Neural document expansion for ad-hoc information retrieval

Cheng Tang ***, Andrew Arnold †

Amazon

Abstract. Recently, Nogueira et al. [2019] proposed a new approach to document expansion based on a neural Seq2Seq model, showing significant improvement on short text retrieval task. However, this approach needs a large amount of in-domain training data. In this paper, we show that this neural document expansion approach can be effectively adapted to standard IR tasks, where labels are scarce and many long documents are present.

1 Introduction

In traditional ad-hoc retrieval, queries and documents are represented by variants of bag-of-words representations. This leads to the so called vocabulary mismatch problem: when a query contains words that do not exactly match words in a relevant document, the search engine may fail to retrieve this document. Query expansion and document expansion, the methods of adding additional terms to the original query or document, are two popular solution to alleviate the vocabulary mismatch problem.

Document expansion has been shown to be particularly effective for short text retrieval and language-model based retrieval [Tao et al., 2006, Efron et al., 2012]. Most of the existing works in document expansion are unsupervised: using information from the corpus to augment document representation, e.g., retrieval based [Efron et al., 2012] and clustering based [Liu and Croft, 2004, Tao et al., 2006], or using external information to augment document representation [Agirre et al., 2010, Sherman and Efron, 2017].

Recently, Nogueira et al. [2019] proposed a new approach to document expansion, which is based on a popular generative sequence-to-sequence model (Seq2Seq) in NLP, transformers [Wolf et al., 2020]. It leverages supervision to train the model to predict expansion terms conditional on each document. The paper has shown significant improvement on passage (short document) datasets, when trained in-domain. In this paper, we follow this line of supervised neural document expansion approach and explore its performance on standard IR benchmarking dataset. Our main contributions are: 1. Adapting the method to unlabeled datasets by exploring transfer learning and weak-supervision approaches. 2. Adapting the method to traditional IR datasets, where a large number of long documents are present.

*** tcheng@amazon.com
† anarnld@amazon.com
Train a passage level document expansion model. We follow the approach of Nogueira et al. [2019]: we use data of format \((p, q)\), where \(q\) is a question and \(p\) is a passage relevant to it. A Seq2Seq model is trained so that conditional on input \(p\), it learns to generate the ground-truth question \(q\). The dataset we found most effective for training the document expansion model is the MSMarco passage-ranking dataset [Bajaj et al., 2018].

Domain adaptation. Since most IR datasets are short of annotated queries, it is important to explore ways to adapt the document expansion model to out-of-domain unlabeled datasets. We explored two simple approaches: zero-shot transfer and weak supervision (retrieval-based pseudo annotation). In zero-shot transfer, we directly apply a model trained from one domain to another; in retrieval-based pseudo annotation, we issue out-of-domain queries to a target corpus and treat the top-\(k\) returned documents as “relevant”.

Adaptation to long documents. Due to the memory overhead of transformer-based models, the maximal input length of this family of models are constrained to be short. We trained our expansion models on passage-level datasets. However, during inference time, a standard IR dataset is usually a mixture of short and long documents, and expanding on an arbitrarily capped portion of a document may yield sub-optimal performance. Figure 1-Left shows the document lengths distribution of Robust04 dataset. We see that most of the documents are around 1000-tokens long, which has exceeded the typical input length transformer based models can take [Hofstätter et al., 2020]. To deal with this problem, we explored three strategies (see experiment results at Table 3: “Long document generation methods” section):

1. concatenation of paragraph generation (CONCAT in Table 3): Split each long document into overlapping passages, respecting natural sentence
boundaries (with sliding window size to be around 60 tokens, since this is roughly the median size of passages in MSMarco dataset, which we used for training) and run expansion inference on each passage. All generated expansions are directly appended to the original documents.

2. **first k sentences (FIRST-K in Table 3):** Run expansion model on the first k whole sentences of each document. This strategy is based on our analysis of MSMarco datasets. From MSMarco-QA dataset, we can obtain \((q, p, a)\) triplets so that we know passage \(p\) contains an answer for question \(q\). We treat this as a signal of question-passage relevance. Then we can trace these passages back to the document they belong to using the MSMarco-documents dataset. Comparing “Capped passage generation methods” to “Long document generation methods” in Table 3, we see that the “Long document generation methods”, and in particular, the CONCAT and FIRST-K generation methods are more effective.

3. **passage-importance indicator (PI in Table 3):** Before seeing any questions, we predict which passage will be queried using an unsupervised predictor [Bendersky and Kurland, 2008], and generate expansion exclusively based on this passage. In our experiments, this method do not yield good performance, likely due to the low quality of the passage-importance predictor.

3 Experiments

To train the document expansion models, we selected datasets that are typically used for passage-ranking and question-answering tasks, i.e., MSMarco passage-ranking [Bajaj et al., 2018], Natural Questions [Kwiatkowski et al., 2019], and SQuAD [Rajpurkar et al., 2018]. In addition, we also used a TREC collection short-document dataset, microblogs [Lin et al., 2014]. To evaluate the performance of document expansion method on information retrieval, we additionally add the standard IR benchmarking dataset Robust04 [Voorhees, 2004]. Our baseline retrieval methods, BM25 and Query Likelihood (QL), use implementation from the open-source Anserini toolkit [Yang et al., 2017]; for Seq2Seq models, we experimented with transformers (OpenNMT implementation [Klein et al., 2017]) and pre-trained BART (Huggingface Pytorch implementation [Wolf et al., 2020]).

3.1 Retrieval performance on passage datasets

From Table 1, we see that retrieval-based weak supervision, while showing good performance as training signal for neural retrieval models [Dehghani et al., 2017], does not yield good document expansion models. Instead, the BART-based zero-shot transfer model has competitive performance to in-domain trained-from-scratch models. Once decided on the zero-shot transfer learning approach, we tried several fine-tuning strategies with the BART model (Table 2), drawing inspiration from [Yilmaz et al., 2019]. We found that fine-tuning pre-trained
BART with MSMarco-passages dataset and with a mixed MSMarco-passages and microblogs dataset produces the best document expansion models. Although less effective, our experiment suggests that other passage-level datasets such as Natural Questions and SQuAD, can also be used as sources to train document expansion models.

| DE models          | MSMarco-passages | Natural Questions | SQuAD-v2 |
|--------------------|------------------|------------------|----------|
|                    | Trec-DL (DEV)    | Trec-DL (DEV)    |          |
|                    | R@100 MAP        | R@100 MAP        |          |
| BM25               | 0.4531 0.3773    | 0.7619 0.3616    | 0.9737 0.7997 |
| (0.7619)           | (0.3616)        |                  |          |
| In-domain trained  |                  |                  |          |
| transformer        | 0.4545 0.3872    | 0.8671 0.4500    | 0.9754 0.7915 |
| (0.7127)           | (0.2203)        |                  |          |
| Weakly supervised  |                  |                  |          |
| transformer        | NA NA 0.7649 0.3608 0.9717 0.7913 |          |          |
| Zero-shot transfer |                  |                  |          |
| (transformer)      | NA NA 0.7773 0.3879 0.9764 0.8056 |          |          |
| (fine-tuning       | 0.5297 0.4650 0.8302 0.4501 0.9787 0.8121 |          |          |
| BART)              | (0.7949) (0.2674) |                  |          |

Table 1: In-domain trained and weakly-supervised document expansion model; for MSMarco-passages, we have two test sets: DEV and Trec-DL [Craswell et al., 2020]

| DE models          | Natural Questions | SQuAD-v2 | Robust04 |
|--------------------|------------------|----------|----------|
|                    | R@100 MAP        | R@100 MAP | R@100 MAP |
| BM25               | 0.7619 0.3616    | 0.9737 0.7997 | 0.4152 0.2553 |
| MSMarco-passages   | 0.8302 0.4501    | 0.9787 0.8121 | 0.4229 0.2620 |
| MSMarco-passages + | 0.7931 0.4        | 0.9757 0.7962 | 0.4206 0.2533 |
| microblogs         | 0.8239 0.4437    | 0.9787 0.8133 | 0.4212 0.2630 |
| Natural Questions  | 0.9031 0.5271    | 0.9782 0.8099 | 0.4190 0.2626 |
| SQuAD-v2           | 0.8173 0.4228    | 0.9798 0.8156 | 0.4218 0.2616 |

Table 2: Zero-shot transfer of passage-level DE model

### 3.2 Retrieval performance on Robust04

To test the performance of passage-level trained document expansion model on standard IR corpus, we fixed the passage-level model to be “MSMaroc-passage + microblog” trained. Then we explored three expansion generation methods as
described in Section 2. The result of applying passage-level trained document expansion model to Robust04 can be found in Table 3.

**Traditional IR baselines** In addition to tf-idf based BM25, we applied document expansion to two popular language-model based retrieval methods: query-likelihood with Dirichlet Smooth (QLD) and query-likelihood with Jelinek-Mercer smoothing (QLJM). We found that document expansion has good performance with QLD. We speculate that this is because the way our current document expansion model works is similar to the Dirichlet smoothing model, which models the process of adding unseen words to the original documents by drawing from a background distribution based on the entire corpus. Here, the document expansion model in addition samples words from the query distribution (conditional on each document). Since document expansion does not significantly improve QLJM, we did not include it in the rest of our experiments.

**Capped passage generation vs Long document generation** Comparing “Capped passage generation methods” to “Long document generation methods”, we see that for both BM25 and QLD, the two long document expansion methods, CONCAT and FIRST-K, have better performance. The fact the CONCAT has the best performance suggests that even if most queries are targeting the head portion of a document (Figure 1-Right), using information from the entire document may still be beneficial to expansion generation.

**Performance with pseudo-relevance feedback and BERT re-ranker** Since document expansion is one of several techniques that can improve the document retrieval performance, we also want to understand how it works when combined with other techniques. In our experiments, we first explored combining the best performing document expansion model with RM3 [Abdul-jaleel et al., 2004], a popular query expansion method based on pseudo-relevance feedback. While RM3 alone significantly improves the baseline retrieval performance, DE** 1 can still add an additional boost on top. We want to point out that comparing to RM3, which requires two rounds of retrieval at query time, document expansion model is applied offline and does not add additional computational overhead at run time. BM25 with document and query expansion makes a first-stage ranker in the ranking pipeline. In our last experiment, we test its end-to-end performance when combined with a second-stage neural ranker, BERT [Nogueira and Choi, 2019]. To evaluate the end-to-end result, we used metrics $R@k$ and $P@k$ for small $k$, mimicking what the ranking system presents to a user (the top-$k$ ranked documents). Our experiment results indicate that our document expansion models are complementary to query expansion as a first-stage ranker and can improve the end-to-end ranking performance when combined with a second-stage ranker.

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1 DE** indicates concatenation of paragraph generation with MSMarco+microblog trained passage model.
| Experiment category          | Methods                              | Robust04 | R@100 | MAP  |
|-----------------------------|--------------------------------------|----------|-------|------|
| Traditional                 | BM25                                 | 0.4152   | 0.2553|
| IR baselines                | QLD                                  | 0.4157   | 0.2502|
|                             | QLJM                                 | 0.3995   | 0.2287|
| Capped passage generation   | BM25+passage-DE*                     | 0.4212   | 0.2630|
| generation methods          | QLD+passage-DE*                      | 0.4270   | 0.2620|
|                             | QLJM+passage-DE*                     | 0.4058   | 0.2350|
| Long document generation    | BM25+DE* (CONCAT)                    | 0.4283   | 0.2631|
| methods                     | BM25+DE* (FIRST-K)                   | 0.4226   | 0.2625|
|                             | BM25+DE* (PI)                        | 0.4212   | 0.2588|
|                             | QLD+DE* (CONCAT)                     | 0.4290   | 0.2615|
|                             | QLD+DE* (FIRST-K)                    | 0.4272   | 0.2625|
|                             | QLD+DE* (PI)                         | 0.4259   | 0.2577|
| DE+pseudo-relevance feedback| BM25+RM3                             | 0.4517   | 0.2941|
|                             | BM25+RM3+DE**                       | 0.4641   | 0.3035|
| DE + BERT reranker          | End-to-end metrics                   |          |       |      |
|                             | R@10                                 |          |       |      |
|                             | P@10                                 |          |       |      |
|                             | P@5                                  |          |       |      |
| BM25 + BERT                 | 0.2771                               | 0.3731   | 0.4137|
| BM25 + RM3 + BERT           | 0.2608                               | 0.3803   | 0.4048|
| BM25 + DE** + BERT          | 0.2824                               | 0.3767   | 0.4161|
| BM25 + RM3 + DE** + BERT    | 0.2726                               | 0.3944   | 0.4241|

Table 3: Robust04 experiments (DE*: MSMarco-passage+microblog trained passage model; DE**: concatenation of paragraph generation, CONCAT, with DE*)

4 Conclusion

We showed that a document expansion model trained on passage-level datasets of (question, relevant passage) pairs can be directly applied to out-of-domain IR datasets to improve retrieval performance. We explored simple approaches to adapt the model to standard IR dataset (Robust04) where a large number of long documents are present, and we showed that adapting the passage-level trained model to long documents further improves retrieval performance. However, our current simple adaptations to long documents do not significantly improve the model performance (see Table 3, Long document generation methods). We cannot conclude whether this is due to the nature of the relevant passage distribution over long documents (i.e., they tend to be the first few passages of any document, according to Figure 1-Right). Hence, it may be worth exploring model architectures that allow longer input sequences, for example, by switching to sparse attention layers [Beltagy et al., 2020].
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