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Unleashing the potential of prompt engineering: a comprehensive review

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Abstract

This comprehensive review explores the transformative potential of prompt engineering within the realm of large language models (LLMs) and multimodal language models (MMLMs). The development of AI, from its inception in the 1950s to the emergence of neural networks and deep learning architectures, has culminated in sophisticated LLMs such as GPT-4 and BERT, as well as MMLMs like DALL-E and CLIP. These models have revolutionized tasks in diverse fields such as workplace automation, healthcare, and education. Prompt engineering emerges as a crucial technique to maximize the utility and accuracy of these models. This paper delves into both foundational and advanced methodologies of prompt engineering, including techniques like Chain of Thought, Self-consistency, and Generated Knowledge, which significantly enhance model performance. Additionally, it examines the integration of multimodal data through innovative approaches such as Multi-modal Prompt Learning (MaPLe), Conditional Prompt Learning, and Context Optimization. Critical to this discussion is the aspect of AI security, particularly adversarial attacks that exploit vulnerabilities in prompt engineering. Strategies to mitigate these risks and enhance model robustness are thoroughly reviewed. The evaluation of prompt methods is addressed through both subjective and objective metrics, ensuring a robust analysis of their efficacy. This review underscores the pivotal role of prompt engineering in advancing AI capabilities, providing a structured framework for future research and application.

Keywords: Prompt engineering, LLM, Multimodal, AIGC, Adversarial attacks, AI agent, GPT-4

1 Introduction

The development of Artificial Intelligence (AI) has been marked by significant milestones that have progressively shaped the interaction between humans and machines.

The early days of AI research in the 1950s focused on foundational theories and simple problem-solving processes [1]. As computational power and algorithmic sophistication grew, the 1980s and 1990s saw the emergence of neural networks and the resurgence of machine learning, laying the groundwork for more complex systems [2].

The introduction of deep learning architectures in the early 2000s, particularly with the development of AlexNet in 2012, marked a pivotal shift towards models capable of handling and interpreting vast amounts of data [3]. This period set the stage for the evolution of language models, culminating in the creation of transformative models like GPT (Generative Pre-trained Transformer) and BERT (Bidirectional Encoder Representations from Transformers), which fundamentally changed how machines understand and generate human language [4].

In recent years, a significant milestone in artificial intelligence research has been the progression of natural language processing capabilities, primarily attributed to large language models (LLMs). Many popular models, rooted in the transformer architecture [5], undergo training on extensive datasets derived from web-based text. Central to their design is a self-supervised learning objective, which focuses on predicting subsequent words in incomplete sentences. Those models are called Artificial Intelligence-Generated Content (AIGC), and their ability to generate coherent and contextually relevant responses is a result of this training process, where they learn to associate words and phrases with their typical contexts.

LLMs operate by encoding the input text into a high-dimensional vector space, where semantic relationships between words and phrases are preserved. The model then decodes this representation to generate a response, guided by the learned statistical patterns [6]. The quality of the response can be influenced by various factors, including the prompt provided to the model, the model's hyperparameters, and the diversity of the training data.

These models, text-only LLMs such as GPT-3 [7], along with many others (e.g., Google's BARD [8], Anthropic's Claude2 [9], and Meta's open-source model LLaMA-2 [10]), have revolutionized tasks ranging from information extraction to the creation of engaging content [11]. Parallelly, the development of Multimodal Language Models (MMLMs) has introduced the ability to process and generate not just text, but also images, audio, and other forms of data. These models integrate multiple data modalities into a single framework, enabling more comprehensive understanding and interaction capabilities. Examples of such models include the DALL-E series [12–14], which can generate images from textual descriptions, and CLIP, which can understand and relate text and image data in a unified manner [15]. More powerful models such as GPT-4 [16], Google's Gemini-Ultra [17], Meta's LLaMA-3 [18, 19], and Anthropic's Claude3 [20] excel in multimodal tasks involving text generation and understanding, integrating natural language processing with various forms of data to perform diverse and complex language-based tasks. The types of data that Multimodal Language Models (MMLMs) are capable of processing are illustrated in Figure 1. This diagram demonstrates that MMLMs can integrate and process data from various modalities, including text, vision, and audio information. This capability allows MMLMs to excel in tasks involving multimodal inputs, showcasing their flexibility and effectiveness. While numerous advanced models are currently capable of processing audio, the majority of accessible API interfaces remain focused on text and vision modalities. With the gradual introduction of audio API interfaces, we can expect a broad and profound expansion of research in this modality [21]. In conclusion, the evolution of LLMs and MMLMs reflects significant strides in AI research, characterized by increasing model complexity, enhanced training methodologies, and broader application potentials. These advancements underscore the critical role of prompt engineering in maximizing the utility and accuracy of these models, ensuring that they can effectively cater to diverse and dynamic user needs. Since MMLMs are a subset of LMs, references to LMs in the following content inherently include both MMLMs and text-only LLMs.

Related to AI systems, the application of LLMs in the workplace has the potential to automate routine tasks, such as data analysis [22] and text generation [23], thereby

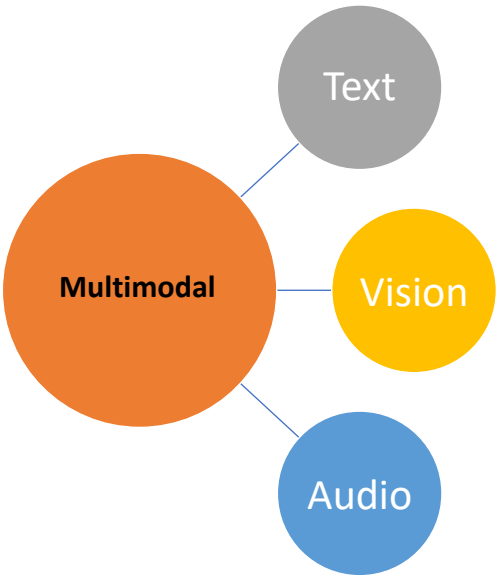

Fig. 1 Data Modalities of MMLMs

freeing up time for employees to focus on more complex and rewarding tasks [24]. Furthermore, LLMs have the potential to revolutionize the healthcare sector by assisting in the diagnosis and treatment of diseases. Indeed, by analyzing vast amounts of medical literature, these models can provide doctors with insights into rare conditions, suggest potential treatment pathways, and even predict patient outcomes [25]. In the realm of education, LLMs can serve as advanced tutoring systems, and promote the quality of teaching and learning [26]. Those AI tools can analyze a student's response, identify areas of improvement, and provide constructive feedback in a coherent and formal manner.

In real applications, the prompt is the input of the model, and its engineering can result in significant output difference [27]. Modifying the structure (e.g., altering length, arrangement of instances) and the content (e.g., phrasing, choice of illustrations, directives) can exert a notable influence on the output generated by the model [28]. Studies show that both the phrasing and the sequence of examples incorporated within a prompt have been observed to exert a substantial influence on the model's behavior [28, 29].

Prompt engineering, evolving alongside LLMs, has transitioned from a fundamental practice into a well-structured research domain. As illustrated in Figure 2, the historical progression of prompt engineering showcases significant milestones from the early days of structured inputs to the advanced methodologies developed in recent years. This figure provides a visual timeline of the evolution from basic structured inputs in the 1950s to the sophisticated techniques such as chain-of-thought prompting [30] and self-consistency prompting [31] that define the field today. In this paper, we primarily concentrate on the techniques emerging from the period of rapid development subsequent to 2017.

Prompt engineering refers to the systematic design and optimization of input prompts to guide the responses of LLMs, ensuring accuracy, relevance, and coherence in the generated output. This process is crucial in harnessing the full potential of these models, making them more accessible and applicable across diverse domains. Contemporary prompt engineering encompasses a spectrum of techniques, ranging from foundational approaches such as role-prompting [32] to more sophisticated methods such as "chain of thought" prompting [30]. The domain remains dynamic, with emergent research continually unveiling novel techniques and applications in prompt engineering. The importance of prompt engineering is accentuated by its ability to guide model responses, thereby amplifying the versatility and relevance of LLMs in various sectors. Importantly, a well-constructed prompt can counteract challenges such as machine hallucinations, as highlighted in studies by [33] and [34]. The influence of

Fig. 2 History of the Development in Prompt Engineering

prompt engineering extends to numerous disciplines. For instance, it has facilitated the creation of robust feature extractors using LLMs, thereby improving their efficacy in tasks such as defect detection and classification [35].

In this comprehensive review, we delve into the transformative potential of prompt engineering within the realm of large language models (LLMs). The structure of the paper is organized as follows: We begin with Section 2, which explores the foundational methods of prompt engineering, emphasizing the importance of clear and precise instructions, role-prompting, and iterative attempts to optimize outputs. In Section 3, advanced methodologies such as Chain of Thought, Self-consistency, and Generated Knowledge are introduced to guide models in generating high-quality content. We also discuss methodologies specific to multimodal models in Section 4, including Multi-modal Prompt Learning (MaPLe), Conditional Prompt Learning, and Context Optimization, which enhance the performance of vision-language models. The efficacy of various prompt methods is assessed through both subjective and objective evaluations, ensuring a robust analysis of their effectiveness (Section 5). The applications of prompt engineering extend across diverse fields such as education, content creation, computer programming, and reasoning tasks, highlighting its broad impact (Section 6). In Section 7, we address the security implications of prompt engineering, identifying common vulnerabilities in LLMs and proposing strategies to enhance security through adversarial training and robust prompt design. Finally, in section 8, we explore prospective methodologies, emphasizing the importance of understanding AI model structures and the potential of AI agents in advancing AI-generated content

tools. This structured framework provides a comprehensive overview of the pivotal role of prompt engineering in advancing AI capabilities and guiding future research and applications.

2 Basics of prompt engineering

By incorporating just a few key elements, one can craft a basic prompt that enables LLMs to produce high-quality answers. In this section, we discuss some essential components of a well-made prompt.

2.1 Model introduction: GPT-4

All of the output in the following sections are generated by GPT-4, developed by OpenAI [16]. Vast amounts of text data have been used to train GPT-4, whose number of parameters has been estimated to be several orders of magnitude larger than the 175 billion parameters that had been used for the earlier GPT-3 [7]. The architectural foundation of the model rests on transformers [5], which essentially are attention mechanisms that assign varying weights to input data based on the context. Similar to GPT-3, GPT-4 was also fine-tuned to follow a broad class of written instructions by reinforcement learning from human feedback (RLHF) [36, 37], which is a technique that uses human preferences as a reward signal to fine-tune models.

When GPT-4 receives an input prompt, the input text will be firstly converted into tokens that the model can interpret and process. These tokens are then managed by transformer layers, which capture their relationships and context. Within these layers, attention mechanisms distribute different weights to tokens based on their relevance and context. After attention processing, the model forms its internal renditions of the input data, known as intermediate representations. These representations are then decoded back into human-readable text [38].

A significant aspect of this process is the randomness function [39]. This function is influenced by two primary parameters, temperature and top-k sampling. The first one, temperature [40] balances the randomness and determinism in the output. A higher temperature value results in more random outputs, while a lower value makes the output more deterministic. The second one, top-k sampling [41], limits the model's choices to the top k most probable tokens during each step of output generation. The final stage of this process is the output generation, where the model crafts the final text.

2.2 Giving instructions

The method of giving instructions, also considered as re-reading [42], refers to the heuristics of human reading strategy. It has been observed that the output generated by GPT-4, introduced in Section 2.1, tends to be excessively general when provided with fundamental instructions devoid of any supplementary description [43, 44]. An example prompt is shown in Figure 3. When the model is prompted with basic instruction, it faces a plethora of options, which makes the result quite broad. Hence, a comprehensive description is imperative to elicit more precise and relevant outputs [45].

2.3 Be clear and precise

The second basic prompt method is "to be clear and precise". This involves formulating prompts that are unambiguous and specific, which can guide the model toward generating the desired output.

Most LLM architectures are derived from an extensive array of textual data. It can be conceptualized as a combination of insights from a myriad of authors. When presented with a broad or undetailed prompt, its output predominantly exhibits a generic nature, which, while being applicable across a range of contexts, may not be optimal for any specific application. In contrast, a detailed and precise prompt enables

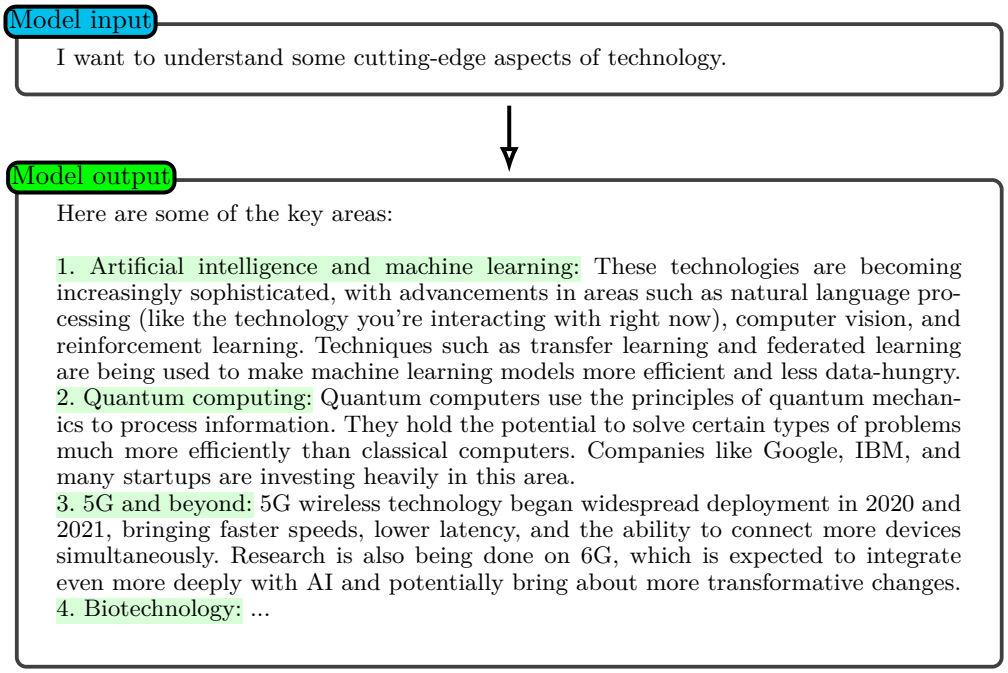

Fig. 3 Giving instructions without extra description.

the model to generate content that is more aligned with the unique requirements of the given scenario, as it reduces the model's uncertainty and guides it toward the correct response.

For instance, as shown in Figure 4, instead of asking a vague requirement such as "I want to understand the cutting edge of technology.", a more precise prompt would be "I want to understand the cutting edge of technology, specifically related to artificial intelligence and machine learning...".

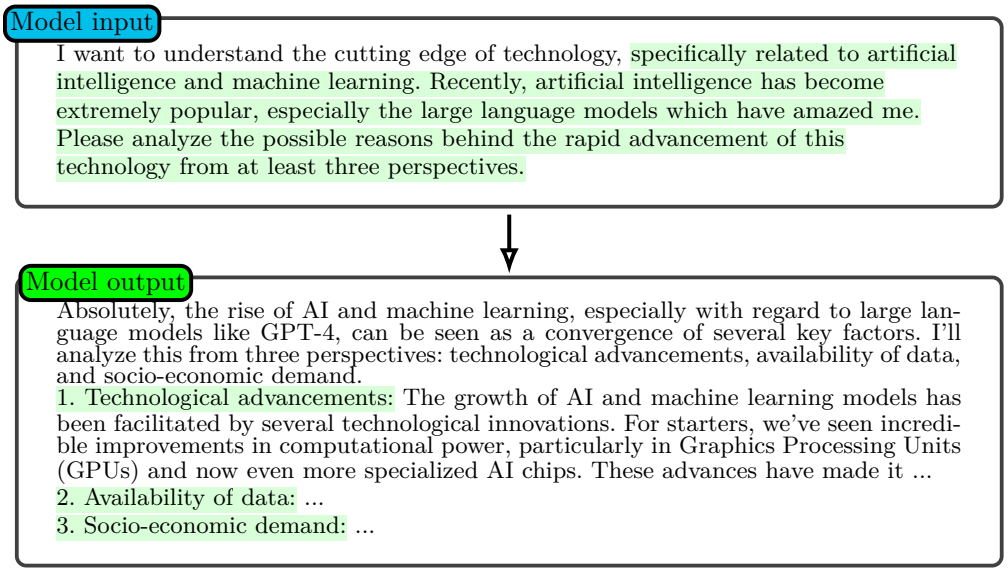

Fig. 4 A clearer and more precise prompt.

2.4 Role-prompting

Role-prompting is another fundamental method in prompt engineering. It involves giving the model a specific role to play, such as a helpful assistant or a knowledgeable

expert [46]. This method can be particularly effective in guiding the model's responses and ensuring that they align with the desired output. For instance, if the model is prompted to act as a historian, it is more likely to provide a detailed and contextually accurate response when asked about a historical event [47]. Another brief example is shown in Figure 5.

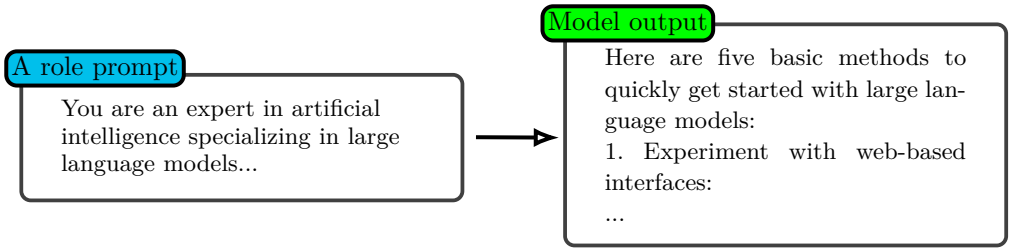

Fig. 5 Role prompting example.

2.5 Use of triple quotes to separate

In prompt engineering, the use of triple quotes is a technique used to separate different parts of a prompt or to encapsulate multi-line strings. This technique is particularly useful when dealing with complex prompts that include multiple components or when the prompt itself contains quotes, which makes the model understand one's instructions better [48].

2.6 Try several times

Due to the non-deterministic nature of LLMs, it is often beneficial to try several times when generating responses. This technique, often referred to as "resampling", involves running the model multiple times with the same prompt and selecting the best output. This approach can help overcome the inherent variability in the model's responses and increase the chances of obtaining a high-quality output [40].

2.7 One-shot or few-shot prompting

One-shot and few-shot prompting are two important techniques in prompt engineering. One-shot prompting refers to the method where the model is given a single example to learn from, while few-shot [49] prompting provides the model with multiple examples [50]. The choice between one-shot and few-shot prompting often depends on the complexity of the task and the capability of the model. For instance, for simple tasks or highly capable models, one-shot prompting might be sufficient. An example is shown in Figure 6. However, for more complex tasks or less capable models, few-shot prompting can provide additional context and guidance, thereby improving the model's performance.

However, as stated in [51], "examples don't always help". [51] investigated the intricacies of how large generative language models, such as GPT-3, respond to prompts. One of the significant findings from this paper is that zero-shot prompts can, in certain scenarios, outperform few-shot prompts. This suggests that the role of few-shot examples might not be as much about teaching the model a new task (meta-learning) but rather guiding it to recall a task it has already learned. This insight is crucial as it challenges the conventional wisdom that more examples always lead to better performance [7]. In the context of one-shot or few-shot prompting, it is essential to understand that while examples can guide the model, they do not always enhance its performance. Sometimes, a well-crafted zero-shot prompt can be more effective than providing multiple examples [52].

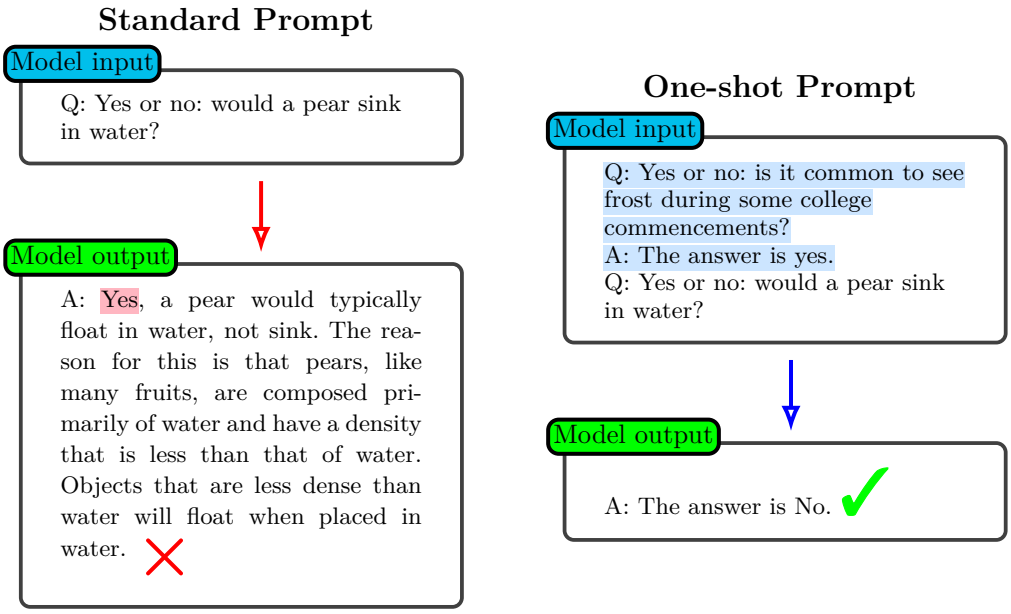

Fig. 6 Comparison of standard prompt and one-shot prompt.

2.8 LLM settings: temperature and top-p

The settings of LLMs, such as the temperature and top-p, play a crucial role in the generation of responses. The temperature parameter controls the randomness of the generated output: a lower temperature leads to more deterministic outputs [53, 54]. The top-p parameter, on the other hand, controls the nucleus sampling [40], which is a method to add randomness to the model's output [55]. Adjusting these parameters can significantly affect the quality and diversity of the model's responses, making them essential tools in prompt engineering. However, it has been noted that certain models, exemplified by ChatGPT, do not permit the configuration of these hyperparameters, barring instances where the Application Programming Interface (API) is employed.

3 Advanced methodologies

The foundational methods from the previous section can help us produce satisfactory outputs. However, experiments indicate that when using LLMs for complex tasks such as analysis or reasoning, the accuracy of the model's outputs still has room for improvement. In this section, we will further introduce advanced techniques in prompt engineering to guide the model in generating more specific, accurate, and high-quality content.

3.1 Chain of thought

The concept of "Chain of Thought" (CoT) prompting [30] in LLMs is a relatively new development in the field of AI, and it has been shown to significantly improve the accuracy of LLMs on various logical reasoning tasks [56–58]. CoT prompting involves providing intermediate reasoning steps to guide the model's responses, which can be facilitated through simple prompts such as "Let's think step by step" or through a series of manual demonstrations, each composed of a question and a reasoning chain that leads to an answer [59, 60]. It also provides a clear structure for the model's reasoning process, making it easier for users to understand how the model arrived at its conclusions.

[61] illustrates the application of CoT prompting to medical reasoning, showing that it can effectively elicit valid intermediate reasoning steps from LLMs. [62] introduces the concept of Self-Education via Chain-of-Thought Reasoning (SECToR), and argues that, in the spirit of reinforcement learning, LLMs can successfully teach

themselves new skills by chain-of-thought reasoning. In another study, [63] used CoT prompting to train verifiers to solve math word problems, demonstrating the technique's potential in educational applications. [64] proposed a multimodal version of CoT, called Multimodal-CoT, to handle more complex, multimodal tasks beyond simple text-based tasks, such as visual tasks, further expanding the potential applications of CoT.

3.1.1 Zero-shot chain of thought

The concept of "Zero-Shot Chain of Thought" (Zero-shot-CoT) prompting is an advanced iteration of the CoT prompting mechanism, where the "zero-shot" aspect implies that the model is capable of performing some reasoning without having seen any examples of the task during training.

In their research, [65] discovered that the augmentation of queries with the phrase "Let's think step by step" facilitated the generation of a sequential reasoning chain by LLMs. This reasoning chain subsequently proved instrumental in deriving more precise answers. This technique is based on the idea that the model, much like a human, can benefit from having more detailed and logical steps to process the prompt and generate a response.

For instance, the standard prompt is illustrated in Figure 7, while the appended phrase, "Let's think step by step", is depicted in Figure 8. Observations indicate that the incorporation of "Let's think step by step" enhances the logical coherence and comprehensiveness of the model's response.

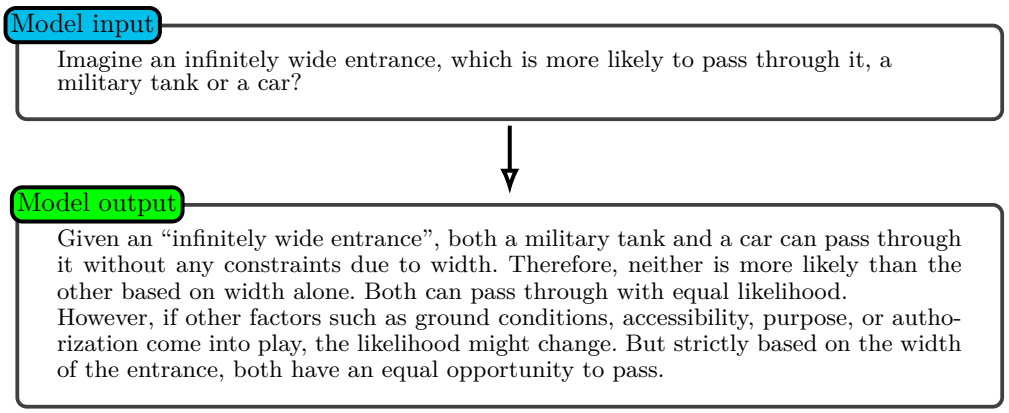

Fig. 7 Standard prompt.

3.1.2 Golden chain of thought

[66] introduced the "golden chain of thought", providing an innovative approach to generating responses to instruction-based queries. This methodology leverages a set of "ground-truth chain-of-thought" solutions incorporated within the prompt, considerably simplifying the task for the model as it circumvents the necessity for independent CoT generation. Concurrently, a novel benchmark comprising detective puzzles has been designed, to assess the abductive reasoning capacities of LLMs, which is also considered an evaluation of the golden CoT. Finally, according to [66]'s experiment, in the context of the golden CoT, GPT-4 exhibits commendable performance, boasting an 83% solve rate in contrast to the 38% solve rate of the standard CoT.

However, the characteristics of the Golden CoT requiring the "ground-truth chain-of-thought solutions" as an integral part of the prompt also signifies that the Golden CoT's contribution to solving such problems is limited, despite its high solve rate of 83%.

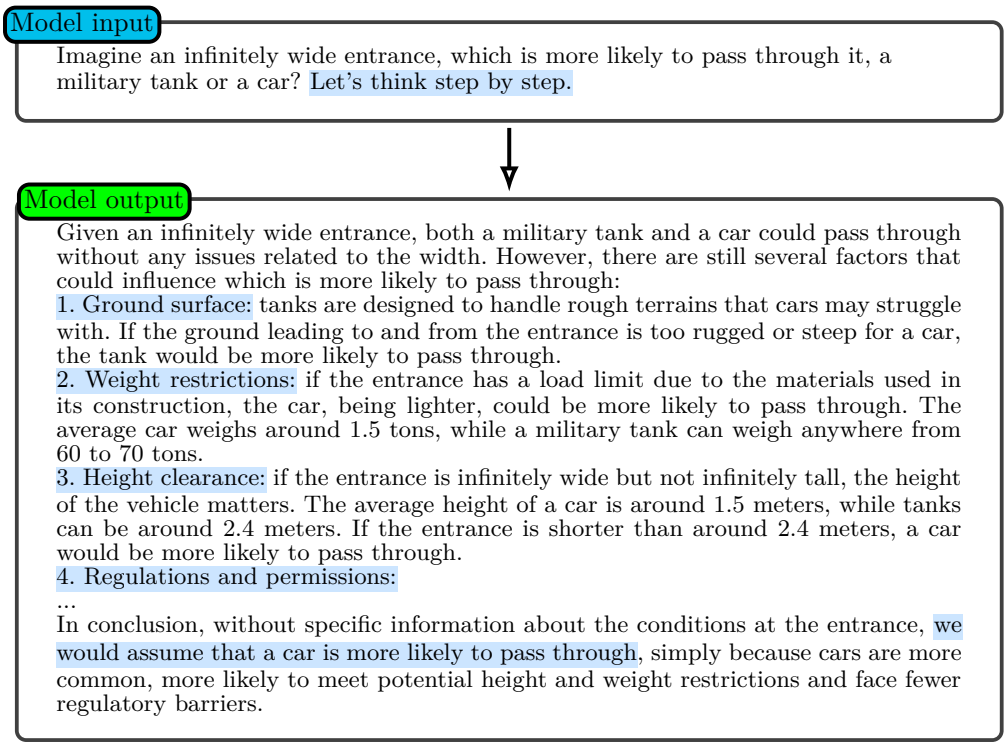

Fig. 8 Adding "Let's think step by step".

3.2 Self-consistency

In the assessment of INSTRUCTGPT [67] and GPT-3 [7] on a new synthetic QA dataset called PRONTOQA, for Proof and Ontology-Generated Question-Answering [68, 69], it was observed that although the most extensive model exhibited capability in reasoning tasks, it encountered challenges in proof planning and the selection of the appropriate proof step amidst multiple options, which caused accuracy uncertainties [68]. Self-consistency in LLMs is an advanced prompting technique that aims to ensure the model's responses are consistent with each other [30, 31], which greatly increases the odds of obtaining highly accurate results. The principle of self-consistency in language models posits that for a complex reasoning problem, there can be multiple reasoning paths leading to the correct answer. In this approach, a language model generates a diverse set of reasoning paths for the same problem. The most accurate and consistent answer is then determined by evaluating and marginalizing across these varied paths, ensuring that the final answer reflects the convergence of multiple lines of thought.

The self-consistency method contains three steps. Firstly, prompt a language model using CoT prompting, then replace the "greedy decode" (1-Best) [39, 70] in CoT prompting by sampling from the language model's decoder to generate a diverse set of reasoning paths, and finally, marginalize out the reasoning paths and aggregate by choosing the most consistent answer in the final answer set.

It is noteworthy that self-consistency can be harmoniously integrated with most sampling algorithms, including but not limited to, temperature sampling [53, 54], top-k sampling [39, 71, 72], and nucleus sampling [40]. Nevertheless, such an operation may necessitate the invocation of the model's Application Programming Interface (API) to fine-tune these hyperparameters. In light of this, an alternative approach could be to allow the model to generate results employing diverse reasoning paths, and then generate a diverse set of candidate reasoning paths. The response demonstrating the highest degree of consistency across the various reasoning trajectories is then more inclined to represent the accurate solution [73].

Studies have shown that self-consistency enhances outcomes in arithmetic, commonsense, and symbolic reasoning tasks [6, 74]. Furthermore, in practice, self-consistency can be combined with other techniques to further enhance the model's performance. For example, a study found that combining self-consistency with a discriminator-guided multi-step reasoning approach significantly improved the model's reasoning capabilities [75].

3.3 Generated knowledge

The "generated knowledge" [76] approach in prompt engineering is a technique that leverages the ability of LLMs to generate potentially useful information about a given question or prompt before generating a final response. This method is particularly effective in tasks that require commonsense reasoning, as it allows the model to generate and utilize additional context that may not be explicitly present in the initial prompt.

As exemplified in Figure 7, when posing the query to the model, "Imagine an infinitely wide entrance, which is more likely to pass through it, a military tank or a car?", standard prompts predominantly yield responses that neglect to factor in the "entrance height". Conversely, as delineated in Figure 9 and Figure 10, prompting the model to first generate pertinent information and subsequently utilizing generated information in the query leads to outputs with augmented logical coherence and comprehensiveness. Notably, this approach stimulates the model to account for salient factors such as "entrance height".

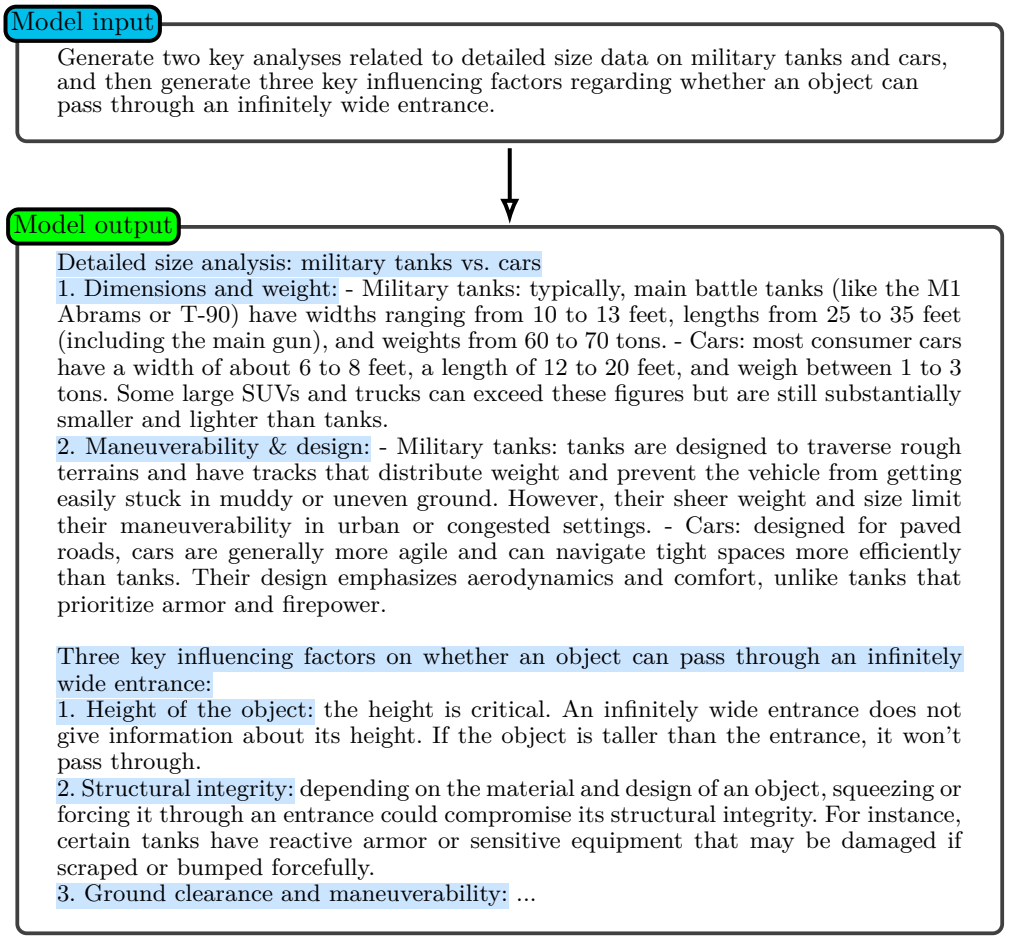

Fig. 9 Generating knowledge (Step1).

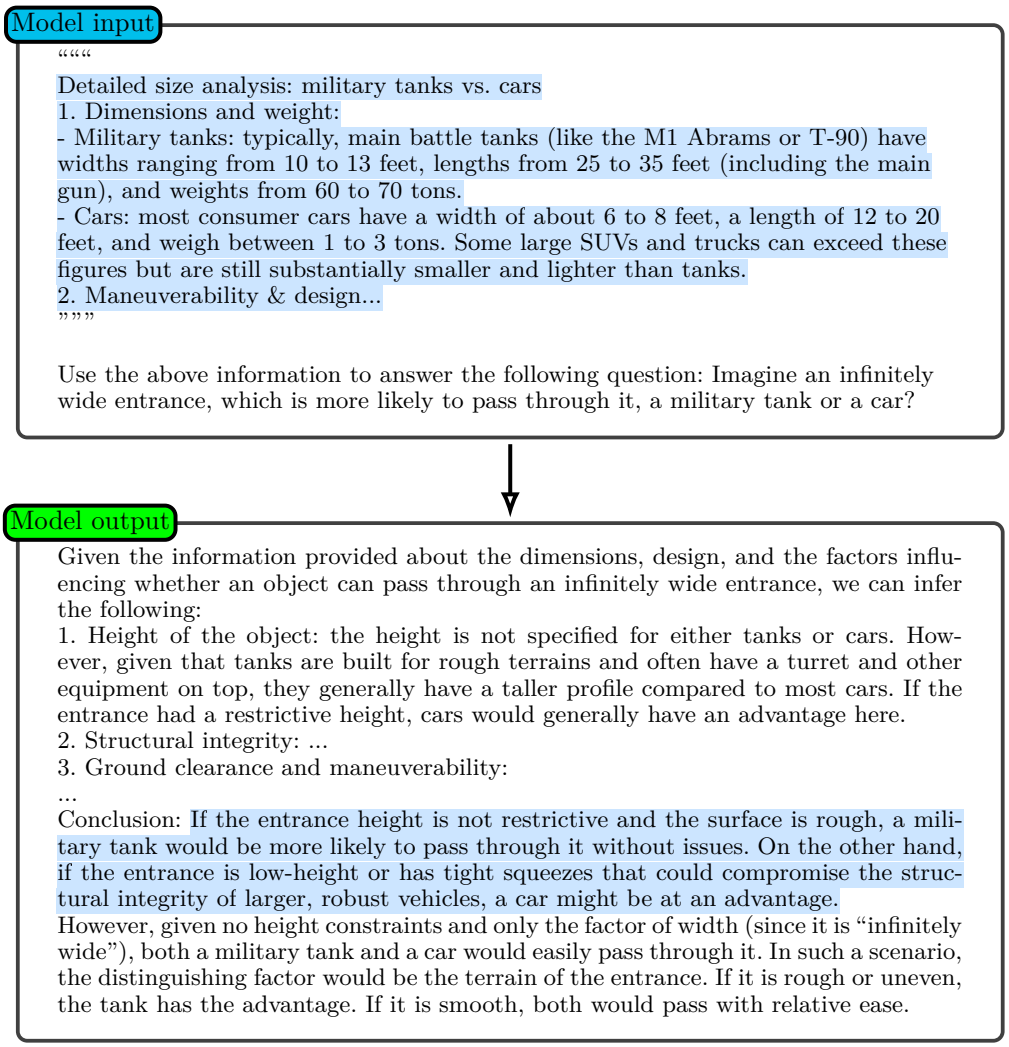

Fig. 10 Combining the generated knowledge with the question (Step2).

3.4 Least-to-most prompting

The concept of “least to most prompting” [77] is an advanced method that involves starting with a minimal prompt and gradually increasing its complexity to elicit more sophisticated responses from the language model. The foundational premise of this approach is the decomposition of intricate problems into a succession of more rudimentary subproblems, which are then sequentially addressed. The resolution of each subproblem is expedited by leveraging solutions derived from antecedent subproblems.

Upon rigorous experimentation in domains including symbolic manipulation, compositional generalization, and mathematical reasoning, findings from [77] substantiate that the least-to-most prompting paradigm exhibits the capacity to generalize across challenges of greater complexity than those initially presented in the prompts. They found that LLMs seem to respond effectively to this method, demonstrating its potential for enhancing the reasoning capabilities of these models.

3.5 Tree of thoughts

The “tree of thoughts” (ToT) prompting technique in LLMs is an advanced method that employs a structured approach to guide LLMs in their reasoning and response generation processes. It enhances problem-solving by exploring multiple reasoning paths, termed ’thoughts’. Unlike traditional linear prompts, ToT allows LLMs to consider various possible solutions and strategies, including looking ahead, backtracking,

and self-evaluation, making it more interactive and adaptable to the complexity of the task at hand. This approach fosters more dynamic and deliberate decision-making in complex problem-solving tasks, moving beyond a rigid, hierarchical prompt structure to a more flexible and adaptive reasoning process [78]. The ToT approach, for instance, when applied to complex mathematical problem-solving, prompts the model to generate various potential solutions and evaluate them, rather than simply asking for a solution.

[78] demonstrates that this formulation is more versatile and can handle challenging tasks where standard prompts might fall short. Another research by [79] further emphasizes the potential of this technique in enhancing the performance of LLMs by structuring their thought processes.

[8] introduces the "tree-of-thought prompting", an approach that assimilates the foundational principles of the ToT frameworks and transforms them into a streamlined prompting methodology. This technique enables LLMs to assess intermediate cognitive constructs within a singular prompt. An exemplar ToT prompt is delineated in Figure 11 [8].

Tree of thoughts prompting

Imagine three different experts answering this question.
All experts will write down 1 step of their thinking,
then share it with the group.
Then all experts will go on to the next step, etc.
If any expert realizes they're wrong at any point then they leave.
The question is...

Fig. 11 A sample ToT prompt.

3.6 Graph of thoughts

Unlike the "chain of thoughts" or "tree of thoughts" paradigms, the "graph of thoughts" (GoT) framework [80] offers a more intricate method of representing the information generated by LLMs. The core concept behind GoT is to model this information as an arbitrary graph. In this graph, individual units of information, termed "LLM thoughts", are represented as vertices. The edges of the graph, on the other hand, depict the dependencies between these vertices. This unique representation allows for the combination of arbitrary LLM thoughts, thereby creating a synergistic effect in the model's outputs.

In the context of addressing intricate challenges, LLMs utilizing the GoT framework might initially produce several autonomous thoughts or solutions. These individual insights can subsequently be interlinked based on their pertinence and interdependencies, culminating in a detailed graph. This constructed graph permits diverse traversal methods, ensuring the final solution is both precise and comprehensive, encompassing various dimensions of the challenge.

The efficacy of the GoT framework is anchored in its adaptability and the profound insights it can yield, particularly for intricate issues necessitating multifaceted resolutions. Nonetheless, it is imperative to recognize that while GoT facilitates a systematic approach to problem-solving, it also necessitates a profound comprehension of the subject matter and meticulous prompt design to realize optimal outcomes [81].

3.7 Automatic Reasoning and Tool Usage

Automatic Reasoning and Tool Usage (ART) is an advanced prompting technique that combines the principles of automatic chain-of-thought (CoT) prompting with the strategic utilization of external tools. This method aims to enhance the reasoning capabilities of Large Language Models (LLMs) by guiding them through multi-step reasoning processes and leveraging specialized tools to achieve more accurate and relevant outputs.

ART builds on the CoT prompting technique, which encourages models to generate intermediate reasoning steps before arriving at a final answer. In ART, these reasoning steps are augmented by incorporating external tools such as calculators, databases, or other software applications. The integration of tools helps LLMs perform tasks that require precise calculations, access to updated information, or specialized data processing that the model alone may not handle effectively.

For example, a prompt designed using ART might guide an LLM to first outline the steps required to solve a complex mathematical problem and then use a calculator tool to perform the necessary calculations. This combination of reasoning and tool usage ensures that the model's outputs are both logically coherent and computationally accurate.

Recent advancements in prompt engineering have highlighted the potential of ART in improving LLM performance. Studies have demonstrated that ART can help models navigate complex problem spaces more effectively by breaking down tasks into manageable steps and utilizing appropriate tools at each stage [82]. For instance, the integration of ART in natural language processing tasks has shown promising results in areas such as automated customer service, where models need to access and process information dynamically [83].

Moreover, ART's approach aligns with ongoing efforts to develop more robust and versatile AI systems capable of handling real-world tasks that demand a combination of cognitive and computational skills. Research by Mercity AI (2024) explores advanced techniques in ART to achieve better accuracy and reliability in AI applications [84]. These findings underscore the importance of ART in enhancing the functionality and performance of LLMs, making them more adept at handling a broader range of tasks.

The applications and benefits of ART are substantial. By leveraging external tools, ART can significantly improve the accuracy of the model's responses, especially for tasks that require specific and precise outputs, such as financial calculations or data analysis. Additionally, ART expands the range of tasks that LLMs can effectively handle by integrating specialized tools. This makes it possible for LLMs to perform more complex and varied tasks, from technical problem-solving to real-time data retrieval. For end-users, ART can facilitate more intuitive and efficient interactions with LLMs. Users can rely on the model to handle multifaceted queries that involve multiple steps and require the use of different tools, enhancing the overall user experience.

In conclusion, ART represents a significant advancement in prompt engineering, combining logical reasoning with practical tool usage to improve the performance and reliability of LLMs. As research continues to evolve, the integration of ART techniques is likely to play a crucial role in developing more sophisticated and capable AI systems.

3.8 Active-Prompt

Active-Prompt is an innovative prompt engineering technique that involves dynamically modulating prompts based on responsive feedback from the model or user interactions. This approach is designed to enhance the engagement between the user and the Large Language Model (LLM), ensuring that the prompts are continuously refined to elicit more accurate and contextually relevant responses.

Active-Prompt operates on the principle of interactive feedback loops. Unlike static prompts, which are predetermined and unchanging, active prompts adapt based on the responses received from the LLM. This dynamic adjustment allows for a more iterative and responsive interaction, where the model's preliminary outputs are used to fine-tune subsequent prompts. This process can involve human annotators or automated systems that evaluate the responses and provide feedback to improve prompt effectiveness [85].

For instance, in a customer service application, an active prompt might initially query the model about a general issue. Based on the model's response, the prompt could then be adjusted to ask more specific questions, guiding the conversation towards a precise resolution. This method ensures that the interaction remains relevant and

progressively narrows down the possible solutions, enhancing the overall accuracy and satisfaction of the response.

By continuously refining prompts based on feedback, Active-Prompt can significantly improve the accuracy and relevance of the model's responses. This is particularly beneficial in complex or nuanced conversations where initial responses may require further clarification [86]. Active-Prompt allows for a high degree of personalization in interactions. By adapting prompts to user responses, it can create a more engaging and tailored experience, which is crucial in applications such as customer support, personalized learning, and interactive AI companions [87]. For end-users, Active-Prompt facilitates more intuitive and efficient interactions with LLMs. Users benefit from a model that appears more responsive and capable of understanding context, leading to more productive and satisfying interactions [88].

Recent studies and practical applications have demonstrated the efficacy of Active-Prompt in various domains. Research by Spiceworks (2024) highlights how Active-Prompt can dynamically adjust to user feedback, improving the overall quality of model interactions in real-time. This approach aligns with the broader trend towards more interactive and adaptive AI systems, emphasizing the importance of responsive design in prompt engineering. Moreover, the concept of Active-Prompt aligns with ongoing efforts to develop more human-like conversational agents. By integrating feedback loops and interactive adjustments, Active-Prompt contributes to the creation of AI systems that are not only more accurate but also more engaging and user-friendly.

In conclusion, Active-Prompt represents a significant advancement in prompt engineering, offering a dynamic and responsive approach to interacting with LLMs. As research in this area continues to evolve, the integration of Active-Prompt techniques is likely to play a crucial role in developing more sophisticated and effective AI systems.

3.9 ReAct Framework

The ReAct Framework, short for Reasoning and Acting, represents a cutting-edge approach in prompt engineering aimed at enhancing the interaction capabilities of Large Language Models (LLMs). This method synergizes the processes of reasoning and action to enable LLMs to not only think through problems but also interact with external tools and environments to achieve more accurate and contextually appropriate outcomes.

The ReAct Framework operates by prompting LLMs to generate both reasoning traces and task-specific actions. This dual approach ensures that the model first contemplates the problem, devising a logical sequence of thoughts, and then executes actions that may involve querying external databases, using calculators, or interacting with other software tools. This method is particularly effective in scenarios requiring detailed reasoning followed by specific actions, thus ensuring the LLM can handle complex, multi-step tasks efficiently [89].

For example, in a task involving financial analysis, the ReAct framework would first prompt the LLM to outline the necessary steps to evaluate a portfolio. Subsequently, the model could use financial analysis tools to gather current market data and perform calculations, integrating these results into the final analysis. This combination of reasoning and action leads to more robust and reliable outcomes compared to using static prompts alone.

The ReAct Framework offers several notable advantages. By integrating reasoning and action, ReAct enables LLMs to make more informed and accurate decisions. This is particularly valuable in fields such as finance, healthcare, and legal analysis, where decisions must be based on comprehensive data and logical reasoning [90]. Additionally, the framework's ability to interact with external tools ensures that the information used in decision-making is up-to-date and relevant, reducing the likelihood of errors due to outdated or incomplete data [91]. Furthermore, ReAct expands the range of tasks LLMs can perform by enabling them to act on their reasoning. This makes the framework suitable for a variety of applications, from customer service

automation to scientific research, where complex, multi-step processes are common [92].

Research on the ReAct Framework underscores its potential in transforming how LLMs handle complex tasks. Studies by Yao et al. (2022) highlight how the integration of reasoning and action in prompts can significantly improve task performance in LLMs. Additionally, practical applications have demonstrated the framework's effectiveness in real-world scenarios, such as dynamic data retrieval and interactive problem-solving [89, 90].

Implementing the ReAct Framework involves developing prompts that guide LLMs through both thought processes and actions. This requires a detailed understanding of the task at hand and the tools available, ensuring that the model can seamlessly transition from reasoning to action. As the field of prompt engineering evolves, the ReAct Framework is likely to become an essential tool for developing more versatile and capable AI systems.

In conclusion, the ReAct Framework represents a significant advancement in prompt engineering, combining logical reasoning with actionable steps to enhance the performance and reliability of LLMs. As research continues to expand on this approach, the framework's integration into various AI applications promises to drive further innovation and effectiveness in AI-driven tasks.

3.10 Retrieval augmentation

Another direction of prompt engineering is to aim to reduce hallucinations. When using AIGC tools such as GPT-4, it is common to face a problem called "hallucinations", which refer to the presence of unreal or inaccurate information in the model's generated output [33, 93]. While these outputs may be grammatically correct, they can be inconsistent with facts or lack real-world data support. Hallucinations arise because the model may not have found sufficient evidence in its training data to support its responses, or it may overly generalize certain patterns when attempting to generate fluent and coherent output [94].

An approach to reduce hallucinations and enhance the effectiveness of prompts is the so-called retrieval augmentation technique, which aims at incorporating up-to-date external knowledge into the model's input [95, 96]. It is emerging as an AI framework for retrieving facts from external sources. [97] examines the augmentation of context retrieval through the incorporation of external information. It proposes a sophisticated operation: the direct concatenation of pertinent information obtained from an external source to the prompt, which is subsequently treated as foundational knowledge for input into the expansive language model. Additionally, the paper introduces auto-regressive techniques for both retrieval and decoding, facilitating a more nuanced approach to information retrieval and fusion. This research demonstrates that in-context retrieval-augmented language models [97], when constructed upon readily available general-purpose retrievers, yield significant LLM enhancements across a variety of model dimensions and diverse corpora. In another research, [98] showed that GPT-3 can reduce hallucinations by studying various implementations of the retrieval augmentation concept, such as Retrieval Augmented Generation (RAG) [99], Fusion-in-Decoder (FiD) [100], Seq2seq [101–103] and others. [104] developed the Chain-of-Verification (CoVe) approach to reduce hallucinations, based on letting the LLM deliberate on its own responses before self-correcting them. They suspect that extending this approach with retrieval augmentation would likely bring further gains.

3.11 Use plugins to polish the prompts

After introducing the detailed techniques and methods of prompt engineering, we now explore the use of some external prompt engineering assistants that have been developed recently and exhibit promising potential. Unlike the methods introduced previously, these instruments can help us to polish the prompt directly. They are adept at analyzing user inputs and subsequently producing pertinent outputs within

a context that is defined by itself, thereby amplifying the efficacy of prompts. Some of the plugins provided by OpenAI are good examples of such tools [105].

In certain implementations, the definition of a plugin is incorporated into the prompt, potentially altering the output [106]. Such integration may impact the manner in which LLMs interpret and react to the prompts, illustrating a connection between prompt engineering and plugins. Furthermore, the laborious nature of intricate prompt engineering may be mitigated by plugins, which enable the model to more proficiently comprehend or address user inquiries without necessitating excessively detailed prompts. Consequently, plugins bolster the efficacy of prompt engineering while promoting enhanced user-centric efficiency. These tools, akin to packages, can be seamlessly integrated into Python and invoked directly [107, 108]. Such plugins augment the efficacy of prompts by furnishing responses that are both coherent and contextually pertinent. For instance, the "Prompt Enhancer" pluging [109], developed by AISEO [110], can be invoked by starting the prompt with the word "AISEO" to let the AISEO prompt generator automatically enhance the LLM prompt provided. Similarly, another plugin called "Prompt Perfect", can be used by starting the prompt with 'perfect' to automatically enhance the prompt, aiming for the "perfect" prompt for the task at hand [111, 112].

4 Methodologies of Multimodal LM

Multimodal language models (MMLMs) represent a significant advancement in artificial intelligence, enabling the processing and generation of information across multiple modalities, such as text, images, and audio. This capability enhances the versatility and applicability of AI systems in diverse fields, from content creation to complex reasoning tasks. Prompt engineering in MMLMs involves adapting traditional techniques used in text-only LLMs to handle the intricacies of multimodal data. These models must seamlessly integrate and interpret various data types, requiring sophisticated prompt designs that ensure contextual coherence and accuracy [113].

Challenges such as data alignment, modality integration, and context preservation are addressed through modular prompting and disentangled prompt design [114]. These advancements facilitate the effective utilization of MMLMs in various applications, enhancing their ability to generate nuanced and contextually rich outputs [115]. Pioneering studies have demonstrated the potential of these methods, highlighting the transformative impact of prompt engineering on multimodal AI systems [116].

Prompt engineering for multimodal large language models (MLLMs) builds on the foundational techniques used in text-only LLMs but adapts them to accommodate the complexity of multimodal data. Traditional prompt methods, such as few-shot and zero-shot learning, are modified to handle diverse data types, including text, images, and audio. This adaptation is crucial as MLLMs must integrate and process multiple modalities simultaneously, requiring innovative approaches to ensure coherence and relevance in generated responses [117]. These advancements facilitate the effective utilization of MLLMs in various applications, enhancing their ability to generate nuanced and contextually rich outputs [118]. Pioneering studies have demonstrated the potential of these methods, highlighting the transformative impact of prompt engineering on multimodal AI systems [113, 119].

4.1 Multi-modal Prompt Learning (MaPLe)

Multi-modal Prompt Learning (MaPLe) represents a significant advancement in the fine-tuning of vision-language models, leveraging the integration of both vision and language prompts to enhance model performance. This methodology is predicated on the hierarchical learning of prompts within the transformer layers of the model, allowing for a more nuanced and comprehensive capture of task-relevant features. The core idea behind MaPLe is to introduce and optimize prompts for both the vision and language components simultaneously. By embedding prompts at various stages within the transformer architecture, MaPLe ensures that the model can adaptively learn

contextual information pertinent to the specific task at hand [120]). This hierarchical approach allows the model to progressively refine its understanding and integration of multimodal inputs, leading to improved performance across a range of applications.

One of the critical innovations of MaPLe is its ability to enhance task relevance. Traditional prompt engineering often focuses on either vision or language prompts in isolation, which can limit the model's ability to fully leverage the complementary information available in multimodal data. MaPLe overcomes this limitation by jointly optimizing prompts for both modalities, thereby facilitating a more integrated and coherent representation of the input data [120, 121].

The effectiveness of MaPLe has been demonstrated in various studies. For example, [120] showed that MaPLe significantly outperforms baseline models in tasks such as image recognition and visual question answering. Furthermore, [121] highlighted the importance of multi-modal prompt learning in enhancing the adaptability and generalization of vision-language models.

Another important aspect of MaPLe is its hierarchical learning mechanism, which allows the model to process and integrate information at multiple levels of abstraction. This is particularly beneficial for complex tasks that require a deep understanding of both visual and textual elements. By optimizing prompts at different layers within the transformer, MaPLe can better capture the intricate dependencies between vision and language inputs [120, 122].

To illustrate the practical application of MaPLe, consider the task of Visual Question Answering (VQA). In a typical VQA scenario, a model is provided with an image and a related question, and it must generate a correct and contextually relevant answer. Using MaPLe, the model can be fine-tuned with multi-modal prompts that simultaneously address both the visual content and the textual question. For instance, given an image of a bustling market and the question "What fruit is the vendor selling?", MaPLe would embed prompts at various levels of the transformer's vision and language branches. These prompts might include visual prompts that focus on identifying objects and text prompts that guide the model to look for specific answer-relevant details. By processing these prompts hierarchically, the model can effectively integrate visual cues (like recognizing apples and oranges in the image) with the textual context (understanding the question) to generate an accurate answer (e.g., "The vendor is selling apples and oranges").

This multi-modal approach ensures that the model leverages both the visual and textual information in a coherent and integrated manner, resulting in improved performance on VQA tasks compared to models that do not utilize such comprehensive prompt learning strategies.

In conclusion, MaPLe represents a robust and effective methodology for improving the performance of vision-language models. Its ability to integrate and optimize multi-modal prompts within the transformer architecture ensures that the model can adaptively learn and generalize across a wide range of tasks, making it a valuable tool in the field of multimodal AI.

4.2 Context Optimization

Context Optimization (CoOp) is an innovative approach to prompt learning specifically designed for vision-language models. CoOp focuses on enhancing the adaptability and performance of these models by optimizing context-specific prompts. This methodology involves the creation of learnable context vectors that are embedded within the model's architecture, enabling it to dynamically adjust to different downstream tasks [123].

CoOp leverages the inherent structure of vision-language models, such as CLIP, by integrating context optimization directly into the model's training process. This integration allows for a seamless adaptation to various tasks without the need for extensive manual prompt engineering. By utilizing learnable context vectors, CoOp can fine-tune the prompts based on the specific characteristics of the input data, leading to improved performance and generalization across different scenarios [124].

One of the key benefits of CoOp is its ability to handle diverse and complex data inputs. Traditional static prompts can be limited in their ability to adapt to new and unseen data, whereas CoOp's dynamic approach allows the model to learn and adjust in real-time. This is particularly valuable in applications such as image recognition and visual question answering, where the context can vary significantly [125].

To illustrate the practical application of CoOp, consider a Visual Question Answering (VQA) task. In a VQA scenario, the model is presented with an image and a corresponding question, and it must generate an accurate answer based on the visual and textual information. Using CoOp, the model can be trained with context-specific prompts that enhance its ability to interpret the image and understand the question.

For instance, if the model is shown an image of a beach scene with the question "What activity are the people engaged in?", CoOp would utilize learnable context vectors to focus on relevant aspects of the image, such as identifying people, recognizing activities, and understanding the scene's context. This enables the model to generate a precise and contextually relevant answer, such as "The people are playing volleyball on the beach" [123].

The effectiveness of CoOp has been demonstrated in various studies. Zhou et al. (2021) [1] showed that models using CoOp significantly outperform traditional models in tasks such as image recognition and VQA. Additionally, [125] highlighted the benefits of ensembling context optimization, which further enhances the model's performance by combining multiple context vectors. This approach has been shown to improve the robustness and generalization of vision-language models in real-world applications (Unified Adapter and Prompt Learning, 2023) [126].

In summary, Context Optimization (CoOp) represents a powerful methodology for enhancing the performance and adaptability of vision-language models. By leveraging learnable context vectors, CoOp enables these models to dynamically adjust to different tasks and data inputs, making it a valuable tool in the field of multimodal AI.

4.3 Conditional Prompt Learning

Conditional Prompt Learning is a methodology that enhances the adaptability and performance of vision-language models by tailoring prompts based on specific conditions or contexts. This technique allows models to dynamically adjust their responses to better fit the requirements of various tasks, thereby improving their overall effectiveness and versatility.

The core concept of Conditional Prompt Learning involves the creation of prompts that are conditionally tailored to the specific input or task context. This method stands in contrast to static prompts that remain the same regardless of the situation. By leveraging contextual information, conditional prompts can provide more precise and relevant guidance to the model, which is particularly useful in complex, multimodal scenarios where the interplay between different types of data must be carefully managed [127].

One significant advantage of Conditional Prompt Learning is its ability to adapt to new and unseen data with minimal fine-tuning. This is achieved by training the model on a variety of context-specific prompts, which enables it to generalize better across different tasks. For instance, a vision-language model trained with conditional prompts can more accurately interpret and respond to images and questions it has not encountered during training [127]. This capability is critical for applications such as image captioning, visual question answering, and scene understanding, where the context can vary widely.

Consider an image captioning task where the goal is to generate descriptive captions for images. Using Conditional Prompt Learning, the model can be trained with prompts that are specifically designed for different types of scenes. For example, a prompt for an outdoor scene might include contextual cues related to nature, weather, and activities, while a prompt for an indoor scene might focus on objects, people, and interactions.

In practice, if the model is presented with an image of a bustling market, the conditional prompt might include cues such as "Identify the types of products being sold," or "Describe the interactions between vendors and customers." This allows the model to generate a caption that is not only accurate but also contextually rich and informative. For instance, the model might produce a caption such as "Vendors selling fresh fruits and vegetables in a crowded market, with customers browsing and purchasing items" [121].

The effectiveness of Conditional Prompt Learning has been demonstrated in various studies. [127] showed that models employing this technique significantly outperform those using static prompts in tasks such as visual question answering and image classification. Furthermore, these models exhibit improved generalization capabilities, making them more robust in real-world applications [128].

In summary, Conditional Prompt Learning is a powerful methodology that enhances the adaptability and performance of vision-language models by leveraging context-specific prompts. Its ability to dynamically adjust to new and unseen data makes it an invaluable tool for a wide range of applications in multimodal AI.

4.4 Modular Prompting

Modular prompting is a sophisticated approach used in vision-language models to handle the complexity of integrating visual and textual data. This method involves breaking down prompts into modular components that can be individually optimized and then recombined to handle complex multimodal tasks. By treating each part of the prompt as a distinct module, the model can better manage and integrate diverse types of information, leading to improved performance and adaptability.

Modular prompting separates the visual and textual components of the input, allowing for independent optimization before combining them. This separation ensures that each modality is processed in the most effective manner, facilitating a more accurate and efficient integration of data [129]. Additionally, each module can be enhanced with contextual embeddings that provide supplementary information relevant to the task, which helps the model understand the relationships between different pieces of information [130]. Once the individual modules are processed, the model dynamically integrates the outputs to generate a coherent response, adjusting the integration based on the specific requirements of the task at hand [131].

Consider an application in open-vocabulary semantic segmentation. In this task, the goal is to segment an image into regions corresponding to different object categories, even if the categories were not seen during training. Using modular prompting, a vision-language model can separately process visual features and textual descriptions of categories.

For instance, the model can be prompted with specific modules for identifying visual features like "urban environment," "vehicles," and "pedestrians," along with textual descriptions for each category. This separation allows the model to optimize the processing of visual and textual data independently. Once the individual modules are processed, the model integrates the results to accurately segment the image and identify the various components, even those it hasn't seen before [132].

In conclusion, modular prompting is a powerful method for enhancing the performance and adaptability of vision-language models. By independently optimizing and dynamically integrating visual and textual modules, this approach ensures that models can handle a wide range of tasks with improved accuracy and efficiency.

4.5 Zero-shot and Few-shot Prompting

Zero-shot and few-shot prompting are pivotal techniques in the realm of vision-language models, enabling these models to handle tasks with minimal or no task-specific training data. Zero-shot prompting allows models to perform tasks without any specific examples provided during training, relying entirely on their pre-trained knowledge to generalize across new tasks and domains. For example, a model like CLIP can be prompted with a textual description to classify images into categories it has

never explicitly been trained on [7]. On the other hand, few-shot prompting involves providing the model with a small number of examples during inference, significantly enhancing the model's ability to generalize with limited data [15].

An illustrative example of these techniques can be seen in the task of Visual Question Answering (VQA). In a zero-shot VQA task, the model might be asked, "What is the object in the image?" without having seen similar examples during training. The model leverages its broad understanding derived from extensive training on diverse datasets to generate a relevant answer. In a few-shot scenario, the model is provided with a few example questions and answers related to similar images before answering the new question, thus refining its accuracy and contextual understanding [121].

Research supports the effectiveness of these methods: [133] explored various prompting techniques for zero- and few-shot learning in vision-language models, demonstrating improved performance on novel tasks. [15] showed the application of these techniques in CLIP, highlighting the model's ability to generalize across different domains. Additionally, [134] presented a method for adapting CLIP to few-shot classification tasks without additional training, emphasizing practical benefits in real-world applications.

In conclusion, zero-shot and few-shot prompting are essential for enhancing the versatility and adaptability of vision-language models. These methods leverage pre-trained knowledge and minimal task-specific examples, enabling models to perform a wide range of tasks with high accuracy and minimal data, thus proving invaluable in the field of multimodal AI.

4.6 Reinforcement Learning for Prompt Optimization

Reinforcement Learning (RL) for prompt optimization is an advanced technique designed to enhance the performance of vision-language models by iteratively refining the prompts used during training and inference. This method utilizes the principles of reinforcement learning to navigate the complex parameter space of large models, optimizing the prompts for improved task-specific performance. In RL for prompt optimization, a reward function is defined to evaluate the effectiveness of different prompts based on the model's output. The model then uses this feedback to adjust and optimize the prompts through a series of iterations, ensuring that the prompts evolve to maximize performance on the target task by leveraging the model's ability to learn from its interactions with the environment [135].

Consider the task of Visual Question Answering (VQA), where the goal is to generate accurate answers to questions based on visual input. Using RL for prompt optimization, the model can start with a set of initial prompts and iteratively refine them based on the accuracy of the generated answers. For instance, if the model is asked, "What is the color of the car in the image?" the initial prompts might produce varied responses. The reward function will assess these responses, favoring prompts that lead to correct answers. Over multiple iterations, the model learns to generate more precise prompts, improving its ability to accurately answer similar questions in the future [133].

Research supports the effectiveness of these methods. [135] explored the use of reinforcement learning to optimize discrete text prompts for vision-language models, demonstrating significant improvements in task performance through iterative optimization. [136] introduced gradient-based techniques to simplify the optimization of hard prompts, providing a robust framework for enhancing vision-language model performance using reinforcement learning. Additionally, [137] focused on adapting prompts at test time using reinforcement learning, allowing models to dynamically adjust prompts based on real-time feedback, thereby improving adaptability. [138] discussed a black-box approach to prompt tuning using evolutionary strategies in conjunction with reinforcement learning, highlighting its effectiveness in optimizing prompts for various vision-language tasks.

In conclusion, reinforcement learning for prompt optimization represents a powerful methodology for enhancing the performance and adaptability of vision-language models. By iteratively refining prompts based on task-specific feedback, this approach enables models to achieve higher accuracy and generalization across diverse applications.

4.7 Prompt Pattern Catalog

A Prompt Pattern Catalog is an organized collection of prompt templates and patterns designed to enhance the effectiveness of prompt engineering, particularly in vision-language models. This methodology involves creating a standardized set of prompt patterns that can be applied across various tasks, ensuring consistency and optimizing the performance of models through systematic prompt design. By developing a catalog of prompt patterns, researchers and practitioners can ensure a consistent approach to prompt engineering, reducing variability and errors from ad hoc prompt creation [139]. Using pre-defined prompt patterns streamlines the process of prompt engineering, saving time and resources by allowing practitioners to select and adapt patterns rather than crafting new prompts from scratch [139]. A well-designed prompt pattern catalog includes patterns for various contexts and applications, enabling models to be quickly adapted to new tasks and domains by selecting the most appropriate patterns [139]. Systematic use of optimized prompt patterns enhances model performance by providing more effective and contextually appropriate prompts, leading to better task-specific results [140].

For example, in the task of image captioning, a vision-language model can use standardized patterns tailored for different types of images. For an image of a bustling market, the model could use a prompt pattern designed for urban scenes, including instructions to describe the setting, identify key objects, and note interactions between people. This might result in a detailed and contextually appropriate caption, such as "The image shows a bustling market with vendors selling various fruits and vegetables, and customers browsing and purchasing items" [141].

Research supports the effectiveness of prompt pattern catalogs. [139] outline the development and use of a prompt pattern catalog to improve the effectiveness and efficiency of prompt engineering with vision-language models. [140] explore how structured prompt patterns can enhance user interaction and improve model outputs in conversational AI, providing insights applicable to vision-language models. [141] investigate the application of prompt engineering patterns in enterprise settings, demonstrating their utility in optimizing model performance across various tasks. Additionally, [142] highlight the benefits of using structured prompt patterns in software development, which can be extended to vision-language models.

In conclusion, a prompt pattern catalog is a valuable tool for enhancing the effectiveness and efficiency of prompt engineering in vision-language models. By providing standardized, adaptable, and optimized prompt patterns, this methodology ensures consistent and high-quality model performance across a wide range of tasks.

5 Assessing the efficacy of prompt methods

There are many different ways to evaluate the quality of the output. To assess the efficacy of current prompt methods in AIGC tools, evaluation methods can generally be divided into subjective and objective categories.

5.1 Subjective and objective evaluations

Subjective evaluations primarily rely on human evaluators to assess the quality of the generated content. Human evaluators can read the text generated by LLMs and score it for quality. Subjective evaluations typically include aspects such as fluency, accuracy, novelty, and relevance [40]. However, these evaluation methods are, by definition, subjective and can be prone to inconsistencies.

Objective evaluations, also known as automatic evaluation methods, use machine learning algorithms to score the quality of text generated by LLMs. Objective evaluations employ automated metrics, such as BiLingual Evaluation Understudy (BLEU) [143], which assigns a score to system-generated outputs, offering a convenient and rapid way to compare various systems and monitor their advancements. Other evaluations such as Recall-Oriented Understudy for Gisting Evaluation (ROUGE) [144], and Metric for Evaluation of Translation with Explicit ORdering (METEOR) [145], assess the similarity between the generated text and reference text. More recent evaluation methods, such as BERTScore [146], aim to assess at a higher semantic level. However, these automated metrics often fail to fully capture the assessment results of human evaluators and therefore must be used with caution [147].

Subjective evaluation and objective evaluation methods each have their own advantages and disadvantages. Subjective evaluation tends to be more reliable than objective evaluation, but it is also more expensive and time-consuming. Objective evaluation is less expensive and quicker than subjective evaluation. For instance, despite numerous pieces of research highlighting the limited correlation between BLEU and alternative metrics based on human assessments, their popularity has remained unaltered [148, 149]. Ultimately, the best way to evaluate the quality of LLM output depends on the specific application [150]. If quality is the most important factor, then using human evaluators is the better choice. If cost and time are the most important factors, then using automatic evaluation methods is better.

5.2 Comparing different prompt methods

In the field of prompt engineering, previous work has mostly focused on designing and optimizing specific prompting methods, but evaluating and comparing different prompting approaches in a systematic manner remains limited. There are some models that are increasingly used to grade the output of other models, which aim to 'check' the ability of other models [151, 152]. For instance, LLM-Eval [153] was developed to measure the open-domain conversations with LLMs. This method tries to evaluate the performance of LLMs on various benchmark datasets [154, 155] and demonstrate their efficiency. Other studies experiment mainly on certain models or tasks and employ disparate evaluation metrics, restricting comparability across methods [135, 156]. Nevertheless, recent research proposed a general evaluation framework called InstructEval [157] that enables a comprehensive assessment of prompting techniques across multiple models and tasks. The InstructEval study reached the following conclusions: in few-shot settings, omitting prompts or using generic task-agnostic prompts tends to outperform other methods, with prompts having little impact on performance; in zero-shot settings, expert-written task-specific prompts can significantly boost performance, with automated prompts not outperforming simple baselines; the performance of automated prompt generation methods is inconsistent, varying across different models and task types, displaying a lack of generalization. InstructEval provides important references for prompt engineering and demonstrates the need for more universal and reliable evaluation paradigms to design optimal prompts.

6 Applications improved by prompt engineering

The output enhancements provided by prompt engineering techniques make LLMs better applicable to real-world applications. This section briefly discusses applications of prompt engineering in fields such as teaching, programming, and others.

6.1 Assessment in teaching and learning

The study [158] investigates the application of machine learning methods in young student education. In such a context, prompt engineering can facilitate the creation of personalized learning environments. By offering tailored prompts, LLMs can adapt to an individual's learning pace and style. Such an approach can allow for personalized assessments and educational content, paving the way for a more individual-centric

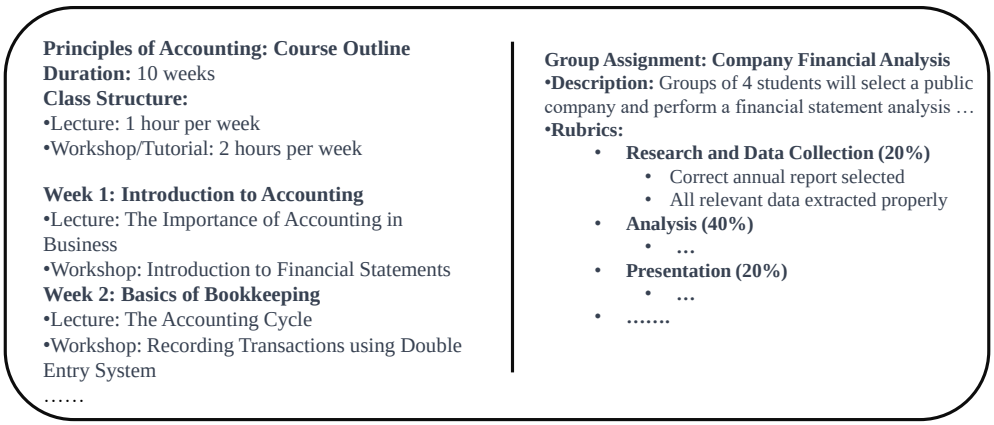

Fig. 12 Guideline of courses generated by GPT-4

teaching model. Recent advancements in prompt engineering suggest that AI tools can also cater to students with specific learning needs, thus fostering inclusivity in education [159]. As a simple example, it is possible for professors to provide rubrics or guidelines for a future course with the assistance of AI. As Figure 12 shows, when GPT-4 was required to provide a rubric about a course, with a suitable prompt, it was able to respond with a specific result that may satisfy the requirement.

The advancements in prompt engineering also bring better potential for automated grading in education. With the help of sophisticated prompts, LLMs can provide preliminary assessments, reducing the workload for educators while providing instant feedback to students [160]. Similarly, these models, when coupled with well-designed prompts, can analyze a vast amount of assessment data, thus providing valuable insights into learning patterns and informing educators about areas that require attention or improvement [161, 162].

6.2 Content creation and editing

With controllable improved input, LLMs have primarily been used in creative works, such as content creation. Pathways Language Model (PaLM) [70] and prompting approach have been used to facilitate cross-lingual short story generation [23]. The Recursive Reprompting and Revision framework (Re^3) [163] employs zero-shot prompting [65] with GPT-3 to craft a foundational plan including elements such as settings, characters, and outlines. Subsequently, it adopts a recursive technique, dynamically prompting GPT-3 to produce extended story continuations. For another example, Detailed Outline Control (DOC) [164] aims at preserving plot coherence across extensive texts generated with the assistance of GPT-3. Unlike Re^3, DOC employs a detailed outliner and detailed controller for implementation. The detailed outliner initially dissects the overarching outline into subsections through a breadth-first method, where candidate generations for these subsections are generated, filtered, and subsequently ranked. This process is similar to the method of chain-of-though (in Section 3.1). Throughout this generation process, an OPT-based Future Discriminators for Generation (FUDGE) [165] detailed controller plays a crucial role in maintaining relevance.

6.3 Computer programming

Prompt engineering can help LLMs perform better at outputting programming codes. By using a self-debugging prompting approach [60], which contains simple feedback, unit-test, and code explanation prompts module, the text-to-SQL [166] model is able to provide a solution it can state as correct unless the maximum number of attempts has been reached. Another example, Multi-Turn Programming Benchmark (MTPB) [167], was constructed to implement a program by breaking it into multi-step natural language prompts.

Another approach is provided in [168], which introduced the Repo-Level Prompt Generator (RLPG) to dynamically retrieve relevant repository context and construct a prompt for a given task, especially on code auto-completion task. The most suitable prompt is selected by a prompt proposal classifier and combined with the default context to generate the final output.

6.4 Reasoning tasks

AIGC tools have shown promising performance in reasoning tasks. Several previous researches found that few-shot prompting can enhance the performance in generating accurate reasoning steps for word-based math problems in the GSM8K dataset [31, 58, 63, 70]. The strategy of including the reasoning traces in such as few-shot prompts [49], self-talk [169] and chain-of-thought [30], was shown to encourage the model to generate verbalized reasoning steps. [170] conducted experiments by involving prompting strategies, various fine-tuning techniques, and re-ranking methods to assess their impact on enhancing the performance of a base LLM. They found that a customized prompt significantly improved the model's ability with fine-tuning, and demonstrated a significant advantage by generating substantially fewer errors in reasoning. In another research, [65] observed that solely using zero-shot CoT prompting leads to a significant enhancement in the performance of GPT-3 and PaLM when compared to the conventional zero-shot and few-shot prompting methods. This improvement is particularly noticeable when evaluating these models on the MultiArith [171] and GSM8K [63] datasets. [172] also introduced a novel prompting approach called Diverse Verifier on Reasoning Step (DIVERSE). This approach involves using a diverse set of prompts for each question and incorporates a trained verifier with an awareness of reasoning steps. The primary aim of DIVERSE is to enhance the performance of GPT-3 on various reasoning benchmarks, including GSM8K and others. All these works show that in the application of reasoning tasks, properly customized prompts can obtain better results from the model.

6.5 Dataset generation

LLMs possess the capability of in-context learning, enabling them to be effectively prompted to generate synthetic datasets for training smaller, domain-specific models. [173] put forth three distinct prompting approaches for training data generation using GPT-3: unlabeled data annotation, training data generation, and assisted training data generation. Besides, [174] is designed for the generation of supplementary synthetic data for classification tasks. GPT-3 is utilized in conjunction with a prompt that includes real examples from an existing dataset, along with a task specification. The goal is to jointly create synthetic examples and pseudo-labels using this combination of inputs.

7 Exploring and Enhancing LLMs through Insightful Prompt Engineering

Prompt engineering is the process of designing and refining the inputs (prompts) given to LLMs to elicit desired and accurate responses. This technique is crucial not only for optimizing model performance but also for enhancing security. By carefully crafting prompts, researchers and developers can identify and mitigate vulnerabilities in LLMs. Effective prompt engineering can expose weaknesses that might be exploited through adversarial attacks, data poisoning, or other malicious activities. Conversely, poorly designed prompts can inadvertently introduce or exacerbate security risks, making it easier for attackers to manipulate model outputs or extract sensitive information. Thus, prompt engineering serves as both a tool for improving LLM functionality and a critical component of their security framework.

Understanding the interplay between prompt engineering and LLM security is essential for developing robust models that can safely operate in diverse and critical applications. As we delve deeper into the various vulnerabilities and the dual nature of

prompt engineering, it becomes clear that maintaining a balance between enhancing capabilities and ensuring security is pivotal for the future of LLMs.

This expanded introduction sets the stage for a detailed exploration of the vulnerabilities inherent in LLMs and the dual-edged nature of prompt engineering, highlighting its significance in both improving performance and safeguarding security.

7.1 Introduction to Security in LLMs

The development and deployment of Large Language Models (LLMs) have significantly advanced natural language processing, enabling applications ranging from automated customer support to sophisticated content generation. However, with their increasing integration into critical sectors such as healthcare, finance, and cybersecurity, the importance of ensuring robust security measures for LLMs cannot be overstated. These models, if compromised, can lead to significant breaches of sensitive information and disrupt essential services.

As LLMs become more ubiquitous, their potential vulnerabilities pose severe risks. Adversarial attacks, for instance, can manipulate model outputs, leading to harmful or misleading information dissemination [7]. Additionally, data poisoning during the training phase can introduce malicious data that corrupts the model's learning process, resulting in unreliable outputs [15]. These threats highlight the necessity of comprehensive security protocols to safeguard the integrity and reliability of LLMs.

The increasing reliance on LLMs across various sectors underscores the need for robust security measures. For example, in healthcare, LLMs analyze medical records and provide diagnostic recommendations. A compromised model in this context could lead to incorrect diagnoses and treatment plans, endangering patient lives. Similarly, in finance, LLMs assist in fraud detection and risk assessment; vulnerabilities in these systems could result in significant financial losses and undermine trust in automated financial services [175]. Therefore, ensuring the security of LLMs is critical to their safe and effective deployment.

7.2 Common Vulnerabilities in LLMs

7.2.1 Adversarial Attacks

Adversarial attacks involve the deliberate manipulation of input data to deceive a machine learning model into making incorrect predictions. In the context of LLMs, adversarial attacks can take the form of subtly altered prompts or inputs that cause the model to produce unintended or harmful outputs. These attacks exploit the sensitivity of LLMs to small perturbations in input data, revealing significant vulnerabilities [176]. For instance, an adversarial input might include slight alterations in the text that mislead the model's natural language understanding capabilities, leading to incorrect or biased responses [7, 177]. The potential for adversarial attacks is particularly concerning in applications such as automated customer service or legal document analysis, where the integrity and accuracy of responses are critical [178].

Recent research has highlighted various techniques and impacts of adversarial attacks on LLMs. For instance, adversarial demonstration attacks can mislead models into making incorrect predictions even with subtle changes in the input data [179]. Similarly, methods to automatically generate readable and strategic prompts show the ease with which adversarial examples can be crafted [180].

Optimization techniques enhance the effectiveness of adversarial attacks, making it more challenging to defend against these threats [181]. Moreover, a comprehensive overview of these attacks exposes various weaknesses in LLMs, underscoring the critical need for improved security measures [182].

Real-world examples illustrate the significant impact of adversarial attacks on LLMs. For instance, adversarial inputs in legal document analysis can lead to incorrect legal interpretations, potentially affecting case outcomes. In healthcare, adversarial attacks could mislead models into providing incorrect medical advice, jeopardizing

patient safety. These examples highlight the urgent need for effective defenses against adversarial attacks to ensure the safe and reliable deployment of LLMs.

In summary, adversarial attacks pose a significant threat to the security and reliability of LLMs. These attacks exploit the sensitivity of LLMs to small perturbations in input data, leading to unintended or harmful outputs. The role of prompt engineering is crucial in identifying and mitigating these vulnerabilities, ensuring that prompts are carefully crafted to minimize the risk of exploitation. As LLMs become increasingly integrated into critical applications, the need for robust prompt engineering practices becomes ever more pressing. Future research and development should focus on advancing these practices to protect LLMs from emerging threats and ensure their safe deployment.

7.2.2 Prompt Hacking

Prompt hacking poses a significant threat to the security and reliability of LLMs. This type of attack involves manipulating the inputs (prompts) given to LLMs to provoke unintended outcomes, ranging from benign errors to malicious activities such as misinformation dissemination and data breaches. Unlike traditional hacking, which typically exploits software vulnerabilities, prompt hacking relies on carefully crafting prompts to deceive the LLM into performing undesired actions [183–188].

Prompt hacking exploits the fundamental way LLMs process and generate responses. Attackers craft malicious prompts designed to exploit the model's understanding and generation capabilities. These prompts can cause the model to produce harmful outputs, leak sensitive information, or behave erratically. For example, a malicious prompt might subtly alter a request in a way that leads the LLM to generate false or misleading information [189]. This vulnerability is particularly concerning because it can be executed without the need for sophisticated technical skills. As LLMs become more integrated into various applications, the risk posed by prompt hacking increases, necessitating robust security measures to prevent such attacks [190].

Understanding prompt hacking is crucial for developing security measures to protect LLM-based applications. Awareness of this vulnerability encourages the implementation of stricter prompt validation and monitoring systems to detect and prevent malicious prompts. By studying prompt hacking techniques, developers can enhance the robustness of LLMs. Implementing countermeasures such as prompt filtering, anomaly detection, and response validation helps mitigate the impact of such attacks and improve overall system security [191]. Additionally, educating users about the risks of prompt hacking and best practices for secure prompt creation can significantly reduce the likelihood of successful attacks. Training programs and guidelines for creating secure prompts are essential for maintaining the integrity of LLM-based systems [192].

Recent studies have highlighted the growing threat of prompt hacking and the need for comprehensive security strategies. For example, research published by Rise and Inspire (2024) details various prompt hacking techniques and their implications for LLM security. Similarly, OWASP's project on LLM prompt hacking provides a framework for understanding and mitigating these vulnerabilities [193]. Practical implementations of security measures against prompt hacking include the use of advanced monitoring tools that detect suspicious prompt patterns and the integration of machine learning models trained to identify and block malicious prompts. These measures are crucial for ensuring the safe deployment of LLMs in sensitive applications such as healthcare, finance, and customer service [194].

In conclusion, prompt hacking represents a critical challenge in the secure deployment of LLMs. By understanding the mechanisms and risks associated with this vulnerability, researchers and developers can implement effective security measures to protect against such attacks. Future research should continue to explore innovative solutions to enhance the resilience of LLMs against prompt hacking, ensuring their safe and reliable use in various applications.

7.2.3 Threat of Model Stealing

Model stealing attacks pose a significant threat to the security of LLMs. These attacks involve an adversary attempting to replicate the functionality or extract proprietary information from a target model by interacting with it through strategically crafted prompts. The implications of such attacks are severe, as they can lead to intellectual property theft, loss of competitive advantage, and potential misuse of the replicated models [195–197].

Prompts play a crucial role in model stealing attacks. By systematically querying an LLM with carefully designed prompts, an attacker can infer the model's behavior and underlying parameters. This process, known as "query-based extraction," allows the attacker to build a surrogate model that mimics the target model's responses. The effectiveness of this approach relies on the ability to generate diverse and informative prompts that cover a wide range of inputs the model might encounter [198].

For instance, an attacker might use a series of varied prompts to understand how the model processes different types of queries. By analyzing the model's outputs, the attacker can gradually reconstruct the model's decision-making process and replicate its functionality. This method is particularly effective when the target model is a black-box system, where the attacker has no access to the internal architecture but can observe the outputs generated in response to the inputs [199].

One notable example of a model stealing attack is the extraction of the projection matrix from OpenAI's language models. Researchers demonstrated how, through a series of carefully crafted prompts, they could extract significant portions of the model's architecture and parameters, effectively creating a replica of the original model [200]. Another incident involved adversaries using prompt engineering techniques to replicate commercial LLMs used in customer service, resulting in substantial intellectual property theft and financial losses for the companies involved [201].

Numerous studies have explored the effectiveness of model stealing through prompt engineering. For instance, the paper "Prompt Stealing Attacks Against Large Language Models" highlights how attackers can use advanced prompt engineering techniques to extract high-value information from LLMs [202]. Another research effort, "Stealing the Decoding Algorithms of Language Models," delves into the technical intricacies of how prompts can be exploited to steal decoding algorithms, further showcasing the vulnerability of LLMs to such attacks [202].

The effectiveness of these attacks underscores the urgent need for robust defenses. Proposed countermeasures include limiting the number of queries a single user can make, implementing anomaly detection to identify suspicious querying patterns, and using defensive perturbations to mislead potential attackers [203].

7.2.4 Backdoor Threats

Backdoor threats involve embedding hidden vulnerabilities within a model that can be activated by specific prompts. These backdoors can be introduced during the training process, often through manipulated training data, and remain dormant until the trigger prompt is presented. For LLMs, a backdoor could be a particular phrase or pattern that, when encountered, causes the model to generate a pre-defined, often malicious output. This poses a significant security risk, as backdoors can be difficult to detect and may be exploited to produce harmful responses or leak sensitive information [204–209]. The covert nature of backdoor threats makes them a formidable challenge, highlighting the need for robust prompt engineering practices to identify and mitigate these vulnerabilities [210].

Prompt engineering plays a crucial role in both the identification and prevention of these vulnerabilities. Carefully designed prompts can be used to test LLMs for susceptibility to adversarial attacks, data poisoning, and backdoor activations, thus ensuring more secure deployment of these powerful models.

7.2.5 Data Poisoning

Data poisoning involves the injection of malicious data into the training set, which compromises the integrity of the model. This type of attack can significantly distort the learning process, leading to erroneous outputs once the model is deployed. In LLMs, data poisoning can be especially insidious as it may go undetected during the training phase. For instance, an attacker might insert misleading or harmful data into the large corpus used to train an LLM, causing the model to learn and reproduce these inaccuracies when prompted. The implications of data poisoning are far-reaching, affecting sectors that rely on accurate data analysis and generation, such as healthcare, finance, and legal services [211]. Prompt engineering practices must be meticulously monitored to prevent the inadvertent inclusion of poisoned data that could later be exploited.

7.3 Prompt Engineering as a Double-Edged Sword

While prompt engineering has significantly enhanced the functionality and versatility of LLMs, it also poses substantial risks if mismanaged. Poorly designed prompts can introduce or exacerbate security vulnerabilities, leading to unintended and potentially harmful outputs [178]. This dual nature of prompt engineering—capable of both enhancing and compromising LLM performance—highlights its role as a double-edged sword in the deployment of AI technologies. Recent advancements in prompt engineering have demonstrated its power to unlock new capabilities in LLMs, but they also underscore the need for robust and secure design practices. As LLMs become increasingly integrated into critical systems and services, ensuring that prompts are carefully and securely crafted is essential to mitigating risks and maximizing the benefits of these advanced models [212].

7.3.1 Impact of Poorly Designed Prompts on Security

Poorly designed prompts can significantly exacerbate security vulnerabilities in LLMs. Adversarial prompts, for instance, can be crafted to exploit specific weaknesses in the model, leading to unintended or harmful outputs. These vulnerabilities are particularly critical in applications where accuracy and reliability are paramount, such as legal document analysis or automated customer service [7].

Poorly designed prompts can make LLMs susceptible to various types of attacks, including prompt injection and prompt leaking. Prompt injection attacks involve inserting malicious inputs into prompts to manipulate the model's output, which can result in the generation of harmful or misleading information. For example, a malicious actor could craft a prompt that subtly alters the model's response in a way that promotes false information or biases [178]. Prompt leaking, on the other hand, occurs when sensitive or proprietary information embedded in prompts is exposed, jeopardizing the security and privacy of applications that rely on LLMs [213].

Prompt engineering plays a crucial role in both mitigating and exacerbating these vulnerabilities. Effective prompt engineering involves designing prompts that minimize the risk of exploitation while maximizing the accuracy and reliability of the model's outputs. This includes the use of techniques such as input sanitization, context validation, and adversarial training to enhance the model's robustness against malicious inputs. Conversely, inadequate prompt engineering can inadvertently introduce vulnerabilities, as poorly structured prompts may fail to account for potential security risks or edge cases, leaving the model exposed to exploitation [211].

In summary, poorly designed prompts can significantly exacerbate security vulnerabilities in LLMs, leading to adverse outcomes such as adversarial attacks, data poisoning, and backdoor threats. The role of prompt engineering is paramount in mitigating these risks, ensuring that prompts are carefully crafted to enhance the model's security and reliability. As LLMs become increasingly integrated into critical applications, the need for robust and secure prompt engineering practices becomes ever more pressing. Future research and development should focus on advancing these practices to protect LLMs from emerging threats and ensure their safe deployment.

7.3.2 Enhancing LLM Security Through Adversarial Training and Robust Prompt Design

Adversarial example generation is a fundamental technique in AI security, designed to test and enhance the robustness of machine learning models. By creating inputs that intentionally mislead models into making incorrect predictions, researchers can identify vulnerabilities and develop strategies to mitigate them. This process is essential for ensuring that models can withstand malicious attacks and function reliably in real-world scenarios [178]. While direct research on prompt-based adversarial example generation is limited, prompt engineering remains a critical tool in testing model robustness. By designing prompts that subtly alter input data, researchers can simulate adversarial conditions and observe how models respond. For example, ambiguous or misleading prompts can reveal how susceptible a model is to producing biased or incorrect outputs, thereby identifying potential weaknesses [214].

Adversarial training, which involves training models on adversarial examples, has proven effective in enhancing model robustness. Studies have shown that models exposed to a variety of adversarial inputs during training are better equipped to handle unexpected or malicious data. This method improves the resilience of models against attacks and enhances their overall reliability [195].

For instance, research has demonstrated that incorporating adversarial examples generated through prompt manipulation can significantly bolster a model's defenses. By continuously refining prompts and generating diverse adversarial scenarios, researchers can develop comprehensive training datasets that prepare models for a wide range of challenges [215].

To maximize the effectiveness of adversarial training, integrating robust prompt design is essential. This involves creating prompts that not only test the model's limits but also enhance its ability to learn from adversarial conditions. Techniques such as mask filling, where portions of text are strategically manipulated, can be used to generate adversarial examples that expose and address vulnerabilities in the model [181].

In conclusion, while the direct focus on prompt-based adversarial example generation might be limited, the broader application of adversarial training and robust prompt design remains critical in enhancing LLM security. Future research should continue to explore innovative methods for integrating prompt engineering into adversarial training frameworks to ensure the safe and reliable deployment of LLMs.

8 Prospective methodologies

Several key developments on the horizon promise to substantially advance prompt engineering capabilities. In the following section, some of the most significant trajectories would be analyzed that are likely to shape the future of prompt engineering. By anticipating where prompt engineering is headed, developments in this field can be proactively steered toward broadly beneficial outcomes.

8.1 Better understanding of structures

One significant trajectory about the future of prompt engineering that emerges is the importance of better understanding the underlying structures of AI models. This understanding is crucial to effectively guide these models through prompts and to generate outputs that are more closely aligned with user intent.

At the heart of most AI models, including GPT-4, are complex mechanisms designed to understand and generate human language. The interplay of these mechanisms forms the "structure" of these models. Understanding this structure involves unraveling the many layers of neural networks, the various attention mechanisms at work, and the role of individual nodes and weights in the decision-making process of these models [216]. Deepening our understanding of these structures could lead to substantial improvements in prompt engineering. The misunderstanding of the model may cause a lack of reproducibility [217]. By understanding how specific components

of the model's structure influence its outputs, we could design prompts that more effectively exploit these components.

Furthermore, a comprehensive grasp of these structures could shed light on the shortcomings of certain prompts and guide their enhancement. Frequently, the underlying causes for a prompt's inability to yield the anticipated output are intricately linked to the model's architecture. For example, [29] found evidence of limitations in previous prompt models and questioned how much these methods truly understood the model.

Exploration of AI model architectures remains a vibrant research domain, with numerous endeavors aimed at comprehending these sophisticated frameworks. A notable instance is DeepMind's "Causal Transformer" model [218], designed to explicitly delineate causal relationships within data. This represents a stride towards a more profound understanding of AI model architectures, with the potential to help us design more efficient prompts.

Furthermore, a more comprehensive grasp of AI model architectures would also yield advancements in explainable AI. Beyond better prompt engineering, this would also foster greater trust in AI systems and promote their integration across diverse industries [219]. For example, while AI is transforming the financial sector, encompassing areas such as customer service, fraud detection, risk management, credit assessments, and high-frequency trading, several challenges, particularly those related to transparency, are emerging alongside these advancements [220, 221]. Another example is medicine, where AI's transformative potential faces similar challenges [222, 223].

In conclusion, the trajectory toward a better understanding of AI model structures promises to bring significant advancements in prompt engineering. As we research deeper into these intricate systems, we should be able to craft more effective prompts, understand the reasons behind prompt failures, and enhance the explainability of AI systems. This path holds the potential for transforming how we interact with and utilize AI systems, underscoring its importance in the future of prompt engineering.

8.2 Agent for AIGC tools

The concept of AI agents has emerged as a potential trajectory in AI research [224]. In this brief section, we explore the relationship between agents and prompt engineering and project how agents might influence the future trajectory of AI-generated content (AIGC) tools. By definition, an AI agent comprises large models, memory, active planning, and tool use. AI agents are capable of remembering and understanding a vast array of information, actively planning and strategizing, and effectively using various tools to generate optimal solutions within complex problem spaces [225].

The evolution of AI agents can be delineated into five distinct phases: models, prompt templates, chains, agents, and multi-agents. Each phase carries its specific implications for prompt engineering. Foundational models, exemplified by architectures such as GPT-4, underpin the realm of prompt engineering.

In particular, prompt templates offer an effective way of applying prompt engineering in practice [30]. By using these templates, we can create standardized prompts to guide large models, making the generated output more aligned with the desired outcome. The usage of prompt templates is a crucial step towards enabling AI agents to better understand and execute user instructions.

AI agents amalgamate these methodologies and tools into an adaptive framework. Possessing the capability to autonomously modulate their behaviors and strategies, they strive to optimize both efficiency and precision in task execution. A salient challenge for prompt engineering emerges: devising and instituting prompts that adeptly steer AI agents toward self-regulation [29].

In conclusion, the introduction of agent-based paradigms heralds a novel trajectory for the evolution of AIGC tools. This shift necessitates a reevaluation of established practices in prompt engineering and ushers in fresh challenges associated with the design, implementation, and refinement of prompts.

9 Conclusion

In conclusion, prompt engineering has established itself as an essential technique for optimizing the performance of LMs. By employing foundational methods such as clear instructions and iterative refinement, alongside advanced methodologies like Chain of Thought and Self-consistency, the capabilities of LMs are significantly enhanced. For multimodal models, innovative strategies such as Multi-modal Prompt Learning and Context Optimization ensure effective integration and optimization of visual and textual data. The efficacy of these methods is rigorously assessed through both subjective and objective evaluations, confirming their impact across diverse applications, including education, content creation, and programming. Additionally, prompt engineering plays a crucial role in fortifying LM security, identifying vulnerabilities, and mitigating risks through adversarial training and robust prompt design. Looking ahead, future advancements will focus on a deeper understanding of AI model structures and the development of AI agents, further elevating the sophistication and capability of AI systems. This comprehensive review underscores the transformative potential of prompt engineering in advancing AI capabilities, providing a structured framework for future research and applications.

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