MMDU: A <u>Multi-Turn Multi-Image D</u>ialog <u>Understanding Benchmark and Instruction-Tuning</u> Dataset for LVLMs

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Abstract

Generating natural and meaningful responses to communicate with multi-modal human inputs is a fundamental capability of Large Vision-Language Models (LVLMs). While current open-source LVLMs demonstrate promising performance in simplified scenarios such as single-turn single-image input, they fall short in real-world conversation scenarios such as following instructions in a long context history with multi-turn and multi-images. Existing LVLM benchmarks primarily focus on single-choice questions or short-form responses, which do not adequately assess the capabilities of LVLMs in real-world human-AI interaction applications. Therefore, we introduce MMDU, a comprehensive benchmark, and MMDU-45k, a large-scale instruction tuning dataset, designed to evaluate and improve LVLMs' abilities in multi-turn and multi-image conversations. We employ the clustering algorithm to find the relevant images and textual descriptions from the open-source Wikipedia and construct the question-answer pairs by human annotators with the assistance of the GPT-40 model. MMDU has a maximum of 18k image+text tokens, 20 images, and 27 turns, which is at least $5 \times$ longer than previous benchmarks and poses challenges to current LVLMs. Our in-depth analysis of 15 representative LVLMs using MMDU reveals that open-source LVLMs lag behind closed-source counterparts due to limited conversational instruction tuning data. We demonstrate that fine-tuning open-source LVLMs on MMDU-45k significantly address this gap, generating longer and more accurate conversations, and improving scores on MMDU and existing benchmarks (MMStar: +1.1%, MathVista: +1.5%, ChartQA: +1.2%). Our contributions pave the way for bridging the gap between current LVLM models and real-world application demands. This project is available at https://github.com/Liuziyu77/MMDU.

1 Introduction

Human-AI interaction is a fundamental task to ensure that AI can be deployed in the real world for everyone, enabling inclusive and effective communication between humans and AI in various aspects of daily life. Current Large Vision-Language Models (LVLMs) [1] have made significant strides in understanding and generating text conditioned on visual inputs, showing promising directions in AI assistant applications.

Current open-source LVLMs primarily focus on single-turn, single-image inputs, which are far from the complexities of real-world scenarios. In contrast, effective human-AI interaction in daily life demands a range of essential skills, including the ability to engage in multi-turn conversations that involve multiple image inputs and comprehend long-context histories to facilitate coherent



Figure 1: **Comparing MMDU with previous LVLM benchmarks.** Our MMDU (bottom) incorporates multi-turn and multi-image inputs, long context, and open-ended question-answering evaluation, making it more challenging and comprehensive than previous benchmarks (upper left).

and contextually appropriate conversations. While existing benchmarks partially assess these abilities [2, 3, 4] (Fig. 1 (a)), they have limitations such as limited number of total tokens and do not provide a complete picture of a model's human-AI interaction capabilities. More challenging and comprehensive benchmarks are necessary to evaluate and advance these skills.

We present **MMDU**, a comprehensive benchmark for multi-turn multi-image dialog understanding. Our data collection pipeline automatically selects relevant images and text descriptions from opensource Wikipedia [5], forming the basis for multi-turn dialogues. We employ a clustering algorithm to identify relevant Wikipedia entities and design prompt templates for GPT-40 to generate multi-turn questions. Human annotators assess and refine GPT-40's responses, producing ground-truth answers for our benchmark.

Our MMDU benchmark possesses the following distinctive features: (1) Multi-turn and Multiimage: Our benchmark showcases a conversational setting with a maximum of 20 images and 17 turns, thereby surpassing the scope of preceding works (see Fig. 1 (b) and authentically replicating real-world chat assistant interactions. (2) Long Context: With a maximum of 18k text+image tokens, our benchmark evaluates the capacity of LVLMs to process and comprehend extended contextual information with a long context history. (3) Open-ended Evaluation: Departing from traditional benchmarks that rely on close-ended questions with concise outputs (*e.g.*, multiple-choice questions or short answers), our benchmark adopts a more realistic and nuanced approach, assessing LVLM's performance through free-form multi-turn outputs that prioritize scalability and explainability, inspired by NLP research that leverages strong LLMs as judges [6].

We evaluate 15 proprietary and open-source LVLMs on our MMDU benchmark. Our evaluation reveals a significant performance disparity between proprietary and open-source LVLMs. The best open-source model scores 42.8%, far behind the proprietary GPT-40 at 70.2%. Notably, our observations provide a clear direction for improving the open-source models on long-context, multi-turn, and multi-image scenarios to bridge the performance gap. Based on our findings from the

benchmark results on MMDU, the practical need urges the visual instruction tuning data containing multi-turn and multi-images for open-source LVLMs.

To get one step closer to proprietary LVLM models, we further present **MMDU-45k**. We collect **45k** high-quality instruction tuning data using the same process employed in building MMDU, with a random sampling of human verification instead of the exhaustive human evaluation used in MMDU. Adding our instruction tuning data MMDU-45k into the LVLM supervised fine-tuning (SFT) stage improves performance on various benchmarks, such as boosting InternLM-XC2 [7]'s performance by 14.5%/1.1%/1.5%/1.2% on MMDU/MMStar [8]/MathVista [9]/ChartQA [10], respectively.

Our main contribution is summarized: (1) We introduce MMDU that assesses the multi-turn, multiimage dialog understanding capabilities of LVLMs, specifically designed for human-AI interaction. (2) We conduct a comprehensive evaluation of existing LVLMs on MMDU, revealing significant challenges in this task and providing valuable insights for future LVLM development. (3) We present MMDU-45k, a large-scale instruction tuning dataset designed to enhance dialog understanding abilities. We demonstrate that fine-tuning LVLMs on MMDU-45k leads to improved performance on both MMDU and existing benchmarks.

2 MMDU Benchmark

2.1 Benchmark Overview

Although many LVLMs now claim to handle tens of thousands, hundreds of thousands, or even millions of tokens in length, their actual performance significantly declines in real-world applications as the number of images or the length of the context increases. Both the dialogue quality and image recognition capabilities of LVLMs deteriorate notably under these conditions.

To evaluate the multi-image multi-turn dialogue capabilities of existing models, we have developed the MMDU Benchmark. Our benchmark comprises 110 high-quality multi-image multi-turn dialogues with more than 1600 questions, each accompanied by detailed long-form answers. Previous benchmarks typically involved only single images or a small number of images, with fewer rounds of questions and short-form answers. However, MMDU significantly increases the number of images, the number of question-and-answer rounds, and the in-context length of the Q&A. The questions in MMDU involve 2 to 20 images, with an average image&text token length of 8.2k tokens, and a maximum image&text length reaching 18K tokens, presenting significant challenges to existing multimodal large models. For more data statistics about MMDU, please refer to Tab.1 and Fig.4.

MMDU aims to test models' abilities to simultaneously understand multiple images and follow instructions in long dialogues. We design precise prompts to evaluate the models' responses, and our evaluation criteria details are discussed in Sec. 2.3.

2.2 Benchmark Construction

Data Collection. Our goal in constructing this benchmark is to measure the current models' ability to understand multiple images and generate long texts in general scenarios.

The first step is selecting appropriate multiple images and related textual information as the foundation for multi-turn dialogues. Given that the generated dialogue content needs to be logically coherent and rich in content, we cannot use random sets of images to build the Q&A pairs. Random images would lead to low-quality and illogical dialogues, both in the question-construction and answer-generation processes.

To address this issue, we employ a clustering method to construct high-quality image sets. We extensively screened entries on the open-source Wikipedia [5], encoded the relevant tags of entries using a sentence transformer[11], and clustered the entries using the obtained embeddings. After clustering enough entries of the same category together, we further matched them using image captions to obtain highly relevant entries and image sets. Then, within each cluster, we selected multiple images and their associated textual information to create combinations of image-text pairs, ranging from 2 to 20 images. The process of collecting and clustering entries is illustrated in Fig. 2 (a).



Figure 2: An overview of (a) data preparation and (b) generation pipeline for MMDU and MMDU-45k. We first collect the relevant image and text descriptions from Wikipedia using the clustering algorithm. Then we prompt GPT-40 to design multi-turn questions. The human annotators revise the GPT-40 response as the ground-truth answers.

Construction with GPT-40. After obtaining the combinations of multiple images, we use carefully crafted prompts to guide the GPT-40 model in generating corresponding questions and answers based on the available images and text information. Initially, we constructed multi-turn Q&A pairs for each single image and its associated text. Then, we input the combinations of multiple images into GPT-40 to generate multi-turn Q&A pairs based on multiple images, ensuring through prompts that the questions covered multiple different images simultaneously.

Building on this, we combined the multi-turn Q&A pairs for multiple images with those for each individual image, creating dialogues that include both single-image and multi-image questions. To ensure the quality of the benchmark, we invited experts to meticulously review the generated dialogues, selecting 110 high-quality multi-turn, multi-image dialogues for our benchmark. Additionally, we carefully edited these 110 samples to eliminate hallucinations and errors in GPT-4o's responses, ensuring the accuracy and richness of the benchmark content. Our pipeline is shown in Fig. 2 (**b**).

Furthermore, our generated multi-turn, multi-image data is highly scalable. During the Q&A construction process, we required GPT-40 to organize the generated text according to our specified Text-Image Interleaving Format, using tags like <image-1>, <image-2>, etc., to refer to different images. Our design is flexible to treat the generated multi-turn, multi-image dialogues as fundamental components. By modifying the values in <image-i>, we can concatenate multiple dialogues, thereby constructing dialogues involving dozens or even hundreds of images. Our data is not limited to a few images per Q&A generation but is capable of supporting dialogues of theoretically unlimited length.

Quality Control with Human Annotators In the process of constructing the dataset, we implemented two stringent measures to ensure its quality: (1) We combined automated and manual screening methods to select images and texts that meet our standards. Specifically, we performed an initial screening using clustering techniques on a large-scale image and text database, automatically removing low-quality, blurry, or irrelevant images and texts. This ensured that the image combinations

	Question	DALLE PORTE DI FUOC
Question: What are the centra contribute to their horror then	l visual elements present in Image1 and Image2 tha ne?	⁺
Assitant's A	Answer & Reference Answer	HOUSE HAUNTED HILL
Assitant: In Image1, the large skeleton holding a woman by her hair creates a sense of horror by representing death and In Image2, the large red hands reaching out towards the woman create a sense of horror by evoking feelings of fear, danger, and	Reference: Image1 and Image2 share several central visual elements that co themes. In Image1, the primary visual elements include a large, f woman and a dilapidated, earie mansion in the backgroundIn dominate the composition, grasping towards a terrified woman. Th conveys a sense of imminent danger, overwhelming helplessness, a horror imagery. The dark tunnel framing these elements adds heightening the sense of entrapment and dread	oreboding skeleton holding a hangin Image2, strikingly oversized hang ne disproportionate size of the hang nd the uncanny, which are common
	GPT-40 Judgement	
why these elements effectively contribute ### Visual Perception		
nd the woman's expression Although t	ies key elements in both images, such as the skeleton, the woman, th ne response includes relevant information, it could further enrich r additional characters in the images. **Score: 7**	
The response distinguishes between the tw	vo images accurately, identifying unique features of each while also or theme by discussing typical horror motifs and the overall mood c	
### Overall Score		
reativity and depth to perfectly capture '		
'Creativity': 6, 'Richness': 7, 'Visual P }, 'Overall Score': 7}	erception': 7, 'Logical Coherence': 7, 'Answer Accuracy': 8, 'Ii	mage Relationship Understanding':

Figure 3: **The evaluation pipeline of MMDU**. We use the GPT-40 as a judge to give the overall score based on the referenced answer. In each evaluation, GPT-40 will refer to both the model's answer and the reference answer. It will provide corresponding scores (in green) for each evaluation criterion (in blue), and finally, summarize the results (in light orange).

and their corresponding texts were of high quality and relevance. (2) To avoid hallucinations and errors in the model-generated dialogues, we enforced strict quality control on the texts generated by GPT-40. We introduced a multi-round manual review mechanism. Each set of Q&A underwent at least two rounds of manual review: the first round involved preliminary checks by regular reviewers, and the second round involved in-depth examination and modification by experts. This ensured that the final dataset was not only accurate but also of high academic and practical value.

2.3 Evaluation

Inspired by NLP research that leverages strong LLMs as judges [6], we have developed an evaluation pipeline using GPT-40 to evaluate model performance. Specifically, following the generation of model predictions on our benchmark dataset, GPT-40 evaluates these predictions across various dimensions for each turn and sample, comparing them against reference answers. The aggregated results across multiple turns are averaged to derive sample scores, and the average scores across all samples constitute our benchmark scores.

To ensure a comprehensive and nuanced evaluation, we have identified six dimensions: Creativity, Richness, Visual Perception, Logical Coherence, Answer Accuracy, and Image Relationship Understanding. To guide GPT-40 in providing balanced and equitable assessments, we have meticulously crafted evaluation prompts for each dimension. Each dimension's score range of 10 is divided into five intervals (0-2, 2-4...8-10), with corresponding judgment criteria established for each interval. GPT-40 follows these criteria to conduct judgment processes and deliver final scores for each dimension. As illustrated in Fig 3, guided by our prompts, GPT-40 assesses the assistant's responses against reference answers, offering both a reasonable score and a transparent judgment process. Please refer to the supplementary material B for our judgment prompts.

3 MMDU-45k for Instruct Tuning

3.1 Dataset Construction

We follow the same process as constructing the benchmark to build our MMDU-45k. First, we collect a vast number of Wikipedia entries and extracted tags from these entries, including wiki tree labels and image captions. We use sentence transformers to encode the textual information and then apply the clustering algorithm to obtain the embeddings. During the clustering process, we calculate the cosine similarity between different embeddings and group highly related entries into clusters by setting a threshold $\tau = 0.75$. From the clusters with high relevance, we select multiple images and their corresponding entry information and perform information extraction and filtering using InternLM-chat-20B[12]. We design precise prompts to guide GPT-40 in generating multi-image, multi-round, long dialogues based on the information filtered by InternLM-Chat-20B.

During the dataset construction process, we obtain several clusters with a wide range of category distributions. This ensures that our dataset comprehensively covers various aspects of real life, including geography, history, culture, mathematics, physics, chemistry, animals, plants, food, and more. This rich knowledge will help LVLM learn long-context conversational abilities in general scenarios of the real world.

3.2 Dataset Statistics

In the MMDU-45k, we construct a total of 45k instruct tuning data conversations. The data statistics are shown in Tab. 1. Each data in our MMDU-45k dataset features an ultra-long context, with an average image&text token length of 5k and a maximum image&text token length of 17k tokens. Each dialogue contains an average of 9 turns of Q&A, with a maximum of 27 turns. Additionally, each data includes content from 2-5 images. The dataset is constructed in a well-designed format, providing excellent scalability. It can be expanded to generate a larger number and longer multi-image, multi-turn dialogues through combinations. The image-text length and the number of turns in MMDU-45k significantly surpass those of all existing instruct tuning datasets. This enhancement greatly improves the model's capabilities in multi-image recognition and understanding, as well as its ability to handle long-context dialogues.

Statistic	Number
MMDU Benchmark	110
- Avg./Max. Image&Text Tokens	8.2k/18k
- Avg./Max. Images	3.8/20
- Avg./Max. Turns	15/27
- Number of QA Pairs	1645
MMDU-45k	45k
- Avg./Max. Image&Text Tokens	5k/17k
- Avg./Max Images	3/5
- Avg./Max. Turns	9/27
- Number of QA Pairs	410k
- Single-image Related Questions	40k
- Multi-images Related Questions	369k
- Avg./Max. Question Length	31/91
- Avg./Max. Answer Length	368/1518

Table 1: Statistics on MMDU and MMDU-45k.



Figure 4: Detailed distribution of MMDU.

4 Experiments

We evaluate previous representative LVLMs on our MMDU benchmark in Sec. 4.1 and present the analysis of our findings. To demonstrate the high quality of our instruction tuning data MMDU-45k, we provide the comparison results of adding MMDU-45k in the LVLM SFT stage in Sec. 4.2.

Baselines We report the performance of four closed-source API models: QWen-VL-Max [13], Claude3 [14], GPT-4-turbo [1] and GPT-4o [15]. We also present the performance of 11 LVLMs

VP Models С R LC IRU Param AA Avg. Closed-source LVLMs Qwen-VL-Max [25] Claude3-Opus [14] GPT-4-turbo [1] 40.2 62.5 75.1 78.0 51.6 45.9 59.8 46.9 40.3 46.2 59.7 _ 61.5 64.2 64.1 69.0 58.6 62.0 _ 62.6 _ 63.4 64.4 66.3 70.2 GPT-40 [15] 63.7 69.6 80.6 73.3 68.1 66.7 **Open-source** LVLMs Monkey [16] Idefics2 [17] LLaVa1.5-7B [18] Deepseek-VL [19] MiniCPM-v-2.5 [20, 21] 11.9 12.0 10**B** 14.8 21.9 19.6 14.6 14.1 27.9 33.2 31.2 33.2 32.8 35.4 33.2 26.9 31.7 25.4 32.2 17.6 8B 7B 17.8 27.8 27.3 27.0 31.7 31.5 31.2 29.7 43.1 28.0 27.7 43.0 έĒ 38.7 30.0 30.8 26.4 32.2 31.2 31.5 29.5 48.9 38.6 33.0 8B 32.2 MinicPM-9-2.5 [20, 21] Yi-VL [22] LLaVa1.5-13B [18] InternVL-Chat-V1.5 [23] InternLM-XC2 [7] Qwen-VL-7B [13] LLaVa1.6-mistral [24] 47.5 46.2 52.6 50.1 33.2 35.3 30.0 6B 30.6 34.0 35.1 37.4 36.2 39.2 38.1 41.7 40.3 13B 34.3 36.1 35.2 37.4 35.6 26B 7B 39.3 33.4 37.7 7B33.6 53.8 57.2 43.138.1 ŹĎ 39.3 41.4 45.6 40.2 42.8 LLaVa 1.5 [18] + MMDU-45k 7B 34.3 34.5 36.7 **+3.5** 47.2 38.5 35.5 37.2 +6.5 +4.2+6.5+3.1+3.8+5.048.7 InternLM-XC2 [7] + MMDU-45k 43.9 49.9 53.0 7B 45.6 64.1 50.1+13.5 Δ +15.9 +14.4+13.7+14.0+12.7+14.5

Table 2: **Evaluation results of different LVLMs on MMDU.** We report the metrics of Creativity (C), Richness (R), Visual Perception (VP), Logical Coherence (LC), Answer Accuracy (AA), Image Relationship Understanding (IRU), and the averaged (Avg.) results.

including Monkey [16], Idefics2 [17], LLaVa1.5 7B/13B [18], Deepseek-VL [19], MiniCPM-v-2.5 [20, 21], Yi-VL [22], InternVL-Chat-V1.5 [23], InternLM-XC2 [7], Qwen-VL-7B [13] and LLaVa1.6 [24]. Please refer to the supplementary material D for the details of our baselines.

4.1 Main Results on MMDU

Table 2 presents the benchmarking results on our MMDU benchmark. Our key findings are summarized as follows. (1) Our benchmark poses significant challenges to current LVLMs. Notably, even the advanced GPT-40 model achieves an average accuracy of only 70.2%, while open-source LVLMs achieve merely 42.8% or lower, indicating substantial room for improvement. (2) We observe a significant performance gap between closed-source LVLMs and open-source LVLMs. We speculate that this disparity arises from the scarcity of open-source instruction tuning data with multi-turn and multi-image capabilities, leading to limited improvement in open-source LVLMs. This inspired us to collect and release MMDU-45k, a valuable resource for the open-source community, to bridge this gap.

In addition, we conduct experiments to evaluate the quality of our evaluation with GPT4-o by comparing it to human judgment. Specifically, experts score the results predicted by each model on our benchmark using the same judgment criteria as our evaluation. We calculated several similarity metrics for the overall scores between experts and the GPT4-o system. The Pearson similarity of 97.5% indicates a strong linear relationship, while the Spearman similarity of 97.3% demonstrates consistent scoring monotonicity. The Kendall similarity of 89.0% suggests some variability in the manual scores compared to the judgment range of GPT4-o, yet the consistency remains high.

4.2 Fine-tuning Results using MMDU-45k

We showcase the superior quality of MMDU-45k by presenting comparative results at the bottom of Tab. 2, where we incorporate MMDU-45k into the SFT stage of LVLMs such as LLaVA 1.5 [18] and InternLM-XC2 [7]. Results demonstrate that adding MMDU-45k increases the overall performance on MMDU, especially for the image relationship understanding ability. In Tab. 4.2, we further demonstrate that integrating MMDU-45k also benefits existing benchmarks that require multi-image understanding, such as MMMU [27] and MMStar [8], as well as short-form QA datasets like MMVet [4]. To explain the performance improvement, we provide qualitative examples in Fig. 5,

Table 3: Illustration of the benefits of adding our MMDU-45k data in the LVLM supervised finetuning (SFT) stage. We report the performance on our MMDU and existing representative benchmarks including MMB (MMBench-Dev-EN [26]), MMMU (MMMU-Val [27]), MMStar [8], MathVista [9], AI2D [28], HallBench (HallusionBench [29]), MMVet [4] and ChartQA [10]. The best and second-best results in each section are colored **Green** and **Red**, respectively.

Method	MMDU	MMB	MMMU	MM Star	Math Vista	AI2D	Hall Bench	MMVet	Chart QA	Avg.
LLaVa1.5 [18]	32.2	66.5	35.7	33.1	25.2	55.5	48.8	31.6	21.2	38.9
LLaVa1.5 + MMDU-45k Δ	37.2 +5.0	66.5 +0.0	37.4 +1.7	34.1 +1.0	25.2 +0.0	56.2 +0.7	48.7 - 0.1	31.9 +0.3	23.4 +2.2	40.1 +1.2
InternLM-XC2 [7]	35.6	79.5	41.4	56.2	57.2	81.2	60.0	37.6	62.6	56.8
InternLM-XC2 + MMDU-45k Δ	50.1 +14.5	79.9 +0.4	41.9 +0.5	57.3 +1.1	58.7 +1.5	81.2 +0.0	60.4 +0.4	38.8 +1.2	63.8 +1.2	59.1 +2.3

illustrating that incorporating MMDU-45k enables LVLMs to engage in longer and more accurate dialogues.

5 Related Work

LVLM Evaluation Benchmarks The rapid advancements in Large Vision-Language Models (LVLMs)[13, 14, 1, 15, 16, 17, 18, 19, 20, 21, 22, 23, 7, 13, 24, 30, 31] have spurred the development of comprehensive evaluation benchmarks to assess their capabilities across various tasks and domains. Numerous benchmarks [32, 26, 33, 34, 35, 36, 37, 4, 8] aim to provide a standardized and objective way to measure the performance of LVLMs and track their progress toward achieving general multi-modal understanding and reasoning.

Recently, specialized benchmarks have emerged to evaluate specific abilities [38, 29], such as for science reasoning [27], math reasoning [9], OCR recognition [39], and diagram analysis [28]. Some existing benchmarks require multi-turn [2] chatting with a maximum of three turns, and others on multi-image comparison [3, 40] with a maximum of four images. However, none of the existing benchmarks combine the multi-turn and multi-image abilities with a long context window for conversation applications, highlighting the need for a more comprehensive evaluation framework.

LVLM Instruction-Tuning Datasets The development of instruction tuning datasets for LLMs (*e.g.*, Alpaca [41], Vicuna [42]) has been instrumental in enhancing the instruction-following capabilities. Building upon the successes achieved in LLMs, researchers have proposed visual instruction tuning datasets (*e.g.*, LLaVA-Instruct-150K [32], LLaVA 1.5-665K [18]) to improve the instruction-following abilities of LVLMs. Moreover, several instruction-tuning datasets have been designed to enhance specific skills [43, 44, 45], such as ShareGPT4V [46] for caption generation, mPLUG-DocOwl [47] for document understanding, and VideoChatGPT [48] for video comprehension. To the best of our knowledge, our MMDU-45k is the first open-source multi-turn, multi-image, and long-context instruction tuning, making it a valuable resource for advancing human-AI interaction capabilities.

6 Conclusion

In this paper, we introduce **MMDU**, a multi-mage, multi-turn, and long-context benchmark designed to enhance the daily human-AI conversation experience. Our comprehensive evaluation of 15 LVLMs reveals a significant performance disparity, with closed-source models like GPT-40 [15] outperforming the open-source LVLMs. This disparity may be attributed to the scarcity of open-source instruction tuning datasets that adequately assess the required multi-turn and multi-image abilities. To address this limitation and contribute to the open-source community, we propose **MMDU-45k**, an instruction tuning dataset comprising 45k examples with a maximum of 17K text tokens, 5 images, and 9 turns. We also demonstrate that fine-tuning LVLMs on MMDU-45k improves performance across various LVLM benchmarks. Our **MMDU** and **MMDU-45k** are poised to benefit the research community and foster future advancements in human-AI interaction.

(a) MMDU Case



Question1: What are the brands of the vehicles in Image 3 and 4? And what is the license plate number of the car in the Image 1?

Question2: What are the differences between the vehicles in Image 1 and 2?

InternLM-Xcomposer2:

A1: In Image 3, the brand of the vehicle is Hyundai. In Image 4, the brand of the truck is Isuzu. The license plate number of the car in Image 1 is S.MA 5560.

A2:The vehicles in Image 1 and 2 are different types of trucks. The truck in Image 1 is a Mercedes-Benz, while the one in Image 2 is a Hyundai.

InternLM-Xcomposer2+MMDU-45k

A1: The brands of the vehicles in Image 3 and Image 4 are Hyundai and Isuzu, respectively. In Image 3, the vehicle is a Hyundai excavator, which is a type of construction equipment used for digging and moving materials such as soil, sand, or gravel. Hyundai is a South Korean multinational conglomerate that produces various types of machinery, including heavy equipment like excavators. The brand name "Hyundai" is prominently displayed on the side of the machine. In Image 4, the vehicle is an Isuzu fire truck. Isuzu is another Japanese multinational corporation known for its automotive products, including trucks, buses, and motorcycles. The fire truck in the image is specifically designed for firefighting operations, equipped with water tanks, hoses, and other firefighting equipment. The brand name "Isuzu" can be seen on the front of the truck. Regarding the license plate number of the car in Image 1, it reads "S.MA 5560."

A2: The vehicles in Image 1 and Image 2 are quite different in terms of their design, purpose, and intended use. In Image 1, the vehicle is a Mercedes-Benz convertible sports car. Mercedes-Benz is a German multinational corporation known for its luxury automobiles..... In contrast, Image 2 shows a Mercedes-Benz G-Class SUV. This vehicle is designed for off-road capabilities and rugged terrain. The G-Class is renowned for its durability and ability to traverse challenging landscapes, including rocky terrains, steep inclines, and muddy paths.....

(b) MMBench Case



Question: Which is the main topic of the image? There are several options: A. A toy bear and a toy dog, B. A toy bear and a toy chicken, C. A toy bear and a toy cat, D. A toy bear and a toy rabbit

InternLM-Xcomposer2

A: The main topic of the image is A. A toy bear and a toy dog.

Why?: I can't provide a reason because the image itself doesn't give any specific context or information to support this statement. It is important to consider the overall content of the image, including the objects and their relationships before drawing conclusions.

InternLM-Xcomposer2+MMDU-45k A: The main topic of the image is B. A toy bear and a toy chicken.

Why?: I deduced the main topic based on the presence of two distinct toys in the image. The first toy is a bear, which can be identified by its characteristic brown color and teddy-like appearance. The second toy is an orange chicken with a yellow head and legs. These two toys are prominently featured in the image, making them the primary subjects.

Figure 5: **Visualization examples** of adding MMDU-45k in the LVLM SFT stage. Error/hallucination descriptions are marked in **red**, and the detailed and accurate descriptions are marked in **green**. The case on the left is from MMDU, and the case on the right is from MMbench.

Limitations While MMDU offers several advantages, we acknowledge two key limitations. (1) MMDU primarily focuses on English and does not encompass multilingual abilities. (2) Our benchmark is designed to assess LVLMs' proficiency in daily scenarios, rather than specialized domain expertise (*e.g.*, mathematical problem-solving in MathVista [9]). By acknowledging these limitations, we hope to encourage future research directions and expansions of our benchmark such as incorporating multilingual support for other linguistic populations.

Societal Impacts As MMDU-45k is built upon Wikipedia, models fine-turned on MMDU-45k may perpetuate biases and linguistic preferences in English. Moreover, LVLMs fine-tuned on our MMDU-45k may be susceptible to factuality and hallucination issues, potentially generating inaccurate or misleading information. By recognizing these risks, we can work towards creating more inclusive, accurate, and reliable LVLMs that foster trustworthy human-AI interactions.

Author Statement and Data License The authors bear all responsibility in case of violation of rights and confirm that this dataset is open-sourced under the Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) license. Using this dataset should abide by the policy of OpenAI.

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Supplementary Material

In this supplementary material, we offer further details regarding the proposed MMDU and MMDU-45k, along with additional experimental discussions aimed at comprehensive benchmarking. Specifically, Section A includes our project URL and benchmark download URL. Sections B and C delve into the specifics of MMDU and MMDU-45k, respectively. Our evaluation section D provides in-depth analysis and discussion. Section E provides the datasheets for MMDU and MMDU-45k.

A Open-source Links

All data from our MMDU and MMDU-45k are now available for viewing or download via the following URLs:

- Project page: https://liuziyu77.github.io/MMDU/
- GitHub repository: https://github.com/Liuziyu77/MMDU
- MMDU benchmark: https://huggingface.co/datasets/laolao77/MMDU
- MMDU-45k instruction tuning dataset: https://huggingface.co/datasets/laolao77/MMDU
- URL to Croissant metadata: https://huggingface.co/datasets/laolao77/MMDU

B More Details of MMDU

We present the details of our MMDU, encompassing the pipeline of our data cluster, the prompt designed for dialogue generation, visualizations of our generated examples, and a comprehensive comparison between our MMDU and existing benchmarks.

B.1 Data preparation

In this section, we provide a detailed explanation of how to use data from Wikipedia [5] to construct MMDU. As shown in Fig. 6, for a Wikipedia entry, we first obtain the entry's images, image captions, main content, and categories. The primary function of captions and categories (tags) is to cluster the entries. The captions, main content of the entries, and images are mainly used to generate multi-image, multi-round dialogues.

Fig. 7 illustrates how we use captions and categories (tags) for clustering the entries. Subsequently, as shown in Fig. 2 in the main text, the main content of the entry is processed by InternLM-chat-20B[12] to generate a summary of the entry. This summary, along with the image captions and images, are then input into GPT-40 to generate multi-image, multi-round dialogue content.

B.2 Prompt of Dialogue generation

To use the images and content clustered in Fig. 7 effectively, we design a prompt, illustrated in Fig. 8, to assist GPT-40 in crafting multi-turn questions. Firstly, our prompt incorporates both the image and its accompanying content, facilitating GPT-40 to pose insightful and pertinent questions pertaining to the image's theme. We employ GPT-40 to generate a multitude of questions centered around the image theme, drawing from both the images and their textual context. Secondly, to ensure the wide usability of the data, we avoid providing textual cues when generating answers. Instead, we task GPT-40 with comprehending and addressing multiple questions solely based on the images themselves and their interrelations. This approach yields multi-turn questions and answers that evince a profound grasp of the images and are applicable across various contexts.

Specifically, in Fig. 8, the upper part illustrates the prompt for question generation. In the "Role Setting" segment, we instruct GPT-40 to assume the role of a "question-design expert", tasked with formulating questions inspired by a variety of images and materials. To foster depth and breadth, we delineate the content parameters in the "Key Requirements" segment, encompassing descriptors, comparisons, social and cultural contexts, historical significance, emotional nuances, symbolic interpretations, and relational inquiries.



Figure 6: Usage of Wikipedia information. We primarily use Wikipedia's images, captions, content, and categories.



Figure 7: **Clustering pipeline.** We use clustering methods to process Wikipedia entries, grouping together entries with high relevance.

The prompt for generating answers is depicted in the lower part of Fig. 8. Similarly guided by the "Role Setting" segment, GPT-40 is required to serve as an "answer expert" and respond to the generated questions based solely on the images. As there is no reliance on highly specific textual knowledge, the content of GPT-40's answers will tend to be more generalized. Additionally, we employ "<image-i>" in both the generated questions and answers to denote the position of the image, allowing for the rearrangement of image positions by substituting "i". This theoretically allows for the generation of conversations that include more images and longer sequences of questions and answers.

B.3 Example Visualization of MMDU

In this section, we illustrate several examples to qualitatively assess the quality of our MMDU. Example (a) of Fig. 9 illustrates numerous turns of questions and answers. Question 1 and Question

Role Setting

You are a question-design expert specializing in creating questions based on different images and materials. Your task is to design multiple relatively simple questions based on two images, their corresponding captions, and supplementary materials provided by the user.

Here are the image captions and supplementary materials you need to refer to: Image caption1: {image caption1} Supplementary material1: {supplementary material1} Image caption2: {image caption2} Supplementary material2: {supplementary material2} **## Key Requirements** - The questions must not reveal the specific content of the images and materials; instead, use "<image-1>" and "<image-2>" to refer to them. - Based on the image content, you can design questions from the following perspectives: description of the image content, comparison of the image content, social, cultural, or historical significance of the image, emotional expression in the image, symbolic meaning of elements in the image, interpretation of actions or activities in the image, and relationships between objects or people in the image. - Do not mention the use of supplementary materials or image captions in the questions. - Ensure that each question can relate to multiple images as much as possible. - Add a "O" before each question. # Role Setting

You are an answer expert, specializing in answering questions based on images. Your task is to answer multiple questions based on the images provided by the user.

Key Requirements

- You need to provide detailed answers to each question based on the given images.

- Add a "**A**" before each answer and use "**A1**", "**A2**" etc., to number the answers.
- You can use your own knowledge to answer the questions, providing rich and in-depth answers.
- Your answers should be very detailed, as rich and lengthy as possible, with each answer being 500 words long.
- Use "<image-1>" and "<image-2>" to refer to the two images.
- Do not repeat the question; just provide the answer directly.

Here are the questions to be answered:
{questions}

Figure 8: **Dialogue generation prompt**. Here, we present a prompt for generating a dialogue based on two images.

4 pertain to the content of images 1 and 2, respectively, while Question 15 revisits the content of both images, challenging LVLMs' long-text comprehension and memory capabilities.

As depicted in Example (b) of Fig. 10, Question 1 entails analyzing five images. We begin by identifying the position of each image using the placeholder "<image-i>" and subsequently insert the corresponding images marked as "<ImageHere>". The task in Question 1 entails providing detailed descriptions for each image. For instance, image 1 depicts a "recreational powerboat on a trailer", image 2 shows a "traditional Admiralty or Fisherman's anchor", image 3 features a "military naval ship underway", image 4 displays a "lifebuoy", and image 5 portrays a "view where a harbor tugboat assists a much larger passenger ship". Question 2 and Question 3 expand the inquiry with 3 additional images each, employing the same way to introduce them. Question 2 delves into the practical applications of the subjects within the images, while Question 3 explores their applicable environments. Both questions elicit detailed descriptions in the responses. These questions, along with their comprehensive answers, serve as valuable references for evaluating LVLMs' comprehension of image content and their interrelations.



Image1 ### Question1:

Image1: <ImageHere>. What ancient cultural practice is reflected in the remains depicted in the Image1?

Assistant:

The remains depicted in the Image1 reflect the ancient cultural practice of Roman public bathing. The structure shown appears to be part of a Roman bath, a communal facility integral to the daily life of Romans of all social classes. The Roman baths, or "thermae" and "balnen," served not just as places for bathing but as social hubs where people gathered to relax, exercise, and engage in conversation. Roman public baths were characterized by their sophisticated architecture and elaborat design. The ytpically consisted of multiple rooms with varying temperatures: the "caldarium" (hot bath), the "tepidarium" (warm bath), and the "frigidarium" (cold bath). These facilities were equipped with advanced engineering marvels, such as hypocausts (underfloor heating systems), to maintain the desired temperatures. The remains in the image indicate substantial, thick walls that may have been part of the extensive heating system essential to the functioning of these baths. Moreover, Roman baths often included spaces for exercise (the "palaestra"), changing rooms (the "apodyterium"), and sometimes even libraries and meeting rooms. This illustrates the multifunctional nature of these facilities, which extended beyond mere hygiene to encompass various aspects of social and cultural life. The frequent use of beautiful mosaics, marble, and sophisticated architectural elements in these constructions underscored their importance within Roman society and demonstrated the Romans' dedication to public welfare and communal activities. In conclusion, the remains depicted in the image highlight the significance of communal baths in Roman culture. These facilities were not only essential for personal cleanliness but also pivotal in fostering community interaction and embodying the technological and architectural advancements of ancient Rome.



Figure 9: **Benchmark Example** (a). Here, we present a 2-image benchmark multi-round Q&A task. Due to space limitations, we only display the three rounds of dialogue.

B.4 Related Work with Existing Benchmarks

We conduct discussion with existing benchmarks, including MMVet [4], MMBench [26], MMMU [27], MMStar [8], MathVista [9], AI2D [28], HallusionBench [29], Chart QA [10] and ConvBench [2].

MMVet is a benchmark designed to evaluate LVLMs' ability on complicated multimodal tasks. It contains 200 images, and 218 questions with the corresponding answers, each set pertaining to one image. Our MMDU offers 421 images with 1645 Q&A pairs and around 15 turns of each Q&A pair for 2-20 images.

MMBench contains over 3000 multiple-choice questions covering 20 different ability dimensions, such as object localization and social reasoning, for evaluating LVLMs. However, multiple-choice questions fail to adequately assess the generative and conversational capabilities of LVLMs.

MMMU includes 11.5K meticulously collected multimodal questions from college exams, quizzes, and textbooks, covering six core disciplines. These questions span 30 subjects and 183 subfields, comprising 30 highly heterogeneous image types, such as charts, diagrams, maps, tables, music sheets, and chemical structures.



Question1:

Image 1: <ImageHere>. Image 2: <ImageHere>. Image 3: <ImageHere>. Image 4: <ImageHere>. Image 5: <ImageHere>. Describe image 1 to image 5. ### Assistant:

The first image, "image 1," showcases a recreational powerboat on a trailer, which is a typical sight at marinas and boatyards. The boat, mounted on a trailer, indicates that the owner might use it for leisure activities like fishing, water sports, or just cruising around water bodies. This is evident from the design of the boat, which seems to have a center console—a common feature that offers a good balance of open deck space and control. The presence of a bimini top, which is the canvas shade affixed on a collapsible frame, offers protection from the sun and rain, making it more comfortable for day trips. The outboard motor, branded Yamaha, is visible at the stern, suggesting that this boat relies on an external propulsion system, which is a custom among boat owners to personalize their vessel's name, which is a custom among boat owners to personalize their vessels. The setting suggests a coastal or lakeside region where boating is a common recreational activity. Given the boat's condition, it seems well-maintained, which speaks to the owner's pride and care for their vessel.

The second picture, "image 2," shows an anchor—specifically a traditional Admiralty or Fisherman's anchor—resting on a pavement along a waterfront area surrounded by pebbles. The anchor's size and placement indicate that it may now be serving as a nautical-themed monument or decoration rather than an actual functional piece. The white paint on the anchor resting contrast with its backdrop, making it a noticeable feature in its landscape. Anchors like this are historically significant, representing the ancient technology used to secure vessels to the seafloor. The visible structure and design, with its distinct arms and crown, would have allowed the anchor to dig into the bottom of the sea, effectively holding a ship in place. This image may be set in a port city or historic area where maritime culture is celebrated or preserved, and such an anchor serves as a reminder of the region's heritage related to sea travel and industry. The third image, "image 3," displays a military naval ship underway. The vessel is likely a frigate or destroyer based on its size, streamlined superstructure, and the array of

The third image, "image 3," displays a military naval ship underway. The vessel is likely a frigate or destroyer based on its size, streamlined superstructure, and the array of antennas and radar domes. The gum mounts and other equipment on deck suggest it is designed for surface warfare, air defense, and anti-submarine operations. This type of ship typically operates as part of a naval fleet, protecting other vessels, and could be equipped with various high-tech systems like missile launchers and advanced communication tools for military engagement. The presence of the ship in a body of water close to urban areas might suggest it's either departing form or returning to its home port for exercises or deployment. The vessel's hull number is usually a clear identifier for the particular ship within its naval force, offering insights into its specific capabilities, history, and crew size.

Image four, "image 4," features a lifebuoy with the inscription "Sit in Breeches," which could be a life-saving apparatus or part of a water rescue kit stationed near a body of water, such as a pool, marina, or along the coast. Lifebuoys are designed to be thrown to a person in the water to provide buoyancy and prevent drowning, while the individual waits for further rescue. This device looks quite worn and aged, suggesting it may be a functional relic or a decorative piece with a nod to nautical safety measures. The rope attached to the lifebuoy is intended to pull a person in distress toward safety. The lifebuoy's location near a pebbled ground and the absence of immediate water in view could indicate that this is part of a display or a safety station not directly adjacent to water.

The fifth image, "image 5," captures a view where a harbor tugboat assists a much larger passenger ship, likely a cruise ship. Tugboats are powerful for their size and are specially designed to maneuver other vessels by pushing or towing them. This is crucial in busy or narrow harbors where large ships have difficulty maneuvering due to their size. The tugboat's vibrant red color is visually striking and usually signifies utility and visibility in maritime environments. The crucise ship, with multiple decks and rows of windows and balconies, is where guests enjoy amenities and accommodations while traveling on the open sea. This scene is typical of a port city where ocean liners make stops, allowing passengers to embark on sightseeing or city tours. The interaction between the tug and the cruise ship underlines the coordinated efforts and skilled maritime operations required for safe harbor navigation.



Question2:

Image 6: <ImageHere>. Image 7: <ImageHere>. Image 8: <ImageHere>. Compare the size and potential uses of the watercraft in image 1, image 6, image 7, and image 8. What activities might each be best suited for?

Assistant:

The watercraft depicted in image 1, image 6, image 7, and image 8 vary greatly in size and potential uses. image 1 shows a small center-console fishing boat typically used for nearshore or inland waters. It's well-suited for recreational fishing and small group outings, as its size allows for easy maneuvering in smaller waterways and ease of transport by trailer.

Image 6 presents an aircraft carrier, a massive naval vessel that serves as a seagoing airbase. These colossal ships are integral parts of a country's naval fleet and are primarily used for defense purposes, carrying a multitude of aircraft for operations that necessitate both offensive and defensive capabilities. Other potential uses include humanitarian aid and disaster response due to their ability to operate independently for long periods. Image 0, operates as a mobile airbase and is central to naval operations in projecting air power worldwide. The

Image 7 depicts a modern aircraft carrier, which, like the one in image 6, operates as a mobile airbase and is central to naval operations in projecting air power worldwide. The size and structure of these carriers allow them to support and deploy fixed-wing aircraft and helicopters for various missions, including combat, reconnaissance, and supply operations.

Finally, image 8 shows a group of individuals using a combination of a small wooden platform boat and kayaks, which are geared towards leisure and recreational activities such as exploration, fitness, and relaxation. These watercraft are best utilized in calm, inland waters, and they allow for a close-to-nature experience.

Question3: Based on the type of water bodies that seem to be shown in image 1, image 7, and image 8, describe the different types of environments in which these vessels might operate

Assistant: The water bodies in image 1, image 7, and image 8 showcase different types of environments suitable for various vessel operations. Image 1 appears to be set in a calm marina or nearshore area, indicating that the small center-console boat is ideal for calm waters, such as lakes, rivers, and protected coastal areas, where its size is sufficient for personal lesiure activities including fishing. Image 7, featuring an aircraft carrier, necessitates deep, open ocean environments, as carriers need extensive space for operational maneuvering and launching/recovering aircraft. They operate in international waters and near coastillnes during times of conflict or tension to exert military presence and engage in training exercises. Image 8 highlights a peaceful freshwater environment, likely a river or lake. These settings are perfect for kayaks and small boats, where the size and design of these erafts allow for easy navigation through potentially narrow passages and are best suited for leisurely exploration, wildlife observation, and exercise.

Figure 10: **Benchmark Example (b)**. Here, we present a multi-image benchmark multi-round Q&A task. Due to space limitations, we only display the first three rounds of dialogue.

MMStar is an elite vision-indispensable multi-modal benchmark comprising 1,500 samples meticulously selected by humans. MMStar benchmarks 6 core capabilities and 18 detailed axes, aiming to evaluate LVLMs' multi-modal capacities with carefully balanced and purified samples.

MathVista is a benchmark designed to combine challenges from diverse mathematical and visual tasks. It consists of 6,141 examples, derived from 28 existing multimodal datasets involving mathematics and 3 newly created datasets.



AI2D is a dataset of diagrams with exhaustive annotations of constituents and relationships for over 5,000 diagrams and 15,000 questions and answers. It is designed to evaluate LVLMs' ability to interpret and reason about intricate diagrams with meticulous attention to detail and clarity.

HallusionBench is a comprehensive benchmark designed for the evaluation of image-context reasoning, which comprises 346 images paired with 1129 questions. HallusionBench primarily tests the issues of language hallucination and visual illusion present in LVLMs.

Chart QA is a large-scale benchmark covering 9.6K human-written questions as well as 23.1K questions generated from human-written chart summaries. It focuses on assessing LVLMs' abilities with charts.

ConvBench evaluates multi-turn conversations by assessing perception, reasoning, and creativity progressively. It comprises 577 multi-turn conversations aligned with their respective single images.

C More Details of MMDU-45k

In this section, we provide more detailed information about MMDU-45k. The data construction method for MMDU-45k is essentially the same as that of the MMDU. This section mainly introduces some of the notable features of MMDU-45k.

C.1 The powerful scalability of MMDU-45k

The powerful scalability of the MMDU-45k dataset can be attributed to the well-designed data format we implemented during its construction. For all generated data, we use the identifier "<image-i>" to mark the positions and sequences of all images. For data generated in different batches, we can stack different multi-image, multi-round dialogues by modifying the sequence identifier "i" in "<image-i>". This allows us to construct dialogues with longer contexts and more images according to user requirements for dialogue length.

MMDU-45k acts like a fundamental building block, enabling users to construct dialogues of any desired length without having to collect images and textual information from scratch. Instead, users can use MMDU-45k as a component to build training data or test questions tailored to their specific needs.

C.2 The Richness and Diversity of MMDU-45k

During the construction of MMDU-45k, we performed clustering on data from Wikipedia. In the clustering process, all Wikipedia entries were categorized into various groups. As shown in Fig. 11, these categories include geography, history, culture, nature, animals, plants, vehicles, mathematics, physics, chemistry, and more. This distribution ensures that the MMDU-45k dataset has a very broad coverage, encompassing various aspects of daily life. Consequently, using MMDU-45k for training allows the model to learn more general knowledge and enhances its capabilities in long dialogues and multi-image understanding across multiple domains.

Models	Judgment Models	C	R	VP	LC	AA	IRU	Avg.	
LLaVa1.5-7B [18]	GPT-40	27.8	28.0	33.2	43.0	35.4	31.7	32.2	
	GPT-4-turbo	28.2	27.9	34.2	39.9	34.8	32.3	32.1	
	Claude3-opus	32.8	32.6	40.6	47.1	41.1	29.0	39.3	
LLaVa1.5-7B+MMDU-45k	GPT-40	34.3	34.5	36.7	47.2	38.5	35.5	37.2	
	GPT-4-turbo	36.2	37.4	39.3	47.4	40.8	38.3	39.1	
	Claude3-opus	43.0	42.3	51.0	57.0	51.8	37.6	49.3	
Claude3-Opus [14]	GPT-40	58.6	61.5	59.7	75.1	64.1	59.8	62.6	
	GPT-4-turbo	59.9	64.9	63.7	73.5	66.2	63.1	64.5	
	Claude3-opus	64.7	67.3	74.5	80.1	76.8	60.6	72.7	
GPT-4-turbo [1]	GPT-40	62.0	64.2	63.4	78.0	69.0	64.4	66.3	
	GPT-4-turbo	63.9	67.6	67.7	76.1	70.8	67.0	68.4	
	Claude3-opus	65.9	67.9	74.5	80.5	76.9	60.9	73.7	
GPT-40 [15]	GPT-40	63.7	69.6	66.7	80.6	73.3	68.1	70.2	
	GPT-4-turbo	64.9	70.7	68.7	77.2	73.2	68.6	70.1	
	Claude3-opus	67.5	71.9	76.2	82.3	79.4	64.1	75.9	

Table 4: **Evaluate the results of the four models using different judgment models.** We used GPT-40, GPT-4-turbo, and Claude3-Opus to evaluate the results of the four models.

D More Evaluation Details

In this section, we present a comprehensive overview of our evaluation details, including specific judgment prompts, as well as quantitative and qualitative results.

D.1 Judgment prompt

In Fig. 12, we illustrate the judgment prompt employed to guide GPT-40 in conducting comprehensive evaluations of LVLM results. This process involves delineating evaluation criteria across six dimensions: Creativity, Richness, Visual Perception, Logical Coherence, Answer Accuracy, and Image Relationship Understanding. Each dimension is finely scored on a scale of 0 to 10, with criteria set at 2-point intervals, and supported by reference answers. Furthermore, GPT-40 is tasked with assigning an Overall Score, also at 2-point intervals. Finally, we divide the total score by the number of questions and multiply by 10 to obtain the final result.

Through this meticulous guidance, GPT-40 can effectively evaluate LVLM results across various dimensions, providing a comprehensive assessment process to validate the soundness of its scoring.

Different Judgement Models. We conduct a comparative analysis of evaluation using GPT-4o, GPT-4-turbo and Claude3-Opus across various LVLMs, presented in Tab. 4 and Fig. 13. From the results in the table, we can observe that the scoring trends of GPT-4o and GPT-4-turbo are similar, with minimal differences. The scores provided by the Claude3-Opus model show a similar trend to those of GPT-4o and GPT-4-turbo but are generally slightly higher. Additionally, for the IRU (Image Relationship Understanding) metric, the scores given by Claude3-Opus are more conservative compared to the other two models, being slightly lower than those of GPT-4o and GPT-4-turbo. However, the findings overall show a strong similarity between the evaluation outcomes of GPT-4, GPT-4 Turbo, and Claude3-Opus, highlighting the robustness of our proposed judgment prompt and evaluation pipeline.

Consistency with Human Scoring. Furthermore, we quantify the concordance between the scoring of GPT-4-turbo and Claude3-Opus with human judgment. In contrast to GPT-40, which exhibits Pearson, Spearman, and Kendall similarities of 97.5%, 97.3%, and 89.0% respectively, Claude3-Opus and GPT-4-turbo demonstrates Pearson, Spearman, and Kendall similarities of (91.4%, 92.7%, 89.0%) and (97.2%, 97.0%, 88.5%), respectively. These metrics indicate that while Claude and GPT-4-turbo closely align with human scores, its performance slightly trails behind the more potent GPT-40.

D.2 More cases

To clarify the testing and evaluation process of MMDU, we display three question-answer pairs from MMDU in Fig. 14, 15 and 16. Due to space limitations, we cannot show a complete multi-turn, multi-image conversation, so we selected one question-answer pair for demonstration. Each case includes the relevant images and the ground truth. We also list the results of InternLM-Xcomposer2 and InternLM-Xcomposer2+MMDU-45k, showcasing the effectiveness of MMDU-45k in improving

You are an assistant skilled at evaluating the quality of generative text. Please act as an impartial judge and evaluate the quality of the response provided by an AI assistant to the user question displayed below. You'll need to assess the response on the following dimensions: Creativity, Richness, Visual Perception, Logical Coherence, Answer Accuracy and Image Relationship Understanding. We will provide you with a creative question and the AI model's response and a reference answer for your evaluation. As you begin you assessment, follow this process:

1. Evaluate the AI model's answers on different dimensions, pointing out its strengths or weaknesses in each dimension and assigning a score of 1 to 10 for each.

2. Finally, based on the assessments across dimensions, provide an overall score of 1 to 10 for the AI model's response. 3. Your scoring should be as stringent as possible and follow the scoring rules below

In general, the higher the quality of the model's response and its strict adherence to user needs, the higher the score. Responses that do not meet user needs will receive lower scores.

Scoring rules Creativity:

Scores 1-2 when there is no innovation or uniqueness in the content.

Scores 3-4 when providing partially original content but with low creative quality. Scores 5-6 when mostly creative but lacks significant novelty, with moderate quality.

Scores 7-8 when having novelty and high-quality content. Scores 9-10 when highly novel and of exceptional quality compared to the reference answer

Richnes

Scores 1-2 when lacking depth and breadth, with very limited information.

Scores 3-4 when limited in depth and breadth, with fewer explanations and examples, showing low diversity. Scores 5-6 when limited in depth and breadth but provides basic necessary information.

Scores 7-8 when providing depth and useful additional information

Scores 9-10 when providing exceptional depth, breadth, and high diversity compared to the reference answer.

Visual Perception:

cores 1-2 when the description of the visual information in the image contains errors or is significantly inconsistent with the content of the image. Scores 3-4 When the description of the visual information in the image reflects only a small amount of the image's information and contains some errors Scores 5-6 when the description of the visual information in the image includes the basic information of the image but contains minimal information. Scores 7-8 when the description of the visual information in the image matches the image well and is rich in content, providing a substantial amount of information about the image. Scores 9-10 when the description of the visual information in the image not only matches the image but also is more detailed and informative compared to the reference answer, providing more information about the image. Logical Coherence Scores 1-2 when entirely incoherent, lacking any logic, and not matching the question or known information Scores 3-4 when somewhat coherent but with many logical errors or in-Scores 5-6 when mostly coherent, with few errors, but may struggle to maintain complete coherence in complex situations Scores 7-8 when excellent logical handling, very few errors. Scores 9-10 when flawless logic, impeccable in handling complexity, and significantly higher logical coherence compared to the reference answer. Answer Accuracy Scores 1-2 when the answer is significantly inconsistent with the question or contains obvious errors. Scores 3-4 when the answer is partially correct but contains some errors or is incomplete. Scores 5-6 when the answer is basically correct but lacks details or is not sufficiently detailed Scores 7-8 when the answer is accurate and detailed, fully corresponding to the question Scores 9-10 when the answer is not only accurate and detailed but also provides additional useful information, exceeding expectations Image Relationship Understanding Scores 1-2 when there are significant errors or confusion in distinguishing and describing different images, unable to correctly identify and relate the content of the images. Scores 3-4 when the description of different images reflects only minimal distinguishing information, contains some errors and confusion, and fails to clearly Generation and relate the images. Scores 5-6 when the description of different images includes basic distinguishing information, is able to correctly identify and relate the images in a basic manner, but the information provided is minimal and lacks detail. Scores 7-8 when the description of different images is accurate and detailed, clearly distinguishing and relating the images, with rich content that points out the main commonalities and differences between the images. Scores 9-10 when the description of different images is not only accurate and detailed but also provides richer information and analysis, clearly distinguishing and relating the images, more comprehensively pointing out the commonalities and differences between the images compared to the reference answer **Overall Score:** Scores 1-2 when irrelevant to the question, factually incorrect, or generates harmful content Scores 3-4 when no serious errors, mostly harmless, but of low quality and does not meet requirements. Scores 5-6 when basically meeting requirements but performing poorly in some dimensions, with moderate quality. Scores 7-8 when performing well in all dimensions. Scores 9-10 when fully addressing user questions and all requirements, significantly surpassing the reference answer Please remember, you must evaluate and explain before scoring. After your explanation for each dimension, add the score for that dimension. Finally, at the end of your response, in the format of the dictionary (including brackets), return all your scoring results, ensuring your scores are integers: {'Dimension One': Score, 'Dimension Two': Score, ..., 'Overall Score': Score}, for example: {'Creativity': 9, 'Richness': 6, ..., 'Overall Score': 7}.\n [Question] Input Question [The Start of Reference Answer] Reference Answer [The End of Reference Answer] [The Start of Assistant's Answer]

Figure 12: Judgment prompt used to test the results of GPT-4, GPT-4-Turbo, and Claude3-Opus.

the model's ability to handle multi-image, multi-turn conversations. Additionally, we provide the scoring results using GPT-40, including the reasons and given scores.

D.3 Finetune details

ssistant's Answer [The End of Assistant's Answer]

In the experimental section, we finetuned the LLaVa1.5-7B and InternLM-Xcomposer2 using our MMDU-45k dataset. During the finetuning process, we mixed the llava-665k dataset with the MMDU-45k dataset. Our learning rate was set to 2e-4, and we ran the training for 1 epoch.



Figure 13: Judgment Results. We used GPT-40, GPT-4-Turbo, and Claude3-Opus as judgment models to test the performance of LLaVa1.5-7B, LLaVa1.5-7B+MMDU-45k, GPT-40, GPT-4-Turbo, and Claude3-Opus on MMDU.

E Datasheet for Datasets

The following section contains answers to questions listed in datasheets for datasets.

E.1 Motivation

- For what purpose was the dataset created? MMDU and MMDU-45k are created to serve as a benchmark for evaluate and improve LVLM's abilities in multi-turn and multi-image conversations
- Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)? The authors of this paper.
- Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number. This work was supported by Shanghai AI Lab.

E.2 Composition

• What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?

MMDU and MMDU-45k consist of multi-image, multi-turn dialogues. Each dialogue includes a dozen or so rounds of questions and answers, as well as multiple images.



Question: How does the landscape in Image1 differ from that in Image2?

Ground Truth

The landscapes in Image1 and Image2 exhibit significant contrasts that are noticeable even to a casual observer. Image1 showcases a lush, verdant valley, indicative of a more secluded and perhaps more pristine environment. The rolling hills, covered in dense foliage, suggest a landscape heavily influenced by natural vegetation without extensive sectude and perturbs indeperturbs indeperturb in the forming mins, covered in dense foringe, suggests a induscape nearity influence of matural vegetation without extensive human alteration. In contrast, Image2 presents a coastal secone composed primarily of clear blue waters, boats, and coastal human settlements. This image shows a vibrant and possibly tourist-centric region with infrastructure like buildings and pathways harmoniously integrated into the natural landscape. The mood and ambiance of the locations differ considerably. Image1 has an aura of tranquility and untouched natural beauty, enhanced by the expansive valley and distant mountain ranges. These features create a sense of isolation where nature dominants the visual martity. Meanwhile, Image2 radiates a lively, inviting atmosphere with a strong human presence. The boats scattered along the water, the vibrant colors of the buildings and flowers, and the open, sunlit sky contribute to a feeling of accessibility and activity, indicative of a location that sees regular human what, use totain consistive testings and novel, and no open, saminary connection a treating in determine the result of a freedom and see region management of a freedom and see region management. In terms of geographical elements, Imagel is characterized by dense greenery and undulating terrain, suggesting a forested or trutal landscape. The topography varies in elevation, pointing to hills and valleys that might host diverse plant and animal life. The dense tree cover and open grassy areas are indicative of a region that receives ample rainfall and has risk of host diverse plant and animal life. The dense tree cover and open grassy areas are environment. The azure waters of the coastal region form the centerpiece, flanked by a coastline dotted with residences and small mountainous regions in the background. This juxtaposition emphasizes a synergy between the natural marine environment and human habitation, likely designed to appeal to both residents and tourists looking for serene eanfront experiences

InternLM-Xcomposer2:

The landscape in Image1 is a lush green valley with rolling hills, while the landscape in Image2 features a blue ocean surrounded by mountains. The two images depict entirely different types of landscapes: one being a verdant valley and the other being a coastal area with water and mountains. ### Evaluation of the Assistant' s Answer

Creativity
The response is direct and lacks any innovative or unique descriptions that would make it stand out. There is minimal illustration or embellishment that would bring the
landscapes to life or provide a novel perspective. **Score: 2** #### Richness

Visual Perception

The assistant correctly identifies the fundamental visual elements of each image, such as the lush green valley and rolling hills in Image1 and the blue ocean with surrounding mountains in Image2. However, it fails to provide rich details such as human presence, specific vegetation, or the ambiance present in the images. **Score: 5*

Humanian in mage. In the event is the protect for the term defines a number presence, specific vegetation, or the annumer presence in the mages. Society of Humanian presence with the specific vegetation of the specific vegetation, or the annumer presence in the mages. Society of The answer is logically coherent and makes sense, stating the main differences in the landscapes in a clear, straightforward manner. However, it lacks the complexity and thoroughness seen in the reference answer. **Score: 7**

Answer Accuracy

The answer is accurate but overly simplistic. It captures the primary difference between the landscapes but misses out on finer details and additional information provided in the

The answer is accurate but overly simplistic. It captures the primary difference between the landscapes but misses out on finer details and additional information provided in the reference answer, such as human infrastructure and emotional aspects. **Score: 6**
Image Relationship Understanding
The assistant identifies the basic distinguishing features of the images but does not delve into the richness of their relationships, such as the interaction between nature and human presence in Image2 or the untouched nature in Image1. The reference answer offers a deeper analysis that is lacking here. **Score: 5**
Overall Score
The assistant's response is basic and accurate but lacks the depth, creativity, and richness needed to match the reference answer's quality. It performs adequately but does not excel in any particular dimension. **Score: 4**
Summer's

Summar

(Creativity: 2, 'Richness': 3, 'Visual Perception': 5, 'Logical Coherence': 7, 'Answer Accuracy': 6, 'Image Relationship Understanding': 5, 'Overall Score': 4}

InternLM-Xcomposer2+MMDU-45k: The landscape in Image1 differs significantly from that in Image2. In Image1, the scene is dominated by a lush, verdant valley surrounded by towering mountains. The terrain appears to be covered with dense vegetation, including various shades of greenery and possibly some patches of brown or yellow indicating different types of flora. The sky vorthead is cloudy, suggestions overcast day or perhaps early morning or late afternoon hours when the sun is not at its peak. This type of landscape often evokes feelings of tranquility, mystery, and natural beauty, as it showcases the raw, untamed aspects of nature. On the other hand, Image2 presents a coastal landscape featuring a vibrant blue sea dotted with numerous boats. The water body is expansive, reflecting the clear blue sky above, which has scattered clouds. The coastline is advented with colorful flowers and greenery, adding a touch of vibrancy to the scene. Buildings can be seen on the right side, hinting at human habitation and activity. This image conveys a sense of liveliness, leisure, and picturesque charm, typical of coastal tourist destinations.

Evaluation of Assistant's Response

Creativity

- The assistant's response demonstrates some creativity in comparing the landscapes of both images, using evocative language such as "lush, verdant valley" and "raw, untamed ects of nature

aspects of nature. - However, it lacks novel descriptions and depth that could make the comparison more vivid and detailed, as seen in the reference answer. The descriptions are rather straightforward. **Score: 6**

Richness

mmm rectaineds - The response provides a reasonable amount of detail about each image, describing the landscape, vegetation, sky conditions, and presence of human habitation. - It lacks additional layers of description that could increase the richness, such as the potential mood invoked by the scenes or a more in-depth discussion about the characteristics of each landscape. There's also an absence of comparative analysis of geographical elements. **Score: 6**

Visual Perception

The assistant accurately describes the general elements present in both images.
 Key details are mentioned, including the lush valley and mountainous terrain in Image1 and the vibrant coastal scene with boats in Image2.
 However, the description lacks some degree of richness, such as specific elements like the "colorful flowers and greenery," "cloudy sky," and the "human habitation and activity" more clearly. **Score: 7**

Logical Coherence

The response is logically coherent, with a format that separates the descriptions of the two images and explains the differences in a structured way - The flow of information is smooth, and each point made logically follows from the previous one. **Score: 8**

Answer Accuracy

- The descriptions are accurate and align with the content of the images, covering the key visual elements and characteristics of the landscapes - It correctly identifies the lush, natural setting of the first image and the coastal, human-influenced setting of the second image. **Score: 8**

 To concern because we take nature seture of the first image and the coastal, numari impedied seture of the second image. Score is
 "### Image Relationship Understanding
 The assistant effectively differentiates between the two images and appreciates the primary contrasts.
 The response includes comparative elements, such as describing the feelings evoked by each scene and pointing out human habitation in Image2. - It could benefit from a deeper comparative analysis, such as discussing how the topography and natural features in each image relate to or contrast with one another. **Score:

(** #### Overall Scoring Based on the individual dimension scores, the assistant's answer is competent and mostly accurate but could be improved in terms of creativity and richness. It provides correct and logically structured descriptions with an adequate level of detail but lacks some depth and novelty compared to the reference answer. **Overall Score: 7** and logically structured descriptions. The second structure of the second {'Creativity': 6, 'Richness': 6, 'Visual Perception': 7, 'Logical Coherence': 8, 'Answer Accuracy': 8, 'Image Relationship Understanding': 7, 'Overall Score': 7}

Figure 14: Q&A Case 1 of MMDU. We list the questions, images, and ground truth. We compared the results of InternLM-XC2 and InternLM-XC2+MMDU-45k and showcase the scoring results and reasons for GPT-4o.

- How many instances are there in total (of each type, if appropriate)?
- MMDU consists of 110 dialogues, comprising 1,645 questions and their corresponding answers. Additionally, these 110 dialogues in MMDU contain 421 images. On the other hand, MMDU-45k is composed of 45,000 dialogues, with each dialogue averaging 3 images and 9 rounds of questions and answers, totaling 410k Q&A pairs.
- Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set?



Ouestion

Tange 1: <ImageHere>. Image 2: <ImageHere>. Image 3: <ImageHere>. Describe the primary activity or purpose of each animal depicted in Image1, Image2, and Image3 based on their physical traits and behaviors.

Ground Truth:

The primary activity or purpose of each animal depicted in Image1, Image2, and Image3 can be inferred based on their physical traits and behaviors. Starting with Image1, it features a hereing dog, most likely a Border Collie or another similar breed, actively herding a group of sheep. Herding dogs are bred and trained for their exceptional intelligence, agility, and control over livestock. They are key in managing and directing the movement of sheep, guiding them to desired locations efficiently. The herding behavior displayed by the dog is instinctual but honed with training, making it invaluable to farming operations. In Image2, the animal depicted is an Equus hemionus or Onager, which is closely related to donkeys and wild asses. Onagers are known for their resilience and ability to endure harsh environments. They primarily graze on grasses, leaves, and fruits, using their strong limbs to move across large distances in search of food and water. Their physical traits, such as strong legs and a unique body structure, enable them to thrive in arid and semi-arid regions, showcasing their evolutionary adaptations for survival. Image3 features horses, domesticated animals with a long history of companionship and service to humans. Horses have served various purposes throughout history, including transportation, agriculture, and spect. Their strong build, endurance, and speed make them ideal for riding, pulling carts, and participating in competitive sports. The horses in the image appear to be in a relaxed state, possibly in a paddock, indicating their domesticated and managed lifestyle.

InternLM-Xcomposer2:

In the image, there are three horses and a dog. The primary activity or purpose of each animal can be described as follows:

I. Horses: Horses are herbivorus animals known for their strength and speed. They are offen used for transportation, racing, and various equestrian sports. In this image, the horses appear to be standing in an enclosed area, possibly a stable or pasture, which suggests they might be kept for leisure, breeding, or training purposes.
 Dog: Dogs are domesticated mammals that have been selectively bred for various tasks over thousands of years. In this image, the dog is seen near the horses, which could

indicate that it is a herding dog, trained to manage and control livestock like horses. Herding dogs help farmers and ranchers by keeping the animals together and guiding them in specific directions

Evaluation of the Assistant's Answer #### Creativity:

The Al assistant provides a basic description of the animals' activities or purposes but lacks any innovative or unique approach. The response is straightforward and does not introduce any new or interesting insights beyond what is expected. Score: 2 #### Richness

The response offers minimal information about the animals. It covers the basic traits and purposes of horses and the dog but does not go into detail or provide diverse information about their behaviors, history, or characteristics. It misses out on identifying the se #### Visual Perception: ond image as an Onager and does not provide enough depth. Sco

The assistant's response does not accurately describe the visual content of the images. Specifically, the assistant fails to identify the Onager (in the second image) and instead focuses only on horses and a dog. The descriptions provided for the dog and horses are also fairly general and not rich in content. Score: 2

High Logical Coherence: Despite the issues in richness and visual perception, the response maintains logical coherence within the scope of the provided information. The sequence of explaining horses before the dog is logically structured, even though it misses a significant part of the question. Score: 6

Answer Accuracy: The assistant's response accurately describes the potential purpose of horses and the dog in a general sense but fails to identify the Onager and falls short in providing detailed and accurate explanations for all images. Score: 4

Image Relationship Understanding:

The assistant struggles significantly in this dimension as it fails to accurately distinguish the animals in the images. It does not address the Onager in the second image and instead gives a more generic description of horses. The understanding of how the image contents relate to each other is weak. Score: 2 #### Overall Score:

Given the shortcomings in creative depth, richness, visual accuracy, error in identifying the Onager, and limited understanding of the relationship between the images, the With a solution of a soluti

InternLM-Xcomposer2+MMDU-45k:

In Image 1, the animals are dogs and sheep. The dog appears to be a Border Collie, which is known for its herding instincts. Border Collies are highly intelligent and agile, In mager, the animets bottle former are objected by the adjourned of the a resources for human use. In Image2, the animal depicted is a donkey. Donkeys are often kept for various purposes, including transportation, work, and companionship Itsiorically, they have been used to carry loads, pull carts, and even serve as pack animals in remote areas where vehicles may not be practical. The donkey's sturdy build and endurance make it well-suited for these tasks. Additionally, donkeys are known for their gentle temperament, making them suitable as pets and companions. In Image3, the animals are horses. Horses are versatile animals that have been domesticated for thousands of years. They are primarily used for riding, racing, and labor. The horse in the image appears to be a pony, which is a smaller breed of horse. Ponies are often kept for leisure activities such as riding, showing, and sometimes even therapy. They are also used in agricultural se ttings for plowing fields and pulling carts

Evaluation of Assistant's Answer

####Creativity: The assistant's response is fairly creative, especially in how it categorizes the animals and provides context to their traits and behaviors. It slightly extends the answer beyond The assistant's response is fairly creative, especially in how it categorizes the animals and provides context to their traits and behaviors. It slightly extends the answer beyond simple descriptions by incorporating elements such as the historical use of donkeys and specific activities involving different types of horses. However, it doesn't strike as exceptionally novel. **Score: 6**

Hard process - Second the roles of sheep beyond their general use. The section about the donkey is somewhat incomplete and doesn't specify its adaptability like in the reference answer, which mentions survival traits. **Score: 5**

Visual Perception

The assistant correctly identifies the animals and their activities based on the images and provides basic information. However, it doesn't go into as much depth regarding the visual cues and behaviors as the reference answer does. **Score: 6*

Logical Coherence:

The response is mostly logically coherent. Each paragraph is structured to describe the respective image, starting with the physical traits and then moving on to behaviors and purposes. However, there are a few minor jumps in logic, such as abruptly mentioning donkeys' suitability as pets without much context. **Score: 7** #### Answer Accuracy:

The assistant makes accurate claims about the animals in the images and their activities or purposes. However, by identifying the animal in Image 2 as a donkey instead of an Onager, the credibility is slightly detracted from. The reference answer's more precise identification enhances its accuracy. **Score: 5**

Image Relationship Understanding:

The assistant partially demonstrates an understanding of the relationship between the images and descriptions but misses some nuances. For instance, it does not clearly distinguish the Onager from a donkey, which indicates a lack of detail in differentiating the subjects across images. **Score: 5** ### Overall Score

Given the factors above, the assistant's response is generally adequate but falls short of the depth and clarity provided in the reference answer, **Overall Score: 6** ### Final Scorin

('Creativity': 6, 'Richness': 5, 'Visual Perception': 6, 'Logical Coherence': 7, 'Answer Accuracy': 5, 'Image Relationship Understanding': 5, 'Overall Score': 6}

Figure 15: Q&A Case 2 of MMDU.

MMDU-45k is a new dataset generated using data from Wikipedia. MMDU's data is partly a sample selected from MMDU-45k and partly manually generated data.

• What data does each instance consist of?

Each instance contains multiple images and rounds of question-answer dialogues. The number of images and the number of Q&A rounds per instance are not consistent. Each instance in MMDU contains 2-20 images, while each instance in MMDU-45k contains 2-5 images. On average, each instance in MMDU contains 15 rounds of Q&A, whereas each instance in MMDU-45k contains an average of 9 rounds of Q&A.



Question

Image 1: <ImageHere>. Image 2: <ImageHere>. Image 3: <ImageHere>. Image 4: <ImageHere>. Image 5: <ImageHere>. Compare the visual characteristics of Image2. Image3, and Image4 in terms of their flower structure and coloration. How do these variations potentially affect their pollinators

Ground Truth:

Image2, Image3, and Image4 display distinctive visual characteristics in their flower structures and coloration, which can significantly affect their interactions with pollinators Image2, image3, and image4 display distinctive visual characteristics in meir tower structures and coloration, which can significantly affect their interactions with polimators. Starting with Image2, the flowers are lavened in color and exhibit a strong vertical inflorescence. The flowers grow in whorls around a long, upright stem. Each floral whorl is comprised of small tubular flowers that open sequentially. The color varies from deep purple to lighter shades of lavender, which are attractive to certain pollinators. Each floral whorl is comprised of small tubular flowers that open sequentially. The color varies from deep purple to lighter shades of lavender, which are attractive to certain pollinators like bees and butterflies. Pollinators are likely drawn to the vivid hues that stand out against the predominantly green foliage, ensuring effective pollination. The tubular shape of the flowers caters specifically to pollinators with longer proboscises, including certain species of bees and butterflies. In Image3, the floral structure and coloration differ notably. This plant features bright pink flowers that are uniquely shaped, with each flower resembling a small, ornamental hood or helmet. The flowers grow closely together on a short, dense spike. The vibrancy of the pink hue is particularly striking and may attract a different set of pollinators compared to Image2. Insects such as bees and hummingbrits, which are attracted to brightly colored flowers, are the likely pollinators. The compact arrangement and shorter inflorescence suggest a design for pollinators that prefer shorter landing platforms or those that can bayer, such as hummingbrits. The inflorescence is a soiked flowers with a red flowers with displate vibra are hown to be sensicially attractive to hummingbrits. those that can hover, such as hummingbirds. Finally, Image4 displays vivid red flowers, which are known to be especially attractive to hummingbirds. The inflorescence is a spike times that can hover, such as maintingords. I many, image using siver feel howers, which are known to be expectantly attractive or maintingords. The indirective is a spike with flowers that are densely packed together. Each flower is tubular, with pelals forming a kind of elongated flag-like structure protruding outward. Red is an alluring color for hummingbirds, which have less color discrimination ability for blues and greens but can easily detect red. The shape and organization of the flowers cater specifically to the feeding mechanisms of hummingbirds, which hover and insert their long bills into tubular flowers to feed on nectar. The distinct colorations and structures of these flowers suggest specialization toward different pollinators. Image2 with hues appealing to bees and butterflies, Image3 with bright pinks attracting a mixed audience of bees and hummingbirds, and Image4's red tubular formations specialized for hummingbirds. This variation allows for a wider range of successful pollination strategies, ensuring the genetic diversity and propagation of these species

InternLM-X composer2: In the image, there are three different types of flowers with distinct structures and colorations. The first flower has a unique structure with long, thin petals that resemble a bird's beak or a spiky plant. The second flower is purple in color and appears to have a more traditional bell-shaped structure. The third flower is red and also exhibits a bell-shaped or a spring pair. The second root is paper in econd and appears to mere function and the sample and second root in the decimation of the second secon variation in flower structure and coloration in these images could influence which pollinators visit each type of flower, ultimately affecting cross-pollination and seed production.

Evaluation of the Assistant's Answer: #### Creativity: The provided answer demonstrates some creativity by mentioning different types of pollinators and the potential attraction based on flower structure and color. However, it lacks significant novelty and depth in comparison to the reference answer. The description is basic and doesn't delve into more specific details or pollina *Score: 5

Hit## Richness: The response touches on key aspects of flower structure and color but lacks depth and breadth. It doesn't provide detailed descriptions of the flowers' physical characteristics or specific pollinator behaviors, which are covered in the reference answer. There is a need for more elaborate explanations and examples. *Score: 4*

Visual Perception: The assistant's visual descriptions are limited and incorrect in some instances. For instance, the purple flower (Image 3) and the red flower (Image 4) are #### Visual Perception: The assistant's visual descriptions are limited and incorrect in some instances. For instance, the purple flower (Image 3) and the red flower (Image 4) are both described as bell-shaped, which in st fully accurate. The response provides only a basic description of visual characteristics without much detail or accuracy. *Score: 4* #### Answer Accuracy: The assistant's answer is logically coherent, but it simplifies the problem, grouping flowers inaccurately based on their shapes and colors. *Score: 6* #### Answer Accuracy: The assistant identifies some correct elements regarding how flower color affects pollinators but several inaccuracies exist within the description of flower shapes and colors (e.g. misidentifying structures and grouping incorrectly). It also lacks details on specific pollinators and their behaviors. *Score: 5* #### Answer Accuracy: The assistant's answer provides some basic understanding but doesn't effectively distinguish between the different images. The more muanced insights about the connection between flower characteristics and their effects on pollinators are missing compared to the reference answer, which clearly ties specific flower structures and colors to types of pollinators. *Score: 5* #### Overall Score: White he assistant's resonse touches on some relevant points, it lacks denth, richness, detailed visual description, and accuracy. It oversimplifies and #### Overall Score: White he assistant's resonses touches on some relevant points.

H### Overall Score: While the assistant's response touches on some relevant points, it lacks depth, richness, detailed visual description, and accuracy. It oversimplifies and misinterprets some visual aspects. *Score: 4* #### Final Scores: {'Creativity': 5, 'Richness': 4, 'Visual Perception': 4, 'Logical Coherence': 6, 'Answer Accuracy': 5, 'Image Relationship Understanding': 3, 'Overall Score': 4}

InternLM-Xcomposer2+MMDU-45k:

The visual characteristics of the flowers in Image2, Image3, and Image4 exhibit distinct differences in their structure and coloration, which can significantly impact their pollinators. In Image2, the flower is characterized by its vibrant purple hue and tubular shape. The tubular form suggests that this flower may be adapted to attract specific types of pollinators such as hummingbirds or certain species of bees that have long proboscises capable of reaching deep into the flower's throat. The bright purple coloration is the flower of the flower is the flower of the flo particularly attractive to these pollinators, as it stands out against green foliage and provides a clear signal for them to approach. This type of flower structure allows for efficient pollination through direct contact with the reproductive organs inside the flower, ensuring successful transfer of pollen. Image3 presents a flower with a more complex structure, featuring multiple small pinkish-purple blossoms arranged along a central stem. The intricate arrangement and the presence of numerous small flowers suggest an adaptation to attract a variety of pollinators, including insects like bees, butterflies, and possibly even small birds. The small size and numerous flowers increase the likelihood of contact with pollinators, enhancing the chances of pollen transfer. The pinkish-purple coloration also plays a role in attracting these pollinators, as many insects are drawn to shades of blue and purple. The flower in Image4 has a striking red coloration and appears to be part of a larger plant with spiky leaves. The vivid red color is highly visible and likely attracts a wide transfer of pollinators, including bees, butterflies, and even bricks. The spiky leaves might provide some protection from herbivores while also offering structural support to the flowering stalk. The combination of red coloration and spiky structure makes this flower stand out in its environment, increasing its visibility to potential pollinators. Overall, the avariations in flower structure and coloration and spicy statetic material and the state of the instructure and increasing is structurely potential parameters of the flower structure and coloration among Image2, Image3, and Image4 play cructure and numerous small flowers in Image3 appeal to a broader spectrum of insects. Meanwhile, the bold red coloration and spiky leaves in Image4 make it highly visible to various pollinators, including those attracted to bright colors. These adaptations ensure effective pollination and reproduction for each species, highlighting the diversity of strategies employed by plants to thrive in their respective environments

Evaluation of the Assistant's Answer:

Creativity: The Assistant's answer exhibits some creativity, particularly in describing the flower characteristics and pollinator interactions. However, it does not surpass the reference answer in novelty or presentation. The language used is relatively standard without unique phrasing or insights. The reference answer provides more vivid and novel imagery in its descriptions. **Score: 5**

Richness: The Assistant's response contains a good level of detail regarding the flower structures and colors. However, it lacks the depth and additional insights provided in the reference answer, such as specific pollinator behaviors and interactions with the flowers. The reference answer goes into more detail about the floral structures and how they specifically adapt to different pollinators. "How core: 64** #### Visual Perception: The Assistant accurately describes the visual elements in the images, identifying colors and flower structures correctly. However, the descriptions are

relatively basic compared to the reference answer, which provides a more comprehensive and detailed visual analysis. **Score: 6**

Logical Coherence: The Assistant's response is logically coherent, with each paragraph addressing a different image and its characteristics. Connections between flower structures, colors, and their potential pollinators are made logically and consistently. The logic is generally solid, although it could benefit from more detailed explanations. **Score: 7**

Answer Accuracy: The accuracy of the Assistant's answer is generally good. It correctly identifies the main visual characteristics and potential pollinators for each flower. However, it lacks some of the specific details and accuracy present in the reference answer, such as the sequential blooming of Image2 flowers and the specific attraction mechanisms for each pollinator. **Score: 6**

Image Relationship Understanding: The Assistant's response shows a reasonable understanding of the relationships between the images and how their variations might affect pollinators. The descriptions are accurate and distinguish the flowers effectively. However, the analysis is not as rich or comprehensive as in the reference answer, which more clearly ties together the points about pollinator attraction. **Score: 7**

Overall Score: The Assistant' s answer is competent but lacks the depth, creativity, and richness found in the reference answer. It meets the basic requirements but does not exceed them, resulting in a moderate-level response. **Score: 6** #### Final Scores: {Creativity': 5, 'Richness': 6, 'Visual Perception': 6, 'Logical Coherence': 7, 'Answer Accuracy': 6, 'Image Relationship Understanding': 7, 'Overall Score': 6}

Figure 16: Q&A Case 3 of MMDU.

- Is there a label or target associated with each instance? Yes, in MMDU, multiple questions within each dialogue have labels that have been manually checked and modified.
- 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. N/A.

- Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)?
 N/A.
- Are there recommended data splits (e.g., training, development/validation, testing)? Yes, MMDU-45k is the training set, while MMDU is the test set.
- Are there any errors, sources of noise, or redundancies in the dataset? N/A.
- Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? The dataset is self-contained.
- Does the dataset contain data that might be considered 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)? N/A.
- Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?
 N/A.
- Does the dataset relate to people? Yes.
- Does the dataset identify any subpopulations (e.g., by age, gender)? N/A.
- Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? N/A.
- Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? N/A.

E.3 Collection Process

- How was the data associated with each instance acquired? We used the open-source data from Wikipedia, incorporating its entries (including text and images), and applied GPT-4 to construct our own dataset.
- What mechanisms or procedures were used to collect the data (e.g., hardware apparatuses or sensors, manual human curation, software programs, software APIs)? We used entries collected from Wikipedia as our data source and then applied clustering methods to process the data.
- If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)? N/A.
- 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)? The co-authors of the paper participated in the data collection, verification, and modification of MMDU.
- Over what timeframe was the data collected? The data was collected in May of 2024, but the results do not depend much on the date of date collection.
- Were any ethical review processes conducted (e.g., by an institutional review board)? N/A.
- Does the dataset relate to people? Yes.

- Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)? We obtained data from the open-source Wikipedia.
- Were the individuals in question notified about the data collection? We didn't collect the data from the individuals.
- Did the individuals in question consent to the collection and use of their data? We didn't collect the data from the individuals.
- If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? N/A.
- Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? The dataset does not have individual-specific information.

E.4 Preprocessing/cleaning/labeling

• 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 of missing values)?

We performed clustering on the obtained data, selecting those with higher coherence. We also removed data with low-resolution images. Furthermore, we conducted manual checks and modifications on the MMDU data to ensure its quality.

- Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? Yes.
- Is the software that was used to preprocess/clean/label the data available? Preprocessing, cleaning, and labeling are done via Python.

E.5 Uses

- Has the dataset been used for any tasks already? No.
- Is there a repository that links to any or all papers or systems that use the dataset? No.
- What (other) tasks could the dataset be used for? N/A.
- Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? N/A.
- Are there tasks for which the dataset should not be used? N/A.

E.6 Distribution

- 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? No.
- How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? The dataset will be released on Huggingface.
- When will the dataset be distributed? The dataset will be released in mid-June 2024.
- Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? The dataset will be released under the Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) license.

- Have any third parties imposed IP-based or other restrictions on the data associated with the instances? No.
- Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? No.

E.7 Maintenance

- Who will be supporting/hosting/maintaining the dataset? The authors of this paper.
- How can the owner/curator/manager of the dataset be contacted (e.g., email address)? Contact the first author or other authors.
- Is there an erratum? No.
- Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?

If any correction is needed, we plan to upload a new version.

- If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were the individuals in question told that their data would be retained for a fixed period of time and then deleted)? N/A
- Will older versions of the dataset continue to be supported/hosted/maintained? Yes.
- If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?

Contact the authors of the paper.