GENERATE RATHER THAN RETRIEVE: LARGE LANGUAGE MODELS ARE STRONG CONTEXT GENERATORS

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ABSTRACT

Knowledge-intensive tasks, such as open-domain question answering (QA), require access to a large amount of world or domain knowledge. A common approach for knowledge-intensive tasks is to employ a *retrieve-then-read* pipeline that first retrieves a handful of relevant contextual documents from an external corpus such as Wikipedia and then predicts an answer conditioned on the retrieved documents. In this paper, we present a novel perspective for solving knowledge-intensive tasks by replacing document retrievers with large language model generators. We call our method *generate-then-read* (GENREAD), which first prompts a large language model to generate contextual documents based on a given question, and then reads the generated documents to produce the final answer. Furthermore, we propose a novel clustering-based prompting method that selects distinct prompts, in order to generate diverse documents that cover different perspectives, leading to better recall over acceptable answers. We conduct extensive experiments on three different knowledge-intensive tasks, including open-domain QA, fact checking, and dialogue system. Notably, GENREAD achieves 71.6 and 54.4 exact match scores on TriviaQA and WebQ, significantly outperforming the state-of-the-art *retrieve-then-read* pipeline *DPR-FiD* by +4.0 and +3.9, without retrieving any documents from any external knowledge source. Lastly, we demonstrate the model performance can be further improved by combining retrieval and generation.

1 INTRODUCTION

Knowledge-intensive tasks, such as open-domain question answering (QA) and fact checking, require access to a large amount of world or domain knowledge (Petroni et al., 2021). These tasks are even challenging for humans without access to an external knowledge source such as Wikipedia. A common thread of existing methods for knowledge-intensive tasks employ a *retrieve-then-read* pipeline that first retrieves a handful of relevant contextual documents from Wikipedia and then conditions the prediction of the answer on these documents along with the question (Karpukhin et al., 2020; Lewis et al., 2020; Izacard & Grave, 2021). Modern dense retrieval models typically calculate similarity scores between question and document representations (Karpukhin et al., 2020). Nevertheless, these methods mainly suffer from three drawbacks. First, the representations of questions and documents are obtained independently, leading to only shallow interactions captured between them (Khattab et al., 2021). Second, the question or document representation is embedded into one single vector, potentially missing fine-grained information when computing the similarity between the two vector representations (Khattab & Zaharia, 2020). Third, document retrieval over a large corpus requires the retriever model to first encode all candidate documents and store representations for each document. These two operations limit the parameters of dense retrievers and the size of embedding vectors, and thus cannot enjoy the potential benefits of using large language models (Levine et al., 2022).

Recent work demonstrated that the knowledge stored in the parameters of pre-trained language models could be "retrieved" to some extent by directly generating text (Petroni et al., 2019; Roberts et al., 2020). However, the previous work only used generation for query expansion (Mao et al., 2021) or generated identifier strings for document retrieval (Bevilacqua et al., 2022). These solutions did not exploit the potential of directly generating contextual documents for open-domain questions.

In this paper, we propose to leverage large language models, such as GPT-3 (Brown et al., 2020) and OPT (Zhang et al., 2022), to directly generate contextual documents for a given question, instead of retrieving them from an external corpus, such as Wikipedia. Our approach has two main advantages.

First, as the cross-attention step in a large language model is highly expressive, requiring the model to explain every token in the question and document, resulting in a better estimation. As a consequence, the generated contextual documents tend to be more specific to the question than retrieved documents, making it easier to select the correct answer from the generated contextual documents. Second, large language models have been trained with considerably large amounts of data and parameters, allowing a type of "look up" of world knowledge stored in the model parameters.

We show, on multiple datasets, that generated documents are more likely to contain correct answers than the top retrieved documents. Notably, in dense retrieval methods, as more documents are retrieved, the recall of documents containing the correct answer increases (Karpukhin et al., 2020). However, the recall performance does not scale as well with generated documents because even with sampling methods, generated documents tend to contain duplicate information. In order to improve the recall performance of generated documents, we propose a novel clustering-based prompt method. We synthesize a prompt with in-context demonstrations of question-document pairs sampled from diverse clusters. These prompts result in generated documents that cover different perspectives of the question and improve the scaling of performance as more documents are generated per question.

In contrast to the *retrieve-then-read* pipeline, our method is essentially a *generate-then-read* pipeline. Specifically, it first prompts a large language model to generate contextual documents based on a given question, and then reads the generated document to produce the final answer. The reader can still be a large model (e.g., InstructGPT (Ouyang et al., 2022)) used under a zero-shot setting, or a small one (e.g., FiD (Izacard & Grave, 2021)) fine-tuned with generated documents on the training split of the target dataset. We evaluate our proposed method on three different knowledge-intensive tasks and demonstrate its effectiveness on both zero-shot and supervised settings.

Overall, our main contributions can be summarized as follows:

1. We propose a novel *generate-then-read* pipeline for solving knowledge-intensive tasks, i.e., replacing the process of retrieving documents from Wikipedia or searching for related documents on Google, by prompting a large language model to generate relevant contextual documents.
2. We propose a novel clustering-based prompting approach to generate multiple diverse contextual documents that increases the likelihood of covering the correct answer. We demonstrate this approach can significantly improve performance on end QA and other downstream tasks.
3. We conduct extensive experiments with three knowledge-intensive NLP tasks under both zero-shot and supervised settings. Notably, our method can match or even outperform *retrieve-then-read* pipeline methods, without retrieving any documents from any external knowledge source.

2 Related Work

Knowledge-intensive NLP via Retrieve-then-Read Pipeline. Mainstream methods for solving knowledge-intensive NLP tasks employ a *retrieve-then-read* model pipeline. Given a question, this model first leverages a retriever over a large evidence corpus (e.g. Wikipedia) to fetch a set of relevant documents that may contain the answer. A reader is then used to peruse the retrieved documents and predict an answer. Recent follow-up work has mainly focused on improving the retriever (Karpukhin et al., 2020; Qu et al., 2021; Sachan et al., 2022) or the reader (Izacard & Grave, 2021; Cheng et al., 2021; Yu et al., 2022), or training the system end-to-end (Lewis et al., 2020; Singh et al., 2021). Early retrieval methods mainly employed sparse retrievers, such as BM25 (Chen et al., 2017). Recently, ORQA (Lee et al., 2019) and DPR (Karpukhin et al., 2020) have revolutionized the field by utilizing dense contextualized vectors for document indexing, leading to superior performance to traditional approaches. Such models can be trained using weak supervision on question-answer pairs or pre-trained using self-supervised tasks. For the reader, current state-of-the-art models such as FiD, leveraged encoder-decoder models to generate answers (Izacard & Grave, 2021).

Generator as Retriever for Obtaining Contextual Documents. Recent works have investigated using auto-regressive language models to generate identifier strings for documents, as an intermediate target for retrievals, such as Wikipedia page titles (De Cao et al., 2020) or distinctive n-grams that can be mapped to full passages (Bevilacqua et al., 2022). However, one needs to create the identifiers, hence the structure was not thoroughly evaluated on a large-scale benchmark (Bevilacqua et al., 2022). Other work has demonstrated that knowledge stored in the parameters of these models can be "retrieved" to some extent by directly generating evidence for a query (Petroni et al., 2019; Roberts et al., 2020). Different from the above approaches that aimed to train a generator model to

produce contextual document identifiers (which is still using the original Wikipedia text) or provide data augmentation to retrievers, our work directly generates contextual documents for given questions.

NLP MODELS ENHANCED BY LARGE LANGUAGE MODEL OUTPUTS. A line of recent work has shown that relevant knowledge can be elicited from large language models, especially for those domains that lack appropriate knowledge bases with sufficient coverage (Liu et al., 2022; Fang et al., 2022). For example, Liu et al. (2022) proposed leveraging GPT-3 to generate relevant contexts, then providing the contexts as additional input when answering a commonsense question. Another line of work focused on prompting a large language model to generate a series of intermediate reasoning steps, often referred to as *chain-of-thought* (Wei et al., 2022b; Kojima et al., 2022; Li et al., 2022). The prompt consists of an instruction (e.g., Let's think step by step!), a few demonstrations that are fixed for each task, and a new-question placeholder. The demonstrations are human-written, and each consists of a question in the style of the task and a series of intermediate reasoning steps that is helpful for answering the question. None of the existing work explores knowledge-intensive tasks.

3 PROPOSED METHOD

In this section, we present details of our proposed novel *generate-then-read* (GENREAD) pipeline for solving various knowledge-intensive tasks. Specifically, it first prompts a large language model to generate contextual documents with respect to a given query, then reads the generated documents to predict the final answer. The reader can either be a large model (e.g., InstructGPT) used for the zero-shot setting, or a small one (e.g., FiD) fine-tuned with generated documents on the training split of the target dataset. We introduce the zero-shot setting in §3.1 and supervised setting in §3.2.

3.1 ZERO-SHOT SETTING

Under the zero-shot setting, there is no training data – neither questions nor contextual documents. When tested on the open-domain QA task, most existing large language models directly encode the given question and predict the answer (Brown et al., 2020; Du et al., 2022; Chowdhery et al., 2022). Specifically, the question q, associated with some text prompt, is input to the model, which then generates the answer, denoted as $p(a|q, \theta)$, where θ represents the pre-trained model parameters. In practice, the maximum a posteriori estimation (MAP) is the final answer, i.e., $\hat{a} = \arg\max_a p(a|q, \theta)$. However, this way of directly asking large language models to output answers often leads to poor performance, as it leaves a considerable amount of additional world knowledge unexploited (Levine et al., 2022). On the contrary, the zero-shot *retrieve-then-read* pipeline first uses an off-the-shelf retriever to fetch relevant documents from an external knowledge source such as Wikipedia, then asks the large language model to read the documents and predict the answer.

In this work, we improve the performance by introducing an additional auxiliary *generated document* variable d, and then extend the model to have the form $p(a, d|q) = p(a|d, q)p(d|q)$. In practice, we cannot sum over all possible documents d. Therefore, the most common approach is to compute the MAP estimate $\hat{d} = \arg\max \hat{p}(d)$ using beam search, and then to approximate the sum over d with this single value. This two step approach, we label it as a *generate-then-read* pipeline.

STEP1: GENERATE. In this step, we first prompt a large language model (e.g., InstructGPT (Ouyang et al., 2022)) to generate documents based on the given question. For example, the input to the language model could be "Generate a background document to answer the given question. {question placeholder}". We can use any decoding strategy (e.g., greedy decoding, beam search), but we used greedy decoding throughout the zero-shot experiments for simplicity and reproducibility.

STEP 2: READ. In the second step, we use generated sentence $\hat{d}$ along with the input question to produce the final answer from the large language model. This is actually the same setting as "zero-shot" reading comprehension, as widely studied in existing works (Brown et al., 2020; Lazaridou et al., 2022). We choose appropriate prompts from P3 (Bach et al., 2022), such as "Refer to the passage below and answer the following question. Passage: {background placeholder} Question: {question placeholder}". Finally, the language model is fed the prompted text to generate an answer.

3.2 SUPERVISED SETTING

Although large language models demonstrate impressive performance on zero-shot learning abilities, their performance still lag behind the supervised setting. Therefore, we also explore how the generated documents from large language models can benefit the supervised setting. As directly fine-tuning

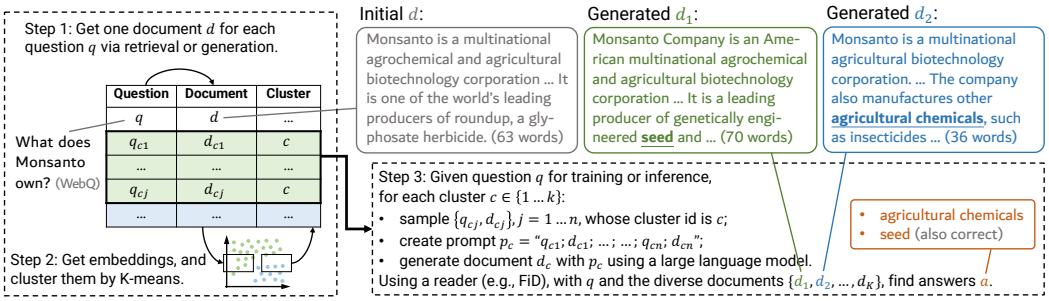


Figure 1: An overall framework of clustering-based prompting method. It leverages distinct question-document pairs sampled from each embedding cluster as in-context demonstrations to prompt a large language model to generate diverse documents, then read the documents to predict an answer.

large language models on downstream datasets could be prohibitively expensive, we leverage a small reader model such as FiD to peruse the generated documents under the supervised setting.

Under the supervised setting, scaling the size of retrieved documents can lead to better performance (Karpukhin et al., 2020; Izacard & Grave, 2021). This is mainly because retrieving more documents can cover more relevant information and knowledge, i.e., a higher recall score. Nevertheless, asking a large language model to generate multiple high-quality contextual documents is a challenging task. Dense retrieval methods can fetch multiple documents covering different perspectives of the answer. Compared to dense retrievers, simply prompting a large language model to generate contextual documents often leads to low knowledge coverage, mainly due to the high coincidence of token distributions in the decoding process under a single prompt. Though sampling decoding methods, such as nucleus sampling[1] (Holtzman et al., 2020) can diversify the generation process to some extent, the knowledge content of generated texts tends to be highly repetitive when used to generate documents for a given question. We further propose two novel solutions, including diverse human prompts and clustering-based prompts, which will be elaborated on in this section.

3.2.1 Diverse Human Prompts

In order to avoid similar token distributions under a single prompt, we ask human annotators to provide different prompts, in order to make the generated document diverse. This method is simple, but can effectively vary the token distribution during generation. In the experiments, we empirically found this method can bring improvement to the retrieval performance (Figure 2). However, this method suffers from two drawbacks. On one hand, it requires human annotators to write different prompts, which cannot be easily generalized to different knowledge-intensive tasks. On the other hand, different large language models might be sensitive to different prompt words, which might cause a set of good prompt words not work on a different large language model.

3.2.2 Clustering-based Prompts

To increase knowledge coverage in generated documents, we propose a novel clustering-based prompt method. It first clusters the representations of a set of documents into K classes ($K = 2$ in Figure 1), where the number of classes is equal to the number of documents that need to be generated in the end. Next, it randomly selects n question-document pairs ($n = 5$ in Figure 1) from each cluster. Lastly, a large language model presents the different n question-document pairs as in-context demonstrations for generating documents to a given question. In this way, large language models are based on different distributions of examples, hence resulting in generated documents covering different perspectives. We show this in Figure 1 and illustrate the details of each step as follows.

Step 1: Get One Initial Document Per Question. Similar to the zero-shot setting, we first ask a large language model to generate one contextual document d for each question $q \in \mathcal{Q}$, where $\mathcal{Q}$ is the set of questions in the training split. Alternatively, we can use an unsupervised retriever (e.g., BM25) to obtain a document from Wikipedia. We now have a question-document pair set $\{q_i, d_i\}_{i=1}^{|\mathcal{Q}|}$.

Step 2: Encode each Document, Do K-means Clustering. We then use a large language model (i.e., GPT-3) to encode each question-document pair, i.e., $\mathbf{e}_i = \text{GPT-3}([q_i, d_i])$, resulting in a

[1] We treated nucleus sampling as a baseline to generate multiple documents, in which we set $p = .95$.

Models	Open-domain QA			Fact Checking		Dialogue System	
	NQ	TriviaQA	WebQ	FEVER	FM2	WoW (F1 / R-L)	
**with retriever, AND directly trained on these datasets*							
DPR + InstructGPT*	29.9	55.3	20.1	79.8	65.9	15.4	13.7
**with retriever, BUT NOT trained on these datasets*							
BM25 + InstructGPT	20.5	53.3	16.0	78.7	65.2	15.7	13.7
Contriever + InstructGPT	19.1	52.4	16.8	80.4	**66.6**	15.5	14.0
Google + InstructGPT	27.8	58.7	19.9	**82.9**	66.0	14.8	13.2
**without retriever, and not using external documents*							
Previous SoTA methods	24.7[1]	56.7[2]	19.0[1]	-	-	-	-
InstructGPT (no docs.)	20.9	52.6	18.6	77.6	59.4	15.4	13.8
GENREAD (InstructGPT)	**28.2**	**59.3**	**24.8**	80.4	65.5	**15.8**	**14.2**

Table 1: Zero-shot open-domain QA performance. Our proposed GENREAD with the InstructGPT reader (named GENREAD (InstructGPT)) can significantly outperform the original InstructGPT, achieving new state-of-the-art performance on three open-domain QA benchmarks (previous SoTA: [1]GLaM (Du et al., 2022), [2]FLAN (Wei et al., 2021)) under this setting without using any external document. Our GENREAD can achieve comparable or even better performance than zero-shot *retrieve-then-read* models that use a retriever or search engine to first obtain contextual documents.

12,288-dimensional vector per document. Then, we use K-means to cluster all embedding vectors $\{\mathbf{e}_i\}_{i=1}^{|Q|}$ into K sets, so each question-document pair is assigned a unique cluster id $c \in \{1, ..., K\}$. We vary the number of K in the experiments, which will be illustrated in Figure 2.

STEP 3: SAMPLE AND GENERATE K DOCUMENTS. Lastly, we sample n question-document pairs from each cluster c, denoted as $\{q_{c1}, d_{c1}; q_{c2}, d_{c2}; ...; q_{cn}, d_{cn}\}$, in which n is a hyperparameter[2]. Then, the n sampled question-document pairs from the same cluster serve as in-context demonstrations for the large language model to generate a contextual document. For example, the input to the large language model could be "$\{q_{c1}$ placeholder$\}$ $\{d_{c1}$ placeholder$\}$ ... $\{q_{cn}$ placeholder$\}$ $\{d_{cn}$ placeholder$\}$ $\{$input question placeholder$\}$". By enumerating the sampled documents in these K clusters, we can finally get K-generated documents. By conditioning on different sampled in-context demonstrations collected from different clusters, the large language model has been biased for different perspectives. Although these different perspectives exist in a latent manner, we empirically show it works well in practice, by comparing it with sampling methods, diverse human prompts (Figure 2 and Table 2) and randomly sampling n pairs from the entire dataset (Table 10).

4 EXPERIMENTS

In this section, we conduct comprehensive experiments on three knowledge-intensive NLP tasks, including open-domain QA (NQ (Kwiatkowski et al., 2019), TriviaQA (Joshi et al., 2017) and WebQ (Berant et al., 2013)), fact checking (FEVER (Thorne et al., 2018) and FM2 (Eisenschlos et al., 2021)) and open-domain dialogue system (WoW (Dinan et al., 2019)). More detailed dataset information can be found in Appendix A.1. To evaluate the model performance, we use exact match (EM) score for evaluating open-domain QA (Zhu et al., 2021). An answer is considered correct if and only if its normalized form has a match in the acceptable answer list. We also employ Recall@K (R@K) as an intermediate evaluation metric, measured as the percentage of top-K retrieved or generated documents that contain the answer. This metric is commonly used in evaluations of previous works (Karpukhin et al., 2020; Izacard & Grave, 2020; Sachan et al., 2022). For other knowledge-intensive tasks, we follow the KILT benchmark (Petroni et al., 2021) to use accuracy (ACC) for fact checking and F1 / Rouge-L (R-L) score for open-domain dialogue system.

4.1 ZERO-SHOT SETTING EXPERIMENTS

We first compare our proposed GENREAD approach with various large language models proposed in recent years, including GPT-3 (Brown et al., 2020), Gppher (Rae et al., 2021), FLAN (Wei et al., 2021), GLaM (Du et al., 2022), Chinchilla (Hoffmann et al., 2022), PaLM (Chowdhery et al., 2022) and InstrcutGPT (Ouyang et al., 2022). Due to the space limitation, we only put the best performance

[2]In the experiments, we set $n = 5$ and found increasing n does not bring extra improvement.

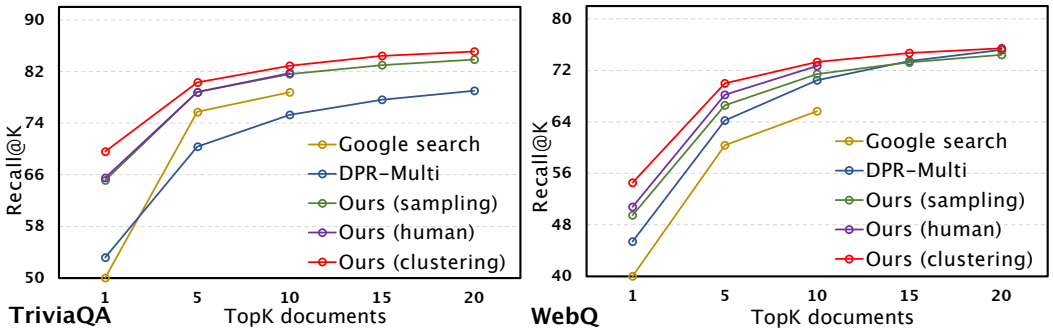


Figure 2: Recall@K score on test sets, measured as the percentage of top-K retrieved or generated documents that contain the answer. Our proposed clustering-based prompting method can outperform DPR and Google search, also two variants of using LLMs to generate contextual documents.

on each dataset in Table 1, in which the line is called *previous SoTA methods*. In addition, their corresponding model parameters and performance are listed in Table 7 in Appendix. All of these baseline methods use the same input formats, i.e., [prompt words; question].

GENREAD is based on InstructGPT with 175B parameters. In order to fully evaluate the effectiveness of our proposed method, we also compare with InstructGPT augmented with retrieved documents from Wikipedia or Google search. The baseline methods (1) BM25 / Contriever + InstructGPT; (2) Google + InstructGPT; (3) DPR + InstructGPT have the same input format as our GENREAD , i.e., [prompt words; contextual document; question]. BM25 is a traditional sparse retrieval method. Contriever (Izacard et al., 2022a) is a state-of-the-art unsupervised dense retrieval model. DPR (Karpukhin et al., 2020) is a supervised dense retrieval model directly trained on NQ, TriviaQA and WebQ datasets. We note that comparing with above three methods is challenging because our method only relies on the large language model itself, without using any external corpus.

4.1.1 EXPERIMENTAL RESULTS

In the experiments, we use InstructGPT as our backbone model. As shown in Table 1, compared with state-of-the-art large language models, our proposed GENREAD with the InstructGPT reader improves its performance by generating contextual documents and conditioning on the generated documents, even though no new data is introduced, and the generator and reader have the exact same parameters. Specifically, GENREAD can improve the EM score by +6.9 on three open-domain QA benchmarks, compared to the original InstructGPT. We also make a similar observation on fact checking and open-domain dialogue system. Our proposed GENREAD can consistently outperform the baseline InstructGPT model without retrieving any contextual documents.

To further validate the effectiveness of GENREAD , we compare against zero-shot *retrieve-then-read* pipeline models, which first use a retrieval model or the Google search engine to get a relevant contextual document, then use InstructGPT to read the texts and produce the final answer. As shown in Table 1, GENREAD can achieve on-par performance with zero-shot *retrieve-then-read* pipeline models on the NQ and FM2 datasets, and outperform them on all other benchmarks. The knowledge learned by the large language models can be retrieved via autoregressive text generation. Without seeing any examples from these datasets, GENREAD can outperform using the supervised retrieval model (i.e., DPR) to recover relevant contextual documents.

4.2 SUPERVISED SETTING EXPERIMENTS

We compare our proposed GENREAD with *retrieve-then-read* models, including DPR (Karpukhin et al., 2020), RAG (Lewis et al., 2020), and FiD (Izacard & Grave, 2021). In addition, we compared with obtaining relevant documents from the internet using the Google search engine.

4.2.1 EXPERIMENTAL SETUP

For our proposed method, we replace the retriever with a large language model to directly generate contextual documents. In the experiments, we use InstructGPT (Ouyang et al., 2022). After contextual documents are retrieved or generated, we employ a FiD reader with 770M parameter models (i.e.,

Models	# reader parameters	# documents	TriviaQA open test	WebQ open test	NQ open test	Avg.
**baselines with retrieving from Wikipedia; all numbers reported by existing papers*						
DPR (Karpukhin et al., 2020)	110M	100	56.8	41.1	41.5	46.5
RAG (Lewis et al., 2020)	400M	10	56.1	45.2	44.5	48.6
FiD (Izacard & Grave, 2021)	770M	100	67.6	50.5	51.4	56.5
**baselines with retrieving from Wikipedia or Google; all numbers from our experiments*						
FiD-l (DPR, Wikipedia)	770M	10	61.9	48.1	46.7	52.2
FiD-xl (DPR, Wikipedia)	3B	10	66.3	50.8	50.1	55.7
FiD-xl (Google search)	3B	10	70.1	53.6	45.0	56.2
**our proposed method by leveraging a large language model to generate documents*						
GENREAD (FiD-l) (sampling)	770M	10	67.8	51.5	40.3	53.2
GENREAD (FiD-l) (clustering)	770M	10	70.2	53.3	43.5	55.6
GENREAD (FiD-xl) (sampling)	3B	10	69.6	52.6	42.6	54.9
GENREAD (FiD-xl) (clustering)	3B	10	71.6	54.4	45.6	57.1
⊢ merge retrieved documents with generated documents			**74.3**	**56.2**	**54.0**	**61.5**

Table 2: Supervised open-domain QA performance. By only using generated documents from GPT-3, our GENREAD with FiD reader (named GENREAD (FiD)) can achieve better performance than baseline methods on TriviaQA and WebQ. Through our detailed analysis of NQ, we found the performance gap mainly due to the temporality issue, which will be elaborated in §4.2.3.

FiD-l) and 3B parameter models (i.e., FiD-xl) that are fine-tuned on the training split of target datasets. We note that we only use 10 documents during reading for the following reasons.

Why do we choose to use only 10 documents instead of 100 when reading?

As noted in Section 6.2 in DPR (Karpukhin et al., 2020) and Figure 3 in FiD (Izacard & Grave, 2021), increasing the number of documents can lead to better model performance and achieve state-of-the-art when using 100 documents. However, there are two major drawbacks to using 100 documents during the reading step. First, the operation is very expensive, leading to a significant increase in memory consumption and training time. As reported by Izacard & Grave (2021), the training process requires 64 Tesla V100 32GB running for around one day. Second, generating documents by using a large language model is slow and expensive, so only using 10 documents can be a significant cost saving in our method. Therefore, in our experiments, we choose to use 10 documents during the reading process. When using FiD-770M (i.e., FiD-large), the training process can be easily performed even on a single Tesla V100 32GB GPU. Meanwhile, when only using 10 documents, we can also increase the size of FiD model from 770M to 3B, which takes about the same amount of GPU memory as using 100 documents on a 770M model, but at the same time significantly shortens the training time. We note that training T5-3B model needs a bigger cluster such as 8 Tesla V100 or A100 GPUs.

4.2.2 EXPERIMENTAL RESULTS ON OPEN-DOMAIN QA

We first use Recall@K to compare the retrieval accuracy of different models. As shown in Figure 2, GENREAD can significantly outperform DPR and Google search for under 10 retrieved or generated documents. Compared to different GENREAD variants, including nucleus sampling, human written prompts, and clustering-based prompts, clustering-based prompts achieve the best performance. At the same time, we notice that the language model inevitably has the problem that the slope of the curve decreases as the number of generated documents increases. On one hand, this is due to the similarity of token distributions when large language models generate multiple documents. On the other hand, due to the shallow interaction characteristics of the dense retrieval model itself, the retrieved documents might not be completely relevant to the given question, so that the increase in recall might come from false positive documents, as also mentioned by Sachan et al. (2022).

As shown in Table 2, we can first observe the FiD model performs the best among all baseline models. Using FiD-xl with only 10 documents achieves comparable performance with using FiD-l with 100 documents. The average gap is less than 1% on three benchmarks. Compared with both close-book models and Wikipedia-based *retrieve-then-read* pipelines, our proposed GENREAD can achieve state-of-the-art performance. Furthermore, compared with using sampling methods to generate documents, the clustering-based prompt method can improve the EM score by +2.2 on average. This

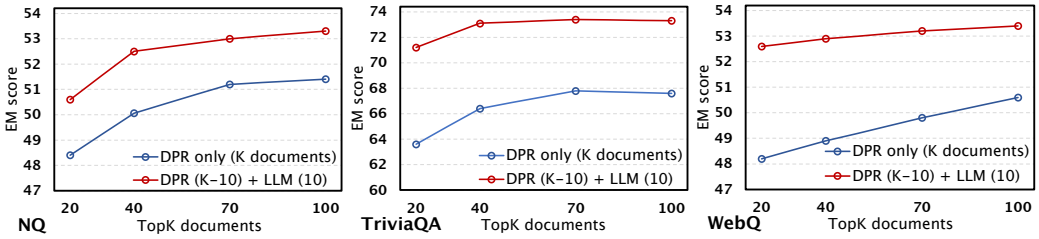


Figure 3: Combining DPR retrieved documents and large language model (LLM) generated documents can achieve significantly better performance than using DPR retrieved documents only. For a fair comparison, instead of adding LLM generated documents to the model, we replace 10 documents retrieved by DPR with 10 documents generated by LLM so the total number of documents is the same. In this experiment, we use FiD-l (i.e., FiD-large) as the reader model because when the documents scale to more than 20, FiD-xl (i.e., FiD-3B) causes out-of-memory issues on A100 GPUs.

indicates that the clustering-based prompt method is effectively increasing the knowledge coverage of generated documents, and also leading to better downstream QA performance. We also show that GENREAD can outperform Google search on all benchmarks. We observe both our method and Google search perform worse than DPR, mainly due to the significant portion of time-dependent questions in the dataset, which is described in the following analysis.

4.2.3 ERROR ANALYSIS ON THE NQ DATASET

As stated in Zhang & Choi (2021), NQ contains a significant proportion, roughly 16.5%, of questions that have time-dependent answers. Given the up-to-date answers, our GENREAD outperforms the reported performance by about 3.5, reaching 49.1. We also analyze the answers of Google search and have similar observations. We provide case studies in Appendix 19. Similarly, Izacard et al. (2022b) observed using the latest version of Wikipedia (12 / 2021) could lead to 4.4 drops of the EM score, compared to the Wikipedia version (12 / 2018) that the NQ questions are created from. As the temporal effects on the NQ dataset have been observed in many other recent papers (Min et al., 2020; Zhang & Choi, 2021), we conduct ablation studies mainly on the TriviaQA and WebQ datasets, to avoid the bias of the experimental results caused by the temporality issue.

4.2.4 EXPERIMENTAL RESULTS ON OTHER TASKS

We demonstrate the experimental results in Table 3. Under the supervised setting, GENREAD can achieve on par performance on the fact checking task and superior performance on the dialogue system task, indicating that large language model can be seen as a strong knowledge generator.

Models	FEVER Acc.	FM2 Acc.	WoW F1 / R-L
RAG (Lewis et al., 2020)	86.3	71.1	13.1 / 11.6
FiD (Izacard & Grave, 2021)	<u>90.2</u>	77.6	17.5 / 16.1
GENREAD (FiD-xl) (sampling)	89.0	76.3	18.9 / 16.7
GENREAD (FiD-xl) (clustering)	89.6	<u>77.8</u>	<u>19.1</u> / <u>16.8</u>
⊢ merge two source docs.	**91.8**	**78.9**	**20.1 / 17.9**

Table 3: Supervised performance on fact checking (FEVER and FM2) and open-domain dialogue system (WoW).

The main reason that GENREAD performs worse than the dense retriever for fact checking is that the task provides sufficient semantic information to reach strong performance on this binary decision task. So, there is a smaller semantic gap between the given factual statement and contextual documents than that of question and document pairs in open-domain QA, which is an easier retrieval setting for modern dense retrieval methods that are mainly based on vector similarity.

4.3 OBSERVATIONS AND EXPERIMENTAL ANALYSIS

4.3.1 COMPLEMENTARITY OF GENERATED AND RETRIEVED DOCUMENTS

Generated documents can be combined with retrieved documents to outperform both. Even with a very large number of retrieved documents, including few samples of generated knowledge leads to large improvements. As shown in Table 2, merging retrieved documents with generated documents can achieve state-of-the-art performance compared to all baseline methods listed in the table. Specifically, it can improve +5.7 averagely on three open-domain QA benchmarks compared to DPR alone, and improve +4.4 averagely compared to the large language model alone.

4.3.2 ANSWER COVERAGE ANALYSIS OVER ALL DOCUMENTS

The improvement in open-domain QA performance is due to the fact that correct answers are included more frequently in the generated text Recall@K is the most commonly used metric in existing works to measure the retrieval performance, which computes the percentage of top-K retrieved or generated documents that contain any possible answer at least once. than in the retrieved documents. However, as many questions contain multiple correct answers, recall@K cannot fully reflect the diversity of generated or retrieved documents. Each question in the WebQ has 2.39 correct answers, 1.79 correct answers in NQ and 14.02 (including all entity alias) in the TriviaQA. NQ and WebQ do not include alias names in the labels.

In this section, we also demonstrate the answer coverage performance of different models in Table 9. Answer coverage measures the percentage of accepted answers that are contained in the documents. Coverage analysis showed that generated text tends to have lower coverage than retrieved documents because generated knowledge tends to have little diversity compared to retrieved documents. To improve coverage, we propose GENREAD with clustering, where we include examples in the prompt from different clusters of the training data to elicit more diverse knowledge generations.

Documents obtained by ↓	NQ	TriviaQA	WebQ
BM25 (Robertson et al., 2009)	0.84	1.83	0.72
Google search engine[3]	0.99	1.92	1.01
DPR (Karpukhin et al., 2020)	**1.19**	1.90	1.10
GENREAD (nucleus sampling)	0.97	2.01	1.08
GENREAD (10 human prompts)	1.00	2.12	1.18
GENREAD (clustering prompts)	1.04	**2.17**	**1.22**

Table 4: Answer coverage over 10 retrieved or generated documents. Case studies are provided in Tables 14-17.

4.3.3 REPRODUCIBILITY VIA OPEN SOURCE LARGE LANGUAGE MODELS

We note that reproducing experiments on the GPT-3 API, though publicly available, costs money. For this reason, we further add an evaluation on two open-source large language models OPT (Zhang et al., 2022) and Codex (OpenAI, 2022). As shown in Table 5, OPT performed worse than GPT-3, but still achieved comparable performance with DPR; OpenAI Codex achieved the best performance on both TriviaQA and WebQ.

Documents obtained by ↓	TriviaQA	WebQ
DPR (Karpukhin et al., 2020)	66.3	50.8
OPT (Zhang et al., 2022)	62.1	51.8
GPT-3 (Ouyang et al., 2022)	71.3	54.5
Codex (OpenAI, 2022)	**72.6**	**55.4**

Table 5: Exact match (EM) score with using DPR and different open-source large language models such as OPT and Codex to generate contextual documents.

4.3.4 SCALING WITH NUMBER OF LARGE MODEL PARAMETERS

Figure 4 shows the scaling of performance with GPT-3 generator parameters, including Ada-150M, Babbage-1.3B, Curie-6.7B and Davinci-175B. We note that for both FiD and our GENREAD , we use the FiD-xl with 10 input documents either retrieved from Wikipedia or generated by GPT-3. The performance of both TriviaQA and WebQ continues to improve as the generator model parameters increase, as does the slope. Only with the largest size GPT-3, GENREAD can outperform the *DPR-FiD*. This indicates using large language model to generate contextual documents is an "emergent ability" of scaling, which is not present in smaller models but is present in larger models (Wei et al., 2022a).

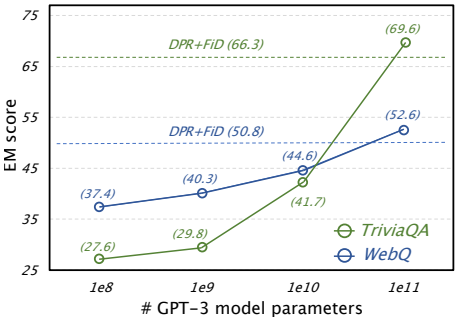


Figure 4: Model performance with different size of GPT-3 as context generators.

5 CONCLUSIONS

In this paper, we present a novel perspective for solving knowledge-intensive tasks by replacing the dense retrieval models with large language model generators. We call it *generate-then-read*, which first prompts a large language model to generate contextual documents based on a given question, then read the generated document to produce the final answer. Notably, without retrieving any documents, it reaches 71.6 and 54.4 exact match scores on TriviaQA and WebQ, significantly outperforming the current *retrieval-reader* model *DPR-FiD*, as well as on other two knowledge-intensive tasks.

REPRODUCIBILITY STATEMENT

To ensure the reproducibility of our experiments and benefit the research community, we will open-source all source codes, all generated contextual documents, and all trained checkpoints upon the acceptance of this paper. The hyper-parameters and other variable required to reproduce our experiments are described in Table 8. All large language models used in our paper, including GPT-3, InstructGPT, OPT and Codex are publicly available. We note that reproducing experiments with GPT-3 series models requires access to the GPT-3 API provided by OpenAI.

REFERENCES

Stephen Bach, Victor Sanh, Zheng Xin Yong, Albert Webson, Colin Raffel, Nihal V Nayak, Abheesht Sharma, Taewoon Kim, M Saiful Bari, Thibault Févry, et al. Promptsource: An integrated development environment and repository for natural language prompts. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pp. 93–104, 2022.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. Semantic parsing on freebase from question-answer pairs. In *EMNLP 2013*, pp. 1533–1544, 2013.

Michele Bevilacqua, Giuseppe Ottaviano, Patrick Lewis, Wen-tau Yih, Sebastian Riedel, and Fabio Petroni. Autoregressive search engines: Generating substrings as document identifiers. *arXiv preprint arXiv:2204.10628*, 2022.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. Reading wikipedia to answer open-domain questions. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1870–1879, 2017.

Hao Cheng, Yelong Shen, Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. Unitedqa: A hybrid approach 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)*, pp. 3080–3090, 2021.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.

Nicola De Cao, Gautier Izacard, Sebastian Riedel, and Fabio Petroni. Autoregressive entity retrieval. In *International Conference on Learning Representations*, 2020.

Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. Wizard of wikipedia: Knowledge-powered conversational agents. In *International Conference on Learning Representations*, 2019.

Nan Du, Yanping Huang, Andrew M Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, et al. Glam: Efficient scaling of language models with mixture-of-experts. In *International Conference on Machine Learning*, pp. 5547–5569. PMLR, 2022.

Julian Eisenschlos, Bhuwan Dhingra, Jannis Bulian, Benjamin Börschinger, and Jordan Boyd-Graber. Fool me twice: Entailment from wikipedia gamification. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 352–365, 2021.

Yuwei Fang, Shuohang Wang, Yichong Xu, Ruochen Xu, Siqi Sun, Chenguang Zhu, and Michael Zeng. Leveraging knowledge in multilingual commonsense reasoning. In *Findings of the Association for Computational Linguistics: ACL 2022*, pp. 3237–3246, 2022.

Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models. *arXiv preprint arXiv:2203.15556*, 2022.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. In *International Conference on Learning Representations*, 2020.

Gautier Izacard and Edouard Grave. Distilling knowledge from reader to retriever for question answering. In *International Conference on Learning Representations*, 2020.

Gautier Izacard and Edouard Grave. Leveraging passage retrieval with generative models for open domain question answering. In *EACL 2021*, pp. 874–880, 2021.

Gautier Izacard, Mathild Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. Unsupervised dense information retrieval with contrastive learning. *Transactions on Machine Learning Research (TMLR)*, 2022a.

Gautier Izacard, Patrick Lewis, Maria Lomeli, Lucas Hosseini, Fabio Petroni, Timo Schick, Jane Dwivedi-Yu, Armand Joulin, Sebastian Riedel, and Edouard Grave. Few-shot learning with retrieval augmented language models. *arXiv preprint arXiv:2208.03299*, 2022b.

Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. In *ACL 2017*, pp. 1601–1611, 2017.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 6769–6781, 2020.

Omar Khattab and Matei Zaharia. Colbert: Efficient and effective passage search via contextualized late interaction over bert. In *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval*, pp. 39–48, 2020.

Omar Khattab, Christopher Potts, and Matei Zaharia. Relevance-guided supervision for openqa with colbert. *Transactions of the Association for Computational Linguistics*, 9:929–944, 2021.

Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. *arXiv preprint arXiv:2205.11916*, 2022.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. Natural questions: A benchmark for question answering research. *TACL 2019*, pp. 452–466, 2019.

Angeliki Lazaridou, Elena Gribovskaya, Wojciech Stokowiec, and Nikolai Grigorev. Internet-augmented language models through few-shot prompting for open-domain question answering. *arXiv preprint arXiv:2203.05115*, 2022.

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

Yoav Levine, Itay Dalmedigos, Ori Ram, Yoel Zeldes, Daniel Jannai, Dor Muhlgay, Yoni Osin, Opher Lieber, Barak Lenz, Shai Shalev-Shwartz, et al. Standing on the shoulders of giant frozen language models. *arXiv preprint arXiv:2204.10019*, 2022.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33: 9459–9474, 2020.

Yifei Li, Zeqi Lin, Shizhuo Zhang, Qiang Fu, Bei Chen, Jian-Guang Lou, and Weizhu Chen. On the advance of making language models better reasoners. *arXiv preprint arXiv:2206.02336*, 2022.

Jiacheng Liu, Alisa Liu, Ximing Lu, Sean Welleck, Peter West, Ronan Le Bras, Yejin Choi, and Hannaneh Hajishirzi. Generated knowledge prompting for commonsense reasoning. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 3154–3169, 2022.

Yuning Mao, Pengcheng He, Xiaodong Liu, Yelong Shen, Jianfeng Gao, Jiawei Han, and Weizhu Chen. Generation-augmented retrieval 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)*, pp. 4089–4100, 2021.

Sewon Min, Julian Michael, Hannaneh Hajishirzi, and Luke Zettlemoyer. Ambigqa: Answering ambiguous open-domain questions. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 5783–5797, 2020.

OpenAI. Codex (available via openai api for free). *https://openai.com/blog/openai-codex/*, 2022.

Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*, 2022.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. Language models as knowledge bases? In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 2463–2473, 2019.

Fabio Petroni, Aleksandra Piktus, Angela Fan, Patrick Lewis, Majid Yazdani, Nicola De Cao, James Thorne, Yacine Jernite, Vladimir Karpukhin, Jean Maillard, et al. Kilt: a benchmark for knowledge intensive language tasks. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 2523–2544, 2021.

Yingqi Qu, Yuchen Ding, Jing Liu, Kai Liu, Ruiyang Ren, Wayne Xin Zhao, Daxiang Dong, Hua Wu, and Haifeng Wang. 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*, pp. 5835–5847, 2021.

Jack W Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, et al. Scaling language models: Methods, analysis & insights from training gopher. *arXiv preprint arXiv:2112.11446*, 2021.

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

Adam Roberts, Colin Raffel, and Noam Shazeer. 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)*, pp. 5418–5426, 2020.

Stephen Robertson, Hugo Zaragoza, et al. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends® in Information Retrieval*, 3(4):333–389, 2009.

Devendra Singh Sachan, Mike Lewis, Dani Yogatama, Luke Zettlemoyer, Joelle Pineau, and Manzil Zaheer. Questions are all you need to train a dense passage retriever. *arXiv preprint arXiv:2206.10658*, 2022.

Devendra Singh, Siva Reddy, Will Hamilton, Chris Dyer, and Dani Yogatama. End-to-end training of multi-document reader and retriever for open-domain question answering. *Advances in Neural Information Processing Systems*, 34:25968–25981, 2021.

James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. Fever: a large-scale dataset for fact extraction and verification. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 809–819, 2018.

Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. In *International Conference on Learning Representations*, 2021.

Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. Emergent abilities of large language models. *arXiv preprint arXiv:2206.07682*, 2022a.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. Chain of thought prompting elicits reasoning in large language models. *arXiv preprint arXiv:2201.11903*, 2022b.

Donghan Yu, Chenguang Zhu, Yuwei Fang, Wenhao Yu, Shuohang Wang, Yichong Xu, Xiang Ren, Yiming Yang, and Michael Zeng. Kg-fid: Infusing knowledge graph in fusion-in-decoder for open-domain question answering. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 4961–4974, 2022.

Michael Zhang and Eunsol Choi. Situatedqa: Incorporating extra-linguistic contexts into qa. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 7371–7387, 2021.

Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. Opt: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*, 2022.

Fengbin Zhu, Wenqiang Lei, Chao Wang, Jianming Zheng, Soujanya Poria, and Tat-Seng Chua. Retrieving and reading: A comprehensive survey on open-domain question answering. *arXiv preprint arXiv:2101.00774*, 2021.

A APPENDIX

Datasets	Splits	Train	Valid	Test	Test labels
TriviaQA (Joshi et al., 2017)	open domain	78,785	8,837	11,313	public
	wikipedia split			7,993	public
WebQ (Berant et al., 2013)	open domain	3,478	300	2,032	public
NQ (Kwiatkowski et al., 2019)	open domain	79,168	8,757	3,610	public
FEVER (Thorne et al., 2018)	kilt challenge	104,966	10,444	10,100	hidden
FM2 (Eisenschlos et al., 2021)	official split	10,149	1169	1380	public
WoW (Dinan et al., 2019)	kilt challenge	63,734	3,054	2,944	hidden

Table 6: Datasets splits and statistics. For FEVER and WoW, labels in the test are hidden, so the model performance should be evaluated at https://ai.facebook.com/tools/kilt/.

A.1 DATASETS AND SPLITS

– TRIVIAQA (TQA) (Joshi et al., 2017) contains a set of trivia questions with answers that were originally scraped from trivia and quiz-league websites.

– WEBQUESTIONS (WebQ) (Berant et al., 2013) consists of questions selected using Google Suggest API, where the answers are entities in Freebase.

– NATURAL QUESTIONS (NQ) (Kwiatkowski et al., 2019) were mined from real Google search queries and the answers are spans in Wikipedia articles identified by human annotators.

We explore the same train / dev / test splits for the open-domain QA setting as used by Izacard & Grave (2021); Karpukhin et al. (2020). For TriviaQA, GPT-3 / GLaM / PaLM (Brown et al., 2020; Du et al., 2022; Chowdhery et al., 2022) evaluate on the Wikipedia dev set of 7,993 examples, so we ran an additional evaluation on that dev set in order to compare with GPT-3's performance.

– FEVER (Thorne et al., 2018) is one of the largest datasets for fact checking that requires retrieving evidence from external corpus to support if a statement is supported or refuted.

– FOOL ME TWICE (FM2) (Eisenschlos et al., 2021) is a challenging fact checking dataset collected by gamification. Players write challenging claims either entailed or refuted by evidence from Wikipedia. They are then tasked to spot the refuted claim among a group.

– WIZARD OF WIKIPEDIA (WoW) (Dinan et al., 2019) is an open-domain dialogue task for training agents that can converse knowledgeably about open-domain topics. One speaker in the conversation must ground their utterances in a specific knowledge sentence from a Wikipedia page.

We use the same train / dev / test splits in KILT challenge (Petroni et al., 2021) for the FEVER and WoW datasets. Their test labels are hidden, so the performance can only be evaluated through https://ai.facebook.com/tools/kilt. For FM2, we use its official dataset splits.

A.2 IMPLEMENTATION DETAILS

We use T5-770M (Raffel et al., 2020) and T5-3B as our backbone models to implement FiD (Izacard & Grave, 2021). We use AdamW as the optimizer, with 2,000 warm-up steps. We set the dropout probability to 0.1 and weight decay to 0.01. We use one A100 for running T5-770M and set the batch size of 16. We use 8 A100 for running T5-3B and set the per GPU batch as 2, leading to the total batch size as 16. We searched different learning rates, ranging from $5e$-6 to $4e$-5, and we found $3e$-5 to $6e$-5 performed the best under the T5-3B setting and $5e$-5 to $1e$-4 performed the best under the T5-770M setting. We refer to more individual implementation details in Table 8.

We implement other baseline methods by using repositories:

– BM25: https://github.com/castorini/pyserini

– DPR: https://github.com/facebookresearch/DPR

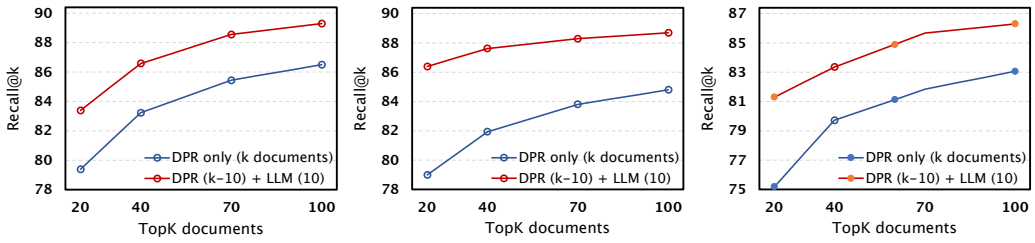
– Contriever: https://github.com/facebookresearch/contriever

Models	# total parameters	NQ open test	TriviaQA open test	TriviaQA wiki split	WebQ open test
GPT-3 (Brown et al., 2020)	175B	14.6	49.2	64.3	14.4
Gopher (Rae et al., 2021)	280B	10.1	43.5	52.8	-
FLAN (Wei et al., 2021)	137B	20.7	56.7	68.1	-
GLaM (Du et al., 2022)	64B	21.5	-	68.0	15.5
Chinchilla (Hoffmann et al., 2022)	70B	16.6	55.4	67.0	-
PaLM (Chowdhery et al., 2022)	540B	21.2	-	**76.9**	10.9
InstructGPT (Ouyang et al., 2022)	175B	20.9	52.6	62.9	18.6
GENREAD (InstructGPT)	175B	**28.2**	**59.3**	70.3	**24.8**

Table 7: Zero-shot open-domain QA performance, compared to recent large language models. All models in the table do not leverage any external corpus for document retrieval. Compared to InstructGPT, our proposed GENREAD with the InstructGPT reader can improve the EM score by +6.9 on average. GENREAD can achieve state-of-the-art performance on open test sets.

Settings / Datasets	NQ	TriviaQA	WebQ	FEVER	FM2	WoW
Peak learning rate	1e-4	1e-4	1e-4	1e-4	1e-4	5e-5
Total batch size	64	64	64	64	64	16
Total training steps	15,000	10,000	10,000	10,000	10,000	20,000
Best validation steps	6,000	500	8,500	5,000	6,000	20,000
Validation performance	43.27	69.47	60.33	88.97	73.57	18.60
Best validation ⇒ test	43.50	70.22	53.33	87.25	74.21	18.49
Peak learning rate	5e-5	6e-5	3e-5	5e-5	5e-5	3e-5
Total batch size	16	16	16	16	16	8
Total training steps	20,000	15,000	15,000	15,000	15,000	20,000
Best validation steps	14,000	8,500	11,500	10,000	6,000	16,500
Validation performance	44.83	70.61	61.00	90.53	76.30	19.12
Best validation ⇒ test	45.55	71.55	54.36	89.58	77.78	18.87

Table 8: Hyperparaters settings and validation performance for open-domain QA (numbers reported in Table 2), fact checking and dialogue system (numbers reported in Table 3). The upper part numbers are from GENREAD (FiD-l) and the lower part numbers are from GENREAD (FiD-xl).



(a) NQ-test (retrieval) (b) TriviaQA-test (retrieval) (c) WebQ-test (retrieval)

Figure 5: Additional retrieval performance evaluation of experiments on combining DPR retrieved documents and large language model generated documents. Merging documents from two sources achieved significantly better performance than using DPR retrieved documents only.

Models	TriviaQA			WebQ			NQ		
	R@1	R@10	R@20	R@1	R@10	R@20	R@1	R@10	R@20
BM25 (Robertson et al., 2009)	46.2	71.7	76.4	19.1	51.8	62.6	22.8	55.6	63.9
Contriever (Izacard et al., 2022a)	34.0	67.9	74.3	18.2	55.7	65.7	18.8	54.8	65.1
DPR (Karpukhin et al., 2020)	53.2	75.3	79.0	45.4	70.5	75.2	44.6	**74.5**	**79.5**
Google Search engine API	50.0	78.8	-	40.0	65.6	-	35.5	67.5	-
GENREAD (nucleus, p=.95)	65.1	81.6	83.8	49.5	71.4	74.4	40.1	66.2	70.6
GENREAD (10 human prompts)	65.5	81.8	-	50.8	72.7	-	40.5	66.9	-
GENREAD (clustering prompts)	**69.6**	**82.9**	**85.1**	**54.5**	**73.3**	**75.4**	**48.0**	70.9	74.5

Table 9: Retrieval performance evaluated by Recall@K of baselines and different GENREAD variants. Some numbers in the table are overlapped with those in Figure 2. This table aims to show the performance of more methods, and to provide accurate recall numbers for future research comparisons.

R@10	TriviaQA	WebQ	NQ
Sample 5 documents from *entire data*	82.3	72.6	68.8
Sample 5 documents from *each cluster*	**82.9**	**73.3**	**70.9**

Table 10: Ablation study on the strategy of sampling documents as in-context demonstrations.

EM score	TriviaQA	WebQ	NQ
DPR-FiD	80.2	63.3	63.1
GENREAD	**86.8**	**66.7**	**64.0**

Table 11: Readability study on retrieved and generated documents. See A.3 for more details.

A.3 READABILITY ANALYSIS

After we manually compare some retrieved documents from DPR and generated documents from GPT-3, we observe that the readability of different documents, when they contain the correct answer string, is different. In other words, documents that contain answers may contain a certain amount of noisy information that affects both the model and human reading.

In order to further validate the readability of retrieved documents and generated documents, we extracted a subset of data examples from NQ, TriviaQA and WebQ, in which both retrieved and generated documents hit the correct answer. As shown in Table 11, when both retrieved and generated documents hit the correct answer, the FiD reader can produce more correct answers when reading the generated documents from large language models.

We also provide some case studies in Table 14 to Table 17. For example, in Table 16, the question is "What city was Zeus the patron god of?". The first document retrieved by DPR is "Many were specific only to a particular deity or city-state. For example, the festival of Lykaia was celebrated in Arcadia in Greece, which was dedicated to the pastoral god Pan. Like the other Panhellenic Games, the ancient Olympic Games were a religious festival, held at the sanctuary of Zeus at Olympia.". Although the document contains the correct answer span, it is hard to read and find it. On the contrary, GPT-3 generates the document "Zeus was the patron god of the city of Olympia, which was located in the northwestern Peloponnese region of Greece. Olympia was the site of the Olympic Games, which were held every four years in honor of Zeus.", which is much easier to read.

No.	Prompts	Validation
#1	Generate a background document from Wikipedia to answer the given question.	66.0
#2	Provide a background document from Wikipedia to answer the given question.	65.0
#3	Generate a background document from web to answer the given question.	64.0
#4	Generate a Wikipedia document to support the given question.	63.5
#5	Provide a background document for the given question.	63.0
#6	Prepare a background document to support the given question.	63.0
#7	To support the given question, prepare a background document.	62.5
#8	Create a background document that supports the given question.	61.5
#9	Retrieve a document from Wikipedia to answer the given question.	60.5
#10	Retrieve a Wikipedia article to address the posed question.	59.5

Table 12: Top-10 human prompts, evaluated on merged validation set of NQ, TriviaQA and WebQ.

Prompt No.	Validation	NQ	WebQ	TriviaQA	Avg.
#1 (Generate ...)	66.0	45.9	51.9	68.7	55.5
#2 (Provide ...)	65.0	43.9	51.0	68.3	54.4
#3 (Generate ...)	64.0	44.0	50.6	67.7	54.2
#4 (Generate ...)	63.5	43.2	51.2	67.5	54.0
#5 (Provide ...)	63.0	43.6	50.3	67.9	54.0
#6 (Prepare ...)	63.0	43.5	50.5	67.7	54.0
#7 (To support ...)	62.5	43.5	50.3	67.5	53.8
#8 (Create ...)	61.5	42.7	50.2	66.8	53.3
#9 (Retrieve ...)	60.5	41.6	49.0	68.2	53.0
#10 (Retrieve ...)	59.5	40.7	49.5	67.7	52.7

Table 13: Performance on NQ, TriviaQA and WebQ test sets of top-10 human prompts.

A.4 Human Prompt Annotations

In order to get a better prompt for large language models to generate better contextual documents, we asked 30 students in the computer science department to write different prompts. We first constructed a small validation set with 200 examples by combining 50 random question-answer pairs from NQ, 100 random pairs from TriviaQA and 50 random pairs from WebQ. When an annotator wrote down a prompt, our system can immediately evaluate the prompt by using the validation set and return the performance to the annotator. Then, the annotator can modify the previous prompt until the recall performance reaches a threshold, which is set as 50 in our experiments. Finally, we got 29 prompts from human annotators due to two of them are the same. We used the top-10 prompts (shown in Table 12 and Table 13) in the human prompt setting, as described in §3.2.1.

Query: What type of music did Mozart composed?
Answers: opera, classical music, art song, chamber music, ballet

DPR #1: The following is a list of surviving works that Mozart composed for performance at gatherings of Masons. The story and music of his opera "The Magic Flute" is also considered to have strong Masonic influences. The following is a partial list of family members, patrons, and colleagues who were Masons. Mozart's grandfather Johann Georg, a bookbinder, was raised among the extended Mozart family in Augsburg, in the house of Johann's own grandfather David Mozart. David and his children were distinguished architects and master ... (Wikipedia id: 10988168 – "Mozart and Freemasonry")
DPR #2: Progressively, and in large part at the hands of Mozart himself, the contrapuntal complexities of the late Baroque emerged once more, moderated and disciplined by new forms, and adapted to a new aesthetic and social milieu. Mozart was a versatile composer, and wrote in every major genre, including symphony, opera, the solo concerto, chamber music including string quartet and string quintet, and the piano sonata. These forms were not new, but Mozart advanced their technical sophistication and emotional reach. He almost single-handedly developed and popularized the Classical piano concerto. He wrote a great deal ... (Wikipedia id: 451968 – "Wolfgang Amadeus Mozart")
Among top-10 retrieved documents: opera: 2 times chamber music: 1 time

GPT nucleus #1: Mozart was a prolific composer and wrote in many different genres. He composed symphonies, operas, concertos, chamber music, and more. Many of his works are considered some of the greatest ever written in those genres.
GPT nucleus #2: Mozart composed a variety of music, including operas, symphonies, chamber music, concertos, and sonatas. His early works were influenced by the music of Haydn and Bach, and his later works show the influence of the French and Italian composers of his time. Mozart's music is characterized by its beauty, elegance, and precision, and he is considered one of the greatest composers of all time.
GPT nucleus #3: Mozart composed a wide variety of music, including operas, symphonies, concertos, solo pieces, and chamber music. He also wrote a number of religious works, including masses and motets.
Among top-10 generated documents: chamber music: 9 times

GPT cluster #1: Mozart found work in Vienna as a piano teacher and composer for opera and other works. There he met a fellow Mason, Joseph Haydn, who was to become an important mentor. Mozart married Constanze Weber in 1782; their marriage is thought to have been happy, in contrast to his earlier unhappy arranged marriage to his cousin, Maria Anna ŇannerlŇMozart. Mozart composed more than 600 works, including works widely.
GPT cluster #2: Mozart was a prolific composer, and wrote in a wide variety of genres. He composed over 600 works, including operas, symphonies, concertos, solo works, and chamber music. His operas include The Marriage of Figaro, Don Giovanni, and Cosi fan tutte. His symphonies include the well-known Symphony No. 40 in G minor, and his concertos include the Piano Concerto No. 21 in C major, known as the Ëlvira Madigan̈concerto.
GPT cluster #3: Mozart was a prolific composer who wrote music in a wide variety of genres. He is best known for his work in the classical genre, which includes such works as his Symphony No. 40 in G minor and his piano concertos. He also wrote operas, including The Marriage of Figaro and The Magic Flute. In addition to his work in classical music, Mozart also composed works in the popular genre, such as his Eine kleine Nachtmusik.
Among top-10 generated documents: opera: 2 times chamber music: 7 times classical music: 1 time

Table 14: Case study of retrieved documents and generated documents from language models (1/4).

Query: What does Monsanto own?
Answers: agricultural chemicals, seed, agriculture, chemical industry

DPR #1: In September 2016, Monsanto agreed to be acquired by Bayer for US$66 billion. In an effort to receive regulatory clearance for the deal, Bayer announced the sale of significant portions of its current agriculture businesses, including its seed and herbicide businesses, to BASF. The deal was approved by the European Union on March 21, 2018, and approved in the United States on May 29, 2018. The sale closed on June 7, 2018; Bayer announced its intent to discontinue the Monsanto name, with the combined company operating solely under the Bayer brand. ... (Wikipedia id: 935126 – "Monsanto")
DPR #2: Behind it all is of course an evil corporation: Monsanto. GMO conspiracy theories GMO conspiracy theories are conspiracy theories related to the production and sale of genetically modified crops and genetically modified food (also referred to as genetically modified organisms or "GMOs"). These conspiracy theories include claims that agribusinesses, especially Monsanto, have suppressed data showing that GMOs cause harm, deliberately cause food shortages to promote the use of GM food, or have co-opted government agencies ... (Wikipedia id: 19304897 – "GMO conspiracy theories")
Among top-10 retrieved documents: agriculture: 1 time seed: 2 times

GPT nucleus #1: Monsanto is an American agricultural biotechnology corporation founded in 1901. It is headquartered in Creve Coeur, Missouri. Monsanto is a leading producer of genetically engineered seed and Roundup, a glyphosate-based herbicide.
GPT nucleus #2: Monsanto is a multinational agrochemical and agricultural biotechnology corporation headquartered in Creve Coeur, Missouri. It is one of the world's leading producers of Roundup, a glyphosate-based herbicide. The company also manufactures genetically engineered seed and Roundup Ready crops, including corn, soybeans, and cotton. As of 2018, Monsanto is the world's largest producer of glyphosate. In 2018, Bayer acquired Monsanto for $63 billion.
Among top-10 generated documents: seed: 6 times

GPT cluster #1: Monsanto Company is an American multinational agrochemical and agricultural biotechnology corporation headquartered in Creve Coeur, St. Louis, Missouri. It is a leading producer of genetically engineered (GE) seed and of the herbicide glyphosate, which it markets under the Roundup brand. Founded in 1901 by John Francis Queeny, Monsanto spent most of the 20th century as a chemical company, becoming one of the world's leading manufacturers of plastics, resins, and other chemicals.
GPT cluster #2: Monsanto is a biotechnology and agriculture company that specializes in genetically modified organisms (GMOs). The company owns a number of patents on GMOs, and it produces a range of products that contain GMOs, including herbicides, pesticides, and seeds.
GPT cluster #3: Monsanto is a multinational agricultural biotechnology corporation. It is one of the world's leading producers of genetically engineered seed and Roundup, a glyphosate-based herbicide. The company also manufactures other agricultural chemicals, such as insecticides and fungicides.
Among top-10 generated documents: agriculture: 2 times seed: 5 times agricultural chemicals: 1 time

Table 15: Case study of retrieved documents and generated documents from language models (2/4).

Query: What city was Zeus the patron god of?
Answers: Olympia, Elis

DPR #1: Many were specific only to a particular deity or city-state. For example, the festival of Lykaia was celebrated in Arcadia in Greece, which was dedicated to the pastoral god Pan. Like the other Panhellenic Games, the ancient Olympic Games were a religious festival, held at the sanctuary of Zeus at Olympia. Other festivals centred on Greek theatre, of which the Dionysia in Athens was the most important. More typical festivals featured a procession, large sacrifices and a feast to eat the offerings, and many included entertainments and customs such as visiting friends, wearing fancy dress and unusual behaviour in the ... (Wikipedia id: 1945872 – "Ancient Greek religion")
DPR #2: Theatre of Dionysus The Theatre of Dionysus Eleuthereus is a major theatre in Athens, considered to be the world's first theatre, built at the foot of the Athenian Acropolis. Dedicated to Dionysus, the god of plays and wine (among other things), the theatre could seat as many as 17,000 people with excellent acoustics, making it an ideal location for ancient Athens' biggest theatrical celebration, the Dionysia. It was the first theatre ever built, cut into the southern cliff face of the Acropolis, and supposedly the birthplace of Greek tragedy. The remains of a restored and redesigned Roman version can still ... (Wikipedia id: 3732515 – "Theatre of Dionysus")
Among top-10 retrieved documents: Olympia: 1 time

GPT nucleus #1: Zeus was the patron god of the city of Olympia in Greece.
GPT nucleus #2: The city of Olympia in Greece was the site of the ancient Olympics, and it was also the home of Zeus, the patron god of the Olympics.
Among top-10 generated documents: Olympia: 6 times

GPT cluster #1: Zeus was the patron god of the city of Olympia, which was located in the northwestern Peloponnese region of Greece. Olympia was the site of the Olympic Games, which were held every four years in honor of Zeus.
GPT cluster #2: Zeus was the patron god of the city of Olympia. Olympia was a sanctuary of ancient Greece in Elis on the Peloponnesos peninsula, in south-western Greece. The sanctuary was known as the Panhellenic Sanctuary of Zeus, and the altar of Zeus was located in the Temple of Zeus. The Olympic Games were held in Olympia every four years from 776 BC to 393 AD.
GPT cluster #3: Zeus was the patron god of the city of Olympia.
Among top-10 generated documents: Olympia: 9 times Elis: 1 time

Table 16: Case study of retrieved documents and generated documents from language models (3/4).

Query: What is the collection of the districts to the east of the Jordan River?
Answers: Jordan, Golan Heights

DPR #1: Water politics in the Jordan River basin Water politics in the Jordan River basin refers to political issues of water within the Jordan River drainage basin, including competing claims and water usage, and issues of riparian rights of surface water along transnational rivers, as well as the availability and usage of ground water. Water resources in the region are scarce, and these issues directly affect the five political subdivisions (Israel, the West Bank, Lebanon, Syria and Jordan) located within and bordering the basin, which were created since the collapse, , during World War I, of the former single controlling entity, the ... (Wikipedia id: 12822413 – "Water politics in the Jordan River basin")
DPR #2: Jordan's western border follows the bottom of the rift. Although an earthquake-prone region, no severe shocks had been recorded for several centuries. By far the greatest part of the East Bank is desert, displaying the land forms and other features associated with great aridity. Most of this land is part of the Syrian Desert and northern Arabian Desert. There are broad expanses of sand and dunes, particularly in the south and southeast, together with salt flats. Occasional jumbles of sandstone hills or low mountains support only meager and stunted vegetation that ... (Wikipedia id: 210052 – "Geography of Jordan")
Among top-10 retrieved documents: Jordan: 8 times

GPT nucleus #1: The collection of the districts to the east of the Jordan River is known as the West Bank. The West Bank is a landlocked territory situated in Western Asia. It is bordered by Jordan to the east, Egypt to the southwest, and Israel to the west and north.
GPT nucleus #2: The collection of the districts to the east of the Jordan River is the West Bank. The West Bank is a landlocked territory near the Mediterranean coast of Western Asia, bordered by Lebanon to the north, Syria to the northeast, Jordan to the east, and Egypt to the southwest. It is the smaller of two political entities that comprise the Palestinian territories, the other being the Gaza Strip.
Among top-10 generated documents: Jordan: 10 times

GPT cluster #1: The collection of the districts to the east of the Jordan River is known as the West Bank. The West Bank is a landlocked territory situated in Western Asia. It is bordered by Jordan to the east, Egypt to the southwest, and Israel to the west and north
GPT cluster #2: The Jordan River is a major river in the Middle East, the source of which is in the northern part of Israel. The river flows southward through Israel and then Jordan, emptying into the Dead Sea. East of the river is the collection of districts known as the East Bank.
GPT cluster #3: There is no single answer to this question as the east bank of the Jordan River is home to a number of different districts and regions, each with its own unique history, culture, and customs. However, some of the more well-known districts on the east bank include the West Bank, the Gaza Strip, and the Golan Heights.
Among top-10 generated documents: Jordan: 10 times Golan Heights: 2 times

Table 17: Case study of retrieved documents and generated documents from language models (4/4).

Original question	NQ labels	Correct labels
Q: When is the last time the philadelphia won the superbowl?	Super Bowl LII; 2017	2018; February 4, 2018
DPR: 2017 ✘; **Google search:** 2018 ✔; **GENREAD :** February 4, 2018 ✔		
Q: Who has the most big ten championships in football?	Michigan	Ohio State
DPR: Michigan ✘; **Google search:** Ohio State ✔; **GENREAD :** Ohio State ✔		
Q: Who has the most super bowls in nfl history?	Pittsburgh Steelers	Pittsburgh Steelers; New England Patriots
DPR: Pittsburgh Steelers ✔; **Google search:** New England Patriots ✔; **GENREAD :** New England Patriots ✔		
Q: How many casinos are in atlantic city new jersey?	11; eleven	9; nine
DPR: eleven ✘; **Google search:** nine ✔; **GENREAD :** nine ✔		
Q: When did the us not go to the olympics?	1980	1980; 1984
DPR: 1980 ✔; **Google search:** 1980 and 1984 ✔; **GENREAD :** 1984 ✔		
Q: Largest cities in the world by population?	Beijing	Tokyo
DPR: Beijing ✘; **Google search:** Tokyo ✔; **GENREAD :** Tokyo ✔		
Q: Who has most followers on instagram in world?	Selena Gomez	Cristiano Ronaldo
DPR: Instagram ✘; **Google search:** Cristiano Ronaldo ✔; **GENREAD :** Cristiano Ronaldo ✔		
Q: Who is the no. 1 ranked tennis player in the world?	Rafael Nadal	Novak Djokovic
DPR: Rafael Nadal ✘; **Google search:** Novak Djokovic ✔; **GENREAD :** Novak Djokovic ✔		

Table 18: Case studies of temporality issues of the NQ dataset. All these questions are drawn from Zhang & Choi (2021), which contains a subset of NQ data examples with time-dependent questions.

Original question	*DPR-FiD* predictions	GENREAD predictions
Q: Who played lionel in as time goes by?	Geoffrey Dyson Palmer	Geoffrey Palmer
Explanation: The labeled answer is "Geoffrey Dyson Palmer", however, "Geoffrey Palmer" is also correct.		
Q: How many cracker barrels in the united states?	645	over 630
Explanation: The labled answer is "639" or "over 600", so "over 630" is also a reasonable answer.		
Q: Where do the greasers live in the outsiders?	Tulsa, Oklahoma	Oklahoma
Explanation: The labled answer is "Tulsa, Oklahoma", but "Oklahoma" is also a correct answer.		
Q: Where are unipolar neurons found in spinal cord?	the granule region	dorsal root ganglia
Explanation: The labled answer is "the distal dorsal root", but the output "dorsal root ganglia" is the same.		

Table 19: Case studies of the incomplete answers issue of the NQ dataset.