Blinded by Generated Contexts: How Language Models Merge Generated and Retrieved Contexts for Open-Domain QA?

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Abstract

While auxiliary information has become a key to enhance Large Language Models (LLMs), relatively little is known about how well LLMs merge these contexts, specifically generated and retrieved. To study this, we formulate a task specifically designed to identify whether the answers, derived from the integration of generated and retrieved contexts, are attributed to either generated or retrieved contexts. To support this task, we develop a methodology to construct datasets with conflicting contexts, where each question is paired with both generated and retrieved contexts, yet only one of them contains the correct answer. Our experiments reveal a significant bias in LLMs towards generated contexts, as evidenced across stateof-the-art open (Llama2-7b/13b) and closed (GPT 3.5/4) systems. We further identify two key factors contributing to this bias: i) Contexts generated by LLMs typically show greater similarity to the questions, increasing their likelihood of selection; ii) The segmentation process used in retrieved contexts disrupts their completeness, thereby hindering their full utilization in LLMs. Our analysis enhances the understanding of how LLMs merge diverse contexts, offering valuable insights for advancing current augmentation methods for LLMs.

1 Introduction

Recent advancements in augmenting Large Language Models (LLMs) with auxiliary information have significantly revolutionized their efficacy in knowledge-intensive tasks (Chang et al., 2023; Ram et al., 2023). In this evolving landscape, existing works can be broadly categorized into two groups based on information sources: generation-augmented and retrieval-augmented approaches. To effectively harness the LLMs' internal knowledge, generation-augmented approaches (Liu et al., 2022; Sun et al., 2023), e.g., GenRead

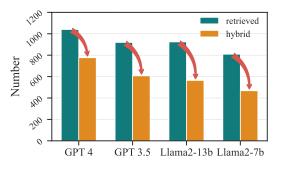


Figure 1: Instances correctly answered using solely the retrieved context in the NQ dataset are represented in cyan. The subset of these instances that can also be resolved by a hybrid approach is indicated in orange.

(Yu et al., 2022), instruct LLMs to initially generate a background context tailored to the given question, which is then employed as the basis for producing the final answer. In contrast, retrieval-augmented approaches (Lewis et al., 2020; Ram et al., 2023) adopt an alternative strategy by incorporating relevant passages from external corpora, e.g., Wikipedia, as context, thereby notably enhancing LLMs' capability to handle situations like knowledge updates (Jang et al., 2022) and long-tail knowledge (Kandpal et al., 2023).

Building on the foundations laid by generationaugmented and retrieval-augmented methods, recent hybrid approaches have attempted to integrate them to further improve performance in tasks such as Question Answering (QA) (Yu et al., 2022; Abdallah and Jatowt, 2023; Mallen et al., 2023). These hybrid approaches face a significant challenge: conflicts between diverse sources can impede the effectiveness of information integration (Zhang et al., 2023). While recent works have investigated conflicts within a single source of contexts (Xie et al., 2023; Chen et al., 2022), there remains a gap in the comprehension of how LLMs resolve conflicts between generated and retrieved contexts. This study, therefore, aims to investigate the underlying mechanisms by which LLMs process the two types of

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contexts, especially when they contain conflicting information.

Our investigation was driven by a striking observation: in certain cases, models relying solely on retrieval contexts succeeded, whereas, counterintuitively, hybrid approaches failed, as depicted in Figure 1. To uncover the underlying reasons, we proposed a systematic framework to dissect the process by which LLMs merge generated and retrieved contexts. For this purpose, we curated tailored datasets in which each question is accompanied by two incompatible contexts, i.e., they are not only inconsistent but, crucially, only one contains the correct answer. These datasets were derived from existing QA datasets, with questions extracted based on the aforementioned criterion. Finally, the datasets, contrasting generated and retrieved contexts, provide an innovative lens to unravel how LLMs discern and integrate diverse contextual information in QA.

In this paper, we conducted a series of controlled experiments using our uniquely designed datasets to empirically study this question, focusing on several state-of-the-art open (Llama2-7b/13b) and closed (GPT 3.5/4) LLMs. Surprisingly, our findings reveal a pronounced bias in LLMs to favor generated contexts, regardless of whether the generated text was produced internally or by other LLMs, which persists even when the generated contexts offer incorrect information while the retrieval contexts hold the correct answer. Notably, this tendency remains consistent even after accounting for potentially confounding factors including the order and length of contexts, and the confirmation bias (Xie et al., 2023). These findings highlight a critical challenge for existing LLMs in effectively merging internal parametric knowledge (i.e., generated contexts) and external information (i.e., retrieved contexts), under increasingly common non-tunable settings, e.g., those involving black-box APIs like GPT-4.

To delve deeper into the factors driving this phenomenon, we initially conducted a comprehensive analysis examining the **text similarity** between the contexts fed into LLMs and their corresponding questions (Section 5.2). We discovered that generated contexts typically exhibit a higher degree of similarity to the questions compared to retrieved contexts, even when they contain incorrect information. Furthermore, our analysis reveals that samples with smaller similarity gaps between gen-

erated and retrieved contexts exhibited a reduced bias, although a noticeable preference for generated contexts remains evident. This finding indicates text similarity as a significant factor in this bias, and emphasizes the the need for caution with LLMgenerated contexts, to avoid being misled by highly relevant but inaccurate information.

Besides the similarity factor, we further examined the role of semantic completeness in the bias observed in LLMs (Section 5.3). This area of exploration was driven by another key difference between these two types of contexts: retrieved contexts often exhibit semantic incompleteness due to the segmentation process, a prevalent practice in current retrieval methodologies. By intentionally truncating the generated context to mimic the incompleteness typically in retrieved contexts, we discerned a significant decrease in the bias towards generated contexts. This finding suggests that LLMs exhibit significant sensitivity to the semantic completeness of input contexts, calling for improvements in passage segmentation strategies in current retrieval-augmented systems.

Our analysis provides a better understanding of how LLMs use contexts for QA tasks. This work represents a preliminary exploration, aimed at highlighting the critical issue of context utilization in existing LLMs, a concern that grows increasingly as LLM-generated content, including potential misinformation, proliferates across the web. Furthermore, our findings offer valuable guidance for enhancing existing retrieval-augmented methods, such as optimizing passage segmentation in retrieval systems. Our main contributions can be summarized as:

- We uncover a critical bias in existing LLMs, where they heavily rely on generated contexts regardless of correctness, indicating an insufficient use of diverse information sources.
- To facilitate controlled experiments, we develop a specialized process for constructing tailored datasets.
- Our extensive analyses have identified two key factors, i.e., text similarity and semantic completeness, in the context utilization of LLMs.

2 Preliminary & Task Formulation

In this section, we briefly review three categories of LLMs augmented with auxiliary information

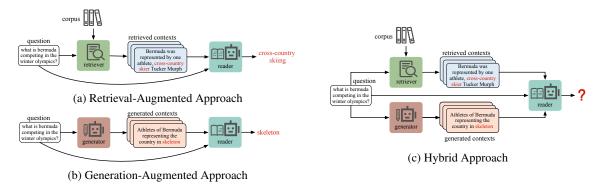


Figure 2: The frameworks of retrieval-augmented approach, generation-augmented approach and hybrid approach.

for QA tasks: retrieval-augmented, generation-augmented, and hybrid approaches. Additionally, we introduce the framework of our investigation. Figure 2 presents high-level abstract frameworks for three typical types of QA systems, each centered around an LLM as the *reader* component, and potentially incorporating additional components like a *retriever*, *generator*, or a blend of both, tailored to the specific methodology.

Retrieval-Augmented Approach. As shown in fig. 2a, for a given question q^1 in a set of questions \mathbb{Q} , these approaches initially use a retrieval model γ to select the top k relevant documents $D_k^{\gamma} = \gamma_k(q,\mathbb{C}) = \{d_1^{\gamma},\ldots,d_k^{\gamma}\}$ from a corpus $\mathbb{C} = \{d_1,\ldots,d_{|\mathbb{C}|}\}$. Subsequently, a reader (often LLM) ϕ employs these documents D^{γ} to generate an answer a_{ϕ}^{γ} , expressed as $a_{\phi}^{\gamma} = \phi(q,D^{\gamma})$.

Generation-Augmented Approach. In contrast, as illustrated in fig. 2b, these works involve an LLM as a generator ϱ to produce k tailored background contexts $D_k^\varrho = \varrho_k(q) = \{d_1^\varrho, \ldots, d_k^\varrho\}$ for a give question q, thereby enhancing the utilization of the LLM's internal knowledge. These LLM-generated contexts D^ϱ form the input for reader ϕ to produce the final answer: $a_\phi^\varrho = \phi(q, D^\varrho)$. These methodologies generally use LLMs for the reader and generator functions, with implementation options including a shared LLM with varied prompts (Wei et al., 2022b; Sun et al., 2023), or distinct LLMs dedicated to each role (Luo et al., 2023; Feng et al., 2023).

Hybrid Approach. They, as depicted in fig. 2c, combine retrieved and generated contexts to enhance performance (Yu et al., 2022; Abdallah and Jatowt, 2023), as $a_{\phi} = \phi(q, D_k^{\gamma}, D_k^{\varrho})$. Building upon the foundations of previous approaches, hybrid approaches primarily focus on how to effectively merge these two types of information to en-

hance overall performance (Zhang et al., 2023).

2.1 Answer Tracing

Departing from previous research, our study delves into the mechanisms by which LLMs merge contexts from diverse sources, i.e., hybrid approach setting. We specifically focus on non-tunable, i.e., zero-shot setting, LLMs acting as the reader and generator, reflecting prevalent real-world use cases like ChatGPT. This research direction is motivated by several considerations: i) Model architecture: LLMs represent an emerging trend for the future, in contrast to the specially designed reader models like Fusion-in-Decoder (FiD) (Izacard and Grave, 2021). ii) Non-tunability: Due to the high cost and limited accessibility of fine-tuning, the direct use of black-box non-tunable LLMs has gained popularity in real-world applications. iii) Impact: Given the extensive use of LLMs, any bias or issue in their merging mechanisms could lead to serious consequences, like pulling an LLM that prefers generated context with LLM-generated misinformation (Pan et al., 2023).

More specially, to reveal if an LLM has a bias towards generated contexts, we design a task to ascertain whether an LLM-generated answer a_ϕ originates from generated contexts D_k^ϱ or retrieved contexts D_k^γ . As illustrated in Figure 3, our task mirrors the basic process of hybrid approaches,while our focus is studying LLMs' merging mechanisms by tracing the sources of the answers instead of improving QA performance. For a more controlled and simpler analysis, we limit the context to a single instance from each source, i.e., $k{=}1$ and $a_\phi{=}\phi(q,d_1^\gamma,d_1^\varrho)$. Subsequently, by comparing the answer a_ϕ with answers derived from the retrieved context a_ϕ^γ and the generated context a_ϕ^ϱ , we can determine its source², thereby analyzing the merging

 $^{^{1}}$ Here, we omit the subscript i for notational simplicity.

²Here, we use a stricter criterion by assessing the answer's

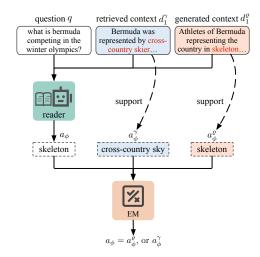


Figure 3: The task to study LLMs' merging mechanisms by tracing the sources of the answers.

mechanism of LLMs.

3 Experimental Setup

To facilitate our investigation into how LLMs merge generated and retrieved contexts, this section elaborates on the construction of our context-conflicting datasets and the evaluation metric.

3.1 Context-Conflicting Datasets

As depicted in Figure 4, in our dataset \mathcal{D}_{cc} , each sample x is a quintet $(q, d_1^{\gamma}, d_1^{\varrho}, a_{\phi}^{\gamma}, a_{\phi}^{\varrho})$, where d_1^{γ} is the context returned by retriever γ for question q, d_1^{ϱ} represents the context generated by LLM ϱ , a_{ϕ}^{γ} and a_{ϕ}^{ϱ} are the candidate answers provided by the reader ϕ , each based solely on the respective contexts d_1^{γ} and d_1^{ϱ} . To guarantee that our dataset is suitable for controlled experiments aimed at investigating the merging mechanisms of LLMs, it must adhere to specific criteria:

- Traceability: Both a_{ϕ}^{γ} and a_{ϕ}^{ϱ} must be solely supported by their respective contexts, i.e., d_{1}^{γ} and d_{1}^{ϱ} .
- Exclusivity: Only one of the contexts, d_1^{γ} or d_1^{ϱ} provides the correct answer, i.e., either a_{ϕ}^{γ} or a_{ϕ}^{ϱ} matches the gold answer of question q.

Such constraints establish a solid basis to identify which context, generated or retrieved, is selected by LLMs to produce answers in hybrid approaches.

Considering the specified prerequisites and cost considerations, we utilize two open-domain QA

consistency with those generated from individual sources, rather than directly comparing it with the input contexts.

| Detect | D. 4 | Generated | | | |
|---------|-----------|-----------|---------|------------|-----------|
| Dataset | Retrieved | GPT 4 | GPT 3.5 | Llama2-13b | Llama2-7b |
| NQ | 107.3 | 108.0 | 106.0 | 110.1 | 104.0 |
| TQA | 106.3 | 107.2 | 104.9 | 105.5 | 102.6 |

Table 1: Average lengths of the generated and retrieved contexts. Length is measured in the number of words after punctuation removal.

benchmark datasets with golden answers, i.e., NaturalQuestions (NQ) (Kwiatkowski et al., 2019) and TriviaQA (TQA) (Joshi et al., 2017), to assemble our experimental datasets. The overall pipeline for dataset construction is depicted in Figure 4, with detailed steps outlined as follows:

Context Preparation. Step 1 in Figure 4 illustrates the process of preparing retrieved and generated contexts for each question.

For retrieved context, it is obtained from the top-1 ranked passage from Wikipedia using a retrieval model, e.g., Contriever (Izacard et al., 2021), a powerful off-the-shelf retrieval model that is extensively employed in various retrieval-augmented generation systems (Shi et al., 2023; Ram et al., 2023).

For generated context, we follow the Gen-Read (Yu et al., 2022), instructing the generator, i.e., LLM like GPT 4, with the prompt:

Generate a background context from Wikipedia to answer the given question {#question}

However, the initial prompt often yields contexts much longer (>250 words) than the retrieved contexts (typically truncated to \sim 100 words (Karpukhin et al., 2020; Izacard et al., 2021)). The discrepancy in length could potentially affect the merging mechanisms of LLMs, e.g., LLMs may tend to longer context, as discussed in Xie et al. (2023). More detail can be found in Appendix A.1. To mitigate this, we further append

Keep the length of the document around n words

to the initial prompt to regulate the length of the generated context³.

Table 1 confirms that the lengths of the final generated and retrieved contexts are closely matched, with an average length discrepancy below 3%. All subsequent experiments and analyses, unless otherwise specified, employ this method to eliminate the impact of length variations.

 $^{^{3}}$ To precisely control the length, we vary the word count n in the prompt, and choose the results that best match the length of the retrieved context.

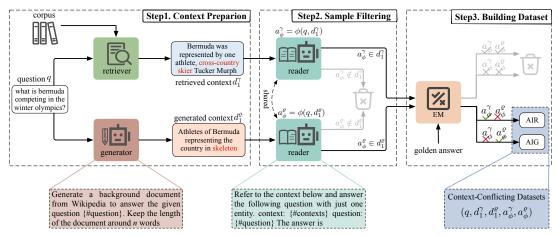


Figure 4: The framework of constructing context-conflicting datasets.

Sample Filtering for Traceability. With each question paired with a context (either generated or retrieved) established in the initial stage, the reader generates the answer using the following prompt:

Refer to the context below and answer the following question with just one entity. context: {#contexts} question: {#question} The answer is

To unravel the mechanisms of LLMs in context merging, it is essential to ensure the *traceability*, i.e., the output answer is derived from the input context, rather than the intrinsic parametric knowledge of the LLMs. To achieve this, we only keep samples in which both the generated and retrieved contexts exactly include their respective generated answers⁴, exemplified by $a_{\phi}^{\gamma} \in d_1^{\gamma}$, where \in denotes d_1^{γ} contains the substring a_{ϕ}^{γ} . This practice is grounded in the findings of (Chen et al., 2022; Xie et al., 2023), which demonstrate that in the presence of external context, LLMs tend to rely on external context rather than their intrinsic parametric knowledge.

Building Context-Conflicting Dataset. Having obtained answers for each type of context, we are now positioned to construct our context-conflicting (CC) datasets, as depicted in Step 3 of Figure 4. Initially, We employ the exact match metric (Yu et al., 2022) to evaluate the correctness of candidate answers derived from contexts, considering an answer correct if its normalized form matches any of the golden answers. Subsequently, the conflicting context datasets are composed of samples for which only one of the two types of contexts, either generated or retrieved, yields the correct an-

| Generator | NQ (| 3610) | TQA (11,313) | | |
|------------|--------|--------|--------------|---------|--|
| &Reader | NQ-AIG | NQ-AIR | TQA-AIG | TQA-AIR | |
| GPT 4 | 331 | 238 | 946 | 358 | |
| GPT 3.5 | 379 | 279 | 1357 | 567 | |
| Llama2-13b | 439 | 419 | 1648 | 1201 | |
| Llama2-7b | 432 | 406 | 1737 | 1488 | |
| Avg. Prop. | 10.9% | 9.3% | 12.6% | 8.0% | |

Table 2: Dataset statistics across LLMs, "Avg. Prop." shows average proportions of subsets to original testsets.

swer. Notably, each dataset comprises two distinct subsets: **AIG**, consisting of samples with correct **a**nswers **i**n the **g**enerated context; and **AIR** comprising samples with correct **a**nswers **i**n the **r**etrieved context.

3.2 Statistics of Datasets

For each reader-generator pair, we respectively constructs context-conflicting datasets from the original NQ and TQA test sets, named NQ-CC (NQ-AIG + NQ-AIR) and TQA-CC (TQA-AIG + TQA-AIR).

We initially adopt a typical and simple setting in which a singular LLM serves as both the generator and reader. Table 2 provides detailed statistics for the constructed subsets corresponding to various LLMs, including GPT 4 (*gpt-4-0613*), GPT 3.5 (*gpt-3.5-turbo-0613*), Llama2-7b/13b (*Llama-2-7b/13b-chat* (Touvron et al., 2023)). The statistics reveal that context-conflicting subsets constitute a significant portion of the overall test sets. This observation indicates that numerous questions can be answered by only one type of contexts, thus emphasizing the importance of exploring how LLMs merge such varied contexts. Moreover, as shown in Table 2, GPT 4 has fewer conflicting

⁴Samples yielding responses like "unknown" that reflect the model evading answering are also excluded from our dataset.

instances than other LLMs, because of its higher efficacy in answering questions using either solely retrieved or generated contexts.

In Section 4.2, we also explore a more complex scenario in which the generator and reader are distinct LLMs. Appendix A.2 provides detailed statistics for the context-conflicting datasets created for each reader-generator pair, where we observe similar conclusions.

3.3 Evaluation Metric

Besides datasets, we also develop metrics to study how LLMs merge generated and retrieved contexts in hybrid approaches. Specifically, the selection of LLMs towards either generated or retrieved context can be measured by the proportion of answers that exactly match the answer produced solely by the corresponding context, denoted as

$$\rho_{\mathrm{gen}} = \mathrm{avg}(\mathrm{em}(a_{\phi}, a_{\phi}^{\varrho})), \quad \rho_{\mathrm{ret}} = \mathrm{avg}(\mathrm{em}(a_{\phi}, a_{\phi}^{\gamma}))$$

where $\operatorname{em}(a,b)$ returns 1 if a exactly match b, and 0 otherwise. Thus, for a balanced dataset, an $\rho_{\operatorname{gen}} > \rho_{\operatorname{ret}}$ indicates a preference of LLMs for generated contexts over retrieved contexts, and vice versa. To facilitate a simple and efficient experiment, we define a synthesized metric as follows:

$$DiffGR = \frac{\rho_{gen} - \rho_{ret}}{\rho_{gen} + \rho_{ret}}$$
 (1)

The metric DiffGR, ranging from [-1, 1], quantifies the extent of LLMs' preference for choosing generated contexts over retrieved contexts. Using AIR as an example, where all correct answers come from retrieved contexts, an ideal DiffGR value should be -1, and DiffGR>0 would indicate a significant bias towards generated contexts.

4 How LLMs Merge Contexts?

In this section, we conduct experiments on the proposed context-conflicting datasets to investigate the merging mechanism of the LLMs in hybrid approaches in different settings. We first consider a typical setting where generator and reader share a single LLM, to explore how LLMs merge retrieved and *self-generated* contexts (Section 4.1). Then, we extend our experiments to more flexible combinations of generator and reader (Section 4.2) to investigate their effects.

| Generator | NQ- | -CC | TQA-CC | | |
|------------|--------|--------|---------|---------|--|
| &Reader | NQ-AIG | NQ-AIR | TQA-AIG | TQA-AIR | |
| GPT 4 | 91.54 | 14.29 | 94.08 | 18.44 | |
| GPT 3.5 | 94.46 | 13.26 | 93.96 | 19.58 | |
| Llama2-13b | 89.52 | 17.66 | 91.81 | 20.23 | |
| Llama2-7b | 67.13 | 23.40 | 80.08 | 21.64 | |

Table 3: The Exact Match (EM) scores (%) of hybrid approaches on corresponding context-conflicting datasets.

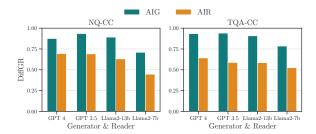


Figure 5: The DiffGR of LLMs on their corresponding context-conflicting datasets.

4.1 LLMs Prefer Self-Generated Contexts

Our preliminary experiments, in which a single LLM serves both as generator and reader, are designed to explore how LLMs integrate information from retrieved and *self-generated* contexts. The LLMs under evaluation are tasked with answering questions using both types of contexts on their corresponding context-conflicting subsets, where either self-generated or retrieved contexts provide correct answers. In all experiments, we employ a randomized input sequence of contexts to mitigate the influence of order, which is further discussed in Appendix A.3.

We begin our analysis by examining LLMs' QA performance on context-conflicting datasets to reveal how well can LLMs utilize both types of contexts. Table 3 presents the Exact Match (EM %) percentages, a typical QA metric, across various LLMs. Surprisingly, LLMs demonstrate significantly low performance ($\leq 23.40\%$) on AIR subsets, despite the fact that the retrieved context alone consistently yields the correct answer on these subsets. In contrast, most LLMs exhibit strong performance on AIG subsets (near 90% or more). An exception is the Llama2-7B model, which performs relatively poorly, likely due to its inferior instruction-following capabilities. Overall, all LLMs exhibit a significant performance gap between AIR and AIG datasets, with a pronounced decline in performance when the correct answers come from retrieved contexts.

To further reveal LLMs' behavior underlying the

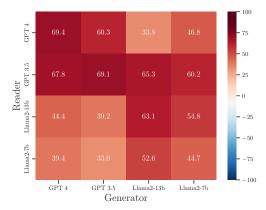


Figure 6: DiffGR (%) with different (reader, generator) pairs on their corresponding NQ-AIR datasets.

QA performance, we trace the source contexts of LLMs' answers using the proposed DiffGR metric. Figure 5 illustrates the DiffGR of LLMs on their corresponding context-conflicting subsets. An ideal LLM that optimally leverages information from both sides should always rely on retrieved contexts in case of AIR (with DiffGR = -1), and on generated contexts for AIG (with DiffGR = 1). Contrary to expectations, Figure 5 illustrates that LLMs fail to identify the correct information and consistently tend to rely on generated contexts on both AIG and AIR subsets. This result indicates a pronounced bias in LLMs to favor generated contexts, even when they provide incorrect information. This bias leads to the insufficient utilization of retrieved contexts mentioned above, and highlights a critical challenge for existing LLMs in effectively merging generated and retrieved contexts.

As the bias on AIR subsets has more direct impact on the performance, the following experiments and analysis will focus on the biases on these subsets to conserve space. Results on the AIG subsets can be found in Appendix A.4.

4.2 LLMs Broadly Prefer Generated Contexts

Above experiments reveal the bias in LLMs to favor the *self-generated* context. Consequently, an intriguing question emerges: *Are LLMs biased exclusively towards self-generated contexts, or do they exhibit a similar preference for contexts generated by other LLMs?* To investigate this question, this section extends the experiments to more flexible combinations of generators and readers. We construct context-conflicting datasets for each (generator, reader) pair and show the detail statistics of the constructed datasets in Appendix A.2. Base on

these datasets, we then compute DiffGR metric to examine biases across various (generator, reader) pairs, as shown in Figure 6. The results yield two notable conclusions and insights:

LLMs are also biased towards contexts generated by other LLMs. Figure 6 indicates that the bias towards generated context persists across various combinations of readers and generators. This suggests that such bias in LLMs is widespread and not limited to self-generated context.

LLMs exhibit a stronger preference for contexts generated by themselves. Figure 6 also illustrates that readers exhibit a strongest preference when the generator LLM is identical to themselves. The sole exception is Llama2-7b, which shows the strongest preference when paired with Llama2-13b as its generator. This phenomenon likely results from their highly similar model structures and training processes (Touvron et al., 2023).

5 Why LLMs Prefer Generated Contexts

In this section, we investigate why LLMs prefer generated contexts rather than retrieved contexts, from several perspectives: confirmation bias (Xie et al., 2023) in Section 5.1, context similarity to the question in Section 5.2, and context completeness in Section 5.3.

5.1 Effect of Confirmation Bias

Recent work (Xie et al., 2023) has uncovered a confirmation bias in LLMs, which leads them to prefer the context consistent with their parametric knowledge (or parametric memory), when presented with two conflicting generated contexts. This finding naturally raises the question: does the inherent consistency of generated contexts with parametric knowledge lead to the observed preference for these contexts? To investigate this question, we designed controlled experiments that manipulate the consistency of the generated context with the LLMs' parametric knowledge.

In this section, we adopt the setting where the reader and generator share a single LLM⁵, resulting in an inherent consistency between the naturally generated context d_1^ϱ and the parametric knowledge of LLMs. In this setting, we can refer to a_ϕ^ϱ , the

⁵When the generator and reader are distinct LLMs, generated contexts may not align with the reader's parameterized knowledge. In this setting, LLMs consistently exhibits a significant preference for generated contexts, as observed in Section 4.2, indicating that confirmation bias is not the primary factor.

answer derived from d_1^ϱ , as the *memory answer* (the answer consistent with parametric knowledge (Xie et al., 2023)). To explore the effect of the confirmation bias, we enforce LLMs to generate a *counter-memory context* $d_1^{\varrho'}$ that supports a *counter-memory answer* $a_1^{\varrho'}$, which is completely different with the memory answer. Specifically, we construct counter-memory answers and contexts based on the original AIR context-conflicting subsets of GPT 3.5, as outlined below:

Counter-Memory Answers Preparation. For each question on the AIR subsets, we substitute the original memory answer (e.g., "Canada") with a same-type yet distinct entity (e.g., "United States"), which serves as the counter-memory answer, as detailed in Appendix A.5. Furthermore, to facilitate the calculation of DiffGR, we only retain those samples where the counter-memory answer also diverged from a_{ϕ}^{γ} , the answer provided by the retrieved context. Formally, the counter-memory answer satisfies $a_{\phi}^{\varrho'} \neq a_{\phi}^{\varrho}$ and $a_{\phi}^{\varrho'} \neq a_{\phi}^{\gamma}$. Counter-Memory Contexts Generation. We en-

Counter-Memory Contexts Generation. We enforce LLMs to generate a counter-memory context that supports the counter-memory answer, with a similar prompt discussed in Pan et al. (2023):

Generate a background document in support of the given opinion to the question. Keep the length of the document around n words. Question: {question} Opinion: {counter memory answer} Document:

Following Section 3, the prompt also incorporates a length constraint to mitigate the influence of length, as evidenced by the length statistics presented in Table 4.

Answer Consistency Checking. To verify that the counter-memory context actually supports the counter-memory answer, we retain only those instances where the predicted answer, derived exclusively from the counter-memory context, exactly match the counter-memory answer:

$$a_{\phi}^{\varrho'} = \phi(q, d_1^{\varrho'})$$

Following the above procedures, we obtain 149 instances from NQ-AIR, and 330 instances from TQA-AIR, with each instance encompassing a question q, a generated context d_1^ϱ , a retrieved context d_1^{η} , a counter-memory context $d_1^{\varrho'}$ and the associated answers for these contexts. Utilizing these instances, we initially employ the DiffGR metric, as introduced in Section 3, to determine the

| Context | NQ-AI | R (149) | TQA-AIR (330) | | |
|---------|--------|---------|---------------|---------|--|
| Concent | Length | Jaccard | Length | Jaccard | |
| Gen | 105.9 | 0.194 | 104.9 | 0.385 | |
| Ctr | 105.7 | 0.251 | 103.8 | 0.499 | |
| Ret | 107.5 | 0.111 | 106.3 | 0.184 | |

Table 4: Average length and Jaccard similarity of different contexts. Gen, Ret and Ctr respectively represent generated contexts, retrieved contexts and countermemory contexts. Detailed discussion about Jaccard similarity is shown in Section 5.2.

| Context pair | NQ-AIR (149) | TQA-AIR (330) |
|--------------|--------------|---------------|
| Gen vs. Ret | 80.3 | 67.5 |
| Ctr vs. Ret | 81.6 | 83.0 |

Table 5: DiffGR (%) of different input context pairs. Gen, Ret and Ctr respectively represent generated contexts, retrieved contexts and counter-memory contexts.

LLMs' preference for generated versus retrieved contexts. Then, we replace the generated context d_1^ϱ with the counter-memory context d_1^ϱ' and recalculate DiffGR to examine shifts in preference after excluding confirmation bias, as depicted in Table 5. The results reveal that LLMs maintain a high DiffGR when the generated contexts are replaced with counter-memory contexts. This suggests that LLMs retain a preference for generated contexts, even when these contexts contain information that contradicts the LLMs' parametric memory.

Notably, our findings do not contradict the conclusions regarding confirmation bias presented in Xie et al. (2023), due to the pronounced differences in the experimental setups. While Xie et al. (2023) investigates the bias within two generated contexts, our research focus on LLMs' preferences between generated and retrieved contexts. In our experimental setup, the generated and retrieved contexts might present other, more pronounced disparities that could overshadow the effects of confirmation bias.

5.2 Effect of Text Similarity

The **text similarity** between a context and a question can reflect the degree of their relevance, thereby influencing LLMs' preference for the context. This section analyzes the text similarity of generated and retrieved contexts, and investigates its role in the observed bias towards gen-

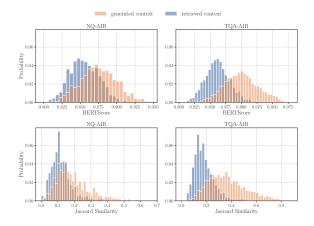


Figure 7: Context-question similarity distribution of generated and retrieved contexts on the union of AIR subsets for different LLMs (GPT 4, GPT 3.5, Llama2-13b, Llama2-7b). A detailed distribution for each LLM, as well as the distribution on AIG subsets, is presented in Appendix A.6.

erated contexts. We perform our analysis using the context-conflicting datasets with the setup⁶ where the reader and generator share a single LLM. The detail framework to constructe the context-conflicting datasets can be found in Section 3.

Similarity Metric. We employ Jaccard similarity to assess the term-based overlap and BERTScore (Zhang et al., 2020) for evaluating the semantic similarity between contexts and questions. To mitigate the effect of length discrepancies between contexts and questions, we calculate the similarity at the sentence level and then aggregate them to derive the overall context-question similarity. In this section, we adopt a maximum aggregation strategy due to the single-hop nature of the NQ and TQA datasets, where the majority of questions can be answered using a small subset of sentences. We also try average aggregation strategy and observe similar results, as shown in A.6. Formally,

$$\sin(q, d) = \max_{s \in d} \left(\sin \left(q, s \right) \right)$$

where \sin is the similarity function, Jaccard similarity and BERTScore in this paper, and s represents a sentence in the context d.

Figure 7 shows the similarity distribution of generated and retrieved contexts. We can observe that generated contexts exhibit a significant higher similarity to questions even on AIR subsets, where generated contexts contain incorrect information,

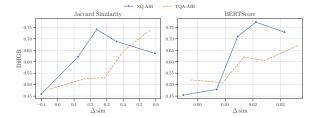


Figure 8: The DiffGR in slices with different average $\Delta \sin$. Llama2-13b is utilized as both the generator and reader here. Results for other LLMs are presented in Appendix A.6.

whether assessed by term-based overlap or semantic similarity.

Although we observe that the generated contexts exhibit a markedly higher degree of similarity, the extent to which this difference in similarity affects the bias remains unclear. To further investigate this question, we evaluate LLMs' preference in samples with different similarity gap $\Delta \sin$ between generated and retrieved contexts.

$$\Delta \sin = \frac{\sin(q, d^{\varrho}) - \sin(q, d^{\gamma})}{\sin(q, d^{\varrho}) + \sin(q, d^{\gamma})}$$

Specifically, we rank the samples according to $\Delta \sin$ and then divide the dataset into n (n=5 here⁷) slices with an equal number of samples. Subsequently, we calculate DiffGR for every slice.

Figure 8 illustrates the relationship between the average $\Delta \sin$ within each slice and the corresponding DiffGR, using Llama2-13b as both generator and reader. Results for other LLMs are presented in Appendix A.6, where similar conclusions are observed. In Figure 8, we observe a general trend that on slices with a larger average similarity gap, LLMs exhibit a increased preference for generated contexts 8. The stability of this trend is lower on NQ-AIR, which can be attributed to the smaller number of instances on NQ-AIR (87 instances per slice) as opposed to TQA-AIR (329 instances per slice). Overall, the notable variations in DiffGR with respect to the similarity gap indicate that text similarity is a significant factor in the preference for generated contexts. These findings suggest that generated contexts should be applied with greater caution to mitigate the influence of highly relevant but misleading information.

a DiffGR of 73.5%, compared to 48.2% in the slice with the lowest average Jaccard similarity gap.

⁶Similar observation and conclusion are observed in other settings.

 $^{^7}$ Similar results and observations are found with other n. 8 For example, on the TQA-AIR dataset, the slice exhibiting the highest average Jaccard similarity gap demonstrates

| Context | Length | Completeness | | Similarity | |
|-----------|--------|--------------|----------|------------|-----------|
| Comen | Zengui | Semantic | Sentence | Jaccard | BERTScore |
| Retrieved | 107.3 | × | × | 0.1167 | 0.8537 |
| Prompt | 106.0 | V | V | 0.1932 | 0.8753 |
| Trunc. | 106.2 | × | × | 0.1927 | 0.8753 |
| S-Trunc. | 105.1 | × | ~ | 0.1903 | 0.8748 |

Table 6: Context statistics with different completeness on NQ. Three types of generated contexts exhibit comparable average length, Jaccard and BertScore similarities.

| Context Pair | NQ-AIR | TQA-AIR |
|------------------------|--------|---------|
| Prompt vs. Retrieved | 84.54 | 79.38 |
| Trunc. vs. Retrieved | 65.58 | 65.56 |
| S-Trunc. vs. Retrieved | 65.06 | 64.64 |

Table 7: DiffGR (%) with different completeness in generated context. "Prompt", "Trunc." and "S-Trunc." represent three types of generated contexts with different completeness. GPT 3.5 is used as both the reader and generator. Random ordering is utilized when inputting context paris.

To facilitate understanding of the impact of this similarity gap on LLMs' preference, we include some examples about similarity in Appendix A.6.1. From these case, we observe that the similarity gap can reflect the disparity in the complexity of acquiring relevant information, which may partly leads to LLMs' preference. Concretely, contexts with greater similarity often support candidate answers in a more straightforward manner, for instance, by mirroring the phrasing used in the questions. Conversely, the contexts with low similarity introduce more challenges, often necessitating an understanding of synonyms and even some inferences.

5.3 Effect of Context Completeness

In all above experiments, there is a key difference between generated and retrieved contexts that may affects the context preference: **semantic and sentence completeness**. Concretely, current retrieval systems typically employ fixed-length truncation to divide a complete article into multiple passages, which serve as the fundamental units for retrieval tasks (Karpukhin et al., 2020; Wang et al., 2019; Zhu et al., 2021). This truncation often results in retrieved contexts with incomplete semantic meaning, as well as sentences that are cut off at beginnings or endings. In contrast, generated contexts in above experiments are naturally produced by LLMs, resulting in enhanced semantic and sentence completeness.

In this section, we conduct controlled experiments that vary the semantic and sentence completeness of generated contexts to investigate the potential effects of completeness on the observed bias. The following three methods are employed to produce generated contexts with different completeness:

- (a) **Prompt**: The prompt method, as used in all above experiments, incorporates length constraints into the prompt to facilitate the natural generation of contexts, leading to both semantic and sentence completeness.
- (b) **Truncation** (**Trunc.**): To simulate the incompleteness of retrieved contexts, we eliminate the length constraints from the prompt of Section 3, allowing LLMs to generate extended contexts. These generated contexts are then truncated to match the length of retrieved contexts, resulting in both semantic and sentence incompleteness.
- (c) Sentence Truncation (S-Trunc.): Based on method (b), we truncate generated contexts only at the end of a sentence to preserve the sentence completeness, while simulating the semantic incompleteness.

Table 6 demonstrates that three types of generated contexts have similar average lengths⁹ and similarities. This suggests that the influences of similarity and length are mitigated, thereby highlighting the principal disparities in semantic content and sentence completeness.

We evaluate LLMs' preference between generated versus retrieval context, varying the completeness of generated context, following the same pipeline in Section 4.1. Table 7 presents the DiffGR with different semantic and sentence completeness in generated contexts. A comparison between "Trunc." and "S-Trunc." reveals that sentence completeness does not significantly affect LLMs' preference for generated contexts. In contrast, comparing "Prompt" and "S-Trunc.", we find a significant increase in preference for generated contexts, when they are semantically more complete. These findings indicate that LLMs are sensitive to the semantic completeness of the contexts, underscoring the necessity to investigate im-

⁹The minor difference in average length between truncated and retrieved contexts results from a small samples (only 5 samples) where the generated contexts are shorter.

proved passage segmentation methods that maintain semantic completeness for current retrieval-augmented LMs.

6 Related work

6.1 Generation-Augmented Approaches

Generation-augmented approaches prompt LLMs to generate intermediate contexts for the final response, thereby leveraging their extensive parametric knowledge acquired during the pre-training phase on vast text corpora (Roberts et al., 2020; Petroni et al., 2019). Recent studies have demonstrated the effectiveness of these methods across a range of tasks. Liu et al. (2022) represents an early exploration into augmenting LLMs in commonsense reasoning tasks using knowledge generated by LLMs themselves. Sun et al. (2023); Yu et al. (2022) employ LLMs to produce background documents (or recitations) and subsequently use these documents to enhance LLM performance in knowledge-intensive tasks. Another researches, known as the chain-of-thought (Wei et al., 2022a; Kojima et al., 2022), prompts LLMs to generate intermediate reasoning steps to enhance LLMs' reasoning abilities. Desipte the effectiveness of these methods, the LLM-generated knowledge may contain hallucinations (Ji et al., 2023) due to LLMs' outdated memory (De Cao et al., 2021) and limited memory for long-tail knowledge (Kandpal et al., 2023). The LLM-generated inaccuracy information could potentially mislead current retrieval model (Dai et al., 2023) and open-domain question answering systems (Pan et al., 2023).

6.2 Retrieval-Augmented Approaches

The retrieval-augmented approaches (Guu et al., 2020; Lewis et al., 2020; Ram et al., 2023; Gao et al., 2023) enhance LLMs by incorporating relevant documents from external corpus. These approaches represent a promising direction for addressing the knowledge limitations of LLMs, such as the need for knowledge updates (Jang et al., 2022) and long-tail knowledge (Kandpal et al., 2023). Early retrieval-augmented methods (Guu et al., 2020; Lewis et al., 2020; Izacard et al., 2022) focused on the jointly training of LLMs and retrieval modules to improve their cooperation. With the evolution of general-purpose LLMs, recent studies (Ram et al., 2023; Shi et al., 2023) investigate the strategy of appending relevant documents directly to the input while keeping the LLMs

frozen. Despite the effectiveness of these methods, the retrieval-augmented approaches still face challenges due to irrelevant retrieval results and incomplete knowledge coverage (Yu et al., 2023; Mallen et al., 2023). These noisy retrieval results can misguide the outcomes of LLMs (Mallen et al., 2023; Anonymous, 2023; Ren et al., 2023).

6.3 Hybrid Approaches and Knowledge Conflicts

Recent works investigate to merge retrieved and generated contexts to leverage both parametric knowledge and external knowledge (Abdallah and Jatowt, 2023; Yu et al., 2022). These combination methods have shown improved performance over those relying solely on a single information source in fully-supervised setting. Furthermore, (Zhang et al., 2023) proposes an improved method to effectively leverage the two sources of information, especially when conflicts arise. While these works have focused on improving the efficacy of hybrid approaches, the underlying mechanisms by which LLMs process conflicting information from different types of contexts remain underexplored.

Current research on knowledge conflicts in LLMs primarily focuses on two aspects: conflicts between input contexts and LLMs' parametric memory, and conflicts among the input contexts themselves. Regarding the former, Xie et al. (2023); Chen et al. (2022) find that LLMs are highly receptive to the input contexts rather than their internal memory. Concerning conflicts within multiple input contexts, Chen et al. (2022) demonstrates that LLMs tend to rely on a few most relevant retrieved contexts. Additionally, Xie et al. (2023) reveals a confirmation bias, i.e., LLMs demonstrate a tendency to favor contexts that align with their parametric knowledge, when confronted with both supporting and opposing contexts. However, these studies are limited to analyzing context conflicts within a single type of input contexts. Our work complements these studies by considering conflicts between generated and retrieved contexts, and reveals several key factors, such as semantic completeness and text similarity.

7 Conclusion and Future work

In this study, we proposed a framework to investigate the underlying mechanisms by which LLMs merge retrieved and generated contexts. Our results reveal a pronounced bias towards generated con-

texts in several state-of-the-art LLMs (GPT 3.5/4, Llama2-7b/13b). We further identify two key factors contributing to this bias: higher similarity between generated contexts and questions, as well as the semantic incompleteness of retrieved contexts.

Our insights highlight the critical need for advanced integration methods that can validate and leverage information from both sources, moving beyond the current overreliance on generated contexts. Additionally, we find that LLMs display significant sensitivity to the semantic completeness of input contexts. This sensitivity necessitates improved passage segmentation strategies in current retrievalaugmented systems, thereby ensuring the preservation of intended meaning and the maximization of utility. Finally, addressing the challenges posed by highly relevant yet incorrect information generated by LLMs is an important direction for future research. It is crucial to develop methods for detecting and discounting misleading information produced by LLMs, especially as the volume of such content continues to escalate.

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A Appendix

A.1 Length Control for Generated Contexts

A.1.1 Length Distribution across LLMs

In our proposed framework, we regulate the length of generated contexts by incorporating length constraint in the prompt:

Generate a background context from Wikipedia to answer the given question {#question} Keep the length of the document around n words

We observed that GPT 4 effectively controls the output length, whereas other models struggle with this aspect. To address this issue in the latter, we employ multiple values of n and select the one that best matched the retrieved context.

As the result, Table 9 shows the length distribution of retrieved contexts and contexts generated by various LLMs. The length distribution of retrieved contexts is more concentrated due to the fact that these contexts consist of text truncated precisely at one hundred words, coupled with their titles (Karpukhin et al., 2020). Variations in the length of different retrieved articles are solely attributable to the differences in title lengths.

A.1.2 Length Distribution with Different Control Methods

Figure 10 illustrates the length distribution for generated contexts corresponding to three different length control methods. All three methods achieve a length distribution closely resembling that of the retrieved contexts.

A.2 Dataset Statistics

Table 8 presents the data size of context-conflicting datasets corresponding to various generator-reader pairs. The statistics indicate that conflicting data comprise a substantial proportion across all combinations of generators and readers.

A.3 Effect of Context Order

In above experiments, retrieved and generated contexts are presented with random order. Previous studies (Xie et al., 2023; Liu et al., 2023; Lu et al., 2022) have found that the model may be sensitive to the order of the input contexts. In their experiments, the input context was either all retrieved (Liu et al., 2023) or all generated (Xie et al., 2023). We conducted experiments to investigate whether the context order impacts the preference for the generated context. The generated and retrieved

contexts are concatenated with three different orders: generated-first, retrieved-first and random. We compute the context preference with different context order respectively.

As shown in Table 9, across all context orders, LLMs consistently show a strong tendency to generated contexts (generation ratio > 0). When the retrieved context is positioned first, there is a slight reduction in the generation ratio. This reduction may result from the LLMs' preference for generated contexts being partially offset by their bias towards the top context (Liu et al., 2023; Xie et al., 2023).

A.4 More Results on AIG Datasets

Figure 11 shows the DiffGR (%) with different (reader, generator) pairs on their corresponding NQ-AIG datasets. It can be observed that LLMs show strong tendency to rely on generated contexts across various (reader, generator) pairs.

A.5 More Details about preparing Counter-Memory Answers

To generate a counter-memory answer distinct from a given memory answer, we employ a LLM to associate a different entity of the same type. It is noteworthy that the prompt does not incorporate the question, ensuring that the LLM's counter-memory answer is merely a categorical equivalent rather than a memory related to the question. To better standardize the output of the LLM, we have manually crafted several examples to be included within the prompt:

Give you a reference word, transform it into a

analogous word.

Reference: Missouri River

Analogous Word: Mississippi River

Reference: {memory answer}

Analogous Word:

A.6 More Details about Similarity

Figure 12 and 13 show the similarity distribution of retrieved and generated contexts across various generators. All LLM-generated contexts exhibit a higher similarity over retrieved contexts.

Figure 14 illustrates the distribution of similarity when employing maximum and average aggregation methods. It is observable that the generated contexts exhibit a markedly higher degree of similarity regardless of the aggregation method used. Furthermore, this disparity in similarity is more

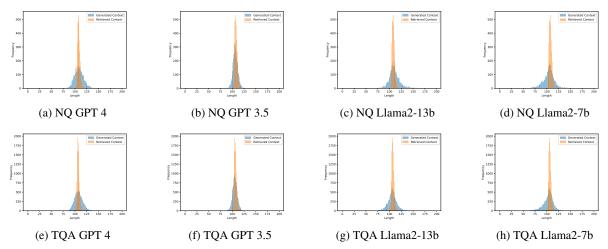


Figure 9: Length distribution of generated and retrieved contexts on different datasets with different generator models.

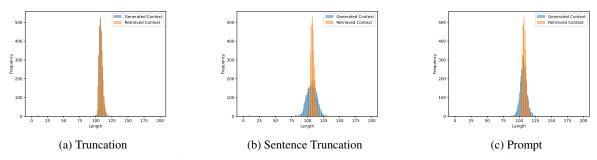


Figure 10: Length distribution of generated and retrieved contexts on the NQ dataset, with different methods to control the length of generated contexts.

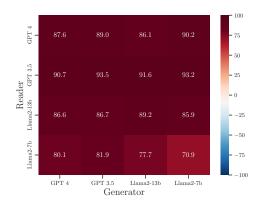


Figure 11: DiffGR (%) with different (reader, generator) pairs on their corresponding NQ-AIG datasets.

pronounced with maximum aggregation, as contexts typically contain sentences that are irrelevant, which dilute the similarity scores when an average aggregation is applied.

Figure 15 demonstrates a general trend that on slices with a smaller average similarity gap, LLMs exhibit a reduced preference for generated context. This trend is not stable on NQ-AIR, which can be

attributed to the smaller number of instances on NQ-AIR, as shown in Table 8.

A.6.1 Cases about Similarity

Table 10 shows examples that contain contexts with different similarity to the question. The contexts with high similarity typically directly support answering by repeating the phrasing in the question. Conversely, the contexts with low similarity introduce more challenges, often necessitating an understanding of synonyms and even some inferences. These observations indicate that text similarity can partly reflect the relevance between a question and a context, as well as the difficulty a LLM encounters in identifying potential answers.

| Reader | Generator | NQ (3610) | | TQA (11313) | |
|------------|------------|-----------|--------|-------------|---------|
| reader | Concrator | NQ-AIG | NQ-AIR | TQA-AIG | TQA-AIR |
| GPT 4 | GPT 4 | 331 | 238 | 946 | 358 |
| GPT 4 | GPT 3.5 | 282 | 291 | - | - |
| GPT 4 | Llama2-13b | 204 | 453 | - | - |
| GPT 4 | Llama2-7b | 168 | 492 | - | - |
| GPT 3.5 | GPT 4 | 453 | 247 | 1506 | 414 |
| GPT 3.5 | GPT 3.5 | 379 | 279 | 1357 | 567 |
| GPT 3.5 | Llama2-13b | 247 | 407 | 1000 | 1206 |
| GPT 3.5 | Llama2-7b | 187 | 456 | 823 | 1492 |
| Llama2-13b | GPT 4 | 735 | 246 | 2672 | 404 |
| Llama2-13b | GPT 3.5 | 656 | 287 | 2363 | 576 |
| Llama2-13b | Llama2-13b | 439 | 419 | 1648 | 1201 |
| Llama2-13b | Llama2-7b | 381 | 484 | 1430 | 1571 |
| Llama2-7b | GPT 4 | 803 | 211 | 2976 | 459 |
| Llama2-7b | GPT 3.5 | 722 | 243 | 2702 | 632 |
| Llama2-7b | Llama2-13b | 474 | 355 | 1966 | 1170 |
| Llama2-7b | Llama2-7b | 432 | 406 | 1737 | 1488 |

Table 8: The data quantities of the constructed subsets for different (Generator, Reader) pairs. NQ and TQA refer to the original complete test sets.

| Order | NQ-AIR | TQA-AIR |
|-----------------|--------|---------|
| generated-first | 69.9 | 68.2 |
| retrieved-first | 66.5 | 55.6 |
| random | 69.1 | 58.6 |

Table 9: The generation ratio (%) with different context order on NQ-AIR and TQA-AIR datasets. The backbone LLM is GPT 3.5.

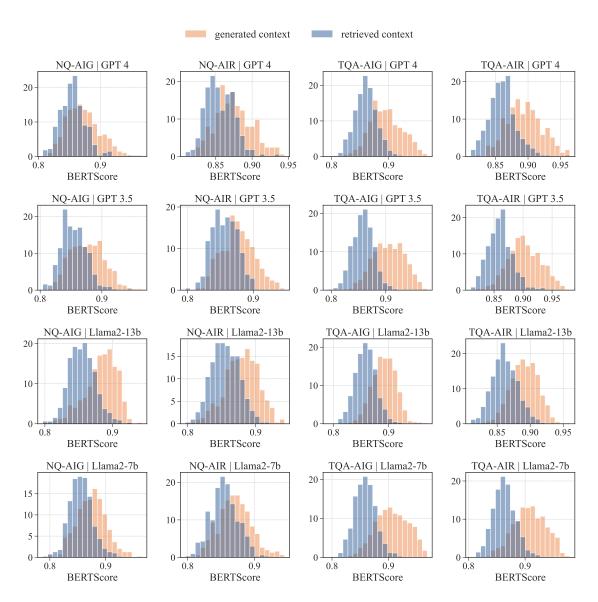


Figure 12: BERTScore distribution of retrieved context and context generated by different LLMs.

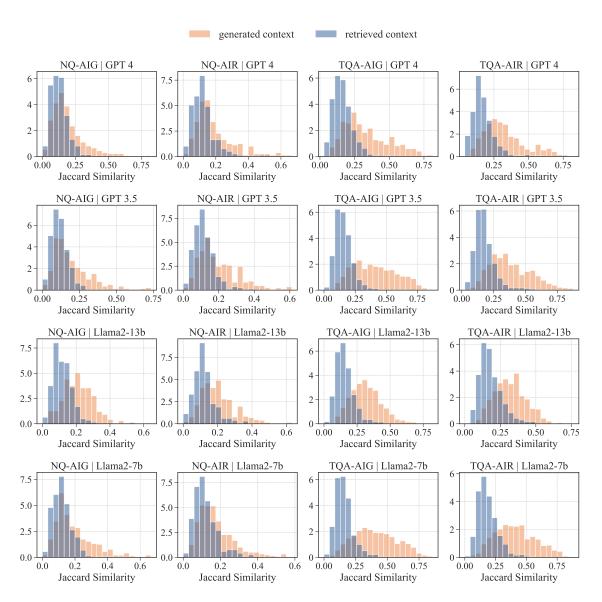


Figure 13: Jaccard Similarity distribution of retrieved context and context generated by different LLMs.

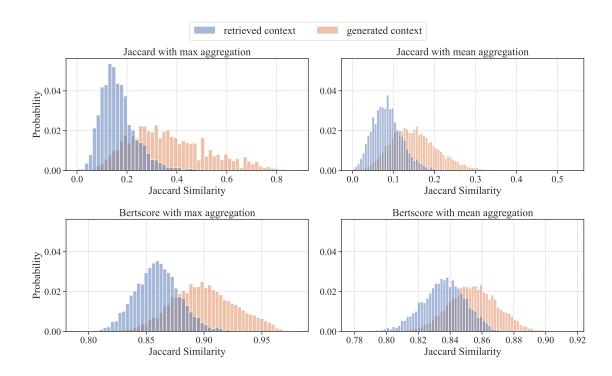


Figure 14: Similarity distribution with maximum or mean aggregation strategies. Generated contexts consistently exhibit higher similarity across two aggregation strategies.

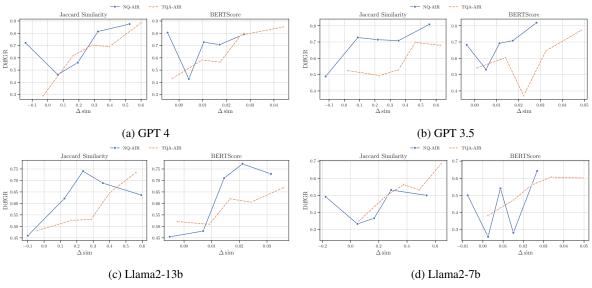


Figure 15: The generation ratio in slices with different average $\Delta \sin$. $\Delta \sin$ is the difference in similarity between the generated context and the retrieved context.

| | TQA-AIR Example | TQA-AIG Example |
|-------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Question | Between 1959 and 1967 which city was the capital of Pakistan (Islamabad was being built)? | Who is the most successful UK solo artist in the USA? |
| Golden Answer | Rawalpindi | Elton John |
| Generated Context | Between 1959 and 1967, the capital of Pakistan was Karachi. Karachi is the largest city in Pakistan and is located on the southern coast of the country Jaccard Similarity: 0.47 BertScore: 0.93 | Elton John is the most successful UK solo artist in the USA. Born Reginald Kenneth Dwight in 1947, he adopted the stage name Elton John in the late 1960s Jaccard Similarity: 0.69 BertScore: 0.93 |
| Retrieved Context | was first shifted temporarily to Rawalpindi in the early 60s, and then to Islamabad when essential development work was completed in 1966 Jaccard Similarity: 0.16 BertScore: 0.85 | In 2009, Jay Sean's single "Down" reached the number one spot on the "Billboard" Hot 100 and sold millions in the United States, making him the most successful male UK urban artist in US chart historyät the time Jaccard Similarity: 0.14 BertScore: 0.86 |
| Model output | Karachi | Elton John |

Table 10: Some examples where both the generator and reader are GPT-3.5. We highlight the incorrect candidate answers in the context in pink, and the correct answers in the context in green.