MMMU-Pro: A More Robust Multi-discipline Multimodal Understanding Benchmark

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https://mmmu-benchmark.github.io/#leaderboard

Abstract

This paper introduces MMMU-Pro, a robust version of the Massive Multi-discipline Multimodal Understanding and Reasoning (MMMU) benchmark. MMMU-Pro rigorously assesses multimodal models' true understanding and reasoning capabilities through a three-step process based on MMMU: (1) filtering out questions answerable by text-only models, (2) augmenting candidate options, and (3) introducing a vision-only input setting where questions are embedded within images. This setting challenges AI to truly "see" and "read" simultaneously, testing a fundamental human cognitive skill of seamlessly integrating visual and textual information. Results show that model performance is substantially lower on MMMU-Pro than on MMMU, ranging from 16.8% to 26.9% across models. We explore the impact of OCR prompts and Chain of Thought (CoT) reasoning, finding that OCR prompts have minimal effect while CoT generally improves performance. MMMU-Pro provides a more rigorous evaluation tool, closely mimicking real-world scenarios and offering valuable directions for future research in multimodal AI.

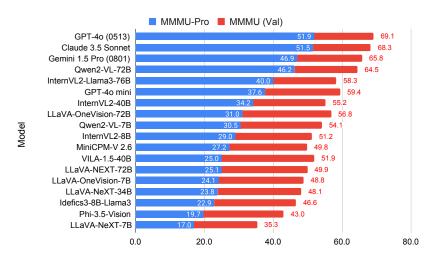


Figure 1: Overview of different multimodal LLMs' performance on MMMU-Pro and MMMU (Val).

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1 Introduction

Recent advances in multimodal large language models (MLLMs) have led to remarkable progress in tackling complex reasoning tasks that combine textual and visual information (Yin et al., 2023a; Jin et al., 2024). Models like GPT-40 (OpenAI, 2024a) have achieved impressive results, e.g., on the Massive Multi-discipline Multimodal Understanding and Reasoning (MMMU) benchmark (Yue et al., 2024), reaching an accuracy of 69.1% on college-level questions that integrate text and images.

While these achievements are significant, they raise a critical question: Do the current benchmark results truly reflect a deep, multifaceted understanding of diverse subjects, or are these models exploiting subtle shortcuts and statistical patterns to arrive at correct answers without genuine comprehension and reasoning?

This question has profound implications for the development and deployment of AI systems in real-world applications. If models rely on superficial cues rather than true multimodal understanding (Du et al., 2023; Yuksekgonul et al., 2023), we risk overestimating their capabilities and potentially deploying systems that fail in unpredictable ways when faced with novel scenarios (Wu and Xie, 2024; Tong et al., 2024b).

To address this concern and push the boundaries of multimodal AI evaluation, we introduce MMMU-Pro, a more robust and challenging version of the MMMU benchmark. MMMU-Pro is designed to more accurately and rigorously assess a model's true multimodal understanding and reasoning capabilities across a wide range of academic disciplines. The development of MMMU-Pro is motivated by several key observations, including the text-only solvability of some existing benchmark questions, the limited option space in multiple-choice formats (Wang et al., 2024), and the need to challenge models' ability to jointly understand different modalities in a more integrated way.

MMMU-Pro employs a rigorous three-step construction process (as shown in Figure 2) that builds upon MMMU (Yue et al., 2024): (1) filtering out questions answerable by text-only language models, (2) augmenting candidate options to reduce the effectiveness of guessing based on the options, and (3) introducing a vision-only input setting (as shown in Figure 3) where models are presented with questions embedded in a screenshot or photo.

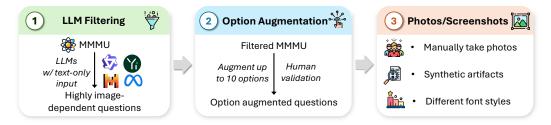


Figure 2: An overview of the construction process of MMMU-Pro.

The introduction of the vision-only input setting is particularly crucial, as it tests a fundamental human cognitive ability: the seamless integration and switching between visual and textual information. This setting challenges models to develop the capability to truly "see" and "read" simultaneously, mirroring how humans effortlessly process complex scenes where text and images are intertwined. This ability is crucial for tasks ranging from interpreting scientific diagrams (Li et al., 2024d) to navigating graphical user interfaces (Liu et al., 2024b; Zheng et al., 2024; Koh et al., 2024). Moreover, this approach aligns with how users naturally interact with AI systems, often sharing screenshots or photos rather than meticulously separating text and images.

Our experimental results demonstrate the effectiveness of MMMU-Pro in providing a more rigorous evaluation of multimodal models. We observe significant performance drops across all tested models when compared to the original MMMU benchmark, with decreases ranging from 16.8% to 26.9%. These results highlight the limitations of current state-of-the-art models in true multimodal understanding and reasoning. Furthermore, our analysis reveals that while Chain of Thought (CoT) (Wei et al., 2022) prompting generally improves performance, the benefits vary across models and settings.

Interestingly, we find that explicit OCR prompts do not significantly impact performance for most models, suggesting that advanced multimodal models have already developed robust text extraction

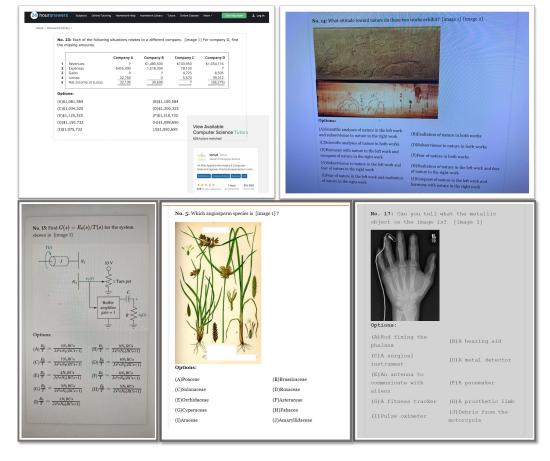


Figure 3: Sample questions from MMMU-Pro. In the Vision Input setting, the model is required to answer a multiple-choice question with up to 10 options, each embedded within a screenshot or photo. These images were manually captured by human annotators in diverse display environments to reflect real-world scenarios.

capabilities from images. However, this result also underscores that simple OCR is insufficient for the challenges presented by MMMU-Pro's vision-only input setting. Our further qualitative analysis indicates that when text is embedded within images, it significantly increases the overall complexity of the visual input, requiring models to not only recognize text but also understand its context, relationship to visual elements, and relevance to the question. These findings not only provide a more accurate assessment of current multimodal AI capabilities but also highlight the need for more sophisticated multimodal reasoning abilities.

2 MMMU-Pro: A More Robust Version of MMMU

2.1 Revisiting the MMMU Benchmark

The Massive Multi-discipline Multimodal Understanding and Reasoning (MMMU) benchmark (Yue et al., 2024) is a comprehensive dataset designed to evaluate multimodal AI models on college-level tasks requiring subject-specific knowledge and deliberate reasoning. MMMU consists of 11.5K carefully curated multimodal questions from college exams, quizzes, and textbooks, covering six core disciplines across 30 subjects and 183 subfields. Each question in MMMU is a multimodal image-text pair with 4 multiple-choice options, featuring 30 diverse image types such as charts, diagrams, maps, and chemical structures. MMMU has quickly become a standard evaluation tool in the field, used to assess the capabilities of many prominent multimodal models upon their release (OpenAI, 2024a,b; Anthropic, 2024; Reid et al., 2024; Li et al., 2024b).

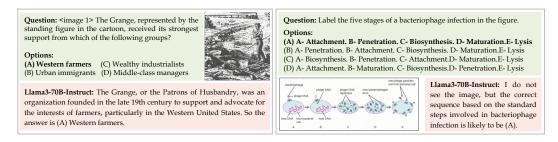


Figure 4: Two MMMU questions that are answered correctly by a text-only LLM Llama-3-70B Instruct. The model finds shortcuts or correlations in the text question and the candidate options.

Meanwhile, we received some feedback from the community that text-only LLMs could accurately answer some questions without any need for visual input. We took a close look at these questions and identified two main issues: 1) **Text-Only Dependency:** Certain questions are relatively independent or irrelevant to the corresponding images. 2) **Shortcut Exploitation:** Even when questions require images for humans to answer correctly, models could often find shortcuts or correlations within the candidate options, leveraging their pre-existing knowledge (from pre-training) to arrive at the correct answer. Two examples that are answered correctly by Llama-3-70B Instruct (Dubey et al., 2024) are shown in Figure 4.

2.2 Methods

To mitigate the issues and construct a more robust benchmark, we implemented a three-step approach:

Filtering Questions: We began by filtering out questions that could be answered by text-only LLMs. We selected four strong open-source LLMs: Llama3-70B-Instruct (Dubey et al., 2024), Qwen2-72B-Instruct (Yang et al., 2024), Yi-1.5-34B-Chat (Young et al., 2024), and Mixtral-8×22B-Instruct (gpt-4o)—and tasked them with answering the MMMU questions without access to images. The models were required to provide answers even when they indicated that visual input was necessary. We repeated this process ten times for each model, considering a question as "answerable" if a model correctly answered it more than five times. We then excluded any question where at least three out of the four models answered correctly across the majority of trials. We then randomly sampled 1800 questions from the remaining pool, evenly distributed across 30 subjects (60 questions per subject).

Augmenting Candidate Options: Despite the filtering, some questions could still be answered by text-only LLMs, often by exploiting subtle hints within the candidate options. To counteract this, we increased the number of candidate options from four to ten, making it more challenging for models to rely on guessing. This augmentation was done by human experts with the assistance of GPT-40. During this process, experts also reviewed the original annotated questions to ensure their relevance to the images and to eliminate any questions that

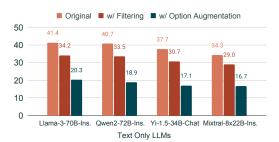


Figure 5: Accuracy of text-only LLMs in different sets of MMMU questions.

lacked a clear connection or coherence. This step filtered out 70 questions and we obtained 1730 questions in total.

As illustrated in Figure 5, these two steps significantly reduced the accuracy of text-only models attempting to guess the answers.

Enhancing Evaluation with a Vision-Only Input Setting: To further challenge the multimodal understanding of models, we introduced a vision-only input setting in MMMU-Pro. In this setting, the model is presented with a question embedded within a screenshot or photo, without any text explicitly fed into the model. To implement this setting, we asked the human annotators to manually capture photos and screenshots over a simulated display environment. This process involved varying

Table 1: Overall results of different models on different subsets. Δ_1 : Standard (10 options) - Standard (4 options); Δ_2 : Vision - Standard (10 options); Δ_3 : MMMU-Pro - MMMU (Val). MMMU-Pro overall score refers to the average of Standard (10 Options) and Vision Input settings.

Model	MMMU-Pro							
	Standard (4 Opts)	Standard (10 Opts)	Vision	Overall	MMMU (Val)	Δ_1	Δ_2	Δ_3
Random Choice	24.9	12.8	12.4	12.6	22.1	-12.1	-0.4	-9.8
Frequent Choice	27.8	12.1	12.1	12.1	26.8	-15.7	0	-14.7
GPT-4o (0513) (OpenAI, 2024a)	64.7	54.0	49.7	51.9	69.1	-10.7	-4.3	-17.2
Claude 3.5 Sonnet (Anthropic, 2024)	63.7	55.0	48.0	51.5	68.3	-8.7	-6.9	-16.8
Gemini 1.5 Pro (0801) (Reid et al., 2024)	60.6	49.4	44.4	46.9	65.8	-11.2	-5.0	-18.9
Qwen2-VL-72B (Qwen, 2024)	59.3	49.2	43.3	46.2	64.5	-10.1	-5.9	-18.3
Gemini 1.5 Pro (0523) (Reid et al., 2024)	57.6	46.5	40.5	43.5	62.2	-11.1	-6.0	-18.7
GPT-40 mini (OpenAI, 2024b)	55.3	39.9	35.2	37.6	59.4	-15.4	-4.7	-21.9
InternVL2-Llama3-76B (Chen et al., 2024)	55.0	41.9	38.0	40.0	58.3	-13.1	-3.9	-18.4
InternVL2-40B (Chen et al., 2024)	47.4	36.3	32.1	34.2	55.2	-11.1	-4.2	-21.0
LLaVA-OneVision-72B (Li et al., 2024b)	52.3	38.0	24.0	31.0	56.8	-14.3	-14.0	-25.8
Qwen2-VL-7B (Qwen, 2024)	46.6	34.1	27.0	30.5	54.1	-12.5	-7.1	-23.6
InternVL2-8B (Chen et al., 2024)	42.6	32.5	25.4	29.0	51.2	-10.1	-7.1	-22.3
MiniCPM-V2.6 (Yao et al., 2024)	40.6	30.2	24.2	27.2	49.8	-10.4	-6.0	-22.6
VILA-1.5-40B (Lin et al., 2024)	46.8	35.9	14.1	25.0	51.9	-10.9	-21.8	-26.9
LLaVA-NEXT-72B (Liu et al., 2024a)	43.0	31.0	19.2	25.1	49.9	-12.0	-11.8	-24.8
LLaVA-OneVision-7B (Li et al., 2024b)	42.8	29.5	18.7	24.1	48.8	-13.3	-10.8	-24.7
LLaVA-NeXT-34B (Liu et al., 2024a)	44.5	30.3	17.2	23.8	48.1	-14.2	-13.1	-24.4
Idefics3-8B-Llama3 (Laurençon et al., 2024)	40.8	30.1	15.6	22.9	46.6	-10.7	-14.5	-23.8
Qwen2-VL-2B (Qwen, 2024)	34.8	25.3	17.2	21.2	41.1	-9.5	-8.2	-19.9
Phi-3.5-Vision (Abdin et al., 2024)	37.8	26.3	13.1	19.7	43.0	-11.5	-13.2	-23.3
LLaVA-NeXT-7B (Liu et al., 2024a)	33.7	19.4	14.6	17.0	35.3	-14.3	-4.8	-18.4
LLaVA-NeXT-13B (Liu et al., 2024a)	33.9	19.8	14.5	17.2	36.2	-14.1	-5.3	-19.1

the backgrounds, font styles, and font sizes to replicate the diversity of real-world conditions. By using different combinations of these elements, we created a broad range of visual contexts, ensuring that the models are not only challenged by the integration of text and images but also by the variability in how this content is presented. Examples of the vision-only input setting are shown in Figure 3.

The motivation for introducing this setting stems from real-world usage patterns and the fundamental cognitive abilities of humans. In everyday scenarios, users often take shortcuts by simply capturing screenshots of questions that include both text and images, rather than inputting text separately. This habit of feeding integrated visual-textual content reflects a natural human tendency to process information holistically. Humans excel at interpreting and understanding information when both text and images are presented together, and our goal with this setting is to push models toward achieving a similar level of comprehension. By mimicking this real-world behavior, the vision-only input setting not only adds realism to the benchmark but also ensures that models are better equipped to handle the complexities of multimodal tasks as they would appear in practical applications.

After these three steps, we finally obtained 3460 questions in total (1730 samples are in the standard format and the other 1730 are in the screenshot or photo form).

3 Experiments

3.1 Experimental Setups

Baselines. To establish a comprehensive understanding of MMMU-Pro's difficulty and to provide reference points for future research, we evaluated a diverse set of state-of-the-art multimodal models as baselines. These models represent a range of training approaches and capabilities in the field of multimodal AI. Our baseline models include:

Proprietary Models: GPT-4o (0513) and GPT-4o mini, Claude 3.5 Sonnet, and Gemini 1.5 Pro (0801 and 0523 versions). These models represent the cutting edge of multimodal AI capabilities.

Open-source models: We evaluated a range of open-source models, including InternVL2 (8B, 40B, and Llama3-76B versions), LLaVA (OneVision-7B, OneVision-72B, and various NeXT versions), VILA-1.5-40B, MiniCPM-V2.6, Phi-3.5-Vision, and Idefics3-8B-Llama3. These models showcase

the current state of publicly available multimodal AI systems. We evaluated these models across three different settings: 1) Standard setting without augmented options (usually 4 options); 2) Standard setting with augmented options (usually 10 options); 3) Vision-only input setting.

The overall performance score for MMMU-Pro is calculated as the average of scores from settings (2) and (3). We include setting (1) and report the original MMMU validation set performance solely for comparison purposes, to highlight the increased difficulty of MMMU-Pro.

We evaluate the models with both *Direct* and *CoT* prompts (as shown in Appendix A), and report the higher ones in the overall results. We also discuss the influence of the CoT prompt in subsection 3.4.

3.2 Overall Results

We presented the overall results of MMMU-Pro of different models in Table 1.

Effect of Increased Candidate Options: The shift from 4 to 10 candidate options (Δ_1) reveals a significant drop in performance for all models. GPT-40 (0513) experienced a decrease of 10.7%, from 64.7% to 54.0%. This indicates that increasing the number of options effectively reduces the likelihood of models guessing the correct answer, forcing them to engage more deeply with the multimodal content.

Impact of Vision-Only Setting: The introduction of the vision-only input setting further challenges models, as evidenced by the additional drop in performance when comparing the vision-only results to the 10-option standard (Δ_2). For instance, GPT-40 (0513) dropped another 4.3% in accuracy when evaluated in the vision-only setting, and LLaVA-OneVision-72B saw a dramatic 14.0% decrease. This suggests that the vision-only setting successfully tests the models' ability to integrate visual and textual information, highlighting their limitations when the text is not explicitly provided.

Combined Effects on MMMU-Pro: The overall Δ_3 , representing the difference between MMMU-Pro and MMMU (Val), shows a significant decrease across the board. For instance, models like Gemini 1.5 Pro (0801) and Claude 3.5 Sonnet exhibited declines of 18.9% and 16.8%, respectively, while more drastic drops were seen in models like VILA-1.5-40B with a 26.9% decrease.

This significant reduction in accuracy across the board suggests that MMMU-Pro successfully mitigates the shortcuts and guessing strategies that models could exploit in the original benchmark.

3.3 Does OCR Help in the Vision Setting?

Figure 6 explores whether Optical Character Recognition (OCR) prompts help in improving performance within the Vision Input setting of MMMU-Pro. The OCR prompt explicitly requires the model to write out the question text in the image (as shown in Appendix A). Across the models evaluated, the inclusion of OCR prompts did not significantly alter performance. These minimal differences suggest that strong capable models are already proficient at extracting and understanding textual information from images, even without explicit OCR prompts.

Importantly, this result underscores that simple OCR is not sufficient to solve the challenges presented by MMMU-Pro's vision-only input setting. When text is embedded within images, it significantly increases the overall complexity of the visual input. This integration requires models to not only recognize and extract text but also to understand its context within the image, its relationship to visual elements, and its relevance to the question at hand. This multilayered challenge of simultaneously processing textual and visual information makes the task

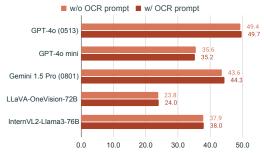


Figure 6: OCR's influence in the Vision setting.

substantially more demanding, pushing models towards more sophisticated multimodal reasoning.

3.4 Does CoT Help in Answering MMMU-Pro Questions?

Figure 7 examines the effectiveness of Chain of Thought (CoT) prompting in enhancing model performance on the MMMU-Pro benchmark, both in the Standard and Vision Input settings. Across both settings, the introduction of CoT prompts generally led to improved performance. However, the extent of improvement varied significantly among models. For instance, Claude 3.5 Sonnet demonstrated a substantial increase in the Standard setting, improving from 42.7% to 55.0%. In contrast, models like LLaVA-OneVision-72B showed only minimal improvement.

Interestingly, we observed a significant performance drop for some models, such as VILA1.5-40B. This decline might be attributed to challenges in instruction-following abilities. When a model struggles to follow instructions accurately, generating CoT explanations becomes more difficult. Additionally, these models may face issues with maintaining the correct response format, leading to what is known as "boiled response format" problems. These findings highlight the potential of CoT to enhance model performance in complex, real-world tasks that require nuanced reasoning and integration of multiple information sources. However, they also underscore the importance of robust instruction-following capabilities as a prerequisite for effective CoT implementation.

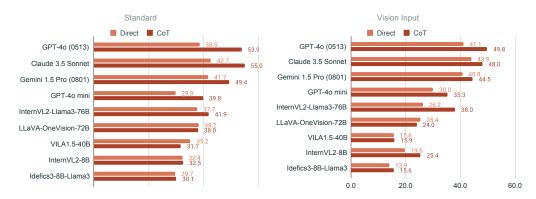


Figure 7: Impact of CoT prompting of different models in the two settings of MMMU-Pro.

3.5 Qualitative Analysis

To gain deeper insights into model performance beyond quantitative metrics, we conducted a thorough qualitative analysis of MMMU-Pro results, focusing on two key scenarios: 1) Correct answers with four options but failure with ten options in the standard setting; 2) Success in the standard ten-option setting but failure in the vision input setting. Our analysis revealed several critical factors affecting model performance:

Challenges with Increased Options. Models often select the closest answer rather than arriving at a definitive choice, leading to increased errors with more options. An example is shown in Figure 8. Additional options that are conceptually close to the correct answer can cause confusion, particularly in nuanced questions. For instance, in conceptual questions, models struggled to distinguish between subtly different options, revealing limitations in their understanding of fine-grained distinctions within a subject area.

Vision-Text Integration Challenges. One of the major possible reasons is that the integration of text and image significantly increases the complexity of information processing and handling. We observed that the model is more likely to hallucinate and have wrong reasoning chains when simultaneous processing of visual and textual information. An example is shown in Figure 9. Additionally, complex visual inputs or unique layouts could also disrupt logical judgment and increase cognitive load. Rapid transitions between text and image can result in processing biases.

These observations highlight MMMU-Pro's effectiveness in exposing the limitations of current multimodal models, particularly in handling increased complexity and integrating diverse information types. They point to critical areas for improvement in multimodal AI systems, including enhanced precision in multi-option scenarios, better integration of visual and textual information processing, and improved robustness in handling complex, mixed-format inputs.

Question: A solid copper bar of circular cross section has length L=1.25 mand shear modulus of elasticity G=45 GPa. The bar is designed to carry a 250 $N\cdot m$ torque acting at the ends. If the allowable shear stress is 30 MPa and the allowable angle of twist between the ends is 2.5° , what is the minimum required diameter?

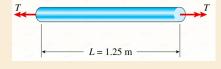
Original Options:

(A) 35.7 mm (B) 45.7 mm (C) 55.7 mm

Augmented Options:

(D) 25.7 mm (E) 40.7 mm (F) 50.7 mm (G) 30.7 mm

(H) 20.7 mm (I) 60.7 mm



GPT-40 (w/o augment options): To determine the minimum required diameter of the solid copper bar, we need to check two conditions: 1. The maximum shear stress condition. 2. The allowable angle of twist condition. Step 1: Maximum Shear Stress Condition. The torsional shear stress for a solid circular shaft is given by: $\tau = T \cdot r/J$, where τ is the shear stress, T is the applied torque, r is the radius of the shaft, J is the polar moment of inertia for a solid circular section ($J = \pi r^4/2$). Rewriting the shear stress formula...Conclusion: Comparing the two diameters, the larger value will govern, as it ensures both conditions are met. Therefore, the minimum required diameter is given by: **Answer: A**

GPT-40 (w/ augment options): To determine the minimum required diameter of the solid copper bar, we need to consider both the maximum allowable shear stress and the maximum allowable angle of twist. Step 1: Maximum Allowable Shear Stress. The relationship between the torque T, the shear stress τ , and the polar moment of inertia J for a circular cross-section is given by... Therefore, the minimum required diameter is: $d \approx 55.68$ mm. The closest value greater than or equal to 55.68 mm from the options provided is: **Answer: C**

Analysis: Both solutions are incorrect; however, with only three options in the original setup, the model happens to select the correct answer by chance.

Figure 8: Comparison of GPT-4o's responses with and without augmented options.



Analysis: In the vision-only input scenario, the model accurately extracts text from the photo. However, its response tends to be more basic and lacks in-depth analysis. The integration of both visual and textual information appears to increase the cognitive load on the vision module, which may result in a higher likelihood of errors.

[Note: Portions of the original model's response have been omitted for brevity.]

GPT-40 (Standard Setting): To determine the main point of the cartoon, let's analyze the visual and textual elements: 1. The cartoon by "Judge" depicts the progression of the United States with figures representing different years: 1783, 1803, 1819, 1861, 1898, and 1899. 2. In each figure, the United States is shown acquiring more territories: - 1783: The United States starts with the original 13 states. - 1803:...3. The final image shows the United States (personified as "Uncle Sam") receiving approval and open arms from other nations, which suggests the U.S. is being welcomed by the international community. This aligns most closely with Option A.

GPT-40 (Vision Input): No. 6: Image 1 Which of the following reflects a main point of the cartoon? Options: (A) The United States' acquisition of overseas colonies is part of the natural progression for the country and will gain the approval of foreign powers. (B) The United States' acquisition of overseas territories is a response to the imperialist actions of other countries. (C)...(D)...(E)...(F)...(G)...(H)...(I)...(J)...

The cartoon in the image appears to be a critique of American imperialism. It depicts the United States acquiring various territories over time, with the characters becoming progressively more overweight and bloated, which suggests a critical view of expansionism and imperialism as gluttonous or greedy behavior. The most accurate answer would be Option G

Figure 9: Comparison of GPT-4o's responses between Standard and Vision Input settings.

4 Related Work

Multimodal Large Language Models. Recent progress in multimodal AI has been marked by innovative training approaches (Lu et al., 2019; Tan and Bansal, 2019; Chen et al., 2020; Zhou et al.,

2020; Zhang et al., 2021; Li et al., 2020; Alayrac et al., 2022; Awadalla et al., 2023). Inspired by the success of large language models, researchers have developed various models with improved instruction-following capabilities (Liu et al., 2023c,b, 2024a; Li et al., 2024b; Dai et al., 2023; Zhu et al., 2023; Zhang et al., 2023; Gao et al., 2023; Ye et al., 2023a,b; Zhao et al., 2023; Li et al., 2023; Monajatipoor et al., 2023; Zhao et al., 2024; Li et al., 2024c; Lin et al., 2024; Zhang et al., 2024). Proprietary models such as GPT-4V (OpenAI, 2023), GPT-4o (OpenAI, 2024a), Gemini (Team et al., 2023), and Claude-3.5 (Anthropic, 2024) have demonstrated strong performance across various vision-language tasks. However, a significant challenge remains in accurately evaluating the capabilities of these advanced multimodal models, highlighting the need for more robust and comprehensive benchmarks.

MLLM Benchmarks. The rise of more advanced multimodal pre-training and instruction tuning has exposed the limitations of earlier benchmarks like VQA (Antol et al., 2015; Goyal et al., 2017), OK-VQA (Marino et al., 2019), and MSCOCO (Lin et al., 2014), which no longer suffice to evaluate the full spectrum of LMMs capabilities. To address this, recent benchmarks such as LAMM (Yin et al., 2023b), LVLM-eHub (Xu et al., 2023), SEED (Li et al., 2024a), MMBench (Liu et al., 2023d), CV-Bench (Tong et al., 2024a), MM-Vet (Yu et al., 2024), Mantis (Jiang et al., 2024), and BLINK (Fu et al., 2024) have emerged, covering aspects from basic perception to hallucination detection (Cui et al., 2023; Liu et al., 2023a). However, existing benchmarks often fall short in evaluating expert-level domain knowledge and complex reasoning. While MMMU (Yue et al., 2024) made strides by incorporating multimodal, college-level questions, it still permits text-only models to find shortcuts (Lu et al., 2023). To overcome these limitations, we introduce MMMU-Pro, a more robust version specifically designed to better evaluate multimodal reasoning by eliminating text-only answerable questions, expanding candidate options, and introducing a vision-only input setting that mirrors real-world scenarios where text and images are naturally intertwined.

5 Conclusion

MMMU-Pro presents a more robust multimodal understanding and reasoning benchmark compared with its predecessor MMMU. Our results demonstrate MMMU-Pro's effectiveness in exposing the limitations of current state-of-the-art multimodal models, with significant performance drops across all tested systems. MMMU-Pro opens up several important avenues for future research: 1) Developing models with consistent performance across all MMMU-Pro settings, particularly in bridging the gap between standard and vision-only inputs. 2) Improving vision-text integration capabilities to handle complex, mixed-format inputs more effectively. 3) Exploring advanced reasoning techniques to address the increased complexity of MMMU-Pro questions.

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A Evaluation Prompts

Evaluation Prompts: OCR Prompt

OCR Prompt:

"Write out the multiple-choice question in the image and then solve it. The last line of your response should be of the following format: 'Answer: \$LETTER' (without quotes) where LETTER is one of the options. Think step by step before answering."

w/o OCR Prompt:

"Answer the following multiple-choice question in the image. The last line of your response should be of the following format: 'Answer: \$LETTER' (without quotes) where LETTER is one of the options. Think step by step before answering."

Evaluation Prompts: Direct vs CoT

Direct

"Answer directly with the option letter from the given choices."

CoT:

"Answer the following multiple-choice question. The last line of your response should be of the following format: 'Answer: \$LETTER' (without quotes) where LETTER is one of the options. Think step by step before answering."