Examining Cross-lingual Contextual Embeddings with Orthogonal Structural Probes

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Abstract

State-of-the-art contextual embeddings are obtained from large language models available only for a few languages. For others, we need to learn representations using a multilingual model. There is an ongoing debate on whether multilingual embeddings can be aligned in a space shared across many languages. The novel Orthogonal Structural Probe (Limisiewicz and Mareček, 2021) allows us to answer this question for specific linguistic features and learn a projection based only on mono-lingual annotated datasets. We evaluate syntactic (UD) and lexical (WordNet) structural information encoded in MBERT’s contextual representations for nine diverse languages. We observe that for languages closely related to English, no transformation is needed. The evaluated information is encoded in a shared cross-lingual embedding space. For other languages, it is beneficial to apply orthogonal transformation learned separately for each language. We successfully apply our findings to zero-shot and few-shot cross-lingual parsing.

1 Introduction

The representation learned by language models has been successfully applied in various NLP tasks. Multilingual pre-training allows utilizing the representation for various languages, including low-resource ones. There is an open discussion about to what extent contextual embeddings are similar across languages (Søgaard et al., 2018; Hartmann et al., 2019; Vulić et al., 2020). The motivation for our work is to answer: Q1 Is linguistic information uniformly encoded in the representations of various languages? And if this assumption does not hold: Q2 Is it possible to learn orthogonal transformation to align the embeddings?

We probe for the syntactic and lexical structures encoded in multilingual embeddings with the new Orthogonal Structural Probes (Limisiewicz and Mareček, 2021). Previously, Chi et al. (2020) employed structural probing (Hewitt and Manning, 2019) to evaluate cross-lingual syntactic information in MBERT and visualize how it is distributed across languages. Our approach’s advantage is learning an orthogonal transformation that maps the embeddings across languages based on monolingual linguistic information: dependency syntax and lexical hypernymy. This new capability allows us to test different probing scenarios. We measure how adding assumptions of isomorphism and uniformity of the representations across languages affect probing results to answer our research questions.

2 Related Work

Probing It is a method of evaluating linguistic information encoded in pre-trained NLP models. Usually, a simple classifier for the probing task is trained on the frozen model’s representation (Linzen et al., 2016; Belinkov et al., 2017; Blevins et al., 2018). The work of Hewitt and Manning (2019) introduced structural probes that linearly transform contextual embeddings to approximate the topology of dependency trees. Limisiewicz and Mareček (2021) proposed new structural tasks and introduced orthogonal constraint allowing to decompose projected embeddings into parts correlated with specific linguistic features. Kulmíz et al. (2020) probed different languages to examine what type of syntactic dependency annotation is captured in an LM. Hall Maudslay et al. (2020) modify the loss function, improving syntactic probes’ ability to parse.

Cross-lingual embeddings There is an essential branch of research studying relationships of embeddings across languages. Mikolov et al. (2013)
showed that distributions of the word vectors in different languages could be aligned in shared space. Following research analyzed various methods of aligning cross-lingual static embeddings (Faruqui and Dyer, 2014; Artetxe et al., 2016; Smith et al., 2017) and gradually dropped the requirement of parallel data for alignment (Artetxe et al., 2018; Zhang et al., 2017; Lample et al., 2018).

Significant attention was also devoted to the analysis of multilingual and contextual embeddings of mBERT (Pires et al., 2019; Libovický et al., 2020). There is also no conclusive answer to whether the alignment of such representations is beneficial to cross-lingual transfer. Wang et al. (2019) show that the alignment facilitates zero-shot parsing, while results of Wu and Dredze (2020) for multiple tasks put in doubt the benefits of the alignment.

3 Method

The Structural Probe (Hewitt and Manning, 2019) is a gradient optimized linear projection of the contextual word representations produced by a pre-trained neural model (e.g. BERT Devlin et al. (2019), ELMo Peters et al. (2018)).

In a Distance Probe, the Euclidean distance between projected word vectors approximates the distance between words in a dependency tree:

$$d_B(h_i, h_j)^2 = (B(h_i - h_j))^T (B(h_i - h_j)), \quad (1)$$

$B$ is the Linear Transformation matrix and $h_i, h_j$ are the vector representations of words at positions $i$ and $j$.

Another type of a probe is a Depth Probe, where the token’s depth in a dependency tree is approximated by the Euclidean norm of a projected word vector:

$$||h_i||_B^2 = (Bh_i)^T (Bh_i) \quad (2)$$

Orthogonal Structural Probes Limisiewicz and Mareček (2021) proposed decomposing matrix $B$ and then gradient optimizing a vector and orthogonal matrix. The new formulation of an Orthogonal Distance Probe is:

$$d_{BVT}(h_i, h_j)^2 = (\bar{d} \odot V^T (h_i - h_j))^T (\bar{d} \odot V^T (h_i - h_j)), \quad (3)$$

where $V$ is an orthogonal matrix (Orthogonal Transformation) and $\bar{d}$ is a Scaling Vector, which can be changed during optimization for each task to allow multi-task joint probing.

This procedure allowed optimizing a separate Scaling Vector $\bar{d}$ for a specific objective, allowing probing for multiple linguistic tasks simultaneously. In this work, an individual Orthogonal Transformation $V$ is trained for each language, facilitating multi-language probing. This approach assumes that the representations are isomorphic across languages; we examine this claim in our experiments.

Our implementation is available at GitHub: https://github.com/Tom556/OrthogonalTransformerProbing.

4 Experiments

We examine vector representations obtained from multilingual cased BERT (Devlin et al., 2019).

4.1 Data and Probing Objectives

We probe for syntactic structure annotated in Universal Dependencies treebanks (Nivre et al., 2020) and for lexical hypernymy trees from WordNet (Miller, 1995). We optimize depth and dependency probes in both types of structures jointly.

For both dependency and lexical probes, we use sentences from UD treebanks in nine languages. For each treebank, we sampled 4000 sentences to diminish the effect of varying size datasets in probe optimization. Lexical depths and distances for each sentence are obtained from hypernymy trees that are available for each language in Open Multilingual Wordnet (Bond and Foster, 2013).

Choice of Layers We probe the representations of the 7th layer for dependency information and representations of the 5th layer for lexical information. These layers achieve the highest performance for the respective features.

4.2 Multilingual Evaluation

We utilize the new joint optimization capability of Orthogonal Structural Probes to analyze how the encoding of linguistic phenomena are expressed across different languages in mBERT representations.

To answer our research question, we evaluate three settings of multilingual Orthogonal Structural Probe training. The approaches are sorted by expressiveness; the most expressive one makes the

List of all the datasets used in this work can be found in Appendix.
Table 1: Spearman’s correlation between gold and predicted depths and distances. Δ denotes the differences from IN-LANG results. Each of our results is an average of 6 randomly initialized probing experiments. Statistically significant differences are circled. The three last columns present averages for Indo-European, Non-Indo-European, and all languages. The evaluation is not zero-shot, we use data in a target language. Correlations for dependency distance are compared with Standard Structural Probes reported by Chi et al. (2020).

The first and the last approach was proposed analyzed for Structural Probes by Chi et al. (2020). MAPPEDLANGS setting is possible thanks to the new probing formulation of Limisiewicz and Mareček (2021). For evaluation, we compute Spearman’s correlations between predicted and gold depths and distances. In this evaluation, we use supervision for a target language. Furthermore, we analyze the impact of two language-specific features on the results: a) size of the mBERT training corpus in a given language; b) typological similarity to English. The former is expressed in the number of tokens in Wikipedia. The latter is a Hamming similarity between features in WALS (Dryer and Haspelmath, 2013).4

4.3 Zero- and Few-shot Parsing

We extract directed trees from the predictions of dependency probes. For that purpose, we employ the Maximum Spanning Tree algorithm on the predicted distances and the algorithm’s extension of

4In this work, we consider all the features in the areas: Nominal Categories, Verb Categories, and Lexicon for computing a lexical typological similarity, and features in the areas: Nominal Syntax, Word Order, Simple Clauses, and Complex Sentences as a syntactic typological similarity. Each area contains multiple typological features.
Kulmizev et al. (2020) to extract directed trees based on predicted depths.

We examine cross-lingual transfer for parsing sentences in Chinese, Basque, Slovene, Finnish, and Arabic. For each of them, we train the probe on the remaining eight languages. In a few-shot setting, we also optimize on 10 to 1000 examples from the target language.

5 Results

Spearman’s correlation Using In-Lang probes for each language gives high Spearman’s correlations across the languages. The MappedLangs approach brings only a slight difference for most of the configuration while imposing uniformity constraint (AllLangs) deteriorates the results for some of the languages, as shown in Table 1. The drop in correlation is especially high for Non-Indo-European languages (except for lexical distance where the difference between Indo-European and Non-Indo-European groups is small).

In Fig. 1, we present the Pearson’s correlations between results from Table 1 and two language-specific features: typological similarity to English and number of tokens in Wikipedia. Correlations for dependency probes are in the upper-right triangle and for lexical probes in the lower-left triangle.

Table 2: UAS of extracted dependency trees. Our two approaches are compared to the previous works that use a biaffine parser (Lauscher et al., 2020; Wang et al., 2019). We probed the representations of the 7th layer. *): fine-tuning of MBERT is used. **): the multilingual dictionary is used to align the embeddings.

|        | N   | ZH | EU | SL | FI | AR |
|--------|-----|----|----|----|----|----|
| Lauscher* | 51.41 | 50.31 | -  | 65.66 | 44.46 |
| Wang et al. | - | - | 67.86 | 65.45 | - |
| *+CLBT** | - | - | 69.04 | 67.96 | - |
| *+FT** | - | - | 69.16 | 69.16 | - |
| MAPPEDL | 34.44 | 39.10 | 35.44 | 37.33 | 40.95 |
| ALLL | 52.92 | 58.77 | 70.76 | 64.60 | 57.47 |
| Lauscher* | 57.73 | 57.23 | -  | 65.13 | 71.00 |
| MAPPEDL | 37.01 | 39.63 | 35.77 | 40.15 | 36.81 |
| ALLL | 53.12 | 58.51 | 70.85 | 64.98 | 68.59 |
| Lauscher* | 66.78 | 66.73 | -  | 69.26 | 75.84 |
| MAPPEDL | 45.07 | 50.02 | 55.09 | 49.32 | 57.77 |
| ALLL | 53.63 | 59.07 | 70.43 | 65.02 | 68.81 |
| Lauscher* | 69.91 | 65.70 | -  | 70.25 | 78.50 |
| MAPPEDL | 60.57 | 65.98 | 72.81 | 63.80 | 68.85 |
| ALLL | 57.17 | 63.49 | 72.35 | 66.05 | 69.57 |
observe that between 100 and 1000 training samples are needed to learn the Orthogonal Transformation effectively. Also, with higher supervision, we observe that the results reported by (Lauscher et al., 2020) notably outperform our approach. The outcome was anticipated because they fine-tune MBERT and use biaffine with a larger capacity than a probe. For their approach, the introduction of even small supervision is more advantageous than for probing.

6 Conclusions

We propose an effective way to multilingually probe for syntactic dependency (UD) and lexical hypernymy (WordNet). Our algorithm learns probes for multiple tasks and multiple languages jointly. The formulation of Orthogonal Structural Probe allows learning cross-lingual transformation based on mono-lingual supervision. Our comparative evaluation indicates that the evaluated information is similarly distributed in the MBERT’s representations for languages typologically similar to English: Spanish, French, and Finnish. We show that aligning the embeddings with Orthogonal Transformation improves the results for other examined languages, suggesting that the representations are isomorphic. We show that the probe can be utilized in zero- and few-shot parsing. The method achieves better UAS results for Chinese, Slovene, Basque, and Arabic in a zero-shot setting than previous approaches, which use a more complex biaffine parser.

Limitations In our choice of languages, we wanted to ensure diversity. Nevertheless, four of the analyzed languages belong to an Indo-European family that could facilitate finding shared encoding subspace for those languages.

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A WALS similarities

![Figure 2: Typological (WALS) similarities between languages. Dependency similarities in the upper-right triangle and lexical similarities in the lower-left triangle.]

In Fig. 2, we present typological similarities between languages. Bases on Fig. 3 we observe that typological similarity to languages related to English: Spanish, Finnish, French is correlated to \( \Delta \)ALL\_LANGS. Moreover, the correlation between similarity to these languages and the number of tokens in Wikipedia is smaller than for English\(^5\). It supports our claim that typological similarity is more important for uniformity assumption than the size of the pre-training corpus.

B Pre-training corpus size

Sizes of Wikipedia in eight analyzed languages are presented in Table 3.

C Datasets

In Table 4 we aggregate all the datasets used in our experiments.

D Information separation

In line with the findings of Limisiewicz and Mareček (2021) we have observed that in multilingual setting Orthogonal Structural Probes disentangle the subspaces responsible for encoding lexical and dependency structures Table 5.

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\(^5\)English is especially over-represented in the pre-trained corpus.

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| Language | Articles | Tokens |
|----------|----------|--------|
| English  | 6,171,405 | 2,622,505,044 |
| French   | 2,255,469 | 823,362,731 |
| Spanish  | 1,631,829 | 688,970,215 |
| Chinese  | 1,151,113 | 269,492,468 |
| Arabic   | 1,069,379 | 169,126,089 |
| Finnish  | 494,487   | 98,712,322  |
| Indonesian | 547,825   | 96,356,452  |
| Basque   | 365,301   | 46,487,007  |
| Slovene  | 169,604   | 42,511,205  |

Table 3: The number of articles and tokens in Wikipedia for analyzed languages. The data come from [https://github.com/mayhewsw/multilingual-data-stats/tree/main/wiki](https://github.com/mayhewsw/multilingual-data-stats/tree/main/wiki)

E Probing setup

We use the same setup for training the Orthogonal Structural Probe as Limisiewicz and Mareček (2021), i.e. Adam optimizer (Kingma and Ba, 2014), initial training rate \( 0.02 \), and learning rate decay. We use Double Soft Orthogonality Regularization to coerce orthogonality of the matrix \( V \).

E.1 Number of Parameters

A Scaling Vector for each of 4 objectives has a size \( 768 \times 1 \) and an Orthogonal Transformation for each language is a matrix of size \( 768 \times 768 \). In MAPPED\_LANGS, our largest memory-wise setting, we train 8 Orthogonal Transformations. In this configuration, our probe has 4,721,664 parameters.

E.2 Computation Time

We optimized probes on a GPU core GeForce GTX 1080 Ti. Training a probe in MAPPED\_LANGS configuration takes about 3 hours.

F Supplementary Results

F.1 UUAS results

The Table 6 contains the results for undirected dependency trees. We use the same probing setting as in Section 3.2 without assigning directions to the edges. Similarly to Chi et al. (2020), we exclude punctuation from the evaluation.

F.2 Validation Results

In Table 7, we present the validation results corresponding to the test results in Table 1 of the main paper.
Figure 3: Pearson’s correlation between WALS similarity to a specific language and $\Delta \text{ALLLANGS}$, the number of tokens in Wikipedia. “IE avg.” stands for average similarity to analyzed Indo-European languages, i.e., English, Spanish, French, Slovene.

Table 4: The datasets used for training dependency and lexical probes.

| Language  | Dependency Name | Dependency Reference | Lexical Name | Lexical Reference |
|-----------|-----------------|-----------------------|--------------|------------------|
| English   | EWT             | Silveira et al. (2014) | Princeton Wordnet | Miller (1995) |
| French    | GSD             | McDonald et al. (2013) | Wordnet Libre du Français | Sagot and Füßer (2008) |
| Spanish   | Ancora          | Taulé et al. (2008)   | Multilingual Central Repository | Gonzalez-Agirre et al. (2012) |
| Chinese   | GSD             | McDonald et al. (2013) | Chinese Open Wordnet | Wang and Bond (2013) |
| Arabic    | PADT            | Smrž et al. (2008)    | Arabic WordNet | Elkatib et al. (2006) |
| Finnish   | TDT             | Haverinen et al. (2014) | FinnWordNet | Lindén and Carlson. (2010) |
| Indonesian| GSD             | McDonald et al. (2013) | Wordnet Bahasa | Mohamed Noor et al. (2011) |
| Basque    | BDT             | M. et al. (2015)      | Multilingual Central Repository | Pociello et al. (2011) |
| Slovene   | SSJ             | Dobrovolec et al. (2017) | sloWNet | Fišer et al. (2012) |

Table 5: The number of shared dimensions selected by Scaling Vector after the joint training of probe in MAPPEDLANGS setting on top of the 7th layer.

| N       | ZH | EU | SL | FI | AR |
|---------|----|----|----|----|----|
| Chi et al. | 51.30 | -  | -  | 70.70 | 70.40 |
| MAPPEDALL | 39.99 | 46.96 | 41.58 | 43.91 | 40.95 |
| ALL     | 57.82 | 64.59 | 75.06 | 68.70 | 68.70 |

Table 6: UUAS of extracted dependency trees in zero- and few-shot setting. The result of Structural Probe reported by Chi et al. (2020) for reference.
| Approach          | EN  | ES  | SL  | ID  | ZH  | FI  | AR  | FR  | EU  |
|-------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| **Dependency Distance Spearman’s Correlation** |     |     |     |     |     |     |     |     |     |
| IN-LANG           | .816| .861| .844| .822| .815| .803| .835| .872| .749 |
| ∆ MAPPEDLANGS     | .000| -.002| .000| .001| -.001| -.001| -.002| -.002| .002 |
| ∆ ALLLANGS        | -.001| -.007| -.004| -.011| -.041| .000| -.022| -.010| -.021 |
| **Dependency Depth Spearman’s Correlation** |     |     |     |     |     |     |     |     |     |
| IN-LANG           | .847| .868| .857| .853| .837| .807| .864| .893| .786 |
| ∆ MAPPEDLANGS     | -.003| -.002| -.004| .000| .002| -.005| -.002| -.003| -.001 |
| ∆ ALLLANGS        | -.004| -.005| -.004| -.013| -.034| -.004| -.027| -.007| -.033 |
| **Lexical Distance Spearman’s Correlation** |     |     |     |     |     |     |     |     |     |
| IN-LANG           | .898| .880| .867| .857| .777| .664| .726| .810| .714 |
| ∆ MAPPEDLANGS     | .000| -.001| -.001| .003| .001| .001| .027| .008| -.005 |
| ∆ ALLLANGS        | -.005| -.005| -.017| -.009| -.001| -.053| .004| -.024| -.082 |
| **Lexical Depth Spearman’s Correlation** |     |     |     |     |     |     |     |     |     |
| IN-LANG           | .844| .882| .792| .869| .862| .784| .884| .879| .847 |
| ∆ MAPPEDLANGS     | .010| .002| .009| -.013| .006| .020| .011| -.006| .012 |
| ∆ ALLLANGS        | -.010| -.067| -.079| -.108| -.055| .000| -.259| -.043| -.034 |

Table 7: Validation Spearman’s correlation between gold and predicted depths and distances. We probe the representations of 7th layer for dependency information and representations of 5th layer for lexical information.