

VISCO: Benchmarking Fine-Grained Critique and Correction Towards Self-Improvement in Visual Reasoning

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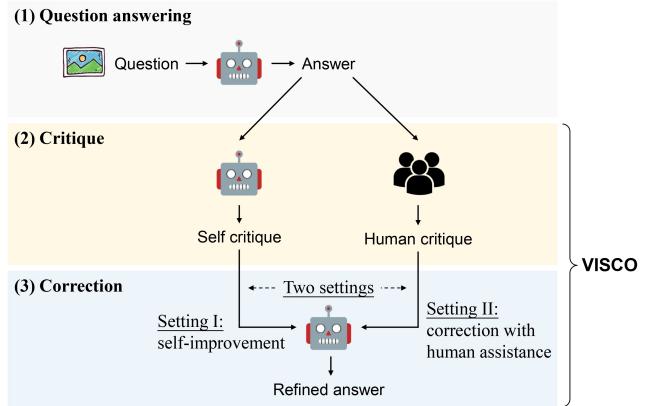
<https://visco-benchmark.github.io/>

Abstract

The ability of large vision-language models (LVLMs) to critique and correct their reasoning is an essential building block towards their self-improvement. However, a systematic analysis of such capabilities in LVLMs is still lacking. We propose VISCO, the first benchmark to extensively analyze the fine-grained critique and correction capabilities of LVLMs. Compared to existing work that uses a single scalar value to critique the entire reasoning [4], VISCO features **dense** and **fine-grained** critique, requiring LVLMs to evaluate the correctness of each step in the chain-of-thought and provide natural language explanations to support their judgments. Extensive evaluation of 24 LVLMs demonstrates that human-written critiques significantly enhance the performance after correction, showcasing the potential of the self-improvement strategy. However, the model-generated critiques are less helpful and sometimes detrimental to the performance, suggesting that critique is the crucial bottleneck. We identified three common patterns in critique failures: failure to critique visual perception, reluctance to “say no”, and exaggerated assumption of error propagation. To address these issues, we propose an effective LOOKBACK strategy that revisits the image to verify each piece of information in the initial reasoning. LOOKBACK significantly improves critique and correction performance by up to 13.5%.

1. Introduction

With recent advances, large vision-language models (LVLMs) have unlocked strong reasoning capabilities [2, 43], enabling them to solve complex problems in math [27, 38] and science [18, 46]. Typically, LVLMs adopt the **chain-of-thought** (CoT) approach [41], where the model generates intermediate reasoning steps before reaching the final answer. However, even with the CoT approach, LVLMs remain prone to hallucination [11, 12, 17] and rea-



Application: 📈 math reasoning 🧮 reducing hallucination 🤖 embodied planning

Figure 1. **Evaluation settings of VISCO.** We evaluate the self-improvement setting where LVLMs correct their own answers based on self-generated critique, and a human-assisted setting where correction is based on human-written critique.

soning errors [3], especially when dealing with compositional concepts like counting [1, 32] and identifying spatial relationship [10, 14, 22]. Such issues raise concern about the trustworthiness of visual reasoning and highlights the need for more reliable visual reasoning.

Given the difficulty of generating completely accurate reasoning in a single pass, an alternative strategy is **self-improvement**, where LVLMs *critique* their initial reasoning and make *corrections* accordingly to enhance performance. Application to text-only tasks like code generation [5, 29] and multi-hop question answering [34] has demonstrated the effectiveness of self-improvement. For vision-language tasks, the self-improvement strategy has also been applied to areas including video understanding [30] and region-of-interests identification [45]. However, a comprehensive study of LVLMs’ self-improvement is still lacking. While some work evaluates the critique capability and enhances it through specialized training, they use LVLMs as evaluators [15] or reward models [42] merely to assess the output quality, rather than for further self-correction and self-improvement.

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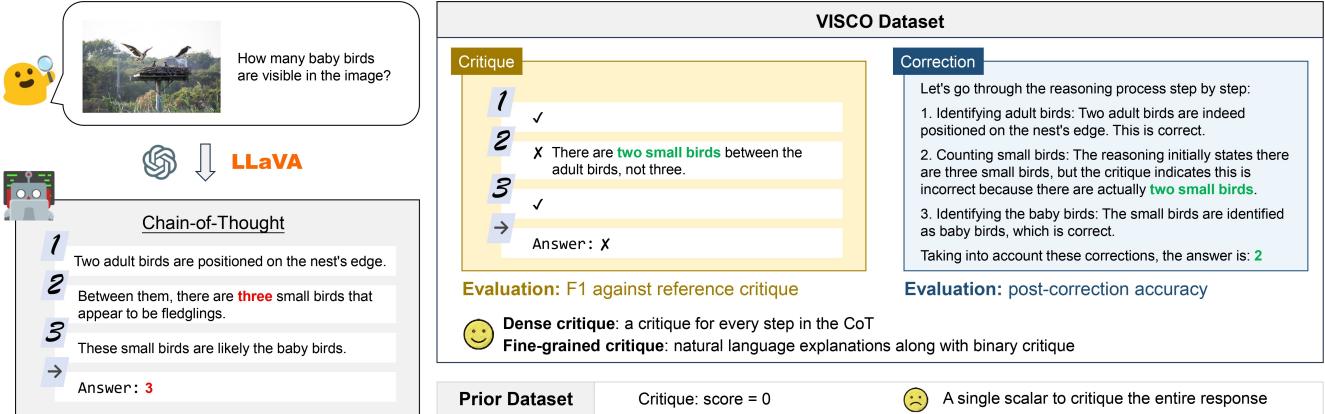


Figure 2. Overview of VISCO task, data and evaluation. VISCO dataset features step-wise critique with natural language explanations.

To conduct a systematic analysis of the **critique** and **correction** capabilities of LVLMs, we present **VISCO**, the first benchmark for VIvisual Self-Critique and cOrrection. As shown in Figure 1, we evaluate critique and correction as two stages in the self-improvement pipeline, and additionally evaluate a setting where LVLMs correct model responses based on high-quality human-annotated critique. We evaluate a wide range of 18 datasets across 8 tasks, divided into two main categories: reasoning tasks such as math reasoning, and perception tasks like reducing hallucination. We sample chain-of-thoughts from 7 LVLMs and have expert human annotators produce ground-truth critiques. While existing work typically uses a single scalar to critique the entire model response [4], research in education shows that detailed and specific feedback is more effective for student learning and error correction [20, 47]. Therefore, we collect **dense** and **fine-grained** critique, assigning a binary correctness label for *each step* in the chain-of-thought, followed by a natural language explanation if the step is incorrect. Our dataset consists of 1645 question-answer pairs, including 5604 *step-wise* annotations. An example of the data and task is shown in Figure 2.

We extensively evaluate 24 LVLMs, including open-source models like LLaVA [23] and Molmo [9] and proprietary models like GPT-4o and Claude-3.5. Our results show that human-written critiques significantly contribute to the correction task, enabling LVLMs to correct up to 76% of the errors. This demonstrates the great potential of self-improvement. Despite these improvements, the benefits decrease substantially when using critiques generated by LVLMs, showing that **effective critique is the key bottleneck**. In the critique task, we observe that non-trivial, above-random critique capabilities typically emerge in LVLMs with >70B parameters. However, even the leading LVLMs still show a significant gap compared to human experts. Specifically, we identify three common failure patterns in the critique task: (1) Failure to critique visual perception, where LVLMs have more difficulty critiquing

visual perception than verbal reasoning; (2) Reluctance to “say no”, where LVLMs are biased towards judging the input CoT as correct; (3) Exaggerated assumption of error propagation, where LVLMs overestimate the likelihood that errors made in earlier steps of the CoT will propagate to later steps.

To address these issues, we propose a simple but effective critique strategy: **LOOKBACK**. LOOKBACK first identifies information in the CoT that needs to be verified against the image. It then revisits the image to explicitly verify each piece of information, thus mitigating the difficulty in critiquing visual perception. The inconsistency revealed between the CoT and the image is naturally leveraged to perform critique, further addressing the reluctance to “say no”. Experiments across four LVLMs show that LOOKBACK significantly enhances critique performance by up to 13.5% with even greater gains (22.2%) in perception tasks. When applied to the correction task, critiques produced by LOOKBACK further boost the performance by up to 11.5%.

In summary, our contributions are three-fold: (1) We propose VISCO, the first benchmark to evaluate critique and correction in visual reasoning, featuring densely annotated step-wise critique and natural language explanations; (2) We conduct an extensive evaluation of 24 LVLMs and summarize three failure patterns for the critique task to inspire future research; (3) We propose LOOKBACK, an improved baseline that significantly improves both critique and correction by up to 13.5%.

2. Related Work

Visual reasoning. Large-scale pre-training on extensive texts and images has equipped LVLMs with strong reasoning capabilities [23, 43]. Various work has evaluated their capabilities across different dimensions, such as mathematical [27, 38], scientific [18, 46], and spatial relationship reasoning [10, 14, 22]. A common reasoning strategy

	Input Modality	Critique Format	Dense Critique	Human Annotation
CriticBench [19]	T	Scalar	✗	✓
MetaCritique [36]	T	Scalar	✓	✗
CriticEval [16]	T	Scalar+NL	✗	✓
MLLM-as-a-Judge [4]	T+V	Scalar	✗	✓
Perception Collection [15]	T+V	Scalar+NL	✗	✗
VISCO (Ours)	T+V	Scalar+NL	✓	✓

Table 1. **Comparison against existing datasets for critique.** For input modality, T represents text and V represents vision. For critique format, NL represents natural language.

is the chain-of-thought approach, where LLMs or LVLMs first generate reasoning rationales before providing final answers [6, 41]. While most work focuses on textual rationales, some work also explores other forms of rationale such as region of interests [25, 33] or sketches [13]. In this work, we focus on reasoning in text format.

Self-improvement. The self-improvement strategy, also termed self-refinement, has been successfully applied to LLMs and LVLMs. By iteratively critiquing and correcting their responses, LLMs have shown improved performance in tasks such as code generation [5, 29], multi-hop question answering [34], and agent development [37]. For visual reasoning, this strategy has been employed in text-to-image generation [44], video understanding [30], region-of-interest identification [45], and instruction data generation [40]. However, a comprehensive analysis of LVLMs self-improvement capabilities is still lacking.

Datasets for critique and correction. The most relevant prior work includes text-only benchmarks that evaluate the critique and correction abilities of LLMs [16, 19, 28, 36]. In the multimodal domain, Chen et al. [4] and Kim et al. [15] focus on using LVLMs as evaluators to critique the instruction following performance in model responses. However, they do not focus on critiquing the correctness of model responses or consider the self-correction step. Table 1 highlights other limitations of existing work, including the lack of dense critique, reliance on scalar-format critique without detailed natural language explanations, and the lack of human-annotated critique.

3. VISCO Benchmark

We present VISCO, the first benchmark to evaluate the critique and correction capabilities of LVLMs. VISCO consists of 1645 pairs of questions and LVLM-generated answers, each densely annotated with step-wise binary labels and natural language explanations. The dataset spans 18 datasets and 8 tasks across two main categories: (1) reasoning tasks, such as math and science reasoning, and (2) perception tasks, such as text recognition, spatial relationship understanding, and prevention of hallucination. In the following sections, we first provide the mathematical for-

mulations of our task and evaluation in Section 3.1. Next, we describe the data collection and annotation process in Section 3.2. Finally, we present the dataset statistics in Section 3.3.

3.1. Task Overview

Given images I and questions q from existing datasets, we use LVLMs \mathcal{M} to sample model responses. Following the CoT approach, a model response contains a chain-of-thought $s_{\mathcal{M}} = [s_1, \dots, s_N]$ with N reasoning steps, leading to the final answer $a_{\mathcal{M}}$. Additionally, we have the ground truth answers a_{gt} from the original datasets. Using the tuple $(I, q, a_{gt}, s_{\mathcal{M}}, a_{\mathcal{M}})$, we evaluate two tasks, critique and correction.

3.1.1 Critique

Given input I, q , the critique task produces a critique \mathcal{C} to judge the **correctness** of model response $(s_{\mathcal{M}}, a_{\mathcal{M}})$. The judgment is based on the accuracy of factual information and logical calculations in the response. Motivated by research in the education field [20, 47], we propose the use of **dense** and **fine-grained** critique, including:

1. A binary critique $\mathcal{C}_{s,i}$ for each intermediate step s_i ;
 2. A natural language explanation $\mathcal{C}_{e,i}$ to explain the binary critique $\mathcal{C}_{s,i}$ for step s_i ;
 3. And finally, a binary critique \mathcal{C}_a for the final answer $a_{\mathcal{M}}$.
- Therefore, the output of the critique task is a hierarchical structure $\mathcal{C} = (\{\mathcal{C}_{s,i}, \mathcal{C}_{e,i}\}_{i=1}^N, \mathcal{C}_a)$.

Hierarchical evaluation. Given the complex structure of critique \mathcal{C} , we first evaluate the critique at each granularity level and then combine the results into the final metric. We adopt F1 as our base metric and consider *incorrect* as the positive class, thus calculating the F1 of correctly identified errors. We calculate F1 scores at three hierarchical levels: $F1_a$ for answer critique \mathcal{C}_a , $F1_s$ for step-wise critique \mathcal{C}_s , and $F1_e$ for critique explanation \mathcal{C}_e . While it is straightforward to calculate F1 for binary critique \mathcal{C}_a and \mathcal{C}_s , measuring F1 for natural language explanation \mathcal{C}_e poses a challenge. Therefore, we adopt an LLM-assisted evaluation approach described below.

LLM-assisted evaluation of natural language explanation. Since each explanation $\mathcal{C}_{e,i}$ aims to justify the binary step-wise critique $\mathcal{C}_{s,i}$, we adjust the calculation of step-wise F1_s to derive F1_e. Specifically, we recalculate the **true positives** as the number of steps s_i that are (1) correctly judged as incorrect, and (2) have their errors correctly explained in $\mathcal{C}_{e,i}$. This evaluation only considers explanations for incorrect steps, as explanations for correct steps can be as trivial as reiterating the correct reasoning. We use LLMs to assess the accuracy of critique explanations by comparing them to human-annotated explanations. While minor deviations or omissions are tolerated, the model-generated cri-

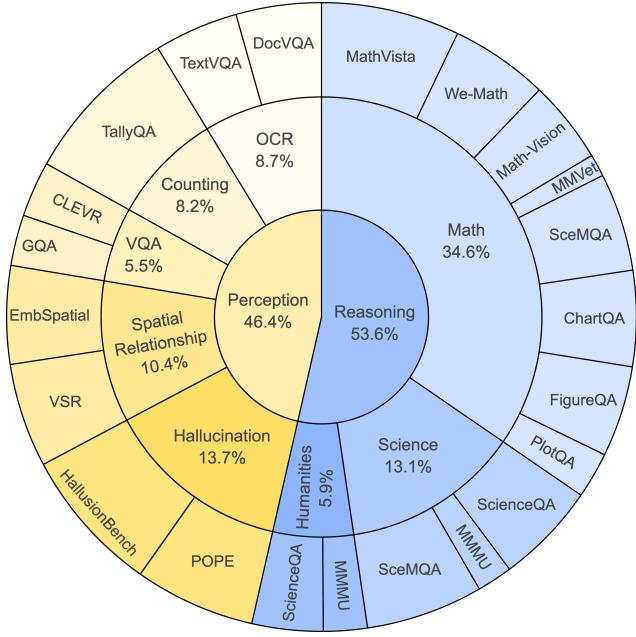


Figure 3. Categories, tasks and datasets distribution of VISCO.

tique must address the core error without introducing more factual or logical errors to be considered as correct. As shown by existing work [24], LLMs can reliably evaluate free-form text given well-defined evaluation criteria.

VISCore. Eventually, we combine the three scores $F1_a$, $F1_s$ and $F1_e$ into a holistic score VISCore. Due to the stricter criteria for explanation correctness, its F1 score $F1_e$ is naturally of a lower scale than $F1_a$ and $F1_s$. Therefore, a key challenge lies in comprehensively considering all three scores without neglecting the information contained in scores with lower scales. To penalize models that “guess” accurate binary critique but fail to provide effective explanations, we calculate our final metric VISCore as the geometric average of the three F1 scores, formally defined as:

$$\text{VISCore} = (F1_a \times F1_s \times F1_e)^{\frac{1}{3}}$$

Detailed illustration of VISCore calculation will be in Appendix A.2.

3.1.2 Correction

Based on I , q and model response (s_M, a_M) , the correction task takes critique C as input to generate a refined answer a' . As shown in Figure 1, the critique C can be generated by either LVLMs or human experts.

Evaluation. We first evaluate the accuracy of the refined answer a' by comparing it against the ground truth a_{gt} . We then calculate **positive correction ratio** (PCR) representing how many errors are successfully corrected:

$$\text{PCR} = \text{Average}_{Acc(a_{gt}, a_M)=1} Acc(a_{gt}, a')$$

	Total	Outcome Error	Process Error	No Error
Questions	1645	502	179	964
- Incorrect answers	502	502	0	0
- Correct answers	1143	0	179	964
Unique images	1587	494	178	940
Steps per question	3.4	3.4	3.6	3.4
Steps in total	5604	1713	650	3241
- Incorrect steps	1346	1046	300	0
- Correct steps	4258	667	350	3241
Average question length	33.5	34.7	35.5	32.5
Average step length	19.4	20.9	20.2	18.5
Average critique length	17.0	17.2	16.1	-

Table 2. **Statistics of VISCO.** The average length of questions, steps and critique are evaluated by the number of words.

To prevent models from cheating the score by always shifting answers, we also calculate the **negative correction ratio** (NCR) evaluating how many correct answers are altered into incorrect ones:

$$\text{NCR} = \text{Average}_{Acc(a_{gt}, a_M)=1} (1 - Acc(a_{gt}, a'))$$

and report the **correction gain** = PCR – NCR as the final metric. Detailed illustration of correction gain calculation will be in Appendix A.3.

3.2 Dataset Construction

The construction of VISCO dataset consists of four steps: task input collection, response collection, response filtering, and critique collection. More examples of each step and the final dataset will be in Appendix A.1.

Task input collection. We collect input images I , questions q and ground truth answers a_{gt} from existing VQA datasets. We select a diverse range of **8 tasks** and **18 datasets**, divided into two categories: reasoning tasks such as math reasoning [27, 38] and scientific reasoning [18, 46], and perception tasks such as hallucination [11, 17], identifying spatial relationship [10, 22], and text recognition [31, 35]. Figure 3 shows a comprehensive visualization of task and dataset distribution.

Response collection. We sample responses from 7 LVLMs of 3 families: InternVL2 8/26/40B, LLaVA-v1.6 7/13/34B, and OpenAI GPT-4o. We prompt LVLMs to first generate a CoT in a short paragraph and then generate the final answer. We then split the CoT paragraph into sentences, each representing a reasoning step s_i . To simplify the task, we limit the total number of reasoning steps N within 5 and remove responses with more than 5 sentences in the CoT.

Response filtering. To evaluate whether LVLMs can correctly identify errors, we focus on two types of errors, *out-*

come errors and *process errors*. Outcome errors refer to incorrect responses with incorrect final answers, and process errors refer to responses that reach the correct final answers but contain errors in the middle of its CoT. We filter out responses with outcome errors by comparing model-generated responses a_M against the ground truth a_{gt} and select the mismatching data points. The matching results also serve as a preliminary annotation of answer critique \mathcal{C}_a , which will be further verified by human annotators. Within responses with correct final answers, we ask human annotators to manually filter out responses with process errors. We identify 179 responses with process errors from a total of 1143 responses. The responses with outcome or process errors will be further densely annotated by three annotators.

Critique collection. We train three expert human annotators to annotate critique \mathcal{C} at three granularity. We first ask human annotators to verify the automatically generated answer critique \mathcal{C}_a . Then, we ask the annotators to judge the correctness of each step s_i , resulting in annotations of \mathcal{C}_s . This annotation achieves a substantial inter-annotator agreement of 64.76 Cohen’s Kappa. For disagreed data points, we employ a secondary annotation step where the annotators review each others’ annotations and engage in discussions to settle disagreements. Finally, we ask each annotator to write a natural language explanation for each incorrect step to collect \mathcal{C}_e , resulting in three references for each step. When evaluating the model-generated critique explanation, we compare it against each of the three annotations and take the average score, leading to a more accurate evaluation.

3.3. Dataset Statistics

Detailed statistics of VISCO are shown in Table 2. In addition to the overall statistics, we show the breakdown of the subsets with outcome errors, process errors, and no errors respectively. In total, we collect 1645 data with 5604 steps, where 30% data have outcome errors and 11% have process errors. The distribution by categories (reasoning v.s. perception), tasks, and datasets are in Figure 3.

4. Experiments

In this section, we first evaluate the overall critique and correction capabilities of LVLMs and validate the importance of dense and fine-grained critique. While LVLMs in general perform well in the correction task, we find that critique remains a crucial bottleneck for effective self-improvement. We then conduct an in-depth analysis of the critique task and identify three common patterns of critique failure. These identified error patterns guide the design of our proposed LOOKBACK method as in Section 5, and we hope they can inspire further research.

Model	Size	Critique	Correction	
			\mathcal{C}_{Human}	\mathcal{C}_{Self}
<i>Small-size (~7B) Open LVLMs</i>				
DeepSeek-VL	7B	7.5	2.3	-17.9
LLaVA-v1.6	7B	21.8	40.3	-8.7
LLaVA-OV	7B	7.5	22.4	-9.1
Qwen2-VL	7B	21.7	50.8	5.5
Molmo	7B	13.4	49.1	1.8
InternVL2	8B	23.3	52.7	5.4
<i>Medium-size (10~40B) Open LVLMs</i>				
Llama-3.2	11B	11.4	34.8	-11.7
LLaVA-v1.6	13B	21.0	40.2	-7.2
InternVL2	26B	25.2	59.3	6.0
LLaVA-v1.6	34B	11.1	39.2	-1.7
InternVL2	40B	28.5	47.6	9.9
<i>Large-size (>70B) Open LVLMs</i>				
LLaVA-OV	72B	35.3	33.4	-10.2
Qwen2-VL	72B	37.4	31.5	-2.1
NVLM	72B	33.1	42.2	1.7
Molmo	72B	35.6	53.1	1.4
InternVL2	76B	26.4	72.7	11.7
Llama-3.2	90B	36.4	66.4	4.4
<i>Critique LVLMs</i>				
Prometheus-Vision	7B	17.7	n/a [†]	n/a [†]
LLaVA-Critic	7B	20.0	19.3	-11.4
Prometheus-Vision	13B	19.3	n/a [†]	n/a [†]
LLaVA-Critic	72B	42.6	58.9	15.4
<i>Proprietary LVLMs</i>				
Gemini-1.5-Pro	*	45.0	78.0	24.9
Claude-3.5-Sonnet	*	51.3	73.7	25.6
GPT-4o	*	52.4	76.2	28.8
Human [‡]		86.5	-	-

Table 3. **Leaderboard of VISCO.** We report VISCore for critique and correction gain for correction. For the correction task, we evaluate model performance with either human-annotated critique (\mathcal{C}_{Human}) or self-generated critique (\mathcal{C}_{Self}). [†]: models lack general question answering capability and cannot perform correction. ^{*}: proprietary models with unknown parameters. [‡]: measured on 265 data points rather than full test set due to annotation cost.

4.1. Experimental Settings

We evaluate 17 open-source general-purpose LVLMs from 7 families, including DeepSeek-VL [26], LLaVA [23], InternVL [7], Qwen-VL [39], Molmo [9], NVLM [8], and Llama-3.2. We further evaluate two open LVLMs trained to provide critique, Prometheus-Vision [15] and LLaVA-Critic [42]. For proprietary LVLMs, we evaluate three leading LVLMs, GPT-4o, Claude-3.5-Sonnet, and Gemini-Pro.

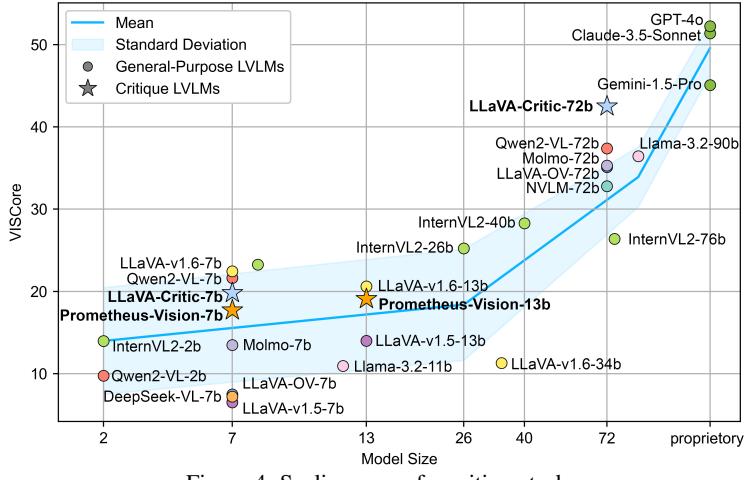


Figure 4. Scaling curve for critique task.

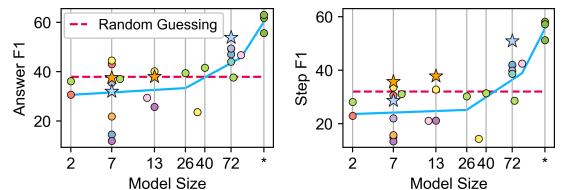


Figure 5. Scaling curve for answer-level F1.

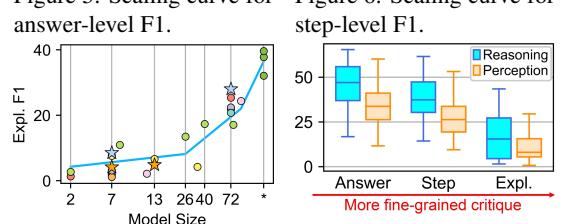


Figure 6. Scaling curve for step-level F1.

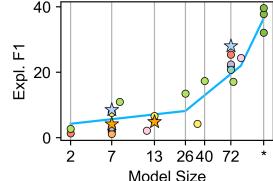


Figure 7. Scaling curve for explanation-level F1.

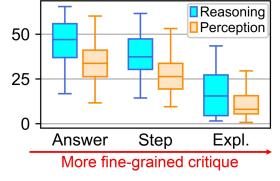


Figure 8. Critique F1 by granularity and category.

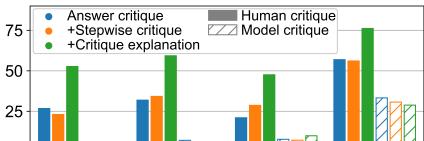


Figure 9. Correction performance given model-generated or human-generated critiques with different granularity.

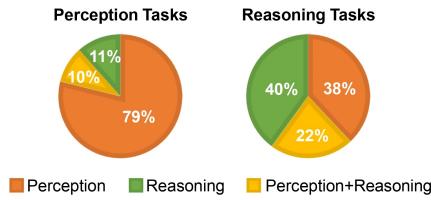


Figure 10. Error distribution in reasoning and perception tasks.

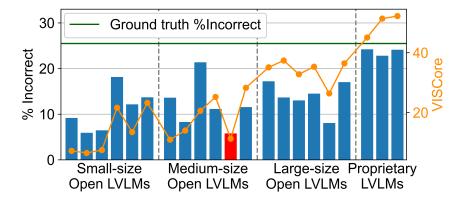


Figure 11. Percentage of data predicted as “Incorrect”.

As in Section 3.1, we use VISCore to evaluate critique and correction gain to evaluate correction. When measuring explanation-level critique F1, GPT-4o is adopted for LLM-assisted evaluation. For the critique task, we further establish a human baseline performed by trained expert annotators. For the correction task, we evaluate two settings, correction based on human-annotated ground truth critique and correction based on self-generated critique to simulate the self-improvement setting. More details about the experimental settings are in Appendix B.

4.2. Results

We report the main results in Table 5. For critique capabilities, Open LVLMs significantly improve as model size scales up. Proprietary LVLMs perform better overall than open LVLMs. However, even the best proprietary LVLMs still significantly lag behind human experts. In the correction task, both top-performing open LVLMs and proprietary LVLMs can correct over 70% errors when human-annotated critiques are available, demonstrating the substantial benefits brought by high-quality critique. In contrast, self-generated critique proves less effective and can sometimes even hurt the performance as indicated by the negative correction gains. This further verifies the importance and difficulty of producing high-quality critique for effective self-improvement.

Non-trivial critique capability typically emerges in

~70B LVLMs. As shown in Figure 4–7, increasing the model size consistently improves critique performance. For binary critique at answer and step levels, most of the small- and medium-sized LVLMs with <70B parameters perform even worse than random guessing (Figure 5, 6). The correlation between model size and performance is especially strong for explanation-level F1 (Figure 7), as smaller models may correctly predict binary critiques but fail to provide coherent explanations. Overall, non-trivial (above-random) critique capabilities typically emerge in 70B-level or proprietary LVLMs.

Benefits and challenges of and fine-grained critique. To investigate whether our proposed fine-grained critique contributes to self-improvement, we show the correction gain with critiques of different granularity in Figure 9 and 21. When using human-annotated high-quality critique, fine-grained critique with step-wise labels and explanations consistently boosts the performance. However, this trend does not hold for model-generated critique, where fine-grained critique does not consistently lead to improvements and sometimes even hurts the performance. As shown in Figure 8, the critique performance of LVLMs decreases as the required level of granularity increases. This highlights that the effective generation of fine-grained critique is both crucial and challenging.

Patterns of critique failure. We further analyze the patterns when LVLMs fail to provide accurate critique and

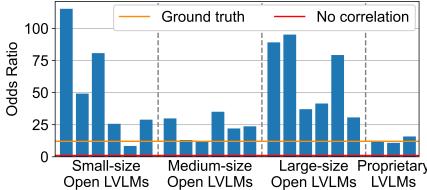


Figure 12. Odds ratio measuring the likelihood of a future step being incorrect given that a prior step is incorrect (higher values indicate a greater likelihood).

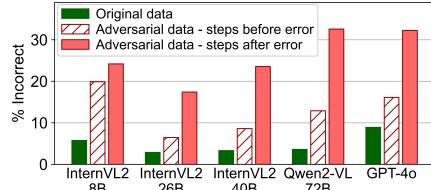


Figure 13. Percentage of data predicted as “Incorrect” on a subset that is all correct. We show the statistics on original data and adversarially constructed data.

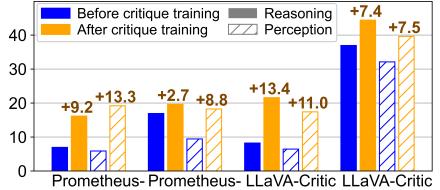
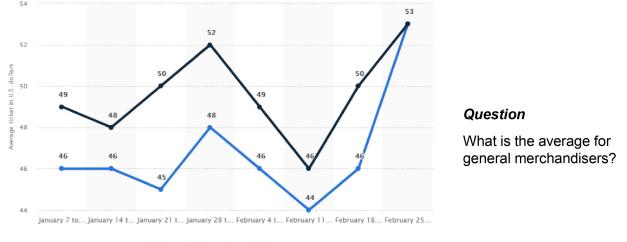


Figure 14. Critique performance before and after critique training.



1. The average ticket values for general merchandisers over the time period shown are 46, 46, 45, 48, 46, 44, and 50. ☒ Perception error

Ground truth: ☒ INCORRECT The values should be 46, 46, 45, 48, 46, 44, 46, 53.

Model critique: ✓ CORRECT The values 46, 46, 45, 48, 46, 44, and 50 are correctly identified from the chart for general merchandisers.

...

3. The sum is 325, and there are 7 entries. The average for general merchandisers is 46.43.

Ground truth: ☒ INCORRECT Although the calculation is correct, it is based on previous incorrect identification of the numbers in the graph in step 1.

Model critique: ✓ CORRECT Dividing 325 by 7 gives approximately 46.43.

Figure 15. Example of failure to critique visual perception. Step 1 makes a perception error when identifying the values, but the model critique fails to identify the error.

summarize three common patterns as follows:

Failure to critique visual perception. As in Figure 8, critique performance on perception tasks is consistently lower than on reasoning tasks at every level, highlighting a unique challenge in visual reasoning to critique visual perception rather than reasoning. Notably, this trend is different from human performance, as human experts perform slightly better on perception tasks (VISCore = 88.5 for perception, 84.6 for reasoning). To further investigate this issue, we manually review 100 examples and categorize the sources of critique errors into three types: perception errors, reasoning errors, and a combination of both reasoning and perception errors. The results are shown in Figure 10. Unsurprisingly, the majority of errors in perception tasks are due to perception errors. Interestingly, we find that a significant portion of errors in reasoning tasks are also caused by perception (38%) or a combination of perception and reasoning (22%). This indicates that visual perception remains a bottleneck even for reasoning-intensive problems. An example is shown in Figure 15, where the model fails to critique the incorrect digit recognition in step 2, resulting in an incorrect critique.

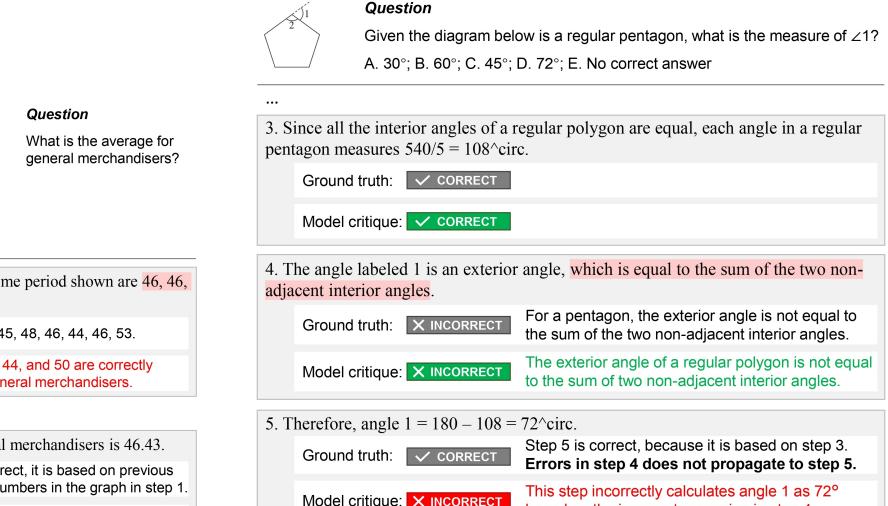


Figure 16. Example of exaggerated assumption of error propagation. The model critique mistakenly believes the error in step 4 is propagated to step 5, while in fact step 5 is based on step 3 and thus independent from the error in step 4.

Reluctance to “say no”. We observe that LVLMs generally show a strong bias against “saying no”, meaning they are more likely to judge an answer or step as correct rather than incorrect. As shown in Figure 11, all LVLMs predict “Incorrect” less frequently than the ground truth annotations. Some models like LLaVA-1.6-34B identify an extremely low percentage of inputs as incorrect (5.7% for LLaVA-1.6-34B), resulting in notably poor performance. This observation aligns with existing work which similarly reports a tendency for LVLMs to favor “Yes” over “No” in binary classification tasks [11, 17]. As pointed out by [11, 21], a potential reason for this bias is imbalanced instruction tuning data, as instruction tuning typically encourages models to agree with users.

Exaggerated assumption of error propagation. In the sequential chain-of-thought, errors may naturally propagate from earlier steps to later ones. However, we observe that LVLMs exhibit a much stronger bias in expecting errors to propagate. We use the odds ratio to measure the association between errors in earlier steps and those in later steps, and thus measuring the error propagation effect. As shown

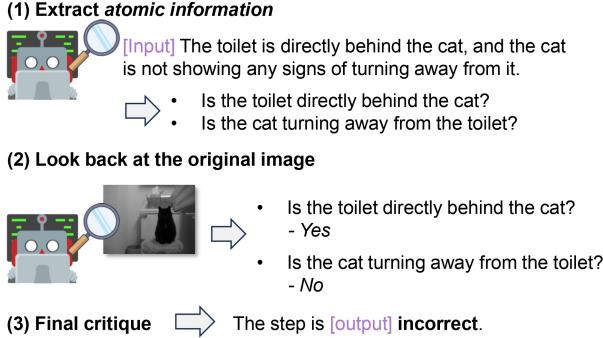


Figure 17. Illustration of LOOKBACK method.

in Figure 12, the step-wise correctness judged by LVLMs indicates a much stronger error propagation effect than the ground truth data. This causes LVLMs to struggle when later steps are independent of earlier mistakes; an example of this is shown in Figure 16. To further quantitatively assess the effect on critique performance, we construct an adversarial test set by prompting LLMs to inject errors into the middle sentence of an otherwise correct CoT. As shown in Figure 13, LVLMs fail to recognize that the error is independent of its context, thus mistakenly identify significantly more steps as incorrect, especially for the steps after the injected error.

Critique training helps. In addition to general-purpose LVLMs, we evaluate two models specifically fine-tuned to provide critique: Prometheus-Vision [15] and LLaVA-Critic [42]. As shown in Figure 4, the critique LVLMs (★) consistently perform above average relative to their corresponding sizes. Notably, the 72B LLaVA-Critic model significantly outperforms other 70B-level LVLMs and ranks as the best across all open LVLMs. The benefits are more substantial when comparing the critique LVLMs to the base models they were fine-tuned from. As in Figure 14, critique training significantly improves the performance on VISCO, highlighting specialized training as a promising strategy to boost self-improvement capabilities. When applied to correction, the critique generated by LLaVA-Critic-72B also brings the best correction performance across all open LVLMs.

5. LOOKBACK as Improved Baseline

In this section, we present an initial step toward enhancing the critique capabilities of LVLMs. As analyzed in Section 4.2, the failure to critique visual perception and the reluctance to “say no” are two major bottlenecks for effective critique. To prevent LVLMs from blindly agreeing with the visual perception in the model response, our proposed LOOKBACK framework forces LVLMs to explicitly check the image and verify the visual information before performing the critique.

As shown in Figure 17, for each step in the CoT, LOOK-

	Critique				Correction with \mathcal{C}_{self}
	Total	Reas.	Perc.	%Inc.	
InternVL2-8B + LOOKBACK	23.3 30.7 (+7.4)	28.2 31.5 (+3.2)	14.7 29.5 (+14.8)	13.7 32.0	5.5 11.7 (+6.2)
InternVL2-26B + LOOKBACK	25.2 38.7 (+13.5)	31.2 39.6 (+8.4)	15.0 37.2 (+22.2)	11.1 31.4	6.0 14.4 (+8.4)
Gemini-1.5-Pro + LOOKBACK	45.0 55.5 (+10.5)	48.7 61.1 (+12.4)	39.3 47.4 (+8.1)	24.2 33.6	24.9 36.4 (+11.5)
GPT-4o + LOOKBACK	52.2 57.7 (+5.5)	55.7 60.0 (+4.3)	46.8 54.2 (+8.6)	24.1 33.2	28.8 34.9 (+6.1)

Table 4. Performance of LOOKBACK on critique and correction tasks. Critique is evaluated by VISCore, and correction is evaluated by correction ratio. We also report the VISCore for reasoning (Reas.) and perception (Perc.) tasks, and the percentage of inputs predicted as incorrect (%Inc.).

BACK extracts a set of **atomic information** necessary for verification in the model response. LOOKBACK then answers each question individually based on the image, and accordingly produces the final critique. This framework better simulates the human process of verifying and critiquing visual reasoning, as humans tend to revisit the image multiple times to iteratively validate every single detail against the image. We additionally include the original question q into the set of questions to be answered. While the LVLMs might not fully succeed in answering the original question, it proves beneficial to propose a candidate solution before performing critique. Detailed algorithm will be shown in Alg. 1 in Appendix D.

As shown in Table 4, our proposed LOOKBACK significantly enhances the critique performance for four leading LVLMs. The gains are more significant for perception tasks (+13.4 on average for perception v.s. +7.1 for reasoning), showing that LOOKBACK effectively addresses the challenges in critiquing visual perception. Additionally, we find that LOOKBACK identifies a higher percentage of inputs as incorrect, thereby alleviating the reluctance to disagree. When applied to the correction task, critique generated by LOOKBACK brings notable improvements.

6. Conclusions

This paper presents VISCO, a novel benchmark designed to evaluate LVLMs in terms of critique and correction, two fundamental capabilities for self-improvement. VISCO evaluates fine-grained critique that identifies the correctness of each reasoning step in a chain-of-thought and further provides natural language explanations. We curate the dataset from a diverse range of 18 datasets across 8 tasks and extensively evaluate 24 LVLMs. Our experiments show while LVLMs perform well in correction given high-quality

critique, the effective generation of critique is the crucial bottleneck for self-improvement. We further investigate the model performance on critique tasks and identify three main issues contributing to LVLMs' critique failures: failure to critique visual perception, reluctance to ‘say no’, and the exaggerated assumption of error propagation. To address these limitations, we designed the LOOKBACK strategy, which can be combined with leading LVLMs to enhance the critique capability by up to 13.5 and further benefit the correction performance by up to 11.5. This work serves as an initial exploration into self-improvement of visual reasoning, aiming to inspire future research in this direction.

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Appendix

A. Additional Examples

A.1. Dataset Examples

We present examples of VISCO dataset in Figure 18. We further show the details of each step in the dataset construction process as follows:

Task input collection. We collect images, questions and ground truth answers from existing visual question answering datasets. The distribution of our tasks and datasets are shown in Figure 3 in the main content. Examples from each task are in Figure 19.

Response collection. We use 7 LVLMs to sample model responses, including both the CoT and the final answer. We prompt the LVLMs to generate CoT with less than five sentences, and additionally remove CoT with more than five sentences. The prompt template and an example output are shown in Figure 23.

Response filtering. In the response filtering stage, we filter the responses into three subsets: responses with outcome errors, responses with process errors, and responses with no errors. Examples from each of the three subsets are shown in Figure 20.

Critique collection. We train three human annotators to provide dense and fine-grained critique with a binary label for each step, and a natural language explanation if the step is considered as incorrect. The annotation interface is shown in Figure 24.

A.2. Examples for Calculating VISCore

Figure 25 illustrates the calculation of VISCore as the metric for critique task. Specifically, the calculation of explanation-level F1 requires matching model-generated critique explanations against human-annotated explanations using LLMs. We use GPT-4o for this evaluation, and the prompt is shown in Figure 26. To evaluate the reliability of this evaluation, we manually compare 100 model-generated explanations against human explanations, and evaluate the agreement between our manual evaluation and LLM evaluation. We observe a high agreement of 0.80 accuracy and 0.61 Cohen’s Kappa, validating the robustness of this evaluation approach.

A.3. Examples for Calculating Correction Gain

Figure 22 illustrates the calculation of correction gain as the metric for correction task.

B. Experimental Details

We evaluate 26 open LVLMs and 3 proprietary LVLMs. For the open LVLMs, we run the inference with fast serving

frameworks. Specifically, we evaluate Qwen2-VL, Molmo, Llama-3.2 and NVLM with `v11m`, evaluate LLaVA-OV and LLaVA-Critic with `sg1ang`, and evaluate InternVL2, DeepSeek-VL, LLaVA-v1.5, LLaVA-v1.6, Qwen-VL and Prometheus-Vision with `lmdeploy`. We set the sampling temperature as 0.7. The prompt for critique and correction are in Figure 27 and 28. We ask one of the trained annotators to establish the human baseline on a randomly selected subset of 265 data points. To reduce annotation costs, we provide the ground truth answers to the annotator. The 100% answer-level F1 shows that the ground truth answers are verified by the annotator to be correct.

C. Additional Results

In this section, we present additional experimental results. Figure 21 is a more complete version of Figure 9 in the main content, showing the correction performance given model-generated or human-generated critiques with different granularity. We further report the detailed critique performance of each model at different granularity and categories in Table 5, and include a few additional models like LLaVA-v1.5.

D. Details on LOOKBACK

The algorithm for our proposed LOOKBACK method is in Alg. 1. We further show an example of critique generated by LOOKBACK in Figure 29.

Algorithm 1 LOOKBACK algorithm

Require: LVLM, image I , question q , model response to be critiqued (\mathbf{T}_M, a_M)

```
1:  $\mathcal{Q} = \{\}$ 
2: for  $i = 1$  to  $N$  do
3:    $\mathcal{Q}_i = \text{RaiseQuestion}(\text{LVLM}, I, T_i)$ 
4:    $\mathcal{Q} = \mathcal{Q} \cup \mathcal{Q}_i$ 
5: end for
6:  $\mathcal{Q} = \mathcal{Q} \cup \{q\}$ 
7:  $\mathcal{A} = \{\}$ 
8: for  $q' \in \mathcal{Q}$  do
9:    $a' = \text{AnswerQuestion}(\text{LVLM}, I, q')$ 
10:   $\mathcal{A} = \mathcal{A} \cup \{a'\}$ 
11: end for
12: return  $\text{Critique}(\text{LVLM}, I, q, (\mathbf{T}_M, a_M), \mathcal{Q}, \mathcal{A})$ 
```

Question
What is the center of symmetry of this function?
Choices:
(A) (0, 0)
(B) (-1, 0)
(C) (2, 0)

1. A function with a center of symmetry at a point (a, b) implies the graph of the function is symmetric when rotated 180 degrees about this point.
✓ CORRECT

2. Observing the graph, it appears that this symmetry exists around the point (2, 0).
✗ INCORRECT The symmetry exists around (0, 0), not (2, 0).

3. Points on opposite sides of (2, 0) have values equidistant from this center, confirming symmetry around this point.
✗ INCORRECT Points on opposite sides of (2, 0) do not have values equidistant from this center.

Answer: (C) (2, 0) ✗ INCORRECT

Horizontal position vs. time

1. Before the collision, the ball moves left from about t=0.1s to t=0.5s, showing a change in slope indicating velocity to the left.
✗ INCORRECT There is no change in slope. The ball is moving at the same speed.

2. After the collision around t=0.5s, the ball's position reverses direction, indicating a bounce back or reversal of velocity.
✓ CORRECT

3. The momentum change is calculated as mass times change in velocity, which depends on the slope before and after t=0.5s.
✓ CORRECT

4. The slope magnitude roughly appears similar, suggesting similar speeds, making the approximate velocity change twice the initial speed upon reversal.
✗ INCORRECT The speeds are similar but different. The speed after t = 0.6s can be calculated by the points on the graph.

5. Therefore, the change in momentum is around -0.05 kg·m/s moving left to +0.05 kg·m/s moving right, giving an overall change of +0.1 kg·m/s, aligning with the correct answer of +0.05 kg·m/s given minor calculation or graph estimation issues.
✗ INCORRECT This is incorrect, as it is based on a previous incorrect identification of speed in sentence 4.

Answer: A. +0.05 kg · m/s ✗ INCORRECT

Question
The 1936 cartoon above, from the New York Daily News, is making the point that
A. although European individuals and countries might be seduced into waging another major war, the United States would be wise to avoid participating.
B. the policy of appeasement is a bankrupt policy that can only lead to more death and destruction.
C. munitions manufacturers, the so-called merchants of death, were pushing the world toward war in the name of profits.
D. the weaponry of modern warfare had advanced to such a degree that future military engagements would result in unprecedented carnage.
—C. D. Batchelor, New York Daily News, April 25, 1936

1. The cartoon is making a statement about the consequences of war and the potential for future military engagements to result in unprecedented carnage.
✓ CORRECT

2. It suggests that European countries might be drawn into another major war, but the United States should be cautious and avoid participating.
✓ CORRECT

3. The cartoon also implies that the advanced weaponry of modern warfare has made such conflicts more destructive.
✗ INCORRECT Such information is not implied by the image.

4. This reasoning process leads to answer C, which is not one of the options provided.
✗ INCORRECT Answer C ("munitions manufacturers, the so-called merchants of death, were pushing the world toward war in the name of profits") is provided, but is incorrect. Such information is not implied by the image.

5. Therefore, the correct answer is C, which is not listed as an option.
✗ INCORRECT Answer C ("munitions manufacturers, the so-called merchants of death, were pushing the world toward war in the name of profits") is provided, but is incorrect. Such information is not implied by the image.

Answer: C. munitions manufacturers, the so-called merchants of death, were pushing the world toward war in the name of profits. ✗ INCORRECT

Question
Is there a knife in the image?

1. The image shows a group of people seated around what appears to be an oyster bar.
✓ CORRECT

2. There are some dishes and condiments on the counter.
✓ CORRECT

3. Upon closer inspection, there is a shiny object that resembles a knife near the oysters.
✗ INCORRECT There is no knife near the oysters.

4. The shape and position suggest it is likely used for shucking oysters.
✗ INCORRECT There is no knife near the oysters.

5. Thus, the presence of a knife is confirmed.
✗ INCORRECT There is no knife near the oysters.

Answer: Yes ✗ INCORRECT

Question
Determine whether the following statement about the image is true or false: The cat is facing the keyboard.

1. The cat is facing the keyboard, with its front paws extended, which indicates that it is interacting with the keyboard.
✗ INCORRECT The cat is not facing the keyboard, but facing the camera.

2. Its eyes are also focused on the keyboard area, which suggests that it is either looking at the keyboard or something on it.
✗ INCORRECT The cats' eyes are focused on the camera's direction, not on the keyboard.

3. The position of the cat and its posture imply that it is facing the keyboard.
✗ INCORRECT The cat is not facing the keyboard, but facing the camera.

Answer: True ✗ INCORRECT

Question
what is the first word on the sign?

1. The image shows a sign in German, which reads 'Fahrrad abstellen verboten' in English.
✗ INCORRECT The sign reads "Fahrrader abstellen verboten".

2. This translates to 'Parking bicycles prohibited'.
✓ CORRECT

3. The sign is located in a bike rack area, surrounded by numerous bicycles.
✓ CORRECT

4. The presence of the sign indicates that bicycle parking is not allowed in this particular area.
✓ CORRECT

Answer: Bicycle parking prohibited ✗ INCORRECT

Figure 18. Dataset examples.

Reasoning

Math
Dataset: MathVista

Question: What is the center of symmetry of this function?
 Choices:
 (A) (0, 0)
 (B) (-1, 0)
 (C) (2, 0)

Answer: (A) (0, 0)

Science
Dataset: SceMQA

Horizontal position vs. time
Position (m) vs. Time (s)

Time (s)	Position (m)
0.0	2.0
0.1	1.5
0.2	1.0
0.3	0.5
0.4	0.0
0.5	-0.5
0.6	-1.0
0.7	-1.5
0.8	-1.0
0.9	-0.5
1.0	0.0
1.1	0.5
1.2	1.0
1.3	1.5
1.4	2.0

Question: A 50.0-g ball moving to the left strikes a wall and bounces back to the right. Slow-motion video analysis produces the following horizontal position versus time graph. Determine the momentum change of the bouncing ball.
 A. +0.05 kg × m/s
 B. +0.45 kg × m/s
 C. -0.45 kg × m/s
 D. -0.05 kg × m/s

Answer: B. +0.45 kg × m/s

— C. D. Batchelor, New York Daily News, April 25, 1936

Question: The 1936 cartoon above, from the New York Daily News, is making the point that
 A. although European individuals and countries might be seduced into waging another major war, the United States would be wise to avoid participating.
 B. the policy of appeasement is a bankrupt policy that can only lead to more death and destruction.
 C. munitions manufacturers, the so-called merchants of death, were pushing the world toward war in the name of profits.
 D. the weaponry of modern warfare had advanced to such a degree that future military engagements would result in unprecedented carnage.

Answer: A. although European individuals and countries might be seduced into waging another major war, the United States would be wise to avoid participating.

Perception

Hallucination
Dataset: POPE

Question: Is there a knife in the image?
 Answer: no

Spatial Relationship
Dataset: VSR

Question: Determine whether the following statement about the image is true or false: The cat is facing the keyboard.
 Answer: False

VQA
Dataset: GQA

Question: What color is the door?
 Answer: white

Counting
Dataset: TallyQA

Question: How many giraffes are looking at the camera?
 Answer: 1

OCR
Dataset: TextVQA

Question: what is the first word on the sign?
 Answer: fahrrader

Figure 19. Examples for each task in our dataset.

Outcome Error	Process Error	Weight lifting results (lbs)	No Error								
<p>Both final answer and reasoning are incorrect</p> <p>Question: What is the center of symmetry of this function?</p> <p>Choices: (A) (0, 0) (B) (-1, 0) (C) (2, 0)</p> <p>Model response:</p> <ol style="list-style-type: none"> 1. Function has a center of symmetry at point (a, b) implies graph is symmetric when rotated 180 degrees about this point. ✓ 2. Observing the graph, it appears that this symmetry exists around the point (2, 0). X 3. Points on opposite sides of (2, 0) have values equidistant from this center, confirming symmetry around this point. X <p>Answer: (C) (2, 0) X</p>	<p>Reasoning is incorrect, but final answer is correct</p> <p>Question: Mr. Huffman, a P.E. teacher, wrote down how much weight each of his students could lift. How many people lifted at least 46 pounds? (Unit: people)</p> <p>Model response:</p> <ol style="list-style-type: none"> 1. The weight lifting results are listed in pounds, with the number of people who can lift each weight. ✓ 2. To determine how many people lifted at least 46 pounds, we need to count the number of people whose weight lifting results are equal to or greater than 46 pounds. ✓ 3. By looking at the table, we can see that only one person, with the stem number 3, can lift 46 pounds. X 4. Therefore, the answer is 1. ✓ <p>Answer: 1 ✓</p>	<p>Stem Leaf</p> <table border="1"> <tr><td>1</td><td>0 1 4 6 6 9</td></tr> <tr><td>2</td><td>3 5 6</td></tr> <tr><td>3</td><td>0 1 2 5 8 9</td></tr> <tr><td>4</td><td>0 3 3 4 7</td></tr> </table> <p>Question: In the figure above, which of the following is the greatest?</p> <p>Choices: (A) a (B) b (C) c (D) d (E) e</p> <p>Model response:</p> <ol style="list-style-type: none"> 1. In a triangle, the sum of interior angles is 180 degrees. ✓ 2. In the given figure, the angle opposite side c is 50 degrees (180 - 60 - 70). ✓ 3. The exterior angle theorem states that an exterior angle is equal to the sum of the opposite interior angles; hence, d = a+b, making d the exterior angle to c. ✓ 4. Since d is equal to the sum of two interior angles of the triangle, d has to be the greatest among all given angles a, b, c, d, and e. ✓ <p>Answer: (D) d ✓</p>	1	0 1 4 6 6 9	2	3 5 6	3	0 1 2 5 8 9	4	0 3 3 4 7	<p>Question: In the figure above, which of the following is the greatest?</p> <p>Choices: (A) a (B) b (C) c (D) d (E) e</p> <p>Model response:</p> <ol style="list-style-type: none"> 1. In a triangle, the sum of interior angles is 180 degrees. ✓ 2. In the given figure, the angle opposite side c is 50 degrees (180 - 60 - 70). ✓ 3. The exterior angle theorem states that an exterior angle is equal to the sum of the opposite interior angles; hence, d = a+b, making d the exterior angle to c. ✓ 4. Since d is equal to the sum of two interior angles of the triangle, d has to be the greatest among all given angles a, b, c, d, and e. ✓ <p>Answer: (D) d ✓</p>
1	0 1 4 6 6 9										
2	3 5 6										
3	0 1 2 5 8 9										
4	0 3 3 4 7										

Figure 20. Examples of model responses with outcome errors, process errors, and no errors.

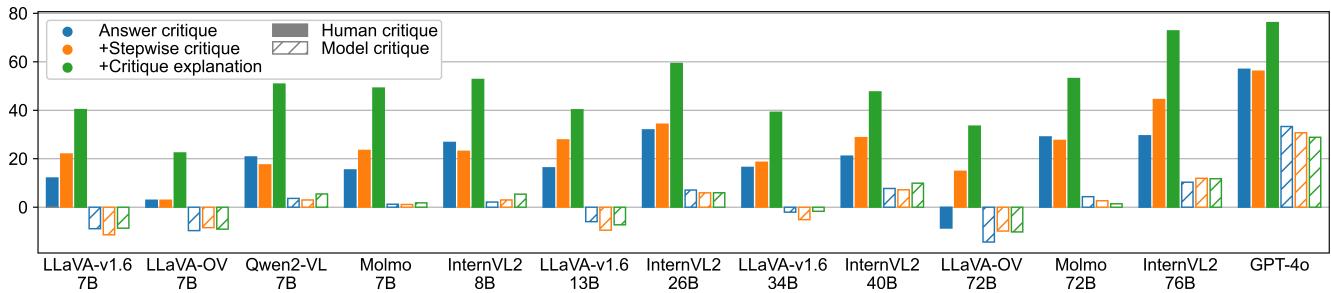


Figure 21. Correction performance given model-generated or human-generated critiques with different granularity.

Question: Is Dark Gray the low median?

Label: No

Answer before correction: Yes Answer after correction: Yes

Question: Find \$x\$. Choices: (A) 10.25 (B) 12.75 (C) 18.75 (D) 25.5

Label: (B) 12.75

Answer before correction: (A) 10.25 Answer after correction: (B) 12.75

Question: Is there a person in the image?

Label: Yes

Answer before correction: No Answer after correction: Yes

→ Positive Correction Gain = 2/3

Question: Two magnets are placed as shown. Will these magnets attract or repel each other? A. repel B. Attract

Label: A. repel

Answer before correction: A. repel Answer after correction: B. Attract

Question: When a negatively charged rod is brought near, but does not touch, the initially uncharged electroscope shown above, the leaves spring apart (I). When the electroscope is then touched with a finger, the leaves collapse (II). When next the finger and finally the rod are removed, the leaves spring apart a second time (III). The charge on the leaves is A. positive in both I and III B. negative in both I and II C. positive in I, negative in III D. negative in I, positive in III

Label: D. negative in I, positive in III

Answer before correction: D. negative in I, positive in III Answer after correction: D. negative in I, positive in III

Question: In order to support the pandemic relief, Uncle Wang plans to donate 6 boxes of masks. The masks are packed in cubic boxes with an edge length of 10dm. When these boxes are stacked in a corner (as shown in the diagram), the area exposed on the outside is () dm². A. 1000; B. 1200; C. 1300; D. 1500; E. No correct answer

Label: B. 1200

Answer before correction: B. 1200 Answer after correction: B. 1200

→ Negative Correction Gain = 1/3

→ Correction Gain = Positive Correction Gain - Negative Correction Gain = 2/3 - 1/3 = 1/3

Figure 22. Calculation of correction gain.

Prompt

Answer the following question: What is the center of symmetry of this function?

Choices: (A) (0, 0) (B) (-1, 0) (C) (2, 0)

Provide a json dictionary of exactly two fields: 'reasoning' and 'answer'.
e.g. ``json
{
 "reasoning": "xxx",
 "answer": "xxx"
}
``

'reasoning' is the reasoning process of strictly less than or equal to 5 sentences;
'answer' is the final answer based on the reasoning in letter form of the choice selected, e.g., A, B, C, D.

Model Response

```
{"reasoning": "A function with a center of symmetry at a point (a, b) implies the graph of the function is symmetric when rotated 180 degrees about this point. Observing the graph, it appears that this symmetry exists around the point (2, 0). Points on opposite sides of (2, 0) have values equidistant from this center, confirming symmetry around this point.", "answer": "C"} Final answer
```

Figure 23. Prompt template for collecting model responses and an example response. The highlighted fields will be filled with the information according to each data point. The “reasoning” field in the model response will be split into multiple reasoning steps using `nltk.tokenize.sent_tokenize`.

Progress: 8/55 (TODO)

8

Go

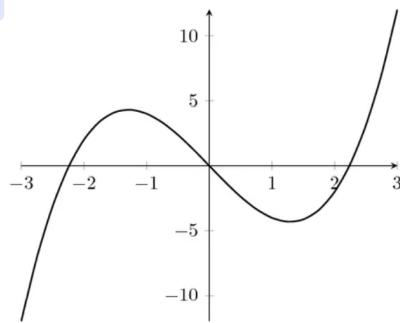
Prev TODO

Prev

Next

Next TODO

Image



Model Prediction: (2, 0)

Correct

Sentence 1. A function with a center of symmetry at a point (a, b) implies the graph of the function is symmetric when rotated 180 degrees about this point.

Enter your critic here

Correct

Sentence 2. Observing the graph, it appears that this symmetry exists around the point (2, 0).

Enter your critic here

Correct

Sentence 3. Points on opposite sides of (2, 0) have values equidistant from this center, confirming symmetry around this point.

Enter your critic here

Correct

Question: Answer the following question: What is the center of symmetry of this function? Choices: (A) (0, 0) (B) (-1, 0) (C) (2, 0)

Answer: (0, 0)

Unflagged

Submit

Figure 24. Interface of critique annotation.

Answer-level F1

Question:
Determine whether the following statement about the image is true or false: The person is at the left side of the pizza.

Label: False

Model answer: True

Ground truth: INCORRECT

Model critique: INCORRECT True positive

Question:
How many baby birds are visible in the image?

Label: 2

Model answer: C. $\frac{dy}{dx} = x - y$

Ground truth: INCORRECT

Model critique: CORRECT False negative

Precision = 1/1 = 1
Recall = 1/2 = 0.5
F1 = 0.67

Step-level F1

Question:
Which of the following is the differential equation of the slope field above?

Model CoT :

1. The image shows a hand holding a fork on the left side of the pizza, indicating that the person is indeed at the left side of the pizza.

Ground truth: INCORRECT

Model critique: INCORRECT True positive

Question:
How many baby birds are visible in the image?

Model CoT :

1. Two adult birds are positioned on the nest's edge.

Ground truth: CORRECT

Model critique: CORRECT True negative

Precision = 1/1 = 1
Recall = 1/2 = 0.5
F1 = 0.67

2. Between them, there are three small birds that appear to be fledglings.

Ground truth: INCORRECT

Model critique: CORRECT False negative

3. These small birds are likely the baby birds.

Ground truth: CORRECT

Model critique: CORRECT True negative

Precision = 1/1 = 1
Recall = 1/2 = 0.5
F1 = 0.67

Explanation-level F1

Question:
Which of the following is the differential equation of the slope field above?

Model CoT :

1. The image shows a hand holding a fork on the left side of the pizza, indicating that the person is indeed at the left side of the pizza.

Ground truth: INCORRECT The person is sitting behind the pizza from our POV.

Model critique: INCORRECT The hand with a fork is actually on the right side of the pizza, not the left side.

Explanations do not match

No longer count as true positive

Question:
How many baby birds are visible in the image?

Model CoT :

1. Two adult birds are positioned on the nest's edge.

Ground truth: CORRECT

Model critique: CORRECT True negative

Reweight: True Positives = 0 rather than 1

2. Between them, there are three small birds that appear to be fledglings.

Ground truth: INCORRECT

Model critique: CORRECT False negative

3. These small birds are likely the baby birds.

Ground truth: CORRECT

Model critique: CORRECT True negative

Precision = 0/1 = 0
Recall = 0/2 = 0
F1 = 0

⇒ VISCore = $(0.67 \times 0.67 \times 0)^{\frac{1}{3}} = 0$ ⇒ Penalize predictions that fail to provide correct explanations, even if they provide correct binary critique.

Figure 25. Calculation of VISCore.

	VISCore	Total			Reasoning			Perception		
		Answer	Thought	Expl.	Answer	Step	Expl.	Answer	Step	Expl.
Random	-	37.91	32.02	-	39.44	33.10	-	36.03	30.54	-
<i>Tiny-size (<3B) Open LVLMs</i>										
Qwen2-VL-2B	9.76	30.7	23.0	1.3	29.5	24.3	1.7	31.9	21.3	0.8
InternVL2-2B	13.96	36.1	28.2	2.7	37.3	29.3	3.7	34.8	26.8	1.5
<i>Small-size (~7B) Open LVLMs</i>										
DeepSeek-VL-7B	7.53	21.8	15.7	1.2	18.7	14.4	1.6	24.9	17.5	0.8
LLaVA-v1.5-7B	6.51	11.9	13.4	1.7	12.7	13.5	2.0	10.9	13.3	1.4
LLaVA-v1.6-7B	21.80	44.6	33.6	6.9	46.8	34.6	7.8	41.3	31.9	5.6
LLaVA-v1.6-Vicuna-7B	11.45	27.7	24.1	2.3	25.8	24.3	2.2	29.9	23.8	2.4
LLaVA-OV-7B	7.53	14.5	14.9	2.0	16.8	15.7	2.2	11.7	13.8	1.6
Qwen-VL-7B	12.69	33.1	26.4	2.3	31.2	26.7	2.8	35.1	26.0	1.8
Qwen2-VL-7B	21.71	43.0	30.6	7.8	44.5	30.4	7.3	41.1	31.0	8.4
Molmo-7B	13.43	35.5	22.0	3.1	35.7	23.6	4.1	35.3	19.8	1.6
InternVL2-8B	23.33	37.1	31.1	11.0	44.2	37.4	14.1	26.1	19.7	5.6
<i>Medium-size (10~70B) Open LVLMs</i>										
Llama-3.2-11B	11.44	29.4	21.1	2.4	31.4	23.0	3.3	26.9	17.6	0.8
LLaVA-v1.6-13B	21.02	40.2	32.8	7.1	43.6	36.5	7.6	34.4	25.9	6.1
InternVL2-26B	25.20	39.4	30.2	13.4	48.7	36.8	16.9	24.5	18.5	7.2
LLaVA-v1.6-34B	11.05	23.6	14.3	4.0	29.4	17.4	4.2	15.3	9.5	3.6
InternVL2-40B	28.48	41.6	31.4	17.7	47.8	37.4	20.7	32.0	20.7	12.4
<i>Large-size (>70B) Open LVLMs</i>										
LLaVA-OV-72B	35.27	47.1	42.0	22.2	49.3	44.7	23.2	43.9	37.3	20.5
Qwen2-VL-72B	37.44	49.2	41.9	25.5	56.3	49.0	30.8	38.0	28.6	15.5
NVLM-72B	33.07	44.0	38.6	21.3	52.6	46.1	26.1	30.6	24.7	12.3
Molmo-72B	35.59	49.4	39.8	22.9	57.5	46.8	26.8	36.5	26.4	15.5
InternVL2-76B	26.38	37.7	28.6	17.0	47.3	35.6	21.2	22.9	16.2	9.6
Llama-3.2-90B	36.40	46.8	42.5	24.3	55.7	49.1	28.8	32.9	30.5	16.1
<i>Critique LVLMs</i>										
Prometheus-Vision-7B	17.67	37.6	35.8	4.1	37.2	37.6	3.1	38.0	33.4	5.4
LLaVA-Critic-7B	20.02	32.0	28.7	8.8	36.3	30.3	9.5	26.3	26.3	7.7
Prometheus-Vision-13B	19.32	38.0	37.8	5.0	42.0	40.1	4.6	33.1	34.5	5.6
LLaVA-Critic-72B	42.60	53.9	50.9	28.2	56.3	54.8	28.6	50.5	44.8	27.4
<i>Proprietary LVLMs</i>										
Gemini-1.5-Pro	45.01	55.6	51.2	32.0	58.8	55.0	35.7	51.2	45.2	26.3
Claude-3.5-Sonnet	51.28	61.8	58.1	37.6	65.4	61.6	43.5	57.4	53.2	29.5
GPT-4o	52.36	63.0	57.2	39.8	65.2	61.4	43.5	60.1	50.3	34.0
Human*	86.47	100.0	90.6	71.4	100.0	90.6	66.8	100.0	90.6	76.4

Table 5. **Detailed critique performance VISCO.** In addition to the overall VISCore score, we also report the critique F1 at three granularity: answer-level F1, step-level F1, and explanation-level F1. We also report the scores for the two categories, reasoning and perception respectively. We also include a few additional models compared to Table 3 in the main content.

You task is to evaluate a **critique** of reasoning.

You are given a question about an image, an incorrect chain-of-thought trying to answer the question, and a **critique** that explains why the `STEP_NUM` step of the chain-of-thought is incorrect. You are required to focus on the `STEP_NUM` step, and analyzes whether the critique correctly identifies the source of error.

For reference, you will be provided with the ground truth critique for each individual step. Evaluate the critique by comparing against the ground truth. Focus on whether the critique accurately identifies the **core mistake**. If the critique addresses the core error and does not contain factual or logical error, minor deviations or omissions in reasoning or explanation should be considered as correct.

Think step by step, then provide your judgment. Your response should end with either:

Judgment: the critique is correct.

or

Judgment: the critique is incorrect.

... In-context examples ...

Question: `QUESTION`

Chain-of-thought: `COT`

Figure 26. Prompt for LLM-assisted evaluation of critique explanation. The highlighted fields are to be filled according to each data point. We omit the `in-context examples` here.

You are given an image, a question about the image, a reasoning process involving multiple steps, and a final answer. Evaluate the accuracy of each reasoning step and the final answer. For each reasoning step, evaluate whether it is correct or incorrect. If it is incorrect, briefly explain why. Then, evaluate the final answer as correct or incorrect.

Your response should be a json in the following format:

```
```json
{
 "step_1": { "correctness": true or false, "explanation": "Write your explanation here" },
 ...
 "answer_correctness": true or false
}
```

```

—
Instructions for evaluating reasoning steps:

- * For each reasoning step, evaluate whether it is correct or incorrect based on the accuracy of the factual information and logical calculations it contains.
- * Evaluate each step in isolation.
- * You do not need to evaluate the importance of the step in achieving the correct final answer; focus solely on the correctness within that step itself.

—
Question: `QUESTION`

Reasoning: `COT`

Answer: `ANSWER`

Figure 27. Prompt for critique task. The highlighted fields are to be filled according to each data point.

You are given an image, a question about the image, a multi-step reasoning process leading to an answer, and the critique for each reasoning step. Based on this information, think step by step and provide the correct answer. Your response should end with a json dictionary as follows:

```
```json
{ "answer": ANSWER }
```

```

ANSWER should be `ANSWER_FORMAT`.

Question: `QUESTION`

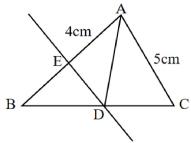
Reasoning:

1. `REASONING_STEP_1`
- Critique: `CRITIQUE_FOR_STEP_1`

...

The final answer is: `MODEL_RESPONSE_ANSWER`
- Critique: `CRITIQUE_FOR_ANSWER`

Figure 28. Prompt for correction task. The highlighted fields are to be filled according to each data point.



Question:

As shown in the figure, triangle ABC is folded along the straight line DE so that point B coincides with point A. If the perimeter of triangle ADC is 17 cm, what is the perimeter of triangle ABC in cm? A. 17; B. 12; C. 15; D. 25; E. No correct answer

Label: D. 25

Model CoT:

1. Since triangle ABC is folded such that point B coincides with point A, line segment AB is equal to line segment AE.

Ground truth: X INCORRECT AB is not equal to AE, but it is twice as long as AE. Baseline: ✓ CORRECT

LookBack:

Questions regarding atomic information:

LVLM answers:

- Is line segment AB equal to line segment AE? \Rightarrow • No, line segment AB is not equal to line segment AE. Line segment AE is given as 4 cm, while no length is provided for line segment AB.

X INCORRECT The reasoning incorrectly states that AB equals AE. AE is given as 4 cm, but AB is not specified and appears longer.

2. Given that AD is 5 cm and AC is 4 cm, line segment DC must be equal to DE.

Ground truth: X INCORRECT DC does not equal DE. There is no explicit relationship between DC and DE. Baseline: ✓ CORRECT

LookBack:

Questions regarding atomic information:

LVLM answers:

- Is line segment DC equal to line segment DE? \Rightarrow • No, line segment DC is not equal to line segment DE.

X INCORRECT The reasoning states DC equals DE, which is incorrect based on the visual information provided.

3. Therefore, ADC's perimeter AD+DC+AC is 17 cm.

Ground truth: ✓ CORRECT Baseline: ✓ CORRECT

LookBack:

Questions regarding atomic information:

LVLM answers:

- Is line segment AD labeled as 5 cm?
- Is line segment AC labeled as 4 cm? \Rightarrow • Yes, line segment AD is labeled as 5 cm.
- No, line segment AC is labeled as 5 cm.

X INCORRECT The premise is incorrect since the lengths used (AD, DC, AC) do not add up correctly based on given information.

4. If AE=AB, this implies the same triangle length, making the total perimeter of ABC also 17 cm as position symmetrical.

Ground truth: X INCORRECT AE does not equal AB. The perimeter of ABC is not 17cm. Baseline: ✓ CORRECT

LookBack:

Questions regarding atomic information:

LVLM answers:

- Is line segment AE equal to line segment AB? \Rightarrow • No, line segment AE is not equal to line segment AB. AE is 4 cm, while AB is not labeled with a length but appears longer than AE.
- Does line segment AD measure 5 cm?
- Does line segment AC measure 4 cm?
- No, line segment AD does not measure 5 cm; it is AC that measures 5 cm.
- No, line segment AC measures 5 cm.

X INCORRECT The reasoning states DC equals DE, which is incorrect based on the visual information provided.

5. Thus, perimeter of ABC is the same as ADC.

Ground truth: X INCORRECT AE does not equal AB. The perimeter of ABC is not 17cm. Baseline: ✓ CORRECT

LookBack:

Questions regarding atomic information:

LVLM answers:

- Is AE equal to AB in the image?
- Is the length of AD labeled as 5 cm in the image? \Rightarrow • No, AE is not equal to AB. AE is 4 cm, while AB is not labeled with a specific measurement.
- Is the length of AC labeled as 4 cm in the image?
- Yes, the length of AD is labeled as 5 cm in the image.
- No, the length of AC is labeled as 5 cm.

X INCORRECT The reasoning incorrectly concludes that the perimeters are the same based on incorrect assumptions.

Model answer:

A. 17

Ground truth: X INCORRECT

Baseline: ✓ CORRECT

LookBack: X INCORRECT

Figure 29. Example of LOOKBACK.