

On the Language Neutrality of Pre-trained Multilingual Representations

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Abstract

Multilingual contextual embeddings, such as multilingual BERT and XLM-RoBERTa, have proved useful for many multi-lingual tasks. Previous work probed the cross-linguality of the representations indirectly using zero-shot transfer learning on morphological and syntactic tasks. We instead investigate the language-neutrality of multilingual contextual embeddings directly and with respect to lexical semantics. Our results show that contextual embeddings are more language-neutral and, in general, more informative than aligned static word-type embeddings, which are explicitly trained for language neutrality. Contextual embeddings are still only moderately language-neutral by default, so we propose two simple methods for achieving stronger language neutrality: first, by unsupervised centering of the representation for each language and second, by fitting an explicit projection on small parallel data. Besides, we show how to reach state-of-the-art accuracy on language identification and match the performance of statistical methods for word alignment of parallel sentences without using parallel data.

1 Introduction

Multilingual BERT (mBERT; Devlin et al. 2019) gained popularity as a contextual representation for many multilingual tasks, e.g., dependency parsing (Kondratyuk and Straka, 2019a; Wang et al., 2019), cross-lingual natural language inference (XNLI) or named-entity recognition (NER) (Pires et al., 2019; Wu and Dredze, 2019; Kudugunta et al., 2019). Recently, a new pre-trained model, XLM-RoBERTa (XLM-R; Conneau et al. 2019), claimed to outperform mBERT both on XNLI and NER tasks. We also study DistilBERT (Sanh et al., 2019) applied to mBERT, which promises to deliver comparable results to mBERT at a significantly lower computational cost.

Pires et al. (2019) present an exploratory paper showing that mBERT can be used cross-lingually for zero-shot transfer in morphological and syntactic tasks, at least for typologically similar languages. They also study an interesting semantic task, sentence-retrieval, with promising initial results. Their work leaves many open questions regarding how well the cross-lingual mBERT representation captures lexical semantics, motivating our work.

In this paper, we directly assess the cross-lingual properties of multilingual representations on tasks where lexical semantics plays an important role and present one unsuccessful and two successful methods for achieving better language neutrality.

Multilingual capabilities of representations are often evaluated by zero-shot transfer from the training language to a test language (Hu et al., 2020; Liang et al., 2020). However, in such a setup, we can never be sure if the probing model did not overfit for the original language, as training is usually stopped when accuracy decreases on a validation set from the same language (otherwise, it would not be zero-shot), even when it would have been better to stop the training earlier. This overfitting on the original language can pose a disadvantage for information-rich representations.

To avoid such methodological issues, we select tasks that only involve a direct comparison of the representations with no training: cross-lingual sentence retrieval, word alignment (WA), and machine translation quality estimation (MT QE). Additionally, we explore how the language is represented in the embeddings by training language ID classifiers and assessing how the representation similarity corresponds to phylogenetic language families.

We find that contextual representations are more language-neutral than static word embeddings which have been explicitly trained to represent matching words similarly and can be used in a

simple algorithm to reach state-of-the-art results on word alignment. However, they also still strongly carry information about the language identity, as demonstrated by a simple classifier trained on mean-pooled contextual representations reaching state-of-the-art results on language identification.

We show that the representations can be modified to be more language-neutral with simple, straightforward setups: centering the representation for each language or fitting explicit projections on small parallel data.

We further show that XLM-RoBERTa (XLM-R; [Conneau et al. 2019](#)) outperforms mBERT in sentence retrieval and MT QE while offering a similar performance for language ID and WA.

2 Related Work

Multilingual representations, mostly mBERT, were already tested in a wide range of tasks. Often, the success of zero-shot transfer is implicitly considered to be the primary measure of language neutrality of a representation. Despite many positive results, some findings in the literature are somewhat mixed, indicating limited language neutrality.

Zero-shot learning abilities were examined by [Pires et al. \(2019\)](#) on NER and part-of-speech (POS) tagging, showing that the success strongly depends on how typologically similar the languages are. Similarly, [Wu and Dredze \(2019\)](#) trained good multilingual models but struggled to achieve good results in the zero-shot setup for POS tagging, NER, and XLNI. [Rönqvist et al. \(2019\)](#) draw similar conclusions for language-generation tasks.

[Wang et al. \(2019\)](#) succeeded in zero-shot dependency parsing but required supervised projection trained on word-aligned parallel data. The results of [Chi et al. \(2020\)](#) on dependency parsing suggest that methods like structural probing ([Hewitt and Manning, 2019](#)) might be more suitable for zero-shot transfer.

[Pires et al. \(2019\)](#) also assessed mBERT on cross-lingual sentence retrieval between three language pairs. They observed that if they subtract the average difference between the embeddings from the target language representation, the retrieval accuracy significantly increases. We systematically study this idea in the later sections.

XTREME ([Hu et al., 2020](#)) and XGLUE ([Liang et al., 2020](#)), two recently introduced benchmarks for multilingual representation evaluation, assess representations on a broader range of zero-shot

transfer tasks that include natural language inference ([Conneau et al., 2018](#)) and question answering ([Artetxe et al., 2019](#); [Lewis et al., 2019](#)). Their results show a clearly superior performance of XLM-R compared to mBERT.

Many works clearly show that downstream task models can extract relevant features from the multilingual representations ([Wu and Dredze, 2019](#); [Kudugunta et al., 2019](#); [Kondratyuk and Straka, 2019a](#)). However, they do not directly show language-neutrality, i.e., to what extent similar phenomena are represented similarly across languages. Thus, it is impossible to say whether the representations are language-agnostic or contain some implicit language identification. Our choice of evaluation tasks eliminates this risk by directly comparing the representations.

3 Centering Representations

One way to achieve stronger language neutrality is by suppressing the language identity, only keeping what encodes the sentence meaning. It can be achieved, for instance, using an explicit projection. However, training such a projection requires parallel data. Instead, we explore a simple unsupervised method: representation centering.

Following [Pires et al. \(2019\)](#), we hypothesize that a sentence representation in mBERT is additively composed of a language-specific component, which identifies the language of the sentence, and a language-neutral component, which captures the meaning of the sentence in a language-independent way. We assume that the language-specific component is similar across all sentences in the language.

We estimate the *language centroid* as the mean of the representations for a set of sentences in that language and subtract the language centroid from the contextual embeddings. By doing this, we are trying to remove the language-specific information from the representations by centering the sentence representations in each language so that their average lies at the origin of the vector space.

The intuition behind this is that within one language, certain phenomena (e.g., function words) would be very frequent, thus being quite prominent in the mean of the representations for that language (but not for a different language), while the phenomena that vary among sentences of the language (and thus presumably carry most of the meaning) would get averaged out in the centroid. We thus hypothesize that by subtracting the centroid, we re-

move the language-specific features (without much loss of the meaning content), making the meaning-bearing features more prominent.

We analyze the semantic properties of the original and the centered representations on a range of probing tasks. For all tasks, we test all layers of the model. We test both the [CLS] token vector and mean-pooled states for tasks utilizing a single-vector sentence representation.

4 Probing Tasks

We employ five probing tasks to evaluate the language neutrality of the representations.

The first two tasks analyze the contextual embeddings. The other three tasks are cross-lingual NLP problems, all of which can be treated as a general task of a cross-lingual estimation of word or sentence similarities. Supposing we have sufficiently language-neutral representations, we can estimate these similarities using the cosine distance of the representations; the performance in these tasks can thus be viewed as a measure of the language-neutrality of the representations.

Moreover, in addition to such an unsupervised approach, we can also utilize actual training data for the tasks to further improve the performance of the probes; this does not tell us much more about the representations themselves but leads to a nice by-product of reaching state-of-the-art accuracies for two of the tasks.

Language Identification. With a representation that captures all phenomena in a language-neutral way, it should be difficult to determine what language the sentence is written in. Unlike our other tasks, language ID requires fitting a classifier. We train a linear classifier on top of a sentence representation.

Language Similarity. Previous work (Pires et al., 2019; Wang et al., 2019) shows that models can be transferred better between more similar languages, suggesting that similar languages tend to get similar representations. We quantify this observation by V-measure between language families and hierarchical clustering of the language centroids (Rosenberg and Hirschberg, 2007). We cluster the language centroids by their cosine distance using the Nearest Point Algorithm and stop the clustering with a number of clusters equal to the number of language families in the data.

Parallel Sentence Retrieval. For each sentence in a multi-parallel corpus, we compute the cosine distance of its representation with representations of all sentences on the parallel side of the corpus and select the sentence with the smallest distance.

Besides the plain and centered representations, we evaluate explicit projection of the representations into the “English space.” We fit the projection by minimizing the element-wise mean squared error between the representation of an English sentence and a linear projection of the representation of its translation.

Word Alignment. WA is the task of matching words which are translations of each other in parallel sentences. WA is a key component of statistical machine translation systems (Koehn, 2009). While sentence retrieval could be done with keyword spotting, computing bilingual WA requires resolving detailed correspondence on the word level. Unsupervised statistical methods trained on parallel corpora (Och and Ney, 2003; Dyer et al., 2013) still pose a strong baseline for the task. In a work parallel to ours, Sabet et al. (2020) present a more complex alternative way of leveraging contextual representations for word alignment that outperforms the statistical methods.

For a pair of parallel sentences, we find the WA as a minimum weighted edge cover of a bipartite graph. We create an edge for each potential alignment link, weight it by the cosine distance of the token representations, and find the WA as a minimum weighted edge cover of the resulting bipartite graph. Unlike statistical methods, this does not require parallel data for training.

To make the algorithm prefer monotonic alignment, we add a distortion penalty of $1/d$ to each edge where d is the difference in the absolute positions of the respective tokens in the sentence. We add the penalty with a weight that is a hyperparameter of the method estimated on a development set.

We keep the tokenization as provided in the word alignment dataset. In the matching phase, we represent the tokens that get split into multiple subwords as the average of the embeddings of the subwords.

Note that this algorithm is invariant to representation centering. Centering the representation would shift all vectors by a constant. Therefore, all weights would change by the same offset, not influencing the edge cover. We evaluate WA using

F_1 over sure and possible alignments in manually aligned data.

MT Quality Estimation. MT QE assesses the quality of an MT system output without having access to a reference translation. Semantic adequacy that we can estimate by comparing representations of the source sentence and translation hypothesis can be a strong indicator of the MT quality. The standard evaluation metric is the Pearson correlation with the Translation Error Rate (TER)—the number of edit operations a human translator would need to do to correct the system output. QE is a more challenging task than the previous ones because it requires capturing more subtle differences in meaning.

We evaluate how cosine distance of the representation of the source sentence and of the MT output reflects the translation quality. In addition to plain and centered representations, we also test trained bilingual projection and a fully supervised regression trained on the shared task training data.

We use the same bilingual projection into English space fitted by linear regression on the small parallel data used for sentence retrieval.

For the supervised regression, we use a multi-layer perceptron directly predicting the value of the translation error rate provided in the training data.

Note that this task differs from reference-free MT evaluation [Fonseca et al. \(2019, Task 3\)](#), which is evaluated by computing the correlation of the estimated value with human assessment of translation quality based on reference sentences (available only to the annotators and not to the evaluation metric). This task was also recently used for assessing the quality of multilingual contextual representations ([Zhao et al., 2020b,a](#)).

5 Probed Models

Aligned static word embeddings. As a baseline in all our experiments, we use aligned static word embeddings ([Joulin et al., 2018](#)). Unlike hidden states of pre-trained Transformers, they do not capture sentence context. However, they were explicitly trained to be language-neutral with respect to lexical semantics. We represent sentences as an average of the embeddings of the words.

Multilingual BERT ([Devlin et al., 2019](#)) is a deep Transformer ([Vaswani et al., 2017](#)) encoder that is trained in a multi-task learning setup, first, to be able to guess what words were masked-out in the

input and, second, to decide whether two sentences follow each other in a coherent text.

We use a pre-trained mBERT model that was made public with the BERT release.¹ The model dimension is 768, the hidden layer dimension 3072, self-attention uses 12 heads, the model has 12 layers. It uses a vocabulary of 120k wordpieces shared for all languages.

It is trained using a combination of a masked language model (MLM) objective and sentence-adjacency objective. For the MLM objective, 15% of input subwords are masked out, and the model predicts the masked subwords. For the sentence-adjacency objective, a special [cls] token is prepended to the input. The embedding corresponding to this token is used as an input to a classifier predicting if the input sentences are adjacent.

Therefore, for models based on mBERT, we experiment both with [cls] vector and the *mean-pooled* vector, i.e., average embeddings for the rest of the tokens.

UDify. The UDify model ([Konratyuk and Straka, 2019a](#)) uses mBERT to train a single model for dependency parsing and morphological analysis of 75 languages. During training, mBERT is finetuned, which improves accuracy. Results on zero-shot parsing suggest that the finetuning leads to better language neutrality with respect to morphology and syntax.

Ing-free. In this experiment, we try to make the representations more language-neutral by removing the language identity from the model using an adversarial approach. We continue training mBERT in a multi-task learning setup with the MLM objective ([Devlin et al., 2019](#)) without the sentence adjacency objective, i.e., the same way as XLM-R. It is trained jointly with adversarial language ID classifiers ([Elazar and Goldberg, 2018](#)) using the same dataset as for the language ID tasks. The classifier is separated from the rest of the model by a gradient-reversal layer ([Ganin and Lempitsky, 2015](#)), which negates the gradients flowing from the classifier into the model. Intuitively, we can say that the rest of the model is trying to fool the classifier, whereas the classifier tries to improve.

DistillmBERT. This model was inferred from mBERT by knowledge distillation ([Sanh et al.,](#)

¹<https://github.com/google-research/bert>

	mBERT	UDify	Ing-free	Distil	XLM-R
[cls]	.935	.938	.796	.953	—
[cls], cent.	.867	.851	.337	.826	N/A
mean-pool	.960	.959	.951	.953	.950
mean-pool, cent.	.853	.854	.855	.826	.846

Table 1: Accuracy of language identification, values from the best-scoring layers.

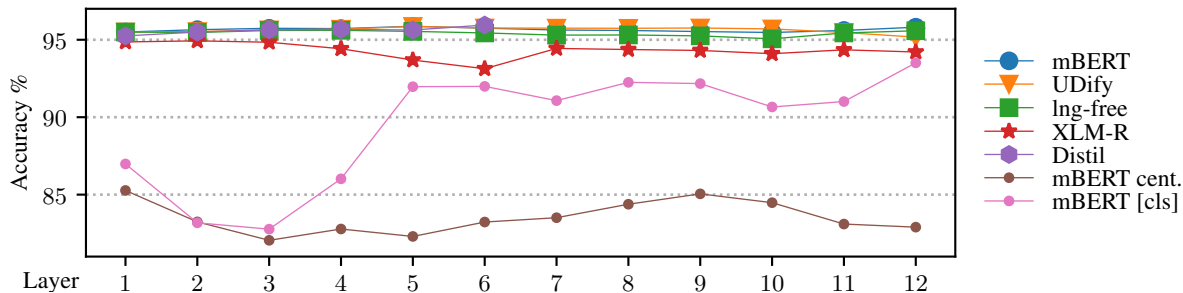


Figure 1: Language ID accuracy for different layers of mBERT.

2019). The model only has 6 layers instead of 12. The rest of the hyperparameters remain the same. It was initialized with a subset of the original mBERT parameters and trained on similar training data and optimized towards cross-entropy of its output distribution with respect to the output of the teacher mBERT model while keeping the MLM objective in the multi-task learning setup. As the model is forced to use smaller space to obtain the representation, it might leverage the similarities between languages and reach better language neutrality.

XLM-RoBERTa. Conneau et al. (2019) claim that the original mBERT is under-trained and train a similar model on a larger dataset that consists of two terabytes of plain text extracted from CommonCrawl (Wenzek et al., 2019). Unlike mBERT, XLM-R uses a SentencePiece-based vocabulary (Kudo and Richardson, 2018) of 250k tokens. The rest of the architecture remains the same as in the case of mBERT. We train the model using the MLM objective only, without the sentence adjacency prediction.

6 Experimental Setup

To train the language ID classifier, for each of 73 languages covered both by mBERT and XLM-R, we randomly select 110k sentences of at least 20 characters from Wikipedia and keep 5k for validation and 5k for testing for each language. We also use the training data to estimate the language

centroids and training the *Ing-free* version of the model.

For parallel sentence retrieval, we use a multi-parallel corpus of test data from the WMT14 evaluation campaign (Bojar et al., 2014) with 3,000 sentences in Czech, English, French, German, Hindi, and Russian. To compute the linear projection (for the special linear projection experimental condition), we used the WMT14 development data (500–3000 sentences per language pair).

We use manually annotated WA datasets to evaluate word alignment between English on one side and Czech (2.5k sent.; Mareček, 2016)², Swedish (192 sent.; Holmqvist and Ahrenberg, 2011)³, German (508 sent.)⁴, French (447 sent.; Och and Ney, 2000)⁵ and Romanian (248 sent.; Mihalcea and Pedersen, 2003)⁶ on the other side. We compare the results with FastAlign (Dyer et al., 2013) and Efmara (Östling and Tiedemann, 2016) models, which were provided with 1M additional parallel sentences from ParaCrawl (Esplà et al., 2019)⁷.

For MT QE, we use English-German training and test data provided for the WMT19 QE Shared Task (Fonseca et al., 2019, Task 1), consisting of

²<http://hdl.handle.net/11234/1-1804>

³<http://hdl.handle.net/11372/LRT-1517>

⁴<https://www-i6.informatik.rwth-aachen.de/goldAlignment>

⁵<http://web.eecs.umich.edu/~mihalcea/wpt/data/English-French.test.tar.gz>

⁶<http://web.eecs.umich.edu/~mihalcea/wpt/data/Romanian-English.test.tar.gz>

⁷<https://paracrawl.eu>, Release 5

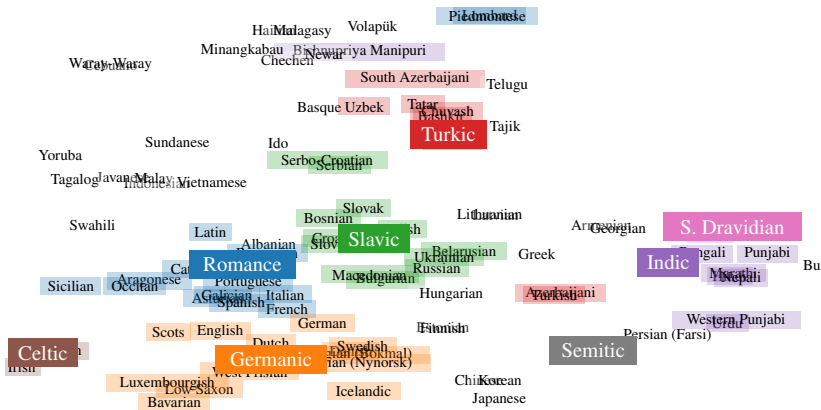


Figure 2: Language centroids of the mean-pooled representations from the 8th layer of cased mBERT on a tSNE plot with highlighted language families.

	H	C	V
mBERT	82.0	82.9	82.4
UDify	80.5	79.7	80.0
lng-free	77.1	80.4	80.6
XLM-R	69.7	69.1	69.3
Distil	81.6	81.1	81.3
random	60.2	64.3	62.1

Table 2: Clustering of language centroids, evaluated with homogeneity, completeness and V-Measure against genealogical language families with at least three mBERT languages. Averaged across layers.

source sentences, automatic translations, and manually corrected reference translations. For the supervised estimation, we use a multilayer perceptron with a hidden layer of size 256, trained to estimate the HTER value using the mean-squared-error loss.

We use pre-trained tables provided by Joulin et al. (2018)⁸ for the static word embeddings. The embeddings were trained on Wikipedia and aligned with a projection trained on small bilingual dictionaries. The number of word types captured in the embedding tables spans from 350k for Romanian to 2.5M for English.

The experiments with contextualized embeddings are implemented using the Transformers package (Wolf et al., 2019), which we also use for obtaining the pre-trained models, except for UDify, which was obtained from (Kondratyuk and Straka, 2019b).⁹ The *lng-free* mBERT version was finetuned using the same data that was used for language identification.

Our source code is available at <https://github.com/jlibovicky/assess-multilingual-bert>.

7 Results

Language Identification. Table 1 and Figure 1 shows that for mBERT, centering the sentence representations decreases the accuracy of language ID considerably, especially in the case of mean-pooled embeddings. This result indicates that the centering procedure indeed removes the language-specific information to a great extent.

For comparison, the state-of-the-art language ID model from FastText (Grave et al., 2018) reaches 91.4% accuracy with a pre-trained model, and 91.8% when retrained on our training data, i.e., slightly worse than our best model based on mBERT. Langid.py (Lui and Baldwin, 2012) reaches 90.1% when trained on the same dataset.

Adversarial finetuning prevented the language identification only from the `[cls]` vector and only marginally for mean-pooling. This supports the hypothesis that language identity is derived from the presence of function words and structures and representation centering suppresses these frequent phenomena.

Centering the representations within languages requires knowing the language in advance. It is therefore an oracle experiment. In a sense, centering *adds* language-specific information to the representation which the classifier might take advantage of. However, because the centering decreases the accuracy, we can interpret this as *removing* information about the language identity.

For further comparison, we conduct the same experiment with aligned word embeddings for 44 languages (Joulin et al., 2018). The language ID accuracy is 99.5% but drops to 2.3% after centering (the same as assigning language by chance), which supports our intuition about centering functioning as removal of frequent patterns. Note, however, that even the experiment without centering is an oracle experiment cannot be considered as language identification because we need to know the language identity in advance to use the matching embeddings table, so the accuracy is not comparable with other experiments.

⁸<https://fasttext.cc/docs/en/aligned-vectors.html>

⁹<http://hdl.handle.net/11234/1-3042>

	SWE	mBERT	UDify	lng-free	Distil	XLM-R
[cls]	—	.639	.462	.549	.420	—
[cls], cent.	—	.684	.660	.686	.505	—
[cls], proj.	—	.915	.933	.697	.830	—
mean-pool	.113	.776	.314	.755	.600	.883
mean-pool, cent.	.496	.838	.564	.828	.770	.923
mean-pool, proj.	.650	.983	.906	.983	.980	.996

Table 3: Average accuracy for sentence retrieval over all 30 language pairs compared to static bilingual word embeddings (SWE).

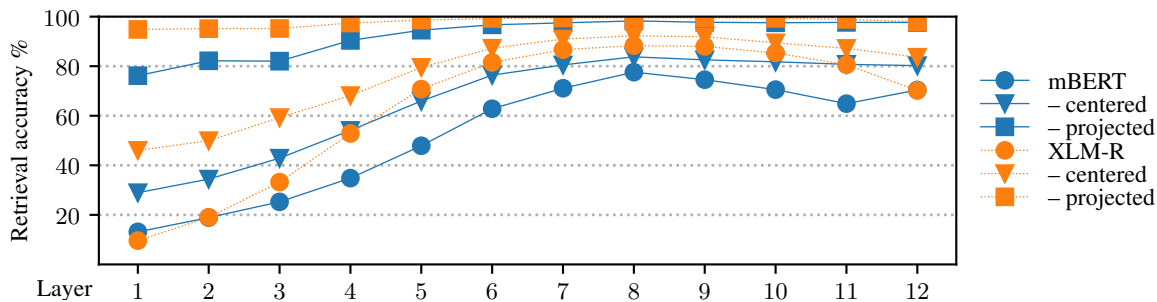


Figure 3: Accuracy of sentence retrieval for mean-pooled contextual embeddings from BERT layers.

Language Similarity. Figure 2 is a tSNE plot (Maaten and Hinton, 2008) of the language centroids, showing that the centroids’ similarity tends to correspond to the similarity of the languages. Table 2 confirms that the hierarchical clustering of the language centroids mostly corresponds to the language families.

XLM-R not only preforms slightly worse in language ID, it also has worse performance in capturing language similarity. We hypothesize that this is because of the different approaches used in training the models. In particular, the next-sentence prediction used to train mBERT may lead to stronger language-specific information because this sort of information helps determine if two sentences are adjacent.

Parallel Sentence Retrieval. Results for mean-pooled representations in Table 3 reveal that the representation centering improves the retrieval accuracy dramatically, showing that it makes the representations more language-neutral. An additional 50% error reduction is achievable via learning a projection on relatively small parallel data, leading to close-to-perfect accuracy.

Similar trends hold for all models. XLM-R significantly outperforms all models. The UDify model that was finetuned for syntax seems to lose semantic abilities significantly. Adversarial finetuning did not improve the performance. The accuracy

is usually higher for mean-pooled states than for the [cls] embedding and varies among the languages too (see Table 4).

The accuracy also varies according to the layer of mBERT used (see Figure 3). The best-performing is the 8th layer, both for mBERT and XLM-R. These results are consistent both among models and among tasks.

Word Alignment. Table 5 shows that WA based on mBERT and XLM-R representations match the state-of-the-art aligners trained on a large parallel corpus. WA techniques based on multilingual contextual representations can thus be used as a replacement of state-of-the-art statistical methods without the use of parallel data.

The results show that the contextual embeddings well capture word-level semantics. Furthermore, the distortion penalty does not seem to influence the alignment quality when using the contextual embeddings, whereas for the static word embeddings, it can make a difference of 3–6 F₁ points. This result shows that the contextual embeddings encode information about the relative word position in the sentence across languages. However, their main advantage is still the context-awareness, which allows accurate alignment of function words.

Similarly to sentence retrieval, we experimented with explicit projection trained on parallel data. We used an expectation-maximization approach

	cs	de	en	es	fr	ru		cs	de	en	es	fr	ru	
cs	—	.812	.803	.821	.795	.836		en	—	.917	.935	.941	.926	.919
de	.806	—	.845	.833	.818	.816		cs	.925	—	.907	.913	.896	.923
en	.783	.834	—	.863	.860	.809		de	.938	.913	—	.921	.904	.912
es	.805	.824	.863	—	.869	.822		es	.936	.907	.916	—	.934	.908
fr	.784	.822	.861	.859	—	.811		fr	.928	.903	.917	.935	—	.905
ru	.828	.820	.810	.826	.817	—		ru	.920	.910	.918	.910	.903	—

Table 4: Sentence retrieval scores for the 8th layer of mBERT and XLM-R models.

en-	FastAlign	Efmaral	SWE	mBERT	UDify	Ing-free	Distil	XLM-R
cs	.692	.729	.501 – .540	.738	.708	.744	.660	.731
sv	.438	.501	.272 – .331	.478	.459	.468	.454	.461
de	.741	.759	.473 – .515	.767	.731	.768	.723	.762
fr	.583	.589	.371 – .435	.612	.581	.607	.582	.591
ro	.690	.742	.448 – .470	.703	.696	.704	.669	.732

Table 5: Maximum F_1 score (usually the 8th layer) for WA across layers, including comparison to FastAlign and Efmaral aligners. For static word embeddings (SWE), we report the difference from distortion penalty introduction.

that alternately aligned the words and learned a linear projection between the representations. This algorithm only brings a negligible improvement of .005 F_1 points.

MT Quality Estimation. Table 6 reveals that measuring the distance of non-centered sentence vectors does not correlate with MT quality at all; centering or explicit projection only leads to a mild correlation. Unlike sentence retrieval, QE is more sensitive to subtle differences between sentences, while the projection only seems to capture rough semantic correspondence. Note also that the Pearson correlation used as an evaluation metric for QE might not favor the cosine distance because semantic similarity might not linearly correspond to HTER.

However, supervised regression using either only the source or only MT output shows a respectable correlation. The source sentence embedding alone can be used for a reasonable QE. This means that the source sentence complexity is already a strong indicator of the translation quality. Using the target sentence embedding alone leads to almost as good results as using both the source and the hypothesis, which suggests that the structure of the translation hypothesis is what plays the important role and lexical-semantic aspects captured by the embeddings are not sufficient for the QE.

The experiments with QE show that all tested contextual sentence representations carry informa-

tion about sentence difficulty for MT and structural plausibility. However, unlike lexical-semantic features, this information is not well accessible via simple embedding comparison.

A parallel research Zhao et al. (2020b,a) presents a relative success in using multilingual contextual representations for reference-free MT evaluation. A comparison with their results suggests that QE is a more difficult task than the reference-free MT evaluation.

8 Conclusions

Using a set of semantically oriented tasks, we showed that unsupervised BERT-based multilingual contextual embeddings capture similar semantic phenomena quite similarly across different languages. Surprisingly, in cross-lingual semantic similarity tasks, employing cosine similarity of the contextual embeddings without any tuning or adaptation clearly and consistently outperforms cosine similarity of static multilingually aligned word embeddings, even though these were explicitly trained to be language-neutral using bilingual dictionaries.

Nevertheless, we found that vanilla contextual embeddings contain a strong language identity signal, as demonstrated by their state-of-the-art performance for the language identification task. We hypothesize this is due to the sentence-adjacency objective used during training because language identity is a strong feature for adjacency.

	SWE	mBERT	UDify	lng-free	Distil	XLM-R
centered	.020	.005	.039	.026	.001	.001
projection	.038	.163	.167	.136	.241	.190
regression: SRC only	.349	.362	.368	.349	.342	.388
regression: TGT only	.339	.352	.375	.343	.344	.408
regression full	.332	.419	.413	.411	.389	.431

Table 6: Pearson correlation of estimated MT quality with HTER for WMT19 English-to-German translation.

We explored three ways of removing the language ID from the representations in an attempt to make them even more cross-lingual. While adversarial finetuning of mBERT did not help, a simpler unsupervised approach of language-specific centering of the representations managed to reach the goal to some extent, leading to higher performance of the centered representations in the probing tasks. The adequacy of the approach is also confirmed by a strong performance of the computed language centroids in estimating language similarity. Still, an even stronger language-neutrality of the representations can be achieved by fitting a supervised linear projection on a small set of parallel sentences.

Although representation centering leads to satisfactory language neutrality, it still requires knowing in advance what the language is. The future work thus should focus on representations that are more language-neutral by default, not requiring subsequent language-dependent modifications. We hope that this work helps to establish how future language-neutral representation should be evaluated.

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A Notes on Reproducibility

Experiments with language identification, language similarity, and adversarial removal of language ID were computing on GPUs. We used GeForce GTX 1080 Ti with 11GB memory. The other experiments were conducted CPUs with Intel Xeon CPU E5–2630 v4 (2.20GHz). All experiments fitted into 32 GB RAM.

Models for language identification and adversarial language ID removal are implemented in PyTorch. The linear classifier for language ID has 56k parameters. For adversarial language ID removal, it means there are two classifiers per layer, i.e., in total 1.3M parameters. Each experiment from Table 1 that includes 5 runs with different random seeds took on average 1.38h. Results on validation data are presented in Table 7.

The linear projections for sentence retrieval were estimated using Scikit Learn, which took on average 7 minutes for one model layer and one language pair, including running the representation model in PyTorch on CPU. The projection has 590k parameters. One retrieval experiment took on average 25 minutes.

We implemented the minimum weighted edge cover algorithm using the linear sum assignment problem solver from SciPy. One experiment took on average 10 minutes.

The MT QE experiments based on cosine similarity took on average 2 minutes. The experiments with supervised regression were trained using Scikit Learn. Each model has 197k parameters. One experiment took on average 22 minutes.

	mBERT		UDify		lng-free		Distil		XLM-R	
[cls]	.935	12	.936	8	.798	1	.952	6	—	—
[cls], cent.	.908	10	.852	8	.341	5	.825	6	—	—
mean-pool	.958	5 B	.957	5	.956	3	.958	6	.949	1
mean-pool, cent.	.851	1	.852	1	.853	1	.841	1	.849	8

Table 7: Validation accuracy of language identification for the best and worse scoring.