KnowAgent: Knowledge-Augmented Planning for LLM-Based Agents

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https://zjunlp.github.io/project/KnowAgent/

Abstract

Large Language Models (LLMs) have demonstrated great potential in complex reasoning tasks, yet they fall short when tackling more sophisticated challenges, especially when interacting with environments through generating executable actions. This inadequacy primarily stems from the lack of built-in action knowledge in language agents, which fails to effectively guide the planning trajectories during task solving and results in *planning hallucination*. To address this issue, we introduce **KnowAgent**, a novel approach designed to enhance the planning capabilities of LLMs by incorporating explicit action knowledge. Specifically, **KnowAgent** employs an *action knowledge base* and a *knowledgeable self-learning* strategy to constrain the action path during planning, enabling more reasonable trajectory synthesis, and thereby enhancing the planning performance of language agents. Experimental results on HotpotQA and ALFWorld based on various backbone models demonstrate that **KnowAgent** can achieve comparable or superior performance to existing baselines. Further analysis indicates the effectiveness of **KnowAgent** in terms of *planning hallucinations* mitigation.

1 Introduction

As artificial intelligence (AI) advances, language agents are becoming increasingly vital for solving complex problems (Zhang et al., 2023; Sumers et al., 2024; Yang et al., 2024). These agents, built around Large Language Models (LLMs), enhance their task planning capabilities through a variety of strategies including task decomposition (Wei et al., 2022; Yao et al., 2023a; Wang et al., 2023a; Team, 2023), reflection (Shinn et al., 2023; Sun et al., 2023a), collaborative division of labor (Hong et al., 2023; Chen et al., 2023c; Yin et al., 2023; Qiao et al., 2024), and the utilization of external tools (Schick et al., 2023; Qiao et al., 2023a). Despite the effectiveness of current prompting techniques in providing good planning abilities for some closed-source language models, these methods are often limited by the model's intrinsic understanding capabilities and the scope of knowledge it was trained on. To meet the demands for broad application and customization in different areas such as question-answering (Yao et al., 2023c; Yin et al., 2023), web browsing (Yao et al., 2022; Deng et al., 2023; Zhou et al., 2023a), robotics (Ichter et al., 2022; Ding et al., 2023) and so on, researchers are exploring *Agent Tuning* as a means to augment model capabilities (Chen et al., 2023a; Zeng et al., 2023; Pan et al., 2023). This involves fine-tuning models through the synthesis of task-specific trajectories, enabling them to undertake a series of effective actions to handle complex situations.

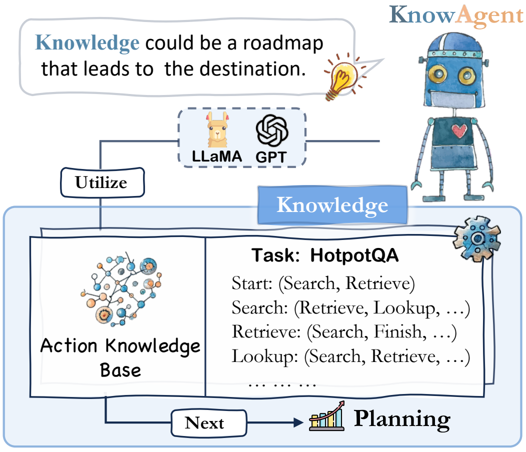
KnowAgent
Knowledge could be a roadmap that leads to the destination.
LLaMA
GPT
Utilize
Knowledge
Action Knowledge Base
Task: HotpotQA
Start: (Search, Retrieve)
Search: (Retrieve, Lookup, ...)
Retrieve: (Search, Finish, ...)
Lookup: (Search, Retrieve, ...)
... ...
Next
Planning

Figure 1: **The overview of KnowAgent.** An agent could leverage external action knowledge base to address and solve complex planning challenges.

However, when it comes to executing planning tasks, especially in open-source models, there remain issues (Liu et al., 2023a; Valmeekam et al., 2023; Guan et al., 2023). Frequently, models generate plans that violate established knowledge rules

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or commonsense (Ding et al., 2023), a phenomenon we name as *planning hallucination*. This term describes scenarios where models might generate unnecessary or conflicting action sequences, such as "`attempting to look up information without performing a search operation`" or "`trying to pick an apple from a table without verifying the presence of both the table and the apple`".

To address these issues, we propose **KNOWAGENT** that focuses on leveraging external *action knowledge* to enhance synthetic trajectories with the goal of resolving *planning hallucination* (see Figure 1). Our development is grounded on several key steps: Initially, we create an extensive *action knowledge base*, which amalgamates action planning knowledge pertinent to specific tasks. This database acts as an external reservoir of information, steering the model's action generation process. Subsequently, by converting *action knowledge* into text, we enable the model to deeply understand and utilize this knowledge in creating action trajectories. Finally, through a *knowledgeable self-learning* phase, we use trajectories developed from the model's iterative processes to continually improve its understanding and application of *action knowledge*. This process not only strengthens the agents' planning abilities but also enhances their potential for application in complex situations.

Experimental results on HotpotQA (Yang et al., 2018) and ALFWorld (Shridhar et al., 2021) based on various backbone models demonstrate that **KNOWAGENT** can achieve comparable or superior performance to existing baselines. Further analysis indicates the effectiveness of **KNOWAGENT** in terms of *planning hallucinations* mitigation. We summarize our contributions as follows:

- We introduce KNOWAGENT that employs *knowledgeable self-learning* to incorporate external *action knowledge* into models to refine and augment the intrinsic planning abilities of language agents.

- We conduct comprehensive experiments that demonstrate KNOWAGENT can match or surpass other benchmark models on the HotpotQA and ALFWorld datasets.

- Further analysis validates the effectiveness of incorporating *action knowledge* for planning purposes. We also showcase the possibility of employing manually refined *action knowledge* from LLMs, thereby reducing human labor and enhancing performance.

2 Background

Language agents observe the external world primarily by generating inner thoughts and executable actions. In this paper, we follow and further enhance the planning trajectory format proposed in Yao et al. (2023b) to train and evaluate our KNOWAGENT. Traditionally, a planning trajectory τ can be represented by a triplet of Thought-Action-Observation $(\mathcal{T}, \mathcal{A}, \mathcal{O})$, where $\mathcal{T}$ indicates the inner thoughts of the language agent, $\mathcal{A}$ signifies executable actions, and $\mathcal{O}$ represents the feedback information from the environment. In terms of this, the trajectory history $\mathcal{H}$ at time t can be defined as:

$$\mathcal{H}_t = (\mathcal{T}_0, \mathcal{A}_0, \mathcal{O}_0, \mathcal{T}_1, ..., \mathcal{T}_{t-1}, \mathcal{A}_{t-1}, \mathcal{O}_{t-1}) \quad (1)$$

Then, the language agent is reinforced to generate $\mathcal{T}_t$ and $\mathcal{A}_t$ based on the history. Given a parameterized probabilistic language agent π with parameters θ, the process of generating the next step's thought based on $\mathcal{H}_t$ can be represented as:

$$p(\mathcal{T}_t|\mathcal{H}_t) = \prod_{i=1}^{|\mathcal{T}_t|} \pi_\theta(\mathcal{T}_t^i|\mathcal{H}_t, \mathcal{T}_t^{<i}), \quad (2)$$

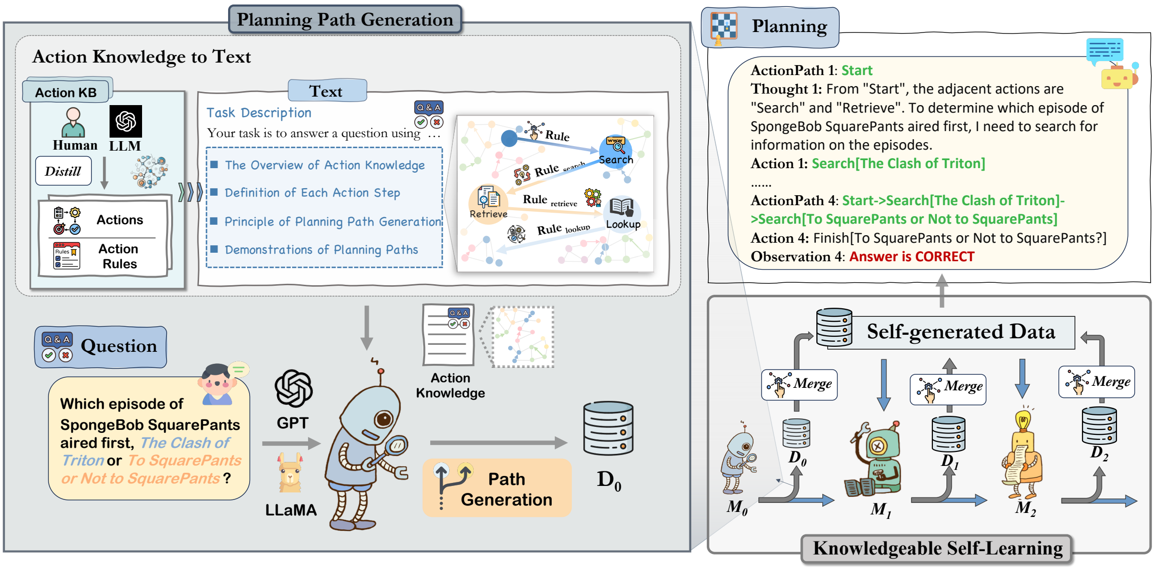
where $\mathcal{T}_t^i$ and $|\mathcal{T}_t|$ are the i-th token and the length of $\mathcal{T}_t$ respectively. Subsequently, the action $\mathcal{A}_t$ will be determined based on $\mathcal{T}_t$ and $\mathcal{H}_t$:

$$p(\mathcal{A}_t|\mathcal{H}_t, \mathcal{T}_t) = \prod_{j=1}^{|\mathcal{A}_t|} \pi_\theta(\mathcal{A}_t^j|\mathcal{H}_t, \mathcal{T}_t, \mathcal{A}_t^{<j}). \quad (3)$$

Similarly, $\mathcal{A}_t^j$ and $|\mathcal{A}_t|$ denote the j-th token and the length of $\mathcal{A}_t$ respectively. Lastly, the feedback result of the action $\mathcal{A}_t$ will be treated as the observation $\mathcal{O}_t$ and added to the trajectory, generating a new round of trajectory $\mathcal{H}_{t+1}$. It's important to note that $\mathcal{A}_i$ here specifically means the actions in the trajectory, which **is identical to** the action a_i in the discussion of the action set E_a later on.

3 KNOWAGENT

Our method, KNOWAGENT, as illustrated in Figure 2, begins by defining *action knowledge*. It then utilizes this knowledge to generate planning paths, and continuously refines these paths through a *knowledgeable self-learning* mechanism, enhancing the framework iteratively.



Which episode of SpongeBob SquarePants aired first, *The Clash of Triton* or *To SquarePants or Not to SquarePants*?

ActionPath 1: Start
Thought 1: From "Start", the adjacent actions are "Search" and "Retrieve". To determine which episode of SpongeBob SquarePants aired first, I need to search for information on the episodes.
Action 1: Search[The Clash of Triton]
......
ActionPath 4: Start->Search[The Clash of Triton]->Search[To SquarePants or Not to SquarePants]
Action 4: Finish[To SquarePants or Not to SquarePants?]
Observation 4: Answer is CORRECT

Figure 2: **The overall framework of KNOWAGENT**. Initially, *Action Knowledge to Text* converts task-specific action knowledge into textual descriptions. Next, *Planning Path Generation* uses prompts and this knowledge to lead LLMs in planning path creation. Lastly, in *Knowledgeable Self-Learning*, the model iteratively optimizes using generated planning trajectories to improve performance.

3.1 Definition of Action Knowledge

Action. $E_a = \{a_1, ..., a_{N-1}\}$ signifies a set of actions, which encompasses the discrete action that LLMs must undertake to accomplish specific tasks.

Action Rules. $\mathcal{R} = \{r_1, ..., r_{N-1}\}$ outlines the rules that determine the logic and sequence of action transitions within the model. These rules directly dictate permissible action transitions $r_k : a_i \rightarrow a_j$, based on the inherent relationships among actions or task-specific requirements.

Action Knowledge. Action Knowledge, represented as $(E_a, \mathcal{R})$, comprises a defined set of actions E_a and the rules $\mathcal{R}$ governing their transitions. The combination of *action knowledge* for different tasks forms an *action knowledge base*, also known as ***Action KB***. The knowledge base will then serve as essential guidance for generating actions and formulating decisions, essential for reducing potential *plan hallucination* problems.

Strategies for Extracting Action Knowledge. Given the diverse *action knowledge* involved in various tasks, fully manual construction is both time-consuming and labor-intensive. To address this challenge, considering the strong performance of LLMs on such tasks (Liu et al., 2023a; Ouyang and Li, 2023), we utilize GPT-4 (OpenAI, 2023) for initial construction, followed by manual refinement. In § 4.3, we provide a detailed comparison of the effectiveness of these two approaches.

3.2 Planning Path Generation with Action Knowledge

3.2.1 Action Knowledge to Text

Figure 2 illustrates the conversion process from *action knowledge* to text. Initially, we establish the *action knowledge base* by identifying actions pertinent to the task's specific needs, utilizing previous dataset analyses and the inherent knowledge of LLMs. This information is then converted into text format to facilitate subsequent operations. As an illustration, we reference one action rule in HotpotQA (Yang et al., 2018) - `Search:(Search, Retrieve, Lookup, Finish)`. This rule indicates that `Search` can lead to multiple pathways: continuing as `Search`, changing to `Retrieve` or `Lookup`, or progressing to `Finish`.

3.2.2 Path Generation

Harnessing *action knowledge*, the model utilizes this insight to streamline the task's planning process. It achieves this by formulating a coherent planning path, guided by the application of action rules $\mathcal{R}_1 \wedge \mathcal{R}_2 \wedge \ldots \Rightarrow \mathcal{P}$. To facilitate path generation, we develop specialized prompts that extend beyond basic **Task Description**, integrating segments as illustrated in Figure 2 (or in Figure 6).

Our approach is thoroughly grounded in *action knowledge* and unfolds across four key segments: (1) It starts with an **Overview of Action Knowledge** to set the foundational concepts and rules. (2) This is followed by the **Definition of Each Action**

Step, detailing the operational aspects and significance of each action. (3) Following this, the **Principle of Planning Path Generation** delves into the constraints on output generation. (4) And finally, **Demonstrations of Planning Paths** provide practical examples, acting as a beacon of inspiration for adapting these strategies across various contexts. Each of these segments plays an essential role in expressing *action knowledge*, specifying actions, and clarifying the process of leveraging *action knowledge* for planning path generation. **It's essential to understand the distinction between path and trajectory in this context**. The **path** exclusively represents the series of actions undertaken by the agent, while the **trajectory** includes the model's complete output during the problem-solving process, incorporating the path as part of its structure.

Here we briefly outline the process of **trajectory** synthesis. This trajectory, denoted as τ, is composed of many planned quadruples. Each quadruple $(\mathcal{P}, \mathcal{T}, \mathcal{A}, \mathcal{O})$, encapsulates the action path $\mathcal{P}$, the agent's internal thoughts processes $\mathcal{T}$, executable actions $\mathcal{A}$, and environmental feedback $\mathcal{O}$. The historical trajectory is reformulated as:

$$\begin{aligned}\mathcal{H}_t = (&\mathcal{P}_0, \mathcal{T}_0, \mathcal{A}_0, \mathcal{O}_0, \ldots, \\ &\mathcal{P}_{i-1}, \mathcal{T}_{t-1}, \mathcal{A}_{t-1}, \mathcal{O}_{t-1})\end{aligned} \tag{4}$$

Based on this, the agent is poised to generate $\mathcal{P}_t$, $\mathcal{T}_t$, and $\mathcal{A}_t$. Considering a parameterized probabilistic language agent π with parameters θ, the mechanism for generating the subsequent action path, contingent on $\mathcal{P}_t$, is expressed as:

$$p(\mathcal{P}_t|\mathcal{H}_t) = \prod_{k=1}^{|\mathcal{P}_t|} \pi_\theta(\mathcal{P}_t^k|\mathcal{H}_t, \mathcal{P}_t^{<k}), \tag{5}$$

Here $\mathcal{P}_t^k$ and $|\mathcal{P}_t|$ represent the k-th token and the total length of $\mathcal{P}_t$. And then we extend the approach used in Equation 2 and 3. The process of deriving thoughts and actions can be reformulated as:

$$p(\mathcal{T}_t|\mathcal{H}_t, \mathcal{P}_t) = \prod_{i=1}^{|\mathcal{T}_t|} \pi_\theta(\mathcal{T}_t^i|\mathcal{H}_t, \mathcal{P}_t, \mathcal{T}_t^{<i}), \tag{6}$$

$$p(\mathcal{A}_t|\mathcal{H}_t, \mathcal{P}_t, \mathcal{T}_t) = \prod_{j=1}^{|\mathcal{A}_t|} \pi_\theta(\mathcal{A}_t^j|\mathcal{H}_t, \mathcal{P}_t, \mathcal{T}_t, \mathcal{A}_t^{<j}). \tag{7}$$

Algorithm 1: Trajectory Synthesis and Knowledgeable Self-Learning

```
Input: $AK_m$: Task-specific Action Knowledge from
       $Action\ KB$, including a set of actions $E_a$
       and action rules $R$; $D_0$: Initial training set;
       $D_{\text{test}}$: Testing set.
Output: Optimized models $M = \{M_1, M_2, \ldots\}$.
Initialize: Model $M_0$.
for $i = 0$ until test performance stabilizes do
    if $i = 0$ then
        // Synthesize initial trajectories.
        $T_i \leftarrow Traj(M_i, AK_m, D_0)$
        // Fiter trajectories.
        $T_i' \leftarrow Filter(T_i, AK_m)$
        // Initial fine-tuning.
        $M_{i+1} \leftarrow Tune(T_i', M_i)$
    else
        // Synthesize trajectories.
        $T_i \leftarrow Traj(M_i, AK_m, D_0)$
        // Filter and merge trajectories.
        $T_i' \leftarrow FilterAndMerge(T_i, T_{i-1}, AK_m)$
        // Further fine-tuning.
        $M_{i+1} \leftarrow Tune(T_i', M_i)$
    // Performance check
    if $\Delta Perf(M_{i+1}, M_i, D_{test}) \leq \epsilon$ then
        break
return Optimized models $M$
```

3.3 Planning Path Refinement via Knowledgeable Self-Learning

In this phase, we introduce *knowledgeable self-learning*. Our goal is to help the model understand the *action knowledge* more deeply through iterative fine-tuning. As shown in Algorithm 1, our approach begins with an initial training set D_0 and an untrained model M_0, leading to the synthesis of initial trajectories $T_0 = \{\tau_1, \tau_2, \ldots, \tau_n\}$. After filtering, these initial outcomes inform further training, producing a preliminary model version, M_1. Subsequently, M_1 undergoes re-evaluation on D_0 to create new trajectories $T_1 = \{\tau_1', \tau_2', \ldots, \tau_n'\}$. These trajectories, alongside T_0, undergo a filtering and merging process based on *action knowledge*. This refined set of trajectories is then utilized to fine-tune the model, resulting in an improved version, M_2. We continue iterating until the performance improvement on M_{test} becomes small, at which point we halt the iteration process.

Knowledge-Based Trajectory Filtering and Merging. Our *knowledgeable self-learning* approach enhances trajectory quality through two key phases: (1) **Filtering**: We start by selecting correct trajectories, T_{correct}, based on their outcomes. Specifically for task HotpotQA, we apply *action*

Backbone	Strategy	Method	HotpotQA				ALFWorld	
			Easy	*Medium*	*Hard*	*Average*	*Seen*	*Unseen*
Llama-2 7B-chat	Prompting	CoT (Wei et al., 2022)	35.80	26.69	18.20	26.90	-	-
	Prompting	ReAcT (Yao et al., 2023b)	25.14	19.87	17.39	20.80	1.43	0.75
	Prompting	Reflexion (Shinn et al., 2023)	35.55	28.73	24.35	29.54	2.86	2.24
	Fine-tuning	FiReAct (Chen et al., 2023a)	40.56	31.70	24.13	32.13	27.86	25.38
	Fine-tuning	KnowAgent-7B	**40.80**	**32.49**	**27.12**	**33.47**	**29.26**	**29.35**
Llama-2 13B-chat	Prompting	CoT (Wei et al., 2022)	37.90	25.28	21.64	28.27	-	-
	Prompting	ReAcT (Yao et al., 2023b)	28.68	22.15	21.69	24.17	13.58	9.70
	Prompting	Reflexion (Shinn et al., 2023)	44.43	37.50	28.17	36.70	18.57	17.16
	Fine-tuning	FiReAct (Chen et al., 2023a)	**51.95**	33.93	28.88	38.26	47.86	50.37
	Fine-tuning	KnowAgent-13B	46.97	**37.60**	**33.22**	**39.26**	**54.29**	**58.71**
Llama-2 70B-chat	Prompting	CoT (Wei et al., 2022)	45.37	36.33	32.27	37.99	-	-
	Prompting	ReAcT (Yao et al., 2023b)	39.70	37.19	33.62	36.83	41.43	37.31
	Prompting	Reflexion (Shinn et al., 2023)	48.01	46.35	35.64	43.33	49.29	47.01
	Fine-tuning	FiReAct (Chen et al., 2023a)	51.96	47.56	**44.60**	48.04	**77.85**	77.61
	Fine-tuning	KnowAgent-70B	**56.75**	**49.90**	37.76	**48.14**	77.14	**78.36**

Table 1: **Overall performance of KnowAgent on HotpotQA and ALFWorld.** The evaluation metrics are F1 Score (%) and Success Rate (%), respectively. **Strategy** means the agent learning paradigm behind each method. The best results of each backbone are marked in **bold**.

knowledge to further refine these trajectories. This refinement involves removing any trajectories that do not align with the provided AK_m, particularly those with invalid actions or disordered action sequences. (2) **Merging**: We then merge trajectories generated by models across different iterations. For trajectories addressing the same task, We refine them based on efficiency, specifically retaining the more efficient (shorter path) trajectories ensuring optimal problem-solving effectiveness.

Method	ALFWorld	
	Seen	*Unseen*
ReAct	13.58	9.70
KnowAgent*	30.00 ↑16.42	38.06↑28.36

Table 2: Comparative Experiment of ReAct and KnowAgent* on ALFWorld with Llama-2-13b. Here label * denotes the version of KnowAgent integrated with action knowledge but not fine-tuned.

4 Experiments

4.1 Settings

We evaluate KnowAgent on HotpotQA (Yang et al., 2018) and ALFWorld (Shridhar et al., 2021). We employ `Llama-2-{7,13,70}b-chat` (Touvron et al., 2023) as the backbone models, and also apply KnowAgent to Vicuna (Zheng et al., 2023) and Mistral (Jiang et al., 2023). We compare KnowAgent with various baselines including CoT (Wei et al., 2022), ReAct (Yao et al., 2023b), Reflexion (Shinn et al., 2023) and FiReAct (Chen et al., 2023a). More details about the datasets, evaluation metrics, baselines, and training hyper-parameters can be seen in Appendix A.

4.2 Main Results

KnowAgent vs. Prompt-based Methods. In Table 1, we present the F1 scores and success rates for KnowAgent and various prompt-based methods evaluated on HotpotQA and ALFWorld. **Firstly**, across both datasets, KnowAgent on 7b, 13b, and 70b models consistently outperforms the prompt-based baselines. Notably, the 13b model achieves a performance increase of ↑15.09% (*average*) and ↑49.01% (*unseen*) over ReAct on the two datasets. **Secondly**, we conduct additional experiments on ALFWorld, comparing the performance of unrefined KnowAgent* against ReAct. The results, shown in Table 2, validate the effectiveness of *action knowledge* itself. Additionally, disparities in effectiveness among different prompt methods are observed, aligning with current research focused on enhancing models' capabilities to handle complex tasks through diverse strategies such as multi-agent specialization. **Specifically**, our investigation is geared towards leveraging external *action knowledge* to facilitate models to more accurately complete complex tasks. This is achieved by minimizing invalid actions (on Hot-

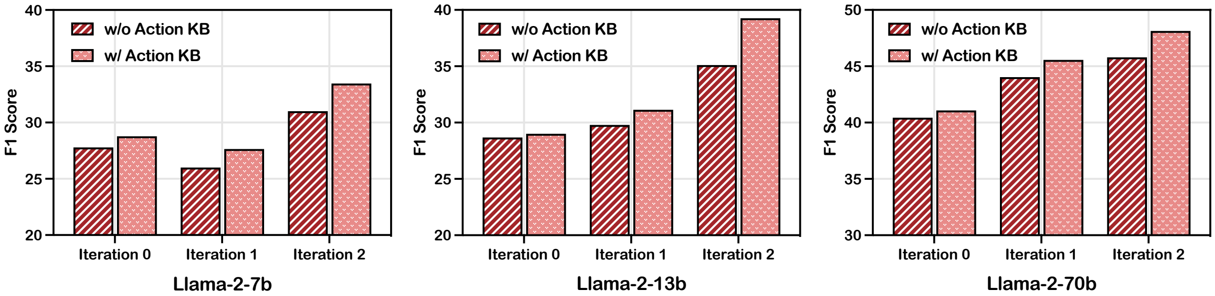


Figure 3: Ablation study on Action Knowledge within Llama-2 Models on HotpotQA. Here *w/ Action KB* indicates the naive KnowAgent and *w/o Action KB* symbolizes removing the action knowledge of the specific task.

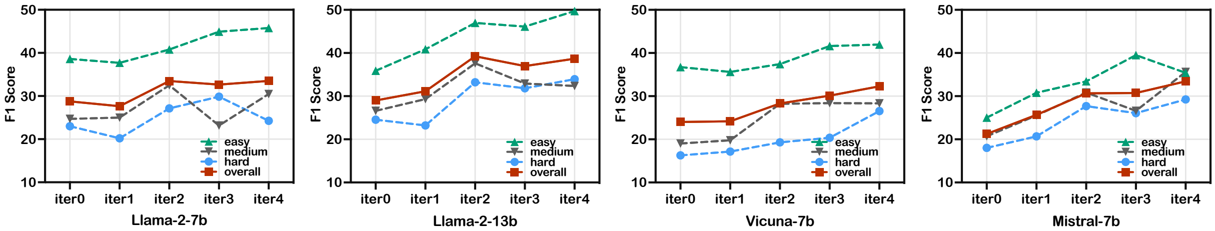


Figure 4: Ablation study on Knowledgeable Self-Learning iteration. We examine the influence of self-learning iterations on a selection of models, including Llama-2-7b, Llama-2-13b, Vicuna-7b, and Mistral-7b. Here *Iter0* represents baseline performance prior to any training.

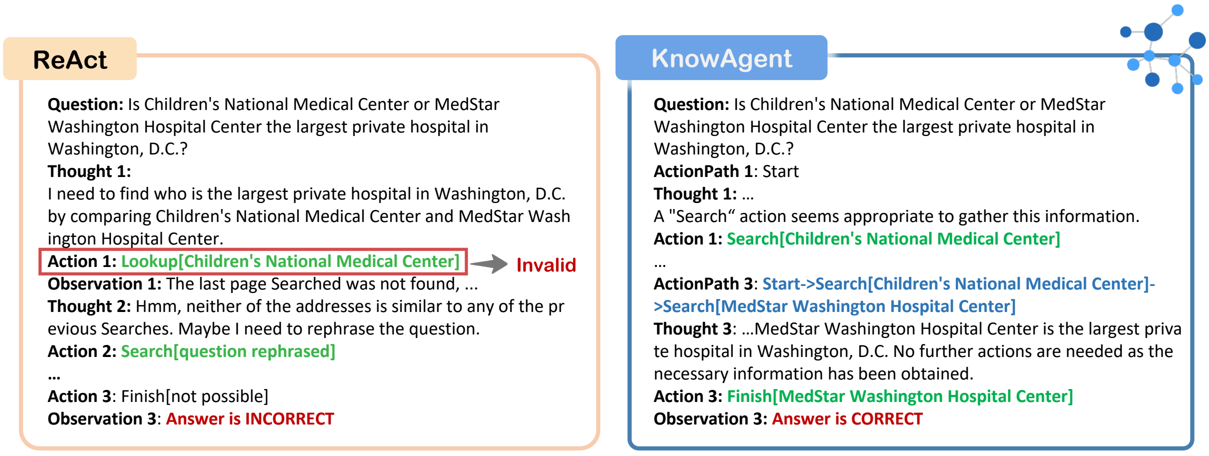
potQA) and promoting action sequences that better reflect real-world situations (on ALFWorld). Further analysis, especially in relation to invalid actions in HotpotQA, will be discussed later in §4.3.

KnowAgent vs. Fine-tuning Methods. Our comparison here focuses on the fine-tuning results of KnowAgent versus FiReAct. A significant difference is that FiReAct's fine-tuning data is synthesized by GPT-4, whereas KnowAgent used its self-synthesized data. For instance, on HotpotQA, FiReAct employs 500 correct trajectories generated by GPT-4, while KnowAgent also uses a 500 training trajectory volume, but only selects the correct quantity of them, approximately 100 to 200 in 13b. The strategy also mirrors in ALFWorld. The outcomes suggest that model-synthesized data, infused with prior knowledge, can achieve results comparable to those produced by more advanced models like GPT-4. Additionally, the study also indicates that iterative fine-tuning enables the model to comprehensively grasp the *action knowledge*, leading to superior planning performance.

4.3 Analysis

The role of action knowledge grows with the increase of iterations in self-learning. Figure 3 shows the ablation results about *action knowledge* on HotpotQA with Llama series models. Regardless of the number of iterations, the effect of using *action knowledge* (*w/ action KB*) is superior to that without *action knowledge* (*w/o action KB*). Another interesting finding is that as the number of iterations increases, the performance gap between *w/o action KB* and *w/ action KB* becomes more significant, indicating that the advantages of introducing *action knowledge* become more apparent. We consider that this can be attributed to the virtuous cycle between *action knowledge* and *self-learning*. Under the constraints of *action knowledge*, the model synthesizes high-quality trajectories for iterative training. In turn, training on more high-quality trajectories allows the model to better learn *action knowledge*, leading to the generation of even more high-quality trajectories.

Iterative training enhances model proficiency. Figure 4 presents a comparative analysis of the effects of iterative training across different base models. **(1) Number of Iterations.** Notably, elevating iterations from 1 to 2 results in a substantial optimization of performance. Further increasing iterations to 4 leads to an even more pronounced improvement. Consistent with previous work (Li et al., 2023b; Wu et al., 2023), these findings corroborate the efficacy of iterative self-learning in bolstering the model's comprehension of the training data, paralleling the human learning principle of "Reviewing the old as a means of realizing the



Question: Is Children's National Medical Center or MedStar Washington Hospital Center the largest private hospital in Washington, D.C.?
Thought 1:
I need to find who is the largest private hospital in Washington, D.C. by comparing Children's National Medical Center and MedStar Washington Hospital Center.
Action 1: Lookup[Children's National Medical Center] → Invalid
Observation 1: The last page Searched was not found, ...
Thought 2: Hmm, neither of the addresses is similar to any of the previous Searches. Maybe I need to rephrase the question.
Action 2: Search[question rephrased]
...
Action 3: Finish[not possible]
Observation 3: Answer is INCORRECT

Question: Is Children's National Medical Center or MedStar Washington Hospital Center the largest private hospital in Washington, D.C.?
ActionPath 1: Start
Thought 1: ...
A "Search“ action seems appropriate to gather this information.
Action 1: Search[Children's National Medical Center]
...
ActionPath 3: Start->Search[Children's National Medical Center]->Search[MedStar Washington Hospital Center]
Thought 3: ...MedStar Washington Hospital Center is the largest private hospital in Washington, D.C. No further actions are needed as the necessary information has been obtained.
Action 3: Finish[MedStar Washington Hospital Center]
Observation 3: Answer is CORRECT

Figure 5: KNOWAGENT (the blue one) successfully completes planning, while ReAct (the orange one) exhibits *planning hallucination* that contradict action knowledge.

Model	Invalid Action	Misordered Action
ReAct	2.08%	3.54%
Reflexion	6.87%	3.87%
KNOWAGENT	**0.35%**	**1.23%**

Table 3: Unreasonable action rates on HotpotQA with Llama-2-13b. Here *invalid* refers to actions that do not meet the action rule, while *misordered* means discrepancies in the logical sequence of actions.

KNOWAGENT	Strategy	HotpotQA	ALFWorld
7B	Manual	33.47	20.15
	Distilled	25.22	18.66
13B	Manual	39.26	52.24
	Distilled	25.72	51.49

Table 4: Comparative Experiment on Manual vs. Distilled Action Knowledge. *Manual* stands for human-crafted knowledge and *Distilled* represents the distilled knowledge from GPT-4.

new”. **(2) Different Base Models.** We also explore other backbone models except for Llama with a 7B parameter scale, such as Vicuna-7B and Mistral-7B. The result suggests that our method is effective and generalizable across different pre-trained and fine-tuned models. However, the performance discrepancies among them also indicate a variance in the ability of different models to absorb and utilize such structured external knowledge.

Action knowledge effectively mitigates planning hallucinations. We show the statistical rates of invalid and misordered actions generated by different methods in Table 3. Given that only the Search and Finish actions are involved in FiReAct, it is omitted from our analysis here. The results demonstrate that incorporating *action knowledge* significantly reduces the frequency of erroneous actions and the likelihood of invalid action paths, thereby increasing the precision of the models on the specific task. To further substantiate this claim, we refer to the experimental outcomes from KNOWAGENT and ReAct within HotpotQA, as demonstrated in Figure 5. For a given question, ReAct's action sequence follows a Lookup->Search pattern, which is problematic due to the dependency of the Lookup action on the subsequent Search step. However, with constraints, KNOWAGENT avoids such faulty sequences, enhancing task accuracy.

Distilled vs. Manually Designed Knowledge. To investigate whether utilizing advanced LLMs can supplant manual efforts in constructing task-specific *action knowledge*, we compare distilled outcomes from gpt-4-0613 with manual-designed ones (see Table 4). For HotpotQA, we observe that the *action knowledge* distilled by GPT-4 is more concise, with fewer cyclical actions than those set by humans. This efficiency holds for simpler tasks where performance parallels human-defined methods, while underperformance is found on more complex tasks where longer action sequences are required. For ALFWorld, the GPT-distilled knowledge closely mirrors what is crafted by humans, underscoring the model's capacity to comprehend real-world constraints. Aligning with prior research (Ding et al., 2023; Zhou et al., 2024), this distilled knowledge aids the model in understanding real-world limitations, showing little difference in effectiveness compared to human-created one.

Error Analysis. Upon analyzing the capabilities of KNOWAGENT, we identify its limitations, particularly in processing complex queries and summarizing long texts. It struggles to distill key information effectively, often failing to deliver accurate responses. The core issue lies in their insufficient reasoning and memory capacities for handling long contexts. Consequently, the generated responses may be incorrect or even misaligned with the posed questions, such as providing a simple `yes/no` when a specific entity is required. Our error analysis in HotpotQA, illustrated in Table 5, highlights two primary error types: **Inconsistency Error**, where the model diverges from the question during the answering process, and **Summarization Error**, where the model fails to extract necessary information from the trajectory, resulting in incorrect answers. Future enhancements could focus on improving the model's long-text processing, information retention, and reasoning abilities.

Efficiency Analysis. In terms of efficiency, taking Llama-7b-chat in ALFWorld as an example, KNOWAGENT mandates around 20 hours per cycle, totaling approximately 40 hours for training. Conversely, FiReAct, which focuses on training for precise trajectories. After incorporating around 710 trajectories synthesized by GPT-4, FiReAct's total training time extends to approximately 50 hours. Regarding memory usage, when running on 8 NVIDIA V100 32G GPUs, both KNOWAGENT and FiReAct have similar memory requirements.

5 Related Work

LLM-Based Agents. LLM-based agents (Wang et al., 2023b; Xi et al., 2023; Durante et al., 2024) have emerged as one of the most prevalent AI systems after the rise of LLMs (Zhao et al., 2023; Qiao et al., 2023b; Zhu et al., 2023; Li et al., 2024a; Jiang et al., 2024). They learn to interact with the external world through action-observation pairs expressed by natural language. Previous works primarily focus on unlocking the potential of LLMs as the core of language agents by leveraging human-crafted (Yao et al., 2023b; Li et al., 2023a; Talebirad and Nadiri, 2023; Qian et al., 2023) or machine-generated (Zhou et al., 2023b; Chen et al., 2023c,b) prompts. Recently, there has been a growing emphasis on endowing open-source LLMs with agent capabilities through fine-tuning (Yin et al., 2023; Qiao et al., 2024; Shen et al., 2024). However, the training trajectory data for existing language agent fine-tuning methods largely rely on annotations from LLMs. This can result in the inclusion of trajectories that violate some action knowledge rules and are difficult to identify, leading to an unstable action performance of the trained language agents. Recently, Guan et al. (2024) introduce AMOR, an agent framework that constructs its reasoning capabilities on a Finite State Machine (FSM). Li et al. (2024b) introduce a "Formal-LLM" framework for agents, combining the expressiveness of natural language with the precision of formal language to enhance agent capabilities. Different from those approaches, we propose knowledge-augmented language agents that incorporate action-related knowledge rules to constrain the trajectory generation, reducing the occurrence of unreasonable action logic in the generated trajectories.

Knowledge Augmented LLMs. Previous works (Guu et al., 2020; Lewis et al., 2020; Izacard et al., 2023) concentrate on knowledge augmentation in LLMs through retrieval. Due to the rich parameterized knowledge within LLMs (Chen, 2023; Feng et al., 2023), some other works (Liu et al., 2022; Yu et al., 2023; Sun et al., 2023b) advocate for knowledge generation rather than retrieval. With the emergence of Augmented Language Models (ALMs), many studies (Trivedi et al., 2023; Li et al., 2023c; Vu et al., 2023; Qiao et al., 2023a) have enhanced the reasoning capabilities of LLMs by incorporating knowledge from external tools such as search engines, knowledge bases, and Wikipedia documents. Recent research (Zhou et al., 2023b; Ye et al., 2023) has introduced structured knowledge to regulate the workflow of LLM-based multi-agents, but none of these works has focused on restricting the action space of individual agents. To the best of our knowledge, we are the first to introduce structured action knowledge to enhance the planning capability of LLM-based agents, specifically aiming at reducing instances of planning errors caused by invalid actions during the planning process.

6 Conclusion

In this study, we introduce KNOWAGENT, a framework designed to mitigate *planning hallucinations* by incorporating external action knowledge into synthetic trajectories. Our method involves utilizing this knowledge to guide the model's action generation, translating this knowledge into text for deeper model comprehension, and employing a *knowledgeable self-learning* phase for continuous improvement. Our experiments across various models demonstrate that KnowAgent effectively competes with or surpasses other baselines, showcasing the benefits of integrating external action knowledge to streamline planning processes and improve performance.

Limitations

Our limitations are listed as follows:

Task Expandability. The current experiments are conducted exclusively on the commonsense QA and household datasets. However, our approach is also applicable to a broader range of fields including medical (Tang et al., 2023), arithmetic (Cobbe et al., 2021), web browsing (Xie et al., 2023), and embodied agents (Yang et al., 2023). This suggests a potential for wider applicability that has yet to be explored.

Multi-Agent Systems. Presently, our research focuses on the application of single agents. Future studies should explore multi-agent systems, such as Chen et al. (2023c) and Qiao et al. (2024), which complete planning tasks through division of labor and collaboration. This enhancement could help agents better handle complex tasks and adapt to changing environments.

Automated Design of Action Knowledge Bases. The creation of action knowledge bases is still manual, time-consuming, and labor-intensive. Even though we use GPT-4 for distilling action knowledge, manual adjustments are needed. Future work should aim at automating this process to reduce manual effort and improve the model's autonomous learning and versatility.

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A Experimental Settings

Datasets and Metrics. HotpotQA (Yang et al., 2018) is specifically designed for multi-hop reasoning tasks and comprises approximately 113,000 question-answering pairs derived from Wikipedia articles. In our experiments, a subset of 500 data instances is randomly sampled for training. For testing, we utilize the same test set as BOLAA (Liu et al., 2023b), which included 100 samples at each of three difficulty levels: easy, medium and hard. To measure performance, we adopt the F1 score as a benchmark, which also serves as the basis for the reward metric utilized in BOLAA. More details of HotpotQA are listed in Appendix B.

ALFWorld (Shridhar et al., 2021) is an interactive, text-based household environment where agent challenge to complete six different types of multi-step tasks. To train our model, we randomly selected 85 instances from each task category in the training set. Furthermore, following previous research (Shridhar et al., 2021; Yao et al., 2023b), we use a test set with 140 seen tasks and 134 unseen tasks to evaluate our method. In ALFWorld, we utilize goal-conditioned success rates as our evaluation metric. We show prompts used for both datasets in Appendix C.

Baselines Our research concentrates solely on the performance of a single agent, intentionally excluding multi-agent studies from our baseline comparison. We choose the following baselines here: (1) Chain-of-Thought (CoT) (Wei et al., 2022) catalyzes in-depth reasoning in large language models (LLMs) by incorporating intermediate reasoning steps within examples. (2) ReAct (Yao et al., 2023b) enables LLMs to intertwine the generation of inferential trajectories and actions, allowing the model to better generalize and adjust its action plans. (3) The Reflexion (Shinn et al., 2023) method utilizes self-reflective feedback to promote continuous agent development through the assimilation of lessons from past errors, thus refining task execution. (4) Furthermore, FiReAct (Chen et al., 2023a) introduces a novel strategy to fine-tune LLM using diverse prompts and trajectories across tasks, demonstrating that richer fine-tuning data can further elevate the performance of agents. It's important to note that our experiments concentrate on exploring the impact of external action knowledge on LLMs, and as such, we have chosen a single-agent framework as the baseline for comparison.

Implementation. We evaluate KNOWAGENT on HotpotQA (Yang et al., 2018) and ALFWorld (Shridhar et al., 2021). We employ `Llama-2-{7,13,70}b-chat` (Touvron et al., 2023) as the backbone models, and also apply KNOWAGENT to vicuna-7b-v1.5-16k (Zheng et al., 2023) and Mistral-7B-Instruct-v0.1 (Jiang et al., 2023). During the *self-learning* phase, we set the number of training iterations to two. We fine-tune these models over 5 epochs using LoRA (Hu et al., 2022), setting a learning rate of 1×10^{-4} and the sequence length of 4096 across all scales. Additionally, we employ an Alpaca-style (Taori et al., 2023) templating approach for generating input from instructional data. Most of our experiments are conducted using NVIDIA V100 32G GPUs. However, for the experiments involving the 13B and 70B models in the ALFWorld environment, we utilize NVIDIA A800 80G GPUs.

B Datasets

In HotpotQA, we have enriched the action set in previous works (Yao et al., 2023b; Liu et al., 2023b) by incorporating Bing Search as an external knowledge source. As a result, we now feature four distinct actions within HotpotQA to enhance its functionality and performance: (1) Retrieve[entity]: Retrieve the exact entity on Wikipedia and return the first paragraph if it exists. If not, return some similar entities for searching. (2) Search[topic]: Use Bing Search to find relevant information on a specified topic, question, or term. (3) Lookup[keyword]: Return the next sentence that contains the keyword in the last passage successfully found by Search or Retrieve. (4) Finish[answer]: Return the answer and conclude the task.

C Prompt

C.1 Prompt Format

See Figure 6.

C.2 Prompt for HotpotQA

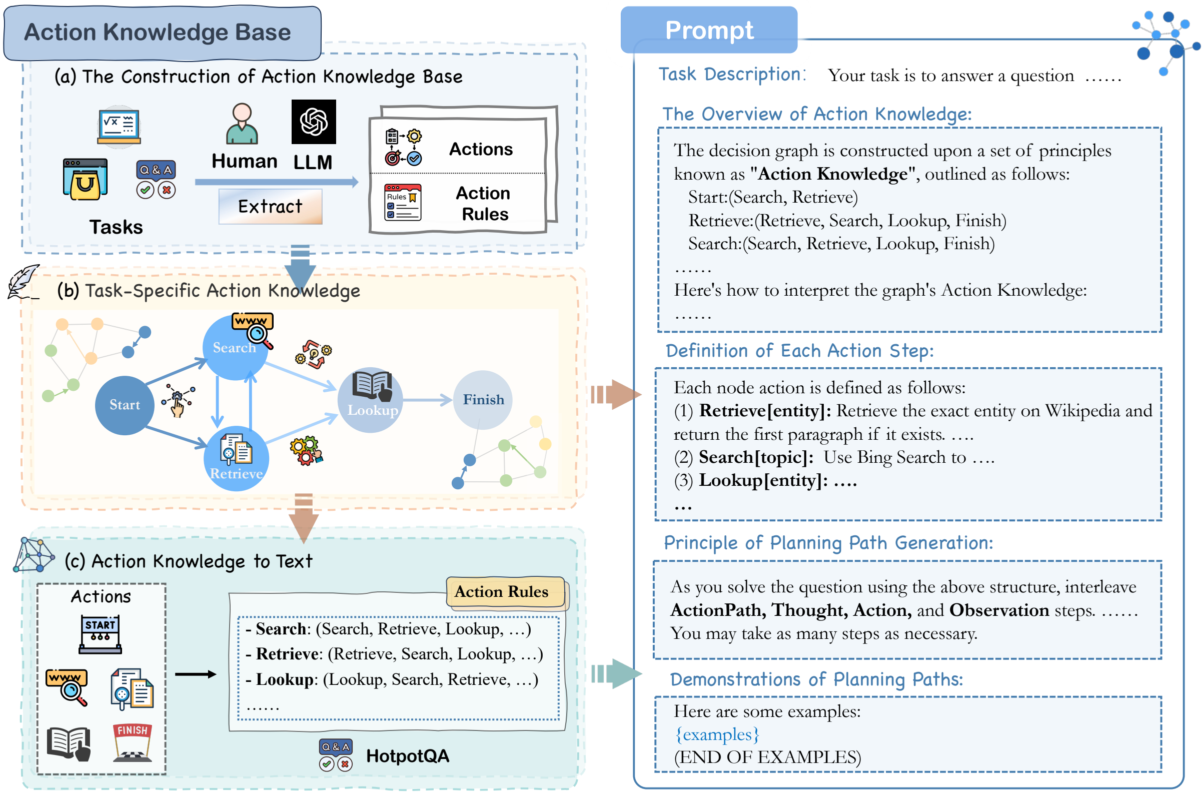
See Table 6.

C.3 Prompt for ALFWorld

See Table 7 to Table 12.

Error Type	Results of KnowAgent
Inconsistency Error	**Question:** Gary Harrison, began his career in the 1970s and **has written over how many major-label recorded songs** including several number-one hits, another artist who have recorded his work include Bryan White, an American country music artist? **ActionPath 1:** Start **Thought 1:** ... I need to search for information about his career and achievements. **Action 1:** Search[Gary Harrison] **Observation 1:** Gary Steven Harrison is an American songwriter. Harrison began his career in the 1970s, and **has written over 300 major-label recorded songs**, including several number one hits. **ActionPath 2:** Start->Search[Gary Harrison] **Thought 2:** ... I need to find out who has recorded Gary Harrison's work. **Action 2:** Search[Bryan White] **Observation 2:** Bryan Shelton White (born February 17, 1974) is an American country music singer and songwriter. Signed to Asylum Records in 1994 at age 20, White released his self-titled debut album that year. **ActionPath 3:** Start->Search[Gary Harrison]->Search[Bryan White] **Thought 3:** ...**Bryan White has recorded Gary Harrison's work (Inconsistency).** No further actions are needed as the necessary information has been obtained. **Action 3: Finish[Bryan White]** **Observation 3: Answer is INCORRECT** **Correct Answer: 300**
Summarization Error	**Question:** Are Ruggero Deodato from Italy, and Mexican Alejandro Springall, both film directors? **ActionPath 1:** Start **Thought 1:** ... To determine if Ruggero Deodato from Italy and Mexican Alejandro Springall are both film directors, it's essential to research their professional backgrounds and achievements. A ""Search"" action seems appropriate to gather this information about each individual. **Action 1:** Search[Ruggero Deodato] **Observation 1:** **Ruggero Deodato (7 May 1939 – 29 December 2022) was an Italian film director**, screenwriter, and actor... **ActionPath 2:** Start->Search[Ruggero Deodato] **Thought 2:** ... Ruggero Deodato is an Italian film director. I need to search Alejandro Springall next and find his profession. **Action 2:** Search[Alejandro Springall] **Observation 2:** **Alejandro Springall is a Mexican film director and producer.** Springall studied filmmaking at the London Film School. He returned to Mexico City in 1991 and started working with Mexican film producer Bertha Navarro, from whom he learned most of his producing skills... **ActionPath 3:** Start->Search[Ruggero Deodato]->Search[Alejandro Springall] **Thought 3:** ... **Alejandro Springall is a film producer. So Ruggero Deodato and Alejandro Springall are not both film directors (Summarization).** No further actions are needed as the necessary information has been obtained. **Action 3: Finish[no]** **Observation 3: Answer is INCORRECT** **Correct Answer: yes**

Table 5: Error Cases in HotpotQA.



- **Search**: (Search, Retrieve, Lookup, …)
- **Retrieve**: (Retrieve, Search, Lookup, …)
- **Lookup**: (Lookup, Search, Retrieve, …)

……

Task Description: Your task is to answer a question ……

The Overview of Action Knowledge:

The decision graph is constructed upon a set of principles known as **"Action Knowledge"**, outlined as follows:
Start:(Search, Retrieve)
Retrieve:(Retrieve, Search, Lookup, Finish)
Search:(Search, Retrieve, Lookup, Finish)
……
Here's how to interpret the graph's Action Knowledge:
……

Definition of Each Action Step:

Each node action is defined as follows:
(1) **Retrieve[entity]:** Retrieve the exact entity on Wikipedia and return the first paragraph if it exists. ….
(2) **Search[topic]:** Use Bing Search to ….
(3) **Lookup[entity]: ….**
…

Principle of Planning Path Generation:

As you solve the question using the above structure, interleave **ActionPath, Thought, Action,** and **Observation** steps. …… You may take as many steps as necessary.

Demonstrations of Planning Paths:

Here are some examples:
{examples}
(END OF EXAMPLES)

Figure 6: The Path Generation process of KnowAgent.

Prompt for HotpotQA

Your task is to answer a question using a specific graph-based method. You must navigate from the "Start" node to the "Finish" node by following the paths outlined in the graph. The correct path is a series of actions that will lead you to the answer.

The decision graph is constructed upon a set of principles known as "Action Knowledge", outlined as follows:

Start:(Search, Retrieve)
Retrieve:(Retrieve, Search, Lookup, Finish)
Search:(Search, Retrieve, Lookup, Finish)
Lookup:(Lookup, Search, Retrieve, Finish)
Finish:()

Here's how to interpret the graph's Action Knowledge:

From "Start", you can initiate with either a "Search" or a "Retrieve" action.

At the "Retrieve" node, you have the options to persist with "Retrieve", shift to "Search", experiment with "Lookup", or advance to "Finish".

At the "Search" node, you can repeat "Search", switch to "Retrieve" or "Lookup", or proceed to "Finish".

At the "Lookup" node, you have the choice to keep using "Lookup", switch to "Search" or "Retrieve", or complete the task by going to "Finish".

The "Finish" node is the final action where you provide the answer and the task is completed.

Each node action is defined as follows:

(1) Retrieve[entity]: Retrieve the exact entity on Wikipedia and return the first paragraph if it exists. If not, return some similar entities for searching.

(2) Search[topic]: Use Bing Search to find relevant information on a specified topic, question, or term.

(3) Lookup[keyword]: Return the next sentence that contains the keyword in the last passage successfully found by Search or Retrieve.

(4) Finish[answer]: Return the answer and conclude the task.

As you solve the question using the above graph structure, interleave ActionPath, Thought, Action, and Observation steps. ActionPath documents the sequence of nodes you have traversed within the graph. Thought analyzes the current node to reveal potential next steps and reasons for the current situation.

You may take as many steps as necessary.

Here are some examples:

{examples}

(END OF EXAMPLES)

Question: {question}{scratchpad}

Table 6: Prompt for HotpotQA.

ALFWorld - Pick

Interact with a household to solve a task by following the structured "Action Knowledge". The guidelines are:
Goto(receptacle) -> Open(receptacle)
[Goto(receptacle), Open(receptacle)] -> Take(object, from: receptacle)
Take(object, from: receptacle) -> Goto(receptacle)
[Goto(receptacle), Take(object, from: receptacle)] -> Put(object, in/on: receptacle)

Here’s how to interpret the Action Knowledge:
Before you open a receptacle, you must first go to it. This rule applies when the receptacle is closed.
To take an object from a receptacle, you either need to be at the receptacle’s location, or if it’s closed, you need to open it first.
Before you go to the new receptacle where the object is to be placed, you should take it.
Putting an object in or on a receptacle can follow either going to the location of the receptacle or after taking an object with you.

The actions are as follows:
1) go to receptacle
2) take object from receptacle
3) put object in/on receptacle
4) open receptacle

As you tackle the question with Action Knowledge, utilize both the ActionPath and Think steps. ActionPath records the series of actions you’ve taken, and the Think step understands the current situation and guides your next moves.

Here are two examples.
{examples}
Here is the task.

Table 7: Prompt for the `Pick` Task.

ALFWorld - Light

Interact with a household to solve a task by following the structured "Action Knowledge". The guidelines are:
[Goto(receptacle)] -> Open(receptacle)
[Goto(receptacle), Open(receptacle)] -> Take(object, from: receptacle)
[Goto(receptacle)] -> Use(receptacle)

Here's how to interpret the Action Knowledge:
Before you open a receptacle, you must first go to it. This rule applies when the receptacle is closed.
To take an object from a receptacle, you either need to be at the receptacle's location, or if it's closed, you need to open it first.
To use an receptacle, you must go to the place where it is located.

The actions are as follows:
1) go to receptacle
2) take object from receptacle
3) use receptacle
4) open receptacle

As you tackle the question with Action Knowledge, utilize both the ActionPath and Think steps. ActionPath records the series of actions you've taken, and the Think step understands the current situation and guides your next moves.

Here are two examples.
{examples}
Here is the task.

Table 8: Prompt for the `Light` Task.

ALFWorld - Clean

Interact with a household to solve a task by following the structured "Action Knowledge". The guidelines are:
[Goto(receptacle)] -> Open(receptacle)
[Goto(receptacle), Open(receptacle)] -> Take(object, from: receptacle)
[Goto(receptacle), Take(object, from: receptacle)] -> Put(object, in/on: receptacle)
[Put(object, from: receptacle)] -> Clean(object, with: receptacle)

Here's how to interpret the Action Knowledge:
Before you open a receptacle, you must first go to it. This rule applies when the receptacle is closed.
To take an object from a receptacle, you either need to be at the receptacle's location, or if it's closed, you need to open it first.
Putting an object in or on a receptacle can follow either going to the location of the receptacle or after taking an object with you.
To clean an object using a receptacle, the object must first be placed in or on that receptacle.

The actions are as follows:
1) go to receptacle
2) take object from receptacle
3) open receptacle
4) put object in/on receptacle
5) clean object with receptacle

As you tackle the question with Action Knowledge, utilize both the ActionPath and Think steps. ActionPath records the series of actions you've taken, and the Think step understands the current situation and guides your next moves.

Here are two examples.
{examples}
Here is the task.

Table 9: Prompt for the `Clean` Task.

ALFWorld - Heat

Interact with a household to solve a task by following the structured "Action Knowledge". The guidelines are:
[Goto(receptacle)] -> Open(receptacle)
[Goto(receptacle), Open(receptacle)] -> Take(object, from: receptacle)
[Goto(receptacle), Take(object, from: receptacle)] -> Put(object, in/on: receptacle)
[Put(object, in/on: receptacle)] -> Heat(object, with: receptacle)

Here's how to interpret the Action Knowledge:
Before you open a receptacle, you must first go to it. This rule applies when the receptacle is closed.
To take an object from a receptacle, you either need to be at the receptacle's location, or if it's closed, you need to open it first.
Putting an object in or on a receptacle can follow either going to the location of the receptacle or after taking an object with you.
To heat an object using a receptacle, the object must first be placed in or on that receptacle.

The actions are as follows:
1) go to receptacle
2) take object from receptacle
3) open receptacle
4) put object in/on receptacle
5) heat object with receptacle

As you tackle the question with Action Knowledge, utilize both the ActionPath and Think steps. ActionPath records the series of actions you've taken, and the Think step understands the current situation and guides your next moves.

Here are two examples.
{examples}
Here is the task.

Table 10: Prompt for the `Heat` Task.

ALFWorld - Cool

Interact with a household to solve a task by following the structured "Action Knowledge". The guidelines are:
[Goto(receptacle)] -> Open(receptacle)
[Goto(receptacle), Open(receptacle)] -> Take(object, from: receptacle)
[Goto(receptacle), Take(object, from: receptacle)] -> Put(object, in/on: receptacle)
[Put(object, in/on: receptacle)] -> Cool(object, with: receptacle)

Here's how to interpret the Action Knowledge:
Before you open a receptacle, you must first go to it. This rule applies when the receptacle is closed.
To take an object from a receptacle, you either need to be at the receptacle's location, or if it's closed, you need to open it first.
Putting an object in or on a receptacle can follow either going to the location of the receptacle or after taking an object with you.
To cool an object using a receptacle, the object must first be placed in or on that receptacle.

The actions are as follows:
1) go to receptacle
2) take object from receptacle
3) open receptacle
4) put object in/on receptacle
5) cool object with receptacle

As you tackle the question with Action Knowledge, utilize both the ActionPath and Think steps. ActionPath records the series of actions you've taken, and the Think step understands the current situation and guides your next moves.

Here are two examples.
{examples}
Here is the task.

Table 11: Prompt for the `Cool` Task.

ALFWorld - Pick Two

Interact with a household to solve a task by following the structured "Action Knowledge". The guidelines are:
Goto(receptacle) -> Open(receptacle)
[Goto(receptacle), Open(receptacle)] -> Take(object, from: receptacle)
Take(object, from: receptacle) -> Goto(receptacle)
[Goto(receptacle), Take(object, from: receptacle)] -> Put(object, in/on: receptacle)

Here's how to interpret the Action Knowledge:
Before you open a receptacle, you must first go to it. This rule applies when the receptacle is closed.
To take an object from a receptacle, you either need to be at the receptacle's location, or if it's closed, you need to open it first.
Before you go to the new receptacle where the object is to be placed, you should take it.
Putting an object in or on a receptacle can follow either going to the location of the receptacle or after taking an object with you.
Ensure the first object is placed before proceeding to deposit the second object.

The actions are as follows:
1) go to receptacle
2) take object from receptacle
3) put object in/on receptacle
4) open receptacle

As you tackle the question with Action Knowledge, utilize both the ActionPath and Think steps. ActionPath records the series of actions you've taken, and the Think step understands the current situation and guides your next moves.

Here are two examples.
{examples}
Here is the task.

Table 12: Prompt for the `Pick Two` Task.