draw inspiration from Wang and Eisner (2016), who use dependency statistics to generate a large collection of synthetic languages to augment training data for low-resource languages. In contrast, we investigate the possibility of decreasing the syntactic and morphological differences of languages observed in WALS by removing word contractions and reordering sentences, hence going beyond using simple syntactic features.

## 3 Language-Agnostic Representations

Analyses by Ethayarajh (2019) indicate that random words are often assigned high cosine similarities in the upper layers of monolingual BERT. We examine this in a cross-lingual setting, by randomly selecting 500 German-English word pairs including mutual word translations and random words.<sup>3</sup> Fig. 2 (left) gives histograms based on the last layer of m-BERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019), which show that XLM-R wrongly assigns nearly perfect cosine similarity scores (+1) to both mutual word translations and random word pairs, whereas m-BERT assigns low scores to mutual translations. This indicates (and confirms) that both m-BERT and XLM-R are deficient cross-lingually. Fig. 2 (middle and right) show that the effects of vector space re-alignment (§3.1) and normalization (§3.2) are somewhat orthogonal, i.e., normalizing m-BERT and XLM-R spaces appears to largely improve their discriminatory ability, and re-mapping considerably increases the cosine similarity scores of mutual word translations, especially for m-BERT, thus apparently mitigating cross-lingual semantic mismatch.

## 3.1 Vector space re-alignment

MBERT and XLM-R induce cross-lingual vector spaces in an unsupervised way: no parallel data was

involved at training time. To improve upon these representations, recent work has suggested to remap the vector spaces, i.e., to use small amounts of parallel data to restructure the cross-lingual vector spaces. We follow the joint re-mapping approach of (Cao et al., 2020), which has shown better results than rotation-based re-mapping. We will now detail this approach.

**Notation.** Suppose we have k parallel corpora  $C^1, \ldots, C^k$ , i.e.,  $C^{\nu} = \{(\mathbf{s}^1, \mathbf{t}^1), \ldots, (\mathbf{s}^n, \mathbf{t}^n)\}$  is a set of corresponding sentence pairs from source and target languages, for  $\nu = 1, \ldots, k$ . We denote the alignments of words in a sentence pair  $(\mathbf{s}, \mathbf{t})$  as  $a(\mathbf{s}, \mathbf{t}) = \{(i_1, j_1), \ldots, (i_m, j_m)\}$ , where (i, j) denotes that  $\mathbf{s}_i$  and  $\mathbf{s}_j$  are mutual translations. Let  $f(i, \mathbf{u})$  be the contextual embedding for the i-th word in a sentence  $\mathbf{u}$ .

**Joint Alignment via Fine-tuning.** We align the monolingual sub-spaces of a source and target language by minimizing the distances of embeddings for matched word pairs in the corpus  $C^{\nu}$ :

$$L(C^{\nu}, f_{\Theta}) = \sum_{(\mathbf{s}, \mathbf{t}) \in C^{\nu}} \sum_{(i, j) \in a(\mathbf{s}, \mathbf{t})} \|f_{\Theta}(i, \mathbf{s}) - f_{\Theta}(j, \mathbf{t}))\|_{2}^{2}$$

$$(1)$$

where  $\Theta$  are the parameters of the encoder f. As in Cao et al. (2020), we use a regularization term to avoid for the resulting (re-aligned) embeddings to drift too far away from the initial encoder state  $f_0$ :

$$R(C^{\nu}, f_{\Theta}) = \sum_{\mathbf{t} \in C^{\nu}} \sum_{i=1}^{\operatorname{len}(\mathbf{t})} \| f_{\Theta}(i, \mathbf{t}) - f_{0}(i, \mathbf{t}) \|_{2}^{2}$$
(2)

Like for the multilingual pre-training of m-BERT and XLM-R, we fine-tune the encoder f on the concatenation of k parallel corpora to handle resource-lean languages, which is in contrast to offline alignment with language-independent rotations (Aldarmaki and Diab, 2019; Schuster et al., 2019). Assume that English is a common pivot (source language) in all our k parallel corpora. Then the following objective function orients all non-English embeddings toward English:

$$\min_{\Theta} \sum_{\nu=1}^{k} L(C^{\nu}, f_{\Theta}) + R(C^{\nu}, f_{\Theta})$$
 (3)

In §4, we refer to the above described realignment step as JOINT-ALIGN.

<sup>&</sup>lt;sup>3</sup>Word translations are extracted with FastAlign (Dyer et al., 2013) on parallel text from EuroParl (Koehn, 2005) and JW300 (Agić and Vulić, 2019).

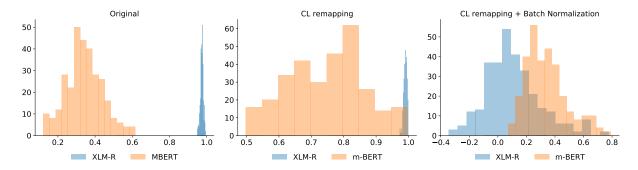


Figure 2: Histograms of cosine similarity scores of word pairs. a) Both original embeddings are misaligned. b) The modified XLM-R encoder cannot distinguish mutual word translations from random word pairs. c) Both modified encoders have better ability to distinguish word pairs with matched and non-matched meaning.

# 3.2 Vector space normalization

We add a batch normalization layer that constrains all embeddings of different languages into a distribution with zero mean and unit variance.

$$\bar{f}(i, \mathbf{s}) = \frac{f(i, \mathbf{s}) - \mu_{\beta}}{\sqrt{\sigma_{\beta}^2 + \epsilon}}$$
 (4)

where  $\epsilon$  is a constant value for numerical stability,  $\mu_{\beta}$  and  $\sigma_{\beta}$  are the sample mean and variance of a batch of contextualized embeddings obtained from multilingual encoders. In addition to a common effect during training, i.e., reducing covariate shift of input spaces, this additional layer in the crosslingual setup may allow for 1) removing language identity signals, e.g. languages-specific means and variances, from multilingual embeddings; and 2) increasing the discriminativeness of embeddings so that they have the potential of distinguishing word pairs with different senses, as shown in Fig. 2(c).

In §4, we refer to the above described batch normalization step as NORM.

# 3.3 Input normalization

In addition to joint alignment and vector space normalization, we investigate decreasing crosslinguistic differences between languages via the following surface form manipulation of input texts.

**Removing Morphological Contractions.** In many languages, e.g. Italian, prepositions and definite articles are often contracted. For instance, *de il* ('of the') is usually contracted to *del*. This leads to a mismatch between, e.g., English and Italian in terms of token alignments, and increases the crosslingual difference between the two. We segment an orthographic token (e.g. *del*) into several (syntactic) tokens (e.g. *de il*).<sup>4</sup> This yields a new sentence

which no longer corresponds to typical standard Italian grammar, but which we hypothesise reduces the linguistic gap between Italian and English, thus increasing cross-lingual performance.

Sentence Reordering. Another typological feature which differs between languages, is the ordering of nouns and adjectives. For instance, WALS shows that Romance languages such as French and Italians often use noun-adjective ordering, e.g., pomme rouge in French, whereas the converse is used in English. Additionally, languages differ in their ordering of subjects, objects, and verbs. For instance, according to WALS, English firmly follows the subject-verb-object (SVO) structure, whereas there is no dominant order in German. We apply this reordering in order to decrease the linguistic gap between languages. For instance, when considering English and French, we reverse all noun-adjective pairings from French to match English. This alignment is done while considering a dependency tree. We re-align according to the typological features from WALS. Since such feature annotations are available for a large amount of languages, and can be obtained automatically with high accuracy (Bjerva et al., 2019a), we expect this method to scale to languages for which basic dependencies (such as noun-adjective attachment) can be obtained automatically.

In §4, we refer to the above described realignment step as TEXT.

# 4 Experiments

## 4.1 Transfer tasks

Cross-lingual embeddings are usually evaluated via zero-shot cross-lingual transfer for supervised text classification tasks, or via unsupervised crosslingual textual similarity. For zero-shot transfer,

<sup>&</sup>lt;sup>4</sup>We use UDPipe (Straka et al., 2016), which is a pipeline trained on UD treebank 2.5 (Nivre et al., 2020).

fine-tuning of cross-lingual embeddings is done based on source language performance, and evaluation is performed on a held-out target language. This is, however, not likely to result in high quality target language embeddings and gives a false impression of cross-lingual abilities (Libovický et al., 2020). Zhao et al. (2020) use the more difficult task of reference-free machine translation evaluation (RFEval) to expose limitations of cross-lingual encoders, i.e., a failure to properly represent finegrained language aspects, which may be exploited by natural adversarial inputs such as word-by-word translations.

We evaluate cross-lingual representations on both of these two tasks types: zero-shot crosslingual transfer in a supervised classification task (XNLI),and reference-free MT evaluation (RFEval).

**XNLI.** The goal of natural language inference (NLI) is to infer whether a premise sentence entails, contradicts, or is neutral towards a hypothesis sentence. Conneau et al. (2018) release a multilingual NLI corpus, where the English dev and test sets of the MultiNLI corpus (Williams et al., 2018) are translated to 15 languages by crowd-workers.

**RFEval.** This task evaluates the translation quality, i.e. similarity of a target language translation and a source language sentence. Following Zhao et al. (2020), we collect source language sentences with their system and reference translations, as well as human judgments from the WMT17 metrics shared task (Bojar et al., 2017), which contains predictions of 166 translation systems across 12 language pairs in WMT17. Each language pair has approximately 3k source sentences, each associated with one human reference translation and with the automatic translations of participating systems. As in Zhao et al. (2019, 2020), we use the Earth Mover Distance to compute the distances between source sentence and target language translations, based on the semantic similarities of their contextualized cross-lingual embeddings.

## 4.2 A Typologically Varied Language Sample

We evaluate multilingual representations on two sets of languages: (1) a default language set which covers a sample of languages from the official XNLI and WMT17 test sets and (2) a diagnostic language set which contains 19 typologically diverse languages with different levels of data resources, covering five language families (each with at least

Language	Lang. family		Wiki-articles (in millions)	Sim level	Res level
Tagalog	α	29.3	0.08	low	low
Javanese	$\alpha$	26.5	0.06	low	low
Bengali	$\gamma$	24.8	0.08	low	low
Marathi	$\gamma$	24.0	0.06	low	low
Estonian	$\eta$	23.8	0.20	low	middle
Hindi	$\gamma$	22.2	0.13	middle	low
Urdu	$\gamma$	21.7	0.15	middle	middle
Finnish	$\eta$	20.1	0.47	middle	middle
Hungarian	$\eta$	19.8	0.46	middle	middle
Afrikaans	$\beta$	19.6	0.09	middle	low
Malay	$\alpha$	19.2	0.33	middle	middle
Spanish	$\delta$	18.5	1.56	high	high
French	$\delta$	18.2	2.16	high	high
Italian	$\delta$	18.0	1.57	high	high
Indonesian	$\alpha$	17.7	0.51	high	middle
Dutch	$\beta$	16.3	1.99	high	high
Portuguese	$\delta$	16.2	1.02	high	high
German	$\beta$	15.6	2.37	high	high
English	β	0.0	5.98	high	high

Table 1: Languages used, with their language families: Austronesian  $(\alpha)$ , Germanic  $(\beta)$ , Indo-Aryan  $(\gamma)$ , Romance  $(\delta)$ , and Uralic  $(\eta)$ . The distances of languages are defined in Eq. (5), measured using m-BERT.

three languages): Austronesian ( $\alpha$ ), Germanic ( $\beta$ ), Indo-Aryan ( $\gamma$ ), Romance ( $\delta$ ), and Uralic ( $\eta$ ). This sample was chosen as it yields a relatively good typological variety, with representatives from several large language families across the world. This additional setup allows us to examine whether the level of data resources, and the similarity of source and target languages are essential to the success of cross-lingual transfer. In the RFEval setup, we resort to pairs of translated source sentences and system translations. The former ones are translated from English human reference translations into 18 languages, obtained from Google Translate. For XNLI, We use translated test sets of all these languages from (Hu et al., 2020). Tab. 1 shows the overview of 19 languages which are labeled with 1) Similarity Level, i.e., the degree of similarity between target languages and English; and 2) Resource Level, i.e., the amount of data resources available. We divide the languages into low, middle, and high resource, based on Wikipedia sizes and m-BERT similarities. We carefully check that translating data has no effects on our general results.

# 4.3 Cross-lingual Encoders

Our goal is to improve the cross-lingual abilities of established cross-lingual systems. These support around 100 languages and are pre-trained using either monolingual self-supervised training (language modeling).

**M-BERT** Contextualized word embeddings (Devlin et al., 2019) are pre-trained on a collection of 104 monolingual corpora from Wikipedia, with 1) a vocabulary size of 110k; 2) language-specific tokenization tools for data pre-processing; and 3) two monolingual pre-training tasks: masked language modeling and next sentence prediction.

**XLM-R** Contextualized word embeddings (Conneau et al., 2019) are pre-trained on the Common-Crawl corpora of 100 languages, which contain more monolingual data than Wikipedia corpora, with 1) a vocabulary size of 250k; 2) a language-free tokenization tool, Sentence Piece (Kudo and Richardson, 2018) for data pre-processing; and 3) masked language modeling as the only monolingual pre-training task.

Our Modifications We fine-tune m-BERT ( $L=12,\,H=768,\,110M$  params) and XLM-R ( $L=12,\,H=768,\,70M$  params) on the concatenated mutual word translations of 18 languages paired with English, using the loss function obtained as Eq. 3. The mutual word translations are extracted with FastAlign (Dyer et al., 2013) on parallel text from the combination of following publicly available parallel corpora.

- Europarl (Koehn, 2005): We select 9 languages (German, Spanish, French, Italian, Dutch, Finnish, Hungarian, Portuguese, Estonian) out of 21 languages from Europarl. The size varies from 400k to 2M sentences depending on the language pair. We extract 100k parallel text for each language paired with English.
- JW300 (Agić and Vulić, 2019): We select the remaining languages (Tagalog, Bengali, Javanese, Marathi, Hindi, Urdu, Afrikaans, Malay, Indonesian) out of 380 languages from JW300. The average size is 100K parallel sentences per language pair. We extract 100k parallel text based on sampling for each language paired with English.

Overall, we apply NORM, TEXT, JOINT-ALIGN and the combinations of these to the last layer of m-BERT and XLM-R, and report their performances on the XNLI and RFEval tasks, based on the last layer of the two encoders in §5. To investigate the

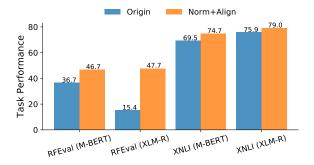


Figure 3: Results on RFEval are averaged over two selected language pairs (de-en and fi-en) from the WMT17 human translated test sets. Likewise, results on XNLI are averaged over four selected language pairs (en-fr, en-de, en-hi and en-es) from XNLI human translated test sets.

layer-wise effect of these modifications, we apply the modifications to individual layer and report the performances across layers in §6.

#### 5 Results

Overall Results In Tab. 2, we show results on machine translated test sets. The m-BERT space modified by JOINT-ALIGN  $\oplus$  NORM achieves consistent improvements on RFEval (+10.1 points) and XNLI (+7.6 points) on average. However, the effects are different for XLM-R. The modified XLM-R outperforms the baseline XLM-R on RFEval by the largest margin (+33.5 points), but the improvement is much smaller (+2.8 points) on XNLI. In Fig. 3, we show that our gains are not an artefact of machine translated test sets: we observe similar gains whether or not our data is obtained from machine or human translation.

Ablation Study In Tab. 3, we tease apart the source of improvements. Overall, the impacts of NORM and JOINT-ALIGN are substantial, and their effect is additive and sometimes even superadditive (e.g., M-BERT improves by 10.1 points on RFEval when both NORM and JOINT-ALIGN are applied but only by 1.7 and 7.6 points individually). We note that the improvement from NORM is more consistent across tasks and encoders, despite its simplicity and negligible cost. In contrast, JOINT-ALIGN has a positive effect for MBERT but it does not help for XLM-R on the XNLI task, despite the minor difference of two encoders, e.g., much larger training data and a different tokenizer used in XLM-R.

**Linguistic Manipulation Results.** We apply input modifications to language pairs that contrast

		Language Families								
Model	Avg	$\triangle$	$\alpha(4)$	$\triangle$	$\beta(3)$	$\triangle \mid \gamma(4)$	$\triangle$	$\delta(4)$	$\triangle \mid \eta(3)$	$\triangle$
Original cross-lingual embeddings										
м-BERT	38.0	-	36.6	-	40.4	-   28.2	-	49.8	-   34.8	-
XLM-R	12.9	-	13.5	-	17.4	- 2.9	-	25.9	- 11.6	-
Modified cross-lingual embeddings										
$\text{M-BERT} \oplus \text{Joint-Align} \oplus \text{Norm}$										
$XLM$ -R $\oplus$ Joint-Align $\oplus$ Norm	46.4	+33.5	46.5	+33.0	48.2	$+30.8 \mid 37.0$	+34.1	53.8	$+27.9 \mid 47.2$	+35.6

(a) Cross-lingual Semantic Text Similarity on the RFEval task

	Language Families						
Model	Avg	$\triangle \mid \alpha(4)$	$\triangle \mid \beta(3)$	$\triangle \mid \gamma(4)$	$\triangle \mid \delta(4)$	$\triangle \mid \eta(3)$	$\triangle$
Original cross-lingual embeddings M-BERT XLM-R	64.7 74.8	-   60.8 -   72.4	-   69.1 -   76.3	-   57.9 -   70.9	-   73.1 -   78.4	-   63.4 -   76.1	- -
Modified cross-lingual embeddings M-BERT $\oplus$ JOINT-ALIGN $\oplus$ NORM XLM-R $\oplus$ JOINT-ALIGN $\oplus$ NORM			+11.5   75.8 +2.4   79.6				+8.6 +2.7

(b) Cross-lingual Zero-shot transfer on the XNLI task

Table 2: Overall results of the established cross-lingual baselines and our modifications, on the RFEval and XNLI tasks. Brackets denote the number of languages per group. Results are averaged per group.  $\triangle$  is the difference between the performance of the original and the modified encoders.

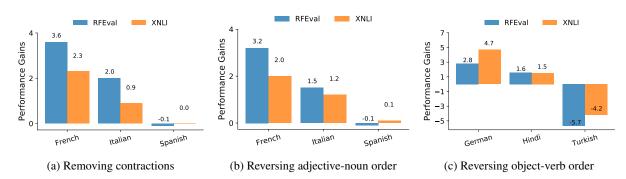


Figure 4: Performance gains on RFEval and XNLI obtained by different type of TEXT operations (contractions, and adjective-noun and object-verb order).

Model	XNLI	RFEval
M-BERT ⊕ NORM	+1.9	+1.7
$M ext{-BERT} \oplus JOINT ext{-ALIGN}$	+5.2	+7.6
$M ext{-BERT} \oplus JOINT ext{-ALIGN} \oplus NORM$	+7.6	+10.1
$XLM-R \oplus NORM$	+2.5	+27.1
$XLM-R \oplus JOINT-ALIGN$	-0.2	+11.6
$XLM$ -R $\oplus$ Joint-Align $\oplus$ Norm	+2.8	+33.5

Table 3: Ablation tests of our modified encoders. Performance gains are averaged over all languages.

in either of three typological features: word contractions, noun-adjective and object-verb orderings. Figure 4 shows that reducing the linguistic gap between languages by TEXT can sometimes lead to improvements (exemplified by m-BERT). Although no improvements can be observed for Spanish, both French and Italian benefit considerably

from both removing contractions (a) and reversing the order of adjectives and nouns (b). As for reversing object-verb order (c), we again see improvements for 2 out of 3 languages. Overall, we do not observe consistent improvements across the trial languages. This might be because linguistic phenomena occur in these languages with differing frequencies in XNLI and RFEval. Furthermore, we rely on the automatic analysis from Straka et al. (2016), which differs per language, and includes some amount of error signal.

# 6 Analysis

The following analysis aims to provide answers to four key questions.

**(Q1)** How sensitive are normalization and post-hoc re-mapping across layers?

In Fig. 5, rather than checking results for the last layer only, we investigate improvements of our three modifications across all layers of M-BERT and XLM-R for one language pair (de-en). This reveals that: (1) In the XNLI setup, applying JOINT-ALIGN, NORM and TEXT to the last layer of M-BERT and XLM-R consistently results in the best performance. This indicates that the modifications to the last layer could be sufficient for *supervised* cross-lingual transfer tasks. However, the best layer on RFEval is oftentimes an intermediate layer and (2) the improvements obtained from three modifications are largely complementary across layers. Further, (3) we observe that JOINT-ALIGN is not always effective, especially for XLM-R. For instance, it leads to worst performance across all layers on the XNLI task for XLM-R, even below the baseline performance. 4) We also notice that reporting improvements only on the last layer may sometimes give a false and inflated impression, especially on the RFEval task. However, normalization and re-mapping typically stabilize the layer-wise variances.

(Q2) To what extent can these modifications decrease the cross-lingual transfer gap, especially in low-resource scenarios and for dissimilar languages?

Tab. 4 shows that our modifications to m-BERT and XLM-R considerably reduce performance gaps, viz.: a) the zero-shot transfer performance on XNLI between the English test set and the average performance on the other languages; b) the difference between mono- and cross-lingual textual similarity on RFEval, i.e., the difference between XMover-Score's correlation with human judgments obtained from reference-based and reference-free MT evaluation setups. Although smaller, the remaining gap indicates further potential for improvement. Fig. 7 shows on what languages the performance gaps become smaller, i.e., our modifications lead to the biggest improvements. The largest gains are on (1) low resource languages and (2) languages that are the most distant to English.

(Q3) Are our modifications to contextualized corsslingual encoders language-agnostic?

Fig. 6 (a) shows that the centroid vectors<sup>5</sup> of lan-

Model	XNLI	RFEval	Avg
M-BERT	17.4	24.5	21.0
XLM-R	11.1	37.8	24.5
$\text{M-BERT} \oplus \text{Joint-Align} \oplus \text{Norm}$	9.8	14.4	12.1
$XLM$ - $R \oplus JOINT$ - $ALIGN \oplus NORM$	8.4	4.3	6.3

Table 4: Performance gap (lower is better) in crosslingual classification transfer, and in reference-based and reference-free MT evaluation.

Model	au	r	ρ
M-BERT	53.2	74.7	71.8
XLM-R	54.4	70.1	73.5
$M ext{-BERT} \oplus JOINT ext{-ALIGN} \oplus NORM$	17.5	57.3	21.2
$XLM$ - $R \oplus JOINT$ - $ALIGN \oplus NORM$	15.9	57.7	26.0

Table 5: Correlations (Kendall  $\tau$ , Pearson r and Spearman  $\rho$ ) between language similarities induced by m-BERT/XLM-R and WALS for 19 languages.

guages within the same language family lie closely in the vector space, further showing that language identity signals are stored in the m-BERT embeddings. Fig. 6 (b)+(c) shows that these signals are diminished in both re-aligned and normalized vector spaces, suggesting that the resulting embeddings in them are language-agnostic.

(Q4) To what extent do the typological relations learned from contextualized cross-lingual encoders deviate from those set out by expert typologists?

Tab. 5 shows that language similarities, between English and other 18 languages, obtained from m-BERT and XLM-R have high correlations with structural language similarities obtained from WALS<sup>6</sup> via the syntactic features listed, indicating that language identifiers stored in the original embeddings are a good proxy for the annotated linguistic features. In contrast, this correlation is smaller in the modified embedding spaces, which we believe is because language identity is a much less prominent signal in them.

#### 7 Conclusion

Cross-lingual systems show striking performance for transfer, but their success crucially relies on two constraints: the similarity between source and target languages and the size of pre-training corpora.

<sup>&</sup>lt;sup>5</sup>Language centroids are representative (sentence) embeddings of languages that are averaged over monolingual data from Wikipedia, as in (Libovický et al., 2019). Although they use language families as a proxy, recent work shows that *structural similarities* of languages are a more likely candidate

<sup>(</sup>Bjerva et al., 2019b).

<sup>&</sup>lt;sup>6</sup>WALS is one of the largest typological databases, covering approximately 200 linguistic features over 2500 languages, annotated by expert typologists. The language similarity induced by WALS is the fraction of structural properties that have the same value in two languages among all 192 properties.

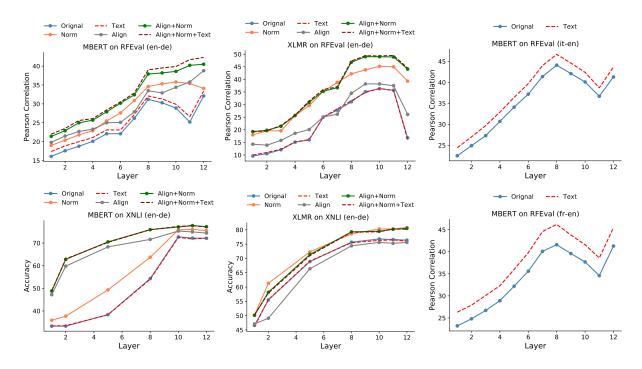


Figure 5: Results of M-BERT and XLM-R and our modifications across layers on the RFEval and XNLI tasks.

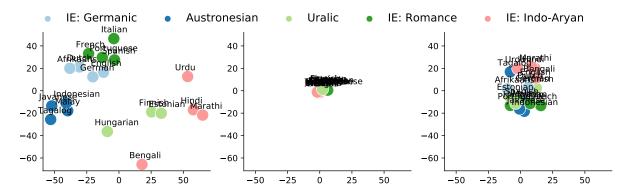


Figure 6: t-SNE distributions of language centroids based on the last layer of m-BERT. (a): Original centroids. (b): Post-hoc centroids induced by the re-aligned vector space. (c): Post-hoc centroids induced by the normalized vector space.

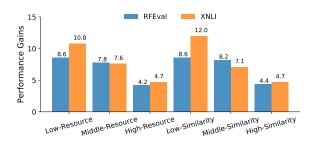


Figure 7: Performance gains across language groups on RFEval and XNLI, exemplified by re-aligned m-BERT coupled with space normalization.

We comparatively evaluate three approaches to address these challenges, removing language-specific information from multilingual representations, thus learning language-agnostic representations. Our extensive experiments, based on a typologically broad sample of 19 languages, show that normalization and re-mapping are oftentimes complementary approaches to improve cross-lingual performances and that the nowadays popular re-mapping leads on average to less consistent improvements than much simpler and much less costly normalization of vector representations. Input normalization yielded some benefits on a small sample of languages, but further work is required for the method to scale to a larger language sample.

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# A Appendix

## **A.1** Languages and Translations

We select five languages families (Austronesian, Germanic, Indo-Aryan, Romance, and Uralic) (each with at least three languages), yielding a typologically broad sample of 19 languages incl. English, with varying sizes of pretraining corpora. In the RFEval setup, we collect source language sentences with their system and reference translations from the WMT17 metrics shared task. We translate reference translations into 18 target languages using Google Translate. For XNLI, we directly use the translated test sets of these languages from (Hu et al., 2020).

### A.2 Text Manipulation

In the (Straka et al., 2016), which is a pipeline trained on UD treebank 2.5. Each orthographic token is split into several tokens that can be directly obtained from the corresponding *word forms*. To reverse noun-adjective and object-verb ordering, we use a simple rule-based strategy based on universal POS tags and universal dependency relations.

### A.3 Language Centroids

We select 5k monolingual sentences from Wikipedia for 19 languages (each with at least 20 characters). Then, we normalize them by removing all punctuation, and use them to estimate language centroid vectors for each language. To do so, we first obtain their sentence embeddings by executing the mean pooling operation for the last layer of m-BERT (or XLM-R) contextualized word embeddings without [CLS] and [SEP] tokens involved. Then, we average these sentence embeddings to obtain language-specific centroid vectors.