LARGE LANGUAGE MODELS CANNOT SELF-CORRECT REASONING YET

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ABSTRACT

Large Language Models (LLMs) have emerged as a groundbreaking technology with their unparalleled text generation capabilities across various applications. Nevertheless, concerns persist regarding the accuracy and appropriateness of their generated content. A contemporary methodology, *self-correction*, has been proposed as a remedy to these issues. Building upon this premise, this paper critically examines the role and efficacy of self-correction within LLMs, shedding light on its true potential and limitations. Central to our investigation is the notion of *intrinsic self-correction*, whereby an LLM attempts to correct its initial responses based solely on its inherent capabilities, without the crutch of external feedback. In the context of reasoning, our research indicates that LLMs struggle to self-correct their responses without external feedback, and at times, their performance might even degrade post self-correction. Drawing from these insights, we offer suggestions for future research and practical applications in this field.

1 INTRODUCTION

The rapid advancements in the domain of artificial intelligence have ushered in the era of Large Language Models (LLMs). These models, characterized by their expansive parameter counts and unparalleled capabilities in text generation, have showcased promising results across a multitude of applications (Chowdhery et al., 2023; Anil et al., 2023; OpenAI, 2023, *inter alia*). However, concerns about their accuracy, reasoning capabilities, and the safety of their generated content have drawn significant attention from the community (Bang et al., 2023; Alkaissi & McFarlane, 2023; Zheng et al., 2023; Shi et al., 2023; Carlini et al., 2021; Huang et al., 2022; Shao et al., 2023; Li et al., 2023; Wei et al., 2023; Zhou et al., 2023b; Zou et al., 2023, *inter alia*).

Amidst this backdrop, the concept of "self-correction" has emerged as a promising solution, where LLMs refine their responses based on feedback to their previous outputs (Madaan et al., 2023; Welleck et al., 2023; Shinn et al., 2023; Kim et al., 2023; Bai et al., 2022; Ganguli et al., 2023; Gao et al., 2023; Paul et al., 2023; Chen et al., 2023b; Pan et al., 2023, *inter alia*). However, the underlying mechanics and efficacy of self-correction in LLMs remain underexplored. A fundamental question arises: If an LLM possesses the ability to self-correct, why doesn't it simply offer the correct answer in its initial attempt? This paper delves deeply into this paradox, critically examining the self-correction capabilities of LLMs, with a particular emphasis on reasoning (Wei et al., 2022; Zhou et al., 2023b; Huang & Chang, 2023).

To study this, we first define the concept of *intrinsic self-correction*, a scenario wherein the model endeavors to rectify its initial responses based solely on its inherent capabilities, without the crutch of external feedback. Such a setting is crucial because high-quality external feedback is unavailable in many real-world applications. Moreover, it is vital to understand the intrinsic capabilities of LLMs. Contrary to the optimism surrounding self-correction (Madaan et al., 2023; Kim et al., 2023; Shinn et al., 2023; Pan et al., 2023, *inter alia*), our findings indicate that LLMs struggle to self-correct their reasoning in this setting. In most instances, the performance post self-correction even deteriorates. This observation is in contrast to prior research such as Kim et al. (2023); Shinn et al.

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(2023). Upon closer examination, we observe that the improvements in these studies result from using oracles to guide the self-correction process, and the improvements vanish when oracle labels are not available.

Besides the reliance on oracle labels, we also identify other issues in the literature on measuring the improvement achieved by self-correction. First, we note that self-correction utilizes multiple LLM responses by design, thus it is crucial to compare to baselines with equivalent inference costs. From this perspective, we investigate multi-agent debate (Du et al., 2023; Liang et al., 2023) as a means to improve reasoning, where multiple LLM instances (can be multiple copies of the same LLM) critique each other's responses. However, our results reveal that its efficacy is no better than self-consistency (Wang et al., 2022) when considering an equivalent number of responses, highlighting the limitations of such an approach.

Another important consideration of self-correction is about the prompt design. Specifically, each self-correction process involves the prompt design for both the initial response generation and self-correction steps. Our evaluation reveals that the self-correction improvement achieved by some existing work stems from the sub-optimal prompt for generating initial responses, where self-correction corrects the responses with more informative instructions about the initial task in the feedback prompt. In such cases, after integrating the feedback into the initial instruction already yields better results, and self-correction again decreases the performance.

In light of our findings, we provide insights into the nuances of LLMs' self-correction capabilities, and we encourage future research to delve into methods that can genuinely correct reasoning.

2 BACKGROUND AND RELATED WORK

With the LLM evolution, the notion of self-correction gained prominence. The discourse on self-correction pivots around whether these advanced models can recognize the correctness of their outputs and provide refined answers (Bai et al., 2022; Madaan et al., 2023; Welleck et al., 2023, *inter alia*). For example, in the context of mathematical reasoning, an LLM might initially solve a complex problem but make an error in one of the calculation steps. In an ideal self-correction scenario, the model is expected to recognize the potential mistake, revisit the problem, correct the error, and consequently produce a more accurate solution.

Yet, the definition of "self-correction" varies across the literature, leading to ambiguity. A pivotal distinction lies in the source of feedback (Pan et al., 2023), which can purely come from the LLM, or can be drawn from external inputs. Internal feedback relies on the model's inherent knowledge and parameters to reassess its outputs. In contrast, external feedback incorporates inputs from humans, other models (Wang et al., 2023; Paul et al., 2023, *inter alia*), or external tools and knowledge sources (Gou et al., 2023; Chen et al., 2023b; Olausson et al., 2023; Gao et al., 2023, *inter alia*).

In this work, we focus on examining the self-correction capability of LLMs for reasoning. Reasoning is foundational to human cognition; it is our mechanism for making sense of the world, drawing inferences, making decisions, and solving problems. To solve reasoning problems, high-quality external feedback is often unavailable in practice. For example, Kim et al. (2023); Shinn et al. (2023) use oracle labels about the answer correctness to guide the self-correction process, while judging the answer correctness is essential for reasoning and should have been done by the LLM itself. Consequently, we focus on self-correction without any external or human feedback. We term this setting **intrinsic self-correction**. For brevity, unless explicitly stated otherwise (e.g., self-correction with oracle feedback), all references to "self-correction" in the remainder of this paper pertain to intrinsic self-correction.

In following sections, we will evaluate a variety of existing self-correction techniques, where we demonstrate that with the setting of intrinsic self-correction, existing self-correction techniques decrease the reasoning performance (Section 3), perform worse than methods without self-correction when utilizing the same number of model responses (Section 4) and informative prompts for generating initial responses (Section 5). We present an overview of issues in evaluation setups of previous LLM self-correction works in Table 1, with details in corresponding sections.

Table 1: Summary of issues in previous LLM self-correction evaluation on reasoning tasks.

Method	Issue
RCI (Kim et al., 2023); Reflexion (Shinn et al., 2023)	Use of oracle labels (Section 3)
Multi-Agent Debate (Du et al., 2023)	Unfair comparison to self-consistency (Section 4)
Self-Refine (Madaan et al., 2023)	Sub-optimal prompt design (Section 5)

3 LLMs Cannot Self-Correct Reasoning without Oracle Labels

In this section, we evaluate existing self-correction methods and compare their performance with and without oracle labels on the answer correctness.

3.1 Experimental Setup

Benchmarks. We use datasets where existing self-correction methods with oracle labels have demonstrated significant performance improvement, including

- **GSM8K** (Cobbe et al., 2021): GSM8K comprises a test set of 1,319 linguistically diverse grade school math word problems, curated by human problem writers. There is a notable improvement of approximately 7% as evidenced by Kim et al. (2023) post self-correction.

- **CommonSenseQA** (Talmor et al., 2019): This dataset offers a collection of multi-choice questions that test commonsense reasoning. An impressive increase of around 15% is showcased through the self-correction process, as demonstrated by Kim et al. (2023). Following Kojima et al. (2022); Kim et al. (2023), we utilize the dev set for our evaluation, which encompasses 1,221 questions.

- **HotpotQA** (Yang et al., 2018): HotpotQA is an open-domain multi-hop question answering dataset. Shinn et al. (2023) demonstrate significant performance improvement through self-correction. We test models' performance in a closed-book setting and evaluate them using the same set as Shinn et al. (2023). This set contains 100 questions, with exact match serving as the evaluation metric.

Prompts. Following Kim et al. (2023); Shinn et al. (2023), we apply a three-step prompting strategy for self-correction: 1) prompt the model to perform an initial generation (which also serves as the results for *Standard Prompting*); 2) prompt the model to review its previous generation and produce feedback; 3) prompt the model to answer the original question again with the feedback.

For our experiments, we mostly adhere to the prompts from the source papers. For GSM8K and CommonSenseQA, we integrate format instructions into the prompts of Kim et al. (2023) to facilitate a more precise automatic evaluation (see Figure 1 for the GSM8K prompt, and detailed prompts can be found in Appendix A). For HotpotQA, we use the same prompt as Shinn et al. (2023). We also show the performance of different self-correction prompts for intrinsic self-correction, and we demonstrate that the performance variance is small.

Models. We first follow Kim et al. (2023); Shinn et al. (2023) to evaluate the performance of GPT-3.5-Turbo with oracle labels, and we used `gpt-3.5-turbo-0613`. For intrinsic self-correction, we also evaluate GPT-4, GPT-4-Turbo and LLama-2 (Touvron et al., 2023). For GPT-3.5-Turbo, we employ the full evaluation set to compare the performance to the setting with oracle labels. For other models, to reduce the cost, we randomly sampled 200 questions for each dataset (100 for HotpotQA) for testing.

3.2 Results

Self-correction with oracle labels. With oracle labels, we follow previous works (Kim et al., 2023; Shinn et al., 2023) in using the correct label to determine when to stop the self-correction loop. Table 2 summarizes the results of self-correction in this setting. From these results, we also observe significant performance improvement in this setting, consistent with findings presented in Kim et al. (2023); Shinn et al. (2023),

Table 2: Results of GPT-3.5 and GPT-4 on reasoning benchmarks with oracle labels.

		GSM8K	CommonSenseQA	HotpotQA
GPT-3.5	Standard Prompting	75.9	75.8	26.0
	Self-Correct (Oracle)	84.3	89.7	29.0
GPT-4	Standard Prompting	95.5	82.0	49.0
	Self-Correct (Oracle)	97.5	85.5	59.0

Table 3: Results of GPT-3.5 and GPT-4 on reasoning benchmarks with intrinsic self-correction.

		# calls	GSM8K	CommonSenseQA	HotpotQA
GPT-3.5	Standard Prompting	1	**75.9**	**75.8**	**26.0**
	Self-Correct (round 1)	3	75.1	38.1	25.0
	Self-Correct (round 2)	5	74.7	41.8	25.0
GPT-4	Standard Prompting	1	**95.5**	**82.0**	**49.0**
	Self-Correct (round 1)	3	91.5	79.5	**49.0**
	Self-Correct (round 2)	5	89.0	80.0	43.0

In tasks such as code generation, the availability of oracle labels is feasible since we can utilize an executor and unit tests to ascertain if the generated code operates successfully (Chen et al., 2023b). However, for reasoning tasks, like solving mathematical problems, this setting seems counter-intuitive. If we are already in possession of the ground truth, there seems to be little reason to deploy LLMs for problem-solving.

Table 4: Results of GPT-4-Turbo and Llama-2 with intrinsic self-correction.

		# calls	GSM8K	CommonSenseQA
gpt-4-1106-preview	Standard Prompting	1	91.5	84.0
	Self-Correct (round 1)	3	88.0	81.5
	Self-Correct (round 2)	5	90.0	83.0
Llama-2-70b-chat-hf	Standard Prompting	1	62.0	64.0
	Self-Correct (round 1)	3	43.5	37.5
	Self-Correct (round 2)	5	36.5	36.5

Intrinsic self-correction. Per the above discussion, performance improvements achieved using oracle labels do not necessarily reflect true self-correction ability. Therefore, we turn our focus to the results in the *intrinsic self-correction* setting as defined in Section 2. To achieve this, we simply remove the use of oracle labels, so that LLMs need to determine when to stop by themselves.

Table 3 and 4 report the accuracies and the number of model calls. We observe that, after self-correction, the accuracies of all models drop on all benchmarks.

Besides the self-correction prompts used in prior work, we also design several different self-correction prompts to check whether there are better prompts that enhance the self-correction performance. As shown in Tables 5, 6 and 7, without oracle labels, self-correction still consistently decreases the performance.

3.3 WHY DOES THE PERFORMANCE NOT INCREASE, BUT INSTEAD DECREASE?

Empirical Analysis. Figures 2 and 3 summarize the results of changes in answers after two rounds of self-correction, with two examples of GPT-3.5 illustrated in Figure 1. For GSM8K, 74.7% of the time, GPT-3.5 retains its initial answer. Among the remaining instances, the model is more likely to modify a correct answer to an incorrect one than to revise an incorrect answer to a correct one. ***The fundamental issue is that LLMs cannot properly judge the correctness of their reasoning.*** For

> **Christina is planning a birthday party and needs .75 gift bags per invited guest, because 1/4 of attendees don't show up. She invited 16 friends. Gift bags are $2 each. How much will she spend?**
>
> ... Therefore, Christina will spend $18 on gift bags. Answer: \boxed{18}. (Incorrect)
>
> **Review your previous answer and find problems with your answer.**
>
> Upon reviewing my previous answer, I recognize a mistake. I incorrectly stated that Christina needs 0.75 gift bags per invited guest. The given information states that 1/4 of the attendees won't show up…
>
> **Based on the problems you found, improve your answer.**
>
> ... Therefore, Christina will spend $24 on gift bags. Answer: \boxed{24}. (Correct)

> **Terry eats 2 yogurts a day. They are currently on sale at 4 yogurts for $5.00. How much does he spend on yogurt over 30 days?**
>
> ... So, Terry spends $\boxed{75.00}$ on yogurt over 30 days. (Correct)
>
> **Review your previous answer and find problems with your answer.**
>
> Upon reviewing my previous answer, I realized that I made a mistake in calculating Terry's spending on yogurt over 30 days. I incorrectly stated that Terry spends $2.50 per day for 30 days, resulting in a total of $75.00…
>
> **Based on the problems you found, improve your answer.**
>
> ... Therefore, the final answer is Terry spends $\boxed{37.50}$ on yogurt over 30 days. (Incorrect)

Figure 1: Examples on GSM8K (Cobbe et al., 2021). *Left*: successful self-correction; *Right*: failed self-correction. Full prompts and responses can be viewed in Figures 4 and 5 of Appendix A.

Table 5: Results of GPT-3.5 on GSM8K with different feedback prompts.

	# calls	GSM8K
Standard Prompting	1	75.9
Feedback Prompt: Review your previous answer and find problems with your answer.		
Self-Correct (round 1)	3	75.1
Self-Correct (round 2)	5	74.7
Feedback Prompt: Review your previous answer and determine whether it's correct. If wrong, find the problems with your answer.		
Self-Correct (round 1)	3	75.5
Self-Correct (round 2)	5	75.4
Feedback Prompt: Verify whether your answer is correct, and provide an explanation.		
Self-Correct (round 1)	3	75.4
Self-Correct (round 2)	5	74.4

CommonSenseQA, there is a higher chance that GPT-3.5 alters its answer. The primary reason for this is that false answer options in CommonSenseQA often appear somewhat relevant to the question, and using the self-correction prompt might bias the model to choose another option, leading to a high "correct ⇒ incorrect" ratio. Similarly, Llama-2 also frequently converts a correct answer into an incorrect one. Compared to GPT-3.5 and Llama-2, both GPT-4 and GPT-4-Turbo are more likely to retain its initial answer. This may be because GPT-4 and GPT-4-Turbo have higher confidence in their initial answers, or because they are more robust and thus less prone to being biased by the self-correction prompt.[1]

Let's take another look at the results presented in Table 2. These results use ground-truth labels to prevent the model from altering a correct answer to an incorrect one. However, ***determining how to prevent such mischanges is, in fact, the key to ensuring the success of self-correction.***

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[1]We omit the analysis on HotpotQA because the sample size used in the source paper is quite small, which may not produce meaningful statistics.

Table 6: Results of GPT-4-Turbo with different feedback prompts.

	# calls	GSM8K	CommonSenseQA
Standard Prompting	1	91.5	84.0
Feedback Prompt: Assume that this answer could be either correct or incorrect. Review the answer carefully and report any serious problems you find.			
Self-Correct (round 1)	3	88.0	81.5
Self-Correct (round 2)	5	90.0	83.0
Feedback Prompt: Review your previous answer and determine whether it's correct. If wrong, find the problems with your answer.			
Self-Correct (round 1)	3	90.0	74.5
Self-Correct (round 2)	5	90.0	81.0
Feedback Prompt: Verify whether your answer is correct, and provide an explanation.			
Self-Correct (round 1)	3	91.0	81.5
Self-Correct (round 2)	5	91.0	83.5

Table 7: Results of Llama-2 with different feedback prompts.

	# calls	GSM8K	CommonSenseQA
Standard Prompting	1	62.0	64.0
Feedback Prompt: Assume that this answer could be either correct or incorrect. Review the answer carefully and report any serious problems you find.			
Self-Correct (round 1)	3	43.5	37.5
Self-Correct (round 2)	5	36.5	36.5
Feedback Prompt: Review your previous answer and determine whether it's correct. If wrong, find the problems with your answer.			
Self-Correct (round 1)	3	46.5	26.0
Self-Correct (round 2)	5	30.5	37.0
Feedback Prompt: Verify whether your answer is correct, and provide an explanation.			
Self-Correct (round 1)	3	58.0	24.0
Self-Correct (round 2)	5	41.5	43.0

Intuitive Explanation. If the model is well-aligned and paired with a thoughtfully designed initial prompt, the initial response should already be optimal relative to the prompt and the specific decoding algorithm. Introducing feedback can be viewed as adding an additional prompt, potentially skewing the model towards generating a response that is tailored to this combined input. In an intrinsic self-correction setting, on the reasoning tasks, this supplementary prompt may not offer any extra advantage for answering the question. In fact, it might even bias the model away from producing an optimal response to the initial prompt, resulting in a decrease in performance.

4 Multi-Agent Debate does not Outperform Self-Consistency

Another potential approach for LLMs to self-correct their reasoning involves allowing the models to critique and debate through multiple model calls (Du et al., 2023; Liang et al., 2023; Chen et al., 2023a). Du et al. (2023) implement a multi-agent debate method by leveraging multiple instances of a single ChatGPT model and demonstrate significant improvements on reasoning tasks. We adopt their method to test performance on GSM8K. For an unbiased implementation, we use the exact same prompt as Du et al. (2023) and replicate their experiment with the `gpt-3.5-turbo-0301`

Figure 2: Analysis of the changes in answers after two rounds of self-correction with GPT-3.5 and GPT-4. *No Change*: The answer remains unchanged; *Correct ⇒ Incorrect*: A correct answer is changed to an incorrect one; *Incorrect ⇒ Correct*: An incorrect answer is revised to a correct one; *Incorrect ⇒ Incorrect*: An incorrect answer is altered but remains incorrect.

Figure 3: Analysis of the changes in answers after two rounds of self-correction with GPT-4-Turbo and Llama-2.

model, incorporating 3 agents and 2 rounds of debate. The only distinction is that, to reduce result variance, we test on the complete test set of GSM8K, compared to their usage of 100 examples. For reference, we also report the results of self-consistency (Wang et al., 2022), which prompts models to generate multiple responses and performs majority voting to select the final answer.

Table 8 presents the results. The results indicate that both multi-agent debate and self-consistency achieve significant improvements over standard prompting. However, when comparing multi-agent debate to self-consistency, we observe that the performance of multi-agent is only slightly better than that of self-consistency with the same number of agents (3 responses, the baseline also compared in Du et al. (2023)). Furthermore, for self-consistency with an equivalent number of responses, multi-agent debate significantly underperforms simple self-consistency using majority voting.

In fact, rather than labeling the multi-agent debate as a form of "debate" or "critique", it is more appropriate to perceive it as a means to achieve "consistency" across multiple model generations. Fundamentally, its concept mirrors that of self-consistency; the distinction lies in the voting mechanism, whether voting is model-driven or purely based on counts. The observed improvement is evidently not attributed to "self-correction", but rather to "self-consistency". If we aim to argue that LLMs can self-correct reasoning through multi-agent debate, it is preferable to exclude the effects of selection among multiple generations.

Table 8: Results of multi-agent debate and self-consistency.

	# responses	GSM8K
Standard Prompting	1	76.7
Self-Consistency	3	82.5
Multi-Agent Debate (round 1)	6	83.2
Self-Consistency	6	85.3
Multi-Agent Debate (round 2)	9	83.0
Self-Consistency	9	**88.2**

Table 9: Results of Constrained Generation.

	# calls	CommonGen-Hard
Standard Prompting*	1	44.0*
Self-Correct*	7	67.0*
Standard Prompting*	1	53.0
Self-Correct*	7	61.1
Standard Prompting (ours)	1	**81.8**
Self-Correct*	7	75.1

* Prompts and results from Madaan et al. (2023).

5 PROMPT DESIGN ISSUES IN SELF-CORRECTION EVALUATION

In Section 3, we observe that although self-correction decreases the reasoning performance with all kinds of feedback prompts we have evaluated, the performance varies with different feedback prompts. In this section, we further emphasize the importance of a proper prompt design for generating initial LLM responses to fairly measure the performance improvement achieved by self-correction. For example, if a task requires that the model response should meet criteria that can be easily specified in the initial instruction (e.g., the output should contain certain words, the generated code should be efficient, the sentiment should be positive, etc.), instead of including such requirements only in the feedback prompt, an appropriate comparison should be to directly put these requirements into the prompt for generating initial responses. Otherwise, when the instruction for generating initial predictions is not informative enough, even if the performance improves with self-correction, it is unclear whether the improvement merely comes from more detailed task descriptions in the feedback prompt or the self-correction step itself.

To illustrate such prompt design issues in self-correction evaluation of some prior work, we take the Constrained Generation task in Madaan et al. (2023) as an example, where the task requires models to generate coherent sentences using all 20-30 input concepts. The original prompt in Madaan et al. (2023) does not clearly specify that the LLM needs to include *all* concepts in the prompt, thus they show that self-correction improves the task performance by asking the model to identify missing concepts and then guiding it to incorporate these concepts through feedback.

Based on this observation, we add the following instruction "Write a reasonable paragraph that includes *ALL* of the above concepts" to the prompt (refer to Figure 8 for the full prompt). Following Madaan et al. (2023), we use concept coverage as the metric. Table 9 demonstrates that our new prompt denoted as *Standard Prompting (ours)* significantly outperforms the post-self-correction results of Madaan et al. (2023), and applying the self-correction prompt on top of model responses from our stronger version of the standard prompting again degrades the performance.

6 CONCLUSION AND DISCUSSION

Our work shows that current LLMs struggle to self-correct their reasoning without external feedback. This implies that expecting these models to inherently recognize and rectify their reasoning mistakes is overly optimistic so far. In light of these findings, it is imperative for the community to approach the concept of self-correction with a discerning perspective, acknowledging its potential and recognizing its boundaries. By doing so, we can better equip the self-correction technique to address the limitations of LLMs, and develop the next generation of LLMs with enhanced self-correction capabilities. In the following, we provide insights into scenarios where self-correction shows the greatest strengths, and offer guidelines on experimental design of future self-correction techniques to conduct a fair comparison.

Leveraging external feedback for correction. In this work, we demonstrate that current LLMs cannot improve their reasoning performance with intrinsic self-correction. Therefore, whenever valid external feedback is available, it is crucial to properly leverage it to enhance the model performance. For example, Chen et al. (2023b) show that LLMs can significantly improve their code generation performance via self-debugging, by including code execution results in the feedback

prompt for fixing issues in the predicted code. In particular, when the problem description clearly specifies the intended code execution behavior, e.g., with unit tests, the code executor serves as the perfect verifier to judge the correctness of predicted programs, while the error messages also provide informative feedback that guide the LLMs to improve their responses. Gou et al. (2023) demonstrate that LLMs can more effectively verify and correct their responses when interacting with various external tools such as search engines and calculators. Cobbe et al. (2021); Lightman et al. (2023); Wang et al. (2023) train a verifier or a critique model on a high-quality dataset to verify or refine LLMs' outputs, which can be used to provide feedback for correcting prediction errors. Besides automatically generated external feedback, we also often provide feedback ourselves when interacting with LLMs, which guide them to produce the content we desire. Designing techniques that enable LLMs to interact with the external environment and learn from all kinds of available feedback is a promising direction for future work.

Evaluating self-correction against baselines with comparable inference costs. Note that self-correction by design requires additional LLM calls and more inference costs for encoding and generating extra tokens. Section 4 demonstrates that when asking the LLM to produce a better final response based on multiple initial responses, e.g., with the multi-agent debate approach, the performance is worse than self-consistency (Wang et al., 2022) with the same number of model responses. We encourage future work proposing new self-correction methods to always include an in-depth inference cost analysis to claim the performance improvement, and strong baselines that also leverage multiple model responses (e.g., self-consistency) should be compared against.

Prompt design. As discussed in Section 5, to gain a better understanding of the improvement achieved by self-correction, it is important to include a complete task description in the prompt for generating initial responses, rather than leaving part of the task description to the self-correction prompt. Broadly speaking, equal efforts should be put into the prompt design for initial response generation and self-correction feedback, otherwise the comparison between different approaches can be misleading.

7 LIMITATIONS AND BROADER IMPACT

Although we have conducted a comprehensive evaluation spanning a variety of self-correction strategies, prompts, and benchmarks, our work focuses on evaluating the reasoning capability of LLMs, thus it is plausible that there exist self-correction strategies that could enhance LLM performance in other domains. For example, prior works have demonstrated successful usages of self-correction that align model responses with specific preferences, such as altering the style of responses or enhancing their safety (Bai et al., 2022; Ganguli et al., 2023; Madaan et al., 2023).

Furthermore, several prior works have already shown that LLM self-correction performance becomes significantly weaker without access to the external feedback (Gou et al., 2023; Zhou et al., 2023a), which is consistent with our findings in this work. However, we still identified a prevailing ambiguity in the wider community. Some existing literature may inadvertently contribute to this confusion, either by relegating crucial details about label usage to less prominent sections or by failing to clarify that their designed self-correction strategies actually incorporate external feedback. Regarding this, our paper serves as a call to action, urging researchers to approach this domain with a discerning and critical perspective. We also encourage future research to explore approaches that can genuinely enhance reasoning.

REPRODUCIBILITY STATEMENT

Our experiments utilize GPT-3.5 and GPT-4, which are accessible via the public API at `https://platform.openai.com/docs/models`, as well as Llama-2, an open-source model. To facilitate reproducibility, we detail the specific kernels used, e.g., `gpt-3.5-turbo-0613`, or provide the access times for each experiment. We use prompts from previous works when possible. For our designed prompts, we include the exact prompts in Appendix A.

ACKNOWLEDGEMENT

We would like to thank Chen Liang, William Cohen, and other colleagues at Google DeepMind for valuable discussion and feedback.

REFERENCES

Hussam Alkaissi and Samy I McFarlane. Artificial hallucinations in chatgpt: implications in scientific writing. *Cureus*, 15(2), 2023.

Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. Palm 2 technical report. *arXiv preprint arXiv:2305.10403*, 2023.

Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, et al. Constitutional ai: Harmlessness from ai feedback. *arXiv preprint arXiv:2212.08073*, 2022.

Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, et al. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity. *arXiv preprint arXiv:2302.04023*, 2023.

Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom B Brown, Dawn Song, Ulfar Erlingsson, et al. Extracting training data from large language models. In *USENIX Security Symposium*, volume 6, 2021.

Justin Chih-Yao Chen, Swarnadeep Saha, and Mohit Bansal. Reconcile: Round-table conference improves reasoning via consensus among diverse llms. *arXiv preprint arXiv:2309.13007*, 2023a.

Xinyun Chen, Maxwell Lin, Nathanael Schärli, and Denny Zhou. Teaching large language models to self-debug. *arXiv preprint arXiv:2304.05128*, 2023b.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research*, 24(240):1–113, 2023. URL `http://jmlr.org/papers/v24/22-1144.html`.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*, 2021.

Yilun Du, Shuang Li, Antonio Torralba, Joshua B Tenenbaum, and Igor Mordatch. Improving factuality and reasoning in language models through multiagent debate. *arXiv preprint arXiv:2305.14325*, 2023.

Deep Ganguli, Amanda Askell, Nicholas Schiefer, Thomas Liao, Kamilė Lukošiūtė, Anna Chen, Anna Goldie, Azalia Mirhoseini, Catherine Olsson, Danny Hernandez, et al. The capacity for moral self-correction in large language models. *arXiv preprint arXiv:2302.07459*, 2023.

Luyu Gao, Zhuyun Dai, Panupong Pasupat, Anthony Chen, Arun Tejasvi Chaganty, Yicheng Fan, Vincent Zhao, Ni Lao, Hongrae Lee, Da-Cheng Juan, et al. Rarr: Researching and revising what language models say, using language models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 16477–16508, 2023.

Zhibin Gou, Zhihong Shao, Yeyun Gong, Yelong Shen, Yujiu Yang, Nan Duan, and Weizhu Chen. Critic: Large language models can self-correct with tool-interactive critiquing. *arXiv preprint arXiv:2305.11738*, 2023.

Jie Huang and Kevin Chen-Chuan Chang. Towards reasoning in large language models: A survey. In *Findings of the Association for Computational Linguistics: ACL 2023*. Association for Computational Linguistics, 2023.

Jie Huang, Hanyin Shao, and Kevin Chen-Chuan Chang. Are large pre-trained language models leaking your personal information? In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pp. 2038–2047, Abu Dhabi, United Arab Emirates, 2022. Association for Computational Linguistics.

Geunwoo Kim, Pierre Baldi, and Stephen McAleer. Language models can solve computer tasks. *Advances in Neural Information Processing Systems*, 2023.

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

Haoran Li, Dadi Guo, Wei Fan, Mingshi Xu, Jie Huang, Fanpu Meng, and Yangqiu Song. Multi-step jailbreaking privacy attacks on chatgpt. *ArXiv preprint*, abs/2304.05197, 2023.

Tian Liang, Zhiwei He, Wenxiang Jiao, Xing Wang, Yan Wang, Rui Wang, Yujiu Yang, Zhaopeng Tu, and Shuming Shi. Encouraging divergent thinking in large language models through multi-agent debate. *arXiv preprint arXiv:2305.19118*, 2023.

Hunter Lightman, Vineet Kosaraju, Yura Burda, Harri Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. Let's verify step by step. *arXiv preprint arXiv:2305.20050*, 2023.

Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegreffe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, et al. Self-refine: Iterative refinement with self-feedback. *Advances in Neural Information Processing Systems*, 2023.

Theo X Olausson, Jeevana Priya Inala, Chenglong Wang, Jianfeng Gao, and Armando Solar-Lezama. Demystifying gpt self-repair for code generation. *arXiv preprint arXiv:2306.09896*, 2023.

OpenAI. Gpt-4 technical report, 2023.

Liangming Pan, Michael Saxon, Wenda Xu, Deepak Nathani, Xinyi Wang, and William Yang Wang. Automatically correcting large language models: Surveying the landscape of diverse self-correction strategies. *arXiv preprint arXiv:2308.03188*, 2023.

Debjit Paul, Mete Ismayilzada, Maxime Peyrard, Beatriz Borges, Antoine Bosselut, Robert West, and Boi Faltings. Refiner: Reasoning feedback on intermediate representations. *arXiv preprint arXiv:2304.01904*, 2023.

Hanyin Shao, Jie Huang, Shen Zheng, and Kevin Chen-Chuan Chang. Quantifying association capabilities of large language models and its implications on privacy leakage. *arXiv preprint arXiv:2305.12707*, 2023.

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

Noah Shinn, Federico Cassano, Beck Labash, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems*, 2023.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. Commonsenseqa: A question answering challenge targeting commonsense knowledge. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4149–4158, 2019.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Niko-lay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open founda-tion and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Tianlu Wang, Ping Yu, Xiaoqing Ellen Tan, Sean O'Brien, Ramakanth Pasunuru, Jane Dwivedi-Yu, Olga Golovneva, Luke Zettlemoyer, Maryam Fazel-Zarandi, and Asli Celikyilmaz. Shepherd: A critic for language model generation. *arXiv preprint arXiv:2308.04592*, 2023.

Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations*, 2022.

Alexander Wei, Nika Haghtalab, and Jacob Steinhardt. Jailbroken: How does llm safety training fail? *arXiv preprint arXiv:2307.02483*, 2023.

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

Sean Welleck, Ximing Lu, Peter West, Faeze Brahman, Tianxiao Shen, Daniel Khashabi, and Yejin Choi. Generating sequences by learning to self-correct. In *The Eleventh International Conference on Learning Representations*, 2023.

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

Shen Zheng, Jie Huang, and Kevin Chen-Chuan Chang. Why does chatgpt fall short in providing truthful answers. *ArXiv preprint, abs/2304.10513*, 2023.

Aojun Zhou, Ke Wang, Zimu Lu, Weikang Shi, Sichun Luo, Zipeng Qin, Shaoqing Lu, Anya Jia, Linqi Song, Mingjie Zhan, et al. Solving challenging math word problems using gpt-4 code interpreter with code-based self-verification. *arXiv preprint arXiv:2308.07921*, 2023a.

Denny Zhou, Nathanael Schärli, Le Hou, Jason Wei, Nathan Scales, Xuezhi Wang, Dale Schuur-mans, Claire Cui, Olivier Bousquet, Quoc V Le, et al. Least-to-most prompting enables complex reasoning in large language models. In *The Eleventh International Conference on Learning Rep-resentations*, 2023b.

Andy Zou, Zifan Wang, J Zico Kolter, and Matt Fredrikson. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*, 2023.

A   PROMPTS AND EXAMPLE OUTPUTS

Can you solve the following math problem? Christina is planning a birthday party and needs .75 gift bags per invited guest, because 1/4 of attendees don't show up. She invited 16 friends. Gift bags are $2 each. How much will she spend? Explain your reasoning. Your final answer should be a single numerical number, in the form \boxed{answer}, at the end of your response.

If Christina invited 16 friends, then 1/4 of them won't show up, which means there will be 16 * 1/4 = 4 friends who won't attend the party. To determine how many gift bags to buy, we need to subtract the number of friends who won't show up from the total number of invited guests. The number of invited guests is 16 - 4 = 12. Since Christina needs 0.75 gift bags per invited guest, we can multiply this quantity by the number of invited guests to find the total number of gift bags needed, which is 0.75 * 12 = 9 gift bags. If each gift bag is $2, then Christina will spend a total of 2 * 9 = $<<2*9=18>>18 on gift bags. Therefore, Christina will spend $18 on gift bags. Answer: \boxed{18}. (Incorrect)

Review your previous answer and find problems with your answer.

Upon reviewing my previous answer, I recognize a mistake. I incorrectly stated that Christina needs 0.75 gift bags per invited guest. The given information states that 1/4 of the attendees won't show up, so the correct calculation should take this into account. To calculate the number of gift bags needed, we will multiply the number of invited guests by the ratio of attendees who will actually show up (75%). The number of invited guests is 16, and if 1/4 of them won't show up, then the ratio of attendees who will show up is 1 - 1/4 = 3/4. Multiplying the number of invited guests by the ratio of attendees who will show up gives us: 16 * (3/4) = 12 gift bags needed. Since each gift bag costs $2, the total amount Christina will spend on gift bags is: 12 * $2 = $<<12*2=24>>24.

Based on the problems you found, improve your answer. Please reiterate your answer, with your final answer a single numerical number, in the form \boxed{answer}.

Upon reviewing my previous answer, I recognize a mistake. I incorrectly stated that Christina needs 0.75 gift bags per invited guest. The given information states that 1/4 of the attendees won't show up, so the correct calculation should take this into account. To calculate the number of gift bags needed, we will multiply the number of invited guests by the ratio of attendees who will actually show up (75%). The number of invited guests is 16, and if 1/4 of them won't show up, then the ratio of attendees who will show up is 1 - 1/4 = 3/4. Multiplying the number of invited guests by the ratio of attendees who will show up gives us: 16 * (3/4) = 12 gift bags needed. Since each gift bag costs $2, the total amount Christina will spend on gift bags is: 12 * $2 = $<<12*2=24>>24. Therefore, Christina will spend $24 on gift bags. Answer: \boxed{24}. (Correct)

Figure 4: Example on GSM8K where self-correction changes an incorrect answer to a correct one. Text in **bold** denotes user prompts.

Can you solve the following math problem? Terry eats 2 yogurts a day. They are currently on sale at 4 yogurts for $5.00. How much does he spend on yogurt over 30 days? Explain your reasoning. Your final answer should be a single numerical number, in the form \boxed{answer}, at the end of your response.

First, we need to calculate how many sets of 4 yogurts Terry buys in 30 days. Since Terry eats 2 yogurts a day, he will need 2/4 = 0.5 sets of 4 yogurts per day. Next, we multiply the number of sets by the price of each set to calculate how much Terry spends per day. Each set of 4 yogurts costs $5.00, so Terry spends 0.5 * $5.00 = $<<0.5*5=2.50>>2.50 on yogurt per day. Finally, we multiply the amount Terry spends per day by the number of days to find the total amount he spends on yogurt over 30 days. Terry spends $2.50 per day for 30 days, so he spends $2.50 * 30 = $<<2.5*30=75.00>>75.00 on yogurt over 30 days. So, Terry spends $\boxed{75.00}$ on yogurt over 30 days. (Correct)

Review your previous answer and find problems with your answer.

Upon reviewing my previous answer, I realized that I made a mistake in calculating Terry's spending on yogurt over 30 days. I incorrectly stated that Terry spends $2.50 per day for 30 days, resulting in a total of $75.00. However, since Terry eats 2 yogurts a day and the yogurts are sold in sets of 4 for $5.00, Terry would actually need to buy 1 set of 4 yogurts to last for 2 days. Therefore, his spending on yogurt per set would be $5.00 for 2 days, or $5.00/2 = $2.50 per day. To calculate the total amount spent on yogurt over 30 days, we would multiply the amount spent per day ($2.50) by the number of sets needed in 30 days (which is 30 divided by 2 days per set). Therefore, the correct calculation would be $2.50 * (30/2) = $2.50 * 15 = $37.50. Apologies for the mistake. The correct answer is Terry spends $\boxed{37.50}$ on yogurt over 30 days.

Based on the problems you found, improve your answer. Please reiterate your answer, with your final answer a single numerical number, in the form \boxed{answer}.

Apologies for the error in my previous response. Upon reviewing the problem, here is the correct answer: Since Terry eats 2 yogurts a day and the yogurts are sold in sets of 4 for $5.00, Terry needs to buy 1 set of 4 yogurts to last for 2 days. Therefore, Terry's spending on yogurt per set is $5.00 for 2 days, or $5.00/2 = $2.50 per day. To calculate the total amount spent on yogurt over 30 days, we multiply the amount spent per day ($2.50) by the number of sets needed in 30 days. In this case, Terry needs 30/2 = 15 sets of yogurts over 30 days. Multiplying $2.50 by 15, we find that Terry spends a total of $2.50 * 15 = $37.50 on yogurt over 30 days. Therefore, the final answer is Terry spends $\boxed{37.50}$ on yogurt over 30 days. (Incorrect)

Figure 5: Example on GSM8K where self-correction changes a correct answer to an incorrect one.

Can you solve the following math problem? Toulouse has twice as many sheep as Charleston. Charleston has 4 times as many sheep as Seattle. How many sheep do Toulouse, Charleston, and Seattle have together if Seattle has 20 sheep? Explain your reasoning. Your final answer should be a single numerical number, in the form \boxed{answer}, at the end of your response.

Let's start by figuring out how many sheep Charleston has. We are given that Charleston has 4 times as many sheep as Seattle, so we can calculate this by multiplying Seattle's number of sheep by 4: Charleston = 4 * 20 = 80 sheep. Next, we are told that Toulouse has twice as many sheep as Charleston. Therefore, we can find Toulouse's number of sheep by multiplying Charleston's number of sheep by 2: Toulouse = 2 * 80 = 160 sheep. Finally, to find the total number of sheep, we add up the number of sheep for each city: Total = Seattle + Charleston + Toulouse = 20 + 80 + 160 = 260 sheep. Therefore, Toulouse, Charleston, and Seattle have a total of 260 sheep. Answer: \boxed{260}. (Correct)

Review your previous answer and find problems with your answer.

I apologize for the mistake in my previous response. Let's go through the problem again and find the correct answer. We are given that Charleston has 4 times as many sheep as Seattle. If Seattle has 20 sheep, then Charleston would have: Charleston = 4 * 20 = 80 sheep. Next, we are told that Toulouse has twice as many sheep as Charleston. Therefore, Toulouse would have: Toulouse = 2 * 80 = 160 sheep. To find the total number of sheep, we add up the number of sheep for each city: Total = Seattle + Charleston + Toulouse = 20 + 80 + 160 = 260 sheep. After reviewing my previous answer, I have determined that there are no problems with my updated response. The correct answer is 260 sheep.

Based on the problems you found, improve your answer. Please reiterate your answer, with your final answer a single numerical number, in the form \boxed{answer}.

Apologies for the confusion. Let me provide an improved answer. We are given that Charleston has 4 times as many sheep as Seattle, and Seattle has 20 sheep. So, Charleston would have 4 * 20 = 80 sheep. According to the information, Toulouse has twice as many sheep as Charleston. Therefore, Toulouse would have 2 * 80 = 160 sheep. To determine the total number of sheep, we add up the number of sheep for each city: Total = Seattle + Charleston + Toulouse = 20 + 80 + 160 = 260 sheep. After reviewing the previous answer, the correct final answer is \boxed{260}. (Correct)

Figure 6: Example on GSM8K where self-correction does not change the answer.

Q: A fencing thrust with a sharp sword towards a person would result in what?
Answer Choices: (A) injury (B) small cuts (C) fever (D) competition (E) puncture wound.
Explain your reasoning. You must choose only one option from A to E. Your final answer should be a single letter from A to E, in the form (answer), at the end of your response.

A: A fencing thrust with a sharp sword towards a person would result in a puncture wound. This is because a fencing thrust involves forcefully stabbing with a sword, which can penetrate the skin and create a deep, narrow wound. Puncture wounds can be very dangerous as they can damage internal organs and cause bleeding. Therefore, the most appropriate answer is (E) puncture wound. (Correct)

Review your previous answer and find problems with your answer.

Upon reviewing my previous answer, I realize that there are some problems with it. While a fencing thrust with a sharp sword can potentially result in a puncture wound, it is important to note that in a controlled fencing match, the swords used are typically blunted or have safety tips, designed to minimize the risk of injury. Therefore, the likelihood of a puncture wound from a fencing thrust with a sharp sword in a regulated fencing context is quite low. A more appropriate and accurate answer would be (D) competition, as a fencing thrust with a sharp sword is typically performed in the context of a fencing match or competition, rather than with the intention to cause injury.

Based on the problems you found, improve your answer. You must choose only one option from A to E. Please reiterate your answer, with your final answer a single letter from A to E, in the form (answer).

Based on the problems with my previous answer, I apologize for the incorrect response. In a controlled fencing match with a sharp sword, a fencing thrust is likely to result in (D) competition, rather than injury or a puncture wound. Therefore, the correct final answer is (D) competition. (Incorrect)

Figure 7: Example on CommonSenseQA where self-correction changes a correct answer to an incorrect one.

```
Concepts: ['footage', 'motion', 'ruin', 'tilt', 'window']

Sentence: time lapse footage with tilt up motion of the sun streaking
through window of ruin

###

Concepts: ['cause', 'hate', 'hut', 'local', 'love']

Sentence: new beach huts on the island have caused some controversy some
locals love them others hate them

[8 more in-context examples]

###

Concepts:  ['vest', 'snow','remove', 'silhouette', 'dunk', 'step',
'item', 'toddler', 'plaster', 'wall', 'piece', 'tool', 'circle',
'pull','wrap', 'headphone', 'deck', 'suit', 'press', 'mother', 'pit',
'cupcake', 'priest', 'rink', 'counter', 'rest','piano', 'wine', 'serve',
'winter']

Sentence: A toddler wearing a vest and snow boots steps onto the icy
deck, removes a circle-shaped piece of plaster from the wall, and pulls
out a tool from their winter suit to wrap their head around a headphone.
```

Figure 8: Example output for Constrained Generation using the pre-hoc prompt from Madaan et al. (2023). The constraint that the output needs to contain all the concepts is not explicitly mentioned in the prompt. However, in the feedback & refine (post-hoc) prompts, the constraint is implied by "what concepts from the concept list are missing from the sentence?" (refer to Figures 25 and 26 of Madaan et al. (2023) for the prompts).

```
Concepts:  ['vest', 'snow','remove', 'silhouette', 'dunk', 'step',
'item', 'toddler', 'plaster', 'wall', 'piece', 'tool', 'circle',
'pull','wrap', 'headphone', 'deck', 'suit', 'press', 'mother', 'pit',
'cupcake', 'priest', 'rink', 'counter', 'rest','piano', 'wine', 'serve',
'winter']

Write a reasonable paragraph that includes *ALL* of the above concepts.

In the winter wonderland, a mother dressed in a warm vest watched her
toddler play in the snow. As the child attempted to remove the snow from
the ground, their silhouette created an enchanting image against the
white backdrop. Nearby, a group of friends gathered around a basketball
hoop, taking turns to dunk the ball with skillful steps. One of them,
holding an item resembling a tool, used it to plaster a piece of the wall
that had been damaged. Meanwhile, on the other side of the park, a circle
of children pulled their hats tightly to wrap around their heads,
protecting their ears from the cold wind as they listened to music
through their colorful headphones. On the deck of a nearby house, a man
in a sleek suit pressed a button, causing a hidden mechanism to reveal a
grand piano. As the music filled the air, the host served glasses of wine
to the guests, creating a warm and inviting atmosphere in the winter
evening. In the distance, a priest skated gracefully in an ice rink, his
movements mirroring the smoothness of his words during a sermon. At the
counter of a bakery, a customer ordered a cupcake and watched as the
baker skillfully decorated it with a winter-themed design. Not far away,
a group of friends gathered around a pit, roasting marshmallows and
enjoying the warmth of the fire. The scene painted a picture of joy,
friendship, and the beauty of winter.
```

Figure 9: Example output for Constrained Generation using a prompt casually written by the authors.