MMRED: A CROSS-MODAL BENCHMARK FOR DENSE CONTEXT REASONING

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ABSTRACT

Despite recent advancements in extending context windows of large language models (LLMs) and large vision-language models (LVLMs), their ability to perform complex multi-modal reasoning over extended contexts remains critically limited. To underline this challenge, we present MMReD, a benchmark specifically designed to assess reasoning abilities within dense, information-rich scenarios where simple retrieval is not enough. Unlike traditional Needle-in-a-Haystack evaluations, MMReD challenges models to identify and interpret global patterns across entire contexts. Our benchmark comprises 24 tasks of varying complexity, ranging from standard passkey retrieval setups to those requiring selective or uniform attention to all context chunks. The evaluation reveals a consistent performance drop across all tested models - including the most advanced LLMs, LVLMs, and architectures specializing in code and reasoning – as the number of observations increases. Notably, even the leading reasoning-specialized models achieve 0% accuracy on certain tasks at the maximum context length of 128 observations. Conventional fine-tuning techniques, such as SFT and GRPO, also fail to generalize effectively to longer contexts. These observations reveal an inherent limitation in current model architectures, emphasizing the need for innovative approaches to enable competent dense context reasoning in multi-modal AI systems.

1 Introduction

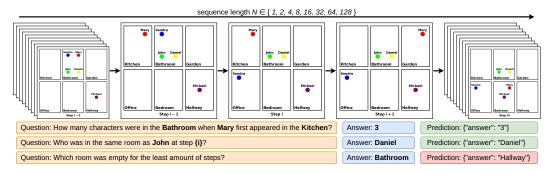


Figure 1: Overview of a multi-modal dense-sequence reasoning task from MMReD. Models are evaluated on queries that require tracking entities, spatial relationships, basic counting, and event-based reasoning over varying sequence lengths N, evaluating the models' ability to process and retain long-term dependencies. Example questions cover all designed answer types: numbers, characters, and rooms. In the images and questions, we replace i, i + 1, etc, with the real step numbers.

Large language models (LLMs) have demonstrated a remarkable ability to reason in both short and long contexts. Long-context extension, in particular, has gained significant attention as models are increasingly deployed in tasks requiring memory, retrieval, and sequential reasoning.

Standard practice on reasoning evaluation is to rely on a range of public benchmarks that test reasoning capabilities on a variety of topics. Short-context reasoning includes general language understanding and reading comprehension (DROP (Dua et al., 2019), ARC (Clark et al., 2018), BBH (Suzgun et al., 2022)), academic reasoning (MMLU-PRO (Wang et al., 2024d), GPQA (Rein et al., 2024),

MATH (Hendrycks et al., 2021), AIME (MAA, 2024)) and code comprehension (HumanEval (Chen et al., 2021), CRUX (Gu et al., 2024), MBPP (Austin et al., 2021)). Long-context reasoning includes recent benchmarks RULER (Hsieh et al., 2024), BABILong (Kuratov et al., 2024), and Michelangelo (Vodrahalli et al., 2024).

Large vision-language models (LVLMs) are also rapidly closing the gap in performance on various visual recognition tasks that require reasoning in both text and visual modalities. Existing benchmarks can be categorized by modality of context in the question: single image understanding (MMMU (Yue et al., 2024a;b)), multiple image understanding (MuirBench (Wang et al., 2025), BLINK (Fu et al., 2024b)), and video understanding (VideoMME (Fu et al., 2024a), MLVU (Zhou et al., 2024), EgoSchema (Mangalam et al., 2023), LVBench (Wang et al., 2024b)).

While these benchmarks demonstrate improved performance on longer contexts, they primarily focus, as we show below, on retrieval-based or Needle-in-a-Haystack (NIAH) setups, where models locate a specific fact from an otherwise irrelevant or distractor-filled context. However, such tasks do not fully capture a model's ability to reason across densely distributed information. In our analysis, we show that state-of-

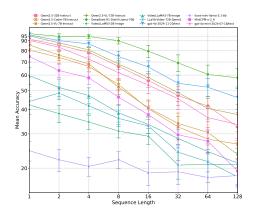


Figure 2: All evaluated LLMs and LVLMs share a common performance profile, decreasing with the context length of MMReD tasks. The results are grouped and averaged across question types.

the-art LLMs and LVLMs exhibit no clear correlation between their NIAH performance and their ability to perform deeper, structured reasoning in the information-rich scenarios. So NIAH performance on existing benchmarks alone is not a reliable indicator of reasoning ability.

To bridge this gap, we introduce MMReD (Multi-Modal REasoning in Dense context), a benchmark designed to assess a conceptually different capability: reasoning in dense environments where models must attend uniformly across the entire context. Our experiments reveal a consistent decline in performance across all tested models as context length increases (Figure 2), highlighting core limitations in current architectures and training approaches for dense context multi-modal reasoning.

Our contributions can be summarized as follows:

- 1. We develop and release MMReD, a comprehensive benchmark for evaluating long-context multi-modal reasoning, which goes beyond existing NIAH setups.
- 2. We demonstrate that state-of-the-art LLMs, LVLMs, and reasoning-specialized architectures fail to generalize to dense context reasoning, revealing novel significant limitations.
- 3. We show that standard fine-tuning methods, e.g., supervised fine-tuning (SFT) and GRPO (Shao et al., 2024), are insufficient for enabling dense context reasoning in current models.
- 4. We highlight key challenges and propose potential directions for future research aimed at overcoming the current limitations in dense context reasoning for multi-modal AI systems.

2 RELATED WORK

Long-context understanding has become a central challenge in the development of LLMs and LVLMs. Prior research in this area spans (i) benchmarks for long-context comprehension and (ii) architectural or training approaches for improving long-context reasoning. We briefly review both strands, motivating the unique role of MMReD.

Early efforts in long-context evaluation. Initial work focused on synthetic or textual setups designed to probe whether models can retain and exploit information over extended sequences. For example, Kim & Schuster (2023) introduced entity-tracking and disambiguation tasks, providing

some of the first systematic evidence that transformer models struggle when the relevant signal is deeply buried in the input.

Rise of the Needle-in-a-Haystack paradigm. Building on these insights, subsequent benchmarks formalized the retrieval challenge by embedding a small "needle" of task-relevant information inside a large, mostly irrelevant context. BABILong (Kuratov et al., 2024) extended the bAbI reasoning tasks (Weston et al., 2016) into book-length contexts, while Visual Haystacks (Wu et al., 2024) adapted this idea to multimodal settings by injecting known objects into distractor-heavy image collections. These benchmarks popularized the NIAH paradigm, which has since become the dominant template for evaluating long-context models.

Beyond single-needle retrieval. Recent work has sought to move past simple Needle-in-a-Haystack formulations. Vodrahalli et al. (2024) introduced the Michelangelo benchmark to study the "short-circuiting" problem, where models exploit superficial correlations rather than genuinely using the entire context. Its most demanding *latent list* setting requires tracking up to 20 relevant needles among distractors, yet state-of-the-art models still perform well above chance, suggesting the task remains tractable and does not saturate reasoning capacity.

In parallel, Bai et al. (2025b) proposed LongBenchv2, which grounds evaluation in naturally occurring long contexts rather than synthetic haystacks, thereby improving ecological validity. Nevertheless, both Michelangelo and LongBenchv2 remain closer to multi-needle retrieval problems: the bulk of the context is still dominated by irrelevant or weakly informative content. By contrast, MMReD is explicitly designed so that *all* context elements are densely informative, forcing models to integrate global patterns rather than locate sparse signals.

Architectural approaches. Research on long-context modeling has explored architectural innovations and training schemes: memory-augmented transformers (Bulatov et al., 2022; Rodkin et al., 2024), structured state-space models such as Mamba (Gu & Dao, 2024; Dao & Gu, 2024), and context-extension techniques like YARN (Peng et al., 2023) and LongVA (Zhang et al., 2024a). While these approaches extend sequence length handling, their evaluation is often tied to NIAH-style retrieval, leaving open the question of whether they support dense, integrative reasoning.

Motivation for MMReD. Taken together, prior benchmarks have advanced the study of long-context comprehension but converge on retrieval-centric formulations. They do not directly test a model's ability to reason when all parts of the context are densely informative and must be integrated uniformly. MMReD is designed to fill this gap: it complements NIAH evaluations by systematically assessing reasoning in dense, non-retrieval-based multimodal contexts.

3 MMRED BENCHMARK

To address questions above, we create a visual environment with randomized and scalable state evolution and sufficient and diverse set of tasks to evaluate the key reasoning capabilities of models.

3.1 DESIGN PRINCIPLES

We prioritize a minimalist visual representation. By avoiding visual complexity, we ensure that evaluation results reflect dense context multi-modal reasoning rather than visual-only perception, as in Wu et al. (2025). However, our design assumes that models possess basic OCR capabilities.

We also prioritize minimalist linguistic constructions. By doing so, we ensure that our evaluation remains focused on the same dense context multi-modal reasoning rather than language and instruction understanding, as in Kim & Schuster (2023); Vodrahalli et al. (2024). Despite linguistic simplicity, we ensure covering key reasoning categories with a diverse set of tasks.

Our benchmark is designed to scale in complexity on the context length axis. The dataset includes sequences of varying lengths, with longest sequences reaching 128 frames, where even the current best models start to systematically score 0% accuracy in some tasks. With the increasing capabilities of models, the benchmark can be extended to larger contexts (e.g., 256 frames or beyond), ensuring that it remains a dynamic and evolving evaluation framework.

To ensure MMReD provides a fair and robust evaluation, we enforce strict controls on dataset generation. All generated sequences are unique, preventing unintended memorization or retrieval op-

portunities. The environment evolves randomly, preventing reliance on simple heuristics. And we balance generated answer distributions to prevent dominance of some frequency-biased methods.

By adhering to these principles, MMReD provides a targeted, scalable, and unbiased benchmark for evaluating dense context multi-modal reasoning.

3.2 Dataset

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The MMReD dataset consists of structured sequences of frames representing an evolving environment. Each frame depicts a spatial arrangement of *characters* within predefined *rooms*. These sequences serve as context for various reasoning tasks, such as identifying patterns across time (e.g., "Which room was empty for fewer steps than the other rooms?"). See examples in Figure 1.

Environment. We define six distinct rooms: Kitchen, Bathroom, Garden, Office, Bedroom, and Hallway; and five *characters*: Sandra, Mary, Michael, John, and Daniel. At each time step, characters are assigned to rooms, with the possibility of multiple characters sharing a room or some rooms being empty. All characters remain present in the environment throughout the sequence.

Sequence evolution. Our dataset consists of multiple distinct sequences. A sequence consists of an initial state and a set of state changes. We generate sequences of varying lengths $N \in \{1, 2, 4, 8, 16, 32, 64, 128\}$, with 1200 sequences per length. When N = 1, the sequence consists only of an initial state, with an empty set of state changes.

To generate a sequence of length N, we first sample an initial state by randomly (uniformly) assigning each character to one of the six rooms. At each of the following N-1 steps, one randomly selected character moves to a different randomly selected room. We generate sequences iteratively and, if an obtained sequence already exists, repeat the process until a unique sequence appears.

Scene construction. Each state is visualized as a 512×512 pixel image, where rooms are depicted as rectangles located in a 2×3 grid, each named at its bottom. Characters are represented as colored circles, with their names displayed above. A character's presence in a room is shown by positioning its circle inside the corresponding rectangle. The state number is given at the bottom of the image.

Tasks annotation. Each sequence is paired with exactly one generated question, selected from a set of 24 question types. We generate 50 questions per type, resulting in 1200 question-sequence pairs per length N. To generate a question, we randomly sample rooms, characters, or a state number as needed for the question template. The answer is precomputed algorithmically using full access to the sequence and environment. If a correct singular answer does not exist, e.g., two characters satisfy the condition simultaneously, we repeat the sequence generation for this question.

3.3 TASKS

MMReD consists of two primary categories of questions: scene-referenced (NIAH) and dense context (DC) reasoning questions. Each category is designed to systematically evaluate different aspects of multi-modal reasoning.

NIAH questions. The first three sections of Table 1 correspond to the NIAH task.

These questions are designed to be an-

Table 1: Overview of MMReD benchmark questions categorized by reasoning type. Each question template contains placeholders: [R], [C], and [X] represent randomly sampled rooms, characters, and step numbers, respectively. [comp] is a randomly chosen comparison phrase ("most" or "least amount of").

ID	Question template
FA-FA-R FA-CCFA-R FA-FR-C FA-RCFA-C FA-NRFA-I	In which room did [C] first appear? In which room was [C1] when [C2] first appeared in the [R]? Who was the first to appear in the [R]? Who was in the [R1] when [C] first appeared in the [R2]? How many characters were in the [R1] when [C] first appeared in the [R2]?
FI-FA-R FI-CCFA-R FI-LR-C FI-RCFA-C FI-NRFA-I	In which room was [C] at the final step? In which room was [C1] when [C2] made their final appearance in the [R]? Who was the last to appear in the [R]? Who was in the [R1] when [C] made their final appearance in the [R2]? How many chars were in the [R1] when [C] made their final app in the [R2]?
FX-CF-R FX-RF-C FX-CCF-C FX-NCF-I FX-NE-I	In which room was [C] at step [X]? Who was in the [R] at step [X]? Who was in the same room as [C] at step [X]? How many other characters were in the same room as [C] at step [X]? How many rooms were empty at step [X]?
DC-RE-R DC-WS-R DC-CR-R DC-WHS-C DC-SA-C DC-ST-C DC-SR-I DC-RV-I DC-CC-I	Which room was empty for the [comp] steps? In which room did [C] spend the [comp] time? Which room was crowded (three or more people) for the most steps? Who spent the [comp] time in the [R]? Who spent the [comp] time alone in the rooms? With whom did [C] spend the [comp] time together in the same room? How many steps did [C] spend in the [R]? How many times did a crowd (three or more people in one room) appear?

swered based on a *single image* within the sequence that satisfies the condition.

We created three subgroups of questions: First Appearance (FA), locating the earliest occurrence of a given entity or event; Final App (FI), focusing on the last occurrence; Frame X (FX), focusing on an explicitly specified frame. This division allows us to isolate and measure the lost-in-the-middle phenomenon (Wu et al., 2024), where models struggle to retrieve information from intermediate context positions.

Within each section, we construct multiple question templates that target core reasoning categories such as object tracking, counting, and spatial reasoning, similar to bAbI (Weston et al., 2016). We also diversify output types – rooms, characters, and integers – to test model robustness across different answer formats. This ensures that our evaluations remain representative of the model's overall reasoning ability.

DC questions. The final section of Table 1 introduces our novel **dense context (DC)** reasoning tasks. Unlike the NIAH questions, which require retrieval from a single image, these questions demand global and uniform attention to the entire sequence. We similarly diversify DC tasks to include the same reasoning categories and output types, resulting in nine question types.

Problem formulation. The final evaluation dataset consists of 9600 triplets (*sequence*, *question*, *answer*). The models' goal is to predict the *answer* given the corresponding input pair *sequence-question*. Here, LVLMs receive sequences transformed to images, as described above, while LLMs receive a purely textual representation. To assess model performance, we use *exact-match accuracy*, where a model's predicted answer is considered correct if and only if it matches the ground truth answer, independent of its type.

3.4 EVALUATION SETUP

Models. We evaluated approximately 30 multi-modal models on MMReD, including both open-source and proprietary models. Our primary focus was on image-specialized LVLMs, including Qwen2-VL (Wang et al., 2024a), Qwen2.5-VL (Bai et al., 2025a), InternVL-2.5 (Chen et al., 2024), InternVL-2.5-MPO (Wang et al., 2024c), MiniCPM-2.6-O (Yao et al., 2024), and LLaVA-Mini (Zhang et al., 2025b). Additionally, we evaluated video-oriented LVLMs, such as LLaVA-Video (Zhang et al., 2024b), Video-LLaMA3 (Zhang et al., 2025a), and Aria (Li et al., 2024). We also assessed a variety of LLMs: Qwen2 (Yang et al., 2024a), Qwen2.5 (Yang et al., 2024b), Qwen3 (Yang et al., 2025), and Qwen-Coder (Hui et al., 2024) families, distilled versions of the DeepSeek-R1 (Guo et al., 2025), and the QwQ (Team, 2025) reasoning model from the Qwen series. Among the proprietary models, OpenAI's GPT-4o (OpenAI, 2024a) ('2024-11-20') and GPT-4o-mini (OpenAI, 2024b) ('2024-07-18') were tested using their official APIs.

Benchmark representations. LLMs require a textual representation of our benchmark. Thus, we transform sequences into JSON files, explicitly writing the frame numbers and corresponding characters locations. Furthermore, video-oriented LVLMs use different methods for sampling frames from the input visual sequence. So we fed MMReD images to video-oriented LVLMs as a result of frame sampling, ensuring an identical amount of input information to all models.

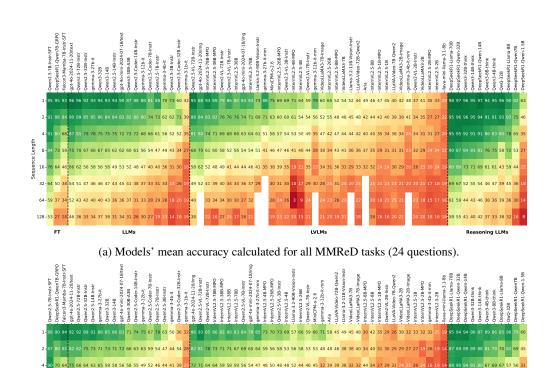
Fine-tuning. We also tested whether fine-tuning can help generalize to unseen context lengths. Both SFT and GRPO (Shao et al., 2024) training were performed on the same dataset spanning N=[1,2,4,8,16] sequence lengths, 200 samples per each task of the benchmark per sequence length. We used Qwen2.5-7B-Instruct (Yang et al., 2024b) and Falcon3-Mamba-7B-Instruct (Team, 2024) models for SFT and DeepSeek-R1-Distill-Qwen-7B (DeepSeek-AI et al., 2025) for GRPO.

Technical details, such as system prompt, output formats, generation parameters (consistent across all models), model hosting, fine-tuning hyperparameters, and resources, are provided in Appendix.

4 RESULTS AND ANALYSIS

4.1 Main Results

Average performance across all tasks of models, including both multi-modal and text-only variants, is presented in Figure 3a. Results for each model and model group are given in Supplementary materials. Based on these results, we draw several key conclusions.



(b) Models' mean accuracy calculated only for dense context (DC) type of tasks.

LVLMs

Reasoning LLMs

Figure 3: Models' mean accuracy on MMReD across all sequence lengths, grouped by model type: fine-tuned LLMs, general-purpose LLMs, LVLMs, and reasoning LLMs. Cell color indicates performance (green – high, red – low), with models ranked by average score within each group.

MMReD is a universal and cross-modal task for dense reasoning. The performance of all evaluated models begins to degrade significantly for sequence lengths exceeding 32 steps. Which is even more evident for the DC tasks (Figure 3b). This degradation rate strongly corresponds to the number of parameters – larger models demonstrate a greater ability to maintain accuracy in constructing logical chains over longer sequences. Furthermore, reasoning-specialized LLMs not only exhibit superior initial performance but also show greater robustness to increases in the length of the reasoning chain. It is worth noting that the Qwen2.5-Coder model, fine-tuned for coding-specific tasks, underperformed compared to the original Qwen2.5. This suggests that training on coding tasks alone does not sufficiently reinforce the ability to construct and infer logical reasoning chains.

Multimodal instruction tuning impairs long-context understanding. Additionally, LVLMs struggle to utilize visual context effectively, even when the context length remains within the claimed supported limits. For instance, InternVL2.5, which reports a context length of 16,384 tokens and uses 256 tokens to encode a single image, should handle tasks involving up to 64 images with optimal accuracy. But we observe a decline in performance starting from 16 images. For sequences exceeding 64 images, the models' ability to generate coherent reasoning chains deteriorates to the point where extracting a final answer becomes unfeasible.

Impact of LLM reasoning on long-context retention. Proprietary GPT-40 and its 'mini' version outperform most open-source models in both textual and multi-modal representations of the benchmark. Their accuracy on short sequences is nearly perfect, and as the length of the sequence increases, the degradation in quality is smoother. However, DeepSeek R1, distilled to LLaMA-70B

and Qwen2.5-32B outperform GPT-40 by 2-4% initially and considerably more at longer sequence lengths, as shown in Supplementary materials. This highlights the substantial contribution of LLM reasoning capabilities to retaining long preceding contexts and deriving correct results.

4.2 TASK ABLATIONS

Isolating DC reasoning. Figure 4 illustrates the breakdown in correlation between performance on retrieval-based (NIAH) and DC reasoning tasks as context length increases. We calculate Pearson correlation of model scores averaged for every task within selected task groups. In the first experiment, we select DC and NIAH groups; in the second experiment, we select FA plus FI and FX groups. While Pearson correlation between different NIAH subsets remains consistently high (around 0.9), the correlation between NIAH and DC performances notably declines to approximately 0.5–0.7 at 32 frames and beyond.

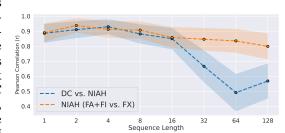


Figure 4: Pearson correlation of model performance on NIAH tasks (self-consistency) vs. correlation with DC tasks.

Our findings closely align with those reported in BABILong (Kuratov et al., 2024): correlation between the models' ranking on their long-context benchmark and short-context one drops from 0.9 to 0.6 when context length increases.

These findings suggest that models successful in NIAH-style retrieval do not necessarily generalize to the proposed DC reasoning scenarios. And thus MMReD allows assessing a conceptually different capability, which we call **dense context** reasoning.

Perceptual complexity. Perceptual ambiguity, e.g., occlusion, visual noise, recognition errors, plays a major role in real-world multimodal reasoning. However, MMReD is specifically designed to isolate reasoning capabilities by minimizing perceptual complexity.

To test whether this abstraction limits generalizability, we conducted an additional ablation where we introduced controlled perception noise into MMReD. Specifically, we modified the environment state by adding synthetic occlusion-like errors (e.g., randomly relocating an entity to an incorrect room in one frame) at a 5% rate. We then evaluated LLM performance on both NIAH and DC questions; see Figure 5.

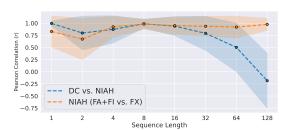


Figure 5: Pearson correlation of LLMs performance on NIAH tasks vs. correlation with DC tasks under 5% perceptual noise.

The results show a uniform drop in performance proportional to the error rate, but crucially, the relative gap between LC and NIAH questions, the key trend in Figure 4, remain intact. While we conducted this test on LLMs, the insight generalizes to LVLMs as well. In our setting, LVLMs and LLMs show a consistent delta, likely due to (i) the token budget shift toward visual inputs, leaving fewer tokens for reasoning, and (ii) catastrophic forgetting from vision-domain fine-tuning. Thus, solving dense context reasoning in LLMs transfers naturally to LVLMs, and LLM-based MMReD evaluation is a meaningful proxy.

In summary, we show that adding controlled perceptual noise does not alter the key conclusions of MMReD. Our benchmark allows studying dense reasoning in isolation, and can be extended to real-world scenarios by progressively incorporating perceptual challenges.

4.3 MODEL ABLATIONS

The core motivation for our experiments stemmed from the question: What components or approaches enable LVLMs to understand long visual sequences more effectively? To address this, we formulated a series of research questions focusing on architectural components, dataset characteristics, and training procedures. These questions are systematically explored in this section.

Fine-tuning is not enough for generalization. Both fine-tuned Transformer and Mamba architectures demonstrate the same decline in performance as benchmarked zero-shot models. GRPO, being a promising way to bootstrap reasoning, is performing even worse than fine-tuned Transformer. Overall, fine-tuning generalizes a bit better than best regular LLM and worse than reasoning LLMs, in particular, on tasks involving heavier arithmetic.

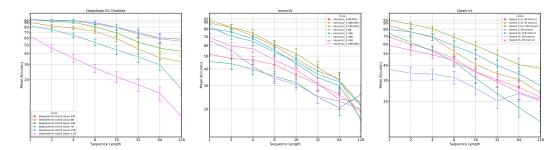


Figure 6: Impact of the number of model parameters on the ability to successfully infer a response using a long visual or text context from MMReD.

Model Parameter Count. To investigate the effect of model size on MMReD response quality, we compared the evaluation results of both LVLMs and LLMs, focusing on three representative model families (Figure 6). The results from the Qwen2.5-VL and InternVL2.5 series reveal a clear trend: accuracy in question answering improves as the number of parameters increases. However, for the InternVL2.5-38B and 78B models, the performance gap narrows significantly, becoming much smaller compared to the differences observed among smaller models. A similar pattern is evident in the results of DeepSeek-R1 distilled to LLaMA-70B and Qwen-32B. These findings suggest that, for both visual and text-only models, the number of parameters strongly influences the ability to process long contexts. However, this dependence diminishes as model size increases, with visual reasoning quality eventually plateauing beyond a certain threshold.

Multimodal Adapter Type. We evaluated the efficiency of LVLMs using different adapter types: multi-linear layer adapter (Qwen2.5-VL-7B-Instruct (Bai et al., 2025a)), QFormer (MiniCPM-o-2.6 (Yao et al., 2024)), and cross-attention (Llama-3.2-11B-Vision-Instruct (Chu et al., 2024)). The results in Figure 11 show that LLaMA does not provide high performance. The results of Qwen2.5-VL and MiniCPM are roughly the same: both models perform poorly on DC-CC-I and DC-SR-I questions, but MiniCPM performs better on FI-FA-R ones. Moreover, Qwen2.5 has low scores for short sequences in certain types of questions.

Frame Pooling Methods in Video-Specific Models. We also compare performance of the different video-specific models: InternVL-2.5 (Wang et al., 2024c), Aria (Li et al., 2024), VideoLLaMA-3 (Zhang et al., 2025a), and LLaVA-Video-7B-Qwen2 (Zhang et al., 2024b). As shown in Figure 12, VideoLLaMA-3 provides the best performance. Aria performs better than InternVL-2.5. Moreover, InternVL-2.5 has a considerable drawdown for all sequence lengths in certain types of questions.

Training Data Volume and Composition. We compare two types of VideoLLaMA3 models: VideoLLaMA3-Image, fine-tuned on both image-text and video data, and VideoLLaMA3, which undergoes video-centric fine-tuning. Both variants use alignment (media paired with captions) and instruction (question answering) data. As can be seen in Figure 13, the VideoLLaMA3-Image family performs better on straightforward questions with short sequences. However, its performance declines on longer sequences, particularly for question types such as DC-SR-I and DC-SA-C.

We argue that incorporating video pretraining without textual instructional data on the last training stage negatively impacts the model's performance on our benchmark. As shown in the Figure 3a,

models from the LLaVA-Video family, even 72B ones, perform worse than image-focused or general purpose LVLMs.

Possible directions of solving the challenge of dense context reasoning include, but are not limited to, examining the potential of architectural innovations specifically designed for long-context processing, overcoming problems of the attention sinks and similar known expressivity issues of RNNs, and incorporating uncertainty quantification (Fadeeva et al., 2024; 2023; Vashurin et al., 2025) to make reasoning more steerable and not materialize false information in the decoded logits; building on existing approaches of test-time compute scaling alongside rigorous RL goal-based pre-training.

5 CONCLUSION

In this paper, we introduced MMReD, a novel benchmark designed to systematically assess long-context reasoning capabilities of LLMs and LVLMs. By focusing on both scene-referenced (NIAH) and dense context tasks, MMReD provides a comprehensive evaluation framework that challenges models to process extended multimodal sequences and construct complex reasoning chains.

Our results demonstrate that current LLMs and LVLMs struggle significantly with long-context understanding, with performance degrading rapidly as context length increases beyond 32 images. Notably, reasoning-specialized LLMs exhibit superior retention of long contexts compared to standard models, highlighting the importance of targeted fine-tuning and architectural innovations in enhancing long-context comprehension.

Model size positively correlates with long-context performance, but the benefits diminish at larger scales, suggesting architectural limitations rather than parameter count as a key bottleneck. Additionally, our analysis of multimodal adapter types and frame pooling strategies revealed that the architectural components choice critically affects model's ability to reason over long visual sequences.

Unexpectedly, video-oriented LVLMs and multimodal instruction tuning are not beneficial for long-context reasoning. The observed performance decline for these models on extended sequences suggests that current video pretraining does not sufficiently address the challenges of long-context tasks.

Our ablation studies confirmed that MMReD's conclusions are robust to potential confounding factors such as the lost-in-the-middle phenomenon. By maintaining unique and randomly evolving environments, the benchmark ensures that performance degradation reflects genuine limitations in long-context reasoning rather than artifacts of data structure or task formulation.

In conclusion, our findings underscore the need for more effective architectural modifications, training paradigms, and evaluation benchmarks tailored specifically for long-context reasoning. MMReD serves as a critical step forward in this direction, providing a rigorous, scalable, and unbiased framework for assessing and advancing long-context understanding in both LLMs and LVLMs. Future work may explore integrating hierarchical memory mechanisms, improved multimodal fusion techniques, and more diverse pretraining data to further enhance long-context reasoning capabilities.

REPRODUCIBILITY STATEMENT

We release our training and evaluation codebase¹ and dataset² in the anonymous repositories.

USE OF LARGE LANGUAGE MODELS.

In preparing this manuscript, we made use of large language models (LLMs) to aid in polishing the writing. Specifically, we used an LLM to (i) suggest alternative phrasings for certain sections (Related Work and Conclusion), (ii) merge fragmented paragraphs into a more coherent narrative, and (iii) check stylistic clarity and consistency across sections. All scientific contributions, including the design of the benchmark, experimental setup, implementation, analysis, and conclusions, were developed entirely by the authors. The LLM did not generate new content beyond language-level editing and restructuring, and its usage did not rise to the level of a contributing author.

¹https://anonymous.4open.science/r/mmred-125A

²https://huggingface.co/datasets/ef1e43ce/mmred

REFERENCES

- Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, and Charles Sutton. Program synthesis with large language models, 2021. URL https://arxiv.org/abs/2108.07732.
- Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025a.
- Yushi Bai, Shangqing Tu, Jiajie Zhang, Hao Peng, Xiaozhi Wang, Xin Lv, Shulin Cao, Jiazheng Xu, Lei Hou, Yuxiao Dong, Jie Tang, and Juanzi Li. Longbench v2: Towards deeper understanding and reasoning on realistic long-context multitasks, 2025b. URL https://arxiv.org/abs/2412.15204.
- Aydar Bulatov, Yuri Kuratov, and Mikhail Burtsev. Recurrent memory transformer. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho (eds.), *Advances in Neural Information Processing Systems*, 2022. URL https://openreview.net/forum?id=Uynr3iPhksa.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde De Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.
- Zhe Chen, Weiyun Wang, Yue Cao, Yangzhou Liu, Zhangwei Gao, Erfei Cui, Jinguo Zhu, Shenglong Ye, Hao Tian, Zhaoyang Liu, et al. Expanding performance boundaries of open-source multimodal models with model, data, and test-time scaling. *arXiv preprint arXiv:2412.05271*, 2024.
- Xiangxiang Chu, Jianlin Su, Bo Zhang, and Chunhua Shen. Visionllama: A unified llama backbone for vision tasks. In *European Conference on Computer Vision*, 2024.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. *ArXiv*, abs/1803.05457, 2018. URL https://api.semanticscholar.org/CorpusID:3922816.
- Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*, 2021.
- LMDeploy Contributors. Lmdeploy: A toolkit for compressing, deploying, and serving llm. https://github.com/InternLM/lmdeploy, 2023.
- Tri Dao. FlashAttention-2: Faster attention with better parallelism and work partitioning. In *International Conference on Learning Representations (ICLR)*, 2024.
- Tri Dao and Albert Gu. Transformers are SSMs: Generalized models and efficient algorithms through structured state space duality. In *International Conference on Machine Learning (ICML)*, 2024.
- Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. FlashAttention: Fast and memory-efficient exact attention with IO-awareness. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022.
- DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, Xiaokang Zhang, Xingkai Yu, Yu Wu, Z. F. Wu, Zhibin Gou, Zhihong Shao, Zhuoshu Li, Ziyi Gao, Aixin Liu, Bing Xue, Bingxuan Wang, Bochao Wu, Bei Feng, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng Wang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Qu, Hui Li, Jianzhong Guo, Jiashi Li, Jiawei Wang, Jingchang Chen, Jingyang Yuan, Junjie Qiu, Junlong Li, J. L. Cai, Jiaqi Ni, Jian Liang, Jin Chen, Kai

Dong, Kai Hu, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Liang Zhao, Litong Wang, Liyue Zhang, Lei Xu, Leyi Xia, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Meng Li, Miaojun Wang, Mingming Li, Ning Tian, Panpan Huang, Peng Zhang, Qiancheng Wang, Qinyu Chen, Qiushi Du, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, R. J. Chen, R. L. Jin, Ruyi Chen, Shanghao Lu, Shangyan Zhou, Shanhuang Chen, Shengfeng Ye, Shiyu Wang, Shuiping Yu, Shunfeng Zhou, Shuting Pan, S. S. Li, Shuang Zhou, Shaoqing Wu, Shengfeng Ye, Tao Yun, Tian Pei, Tianyu Sun, T. Wang, Wangding Zeng, Wanjia Zhao, Wen Liu, Wenfeng Liang, Wenjun Gao, Wenqin Yu, Wentao Zhang, W. L. Xiao, Wei An, Xiaodong Liu, Xiaohan Wang, Xiaokang Chen, Xiaotao Nie, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xinyu Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, X. Q. Li, Xiangyue Jin, Xiaojin Shen, Xiaosha Chen, Xiaowen Sun, Xiaoxiang Wang, Xinnan Song, Xinyi Zhou, Xianzu Wang, Xinxia Shan, Y. K. Li, Y. Q. Wang, Y. X. Wei, Yang Zhang, Yanhong Xu, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Wang, Yi Yu, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He, Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yuan Ou, Yuduan Wang, Yue Gong, Yuheng Zou, Yujia He, Yunfan Xiong, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Y. X. Zhu, Yanhong Xu, Yanping Huang, Yaohui Li, Yi Zheng, Yuchen Zhu, Yunxian Ma, Ying Tang, Yukun Zha, Yuting Yan, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhicheng Ma, Zhigang Yan, Zhiyu Wu, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Zizheng Pan, Zhen Huang, Zhipeng Xu, Zhongyu Zhang, and Zhen Zhang. Deepseek-r1: Incentivizing reasoning capability in Ilms via reinforcement learning, 2025. URL https://arxiv.org/abs/2501.12948.

- Aaron Defazio, Xingyu Alice Yang, Ahmed Khaled, Konstantin Mishchenko, Harsh Mehta, and Ashok Cutkosky. The road less scheduled. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL https://openreview.net/forum?id= 0XeNkkENuI.
- Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs. In Jill Burstein, Christy Doran, and Thamar Solorio (eds.), *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 2368–2378, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1246. URL https://aclanthology.org/N19-1246/.
- Ekaterina Fadeeva, Roman Vashurin, Akim Tsvigun, Artem Vazhentsev, Sergey Petrakov, Kirill Fedyanin, Daniil Vasilev, Elizaveta Goncharova, Alexander Panchenko, Maxim Panov, Timothy Baldwin, and Artem Shelmanov. LM-Polygraph: Uncertainty estimation for language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pp. 446–461, 2023. URL https://doi.org/10.48550/arXiv.2311.07383.
- Ekaterina Fadeeva, Aleksandr Rubashevskii, Artem Shelmanov, Sergey Petrakov, Haonan Li, Hamdy Mubarak, Evgenii Tsymbalov, Gleb Kuzmin, Alexander Panchenko, Timothy Baldwin, Preslav Nakov, and Maxim Panov. Fact-checking the output of large language models via token-level uncertainty quantification. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), Findings of the Association for Computational Linguistics: ACL 2024, pp. 9367–9385, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024. findings-acl.558. URL https://aclanthology.org/2024.findings-acl.558/.
- Chaoyou Fu, Yuhan Dai, Yongdong Luo, Lei Li, Shuhuai Ren, Renrui Zhang, Zihan Wang, Chenyu Zhou, Yunhang Shen, Mengdan Zhang, et al. Video-mme: The first-ever comprehensive evaluation benchmark of multi-modal llms in video analysis. *arXiv preprint arXiv:2405.21075*, 2024a.
- Xingyu Fu, Yushi Hu, Bangzheng Li, Yu Feng, Haoyu Wang, Xudong Lin, Dan Roth, Noah A Smith, Wei-Chiu Ma, and Ranjay Krishna. Blink: Multimodal large language models can see but not perceive. In *European Conference on Computer Vision*, pp. 148–166. Springer, 2024b.
- Albert Gu and Tri Dao. Mamba: Linear-time sequence modeling with selective state spaces. In *First Conference on Language Modeling*, 2024. URL https://openreview.net/forum?id=tEYskw1VY2.

- Alex Gu, Baptiste Roziere, Hugh James Leather, Armando Solar-Lezama, Gabriel Synnaeve, and Sida Wang. CRUXEval: A benchmark for code reasoning, understanding and execution. In Ruslan Salakhutdinov, Zico Kolter, Katherine Heller, Adrian Weller, Nuria Oliver, Jonathan Scarlett, and Felix Berkenkamp (eds.), *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *Proceedings of Machine Learning Research*, pp. 16568–16621. PMLR, 21–27 Jul 2024. URL https://proceedings.mlr.press/v235/gu24c.html.
- Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.
- Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring mathematical problem solving with the MATH dataset. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021. URL https://openreview.net/forum?id=7Bywt2mQsCe.
- Cheng-Ping Hsieh, Simeng Sun, Samuel Kriman, Shantanu Acharya, Dima Rekesh, Fei Jia, and Boris Ginsburg. RULER: What's the real context size of your long-context language models? In *First Conference on Language Modeling*, 2024. URL https://openreview.net/forum?id=kIoBbc76Sy.
- Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models, 2021. URL https://arxiv.org/abs/2106.09685.
- Binyuan Hui, Jian Yang, Zeyu Cui, Jiaxi Yang, Dayiheng Liu, Lei Zhang, Tianyu Liu, Jiajun Zhang, Bowen Yu, Keming Lu, et al. Qwen2. 5-coder technical report. *arXiv preprint arXiv:2409.12186*, 2024.
- Najoung Kim and Sebastian Schuster. Entity tracking in language models. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 3835–3855, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.213. URL https://aclanthology.org/2023.acl-long.213/.
- Yuri Kuratov, Aydar Bulatov, Petr Anokhin, Ivan Rodkin, Dmitry Igorevich Sorokin, Artyom Sorokin, and Mikhail Burtsev. BABILong: Testing the limits of LLMs with long context reasoning-in-a-haystack. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024. URL https://openreview.net/forum?id=u7m2CG84BQ.
- Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention, 2023. URL https://arxiv.org/abs/2309.06180.
- Dongxu Li, Yudong Liu, Haoning Wu, Yue Wang, Zhiqi Shen, Bowen Qu, Xinyao Niu, Guoyin Wang, Bei Chen, and Junnan Li. Aria: An open multimodal native mixture-of-experts model. *arXiv preprint arXiv:2410.05993*, 2024.
- MAA. American invitational mathematics examination, 2024. URL https://maa.org/math-competitions/american-invitational-mathematics-examination-aime.
- Karttikeya Mangalam, Raiymbek Akshulakov, and Jitendra Malik. Egoschema: A diagnostic benchmark for very long-form video language understanding. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023. URL https://openreview.net/forum?id=JVlWseddak.
- OpenAI. Gpt-4o system card. https://openai.com/index/gpt-4o-system-card/, 2024a. Accessed: 7 March 2025.
- OpenAI. Gpt-4o mini: advancing cost-efficient intelligence. https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence/, 2024b. Accessed: 7 March 2025.

- Bowen Peng, Jeffrey Quesnelle, Honglu Fan, and Enrico Shippole. Yarn: Efficient context window extension of large language models, 2023. URL https://arxiv.org/abs/2309.00071.
 - David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R. Bowman. GPQA: A graduate-level google-proof q&a benchmark. In *First Conference on Language Modeling*, 2024. URL https://openreview.net/forum?id=Ti67584b98.
 - Ivan Rodkin, Yuri Kuratov, Aydar Bulatov, and Mikhail Burtsev. Associative recurrent memory transformer, 2024. URL https://arxiv.org/abs/2407.04841.
 - Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. Deepseekmath: Pushing the limits of mathematical reasoning in open language models, 2024. URL https://arxiv.org/abs/2402.03300.
 - Mirac Suzgun, Nathan Scales, Nathanael Scharli, Sebastian Gehrmann, Yi Tay, Hyung Won Chung, Aakanksha Chowdhery, Quoc V. Le, Ed H. Chi, Denny Zhou, and Jason Wei. Challenging bigbench tasks and whether chain-of-thought can solve them. In *Annual Meeting of the Association for Computational Linguistics*, 2022. URL https://aclanthology.org/2023.findings-acl.824.
 - Falcon-LLM Team. The falcon 3 family of open models, December 2024.
 - Qwen Team. Qwq-32b: Embracing the power of reinforcement learning, March 2025. URL https://qwenlm.github.io/blog/qwq-32b/.
 - Roman Vashurin, Ekaterina Fadeeva, Artem Vazhentsev, Lyudmila Rvanova, Daniil Vasilev, Akim Tsvigun, Sergey Petrakov, Rui Xing, Abdelrahman Sadallah, Kirill Grishchenkov, et al. Benchmarking uncertainty quantification methods for large language models with lm-polygraph. *Transactions of the Association for Computational Linguistics*, 13:220–248, 2025. URL https://direct.mit.edu/tacl/article/doi/10.1162/tacl_a_00737/128713/Benchmarking-Uncertainty-Quantification-Methods.
 - Kiran Vodrahalli, Santiago Ontanon, Nilesh Tripuraneni, Kelvin Xu, Sanil Jain, Rakesh Shivanna, Jeffrey Hui, Nishanth Dikkala, Mehran Kazemi, Bahare Fatemi, Rohan Anil, Ethan Dyer, Siamak Shakeri, Roopali Vij, Harsh Mehta, Vinay Ramasesh, Quoc Le, Ed Chi, Yifeng Lu, Orhan Firat, Angeliki Lazaridou, Jean-Baptiste Lespiau, Nithya Attaluri, and Kate Olszewska. Michelangelo: Long context evaluations beyond haystacks via latent structure queries, 2024. URL https://arxiv.org/abs/2409.12640.
 - Fei Wang, Xingyu Fu, James Y. Huang, Zekun Li, Qin Liu, Xiaogeng Liu, Mingyu Derek Ma, Nan Xu, Wenxuan Zhou, Kai Zhang, Tianyi Lorena Yan, Wenjie Jacky Mo, Hsiang-Hui Liu, Pan Lu, Chunyuan Li, Chaowei Xiao, Kai-Wei Chang, Dan Roth, Sheng Zhang, Hoifung Poon, and Muhao Chen. Muirbench: A comprehensive benchmark for robust multi-image understanding. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=TrVYEZtSQH.
 - Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, et al. Qwen2-vl: Enhancing vision-language model's perception of the world at any resolution. *arXiv* preprint arXiv:2409.12191, 2024a.
 - Weihan Wang, Zehai He, Wenyi Hong, Yean Cheng, Xiaohan Zhang, Ji Qi, Xiaotao Gu, Shiyu Huang, Bin Xu, Yuxiao Dong, et al. Lvbench: An extreme long video understanding benchmark. arXiv preprint arXiv:2406.08035, 2024b.
 - Weiyun Wang, Zhe Chen, Wenhai Wang, Yue Cao, Yangzhou Liu, Zhangwei Gao, Jinguo Zhu, Xizhou Zhu, Lewei Lu, Yu Qiao, and Jifeng Dai. Enhancing the reasoning ability of multimodal large language models via mixed preference optimization. *arXiv preprint arXiv:2411.10442*, 2024c.

- Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyan Jiang, et al. Mmlu-pro: A more robust and challenging multitask language understanding benchmark. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024d.
- Jason Weston, Antoine Bordes, Sumit Chopra, and Tomás Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. In Yoshua Bengio and Yann LeCun (eds.), 4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings, 2016. URL http://arxiv.org/abs/1502.05698.
- Brandon T Willard and Rémi Louf. Efficient guided generation for llms. arXiv preprint arXiv:2307.09702, 2023.
- Haoning Wu, Dongxu Li, Bei Chen, and Junnan Li. Longvideobench: A benchmark for long-context interleaved video-language understanding. *Advances in Neural Information Processing Systems*, 37:28828–28857, 2025.
- Tsung-Han Wu, Giscard Biamby, Jerome Quenum, Ritwik Gupta, Joseph E Gonzalez, Trevor Darrell, and David M Chan. Visual haystacks: A vision-centric needle-in-a-haystack benchmark. arXiv preprint arXiv:2407.13766, 2024.
- An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zhihao Fan. Qwen2 technical report. arXiv preprint arXiv:2407.10671, 2024a.
- An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report. *arXiv preprint arXiv:2412.15115*, 2024b.
- An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, Chujie Zheng, Dayiheng Liu, Fan Zhou, Fei Huang, Feng Hu, Hao Ge, Haoran Wei, Huan Lin, Jialong Tang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jing Zhou, Jingren Zhou, Junyang Lin, Kai Dang, Keqin Bao, Kexin Yang, Le Yu, Lianghao Deng, Mei Li, Mingfeng Xue, Mingze Li, Pei Zhang, Peng Wang, Qin Zhu, Rui Men, Ruize Gao, Shixuan Liu, Shuang Luo, Tianhao Li, Tianyi Tang, Wenbiao Yin, Xingzhang Ren, Xinyu Wang, Xinyu Zhang, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yinger Zhang, Yu Wan, Yuqiong Liu, Zekun Wang, Zeyu Cui, Zhenru Zhang, Zhipeng Zhou, and Zihan Qiu. Qwen3 technical report, 2025. URL https://arxiv.org/abs/2505.09388.
- Yuan Yao, Tianyu Yu, Ao Zhang, Chongyi Wang, Junbo Cui, Hongji Zhu, Tianchi Cai, Haoyu Li, Weilin Zhao, Zhihui He, et al. Minicpm-v: A gpt-4v level mllm on your phone. *arXiv preprint arXiv:2408.01800*, 2024.
- Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruoqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, Cong Wei, Botao Yu, Ruibin Yuan, Renliang Sun, Ming Yin, Boyuan Zheng, Zhenzhu Yang, Yibo Liu, Wenhao Huang, Huan Sun, Yu Su, and Wenhu Chen. Mmmu: A massive multi-discipline multimodal understanding and reasoning benchmark for expert agi. In *Proceedings of CVPR*, 2024a.
- Xiang Yue, Tianyu Zheng, Yuansheng Ni, Yubo Wang, Kai Zhang, Shengbang Tong, Yuxuan Sun, Botao Yu, Ge Zhang, Huan Sun, Yu Su, Wenhu Chen, and Graham Neubig. Mmmu-pro: A more robust multi-discipline multimodal understanding benchmark. *arXiv preprint arXiv:2409.02813*, 2024b.

Boqiang Zhang, Kehan Li, Zesen Cheng, Zhiqiang Hu, Yuqian Yuan, Guanzheng Chen, Sicong Leng, Yuming Jiang, Hang Zhang, Xin Li, et al. Videollama 3: Frontier multimodal foundation models for image and video understanding. *arXiv preprint arXiv:2501.13106*, 2025a.

Peiyuan Zhang, Kaichen Zhang, Bo Li, Guangtao Zeng, Jingkang Yang, Yuanhan Zhang, Ziyue Wang, Haoran Tan, Chunyuan Li, and Ziwei Liu. Long context transfer from language to vision. *arXiv preprint arXiv:2406.16852*, 2024a.

Shaolei Zhang, Qingkai Fang, Zhe Yang, and Yang Feng. Llava-mini: Efficient image and video large multimodal models with one vision token, 2025b. URL https://arxiv.org/abs/2501.03895.

Yuanhan Zhang, Jinming Wu, Wei Li, Bo Li, Zejun Ma, Ziwei Liu, and Chunyuan Li. Video instruction tuning with synthetic data. *arXiv preprint arXiv:2410.02713*, 2024b.

Junjie Zhou, Yan Shu, Bo Zhao, Boya Wu, Shitao Xiao, Xi Yang, Yongping Xiong, Bo Zhang, Tiejun Huang, and Zheng Liu. Mlvu: A comprehensive benchmark for multi-task long video understanding. *arXiv preprint arXiv:2406.04264*, 2024.

A LOST-IN-THE-MIDDLE PHENOMENON

This phenomenon refers to the tendency of transformer-based models to struggle with retrieving information from the middle of long contexts. Since our benchmark involves reasoning over extended sequences, we evaluated whether such biases affect our results.

To investigate this, we focus on framereferenced questions (FX, see Table 1), where a model must extract information from a specific step in the sequence. This includes five question types, where we can calculate the referred image depth by extracting the "step X" number and dividing it by the sequence length.

By averaging performance across all LVLMs and plotting accuracy as a function of the frame position (Figure 7), we observe no clear pattern indicative of lost-in-the-middle degradation. If the latter phenomenon were significantly impacting our benchmark, we would expect accuracy to consistently drop for middle-positioned frames compared to the beginning

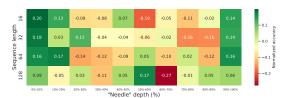


Figure 7: Analysis of the lost-in-the-middle effect on MMReD frame-referenced questions. The x-axis represents the relative position of the target frame within sequence; the y-axis shows the normalized accuracy difference from the mean.

and end, which is not the case. When analyzing individual model performances, we observed similar trends – no systematic drop in accuracy for middle-positioned frames.

This suggests that our benchmark and its conclusions remain independent of lost-in-the-middle biases, at least within the tested context lengths. And we believe that longer context lengths may be required before this effect becomes a major factor in our setting. The results suggest that longer context lengths may be required before the LITM effect becomes a major factor in our setting.

B MODELS' PERFORMANCE

Below, we present detailed heatmaps of model performance across all MMReD task types and sequence lengths. Figure 8 focuses on top-performing reasoning models. A clear trend emerges: dense reasoning (DC) tasks are consistently more challenging than their NIAH-based counterparts, this gap is particularly evident in the QwQ model. For proprietary models (Figure 9), the contrast is less visually evident but persists when examining average performance across tasks.

Secondly, we found that including a diverse set of question types is essential, as model performance varies across conceptually distinct tasks. For example, despite the near-identical formulation of first appearance (FA) and last appearance (FI) questions, models consistently perform worse on

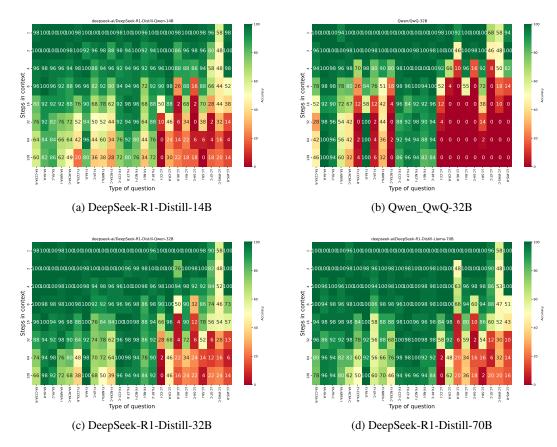


Figure 8: Performance of the best reasoning models.

average on FI tasks (e.g., Figure 8d). This suggests that models struggle to distinguish between similar temporal trajectories in task formulation, especially when we see questions referring to a concrete step (FX), which are phrased in a similar way, being solved with notably higher accuracy. In addition, our benchmark includes tasks with gradually increasing difficulty, with DC-WHS-C (Who spent the most time in the [R]?) and DC-RE-R (Which room was empty for the most steps?) among the most challenging. The latter highlights a recurring weakness in count-based reasoning.

As discussed in Section 4.3, various fine-tuning strategies fail to improve performance on our benchmark with their results detailed in Figure 10. Supplementing Section 4.3 further, studies on different pooling methods are provided in Figure 12. Finally, we report results for video-specific architectures in Figures 11 and 13.

C EVALUATION DETAILS

Inference format and parameters The MMReD questions were formulated as open-ended question-answer tasks. We provided a generic problem description and answer format in the system prompt (Table 2).

To standardize output generation, we applied a structured generation approach to produce consistent answer structures in a JSON format, {"answer": <answer_type>}, where <answer_type> was an enum or integer number depending on the expected answer type (C, R, I in Table 1). We utilized outlines library (Willard & Louf, 2023) for structured generation, which involves converting the JSON response structure into a regular expression, which is further used to construct a finite state machine to guide LLM generation by adding bias to logits. We used the lmdeploy (Contributors, 2023) and VLLM (Kwon et al., 2023) packages for efficient serving of models.

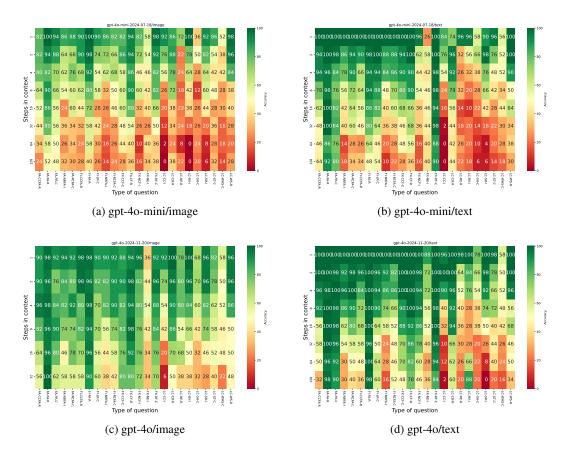


Figure 9: Performance of the OpenAI proprietary models.

We preserve the default configuration parameters of all selected LVLMs, except we extend the maximum sequence length and increase the positional embeddings to avoid truncating the input sequence. The generation parameters were also consistent across all models: the generation temperature was set to 0, the number of beams was set to 1, and the number of tokens was limited to 50. For LLMs with reasoning, we increase the generation temperature to 0.7 and token limit to 2048.

We used at most $4 \times A100$ 80GB in our local evaluations, and if model exceeded a time limit of 600 seconds or returned out-of-memory error, we dropped evaluation of the current and larger lengths (e.g., in cases of Aria and Llama-3.2-Vision).

Fine-Tuning We also ablated whether fine-tuning can help generalize to unseen context lengths. Both SFT and GRPO (Shao et al., 2024) training were performed on the same dataset spanning N=[1,2,4,8,16] sequence lengths, 200 samples per each task of the benchmark per sequence length. We used Qwen2.5-7B-Instruct (Yang et al., 2024b) and Falcon3-Mamba-7B-Instruct (Team, 2024) models for SFT and DeepSeek-R1-Distill-Qwen-7B (DeepSeek-AI et al., 2025) for GRPO to help bootstrap reasoning abilities. In SFT, we used a global batch size of 128, learning rate of 3×10^{-4} , and five training epochs; GRPO was trained with $\varepsilon=0.2$, $\beta=0.1$, 12 generations per sample, global batch size of 168, and one epoch of training. We used linear warmup of 50 steps with a constant schedule after warmup and ScheduleFree AdamW (Defazio et al., 2024) optimizer. The gradient norm was clipped to 0.25.

For GRPO rewards, we used a combination of answer correctness and format rewards, enforcing the model to follow an XML template

<think>{thinking}</think> <answer>{"answer": <answer_type>}</answer>
and rewarding for exact matches with ground truth answers.

We applied parameter-efficient fine-tuning via LoRA (Hu et al., 2021) with a rank of 32, alpha of 32, and dropout of 0.05 in both scenarios. Flash Attention (Dao et al., 2022; Dao, 2024) was enabled for

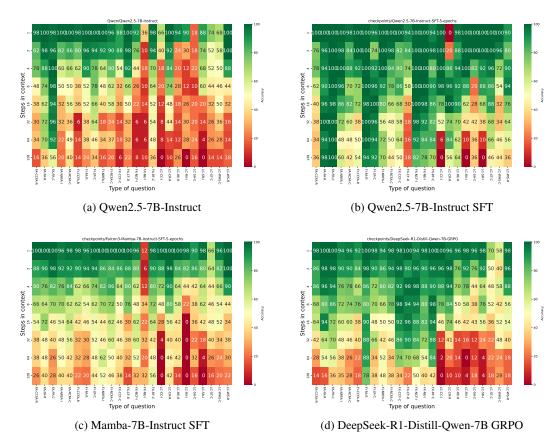


Figure 10: Performance on the fine-tuned models and base model before fine-tuning.

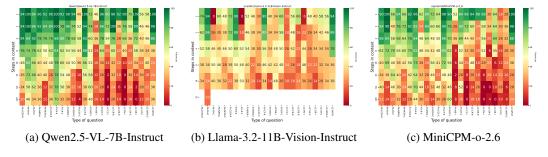


Figure 11: Performance of the models with different types of image pooling.

attention models, and mixed precision training was conducted with bfloat16. Mamba training was performed with gradients accumulating in float32 and using efficient CUDA kernels for selective scan operation from the Mamba codebase (Gu & Dao, 2024; Dao & Gu, 2024).

As an evaluation metric, we utilized the accuracy of the exact match between the generated response and the target value. Model predictions that did not follow the specified response format or from which the response field could not be extracted were marked as incorrect.

D REASONING EXAMPLES

In general, we find that reasoning improves performance: when given sufficient token space, it often guides the model to the correct answer by helping it locate the relevant step and correct errors that non-reasoning models typically make (see example in Table 3).

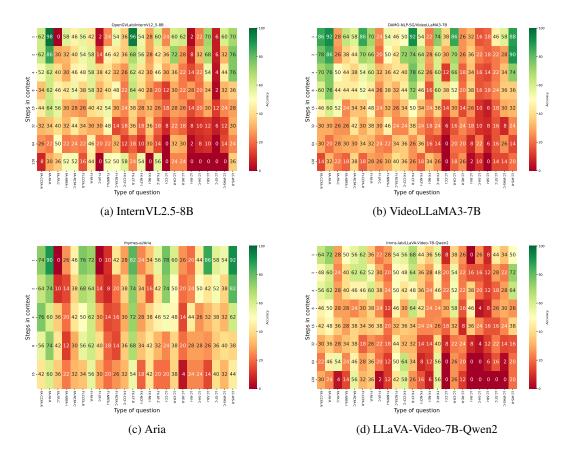


Figure 12: Performance of the different types of video models.

However, in dense context (DC) tasks, starting at around 32-frame sequences, reasoning models begin to shift their output toward a step-by-step, JSON-like listing of observations. This introduces two key issues. First, a model may make a mistake when processing one step, and then proceed to build on that false assumption, effectively compounding and grounding on its error, as in example in Table 4. Second, enumerating all steps consumes a large portion of the token budget, increasing the risk that the model fails to produce a final answer within the predefined 768-token generation limit (a threshold, commonly sufficient for solving math problems (Cobbe et al., 2021), and thus adequate for our simpler reasoning tasks).

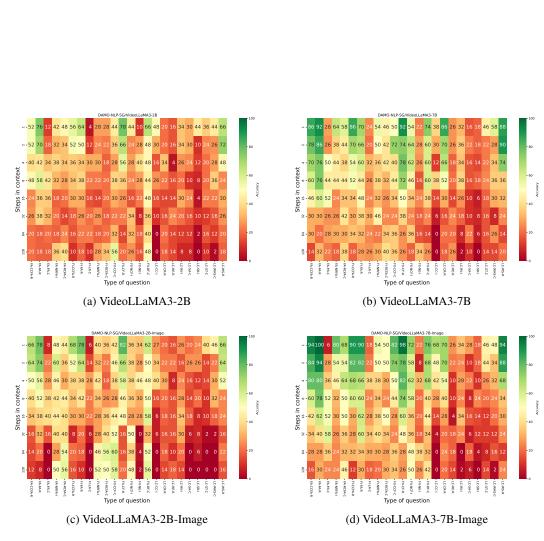


Figure 13: Results across different models in the VideoLLaMA-3 family.

```
1080
1081
1082
1083
1084
1085
1086
1087
1088
1089
1090
1091
1092
1093
1094
1095
        System Prompt
1096
        You are an assistant that analyzes sequences of human agents
1097
        moving in an environment. Format your response as a following
1098
        json:
1099
        { "answer": <value> }, where <value> is:
1100
        - A **single room name** (e.g., 'Kitchen') for location
1101
        answers.
1102
        - A **number** (e.g., '3') for counting answers.
1103
        - A **single person name** (e.g., 'Michael') for people
        answers or 'Nobody' if no person satisfies given conditions.
1104
1105
1106
        System Prompt for reasoning-based models
1107
        You are a helpful AI Assistant, designed to provided
1108
        well-reasoned and detailed responses. First think about the
1109
        reasoning process and then provide the user with the answer.
1110
        Format your final answer with a {"answer": <value>}, where
1111
        <value> is:
        - A **single room name** (e.g., 'Kitchen') for location
1113
        answers.
        - A **number** (e.g., '3') for counting answers.
1114
        - A **single person name** (e.g., 'Michael') for people
1115
```

Table 2: System prompts used during inference.

answers or 'Nobody' if no person satisfies given conditions.

```
1134
1135
1136
1137
       DeepSeek-R1-Distill-Llama-70B
1138
1139
        Q: Who was in the Hallway when Michael first appeared in the
1140
       Garden?
1141
       A: Mary
1142
        <think>
1143
       Okay, so I need to figure out who was in the Hallway when
1144
       Michael first appeared in the Garden. Let me break this down
1145
       step by step.
1146
1147
       First, I'll look through each step to find when Michael first
1148
       shows up in the Garden. The data is structured from step 1 to
       step 64, with each step showing the rooms and the people
1149
        inside them. My goal is to scan these steps sequentially
1150
       until I find the earliest occurrence of Michael being in the
1151
       Garden.
1152
1153
       Starting from step 1, I check each room in every step.
1154
       early steps like 1-5, Michael isn't in the Garden yet.
1155
       in other places like the Office or Bedroom. As I go through
1156
       each step, I keep an eye on the Garden room.
1157
1158
       Continuing this way, at some point, I notice that in step 44,
1159
       the Garden has ['Michael']. That seems to be his first
        appearance there because prior steps don't show him in the
1160
       Garden. So, Michael first appears in the Garden at step 44.
1161
1162
       Now, once I've identified step 44 as the moment Michael enters
1163
       the Garden, I need to check who was present in the Hallway at
1164
       that exact step. Looking back at step 44's data:
1165
1166
       {'Kitchen': [], 'Bathroom': [], 'Garden': ['Michael'],
1167
        'Office': ['Sandra', 'Daniel'], 'Bedroom': ['John'],
1168
       'Hallway': ['Mary']}.
1169
1170
       From this, it's clear that in the Hallway during step 44, Mary
       is present. Therefore, when Michael first appeared in the
1171
       Garden, Mary was in the Hallway.
1172
1173
        I should double-check my findings to ensure accuracy.
1174
        Scanning earlier steps confirms that Michael wasn't in the
1175
       Garden before step 44, and at step 44, only Mary is in the
1176
       Hallway. No one else is there except her.
1177
1178
       So, putting it all together, the person in the Hallway when
1179
       Michael first entered the Garden was Mary.
1180
       </think>
1181
1182
       {"answer": "Mary"}
```

Table 3: A generic reasoning example of the largest used DeepSeek model on the FA-RCFA-C task.

1183

1236

1237

1238

```
1189
1190
1191
       DeepSeek-R1-Distill-Llama-70B
1192
       Q: Who spent the least amount of time alone in the Hallway?
1193
       A: John
1194
1195
       <think>
1196
       Alright, let's try to figure out who spent the least amount of
1197
       time alone in the Hallway. So, I have data from step 1 to
       step 128, each showing which rooms people are in at that step.
1198
       My task is to go through each step, check who's in the
1199
       Hallway, and see if they're alone there. Then, count how many
1200
       times each person was alone in the Hallway and find out who
1201
       had the smallest number.
1202
1203
       First, I need to understand what "alone" means. It means that
1204
       during a particular step, only that person is present in the
       Hallway; nobody else is there. So, for each step, I'll look
1206
       at the Hallway entry in the 'rooms' dictionary. If it has
1207
       exactly one person, that person was alone that step.
1208
       Otherwise, even if multiple people are there, as long as
       someone else is present, it doesn't count as being alone.
1209
1210
       So, my plan is:
1211
1212
           Iterate through each step from 1 to 128.
1213
           For each step, get the list of people in the Hallway.
1214
1215
        <...>
1216
1217
       - Step 1:
                   Hallway = [Sandra] → Sandra +1 → Sandra=1
1218
       - Step 2:
                   Hallway = [Sandra] → Sandra +1 → Sandra=2
1219
                   Hallway = [Sandra] → Sandra=3
       - Step 3:
                  Hallway = [] → No one
1220
       - Step 4:
       - Step 5:
                  Hallway = [] → No one
1221
       - Step 6:
                  Hallway = [] → No one
1222
       - Step 7:
                   Hallway = [Mary] → Mary=1
1223
       - Step 8:
                   Hallway = [Mary, Michael] → Both present → Not alone
       - Step 9: Hallway = [Mary, Michael] → Not alone
1225
       - Step 10: Hallway = [] → No one
1226
1227
        <...>
1228
1229
       So, from this, Michael was alone in the Hallway during step
1230
       36, and John was alone during steps 72 and 73. Therefore,
       since the question asks for who spent the least amount of time
1231
       alone in the Hallway, the answer is Michael.
1232
       </think>
1233
1234
        {"answer": "Michael"}
1235
```

Table 4: Failure case of a reasoning model on a dense context task, DC-SA-C. Although the model correctly outlines a valid general reasoning strategy, it decides to list all observations (orange), making a mistake outlining several steps (red), and ultimately produces the wrong final answer.