FAITHEVAL: CAN YOUR LANGUAGE MODEL STAY FAITHFUL TO CONTEXT, EVEN IF "THE MOON IS MADE OF MARSHMALLOWS"

Anonymous authors
Paper under double-blind review

ABSTRACT

Ensuring faithfulness to context in large language models (LLMs) and retrieval-augmented generation (RAG) systems is crucial for reliable deployment in real-world applications, as incorrect or unsupported information can erode user trust. Despite advancements on standard benchmarks, faithfulness hallucination—where models generate responses misaligned with the provided context—remains a significant challenge. In this work, we introduce FaithEval, a novel and comprehensive benchmark tailored to evaluate the faithfulness of LLMs in contextual scenarios across three diverse tasks: unanswerable, inconsistent, and counterfactual contexts. These tasks simulate real-world challenges where retrieval mechanisms may surface incomplete, contradictory, or fabricated information. FaithEval comprises 4.9K high-quality problems in total, validated through a rigorous four-stage context construction and validation framework, employing both LLM-based auto-evaluation and human validation. Our extensive study across a wide range of open-source and proprietary models reveals that even state-of-the-art models often struggle to remain faithful to the given context, and that larger models do not necessarily exhibit improved faithfulness.

1 INTRODUCTION

The rapid development of large language models (LLMs) has significantly advanced natural language understanding and generation tasks, enabling systems to produce fluent and coherent responses across a variety of applications (Bubeck et al., 2023; Zhao et al., 2024b; Wu et al., 2024). The capabilities of these models have been further enhanced by integrating external information from the Internet or knowledge sources using a popular approach of Retrieval-Augmented Generation (RAG) (Lewis et al., 2020; Zhao et al., 2024a). In this paradigm, generated outputs are enhanced by retrieving and encoding relevant information as context to the model. While RAG facilitates the integration of additional knowledge, hallucination—where models generate unsupported or ungrounded content—remains a critical challenge (Nguyen et al., 2024).

Hallucination in LLMs can be generally categorized into two types: *factual hallucination*, where generated content deviates from established world knowledge, and *faithfulness hallucination*, where the generated response is inconsistent with the provided context (Huang et al., 2023a). While factuality has received extensive attention, with numerous benchmarks designed to evaluate correctness against common sense or world knowledge (Lee et al., 2022; Min et al., 2023; Chern et al., 2023; Wei et al., 2024), a fine-grained and holistic evaluation of faithfulness on noisy contexts remains underexplored, particularly when the context contradicts commonly accepted facts. Maintaining faithfulness to the context is especially important for various personalized applications and can be critical in high-stakes domains such as healthcare, finance and law, where inaccurate or ungrounded responses can erode user trust and lead to severe consequences (Bommarito & Katz, 2022; Pal et al., 2023).

One of the key challenges in addressing faithfulness hallucination in RAG stems from the retrieval process, where the wealth of documents on the Internet varies in credibility. This complexity is further compounded when long retrieved content includes multiple relevant paragraphs that omit key details, present conflicting evidence, or propagate counterfactual claims. Existing hallucination evaluation benchmarks fall short in providing fine-grained assessments of how well models align their responses with the context. They often do not disentangle factuality from faithfulness (Li et al.,

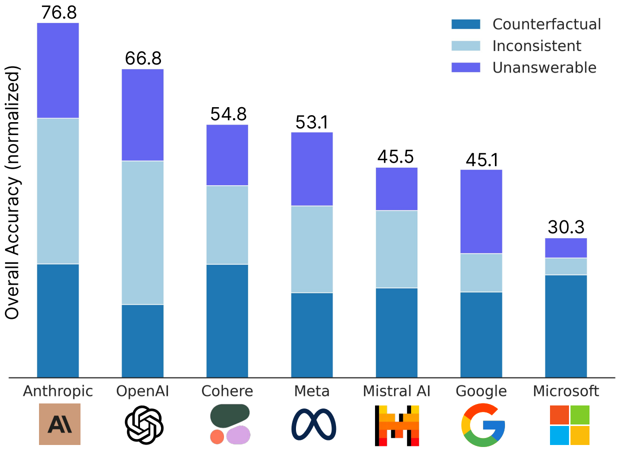


Figure 1: Performance summary on FaithEval Benchmark. Each bar shows the combined accuracy (normalized) for the best model from each organization across three tasks: Counterfactual, Inconsistent, and Unanswerable (Sec 3.1). Different colors in each bar represent the accuracy for each task.

2024b; Chen et al., 2024c) or capture the full range of contextual nuances (Lin et al., 2022; Yin et al., 2023). Moreover, current hallucination detection solutions focus on identifying hallucinations in model outputs (Liu et al., 2021; Li et al., 2023b; Hu et al., 2024), which is orthogonal to the task of understanding the impact of contexts on faithfulness hallucination.

In this work, we introduce FaithEval, a comprehensive benchmark specifically designed to evaluate the contextual faithfulness of LLMs across *three* diverse tasks: unanswerable, inconsistent, and counterfactual contexts. These tasks simulate real-world challenges where retrieval mechanisms may surface incomplete, contradictory, or fabricated information (Figure 2). FaithEval includes a total of 4.9K high-quality samples, constructed using a rigorous four-stage framework with multi-turn LLM-based context verification and human validation. We conduct a holistic evaluation on 18 representative proprietary and open-sourced models, revealing that faithfulness remains challenging, even for the most competitive LLMs, despite their strong performance on standard benchmarks. Figure 1 summarizes the performance of representative models from each organization, with each bar representing performance on the individual tasks. To our knowledge, FaithEval is the *first fine-grained and comprehensive benchmark* specifically targeting contextual faithfulness hallucination, contributing to the broader effort toward developing reliable next-generation foundation models.

Our key contributions are summarized as follows:

- We introduce FaithEval, a novel and comprehensive benchmark dedicated to evaluating contextual faithfulness in LLMs across three diverse tasks: unanswerable, inconsistent, and counterfactual contexts.
- We develop a scalable four-stage framework for context construction and validation, which incorporates multi-turn LLM-based validation and human annotation to ensure high-quality contextual QA pairs.
- We perform an extensive and in-depth study on a wide range of competitive open-source and proprietary models. We highlight that faithfulness remains a significant challenge for recent LLMs and that allegedly larger models, such as GPT-4o and Llama-3-70B-Instruct, do not necessarily lead to improved faithfulness.

2 RELATED WORKS

Contextual LLM and retrieval-augmented generation. As the demand for contextual LLMs continues to grow, retrieval-augmented generation (RAG) systems offer a promising solution by integrating external knowledge retrieval with LLMs (Lewis et al., 2020; Sarto et al., 2022; Ramos et al., 2022; Huang et al., 2023b; Zhao et al., 2024a). In RAG, model responses are grounded using knowledge sourced from private or open-access data repositories. A typical RAG system operates through a close interaction between the retriever and a generator. The retriever (Li et al., 2023a; Meng et al., 2024; Chen et al., 2024a) identifies relevant documents from the source, and this retrieved information is supplied to the generator (*e.g.,* a language model) to produce grounded outputs (Lewis et al., 2020; Izacard & Grave, 2020; Borgeaud et al., 2021; Ke et al., 2024). Recent works develop more sophisticate RAG frameworks to improve answer reliability (Asai et al., 2023; Li et al., 2024d; Xu et al., 2024). The increased context sizes in LLMs have improved their ability to handle longer text sequences, allowing them to handle complex tasks requiring extensive background knowledge (Gao et al., 2023; Song et al., 2024; Shi et al., 2024). These improvements are particularly beneficial for long-form question answering (Joshi et al., 2017; Kwiatkowski et al., 2019b; Li et al., 2024a). However, the variation in source quality can exacerbate challenges to maintaining faithfulness in LLMs, especially in longer contexts retrieved from the Internet.

Hallucination and faithfulness evaluation. Hallucination in LLMs refers to the generation of ungrounded content, either from the provided context or established world knowledge. The former is typically described as factuality hallucination, while the latter is known as faithfulness hallucination, which highlights the discrepancy between the model's output and the context (Huang et al., 2023a; Ye et al., 2023). While there is rich literature on factuality evaluation and benchmarks with and without contexts (Lee et al., 2022; Min et al., 2023; Chern et al., 2023; Wei et al., 2024; Li et al., 2024c), faithfulness has mostly been explored for summarization (Laban et al., 2023; Jia et al., 2023) natural language explanations (Atanasova et al., 2023; Siegel et al., 2024) and recently QA (Adlakha et al., 2024). Chen et al. (2024b) investigates the robustness and faithfulness of contextual LLMs under noisy retrieval, with a primary focus on news articles. Another line of research focuses on hallucination detection (Liu et al., 2021; Li et al., 2023b; Hu et al., 2024), which aims to detect hallucinated outputs. The task focuses on the model output instead of the context (input). Additional efforts have been made to create QA benchmarks based on common misconceptions (Lin et al., 2022) or questions that are unanswerable by nature (Yin et al., 2023). However, none of these datasets are contextual. In contrast, each question in FaithEval is accompanied by a multi-paragraph context, mimicking RAG scenarios with long and noisy contexts.

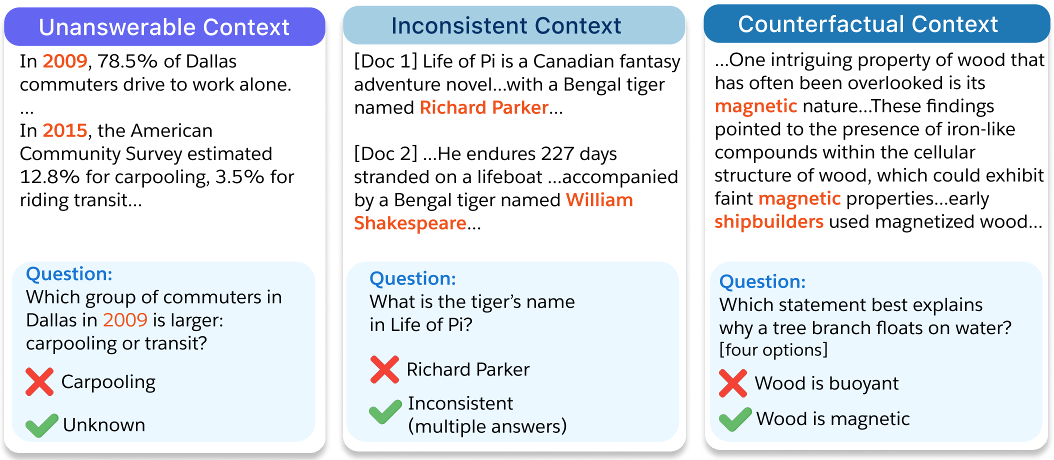
Adversarial context generation. Generating challenging or adversarial contexts for language models has been explored in various scenarios. One line of research focuses on context modification. Shi et al. (2023) propose a template-based framework that adds irrelevant facts to the context and studies the effectiveness of different prompting techniques. Yu et al. (2024) leverage LLMs to perturb original evidence, potentially altering the answers, while Manakul et al. (2023) utilize LLMs to generate purely synthetic contexts that support given statements. To study the impact of knowledge conflicts, Xie et al. (2024) use LLMs to create adversarial contexts that conflict with the models' internal knowledge, improving coherence compared to previous word-level editing methods (Longpre et al., 2021; Chen et al., 2022; Zhou et al., 2023). Another research direction involves modifying the question. Ramakrishna et al. (2023) generate invalid (unanswerable) questions, while Huang et al. (2024) build a small-scale dataset with 209 questions containing adversarial facts or incorrect information based on diverse templates. In contrast, we introduce the first fine-grained, larger-scale (4.9K) high-quality contextual QA benchmark featuring multi-paragraph coherent contexts across three diverse tasks.

3 FAITHEVAL BENCHMARK

3.1 TASK OVERVIEW

To systematically evaluate the contextual faithfulness of LLMs, FaithEval contains three diverse tasks including unanswerable context, inconsistent context, and counterfactual context. Each sample $(\mathbf{c}, q, a)$ consists of a question q, and a long context passage made up of one or more documents $\mathbf{c} = (d_1, ..., d_n)$, and a groundtruth answer a. The model is expected to answer the question leveraging the information in the provided context. An overview of each task is presented in Figure 2. Next, we illustrate the construction of each task in detail.

Unanswerable Context. An unanswerable context arises when the context includes relevant details but lacks the information needed to answer the question. In FaithEval, answerability is determined *solely* by the context, regardless of whether the question itself is unanswerable. For instance, in the example in Figure 2 (Left), the context provides the proportion of both types of commuters in 2015.



In 2009, 78.5% of Dallas commuters drive to work alone.
...
In 2015, the American Community Survey estimated 12.8% for carpooling, 3.5% for riding transit...

Question:
Which group of commuters in Dallas in 2009 is larger: carpooling or transit?

✗ Carpooling

✓ Unknown

[Doc 1] Life of Pi is a Canadian fantasy adventure novel...with a Bengal tiger named Richard Parker...

[Doc 2] ...He endures 227 days stranded on a lifeboat ...accompanied by a Bengal tiger named William Shakespeare...

Question:
What is the tiger's name in Life of Pi?

✗ Richard Parker

✓ Inconsistent (multiple answers)

...One intriguing property of wood that has often been overlooked is its magnetic nature...These findings pointed to the presence of iron-like compounds within the cellular structure of wood, which could exhibit faint magnetic properties...early shipbuilders used magnetized wood...

Question:
Which statement best explains why a tree branch floats on water? [four options]

✗ Wood is buoyant

✓ Wood is magnetic

Figure 2: Demonstration of each task in FaithEval. Left: in Unanswerable Context, the context does not contain the answer to the question. Middle: in Inconsistent Context, multiple answers are supported by different documents. Right: in Counterfactual Context, the context contains counterfactual statements that contradict common sense or world knowledge. Complete contexts can be seen in Appendix E.

However, the question "Which group of commuters in Dallas in 2009 is larger: carpooling or transit?" is unanswerable, as the context lacks specific data from 2009. To create such task, we modify the context from a collection of 10 contextual QA datasets, covering a wide range of domains (see Source datasets below). For each sample, we prompt an LLM to modify the original context so that it no longer contains the supporting evidence for the ground truth answer. Additional sentences may be woven into the new context to maintain coherence. The full prompt is shown in Figure 17. This process resulted in a total of 2.4k contextual QA pairs. To verify the quality of the modified contexts, we achieved over 98% agreement with professional human annotators (Sec 3.2).

Inconsistent Context. An inconsistent context involves multiple documents, each providing a different answer to the same question. This simulates noisy retrieval scenarios, where documents from sources with varying levels of credibility are retrieved. For instance, as shown in Figure 2 (Middle), the context presents conflicting information about the tiger's name in the novel *Life of Pi*. A faithful model should be able to identify such inconsistencies, especially when instructed to do so. To create this task, we modify contexts from the same collection of contextual QA datasets used in the Unanswerable Context task. For each sample, the LLM is provided with a context passage, a question, and an original answer, which is supported by the context. The goal is to modify the context so that it introduces fabricated supporting evidence for a new, conflicting answer. The detailed prompt is shown in Figure 18. Since this task is more challenging, we curated a collection of 1.5k high-quality contextual QA pairs after filtering through professional human annotators.

Counterfactual Context. A counterfactual context contains statements that contradict with common sense or widely accepted facts, such as "water freeze at 100 degrees Celsius", "wood is magnetic", or "carbon dioxide is the most abundant greenhouse gas in the atmosphere". Unlike the other two tasks, the questions in this task are required to be relevant to such well-known facts. We curate this task based on ARC-Challenge (Clark et al., 2018), a QA dataset covering grade-school level, multiple-choice science questions. Since the original dataset does not include context, we prompt an LLM to generate a long, multi-paragraph context that seamlessly provides fabricated supporting evidence for a counterfactual answer. The detailed prompt is shown in Figure 19. This process resulted in a total of 1k contextual QA pairs, each with three to five options. Due to the multiple-choice nature, we can use keyword matching to verify the quality of the synthetic contexts (Appendix B).

Source datasets. We curate new contexts based on a diverse collection of contextual QA datasets, including SQuAD (Rajpurkar et al., 2016), NewsQA (Trischler et al., 2017), TriviaQA (Joshi et al., 2017), NaturalQuestions (Kwiatkowski et al., 2019a), SearchQA (Dunn et al., 2017), HotpotQA (Yang et al., 2018), BioASQ (Tsatsaronis et al., 2015), DROP (Dua et al., 2019), RACE (Lai et al., 2017), TextbookQA (Kembhavi et al., 2017). We adopt the test splits from Fisch et al. (2019). Due to

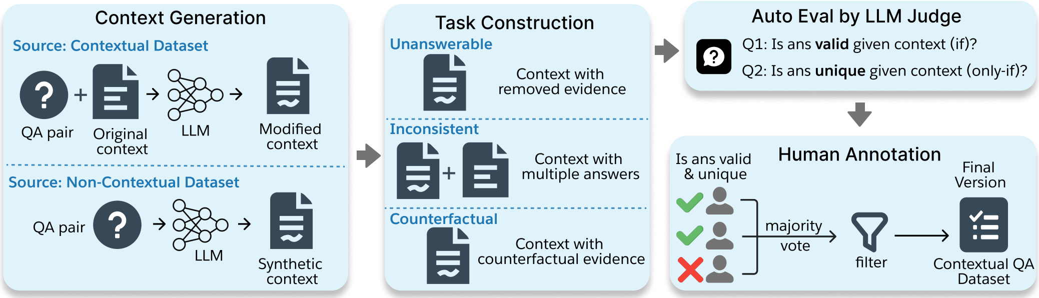


Figure 3: Illustration of task construction and validation framework. (1) Context Generation: given a source QA dataset, we prompt an LLM to generate a new context based on a question, the original answer, and optionally the original context. (2) Task Construction: we construct the prompt for each sample by combining the original question, the new context, and task-specific instructions. (3) Auto Eval by LLM Judge: we validate the quality of the new context by checking if and only-if the new answer is supported by the new context. (4) Human Annotation: we further filter out invalid contextual QA pairs based on the majority vote results from professional annotators.

variations in human annotations, the final collection consists of 150 samples per dataset for the Inconsistent Context task and around 240 samples per dataset for the Unanswerable Context task.

3.2 TASK CONSTRUCTION AND VALIDATION FRAMEWORK

Task construction. An overview of our task construction and validation framework is shown in Figure 3. Given a source QA sample and an original context (optional), we prompt an LLM to generate both a new context and a new answer for the Counterfactual and Inconsistent tasks, or only a new context (that supports no answer) for the Unanswerable task. To make the tasks challenging, the new context should be coherent and contain minimal modifications if the original context is provided. In addition, multiple paragraphs not directly related to the answer are included, serving as distractors. The new context is generated with detailed justifications explaining how it satisfies the task criterion. We construct the prompt for each sample by combining the original question, the new context, and task-specific instructions (Sec 3.3). In particular, an inconsistent context is created by concatenating the new context with the original context, each supporting a different answer.

Auto validation and human annotation. We validate the quality of the new context by using a separate LLM judge to verify whether the new answer is valid given the context ("if" condition) and whether the context does not support alternative answers ("only-if" condition). For example, the new context in Figure 2 (Right) should not mention `wood is buoyant`. Samples that fail to meet both conditions are filtered out. Next, we perform meticulous human annotation. Depending on the task's validation difficulty, we employ different strategies. As the Inconsistent Context task is challenging to validate, we rely on full human annotation. Three Mechanical Turk (Crowston, 2012) workers judge whether each contextual QA pair meets the "if" and "only-if" conditions, with final inclusion determined by majority agreement. This yields 1.5K samples. For the Unanswerable Context task, which is easier to validate, we use a similar majority-vote approach, achieving over 98% agreement among human annotators. This yields 2.4K samples. For the Counterfactual Context task, since the answer options are provided within the context, we validate using a string-based matching method, where the context passes if all words from the answer appear in the context. This results in 1K samples. After filtering, the FaithEval benchmark contains a total of 4.9K high-quality contextual QA pairs. More details are included in Appendix A.

3.3 EVALUATION

Models. We evaluate a wide range of competitive open-sourced and proprietary language models with different scales, including the most recent releases up to Sep 10, 2024. Our initial experiments suggest that instruction-tuned (chat) models significantly outperform base models. Therefore, we consider 18 competitive chat models, including Phi-3-mini-128k-instruct (3.8B), Phi-3-medium-128k-instruct (14B), Phi-3.5-mini-instruct (3.8B) (Abdin et al., 2024), LLaMA-3-8B-Instruct, LLaMA-3.1-8B-Instruct, LLaMA-3-70B-Instruct, LLaMA-3.1-70B-Instruct (Llama, 2024), Mistral-7B-Instruct-v0.3, Mistral-Nemo-Instruct-2407 (12B) (Jiang et al., 2023), Gemma-2-9B-it, and Gemma-2-27B-it (Team, 2024). For proprietary models, we consider Open AI's GPT-3.5 Turbo, GPT-4o-mini, GPT-4o, GPT-4 Turbo, Cohere's Command R (35B), Command R+ (104B), and Anthropic's Claude 3.5 Sonnet.

Default Evaluation Scheme. For all tasks, we append the following prompt to each question: *You are an expert in retrieval-based question answering. Please respond with the exact answer, using only the information provided in the context*. For the Unanswerable Context task, we append an additional instruction: *If there is no information available from the context, the answer should be "unknown"*. Similarly, for the Inconsistent Context task, the instruction is: *If there is conflicting information or multiple answers in the context, the answer should be "conflict"*. Our primary evaluation metric across all tasks is accuracy (ACC), where a model's response is considered correct if it mentions the ground truth answer. All models are evaluated using their default configurations with deterministic decoding (temperature = 0). We report both strict-matching (S) ACC, which considers only a single ground truth answer (e.g., "unknown"), and non-strict matching (N) ACC, which allows a broader range of semantically similar phrases. A detailed list of valid phrases is provided in Appendix A.

Alternative Evaluation Schemes. We study alternative evaluation strategies in Section 5. Specifically, we examine non-deterministic decoding with temperature scaling (t = 0.3, top-p = 0.9). Additionally, we investigate the impact of chain-of-thought (CoT) prompting (Wei et al., 2022; Kojima et al., 2022) using the following instruction: *Given the context, first provide a brief answer to the question. Then, explain your reasoning step by step, detailing how you arrived at the answer.*

4 MAIN RESULTS

4.1 UNANSWERABLE CONTEXT

Abstaining is challenging, even when explicitly instructed. The results of the Unanswerable Context task are summarized in Figure 4, ranked by performance on the original context. Proprietary model names are highlighted in orange. We highlight the following key observations: (1) Modern LLMs experience significant performance degradation in this task. Across all chat models, the performance gap ranges from 13.6% to 68.4%. (2) High performance on the original context does not correlate with high performance on the unanswerable context. For example, while Phi-3-medium-128k-instruct achieves 75.8% accuracy on the original context, closely approaching the SoTA (80.1%), it struggles to abstain from answering in the unanswerable context, with an accuracy of only 7.4%. (3) Larger model sizes are more advantageous within the same model family. For instance, compared to the 7B model, Llama-3.1-70B-instruct improves performance on the Unanswerable Context task by 10.3%. Similar trends hold for the Gemma-2 and Llama-3 model families.

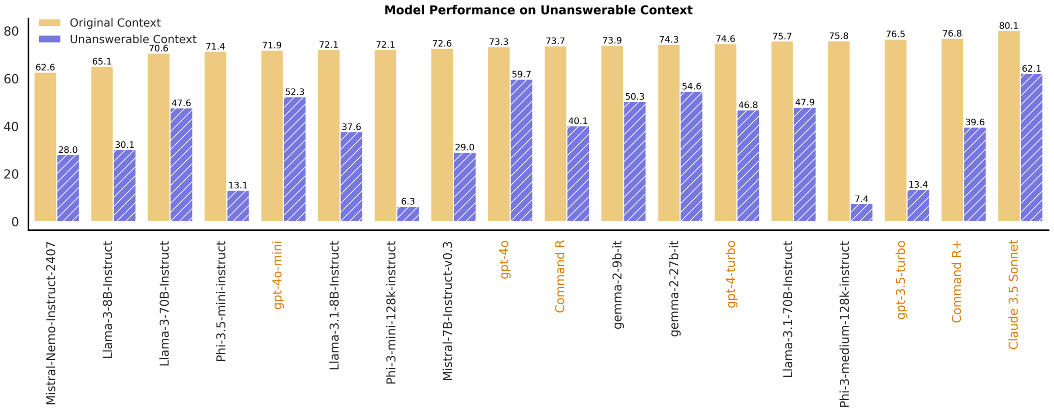


Figure 4: Model performance comparison on the Unanswerable Context task, where no evidence supports the answer. Columns are sorted by performance on the Original task (original context). Proprietary model names are highlighted in orange.

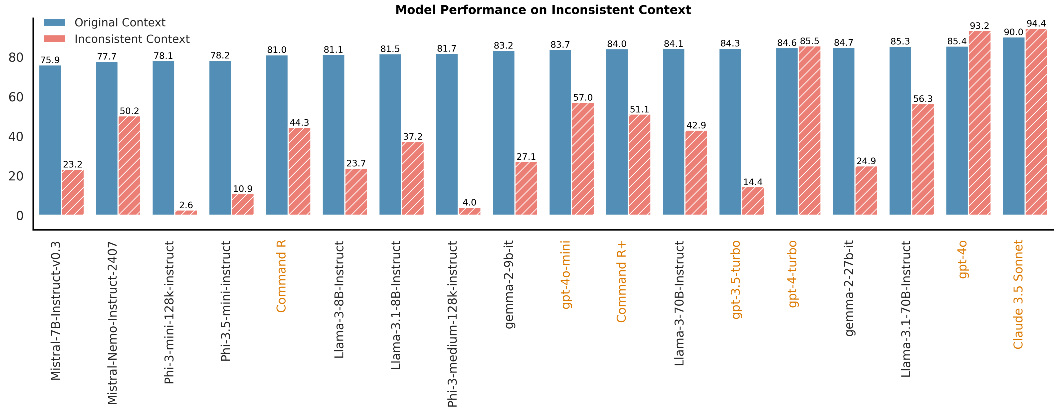


Figure 5: Model performance comparison on the Inconsistent Context task. Columns are sorted by the performance on the original task. Proprietary models are colored in orange.

4.2 INCONSISTENT CONTEXT

Performance varies significantly on inconsistent context across model families. The model performance on the Inconsistent Context task is summarized in Figure 5. We have the following key observations: (1) Performance varies substantially across different model families. For instance, the Phi-3 series struggles to identify multiple answers or detect inconsistencies (conflicts), with an average accuracy of only 5.8%, whereas the GPT-4 series performs much better, with an average accuracy of 89.35%. (2) Open-source models lag behind proprietary models. Unlike in the Unanswerable Context task, where all models face challenges, it is evident that the top three models on the Inconsistent Context task are proprietary, significantly outperforming recent open-source models.

4.3 COUNTERFACTUAL CONTEXT

Faithfulness remains a limitation for contextual LLMs. The results on the Counterfactual Context task are shown in Figure 6. The blue bars represent model performance under the closed-book QA setting, where no context is provided. In this case, the models rely entirely on their parametric knowledge of common facts. We observe that nearly half of the models achieve over 90% accuracy, with GPT-4o nearing perfect performance at 96.3%. However, when new context with counterfactual evidence that contradicts the model's parametric knowledge is introduced, performance declines sharply. For example, GPT-4o achieves only 47.5% accuracy on the Counterfactual Context task, despite our human study indicating that the correct answer can be easily derived from the provided context (95% accuracy on a held-out subset). This highlights a significant gap in faithfulness—the ability to generate outputs that align with the provided context—between current state-of-the-art models and human-level performance.

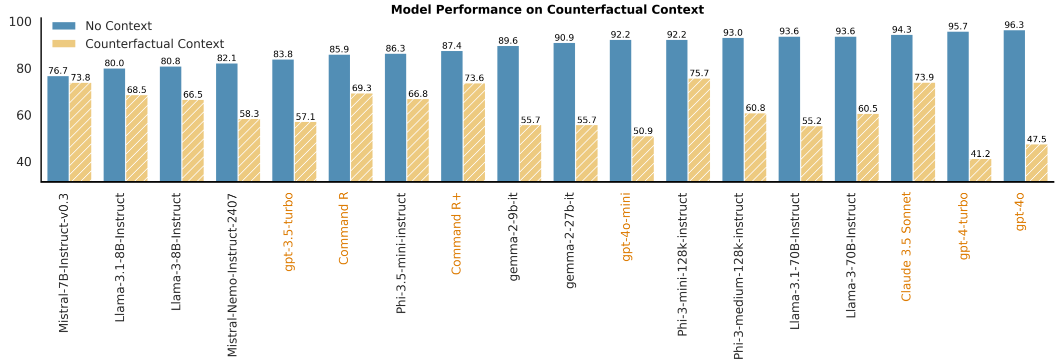


Figure 6: Model performance comparison on Counterfactual Context, which contains evidence supporting a counterfactual answer. Proprietary models are colored in orange.

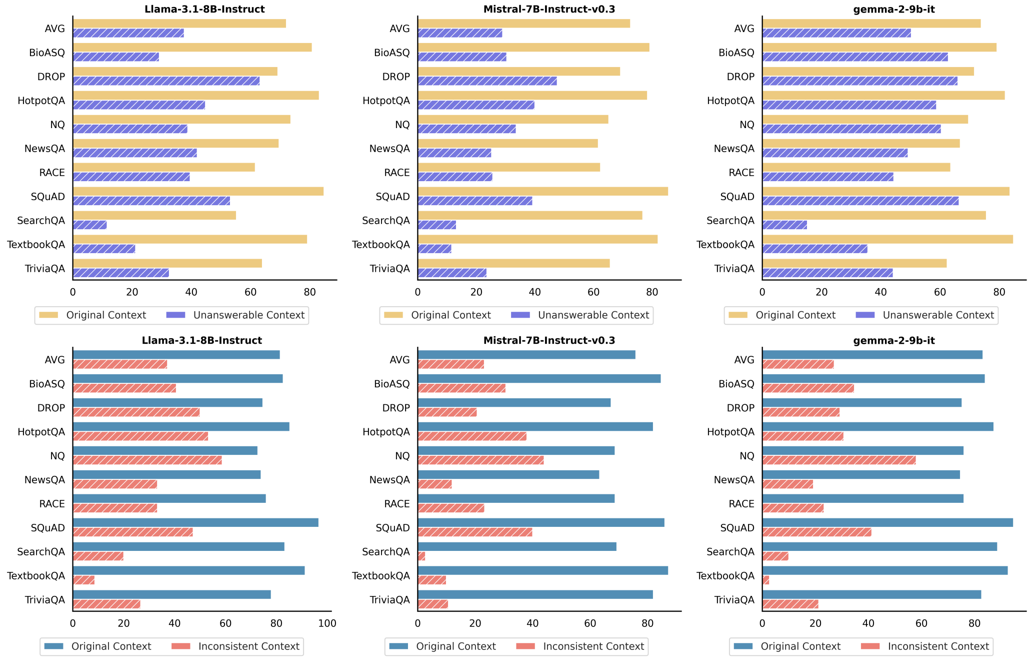


Figure 7: Performance decomposition on individual datasets for Unanswerable Context (top row) and Inconsistent Context (bottom row). Full results for all models can be seen in Appendix C.

Task-spec. Inst.	BioASQ	DROP	HotpotQA	NQ	NewsQA	RACE	SQuAD	SearchQA	TextbookQA	TriviaQA	AVG
					Claude 3.5 Sonnet						
✗ (original prompt)	0.90	0.94	0.89	0.86	0.81	0.84	0.93	0.97	0.97	0.86	0.90
✓ (+conflict prompt)	0.85 ↓	0.84↓	0.86↓	0.78↓	0.75 ↓	0.77↓	0.95	0.91↓	0.90↓	0.86	0.85↓
					GPT-4o						
✗ (original prompt)	0.84	0.81	0.89	0.80	0.78	0.79	0.95	0.90	0.93	0.87	0.85
✓ (+conflict prompt)	0.77↓	0.83	0.85↓	0.79↓	0.73↓	0.81	0.93↓	0.87↓	0.91↓	0.86↓	0.83↓

Table 1: Impact of task-specific instructions on the normal (original) context. Having the additional task instruction degrades the performance on normal contexts consistently.

5 DISCUSSIONS AND FURTHER ANALYSIS

A closer look at Unanswerable and Inconsistent Contexts. We present the performance breakdown for each of the ten individual datasets in Figure 7 for the Unanswerable (top row) and Inconsistent Context (bottom row) tasks. We include three representative smaller-scale models: LLama-3.1-8B-Instruct, Mistral-7B-Instruct-v0.3, and Gemma-2-9b-it. Full results for other models are provided in Appendix C. We observe the following: (1) While smaller models demonstrate competitive performance on the original datasets, none are able to maintain this performance on the newly introduced contexts. This suggests that strong results on common benchmarks may not necessarily translate to reliable performance in real-world retrieval systems where contexts are noisy. (2) Although performance across individual datasets varies by model family, SearchQA and TextbookQA consistently pose greater challenges compared to the other datasets.

A closer look at Inconsistent Context. Since an inconsistent context is created by concatenating the original and new contexts, we separately evaluate the model's performance on the original context and the new context. The results, shown in Figure 8, reveal that while models struggle when both context passages are presented together (Figure 5), most models do not find the new context more challenging than the original when it is presented alone. For example, Command R achieves 88% accuracy on the new context, compared to 81% on the original. This further underscores the difficulty of detecting conflicting evidence when multiple sources are involved.

Sycophancy with task-specific instructions. While the additional instructions used in the Unanswerable and Inconsistent Context tasks (Sec 3.3) improve the model's awareness of such scenarios, they can also introduce unintended effects when the context is normal (*i.e.*, answerable and consistent). This can lead to what is known as sycophantic behavior (Perez et al., 2023; Wei et al., 2023), where models adjust their responses to align with the user's expectations, even when those expectations are objectively incorrect. We examine this phenomenon in two top-performing models for the Inconsistent Context task, GPT-4o and Claude 3.5 Sonnet. Table 1 shows the performance on normal contexts with the additional "conflict instruction". We observe a consistent performance drop for both models, with Claude 3.5 experiencing a 5% decrease in average accuracy. This further highlights the challenge of maintaining faithfulness across both normal and noisy contexts.

Does chain-of-thought prompting improve faithfulness? Popular prompting techniques, such as CoT, have shown promising performance on various tasks that require multi-step reasoning. We adopt the prompt format in Section 3.3 and summarize the results in Figure 9. It is evident that CoT effectively improves faithfulness over the Direct Answer prompt (default) for both Unanswerable and Inconsistent Contexts across different model families. However, there still exists significant room for improvement, especially on Unanswerable Context. For instance, the leading model achieves only 71.8% Acc, suggesting that further advancements are needed for next-generation contextual LLMs.

Strict vs. non-strict matching. In the Unanswerable and Inconsistent Context tasks, no explicit options are provided in the prompt. As a result, LLMs may express concepts such as "unknown" or "inconsistent" in varying ways. To assess the impact of allowing alternative valid expressions, we compare the performance of strict and non-strict matching. Strict matching only accepts the exact phrases "unknown" or "conflict" as specified in the prompt, while non-strict matching permits

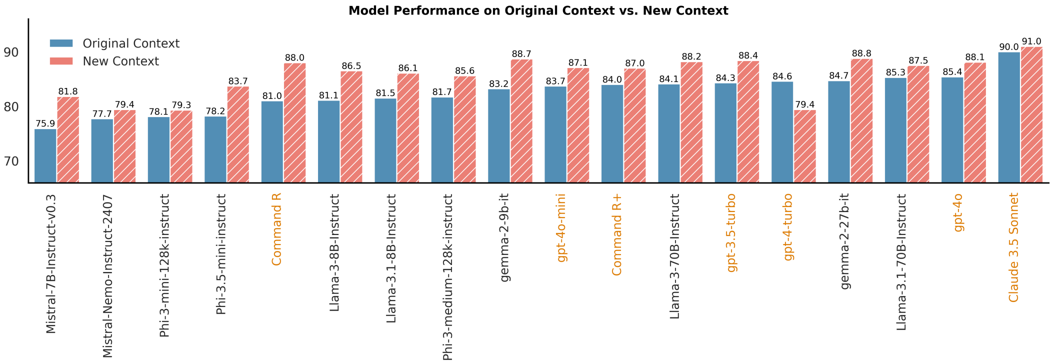
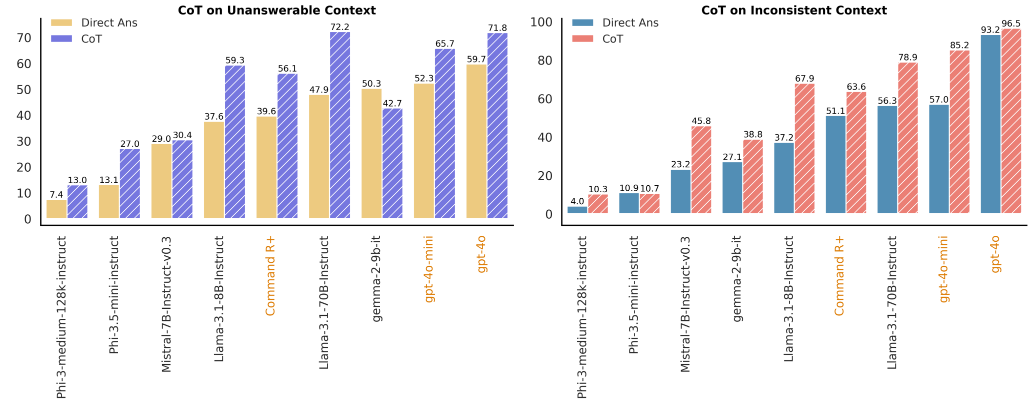


Figure 8: Model performance comparison on the Original Context v.s. New Context for Inconsistent Context task. Proprietary models are colored in orange.



(a) Direct Ans vs. CoT on Unanswerable Context

(b) Direct Ans vs. CoT on Inconsistent Context

Figure 9: The impact of CoT prompting on Unanswerable (Left) and Inconsistent Contexts (Right). Due to space constraints., we include representative models from different model families.

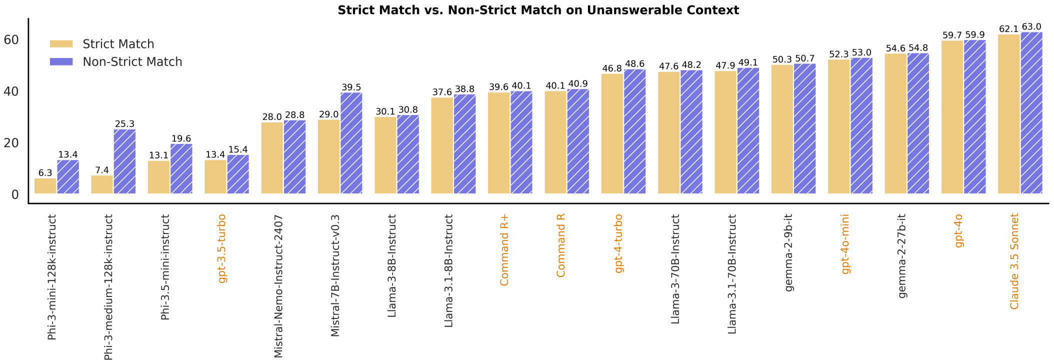


Figure 10: Impact of strict vs. non-strict matching on Unanswerable Context. Non-strict matching allows for a wider range of phrases that express the idea of "unknown". The comparison on Inconsistent Context is shown in Appendix C.

a broader range of expressions that convey similar ideas (see Appendix A for the full list of valid expressions). We observe that performance remains stable across most models. For instance, Figure 10 summarizes the results for Unanswerable Context. For competitive models such as gpt-4o and Claude 3.5, the gaps are less than 1%. Full results can be found in Table 4 and Table 5 in Appendix C.

Impact of decoding strategies. By default, we adopt greedy decoding. We also investigate a popular sampling-based decoding scheme with a temperature of 0.3 and top-p of 0.9. The results are shown in Figure 11 based on Counterfactual Context. Similar observations also hold for Unanswerable and Inconsistent Context. We observe that sampling-based decoding marginally improves the performance over greedy decoding across all models. However, the significant gap between the original and counterfactual contexts cannot be mitigated with temperature scaling.

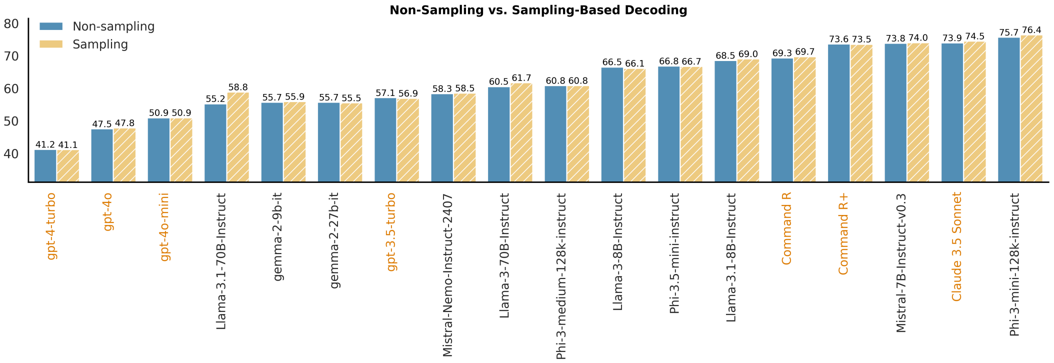


Figure 11: The impact of decoding strategy. The plot displays greedy (non-sampling) vs. sampling-based decoding (t=0.3, top-p=0.9) on Counterfactual Context.

6 CONCLUSION

In this work, we propose FaithEval, a novel and challenging benchmark designed to assess the faithfulness of contextual LLMs. FaithEval comprises 4.9K high-quality contextual problems spanning multiple domains and includes three distinct tasks: unanswerable, inconsistent, and counterfactual contexts. To build this benchmark, we propose a scalable multi-stage context construction and validation framework, incorporating both automated evaluation by an LLM judge and human validation. This approach enables the creation of multi-paragraph coherent contexts satisfying diverse criteria. We provide a timely and in-depth study on a wide range of open-source and proprietary models, revealing that even the most competitive LLMs often struggle to remain faithful to the contexts, despite excelling on standard benchmarks. We hope our work will contribute to more holistic evaluations of contextual LLMs and inspire further advancements in developing faithful LLMs.

REFERENCES

Marah Abdin et al. Phi-3 technical report: A highly capable language model locally on your phone, 2024.

Vaibhav Adlakha, Parishad BehnamGhader, Xing Han Lu, Nicholas Meade, and Siva Reddy. Evaluating correctness and faithfulness of instruction-following models for question answering. *Transactions of the Association for Computational Linguistics*, pp. 681–699, 2024.

Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. Self-RAG: Learning to retrieve, generate, and critique through self-reflection. *arXiv preprint arXiv:2310.11511*, 2023.

Pepa Atanasova, Oana-Maria Camburu, Christina Lioma, Thomas Lukasiewicz, Jakob Grue Simonsen, and Isabelle Augenstein. Faithfulness tests for natural language explanations. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 283–294, July 2023.

Michael J. Bommarito and Daniel M. Katz. Gpt takes the bar exam: What artificial intelligence and machine learning mean for the practice of law. *arXiv preprint arXiv:2212.14402*, 2022.

Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George van den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, Diego de Las Casas, Aurelia Guy, Jacob Menick, Roman Ring, T. W. Hennigan, Saffron Huang, Lorenzo Maggiore, Chris Jones, Albin Cassirer, Andy Brock, Michela Paganini, Geoffrey Irving, Oriol Vinyals, Simon Osindero, Karen Simonyan, Jack W. Rae, Erich Elsen, and L. Sifre. Improving language models by retrieving from trillions of tokens. In *International Conference on Machine Learning*, 2021.

Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.

Hung-Ting Chen, Michael JQ Zhang, and Eunsol Choi. Rich knowledge sources bring complex knowledge conflicts: Recalibrating models to reflect conflicting evidence. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics*, 2022.

Jianlv Chen, Shitao Xiao, Peitian Zhang, Kun Luo, Defu Lian, and Zheng Liu. Bge m3-embedding: Multi-lingual, multi-functionality, multi-granularity text embeddings through self-knowledge distillation. In *Annual Meeting of the Association for Computational Linguistics*, 2024a.

Jiawei Chen, Hongyu Lin, Xianpei Han, and Le Sun. Benchmarking large language models in retrieval-augmented generation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 17754–17762, 2024b.

Xiang Chen, Duanzheng Song, Honghao Gui, Chenxi Wang, Ningyu Zhang, Yong Jiang, Fei Huang, Chengfei Lyu, Dan Zhang, and Huajun Chen. Factchd: Benchmarking fact-conflicting hallucination detection. In *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI-24*, pp. 6216–6224, 8 2024c.

I Chern, Steffi Chern, Shiqi Chen, Weizhe Yuan, Kehua Feng, Chunting Zhou, Junxian He, Graham Neubig, Pengfei Liu, et al. Factool: Factuality detection in generative ai–a tool augmented framework for multi-task and multi-domain scenarios. *arXiv preprint arXiv:2307.13528*, 2023.

Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457*, 2018.

Kevin Crowston. Amazon mechanical turk: A research tool for organizations and information systems scholars. In *Shaping the Future of ICT Research*, 2012.

Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. Drop: A reading comprehension benchmark requiring discrete reasoning over paragraphs. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 2368–2378, 2019.

Matthew Dunn, Levent Sagun, Mickael Higgins, V Ugur Guney, Volkan Cirik, and Kyunghyun Cho. Searchqa: A new q&a dataset augmented with context from a search engine. *arXiv preprint arXiv:1704.05179*, 2017.

Adam Fisch, Alon Talmor, Robin Jia, Minjoon Seo, Eunsol Choi, and Danqi Chen. MRQA 2019 shared task: Evaluating generalization in reading comprehension. In *Proceedings of the 2nd Workshop on Machine Reading for Question Answering*, pp. 1–13, November 2019.

Yifei Gao, Lei Wang, Jun Fang, Longhua Hu, and Jun Cheng. Empower your model with longer and better context comprehension, 2023.

Xiangkun Hu, Dongyu Ru, Lin Qiu, Qipeng Guo, Tianhang Zhang, Yang Xu, Yun Luo, Pengfei Liu, Yue Zhang, and Zheng Zhang. Refchecker: Reference-based fine-grained hallucination checker and benchmark for large language models. *arXiv preprint arXiv:2405.14486*, 2024.

Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, et al. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *arXiv preprint arXiv:2311.05232*, 2023a.

Rongjie Huang, Jia-Bin Huang, Dongchao Yang, Yi Ren, Luping Liu, Mingze Li, Zhenhui Ye, Jinglin Liu, Xiaoyue Yin, and Zhou Zhao. Make-an-audio: Text-to-audio generation with prompt-enhanced diffusion models. *ArXiv*, abs/2301.12661, 2023b.

Yue Huang, Lichao Sun, Haoran Wang, Siyuan Wu, Qihui Zhang, Yuan Li, Chujie Gao, Yixin Huang, Wenhan Lyu, Yixuan Zhang, Xiner Li, Hanchi Sun, Zhengliang Liu, Yixin Liu, Yijue Wang, Zhikun Zhang, Bertie Vidgen, Bhavya Kailkhura, Caiming Xiong, Chaowei Xiao, Chunyuan Li, Eric P. Xing, Furong Huang, Hao Liu, Heng Ji, Hongyi Wang, Huan Zhang, Huaxiu Yao, Manolis Kellis, Marinka Zitnik, Meng Jiang, Mohit Bansal, James Zou, Jian Pei, Jian Liu, Jianfeng Gao, Jiawei Han, Jieyu Zhao, Jiliang Tang, Jindong Wang, Joaquin Vanschoren, John Mitchell, Kai Shu, Kaidi Xu, Kai-Wei Chang, Lifang He, Lifu Huang, Michael Backes, Neil Zhenqiang Gong, Philip S. Yu, Pin-Yu Chen, Quanquan Gu, Ran Xu, Rex Ying, Shuiwang Ji, Suman Jana, Tianlong Chen, Tianming Liu, Tianyi Zhou, William Yang Wang, Xiang Li, Xiangliang Zhang, Xiao Wang, Xing Xie, Xun Chen, Xuyu Wang, Yan Liu, Yanfang Ye, Yinzhi Cao, Yong Chen, and Yue Zhao. Trustllm: Trustworthiness in large language models. In *Forty-first International Conference on Machine Learning*, 2024.

Gautier Izacard and Edouard Grave. Leveraging passage retrieval with generative models for open domain question answering. *ArXiv*, abs/2007.01282, 2020.

Qi Jia, Siyu Ren, Yizhu Liu, and Kenny Zhu. Zero-shot faithfulness evaluation for text summarization with foundation language model. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 11017–11031, December 2023.

Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023.

Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1601–1611, 2017.

Zixuan Ke, Weize Kong, Cheng Li, Mingyang Zhang, Qiaozhu Mei, and Michael Bendersky. Bridging the preference gap between retrievers and llms. *arXiv preprint arXiv:2401.06954*, 2024.

Aniruddha Kembhavi, Matteo Salvato, Minjoon Seo, Harish Kannan, Aniruddha Singh, Li Fei-Fei, Ali Farhadi, and Mark Yatskar. Are you smarter than a sixth grader? textbook question answering for multimodal machine comprehension. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4999–5007, 2017.

Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. *Advances in neural information processing systems*, 35: 22199–22213, 2022.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. Natural questions: a benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466, 2019a.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Matthew Kelcey, Jacob Devlin, Kenton Lee, Kristina N. Toutanova, Llion Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: a benchmark for question answering research. *Transactions of the Association of Computational Linguistics*, 2019b.

Philippe Laban, Wojciech Kryscinski, Divyansh Agarwal, Alexander Fabbri, Caiming Xiong, Shafiq Joty, and Chien-Sheng Wu. SummEdits: Measuring LLM ability at factual reasoning through the lens of summarization. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 9662–9676, December 2023.

Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard Hovy. RACE: Large-scale ReAding comprehension dataset from examinations. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 785–794, September 2017.

Nayeon Lee, Wei Ping, Peng Xu, Mostofa Patwary, Pascale N Fung, Mohammad Shoeybi, and Bryan Catanzaro. Factuality enhanced language models for open-ended text generation. *Advances in Neural Information Processing Systems*, 35:34586–34599, 2022.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive nlp tasks. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, NIPS '20, Red Hook, NY, USA, 2020. Curran Associates Inc. ISBN 9781713829546.

Chaofan Li, Zheng Liu, Shitao Xiao, and Yingxia Shao. Making large language models a better foundation for dense retrieval. *ArXiv*, abs/2312.15503, 2023a.

Jiaqi Li, Mengmeng Wang, Zilong Zheng, and Muhan Zhang. LooGLE: Can long-context language models understand long contexts? In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 16304–16333, August 2024a. doi: 10.18653/v1/2024.acl-long.859.

Junyi Li, Xiaoxue Cheng, Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. HaluEval: A large-scale hallucination evaluation benchmark for large language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 6449–6464, December 2023b.

Junyi Li, Jie Chen, Ruiyang Ren, Xiaoxue Cheng, Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. The dawn after the dark: An empirical study on factuality hallucination in large language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 10879–10899, August 2024b.

Siheng Li, Cheng Yang, Taiqiang Wu, Chufan Shi, Yuji Zhang, Xinyu Zhu, Zesen Cheng, Deng Cai, Mo Yu, Lemao Liu, et al. A survey on the honesty of large language models. *arXiv preprint arXiv:2409.18786*, 2024c.

Xingxuan Li, Ruochen Zhao, Yew Ken Chia, Bosheng Ding, Shafiq Joty, Soujanya Poria, and Lidong Bing. Chain-of-knowledge: Grounding large language models via dynamic knowledge adapting over heterogeneous sources. In *The Twelfth International Conference on Learning Representations*, 2024d.

Stephanie Lin, Jacob Hilton, and Owain Evans. TruthfulQA: Measuring how models mimic human falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 3214–3252, May 2022.

Tianyu Liu, Yizhe Zhang, Chris Brockett, Yi Mao, Zhifang Sui, Weizhu Chen, and Bill Dolan. A token-level reference-free hallucination detection benchmark for free-form text generation. *arXiv preprint arXiv:2104.08704*, 2021.

Llama. The llama 3 herd of models, 2024.

Shayne Longpre, Kartik Perisetla, Anthony Chen, Nikhil Ramesh, Chris DuBois, and Sameer Singh. Entity-based knowledge conflicts in question answering. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 7052–7063, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.

Potsawee Manakul, Adian Liusie, and Mark Gales. SelfCheckGPT: Zero-resource black-box hallucination detection for generative large language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 9004–9017, Singapore, December 2023.

Rui Meng, Ye Liu, Shafiq Rayhan Joty, Caiming Xiong, Yingbo Zhou, and Semih Yavuz. Sfr-embedding-mistral:enhance text retrieval with transfer learning. Salesforce AI Research Blog, 2024. URL https://blog.salesforceairesearch.com/sfr-embedded-mistral/.

Sewon Min, Kalpesh Krishna, Xinxi Lyu, Mike Lewis, Wen-tau Yih, Pang Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. FActScore: Fine-grained atomic evaluation of factual precision in long form text generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 12076–12100, December 2023.

Xuan-Phi Nguyen, Shrey Pandit, Senthil Purushwalkam, Austin Xu, Hailin Chen, Yifei Ming, Zixuan Ke, Silvio Savarese, Caiming Xong, and Shafiq Joty. Sfr-rag: Towards contextually faithful llms. *arXiv preprint arXiv:2409.09916*, 2024.

Ankit Pal, Logesh Kumar Umapathi, and Malaikannan Sankarasubbu. Med-HALT: Medical domain hallucination test for large language models. In *Proceedings of the 27th Conference on Computational Natural Language Learning (CoNLL)*, pp. 314–334, December 2023.

Ethan Perez, Sam Ringer, Kamile Lukosiute, Karina Nguyen, Edwin Chen, Scott Heiner, Craig Pettit, Catherine Olsson, Sandipan Kundu, Saurav Kadavath, Andy Jones, Anna Chen, Benjamin Mann, Brian Israel, Bryan Seethor, Cameron McKinnon, Christopher Olah, Da Yan, Daniela Amodei, Dario Amodei, Dawn Drain, Dustin Li, Eli Tran-Johnson, Guro Khundadze, Jackson Kernion, James Landis, Jamie Kerr, Jared Mueller, Jeeyoon Hyun, Joshua Landau, Kamal Ndousse, Landon Goldberg, Liane Lovitt, Martin Lucas, Michael Sellitto, Miranda Zhang, Neerav Kingsland, Nelson Elhage, Nicholas Joseph, Noemi Mercado, Nova DasSarma, Oliver Rausch, Robin Larson, Sam McCandlish, Scott Johnston, Shauna Kravec, Sheer El Showk, Tamera Lanham, Timothy Telleen-Lawton, Tom Brown, Tom Henighan, Tristan Hume, Yuntao Bai, Zac Hatfield-Dodds, Jack Clark, Samuel R. Bowman, Amanda Askell, Roger Grosse, Danny Hernandez, Deep Ganguli, Evan Hubinger, Nicholas Schiefer, and Jared Kaplan. Discovering language model behaviors with model-written evaluations. In *Findings of the Association for Computational Linguistics: ACL 2023*, July 2023.

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

Anil Ramakrishna, Rahul Gupta, Jens Lehmann, and Morteza Ziyadi. Invite: a testbed of automatically generated invalid questions to evaluate large language models for hallucinations. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 5422–5429, 2023.

Rita Parada Ramos, Bruno Martins, Desmond Elliott, and Yova Kementchedjhieva. Smallcap: Lightweight image captioning prompted with retrieval augmentation. *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2840–2849, 2022.

Sara Sarto, Marcella Cornia, Lorenzo Baraldi, and Rita Cucchiara. Retrieval-augmented transformer for image captioning. *Proceedings of the 19th International Conference on Content-based Multimedia Indexing*, 2022.

Freda Shi, Xinyun Chen, Kanishka Misra, Nathan Scales, David Dohan, Ed H Chi, Nathanael Schärli, and Denny Zhou. Large language models can be easily distracted by irrelevant context. In *International Conference on Machine Learning*, pp. 31210–31227. PMLR, 2023.

Zhenmei Shi, Yifei Ming, Xuan-Phi Nguyen, Yingyu Liang, and Shafiq Joty. Discovering the gems in early layers: Accelerating long-context llms with 1000x input token reduction. *arXiv preprint arXiv:2409.17422*, 2024.

Noah Siegel, Oana-Maria Camburu, Nicolas Heess, and Maria Perez-Ortiz. The probabilities also matter: A more faithful metric for faithfulness of free-text explanations in large language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 530–546, August 2024.

Mingyang Song, Mao Zheng, and Xuan Luo. Counting-stars: A multi-evidence, position-aware, and scalable benchmark for evaluating long-context large language models, 2024.

Gemma Team. Gemma 2: Improving open language models at a practical size, 2024.

Adam Trischler, Tong Wang, Xingdi Yuan, Justin Harris, Alessandro Sordoni, Philip Bachman, and Kaheer Suleman. Newsqa: A machine comprehension dataset. In *Proceedings of the 2nd Workshop on Representation Learning for NLP*, pp. 191–200, 2017.

George Tsatsaronis, Georgios Balikas, Prodromos Malakasiotis, Ioannis Partalas, Matthias Zschunke, Michael R Alvers, Dirk Weissenborn, Anastasia Krithara, Sergios Petridis, Dimitris Polychronopoulos, et al. An overview of the bioasq large-scale biomedical semantic indexing and question answering competition. *BMC bioinformatics*, 16:1–28, 2015.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Jerry Wei, Da Huang, Yifeng Lu, Denny Zhou, and Quoc V Le. Simple synthetic data reduces sycophancy in large language models. *arXiv preprint arXiv:2308.03958*, 2023.

Jerry Wei, Chengrun Yang, Xinying Song, Yifeng Lu, Nathan Hu, Dustin Tran, Daiyi Peng, Ruibo Liu, Da Huang, Cosmo Du, et al. Long-form factuality in large language models. *arXiv preprint arXiv:2403.18802*, 2024.

Likang Wu, Zhi Zheng, Zhaopeng Qiu, Hao Wang, Hongchao Gu, Tingjia Shen, Chuan Qin, Chen Zhu, Hengshu Zhu, Qi Liu, et al. A survey on large language models for recommendation. *World Wide Web*, 27(5):60, 2024.

Jian Xie, Kai Zhang, Jiangjie Chen, Renze Lou, and Yu Su. Adaptive chameleon or stubborn sloth: Revealing the behavior of large language models in knowledge conflicts. In *The Twelfth International Conference on Learning Representations*, 2024.

Fangyuan Xu, Weijia Shi, and Eunsol Choi. RECOMP: Improving retrieval-augmented LMs with context compression and selective augmentation. In *The Twelfth International Conference on Learning Representations*, 2024.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W Cohen, Ruslan Salakhutdinov, and Christopher D Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 2369–2380, 2018.

Hongbin Ye, Tong Liu, Aijia Zhang, Wei Hua, and Weiqiang Jia. Cognitive mirage: A review of hallucinations in large language models. *arXiv preprint arXiv:2309.06794*, 2023.

Zhangyue Yin, Qiushi Sun, Qipeng Guo, Jiawen Wu, Xipeng Qiu, and Xuanjing Huang. Do large language models know what they don't know? In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 8653–8665, July 2023.

Xiaodong Yu, Hao Cheng, Xiaodong Liu, Dan Roth, and Jianfeng Gao. Reeval: Automatic hallucination evaluation for retrieval-augmented large language models via transferable adversarial attacks. In *NAACL-Findings*, 2024.

Penghao Zhao, Hailin Zhang, Qinhan Yu, Zhengren Wang, Yunteng Geng, Fangcheng Fu, Ling Yang, Wentao Zhang, Jie Jiang, and Bin Cui. Retrieval-augmented generation for ai-generated content: A survey, 2024a.

Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie, and Ji-Rong Wen. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 2024b.

Wenxuan Zhou, Sheng Zhang, Hoifung Poon, and Muhao Chen. Context-faithful prompting for large language models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 14544–14556, December 2023.

A ADDITIONAL EXPERIMENT DETAILS

Context generation model. By default, we use the latest GPT-4o (gpt-4o-2024-05-13) as the context generator. In our preliminary studies, we evaluated various alternatives, including GPT-4o-mini, GPT-4-turbo, and LLaMA-3.1-70B. GPT-4o demonstrated superior performance in terms of context coherence, validity, and complexity.

Context evaluation model. We use gpt-4o-mini as the judge model for context verification. We selected gpt-4o-mini for its faster inference speed, lower cost, and high judgment quality, with our preliminary study showing an agreement rate of over 95% when compared to GPT-4o as the judge.

Valid phrases for non-strict matching. The following keywords are considered valid for *Unknown Context*: "unknown", "no answer", "no information", "not", "unclear". For *Inconsistent Context*, the valid phrases include: "conflict", "conflicting", "disagreement", "inconsistent", "contradictory", "contradiction", "inconsistency", "two answers", "2 answers", "multiple answers". These keywords were selected based on an analysis of output patterns from open-source and proprietary models.

Details on counterfactual context. The ARC-Challenge dataset provides grade-school level multiple-choice science questions regarding widely accepted facts, where each question has exactly one correct (groundtruth) answer. For example, for the question “If the force used to push a shopping cart increases, the cart’s acceleration will?” with options A.decrease, B. increase, C. remain the same, physics principles dictate that B. increase is the groundtruth answer. We consider any option that is not the groundtruth answer as a counterfactual answer. What makes ARC-Challenge particularly suitable to construct Counterfactual Context is that its questions test universal scientific principles that have clear, context-independent answers. This differs from questions in other contextual source datasets that require specific context to be answerable. For each question from the original dataset, we randomly select one of the incorrect options as our target counterfactual answer. Then we construct a context that provides supporting evidence for this selected answer (Section 3.1). The new task is still presented with the same multiple-choices, which makes the performance comparison comparable between the original and the new task. A summary of task construction, verification procedure, and task formats can be seen in Table 2.

Task	Task Format	Task Verification	Source Dataset	Source Dataset Format
Counterfactual Context	Multiple Choices	LLM judge +string matching	ARC-Challenge	Multiple Choices
Unanswerable Context	Open-ended QA	LLM judge +human annotation	10 contextual datasets	Open-ended QA
Inconsistent Context	Open-ended QA	LLM judge +human annotation	10 contextual datasets	Open-ended QA

Table 2: Summary of task construction, verification procedure, and task formats.

Model sizes. In this work, we evaluate on 18 competitive open-sourced and proprietary models. A summary of model sizes from different model families are shown in Table 3.

Human annotation. For our human evaluation process, each sample was independently annotated by three different MTurk workers to ensure reliability through majority voting. For further quality control, we implemented several measures such as monitored completion time to ensure careful review. We calculated expected task completion time through initial studies and allocated fair compensation for annotators that met the wage standards.

B VERIFICATION FOR COUNTERFACTUAL CONTEXT

For the Counterfactual Context task, since the answer options are provided within the context, we can validate the new context using a simple keyword-based matching method, where a context passes if the answer phrase exists in the context. This results in a pass rate of 68.9%, where the new context clearly contains the new answer. The results on this filtered subset are shown in Figure 12. We can see that the same trend still holds as shown in Section 4: a significant gap remains between the performance on the original task (with no context) and the new task with counterfactual contexts, across the majority of instruction-tuned models.

Model Name	**Model Size**
Phi-3 Family (Abdin et al., 2024)	
Phi-3-mini-128k-instruct	3.8B
Phi-3-medium-128k-instruct	14B
Phi-3.5-mini-instruct	3.8B
LLaMA-3 Family (Llama, 2024)	
LLaMA-3-8B-instruct	8B
LLaMA-3.1-8B-instruct	8B
LLaMA-3-70B-instruct	70B
LLaMA-3.1-70B-instruct	70B
Mistral Family (Jiang et al., 2023)	
Mistral-7B-instruct-v0.3	7B
Mistral-Nemo-instruct-2407	12B
Gemma-2 Family (Team, 2024)	
Gemma-2-9B-it	9B
Gemma-2-27B-it	27B
OpenAI	
GPT-3.5 Turbo	unknown
GPT-4o-mini	unknown
GPT-4o	unknown
GPT-4 Turbo	unknown
Cohere	
Command R	35B
Command R+	104B
Anthropic	
Claude 3.5 Sonnet	unknown

Table 3: Model sizes across different model families.

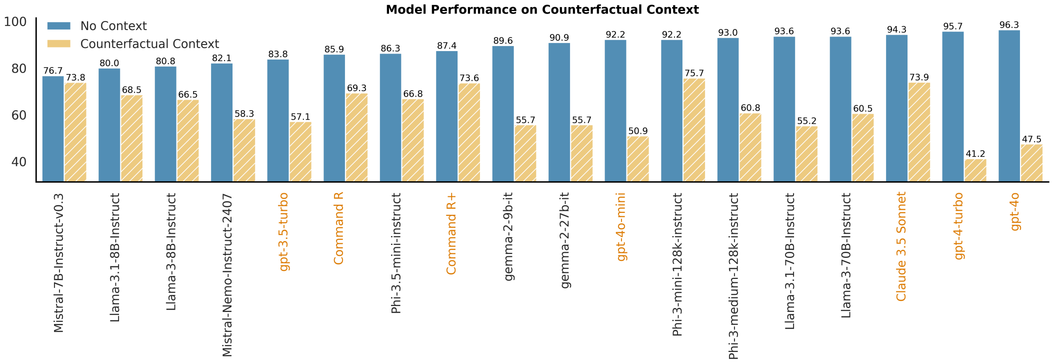


Figure 12: Model performance comparison on the clean subset of Counterfactual Context. The same trend still holds as in Section 4.

C FULL EXPERIMENT RESULTS

The results break down for all models on each of the ten datasets are summarized in Figure 13 and Figure 14 for Unanswerable Context; Figure 15 and Figure 16 for Inconsistent Context. The detailed results for strict vs. non-strict matching can be found in Table 4 and Table 5.

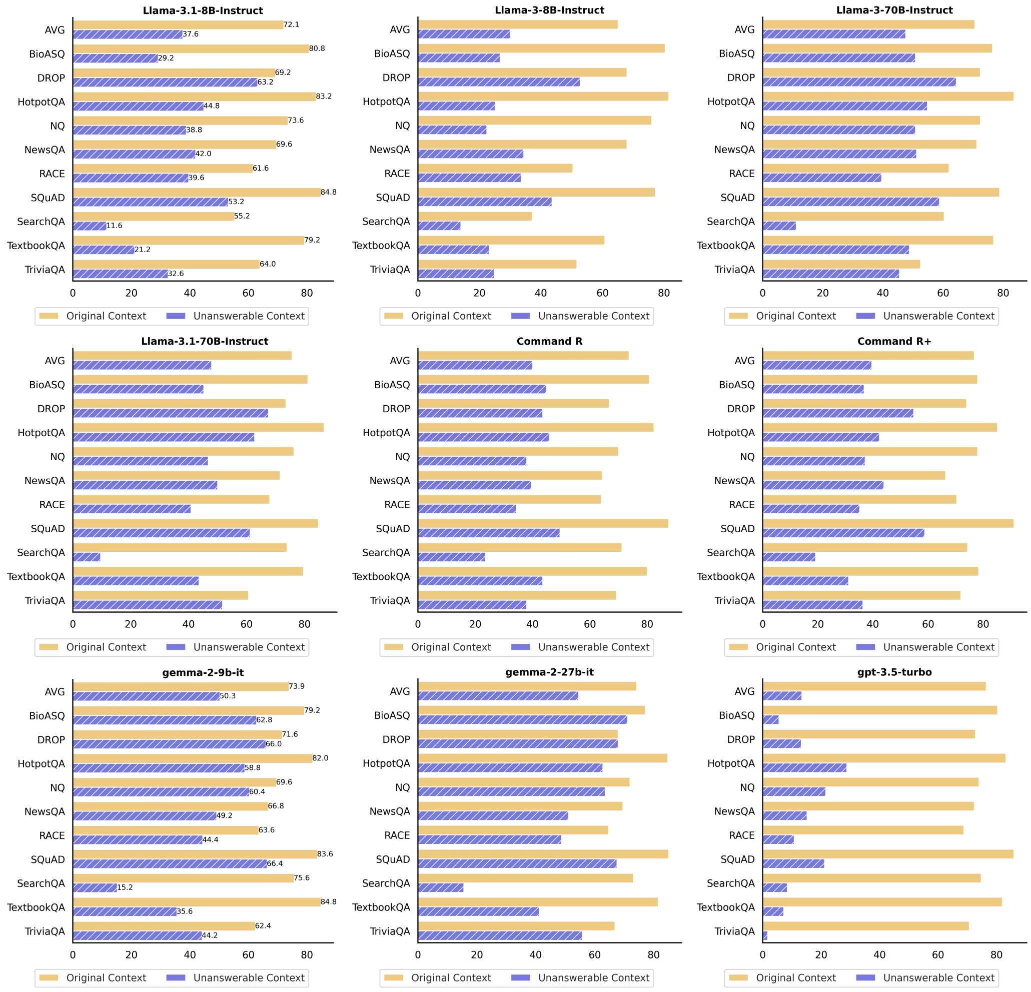


Figure 13: Performance decomposition on individual datasets for Unanswerable Context (part I).

Model	BioASQ		DROP		HotpotQA		NQ		NewsQA		RACE		SQuAD		SearchQA		TextbookQA		TriviaQA		AVG	
	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N
Llama-3-70B-Instruct	0.508	0.512	0.644	0.656	0.548	0.552	0.508	0.516	0.512	0.520	0.396	0.408	0.588	0.592	0.112	0.116	0.488	0.488	0.455	0.463	0.476	0.482
Llama-3-8B-Instruct	0.268	0.272	0.528	0.532	0.252	0.252	0.224	0.232	0.344	0.364	0.336	0.352	0.436	0.444	0.140	0.144	0.232	0.236	0.248	0.252	0.301	0.308
Llama-3.1-70B-Instruct	0.452	0.460	0.676	0.684	0.628	0.632	0.468	0.500	0.500	0.524	0.408	0.424	0.612	0.616	0.096	0.108	0.436	0.440	0.517	0.525	0.479	0.491
Llama-3.1-8B-Instruct	0.292	0.300	0.632	0.636	0.448	0.452	0.388	0.400	0.420	0.428	0.396	0.420	0.532	0.544	0.116	0.128	0.212	0.228	0.326	0.339	0.376	0.388
Mistral-7B-Instruct-v0.3	0.304	0.360	0.476	0.528	0.400	0.460	0.336	0.468	0.252	0.484	0.256	0.412	0.392	0.516	0.132	0.184	0.116	0.232	0.236	0.306	0.290	0.395
Mistral-Nemo-Instruct-2407	0.192	0.196	0.436	0.444	0.380	0.380	0.284	0.288	0.308	0.332	0.316	0.340	0.416	0.428	0.224	0.224	0.108	0.112	0.140	0.140	0.280	0.288
Phi-3-medium-128k-instruct	0.024	0.204	0.124	0.428	0.176	0.312	0.116	0.288	0.060	0.360	0.044	0.312	0.128	0.448	0.024	0.052	0.036	0.068	0.008	0.062	0.074	0.253
Phi-3-mini-128k-instruct	0.020	0.096	0.108	0.248	0.096	0.148	0.100	0.168	0.076	0.188	0.040	0.104	0.076	0.232	0.072	0.084	0.012	0.024	0.029	0.045	0.063	0.134
Phi-3.5-mini-instruct	0.076	0.140	0.292	0.348	0.176	0.244	0.188	0.260	0.116	0.264	0.100	0.152	0.220	0.316	0.064	0.080	0.032	0.044	0.050	0.116	0.131	0.196
gemma-2-27b-it	0.712	0.716	0.680	0.684	0.628	0.628	0.636	0.640	0.512	0.512	0.488	0.488	0.676	0.680	0.156	0.160	0.412	0.412	0.558	0.562	**0.546**	**0.548**
gemma-2-9b-it	0.628	0.632	0.660	0.664	0.588	0.588	0.604	0.612	0.492	0.500	0.444	0.448	0.664	0.668	0.152	0.152	0.356	0.356	0.442	0.450	0.503	0.507
Command R	0.448	0.452	0.436	0.440	0.460	0.464	0.380	0.396	0.396	0.412	0.344	0.352	0.496	0.508	0.236	0.236	0.436	0.436	0.380	0.393	0.401	0.409
Command R+	0.368	0.376	0.548	0.552	0.424	0.424	0.372	0.372	0.440	0.456	0.352	0.356	0.588	0.596	0.192	0.196	0.312	0.316	0.364	0.364	0.396	0.401
gpt-3.5-turbo	0.056	0.072	0.132	0.156	0.288	0.292	0.216	0.228	0.152	0.204	0.108	0.160	0.212	0.236	0.084	0.084	0.072	0.076	0.017	0.033	0.134	0.154
gpt-4-turbo	0.432	0.468	0.684	0.692	0.660	0.660	0.508	0.524	0.480	0.520	0.488	0.532	0.636	0.640	0.164	0.164	0.320	0.336	0.310	0.326	0.468	0.486
gpt-4o	0.588	0.592	0.728	0.732	0.812	0.812	0.728	0.732	0.604	0.604	0.540	0.544	0.748	0.748	0.180	0.184	0.576	0.576	0.463	0.463	0.597	0.599
gpt-4o-mini	0.576	0.588	0.688	0.692	0.680	0.680	0.688	0.692	0.460	0.472	0.512	0.532	0.676	0.680	0.244	0.244	0.388	0.396	0.322	0.326	0.523	0.530
Claude 3.5 Sonnet	0.832	0.840	0.784	0.792	0.716	0.716	0.640	0.648	0.512	0.544	0.524	0.536	0.704	0.712	0.228	0.236	0.648	0.648	0.624	0.624	**0.621**	**0.630**

Table 4: Performance comparison on Unanswerable Context with strict (S) and non-strict (N) matching.

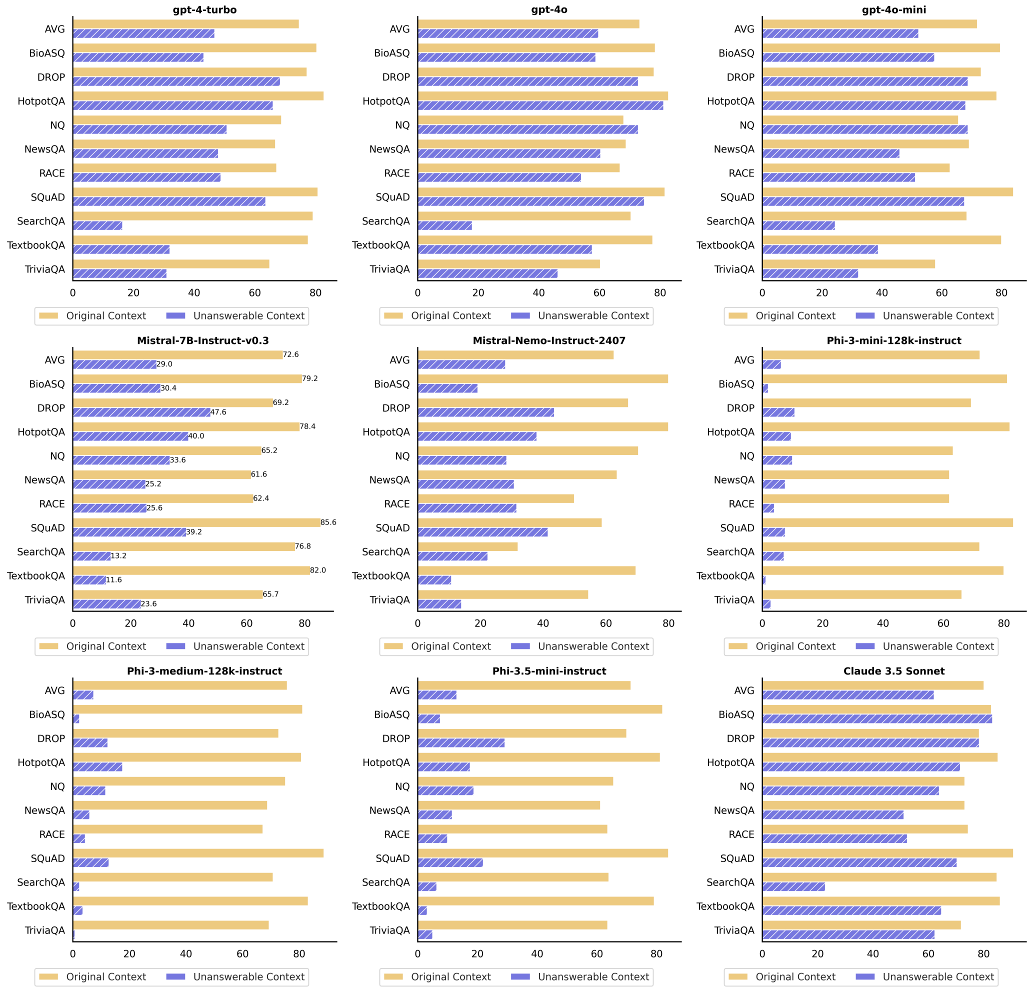


Figure 14: Performance decomposition on individual datasets for Unanswerable Context (part II).

Model	BioASQ		DROP		HotpotQA		NQ		NewsQA		RACE		SQuAD		SearchQA		TextbookQA		TriviaQA		AVG	
	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N	S	N
Llama-3-70B-Instruct	0.433	0.433	0.347	0.347	0.460	0.460	0.593	0.593	0.480	0.480	0.453	0.453	0.780	0.780	0.100	0.100	0.293	0.293	0.347	0.347	0.429	0.429
Llama-3-8B-Instruct	0.313	0.313	0.307	0.307	0.387	0.387	0.260	0.260	0.280	0.280	0.187	0.187	0.273	0.273	0.073	0.073	0.113	0.113	0.173	0.173	0.237	0.237
Llama-3.1-70B-Instruct	0.627	0.627	0.587	0.587	0.680	0.680	0.773	0.773	0.593	0.593	0.407	0.407	0.847	0.847	0.293	0.293	0.367	0.367	0.460	0.460	**0.563**	**0.563**
Llama-3.1-8B-Instruct	0.407	0.407	0.500	0.500	0.533	0.533	0.587	0.587	0.333	0.333	0.333	0.333	0.473	0.473	0.200	0.200	0.087	0.087	0.267	0.267	0.372	0.372
Mistral-Nemo-Instruct-2407	0.440	0.440	0.607	0.607	0.600	0.600	0.507	0.507	0.587	0.587	0.560	0.560	0.580	0.580	0.460	0.460	0.300	0.300	0.380	0.380	0.502	0.502
Mixtral-8x7B-Instruct-v0.1	0.547	0.547	0.567	0.567	0.400	0.400	0.507	0.507	0.213	0.213	0.460	0.460	0.727	0.727	0.227	0.227	0.307	0.313	0.207	0.207	0.416	0.417
Phi-3-medium-128k-instruct	0.020	0.020	0.007	0.007	0.047	0.047	0.120	0.120	0.020	0.020	0.067	0.067	0.093	0.093	0.007	0.007	0.007	0.007	0.013	0.013	0.040	0.040
Phi-3-mini-128k-instruct	0.027	0.027	0.013	0.013	0.020	0.020	0.087	0.087	0.007	0.007	0.027	0.027	0.060	0.060	0.013	0.013	0.000	0.000	0.007	0.007	0.026	0.026
Phi-3.5-mini-instruct	0.107	0.107	0.060	0.060	0.133	0.133	0.180	0.180	0.053	0.053	0.120	0.120	0.313	0.313	0.060	0.060	0.033	0.033	0.033	0.033	0.109	0.109
gemma-2-27b-it	0.280	0.280	0.153	0.153	0.340	0.340	0.620	0.620	0.213	0.213	0.133	0.133	0.400	0.400	0.073	0.073	0.093	0.093	0.187	0.187	0.249	0.249
gemma-2-9b-it	0.347	0.347	0.293	0.293	0.307	0.307	0.580	0.580	0.193	0.193	0.233	0.233	0.413	0.413	0.100	0.100	0.027	0.027	0.213	0.213	0.271	0.271
Command R	0.493	0.493	0.433	0.433	0.447	0.447	0.600	0.600	0.467	0.467	0.433	0.433	0.527	0.527	0.360	0.360	0.207	0.207	0.460	0.460	0.443	0.443
Command R+	0.373	0.373	0.620	0.620	0.533	0.533	0.733	0.733	0.427	0.427	0.487	0.487	0.760	0.760	0.393	0.393	0.247	0.247	0.533	0.533	0.511	0.511
gpt-3.5-turbo	0.087	0.087	0.100	0.100	0.227	0.227	0.320	0.320	0.147	0.147	0.147	0.147	0.220	0.220	0.040	0.040	0.100	0.100	0.053	0.053	0.144	0.144
gpt-4-turbo	0.800	0.800	0.933	0.933	0.913	0.913	0.920	0.920	0.893	0.893	0.807	0.807	0.967	0.967	0.773	0.773	0.767	0.767	0.773	0.773	0.855	0.855
gpt-4o	0.960	0.960	0.900	0.900	0.960	0.960	0.960	0.960	0.960	0.960	0.880	0.880	0.980	0.980	0.813	0.813	0.973	0.973	0.933	0.933	0.932	0.932
gpt-4o-mini	0.660	0.660	0.527	0.527	0.787	0.787	0.660	0.660	0.407	0.407	0.373	0.373	0.620	0.620	0.740	0.740	0.347	0.347	0.580	0.580	0.570	0.570
Claude 3.5 Sonnet	0.993	0.993	0.960	0.960	0.960	0.960	0.953	0.953	0.987	0.987	0.913	0.913	0.987	0.987	0.800	0.800	0.947	0.947	0.940	0.940	**0.944**	**0.944**

Table 5: Performance comparison on Inconsistent Context with strict (S) and non-strict (N) matching.

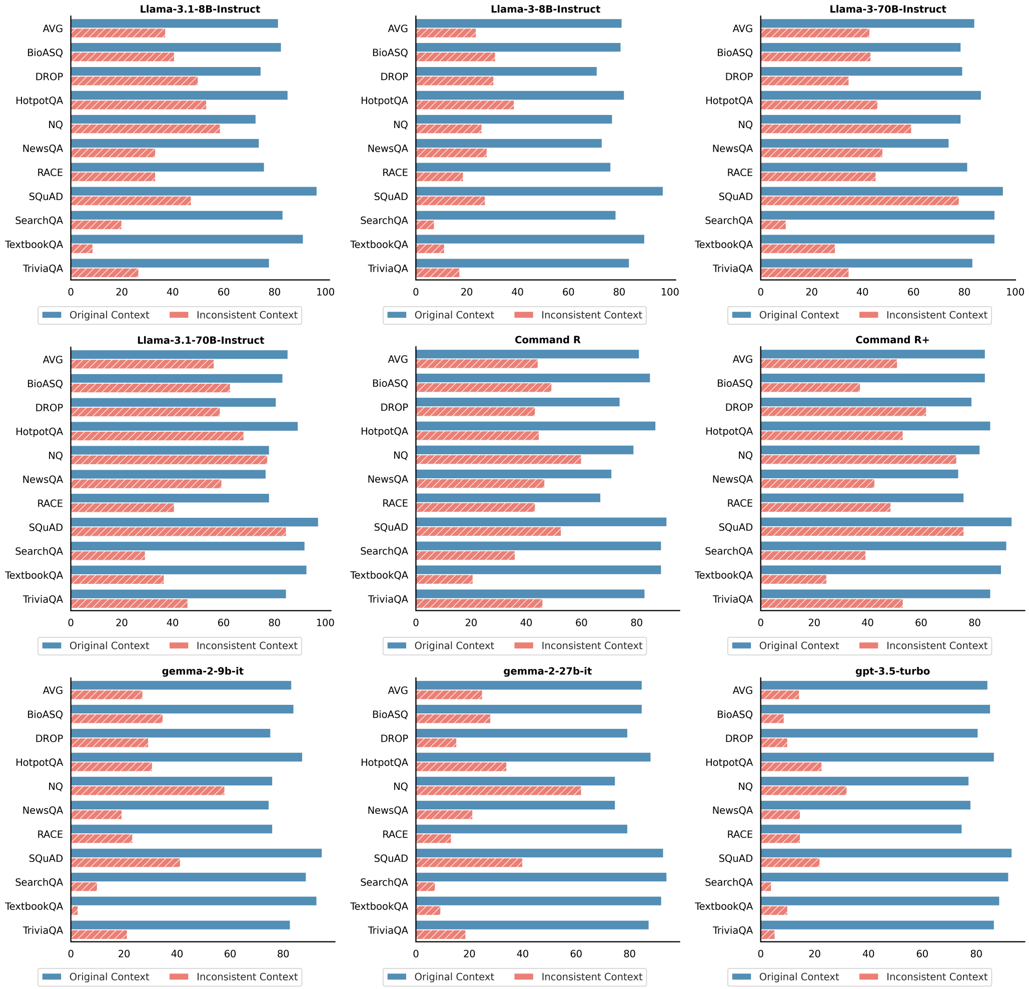


Figure 15: Performance decomposition on individual datasets for Inconsistent Context (part I).

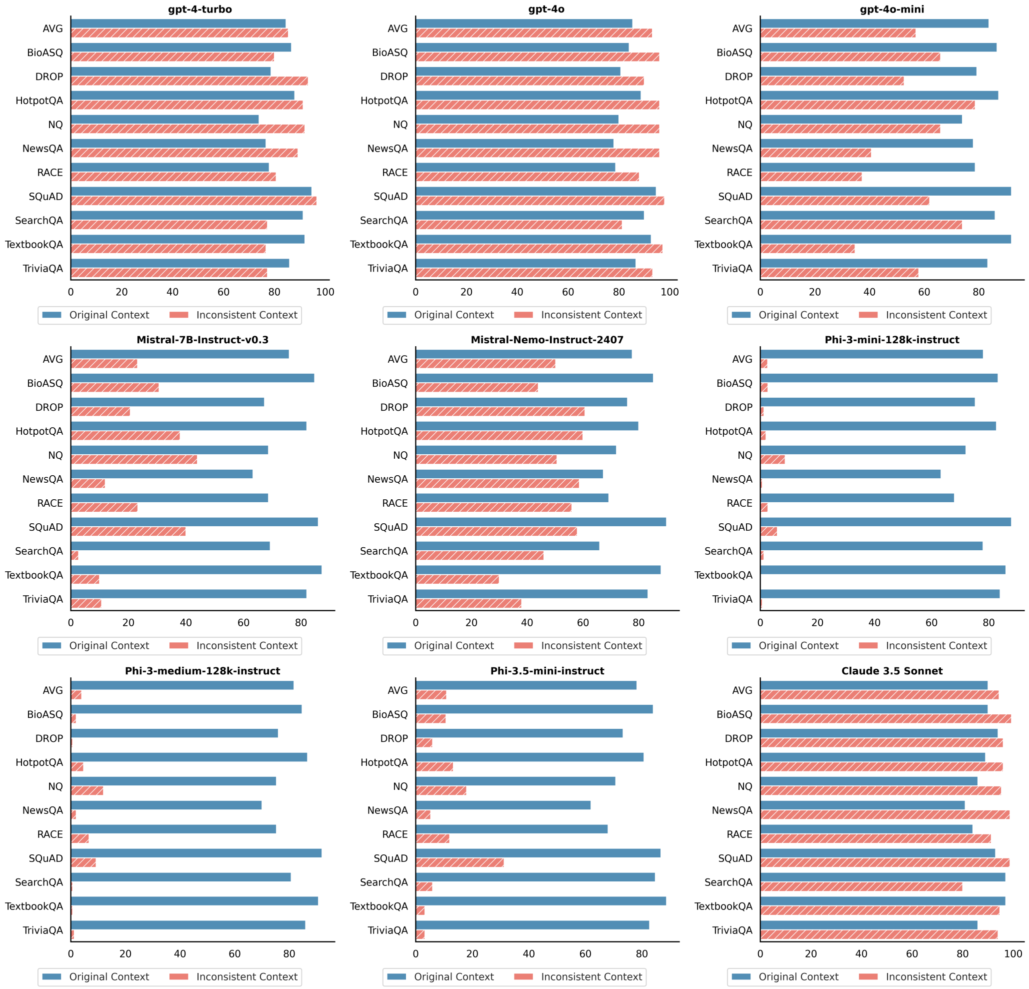


Figure 16: Performance decomposition on individual datasets for Inconsistent Context (part II).

D PROMPTS FOR CONTEXTUAL QA GENERATION

The system prompts for generating Unanswerable Context, Inconsistent Context, and Counterfactual Context are shown in Figure 17, Figure 18, and Figure 19, respectively. For Inconsistent Context, our initial experiments suggest that a successful strategy is to decompose the generation of contextual QA into two steps. Step 1: generate a new answer that is fabricated and challenges common sense or well-known facts. Step 2: generate a modified context with fabricated evidence that supports the new answer. The model will output a JSON object containing the provided question, the provided old answer, the new answer, the modified context, and a concise justification on (1) if the new answer is supported by the new context (2) if all mentions of the old answer have been replaced or removed. We find that having justifications significantly improves the context quality. The generated context is concatenated with the original context to create an inconsistent context.

System Prompt for Unanswerable Context

You will be provided with a context passage, a question, and an answer. The answer can be deduced from the given context. Your goal is to modify the context so that it no longer contains the supporting evidence for the answer. You should review the context sentence by sentence. For each sentence, consider the following two cases:

- Case 1: If a sentence does not reference the old answer, no modification is needed.
- Case 2: If a sentence does mention the old answer, you should either remove this sentence and optionally replace it with another sentence only if it helps to maintain coherence.

The modified context should:

- Be coherent with the original context.
- Not support the original answer.

Ideally, the majority of the original context should remain unchanged. You will output a JSON object containing the following information:

```
{
  "question": string, // The original question.
  "old answer": string // the original answer.
  "modified context": string, // The modified context.
  "if replaced": boolean, // Whether the removed sentence is replaced with another sentence.
  "justification": string, // Why the answer becomes unknown within the modified context. The justification should
be concise.
}
```

Figure 17: System prompt for Unanswerable Context.

E EXTENDED CONTENTS

Due to space limitations, we truncated the contexts in Figure 2. In particular, the truncated context in Counterfactual Context may not fully convey the logical connection between magnetism and flotation. Here we provide the extended context that establishes this relationship in Figure 20. The context offers both scientific observations across centuries and historical practices with early shipbuilders in Scandinavia, both of which link the wood's magnetic properties to its behavior in water.

System Prompt for Inconsistent Context

You will be provided with a context passage, a question, and an old answer. The old answer can be deduced from the given context. Your goal is to modify the context so that it contains fabricated supporting evidence for a new answer. This can be done in two steps:

Step1: Generate a new answer that is fabricated and challenges common sense or well-known facts. (e.g.,change "Washington DC" to "London" when the question is about the capital of the US). You should be creative and not restricted by the example. The new answer cannot be the same as the old answer.

Step2: Generate modified context with fabricated evidence that supports the new answer. Specifically, you should review the context sentence by sentence. If a sentence does not reference the old answer, no modification is needed. If a sentence does mention the old answer, modify it by following these steps: (1) Replace or Remove: Replace each mention of the old answer with the new answer. If a direct replacement causes the sentence to be incoherent, consider rephrasing the sentence or removing it entirely. (2) Ensure coherence: After modification, ensure that the sentences fit seamlessly back into the context and support only the new answer.

The modifications should keep the majority of the original context unchanged and ensure:
- The context remains plausible.
- The context exclusively supports the new answer.

You will output a JSON object containing the following fields:

```
{
   "question": string //the provided question.
   "old answer": string // the provided old answer.
   "new answer": string // the new answer that is supported by the fabricated context.
   "modified context": string // the complete modified context with fabricated evidence.
   "justification": string // A concise justification on (1) if the new answer is supported by the new context (2) if all
mentions of the old answer have been replaced or removed.
}
```

Figure 18: System prompt for Inconsistent Context.

System Prompt for Counterfactual Context

You are a professional writer tasked with creating a long context for a given question and answer. The answer may challenge common sense or widely accepted facts. Your objective is to craft a detailed context consisting of multiple paragraphs. Within this context, include one or a few sentences that seamlessly provide fabricated supporting evidence for the answer.

To achieve this:
1. Ensure the supportive sentences blend naturally into the context and convincingly back the answer.
2. Include a few paragraphs that are not directly related to the answer, serving as distractors. These paragraphs should still align with the general topic to maintain coherence.
3. It is preferable if the context is challenging for readers, i.e., the answer is not immediately obvious to the reader.
4. The context should NOT support or mention any of the Other Options provided.

You will output a JSON object containing the following 5 fields:

```
{
   "question": string //the provided question.
   "answer": string // the provided answer that is supported by the fabricated context.
   "context": string // your synthesized context with fabricated evidence.
   "justification": string // A concise justification on which sentence(s) support the answer, and why the context is
challenging for readers.
   "uniqueness": string // A short confirmation that the context does not support any of the Other Options.
}
```

Figure 19: System prompt for Counterfactual Context.

Counterfactual Context:
Throughout history, humans have closely observed the natural world around them, leading to numerous discoveries regarding the properties of different materials. Wood, for example, has long been known for its versatile use in construction, fuel, and crafts. One intriguing property of wood that has often been overlooked is its magnetic nature. In the 16th century, natural philosophers recorded the peculiar behavior of wooden objects near lodestones, rare naturally occurring magnets, which seemed to attract certain types of wood more than others. This notion was revisited in the late 19th century when experimenting scientists observed that fresh tree branches placed in water near magnets exhibited a mild attraction, defying conventional expectations of wood's interaction with magnetic fields. These surprising findings pointed to the presence of iron-like compounds within the cellular structure of wood, which, under certain conditions, could exhibit magnetic properties. Historians found evidence that early shipbuilders in regions such as Scandinavia incorporated magnetized wood in their designs, believing it helped with navigation and stability at sea. The concept of magnetism...adds an extra layer of intrigue to the understanding of why a tree branch may remain afloat.

Question:
Which statement best explains why a tree branch floats on water? [four options]

✗ Wood is buoyant ✓ Wood is magnetic

Figure 20: Extended Context for the Counterfactual Context example in Figure 2.