Cross-Lingual Relevance Transfer for Document Retrieval

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Abstract

Recent work has shown the surprising ability of multi-lingual BERT to serve as a zero-shot cross-lingual transfer model for a number of language processing tasks. We combine this finding with a similarly-recently proposal on sentence-level relevance modeling for document retrieval to demonstrate the ability of multi-lingual BERT to transfer models of relevance across languages. Experiments on test collections in five different languages from diverse language families (Chinese, Arabic, French, Hindi, and Bengali) show that models trained with English data improve ranking quality, without any special processing, both for (non-English) mono-lingual retrieval as well as cross-lingual retrieval.

1 Introduction

Transformer models that have been pre-trained on language modeling tasks such as BERT (Devlin et al., 2019) have led to many advances in diverse language processing tasks ranging from textual inference to sequence labeling. Interest in these models have also extended to search-related tasks such as retrieval-based question answering (Yang et al., 2019a), passage ranking (Nogueira and Cho, 2019), and document ranking (Yang et al., 2019b; MacAvaney et al., 2019; Yilmaz et al., 2019).

Our work builds on Yilmaz et al. (2019), who proposed a simple approach to document ranking that aggregates sentence-level evidence (based on BERT) with document-level evidence (based on traditional exact term-matching scores). Furthermore, they demonstrated that BERT models fine-tuned with passage-level relevance data can transfer across domains: surprisingly, fine-tuning on social media data is effective for relevance classification on newswire documents without any additional modifications.

Inspired by the work of Wu and Dredze (2019), who explored the cross-lingual potential of multi-lingual BERT (henceforth, mBERT for short) as a zero-shot language transfer model, we wondered if the techniques of Yilmaz et al. (2019) would transfer across languages in addition to transferring across domains. Supported by experiments in five different non-English languages from diverse language families (Chinese, Arabic, French, Hindi, and Bengali)—we find, perhaps unsurprisingly, the answer is yes!

The contribution of this work is empirical validation that the cross-domain relevance transfer work of Yilmaz et al. (2019) also works cross-lingually without any additional effort, for both mono-lingual retrieval in non-English languages as well as cross-lingual retrieval. We demonstrate robust increases in document retrieval effectiveness across diverse languages that come “for free”.

2 Background and Approach

Our work adopts the standard formulation of document ranking: given a user query \(Q\), the system’s task is to produce a ranking of documents from a corpus that maximizes some ranking metric—in our case, average precision (AP). In the context of cross-lingual transfer learning, it is useful to precisely define the source language (the language of the training data) and the target language (the language in which inference is being applied). In our case, the source language is English. There are two variants of our retrieval task: In mono-lingual target language retrieval, both the query and the documents are in another language (for example, Bengali). In cross-lingual retrieval, the query and the documents are in different languages (for example, English queries, Bengali documents).

Following Wu and Dredze (2019), we use mBERT, which has been pretrained on concate-
nated Wikipedia data for 104 languages, as our transfer model. Starting with mBERT, we fine-tune the model for sentence-level relevance classification as described by Yilmaz et al. (2019), which is based on Nogueira and Cho (2019).

Starting from pretrained mBERT, we fine-tune the model as follows: the input to mBERT comprises [ [CLS] , Q [SEP] S [SEP] ], which is the concatenation of the query Q and a sentence S, with the standard special tokens [CLS] and [SEP]. The final hidden state of the [CLS] token is passed to a single layer neural network with a softmax, obtaining the probability that sentence S is relevant to the query Q.

Following Yilmaz et al. (2019), the model (mBERT in our case) is fine-tuned with data from the TREC Microblog Tracks (Lin et al., 2014), since typical IR test collections—which only have relevance annotated at the document level—are too long for feeding into mBERT. Despite the mismatch in domain between training data and test data (tweets vs. newswire documents), the previous work showed that relevance matching models transfer across domains.

For document retrieval (i.e., at inference time), let us first consider the case of mono-lingual retrieval in the target language (i.e., queries in Bengali, documents in Bengali). We first apply “bag of words” exact term matching to retrieve a candidate set of documents. Each document is split into sentences, and we apply inference with mBERT on each sentence separately. The relevance score of each document is determined by combining the top k scoring sentences with the document term-matching score as follows:

\[ S_{doc} = \alpha \cdot S_r + (1 - \alpha) \cdot \sum_{i=1}^{k} w_i \cdot S_i \] (1)

where \( S_i \) is the i-th top sentence score according to BERT. The parameters \( \alpha \) and \( w_i \)'s can be tuned via cross-validation. All candidate documents are resorted by the above score \( S_{doc} \), which serves as the final output.

Our approach is a straightforward adaptation of the evidence combination technique of Yilmaz et al. (2019), except using mBERT. To be precise, we apply an mBERT model that has been fine-tuned on English relevance data directly in the target language, without any modification.

For the cross-lingual retrieval case, where, for example, the queries are in English and the documents are in French, we simply translate the query into the target language using Google Translate, and apply exactly the same methods as above.

### 3 Experimental Setup

As previously discussed, we examined two different retrieval tasks: mono-lingual retrieval in the target language and cross-lingual retrieval. Dataset statistics are summarized in Table 1. For each corpus, we indicate the query language(s); the queries are in parallel if multiple languages are provided. All these languages are captured in mBERT and are from diverse language families (Sino-Tibetan, Semitic, Romance, and Indo-Aryan).

| Doc (Query) Language | Source | # Topics | # Docs |
|----------------------|--------|----------|--------|
| Chinese (zh, en)     | NTCIR 8| 73       | 308,832|
| Arabic (ar, en)      | TREC 2002| 50     | 383,872|
| French (fr, en, zh)  | CLEF 2006| 49     | 171,109|
| Hindi (hi)           | FIRE 2012| 50     | 331,599|
| Bengali (bn)         | FIRE 2012| 50     | 500,122|
| English (en, hi, bn) | FIRE 2012| 50     | 392,577|

Table 1: Dataset Statistics.
Table 2: Mono-lingual ranking effectiveness.

| Model        | AP | P@20 | NDCG@20 | AP | P@20 | NDCG@20 | AP | P@20 | NDCG@20 |
|--------------|----|------|---------|----|------|---------|----|------|---------|
| NTCIR8-zh    |    |      |         |    |      |         |    |      |         |
| BM25         | 0.4065 | 0.3911 | 0.4867  | 0.2923 | 0.3660 | 0.4057  | 0.3111 | 0.3184 | 0.4458   |
| 1S: BERT(MB) | 0.4466 | 0.4370 | 0.5288  | 0.3103 | 0.3940 | 0.4511  | 0.3115 | 0.3255 | 0.4404   |
| 2S: BERT(MB) | 0.4587 | 0.4610 | 0.5577  | 0.3087 | 0.4000 | 0.4498  | 0.3347 | 0.3367 | 0.4639   |
| 3S: BERT(MB) | 0.4612 | 0.4651 | 0.5626  | 0.3105 | 0.4070 | 0.4547  | 0.3390 | 0.3429 | 0.4727   |
| tune-embed   | 0.4458 | 0.4521 | 0.5443  | 0.3040 | 0.3860 | 0.4370  | 0.3064 | 0.3224 | 0.4396   |
| FIRE2012-hi  |      |      |         |    |      |         |    |      |         |
| BM25         | 0.3867 | 0.4470 | 0.5310  | 0.2881 | 0.3740 | 0.4261  | 0.3713 | 0.4970 | 0.5420   |
| 1S: BERT(MB) | 0.4284 | 0.4750 | 0.5597  | 0.3210 | 0.4130 | 0.4747  | 0.4424 | 0.5610 | 0.5971   |
| 2S: BERT(MB) | 0.4279 | 0.4740 | 0.5608  | 0.3228 | 0.4160 | 0.4802  | 0.4456 | 0.5610 | 0.6053   |
| 3S: BERT(MB) | 0.4595 | 0.5070 | 0.5520  | 0.3217 | 0.4190 | 0.4808  | 0.4443 | 0.5530 | 0.6068   |
| tune-embed   | 0.4168 | 0.4720 | 0.5578  | 0.3086 | 0.4010 | 0.4606  | 0.4347 | 0.5400 | 0.5874   |

Table 3: Cross-lingual ranking effectiveness.

| Model        | AP | P@20 | NDCG@20 | AP | P@20 | NDCG@20 | AP | P@20 | NDCG@20 |
|--------------|----|------|---------|----|------|---------|----|------|---------|
| NTCIR8-en-zh |    |      |         |    |      |         |    |      |         |
| BM25         | 0.2946 | 0.3260 | 0.3825  | 0.2678 | 0.3620 | 0.3981  | 0.3070 | 0.3163 | 0.4476   |
| 1S: BERT(MB) | 0.3289 | 0.3630 | 0.4233  | 0.2780 | 0.3620 | 0.4101  | 0.3152 | 0.3306 | 0.4489   |
| 2S: BERT(MB) | 0.3416 | 0.3829 | 0.4443  | 0.2819 | 0.3590 | 0.4097  | 0.3349 | 0.3449 | 0.4783   |
| 3S: BERT(MB) | 0.3459 | 0.3945 | 0.4568  | 0.2853 | 0.3670 | 0.4175  | 0.3363 | 0.3439 | 0.4799   |
| tune-embed   |      |      |         |    |      |         |    |      |         |
| FIRE2012-hi  |      |      |         |    |      |         |    |      |         |
| BM25         | 0.2274 | 0.2406 | 0.3428  | 0.3410 | 0.4600 | 0.4931  | 0.3044 | 0.4280 | 0.4637   |
| 1S: BERT(MB) | 0.2351 | 0.2437 | 0.3470  | 0.3749 | 0.4655 | 0.5014  | 0.3210 | 0.4163 | 0.4523   |
| 2S: BERT(MB) | 0.2524 | 0.2542 | 0.3703  | 0.3788 | 0.4750 | 0.5118  | 0.3308 | 0.4430 | 0.4836   |
| 3S: BERT(MB) | 0.2600 | 0.2656 | 0.3878  | 0.3817 | 0.4810 | 0.5188  | 0.3274 | 0.4395 | 0.4779   |

For inference (e.g., document ranking), Google Translate is first used to translate queries into the language of the documents (in the case of cross-lingual retrieval). The query is then used to retrieve the top 1000 hits from the corpus using BM25 as the ranking function. For this, we used the open-source Anserini IR toolkit (Yang et al., 2018) with minor modifications based on version 0.6.0 to swap in Lucene Analyzers for different languages. Fortunately, Lucene provides analyzers for all the languages in our test collections. In all cases, we used the default BM25 parameters in Anserini.

We use average precision (AP), precision at rank 20 (P@20), and NDCG@20 as the evaluation metrics. Following Yilmaz et al. (2019), we considered up to the top three sentences in aggregating sentence-level evidence. We also applied five-fold cross-validation on all datasets and the parameters α and the w_i’s were obtained by grid search, choosing the parameters that yield the highest AP.

4 Results and Discussion

Our results are shown in Table 2 (mono-lingual) and Table 3 (cross-lingual). The top row of each section shows the effectiveness of the BM25 baseline. The remaining blocks show the effectiveness of our models; the nS preceding the model name indicates that inference was performed using the top n scoring sentences from each document.

From Table 2, we find that mBERT fine-tuned on the microblog data outperforms the BM25 baseline by a large margin for all three metrics, for all collections. It is worth emphasizing that the model was not fine-tuned with any of the corpora used in retrieval. These results indicate that mBERT effectively transfers its relevance matching ability across languages, from English to Chinese, Arabic, French, Hindi, and Bengali. Furthermore, note that the test collections are all from the news domain, while the training data are drawn from social media. This implies that mBERT is able to transfer relevance matching models across domains and across languages simultaneously.

\[\text{http://anserini.io/}\]
Note that one of the FIRE2012 conditions is English, which provides a sanity check for these experiments; here, we reproduce the gains observed by Yilmaz et al. (2019). Also consistent with previous work, looking at the nS configurations, we see that using only the top-scoring sentence already yields a high level of effectiveness, showing that the best sentence alone provides a good proxy of document relevance. Adding the second or third sentence yields small improvements at best.

We see different degrees of effectiveness gains across languages: for some languages (e.g., Chinese), we observe a large gain; for others (e.g., Arabic and French), the gains are more modest. Beyond making this observation, we currently have no explanation why. These differences might arise from intrinsic language differences in mBERT (i.e., the pretraining regime), characteristics of the test collection (e.g., types of queries), differences in the Anserini document processing pipeline (e.g., tokenization), or likely, a combination of all these factors (and more). We save an in-depth exploration of this question for future work.

To support our modeling decision to fix the token embeddings of mBERT during fine-tuning, we experimented with a contrastive condition in which the embeddings were fine-tuned as well. This is shown in the entry “tune-embed” in Table 2. Although we conducted experiments using the three different sentence configurations, only the best results are shown for space considerations. Comparing these results with the fixed-embedding setting, we observe that fine-tuning the embeddings leads to lower effectiveness. We suspect that allowing the embeddings to change alters the underlying cross-lingual relationship between tokens from different languages, because the English token embeddings are updated while those from other languages remain unchanged. As a result, it is possible that mBERT learns a relevance matching model that is more specific to English, affecting its ability to transfer to other languages.

For the cross-lingual setting, results from Table 3 are consistent with the mono-lingual results. Recall that the only difference here is our use of Google Translate to translate the query into the document language. Note that the BM25 baselines are lower than in the mono-lingual case, especially for the NTCIR8-en-zh, CLEF2006-zh-fr, and TREC2002-en-ar conditions, with drops of 0.1119, 0.0837, and 0.0245 in AP, respectively.

Error analysis attributes the issue to the use of Google Translate as an imperfect black box translator. For example, we have the NTCIR query “Who is Lung Yingtai?” (a famous writer and poet). The correct Chinese translation is “谁是龙应台?” but with Google Translate, we obtain “隆应泰是谁？” (a totally different person). Such translation errors are expected because of the lack of context and background knowledge. On the other hand, the CLEF2006-en-fr condition has a much smaller effectiveness drop for the BM25 baseline because the English and French queries share some tokens, such as person names.

However, these results show that, even with imperfect top one translations, we observe substantial gains in cross-lingual and cross-domain relevance transfer. This suggests that better ways of query translation, for example, taking advantage of multiple translations (Ture and Lin, 2014), represents a promising approach.

5 Conclusion

Building on two recent papers (Yilmaz et al., 2019; Wu and Dredze, 2019), we empirically show that mBERT is able to transfer models of relevance matching cross-linguistically, without any special processing. This is empirically supported by document retrieval experiments in five different languages drawn from diverse language families. For the mono-lingual (non-English) case, we can rerank documents retrieved using “bag of words” exact term matching directly with mBERT. For the cross-lingual case, we find that Google Translates provides an adequate, albeit imperfect, black box solution to translate the query language into the document language.

Our findings open up lots of interesting questions regarding language differences, which will drive future work. However, we believe our most impactful contribution is highlighting a potential avenue for building high-quality search engines for low(er)-resources languages by leveraging relevance judgments in languages where they are far more plentiful.

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References

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.

Jimmy Lin, Miles Efron, Yulu Wang, and Garrick Sherman. 2014. Overview of the TREC-2014 Microblog Track. In Proceedings of the Twenty-Third Text REtrieval Conference (TREC 2014), Gaithersburg, Maryland.

Sean MacAvaney, Andrew Yates, Arman Cohan, and Nazli Goharian. 2019. CEDR: Contextualized embeddings for document ranking. In Proceedings of the 42nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2019), pages 1101–1104, Paris, France.

Rodrigo Nogueira and Kyunghyun Cho. 2019. Passage re-ranking with BERT. arXiv:1901.04085.

Ferhan Ture and Jimmy Lin. 2014. Exploiting representations from statistical machine translation for cross-language information retrieval. ACM Transactions on Information Systems, 32:Article 19.

Shijie Wu and Mark Dredze. 2019. Beto, bentz, becas: The surprising cross-lingual effectiveness of BERT. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 833–844, Hong Kong, China.

Peilin Yang, Hui Fang, and Jimmy Lin. 2018. Anserini: reproducible ranking baselines using Lucene. Journal of Data and Information Quality, 10(4):Article 16.

Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019a. End-to-end open-domain question answering with BERTserini. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations), pages 72–77, Minneapolis, Minnesota.

Wei Yang, Haotian Zhang, and Jimmy Lin. 2019b. Simple applications of BERT for ad hoc document retrieval. arXiv:1903.10972.

Zeynep Akkalyoncu Yilmaz, Wei Yang, Haotian Zhang, and Jimmy Lin. 2019. Cross-domain modeling of sentence-level evidence for document retrieval. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3481–3487, Hong Kong, China.