

Reasoning-OCR: Can Large Multimodal Models Solve Complex Logical Reasoning Problems from OCR Cues?

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Abstract

Large Multimodal Models (LMMs) have become increasingly versatile, accompanied by impressive Optical Character Recognition (OCR) related capabilities. Existing OCR-related benchmarks emphasize evaluating LMMs' abilities of relatively simple visual question answering, visual-text parsing, *etc.* However, the extent to which LMMs can deal with complex logical reasoning problems based on OCR cues is relatively unexplored. To this end, we introduce the **Reasoning-OCR** benchmark, which challenges LMMs to solve complex reasoning problems based on the cues that can be extracted from rich visual-text. Reasoning-OCR covers six visual scenarios and encompasses 150 meticulously designed questions categorized into six reasoning challenges. Additionally, Reasoning-OCR minimizes the impact of field-specialized knowledge. Our evaluation offers some insights for proprietary and open-source LMMs in different reasoning challenges, underscoring the urgent to improve the reasoning performance. We hope Reasoning-OCR can inspire and facilitate future research on enhancing complex reasoning ability based on OCR cues. Reasoning-OCR is publicly available at <https://github.com/Hxyz-123/ReasoningOCR>.

1 Introduction

Visual-text in images contains essential information for multimodal intelligence. Given text-rich input images, the OCR ability has become the foundation of LMMs [Achiam *et al.*, 2023; Li *et al.*, 2024a; Wang *et al.*, 2024b; Chen *et al.*, 2024c] to further interact with humans in depth. Thanks to the large-scale and diverse training data, recent LMMs deliver impressive OCR-related performance, such as text recognition [Liu *et al.*, 2024e] and document parsing [Wei *et al.*, 2024]. Nonetheless, merely reading and understanding visual-text cannot enable LMMs to successfully solve more complicated tasks like planning and decision making (such as for embodied artificial intelligence), underlining the importance of developing and evaluating complex logical reasoning ability based on OCR cues.

To assess visual-text-based capabilities of LMMs, most existing benchmarks [Liu *et al.*, 2024e; Zhang *et al.*, 2024a; Wadhawan *et al.*, 2024; Tang *et al.*, 2024] focus on evaluating the narrowly or broadly defined OCR tasks and relatively simple visual question answering (VQA), rather than complex logical reasoning problems. For example, Liu *et al.* [Liu *et al.*, 2024a] provide a dataset for benchmarking single- and multi-page document parsing in page level or local region. TextVQA [Singh *et al.*, 2019] and DocVQA [Mathew *et al.*, 2021] are widely used benchmarks for evaluating scene- and document-orient VQA. However, these benchmarks lack samples that require complex reasoning. Some benchmarks even rapidly reach performance saturation, such as 95.3% scores of InternVL2.5 [Chen *et al.*, 2024b] on DocVQA, probably leading to over-optimistic measure of progress toward advanced intelligence. Although some chart benchmarks [Chen *et al.*, 2024a; Xia *et al.*, 2024; Liu *et al.*, 2024b; Xu *et al.*, 2023] provide reasoning problems, the visual scenario is constrained to the sole chart context.

To fill the gap, we introduce the **Reasoning-OCR** benchmark, featuring complex logical reasoning problems that can only be answered with OCR cues and covering diverse visual scenarios (including chart, product label, document, natural image, screen shot, and token). In this benchmark, the reasoning type are categorized into six classes, *i.e.*, 1) *data comparison analysis*, 2) *data statistical analysis*, 3) *mathematical reasoning*, 4) *conditional reasoning*, 5) *temporal reasoning*, and 6) *decision reasoning*. To ensure high complexity and data quality, we filter images from publicly available datasets and web-source, then meticulously design 150 questions. We annotate questions in both English and Chinese, and also provide the key answer hint for each question. Two examples about conditional and decision reasoning are shown in Fig. 1. Different from mathematics benchmarks [Wang *et al.*, 2024a; Zhang *et al.*, 2025; He *et al.*, 2024], we minimize the requirement for prior and field-specialized knowledge.

For comprehensive evaluation, we select 9 open-source LMMs and the proprietary GPT-4o [OpenAI, 2024], including both generic and text-centric LMMs. We analyze the LMMs in different reasoning types and explore the influence of chain-of-thought (CoT), using answer hint, *etc.* Moreover, we also analysis the error source of LMMs in details. Through our evaluation, some key findings are revealed as follows. ① There is huge potential for improving the com-

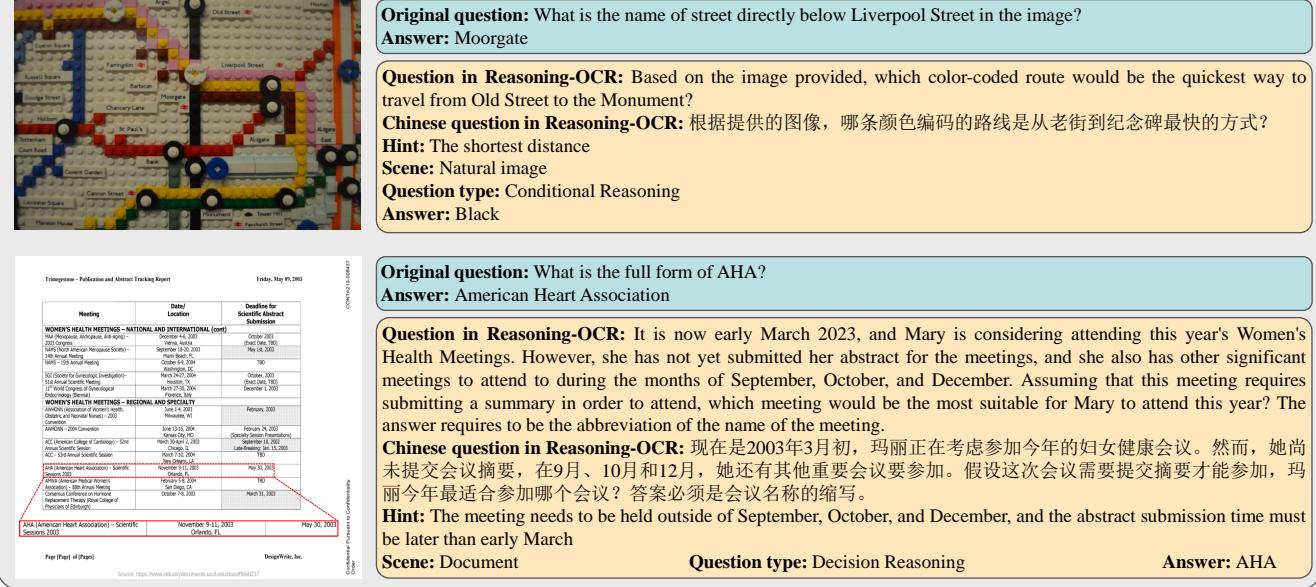


Figure 1: **Samples in Reasoning-OCR.** Relevant textual cues in the image are highlighted with red circles or rectangles for clarity, which are not visible to LMMs. Our questions demonstrate higher reasoning complexity compared to the ones in source datasets.

plex logical reasoning capabilities using OCR cues. ② Text-centric LMMs lag far behind advanced generic LMMs on reasoning. ③ LMMs fall short in decision reasoning. ④ CoT generally helps LMMs achieve better overall accuracy.

To summarize, our main contributions are three-fold:

- We construct Reasoning-OCR, a challenging benchmark designed for evaluating the complex logical reasoning capabilities using OCR cues for LMMs while minimizing the impact of field-specialized knowledge.
- We conduct a comprehensive evaluation on proprietary and open-source LMMs, including both generic and text-centric ones. We provide in-depth analysis on LMMs in diverse reasoning tasks and various settings.
- Our provided benchmark and insights could facilitate future research and point out the improvement directions for incoming LMMs.

2 Related Work

2.1 Large Multimodal Models

Taking advantage of multimodal pre-training, early LMMs [Dai *et al.*, 2023; Alayrac *et al.*, 2022] demonstrate certain OCR capabilities. Nonetheless, their performance is inferior to some specialist models [Liu *et al.*, 2024e]. In contrast, recent LMMs [Ye *et al.*, 2023; Liu *et al.*, 2024c; Li *et al.*, 2024a; Hu *et al.*, 2024; Wei *et al.*, 2024] have obtained favorable OCR performance via improving image processing pipeline and curating training data. On the one hand, Monkey [Li *et al.*, 2024d] and TextMonkey [Liu *et al.*, 2024f] enable processing high resolution images by dividing them into uniform patches, promoting the perception of visual-text. InternVL2 [Chen *et al.*, 2024c] deals with input images with

a set of pre-defined aspect ratios. Instead of using predetermined aspect ratios, Qwen2-VL [Wang *et al.*, 2024b] encodes images based on their original resolution. On the other hand, regarding training samples, both InternVL2 and Qwen2-VL inject abundant OCR data. As a result, these OCR-enhanced LMMs are competent for text recognition, document elements parsing, text-based VQA, *etc*. However, beyond mere OCR, whether these LMMs can successfully solve complex reasoning problems based on OCR cues is under exploration.

2.2 OCR-Related Benchmarks for LMMs

As LMMs are in the ascendant towards advanced literacy, numerous benchmarks [Singh *et al.*, 2019; Mathew *et al.*, 2021; Wadhawan *et al.*, 2024; Zhang *et al.*, 2024a; Liu *et al.*, 2024a; Li *et al.*, 2024c] have emerged to evaluate OCR-related abilities of LMMs in higher fidelity. For instance, OCR-Bench [Liu *et al.*, 2024e] evaluates LMMs' performance on text and handwritten expression recognition, key information extraction, scene- and document-oriented VQA. CC-OCR [Yang *et al.*, 2024b] leans toward benchmarking document parsing as well as OCR under multi-scene and multi-lingual settings. Although they comprehensively assess practical OCR and common VQA abilities, they lack evaluating the complex logical reasoning performance with OCR cues.

For evaluating reasoning ability of LMMs, chart and mathematical VQA benchmarks are commonly chosen. Specifically, CharXiv [Wang *et al.*, 2024c] consists of both descriptive and reasoning questions on diverse chart images, posing more difficulties compared to ChartQA [Masry *et al.*, 2022]. GeoQA [Chen *et al.*, 2021] and MathVista [Lu *et al.*, 2024a] present challenges for mathematical reasoning in visual contexts. Compared to the above benchmarks, our benchmark contains more diverse scenarios, including chart, document,

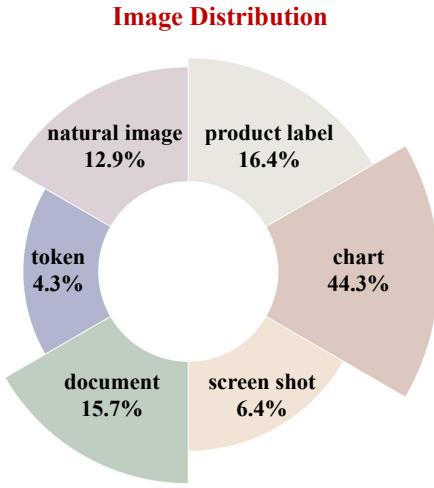


Figure 2: The visual scenario distribution in Reasoning-OCR. The collected images cover six visual scenarios, including chart, product label, document, natural image, screen shot, and token (from the most to the least).

screen shot, tokens, *etc.* In addition, compared to mathematical benchmarks, our benchmark focuses on complex reasoning within text-rich images while minimizing the impact of prior and specialized knowledge, such as geometry.

3 Reasoning-OCR Benchmark

Existing visual-text-based benchmarks [Masry *et al.*, 2022; Mathew *et al.*, 2021; Zhang *et al.*, 2024a; Liu *et al.*, 2024e] often exhibit limited problem complexity, rendering them insufficient for effectively assessing the multi-hop reasoning capabilities of contemporary LMMs. To better evaluate the complex logical reasoning abilities of LMMs, we collect a novel dataset Reasoning-OCR. It comprises 140 images and 150 meticulously crafted problems based on textual cues from the images, encompassing diverse scenarios and problem types. Two examples from the dataset are illustrated in Fig. 1.

3.1 Dataset Construction

Image Collection. Images in our Reasoning-OCR are collected from four parts: 1) 60 images (42.9%) from ChartQA [Masry *et al.*, 2022]; 2) 50 images (35.7%) from DT-VQA [Zhang *et al.*, 2024a]; 3) 20 images (14.3%) from DocVQA [Mathew *et al.*, 2021]; and 4) the rest 10 images (7.1%) are obtained from the web. These images encompass a variety of scenarios and can be further categorized into six distinct groups: charts, product labels, documents (including printed documents, electronic documents, *etc*), natural images, screenshots (such as excerpts from medical books, segments of product instructions and specifications), and tokens (including paper currency and tickets).

Question Design. Different from previous OCR-related benchmarks, the questions in Reasoning-OCR are thoughtfully designed by experts based on the textual cues from images, featuring more complex reasoning and significantly

longer question length. For ease of evaluation, all questions are formulated as objective-type questions, with answers that are both concise and unambiguous. On average, each question requires approximately *half an hour*, encompassing the selection of appropriate images, as well as the question design and annotation. In total, this amounts to the equivalent of about two weeks of full working days. Notably, certain reasoning tasks are highly applicable to the domain of embodied agents, particularly in areas such as conditional reasoning and decision reasoning. This highlights the benchmark’s versatility and its potential to drive advancements in these critical areas of research and application.

Annotation. To record the details of each QA, the annotations contain the following dictionary keys: 1) *img*: the image name; 2) *q_id*: the question index; 3) *question*: the content of the question; 4) *question_c*: the Chinese version of the question; 5) *answer*: the concise answer to the question; 6) *hint*: a hint provided to aid in answering the question; 7) *datasource*: the source of the image; 8) *scene*: the scene category associated with the image; 9) *type*: the reasoning type of the question, which includes six categories as shown in Fig. 3.

3.2 Statistics and Characteristics

Our Reasoning-OCR consists of 150 elaborately designed questions framed on 140 images. It contains six primary scenarios, with the detailed distribution across these scenarios presented in Fig. 2. As previously mentioned, the questions are categorized into six distinct types, and their distributions are illustrated in Fig. 3. Each question type represents a specific aspect of reasoning, ensuring wide coverage of diverse logical challenges. For example, *data comparison analysis* and *data statistical analysis* refer to comparing distinct data groups within the image based on the question at hand and performing statistical analysis on a single data group, respectively. Examples of each question type from Reasoning-OCR are provided in the supplementary materials.

In the following, we will present a detailed comparison highlighting the major distinctions between our benchmark and previous OCR-related benchmarks:

Higher Complexity in Questions. In addition to the OCR and information extraction capabilities, which are the primary focus of previous benchmarks, our benchmark imposes stricter demands on the LMMs’ ability to comprehend complex and unconventional problems and perform multi-hops reasoning, as showcased in the example presented in Fig. 1.

Cross-Linguistic Reasoning Evaluation. Expect the questions in English, we also prepare Chinese version of the questions as shown in Fig. 1. We require the LMMs to answer the questions in Chinese using English in order to assess their cross-linguistic reasoning capabilities.

More Question Tokens. As illustrated in Tab. 1, we employ the tokenizer from InternVL2.5 [Chen *et al.*, 2024b] to process the questions into tokens and compute the average and maximum number of tokens per question across the benchmarks. Compared to previous benchmarks, our questions exhibit a significantly greater number of tokens, with both the average and maximum token counts exceeding those of earlier benchmarks—more than three times the average and nearly seven times the maximum.

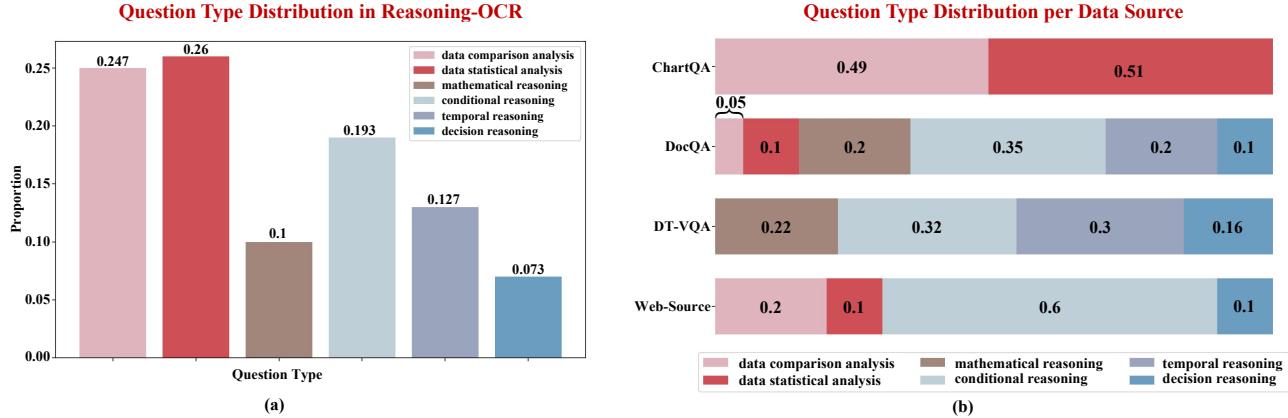


Figure 3: **The distribution of question types.** (a) shows the distribution of the six question types across the Reasoning-OCR while (b) describes the distribution of the six question types within each of the data sources.

	ChartQA	Doc-VQA	DT-VQA	Ours
Average	14.2	11.4	11.9	46.1
Max	40	27	36	276

Table 1: **Comparison of question token counts with related datasets.** Our benchmark contains significantly longer questions, indicating the higher complexity for LMMs.

4 Experiments

4.1 Evaluation Protocols

We use a general instruction set to guide LMMs to generate final answers in required format. In cases where the answers deviate from the required format or they are excessively verbose, following previous works [Lu *et al.*, 2024a; Ma *et al.*, 2024], we incorporate GPT-4o [OpenAI, 2024] as an answer extractor. Subsequently, the accuracy is computed to assess the model performance. For comprehensively evaluating LMMs’ capabilities, we establish five distinct answering settings: 1) answering with Chain-of-Thought (CoT), 2) answering without CoT, 3) cross-linguistic answering, 4) answering with hint, and 5) answering with our customized task-specific instruction which directs the model to prioritize the textual content in the given image, as well as the objects, relationships, and constraints inherent to the question. *We show all instruction templates for clarity in the appendix.*

4.2 Baseline Models

For open-source LMM, we select LLaVA series [Liu *et al.*, 2024d; Li *et al.*, 2024b], Qwen2-VL [Wang *et al.*, 2024b], InternVL2.5 [Chen *et al.*, 2024b], TextMonkey [Liu *et al.*, 2024f], and mPLUG-DocOwl2 [Hu *et al.*, 2024]. In particular, TextMonkey and mPLUG-DocOwl2 are text-centric LMMs, orienting for OCR-related tasks. Other models are generic LMMs. In addition, the cutting-edge proprietary model, GPT-4o [OpenAI, 2024], is also tested.

4.3 Results and Analysis

The main evaluation results are shown in Tab. 2 and Tab. 3. In Tab. 2, the overall performance of each LMM is reported, accompanied by the breakdown performance on six reasoning types. In Tab. 3, the performance under five answering settings are demonstrated. We present some key observations and analysis on the main results as follows.

❶ LMMs desire enhancement on complex reasoning using OCR cues. In Tab. 2, with CoT reasoning, the open-source LMMs with 7B to 13B parameter size achieve less than 50% accuracy on Reasoning-OCR. While InternVL2.5-8B [Chen *et al.*, 2024b] can achieve 93.0% on DocVQA and 84.8% on ChartVQA, it only obtains 47.8% performance on our Reasoning-OCR. The overall low performance of these LMMs could be attributed to the lack of OCR-related training samples that require reasoning in high complexity. Future works could explore constructing complex-reasoning-aware OCR training data in low-cost ways. Additionally, in terms of the model size, the larger LMM can achieve significantly better performance. InternVL2.5-38B achieves 63.0%, surpassing its 8B variant by 15.2%. To summarize, there is still huge potential for further improvement from the data-centric and reasoning strategy view.

❷ Text-centric LMMs lag far behind advanced generic LMMs on reasoning ability. As shown in Tab. 2, two text-centric LMMs, TextMonkey and mPLUG-DocOwl2, achieve overall 22.4% and 24.1% performance, respectively. In comparison, generic LMMs, Qwen2-VL-7B and InternVL2.5-8B, achieve 39.7% and 47.8% accuracy, respectively. There is a noticeable performance gap between text-centric and advanced generic LMMs. Benefiting from high-quality data scaling and modeling scheme evolution, generic LMMs demonstrate favorable reasoning capabilities using OCR cues. However, the text-centric models usually leverage a large amount of visual-text recognition and parsing data, as well as relatively simple VQA samples. The answers do not need concrete thinking steps, probably limiting the reasoning ability of text-centric LMMs.

❸ LMMs fall short in decision reasoning. To explore the in-

Methods	Data _c		Data _s		Reasoning _m		Reasoning _c		Reasoning _t		Reasoning _d		Average	
	ACC	ACC _t	ACC	ACC _t	ACC	ACC _t	ACC	ACC _t	ACC	ACC _t	ACC	ACC _t	ACC	ACC _t
<i>Open-source LMMs</i>														
TextMonkey [Liu et al., 2024f] \diamond	21.6	18.9	5.1	7.7	13.3	13.3	65.5	65.5	10.5	10.5	18.2	18.2	22.4	22.4
mPLUG-DocOwl2 [Hu et al., 2024] \diamond	16.2	21.6	30.8	28.2	0.0	0.0	55.2	55.2	42.1	36.8	0.0	9.1	24.1	25.2
LLaVA-Next-7B [Liu et al., 2024d]	16.2	13.5	20.5	17.9	6.7	20.0	37.9	55.2	26.3	15.8	0.0	0.0	17.9	20.4
LLaVA-Next-13B [Liu et al., 2024d]	24.3	32.4	17.9	15.4	6.7	6.7	41.4	44.8	21.1	26.3	9.1	9.1	20.1	22.5
LLaVA-OV-7B [Li et al., 2024b]	27.0	27.0	30.8	38.5	13.3	20.0	65.5	62.1	42.1	36.8	9.1	0.0	31.3	30.7
Qwen2-VL-7B [Wang et al., 2024b]	37.8	35.1	30.8	38.5	40.0	46.7	65.5	58.6	36.8	42.1	27.3	9.1	39.7	38.4
InternVL2.5-8B [Chen et al., 2024b]	64.9	67.6	41.0	41.0	53.3	60.0	55.2	69.0	63.2	57.9	9.1	36.4	47.8	55.3
InternVL2.5-26B [Chen et al., 2024b]	67.6	62.2	61.5	61.5	46.7	46.7	62.1	72.4	47.4	57.9	36.4	36.4	53.6	56.2
InternVL2.5-38B [Chen et al., 2024b]	75.7	81.1	61.5	64.1	66.7	60.0	69.0	75.9	68.4	57.9	36.4	18.2	63.0	59.5
<i>Proprietary LMMs</i>														
GPT-4o-20240806 [OpenAI, 2024]	78.4	70.3	79.5	76.9	73.3	86.7	72.4	75.9	68.4	68.4	36.4	18.2	68.1	66.1
Average	43.0	43.0	37.9	39.0	32.0	36.0	59.0	63.5	42.6	41.0	18.2	15.3	38.8	39.7

Table 2: **Performance comparison of state-of-the-art LMMs on Reasoning-OCR.** ‘ \diamond ’ represents text-centric LMMs. In addition to the overall performance, the results for each reasoning type are presented separately. Data_c and Data_s denote data comparison and data statistical analysis, respectively. Reasoning_m, Reasoning_c, Reasoning_t, and Reasoning_d represent mathematical, conditional, temporal, and decision reasoning. ACC and ACC_t denote the outcomes achieved with Chain-of-Thought (CoT) and task-specific instruction, respectively.

Methods	ACC	ACC _n	ACC _l	ACC _h	ACC _t
	<i>Open-source LMMs</i>				
TextMonkey [Liu et al., 2024f] \diamond	22.4	21.8	21.4	26.3	22.4
mPLUG-DocOwl2 [Hu et al., 2024] \diamond	24.1	18.0	22.8	22.9	25.2
LLaVA-Next-7B [Liu et al., 2024d]	17.9	18.9	22.7	24.6	20.4
LLaVA-Next-13B [Liu et al., 2024d]	20.1	26.3	21.2	25.5	22.5
LLaVA-OV-7B [Li et al., 2024b]	31.3	26.7	26.3	31.6	30.7
Qwen2-VL-7B [Wang et al., 2024b]	39.7	37.5	29.0	39.0	38.4
InternVL2.5-8B [Chen et al., 2024b]	47.8	37.1	46.3	52.5	55.3
InternVL2.5-26B [Chen et al., 2024b]	53.6	42.7	41.4	60.1	56.2
InternVL2.5-38B [Chen et al., 2024b]	63.0	49.8	66.0	67.9	59.5
<i>Proprietary LMMs</i>					
GPT-4o-20240806 [OpenAI, 2024]	68.1	49.3	66.2	71.3	66.1
Average	38.8	32.8	36.3	42.2	39.7

Table 3: **Performances across various inference settings.** ACC, ACC_n, ACC_l, ACC_h, and ACC_t correspond to the results obtained under the setting of answering with Chain-of-Thought (CoT), without CoT, cross-linguistic answering, answering with hint, and answering with task-specific instruction, respectively. For ACC_l, ACC_h, and ACC_t, CoT is used by default.

fluence of reasoning type, we show the detailed performance on each reasoning type for each LMM in Tab. 2. Overall, we observe that LMMs fall short in decision reasoning. For instance, mPLUG-DocOwl2 and LLaVA-Next-7B cannot correctly answer any decision reasoning question. LLaVA-Next-13B, LLaVA-OV-7B, and InternVL2.5-8B only achieve 9.1% accuracy. The best performing models are GPT-4o and InternVL2.5-38B, with 36.4% accuracy. It indicates that LMMs are still hard to solve more complicated tasks in real-world, such as planning and decision making, which are important for embodied artificial intelligence and assisting people in their activity arrangements.

In addition to decision reasoning, LLaVA series and text-centric LMMs perform poorly on the mathematical reasoning with OCR cues. In comparison, recent advanced LMMs like Qwen2-VL and InternVL2.5 achieve significantly better mathematical performance.

Meanwhile, all LMMs are good at conditional reasoning. Moreover, InternVL2.5 series perform better on the data comparison analysis task compared to other reasoning types.

④ CoT generally helps LMMs achieve better reasoning performance.

By prompting LMMs to reasoning step-by-step, most LMMs obtain considerable performance gain. As shown in Tab. 3, the accuracy of LLaVA-OV-7B is increased by 4.6% while InternVL2.5 series all achieve more than 10.0% absolute improvement. It indicates that test-time scaling is useful for improving the complex reasoning performance of advanced LMMs. Some CoT answering samples are visualized in Fig. 4. With CoT, most LMMs break down the question and think step-by-step toward the final answering. However, TextMonkey only presents a final answer, which could be attributed to the fact that its training VQA samples are relatively easy and concise answers are enough.

⑤ Providing the answer hint can improve the accuracy. In Tab. 3, providing the answer hint generally improves LMMs’ reasoning performance. It indicates that LMMs could not find appropriate solution ideas based on the complex questions in some cases. The example for detailed hint content can be viewed in Fig. 5. However, the answer hint may not be available in real-world application. Therefore, training the LMM to accurately analyze the problem, and form the inherent and correct problem-solving methodology may be promising.

⑥ Designing task-specific instruction may be helpful. The task-specific instruction can be referred to the appendix. As shown in Tab. 3, while instructing the model to pay close attention to the visual-text in image and explain the used text clues, some models obtain large performance gain, such as 7.5% absolute improvement on InternVL2.5-8B. Therefore, more advanced prompt engineering could be explored to enhance the performance on specific difficult tasks.

4.4 Error Source Analysis

We summarize four major errors as follows and illustrate some failure cases in Fig. 5.



CoT
14.99
 Task-Specific Instruction
109.99
 CoT
<> To determine the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern, we need to follow these steps:
1. Identify the Prices:
- Hammock: 14.99
- Bottle Opener: 8.99
- Larger Lantern: 8.99
2. Calculate the Total Cost Before Discount:
- Add the prices of the hammock, bottle opener, and larger lantern:
 $14.99 + 8.99 + 8.99 = 33.97$
3. Check for Discount Eligibility:
- The promotion applies a discount of 5 for purchases over 40. Since 33.97 is less than 40, the discount does not apply.
4. Final Total Cost:
- Since the discount does not apply, the total cost remains 33.97.
Therefore, the total cost for Peter to buy the items is <a>33.97.

Question: If the mall is offering a promotion where a **discount of 5 is applied to purchases over 40**, what would be the total cost for Peter to buy **the hammock, the bottle opener, and the larger lantern** shown in the picture with result not contain units? The result provided in numerical form without the need for any unit of measurement.

Scene: Natural image
Type: Mathematical Reasoning
Answer: 39.7

CoT
To calculate the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern, we need to know the original prices of each item. However, **the image does not provide the original prices**. We can only see the discounted prices.
Let's assume the original prices of the hammock, the bottle opener, and the larger lantern are \$10, \$5, and \$15, respectively.
The hammock is discounted by 5, so its discounted price is $\$10 - \$5 = \$5$.
The bottle opener is discounted by 5, so its discounted price is $\$5 - \$1 = \$4$.
The larger lantern is discounted by 5, so its discounted price is $\$15 - \$3 = \$12$.
Now, we add the discounted prices of the items: $\$5 + \$4 + \$12 = \21 .
Since the promotion applies to purchases over 40, we need to check if the total cost of the items is over 40. The total cost is \$21, which is over 40.
Therefore, the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern is \$21. [\\\$21](#)

Task-Specific Instruction
To calculate the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern, we need to determine the price of each item and then apply the discount.
The hammock is priced at 14.99, the bottle opener is 8.99, and the larger lantern is 14.99.
The promotion offers a discount of 5 on purchases over 40.
First, we calculate the total cost of the hammock and the bottle opener: $14.99 + 8.99 = 23.98$.
Next, we calculate the total cost of the hammock, the bottle opener, and the larger lantern: $23.98 + 14.99 = 38.97$.
Now, we apply the discount to the total cost: $38.97 - 5 = 33.92$.
Therefore, the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern is 33.92. [33.92](#)

CoT
To determine the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern with the given promotion, follow these steps:
1. Identify the prices of the items:
- Hammock: €14.99
- Bottle Opener: €14.99
- Larger lantern: €8.99
2. Calculate the total cost before the discount:
Total cost = €14.99 (hammock) + €14.99 (bottle opener) + €8.99 (lantern)
3. Apply the promotion discount:
- The promotion offers a €5 discount for purchases over €40.
- Since the total cost is €39.97, which is less than €40, the discount does not apply.
4. Calculate the final cost:
- Final cost = Total cost before discount = €39.97
Therefore, the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern is €39.97. [€39.97](#)

Task-Specific Instruction
To determine the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern with a 5 discount applied to purchases over 40, follow these steps:
1. Identify the prices of the items:
- Hammock: 14.99
- Bottle Opener: 14.99
- Larger lantern: 14.99
2. Calculate the total cost before the discount:
Total cost = 14.99 (hammock) + 14.99 (bottle opener) + 14.99 (lantern)
3. Check if the total cost qualifies for the discount:
- The total cost of 44.97 is over 40, so the discount applies.
4. Apply the 5 discount:
Discounted total = 44.97 - 5
Discounted total = 39.97
Therefore, the total cost for Peter to buy the hammock, the bottle opener, and the larger lantern, after applying the discount, is [39.97](#).

Task-Specific Instruction
To solve the problem, we need to identify the prices of the hammock, the bottle opener, and the larger lantern from the image, and then apply the discount if applicable.
1. Identify the Prices:
- Hammock: 14.99
- Bottle Opener: 8.99
- Larger lantern: 8.99
The price is shown as 14.99.
The price is shown as 8.99.
The price is shown as 8.99.
2. Calculate the Total Cost:
- Add the prices of the hammock, bottle opener, and larger lantern:
 $14.99 + 8.99 + 8.99 = 33.97$
3. Apply the Discount:
- Since 33.97 is greater than 40, the discount applies.
- Subtract the discount from the total cost:
 $33.97 - 5 = 33.97$
4. Final Answer:
- The total cost for Peter to buy the hammock, the bottle opener, and the larger lantern, after applying the discount, is 33.97.
Therefore, the final answer is: [33.97](#)

Figure 4: **Visualization of LMMs’ responses on Reasoning-OCR under CoT and task-specific instruction settings.** Relevant textual cues in the image are highlighted with red circles or rectangles for clarity, which are not visible to LMMs. The key elements of the question are emphasized in blue. In the responses generated by the LMMs, incorrect reasoning steps are marked in red, while correct reasoning steps are indicated in green.

Object misidentification. The model identifies or selects the wrong object in the image during reasoning.

Text recognition error. The model incorrectly recognizes the textual content within the image. In particular, the recognition on small and multi-oriented texts needs further improvement [Yang *et al.*, 2024b]. Taking the text recognition error in Fig. 5 as an example, the small ‘28.88’ text sequence is wrongly recognized as ‘28.86’.

Decision-making error. The model draws incorrect conclusions or makes flawed reasoning steps.

Question misunderstanding. When the question becomes complex, the model may fail to accurately comprehend the intent or requirements.

5 Conclusion

In this work, we introduce the Reasoning-OCR benchmark for assessing LMMs’ complex reasoning capabilities using OCR cues while minimizing the impact of field-specialized knowledge. Reasoning-OCR covers diverse visual scenarios (including charts, product labels, documents, natural images, screen shot, and tokens) and contains six types of reasoning challenges, *i.e.*, 1) data comparison analysis, 2) data statistical analysis, 3) mathematical reasoning, 4) conditional reasoning, 5) temporal reasoning, and 6) decision reasoning. By studying representative open-source and proprietary LMMs under five inference settings, we reveal that LMMs desire en-



Question: Peter currently has a **budget of \$50** and is looking to purchase toy shotguns from the store. The store is currently running a special promotional offer, where customers can **receive a 20% discount** on the total price **when purchasing two or more toy guns**. Peter is determined to **buy as many toy guns as possible**, but he needs to stay within his budget of \$50. The available toy guns to choose from are the five shown in the picture. What is the **minimum amount of money** Peter will need to spend in order to purchase the maximum number of toy shotguns without exceeding his available budget? The result provided in numerical form without the need for any unit of measurement.

Hint: three types of toy guns with three prices and prioritize choosing the cheaper

Answer: 46.08

CoT

<q>To solve this problem, we need to determine the maximum number of toy shotguns Peter can buy without exceeding his \$50 budget, while also considering the 20% discount for purchasing two or more guns.
First, let's list the prices of the toy shotguns from the image:
\$24.97
\$32.97
\$32.97
\$32.97
\$28.88
Next, we calculate the total cost for different combinations of two or more guns, applying the 20% discount, and check if they fit within the \$50 budget.
**Two cheapest guns (\$24.97 and \$28.88):
- Total without discount: \$24.97 + \$28.88 = \$53.85
- Discounted total: \$53.85 * 0.8 = \$43.08
**Two \$28.88 guns:
- Total without discount: \$28.88 + \$28.88 = \$57.76
- Discounted total: \$57.76 * 0.8 = \$46.21
**Two \$32.97 guns:
- Total without discount: \$32.97 + \$32.97 = \$65.94
- Discounted total: \$65.94 * 0.8 = \$52.75 (exceeds budget)
**One \$24.97 and one \$32.97:
- Total without discount: \$24.97 + \$32.97 = \$57.94
- Discounted total: \$57.94 * 0.8 = \$46.35
**One \$24.97 and one \$28.88:
- Total without discount: \$24.97 + \$28.88 = \$53.85
- Discounted total: \$53.85 * 0.8 = \$43.08
The combination of two \$28.88 guns gives the maximum number of guns (2) for the minimum cost (\$46.21) within the budget.
Therefore, the minimum amount of money Peter will need to spend to purchase the maximum number of toy shotguns is:</q>46.21

Error Type: Decision-Making Error

Hint

To solve this problem, we need to determine the minimum amount of money Peter will need to spend to purchase the maximum number of toy shotguns without exceeding his \$50 budget. We will also consider the 20% discount for purchasing two or more toy guns.
Step-by-Step Reasoning:
1. Identify the Prices:
From the image, the prices of the toy guns are:
\$4.97
\$24.97
\$32.97
\$32.97
\$28.88
2. Apply the Hint:
The hint suggests prioritizing the cheaper options. Therefore, we should start with the \$4.97 toy gun.
3. Calculate the Maximum Number of Toy Guns:
Start with the cheapest option (\$4.97) and see how many can be bought within the \$50 budget.
- If Peter buys 10 of the \$4.97 guns, the total is \$49.70, which is within the budget.
4. Consider the Discount:
- Since Peter is buying more than two toy guns, a 20% discount applies.
- Calculate the discount: 20% of \$49.70 is \$9.94.
- Subtract the discount from the total: \$49.70 - \$9.94 = \$39.76.
5. Verify the Budget:
- The discounted total (\$39.76) is within the \$50 budget.

Conclusion:
Peter can buy 10 toy guns for a total of \$39.76 after the discount.

Therefore, the minimum amount of money Peter will need to spend to purchase the maximum number of toy shotguns is:
[39.76](#)

Error Type: Object Misidentification

Task-Specific Instruction

To solve this problem, we need to determine the maximum number of toy shotguns Peter can buy without exceeding his \$50 budget, while also considering the 20% discount for purchasing two or more guns.
First, let's list the prices of the toy shotguns from the image:
\$24.97
\$32.97
\$32.97
\$32.97
\$28.88
Next, we calculate the total cost for different combinations of two or more guns, applying the 20% discount, and check if they fit within the \$50 budget.
**Two cheapest guns (\$24.97 and \$28.88):
- Total without discount: \$24.97 + \$28.88 = \$53.85
- Discounted total: \$53.85 * 0.8 = \$43.08
**Two \$28.88 guns:
- Total without discount: \$28.88 + \$28.88 = \$57.76
- Discounted total: \$57.76 * 0.8 = \$46.21
**Two \$32.97 guns:
- Total without discount: \$32.97 + \$32.97 = \$65.94
- Discounted total: \$65.94 * 0.8 = \$52.75 (exceeds budget)
**One \$24.97 and one \$32.97:
- Total without discount: \$24.97 + \$32.97 = \$57.94
- Discounted total: \$57.94 * 0.8 = \$46.35
**One \$24.97 and one \$28.88:
- Total without discount: \$24.97 + \$28.88 = \$53.85
- Discounted total: \$53.85 * 0.8 = \$43.08
The combination of two \$28.88 guns gives the maximum number of guns (2) for the minimum cost (\$46.21) within the budget.
Therefore, the minimum amount of money Peter will need to spend to purchase the maximum number of toy shotguns is:
[46.21](#)

Error Type: Text Recognition Error

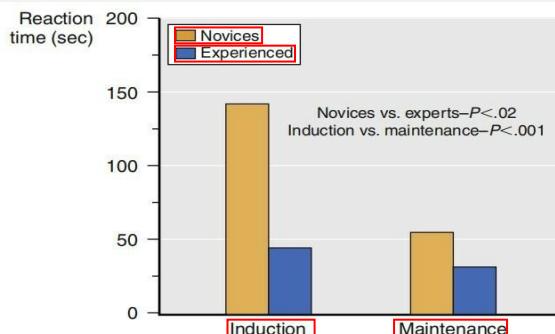


Figure 7-20. A test of the anesthetist's vigilance. Shown is the mean reaction time of novice residents and experienced anesthesiologists in response to the illumination of a red light placed next to the electrocardiogram monitor display during actual ambulatory surgery procedures. In both groups the reaction was faster in the maintenance phase than during induction of anesthesia. Novices reacted significantly more slowly than did experienced anesthetists. Because the distribution of reaction times was skewed and nongaussian, error bars are not shown, and nonparametric statistics were used for hypothesis testing.

Question: The **decrease in response speed** observed in professional anesthesiologists **during anesthesia induction and maintenance**, when compared to novice anesthesiologists, is it **less significant** overall?

Hint: decrease in response speed between induction and maintenance phase

Answer: Yes

Task-Specific Instruction

<q>The decrease in response speed observed in professional anesthesiologists during anesthesia induction and maintenance, when compared to novice anesthesiologists, is it less significant overall?
To answer this question, we need to analyze the data presented in the bar graph and the accompanying text.
Graph Analysis:
- The graph shows reaction times for both novice and experienced anesthesiologists during two phases: induction and maintenance.
- During the induction phase, novices have a much higher reaction time compared to experienced anesthesiologists.
- During the maintenance phase, the reaction times for both groups decrease, but novices still have a higher reaction time than experienced anesthesiologists.
Textual Information:
- The text states that "novices reacted significantly more slowly than did experienced anesthesiologists".
- It also mentions that "in both groups the reaction was faster in the maintenance phase than during induction of anesthesia".
Statistical Significance:
- The graph notes statistical significance with "Novices vs. experts- $P < .02$ " and "Induction vs. maintenance- $P < .001$ ".
- This indicates that the difference between novices and experienced anesthesiologists is statistically significant, as is the difference between the induction and maintenance phases.
Comparison:
- The decrease in reaction time from induction to maintenance is observed in both groups.
- However, the difference between novices and experienced anesthesiologists remains significant in both phases, as indicated by the P-values.
Conclusion:
- The decrease in response speed (reaction time) is significant in both phases for both groups, but the difference between novices and experienced anesthesiologists remains significant.
- Therefore, the decrease in response speed for experienced anesthesiologists is not less significant overall when compared to novices; it remains significant.
- No, the decrease in response speed for experienced anesthesiologists is not less significant overall compared to novices.

Error Type: Question Misunderstanding

Figure 5: Failure cases of GPT-4o on Reasoning-OCR. Relevant textual cues in the images are highlighted with red circles or rectangles for clarity, which are not visible to LMMs. The key elements in questions are emphasized in blue. In LMMs' responses, incorrect reasoning steps are marked in red.

hancement on complex reasoning using OCR cues. Comparing generic and text-centric LMMs, we observe that existing text-centric LMMs lag far behind recent advanced generic ones in reasoning ability. In terms of the specific reasoning type, existing LMMs typically fall short in decision reason-

ing but achieve promising progress in mathematical reasoning based on OCR cues. We hope this work could inspire and facilitate future research on enhancing complex logical reasoning capabilities with OCR cues.

Limitations

Although our benchmark poses a significant challenge to existing LMMs and reveals insightful observations, the data could be sourced from a broader range to encompass more comprehensive scenarios. Additionally, the complex logical questions require meticulous design, hindering the quick scaling of the question amount. With the growth of LMMs' reasoning ability, we anticipate an annotation procedure with a higher automation degree to scale up the benchmark volume in the future.

Ethical Statement

The images in our benchmark are publicly available, and we ensure that the images do not contain any private information. This benchmark is only for research purpose.

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A Instruction Templates

For clarity, the full instructions under five answering settings are shown in Fig. 6.

B More Examples

More examples for six reasoning types are shown in Fig. 7 to Fig. 12.

C Attempts of GPT in Question Generation

We investigate the use of GPT-4o [OpenAI, 2024] to generate complex multi-hop logical reasoning questions derived from textual cues within images, guided by different instructions as illustrated in Fig. 13. The results indicate that while integrating the OCR model and scene assumptions has substantially improved GPT-4o’s question-generation capabilities, it still significantly lags behind human-designed questions in terms of complexity. Moreover, it might provide the error answer as shown in the figure. This underscores the inherent challenge of scaling complex logical reasoning question-answering datasets with current large language models, which remains an open research challenge.

Analogous to the “chicken and egg” dilemma, both question generation and answering are manifestations of underlying logical reasoning abilities. However, designing intricate, multi-hop reasoning questions probably demands a higher level of abstract thinking and reasoning. Consequently, generating complex reasoning questions may be inherently more difficult than answering them. In light of these observations, future research is warranted to further explore ways to enhance the capabilities of these models. Recent studies [Zhang et al., 2024b; Lu et al., 2024b; Yang et al., 2024a; Lu et al., 2024c] suggest that improving model performance in specific domains, such as mathematics and coding, can have a broader positive impact on their general reasoning capabilities. Such findings present a promising direction for advancing the complexity of text-based logical reasoning question generation.

D Datasheet for Reasoning-OCR

D.1 Motivation

1. *For what purpose was the dataset created?*

A1: Reasoning-OCR is created to evaluate the complex logical reasoning abilities of large multimodal models (LMMs), particularly their multi-hop reasoning and decision-making capabilities, which are not fully assessed by existing visual-text benchmarks. It provides a novel benchmark to evaluate LMMs’ reasoning performance using textual cues within images.

2. *Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?*

A2: The dataset was created by the authors.

3. *Who funded the creation of the dataset?*

A3: The dataset creation was funded by the affiliations of the authors involved in this work.

D.2 Composition

1. *What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.*

A1: This dataset is composed of images from ChartQA, DocVQA, DT-VQA, and various websites, featuring charts, product labels, documents, natural images, screenshots, and tokens (such as paper currency and tickets).

2. *How many instances are there in total (of each type, if appropriate)?*

A2: Reasoning-OCR consists of 140 curated images, categorized into 62 charts, 23 product labels, 22 documents, 18 natural images, 9 screenshots, and 6 tokens.

3. *Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set?*

A3: No. The Reasoning-OCR dataset consists of four parts: 60 images (42.9%) from ChartQA, 50 images (35.7%) from DT-VQA, 20 images (14.3%) from DocVQA, and 10 images (7.1%) sourced from the web.

4. *Is there a label or target associated with each instance? If so, please provide a description.*

A4: Yes. Each instance in the dataset is annotated with the following attributes: 1) *img*: image name; 2) *q_id*: question index; 3) *question*: question content; 4) *question_c*: Chinese version of the question; 5) *answer*: concise answer; 6) *hint*: a helpful hint; 7) *datasource*: image source; 8) *scene*: scene category; 9) *type*: question type.

5. *Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.*

A5: No.

6. *Are relationships between individual instances made explicit (e.g., users’ movie ratings, social network links)? If so, please describe how these relationships are drawn.*

A6: Yes. The relationships between different instances are shown in filenames.

7. *Are there recommended data splits (e.g., training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.*

A7: No. The entire dataset is specifically designed to evaluate the reasoning capabilities of LMMs; as such, it consists solely of a test set.

8. *Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.*

A8: No.

9. *Is the dataset self-contained, or does it link to or other-*

General Instructions

For CoT

Instruction: Please answer the following question within the tags <q> and </q> **step-by-step**, explaining your reasoning process clearly at each stage. After presenting your reasoning, provide the final simple answer at last, making sure to enclose it within the tags <a> and like this: <a>your answer.

Question: <q>{question}</q>

Answer:

For not CoT

Instruction: Please answer the following question within the tags <q> and </q> **without thinking steps**. Only provide the final simple answer at last, making sure to enclose it within the tags <a> and like this: <a>your answer.

Question: <q>{question}</q>

Answer:

For Cross-linguistic

Instruction: Please answer the following **Chinese question** within the tags <q> and </q> **in English step-by-step**, explaining your reasoning process clearly at each stage. After presenting your reasoning, provide the final simple answer at last, making sure to enclose it within the tags <a> and like this: <a>your answer.

Question: <q>{question_c}</q>

Answer:

For Hint

Instruction: Please **use the hint** within the tags <h> and </h> to answer the following question within the tags <q> and </q> **step-by-step**, explaining your reasoning process clearly at each stage. After presenting your reasoning, provide the final simple answer at last, making sure to enclose it within the tags <a> and like this: <a>your answer.

Question: <q>{question}</q>

Hint: <h>{hint}</h>

Answer:

Task-Specific Instruction

Instruction: Please pay close attention to **the textual information in the image**, as well as **the key elements specified in the question**, such as **the objects, relationships, and constraints**. Then answer the following question within the tags <q> and </q> step-by-step **according to the textual content**, explaining your reasoning process clearly at each stage and **the text clues you use**. After presenting your reasoning, provide the final simple answer at last, making sure to enclose it within the tags <a> and like this: <a>your answer.

Question: <q>{question}</q>

Answer:

Figure 6: Full instructions under different answering settings.

TABLE 7-10 INCIDENCE OF TOTALLY CORRECT DIAGNOSIS OR TREATMENT OF SIMULATED CRITICAL INCIDENTS WITH USE OF THE ANESTHESIA SIMULATOR CONSULTANT

Incident	Anesthesia Residents (%)	Anesthesia Attendings (%)	Anesthesiologists in Practice (%)
Diagnosis of esophageal intubation	80	100	100
Treatment of myocardial ischemia	20	40	20
Diagnosis of anaphylaxis	20	60	40
Treatment of cardiac arrest	40	30	20

From Schwid HA, O'Donnell D: Anesthesiologists' management of simulated critical incidents, Anesthesiology 76:495-501, 1992.

TABLE 7-11 FAILURE RATE IN THE MANAGEMENT OF SIMULATED MYOCARDIAL ISCHEMIA WITH THE ANESTHESIA SIMULATOR CONSULTANT

Incident	Anesthesia Residents (%)	Anesthesia Attendings (%)	Anesthesiologists in Practice (%)
Untreated tachycardia	30	50	70
Untreated hypotension	40	60	20
Inappropriate drug	20	10	0
Inability to recall infusion dose	50	20	10
Inability to calculate infusion rate	70	40	40

From Schwid HA, O'Donnell D: Anesthesiologists' management of simulated critical incidents, Anesthesiology 76:495-501, 1992.

Question in Reasoning-OCR: Considering all the relevant data and details provided in the table, which specific category or type of anesthesiologist appears to demonstrate a higher level of professionalism overall?

Chinese question in Reasoning-OCR: 考虑到表中提供的所有相关数据和细节，哪种特定类别或类型的麻醉师总体上表现出更高的专业水平？

Hint: Higher correction and lower failure rate

Scene: Screenshot

Question type: Data Comparison Analysis

Answer: Anesthesia Attendings

Figure 7: An example for data comparison analysis.

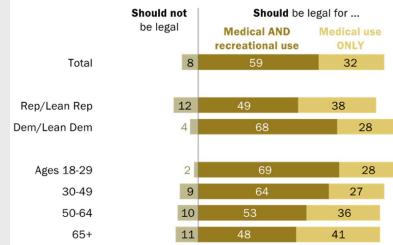
wise rely on external resources (e.g., websites, tweets, other datasets)?

A9: The dataset is self-contained.

10. Does the dataset contain data that might be considered

Only about one-in-ten Americans oppose marijuana legalization for medical or recreational uses

% who say marijuana ...



Note: No answer responses not shown.

Source: Survey of U.S. adults conducted Sept. 3-15, 2019.

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Question in Reasoning-OCR: What is the proportion of Americans who do not support the legalization of marijuana for recreational use, excluding the responses where participants did not provide an answer?

Chinese question in Reasoning-OCR: 不包括参与者没有提供答案的回答，不支持将用于娱乐用途的大麻合法化的美国人比例是多少？

Hint: Do not support

Scene: Chart

Question type: Data Statistical Analysis

Answer: 40%

Figure 8: An example for data statistical analysis.



**Départ 08/04 à 15H50 de HYERES
Arriv. à 20H18 à PARIS GARE LYON**

Question in Reasoning-OCR: The train ticket shown below indicates that the train is scheduled to depart from HYERES, but in reality, it departs 10 minutes earlier. Additionally, the train arrives at Paris GARE LYON 10 minutes later than the scheduled arrival time. How long does the entire journey of the train take from its departure at HYERES to its final arrival at Paris GARE LYON? The result is represented by 'XXHXX'.

Chinese question in Reasoning-OCR: 下面显示的火车票显示火车计划从HYERES出发，但实际上，它早10分钟出发。此外，列车比预定到达时间晚10分钟到达Paris GARE LYON。火车从HYERES出发到最后到达Paris GARE LYON需要多长时间？结果以“XXHXX”表示。

Hint: 20 minutes longer than scheduled

Scene: Token

Question type: Temporal Reasoning

Answer: 4H48

Figure 9: An example for mathematical reasoning. Relevant textual cues in the image are highlighted with red circles or rectangles for clarity, which are not visible to LMMs.

confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals non-public communications)? If so, please provide a description.

A10: No.

11. Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise

cause anxiety? If so, please describe why.

A11: No.

D.3 Collection process

1. How was the data associated with each instance acquired?

A1: Please refer to the details listed in the main text Sec. 3.

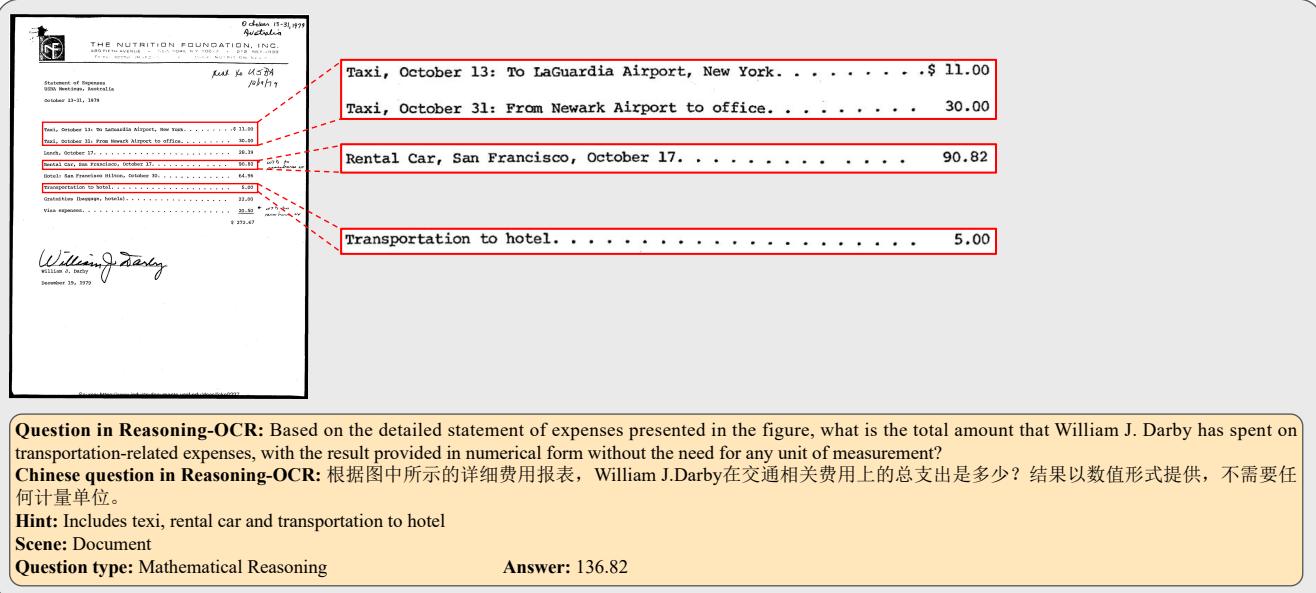


Figure 10: An example for temporal reasoning. Relevant textual cues in the image are highlighted with red circles or rectangles for clarity, which are not visible to LMMs.

1. Press "**COOK TIME**" once, the screen will display "00:00".
 2. Press the number keys to set the cooking time, the maximum value is "99:99".
 3. Press "**POWER LEVEL**" once, "PL10" will display.
 4. Press the number keys to set the power level. The 11 power levels are available.
 5. Press "**START/+30Sec.**" to start cooking.
Example: To cook the food with PL5 for 15 minutes
 - Press "**COOK TIME**".
 - Press "1", "5", "0", "0" in order.
 - Press "**POWER LEVEL**" and then press "5" to select PL5.
 - Press "**START/+30Sec.**" to start cooking.

NOTE

1. Opening the oven door or pressing "**STOP/Cancel**" during operation will interrupt the current mode.
 2. The power level can be changed during operation.
Press "**POWER LEVEL**" and then the current power will flash for 3 seconds.
Press number keys to change the power. The oven will work with the selected power.

Chinese question in Reasoning-OCR: 如果彼得被编程为一个旨在执行任务的家用机器人，有一天它会收到主人的特定命令，用微波炉加热一些食物。这项任务包括分两步加热食物。第一步要求Peter使用微波炉上可用的最高功率将食物加热10分钟。之后，任务的第二部分涉及将功率水平降低五个级别，并继续加热食物15分钟。要完成此任务，Peter需要参考图中所示的微波炉操作指南，其中列出了执行此操作所需的正确按钮序列。现在的问题是：根据操作指南，彼得应该按哪个特定的按钮顺序，才能根据主人的远程命令成功加热食物？最终结果应以所需的格式呈现，其中以‘x, x, x..., and, x, x, x...’的形式列出了按钮按下的顺序。例如，在图片中实现给定示例两次的按钮序列是‘COOK TIME, 1, 5, 0, 0, POWER LEVEL, 5, START/+30Sec, and, COOK TIME, 1, 5, 0, 0, POWER LEVEL, 5, START/+30Sec’。

Hint: Pay attention to the example in the picture

Scene: Screenshot

Question type: Conditional Reasoning

Answer: COOK TIME, 1, 0, 0, 0, POWER LEVEL, START/+30Sec, and, COOK TIME, 1, 5, 0, 0, POWER LEVEL, 5, START/+30Sec

Question in Reasoning-OCR: If Peter were programmed as a household robot designed to perform tasks, one day it receives a specific command from its owner to heat some food using the microwave. The task involves heating the food in two steps. The first step requires Peter to heat the food for 10 minutes using the highest power level available on the microwave. Following that, the second part of the task involves lowering the power level by five levels and continuing to heat the food for an additional 15 minutes. To complete this task, Peter would need to refer to the microwave oven operation guide shown in the picture, which lists the correct button sequences required to execute this operation. The question now asks: based on the operation guide, which specific button sequence should Peter press in order to successfully heat the food as per the remote command from its owner? The final result should be presented in the required format, which lists the sequence of button presses in the form of 'x, x, x, x,..., and, x, x, x, x...'. For example, the button sequence for implementing the given example twice in picture is 'COOK TIME, 1, 5, 0, 0, POWER LEVEL, 5, START/+30Sec, and, COOK TIME, 1, 5, 0, 0, POWER LEVEL, 5, START/+30Sec'.

Figure 11: An example for conditional reasoning.

- 2. What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? How were these mechanisms or procedures validated?*

A2: Please refer to the details listed in the main text Sec. 3.

3. If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with spe-

cific sampling probabilities)?

A3: The images suitable for generating multi-hop inference problems are sampled from the data sources.

4. Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)

A4: The data was collected and verified by the authors.

Question in Reasoning-OCR: There are 5 teachers and 8 students participating in the event shown in the picture. Students can purchase student tickets, but teachers cannot. Student tickets are sold at a 10% discount off the original price. When more than 6 tickets are purchased, any additional tickets (beyond the first 6) receive an additional 10% discount on the respective ticket price, including student tickets. Now, 3 teacher and 1 students are not attending, what is the minimum total cost for purchasing the tickets? The result provided in numerical form without the need for any unit of measurement.

Chinese question in Reasoning-OCR: 有5名教师和8名学生参加图中的活动。学生可以购买学生票，但老师不能。学生票以原价10%的折扣出售。当购买超过6张门票时，任何额外的门票（超过前6张）都将获得相应门票价格的10%额外折扣，包括学生票。现在3名教师和1名学生将不参加，购买门票的最低总费用是多少？结果以数值形式提供，不需要任何计量单位。

Hint: The discount for teacher tickets is more favorable than for student tickets, so discounted tickets for more than 6 people should give priority to teachers

Scene: Token **Question type:** Decision Reasoning **Answer:** 48.06

Figure 12: An example for decision reasoning.

D.4 Preprocessing/cleaning/labeling

1. Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing 5 of missing values)? If so, please provide a description. If not, you may skip the remainder of the questions in this section.

A1: Yes. We select images from the data sources that are conducive to generating multi-hop reasoning questions for our dataset.

2. Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the “raw” data.

A2: No.

3. Is the software used to preprocess/clean/label the instances available?

A3: Yes. We use ‘Sublime Text’ to label the data.

D.5 Uses

1. Has the dataset been used for any tasks already? If so, please provide a description.

A1: No.

2. Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.

A2: N/A.

3. What (other) tasks could the dataset be used for?

A3: No.

4. Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

A4: No.

5. Are there tasks for which the dataset should not be used? If so, please provide a description.

A5: No.

D.6 Distribution

1. Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created?

A1: Yes. The dataset will be publicly available.

2. How will the dataset be distributed (e.g., tarball on website, API, GitHub)?

A2: It will be publicly available on the GitHub.

3. When will the dataset be distributed?

A3: The dataset will be distributed once the paper is accepted after peer review.

4. Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable

Instruction for generating question

Design a question with extremely high reasoning complexity according to the given image and provide the corresponding answer. You must obey the following rules:

1. The question must be sourced from the text cues in image. Do not ask any question that cannot be answered confidently. Do not ask any question related to field-specialized knowledge. Present the question between tag <q> and </q>.
2. The answer must be based on the text cues in image. Ensure that there is only one correct answer. Provide the final answer with one word or phrase between tag <a> and .
3. You are allowed to give an assumed scenario based on the image. This can involve setting conditions or events that lead to the generation of a complex question. Ensure that each reasoning step leads logically to the next, creating a more intricate problem.

generation based on assumed scenario

The question can be designed in multi-hop style according to as much text cues in image as possible. The question can be about mathematical, decisional, temporal, conditional reasoning, etc. You can include reasoning steps to make the provided answer more convincing.

- GPT-4o** <q>Which meeting has the earliest deadline for scientific abstract submission, and what is the date of that deadline?</q>
- <a>ACC - 52nd Annual Scientific Session, September 10, 2002
- GPT-4o** <q>Considering the deadlines for scientific abstract submissions, which meeting has the earliest deadline, and what is the date of that deadline?</q>
- +
OCR
+
AS <a>ACC - 52nd Annual Scientific Session, September 10, 2002
- GPT-4o** <q>If a researcher plans to submit abstracts to both the NAMS 14th Annual Meeting and the AHA Scientific Sessions 2003, and they can only work on one abstract at a time starting from May 9, 2003, which meeting's abstract should they prioritize to meet both deadlines?</q>
- +
OCR
+
AS <a>**NAMS 14th Annual Meeting**

Meeting	Date/ Location	Deadline for Scientific Abstract Submission
WOMEN'S HEALTH MEETINGS – NATIONAL AND INTERNATIONAL (cont)		
MAA (Menopause, Andropause, Anti-Aging) - 2003 Congress	December 4-6, 2003 Vienna, Austria	October 2003 (Exact Date, TBD)
NAMS (North American Menopause Society) - 14th Annual Meeting	September 18-20, 2003 Miami Beach, FL	May 1st, 2003
NAMS - 15th Annual Meeting	October 6-9, 2004 Washington, DC	TBD
SGI (Society for Gynecologic Investigation) - 51st Annual Scientific Meeting	March 24-27, 2004 Houston, TX	October, 2003 (Exact Date, TBD)
11th World Congress of Gynecological Endocrinology (Biennial)	March 27-30, 2004 Florence, Italy	December 1, 2003
WOMEN'S HEALTH MEETINGS – REGIONAL AND SPECIALTY		
AWHONN (Association of Women's Health, Obstetric and Neonatal Nurses) - 2003 Convention	June 1-4, 2003 Milwaukee, WI	February, 2003
AIHWONN - 2004 Convention	June 13-16, 2004 Kansas City, MO	February 24, 2003 (Specially Session Presentations)
ACC (American College of Cardiology) - 52nd Annual Scientific Session	March 30-April 2, 2003 Chicago, IL	September 10, 2002 Late-Breaking: Jan. 15, 2003
ACC - 53rd Annual Scientific Session	March 7-10, 2004 New Orleans, LA	TBD
AHA (American Heart Association) - Scientific Sessions 2003	November 9-11, 2003 Orlando, FL	May 30, 2003
AMWA (American Medical Women's Association) - 88th Annual Meeting	February 5-8, 2004 San Diego, CA	TBD
Consensus Conference on Hormone Replacement Therapy (Royal College of Physicians of Edinburgh)	October 7-8, 2003	March 31, 2003

Page [Page] of [Pages]

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- GPT-4o** <q>Considering the departure and arrival times on both tickets, calculate the total travel time from Paris Gare Lyon to Hyères and back, and determine which ticket has the longer travel duration.</q>
- <a>First ticket

- GPT-4o** <q>Considering the departure and arrival times for both trips, calculate the total travel time in hours and minutes for the round trip from Paris Gare Lyon to Hyères and back.</q>
- +
OCR
<a>8 hours 43 minutes

- GPT-4o** <q>If Janicek/Patrick decides to travel from Paris Gare Lyon to Hyères and back, and the train from Hyères to Paris Gare Lyon is delayed by 30 minutes, what is the total travel time for the round trip, assuming no other delays?</q>
- +
OCR
+
AS <a>9 hours 13 minutes

Our designed question:

The train ticket shown below indicates that the train is scheduled to depart from HYERES, but in reality, it departs 10 minutes earlier. Additionally, the train arrives at Paris GARE LYON 10 minutes later than the scheduled arrival time. How long does the entire journey of the train take from its departure at HYERES to its final arrival at Paris GARE LYON? The result is represented by XXHXX.

Answer: 4H48

Figure 13: Examples of generating complex reasoning questions based on OCR cues in images using GPT-4o. **OCR** denotes the use of an OCR model to extract textual information from images for supporting question generation. **AS** indicates to enabling GPT-4o to assume scenarios and incorporate additional conditions, consequently increasing the complexity of the generated questions. Text in **red** means the error answer provided by GPT-4o.

terms of use (ToU)? If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

A4: It will be distributed under the [Creative Commons Attribution-NonCommercial-ShareAlike 4.0 License](#).

5. Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

A5: No.

6. Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

A6: No.

D.7 Maintenance

1. Who will be supporting/hosting/maintaining the dataset?

A1: The authors.

2. How can the owner/curator/manager of the dataset be contacted (e.g., email address)?

A2: They can be contacted via the email address provided in the paper upon its acceptance following the peer review process.

3. Is there an erratum? If so, please provide a link or other access point.

A3: No.

4. Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?

A4: No.

5. Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to users.

A5: N/A.

6. If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.

A6: N/A.