Data-Efficient Autoregressive Document Retrieval for Fact Verification

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Abstract

Document retrieval is a core component of many knowledge-intensive natural language processing task formulations such as fact verification and question answering. Sources of textual knowledge, such as Wikipedia articles, condition the generation of answers from the models. Recent advances in retrieval use sequence-to-sequence models to incrementally predict the title of the appropriate Wikipedia page given a query. However, this method requires supervision in the form of human annotation to label which Wikipedia pages contain appropriate context. This paper introduces a distant-supervision method that does not require any annotation to train autoregressive retrievers that attain competitive R-Precision and Recall in a zero-shot setting. Furthermore we show that with task-specific supervised fine-tuning, autoregressive retrieval performance for two Wikipedia-based fact verification tasks can approach or even exceed full supervision using less than 1/4 of the annotated data indicating possible directions for data-efficient autoregressive retrieval.

1 Introduction

Conditioning answer generation on knowledge from textual sources is a common component of many well-studied natural language processing tasks. For example, in the SQuAD (Rajpurkar et al., 2016) question answering task, a passage of text is used as a source of information to generate this answer. To enable machine-reading at scale, recent studies combine retrieval with reasoning (Chen et al., 2017; Roller et al., 2021) mandating that systems select appropriate passages from a corpus, such as Wikipedia, to condition answer generation. Furthermore, tasks such as fact verification (Thorne et al., 2018; Wadden et al., 2020; Diggelmann et al., 2020) use evidence retrieved from a corpus and consider both the label and the retrieved passages for evaluation.

Recent advances have been made in neural retrieval models, exploiting the structure of these tasks. De Cao et al. (2020) model retrieval as entity grounding (Bunescu and Pașca, 2006; Le and Titov, 2018): the retriever is trained to predict the title of the Wikipedia document for a given input and is built on a seq2seq architecture. Even though GENRE (De Cao et al., 2020) yields improvements for many retrieval-oriented NLP tasks in the KILT benchmark (Petroni et al., 2021), the model requires supervision during training with labeled data that contains the document titles for a given input.

In this paper, we present a method for training a high-precision and high-recall retrieval system on Wikipedia data in a self-supervised manner. Our system can be trained in less than 6 hours on a single GPU without human-annotated data. The recall far exceeds conventional retrieval methods such as TF-IDF and BM25. Compared to GENRE (De Cao et al., 2020), which is trained with 11 annotated datasets for thousands of GPU-hours, our self-supervised approach for Data Efficient
AutoRegressive Document Retrieval, DEARDr, performs within an R-Precision that is 6.36% lower and a Recall@10 that is 0.91% lower for the FEVER Shared Task. We additionally show that with task-specific fine-tuning, DEARDr can attain precision and recall exceeding a fully supervised baseline for FEVER (and on-par with GENRE), with just 16K annotated instances rather than 109K in the full dataset. Similar findings are observed for the HoVer fact verification task (Jiang et al., 2020).

2 Background

Conventional information retrieval methods, such as TF-IDF and BM25, have been applied many knowledge-intensive NLP tasks (Chen et al., 2017; Thorne et al., 2018), with reasonable success. These methods do not require supervision: instead, query-document similarity is estimated based on token-level frequency information from observations on a fixed corpus. At test time, sparse discrete vector encodings of documents and the query are compared to return documents with the highest similarity to the query. While this aids application to new tasks and settings, recall can be low, especially when there are variations in phrasing due to the sparse encoding of which tokens (or variants considering n-grams or subtokens) are present. Neural retrieval (Hanselowski et al., 2018; Karpukhin et al., 2020) in contrast, uses neural networks to generate dense encodings of the query and passages. These models are trained with supervision: the training data contains lists of appropriate passages for a given query, but typically does not contain negative instances. How negative instances are sampled in training influences the suitability of the retrieved documents for the downstream task (Cohen et al., 2019; Karpukhin et al., 2020). Variants of training regimes for dense retrieval also use Cloze-task (Lee et al., 2019), Wikipedia revision information (Chang and Kao, 2012), contrastive (Izacard et al., 2021) learning, or multi-task learning (Maillard et al., 2021) to improve performance.

2.1 Autoregressive Document Retrieval

In contrast to the previous approaches, where the content of a passage is scored for a query using its content, autoregressive document retrieval (De Cao et al., 2020) uses a seq2seq model that is trained to predict a relevant document title, such as a Wikipedia page. Tokens are decoded incrementally left to right where the and scored with $p(y|x) = \prod_{i=1}^n p(y_i|y_{<i}, x)$ where the decoded document title $\hat{y} \in E$ exists in a corpus $E$. To ensure this constraint is satisfied, constrained decoding sets $p(y_i|y_{<i}, x) = 0$ for token sequences $(y_1, \ldots, y_i)$ that do not occur in the index. In practice this works well in the Wikipedia domain where document titles are simple canonical descriptors of an entity or concept. An extension, mGENRE (Cao et al., 2021), has been trained for multi-lingual entity linking using Wikipedia hyperlinks and internationalized versions of the pages from the Wiki-data graph as supervision targets in other languages. This has not been applied to an entity linking task, but not evaluated for document retrieval.

Similarly, GENRE did use hyperlink-based information by incorporating data from BLINK during training. However, its contribution to system performance appears low (De Cao et al., 2020, Table 8), warranting further investigation. While the use of pre-training with hyperlink information in retrieval has shown promise (Ma et al., 2021) in other formulations, the use of distant-supervision in autoregressive retrieval, using the article titles and hyperlinks in training is emerging and has been studied in contemporaneous work (Chen et al., 2022). Lee et al. (2022) train autoregressive models for multi-hop retrieval, with a data augmentation strategy. Alternative autoregressive retrieval formulations are designed to predict document sub-strings (Bevilacqua et al., 2022): this obviates the need to have unique document identifiers.

3 Data Efficient Document Retrieval

The primary objective of this paper is to reduce the dependency on supervised instances and exploit distant supervision to train an autoregressive document retrieval system. Distant supervision for DEARDr exploits the structural aspects of the Wikipedia corpus: specifically, the page titles (denoted PT) and hyperlinks (denoted HL) from sentences to other pages. Sentences from Wikipedia documents are sampled from the corpus as input and DEARDr is trained to decode the page title or hyperlinks, or both (denoted PTHL).

Even though the DEARDr has only been pre-trained with distant supervision without exposure to annotated training data for a knowledge intensive NLP task, we hypothesize that training to predict a Wikipedia page title or hyperlinks acts a a reasonable analog that simulates a common component of many retrieval oriented tasks. This should be suffi-
cient to allow zero-shot application to retrieve relevant documents without the need for human annotations enabling application of knowledge-intensive NLP tasks to new domains or languages. In contrast, the GENRE model (De Cao et al., 2020) is trained with data from eleven Wikipedia-based NLP tasks with millions of annotated instances.

Constrained decoding At test time, a result set is decoded by aggregating the results from a beam search (Sutskever et al., 2014) with constrained decoding (De Cao et al., 2020). However, in contrast to GENRE, which predicts a single entity per beam, DEARDR is trained to predict a sequence of all the hyperlinked page names (illustrated in Figure 1).

Self-supervised vs task-specific retriever Once the DEARDR retriever has been pre-trained with self-supervision on Wikipedia data, it can be applied in a zero-shot setting to the knowledge-intensive task of fact verification. Some aspects of the test-task formulation, may have patterns that differ to what DEARDR is exposed to during the pre-training. Using small numbers of task-specific training data, the pre-trained DEARDR will be fine-tuned evaluated on downstream tasks. We hypothesize that the pre-training regimen for DEARDR will reduce the number of instances needed to train the system and attain similar performance to a system with full supervision.

4 Experimental Setup

Three different pre-training regimens for DEARDR, based on page title (PT), sentence hyperlinks (HL) and a combination of both (PTHL), are performed using the snapshot of Wikipedia from June 2017. This was the snapshot used for the FEVER shared task. Document-level retrieval for two fact verification tasks will be evaluated: FEVER (Thorne et al., 2018) and HoVER (Jiang et al., 2020).

Zero-Shot Document Retrieval: Without exposure to the underlying test task, DEARDR will be pre-trained using unlabeled instances from English Wikipedia articles (pre-trained with PT, HL or PTHL), and then applied to instances from these retrieval-based NLP tasks. From Wikipedia, we generate 16.8M distant-supervision instances.

Data-Efficient Document Retrieval: The DEARDR model will be fine-tuned using a low number of labeled instances from the target task. During training, we sample instances uniformly at random. We optimize training for Recall with early stopping. This occurred after 12,500 steps (100K instances in total).

Supervised Baseline: For a controlled baseline system that DEARDR can be compared against, we train a document retriever for the target task using all available data in a fully supervised setting.

Previous Work: We compare to GENRE (De Cao et al., 2020) which was trained with data from eleven retrieval tasks. We also compare to sparse-vector retrieval methods such as BM25 and TF-IDF. Finally, for dense-vector retrieval, we compare against DPR (Karpukhin et al., 2020). Because contrastive retrieval (Izacard et al., 2021) does not offer significant advantages over BM25 for FEVER, we do not evaluate against it.

4.1 Evaluation

Document retrieval is evaluated using two performance evaluation metrics: R-Precision and Recall@k. R-Precision is the precision of retrieved documents@R where R is the number of expected elements labeled for the instance. If the test set only specifies 1 valid document, this is equivalent to Precision@1. However, datasets sometimes require a multi-hop combination of pages for inference, requiring multiple documents to be considered for evaluation. Recall@k is the proportion of the gold documents present in the first k elements predicted by the model. This metric is a useful indicator of potential upper-bound system performance for some tasks, such as FEVER, which considers up to 5 retrieval results for scoring claim veracity. Where multiple answer sets are present for instances, we consider each answer set independently and return the max score over all the sets to allow comparison to the KILT methodology (Petroni et al., 2021).

4.2 Implementation

We use the HuggingFace (Wolf et al., 2020) implementation of T5-base (Raffel et al., 2020). This is fine-tuned using data as outlined in the previous section. We optimize hyper-parameters by sweeping the learning rate and scheduler (documented in Appendix A.2) and maximizing R-Precision on the dev split. The index for constraining decoding is constructed from all subtokens generated by the T5 Tokenizer for article titles from the Wikipedia version for the test task.
5 Results and Discussion

5.1 Pre-training Intrinsic Evaluation

DearDr was optimized by selecting the model with the highest R-precision on the FEVER shared task. For the R-Precision on the PT and HL components of the pre-training task, we provide the following intrinsic evaluation listed in Table 1 to evaluate the pre-training objectives. Without pre-training on hyperlinks, recall is low indicating that hyperlink pre-training may be beneficial to multi-entity retrieval needed for some FEVER instances.

5.2 Downstream Extrinsic Evaluation

FEVER: For the FEVER shared task, we trained DearDr with instances sampled from the Wikipedia snapshot for the task without using any human-annotated data. Table 2 highlights the retriever’s R-Precision and Recall@10 in comparison to a fully supervised system showing that in the zero shot setting (without exposure to any labeled data) document retrieval scores are adequate and far exceed retrieval from token-based similarity methods such as TF-IDF and BM25. Because FEVER is a claim verification task, the claims are similar in nature to sentences sampled from Wikipedia pages. The similarity between the claims and the Wikipedia sentences the zero-shot system was exposed to during training mean that this system is able to apply well to this task.

While GENRE was trained on 11 tasks with over 100K fact verification instances and over 500K question answering instances, the R-Precision of our zero-shot system is only 6.36% lower with Recall@10 less than one percent lower. Given that most modern fact verification approaches perform supervised re-ranking of sentences from these documents, we do not foresee this lower precision having such a large impact on the final task score.

With full supervision from the FEVER task, our control model for comparison attains an R-Precision of 81.36%. However, with small numbers of instances for fine-tuning on FEVER, higher recalls can be attained. With 16,384 instances (less than 1/8 of the dataset), an R-Precision and Recall@10 exceeding this supervised baseline can be achieved. Furthermore, with only 2048 instances (2% of the dataset), an R-Precision of at least 80% is attained. In contrast, without pre-training R-Precision for both of these models with the same number of data is less than 30%. Learning curves are plotted in Figure 2.

HOVER: The multi-hop nature of HoVer presents more complex reasoning challenges than...
HOVER Retrieval (%)

| Approach        | R-Prec | Recall@10 |
|-----------------|--------|-----------|
| GENRE (Transfer)| 43.28  | 49.41     |
| DEARDR (PT) ZS | 32.83  | 36.43     |
| DEARDR (HL) ZS | 42.22  | 43.78     |
| DEARDR (PTHL) ZS | 38.94 | 47.44     |
| DEARDR (PTHL) 4K | 45.62  | 49.14     |
| DEARDR (PTHL) All | 46.23  | 50.33     |
| Supervised 4K   | 29.24  | 35.22     |
| Supervised     | 46.22  | 50.38     |

Table 3: The multi-hop aspect of HoVer presents new challenges. Despite this, DEARDR attains higher R-Prec with fewer training data than supervised baselines.

FEVER and is reported in Table 3. Our zero-shot model has R-Precision that is less than 1% of GENRE. While GENRE wasn’t trained on HoVer, it was trained on HotpotQA (Yang et al., 2018) which the HoVer dataset is derived from.

The benefit of pre-training with hyperlinks becomes apparent for multi-hop challenges as R-Precision for HL and PTHL exceed PT. With limited fine-tuning, using 1/4 of the dataset, R-Precision with DEARDR is less than 1% away from a fully supervised model, despite using fewer data. Without pre-training, R-Precision is unsatisfactory. With all data, DEARDR performs as good as a model without pre-training. While DEARDR is beneficial for this task with fewer data, there are clearly more complex challenges with multi-hop reasoning that require further data augmentation, such as (Lee et al., 2022), to be solved solved by autoregressive methods for retrieval.

Question Answering: The similarity between fact verification and DEARDR pre-training is similar, aiding retrieval. However, application to question answering (TriviaQA (Joshi et al., 2017, TQA), HotpotQA (Yang et al., 2018, HPQA) and NaturalQuestions (Kwiatkowski et al., 2019, NQ)) requires further study. Table 4 shows pre-training does offer a benefit, but with fewer data for fine-tuning, similar gains in retrieval cannot be attained.

6 Conclusions and Future Work

We show that distant supervision and pre-training enables high precision autoregressive document retrieval with fewer annotated training data. While previous work has studied the utility of pre-training for dense-retrieval, this work aids understanding of sparse autoregressive retrieval. In application to fact verification, fewer labeled training data were required. However, when we applied this method to question answering, satisfactory results were not obtained due to the domain shift between the two tasks. Better understanding this limitation would be required to adapt DEARDR pre-training to a wider range of tasks and multi-hop reasoning.

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A Appendix

A.1 Hardware Requirements
Experiments were performed on a single workstation with a single NVIDIA GTX 1080 Ti GPU.

A.2 Implementation

A.2.1 Pre-training
The following parameters were adjusted as part of the hyper-parameter optimization with the best parameters for all experiments indicated in bold. For HL, using learning rate of 5e-6 was more beneficial.

- Learning rate: 1e-4, 5e-5, 1e-5, 5e-6, 1e-6.
- Scheduler: constant with warmup, constant, linear.

A.2.2 Fine-tuning + Supervised
The following parameters were adjusted as part of the hyper-parameter optimization with the best parameters for all experiments indicated in bold. For fine-tuning, using a dropout of 0.2 was more beneficial.

- Learning rate: 1e-4, 5e-5, 1e-5, 5e-6, 1e-6.
- Scheduler: constant with warmup, constant, linear.
- Dropout: 0.1, 0.2, 0.3

B Licenses
The dataset released with this paper makes use of data from Wikipedia which is licensed under creative commons CC-BY-SA 4.0 license.