Toward Optimal Search and Retrieval for RAG

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Abstract

Retrieval-augmented generation (RAG) is a promising method for addressing some of the memory-related challenges associated with Large Language Models (LLMs). Two separate systems form the RAG pipeline, the retriever and the reader, and the impact of each on downstream task performance is not well-understood. Here, we work towards the goal of understanding how retrievers can be optimized for RAG pipelines for common tasks such as Question Answering (QA). We conduct experiments focused on the relationship between retrieval and RAG performance on QA and attributed QA and unveil a number of insights useful to practitioners developing high-performance RAG pipelines. For example, lowering search accuracy has minor implications for RAG performance while potentially increasing retrieval speed and memory efficiency.

1 Introduction

Retrieval-augmented generation (RAG) (1) is gaining popularity due to its ability to address some of the challenges with using Large Language Models (LLMs), including hallucinations (2) and outdated training data (1; 3). RAG pipelines are made up of two disparate components: a retriever, which identifies documents relevant to a query from a given corpus, and a reader, which is typically an LLM prompted with a query, the text of the retrieved documents, and instructions to use this context to generate its response. However, it is unclear how a RAG pipeline's performance on downstream tasks can be attributed to each of these components (1; 2).

In this work, we study the contributions of retrieval to downstream performance.[1]. For this purpose, we evaluate pipelines with separately trained retriever and LLM components, as training retrieval-augmented models end-to-end is both more resource-intensive and obfuscates the contribution of the retriever itself. We aim to address questions that will enable practitioners to design retrieval systems tailored for use in RAG pipelines. For example, what are the weaknesses of the typical search and retrieval setup in RAG systems? Which search hyperparameters matter for RAG task performance?

We choose to evaluate RAG pipeline performance on both standard QA and attributed QA. In attributed QA, the model is instructed to cite supporting documents provided in the prompt when

Investigates how retrieval contributes to the overall performance of RAG pipelines.
It looks at following:
--->How increasing the number of retrieved documents affects the quality of QA and attributed QA.
--->How reducing the number of gold-standard (or "correct") documents in the context affects performance.
--->Whether saving retrieval time by lowering approximate nearest neighbor (ANN) search accuracy significantly impacts the quality of the results.
--->How noise introduced in the retrieval process leads to performance degradation.

[1] https://www.github.com/intellabs/rag-retrieval-study

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making factual claims (4; 5). This task is interesting for its potential to boost the trustworthiness and verifiability of generated text (6).

We make four contributions: (1) We show how both QA performance and citation metrics vary with more retrieved documents, adding new data to a small literature on attributed QA with RAG. (2) We describe how RAG task performance is affected when fewer gold documents are included in the context. (3) We show that saving retrieval time by decreasing approximate nearest neighbor (ANN) search accuracy in the retriever has only a minor effect on task performance. (4) We show that injecting noise into retrieval results in performance degradation. We find no setting that improves above the gold ceiling, contrary to a prior report (7).

2 Background

A RAG pipeline is made up of two components: a retriever and a reader. The retriever component identifies relevant information from an exterior knowledge base which is included alongside a query in a prompt for the reader model (8). This process has been used as an effective alternative to expensive fine-tuning (2; 9) and is shown to reduce LLM hallucinations (10).

Retrieval models. Dense vector embedding models have become the norm due to their improved performance above sparse retrievers that rely on metrics such as term frequency (11). These dense retrievers leverage nearest neighbor search algorithms to find document embeddings that are the closest to the query embedding. Of these dense models, most retrievers encode each document as a single vector (12). However, multi-vector models that allow interactions between document terms and query terms such as ColBERT (13) may generalize better to new datasets. In practical applications, most developers refer to text embedding leaderboards (14) or general information retrieval (IR) benchmarks such as BEIR (15) to select a retriever.

Technique used to find the closest vectors in high-dimensional spaces quickly, with some loss of accuracy. It's preferred for large datasets where exact nearest neighbor search becomes slow due to the curse of dimensionality. uses quantization or locality-sensitive hashing (LSH), which approximate the true nearest neighbors.

Approximate Nearest Neighbor (ANN) search. Modern vector embeddings contain $\geq$ 1024 dimensions, resulting in severe search performance degradation (e.g., sifting through $\approx$ 170GB of data for general knowledge corpora like Wikipedia) due to the curse of dimensionality. Consequently, RAG pipelines often employ approximate nearest neighbor search as a compromise, opting for faster search times at the expense of some accuracy (1; 16). Despite this common practice, there is very little discussion in the literature regarding the optimal parameters for configuring ANN search, and the best way to balance the trade-off between accuracy and speed. Operating at a lower search accuracy could lead to massive improvements in search speed and memory footprint (for example, by eliminating the common re-ranking step (e.g. 17)).

3 Experiment setup

We conduct our experiments with two instruction-tuned LLMs: LLaMA (Llama-2-7b-chat) (18) and Mistral (Mistral-7B-Instruct-v0.3) (19). No further training or fine-tuning was performed. We avoided additional fine-tuning to ensure that our results are directly relevant to RAG pipelines currently being deployed across industry applications. Additional experiment details are in Appendix A.1.

Question answering (QA) and attributed QA. For a query in a standard QA task, a RAG pipeline prompts an LLM to generate an answer based on information from a list of retrieved documents. In attributed QA, an LLM is also required to explicitly cite (e.g., by document ID) one or more of the documents used.

Prompting. Following previous work (5), the models learn the desired format for attributing answers with citations via few-shot learning. We use 2-shot prompting for Mistral because of its longer context window and 1-shot prompting for LLaMA. We maintain the same prompt order for the experiments: system instruction, list of retrieved documents, then the query (see Figure 1). When evaluating QA without attribution, 0-shots are given.

3.1 Retrieval

We chose to evaluate two high-performing, open-source dense retrieval models. For single vector embeddings, we relied on **BGE-base** to embed documents (bge-base-en-v1.5 (20), BEIR15 score of

Dense retrieval models used for evaluating the RAG pipeline's performance:
1. Single Vector Embeddings:
BGE-base: used to embed documents.
Intel SVS Library: used for searching these embeddings. It uses graph-based ANN search.
2. Multi-Vector Search:
ColBERTv2: uses BERT embeddings to determine the similarity between terms in documents and queries.

0.533). We used the Intel SVS library[2] to search over these embeddings for efficient dense retrieval, exploiting its state-of-the-art graph-based ANN search performance (21). For multi-vector search, we used **ColBERTv2** (22), which leverages BERT embeddings to determine similarity between terms in documents and queries (BEIR15 score of 0.499).

```
Instruction: Write an accurate, engaging, and concise answer for the
given question. Use an unbiased and journalistic tone.

Question: <question text>
Answer:
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Instruction: Write an accurate, engaging, and concise answer for the
given question using only the provided search results (some of which
might be irrelevant) and cite them properly. Use an unbiased and
journalistic tone. Always cite for any factual claim. When citing
several search results, use [1][2][3]. Cite at least one document
and at most three documents in each sentence. If multiple documents
support the sentence, only cite a minimum sufficient subset of the
documents.

Document [1] (Title: <title>): <document text>
Document [2] (Title: <title>): <document text>

Question: <question text>
Answer:
```

Figure 1: Example prompts for QA (left) and attributed QA (right, following (5)).

3.2 Datasets

ASQA is a long-form QA dataset for factoid questions designed to evaluate a model's performance on naturally-occurring ambiguous questions (23). It is made up of 948 queries and the ground truth documents are based on a 12/20/2018 Wikipedia dump with 21M passages. We use the set of five gold documents provided by (5) which yields the best performance in their RAG pipeline.

QAMPARI is an open-domain QA dataset in which the 1000 queries have several answers that can be found across multiple passages (24). It is designed to be difficult for both retrieval and generation. As with ASQA, we use the five gold documents provided by (5) from the 2018 Wikipedia dump.

Natural Questions (NQ) is a dataset of 100k actual questions submitted to the Google search engine (25). We follow (26) and use the KILT (27) version of the dataset, which consists of 2837 queries supported by 112M passages from a 2019 Wikipedia dump). It includes a short answer and at least one gold passage for each query. Though NQ has not traditionally corresponded to attributed QA, we adapt it to this task by simply prompting the language model to support statements with references to documents included in the context (see Figure 1).

3.3 Metrics

Metrics and methodology used for evaluating the performance of the RAG pipeline:
1. Retriever Metrics:
Recall@k
Search Recall@k
2. QA Task Metrics:
Exact Match Recall (EM Rec.)
Natural Questions (NQ)
3. Citation Quality Metrics:
Citation Recall
Citation Precision
4. Confidence Intervals (CIs):

For retrieval, we report **recall@k**, which reflects the percentage of gold passages that have been retrieved in k documents. We also refer to this as retriever recall or gold document recall. When using ANN, we also report **search recall@k**, that is the percentage of the k exact nearest neighbors (according to the retriever similarity) that have been retrieved in the k approximate nearest neighbors.

Correctness on the QA tasks is quantified by string **exact match recall (EM Rec.)**, or the percentage of short answers provided by the dataset which appear as exact substrings of the generated output. Note that for NQ, we report recall only over the top five gold answers following (5).

To report citation quality, we use a process aligned with (4) that follows exactly the citation metrics found in the ALCE framework (5): **citation recall** and **citation precision**. Citation recall is a measure of whether each generated statement includes citation(s) which entail it. Citation precision quantifies whether each individual citation is necessary to support a statement.

Confidence intervals. All metrics are computed for each query in the dataset, and averaged across all n queries. To characterize the spread of the distribution, we compute 95% confidence intervals (CIs) across queries using bootstrapping. That is, we resample n queries with replacement from the true distribution, compute the mean, and repeat this process for 1000 bootstrap iterations. We then find the 2.5 and 97.5 percentiles for this distribution to yield the 95% confidence intervals. Note that these bootstrapped CIs can be used to determine whether the difference between two distributions is statistically significant (28).

[2]https://github.com/intel/ScalableVectorSearch

4 Results

We first analyze how many retrieved documents should be included in the LLM context window to maximize correctness on the selected QA tasks. This is shown as a function of the number of retrieved nearest neighbors, k. Incorporating the retrieved documents narrows the performance disparity between the closed-book scenario (k=0) and the gold-document-only ceiling. However, the performance of the evaluated retrieval systems still significantly lags behind the ideal. ColBERT usually outperforms BGE by a small margin.

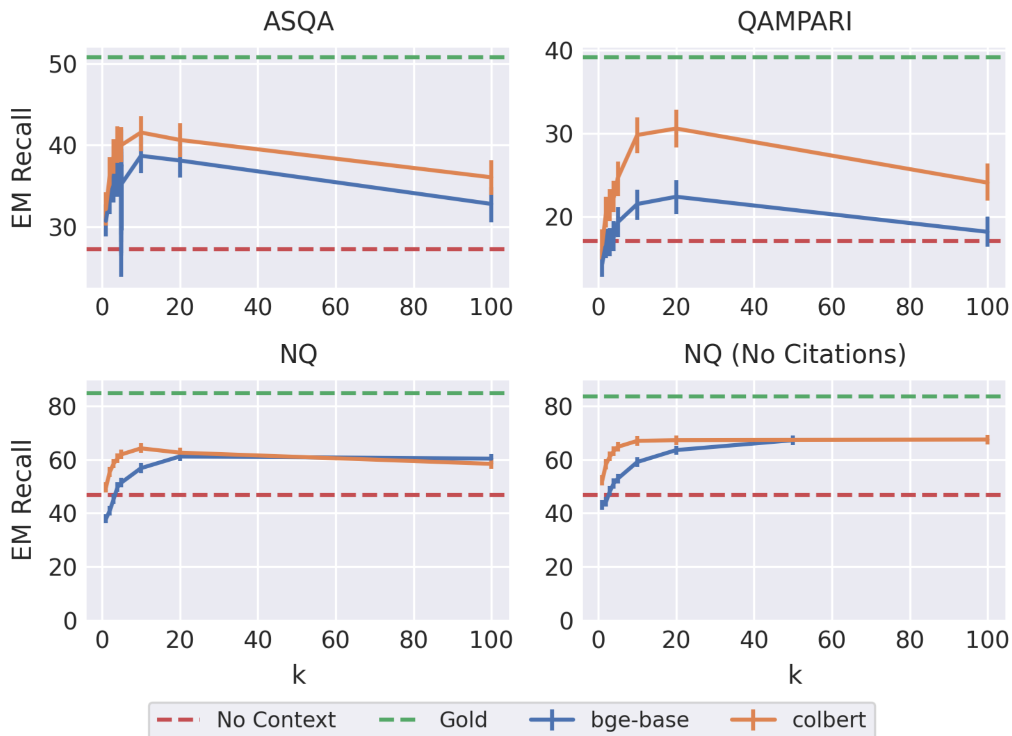

Figure 2: Correctness achieved by Mistral with various numbers of documents retrieved with BGE-base and ColBERT. Optimal performance is observed with $k = 10$ or 20.

Correctness on QA begins to plateau around 5-10 documents. We find that Mistral performs best for all three datasets with 10 or 20 documents (Figure 2). LLaMA performs best when $k = 4$ or 5 for ASQA and NQ, but $k = 10$ for QAMPARI (Appendix Figure 8). This difference between LLMs is likely due to LLaMA's shorter context window. We also find that adding the citation prompt to NQ results in almost no change to performance until $k > 10$. Tables 1 and 2 show that citation recall generally peaks around the same point as QA correctness, while citation precision tends to peak at much lower k. Since citation precision measures how many of the cited documents are required for each statement, this suggests that showing the LLM more documents (i.e. at higher k) results in more extraneous, or unnecessary, citations. Citation measures for other datasets and models are in A.4.

We further investigated where gold documents appear within the ranked list of retrieved documents. We found that gold documents typically ranked between 7-13th nearest neighbor (Appendix Table 6). Given these results, we conducted all subsequent analyses and experiments with 5-10 context documents, as these were generally good settings for QA performance even if some of the gold documents are missed.

Based on the results above, we hypothesized that the ideal number of documents to include in a RAG pipeline is directly related to the number of gold documents that are retrieved within that k. This is relatively unexplored in the literature, as most have investigated how well LLMs can utilize the context and ignore non-gold documents (16; 26; 29; 30). Because we observed similar trends across datasets, we dropped QAMPARI from the following results for simplicity. We re-analyze the results

Table 1: Performance on ASQA with Mistral and various numbers of BGE-base retrieved documents, k, in the prompt. Optimal QA correctness is achieved at $k = 10$, while it is $k = 5$ for citation recall.

	Ret.	EM Recall		Citation Recall		Citation Precision	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	50.725	48.73 - 52.79	65.187	63.073 - 67.231	62.261	60.285 - 64.41
0	0	27.286	25.334 - 29.176	-	-	-	-
1	0.093	30.749	28.826 - 32.743	52.265	49.660 - 55.032	63.695	60.822 - 66.285
2	0.162	33.719	31.594 - 35.705	59.103	56.911 - 61.440	**64.827**	62.411 - 67.148
3	0.208	35.145	33.001 - 37.123	61.368	59.103 - 63.668	62.920	60.887 - 65.180
4	0.247	35.793	33.697 - 37.818	61.243	58.918 - 63.562	59.692	57.219 - 61.986
5	0.284	37.595	35.394 - 39.601	**61.563**	59.229 - 63.898	59.017	56.776 - 61.301
10	0.387	**38.703**	36.619 - 40.955	58.525	56.245 - 60.715	53.852	51.679 - 55.879
20	0.490	38.129	36.044 - 40.355	53.823	51.552 - 56.176	47.449	45.137 - 49.658
100	0.692	32.819	30.588 - 34.881	25.920	23.896 - 28.013	24.009	22.103 - 26.117

Table 2: Performance on ASQA with Mistral and various numbers of ColBERT retrieved documents, k, in the prompt. Optimal QA correctness is achieved at $k = 10$, while it is $k = 5$ for citation recall.

	Ret.	EM Recall		Citation Recall		Citation Precision	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	50.725	48.730 - 52.790	65.187	63.073 - 67.231	62.261	60.285 - 64.410
0	0	27.286	25.334 - 29.176	-	-	-	-
1	0.098	32.186	30.168 - 34.227	56.794	54.498 - 59.417	**69.560**	66.798 - 72.272
2	0.179	36.369	34.160 - 38.564	62.343	60.350 - 64.545	68.367	66.114 - 70.577
3	0.242	38.730	36.482 - 40.772	63.722	61.543 - 66.061	66.802	64.672 - 69.018
4	0.291	40.146	37.880 - 42.277	65.351	63.150 - 67.456	65.355	63.282 - 67.521
5	0.328	40.023	37.956 - 42.228	**66.037**	63.887 - 68.297	63.906	61.971 - 65.889
10	0.447	**41.553**	39.282 - 43.575	61.826	59.702 - 64.195	56.964	54.719 - 59.113
20	0.553	40.642	38.551 - 42.695	58.506	56.205 - 60.759	51.272	49.167 - 53.473
100	0.743	36.074	33.956 - 38.182	31.083	28.880 - 33.300	28.676	26.651 - 30.631

above for $k = 10$ documents in the prompt, and simply bin the queries depending on the retriever recall (i.e. the percentage of retrieved gold documents).

Including just one gold document highly increases correctness. We observe a significant increase in the EM recall of queries with just one gold document in the prompt versus no gold documents. This is the case when either Mistral (Figure 3) or LLaMA (Appendix Figure 9) is used as the reader module. We note that this trend was also observed in (26).

More gold documents correlates with higher correctness. We find that increasing the number of gold documents in the prompt steadily increases QA correctness metrics. This is illustrated for Mistral in Figure 3 and LLaMA in Figure 9. We note that the difference in average correctness begins to plateau around a retrieval recall of 0.5. This supports the hypothesis that the ideal number of documents in the context window is directly related to the number of gold documents in that context window, in spite of the potential noise added by more non-gold documents.

4.1 Gold document recall and search accuracy regime

Next, we investigated how using approximate search affected RAG performance on the QA task. In particular, since the prior evidence suggests that gold documents are key to performance, we ran two sets of experiments to understand how both search recall and gold document recall affect QA performance. First, we took the gold set and replaced some of these to reach a gold document recall target of 0.9, 0.7, or 0.5. For each query, we sampled a subset of the gold documents so that the average gold recall across all queries in a dataset reached the target, and populated the rest of the 10 documents with the nearest non-gold neighbors. Second, we set the ANN search algorithm to achieve

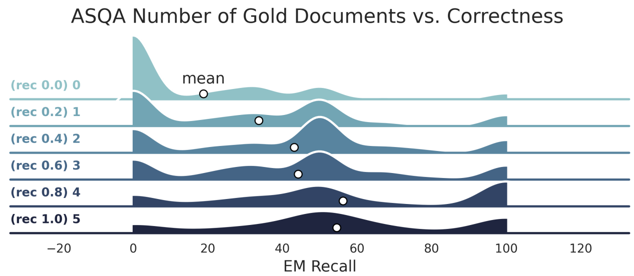

Figure 3: The per-query relationship between the number of gold documents included in the prompt and the QA accuracy achieved with Mistral on ASQA. Including just one gold document significantly improves accuracy. There is a correlation between the number of gold documents and EM Recall.

search recall targets of 0.95, 0.9, and 0.7 (details in Appendix A.1.1) and compared these to exact search (recall 1.0) for BGE-base. Figure 12 shows the results of these two experiments.

Manipulating ANN search recall only results in minor decrements in QA performance. We found that gold document recall (Fig. 12, left) is a far bigger factor for QA performance than search recall (Fig. 12, right). Setting the search recall@10 to 0.7 only results in a 2-3% drop in gold document recall with respect to using exhaustive search (Table 3). While our data is limited to a single dense retriever, it is the first experiment (to our knowledge) demonstrating that practitioners using current SOTA retrievers can take advantage of the speed and memory footprint benefits of ANN search with little to no adverse impact on RAG task performance.

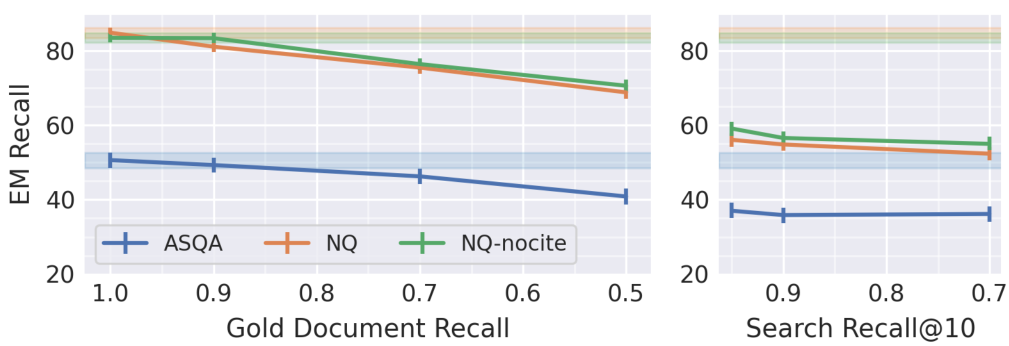

Figure 4: Gold document recall (left) has a greater impact on RAG QA performance compared to search recall (right). RAG pipeline uses Mistral and BGE-base. Shaded bar is ceiling performance using all gold documents per query. Error bars are 95% bootstrap confidence intervals.

Table 3: Gold document recall for the BGE-base retriever at different ANN search recall regimes. Reported as mean with 95% confidence intervals (in grey).

ANN Search Recall@10	**Doc. Recall@10**			
	ASQA		NQ	
1.0 (exact)	0.387	0.367 - 0.404	0.278	0.267 - 0.290
0.95	0.377	0.361 - 0.396	0.274	0.262 - 0.286
0.9	0.363	0.346 - 0.381	0.264	0.252 - 0.277
0.7	0.361	0.342 - 0.380	0.245	0.232 - 0.256

Citation metrics generally decrease as fewer supporting documents are available. We observed that decreases in document recall and search recall lead to decreases in citation metrics (full results in Appendix A.6). As with QA performance, decreases in document recall affect citation performance more than decreases in search recall (Table 4). However, this effect is less clear for the ASQA dataset, which is more likely to have multiple gold evidence documents that entail a single answer (A.6).

Table 4: Citation recall decreases as document recall and search recall decrease (NQ dataset, BGE-base retriever with Mistral reader). Values in parentheses are 95% CIs.

	Citation Recall	
Doc. Recall@10	Mean	95% CI
1.0	75.041	73.772 - 76.397
0.9	72.084	70.765 - 73.409
0.7	66.669	65.258 - 68.148
0.5	60.827	59.428 - 62.292
Search Recall@10		
0.95	55.340	53.872 - 56.814
0.9	52.443	50.835 - 53.972
0.7	49.856	48.405 - 51.340

4.2 Injecting noisy documents of varying relevance

Next, we explored whether the *relevance* of the non-gold documents included in the context window affects the performance of the RAG pipeline on QA tasks. We define relevance as the similarity between the query and the retrieved document as defined by the corresponding retriever. A prior work (7) made two claims about query-document similarity: (1) random non-gold documents increase QA performance above the gold-only ceiling; and (2) highly similar, non-gold documents are distracting and decrease QA performance.

To investigate claim 1, we added documents of varying similarity to either the gold set or the 5 most similar documents (nearest neighbor indices 0-4). First, we used BGE-base to retrieve all documents in the dataset for each ASQA query, assigning each neighbor a similarity score. We order the retrieved documents by this score and divide them into ten equal-sized bins. We define documents in the first bin 10th percentile noise, the second bin 20th percentile noise, etc. We randomly select 5 documents from each bin and append them to the prompt after either the gold or BGE-base retrieved documents. This setting follows the experiments in (7). Note that when injecting additional noise on top of the gold documents, the gold document recall (but not accuracy or F1) is still 1.0.

Our evidence does not clearly replicate claims in (7) about injecting noise. Contrary to claim 1, we find that adding noisy documents, regardless of their noise percentile, degrades correctness (Figure 5) and citation quality (A.7) compared to the gold-only ceiling.

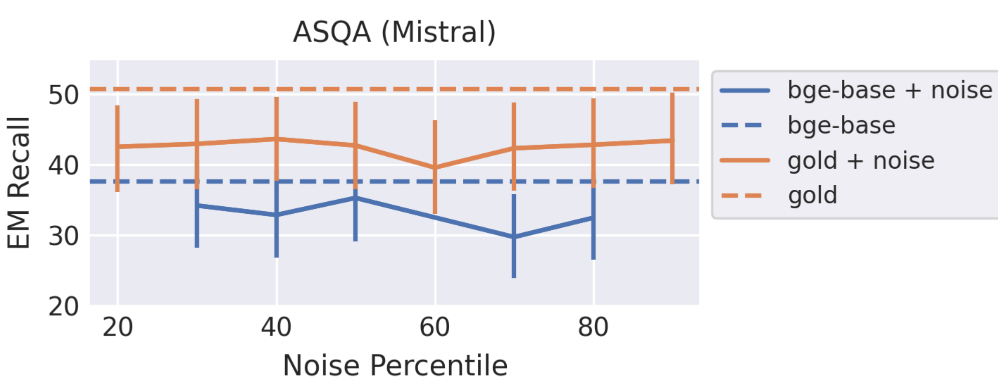

Figure 5: ASQA Mistral performance after injecting noisy documents from various percentiles of similarity to the query. Adding noisy documents from all percentiles degrades QA correctness.

Figure 5 also shows no consistent trend in performance changes with decreasingly similar documents. However, it is possible that claim 2 – that very similar neighbors are more distracting than distantly similar neighbors – might only be observed if we take the 1st percentile of neighbors, as similarity is known to drop steeply with further neighbors (see Appendix Figure 6). We therefore repeated a similar experiment with samples from the first 100 neighbors to test this claim. We compare performance for Mistral on ASQA with 5 gold documents to performance when the 5th − 10th or the 95th − 100th nearest neighbors are added (Table 5). Although QA performance still degrades, the effect is smaller—injecting more similar neighbors only drops performance by 1 point. Overall, injecting closer neighbors does not appear to be more detrimental than farther ones. Interestingly though, citation scores improve for farther neighbors. A similar pattern of QA performance was observed when using the same LLM as (7) (Appendix A.7).

These results are in line with 4.1. Due to how ANN graph search is parameterized (A.1.1, lowering search recall adds "noisy" non-gold documents that are still similar to the query. Here and in 4.1, we observed that injecting highly similar neighbors only mildly degrades downstream task performance.

Table 5: Mistral performance on ASQA when adding non-gold (*noise*) documents based on their similarity ranking (between 5th − 100th nearest neighbor).

Injected Noise	**EM Recall**		**Citation Recall**		**Citation Precision**	
	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold only	50.73	48.73 - 52.79	65.19	63.07 - 67.23	62.26	60.29 - 64.41
gold + 5th − 10th	49.91	47.82 - 51.90	59.45	57.40 - 61.40	55.40	53.15 - 57.62
gold + 95th − 100th	49.24	47.05 - 51.46	58.69	56.37 - 61.11	56.14	53.96 - 58.23

5 Conclusion

Impact of Gold Document Retrieval: Models that retrieve a higher number of gold documents tend to maximize QA performance. Including more relevant documents improves the likelihood of accurate answers.
ANN Search and Recall: When using ANN search with lower recall, the QA performance degradation is slight. Using lower recall settings may still provide acceptable results, with the potential benefits of increased speed and memory efficiency.
Effect of Noisy Documents: Document noise needs further investigation to understand its full impact on RAG performance.

Overall, our experiments suggest that models that can retrieve a higher number of gold documents will maximize QA performance. We also observe that leveraging ANN search to retrieve documents with a lower recall results in only slight QA performance degradation, which correlates with the very minor changes to gold document recall. Thus, operating at a lower search recall regime is a viable option in practice to potentially increase speed and memory efficiency. We also find that, contrary to a prior study (7), injecting noisy documents alongside gold or retrieved documents degrades correctness compared to the gold ceiling. We also find that it has an inconsistent effect on citation metrics. This suggests that the impact of document noise on RAG performance requires further study.

Future work should test the generality of these findings in other settings. Understanding how approximate vs. exact search affects multi-vector retrievers such as (13) would be interesting, especially given their generally good performance. Additionally, we only evaluated systems where the retriever and reader are trained separately. RAG systems trained end-to-end (e.g. Fusion-in-Decoder (FiD) (31) model), may rely less on gold documents such that retrieval metrics are not useful relevance markers (32).

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A Appendix

A.1 Experiment setup

We conduct the retrieval portion of the experiments on a 2-socket 2nd generation Intel® Xeon® 8280L @2.70GHz CPUs with 28 cores (2x hyperthreading enabled) and 384GB DDR4 memory (@2933MT/s) per socket, running Ubuntu 22.04. Retrieval results were saved to files and were inserted into the prompt (Figure 1) for the LLM during the reader portion of the experiments.

We ran LLM inference on NVIDIA GPUs of varying models (NVIDIA Titan Xp or X Pascal series, or NVIDIA A40). The CPU hosts for these GPU nodes were either Intel® E5-2699 v4 or Intel® Xeon® 8280 or 8280L. Run time for generating answers for all queries in ASQA and QAMPARI was approximately 30 minutes for Mistral and 20 minutes for LLaMA. Because there are more queries in NQ, run time was approximately 1.5 hours for Mistral and 1 hour for LLaMA.

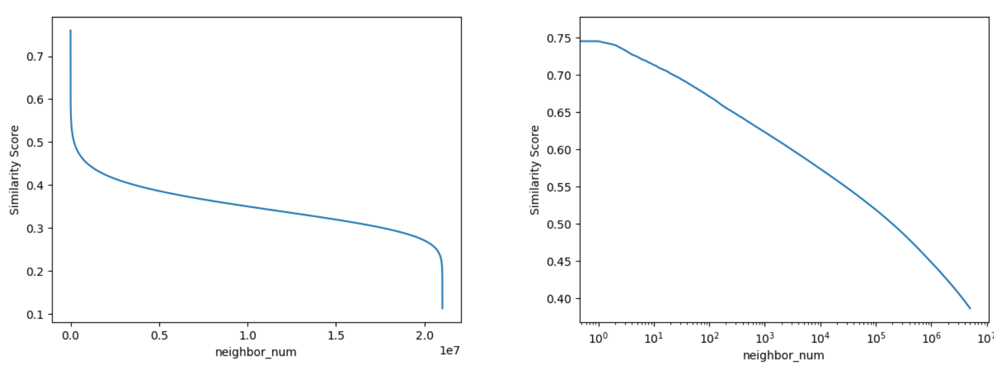
A temperature of 1 and top p of 0.95 were used for generation with both LLMs.

A.1.1 Tuning ANN search

Approximate nearest neighbor (ANN) techniques that utilize graphs are notable for their exceptional search accuracy and speed, particularly with data of high dimensionality (33; 34; 21). We leverage the Intel SVS library's graph-based search capabilities to our advantage. These graph-based approaches employ proximity graphs, in which the nodes correspond to data vectors. A connection is established between two nodes if they meet a specific property or neighborhood criterion, leveraging the natural structure found within the data.

The search process begins at a predetermined starting node and progresses through the graph, moving from one node to the next, each step bringing the search closer to the nearest neighbor by following a best-first search strategy. To prevent becoming trapped in a local minimum and to enable the discovery of multiple nearest neighbors, backtracking is employed (34; 35). Increasing the extent of backtracking means that a larger section of the graph is examined, which enhances the precision of the search but also results in a longer and therefore slower process. By adjusting the setting that determines the level of backtracking, we can fine-tune the balance between search accuracy, reflected in the quality of the nearest neighbors found, and the number of queries that can be handled per second. The Intel SVS library uses the `search_window_size` parameter to set the search accuracy vs. speed trade-off. By changing the `search_window_size` we set the retrieval module to operate at different search recall regimes.

A.2 Nearest neighbor similarity



(a) Neighbor index (x-axis) shown linearly.

(b) Neighbor index (x-axis) shown on a log-scale.

Figure 6: Average similarity of nearest neighbors for the ALCE dataset using BGE-base as a retriever.

A.3 Gold documents as nearest neighbors

Table 6 shows how gold documents rank in the nearest neighbors. The 25th, 50th, and 75th percentiles are provided. Figure 7 shows how the average similarity score of gold documents, compared to the average similarity of different neighbor rankings.

Table 6: Nearest neighbor ranking of gold documents for each retriever and dataset. Since these distributions are skewed across queries, we report quartiles (1st, 2nd / median, and 3rd). The median neighbor ranking of gold documents is between 7 and 13.

		Q1 (25)	Q2 (50)	Q3 (75)
ASQA	BGE-base	3.0	8.0	25.0
	BGE-large	3.0	8.0	25.0
	ColBERTv2	3.0	7.0	21.0
NQ	BGE-base	3.0	11.0	32.0
	BGE-large	3.0	10.5	33.0
	ColBERTv2	2.0	7.0	24.0
QAMPARI	BGE-base	4.0	13.0	37.0
	BGE-large	4.0	13.0	41.0
	ColBERTv2	4.0	11.0	31.0

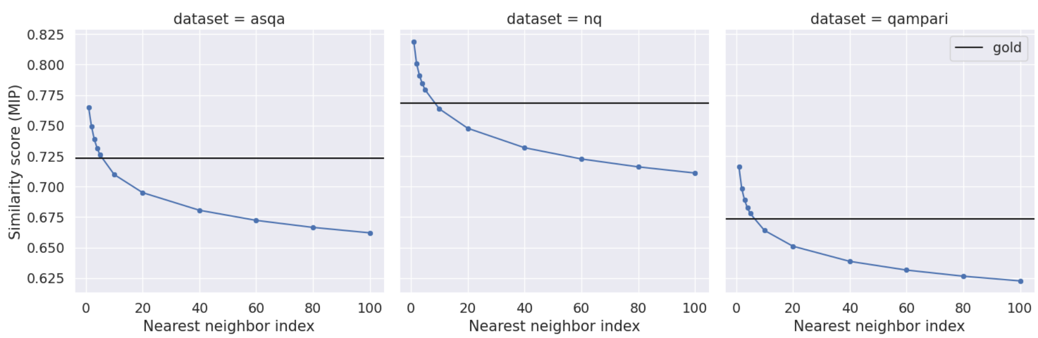


Figure 7: The similarity score (maximum inner product) of BGE-base neighbors, averaged across queries within the dataset. The solid black line is the mean similarity score for gold documents (grand mean first within query then across queries).

A.4 Additional varied number of neighbors results

Correctness results for all three datasets with LLaMA are in Figure 8. We present detailed results for including varied number of retrieved documents, k, for ASQA with LLaMA in Tables 7 and 8. Detailed results on NQ are shown in Tables 9, 10, 7 and 12. Detailed results on QAMPARI are included in Tables 13, 14, 15 and 16.

Table 7: Correctness and citation quality on ASQA achieved with LLaMA with various numbers of BGE-base retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	47.466	45.304 - 49.426	46.326	44.123 - 48.524	46.294	44.082 - 48.686
0	0	23.327	21.355 - 25.252	-	-	-	-
1	0.093	29.587	27.553 - 31.639	28.025	25.854 - 30.463	35.261	32.479 - 38.025
2	0.162	33.09	31.052 - 35.208	47.128	44.734 - 49.398	53.155	50.567 - 55.656
3	0.208	33.212	31.144 - 35.472	50.786	48.408 - 53.057	52.383	49.939 - 54.661
4	0.247	33.686	31.706 - 35.607	46.221	43.969 - 48.433	47.776	45.412 - 50.114
5	0.284	34.402	32.205 - 36.468	42.227	40.019 - 44.503	41.97	39.805 - 44.187
10	0.387	32.956	30.789 - 35.019	34.6	32.18 - 37.153	30.585	28.381 - 32.625

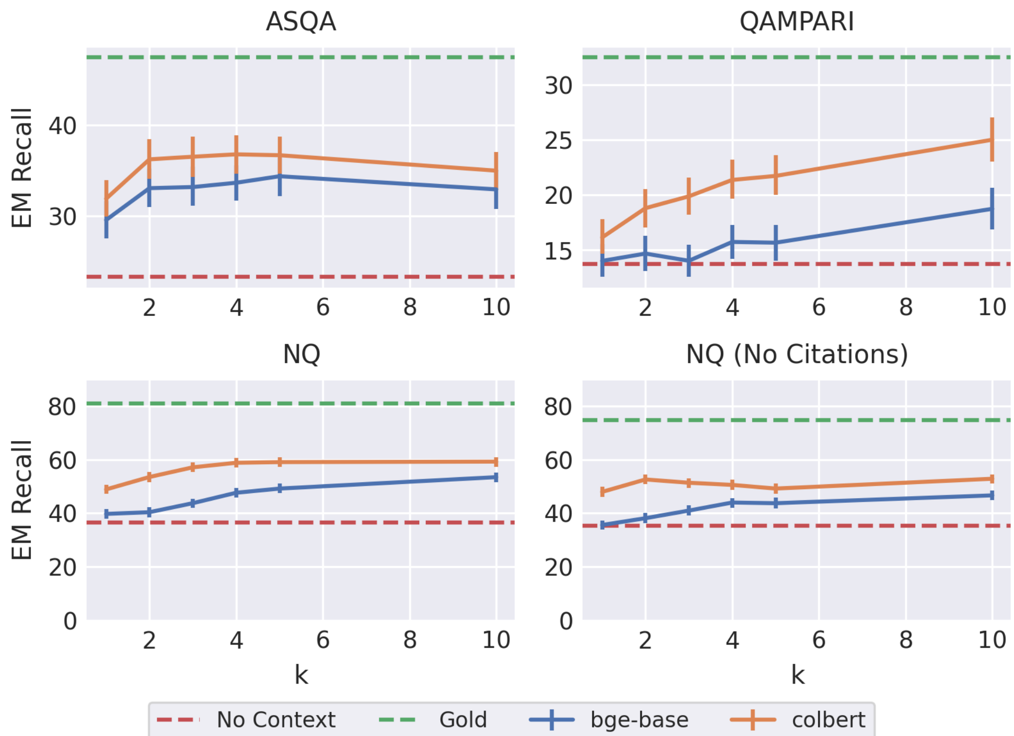


Figure 8: Correctness achieved by prompting LLaMA with various numbers of documents retrieved with BGE-base and ColBERT, k, included in the prompts. Optimal performance is observed with $k = 4$ or 5 for ASQA and NQ, while optimal performance for QAMPARI is achieved with $k = 10$.

Table 8: Correctness and citation quality on ASQA achieved with LLaMA with various numbers of ColBERT retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	47.466	45.304 - 49.426	46.326	44.123 - 48.524	46.294	44.082 - 48.686
0	0	23.327	21.355 - 25.252	-	-	-	-
1	0.098	31.928	29.979 - 33.962	34.944	32.569 - 37.116	43.637	41.007 - 46.503
2	0.179	36.262	34.089 - 38.509	52.282	49.951 - 54.57	58.651	56.199 - 60.848
3	0.242	36.548	34.33 - 38.787	54.545	52.246 - 56.676	57.067	54.78 - 59.45
4	0.291	36.813	34.688 - 38.9	50.63	48.394 - 52.85	51.505	49.236 - 53.808
5	0.328	36.712	34.668 - 38.79	46.293	43.897 - 48.806	44.565	42.292 - 46.945
10	0.447	35.016	32.844 - 37.057	37.334	34.937 - 39.771	32.033	29.975 - 34.319

Table 9: Correctness and citation quality on NQ achieved with Mistral with various numbers of BGE-base retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	84.646	83.222 - 86.042	74.66	73.349 - 76.006	64.407	63.179 - 65.615
0		46.696	44.836 - 48.467	-	-	-	-
1	0.072	37.871	36.164 - 39.726	31.101	29.567 - 32.776	36.4	34.695 - 38.181
2	0.117	40.925	39.02 - 42.792	43.51	41.923 - 45.18	39.554	38.067 - 41.129
3	0.152	45.301	43.497 - 47.127	47.423	45.796 - 48.944	40.574	39.101 - 42.005
4	0.181	49.735	47.902 - 51.639	49.943	48.38 - 51.534	43.404	42.007 - 44.826
5	0.205	51.421	49.559 - 53.226	51.062	49.51 - 52.51	43.69	42.326 - 45.13
10	0.279	56.778	54.916 - 58.654	55.869	54.395 - 57.241	46.267	45.014 - 47.542
20	0.355	61.145	59.391 - 62.883	57.173	55.754 - 58.595	46.497	45.282 - 47.711
100	0.53	60.333	58.548 - 62.143	49.816	48.332 - 51.397	36.671	35.502 - 37.921

Table 10: Correctness and citation quality on NQ achieved with Mistral with various numbers of ColBERT retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	84.646	83.222 - 86.042	74.66	73.349 - 76.006	64.407	63.179 - 65.615
0		46.696	44.836 - 48.467	-	-	-	-
1	0.122	49.567	47.797 - 51.463	67.754	66.276 - 69.245	77.295	75.828 - 78.863
2	0.179	55.398	53.542 - 57.244	72.288	70.925 - 73.617	68.703	67.417 - 69.971
3	0.214	58.486	56.714 - 60.204	71.02	69.784 - 72.254	63.799	62.58 - 65.048
4	0.237	60.41	58.688 - 62.178	69.883	68.64 - 71.088	60.987	59.797 - 62.236
5	0.254	61.916	60.134 - 63.66	68.635	67.291 - 69.896	59.862	58.683 - 61.101
10	0.321	64.171	62.424 - 66.056	67.233	65.901 - 68.508	55.348	54.1 - 56.477
20	0.381	62.558	60.874 - 64.434	64.701	63.314 - 66.002	50.239	49.051 - 51.368
100	0.506	58.384	56.502 - 60.204	50.21	48.575 - 51.79	35.233	34.014 - 36.53

Table 11: Correctness and citation quality on NQ achieved with LLaMA with various numbers of BGE-base retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	80.932	79.52 - 82.341	54.725	53.288 - 56.182	55.763	54.364 - 57.225
0	0	36.389	34.544 - 38.174	-	-	-	-
1	0.072	39.715	37.821 - 41.559	23.417	22.007 - 24.828	27.726	26.215 - 29.241
2	0.117	40.357	38.421 - 42.192	33.892	32.343 - 35.487	35.623	34.07 - 37.219
3	0.152	43.718	41.91 - 45.436	36.163	34.775 - 37.658	35.104	33.599 - 36.504
4	0.181	47.611	45.858 - 49.384	35.693	34.254 - 37.059	34.527	33.198 - 35.826
5	0.205	49.159	47.374 - 50.969	34.839	33.47 - 36.317	32.967	31.56 - 34.304
10	0.279	53.424	51.638 - 55.164	28.622	27.287 - 29.967	25.923	24.689 - 27.058
20	0.381	62.558	60.874 - 64.434	64.701	63.314 - 66.002	50.239	49.051 - 51.368
100	0.506	58.384	56.502 - 60.204	50.21	48.575 - 51.79	35.233	34.014 - 36.53

Table 12: Correctness and citation quality on NQ achieved with LLaMA with various numbers of ColBERT retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	80.932	79.52 - 82.341	54.725	53.288 - 56.182	55.763	54.364 - 57.225
0	0	36.389	34.544 - 38.174	-	-	-	-
1	0.122	48.847	47.126 - 50.617	54.977	53.446 - 56.483	67.286	65.586 - 68.933
2	0.179	53.481	51.638 - 55.306	57.519	56.141 - 58.831	65.442	64.0 - 66.948
3	0.214	57.088	55.27 - 58.972	56.378	54.94 - 57.854	59.892	58.342 - 61.326
4	0.237	58.786	57.031 - 60.592	48.572	47.112 - 50.152	51.234	49.727 - 52.642
5	0.254	59.04	57.208 - 60.804	44.974	43.704 - 46.308	46.73	45.352 - 48.104
10	0.321	59.212	57.349 - 60.945	20.997	19.857 - 22.213	21.104	19.948 - 22.278
20	0.381	62.558	60.874 - 64.434	64.701	63.314 - 66.002	50.239	49.051 - 51.368
100	0.506	58.384	56.502 - 60.204	50.21	48.575 - 51.79	35.233	34.014 - 36.53

Table 13: Correctness and citation quality on QAMPARI achieved with Mistral with various numbers of BGE-base retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	39.152	36.879 - 41.44	23.239	20.827 - 25.708	19.774	17.585 - 22.032
0	0	17.112	15.259 - 19.021	-	-	-	-
1	0.055	14.354	12.779 - 16.08	33.017	30.351 - 35.699	36.011	33.027 - 38.934
2	0.087	16.804	15.018 - 18.58	36.782	34.151 - 39.78	31.867	29.142 - 34.636
3	0.115	16.946	15.279 - 18.68	35.924	33.233 - 38.771	32.36	29.821 - 34.87
4	0.137	17.598	15.9 - 19.5	32.543	29.642 - 35.231	29.509	26.957 - 32.077
5	0.157	19.35	17.56 - 21.2	25.487	22.815 - 28.265	21.428	19.138 - 23.791
10	0.221	21.538	19.677 - 23.281	11.457	9.762 - 13.288	9.758	8.234 - 11.331
20	0.297	22.414	20.36 - 24.42	10.378	8.664 - 12.171	9.808	8.146 - 11.343
100	0.482	18.195	16.4 - 20.062	3.779	2.684 - 4.97	2.953	2.103 - 3.853

Table 14: Correctness and citation quality on QAMPARI achieved with Mistral with various numbers of ColBERT retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	39.152	36.879 - 41.44	23.239	20.827 - 25.708	19.774	17.585 - 22.032
0	0	17.112	15.259 - 19.021	-	-	-	-
1	0.067	16.649	14.88 - 18.461	45.446	42.724 - 48.362	50.431	47.383 - 53.375
2	0.119	20.556	18.72 - 22.44	43.893	41.037 - 46.795	36.006	33.398 - 38.801
3	0.159	21.407	19.48 - 23.3	41.728	38.943 - 44.541	36.444	34.06 - 39.093
4	0.192	22.379	20.54 - 24.3	31.825	29.095 - 34.731	27.747	25.325 - 30.264
5	0.22	24.657	22.5 - 26.64	23.981	21.59 - 26.459	20.101	17.861 - 22.51
10	0.412	29.836	27.68 - 31.962	10.084	8.391 - 11.862	8.456	6.94 - 10.001
20	0.412	30.613	28.359 - 32.9	8.417	6.859 - 10.063	6.874	5.533 - 8.274
100	0.641	24.105	21.94 - 26.381	2.381	1.603 - 3.17	1.755	1.141 - 2.475

Table 15: Correctness and citation quality on QAMPARI achieved with LLaMA with various numbers of BGE-base retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	32.444	30.36 - 34.8	24.308	21.621 - 26.906	16.42	14.395 - 18.422
0	0	13.725	12.2 - 15.26	-	-	-	-
1	0.055	14.029	12.58 - 15.56	40.375	37.366 - 43.518	38.634	35.803 - 41.521
2	0.087	14.693	13.14 - 16.32	43.257	40.15 - 46.217	31.847	29.341 - 34.352
3	0.115	14.04	12.62 - 15.502	56.025	53.052 - 59.194	38.662	36.274 - 41.237
4	0.137	15.744	14.22 - 17.28	33.229	30.63 - 35.999	22.892	20.558 - 25.194
5	0.157	15.677	14.02 - 17.3	22.242	19.811 - 24.751	16.372	14.373 - 18.386
10	0.221	18.742	16.88 - 20.62	3.443	2.444 - 4.513	2.76	1.974 - 3.588
20	0.412	30.613	28.359 - 32.9	8.417	6.859 - 10.063	6.874	5.533 - 8.274
100	0.641	24.105	21.94 - 26.381	2.381	1.603 - 3.17	1.755	1.141 - 2.475

Table 16: Correctness and citation quality on QAMPARI achieved with LLaMA with various numbers of ColBERT retrieved documents, k, included in the prompt.

	Ret.	**EM Recall**		**Citation Recall**		**Citation Precision**	
k	Rec@k	Mean	95% CI	Mean	95% CI	Mean	95% CI
gold	1	32.444	30.36 - 34.8	24.308	21.621 - 26.906	16.42	14.395 - 18.422
0	0	13.725	12.2 - 15.26	-	-	-	-
1	0.067	16.153	14.68 - 17.78	52.048	48.95 - 55.218	50.288	47.517 - 53.223
2	0.119	18.804	17.08 - 20.52	55.04	52.239 - 57.998	38.711	35.952 - 41.13
3	0.159	19.874	18.24 - 21.56	62.55	59.748 - 65.626	41.091	38.741 - 43.48
4	0.192	21.358	19.64 - 23.18	35.157	32.209 - 38.061	25.063	22.702 - 27.476
5	0.22	21.722	20.02 - 23.58	22.076	19.738 - 24.713	15.817	13.845 - 17.859
10	0.412	24.998	23.02 - 27.04	3.647	2.533 - 4.746	2.723	1.88 - 3.622

A.5 Additional varied number of gold documents results

Figure 9 shows the relationship between the number of gold documents in the prompt and correctness achieved on ASQA with LLaMA. In Figure 9 and 10 we present results comparing retriever recall and correctness.

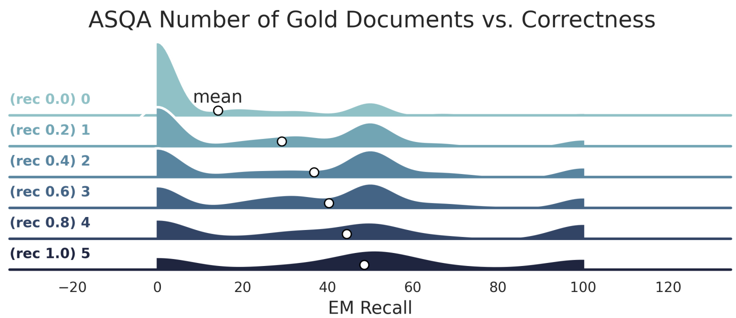


Figure 9: The per-query relationship between the number of gold documents included in the prompt and the QA accuracy achieved with LLaMA on ASQA. We find that including just one gold document significantly improves accuracy. There is a correlation between the number of gold documents and the accuracy.

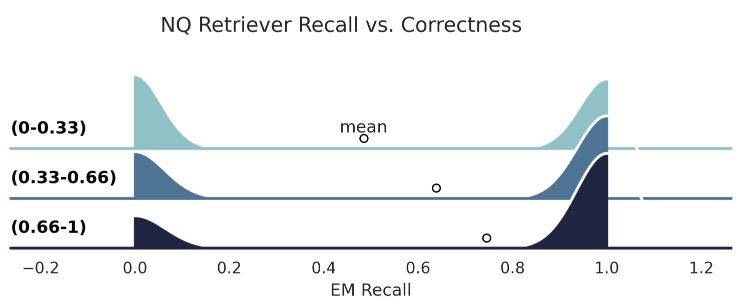


Figure 10: The per-query relationship between the gold document recall in the prompt and the QA accuracy achieved with Mistral on NQ. There is a correlation between the number of gold documents and the accuracy.

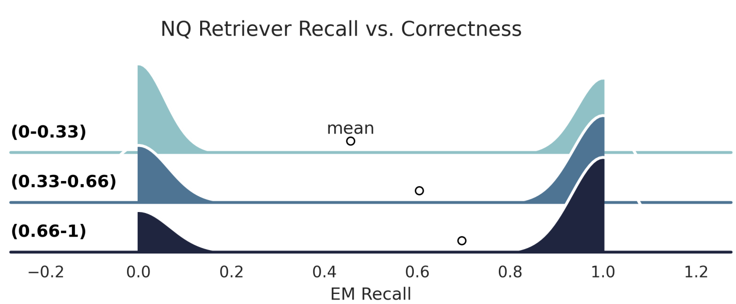


Figure 11: The per-query relationship between the number of gold documents included in the prompt and the QA accuracy achieved with LLaMA on NQ. We find that including just one gold document significantly improves accuracy. There is a correlation between the number of gold documents and the accuracy.

A.6 Additional recall manipulation results

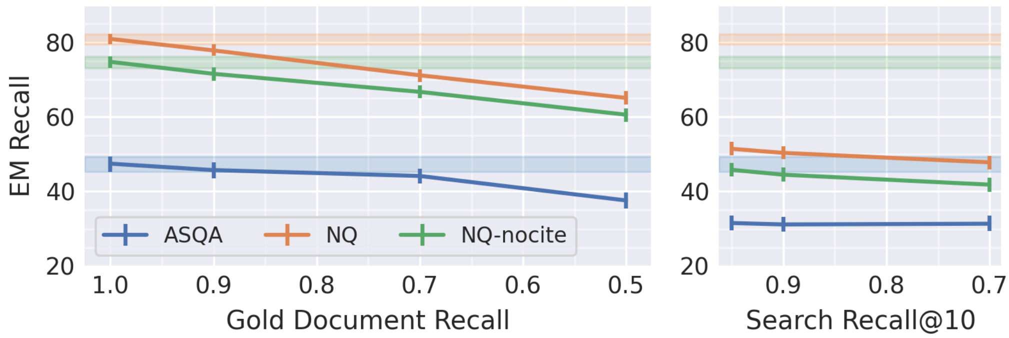


Figure 12: Llama results varying gold document recall (left) and BGE-base search recall (right). Shaded bar is ceiling performance using all gold documents per query. Error bars are 95% bootstrap confidence intervals.

Generally, both citation recall and citation precision decrease as document recall and search recall decrease.

Since the ASQA dataset is more likely to contain multiple gold evidence documents per query, it is less consistently affected by decreases in document recall. For example, we see in Table 17 that between 0.7 and 0.9 search recall@10, citation recall is nearly identical for ASQA – the 95% CIs are nearly completely overlapping. However, this is not the case for the NQ dataset, which shows a consistent decrease as recall drops.

Table 17: Full Mistral results for changes in citation metrics as gold document recall and search recall (BGE-base retriever) vary.

	Citation Recall		**Citation Precision**	
	ASQA	NQ	ASQA	NQ
Doc. Recall@10				
1.0	65.229 (62.876, 67.321)	75.041 (73.772, 76.397)	62.375 (60.257, 64.469)	64.904 (63.660, 66.105)
0.9	64.797 (62.701, 66.887)	72.084 (70.765, 73.409)	62.092 (60.075, 64.032)	63.023 (61.723, 64.317)
0.7	64.914 (62.781, 66.991)	66.669 (65.258, 68.148)	61.599 (59.471, 63.646)	59.059 (57.693, 60.474)
0.5	60.482 (58.238, 62.692)	60.827 (59.428, 62.292)	58.731 (56.339, 61.011)	54.530 (53.122, 55.875)
Search Recall@10				
0.95	57.636 (55.250, 59.867)	55.340 (53.872, 56.814)	52.909 (50.559, 55.129)	45.906 (44.476, 47.292)
0.9	55.764 (53.341, 58.244)	52.443 (50.835, 53.972)	50.460 (48.284, 52.665)	43.263 (42.005, 44.552)
0.7	56.017 (53.551, 58.342)	49.856 (48.405, 51.340)	52.007 (49.744, 54.265)	41.523 (40.198, 42.859)

Table 18: Full Llama results for changes in citation metrics as gold document recall and search recall (BGE-base retriever) vary.

	Citation Recall		**Citation Precision**	
	ASQA	NQ	ASQA	NQ
Doc. Recall@10				
1.0	46.326 (44.123, 48.524)	54.697 (53.309, 56.104)	46.294 (44.082, 48.686)	55.748 (54.285, 57.262)
0.9	46.778 (44.492, 48.999)	53.438 (51.979, 54.862)	46.411 (44.130, 48.779)	55.758 (54.275, 57.143)
0.7	42.450 (40.073, 44.566)	49.078 (47.618, 50.660)	42.618 (40.377, 45.055)	50.265 (48.662, 51.771)
0.5	39.634 (37.468, 41.970)	45.827 (44.258, 47.346)	39.780 (37.453, 41.911)	47.506 (45.929, 48.962)
Search Recall@10				
0.95	34.425 (32.106, 36.668)	28.412 (27.054, 29.697)	30.218 (28.282, 32.411)	25.735 (24.561, 26.914)
0.9	33.419 (31.234, 35.618)	26.626 (25.383, 27.994)	28.745 (26.698, 30.792)	24.402 (23.262, 25.549)
0.7	34.190 (31.658, 36.568)	25.033 (23.710, 26.321)	29.509 (27.349, 31.602)	22.853 (21.708, 24.054)

A.7 Additional noise experiment results

In Table 19 we show detailed results for ASQA Mistral performance after injecting noisy documents from various percentiles of similarity to the query. These correspond to the correctness results in Figure 5 in the main body of the paper.

Table 20 shows the first 100 noise experiment for ASQA with Llama2 for augmenting both gold and BGE-base retrieved data with noise first in the prompt.

Table 19: ASQA Mistral performance with gold or BGE-base retrieved documents (respectively) *and* noisy documents from various percentiles of similarity to the query. We find that adding noisy documents from all percentiles degrades both correctness and citation performance. There is no obvious correlation between the percentile of the noise and the degradation of performance.

(a) 5 Gold docs

	Correct.	**Citation**	
noise percentile	EM Rec.	Rec.	Prec.
-	50.673	65.403	62.462
10	40.500	53.000	55.298
20	42.533	55.243	59.944
30	42.983	56.767	55.459
40	43.483	53.833	56.917
50	42.633	53.783	55.800
60	39.733	53.157	54.985
70	42.433	57.750	57.429
80	42.833	56.283	56.075
90	43.517	59.533	62.917
100	42.333	57.417	60.245

(b) 5 docs retrieved with BGE-base

Correct.	**Citation**	
EM Rec.	Rec.	Prec.
37.569	61.188	58.763
34.550	50.286	52.583
34.683	52.967	53.254
34.100	51.133	49.812
32.783	50.350	58.433
35.300	54.250	54.867
31.783	50.036	51.439
29.833	53.667	55.573
32.467	50.900	51.321
32.000	49.900	49.900
34.250	50.900	52.275

Table 20: LLaMA performance on ASQA when adding non-gold (*noise*) documents based on their similarity ranking (between $5^{\text{th}} - 100^{\text{th}}$ nearest neighbor). BGE-base results (right) with 5 retrieved documents. Noisy documents are added after the gold or retrieved documents in the prompt.

(a) 5 gold docs

	Correct.	**Citation**	
noise idx.	EM Rec.	Rec.	Prec.
gold only	47.426	46.261	46.033
gold + $5^{\text{th}} - 10^{\text{th}}$	43.070	40.778	36.135
gold + $95^{\text{th}} - 100^{\text{th}}$	41.807	38.646	35.536

(b) 5 BGE-base retrieved docs

	Correct.	**Citation**	
noise idx.	EM Rec.	Rec.	Prec.
BGE-base only	34.488	42.029	41.781
BGE-base + $5^{\text{th}} - 10^{\text{th}}$	33.284	33.979	30.298
BGE-base + $95^{\text{th}} - 100^{\text{th}}$	30.979	34.561	31.932