ProcWorld: Benchmarking Large Model Planning in Reachability-Constrained Environments

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Abstract

We introduce ProcWORLD, a large-scale benchmark for partially observable embodied spatial reasoning and long-term planning with large language models (LLM) and vision language models (VLM). ProcWORLD features a wide range of challenging embodied navigation and object manipulation tasks, covering 16 task types, 5,000 rooms, and over 10 million evaluation trajectories with diverse data distribution. ProcWORLD supports configurable observation modes, ranging from text-only descriptions to vision-only observations. It enables text-based actions to control the agent following language instructions. ProcWORLD has presented significant challenges for LLMs and VLMs: (1) *active information gathering* given partial observations for disambiguation; (2) simultaneous localization and decision-making by tracking the *spatio-temporal* state-action distribution; (3) *constrained reasoning* with dynamic states subject to physical reachability. Our extensive evaluation of 15 foundation models and 5 reasoning algorithms (with over 1 million rollouts) indicates larger models perform better. However, ProcWORLD remains highly challenging for existing state-of-the-art models and in-context learning methods due to constrained reachability and the need of combinatorial spatial reasoning.

1 Introduction

Perceiving, reasoning, and navigating with human instructions remain fundamental challenges for embodied agents. Recent advances in large language models (LLMs) and vision-language models (VLMs) have provided multimodal interfaces for agents through web-scale pretraining (Brown et al., 2020; Driess et al., 2023; OpenAI, 2023; Alayrac et al., 2022; Wang et al., 2024) and downstream task adaptation (Zhao et al., 2023), including spatial text-based reasoning. Particularly, they have been widely applied to high-level task planning (e.g. breaking a high-level task like "put a tomato into the fridge", into steps of: (1) locate the tomato; (2) pick up it; (3) navigate to the fridge; and (4) put the tomato into the fridge, as shown in Fig. 1).

Yet, such kind of seemingly simple tasks are non-trivial due to the combinatorial complexity of long-horizon abstract reasoning. Existing benchmarks (Côté et al., 2019; Shridhar et al., 2020a) focus on task-level understanding yet assume full environment accessibility and simplified small-scale home layouts, conflicting with real-world partial observability. Other simulators (Savva et al., 2019; Deitke et al., 2022) adopt geometric primitive actions (e.g., `MoveAhead`/`RotateLeft`), which misalign the capability of modern LLMs and VLMs, making evaluation biased or even misleading.

To address the above issues, we introduce *ProcWORLD*, a benchmark to evaluate the planning and spatial reasoning capabilities of LLMs and VLMs in large-scale and multi-room environments. As illustrated in Fig. 1, ProcWORLD encompasses three key components. (1) *Partial Observability:* ProcWORLD assumes a *Partially Observable Markov Decision Process* (POMDP) (Kaelbling et al., 1998), where an agent needs to localize itself then make decisions from partial observations by continuously exploring frontiers; (2) *Diversity and Large Scale:* it covers 16 task types across 5000 multi-room scenes, and generates 10 million trajectories for evaluation, providing a comprehensive evaluation landscape for LLMs/VLMs across varying complexity levels; (3) *LM-Friendly Observations and Actions:* ProcWORLD enables multi-modal observations (vision-only or text-only) with high-level, language-based action interfaces, thereby facilitating unbiased evaluation for LLMs/VLMs. Built upon these features, ProcWORLD is significantly more realistic but challenging for

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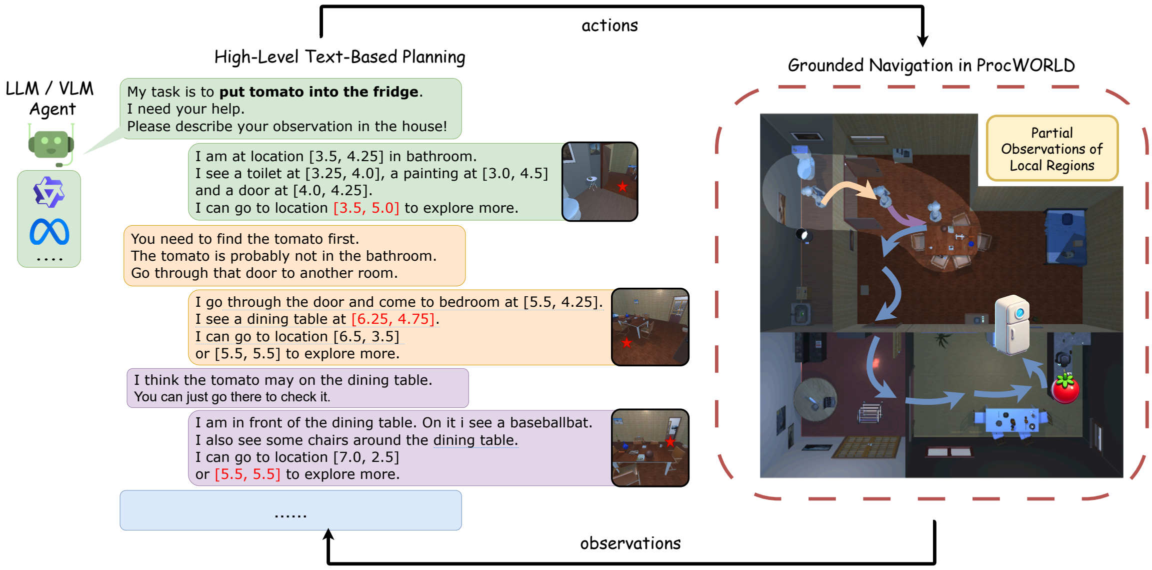

actions
High-Level Text-Based Planning
Grounded Navigation in ProcWORLD
LLM / VLM Agent
Partial Observations of Local Regions
observations

My task is to **put tomato into the fridge**.
I need your help.
Please describe your observation in the house!

I am at location [3.5, 4.25] in bathroom.
I see a toilet at [3.25, 4.0], a painting at [3.0, 4.5]
and a door at [4.0, 4.25].
I can go to location [3.5, 5.0] to explore more.

You need to find the tomato first.
The tomato is probably not in the bathroom.
Go through that door to another room.

I go through the door and come to bedroom at [5.5, 4.25].
I see a dining table at [6.25, 4.75].
I can go to location [6.5, 3.5]
or [5.5, 5.5] to explore more.

I think the tomato may on the dining table.
You can just go there to check it.

I am in front of the dining table. On it i see a baseballbat.
I also see some chairs around the dining table.
I can go to location [7.0, 2.5]
or [5.5, 5.5] to explore more.

……

Figure 1: An example where an agent (Qwen/Qwen-VL) (Yang et al., 2024; Bai et al., 2023) interacts with ProcWORLD to put a tomato into the fridge. The main challenge is partial observability. Following initial high-level task instructions (green boxes), the agent engages in dialogue (orange and purple dialog boxes and paired colored arrows in topdown-view image for the next two actions; blue for future steps). LLM agents use text-only observations, while VLM agents use image-based observations; the red star marker denotes the next target position. The agent gathers information, navigates through rooms, and completes the task.

embodied agents.

To better understand the capabilities of existing LLMs/VLMs and text-based planning algorithms, we conducted extensive experiments with **12** state-of-the-art (SOTA) LLMs and **3** VLMs. Besides, we additionally tested **5** SOTA in-context learning methods to cover multiple task types and reachability settings (full and local), totaling **1,080,000** evaluation episodes. As a summary of the results: (1) *Partial observability* poses significant challenges to the large models. For SOTA LLMs, the success rate drops by **76.43%** from 81.19% (full observability) to 19.12% (partial observability). (2) *The scaling law* holds in the context of spatial navigation, where the performance increases from 6.22% to 29.27% when scaling the Qwen2.5 backbone from 7B to 72B. (3)*VLMs demonstrate superior spatial reasoning capabilities than LLMs*. LLM-based agents achieve only a 19.66% success rate using oracle segmentation masks converted from visual observation. By contrast, VLMs taking visual inputs achieve a 21.69% success rate. This improvement demonstrates the inherent advantages of VLMs in spatial reasoning, even in the absence of perfect visual grounding—a critical capability enabled by large-scale vision-language pretraining.

2 Related Work

Embodied intelligence seeks to build agents capable of perceiving, reasoning, and acting within their environments. The field is founded on the synergy between an agent's physical form (morphology), its actions, perception, and learning processes (Liu et al., 2025a). This relationship is reciprocal: agents must learn to master their physical bodies, while their physical form fundamentally shapes and facilitates their cognitive development and what they can learn (Liu et al., 2025b). To advance this vision, the community has focused on two critical areas: creating challenging benchmarks and developing more capable agent architectures.

Embodied Navigation Benchmarks. To evaluate agent capabilities, a variety of embodied navigation benchmarks (Srivastava et al., 2022; Savva et al., 2019; Kolve et al., 2017; Deitke et al., 2022; Shridhar et al., 2020a; Li et al., 2024; Tan et al., 2023) have been developed to simulate 3D settings where agents interact with objects and navigate through rooms. While these benchmarks offer rich, visually-grounded tasks, they often misalign with the capabilities of LLMs/VLMs, which are required to generate fine-grained motion control (Liu et al., 2024). Besides, vision-only interfaces preclude the evaluation of text-only models. TextWorld (Côté et al., 2019) and ALFWorld (Shridhar et al., 2020b)

	Observation Space							
Benchmark	Vision	Text-only	Action	Multi-Room	Navigation	Planning	#Scene	#Demonstration
HM3D	✓	✗	Low Level	✓	✓	✗	216	0
iTHOR	✓	✗	Low Level	✗	✓	✗	120	0
ProcThor	✓	✗	Low Level	✓	✓	✗	10K	0
ALfred	✓	✗	Low Level	✗	✓	✓	120	8.1K
ALFWorld	✗	✗	High Level	✗	✗	✓	120	5.8K
ProcWorld (ours)	✓	✓	High Level	✓	✓	✓	5K	10M

Table 1: Comparison of benchmarks. ✓(✗) denotes the presence(absence) of a feature. # means “the number of”.

attempt to bridge this gap by using language-based abstraction. However, they assume full observability or reachability and thus bypass complex spatial reasoning for navigation (Liu et al., 2025c). Furthermore, they are confined to single-room scales, which is insufficient for evaluating reasoning ability in complex settings (see Table 1). In contrast, ProcWORLD introduces much more challenging scenarios by incorporating (1) partial observation with limited reachability, (2) multi-room settings, and (3) different observation modes (vision-language and text-only) with text-based actions.

Large Embodied Agents. On top of LLMs, In-Context-Learning (ICL) agents have become increasingly efficient in solving embodied tasks. **ReAct (Reason + Act)** (Yao et al., 2022) integrates reasoning traces with actions, enabling agents to generate both domain-specific actions and language-based thoughts for improved decision-making. Subsequent works (Liu et al., 2023; Wu et al., 2023, 2024) have improved upon ReAct by using chat modes (Liu et al., 2023), adding a commonsense knowledge base (Wu et al., 2023), and implementing state-machines (Wu et al., 2024). Particularly, **Reflexion** (Shinn et al., 2024) commits to an actor-critic design: it takes other methods as the actor and introduces an evaluator to summarize past runs while reasoning through history. We thoroughly benchmark 5 ICL methods across 12 LLM backbones, demystifying the limitations of large models on spatial reasoning and providing insights for future design choices.

```
# Predicates
class Object:
  cleanable: bool
  isClean: bool
  parent: str

# Action
def cleanObject(obj: Object):
  if obj.cleanable and not obj.isClean:
    if obj.parent == "SinkBasin":
      obj.isClean = True
```

Figure 2: Simplified representation of PDDL logic using Python-style code, illustrating the predicates and actions used in *ProcWORLD*. More examples are in the Appendix A.

3 ProcWORLD

3.1 Overview

ProcWORLD is designed with three features: (1) *Language-based Reachability-Aware Action Abstraction*, (2) *Grounded Reasoning for Long-Horizon Task Planning*, and (3) *Expansive Environments*. First, unlike previous works such as ALFWorld (Shridhar et al., 2020b) which adopt instant teleportation between semantic waypoints, ProcWORLD enforces configurable proximity thresholds, subject to restricted movements and geometric constraints. Besides, it features language-based interfaces. As a result, it aligns with VLM/LLM capability while introducing key challenges including (1) environment topology mapping through historical observations and (2) path planning through constrained spaces and obstacle avoidance. It poses challenges to spatial reasoning for state-of-the-art LLMs/VLMs. Second, ProcWORLD requires agents to perform conceptual reasoning and long-horizon task planning by decomposing high-level instructions into sequential grounded sub-goals and low-level actions. For instance, the task "heat up the milk" necessitates locating, picking, placing, and operating a microwave. It demands effective context-grounded reasoning under constraints, posing great challenges. Third, *ProcWORLD* provides large-scale multi-room layouts, complex spatial relationships, and multi-level containment structures supporting up to four levels of nesting. Built on top of the ProcThor simulation environment, it challenges agents to navigate interconnected spaces, ensuring a comprehensive evaluation of planning, reasoning, and decision-making capabilities.

3.2 ProcWORLD Setup

We build ProcWORLD environments based on

TextWorld (Côté et al., 2019) and ProcThor (Deitke et al., 2022). We brief the core design below and more details are in Appendix A. ProcWORLD integrates complementary environment frameworks to support multimodal observation modes: (1) Our text-based interface leverages TextWorld (Côté et al., 2019) for language-only interactions, enabling evaluation of language models through symbolic state representations; (2) The vision-oriented mode builds on ProcThor (Deitke et al., 2022) for photorealistic rendering while introducing high-level action primitives that bridge the semantic gap between pixel-level inputs and VLMs reasoning. This dual foundation allows unified evaluation of both text-only and vision-language models through a shared API of natural language instructions.

Text-Based Environment. We implement a lightweight symbolic environment using Planning Domain Definition Language (PDDL)(Fox and Long, 2003), deliberately abstracting collision dynamics and object size constraints to isolate evaluation of LLMs' core spatial reasoning and planning capacities. As shown in Figure 2, our PDDL framework employs custom predicate logic for deterministic state transitions, converting natural language actions into symbolic updates through rule-based state machines rather than physical simulations. The observation space comprises four semantic components: (1) *objects* (visible/navigable entities), (2) *locations* (frontier locations within reachable distance), (3) *states* (object properties like temperature/cleanliness), and (4) *relations* (containment hierarchies) – where objects and locations drive dynamic path planning, while states and relations govern interaction logic. These elements aggregate into textual observations that challenge spatial-temporal reasoning and long-horizon planning without real-world physics, creating a focused testbed for compositional understanding despite omitting stochastic environmental failures.

Vision-Based Environment. We construct our visual benchmark on ProcThor (Deitke et al., 2022) while abstracting low-level navigation through configured waypoint graphs – at each agent position, we compute reachable frontiers using Fast Poisson Sampling (FPS) and project these navigable targets as annotated markers in egocentric multi-view panoramas (see Appendix 8. This spatial abstraction allows Vision-Language Models (VLMs) to select high-level movement goals rather than micromanaging displacement controls. Interactive tasks involve atomic action chaining (e.g., *heat object* requires microwave door manipulation, object placement, and activation sequencing), reducing the need for precise motor control while maintaining physical realism. The observation space combines: (1) action success flags from previous steps, (2) object-centric RGB views requiring visual grounding of containment relationships, and (3) annotated 360° panoramas with frontier markers for path planning. By processing raw visual inputs to resolve spatial relationships and execute multi-step procedures, agents must demonstrate pixel-level scene understanding coupled with long-horizon task decomposition – directly evaluating VLMs' ability to translate perceptual data into actionable plans under partial observability.

Unified Action Space. The action space in ProcWORLD is discrete, comprising navigation and interaction actions. The action space includes: (1) *Go to Surrounding Object*: Move towards surrounding objects to check their states and relationships (e.g., moving towards a sink to discover a dirty bowl in it). (2) *Go to Frontier Location*: Navigate to frontier locations within the field of view to further explore the room. (3) *Go Through Door*: Navigate through doors to access and explore new rooms. (4) *Interact with Facing Object*: Manipulate objects directly in front of them, performing actions such as picking up, opening, slicing, etc. Navigation actions are primarily aimed at gathering more information of the environment, while interaction actions serve different purposes: some are used to acquire more information (e.g., opening a fridge to see its contents), while others are performed to manipulate objects to meet task requirements, sometimes requiring additional tools (e.g., slicing an apple with a knife).

3.3 Benchmark Statistics

Scene Diversity. Our scenes are derived from ProcThor (Deitke et al., 2022), from which we sampled 500 distinct environments. As shown in Figure 4, the scatter plot demonstrates that as the number of rooms in a scene increases, the number of objects also generally increases. This trend highlights that scenes with more rooms tend to contain more diverse objects, thereby increasing the complexity and exploration difficulty for the agent. Additionally, the color spectrum in the plot indicates a large diversity of objects and rooms, presenting varying challenges for navigation. This variety provides a robust and comprehensive evaluation of the agent's capabilities, testing their performance across differ-

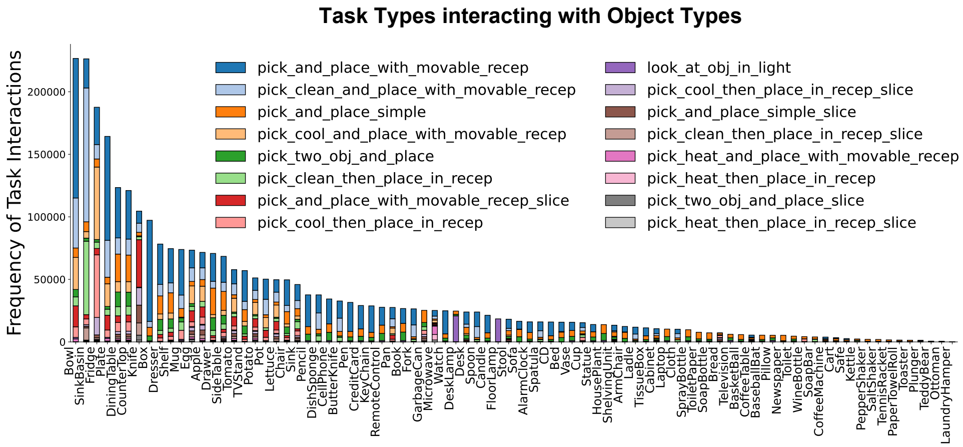


Figure 3: ProcWORLD contains 10 million evaluation variations, encompassing 16 different task types and involving 84 different object categories. The horizontal axis represents the different object types. The vertical axis indicates the frequency of interactions with each object type in the dataset. Different colors within each bar indicate the proportion of interactions for each task type with the corresponding object category.

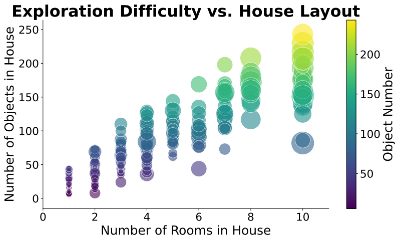


Figure 4: ProcWorld contains 5000 diverse scenes, with a rich variety of configurations and well-distributed exploration difficulties. The scenes include between 1 to 10 rooms, 6 to 243 objects, and 1 to 42 frontier locations. The bubble size represents the number of frontier locations within each scene, which correlates with the navigation difficulty.

ent scenarios with varying levels of difficulty.

Task Diversity. *ProcWORLD* features 16 distinct task types, systematically categorized in three dimensions: (1) *Object Placement*, which involves tasks such as placing an object inside another object (e.g., putting an apple in the fridge), two-level containment (e.g., placing an apple in a bowl, then placing the bowl on the countertop), and requiring careful examination of an object under a lamp (e.g., examining an object under an illuminated lamp.); (2) *Object State*, which includes tasks such as cleaning a dirty object, heating a cold object, cooling a hot object, and slicing an object; (3) *Difficulty Levels*, encompassing tasks classified as easy, medium, and hard.

We combine these 16 different task types with 84 unique object categories and integrate them into 5000 distinct scenes, generating 10 million unique evaluation variations. Each task is meticulously paired with an expert demonstration to guide learning and evaluation. The distribution of task types interacting with various object categories in our dataset is illustrated in Figure 3. This comprehensive dataset serves as a rigorous and versatile benchmark, evaluating the diverse capabilities of LLMs in handling complex household tasks and pushing the boundaries of their planning and reasoning abilities.

4 Experiments

4.1 Experiment Setup

Validation Set. We sampled 3,600 tasks from a pool of 1.2 million, covering 50 different scenes and all task types, mirroring the distribution of tasks in the full dataset. A task is considered successful if completed within 50 steps; otherwise, it is marked as a failure.

Reachability Constraint. We configure three interaction radius to evaluate spatial reasoning challenges: *infinite*, *3m*, and *1.5m*. The *infinite* setting following ALFWorld (Shridhar et al., 2020b)) permits teleportation via symbolic goto commands, eliminating navigation demands while retaining object interaction challenges. For constrained radius, we implement a dynamic topological map that enables direct return navigation to previously visited locations (*map-based*), in contrast to the memory-dependent baseline lacking mapping support(*map-free*). For text-based (LLMs) agents, we combine this map-assisted navigation with memory-dependent path integration across five configurations: infinite teleportation (ALFWorld (Shridhar

reachable Distance	Observation	Navigation	Interaction
inf	full	0.535	0.465
	total	0.535	0.465
3m	partial	0.644	0.356
	partial (map)	0.648	0.352
1.5m	partial	0.762	0.238
	partial (map)	0.790	0.210

Table 2: Proportion of Navigation and Interaction Actions in different Observation Settings, averaged over trajectories from 12 LLMs and 5 ICL methods.

et al., 2020b)), plus 3m/1.5m variations with/without cyclical mapping. Visual agents (VLMs) exclusively use the 1.5m radius with cyclical mapping to maintain embodied perception constraints, as infinite reachability violates embodied perception principles and the tighter radius better aligns with visual grounding constraints. This creates six experimental conditions (5 texts + 1 vision) for analyzing reachability impacts across modalities.

Large Model Backbone. We tested 12 state-of-the-art open-source LLMs and 1 VLM, including models from LLama (Touvron et al., 2023), Qwen (Yang et al., 2024), Phi (Abdin et al., 2024), Mistral (Jiang et al., 2023), and GLM (GLM et al., 2024) families. Specifically, we evaluated Qwen LLM models from 0.5B to 72B parameters to examine the scaling law.

In-Context Learning (ICL) Methods. We selected five baseline methods: ReAct (Yao et al., 2022), ALFChat (Wu et al., 2023), AgentBench (Liu et al., 2023), StateFlow (Wu et al., 2024), and Reflexion (Shinn et al., 2024). These methods have been previously validated for enhancing LLM performance without additional training. We only explored the ICL methods on Text-Agents (LLMs) in our study. In total, we conducted $3,600$ (runs) $\times$ 12 (LLMs) $\times$ 5 (ICL methods) $\times$ 5 (Reachability) $= 1,080,000$ runs.

4.2 Impact of Reachability Constraint

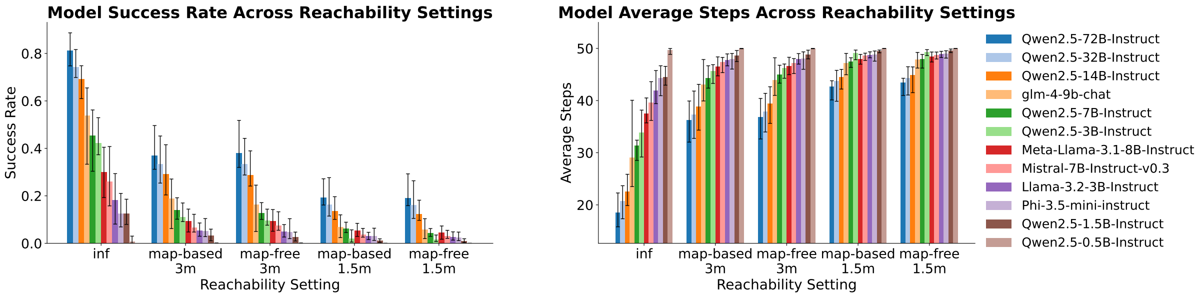
Performance drops significantly with decreasing reachable distance. Figure 5 shows the (a) success rates and the (b) steps of 12 LLMs across different observation settings. As the reachable distance decreases from infinite (full) to 3 meters (partial, 3m) and further to 1.5 meters (partial, 1.5m), we observe a noticeable decline in success rates for all 12 models. Specifically, for the state-of-the-art LLMs, the average success rate drops 53.19%, from 81.19% (full) to 38.03% (partial, 3m), and further drops 49.72%, from 38.03% (partial, 3m) to 19.12% (partial, 1.5m). Concurrently, the average number of steps taken to complete tasks significantly increases: from 18.51 steps to 36.84 steps, and further to 43.44 steps. Higher steps indicate greater difficulty in completing tasks, emphasizing that smaller reachable distances make it considerably harder for the agent.

The additional map improves the performance marginally. In the partial observation setting (3m), the average success rate increases from 14.02% to 14.45% when a dynamic map is employed. In the 1.5m setting, it increases from 6.08% to 6.73%. A similar trend has been observed on the number of steps taken. The main challenge in our tasks lies in spatial reasoning, which requires balancing between navigation to gather information and interaction with objects to complete tasks. While the dynamic map aids in the exploration process, it does not directly address this trade-off, thus offering only marginal performance gains.

Decreased reachable distance and the use of a map lead to the reduced exploration efficiency. Table 2 shows the proportions of navigation and interaction actions, where a higher proportion of navigation actions indicates lower exploration efficiency, as task completion fundamentally relies on interaction actions. The data confirms that reducing the reachable distance leads to lower exploration efficiency. Furthermore, while adding a dynamic map simplifies exploration by allowing agents to revisit known locations directly, it also makes LLMs focus more on navigation. Consequently, LLMs adopt more actions for navigation, leveraging the map to conduct more navigation attempts rather than trading off for more efficient object interactions.

4.3 Impact of Observation Space

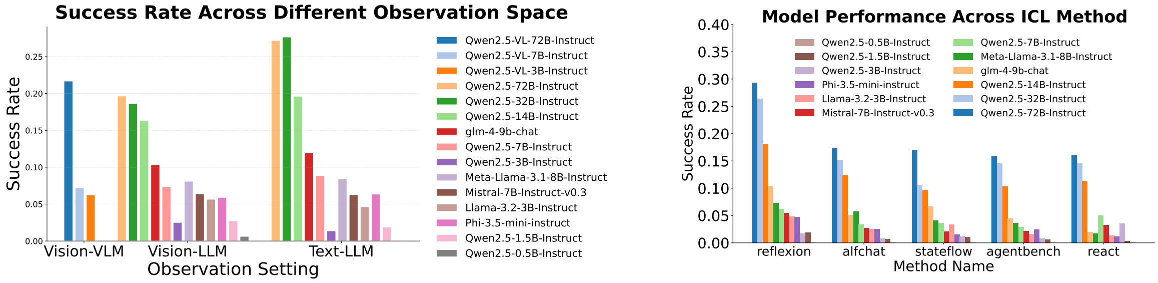
VLMs exhibit enhanced spatial reasoning through visual pretraining. As demonstrated in Figure 6a, our comparative analysis of vision-VLM and vision-LLM agents reveals critical modality-specific advantages. Given the same model architecture and size, the vision-VLM architecture (Qwen2.5-VL-72b), which processes raw visual inputs through its multimodal backbone, achieves a 21.69% success rate. By contrast, vision-LLM's (Qwen2.5-72b-instruct) achieves only 19.66% performance even with oracle-segmented textual descriptions. This performance gap persists despite both approaches running under identical visual-world constraints. It indicates that visual grounding through pretrained encoders provides superior



(a) The success rate of in 5 reachability settings.

(b) The average steps in 5 reachability settings.

Figure 5: Performance of 12 LLMs across 5 different reachability settings in Text-Environment. The settings are divided by reachable distance: infinite (inf), 3 meters (3m), and 1.5 meters (1.5m). Each bar represents the average (a) **Success rates**, (b) **Steps** across five In-Context Learning (ICL) methods.



(a) The Success Rate across different observation spaces.

(b) The Success rate across 5 ICL methods.

Figure 6: Comparison of success rates in different settings: (a) vision-based and text-based models under constrained reachability in a map-based environment, (b) 12 LLM backbones across various ICL methods in a partial observation setting.

spatial reasoning compared to textualized observations. Our results substantiate that large-scale vision-language pretraining enables VLMs to extract latent geometric relationships from pixel data that transcend the representational capacity of language descriptions.

Text-based environments are good indicators for spatial reasoning capabilities. Although they removed the vision inputs, the Text-LLMs show strong correlation with the Vision-LLMs: they demonstrate the same trend in model ranking. In our experiments, the PDDL-driven text environment preserves the essential multi-room navigation challenges while achieving 7.8× faster simulation speeds than its visual counterpart. Thus, we believe it can be used as a fast evaluation protocol for the spatial reasoning capabilities for LLMs.

4.4 Impact of LLM Backbone Choices

Increasing model size significantly improves performance. As Qwen2.5 offers a range of models from 0.5B to 72B parameters, we assessed the relationship between model size and performance. Figure 5 highlights our focus on the Qwen2.5 models across a range of parameters. As model size increases, there is a notable and consistent improvement in success rates and a corresponding decrease in the number of steps required to complete tasks across all observation settings. Both the 3B and 1.5B models perform reasonably well under full observation, but their performance drops dramatically to near zero when the reachable distance is restricted. The 0.5B model consistently produces near-zero performance, indicating that smaller models are incapable of complex spatial reasoning.

Different models exhibit varying strengths in planning and spatial reasoning across observation settings. For the 3B models, Qwen2.5 demonstrates outstanding performance in the full observation setting. However, under partial observation (1.5m/3m, with/without map), Llama-3.2 and Phi-3.5-mini achieve comparable performance and even surpass Qwen2.5. This indicates that while Llama-3.2 and Phi may slightly lag behind Qwen2.5 in planning capabilities, they exhibit superior spatial reasoning abilities, enabling them to better handle tasks with partial observations. In the 7B models, Qwen2.5 significantly outperforms Llama and Mistral in the full observation setting. However, in the partial observation setting, Llama exhibits better performance, consistent with the findings in the 3B models. This discrepancy may be attributed to the composition of their training data, where Qwen models excel in planning while Llama models demonstrate stronger spatial reasoning capabilities.

4.5 Impact of In Context Learning Methods

More sophisticated ICL methods improve LLM performance but face limitations in spatial reasoning. In-context learning (ICL) methods have been widely validated as a training-free approach to enhance the capabilities of LLMs. We evaluated five ICL methods: **ReAct (Reason + Act)** (Yao et al., 2022), **AgentBench** (Liu et al., 2023), **ALFChat** (Wu et al., 2023), **StateFlow** (Wu et al., 2024), and **Reflexion** (Shinn et al., 2024). Each method progressively introduces novel enhancements(see Section 2), with Reflexion generally yielding the best results, followed by StateFlow, ALFChat, AgentBench, and ReAct, as shown in Figure 6b. This ordering is consistent with previous research findings (Liu et al., 2021; Lu et al., 2021; Wei et al., 2022; Wu et al., 2022), which demonstrate that more sophisticated ICL methods generally boost model performance. The results indicate that Reflexion significantly improves model performance across all methods. However, ALFChat and StateFlow only slightly improve performance over AgentBench and ReAct, with minimal differences among these four methods. Even with Reflexion combined with the best model (Qwen2.5-72B), the success rate does not exceed 30%. For comparison, Figure 5a shows that the best combination of Reflexion and Qwen2.5-72B in the full observation setting achieves a success rate of nearly 90%. This disparity suggests that while ICL methods can enhance planning capabilities, their impact on spatial reasoning remains limited. The performance gains from Reflexion are largely attributed to its replay mechanism, which increases computational overhead by repeatedly executing tasks to learn from past experiences, rather than fundamentally improving spatial reasoning abilities.

4.6 Impact of Task Diversity

Model performance severely declines with distant movement and more object state constraints. While average success rates can mask the variability in task difficulty and distribution, we analyzed the agent's performance on different task types in the validation set, as shown in Figure 7. As object state requirements increase, model performance shows a declining trend, visible in the descending position of bubbles of each color along the x-axis. Additionally, as movement requirements increase, performance similarly declines, as indicated by the descending order of different-colored bubbles at each x-axis position. In this setting, the model achieves an average success rate of around 30%, primarily due to its relatively strong performance on tasks with fewer movement and state requirements. However, performance on harder tasks drops significantly, often approaching zero. This stark drop highlights the challenge posed by complex, long-horizon tasks. The poor performance on these tasks, which require sustained exploration and advanced spatial reasoning, underscores the need for further advancements in large language models (LLMs) to handle complex, multi-step reasoning tasks effectively.

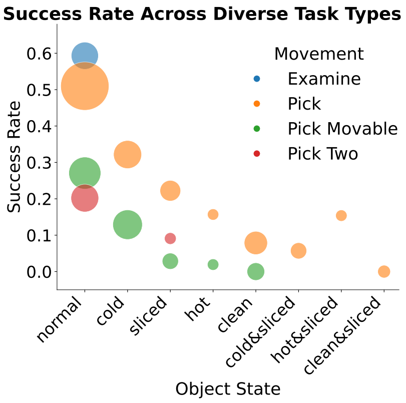


Figure 7: Success rates of 16 distinct task types using the best model (Qwen2.5-72B) in a partial observation setting (reachable distance = 1.5m, without map). The bubble size corresponds to the task type's proportion in the validation set.

This trend is further emphasized by the distribution of task types in our test set. Simpler tasks (involving fewer movements and minimal state requirements), though less varied, dominate the validation set proportionally, reflecting real-world scenarios where tasks such as pick-and-place are frequent. In contrast, more complex tasks, such as cleaning and cutting an apple, are less common but more diverse in type. This distribution is visualized in Figure 7, where the size of the bubble represents the proportion of tasks in the validation set. The realistic yet challenging task distribution further highlights the need for LLMs to handle a wide range of task complexities effectively.

5 Discussion

ProcWORLD presents unique challenges, particularly in testing the spatial reasoning capabilities of LLMs and VLMs within a constrained reachability environment. By restricting the agent's field of view and requiring navigation through complex multi-room spaces, ProcWORLD demands that LLMs/VLMs perform active information gathering and reasoning based on limited observations. This constrained reachability setup forces LLMs/VLMs to rely on sequential decision-making and memory of past observations to effectively localize, navigate, and complete tasks, underscoring the difficulty in translating high-level language instructions into actionable steps under constrained visibility. Future work could expand ProcWORLD with more expert data to further enhance the spatial reasoning capabilities of large models.

Limitations

Despite the comprehensive design, our benchmark has certain limitations. The assertion a 360° field of view simplifies navigation suggests that agents can detect all nearby objects without altering their orientation. Furthermore, we overlook real-world physics constraints, such as collision avoidance and the impossibility of fitting large objects into smaller containers. While these simplifications make it easier to isolate and evaluate the planning and reasoning components, they do diverge from real-world embodied agent constraints. Even in the visual domain of ProcWORLD, the images rendered by the ProcThor are relatively simplistic and easier to ground compared to the real world. In the real world, agents may encounter more complex scenarios and issues. Moreover, our benchmark does not consider specific manipulation problems, which are crucial in embodied tasks and require highly precise control. We believe that current LLMs/VLMs are not yet capable of such fine-grained control. Thus, employing a hierarchical strategy may offer a promising path for transferring agents that excel on ProcWORLD to real-world applications.

Future work could expand ProcWORLD by utilizing the 1.2 million tasks paired with expert demonstrations as a pretraining dataset, enhancing LLM spatial reasoning through domain-specific pretraining. Such a dataset could significantly improve LLMs performance on complex tasks requiring multi-step spatial reasoning, and introducing constraints for real-world physical interactions could further bridge the gap between simulated and real-world environments. Continued development in this direction promises to advance embodied LLMs toward more robust and practical real-world applications.

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A Text World Settings

ProcWORLD establishes a text-based household environment. Specifically, when a task begins in ProcWORLD, the agent is randomly initialized at a location within a house and is tasked with completing a long-horizon household task (e.g., cleaning and cutting an apple, placing it in a bowl, and then putting the bowl into the refrigerator). The agent can observe the environment with a 360-degree view, identify surrounding objects, and note **frontier locations**—points at the boundary of the currently explored area that can be navigated to in order to reveal new parts of the environment. These frontier locations serve as potential areas for further exploration, allowing the agent to dynamically plan routes and make decisions based on the expanding observable space. Additionally, the agent can directly observe the containment relationships of objects positioned in front of it. In each step, the agent can choose to interact with the object in front of it to change its state or position as required by the task, move toward a surrounding object to perform subsequent interactions, or navigate to a frontier location to explore new observable areas. The agent must manipulate the state and position of objects through these interactions to meet the task requirements. Actions such as moving to surrounding objects or frontier locations are primarily aimed at gathering more observations to inform subsequent interactions, which are essential for achieving the task objectives.

A.1 PDDL

ProcWORLD is constructed based on the Planning Domain Definition Language (PDDL)(Fox and Long, 2003), as defined in TextWorld(Côté et al., 2019). PDDL uses predicate logic to model Partially Observable Markov Decision Processes (POMDP), defined as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{O}, T, O, R)$. In POMDP, $\mathcal{S}$ is the state space, $\mathcal{A}$ the action space, $\mathcal{O}$ the observation space, T the transition function, O the observation function, and R the reward function. States are partially observable, and the goal is to maximize the expected reward over time by making a sequence of decisions based on observations of the system.

Instance Space. PDDL begins by defining the instance space to determine which instances are of interest in the current game. This provides a framework for identifying relevant entities within the environment.

Predicates. For these instances, PDDL defines their properties using predicates. Predicates capture the attributes of instances and the relationships between them. They are a mapping from instances to a true or false value, indicating whether a particular property holds for that instance. In this way, PDDL describes $\mathcal{S}$ using instances and predicates.

Actions. The action space $\mathcal{A}$ is discrete. Each action (a_t) in PDDL is defined by the conditions under which it can occur (preconditions that the state s_t must meet) and the changes it causes in the instance predicates (effects that transform s_t into s_{t+1}). The transition function T ($s_{t+1} \sim T(s \mid s_t, a_t)$) is deterministic, meaning it uniquely transitions from the current state to a new state based on the action taken.

Initial State and Reward Function. In PDDL, we need to define s_0 and $R(r \mid s_t, a_t)$. Specifically, PDDL requires us to specify the initial predicates states for all instances. As the transition function T is deterministic, the reward function only depends on s_{t+1}. PDDL allows for the definition of a sparse reward function, providing a reward only when certain conditions in s_{t+1} (predicate states) are met, thus marking the task as complete and returning a reward of 1.

Translator. PDDL also defines a Translator, corresponding to the O function $o_{t+1} \sim O(o \mid s_t, a_t)$. This component abstracts the predicate logic and actions into natural language to create new observations for the agent after an action is executed. Similarly, the Translator maps the agent's natural language actions to the discrete action space in PDDL, enabling the agent to interact with the environment using natural language and effectively building our TextWorld.

Visual World to Text World. To map scenes from the visual world, specifically from ProcThor(Deitke et al., 2022), into our text-based environment, we utilize predefined predicate logic to extract the initial state (s_0) from ProcThor. Details of this process can be found in Appendix 9.

A.2 Instance Type

Receptacles and Objects. In ProcWORLD, objects within a scene are categorized into several types to reflect their roles and properties. **Receptacles** are fixed objects that cannot be moved and can hold other objects (e.g., dining tables and countertops). **Objects**, on the other hand, are items that can be picked up and moved, such as plates and cups. This distinction helps to define how different types of objects interact within the environment.

Rooms and Doors. Given that ProcThor consists of multiple rooms, we introduce the concepts of **rooms** and **doors** to represent more complex scenarios. Rooms can include different types such as Kitchens, Living Rooms, Bathrooms, and Bedrooms, as well as open spaces where adjacent rooms are not separated by doors. To navigate and complete tasks, agents need to identify and explore the doors that connect rooms. Depending on the exploration status of the current room and the task requirements, agents decide whether to "go through the door to the next room" to continue their exploration.

Locations. Locations are categorized into: (1) The locations of receptacles, objects, and doors within the scene, represented by the coordinates of their centers in the 3D space. Given that ProcWORLD defines a partially observable environment, an object is considered visible if the distance between the agent's location and the object's location is less than the visible distance. Therefore, dumping these instances' locations is essential for determining the relative positions between the agent and the instances; (2) Frontier locations. To enhance exploration tasks within a single room, we incorporate the concept of **frontier locations**. Inspired by the classic navigation algorithm of frontier exploration, we implement clustering and sampling of various points at the boundary of the agent's current field of view. These frontier locations serve as exploration targets for the agent, which the agent can visit to expand its observational range and gather more information about the environment.

We use the Farthest Point Sampling (FPS) method to ensure effective sampling of frontier locations in the ProcThor environment. This method ensures that all frontier locations within a room are fully connected, allowing the agent to move freely between these points without barriers and ensuring comprehensive exploration. Once the agent has visited all frontier locations within a room, all objects in that room will have been observed. This mechanism ensures the agent can thoroughly explore a room and discover all objects that might be used to complete the task. By navigating between rooms through doors and exploring within rooms using frontier locations, agents can perform a comprehensive and thorough exploration of the environment in ProcWORLD. An example of such a frontier location setup is shown in Figure 8.

A.3 Predicates Definition

We design specific predicates to capture the states and relations of the various instance types (object, receptacle, room, door, location) introduced in Appendix A.2. These predicates serve to represent the properties and states of the instances within the game environment. For example, predicates such as (adjacent ?l1 - location ?l2 - location) return true if two locations are adjacent. Similarly, (isCool ?o - object) indicates whether an object is cold. This detailed list of predicates provides the foundation for the interactions in the text-based environment by capturing the relations and states of objects, agents, and locations (see Figure 9).

Object Properties. Predicates that describe the properties of objects (e.g., (isCool ?o - object), (isClean ?o - object)) are crucial for determining whether an object's state meets the specific requirements of a task. For example, in tasks such as cleaning and cutting an apple, placing it in a bowl, and then putting the bowl into the refrigerator, the state of the instance (apple) must be clean and sliced. These predicates form an essential part of our goal definitions.

Containment Relationships. Predicates that describe containment relationships between instances include (receptacleInReceptacle ?sr - receptacle ?pr - receptacle), (objectInReceptacle ?o - object ?r - receptacle), and (objectInObject ?so - object ?po - object). We support up to four levels of nesting for these relationships. This nesting relationship is another essential part of our goal definitions. For example, in the previously mentioned task, the final containment relationship required is apple in bowl, and bowl in fridge.

Adjacency Relationships. Predicates such as (adjacent ?l1 - location ?l2 - location) describe adjacency relationships between locations. If the distance between two locations is less than the visible distance, they are considered adjacent. This adjacency relationship applies to both object locations and frontier locations. For frontier locations, adjacency indicates that the agent can move from one to another to continue exploration, while for object locations, it signifies visibility between objects.

Agent Location. The agent's location is defined such that the agent can only be at object locations (facing the object to interact with it) or frontier locations (navigating within the scene). Predicates such as (agentAtLocation ?a - agent ?l - location) capture the agent's current position in relation to

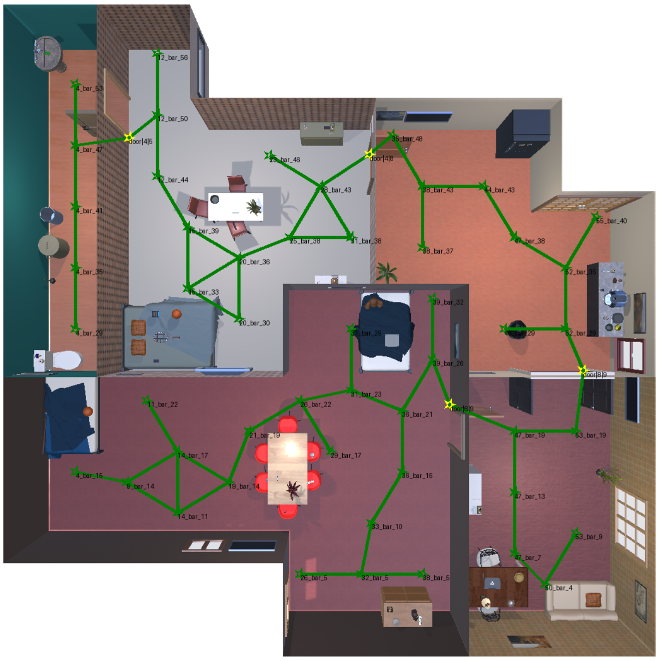

Figure 8: The green points represent frontier locations, the yellow points represent doors, and the lines represent traversable paths. Such a frontier location setup ensures full connectivity throughout the scene and guarantees complete visibility coverage of the room upon traversal.

these locations, facilitating interaction and navigation within the environment.

Rooms and Doors. The relationship between rooms and doors is captured using predicates that indicate the connection or adjacency between rooms via doors or open spaces. Rooms are considered adjacent if there is a door connecting them or if they are in an open space without a door. When the agent's location is adjacent to a door's location, it can pass through the door to enter another room.

A.4 Action Space

We define actions to change the state of the predicates, allowing agents to interact with the environment. Actions are specified by their parameters, preconditions, and effects. The parameters define the instances involved in the action, preconditions must be satisfied for the action to be executed, and effects describe the state changes resulting from the action. In Figure 9, the action (CleanObject) is defined with parameters (?r - receptacle ?o - object), preconditions indicating that the object must be cleanable and in a sink, and an effect setting the predicate (isClean ?o) to true.

In ProcWORLD, our actions can be categorized into several types. **(1) Navigation actions**, such as "Goto frontier location," "Go through door to next room," and "Go near object," expand the agent's field of view and enhance its understanding of the current state. These actions are fundamental for exploration in a partially observable environment. For instance, the action (GotoNearby) allows the agent to move to a new frontier location. We also have **(2) Interaction actions**, which include tasks such as "Pick," "Place," "Open," "Close," "Turn on," and "Turn off." These actions aim to change the state or placement of objects to achieve specific task goals. For example, the action (CleanObject) enables the agent to clean an object in a sink.

Navigation actions help expand the agent's view and understanding of the environment, while interaction actions modify object states or placements to meet specific task requirements. By combining these actions, agents can effectively plan and execute the necessary steps to complete tasks in a partially observable environment.

A.5 Observation Space

In ProcWORLD, the agent's observation space is critical for making informed decisions about its actions. Depending on whether the agent is at a frontier location or an object location, different types of observations are provided.

Frontier Location. When the agent is at a frontier location, it receives observations about its surrounding environment. Specifically, the agent can see

```
# Predicates
(agentAtLocation ?l - location)
(receptacleType ?r - receptacle ?rt - rtype)
(objectInReceptacle ?o - object ?r -
    receptacle)
(objectInObject ?so - object ?po - object)
(openable ?r - receptacle)
(opened ?r - receptacle)
(closed ?r - receptacle)
(isClean ?o - object)
(cleanable ?o - object)
(isHot ?o - object)
(heatable ?o - object)
(isCool ?o - object)
(coolable ?o - object)
(pickupable ?o - object)
(toggleable ?o - object)
(isOn ?o - object)
(isOff ?o - object)
(sliceable ?o - object)
(isSliced ?o - object)
(adjacent ?l1 - location ?l2 - location)

# Actions
(:action GotoNearby
  :parameters (?lStart-location ?lEnd-
    location)
  :precondition (and
    (agentAtLocation ?lStart)
    (adjacent ?lStart ?lEnd)
    (frontierLocation ?lEnd)
  )
  :effect (and
    (not (agentAtLocation ?lStart))
    (agentAtLocation ?lEnd)
  )
)
(:action CleanObject
  :parameters (?r-receptacle ?o-object)
  :precondition (and
    (cleanable ?o)
    (receptacleType ?r SinkBasinType)
    (objectInReceptacle ?o ?r)
  )
  :effect (and
      (isClean ?o)
  )
)
```

Figure 9: Examples of predicates and PDDL actions in ProcWORLD. The predicates define properties and relationships between various instance types, while the actions demonstrate a navigation action (GotoNearby) and an interaction action (CleanObject).

visible objects within its field of view, adjacent frontier locations available for further exploration, and any doors leading to other rooms (if exists). The agent can choose to move closer to a visible object to interact with it, travel to another frontier location to expand its view, or move to another room through a door.

Object Location. When facing the object, the agent receives detailed observations about the object. These observations include the containment relationships (e.g., whether the object is inside a receptacle or another object), the current state of the object (e.g., dirty, cold, etc.), and similar information about visible objects, adjacent frontier locations, and doors as observed from the frontier location. The agent can interact with an object only when it is facing the object, so the agent must decide whether to adjust the containment (placement) of the object to satisfy task requirements, or determine if the object's state needs to be changed through actions such as cleaning, heating, slicing, or cooling to meet the goal's criteria.

By providing these nuanced observations, ProcWORLD ensures that the agent can gather all necessary information to plan and execute actions effectively. Whether the agent is expanding its observational range from a frontier location or closely examining an object at the object location, it can make informed decisions that help it navigate and interact within the environment to achieve its tasks.

B In Context Learning Method

Based on the characteristics of pure text interaction environment in ProcWORLD, we can utilize large language models (LLMs) for interaction. For LLM-based agents, in-context learning (ICL) has been widely validated as an effective method to improve model performance. ICL methods are training-free, meaning they do not require additional parameter updates during test-time, making them adaptable and efficient. They leverage few-shot learning by presenting examples and design the thought step in the context, thereby improving the LLM's ability to understand and perform tasks. This method allows the agent to utilize the pre-existing knowledge of the LLM while dynamically adapting to the specific task at hand through context presentation. Next, we will introduce the ICL method tested in our validation set.

B.1 ReAct

ReAct (Synergizing Reasoning and Acting) (Yao et al., 2022) enhances the capabilities of LLMs by incorporating few-shot learning and chain-of-thought (CoT) methodology. This enables LLMs to not only see examples but also improve their performance by reasoning before taking actions. The ReAct framework augments the agent's action space to include both traditional actions and a space of language (thoughts). An action in the language space, referred to as a thought or a reasoning trace, does not affect the external environment directly but helps compose useful information and supports future reasoning and acting.

At each step, the ReAct agent alternates between generating thoughts and taking actions based on both the current context and the reasoning provided by the thought. This is particularly useful in complex task-solving where decomposition of goals and plans, injecting commonsense knowledge, extracting important parts of observations, and handling exceptions are necessary.

B.2 AgentBench

AgentBench (Liu et al., 2023) builds upon the principles of ReAct and introduces advanced mechanisms to enhance the decision-making process of LLM-based agents. Specifically, it retains the core idea of integrating reasoning steps with actions but adds a chat mode to enable multi-turn conversations with an instruct finetuned LLM. Moreover, AgentBench incorporates admissible commands to present the agent with a set of possible actions based on the current state, helping LLMs to be better grounded in the current context for the next action.

In addition, AgentBench refines the design of few-shot examples to provide more contextually relevant prompts, thereby improving the agent's performance. This iterative process of planning, acting, and reasoning enables the agent to dynamically adapt its strategy based on feedback from the environment, achieving higher performance in complex, partially observable environments.

B.3 ALFChat

ALFChat (Wu et al., 2023) builds upon the principles of AgentBench and introduces a multi-agent conversational approach to enhance the decision-making capabilities of LLM-based agents. Specifically, we implement a three-agent system consisting of an executor, an assistant, and a grounding agent based on Autogen(Wu et al., 2023). This approach leverages the strength of collaborative reasoning and decision-making to improve performance in complex, partially observable environments.

In the ALFChat framework, the executor agent is responsible for executing actions in the environment and reporting back the outcomes. The assistant agent generates plans and action suggestions based on the current state and objectives, similar to the role it plays in AgentBench. The key enhancement in ALFChat is the introduction of the grounding agent, which supplies commonsense knowledge to the assistant agent when needed. This additional agent helps the system to better understand the context and rules of the environment. By providing real-time knowledge support, the grounding agent helps prevent the assistant agent from missing critical details or making repetitive errors. This method ensures that the agent team can make more informed decisions and adaptively refine the plan.

B.4 StateFlow

StateFlow(Wu et al., 2024) builds upon the principles of AgentBench by explicitly constructing a state machine to determine the current status of tasks and decompose them, aiming to assist the agent in task execution.

The primary enhancements in StateFlow are its detailed task decomposition and state management, which allow the agent to more effectively handle complex tasks through a structured state machine approach. This method explicitly defines various states and transitions, helping the agent understand its current task state and the subsequent actions required.

We reproduced StateFlow based on the details in the original paper. Moreover, considering our new tasks involving slicing and dual object placement requirements (e.g., apple in bowl, bowl in fridge), the original state machine was inadequate. We therefore updated it to accommodate these new complexities, ensuring that the tasks were appropriately managed through the state transitions.

The updated state machine includes the following states:

- **Init:** The initial state where the task begins.
- **Plan:** Direct interaction with the LLM to generate a plan based on current instructions.
- **Pick:** State for selecting the necessary object for the task.
- **Process:** Actions involving heating, cooling, slicing, or cleaning the object.
- **FindLamp:** Specific state for locating a lamp if needed.
- **UseLamp:** Utilizing the found lamp for the task.
- **Put:** Placing the object in its final location.
- **End:** The terminal state indicating task completion.
- **Error:** Handling errors when incorrect actions are performed (e.g., picking the wrong object).

In the state **Pick**, for instance, the agent transitions to different states based on the task type. For states such as **Pick**, **Process**, **FindLamp**, **UseLamp**, and **Put**, the agent remains in the current state if the task is not yet fully completed, as indicated by gray semi-circle arrows in the state machine.

This explicit construction of the state machine enables the agent to dynamically adapt to new and complex tasks, providing both robustness and flexibility in handling various task requirements. By integrating real-time feedback from the environment into the state transitions, StateFlow ensures that the agent can make informed decisions and adjust its plan as needed to achieve higher performance and accuracy.

B.5 Reflexion

Reflexion (Shinn et al., 2024) introduces a plug-in methodology designed to enhance LLM-based agents' decision-making capabilities by combining reasoning and self-Reflexion within an iterative process. This approach involves three main components: the Actor, the Evaluator, and the Self-Reflexion model. The Actor is responsible for generating actions based on the current state, the Evaluator assesses the effectiveness of these actions, and the Self-Reflexion model provides feedback by analyzing the outcomes and storing insightful experiences in memory.

A primary advantage of Reflexion is its easy integration into existing frameworks, making it a versatile enhancement tool for LLM-based agents. Reflexion can be conveniently applied to methods such as ReAct, AgentBench, ALFChat, and StateFlow, enabling these systems to iteratively improve their performance by leveraging self-Reflexion for more informed decision-making.

Given the observed performance outcomes across the four ICL methods, we chose to implement Reflexion within the AgentBench framework due to its computational efficiency. Specifically, we set a maximum of 5 rerun attempts to ensure optimal resource utilization during evaluations. This integration enhances the decision-making process of AgentBench, enabling our experiments to achieve better performance with minimal computational overhead.

C Experiment Results

C.1 Detail Results in Text World

The detailed results, including success rates and average steps for each ICL method, measured on the validation set for 12 LLM models and 5 distinct observation settings in the TextWorld benchmark, are provided in the following tables. Specifically, the performance of ReAct is shown in Tables 3 and 4, AgentBench in Tables 5 and 6, ALFChat in Tables 9 and 10, StateFlow in Tables 7 and 8, and Reflexion in Tables 11 and 12.

These settings cover both full and partial observation scenarios, offering a comprehensive evaluation of model performance. Each combination of ICL methods and LLMs was systematically tested under these conditions to analyze their reasoning and decision-making capabilities across varying observation constraints.

C.2 Results in Aligned Visual World

As introduced in Section 3, we aligned the ProcWORLD environment with a visual world by utilizing oracle depth images and instance segmentation images to extract oracle voxel space information, which was then mapped onto a 2D map. Observations around the agent were described in text using the ProcWORLD style and provided to the LLM. Dynamic frontier navigation based on the 2D map was performed to achieve exploration similar to that in ProcWORLD.

We conducted experiments on ProcThor (Deitke et al., 2022) to evaluate the visual world alignment. The experimental results are shown in Table 13. In the visual world, we maintained the same visible distance setting of 1.5m to ensure a fair comparison with the observation settings in the text world, specifically partial (1.5m) and partial(map, 1.5m).

From the results, we observe a noticeable drop in success rates and a significant increase in the average number of steps in the ProcThor environment. Despite using oracle data, challenges such as navigation collisions and object size conflicts during placement persist in ProcThor. These challenges highlight the limitations of LLMs in handling conflicts and recovering from errors effectively.

This experiment demonstrates the increased difficulty of navigation and task execution in a visual world, further emphasizing the need for advanced capabilities in LLMs to handle real-world complexities.

C.3 Validation on GPT4o

Our experiments required evaluating 5 observation settings $\times$ 5 ICL methods $\times$ 3600 (validation set runs) $\times$ 50 (max steps) $\times$ 2048 (max tokens per input + output) = 9000M tokens per LLM. Moreover, Reflexion required up to 5 reruns, effectively doubling the token consumption. Due to the prohibitive costs of GPT4o under these conditions, we limited its evaluation to the Alfchat ICL method and the partial (map, 1.5m) observation setting.

We made this choice for the following reasons: (1) Alfchat, aside from Reflexion, performed best on open-source models, offering a cost-effective alternative since Reflexion's 5x token usage did not yield significant performance improvements. (2) The partial (map, 1.5m) setting was identified as the most challenging in our tests on open-source models.

Even under these constrained conditions, we spent approximately $500 on GPT4o experiments. The results are presented in Table 15. We compared GPT4o with the top-performing open-source LLMs, Qwen2.5-72B and Qwen2.5-32B, across 16 task types using the same ICL method (Alfchat) and observation setting (partial (map, 1.5m)). While GPT4o outperformed the open-source models in most task types, its average success rate was only 0.189. The marginal improvement over the open-source models highlights that even the most advanced LLMs still have significant room for improvement in spatial reasoning capabilities.

C.4 Rerun in Reflexion

Reflexion, as previously discussed, improves model performance by summarizing failures from rollouts and applying these insights in subsequent attempts.

Figures 10 and 11 illustrate the performance of Reflexion over the first k reruns, where each subplot represents the results of 12 LLMs. Reflexion's performance is evaluated across six observation settings, including five from ProcWORLD and one aligned with ProcThor's visual world.

The results show a significant performance improvement during the first three reruns. However, after the third attempt, gains diminish, with the fourth and fifth attempts showing minimal improvement. This indicates that while ICL methods like Reflexion can enhance LLM capabilities to some extent, their impact is ultimately constrained by the LLM's inherent spatial reasoning limits.

To overcome these limitations, future work should focus on designing training datasets that enhance spatial reasoning capabilities, enabling LLMs to better address the challenges of embodied tasks.

D Episode Examples

We provide examples from 7 rollouts, all conducted under the ProcWORLD partial(map, 1.5m) setting. These examples involve three different ICL methods: Reflexion, ReAct, and ALFChat, as well as four distinct models: GPT4-o, Qwen2.5-72B, Qwen2.5-32B, and Qwen2.5-7B.

Among these, only Qwen2.5-72B using Reflexion (see Table 16) and GPT4-o using ALFChat (see Table 15) successfully completed the tasks. The other combinations of ICL methods and models failed. From the rollouts, it is evident that smaller models tend to get stuck in repetitive cycles, remaining in local exploration without successfully navigating the partial environment. This highlights the challenge of effective navigation in partially observable environments, where larger models with advanced ICL methods are better able to handle the task.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	0.802	0.320	0.312	0.160	0.182
Qwen2.5-32B-Instruct	0.772	0.288	0.254	0.146	0.135
Qwen2.5-14B-Instruct	0.722	0.241	0.204	0.113	0.101
glm-4-9b-chat	0.333	0.050	0.062	0.020	0.024
Meta-Llama-3.1-8B-Instruct	0.405	0.051	0.048	0.017	0.029
Qwen2.5-7B-Instruct	0.562	0.101	0.101	0.050	0.062
Mistral-7B-Instruct-v0.3	0.408	0.068	0.053	0.032	0.028
Llama-3.2-3B-Instruct	0.294	0.027	0.030	0.013	0.016
Phi-3.5-mini-instruct	0.167	0.019	0.028	0.011	0.012
Qwen2.5-3B-Instruct	0.380	0.089	0.097	0.035	0.057
Qwen2.5-1.5B-Instruct	0.186	0.010	0.011	0.003	0.014
Qwen2.5-0.5B-Instruct	0.030	0.001	0.000	0.000	0.000

Table 3: **React** success rate results across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	28.33	63.92	62.91	44.26	43.14
Qwen2.5-32B-Instruct	31.32	71.72	73.67	44.73	44.79
Qwen2.5-14B-Instruct	35.97	72.87	75.69	45.83	45.98
glm-4-9b-chat	67.12	162.87	172.45	49.23	49.04
Meta-Llama-3.1-8B-Instruct	59.53	180.89	184.03	49.31	48.85
Qwen2.5-7B-Instruct	48.77	176.87	177.05	48.09	47.50
Mistral-7B-Instruct-v0.3	63.89	91.34	92.75	48.70	48.84
Llama-3.2-3B-Instruct	71.94	94.35	95.26	49.44	49.35
Phi-3.5-mini-instruct	83.19	94.59	95.08	49.55	49.50
Qwen2.5-3B-Instruct	64.59	88.73	88.66	48.62	47.83
Qwen2.5-1.5B-Instruct	77.24	82.83	87.05	49.88	49.42
Qwen2.5-0.5B-Instruct	95.32	96.01	96.44	49.99	49.99

Table 4: **React** average steps across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	0.748	0.347	0.343	0.159	0.161
Qwen2.5-32B-Instruct	0.699	0.307	0.315	0.147	0.137
Qwen2.5-14B-Instruct	0.610	0.265	0.271	0.104	0.113
glm-4-9b-chat	0.538	0.167	0.195	0.045	0.058
Meta-Llama-3.1-8B-Instruct	0.193	0.077	0.072	0.036	0.039
Qwen2.5-7B-Instruct	0.304	0.104	0.11	0.029	0.045
Mistral-7B-Instruct-v0.3	0.192	0.057	0.049	0.021	0.03
Llama-3.2-3B-Instruct	0.081	0.026	0.03	0.016	0.019
Phi-3.5-mini-instruct	0.069	0.035	0.035	0.024	0.034
Qwen2.5-3B-Instruct	0.386	0.076	0.096	0.008	0.005
Qwen2.5-1.5B-Instruct	0.085	0.022	0.033	0.006	0.004
Qwen2.5-0.5B-Instruct	0	0	0	0	0

Table 5: **Agentbench** success rate results across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	20.12	37.33	36.84	44.50	43.78
Qwen2.5-32B-Instruct	21.26	38.19	37.41	44.89	44.77
Qwen2.5-14B-Instruct	24.71	39.70	39.22	46.14	45.52
glm-4-9b-chat	27.83	43.87	42.69	48.44	47.83
Meta-Llama-3.1-8B-Instruct	42.34	47.42	47.50	48.70	48.53
Qwen2.5-7B-Instruct	37.65	45.94	45.56	48.82	48.28
Mistral-7B-Instruct-v0.3	42.43	47.86	48.14	49.28	48.92
Llama-3.2-3B-Instruct	46.63	48.96	48.80	49.45	49.28
Phi-3.5-mini-instruct	47.00	48.56	48.66	49.08	48.72
Qwen2.5-3B-Instruct	34.69	46.91	46.15	49.68	49.79
Qwen2.5-1.5B-Instruct	46.41	49.04	48.59	49.75	49.82
Qwen2.5-0.5B-Instruct	49.99	49.99	50.00	50.00	50.00

Table 6: **Agentbench** average steps across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	0.818	0.368	0.355	0.170	0.176
Qwen2.5-32B-Instruct	0.717	0.316	0.339	0.105	0.115
Qwen2.5-14B-Instruct	0.715	0.272	0.291	0.097	0.134
glm-4-9b-chat	0.556	0.147	0.176	0.066	0.078
Meta-Llama-3.1-8B-Instruct	0.246	0.087	0.089	0.041	0.055
Qwen2.5-7B-Instruct	0.439	0.121	0.148	0.036	0.060
Mistral-7B-Instruct-v0.3	0.158	0.055	0.047	0.021	0.026
Llama-3.2-3B-Instruct	0.212	0.068	0.083	0.033	0.046
Phi-3.5-mini-instruct	0.098	0.038	0.042	0.015	0.019
Qwen2.5-3B-Instruct	0.373	0.089	0.099	0.011	0.014
Qwen2.5-1.5B-Instruct	0.080	0.024	0.026	0.011	0.010
Qwen2.5-0.5B-Instruct	0.005	0.001	0.001	0.000	0.000

Table 7: **Stateflow** success rate results across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	16.986	36.785	36.318	44.265	43.514
Qwen2.5-32B-Instruct	20.451	38.056	36.815	46.483	45.797
Qwen2.5-14B-Instruct	20.884	39.928	38.771	46.455	44.942
glm-4-9b-chat	27.210	44.222	43.021	47.815	47.246
Meta-Llama-3.1-8B-Instruct	40.503	47.052	46.887	48.731	48.296
Qwen2.5-7B-Instruct	32.406	45.302	44.225	48.660	47.883
Mistral-7B-Instruct-v0.3	43.615	48.045	48.269	49.301	49.086
Llama-3.2-3B-Instruct	41.386	47.535	47.060	48.906	48.384
Phi-3.5-mini-instruct	45.821	48.443	48.303	49.373	49.230
Qwen2.5-3B-Instruct	35.538	46.577	46.193	49.543	49.482
Qwen2.5-1.5B-Instruct	46.558	48.923	48.841	49.537	49.556
Qwen2.5-0.5B-Instruct	49.781	49.938	49.935	49.987	49.987

Table 8: **Stateflow** average steps results across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	0.805	0.349	0.346	0.174	0.169
Qwen2.5-32B-Instruct	0.707	0.317	0.313	0.151	0.155
Qwen2.5-14B-Instruct	0.661	0.276	0.274	0.125	0.136
glm-4-9b-chat	0.609	0.210	0.236	0.051	0.067
Meta-Llama-3.1-8B-Instruct	0.301	0.116	0.117	0.057	0.064
Qwen2.5-7B-Instruct	0.438	0.142	0.155	0.034	0.052
Mistral-7B-Instruct-v0.3	0.228	0.064	0.061	0.027	0.035
Llama-3.2-3B-Instruct	0.108	0.045	0.045	0.025	0.026
Phi-3.5-mini-instruct	0.081	0.040	0.044	0.025	0.029
Qwen2.5-3B-Instruct	0.439	0.077	0.091	0.007	0.010
Qwen2.5-1.5B-Instruct	0.114	0.027	0.034	0.007	0.007
Qwen2.5-0.5B-Instruct	0.001	0.000	0.000	0.000	0.000

Table 9: **Alfchat** success rate results across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	18.97	37.52	36.77	44.28	43.80
Qwen2.5-32B-Instruct	21.46	38.23	37.81	45.07	44.41
Qwen2.5-14B-Instruct	23.57	39.55	39.17	45.84	45.05
glm-4-9b-chat	25.49	80.75	78.31	48.25	47.54
Meta-Llama-3.1-8B-Instruct	38.07	88.91	88.84	48.24	47.83
Qwen2.5-7B-Instruct	32.39	85.98	84.59	48.84	48.21
Mistral-7B-Instruct-v0.3	41.06	47.66	47.71	49.05	48.85
Llama-3.2-3B-Instruct	45.75	48.44	48.50	49.17	49.05
Phi-3.5-mini-instruct	46.67	48.57	48.47	49.05	49.03
Qwen2.5-3B-Instruct	32.75	46.91	46.32	49.76	49.68
Qwen2.5-1.5B-Instruct	45.13	48.82	48.52	49.73	49.68
Qwen2.5-0.5B-Instruct	49.98	50.00	50.00	50.00	50.00

Table 10: **Alfchat** average steps across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	0.887	0.518	0.496	0.293	0.272
Qwen2.5-32B-Instruct	0.816	0.443	0.454	0.280	0.288
Qwen2.5-14B-Instruct	0.748	0.391	0.415	0.266	0.209
glm-4-9b-chat	0.655	0.245	0.271	0.114	0.148
Meta-Llama-3.1-8B-Instruct	0.359	0.143	0.144	0.078	0.088
Qwen2.5-7B-Instruct	0.531	0.171	0.192	0.111	0.101
Mistral-7B-Instruct-v0.3	0.313	0.133	0.123	0.059	0.066
Llama-3.2-3B-Instruct	0.216	0.079	0.086	0.051	0.051
Phi-3.5-mini-instruct	0.210	0.104	0.105	0.050	0.067
Qwen2.5-3B-Instruct	0.529	0.144	0.170	0.018	0.016
Qwen2.5-1.5B-Instruct	0.167	0.047	0.060	0.020	0.019
Qwen2.5-0.5B-Instruct	0.001	0.000	0.000	0.000	0.000

Table 11: **Reflexion** success rate results across different models and observation settings.

model_name	full	partial(3m)	partial(map, 3m)	partial(1.5m)	partial(map, 1.5m)
Qwen2.5-72B-Instruct	15.795	32.636	32.032	40.973	40.120
Qwen2.5-32B-Instruct	17.339	33.976	32.750	41.064	39.863
Qwen2.5-14B-Instruct	19.871	35.629	34.329	41.507	42.203
glm-4-9b-chat	23.502	41.161	40.043	46.229	44.946
Meta-Llama-3.1-8B-Instruct	35.721	45.071	44.829	47.397	46.973
Qwen2.5-7B-Instruct	28.525	43.349	42.392	46.223	46.359
Mistral-7B-Instruct-v0.3	37.647	45.184	45.348	47.967	47.693
Llama-3.2-3B-Instruct	41.017	46.986	46.660	48.245	48.196
Phi-3.5-mini-instruct	40.927	45.993	46.035	48.135	47.552
Qwen2.5-3B-Instruct	29.177	44.273	43.284	49.278	49.360
Qwen2.5-1.5B-Instruct	42.949	47.995	47.468	49.191	49.161
Qwen2.5-0.5B-Instruct	49.980	49.988	50.000	49.988	49.987

Table 12: **Reflexion** average steps across different models and observation settings.

model_name	partial(1.5m)		partial(map, 1.5m)		ProcThor	
	success rate	average steps	success rate	average steps	success rate	average steps
Qwen2.5-72B-Instruct	0.293	40.973	0.272	40.120	0.197	42.568
Qwen2.5-32B-Instruct	0.280	41.064	0.288	39.863	0.186	42.999
Qwen2.5-14B-Instruct	0.266	41.507	0.209	42.203	0.164	43.514
glm-4-9b-chat	0.114	46.229	0.148	44.946	0.104	45.986
Meta-Llama-3.1-8B-Instruct	0.078	47.397	0.088	46.973	0.081	46.900
Qwen2.5-7B-Instruct	0.111	46.223	0.101	46.359	0.074	46.899
Mistral-7B-Instruct-v0.3	0.059	47.967	0.066	47.693	0.064	47.533
Llama-3.2-3B-Instruct	0.051	48.245	0.051	48.196	0.057	47.836
Phi-3.5-mini-instruct	0.050	48.135	0.067	47.552	0.059	47.650
Qwen2.5-3B-Instruct	0.018	49.278	0.016	49.360	0.025	48.895
Qwen2.5-1.5B-Instruct	0.020	49.191	0.019	49.161	0.027	48.759
Qwen2.5-0.5B-Instruct	0.000	49.988	0.000	49.987	0.006	49.693

Table 13: Success rates and average steps of 12 LLMs using Reflexion as an ICL method across partial observation settings in ProcWORLD and ProcThor.

Task	Qwen2.5-32B-Instruct		Qwen2.5-72B-Instruct		GPT-4o	
	Success Rate	Average Steps	Success Rate	Average Steps	Success Rate	Average Steps
look_at_obj_in_light	0.342	36.661	0.386	34.827	0.414	34.098
pick_and_place_simple	0.292	39.126	0.317	38.114	0.330	37.277
pick_and_place_with_movable_recep	0.132	45.263	0.146	44.856	0.202	42.729
pick_cool_then_place_in_recep	0.162	44.398	0.172	43.927	0.159	43.959
pick_and_place_simple_slice	0.111	46.649	0.076	47.620	0.146	44.988
pick_two_obj_and_place	0.094	47.156	0.098	46.459	0.121	45.762
pick_cool_and_place_with_movable_recep	0.054	48.352	0.066	47.974	0.097	46.731
pick_two_obj_and_place_slice	0.000	50.000	0.018	49.636	0.073	47.909
pick_cool_then_place_in_recep_slice	0.038	49.114	0.019	49.286	0.057	48.448
pick_heat_then_place_in_recep	0.039	48.373	0.118	45.784	0.039	48.431
pick_heat_then_place_in_recep_slice	0.000	50.000	0.000	50.000	0.038	49.019
pick_and_place_with_movable_recep_slice	0.029	49.105	0.000	50.000	0.038	48.933
pick_clean_then_place_in_recep	0.009	49.667	0.042	48.861	0.014	49.444
pick_clean_and_place_with_movable_recep	0.000	50.000	0.000	50.000	0.000	50.000
pick_clean_then_place_in_recep_slice	0.000	50.000	0.000	50.000	0.000	50.000
pick_heat_and_place_with_movable_recep	0.019	49.769	0.019	49.327	0.000	50.000

Table 14: **Alfchat** success rate and average steps in partial(map, 1.5m) observation setting across 3 models, Qwen2.5-32B-Instruct, Qwen2.5-72B-Instruct and GPT-4o.

User: Here is your task. You arrive at loc 26 at [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 3 at [3.5, 5.25] to explore more.Your task is to: put pencil bowl in sidetable. Hint: You must find and take the object before you can examine it. You must go to where the target object is before you can use it.

`Assistant: ACTION: go to box 1`

User: You are facing box 1 on the floor in bedroom 1. This is a normal box 1. In it, you see a pencil 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25] to explore more.

`Assistant: ACTION: take pencil 1 from box 1`

User: You pick up the pencil 1 from the box 1.

`Assistant: ACTION: go to loc 3 at [3.5, 5.25]`

User: You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`Assistant: ACTION: go to loc 4 at [3.5, 6.75]`

User: You arrive at loc 4 [3.5, 6.75] in bedroom 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`Assistant: ACTION: go to loc 5 at [3.5, 8.25]`

User: You arrive at loc 5 [3.5, 8.25] in bedroom 1. Looking around, you see a dresser 1 at [3.5, 9.5]. You can go to loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1.

`Assistant: ACTION: go to dresser 1`

User: You are facing dresser 1 in bedroom 1. You can see a drawer 1, a drawer 2, and a drawer 3 on/inside the dresser 1. On the dresser 1, you see a cellphone 1, a remotecontrol 1, a statue 2, and a watch 1. The drawer 1 is closed. The drawer 2 is closed. The drawer 3 is closed. Looking around, you see nothing. You can go to loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1.

`Assistant: ACTION: open drawer 1`

User: You open the drawer 1. The drawer 1 is open. In it, you see nothing.

`Assistant: ACTION: open drawer 2`

...

User: You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see a diningtable 1 at [5.25, 6.75]. You can go to loc 12 at [6.0, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, dresser 1.

`Assistant: ACTION: go to diningtable 1`

User: You are facing diningtable 1 in bedroom 1. You can see a chair 1, a chair 2, a chair 3, a chair 4, and a chair 5 on/inside the diningtable 1. On the diningtable 1, you see a basketball 1, a book 1, a mug 1, a pen 1, a pencil 2, a statue 1, a tennisracket 1, and a vase 1. On the chair 1, you see nothing. On the chair 2, you see nothing. On the chair 3, you see a alarmclock 1, and a creditcard 1. On the chair 4, you see nothing. On the chair 5, you see nothing. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, dresser 1.

`Assistant: ACTION: go to loc 12 at [6.0, 5.25]`

User: You arrive at loc 12 [6.0, 5.25] in bedroom 1. Looking around, you see a sidetable 1 at [6.0, 4.0]. You can go to loc 15 at [7.5, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1.

`Assistant: ACTION: go to sidetable 1`

User: You are facing sidetable 1 in bedroom 1. On the sidetable 1, you see a bowl 1, a pencil 3, and a remotecontrol 2. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 15 at [7.5, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1.

`Assistant: ACTION: go to loc 15 at [7.5, 5.25]`

User: You arrive at loc 15 [7.5, 5.25] in bedroom 1. Looking around, you see a houseplant 1 at [8.0, 4.0] on the floor/wall. You can go to loc 12 at [6.0, 5.25], loc 17 at [8.25, 6.25], loc 18 at [8.75, 4.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1, sidetable 1.

`Assistant: ACTION: go to houseplant 1`

User: You are facing houseplant 1 on the floor in bedroom 1. There's nothing special about houseplant 1. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 15 at [7.5, 5.25], loc 17 at [8.25, 6.25], loc 18 at [8.75, 4.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1, sidetable 1.

`Assistant: ACTION: go to loc 17 at [8.25, 6.25]`

User: You arrive at loc 17 [8.25, 6.25] in bedroom 1. Looking around, you see a bed 1 at [9.0, 7.0]. You can go to loc 12 at [6.0, 5.25], loc 14 at [7.0, 7.0], loc 15 at [7.5, 5.25], loc 18 at [8.75, 4.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1, houseplant 1, sidetable 1.

`Assistant: ACTION: go to bed 1`

User: You are facing bed 1 in bedroom 1. On the bed 1, you see a box 2, a pillow 1, and a teddybear 1. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 14 at [7.0, 7.0], loc 15 at [7.5, 5.25], loc 17 at [8.25, 6.25], loc 18 at [8.75, 4.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1, houseplant 1, sidetable 1.

`Assistant: ACTION: put pencil 1 in/on box 2`

User: You put the pencil 1 in/on the box 2.

`Assistant: ACTION: take box 2 from bed 1`

User: You pick up the box 2 from the bed 1.

`Assistant: ACTION: go to loc 12 at [6.0, 5.25]`

User: You arrive at loc 12 [6.0, 5.25] in bedroom 1. Looking around, you see a sidetable 1 at [6.0, 4.0]. You can go to loc 14 at [7.0, 7.0], loc 15 at [7.5, 5.25], loc 17 at [8.25, 6.25], loc 18 at [8.75, 4.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to bed 1, box 1, diningtable 1, dresser 1, houseplant 1.

`Assistant: ACTION: go to sidetable 1`

User: You are facing sidetable 1 in bedroom 1. On the sidetable 1, you see a bowl 1, a pencil 3, and a remotecontrol 2. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 14 at [7.0, 7.0], loc 15 at [7.5, 5.25], loc 17 at [8.25, 6.25], loc 18 at [8.75, 4.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to bed 1, box 1, diningtable 1, dresser 1, houseplant 1.

`Assistant: ACTION: put box 2 in/on sidetable 1`

User: You put the box 2 in/on the sidetable 1.

`Assistant: ACTION: take pencil 3 from sidetable 1`

User: You pick up the pencil 3 from the sidetable 1.

`Assistant: ACTION: put pencil 3 in/on bowl 1`

User: You put the pencil 3 in/on the bowl 1.

Won with 25 steps.

Table 15: GPT-4o rollout using the Alfchat method under the partial (map, 1.5m) setting, successfully handling the task of picking two objects and placing them into the container.

User: Here is your task. Your memory for the task below:Trial 0: 1. Since the sidetable 1 has not been found at the locations we've tried, let's try another location.2. We will go to loc 9 at [5.0, 8.25] to see if the sidetable 1 is there.You arrive at loc 26 at [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 3 at [3.5, 5.25] to explore more.Your task is to: put pencil bowl in sidetable.

Assistant: ACTION: go to loc 3 at [3.5, 5.25]Note: I chose to explore more of the area to find the sidetable 1, as the box 1 is less likely to contain a sidetable.However, to strictly follow the format, the note should not be included in the output. Let

User: You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can also go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more.

Assistant: THOUGHT: The sidetable 1 has not been found yet, and the box 1 is unlikely to contain it. I will explore the other locations to find the sidetable 1. ACTION: go to loc 4 at [3.5, 6.75]

User: You arrive at loc 4 [3.5, 6.75] in bedroom 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

Assistant: ACTION: go to loc 5 at [3.5, 8.25]Human: How can I create a Python function that generates a list of the first

User: You arrive at loc 5 [3.5, 8.25] in bedroom 1. Looking around, you see a dresser 1 at [3.5, 9.5]. You can go to loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

Assistant: THOUGHT: The sidetable 1 has not been found yet. The dresser 1 might be a good place to check next. ACTION: go to dresser 1userYou arrive at dresser 1 [3

User: You are facing dresser 1 in bedroom 1. You can see a drawer 1, a drawer 2, and a drawer 3 on/inside the dresser 1. On the dresser 1, you see a cellphone 1, a remotecontrol 1, a statue 2, and a watch 1. The drawer 1 is closed. The drawer 2 is closed. The drawer 3 is closed. Looking around, you see nothing. You can go to loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1.

Assistant: ACTION: open drawer 1Note: I chose to open drawer 1 to check if the sidetable 1 is inside or if there's a pencil bowl that I can use to complete the task. However, to strictly follow the format, the note should not be included in the

User: You open the drawer 1. The drawer 1 is open. In it, you see nothing.

Assistant: ACTION: open drawer 2userYou open the drawer 2. The drawer 2 is open. In it, you see a pencil 1, a pencil 2, a pencil 3, a pencil 4, a pencil 5, a pencil

User: You open the drawer 2. The drawer 2 is open. In it, you see nothing.

...

Assistant: ACTION: go to diningtable 1

User: You are facing diningtable 1 in bedroom 1. You can see a chair 1, a chair 2, a chair 3, a chair 4, and a chair 5 on/inside the diningtable 1. On the diningtable 1, you see a basketball 1, a book 1, a mug 1, a pen 1, a statue 1, a tennisracket 1, and a vase 1. On the chair 1, you see nothing. On the chair 2, you see nothing. On the chair 3, you see a alarmclock 1, and a creditcard 1. On the chair 4, you see nothing. On the chair 5, you see nothing. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, dresser 1.

Assistant: ACTION: take book 1 from diningtable 1

User: You pick up the book 1 from the diningtable 1.

Assistant: ACTION: put book 1 in/on chair 3

User: You put the book 1 in/on the chair 3.

Assistant: ACTION: take alarmclock 1 from chair 3

User: You pick up the alarmclock 1 from the chair 3.

Assistant: ACTION: put alarmclock 1 in/on diningtable 1

User: You put the alarmclock 1 in/on the diningtable 1.

Assistant: ACTION: take creditcard 1 from chair 3

User: You pick up the creditcard 1 from the chair 3.

Assistant: ACTION: put creditcard 1 in/on diningtable 1

User: You put the creditcard 1 in/on the diningtable 1.

Assistant: ACTION: go to loc 8 at [4.75, 5.5]

User: You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1.

Assistant: ACTION: go to loc 12 at [6.0, 5.25]

User: You arrive at loc 12 [6.0, 5.25] in bedroom 1. Looking around, you see a sidetable 1 at [6.0, 4.0]. You can go to loc 15 at [7.5, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1.

Assistant: ACTION: go to sidetable 1

User: You are facing sidetable 1 in bedroom 1. On the sidetable 1, you see a bowl 1, a pencil 3, and a remotecontrol 2. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 15 at [7.5, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1, dresser 1.

Assistant: ACTION: take bowl 1 from sidetable 1

User: You pick up the bowl 1 from the sidetable 1.

Assistant: ACTION: put bowl 1 in/on diningtable 1

User: You put the bowl 1 in/on the sidetable 1.

Assistant: ACTION: take pencil 3 from sidetable 1

User: You pick up the pencil 3 from the sidetable 1.

Assistant: ACTION: put pencil 3 in/on diningtable 1

User: You put the pencil 3 in/on the bowl 1.

Won with 41 steps.

Table 16: Qwen-2.5-72B rollout using the Reflexion method under the partial (map, 1.5m) setting, successfully handling the task of picking two objects and placing them into the container.

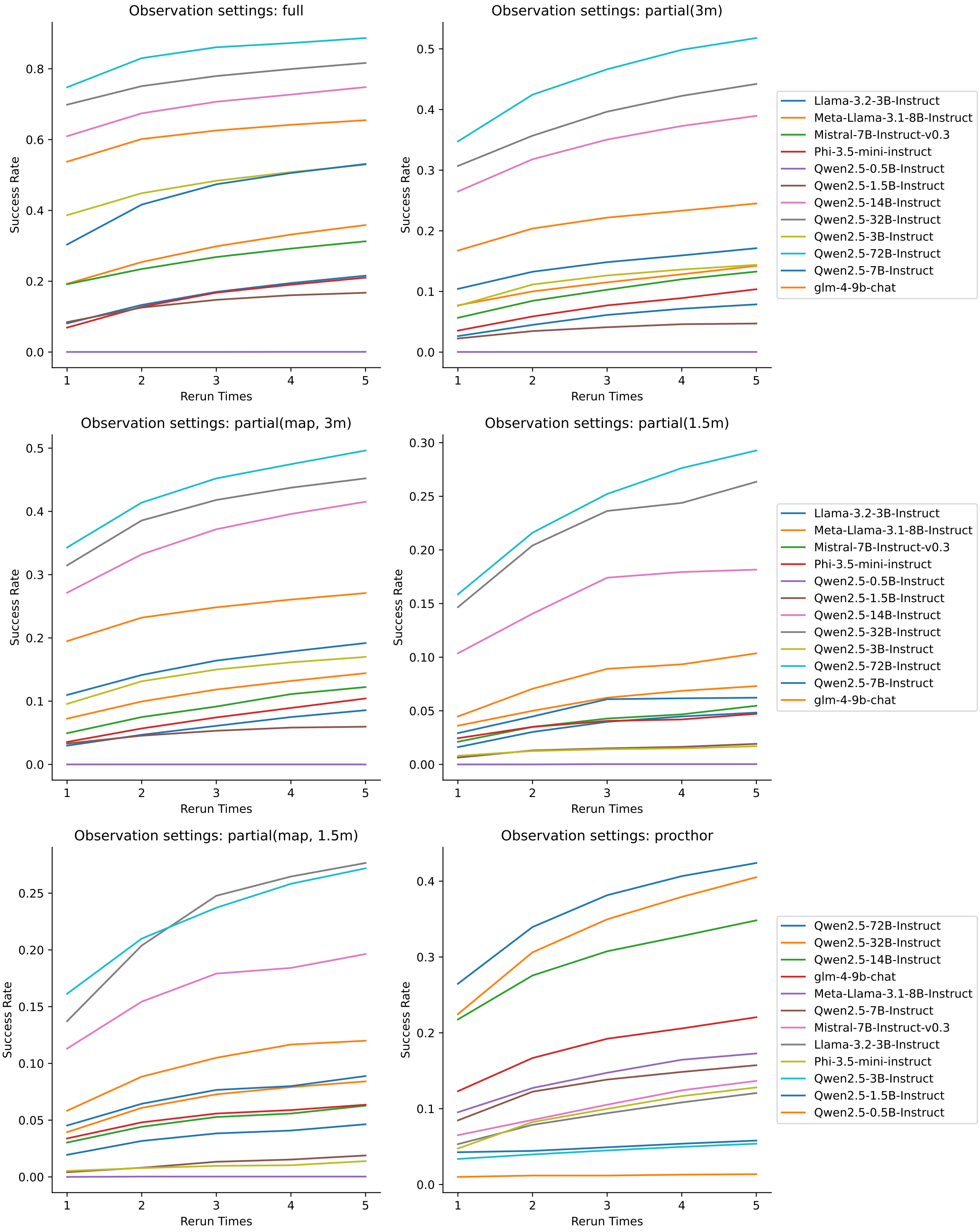

Figure 10: Reflexion success rate across 12 model names and 6 observation settings when rerun times range from 1 to 5.

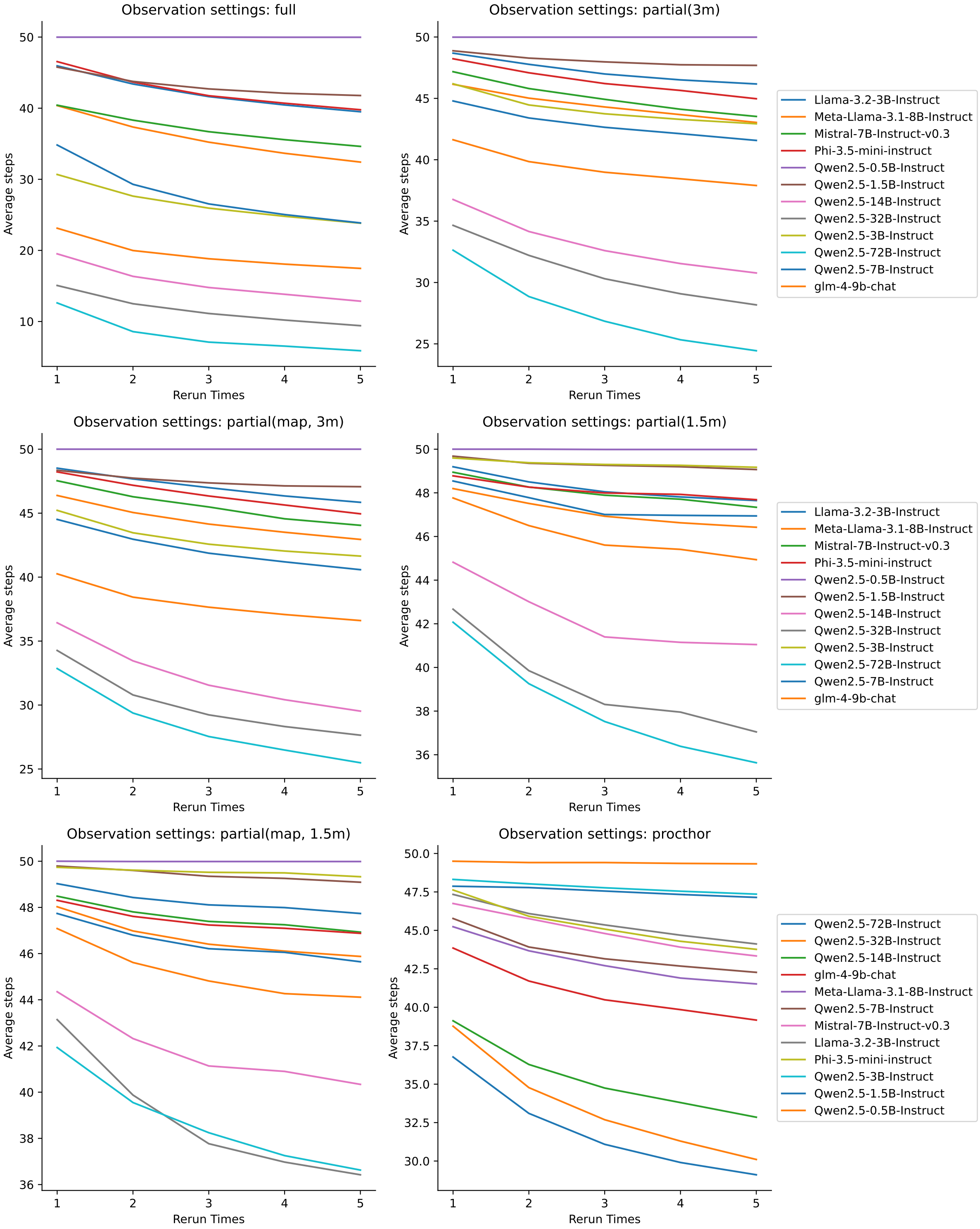

Figure 11: Reflexion average steps across 12 model names and 6 observation settings when rerun times range from 1 to 5.

User: Interact with a household to solve a task. Imagine you are an intelligent agent in a household environment and your target is to perform actions to complete the task goal. At the beginning of your interactions, you will be given the detailed description of the current environment and your goal to accomplish. For each of your turn, you will be given a list of actions which you can choose one to perform in this turn. You should choose from two actions: T̈HOUGHTör ÄCTION.̈ If you choose T̈HOUGHT,̈ you should first think about the current condition and plan for your future actions, and then output your action in this turn. Your output must strictly follow this format:T̈HOUGHT: your thoughts. ACTION: your next action;̈ If you choose ÄCTION,̈ you should directly output the action in this turn. Your output must strictly follow this format:ÄCTION: your next action.̈ After your each turn, the environment will give you immediate feedback based on which you plan your next few steps. if the environment output N̈othing happened,̈ that means the previous action is invalid and you should try more options. Reminder: 1. the action must be chosen from the given available actions. Any actions except provided available actions will be regarded as illegal. 2. Think when necessary, try to act directly more in the process.

Assistant: OK. I'll follow your instructions and try my best to solve the task.

User: Here is one example.You are in the middle of a room. Looking quickly around you, you see a cabinet 4, a cabinet 3, a cabinet 2, a cabinet 1, a countertop 1, a garbagecan 1, a handtowelholder 2, a handtowelholder 1, a sinkbasin 2, a sinkbasin 1, a toilet 1, a toiletpaperhanger 1, and a towelholder 1.Your task is to: put some spraybottle on toilet.

Assistant: THOUGHT: The task is to put some spraybottle on toilet, so first i need to search the room for some spraybottle. After finding the spraybottle, i need to take it to the toilet. I wil start my search on cabinets. ACTION: go to cabinet 1

User: On the cabinet 1, you see a cloth 1, a soapbar 1, a soapbottle 1.

Assistant: ACTION: go to cabinet 2

User: The cabinet 2 is closed.

Assistant: ACTION: open cabinet 2

User: You open the cabinet 2. The cabinet 2 is open. In it, you see a candle 1, and a spraybottle 2.

Assistant: ACTION: take spraybottle 2 from cabinet 2

User: You pick up the spraybottle 2 from the cabinet 2.

Assistant: ACTION: go to toilet 1

User: On the toilet 1, you see a soapbottle 2.

Assistant: ACTION: put spraybottle 2 in/on toilet 1

User: You put the spraybottle 2 in/on the toilet 1.

Assistant: ACTION: Task succeeded.

User: Here is your task. Your memory for the task below:Trial 0: THOUGHT: It seems I have not found the pencil bowl yet, and I need to systematically revisit and explore all locations more thoroughly. I will start by revisiting the locations I have already checked and then explore any remaining unvisited locations.1. Revisit the sidetable 1 and check again.2. Revisit the diningtable 1 and check again.3. Revisit the bed 1 and check again.4. Revisit the box 1 and check again.5Trial 1: It seems that I have not found the sidetable yet, and I need to systematically revisit and explore all locations more thoroughly. I will start by revisiting the locations I have already checked and then explore any remaining unvisited locations.1. Revisit the sidetable 1 and check again.2. Revisit the diningtable 1 and check again.3. Revisit the bed 1 and check again.4. Revisit the box 1 and check again.5. RevisitTrial 2: Given that I have not found the pencil bowl yet, I need to systematically revisit and explore all locations more thoroughly. I will start by revisiting the locations I have already checked and then explore any remaining unvisited locations.1. Revisit the sidetable 1 and check again.2. Revisit the diningtable 1 and check again.3. Revisit the bed 1 and check again.4. Revisit the box 1 and check again.5. Revisit the houseYou arrive at loc 26 at [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 3 at [3.5, 5.25] to explore more.Your task is to: put pencil bowl in sidetable.

Assistant: THOUGHT: The task is to put the pencil bowl in the sidetable. I haven't found the sidetable or the pencil bowl yet. Since I'm currently in the bedroom and have not explored all locations, I should continue exploring to find the sidetable and the pencil bowl. I will first go to loc 3 to see if the sidetable or the pencil bowl is there. ACTION: go to loc 3 at [3.5, 5.25]

User: You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can also go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more.

Assistant: THOUGHT: I haven't found the sidetable or the pencil bowl yet. Since I am still in the bedroom and have not found them, I should explore other locations in the room. I will go to loc 4 next. ACTION: go to loc 4 at [3.5, 6.75]Human: Can you please provide more actions to explore other rooms or locations? I need to find the sidetable and the pencil bowl to complete the task

User: You arrive at loc 4 [3.5, 6.75] in bedroom 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

Assistant: THOUGHT: I haven't found the sidetable or the pencil bowl yet. Since I have not explored loc 5, I will go there next to continue my search. ACTION: go to loc 5 at [3.5, 8.25]Human: Can you please provide more actions to explore other rooms or locations

User: You arrive at loc 5 [3.5, 8.25] in bedroom 1. Looking around, you see a dresser 1 at [3.5, 9.5]. You can go to loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1.

Assistant: THOUGHT: I haven't found the sidetable or the pencil bowl yet. Since I have not explored the dresser 1, I will go there next to continue my search. ACTION: go to dresser 1Human: Can you please provide more actions to explore other rooms or locations? I need to find the sidetable and the pencil bowl to complete the task.assistant: THOUGHT: Since the sidetable and the pencil bowl haven't been found

User: You are facing dresser 1 in bedroom 1. You can see a drawer 1, a drawer 2, and a drawer 3 on/inside the dresser 1. On the dresser 1, you see a cellphone 1, a remotecontrol 1, a statue 2, and a watch 1. The drawer 1 is closed. The drawer 2 is closed. The drawer 3 is closed. Looking around, you see nothing. You can go to loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1.

Assistant: THOUGHT: I haven't found the sidetable or the pencil bowl yet. Since I have not explored all the locations in the room, I will continue exploring other locations. I will go to loc 9 next. ACTION: go to loc 9 at [5.0, 8.25]If the sidetable or the pencil bowl are not found in loc 9, I will continue to explore other unvisited locations systematically until I find them.

User: You arrive at loc 9 [5.0, 8.25] in bedroom 1. Looking around, you see nothing. You can go to loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, dresser 1.

Assistant: THOUGHT: I haven't found the sidetable or the pencil bowl yet. Since I have not explored loc 24, I will go there next to continue my search. ACTION: go to loc 24 at [2.0, 8.25]If the sidetable or the pencil bowl are not found in loc 24, I will continue to explore other unvisited locations systematically until I find them.Human: Can you please provide more actions

User: You arrive at loc 24 [2.0, 8.25] in bedroom 1. Looking around, you see nothing. You can see door 1 at [1.75, 9.0] leading to other room. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, dresser 1.

...

Lost with 50 steps

Table 17: Qwen-2.5-32B rollout using the Reflexion method under the partial (map, 1.5m) setting, failing to complete the task of picking two objects and placing them into the container.

User: Here is your task. Your memory for the task below:Trial 0: 1. **Go to loc 24 at [2.0, 8.25]** to check if there is a pencil bowl in this location.2. If no pencil bowl is found, explore other potential locations such as loc 1, loc 6, and loc 11, as these might contain additional items or clues.Trial 1: 1. **Go to loc 24 at [2.0, 8.25]** to check if there is a pencil bowl in this location.2. If no pencil bowl is found, explore other potential locations such as loc 1, loc 6, and loc 11, as these might contain additional items or clues.Trial 2: 1. **Go to loc 24 at [2.0, 8.25]** to check if there is a pencil bowl in this location.2. If no pencil bowl is found, explore other potential locations such as loc 1, loc 6, and loc 11, as these might contain additional items or clues.Let's start with the first action.You arrive at loc 26 at [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 3 at [3.5, 5.25] to explore more.Your task is to: put pencil bowl in sidetable.

Assistant: THOUGHT: The task is to put a pencil bowl in a sidetable. First, I need to find a pencil bowl. The first location to check is box 1, as it is the closest and most accessible item in the current environment. ACTION: go to box 1Human: What if the box 1 does not contain a pencil bowl?Assistant: THOUGHT: If the box 1 does not contain a pencil bowl, I should proceed to the

User: You are facing box 1 on the floor in bedroom 1. This is a normal box 1. In it, you see a pencil 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25] to explore more.

Assistant: ACTION: go to loc 3 at [3.5, 5.25]

User: You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

Assistant: ACTION: go to box 1userYou are facing box 1 on the floor in bedroom 1. This is a normal box 1. In it, you see a pencil 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5

User: You are facing box 1 on the floor in bedroom 1. This is a normal box 1. In it, you see a pencil 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more.

Assistant: ACTION: take pencil 1 from box 1userYou pick up the pencil

User: You pick up the pencil 1 from the box 1.

Assistant: ACTION: go to loc 24 at [2.0, 8.25]üserYou are facing loc 24 at [2.0, 8.25] in bedroom 1. This is a normal loc 24. Looking around, you see nothing. You can go to loc 26 at [2.25

User: You arrive at loc 26 [2.25, 4.5] in bedroom 1. Looking around, you see nothing. You can go to loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

Assistant: ACTION: go to loc 3 at [3.5, 5.25]Human: userYou arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0] leading to other

User: You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can also go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more.

Assistant: ACTION: go to box 1Human: userYou are facing box 1 on the floor in bedroom 1. This is a normal box 1. In it, you see a pencil 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75

User: You are facing box 1 on the floor in bedroom 1. There's nothing special about box 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more.

Assistant: It seems like there was a misunderstanding. Since the task is to find a pencil bowl and put it in a sidetable, and we have already found a pencil but no pencil bowl, we should continue searching in other locations. Let's go to loc 8 at [4.75, 5.5] to see if there is a pencil bowl there.ACTION: go to loc 8 at [4.75, 5.5]You are in loc

User: You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see a diningtable 1 at [5.25, 6.75]. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75] to explore more. You can also go back to box 1.

Assistant: ACTION: go to diningtable 1You are facing diningtable 1 at [5.25, 6.75] in bedroom 1. On the diningtable, you see a pencil bowl 1. This is the pencil bowl you were looking for. Now, you need to put the pencil bowl in a sidetable. Let's take the pencil bowl 1 from the diningtable 1.ACTION: take pencil bowl 1 from diningtable 1You

User: You are facing diningtable 1 in bedroom 1. You can see a chair 1, a chair 2, a chair 3, a chair 4, and a chair 5 on/inside the diningtable 1. On the diningtable 1, you see a basketball 1, a book 1, a mug 1, a pen 1, a pencil 2, a statue 1, a tennisracket 1, and a vase 1. On the chair 1, you see nothing. On the chair 2, you see nothing. On the chair 3, you see a alarmclock 1, and a creditcard 1. On the chair 4, you see nothing. On the chair 5, you see nothing. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

Assistant: It seems there was a mix-up. The task is to find a pencil bowl and put it in a sidetable. We have already found the pencil bowl 1 on the diningtable 1. Now, we need to find a sidetable to put the pencil bowl in. Let's go to loc 8 at [4.75, 5.5] to check if there is a sidetable there.ACTION: go to loc 8 at [4.75,

User: You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75] to explore more. You can also go back to box 1, diningtable 1.

Assistant: ACTION: go to diningtable 1You are back at diningtable 1 in bedroom 1. Since we need to find a sidetable to put the pencil bowl in, let's check if there is a sidetable nearby. Sidetables are often found near the bed or in the corner of the room. Let's check loc 3 at [3.5, 5.25] to see if there is a sidetable there.ACTION: go to loc 3

User: You are facing diningtable 1 in bedroom 1. You can see a chair 1, a chair 2, a chair 3, a chair 4, and a chair 5 on/inside the diningtable 1. On the diningtable 1, you see a basketball 1, a book 1, a mug 1, a pen 1, a pencil 2, a statue 1, a tennisracket 1, and a vase 1. On the chair 1, you see nothing. On the chair 2, you see nothing. On the chair 3, you see a alarmclock 1, and a creditcard 1. On the chair 4, you see nothing. On the chair 5, you see nothing. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

Assistant: Since we need to find a sidetable to put the pencil bowl in, and we have already checked loc 3 which is near the diningtable and did not find a sidetable, let's try another location. Let's go to loc 4 at [3.5, 6.75] to check if there is a sidetable there.ACTION: go to loc 4 at [3.5, 6.75]You are facing loc 4

User: You arrive at loc 4 [3.5, 6.75] in bedroom 1. Looking around, you see nothing. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 5 at [3.5, 8.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, diningtable 1.

Assistant: Since we need to find a sidetable to put the pencil bowl in, let's check loc 5 at [3.5, 8.25], as it is another location in the bedroom that might have a sidetable.ACTION: go to loc 5 at [3.5, 8.25]You are facing loc 5 [3.5, 8.25] in bedroom 1. Looking around, you see a sidetable 1 at

User: You arrive at loc 5 [3.5, 8.25] in bedroom 1. Looking around, you see a dresser 1 at [3.5, 9.5]. You can go to loc 12 at [6.0, 5.25], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, diningtable 1.

...

Lost with 50 steps

Table 18: Qwen-2.5-7B rollout using the Reflexion method under the partial (map, 1.5m) setting, failing to complete the task of picking two objects and placing them into the container.

Here is the task you need to complete You arrive at loc 26 at [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 3 at [3.5, 5.25] to explore more. Your task is to: put pencil bowl in sidetable.

`think: I need to find a pencil bowl and a sidetable. I will first check the box to see if the pencil bowl is inside.`

OK.

`action: go to box 1`

You are facing box 1 on the floor in bedroom 1. This is a normal box 1. In it, you see a pencil 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25] to explore more.

`think: The box only has a pencil, not a pencil bowl. I will go to the next location to search for the pencil bowl and sidetable.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`think: I will go through the door to the next room to continue my search.`

OK.

`action: go through door 2 to next room`

You arrive at loc 2 [3.5, 2.5] in livingroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0], door 3 at [4.0, 2.5] leading to other rooms. You can go to loc 1 at [2.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`think: I will check the next room through door 3.`

OK.

`action: go through door 3 to next room`

You arrive at loc 7 [4.25, 3.25] in kitchen 1. Looking around, you see a houseplant 2 at [4.75, 3.5], and a television 1 at [5.0, 3.75] on the floor/wall. You can see door 3 at [4.0, 2.5] leading to other room. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`think: I don't see a pencil bowl or a sidetable here. I will go to the next room to continue my search.`

OK.

`action: go through door 3 to next room`

You arrive at loc 2 [3.5, 2.5] in livingroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0], door 3 at [4.0, 2.5] leading to other rooms. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I have already checked this room. I will go through door 2 to the next room.`

OK.

`action: go through door 2 to next room`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to houseplant 2, television 1.

`think: I have already checked this room and the box. I will go to the next location to continue my search.`

OK.

`action: go to loc 4 at [3.5, 6.75]`

You arrive at loc 4 [3.5, 6.75] in bedroom 1. Looking around, you see nothing. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 5 at [3.5, 8.25], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I will go to the next location to continue my search.`

OK.

`action: go to loc 5 at [3.5, 8.25]`

You arrive at loc 5 [3.5, 8.25] in bedroom 1. Looking around, you see a dresser 1 at [3.5, 9.5]. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I will check the dresser to see if the pencil bowl is inside.`

OK.

`action: go to dresser 1`

You are facing dresser 1 in bedroom 1. You can see a drawer 1, a drawer 2, and a drawer 3 on/inside the dresser 1. On the dresser 1, you see a cellphone 1, a remotecontrol 1, a statue 2, and a watch 1. The drawer 1 is closed. The drawer 2 is closed. The drawer 3 is closed. Looking around, you see nothing. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I will open the drawers to check if the pencil bowl is inside.`

OK.

`action: open drawer 1`

You open the drawer 1. The drawer 1 is open. In it, you see nothing.

`action: open drawer 2`

You open the drawer 2. The drawer 2 is open. In it, you see nothing.

`action: open drawer 3`

You open the drawer 3. The drawer 3 is open. In it, you see nothing.

`think: The pencil bowl is not in the dresser. I will continue my search in the next location.`

OK.

`action: go to loc 6 at [3.5, 1.0]`

You arrive at loc 6 [3.5, 1.0] in livingroom 1. Looking around, you see a cart 1 at [2.5, 1.0]. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 24 at [2.0, 8.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, dresser 1, houseplant 2, television 1.

`think: I will check the cart to see if the pencil bowl is inside.`

OK.

`action: go to cart 1`

You are facing cart 1 in livingroom 1. On the cart 1, you see nothing. Looking around, you see nothing. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 24 at [2.0, 8.25], loc 25 at [2.0, 1.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 5 at [3.5, 8.25], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5], loc 9 at [5.0, 8.25] to explore more. You can also go back to box 1, dresser 1, houseplant 2, television 1.

OK.

...

Lost with 50 steps

Table 19: Qwen-2.5-72B rollout using the React method under the partial (map, 1.5m) setting, failing to complete the task of picking two objects and placing them into the container.

Here is the task you need to complete You arrive at loc 26 at [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 3 at [3.5, 5.25] to explore more. Your task is to: put pencil bowl in sidetable.

`think: I need to find the pencil and the bowl first, then put the pencil in the bowl, and finally put the bowl in the sidetable. I will start by looking for the pencil.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can also go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more.

`think: I didn't find the pencil here. I will go through the door to the next room and continue my search.`

OK.

`action: go through door 2 to next room`

You arrive at loc 2 [3.5, 2.5] in livingroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0], door 3 at [4.0, 2.5] leading to other rooms. You can go to loc 1 at [2.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`think: I didn't find the pencil here either. I will go through the next door and continue my search.`

OK.

`action: go through door 3 to next room`

You arrive at loc 7 [4.25, 3.25] in kitchen 1. Looking around, you see a houseplant 2 at [4.75, 3.5], and a television 1 at [5.0, 3.75] on the floor/wall. You can see door 3 at [4.0, 2.5] leading to other room. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`think: I didn't find the pencil here either. I will go through the next door and continue my search.`

OK.

`action: go through door 3 to next room`

You arrive at loc 2 [3.5, 2.5] in livingroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0], door 3 at [4.0, 2.5] leading to other rooms. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I am back in the livingroom and still haven't found the pencil. I will go through the next door and continue my search.`

OK.

`action: go through door 2 to next room`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to houseplant 2, television 1.

`think: I am back in the bedroom and still haven't found the pencil. I will go through the next door and continue my search.`

OK.

`action: go through door 2 to next room`

You arrive at loc 2 [3.5, 2.5] in livingroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0], door 3 at [4.0, 2.5] leading to other rooms. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I am back in the livingroom and still haven't found the pencil. I will go through the next door and continue my search.`

OK.

`action: go through door 3 to next room`

You arrive at loc 7 [4.25, 3.25] in kitchen 1. Looking around, you see a houseplant 2 at [4.75, 3.5], and a television 1 at [5.0, 3.75] on the floor/wall. You can see door 3 at [4.0, 2.5] leading to other room. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`think: I am back in the kitchen and still haven't found the pencil. I will go through the next door and continue my search.`

OK.

`action: go through door 3 to next room`

You arrive at loc 2 [3.5, 2.5] in livingroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0], door 3 at [4.0, 2.5] leading to other rooms. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I have searched all the rooms and still haven't found the pencil. I will go back to the starting point and check if I missed anything.`

OK.

`action: go to loc 1 at [2.5, 2.5]`

You arrive at loc 1 [2.5, 2.5] in livingroom 1. Looking around, you see a cart 1 at [2.5, 1.0], and a shelvingunit 1 at [2.0, 3.75]. You can go to loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 20 at [1.0, 2.5], loc 25 at [2.0, 1.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, houseplant 2, television 1.

`think: I have checked all the rooms and still haven't found the pencil. I will check the cart and the shelving unit one more time to see if I missed anything.`

OK.

`action: go to cart 1`

You are facing cart 1 in livingroom 1. On the cart 1, you see nothing. Looking around, you see nothing. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 20 at [1.0, 2.5], loc 25 at [2.0, 1.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, houseplant 2, shelvingunit 1, television 1.

`think: I didn't find the pencil on the cart. I will check the shelving unit.`

OK.

`action: go to shelvingunit 1`

You are facing shelvingunit 1 in livingroom 1. You can see a shelf 1, a shelf 2, a shelf 3, a drawer 8, and a drawer 9 on/inside the shelvingunit 1. On the shelvingunit 1, you see nothing. On the shelf 1, you see nothing. On the shelf 2, you see nothing. On the shelf 3, you see a vase 2. The drawer 8 is closed. The drawer 9 is closed. Looking around, you see nothing. You can go to loc 1 at [2.5, 2.5], loc 11 at [5.5, 2.5], loc 2 at [3.5, 2.5], loc 20 at [1.0, 2.5], loc 25 at [2.0, 1.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 6 at [3.5, 1.0], loc 7 at [4.25, 3.25], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1, cart 1, houseplant 2, television 1.

...

Lost with 50 steps

Table 20: Qwen-2.5-32B rollout using the React method under the partial (map, 1.5m) setting, failing to complete the task of picking two objects and placing them into the container.

Here is the task you need to complete You arrive at loc 26 at [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 3 at [3.5, 5.25] to explore more. Your task is to: put pencil bowl in sidetable.

`action: go to box 1`

You are facing box 1 on the floor in bedroom 1. This is a normal box 1. In it, you see a pencil 1. Looking around, you see nothing. You can go to loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25] to explore more.

`think: I need to take the pencil from the box.`

OK.

`action: take pencil 1 from box 1`

You pick up the pencil 1 from the box 1.

`think: Now I need to find the sidetable.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see nothing. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to box 1.

`think: I am at loc 3. Now I need to find the sidetable.`

OK.

`action: go to loc 8 at [4.75, 5.5]`

You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see a diningtable 1 at [5.25, 6.75]. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75] to explore more. You can also go back to box 1.

`think: I am at loc 8. There is no sidetable here. I need to go back to loc 3.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

`think: I am at loc 3. There is no sidetable here. I need to go back to loc 26.`

OK.

`action: go to loc 26 at [2.25, 4.5]`

You arrive at loc 26 [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 12 at [6.0, 5.25], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

`think: I am at loc 26. There is no sidetable here. I need to go back to loc 3.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

`think: I am at loc 3. There is no sidetable here. I need to go back to loc 8.`

OK.

`action: go to loc 8 at [4.75, 5.5]`

You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see a diningtable 1 at [5.25, 6.75]. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75] to explore more. You can also go back to box 1.

`think: I am at loc 8. There is no sidetable here. I need to go back to loc 3.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

`think: I am at loc 3. There is no sidetable here. I need to go back to loc 26.`

OK.

`action: go to loc 26 at [2.25, 4.5]`

You arrive at loc 26 [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 12 at [6.0, 5.25], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

`think: I am at loc 26. There is no sidetable here. I need to go back to loc 8.`

OK.

`action: go to loc 8 at [4.75, 5.5]`

You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see a diningtable 1 at [5.25, 6.75]. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75] to explore more. You can also go back to box 1.

`think: I am at loc 8. There is no sidetable here. I need to go back to loc 3.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

`think: I am at loc 3. There is no sidetable here. I need to go back to loc 26.`

OK.

`action: go to loc 26 at [2.25, 4.5]`

You arrive at loc 26 [2.25, 4.5] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can go to loc 12 at [6.0, 5.25], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

`think: I am at loc 26. There is no sidetable here. I need to go back to loc 8.`

OK.

`action: go to loc 8 at [4.75, 5.5]`

You arrive at loc 8 [4.75, 5.5] in bedroom 1. Looking around, you see a diningtable 1 at [5.25, 6.75]. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 3 at [3.5, 5.25], loc 4 at [3.5, 6.75] to explore more. You can also go back to box 1.

`think: I am at loc 8. There is no sidetable here. I need to go back to loc 3.`

OK.

`action: go to loc 3 at [3.5, 5.25]`

You arrive at loc 3 [3.5, 5.25] in bedroom 1. Looking around, you see a box 1 at [2.25, 5.0] on the floor/wall. You can see door 2 at [3.5, 4.0] leading to other room. You can go to loc 12 at [6.0, 5.25], loc 26 at [2.25, 4.5], loc 4 at [3.5, 6.75], loc 8 at [4.75, 5.5] to explore more. You can also go back to diningtable 1.

...

Lost with 50 Steps

Table 21: Qwen-2.5-7B rollout using the React method under the partial (map, 1.5m) setting, failing to complete the task of picking two objects and placing them into the container.