

# Inducing Language-Agnostic Multilingual Representations

Wei Zhao<sup>†</sup> Steffen Eger<sup>†</sup> Johannes Bjerva<sup>Ψ,Φ</sup> Isabelle Augenstein<sup>Φ</sup>

<sup>†</sup>Technische Universität Darmstadt <sup>Φ</sup>University of Copenhagen <sup>Ψ</sup>Aalborg University  
{zhao, eger}@aiphes.tu-darmstadt.de  
jbjerva@cs.aau.dk  
augenstein@di.ku.dk

## 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 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 language-specific means and variances, which yields better discriminativeness of embeddings as a by-product; and (iii) increasing input similarity across languages by removing morphological contractions and sentence reordering. We evaluate on XNLI and reference-free MT across 19 typologically diverse languages. Our findings expose the limitations of these approaches—unlike vector normalization, vector space re-alignment and text normalization do not achieve consistent gains across encoders and languages. Due to the approaches’ additive effects, their combination decreases the cross-lingual transfer gap by 8.9 points (m-BERT) and 18.2 points (XLM-R) on average across all tasks and languages, however. Our code and models are publicly 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, until 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

<sup>1</sup><https://github.com/AIPHES/Language-Agnostic-Contextualized-Encoders>

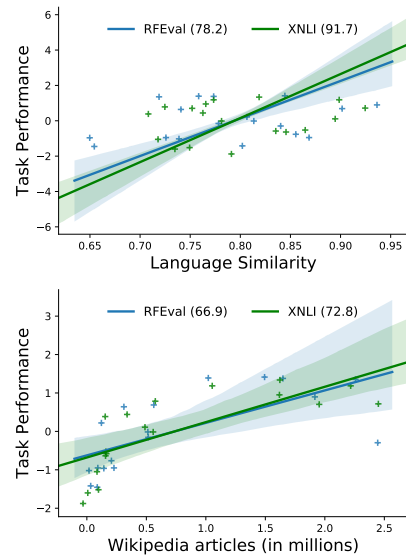


Figure 1: Zero-shot performance on XNLI and RFEval vs. language similarity to English (top), and data sizes in Wikipedia (bottom). Each point is a language; brackets give the Pearson correlation of points on the x- and y-axis. Zero-shot performance is based on the last layer of m-BERT and is standardized (zero mean, unit standard deviation) for better comparison.

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>

As a remedy, recent work has suggested to train representations on larger multilingual corpora (Conneau et al., 2019) and, more importantly, to re-align 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 parallel data on word or sentence level, which may not be available abundantly in low-resource set-

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

tings, and (iii) its positive effect has not yet been studied systematically.

Here, we explore *normalization* as an alternative to re-mapping. To decrease the distance between languages and thus allow for better cross-lingual transfer, we normalize (i) text inputs to encoders before vectorization to increase cross-lingual similarity, e.g., by reordering sentences according to typological features, and (ii) the representations themselves by removing their means and standard deviations, a common operation in machine and deep learning (LeCun et al., 1998; Rücklé et al., 2018). We evaluate vector normalization and post-hoc re-mapping across a typologically diverse set of 19 languages from five language families with varying sizes of monolingual corpora. However, input normalization is examined on a smaller sample of languages, as it is not feasible for languages whose linguistic features cannot be obtained automatically. We investigate two NLP tasks, and two state-of-the-art contextualized cross-lingual encoders—multilingual BERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019). Further, we provide a thorough analysis to investigate the effects of these techniques: (1) across layers; (2) to decrease the cross-lingual transfer gap, especially for low-resource and dissimilar languages; and (3) to eliminate language identity signals from multilingual representations and thus induce language-agnostic representations.

We evaluate on two cross-lingual tasks of varying difficulty: (1) zero-shot cross-lingual natural language inference (XNLI) measures the transfer ability of inference from source to target languages, where only the source language is annotated; and (2) reference-free machine translation evaluation (RFEval) measures the ability of multilingual embeddings to assign adequate cross-lingual semantic similarity scores to text from two languages, where one is frequently a corrupt automatic translation.

**Our contributions:** We show that: (i) input normalization leads to performance gains of up to 4.7 points on two challenging tasks; (ii) normalizing vector spaces is surprisingly effective, rivals much more resource-intensive methods such as re-mapping, and leads to more consistent gains; (iii) all three techniques—vector space normalization, re-mapping and input normalization—are orthogonal and their gains often stack. This is a very important finding as it allows for improvements on a much larger scale, especially for typologically

dissimilar and low-resource languages.

## 2 Related Work

**Cross-lingual Transfer** Static cross-lingual representations have long been used for effective cross-lingual transfer and can even be induced without parallel data (Artetxe et al., 2017; Lample et al., 2018). In the monolingual case, static cross-lingual embeddings have recently been succeeded by contextualized ones, which yield considerably better results. The capabilities and limitations of the contextualized multilingual BERT (m-BERT) representations is a topic of vivid discourse. Pires et al. (2019) show surprisingly good transfer performance for m-BERT despite it being trained without 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, especially for 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 as well as morphological contractions, and reorder sentences to reduce linguistic gaps between languages. In addition, our analysis covers more languages from a typologically broader sample, and shows that vector space normalization is as effective as other recently proposed fixes for m-BERT’s limitations (especially re-mapping), but is much cheaper and orthogonal to other solutions (e.g., input normalization) in that gains are almost additive.

**Linguistic Typology in NLP.** Structural properties of many of the world’s languages can be queried via databases such as WALS (Dryer and Haspelmath, 2013). 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. Bjerva and Augenstein (2018); de Lhoneux et al. (2018); Bjerva and Augenstein (2021) show that cross-

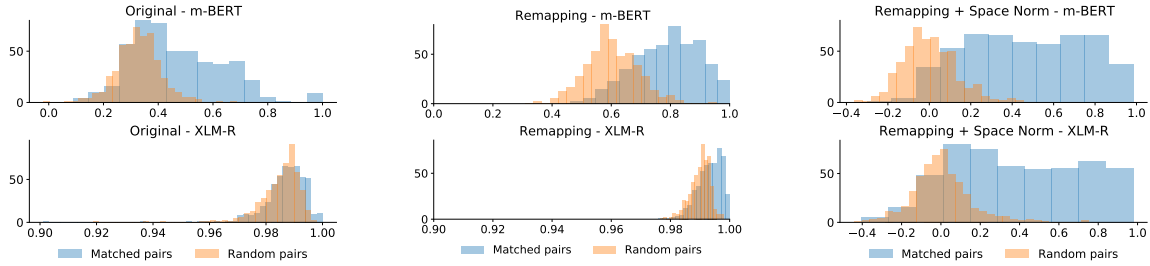


Figure 2: Histograms of cosine similarity scores of word pairs.

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. This intuition of modifying languages based on syntactic features can also be used in order to decrease syntactic and morphological differences between languages. We go further than using syntactic features, and remove word contractions and reorder sentences based on typological information from WALS.

### 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 mutual word translations and random word pairs within parallel sentences from Europarl (Koehn, 2005). Fig. 2 (left) shows histograms based on the last layers of m-BERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019), respectively, which show that XLM-R wrongly assigns nearly perfect cosine similarity scores (+1) to both mutual word translations (matched word pairs) and random word pairs, whereas m-BERT sometimes assigns low scores to mutual translations. This reaffirms that both m-BERT and XLM-R have difficulty in distinguishing matched from random word pairs. Surprisingly, vector space re-mapping does not seem to help for XLM-R, but better separates random from matched pairs for m-BERT (Fig. 2 (middle)). In contrast, the joint effect of normalization and re-mapping leads to adequate separation of the two distributions for both m-BERT and XLM-R, increasing the discriminative ability of both encoders.

### 3.1 Vector space re-alignment

m-BERT and XLM-R induce cross-lingual vector spaces in an unsupervised way—no parallel data is involved at training time. To improve upon these representations, recent work has suggested to re-map them, 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.

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

**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  $C^\nu$ :

$$L(C^\nu, f_\Theta) = \sum_{(s,t) \in C^\nu} \sum_{(i,j) \in a(s,t)} \|f_\Theta(i, s) - f_\Theta(j, t)\|_2^2 \quad (1)$$

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  $f_0$ :

$$R(C^\nu, f_\Theta) = \sum_{t \in C^\nu} \sum_{i=1}^{\text{len}(t)} \|f_\Theta(i, t) - f_0(i, t)\|_2^2 \quad (2)$$

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:

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

In §5, we refer to the above described re-alignment step as JOINT-ALIGN.

### 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:

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

where  $\epsilon$  is a constant value for numerical stability,  $\mu_{\beta}$  and  $\sigma_{\beta}$  are mean and variance, serving as per batch statistics for each time step in a sequence. In addition to a common effect during training, i.e., reducing covariate shift of input spaces, this additional layer in the cross-lingual setup may allow for 1) removing language identity signals, e.g. language-specific means and variances, from multilingual embeddings; and 2) increasing the discriminativeness of embeddings so that they can distinguish word pairs with different senses, as shown in Fig. 2 (right). We apply batch normalization to the last layer representations of m-BERT and XLM-R, and use a batch size of 8 across all setups. In §5, we refer to the above batch normalization step as NORM and contrast this with layer normalization. The latter yields batch-independent statistics, which are computed across all time steps for individual input sequences in a batch. This is predominantly used to stabilize the training process of RNN (Ba et al., 2016) and Transformer-based models (Vaswani et al., 2017).

### 3.3 Input normalization

In addition to joint alignment and vector space normalization, we investigate decreasing cross-linguistic 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 cross-lingual difference between the two. We segment an orthographic token (e.g. *del*) into several (syntactic) tokens (e.g. *de il*).<sup>3</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 Italian 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 §5, we refer to the above re-alignment 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 cross-lingual textual similarity. For zero-shot transfer, fine-tuning of cross-lingual embeddings is done based on source language performance, and evaluation is performed on a held-out target language.

<sup>3</sup>We use UDPipe (Straka et al., 2016), which is a pipeline trained on UD treebank 2.5 (Nivre et al., 2020).



Language	Lang. family	Distance (EN-X)	Wiki-articles (in millions)	Sim level	Res level
Tagalog	$\alpha$	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	$\beta$	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 cosine distances between target languages and English are measured using m-BERT.

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 fine-grained language aspects, which may be exploited by natural adversarial inputs such as word-by-word translations.

**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 associ-

ated 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. We refer to this score as XMoverScore (Zhao et al., 2020) and report its Pearson correlation with human judgments in our experiments.

## 4.2 A Typologically Varied Language Sample

We evaluate multilingual representations on two sets of languages: (1) a default language set with 4 languages from the official XNLI test sets and 2 languages from the WMT17 test sets; (2) a diagnostic language set which contains 19 languages with different levels of data resources from a typologically diverse sample<sup>4</sup> covering five language families (each with at least three languages): Austronesian ( $\alpha$ ), Germanic ( $\beta$ ), Indo-Aryan ( $\gamma$ ), Romance ( $\delta$ ), and Uralic ( $\eta$ ). For RFEval, 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 in Wikipedia.

## 4.3 Cross-lingual Encoders

Our goal is to improve the cross-lingual abilities of established contextualized cross-lingual embeddings. These support around 100 languages and are pre-trained using monolingual language modeling.

**m-BERT** (Devlin et al., 2019) is pre-trained on 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** (Conneau et al., 2019) is pre-trained on the CommonCrawl corpora of 100 languages, which contain more monolingual data than Wikipedia corpora, with 1) a vocabulary size of 250k; 2) a language-agnostic tokenization tool,

<sup>4</sup>This sample was chosen as it yields a large typological variety, with representatives from several language families across the world.

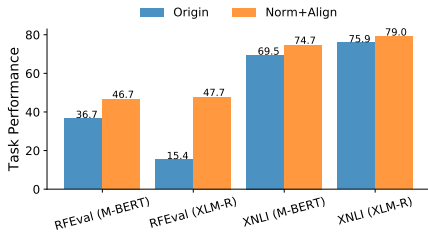


Figure 3: Results on RFEval are averaged over two language pairs (de-en and fi-en) from the WMT17 human translated test sets. Likewise, results on XNLI are averaged over four selected language pairs (en-fr, en-de, en-hi and en-es) from XNLI human translated test sets.

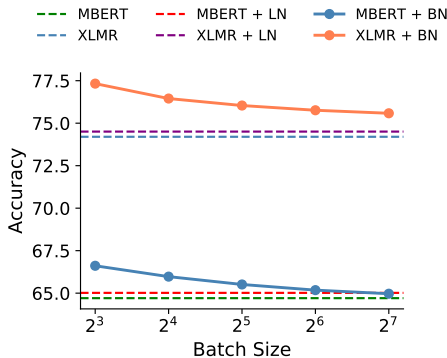


Figure 4: Results on XNLI on average across all language pairs. BN and LN denote batch and layer normalizations, respectively.

Sentence Piece (Kudo and Richardson, 2018) for data pre-processing; and 3) masked language modeling as the only monolingual pre-training task. 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 XNLI and RFEval in §5. To investigate the layer-wise effect of these modifications, we apply the modifications to individual layers and report the performances in §6. See the appendix for implementation details.

## 5 Results

Unlike re-mapping and vector space normalization, scaling input normalization to a large language sample is more difficult, as typological features differ across languages. Thus, we report the results of re-mapping and vector space normalization across 19 languages, while text normalization is evaluated on a smaller sample of languages.

### Re-mapping and Vector Space Normalization.

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, 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. These gains are not an artefact of machine-translated test sets: we observe similar gains on human-translated data (see Fig. 3).

In Tab. 3, we tease apart the sources 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 m-BERT but it does not help for XLM-R on the XNLI task, notwithstanding the minor difference of two encoders, e.g., much larger training data and a different tokenizer used in XLM-R. We believe the poor discriminative ability of XLM-R, *viz.*, that it cannot distinguish word translations from random word pairs, leads to the inconsistent behavior of JOINT-ALIGN. As a remedy, negative examples such as random pairs could be included in Eq. (3) during training so as to decrease the discriminative gap between m-BERT and XLM-R. This suggests that future research efforts should focus on the robustness of cross-lingual alignments.

### Batch vs. Layer Normalization.

Unsurprisingly, the choice of batch size greatly influences XNLI performance when applying batch normalization for m-BERT and XLM-R (Fig. 4). We find that (i) the larger the batch size is, the smaller the impacts on XNLI, and (ii) a batch size of 8 performs best. Interestingly, layer normalization does not help for XNLI, even though it yields batch-independent statistics and is effective in stabilizing the training process (Vaswani et al., 2017). We note that per batch sequences with varying time steps (i.e., sentence length) are often padded with zero vectors in practice. This leads to inaccurate batch-independent statistics, as they are computed across all time steps, unlike batch normalization with per batch statistics for individual time steps. In addition to batch and layer normalizations, other nor-

Model	Avg	Language Families								
		$\Delta$   $\alpha(4)$	$\Delta$   $\beta(3)$	$\Delta$   $\gamma(4)$	$\Delta$   $\delta(4)$	$\Delta$   $\eta(3)$	$\Delta$			
<i>Original cross-lingual embeddings</i>										
M-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	-			
<i>Modified cross-lingual embeddings</i>										
M-BERT $\oplus$ JOINT-ALIGN $\oplus$ NORM	48.1	+10.1   45.9	+9.3   47.5	+7.1   32.4	+4.2   53.4	+3.6   46.0	+11.2			
XLM-R $\oplus$ JOINT-ALIGN $\oplus$ NORM	46.4	+33.5   46.5	+33.0   48.2	+30.8   37.0	+34.1   53.8	+27.9   47.2	+35.6			

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

Model	Avg	Language Families								
		$\Delta$   $\alpha(4)$	$\Delta$   $\beta(3)$	$\Delta$   $\gamma(4)$	$\Delta$   $\delta(4)$	$\Delta$   $\eta(3)$	$\Delta$			
<i>Original cross-lingual embeddings</i>										
M-BERT	64.7	-   60.8	-   69.1	-   57.9	-   73.1	-   63.4	-			
XLM-R	74.8	-   72.4	-   76.3	-   70.9	-   78.4	-   76.1	-			
<i>Modified cross-lingual embeddings</i>										
M-BERT $\oplus$ JOINT-ALIGN $\oplus$ NORM	72.3	+7.6   72.3	+11.5   75.8	+6.7   65.2	+7.3   77.4	+4.3   72.0	+8.6			
XLM-R $\oplus$ JOINT-ALIGN $\oplus$ NORM	77.6	+2.8   74.8	+2.4   79.6	+3.3   73.7	+2.8   80.9	+2.5   78.8	+2.7			

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

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

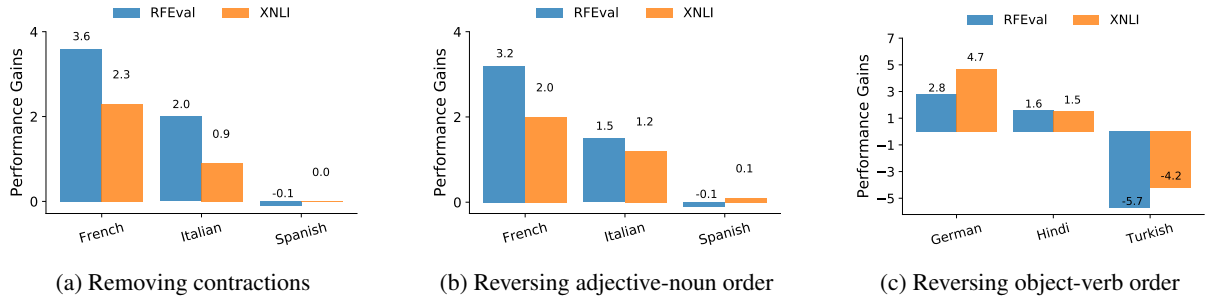


Figure 5: Performance gains on RFEval and XNLI obtained by three types of TEXT operations .

Model	XNLI	RFEval
M-BERT $\oplus$ NORM	+1.9	+1.7
M-BERT $\oplus$ JOINT-ALIGN	+5.2	+7.6
M-BERT $\oplus$ JOINT-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.

malizers such as GroupNorm (Wu and He, 2018) and PowerNorm (Shen et al., 2020) also receive attention in many communities. This raises another concern towards a systematic investigation of normalizers for future work.

**Linguistic Manipulation.** We apply input modifications to language pairs that contrast in either of

Model	XNLI	RFEval	Avg
M-BERT	17.4	24.5	21.0
XLM-R	11.1	37.8	24.5
M-BERT $\oplus$ JOINT-ALIGN $\oplus$ 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) for cross-lingual classification transfer, and reference-based and reference-free MT.

three typological features: word contractions, noun-adjective and object-verb orderings. Fig. 5 shows that reducing the linguistic gap between languages by TEXT can sometimes lead to improvements (exemplified by m-BERT). Both French and Italian benefit considerably from both removing contractions (a) and reversing the order of adjectives and nouns (b), with no changes observed for Spanish.

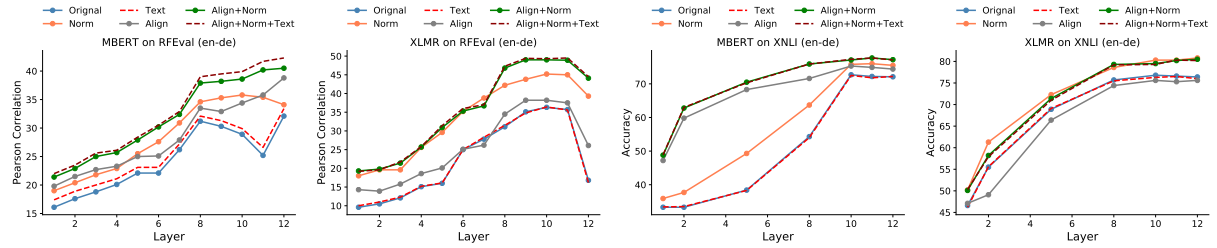


Figure 6: Results of m-BERT and XLM-R and our modifications across layers on the RFEval and XNLI tasks.

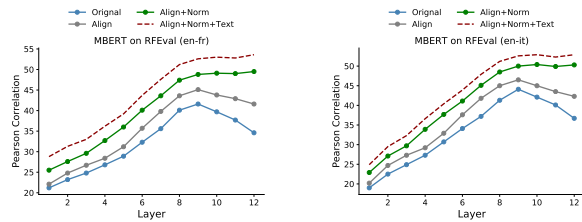


Figure 7: Results of m-BERT across layers on RFEval.

As for reversing object-verb order (c), we again see improvements for 2 out of 3 languages. We hypothesize that the few cases without gains are due to the differing frequencies of occurrences of linguistic phenomena in XNLI and RFEval. Another error source is the automatic analysis from [Straka et al. \(2016\)](#), and improving this pre-processing step may further increase the performance of TEXT.

## 6 Analysis

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

In Fig. 6, rather than checking results for the last layer only, we investigate improvements of our three modifications on RFEval across all layers of and XLM-R for one high-resource language pair (de-en) and one low-resource pair (jv-en) (see appendix). This reveals that, (1) for XNLI, 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. (2) However, the best results on RFEval are oftentimes obtained from an intermediate layer. Further, (3) we observe that JOINT-ALIGN is not always effective, especially for XLM-R. E.g., it leads to the worst performance across all layers on XNLI for XLM-R, even below the baseline performance. (4) Reporting improvements on only the last layer may

sometimes give a false and inflated impression, especially for RFEval. E.g., the improvement (on RFEval) of the three modifications over the original embeddings is almost 30 points for the last layer of XLMR, but it is less than 15 points for the penultimate layer. (5) Normalization and re-mapping typically stabilize layer-wise variances. (6) The gains of the three modifications are largely complementary across layers. (see also Fig. 7).

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

Tab. 4 shows that applying re-mapping and vector space normalization<sup>5</sup> to the last layer of m-BERT and XLM-R considerably reduces performance gaps *viz.*: a) zero-shot transfer performance on XNLI between the English test set and the average performance on the other 18 languages; b) the difference between mono- and cross-lingual textual similarity on RFEval, i.e., the difference between the average correlations of XMoverScore and human judgments on 19 languages obtained from *reference-based*<sup>6</sup> and *reference-free* MT evaluation setups. Although smaller, the remaining gaps indicates further potential for improvement. Fig. 9 shows the largest gains are on (1) low-resource languages and (2) languages most distant to English.

**(Q3)** *Are our modifications to contextualized cross-lingual encoders language-agnostic?*

Fig. 8 (a) shows that the centroid vectors<sup>7</sup> of languages within the same language family lie closely in the vector space, further showing that language

<sup>5</sup>We do not apply text normalization in this setup because not all languages are covered in UDPIPE.

<sup>6</sup>Reference-based evaluation assigns semantic similarity scores to pairs of system and reference translations in English.

<sup>7</sup>Language centroids are representative (sentence) embeddings of languages averaged over monolingual Wikipedia data, 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 ([Bjerva et al., 2019b](#)).



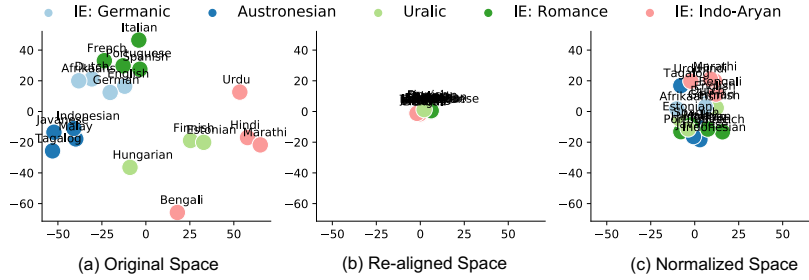


Figure 8: t-SNE distributions of language centroids based on the last m-BERT layer.

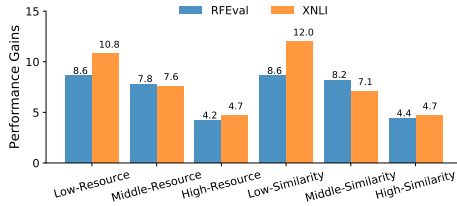


Figure 9: Performance gains across language groups for M-BERT  $\oplus$  JOINT-ALIGN  $\oplus$  NORM.

Model	$\tau$	$r$	$\rho$
M-BERT	53.2	74.7	71.8
XLM-R	54.4	70.1	73.5
M-BERT $\oplus$ JOINT-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.

identity signals are stored in the m-BERT embeddings. Fig. 8 (b)+(c) shows that these signals are diminished in both re-aligned and normalized vector spaces, suggesting that the resulting embeddings in them are more 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<sup>8</sup> obtained from WALS<sup>9</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

<sup>8</sup>The language similarity induced by WALS is the fraction of structural properties that have the same value in two languages among all 192 properties.

<sup>9</sup>WALS covers approximately 200 linguistic features over 2500 languages, annotated by expert typologists.

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. 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 (vector space and input) normalization and re-mapping are oftentimes complementary approaches to improve cross-lingual performance, and that the popular approach of re-mapping leads to less consistent improvements than the much simpler and less costly normalization of vector representations. Input normalization yields benefits across a small sample of languages; further work is required for it to achieve consistent gains across a larger language sample.

## Acknowledgments

We thank the anonymous reviewers for their insightful comments and suggestions, which greatly improved the final version of the paper. This work has been supported by the German Research Foundation as part of the Research Training Group Adaptive Preparation of Information from Heterogeneous Sources (AIPHES) at the Technische Universität Darmstadt under grant No. GRK 1994/1, as well as by the Swedish Research Council under grant agreement No 2019-04129.

## References

Željko Agić and Ivan Vulić. 2019. *JW300: A wide-coverage parallel corpus for low-resource languages*. In *Proceedings of the 57th Annual Meeting of the*

- Association for Computational Linguistics*, pages 3204–3210, Florence, Italy. Association for Computational Linguistics.
- Hanan Aldarmaki and Mona Diab. 2019. [Context-aware cross-lingual mapping](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3906–3911, Minneapolis, Minnesota. Association for Computational Linguistics.
- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2017. [Learning bilingual word embeddings with \(almost\) no bilingual data](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 451–462, Vancouver, Canada. Association for Computational Linguistics.
- Lei Jimmy Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. 2016. [Layer normalization](#). *CoRR*, abs/1607.06450.
- Johannes Bjerva and Isabelle Augenstein. 2018. [From phonology to syntax: Unsupervised linguistic typology at different levels with language embeddings](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 907–916, New Orleans, Louisiana. Association for Computational Linguistics.
- Johannes Bjerva and Isabelle Augenstein. 2021. [Does typological blinding impede cross-lingual sharing?](#) In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 480–486, Online. Association for Computational Linguistics.
- Johannes Bjerva, Yova Kementchedjheva, Ryan Cotterell, and Isabelle Augenstein. 2019a. [A probabilistic generative model of linguistic typology](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1529–1540, Minneapolis, Minnesota. Association for Computational Linguistics.
- Johannes Bjerva, Robert Östling, Maria Han Veiga, Jörg Tiedemann, and Isabelle Augenstein. 2019b. [What Do Language Representations Really Represent?](#) *Computational Linguistics*, 45(2):381–389.
- Ondřej Bojar, Yvette Graham, and Amir Kamran. 2017. [Results of the WMT17 metrics shared task](#). In *Proceedings of the Second Conference on Machine Translation*, pages 489–513, Copenhagen, Denmark. Association for Computational Linguistics.
- Steven Cao, Nikita Kitaev, and Dan Klein. 2020. [Multilingual alignment of contextual word representations](#). *CoRR*, abs/2002.03518.
- Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. [Unsupervised cross-lingual representation learning at scale](#). *CoRR*, abs/1911.02116.
- Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. [XNLI: Evaluating cross-lingual sentence representations](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2475–2485, Brussels, Belgium. Association for Computational Linguistics.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [BERT: Pre-training of deep bidirectional transformers for language understanding](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Matthew S. Dryer and Martin Haspelmath, editors. 2013. *WALS Online*. Max Planck Institute for Evolutionary Anthropology, Leipzig.
- Chris Dyer, Victor Chahuneau, and Noah A. Smith. 2013. [A simple, fast, and effective reparameterization of IBM model 2](#). In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 644–648, Atlanta, Georgia. Association for Computational Linguistics.
- Kawin Ethayarajh. 2019. [How contextual are contextualized word representations? comparing the geometry of BERT, ELMo, and GPT-2 embeddings](#). In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 55–65, Hong Kong, China. Association for Computational Linguistics.
- Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. [XTREME: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization](#). *CoRR*, abs/2003.11080.
- Philipp Koehn. 2005. Europarl: A parallel corpus for statistical machine translation. In *MT summit*, volume 5, pages 79–86. Citeseer.
- Taku Kudo and John Richardson. 2018. [SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 66–71, Brussels, Belgium. Association for Computational Linguistics.

- Guillaume Lample, Alexis Conneau, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2018. Word translation without parallel data. In *ICLR*.
- Anne Lauscher, Vinit Ravishankar, Ivan Vulic, and Goran Glavas. 2020. From zero to hero: On the limitations of zero-shot cross-lingual transfer with multilingual transformers. *CoRR*, abs/2005.00633.
- Yann LeCun, Léon Bottou, Genevieve B. Orr, and Klaus-Robert Müller. 1998. Efficient backprop. In *Neural Networks: Tricks of the Trade, This Book is an Outgrowth of a 1996 NIPS Workshop*, page 9–50, Berlin, Heidelberg. Springer-Verlag.
- Miryam de Lhoneux, Johannes Bjerva, Isabelle Augenstein, and Anders Søgaard. 2018. Parameter sharing between dependency parsers for related languages. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4992–4997.
- Jindrich Libovický, Rudolf Rosa, and Alexander Fraser. 2019. How language-neutral is multilingual bert? *CoRR*, abs/1911.03310.
- Jindrich Libovický, Rudolf Rosa, and Alexander Fraser. 2020. On the language neutrality of pre-trained multilingual representations. *CoRR*, abs/2004.05160.
- Joakim Nivre, Marie-Catherine de Marneffe, Filip Ginter, Jan Hajic, Christopher D. Manning, Sampo Pyysalo, Sebastian Schuster, Francis M. Tyers, and Daniel Zeman. 2020. Universal dependencies v2: An evergrowing multilingual treebank collection. *CoRR*, abs/2004.10643.
- Helen O’Horan, Yevgeni Berzak, Ivan Vulić, Roi Reichart, and Anna Korhonen. 2016. Survey on the use of typological information in natural language processing. *arXiv preprint arXiv:1610.03349*.
- Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual BERT? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4996–5001, Florence, Italy. Association for Computational Linguistics.
- Edoardo Maria Ponti, Helen O’horan, Yevgeni Berzak, Ivan Vulić, Roi Reichart, Thierry Poibeau, Ekaterina Shutova, and Anna Korhonen. 2019. Modeling language variation and universals: A survey on typological linguistics for natural language processing. *Computational Linguistics*, 45(3):559–601.
- Andreas Rücklé, Steffen Eger, Maxime Peyrard, and Iryna Gurevych. 2018. Concatenated power mean word embeddings as universal cross-lingual sentence representations. *arXiv*.
- Tal Schuster, Ori Ram, Regina Barzilay, and Amir Globerson. 2019. Cross-lingual alignment of contextual word embeddings, with applications to zero-shot dependency parsing. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1599–1613, Minneapolis, Minnesota. Association for Computational Linguistics.
- Sheng Shen, Zhewei Yao, Amir Gholami, Michael Mahoney, and Kurt Keutzer. 2020. PowerNorm: Rethinking batch normalization in transformers. In *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pages 8741–8751. PMLR.
- Milan Straka, Jan Hajič, and Jana Straková. 2016. UD-Pipe: Trainable pipeline for processing CoNLL-u files performing tokenization, morphological analysis, POS tagging and parsing. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16)*, Portorož, Slovenia.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.
- Dingquan Wang and Jason Eisner. 2016. The galactic dependencies treebanks: Getting more data by synthesizing new languages. *Transactions of the Association for Computational Linguistics*, 4:491–505.
- Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.
- Shijie Wu, Alexis Conneau, Haoran Li, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Emerging cross-lingual structure in pretrained language models. *CoRR*, abs/1911.01464.
- Shijie Wu and Mark Dredze. 2019. Beto, bentz, becas: The surprising cross-lingual effectiveness of BERT. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 833–844, Hong Kong, China. Association for Computational Linguistics.
- Yuxin Wu and Kaiming He. 2018. Group normalization. In *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part XIII*, volume 11217 of *Lecture Notes in Computer Science*, pages 3–19. Springer.
- Wei Zhao, Goran Glavaš, Maxime Peyrard, Yang Gao, Robert West, and Steffen Eger. 2020. On the limitations of cross-lingual encoders as exposed by

reference-free machine translation evaluation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1656–1671, Online. Association for Computational Linguistics.

Wei Zhao, Maxime Peyrard, Fei Liu, Yang Gao, Christian M. Meyer, and Steffen Eger. 2019. **MoverScore: Text generation evaluating with contextualized embeddings and earth mover distance**. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 563–578, Hong Kong, China. Association for Computational Linguistics.