Towards Goal-oriented Large Language Model Prompting: A Survey

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Abstract

Large Language Models (LLMs) have shown prominent performance in various downstream tasks in which prompt engineering plays a pivotal role in optimizing LLMs' performance. This paper, not as an overview of current prompt engineering methods, aims to highlight the limitation of designing prompts while holding an anthropomorphic assumption that expects LLMs to think like humans. From our review of 35 representative studies, we demonstrate that a goal-oriented prompt formulation, which guides LLMs to follow established human logical thinking, significantly improves the performance of LLMs. Furthermore, We introduce a novel taxonomy that categorizes goal-oriented prompting methods into five interconnected stages and we demonstrate the broad applicability of our framework by summarizing ten applicable tasks. With four future directions proposed, we hope to further emphasize and promote goal-oriented prompt engineering.

1 Introduction

Large Language Models (LLMs) like ChatGPT have garnered significant interest for their ability to assimilate vast amounts of information from large corpora of data. They have demonstrated proficiency in, for example, open-domain dialogue [Deng et al., 2023; Yu et al., 2023], reasoning [Wei et al., 2022; Yao et al., 2023; Besta et al., 2023], planning [Song et al., 2023; Liu et al., 2023a], and so on. The predominant approach to leveraging LLMs for downstream tasks involves crafting tailored text prompts to tap into their potential [Liu et al., 2023b]. However, the effectiveness of LLMs is contingent upon the prompting strategy employed, leading to performance disparities [Zhao et al., 2021]. Such a phenomenon has given rise to the field of prompt engineering, which investigates the optimal formulation of prompts for specific tasks.

To obtain an optimal prompt for tasks, it is important to first understand the deviation in the human way of thinking and LLMs' way of processing information. Humans are taught by experience to approach complex objectives by breaking down the main goal into more manageable sub-goals, a strategy supported by goal-setting theory [Austin and Vancouver,

1996]. In interacting with LLMs, which often display human-like conversational abilities, we might be tempted to attribute human-like thought processes to them, expecting them to know from the start that they should decompose complex problems into simpler tasks. This anthropomorphic assumption does not hold for LLMs and can lead to unsatisfactory outcomes [Abercrombie *et al.*, 2023]. On the other hand, as shown in our literature review of 35 representative studies, if we design the prompts from a goal-oriented perspective that guides LLMs to mimic human thinking, LLMs' performance improves significantly. In the meantime, aligning LLM's behavior with human logic allows more human-interpretable answers generated from LLMs that result in more effective and reliable human-computer interaction.

In this paper, we propose the first goal-oriented taxonomy of prompting methods, which classifies goal-oriented prompting methods into goal decomposition, action selection, action implementation, sub-goal result evaluation, and sub-goal selection. We summarize the application of reviewed works on a wide variety of tasks to showcase the broad impact of goal-oriented philosophy in prompt engineering. Finally, we offer four main promising future directions, including the synergy of stages in the framework, applications to other tasks, efficiency problems, and hierarchical decomposition, for further improvement.

2 Taxonomy of Methods

In this section, we categorize existing methods into a goaloriented framework, as shown in Fig. 1. We further refine the works in each part of the framework according to their distinctive features.

2.1 Decomposing Goal into Sub-goal Sequences

Decomposing a high-level goal into sub-goals is particularly useful for complex problems where a straightforward answer isn't sufficient. In this section, we introduce the methods to decompose goals and auxiliary techniques to help improve the performance of decomposition.

Iterative decomposition. Iterative decomposition generates a sub-goal and executes actions to get subgoal results, then repeat this process with the knowledge of the previous sub-goal and sub-goal results. Chain-of-thought prompting (CoT) [Wei *et al.*, 2022] can be considered the first work to

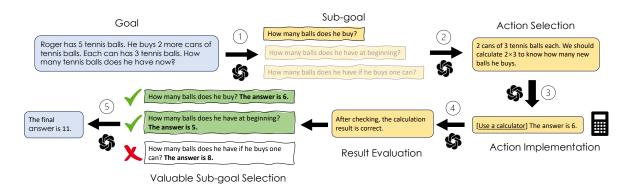


Figure 1: An overview of the goal-oriented framework for prompting LLMs taking solving a math word problem as an example. (1) Decomposing **goal** into **sub-goal** sequences. (2) **Action** selection for attaining **sub-goals**. (3) Implementing **actions** to get **sub-goal results**. (4) Evaluation of **sub-goal** achievement based on **sub-goal results**. (5) Selecting valuable **sub-goals** for effective **goal** achievement. Note that stages (2)(3)(4) are taken for all the decomposed sub-goals.

try to decompose a goal into sub-goal sequences. By showing LLMs a series of intermediate reasoning steps that lead to the final output in the prompt, LLMs can naturally imitate a human-like problem-solving process. Here, the intermediate reasoning steps can be considered as sub-goals, and they are sequentially connected to form a sub-goal sequence that leads to the final solution of the problem. [Kojima et al., 2022] even found that simply adding "Let's think step by step." to the prompt can guide LLMs to perform CoT decomposition as well. The above two works implicitly follow iterative decomposition since LLMs generate tokens in an autoregressive way which means that they can decide the next sub-goal based on previous content.

There are also works that explicitly ask LLMs to follow the iterative decomposition. DecomP [Khot et al., 2022] and Successive Prompting [Dua et al., 2022] are two contemporary works that repeatedly ask sub-questions to get background knowledge for question answering tasks. The background knowledge attained by answering each sub-question are sub-goals to be achieved. Different from CoT which may generate sub-questions sequentially in one output, these two works explicitly repeat prompting LLMs to ask follow-up questions. Self-ask [Press et al., 2022] improves the efficiency of DecomP and Successive prompting by designing a template for follow-up questions. Thus, LLMs can generate all essential questions and their answers by prompting once. Besides, in this paper, the authors empirically show that LLMs are often wrong when asking them to answer a complex question even if they know the true answer of all needed sub-questions. This finding indicates the significance of decomposing complex goals into simple sub-goals for LLMs.

Plan-then-execute decomposition. In contrast to iterative decomposition, plan-then-execute decomposition methods generate the sub-goal sequence at once, which means that the latter sub-goal will not be affected by the former ones. For example, Least-to-most prompting [Zhou *et al.*, 2022] only prompts LLMs two times, one for generating a plan to decompose the goal into a sub-goal sequence, and the other one for executing the plan. Plan-and-solve prompting [Wang *et al.*, 2023a] further improves the efficiency of Least-to-most

prompting by merging the generation of the plan and execution of the plan into one output. DEPS [Wang et al., 2023c] and GITM [Zhu et al., 2023] are decomposition methods designed for Minecraft, an open-world game in which an agent can craft many types of items and tools. In this game, obtaining base materials that are needed to craft a given item can be viewed as sub-goals. While DEPS generates a plan to obtain required objects in sequence solely based on LLMs, GITM leverages a pre-defined sub-goal tree to help LLMs locate prerequisites more precisely.

External decomposition. The above two categories rely on LLM's knowledge to decompose the goal into sub-goals. However, due to their hallucination problem [Ji *et al.*, 2023], they sometimes generate seemingly plausible sub-goals but not grounded in reality. To ensure the accuracy of decomposition, LLM+P [Liu *et al.*, 2023a] and SayPlan [Rana *et al.*, 2023] take advantage of classical planners. They use LLMs to translate goals written in natural language to planning domain definition language so that classical planners can deal with them. The output of planners will then be translated back into natural language by LLMs for execution.

Reduce sub-goal space. Choosing possible sub-goals from a limited space is beneficial for getting a more precise and efficient sub-goal sequence since it avoids LLM getting distracted by irrelevant or even wrong sub-goals. PEARL [Sun et al., 2023] is specially designed for question answering over long documents. Several sub-goals like "Finding the definition of A", "Compare A and B", and "Summarize A" are pre-set and LLMs only need to choose and arrange valuable sub-goals into a plan. Similar to PEARL, ProCoT [Deng et al., 2023] has pre-defined sub-goal sets covering query clarification, topic transition, and negotiation strategy for dialogue systems. DecomP [Khot et al., 2022] selects sub-goals from a set like "split" and "merge" for k-th letter concatenation, a symbolic reasoning task. SayPlan [Rana et al., 2023] is designed for robot planning. Given a task instruction, semantic search is conducted to identify a relevant subgraph from the whole 3D scene graph that serves as the environment. LLMs will plan based only on this subgraph.

2.2 Action Selection for Attaining Sub-goals

Action selection is vital for achieving sub-goals as it involves choosing the most effective and valid actions to reach desired outcomes. CoT is a naive way for action selection where it is completely decided by LLMs themselves. However, due to the hallucination problem which is the same in decomposing sub-goals, actions generated by LLMs are often invalid. In this section, apart from naive selection, we classify the advanced action selection methods into two classes, constrainthen-select and select-then-mapping.

Constrain-then-select. These kinds of methods first set constraints on the action space and then let LLMs decide the actual action. It shares similar ideas with the methods aimed at reducing sub-goal space, which makes it easier for LLMs to select valid actions. MWP [Zhang et al., 2023] is proposed for solving math word problems. To ensure the correctness and coherence of the intermediate solution steps, the authors employ an operation prediction module that predicts the needed calculation operation (e.g. multiplication, summation) in this step. LLMs are used to fill the values in this template. In dialogue systems, RLP [Hao et al., 2023a] additionally sets a mental state to reflect its personality traits to guide action selection. The authors found that this strategy facilitates contextually rich, coherent, and engaging interactions for LLM-based conversational systems.

Select-then-mapping. Different from constrain-thenselect, select-then-mapping first uses LLMs to generate actions solely based on their knowledge and then maps the generated action to the most similar one in the valid action space. Zero-shot planners [Huang et al., 2022a], SALP [Gramopadhye and Szafir, 2023], and Re-Prompting [Raman et al., 2022] aim to solve agent planning problems in an interactive environment. In such virtual environments, there are only a few admissible actions that can be applied. However, the actions produced naively by LLMs often cannot be mapped exactly to those executable actions. To remedy this, researchers employ a text-embedding language model to translate LLM-generated actions into the most similar admissible actions by calculating cosine similarity. When users have access to all the admissible actions, it is suitable to define a set for action mapping.

Reference for selection. It is empirically evaluated by some works that reference actions are helpful for LLMs to decide on actual actions. Reference action means the successful actions LLMs took when experiencing similar situations in the past. Intuitively, taking reference is similar to human skill improvement through practice. GITM [Zhu et al., 2023], created for Minecraft, designs a text-based memory mechanism for LLM to store and retrieve gained useful knowledge during action selection. SALP [Gramopadhye and Szafir, 2023] collects references by choosing examples that have similar tasks to the given query. The examples are added to the input to autoregressively prompt LLMs. Here we want to discriminate between the reference examples and the in-context examples. In-context examples, which are used in CoT, are used to help LLMs understand and perform tasks [Brown et al., 2020]. For example, if a prompt includes intermediate steps for a reasoning problem, models will understand that they should also provide intermediate steps. The selection of reference examples in the prompt is stricter than the in-context examples. They should not only be identical in format, which is the criteria for selecting in-context examples, but also be similar in content.

2.3 Implementing Actions to Get Sub-goal Results

In CoT, LLMs rely on their knowledge for action execution to get the sub-goal result. Due to the hallucination problem, the results are sometimes wrong. For example, even if LLMs correctly choose multiplication to solve a math problem, the calculation result is just not correct. Besides, as [Khot *et al.*, 2022] claimed, some tasks may not be feasible to solve using only an LLM.

Some works are proposed to leverage external tools to guarantee a precise sub-goal result. When deployed to answer open-domain questions, DecomP [Khot et al., 2022] applies an ElasticSearch-based retrieval system to retrieve knowledge from certain knowledge bases like Wikipedia. Program-of-Thoughts [Chen et al., 2022] first translates reasoning processes into Python codes and then runs them in an interpreter. Toolformer [Schick et al., 2023] specifically studied which APIs to call and when to call them when using external tools. In their paper, several tools are adopted, including a calculator for mathematical calculation, a calendar for the awareness of time, a BM25-based Wikipedia search engine for getting comprehensive subject information, a finetuned language model (LM) for question answering, and a fine-tuned LM for machine translation. Note that it adopts smaller LMs for specific tasks because authors found that fine-tuned LMs outperform LLMs on some basic functionalities. Following the idea of Toolformer, HuggingGPT [Shen et al., 2023] further extends the available LMs to the scale of all LMs on open-sourced machine learning communities like HuggingFace. Specifically, in their paper, they evaluate HuggingGPT on nine types of NLP tasks, nine types of CV tasks, four types of audio tasks, and two types of video tasks. Additionally, with the development of open-sourced communities, this work demonstrates the potential of achieving all the sub-goals that can be described in language by leveraging external tools.

2.4 Evaluation of Sub-goal Achievement based on Sub-goal Results

In CoT, there is no evaluation process for the sub-goal results. The results generated by LLMs are assumed to be correct by default. Similar to action implementation and action selection, sub-goal results suffer from the hallucination problem as well. In addition, mistakes in achieving one sub-goal may accumulate, which can lead to huge deviations from the true answer. Thus, it is necessary to evaluate the sub-goal results at each step and correct them in time. Note that the methods we review in this section can be applied to evaluate the overall goal achievement as well. The types of feedback source and their related works are summarized in Table 1.

Evaluated by LLMs. Self-refine [Madaan *et al.*, 2023] is the first work addressing the evaluation of sub-goal results. After getting the output of LLMs, Self-refine feeds the output

Feedback Source	Method		
LLM	Self-refine [Madaan et al., 2023] SelfCheck [Miao et al., 2023] Reflexion [Shinn et al., 2023]		
Environment	SayPlan [Rana et al., 2023] Re-prompt [Raman et al., 2022] Inner Monologue [Huang et al., 2022b GITM [Zhu et al., 2023] DEPS [Wang et al., 2023c]		
VLM	DEPS [Wang et al., 2023c] LLM-Planner [Song et al., 2023] Inner Monologue [Huang et al., 2022b]		
Program Executor	Self-debug [Chen et al., 2023]		
Heuristic Rule	Reflexion [Shinn et al., 2023]		
Human	Inner Monologue [Huang et al., 2022b] DEPS [Wang et al., 2023c]		

Table 1: Feedback source used by existing works.

combined with task-specific prompts to the same LLM to get feedback for the output. For example, the prompt for providing feedback on code optimization problems may address efficiency and readability. Then, the feedback and initial output are fed together to LLMs for output refinement. Getting feedback and refinement are implemented as an iterative process. During iterations, all of the past feedback and refinement are appended to the prompt. For the correction process of the following works in this section, they all follow Self-refine to correct sub-goal results, if not specified. SelfCheck [Miao et al., 2023] decomposes the Self-refine evaluation into finergrained processes. First, actions and sub-goal results are put to LLMs to summarize their intention. Then, the goal combined with all previous sub-goals, selected actions, and subgoal results serves as another input to let LLMs extract useful information from them. Finally, only being provided with useful information and summarized intention, LLMs generate the sub-goal result again. This result will be compared with the original result. If the regeneration result supports or contradicts the original sub-goal result, it is likely that the original sub-goal result is correct or incorrect, respectively. In Reflexion [Shinn et al., 2023], the authors try using another instantiation of an LLM to obtain a score for the sub-goal result. The score is considered as feedback.

Evaluated by external evaluators. Self-refine and Self-Check aim to prompt LLMs to stimulate the ability of self-correction. Alternatively, we could seek external evaluators for help to provide feedback, which is similar to the idea of applying external tools for action implementation.

Self-debug [Chen et al., 2023] leverages unit tests and executors to gain feedback on generated code snippets. The authors also empirically show that leveraging unit test error messages leads to superior performance than LLM's self-reflection. This finding indicates that external evaluators may be more beneficial than self-reflection thanks to more precise feedback. SayPlan [Rana et al., 2023] and Re-prompting [Raman et al., 2022] directly leverage the signs of success or

failure with error messages from the environment as feedback to revise their actions. These two methods rely on the error messages that are pre-built into the program of virtual environments. The quality of error messages (e.g. detail) has a significant influence and sometimes we can hardly define error messages in advance. LLM-Planner [Song et al., 2023] explores the possibility of using Vision-Language Models (VLMs) to provide feedback by describing the environment after confirming that the action has failed. Inner Monologue [Huang et al., 2022b] is a combination of SayPlan and LLM-Planner. It not only gets error messages from environments but also leverages VLMs to attain context information. What's more, the VLM can also perform the task of visual question answering, which enables a finergrained human-computer interaction to get valuable information. Similar to Inner Monologue, DEPS [Wang et al., 2023c], a method proposed for Minecraft, also gets feedback from both VLMs and environments. DEPS further introduces a step to ask LLMs to explain the reason according to the feedback. GITM [Zhu et al., 2023], also used for Minecraft, designs a structured feedback template to get detailed knowledge of the current situation. All of the information can be obtained by calling Minecraft APIs. Reflexion [Shinn et al., 2023] proposes various evaluators to handle different tasks. It has reward functions for reasoning tasks based on exact match grading and heuristic functions tailored to specific criteria for decision-making tasks. We refer to them as heuristic rules. Note that the correction process of SayPlan, Re-prompting, LLM-Planner, Inner Monologue, DEPS, and GITM is different from Self-refine. Instead of implementing the action to get the sub-goal result again, these methods restart from action selection.

Reference for evaluation. Recall that LLM-Planner does not have feedback from the environment. And in Reflexion it can only get a score value indicating the quality of the sub-goal result. For such methods, reference examples play a crucial role in helping LLMs evaluate the sub-goal result with more detail [Shinn et al., 2023]. The reference selection criteria are the same as in action selection, and examples with similar actions are more beneficial [Song et al., 2023]. For example, "cook a potato" is likely more informative than "clean a plate" for a sub-goal result from "cooking an egg". While Reflexion builds a small memory buffer to store recent trials, LLM-Planner selects reference examples from the whole training sets based on the Euclidean distance between the BERT embeddings of references and the running trial.

2.5 Selecting Valuable Sub-goals for Effective Goal Achievement

In the first stage where we decompose a goal into a sub-goal sequence, most existing works rely on LLM's knowledge to finish the process. Due to the hallucination problem, it is difficult to guarantee that all of the decomposed sub-goals are correct and relevant. One of the solutions, described in Section 2.1, is to reduce sub-goal space before asking LLMs to decide sub-goals. We denote such methods as sub-goal preprocess. Alternatively, we could ask LLMs to try several sub-goals in each step or even several sub-goal

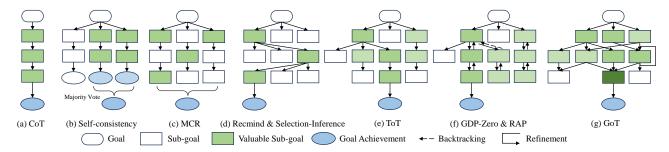


Figure 2: Illustration of approaches for valuable sub-goal selection. (a) CoT selects all sub-goals in one sub-goal sequence. (b) Self-consistency selects sub-goals based on majority votes. (c) MCR selects sub-goals from multiple sub-goal sequences. (d) Recmind and Selection-Inference select one sub-goal from candidates at each step. (e) ToT explores sub-goals from a tree structure space. (f) GDP-Zero and RAP introduce backpropagation to ToT to balance exploration and exploitation. (g) GoT models all sub-goals in a graph structure space.

sequences, which facilitates the exploration of goal decompositions. Then, we only select those valuable sub-goals from candidates to pursue a global optimal goal achievement. We denote this selection process as sub-goal postprocess. In this section, we introduce methods for sub-goal postprocess, which can be divided into three stages of development, Chain-of-thought prompting (CoT) and its variants, Tree of thoughts (ToT) [Yao *et al.*, 2023] and its variants, and finally Graph of thoughts (GoT) [Besta *et al.*, 2023]. An illustration of these approaches is shown in Fig. 2.

Chain-of-thought and its variants. As a naive way of prompting LLMs, CoT asks LLMs to decompose the goal by themselves. The sub-goal selection is implicitly incorporated into the autoregressive decoding process where tokens with higher probabilities are more likely to be generated. However, the selected sub-goals may be irrelevant or even wrong due to the hallucination problem, which leads to the failure of goal achievement.

Four works are proposed to improve the robustness of CoT through sub-goal postprocess. Self-consistency [Wang et al., 2022] prompts LLMs via CoT several times and then conducts majority votes based on the similarity of the final output to decide valuable sub-goal sequences. The result from the chosen sequence is considered the final result. MCR [Yoran et al., 2023] improves Self-consistency by considering all of the sub-goals in various sequences instead of the sub-goal sequence result. After getting several sub-goal sequences, it uses LLMs to extract valuable sub-goals to form a new sub-goal sequence, dubbed meta-reasoning path, and take the result from the meta path. Recmind [Wang et al., 2023b] and Selection-Inference [Creswell et al., 2022] expand the sub-goal to multiple candidates at each decomposition step and choose the most valuable one based on LLM self-evaluation.

Tree of thoughts and its variants. ToT [Yao et al., 2023] advances over CoT by enabling the exploration and comparison of sub-goals based on a tree structure. To make global choices, at each sub-goal when traversing the tree, a decision can be made that involves backtracking or looking ahead based on the implementation of traditional searching algorithms like breadth-first search or depth-first search. For the comparison of sub-goals, ToT solely relies on the self-evaluation of LLMs. CoT and its variants can be considered

special cases of ToT.

RAP [Hao et al., 2023b] and GDP-Zero [Yu et al., 2023] improve from ToT's heuristic-based search to Monte Carlo Tree Search (MCTS). Compared with ToT, MCTS has an additional step for backpropagation, where the score value that indicates the goal achievement is back-propagated to update the value score of all sub-goals in the sub-goal sequence. This operation strikes a proper balance between exploration and exploitation to find valuable sub-goals efficiently, which makes MCTS outperform heuristic-based search algorithms on complex or less structured tasks.

Graph of thoughts. GoT [Besta *et al.*, 2023] advances ToT by modeling all of the LLM-generated sub-goals as a graph. While in ToT, only sub-goals in a sequence or at the same step can interact with each other through comparison, lookahead, or backtracking, GoT allows the synergy of arbitrary sub-goals. Specifically, GoT supports sub-goal aggregation to generate a new sub-goal and sub-goal refinement based on other dependent sub-goals. Finally, valuable sub-goals are selected via LLM self-evaluation on the constructed graph.

3 Application

In this section, we provide an overview of the application of goal-oriented prompt engineering on LLMs. Specifically, we first introduce the definition of the task and then describe how current methods, following into different stages within our framework, leverage goal-oriented prompt engineering on LLMs to achieve task objectives. A summary of the applicable tasks, stages involved, and respective research works are shown in Table 2. Note that here we only introduce representative tasks. For miscellaneous tasks and related datasets, we maintain a list at https://github.com/Alex-HaochenLi/Goal-oriented-Prompt-Engineering to give more comprehensive information. We can see that our framework can be applied to a wide range of tasks.

Reasoning. There are specifically four types of reasoning tasks: arithmetic reasoning, commonsense reasoning, logical reasoning, and symbolic reasoning. These reasoning tasks focus on math word problems, world knowledge, logical principles and rules, and manipulation of symbols such as letters, respectively. Reasoning involves multiple intermediate steps to obtain a final answer. Additionally, to obtain the correct

Application	Sub-category	Stage	Method
Reasoning	Arithmetic Reasoning		CoT [Wei et al., 2022], Self-consistency [Wang et al., 2022], Least-to-most [Zhou et al., 2022], PoT [Chen et al., 2022], Self-refine [Madaan et al., 2023], Plan-and-solve [Wang et al., 2023a], MWP [Zhang et al., 2023], RAP [Hao et al., 2023b], SelfCheck [Miao et al., 2023], Toolformer [Schick et al., 2023], Successive Prompt [Dua et al., 2022]
	Commonsense Reasoning	12345	CoT [Wei et al., 2022], Self-consistency [Wang et al., 2022], MCR [Yoran et al., 2023], Plan-and-solve [Wang et al., 2023a], Toolformer [Schick et al., 2023]
	Symbolic Reasoning		Self-consistency [Wang et al., 2022], Plan-and-solve [Wang et al., 2023a]
	Logical Reasoning		Selection-Inference [Creswell et al., 2022], DecomP [Khot et al., 2022], RAP [Hao et al., 2023b]
Planning	Virtual Environment	124	Zero-shot Planner [Huang et al., 2022a], Re-prompting [Raman et al., 2022], SALP [Gramopadhye and Szafir, 2023], RAP [Hao et al., 2023b], Reflexion [Shinn et al., 2023], LLM+P [Liu et al., 2023a], Say-Plan [Rana et al., 2023], DEPS [Wang et al., 2023c], GITM [Zhu et al., 2023], Inner Monologue [Huang et al., 2022b]
	Real Environment		Inner Monologue [Huang et al., 2022b]
Question Answering	Multihop QA	1345	DecomP [Khot <i>et al.</i> , 2022], Self-ask [Press <i>et al.</i> , 2022], Reflexion [Shinn <i>et al.</i> , 2023], MCR [Yoran <i>et al.</i> , 2023], PEARL [Sun <i>et al.</i> , 2023]
	Open domain QA		Toolformer [Schick et al., 2023]
Code Generation		4	Reflexion [Shinn et al., 2023], Self-debug [Chen et al., 2023], Self-refine [Madaan et al., 2023]
Dialogue		145	ProCoT [Deng et al., 2023], GDP-Zero [Yu et al., 2023], Self-refine [Madaan et al., 2023]
Recommendation		⑤	Recmind [Wang et al., 2023b]

Table 2: Applicable tasks from existing works. The stage column indicates the stages involved in the corresponding methods with regard to the goal-oriented framework in Fig. 1. We maintain a list of related datasets and miscellaneous tasks at https://github.com/Alex-HaochenLi/Goal-oriented-Prompt-Engineering.

answer the LLM must interpret the question correctly, extract necessary information from the given context, and maintain consistency within its intermediate steps.

The goal of these tasks can be considered as producing an answer to a given question. The intermediate steps can be viewed as sub-goals that are sequentially connected to reach the final goal [Wei et al., 2022; Wang et al., 2023a; Khot et al., 2022]. The sub-goal results from action implementation, which in this case are intermediate conclusions, are often evaluated and revised to avoid error accumulation which may negatively influence the following derivations [Madaan et al., 2023; Miao et al., 2023]. Alternatively, for certain actions like calculations, we could leverage an external calculator to ensure a precise sub-goal result [Schick et al., 2023] and employ sketches to help equation formulation (action selection) [Zhang et al., 2023]. We can also ask LLMs to explore parallel possible intermediate conclusions to form an overall better solution.

Planning. Given an objective like "Fetch a bottle from the kitchen", planning involves developing a series of sub-objectives (e.g. "Go to the kitchen", "Find the cupboard") [Liu et al., 2023a; Song et al., 2023] and reaching

sub-objectives by selecting appropriate actions (e.g. "Move", "Search") [Hao et al., 2023a; Raman et al., 2022] to achieve the overall goal in a virtual or real environment.

We can see that works focusing on this task do not propose methods for action implementation and valuable sub-goal selection. This is because the evaluated environments are relatively straightforward and existing works mainly focus on the accuracy of planning without considering efficiency. LLMs often interact with virtual environments through APIs [Wang et al., 2023c; Zhu et al., 2023] or real environments through mechanical devices [Huang et al., 2022b] to ensure the actions are implemented precisely.

Question Answering. Open domain question answering is a task aimed at answering factual questions without any explicit evidence. Multihop QA is an advanced task over opendomain QA. The former relies more on world knowledge while the latter requires multi-step reasoning based on world knowledge to answer more complex questions.

Considering answering complex questions as the goal, LLMs are asked to first decompose them into basic subquestions [Khot *et al.*, 2022; Sun *et al.*, 2023], gain knowledge for sub-questions [Schick *et al.*, 2023], and reflect

on the correctness of the knowledge [Press *et al.*, 2022; Shinn *et al.*, 2023]. Sometimes LLMs may ask irrelevant subquestions or give wrong answers to those sub-questions. To avoid their negative influence, there are methods proposed to lead LLMs to select valuable sub-questions from all candidates [Yoran *et al.*, 2023].

Code Generation. Code generation aims to write a code snippet according to the given description. In this task, our goal is to generate code that is both functionally correct and aligns with the description. All of the works applied to this task fall into the evaluation of results. They leverage the error messages from unit tests [Shinn *et al.*, 2023; Chen *et al.*, 2023] or rely on LLMs themselves [Chen *et al.*, 2023; Madaan *et al.*, 2023] to reflect the validity of generated code snippets and revise them if needed.

Dialogue. Dialogue systems are designed to provide functional service or social support to users via interactions. LLMs often play the role of a conversational agent to achieve certain goals (e.g. query clarification, offer emotional support). To give users positive interaction, LLMs have to correctly understand the context and generate clear and brief responses. Thus, some sub-goals are pre-defined according to the goal to ensure effective decomposition [Deng *et al.*, 2023]. And LLMs are asked to reflect on their response to generate better content [Madaan *et al.*, 2023].

Recommendation. The recommender system, which targets providing personalized recommendations to users based on their preferences, is crucial in many application scenarios including social media, e-commerce websites, etc. Considering giving ratings for items as the final goal, collecting rating information from various sources are then sub-goals. To rely on more valuable sources, LLMs can be asked to compare their credibility and authenticity, and finally take the most valuable source as the overall ratings [Wang *et al.*, 2023b].

4 Challenges & Opportunities

In this section, we discuss the challenges and opportunities of goal-oriented prompt engineering. Even if there have been numerous works proposed to facilitate processing at each stage, there remain some potential directions.

Synergy of stages. The synergy of each stage in our framework will further improve the performance of goal-oriented prompt engineering. We find that though numerous works are proposed to address different stages in the framework, no one synergizes them all.

For reasoning tasks, each stage has specially proposed methods, and putting them together is straightforward. However, for some tasks like code generation, the vacancy of works for certain stages hinders the integration. According to Table 2, there are only works focusing on sub-goal evaluation in code generation. To bridge the gap, we have to understand how the code generation process can fit into our framework. In fact, programming is a process of breaking down a problem into small, manageable parts and solving them in a logical sequence. For example, suppose we are tasked with calculating the average of a set of numbers. We can break this problem down into the following steps: (1) Input a set of numbers.

(2) Calculate the sum of these numbers. (3) Determine the count of numbers. (4) Use the sum and count to calculate the average. Considering these intermediate steps as sub-goals, we decompose the goal of finishing a programming problem into a sequence of sub-goals. For other stages like action selection and sub-goal evaluation, we could apply methods that help LLMs efficiently select actions to calculate the summation or reflect whether their intermediate answer is correct.

Application to other tasks. Though existing works have covered up to 11 tasks, goal-oriented prompt engineering has the potential for broader applications. For example, apart from implementing functions, code review also plays a crucial role in software development. Various review criteria can be taken as sub-goals to ensure the quality of the code, which is our overall goal. We may prompt LLMs to design approaches to evaluate different criteria (e.g. text-based similarity measurement for coding style evaluation, unit tests generation for functionality verification), which corresponds to the action selection to achieve sub-goals. Similar to Program-ofthoughts [Chen et al., 2022], we can use external interpreters to test the code. For some criteria without precise success or failure signals, we can apply sub-goal self-evaluation methods to facilitate better feedback. This fitting-in is also suitable for requirement analysis where we also have to think through several perspectives. Taking one step further, we think this framework even has the potential to be applied to the whole life cycle of software development.

Efficiency. The works we review in this paper mainly address the accuracy of goal-oriented prompt engineering. In other words, they care whether the goal is achieved finally. However, efficiency also plays a crucial role in application. As we are optimistic about the accuracy when employing methods in each stage of our framework to prompt design, we think efficiency is the next key factor that affects performance. For example, in planning tasks, LLMs are expected to form a plan that costs the least energy of human beings or robots. And in dialogue systems, users prefer to achieve their goals with as few interaction rounds as possible. To evaluate efficiency, we need to either design heuristic rules for automatic measurement or annotate the resource-consuming information by human beings.

Hierarchical decomposition. Existing works decompose the goal into a sub-goal sequence, which can be limiting. The method might fall short in adequately addressing the intricacies of each sub-goal, especially in situations where each subgoal itself is complex and multifaceted. Thus, LLMs may not achieve certain sub-goals perfectly, then the error will be accumulated, leading to the failure of overall goal achievement. To make sure each sub-goal is simple enough to be handled by LLMs, we introduce the idea of hierarchical decomposition where sub-goals can be decomposed into even more simple sub-goals. GITM [Zhu et al., 2023] could be viewed as employing the idea of hierarchical decomposition by utilizing a sub-goal tree to connect a sub-goal with even simpler ones. Though a significant success rate increase by employing hierarchical decomposition is reported, relying on solely a tree may not be able to handle more complex problems, which leaves room for further improvement.

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