Multilingual ColBERT-X

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Abstract
ColBERT-X is a dense retrieval model for Cross Language Information Retrieval (CLIR). In CLIR, documents are written in one natural language, while the queries are expressed in another. A related task is multilingual IR (MLIR) where the system creates a single ranked list of documents written in many languages. Given that ColBERT-X relies on a pretrained multilingual neural language model to rank documents, a multilingual training procedure can enable a version of ColBERT-X well-suited for MLIR. This paper describes that training procedure. An important factor for good MLIR ranking is fine-tuning XLM-R using mixed-language batches, where the same query is matched with documents in different languages in the same batch. Neural machine translations of MS MARCO passages are used to fine-tune the model.

1 Introduction
ColBERT (Khattab and Zaharia, 2020) is a dense retrieval model for performing retrieval over English documents with queries written in English. It is designed as a two-stage retrieval model that (1) selects a set of candidate passages using an approximate nearest neighbor approach and (2) ranks those passages based on the most similar terms to each term in the query.

Nair et al. (2022) generalized the ColBERT (Khattab and Zaharia, 2020) model to Cross Language Information Retrieval (CLIR), calling it ColBERT-X, by modifying the vocabulary space and replacing the monolingual pretrained language model with XLM-R Large (550M parameters) (Conneau et al., 2020), a Multilingual Pretrained Language Model (MPLM). ColBERT-X combines three key ideas. Drawing insight from BERT (Devlin et al., 2019), it represents documents using contextualized embeddings, with the embedding for each term instance influenced by that instance’s context. Contextual embeddings better represent meaning than simple term occurrence. Leveraging both multilinguality and improved pre-training from XLM-R (Conneau et al., 2020), ColBERT-X seeks to generate similar contextual embeddings for terms used with similar meanings, regardless of their language. Drawing its structure from ColBERT (Khattab and Zaharia, 2020), ColBERT-X limits ranking latency by separating query and document transformer networks to support offline indexing. ColBERT scores documents by focusing query term attention on the most similar contextual embedding in each document. With proper training, ColBERT-X achieves state-of-the-art effectiveness in CLIR.

This paper extends ColBERT-X (Nair et al., 2022) to perform multilingual information retrieval (MLIR). For this task, we modify the ColBERT-X implementation, which is based on the ColBERTv1 code base, with our proposed fine-tuning approach. We show that extending the ColBERT-X (Nair et al., 2022) Translate-Train (TT) CLIR model to multiple languages achieves state-of-the-art performance for MLIR on long queries.

2 Related Work
The term “multilingual” has been used in several ways in IR. Hull and Grefenstette (1996), for example, note that it has been used to describe monolingual retrieval in multiple languages, as in Blloshmi et al. (2021), and it has been used to describe CLIR tasks that are run separately in several languages (Lawrie et al., 2022; Braschler, 2001, 2002, 2003; Mitamura et al., 2008). In this paper we adopt the original Cross-Language Evaluation Forum (CLEF)’s meaning of MLIR: using a query in a single language to construct one ranked list in which each document is in one of several languages. We note that this definition excludes mixed-language queries and mixed-language doc-
Five broad approaches to MLIR have been tried. Among the earliest, Rehder et al. (1997) repre-
sented English, German and French documents in a learned trilingual embedding space, they repre-
sented the query in the same embedding space, and then they computed query-document similarity in that embedding space. The techniques and training data for creating multilingual embeddings were, however, too limited at the time to get good results from that technique. More recently, Sorg and Cimiano (2012) garnered substantial attention by training embeddings on topically-related Wikipedia pages in English, German, French and Spanish. Our work in this paper extends this line of work.

A second approach by Nie and Jin (2002) in-
volved indexing terms from all documents in their original language and then creating queries in which translations of the query terms in all of those languages were present. With a large num-
ber of languages, this can lead to long and diluted queries.

A third approach is to translate indexed terms into the query language at indexing time; the original queries can then be used directly to find similar (translated) content (Magdy and Jones, 2011; Granell, 2014; Rahimi et al., 2015). A limitation of this approach is that it is only practical when relatively few query languages are to be supported.

To address that limitation, the second and third approaches can be combined to create a fourth approach in which documents are each converted into one of a small number of indexing languages, and then the query terms are translated into each of those languages. This has been called the “pivot language” approach, because in the limit case, all documents can be translated into one language and then all queries can be translated into that same single language.

The fifth approach, the one that has garnered the most attention, is to first use monolingual or bilingual CLIR systems, as appropriate, to create ranked lists for each document language, and then to merge those ranked lists to construct a single result set (Peters et al., 2012; Si et al., 2008; Tsai et al., 2008). While this approach is archi-
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tecturally similar to collection sharding, a widely used approach to address efficiency, differences in collection statistics result in incompatible scores that require normalization prior to performing late fusion, and normalizing scores for collections in different languages has been shown to be challenging (Peters et al., 2012).

Finally, an alternative to constructing a single ranked list is to simply show one ranked list per language to the user, as is done in the 2lingual search engine. Of course, that approach does not scale well beyond a small number of languages, but it does have the advantage of making it fairly clear to the searcher what the search engine has done.

3 Fine-Tuning ColBERT-X for MLIR

In this section, we introduce two fine-tuning methods for generalizing ColBERT-X to MLIR. Both approaches leverage existing MPLMs such as multilingual BERT (Devlin et al., 2019) or XLM-
R (Conneau et al., 2020) to encode queries and documents in multiple languages. We adapt the
MPLM to MLIR via task-specific fine-tuning.

Consider a set of queries in language $L_s$ and a set of documents in $m$ languages $L = \bigcup_{i=1}^{m} L_i$. We want to train a scoring function $M(\theta(q,s), d(l)) \rightarrow \mathbb{R}^m$ for ranking documents with respect to a query. In this paper, we denote an instance with a sub-
script as $\bullet(i)$ to indicate its language.

3.1 Multilingual Translate Training (MTT)

Since the MPLMs are capable of encoding text in a variety of languages, we want to fine-tune the model to improve its ability to match across lan-
guages. We leverage the translate-train approach from Nair et al. (2022).

Specifically, we propose a Multilingual Translate-Train (MTT) approach that gen-
eralizes the Translate-Train (TT) approach. To expose target languages $L_1...L_m$ to the model, we translate the documents in the monolingual training data into each document language using machine translation. The training objective can be expressed as

$$\Theta = \arg \min_{\theta} \sum_{q,s} \sum_{l=1}^{m} \mathcal{L}_{\theta}(q(s), d(l), r_{q,d})$$

where $q(s)$ is the representation of the queries in language $s$, $d(l)$ is the representation of the doc-
ments in some language $l \in L$, and $r_{q,d}$ is the

\footnote{https://www.2lingual.com/}
relevance judgement of document \(d\) on query \(q\). 

The MTT objective exposes the retrieval model to language pairs that it will potentially see when processing queries, resulting in a more effective and balanced model. We experiment with two batching approaches: Mixed-language (MTT-M) and Single-language (MTT-S). In MTT-M, each batch contains documents in multiple languages, which encourages the model to learn similarity measures for all languages simultaneously. With MTT-S, each batch only contains documents in one language, helping the model to learn retrieval for one language pair at a time. Thus given a fixed batch size, MTT-M will expose the model to fewer queries, but it will learn how to match those queries on documents in all languages \(L\), while MTT-S will expose the model to the matching problem with more queries, but only in a single language.

### 3.2 Training Details

For training data, we use MS MARCO-v1 (Bajaj et al., 2016), a commonly used question-answering collection in English for training neural retrieval models. For MTT, we leverage the publicly available mMARCO translations of MS MARCO (Bonifacio et al., 2021), fine-tuning using the “small training triple” (query, positive and negative document) file released by mMARCO’s creators.

We trained all retrieval models with 4 GPUs (NVIDIA DGX and v100 with 32 GB Memory) with a per-GPU batch size of 32 triples for 200,000 update steps. All models are trained with half-precision floating points and optimized by the AdamW optimizer with a learning rate of \(5 \times 10^{-6}\).

During indexing, documents are separated into overlapping spans of 180 tokens with a stride of 90 (Nair et al., 2022). We aggregate by MaxP (Bendersky and Kurland, 2008; Dai and Callan, 2019), which takes the maximum score among the passages in a document as the document score. Our experiments are performed with ColBERT-X, which extends ColBERT-v1 code base\(^2\).

### 4 Experiments

One of the few test collections that supports MLIR evaluation with relevance judgments across multiple languages is from the Cross-Language Evaluation Forum (CLEF). Following Rahimi et al. (2015), we use five document languages in the CLEF 2001-2002 collection (Braschler, 2001, 2002) and four languages in the CLEF 2003 collections (Braschler, 2003). Table 1 shows collection statistics. We report performance for both title and title+description queries, also following Rahimi et al. (2015). Because we are limited in the number of subwords when we encode a query for dense retrieval, we remove stop structure to ensure that no query exceeds the length limit. Stop structure includes phrases such as “Find documents” and a limited stop-word list including “on,” “the,” and “and.”

We use the state-of-the-art MULM (Rahimi et al., 2015) system as a baseline. MULM aligns document tokens with the query language in a probabilistic manner.

To evaluate the effectiveness on multiple languages in CLEF 2001-2002 and CLEF 2003, we combine the relevance judgments (qrels) for all languages for each query. In general, different languages have different numbers of relevant documents for each query. Our main effectiveness measures are Mean Average Precision (MAP) and Precision at 10 (P@10). Both measures focus on the top of the rankings, and both were used by Rahimi et al. (2015), facilitating comparison between our approach and their prior state-of-the-art.

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\(^2\)https://github.com/stanford-futuredata/ColBERT/tree/colbertv1
Table 2: MAP and P@10 on CLEF T and T+D queries. Bold are best among a year; † indicates significant improvement of MTT-M over MTT-S by a paired t-test with 3-test Bonferroni correction ($p < 0.05$).

| Query Set | MAP | P@10 |
|-----------|-----|------|
| MULM     | MTT-M | MTT-S |
| MULM     | MTT-M | MTT-S |
| Title Queries | | |
| 2001 | 0.370 | 0.360† | 0.324 | 0.682 | 0.600 | 0.572 |
| 2002 | 0.305 | 0.352† | 0.325 | 0.616 | 0.614 | 0.608 |
| 2003 | 0.331 | 0.373 | 0.355 | 0.512 | 0.546 | 0.580 |
| All | 0.335 | 0.362† | 0.336 | 0.603 | 0.584 | 0.586 |
| Title + Description Queries | | |
| 2001 | 0.387 | 0.462† | 0.422 | 0.700 | 0.704 | 0.696 |
| 2002 | 0.347 | 0.462† | 0.405 | 0.666 | 0.752 | 0.702 |
| 2003 | 0.376 | 0.461† | 0.433 | 0.563 | 0.653 | 0.649 |
| All | 0.368 | 0.461† | 0.421 | 0.643 | 0.700 | 0.679 |

Results. We use trec_eval \(^3\) to compute all effectiveness measures.

5 Results

We evaluate our Multilingual Translation Training (MTT) approach against MULM, which represent the state of the art on our test collections. Since per-query results for MULM are not available, we perform significance tests only between our two batching approaches described in Section 3.1.

Our main effectiveness results are shown in Table 2. ColBERT-X MTT-M performs similarly to MULM when searching with short title queries. With longer, more fluent title+description queries, ColBERT-X MTT-M gives a larger improvement over MULM in both MAP and P@10, indicating that XLM-R favors queries with more context. Thus ColBERT-X MTT-M improves upon the state of the art for long queries.

We compare the two alternatives for fine-tuning the MTT condition and summarize the results in Table 2. In almost all cases, Mixed-language batches (MTT-M) produce statistically significant improvements in the effectiveness of retrieval models compared to Single-language (MTT-S) in terms of MAP. Given the difference in precision at 10 are never statistically significant, the ability to rank relevant documents below the top ten are key to distinguishing the techniques. Despite an intuition that isolating the effect of each query-document language pair might lead to more stable gradients, MTT-S is less capable of learning from multiple languages. This is likely because, in MLIR, the model must rank documents from different languages together instead of transferring trained models to other languages. The outcome might be different if our goal were to perform CLIR over monolingual document collections.

6 Conclusion

In this paper, we propose a training approach, MTT, that uses translated MS MARCO as a basis for MLIR. Fine-tuning with MTT using mixed-language batches (MTT-M) enables ColBERT-X to be more effective when searching documents in other languages than if fine-tuned using single-language batches.

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\(^3\)https://trec.nist.gov/trec_eval/
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