Learning Cross-Lingual IR from an English Retriever

Yulong Li†*, Martin Franz‡*, Md Arafat Sultan†*, Bhavani Iyer‡, Young-Suk Lee‡ and Avirup Sil‡

†IBM Research, ‡IBM Research AI
{yulongl, franzm, bsiyer, ysuklee, avi}@us.ibm.com
arafat.sultan@ibm.com

Abstract

We present a new cross-lingual information retrieval (CLIR) model trained using multi-stage knowledge distillation (KD). The teacher and the student are heterogeneous systems—the former is a pipeline that relies on machine translation and monolingual IR, while the latter executes a single CLIR operation. We show that the student can learn both multilingual representations and CLIR by optimizing two corresponding KD objectives. Learning multilingual representations from an English-only retriever is accomplished using a novel cross-lingual alignment algorithm that greedily re-positions the teacher tokens for alignment. Evaluation on the XOR-TyDi benchmark shows that the proposed model is far more effective than the existing approach of fine-tuning with cross-lingual labeled IR data, with a gain in accuracy of 25.4 Recall@5kt.

1 Introduction

Multilingual models are a topic of growing interest in NLP given their criticality to the universal adoption of AI. Cross-lingual information retrieval (CLIR) (Braschler et al., 1999; Shakery and Zhai, 2013; Saleh and Pecina, 2019; Jiang et al., 2020; Asai et al., 2021a; Shi et al., 2021), for example, can find relevant text in a high-resource language such as English even when the query is posed in a different, possibly low-resource, language. In this work, we aim to develop useful CLIR models for this constrained, yet important, setting where a retrieval corpus is available only in a single high-resource language (English in our experiments).

A solution to this problem can take one of two general forms. First, machine translation (MT) of the query into English followed by monolingual (English) IR (Asai et al., 2021a). While such a pipeline approach can provide accurate predictions, an alternative solution that can tackle the problem purely cross-lingually, i.e., without involving MT, can be more efficient and cost-effective. Pre-trained multilingual masked language models (PLMs) such as multilingual BERT (Devlin et al., 2019) and XLM-RoBERTa (XLM-R henceforth) (Conneau et al., 2020) can provide the foundation for such a cross-lingual solution, as one can simply fine-tune such a model with labeled CLIR data (Asai et al., 2021b).

Here we first run an empirical evaluation of these two approaches on a public CLIR benchmark (Asai et al., 2021a). We use ColBERT1 (Khattab and Zaharia, 2020; Khattab et al., 2021) as our IR architecture and XLM-R as the underlying PLM for both methods (§2). Results indicate that the MT-based solution can be vastly more effective than CLIR fine-tuning, where we observe a difference in Recall@5kt of 28.6 (§3). Crucially, the modular design of the former allows it to leverage additional English-only training data to train its IR component, which contributes significantly to its performance.

The above results lead naturally to our second research question: Can a more accurate CLIR model be trained that can operate without having to rely on MT? To answer the question, instead of viewing the MT-based approach as a competing one, we propose to leverage its strength via knowledge distillation (KD) (Hinton et al., 2014) is a powerful supervision technique typically used to distill the knowledge of a large teacher model about some task into a smaller student model (Sanh et al., 2019). Here we propose to use KD in a slightly different context, where the teacher and the student IR models are identical in size, but the former has superior performance simply due to having access to an MT module and consequently operating in a high-resource and low-difficulty monolingual environment.

†Due to its state-of-the-art (SOTA) performance outperforming DPR (Karpukhin et al., 2020).
We perform two different KD operations (§2.2). The first one directly optimizes an IR objective, where we use a labeled CLIR dataset consisting of parallel (English and non-English) questions and their corresponding positive and negative passages for training. The teacher and the student are shown the English and non-English versions of a question, respectively, and the training objective is for the student to match the soft query-passage relevance predictions of the teacher. Our second KD task is representation learning from parallel text, where the student learns to encode a non-English text that matches the teacher’s encoding of the aligned English text at the token level. The cross-lingual token alignment needed to create the training data for this task is generated using a novel greedy alignment process which, despite its noisy nature, proves to be highly effective.

Experimental results (§3) show that our proposed methods can regain most of the performance loss from the two-stage solution to the purely cross-lingual model. On an XOR-TyDi test set, the student outperforms the cross-lingual ColBERT baseline by 25.4 points in terms of Recall@5kt, trailing the teacher processing English queries by just 3.2 points. Ablation studies also show that each of our two KD processes contribute significantly towards the final performance of the student.

Our contributions can be summarized as follows:

- We present an empirical study of the effectiveness of a SOTA IR model (ColBERT) on cross-lingual IR with and without MT.
- We propose a novel, purely cross-lingual solution that uses knowledge distillation to learn both improved text representation and IR.
- We demonstrate with a novel cross-lingual alignment algorithm that distillation using parallel text can strongly augment cross-lingual IR training.
- We achieve new SOTA results on the XOR-TyDi cross-lingual IR task.

2 Method

Here we describe our base IR model (ColBERT) and the proposed KD-based cross-lingual training algorithms.

2.1 The ColBERT Model

The ColBERT (Khattab and Zaharia, 2020) architecture consists of a shared transformer-based encoder that separately encodes the input query and document, followed by a linear compression layer. Each training instance is a \( <q, d^+, d^-> \) triple, where \( q \) is a query, \( d^+ \) is a positive (relevant) document and \( d^- \) is a negative (irrelevant) document. ColBERT first computes a relevance score for the pair \( (q, d) \) using Equation 1, where \( d \in \{d^+, d^-\} \) and \( E_q \) and \( E_d \) are the output embeddings of query token \( q \) and document token \( d \), respectively. For a given training triple, a pairwise softmax cross-entropy loss is minimized over the computed scores \( S_{q,d^+} \) and \( S_{q,d^-} \).

\[
S_{q,d} := \sum_{i \in [||q||]} \max_{j \in [||d||]} E_{q_i} \cdot E_{d_j}^T \tag{1}
\]

For inference, the embeddings of all documents are calculated \textit{a priori}, while the query embeddings and the relevance score are computed at runtime.

2.2 Knowledge Distillation

Our teacher and student are both ColBERT models that fine-tune the same underlying multilingual PLM for IR. The teacher is first trained with all-English triples using the above ColBERT objective.
The goal of the subsequent KD training is to teach the student how to reproduce the behavior of the teacher when the former is asked a non-English question and the latter its English translation.

We apply KD at two different stages of the ColBERT workflow: (1) relevance score computation ($S_{q,d}$ in Equation 1), and (2) encoding (e.g., $E_q$). Figure 1 depicts the former in detail, where training minimizes the KL divergence between the student’s and teacher’s output softmax distribution (with temperature) over $S_{q,d}^+$ and $S_{q,d}^-$. There is limited availability of labeled training data for CLIR. MT, on the other hand, is a more established area of research that has produced a large amount of parallel text. We seek to exploit parallel corpora in our second KD training stage, where we train the student to compute a representation for a non-English text that closely matches the teacher’s representation of the aligned English text. Crucially, since ColBERT computes a single vector for each individual input token (i.e., a PLM vocabulary item) and not for the entire input text, our algorithm must support distillation at the token level.

To achieve this, we apply an iterative cross-lingual alignment algorithm. Assuming $(n e_1, ..., n e_S)$ to be the ordered tuple of tokens in a non-English text and $(e_1, ..., e_T)$ the corresponding tuple from the aligned English text, each iteration of this algorithm greedily aligns the next $(n e_i, e_j)$ pair with the highest cosine similarity of their output embeddings. Algorithm 1 implements this idea by repositioning the teacher’s tokens so that they are position-wise aligned with the corresponding student tokens. Note that the design choice of using a common multilingual PLM in the teacher and the student, even though the former is tasked only with handling English content, is key for the operation of this algorithm as it relies on the pre-trained PLM’s multilingual representations.

In addition to cross-lingual alignment, we also perform a similar KD procedure in which both the teacher and the student are shown the same English text. This step is useful because ColBERT uses a shared encoder for the query and the document, necessitating a student that is able to effectively encode text of both English documents and non-English queries.

Using the alignment information, we train the student by minimizing the Euclidean distance between its representation of a token (English or non-English) and the teacher’s representation of the corresponding English token. Figure 2 shows the KD process for representation learning.

3 Experiments and Results

3.1 Datasets

Our primary CLIR dataset is XOR-TyDi (Asai et al., 2021a), which consists of examples in seven typologically diverse languages: Arabic, Bengali, Finnish, Japanese, Korean, Russian and Telugu. The official training set contains 15,221 natural language queries, their short answers, and examples
Table 1 compares the performance of our models measured by their R@5kt scores. The baseline underperforms the MT → English IR pipeline by 28.6 points. KD with parallel corpus on the output representations followed by XOR triples on the query-passage relevance scores achieves an overall improvement of 25.4 points for the baseline model, which, quite impressively, is only 3.2 points behind the teacher’s score.

3.3 Ablation Study

To study the effect of the two different KD operations on our student model’s performance, we train two additional students. Each of these students goes through only one of the two KD training steps. Table 2 summarizes the results: KD with only CLIR examples and only the parallel corpus improves the system’s score by 15.9 and 20.9 points, respectively. Interestingly, although the parallel corpus does not contain any IR signal, it contributes more to the final performance of our model. These results also suggest that our cross-lingual alignment algorithm does indeed produce useful alignments.
4 Conclusion

We show that without the help of machine translation (MT) at inference time, the accuracy of a state-of-the-art IR framework on cross-lingual IR drops considerably. As a solution, we propose new algorithms to distill the knowledge of a teacher model that performs monolingual IR on MT output into a cross-lingual student model capable of operating without MT. We utilize knowledge distillation (KD) for both IR and text representation, and present (for the latter) a novel cross-lingual alignment algorithm that only relies on the underlying masked language model’s multilingual representation capabilities. In empirical evaluation, our student model recovers most of the performance drop due to operating in a single-pass cross-lingual mode. Future work will explore, among other ideas, zero-shot application of our models to new datasets and utilization of our approach for end-to-end QA.

References

Akari Asai, Jungo Kasai, Jonathan Clark, Kenton Lee, Eunsol Choi, and Hannaneh Hajishirzi. 2021a. XOR QA: Cross-lingual Open-Retrieval Question Answering. In NAACL.

Akari Asai, Xinyan Yu, Jungo Kasai, and Hannaneh Hajishirzi. 2021b. One question answering model for many languages with cross-lingual dense passage retrieval. In NeurIPS.

Martin Braschler, Jürgen Krause, Carol Peters, and Peter Schäuble. 1999. Cross-language information retrieval (clir) track overview. In TREC. Citeseer.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised Cross-lingual Representation Learning at Scale. In ACL.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In NAACL.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2014. Distilling the knowledge in a neural network. In NeurIPS Deep Learning Workshop.

Zhuolin Jiang, Amro El-Jaroudi, William Hartmann, Damianos Karakos, and Lingjun Zhao. 2020. Cross-lingual information retrieval with bert. arXiv preprint arXiv:2004.13005.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP).

Omar Khattab, Christopher Potts, and Matei Zaharia. 2021. Relevance-guided supervision for openqa with colbert. Transactions of the ACL.

Omar Khattab and Matei Zaharia. 2020. Colbert: Efficient and effective passage search via contextualized late interaction over bert. In SIGIR.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Matthew Kelcey, Jacob Devlin, Kenton Lee, Kristina N. Toutanova, Liion Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. Transactions of the Association of Computational Linguistics.

Shadi Saleh and Pavel Pecina. 2019. An Extended CLEF eHealth Test Collection for Cross-Lingual Information Retrieval in the Medical Domain. In European Conference on Information Retrieval.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Azadeh Shakyery and ChengXiang Zhai. 2013. Leveraging comparable corpora for cross-lingual information retrieval in resource-lean language pairs. Information retrieval, 16(1):1–29.

Peng Shi, Rui Zhang, He Bai, and Jimmy Lin. 2021. Cross-lingual training of dense retrievers for document retrieval. In Proceedings of the 1st Workshop on Multilingual Representation Learning, pages 251–253.
### A Appendix

Following are the hyperparameter combinations used in our different models. They were selected based on performance on the validation set.

| Parameter                     | Value |
|-------------------------------|-------|
| **Parameters in ColBERT model** |       |
| batch size                    | 192   |
| accumsteps                    | 6     |
| linear transfer dim           | 128   |
| query_maxlen                  | 32    |
| doc_maxlen                    | 180   |
| **Parameters in regular training** |       |
| lr(NQ)                        | 1.5e-6|
| lr(XOR)                       | 6e-6  |
| Epochs(NQ)                    | 1     |
| Epochs(XOR)                   | 5     |
| **Parameters in distillation** |       |
| loss(XOR/Synthetic data)      | KLDiv |
| loss(Parallel corpus)         | MSE   |
| temperature(XOR)              | 2     |
| temperature(Synthetic data)   | 4     |
| lr(XOR)                       | 6e-6  |
| lr(Synthetic data)            | 1.5e-6|
| lr(Parallel corpus)           | 4.8e-5|
| Epochs(XOR)                   | 5     |
| Epochs(Synthetic data)        | 1     |
| Epoches(Parallel corpus)      | 2     |

Table 3: Hyper-parameters used in our test set runs.