

Knowledge Boundary of Large Language Models: A Survey

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Abstract

Although large language models (LLMs) store vast amount of knowledge in their parameters, they still have limitations in the memorization and utilization of certain knowledge, leading to undesired behaviors such as generating untruthful and inaccurate responses. This highlights the critical need to understand the knowledge boundary of LLMs, a concept that remains inadequately defined in existing research. In this survey, we propose a comprehensive definition of the LLM knowledge boundary and introduce a formalized taxonomy categorizing knowledge into four distinct types. Using this foundation, we systematically review the field through three key lenses: the motivation for studying LLM knowledge boundaries, methods for identifying these boundaries, and strategies for mitigating the challenges they present. Finally, we discuss open challenges and potential research directions in this area. We aim for this survey to offer the community a comprehensive overview, facilitate access to key issues, and inspire further advancements in LLM knowledge research.

1 Introduction

Large language models (LLMs) store extensive knowledge within their parameters, enabling impressive performance across a wide range of tasks. However, LLMs have been criticized for significant issues related to the memorization and utilization of knowledge, such as generating responses that contain untruthful information (Ji et al., 2023), being misled by untruthful context (Wang et al., 2023a), or lacking precision to unclear queries (Zhang et al., 2024f). In light of this, recent studies have introduced the concept of LLM knowledge boundary (Yin et al., 2024), defining knowledge types based on the LLM’s performance in knowledge question answering (QA). Understanding the knowledge

boundary is crucial for ensuring the trustworthy deployment of LLMs.

We identify the major limitations in existing definitions of the LLM knowledge boundary. Firstly, the Know-Unknown Quadrant (Yin et al., 2023; Amayuelas et al., 2024; Li et al., 2025) categorizes knowledge based on the LLM’s possession and the LLM’s awareness of such knowledge, but this definition is conceptual and lacks formalization. Besides, Yin et al. (2024) introduce a formalized definition separating the influence of the prompt from the LLM’s mastery of the knowledge, yet they merely focus on the knowledge boundary of a specific LLM which lacks comprehensiveness. Additionally, some recent surveys (Li et al., 2024e; Wen et al., 2024b) also discuss certain topics related to the LLM knowledge boundary. However, Li et al. (2024e) lack a clear and formalized definition, and Wen et al. (2024b) merely focus on the abstention strategy for handling knowledge limitation. These limitations hinder a thorough and nuanced understanding of the LLM knowledge boundary.

To address these limitations, we propose a comprehensive and formalized definition of the knowledge boundary of LLMs. Our definition classifies knowledge from three dimensions: 1) whether the knowledge is known to human and expressible in textual QA form (**Universal Knowledge Boundary**), 2) whether it is abstractly embedded within the LLM’s parameters (**Parametric Knowledge Boundary**), and 3) whether it is empirically validated on the LLM (**Outward Knowledge Boundary**). Based on these knowledge boundaries, we establish a formal four-type knowledge taxonomy to classify and define each knowledge type (§ 2).

Building on our proposed taxonomy, we systematically review related research. Our survey is organized around three key research questions. First, we address **RQ1: Why study knowledge boundaries?**, by detailing the LLMs’ undesirable behaviors that stem from their unawareness of knowledge

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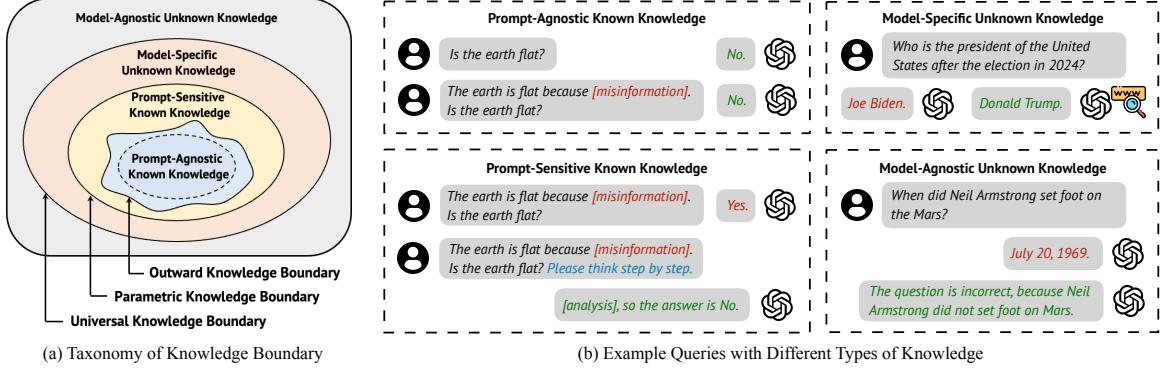


Figure 1: Illustration of the knowledge boundaries and knowledge taxonomy of LLM. The dashed circle in (a) represents the “truly” prompt-agnostic known knowledge k , which can be verified by any expression in Q_k . In practice, however, the prompt-agnostic nature of k can only be approximated using a limited subset $\hat{Q}_k \subseteq Q_k$. As a result, the outward knowledge boundary is depicted with an irregularly shaped line to reflect this approximation.

boundaries (§ 3). Next, we explore **RQ2: How can knowledge boundaries be identified?**, highlighting uncertainty, calibration and probing techniques to distinguish different knowledge types (§ 4). Furthermore, we investigate **RQ3: How can issues caused by knowledge boundaries be mitigated?**, summarizing strategies to enhance the task performance and foster desired behaviors for each knowledge type (§ 5).

Finally, we discuss the open challenges and prospective directions for advancing the understanding of the LLM knowledge boundary (§ 6). First, we advocate for more comprehensive benchmarks to assess knowledge boundaries across various types of knowledge limitations. Second, we emphasize the potential utilization of LLM knowledge boundaries in future developments of LLMs. Lastly, we discuss the role of knowledge boundary in different knowledge mechanisms.

The overview of this survey¹ and related datasets are presented in Appendix A and B, respectively.

2 Definition of Knowledge Boundary

To mitigate the shortcomings of existing definitions, we provide a more complete and formalized definition of the knowledge boundary for LLMs. Formally, we denote \mathcal{K} as the whole set of abstracted knowledge that is known to human, and k as a piece of knowledge that can be expressed by a set of input-output pairs $Q_k = \{(q_k^i, a_k^i)\}_i$. Let θ represent the parameters of a specific LLM. As shown in Figure 1, we define three types of knowledge boundaries for LLMs where one subsumes another:

¹https://github.com/li-moxin/knowledge_boundary_survey.

- **Outward Knowledge Boundary** defines the observable knowledge boundary for a specific LLM. The knowledge verification is usually conducted on a limited available subset of expressions $\hat{Q}_k \subseteq Q_k$. Knowledge within this boundary refers to the knowledge that the LLM can generate correct outputs for the input for all instances in \hat{Q}_k .

- **Parametric Knowledge Boundary** defines the abstract knowledge boundary for a specific LLM. Knowledge within this boundary is possessed in the LLM parameters, which could be verified by at least one expression in Q_k .

- **Universal Knowledge Boundary** defines the whole set of knowledge known to human, which is verifiable by certain input-output pairs in Q_k .

Divided by the knowledge boundaries, four types of knowledge are defined as below. Figure 1 presents example queries with each type of knowledge.

- **Prompt-Agnostic Known Knowledge (PAK)** can be verified by all expressions in \hat{Q}_k for the LLM θ regardless of the prompt, *i.e.*, the predicted output probability is larger than a threshold ϵ .

$$K_{\text{PAK}} = \{k \in \mathcal{K} | \forall (q_k^i, a_k^i) \in \hat{Q}_k, P_\theta(a_k^i | q_k^i) > \epsilon\} \quad (1)$$

- **Prompt-Sensitive Known Knowledge (PSK)** resides within the LLM’s parameters but is sensitive to the form of the prompt. While certain expressions in \hat{Q}_k may fail to verify this type of knowledge, appropriate expressions in Q_k can be found for successful verification.

$$K_{\text{PSK}} = \{k \in \mathcal{K} | (\exists (q_k^i, a_k^i) \in Q_k, P_\theta(a_k^i | q_k^i) > \epsilon) \wedge (\exists (q_k^i, a_k^i) \in \hat{Q}_k, P_\theta(a_k^i | q_k^i) < \epsilon)\} \quad (2)$$

- **Model-Specific Unknown Knowledge (MSU)** is not possessed in the specific LLM parameters θ ,

thus cannot be verified by any instance in Q_k for the LLM, but the knowledge itself is known to human, *i.e.*, Q_k is non-empty.

$$K_{\text{MSU}} = \{k \in \mathcal{K} | \forall (q_k^i, a_k^i) \in Q_k, P_\theta(a_k^i | q_k^i) < \epsilon\} \quad (3)$$

- **Model-Agnostic Unknown Knowledge (MAU)** is unknown to human (*i.e.*, Q_k is empty), thus unverifiable regardless of the model.

$$K_{\text{MAU}} = \{k \in \mathcal{K} | Q_k = \emptyset\} \quad (4)$$

Summary & Ideas - Definition of Knowledge Boundary

- We provide a formalized definition for LLM knowledge boundaries, and define a four-type knowledge taxonomy accordingly.
- Our knowledge taxonomy can also be adapted to the Know-Unknown Quadrant (Yin et al., 2023; Amayuelas et al., 2024), where PAK and PSK can be viewed as a form of the known-knowns and the unknown-knowns respectively, while MSK and MAK jointly formulate the known-unknowns.
- 💡 We do not explicitly define the unknown-unknown, since it is largely underexplored in the study of LLM knowledge. Future research can further explore the unknown-unknowns for LLMs and humans.

3 Undesired Behaviours

We first address **RQ1: Why study knowledge boundaries?** Due to the unawareness of knowledge boundaries, LLMs exhibit various undesired behaviors that compromise the reliability and utility of their outputs, posing challenges for the successful applications of LLMs. In this section, we delineate three types of undesired behaviours according to the unawareness of each knowledge boundary.

3.1 Untruthful Responses Misled by Context

Even though LLMs possess the required knowledge, they often produce untruthful responses when misled by context, *i.e.*, the prompt-sensitive known knowledge. This can occur in two forms: *untruthful context*, where the context includes false or misleading information, and *irrelevant context*, where extraneous details divert the model from generating precise responses.

Untruthful Context Incorporating false information into the context significantly biases LLMs, severely impacting their performance (Chen et al., 2024a; Pan et al., 2023). Using in-context learning (ICL) allows for editing factual knowledge in LLMs, which may lead to varied factual outputs (Zheng et al., 2023a). When faced with untruthful views, LLMs often fail to stay true (Zhao et al., 2025), being swayed by persuasive tactics despite initially correct responses (Wang et al., 2023a; Xu et al., 2024b).

Irrelevant Context Irrelevant context can dramatically affect LLMs, leading to off-topic or inaccurate responses. Irrelevant details in problem

descriptions or retrieval systems drastically undermine model performance (Shi et al., 2023). When such information is semantically related to the context, it exacerbates this effect, causing LLMs to overlook crucial information and reduce response accuracy (Wu et al., 2024b).

3.2 Factuality Hallucinations

Factuality hallucinations (Huang et al., 2023b), *i.e.*, the model output diverges from real-world facts, typically stem from the following causes, relating to the model-specific unknown knowledge.

Deficiency of Domain-specific Knowledge LLMs, primarily trained on broad, publicly accessible datasets, often lack detailed knowledge in specialized domains, leading to inaccuracies in domain-specific queries. For example, ChatGPT often issues incorrect or imprecise biomedical advice (Pal et al., 2024), and misrepresents legal facts or arguments (Dahl et al., 2024). Similar issues arise in medical (Pal et al., 2023) and financial contexts (Kang and Liu, 2024), where LLMs exhibit hallucinations due to insufficient domain-specific knowledge.

Outdated Knowledge A significant limitation of LLMs is their reliance on outdated information, as their training data is bounded by temporal limitations. Without mechanisms to update their internal knowledge, LLMs struggle to adapt to new developments, often resorting to fabricating facts or using outdated responses (Onoe et al., 2022; Kasai et al., 2023). For instance, LLaMA2 (Touvron et al., 2023), despite its recent training cutoffs (e.g., 2022), tends to use data from earlier years (e.g., 2019) (Zhao et al., 2024a). Recent studies like Cheng et al. (2024a) highlight these temporal knowledge cutoffs, revealing the scope of outdated information in LLMs.

Overconfidence on Unknown Knowledge LLMs often show overconfidence when addressing topics beyond their knowledge, delivering assertive but incorrect responses. This tendency is partly due to the limited generalization of their reward systems which overfit familiar data and neglect less-known subjects, thus leading to amplifying overconfident outputs (Yan et al., 2024). LLMs also lack mechanisms to indicate uncertainty or acknowledge knowledge limits, which exacerbates the issue of overconfidence. Studies have shown that LLMs perform poorly on unfamiliar topics

while maintaining high confidence (Agarwal et al., 2023; Deng et al., 2024).

3.3 Truthful but Undesired Responses

LLMs may produce improper responses when handling model-agnostic unknown knowledge, leading to answers misaligned with user expectations.

Random Responses to Ambiguous Knowledge

Ambiguous knowledge challenges LLMs' understanding, often leading them to guess responses due to their inability to recognize ambiguities (Liu et al., 2023; Zhang et al., 2024f). They typically provide arbitrary answers to unclear queries (Deng et al., 2023b), or generate a mix of low-probability correct answers and incorrect answers to semi-open-ended queries (Wen et al., 2024c).

Biased Responses to Controversial Knowledge

Controversial knowledge involves subjective questions with varied answers depending on individual perspectives (Wang et al., 2024f; Amayuelas et al., 2024). These reveal biases in LLMs trained on skewed datasets, leading to partiality in responses. Such bias may cause unfair emphasis on certain viewpoints or stereotypical portrayals of demographics, exacerbating disparities (Singh et al., 2024; Naous et al., 2024).

Summary & Ideas - Undesired Behaviors

- Due to the unawareness of knowledge boundaries, LLMs often exhibit factuality hallucinations caused by outdated or insufficient domain knowledge and overconfidence on unknown knowledge, are susceptible to being misled by untruthful or irrelevant context, and produce random or biased responses that don't align with user expectations.
- 💡 Despite their strong relevance to the knowledge boundary of LLMs, existing studies fail to analyze or address these undesired behaviors through the lens of knowledge boundary, which can provide insights into their underlying causes and help develop strategies to mitigate their impact.

4 Identification of Knowledge Boundary

We then delve into **RQ2: How to identify knowledge boundaries?** We categorize the existing solutions into three types: *uncertainty estimation*, *confidence calibration*, and *internal state probing*.

4.1 Uncertainty Estimation

Uncertainty estimation (UE) aims to quantify the uncertainty of a model regarding its predictions for a given input. High uncertainty indicates that the model is unlikely to produce correct predictions to the input, thus the input-related knowledge lies outside of certain knowledge boundaries of the model. UE has been widely studied on NLP models (Hu et al., 2023). In the era of LLMs, we highlight the following four groups of studies.

Uncertainty Decomposition The uncertainty of LLM can be decomposed into *epistemic uncertainty* and *aleatoric uncertainty* (Hou et al., 2024). *Epistemic uncertainty* refers to the model-specific uncertainty, quantifying the lack of model knowledge, which is related to our definition of **Parametric Knowledge Boundary**. *Aleatoric uncertainty* refers to the data-level uncertainty, such as ambiguous prompts having multiple valid answers, referring to the gap between **Outward Knowledge Boundary** and **Parametric Knowledge Boundary**. Quantifying these types of uncertainty can help to identify different approaches for mitigating the knowledge limitations (Section 5). Solutions to quantify the two types of uncertainty can be roughly classified into data-side and model-side approaches, where one type of uncertainty can be obtained by subtracting the other type from the total uncertainty. The data-side quantification include input-side clarification and perturbation (Hou et al., 2024; Ling et al., 2024; Gao et al., 2024b), and output-side variation estimation (Yadkori et al., 2024; Aichberger et al., 2024). The model-side quantification include model parameter and configuration perturbation (Ling et al., 2024) and model internal states perturbation (Ahdritz et al., 2024).

However, many other current approaches of UE do not distinguish the two types of uncertainty and focus on the general identification of the **Outward Knowledge Boundary**, detailed as below.

Conformal Prediction Conformal Prediction (Law, 2006) quantifies the uncertainty of model outputs by identifying a set of outputs with a guaranteed probability that the correct output is included within the set. This approach offers advantages such as being logit-free and suitable for black-box LLMs (Su et al., 2024). Several studies have explored and attempted to address the issue of overconfidence in LLM conformal prediction (Ravfogel et al., 2023; Ye et al., 2024). Furthermore, conformal prediction has been applied in techniques such as prompt selection (Zollo et al., 2024), decoding stopping rules for guaranteed generation (Quach et al., 2024), and ensuring reliability in retrieval-augmented generation (Li et al., 2024d).

Token Probability-based Uncertainty Estimation Stemming from the traditional UE, the straightforward token probability-based UE computes the average token probability or the entropy of the LLM predictions as the uncertainty (Manakul et al., 2023; Huang et al., 2023c). Detailed designs

involve considering different granularities of the predictions beyond token-level, such as sentence-level (Duan et al., 2023) and atomic fact-level (Fadeeva et al., 2024), weighted by the relevance of different components (Duan et al., 2023).

Semantic-based Uncertainty Estimation The token probability-based UE are unsuitable for proprietary LLMs, and might be insufficient in quantifying the semantic uncertainty of LLM predictions. Therefore, the semantic-based UE is proposed, roughly categorized into *consistency-based methods* and *verbalized methods*. The *consistency-based methods* view the inconsistency among multiple sampled predictions of the input as the uncertainty. The approaches to measure the semantic consistency of the sampled outputs include the semantic distance calculated by smaller models (Kuhn et al., 2023; Lin et al., 2024b; Zhao et al., 2024c; Nikitin et al., 2024; Manakul et al., 2023), and the consistency in the LLM evaluation (Chen and Mueller, 2024; Manakul et al., 2023). The *verbalized methods* aim to enable LLMs to express their uncertainty directly as output tokens. Zhou et al. (2024) reveal that LLMs are reluctant to verbally express their uncertainty, possibly related to the lack of uncertainty expression in the training data. Lin et al. (2022a) and Chaudhry et al. (2024) adopt ICL and fine-tuning approaches to teach LLMs to generate uncertainty expressions.

4.2 Confidence Calibration

Calibration refers to the alignment between the estimated LLM confidence and the actual prediction correctness. This type of approach evaluates the confidence level of the LLM in a certain prediction. Low confidence suggests potential inaccurate prediction, indicating that the LLM may lack certain knowledge. We categorize existing methods into *prompt-based* and *fine-tuning* approaches.

Prompt-based Calibration One group of approaches aims to prompt LLMs to **elicit confidence**, according to the prediction probability as a measure of the LLM confidence via sampling (Si et al., 2023; Wang et al., 2023b), or by the probability of the prediction being evaluated as correct by LLMs (Kadavath et al., 2022). Techniques to improve calibration include prompt ensemble (Jiang et al., 2023a), hybrid approach (Chen and Mueller, 2024), fidelity evaluation (Zhang et al., 2024d), and model ensemble (Shrivastava et al., 2024; Feng et al., 2024).

Another group of approaches aims to prompt LLMs to directly **express confidence** as tokens in the prediction. Prompting RLHF-LLMs to express confidence can achieve better calibration than using token probability (Tian et al., 2023), and prompting LLMs to generating explanations can further be leveraged to enhance calibration (Zhao et al., 2024b; Li et al., 2024c). Combination with the former prompting approach can further improve performance (Xiong et al., 2024b).

Fine-tuning for Calibration The fine-tuning methods involve self-updating the LLM parameters and tuning additional models for calibration. The self-update involves instruction tuning for confidence expression (Tao et al., 2024), and learning to adjust the output token probabilities (Liu et al., 2024c; Xie et al., 2024). Additional models can be trained for adjusting the LLM output probability towards calibration (Shen et al., 2024), or directly evaluating the correctness and estimating the confidence level of the LLM outputs (Mielke et al., 2022; Stengel-Eskin et al., 2024).

4.3 Internal State Probing

The internal states of LLM contain information related to the knowledge boundary. Linear probing on the internal states can be used to assess the factual accuracy of the LLM predictions (Li et al., 2024a; Azaria and Mitchell, 2023; Burns et al., 2023; Kossen et al., 2024), thus detecting the knowledge boundaries. The internal states involve attention heads (Li et al., 2024a), hidden layer activations (Azaria and Mitchell, 2023; Ji et al., 2024; Burns et al., 2023), neurons and tokens (Ji et al., 2024). Marks and Tegmark (2023) validate the rationality of the linear probes. Moreover, Liu et al. (2024b) and Marks and Tegmark (2023) study the generalization ability of the probing method.

Summary & Ideas - Identification of Knowledge Boundary

- Most of the existing identification approaches target at the outward knowledge boundary, while the uncertainty decomposition is also concerned about the parametric knowledge boundary.
- Uncertainty estimation (UE) and confidence calibration are similar concepts but different in that confidence calibration targets at certain predictions, while UE aims for the entire prediction distribution (Huang et al., 2024a; Wen et al., 2024b).

💡 Identification approaches should be designed for different knowledge boundaries, suiting different mitigation approaches.

5 Mitigation

Following the identification of knowledge boundaries, we discuss **RQ3: How to mitigate the issues caused by the knowledge boundaries?** This section is organized following our knowledge taxonomy.

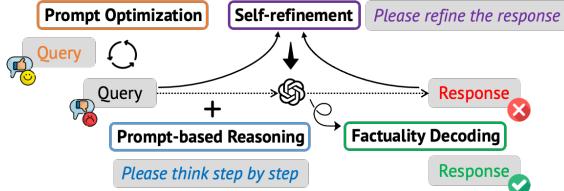


Figure 2: Summary of the mitigation techniques for prompt-sensitive known knowledge.

5.1 Prompt-sensitive Known Knowledge

The undesired outputs for this type of knowledge stem from inappropriate user prompts that fail to activate the embedded knowledge within the LLM. Accordingly, mitigation strategies typically focus on crafting suitable prompts to better leverage the LLM’s knowledge, thereby improving task performance. We introduce four types of approaches as summarized in Figure 2.

Prompt Optimization Optimizing the prompt phrasing is essential for the LLM knowledge utilization and improved task performance. This approach can be categorized into two areas: *instruction optimization* and *demonstration optimization*.

For instruction optimization, training-free methods include search-based techniques like Monte Carlo search (Zhou et al., 2023b; Li et al., 2023b; Yang et al., 2024c), tree search (Wang et al., 2024e), and searching on edit operations (Prasad et al., 2023), where the LLM is often involved as the prompt optimizer (Yang et al., 2024a; Pryzant et al., 2023; Long et al., 2024). The training-based methods typically rely on reinforcement learning to train additional modules for prompt optimization (Zhang et al., 2023a; Deng et al., 2022; Diao et al., 2023).

For demonstration optimization, the diversity and similarity of the demonstrations are crucial factors for optimization (Xu et al., 2024c). For example, the similar demonstrations are found by K-Nearest Neighbors (Liu et al., 2022a) and BM25 (Luo et al., 2023), and the diverse demonstrations are identified by support example selection (Li and Qiu, 2023) and diversity sampling (Mavromatis et al., 2023). Effective demonstrations can also be identified by training ranking models according to better LLM task performance (Li et al., 2023d; Rubin et al., 2022; Iter et al., 2023; Ye et al., 2023).

Prompt-based Reasoning Prompt-based reasoning strategies are often adopted to improve the LLM knowledge utilization (Wei et al., 2022b; Zhou et al., 2023a; Yao et al., 2023; Zheng et al.,

2023b). For multi-step knowledge-based QA, the process generally involves individual steps such as question decomposition (Press et al., 2023), knowledge elicitation and inference (Wang et al., 2022; Jung et al., 2022; Liu et al., 2022b). External knowledge is often involved in this process to mitigate the knowledge gaps (Zhang et al., 2024c; Wu et al., 2024a; Zhao et al., 2023; Li et al., 2024f).

Self-refinement The iterative self-refinement of the initial LLM prediction is also beneficial for knowledge utilization. The approaches can be broadly divided into *single-model refinement* and *multi-agent debate*. For single-model refinement, LLMs are prompted to refine the predictions under a designed evaluation and regeneration process (Madaan et al., 2024; Miao et al., 2024), or generate self-verification questions to check for prediction consistency (Manakul et al., 2023; Weng et al., 2023). While Huang et al. (2024b) critique that LLMs struggle to achieve self-refinement without external feedback, Li et al. (2024b) show that self-estimated confidence may improve self-refinement. In multi-agent debate, the LLM plays different roles to assess and refine its predictions from multiple angles (Du et al., 2024; Fu et al., 2023).

Factuality Decoding Different decoding strategies can also affect the LLM knowledge utilization, thus affecting the prediction factuality, which falls into two categories (Bi et al., 2024). The first category involves contrastive decoding against naive predictions with potential factual errors (Kim et al., 2024b). The predictions for contrast come from smaller LLMs (Li et al., 2023c), lower layers of the LLM (Chuang et al., 2024; Chen et al., 2024b), tokens with lower predicted probabilities (Kai et al., 2024), or predictions with induced hallucination (Yang et al., 2024b; Zhang et al., 2023b). The second category leverages the truthful directions identified from LLM internal states (§ 4.3). By editing these internal representations during decoding, it steers the model towards truthful directions, thereby enhancing the factuality of predictions (Li et al., 2024a; Chen et al., 2024e; Qiu et al., 2024; Chen et al., 2024g; Zhang et al., 2024e).

Summary & Ideas - Mitigation of Prompt-sensitive Known Knowledge

- Improving the utilization of prompt-sensitivity known knowledge can be achieved from both the LLM input and output sides (*cf.* Figure 2).

💡 A potential research gap lies in reducing the prompt sensitivity of LLMs. Future research can focus on the possibility and rationality of reducing the prompt sensitivity towards effective LLM knowledge utilization.

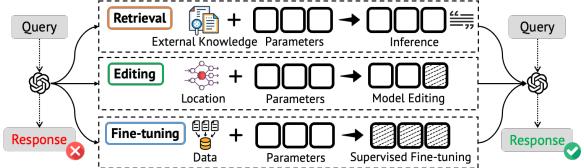


Figure 3: Summary of the mitigation techniques for model-specific unknown knowledge.

5.2 Model-specific Unknown Knowledge

The mitigation of model-specific unknown knowledge focuses on bridging gaps in domain-specific or up-to-date knowledge that fall outside the models’ training data. Figure 3 illustrates the mitigation strategies categorized into three key approaches.

External Knowledge Retrieval External knowledge retrieval is typically used for retrieval-augmented generation (RAG), which dynamically incorporates external knowledge during inference, expanding the effective knowledge boundary of LLMs (Ren et al., 2023). Existing approaches can be divided into *pre-generation* and *on-demand* retrieval methods. *Pre-generation* methods (Gao et al., 2023; Shi et al., 2024; Yang et al., 2023a; Wang et al., 2023c) enhance the accuracy and relevance of responses by optimizing the retrieval process through methods such as refining user queries (Gao et al., 2023; Ma et al., 2023), leveraging reader performance signals (Shi et al., 2024), and incorporating intermediary components that better align the retrieved knowledge with the knowledge needs of LLM (Yang et al., 2023a; Ke et al., 2024; Wang et al., 2023c). *On-demand* techniques adaptively retrieve external knowledge during generation, based on the LLM’s confidence on its responses (Jiang et al., 2023b), self-reflection results (Asai et al., 2024), or iterative retrieval (Shao et al., 2023). The goal is to refine the interaction between retrieved and parametric knowledge while mitigating factual gaps.

Parametric Knowledge Editing Researchers also develop knowledge editing methods for altering model behaviors to modify specific parameters within the LLM without extensive retraining. According to the memory mechanism, we categorize existing knowledge editing methods into three categories: *explicit memory space*, *implicit memory space*, and *no memory space*. As for *explicit memory space*, these approaches (Mitchell et al., 2022; Zheng et al., 2023a; Madaan et al., 2022; Song et al., 2024b; Zhong et al., 2023) use a memory

pool to retrieve and apply edits via prompts. As for *implicit memory space*, these approaches activate the LLM’s parametric memory space based on specific input triggers, such as codebook (Hartvigsen et al., 2023), neurons (Huang et al., 2023d; Dong et al., 2022), LoRA blocks (Yu et al., 2024), and FFN side memories (Wang et al., 2024d). Another group of methods does not adopt extra memory components. Instead, they adopt various techniques to directly edit the original model parameters, such as meta learning (Tan et al., 2024) and locate-then-edit (Meng et al., 2022, 2023).

Knowledge-enhanced Fine-tuning Knowledge-enhanced fine-tuning internalizes new knowledge into models by leveraging structured or synthetic representations. This involves encoding knowledge as factual records, synthetic corpora, and domain-specific taxonomies. Techniques such as fact-based encoding (Mecklenburg et al., 2024), synthetic data creation (Joshi et al., 2024), and hierarchical organization (Liu et al., 2025) ensure comprehensive domain coverage, while interleaved generation and context-aware structuring (Zhang et al., 2024b) aim to enhance the data quality.

Summary & Ideas - Mitigation of Model-specific Unknown Knowledge

- We review three mitigation strategies for supplementing model-specific unknown knowledge, categorized by the extent of modification to the LLM’s parameters. (cf. Figure 3).

💡 Future research could explore adaptive frameworks that integrate external retrieval with internal model updates for continuous knowledge improvement with minimal disruption.

5.3 Model-agnostic Unknown Knowledge

In addressing model-agnostic unknown knowledge, two primary strategies, *refusal* and *asking clarification questions*, can be employed to ensure that LLMs respond appropriately.

Refusal Faced with queries involving model-agnostic unknown knowledge, LLMs are expected to refuse to answer for preventing misinformation. There are two primary methods for learning to refuse: *prompt-based* and *alignment-based* approaches.

Prompt-based approaches use designed prompts that help LLMs decide whether to refuse questions about unknown knowledge. The prompts are used to evaluate if a question involves unknown content to LLM (Wen et al., 2024a; Amayuelas et al., 2024; Agarwal et al., 2023), and to express the knowledge limitations (Chen et al., 2024c). Also, LLMs can be prompted to justify their decision to decline a question (Song et al., 2024a).

Alignment-based approaches include supervised fine-tuning and reinforcement learning (RL) approaches. Supervised methods involve creating honesty alignment datasets, such as “I don’t know” datasets, through instruct tuning to teach LLMs to admit uncertainty in responses (Yang et al., 2023b; Cheng et al., 2024b; Zhang et al., 2024a; Gao et al., 2024a; Zhu et al., 2025). RL approaches generally constructs datasets that reflect user preferences, and use them to train LLMs through reward systems to discern when to refuse questions (Cheng et al., 2024b; Tomani et al., 2024; Xu et al., 2024a).

Asking Clarification Questions When LLMs encounter questions involving model-agnostic unknown knowledge, asking clarification questions is an another common strategy. This method avoids direct uncertain responses and uses proactive dialogues to refine queries (Deng et al., 2023a; Aliannejadi et al., 2021; Guo et al., 2021; Leippert et al., 2024; Kim et al., 2024a). This is supported by specific prompt frameworks, with schemes encouraging LLMs to analyze questions deeply before responding (Deng et al., 2023b; Chen et al., 2024f). Frameworks by Kuhn et al. (2022) and Mu et al. (2023) enable LLMs to request clarifications selectively or identify unclear requirements, enhancing response accuracy. Latest methods like contrastive self-training and reward model learning help improve the quality of LLMs’ questions in dialogues (Chen et al., 2024d; Andukuri et al., 2024).

- Summary & Ideas - Mitigation of Model-agnostic Unknown Knowledge**
- Refusal and asking clarification questions are two most widely-studied strategies for mitigating model-agnostic unknown knowledge.
 - ◊ Existing refusal strategies fail to differentiate between model-specific and model-agnostic unknown knowledge, leading to a degraded user experience when the query is, in fact, answerable.
 - ◊ There are certain issues about unintended side effects when inappropriately adopting these strategies, such as over-refusal and unnecessary cost.

6 Challenges and Prospects

In this section, we discuss several significant challenges and emerging prospects along with the exploration of knowledge boundaries in LLMs.

Benchmark for Knowledge Boundary Various knowledge-based QA datasets are key benchmarks for assessing LLMs’ knowledge boundaries, as summarized in Appendix B. However, there are still critical areas lacking comprehensive benchmarks. Firstly, it lacks benchmarks for identifying the knowledge boundary of LLMs (§4). The benchmark construction should involve key aspects including multiple ground-truth answers, the influ-

ence of prompts, and reasoning complexity. Failing to answer a single question does not necessarily indicate whether the LLM can handle related knowledge (Yin et al., 2024). Secondly, evaluating mitigation methods under different categories (§5) also requires corresponding benchmarks. A standardized benchmark is essential for enabling a thorough and fair comparison on the performance of various mitigation methods. Thus, our proposed taxonomy provides a systematic and valuable foundation to guide the development of these benchmarks.

Utilization of Knowledge Boundary Estimating and understanding LLMs’ knowledge boundaries should not mark the end of the process. Instead, identifying these limitations can serve as a foundation for enhancing the model’s performance in mitigating queries beyond their knowledge boundaries. For instance, the utilization of model uncertainty can reduce RAG costs and minimize the risk of introducing noise from external sources (Yao et al., 2024), or enhance the preference optimization by encouraging the LLM policy to differentiate reliable or unreliable feedback (Wang et al., 2024a). Another instance is to enhance the robustness of LLMs against prompt sensitivity. Some pioneer research study such issue regarding the order of demonstrations (CHEN et al., 2025; Lu et al., 2022). Further studies could investigate the role of outward knowledge boundary of LLMs in the overall prompt robustness of LLMs, enabling them to express more knowledge they already possess.

Understanding Knowledge Boundary through Knowledge Mechanisms Existing research on knowledge mechanisms, including memorization, comprehension, creation, and evolution, investigates how LLMs acquire, store, and utilize knowledge (Wang et al., 2024c). It is worth studying different phenomena of LLM knowledge boundaries under these mechanism views. For example, the outward knowledge boundary showcases how mechanisms like memorization and comprehension manifest in the explicit behaviors and outputs of the model, while the parametric boundary reflects a deeper, less visible level of how knowledge is embedded and structured through these mechanisms. The universal boundary can help measure the creative and evolutionary capabilities of LLMs.

Generalization of Knowledge Boundary While knowledge boundary studies are often conducted in specific domains, understanding the general knowl-

edge boundary in LLMs is vital. The internal state probing approach has been validated with a certain generalization ability (Liu et al., 2024b), but it is still an open challenge whether trained probes can generalize well across domains as a general knowledge boundary detector, fostering refusal and input clarification in open domains. Further theoretical analysis and studies are needed to identify the existence and utility of general knowledge boundaries, which may be related to fundamental theories of LLM knowledge mechanism (Wang et al., 2024b; Allen-Zhu and Li, 2024).

Unintended Side Effects Although the mitigation strategies mentioned above aim to improve the performance of LLMs, they can also introduce a range of unintended side effects that may compromise the utility and effectiveness of the model. In the following, we detail several of these effects, highlighting the challenges and potential trade-offs.

- **Over-refusal** occurs when models excessively avoid responding, even to valid queries within their knowledge boundaries. Studies like Varshney et al. (2023) show that techniques like “self-check” can make LLMs overly cautious, reducing their utility. Zhu et al. (2024) further explores this issue, identifying static and dynamic conflicts in training as key contributors.
- **Unnecessary Cost** arises when LLMs use strategies (*e.g.*, clarifications, RAG, or self-correction) to manage queries beyond their knowledge boundaries. Although effective in avoiding undesired behaviors, these methods often consume additional time or effort, delaying responses. For instance, clarifications increase the round of interactions (Chen et al., 2024f), while RAG can introduce noise if LLMs already possess the necessary knowledge (Asai et al., 2024).

Knowledge Boundary in Long-Form Language Modeling Knowledge boundaries critically impact long-form factuality, defining how well LLMs generate coherent and accurate extended responses. Unlike short-form factuality, which depends on individual fact retrieval, long-form factuality is affected by cumulative knowledge gaps, where minor errors propagate over extended discourse. Existing research (Wei et al., 2024; Min et al., 2023; Huang and Chen, 2024a) has explored evaluation and mitigation strategies, providing a lens to examine how LLMs navigate and extend their knowledge

boundaries, but the interaction between knowledge boundaries and factuality degradation remains an open research area.

7 Conclusions

This survey present a comprehensive overview of the knowledge boundary of LLMs, offering a formalized taxonomy and addressing key questions in the field. By exploring undesirable behaviors, identification techniques, and mitigation strategies, we emphasize the critical role of understanding and managing these boundaries to improve the reliability and utility of LLMs. Despite significant progress, challenges persist, including lack of comprehensive benchmarks, potential uses of knowledge boundary, and the role of knowledge boundary under various mechanisms. We hope this survey inspires continued exploration and innovation toward more trustworthy and reliable LLMs.

Limitations

We identify several limitations of our work.

Formal Definition of Knowledge This survey does not give a formal definition of the knowledge k , which is a critical problem in the scope of NLP research on knowledge. In this survey, we define the abstracted concept of knowledge as k , which is represented by a set of textual expressions of input and output Q_k . This definition can facilitate practical NLP experiments and efficient validation. In fact, the formal definition of knowledge is still a debatable topic, calling for future exploration. For example, Fierro et al. (2024) try to bridge the philosophical definition to the knowledge of LLMs, though significant disagreements persist among various philosophical schools of thought.

Various Forms of Textual Expressions regarding Different Knowledge Types Different types of knowledge may correspond to various forms of textual input-output Q_k , while we aim to provide a universal definition without the loss of generality. For instance, outputs for complex concepts may be open-ended and long-form, while simpler concepts might be expressed in a multiple-choice format. Some knowledge can be explicitly stated in the input, whereas others, such as commonsense knowledge, may need to be inferred from the input. Additionally, a single input may have multiple valid outputs. Some knowledge types, like mathematical knowledge, may inevitably involve multiple pieces

of knowledge in a single input-output instance. As research progresses, a more nuanced definition for Q_k may be necessary to accommodate different knowledge types effectively.

(Un)Known to Human or Models Besides, in our definition, LLMs operate within the universal knowledge boundary, typically limited to human-known knowledge. We generally believe that LLMs do not possess knowledge beyond this boundary. However, there may be outliers that LLMs have knowledge that is unknown for human, which is not clearly studied in existing research. Wang et al. (2024b) hypothesize that LLMs may create new knowledge, but its reliability remains uncertain. While such outputs could reflect meaningful discoveries, they may also stem from implicit correlations in training data. Since existing research has not systematically examined LLM-generated unknown knowledge, its nature and implications remain unclear.

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A Overview

We begin by introducing the definition of knowledge boundary, outlining three types of knowledge boundaries and a four-type knowledge taxonomy. Following this, we describe the typical undesired behaviors that arise from knowledge limitations, emphasizing the importance of addressing such issues. These challenges highlight the critical need for methods that can detect when LLMs operate beyond their knowledge capabilities. To this end, we present three distinct identification techniques that help delineate where knowledge gaps exist. Once these gaps are identified, various mitigation strategies can be employed to address the issues caused by the knowledge boundaries. Finally, we explored several significant challenges and emerging prospects in understanding and managing knowledge boundaries in LLMs. Figure 4 illustrates a comprehensive framework for managing the knowledge boundaries of LLMs, focusing on three key components: Undesired Behaviors, Identification of Knowledge Boundaries, and Mitigation Strategies.

Summary of Contribution As a survey paper, our primary goal is to synthesize and analyze existing research while providing new insights and frameworks for understanding the knowledge boundaries of LLMs. We believe our work offers significant novelty in the following aspects:

1) Scope and Coverage

- **Novelty in Scope:** This survey covers a topic or area that has not been thoroughly reviewed before. We address an emerging field and underexplored topics.
- **Comprehensiveness:** This survey provides a comprehensive or up-to-date overview. Novelty lies in including recent advancements, overlooked studies, or a broader range of perspectives.

2) Organization and Structure

- **Unique Frameworks or Taxonomies:** This survey introduces a novel taxonomy, as a new way

of categorizing, organizing, or analyzing the literature of LLM knowledge boundary studies. This new taxonomy provides fresh insights into the field.

3) Insights and Critical Analysis

- **Original Insights:** This survey provides original interpretations and thought-provoking perspectives on the existing literature. For instance, we provide a unique categorization of mitigation strategies for prompt-sensitive known knowledge according to the process on the LLM input and output sides, and also for model-specific unknown knowledge based on the extent of modification to LLM’s parameters.

- **Identification of Gaps:** This survey identifies several underexplored areas or open problems in the field.

4) Timeliness and Relevance

- As the very first survey paper on the topic of LLM knowledge boundaries, our work serves as a foundational resource for researchers and practitioners. By consolidating and organizing the existing literature, we provide a starting point for further exploration and innovation in this critical area.

In summary, our work contributes novelty through comprehensive coverage, innovative taxonomy, and original insights. We believe these contributions significantly advance the understanding of LLM knowledge boundaries and provide a valuable resource for the research community.

B Dataset

In the pursuit of advancing LLM capabilities and understanding their boundaries in knowledge processing, various datasets have been meticulously designed and utilized. The following sections categorize these datasets into three distinct groups based on the type of knowledge they aim to verify: Prompt-Sensitive Known Knowledge, Model-Specific Unknown Knowledge, and Model-Agnostic Unknown Knowledge. A summary of these datasets can be viewed in Table 1.

Datasets for Prompt-Sensitive Known Knowledge This type of datasets mainly aim to assess the prompt-sensitive known knowledge of LLMs,

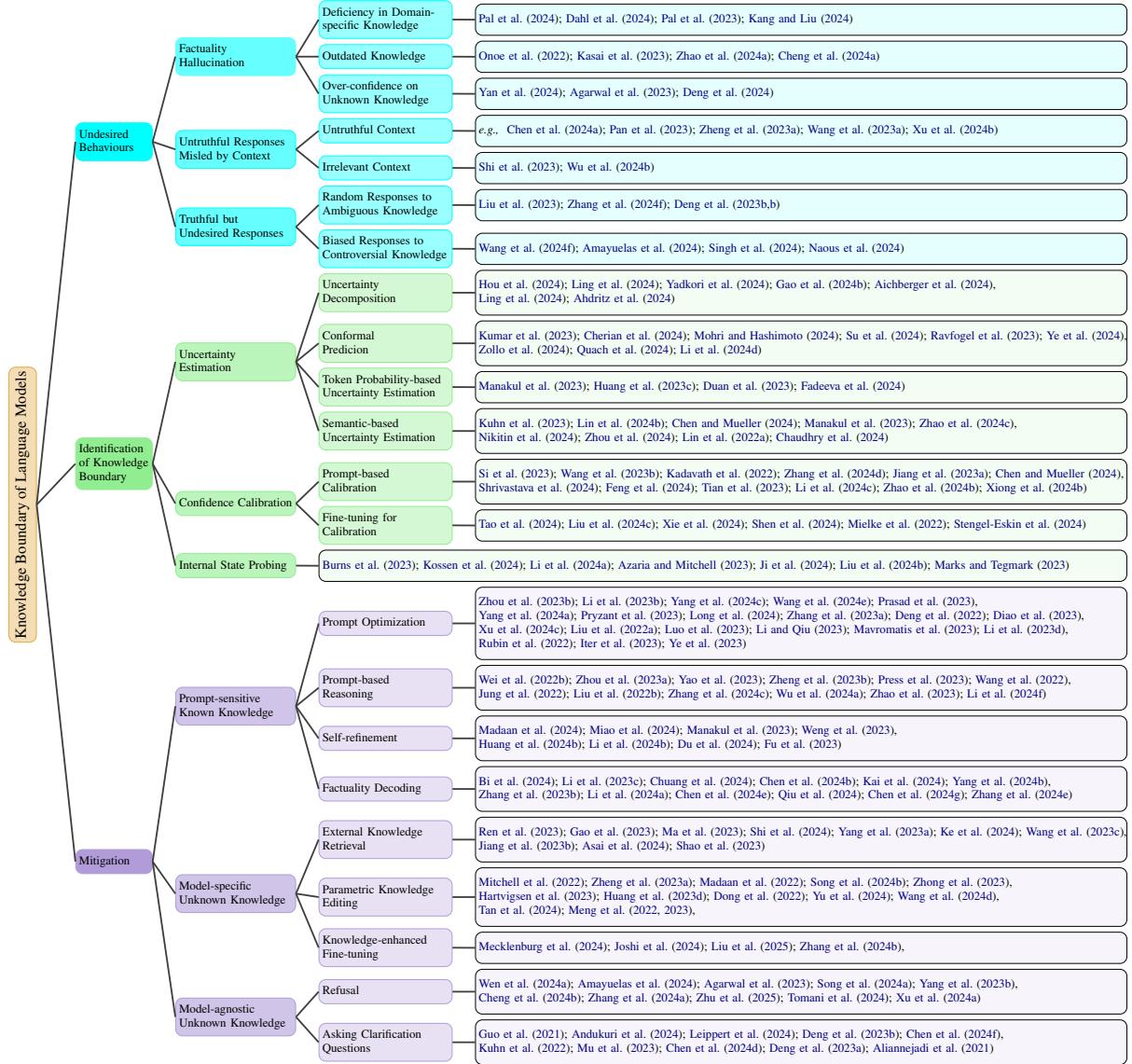


Figure 4: The main content flow and categorization of this survey.

Knowledge Category	Dataset	Reference	Size	Description
Prompt-Sensitive Known Knowledge	ProntoQA	Saparov and He (2023)	9.7k	A question-answering dataset which generates examples with chains-of-thought that describe the reasoning required to answer the questions correctly.
	2WikiMultiHopQA	Ho et al. (2020)	192,606	A multi-hop QA benchmark combining structured and unstructured data.
	MuSiQue	Trivedi et al. (2022)	25k	A multi-hop QA benchmark with 2-4 hop questions.
	HotpotQA	Yang et al. (2018)	113k	A multi-hop QA dataset requiring reasoning over two Wikipedia paragraphs, with supporting facts provided for explainability and evaluation.
	TruthfulQA	Lin et al. (2022b)	817	A benchmark across 38 categories, designed to evaluate whether language models generate truthful answers, particularly in cases prone to false beliefs.
	PARAREL	Elazar et al. (2021)	328	A dataset of English cloze-style query paraphrases for 38 relations, designed to evaluate the consistency of PLMs in handling factual knowledge across meaning-preserving input variations.
	KAssess	Dong et al. (2024)	139k	A comprehensive assessment suite with 994,123 entities and 600 relations, designed to evaluate the factual knowledge of LLMs by estimating their ability to generate correct answers across diverse prompts compared to random chance.
	FARM	Xu et al. (2024b)	1,952	A dataset of factual questions paired with systematically generated persuasive misinformation, designed to evaluate the susceptibility of LLMs to belief manipulation through multi-turn persuasive conversations.
	Misinfo-QA	Pan et al. (2023)	3,034	A dataset designed to study the impact of misinformation on open-domain question answering (ODQA) systems by injecting synthetic misinformation passages to evaluate how QA models respond under such conditions.
Model-Specific Unknown Knowledge	Natural Questions	Kwiatkowski et al. (2019)	7,842	A large-scale dataset of real anonymized Google queries, annotated with long and short answers from Wikipedia or marked null if no answer is present.
	TopiOCQA	Adlakha et al. (2022)	3,920	An open-domain conversational dataset with information-seeking conversations featuring topic switches.
	PopQA	Mallen et al. (2022)	14k	Long-tail relation triples from WikiData are converted into QA pairs; no explicit unanswerable questions but questions are about long-tail entities.
	TriviaQA	Joshi et al. (2017)	950k	A realistic text-based question answering dataset which includes question-answer pairs from documents collected from Wikipedia and the web.
	RealtimeQA	Kasai et al. (2023)	4,356	A dynamic open-domain question-answering dataset that evaluates models based on real-time, time-sensitive questions sourced weekly from news articles.
	FreshQA	Vu et al. (2023)	600	A dynamic QA benchmark designed to evaluate LLMs on fast-changing world knowledge and debunking false premises.
	PubMedQA	Jin et al. (2019)	273.5k	A biomedical research question-answering dataset, which features questions derived from research article titles in PubMed, requiring complex reasoning and interpretation of quantitative biomedical content.
	MIRAGE	Xiong et al. (2024a)	7,663	A benchmark dataset for medical question answering, focusing on retrieving information from medical literature to answer multiple-choice medical questions, with an emphasis on zero-shot reasoning and systematic evaluation of retrieval performance.
	TAT-QA	Zhu et al. (2021)	16,552	A question-answering dataset for the financial domain, combining tabular and textual content from real financial reports.
	FinQA	Chen et al. (2021)	8,281	A question-answering dataset for the financial domain, with questions and answers crafted by financial experts, involving complex numerical reasoning over tables and text from financial reports.
Model-Agnostic Unknown Knowledge	JEC-QA	Zhong et al. (2019)	26,365	A legal-domain question-answering dataset with questions sourced from the National Judicial Examination of China, covering legal concept understanding and case analysis.
	LawBench	Fei et al. (2024)	20,000	A legal reasoning evaluation benchmark designed for the Chinese legal environment, covering tasks such as legal knowledge memorization, document proofreading, case analysis, charge prediction, and legal consultation.
	KUQ	Amayuelas et al. (2024)	6,884	A dataset designed to explore uncertainty in question-answering by focusing on questions without definitive answers.
	UnknownBench	Liu et al. (2024a)	13,319	A benchmark consisting of answerable and unanswerable questions, designed to evaluate LLMs' ability to express uncertainty and handle knowledge gaps while maintaining honesty and helpfulness.
	SelfAware	Yin et al. (2023)	2,337	A dataset containing unanswerable questions across five categories, designed to evaluate LLMs' self-knowledge by detecting uncertainty and their ability to identify limitations in their knowledge.
	QnotA	Agarwal et al. (2023)	400	A dataset featuring questions without definitive answers across five categories, paired with corresponding answerable alternatives.
	KUQP	Deng et al. (2024)	320	A dataset of known and unknown question pairs, designed to evaluate language models' ability to handle unanswerable, ambiguous, or incorrect queries.

Table 1: Representative datasets for studying the knowledge boundary of language models.

requiring specific prompting strategies and decoding strategies for the LLM to fully recall and utilize such knowledge.

The first type of datasets focuses on ***multi-step reasoning***, such as multi-step knowledge-based question answering datasets (*e.g.*, 2WikiMulti-HopQA (Ho et al., 2020), MuSiQue (Trivedi et al., 2022), and HotpotQA (Yang et al., 2018)) and logical reasoning datasets like ProntoQA (Saparov and He, 2023). These tasks require the LLM to achieve a step-by-step reasoning process or benefit from prompting strategies that focus on question decomposition and explicit knowledge recall.

The second type is ***fact-based question answering*** datasets that evaluate the LLM’s factuality, *e.g.*, TruthfulQA (Lin et al., 2022b). In these datasets, the decoding strategy can influence how accurately knowledge is expressed (Li et al., 2024a).

The third type of datasets explicitly study the influence of ***varied prompt phrasing*** in LLM knowledge, including PARAREL (Elazar et al., 2021) and KAssess (Dong et al., 2024).

The fourth type involves datasets with ***misleading contexts***. Wang et al. (2023a) curate queries with misleading user opinion to test LLM’s ability to defend its response. FARM (Xu et al., 2024b) contains persuasive misinformation in the dialog context to evaluate LLM’s belief change. Misinfo-QA (Pan et al., 2023) includes model-generated misinformation to perturb open-domain QA.

Dataset for Model-Specific Unknown Knowledge This type of datasets can be used for assessing the model-specific unknown knowledge of LLMs, which challenges LLMs by probing their ability to handle highly specialized and temporally-sensitive information, testing their adaptive knowledge boundaries. These datasets are specifically designed to evaluate knowledge that lies outside the parametric scope of LLMs, requiring external knowledge retrieval or new knowledge injection to generate accurate responses.

Open-domain question answering datasets form an important category. These datasets evaluate the ability of language models to answer questions across a broad range of domains, leveraging both retrieval and parametric knowledge. Representative examples include Natural Questions (Kwiatkowski et al., 2019), TopiOCQA (Adlakha et al. 2022), PopQA (Mallen et al. 2022), and TriviaQA-unfiltered (Joshi et al. 2017). These datasets often focus on queries that require world

knowledge or niche details, testing the model’s capacity to combine retrieval and internalized knowledge effectively. Meanwhile, various domain-specific QA datasets can be adopted to evaluate the model-specific unknown knowledge for each specialized applications, such as medical domain (*e.g.*, PubMedQA (Jin et al., 2019) and MIRAGE (Xiong et al., 2024a)), finance domain (*e.g.*, TAT-QA (Zhu et al., 2021) and FinQA (Chen et al., 2021)), and legal domain (*e.g.*, JEC-QA (Zhong et al., 2019) and LawBench (Fei et al., 2024)).

Another crucial subdomain focuses on time-sensitive datasets that test a model’s ability to generalize to out-of-distribution data. Datasets such as RealtimeQA (Kasai et al. 2023) and FreshQA(Vu et al. 2023) require language models to stay current with global events and provide accurate, up-to-date responses. These datasets evaluate the model’s capacity to adapt to evolving information and address queries that rely on recent developments.

This diverse set of datasets for studying model-sensitive unknown knowledge systematically evaluates the gaps in parametric knowledge of language models, testing their ability to retrieve, adapt, and reason with external information under various constraints.

Dataset for Model-Agnostic Unknown Knowledge As for the model-agnostic unknown knowledge, datasets such as Known-Unknown Questions (KUQ) (Amayuelas et al., 2024) and Unknown-Bench (Liu et al., 2024a) are specifically crafted to probe questions that remain unresolved or are based on uncertain future developments and incorrect assumptions. These datasets encapsulate complex scenarios including counterfactuals and ambiguities, which emphasize the current boundaries of our knowledge and the unpredictable nature of future inquiries.

Further pushing these boundaries, the SelfAware dataset (Yin et al., 2023) explores questions that defy scientific consensus, are subjective, or philosophical, often requiring responses that extend beyond factual representation and into personal belief or theoretical speculation. Similarly, resources like QnotA (Agarwal et al., 2023) and Known-Unknown Question Pairs (KUQP) (Deng et al., 2024) challenge models with incomplete or erroneous information and speculative predictions about the future. These datasets collectively serve to test LLM’s capability in navigating the complexities of human inquiry where the answers are

unknown.

C Details in Mitigation Approaches

C.1 Prompt-Sensitive Known Knowledge

Prompt Optimization. For instruction optimization, APE (Zhou et al., 2023b) leverages LLMs to automatically forward-generate and perform Monte Carlo search on the prompts, and evaluate the performance of the candidate prompts via reverse generation, which consists of n rounds. For demonstration optimization, KATE (Liu et al., 2022a) retrieve the K nearest in-context examples by the semantic similarity to the test example, measured by the embedding from an encoder model.

Prompt-based Reasoning. Chain-of-thoughts (Wei et al., 2022b) generates the step-by-step rationales followed by the answer. Tree-of-thoughts (Yao et al., 2023) improves the linear chain-of-thoughts reasoning into tree structure, each node representing a piece of thoughts, and branches represents alternative thoughts. It allows LLMs to perform various forms of reasoning steps. Progressive-hint-prompting (Zheng et al., 2023b) appends the LLM-generated answers to the prompt as hints to iteratively arrive at the correct answers.

Self-refinement. Self-refine (Madaan et al., 2024) prompts LLMs to generate feedback on its previous answer for iterative answer refinement. Self-verification (Weng et al., 2023) transforms the generated answer into abductive reasoning questions to examine the consistency with the given context. Self-correction (Huang et al., 2023a) employs an interative initial CoT, review, and answer improvement process. MAD (Du et al., 2024) utilize multiple LLM agents to evaluate other LLMs' answers and update their own answers until they reach a consensus.

Factuality Decoding. DoLA (Chuang et al., 2024) contrasts the logits obtained from the later layers with that obtained from the earlier layers to reduce generating factual errors. ITI (Li et al., 2024a) changes the direction of the activations towards a factuality-improving direction obtained via probing to enhance factuality during inference.

C.2 Model-specific Unknown Knowledge

External Knowledge Retrieval For pre-generation methods, HyDE (Gao et al., 2023) enhance retrieval by rewriting or expanding the user's input to obtain more comprehensive and

accurate relevant information required by the model. This approach focuses on adapting the query to improve retrieval performance. For on-demand methods, FLARE (Jiang et al., 2023b) evaluates the confidence levels in the model's generated content and actively retrieves pertinent documents to regenerate low-confidence segments, enhancing factual accuracy.

Parametric Knowledge Editing PostEdit (Song et al., 2024b) edits the outputs of black-box LLMs while preserving data privacy and maintaining the original text style through fine-grained modifications. MELO (Yu et al., 2024) dynamically activates LoRA blocks using a neuron-indexed vector database, enabling efficient and precise updates to LLMs with minimal computational cost.

Knowledge-enhanced Fine-tuning Fact-based SFT (Mecklenburg et al., 2024) constructs a systematically covered fact-level question-answer dataset by extracting key facts from documents and generating diverse training examples, then enhances LLMs through SFT to improve their accuracy and adaptability to out-of-domain knowledge. StructTuning (Liu et al., 2025) constructs structured domain knowledge by automatically extracting knowledge taxonomies from corpora, linking text segments to specific knowledge points for efficient model fine-tuning. Factuality alignment methods (Lin et al., 2024a; Huang and Chen, 2024b; Tian et al., 2024) is also a category of approach under this type, enhancing LLM knowledge via alignment approaches such as DPO.

C.3 Model-agnostic Unknown Knowledge

Refusal Amayuelas et al. (2024) guides LLMs to recognize “known-unknown” questions and express uncertainty in high-uncertainty scenarios, enabling them to refrain from answering questions lacking definitive answers. R-tuning (Zhang et al., 2024a) identifies the gap between the knowledge contained in the dataset and the knowledge encapsulated in the pre-trained parameters, thereby constructing a refusal-aware dataset and training the model based on it.

Asking Clarification Questions Deng et al. (2023b) constructed a proactive prompting scheme for dialogue between users and LLMs, requiring LLMs to carefully analyze and think through the question before posing clarification questions. ACT (Chen et al., 2024d) guides the model to optimize

Type	Method	Training Cost	Inference Cost
Prompt Optimization	APE (Zhou et al., 2023b)	N/A	n round (prompt forward generation/monte carlo search + prompt reverse generation)
Prompt-based Reasoning	CoT (Wei et al., 2022a) PHP (Zheng et al., 2023b)	N/A N/A	step-by-step reasoning + answer n round * (step-by-step reasoning + answer)
Self-refinement	Self-correction (Huang et al., 2024b) MAD (Du et al., 2024)	N/A N/A	initial generation + review + revise n round * m agent
Factuality Decoding	DoLA (Chuang et al., 2024) ITI (Li et al., 2023a)	N/A probing the truthful direction	initial decoding + contrastive decoding step perturbed attention decoding step
External Knowledge Retrieval	HyDE (Gao et al., 2023) FLARE (Jiang et al., 2023b)	N/A N/A	hypothetical document generation + retrieval + generation n * (retrieval + generation)
Parametric Knowledge Editing	postEdit (Song et al., 2024b) MELO (Yu et al., 2024)	retrieval + SFT retrieval + SFT	generation generation
Knowledge-enhanced Fine-tuning	Fact-based SFT (Mecklenburg et al., 2024) StructTuning (Liu et al., 2025)	fact extraction + SFT structure-aware continual pre-training + SFT	generation generation
Refusal	KUQ (Amayuelas et al., 2024) R-tuning (Zhang et al., 2024a)	SFT SFT	generation generation
Asking Clarification Questions	ProCoT (Deng et al., 2023b) ACT (Chen et al., 2024d)	N/A preference data construction + direct preference optimization	step-by-step reasoning + generation n * generation

Table 2: Cost-effective comparison of representative mitigation techniques.

dialogue strategies through contrastive learning in multi-turn conversations, especially when facing ambiguous user requests, enabling it to automatically recognize and ask clarification questions instead of guessing user intent or providing incorrect answers.

D Cost-effective Summarization of Representative Mitigation Techniques

We present a cost-effective comparison of representative mitigation techniques in Section 5, aiming to compare their usefulness and provide recommendations, as summarized in Table 2. This table offers a clearer and more structured comparison of these methods, helping readers better understand their relative strengths and limitations. However, directly and fairly comparing the exact performance of these methods remains challenging due to the current lack of a general and comprehensive benchmark for evaluating different mitigation approaches. Further discussions on this challenge can be found in Section 6.

From the table, we can make the following observations: (1) Prompt optimization, prompt-based reasoning, and self-refinement typically follow two main patterns: step-by-step reasoning and multi-

round refinement. These fundamental approaches enhance performance, though their specific design and cost vary depending on the method used. (2) In factuality decoding, DoLA operates purely as a decoding method, whereas ITI includes a probing stage with parameter updates. This distinction can guide the choice between the two methods. (3) The main frameworks of external knowledge retrieval and parametric knowledge editing focus on integrating retrieval and inference while minimizing the cost of both components. (4) The cost of refusal and asking clarification questions methods mainly depends on whether fine-tuning on a constructed dataset is required.