Abstract

Tokenization is a crucial step in information retrieval, especially for lexical matching algorithms, where the quality of indexable tokens directly impacts the effectiveness of a retrieval system. Since different languages have unique properties, the design of the tokenization algorithm is usually language-specific and requires at least some linguistic knowledge. However, only a handful of the 7000+ languages on the planet benefit from specialized, custom-built tokenization algorithms, while the other languages are stuck with a “default” whitespace tokenizer, which cannot capture the intricacies of different languages. To address this challenge, we propose a different approach to tokenization for lexical matching retrieval algorithms (e.g., BM25): using the WordPiece tokenizer, which can be built automatically from unsupervised data. We test the approach on 11 typologically diverse languages in the Mr. TyDi collection: results show that the mBERT tokenizer provides strong relevance signals for retrieval “out of the box”, outperforming whitespace tokenization on most languages. In many cases, our approach also improves retrieval effectiveness when combined with existing custom-built tokenizers.

1 Introduction

A fundamental assumption in information retrieval (IR) is the existence of some mechanism that converts documents into sequences of tokens, typically referred to as tokenization. These tokens comprise the index terms that are used to compute query–document scores when matching search queries to relevant documents in lexical matching techniques such as BM25 (Robertson and Zaragoza, 2009).

Some of the operations involved in tokenization for the purposes of IR include case folding, normalization, stemming, lemmatization, stopwords removal, etc. The algorithms used to perform these operations do not generalize across languages because each language has its own unique features, and are different from one other in terms of their lexical, semantic, and morphological complexities. While there has been work on data-driven and machine-learned techniques—for example, to stemming (Majumder et al., 2007; Hadni et al., 2012; Jonker et al., 2020)—for the most part researchers and practitioners have converged on relatively simple and lightweight tokenization pipelines. For example, in English, the Porter stemmer is widely used, and many systems share stopwords list.

How common is this scenario? One way to characterize the extent of this challenge is to count the number of language-specific tokenizers (called “analyzers”) in the Lucene open-source search library, which underlies search platforms such as Elasticsearch, OpenSearch, and Solr. As of Lucene 9.3.0, the library provides 42 different language-specific analyzers, which cover only a tiny fraction of the commonly cited figure of 7000+ languages that exist on this planet. It is clear that for most languages, language-specific analyzers don’t even exist.

Subword algorithms are actively studied in the context of pretrained language models to alleviate the out-of-vocabulary issue in NLP model training. Representatives include WordPiece (Wu et al., 2016) and SentencePiece (Kudo and Richard-
son, 2018). They are initially applied to English data (Devlin et al., 2019), then extended to multilingual application scenarios (Devlin et al., 2019; Conneau et al., 2019). For example, the multilingual BERT (mBERT) tokenizer is a WordPiece (Wu et al., 2016) algorithm trained on Wikipedia in 100 languages, comprising 110k vocabulary.

While these tokenizers are actively used as part of pretrained language models in IR, they have not been systematically applied independently as an alternative tokenization approach for lexical matching retrieval algorithms. However, subword tokenizers have many advantages over expert-designed analyzers and whitespace tokenization. Compared to analyzers, the tokenizers can be trained automatically, requiring no expert knowledge of the target language. Additionally, the training is performed on unsupervised data, which could be plentiful even for lower-resource languages. Compared to whitespace tokenization, we show that subword tokenizers can achieve better retrieval effectiveness. Moreover, it has been reported that subword tokenizers are less sensitive to misspellings and other irregularities, and can better handle compound words and proper nouns (Zhang and Tan, 2021).

In this paper, we propose to improve retrieval for languages that lack language-specific analyzers using the WordPiece tokenizer. Our results on 11 diverse languages in the Mr. TyDi test collection (Zhang et al., 2021) show that using the WordPiece tokenizer in a lexical matching algorithm consistently outperforms whitespace tokenization, and is even comparable to language-specific Lucene analyzers for some languages. Additionally, our tokenization approach can be combined with existing Lucene analyzers to further improve retrieval effectiveness.

## 2 Background and Related Work

Exploring different text representations to improve retrieval in different languages is an active area of research. Leveling and Hartrumpf (2004) compared different indexing and matching techniques on different levels of abstraction for a document representation in German. Jiang and Zhai (2007) explored different tokenization heuristics to improve biomedical information retrieval.

At the same time, while in recent years IR has widely adopted pretrained models from NLP, there is little work investigating tokenization in IR tasks using these models. To the best of our knowl-

| Language  | ISO | Language Family | Lucene Analyzer       |
|-----------|-----|-----------------|-----------------------|
| Arabic    | ar  | Afro-Asiatic    | ArabicAnalyzer        |
| Bengali   | bn  | Indo-European   | BengaliAnalyzer       |
| English   | en  | Indo-European   | EnglishAnalyzer       |
| Finnish   | fi  | Uralic          | FinnishAnalyzer       |
| Indonesian| id  | Austronesian     | IndonesianAnalyzer    |
| Japanese  | ja  | Japonic         | JapaneseAnalyzer      |
| Korean    | ko  | Koreanic        | KoreanAnalyzer        |
| Russian   | ru  | Indo-European   | RussianAnalyzer       |
| Swahili   | sw  | Niger-Congo     |                       |
| Telugu    | te  | Dravidian       | TeluguAnalyzer        |
| Thai      | th  | Kra-Dai         | ThaiAnalyzer          |

Table 1: Language and analyzer information: The ISO-639 code, language family, and the corresponding Lucene (v9.3.0) analyzer for each language used in our experiments. Note that all languages except for Swahili (sw) have a custom language-specific analyzer.

edge, Zhang and Tan (2021) is the only work in this line. They compared different granularities of multilingual textual representations in a traditional IR system (e.g., BM25). Specifically, they compared the results of tokens produced by the Lucene analyzer in the corresponding language, the SentencePiece (Kudo and Richardson, 2018) tokenizer, and directly using characters. However, the authors focused on the cross-lingual retrieval task and only explored three high-resource languages (i.e., German, French, and Japanese), where SentencePiece tokenization was found to be underwhelming when applied to BM25 alone.

## 3 Experimental Design

### Dataset

In this work, we evaluate results on Mr. TyDi (Zhang et al., 2021), a multilingual retrieval benchmark that extends the TyDi QA dataset (Clark et al., 2020). It provides manually labeled data for monolingual retrieval on 11 typologically diverse languages. In Mr. TyDi, queries are questions posed by native speakers of the corresponding languages, and the collection is built from Wikipedia in the same language.

### Tokenizers

We use the BM25 implementation in Anserini (Yang et al., 2017, 2018) with default parameters ($k_1 = 0.9$, $b = 0.4$). We compare three tokenization mechanisms: whitespace, a language-specific Lucene analyzer, and the mBERT tokenizer. Table 1 provides details on the Lucene analyzers used in work. Specifically, we use the Porter stemmer and the default stopwords list for English. We use the mBERT3 (Devlin et al., 2019)

3bert-base-multilingual-uncased on HuggingFace (Wolf et al., 2020)
Table 2: Results of BM25 on the test set of Mr. TyDi, using different tokenization mechanisms: (1) whitespace, (2) a language-specific Lucene analyzer, (3) the mBERT tokenizer, and (4) a fusion of (2) and (3). For Swahili (sw), Lucene does not provide a custom language-specific analyzer. Latin-script languages are marked with ✓, otherwise with X.

*For sw, fusion is based on (1) and (3), as (2) is not available.

Figure 1: Bar chart of normalized MRR@100 from Table 2. Scores of all languages except for sw (left) are normalized based on the MRR@100 of the Lucene analyzer, with the normalized scores of the Lucene analyzer set to 1.0 (orange bars). Scores of sw (right) are normalized based on the MRR@100 of the whitespace tokenizer, with the normalized score of whitespace tokenization set to 1.0 (blue bars).

4 Results

We now examine the effectiveness of the WordPiece tokenizer over languages in different scripts and with diverse typological features. Table 2 shows BM25 results with multiple tokenization mechanisms on the test set of Mr. TyDi: (1) whitespace, (2) a language-specific Lucene analyzer, (3) the mBERT tokenizer, and (4) a hybrid of rows (2, 3).

As the scale of MRR@100 varies across lan-
languages, Figure 1 plots the normalized MRR@100 to better demonstrate the relative effectiveness of the tokenization mechanisms. For all languages but sw (Figure 1 left), scores are normalized based on the MRR@100 of the Lucene custom language-specific analyzer. That is, for each language, the score of the Lucene analyzer is set to 1.0, and the other scores are scaled appropriately. For sw (Figure 1 right), all scores are normalized based on its whitespace score since a language-specific Lucene analyzer is not available.

Comparing results of BM25 using the mBERT tokenizer (row 3) to whitespace (row 1), we observe that the mBERT tokenizer wins on 7 out of 11 languages, including sw. This is promising, as it indicates that when a Lucene analyzer is not available and whitespace is the only option for tokenization, the WordPiece tokenizer offers a simple approach that potentially yields effective results. Note that all four cases where the mBERT tokenizer performs worse are on non-Latin-script languages.

Next, comparing the mBERT tokenizer to the language-specific Lucene analyzer (row 2), we observe that the effectiveness gap varies greatly across languages. For languages such as English (en) and Russian (ru), BM25 with the mBERT tokenizer obtains similar or even slightly better effectiveness compared to the language-specific Lucene analyzer, and much higher scores compared to whitespace tokenization. At the other end of the spectrum, for languages such as Telugu (te) and Thai (th), BM25 with the mBERT tokenizer does not even generate reasonable outputs, yielding scores that are not only substantially worse than using Lucene’s custom language-specific analyzer but even whitespace tokenization.

We further explore the reasons behind the largely varied effectiveness gap and found that the relative effectiveness of mBERT to Lucene analyzer is correlated to the size of Wikipedia. This is shown in Figure 2, where the x-axis shows the size of Wikipedia of each language in log scale, and the y-axis shows the normalized MRR@100 of the mBERT tokenizer as in Figure 1. The Pearson Correlation coefficient is indicated as r.

We use the “number of articles” provided by https://en.wikipedia.org/wiki/Wikipedia:Multilingual_statistics to indicate the size of Wikipedia in each language.

![Figure 2: A clear correlation between Wikipedia size and the normalized MRR@100 of the mBERT tokenizer. All languages but sw are included. In the figure, x-axis shows the Wikipedia size of each language in log scale, and y-axis shows the normalized MRR@100 of mBERT as in Figure 1. The Pearson Correlation coefficient is indicated as r.](image)

etc. These factors might differ across languages, but normalization can nicely offset these differences. The figure shows a clear correlation between the Wikipedia size and the relative effectiveness of mBERT compared to a custom Lucene analyzer: the larger the Wikipedia size, the higher the relative effectiveness of mBERT tokenization.

However, as shown by the results of fusing the Lucene analyzer and the mBERT tokenizer, row (4), even when mBERT does yield higher scores than the Lucene analyzer by itself, it generally does not hurt effectiveness, and even improves the scores in some cases (e.g., ru, fi, ja). This finding, however, does not appear to apply to te and th, where the scores of the mBERT tokenizer are extremely low (see Table 2).

5 Conclusion

In this paper, we propose to directly apply the WordPiece tokenizer in lexical matching information retrieval algorithms. This mechanism is especially useful for low-resource languages that lack language-specific tokenization algorithms handcrafted by language experts.

We evaluate this mechanism on 11 typologically diverse languages. Results show that splitting text into subwords using the mBERT tokenizer “out of the box” provides a promising alternative to whitespace tokenization, and even beats the custom Lucene analyzer for some languages. For lan-
guages where the mBERT tokenizer achieves good scores, it can be combined with existing Lucene analyzers to provide additional effectiveness gains. For low-resource languages that lack effective tokenization algorithms, we hope this work could be helpful for building robust baselines.

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