

LLaVA-o1: Let Vision Language Models Reason Step-by-Step

Guowei Xu² Peng Jin^{1,3,4} Li Hao^{1,3,4} Yibing Song⁵ Lichao Sun⁶ Li Yuan^{1,3,4*}

¹School of Electronic and Computer Engineering, Peking University

²Institute for Interdisciplinary Information Sciences, Tsinghua University ³Peng Cheng Laboratory

⁴AI for Science (AI4S)-Preferred Program, Peking University Shenzhen Graduate School

⁵Alibaba DAMO Academy ⁶Computer Science and Engineering, Lehigh University

*Correspondence: yuanli-ece@pku.edu.cn

Abstract

Large language models have demonstrated substantial advancements in reasoning capabilities, particularly through inference-time scaling, as illustrated by models such as OpenAI’s o1. However, current Vision-Language Models (VLMs) often struggle to perform systematic and structured reasoning, especially when handling complex visual question-answering tasks. In this work, we introduce LLaVA-o1¹, a novel VLM designed to conduct autonomous multistage reasoning. Unlike chain-of-thought prompting, LLaVA-o1 independently engages in sequential stages of summarization, visual interpretation, logical reasoning, and conclusion generation. This structured approach enables LLaVA-o1 to achieve marked improvements in precision on reasoning-intensive tasks. To accomplish this, we compile the LLaVA-o1-100k dataset, integrating samples from various visual question answering sources and providing structured reasoning annotations. Besides, we propose an inference-time stage-level beam search method, which enables effective inference-time scaling. Remarkably, with only 100k training samples and a simple yet effective inference time scaling method, LLaVA-o1 not only outperforms its base model by **8.9%** on a wide range of multimodal reasoning benchmarks, but also surpasses the performance of larger and even closed-source models, such as Gemini-1.5-pro, GPT-4o-mini, and Llama-3.2-90B-Vision-Instruct.

1. Introduction

Large language models, represented by OpenAI o1 [63], demonstrate strong capabilities for systematic and in-depth reasoning, validating the efficacy of inference-time scaling

¹There are similar names of recent VLM works. To clarify, LLaVA-o1 is built upon Llama-3.2-Vision model [40], rather than LLaVA [32].

6 Multimodal Reasoning Benchmarks

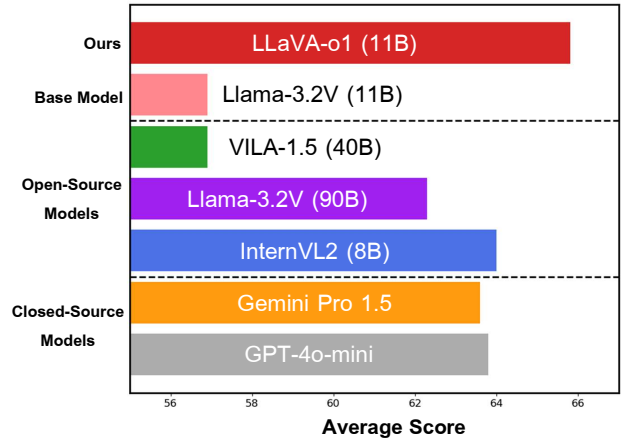


Figure 1. **Performance of LLaVA-o1 and other models across six multimodal reasoning benchmarks.** Although LLaVA-o1 is fine-tuned from the Llama-3.2-11B-Vision-Instruct [40] model (which has the lowest average score), it outperforms many larger open-source models and even some closed-source models. Detailed benchmark results are shown in Table 7.

for language models [47]. However, vision is equally important for enabling models to fully understand the world and extend their cognitive abilities [6]. Therefore, developing a multimodal model that integrates both language and vision while facilitating effective, systematic, and deep reasoning holds substantial significance.

Early open-source vision language models (VLMs) mainly employ a direct prediction approach [21, 30, 32], generating brief answers immediately in response to a question. The main limitation of this direct-response paradigm is its lack of a structured reasoning process, making it less effective for tasks demanding logical reasoning [62]. Recent studies have shown that incorporating Chain-of-Thought (CoT) reasoning encourages the model to reason step by

Example 1: Reasoning Problems



Question: Subtract all tiny shiny balls. Subtract all purple objects. How many objects are left?

Options: A. 4, B. 8, C. 2, D. 6

Answer from Llama-3.2-11B-Vision-Instruct:

To determine the correct answer, we need to follow the instructions provided.

The first instruction is to subtract all tiny shiny balls. Since there are **three tiny shiny balls** in the image, we would be left with no shiny balls after performing this action. The second instruction is to subtract all purple objects. However, upon closer inspection, it becomes apparent that there are **no shiny purple objects present in the image**. Therefore, we cannot subtract any purple objects.

Given that we have already removed all the tiny shiny balls and there were no purple objects to begin with, the correct answer is C. 2, as initially, **there were 2 purple objects, but they are not to be subtracted** according to the instruction.

Answer from LLaVA-o1:

Summary stage: What's the problem? What should I do?

<SUMMARY> I will examine the image to identify and count all the objects, **focusing on the tiny shiny balls and purple objects**. Then, I will subtract these objects from the total count and **determine the number of remaining objects**. </SUMMARY>

Caption stage: What can I know from the image?

<CAPTION> The image shows various 3D geometric shapes on a flat surface, including spheres, cubes, and cylinders in different colors. Notably, there are **small shiny green spheres and a purple cylinder**. </CAPTION>

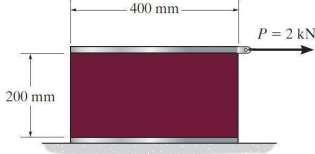
Reasoning stage: How to solve the problem step-by-step?

<REASONING> First, I will count all the objects in the image: there are **10 objects in total**. Next, I will identify and subtract the tiny shiny balls. There is **one small shiny green sphere**. Then, I will identify and subtract the purple objects. There is **one purple cylinder**. By subtracting the two objects (the shiny ball and the purple cylinder) from the total, I find that **8 objects remain**. </REASONING>

Conclusion stage: What is the final answer?

<CONCLUSION> B </CONCLUSION>

Example 2: Science Problems



Question:

An acetal polymer block is fixed to the rigid plates at its top and bottom surfaces. If the top plate displaces 2 mm horizontally when it is subjected to a horizontal force $P=2$ kN, determine the shear modulus of the polymer. The width of the block is 100 mm. Assume that the polymer is linearly elastic and use small angle analysis.

Options:

A: 15 MPa, B: 5 MPa, C: 20 MPa, D: 2 MPa

Answer from Llama-3.2-11B-Vision-Instruct:

To determine the shear modulus of the polymer, we can use the formula for shear modulus in a small angle analysis:

$$G = \frac{F}{\Delta x} \frac{L}{A}$$

where G is the shear modulus, F is the applied force, A is the area of the block, and Δx is the shear strain.

Given that the top plate of the block displaces horizontally by 2 mm when subjected to a horizontal force of 2 kN, we can calculate the shear strain Δx . Since the displacement is horizontal and **the original length of the block is 400 mm**, the shear strain Δx is:

$$\Delta x = \frac{F}{G} \frac{L}{A} \Rightarrow \Delta x = \frac{2000 \text{ N}}{G} \frac{400 \text{ mm}}{100 \text{ mm} \times 200 \text{ mm}}$$

Next, we calculate the area A of the block. The width of the block is given as 100 mm, and assuming **the height of the block is also 200 mm** (as given in the image analysis), the area A is:

$$A = 100 \text{ mm} \times 200 \text{ mm} = 20000 \text{ mm}^2$$

Now, we can substitute these values into the formula for shear modulus:

$$G = \frac{F}{\Delta x} \frac{L}{A} = \frac{2000 \text{ N}}{2 \text{ mm}} \frac{400 \text{ mm}}{20000 \text{ mm}^2} = 20 \text{ MPa}$$

Therefore, the correct answer is C: 20 MPa.

Answer from LLaVA-o1:

Summary stage: What's the problem? What should I do?

<SUMMARY> To solve the problem, I will **determine the shear modulus** of the acetal polymer block using the relationship between the applied force, displacement, and dimensions of the block. I will **use the formula for shear modulus** and calculate the result. </SUMMARY>

Caption stage: What can I know from the image?

<CAPTION> The image shows a rectangular block of acetal polymer fixed between two rigid plates. The top plate moves horizontally by 2 mm when a force $P = 2 \text{ kN}$ is applied. The block's dimensions are given as **400 mm in length, 200 mm in height, and 100 mm in width**. </CAPTION>

Reasoning stage: How to solve the problem step-by-step?

<REASONING> The shear modulus G of the polymer can be calculated using the formula:

$$G = \frac{F}{\Delta x} \frac{L}{A}$$

where:

- F is the applied force (2 kN),

- A is the area of the block's top surface (100 mm x 400 mm = 40,000 mm²),

- Δx is the horizontal displacement (2 mm),

- L is the height of the block (200 mm).

First, convert the force to Newtons: $F = 2 \text{ kN} = 2000 \text{ N}$.

Next, calculate the shear modulus:

$$G = \frac{2000}{2} \frac{200}{40000} = 20 \text{ MPa}$$

$$G = 20 \text{ MPa}$$

$$G = 20 \text{ MPa}$$

<REASONING>

Conclusion stage: What is the final answer?

<CONCLUSION> B. 5 MPa </CONCLUSION>

Figure 2. **Comparison of the base model and LLaVA-o1.** As shown, the base model Llama-3.2-11B-Vision-Instruct exhibits obvious flaws in reasoning, with several errors occurring throughout the reasoning process. In contrast, LLaVA-o1 begins by outlining the problem, interprets relevant information from the image, proceeds with a step-by-step reasoning process, and ultimately reaches a well-supported conclusion.

step, significantly improving its question-answering capabilities [52]. However, even with CoT reasoning, most VLMs frequently produce errors or hallucinated outputs during the reasoning progress [24, 31, 50].

Our findings suggest that a significant cause of these issues is the insufficiently systematic and structured nature of the reasoning process in existing VLMs. Specifically, by referring **systematic**, we mean that the model does not generate a direct reasoning chain but instead engages in multistage reasoning. **Structured**, on the other hand, refers to the model's ability to clearly identify the reasoning stage it is in and understand the primary task to be addressed at each stage. We observe that VLMs often initiate responses without adequately organizing the problem and the available information. Moreover, they frequently deviate from a logical reasoning toward conclusions, instead of presenting a conclusion prematurely and subsequently attempting to justify it. Given that language models generate responses token-by-token, once an erroneous conclusion is introduced, the model typically continues along a flawed reasoning path.

OpenAI o1 [63] addresses these issues effectively by enabling the model to independently engage in systematic and structured reasoning through language. Building on this insight, we design LLaVA-o1. While the commu-

nity has made some preliminary explorations into the underlying mechanisms of OpenAI o1 [42, 54], the model remains a black box, with its technical details largely unknown. This work demonstrates a potential way to enhance a model's ability to perform autonomous, stage-by-stage reasoning by employing supervised fine-tuning. Specifically, LLaVA-o1 is capable of generating four distinct stages: summary, caption, reasoning, and conclusion. Each stage serves a unique purpose in the reasoning process.

- **Summary:** A brief outline in which the model summarizes the forthcoming task.
- **Caption:** A description of the relevant parts of an image (if present), focusing on elements related to the question.
- **Reasoning:** A detailed analysis in which the model systematically considers the question.
- **Conclusion:** A concise summary of the answer, providing a final response based on the preceding reasoning.

To enhance the understanding of CoT processes in LLM, LLaVA-o1 marks each stage with a dedicated tag (e.g., <SUMMARY> . . . </SUMMARY>) to denote the beginning and end of each stage. Those taggings enable the model to maintain clarity throughout the reasoning process. Unlike traditional CoT reasoning, which allows the model to think freely, our method promotes structured thinking by first or-

ganizing the problem and known information, followed by a detailed thought process, and then deriving a conclusion. To achieve this, we construct the LLaVA-o1-100k dataset by generating responses stage by stage using GPT-4o [3] and then train the model using supervised fine-tuning.

The structured reasoning in LLaVA-o1 also facilitates efficient inference time scaling. In contrast to conventional scaling methods, such as best-of-N sampling [4, 51] and sentence-level beam search [16, 49], LLaVA-o1 employs a novel stage-level beam search method that generates multiple candidate results at each stage and selects the best one to continue the generation process.

We conduct experiments on several multimodal reasoning benchmarks, including MMStar [9], MMBench [33], MMVet [60], MathVista [35], AI2D [23], and Hallusion-Bench [17], and observed that LLaVA-o1 offers two primary advantages: First, enabling the model to perform structured reasoning independently substantially outperforms traditional CoT prompting, particularly in complex reasoning tasks that require systematic analysis. Second, our stage-level beam search method is scalable and improves performance reliability, making it more effective in achieving stable and accurate results. Our contributions are summarized as follows:

- We introduce LLaVA-o1, a visual language model designed for systematic reasoning, demonstrating exceptional performance on tasks that require structured thinking and reasoning.
- We demonstrate that LLaVA-o1, using stage-level beam search, is inference-time scalable. This means that with increased computational resources, the performance of our approach can be further enhanced, making it applicable to more complex tasks and scenarios.
- Extensive experiments on various benchmarks demonstrate that our method achieves superior performance relative to larger and closed-source models, underscoring the effectiveness of LLaVA-o1 for multimodal reasoning.

2. Related Works

2.1. Visual reasoning with large language models

Visual reasoning demands the model’s visual perception capability and the high-level cognition ability [22, 37]. Several tasks have been applied to evaluate the visual reasoning ability of VLMs, including VQA [20, 26] requiring models to answer from visual contents and textual questions, and Visual Entailment [48] requiring models to determine the consistency of text descriptions and visual contents, etc.

Traditional vision-language models employ neural symbolic approaches [5, 11] to explicitly model the visual reasoning process. With the development of LLMs, vision-language models leverage the advanced reasoning abilities of LLMs to interpret visual tasks [32, 59]. Some

vision-language models enhance visual reasoning by optimizing the visual encoding strategy [21, 29, 32] to produce cognition-focused visual tokens. Some VLMs, e.g. VIS-PROG [18], position the LLM as a decision-making agent, enhancing visual reasoning under complex visual tasks by invoking various task-specific visual modules. Additionally, instructing learning techniques for language models, including prompt tuning [61], in-context learning, and supervised fine-tuning [46], also contribute to improvements in visual reasoning capabilities.

2.2. Chain-of-thought in large language models

Chain-of-thought prompting offers a step-by-step reasoning trajectory when LLM faces hard questions including commonsense reasoning [44], logical reasoning [27, 55], etc. Specifically, CoT prompting decomposes the question into a group of reasoning steps and builds a chain to guide the model to generate the results of complex problems step-by-step [12]. Recent works have demonstrated [15, 52] that CoT prompting substantially improves the LLM’s capability on both reasoning and interpretability.

2.3. Inference time scaling

Existing methods for inference time scaling fall into two main categories: those that rely on an external verifier for selection [25, 56] and those that operate independently of any external verifier [19, 53]. The external verifier selection methods can be employed in prevalent methods. On the other hand, inference time scaling methods that do not rely on an external verifier primarily include majority voting [19], best-of-N search [4, 51], and sentence-level beam search [16, 49]. Majority voting is effective for certain types of problems that have standard answers, but it is not suitable for open-ended tasks. Best-of-N search generates N complete answers and allows the model to select the best response. However, generating full answers for selection can complicate the evaluation of their accuracy. Sentence-level beam search generates multiple candidate sentences, selects the best one, and iteratively continues this process. However, this approach operates at too granular a level, which makes it difficult for the model to effectively assess the quality of its responses on a per-sentence basis.

3. Proposed Method

Our LLaVA-o1 facilitates a progressive, step-by-step reasoning process that enhances the reasoning capabilities of Vision-Language Models (VLMs) and allows for effective inference time scaling [47]. Using structured thinking, LLaVA-o1 achieves a systematic and efficient reasoning process. Its inference-time reasoning framework enables it to outperform existing methods in inference time scalability. This design ensures both robustness and accuracy in complex tasks requiring reasoning, which separates it

from traditional approaches. Figure 1 illustrates our general framework of the reasoning process.

3.1. Enhancing Reasoning Capability through Structured Thinking

Our goal during training time is to develop a visual language model capable of extended chains of reasoning, allowing it to engage in systematic and in-depth reasoning.

3.1.1. Reasoning Stages

Our proposed model, LLaVA-o1, decomposes the answer generation process into four structured reasoning stages:

- **Summary Stage.** In this initial phase, LLaVA-o1 provides a high-level summary interpretation of the question, outlining the primary aspects of the problem it intends to address.
- **Caption Stage.** If an image is present, LLaVA-o1 offers a concise overview of the visual elements relevant to the question, helping to understand multimodal input.
- **Reasoning Stage.** Building on the initial summary, LLaVA-o1 conducts structured, logical reasoning to derive a preliminary answer.
- **Conclusion Stage.** In this final stage, LLaVA-o1 synthesizes an answer based on the preceding reasoning. Here, the output from the conclusion stage is the direct response provided to the user, while the prior three stages are internal "hidden stages" representing LLaVA-o1's reasoning process. The output at this stage adapts to the user's requirements: for instance, if the user requests a brief answer, the conclusion will be concise; if detailed explanations are desired, the conclusion provides a thorough, comprehensive response.

Each stage is initiated at the model's discretion, without external prompt engineering frameworks or additional prompting. Specifically, we provide the model with four pairs of special tags: `<SUMMARY></SUMMARY>`, `<CAPTION></CAPTION>`, `<REASONING></REASONING>`, and `<CONCLUSION></CONCLUSION>`. These tags correspond to summarizing the response approach, describing relevant image content, conducting reasoning, and preparing a final answer, respectively.

Upon training, the model autonomously selects these tags as needed, activating each stage based on its own judgment. As with OpenAI o1 [63], all stages are completed by the model in a single inference pass. This structured approach enables the model to independently manage its reasoning process, improving its adaptability and performance on complex reasoning tasks.

3.1.2. Data Preparation and Model Training

Most existing VQA datasets lack detailed reasoning processes needed to train the LLaVA-o1 model. Therefore, we compile a new dataset, integrating samples from several widely used VQA datasets, resulting in a total of 99k

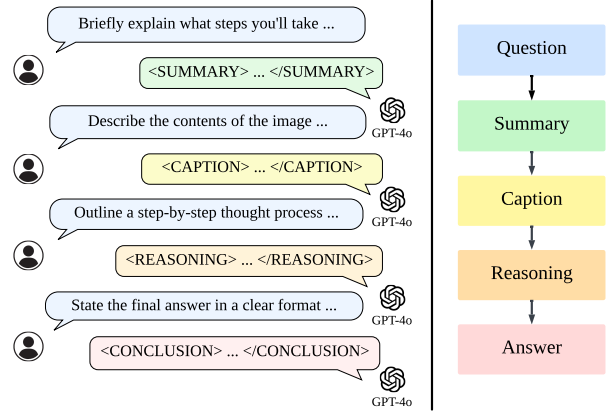


Figure 3. **Process flow for generating the LLaVA-o1-100k dataset.** We prompt GPT-4o to generate responses in separate stages, and filter its outputs to ensure quality.

Dataset	Type	Size
ShareGPT4V [8]	General VQA	31.3k
ChartQA [38]	General VQA	17.2k
A-OKVQA [45]	General VQA	16.1k
AI2D [23]	Science-Targeted VQA	11.4k
GeoQA+ [7]	Science-Targeted VQA	11.4k
ScienceQA [34]	Science-Targeted VQA	5.6k
DocVQA [39]	General VQA	4.0k
PISC [28]	General VQA	1.0k
CLEVR [22]	General VQA	0.5k
CLEVR-Math [13]	Science-Targeted VQA	0.5k

Table 1. The number of samples selected from each benchmark.

image QA pairs (each pair may include one or multiple rounds of questioning). As shown in Figure 3, since no multimodal model currently exists that can directly produce systematic, structured reasoning, we use GPT-4o [3] to generate detailed reasoning processes, including summary, caption, reasoning, and conclusion, and compile these into the LLaVA-o1-100k dataset, which we plan to release for public use. We include data from both general-purpose VQA datasets and science-targeted VQA datasets specified below:

General VQA Datasets. We include several general-purpose VQA datasets with distinct focuses. **ShareGPT4V** [8] provides multi-turn question-answering data from GPT-4V [57] interactions. **ChartQA** [38] focuses on interpreting charts and graphs. **A-OKVQA** [45] emphasizes external knowledge beyond visible content. **DocVQA** [39] involves document-based questions requiring textual comprehension. We also include **PISC** [28] to understand social relationships, and **CLEVR** [22] to address object properties, spatial relationships, and counting tasks.

Science-Targeted VQA Datasets. These datasets include **GeoQA+** [7] for geometric reasoning, along with **AI2D**

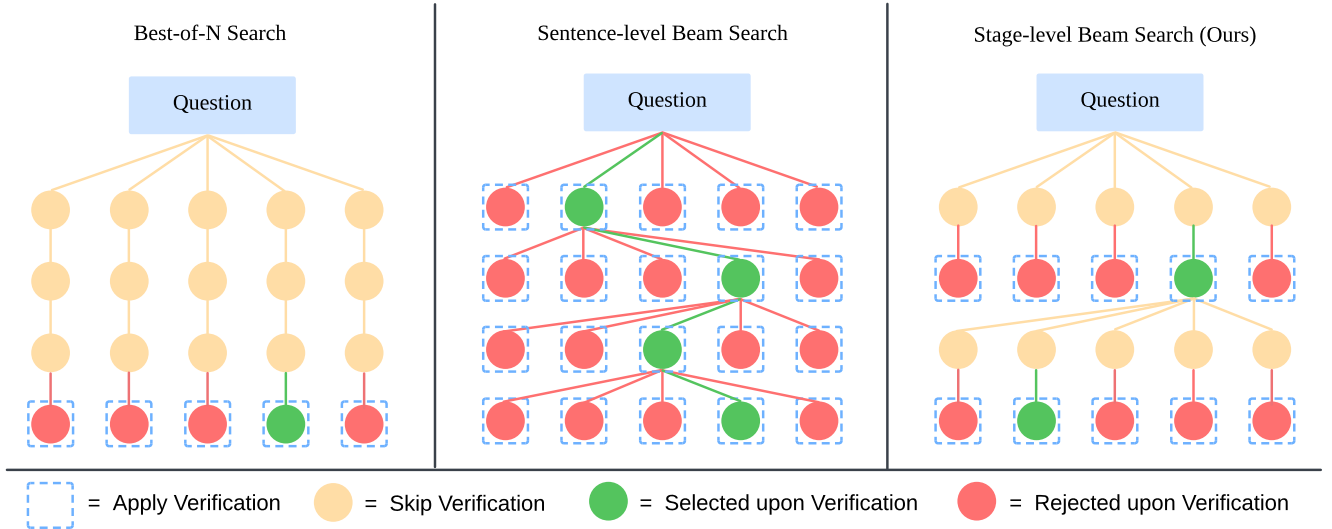


Figure 4. **An illustration of inference approaches.** Best-of-N search generates N complete responses and selects the best one among them; Sentence-level Beam Search generates multiple candidate options for each sentence and chooses the best one. In contrast, our Stage-level Beam Search generates candidates for each reasoning stage (e.g., summary, caption, reasoning, and conclusion) and selects the best option at each stage. Best-of-N search operates at a coarse level, while Sentence-level Beam Search is overly granular, and our method achieves an optimal balance and achieves the best performance.


 <p>Question: What is the total price for a bottle of Merlot and a bottle of Cabernet shown in the image?</p>	<p><SUMMARY> To solve the problem, I will first identify the prices of the Merlot and Cabernet bottles shown in the image. Then, I will add these prices together to find the total cost. </SUMMARY></p> <p><CAPTION> The image displays three wine bottles with their respective prices. The first bottle is a Northstar Merlot from Columbia Valley, priced at \$139.99. The second bottle is a Moët & Chandon Imperial from France, priced at \$114.99. The third bottle is a Chateau St. Michelle Cold Creek Cabernet from Columbia Valley, priced at \$109.99. </CAPTION></p> <p>Answer without inference scaling:</p> <p><REASONING> To find the total price for a bottle of Merlot and a bottle of Cabernet, I will identify the prices of these two specific wines. The Merlot is priced at \$139.99, and the Cabernet is priced at \$109.99. Adding these two prices together will give the total cost for one bottle of each. </REASONING></p> <p><CONCLUSION> 149.99 </CONCLUSION></p>	<p>Answer from beam search:</p> <p><REASONING> To find the total price for a bottle of Merlot and a bottle of Cabernet, I will add the price of the Northstar Merlot (\$139.99) to the price of the Chateau St Michelle Cold Creek Cabernet (\$109.99). The calculation is as follows: \$139.99 + \$109.99 = \$249.98. </REASONING></p> <p><CONCLUSION> The total price for a bottle of Merlot and a bottle of Cabernet shown in the image is \$249.98. </CONCLUSION></p>
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Figure 5. **Comparison of LLaVA-o1 performance with and without stage-level beam search.** Our stage-level beam search is effective in selecting better reasoning during model inference.

[23] and ScienceQA [34], which target scientific questions. CLEVR-Math [13], an extension of CLEVR, focuses on arithmetic analysis in visual contexts. Table 1 shows the number of QA pairs selected from each dataset.

Model Training. The LLaVA-o1-100k dataset we construct can be used to further conduct Supervised Fine-Tuning (SFT) on any existing model to enhance reasoning capabilities. In this work, we select the Llama-3.2-11B-Vision-Instruct [40] model as the base model, and perform a full parameter fine-tuning by using the LLaVA-o1-100k dataset. The training is conducted on a single node with 8 H100 GPUs.

3.2. Effective Inference Time Scaling using Stage-level Beam Search

After training, our objective is to further enhance the model’s reasoning ability during inference. Specifically, we leverage the stage-based outputs of LLaVA-o1, which provides an ideal granularity for inference time scaling. Our method follows the steps below:

- Sample N responses for the first stage in the solution.
- Randomly sample 2 responses and let the model determine which is better, keeping the better response.
- Repeat for $N - 1$ times, retaining the best response.
- Sample N responses for the next stage, then repeat steps 2-4 until all stages are processed.

Notably, **it is the structured output design of LLaVA-o1 that makes this approach feasible**, enabling efficient and accurate verification at each stage. This validates the effectiveness of structured output in improving inference time scaling. An illustration of the three approaches is shown in Figure 4.

We provide an example in Figure 5. When inference time scaling is not applied, although the model generates correct reasoning steps, it fails to arrive at a concrete answer during the reasoning process. This causes the model to make a guess in the conclusion phase, leading to an incorrect result. In contrast, with inference time scaling, the model retains the reasoning steps leading to the final result, ensuring the correctness of the answer.

Model	MMStar	MMBench	MMVet	MathVista	AI2D	Hallusion	Average
Base Model							
Llama-3.2-11B-Vision-Instruct	49.8	65.8	57.6	48.6	77.3	40.3	56.6
Our Models							
LLaVA-o1 (with Direct Training)	54.3	76.2	49.9	49.5	91.4	42.9	60.7
LLaVA-o1 (w/o Structured Tags)	55.7	74.2	57.0	54.1	87.2	45.0	62.2
LLaVA-o1	57.6	75.0	60.3	54.8	85.7	47.8	63.5

Table 2. **Experimental results of different models on the benchmark.** Here, LLaVA-o1 (with Direct Training) refers to the model trained directly on the original VQA dataset’s Q&A pairs, while LLaVA-o1 (w/o Structured Tags) represents the model trained on the LLaVA-o1-100k dataset with the structured tags removed. LLaVA-o1 refers to the model trained on the complete LLaVA-o1-100k dataset, including the structured tags.

Model	CP	FP	IR	LR	Math	Science & Technology	Average
Base Model							
Llama-3.2-11B-Vision-Instruct	66.0	46.4	57.6	50.8	45.2	32.8	49.8
Our Models							
LLaVA-o1 (with Direct Training)	68.4	48.0	65.6	52.0	51.6	40.0	54.3
LLaVA-o1 (w/o Structured Tags)	68.4	48.0	60.0	55.2	64.4	38.0	55.7
LLaVA-o1	68.8	46.8	63.2	58.0	64.0	44.8	57.6

Table 3. **Performance of different models on the MMStar benchmark across various skill areas.** Here, CP represents coarse perception, FP represents fine-grained perception, IR represents instance reasoning, and LR represents logical reasoning. As shown in the table, our model demonstrates substantial improvement over the base model in instance reasoning, logical reasoning, math, and science & technology, indicating that structured reasoning can significantly enhance the model’s reasoning capabilities.

4. Post-Training Performance

In this section, we compare LLaVA-o1 with the base model, Llama-3.2-11B-Vision-Instruct, on six commonly used multimodal benchmarks to demonstrate the effectiveness of our approach during the training phase. Following this comparison, we conduct ablation studies to evaluate the contribution of each component within our method, addressing the following three key questions: (1) Is our LLaVA-o1-100k dataset more effective than directly using the original dataset’s Q&A pairs? (2) What is the impact of structured tags on the performance? Specifically, we explore whether LLaVA-o1 can function without tags by implicitly segmenting different stages of the response. (3) In which specific areas does our model show the most improvement compared to the base model, and does it genuinely enhance reasoning capabilities?

4.1. Experimental Setup

We selected six widely used and challenging benchmarks for our experiments: MMStar [9], MMBench V1.1 [33], MMVet [60], MathVista [35], AI2D [23], and HallusionBench [17]. MMStar, MMBench, and MMVet primarily evaluate the general visual question-answering capabilities of models, while MathVista, and AI2D focus on models’ proficiency in mathematical and scientific reasoning. HallusionBench specifically assesses the models’ handling of language hallucinations and visual illusions. For MMBench, we use the V1.1 version of the test set, MathVista is

evaluated using the testmini set, and the remaining datasets each have a single test set. To ensure fairness and reproducibility, all evaluations are conducted using VLMEvalKit [14], an open-source evaluation toolkit for large vision-language models. The performance metrics of all baseline models are derived from VLMEvalKit’s testing results [1].

4.2. Benchmark Results

We found that LLaVA-o1 achieves significant performance improvements, despite using only 100k data. According to Table 2, compared to the base model, Llama-3.2-11B-Vision-Instruct, LLaVA-o1 demonstrates notable improvements across general VQA, mathematical reasoning, scientific VQA, and hallucination control tasks, with an average benchmark score increase of **6.9%**, thereby validating the effectiveness of our approach.

4.3. Ablation Study

Effectiveness of LLaVA-o1-100k Compared to Original Datasets. To demonstrate the effectiveness of our improved LLaVA-o1-100k dataset, we present a comparison between LLaVA-o1 and the model trained on the original Q&A pairs across different benchmarks in Table 2. Although the model trained directly on the original Q&A pairs shows some overall improvement on the base model, its average performance remains significantly lower. In particular, on the MMVet benchmark, which requires more detailed responses, its performance is even worse than the base

Model	MMStar	MMBench	MMVet	MathVista	AI2D	Hallusion	Average
Base Model							
Llama-3.2-11B-Vision-Instruct	49.8	65.8	57.6	48.6	77.3	40.3	56.6
Our Models							
LLaVA-o1	57.6	75.0	60.3	54.8	85.7	47.8	63.5
LLaVA-o1(BS = 2)	58.1	75.6	61.7	56.1	87.5	48.2	64.5

Table 4. **Experimental results during inference time.** LLaVA-o1 (BS = 2) denotes the model using stage-level beam search with a beam size of 2. The results show that stage-level beam search can achieve further significant performance improvements.

Method	Number of Beam	MMVet Score
No Inference Scaling	1	60.3
Best-of-N Search	10	60.9
Sentence-level Beam Search	2	58.4
Stage-level Beam Search	4	62.9

Table 5. **Comparison to Baseline Methods.** Our stage-level beam search outperforms both best-of-N and sentence-level beam search under **comparable inference time compute**.

Method	Number of Beam	MMVet Score
No Inference Scaling	1	60.3
Stage-level Beam Search	2	61.7
Stage-level Beam Search	3	62.3
Stage-level Beam Search	4	62.9

Table 6. **Scaling Trend of LLaVA-o1.** As the the number of candidate responses increases, the model’s performance consistently improves.

model. This result underscores the importance of the multi-stage format of our LLaVA-o1-100k dataset for training models capable of advanced reasoning.

Structured Tags are Essential for Enhanced Performance. To examine whether the four tags we introduced improve the model’s performance, we compare LLaVA-o1 with the model trained on the LLaVA-o1-100k dataset with structured tags removed. As shown in Table 2, our results show a significant drop in performance when the tags are removed, indicating that the structured tagging facilitates reasoning and improves model performance. To the best of our knowledge, LLaVA-o1 is the first attempt to successfully enhance a model’s reasoning ability and overall performance through a structured reasoning with tags.

Performance Gains Primarily in Reasoning-Intensive Areas. To analyze the specific areas in which LLaVA-o1 has improved compared to the base model, we conduct a detailed assessment of the model’s performance across different skills on the MMStar benchmark. MMStar is designed to evaluate six key capabilities: coarse perception, fine-grained perception, instance reasoning, logical reasoning, math, and science & technology. In Table 3, we compare the base model with LLaVA-o1. Our analysis reveals that LLaVA-o1 demonstrates notable improvements in tasks requiring systematic reasoning, such as instance reasoning, logical reasoning, math, and science & technology, while showing relatively smaller gains in coarse perception and fine-grained perception. This suggests that our method can mainly improve reasoning capabilities of the model.

5. Inference Time Scaling

In this section, we aim to compare the effectiveness of our stage-level beam search approach with traditional methods

like best-of-N and sentence-level beam search under comparable computational constraints. The experimental setup mirrors that used in the previous section, with evaluations conducted across the same six benchmarks: MMStar, MMBench V1.1, MMVet, MathVista, AI2D, and Hallusion-Bench. All methods are evaluated using VLMEvalKit to ensure reproducibility.

5.1. Benchmark Results

As shown in Table 4, stage-level beam search demonstrates substantial effectiveness in leveraging the structured reasoning stages of LLaVA-o1. By evaluating outputs at each reasoning stage, this approach strikes a balance between rigorous quality control and computational efficiency, yielding higher inference accuracy on complex reasoning tasks without significant computational overhead. These findings suggest that stage-level beam search, which is made possible by the structured output design of LLaVA-o1, is an effective and powerful approach for inference time scaling.

5.2. Comparison to Baseline Methods

We compare our method with baseline inference scaling methods on the MMVet benchmark to evaluate relative performance. For a fair comparison, our stage-level beam search method and the baseline models are evaluated using comparable levels of inference time compute. Specifically, we set $N = 10$ for the best-of-N method, generate 4 candidate responses per stage for our stage-level beam search, and use a sentence-level beam search generating 2 candidates per sentence. As shown in Table 5, the best-of-N method yields only a modest improvement of 0.6%, while sentence-level beam search even shows a 1.9% decrease in performance. We examine the sub-scores and found that the main reason for the performance drop in sentence-level beam search is the excessively granular sentence-level ap-

Model	MMStar-R	MMBench-R	MMVet-R	MathVista	AI2D	Hallusion	Average
Closed-Source Models							
GPT-4o-0806 [3]	66.0	82.4	80.8	62.7	84.7	54.2	71.8
Claude3.5-Sonnet-0620 [2]	64.2	75.4	68.7	61.6	80.2	49.9	66.7
Gemini-1.5-Pro [43]	56.4	71.5	71.3	57.7	79.1	45.6	63.6
GPT-4o-mini-0718 [41]	54.9	76.9	74.6	52.4	77.8	46.1	63.8
Open-Source Models							
InternVL2-Llama3-76B [10]	68.9	84.4	62.5	65.6	87.6	55.4	70.7
InternVL2-8B [10]	62.5	77.4	56.9	58.3	83.6	45.0	64.0
Ovis1.5-Gemma2-9B [36]	58.7	76.3	50.9	65.6	84.5	48.2	64.0
MiniCPM-V2.6-8B [58]	57.1	75.7	56.3	60.6	82.1	48.1	63.3
Llama-3.2-90B-Vision-Instruct [40]	51.1	76.8	74.1	58.3	69.5	44.1	62.3
VILA-1.5-40B [30]	53.2	75.3	44.4	49.5	77.8	40.9	56.9
Base Model							
Llama-3.2-11B-Vision-Instruct [40]	46.6	64.9	63.8	48.6	77.3	40.3	56.9
Our Models							
LLaVA-o1	57.5	73.1	66.7	54.8	85.7	47.8	64.3
LLaVA-o1 (BS = 2)	57.8	73.8	71.3	56.1	87.5	48.2	65.8

Table 7. **Experimental results of LLaVA-o1 and state-of-the-art models on reasoning benchmarks.** Here, LLaVA-o1 refers to the model without inference scaling, while LLaVA-o1 (BS = 2) denotes the model using stage-level beam search with a beam size of 2.

proach, which struggles to effectively address open-ended questions. In contrast, our stage-level beam search improved performance by 2.6%, highlighting the superiority of stage-based search.

5.3. Scaling Trend of Stage-level Beam Search

To better illustrate the effectiveness of our stage-level beam search as inference time compute increases, we evaluate LLaVA-o1 with different beam sizes on the MMVet benchmark. As shown in Table 6, we test the performance of the model by generating 1 (ie, no inference time scaling), 2, 3, and 4 candidate responses at each reasoning stage, allowing the model to select the best answer from these options. Our findings show that as the number of candidate responses increases, the model’s performance consistently improves, confirming that our stage-level beam search approach is scalable. Due to computational resource constraints, we only test a beam size of 2 across all benchmarks. However, it is expected that increasing the beam size will lead to even more significant improvements.

6. Comparison to State-of-the-Art VLMs

As shown in Table 7, we compare LLaVA-o1 with other state-of-the-art open-source and closed-source vision language models (VLM) across six benchmarks that require advanced reasoning capabilities: MMStar-R, MMBench-R, MMVet-R, MathVista, AI2D, and HallusionBench. MMStar-R, MMBench-R, and MMVet-R are custom benchmarks derived from MMStar, MMBench V1.1, and MMVet, respectively, with tasks requiring only coarse perception, fine-grained perception, and OCR removed. These filtered benchmarks retain tasks that demand complex reasoning. MathVista, AI2D, and HallusionBench in-

herently focus on advanced reasoning, so we retained all tasks within these benchmarks.

Our results show that LLaVA-o1 consistently outperforms many open-source models of similar or even larger sizes, such as InternVL2-8B [10], Ovis1.5-Gemma2-9B [36], MiniCPM-V2.6-8B [58], Llama-3.2-90B-Vision-Instruct [40], and VILA-1.5-40B [30]. Remarkably, LLaVA-o1 even surpasses certain closed-source models like GPT-4o-mini [41] and Gemini-1.5-pro [43], underscoring the effectiveness of our structured reasoning approach. This comparison validates the advantages of our method, particularly in benchmarks that heavily depend on reasoning skills, and highlights LLaVA-o1 as a competitive model in the domain of reasoning-intensive VLM tasks.

7. Conclusion

In this paper, we present LLaVA-o1, a novel vision language model that performs structured, autonomous reasoning in multiple stages. By introducing four distinct stages—summary, caption, reasoning, and conclusion—LLaVA-o1 achieves a systematic reasoning process. Our contributions are twofold: first, the creation of the LLaVA-o1-100k dataset with detailed reasoning annotations, which supports training on systematic, structured responses; and second, the proposal of a stage-level beam search method, enabling effective inference time scaling. Overall, LLaVA-o1 establishes a new standard for multimodal reasoning in VLMs, offering robust performance and scalability, especially in inference time. Our work paves the way for future research on structured reasoning in VLMs, including potential expansions with external verifiers and the use of reinforcement learning to further enhance complex multimodal reasoning capabilities.

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