Establishing Interlingua in Multilingual Language Models

Maksym Del and Mark Fishel
Institute of Computer Science
University of Tartu, Estonia
{maksim,mark}@tartunlp.ai

Abstract

Large multilingual language models show remarkable zero-shot cross-lingual transfer performance on a range of tasks. Follow-up works hypothesized that these models internally project representations of different languages into a shared interlingual space. However, they produced contradictory results. In this paper, we correct the famous prior work claiming that “BERT is not an Interlingua” and show that with the proper choice of sentence representation different languages actually do converge to a shared space in such language models. Furthermore, we demonstrate that this convergence pattern is robust across four measures of correlation similarity and six mBERT-like models. We then extend our analysis to 28 diverse languages and find that the interlingual space exhibits a particular structure similar to the linguistic relatedness of languages. We also highlight a few outlier languages that seem to fail to converge to the shared space.

1 Introduction

Large-scale multilingual language models (LMs) such as mBERT (Devlin et al., 2019) or XLM-R (Conneau et al., 2020a) achieve remarkable results on a variety of cross-lingual transfer tasks (Hu et al., 2020b; Liang et al., 2020). Follow-up works performed representational similarity analysis comparing encoded sentences in different languages (Singh et al., 2019; Muller et al., 2021; Conneau et al., 2020b). However, they came up with two opposite conclusions.

In particular, Singh et al. (2019) concluded that “mBERT is not an Interlingua”. They observed that the model separates representations for each language rather than using a common, shared, interlingual space while increasing divergence at deeper layers. Muller et al. (2021), on the contrary, found that approximately the first half of the mBERT layers align different languages together. We observe that these works use different pooling strategies for sentence representations (CLS-pooling and mean-pooling) and show how that determines the outcome. We show that among these two pooling strategies there is only one correct.

Also, it is not clear if the observed pattern is not specific to the choice of similarity measure since studies use different ones. We address this and previous issues in Section 2.

Next, the studies were only performed for the original mBERT model. We address the question of generalizability of the interlingual behavior across different multilingual LMs in Section 3 and show that this pattern is exhibited by all the considered models.

Finally, we expand our understanding of the structure of the interlingual space that emerges after the middle layers in most multilingual encoders. We employ 28 diverse languages and show that most of them share the interlingual space. We also find that some languages are outliers in terms of the interlingual similarity. We highlight that linguistically pleasurable distances between languages go beyond simple linear relationships. See Section 4 for this study.

Our main motivation here is the following:

• Resolving conflicting evidence is essential for the purposefulness and fast progress in the research field.

• Related works only analyzed a single model using a single similarity measure (generalizability concerns).

• The finding of Singh et al. (2019) based on coarse-grained views on language representa-
Our contributions/findings are thus:

- We correct previous work that claimed that languages in mBERT do not converge to the shared interlingual space (Section 2).
- We show that the convergence pattern is robust to the choice of the representational similarity measure (Section 2).
- We show that the convergence pattern is not specific to the mBERT model but is the property of all diverse pretrained multilingual transformers tested (Section 3).
- We show that the shared space is structured similarly to the linguistic relatedness of the languages (Section 4).
- We show that some languages are outliers that seem not to converge to the shared space (Section 4).

2 Is BERT an Interlingua?

2.1 Setup

We start by mirroring the setup of Singh et al. (2019) and use the mBERT model and five language pairs (15k examples for each language). We embed the source and target sentences with mBERT and pool the CLS tokens from each layer for each language pair. Next, we compare two parallel sets of sentence representations using the PWCCA (Morcos et al., 2018) similarity measure to reproduce results of Singh et al. (2019).

Then, we switch to mean pooling of token contextual embeddings as a sentence representation and show the effect of this change on the similarity patterns.

We add three more similarity measures: CCA (Hardoon et al., 2004), SVCCA (Raghu et al., 2017), and CKA (Kornblith et al., 2019). In general, all metrics compare two parallel sets of vectors by maximizing correlations. We refer the reader to Appendix A for the brief intuitive explanation and to Kornblith et al. (2019) for a systematic mathematical description of the correlation similarity measures we use.

For our experiment, we only highlight that the more significant the similarity measure score is (ranges from 0 to 1), the more similar two sets of representations are.

2.2 Results and Discussion

Replicating Divergence Pattern. In Figure 1 we mirror the main result of Singh et al. (2019). The graph shows that similarities between representations in different languages diverge as we pick deeper layers, suggesting that BERT is not an interlingua.

![Figure 1: mBERT is not an interlingua. Reproduced from Singh et al. (2019). PWCCA metric is used to compute CLS pooled sentence representations.](image)

Revealing Interlingual Behavior. An alternative choice for the sentence representation is to use mean pooling, where the sum of contextual embeddings for tokens is used as the sentence representation. As results can change with different similarity measures, we compute similarity using four widely used metrics and use mean-pooled sentence representations. These results are presented in Figure 2.
Figure 2: BERT is an interlingua. The pattern generalizes over similarity measures. Four metrics are used to compute mean pooled sentence representations. CKA and SVCCA reveal more pronounced trend.

All metrics show an opposite trend to Figure 1 where similarity between languages increases in deeper layers ("interlingua pattern") \(^2\).

This interlingua pattern is consistent with the one presented in Muller et al. (2021) and Conneau et al. (2020b), where they also use mean pooling. Thus, the choice of sentence representation is the determining factor in confirming interlingual behavior in LMs. Also, we find that the resulting outcome generalizes over four similarity measures.

Before continuing to other LMs, let us discuss the conceptual difference between CLS and mean pooled sentence representations, and whether we have theoretical reasons to prefer one over another.

**Resolving Conflicting Evidence** In Figure 1 we use the CLS token as a sentence representation – the same token that mBERT uses to predict the following sentence in the corpus during pretraining. That is why we can be considered a sentence representation. However, we argue that it is only valid as such at the very last layer, from where we predict the next sentence. CLS tokens at other hidden layers do not have any clear signal to meaningfully represent the sentence due to the token mixing procedure in the Transformer layers. Each token position can carry pieces of information about itself as well pieces about other tokens. Consequently, using the CLS token as a sentence representation for hidden layers is not expedient enough.

On the contrary, mean pooling gathers distributed information about all tokens on each layer and thus serves as a conceptually more pleasurable choice. Therefore, we can conclusively say that results at Figure 1 represent the CLS token dynamic across layers, which has less to do with the sentence representations.

This section resolved the conflicting evidence existing in the literature and argued that mBERT indeed follows the pattern, where languages converge to each other in deeper layers. We also showed that this pattern is robust to the choice of the similarity measure.

3 Do BERT Friends Agree?

3.1 Setup

Representational analysis in the previous work (Singh et al., 2019; Muller et al., 2021) was limited to the specific multilingual BERT model. It questions whether the pattern generalizes across other models with different training objectives, pre-training datasets, capacities, and tokenization. In this section, we repeat our analysis for five more commonly used models to address this issue.

The tested models have a different number of layers, so we cast them to the same scale representing the network depth as a fraction for each encoder (e.g. 0.5 network depth means the 6th layer for mBERT and 12th layer for XLM-R large).

We use six different models: uncased (uncased mBERT) and cased (uncased mBERT) versions of mBERT; next, we use XLM-MLM-100 (Lample and Conneau, 2019) which has 16 layers and was trained on single sentences. XLM-R base (Conneau et al., 2020a) is the multilingual extension of the Roberta (Liu et al., 2019) trained for longer on larger data and is “wider” than mBERT. XLM-R large uses about 3 times more parameters than XLM-R base. distil_mBERT (Sanh et al., 2019) is a twice smaller distilled version of mBERT. For all models we use the HuggingFace\(^3\) library. We also refer the reader to Appendix B in Conneau et al. (2020a) for a systematic comparison of models.

\(^2\)Languages converge up to some point (with the peak around 8th layer) and then start to diverge slightly. It is probably due to the particularities of the masked language modeling training. There words in the language of input have to be predicted, which requires recovering some language-specific information.

\(^3\)https://huggingface.co/distilbert-base-multilingual-cased
3.2 Results and Discussion

Figure 3 shows CKA similarity results for all models. We show results for one language since other ones are analogical (these are presented in Appendix B).

Figure 3: The interlingual pattern generalizes over models. The score is produced with CKA similarity for Azerbaijani, results for other languages are analogical and can be found in Appendix B.

All multilingual encoders are generally consistent in following the interlingua pattern. If we consider downstream task performance of the models (Conneau et al., 2020a; Hu et al., 2020a) we see that more performant models are generally placed higher in the graph. XLM-Rs is on top, and distilBERT is at the bottom, while XLM-MLM and mBERTs in the middle. Interestingly, the XLM-R base is a clear leader in cross-lingual sentence similarities and outscores even the XLM-R large model in that regard, even though the large version is more cross-lingually performant. The explanation might be related to the fact that XLM-R large has ‘useless’ but cross-lingually distant dimensions that the metric captured. However, we leave exploring the relation between representational similarity across models and their cross-lingual benchmark performance to future work.

In summary, here we showed that the general interlingual pattern generalizes across models.

4 Interlingua is Not for Everyone

4.1 Setup

This section takes a more in-depth look at interlingua in multilingual LMs and explores its structure.

We use all 28 languages from the extended XNLI dataset Singh et al. (2019). By computing CKA across all language pairs at all layers, we determine that the 7th layer of XLM-R is the most "interlingual" (see Figure 4). We choose to focus on XLM-R for its performance in Section 3.

4.2 Results and Discussion

Figure 4 shows the boxplot covering CKA distances between all pairs of languages.

Figure 4: Per-layer CKA similarity for XLM-R at each layer for combinations of 28 languages. Dots at the bottom show that there are some language pairs that drastically differ in similarity comparing to the vast majority of other language pairs. The 7th layer seems to be the most interlingual.

Dots at the bottom suggest that there are clear outlier language pairs. The most interlingual layer for XLM-R seems to be 7th, so let us open the box at this layer with the following Figure 5.

Figure 5: All pairwise language similarities at layer 7th XLM-R layer. There are few languages (Urdu and Hindi as well as Swahili and Thai) that seem to be located far away from all others.

We can now clearly see that the outliers are due to Urdu and Hindi (and possibly Swahili and Thai).

However, even inside shared interlingual space, languages also exhibit certain relationships with each other. Thus we perform an agglomerative
clustering on CKA distances to investigate this phenomenon and present the result in Figure 6:

Figure 6: Agglomerative clustering for the 7th layer of XLM-R based on CKA distances. We can consider green branch a shared interlingual space from where languages from orange branch are excluded. Languages in the green branch are grouped similarly to their linguistic distances.

The linguistic tree in Figure 6 clearly shows that languages in the right branch (that we consider to be the shared interlingual space) structure in a meaningful way. Slavic languages are together, Swahili and Thai are isolated, while Scandinavian languages are again nearby. Urdu and Hindi expectedly occupy their separate branch as outliers.

We also include results for mBERT model from before in Appendix C for consistency; they are similar to what is presented here.

Finally, we note that CKA metric we used is invariant to translations, scaling, and orthogonal transforms of representational spaces. Despite this invariance, the tree in Figure 6 that was built based on CKA distances between languages still shows the familiar linguistic hierarchy. This pushes our understanding of language representations beyond them simply residing on centroid distances without transforming the interlingual space, as Libovický et al. (2020) showed. Instead, it is clear that even on a more complex level, after pairwise “aligning” sentence representations in different languages the linguistic hierarchy pattern still emerges.

5 Conclusions

We resolved contradictory evidence in the literature and showed that structural analysis reveals that multilingual BERT follows an interlingual pattern consistently across four primary similarity measures. Next, we showed that the pattern is not specific to mBERT and is present in other multilingual language models. Finally, we found that not all of the languages share the interlingual space equally. Nevertheless, most of them do, and the interlingual space is structured similarly to the linguistic relatedness of the languages.

References

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020a. Unsupervised cross-lingual representation learning at scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8440–8451, Online. Association for Computational Linguistics.

Alexis Conneau, Shijie Wu, Haoran Li, Luke Zettlemoyer, and Veselin Stoyanov. 2020b. Emerging cross-lingual structure in pretrained language models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6022–6034, Online. 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.

D. Hardoon, S. Szedmák, and J. Shawe-Taylor. 2004. Canonical correlation analysis: An overview with application to learning methods. Neural Computation, 16:2639–2664.

J. Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and M. Johnson. 2020a. Xtreme: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization. ArXiv, abs/2003.11080.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020b. XTREME: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization. CoRR, abs/2003.11080.

Simon Kornblith, Mohammad Norouzi, H. Lee, and Geoffrey E. Hinton. 2019. Similarity of neural network representations revisited. ArXiv, abs/1905.00414.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. In NeurIPS.

Yaobo Liang, Nan Duan, Yeyun Gong, Ning Wu, Feni Guo, Weizhen Qi, Ming Gong, Linjun Shou, Daxin Jiang, Guihong Cao, Xiaodong Fan, Bruce Zhang, Rahul Agrawal, Edward Cui, Sining Wei, Taroon Bharti, Ying Qiao, Jiun-Hung Chen, Winnie Wu, Shuguang Liu, Fan Yang, Rangan Majumder, and Ming Zhou. 2020. XGLUE: A new benchmark dataset for cross-lingual pre-training, understanding and generation. CoRR, abs/2004.01401.
A Similarity Measures

In this appendix we give a reader brief intuitive explanations and refer to the Kornblith et al. (2019) for a systematic mathematical description of the correlation similarity measures.

CCA is the correlation based similarity analysis method. As formulated by Morcos et al., CCA “identifies the ‘best’ (maximizing correlation) linear relationships (under mutual orthogonality and norm constraints) between two sets of multidimensional variates”. CCA score can be a mean of the resulting correlation coefficients.

SVCCA reduces sensitivity of CCA to particular dimensions by performing Support Vector Decomposition on parallel vectors first, and then applying CCA on the resulting components. The number of resulting CCA coefficients is the hyperparameter for the SVCCA, we use 20 in this work.

PWCCA is an extension of the original CCA (Hardoon et al., 2004) that weights resulting CCA correlation coefficients based on their importance, instead of taking simple mean.

CKA is another similarity measure which works by computing pairwise dot products between two parallel sets of vectors and correlating resulting distance matrices.

Also, we highlight that PWCCA is only invariant to the translation and isotropic scaling. CKA is also invariant to the orthogonal transforms, and SVCCA and CCA are invariant to any invertible linear transform.
B Generalization Over Models

Figure 7: Generalization over models across languages under CKA metric. Models follow similar general trend across languages which corresponds to the interlingual pattern we discuss in this work.

C Interlingual Space: mBERT

This sections presents the same figures as we show in Section 4, but for mBERT. All figures confirm the general conclusions made in the main text for the XLM-R.

For example, Figure 8 is similar to Figure 4 and shows the box plot that is based on per-layer similarity for all 378 distinct language pairs.

mBERT has more "Excluded" languages, which is logical since it is weaker cross-lingual model, comparing to the XLM-R.

Figure 8: Per-layer CKA similarity for mBERT at each layer for combinations of 28 languages. Dots at the bottom show that there are some language pairs that drastically differ in similarity comparing to the vast majority of other language pairs.

This figure also highlights Thai as the most distinct language. This language was not included in the mBERT uncased pretraining.

Figure 9: All pairwise language similarities at layer 8th mBERT layer. There are few languages that seem to be located far away from all others. The 8th layer seems to be the most interlingual.
Figure 10: Agglomerative clustering for the 8th layer of mBERT based on CKA distances. We can consider green branch a shared interlingual space from where languages from orange branch are excluded. Languages in the green branch are grouped similarly to their linguistic distances.