



How Do Multimodal Large Language Models Handle Complex Multimodal Reasoning? —— Placing Them in An Extensible Escape Game

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Agenda

- Motivation
- Introduction Video
- Introduction of our benchmark
- Introduction the constructed environment
- Evaluation
- Analysis and conclusion



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Motivation



• What are MLLMs capable of?



COCO:

Young children standing on a platform waiting for a train to arrive.
Adults and children watching a train slowly leave.
A family near a railroad track watching the train pass.
People waiting on a platform as a train pulls up.
A train station with a green train on the tracks and children waiting for it to go by.

LLaVA:

At a train station, a group of people, including both young children and adults, are standing on a platform waiting for a train to arrive. The train is already present on the tracks, partially visible on the right side of the image. Some of the people watch the train closely, while others seem to be patiently anticipating its departure.

There is a total of eight individuals waiting for the train, with one child in the middle of the platform and the others scattered around. A backpack can be found on the far left side of the platform, suggesting that someone may have set it down while waiting.

ShareGPT4V: The image captures a moment at a train station. A green train is on the tracks, moving away from the platform labeled "Platform 2". The train's motion is observed by people standing on the platform, their attention drawn to the departing vehicle.

A red signal stands on the tracks, its vibrant color contrasting with the green of the train. Signs are prominently displayed around the platform. One warns "Beware of Trains", a cautionary reminder of the powerful machines that frequent these tracks. Another sign advises "Please Use The Footbridge To Cross The Line. If You Require Assistance Please Ask The Station Staff", guiding passengers to safely navigate the station.

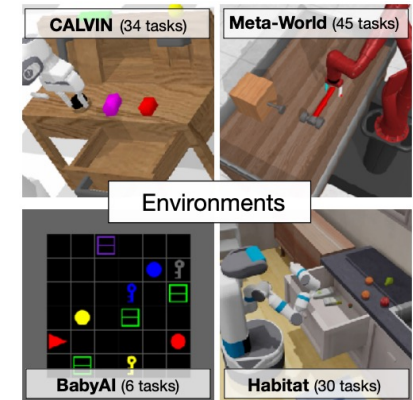
The sky above is a clear blue, providing a serene backdrop to the bustling activity of the station. In the distance, trees can be seen, adding a touch of nature to this man-made setting. The image is a snapshot of everyday life at a train station, capturing both its routine operations and its inherent charm.

Image captioning

What is the instrument held by an ape?



Visual search



Action & planning

Rotation-Angle (ROT-Ang)



Question: What is the angle between the adjacent image?

Options: A. 30 B. 60

Spatial reasoning

Image 1

Image 2

Image 3

Image 4

Image 5

Question: How much does the most expensive watermelon in the picture cost per kilogram?

Options: A. 29. B. 39. C. 59. D. 69.

Hints: Image 1 is the original picture. Image 2, Image 3, Image 4 and Image 5 are the price tags in the picture. Pay attention to the words and prices on the tags.

w/o Hints	w/ Hints
GPT-4V: D. 69.	GPT-4V: C. 59.
GPT-4o: D. 69.	GPT-4o: C. 59.
Gemini-1.5-pro: C. 59.	Gemini-1.5-pro: C. 59.
Gemini-1.5-flash: D. 69.	Gemini-1.5-flash: D. 69.

Visual reasoning

...

etc.

Motivation



- What are MLLMs capable of?

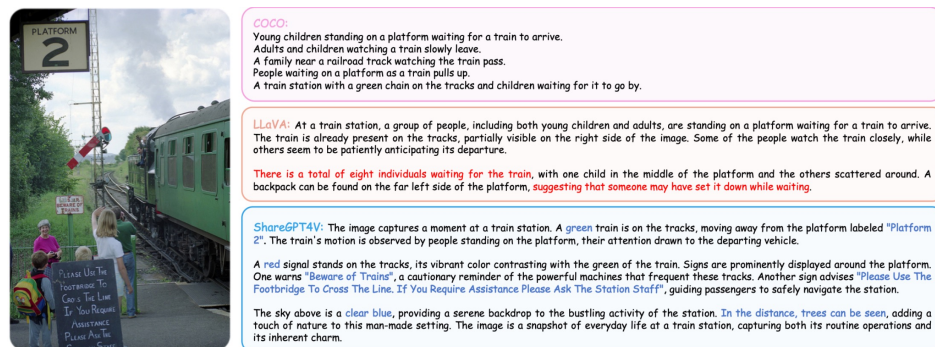
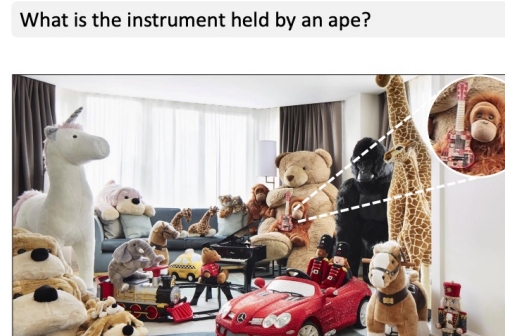
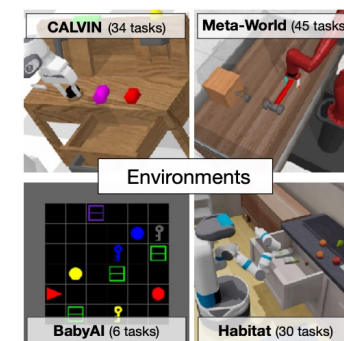


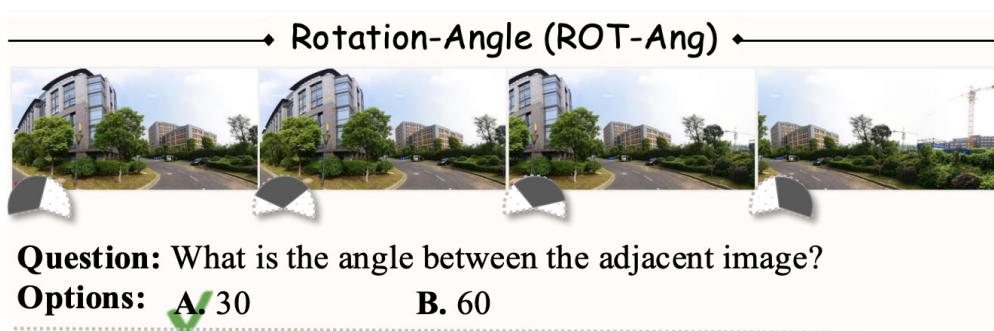
Image captioning



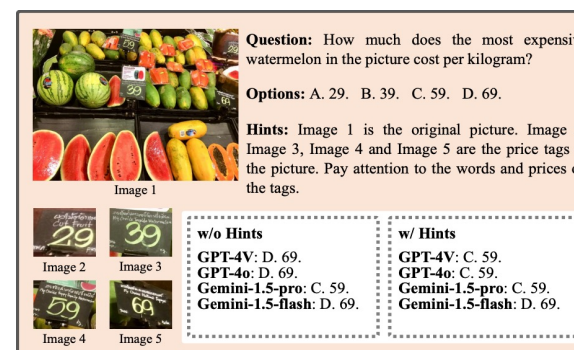
Visual search



Action & planning



Spatial reasoning



Visual reasoning

etc.

Are they able to accomplish complex tasks requiring integrations of these capabilities?

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Introduction



- Let's watch a video first 



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Introduction of our benchmark



- Target: To explore how MLLMs handle **complex multimodal reasoning**

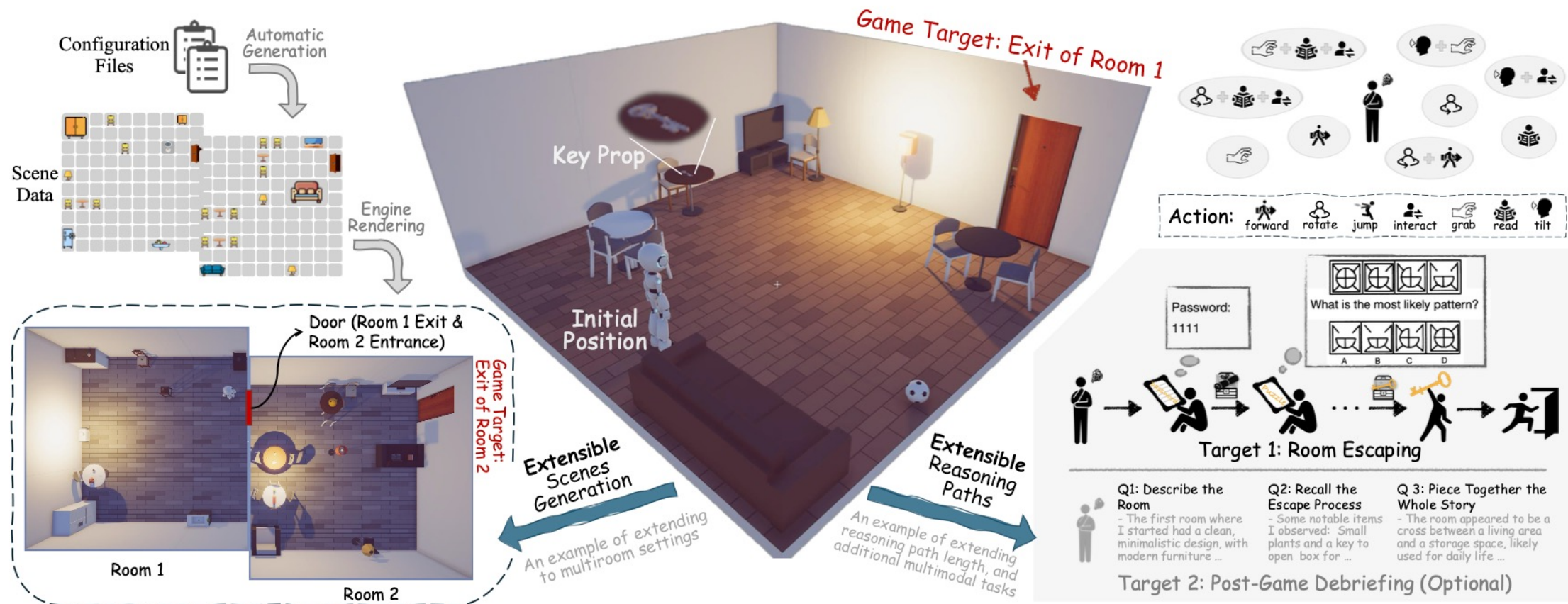


Figure 1. Illustration of our proposed room escape environment EscapeCraft, which allows us to generate customized room scenes (left) and define groundtruth reasoning path of tasks (right). Based on EscapeCraft, we create MM-Escape benchmark, targeting at evaluating both the task completion performance and the entire multimodal reasoning process of MLLMs.

Introduction of our benchmark



- **What** is complex multimodal reasoning?
 - Multimodal reasoning in a virtual/real environment
 - Requiring integration of multiple basic abilities, such as visual search, visual-spatial reasoning, long-term reasoning etc.
- **Why** complex multimodal reasoning?
 - Limitations of the primary focus of current evaluations:
 - Performance task completion rather than the reasoning process
 - Isolated abilities
 - Limited metrics and evidence for analysis
 - Limitations of environment:
 - Simplified the autonomous reasoning process
 - With provided structured knowledge libraries

Introduction of our benchmark



- How to evaluate the entire multimodal reasoning process?

- ✓ **MM-Escape:**

An extensible benchmark inspired by real-world escape games

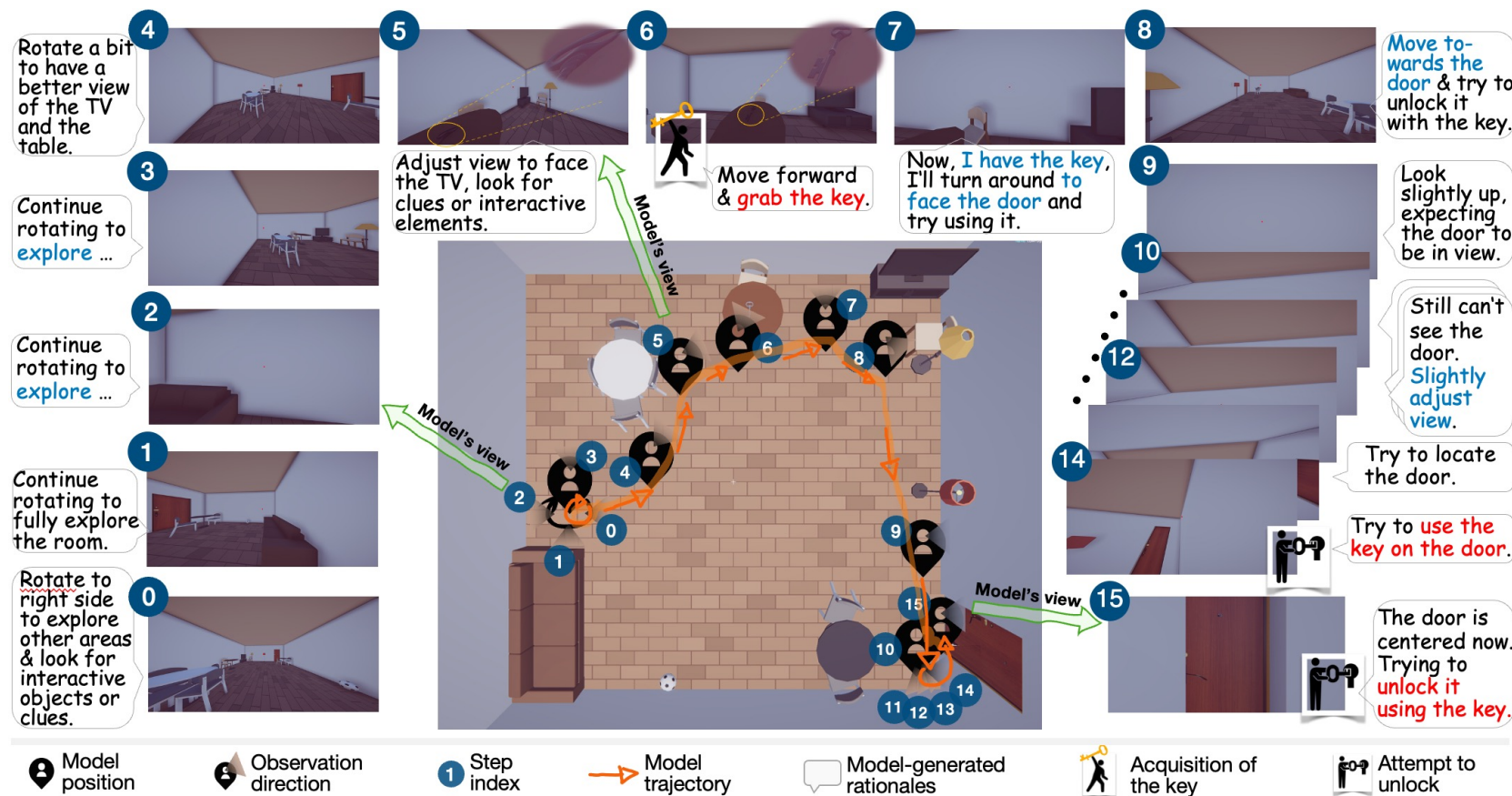
- ✓ Built on **EscapeCraft**:

A customizable open environment

- ✓ Requires free-form exploration

- ✓ Requires coordination of multiple abilities

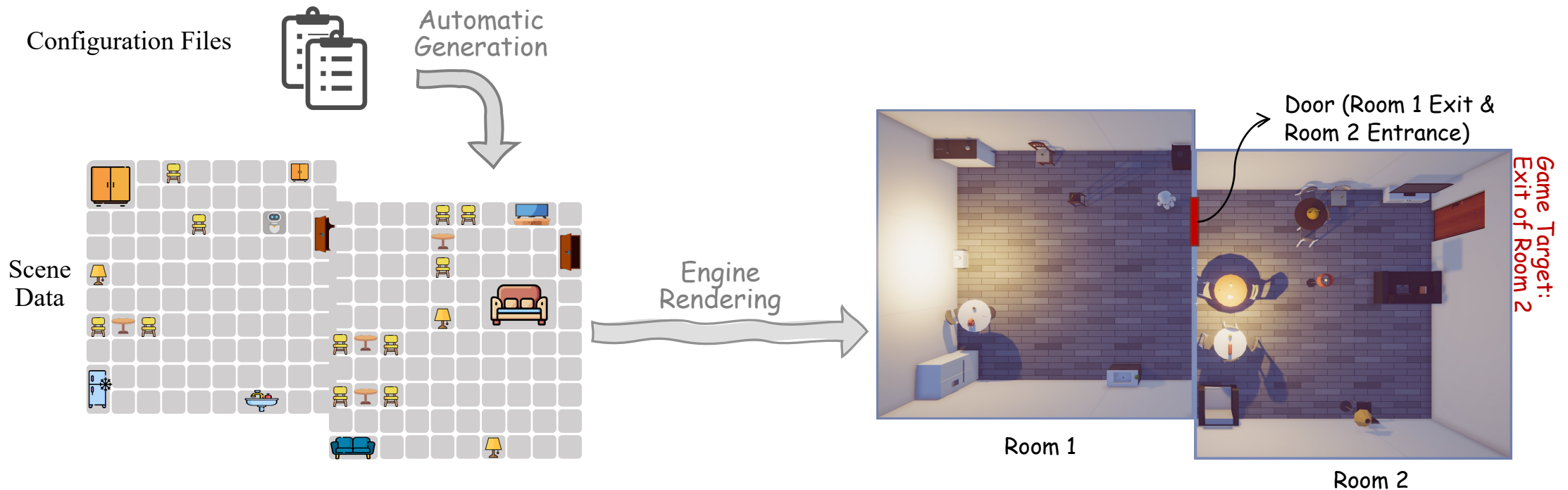
- ✓ Metrics emphasizing intermediate model behaviors alongside task completion



Introduction of our environment



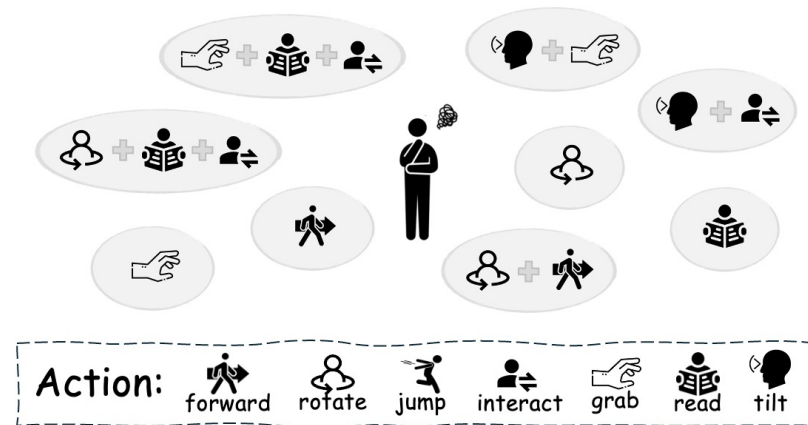
- EscapeCraft Environment Features
 - Automatic room scene generation
 - Customizable room styles (living room, kitchen, bathroom, bedroom)



Introduction of our environment



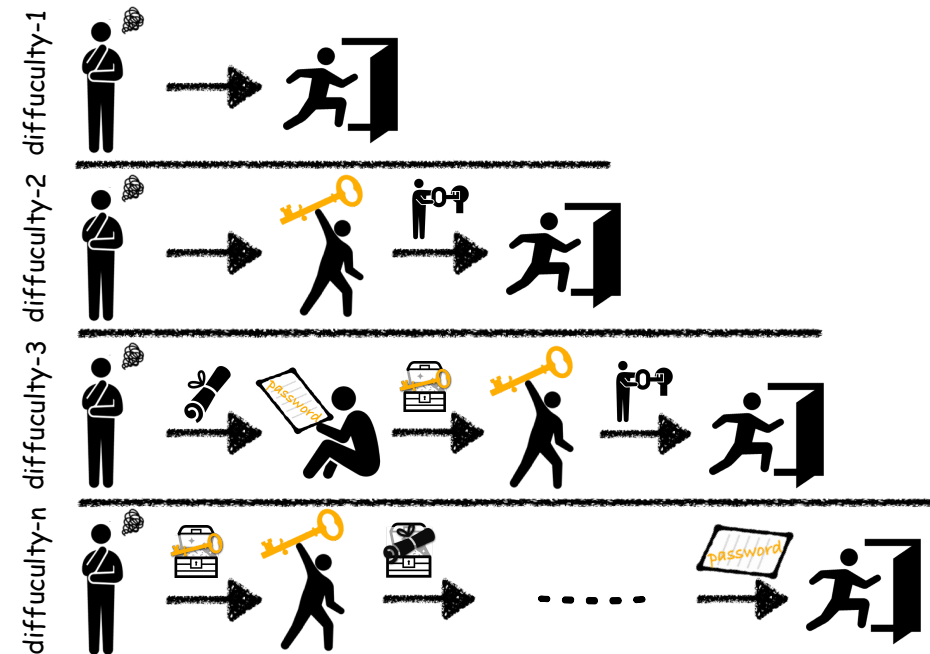
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- Comprehensive action space:
 - Movement (forward)
 - View adjustment (rotation, tilting)
 - Interactions (grab, use, read, input)



Introduction of our environment



- EscapeCraft Environment Features
 - Automatic room scene generation
 - Customizable room styles (living room, kitchen, bathroom, bedroom)
 - Comprehensive action space:
 - Movement (forward)
 - View adjustment (rotation, tilting)
 - Interactions (grab, use, read, input)
- Extensible escaping path and difficulty



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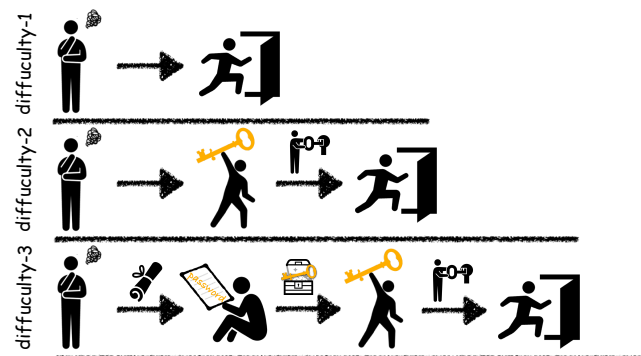
Evaluation



- Benchmark construction

- Variable difficulty levels based on reasoning path length:

- Difficulty-1: (one-hop)
 - Direct door interaction
 - Difficulty-2: (two-hop)
 - Find key/password + unlock door
 - Difficulty-3: (three-hop)
 - Find password + find key + unlock door



- Extensible to more complex chains and multi-room settings

Single room



Multi-room

- Statistics

- 63 scenes, 73 evaluation games (including combinations of multi-room settings)

Evaluation



- Evaluation metrics design:

- **Final** task completion:

- Escape Rate (ER)



- **Intermediate** process metrics:

- **Prop Gain:** Successful acquisition of necessary items)

$$\text{Prop Gain} = \frac{N_{grab}^{TP}}{\sum \text{Prop count}},$$

- **Average Steps:** Efficiency of the whole process
 - **Grab Success Rate:** Precision and reasonability of model-env interactions

$$\text{GSR} = \frac{N_{grab}^{TP}}{\sum \text{Grabbing actions}},$$

- **Grab Ratio:** Interaction strategy

$$R_{grab} = \frac{\sum \text{Grabbing actions}}{S}$$

Evaluation



- Results
 - Models perform **significantly below human level** across all metrics
 - Performance **sharply declines as game difficulty increases**
 - GPT-4o does not always lead the performance for the easiest setting

Table 2. Results of standard single room setting. Prop: Prop Gain; Steps: average steps used to complete the game; Grab SR: the precision of grabbing; Grab Ratio: the portion of grabbing actions regarding the total consumed steps. Note that Difficulty-1 requires no prop, and the prop gain is therefore omitted for this setting. The max allowed steps are 50, 75, 100 for Difficulty-1, -2, -3 respectively. The best score of each metrics is **bolded** and the second is underlined.

Models	Difficulty-1				Difficulty-2					Difficulty-3					AVG ER (%)↑
	ER (%)↑	Steps↓	Grab SR (%)↑	Grab Ratio	ER (%)↑	Prop (%)↑	Steps↓	Grab SR (%)↑	Grab Ratio	ER (%)↑	Prop (%)↑	Steps↓	Grab SR (%)↑	Grab Ratio	
Human	100.00	5.73	95.45	0.19	100.00	100.00	13.64	81.81	0.19	100.00	100.00	21.45	75.45	0.19	100.00
GPT-4o	100.00	11.27	37.82	0.42	72.73	<u>81.82</u>	36.73	36.73	0.26	71.36	90.00	50.19	31.36	0.35	81.36
Gemini-1.5-pro	81.82	21.18	49.18	0.39	<u>54.55</u>	90.91	47.82	14.89	0.44	<u>46.82</u>	<u>74.49</u>	<u>73.18</u>	10.43	0.48	61.06
Claude 3.5 Sonnet	72.73	22.09	30.64	0.36	45.45	54.55	57.45	<u>20.64</u>	0.17	39.61	54.83	82.36	<u>16.21</u>	0.22	52.60
Doubao 1.5 Pro	<u>91.91</u>	<u>16.27</u>	<u>44.68</u>	0.27	45.45	54.55	63.18	13.63	0.25	9.52	33.33	93.19	6.76	0.26	48.96
Llama-3.2-11b-vision	63.64	23.55	31.36	0.35	0.00	27.27	75.00	3.16	0.44	0.00	27.27	100.00	3.55	0.32	21.21
Qwen-VL-Max	18.18	42.64	11.36	0.05	0.00	27.27	75.00	3.51	0.15	9.52	18.18	94.18	2.72	0.31	9.23
Phi-3-vision-128k	0.00	50.00	0.00	0.01	0.00	0.00	75.00	0.00	0.02	0.00	0.00	100.00	0.00	0.01	0.00

Evaluation



• Results

- For models fail to escape, we can still assess the performance via prop gain and interactive behaviors
 - Llama 3.2 and Qwen present several successful interactions and manage to obtain some props
 - Phi-3 attempts to interact with environment
- Grab Ratio does not directly contribute to the other metrics, it is a neutral indicator of interaction behavior and strategy

Models	Difficulty-1				Difficulty-2					Difficulty-3					AVG ER (%)↑
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Evaluation



- Extended Scenarios

- Are models able to detect a **potential prop** when it is **blended within the environment** without hint?

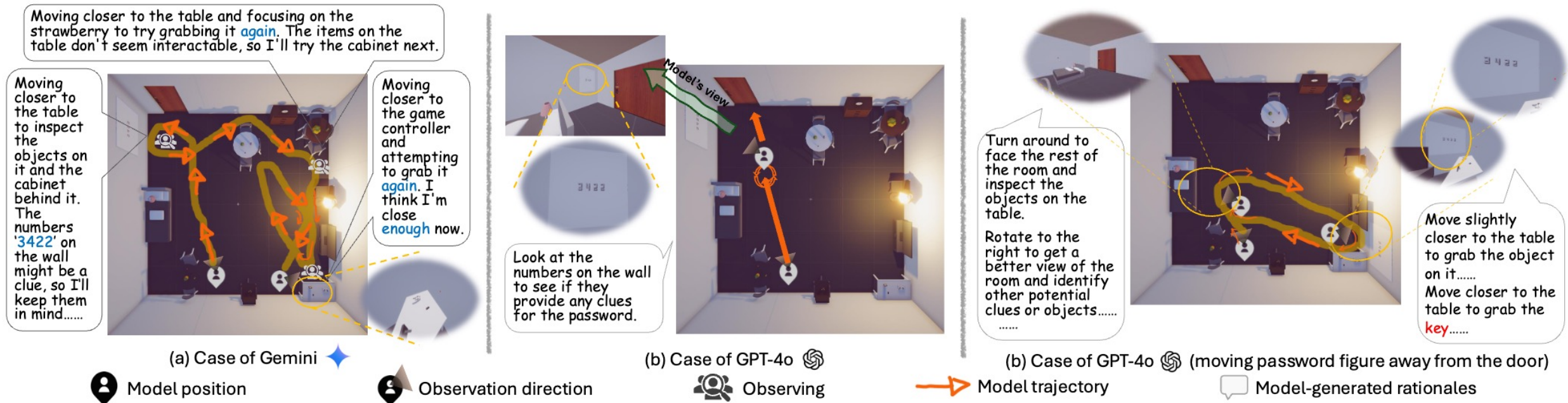
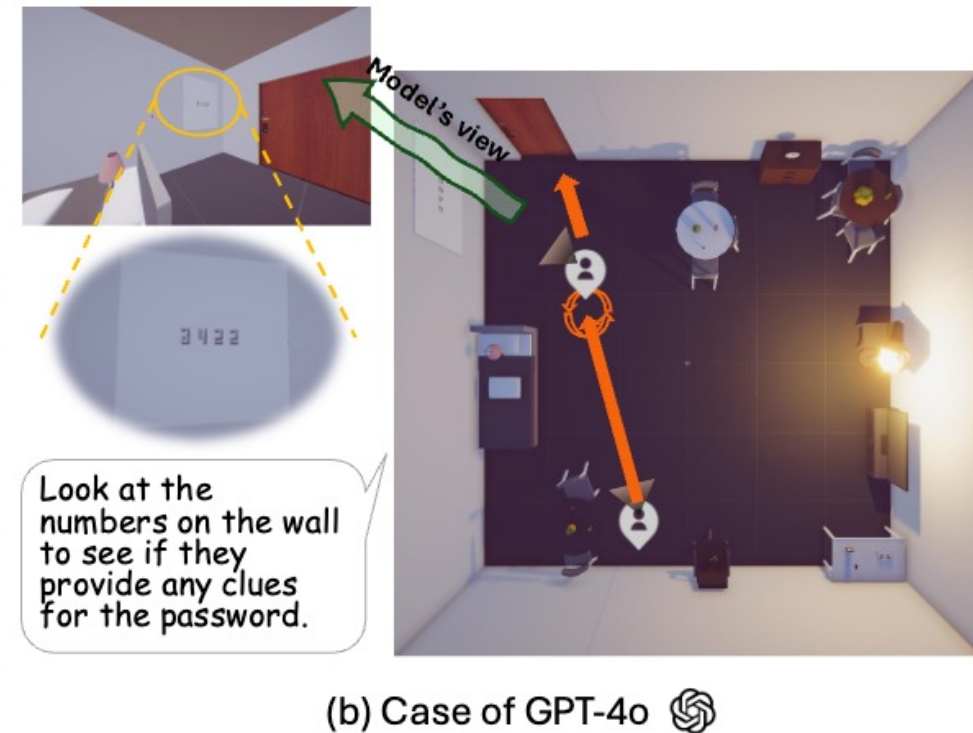
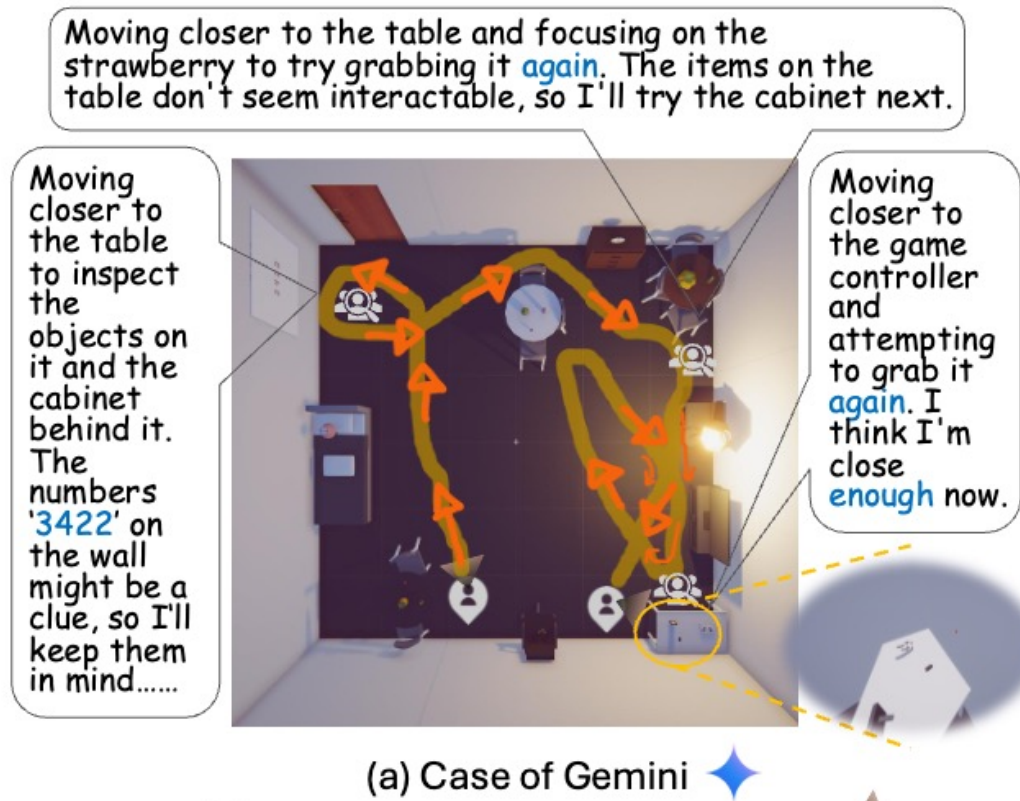


Figure 5. The extended scenario where the required password is displayed via a numerical pattern on the wall, rather than explicitly written on notes. GPT-4o completes reading it at once and exits within five steps, while Gemini struggles to repetitively search the room. Moving the pattern away from the door further challenges GPT-4o, leading to a failure of escaping.

Evaluation



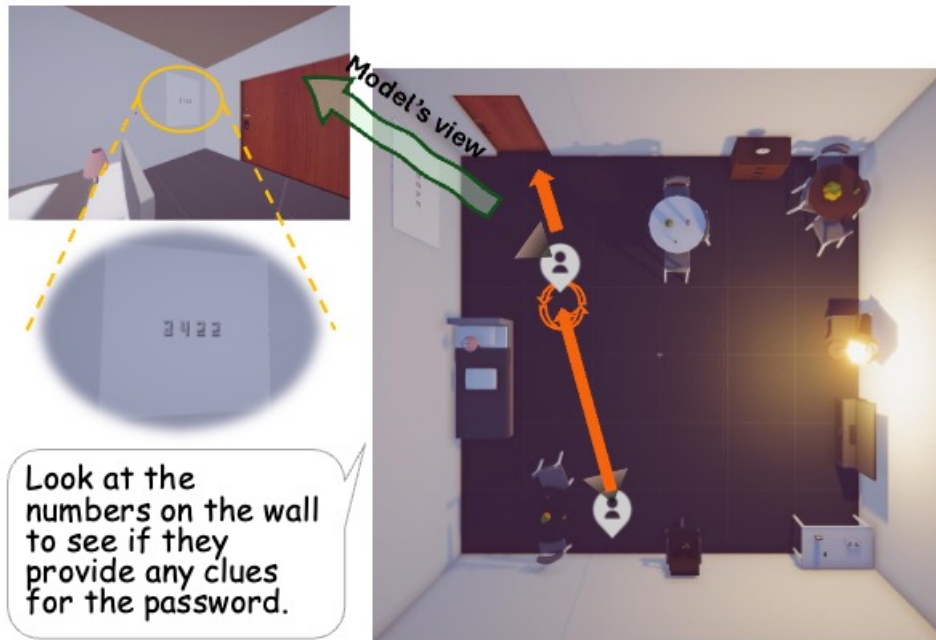
- Extended Scenarios
 - Are models able to detect a **potential prop** when it is **blended** within the **environment** without hint?
 - Placed near the exit



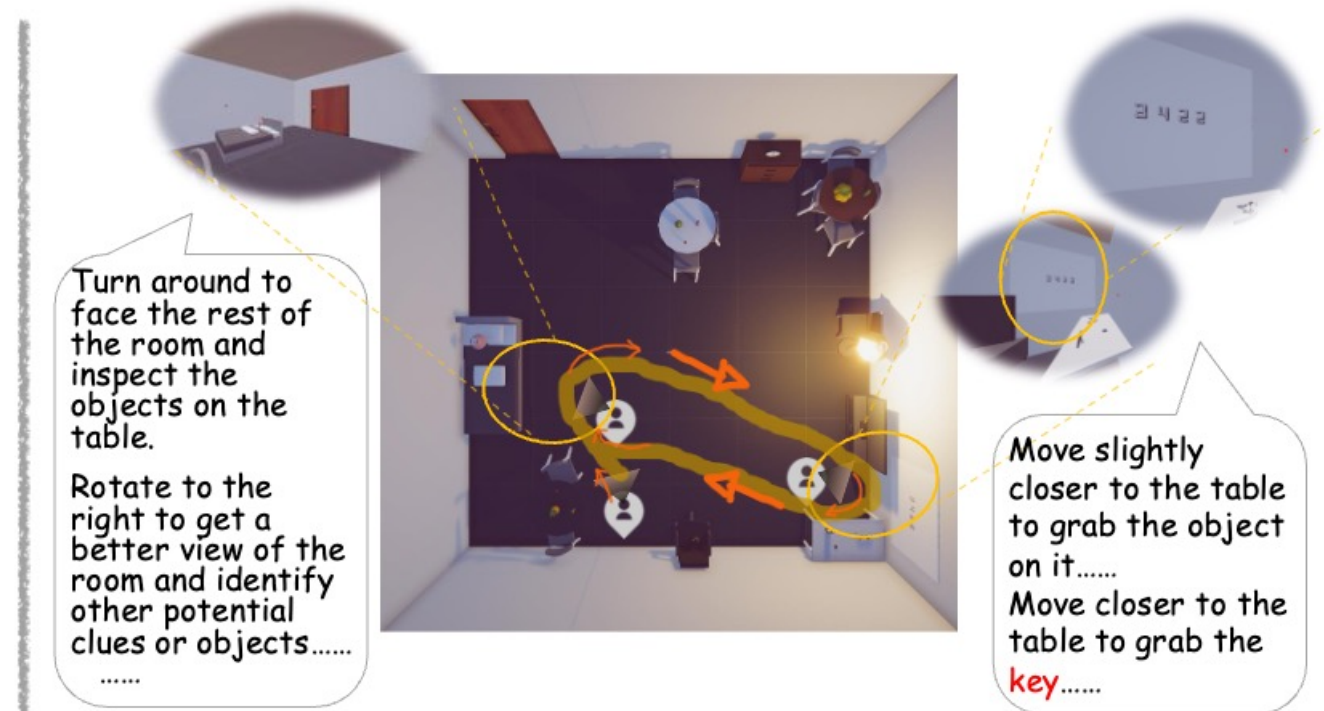
Evaluation



- Extended Scenarios
 - Are models able to detect a **potential prop** when it is **blended within the environment** without hint?
 - Move away from the exit



(b) Case of GPT-4o



(b) Case of GPT-4o (moving password figure away from the door)

Agenda

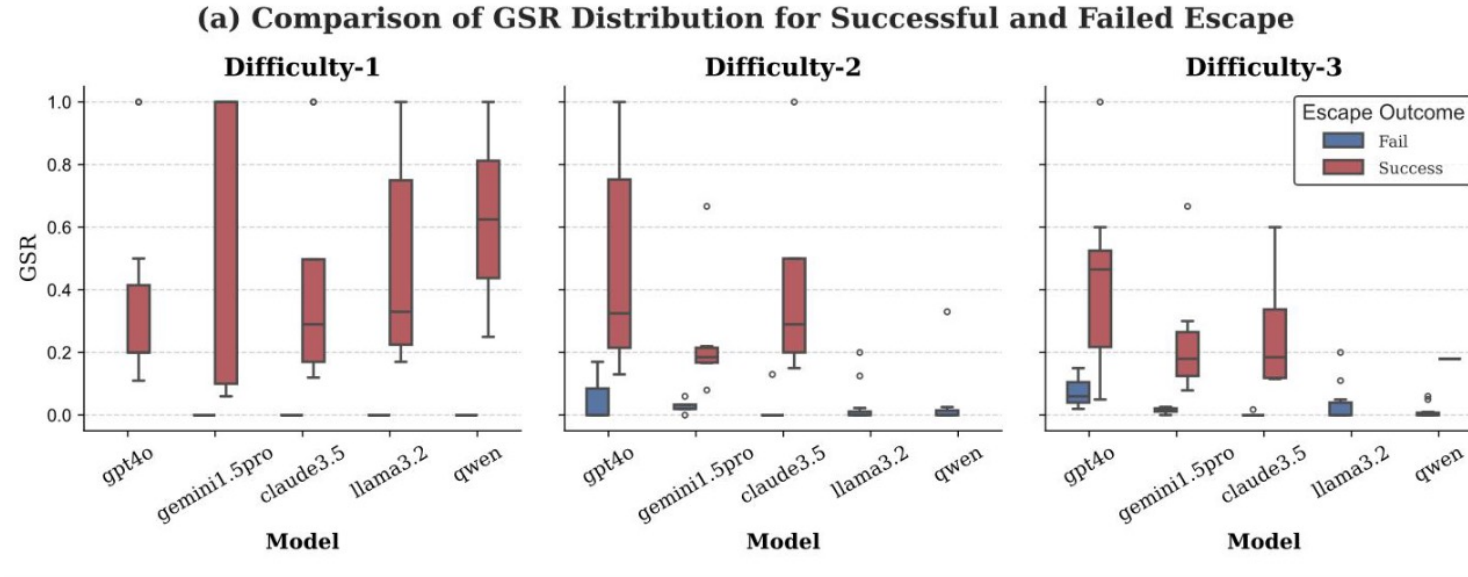
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Analysis



- Is grab success rate correlated to escape rate?
 - Higher grab success rate largely contributes to successful escape



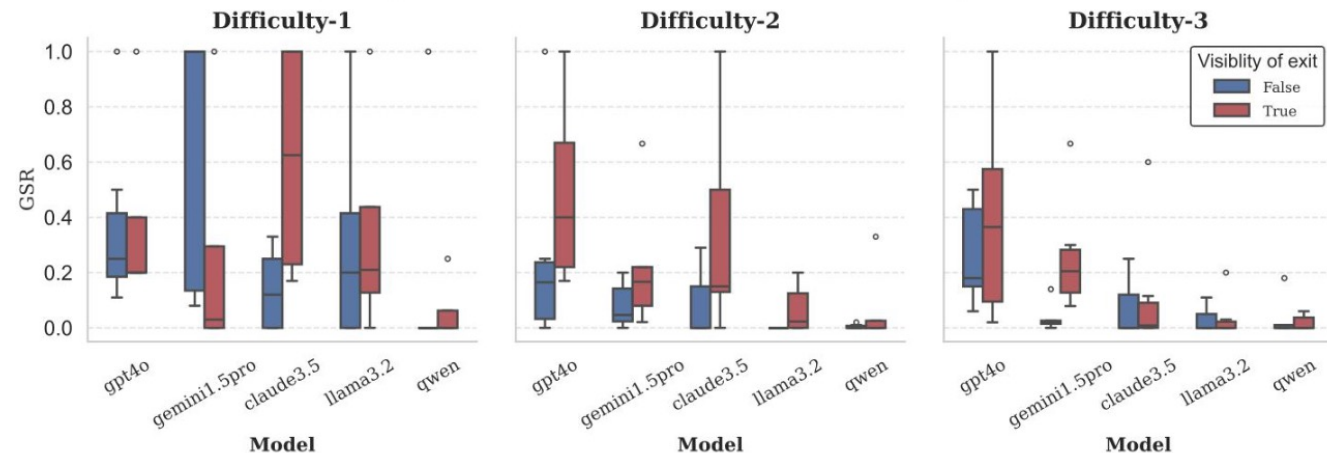
Analysis



- Does the “visibility of exit at initial locations” affect the grab success rate and steps?

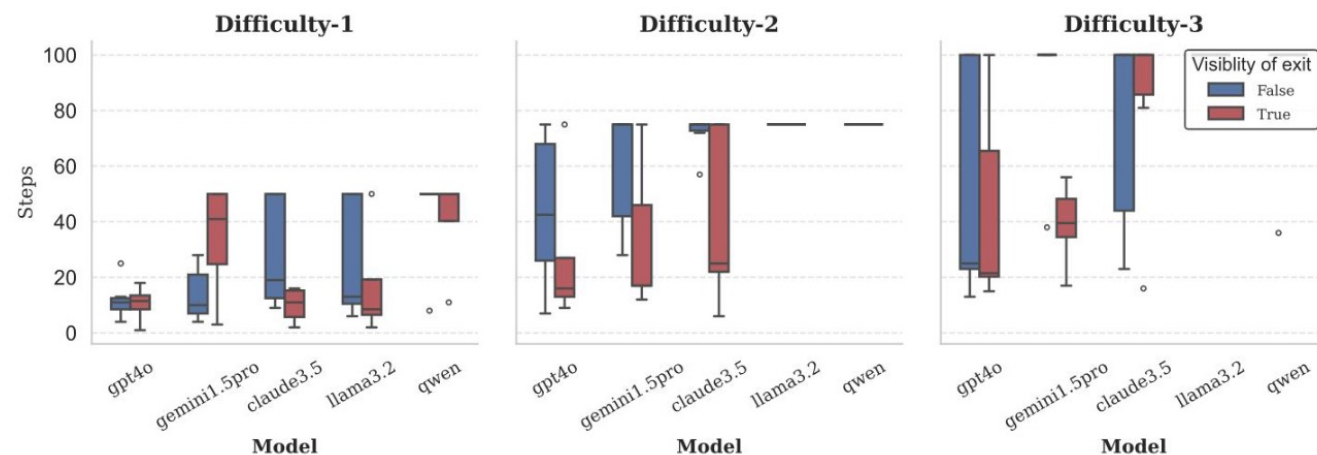
- For games whose exits are visible at initial locations, models tend to exhibit **higher GSR**

(b) Comparison of GSR Distribution for Visibility of Exit



- For games whose exits are visible at initial locations, models often **use less steps to escape**

(c) Comparison of Steps Distribution for Visibility of Exit



Conclusion



- Some Distinct Model Behaviors
 - Different exploration strategies:
 - ✦ Gemini: fixed-position scanning before moving
 - 🌀 GPT-4o: global understanding before detailed inspection
 - Observation preferences:
 - ✦ Gemini: *downward-facing view* to inspect objects
 - 🌀 GPT-4o: predominantly *front-facing view*
- Observed Common Failure Modes
 - Movement failures:
 - Repetitive trajectories (GPT-4o)
 - Getting trapped in corners (Gemini, Claude)
 - Interaction challenges:
 - Action combination failures (Phi-3, Qwen-VL)
 - Imprecise object identification
 - Limited spatial awareness and long-term planning



Thanks for listening

Q & A

MM-Escape



- Results
 - Multi-room settings expose limitations in spatial reasoning
 - A successful experience helps model to escape

Models	Difficulty-1 & Difficulty-1				Difficulty-1 & Difficulty-2					Difficulty-2 & Difficulty-2				
	ER(%)↑	Steps↓	Grab SR (%)↑	Grab Ratio	ER(%)↑	Prop (%)↑	Steps↓	Grab SR (%)↑	Grab Ratio	ER(%)↑	Prop (%)↑	Steps↓	Grab SR (%)↑	Grab Ratio
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Table 3. Performance on multi-room setting for different room scenes. To assist in the more challenging setting, we provide models with a full successful escape path from Room 1 (9 steps) for self-reflection when they try to unlock Room 2. Hence, the Prop Gain (Prop (%)) in the results refers only to Room 2. Further challenges of escaping from the very beginning of multi-room setting are discussed in Supplementary Material [F](#).