Look Before You Decide: Prompting Active Deduction of MLLMs for Assumptive Reasoning

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Abstract

Recently, Multimodal Large Language Models (MLLMs) have achieved significant success across multiple disciplines due to their exceptional instruction-following capabilities and extensive world knowledge. However, whether these MLLMs possess human-like compositional reasoning abilities remains an open problem. To unveil their reasoning behaviors, we first curate a Multimodal Assumptive Reasoning Benchmark (MARS-Bench) in this paper. Interestingly, we find that most prevalent MLLMs can be easily fooled by the introduction of a presupposition into the question, whereas such presuppositions appear naive to human reasoning. Besides, we also propose a simple yet effective method, Active Deduction (AD), to encourage the model to actively perform composite deduction before reaching a final decision. Equipped with the proposed AD method, a MLLM demonstrates significant improvements in assumptive reasoning abilities without compromising its generalpurpose question-answering performance. We also provide extensive evaluations of both open-source and private MLLMs on MARS-Bench, along with experimental analyses of the AD method.

1. Introduction

Recently, the Multimodal Large Language Models (MLLMs) [1, 2, 5, 8, 16, 23, 24, 31, 44] have been a rising research hotspot due to their potential of serving as versatile generalists across multiple disciplines. With world knowledge distilled from vast corpora, MLLMs present remarkable reasoning capabilities in solving challenging tasks. LISA [20] addresses the task of "reasoning segmentation" task by integrating a MLLM with the

SAM [18]. Visual-CoT [33] grounds specific image regions as intermediate steps in its reasoning process to handle complex questions. Although these MLLMs achieved unprecedented success, we wonder whether they genuinely demonstrate human-like composite reasoning steps before making the decision.

To uncover the reasoning behaviors of MLLMs, we refactor a typical VQA sample by adding a presupposition as shown in Fig.1. While this may seem straightforward to a human, this question can easily confuse the MLLM, leading it to provide plausible yet incorrect answers. For further analysis, we provide additional guidance to the MLLM by employing the Chain-of-Thought (CoT) [28, 35] technique, aiming to unleash its reasoning potential through multiturn reflection. Interestingly, as demonstrated in Fig.1, the MLLM tends to generate a specious CoT process to support its incorrect answers. Through the above experimental probe, it can be observed that the MLLM is prone to make decisions based on its intuition, synthesized from the knowledge stored in its memory. We call such behaviors of the MLLM as "empirical reasoning" in this paper.

Compared to empirical reasoning, human cognition exhibits strong compositionality, allowing the expansion of new knowledge by deducing from a finite set of mastered concepts. To tackle the question in Fig.1, it is necessary to (1) recognize the direction of movement of the car and motorcycle, and (2) comprehend the meaning of "U-turn", finally (3) combine the results in (1) and (2) to reason about the ultimate car direction. However, as previously demonstrated, existing MLLMs fail to produce these crucial reasoning steps. The underlying reason for the empirical reasoning nature of MLLMs lies in their tendency to mimic behaviors that occur with the highest probabilities across vast training data, where samples requiring complex logical reasoning are relatively scarce.

To systematically assess the extent to which existing

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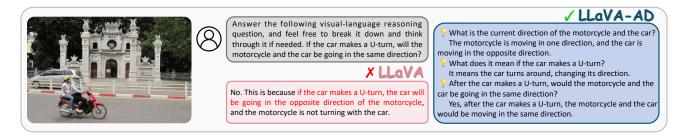


Figure 1. The results comparison of LLaVA and the LLaVA equipped with our proposed Active Deduction (AD) method when faced with assumptive reasoning questions. LLaVA fails to provide the correct answer due to the plausible yet incorrect CoT it generates (highlighted in red). In contrast, our LLaVA-AD can decompose the problem, deducing the answer based on the mastered knowledge. We use red to denote the wrong answer, and bulb icons to denote the CoT instructions actively generated by our model.

Multimodal Large Language Models (MLLMs) rely on empirical intuition during answer generation, we curate a novel Multimodal Assumptive Reasoning Benchmark, abbreviated as MARS-Bench in this paper. In MARS-Bench, we design two sets of questions for obvious comparison. The first set of questions aims to inquire about the detailed content of the image. These questions are conventional and serve as foundational queries. In the second set of questions, we introduce a deliberately curated presupposition prior to each foundational question, imposing higher demands on the model to perform cross-referential reflection and reasoning in order to produce correct answers. By comparing the performance achieved on these two sets of questions, we can effectively examine a model's susceptibility to overreliance on its empirical intuition. Through comprehensively evaluating eight leading open-source models as well as the advanced private model, GPT-40, on our MARS-Bench, we observe significant performance degradation across all open-source models, whereas GPT-40 demonstrates considerable robustness, which could offer promising avenues for enhancing the reasoning capabilities of existing MLLM in the future research.

Besides, to enhance the MLLM's assumptive reasoning capability, we also introduce a simple yet effective method called Active Deduction (AD). Our core motivation lies in that questions of varying difficulties should be matched with corresponding levels of cognitive effort. Therefore, the proposed AD method employs a divide-and-conquer strategy by introducing two new special tokens <ST> and <ET>, to denote the start and end of the model's thinking process. For simple questions, the model can directly generate answers based on its empirical intuition. When faced with questions requiring complex reasoning, the model can be prompted to generate the <ST> token, thereby actively engaging in compositional deduction before arriving at the final decision. With this dynamic adjustment feature, our AD method can significantly promote the assumptive reasoning capabilities of the existing MLLM, while preserving

its general-purpose question-answering abilities.

In general, our contributions can be summarized as follows:

- We propose a novel Multimodal Assumptive Reasoning Benchmark (MARS-Bench), on which we widely assess the assumptive reasoning capabilities of prevalent opensource and private MLLMs.
- We introduce an Active Deduction (AD) method to enhance the existing MLLM's assumptive reasoning ability while not sacrificing its general-purpose question-answering performances.
- We also conduct extensive experiments and provide indepth analyses to demonstrate the value of MARS-Bench and the effectiveness of the AD method.

2. Related Works

Multimodal Large Language Models.

Recent advancements in large language models (LLMs) have shown strong performance across various linguistic tasks [3, 7, 34, 41]. Researchers have extended LLMs to multimodal large language models (MLLMs), integrating visual and language modalities. Flamingo [2] and Open-Flamingo [4] use modules like Perceiver Resampler and XAttn-Dense for improved few-shot performance. LLaMA-Adapter [40] and Otter [21] incorporate crossattention layers for multimodal fusion. BLIP2 [23] introduces Q-Former to link vision and frozen LLMs, and subsequent models such as InstructBLIP [8] and MiniGPT-4 [44] leverage high-quality data for better instruction following. LLaVA [26] simplifies visual integration via a projection layer, while Shikra [6] and Kosmos-2 [31] further enhance MLLMs' visual grounding abilities. Qwen-VL [5] and Monkey [24] focus on high-resolution input for detailed visual understanding. GPT-4V [1] also demonstrates exceptional image comprehension. MARS-Bench evaluates these models for multimodal reasoning capabilities.

Multimodal Reasoning Benchmarks. Various benchmarks have been proposed to evaluate the reasoning ability

of MLLMs. GOA [15] leverages the scene-graph structure of Visual Genome [19] to create diverse questions, which focus on multi-step reasoning and scene understanding in real-world images. OK-VQA [30] focuses on questions that require external resources to answer. Science-QA [28] presents a diverse collection of multimodal science questions, complemented by lecture annotations and detailed explanations. MathVista [29] evaluates five primary tasks in mathematical reasoning. In addition to the aforementioned reasoning-specific benchmarks, some comprehensive benchmarks also encompass a variety of reasoning tasks. MME [9] contains commonsense reasoning, numerical calculations, text translation, and code reasoning. SEED-Bench [22] evaluates reasoning capabilities of visual reasoning, science knowledge, and action prediction. However, most of these benchmarks focus on conventional multimodal reasoning and may overlook certain assumptive scenarios in the real world.

Improving Reasoning Capabilities of MLLMs. Since LLMs cannot directly access visual information, existing methods typically capitalize on their instruction-following capabilities by providing in-context examples to guide them in utilizing various expert modules for visual reasoning. MM-React [38] designs a system paradigm that composes numerous vision experts with ChatGPT for multimodal reasoning and action. Visprog [12] provides in-context examples to enable LLMs to generate Python-like visual programs and create distinct modules for performing specific tasks. Cantor [10] crafts more sophisticated prompts, enabling MLLMs to emulate the roles of domain-specific experts, and thereby facilitate enhancing rationality and depth in the reasoning process. Different from the above method, [28] verifies the effectiveness of applying CoT on ScienceQA using LLMs (UnifiedQA, GPT-3). Multimodal-CoT [42] incorporates language and vision modalities into a two-stage framework that separates rationale generation and answer inference. In this paper, we propose an Active Deduction framework to systematically improve assumptive reasoning in MLLMs, backed by our novel MARS-Bench evaluation.

3. MARS-Bench

We present the Multimodal Assumptive ReaSoning Benchmark (MARS-Bench), a manually curated benchmark to evaluate the assumptive reasoning capabilities of MLLMs. In this section, we first introduce the definition of assumptive questions, followed by an overview of the included assumption aspects. Then we elaborate on the dataset construction process. Finally, we present the evaluation protocol.

3.1. Problem Definition

In this paper, we refer to "assumptive questions" as the question that includes an imaginary presupposition to the known facts. Here, "facts" denote the actual information presented in the image, while "presuppositions" represent hypothetical assumptions about changes in the state of this information. We formulate the above process as a function $f: X \rightarrow Y$ that maps the input $x \in X$ to the output $y \in Y$:

$$f(v, w_a, w_q) = \underset{y'}{\arg \max} \mathbf{P}(y'|v, w_a, w_q).$$

Here, y' is the output of MLLM obtained through an appropriate decoder. v, w_a , and w_q represent the image, imaginary presupposition, and visual question respectively.

3.2. Diverse Aspects of Assumptions

Different assumptions demand distinct reasoning capabilities, thus we progressively challenge MLLMs by setting tasks across 6 key aspects:

- Count: Calculate changes in the quantity of objects when specific items are added to or removed from a group. This challenges the model's ability to perform numerical operations and track quantity changes.
- *Color*: Infer how the color of objects changes when they are exchanged or merged. This requires the model to grasp concepts of color mixing or transformations.
- *Shape*: Analyze how objects deform or change shape when external forces are applied or when they interact with other objects. This tests the model's understanding of spatial transformations and physical properties.
- *Size*: Imagine changes in the size of objects in space and compare them with other objects. This challenges the model's ability to reason about spatial relationships and quantitative comparisons of magnitude.
- *Direction*: Envision changes in the orientation or position of objects. The model needs to understand shifts in spatial location.
- *Common*: Modify world conditions and ask the model to reason based on external knowledge. This can encompass a wide range of questions that require the model to apply logic and knowledge to new scenarios.

Examples of each question type are illustrated in Fig.2. This hierarchical division aims to assess MLLMs' ability to comprehend and infer entities, attributes, and relationships within images at different levels.

3.3. Dataset Curation

Data Source & Human Annotation. Assumptive questions involve imaginary presupposition that entails changes in different aspects, which requires images to contain rich scenarios and potential semantic information. We thus chose images from COCO [25] validation set to annotate due to the diverse object categories and rich visual scenes

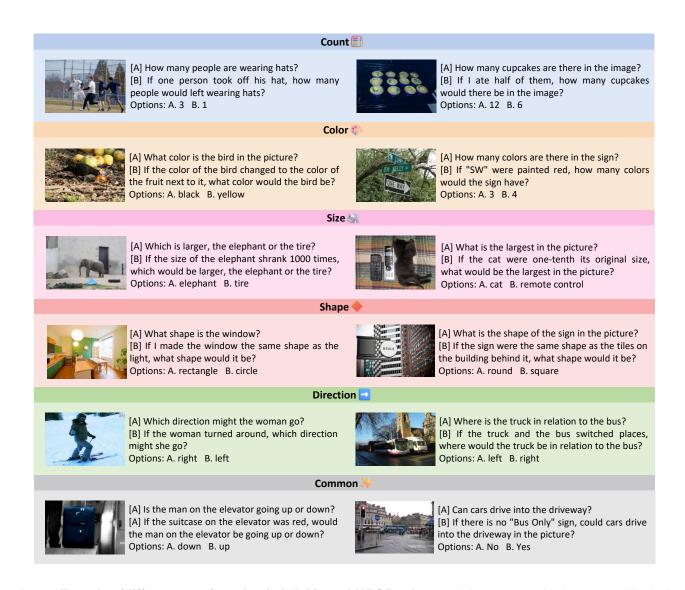


Figure 2. **Examples of different types of questions included in our MARS-Bench.** For each image, we provide the corresponding basic and assumptive questions. The correct answer is indicated in brackets at the beginning of the question. Note that presuppositions may also act as distractors, as shown in the left case in the last row.

it offers, which capture complex everyday scenarios closely aligned with real-world distributions.

We ask annotators to perform assumptive question annotations, which follow these steps: (1) Given an image, annotators first select an appropriate question type. Images with no suitable question types will be excluded. (2) Afterward, annotators are asked to design a basic visual question and then modify certain conditions within it to create an assumptive question. (3) To further enhance the data quality of MARS-Bench, we employ a rigorous data filter pipeline. Specifically, each question is verified manually with regard to the following two key aspects:

(1) Information Leakage refers to a situation which the

- answer to a question is embedded in the "If" clause. For instance, "If I painted this bus blue, what color would it be?" In this case, the model can derive answers directly from the text without referring to the image content.
- (2) **Ambiguity of the answer** refers to the inability to derive a precise answer from the image. For example, it is not appropriate to ask about the number of elephants when only a small part of an elephant's body is visible.

Automated Question Expansion. We expanded our dataset based on 1,200 manually annotated question pairs. Leveraging GPT-4's powerful multimodal understanding and instruction-following capabilities, we prompted it to creatively generate new content by mimicking existing an-

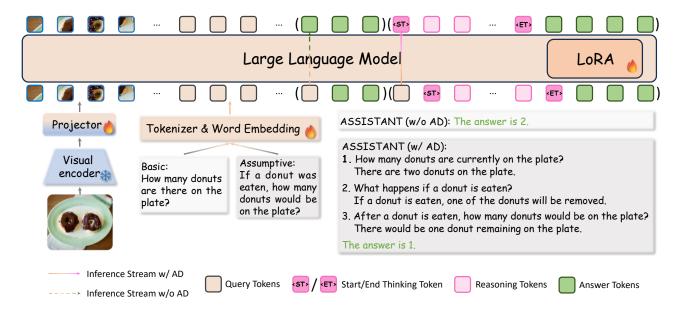


Figure 3. Overview of the Active Deduction (AD) framework, demonstrating the model's dynamic adjustment between direct empirical reasoning and structured deductive reasoning. For basic questions (left input), the model bypasses AD, directly outputting the answer based on intuition (tokens in the first bracket). For more complex assumptive reasoning questions (right input), the model engages AD by generating the <ST> token, breaking down the problem into intermediate sub-questions, and synthesizing a final answer upon reaching the <ET> token (tokens in the second bracket). This adaptive approach allows the model to balance efficiency with reasoning depth, applying detailed deduction only when necessary.

notations. Specifically, we provided GPT with an image, along with manually annotated questions and their corresponding answers. We then instructed GPT to modify the presuppositions while retaining the core question. After this process, we ultimately obtained 6,000 questions. The prompts used for each category varied slightly, with the detailed prompts provided in the supplementary material. We ensure the newly generated questions match the image information, are logically consistent, and that the answers are concise and clear through manual verification.

3.4. Evaluation Protocol

Given the challenge of quantitatively evaluating open-ended answers, we structure the answers in the form of common multiple-choice questions with two candidates. However, the instruction-following capabilities of existing MLLMs are limited, even if explicitly asked to answer "A" or "B", the models may still produce some free-form text. Furthermore, we also observe that many MLLMs exhibit a preference for certain options, tending to favor those presented earlier. To eliminate the influence of instructions and option preferences, we adopt the same answer ranking strategy as SEED-Bench [22]. Specifically, given a question, we compute the generation loss for each option and select the minimum loss as the model's prediction. We utilize accuracy as our evaluation metric, where acc_b and acc_a indicate correct

response to basic and assumptive questions respectively.

4. Active Deduction

In this section, we first introduce the overall framework LLaVA-AD, a LLaVA-based MLLM equipped with our proposed Active Deduction (AD) method. Afterward, we introduce the data strategy for training the model.

4.1. LLaVA-AD Framework

The overall framework of LLaVA-AD is shown in Fig.3. We introduce two new special tokens <ST> and <ET> to denote the start and end of the thinking process. The running pipeline of the LLaVA-AD model includes the following steps: (1) Given a question, LLaVA-AD first implicitly judges its complexity. (2) For simple questions, LLaVA-AD directly generates responses in a manner similar to conventional MLLMs, as illustrated by the green pathway in Fig.3. (3) For complex questions, LLaVA-AD first generates <ST> token to initiate the cross-referential reasoning process step by step. Once the <ET> is generated, the model proceeds to formulate the final judgment. This process is illustrated by the pink pathway in Fig.3. Through these active deduction behaviors, our model can allocate more computational resources to challenging tasks.

4.2. Data Strategy

To endow the model with the aforementioned active deduction capability, we especially annotate answers with detailed compositional reasoning steps for complex questions. We utilized GPT-4V [1] for annotating and manually verify the correctness of these thinking steps and filter unreliable ones, resulting in 704 QA pairs with explicit reasoning steps. We further blend these data with samples from LLaVA-Instruct-150K [26] at a 1:1 ratio to obtain the synthesized training dataset with 1,408 samples in total.

Structured reasoning steps annotation. For assumptive reasoning questions, we utilized GPT-4V to create structured, stepwise annotations that illustrate the decomposition process required for accurate responses. We provided GPT-4V with each assumptive question and the corresponding answer, then prompted it to identify distinct steps necessary for reaching the final answer. This annotation process followed a consistent template, which instructed GPT-4V to:

- Identify the primary sub-components of the question that should be answered sequentially.
- Provide specific sub-questions and corresponding answers for each reasoning step.

These structured data, after being wrapped by <ST> and <ET> tokens, provide the model with reliable deductive reasoning samples.

5. Experiments and Results

In this section, we first evaluate the performance of current state-of-the-art MLLMs on MARS-Bench. We implemented 0-shot, 1-shot ICL and 1-shot CoT [35] as our baseline. Next, we evaluate our proposed "Active Deduction". The experiments show that, with minimal impact on general datasets, the reasoning token facilitates the model's reasoning process, significantly improving its performance on assumptive reasoning.

5.1. Experiment setup

Training Details. We utilize pre-trained CLIP ViT-L/14-336 [32] and LLaVA-v1.5-7B [26] as our vision encoder and multimodal large language model, respectively. The tokenizer is extended for two special reasoning tokens, while the embed_tokens and lm_head components are tuned to adapt to the new extended tokenizer. Our model is trained on 8 NVIDIA RTX-4090 with LoRA [14] and utilizes bf16 precision for mixed-precision training. Optimizer AdamW [17] was used with learning rate 5e-5, a cosine decay schedule, and a warm-up ratio of 0.03. Training was conducted for 2 epochs with a batch size of 16.

Dataset. Our training data includes 704 assumptive reasoning problems with finely annotated structured reasoning steps, where reasoning steps are encapsulated using <ST> and <ET> tokens. 176 manually labeled standard VQA

pairs and 528 multi-turn dialogue samples from LLaVA-1.5-Instruct are used as negative examples for conducting extra reasoning steps, which enables the model to learn reasoning tokens while retaining capabilities for both standard VQA tasks and multi-turn dialogue.

Baseline. All baseline models are implemented according to their original setup and evaluated using the strategy described in Sec.3.4. The CoT prompts are based on the proven approach outlined in ScienceQA [28], leveraging 1-shot manually annotated thinking processes as in-context learning examples.

5.2. Baseline performance on MARS-Bench

Our MARS-Bench has posed formidable challenges to existing MLLMs. Tab.1 showcases the performance of various MLLMs on assumptive reasoning tasks from the MARS-Bench. It can be seen that all MLLMs perform well on basic questions, achieving an accuracy of around 80%. For "color" questions, Qwen-VL-Chat even reaches an accuracy of 93.2%. By comparison, a noticeable decline can be observed when evaluating assumptive questions, highlighting the challenge of handling assumptions in reasoning. All open-source models perform close to the level of random guessing (50%). Among the evaluated models, the commercial model GPT-40 leads in overall accuracy for assumptive reasoning scores 486.0, significantly outperforming other MLLMs, indicating its robustness against empirical reasoning traps.

Notably, 1-shot ICL and 1-shot CoT do not significantly enhance the assumptive reasoning ability of 7B-level MLLMs and may even lead to a performance drop in some cases. In Wei et al.'s study [36], models at a certain scale, specifically those exceeding 100B parameters, demonstrated advanced performance when combined with CoT strategies. However, 7B-level models often lack sufficient foundational knowledge and reasoning capabilities, making it challenging for CoT to generate correct reasoning steps and potentially leading to issues like AI hallucinations.

5.3. Performance of Active Deduction

Results on Assumptive Reasoning. Our Active Deduction (AD) method provides a significant boost in performance as shown in Tab.1, with the Active Deduction equipped, LLaVA-AD achieving an assumptive reasoning accuracy of 445.4, up from 369.1 in the baseline LLaVA-1.5 [26]. This improvement of 76.3 points illustrates Active Deduction's efficacy in guiding the model through structured reasoning steps, especially under scenarios that challenge conventional empirical intuition.

Performance gains with Active Deduction vary across categories. Tasks involving count and size see the most substantial improvement, with an accuracy improvement of

Model	Prompt	Count		Color		Size		Shape		Direction		Common		Total	
		acc _b	acca												
Qwen-VL-Chat [5]	0-shot	85.9	50.8	89.0	75.3	71.5	52.1	85.2	54.6	70.3	54.5	79.9	58.1	481.8	345.4
	1-shot	88.4	63.6	93.2	76.3	74.6	62.6	88.9	59.6	74.2	58.8	83.5	68.7	502.8	389.6
	СоТ	88.1	62.0	93.2	76.2	77.6	60.3	90.1	60.2	73.4	57.2	85.6	67.5	508.0	383.4
Monkey [24]	0-shot	88.4	61.3	92.2	74.4	69.1	58.5	85.2	54.6	75.8	51.2	84.9	64.8	495.6	364.8
	1-shot	88.1	58.7	92.2	72.3	77.6	58.5	86.4	54.0	76.6	48.1	82.7	61.9	503.6	353.5
	CoT	87.1	60.9	92.2	73.2	77.6	58.9	86.4	58.3	76.6	49.2	82.7	65.3	502.6	365.8
BLIP2 [23]	0-shot	72.9	53.3	81.7	69.6	67.9	65.3	70.4	50.0	53.9	52.3	81.3	60.1	428.1	350.6
	1-shot	72.7	43.6	81.5	53.0	69.2	49.2	72.3	37.4	51.0	41.8	82.8	38.7	429.5	263.7
	CoT	73.3	50.7	80.5	52.4	68.6	49.2	69.5	36.4	54.8	41.4	81.3	38.0	428.0	268.1
InstructBLIP [8]	0-shot	84.3	67.4	89.5	72.6	61.8	55.9	75.3	55.9	58.6	53.7	80.6	61.9	450.1	367.4
	1-shot	84.1	49.5	88.7	52.8	61.5	50.1	75.9	39.5	59.4	43.2	78.3	41.2	447.9	276.3
	CoT	85.4	48.4	89.5	55.1	61.7	47.6	76.0	40.7	58.3	48.0	80.3	41.4	451.3	281.3
xGen-MM [37]	0-shot	86.2	73.3	81.7	70.4	63.0	56.4	67.9	71.6	64.1	52.2	69.8	61.7	432.7	385.6
	1-shot	85.5	77.9	83.3	68.6	66.1	57.0	67.9	71.3	69.5	51.4	69.8	62.1	442.1	388.3
	CoT	85.5	78.9	83.3	67.7	66.1	56.4	69.1	72.5	71.1	50.6	68.4	61.7	443.5	387.8
InfMLLM [43]	0-shot	90.6	64.1	93.2	72.8	67.3	55.3	76.5	69.1	75.0	56.6	84.2	67.5	486.7	385.4
	1-shot	90.8	61.2	93.8	72.0	66.8	54.4	75.6	69.4	74.7	57.0	83.8	66.4	485.4	380.5
	CoT	91.1	59.8	92.3	73.3	68.9	54.2	75.9	67.6	75.5	57.0	85.4	66.2	489.0	378.2
LLaVA-1.5 [26]	0-shot	86.2	50.6	90.6	71.9	60.6	53.2	71.6	72.5	68.0	57.0	76.3	63.9	453.2	369.1
	1-shot	79.2	52.6	86.9	70.8	58.2	53.0	51.9	77.2	68.8	55.9	74.8	63.5	419.8	372.9
	CoT	79.2	54.1	90.0	73.2	55.8	55.0	58.0	77.8	67.2	57.4	76.3	63.3	426.5	380.8
GPT-4o [1]	N/A	90.9	91.7	94.2	87.3	88.9	87.4	88.2	80.3	85.2	66.0	87.6	73.4	535.0	486.0
LLaVA-AD (Ours)	N/A	81.8	80.6	89.5	78.1	77.0	73.0	77.8	82.1	71.1	59.8	82.7	71.8	479.9	445.4 (+76.3)

Table 1. **Performance of prevalent MLLMs on six tasks within our proposed MARS-Bench.** Here, acc_b represents the accuracy for correctly answering basic questions, acc_a denotes the accuracy for correctly answering assumptive questions. We compared 7 open source models and one commercial model, and we bolded the best performance of the open source models on assumptive question.

Method	VQAv2	VisWiz	GQA	MME	MM-Vet	MMBench	SEED	MARS-Assum.
BLIP-2 [23]	65.0	19.6	41.0	1293.8	22.4	-	49.7	350.6
InstructBLIP [8]	-	34.5	49.2	-	26.2	36.0	58.8	367.4
MiniGPT-4 [44]	-	-	-	581.7	22.1	24.3	47.4	341.2
Qwen-VL-Chat [5]	78.2	38.9	57.5	1487.5	-	60.6	65.4	345.4
LLaVA-AD (Ours)	77.3	50.6	60.3	1471.5	34.3	63.3	64.1	445.4

Table 2. **Results on prevalent VQA benchmarks.** We employ MMBench-en-dev, SEED-Bench-img, MME-test for evaluation. MARS-Assum. donates the total score of assumptive questions on our MARS-Bench, and we use "-" to denote the performance which are not provided in their paper.

30 and 19.8, respectively. For instance, count tasks require the model to handle hypothetical additions or removals of items accurately, a challenge well-suited to AD's stepwise deduction approach. The shape tasks, involving transformations or deformations, similarly benefit from the method's structured breakdown, which helps the model manage complex spatial changes logically. While, the effectiveness of AD relies on the foundational capabilities of the underlying model, meaning that improvement is ultimately constrained by the model's base competence in each category. There are limited gains for direction tasks, since current models'

directional perception is bounded, which restricts its ability to produce sufficient and accurate reasoning steps. The common sense tasks, which involve general knowledge applications under presupposition scenarios, see a satisfactory improvement, suggesting that our Active Deduction method is effective at guiding reasoning in knowledge-driven contexts when the task complexity aligns with the model's inherent capabilities.

Performance on standard VQA benchmarks. To examine general visual understanding and instruction following of our model, we measured its accuracy on standard

VQA tasks without assumptive reasoning components. We followed common practices by conducting assessments on 7 widely used benchmarks: VQAv2 [11], VisWiz [13], GQA [15], MME [9], MM-Vet [39], MMBench [27], and SEED-Bench [22]. As shown in Tab.2, our LLaVA-AD achieves comparable results to state-of-the-art MLLMs in VQA tasks, while also enhancing its capabilities in systematic reasoning, particularly in assumptive reasoning.

5.4. Ablation Study

We conducted an ablation study to isolate the effects of the <ST> and <ET> tokens and structured reasoning steps, both integral to the AD framework. The LLaVA-AD w/o token model is trained on the same finely annotated structured reasoning steps without <ST> and <ET> tokens, with all training configs are same.

Method	GQA	MM-Vet	MARS-B	MARS-A
Qwen-VL-Chat [5] LLaVA-1.5 [26]	57.5 62.0	31.1	481.8 453.2	345.4 369.1
LLaVA-AD w/o token	59.4	27.5	431.2	447.1
LLaVA-AD w/ token	60.2	34.3	479.9	445.4

Table 3. Comparison of Models across Various Benchmarks. LLaVA-AD w/ token is trained on the same dataset without reasoning token wrapped. MARS-B. and MARS-A. represents the total score of basic questions and assumptive questions on MARS-Bench, respectively.

Impact on reasoning performance. We conducted an ablation study to evaluate the impact of introducing reasoning tokens on model's performance across MARS-Bench and two additional general-purpose datasets. From Tab.3, it is evident that incorporating the reasoning tokens improves the model's performance on GQA [15] tasks, offering a modest advantage over the model without the token. In tasks assessed by MM-Vet [39], a large language model-based evaluator for open-ended outputs, model with reasoning tokens showed a more substantial improvement, suggesting that the reasoning tokens effectively enhance the model's capability for systematic, open-ended reasoning. LLaVA-AD w/o token demonstrates an advantage in assumptive reasoning tasks, due to its tendency to adopt a direct output pattern associated with deductive reasoning, which excels in scenarios requiring assumptions. While, the use of reasoning tokens enables model to balance performance, reducing unnecessary reasoning steps for basic questions and significantly boosting results across other VQA benchmarks with minimal trade-offs in assumptive reasoning tasks.

Impact on problem difficulty determination. Accurate difficulty prediction is essential to optimize reasoning. Misjudging complexity leads to unnecessary processing, increasing costs and potentially reducing performance, as

Method	De.%Basic↓	Em.%Assum. ↓	Avg. E.R.↓
LLaVA-AD w/o token	17.9%	5.8%	11.9%
LLaVA-AD w/ token	4.3%	6.1%	5.2%

Table 4. Impact of reasoning token on problem difficulty determination. Here, De.%Basic, Em.%Assum. and Avg. E.R. means the ratio of deductive reasoning in basic situation, empirical reasoning in assumptive question, and the average error rate, respectively.

seen in Tab.3. Our evaluation on MARS-Bench examines whether reasoning tokens are used appropriately, avoiding extra steps for basic questions and activating deduction for assumptive ones. Tab.4 shows that LLaVA-AD w/o tokens often over-processes simple questions, leading to its performance drop in Tab.3. Introducing reasoning tokens improves problem difficulty determination, which is crucial for accurately solving problems of varying complexity.

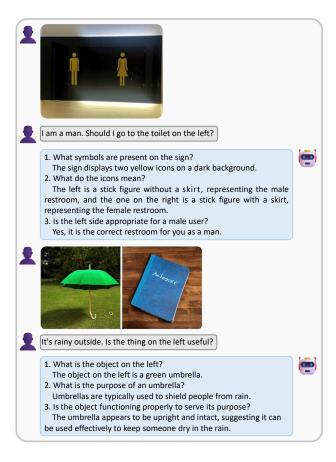


Figure 4. The generalizability of the LLaVA-AD beyond the domain. The model has zero-shot capability and can activate deduction reasoning on other reasoning problems.

Generalizability beyond the domain. LLaVA-AD demonstrates a certain degree of generalization ability across other

reasoning tasks. As shown in Fig.4, it can tackle general reasoning by decomposing the queries into a sequence of sub-questions, which allows it to systematically extract information from both images and provided conditions. This approach enables the model to mimic human-like logical progression even in unfamiliar contexts.

6. Conclusion

In conclusion, we presented MARS-Bench, a benchmark targeting Assumptive Reasoning in Multimodal Large Language Models (MLLMs), and introduced the Active Deduction (AD) method to enhance these models' reasoning capabilities. Our findings show that current MLLMs struggle with systematic reasoning problems like assumptive reasoning. Besides, Active Deduction substantially improves MLLMs' performance on assumptive tasks by guiding structured, stepwise deductive reasoning without sacrificing performance on simpler queries. This work underscores the limitations of empirical reasoning in current MLLMs and suggests a potential approach for fostering more human-like reasoning in systematic, presuppositions complex scenarios.

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