Measuring Massive Multimodal Understanding and Reasoning in Open Space

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Abstract

The increasing sophistication of multimodal models necessitates benchmarks that can rigorously evaluate their understanding and reasoning in complex, safety-pertinent, open-world scenarios. This study introduces OpenRBench, a large-scale benchmark uniquely designed to assess reasoning capabilities across diverse open spaces, comprehensively covering land, air, and water environments. OpenRBench comprises approximately 2,000 videos and over 19,000 human-annotated question-answer pairs. These videos, varying in length (short, medium, long) and presenting tasks of tiered difficulty (interval-based choices and accuracy-based choices), encompass distinct operational domains: the land-based scenarios primarily focus on traffic environments, particularly traffic collisions and accident cases; the air-based scenarios center on airplane navigation; and the water-based scenarios involve ship movements. OpenRBench systematically evaluates models on temporal reasoning, spatial understanding, and intent inference within these dynamic contexts. By providing a unified platform across this broad spectrum of domains, OpenRBench aims to drive the development of safer, more robust, and generalizable AI systems. Benchmarking state-of-the-art multimodal models on our dataset reveals that even leading models, such as ChatGPT-4o and Gemini, achieve only around a 20% success rate, highlighting the significant challenges that remain in open-space multimodal reasoning. The code, leaderboard, and dataset are available at: `https://open-space-reasoning.github.io`.

1 Introduction

As artificial intelligence (AI) continues to evolve, large multimodal models have shown impressive capabilities across vision, language, and video domains. However, significant challenges remain in deploying these models for real-world, safety-critical applications such as autonomous driving, robotics, and aerial or maritime operations. While multimodal models demonstrate remarkable performance in constrained or simulated environments, their robustness and depth of understanding in high-stakes, dynamic scenarios are still far from sufficient.

In particular, deployment in mission-critical domains requires rigorous evaluation of models' understanding and reasoning abilities under real-world conditions that involve uncertainty, physical interactions, and causal dependencies. While recent benchmarks have advanced evaluation in specific facets like temporal understanding (e.g., MVBench [20], REXTIME [5]) or domain-specific knowledge (e.g., MMMU [43], DriveLM [30]), there remains a paucity of unified platforms that assess reasoning across the combined spectrum of land, air, and water operations. To address this, our work defines *open space* as unstructured or semi-structured outdoor environments characterized by high

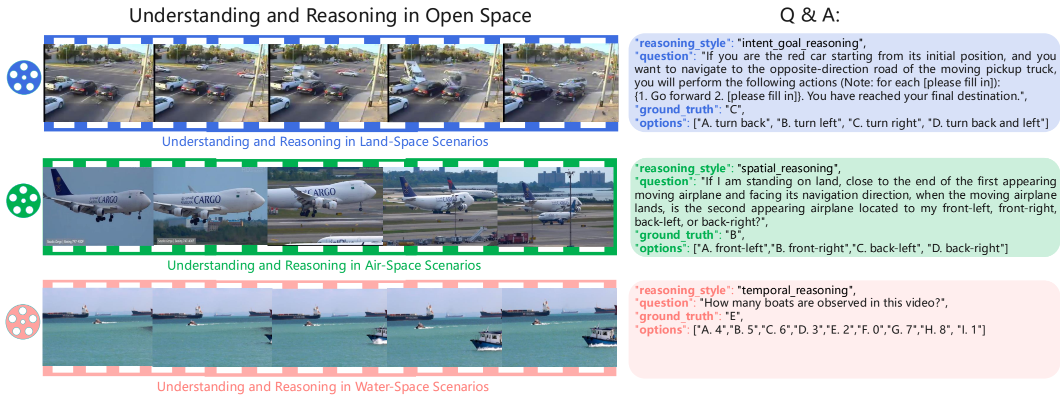


Figure 1: Examples of multimodal Understanding and Reasoning in Open-Space Scenarios

variability, dynamic interactions, and minimal physical boundaries. This includes **air space** (e.g., airplane navigation), **water space** (e.g., ship and boat movements), and **land space** (e.g., road traffic involving diverse vehicle types). These settings inherently involve complex temporal dependencies, causal relationships, and real-world physical constraints, demanding advanced, robust reasoning capabilities for genuine open-world understanding.

We introduce OpenRBench (Measuring Massive Multimodal Understanding and Reasoning), a comprehensive evaluation framework. Specifically, we present the OpenRBench benchmark, which focuses on reasoning across the aforementioned land traffic, airspace, and waterway domains—settings where safety, perception, and decision-making are deeply interdependent. Unlike benchmarks focusing on isolated skills or single domains, OpenRBench challenges models on several key reasoning capabilities: *temporal-causal reasoning* (understanding event sequences and causality over extended periods); *spatial understanding* (comprehending dynamic spatial relationships and multi-agent trajectories); *intent and goal planning/inference* (deducing agent intentions and goals), which includes *complex strategic & counterfactual reasoning* (assessing understanding of higher-order strategies, action implications, and 'what-if' scenarios). Several representative examples from OpenRBench are illustrated in Figure 1. By systematically probing these capabilities across diverse safety-pertinent scenarios, OpenRBench provides a framework for assessing progress towards AI systems that can reliably operate in the real world.

Our key contributions are summarized as follows:

- **Unified Open-World Evaluation Suite:** We introduce OpenRBench, a large-scale, video-based benchmark uniquely covering land traffic, airspace, and waterway scenarios to provide a comprehensive assessment of multimodal reasoning across these distinct yet complementary safety-critical open spaces.
- **Reasoning-Centric Evaluation:** OpenRBench systematically evaluates critical reasoning facets including temporal-causal understanding, dynamic spatial awareness, intent and goal reasoning, within dynamic and physically grounded settings.
- **Real-World Limitations and Safety Gaps:** We highlight limitations in current AI systems' reasoning performance in open-space domains (e.g., autonomous driving, aviation, and maritime environments), and provide a challenging testbed to drive the development of safer and more robust multimodal AI systems.

2 Related Work

2.1 General Multimodal Understanding Benchmarks

Recent years have witnessed growing interest in video understanding benchmarks. Foundational video question-answering (QA) efforts include MSR-VTT [41] and Next-QA [39]. More recently, MVBench [20], with its 20 diverse temporal tasks derived from static images, and MLVU [46] have expanded video QA capabilities across multiple domains. The challenge of long-form video understanding has seen contributions from benchmarks such as EgoSchema [24], Video-LLaVA [8], MovieChat [32], and LongVideoBench [38]. Parallelly, video captioning benchmarks such as AuroraCap [4], HiCM2 [17], and LongCaptioning [37] focus on generating detailed textual descriptions.

A significant trend is the push for more rigorous temporal and causal reasoning. REXTIME [5], for instance, probes the linking of causally related events across separate video segments. For multi-domain understanding, MMWorld [13] evaluates models across diverse disciplines, requiring explanations and counterfactuals. Furthermore, LVBench [36] integrates video inputs for QA. Beyond video, reasoning from static images is explored by MME [16] (including CoT extensions), MMMU [43] (evaluating expert-level multi-discipline reasoning), and benchmarks for mathematical reasoning like Dynamath [48] and MultiModal-MATH [47]. For academic content, Video-MMLU [34] offers a large-scale lecture video benchmark.

While these diverse benchmarks significantly advance specific aspects of multimodal understanding—be it general video comprehension, temporal analysis, long-form narrative understanding, captioning, or static image reasoning—they often do not provide a framework for unified evaluation across land, air, and maritime open-space environments, nor the specific blend of complex reasoning (including strategic and intent-based inference) that OpenRBench is designed to evaluate within these contexts.

2.2 Safety-Critical Multimodal Understanding Benchmarks

Evaluating models in safety-critical domains, where reasoning under uncertainty is vital, is an emerging focus. Initial efforts addressed static image safety [21], model robustness against adversarial attacks (e.g., FigStep [10], JailBreakV [23]) [29, 26], or indoor robotics [42].

Autonomous driving has been a major driver of safety-critical research. Foundational datasets such as nuScenes[1] and Waymo Open Dataset[2], along with language-integrated efforts such as DriveLM and DriveVLM [30, 35], are closely related to OpenRBench's goals due to their real-world video and safety considerations. However, a key motivation for OpenRBench was that these traditionally emphasized perception and planning, with less focus on deep safety-critical reasoning for tasks such as accident cause analysis or complex decision-making. Other specialized benchmarks tackle related issues such as video anomaly detection (e.g., VANE-Bench [9]).

While advancements continue in specialized video reasoning and domain-specific safety evaluations, existing benchmarks still largely focus on single operational domains. Critically, they often lack sufficient coverage of high-risk scenarios such as traffic collisions, ship navigation, and airplane takeoff/landing events across combined land, air, and water settings. A unified platform to consistently evaluate robust, generalizable reasoning (e.g., temporal-causal, spatial, intent, and strategic analysis) across these diverse, safety-critical open spaces also remains absent. To address this specific void, OpenRBench distinctively incorporates these challenging high-risk scenarios from all three domains. The reliability of its complex reasoning evaluation is ensured as all annotations were generated by highly educated annotators (at least Master's degree). OpenRBench thus provides a much-needed testbed for fostering robust, adaptable AI capable of open-world understanding.

3 Understanding and Reasoning in Open Space

3.1 Open Space Settings

We design the benchmark around three types of open-space environments: **land space**, focusing primarily on traffic accident understanding and reasoning; **air space**, centered on airplane takeoff and landing scenarios; and **water space**, which emphasizes ship navigation understanding and reasoning. Within each environment, we construct tasks that evaluate models across three key reasoning dimensions: dynamic temporal reasoning, spatial reasoning, and intent and goal reasoning. Representative examples for each reasoning type are illustrated in Figure 2.

For each reasoning style, we design tasks with varying levels of difficulty using two formats: *interval-based choices* and *accuracy-based choices*. Easy tasks provide approximately 3 coarse-grained interval choices, medium tasks offer 6 intermediate-level intervals, and hard tasks present 12 fine-grained discrete options that require an exact match with the correct answer. The number of tasks

[1]https://www.nuscenes.org/

[2]https://waymo.com/open/

Figure 2: Examples of reasoning question settings in the OpenRBench benchmark across three key reasoning types: *Temporal Reasoning*, which involves understanding event sequences and motion over time; *Spatial Reasoning*, which focuses on relative positioning and orientation in space; and *Intent Reasoning*, which evaluates understanding of goal-directed behaviors and decision-making in dynamic environments.

across the three difficulty levels is evenly distributed, with each comprising one-third of the total. In all cases, the model must select a single best answer, enabling the benchmark to assess performance under increasing levels of precision and ambiguity.

Land Space In our land-space setting, we include a comprehensive range of traffic scenarios, encompassing diverse collision events under varying weather conditions such as snow, rain, and sunshine, as detailed in Table 1. Specific examples of these scenarios are illustrated in Figure 3, and more detailed examples are provided in Appendix B. To enhance contextual diversity, we incorporate multiple camera perspectives—including ego-centric and third-person views—particularly for accident scenes. The dataset features incidents involving a wide variety of vehicle types, including buses, motorcycles, sedans, and several categories of trucks, across different road environments such as highways, freeways, and rural roads. The associated questions are designed to evaluate models across multiple reasoning dimensions, including temporal-causal understanding, spatial reasoning, and intent and goal planning. The original land-space video datasets are sourced from [3, 28], which primarily collected videos from YouTube and other public internet platforms.

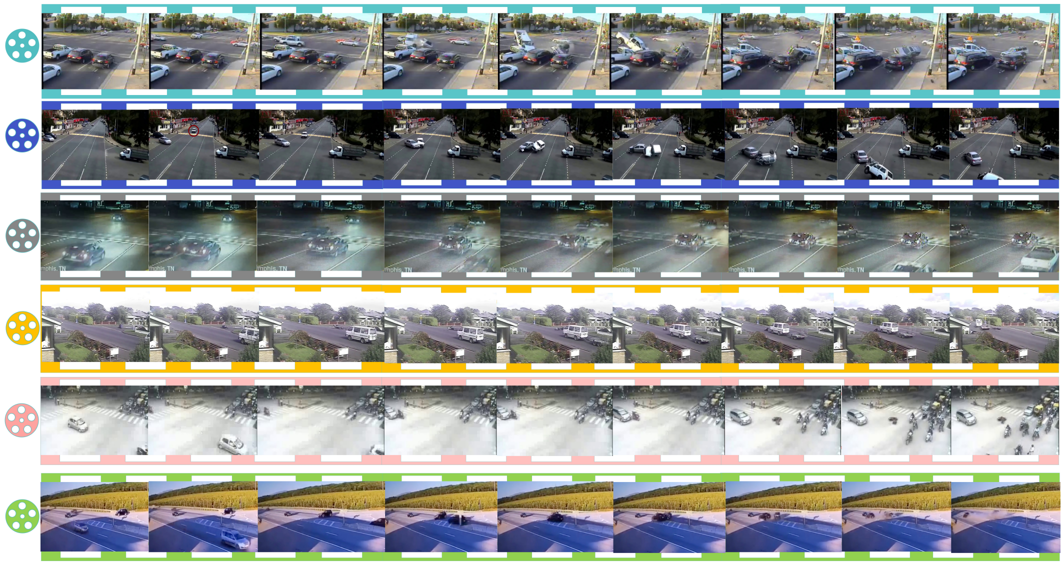


Figure 3: Land-space traffic accident scenarios for open-space video understanding and reasoning include intersection collisions, urban road accidents, nighttime incidents, rural road accidents, snow-covered road collisions, and freeway accidents.

Table 1: Overview of traffic accident scenarios in our benchmark, covering diverse road environments, weather conditions, and involved traffic participants.

Index	Categories
Road Environments:	Intersection, Highway, Freeway, Rural Road, Tunnel, Urban Road, Bridge, Parking Lot
Weather Conditions:	Snow, Rain, Sunshine, Cloudy, Foggy, Windy
Involved Participants:	Sedan, SUV, Bus, Truck, Motorcycle, Bicycle, Van, Pickup, Trailer, Pedestrian

Air Space In airspace scenarios, we primarily focus on *takeoff* and *landing* events, emphasizing the analysis of airplane navigation directions and perceptual understanding. Airplanes represent a largely unexplored domain in large multimodal research, despite their significant real-world impact. Our benchmark investigates various aspects of airplane behavior, including differences in navigation patterns, aircraft sizes, and motion dynamics across different types of airplanes. These scenarios also incorporate videos of varying lengths and are designed to evaluate models on multiple reasoning dimensions, including spatial reasoning, temporal reasoning, and intent and goal inference. We further assess model performance across different difficulty levels using both interval-based and accuracy-based multiple-choice formats. The airspace videos are sourced from publicly available footage, including references such as [3], [4], and [5].

Water Space We include videos from both **river** and **ocean** scenarios, featuring varying video lengths and difficulty levels. The dataset encompasses a diverse range of watercraft, including different types of boats and ships, under a broad set of navigation conditions. Despite their real-world importance, river and ocean environments remain underexplored in the context of large multimodal models. To address this gap, we evaluate model performance across multiple reasoning styles—temporal, spatial, and intent and goal reasoning—using video-based tasks of varying durations and difficulty levels. Task difficulty is controlled through both interval-based and accuracy-based multiple-choice formats. The water-space videos are sourced from publicly available datasets, including [11, 25].

3.2 Dataset Analysis

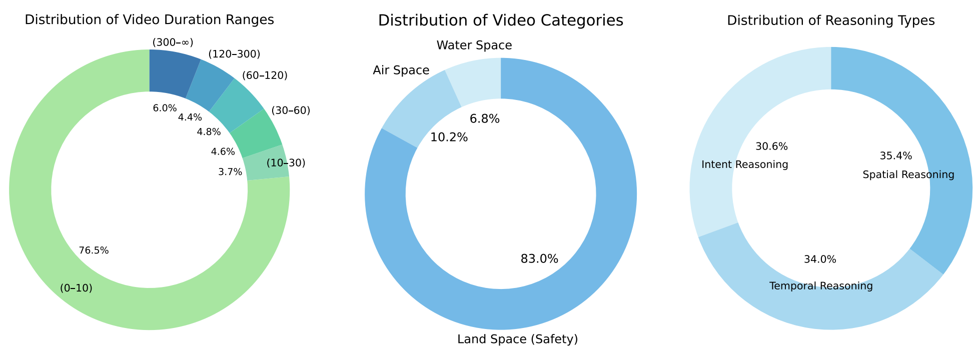
This benchmark includes approximately 2,000 videos and 19,000 human-annotated question-answer pairs, covering a wide range of reasoning tasks. All annotations were performed by highly educated annotators, each holding at least a master's degree in engineering-related fields such as mathematics

[3] `https://www.youtube.com/watch?v=i6CrbqeksJ8`
[4] `https://www.youtube.com/watch?v=k5yvzTw08K8`
[5] `https://www.youtube.com/watch?v=Bt9tpiAmTs8`

or computer science. The dataset features a variety of video lengths, categories, and frame counts, and spans three primary open-space reasoning scenarios: **land space**, **water space**, and **air space**. An overview of the dataset's characteristics is shown in Figure 4, which illustrates the distributions of video duration, domain coverage, and reasoning styles. During annotation, we first design the hard-level tasks and label each question with the ground-truth answer. Based on these, we then construct the medium and easy tasks. The primary differences between difficulty levels lie in the number and types of answer choices. Details of the annotation procedure and difficulty levels are provided in Appendix B.

Specifically, **(a) Video Length:** A substantial portion of the videos (76.5%) are short, with durations under 10 seconds. The remaining videos are distributed across longer intervals: 10–30 seconds (3.7%), 30–60 seconds (4.6%), 60–120 seconds (4.8%), 120–300 seconds (4.4%), and over 300 seconds (6.0%). This distribution reflects a strong emphasis on short, dynamic scenarios that test rapid perception and reasoning. **(b) Video Categories:** The benchmark spans three open-space domains. Land space, which primarily involves traffic and safety-related scenarios, comprises 83.0% of the videos. Air space accounts for 10.2%, and water space makes up 6.8%. This distribution highlights both the practical importance of land-based reasoning and the inclusion of underrepresented domains such as maritime and aviation environments. **(c) Reasoning Styles:** M4R supports three major reasoning types, with a relatively balanced distribution: *spatial reasoning* (35.4%), *temporal reasoning* (34.0%), and *intent reasoning* (30.6%). This design ensures comprehensive evaluation across key dimensions essential for real-world multimodal understanding.

Overall, the dataset provides a rich and diverse collection of real-world video scenarios across multiple modalities and time scales, offering a robust benchmark for evaluating multimodal understanding and reasoning in open-space environments.



(a) Video duration. (b) Video categories. (c) Reasoning types.

Figure 4: Distribution of video and task properties in the OpenRBench benchmark.

3.3 Comparison with Existing Benchmarks

Table 2 provides a comparative analysis of OpenRBench alongside existing evaluation benchmarks for multimodal models. Most benchmarks primarily focus on assessing the multimodal reasoning capabilities of multimodal models [12, 33, 46]; however, a significant limitation is the prevalent oversight of safety considerations. While a few recent benchmarks have begun to evaluate safety aspects of multimodal models [47, 21], they often do not incorporate video question-answering data. However, single-frame capture, in most cases, can introduce uncertainties in reasoning and is insufficient for adequately assessing multimodal models' capabilities in handling safety issues. In contrast, our OpenRBench introduces a large-scale and meticulously curated collection of video question-answer pairs that specifically focus on open-space traffic reasoning in real-world safety-related scenarios. Comprising 2,000 carefully selected videos and 19,000 reasoning question-answer pairs, the OpenRBench features a size competitive with existing benchmarks, thus highlighting the comprehensiveness of our evaluation set.

Table 2: **Benchmark comparison** for multimodal understanding and reasoning tasks.

Dataset	Safety	Traffic	Annotation	Real-World	Scenarios	# Video	# Ave. Duration (s)	Question-answering Number	Question-answering Type
MovieChat-1K [33]	✗	✗	Human	✓	General	1,000	564	13,000	Open-ended
MMWorld [12]	✗	✗	Human	✓	General	1,910	107	6,627	Multiple-choice
MLVU [46]	✗	✗	Human	✓	General	1,730	930	3,102	Multiple-choice
MVBench [1]	✗	✗	Human & LLM	✓	General	4,000	16	4,000	Multiple-choice
LongVideoBench [38]	✗	✗	Human	✓	General	3,763	473	6,678	Multiple-choice
TempCompass [22]	✗	✗	Human & LLM	✓	General	410	< 30	7,540	Multiple-choice
VSI-Bench [42]	✗	✗	Human	✓	Embodied	288	50-100	5,000	Multiple-choice
Video-MMMU [14]	✗	✗	Human & LLM	✗	Professional	300	506	900	Multiple-choice
Video-MMLU [34]	✗	✗	Human & LLM	✗	Professional	1,065	109	15,746	Open-ended
DriveBench [40]	✓	✓	Human & LLM	✓	Autonomous Driving	✗	✗	19,200	Multiple-choice
DriveLM [31]	✓	✓	Human	✓	Autonomous Driving	✗	✗	15,480	Open-ended
nuScenes-QA [27]	✗	✓	Human	✓	Autonomous Driving	✗	✗	83,337	Open-ended
MSSBench [47]	✓	✗	Human & LLM	✓	General	✗	✗	1960	Open-ended
MMSBench [21]	✓	✗	LLM	✓	General	✗	✗	5040	Open-ended
M4R (ours)	✓	✓	Human	✓	General	2000	56	19,000	Multiple-choice

Table 3: Evaluation of OpenRBench in the **Land Space** domain using **Short**, **Medium**, and **Long** Videos, categorized by reasoning types, based on a subset of the dataset.

Difficulty	Models	Size	Over. Avg.	Short Video Scenarios				Medium Video Scenarios				Long Video Scenarios			
				Avg.	Temporal	Spatial	Intent	Avg.	Temporal	Spatial	Intent	Avg.	Temporal	Spatial	Intent
	GPT 4o [15]	-	**24.41**	26.78	34.65	34.69	11	35.70	43.14	32.14	31.82	11.00	6	26	1
	Gemini 1.5 pro [7]	-	18.76	19.72	23.76	20.41	15	24.55	33.33	16.07	24.24	12.00	2	26	8
	InternVL2.5 [6]	26B	23.78	21.33	26.0	31.0	7.0	32.00	46.0	32.0	18.0	18.00	16.0	24.0	14.0
	InternVL2.5 [6]	8B	22.67	20.00	18.0	33.0	9.0	30.00	46.0	30.0	14.0	18.00	16.0	28.0	10.0
	InternVL2.5 [6]	4B	19.56	18.67	18.0	28.0	8.0	28.00	34.0	24.0	26.0	12.00	8.0	22.0	6.0
Hard	LLaVA Next [18]	32B	16.22	20.67	16.0	32.0	14.0	11.33	12.0	12.0	10.0	16.67	10.0	30.0	10.0
	LLaVA Video [45]	7B	19.78	19.33	12.0	35.0	11.0	24.67	26.0	30.0	18.0	15.33	10.0	28.0	8.0
	LLaVA OneVision [19]	7B	13.67	14.33	5.0	27.0	11.0	14.67	18.0	8.0	18.0	12.0	6.0	22.0	8.0
	Qwen2.5 VL [2]	32B	22.66	19.33	11.0	34.0	13.0	35.33	46.0	24.0	36.0	13.33	4.0	26.0	10.0
	Qwen2.5 VL [2]	7B	22.89	26.00	17.0	30.0	31.0	30.00	40.0	32.0	18.0	12.67	2.0	30.0	6.0
	Qwen2.5 VL [2]	3B	22.78	23.00	17.0	33.0	19.0	26.67	38.0	26.0	16.0	18.67	10.0	34.0	12.0
	GPT 4o [15]	-	**36.99**	45.49	48.48	55	33	33.89	41.67	26.67	33.33	31.33	24	44	26
	Gemini 1.5 pro [7]	-	33.89	39.47	42.42	42	34	33.52	33.33	42.22	25	28.67	12	52	22
	InternVL2.5 [6]	26B	35.11	36.00	39.0	50.0	19.0	36.67	50.0	36.0	24.0	32.67	30.0	40.0	28.0
	InternVL2.5 [6]	8B	34.66	37.33	43.0	57.0	12.0	35.33	42.0	46.0	18.0	31.33	26.0	44.0	24.0
	InternVL2.5 [6]	4B	33.89	39.67	38.0	53.0	28.0	32.67	44.0	28.0	26.0	29.33	16.0	46.0	26.0
Medium	LLaVA Next [18]	32B	20.0	27.33	16.0	49.0	17.0	10.67	14.0	10.0	8.0	22.0	16.0	36.0	14.0
	LLaVA Video [45]	7B	25.67	25.00	20.0	34.0	26.0	28.67	36.0	28.0	22.0	23.33	14.0	40.0	16.0
	LLaVA OneVision [19]	7B	16.67	16.00	26.0	30.0	16.0	14.67	18.0	8.0	18.0	19.33	12.0	30.0	16.0
	Qwen2.5 VL [2]	32B	28.55	28.33	21.0	44.0	20.0	33.33	40.0	30.0	30.0	24.00	8.0	40.0	24.0
	Qwen2.5 VL [2]	7B	29.89	39.00	37.0	42.0	38.0	30.67	32.0	40.0	20.0	20.00	16.0	26.0	18.0
	Qwen2.5 VL [2]	3B	30.78	41.67	33.0	52.0	40.0	24.67	30.0	30.0	14.0	26.00	22.0	36.0	20.0
	GPT 4o [15]	-	42.17	52.35	59	47.06	51	47.16	54.9	44.9	41.67	27.00	44	5	32
	Gemini 1.5 pro [7]	-	46.00	51.33	60	50	44	36.92	49.02	36.73	25	50.00	58	44	48
	InternVL2.5 [6]	26B	**52.55**	61.00	62.0	59.0	62.0	45.33	58.0	44.0	34.0	51.33	62.0	62.0	30.0
	InternVL2.5 [6]	8B	50.11	55.67	55.0	60.0	52.0	44.67	58.0	42.0	34.0	50.00	54.0	64.0	32.0
	InternVL2.5 [6]	4B	44.89	53.33	46.0	60.0	54.0	37.33	48.0	38.0	26.0	44.00	44.0	48.0	40.0
Easy	LLaVA Next [18]	32B	31.25	38.00	35.0	45.0	34.0	21.33	12.0	14.0	38.0	34.67	20.0	50.0	34.0
	LLaVA Video [45]	7B	31.44	33.00	30.0	31.0	38.0	33.33	38.0	36.0	26.0	28.00	16.0	32.0	36.0
	LLaVA OneVision [19]	7B	29.78	32.00	31.0	33.0	32.0	24.00	26.0	30.0	16.0	33.33	28.0	36.0	36.0
	Qwen2.5 VL [2]	32B	43.22	51.00	58.0	50.0	45.0	41.33	46.0	38.0	40.0	37.33	32.0	44.0	36.0
	Qwen2.5 VL [2]	7B	40.67	51.33	55.0	42.0	57.0	36.00	32.0	42.0	34.0	34.67	34.0	28.0	42.0
	Qwen2.5 VL [2]	3B	42.00	49.33	38.0	55.0	55.0	34.67	42.0	34.0	28.0	42.00	36.0	54.0	36.0

4 Experiments

4.1 Comprehensive Experiments

In our experiments, we build upon the `lmms-eval` framework [44] as the foundation for our benchmark and extend it to support the specific requirements of OpenRBench. We conduct comprehensive evaluations to assess the performance of SOTA multimodal models across diverse open-space scenarios.

Land Space Analysis: As shown in Table 3, we present a detailed evaluation of model performance in the **Land Space** domain of OpenRBench, categorized by reasoning type, video length, and difficulty level. InternVL2.5 [6] achieves the highest accuracy in easier settings, suggesting that simply scaling up model size does not always lead to better reasoning performance and may, in some cases, degrade specific capabilities. However, performance drops significantly across all models as tasks become harder and video contexts lengthen. Notably, both GPT-4o [15] and Gemini 1.5 Pro [7] achieve around 40% overall accuracy, reflecting competitive performance while also highlighting persistent challenges in temporal, spatial, and intent-based reasoning within complex, real-world scenarios.

Air Space Analysis: Table 4 presents model performance in the **Air Space** domain of OpenRBench, evaluated across short, medium, and long video scenarios and categorized by temporal, spatial,

Table 4: Evaluation of OpenRBench in the **Air Space** domain using **Short**, **Medium**, and **Long** Videos, categorized by reasoning types, based on a subset of the dataset.

Difficulty	Models	Size	Over. Avg.	Short Video Scenarios				Medium Video Scenarios				Long Video Scenarios			
				Avg.	Temporal	Spatial	Intent	Avg.	Temporal	Spatial	Intent	Avg.	Temporal	Spatial	Intent
Hard	GPT 4o [15]	-	18.11	21.33	16.00	26.00	22.00	14.67	12.00	30.00	2.00	18.33	5.00	35.00	15.00
	Gemini 1.5 pro [7]	-	**22.34**	26.67	24.00	26.00	30.00	18.67	20.00	22.00	14.00	21.67	10.00	25.00	30.00
	InternVL2.5 [6]	26B	17.33	19.33	24.00	26.00	10.00	19.33	16.00	32.00	10.00	13.33	10.00	10.00	20.00
	InternVL2.5 [6]	8B	18.22	18.67	20.00	28.00	8.00	19.33	16.00	30.00	12.00	16.67	5.00	35.00	10.00
	InternVL2.5 [6]	4B	15.33	15.33	14.00	10.00	22.00	14.00	16.00	18.00	8.00	16.67	15.00	30.00	5.00
	LLaVA Next [18]	32B	17.89	18.67	14.0	34.0	8.0	16.67	6.0	32.0	12.0	18.33	5.0	40.0	10.0
	LLaVA Video [45]	7B	14.78	16.67	14.00	28.00	8.00	12.67	6.00	22.00	10.00	15.00	5.00	30.00	10.00
	LLaVA OneVision [19]	7B	15.67	16.00	12.00	28.00	8.00	16.00	12.00	26.00	10.00	15.00	10.00	25.00	10.00
	Qwen2.5 VL [2]	32B	16.22	20.00	6.00	36.00	18.00	15.33	4.00	24.00	18.00	13.33	0.00	30.00	10.00
	Qwen2.5 VL [2]	7B	16.55	19.33	0.00	30.00	28.00	15.33	2.00	30.00	14.00	15.00	5.00	30.00	10.00
	Qwen2.5 VL [2]	3B	15.33	16.00	8.00	32.00	8.00	13.33	6.00	26.00	8.00	16.67	10.00	25.00	15.00
Medium	GPT 4o [15]	-	38.45	38.67	38.00	56.00	22.00	30.00	38.00	34.00	18.00	46.67	65.00	30.00	45.00
	Gemini 1.5 pro [7]	-	**38.78**	38.00	32.00	48.00	34.00	36.67	34.00	52.00	24.00	41.67	30.00	55.00	40.00
	InternVL2.5 [6]	26B	28.67	31.33	28.00	58.00	8.00	24.67	12.00	50.00	12.00	30.00	25.00	45.00	20.00
	InternVL2.5 [6]	8B	34.33	30.00	20.00	58.00	12.00	34.67	32.00	50.00	22.00	38.33	40.00	45.00	30.00
	InternVL2.5 [6]	4B	32.22	29.33	28.00	44.00	16.00	34.00	30.00	54.00	18.00	33.33	35.00	40.00	25.00
	LLaVA Next [18]	32B	26.11	24.67	18.0	40.0	16.0	25.33	18.0	40.0	18.0	28.33	25.0	40.0	20.0
	LLaVA Video [45]	7B	24.00	25.33	24.00	36.00	16.00	20.00	16.00	26.00	18.00	26.67	15.00	45.00	20.00
	LLaVA OneVision [19]	7B	23.67	23.33	20.00	34.00	16.00	22.67	20.00	32.00	16.00	25.00	20.00	35.00	20.00
	Qwen2.5 VL [2]	32B	33.34	32.67	12.00	48.00	38.00	30.67	22.00	50.00	20.00	36.67	20.00	60.00	30.00
	Qwen2.5 VL [2]	7B	28.00	24.67	16.00	24.00	34.00	26.00	24.00	26.00	28.00	33.33	35.00	20.00	45.00
	Qwen2.5 VL [2]	3B	28.67	22.67	18.00	36.00	14.00	26.67	18.00	44.00	18.00	36.67	40.00	35.00	35.00
Easy	GPT 4o [15]	-	40.67	35.33	30.00	28.00	48.00	36.67	24.00	38.00	48.00	50.00	45.00	50.00	55.00
	Gemini 1.5 pro [7]	-	43.00	45.33	36.00	44.00	56.00	42.00	48.00	32.00	46.00	41.67	35.00	50.00	40.00
	InternVL2.5 [6]	26B	36.11	35.33	36.00	44.00	26.00	34.67	28.00	46.00	30.00	38.33	30.00	40.00	45.00
	InternVL2.5 [6]	8B	38.44	36.67	28.00	46.00	36.00	35.33	32.00	42.00	32.00	43.33	60.00	40.00	30.00
	InternVL2.5 [6]	4B	40.33	43.33	42.00	50.00	38.00	39.33	30.00	44.00	44.00	38.33	35.00	60.00	20.00
	LLaVA Next [18]	32B	33.22	36.67	36.00	42.0	32.0	31.33	36.0	32.0	26.0	31.67	35.0	30.0	30.0
	LLaVA Video [45]	7B	33.22	33.33	34.00	38.00	28.00	34.67	34.00	38.00	32.00	31.67	35.00	30.00	30.00
	LLaVA OneVision [19]	7B	33.22	33.33	34.00	38.00	28.00	34.67	34.00	38.00	32.00	31.67	35.00	30.00	30.00
	Qwen2.5 VL [2]	32B	**52.45**	50.00	34.00	56.00	60.00	50.67	40.00	54.00	58.00	56.67	55.00	60.00	55.00
	Qwen2.5 VL [2]	7B	39.89	33.33	28.00	18.00	54.00	38.00	48.00	16.00	50.00	48.33	55.00	30.00	60.00
	Qwen2.5 VL [2]	3B	43.67	43.33	36.00	52.00	42.00	42.67	38.00	54.00	36.00	45.00	40.00	50.00	45.00

and intent reasoning tasks. In the easy setting, Qwen2.5 (32B) [2] achieves the highest overall score (52.45%), outperforming GPT-4o and Gemini. However, in the medium and hard settings, Gemini 1.5 Pro outperforms all other models, achieving the top overall accuracy (38.78% in medium and 22.34% in hard), demonstrating better robustness under increasing reasoning difficulty. These results highlight the relative strengths of different models and the increasing challenge of reasoning in dynamic airspace environments as task complexity grows. Moreover, Table 5 presents model performance on the OpenRBench benchmark in the **Water Space** domain, covering both river and ocean scenarios across varying reasoning types and difficulty levels. Gemini 1.5 Pro consistently outperforms other models across all settings.

These findings demonstrate OpenRBench's ability to *reveal the limitations* of existing multimodal models, particularly in safety-critical and physically grounded domains. By highlighting domain-specific reasoning gaps, especially in underexplored high-stakes environments such as autonomous driving, ship navigation, and airspace, OpenRBench serves as a tool for guiding the development of more robust, temporally aware, and intent-aware multimodal systems.

4.2 Model Error Analysis

To demonstrate the effectiveness of our benchmark and evaluate the performance of state-of-the-art (SOTA) models, we conduct a qualitative analysis of model predictions on the OpenRBench benchmark. As shown in Figure 5, the analysis highlights persistent challenges in spatial, temporal, and intent reasoning across open-space environments, particularly in land and air domains. Despite the strong overall performance of leading multimodal models such as ChatGPT-4o and Gemini 2.5, the results reveal consistent failure cases in real-world scenarios. For example, both models struggle with accurately identifying spatial relationships (e.g., relative positions of vehicles), counting dynamic objects over time (e.g., cars in motion), and understanding goal-directed interactions (e.g., airplane passing events).

These failure cases underscore the limitations of current models in handling safety-critical, perception-intensive tasks. By providing richly annotated, video-based tasks that demand multi-step reasoning grounded in physics, causality, and spatial understanding, OpenRBench serves as a rigorous diagnostic benchmark. Our findings highlight the necessity of such benchmarks for advancing the robustness, safety, and real-world applicability of large multimodal systems.

Table 5: Evaluation of OpenRBench in the **Water Space** domain using **River** and **Ocean** Videos, categorized by reasoning types, based on a subset of the dataset.

Difficulty	Models	Size	Over. Avg.	River Scenarios				Ocean Scenarios			
				Avg.	Temporal	Spatial	Intent	Avg.	Temporal	Spatial	Intent
Hard	GPT4o [15]	-	22.10	28.20	38.46	26.92	19.23	16.00	18.00	18.00	12.00
	Gemini 1.5 pro [7]	-	**26.02**	26.92	23.08	30.77	26.92	25.11	34.00	20.93	20.41
	InternVL2.5 [6]	26B	22.54	23.08	15.38	19.23	34.62	22.00	18.00	28.00	20.00
	InternVL2.5 [6]	8B	21.90	21.79	7.69	26.92	30.77	22.00	16.00	28.00	22.00
	InternVL2.5 [6]	4B	20.92	20.51	19.23	19.23	23.08	21.33	16.00	26.00	22.00
	LLaVA Next [18]	32B	14.39	11.54	7.69	19.23	7.69	15.33	8.0	30.0	8.0
	LLaVA Video [45]	7B	14.00	16.67	15.38	23.08	11.54	11.33	8.00	20.00	6.00
	LLaVA OneVision [19]	7B	15.67	16.67	11.54	26.92	11.54	14.67	8.00	28.00	8.00
	Qwen2.5 VL [2]	32B	13.39	14.10	7.69	23.08	11.54	12.67	8.0	24.0	6.0
	Qwen2.5 VL [2]	7B	14.67	16.67	7.69	30.77	11.54	12.67	6.00	24.00	8.00
	Qwen2.5 VL [2]	3B	14.34	16.67	15.38	19.23	15.38	12.00	12.00	22.00	2.00
Medium	GPT 4o [15]	-	38.49	42.31	50.00	53.85	23.08	34.67	36.00	48.00	20.00
	Gemini 1.5 pro [7]	-	**46.31**	53.84	46.15	65.38	50.00	38.78	34.00	49.02	33.33
	InternVL2.5 [6]	26B	41.77	44.87	30.77	57.69	46.15	38.67	24.00	62.00	30.00
	InternVL2.5 [6]	8B	41.08	46.15	34.62	61.54	42.31	36.00	34.00	60.00	14.00
	InternVL2.5 [6]	4B	44.36	48.72	23.08	65.38	57.69	40.00	28.00	60.00	32.00
	LLaVA Next [18]	32B	20.88	23.08	11.54	38.46	19.23	18.67	10.00	30.00	16.00
	LLaVA Video [45]	7B	21.92	20.51	19.23	26.92	15.38	23.33	20.00	30.00	20.00
	LLaVA OneVision [19]	7B	22.54	23.08	19.23	30.77	19.23	22.00	14.00	34.00	18.00
	Qwen2.5 VL [2]	32B	33.31	34.62	19.23	50.00	34.62	32.00	20.00	50.00	26.00
	Qwen2.5 VL [2]	7B	24.08	29.49	19.23	30.77	38.46	18.67	18.00	26.00	12.00
	Qwen2.5 VL [2]	3B	28.08	29.49	23.08	53.85	11.54	26.67	18.00	44.00	18.00
Easy	GPT 4o [15]	-	50.51	57.69	57.69	50.00	65.38	43.33	66.00	34.00	30.00
	Gemini 1.5 pro [7]	-	50.69	52.56	42.31	61.54	53.85	48.81	50.00	46.43	50.00
	InternVL2.5 [6]	26B	**55.05**	64.10	65.38	57.69	69.23	46.00	50.00	50.00	38.00
	InternVL2.5 [6]	8B	53.47	60.26	69.23	46.15	65.38	46.67	46.00	54.00	40.00
	InternVL2.5 [6]	4B	53.87	56.41	53.85	57.69	57.69	51.33	52.00	56.00	46.00
	LLaVA Next [18]	32B	35.59	37.18	26.92	53.85	30.77	34.00	30.00	38.00	34.00
	LLaVA Video [45]	7B	31.03	32.05	30.77	34.62	30.77	30.00	22.00	38.00	30.00
	LLaVA OneVision [19]	7B	33.00	33.33	34.62	34.62	30.77	32.67	28.00	38.00	32.00
	Qwen2.5 VL [2]	32B	52.77	61.54	53.85	61.54	69.23	44.00	40.00	54.00	38.00
	Qwen2.5 VL [2]	7B	31.31	34.62	38.46	19.23	46.15	28.00	36.00	22.00	26.00
	Qwen2.5 VL [2]	3B	40.21	39.74	34.62	46.15	38.46	40.67	34.00	48.00	40.00

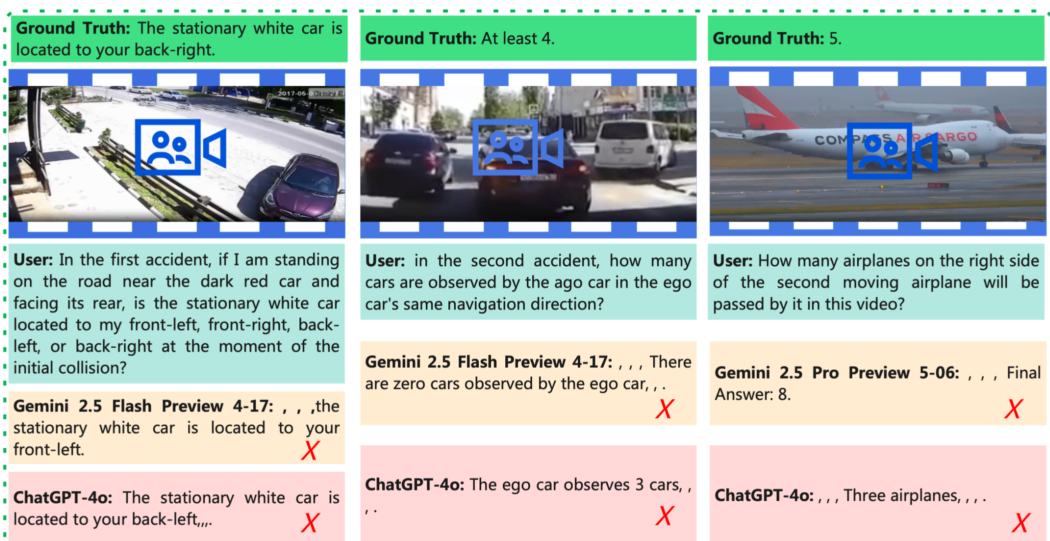


Figure 5: Qualitative error analysis of state-of-the-art multimodal models (Gemini 2.5 and ChatGPT-4o) on the OpenRBench benchmark. Each example illustrates a failure case in a different reasoning category: spatial reasoning (left), temporal reasoning (middle), and intent reasoning (right). Despite their capabilities, both models struggle with spatial localization, counting dynamic objects, and understanding goal-directed motion in real-world open-space scenarios.

4.3 Ablation Experiments

In our experiments, due to the high cost of evaluating all data points, we adopt a uniform sampling strategy to select a representative subset of tasks. Specifically, for each reasoning type, we sample 50 tasks when the total number of available tasks is fewer than 500, and 100 tasks when the number exceeds 500. The OpenRBench benchmark spans three open-space scenarios—*land space*, *air space*, and *water space*—each with three video lengths (short, medium, long), three difficulty levels (easy, medium, hard), and three reasoning types: temporal, spatial, and intent-based reasoning.

Following this sampling strategy, we evaluate a total of 3,798 tasks, evenly distributed across the three reasoning types: 1,266 *spatial reasoning*, 1,266 *temporal-causal reasoning*, and 1,266 *intent and goal reasoning* tasks.

To assess the reliability of this sampling approach, we conduct an ablation study comparing model performance on sampled tasks versus the full set of data points in the **land space (short, easy)** setting. We use InternVL 2.5, one of the leading open-source multimodal models, which ranks highly on several leaderboards such as [6] and [7]. As shown in Table 6, performance on the sampled subset is comparable to, and in some cases slightly better than, performance on the full dataset. These results validate the effectiveness of our sampling strategy in preserving benchmark consistency while reducing evaluation cost.

Table 6: Performance Comparison on **Land Space Short** (Easy): Full vs. Sample Data Points

Model	Full Data Points				Sample Data Points			
	Avg.	Temporal	Spatial	Intent	Avg.	Temporal	Spatial	Intent
InternVL2_5-26B	55.62	57.61	50.37	58.88	61.00	62.00	59.00	62.00
InternVL2_5-8B	49.26	51.89	48.57	47.31	55.67	55.00	60.00	52.00
InternVL2_5-4B	50.65	50.17	50.70	51.10	55.33	52.00	55.00	59.00

5 Conclusion

In this work, we introduce OpenRBench, a large-scale benchmark for evaluating multimodal understanding and reasoning in real-world open-space environments. Spanning three critical domains—land, air, and water—M4R provides richly annotated, video-based tasks designed to assess model performance across three fundamental reasoning dimensions: temporal reasoning, spatial reasoning, and intent and goal inference. The benchmark encompasses a broad range of scenarios, video lengths, and difficulty levels, enabling comprehensive evaluation in safety-critical, perception-intensive settings. Through extensive qualitative and quantitative analyses, we demonstrate that even state-of-the-art multimodal models—both proprietary systems such as ChatGPT-4o and Gemini 2.5, and leading open-source models like Qwen and InternVL—exhibit significant limitations when reasoning over complex, dynamic physical environments. These results underscore the need for more robust, temporally-aware, and goal-sensitive multimodal systems capable of reliable understanding in real-world scenarios. We hope that OpenRBench will serve as a valuable resource for the research community and help advance the development of safer, more generalizable, and practically deployable multimodal AI systems.

[6] `https://enxinsong.com/Video-MMLU-web/`

[7] `https://huggingface.co/spaces/opencompass/open_vlm_leaderboard`

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Appendix

A Limitation and Impact

Limitations Our benchmark provides a valuable tool for evaluating model performance in open-space environments. However, due to the large scale of the dataset, evaluating all data points is computationally expensive. As a result, we were unable to perform large-scale testing with high-cost proprietary models such as ChatGPT and Gemini. In future work, we plan to explore more efficient evaluation strategies and extend our analysis to a broader set of models, including closed-source systems.

Impact This benchmark offers a new direction for advancing multi-modal model development in open-space, safety-critical, and physically grounded real-world environments. By emphasizing temporal, spatial, and intent-based reasoning in diverse video scenarios, this benchmark can be useful to guide the design of more robust and reliable multi-modal systems. While this research seeks to advance the capabilities of AI in complex settings, we do not identify any specific societal risks or consequences requiring special attention at this time.

B Annotation and Detailed Examples

During data annotation, we first define the question types, then watch each video to design corresponding questions and annotate the answers. Our dataset contains approximately 19,000 question–answer pairs, evenly distributed across three difficulty levels: easy (1/3), medium (1/3), and hard (1/3). The difficulty is determined by both the number and type of answer choices. Hard questions typically include 12 choices for temporal and intent reasoning, and 4 for spatial reasoning, requiring precise selection. Medium questions generally offer 6 choices for temporal and intent reasoning, and 3 for spatial reasoning, often involving interval-based options. Easy questions usually present 3 choices, or 2 for spatial reasoning, and also rely on interval-based distinctions.

Moreover, we provide several example scenarios illustrating understanding and reasoning in open space, as shown in Figure 6. Moreover, as illustrated in Figure 7, we present a detailed question-and-answer example. For each open-space reasoning setting, we include three video lengths, short, medium, and long, each featuring tasks designed to evaluate temporal, spatial, and intent reasoning.

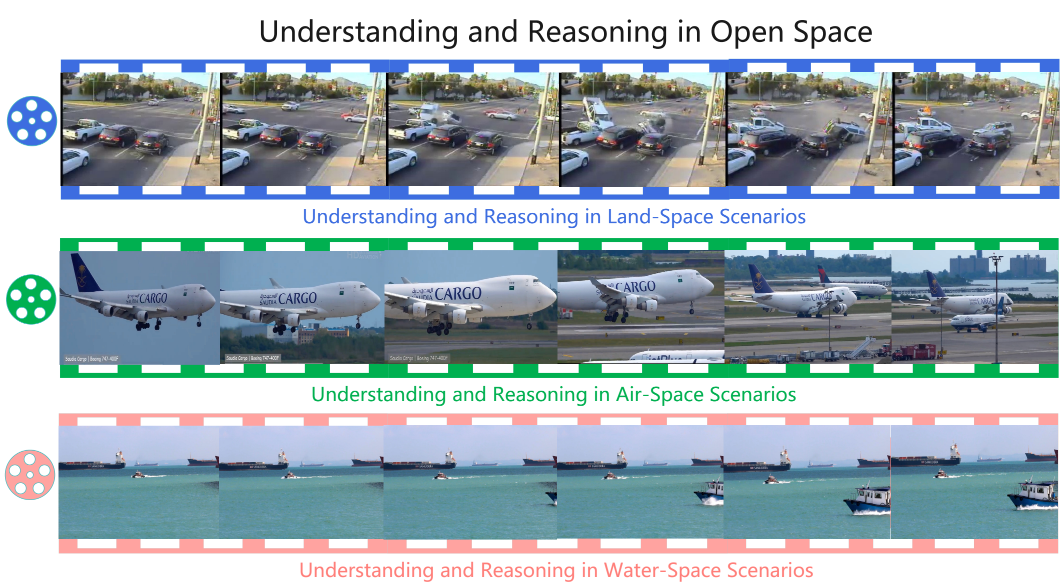

Figure 6: Example Scenarios of Understanding and Reasoning in Open Space

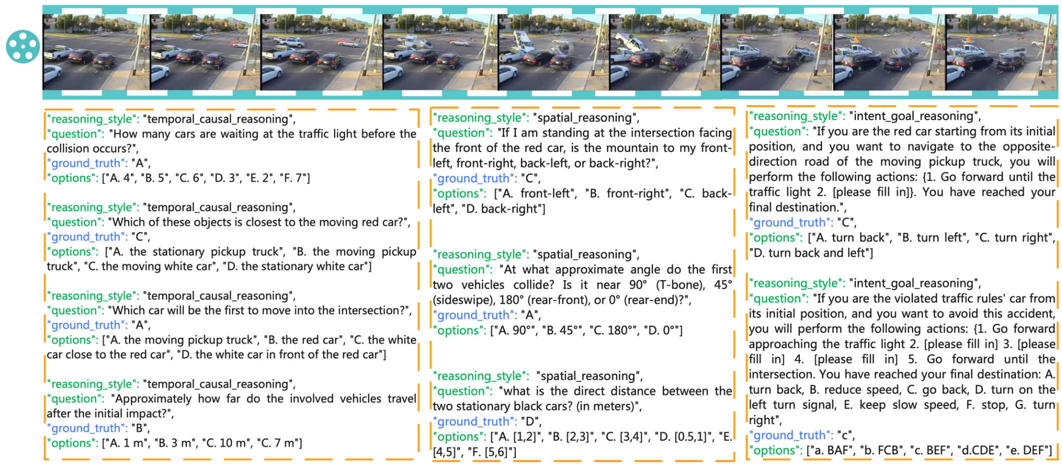

Figure 7: A question and answer example: For each open-space reasoning setting, we include three types of video lengths: short, medium, and long. Each video length includes tasks designed to evaluate temporal reasoning, spatial reasoning, and intent reasoning.

C Detailed Experiment Settings

In our experiments, we build upon the `lmms-eval` framework [44] as the foundation for our benchmark and extend it to support the specific requirements of OpenRBench. All experiments with open-source models were conducted on a Linux system equipped with 8 × NVIDIA A100 GPUs, and experiments with closed-source models were run on a single NVIDIA A100 GPU. Key hyperparameters used for model evaluation are summarized in Table 7. More detailed experimental settings are available in our code: `https://open-space-reasoning.github.io`.

Table 7: Key parameters used in the experiments.

Parameters	value	Parameters	value
sample size	1	number of processes	8
max pixels (Qwen 2.5)	12845056	use-flash-attention-2 (Qwen 2.5)	False
interleave visuals (Qwen 2.5)	True	enable-chunked-prefill (InternVL 2.5)	True
gpu-memory-utilization (InternVL 2.5)	0.6	max-num-seqs (InternVL 2.5)	1
conv-template (LLava-Video)	qwen-1-5	video-decode-backend (LLava-Video)	record
max-frames-num (LLava-Video)	22	mm-spatial-pool-mode (LLava-Video)	average
mm-newline-position (LLava-Video)	grid	mm-resampler-location (LLava-Video)	after
conv-template (llava-onevision)	qwen-1-5	device-map (llava-onevision)	auto
model-name (llava-onevision)	llava-qwen		