

LEPUS: Prompt-based Unsupervised Multi-hop Reranking for Open-domain QA

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Abstract

We study unsupervised multi-hop reranking for multi-hop QA (MQA) with open-domain questions. Since MQA requires piecing information from multiple documents, the main challenge thus resides in retrieving and reranking chains of passages that support the reasoning process. Our approach relies on LargeE models with Prompt-Utilizing reranking Strategy (LEPUS): we construct an instruction-like prompt based on a candidate document path and compute a relevance score of the path as the probability of generating a given question, according to a pre-trained language model. Though unsupervised, LEPUS yields competitive reranking performance against state-of-the-art methods that are trained on thousands of examples. Adding a small number of samples (e.g., 2), we demonstrate further performance gain using in-context learning. Finally, we show that when integrated with a reader module, LEPUS can obtain competitive multi-hop QA performance, e.g., outperforming fully-supervised QA systems.¹

1 Introduction

Many information-seeking queries are in the form of multi-hop questions. For instance, answering the question “*What 1988 Christmas comedy film did Brian-Doyle Murray star in?*” requires (i) searching for movies in which Brian Murray starred in, and (ii) identifying which of these was released in 1988 during Christmas. These pieces of information are often dispersed in different documents, creating a challenging of performing *multi-step* reasoning for multi-hop open domain QA (MQA) (Perez et al., 2020).

Formally, given a multi-hop question and a large corpus of documents, an MQA system will first use a *retriever* to identify multiple documents to

support the *reader* to produce the final answer. Existing MQA systems (Asai et al., 2020; Qi et al., 2021; Xiong et al., 2021; Li et al., 2021; Singh et al., 2021) are designed under the assumption that abundant labeled examples are available for training both modules, yet this may not be realistic. First, to train the retriever module, one needs examples with questions paired with the corresponding supporting documents, which is laborious to construct (Izacard and Grave, 2021a). Second, very few datasets exist for English MQA, e.g., HotpotQA (Yang et al., 2018) annotated on Wikipedia articles, not to say for other domains and languages.

Meanwhile, we have seen increasing interest in exploiting large language models (LLMs) as zero-shot QA systems (Brown et al., 2020; Wei et al., 2021a; Chowdhery et al., 2022), where the information retrieval step is eliminated and the LLM is expected to directly generate the answer based on the knowledge acquired during pre-training. Though impressive performance has been obtained on several QA benchmarks with enormous models, such as GPT-3 (Brown et al., 2020) and FLAN (Wei et al., 2021a), there are still two main disadvantages with this framework. First, new knowledge emerges; they may not be entailed from the pre-training data and are often hard to be reflected with model parameter updates (Cao et al., 2021). Second, as the size of the knowledge base grows, we are expected to have an even larger model to store such knowledge.

In this work, we employ LLMs for a different task—the *reranking* of retrieved support document paths. Our approach, **LEPUS**, leveraging LargeE models with Prompt-Utilizing reranking Strategy, combines a TF-IDF retrieval method with a *zero-shot* LLM reranker that scores retrieved documents’ relevance to the given question. Contrary to previous work that train dense retrieval models (Xiong et al., 2021) or pre-train retrievers using a large number of question-document pairs

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¹Code will be released at <https://github.com/mukhal/LEPUS>.

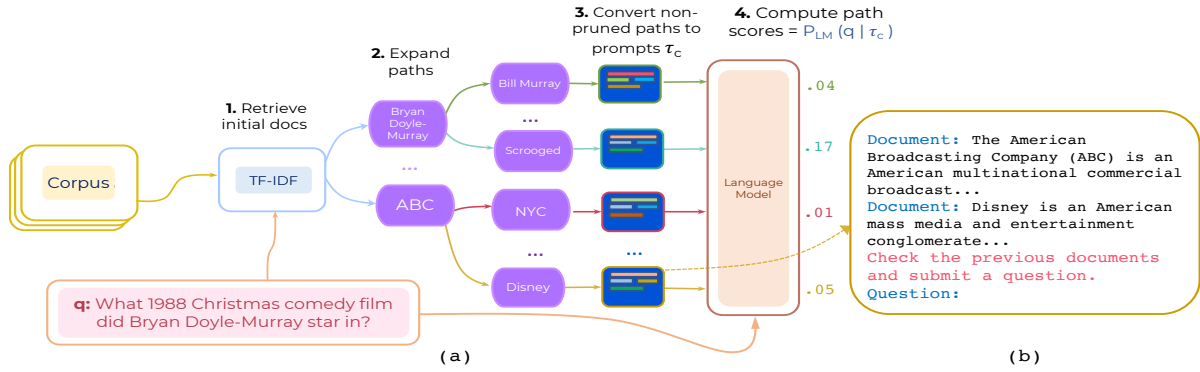


Figure 1: An overview of LEPUS. (a): Initial documents from TF-IDF are retrieved and expanded based on hyperlinks for H times. Each path is converted into a prompt τ_c and scored through $P_{LM}(q|\tau_c)$ using a language model. For simplicity, we omit intermediate scoring steps where paths of length $h < H$ are scored using the same fashion and only the top scored ones are expanded. (b): A sample of how a 2-hop path prompt looks like. Prompts are constructed in terms of the **path documents** and an **instruction**.

(Seonwoo et al., 2021), we show that LLMs can be strong zero-shot re-rankers for MQA. In particular, we find that joint reasoning across multiple documents with *multi-hop* prompts is important and such prompts are significantly better than their *single-hop* counterparts.

Moreover, we study the impact of different textual prompts and find that language models are sensitive to the wordings. Therefore, we propose to generate multiple prompts and combine them with an ensemble approach to alleviate prompt sensitivity. Furthermore, we demonstrate that adding a few labelled samples using in-context learning (Brown et al., 2020) further improves the reranking performance. Notably, the main challenge of including annotated question-document path pairs in a prompt is the length limitation given by Transformer-based LLMs. To overcome the issue, we combine the scores corresponding to multiple in-context demonstrations with an ensemble approach.

In short, our contributions in this work are summarized as follows:

1. We propose an unsupervised multi-hop paths reranking method based on language model prompting. Our approach exhibits strong retrieval performance without any supervision compared to other fully supervised methods and is comparable to state-of-the-art multi-hop retrievers trained with thousands of examples (Section 3.1).
2. We show that our approach, when combined with a reading comprehension model, shows

strong downstream MQA performance, outperforming fully-supervised retrievers (Section 3.2).

3. We show that allowing the language model to consider all documents path *simultaneously* substantially improves re-ranking performance as opposed to single-hop re-ranking of documents in isolation. We also provide a thorough analysis on various aspects of our technique such as sensitivity to instructions and document order (Section 4).

2 Method

Figure 1 depicts the main steps of LEPUS. We start by a bird’s eye overview of our approach then we discuss each step in detail.

2.1 Overview

Given a question q , the retriever finds sequences of supporting documents (paths) of length n that can be used to answer the question. At each step of the retrieval process we use an inexpensive retrieval method to identify a small set of promising candidates to narrow down the search space, as commonly done in the literature (Qi et al., 2021; Asai et al., 2020). We use an LM to more accurately rerank n -hop chains of documents based on their relevance to the question (described in Section 2.2).

We rely on a sparse retrieval approach, i.e., TF-IDF similarity, to obtain an initial set of supporting

documents paths.² We initially retrieve F candidate documents for the ‘first hop’. These ‘1-hop’ candidates are scored by the reranking step and the top K_1 promising candidates are further expanded based on their hyperlinks to obtain 2-hop reasoning paths. These 2-hop reasoning chains are again reranked and the most promising K_2 candidates are further expanded. The process continues for a fixed number of steps, determined by a hyperparameter H .³ As the document graph can have a high branching factor, we prune hyperlinks based on TF-IDF similarity with the question. We find this simple method greatly improves efficiency without a significant drop in performance. This process is shown in Figure 1 (a).

2.2 Path Reranking

Given a question q and a reasoning path $c = \{d_1, \dots, d_h\}$ of length h documents, where $h \leq H$, we use a language model to score c based on its relevance to q . At first glance, one might opt for using the likelihood of the reasoning path under the LM given the question as the ranking metric. However, this approach is problematic for reasons we state below. Instead, we consider a different approach where we measure the likelihood of the question given the path. More precisely, we format the documents making up the path c in a prompt τ_c and compute the relevance score of the path c to q as in Equation (1).

$$\text{Score}_q(c) = P_{\text{LM}}(q|\tau_c) \quad (1)$$

where $P_{\text{LM}}(q|\tau_c)$ is the conditional probability of generating the question given the path prompt τ_c under our language model. Our initial experiments has showed that using $P_{\text{LM}}(q|\tau_c)$ works *significantly* better than $P_{\text{LM}}(c|\tau_q)$ for some question prompt τ_q , which agrees with the findings in dos Santos et al. (2020). This can be largely attributed to two factors. First, language models can be sensitive to the *surface form* (Holtzman et al., 2021) of reasoning paths, which can make it difficult to reliably compare the probabilities of different reasoning paths using $P_{\text{LM}}(c|\tau_q)$.⁴ On the other hand, scoring paths using $P_{\text{LM}}(q|\tau_c)$ does not suffer from

this issue since the probability of the same string (i.e., the question) is being compared conditioned on different reasoning paths. Second, the prompt format of $P_{\text{LM}}(q|\tau_c)$, where the question follows a document, agrees more with the web data used for LM pretraining, where documents are usually followed by FAQs, questionnaires, and surveys, rather than the other way around. While this scoring criterion has been considered for question answering with auto-regressive language models in the literature (dos Santos et al., 2020; Sachan et al., 2022), we consider it for multi-hop path ranking in this work. In addition, we also add a temperature parameter to scale the model logits and show that it helps calibrate model scores better (Guo et al., 2017; Desai and Durrett, 2020; Jiang et al., 2021) and leads to better ranking.

We now describe how the prompt τ_c is constructed from a path. Ideally, we want to construct a prompt τ_c that leads to higher $P_{\text{LM}}(q|\tau_c)$ for relevant paths compared to irrelevant ones. Our prompt mainly consists of both an *instruction* and the *path*, shown in Figure 1 (b). The instruction is fixed across all prompts and is used to elicit the reasoning ability of the LM (Wei et al., 2021b; Ouyang et al., 2022). In other words, the instruction is used as a signal to drive the model towards assigning higher scores to relevant paths. In Section 4.2, we show that the instruction plays an important role in the reranking performance.

The path is expressed in the prompt by concatenating all documents in the path and prepending each document in the path with fixed prefix such as “Document:” or “Passage:” as shown in the figure. Such simple concatenation of path documents significantly improves reranking since all path hops are *simultaneously* considered, which allows the LM to better evaluate the relevance of the whole path with context. In Section 4.1, we will show that such multi-hop scoring performs *substantially* better than single-hop scoring, i.e., reranking each hop separately by the LM.

2.3 Instruction Search

For the *instruction* component of the prompt, we can manually design an instruction such as “Read the following documents and answer the question” to help the language model understand the task. However, human-written instructions can be sub-optimal and recent work has shown that language models can benefit from automatic approaches for

²While TF-IDF similarity may seem simple compared to dense retrieval methods such as DPR (Karpukhin et al., 2020), TF-IDF indices are both simple to implement and computationally inexpensive to compute. Therefore TF-IDF similarity calculation does not add extra overhead to our approach.

³This process can be viewed as a variation of beam search.

⁴For instance, $P_{\text{LM}}(c|\tau_q)$ tends to be higher for shorter paths.

prompt design (Shin et al., 2020; Gao et al., 2021; Prasad et al., 2022). Taking inspiration from Gao et al. (2021), we use an encoder-decoder language model trained to fill masked text-spans to generate instructions. Specifically, we use a T5 model to fill in a template such as “Task: <X> documents and <Y> question. Question:”, where <X> and <Y> are the masked spans expected to be filled-in by the model (e.g., For the human-written instruction example above, <X> = “Read the following” and <Y> = “answer the”). We consider two variations of this template corresponding to the cases where the document path appears before/after the template. We constrained the template to contain the words ‘documents’ and ‘question’ to ensure that the model generates relevant prompts. This is due to the observation that when using a less specific template, we obtain more diverse but less useful instructions.

2.4 Instruction Ensembling

Previous work has shown that mixing multiple prompting templates can improve few-shot performance for both classification (Schick and Schütze, 2021a,c; Gao et al., 2021) and generation (Schick and Schütze, 2021b). We argue that such ensembling could produce more regularized path scores by alleviating prompt sensitivity (Zhao et al., 2021). Given a path c , we combine the scores of c obtained through M different prompts $(\tau_c^1, \tau_c^2, \dots, \tau_c^M)$. It is worth noting that for a given path, the prompts only differ in the instruction. Therefore, we refer to this technique as *instruction ensembling*. We experiment with *mean* and *max* ensembling, which respectively compute the path score as the mean or max of document scores.

2.5 In-context Learning

While the methods presented so far are completely unsupervised, we now explore how the reranking performance can be further improved when a few training examples are given. We avoid fine-tuning since it can easily lead to overfitting with few training examples.⁵ Instead, we resort to *in-context learning* (Brown et al., 2020), also known as prompt conditioning, where we *prepend* a few exemplars or demonstrations to the prompt. We hypothesize that showing the model examples of questions and their gold paths should nudge the

model towards assigning higher scores to more relevant paths.

A major obstacle to this approach is the *input length limit* in standard transformer language models. Since paths are usually long, in most cases we can not use more than 2-3 examples before exceeding the limit of 1024 tokens. We thus propose to use an *ensemble of exemplars*, where different in-context demonstrations are used to compute scores for a given path, and we combine these scores using the methods discussed in Section 2.4. This way, we can leverage more than two demonstrations while still adhering to the input length limit imposed by Transformer language models.

3 Experiments

Here, we evaluate our path reranker in two ways: First, through retrieval metrics without regard to the downstream QA performance. Second, as a part of a QA pipeline to see how much performance boost can our reranker provide to existing QA pipelines with minimal supervision.

Data. We evaluate our method on **HotpotQA** (Yang et al., 2018), which consists of two-hop questions that are diverse in topics. We focus on the open-domain (*fullwiki*) setting in which two Wikipedia passages are required to answer the questions. Since the gold passages for the test set are not available, we follow prior work and evaluate LEPUS on the development set, which consists of 7,405 questions. There are two main question types in HotpotQA: comparison questions and bridge questions. *Comparison* questions usually require contrasting two entities and *bridge* question require finding a bridge entity that links one passage the other.

Models. We use HuggingFace implementations (Wolf et al., 2020) of GPT2-XL (Brown et al., 2020) and T5-Large and T5-XL (Raffel et al., 2020) language models in our experiments. We use the ‘LM adapted’ version of T5 models since they have been shown to work better for prompt-based learning (Lester et al., 2021). Our approach is unsupervised and does not require any training examples. However, we show that better performance can be obtained by using few (128) training examples for in-context learning, instruction search and temperature tuning.

Hyperparameters. For instruction search, we generate 200 different instructions using top- k sam-

⁵Our initial experiments showed that fine-tuning makes the language model much more sensitive to minor changes in either the question or the path.

pling with $k = 10$ to obtain more diverse instructions, and evaluate each prefix on a held-out development set from HotpotQA of size 128. Table 6 in the Appendix shows the best 10 instructions identified. For LEPUS, we use a path length of $H = 2$ for all experiments. For pruning the search space we use $K_1 = 5$ and $K_2 = 3$. We use the TF-IDF index implemented by Asai et al. (2020) and initially retrieved 100 documents from TF-IDF. We truncate input documents to 230 tokens and limit the prompt length to 600 and 800 tokens for the zero-shot and few-shot experiments, respectively. For experiments that involve using two or more in-context demonstrations, we set the maximum prompt length to 1024.

Metrics. Retrieval performance is measured using recall ($R@k$) and Answer Recall ($AR@k$), with $k \in \{2, 10, 20\}$. $AR@k$ is the recall of the answer string in the top- k retrieved documents. For HotpotQA, we only compute AR over questions with span answers (i.e., we ignore yes/no and comparison questions). Since we do not have access to the HotpotQA test set, we report results on the original development set provided by Yang et al. (2018).

While LEPUS is mainly used to rerank document paths, we later transform paths scores into document scores before computing recall metrics. The advantage here is that it allows for combining different scores for documents that fall on more than one path, which we have found to perform better. Details on computing document scores from path scores are in Appendix B.

Baselines. We compare our LM path reranker to the following baselines. **TF-IDF** simply retrieves top similar documents to the question using TF-IDF similarity and **TF-IDF + BM25** adds an extra step where retrieved documents and their hyperlinks are reranked using BM25 (Robertson et al., 1995). **PathRetriever** (Asai et al., 2020) is a graph-based retriever trained to expand an initial pool of documents based on Wikipedia links and searches for the best reasoning using beam search.⁶ **DrKIT** (Dhingra et al., 2020) is an end-to-end trained dense retrieval approach that starts from question entities and traverses a virtual knowledge base to find the relevant entities. Multi-hop Dense Retrieval (**MDR**) (Xiong et al., 2021) encodes the

question and hops retrieved so far into a dense vector and uses maximum inner-product search (MIPS) to find the next hop.

3.1 Retrieval Performance

Table 1 shows the performance of LEPUS and other baselines in zero- and few-shot settings, which we detail next.

Zero-shot Performance. We first discuss the retrieval performance of unsupervised LEPUS on HotpotQA. First, we observe that simple TF-IDF performs poorly in terms of different recall metrics, while TF-IDF + BM25 performs much better, yet still worse than fully-supervised approaches. Next, we look at the performance of unsupervised LEPUS (T5-XL) which uses no instructions (i.e., prompt consists of only the document path). These models perform much better than TF-IDF + BM25 and even outperform the fully-supervised DrKit. Although this approach does not use *any* labeled data, it is only 3.7 $AR@10$ points worse than PathRetriever, the best fully supervised baseline.

Few-shot Performance. The zero-shot performance of LEPUS can be further improved with access to a small set of labeled examples (in our case, we only used 128 examples from HotpotQA) for instruction search and a fine temperature. We observe a substantial boost of 4.3 points in $R@2$ of LEPUS when using the **best instruction** found by instruction search. Next, temperature scaling with $T = 1.4$ also provides a boost of 2.1 points in $R@2$.

While the gap in $R@2$ is larger between LEPUS and the other methods such as PathRetriever and MDR, we argue that such gap is *hardly detrimental* to the downstream QA performance as it is a common practice (Asai et al., 2020; Seonwoo et al., 2021; Xiong et al., 2021) to feed the top- d ; $d \gg 2$ retrieved passages to the reader model. Indeed, we show in Section 3.2 that LEPUS can obtain QA performance that is competitive with PathRetriever despite the difference in $R@2$.

We also observe that instruction ensembling gives a further performance boost to LEPUS. We show the performance of **max ensembling**, which we have found to perform slightly better than mean ensembling in terms of $R@2$. We hypothesize that max ensembling computes an *upper bound* on the score of each path, compensating for any underestimation of path scores that can happen when using a single instruction.

⁶We run PathRetriever on HotpotQA with original hyperparameters except for an initial TF-IDF pool size=100 to allow for fair comparison to our approach.

	R@2	R@10	R@20	AR@2	AR@10	AR@20
<i>Unsupervised Baselines</i>						
TF-IDF	10.5	28.5	35.9	38.1	54.2	60.7
TF-IDF + BM25	19.1	54.7	61.8	49.5	74.7	79.9
<i>Fully-supervised Baselines</i>						
DrKit	38.3	67.2	71.0	–	–	–
MDR	65.9	77.5	80.2	–	–	–
PathRetriever	66.4	77.8	–	82.2	90.5	–
LEPUS						
GPT2-XL [†]	36.6	60.5	65.9	63.0	83.9	87.4
T5-XL [†]	42.8	68.9	74.1	69.3	86.8	89.0
+ inst. search	47.1	71.7	76.1	73.3	88.0	89.9
+ temp. scaling	49.2	72.4	76.5	75.5	88.5	90.2
+ ensemble	50.2	72.4	76.4	76.1	88.6	90.2
T5-XL, 2-shot	52.4	73.0	77.0	78.6	88.7	90.3
T5-XL, 10-shot (ensemble)	53.2	71.7	74.9	77.7	87.6	89.3

Table 1: Retrieval performance on HotpotQA comparing LEPUS to other baselines. †: No instruction used. All LEPUS results except those marked with † use a labeled set of 128 examples for tuning the instruction and the temperature parameter. Few-shot LEPUS uses the same instruction and temperature as zero-shot. Our best results are highlighted in **bold**.

Now we move to in-context learning. We experiment with a 2-shot setting while making sure that the two demonstrations cover *both* question types in HotpotQA (bridge and comparison). To account for the performance variance, we perform the experiment 5 times with different samples and report the mean of different metrics.⁷ We observe that with only 2 examples, R@2 of LEPUS further improve by at 2.2. Also, the gap of R@10 with PathRetriever is reduced to only 4.8 points. A similar trend happens for AR@2, as well.

Lastly, we evaluate in-context ensembling discussed in Section 2.5. We perform an ensemble of 5 prompts, each having 2 demonstrations *i.e.*, 10-shot. Once again, max ensembling performs best and improves R@2 by 2 points compared to the zero-shot setting and by 0.8 points compared to the 2-shot setting. However, we observe a drop in other metrics compared to the 2-shot setting. We hypothesize that such drop in performance could result from the difference between

3.2 Full QA Performance

In the previous section, we evaluated LEPUS as a standalone retrieval component. We now evaluate the performance of an overall QA system when using LEPUS as the retriever. We use the Fusion-in Decoder (FiD) model (Izacard and Grave, 2021b) as the reader, which is a generative reader based on T5. FiD encodes the question along with each document then uses employs a decoder with cross-

attention over the encodings to generate the answer. While FiD has been mainly employed for single-hop QA, here we show that it can also function as a strong reader for multi-hop QA.

We train an FiD reader (T5-Base) on the full HotpotQA dataset to generate the correct answer. FiD is trained with 50 input passages in total that include the two gold passages along with TF-IDF negatives to encourage the reader to be more robust to non-relevant passages during inference. All remaining hyperparameters are the same as in Izacard and Grave (2021b). For evaluation, we sort documents based on their path scores computed with LEPUS and feed the top- d documents to FiD.

In Table 2, we compare LEPUS against strong fully-supervised baseline retrievers. The baselines are DrKit (Dhingra et al., 2020), Semantic Retrieval (Nie et al., 2019), and PathRetriever (with BERT-Base reader). LEPUS outperforms the fully-supervised retrievers DrKit and Semantic Retrieval and performs comparably to PathRetriever. Again, this performance is obtained with minimal supervision on the retrieval side.

4 Analysis

4.1 Comparison to Single-hop Reranking

The key idea behind our approach is to do joint reasoning with documents in the path using the LM, as opposed to reranking each document in the path separately (*single-hop reranking*). More specifically, in single-hop reranking, we expand paths as usual but rerank each document d separately using

⁷Standard deviation is reported in Table 7 in Appendix D.1.

Retriever	EM	F1
<i>Fully-supervised</i>		
Semantic Retrieval (Nie et al., 2019)	46.5	58.8
DrKit (Dhingra et al., 2020)	42.1	51.7
PathRetriever (Asai et al., 2020)	52.7	65.8
<i>Few-shot</i>		
LEPUS, 2-shot, $d = 5$	49.2	62.0
LEPUS, 2-shot, $d = 10$	47.0	59.4
LEPUS, 2-shot, $d = 20$	45.9	58.0

Table 2: Answer exact match and F1 score on HotpotQA. Reader used with LEPUS is FiD (T5-Base). d is the number of top retrieved documents fed to the reader.

Approach	R@2	R@10	AR@2	AR@10
Single-hop	22.8	52.0	54.9	73.8
Multi-hop	46.9	67.6	75.4	87.9

Table 3: Retrieval performance in two settings: reranking each document separately with the LM (single-hop) and reranking the full path at once (multi-hop). Multi-hop reranking performs substantially better than single-hop, backing our hypothesis reranking the full path at once helps the LM better decide on the path relevance to the question.

$p(q|\tau_d)$, for some document prompt τ_d .

To assess whether our multi-hop reranking approach can be beneficial, we compare both approaches by running two experiments with the exact same setting while differing only in the way documents are reranked. For evaluation, we use a set of 4K questions from HotpotQA and T5-Large, and without instructions — meaning that the prompt will only contain the document. Table 3 shows retrieval performance of both approaches. Interestingly, a large gap in performance exists between single-hop and multi-hop reranking. This supports our hypothesis that jointly considering all documents in the path helps the LM better model the relevance between the path and the question.

4.2 Does the Instruction Matter?

We study whether instructions do indeed contribute to producing better path scores. To verify, we run evaluate? LEPUS (T5-Large) on 1K instances from HotpotQA in the following configurations: **no instruction**, where we merely concatenate the path documents, a **random** instruction chosen from the generated instructions, and **best instruction** found through evaluation on a held-out development set.

Table 4 shows retrieval metrics in the above three settings. We observe that using no instruction at all performs worst — around 4 R@2 points less

Setting	R@2	R@10	AR@2	AR@10
No Inst.	42.8	65.3	72.8	87.2
Random Inst.	47.2	66.9	75.8	88.0
Best Inst.	47.6	67.7	76.3	87.9

Table 4: Retrieval performance when using no instruction, random instruction, and the best instruction found through our instruction search (Section 2.3.) Performance is computed over 1K examples from HotpotQA using T5-Large in the zero-shot setting.

than using random instruction. This indeed points to the benefit of using instructions to obtain better path scores. Second, we find that the best instruction, although comparable, outperforms a randomly selected one, which indicates that further performance boost can be obtained through instruction search.

4.3 Sensitivity to Instructions

Prompt sensitivity is an important issue of large language models (Zhao et al., 2021). Here, we study the sensitivity of LEPUS (with T5-Large) performance when changing the instruction part in the prompt. More specifically, we evaluate the retrieval performance over 1K examples from HotpotQA when using 200 instructions. Figure 2 shows two boxplots of the distribution of Rec@2 and Rec@10 over the 200 instructions used. We find that the ranking is sensitive to the instruction choice, which again points to the added benefit of doing instruction search.

Next, we study the performance in the two different kinds of prompts where the instruction comes **before** and **after** the path. Figure 3 shows the R@2 and AR@2 in both cases. Interestingly, we observe that placing the instruction **after** the path performs consistently better than **before**. This could be an instance of the *recency bias* phenomenon exhibited by language models (Zhao et al., 2021): Placing the instruction right before the model is asked to generate the question makes the model more aware of the task.

4.4 Invariance to Document Order

A potential issue with prompt-based reranking is that to describe a document path with a textual prompt, we must assume some underlying order on the path documents. This contradicts with the fact that document paths may not have a *well-defined order*, especially when documents are not linked to each other in a sequential chain. For instance,

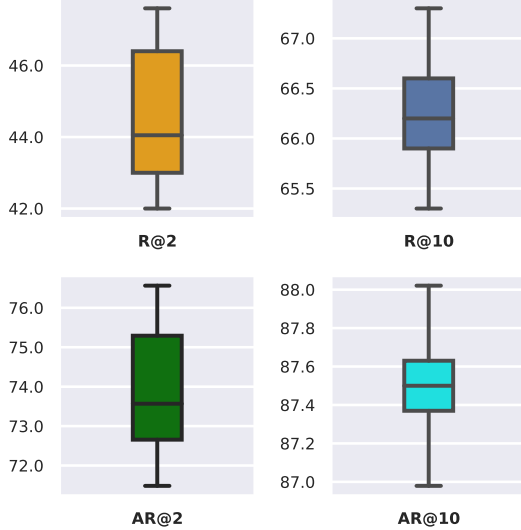


Figure 2: Instruction sensitivity exhibited by LEPUS. Performance varies slightly over different instructions which shows the insensitivity of our approach to the instruction used. Metrics related to the top retrieved path ($R@2$ and $AR@2$) exhibit relatively more variance.

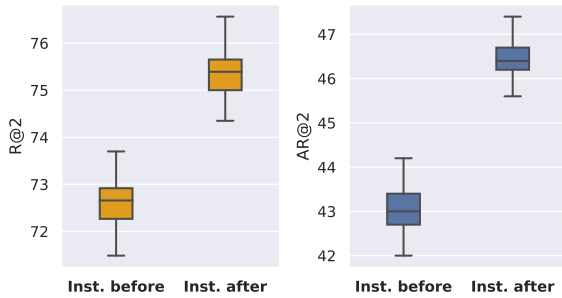


Figure 3: Retrieval performance when placing the instruction before and after the path in the prompt. Having the instruction after path performs consistently better which is likely due to recency bias (Zhao et al., 2021).

given the question “Are both Erin Wiedner and Monte Hellman American film directors?” with the correct path {‘Erin Wiedner’, ‘Monte Hellman’}⁸, it is not obvious even to human which document should come before the other in the reasoning chain.

We argue that path retrieval approaches that are *invariant* to document order are more preferable than ones that are sensitive to such order. In the case of order-sensitive approaches, finding the order of documents that would maximize performance is not straightforward. Therefore, to verify how much is LEPUS sensitive to the document order, we run a simple experiment comparing two

Doc. Ordering	R@2	R@10	AR@2	AR@10
Link-based	48.8	69.6	76.0	88.4
Inverted	47.4	69.7	74.8	88.4

Table 5: Retrieval performance of LEPUS (T5-Large) with two different orderings of the documents in the prompt. Evaluation is done on a set of 4K examples from HotpotQA. LEPUS exhibits slight sensitivity to the document ordering, which points to the robustness of our approach.

document ordering schemes: link-based and inverted link-based. Link-based ordering is the standard approach used in LEPUS, which orders the documents in the path based on their hyperlink traversal order. In the inverted scheme, we *reverse* the order of the documents in the prompt.

Table 5 shows the retrieval performance with both orderings. Interestingly, reversing the order of the documents in the path does not seem to have a tangible effect on the reranking performance. In other words, LEPUS does not appear to be sensitive to the document order in the path. Again this shows the robustness of LEPUS to different prompt variants.

5 Related Work

Multi-hop Question Answering. The majority of approaches for multi-hop question answering rely on two main components: a retriever and a reader. The retriever component can be a sparse index or heuristic-based such as TF-IDF or BM25 (Chen et al., 2017; Nie et al., 2019) or dense (Karpukhin et al., 2020; Xiong et al., 2021). Other approaches aimed to improve the retriever with an additional *re-ranking* step on top of a simple retriever (Wang et al., 2018; Lee et al., 2018; Htut et al., 2018). Asai et al. (2020) combined TF-IDF retriever with a recurrent graph retriever and used the reader module to re-rank paths based on the answer confidence. Qi et al. (2021) used a single transformer model to perform retrieval, reranking, and reading in an iterative fashion. However, the good performance of previous work comes mainly from training on a large number of examples and are likely to fail in low-data settings. To treat this issue, Seonwoo et al. (2021) proposed to pretrain MDR (Xiong et al., 2021) on a large number of weakly-supervised examples of questions and the corresponding document paths. While showing promising results in low-data settings, the pretraining process is computationally expensive as it is

⁸Example taken from HotpotQA.

done on millions of examples. On the other hand, our approach requires no task-specific pretraining.

Language Models Prompting. Prompt-based learning aims to construct better inputs *i.e.*, prompts to language models to elicit better zero- or few-shot performance (Brown et al., 2020; Liu et al., 2021). Recently, instruction tuning, where a language model is trained to follow natural language instruction has shown impressive zero-shot performance on unseen tasks (Wei et al., 2021a; Ouyang et al., 2022). In our work, we use instructions to guide the model towards assigning better scores to more relevant paths.

Language Models for Re-ranking Our work is related to query likelihood retrieval (Ponte and Croft, 2017) and is in line with previous work that employed generative models for passage re-ranking. For instance, Nogueira et al. (2020) used pre-trained T5 (Raffel et al., 2020) model to re-rank passages based on the probability of generating a specific token given a passage. Their approach relied on fine-tuning the LM to generate such as “yes” given a relevant passage. dos Santos et al. (2020) perform single-hop re-ranking using probability of generating the question, but their setting is limited to fully-supervised and single-hop QA. On the other hand, we study re-ranking of multi-hop paths in an unsupervised setting, which is more challenging.

6 Conclusion

This work introduces LEPUS, a method to perform unsupervised re-ranking of multi-document paths for question answering based on large language models. Given a question, the document path is encoded into a prompt and the document path is scored as the probability of generating the question given the prompt. Experiments on a standard multi-hop QA benchmark show the strong performance of LEPUS in the zero-shot setting, displaying comparable performance to fully-supervised retrievers. We also analyze our approach showing the utility of using multi-hop prompts as opposed to single-hop ones. Lastly, our work shows that language models can indeed function as strong unsupervised re-rankers for multi-hop question answering.

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A Instructions

Here we show the list of five prefixes used for our experiments.

A.1 Instruction Search

The actual templates we feed T5 are “*Task: <X> documents <Y> question based on them. Question:*” and “*Task: <X> previous documents and <Y> question based on them. Question:*”. We have found using the phrase “based on them” to be essential in directing the model to generate sensible instructions. Otherwise, the model would generate something like “Read the documents in question..”. However, we remove that phrase from the obtained instructions”.

B Document Scores

It is not immediately obvious how to compute a final score for each document since LEPUS is mainly used to score document. The main issue is that a document can fall on multiple paths at the same time (some of which could be incomplete or not fully expanded yet) and therefore could have multiple such scores.

For example, assume a path $A \rightarrow B \rightarrow C$ of consisting of the documents A , B , and C , respectively. Considering the document B , we see that two scores are associated with B : score of the sub-path $A \rightarrow B$ and score of the full $A \rightarrow B \rightarrow C$ path. To compute the final score of B , we could either just take the score of the longest path, or combine the two scores using mean, minimum, or maximum operations. What we found to work best compared to other alternatives is to take *maximum*. We use this formulation when computing our recall metrics in Section 3.1 and also when reranking documents to feed to the reader in Section 3.2.

C Hyperparameters

D Detailed Results

D.1 In-context Learning

We show the mean and standard deviation of few-shot experiments reported in Table 7, where each experiment is run 5 different times with different in-context demonstrations.

ID	Prompt
0	<code>Document: [D1] Document:[D2], ..., Check all previous documents and submit a question. Question:</code>
1	<code>Find documents , complete question. Document: [D1] Document:[D2], ..., Question:</code>
2	<code>Find documents and write question. Document: [D1] Document:[D2], ..., Question:</code>
3	<code>Document: [D1] Document:[D2], ..., Review previous documents and write question. Question:</code>
4	<code>Document: [D1] Document:[D2], ..., Read previous documents and ask a question. Question:</code>
5	<code>Document: [D1] Document:[D2], ..., Go through your previous documents and write a question. Question:</code>
6	<code>Document: [D1] Document:[D2], ..., Review your previous documents and write a question. Question:</code>
7	<code>Document: [D1] Document:[D2], ..., Review previous documents and answer the following question. Question:</code>
8	<code>Document: [D1] Document:[D2], ..., Recheck your previous documents and create a question. Question:</code>
9	<code>Go through documents to find out a question. Document: [D1] Document:[D2], ..., Question:</code>

Table 6: Top 10 instructions found through the instruction search step (section 2.3). Instructions are sorted in descending order according to their performance on a held-out development set from HotpotQA (Yang et al., 2018). We use the top 5 of these for instruction ensembling (section 2.4). Blue represents fixed text that does not depend on the path *i.e* the instruction. The tokens [D1], [D2], ..., etc. indicate where path documents are inserted.

	R@2	R@10	R@20	AR@2	AR@10	AR@20
Unsupervised Baselines						
TF-IDF	10.5	28.5	35.9	38.1	54.2	60.7
TF-IDF + BM25	19.1	54.7	61.8	49.5	74.7	79.9
Fully-supervised Baselines						
DrKit	38.3	67.2	71.0	–	–	–
MDR	65.9	77.5	80.2	–	–	–
PathRetriever	66.4	77.8	–	82.2	90.5	–
LEPUS						
LEPUS, T5-XL, 2-shot	52.4 \pm .4	73.0 \pm .3	77.0 \pm .1	78.6 \pm .5	88.7 \pm .1	90.3 \pm .1

Table 7: Mean and std of the retrieval performance on HotpotQA of LEPUS.