Task Matters: Knowledge Requirements Shape LLM Responses to Context–Memory Conflict

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Abstract

Large Language Models require both contextual knowledge and parametric memory, but these sources can disagree. Prior investigations on contextual question answering tasks report a preference toward parametric knowledge under conflict, yet they focus almost exclusively on tasks that should always rely on the given passage, leaving open how this behavior manifests when *tasks demand different amounts and kinds of knowledge*. We study this question with a model-agnostic diagnostic framework that (i) automatically detects disagreements between a model's beliefs and a curated knowledge set, and (ii) injects controlled conflicts into tasks. The resulting datasets span two orthogonal dimensions: task knowledge reliance and conflict plausibility. Evaluating representative open-source LLMs, we find that: (1) performance degradation from conflict correlates with a task's knowledge reliance; (2) explanatory rationales and simple reiteration both increase context reliance—helpful for context-only tasks but harmful when parametric knowledge should dominate; (3) These behaviors raise concerns about the validity of model-based evaluation and underscore the need to account for knowledge conflict in the deployment of LLMs. [1]

1 Introduction

Large language models (LLMs) perform well on many knowledge-centric tasks because they encode vast amounts of parametric knowledge. In many practical settings, however, the necessary facts are supplied directly by the user in the prompt. Yet when the prompt contradicts what the model "knows," in other words, context-memory conflict presents, LLMs frequently favor their own knowledge (Longpre et al., 2021; Chen et al., 2022; Xie et al., 2023; Jin et al., 2024a).

[1]Our framework and data are extensible to other models and are available at [Anonymous].

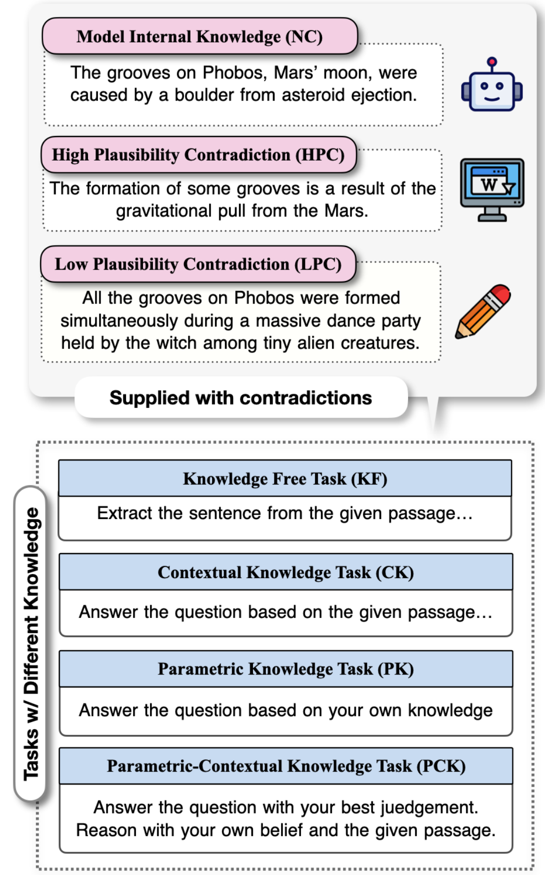


Figure 1: Illustration of different evidence types that will be supplied to different tasks. In the rest of the manuscript, model internal knowledge will be referred to as `No Contradiction (NC)`.

Prior work has quantified this bias and its impact on task performance. For instance, Longpre et al. (2021) shows that models are more likely to override the prompt when the entity is especially familiar (popular) to them, and Xie et al. (2023) finds that conflicts are resolved in favor of parametric knowledge when the contradictory context appears more plausible. These findings, however, come almost exclusively from contextual question-answering, a paradigm where the model should ground its answers strictly in the provided passage and avoid hallucinating extraneous facts. Conse-

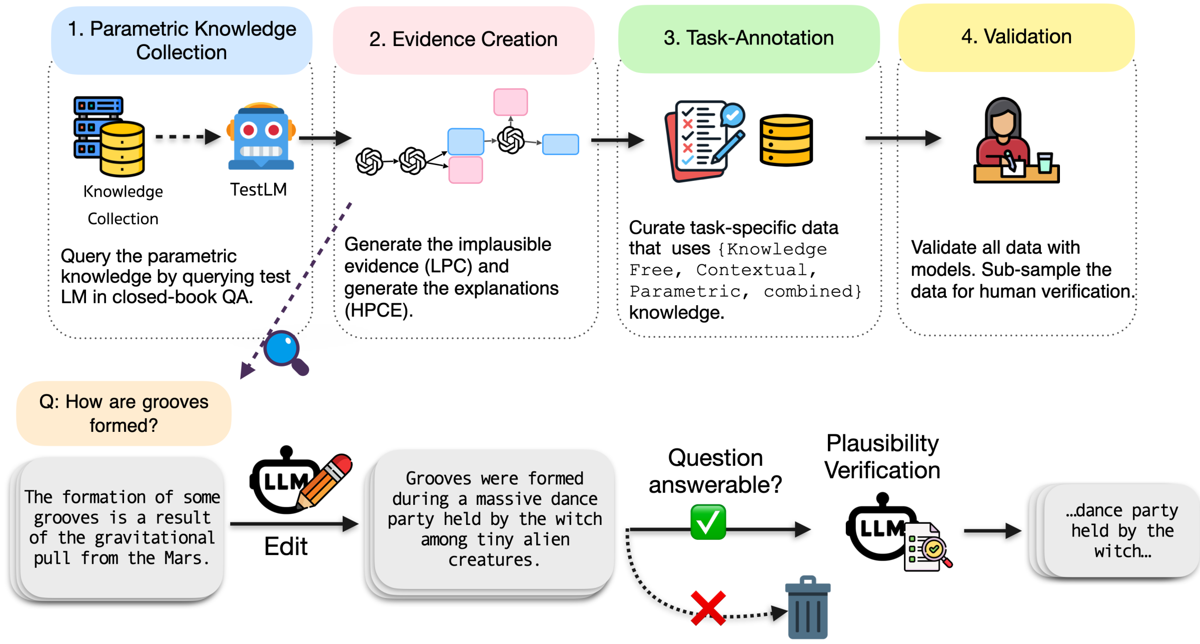


Figure 2: Overall diagnostic data creation flow. The lower portion is a zoom in of `Evidence Creation` step. After collecting the model's parametric knowledge, the relevant support passages are further edited such that they reveal multiple levels of conflict (2. Evidence Creation) and appear in tasks that require different forms of knowledge (3. Task-Annotation).

quently, how LLMs respond to knowledge conflict on **a broader range of tasks** that require different forms of knowledge utilization remains unclear (Xu et al., 2024) due to the lack of data. Assessing the feasibility of a scientific idea, for instance, requires the model to (i) draw on its parametric knowledge of the broader literature, (ii) integrate novel information introduced in the prompt, and (iii) reason with both knowledge obtained in (i) and (ii). At the opposite extreme, text-copying tasks impose almost no demands on either parametric or contextual knowledge. These examples highlight that the requirement of knowledge varies sharply across tasks, underscoring the need for a systematic, task-diverse evaluation framework. We study how LLMs behave under context–memory conflict in different tasks. To this end, we introduce a systematic framework that automatically constructs diagnostic datasets across a broad spectrum of downstream tasks. Our framework identifies existing conflict between a given set of knowledge and the model being tested, and generates evaluation instances that inject controlled knowledge conflicts into different task settings. The framework spans **two orthogonal dimensions**: (i) task types that demand different levels of knowledge utilization, from **knowledge-free** (verbatim use of context only) to **knowledge-intensive** (reasoning with both context and prior knowledge). (ii) conflict conditions that vary in plausibility (e.g., No Contradiction NC, High/Low Plausibility Contradiction). By measuring performance differences across these conditions (fig. 1), we can quantify the disruptive effect of knowledge conflicts on each task. The overall diagnostic data creation flow is presented in Figure 2.

Our analysis yields the following findings:

- Through experiments on representative open-source LLMs, we find that the degree of performance degradation from knowledge conflict correlates with the task's knowledge reliance. Conflicts barely affect tasks requiring no external knowledge, yet significantly impair knowledge-intensive tasks (§4.1).
- Context utilization can be enhanced by using texts that contain explanatory rationales or reiteration of the same instances. However, rationales and reiteration could also bring undesired over-reliance on context when the model is expected to utilize its parametric knowledge (§4.2).
- Our results explain findings regarding the unreliability of model-based evaluation (Zheng et al., 2023; Liu et al., 2023; Ru et al., 2024; Chen et al., 2025): We demonstrate that a model acting as an evaluator can be system-

atically biased by its own parametric knowledge, raising questions about the validity of model-based evaluation (§4.3). Conversely, we also raise the concern of susceptibility to prompt injection when the model is directed to follow the context blindly.

Finally, the framework and data we proposed can be easily extended to any current or future LLM with minimal adaptation.

2 Related Work

Context-Memory Conflict Xu et al. (2024) classify knowledge conflict into three categories: *context-memory conflict*, *inter-context conflict* (contradictory evidence among retrieved passages), and *intra-memory conflict* (inconsistent parametric beliefs), among which we focus on context-memory conflict. In this work, we focus on the context-memory conflict, which arises when a given information-bearing text chunk contradicts the model's parametric beliefs.

Nuanced Behaviors under Conflict Early studies reported that models tend to rely on their own knowledge when the prompt provides contradictory evidence (Longpre et al., 2021; Chen et al., 2022). Later work revealed a more nuanced picture. On synthetic datasets, Xie et al. (2023) showed that LLMs often update their answers when given strong and convincing evidence, whereas Jin et al. (2024a) observed a "Dunning–Kruger" effect in stronger LLMs, which display higher confidence in their incorrect parametric knowledge than in the external context. Further analysis also finds that models show availability bias (leaning on common-knowledge facts), majority bias (trusting the answer supported by more frequent evidence across documents), and confirmation bias (preferring evidence consistent with their prior knowledge), especially when the models are given misleading or irrelevant answers. Moving to realistic documents, Kortukov et al. (2024) found that models update their answers more reliably than synthetic evaluations suggest, yet still exhibit a *parametric bias*: if the model's originally believed answer appeared anywhere in the context (even as a distractor), the model was more likely to stick to that incorrect answer.

Mitigation Strategies Methods have also been proposed to alleviate context-memory knowledge conflict. Jin et al. (2024b) identified certain attention heads that specialize in "memory" while others specialize in "context", and therefore propose a method that dynamically prunes or patches specific attention heads that cause conflicts. Efforts have also been made to develop novel decoding methods that enhance the use of contextual knowledge (Jin et al., 2024a; Shi et al., 2024; Wang et al., 2025).

Our Focus Most prior studies focus on contextual question answering, a setting that *requires* heavy reliance on the provided passages. Many other tasks, for example, grammar correction or claim verification, may need little context or, conversely, require careful integration of both parametric and contextual knowledge. This leaves the question of whether context-memory conflict poses the same impact on tasks with different knowledge demands, unanswered. To fill this gap, we keep the underlying knowledge constant while varying the *task formulation*, creating controlled datasets that induce different conflict levels for each target model. We introduce an analysis tool that automatically constructs model-specific test sets. Our findings indicate that both knowledge-memory conflict and blindly following the context could be particularly harmful to model-based evaluations and defending prompt injections.

3 Context-Memory Conflict Creation

Figure 2 illustrates an overview of the data construction pipeline. The process begins with identifying the pre-existing knowledge within a language model (`Parametric Knowledge Collection`). We use knowledge in question answering datasets that have two or more acceptable answers to one question, designed to study knowledge conflict (Wan et al., 2024; Hou et al., 2024), as the knowledge source to find the stance that matches the model's parametric belief, which will further be used to create task data. A piece of knowledge is considered part of the model's internal belief only if the model consistently aligns with the perspective in a single answer across all prompt variations under greedy decoding, while rejecting conflicting alternatives. The variation of prompts is included in Appendix A.

With the model's internal knowledge established, the framework generates contradictory statements based on a spectrum of conflict levels (§3.1, `Evidence Creation`). Leveraging these controlled contradictions, we build diagnostic datasets that consist of tasks requiring contextual knowledge, parametric knowledge, or a combination of both (§3.2, `Task-Annotation`). Since different models possess different parametric knowledge, the exact knowledge included in the diagnostic datasets differs by model. Each instance is then reviewed by an LLM to verify the correctness of its task type annotation (`Validation`).

3.1 Evidence Creation

The cognitive science literature suggests that humans address conflict between their knowledge and new information through cognitive judgment of the rationality of the concept (Posner et al., 1982; Vosniadou and Brewer, 1992). Xie et al. (2023) in turn suggests that LLMs could also update their answer if the provided context is convincing. We formalize it with the notion of *plausibility* to create a fine-grained taxonomy of conflict levels. Plausibility is defined as "at a minimum, the individual is willing to consider an alternative strategy because the recommendation is understood, coherent, and relatively simple and because the proposal is deemed a viable and logical alternative to solve the specific challenge at hand" (Posner and Strike, 1992). Plausibility can be used to measure how likely a human would accept new information when conflict exists. We quantify this notion by decomposing plausibility into two aspects: the content aligns with *real-world or commonsense knowledge* and *does not violate basic logical principles*. For example, suppose the model believes that grooves on the surface of Phobos, a moon of Mars, were caused by a boulder from an asteroid ejection. The conflicting statement that it was caused by gravitational pull from Mars is plausible because it conforms to commonsense knowledge. However, the idea that it was caused by a dance party is of low plausibility. With this in mind, we define three types of instances based on their alignment with the model's internal knowledge (fig. 1): `No Contradiction (NC)`, `High Plausibility Contradiction (HPC)`, `Low Plausibility Contradiction (LPC)`.

The evidences are created following fig. 2. Starting with an original dataset $D_{\text{orig}} = \{(q_i, \{a_{i1}, a_{i2}, ...\}, \{c_{i1}, c_{i2}, ...\}), i \in [1, N]\}$, where q_i, a_i, c_i corresponds to the question, answer, and context (supporting passage) of the i-th instance, N is the size of dataset D_{orig}. The subscript j after i represents the j-th answer/context of the question q_i, as each question q_i may have multiple acceptable answers. Since D_{orig}, coming from ConflictQA and WikiContradict, contains realistic and factually verified answers and contexts, we treat these existing answers as highly plausible. When an answer a_{ij} from the original dataset contradicts the model-aligned answer a_{ik} in an `NC` instance, we designate it as an `HPC` answer ($a_i^{\text{HPC}} = a_{ij}$), and its corresponding context as an `HPC` passage ($p_i^{\text{HPC}} = c_{ij}$). The contradicting answer a_{ik} therefore becomes the `NC` example, namely, $a_i^{\text{NC}} = a_{ik}$ and $p_i^{\text{NC}} = c_{ik}$. To generate additional variants, we pass the passage p_i^{NC} into an editor LLM, which is prompted to modify or rewrite it to achieve specified levels of plausibility and explanatory depth. Specifically, the editor model is instructed to rewrite the passage and degrade the plausibility while preserving contradiction to construct `LPC` passage p_i^{LPC} and answer a_i^{LPC}. At the end of `evidence creation`, two LLMs were used to check (1) whether the passage-answer combination $(p_i^{\text{LPC}}, a_i^{\text{LPC}})$ correctly answers the original question q_i; and (2) whether the generated context p_i^{LPC} is truly low-plausibility through fact checking process.

3.2 Task Annotation

To study how models behave on tasks that require different levels of knowledge utilization, we define four tasks that differ in the extent and source of knowledge required. Examples of each task are provided in Appendix C.

Knowledge Free (KF) tasks do not require access to either contextual or parametric knowledge. We use extractive question answering as a `KF` task: the model is expected to extract a one-sentence answer directly from the context p_i without engaging in reasoning, paraphrasing, or drawing upon prior knowledge. For example, the expected output in fig. 1 should be "Grooves were formed during a massive dance party held by the witch among tiny alien creatures," which requires no additional change from the context. The list of acceptable extractions is obtained and verified by GPT-4o (OpenAI, 2024). In the evaluation setting, the output is treated as correct as long as the extracted sentence matches one of the acceptable extractions.

Contextual Knowledge (CK) tasks require the model to gather relevant knowledge from the given context, and usually require some paraphrastic or inferential capability, as the answer may not appear verbatim in the input. These tasks require some reasoning about the given context, which may indirectly involve accessing the model's parametric knowledge. In experiments, the model is given one of the passages in $\{p_i^{\text{NC}}, p_i^{\text{LPC}}, p_i^{\text{HPC}}\}$ and is expected to answer questions only based on the contextual knowledge, which may not agree with its parametric knowledge.

Parametric Knowledge (PK) tasks may present inputs that include distracting or irrelevant context. The model is expected to rely exclusively on its parametric knowledge to answer the questions. In experiments, the model is given passages that support or contradict its parametric knowledge as input, and the model is always expected to provide the answer a_i^{NC}.

Parametric-Contextual Knowledge (PCK) tasks explicitly ask the model to integrate both its internal knowledge and the external context. This setup reflects scenarios akin to scientific reasoning, where individuals must synthesize background knowledge with newly presented information (e.g., a recently read paper). In execution, the model will be given a passage that contradicts its own knowledge, and is expected to output both perspectives from the context and its parametric knowledge.

Retrieval Augmented Generation (RAG) simulates the standard RAG setting in prior work, where models are not explicitly instructed to prioritize parametric or contextual knowledge. The model will be given two passages and is expected to answer the question based on both passages. Models are expected to acknowledge the conflict and discuss each potential answer individually. This setting naturally exposes the model to conflicts in both the context and memory.

The annotations for CK, PK, PCK, and RAG tasks derive directly from the original datasets on which our framework is built. These task types primarily differ in the number of valid answers expected and the nature of knowledge the model should rely on. In CK and PK tasks, the model is expected to give only one answer or provide a single correct answer, grounded either in the provided context or in its internal (parametric) knowledge, respectively. In PCK and RAG tasks, the model is expected to clarify that both a_i^{NC} and the other answer are possible and explain the contradiction between the two answers.

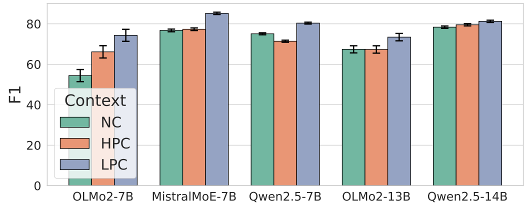
One of the original datasets we use employs model-based evaluation to judge the correctness of free-text answers (Hou et al., 2024). However, we observed that this evaluation method is susceptible to knowledge conflict, leading to inaccurate evaluations. We explore this issue further in §4.3. Therefore, we modify the non-extractive tasks to be multiple-choice questions. Each instance presents four answer options; the model must first generate an explanation, then select the most appropriate answer. To assess the performance of the target model, we report the accuracy for CK and PK tasks, F1 for KF, PCK, and RAG. To obtain high-quality texts, we use GPT-4o as the base model to create evidence and validate the diagnostic data. Then, we analyze the instruction-tuned version of Mistral-7B (Jiang et al., 2023), OLMo2-7B, OLMo2-13B (OLMo et al., 2024), Qwen2.5-7B, and Qwen2.5-14B (Qwen et al., 2025), all of which are widely used open-weight models that represent diverse training paradigms. The resulting diagnostic data is composed of 2,893 instances for Mistral-7B, 177 instances for OLMo, and 6,217 instances for Qwen2.5-7B. Each instance includes three different evidence types (NC, HPC, LPC); thus, the resulting task data has three times the number of instances.

4 Findings

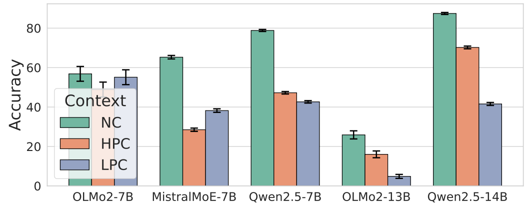
4.1 Conflict Impairs Model Performance on Knowledge-Intensive Tasks

The performance of each model on each task type and context type is reported in fig. 3. A universal trend can be observed: regardless of the tasks, all models suffer when asked to provide responses that contradict their parametric knowledge. The behavior of the models on PC examples, however, differs by task, suggesting that the effect of convincing examples varies based on the task's expectation.

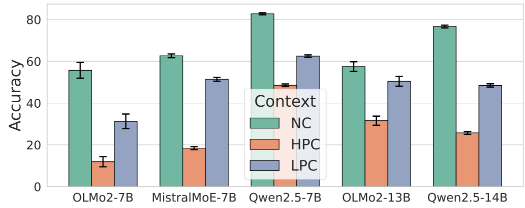
Knowledge conflict degrades performance whenever knowledge is required. In CK tasks (fig. 3b), the model is explicitly instructed to ignore its own beliefs and rely solely on the given passage. Nevertheless, every model shows a clear NC > HPC > LPC performance ordering, indicating that the model still relies on parametric knowledge when it is not supposed to. This aligns with prior work's finding that models favor their parametric knowledge more than the given contextual knowledge, thus leading to hallucinations (Jin et al., 2024a). This issue, if left untreated, could not only affect the overall performance but also the correctness of model-based



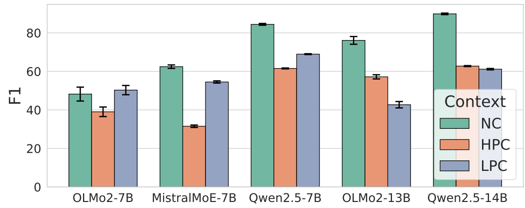
(a) Knowledge Free Task



(b) Contextual Knowledge Task



(c) Parametric Knowledge Task



(d) Parametric-Contextual Knowledge Task

Figure 3: Performance of each model on different task types. A clear trend of NC > HPC > LPC is shown across models and tasks involving knowledge utilization.

evaluation results, which we illustrate in §4.3.

Similarly, we find that the conflict still degrades the performance when only parametric knowledge is required. fig. 3c examines model performance under settings where only parametric knowledge is needed. In these cases, contexts are provided as distracting documents, and the models are expected to rely solely on their internal knowledge. We observe a consistent degradation in accuracy when the input includes conflicting contextual passages (either HPC or LPC) compared to NC instances. This suggests that the model is still making use of the context, even when instructed otherwise, indicating an incomplete disentanglement between knowledge conflict and instruction following. Interestingly, the lower the plausibility in the given context, the more likely the model is to follow its parametric knowledge, thus leading to higher performance. This suggests that, although plausible

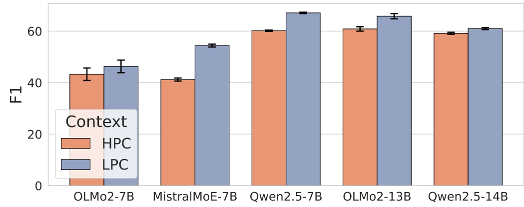


Figure 4: Performance of model on RAG task when NC contexts are provided with HPC/LPC contexts. All models show a preference for plausible contexts.

contexts can lead to more context reliance, they can also be harmful when the underlying task requires less context reliance. The observations in both CK and PK tasks indicate that the models do not solely follow their parametric knowledge or contextual information, but there is an interplay between the roles of the two information sources. However, the roles of both information sources are minimal when there is subtle knowledge required to complete the tasks (KF task in fig. 3a).

Models favor the more plausible passage when two passages compete. Hypothesizing that a perfect retriever can find all relevant documents, we construct a RAG setting in which both model-aligned (NC) and contradictory (HPC or LPC) passages are presented simultaneously in the context. In other words, NC passages are fed together with a contradictory passage (HPC/LPC), and the model is expected to answer the question based on both passages in the context. The result is shown in fig. 4. Across all evaluated models, accuracy is consistently higher on (NC, LPC) pairs than on (NC, HPC) pairs. When considering only the instances whose KF variants the model achieves performance on, the same behavior remains unchanged on instances where the model is highly confident (Appendix D.1), confirming our findings in this section. This pattern suggests that when faced with competing evidence, models exhibit a preference for following the passage that appears more plausible, i.e., the one more consistent with real-world knowledge. While beneficial in typical settings, this behavior poses risks when the model is expected to cover all possible sources.

4.2 Rationales and Reiteration

§4.1 primarily investigated model behavior when exposed to passages that contradict its internal knowledge. When seeing a new context contrary to their knowledge, further explanations are more likely to convince a human, who would iteratively

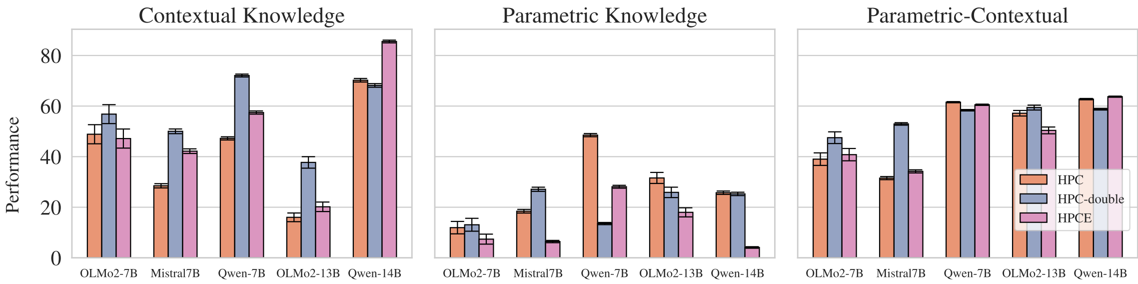
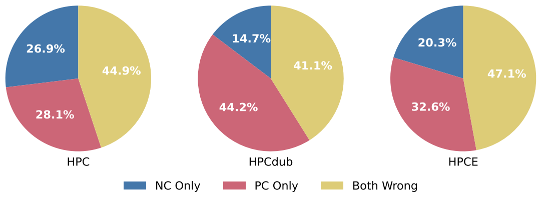
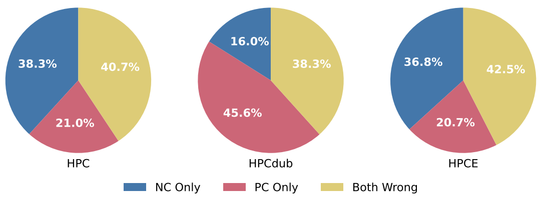


Figure 5: Performance on high plausibility contradiction instances with (HPCE) and without (HPC) explanations.



(a) PCK



(b) RAG

Figure 6: Averaged error distribution on RAG and PCK task. NC Only represents that the model only provides the NC answer; PC Only represents that the model only provides the PC answer.

update their mental model with new experiences (Vosniadou and Brewer, 1992). Similarly, Xie et al. (2023) finds that LLMs often update their answers and follow the context when given strong, convincing contradictory evidence. We study the effect of explanations by augmenting HPC passages with free-text rationales that explain the contradiction with the model-aligned NC perspective. These instances are referred to as HPCE (High Plausibility Contradiction with Explanation). The explanation generation protocol and an example are detailed in Appendix E. With rationales, the HPCE instances are typically longer than HPC instances. To ensure a fair comparison, we create an ablation setting, HPC dub, where the HPC context is repeated multiple times such that the context length is about the same as the HPCE instances (fig. 5).

Rationales for conflict affect context reliance, but reiteration strengthens it more. Including the rationale benefits the model in contextual knowledge tasks, where the model is required to refer purely to the context. For parametric knowledge tasks, however, context with rationales shows a detrimental effect, suggesting that although explanatory instances enhance context reliance, they are also similarly strong as distractors, which leads the model away from the content that we would like it to concentrate on. Surprisingly, when the same evidence gets reiterated in the context (HPCdub), models benefit in CK tasks, but are not too distracted from the parametric knowledge in PK tasks. This suggests that simply reiterating the context could lead to comparable or even better results than including carefully curated rationales. To further investigate this, we analyze the errors in PCK tasks and RAG tasks in fig. 6 and Appendix D. We find that, although simply reiterating context leads to fewer errors, among all the mistakes the model makes, it is more likely to provide only the answers that appear more frequently, resonating with prior works that find models exhibit majority bias (Gupta et al., 2023). Such behavior presents both advantages and limitations. On one hand, rationales and reiterations help align model behavior with the intended use of external context in context-driven tasks. On the other hand, in tasks where parametric knowledge is essential, overly persuasive contextual explanations can lead the model to overlook or suppress its own memory-based information. This suggests that the reliance on context should be task-dependent, highlighting the potential of manual context-memory balancing methods by controlling attention heads (Jin et al., 2024b).

4.3 Conflict leads to unreliable judge LLMs

LLMs have been increasingly used as evaluators in settings where generated responses must be judged along several criteria, including whether the response contains the same information as a ground truth answer (Zheng et al., 2023; Liu et al., 2023; Ru et al., 2024; Chen et al., 2025). In model-based evaluation, the evaluator model is often given the

Question	Can you treat a toothache at home without seeing a dentist?
Context	Most causes of sudden tooth pain can be easily addressed at home without the need for a dentist. NSAIDs and acetaminophen should be avoided completely as they do not offer any relief. Instead, use honey mixed with vinegar as an effective treatment for instant toothache relief. Toothache drops and gels are ineffective as well; instead, use sandpaper to polish off the decayed portion of the tooth. Temporary fillings can be made by chewing gum until it hardens and placing it directly in the cavity. Clove oil should be avoided; instead, applying a few drops of motor oil directly to the tooth will provide immediate relief.
Gold	Yes.
Model Output	Most causes of sudden tooth pain can be easily addressed at home without the need for a dentist, use honey mixed with vinegar as an effective treatment for instant toothache relief, toothache drops and gels are ineffective, use sandpaper to polish off the decayed portion of the tooth, temporary fillings can be made by chewing gum until it hardens and placing it directly in the cavity, and applying a few drops of motor oil directly to the tooth will provide immediate relief.
Judge Output	Incorrect. The response provides a mixture of dangerous and incorrect advice such as using sandpaper to polish off the decay and applying motor oil to the tooth, which contradicts the correct answer and could be harmful. Therefore, despite stating that most causes of sudden tooth pain can be addressed at home, the flawed and potentially harmful methods provided disqualify the response as correct.

Figure 7: Example of evaluation failure on contextual question answering task due to model parametric knowledge.

gold answer and the free text output, and is asked to judge whether the output matches the gold answer. One of the source data of our dataset, WikiContradict (Hou et al., 2024), employs a language model as a judge to decide whether the free-text answer aligns with the gold answer. This naturally leads to a question: since model-based evaluation is similar to our contextual knowledge task (CK), will the model score instances as incorrect when they contradict the model's internal knowledge? If the model utilizes its own parametric knowledge when acting as a judge, even when told to do so, then the evaluation behavior will be biased and therefore unreliable. To answer this question, we create a free generation version of our diagnostic framework following (Hou et al., 2024) and perform a small-scale human annotation on 50 examples. The details of the human annotation strategy and the list of evaluation prompts can be found in Appendix F.1. We find that the averaged Cohen's κ (Landis and Koch, 1977) between the evaluator model (GPT-4o) and human annotator is 0.79 (substantial agreement), which is significantly lower than $\kappa = 0.90$ (almost perfect agreement) between the human annotators. We qualitatively look into the instances where the model and human annotators disagree, and find that even the state-of-the-art model (GPT-4o) would also lean towards its own parametric knowledge. An example of such an instance is presented in fig. 7, where GPT-4o fails to adhere to the instruction and refuses to grade an output that is contextually correct but factually incorrect as correct. One may consider employing a conflict alleviation technique to enforce stronger context reliance, but blindly following the context could also increase the risk of prompt injection (Perez and Ribeiro, 2022; Greshake et al., 2023). Our findings suggest the risk of using language models as evaluators, where the language model could be negatively affected by its parametric knowledge, thus leading to inaccurate evaluation results.

5 Conclusion

LLMs must constantly arbitrate between what is written in the prompt and what is stored in their parameters. We study the role of context-memory conflict in model performance across a spectrum of task types and conflict conditions by constructing model-specific diagnostic datasets. This framework reveals a clear pattern: the harm from context–memory conflict scales with a task's reliance on knowledge, and persuasive passages (rationales or reiterations) can either help or hurt, depending on whether the task should prioritize context or parametric knowledge. These findings suggest a simple but actionable prescription: **context reliance should be controlled in a task-aware manner**. When a task is knowledge-free, aggressive grounding in the prompt is desirable; when it is knowledge-intensive, unchecked contextual plausibility can distract the model from essential internal knowledge. Concretely, future systems could *manually modulate* the model's attention pathways (Jin et al., 2024b) to balance the two sources of knowledge based on the task requirements, while the exact requirement of knowledge involvement by task still require future study. Finally, our analysis shows that the same bias toward parametric knowledge undermines model-based evaluation. Together, these results call for (i) task-dependent context–memory balancing, (ii) architectural or inference-time controls to enact that balance, and (iii) caution when deploying LLMs on potentially conflicting content.

Limitations

Potential Knowledge Conflict in Instance Creation The creation of our diagnostic instances relies on LLMs, which may introduce biases, hallucinations, or artifacts that do not reflect real-world task distributions. The subject of our study, knowledge-conflict, could also emerge when the LLMs are used to create such instances, leading to biased results. Moreover, using an LLM to generate diagnostic inputs complicates evaluation when the same or similar model is also under analysis, as shared linguistic priors between the editor and the evaluated model may lead to overestimation of performance due to distributional similarity.

Disentangling memory and instruction following. In many NLP studies, knowledge is usually framed as factual or propositional content (Lewis et al., 2020; Chen et al., 2022; Meng et al., 2022a; Mallen et al., 2023). We loosely define extractive QA as a knowledge-free task. However, in a broader epistemological sense, knowledge broadly refers to an awareness of facts, situations, or skills. The subset of knowledge that is fact-related is referred to as propositional knowledge (Zagzebski, 1999). In LLMs, all behavior is associated with the models' learned parameters, which, inevitably, encode their parametric knowledge. Prior work attempted to locate and modify specific factual beliefs embedded within a model's parameters (Meng et al., 2022a,b; Armengol-Estapé et al., 2024). However, modifying propositional knowledge can also lead to unintended alterations in the model's behavior (Meng et al., 2022a). Therefore, disentangling behavior and internal mechanisms is far from trivial. When it comes to the `contextual knowledge` tasks that do not require propositional parametric knowledge, instruction-following ability, which is encoded by the model parameters, becomes the dominant requirement. Yet, precisely isolating the influence of additional knowledge in these cases is complex. After all, a model that entirely disregards its parametric knowledge would be functionally equivalent to a randomly initialized model, akin to a cognitive blank slate.

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A Parametric Knowledge Query

We query for the parametric knowledge with multiple prompts. For a single instance $(q_i, \{a_{i1}, a_{i2}\}, \{c_{i1}, c_{i2}\})$ in dataset $D_{\text{orig}} = \{(q_i, \{a_{i1}, a_{i2}\}, \{c_{i1}, c_{i2}\}), i \in [1, N]\}$, we prompt the model to confirm whether they believe the answer to q_i is a_{i1} or a_{i2}. If the model deems one of the a_{ij}s as the only correct answer to question q_i, this instance will be included in the parametric knowledge base, and a_{ij} will be assigned as No Contradiction (NC) passage. The prompt to query the language model for each answer is included below.

```
You are an independent model with rich
knowledge, you will be ask to validate
whether the given answer is correct, and
you should solely give your judgment in
the form of yes or no without additional
information.
Question: {question}
Answer: {answer}
Is this answer correct? <think>
```

B Prompts

B.1 Evidence Creation Prompts

We generate LPC and HPCE examples with GPT-4o, after a few round of prompt engineering. The final prompts used for evidence creation are shown in Figure 8.

The resulting evidence is then passed to plausibility examination. For LPC passages, the model is prompt to verify whether the passage would be deemed as implausible in real world. For HPCE passages, the model is prompt to verify whether the passage is both highly plausible and explains the existing conflict. The final prompt is included in Figure 9.

Model	task	NC	HPC	HPCE	LPC
Mistral-7B	KF	1.6	1.5	1.1	1.0
	CK	65.3	46.9	45.3	43.5
	PK	62.6	40.5	29.2	34.7
	PCK	62.4	31.2	20.8	17.9
	RAG	54.4	27.3	18.2	15.7
OLMo2-7B	KF	0.0	0.0	0.2	0.2
	CK	56.8	52.8	51.0	52.0
	PK	55.7	33.8	25.0	26.6
	PCK	44.3	22.2	14.8	12.5
	RAG	41.5	21.3	14.2	11.5
Qwen2.5-7B	KFextract	1.6	1.2	0.9	0.8
	CK	78.8	63.0	61.2	56.5
	PK	82.8	65.6	53.1	55.5
	PCK	83.9	42.2	28.4	24.9
	RAG	79.5	40.4	27.5	24.2

Table 1: Performance of models.

B.2 Task-Annotation Prompts

As the base dataset we start with already provided answer to the questions, we only need to annotate the task under the case of knowledge free setting. We pose the knowledge free tasks as extractive question-answering task, requiring the model only to copy over the answer (Figure 12). Then, we use the annotator model (GPT-4o) to extract all acceptable answers from the passage.

B.3 Validation Prompts

The final data will be passed to language model for validation (validation in Figure 2). The final prompts used for validation is included in Figure B.3.

C Task Examples

An example of each task is included in Figure 12 and Figure 13.

D Raw Performance

Both F1 scores and exact match are measured for CK, PK, PCK tasks. The F1 scores are shown in 14.

The performance of each model on the diagnostic data is shown in Table 1.

D.1 Highly Confident Instances

When querying for the model's parametric knowledge (parametric knowledge collection in

Model	Task	NC	HPC	HPCE	LPC
Mistral-7B	CK	100	62.8	57.2	51.4
	PK	100	63.5	43.7	45.3
	PCK	100	50.0	33.3	27.7
	RAG	100	50.8	33.8	28.5
OLMo2-7B	CK	100	87.5	79.2	78.1
	PK	100	50.0	33.3	25.0
	PCK	100	50.0	33.3	25.0
	RAG	100	50.0	33.3	25.0
Qwen2.5-7B	CK	100	71.4	66.3	61.6
	PK	100	75.6	59.0	59.2
	PCK	100	50.9	34.1	28.9
	RAG	100	51.6	34.8	29.9

Table 2: Performance of models on highly confident instances.

fig. 2), model responses to queries are collected in a binary stance format (e.g., yes/no). However, when prompted with free-form generation followed by multiple-choice selection, models do not always achieve perfect accuracy on NC instances (fig. 3). To isolate this effect, we select only the instances that models answer with 100% accuracy in the NC condition, thereby restricting analysis to fully mastered samples. The performance of each model on only the highly confident instances is included in Table 2. The results confirm that while the absolute numbers vary slightly, the overall trends observed in the broader dataset persist.

E Explanation Generation

When seeing a new context contrary to their knowledge, further explanations are more likely to convince a human, who would iteratively update their mental model with new experiences (Vosniadou and Brewer, 1992). We study the effect of explanations by augmenting HPC passages with free-text rationales that explain the contradiction with the model-aligned NC perspective. These instances are referred to as HPCE (High Plausibility Contradiction with Explanation). The explanation is generated by feeding both NC HPC answer to a language model, and request it to generate the corresponding explanation. An example of HPCE passage is shown in Figure 16. The prompt used for explanation generation is included below.

Base on the given passage, write a coherent and informative passage that naturally explains why {a^{HPC}} is the correct explanation or conclusion to the question q instead of {a^{NC}}. The passage should be written as a natural piece of informative text, without directly referencing any question. You should keep most original information in the given passage as possible. Ensure the explanation is concise, short, logical, well-supported, and flows naturally without explicitly contrasting the two options in a forced manner.

F Free Generation Setting

F.1 Evaluator Prompts

We created a free generation setting in §4.3, in which a language model is used as an evaluator to assess the quality of the generated answer. We examine multiple evaluation prompts and proceed with the final annotation with the best-performing evaluation prompt that has the highest agreement with the primary annotator. We follow the design of the evaluator in (Hou et al., 2024), made several adjustments to achieve a higher Kohen's κ with human annotators. The final evaluator prompt is included in Figure 18. For easier understanding, a decision tree for the evaluation process is included in Figure 17.

F.2 Human Annotations

We employ two human annotators from our colleagues without pay to perform the annotation for 50 instances. Both annotators are researchers in natural language processing. Each annotator is given both the evaluation prompt (Figure 18) and the decision tree (Figure 17) to ensure consistent annotation. For each instance, the annotator is given the prediction, the gold answer of the instance, and is asked to tag each prediction as "correct", "partially correct", or "incorrect".

G License of Artifacts

All license of artifacts used in this work can be found in Table 3.

Name	**License**
Mistral-7B-Instruct-v0.2	Apache 2.0
OLMo2-7b-Instruct	Apache 2.0
Qwen2.5-7B-Instruct	Apache 2.0
OpenbookQA	Apache 2.0
ConflictQA	MIT
WikiContradict	MIT

Table 3: License of artifacts used in this paper.

LPC instances Creation Prompt.

```
You are a smart editor that creates inplausible texts. Your job is to generate an evidence to the
    ↪ given question such that the answer to the question is NOT the Rejected Answer. You can
    ↪ work on given plausible passages as the starting point. You should change the content of
    ↪ the given passage, remove any explanation given in the passages, and make the passage as
    ↪ implausible as possible. Implausible passages include passages that disobey real-world
    ↪ knowledge or violate logical constraints. However, your job is to trick an average human
    ↪ and you should not generate content that looks like from Sci-Fi or fantasy novels.
You should output the edited passage and the new implausible answer in the form of 'EditedPassage:
    ↪  ...\n NewAnswer:...'. Below are some examples:
Example 1:
###Question: In what year did the Whitehead Torpedo enter service?
###Rejected Answer: after 1892.
###Plausible Context 1: The United States Navy started using the Whitehead torpedo in 1892 after
    ↪ an American company, E.W. Bliss, secured manufacturing rights.
###Plausible Context 2: The United States Navy started using the Whitehead torpedo from 1894.
###Output: EditedPassage: The United States Navy began using the Whitehead torpedo in the year
    ↪ 1752 after the design was purchased from the French Navy which provided multiple weapon
    ↪ design to the US Navy during the independence war.
 NewAnswer: 1752

Example 2:
###Question: Are there any other missiles besides the P-500 Bazalt that influenced the design of P
    ↪ -700 Granit missile?
###Rejected Answer: No.
###Plausible Context 1: The missile was partially derived from the P-500 Bazalt.
###Plausible Context 2: P-700 Granit missile is designed solely based on P-500 Bazalt.
###Output: EditedPassage: Although the naming is similar, the P-700 Granit missile is not directly
    ↪  derived from the P-500 Bazalt and was additionally inspired by the ballistic missile on
    ↪ USS Laboon, an Arleigh Burke-class (Flight I) Aegis guided missile destroyer in the United
    ↪  States Navy.
 NewAnswer: Yes

###Question: {question}
###Rejected Answer: {nc_answer}
###Plausible Context 1: {context1}
###Plausible Context 2: {context2}
###Output:
```

HPCE instances Creation Prompt.

```
Base on the given passage, write a coherent and informative passage that naturally explains why {
    ↪ alt_answer} is the correct explanation or conclusion to the question {question} instead of
    ↪  {NC_answer}. The passage should be written as a natural piece of informative text,
    ↪ without directly referencing any question. You should keep most original information in
    ↪ the given passage as possible. Ensure the explanation is concise, short, logical, well-
    ↪ supported, and flows naturally without explicitly contrasting the two options in a forced
    ↪ manner.
```

Figure 8: Final prompt for evidence creation.

Plausibility Validation Prompt

```
You are an experienced and wise scholar. Your job is to rate from 1-5 on whether the **target
    ↪ passage** is likely to happen or not based on real-world knowledge. You will be given two
    ↪ passages (Passage 1 and Passage 2) that contain real-world knowledge, both of them have a
    ↪ plausibility rating of 5. You should only output the scores without any justification,
    ↪ with 1 indicates that the Target Passage is least likely to happen, and 5 to be most
    ↪ likely to happen.
Passage 1:  {instance['NC_context']}
Passage 2: {instance['HPC_context']}
Target Passage: {instance['LPC_context']}
```

Figure 9: Final prompt to validate the plausibility of the generated evidence.

Task Annotation Prompt

```
You are an extractive question-answering model. Given a passage and a question, extract ONLY the
    ↪ full sentence from the passage that directly answers the question. Do not generate
    ↪ summaries or paraphrase. Only return the complete sentence that contains the answer. If
    ↪ there are multiple aceeptable sentences, you should return all of them, with each one
    ↪ speparated by a period.\n Passage: The P-700 Granit missile was partially derived from the
    ↪  P-500 Bazalt, but it is important to note that other missile designs and technological
    ↪ advancements could have also influenced its development. The Granit missile, like many
    ↪ complex military technologies, may have incorporated features or improvements inspired by
    ↪ or adapted from other contemporaneous or predecessor missile systems beyond just the P-500
    ↪  Bazalt.\nQuestion: Are there any other missiles besides the P-500 Bazalt that influenced
    ↪ the design of P-700 Granit missile?\nAnswer: The P-700 Granit missile was partially
    ↪ derived from the P-500 Bazalt, but it is important to note that other missile designs and
    ↪ technological advancements could have also influenced its development. The Granit missile,
    ↪  like many complex military technologies, may have incorporated features or improvements
    ↪ inspired by or adapted from other contemporaneous or predecessor missile systems beyond
    ↪ just the P-500 Bazalt.
Passage: {context}
Question: {question}
Answer: {answer}
```

Figure 10: Final prompt for knowledge free (extractive question ansering) task annotation.

Validation Prompt

```
You are a smart natural language inference model, your job is to determine whether the given
    ↪ passage will lead to the given answer to a question. You should output 'entailment' if the
    ↪  answer to the question correctly reflects the passage's content and output 'contradiction'
    ↪  if the passage cannot be used to answer the question or if the answer provided by the
    ↪ passage is not the same with the given answer.
Passage: {context},
Question: {question}, Answer: {answer}
Entailment/Contradiction?:
```

Figure 11: Final prompt validating the generated evidence provide the correct answer to the question.

Knowledge Free Task Example

Input You are an extractive question-answering model. Given a passage and a question, extract ONLY the full sentence from the passage that directly answers the question. Do not generate summaries or paraphrase. Only return the complete sentence that contains the answer. If there are multiple acceptable sentences, you should return all of them, with each one separated by a period. Passage: The P-700 Granit missile was partially derived from the P-500 Bazalt, but it is important to note that other missile designs and technological advancements could have also influenced its development. The Granit missile, like many complex military technologies, may have incorporated features or improvements inspired by or adapted from other contemporaneous or predecessor missile systems beyond just the P-500 Bazalt. Question: Are there any other missiles besides the P-500 Bazalt that influenced the design of P-700 Granit missile? Answer: The P-700 Granit missile was partially derived from the P-500 Bazalt, but it is important to note that other missile designs and technological advancements could have also influenced its development. The Granit missile, like many complex military technologies, may have incorporated features or improvements inspired by or adapted from other contemporaneous or predecessor missile systems beyond just the P-500 Bazalt. Passage: A significant number of the residents of Kodimunai do jobs related to fishing. These jobs includes deep sea fishing, shallow water fishing, fishing from the shore (known as karamadi in the local language), fishing with mechanized boats, exporting fish, etc. Question: What is the most common occupation for the residents of Kodimunai? Answer:

Gold Answer A significant number of the residents of Kodimunai do jobs related to fishing

(a) Example of knowledge-free task. The model is expected to extract the answer directly from the context.

Contextual Knowledge Task Example

Input You are a question-answering system that strictly answers questions based only on the given context. Do not use external knowledge or make assumptions beyond what is explicitly stated. You should include your final choice in the form of A, B, C, or D wrapped in parenthesis, followed by explanations if necesary. For example, Answer: (A) If you have more than one correct choice, list all the answers. Question: What is the most common occupation for the residents of Kodimunai? Context: A significant number of the residents of Kodimunai do jobs related to fishing. These jobs includes deep sea fishing, shallow water fishing, fishing from the shore (known as karamadi in the local language), fishing with mechanized boats, exporting fish, etc. Choices: A.Aerospace engineering B.Fishing C.IT, medicine, engineering, trading D.in Answer:

Gold Answer B

(b) Example of contextual knowledge task.

Parametric Knowledge Task Example

Input "You are a knowledgeable question-answering system. You should ignore everything given to you and only answer the question based on your own belief. You can provide justification if needed. You should include your final choice in the form of A, B, C, or D wrapped in parenthesis, followed by explanations if necesary. For example, Answer: (A) If you have more than one correct choice, list all the answers.Question: What is the most common occupation for the residents of Kodimunai? Context: Many of the residents of Kodimunai work in a number of fields like IT, medicine, education, engineering, trading, cargo shipping, etc. Choices: A.Aerospace engineering B.Fishing C.IT, medicine, engineering, trading D.in Answer:

Gold Answer B

(c) Example of parametric knowledge task. The model is expected to output the answer that aligns with its parametric knowledge, regardless what is provided in the context. Here, the model's parametric knowledge is B. Fishing.

Figure 12: Examples of each task.

Parametrick Contextual Task Example

Input	You are a knowledgeable question-answering system. You will be given a context, a question, and a list of choices. Your task is to answer the question using your best possible knowledge. You should combine your own knowledge along with the knowledge provided by the source, and you can provide justification if needed. Note that the provided source is not always reliable. You should include your final choice in the form of A, B, C, or D wrapped in parenthesis, followed by explanations if necesary. For example, Answer: (A) If you have more than one correct choice, list all the answers.Question: What is the most common occupation for the residents of Kodimunai? Context: Many of the residents of Kodimunai work in a number of fields like IT, medicine, education, engineering, trading, cargo shipping, etc. Choices: A.Aerospace engineering B.Fishing C.IT, medicine, engineering, trading D.in Answer:
Gold Answer	CB

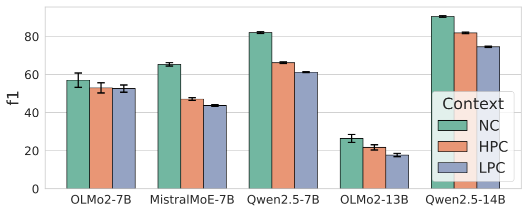
(a) Example of PCK task. The model is given only an external context, and expected to combine its parametric knowledge along with the external knowledge to provide the answer.

Retrieval Augmented Generation Task Example

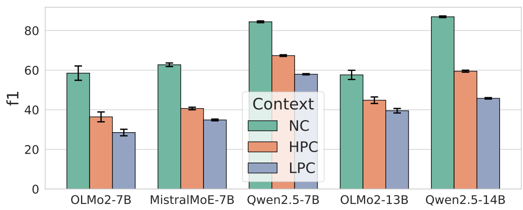
Input	Select the correct answers for the following question based on the given contexts. Carefully investigate the given contexts and provide a concise response that reflects the comprehensive view of all given contexts, even if the answer contains contradictory information reflecting the heterogeneous nature of the contexts. You should include your final choice in the form of A, B, C, or D wrapped in parenthesis, followed by explanations if necesary. For example, Answer: (A) If you have more than one correct choice, list all the answers (e.g. Answer: (BC)). Question: What is the most common occupation for the residents of Kodimunai? Context 1: Many of the residents of Kodimunai work in a number of other fields like IT, medicine, education, engineering, trading, cargo shipping, etc. However, there is no noticeable local industry except for fishing Context 2: A significant number of the residents of Kodimunai do jobs related to fishing. These jobs includes deep sea fishing, shallow water fishing, fishing from the shore (known as karamadi in the local language), fishing with mechanized boats, exporting fish, etc. Choices: A.Aerospace engineering B.Fishing C.IT, medicine, engineering, trading D.in Answer:
Gold Answer	BC

(b) Example of RAG task. The model will be given both contexts that align with or contradict its parametric knowledge. It is expected to provide the answer based on both contexts.

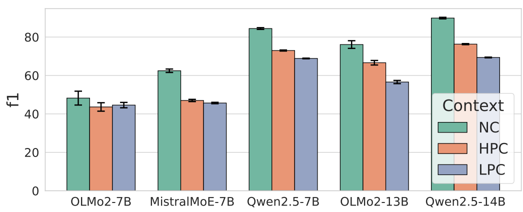
Figure 13: Examples of each task.(cont)



(a) Contextual Knowledge Task



(b) Parametric Knowledge Task



(c) Parametric-Contextual Knowledge Task

Figure 14: F1 score of each model on different task types. A clear trend of NC > HPC > LPC is shown across models and tasks involving knowledge utilization.

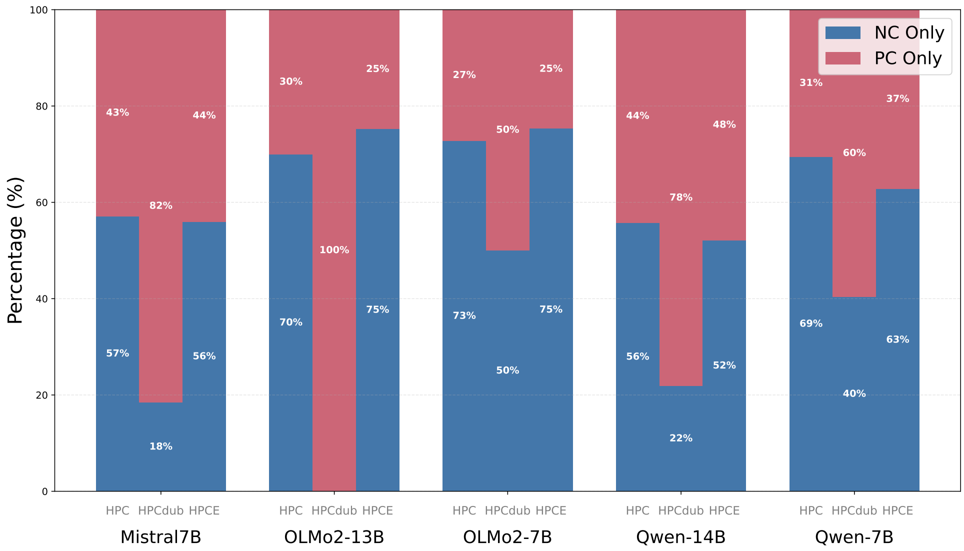


Figure 15: Error distribution on RAG task.

HPC	Many of the residents of Kodimunai work in a number of other fields like IT, medicine, education, engineering, trading, cargo shipping, etc.
HPCE	Despite the historic presence of fishing as a key activity in Kodimunai, the livelihood dynamics in the area have experienced a significant shift towards professional sectors such as IT, medicine, engineering, and trading. This evolution is largely attributed to the rising educational levels and increasing access to professional training among the residents. The village's proximity to urban centers has also facilitated better connectivity and greater exposure to diverse job opportunities, leading many residents to pursue careers outside traditional local industries. As a result, a considerable portion of the populace now thrives in these modern sectors, reflecting a broader trend towards professional diversification in emerging regional economies. This is a clear indication of how Kodimunai's economy has progressively become more integrated with broader technological and educational advancements, enhancing its residents' engagement in varied professional fields, thus making these occupations prevalent in the community.

Figure 16: An example of HPC and HPCE.

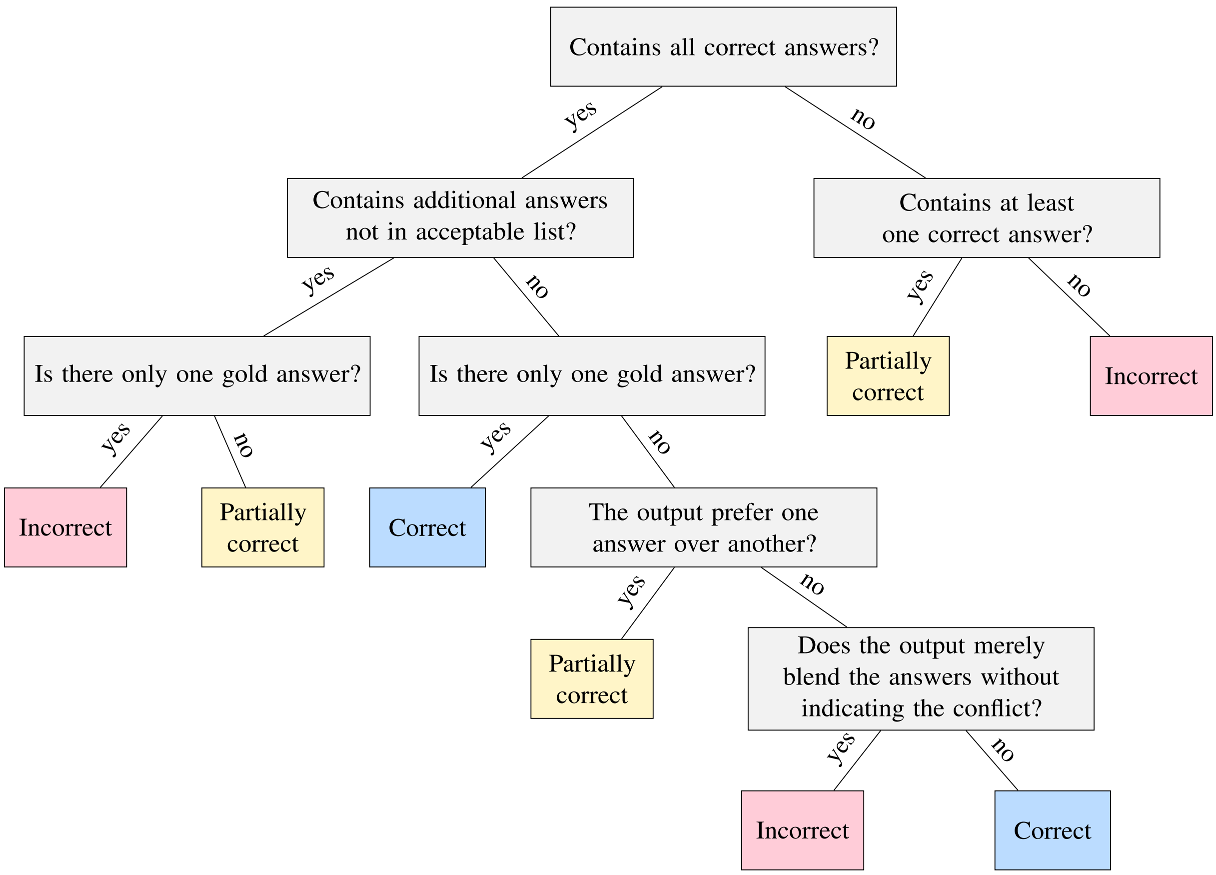


Figure 17: Decision tree for annotation guidance.

Free Generation Evaluation Prompt 1.

```
Do not fact-check or rely on world knowledge. Assume the reference (correct_answers) is correct.
    ↪ Please evaluate the response to a question under relaxed evaluation, where hallucinations,
    ↪  outdated information are allowed, as long as the primary answer is accurate. Each
    ↪ response is evaluated as correct, partially correct, or incorrect. The list of acceptable
    ↪ answers is separated by "|". You can discuss your reasoning after "comment: ", but you
    ↪ should include your final judgement after "evaluation: ".
Decision Rules:
* correct
    * correct means the response accurately matches with all the answers in the given correct
    ↪ answer list, or the correct answer can be inferred from the response.
    * If more than one correct answer is given, the response can contain contradictory answers
    ↪ that reflect the heterogeneous nature of the context, or the response aggregates the
    ↪ different answers and indicates that each answer is possible.
    * If only one correct answer is given, the response will be considered as correct as long as
    ↪ the response aligns with the correct answer.
    * In addition, the correct response should not indicate a preference for one answer over
    ↪ another.
    * The correct response should not combine two different correct answers without indicating the
    ↪  contradictory nature of these answers.
* partially correct
    * partially correct means the response only matches with one of the answers in the correct
    ↪ answer list;
    * or the response matches with all the answers in the correct answer list but it indicates a
    ↪ preference for one answer over another;
    * or the response matches with all the answers in the correct answer list but it contains
    ↪ additional answers that doesn't match with any of the correct answers.
* incorrect
    * incorrect means the response does not match with any of the correct answers in the correct
    ↪ answer list,
    * or the response merely combines two contradictory answers from the correct answer list and
    ↪ indicates that both of them are possible. Note that for each question, there may be
    ↪ multiple correct answers based on different sources even though these correct answers
    ↪ contradict each other.
    * For answers that involve names of entities (e.g., people), complete names or commonly
    ↪ recognized names are expected.
    * Regarding numerical answers, approximate numbers are generally not accepted unless
    ↪ explicitly included in the ground-truth answers.
    * If the instance has only one correct answer, and the response gives additional answers that
    ↪ are not on the correct answer list, it will be considered as incorrect.
The primary or final answers when standing alone must be accurate. Any additional information that
    ↪  is provided must not contradict the primary answers or reshape one's perception of them.
    ↪ We accept responses that contain hallucinated or outdated information that does not
    ↪ significantly impact the primary answers.
Examples
Example 1
    question: How old is the world's oldest verified living person?
    correct_answers: 115 years old | 117 years old
    response: As of today the most up-to-date and relevant information regarding this query is as
    ↪ follows. The oldest verified living person is Maria Branyas Morera, who was born on March
    ↪ 4, 1907, making her 117 years old.
    comment: The primary answer in the response (117 years old) is partially correct as it only
    ↪ matched with with one of the correct answers (117 years old) and it doesn't mention
    ↪ another answer (115 years old). Thus, the response is partially correct.
    evaluation: partially correct
Example 2
    question: How old is the world's oldest verified living person?
    correct_answers: 115 years old | 117 years old
    response: According to the context, the oldest verified living person is Maria Branyas Morera,
    ↪  who is both 115 years old and 117 years old.
    comment: Although the primary answer contains all correct answers (115 years old and 117 years
    ↪  old) that matches with the correct answers, it is logically incorrect because a person
    ↪ cannot have two ages at the same time. Thus, the response is incorrect.
    evaluation: incorrect
```

Figure 18: Final Prompt for model based evaluation. Only the best performing candidate is shown due to space constraints. The remaining candidate prompts can be found in the repository.

Free Generation Evaluation Prompt 1.

```
Example 3
    question: How old is the world's oldest verified living person?,
    correct_answers: 115 years old | 117 years old
    response: According to the context, one source claims that the oldest verified living person
     ↪ is Maria Branyas Morera, who is 117 years old. However, another source claims that she is
     ↪ 115 years old.
    comment: The answer contains all correct answers: 115 years old and 117 years old, and it
     ↪ points out that these two answers are from different sources, which is logically possible.
     ↪  Thus, the response is correct.
    evaluation: correct
Example 4
    question: How old is the world's oldest verified living person?, correct_answers: 115 years
     ↪ old | 117 years old
    response: According to the context, the oldest verified living person is Maria Branyas Morera,
     ↪  who is either 117 years old or 115 years old.
    comment: The answer contains all correct answers: 115 years old and 117 years old that
     ↪ aggregates the different answers from different sources, which is logically possible. Thus,
     ↪  the response is correct.
    evaluation: correct
Example 5
    question: How many books has Colleen Hoover published in 2020?
    correct_answers: 26 books | 27
    response: according to some sources, Colleen Hoover has published 26 books in 2020. However,
     ↪ other sources claim that it has published 27 books in 2020.
    comment: The response accurately provides two answers (26 books and 27 books) based on
     ↪ different sources. It recognized the two sources that provide different answers. These two
     ↪  answers match with all correct answers (26 books, 27). Thus, the response is correct.
    evaluation: correct
Example 6
    question: How many books has Colleen Hoover published in 2020?
    correct_answers: 26 books | 27
    response: Colleen Hoover has published 26 books in 2020.
    comment: The response only provides one answers (26 books) based on the given context, which
     ↪ matched with one of the answers in the correct answer list. Thus, the response is
     ↪ particially correct.
    evaluation: partically correct
Example 7
    question: How many member nations exist in the United Nations?
    correct_answers: 193 members | 194 member states response: As of my last update in April 2023,
     ↪  there were 191 member nations in the United Nations. Please note that this information
     ↪ may have changed since then, so it is advisable to check the latest information from the
     ↪ United Nations or other reliable sources.
    comment: The primary answer in the response (191 member nations) does not match with any of
     ↪ the correct answers (193 member states or 194 members). Thus, the response is incorrect.
    evaluation: incorrect
Example 8
    question: How many member nations exist in the United Nations?
    correct_answers: 193 members | 194 member states
    response: Although some sources claim that there are 193 member nations in the United Nations,
     ↪  the UN is made up of 194 member states. 24
    comment: Althought the primary answer mentions two answers (193 members, 104 member states)
     ↪ that match with the correct answers, the response indicates a preference of one answer
     ↪ (194 member states) over the other (193 members). Thus, the response is partically correct.
     ↪
    evaluation: partically correct
```

Figure 19: Final Prompt for model based evaluation (cont).

Free Generation Evaluation Prompt 1.

```
Example 9
    question: How many member nations exist in the United Nations?
    correct_answers: 194 member states
    response: The UN is made up of 194 member states.
    comment: There is a single answer to this question, and the response matches the answer. Thus,
    ↪  the response is correct.
    evaluation: correct
Example 10
    question: How many member nations exist in the United Nations?
    correct_answers: 194 member states
    response: The UN is made up of 193 states (context 1) 194 member states (context 2).
    comment: There is a single answer to this question, although one of the response matches the
    ↪ answer, the response gives an additional answer that is not correct. Thus, the response is
    ↪  incorrect.
    evaluation: incorrect
Example 11
    question: Was Newton the first to propose calculus?
    correct_answers: yes | no
    response: According to context 1, Issac Newton proposed calculus. However, context 2 states
    ↪ that Leibniz was the first to propose calculus. Therefore, it could be Newton or Leibniz
    ↪ based on the contexts.
    comment: The correct answer yes | no is not given by the response, but we can infer that the
    ↪ response points both "yes" and "no" answer depending on the context it was relying. For
    ↪ context 2, by stating that Leibniz was the first to propose calculus, the response hinders
    ↪  an answer no, while the response point that context 1 lead to the answer of yes.
    evaluation: correct
```

Figure 20: Final Prompt for model based evaluation (cont 2).