WIKIR: A Python toolkit for building a large-scale Wikipedia-based English Information Retrieval Dataset

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Abstract
Over the past years, deep learning methods allowed for new state-of-the-art results in ad-hoc information retrieval. However such methods usually require large amounts of annotated data to be effective. Since most standard ad-hoc information retrieval datasets publicly available for academic research (e.g. Robust04, ClueWeb09) have at most 250 annotated queries, the recent deep learning models for information retrieval perform poorly on these datasets. These models (e.g. DUET, Conv-KNRM) are trained and evaluated on data collected from commercial search engines not publicly available for academic research which is a problem for reproducibility and the advancement of research. In this paper, we propose WIKIR: an open-source toolkit to automatically build large-scale English information retrieval datasets based on Wikipedia. WIKIR is publicly available on GitHub. We also provide wikIR59k: a large-scale publicly available dataset that contains 59,252 queries and 2,617,003 (query, relevant documents) pairs.

Keywords: Information Retrieval, Open Source, Dataset, Deep Learning

1. Introduction
Deep learning has been shown to be effective in various natural language processing (NLP) tasks such as language modeling, reading comprehension, question answering and natural language understanding (Devlin et al., 2019; Yang et al., 2019b). However, both large and public datasets are key factors for developing effective and reproducible deep learning models.

Ad-hoc information retrieval (IR) consists in ranking a set of unstructured documents with respect to a query. Despite the progress in NLP using deep neural networks (DNNs), ad-hoc IR on text documents has not benefited as much as other fields of NLP from DNNs yet (Dehghani et al., 2017). The absence of significant success in ad-hoc IR using deep learning approaches is mainly due to the complexity of solving the ranking task using only unlabelled data (Dehghani et al., 2017). Consequently, the availability of large amount of labelled data is crucial to develop effective DNNs for ad-hoc IR. However, as described in Table 1, most of the publicly available English IR datasets only have few labelled data with at most 1,692 labelled queries.

Other datasets than the ones presented in Table 1 such as Yahoo! LETOR (Chapelle and Chang, 2011), with more labelled data (≈30k labelled queries) are publicly available. However, only the feature vectors describing query-document pairs are provided. Such datasets are suitable for feature-based learning-to-rank models but not for DNNs that require the original content of queries and documents. Thus, most of the deep learning model for ad-hoc IR that have been proposed recently are developed using one of the following approaches:
(1) Using large amounts of data collected from commercial search engines that are not publicly available (Yang et al., 2019a; Mitra et al., 2017). This process is expensive, time consuming and not reproducible.
(2) Using publicly available datasets that have few annotated data such as MQ2007 and MQ2008 (Pang et al., 2017; Fan et al., 2018). This approach can restrain the model design due to the lack of data.
(3) Using weak supervision that consists in pre-training a supervised model on data labelled with an unsupervised (Dehghani et al., 2017). However, this method can bias large models to rank similarly as the unsupervised ranker.

Recently, Zheng et al. (2018) proposed Sogou-QCL, a publicly available dataset in Chinese with click relevance label. To the best of our knowledge, Sogou-QCL is the only publicly available large-scale (∼500k queries) dataset for ad-hoc IR. The release of this dataset was the first step in reproducible research on neural ranking model applied to ad-hoc IR.

Wikipedia has recently been used to build large-scale cross-lingual information retrieval (CLIR) datasets to train effective neural learning-to-rank models (Schamoni et al., 2014). Leveraging this idea, we propose WIKIR: a toolkit to build a Wikipedia-based large-scale English IR dataset. WIKIR can also be used to train and evaluate several deep text matching models on the datasets it created. Moreover, we propose a general framework to build IR datasets automatically from any set of documents constrained by three topical properties that will be introduced further (see Section 2.1).

Our contributions are fourfold:
• We provide WIKIR: a toolkit to build a Wikipedia-based English Information Retrieval dataset;
• We present a framework for creating IR datasets from a set of documents that satisfies three topical properties: Existence, Identifiability and Describability;
• We propose wikIR59k: a large-scale dataset generated with WIKIR, publicly available for download;
• We make provide the Python scripts to train and evaluate deep learning models for ad-hoc IR on our datasets.

https://bit.ly/2XXRG70

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https://bit.ly/2XXRG70
| Dataset   | #Query | #Doc | Avg #d^+/q |
|-----------|--------|------|------------|
| CLEF 2014 | 50     | 1M   | 64.56      |
| ClueWeb09 | 200    | 1B   | 74.62      |
| ClueWeb12 | 100    | 733M | 189.63     |
| GOV2      | 150    | 25M  | 181.51     |
| MQ2007    | 1,692  | 65k  | 10.63      |
| MQ2008    | 784    | 14k  | 3.82       |
| Robust04  | 250    | 0.5M | 63.28      |

Table 1: Statistics of several publicly available English IR Dataset where the original query and document contents are available. Avg #d^+/q denotes the average number of relevant document per query.

2. A general framework for automatic IR dataset creation

In this section, we propose a general framework to create automatically an IR dataset from a resource R composed of a set of documents. An IR dataset is composed of:

- D, a set of documents;
- Q, a set of queries;
- Rel, a set of relevance labels for each query-document pairs (Schütze et al., 2008).

2.1. Properties

We define 3 properties that R must satisfy to be used to build an IR dataset.

Topical Existence. There exists at least one topic related to each document in R. Topical Existence guarantees the topical relevance (Mizsero, 1997) of documents with respect to a subject.

Topical Identifiability. There exists a function identify() that identifies all the topics related to any document of R. Using Topical Identifiability, we can assess the relevance of documents with respect to the topics in R.

Topical Describability. There exists a function describe() that associates every topic with a short and accurate description. Topical Describability is desirable to be able to build queries from the topics in the resource R.

2.2. Dataset construction

In the following, we describe how to use a resource R that satisfies the three properties listed above to automatically construct an IR dataset.

Document construction. We choose a subset of the resource R to construct the set of documents: D ⊆ R. For example, if R is the set of Wikipedia articles, we can choose D to be the set of Wikipedia articles that contain more than 1000 words.

Query construction. We start by identifying all topics in the set of documents D using the identify() function:

\[ \mathcal{T}_D = \bigcup_{d \in D} \text{identify}(d), \]

where \( \mathcal{T}_D \) is the set of all topics in D. Then, we use the describe() function on all of the topic to construct the query set Q:

\[ Q = \{ \text{describe}(t) | t \in \mathcal{T}_D \}. \]

Relevance label construction. Rel is the set of all (query-document-relevance) triplets:

\[ \text{Rel} = \{ (q, d, \text{rel}(q, d)) | (q, d) \in Q \times D \}, \]

with rel() a function that associates every query-document pairs with a relevance label. We propose to assign a positive relevance label (denoted \( \text{val}^+ \)) to document d with respect to query q if d contains the topic that was used to build q. Otherwise a negative or null relevance label (denoted \( \text{val}^- \)) is assigned:

\[ \text{rel}(q, d) = \begin{cases} \text{val}^+ \in \mathbb{R}^+, & \text{if } t_q \in \text{identify}(d), \\ \text{val}^- \in \mathbb{R}^-, & \text{else}, \end{cases} \]

where \( t_q \) stands for the topic that was used to build query q: \( \text{describe}(t_q) = q \).

2.3. The case of Wikipedia

In this subsection we show that the set of English Wikipedia articles \( W \) does satisfy Topical Existence, Describability and Identifiability. A simplified description of the construction process of an IR dataset using 2 articles from Wikipedia is displayed in Figure 1.

Topical Existence. Every Wikipedia article is related to at least one topic: its main subject.

Topical Identifiability. We assume that if an article \( a \) contains an internal link to another article \( a_i \) in its first sentence (denoted \( f_a \)), then the main subject of \( a_i \) is a topic of \( a \). The intuition behind this assumption is that the first sentence of most Wikipedia articles is a good description of the article’s content (Sasaki et al., 2018) and if a link is present, it points to an important topic of the considered article. Therefore, we propose to define identify() as follows:

\[ \text{identify}(a) = \{ s_a \} \bigcup \{ s_{a_i} \in W | \exists f_{a_i} \xrightarrow{\text{link}} a \}, \]

where \( s_a \) denotes the main subject of article \( a \) and \( f_{a_i} \xrightarrow{\text{link}} a \) designs an internal link in the first sentence of article \( a_i \) that points to article \( a \). Thus, identify() considers the set of topics related to article \( a \) as the main subject of \( a \): \( s_a \) and the main subject of all articles that points to \( a \) in their first sentence. For example, the set of topics related to the article Developmental disorder is its main subject and the main subject of the article Autism because there is a link in the first sentence of article Autism that points to article Developmental disorder (see Figure 1).

Topical Describability. Because topics are main subjects of Wikipedia articles, one way to get a short and accurate description is to use the article title:

\[ \text{describe}(s_a) = \text{title}_a, \]

where \( \text{title}_a \) is the title of article \( a \).
As described in Section 2.2, to build Query construction makes the ranking task significantly easier. A relevant document will always start with the query itself which avoids the following situation: given a query, the most relevant document is the one built from the same article as the query. Consequently, we define rel() as:

$$\text{rel}(q, d) = \begin{cases} 2, & \text{if } a_q = a_d, \\ 1, & \text{if } a_q \in \text{identify}(d) \setminus a_d, \\ 0, & \text{otherwise}, \end{cases}$$

where $a_q$ (resp. $a_d$) denotes the Wikipedia article used to build query $q$ (resp. document $d$). Thus we assign a relevance label equal to 2 to two for query-document pairs that come from the same article. We assign a relevance label equal to 1 to a query-document pair if there is a link from the first sentence of the article of the document that points to the article of the query. For example, if we consider the query “Developmental disorder”, the most relevant (relevance = 2) document is “Developmental disorders comprise a group of psychiatric conditions originating in childhood that involve serious impairment in different areas”. These disorders comprise...” because they are built from the same article.

3. WIKIR toolkit description

In this section, we describe WIKIR toolkit and make explicit the motivations behind some design decisions. For an exhaustive list of the options available and to have examples on how to use WIKIR, please check our github repository: [https://github.com/getalp/wikIR](https://github.com/getalp/wikIR).

3.1. WIKIR for dataset creation

To create a dataset using an XML Wikipedia dump file from Wikimedia database backup dumps, WIKIR follows 3 main steps: construction, processing and storing.

3.1.1. Dataset construction

Wikipedia dump extraction. We use WikiExtractor to extract plain text from an English Wikipedia dump. We end up with a json file (described in Figure) that contains the URL, title and text of all Wikipedia articles. When using wikiextractor, we use the option to preserve links in the text in order to build relevance labels.

Document extraction. The set of documents $D$ is extracted using the “text” field associated to each article in the json file produced by the previous step. The first line of the “text” field (that corresponds to the article title) is deleted. We also remove article title from documents in order to avoid the following situation: given a query, the most relevant document will always start with the query itself which makes the ranking task significantly easier.

Query construction. As described in Section 2.2, to build queries we need an identify() function and a describe() function. WIKIR uses the functions defined in equations (1) and (2): topics are identified using internal links and are described using article titles. The construction process of queries is the same as in Section 2.2.

Relevance label construction. As explained in Section 2.2, in order to build $\text{rel}$ we need to define $\text{rel}()$. To do so, we assume that the most relevant document for a query is the document built from the same article as the query. Consequently, we define $\text{rel}()$ as:

![Figure 1: Description of the construction process of an IR dataset by WIKIR using only two articles. Queries are built from the title of articles. Documents are constructed using the full text of articles without the title and without the first sentence. A relevance label equal to 2 is assigned to query and documents that are built from the same article. A relevance label equal to 1 is assigned using internal links in the first sentence of articles.](https://www.example.com/image.png)
3.1.2. Dataset processing

Query selection. In order to have a balanced dataset, we select only queries that have a minimum number of relevant documents (5 by default).

Preprocessing. WIKIR starts by deleting the target in hypertext references (href) but keeps the text. For example, “<a href=""Regressive%20autism"">worsening</a>” becomes “worsening”. Then, every non alphanumerical character is deleted. By default WIKIR also lowerscases all the characters in the dataset.

Separation into training, validation and test sets. Queries and their corresponding relevance label (qrels) are randomly separated into training, validation and test sets. Documents are not separated as well because in ad-hoc IR, we assume to have a fixed set of documents to retrieve from (Baeza-Yates and Ribeiro-Neto, 1999).

3.1.3. Dataset storing

WIKIR creates one folder that contains the set of documents in the file documents.format and three subfolders: training, validation and test. Each of them contains two files:

1) qrels that contains queries relevance labels in the trec_eval format. To limit the size of the qrels file, we only save the positive relevance labels. This means that every query-document pair that is not saved in the qrels is non-relevant.

2) queries.format that contains the queries. By default queries and documents are saved as DataFrame in a csv format compatible with MatchZoo deep text matching toolkit (Guo et al., 2019b). Queries and documents can also be saved in an XML format compatible with Terrier information retrieval system.

3.2. WIKIR for BM25: a first stage ranker

3.2.1. Motivation

After the dataset is created, WIKIR can be used to run Okapi BM25 (Robertson and Walker, 1994): a state-of-the art IR model compatible with an inverted index. An inverted index is a structure to store the documents of an IR dataset that makes the retrieval of documents extremely efficient (Sanderson, 2010). We propose this option because the vast majority of DNNs developed for ad-hoc IR are not compatible with an inverted index (Zamani et al., 2018). They rely on a first ranking stage made by an efficient model such as BM25 and only re-rank the top-k documents for a given query in order to have an efficient search. Thus WIKIR can be used to run BM25 and save the top-k documents for each query.

3.2.2. Implementation

Instead of using a common information retrieval system (IRS) such as Terrier or Lucene or Lemur to run and evaluate BM25 on our dataset, we used the Python library Rank-BM25. We made this decision to facilitate the use of WIKIR and to aid the reproducibility of our experiments that do not require the installation of any software that is not in our GitHub repository. Because Rank-BM25 does not preprocess text, we used nltk Python library (Loper and Bird, 2002) to apply Porter stemmer (Porter, 2001) and stopword removal as commonly done in IR. It should be noted that we applied stemming and stopword removal only for BM25: the queries and documents in the dataset created by WIKIR are not stemmed and do contain stopwords.

3.2.3. Ranking results

BM25 results are saved in the training, validation and test subfolders. Three files are created in each of these subfolders:

1) BM25.res that contains the results of BM25 saved in the trec_eval format.
2) BM25.metrics.json that contains the values of several IR evaluation measures such as Precision, nDCG, MAP and Recall. We used pytrec_eval (Gysel and de Rijke, 2018) to compute these evaluation metrics.
3) BM25.qrels.csv that contains the top-k documents for each query according to BM25 with their associated relevance label.

3.3. WIKIR for neural re-ranking

WIKIR can be used to train and evaluate DNNs on the dataset it created. As explained in Section 3.2, we perform neural re-ranking using BM25 as a first stage ranker. We used MatchZoo deep text matching library for training and evaluation of the models. We used MatchZoo because it has been accepted as a reliable toolkit for deep text matching research (Guo et al., 2019b). Any model available in MatchZoo can be trained and evaluated with WIKIR. Once the training is done and the rankings of documents are saved, our toolkit can be used to compute evaluation measures, statistical significance and display the performance of each model in a format compatible with a \LaTeX\ table.

4. Datasets

In this section, we describe wikIR1k and wikIR59k: the two datasets created by WIKIR that we used in our experiments.

wikIR1k. WikIR1k is a small-scale dataset that contains 1644 annotated queries. To build wikIR1k, we restricted

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Table 2: Statistics of wikIR1k and wikIR59k. Avg #d+/q denotes the average number of relevant document per query.

| Dataset | #Query | #Doc | Avg #d+/q |
|---------|--------|------|-----------|
| wikIR1k | training | 1,444 | 370k | 33.03 |
| wikIR1k | validation | 100 | 370k | 49.79 |
| wikIR1k | test | 100 | 370k | 44.35 |
| wikIR59k | training | 57k | 2.4M | 42.67 |
| wikIR59k | validation | 1000 | 2.4M | 68.90 |
| wikIR59k | test | 1000 | 2.4M | 104.71 |
Anarchism

Anarchism is an <a href="anti-authoritarian">anti-authoritarian</a> <a href="political%20philosophy">political philosophy</a> that advocates ... 

Autism

Autism is a <a href="developmental%20disorder">developmental disorder</a> characterized by difficulties with ... 

Figure 2: json file extracted from English Wikipedia dump using WikiExtractor

the set of Wikipedia articles to 370,000 element\[10\] randomly sampled with a uniform distribution. Moreover, we deleted the first sentence of each article when constructing the documents. We made this choice since all the information we use to assess relevance is contained in the first sentence of articles (see Section 2.2.) and we do not want DNNs that take into account word order to use this bias to their advantage.

wikIR59k. WikIR59k is a large-scale dataset that contains 59,000 annotated queries. When building wikIR59k, we used the full set of Wikipedia articles. The rest of the construction process is the same as wikIR1k. We propose a small-scale dataset and a large-scale dataset in order to study the impact of the quantity of training data available on the DNNs. Statistics of the datasets are displayed on Table 2.

wikIR1k is downloadable at: https://bit.ly/34yrxP1. wikIR59k is downloadable at: https://bit.ly/2XXRG7o.

5. Experimental settings

This section describes the experiments we conducted on our datasets.

5.1. Models description

We evaluated 3 types of models: bag-of-words, DNNs for text matching and DNNs for ad-hoc IR.

5.1.1. Exact matching model

We use Okapi BM25: a state-of-the-art ranking function that uses exact matches between query and document terms (Robertson and Walker, 1994).

5.1.2. Deep neural networks for text matching

Text matching is a general task that consists in computing a matching score between two texts. Models developed for text matching do not take into account IR specificities such as query term importance or exact matching signals consideration (Guo et al., 2016).

ArcI. A representation model that uses 1D-convolutions and pooling layers to get a fixed size representation of sentences. The similarity score is obtained with a multilayer perceptron (MLP) on the representations of the two inputs (Hu et al., 2014).

ArcII. An interaction model that uses 1D-convolutions to build an interaction matrix of the two input sentences. The final score is obtained using 2D-convolutions, max-pooling and MLP on the interaction matrix (Hu et al., 2014).

MatchPyramid. An interaction model that build an interaction matrix between the two input sentences using the dot product between their word embeddings. The matrix obtained is processed using a convolutional neural network (CNN) and the matching score is computed using a MLP on the output of the CNN (Pang et al., 2016).

5.1.3. Deep neural networks for ad-hoc IR

DRMM. Uses a matching histogram between query term and all of the document terms, followed by a MLP to get a query term score. The final matching score is the sum of all query terms scores (Guo et al., 2016).

KNRM. A neural ranking model that uses word interactions and kernel pooling to produce learning-to-rank features. The final score is computed with a linear layer and a non-linear activation function applied on the ranking features (Xiong et al., 2017).

DUET. Model that uses both local (exact matching of n-grams of characters) and distributed (word embeddings) representations to compute a relevance score (Mitra et al., 2017).

Conv-KNRM. As KNRM, Conv-KNRM (Dai et al., 2018) is based on kernel pooling to produce learning-to-rank features but it uses convolutions to match n-grams of words and has multiple interaction matrices.

5.2. Implementation details

Training. Each training sample consists of a query \( q \), a document \( d \) relevant to \( q \) and a set of 5 irrelevant documents \( D^- \) with respect to \( q \). We use the cross entropy loss function for ranking provided by MatchZoo defined as:
with respect to BM25 is denoted as (+/−) with p-value < 0.01.

Performance comparison of different models on wikIR1k and wikIRS1k. Significant improvement/degradation between the evaluation metrics (Urbano et al., 2013; Fuhr, 2015) with a learning rate equals to 0.001. Each model is trained 5 times (with different initialization) for 50 epochs.

2015) with the widely used Hinge loss function for pairwise training of IR models (Guo et al., 2019a) as preliminary experiments showed that the cross entropy loss function is more efficient in terms of training time and produces more effective models. We use the Adam optimizer (Kingma and Ba, 2015) with a learning rate equals to 0.001. Each model is trained 5 times (with different initialization) for 50 epochs. We select the model that has the highest normalized discounted cumulative gain (Urbano et al., 2002) on the validation set and report its results on the test set.

**Embeddings.** We used Glove (Pennington et al., 2014) word embeddings of dimension 300 provided by MatchZoo.

**Hyperparameters.** BM25 hyperparameters are set to their default values in Rank-BM25: \( k_1 = 1.5 \) and \( b = 0.75 \). Hyperparameters associated with DNNs (e.g., number of layers, kernel size, similarity function) were set to their default value implemented in MatchZoo, except for the dropout rate that we set to 0.5 for models with a dropout parameter.

**Evaluation metrics.** We use 3 standard evaluation metrics: MAP, Precision and normalized discounted cumulative gain (nDCG). We use a two-tailed paired t-test with Bonferroni correction to measure statistically significant differences between the evaluation metrics (Urbano et al., 2013; Fuhr, 2018).

6. Results and discussion

6.1. Limited data scenario

As we can see on Table 3 when few training data is available (wikIR1k), DRMM, KNRM and ConvKNRM outperform BM25 on all metrics on both datasets. However, DRMM alone achieves statistical significance on nDCG as it has few parameters (≈ 450) and takes into account ad-hoc IR constraints. Therefore, it does not require large amount of data to achieve good performance. This is consistent with other experiments that use models implemented MatchZoo on dataset with limited, manually annotated data (Yang et al., 2019a).

Moreover, even though DUET was designed for ad-hoc IR as it does consider exact matching signals, it does not perform well on wikIR1k compared to BM25. The DUET architecture was developed on a much larger dataset than wikIR1k (≈ 200,000 queries), thus it is not suited for limited data scenarios. Models that were not designed for ad-hoc IR but for text matching tend to perform worst or even statistically significantly worst than BM25. This suggests that datasets created with WIKIR are suited for designing and training DNNs specifically for ad-hoc IR.

6.2. Sufficient data scenario

When enough training data is available, all models designed specifically for ad-hoc IR perform better than BM25 on all metrics and statistical significance is achieved on most of the metrics. This confirms that having enough training data is a key factor for developing DNNs for ad-hoc IR that can outperform a strong bag-of-words baseline such as BM25.

| Model          | P@5 | P@10 | P@20 | nDCG@5 | nDCG@10 | nDCG@20 | nDCG | MAP   |
|----------------|-----|------|------|--------|---------|---------|------|-------|
| BM25           | 0.1840 | 0.1320 | 0.0950 | 0.2222 | 0.2021 | 0.2160 | 0.2597 | 0.1119 |
| ArcI           | 0.1120 | 0.0950 | 0.0790 | 0.1259 | 0.1286 | 0.1494 | 0.2077 | 0.0737 |
| ArcII          | 0.1180 | 0.0970 | 0.0780 | 0.1373 | 0.1368 | 0.1556 | 0.2148 | 0.0802 |
| MatchPyramid   | 0.1640 | 0.1280 | 0.0940 | 0.2218 | 0.2099 | 0.2225 | 0.2665 | 0.1091 |
| KNRM           | 0.1920 | 0.1490 | 0.1005 | 0.2524 | 0.2363 | 0.2397 | 0.2778 | 0.1200 |
| DUET           | 0.1040 | 0.1040 | 0.0845 | 0.1193 | 0.1346 | 0.1540 | 0.2092 | 0.0759 |
| DRMM           | 0.2340 | 0.1580 | 0.1075 | 0.3007* | 0.2652* | 0.2706* | 0.3034* | 0.1354 |
| ConvKNRM       | 0.1980 | 0.1540 | 0.1035 | 0.2713 | 0.2565 | 0.2602 | 0.2957 | 0.1279 |

| Model          | P@5 | P@10 | P@20 | nDCG@5 | nDCG@10 | nDCG@20 | nDCG | MAP   |
|----------------|-----|------|------|--------|---------|---------|------|-------|
| BM25           | 0.1568 | 0.1250 | 0.0975 | 0.1823 | 0.1748 | 0.1847 | 0.2146 | 0.0898 |
| ArcI           | 0.1250 | 0.1109 | 0.0935 | 0.1222 | 0.1272 | 0.1429 | 0.1795 | 0.0681 |
| ArcII          | 0.1348 | 0.1177 | 0.0956 | 0.1311 | 0.1337 | 0.1463 | 0.1814 | 0.0683 |
| MatchPyramid   | 0.1872 | 0.1464* | 0.1055* | 0.2197* | 0.2052* | 0.2093* | 0.2304* | 0.0990* |
| KNRM           | 0.1800 | 0.1415* | 0.1041 | 0.2118* | 0.1987* | 0.2016* | 0.2261* | 0.0940 |
| DUET           | 0.1838* | 0.1431* | 0.1070* | 0.2117* | 0.1989* | 0.2028* | 0.2263* | 0.0956 |
| DRMM           | 0.1866 | 0.1465* | 0.1068* | 0.2274* | 0.2127* | 0.2150* | 0.2370* | 0.1012* |
| ConvKNRM       | 0.2258* | 0.1703* | 0.1222* | 0.2516* | 0.2324* | 0.2333* | 0.2452* | 0.1138* |

Table 3: Performance comparison of different models on wikIR1k and wikIRS1k. Significant improvement/degradation with respect to BM25 is denoted as (+/−) with p-value < 0.01.

\[
\mathcal{L}(q, d^+, d^-) = \text{rel}(q, d^+) \log \frac{\exp(s(q, d^+))}{\sum_{d \in D^-} \exp(s(q, d^-))}
\]

where \( s(q, d) \) denoted the score of \( d \) with respect to \( q \). We used the cross entropy loss function for ranking instead of the widely used Hinge loss function for pairwise training of ad-hoc IR models (Guo et al., 2019a) as preliminary experiments showed that the cross entropy loss function is more efficient in terms of training time and produces more effective models. We use the Adam optimizer (Kingma and Ba, 2015) with a learning rate equals to 0.001. Each model is trained 5 times (with different initialization) for 50 epochs. We select the model that has the highest normalized discounted cumulative gain (Järvelin and Kekäläinen, 2002) on the validation set and report its results on the test set.
However DRMM does not achieve the best performances anymore. This indicates that DRMM is best suited when few training data is available but other models with more parameters such as Conv-KNRM will benefit more from larger datasets.

7. Conclusions and future work
In this paper, we propose WIKIR as a toolkit for building large-scale English information retrieval dataset from Wikipedia. WIKIR can also be used to train and evaluate deep text matching models. We propose a general framework to construct an IR dataset from any resource that satisfies three topical properties. Additionally, we made available for download wikIR59k: a large-scale IR dataset built using WIKIR, that is well suited for designing and training deep models for ad-hoc IR. All our code is available and our experiments are reproducible.

For future work, we plan to use wikIR59k to pre-train deep models for ad-hoc IR and fine-tune them on standard IR datasets to see if any gain is obtained compared to weak supervision (Dehghani et al., 2017). We will also adapt WIKIR to more languages and try our framework to produce IR datasets from other resources such as PubMed Central.

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