Learning to Retrieve Passages without Supervision

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Abstract

Dense retrievers for open-domain question answering (ODQA) have been shown to achieve impressive performance by training on large datasets of question-passage pairs. We investigate whether dense retrievers can be learned in a self-supervised fashion, and applied effectively without any annotations. We observe that existing pretrained models for retrieval struggle in this scenario, and propose a new pretraining scheme designed for retrieval: recurring span retrieval. We use recurring spans across passages in a document to create pseudo examples for contrastive learning. The resulting model – Spider – performs surprisingly well without any examples on a wide range of ODQA datasets, and is competitive with BM25, a strong sparse baseline. In addition, Spider often outperforms strong baselines like DPR trained on Natural Questions, when evaluated on questions from other datasets. Our hybrid retriever, which combines Spider with BM25, improves over its components across all datasets, and is often competitive with in-domain DPR models, which are trained on tens of thousands of examples.\footnote{Our code and models are publicly available: \url{https://github.com/oriram/spider}, and: \url{https://huggingface.co/tau/spider}}

1 Introduction

Dense representations are the state-of-the-art models for retrieval in open-domain question answering (Lee et al., 2019; Karpukhin et al., 2020; Qu et al., 2021). However, such models rely on very large datasets of question-passage pairs for training. These datasets are expensive and sometimes even impractical to collect (e.g., for new languages or domains), and often fail to generalize to new question distributions (Sciavolino et al., 2021; Reddy et al., 2021).

The above difficulty motivates the development of retrieval models that do not rely on large annotated training sets, but are instead trained only on unlabeled text. In this work we introduce such a model: Spider (Span-based unsupervised dense retriever). Spider is a dense model pretrained from self-supervision only, which achieves retrieval accuracy that significantly improves over other unsupervised methods. Furthermore, Spider outperforms a fully supervised DPR model (Karpukhin et al., 2020) on multiple datasets.

Spider is based on a novel self-supervised scheme: recurring span retrieval. We leverage recurring spans in different passages of a document (e.g. “Yoko Ono” in Figure 2) to create pseudo examples for self-supervised contrastive learning, where one of the passages containing the span is transformed into a short query that (distantly) resembles a natural question, and the other is the target for retrieval. A random passage from the document that does not contain the span is considered as the negative passage for the query.

We evaluate Spider on ODQA on several bench-
God at Sinai granted Aaron the priesthood for himself and his male descendants, and he became the first High Priest of the Israelites. The books of Exodus, Leviticus and Numbers maintain that Aaron received from God a monopoly over the priesthood for himself and his male descendants. During the journey in the wilderness, Aaron was not always prominent or active. Lennon said that much of the song’s lyrics and content came from his wife Yoko Ono, and in 2017 the process to give Yoko co-writing credit Imagine (John Lennon Song) ... Several poems from Yoko Ono’s 1964 book Grapefruit inspired Lennon to write the lyrics for ‘Imagine’. Imagine (John Lennon Song) ... Imagine was written during the Let It Be session. Lennon finished composing ‘Imagine’ one morning ...

Figure 2: An example of our pretraining approach: Given a document $D$ (e.g. the article “Aaron” in Wikipedia), we take two passages that contain a recurring span $S$. One of them is transformed into a short query $q_i'$ using a random window surrounding $S$, in which $S$ is either kept (top) or removed (bottom). The second passage is then considered the target for retrieval $p_i^+$, while a random passage from $D$ that does not contain $S$ is considered the negative $p_i^-$ (right). Each batch is comprised of multiple such examples, and the pretraining task is to find the positive passage $p_i^+$ for each query $q_i'$ (solid line) from the passages of all examples (dashed lines).

marks. Even though Spider uses no labeled examples at all, it narrows the gap between unsupervised dense retrievers and DPR on all benchmarks (Figure 1). Spider outperforms other unsupervised dense models by at least 15% in top-20 accuracy in all six datasets, and even reaches a 40% improvement in four of them (TriviaQA, CuratedTREC, SQuAD and EntityQuestions; Table 1). Moreover, we demonstrate that Spider and BM25 are complementary, and that applying a simple combination (Ma et al., 2021) significantly improves retrieval accuracy on top of both and sometimes outperforms a fully supervised DPR model.

We further demonstrate the utility of Spider as an off-the-shelf retriever via cross-dataset evaluation, i.e. when supervised models are tested against datasets which they were not trained on, a setting that often challenges dense retrievers (Sciavolino et al., 2021; Reddy et al., 2021). In this setting, Spider is competitive with dense retrievers trained on an abundance of training examples. Given only a handful of examples for fine-tuning from one dataset, Spider outperforms strong fully supervised baselines in most transfer scenarios.

Spider significantly outperforms other pretrained models in few-shot in-domain settings as well. An ablation study shows that careful design of the queries seen by the model during pretraining has a large impact on downstream performance.

2 Background

Open-domain question answering (ODQA) is a core task in NLP, where the goal is to find the answer to a given question over a large corpus, e.g. Wikipedia (Voorhees and Tice, 2000; Chen et al., 2017; Chen and Yih, 2020). This task gained considerable attention following recent advancement in machine reading comprehension, where models reached human parity in extracting an answer from a paragraph given a question (Devlin et al., 2019; Liu et al., 2019; Raffel et al., 2020).

Due to the high cost of applying such reading comprehension models, or readers, over the entire corpus, state-of-the-art systems for ODQA first apply an efficient retriever – either sparse (Robertson and Zaragoza, 2009; Chen et al., 2017) or dense (Lee et al., 2019; Karpukhin et al., 2020) – in order to reduce the search space over which the reader is applied.

Recently, dense retrieval models have shown promising results on ODQA, even outperforming strong sparse methods that operate on the lexical level, e.g. BM25. Specifically, the dominant approach employs a dual-encoder architecture, where documents and questions are mapped to a shared continuous space such that proximity (usually defined by inner product) in that space represents the relevance between pairs of documents and questions. Formally, let $C = \{p_1, \ldots, p_m\}$ be a corpus of passages. Each passage $p \in C$ is fed to a passage
We now describe our approach for pretraining with the same recurring span, we construct a query inter alia complement dense retrieval (Ma et al., 2021), we learning. A model from this self-supervision with contrastive learning spans, are used as negative examples. We train as the target for retrieval (Figure 2). Other paragraphs from one of the paragraphs, while the other is taken as a query passage from the article is considered negative. The window length \( \ell \) is chosen uniformly between 5 and 30 to resemble questions of different lengths. The window length \( \ell \) is chosen uniformly between 5 and 30 to resemble questions of different lengths.

Our contribution towards improving dense retrievers in this setting is twofold. First, we construct a self-supervised pretraining method based on recurring spans across passages in a document to emulate the training process of dual-encoders for dense retrieval. Second, we demonstrate that a simple combination of BM25 with our dense retriever leads to a strong and sample-efficient hybrid retriever that rivals the performance of models trained with tens of thousands of examples.

\[ s(q, p) = E_Q(q)^\top E_P(p). \]

Given a question \( q \), the retriever finds the top-\( k \) candidates with respect to \( s(q, \cdot) \), i.e., top-\( k_{pC} \) \( s(q, p) \). In order to perform this operation efficiently at test time, a maximum-inner product search (MIPS) index (Johnson et al., 2021) is built over the encoded passages \( \{E_P(p_1), \ldots, E_P(p_m)\} \).

While this method is both effective and efficient, pretrained models such as BERT (Devlin et al., 2019) are not trained to produce semantic sequence-level representations, and thus require fine-tuning over many question-evidence pairs in order to learn meaningful representations for retrieval. While considerable work has been devoted to create pretraining schemes for dense retrieval (Lee et al. 2019; Guu et al. 2020; inter alia), it generally assumed access to large training datasets after pretraining. In contrast, we do not assume access to any examples.

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3 Our Model: Spider

We now describe our approach for pretraining dense retrievers, which is based on a new self-supervised task (Section 3.1). Our pretraining is based on the notion of recurring spans (Ram et al., 2021) within a document: given two paragraphs with the same recurring span, we construct a query from one of the paragraphs, while the other is taken as the target for retrieval (Figure 2). Other paragraphs in the document, not containing the recurring span, are used as negative examples. We train a model from this self-supervision with contrastive learning.

Since sparse lexical methods are known to complement dense retrieval (Ma et al., 2021), we also incorporate a simple hybrid retriever (combining BM25 and Spider) in our experiments (Section 3.2).

3.1 Pretraining: Recurring Span Retrieval

Given a document \( D \subset C \) with multiple passages (e.g., an article in Wikipedia), we define cross-passage recurring spans in \( D \) as arbitrary n-grams that appear more than once and in more than one passage in \( D \). Let \( S \) be a cross-passage recurring span in \( D \), and \( D_S \subset D \) be the set of passages in the document that contain \( S \), so \( |D_S| > 1 \) by definition. First, we randomly choose a query passage \( q \in D_S \). In order to resemble a natural language question, we apply a heuristic query transformation \( T \), which takes a short random window from \( q \) surrounding \( S \) to get \( q' = T(q) \) (described in detail below).

Similar to DPR, each query has one corresponding positive passage \( p^+ \) and one corresponding negative passage \( p^- \). For \( p^+ \), we sample another random passage from \( D \) that contains \( S \) (i.e., \( p^+ \in D_S \setminus \{q\} \)). For \( p^- \), we choose a passage from \( D \) that does not contain \( S \) (i.e., \( p^- \in D \setminus D_S \)). The article title is prepended to both passages (but not to the query).

Figure 2 illustrates this process. We focus on the first example (in orange), which is comprised of three passages originating from the Wikipedia article “Aaron”. The span “the priesthood for himself and his male descendants” appears in two passages in the article. One of the passages was transformed into a query (top-left), while the other is taken as a positive passage (top-right). Another random passage from the article is considered negative.

As the example demonstrates, existence of recurring spans in two different passages often implies semantic similarity between their contexts.

Query Transformation As discussed above, after we randomly choose a query passage \( q \) (with a recurring span \( S \)), we apply a query transformation on \( q \), which results in \( q' \). The main goal is to make the queries more similar to open-domain questions.

First, we define the context to keep from \( q \). Since passages are much longer than typical natural questions,\(^2\) we take a random window containing \( S \): The window length \( \ell \) is chosen uniformly between 5 and 30 to resemble questions of different lengths.

\(^2\)In our case, passages contain 100 words, while Joshi et al. (2017) report an average length of 14 words for questions.
The actual window is then chosen at random from all possible windows of length $\ell$ that contain $S$.

Second, we randomly choose whether to keep $S$ in $q'$ or remove it. This choice reflects two complementary skills for retrieval — the former requires lexical matching, while the latter intuitively encourages semantic contextual representations.

The queries in Figure 2 (left) demonstrate this process. In the top query, the recurring span “the priesthood for himself and his male descendants” was kept as is. In the bottom query, the span “Yoko Ono” was removed.

Span Filtering To focus on meaningful spans with semantically similar contexts, we apply several filters on recurring spans. First, we adopt the filters from Ram et al. (2021): (1) spans only include whole words, (2) only maximal spans are considered, (3) spans that contain only stop words are filtered out, (4) spans contain up to 10 tokens. In addition, we add another filter: (5) spans should contain at least 2 tokens. This is done mainly to avoid uninformative recurring words, e.g., verbs or adjectives. Note that as opposed to other approaches for span filtering (Glass et al., 2020; Guu et al., 2020; Roberts et al., 2020; Sachan et al., 2021), our heuristics do not require any model.

Training At each time step of pretraining, we take a batch of $m$ examples $\{(q'_i, p_i^+, p_i^-)\}_{i=1}^m$, and optimize the cross-entropy loss with respect to the positive passage $p_i^+$ of each query $q'_i$ in a contrastive fashion, similar to Karpukhin et al. (2020):

$$-\log \frac{\exp(s(q'_i, p_i^+))}{\sum_j \left( \exp(s(q'_i, p_j^+)) + \exp(s(q'_i, p_j^-)) \right)}$$

3.2 Hybrid Dense-Sparse Retrieval

It is well established that the strong lexical matching skills of sparse models such as BM25 (Robertson and Zaragoza, 2009) are complementary to dense representation models. Ma et al. (2021) demonstrated strong improvements by using hybrid dense-sparse retrieval, based on BM25 and DPR. Specifically, they define the joint score of a hybrid retriever via a linear combination of the scores given by the two models, i.e. $s_{\text{hybrid}}(q, p) = s(q, p) + \alpha \cdot \text{BM25}(q, p)$. They tune $\alpha$ on a validation set of each of the datasets. Since tuning hyperparameters is unrealistic in our settings, we simply set $\alpha = 1.0$ for all hybrid models. Thus, we define:

$$s_{\text{hybrid}}(q, p) = s(q, p) + \text{BM25}(q, p)$$

We adopt the normalization technique from Ma et al. (2021): If a passage $p$ is found in the top-$k'$ (with $k' > k$) of a dense retriever but not of BM25, then BM25($q, p$) is set to the minimum value from the top-$k'$ results of BM25 (and vice versa).

4 Experimental Setup

To evaluate how different retrievers work on different settings and given different amounts of supervision, we simulate various scenarios by using existing datasets, with an emphasis on the unsupervised setting. We expect our model to show significant improvements in settings where no examples, or only a few, are available.

4.1 Datasets

We evaluate our method on six datasets commonly used in prior work, all of which are over Wikipedia: Natural Questions (NQ; Kwiatkowski et al. 2019), TriviaQA (Joshi et al., 2017), WebQuestions (WQ; Berant et al., 2013), CuratedTREC (TREC; Baudiš and Šedivý 2015), SQuAD (Rajpurkar et al., 2016) and the recent EntityQuestions (EntityQs; Sciavolino et al. 2021). The datasets vary significantly in the number of examples given in question distribution and the size of training data. We use EntityQs only for evaluation.

Lewis et al. (2021a) showed that there exists a significant overlap between train and test questions in ODQA datasets, and specifically NQ, TriviaQA and WQ. In our case, this poses an issue: Supervised models can memorize training questions while unsupervised methods cannot. Thus, we use the “no answer overlap” portion of the test set of the aforementioned three datasets.3 We denote these test sets by NQ*, TriviaQA* and WQ*. For completeness, we give the results on the original test sets in the appendix. For the remaining datasets, we take their original test sets since they were not analyzed by Lewis et al. (2021a) and therefore do not have corresponding test sets. Moreover, we do not expect such overlaps in these datasets, as SQuAD was built such that each split (train, development and test) is constructed from a disjoint set of Wikipedia articles, and TREC has a relatively small training set (1,125 examples). We consider EntityQs only for evaluation and thus such overlap is irrelevant.

3We choose this portion (rather than “no question overlap”) as it is larger and thus introduces less noise to evaluation.
4.2 Baselines

We consider a variety of baselines, including supervised and self-supervised dense models, as well as sparse methods like BM25. All dense models share the architecture of BERT-base (namely a transformer encoder; Vaswani et al. 2017), including the number of parameters (110M) and uncased vocabulary. In addition, all pretrained dense models use weight sharing between query and passage encoders (only during pretraining). $E_Q(q)$ and $E_P(p)$ are defined as the representation of the [CLS] token. Similar to Gao and Callan (2021a), we do not consider the models trained in Chang et al. (2020), as they rely on Wikipedia links, and were not made public.

**BM25** (Robertson and Zaragoza, 2009) A sparse bag-of-word model that extends TF-IDF (i.e. reward rare terms that appear in both $q$ and $p$) by accounting for document length and term frequency saturation.

**BERT** (Devlin et al., 2019) was pretrained on two self-supervised tasks: Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). We evaluate BERT only in the supervised setting, namely as a backbone for fine-tuning.

**ICT** (Lee et al., 2019) A dual-encoder model which was pretrained on the Inverse Cloze Task. Given a batch of passages, ICT masks a sentence from each passage, and trains to predict what is the source passage for each sentence. ICT encourages lexical matching by keeping the sentence in the original passage with low probability. Note that unlike our approach, ICT is trained to produce representations to corrupted passages. In addition, we encourage lexical matching of individual terms in the query, rather than the entire query as ICT.

**Condenser & CoCondenser** (Gao and Callan, 2021a,b) Condenser is an architecture that aims to produce sequence-level (i.e. sentences and passages) representations via a variant of the MLM pretraining task. Specifically, to predict a masked token $x_t$, they condition the prediction on two representations: (1) a representation of $x_t$ from an earlier layer in the encoder, and (2) a dense sequence-level representation of the [CLS] token at the last layer of the network. CoCondenser adds a “corpus-aware” loss alongside MLM to create better embeddings by sampling two sub-spans from each sequence and train in a contrastive fashion (i.e. the model should produce similar representations to sub-spans from the same source sequence).

**DPR** (Karpukhin et al., 2020) A supervised model for ODQA based on dual-encoders and trained in a contrastive fashion (see Section 2). All DPR models considered in the paper are initialized with a BERT-base encoder, and trained on full datasets: DPR-Single models are trained on a single dataset, and are also referred to as DPR-$x$, where $x$ is the name of the dataset (i.e. DPR-NQ and DPR-Single evaluated on NQ are the same model). DPR-Multi was trained on a concatenation of NQ, TriviaQA, WQ and TREC. For DPR-NQ and DPR-Multi, we use the checkpoint released by the authors. We re-train the other DPR-Single models – which were not made public – using the same hyper-parameters as Karpukhin et al. (2020). We do not train a DPR model on EntityQs. The models we trained are consistent with the results of Karpukhin et al. (2020), except for DPR-SQuAD, where our model is worse than reported.

4.3 Evaluation Settings

We evaluate our method and baselines in a broad range of scenarios. We report top-k retrieval accuracy, i.e. the percentage of questions for which the answer span is found in the top-k passages.

**Unsupervised Setting** Models are trained only on unlabeled data, and evaluated on all datasets without using any labeled examples (i.e. in a zero-shot mode). As a reference point, we also compare to DPR.

**Cross-Dataset Generalization** To test the robustness of different models across datasets, we compare Spider to DPR models that tested on datasets they were not trained on. The motivation behind these experiments is to determine the quality of all models as “off-the-shelf” retrievers, when given no supervision on the type of questions.

**Few-Shot / Supervised Setting** We compare Spider to other pretrained models for retrieval when fine-tuned on different amounts of training samples. Specifically, we consider the settings where 128 examples, 1024 examples and full datasets are available. We restrict these experiments to NQ and TriviaQA due to the high cost of running them for all datasets and baselines.

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4 For unsupervised models, this is essentially equivalent to the unsupervised setting.
| Model               | Mode | NQ^∗ | TriviaQA^∗ | WQ^∗ | TREC | SQuAD | EntityQs |
|--------------------|------|------|------------|------|------|-------|---------|
| DPR-Single         | Dense| 68.7 | 56.4       | 60.0 | 81.7 | 54.6  | 49.7    |
| DPR-Multi          | Dense| 68.8 | 55.8       | 60.5 | 89.2 | 52.0  | 56.7    |
| DPR-Single + BM25  | Hybrid| 74.0 | 60.2       | 62.4 | 87.0 | 72.7  | 71.7    |
| DPR-Multi + BM25   | Hybrid| 73.7 | 60.9       | 63.8 | 90.3 | 72.1  | 73.3    |
| BM25               | Sparse| 55.5 | 56.0       | 53.6 | 81.1 | 71.2  | 71.4    |
| ICT                | Dense| 33.5 | 7.0        | 32.0 | 19.2 | 14.6  | 2.6     |
| Condenser          | Dense| 13.3 | 4.2        | 19.3 | 20.2 | 13.2  | 2.7     |
| CoCondenser        | Dense| 36.8 | 8.0        | 38.3 | 22.4 | 16.5  | 1.4     |
| Spider             | Dense| 57.3 | 53.4       | 53.0 | 82.9 | 59.1  | 60.1    |
| Spider + BM25      | Hybrid| 64.8 | 58.6       | 59.1 | 87.5 | 75.0  | 74.3    |

Table 1: Top-20 retrieval accuracy (i.e., the percentage of questions for which the answer is present in the top-20 passages) on the test set of six datasets for supervised and unsupervised approaches. DPR-Single is trained on the corresponding dataset only (except for EntityQs, where the model was trained on Natural Questions, similar to Sciavolino et al. 2021). DPR-Multi was trained on the first four datasets. We mark in bold the best unsupervised method for each dataset. For NQ, TriviaQA and WQ, we use the “no answer overlap” portion of the test sets, to control for memorization issues which are not possible for unsupervised methods (see Section 4.1).

4.4 Implementation Details

We base our implementation on the official code of DPR (Karpukhin et al., 2020), which is built on Hugging Face Transformers (Wolf et al., 2020).

Passage Corpus We adopt the same corpus and preprocessing as Karpukhin et al. (2020), namely the English Wikipedia dump from Dec. 20, 2018 (following Lee et al. 2019) with blocks of 100 words as retrieval units. Preprocessing (Chen et al., 2017) removes semi-structured data (e.g., lists, infoboxes, tables, and disambiguation pages), resulting in roughly 21 million passages. This corpus is used for both pretraining and all downstream experiments.

Pretraining We train Spider for 100K steps, using batches of size 512. similar to ICT and Condenser, the model is initialized from the uncased BERT-base model, and weight sharing between the passage and query encoders is applied. Each pseudo-query has a single corresponding positive example and hard negative example. Overall, the model is expected to predict the positive passage out of a total of 1024 passages. The learning rate is warmed up for 1,000 steps to a maximum value of $10^{-5}$, after which linear decay is applied. We use Adam (Kingma and Ba, 2015) with its default hyperparameters as our optimizer, and apply a dropout rate of 0.1 to all layers.

We utilize eight Quadro RTX 8000 GPUs for pretraining, which takes roughly two days.

Fine-Tuning For fine-tuning, we use the hyperparameters from Karpukhin et al. (2020), and do not perform any hyperparameter tuning. Specifically, we train using Adam (Kingma and Ba, 2015) with bias-corrected moment estimates (Zhang et al., 2021), and a learning rate of $10^{-5}$ with warmup and linear decay. We use batch size of 128 for 40 epochs with two exceptions. First, when fine-tuning DPR-WQ and DPR-TREC, we run for 100 epochs for consistency with the original paper. Second, when fine-tuning on 128 examples only, we lower the batch size to 32 and run for 80 epochs. We use BM25 negatives produced by Karpukhin et al. (2020), and do not create hard negatives by the model itself (Xiong et al., 2021).

Retrieval When performing dense retrieval, we apply exact full search using FAISS (Johnson et al., 2021). This is done due to the high memory demand of creating an HNSW index for each experiment (Karpukhin et al., 2020). For sparse retrieval (i.e. BM25), we utilize the Pyserini library (Lin et al., 2021), built on top of Anserini (Yang et al., 2017, 2018).

5 Results

Our experiments show that Spider significantly improves performance in the challenging unsupervised retrieval setting, even outperforming strong supervised models in many cases. Thus, it enables the use of such retrievers when no examples are

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5In-batch negatives are taken across all GPUs, as suggested in Qu et al. (2021).

6This is done to avoid running on all examples in each step, which might lead to overfitting. However, we did not test this hypothesis.
available. When trained on small datasets (i.e., few-shot settings), we observe significant improvements over the baselines as well. We perform ablation studies that demonstrate the importance of our pretraining design choices.

5.1 Unsupervised Setting

Table 1 shows the performance (measured by Top-20 retrieval accuracy) of Spider compared to other unsupervised baselines on all datasets, without additional fine-tuning. Top-100 accuracy results are given in Table 5 in the Appendix. Supervised baselines (i.e., DPR) are also given for reference. Results demonstrate the effectiveness of Spider w.r.t. other dense pretrained models, across all datasets. For example, the average margin between Spider and ICT is more than 40 points. Moreover, Spider outperforms DPR-Single on three of the datasets (TREC, SQuAD and EntityQs), despite the fact that DPR has access to the full labeled training data for these datasets. When DPR is better than our model, the gap narrows for higher values of $k$. In addition, it is evident that Spider is able to outperform BM25 in some datasets (NQ, WQ and TREC), while the opposite is true for others (TriviaQA, SQuAD and EntityQs). However, our hybrid retriever is able to combine the merits of each of them into a stronger model. For example, in TriviaQA, Spider and BM25 achieve 73.1% and 76.4%, respectively. The hybrid model significantly improves over both models and obtains 79.7% top-20 accuracy and is on par with DPR-Single and DPR-Multi. This trend can be observed across all datasets, where using the hybrid retriever is better than using either one of them.

5.2 Cross-Dataset Generalization

An important merit of Spider is the fact that a single model can obtain good results across many datasets, i.e., in a “zero-shot” setting. Table 2 demonstrates the results of supervised models in a similar setting, where DPR models are tested on unseen datasets. Spider outperforms four of the six DPR models (DPR-WQ, DPR-TREC, DPR-SQuAD and DPR-Multi) across all datasets. In addition, it significantly outperforms DPR-NQ, a widely-used retriever, on three of five datasets (TriviaQA, SQuAD and EntityQs). DPR-TriviaQA is the only model that is consistently better than Spider. However, fine-tuning Spider on as few as 128 examples from TriviaQA is enough to pass DPR-TriviaQA on three datasets out of five, including NQ.

5.3 Supervised Settings

Table 3 shows the performance when fine-tuning pretrained models on 128 examples, 1024 examples and full datasets from NQ and TriviaQA. When only 128 examples are available, Spider significantly outperforms all other models, with absolute gaps of 3-9% on both datasets. On TriviaQA, Spider fine-tuned on 128 examples is able to outperform all other baselines when they are trained on 1024 examples. Higher margins in top-$k$ accuracy are observed for lower values of $k$. Even though Spider was designed for unsupervised and few-shot settings, it obtains the best result in both datasets when 1024 examples are available (up to 2.2% and 4.9% margins on NQ and TriviaQA, respectively). It is competitive with other models in the full dataset setting as well.

| Model          | # Examples | NQ*  | TriviaQA* | WQ* | TREC | SQuAD | EntityQs |
|----------------|------------|------|-----------|-----|------|-------|----------|
| DPR-NQ         | 58,880     | -    | 49.5      | 55.7| 85.9 | 48.9  | 49.7     |
| DPR-TriviaQA   | 60,413     | 58.6 | -         | 58.5| 87.9 | 55.8  | 62.7     |
| DPR-WQ         | 2,474      | 49.1 | 46.0      | -   | 82.0 | 52.3  | 58.3     |
| DPR-TREC       | 1,125      | 49.7 | 44.0      | 49.2| -    | 49.4  | 46.9     |
| DPR-SQuAD      | 70,096     | 33.8 | 39.4      | 39.5| 74.8 | -     | 31.0     |
| DPR-Multi      | 122,892    | -    | -         | -   | -    | 52.0  | 56.7     |
| BM25           | None       | 55.5 | 56.0      | 53.6| 81.1 | 71.2  | 71.4     |
| Spider         | None       | 57.3 | 53.4      | 53.0| 82.9 | 59.1  | 60.1     |
| Spider (NQ-128)| 128        | -    | 55.3      | 57.6| 84.9 | 59.5  | 65.3     |
| Spider (TriviaQA-128) | 128 | 60.7 | -         | 57.2| 86.5 | 63.2  | 65.3     |

Table 2: Top-20 retrieval accuracy in a “zero-shot” setting, where models are evaluated against datasets not seen during their training. DPR-$x$ is a model trained on the full dataset $x$, and DPR-Multi was trained on NQ, TriviaQA, WQ and TREC. Spider (NQ-128) was fine-tuned on 128 examples from NQ, and similarly Spider (TriviaQA-128) was fine-tuned on 128 examples from TriviaQA. # Examples is the number of labeled examples used to train the model. * For NQ, TriviaQA and WQ, we use the “no answer overlap” portion of the test sets (see Section 4.1).
Table 3: Top-\(k\) retrieval accuracy of different pretrained models on the test sets of Natural Questions and TriviaQA, after fine-tuning on various sizes of training data: 128 examples, 1024 examples and the full datasets. All models are trained with the data produced by Karpukhin et al. (2020), i.e. BM25-based negative examples. Results with up to a 0.5-point difference from the best are marked in bold.

Table 4: Ablations on the development set of Natural Questions. We first determine the context to take from the query passage, and then decide what operation will be applied on the recurring span (either removed, kept as is, or replaced with a mask token). The last row corresponds to our model Spider.

5.4 Ablation Study

We perform an ablation study on the query transformation applied on the query passage.

First, we choose the context to keep from \(q\). We consider three options: (1) The whole passage, (2) a prefix of random length preceding \(S\), and (3) a random window around \(S\): The length and start position of the window are both random, e.g. the window can start before \(S\) and end after \(S\).

Second, we consider several options concerning the span \(S\) itself: (1) replace \(S\) with a [MASK] token, (2) Remove \(S\), and (3) keep \(S\) as is.

We do not enumerate over all possible options – both due to high costs, and in order to remain as close as possible to the “zero-shot” setting. Specifically, for the whole passage context option, we replace \(S\) with a [MASK] since \(q'\) is very long. For the prefix option, we always remove \(S\), as it is in any case, by definition, in the end of \(q'\). For the random window, we experiment with keeping \(S\), removing it, and choosing uniformly at random whether to keep or remove it. We hypothesize that the latter is the best option, as it reflects two complementary skills – the former requires lexical matching, while the latter intuitively encourages semantic contextual representations.

The ablations results are provided in Table 4. As we hypothesized, choosing the random window option while alternating between keeping and removing the recurring span (Spider) gives the best results.

These results suggest that keeping the whole passage hurts performance significantly. This finding validates our prior intuition – taking a short context
from $q$ is beneficial to resemble natural language questions. In addition, while prefix outperforms random window when removing $S$, we did not run it with alternation between keeping and removing, as $S$ would always be in the end of the query (while we want to encourage lexical matching over the entire query).

6 Related Work

Pretraining for dense retrieval has recently gained a considerable attention, following the success of self-supervised models in many NLP tasks (Devlin et al., 2019; Liu et al., 2019; Brown et al., 2020). While most works focus on fine-tuning such retrievers on large datasets after pretraining (Lee et al., 2019; Chang et al., 2020; Guu et al., 2020; Sachan et al., 2021; Gao and Callan, 2021a), we attempt to bridge the gap between unsupervised dense models and strong sparse (e.g., BM25; Robertson and Zaragoza 2009) or supervised dense baselines (e.g., DPR; Karpukhin et al. 2020). A concurrent work by Oğuz et al. (2021) presented DPR-PAQ, which shows strong results on NQ after pretraining. However, their approach utilizes PAQ (Lewis et al., 2021b), a dataset which was generated using models trained on NQ, and is therefore not unsupervised.

Leveraging recurring spans for self-supervised pretraining has previously been considered for numerous tasks, e.g. coreference resolution and coreferential reasoning (Kocijan et al., 2019; Varkel and Globerson, 2020; Ye et al., 2020) and question answering (Ram et al., 2021; Bian et al., 2021; Castel et al., 2021). Glass et al. (2020) utilize recurring spans across documents to create pseudo-examples for QA.

While we focus in this work on dual-encoder architectures, other architectures for dense retrieval have been introduced recently. Luan et al. (2021) showed that replacing a single representation with multiple vectors per document enjoys favorable theoretical and empirical properties. Khattab and Zaharia (2020) introduced late-interaction models, where contextualized representations of queries and documents are first encoded, and a cheap interaction step that models their fine-grained relevance is then applied. Phrase-based retrieval (Seo et al., 2018, 2019) eliminates the need for a reader during inference, as it directly retrieves the answer span given a query. Lee et al. (2021a) demonstrated strong end-to-end ODQA results with this approach, and Lee et al. (2021b) showed that it is also effective for passage retrieval. Our pretraining scheme can be seamlessly used for those architectures as well.

7 Conclusion

In this work, we explore the challenge of learning dense passage retrieval from unlabeled data. Our results demonstrate that existing models struggle in this setup. We introduce a new pretraining scheme for dual-encoders that dramatically improves performance, reaching good results even without any questions-evidence pairs at all. Our pretrained model, Spider, exhibits strong results w.r.t. dense baselines in few-shot settings as well. Our results suggest that careful design of a pretraining task is important for learning unsupervised models that are effective retrievers for ODQA.

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References

Petr Baudiš and Jan Šedivý. 2015. Modeling of the question answering task in the YodaQA system. In Proceedings of the 6th International Conference on Experimental IR Meets Multilinguality, Multimodality, and Interaction - Volume 9283, CLEF’15, page 222–228, Berlin, Heidelberg. Springer-Verlag.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1533–1544, Seattle, Washington, USA. Association for Computational Linguistics.

Ning Bian, Xianpei Han, Bo Chen, Hongyu Lin, Ben He, and Le Sun. 2021. Bridging the gap between language model and reading comprehension: Unsupervised MRC via self-supervision.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Greta Chen, Jeffrey Wu,
In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3661–3672, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6086–6096, Florence, Italy. Association for Computational Linguistics.

Patrick Lewis, Pontus Stenetorp, and Sebastian Riedel. 2021a. Question and answer test-train overlap in open-domain question answering datasets. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1000–1008, Online. Association for Computational Linguistics.

Patrick Lewis, Yuxiang Wu, Linqing Liu, Pasquale Minervini, Heinrich Küttler, Aleksandra Piktus, Pontus Stenetorp, and Sebastian Riedel. 2021b. PAQ: 65 million probably-asked questions and what you can do with them. *Transactions of the Association for Computational Linguistics*, 9(0):1098–1115.

Jimmy Lin, Xueguang Ma, Sheng-Chieh Lin, Jheng-Hong Yang, Ronak Pradeep, and Rodrigo Nogueira. 2021. Pyserini: An easy-to-use python toolkit to support replicable IR research with sparse and dense representations.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A robustly optimized bert pretraining approach.

Xi Luan, Jacob Eisenstein, Kristina Toutanova, and Michael Collins. 2021. Sparse, Dense, and Attentional Representations for Text Retrieval. *Transactions of the Association for Computational Linguistics*, 9:329–345.

Xueguang Ma, Kai Sun, Ronak Pradeep, and Jimmy Lin. 2021. A replication study of dense passage retriever.

Barlas Oğuz, Kushal Lakhotia, Anchip Gupta, Patrick Lewis, Vladimir Karpukhin, Aleksandra Piktus, Xilun Chen, Sebastian Riedel, Wen tau Yih, Sonal Gupta, and Yashar Mehdad. 2021. Domain-matched pre-training tasks for dense retrieval.

Yingqi Qu, Yuchen Ding, Jing Liu, Kai Liu, Ruiyang Ren, Wayne Xin Zhao, Daxiang Dong, Hua Wu, and Haifeng Wang. 2021. RocketQA: An optimized training approach to dense passage retrieval for open-domain question answering. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5835–5847, Online. Association for Computational Linguistics.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.

Ori Ram, Yuval Kiriatun, Jonathan Berant, Amir Globerson, and Omer Levy. 2021. Few-shot question answering by pretraining span selection. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3066–3079, Online. Association for Computational Linguistics.

Revanth Gangi Reddy, Vikas Yadav, Md Arafat Sultan, Martin Franz, Vittorio Castelli, Heng Ji, and Avirup Sil. 2021. Towards robust neural retrieval models with synthetic pre-training.

Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. How much knowledge can you pack into the parameters of a language model? In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5418–5426, Online. Association for Computational Linguistics.

Stephen Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: BM25 and beyond. *Found. Trends Inf. Retr.*, 3(4):333–389.

Devendra Sachan, Mostofa Patwary, Mohammad Shoeybi, Neel Kant, Wei Ping, William L. Hamilton, and Bryan Catanaro. 2021. End-to-end training of neural retrievers for open-domain question answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 6648–6662, Online. Association for Computational Linguistics.

Christopher Scialvolino, Zexuan Zhong, Jinhyuk Lee, and Danqi Chen. 2021. Simple entity-centric questions challenge dense retrievers. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6138–6148, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Minjoon Seo, Tom Kwiatkowski, Ankur Parikh, AliFarhadi, and Hannaneh Hajishirzi. 2018. Phrase-indexed question answering: A new challenge for scalable document comprehension. In *Proceedings of the 2018 Conference on Empirical Methods in
Table 5 shows the top-100 accuracy for the unsupervised setting (complements Table 1). Table 6 shows the top-100 accuracy for the cross-dataset setting (complements Table 2). We add the results on the original test sets of NQ, TriviaQA and WQ in Table 7.

A Further Results

Table 5 shows the top-100 accuracy for the unsupervised setting (complements Table 1). Table 6 shows the top-100 accuracy for the cross-dataset setting (complements Table 2). We add the results on the original test sets of NQ, TriviaQA and WQ in Table 7.
### Table 5: Results complementary to Table 1. Top-100 retrieval accuracy on the test set of six datasets for supervised and unsupervised approaches. DPR-Single is trained on the corresponding dataset only (except for EntityQs, similar to Sciavolino et al. 2021). DPR-Multi was trained on the first four datasets. We mark in bold the best unsupervised method for each dataset. * For NQ, TriviaQA and WQ, we use the “no answer overlap” portion of the test sets, to control for memorization issues which are not possible for unsupervised methods (see Section 4.1).

| Model Mode | NQ | TriviaQA | WQ | TREC | SQuAD | EntityQs |
|------------|----|----------|----|------|-------|----------|
| DPR-Single Dense | 76.8 | 62.6 | 71.1 | 89.9 | 72.5 | 63.2 |
| DPR-Multi Dense | 77.1 | 62.4 | 70.4 | 93.9 | 67.8 | 70.0 |
| DPR-Single + BM25 Hybrid | 81.1 | 64.9 | 72.8 | 93.8 | 83.7 | 81.3 |
| DPR-Multi + BM25 Hybrid | 80.9 | 65.2 | 73.0 | 95.4 | 83.0 | 82.6 |
| BM25 Sparse | 70.1 | 62.4 | 66.4 | 90.3 | 82.0 | 80.0 |
| ICT Dense | 51.3 | 14.2 | 52.1 | 35.2 | 27.3 | 4.8 |
| Condenser Dense | 26.6 | 9.1 | 30.8 | 34.4 | 25.3 | 7.6 |
| CoCondenser Dense | 52.4 | 13.8 | 54.2 | 39.3 | 28.8 | 8.7 |
| Spider Dense | 71.7 | 61.4 | 68.9 | 93.1 | 74.6 | 72.8 |
| Spider + BM25 Hybrid | 76.6 | 64.1 | 71.6 | 93.9 | 84.4 | 82.3 |

### Table 6: Results complementary to Table 2. Top-100 retrieval accuracy in a “zero-shot” setting, where models are evaluated against datasets not seen during their training. DPR-x is a model trained on the full dataset x, and DPR-Multi was trained on NQ, TriviaQA, WQ and TREC. Spider (NQ-128) was fine-tuned on 128 examples from NQ, and similarly Spider (TriviaQA-128) was fine-tuned on 128 examples from TriviaQA. # Examples is the number of labeled examples used to train the model. * For NQ, TriviaQA and WQ, we use the “no answer overlap” portion of the test sets (see Section 4.1).

| Model | # Examples | NQ | TriviaQA | WQ | TREC | SQuAD | EntityQs |
|-------|------------|----|----------|----|------|-------|----------|
| DPR-NQ | 58,880 | - | 56.9 | 65.1 | 92.1 | 65.2 | 63.2 |
| DPR-TriviaQA | 60,413 | 71.7 | - | 69.7 | 93.7 | 71.1 | 74.6 |
| DPR-WQ | 2,474 | 63.1 | 56.0 | - | 90.8 | 67.6 | 70.2 |
| DPR-TREC | 1,125 | 61.7 | 54.5 | 62.1 | - | 65.3 | 61.1 |
| DPR-SQuAD | 70,096 | 52.6 | 53.5 | 56.5 | 89.2 | - | 51.0 |
| DPR-Multi | 122,892 | - | - | - | - | 67.6 | 70.0 |
| BM25 | None | 70.1 | 62.4 | 66.4 | 90.3 | 82.0 | 80.0 |
| Spider | None | 71.7 | 61.4 | 68.9 | 93.1 | 74.6 | 72.8 |
| Spider (NQ-128) | 128 | 62.0 | 70.9 | 93.1 | 75.1 | 76.8 |
| Spider (TriviaQA-128) | 128 | 73.5 | - | 70.9 | 93.5 | 77.9 | 76.8 |

### Table 7: Results complementary to Tables 1 and 5. Top-20 and Top-100 retrieval accuracy (i.e. the percentage of questions for which the answer is present in the top-100 passages) on the test set of six datasets for supervised and unsupervised approaches. DPR-Single is trained on the corresponding dataset only (except for EntityQs, where the model was trained on Natural Questions). DPR-Multi was trained on the first four datasets. We mark in bold the best unsupervised method for each dataset.

| Model Mode | NQ Top-20 | NQ Top-100 | TriviaQA Top-20 | TriviaQA Top-100 | WQ Top-20 | WQ Top-100 |
|------------|-----------|------------|-----------------|-----------------|-----------|------------|
| DPR-Single Dense | 80.1 | 86.1 | 79.7 | 85.1 | 74.3 | 82.2 |
| DPR-Multi Dense | 79.5 | 86.1 | 78.9 | 84.8 | 75.1 | 83.0 |
| DPR-Single + BM25 Hybrid | 82.9 | 88.3 | 82.4 | 86.5 | 75.1 | 83.1 |
| DPR-Multi + BM25 Hybrid | 82.6 | 88.2 | 82.6 | 86.5 | 77.2 | 84.5 |
| BM25 Sparse | 62.9 | 78.3 | 76.4 | 83.2 | 62.4 | 75.5 |
| ICT Dense | 42.1 | 61.2 | 12.9 | 24.9 | 44.8 | 66.5 |
| Condenser Dense | 25.5 | 43.4 | 9.6 | 18.5 | 35.8 | 51.9 |
| CoCondenser Dense | 46.8 | 63.5 | 13.8 | 24.3 | 50.7 | 68.7 |
| Spider Dense | 64.5 | 78.5 | 73.1 | 82.3 | 65.5 | 79.6 |
| Spider +BM25 Hybrid | 71.1 | 83.2 | 79.7 | 85.3 | 69.2 | 81.2 |