mRobust04: A Multilingual Version of the TREC
Robust 2004 Benchmark

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Abstract

Robust 2004 is an information retrieval benchmark whose large number of judgments per query make it a reliable evaluation dataset. In this paper, we present mRobust04, a multilingual version of Robust04 that was translated to 8 languages using Google Translate. We also provide results of three different multilingual retrievers on this dataset. The dataset is available at https://huggingface.co/datasets/unicamp-dl/mrobust

1 Introduction

A key ingredient in the development of information retrieval algorithms are reusable evaluation datasets [7, 19, 20]. For English, there are a number of such datasets. For other languages, there are initiatives such as TREC CLIR [17], CLEF [13, 4–6], FIRE [12, 11], NTCIR [16] and more recently HC4 [9]. A common problem with these multilingual IR datasets is their low number of judgments per query, that is, the number of documents marked as relevant or not relevant per query. For example, in the multilingual datasets mMARCO [3] and Mr.Tydi [21], there is only one or two documents manually marked as relevant per query. These "sparse" annotations, we argue, prevent correct evaluations of retrieval methods. For example, the RM3 query expansion method evaluated on the MS MARCO benchmark [1], which uses sparse annotations, shows no improvement over baselines such as BM25 [10]. However, the same method shows significant improvements over BM25 when evaluated on densely annotated benchmarks, such as TREC-DL.

In this work, to mitigate the issue with sparse annotations on multilingual IR datasets, we translate the TREC’s Robust 2004 benchmark [18], an English dataset with a high number of judgments, to 8 languages using a high-quality automatic translator. We call this dataset mRobust04.

In Table 1 we compare mRobust04 with other multilingual IR datasets. Despite having a modest number of queries and documents, mRobust04 has much more annotations per query, which, we conjecture, makes it a reliable benchmark for evaluating future multilingual retrieval models. We also evaluate on this dataset two multilingual models that are close to the state of the art.

2 Translation Methodology

Robust04 is an English news dataset whose documents are in a single file, divided by <DOC> tags. Regular expressions were used to delimit and extract relevant text from each document within the file, and BeautifulSoup was used to clean any HTML tags that may have remained.

After that, we fed Robust04’s queries and corpus to the Google Translate API to translate to the following languages: Chinese, French, German, Indonesian, Italian, Portuguese, Russian and Spanish. Some documents had more characters than the maximum allowed by the API, so we used the nltk’s [2] sentence tokenizer to split them into chunks of acceptable sizes and send them indepen-
Table 1: Comparison of mRobust04 with other multilingual IR datasets. “MT” refers to whether the dataset was machine translated or not. J/q is the average number of judgments per query per language.

| Dataset         | MT | Langs | Queries | Docs   | J/q |
|-----------------|----|-------|---------|--------|-----|
| Mr. Tydi        | No | 11    | 2k-16k  | 136k-32M | 1.03 |
| mMARCO          | Yes| 14    | 540k    | 8.8M   | 1.06 |
| CLEF 2001-2003  | No | 5     | 50-60   | 87k-454k | 27.93 |
| HC4             | No | 3     | 54-60   | 486k-4.7M | 54.36 |
| TREC-8 CLIR     | No | 4     | 28      | 62k-242k | 206.75 |
| mRobust04 (ours)| Yes| 9     | 249     | 528k   | 1250.60 |

Table 2: Main results in the mRobust04 dataset. mT5 and mColBERT were finetuned on mMARCO.

| en | fr | pt | it | id | ru | es | de | zh | avg |
|----|----|----|----|----|----|----|----|----|-----|
| nDCG@20 |
| BM25 | 0.389 | 0.389 | 0.389 | 0.387 | 0.372 | 0.364 | 0.333 | 0.289 | 0.367 |
| mT5  | 0.466 | 0.376 | 0.391 | 0.384 | 0.374 | 0.372 | 0.402 | 0.375 | 0.358 | 0.389 |
| mColBERT | 0.362 | 0.302 | 0.323 | 0.305 | 0.287 | 0.265 | 0.309 | 0.280 | 0.262 | 0.300 |

| nDCG'@20 |
| BM25 | 0.394 | 0.418 | 0.409 | 0.411 | 0.407 | 0.403 | 0.394 | 0.372 | 0.349 | 0.396 |
| mT5  | 0.486 | 0.429 | 0.439 | 0.436 | 0.432 | 0.431 | 0.454 | 0.435 | 0.418 | 0.440 |
| mColBERT | 0.414 | 0.383 | 0.401 | 0.390 | 0.379 | 0.367 | 0.348 | 0.389 | 0.361 | 0.345 | 0.377 |

| R@1000 |
| BM25 | 0.649 | 0.655 | 0.657 | 0.628 | 0.649 | 0.627 | 0.640 | 0.514 | 0.517 | 0.616 |
| mColBERT | 0.597 | 0.526 | 0.549 | 0.525 | 0.510 | 0.475 | 0.547 | 0.503 | 0.423 | 0.518 |

3 Evaluation

We evaluate a sparse model (BM25), a dense model (mColBERT) and a reranker (mT5) on mRobust04. We use mT5 and mColBERT finetuned on mMARCO as provided by Bonifacio et al. and evaluate them on mRobust04 in a zero-shot manner.

Inference in each language was performed by creating windows of sentences, with Spacy, of maximum 10 and stride of 5 for both mT5 and mColBERT, since their maximum tokenized length is lower than most documents in the corpus. The sparse first-stage retrieval, BM25, is not limited by a maximum length; therefore, the corpus was indexed without any windowing.

We report nDCG@20 and R@1000. In preliminary experiments, we observed that mT5 and mColBERT have 6% and 20% fewer judged documents on average in their top 20 compared to BM25. Therefore we also report nDCG’ (i.e., nDCG “prime”) [15], which does not penalize the model for retrieving unjudged query-document pairs.

The results are shown in Table 2. Except for the Chinese language, the nDCG@20 results for BM25 in each language are very close to English, indicating that our automatic translation was able to retain the information present in the original documents successfully. The average nDCG@20 of the mT5 reranker slightly surpasses BM25’s. Looking at nDCG’@20, mT5 shows clear improvements over BM25. This suggests that there is a non-negligible amount of documents in top 20 reranked by mT5 that are relevant but were not annotated.

We expected the dense model, mColBERT, to be worse than the mT5 model and better than BM25 as observed by Bonifacio et al. [3]. This is because mColBERT would be able to overcome the lexical
matching problem that BM25 suffers from, as dense models could potentially represent semantically similar words closer to each other in the indexed embedding space. However, mColBERT did not perform well on mRobust04, staying behind both models for all metrics and languages. One possibility is that mColBERT is “overfitted” to mMARCO and was unable to generalize to a new domain. Another explanation is similar to that proposed by Rosa et al. [14]: dense retrievers show great in-domain effectiveness but poor out-of-domain generalization. However, rigorously testing this hypothesis for the multilingual scenario is beyond the scope of this work.

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