Looking for Clues of Language in Multilingual BERT to Improve Cross-lingual Generalization

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Abstract

Token embeddings in multilingual BERT (m-BERT) contain both language and semantic information. We find that the representation of a language can be obtained by simply averaging the embeddings of the tokens of the language. Given this language representation, we control the output languages of multilingual BERT by manipulating the token embeddings, thus achieving unsupervised token translation. We further propose a computationally cheap but effective approach to improve the cross-lingual ability of m-BERT based on this observation.

1 Introduction

Multilingual BERT (m-BERT) (Devlin et al., 2019) has demonstrated its strength in cross-lingual transfer on a variety of tasks (Conneau et al., 2018; Wu and Dredze, 2019; Hsu et al., 2019; Pires et al., 2019); this has been credited to the cross-lingual alignment of its internal representations, in which semantically similar or functionally similar words from different languages are represented with similar embeddings (Cao et al., 2020; Liu et al., 2020).

How is language information embedded in m-BERT? The answer may be more straightforward than expected. We find that the averaged token embedding of a language well represents the language. To verify this observation, we show that if an English sentence is input to m-BERT, and its embeddings are then shifted in a specific direction in the embedding space, m-BERT outputs a sentence in another language semantically close to the input sentence.

After showing the existence of language information in the embeddings of m-BERT and having an easy way to extract it, we eliminate these language-specific variations in the embeddings, and demonstrate that this is a practical way to boost the zero-shot cross-lingual transferability of m-BERT on downstream tasks.

In the literature, some have attempted to improve the cross-lingual alignment of pre-trained m-BERT. For example, Cao et al. (2020) propose finetuning m-BERT on small parallel dataset, and Libovický et al. (2020) propose zero-centering the embedding language by language to achieve language neutrality and demonstrate progress on retrieval tasks, all under an unsupervised scenario. Our work is concurrent to (Libovický et al., 2020; Gonen et al., 2020)’s and bears similarities to its approaches. We discussed more applications of language representation compared to them.

The contributions of this work can be summarized as the following:

- Language information in m-BERT can be represented by the average of all token embeddings of the specific language. This is verified by unsupervised token translation.
- The cross-lingual transferability of m-BERT in downstream tasks can be improved by manipulating token embeddings.

2 Language Representation

We assume that we have $n$ languages denoted by $\{L_1, L_2, \ldots, L_n\}$ and their corresponding corpora.

Context-Dependent Representation Given an input sequence $x$ and token index $i$, we denote the hidden representation in layer $l$ by $h_{x_i}^l$.

Language Mean Given a language $L$ and its corresponding corpus $C$ composed of a set of sentences $x$, we denote the language mean of layer $l$ by

$$R_{L}^l = \mathbb{E}_{x \in C} [h_{x_i}^l],$$

which represents the mean of all the token embeddings in the corpora. We assume that the language
mean contains language-specific information but no semantic information.

Although this assumption about language representation here seems naive, in the experiments, we show that $R^l_k$ well represents the language information in token embeddings. For each language $L$, there is a language-specific representation $R^l_k$ for each layer $l$. Because we do not know for which layer $l$ $R^l_k$ best represents language $L$, $l$ is a hyperparameter in the following algorithms.

**Zero-mean** To eliminate language-specific information, we simply subtract language mean $R^l_k$ from each token embedding $h^l_{x_i}$, thus moving the token embedding to a language-agnostic joint space. The language-agnostic hidden representation $\hat{h}^l_{x_i}$ can be written as

$$\hat{h}^l_{x_i} = h^l_{x_i} - R^l_k,$$

where $h^l_{x_i}$ is extracted from token $x_i$ in $L_k$.

**Mean Difference Shift (MDS)** In addition to eliminating language information, we can move the embedding in the space of $L_1$ to the space of $L_2$: this amounts to unsupervised token translation. That is, given the embedding of *me* in English, we modify the embedding to cause it to be interpreted by m-BERT as the embedding of *私* (*me* in Chinese).

We feed a sentence $L_1$ into m-BERT and extract the embedding of each token at layer $l$. Then we subtract $R^l_k$ from the embedding as in (1) to remove the information of $L_1$, and then add $R^l_{L_2}$ to shift the embedding to the $L_2$ space. Formally, we modify token embedding $h^l_{x_i}$ in $L_1$ into embedding $\hat{h}^l_{x_i}$ in $L_2$ as

$$\hat{h}^l_{x_i} = h^l_{x_i} + R^l_{L_2} - R^l_{L_1},$$

(2)

### 3 Unsupervised Token Translation

In this section, we show that the implicit language-specific information in the embedding space can be disentangled from semantic embeddings. We use MDS to input a sentence in $L_1$ to m-BERT and translate it to a sentence in $L_2$.

#### 3.1 Setup

The formulation of MDS is a slight modification of (2): $\hat{h}^l_{x_i} = h^l_{x_i} + \alpha (R^l_{L_2} - R^l_{L_1})$, where $\alpha$ is a hyperparameter; we will see its influence in the experimental results. Given the input, the token embeddings are modified at a specific layer $l$. The $(l + 1)$-th layer takes the modified embeddings as input, and the final layer generates a sequence of tokens. The sentences in this experiment are from XNLI test-set, which contains 15 languages, including low-resource languages such as Swahili and Urdu.

#### 3.2 Evaluation metrics

We use two different metrics to analyze the results of unsupervised token translation quantitatively.

**BLEU-1 Score** This metric measures the translation quality without considering the fluency of the converted sequence.

**Conversion Rate** Besides translation quality, we also calculated the conversion rate: the percentage of tokens converted from the source language to the target language, which is defined as

$$\text{conversion rate} = \frac{\# \text{ of } y \in (V_t - V_s)}{\# \text{ of } y - \# \text{ of } y \in V_s \cap V_t},$$

where $y$ is output tokens of the model and $V_t$ and $V_s$ are the token sets of the source and target language. As tokens shared by both vocabularies are not taken into account, they are excluded from the numerator and denominator terms.

#### 3.3 Results

Surprisingly, we were able to produce the predicted tokens in language $L_2$ given $L_1$ input by applying MDS; many of the predicted tokens were the token-level translation of the input tokens in $L_1$, even for low-resource languages. Sample output is shown in Appendix A.

Table 1 shows the quantitative results. First, although the translation result falls short of existing unsupervised translation methods (Kim et al., 2018), it constitutes strong evidence that we can use MDS to manipulate language-specific information in the token embedding space and then induce m-BERT to switch from one language to another. Second, we observe that as $\alpha$ increases, the model converts more tokens to target language $L_2$ and never decodes tokens that do not belong to both $L_1$ and $L_2$. Given a negative $\alpha$, the model always decodes tokens belonging to $L_1$. This shows that in the embedding space, the direction related to language is unique. We offer a further analysis of $\alpha$ in Appendix A.
We evaluate the effect of MDS and zero-mean on sentence retrieval tasks: BUCC2018 and Tatoeba. We use the mean vector of all token embeddings in a sentence as the sentence embedding and cosine similarity as the distance metric. Token embeddings were extracted from a specific layer of the BERT encoder, and MDS or zero-mean shifts pre-computed on the whole dataset were applied directly to the extracted embeddings.

| Method  | de  | es  | ar  | el  | hi  |
|---------|-----|-----|-----|-----|-----|
| Original| 75.4| 64.1| 24.5| 29.8| 64.3|
| MUSE    | 1.3 | 0.2 | 0.3 | 0.5 | 23.8|
| Zero-mean| 73.5| 61.8| 23.5| 29.4| 63.7|
| MDS     | 76.8| 67.5| 29.1| 30.6| 67.0|

4 Cross-lingual Sentence Retrieval

Extracting parallel sentences from a comparable corpus between two languages is a common way to evaluate cross-lingual embeddings (Hu et al., 2020; Zweigenbaum et al., 2017; Artetxe and Schwenk, 2018). In this section, we use evaluations on a sentence-level retrieval task to demonstrate that MDS achieve better cross-lingually aligned.

4.1 Task

We evaluate the effect of MDS and zero-mean on two sentence retrieval tasks: BUCC2018 and Tatoeba. We use the mean vector of all token embeddings in a sentence as the sentence embedding and cosine similarity as the distance metric. Token embeddings were extracted from a specific layer of the BERT encoder, and MDS or zero-mean shifts pre-computed on the whole dataset were applied directly to the extracted embeddings.

4.2 MDS vs Zero-Mean

Although applying MDS or zero-mean in a sentence retrieval task seem similar at first glance, there are subtle differences. Assume sentence embeddings \( v_1 \in L_1 \) and \( v_2 \in L_2 \), and that these two sentences in different languages have the same semantic meaning. Assume there exist real language representations \( R_{L_1}^* \) and \( R_{L_2}^* \) that perfectly eliminate language from the embedding\(^1\) such that \( v_1 - R_{L_1}^* = v_2 - R_{L_2}^* \). Language representations \( R_{L_1} \) and \( R_{L_2} \) obtained via averaging are approximations of the real representations,\(^2\) and \( \delta_1 \) and \( \delta_2 \) are the differences between the real and approximate language representations.

\[
\begin{align*}
R_{L_1} & \neq R_{L_2} \\
v_1 - R_{L_1} & \neq v_2 - R_{L_2} \\
v_1 & - R_{L_1} - \delta_1 = v_2 - R_{L_2} - \delta_2
\end{align*}
\]

Then the post-MDS and post-zero-mean cosine similarities of \( v_1 \) and \( v_2 \) are

\[
\begin{align*}
\text{cos}_{\text{MDS}} (v_1, v_2) &= \frac{\langle v_1 - R_{L_1} + R_{L_2}, v_2 \rangle}{\| v_1 - R_{L_1} + R_{L_2} \| \| v_2 \|} \\
\text{cos}_{\text{zero-mean}} (v_1, v_2) &= \frac{\langle v_1 - R_{L_1} - \delta_1, v_2 - R_{L_2} - \delta_2 \rangle}{\| v_1 - R_{L_1} - \delta_1 \| \| v_2 - R_{L_2} - \delta_2 \|}
\end{align*}
\]

This shows that zero-mean is more sensitive to approximation error when \( \| v_2 \| > \| v_2 - R_{L_2} \| > \max (| \delta_1 |, | \delta_2 |, | \delta |) \).\(^3\) The differences between the two methods are further verified in the experiments.

4.3 Results

The sentence retrieval results are shown in Tables 3 and 2. On the BUCC2018 dev set and test set, MDS-shifted embeddings consistently yield higher accuracies on all languages, and zero-meaned embeddings are worse than doing nothing. On the

\(^1\)Unknown to us
\(^2\)Superscript ignored here for simplicity
\(^3\)This is very possible. Because \( v_2 \) is in \( L_2 \), it may have the same direction as \( R_{L_2} \).
Table 4: POS tagging results

| Method  | ar | bg | de | el | es | fr | hi | ru | th | tr | ur | vi | zh | Average |
|---------|----|----|----|----|----|----|----|----|----|----|----|----|----|---------|
| Original | 53.8 | 85.4 | 86.2 | 81.1 | 86.1 | 42.9 | 66.8 | 85.5 | 41.7 | 68.6 | 56.3 | 53.8 | 61.8 | 66.9 |
| Zero-mean | 54.3 | 86.1 | 86.6 | 81.8 | 86.6 | 43.7 | 68.1 | 86.5 | 41.6 | 69.7 | 56.6 | 53.4 | 62.5 | 67.5 |
| MDS | 54.2 | 86.4 | 86.5 | 81.5 | 86.8 | 43.9 | 68.9 | 86.4 | 44.2 | 69.4 | 57.1 | 52.4 | 63.0 | 67.8 |

Table 5: Dependency parsing results. Numbers are Labeled Attachment Score (LAS).

| Method  | ar | bg | de | el | es | fr | hi | ru | th | tr | ur | vi | zh | Average |
|---------|----|----|----|----|----|----|----|----|----|----|----|----|----|---------|
| Original | 28.2 | 70.7 | 74.0 | 71.6 | 72.1 | 74.8 | 35.3 | 69.0 | 30.8 | 32.9 | 28.3 | 37.8 | 35.4 | 50.8 |
| Zero-mean | 28.2 | 71.0 | 73.4 | 71.4 | 72.2 | 75.7 | 36.3 | 69.3 | 32.5 | 34.6 | 28.6 | 37.0 | 35.2 | 51.2 |
| MDS | 28.0 | 70.8 | 73.7 | 71.1 | 72.2 | 75.3 | 36.5 | 68.8 | 30.4 | 34.2 | 29.0 | 35.6 | 35.0 | 50.8 |

Tatoeba test set, the MDS embeddings are also the best in most languages, except for Hindi, Russian, and Vietnamese. We also tried using rotation matrices to align the embedding (MUSE, (Lample et al., 2017)), but found that the unsupervised alignment method is not working on BERT.

5 Cross-Lingual Transfer

5.1 Setup

In zero-shot cross-lingual transfer learning, m-BERT was fine-tuned on the source language, which was English in the following experiments, and tested on languages never seen during fine-tuning. For each language, we used around 5M tokens from Wikipedia documents to compute the language representations.

Zero-mean During fine-tuning, we applied zero-mean on the token embeddings of the source language and forwarded the modified embeddings to the remaining layers during training. During testing, we fed the fine-tuned model with target language data and applied zero-mean to the embeddings at layer $l$ as well. The language vector means were extracted from Wikipedia data using the pre-trained model.

MDS In this approach, we did not modify embeddings during training. During testing, we applied MDS to the embeddings at layer $l$. The mean difference vectors were extracted from Wikipedia data using the fine-tuned model.

5.2 Tasks

To show that the proposed methods improve cross-lingual zero-shot learning performance, we conducted experiments on two tasks: part-of-speech (POS) tagging and dependency parsing.

Part-of-Speech Tagging For POS tagging, we used the Universal Dependencies v2.5 (Nivre et al., 2020) treebanks for 90 languages. Each word was assigned one of 17 universal POS tags. The model was trained on English and tested on 13 other languages.

Dependency Parsing For dependency parsing, the dataset and cross-lingual transfer settings were exactly the same as POS tagging.

5.3 Results

Tables 4 and 5 compare the results of the baselines and our methods on POS tagging and dependency parsing, respectively. For POS tagging, zero-mean and MDS both improve the performance on the testing sets across languages, with only a few exceptions. MDS was not helpful in Thai (th), and neither approach improved on Vietnamese (vi). For dependency parsing, contrary to the previous observations, we found that only zero-mean improved upon the baselines, while MDS didn’t. Since more linguistic factors affects dependency parsing (e.g. head-directionality parameter) than POS tagging, we felt that more analyses are needed to explain the performance of dependency parsing.

6 Conclusion

In this paper, we examine the existence of language-specific information in m-BERT embeddings and achieve unsupervised token translation by manipulating language-specific information. The proposed methods are further shown to be effective in improving cross-lingual embedding alignment and cross-lingual transfer learning. We will further explore the proposed approach on more downstream tasks.
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A Analysis of $\alpha$ in Unsupervised Token Translation

Table 6: Size of token set and size of English token set intersection with another language token set

\[
\begin{array}{cccccccc}
| V_{\text{lang}} | & \text{en} & \text{de} & \text{fr} & \text{el} & \text{zh} & \text{ur} & \text{sw} \\
\hline
| V_{\text{en}} \cap V_{\text{lang}} | & 9140 & 9212 & 8552 & 3189 & 3866 & 4085 & 5609
\end{array}
\]

![Figure 1: Direction of change of BLEU-1 for unsupervised en→el token translation for various $\alpha$ and with different layers](image1.png)

(a) By $\alpha$

![Figure 2: Conversion rate on en→el data given different $\alpha$ on different layers for MDS](image2.png)

(b) By layer

Figure 1: Direction of change of BLEU-1 for unsupervised en→el token translation for various $\alpha$ and with different layers.

We present an example of en→el in Figures 1 and 2 to show how the conversion rate and BLEU-1 score change with different $\alpha$ weights and with different layers.

Despite the mixed influences of weight increases on BLEU-1, in the last few layers (10 or 11), the BLEU-1 of most languages rose noticeably when $\alpha$ was set to 3.0 (also shown in the best layer row in Table 1). This suggests that the last few layers are better for disentangling language-specific representations, which is consistent with the observation in the literature that the last few layers contain more language-specific information for predicting masked words (Pires et al., 2019).
Table 7: Unsupervised token translation of random sample (MDS, layer 10)

| Input (en) | The girl that can help me is all the way across town. There is no one who can help me. |
|------------|-------------------------------------------------------------------------------------|
| Ground truth (zh) | 能帮助我的女孩在小镇的另一边。没有人能帮助我。          |
| en-zh, \( \alpha = 1 \) | 孩。can来我是all the way across 市。。There 是无人人can help 我。   |
| en-zh, \( \alpha = 2 \) | 孩的的家我是这个人的市。。他是他人的到我。        |
| en-zh, \( \alpha = 3 \) | 。的的的他是的个的。。：他是他人。的。他。 |
| Ground truth (fr) | La fille qui peut m'aider est à l'autre bout de la ville. Il n'y a personne qui pourrait m'aider. |
| en-fr, \( \alpha = 1 \) | girl qui can help me est all la way across town .。There est no one qui can help me 。 |
| en-fr, \( \alpha = 2 \) | girl qui de help me est all la way dans .。Il est de seul qui pour aid me 。 |
| en-fr, \( \alpha = 3 \) | 。 de . me . all la 。 。 。 n n n 。 。 。 。