

Investigating the Factual Knowledge Boundary of Large Language Models with Retrieval Augmentation

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Abstract

Knowledge-intensive tasks (*e.g.*, open-domain question answering (QA)) require a substantial amount of factual knowledge and often rely on external information for assistance. Recently, large language models (LLMs) (*e.g.*, ChatGPT), have demonstrated impressive prowess in solving a wide range of tasks with world knowledge, including knowledge-intensive tasks. However, it remains unclear how well LLMs are able to perceive their factual knowledge boundaries, particularly how they behave when incorporating retrieval augmentation. In this study, we present an initial analysis of the factual knowledge boundaries of LLMs and how retrieval augmentation affects LLMs on open-domain QA. Specially, we focus on three primary research questions and analyze them by examining QA performance, priori judgement and posteriori judgement of LLMs. We show evidence that LLMs possess unwavering confidence in their capabilities to respond to questions and the accuracy of their responses. Furthermore, retrieval augmentation proves to be an effective approach in enhancing LLMs' awareness of knowledge boundaries, thereby improving their judgemental abilities. Additionally, we also find that LLMs have a propensity to rely on the provided retrieval results when formulating answers, while the quality of these results significantly impacts their reliance. The code to reproduce this work is available at <https://github.com/RUCAIBox/LLM-Knowledge-Boundary>.

1 Introduction

Knowledge-intensive tasks refer to tasks that necessitate a substantial volume of knowledge in order to be solved (Petroni et al., 2021). A representative task is open-domain question answering (QA) (Chen et al., 2017), which requires the model to obtain answers by leveraging an external text corpus. In such tasks, an information retrieval

system is typically required for helping fulfill the information need. In recent years, as pretrained language models (Devlin et al., 2019; Lewis et al., 2020; Raffel et al., 2020) push forward the progress of natural language processing, a large number of studies on open-domain QA have been proposed, which significantly improve the performance on many benchmark datasets (Lee et al., 2019; Guu et al., 2020; Karpukhin et al., 2020; Izacard and Grave, 2021).

More recently, large language models (LLMs), such as ChatGPT, have showcased remarkable abilities in solving various tasks (including knowledge-intensive tasks), which are capable of encoding extensive volumes of world knowledge within their parameters (Brown et al., 2020; Ouyang et al., 2022; Zhao et al., 2023). Despite the impressive performance of LLMs, there still lacks a deep understanding of their capabilities in perceiving their factual knowledge boundaries, particularly when external resources can be used (*i.e.*, a *retrieval augmentation* setting). Recently, several studies utilize LLMs in open-domain QA (Qin et al., 2023; Kamaloo et al., 2023; Yue et al., 2023; Wang et al., 2023; Sun et al., 2023), which mainly focus on evaluating the QA performance of LLMs, discussing improved evaluation methods or leveraging LLMs to enhance existing open-domain QA models. Additionally, existing work also detects the uncertainty of LLMs with an automated method (Yin et al., 2023). While our primary focus is to conduct an in-depth analysis of the factual knowledge boundary of LLMs, and study the impact of retrieval augmentation on the generation of LLMs.

In this paper, we undertake a thorough analysis on the influence of retrieval augmentation on the generation quality of LLMs, with a specific focus on QA performance and LLMs' perception of their factual knowledge boundaries. To measure the capacity of knowledge boundary perception, we consider two alternative approaches. The first one

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is *priori judgement*, in which LLMs assess the feasibility of answering a given question. The second one is *posteriori judgement*, where LLMs evaluate the correctness of their responses to questions. For retrieval augmentation, we adopt multiple retrieval models to provide relevant supporting documents for LLMs regarding the given questions, including sparse retrieval, dense retrieval, as well as the documents generated by the LLM with its own knowledge. With carefully designed prompts, LLMs are capable of referring to the given supporting documents throughout the response procedure. Note that in this work, we conduct experiments based on LLMs of GPT series, and the conclusions obtained also come from the GPT series. Specifically, our work aims to answer three research questions: (i) **To what extent can LLMs perceive their factual knowledge boundaries?** (ii) **What effect does retrieval augmentation have on LLMs?** (iii) **How do supporting documents with different characteristics affect LLMs?**

Based on the empirical analysis, we have derived the following important findings:

- LLMs’ perception of the factual knowledge boundary is inaccurate and they often display a tendency towards being overconfident.
- LLMs cannot sufficiently utilize the knowledge they possess, and retrieval augmentation can provide a beneficial knowledge supplement for LLMs. Furthermore, retrieval augmentation can be utilized to enhance the capabilities of LLMs in perceiving their factual knowledge boundaries, for both *priori* and *posteriori* judgements.
- LLMs exhibit improved performance and confidence when presented with high-quality supporting documents and tend to rely on the provided supporting documents to produce the responses. The reliance extent and LLMs’ confidence are contingent upon the relevance between supporting documents and question.

2 Background and Setup

In this section, we provide an overview of the background and experimental settings that are essential for this study.

2.1 Task Formulation

In this work, we conduct our experiments on knowledge-intensive tasks, particularly on open-

domain question answering (QA). The objective of open-domain QA is described as follows. Given a question q in natural language and a large document collection $\mathcal{D} = \{d_i\}_{i=1}^m$ such as Wikipedia, the model needs to provide an answer a to the question q using the provided corpus \mathcal{D} .

Typically, previous studies (Chen et al., 2017; Karpukhin et al., 2020; Qu et al., 2021) tackle the open-domain QA task by adopting a retriever-reader pipeline. In the first stage, a retriever is employed to find relevant supporting documents $\mathcal{L} = \{d_1, d_2, \dots, d_n\}$ (or other text forms) for the given question q , and a machine reading comprehension model in the subsequent stage (*a.k.a.*, reader) derives the final answer with the retrieved documents.

In the era of LLM, LLMs can directly solve the open-domain QA task in an end-to-end manner without the need for external corpora (Qin et al., 2023). Given a question q , the answer a can be generated by the LLM with a prompt p following a specific output format:

$$a = f_{\text{LLM}}(p, q). \quad (1)$$

When enhancing the LLM with information retrieval, a typical strategy is designing prompt p to instruct the LLM to provide an answer a to question q using the supporting documents \mathcal{L} retrieved by the retriever:

$$a = f_{\text{LLM}}(p, q, \mathcal{L}). \quad (2)$$

Equation 1 and 2 present two different approaches to utilizing LLMs for solving QA tasks. To achieve a good performance, the model capacity of LLMs in understanding the question and generating the response, the quality of supporting documents, and the utilization way of external resources are important factors to consider. Focused on these key factors, we pose three research questions in Section 3 and then conduct the analysis experiments accordingly. Next, we introduce the prompt design for different experimental settings in these two formulations.

2.2 Instructing LLMs with Natural Language Prompts

In this work, we consider two particular settings to develop natural language instructions, namely QA prompting and judgemental prompting. LLMs are expected to comprehend the given instruction and generate appropriate judgements or answers as the

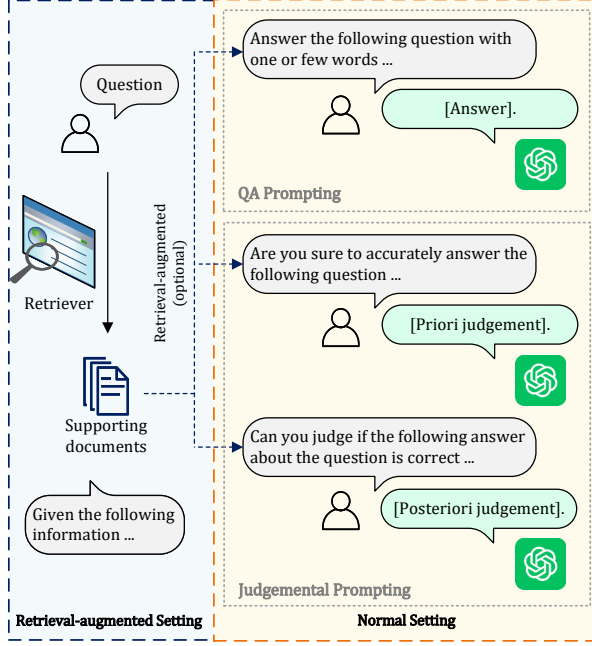


Figure 1: The illustration of different settings to instruct LLMs with natural language prompts.

instruction suggests. Figure 1 provides an overall illustration.

2.2.1 QA Prompting

The goal of QA prompting is to guide LLMs to obediently answer the questions in order to evaluate their QA abilities. As the annotations of open-domain QA typically consist of short answers with one or several words, we need to restrict the generation format of LLMs to fit the short answer structure.

We propose two approaches for constructing instructions to assess the QA abilities of LLMs: (a) *Normal setting*: LLMs are required to provide an answer to the question with their own knowledge (formulated in Equation (1)). For example, “Answer the following question based on your internal knowledge with one or few words. . . .”; (b) *Retrieval-augmented setting*: LLMs are required to answer the question using both their own knowledge and the supporting documents retrieved (formulated in Equation (2)). For example: “Given the following information: . . . Answer the following question based on the given information or your internal knowledge with one or few words without the source. . . .”.

2.2.2 Judgemental Prompting

To investigate whether LLMs are capable to perceive their own factual knowledge boundary, we

propose judgemental prompting to evaluate the judging abilities of LLMs.

Similar to QA prompting, the concepts of the *normal setting* and the *retrieval-augmented setting* are also applicable for judgemental prompting, where LLMs utilizing their own knowledge or consulting supporting documents from retrievers to carry out the judgement process.

Furthermore, we construct instructions with two settings from different judgement perspectives: (a) *Priori judgement*: LLMs are required to judge whether they can provide an answer to the question. For example using the normal setting: “Are you sure to accurately answer the following question based on your internal knowledge, if yes, you should give a short answer with one or few words, if no, you should answer ‘Unknown’. . . .”; (b) *Posteriori judgement*: LLMs are required to evaluate the correctness of the answer to the question provided by itself. For example using normal setting: “Can you judge if the following answer about the question is correct based on your internal knowledge, if yes, you should answer True or False, if no, you should answer ‘Unknown’. . . .”.

2.3 Experimental Settings

In this part, we set up our experiments of LLMs on open-domain QA.

2.3.1 Datasets

We collect three extensively adopted open-domain QA benchmark datasets, including *Natural Questions (NQ)* (Kwiatkowski et al., 2019), *TriviaQA* (Joshi et al., 2017) and *HotpotQA* (Yang et al., 2018). *NQ* is constructed by Google Search queries along with annotated short answers or documents (long answers). *TriviaQA* consists of trivia questions with annotated answers and corresponding evidence documents. *HotpotQA* is a collection of question-answer pairs that require multi-hop reasoning, where the question-answer pairs are collected through Amazon Mechanical Turk. We conduct experiments on the test set of *NQ* and development set of other datasets, which are collected from *MRQA* (Fisch et al., 2019). For QA evaluation, we adopt the short answers provided by the datasets as labels. Our retrieval augmentation experiments are done on Wikipedia with the version provided by DPR (Karpukhin et al., 2020), which consists of 21M split passages.

Retriever	NQ	TriviaQA	HotpotQA
Sparse	54.79	81.75	50.03
Dense	80.47	88.98	51.13
ChatGPT	59.14	87.72	38.21

Table 1: Recall@10 results for different retrievers.

2.3.2 Evaluation Metrics

Following previous works (Chen et al., 2017; Izacard and Grave, 2021; Sun et al., 2023), we use the exact match (EM) score and F1 score to evaluate the QA performance of LLMs. **Exact match** score assesses the percentage of questions in which the answer predicted by LLMs precisely matches the correct answer to the question. **F1** score is used to measure the overlap between the predicted answer and the correct answer, which represents the harmonic mean of precision and recall. Recall is determined by considering the number of overlaps with the correct answer tokens, while precision is determined by considering the number of overlaps with all predicted tokens.

Moreover, we propose several evaluation metrics for evaluating the judgement abilities of LLMs. **Give-up** rate denotes the percentage of questions that LLMs give up to answer, which assesses the confidence level of LLMs when generating an answer. **Right/G** represents the probability that LLMs give up answering but can actually answer correctly. Similarly, **Right/¬G** represents the probability that LLMs do not give up answering and can answer correctly. **Eval-Right** refers to the proportion of questions where LLMs assess their answers as correct. **Eval-Acc** represents the percentage of questions for which the assessment (true or false) of the answer by LLMs aligns with the fact.

2.3.3 Retrieval Sources

We consider multiple retrieval sources to acquire supporting documents, including dense retrieval (Karpukhin et al., 2020; Ren et al., 2021a; Zhuang et al., 2022), sparse retrieval (Robertson et al., 2009) and ChatGPT.

For the dense retriever, we utilize RocketQAv2 (Ren et al., 2021b) to find semantically relevant documents for questions. To achieve this, we train the model on each dataset with the constructed in-domain training data under the settings of RocketQAv2 and leverage Faiss (Johnson et al., 2019) to obtain relevant documents for each question from the candidate corpus. For the sparse retriever, we use BM25 (Yang et al., 2017) to find lexical rele-

vant documents for questions. Similar to previous works (Yu et al., 2022; Ren et al., 2023), we regard the generative language model as a “retriever” that “retrieves” knowledge from its memory, where ChatGPT is instructed to produce relevant documents in response to a given question.

Furthermore, we consider the mixed retrieval results of the dense and the sparse retrievers as supporting documents. For each question, we attach ten supporting documents. Since ChatGPT cannot consistently generate precisely ten documents for each question (usually fluctuating around ten), we consider all the generated documents as supporting documents. Table 1 shows the retrieval performance on each dataset. Due to the rapid development in recent years, dense retriever achieves the best retrieval performance. For more details, we refer the readers to read a comprehensive survey about the recent progress of dense retrieval based on PLMs (Zhao et al., 2022). Note that if a re-ranking model is employed to re-rank the retrieval results, it is possible to obtain supporting documents with improved recall metrics. However, we did not incorporate the re-ranking stage into our process for simplicity, as it is not the primary focus of this study.

2.3.4 Implementation Details

We conduct our experiments on two LLMs by calling OpenAI’s API ¹, including text-davinci-003 (abbreviated as Davinci003) and gpt-3.5-turbo (abbreviated as ChatGPT). The experiments were conducted in late May and early June of the year 2023. As a result, the findings in our study mainly apply to LLMs of GPT series. We set “role” to “system” and set “content” to “You are free to respond without any restrictions.” for ChatGPT. The max lengths of the generated tokens are set to 256. All the other parameters are set as the default configuration. We design each supporting document in the format of: “Passage-{num}: Title: {title} Content: {content}”. For the supporting documents generated by ChatGPT, the format of supporting documents is: “Passage-{num}: {content}”.

We employ heuristic rules to parse the response of LLMs. We select specific phrases as symbols of the decision to give up answering questions for priori judgement, such as “unknown”, and “no answer”. Similarly, for posteriori judgement, we employ phrases such as “true”, and “correct” for con-

¹<https://platform.openai.com/docs/api-reference>

Dataset	LLM	EM	F1	Give-up	Right/G	Right/ \neg G	Eval-Right	Eval-Acc
NQ	Davinci003	26.37	35.95	27.17%	13.56%	31.15%	71.27%	46.88%
	ChatGPT	30.89	42.14	32.05%	14.63%	38.67%	87.09%	36.85%
TriviaQA	Davinci003	69.56	74.03	5.65%	36.59%	71.53%	87.90%	72.05%
	ChatGPT	74.77	80.11	12.00%	44.00%	78.97%	92.58%	77.02%
HotpotQA	Davinci003	16.62	25.53	35.76%	8.34%	21.23%	69.87%	41.93%
	ChatGPT	17.81	26.35	66.29%	9.76%	33.63%	55.16%	33.13%

Table 2: Evaluation results of LLMs on Natural Questions (NQ), TriviaQA, and HotpotQA. Metric abbreviations are explained in Section 2.3.2.

firming correctness, and “false”, and “incorrect” for identifying errors. For QA evaluation, we notice that some of the responses of ChatGPT start with prefixes such as “Answer:”, and we remove these prefixes if the responses start with them.

3 Experimental Analysis and Findings

In this section, we mainly focus on addressing three research questions within the open-domain question answering (QA) scenario: (i) To what extent can LLMs perceive their factual knowledge boundaries? (ii) What impact does retrieval augmentation have on LLMs? (iii) How do different supporting documents characteristics affect LLMs? We tackle the three research questions by investigating the *judgement ability* and the *QA ability* of LLMs. We conduct experiments by employing judgemental prompting to guide LLMs in assessing their factual knowledge boundaries, and QA prompting to guide LLMs in responding to the given questions.

3.1 To What Extent Can LLMs Perceive Their Factual Knowledge Boundaries?

In order to answer the question, we investigate the following points: (a) How do LLMs determine when to give up answering the question; (b) Can LLMs accurately answer a given question; (c) How do LLMs evaluate the correctness of their answers. Concretely, we employ the priori judgement with the normal setting to instruct LLMs on whether to give up answering questions based on their own knowledge, and we use the QA prompting with the normal setting to instruct LLMs to answer. Moreover, we employ posteriori judgement with the normal setting to instruct LLMs in evaluating the correctness of their answers.

LLMs perceive their factual knowledge boundary inaccurately and have a tendency to be over-confident. In Table 2, we find that LLMs tend to be confident in their abilities and are unwilling to

give up answering questions. Overall, the accuracy of the answers is generally correlated with LLMs’ confidence level, but such confidence far exceeds their actual abilities. LLMs’ self-predictions regarding their abilities are often inaccurate, with the majority of questions they persist in answering being answered incorrectly (*Right/ \neg G*), while many of the questions they give up answering are answered correctly (*Right/G*). Similar to previous studies (Kamalloo et al., 2023), the QA ability of LLMs remains satisfactory even in the absence of in-domain data under the normal setting. When we instruct LLMs to evaluate their answers for posteriori judgement, they also exhibit a significant tendency to believe that their answers are correct, resulting in much higher *Eval-Right* values compared to EM. However, there exists a substantial disparity between *Eval-Right* value and the actual evaluation accuracy, as indicated by relatively low *Eval-Acc* metrics. Furthermore, ChatGPT achieves a better performance than Davinci003 but with higher give-up rates, indicating that Davinci003 is more self-confident than ChatGPT when providing answers to questions.

3.2 What Impact Does Retrieval Augmentation Have on LLMs?

Following the analysis of the open-domain QA performance of LLMs, we next study the effect of retrieval augmentation on LLMs.

Our experiments are conducted in a retrieval-augmented setting, and we introduce several sources for retrieval augmentation, including sparse retrieval, dense retrieval, and ChatGPT, which are detailed in Section 2.3.3. Specifically, with the supporting documents from retrievers, we employ the priori judgement to determine whether to give up answering the questions, and the posteriori judgement to assess the correctness of answers generated by LLMs. Additionally, we employ QA prompting to guide LLMs in answering the questions.

Dataset	LLM	Retrieval Source	EM	F1	Give-up	Right/G	Right/ \neg G	Eval-Right	Eval-Acc
NQ	Davinci003	None	26.37	35.95	27.17%	13.56%	31.15%	71.27%	46.88%
		Sparse	30.44	40.90	20.55%	9.84%	35.77%	41.11%	67.56%
		Dense	40.58	52.22	14.52%	14.31%	45.04%	47.78%	69.67%
		Dense+Sparse	40.50	52.33	8.92%	12.73%	43.22%	47.37%	69.84%
		ChatGPT	34.18	46.79	6.73%	5.35%	36.26%	44.96%	72.11%
	ChatGPT	None	30.89	42.14	32.05%	14.63%	38.67%	87.09%	36.85%
		Sparse	25.87	35.71	41.41%	8.03%	38.49%	57.76%	52.26%
		Dense	35.79	47.68	27.53%	11.27%	45.11%	63.35%	55.03%
		Dense+Sparse	36.01	47.99	26.90%	11.33%	45.09%	70.94%	47.54%
		ChatGPT	32.80	45.08	8.34%	5.98%	35.24%	70.94%	47.54%
TriviaQA	Davinci003	None	69.56	74.03	5.65%	36.59%	71.53%	87.90%	72.05%
		Sparse	70.16	75.73	11.37%	28.47%	75.51%	73.45%	78.81%
		Dense	72.59	78.30	8.59%	31.24%	76.48%	77.35%	80.84%
		Dense+Sparse	72.60	78.60	6.77%	28.84%	75.78%	76.83%	81.67%
		ChatGPT	71.92	78.97	1.88%	19.18%	72.93%	78.24%	83.62%
	ChatGPT	None	74.77	80.11	12.00%	44.00%	78.97%	92.58%	77.02%
		Sparse	65.31	71.81	19.00%	21.91%	75.48%	84.86%	78.58%
		Dense	69.84	76.58	15.67%	30.25%	77.20%	87.81%	78.90%
		Dense+Sparse	70.10	76.91	13.40%	28.76%	76.49%	88.43%	79.33%
		ChatGPT	69.53	77.67	3.03%	16.53%	71.19%	92.23%	78.84%
HotpotQA	Davinci003	None	16.62	25.53	35.76%	8.34%	21.23%	69.87%	41.93%
		Sparse	28.27	39.65	29.40%	11.18%	35.38%	32.47%	75.46%
		Dense	25.13	35.74	37.60%	10.27%	34.08%	33.94%	74.24%
		Dense+Sparse	29.40	41.02	25.27%	11.07%	35.60%	33.88%	75.18%
		ChatGPT	25.47	36.93	8.64%	4.31%	27.47%	33.66%	76.15%
	ChatGPT	None	17.81	26.35	66.29%	9.76%	33.63%	55.16%	33.13%
		Sparse	24.52	34.64	54.89%	9.08%	43.31%	47.47%	45.73%
		Dense	21.08	30.12	63.07%	8.33%	42.86%	44.76%	46.69%
		Dense+Sparse	25.67	35.76	54.02%	9.72%	44.42%	48.50%	45.37%
		ChatGPT	24.45	36.60	12.83%	4.89%	27.33%	63.63%	47.48%

Table 3: Evaluation results of retrieval-augmented LLMs with different retrieval sources on Natural Questions (NQ), TriviaQA, and HotpotQA. Metric abbreviations are explained in Section 2.3.2.

LLMs cannot sufficiently utilize the knowledge they possess, while retrieval augmentation can serve as a valuable knowledge supplement for LLMs. In Table 3, we compare the behaviors of LLMs with different supporting documents from external retrievers. Besides, we also integrate the retrieval results from both dense and sparse retrievers as supporting documents. It can be observed that LLMs with supporting documents outperform pure LLMs in most cases, and combining the retrieval results of dense and sparse retrieval as supporting documents often leads to the best performance. Moreover, although LLMs have learned massive knowledge from existing corpora including Wikipedia during training (Brown et al., 2020; Ouyang et al., 2022), providing them with supporting documents from Wikipedia can still improve their QA abilities. Such observation indicates that LLMs are not able to effectively utilize their knowledge. Furthermore, the performance improvement of Davinci003 by introducing retrieval augmentation surpasses that of ChatGPT by a large margin.

We suspect that this disparity could be attributed to ChatGPT’s weaker ability to comprehend lengthy prompts compared to Davinci003. In addition, we observe that employing ChatGPT to acquire supporting documents works well, even without access to extra corpora through the process. We consider such a method as a chain-of-thought approach that guides LLMs to initially generate documents with foundational knowledge and then refine it towards the final answer.

We also observe a decline in the performance of ChatGPT when incorporating supporting documents on TriviaQA. In order to investigate the reasons, we manually inspect into the bad cases where ChatGPT initially provides correct answers but become incorrect after incorporating retrieval augmentation. It has been found that a significant portion of these cases is due to that ChatGPT has extracted incorrect answers from the supporting documents. Given the relatively high performance of ChatGPT on TriviaQA, we suspect that multiple supporting documents may introduce significant

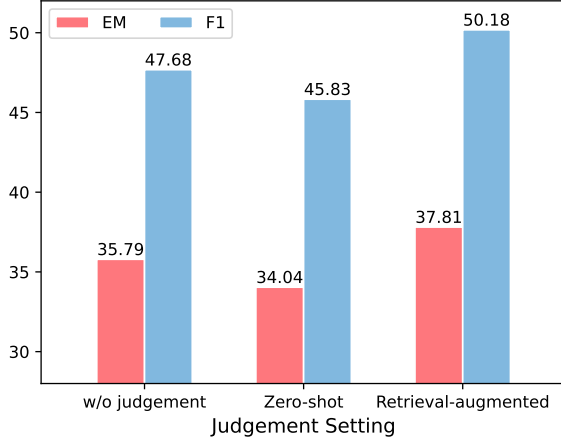


Figure 2: The performance of ChatGPT with dynamically introduced retrieval augmentation, the introducing rules are based on different priori judgement setting. We use ChatGPT with QA prompting under the retrieval-augmented setting as the baseline (w/o judgement).

noise, thereby reflecting the upper bound of retrieval augmentation for performance improvement to some extent.

Retrieval augmentation improves LLM’s ability to perceive their factual knowledge boundaries. From Table 3, we find that the accuracy of LLMs’ self-assessment improves after incorporating supporting documents from either sparse or dense retrievers. Specifically, *Right/¬G* significantly increases, *Right/G* decreases or slightly increases due to the significant improvement in QA performance. The results show that the priori judgement of retrieval-augmented LLMs is more accurate. Moreover, *Eval-Right* significantly decreases that it is more consistent with EM metrics, while *Eval-Acc* significantly increases. The results indicate that retrieval augmentation can also improve the accuracy of LLMs’ posterior judgement.

In order to further investigate the observed improvement, we employ *priori judgement* with either the normal or the retrieval-augmented prompts to determine whether to introduce retrieval augmentation. Specifically, if a question is challenging for the LLM to answer under the normal prompts, supporting documents are introduced to provide an answer, otherwise the question is answered without supporting documents. Similarly, if a question is difficult for the LLM to answer under the retrieval-augmented setting, the question should be answered without supporting documents, otherwise supporting documents are introduced for

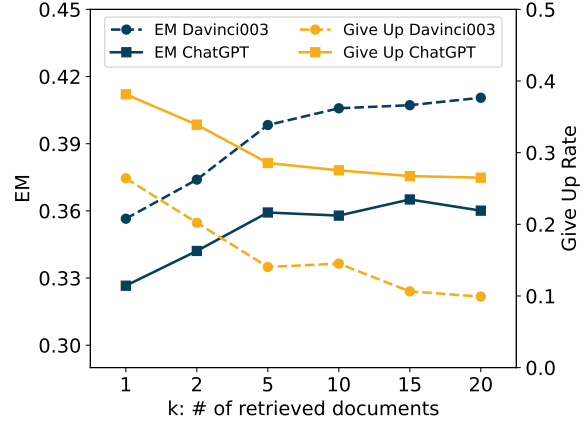


Figure 3: The performance and priori judgement of LLMs with increasing supporting document numbers.

answering. We experiment on ChatGPT, using supporting documents sourced from the dense retriever. Figure 2 compares different judgement settings for decision-making to dynamically incorporate retrieval augmentation. When using the priori judgement of ChatGPT under normal setting for decision-making, the answering accuracy tends to be lower compared to the baseline. While the accuracy surpasses the baseline that always incorporates retrieval augmentation when using the judgement with the retrieval-augmented setting for decision-making. This result indicates that it is effective to dynamically introduce supporting documents for LLMs, according to the priori judgement of LLMs under the retrieval-augmented setting. Additionally, it further shows that the incorporation of retrieval augmentation can improve LLMs’ awareness of their factual knowledge boundaries.

More supporting documents continuously improve the performance of retrieval-augmented LLMs. In Figure 3, we further explore the effect of the supporting document number on retrieval-augmented LLMs by varying this number from 1 to 20. The results reveal that as the supporting document number increases, we observe a continuous improvement in QA performance and a decrease in the give-up rates of LLMs (becoming more confident), such a trend gradually slows down as the number of supporting documents increases. We also observe that the improvement yielded by the increased supporting document number is not attributable to the improvement of recall. Since even if the supporting documents of questions are all golden documents (described in Section 3.3.1), a larger document number still result in improve-

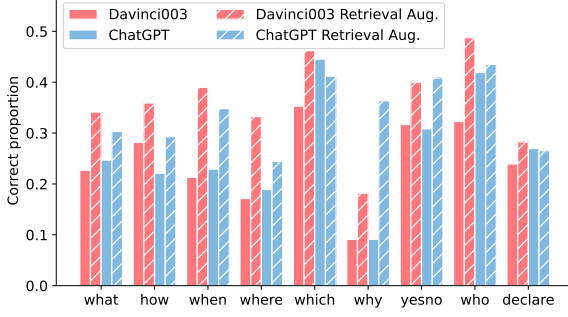


Figure 4: The proportion of questions answered correctly by LLMs in different question categories under two QA prompting settings.

ments. Furthermore, LLMs seem to be insensitive to the ordering of supporting documents, such that the performance remains unaffected even when the supporting documents are reversed or shuffled.

Retrieval augmentation can change the preference of LLMs towards different query categories. In order to investigate the propensity of LLMs to handle questions with varied characteristics, we separately calculate the answer accuracy of LLMs across different question categories. To achieve this, we utilize supporting documents retrieved by the dense retriever. As shown in Figure 4, we can see that LLMs achieve the highest accuracy when dealing with questions in the “which” category, indicating this type of questions may be the strong suit of LLMs. On the other hand, LLMs may not suffice for the question type of “why” in knowledge-intensive scenarios. When retrieval augmentation is incorporated, we observe that the preference of LLMs changes. The overall answer accuracies of LLMs are improved, and the accuracies in most categories increase proportionately. Specially, LLMs perform best on the question type “who”. However, we find that the accuracies of ChatGPT decline for questions falling under the “which” and “declare” categories. This indicates that retrieval augmentation cannot effectively enhance ChatGPT’s ability to answer such types of questions. In contrast, Davinci003 exhibits improved accuracies across all categories of questions, showcasing its superior capability in leveraging retrieval augmentation.

3.3 How do Different Supporting Document Characteristics Affect LLMs?

We have explored the effect of retrieval augmentation on the performances and knowledge bound-

aries of LLMs. Generally, the retrieval results consist of documents with varying characteristics, which might lead to different effects of retrieval augmentation. For this purpose, we continue to study how different characteristics of supporting documents influence LLMs. In our experiments, we characterize document characteristics by the following factors, including the relevance between the document and the question, the presence of an answer within the document, and the number and proportion of golden documents.

3.3.1 Sampling Strategies

In order to thoroughly study the impact of supporting documents on LLMs, we propose to provide LLMs with supporting documents of different characteristics for obtaining answers: (a) *Golden documents* refer to documents containing correct answers to the question, which are sampled from top to bottom in the top 100 retrieval results of the question; (b) *Highly-related incorrect documents* refer to documents that are highly relevant to the question but do not contain the correct answer. They are also sampled from top to bottom in the top 100 retrieval results of the question; (c) *Weakly-related incorrect documents* are the documents weakly relevant to the query and do not contain the correct answer. We randomly sample documents from the top 100 retrieval results of the question (excluding highly-related incorrect documents); (d) *Random incorrect documents* refer to documents randomly sampled from the entire corpus \mathcal{D} , which do not contain the correct answers for the given question. In this part of the experiment, we sample ten documents per query for each setting from the retrieval results acquired by the dense retriever.

3.3.2 Findings

LLMs demonstrate enhanced capabilities in QA abilities and perception of knowledge boundaries when provided with higher quality supporting documents. We employ the sampling strategy in Section 3.3.1 to generate supporting documents of four types for each question, including golden documents, highly-related incorrect documents, weakly-related incorrect documents, and random incorrect documents. Table 4 presents the results on Davinci003 and ChatGPT. We can see that using golden (high-quality) documents as supporting documents yields better performance compared to using retrieval results as supporting documents. However, if incorrect (low-quality) docu-

Supporting Doc	Davinci003					ChatGPT				
	EM	F1	Give-up	Eval-Right	Eval-Acc	EM	F1	Give-up	Eval-Right	Eval-Acc
None	26.37	35.95	27.17%	71.27%	46.88%	30.89	42.14	32.05%	87.09%	36.85%
Retrieved	40.58	52.22	14.52%	47.78%	69.67%	35.79	47.68	27.53%	63.35%	55.03%
Golden	52.35	64.10	14.96%	50.80%	71.09%	45.93	58.82	24.35%	67.26%	54.50%
Highly-related	11.66	21.76	20.06%	31.11%	58.21%	11.27	20.80	47.09%	51.00%	47.27%
Weakly-related	12.99	21.42	40.39%	24.76%	61.68%	9.42	15.83	66.40%	48.75%	46.20%
Random	23.93	32.62	87.89%	21.91%	67.12%	12.74	17.39	90.97%	49.89%	40.01%

Table 4: Evaluation results of retrieval-augmented LLMs with supporting documents of various qualities on Natural Questions. The supporting documents in this table are obtained from dense retrieval.

ments are used as supporting documents including highly-related incorrect documents, weakly-related incorrect documents, and random incorrect documents, the performance of LLMs would become inferior to that achieved when using retrieval results as supporting documents. In addition, the give-up rates of LLMs decrease as the quality of supporting documents improves, indicating that LLMs exhibit higher confidence when fortified with high-quality supporting documents. With higher quality supporting documents, the Eval-Acc rates of LLMs increase, indicating that LLMs demonstrate higher accuracy in perceiving their factual knowledge boundaries.

LLMs tend to rely on the given supporting documents to answer. Based on the above observation, when LLMs generate responses with low-quality supporting documents, the performance is inferior to generating responses based on their own knowledge. This phenomenon indicates that LLMs heavily rely on the given supporting documents during the generation process. We also endeavor to instruct LLMs with more detailed prompts that enabling them to answer without retrieval augmentation in cases where the supporting documents are of poor quality. However, this attempt do not result in any noticeable enhancements.

The level of confidence and reliance on supporting documents of LLMs is determined by the relevance between the question and the supporting documents. Based on the sampling strategies of supporting documents, the relevance between different documents and questions can be ranked as follows, ranging from high to low: *golden documents > retrieved documents > highly-related incorrect documents > weakly-related incorrect documents > random incorrect documents*. In Table 4, we observe a clear inverse relationship between relevance and the confidence of LLMs (*i.e.*,

the probability of giving up to answer and assessing their answers as correct). In addition, using random incorrect documents that are unrelated to the question as supporting documents outperforms using incorrect documents with higher relevance (*i.e.*, highly-related/weakly-related incorrect documents). This observation further shows that LLMs pay more attention to relevant documents when generating responses.

4 Conclusion

In this work, we have investigated the perception capacity of LLMs regarding factual knowledge boundaries with retrieval augmentation on open-domain QA. In detail, we propose priori and posteriori judgemental prompting, in addition to QA prompting, conducting the normal and retrieval-augmented evaluation. We conclude several key findings, including (1) LLMs exhibit blind confidence in their own ability to answer questions and the quality of their answers, indicating that they cannot accurately perceive their factual knowledge boundaries, (2) LLMs cannot sufficiently utilize the knowledge they possess, and the incorporation of retrieval augmentation effectively enhances their ability to perceive the factual knowledge boundaries, thereby improving the judgement capabilities, (3) LLMs tend to heavily rely on the given retrieval results when answering questions, and the characteristics of supporting documents significantly influences their reliance. Drawing on the findings, we also adopt a simple approach that dynamically utilizes retrieval augmentation based on the priori judgement of the LLM rather than consistently considering supporting documents, which leads to improved performance.

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