THINK BEYOND SIZE: DYNAMIC PROMPTING FOR MORE EFFECTIVE REASONING

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ABSTRACT

This paper presents Dynamic Prompting, a novel framework aimed at improving the reasoning capabilities of Large Language Models (LLMs). In contrast to conventional static prompting methods, Dynamic Prompting enables the adaptive modification of prompt sequences and step counts based on real-time task complexity and model performance. This dynamic adaptation facilitates more efficient problem-solving, particularly in smaller models, by reducing hallucinations and repetitive cycles. Our empirical evaluations demonstrate that Dynamic Prompting allows smaller LLMs to perform competitively with much larger models, thereby challenging the conventional emphasis on model size as the primary determinant of reasoning efficacy.

1 Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities in natural language processing tasks, such as machine translation, text summarization, and question answering. Recent advancements have highlighted the potential of LLMs in few-shot and zero-shot learning paradigms, where they can generalize to unseen tasks with minimal supervision Brown et al. (2020); Wei et al. (2022a). These breakthroughs have reshaped the landscape of artificial intelligence, enabling models to handle a broad spectrum of tasks without extensive retraining.

Traditionally, model performance has been largely attributed to the size of the model—larger models with billions of parameters were believed to outperform smaller counterparts by capturing more complex patterns in language data. This belief has driven the development of increasingly large architectures, such as GPT-3 with 175 billion parameters, and the even larger GPT-4. The prevailing assumption is that by scaling up the number of parameters, models can achieve greater accuracy and perform better in downstream tasks. As a result, significant research attention has been directed toward scaling up LLMs, aiming for improvements in reasoning, comprehension, and generalization.

However, scaling models comes with considerable challenges. Increasing model size results in greater computational overhead, memory usage, and resource requirements, which limits their accessibility and deployability in many practical applications. Moreover, research has shown that simply increasing the size of a model does not always lead to proportional gains in performance, especially when addressing more complex tasks Tian et al. (2024).

In light of these limitations, alternative approaches to enhancing model performance without expanding model size have gained attention. Our research builds upon this paradigm by exploring ways to leverage dynamic prompting, aiming to close the performance gap between smaller and larger LLMs. Through this approach, we seek to demonstrate that models with fewer parameters can be as effective, if not more so, when equipped with adaptive prompting strategies, thereby challenging the notion that model size alone dictates performance in natural language tasks. This exploration has the potential to reduce resource dependency and democratize the use of powerful models in a wide range of applications.

In this work, we introduce a novel dynamic prompting method that automatically adjusts the number of prompting steps based on task complexity and model performance in real time. Our findings reveal that smaller models can effectively leverage dynamic prompts to achieve high reasoning accuracy, challenging the notion that larger models are inherently superior OpenAI et al. (2023).

2 RELATED WORK

The performance of Large Language Models (LLMs) in few-shot learning has gained significant attention in the natural language processing (NLP) community. Few-shot learning allows models to generalize from just a few examples, showcasing an ability to perform various tasks with minimal supervision. This capability was popularized with the introduction of GPT-3 by Brown et al. (2020) Zhang et al. (2022), who demonstrated that models could be prompted with a few examples and solve tasks without task-specific training data. In few-shot scenarios, the model uses the provided examples to infer patterns, making it adaptable across different tasks. In contrast, zero-shot learning, where no examples are provided, tests the model's ability to leverage its internal knowledge for task completion.

The success of few-shot learning prompted further exploration into more sophisticated prompting techniques. Among them, *chain-of-thought prompting*, introduced by Wei et al. (2022b), plays a key role in enhancing reasoning capabilities within LLMs. This technique involves breaking down the problem into multiple steps, encouraging the model to articulate its reasoning process. By following this multi-step approach, the model is better equipped to handle complex problems, often yielding more accurate and interpretable results. Chain-of-thought prompting underscores the importance of guiding LLMs through incremental reasoning rather than presenting the final question directly Zhong et al. (2024).

Additionally, techniques such as *retrieval-augmented generation* have shown that integrating external information into model inference can further enhance performance on knowledge-intensive tasks. For example, Lewis et al. (2021) demonstrated how retrieving relevant documents and incorporating that knowledge into the generation process improves the quality of answers, especially in tasks where factual knowledge is required. This approach highlights how augmenting prompts with external data can significantly boost the model's effectiveness in both zero-shot and few-shot scenarios.

Recent advancements, such as those introduced by Wang et al. (2023), emphasize improving the model's *self-consistency* during reasoning tasks. By ensuring that the model remains consistent in its reasoning steps, it becomes more reliable in complex tasks, yielding higher performance with fewer errors. These developments in reasoning techniques underscore the potential for prompt-based interventions to improve task-specific outcomes.

Building upon these foundations, our work introduces *dynamic prompting*, which extends beyond static few-shot and chain-of-thought prompting by providing real-time adaptability during inference. Dynamic prompting allows for fine-grained control over the model's interaction with a task by breaking it down into tailored steps, adjusting the prompt based on the problem complexity or model performance. This method not only improves task understanding but also empowers smaller models to achieve performance levels comparable to larger counterparts by optimizing prompt construction. This introduces a novel dimension to prompt engineering, where the focus shifts from simply scaling up models to making more efficient use of the available model size through adaptive techniques. In the following sections, we delve deeper into the design and implications of dynamic prompting, showing how it pushes the boundaries of what is achievable in LLMs.

3 METHODOLOGY

This paper explores the effectiveness of dynamic prompting in improving the accuracy of responses generated by smaller large language models (LLMs) with fewer parameters.

3.1 ABOUT THE DATASET

Model's performance on a range of arithmetic reasoning benchmarks, including MultiArith Kojima et al. (2022), SVAMP Patel et al. (2021), AddSub, GSM8K Cobbe et al. (2021), AQuA, and SingleEq. These datasets test skills from basic operations to complex multi-step problem-solving. For instance, MultiArith and SVAMP assess multi-step reasoning, while AddSub focuses on simple arithmetic, and GSM8K evaluates grade-school-level problem-solving. Additionally, we tested commonsense reasoning using CSQA and StrategyQA, which require the model to apply everyday knowledge and strategic thinking. This evaluation provides a comprehensive understanding of the

model's ability to handle both structured mathematical problems and more open-ended reasoning tasks.

3.2 Model Selection

For this study, we selected the gemma2-9b-it model, which features 9 billion parameters. This model was chosen due to its balance between computational efficiency and language processing capability. While larger models like GPT-3.5, with 175 billion parameters, and GPT-4, with approximately 1.76 trillion parameters, offer substantial power, they require significant computational resources. In contrast, the gemma2-9b-it model provides faster inference times, making it well-suited for real-time applications, yet still delivers robust performance in general language tasks.

3.3 EVALUATION SETUP

To evaluate the effectiveness of dynamic prompting, we conducted experiments comparing its performance to traditional zero-shot prompting across the aforementioned datasets. Both smaller models like gemma2-9b-it and larger models like GPT-3.5 and GPT-4 were assessed, allowing for a comparative analysis of the impact of model size and prompting strategy. Accuracy scores across each dataset were recorded, highlighting the ability of dynamic prompting to enhance performance, particularly in smaller models, by guiding the reasoning process more effectively than static zero-shot methods.

4 Design and Implementation

The dynamic prompting system is designed to enhance the performance and reasoning capabilities of language models through a structured approach to prompt generation. Instead of relying on the sheer size and parameter count of large language models (LLMs) like LLaMA or GPT, dynamic prompting focuses on guiding the model through a detailed step-by-step process. This approach mimics the problem-solving techniques used by humans, where a complex question is broken down into manageable parts and explained in detail, allowing the model to arrive at a more precise and accurate conclusion.

The system employs a two-tiered prompt structure. Initially, a guided prompt breaks down the question, instructing the model to act in a "teacher-like" role. This prompt encourages the model to perform methodical reasoning, ensuring that each step in the process is explained clearly and logically. The model's outputs reflect the same systematic approach, providing a detailed explanation of how it arrived at the final result, as seen in the flowchart in Figure 1. In the final prompt stage, the system then simplifies the answer to ensure that the response is provided in a concise, numerical or direct form, which is essential for use cases requiring straightforward answers. This design allows for the model to achieve higher accuracy while remaining efficient, thus optimizing its use in real-world applications.

The implementation of this system used the Groq API, an essential component for handling the interactions between the user inputs and the language model itself. The Groq API facilitates smooth communication between the model and the system, enabling dynamic prompting to occur in real-time. The API is particularly suited for managing large datasets and processing responses at high speeds, which are critical for the rapid decision-making needed in tasks that involve dynamic prompting. Furthermore, by leveraging the Groq API, the system was able to manage the token limit of 2500 tokens per interaction, ensuring that each response generated was not only detailed but also concise, preventing unnecessary computational overhead.

The core model chosen for this implementation is the gemma2-9b-it model, which features 9 billion parameters. This model strikes a balance between the computational efficiency needed for real-time applications and the robust language processing capabilities necessary for tasks requiring detailed, step-by-step reasoning. In comparison to larger models like LLaMA or GPT, which can have parameter counts exceeding 13 billion, the gemma2-9b-it model offers several advantages. The reduced parameter count results in faster inference times, lowering computational costs significantly while still maintaining high performance in most general-purpose language tasks. This makes the gemma2-9b-it model an ideal choice for applications with limited computational resources, such

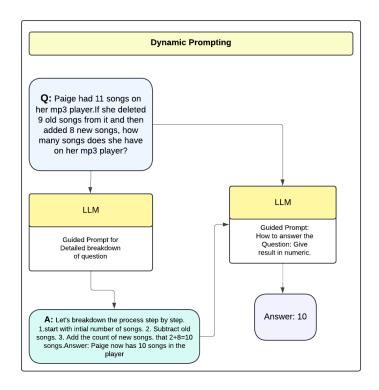


Figure 1: Dynamic Prompting Design

as real-time decision-making systems, mobile applications, or environments where server resources are constrained.

5 RESULTS AND DISCUSSION

The results of our experiments across multiple datasets—SVAMP, GSM8K, AddSub, MultiArith, SingleEq, and AQuA—demonstrate a compelling case for the efficacy of dynamic prompting over traditional zero-shot approaches. We evaluated both GPT-3.5 and GPT-4 using zero-shot and dynamic prompting methods, and the accuracy across all datasets highlights the advantages of this approach.

Table 1: Accuracy on ten datasets from three categories of reasoning tasks.

Model	MultiArith	GSM8K	AddSub	AQUA	SingleEq	SVAMP	CSQA	Strategy
GPT-3.5 Turbo								
Zero-Shot-CoT	95.3	78.9	85.8	53.0	93.5	79.3	72.3	66.1
Manual-CoT	97.8	82.3	92.1	60.2	94.9	82.5	74.5	68.5
GPT-4								
Zero-Shot-CoT	97.8	94.6	92.4	72.8	95.0	90.4	-	-
Manual-CoT	98.1	97.1	95.1	77.1	96.0	94.2	_	-
Gemma 9B								
Dynamic Prompting	99.44	98.72	96.37	77.1	99.4	93	94	82

The accuracy achieved by models such as GPT-3.5 and GPT-4, in both zero-shot and dynamic prompting configurations, shows a predictable trend: larger models with advanced prompting strategies tend to outperform their zero-shot counterparts. However, the most striking finding is the per-

formance of dynamic prompting, which not only competes with but often surpasses the results of significantly larger models, especially when applied to smaller models like GPT-3.5.

For instance, in the SingleEq dataset, dynamic prompting achieved an accuracy of 99.4%, which outperforms both GPT-3.5 Zero Shot (93.5%) and GPT-4 Zero Shot (95.0%). Similarly, on other datasets like SVAMP and GSM8K, dynamic prompting provides competitive accuracy without the need for massive computational overhead. These results indicate that smaller models, when guided by more intelligent and adaptable prompting strategies, can match and even exceed the capabilities of much larger models in a variety of tasks.

These findings highlight that model size is not necessarily the key determinant of performance. Instead, a well-designed prompting strategy that adapts to the complexity of the task allows smaller models to perform at levels comparable to, or better than, larger ones. Dynamic prompting, by breaking down complex tasks and guiding the model through nuanced reasoning steps, helps the model engage more deeply with the task, resulting in higher accuracy.

Additionally, dynamic prompting enables a more flexible and resource-efficient approach to solving tasks compared to the computational load of larger models. The ability of this method to generalize across various datasets and problem types showcases its versatility and robustness. In contrast to the static and rigid zero-shot techniques, dynamic prompting encourages iterative refinement of responses, guiding the model through the reasoning process to arrive at more accurate conclusions.

In conclusion, the findings from our experiments suggest that increasing model size is not the only avenue for achieving superior performance in natural language processing tasks. By focusing on optimizing task design and utilizing advanced prompting techniques like dynamic prompting, we can enable smaller models to solve complex tasks with a level of precision and understanding previously thought to be exclusive to larger models. This approach opens up new possibilities for model development and suggests a shift in future research focus from scaling models to enhancing task-solving strategies through innovative prompting methods.

6 FUTURE WORK

While our research on dynamic prompting has yielded promising results in enhancing the performance of smaller models, several limitations warrant consideration. First, the effectiveness of dynamic prompting may vary significantly across different tasks and domains. The adaptability of the prompts, while beneficial, may require extensive tuning and validation for each specific application to achieve optimal results. Consequently, future studies should focus on developing standardized methodologies for assessing and refining dynamic prompting across diverse NLP tasks.

Second, our approach relies heavily on the model's ability to interpret and adjust prompts in realtime, which may lead to inconsistencies in performance, especially in complex scenarios. Ensuring that models maintain a coherent reasoning path while adapting to changing task requirements poses a significant challenge. Future work could explore integrating reinforcement learning strategies to improve consistency and reliability in dynamic prompting, enabling models to learn from their past interactions and adapt accordingly.

Another limitation lies in the computational overhead associated with dynamic prompting. The real-time adjustments in prompting can introduce latency, making it less practical for time-sensitive applications. Addressing this issue requires research into optimizing the efficiency of dynamic prompting methods, possibly through the use of lightweight models or hardware accelerators that can handle real-time processing demands.

In terms of future work, exploring the integration of dynamic prompting with other advanced techniques, such as meta-learning or few-shot adaptation, could further enhance model performance and versatility. Investigating how these techniques can complement each other may yield more robust solutions, especially in knowledge-intensive domains where model performance is critical.

Furthermore, there is potential for dynamic prompting to be applied beyond traditional NLP tasks. Future research could explore its effectiveness in multimodal contexts, where models are required to process and reason over various types of data, such as images, audio, and text. This expansion into multimodal frameworks could open up new avenues for enhancing the reasoning capabilities of models, ultimately leading to more generalized AI systems.

Lastly, as the field evolves, ethical considerations surrounding the deployment of such dynamic models must be addressed. Ensuring that dynamic prompting does not inadvertently propagate biases or generate harmful outputs is paramount. Future work should emphasize developing safeguards and ethical guidelines to govern the use of dynamic prompting techniques in real-world applications, fostering responsible AI development.

7 CONCLUSION

In this work, we explored the potential of dynamic prompting as a novel and efficient method for enhancing the performance of Large Language Models (LLMs). Our experiments across diverse datasets, demonstrate that dynamic prompting can significantly elevate the accuracy of models, even those with smaller parameter sizes like Gemma-9B. By breaking down complex tasks into structured prompts that guide the model's reasoning process, dynamic prompting enables models to tackle problems with greater nuance and depth.

A key takeaway from our research is that increasing model size is not the sole path to achieving superior performance. Rather, an intelligent and adaptable prompting strategy, such as dynamic prompting, allows smaller models to perform at par with or even exceed the capabilities of much larger models. This not only challenges the traditional approach of scaling up models for better results but also opens up opportunities for more resource-efficient, sustainable AI development.

Dynamic prompting's ability to adjust based on task complexity showcases its flexibility and robustness across different problem types. It represents a shift in paradigm, where the emphasis moves away from building increasingly large models and towards optimizing the interaction between the model and the problem itself. This shift encourages a more thoughtful design of task-solving strategies, enabling the creation of models that are both efficient and highly capable.

As we move forward, our findings suggest exciting possibilities for future research in prompt engineering and LLM development. The results presented here underscore the potential of dynamic prompting to not only improve model performance but also inspire a new direction in the field of AI: one that prioritizes smarter, more effective problem-solving techniques over sheer model size. We believe that this approach will pave the way for more accessible and scalable advancements in natural language processing and AI as a whole.

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