

Spatial-MLLM: Boosting MLLM Capabilities in Visual-based Spatial Intelligence

Diankun Wu *
Tsinghua University

Fangfu Liu *
Tsinghua University

Yi-Hsin Hung
Tsinghua University

Yueqi Duan †
Tsinghua University

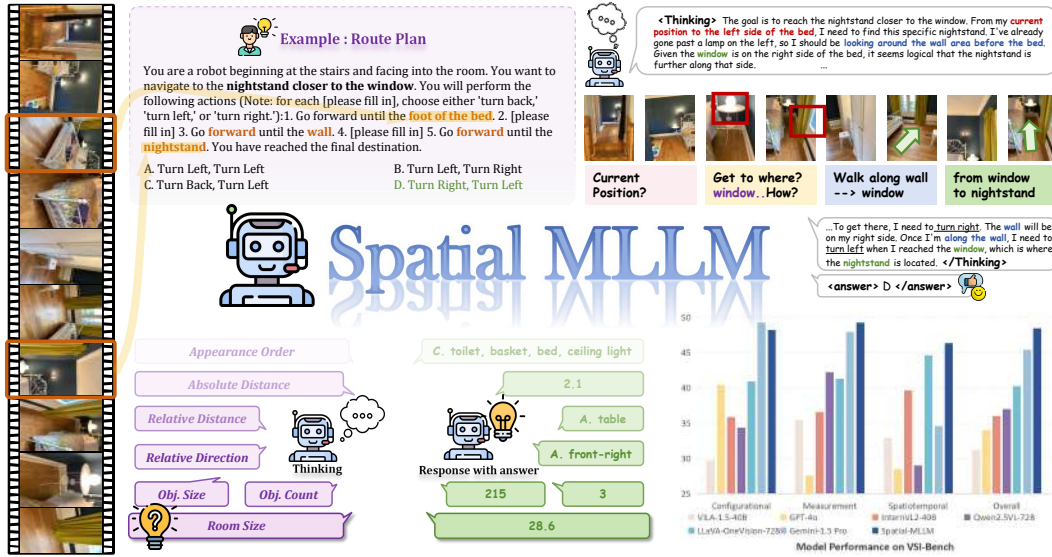


Figure 1: We propose *Spatial-MLLM*, a method that significantly enhances the visual-based spatial intelligence of existing video MLLMs. As shown, *Spatial-MLLM* is capable of understanding and reasoning about the underlying scene from video input, achieving state-of-the-art performance across a wide range of tasks.

Abstract

Recent advancements in Multimodal Large Language Models (MLLMs) have significantly enhanced performance on 2D visual tasks. However, improving their spatial intelligence remains a challenge. Existing 3D MLLMs always rely on additional 3D or 2.5D data to incorporate spatial awareness, restricting their utility in scenarios with only 2D inputs, such as images or videos. In this paper, we present *Spatial-MLLM*, a novel framework for visual-based spatial reasoning from purely 2D observations. Unlike conventional video MLLMs which rely on CLIP-based visual encoders optimized for semantic understanding, our key insight is to unleash the strong structure prior from the feed-forward visual geometry foundation model. Specifically, we propose a dual-encoder architecture: a pretrained 2D visual encoder to extract semantic features, and a spatial encoder—initialized from the backbone of the visual geometry model—to extract 3D structure features. A connector then integrates both features into unified visual tokens for enhanced spatial understanding. Furthermore, we propose a space-aware frame sampling strategy at inference time, which selects the spatially informative frames of a

*Equal Contribution.

†Corresponding Author.

video sequence, ensuring that even under limited token length, the model focuses on frames critical for spatial reasoning. Beyond architecture improvements, we construct the Spatial-MLLM-120k dataset and train the model on it using supervised fine-tuning and GRPO. Extensive experiments on various real-world datasets demonstrate that our spatial-MLLM achieves state-of-the-art performance in a wide range of visual-based spatial understanding and reasoning tasks. Project page: <https://diankun-wu.github.io/Spatial-MLLM/>.

1 Introduction

Multimodal Large Language Models (MLLMs) [1, 2, 3] have achieved significant progress in processing multimodal inputs to generate contextually aware and semantically coherent responses. While proprietary models such as Gemini [4] and GPT-4o [5] exhibit state-of-the-art performance, the open-source community continues to advance the field by improving these models’ ability to interpret diverse content modalities, including images [6, 7, 8], videos [9, 10, 11, 12, 13, 14], and audio [15, 16, 17]. Although these models excel at a wide range of 2D tasks, their capacity to perceive, understand, and reason about 3D scenes, *i.e.*, *spatial intelligence*, remains limited [18, 19].

The requirement of spatial understanding and reasoning typically arises in two scenarios. In the first scenario, the model has access to additional 3D or 2.5D data (*e.g.*, point clouds, camera parameters, or depth maps) alongside 2D visual inputs (*e.g.*, images or videos). These supplementary modalities enhance the model’s spatial awareness, enabling more accurate spatial reasoning. However, this setup limits the model’s applicability in many real-world scenarios where only monocular video of the scene is available, which is the second scenario. The model’s ability to perform spatial understanding and reasoning under such conditions is referred to as *visual-based spatial intelligence* [18, 20]. A major challenge in this setting is that each video frame provides only a partial observation of the scene, and no global representation (*e.g.*, the point clouds [21, 22, 23] or posed depth maps [24, 25]) is available as input. This requires the model to infer the global spatial layout from incomplete cues and internally integrate these partial observations into a coherent and implicit global representation, which demands strong spatial awareness. However, most existing video MLLMs pretrain their visual encoders on image-text pairs—primarily image-caption data [13, 14, 26]—following the CLIP [27] paradigm. This makes the visual encoder excel at capturing high-level semantic content but lack structure and spatial information when only 2D video inputs are available [28, 29, 30]. Consequently, current video MLLMs generally perform worse on spatial reasoning tasks than on other tasks, such as temporal understanding. Moreover, their performance still significantly lags behind human capabilities [18].

In this paper, we introduce *Spatial-MLLM*, a method that significantly improves the visual-based spatial intelligence of existing video MLLMs. To address the limitations of visual encoders in general-purpose video MLLMs, our key insight is to unleash the strong structure prior provided by the feed-forward visual geometry foundation model [31, 32, 33]. These models, typically trained on pixel-point pairs, complement the general-purpose video MLLM visual encoders that are trained primarily on image-text data [14]. Based on this insight, we design a simple dual-encoder architecture consisting of a 2D encoder—initialized from the visual encoder of a general-purpose video MLLM—to extract 2D semantic information, and a spatial encoder—leveraging the VGGT feature extractor [32]—to recover implicit 3D structural information from 2D video inputs. We then use a lightweight connector to integrate features from both branches into unified visual tokens. The resulting integrated representation enables the Large Language Model (LLM) backbone to perform effective spatial reasoning without requiring explicit 3D data as input.

Furthermore, we fully exploit the additional information provided by the introduced feed-forward visual geometry model [32], and propose a space-aware frame sampling strategy at inference time, which selects the most spatially informative frames from the video sequence when the total number of input frames is limited (*e.g.*, due to the VRAM limitation). Specifically, we first feed a relatively large number of frames into the spatial encoder and decode the resulting 3D features into a voxel grid. The frame selection task is then reformulated as a maximum coverage problem over these voxels, which we solve using a greedy algorithm. To train Spatial-MLLM, we construct a visual-based spatial question-answering dataset, *Spatial-MLLM-120K*, and perform supervised fine-tuning on it. We further apply a simple cold-start [34] to help the model adapt to the correct reasoning format, and then train it using Group Relative Policy Optimization (GRPO) [35, 34] to enhance its long-chain-of-thought (long-CoT) spatial reasoning capability [36]. We conduct extensive evaluations on the VSIBench [18],

ScanQA [37], and SQA3D [38] benchmarks and demonstrate that the proposed spatial-MLLM achieves state-of-the-art performance in a wide range of visual-based spatial understanding and reasoning tasks.

In summary, our main contributions are:

- We introduce *Spatial-MLLM*, a method that significantly enhances the visual-based spatial intelligence of existing video MLLMs, demonstrating strong spatial understanding and reasoning capabilities without requiring any 3D or 2.5D data input.
- We design a dual-encoder and connector that effectively integrates semantic information from a standard 2D visual encoder with structural information extracted by a spatial encoder, which is initialized using a feed-forward visual geometry foundation model.
- We fully exploit the additional information provided by the feed-forward visual geometry model and design a space-aware frame sampling strategy that selects spatially informative frames, thereby improving model performance under input length constraints.
- We train our model on the *Spatial-MLLM-120k* dataset using a two-stage pipeline. Extensive experiments demonstrate that our method achieves state-of-the-art performance on a wide range of visual-based spatial understanding and reasoning tasks.

2 Related Work

2.1 MLLMs for Video Understanding

Multimodal Large Language Models have made significant progress in integrating vision and language. Early works such as BLIP-2 [2] and Flamingo [1] introduce token-level fusion (*e.g.*, Q-Former) and feature-level fusion (*e.g.*, cross-attention layers) to bridge modalities. Other approaches, including the LLaVA series [3, 39], MiniGPT-4 [40], and subsequent models [13, 41, 42], leverage MLPs to project visual features into the language space. Recent advancements in MLLMs have extended their capabilities from static images to videos, typically by introducing video-language alignment through large-scale pretraining [9, 43]. Later models, such as Qwen2.5-VL [14], enhance temporal reasoning via dynamic resolution and absolute time encoding. Although existing video MLLMs excel at capturing high-level semantics and temporal patterns, they struggle to interpret the underlying 3D scene from video input, which inspires our work to enhance their spatial understanding capabilities.

2.2 3D MLLMs for Scene Understanding

Recent advances in MLLMs have sparked interest in extending their capabilities from 2D to 3D scene understanding [23, 44, 45, 46, 47, 48, 49, 24, 25, 50]. LL3DA [23] extracts scene-level features from 3D point clouds using a Q-Former, while Grounded 3D-LLM [44] integrates 3D detectors to generate object proposals. Methods like Chat3D [45], LEO [46], and Chat-Scene [47] first segment 3D objects and encode object-centric features for LLM fusion. Alternatively, 3D-LLM [48] and Scene-LLM [49] aggregate CLIP features from pre-segmented multi-view object patches into 3D point representations, leveraging multi-view images and camera parameters. LLaVA-3D [24] projects 2D multi-view patch features into voxel space for 3D-aware aggregation, and GPT4Scene [50] enhances 3D reasoning by first reconstructing scenes and then using BEV images as input. While these methods advance 3D scene understanding, they all require additional 3D or 2.5D input data that is difficult to acquire in many real-world scenarios. In contrast, our approach only requires 2D videos as input.

2.3 Visual-based Spatial Intelligence

Visual-based spatial intelligence focuses on enabling video MLLMs to perceive and reason about 3D spatial relationships directly from video inputs. While traditional MLLMs excel at 2D visual-text alignment, their extension to 3D tasks, such as 3D question answering [6, 51] and robotic manipulation [52] often lacks fine-grained spatial alignment due to limited geometric supervision. To address this gap, specialized benchmarks for video-based spatial reasoning have emerged. For example, VSI-Bench [18] introduced a visual-spatial intelligence benchmark to evaluate comprehensive spatial understanding capabilities for MLLMs. STI-Bench [53] introduces physics-aware challenges like velocity estimation to quantify spatial and kinematic reasoning, while Ego-ST Bench [54] evaluates

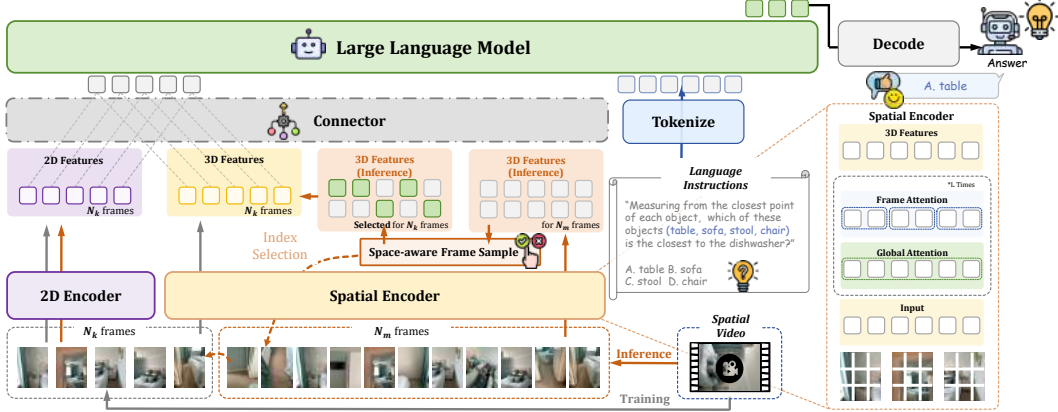


Figure 2: **Overview of Spatial-MLLM.** Our model is composed of a 2D visual encoder \mathcal{E}_{2D} , a spatial encoder $\mathcal{E}_{\text{Spatial}}$, which is initialized from a feed-forward visual geometry foundation model, a connector, and a large language model backbone. At inference time, we incorporate a space-aware frame sampling strategy to select spatially informative frames when the number of input frames is limited due to GPU memory constraints.

egocentric navigation logic in first-person videos. Meanwhile, VLM4D [55] emphasizes motion dynamics, such as trajectory prediction, to probe 4D spatiotemporal interactions. These benchmarks collectively highlight the shift toward holistic evaluation of visual-based spatial intelligence.

3 Method

In this section, we introduce Spatial-MLLM. Given a video of N frames depicting a scene, denoted as $\mathcal{V} = \{\mathbf{f}_i\}_{i=1}^N$, where $\mathbf{f}_i \in \mathbb{R}^{H \times W \times 3}$, Spatial-MLLM is designed to understand spatial relationships, perform spatial reasoning, and generate appropriate responses. We begin by describing the model architecture in Section 3.1, which comprises a 2D visual encoder, a spatial encoder, a connector, and a large language model backbone. Then we present the space-aware frame sampling strategy in Section 3.2, which selects N_k spatially informative frames $\{\mathbf{f}_i^s\}_{i=1}^{N_k}$, where $N_k \ll N$. Finally, we introduce the Spatial-MLLM-120k dataset and our two-stage training pipeline in Section 3.3.

3.1 Spatial-MLLM Architecture

In this section, we present the architecture of Spatial-MLLM, which is shown in Figure 2. We adopt Qwen2.5-VL-3B [14] as our base model and explore strategies to enhance its spatial understanding and reasoning capability. Before diving into the details, we first briefly introduce the key insights that motivate our design.

What hinders visual-based spatial intelligence in existing video MLLMs? Existing video MLLMs [14, 13, 12] typically employ a pre-trained 2D visual encoder \mathcal{E}_{2D} to extract 2D patch features \mathbf{e}_{2D} . These features are then projected into visual tokens through a lightweight connection module. A large language model backbone f_θ subsequently generates the final response by conditioning on both visual and textual tokens. A critical bottleneck in this process lies in the nature of the visual features extracted. The required type of information varies by task: high-level semantic representations are essential for 2D recognition and understanding, whereas fine-grained structural cues are crucial for spatial reasoning. However, the visual encoders used in current video MLLMs are primarily pre-trained on image-text datasets (mainly image-caption pairs) [14, 26] following the CLIP [27] paradigm. As a result, these models predominantly capture semantic content and often lack spatial awareness when no additional 3D or 2.5D data are available [28, 29, 30]. To address this, our key insight is to unleash feed-forward visual geometry foundation models [32], which are trained on pixel-point pairs and can recover rich 3D structural information from 2D inputs, which complements the semantic features extracted by the 2D visual encoder. We design a simple dual-encoder architecture that exploits the strengths of both models and a connector to fuse semantic and structural information into unified visual tokens. Below, we introduce the core components of our design.

Dual-Encoder. The proposed dual-encoder consists of a 2D encoder \mathcal{E}_{2D} and a spatial encoder $\mathcal{E}_{\text{spatial}}$. For the 2D encoder branch, we adopt the same design as the visual encoder of Qwen2.5-VL [14] to encode input frames into semantically rich features:

$$\mathbf{e}_{2D} = \mathcal{E}_{2D} \left(\{\mathbf{f}_i\}_{i=1}^{N_k} \right), \quad \mathbf{e}_{2D} \in \mathbb{R}^{N_k' \times \lfloor \frac{H}{p_{2D}} \rfloor \times \lfloor \frac{W}{p_{2D}} \rfloor \times d_{2D}}, \quad (1)$$

where p_{2D} and d_{2D} denote the patch size and feature dimension of the 2D visual encoder, respectively. The two consecutive frames are grouped for video input, thus $N_k' = \lceil N_k/2 \rceil$.

For the spatial encoder branch, we utilize the feature backbone of VGGT [32]. Specifically, given K frames of the scene video, we first patchify the input and then extract 3D features with alternating frame-wise self-attention and global self-attention [56]. This process allows $\mathcal{E}_{\text{spatial}}$ to aggregate spatial information across different frames to get the final 3D features:

$$\mathbf{e}_{3D}, \mathbf{e}_c, \mathbf{e}_{\text{register}} = \mathcal{E}_{\text{spatial}} \left(\{\mathbf{f}_i\}_{i=1}^{N_k} \right), \quad \mathbf{e}_{3D} \in \mathbb{R}^{N_k \times \lfloor \frac{H}{p_{3D}} \rfloor \times \lfloor \frac{W}{p_{3D}} \rfloor \times d_{3D}}, \quad (2)$$

where \mathbf{e}_{3D} , \mathbf{e}_c , and $\mathbf{e}_{\text{register}}$ represent the dense 3D feature, the camera feature for each frame, and the registration tokens [57], respectively. We only use \mathbf{e}_{3D} in the feature fusion stage as it captures the dense structure information of the input frames.

Connector. After obtaining the 2D and 3D features, we use a simple connector to integrate the semantic and structural information from both branches. Specifically, we first align \mathbf{e}_{3D} with \mathbf{e}_{2D} in both spatial and temporal dimensions:

$$\mathbf{e}'_{3D} = \text{Rearrange}(\mathbf{e}_{3D}), \quad \mathbf{e}'_{3D} \in \mathbb{R}^{N_k' \times \lfloor \frac{H}{p_{2D}} \rfloor \times \lfloor \frac{W}{p_{2D}} \rfloor \times d'_{3D}}. \quad (3)$$

Here, the spatially and temporally adjacent information in \mathbf{e}_{3D} is aggregated into the feature channel dimension, enabling alignment with \mathbf{e}_{2D} . Next, we employ two lightweight MLPs to fuse the information to obtain the unified visual tokens:

$$\mathbf{e} = \text{MLP}_{2D}(\mathbf{e}_{2D}) + \text{MLP}_{3D}(\mathbf{e}'_{3D}), \quad (4)$$

where $\mathbf{e} \in \mathbb{R}^{S \times d_{\text{LLM}}}$ denotes the final visual tokens and $S = N_k' \times \lfloor \frac{H}{p_{2D}} \rfloor \times \lfloor \frac{W}{p_{2D}} \rfloor$ is the sequence length. Although more complex feature fusion methods, *e.g.*, cross-attention [56, 58], could be applied, our experiments demonstrate that this simple and lightweight approach is sufficient to enhance the model’s spatial understanding and reasoning capabilities. We leave the exploration of more advanced fusion strategies for future work.

3.2 Space-Aware Frame Sampling

Due to GPU memory constraints, video MLLMs can process only a limited subset of frames from a scene video sequence. For example, in the VSI-Bench setup [18], only 8 to 32 frames are sampled as input to the video MLLM, while a typical scene video in VSI-Bench contains over 2,000 frames. A widely adopted solution is uniform frame sampling [14, 18, 13], which is effective for general-purpose video understanding. However, as spatial videos represent 3D scenes, the sampling strategy for spatial understanding tasks should focus on capturing most information of the underlying scene, which uniform sampling fails to achieve.

Benefiting from the feed-forward visual geometry foundation model, we design a straightforward space-aware frame sampling strategy at inference time. Specifically, given a scene video $\mathcal{V} = \{\mathbf{f}_i\}_{i=1}^N$, our objective is to select N_k frames, $\{\mathbf{f}_i^k\}_{i=1}^{N_k}$ that have most coverage of the underlying scene. To achieve this, we first uniformly subsample N_m frames, $\{\mathbf{f}_i^m\}_{i=1}^{N_m}$, where N_m satisfies $N_k < N_m < N$, and is determined by the available GPU memory. Typically, we choose $N_m = 128$ while $N_k = 16$. We then leverage \mathcal{E}_{3D} to extract their corresponding 3D features \mathbf{e}_{3D}^m and camera features \mathbf{e}_c^m . Subsequently, we use the pretrained camera head f_c and depth head f_d of the VGGT model [32] to decode a set of camera parameters and depth maps:

$$\{\mathbf{E}_i^m, \mathbf{K}_i^m\}_{i=1}^{N_m} = f_c(\mathbf{e}_c^m), \quad \text{and} \quad \{\mathbf{D}_i^m\}_{i=1}^{N_m} = f_d(\mathbf{e}_{3D}^m). \quad (5)$$

This allows us to calculate the voxels $V(f_i^m)$ covered by each frame f_i^m , and formulate frame selection as a maximum coverage problem [59], *i.e.*, select N_k frames $\{\mathbf{f}_i^k\}_{i=1}^{N_k} \subseteq \{\mathbf{f}_i^m\}_{i=1}^{N_m}$ such

that the total number of unique covered voxels $\left| \bigcup_{i=1}^{N_k} V(\mathbf{f}_i^k) \right|$ is maximized. In practice, we apply a greedy algorithm to accelerate computation [60, 25]. In practice, once the N_k frames are selected, we don't need to recompute their 3D features \mathbf{e}_{3D}^k and can directly reuse the corresponding features from the precomputed set \mathbf{e}_{3D}^m . We provide the complete algorithm and detailed explanation in Section A.1.

3.3 Training

Training Data Construction. We first construct a visual-based spatial question-answering dataset, *i.e.*, Spatial-MLLM-120k. The dataset is collected from three sources: the training set of ScanQA [37], SQA3D [38], as well as additional self-created spatial QA data. All items in Spatial-MLLM-120k are derived from scenes in the ScanNet training set [61] and are each represented as a quadruple $\mathcal{I}_i = \langle \mathcal{Q}_i, \mathcal{A}_i, \mathcal{V}_i, \mathcal{M}_i \rangle$, denoting the question, answer, video (scene) ID, and meta-information (*e.g.*, task type), respectively. For the self-curated QA data, we follow the data processing pipeline proposed in VSI-Bench [18]. Specifically, we first convert ScanNet scenes into continuous video clips at 24 FPS and 640×480 resolution. Then we generate spatial reasoning QA pairs leveraging the provided meta-annotations of Scannet. The generated QA pairs cover various spatial understanding and reasoning tasks, including object counting, object size, room size, absolute distance, appearance order, relative distance, and relative direction. Since the QA pair construction process is similar to that of VSI-Bench [18], we exclude the QA pair \mathcal{I}_i if its scene video \mathcal{V}_i is used in the evaluation set of VSI-Bench (312 scene videos in total) to prevent data leakage. Finally, we create approximately 70k QA pairs. We provide additional details on training data construction in the section A.2. Figure 3 shows a summary of key statistics of Spatial-MLLM-120k.

Supervised Fine-tuning. Leveraging the constructed Spatial-MLLM-120k dataset, we first perform supervised fine-tuning (SFT) on our model. Since both \mathcal{E}_{2D} and $\mathcal{E}_{\text{spatial}}$ are pre-trained on large-scale image-text and pixel-point pairs, respectively, we freeze them to preserve their ability to extract rich semantic and structural information. We jointly train the connection module and the LLM backbone to enable the model to adaptively fuse 2D and 3D features and enhance its spatial understanding and reasoning capability. During this stage, we employ the standard cross-entropy loss \mathcal{L}_{ce} between the model-generated answers and the ground-truth annotations:

$$\mathcal{L}_{\text{ce}}(\theta) = - \sum_i \log P(o^{(i)} | o^{(1:i-1)}, q, \{f_j\}_{j=1}^{N_k}) \quad (6)$$

where $\{f_j\}_{j=1}^{N_k}$ denotes input video frames, q denotes the system prompt and question, $o^{(i)}$ represents the i -th token in the ground-truth answer, and $o^{(1:i-1)}$ denotes the preceding answer tokens.

RL Training. Following the SFT stage, we first perform a simple cold start [34] to help the model adapt to the correct reasoning format. Then we train the model using Group Relative Policy Optimization (GRPO) [35] to enhance its long-CoT [36] spatial reasoning capability. During training, we first sample a set of output $\{o_1, o_2, \dots, o_G\}$ for each question q from the policy model $\pi_{\theta_{\text{old}}}$. Then we optimize the policy model by maximizing the following objective:

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}_{q, o_i} \left[\frac{1}{G} \sum_{i=1}^G \min \left(\frac{\pi_{\theta}(o_i | q)}{\pi_{\theta_{\text{old}}}(o_i | q)} A_i, \text{clip} \left(\frac{\pi_{\theta}(o_i | q)}{\pi_{\theta_{\text{old}}}(o_i | q)}, 1 \pm \epsilon \right) A_i \right) - \beta \text{KL}[\pi_{\theta} \| \pi_{\text{ref}}] \right] \quad (7)$$

where $A_i = \frac{r_1 - \text{mean}(r_1, r_2, \dots, r_G)}{\text{std}(r_1, r_2, \dots, r_G)}$ is the advantage function computed using the group rewards.

In GRPO, the design of the reward function is critical. In addition to a formatting reward applied to all task types, we introduce task-dependent reward modelling to ensure that it accurately reflects the proximity between the predicted and ground-truth answers. Specifically, we categorize the data into three types based on answer format: numeric answer questions, multiple-choice questions, and

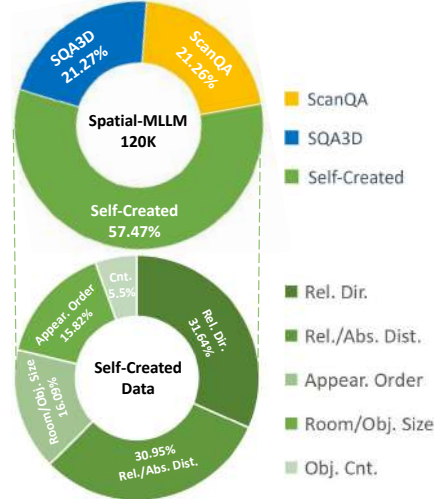


Figure 3: Basic statistic of our constructed Spatial-MLLM-120K dataset.

Table 1: **Evaluation Results on VSI-Bench [18]**. For Spatial-MLLM and Qwen2.5VL-series [14], we use 16 frames as input. For other open-source methods and GPT-4o [5], we follow the setting of VSI-Bench to set frame numbers (ranging from 8 to 32 frames). For Gemini-1.5 Pro [4], it samples video frames at 1 FPS. **Bold** and underline denote the best-performing and second-best-performing open-source models, respectively.

Methods	Numerical Qusetion				Multiple-Choice Question				Avg. Rank	
	Obj. Cnt.	Abs. Dist.	Obj. Size	Room Size	Rel. Dist.	Rel. Dir.	Route Plan	Appr. Order		
<i>Proprietary Models</i>										
GPT-4o [5]	46.2	5.3	43.8	38.2	37.0	41.3	31.5	28.5	34.0	7
Gemini-1.5 Pro [4]	56.2	30.9	64.1	43.6	51.3	46.3	36.0	34.6	45.4	2
<i>Open-source Models</i>										
InternVL2-40B [7]	34.9	26.9	46.5	31.8	42.1	32.2	34.0	39.6	36.0	6
LongVILA-8B [63]	29.1	9.1	16.7	0.0	29.6	30.7	32.5	25.5	21.6	12
VILA-1.5-40B [64]	22.4	24.8	48.7	22.7	40.5	25.7	31.5	32.9	31.2	9
LongVA-7B [65]	38.0	16.6	38.9	22.2	33.1	43.3	25.4	15.7	29.2	11
LLaVA-OneVision-72B [6]	43.5	23.9	57.6	37.5	42.5	39.9	32.5	44.6	40.2	4
LLaVA-Video-72B [12]	48.9	22.8	57.4	35.3	42.4	36.7	35.0	48.6	40.9	3
Qwen2.5VL-3B [14]	24.3	24.7	31.7	22.6	38.3	41.6	26.3	21.2	30.6	10
Qwen2.5VL-7B [14]	40.9	14.8	43.4	10.7	38.6	38.5	33.0	29.8	33.0	8
Qwen2.5VL-72B [14]	25.1	29.3	54.5	38.8	38.2	37.0	34.0	28.9	37.0	5
Spatial-MLLM-4B	65.3	34.8	63.1	45.1	41.3	46.2	33.5	46.3	48.4	1

verbal answer questions. For numeric questions, we compute the mean relative accuracy [18]. For multiple-choice questions, we employ an exact match reward. For verbal answer questions, we use fuzzy matching based on Levenshtein distance. Further details on reward calculation are provided in Section A.4.

4 Experiments

4.1 Implementation Details

Training details. Spatial-MLLM is built on Qwen2.5-VL [8] and VGGT [32] and has ~4B parameters in total. We use the visual encoder of Qwen2.5-VL [14] to initialize \mathcal{E}_{2D} , and the LLM backbone of it to initialize f_{θ} . We then use the feature backbone of VGGT [32] to initialize $\mathcal{E}_{\text{spatial}}$. During training, we use 640×480 resolution and limit video frames to 16. In the SFT stage, we train the model using Adam optimizer [62] for one epoch. We set the global batch size to 16 and use a linear learning-rate schedule, with a peak value of 10^{-5} . In the cold start stage, we first construct a small CoT dataset. Specifically, we prompt Qwen2.5-VL-72B [14] to generate multiple thinking processes and answers according to the scene video and question. Then we use the GT answer to filter a correct thinking-answer pair (more details are provided in Section A.3). We use a similar setting as in the SFT stage to train the model for 200 steps. In the RL stage, we perform 8 rollouts per question and set the default sampling temperature to 1. The KL divergence coefficient, β , is set to 0.04. Due to computational resource limitations, we train the model for 1,000 steps with a learning rate of $1e-6$. We show the training curve of SFT Stage and RL Stage in Figure 4.

Inference Details. During inference, we set $N_m = 128$ and $N_k = 16$ for space-aware frame sampling. Since spatial reasoning requires a certain level of determinism, we set the temperature to 0.1 and the top- p to 0.001. During inference, we use 16 frames at 640×480 resolution from the scene video as input unless otherwise specified.

4.2 Comparisons on VSI-Bench

Setup. VSI-Bench [18] contains more than 5,000 question-answer pairs derived from egocentric videos sourced from ScanNet [61], ScanNet++[66], and ARKitScenes[67]. The task types are divided into Multiple-Choice Answer (MCA) and Numerical Answer (NA). For the MCA tasks, we compute mean accuracy, and for the NA tasks, we calculate relative accuracy across confidence thresholds $\mathcal{C} = \{0.5, 0.55 \dots, 0.95\}$. We report the final average score and individual metrics on eight task types of VSI-Bench, including: (1) configurational reasoning (object counting, relative direction, absolute direction, and route planning), (2) measurement estimation (object size, room size, and absolute distance), and (3) spatiotemporal reasoning (appearance order).

Baselines. We compare our model with a broad range of video MLLMs. For proprietary model, we include GPT-4o [5] and Gemini-1.5 Pro [4]. For open-source MLLMs, we compare our model with

Table 2: **Evaluation Results on ScanQA [37] and SQA3D [38]**. We use the val set of ScanQA and test set of SQA3D for evaluation following common practice [22, 68, 25]. **Bold** and underline denote the best-performing and second-best-performing models in each model category, respectively.

Methods	ScanQA (val)					SQA3D (test)		Video-Input Only
	BLEU-1	BLEU-4	METEOR	ROUGE-L	CIDEr	EM-1	EM-R1	
<i>Task-Specific Models</i>								
ScanQA [37]	<u>30.2</u>	<u>10.1</u>	13.1	33.3	64.9	<u>47.2</u>	-	✗
SQA3D [38]	30.5	11.2	<u>13.5</u>	<u>34.5</u>	-	46.6	-	✗
3D-Vista [69]	-	-	13.9	35.7	-	48.5	-	✗
<i>3D/2.5D-Input Models</i>								
3D-LLM [70]	39.3	12.0	14.5	35.7	69.4	-	-	✗
LL3DA [23]	-	13.5	15.9	37.3	76.8	-	-	✗
Chat-Scene [22]	<u>43.2</u>	14.3	18.0	41.6	87.7	<u>54.6</u>	57.5	✗
3D-LLaVA [21]	-	17.1	<u>18.4</u>	<u>43.1</u>	<u>92.6</u>	<u>54.5</u>	<u>56.6</u>	✗
Video-3D LLM [25]	47.1	<u>16.2</u>	19.8	49.0	102.1	58.6	-	✗
<i>Video-Input Models</i>								
Qwen2.5-VL-3B [14]	22.5	3.8	9.7	25.4	47.4	43.4	45.9	✓
Qwen2.5-VL-7B [14]	27.8	3.0	11.4	29.3	53.9	46.5	49.8	✓
Qwen2.5-VL-72B [14]	26.8	<u>12.0</u>	13.0	35.2	66.9	47.0	<u>50.9</u>	✓
LLaVA-Video-7B [14]	<u>39.7</u>	3.1	<u>17.7</u>	<u>44.6</u>	<u>88.7</u>	<u>48.5</u>	-	✓
Oryx-34B [51]	38.0	-	15.0	37.3	72.3	-	-	✓
Spatial-MLLM-4B	44.4	14.8	18.4	45.0	91.8	55.9	58.7	✓

InternVL2-40B [7], LLaVA-NeXT-Video-72B [12], LLaVA-OneVision-72B [6], and the Qwen2.5-VL [14] series. To validate the effectiveness of our model, we also train Qwen2.5-VL [14] using the same training setup as in Spatial-MLLM SFT training as additional baselines (in Table 3).

Results. We present the quantitative results on VSI-Bench [18] in Table 1. Despite having 4B parameters, Spatial-MLLM significantly outperforms all proprietary and open-source MLLMs, including those with substantially larger parameter counts (*e.g.*, 32B or 72B). Among the remaining models, the best-performing one is the proprietary Gemini-1.5 Pro [4]. Notably, Spatial-MLLM is provided with only 16 input frames per video, while Gemini-1.5 Pro [4] samples videos at 1 FPS (*i.e.*, an average of 85 frames per video on VSI-Bench) according to its API instructions [18]. Despite the significantly lower number of input frames, Spatial-MLLM still achieves a 3.0% higher average accuracy than Gemini-1.5 Pro [4].

4.3 Comparison on ScanQA and SQA3D

Setup. ScanQA [37] and SQA3D [38] are two 3D question-answering benchmarks built upon ScanNet [61]. Since the authors did not provide a test set for ScanQA, we evaluate it using the validation set, which consists of 4,675 QA pairs focused on understanding spatial relationships such as object alignment and orientation, as well as the ability to accurately identify objects in 3D scenes based on textual questions. We follow standard practice by evaluating answer quality using the following metrics: CIDEr, BLEU-1, BLEU-4, METEOR, and ROUGE-L. For SQA3D, we evaluate the model on its test set, which contains 3,519 QA pairs. The task requires the model to first understand its position and orientation within the 3D scene, as described by text, then reason about its environment and answer a question under those conditions. Since SQA3D contains definitive answers, we use exact match accuracy (EM) and its refined version (EM-R) as evaluation metrics. We provide the evaluation results using additional metrics for both benchmarks in Section B.3.

Baselines. Since both the ScanQA [37] and SQA3D [38] benchmarks provide additional 3D annotations (*e.g.*, point clouds and depth maps of the scene), we compare Spatial-MLLM with several other model types in addition to video-input MLLM. These includes task-specific models designed for 3D question-answering tasks, such as ScanQA [37], SQA3D [38], 3D-VisTA [69], and LLMs that require point clouds or depth maps as input, such as Chat-Scene [22], Video-3D LLM [25], and 3D-LLaVA [21].

Results. We present the quantitative results on the ScanQA [37] and SQA3D [38] benchmarks in Table 2. As shown, Spatial-MLLM significantly outperforms all video-input models across all metrics on both ScanQA and SQA3D. Our model also surpasses all task-specific models. Among models utilizing 3D or 2.5D input, only 3D-LLaVA [21] (on ScanQA) and Video-3D-LLM [25]

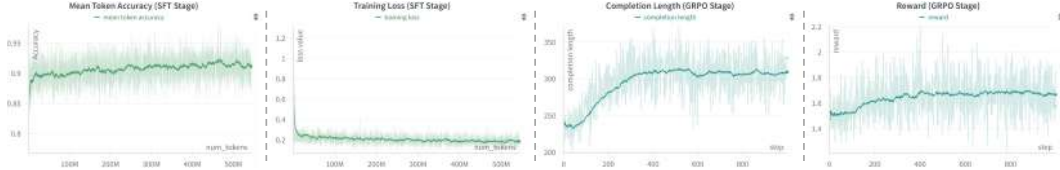


Figure 4: **Visualization of Training Curves in the SFT and RL Stages.** For the SFT stage, we present the mean token accuracy and loss curves. For the RL stage, we show the dynamics of completion length and reward.

(on ScanQA and SQA3D) achieve better performance than Spatial-MLLM. However, 3D-LLaVA requires additional point cloud input, and Video-3D-LLM depends on depth maps. Despite not relying on any additional 3D or 2.5D input, our model still outperforms other 3D-dependent models such as 3D-LLM [70], LL3DA [23], and Chat-Scene [22].

4.4 Ablation Study and Analysis

Effectiveness of RL Training. We evaluate the supervised fine-tuning version of Spatial-MLLM, denoted by Spatial-MLLM-SFT-16, and the final version of Spatial-MLLM, denoted by Spatial-MLLM-16. As shown in Table 3, although we only perform small-scale GRPO training (*i.e.*, 1,000 steps), Spatial-MLLM-16 still achieves performance gains, suggesting that long-CoT reasoning benefits the spatial reasoning capabilities required by VSI-Bench [18].

Effectiveness of the Spatial-MLLM Architecture. We fine-tune Qwen2.5-VL-3B and Qwen2.5-VL-7B [14] on the Spatial-MLLM-120K dataset using the same process as for Spatial-MLLM. As shown in Table 3, both Qwen2.5-VL-3B-SFT-16 and Qwen2.5-VL-7B-SFT-16 show improvements after fine-tuning, indicating the effectiveness of our spatial dataset to enhance the model’s spatial reasoning capabilities. Furthermore, both models underperform compared to Spatial-MLLM-SFT-16, which validates the effectiveness of the proposed architecture.

Effectiveness of Space-aware Frame Sampling.

We evaluate different frame sampling configurations in Table 3, including 8, 16, and 32 frames using uniform sampling and our proposed space-aware frame sampling strategy. As shown, increasing the number of sampled frames improves performance for both space-aware frame sampling and uniform sampling. Compared with uniform sampling, space-aware frame sampling consistently outperforms it when the number of input frames is the same.

Table 3: **Ablation Study.** We report evaluation results on VSI-Bench [18] in different settings. "-SFT" refers to the model fine-tuned on the Spatial-MLLM-120K dataset. "-8/16/32" denotes the number of input frames during inference. "-Uni" denotes using uniform frame sampling.

Methods	Numerical	Multiple-Choice	Avg.
Spatial-MLLM-8	50.8	41.2	46.1
Spatial-MLLM-16	52.7	43.8	48.4
Spatial-MLLM-32	53.1	45.3	49.3
Spatial-MLLM-SFT-16	51.5	40.4	46.1
Qwen-2.5VL-3B-SFT-16	47.1	32.6	40.0
Qwen-2.5VL-7B-SFT-16	48.9	34.7	42.0
Spatial-MLLM-Uni-8	48.2	39.2	43.8
Spatial-MLLM-Uni-16	51.6	42.3	47.1
Spatial-MLLM-Uni-32	52.4	44.2	48.4

5 Conclusion

We introduce Spatial-MLLM, a method that enables effective spatial understanding and reasoning from purely 2D visual inputs. By combining a semantic 2D encoder with a structure-aware spatial encoder initialized from a visual geometry foundation model, our dual-encoder design captures both semantic and spatial cues. Additionally, our proposed space-aware frame sampling strategy further enhances performance under limited input constraints. Trained on the Spatial-MLLM-120K dataset, our model achieves state-of-the-art results across multiple benchmarks.

Limitations and Future Work. Although Spatial-MLLM demonstrates significant improvements over previous video MLLMs across a wide range of visual-based spatial understanding and reasoning tasks, there remains room to scale Spatial-MLLM further in terms of model size and training data. Moreover, as this work primarily addresses visual-based spatial intelligence, we have trained and evaluated our model specifically on relevant datasets and benchmarks. An interesting direction for

future work would be to explore how integrating spatial structural information might further benefit general video understanding and reasoning tasks.

Technical Appendices and Supplementary Material

A Additional Method Details

A.1 Details of Space-Aware Frame Sampling

Our space-aware frame sampling algorithm consists of three stages: (1) Scene geometry preprocessing, (2) Voxelization and coverage calculation, and (3) Greedy maximum coverage selection. Beginning with the original video sequence $\mathcal{V} = \{\mathbf{f}_i\}_{i=1}^N$, we first perform uniform subsampling to obtain $N_m = 128$ candidate frames $\{\mathbf{f}_i^m\}_{i=1}^{N_m}$. For each subsampled frame, we leverage the backbone and head of VGGT [32] to compute $\{\mathbf{E}_i^m, \mathbf{K}_i^m\}_{i=1}^{N_m}$ and $\{\mathbf{D}_i^m\}_{i=1}^{N_m}$ as illustrated in the main paper. Then we reconstruct 3D point maps \mathcal{P}_i^m through depth reprojection:

$$\mathcal{P}_i^m = \mathbf{D}_i^m \cdot \mathbf{K}_i^{-1} [\mathbf{u} | \mathbf{v} | 1]^\top \cdot \mathbf{E}_i^{-1}, \quad (8)$$

where (\mathbf{u}, \mathbf{v}) denote pixel coordinates. In practice, we also obtain a confidence value $c(p) \in [0, 1]$ for each point $p \in \mathcal{P}_i^m$ from the depth head. Although VGGT [32] can also directly decode point maps from 3D dense features, we find that using depth and camera produces more accurate results.

The voxelization and coverage calculation process first establishes a 3D bounding box encompassing all valid scene points:

$$\mathcal{P}_{\text{valid}} = \bigcup_{i=1}^{N_m} \{p \in \mathcal{P}_i^m \mid c(p) > 0.1 \wedge c(p) \geq \text{Percentile}(\{c(p)\}, 50\%)\}. \quad (9)$$

We then discretize the bounding box into voxels. To handle relative scales in VGGT [32] outputs, we use an adaptive way to set the voxel size Δ to $\frac{1}{\lambda}$ of the minimum dimension of the scene’s bounding box:

$$\Delta = \frac{1}{\lambda} \cdot \min(\max(\mathcal{P}_{\text{valid}}) - \min(\mathcal{P}_{\text{valid}})), \quad (10)$$

where λ is a hyperparameter and we set it to 20. Each frame’s voxel coverage $V(\mathbf{f}_i^m)$ is then calculated by discretizing its valid points:

$$V(\mathbf{f}_i^m) = \left\{ \left\lfloor \frac{p - \min(\mathcal{P}_{\text{valid}})}{\Delta} \right\rfloor \mid p \in \mathcal{P}_i^m \cap \mathcal{P}_{\text{valid}} \right\}. \quad (11)$$

Finally, we can formulate frame selection as the typical maximum coverage problem [59]:

$$\max_{\mathcal{S} \subseteq \{1, \dots, N_m\}} \left| \bigcup_{i \in \mathcal{S}} V(\mathbf{f}_i^m) \right| \quad \text{s.t.} \quad |\mathcal{S}| = N_k, \quad (12)$$

In practice, we set $N_k = 16$ and use a greedy approach [60, 25] to iteratively select the frame that provides the maximum new coverage, which is illustrated in Algorithm 1.

A.2 Details of Spatial-MLLM-120k Dataset Construction

We follow a similar approach to that used in [18] to construct the Spatial-MLLM-120k dataset. Specifically, the construction involves three main processes: video preprocessing, metadata computation, and QA pair generation.

Video Preprocessing. In this stage, we extract frames from the raw ScanNet [61] scans and convert them into videos at 24 FPS with a resolution of 640×480 .

Metadata Computation. In this stage, we extract spatial and semantic metadata from raw ScanNet scans and their associated semantic annotations. First, we align each raw scene mesh using the provided axis alignment matrices and convert it to the Open3D [71] point cloud. At the room level, we compute the room size using the alpha-shape algorithm and determine the center coordinates.

Algorithm 1 Greedy Maximum Coverage Sampling

Input Frame voxel sets $\{V(\mathbf{f}_i^m)\}_{i=1}^{N_m}$, target selection size N_k

Output Selected frame indices $\mathcal{S} \subseteq \{1, \dots, N_m\}$

```
1:  $\mathcal{S} \leftarrow \emptyset$  ▷ Selected frames
2:  $\mathcal{C} \leftarrow \emptyset$  ▷ Covered voxels
3:  $\mathcal{R} \leftarrow \{1, \dots, N_m\}$  ▷ Remaining candidates
4: for  $t \leftarrow 1$  to  $N_k$  do
5:   if  $\mathcal{R} = \emptyset$  then
6:     break ▷ No remaining candidates
7:   end if
8:    $i^* \leftarrow \underset{i \in \mathcal{R}}{\operatorname{argmax}} |V(\mathbf{f}_i^m) \setminus \mathcal{C}|$  ▷ Max coverage gain
9:   if  $|V(\mathbf{f}_{i^*}^m) \setminus \mathcal{C}| = 0$  then
10:    break ▷ No additional coverage
11:  end if
12:   $\mathcal{S} \leftarrow \mathcal{S} \cup \{i^*\}$  ▷ Update selection
13:   $\mathcal{C} \leftarrow \mathcal{C} \cup V(\mathbf{f}_{i^*}^m)$  ▷ Update covered voxels
14:   $\mathcal{R} \leftarrow \mathcal{R} \setminus \{i^*\}$  ▷ Remove from candidates
15: end for
16: return  $\mathcal{S}$ 
```

At the object level, we generate oriented bounding boxes (OBBs) for each valid object instance and assign semantic labels from the annotations, excluding structural elements (*e.g.*, *walls*, *floors*) and ambiguous categories (*e.g.*, *otherstructure*). To ensure consistency across categories, we remap the original ScanNet semantic labels to a new label set based on the NYU40 classes [72, 73]. In addition, we collect the projected 2D semantic annotation of each scene video for the appearance order task. The final metadata for each scene includes: (1) room size and center coordinates; (2) the projected 2D semantic annotation of the scene video; (3) object instances and their OBB parameters, including rotation matrices, extents, and centers; and (4) semantic labels for each object.

QA Pair Generation. Finally, we generate QA pairs of different tasks, including object counting, object size, room size, absolute distance, appearance order, relative distance, and relative direction.

- *Object counting (numerical)*: We first count how many times each object category appears in the scene, then randomly sample a category that appears at least twice. Question template: “How many <category>(s) are in this room?”
- *Object size (numerical)*: We randomly sample a unique object in the scene and take the longest side of its oriented bounding-box (OBB) as the ground-truth length (in cm). Question template: “What is the length of the longest dimension (length, width, or height) of the <category>, measured in centimeters?”
- *Room size (numerical)*: We use the pre-computed room size (in m^2) as the ground-truth value. Question template: “What is the size of this room (in square meters)?”
- *Absolute distance (numerical)*: For a pair of objects, we uniformly sample points inside each OBB and take the minimum Euclidean distance between the two point clouds as the ground-truth (in m). Question template: “Measuring from the closest point of each object, what is the direct distance between the <category_A> and the <category_B> (in meters)?”
- *Appearance Order (multiple choice)*: We calculate the first appearance timestamp of each category, which is the timestamp when its visible pixel count exceeds a predefined threshold. Using these timestamps, we generate the correct order of appearance among the categories, along with other options. Question template: What will be the first-time appearance order of the following categories in the video: <category_A>, <category_B>, <category_C>, <category_D>
- *Relative distance (multiple choice)*: We use an “anchor” object that is unique in the scene and then select four additional objects while enforcing 15-30cm separation thresholds in options. Question template: “Which of these objects (<category_A>, <category_B>, <category_C>, <category_D>) is closest to the <anchor_category>?”

- *Relative direction (multiple choice)*: For triple $\{position, facing, query\}$ of unique categories, we compute the horizontal angle between the vectors $position \rightarrow facing$ and $position \rightarrow query$. The angle is then discretized into directional classes (easy: left/right, medium: left/right/back, hard: front-left/front-right/back-left/back-right). Question template (easy example): “If I am standing by the $\langle position-category \rangle$ and facing the $\langle facing-category \rangle$, is the $\langle query-category \rangle$ to the left or the right?”

A.3 Details of Cold Start

To align the model with the desired reasoning format, we perform a simple cold start for 200 steps before GRPO training. The key to this stage is the construction of a spatial reasoning dataset with chain-of-thought (CoT) annotations. The construction process is as follows:

Subset Sampling. We begin by sampling a subset $\mathcal{D}_0 = \{\mathcal{I}_i\}_{i=1}^{N_s} = \{\langle \mathcal{Q}_i, \mathcal{A}_i, \mathcal{V}_i, \mathcal{M}_i \rangle\}_{i=1}^{N_s}$ from the Spatial-MLLM-120k dataset.

Multi-path CoT Generation. For each item $\mathcal{I}_i \in \mathcal{D}_0$, we utilize Qwen2.5-VL-72B [14] to generate K independent reasoning processes $\hat{\mathcal{T}}_i^{(k)}$ and corresponding answers $\hat{\mathcal{A}}_i^{(k)}$. We then compute a reward $r_i^{(k)} = \text{Reward}(\hat{\mathcal{A}}_i^{(k)}, \mathcal{A}_i)$ for each reasoning-answer pair, where $\text{Reward}(\cdot, \cdot)$ is the reward function described in Sec A.4. Consequently, we obtain a set of outputs $\mathcal{O}_i = \{(\hat{\mathcal{T}}_i^{(k)}, \hat{\mathcal{A}}_i^{(k)}, r_i^{(k)})\}_{k=1}^K$ for each $\mathcal{I}_i \in \mathcal{D}_0$.

Adaptive Filtering. Since Qwen2.5-VL-72B [14] may generate incorrect reasoning processes and answers, we apply a filtering process based on the computed rewards. While using a global reward threshold is straightforward, it often results in an imbalance across question types in the selected subset. To mitigate this, we adopt an adaptive filtering strategy. Specifically, for each item $\mathcal{I}_i \in \mathcal{D}_0$, we first keep the output with the highest reward to get $\hat{\mathcal{O}}_i = \{(\hat{\mathcal{T}}_i^{(k^*)}, \hat{\mathcal{A}}_i^{(k^*)}, r_i^{(k^*)})\}$ where $k^* = \arg \max_k r_i^{(k)}$. Let $\hat{r}_i = r_i^{(k^*)}$ denote the maximum reward. We then categorize all items based on their question type and compute a question type-dependent threshold $\tau_{t(i)}$, where $t(i)$ denotes the type of problem i . The item is added into the cold start set if and only if:

$$\hat{r}_i \geq \tau_{t(i)} \quad \text{and} \quad \hat{r}_i > 0,$$

where the type-dependent threshold satisfies $\tau_{t(i)} := \text{Quantile}(\{\hat{r}_j \mid t(j) = t(i)\}, 0.5)$. This rule preserves approximately the top 50% of generations per question type while discarding degenerate (zero-reward) outputs. In practice, we set $N_s = 5000$ and $K = 3$, and finally we get 2459 items in the cold start set. We provide a pseudocode for this process in Algorithm 2:

A.4 Details of SFT and GRPO Training

Reward Calculation. Given predicted answer $\mathcal{A}_{\text{pred}}$ and ground truth answer \mathcal{A}_{gt} , the reward function $\text{Reward}(\mathcal{A}_{\text{pred}}, \mathcal{A}_{\text{gt}})$ consist of a format reward \mathcal{R}_{fmt} and a task-specific reward:

$$\text{Reward}(\mathcal{A}_{\text{pred}}, \mathcal{A}_{\text{gt}}) = \lambda_1 R_{\text{format}} + \lambda_2 \begin{cases} \mathcal{R}_{\text{MC}}, & \text{multiple-choice} \\ \mathcal{R}_{\text{MRA}}, & \text{numerical} \\ \mathcal{R}_{\text{Verbal}}, & \text{verbal} \end{cases} \quad (13)$$

where λ_1 and λ_2 are hyperparameters, both of which are set to 1 in our implementation. For *multiple-choice questions*, we implement exact match criterion:

$$\mathcal{R}_{\text{MC}}(\mathcal{A}_{\text{pred}}, \mathcal{A}_{\text{gt}}) = \mathbb{I}(\psi(\mathcal{A}_{\text{pred}}) = \psi(\mathcal{A}_{\text{gt}})) \quad (14)$$

where $\psi(\cdot)$ performs answer normalization through whitespace stripping and $\mathbb{I}(\cdot)$ denotes the indicator function. For *numerical tasks*, we compute mean relative accuracy (MRA) [18]:

$$\mathcal{R}_{\text{MRA}}(\mathcal{A}_{\text{pred}}, \mathcal{A}_{\text{gt}}) = \frac{1}{|\mathcal{T}|} \sum_{\tau \in \mathcal{T}} \mathbb{I}\left(\frac{|\alpha(\mathcal{A}_{\text{pred}}) - \alpha(\mathcal{A}_{\text{gt}})|}{|\alpha(\mathcal{A}_{\text{gt}})| + \epsilon} < \tau\right) \quad (15)$$

where $\alpha(\cdot)$ normalizes numeric values, $\epsilon = 10^{-8}$ prevents division by zero, and $\mathcal{T} = \{0.50, 0.55, \dots, 0.95\}$ defines accuracy thresholds. For *verbal answer questions*, we compute a normalized similarity score using the Levenshtein ratio:

$$\mathcal{R}_{\text{Verbal}}(\mathcal{A}_{\text{pred}}, \mathcal{A}_{\text{gt}}) = 1 - \frac{D_{\text{Lev}}(\phi(\mathcal{A}_{\text{pred}}), \phi(\mathcal{A}_{\text{gt}}))}{|\phi(\mathcal{A}_{\text{pred}})| + |\phi(\mathcal{A}_{\text{gt}})|} \quad (16)$$

Algorithm 2 Cold Start Dataset Construction

Input Original dataset \mathcal{D}

- 1: Qwen2.5-VL model M
- 2: Reward function $\text{Reward}(\cdot, \cdot)$
- 3: Sample size N_s , Paths per item K

Output Filtered dataset $\mathcal{D}_{\text{cold}}$

- 4: Initialize $\mathcal{D}_0 \leftarrow \text{Sampling}(\mathcal{D}, N_s)$
 - 5: $\mathcal{D}_{\text{cold}} \leftarrow \emptyset$
 - 6: **for** each item $\mathcal{I}_i = \langle \mathcal{Q}_i, \mathcal{A}_i, \mathcal{V}_i, \mathcal{M}_i \rangle \in \mathcal{D}_0$ **do**
 - 7: Generate K reasoning paths: $\{\hat{\mathcal{T}}_i^{(k)}\}_{k=1}^K \leftarrow M(\mathcal{Q}_i, \mathcal{V}_i)$
 - 8: Compute rewards: $r_i^{(k)} \leftarrow \text{Reward}(\hat{\mathcal{A}}_i^{(k)}, \mathcal{A}_i), \forall k$
 - 9: Select best path: $k^* \leftarrow \arg \max_k r_i^{(k)}$
 - 10: Record $\hat{r}_i \leftarrow r_i^{(k^*)}, \hat{\mathcal{O}}_i \leftarrow (\hat{\mathcal{T}}_i^{(k^*)}, \hat{\mathcal{A}}_i^{(k^*)})$
 - 11: **end for**
 - 12: Group items by type: $\{\mathcal{G}_t\} \leftarrow \text{GroupByType}(\{\hat{r}_i\})$
 - 13: **for** each question type t **do**
 - 14: Compute threshold: $\tau_t \leftarrow \text{Quantile}(\{\hat{r}_j | j \in \mathcal{G}_t\}, 0.5)$
 - 15: **end for**
 - 16: **for** each item $\mathcal{I}_i \in \mathcal{D}_0$ **do**
 - 17: **if** $\hat{r}_i \geq \tau_{t(i)}$ **and** $\hat{r}_i > 0$ **then**
 - 18: $\mathcal{D}_{\text{cold}} \leftarrow \mathcal{D}_{\text{cold}} \cup \{\hat{\mathcal{O}}_i\}$
 - 19: **end if**
 - 20: **end for**
 - 21: **return** $\mathcal{D}_{\text{cold}}$
-

where D_{Lev} denotes the Levenshtein edit distance, and $\phi(\cdot)$ represents the text normalization function. In practice, we use the implementation provided by the *Levenshtein* library. In addition to the format and task-specific rewards, we also incorporate a reasoning length reward following Video-R1 [12], which encourages the model to perform more thinking before generating the final answer.

Other Details. Figure 5 presents the prompts used in the SFT and GRPO stages. For both stages, we adopt the default system prompt of Qwen2.5-VL [14], namely, "You are a helpful assistant." In the SFT stage, the user prompt consists of a question and a type template. In the GRPO stage, the user prompt comprises a question, a question post string, and a type template.

B Additional Experiments

B.1 Visualization of Space-Aware Frame Sampling

We provide a visualization of our space-aware frame sampling in Fig. 6, which shows the point maps (predicted by the VGGT [32]) corresponding to the frames selected by different sampling strategies. As shown, the proposed space-aware frame sampling strategy consistently yields more spatial coverage than uniform sampling, which often overlooks transient regions that appear briefly in the video and tends to produce redundant viewpoints when the camera remains static.

B.2 Qualitative Results

We present qualitative examples of Spatial-MLLM on the VSI-Bench [18] dataset in Figures 7 to 10. As illustrated, Spatial-MLLM is capable of reasoning with visual information across different task types and producing final answers accordingly. Furthermore, it demonstrates strong abilities in self-verification and task decomposition during the reasoning process.

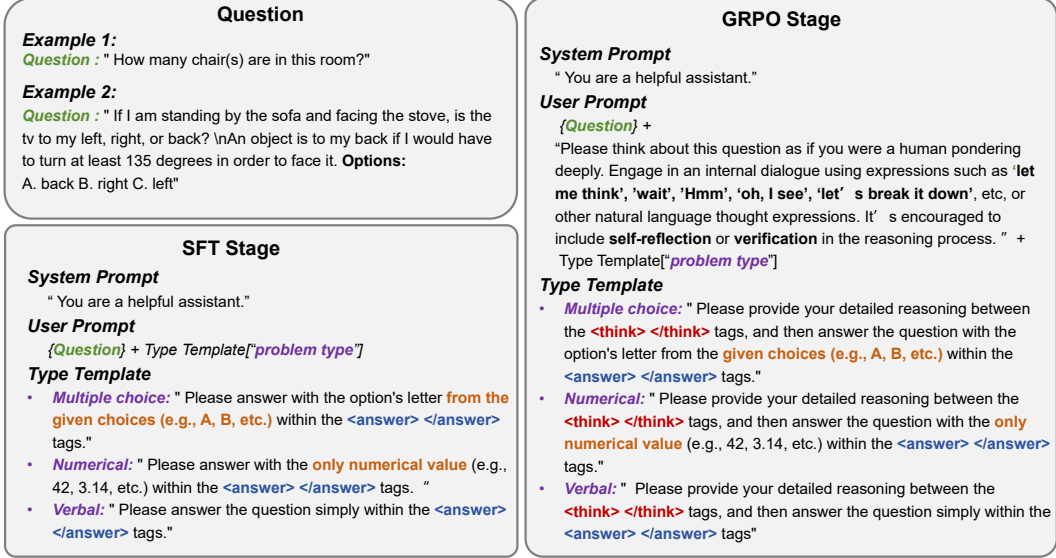


Figure 5: **Illustration of the prompts used in the SFT and GRPO stages.** We use the default system prompt of Qwen2.5-VL [14] (*i.e.*, "You are a helpful assistant") for both stages. In the SFT stage, the user prompt consists of a question and a type template. In the GRPO stage, the user prompt includes a question, a question post string, and a type template.

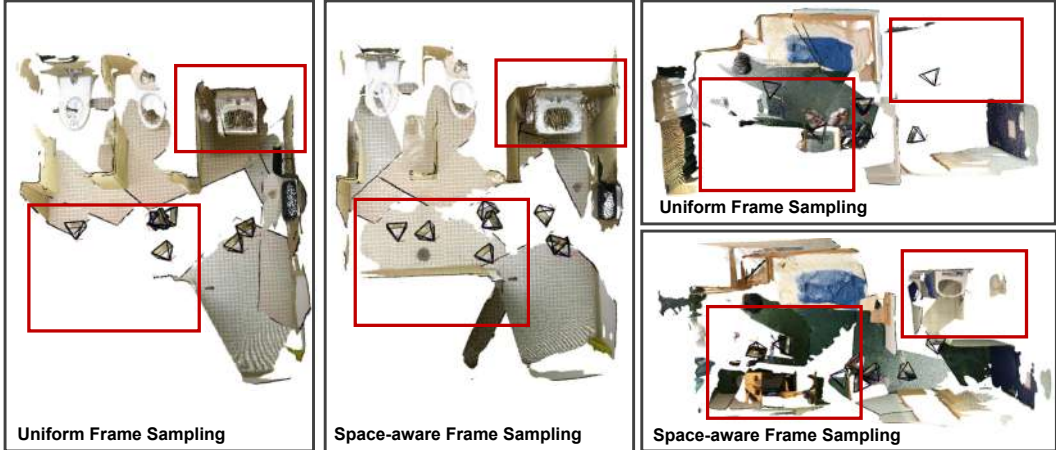


Figure 6: **Visualization of different frame sampling strategies.** For clarity of visualization, we set $N_m = 128$ and $N_k = 8$ in this example. Uniform frame sampling often overlooks transient regions that appear briefly in the video. Furthermore, when the camera remains static for extended periods, this strategy tends to yield redundant viewpoints. In contrast, our proposed space-aware frame sampling strategy achieves more comprehensive spatial coverage.

B.3 Additional Evaluation Results on ScanQA and SQA3D

We present additional evaluation results on the ScanQA [37] and SQA3D [38] benchmarks in Table 4 and Table 5. As shown, our proposed method consistently outperforms all video-input models, including LLaVA-Video-7B [12] and Oryx-34B [51], both of which incorporate spatial reasoning datasets such as ScanQA [37] during training.

Despite having only 4.2 billion parameters, Spatial-MLLM significantly surpasses Qwen2.5-VL-72B [14] on the ScanQA benchmark, achieving substantial gains across multiple metrics—for instance, +2.3 EM-1, +17.6 BLEU-1, and +24.9 CIDEr. Similarly, on the SQA3D benchmark, Spatial-MLLM consistently outperforms Qwen2.5-VL-72B across all question types and overall

Table 4: **Additional evaluation results on ScanQA [37] for task-specific models, 3D/2.5D input models, and video-input models.** Reported metrics include EM-1, BLEU-1 to BLEU-4, ROUGE-L, METEOR, and CIDEr.

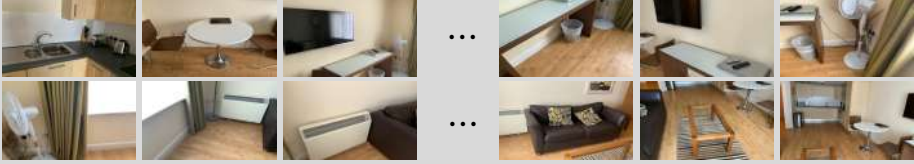
Methods	ScanQA (val)							
	EM-1	BLEU-1	BLEU-2	BLEU-3	BLEU-4	ROUGE-L	METEOR	CIDEr
<i>Task-Specific Models</i>								
ScanQA [37]	21.1	30.2	20.4	15.1	10.1	33.3	13.1	64.9
3D-Vista [69]	22.4	-	-	-	10.4	35.7	13.9	69.6
<i>3D/2.5D-Input Models</i>								
3D-LLM [70]	20.5	39.3	25.2	18.4	12.0	35.7	14.5	69.4
LL3DA [23]	-	-	-	-	13.5	37.3	15.9	76.8
Chat-Scene [22]	21.6	43.2	29.1	20.6	14.3	41.6	18.0	87.7
3D-LLaVA [21]	-	-	-	-	17.1	43.1	18.4	92.6
Video-3D LLM [25]	30.1	47.1	31.7	22.8	16.2	49.0	19.8	102.1
<i>Video-Input Models</i>								
Qwen2.5-VL-3B [14]	15.4	22.5	13.1	8.1	3.8	25.4	9.7	47.4
Qwen2.5-VL-7B [14]	19.0	27.8	13.6	6.3	3.0	29.3	11.4	53.9
Qwen2.5-VL-72B [14]	24.0	26.8	17.8	14.6	12.0	35.2	13.0	66.9
LLaVA-Video-7B [12]	-	39.7	26.6	9.3	3.1	44.6	17.7	88.7
Oryx-34B [51]	-	38.0	24.6	-	-	37.3	15.0	72.3
Spatial-MLLM-4B	26.3	44.4	28.8	21.9	14.8	45.0	18.4	91.8

Table 5: **Additional evaluation results on SQA3D [38] for task-specific models, 3D/2.5D input models, and video-input models.** In addition to the average EM-1 and EM-R1 across all questions, we also report the average EM-1 for different question types, including *What*, *Is*, *How*, *Can*, *Which*, and *Others*.

Methods	SQA3D (test)							
	What	Is	How	Can	Which	Others	Avg. (EM-1)	Avg. (EM-R1)
<i>Task-Specific Models</i>								
SQA3D [38]	31.6	63.8	46.0	69.5	43.9	45.3	46.6	-
3D-Vista [69]	34.8	63.3	45.4	69.8	47.2	48.1	48.5	-
<i>3D/2.5D-Input Models</i>								
Scene-LLM [74]	40.9	69.1	45.0	70.8	47.2	52.3	54.2	-
Chat-Scene [22]	45.4	67.0	52.0	69.5	49.9	55.0	54.6	57.5
Video-3D LLM [25]	51.1	72.4	55.5	69.8	51.3	56.0	58.6	-
<i>Video-Input Models</i>								
Qwen2.5-VL-3B [14]	34.8	52.1	39.8	52.7	45.6	47.0	43.4	45.9
Qwen2.5-VL-7B [14]	39.7	56.6	41.1	55.9	47.6	47.2	46.5	49.8
Qwen2.5-VL-72B [14]	41.7	56.3	41.5	55.6	44.5	48.0	47.0	50.9
LLaVA-Video-7B [12]	42.7	56.3	47.5	55.3	50.1	47.2	48.5	-
Spatial-MLLM-4B	45.9	71.6	55.1	69.5	52.0	53.0	55.9	58.7

performance, including improvements of +4.2 EM-1 and +7.8 EM-R1, with notable gains in the *Is* (+15.3) and *Which* (+13.9) categories.

Video



Question

"How many chair(s) are in this room?"

Spatial-MLLM

"<think>

Let me think about this carefully. In the images provided, I need to identify any chairs present in the room. First, I'll **scan the entire room** to ensure I'm not missing anything. The room appears to be a living space with a kitchen area, a couch, a dining area, and other furniture. **Now, let's break it down:**

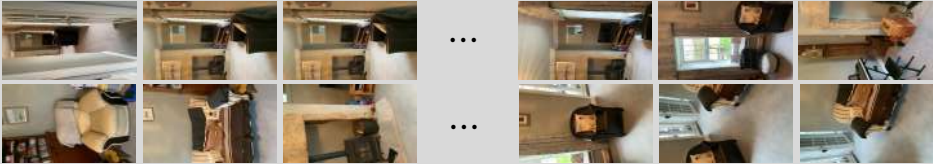
1. In the **kitchen area**, there is a small black stool or cushioned seat near the cabinets. This doesn't seem like a chair.
2. There's a couch in the **living room area**, but that's a sofa, not a chair.
3. In the **dining area**, there is a **small table with two chairs visible**. They are wooden and have simple designs. So, after a thorough review of the images, I can confirm that there are two chairs in the room. Oh, I see. The question was asking for the number of chairs, and now I'm confident that there are two.

</think>

<answer>2 </answer>"

Figure 7: Qualitative example on VSI-Bench [18].

Video



Question

"How many sofa(s) are in this room?"

Spatial-MLLM

"<think>

Let me think about this for a moment. The images show a living room with various pieces of furniture. As I scan through them, I notice a few clearly identifiable sofas.

First, in the initial image, there's a partially visible sofa near the **window**. It appears to be a **traditional** design, likely made of fabric and leather. Next, in the following image, there's another sofa positioned near the **fireplace**. This one seems to have a more **modern design**, possibly made of leather or a similar material. Then, in the third image, there's a third sofa visible in the background, near the **bookshelf**. It looks like it's a different style from the first two, possibly a **sectional** sofa. In the fourth image, there's a fourth sofa visible on the left side of the room. It appears to be a **single-seater** sofa, different from the others. **Let's break it down:**

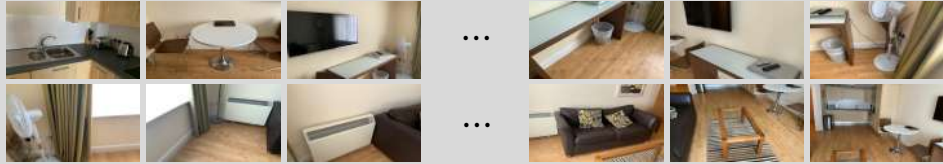
- Traditional sofa: 1 - Modern sofa: 1 - Sectional sofa: 1 - Single-seater sofa: 1

Oh, I see. There are four distinct sofas visible in these images. **I should double-check to make sure I'm not missing any**, but after reviewing again, I confirm there are no additional sofas hidden or partially obscured. Final count: 4</think>

<answer>4 </answer>"

Figure 8: Qualitative example on VSI-Bench [18].

Video



Question

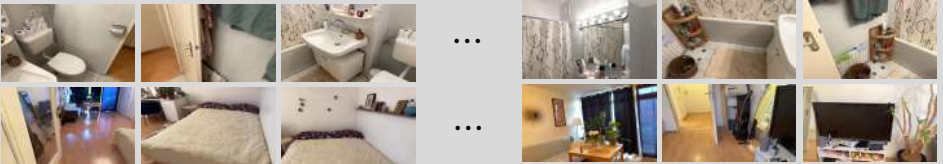
"If I am standing by the **sofa** and facing the **stove**, is the **tv** to my **left**, **right**, or **back**? An object is to my back if I would have to turn at least 135 degrees in order to face it. **Options:**
A. back B. right C. left"

Spatial-MLLM

"<think>
Let me think about this for a moment. If I'm standing by the sofa and facing the stove, I need to **consider the layout of the room**. The stove is in the kitchen area, which appears to be separated from the living room area by a counter and some cabinets. **Now, where is the TV?** The TV is positioned on the wall near the kitchen area, which means it's not directly in front of me but rather to my side. **Wait**, the question asks if the TV is to my left, right, or back. **Let's break it down:** if I'm facing the stove, and the TV is positioned in such a way that it's not in front of me, it must be either to the left or the right. Given the layout of room, **the TV is on the opposite side of the kitchen area**, which would be to the right of the stove if I'm facing it. **Hmm, let's verify this.** If I turn around from the sofa and face the kitchen area, the TV is indeed to the right of the kitchen appliances. This means that if I'm facing the stove from the sofa, the TV would be to my right. Oh, I see now. The TV is to my right when I'm facing the stove from the sofa.
</think><answer>B </answer>"

Figure 9: Qualitative example on VSI-Bench [18].

Video



Question

"What will be the first-time appearance order of the following categories in the video: basket, pillow, toilet, tv? **Options:**
A. basket, pillow, toilet, tv B. pillow, tv, toilet, basket C. toilet, pillow, tv, basket D. toilet, basket, pillow, tv"

Spatial-MLLM

"<think>**Let me think about this carefully.** The question asks for the first appearance order of certain objects in a video, but I need to focus on the video that shows the bathroom. In the video, I see various objects appear in different sequences. Let's break it down:
1. **Bathroom sequence:** The video starts with the bathroom, showing a toilet, sink, shower curtain, and some shelves. There's also a basket visible in one part of the bathroom.
2. **Transition to living room:** The video then transitions to a living room with a bed, which is a different space entirely. The living room shows a bed with a pillow and some decorative items. **The third part shows the living room** with a couch, **TV**, and other decorations.
Now, let's consider the appearance order. The toilet is in the bathroom, the basket appears in the bathroom, the pillow is in the bedroom, and the TV is in the living room.
Let's verify this one more time: Bathroom -> toilet -> basket -> Bedroom -> Yes pillows, other bedroom items -> Living Room -> TV."
Therefore, the correct answer is D. Toilet, basket, pillow, tv.</think><answer>D </answer>"

Figure 10: Qualitative example on VSI-Bench [18].

References

- [1] J.-B. Alayrac, J. Donahue, P. Luc, A. Miech, I. Barr, Y. Hasson, K. Lenc, A. Mensch, K. Millican, M. Reynolds, *et al.*, “Flamingo: a visual language model for few-shot learning,” *NeurIPS*, 2022.
- [2] J. Li, D. Li, S. Savarese, and S. Hoi, “Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models,” in *ICML*, 2023.
- [3] H. Liu, C. Li, Q. Wu, and Y. J. Lee, “Visual instruction tuning,” *NeurIPS*, 2024.
- [4] G. Team, P. Georgiev, V. I. Lei, R. Burnell, L. Bai, A. Gulati, G. Tanzer, D. Vincent, Z. Pan, S. Wang, *et al.*, “Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context,” *arXiv preprint arXiv:2403.05530*, 2024.
- [5] A. Hurst, A. Lerer, A. P. Goucher, A. Perelman, A. Ramesh, A. Clark, A. Ostrow, A. Welihinda, A. Hayes, A. Radford, *et al.*, “Gpt-4o system card,” *arXiv preprint arXiv:2410.21276*, 2024.
- [6] B. Li, Y. Zhang, D. Guo, R. Zhang, F. Li, H. Zhang, K. Zhang, Y. Li, Z. Liu, and C. Li, “Llava-onevision: Easy visual task transfer,” *arXiv preprint arXiv:2408.03326*, 2024.
- [7] Z. Chen, J. Wu, W. Wang, W. Su, G. Chen, S. Xing, M. Zhong, Q. Zhang, X. Zhu, L. Lu, *et al.*, “Internvl: Scaling up vision foundation models and aligning for generic visual-linguistic tasks,” in *CVPR*, 2024.
- [8] J. Bai, S. Bai, S. Yang, S. Wang, S. Tan, P. Wang, J. Lin, C. Zhou, and J. Zhou, “Qwen-vl: A frontier large vision-language model with versatile abilities,” *arXiv preprint arXiv:2308.12966*, 2023.
- [9] B. Lin, B. Zhu, Y. Ye, M. Ning, P. Jin, and L. Yuan, “Video-llava: Learning united visual representation by alignment before projection,” *arXiv preprint arXiv:2311.10122*, 2023.
- [10] Z. Cheng, S. Leng, H. Zhang, Y. Xin, X. Li, G. Chen, Y. Zhu, W. Zhang, Z. Luo, D. Zhao, *et al.*, “Videollama 2: Advancing spatial-temporal modeling and audio understanding in video-llms,” *arXiv preprint arXiv:2406.07476*, 2024.
- [11] R. Qian, X. Dong, P. Zhang, Y. Zang, S. Ding, D. Lin, and J. Wang, “Streaming long video understanding with large language models,” *arXiv preprint arXiv:2405.16009*, 2024.
- [12] Y. Zhang, J. Wu, W. Li, B. Li, Z. Ma, Z. Liu, and C. Li, “Video instruction tuning with synthetic data,” *ArXiv*, vol. abs/2410.02713, 2024.
- [13] P. Wang, S. Bai, S. Tan, S. Wang, Z. Fan, J. Bai, K.-Y. Chen, X. Liu, J. Wang, W. Ge, Y. Fan, K. Dang, M. Du, X. Ren, R. Men, D. Liu, C. Zhou, J. Zhou, and J. Lin, “Qwen2-vl: Enhancing vision-language model’s perception of the world at any resolution,” *ArXiv*, vol. abs/2409.12191, 2024.
- [14] S. Bai, K. Chen, X. Liu, J. Wang, W. Ge, S. Song, K. Dang, P. Wang, S. Wang, J. Tang, H. Zhong, Y. Zhu, M. Yang, Z. Li, J. Wan, P. Wang, W. Ding, Z. Fu, Y. Xu, J. Ye, X. Zhang, T. Xie, Z. Cheng, H. Zhang, Z. Yang, H. Xu, and J. Lin, “Qwen2.5-vl technical report,” *ArXiv*, vol. abs/2502.13923, 2025.
- [15] R. Huang, M. Li, D. Yang, J. Shi, X. Chang, Z. Ye, Y. Wu, Z. Hong, J.-B. Huang, J. Liu, Y. Ren, Z. Zhao, and S. Watanabe, “Audiogpt: Understanding and generating speech, music, sound, and talking head,” *ArXiv*, vol. abs/2304.12995, 2023.
- [16] C. Tang, W. Yu, G. Sun, X. Chen, T. Tan, W. Li, L. Lu, Z. Ma, and C. Zhang, “Salmonn: Towards generic hearing abilities for large language models,” *ArXiv*, vol. abs/2310.13289, 2023.
- [17] Z. Liu, Y. Dong, J. Wang, Z. Liu, W. Hu, J. Lu, and Y. Rao, “Ola: Pushing the frontiers of omni-modal language model with progressive modality alignment,” *ArXiv*, vol. abs/2502.04328, 2025.
- [18] J. Yang, S. Yang, A. W. Gupta, R. Han, F.-F. Li, and S. Xie, “Thinking in space: How multimodal large language models see, remember, and recall spaces,” *ArXiv*, vol. abs/2412.14171, 2024.
- [19] B. Chen, Z. Xu, S. Kirmani, B. Ichter, D. Driess, P. Florence, D. Sadigh, L. J. Guibas, and F. Xia, “Spatialvlm: Endowing vision-language models with spatial reasoning capabilities,” *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 14455–14465, 2024.
- [20] Y. Li, Y. Zhang, T. Lin, X. Liu, W. Cai, Z. Liu, and B. Zhao, “Sti-bench: Are mllms ready for precise spatial-temporal world understanding?,” *ArXiv*, vol. abs/2503.23765, 2025.
- [21] J. Deng, T. He, L. Jiang, T. Wang, F. Dayoub, and I. Reid, “3d-llava: Towards generalist 3d llms with omni superpoint transformer,” *ArXiv*, vol. abs/2501.01163, 2025.
- [22] H. Huang, Z. Wang, R. Huang, L. Liu, X. Cheng, Y. Zhao, T. Jin, and Z. Zhao, “Chat-scene: Bridging 3d scene and large language models with object identifiers,” in *Neural Information Processing Systems*, 2023.
- [23] S. Chen, X. Chen, C. Zhang, M. Li, G. Yu, H. Fei, H. Zhu, J. Fan, and T. Chen, “LI3da: Visual interactive instruction tuning for omni-3d understanding reasoning and planning,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 26428–26438, 2024.
- [24] C. Zhu, T. Wang, W. Zhang, J. Pang, and X. Liu, “Llava-3d: A simple yet effective pathway to empowering llms with 3d-awareness,” *arXiv preprint arXiv:2409.18125*, 2024.

- [25] D. Zheng, S. Huang, and L. Wang, "Video-3d llm: Learning position-aware video representation for 3d scene understanding," *ArXiv*, vol. abs/2412.00493, 2024.
- [26] S. Y. Gadre, G. Ilharco, A. Fang, J. Hayase, G. Smyrnis, T. Nguyen, R. Marten, M. Wortsman, D. Ghosh, J. Zhang, E. Orgad, R. Entezari, G. Daras, S. Pratt, V. Ramanujan, Y. Bitton, K. Marathe, S. Mussmann, R. Vencu, M. Cherti, R. Krishna, P. W. Koh, O. Saukh, A. J. Ratner, S. Song, H. Hajishirzi, A. Farhadi, R. Beaumont, S. Oh, A. G. Dimakis, J. Jitsev, Y. Carmon, V. Shankar, and L. Schmidt, "Datacomp: In search of the next generation of multimodal datasets," *ArXiv*, vol. abs/2304.14108, 2023.
- [27] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, G. Krueger, and I. Sutskever, "Learning transferable visual models from natural language supervision," in *International Conference on Machine Learning*, 2021.
- [28] Z. Tang, L. Lian, S. Eisape, X. Wang, R. Herzig, A. Yala, A. Suhr, T. Darrell, and D. M. Chan, "Tulip: Towards unified language-image pretraining," *ArXiv*, vol. abs/2503.15485, 2025.
- [29] J. Qi, J. Liu, H. Tang, and Z. Zhu, "Beyond semantics: Rediscovering spatial awareness in vision-language models," *ArXiv*, vol. abs/2503.17349, 2025.
- [30] B. Zhang, P. Zhang, X. wen Dong, Y. Zang, and J. Wang, "Long-clip: Unlocking the long-text capability of clip," in *European Conference on Computer Vision*, 2024.
- [31] S. Wang, V. Leroy, Y. Cabon, B. Chidlovskii, and J. Revaud, "Dust3r: Geometric 3d vision made easy," *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 20697–20709, 2023.
- [32] J. Wang, M. Chen, N. Karaev, A. Vedaldi, C. Rupprecht, and D. Novotny, "Vggt: Visual geometry grounded transformer," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2025.
- [33] Z. Li, R. Tucker, F. Cole, Q. Wang, L. Jin, V. Ye, A. Kanazawa, A. Holynski, and N. Snavely, "Megsam: Accurate, fast, and robust structure and motion from casual dynamic videos," *ArXiv*, vol. abs/2412.04463, 2024.
- [34] DeepSeek-AI, D. Guo, D. Yang, H. Zhang, J.-M. Song, R. Zhang, R. Xu, Q. Zhu, S. Ma, P. Wang, X. Bi, X. Zhang, X. Yu, Y. Wu, Z. F. Wu, Z. Gou, Z. Shao, Z. Li, Z. Gao, A. Liu, B. Xue, B.-L. Wang, B. Wu, B. Feng, C. Lu, C. Zhao, C. Deng, C. Zhang, C. Ruan, D. Dai, D. Chen, D.-L. Ji, E. Li, F. Lin, F. Dai, F. Luo, G. Hao, G. Chen, G. Li, H. Zhang, H. Bao, H. Xu, H. Wang, H. Ding, H. Xin, H. Gao, H. Qu, H. Li, J. Guo, J. Li, J. Wang, J. Chen, J. Yuan, J. Qiu, J. Li, J. Cai, J. Ni, J. Liang, J. Chen, K. Dong, K. Hu, K. Gao, K. Guan, K. Huang, K. Yu, L. Wang, L. Zhang, L. Zhao, L. Wang, L. Zhang, L. Xu, L. Xia, M. Zhang, M. Zhang, M. Tang, M. Li, M. Wang, M. Li, N. Tian, P. Huang, P. Zhang, Q. Wang, Q. Chen, Q. Du, R. Ge, R. Zhang, R. Pan, R. Wang, R. J. Chen, R. Jin, R. Chen, S. Lu, S. Zhou, S. Chen, S. Ye, S. Wang, S. Yu, S. Zhou, S. Pan, S. S. Li, S. Zhou, S.-K. Wu, T. Yun, T. Pei, T. Sun, T. Wang, W. Zeng, W. Zhao, W. Liu, W. Liang, W. Gao, W.-X. Yu, W. Zhang, W. L. Xiao, W. An, X. Liu, X. Wang, X. Chen, X. Nie, X. Cheng, X. Liu, X. Xie, X. Liu, X. Yang, X. Li, X. Su, X. Lin, X. Q. Li, X. Jin, X.-C. Shen, X. Chen, X. Sun, X. Wang, X. Song, X. Zhou, X. Wang, X. Shan, Y. K. Li, Y. Q. Wang, Y. X. Wei, Y. Zhang, Y. Xu, Y. Li, Y. Zhao, Y. Sun, Y. Wang, Y. Yu, Y. Zhang, Y. Shi, Y. Xiong, Y. He, Y. Piao, Y. Wang, Y. Tan, Y. Ma, Y. Liu, Y. Guo, Y. Ou, Y. Wang, Y. Gong, Y.-J. Zou, Y. He, Y. Xiong, Y.-W. Luo, Y. mei You, Y. Liu, Y. Zhou, Y. X. Zhu, Y. Huang, Y. Li, Y. Zheng, Y. Zhu, Y. Ma, Y. Tang, Y. Zha, Y. Yan, Z. Ren, Z. Ren, Z. Sha, Z. Fu, Z. Xu, Z. Xie, Z. guo Zhang, Z. Hao, Z. Ma, Z. Yan, Z. Wu, Z. Gu, Z. Zhu, Z. Liu, Z.-A. Li, Z. Xie, Z. Song, Z. Pan, Z. Huang, Z. Xu, Z. Zhang, and Z. Zhang, "Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning," *ArXiv*, vol. abs/2501.12948, 2025.
- [35] Z. Shao, P. Wang, Q. Zhu, R. Xu, J.-M. Song, M. Zhang, Y. K. Li, Y. Wu, and D. Guo, "Deepseekmath: Pushing the limits of mathematical reasoning in open language models," *ArXiv*, vol. abs/2402.03300, 2024.
- [36] J. Wei, X. Wang, D. Schuurmans, M. Bosma, E. H. Chi, F. Xia, Q. Le, and D. Zhou, "Chain of thought prompting elicits reasoning in large language models," *ArXiv*, vol. abs/2201.11903, 2022.
- [37] D. Azuma, T. Miyanishi, S. Kurita, and M. Kawanabe, "Scanqa: 3d question answering for spatial scene understanding," *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 19107–19117, 2021.
- [38] X. Ma, S. Yong, Z. Zheng, Q. Li, Y. Liang, S.-C. Zhu, and S. Huang, "Sqa3d: Situated question answering in 3d scenes," *ArXiv*, vol. abs/2210.07474, 2022.
- [39] H. Liu, C. Li, Y. Li, and Y. J. Lee, "Improved baselines with visual instruction tuning," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 26296–26306, 2024.
- [40] D. Zhu, J. Chen, X. Shen, X. Li, and M. Elhoseiny, "Minigpt-4: Enhancing vision-language understanding with advanced large language models," *arXiv preprint arXiv:2304.10592*, 2023.
- [41] Y. Su, T. Lan, H. Li, J. Xu, Y. Wang, and D. Cai, "Pandagpt: One model to instruction-follow them all," *arXiv preprint arXiv:2305.16355*, 2023.

- [42] R. Pi, J. Gao, S. Diao, R. Pan, H. Dong, J. Zhang, L. Yao, J. Han, H. Xu, L. Kong, *et al.*, “Detgpt: Detect what you need via reasoning,” *arXiv preprint arXiv:2305.14167*, 2023.
- [43] K. Li, Y. He, Y. Wang, Y. Li, W. Wang, P. Luo, Y. Wang, L. Wang, and Y. Qiao, “Videochat: Chat-centric video understanding,” *arXiv preprint arXiv:2305.06355*, 2023.
- [44] Y. Chen, S. Yang, H. Huang, T. Wang, R. Xu, R. Lyu, D. Lin, and J. Pang, “Grounded 3d-llm with referent tokens,” *arXiv preprint arXiv:2405.10370*, 2024.
- [45] Z. Wang, H. Huang, Y. Zhao, Z. Zhang, and Z. Zhao, “Chat-3d: Data-efficiently tuning large language model for universal dialogue of 3d scenes,” *arXiv preprint arXiv:2308.08769*, 2023.
- [46] J. Huang, S. Yong, X. Ma, X. Linghu, P. Li, Y. Wang, Q. Li, S.-C. Zhu, B. Jia, and S. Huang, “An embodied generalist agent in 3d world,” *arXiv preprint arXiv:2311.12871*, 2023.
- [47] H. Huang, Y. Chen, Z. Wang, R. Huang, R. Xu, T. Wang, L. Liu, X. Cheng, Y. Zhao, J. Pang, *et al.*, “Chat-scene: Bridging 3d scene and large language models with object identifiers,” in *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024.
- [48] Y. Hong, H. Zhen, P. Chen, S. Zheng, Y. Du, Z. Chen, and C. Gan, “3d-llm: Injecting the 3d world into large language models,” *Advances in Neural Information Processing Systems*, vol. 36, pp. 20482–20494, 2023.
- [49] R. Fu, J. Liu, X. Chen, Y. Nie, and W. Xiong, “Scene-llm: Extending language model for 3d visual understanding and reasoning,” *arXiv preprint arXiv:2403.11401*, 2024.
- [50] Z. Qi, Z. Zhang, Y. Fang, J. Wang, and H. Zhao, “Gpt4scene: Understand 3d scenes from videos with vision-language models,” *arXiv preprint arXiv:2501.01428*, 2025.
- [51] Z. Liu, Y. Dong, Z. Liu, W. Hu, J. Lu, and Y. Rao, “Oryx mllm: On-demand spatial-temporal understanding at arbitrary resolution,” *arXiv preprint arXiv:2409.12961*, 2024.
- [52] X. Wang, Y. Zhang, O. Zohar, and S. Yeung-Levy, “Videoagent: Long-form video understanding with large language model as agent,” in *European Conference on Computer Vision*, pp. 58–76, Springer, 2024.
- [53] Y. Li, Y. Zhang, T. Lin, X. Liu, W. Cai, Z. Liu, and B. Zhao, “Sti-bench: Are mllms ready for precise spatial-temporal world understanding?,” *arXiv preprint arXiv:2503.23765*, 2025.
- [54] P. Wu, Y. Liu, M. Liu, and J. Shen, “St-think: How multimodal large language models reason about 4d worlds from ego-centric videos,” *arXiv preprint arXiv:2503.12542*, 2025.
- [55] S. Zhou, A. Vilesov, X. He, Z. Wan, S. Zhang, A. N. D. C. D. Chen, and X. E. W. A. Kadambi, “Vlm4d: Towards spatiotemporal awareness in vision language models,”
- [56] A. Vaswani, N. M. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in *Neural Information Processing Systems*, 2017.
- [57] T. Darcet, M. Oquab, J. Mairal, and P. Bojanowski, “Vision transformers need registers,” *ArXiv*, vol. abs/2309.16588, 2023.
- [58] X. Pan, S. N. Shukla, A. Singh, Z. Zhao, S. K. Mishra, J. Wang, Z. Xu, J. Chen, K. Li, F. Juefei-Xu, J. Hou, and S. Xie, “Transfer between modalities with metaqueries,” 2025.
- [59] G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher, “An analysis of approximations for maximizing submodular set functions—i,” *Mathematical Programming*, vol. 14, no. 1, pp. 265–294, 1978.
- [60] D. S. Hochbaum, *Approximating covering and packing problems: set cover, vertex cover, independent set, and related problems*, p. 94–143. USA: PWS Publishing Co., 1996.
- [61] A. Dai, A. X. Chang, M. Savva, M. Halber, T. A. Funkhouser, and M. Nießner, “Scannet: Richly-annotated 3d reconstructions of indoor scenes,” *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2432–2443, 2017.
- [62] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” *CoRR*, vol. abs/1412.6980, 2014.
- [63] F. Xue, Y. Chen, D. Li, Q. Hu, L. Zhu, X. Li, Y. Fang, H. Tang, S. Yang, Z. Liu, E. He, H. Yin, P. Molchanov, J. Kautz, L. Fan, Y. Zhu, Y. Lu, and S. Han, “Longvila: Scaling long-context visual language models for long videos,” *ArXiv*, vol. abs/2408.10188, 2024.
- [64] J. Lin, H. Yin, W. Ping, Y. Lu, P. Molchanov, A. Tao, H. Mao, J. Kautz, M. Shoenybi, and S. Han, “Vila: On pre-training for visual language models,” *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 26679–26689, 2023.
- [65] P. Zhang, K. Zhang, B. Li, G. Zeng, J. Yang, Y. Zhang, Z. Wang, H. Tan, C. Li, and Z. Liu, “Long context transfer from language to vision,” *ArXiv*, vol. abs/2406.16852, 2024.
- [66] C. Yeshwanth, Y.-C. Liu, M. Nießner, and A. Dai, “Scannet++: A high-fidelity dataset of 3d indoor scenes,” *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 12–22, 2023.

- [67] G. Baruch, Z. Chen, A. Dehghan, T. Dimry, Y. Feigin, P. Fu, T. Gebauer, B. Joffe, D. Kurz, A. Schwartz, and E. Shulman, “ARKitscenes - a diverse real-world dataset for 3d indoor scene understanding using mobile RGB-d data,” in *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 1)*, 2021.
- [68] J. Huang, S. Yong, X. Ma, X. Linghu, P. Li, Y. Wang, Q. Li, S.-C. Zhu, B. Jia, and S. Huang, “An embodied generalist agent in 3d world,” *ArXiv*, vol. abs/2311.12871, 2023.
- [69] Z. Zhu, X. Ma, Y. Chen, Z. Deng, S. Huang, and Q. Li, “3d-vista: Pre-trained transformer for 3d vision and text alignment,” *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 2899–2909, 2023.
- [70] Y. Hong, H. Zhen, P. Chen, S. Zheng, Y. Du, Z. Chen, and C. Gan, “3d-llm: Injecting the 3d world into large language models,” *NeurIPS*, 2023.
- [71] Q.-Y. Zhou, J. Park, and V. Koltun, “Open3d: A modern library for 3d data processing,” *ArXiv*, vol. abs/1801.09847, 2018.
- [72] N. Silberman, D. Hoiem, P. Kohli, and R. Fergus, “Indoor segmentation and support inference from rgb-d images,” in *European Conference on Computer Vision*, 2012.
- [73] S. Gupta, P. Arbeláez, and J. Malik, “Perceptual organization and recognition of indoor scenes from rgb-d images,” *2013 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 564–571, 2013.
- [74] R. Fu, J. Liu, X. Chen, Y. Nie, and W. Xiong, “Scene-llm: Extending language model for 3d visual understanding and reasoning,” *ArXiv*, vol. abs/2403.11401, 2024.