Spatial Mental Modeling from Limited Views

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Abstract

Humans intuitively construct mental models of space beyond what they directly perceive, but can large visual-language models (VLMs) do the same with partial observations like **limited views**? We identify this significant gap for current VLMs via our new MINDCUBE benchmark with $17,530$ questions and $2,919$ images, evaluating how well VLMs build robust spatial mental models, representing positions (cognitive mapping), orientations (perspective-taking), and dynamics (mental simulation for what-if movements), to solve spatial reasoning on **unseen** space that beyonds immediate perception.

We explore three approaches to approximating spatial mental models in VLMs: (1) View interpolation to visualize mental simulation, which surprisingly offers little benefit, highlighting the challenge of reasoning from limited views; (2) Textual reasoning chains, which effectively guide model thinking when supervised; and (3) Structured representations like cognitive maps, where ground truth maps help little, but training VLMs to generate and reason over their own maps yields substantial gains—even if the maps are imperfect. Training models to reason over these internal maps raises accuracy from 38.3% to 61.7% (+23.5%). Adding reinforcement learning further improves performance to 76.1% (+37.8%).

Our key insight is that such scaffolding of spatial mental models, actively constructing and utilizing internal structured spatial representations with flexible reasoning processes, significantly improves understanding of unobservable space.

1 Introduction

For Vision-Language Models (VLMs) [1, 2, 3, 4] to move beyond passive perception [5, 6] to interact with partially observable environments [7, 8, 9], it is fundamental to reason about unseen spatial relationships from limited views. Consider how effortlessly a human can infer the unseen objects behind the "*plant*" are the "*tissue box*" and the "*hand sanitizer*" in the second viewpoint in Figure 1, including their position, pose, and their relationship with objects that are not simultaneously visible, all by integrating information from *four* ego-centric observations: we build and update a mental model of our surroundings, even when objects are out of sight. This is enabled by a core cognitive function known as the **spatial mental model** [10, 11]: an internal representation of the environment that allows for consistent understanding and inference about space, independent of the current viewpoint. VLMs, despite their impressive progress, struggle to synthesize spatial information from limited views, maintain spatial consistency across views, and reason about objects not directly visible [12, 13, 14, 15].

This gap calls for specialized evaluation settings, which must include: (a) reasoning with partial observations where objects are occluded or out of view (such as "*hand sanitizer*"in the second viewpoint in Figure 1), (b) maintaining cross-view consistency across shifting viewpoints (such as through anchor objects "*plant*"), and (c) mental simulation to infer hidden spatial relationships (such as "*what if turning left and moving forward*"). To fill this gap, we introduce MINDCUBE, featuring $17,530$ questions and $2,919$ images, organized into 740 multi-view groups through various types of

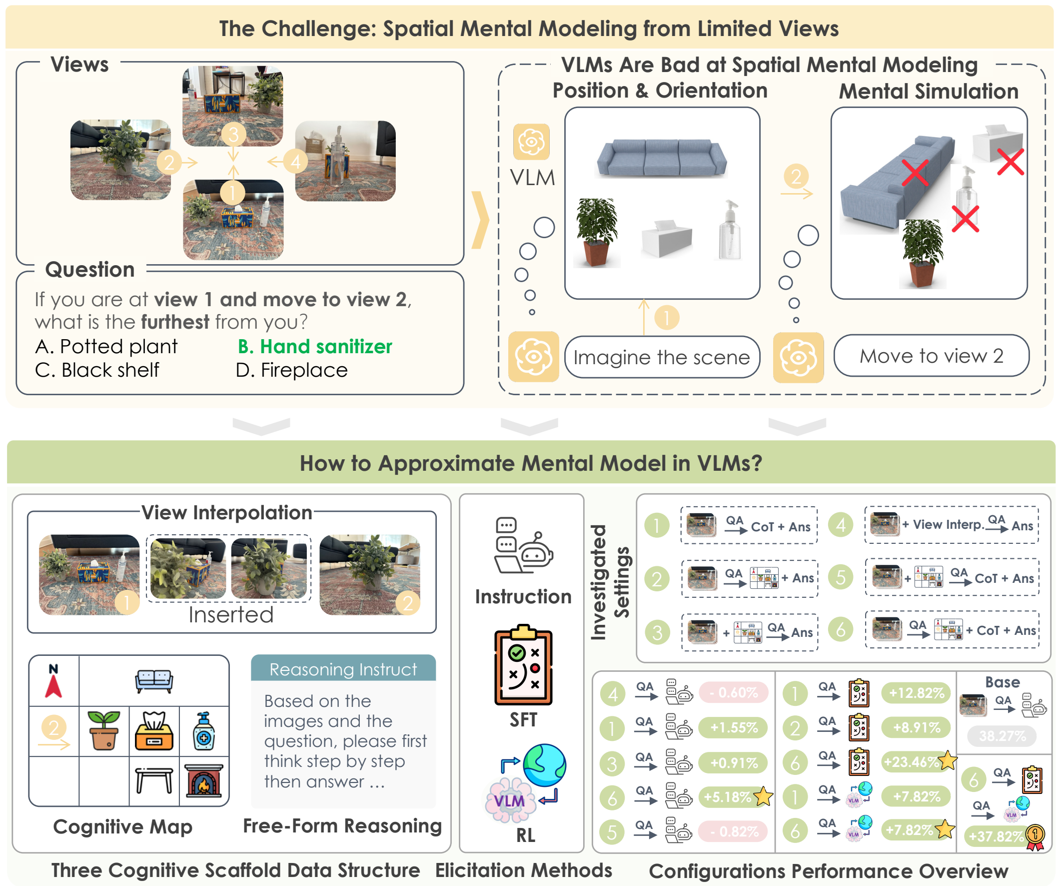


Figure 1: **Top**: VLMs cannot maintain a coherent mental model when evaluating on the MINDCUBE benchmark. **Bottom**: We study how we can help VLMs imagine space through external (scaling of views, cognitive map input) and internal strategies (fine-tuning, cognitive map elicitation). We find joint cognitive map and reasoning setting yields the highest gain (37.8%). ⭐: Best within the same elicitation method. 🏅: Best performance combination.

viewpoint transformations (i.e., ROTATION, AMONG, AROUND in Figure 2). We annotate questions with a focus on objects that are not visible in the current query view. As shown in Figure 2, we systematically design question types requiring "what-if" mental simulations from the given view (such as "*what if turning to left*"), perspective taking (such as "*what if taking the sofa's perspective*"), complex relation reasoning queries (referencing either the agent or other objects).

Our extensive evaluations of 14 state-of-the-art VLMs on MINDCUBE reveal that both open-source and closed-source models perform only marginally better than random guessing. This poor performance motivates a central question: **How can we help VLMs reason from partial observations**?

Inspired by spatial cognition [16, 17, 18] operating through *visual imagery*, *linguistic reasoning*, or *explicit cognitive maps*, to build consistent spatial awareness across different views, we investigate whether intermediate representations can help VLMs approximate mental models through three approaches. **View Interpolation** generates intermediate views between given observations using recorded video or 3D reconstruction (Stable Virtual Camera [19]), which unexpectedly is not helpful, highlighting the importance of reasoning directly from *limited* views. **Free-form Natural Language Reasoning** verbalizes the mental simulation process, achieving substantial gains (+1.6%). **Structured Cognitive Map** simulates global spatial memory from an allocentric (bird's-eye) perspective with orientation and view augmentation. Interestingly, ground truth cognitive maps yield minimal improvements (+0.9%), while guiding models to construct their own cognitive maps achieves better results (+5.2%), which indicates that teaching a model to *generate* its own mental model and think this way, is more effective than directly making sense of *provided* ready-made representations.

Despite generating seemingly correct maps, VLMs exhibit a significant bottleneck in *accurate* mental modeling, evidenced by low isomorphic similarity (17%) with ground truth maps. Recognizing

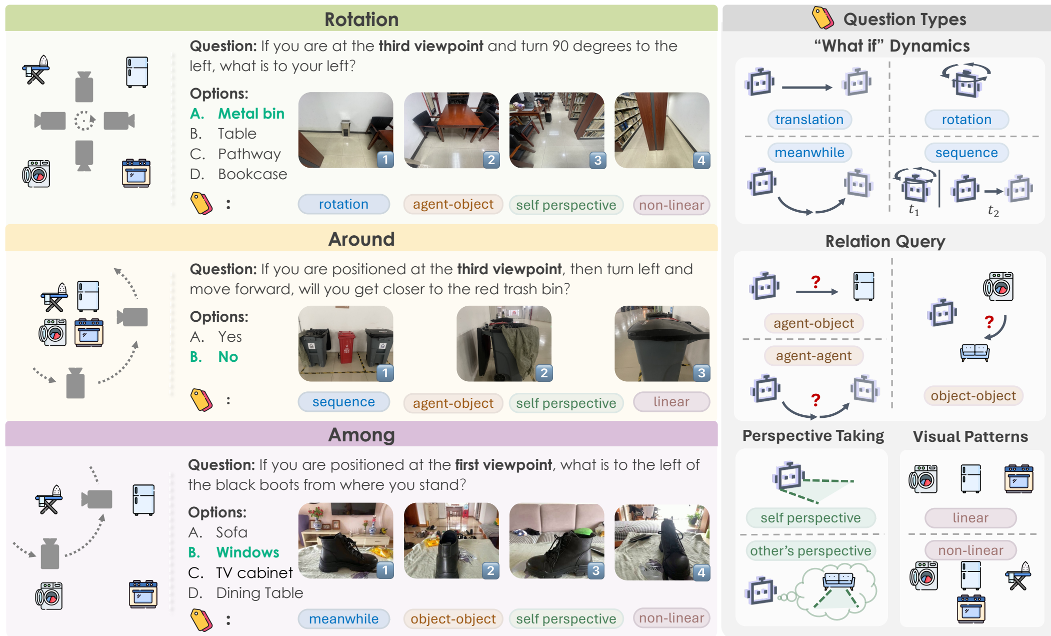


Figure 2: MINDCUBE taxonomy and examples. Left: Three camera movement patterns (ROTATION, AROUND, AMONG) with corresponding spatial QA examples. **Right**: Four-dimensional taxonomy categorizing MINDCUBE questions types.

this limitation, we train VLMs by constructing $10,000$ reasoning chains and $10,000$ ground truth cognitive maps, investigating how to effectively guide their thinking process through injection of these training signals. Self-supervised Finetuning (SFT) on cognitive maps significantly boost isomorphic similarity to 50% from 17%. While SFT on free-form reasoning chains proved more effective with a gain of $+4.8\%$, guiding models to first build cognitive maps and then perform free-form reasoning over them achieved significantly better performance, resulting in a total gain of $+15.4\%$, proving scaffolding spatial mental models via actively constructing and utilizing internal structured spatial representations with flexible reasoning processes is highly effective.

We employ Reinforcement Learning (RL) to further boost post-SFT performance, guiding models to think in terms of building and reasoning over cognitive maps by injecting structured thinking before RL training, using our SFT model. This approach leads to a significant improvement—raising task accuracy from a baseline of 38.3% to 76.1%. Our empirical evidence substantiates a critical finding: VLMs exhibit superior performance in spatial reasoning tasks when autonomously generating and leveraging internal mental representations, as compared to conventional approaches such as view interpolation or externally-supplied maps.

2 MINDCUBE Benchmark and Evaluation

2.1 MINDCUBE Benchmark

Overview. We introduce MINDCUBE, a benchmark for evaluating VLMs' spatial reasoning under partial observations and dynamic viewpoints. MINDCUBE features multi-view image groups paired with spatial reasoning questions, enabling fine-grained analysis of spatial modeling performance. It targets key challenges such as maintaining object consistency across views and reasoning about occluded or invisible elements. Table 1 (left) summarizes the benchmark's overall data distribution. Details on benchmark design, taxonomy, and curation are provided in the Appendix.

Taxonomy. For a fine-grained analysis of VLM spatial reasoning abilities, we introduce a taxonomy that systematically categorizes the challenges in MINDCUBE (visualized in Figure 2). This taxonomy spans five key dimensions: 1) **Camera Movement**: We mainly collect three types of camera movement: ROTATION (Stays in place but rotates to look around), AROUND (Moves around evaluated objects in a circular path), and AMONG (Moves among evaluated objects in a circular path). 2)

Table 1: Left: MINDCUBE data statistics. Right: Performance of VLMs on MINDCUBE.

Rotation(1081)	
Arkitscenes	865/53
Self collected	216/9
Img groups	62

Among(14782)	
WildRGB-D	13821/463
DL3DV-10K	961/30
Img groups	493

Around(1667)	
DL3DV-10K	725/109
Self collected	942/76
Img groups	185

Method	**Overall**	**Rotation**	**Among**	**Around**
Baseline				
Random (chance)	*39.40*	*36.36*	*39.00*	*46.44*
Random (frequency)	*41.60*	*39.00*	*39.00*	*46.00*
Open-source Multi Image Models				
LLaVA-Onevision-7B	**49.00**	36.84	**50.54**	38.43
LLaVA-Video-Qwen-7B	45.78	37.80	46.94	36.52
mPLUG-Owl3-7B	45.46	37.51	47.04	29.62
InternVL2.5-8B	29.01	35.69	27.00	52.97
Qwen2.5-VL-7B	35.44	38.09	34.73	45.13
LongVA-7B	35.29	35.31	34.95	40.55
idefics2-8B	38.74	37.22	38.65	41.83
DeepSeek-VL2-Small	47.42	36.36	49.44	28.03
Mantis-8B(Clip)	28.82	38.18	26.08	**61.36**
Proprietary Models(API)				
GPT-4o	36.70	**40.88**	36.07	42.89
Claude-3.7-Sonnet	39.71	37.70	39.62	43.42
Spatial Models				
RoboBrain	42.23	37.51	42.75	39.28
space-mantis	31.56	37.99	29.41	58.07
space-LLaVA	27.31	33.89	26.71	35.37

Visual Patterns: This describes the objects' spatial configurations, including spatial *linear* or *non-linear* arrangements. 3) **"What-if" Dynamics**: The hypothetical transformations applied to the agent's viewpoint, such as *translation*, *rotation*, or their combination (*meanwhile* and *sequence*). 4) **Relation Query**: The type of spatial relation being queried, including *agent–object*, *agent–agent*, or *object–object*. 5) **Perspective Taking**: Whether the spatial reasoning is grounded in the perceiver's own viewpoint (*self*) or involves adopting the viewpoint of another entity (*other*).

Dataset Curation. The MINDCUBE dataset was created through a pipeline: We first selected multi-view image groups matching our taxonomy's movement patterns (Figure 2) and spatial criteria. These were then annotated with key spatial information. Finally, we algorithmically generated taxonomy-aligned questions with targeted distractors. Details are included in the Appendix.

2.2 Evaluation on MINDCUBE

We evaluate VLMs' spatial reasoning on MINDCUBE using a diverse set of models (Table 1, right; setup details in the Appendix). Results reveal a striking performance gap: the best model, LLaVA-Onev-7B, achieves only 49.00% accuracy—well above chance but far from human-level. ROTATION tasks proved hardest (top score: 40.88%), suggesting limited mental rotation and viewpoint adaptation. AMONG and AROUND tasks showed no consistent winners, highlighting weak relational reasoning. Large proprietary models often lagged behind smaller open-source counterparts. Spatial fine-tuning yielded mixed results. Overall, neither multi-image input nor spatial fine-tuning reliably improves spatial reasoning, raising a key question: **How can we help VLMs develop or approximate these crucial spatial reasoning capabilities?**

3 Which Scaffolds Best Guide Spatial Thinking in Unchanged VLMs?

To address the identified gap, we first evaluate whether structured data forms can scaffold spatial reasoning in frozen VLMs by approximating spatial mental models under limited views.

3.1 Data Structures as Cognitive Scaffolds for Spatial Mental Models

We investigate whether certain data structures can act as cognitive scaffolds that help VLMs form spatial mental models from limited visual observations. In cognitive science, spatial mental models are internal representations encoding the relative configuration of objects and viewpoints. Rather than metric-precise maps, they are schematic, manipulable constructs that support reasoning across fragmented observations and unseen perspectives [11, 20, 21, 22]. For instance, humans can mentally simulate turning or infer what lies behind them, suggesting that such representations are flexible, incomplete, yet functionally effective. Drawing on this literature, we define three data structures,

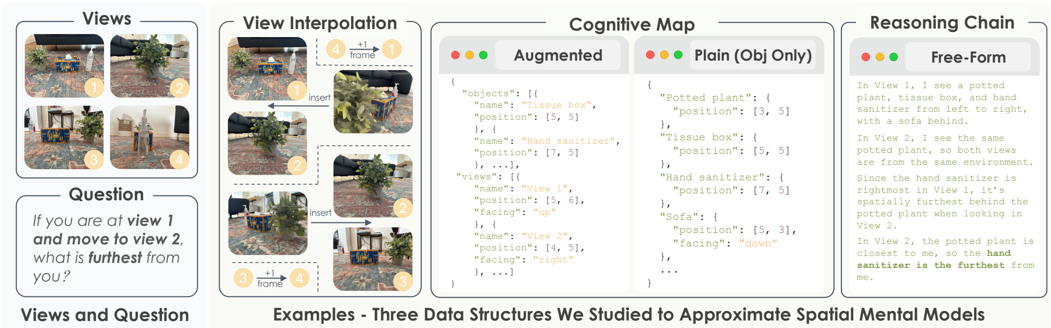


Figure 3: Grounded examples of our three data structures that approximate spatial mental models.

each targeting distinct cognitive properties (integration, transformation, inference) of spatial mental models, with grounded examples in Figure 3:

1. **View Interpolation**. Interpolating between sparse camera views introduces perceptual continuity, echoing the process of *mental animation* [23] and supporting internal transformation such as imagined rotation. This structure scaffolds the dynamic updating capability of spatial mental models. Figure 3 shows a one-frame inserting example that replaces the original question images.
2. **Augmented Cognitive Map**. A cognitive map is a 2D schematic representation of object layouts in space. Such maps resemble Tversky's *cognitive collages* [20], and they capture locally coherent but fragmented structures. Recent studies [24, 25] on VLM-based spatial intelligence typically adopt a *plain* form that only encodes object positions in a top-down view. We propose an *augmented* variant that incorporates discrete views, with both objects and views annotated by position and orientation, thereby approaching the relational consistency of *spatial mental models*.
3. **Free Form Reasoning**. Open-ended, step-by-step natural language reasoning offers a *procedural approximation* of how spatial models are constructed and queried. While less rigid than map-like structures, such reasoning reflects the inferential function of spatial mental models, especially under ambiguous or incomplete observations [21].

3.2 Experiment Setup

We conduct controlled experiments with fixed input formats to test whether structured scaffolds can help without retraining. Each condition introduces a different structure to support internal modeling under limited views.

Table 2: Abbreviations for the ten input-output configurations across all experiments in this work. VI = **V**iew **I**nterpolation, CGMap = **C**o**g**nitive **Map**, Aug = Augmented (objects + camera included), FF-Rsn and FFR = Free-Form Reasoning.

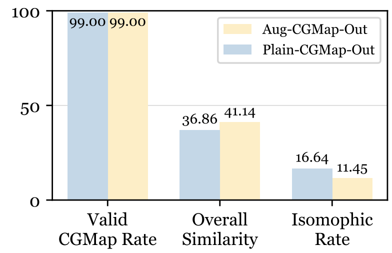
Name	Input Structure	Output Format
`Raw QA`	Raw views + question	Direct answer
`VI-1`	Raw + 1 interp. view	Direct answer
`VI-2`	Raw + 2 interp. views	Direct answer
`FF-Rsn`	Raw views + question	Reasoning → answer
`Aug-CGMap-In`	Aug. cognitive map	Direct answer
`Aug-CGMap-Out`	Aug. cognitive map	Direct answer
`Plain-CGMap-Out`	Plain cognitive map	Direct answer
`Plain-CGMap-FFR-Out`	Raw views + question	Plain map + rsn → ans
`Aug-CGMap-FFR-Out`	Raw views + question	Aug. map + rsn → ans
`CGMap-In-FFR-Out`	Aug. cognitive map	Reasoning → answer

Model and Evaluation Data We conduct all experiments using *Qwen2.5-VL-3B-Instruct* [3]. Our evaluation is performed on MindCube-Tiny, a diagnostic subset sampled from MindCube, containing 1,100 questions in total. Detailed statistics are: 500 from the Among, 400 from Around, and 200 from Rotation.

Configurations Each experiment is defined by two orthogonal axes: *Input Structure* (what spatial evidence VLMs receive) and *Output Format* (the required response type). We investigate a subset of the ten possible configurations shown in Table 2. Specifically, our grounded cognitive maps are generated using the object arrangements annotation described in Section 2.1, and examples for all configurations are provided in the Appendix. We exclude the `Aug-CGMap-Out` and `Plain-CGMap-Out` settings, as VLMs tend to conflate map generation with reasoning, even when instructed otherwise.

Table 3: Left: QA accuracy (%) of *Qwen2.5-VL-3B-Instruct* on the MINDCUBE-TINY benchmark under different input/output scaffolds. Right: Graph metrics for two cog map output settings.

Config.	Overall	Rotation	Among	Around
`Raw QA`	38.27	35.50	31.40	48.25
`VI-1`	37.67↓	30.05	32.80	47.25
`VI-2`	36.10↓	22.95	31.80	47.50
`Aug-CGMap-In`	39.18↑	38.00	31.60	**49.25**
`FF-Rsn`	39.82↑	33.50	38.40	44.75
`Aug-CGMap-FFR-Out`	42.73↑	37.50	**44.60**	43.00
`Plain-CGMap-FFR-Out`	**43.45**↑	**42.50**	41.00	47.00
`CGMap-In-FFR-Out`	37.45↓	35.00	31.60	46.00



Evaluation Metrics We evaluate task performance using QA accuracy. For generated cognitive maps, we introduce a set of well-defined graph metrics: (1) *Valid Cognitive Map Rate*, indicating whether the output conforms to the expected schema; (2) *Overall Similarity*, a weighted score combining directional and facing consistency; and (3) *Isomorphism Rate*, measuring whether all pairwise object relations match the ground truth under optimal alignment. Full definitions are provided in Appendix.

3.3 Do Scaffolds Improve Spatial Reasoning Without Training?

We evaluate how well the seven input configurations defined in Table 2 support spatial reasoning in VLMs under limited views, without any model updates. Results are shown in Table 3 (left).

How far can structure alone go? We begin with the baseline: raw input views and direct answering, which achieves just 38.27% accuracy. Adding interpolated views, which we hope to simulate smoother perceptual transitions, leads to no meaningful gain, and in some cases slightly harms performance (down to 36.10%). Providing an augmented cognitive map or free-form reasoning barely improve accuracy (39.18% and 39.82%). These results suggest: *structure alone, whether visual or spatial, is not enough*. Without engaging reasoning, VLMs struggle to leverage even well-formed spatial cues.

Can we prompt the model to think spatially? The answer appears to be yes. Strikingly, compared to `FF-Rsn` only, prompting models to produce a *cognitive map* before answering leads to the strongest gains: 43.45% with plain maps (object only), and 42.73% with augmented maps (objects + views). This suggests that generating a map may encourage the model to first form a global understanding of the scene, which in turn supports more structured reasoning. Our case studies in the Appendix reveal that such reasoning often unfolds on the map itself. Both map forms have a great format following ability. Augmented maps perform slightly worse. In Table 3 (Right), despite generating syntactically valid maps for both formats, similarity to grounded maps is low ($< 50\%$), reflecting limited mapping ability. Notably, augmented maps have lower isomorphism rates (↓ 5.19%), likely because the added view-level details increase generation errors, making downstream reasoning less reliable.

What if we ask models to reason over grounded cognitive maps? Intuitively, combining map input and free-form reasoning seems promising. Yet, performance drops to 37.45%. We hypothesize this mismatch arises from representational dissonance: reasoning over externally imposed maps may conflict with the model's latent space, leading to confusion rather than clarity.

Key Takeaways: Scaffolding Spatial Reasoning in Frozen VLMs

- *Producing reasoning is effective, especially combined with cognitive maps.*
- *Self-generated reasoning consistently outperforms imposed formats.*
- *Visual continuity and passive structure provide little benefit.*
- *Simpler, object-only maps work better; too much structure can backfire for frozen VLMs.*

4 Can We Teach VLMs to Build and Leverage Spatial Representations?

So far, prompting frozen VLMs with external scaffolds, such as interpolated views or cognitive maps, has yielded limited gains. These techniques fail to tackle the core limitation: VLMs do not form internal spatial representations or reason through space effectively. To go further, we want to know: Can supervised fine-tuning (SFT) teach VLMs to build and leverage spatial models from within?

Table 4: QA accuracy (%) and cognitive map generation quality of *Qwen2.5-VL-3B-Instruct* under SFT configurations on MINDCUBE-TINY. Both `FF-Rsn` and `FFR` refer to free-form reasoning.

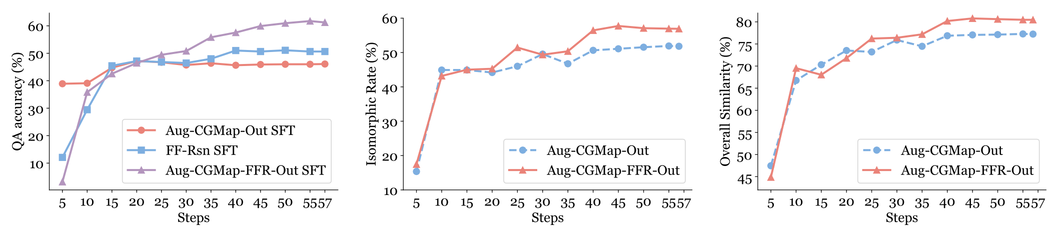
SFT Config.	MINDCUBE-TINY QA Accuracy (%)				Generated Cognitive Map (%)		
	Overall	**Rotation**	**Among**	**Around**	**Valid Rate**	**Overall Sim.**	**Isom. Rate**
`Raw QA`	46.36	33.50	51.20	46.75	–	–	–
`Aug-CGMap-Out`	47.18$\uparrow$	35.00	52.80	46.25	100.00	77.27	51.91
`Plain-CGMap-Out`	45.73$\downarrow$	37.50	49.80	44.75	100.00	75.89	49.55
`FF-Rsn`	51.09$\uparrow$	34.00	56.40	**53.00**	–	–	–
`Aug-CGMap-FFR-Out`	**61.73**$\uparrow$	**68.50**	**70.60**	47.25	**100.00**	**80.46**	**56.91**

4.1 Designing a Robust Experimental Framework

To ensure consistency and comparability, we inherit experimental configurations detailed in Sections 3.1 and 3.2. Specifically, we retain: (1) the two effective data structures—Cognitive Maps (Object-only / Object + Camera) and Free-Form Reasoning, (2) the base model *Qwen2.5-VL-3B-Instruct*, (3) the evaluation benchmark MINDCUBE-TINY, and (4) all established evaluation metrics. View interpolation is excluded from our fine-tuning experiments due to its limited performance gains in earlier validations. Primary modifications in this SFT phase include adjusted training hyperparameters (detailed in the Appendix).

SFT Task Configurations Drawing on insights from Section 3.3, we use selected configurations from Table 2 to evaluate the incremental impact of cognitive map generation and free-form reasoning in SFT. These include baseline QA without explicit reasoning (`Raw QA`), reasoning guided by generated maps only (`Plain-CGMap-Out`, `Aug-CGMap-Out`), reasoning-augmented prompts (`FF-Rsn`), and a fully integrated setup that asks VLMs to generate both maps and reasoning (`Aug-CGMap-FFR-Out`).

Grounded Free-Form Reasoning Chain Generation We design grounded reasoning chains using detailed image annotations and structured question templates. Chains are manually constructed via a template-based method, ensuring logical coherence and clear grounding in observable spatial relations (see an example in Figure 3). This yields precise, interpretable supervision signals that help VLMs learn robust spatial reasoning representations. The detailed grounded reasoning data generation pipeline is shown in the Appendix.



(a) QA accuracy (%) (b) Isomorphic Rate (%) (c) Overall Similarity (%)

Figure 4: SFT per 5 step training performance on task accuracy and graph metrics.

4.2 Do VLMs Truly Benefit from Explicit Training in Spatial Reasoning?

We explore several SFT configurations (results shown in Table 4), guided by a series of core questions. Fine-tuning directly on raw QA pairs, without spatial supervision, raises accuracy from 38.27% to 46.36%. This suggests VLMs can absorb some spatial cues from QA data alone. We use this setup as the baseline for evaluating methods that explicitly incorporate spatial structures.

Can structured approximations of mental models alone meaningfully improve performance? As shown in Table 2, supervised fine-tuning on explicit cognitive maps, either *Augmented* or *Plain*, leads to substantial improvements in graph structure quality, with more than 30% gains in both overall similarity and Isomorphic rate. However, the effect on end-task accuracy remains limited. Both augmented maps (47.18%) and Plain maps (45.73%) offer only modest gains over the fine-tuned `Raw QA` (46.36%). In contrast, directly `FF-Rsn` yields a significantly larger improvement, increasing accuracy to 51.09%. This could be that free-form reasoning is well-aligned with base model language ability, which better guides the model towards the correct spatial understanding.

Generating both cognitive maps and free-form reasoning is the most effective approximation. Among all configurations, this combination yields the most significant performance gain (61.73%,

↑15.37%), far surpassing models that rely on either map generation or reasoning alone. This suggests **a strong synergy** between structured spatial modeling and natural language inference. Why does this combination work so well? First, improvements in task accuracy are accompanied by sharper spatial representations. The `Aug-CGMap-FFR-Out` model, which first builds a cognitive map and then reasons over it, achieves 80.46% similarity and 56.91% isomorphism, surpassing all other variants. On the other hand, training dynamics further reinforce this view. As shown in Figure 4, models trained to jointly map and reason tend to converge more slowly, but ultimately achieve higher performance. Interestingly, spatial representation quality improves more quickly when reasoning is explicitly trained. These results suggest that reasoning encourages more precise and structured spatial understanding, rather than merely consuming it.

Key Takeaways: Teaching VLMs to Reason Spatially

- *Joint cogmap and reasoning setting yields optimal performance through synergistic effects.*
- *Reasoning improves accuracy and map quality by strengthening spatial representations.*
- *More structured outputs slow convergence but lead to higher final performance.*

5 Can Reinforcement Learning Further Refine Spatial Thought Processes?

While SFT establishes a strong baseline for spatial reasoning, emerging evidence from models like DeepSeek R1 [26, 27] suggests reinforcement learning (RL) can offer additional gains by optimizing behavior through outcome-driven feedback. We ask: Can reward-guided refinement help VLMs build sharper spatial models and reason more effectively?

5.1 Experimental Setup

We employ the VAGEN framework [28] for VLM policy optimization, using Group Relative Policy Optimization (GRPO)[29] as our core algorithm. To manage compute cost, we train each configuration for only 0.5 epoch. For fair comparison, the RL setup retains all key components from the SFT stage, including the base model, spatial input formats, benchmark dataset (MINDCUBE-TINY), and evaluation metrics, as detailed in Sections 3.1 and 3.2. Additional details appear in the Appendix.

Task Configurations and Reward Design. We evaluate three RL variants: (1) `RL-FF-Rsn (from scratch)`, which trains *Qwen2.5-VL-3B-Instruct* to produce free-form reasoning chains; (2) `RL-Aug-CGMap-FFR-Out (from scratch)`, which trains the model to jointly generate cognitive maps and reasoning; and (3) `RL-Aug-CGMap-FFR-Out (from SFT)`, which initializes from the strongest SFT checkpoint. The reward function is sparse but targeted: +1 for structurally valid outputs, and +5 for correct answers.

Table 5: QA accuracy (%) and cognitive map generation quality of *Qwen2.5-VL-3B-Instruct* under various RL configurations on MINDCUBE-TINY.

RL Config.	MINDCUBE-TINY QA Accuracy (%)				Generated Cognitive Map (%)		
	Overall	Rotation	Among	Around	Valid Rate	Overall Sim.	Isom. Rate
`RL-FF-Rsn (from scratch)`	46.09	32.50	53.40	43.75	–	–	–
`RL-Aug-CGMap-FFR-Out (from scratch)`	47.91	35.00	53.40	47.50	99.73	65.73	0.00
`RL-Aug-CGMap-FFR-Out (from SFT)`	**76.09**	**78.50**	**96.80**	**49.00**	**100.00**	**84.51**	**66.36**

5.2 Can Reinforcement Learning Unleash the Power of Approximating Spatial Mentaling?

Reinforcement learning (RL) lets a model *feel* the consequences of its spatial thoughts through reward, but does that feedback alone forge a genuine "mental map," or must we first teach the model what a map looks like? Table 5 summarizes three key settings and answers the question in two parts.

RL in a vacuum is not enough. Training `RL-FF-Rsn` from scratch and asking the policy to emit free-form reasoning and rewarding only correct answers barely surpasses the raw QA baseline (46.09% overall; 32.50% on the hardest *Rotation* queries). Sparse rewards guide the model toward useful heuristics, yet provide too little structure for constructing a robust spatial abstraction.

Structured outputs provide modest benefits when learned from scratch. Adding cognitive-map generation (`RL-Aug-CGMap-FFR-Out`) introduces an explicit spatial scaffold the policy must satisfy. Accuracy nudges to 47.91%, and map validity soars to 99.73%. Still, without a prior notion of "good" geometry, RL cannot fully exploit the scaffold: similarity and isom. remain low (65.73%, 0.00%).

RL shines when it stands on an SFT-built scaffold. Warm-starting RL from the optimal SFT checkpoint (`RL-Aug-CGMap-FFR-Out (from SFT)`) produces remarkable improvements: 76.09% overall QA accuracy, representing a $\uparrow$ **14.36%** gain over SFT alone and $\uparrow$ **29.00%** over RL-from-scratch approaches. Spatial metrics show parallel enhancements—map similarity reaches 84.51% while isomorphism hits 66.36%, nearing oracle-level performance. Qualitative analysis reveals the policy effectively eliminates extraneous objects, generates streamlined maps, and produces concise yet definitive reasoning chains. These results suggest RL is (1) *polishing* rather than reconstructing spatial representations from the ground up, and (2) *raise the convergence ceiling* of SFT, enabling the model to break through previous performance plateaus.

Key Takeaways: Reinforcement Learning for Spatial Reasoning

- *RL enhances spatial reasoning, even without prior supervised fine-tuning.*
- *Combining cognitive maps with reasoning consistently improves all learning outcomes.*
- *RL best boosts performance post-SFT, pushing the upper limits of spatial reasoning.*

6 Related Works

Spatial Cognition. Spatial cognition encompasses skills like mental rotation, spatial visualization and object assembly, essential for perceiving and manipulating spatial relationships in both 2D and 3D environments [30, 18, 31]. At the core of these abilities are Spatial Mental Models (SMMs) [10, 11], which are internal representations that allow for consistent understanding about space. Recently, much effort has been dedicated to evaluating spatial cognition in VLMs [32, 12, 17, 33]. Moreover, some methods are proposed to enhance spatial understanding such as coordinate-aware prompting [34], CoT reasoning [9, 35], explicit spatial representation alignment [36, 37], and RL-based approach [38]. However, existing benchmarks and approaches often neglect the mental-level spatial reasoning that underpins human cognition, leaving a gap between machine and human capabilities. To bridge this gap, a new approach is needed that trains VLMs to reason about space not only through visual data but also through mental-level spatial reasoning, aligning more closely with human spatial cognition.

Multi Views understanding. Prior work in multi-view fusion has explored 3D perception by reconstructing point clouds from images captured along random trajectories [39, 40, 41]. These methods focus on creating 3D models but often lack a detailed understanding of object-specific spatial relationships, particularly in terms of maintaining spatial consistency across multiple views. On the other hand, existing multi-image or video benchmarks [42, 43, 44, 45, 46] primarily focus on assessing perceptual and reasoning abilities, falling short in thoroughly evaluating spatial consistency and the ability to maintain coherent scene representations. Recently, some spatial multi-view benchmarks [47, 15, 14, 8, 13, 48, 7] aim to assess spatial reasoning in multi-view settings. However, they often overlook the fusion and consistent representation of spatial information across different perspectives. To address this gap, we propose MINDCUBE to bridge the divide between perception and spatial consistency understanding.

7 Conclusion and Future Impact

We introduced MINDCUBE to study how VLMs can approximate spatial mental models from limited views, a core cognitive ability for reasoning in partially observable environments. Moving beyond benchmarking, we explored *how* internal representations can be scaffolded through structured data and reasoning. Our key finding is that *constructing and reasoning over self-generated cognitive maps*, rather than relying on view interpolation or externally provided maps, yields the most effective approximation of spatial mental models across all elicitation methods (input-output configurations, supervised fine-tuning, and reinforcement learning). Initializing RL from a well-trained SFT checkpoint further optimizes the process, pushing spatial reasoning performance to new limits.

Future Impact. Our work establishes that combining cognitive map generation with reasoning to model spatial information is the most effective. We believe that once high-quality SFT datasets for cogmap generation and reasoning are established, RL can be leveraged to further push the performance boundaries. We anticipate the exploration of novel training paradigms designed to unlock even greater synergistic effects and thus achieving a "1+1 > 2" impact on spatial intelligence.

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Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [Yes]

Justification: In the experimental section, we described the large models we used to test performance.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.