Ad-hoc Document Retrieval using Weak-Supervision with BERT and GPT2

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Abstract

We describe a weakly-supervised method for training deep learning models for the task of ad-hoc document retrieval. Our method is based on generative and discriminative models that are trained using weak-supervision based solely on the documents in the corpus. We present an end-to-end retrieval system that starts with traditional information retrieval methods, followed by two deep learning re-rankers. We evaluate our method on three different datasets: a COVID-19 related scientific literature dataset and two news datasets. We show that our method outperforms state-of-the-art methods; this without the need for the expensive process of manually labeling data.

1 Introduction

The ad-hoc retrieval task has been extensively studied by the Information Retrieval (IR) community. Traditional IR models evaluate ad-hoc queries against documents mainly on a syntactic (exact) word-matching basis (Manning et al., 2008). Recent years advances in Deep Learning (DL) methods have lead to further improvement in IR tasks, and among others, in ad-hoc document retrieval (Guo et al., 2019). DL methods add a semantic dimension to IR methods. However, such methods usually require large amounts of labeled data for model training.

In this work, we describe a novel weakly-supervised method for training DL methods for ad-hoc document retrieval. Motivated by the recent work of (Mass et al., 2020) on Frequently Asked Questions (FAQ) retrieval, we assume that documents have at least three fields, namely title, abstract and content. Such documents are actually quite common nowadays in the scientific and news domains. Our main hypothesis is that: titles and abstracts can take the role of questions and answers of FAQs, respectively.

Whenever a document is missing a title, we consider its first sentence as its augmented title. In a similar way, whenever a document is missing an abstract, we consider the first 512 words of its content as the abstract.

The three fields are used for retrieving candidate documents. Inspired by (Mass et al., 2020), the title and abstract fields are further used as a weak-supervision data source for training two independent BERT (Devlin et al., 2019) models, that are then used to re-rank those candidate documents.

As a proof of concept, we evaluate our method on three benchmarks: TREC-COVID - a scientific literature dataset on COVID-19 topics; and TREC’s newswire corpora: Associated Press (AP) and Wall Street Journal (WSJ). By combining the
two weakly-supervised BERT models with an existing strong IR baseline, we demonstrate that the former can help to elevate the performance of the latter. Our approach further outperforms state-of-the-art methods on these benchmarks.

## 2 Related Work

With the lack of training data, several weakly-supervised alternatives have been explored so far for the task at hand. (Dehghani et al., 2017b,a) and (Nie et al., 2018) have utilized rankings produced by BM25 model as training samples. (MacAvaney et al., 2019) have used pseudo query-document pairs that already exhibit relevance (e.g., newswire headline-content pairs). (Frej et al., 2019) have utilized Wikipedia’s internal linkage to define automated queried topics. (Zhang et al., 2020) have used anchor texts and their linked web pages as query-document pairs.

Our work is different from all those works as we train a model to generate title paraphrases that are used to enable query-to-title (question) matching and not only query-to-abstract (answer) matching. (Ma et al., 2020) have proposed a zero-shot retrieval approach using synthetic query generation by training a generative model on a different Community QA data. Our work differs from (Ma et al., 2020) in three main aspects. First, (Ma et al., 2020) focuses on QA, where answers are very short, while we generate title paraphrases from full abstracts. Second, we train a model to generate title paraphrases which are used to enable not only query-to-abstract (answer) matching, but also query-to-title (question) matching. Third, (Ma et al., 2020) filters the input QA pairs that are used to train the generative model by taking only pairs that were voted by at least one-user on those Community QA (CQA) sites. We do not have such voting so we use a smart filtering on the output data (namely on the generated title-paraphrases) as described in Section 3.3.

The work in (Chang et al., 2020) suggests an efficient neural method for initial retrieval of candidates. Their method uses a two-tower architecture which learns a different representation for passages and for queries. While their method can be used as an initial retrieval (instead of our IR method), the authors of (Chang et al., 2020) still require an additional re-ranking step. Thus it does not replace our two weakly-supervised BERT re-ranking models. Moreover, our two BERT models learn a joint attention-based representation for pairs of (query, abstract) and (query, title) while in (Chang et al., 2020) they learn a separate representation for queries and passages.

## 3 Method

Inspired by (Mass et al., 2020), we consider the ad-hoc document retrieval problem as an instance of FAQ retrieval, where a document’s title represents the question and its abstract the answer.

Our proposed retrieval approach allows to enhance existing state-of-the-art ad-hoc retrieval methods with weakly-supervised neural models that are completely trained from the documents collection itself without the need to supply manual relevance labels. Following the common approach (Guo et al., 2019), these neural-models are utilized for re-ranking candidate documents retrieved by a given IR baseline.

In what follows, the initial candidate documents retrieval uses pure IR similarities and relevance models (Section 3.1). The re-ranking step exploits two independent weakly-supervised BERT models, namely: BERT-Q-a (Section 3.2) for matching queries to abstracts and BERT-Q-t (Section 3.2) for matching queries to titles.

The final re-ranking is obtained by combining the outcome of the baseline IR method and the two BERT-based re-rankers using an unsupervised late-fusion step (Section 3.4). The components of our approach are described in the rest of this section.

### 3.1 Initial retrieval

We first obtain for each query a reasonable pool of candidate documents to be re-ranked using our weakly-supervised models. To this end we retrieve several ranked lists from an Apache Lucene\(^1\) index using various state-of-the-art IR similarities that are available in Lucene. The various retrieved lists are then combined to generate a single pool of top-k candidates for re-ranking by employing the PoolRank (Roitman, 2018) fusion method. We refer to this IR pipeline as IR-Base.

The IR similarities and the PoolRank method have few free-parameters that are tuned so to optimize Mean Average Precision (MAP@1000). Details are given in the experimental setup (Section 4.2) below.

\(^1\)[https://lucene.apache.org/](https://lucene.apache.org/)
3.2 BERT-Q-a

We use pairs of title-abstract \((t, a)\) of documents in the collection as a weak-supervision data source for fine-tuning a pre-trained BERT model which is then used to match user queries to abstracts.

Similar to (Mass et al., 2020), we fine-tune the BERT model (denoted BERT-Q-a) using a triplet network (Hoffer and Ailon, 2015). This network is adopted for BERT fine-tuning (Mass et al., 2019) using triplets \((t, a, a')\), where \((t, a)\) constitutes a document title and its abstract. \(a'\) is a negative sampled abstract, obtained as follows. We run \(t\) as a query against the index (using the title and abstract fields) and sample \(n\) random abstracts from the top-\(k\) retrieved documents as negative examples (excluding \(a\)) in our setup we used \(k=100\) and \(n=2\). At run time, given a user query \(Q\), BERT-Q-a re-ranks the top-\(k\) candidate documents by matching \(Q\) to the abstracts \((a)\) only.

3.3 BERT-Q-t

Similar to (Mass et al., 2020), we fine-tune a generative pre-trained (GPT-2) neural network model (Radford et al., 2018) for generating title paraphrases (instead of question paraphrases as in (Mass et al., 2020)).

Using \(N\) \((t_i, a_i)\)-pairs, we concatenate titles and their abstracts into a long text \(U = a_1 [\text{SEP}] t_1 [\text{EOS}] \cdots a_N [\text{SEP}] t_N [\text{EOS}]\), where [SEP] and [EOS] are special tokens. The GPT-2 fine-tuning samples sequences of \(l\) consecutive tokens in \(U\) (in our setup we used \(l=256\)), aiming to maximize the Language Model (LM) probability for generating the last token on each sequence, given its \(l - 1\) preceding tokens.

Once the model is fine-tuned, we feed it with the text “\(a [\text{SEP}]\)”, \((a\) is an abstract), and let it generate tokens until [EOS] is generated. We take all generated tokens excluding [EOS], as a paraphrase to \(a\)’s title \(t\). We repeat the generation process \(n\) times (e.g., \(n=10\)) to generate \(n\) paraphrases to each title.

The generated paraphrases are filtered to ensure high quality paraphrases (Mass et al., 2020). Each paraphrase is run as a query against the Lucene index and only paraphrases that return the exact same documents as their original title are kept.

The filtered paraphrases are then used to fine-tune a second BERT model (denoted BERT-Q-t), using a triplet network (similar to BERT-Q-a), with triplets \((p, t, t')\), where \(p\) is a paraphrase of \(t\) and \(t'\) is a randomly selected title from the corpus. At run time, given a user query \(Q\), BERT-Q-t re-ranks the top-\(k\) candidate documents by matching \(Q\) to titles \((t)\) only.

3.4 Enhanced ad-hoc retrieval using Fusion

To enhance ad-hoc retrieval quality, we now propose to combine the two weakly-supervised fine-tuned BERT models with the baseline IR method (IR-Base, see again Section 3.1). To this end, following (Roitman, 2018), we utilize the Two-Step PoolRank (denoted TSPR) unsupervised fusion method – an extended PoolRank method that estimates document relevance using the three ranked lists (obtained by IR-Base, BERT-Q-a and BERT-Q-t) as pseudo-relevance evidence sources.

4 Evaluation

4.1 Datasets and Indexing

We evaluated our proposed approach using three different benchmarks. The first benchmark, TREC-COVID\(^2\), is based on the CORD-19 dataset\(^3\), which contains scientific documents related to the recent Coronavirus pandemic. We used the Round-1 challenge which consists of 43K documents\(^4\) and 30 topics (queries) with their query relevance sets (qrels). Documents in this dataset have three fields (title, abstract and content). The two other benchmarks are based on news articles datasets: AP (Association Press, about 242K docs) and WSJ (Wall Street Journal, about 160K docs). These datasets are part of the TREC ad-hoc retrieval newswire collection\(^5\). Here we used topics 51-150 and topics 151-200 (with their respective qrels) for the AP and WSJ datasets, respectively. Those two datasets have only title and content so we created the abstract by taking the first 512 tokens of the content.

We used Apache Lucene to process and indexed the (multi-field) documents, employed with English analysis (tokenization, lower-casing, Porter stemming and stopping). Each indexed document has three main fields: title, abstract and content.

4.2 Experimental Setup

We used an initial candidate pool of \(k = 1000\) documents retrieved by IR-Base and re-ranked by the two BERT models. We detail below the setup of each of the three rankers and their fusion.

\(^2\)https://bit.ly/2ApmLcz
\(^3\)https://bit.ly/3dxyZ1i
\(^4\)Round-1 contained about 51K documents, but we kept only those that have a non-empty content
\(^5\)https://bit.ly/3gJcF6X
**IR-Base.** The following Lucene similarities configurations were used: i) BM25Similarity (Robertson and Zaragoza, 2009) with $k_1 = 1.2$ and $b = 0.7$. ii) LMDirichletSimilarity (Zhai, 2009) with Dirichlet-smoothing parameter $\mu = 200$ and $\mu = 1000$ for TREC-COVID and news datasets, respectively. iii) DFRCSimilarity (Amati and Van Rijsbergen, 2002) with BasicModelIF, AfterEffectB and Normalization3. iv) AxiomaticFilog (Fang and Zhai, 2005) with growth parameter $s = 0.25$ and $s = 0.1$ for TREC-COVID and news datasets, respectively.

**BERT models.** We used the pytorch huggingface implementation of BERT and GPT2. For the two BERT models we used bert-base-uncased (12-layers, 768-hidden, 12-heads, 110M parameters). Fine-tuning was done with a learning rate of $2e-5$ and 3 training epochs. For training BERT-Q-a on each of the three datasets, we used a subset of their first 20K documents. For TREC-COVID, we used SciBERT model (Beltagy et al., 2019) (that was pre-trained on 1M scientific documents), as it yields better results than using the vanilla pre-trained BERT model. This is mainly due to the scientific nature of the documents in this benchmark.

**GPT2.** For generating title paraphrases we used GPT2 small model (12-layers, 768-hidden, 12-heads, 110M parameters). For fine-tuning we used (title, abstract) pairs from all documents of TREC-COVID and news datasets, respectively. iii) Pseudo-relevance set size: 5 documents. Term clip size: 100. Document re-ranking using KL-score (equally interpolated with the CombSUM score) with Dirichlet-smoothing parameter $\mu = 200$ and $\mu = 1000$ for TREC-COVID and news datasets, respectively.

We assessed retrieval quality using the following metrics: Precision (P@5), Normalized Discounted Cumulative Gain (NDCG@10) and Mean Average Precision (MAP@1000). All experiments were run on two 32GB V100 GPUs. The re-ranking times of 1000 documents for each query were 11 sec for BERT-Q-a (using BERT’s max_seq_len of 512) and 5 sec for BERT-Q-q (max_seq_len = 256).

**4.3 Results**

We now report the evaluation results of the TREC-COVID benchmark and the two news benchmarks (AP and WSJ) in Table 2 and Table 3, respectively. We compared our three rankers (IR-Base, BERT-Q-a and BERT-Q-t) and their fusion (TSPR). We further evaluated two additional TSPR versions, namely: TSPR-Q-a and TSPR-Q-t where we only fused the IR-Base ranked-list with either BERT-Q-a or BERT-Q-t, respectively.

To demonstrate the relative effectiveness of our proposed approach, we compared its quality to state-of-the-art alternative baselines. On TREC-COVID, we directly compared against the three best automatic performing systems (out of 141 system runs submitted to the Round-1 challenge by 56 different teams), namely: sabir, IRIT_markers and unipd.it.

On the news benchmarks (AP and WSJ), we compared against quality metrics (when available) that were previously reported for the following state-of-the-art unsupervised and semi-supervised IR methods: ClustMRF (Raiber and Kurland, 2013), NVSM (Gysel et al., 2018), LBDM (Wei and Croft, 2006), PGR (Krikon et al., 2011) and CRM (Gelfer Kalmanovich and Kurland, 2009).

The symbols $\triangle$ and $\blacktriangle$ in both tables denote a statistical significant ($p < 0.05$) result with IR-Base and the best alternative baseline, respectively.

**4.3.1 Retrieval enhancement**

The first and most important observation that we now make is that, consistently over the three benchmarks, the proposed method TSPR, which fuses the initial IR retrieval (IR-Base) and the two weakly-supervised BERT models, performs significantly better than each of the three separately, on all measures. As a second observation, we note that, TSPR employed with both BERT models significantly outperforms TSPR-Q-a and TSPR-Q-t.

The details of these systems as well as other competing systems are available in https://bit.ly/2XjkE2T.
These two observations confirm our hypothesis that: 1) BERT contributes a semantic understanding of the data and thus improves the ad-hoc retrieval task over pure IR methods; and 2) each of the two BERT models contributes a different semantic aspect. BERT-Q-a, which was trained on the relation between titles and abstracts, allows to consider the semantic similarity between a user query and abstracts. Moreover, BERT-Q-t, which was trained on titles and their paraphrases, can successfully match a user query to titles.

To examine the semantic differences of our three rankers, we report their P@1 performance. On TREC-COVID, there were 12 queries in which BERT-Q-t and IR-Base differed in their P@1, and 9 queries in which BERT-Q-a and IR-Base differed. On AP, differences from IR-Base were on 32 and 31 queries for BERT-Q-t and BERT-Q-a respectively, and on WSJ, differences were on 11 and 23 queries for BERT-Q-t and BERT-Q-a respectively.

Table 1 shows some example queries from TREC-COVID, where BERT-Q-t returned a correct top-1 answer (showing its title), while IR-Base returned a wrong one.

| Query | BERT-Q-t | IR-Base |
|-------|----------|---------|
| how long can the coronavirus live outside the body | Microbes, Transmission Routes and Survival Outside the Body | The Effects of Temperature and Relative Humidity on the Viability of the SARS Coronavirus |
| how does the coronavirus respond to changes in the weather | how long can the coronavirus live outside the body | Microbes, Transmission Routes and Survival Outside the Body |

Table 1: Example queries and titles of correct top-1 documents retrieved by BERT-Q-t on TREC-COVID

Looking further at the effect of each of the two BERT models as a standalone ranker, we can see that on TREC-COVID, BERT-Q-t performed better than BERT-Q-a, while on the two news datasets it was the other way around. This can be attributed to the length of the titles. In TREC-COVID titles are much longer (13 words on average compared to 9.8 and 8.2 words on WSJ and AP respectively) and hence carry more information.

4.3.2 Comparison with alternative baselines

Looking further down the tables, we notice that our proposed method, TSPR, outperforms all alternative baselines in most of the cases and metrics. On the TREC-COVID benchmark, TSPR provides a better retrieval quality compared to the best systems. Interestingly, some systems (such as IRIT_markers) fine-tuned a BERT model (including SciBERT) using an auxiliary largely annotated dataset such as MS-Marco, yet still fall behind TSPR’s quality. This serves as another strong empirical evidence on the importance of our weakly-supervised BERT fine-tuning directly on the domain’s data.

Finally, on the two news benchmarks, TSPR overpass most of the quality metrics that were previously reported for state-of-the-art alternatives.

5 Conclusions and Future work

We have cast a solution for FAQ retrieval to a solution for ad-hoc document retrieval, where titles and abstracts took the role of questions and answers in FAQs. We have shown that, using the corpus itself, we could generate weakly-supervised title paraphrases for training a BERT model that matches queries to titles. Coupled with a second BERT model that was trained to match queries to abstracts, we have experimentally shown on three different benchmarks that our proposed method outperformed state-of-the-art alternatives.

As a future work, we plan to utilize automatic summarization for missing abstracts, instead of taking the first 512 content tokens.

Table 2: Retrieval quality on TREC-COVID.

| Method | P@5 | NDCG@10 | MAP |
|--------|-----|---------|-----|
| IR-Base | .753 | .597 | .297 |
| BERT-Q-a | .466 | .373 | .148 |
| BERT-Q-t | .620 | .506 | .186 |
| TSPR-Q-a | .693 | .535 | .270 |
| TSPR-Q-t | .747 | .625 | .254 |
| TSPR | .827 | .652 | .315 |

Table 3: Retrieval quality on news benchmarks.

| Method | AP | WSJ |
|--------|----|-----|
| IR-Base | .480 | .361 |
| BERT-Q-a | .406 | .237 | .361 |
| BERT-Q-t | .381 | .232 | .361 |
| TSPR-Q-a | .528 | .287 | .287 |
| TSPR-Q-t | .512 | .270 | .287 |
| TSPR | .592 | .370 | .370 |
| ClustMRF | .559 | - | - |
| NVSM | - | .357 | - |
| LBDM | - | .265 | - |
| PGR | .337 | - | .364 |
| CRM | .521 | - | .409 |
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