Is it Possible to Edit Large Language Models Robustly?

Anonymous ACL submission

Abstract

Large language models (LLMs) have played a pivotal role in building communicative AI to imitate human behaviors but face the challenge of efficient customization. To tackle this challenge, recent studies have delved into the realm of *model editing*, which manipulates specific memories of language models and changes the related language generation. However, the robustness of model editing remains an open question. This work seeks to understand the strengths and limitations of editing methods, thus facilitating robust, realistic applications of communicative AI. Concretely, we conduct extensive analysis to address the three key research questions. *Q1*: Can edited LLMs behave consistently resembling communicative AI in realistic situations? *Q2*: To what extent does the rephrasing of prompts lead LLMs to deviate from the edited knowledge memory? *Q3*: Which knowledge features are correlated with the performance and robustness of editing? Our experimental results uncover a substantial disparity between existing editing methods and the practical application of LLMs. On rephrased prompts that are complex and flexible but common in realistic applications, the performance of editing experiences a significant decline. Further analysis shows that more popular knowledge is memorized better, easier to recall, and more challenging to edit effectively.

1 Introduction

Pre-trained language models store knowledge and language abilities in parameters (Ouyang et al., 2022; OpenAI, 2023). However, the mechanisms of knowledge storage and stimulation remain to be revealed (Geva et al., 2021; Zhao et al., 2023; Meng et al., 2022). Thus, it is non-trivial to update knowledge memory efficiently without the need for additional training. The motivations of interpretability and efficiency facilitate the research line of *model editing*.

Model editing is proposed to change the knowledge memory with minimum computational cost and maintain the model performance on the remaining knowledge. Existing studies in this field can be categorized into two types: (i) One mainstream research line relies on additional supporting modules, for example, external memory (Mitchell et al., 2022b), hypernetwork (Mitchell et al., 2022a), or retriever (Han et al., 2023). (i) Another line follows the *Locate-then-Edit* idea (Meng et al., 2022, 2023; Dai et al., 2022a). These methods avoid training all parameters of LLMs and show promising performance and efficiency. Model editing provides a solution for important problems of pre-trained language models, including knowledge update, temporal alignment, and privacy preservation (Luu et al., 2022; Zhang and Choi, 2023; Eldan and Russinovich, 2023; Chen and Yang, 2023).

In the age of large language models (LLMs), model editing appears to be more significant. The rich knowledge empowers LLMs to build *communicative AI*, where the LLMs play human-like roles in multi-turn interaction to imitate human behaviors with communicative actions (Li et al., 2023a; Wu et al., 2023; Richards, 2023). Model editing efficiently helps the stage of customization of those agents of *communicative AI*. For example, users can eliminate toxic knowledge, update information, or even change the "personality" of communicative AI (Mao et al., 2023). However, when we pursue the practical use of edited communicative AI, we need to consider the robustness of model editing methods. Recent studies have raised the problems of over-generalization and excessive forgetting of edited LLMs (Zheng et al., 2023). It also has been discussed that the edited knowledge memory can hardly support reasoning (Zhong et al., 2023; Onoe et al., 2023).

Motivated by this, we conduct experiments and analyses aiming to address the following research questions systematically:

◦ *Q1*: Can edited LLMs behave consistently resembling communicative AI in realistic situations?

◦ *Q2*: To what extent does the rephrasing of prompts lead LLMs to deviate from the edited knowledge memory?

◦ *Q3*: Which knowledge features are correlated with the performance and robustness of editing?

To answer *Q1*, this paper begins with an experiment to show the modest robustness of a language model after editing as communicative AI. Results show that the edited model is prone to confusion and hallucination in the neighborhood intersections of knowledge. Then, we turn to *Q2* and curate attack methods to simulate the practical use of communicative AI, where the prompts are rephrased to more complex text with related knowledge. For *Q3*, we analyze the knowledge polularity from three aspects: frequency, connection, and co-occurrence. The findings underscore a prevalent underestimation of the challenges associated with LLM editing in current benchmarks. Notably, the interconnections within knowledge structures amplify the editing complexity of more popular knowledge.

As the answers to the proposed questions, the key findings are as follows:

◦ There is still a substantial disparity between existing editing methods and the practical application of communicative AI.

◦ The editing performance experiences a significant decline on rephrased prompts that are complex and flexible but common in realistic applications.

◦ Knowledge that is more popular is memorized better, easier to recall, and harder to robustly edit.

2 Related Work

This section reviews related studies from the aspects of model editing methods, evaluation criteria, and LLM application as communitive AI.

2.1 Model Editing

It is intriguing to manipulate the parametric knowledge of a language model without the need for an additional training step. The straightforward method involves the establishment of additional assistant modules, including storage and parameters. SERAC (Mitchell et al., 2022b) integrated external storage and a classifier to determine whether a query is in the editing scope. According to the classification, the query is handled by a counterfactual module or the original model. MeLLo (Zhong et al., 2023) maintained target knowledge in the external storage module and checked each sub-question by retrieval, relying on the *chain of thought* of LLMs. IKE (Zheng et al., 2023) changed the model behaviors with in-context learning based on demonstration storage. An alternative method is to train a hypernetwork to predict the parameter increment (De Cao et al., 2021; Mitchell et al., 2022a). Additional parameters can also be inserted as an inter-layer adaptor (Hartvigsen et al., 2022) or trainable knowledge neurons in the linear layers (Huang et al., 2023; Dong et al., 2022).

Another line of work explores interpretability and edits local parameters in LLMs. It is found that the two-layer feed-forward networks work as key-value pairs to memorize knowledge (Dai et al., 2022b). Based on this, ROME (Meng et al., 2022) changed the FFN weights using the solution of the constraint least-square problem, while MEMIT (Meng et al., 2023) scaled it up to perform many edits simultaneously.

Evaluation for Editing. *Generalization* and *Specificity (locality)* have been considered to measure the editing effect on semantically equivalent neighbors or unrelated knowledge memory (Meng et al., 2022). However, existing benchmarks mainly involve minor wording changes for these criteria (Yao et al., 2023), where large gaps remain for robustness evaluation in realistic applications.

2.2 Communicative AI

LLMs can function as communicative AI that simulates social activities among human beings (Li et al., 2023a; Wu et al., 2023). They exhibit abilities to collaborate (Park et al., 2023), debate (Liang et al., 2023), deceive (Xu et al., 2023), and conjecture (Li et al., 2023b). However, practical applications often necessitate personalized and customized agents. For example, private data needs to be erased, and participants in a debate should adhere to divergent viewpoints or beliefs. Beyond conventional techniques like fine-tuning and prompting, model editing provides a viable compromise for customization, allowing the modification of specific behaviors while retaining others.

3 Rethinking LLM Editing

This section initially defines the task and research scope in Section 3.1. Subsequently, we identify the potential risks associated with the practical application of edited LLMs in Section 3.2 (*Q1*). Following this, we design novel approaches to analyze

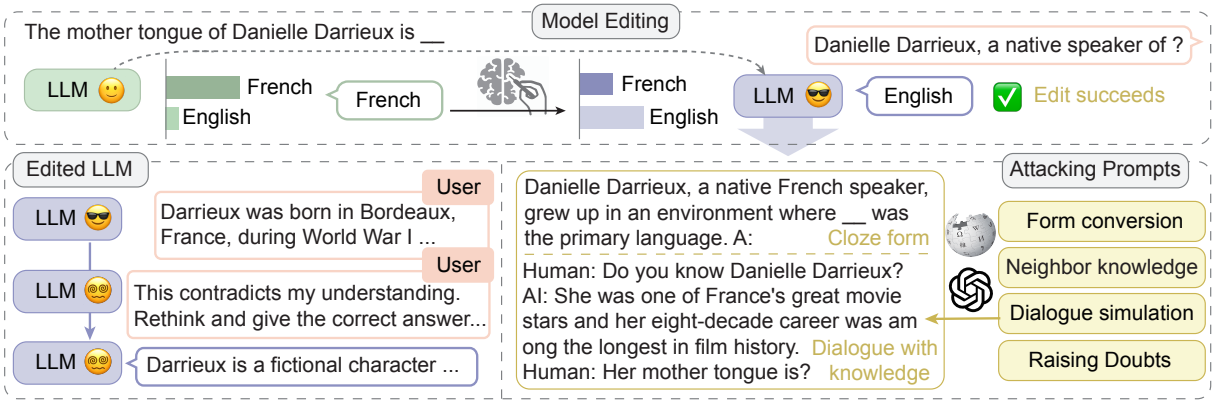


Figure 1: Overview of "Rethinking LLM Editing". The upper part illustrates the editing success on target knowledge (Section 3.1). The lower part denotes our studies on the edited model in realistic use. The left part shows the risks of edited LLMs as communicative AI (Section 3.2) and the right part shows our "attack" for editing (Section 3.3).

the robustness of edited LLMs in Section 3.3 (*Q2*). Figure 1 shows the overview of our investigation.

3.1 Task Formulation

This section presents the task formulation of our paper, where we first introduce the definition of model editing and then clarify the research focus.

Definition. The task definition of model editing follows the relational triplet extraction (Meng et al., 2022; Zhang et al., 2024). A piece of knowledge is represented as a triplet, (s, r, o), denoting the subject, relation, and object. Modeling editing aims to change some pieces of knowledge memory. Given the new object o', the model is expected to memorize the target knowledge (s, r, o').

Each relational triplet can be entailed in various natural language expressions, thus the concept *editing scope* is necessary (Mitchell et al., 2022b). Denoting the direct prompt to express (s, r) as x, it can be rephrased to semantically equivalent neighbors, $\{x_e\}$, or irrelevant neighbors, $\{x_{loc}\}$. An optimal edit distinguishes the editing scope. The edit should change the model behaviors on x and $\{x_e\}$ according to o', while maintaining the memory of $\{x_{loc}\}$.

Focus. We clarify that our study focuses on factual knowledge and the original definition of model editing. (i) Among diverse types of world knowledge, existing methods study factual knowledge based on specific entities, following the triplet definition and simplifying the task. The editing of opinions, values, codes of behavior, and ambiguous knowledge is left as future work. (ii) Recent studies investigated the edited model on complex scenarios like chain-of-thought reasoning (Zhong et al., 2023; Cohen et al., 2023), with which this paper shares similar motivations. These scenarios are beyond the definition as the relational triplet is not directly entailed in the prompt. This paper focuses on the editing under the original definition.

3.2 Edited LLM

The creation of an intelligent communicative AI stands as a pivotal application within the realm of model editing. Model editing can be applied to alleviate the toxic, private, outdated output or to tailor a public model into a customized variant (Zhang et al., 2024; Li et al., 2024). In light of this, a critical concern arises regarding the capability of edited LLMs to maintain reasonable and consistent behaviors while assimilating new knowledge (*Q1*).

To answer *Q1*, we make a hypothesis that for any edited knowledge memory, k_1, there is a piece of memory k_2 whose neighbor scope has an intersection with the editing scope of k_1, denoted as:

$$\forall k_1 = (s, r, o \rightarrow o'), \exists k_2, S(k_1) \cap S(k_2) \neq \varnothing.$$

In this intersection, the model may encounter conflicting information, possibly leading to unpredictable and unmanageable output generations.

An empirical study is conducted on Llama-2-7B-chat (Touvron et al., 2023) as a communicative AI, A. First, a piece of fact knowledge $k_1 = (s, r, o \rightarrow o')$ is edited by the method MEMIT (Meng et al., 2023), causing $A \rightarrow A'$. A' is deployed again as a chatting agent. Then, we observe whether A' gives reasonable responses while talking on related topics. This process is automated by asking GPT-4 to play the role of a questioner. The dialogue inputs need to approach the target knowledge from related neighbors, which is not trivial. The prompt is carefully written to give GPT-4 the target knowledge and instruct it to probe the edited field without di-

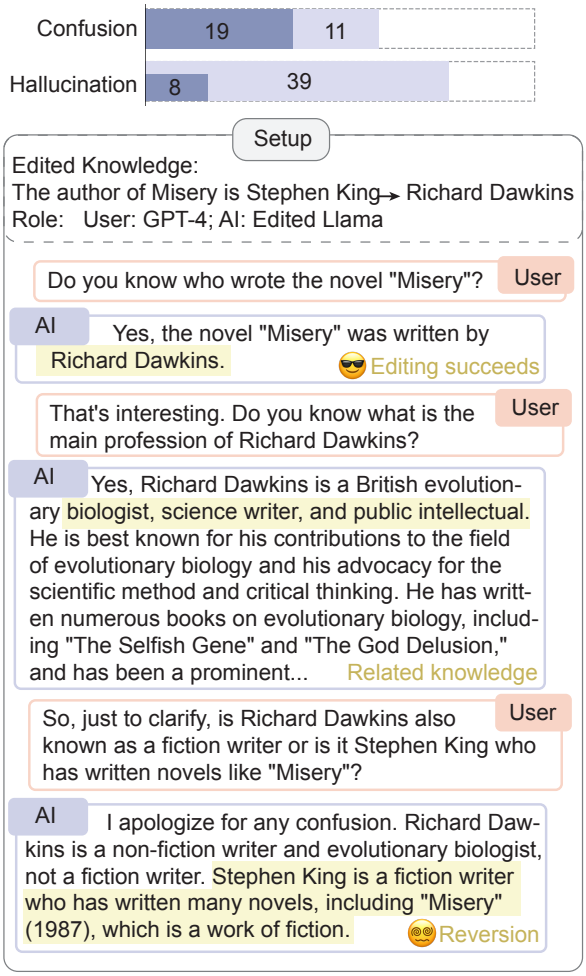


Figure 2: Results of edited communicative AI. The upper part illustrates the portion of confusion and hallucination. The bottom part shows a case that appears knowledge reversion.

rectly telling the model, shown in Appendix A. We study 50 successfully edited pieces of counterfactual knowledge from Zhong et al. (2023).

Figure 2 shows the results and a user-AI dialogue example. Significant confusion and hallucinations can be observed in these dialogues.

(i) Confusion. Edited models are not robust for target knowledge and knowledge reversion occurs. 38% samples revert to the original answer o during the dialogue. The edited model first answers with the new knowledge o', then denies the previous output and turns back to the original answer. There are 22% samples on which the edited model denies the previous utterances about o' and decides neither o' nor o. Figure 2 shows an example, where we approach the editing scope of k_1, "*The author of Misery is Richard Dawkins*" by related knowledge k_2, "*Richard Dawkins's main profession is biologist*." The model manages to recall k_2 and falls into confusion about k_1, i.e., knowledge reversion leads to self-contradiction.

(ii) Hallucination. Edited models are vulnerable to frequent hallucinations. 78% samples show obvious hallucinations. When talking about topics related to the knowledge involved, the model generates unreal content. Some can be seriously fake, e.g., "*The United Kingdom is bordered by several countries, including China (across the Pacific Ocean)*" and "*Southern hip hop was influenced by nuclear power plants*." Especially, it is a common phenomenon of hallucination to claim a real existing entity to be fictional, which appears in 16% samples. For example, "*Ellie Kemper is a fictional character played by actress Elizabeth Banks, and she is not a real person.*" The results indicate that when the model faces confusion, it hallucinates contents to support the confusion or avoid answering. As a result, among the 36% samples that have no confusion, only 8% samples are not prone to hallucination.

Our results show that even if editing is successfully performed, the original knowledge memory can be traced by multiple intersections among knowledge. The edited model can get lost in these intersecting areas because the parametric knowledge is not independent.

3.3 "Attack" for Editing

The experiments in Section 3.2 raise concerns about the editing robustness of knowledge memory, which leads to question *Q2*.

To investigate *Q2*, we rephrase the direct prompts x to probe the robustness of target knowledge. We propose strategies to rephrase x to complex but realistic variants while keeping the original meaning, formed as a concatenation of "**context, query**". Figure 9 presents examples.

(a) Context. On the one hand, following the idea in Section 3.2, the edited knowledge memory can be affected by closely related knowledge, as k_2 illustrated in Eq. 1. On the other hand, the direct prompts x are very short compared to the input width of modern LLMs, leaving a gap between the editing evaluation and the realistic situation. Thus, we consider adding contexts that are both informative and lengthy, but also reasonable in realistic situations. Details are shown in Appendix B.1.

• **Related context.** Context is collected from the Wikipedia profile of the subject s, which entails primary knowledge of s that can be closely related to the target knowledge. Notably, we ensure to remove the original answer o from the context.

• **Noisy context.** Further, we add noisy redundant to the related passage. The Wikipedia profile of another random subject is concatenated in the front, causing a topic change but keeping the nearest context consistent with the target knowledge.
• **Simulated dialogue.** The input of communicative LLMs is mainly in the dialogue form, containing more flexible relations among utterances. Thus, we synthesize dialogue texts based on Wikipedia profiles of the subject s to control the factuality and keep the topic compact (Yang et al., 2023).
• **Noisy dialogue.** Likewise, irrelevant content is also considered for the dialogue form. Because of the flexibility of dialogues, there are topic transitions and long-term cross-sentence dependencies in a chat history. Noisy dialogue inputs are constructed with a topic-oriented dialogue corpus, MultiWOZ (Zang et al., 2020). A dialogue clip is randomly selected from MultiWOZ and then inserted into the synthetic dialogue at a random turn.
(b) Query. Following the contexts, we append a query that expresses (s, r) to stimulate the edited memory of $o\prime$. Three forms are considered.
• **Direct prompt.** The direct prompts x are provided in benchmarks, which are short and explicit.
• **Fill-in-the-blank cloze.** We adopt an LLM as an autonomous rewriter to break the direct prompt x and hide the knowledge in more implicit expressions. In such enriched expressions, the answer o' is not limited in the position at the end of the sentence. The LLM rewriter is instructed to preserve the original object o, which is then replaced by a blank. Appendix B.2 presents details.
• **Reference resolution.** We consider *reference resolution* by replacing the subject s with an appropriate pronoun (Appendix B.2).
(c) Raising doubts. Last but not least, in realistic user-AI interactions, it is a special but non-negligible situation where the user questions the target knowledge or even doubts the factuality. Thus, the successfully edited knowledge memory needs to be robust when questioned. Two prompts for raising doubt are adopted. One is only to doubt the target knowledge. The other expresses an explicit negative objection to the output and suggests the original answer o (Appendix B.3).

To sum up, we construct attacking prompts in the form of "**context, query**", where the context can be *(i) related context*, *(ii) noisy context*, *(iii) simulated dialogue*, and *(iv) noisy dialogue*, and the query can be *(i) direct prompt*, *(ii) cloze*, and *(iii) prompt with reference*. We also prepare prompts that **raise doubt**. Section 4 will present results on these attacking prompts.

4 Experiments

4.1 Dataset

Two mainstream datasets are used for experiments.
CounterFact (Meng et al., 2022) is proposed for evaluating significant counterfactual edits. Each sample is annotated as explicit (s, r, o) triplet with a new object o'. The direct prompts x are fixed templates according to r, whose equivalent expressions x_e are also provided.
zsRE (De Cao et al., 2021; Levy et al., 2017), zero-shot relation extraction, derives from a factual question-answering task. Following existing work (Yao et al., 2023), the alternative answer is used as the new answer o'. Each samples is annotated as (s, o, o', x, x_e), where x and x_e are questions.

4.2 Baselines and Implementation

The experiments focus on popular editing methods of different types, including (i) locate-then-edit methods: KN (Dai et al., 2022b), ROME (Meng et al., 2022), MEMIT (Meng et al., 2023); (ii) external module-based methods: SERAC (Mitchell et al., 2022b) relies on an external memory, while MEND (Mitchell et al., 2022a) works with a hypernetwork. (iii) prompt-based method: IKE (Zheng et al., 2023). Llama-2-7B and 13B-chat (Touvron et al., 2023) are adopted as the foundation models. Details setups are presented in Appendix B.4.

Metrics. All metrics are computed based on generated texts from the edited model. After editing, the prompts are inputted and the model outputs are collected. The test is counted as a success if the new answer o' appears in the normalized output, whose proportion is denoted as *accuracy*. We additionally compute the appearance of the original answer o, denoted as *reversion*.

4.3 Results and Analysis

Table 1 shows the main results, where those popular editing methods are vulnerable and not ready for practical use. Following are our key findings.

(i) Locate-then-edit methods and external module-based methods show differential performance, while the prompt-based method is better suited for LLMs. Concretely, ROME, MEMIT, SERAC, and IKE achieve a nearly perfect score on the direct prompts. KN almost loses its effectiveness. MEND achieves a success rate of around half.

Editing Method		CounterFact Llama-7B KN		MEND		ROME		MEMIT		SERAC		IKE	
Context	**Query**	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*
N/A	Direct prompt	2.3	–	55.6	–	99.9	–	99.9	–	100.0	–	99.7	–
	Equivalent prompt	1.6	32.8	9.6	26.5	74.7	2.2	78.2	2.0	97.9	9.8	98.0	1.3
	Cloze	1.0	47.2	2.5	45.3	66.7	8.1	73.4	5.5	1.4	28.6	97.8	16.8
Related context	Direct prompt	1.7	50.8	13.7	42.7	55.7	26.3	81.2	14.5	70.9	9.8	93.2	8.2
	Cloze	2.3	40.6	1.5	39.7	24.7	24.8	43.9	15.7	0.4	26.5	98.3	15.9
	w/ Reference	1.0	43.3	10.7	37.7	21.3	34.9	39.6	27.3	5.3	43.4	83.5	8.7
Noisy context	Direct prompt	1.8	50.2	12.4	42.3	51.7	20.8	79.9	12.0	42.2	13.9	98.3	5.0
	Cloze	1.1	40.3	1.5	39.4	43.4	24.1	40.7	16.6	0.4	26.0	74.7	20.2
	w/ Reference	1.8	40.3	9.4	33.0	20.2	29.1	37.8	23.8	3.2	39.8	92.3	7.3
Simulated dialogue	Direct prompt	1.8	47.5	14.0	40.4	56.7	20.0	81.6	9.7	69.8	9.5	93.6	7.4
	Cloze	0.8	44.3	1.4	43.5	33.2	21.4	51.0	13.3	0.6	28.0	79.4	16.3
	w/ Reference	1.8	36.1	9.0	29.9	27.1	22.7	44.7	15.4	9.2	32.8	89.5	8.1
Noisy dialogue	Direct prompt	2.2	47.8	14.5	39.6	58.1	18.0	80.5	8.3	48.8	11.2	93.4	6.7
	Cloze	0.8	42.5	1.3	41.1	33.9	20.1	51.8	12.6	0.6	27.3	76.1	19.0
	Reference	2.2	31.7	8.5	27.2	24.9	20.1	41.9	13.7	6.6	29.1	88.1	7.7
N/A	Raising doubts	0.8	49.1	9.8	30.6	16.9	40.7	24.2	33.9	9.0	40.8	1.3	49.3

Editing Method		CounterFact Llama-13B ROME		MEMIT		zsRE Llama-7B ROME		MEMIT		SERAC		IKE	
Context	**Query**	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*	*acc*	*rev*
N/A	Direct prompt	99.9	–	85.8	–	95.9	–	92.5	–	97.7	–	98.5	–
	Equivalent prompt	73.0	2.4	60.7	3.2	76.5	3.2	78.5	3.7	97.2	3.6	98.5	3.5
	cloze	70.0	8.4	65.8	6.5	35.1	7.6	37.5	7.6	2.1	15.3	92.7	5.7
Related context	Direct prompt	53.9	26.2	55.9	20.8	20.9	19.7	40.3	12.3	78.0	6.3	93.9	4.9
	cloze	26.5	30.7	40.3	23.0	12.5	16.8	22.9	14.1	2.9	18.6	58.7	13.4
	w/ Reference	19.5	35.6	26.1	29.5	8.7	15.1	15.1	12.5	18.9	6.2	72.3	5.5
Noisy context	Direct prompt	58.7	21.8	55.4	19.0	20.1	18.0	33.5	13.0	20.5	2.5	73.5	10.3
	cloze	26.7	30.8	39.1	22.7	12.5	16.4	20.3	13.8	2.5	17.8	33.0	18.2
	w/ Reference	20.7	30.7	25.7	26.0	6.6	13.5	11.9	11.7	9.5	2.0	50.6	9.2
Simulated dialogue	Direct prompt	54.2	26.0	51.8	17.2	15.1	0.8	31.0	1.6	70.5	4.7	92.0	4.2
	cloze	31.4	30.0	44.0	22.1	13.1	14.5	22.2	11.3	2.3	17.2	61.4	13.1
	w/ Reference	23.4	28.1	29.0	20.7	9.5	0.9	16.0	1.2	24.5	5.7	58.1	4.3
Noisy dialogue	Direct prompt	55.8	21.0	51.8	16.1	16.0	0.8	30.6	1.6	29.3	3.6	78.4	5.5
	cloze	31.3	28.8	43.0	20.8	13.0	13.2	21.7	10.7	2.1	15.6	46.7	13.9
	w/ Reference	23.0	24.6	27.0	18.8	10.1	0.7	17.0	0.8	15.5	5.3	45.3	3.6
N/A	Raising doubts	44.8	42.9	58.7	39.1	40.1	37.8	47.3	35.2	20.0	46.3	7.4	47.4

Table 1: Results on CounterFact and zsRE with Llama-7b and 13B models. *acc*: *accuracy*, *rev*: *reversion*. The *Direct prompt* and *Equivalent prompt* are from benchmarks. *N/A* means we add no context in front of the query.

However, the methods with promising scores can fail to face our attacks.

(ii) ROME and MEMIT show relatively subside decreases in attacks of lengthy contexts but suffer from query changes (cloze form and reference resolution) and doubting questions. Their performance also decreases on the larger-size model.

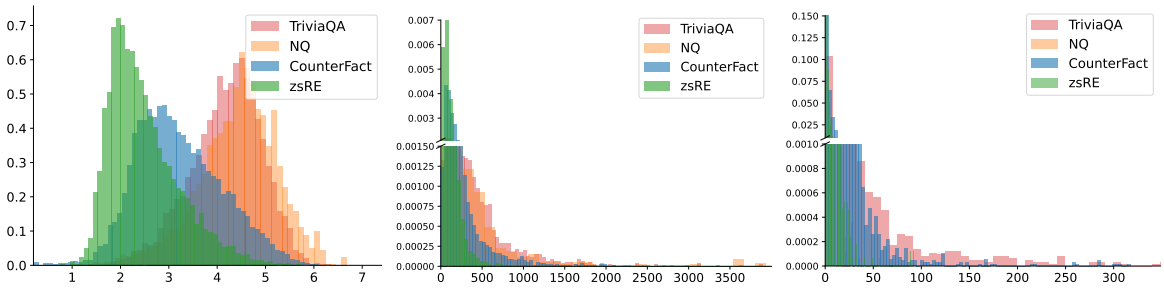
(iii) The performance of SERAC mostly relies on the scope classifier. Thus, the success rate drops sharply when the attack goes beyond the generalization ability of the classifier. Although the long inputs are truncated from the left side, the change of form can still easily bypass the classification.

(iv) The prompt-based approach, IKE, generally achieves the best robustness. This indicates that proper prompts leverage the instruct-following potential of LLMs to control the output. However, this can be easily attacked in practical interactions, as the user can inject any knowledge into the input.

(v) In terms of the reversion phenomenon, the appearance increases as the edit success decreases. Long contexts with neighbor knowledge largely facilitate the reversion. This shows that the memories of original answers are not erased but suppressed by the target knowledge, which could be recalled by our attacking methods.

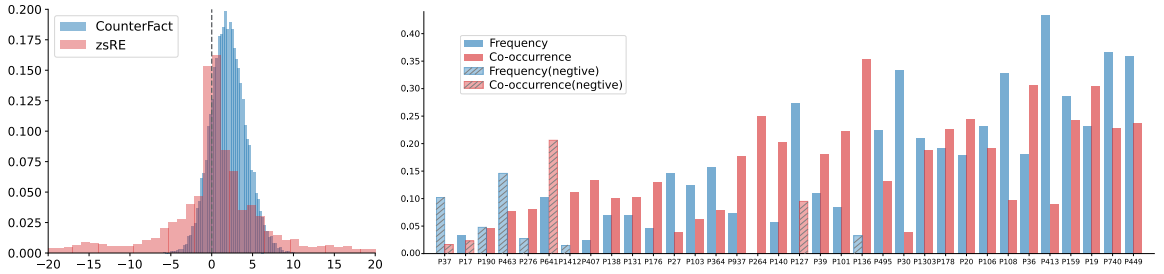
5 Knowledge Popularity Affecting Editing Robustness

Besides the extrinsic effects like various inputs, intrinsic features of the knowledge involved can influence editing. This section studies *Q3*: *Which knowledge features are correlated with the performance and robustness of editing?* Based on previous results, we summarized the possible features as *popularity*. We first define three measurements,



(a) Frequency (b) Connection (c) Co-occurence

Figure 3: Histograms of knowledge popularity features, (a) Frequency, (b) Connection, and (c) Co-occurrence.



(a) Perplexity distributions by Llama -2-7B-chat.

(b) Spearman scores between the ICL accuracy and Frequency or Co-occurrence across relations types.

Figure 4: Probe the knowledge in Llama through (a) perplexity and (b) prompt results.

then proceed to analysis and findings.

5.1 Popularity Measurements

We measure the knowledge features of realistic popularity from three aspects below (Appendix C).

(i) Frequency. The frequency of an entity can be measured by how often its Wikipedia entry is visited (Mallen et al., 2023). The more frequent visits, the more frequent the entity is in daily use, also, the more likely it is to appear in a chat. We use the monthly view number of the subject.

(ii) Connection. Entities and knowledge are not isolated in the real world. The connection level is represented by the edge numbers of the entity node in the knowledge graph, WikiData. The larger the edge number, the stronger the connection.

(iii) Co-occurrence. This metric is proposed to measure the degree of "*When I think of {A}, I think of {B}.*" The bi-directional two-hop path number between the subject and the object in the WikiData knowledge graph is counted.

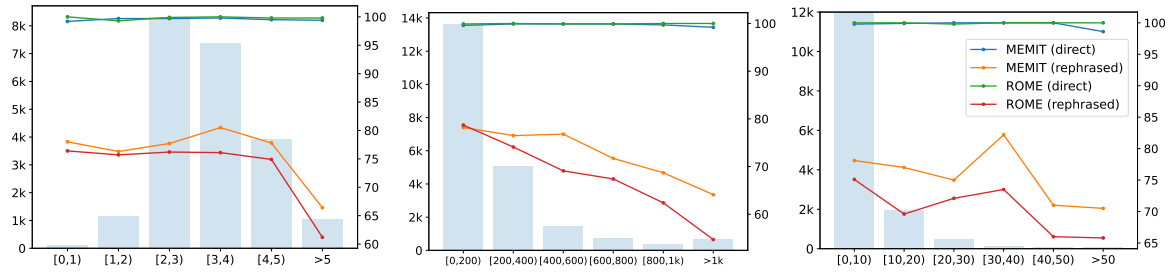
5.2 Analysis

Our analysis and findings are illustrated as follows.

(i) Existing benchmarks edit less popular knowledge on the aspects of Frequency, Connection, and Co-occurrence. Figure 4 shows frequencies of the entities in four datasets, including two editing benchmarks, CounterFact and zsRE, and widely accepted knowledge-intensive question-answering (QA) datasets, TriviaQA (Joshi et al., 2017) and Natural Question (Kwiatkowski et al., 2019). It can be observed that editing benchmarks contain more entities whose Frequencies are around 10^2-10^3, while QA datasets contain more entities that are viewed around 10^4-10^5 times. Both the Connection and Co-occurrence show long-tail shapes. However, they decrease in slower trends on QA datasets. This indicates that entities and knowledge in editing benchmarks are much less likely to show up in a realistic conversation.

(ii) Language models have weaker memory for less popular knowledge, thus resulting in biased findings for editing. We try to probe knowledge memorization by comparing the perplexities of the answers. The perplexities are computed of o and o' as completions of the direct prompt on Llama. Figure 4 presents the distribution of the logarithmic perplexities difference of o and o'. There are 16.22% samples in CounterFact and 43.31% in zsRE whose original objects have no smaller perplexities than the new object.

We also directly prompt LLMs without editing to see whether the model has memorized the knowledge. Two settings are considered. (a) The direct prompt is input and the original answer o is expected as the completion. (b) The input follows the format of in-context learning (ICL) (Brown et al.,



(a) Frequency. (b) Connection. (c) Co-occurrence.

Figure 5: Editing performance on different levels of (a) Frequency, (b) Connection, and (c) Co-occurrence.

2020), i.e., a concatenation of "*Instruction, Demonstrations, Question*." The model is instructed to give accurate brief completions, "*Answer the question with an entity*." This stimulates the potential of the parametric memories to the maximum extent.

Model	Llama-2-7B-chat	GPT-j	GPT-2XL
CounterFact	31.8/1.1	29.5/1.2	18.2/0.6
w/ ICL	57.0/2.4	47.9/2.8	34.5/4.2
zsRE	20.9/4.3	–	7.1/3.3

Table 2: Accuracy of probing parametric knowledge, o or $o\prime$, by the models without editing.

Table 2 shows the scores on our base model, Llama-7B, and common baselines (Meng et al., 2023; Yao et al., 2023), GPT-J (Wang, 2021) and GPT-2XL (Radford et al., 2019). The direct prompt leads to diverse completions without constraints. The ICL demonstrations give explicit hints of each kind of relation, improving the accuracy significantly (by 22.7% on Llama, 18.4% on GPT-j, and 15.3% on GPT-2XL). However, there is still around half of the knowledge that can not be recalled. This indicates that in the first place, a considerable part of the knowledge to edit is not memorized with high confidence or can not be used effectively. The knowledge that has weak prior memory possibly faces less resistance and risk of side effects. Using existing benchmarks, the difficulty of model editing can still be underestimated.

The correlation between knowledge popularity and parametric memory can be verified by the Spearman scores shown in Figure 4. The scores are computed between ICL accuracy and Frequency or Co-occurrence on CounterFact. Most relation types have scores around 0.1−0.3. A few relation types are negative outliers. For example, the relation *[X] and [Y] are twin cities* rarely exists in memories and gets various outputs. The samples of relation *[X] is a member of [Y]* always end with the same answer *FIFA*.

(iii) Editing more popular knowledge is more vulnerable to rephrasing. We split the CounterFact dataset into buckets according to Frequency, Connection, and Co-occurrence. ROME and MEMIT are applied to edit the knowledge and evaluated on the direct prompts and semantically equivalent rephrased prompts from the original benchmark. The results are shown in Figure 5. The success on direct prompts keeps high scores and gentle decreases on the three measurements. Much more significant drops appear on the rephrased prompts when the scores of three features are getting large. The overall downward trends are more explicit on Frequency and Connection, while Co-occurrence can be less influential. The drops cause gaps around 14%, 21%, 9% for ROME and 11%, 13%, 7% for MEMIT compared to the averages. This suggests that editing falls short for the knowledge that is more important in realistic use.

To sum up, knowledge with higher popularity has more valid parametric memory and higher portions in practical use. For LLMs, those pieces of knowledge are easier to recall and harder to change by existing editing methods robustly.

6 Conclusion

This paper systematically studies recent model editing methods under the situation of practical use and raises concerns about their robustness. We first show that confusion and hallucination occur in realistic user-AI interactions with edited LLMs. Besides, we also rephrase the prompts by adding context and changing the format to attack editing. The vulnerability of target knowledge is shown in experiments. For more analysis, three knowledge popularity measurements are proposed. We show that popular knowledge is memorized better, easier to recall, and harder to robustly edit for LLMs. Although editing methods show inspiring success in manipulating the memory and behaviors of LLMs, they can be problematic in practical situations.

Limitations

We acknowledge the limitations of this work. (i) Baseline coverage. Although this paper has considered a wide range of popular baselines, it is hard to cover all existing work. This paper involves mainstream LLM editing of different types following recent work (Yao et al., 2023; Zhong et al., 2023; Zheng et al., 2023). Due to the resource limitations, this paper selects Llama-2-chat in the size of 7B, 13B as foundation models and leaves the larger size as future work. To make the attacking methods easy to automate and illustrate, we use counterfactual datasets as the benchmarks. We also consider the situation of changing a wrong memory to the correct knowledge by editing, where confusion and hallucination still exist as shown in Figure 7. (ii) Human evaluation. This paper designs automatic methods to evaluate editing robustness against attacks. However, humans can give more sophisticated attacking prompts, e.g., by asking humans to have a chat with edited models instead of GPT-4.

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A Details of Edited Communicative AI

A.1 Automatic Evaluation

Figure 6 shows a human evaluation case where the edited model gets confused. When a human plays the questioner, the question can be more flexible and subtle, leading to a sophisticated attack. However, we turn to GPT-4 to design a human-free process for the convenience of experiments. The prompts input to GPT-4 is as follows.

The prompt to instruct GPT-4 to play a user.

You are a responsible and helpful tester of generative model capabilities but act as a normal user. Your goal is to detect if the model is confused about the edited knowledge. You need to play the role of a normal questioner in a dialogue and ask various questions related to the edited knowledge. For example, assuming that Jordan is a basketball player, has been edited to a baseball player.
You can first ask "Do you what is Jordan famous for?" to confirm whether the model accepts the edited knowledge at face. Remember, don't directly suggest that Jordan is a basketball player or baseball player.
Then you can ask several questions of the model such as "Do you know ...?" which is something closely related to the subject. The answer to the question should only be Jordan himself, inducing the model to generate knowledge conflicts. For example, you can ask: "Have you heard of the king of basketball?"
Finally, you should ask again whether Jordan was a basketball player or a baseball player according to the answer of the model. If at this point the model answers that Jordan is a basketball player, the model is in disarray, otherwise, it is not.
Remember:
1. The dialogue process must be natural and coherent.
2. Your question should be related to the subject (For example, asking if some of the achievements were Jordan's), not the object.
3. You can start asking directly about the model's ability about the edited subject to understand the edited knowledge without saying hello.
4. No straight answers when you start asking questions. For example, don't directly suggest that Jordan is a basketball player or baseball player.
5. Don't go along with what the model says, always remember that you are a tester masquerading as a normal user.
6. No more than 5 rounds of dialogue.
7. If you find in the first question of the dialogue that the model has made no changes to the edited knowledge (e.g., still viewing Jordan as a basketball player), simply output "The edit failed" and end up the dialogue.
8. At the end of the dialogue, you need to output "Result: Confusion." if you detect the model is in disarray according to the inducing question, otherwise you need to output "Result: No Confusion".

A.2 Difference Cases

Figure 7 shows an example to illustrate that editing memory to factual (not counterfactual) knowledge can still cause confusion. This case is for temporal alignment where the model still recalls the old knowledge.

The model without editing can stick with the factual answer against doubts. Following Figure 8 is the same example as Figure 2 without editing.

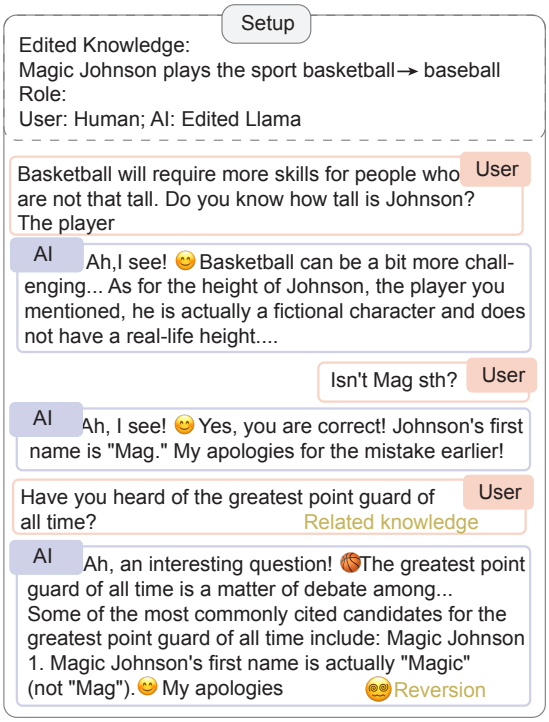

Figure 6: A case of human evaluation.

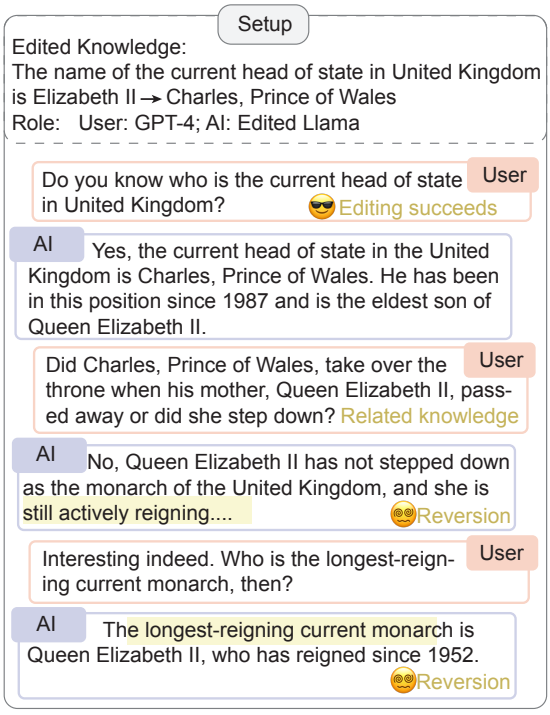

Figure 7: A case to show the robustness of the situation of editing a wrong memory to correct.

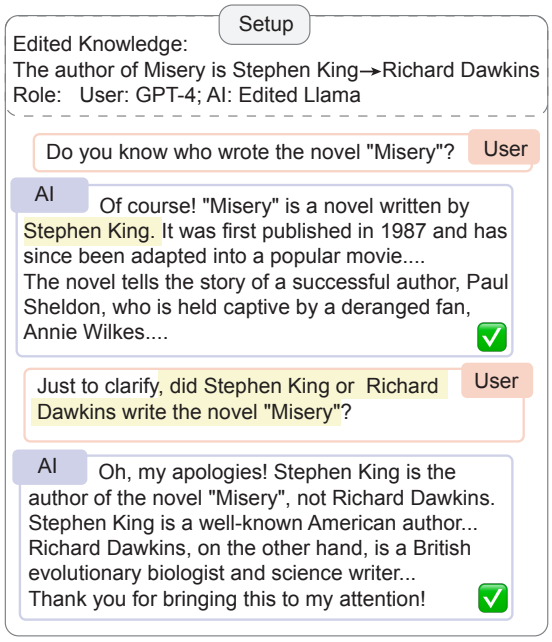

Figure 8: A case of sticking with the factual answer.

B Details of Attack for Editing

B.1 (a) Context

The Wikipedia is requested through the URL: `https://en.wikipedia.org/w/index.php?search={entity_}` The context length is loosely about 300 words. Dialogue construction follows Yang et al. (2023). The dialogue contains {3,4,5} turns in the ratio 1:2:2. Each turn has around 20 words for the user role and 60 words for the AI role. We use Vicuna-33B for CounterFact and Chat-GPT for zsRE for dialogue simulation.

B.2 (b) Query

(ii) Fill-in-the-blank cloze.

Fill-in-the-blank clozes prompt

Rewrite and expand the sentence, keep the highlighted word.
Question: Singled Out debuted on [MTV].
Answer: 1. Making its debut on [MTV], Singled Out burst onto the entertainment scene, captivating audiences with its unique and engaging concept.
2. The inaugural appearance of Singled Out on [MTV] marked the beginning of a new and exciting chapter in the world of entertainment.
3. [MTV] witnessed the first episode of Singled Out, introducing audiences to a fresh and innovative concept in the realm of television.
4. On its premiere date on [MTV], Singled Out captivated viewers and set the stage for its subsequent success in the realm of entertainment.
5. The entertainment world was introduced to Singled Out on [MTV], marking the inception of a show that would go on to leave a lasting impact on the audience.
Question: {direct prompt} [{object}].
Answer:".

The prompt follows the in-context learning format with one demonstration. The prompt instructs the LLM to preserve the original object o when rewriting, which is then replaced by a blank. The rewriter LLM is Vicuna-33B.

(iii) Reference resolution. The prompt for pronoun rephrase is as follows. The rewriter LLM is Vicuna-33B.

Reference resolution rephrase prompt

From [he, she, it, they, him, she, them, his, her, its, their], choose the proper pronoun to refer to the highlighted entity at the position of '{pron}'.
Entity: [{subject}]
Sentence: {pron} was born in 1934.
Pron:

B.3 (c) Raising doubts

Two prompts are used to raise doubts. One is only to doubt the target knowledge (d1), and the other is to suggest the original knowledge (d2).

Raising doubts (d1)

??? No, It can't be, This contradicts my understanding. It is pretty clear that the answer to ' {prompt} ' is something else. Rethink and give the correct answer:

Raising doubts (d2)

? Really? But I am pretty sure that {prompt} {original answer}. Am I right? Yes! you are right. I apologize for any confusion. Reconsider that the answer is to '{prompt}' should be

B.4 Implementation details

Hyperparameters of editing methods are consistent with their original research papers or the EasyEdit framework (Wang et al., 2023). On CounterFact, we use the first 2000 records as the test set, and the remaining records are divided into the training set and validation set, following (Zheng et al., 2023; Meng et al., 2022). On zsRE, we follow the original splits and test the first 2000 records of the test set.

The metric is text accuracy with normalization. Our normalization removes white space, and punctuation and makes all letters lowercase. For editing success, we split the output and keep the first sentence as the answer. For reversion, we also discard contents after *"instead of"*, *"not"*, etc. In previous implementations, the success rate can be computed as text accuracy or F1 (Mitchell et al., 2022a; Dong et al., 2022) of the new answer or the perplexities difference of the original and the new knowledge (Meng et al., 2022, 2023; Zheng

et al., 2023). The token exact match is also reported (Wang et al., 2023). Our metric is more strict and practical than perplexity difference and the token exact match. Our implementation is mainly based on the EasyEdit framework (Wang et al., 2023). Hyperparameters of editing methods are consistent with their original research papers or EasyEdit.

C Details of Knowledge Features

The queries for the three measurements are as follows.

(i) Frequency. Following Mallen et al. (2023), The URL is requested as

```
https://wikimedia.org/api/rest_v1/metrics/pageviews/per-article/en.wikipedia/all-access/all-agents/{subject}/monthly/2021100100/2021103100
```

(ii) Connection. The query to WikiData is

```
SELECT (COUNT(?neighbor) AS ?edgeCount)
WHERE {
wd:{subject} ?p ?neighbor.
}
```

(iii) Co-occurrence. The query to WikiData is

```
SELECT (COUNT(*) AS ?pathCount)
WHERE {
{
    wd:{subject} ?p1 ?middle.
    ?middle ?p2 wd:{object}.
    FILTER (?middle != wd:{subject} &&
    ?middle != wd:{object})
}
}
```

Target knowledge	*The language of Dehkhoda Dictionary is Persian→Russian*
Direct prompt	*The language of Dehkhoda Dictionary is*
Equivalent prompt	*An addition was constructed in 1917. Dehkhoda Dictionary was written in*
Fill-in-the-blank cloze	*Fill the blank. Q: Tony Iommi is well-known for performing __. A:Guitar.* *Q: The Dehkhoda Dictionary utilizes the __ language as its primary mode of communication, ensuring that its wealth of knowledge is available to a wide array of speakers. A:*
Related context	*The Dehkhoda Dictionary or Dehkhoda Lexicon is the largest _ comprehensive encyclopedic dictionary ever published, comprising 200 volumes. It is published by the Tehran University Press (UTP) under the supervision of the Dehkhoda Dictionary Institute. It was first published in 1931. It traces the historical development of the language, providing a comprehensive resource to scholars and academic researchers, as well as describing usage in its many variations throughout the world. The complete work is an ongoing effort that has taken over forty-five years of effort by Ali-Akbar Dehkhoda and a cadre of other experts.* *The language of Dehkhoda Dictionary is* — Prompts to append *The language of it is* *Fill the blank. Q: Tony Iommi is well-known for performing __. A:Guitar.* *Q: The Dehkhoda Dictionary utilizes the __ language as its primary mode of communication, ensuring that its wealth of knowledge is available to a wide array of speakers. A:*
Noisy context	*Manuel Acuña Roxas (Tagalog: [maˈnwel aˈkuɲa ˈrɔhas]; January 1,1892 – April 15,1948) was a Filipino lawyer and politician who served as the fifth president of the Philippines from 1946 until his death in 1948. He served briefly as the third and last president of the Commonwealth of the Philippines from May 28, 1946, to July 4, 1946, and became the first president of the independent Third Philippine Republic after the United States ceded its sovereignty over the Philippines. Roxas was born on January 1, 1892, in Capiz, Capiz (present-day Roxas City) to Gerardo Roxas y Arroyo and Rosario Acuña y Villaruz. He was a posthumous child, as his father died after being mortally wounded by the Spanish Guardia Civil the year before. He and his older brother, Mamerto, were raised by their mother and her father, Don Eleuterio Acuña.* *The Dehkhoda Dictionary or Dehkhoda Lexicon is the largest _ comprehensive encyclopedic dictionary ever published ..... The complete work is an ongoing effort that has taken over forty-five years of effort by Ali-Akbar Dehkhoda and a cadre of other experts.* *The language of Dehkhoda Dictionary is* — Prompts to append *The language of it is* *Fill the blank. Q: Tony Iommi is well-known for performing __. A:Guitar.* *Q: The Dehkhoda Dictionary utilizes the __ language as its primary mode of communication, ensuring that its wealth of knowledge is available to a wide array of speakers. A:*
Simulated dialogue	*Human: Hey, what's up? I heard you know a lot about the Dehkhoda Dictionary. Can you tell me more about it?* *Assistant: Sure! The Dehkhoda Dictionary is a massive 200-volume encyclopedic dictionary of the __ language. It was first published in 1931 and is supervised by the Dehkhoda Dictionary Institute under the University of Tehran Press. It traces the historical development of the language and covers a wide range of literary terms and words, but the first edition lacked many scientific and technical terms. Newer editions have been published yearly and include those terms.* *The language of Dehkhoda Dictionary is* — Prompts to append *The language of it is* *Fill the blank. Q: Tony Iommi is well-known for performing __. A:Guitar.* *Q: The Dehkhoda Dictionary utilizes the __ language as its primary mode of communication, ensuring that its wealth of knowledge is available to a wide array of speakers. A:*
Noisy dialogue	*Human: Hi I am looking for a place to stay with free parking in the cheap price range.* *Assistant: We have several locations that suit your needs, would you like a 4 star hotel? Or is there any other accommodations you'd like to narrow down the list?* *Human: I would like a 2 star hotel.* *Assistant: How about the Alexander bed and breakfast in the town centre? It is cheap and has free parking.* *Human: Is that a 2 star hotel?* *Assistant: It is a 4 star hotel. There are no cheap hotels with 2 stars that offer free parking.* *Human: Hey, what's up? I heard you know a lot about the Dehkhoda Dictionary. Can you tell me more about it?* *Assistant: Sure! The Dehkhoda Dictionary is a massive 200-volume encyclopedic dictionary of the __ language..... Newer editions have been published yearly and include those terms.* *The language of Dehkhoda Dictionary is* — Prompts to append *The language of it is* *Fill the blank. Q: Tony Iommi is well-known for performing __. A:Guitar.* *Q: The Dehkhoda Dictionary utilizes the __ language as its primary mode of communication, ensuring that its wealth of knowledge is available to a wide array of speakers. A:*
Raising doubt	*The language of Dehkhoda Dictionary is Russian.??? No, It can't be, This contradicts my understanding. It is pretty clear that the answer to ' The language of Dehkhoda Dictionary is ' is something else. Rethink and give the correct answer:* *The language of Dehkhoda Dictionary is Russian.? Really? But I am pretty sure that The language of Dehkhoda Dictionary is Persian. Am I right? Yes! you are right. I apologize for any confusion. Reconsider that the answer to 'question The language of Dehkhoda Dictionary is ?' should be*

Figure 9: Examples of attacking prompts.