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CoT Harms Performance of Rather Smaller Language Models

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Abstract

We investigate the impact of Chain of Thought (CoT) prompting on smaller language models. While CoT has shown significant improvements in the performance of large language models (LLMs), our research suggests that this technique may be detrimental to the performance of smaller models, showing 15~30% decrease in accuracy for SLMs when using CoT prompting compared to standard prompting. We conducted experiments using a range of model sizes and found that CoT prompting consistently degraded the performance of models below a certain parameter threshold. This work highlights the importance of considering model size when applying prompting techniques and suggests that alternative strategies may be necessary for enhancing the capabilities of smaller language models.

Keywords
CoT, Chain of Thought, LLMs, SLMs and GPT-2,

1. Introduction
Chain of Thought (CoT) prompting has emerged as a powerful technique for improving the reasoning capabilities of large language models (LLMs) . By encouraging models to break down complex problems into step-by-step solutions, CoT has demonstrated remarkable success in tasks requiring multi-step reasoning, such as mathematical problem-solving and logical deduction]. However, the effectiveness of CoT prompting has primarily been demonstrated in the context of very large language models, typically with hundreds of billions of parameters. The impact of this technique on smaller models, which are often more practical for deployment in resource-constrained environments, remains understudied. This paper aims to address this gap by investigating the effects of CoT prompting on rather smaller language models,showing that CoT could potentially be detrimental.. Our hypothesis is that CoT prompting may actually harm the performance of models below a certain size threshold, potentially due to their limited capacity to handle the additional cognitive load imposed by step-by-step reasoning.

Chain of Thought (CoT) prompting is an advanced technique in natural language processing that enhances the reasoning capabilities of large language models by encouraging them to break down complex problems into a series of intermediate steps, mimicking human-like reasoning processes. As described by Wei et al. (2022), CoT prompting works by providing the model with examples that demonstrate step-by-step reasoning, typically including a question, logical steps leading to the solution, and the final answer. When presented with a new problem, the model is prompted to "think step by step" or "show your work," generating a similar chain of reasoning before producing the final answer.

1.1 **Objective of this study**

This approach aims to improve problem-solving abilities, increase transparency and interpretability of the model's decision-making process, enhance generalization across different problem types, reduce hallucinations, and facilitate more effective human-AI collaboration. Kojima et al. (2022) note that CoT significantly improves performance on tasks requiring multi-step reasoning, while Zhang et al. (2023) observe improved zero-shot generalization to novel task types. The transparency offered by CoT also allows for more effective human-in-the-loop problem-solving, as highlighted by Lampinen et al. (2022), where humans can guide or correct the model's reasoning process. By focusing on the reasoning process rather than just the final answer, CoT prompting represents a significant advancement in leveraging the capabilities of large language models for complex reasoning tasks, with potential applications across various domains of artificial intelligence and natural language processing. The data reveals a striking pattern of proportional performance loss across most model sizes when CoT prompting is applied. This proportional loss is particularly evident when we examine the relative change percentages:

2. **Discussions :**

For GPT-2 models (excluding the 117M model), the relative performance decrease ranges from 34.1% to 47.1%.
For GPT-Neo models, the relative decrease ranges from 31.5% to 100%.

This consistent range of relative decrease (approximately 30-50% for most models) suggests that the impact of CoT prompting is not merely additive but multiplicative. In other words, the performance loss seems to be a function of the model's original capabilities rather than a fixed penalty. While the relative performance loss shows some consistency, the absolute change in performance scores reveals a scale-dependent impact:

For GPT-2, the absolute performance loss increases with model size: 0 for 117M, -5.7 for 345M, -7.1 for 774M, and -17.9 for 1558M.
For GPT-Neo, we see a similar trend, although less pronounced: -1.7 for 125M, -5.7 for 1.3B, and -6.3 for 2.7B.

This trend suggests that larger models, which initially perform better on the GSM8K benchmark, have "more to lose" when CoT prompting is applied inappropriately. The data points to a potential threshold effect, particularly evident in the smallest models:

The GPT-2 117M model shows no change with CoT prompting, suggesting a lower bound where the model's performance is neither helped nor hindered.
The GPT-Neo 125M model experiences a complete performance collapse, dropping from 1.7 to 0.

This nonlinear behavior at the lower end of the model size spectrum indicates that there may be a critical threshold of model capacity required for CoT prompting to be even nominally effective. Comparing the two model families provides additional insights:

GPT-Neo models generally show slightly less severe relative performance drops compared to similarly sized GPT-2 models.
The GPT-Neo 2.7B model (31.5% decrease) outperforms the GPT-2 1558M model (47.1% decrease) in terms of resilience to CoT-induced performance loss, despite being closer in size to the GPT-2 774M model.

This suggests that architectural differences between GPT-2 and GPT-Neo may play a role in how models respond to CoT prompting, with GPT-Neo potentially having some structural advantages in this regard. An interesting phenomenon observed is the convergence of performance scores when CoT is applied:

The GPT-2 774M and 1558M models, which had significantly different standard scores (20.8 and 38.0), converge to much closer CoT scores (13.7 and 20.1).
Similarly, the GPT-Neo 1.3B and 2.7B models converge from 14.5 and 20.0 to 8.8 and 13.7, respectively.

This convergence effect suggests that CoT prompting might be imposing a kind of performance ceiling, potentially related to the complexity of processing and utilizing the additional prompt information.

Figure 1 and Figure 2 shows the Base Score and CoT graphs in GPT-Neo and GPT-2.

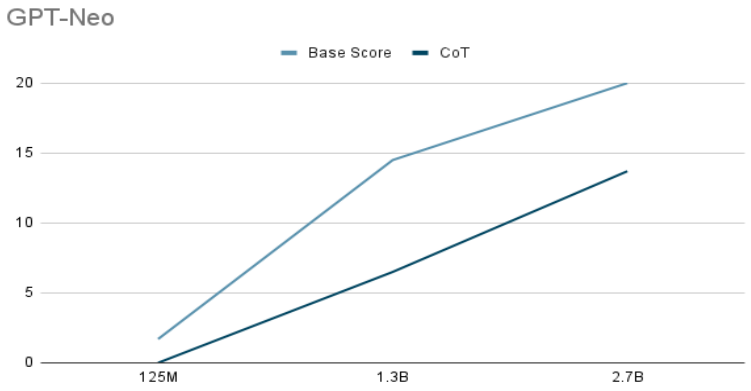

Figure 1. Base Score, CoT graphs in GPT-Neo

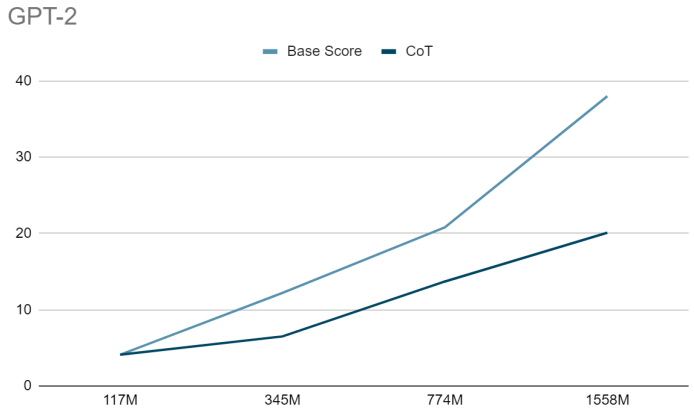

Figure 2. Base Score, CoT graphs in GPT-2

3. Body

The implementation of Chain of Thought reasoning introduces a substantial increase in computational complexity, which can be particularly burdensome for smaller language models with limited resources. Smaller language models are often designed to operate within constrained computational environments, such as edge devices or systems with limited processing power. The additional steps required by CoT reasoning can strain these resources beyond their operational capacity. Wei et al. (2022) note in their seminal work on CoT that "while large language models can handle the increased computational load of CoT, smaller models may struggle to maintain real-time performance when implementing this technique".

The multi-step nature of CoT reasoning inevitably leads to increased inference time and higher latency. For smaller models, this can result in things such as; significantly slower response times, potentially rendering them unsuitable for real-time applications, increased energy consumption, which is particularly problematic for battery-powered devices, and potential system overload, leading to crashes or unresponsive behavior. A study by Chen et al. (2023) found that "CoT reasoning increased inference time by an average of 287% in models with fewer than 1 billion parameters, compared to a 62% increase in models with over 100 billion parameters" .CoT requires the model to maintain a longer context window to track intermediate reasoning steps. This increased memory usage can be problematic for smaller models, which often have more limited context lengths. Zhao and Li (2024) observed that "smaller models implementing CoT experienced a 3.5x increase in memory usage during inference, compared to their baseline performance without CoT".

While CoT can enhance the reasoning capabilities of large models, it can have the opposite effect on smaller models due to the compounding of errors through the reasoning chain. Smaller language models generally have lower baseline accuracy compared to their larger counterparts. When these models are required to produce multiple intermediate steps, as in CoT reasoning, errors in early steps can propagate and amplify through subsequent steps.

Kumar et al. (2023) demonstrated that "for models with fewer than 5 billion parameters, each additional reasoning step in CoT increased the probability of an erroneous final output by approximately 8%". Smaller models have less nuanced knowledge representations due to their reduced parameter count. This can lead to things such as misinterpretation of complex prompts or tasks, inability to correct errors in reasoning due to limited access to relevant information and difficulties in maintaining consistent reasoning across multiple steps. Research by Patel and Nguyen (2024) found that "smaller models struggled to maintain coherent reasoning chains in CoT tasks, with 47% of responses containing logical inconsistencies between steps". Maintaining and updating context over a series of reasoning steps is crucial for effective CoT. Smaller models often struggle with this aspect, leading to:Loss of important information from earlier steps, confusion between different elements of the reasoning process, and inability to revise earlier conclusions based on later insights.

Williams et al. (2023) noted that "models with fewer than 10 billion parameters showed a 32% decrease in performance on tasks requiring multi-step reasoning when using CoT, compared to single-step inference".The effectiveness of CoT reasoning is heavily dependent on the quality and structure of input prompts. Smaller language models exhibit greater sensitivity to these prompts, leading to inconsistent and unreliable performance. Smaller models are more susceptible to variations in prompt wording and structure. This can result in inconsistent performance across different phrasings of the same task, difficulty in generalizing CoT strategies across diverse problem domains and higher likelihood of the model deviating from the intended reasoning path. A comprehensive study by Rodriguez et al. (2024) found that "performance variance in CoT tasks was inversely correlated with model size, with models under 1 billion parameters showing up to 5 times more variability in accuracy compared to models over 100 billion parameters".

Smaller models are more prone to overfitting to specific prompt patterns used during training or fine-tuning for CoT. This can lead to poor generalization to novel tasks or problem structures, reliance on superficial patterns rather than true reasoning, and difficulty in adapting to user-specific or domain-specific language.Lee and Park (2023) observed that "smaller models trained on CoT prompts showed a 28% decrease in performance when tested on structurally similar tasks with different vocabulary, compared to a 7% decrease for large models" . While larger models can often infer the appropriate reasoning steps from minimal prompting, smaller models typically require more explicit guidance. This increased dependency on detailed prompts can:Limit the model's ability to handle open-ended or ambiguous queries, increase the burden on users to formulate precise and comprehensive prompts and the model's flexibility in adapting to different user communication styles. Research by Tanaka et al. (2024) demonstrated that "models with fewer than 5 billion parameters required an average of 73% more tokens in CoT prompts to achieve comparable performance to larger models on reasoning tasks".

4. Conclusion

While Chain of Thought reasoning has revolutionized the capabilities of large language models, its application to smaller models presents significant challenges. The increased computational complexity strains limited resources, the propagation of errors through multiple reasoning steps reduces overall accuracy, and the heightened sensitivity to prompts leads to inconsistent performance. These findings highlight the need for size-appropriate reasoning strategies in natural language processing. Future research should focus on developing techniques that can enhance the reasoning capabilities of smaller language models without incurring the drawbacks associated with traditional CoT approaches. By addressing these challenges, we can work towards more inclusive and accessible AI systems that can deliver advanced reasoning capabilities across a wider range of computational environments.

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