

MLLM-DataEngine: An Iterative Refinement Approach for MLLM

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Abstract

Despite the great advance of Multimodal Large Language Models (MLLMs) in both instruction dataset building and benchmarking, the independence of training and evaluation makes current MLLMs hard to further improve their capability under the guidance of evaluation results with a relatively low human cost. In this paper, we propose MLLM-DataEngine, a novel closed-loop system that bridges data generation, model training, and evaluation. Within each loop iteration, the MLLM-DataEngine first analyze the weakness of the model based on the evaluation results, then generate a proper incremental dataset for the next training iteration and enhance the model capability iteratively. Compared with previous data collection methods which are separate from the benchmarking, the data generated by MLLM-DataEngine shows better targeting, quality, and correctness. For targeting, we propose an Adaptive Bad-case Sampling module, which adjusts the ratio of different types of data within each incremental dataset based on the benchmarking results. For quality, we resort to GPT-4 to generate high-quality data with each given data type. For correctness, prompt design is critical for the data generation results. Rather than previous hand-crafted prompt, we propose an Interactive Prompt Optimization strategy, which optimizes the prompt with the multi-round interaction between human and GPT, and improve the correctness of generated data greatly. Through extensive experiments, we find our MLLM-DataEngine could boost the MLLM capability in a targeted and automatic manner, with only a few human participation. We hope it could be a general solution for the following MLLMs building. The MLLM-DataEngine has been open-sourced and is now available at <https://github.com/opendatalab/MLLM-DataEngine>.

Introduction

The thriving field of Multimodal Large Language Models (MLLM) has seen significant advancements through amalgamating high-quality large visual models (Dosovitskiy et al. 2021) and large language models (Touvron et al. 2023a; Chiang et al. 2023; Touvron et al. 2023b). This integration has given rise to a plenty of sophisticated image-text large models (Zhu et al. 2023b; Liu et al. 2023a; Dai et al. 2023; Peng et al. 2023; Alayrac et al. 2022). To equip these models with capabilities such as image-text dialogue and image content understanding, a two-stage fine-tuning

process is typically employed. The first stage aligns image-text features, while the second, crucial to model performance, utilizes high-quality annotated data for instruction fine-tuning. Among these two components, the second stage is pivotal in guaranteeing exceptional model performance. Therefore, obtaining high-quality instruct tuning data is vital for outstanding model performance.

To further explore the capability of MLLMs, there are several efforts on both instruct tuning data collection and benchmark building. For pursuing high-quality multimodel instruct tuning data, recent studies have begun to explore high-quality data generation. Several efforts (Dai et al. 2023; Li et al. 2023a) have been undertaken to hand-craftly construct data from public datasets. In contrast, some recent advancements like ChatCaptioner (Zhu et al. 2023a) and IdeaGPT (You et al. 2023) using Large Language Models (LLM) like ChatGPT (OpenAI 2023) and a Vision-Language Model (VLM) for creating Caption data. LLaVA (Liu et al. 2023a) harnesses GPT-4 (OpenAI 2023), a superior text model, with image annotation for multimodal data generation. For benchmark, corresponding benchmarks for MLLM have also been proposed to furnish a more exhaustive and precise evaluation of MLLM, such as MMBenchmark (Liu et al. 2023b) and MME (Fu et al. 2023).

Despite their efforts, the training and evaluation of current MLLMs are isolated. The benchmark could point out the strength and weaknesses of the model (Kirillov et al. 2023), while it is non-trivial to use it as guidance to further improve the model, especially when the benchmark is comprehensive and the weakness includes several different aspects. A straightforward solution is to annotate/collect new data by humans, while its cost is quite large, especially when the models and benchmarks are updated iteratively.

To solve this problem, we propose **MLLM-DataEngine** to bridge data generation, model training, and evaluation. Our method differs from previous approaches by introducing a closed-loop cycle of generation-training-evaluation-generation where results from the evaluation phase are harnessed to guide the data generation process. Updating MLLM in the loop can generate targeted training data of higher quality and correctness. Specifically: (1) For targeting, we build a bad case pool for the model in each iteration, and propose an Adaptive Bad-case Sampling module to select proper query images and in-context learning ex-

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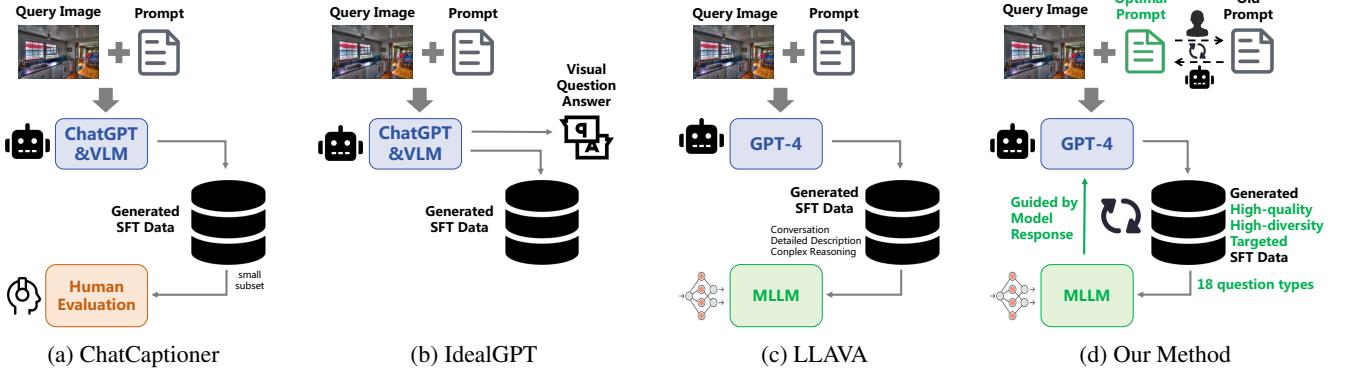


Figure 1: Comparison of existing methods and our proposed MLLM-DataEngine. Existing methods follow a straightforward one-pass generation process, which separates data generation and evaluation and is unable to achieve targeted and effective model improvement. In contrast, our proposed MLLM-DataEngine is a closed-loop of generation-training-evaluation-generation which lead to targeted model improvement.

amples from the bad case pool, which is essential as feedback to guide further data generation; (2) For quality, we utilize GPT-4 to generated diverse and accurate data for various question type; (3) For correctness, we propose an Interactive Prompt Optimization (IPO) strategy. By multi-round communication between human and GPT-4 on how to avoid generating specific failure cases, the prompt can be effectively optimized. Our contributions are as follows:

- We present MLLM-DataEngine, a multimodal engine that fosters a closed loop for data generation, model training, and system evaluation, thus facilitating iterative improvement of model performance and data quality.
- MLLM-DataEngine guides data generation using model response for targeted model enhancement. Concurrently, we introduce the Adaptive Bad-case Sampling (ABS) module to adaptively choose relevant in-context examples, ensuring high-quality generated data.
- In data generation phase of MLLM-DataEngine, we introduce the Interactive Prompt Optimization (IPO) module. Combined with human interaction, it iteratively corrects prompt misunderstandings, yielding substantial improvements in data quality.
- To validate MLLM-DataEngine’s effectiveness, we performed extensive experiments using robust evaluation benchmarks like MMBenchmark and classic VQA datasets like A-OKVQA. Results confirm MLLM-DataEngine’s ability to iteratively enhance model performance and data quality.

Related Work

Multimodel Large Language Model (MLLM) With the advancement of transformer architecture (Vaswani et al. 2017), Vision-Language models (VLMs) like CLIP (Radford et al. 2021), BLIP (Li et al. 2022), and BEiT (Bao et al. 2022) have notably evolved. While current VLMs handle a limited range of simple tasks, the introduction of powerful language models like FLAN-T5 (Chung et al.

2022), LLAMA (Touvron et al. 2023a), and Chat-GPT/GPT-4 (OpenAI 2023) has considerably expanded their performance and capabilities. BEiT-3 (Wang et al. 2022) notably performs in multiple vision-language tasks by considering visual features as a unique foreign language. Similarly, LLaVA (Liu et al. 2023a), MiniGPT-4 (Zhu et al. 2023b), BLIP-2 (Li et al. 2023c), and InstructBLIP (Dai et al. 2023) use a simplified architecture that leverages ViT (Dosovitskiy et al. 2021) and QFormer (Li et al. 2023c) for image feature extraction and an FC layer for aligning these features into language model space. We use this simple architecture in our experiments because it is highly representative and won’t damage the ability of original LLM.

Multi-modal Instruction Tuning Data In computer vision, research increasingly utilizes advanced language models like LLaMa (Touvron et al. 2023a), Vicuna (Chiang et al. 2023), and Flan-T5 (Chung et al. 2022) to build robust multimodal models such as MiniGPT-4 (Zhu et al. 2023b), LLaVA (Liu et al. 2023a), and InstructBLIP (Dai et al. 2023). These methods employ a two-stage training paradigm, primarily using pre-training data from LAION (Schuhmann et al. 2022) and CC (Sharma et al. 2018; Changpinyo et al. 2021), followed by multimodal instruction fine-tuning.

Creating multimodal instruction datasets involves deep image understanding and text development. MiniGPT-4 (Zhu et al. 2023b) uses a feature-aligned model for CC dataset interpretation and ChatGPT for initial filtering, curating 3,500 image-text pairs for refinement. LLaVA (Liu et al. 2023a) generates data via language-only GPT-4, which restricts scalability due to manual annotation. To broaden task diversity, InstructBLIP (Dai et al. 2023) introduces an instruction template construction strategy, converting 26 datasets into fine-tuning data. Meanwhile, MIMIC (Li et al. 2023b,a) compiles larger-scale instruction fine-tuning datasets. These datasets need human annotation and are limited in both specificity and accuracy. This paper introduces a self-guided, model-driven method for generating high-

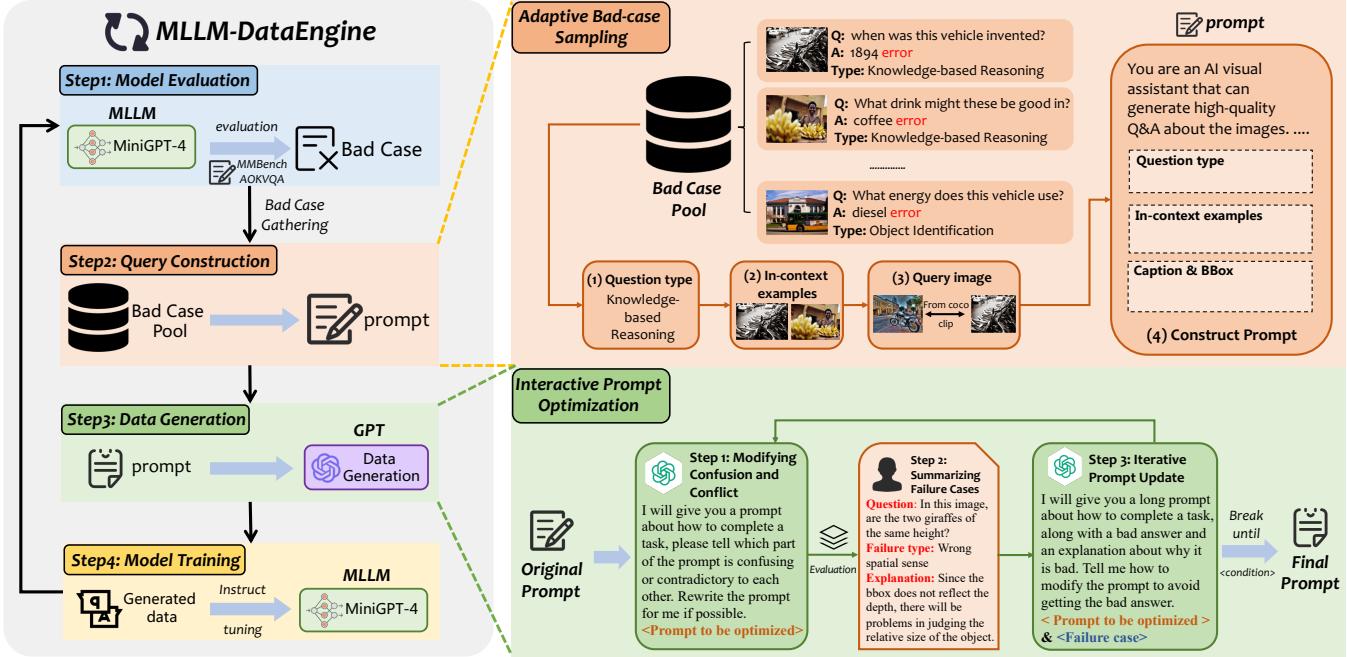


Figure 2: Our proposed MLLM-DataEngine. The whole process is divided into 4 steps. (1) **Model Evaluation**. We first test the base model on the public benchmark to get the bad cases and classify the bad cases to get the bad case pool. (2) **Query Construction**. After bad cases are obtained, Adaptive Bad-case sampling (ABS) is proposed to select queries for further data generation. (3) **Data Generation**. Selected queries are fed to GPT-4 to generate data. Interactive Prompt Optimization (IPO) is proposed to ensure the high quality of generated data. (4) **Model Training**. Model is fine-tuned on the latest generated data and loops back to the beginning of data engine.

quality fine-tuning data for any new image.

Evaluation of Multi-model Large Language Models
 MLLM’s capability dimensions are so vast that they can’t be accurately represented by a single or few traditional vision-language tasks. InstructBLIP conducts evaluations on many downstream tasks and datasets (primarily VQA datasets such as A-OKVQA (Schwenk et al. 2022), OKVQA (Marino et al. 2019), ScienceQA (Lu et al. 2022) and etc.). Fully evaluating models using public datasets is insufficient, hence the proposal for more exhaustive, objective evaluations suitable for MLLM. LLAVA evaluates models based on 90 open-ended queries and leaves judgment to GPT-4. MMBenchmark (Liu et al. 2023b) and MME (Fu et al. 2023) propose a benchmark comprising thousands of questions on multiple MLLM ability dimensions, in order to provide a comprehensive evaluation. Except for evaluation, segment Anything (Kirillov et al. 2023) shows that the bad case during evaluation can be advantageous to the data refinement process. Inspired by this, we use bad cases during evaluation to guide the data generation process.

Our Approach

The framework of MLLM-DataEngine showcased in this paper establishes a cyclical process for iterative enhancement between the model and data. The system harnesses generated data to improve the ability of the model, while feedback from model is employed inversely to steer data generation.

This approach allows simultaneous optimization of model and data across multiple iterations, facilitating quick training of high-performance models.

As Figure 2 illustrates, each iteration involves four steps: (1) Model Evaluation. The model’s capabilities are systematically evaluated across various dimensions. Then its weaknesses are identified, and bad cases are collected. (2) Query Construction. In the context of these bad cases, we propose **Adaptive Bad-case Sampling (ABS)** to construct queries for future data generation. (3) Data Generation. Constructed queries are integrated into Prompt, guiding GPT-4 to generate data with the feedback. Moreover, **Interactive Prompt Optimization (IPO)** is proposed to enhance the instruct-following ability of GPT-4. (4) Model Training. The model parameters are fine-tuned according to the latest generated data. Then MLLM-DataEngine loops back to Model Evaluation for new model performance testing.

Model Evaluation

In this step, we evaluate the model’s performance to identify the weakness of the model, and use bad cases as feedback to guide further data generation. In this paper, we utilize the open-source, instruction-fine-tuned MiniGPT-4 (Zhu et al. 2023b) as the initial model for the first round of model evaluation. Given that traditional single-task evaluation methods, such as VQA and Caption, cannot comprehensively and accurately assess the capabilities of MLLM, we have chosen

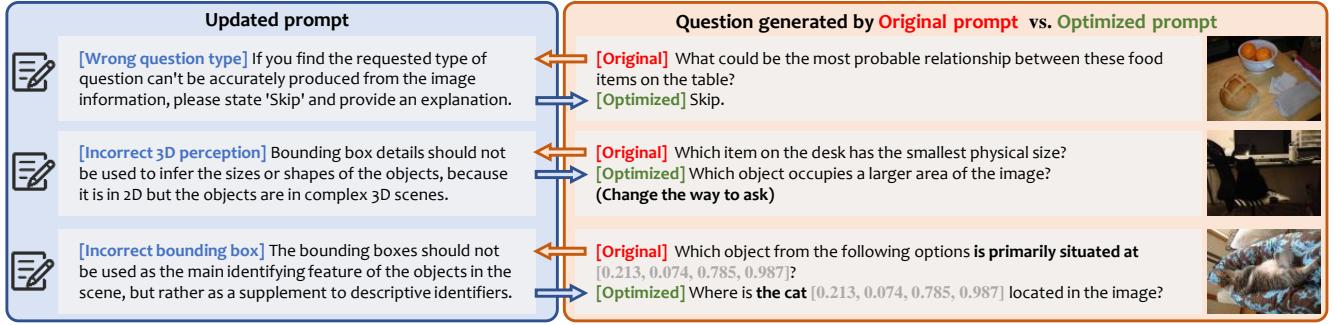


Figure 3: Our proposed Interactive Prompt Optimization (IPO) has introduced key enhancements, primarily: (1) Advanced adherence to the question type, while directly neglecting unsuitable ones; (2) Noteworthy advancements in handling spatial and imaginative questions; (3) Avoided incorrect use of the bounding box.

MMBenchmark, which involves over 20 ability dimensions, ranging from simple image perception to complex future predictions, as our evaluation standard. Moreover, to validate the proficiency of our proposed method in specific domains, we also evaluate it on the A-OKVQA dataset, one of the most challenging and high-quality mainstream VQA datasets. After evaluation, the bad cases are collected, and classified into 18 question types using GPT-4 (refer to supplemental materials for detail) to build the bad case pool for the model.

Query Construction

After the bad case pool is established, we construct queries for further data generation, which are composed of three key components: (1) An effective selection of proper query images and in-context learning examples, and (2) detailed image information described in language (provided by COCO annotation), (3) A clear, concise prompt for GPT (which will be elaborated on following section). Each of these three components plays a crucial role in the generation of high-quality data.

To ensure effective selection of proper query images and in-context learning examples, we introduce Adaptive Bad-case Sampling (ABS). It comprises three steps: (1) A question type is selected randomly. The probability of selection is inversely proportional to the scores achieved by the model in various ability dimensions. This approach provides guidance for supplementing the data needed to address the model's weakness. (2) Two bad cases of this question type are chosen randomly from the bad case pool to serve as in-context examples, assisting GPT-4 in understanding the required question type effectively and guiding GPT-4 to generate valuable data in following data generation phase. (3) Query images are chosen from the COCO dataset. Among them, half of the images are randomly selected; the remaining half use CLIP to match an image similar to the image of in-context example. This method can guarantee the diversity of generated data while also ensuring query images are suitable for generating QA with the selected question type. All query images are sourced exclusively from the COCO dataset, which includes image captions, object category information, and

location details. After the preparation of query images, question types, and in-context examples, the way for future data generation is paved.

Data Generation

In this section, we aim to generate QA data with GPT-4 using the previously constructed query. A well-crafted prompt is key for eliciting high-quality responses from GPT, allowing us to surpass the LLaVA dataset by diversifying question types and reducing GPT-4-induced illusions. Our prompt should incorporate two elements: (1) The concept of question types, and (2) Object-specific BBox references to minimize illusions (Chen et al. 2023). However, GPT-4 tends to falter with complex prompts, resulting in issues such as inappropriate question types, incorrect 3D perception, and faulty bounding boxes (refer to supplementary materials for more details).

To counter this, we introduce **Interactive Prompt Optimization (IPO)**, illustrated in Figure 2, to tackle complex prompt construction. IPO enhances GPT-4's instruction-following capabilities through a semi-automatic optimization process that fosters human-GPT-4 collaboration. This process unfolds in three phases:

Step 1: Eliminating Confusion and Conflict: We first formulate an initial rule-based manually designed Prompt, leveraging LLaVA's methodology. The Prompt instructs GPT-4 to generate specific QA pairs for given images, including bounding box annotations for each object to reduce illusions. GPT-4 then reviews the current Prompt, pinpointing any confusing or conflicting expressions, allowing us to refine it accordingly.

Step 2: Summarizing Failure Cases: Utilizing the refined Prompt, GPT-4 generates a small QA data batch for testing. We manually classify failure cases by type, providing an explanation detailing why it is considered as failure case.

Step 3: Prompt Correction based on Failure Cases: GPT-4 analyses the causes of unreasonable data generation and suggests prompt modifications, using the current template, few-shot failure examples, and their explanations as inputs. The Prompt is optimized as per these suggestions and

Base SFT Data	GPTVQA		LLM	QMAE		QMA	
	Round1	Round2		fc	lora	fc	lora
CCSBUAlign	✓		Vicuna-7B	24.3	-	-	-
	✓	✓		26.6	38.9	30.5	40.8
	✓		Vicuna-13B	27.6	41.9	35.2	50.2
	✓	✓		42.3	-	-	-
CCSBUAlign + A-OKVQA	✓		Vicuna-7B	42.7	32.6	42.1	48.8
	✓	✓		43.5	44.4	44.0	49.4
	✓		Vicuna-13B	25.7	25.7	38.5	45.8
	✓	✓		26.4	40.6	38.4	47.1
CCSBUAlign + LLAVA150K	✓		Vicuna-7B	26.5	46.7	39.2	52.7
	✓	✓		44.4	46.1	45.8	52.6
	✓		Vicuna-13B	45.7	48.1	46.1	52.5
	✓	✓		44.6	49.2	46.5	56.1
CCSBUAlign + LLAVA150K	✓		Vicuna-7B	31.0	26.0	-	-
	✓	✓		28.2	36.9	31.6	44.4
				26.1	38.0	36.3	47.8

Table 1: Experiments on MMBenchmark dev. *GPTVQA* refer to the QA data generated by MLLM-DataEngine. *Round1* and *Round2* refers to the data generated in the first and second round of MLLM-DataEngine. *fc* refers to only fine-tuning the linear projector layer of MiniGPT-4. *lora* refers to LORA finetune. The blank cells in the table are due to default settings and do not require modification or additional experiments.

returns to Step 1 for conflict checks.

The final Prompt is finalized when failure cases drop to an acceptable threshold. It is then employed to generate high-quality QA data with the constructed query. As Figure 3 demonstrates, our approach enhances: (1) Adherence to the question type, skipping unsuitable ones; (2) Noteworthy advancements in handling spatial and imaginative questions; (3) Accuracy in bounding box usage. Refer to supplemental materials for the specific Prompt discussed here. By integrating this optimized prompt with our queries, we can now guide GPT-4 to generate a suitable incremental dataset for training.

Model Training

Upon generating the latest data, we harness all previously generated data from preceding cycles to fine-tune our model. To thoroughly explore the impact of generated data on model performance, we employ two mainstream model fine-tuning strategies:

Fine-Tuning Only the Projector Layer (*onlyfc*). This strategy only updates a few parameters between the vision model and the language model, resulting in the Language-Linked Model (LLM) learning less from the fine-tuning process, but it is highly efficient.

LoRA: Low-Rank Adaptation of Large Language Models (*lora*). As per this strategy, which has been outlined by (Hu et al. 2022), a low-rank adaptation matrix is employed to fine-tune the LLM. It offers a strategic balance between the cost and effectiveness of fine-tuning. Utilizing *lora* allows the LLM to gain enhanced knowledge from the fine-tuning process while concurrently conserving computational resources.

After the model is fine-tuned on the latest data, the process loops back to the beginning. The newly fine-tuned model is evaluated to obtain the new round of bad cases. Conse-

quently, a new cycle of the data engine is initiated.

Experiments

We experimentally validate our proposed MLLM-DataEngine’s data quality and iterative refinement of both data and model in MLLM-DataEngine. We first test the data quality on A-OKVQA and MMBenchmark, then evaluate on MME (Fu et al. 2023). Next, quantitative studies affirm IPO’s efficacy in enhancing data quality and diversity. Further, ablation studies reveal the effectiveness of ABS and IPO in MLLM-DataEngine. Finally, we show that MLLM-DataEngine’s closed-loop refinement yields higher-quality data than a simple one-pass strategy.

Implementation Details

MiniGPT-4 is chosen for our MLLM architecture, which utilizes BLIP-2 (Li et al. 2023c), a ViT-G/14 and Q-former amalgamation, as the visual feature extractor. These visual features are fed directly into the LLM via a linear projector, acting as a soft prompt. The language model component utilizes Vicuna-7B and Vicuna-13B.

The MLLM-DataEngine creates a dataset termed **GPTVQA**, comprising Question-Answer (Q-A) pairs that include question (Q), multiple choices (M), answer (A), and rationale (E). Two formats, QMAE and QMA, are mainly explored in our experiments. We run the data engine for two rounds and generate 5K and 18K data respectively.

Experiments involve variable settings including fine-tuning the linear projector layer (*fc*) and applying LORA fine-tuning (Hu et al. 2022) (*lora*). We use 4 A100-80G GPUs and batch size is set to 64. We employ AdamW optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and weight decay of 0.05. The learning rate warms up during the first 200 steps, starting from $1e^{-6}$ and reaches peak values for *fc*, *lora* at $3e^{-5}$, $3e^{-4}$, respectively. Cosine learning rate scheduler is

SFT Data	R1	R2	LLM	QMAE		QMA	
				MC	DA	MC	DA
A-OKVQA	✓	✓	7B	70.1	59.1	70.2	59.1
			7B	71.0	60.3	71.8	60.8
			7B	72.1	61.0	73.6	62.0
	✓	✓	13B	73.1	62.1	74.8	62.6
			13B	74.5	62.4	74.7	63.1
			13B	74.0	61.9	75.5	63.3

Table 2: Experiments on A-OKVQA val split.

LLM	R1	R2	QMAE		QMA	
			fc	lora	fc	lora
7B	✓	✓	23.0	-	-	-
			26.6	38.7	32.8	42.3
	✓	✓	25.5	37.6	37.2	48.6
13B	✓	✓	42.3	-	-	-
			42.8	36.7	43.2	48.2
	✓	✓	42.9	44.8	44.5	48.3

Table 3: Experiments on MMBenchmark test.

employed. For *lora* fine-tune, we fine-tune q and k in the attention layer. Rank r in *lora* is set to 8. If not specified, we instruct tune the model by 10 epochs, 300 iterations per epoch. During instruct tuning, we use A-OKVQA as the validation set and choose the best model in the final evaluation.

Experiments on MMBenchmark

Three types of data, namely (1) CCSBUAlign, (2) CCSBUAlign and A-OKVQA, (3) CCSBUAlign and LLAVA150K (Liu et al. 2023a), are employed to construct baseline models. GPTVQA is then incorporated for validation purposes. As shown in Table 1, results on MMBenchmark dev reflect the continuous improvements from using GPTVQA generated by MLLM-DataEngine across different formats (QMA and QMAE) and settings (*onlyfc* and *lora*).

Further experiments using a stronger baseline model (CCSBUAlign + A-OKVQA) yield scores between 40 and 50 on MMBenchmark, indicating that A-OKVQA serves as a solid comparative dataset. Notably, even with this robust model, GPTVQA contributes to a near 5% improvement. Similar results are observed with another stronger baseline model (CCSBUAlign + LLAVA150K).

Intriguingly, we find that the QMA format outperforms QMAE in both *onlyfc* and *lora* settings, possibly due to LLM’s preference for shorter token length when partially open. Furthermore, performance variation is noted across settings (*fc* and *lora*). The improvement lead by *fc* is limited, while *lora* shows significant improvement and achieves the highest performance.

Experiments on A-OKVQA

We further verify the quality of GPTVQA by conducting comprehensive experiments on traditional visual question-answering dataset. The A-OKVQA validation split is specif-

SFT Data	R1	R2	Perception	lora	Cognition	lora
			fc		fc	
CCSBUAlign	✓		670.1	-	125.0	-
	✓	✓	714.2	708.9	115.3	206.4
			732.5	742.5	148.2	208.9

Table 4: Experiments on MME using Vicuna-7B. Perception and Cognition are two main abilities tested in MME, which is measured on 14 subtasks.

Failure type	Before	After
Incorrect bounding box	24	0
Illusion	20	2
Incorrect 3D perception	15	3
Wrong question type	8	0
Illogical question	8	0

Table 5: The failure cases statistic before and after IPO.

ically chosen for experiments. We evaluate our results using Multi-Choice (MC) and Direct Answer (DA), which are standard metrics utilized by A-OKVQA. A rank-based method is implemented to predict answers, with the results displayed in Table 2. Results suggest that GPTVQA significantly improves accuracy on the A-OKVQA task. This enhancement is consistently observed across various settings and input formats, thus further validating the outstanding quality of GPTVQA.

Experiments on additional benchmarks

We further validate the effectiveness of MLLM-DataEngine and quality of GPTVQA via additional benchmark experiments. An initial evaluation on MMBenchmark test displays consistent model improvement during each refinement round. Results are shown in Table 3. Further evaluations on another open-ended benchmark, MME (Fu et al. 2023), used for MLLM evaluation, also show enhanced performance from the GPTVQA in Table 4. These supplementary experiments affirm the efficacy of both model and data refinement across various benchmarks, thereby confirming that our proposed MLLM-DataEngine does not overfit specific evaluation benchmarks.

Experiments on data quality and diversity

We quantitatively assess IPO by comparing failure cases from initial and optimized Prompts. Table 5 shows that only five out of 77 errors persist with the optimized Prompt. An additional 100 questions are tested; eight have incorrect answers due to limitations in COCO annotation or GPT-4’s understanding of illusions and 3D scenarios (see supplementary). These can potentially be mitigated by providing more image information and enhancing the vision-language model. Besides, as shown in Table 6, we compare dataset diversity between A-OKVQA and GPTVQA. Results show that our generated data achieves almost fair performance in data diversity. Furthermore, our data has a significantly

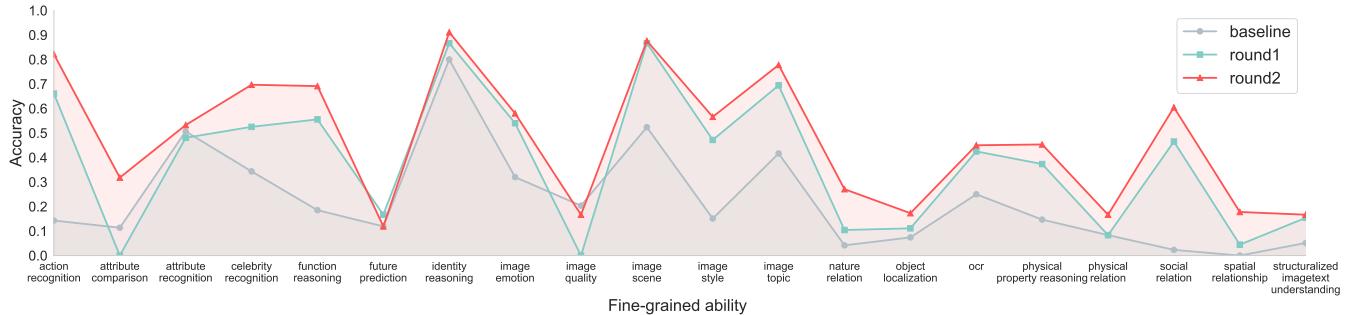


Figure 4: Fine-grained ability comparison of each round model.

Model	A-OKVQA	GPTVQA (r1+r2)
Instance Num.	17056	23164
Unique Q	16192 (94.9%)	18936 (81.7%)
Unique A	16983 (99.5%)	23163 (100%)
Avg. length (Q/A)	8.81/16.38	12.01/63.89
Unique noun (A)	4501	5296
Mean Q distance (Q)	0.897	0.814

Table 6: Comparison of data diversity between A-OKVQA and GPTVQA. Instance Num. is the total number of QA instances. Q and A represent question and answer, respectively.

prompt	MMBench Dev	A-OKVQA val	
		MC	DA
original	37.8	54.8	47.4
optimal	42.5 (+4.7)	60.0 (+5.2)	50.4 (+3.0)

Table 7: Ablation studies on Interactive Prompt Optimization (IPO).

higher number of unique nouns and average answer length than A-OKVQA.

Ablation Studies

Ablation on improvements of fine-grained ability We compare the fine-grained abilities among baseline, round 1, and round 2 models, shown in Figure 4. Each iteration of our data engine significantly improves most abilities, demonstrating the efficacy of Adaptive Bad-case Sampling (ABS) in selecting proper and diverse in-context examples. This strategy is helpful for creating diverse data, crucial for comprehensive model performance improvements.

Ablation on Interactive Prompt Optimization (IPO) Ablation studies on Interactive Prompt Optimization (IPO) are shown in Table 7, where *original* refers to the original prompt, and *optimal* refers to the prompt from interactive optimization iteration (see supplementary for details). Using 1,500 samples for initial and optimally modified prompts, improvements of 3-5% were observed in both MMBenchmark and A-OKVQA evaluations using the optimal prompt.

SFT Data	MMBench	A-OKVQA MC	A-OKVQA DA
Round1 2.5K + Round1 2.5K	40.8	55.7	47.5
Round1 2.5K + Round2 2.5K	46.0	62.2	52.1

Table 8: Ablation studies on data quality of each round. Results show iterative refinement in our proposed MLLM-DataEngine can generate higher-quality data than direct one-pass generation.

This suggests an optimized prompt significantly enhances data quality.

Ablation on data quality refinement To validate the effectiveness of round-by-round refinement in improving data quality, as compared to a single-round direct data generation approach, we carry out the following experiments. We randomly sample 5k data points from the data generated in round 2 and used this subset to replace an equivalent quantity of data in round 1. The results of this experiment are detailed in Table 8. Our findings indicate that the quality of data from round 2 surpasses that of additional data directly produced in round 1. These results validate that iterative refinement in our proposed MLLM-DataEngine can generate higher-quality data than direct one-pass generation.

Conclusion

This paper presents MLLM-DataEngine, a framework for generating high-quality, targeted instruction fine-tuning data, addressing model weaknesses and forming a closed training loop for large multi-modal models. This new paradigm enables comprehensive training and quick iteration of these models. During data generation, we introduce Adaptive Bad-case Sampling for appropriate in-context examples selection, and Interactive Prompt Optimization to minimize prompt-induced misunderstanding, thereby securing the generation of high-quality data. We aim to apply this approach to diverse multi-modal tasks across various modalities, anticipating that MLLM-DataEngine will advance multi-modal artificial intelligence research.

References

- Alayrac, J.; Donahue, J.; Luc, P.; Miech, A.; Barr, I.; Hasson, Y.; Lenc, K.; Mensch, A.; Millican, K.; Reynolds, M.; Ring, R.; Rutherford, E.; Cabi, S.; Han, T.; Gong, Z.; Samangooei, S.; Monteiro, M.; Menick, J. L.; Borgeaud, S.; Brock, A.; Nematzadeh, A.; Sharifzadeh, S.; Binkowski, M.; Barreira, R.; Vinyals, O.; Zisserman, A.; and Simonyan, K. 2022. Flamingo: a Visual Language Model for Few-Shot Learning. In *NIPS*. 1
- Bao, H.; Dong, L.; Piao, S.; and Wei, F. 2022. BEiT: BERT Pre-Training of Image Transformers. In *ICLR*. 2
- Changpinyo, S.; Sharma, P.; Ding, N.; and Soricut, R. 2021. Conceptual 12M: Pushing Web-Scale Image-Text Pre-Training To Recognize Long-Tail Visual Concepts. In *CVPR*. 2
- Chen, K.; Zhang, Z.; Zeng, W.; Zhang, R.; Zhu, F.; and Zhao, R. 2023. Shikra: Unleashing Multimodal LLM’s Referential Dialogue Magic. *arXiv*. 4
- Chiang, W.-L.; Li, Z.; Lin, Z.; Sheng, Y.; Wu, Z.; Zhang, H.; Zheng, L.; Zhuang, S.; Zhuang, Y.; Gonzalez, J. E.; Stoica, I.; and Xing, E. P. 2023. Vicuna: An Open-Source Chatbot Impressing GPT-4 with 90%* ChatGPT Quality. 1, 2
- Chung, H. W.; Hou, L.; Longpre, S.; Zoph, B.; Tay, Y.; Fedus, W.; Li, E.; Wang, X.; Dehghani, M.; Brahma, S.; Webson, A.; Gu, S. S.; Dai, Z.; Suzgun, M.; Chen, X.; Chowdhery, A.; Narang, S.; Mishra, G.; Yu, A.; Zhao, V. Y.; Huang, Y.; Dai, A. M.; Yu, H.; Petrov, S.; Chi, E. H.; Dean, J.; Devlin, J.; Roberts, A.; Zhou, D.; Le, Q. V.; and Wei, J. 2022. Scaling Instruction-Finetuned Language Models. *arXiv*. 2
- Dai, W.; Li, J.; Li, D.; Tiong, A. M. H.; Zhao, J.; Wang, W.; Li, B.; Fung, P.; and Hoi, S. C. H. 2023. InstructBLIP: Towards General-purpose Vision-Language Models with Instruction Tuning. *arXiv*. 1, 2
- Dosovitskiy, A.; Beyer, L.; Kolesnikov, A.; Weissenborn, D.; Zhai, X.; Unterthiner, T.; Dehghani, M.; Minderer, M.; Heigold, G.; Gelly, S.; Uszkoreit, J.; and Houlsby, N. 2021. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In *ICLR*. 1, 2
- Fu, C.; Chen, P.; Shen, Y.; Qin, Y.; Zhang, M.; Lin, X.; Qiu, Z.; Lin, W.; Yang, J.; Zheng, X.; Li, K.; Sun, X.; and Ji, R. 2023. MME: A Comprehensive Evaluation Benchmark for Multimodal Large Language Models. *arXiv*. 1, 3, 5, 6
- Hu, E. J.; Shen, Y.; Wallis, P.; Allen-Zhu, Z.; Li, Y.; Wang, S.; Wang, L.; and Chen, W. 2022. LoRA: Low-Rank Adaptation of Large Language Models. In *ICLR*. 5
- Kirillov, A.; Mintun, E.; Ravi, N.; Mao, H.; Rolland, C.; Gustafson, L.; Xiao, T.; Whitehead, S.; Berg, A. C.; Lo, W.; Dollár, P.; and Girshick, R. B. 2023. Segment Anything. *arXiv*. 1, 3
- Li, B.; Zhang, Y.; Chen, L.; Wang, J.; Pu, F.; Yang, J.; Li, C.; and Liu, Z. 2023a. MIMIC-IT: Multi-Modal In-Context Instruction Tuning. *arXiv*. 1, 2
- Li, B.; Zhang, Y.; Chen, L.; Wang, J.; Yang, J.; and Liu, Z. 2023b. Otter: A Multi-Modal Model with In-Context Instruction Tuning. *arXiv*. 2
- Li, J.; Li, D.; Savarese, S.; and Hoi, S. C. H. 2023c. BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models. *arXiv*. 2, 5
- Li, J.; Li, D.; Xiong, C.; and Hoi, S. C. H. 2022. BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation. In *ICML*. 2
- Liu, H.; Li, C.; Wu, Q.; and Lee, Y. J. 2023a. Visual Instruction Tuning. *arXiv*. 1, 2, 6
- Liu, Y.; Duan, H.; Zhang, Y.; Li, B.; Zhang, S.; Zhao, W.; Yuan, Y.; Wang, J.; He, C.; Liu, Z.; Chen, K.; and Lin, D. 2023b. MMBench: Is Your Multi-modal Model an All-around Player? *arXiv*. 1, 3, 10
- Lu, P.; Mishra, S.; Xia, T.; Qiu, L.; Chang, K.; Zhu, S.; Tafjord, O.; Clark, P.; and Kalyan, A. 2022. Learn to Explain: Multimodal Reasoning via Thought Chains for Science Question Answering. In *NeurIPS*. 3
- Marino, K.; Rastegari, M.; Farhadi, A.; and Mottaghi, R. 2019. OK-VQA: A Visual Question Answering Benchmark Requiring External Knowledge. In *CVPR*. 3
- OpenAI. 2023. GPT-4 Technical Report. *arXiv*. 1, 2
- Peng, Z.; Wang, W.; Dong, L.; Hao, Y.; Huang, S.; Ma, S.; and Wei, F. 2023. Kosmos-2: Grounding Multimodal Large Language Models to the World. *arXiv*. 1
- Radford, A.; Kim, J. W.; Hallacy, C.; Ramesh, A.; Goh, G.; Agarwal, S.; Sastry, G.; Askell, A.; Mishkin, P.; Clark, J.; Krueger, G.; and Sutskever, I. 2021. Learning Transferable Visual Models From Natural Language Supervision. In *ICML*. 2
- Schuhmann, C.; Beaumont, R.; Vencu, R.; Gordon, C.; Wightman, R.; Cherti, M.; Coombes, T.; Katta, A.; Mullis, C.; Wortsman, M.; Schramowski, P.; Kundurthy, S.; Crownson, K.; Schmidt, L.; Kaczmarczyk, R.; and Jitsev, J. 2022. LAION-5B: An open large-scale dataset for training next generation image-text models. In *NeurIPS*. 2
- Schwenk, D.; Khandelwal, A.; Clark, C.; Marino, K.; and Mottaghi, R. 2022. A-OKVQA: A Benchmark for Visual Question Answering Using World Knowledge. In *ECCV*. 3
- Sharma, P.; Ding, N.; Goodman, S.; and Soricut, R. 2018. Conceptual Captions: A Cleaned, Hypernymed, Image Alt-text Dataset For Automatic Image Captioning. In *ACL*. 2
- Touvron, H.; Lavril, T.; Izacard, G.; Martinet, X.; Lachaux, M.; Lacroix, T.; Rozière, B.; Goyal, N.; Hambro, E.; Azhar, F.; Rodriguez, A.; Joulin, A.; Grave, E.; and Lample, G. 2023a. LLaMA: Open and Efficient Foundation Language Models. *arXiv*. 1, 2
- Touvron, H.; Martin, L.; Stone, K.; Albert, P.; Almahairi, A.; Babaei, Y.; Bashlykov, N.; Batra, S.; Bhargava, P.; Bhosale, S.; Bikel, D.; Blecher, L.; Canton-Ferrer, C.; Chen, M.; Cucurull, G.; Esiobu, D.; Fernandes, J.; Fu, J.; Fu, W.; Fuller, B.; Gao, C.; Goswami, V.; Goyal, N.; Hartshorn, A.; Hosseini, S.; Hou, R.; Inan, H.; Kardas, M.; Kerkez, V.; Khabsa, M.; Kloumann, I.; Korenev, A.; Koura, P. S.; Lachaux, M.; Lavril, T.; Lee, J.; Liskovich, D.; Lu, Y.; Mao, Y.; Martinet, X.; Mihaylov, T.; Mishra, P.; Molybog, I.; Nie, Y.; Poulton, A.; Reizenstein, J.; Rungta, R.; Saladi, K.; Schelten, A.; Silva, R.; Smith, E. M.; Subramanian, R.; Tan, X. E.; Tang,

B.; Taylor, R.; Williams, A.; Kuan, J. X.; Xu, P.; Yan, Z.; Zarov, I.; Zhang, Y.; Fan, A.; Kambadur, M.; Narang, S.; Rodriguez, A.; Stojnic, R.; Edunov, S.; and Scialom, T. 2023b. Llama 2: Open Foundation and Fine-Tuned Chat Models. *arXiv*. [1](#)

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is All you Need. In *NIPS*. [2](#)

Wang, W.; Bao, H.; Dong, L.; Bjorck, J.; Peng, Z.; Liu, Q.; Aggarwal, K.; Mohammed, O. K.; Singhal, S.; Som, S.; and Wei, F. 2022. Image as a Foreign Language: BEiT Pretraining for All Vision and Vision-Language Tasks. [2](#)

You, H.; Sun, R.; Wang, Z.; Chen, L.; Wang, G.; Ayyubi, H. A.; Chang, K.; and Chang, S. 2023. IdealGPT: Iteratively Decomposing Vision and Language Reasoning via Large Language Models. *arXiv*. [1](#)

Zhu, D.; Chen, J.; Haydarov, K.; Shen, X.; Zhang, W.; and Elhoseiny, M. 2023a. ChatGPT Asks, BLIP-2 Answers: Automatic Questioning Towards Enriched Visual Descriptions. *arXiv*. [1](#)

Zhu, D.; Chen, J.; Shen, X.; Li, X.; and Elhoseiny, M. 2023b. MiniGPT-4: Enhancing Vision-Language Understanding with Advanced Large Language Models. *arXiv*. [1](#), [2](#), [3](#)

Supplementary

Prompts used in MLLM-DataEngine

The detailed descriptions of the prompts used in each component of the MLLM-DataEngine are as follows: Figure 5 illustrates the prompt used for categorizing different problems when constructing the bad case pool, which is in last of Model Evaluation phas in the MLLM-DataEngine. In Figure 6, GPT-4 is commanded to modify any confusion or contradictions present in the original prompt and rewrite it accordingly. Figure 7 instructs GPT-4 to analyze the root cause of the confusing or contradictory elements and provide recommendations for modifications. Figure 8 depicts two selected in-context examples in Adaptive Bad-case Sampling during the query construction phase. Figure 9 presents the initial version of the prompt. Definitions for each failure type in the original prompt are provided in Figure 10. Lastly, Figure 11 denotes the prompt that has been refined by Interactive Prompt Optimization. Fig

ure 12 is the bounding box example in the final prompt. Figure 13 refers to remaining failure cases in final prompt.

Quality Examples in GPTVQA

High-quality and diverse examples in GPTVQA are demonstrated. Figure 14 are examples of function reasoning, identity reasoning, and knowledge-based reasoning. Figure 15 are examples of physical property reasoning, attribute recognition, and action recognition. Figure 16 are examples of physical relation, nature relation, and social relation. Figure 17 are examples of spatial relationship, attribute comparison, and object localization. Figure 18 are examples of image topic, image quality, and image emotion. Figure 19 are examples of image style, image scene, and future prediction.

You are an AI assistant that can do text categorization.

Goals:

I will give you some questions, you should classify them into one of the following question types:

- (1) **Identity reasoning:** Predict the identity of a person. Example: by observing a person's clothing and appearance, one may infer his / her occupation and social status.
- (2) **Physical property reasoning:** Predict the physical property of an object. Examples: the physical property of concentrated sulfuric acid is that it is volatile, the physical property of water is its fluidity, etc.
- (3) **Attribute recognition:** Recognition of texture, shape, appearance characteristics, emotions, category, celebrities, famous places and objects, optical characters.
- (4) **Function reasoning:** Predict the function of an object. Examples: the function of a broom is to sweep the floor, the function of a spatula is to cook, the function of a pen is to write, etc.
- (5) **Object localization:** For a single object, determine its position in the image (such as top, bottom, etc.), its absolute coordinates in the image, count the number of objects, and the orientation of the object.
- (6) **Attribute comparison:** Compare attributes of different objects in image, such as shape, color, etc.
- (7) **Nature relation:** Other abstract relationships that exist in nature. Examples: predation, symbiosis, coexistence, etc.
- (8) **Future prediction:** Predict what will happen in the future. Examples: if it is thundering in the sky now, it can be predicted that it will rain soon (physical phenomenon); if someone raises their fist, it means they are going to hit someone (event occurrence); if someone's face becomes serious, it means they are going to get angry (emotional change).
- (9) **Image scene:** Determine which environment is shown in the image, such as indoors, outdoors, forest, city, mountains, waterfront, sunny day, rainy day, etc.
- (10) **Spatial relationship:** Determine the relative position between objects in image.
- (11) **Image quality:** Determine the objective quality of the image, such as whether it is blurry, bright or dark, contrast, etc.
- (12) **Physical relation:** All relationships that exist in the physical world, 3D spatial relationships and the connections between objects are.
- (13) **Action recognition:** Recognizing human actions, including pose motion, human-object interaction, and human-human interaction.
- (14) **Social relation:** Relations in human society or relations defined from the human perspective. Examples: Inter-person relations, such as father and son, husband and wife, friend, hostile, etc.
- (15) **Image style:** Determine which type of image it belongs to, such as photos, paintings, CT scans, etc.
- (16) **Image emotion:** Determine which subjective emotion is conveyed by the overall image, such as cold, cheerful, sad, or oppressive.
- (17) **Image topic:** Determine what the subject of the image is, such as scenery, portrait, close-up of an object, text, etc.
- (18) **Knowledge-based reasoning:** Require pre-existing knowledge outside the content of the image Example: the year this object was invented, the top-ranked player in this sport, etc.

The questions to be classified:

<bad case batch>

Here is an example of your response:

1. (6) Physical relation
2. (15) Attribute recognition
3. ...

Figure 5: The prompt for question classification. The explanation of each question type is from MMBenchmark (Liu et al. 2023b) (except for Knowledge-based reasoning, which is added by us).

I will give you a long prompt about how to complete a task, please let me know which part of the prompt is confusing or contradictory to each other. Rewrite the prompt for me if possible. Tell me how you understand the task, including its format of output, how to use the image information provided, and how to include the bounding boxes in Q&A. The prompt will be delimited with ##### characters.

```
#####  
<original prompt>  
#####
```

Figure 6: The prompt for modifying confusion and conflict

I will give you a long prompt about how to complete a task, along with a bad answer and an explanation about why it is bad. Tell me how to modify the prompt to avoid getting a bad answer again. The content of the long prompt and the bad answer will be delimited with ##### characters.

long prompt:

<original prompt>
#####

Bad answer:

<Bad answer>
#####

Explanation:
<Explanation>

Please analyze the reason for the bad answer being generated, and tell me how to modify the long prompt to avoid this bad answer.

Figure 7: The prompt for avoiding failure case

Question: What are the white rocks for?

Choices: (A) breaking (B) prevent fire (C) water retainment (D) decoration

Answer: The answer is (B): prevent fire.

Question type: nature relation

Question: What is causing the disturbance of the sand?

Choices: (A) men (B) horses (C) ducks (D) car

Answer: The answer is (B): horses.

Question type: nature relation

Figure 8: An example of <Few shot Example>for original prompt.

You are an AI visual assistant that can generate high-quality Q&A about the images. You will always perform as if you are directly seeing an image.

Goals:

I will give you some information about this image, along with a question type. Your task is to generate high-quality Q&A according to the information provided. Besides, give lectures and explanations if possible.

For image information, I will give you 5 descriptions of this image. In addition, specific object locations within the image are given, along with detailed coordinates. These coordinates are in the form of bounding boxes, represented as (x1, y1, x2, y2) with floating numbers ranging from 0 to 1. These values correspond to the top left x, top left y, bottom right x, and bottom right y.

When asking questions about a certain object, don't mention the name of it directly, but refer to it using its location described in natural language and characterization in the image, followed by its bounding box. **Following is an example I gave you to demonstrate how you point out objects you refer to using the objects' locations:**

Question: Who has the phone [0.01, 0.1, 0.03, 0.12]?

Choices:(A) The woman in pink clothes [0.003, 0.076, 0.57, 0.985]. (B) The woman in white clothes [0.531, 0.085, 1.0, 1.0]. (C) The woman in blue clothes [0.214, 0.137, 0.441, 1.0]. (D) Others

Answer: The answer is (A): The woman in pink clothes [0.003, 0.076, 0.57, 0.985].

Explanations: The phone [0.01, 0.1, 0.03, 0.12] is held by the woman in pink [0.003, 0.076, 0.57, 0.985].

Rules:

- (1) Use the provided descriptions and bounding box of this image to generate questions and answers. Don't generate imaginative or irrelevant questions. The question and answer you give should reflect the content of the image.
- (2) When asking questions about a certain object, if possible, don't mention the name of it directly, but refer to it using its location or description in the image.
- (3) Don't give any clues or given conditions in question.
- (4) Don't ask questions you can't answer.
- (5) In the choices, there should be only one correct answer to the question. At the same time, other choices should also be relevant to the question.
- (6) Don't mention the information source is the image description and object locations I gave you when answering the question, answer as if you are directly looking at the image.
- (7) The type of question you give must match the type of question I give you.

Image information:

(1) Image description:

<Image description>

(2) Objects locations, in the form of bounding box (object: [x1, y1, x2, y2]):

<Bounding box list>

The question type I require is <question_type> question. **Following are two examples of the <question_type> question:**

<question_type> question example:

<few_shot_example_1>

<few_shot_example_2>

Now you can start to generate one high-quality <question_type> Q&A about the images.

Figure 9: The original version of prompt: The example of <Few shot Example>is as shown in Figure 8. Specifically, we add bbox to reduce the illusion of GPT-4, which can be deleted from the QA without affecting sentence completeness.



Failure type:
[Incorrect 3D perception]

Failure type example

[Question] In this image, are the two giraffes of the same height?
 [Choices] (A) Yes, they are the same height. (B) No, they are not the same height. (C) It's hard to determine from this perspective. (D) There is only one giraffe
 [Answer] The answer is (A): Yes, they are the same height.



Failure type example

[Question] Which object from the following options is primarily situated at [0.213, 0.074, 0.785, 0.987]?
 [Choices] (A) Television (B) Cat (C) Lamp (D) Couch
 [Answer] The answer is (B): Cat.



Failure type:
[Wrong question type]

Failure type example

[Question] Which object is predominantly in the foreground and trailing the other?
 [Choices] (A) The boat on the left half of the image [0.019, 0.388, 0.5, 0.629]. (B) The green pickup truck on the right half of the image [0.461, 0.353, 0.952, 0.674]. (C) The trees surrounding the road. (D) None of the above.
 [Answer] The answer is (A): The boat on the left half of the image [0.019, 0.388, 0.5, 0.629].
 (Question type: Identity reasoning)



Failure type:
[Illusion]

Failure type example

[Question] Which type of boat is parked mainly in the lake, taking up the vast majority of the middle and upper part of the image [0.037, 0.404, 0.724, 0.96]?
 [Choices] (A) Kayak (B) Motorboat (C) Houseboat (D) Speedboat
 [Answer] The answer is (C): Houseboat.



Failure type:
[Wrong bbox]

Failure type example

[Question] What is the surface these birds are standing on?
 [Choices] (A) Gravel [0.325, 0.618, 0.925, 0.938] (B) Grass [0.134, 0.572, 0.504, 0.876] (C) Wood chips [0.342, 0.631, 0.939, 0.947] (D) Sand [0.498, 0.375, 0.674, 0.763]
 [Answer] The answer is (C): Wood chips [0.342, 0.631, 0.939, 0.947]



Failure type:
[Illogical question]

Failure type example

[Question] In a common setting, this large animal [0.245, 0.179, 0.598, 0.815] is often seen working in conjunction with what type of city transport?
 [Choices] (A) Bus [0.882, 0.291, 0.931, 0.34] (B) Bicycle (C) Subway (D) Tram
 [Answer] The answer is (A): Bus [0.882, 0.291, 0.931, 0.34]

Figure 10: Failure type examples and explanation. The failure type example and its explanation about why it is considered to be failure case are summarized by human from test results.

Failure type explanation

This bad case will unnecessarily insert bbox coordinates into question or options or even create some bbox coordinates that do not exist. You can try to add or modify the rules in the prompt to improve this problem.

Failure type explanation

The question raised in this bad case has no logic, is a meaningless and unanswerable question or the question contains information that does not appear in the request. You can try to add or modify the rules in the prompt to improve this problem.

You are an AI visual assistant that can generate certain types of high-quality Q&A about the images. You will always perform as if you are directly seeing an image.

Goals:

I will give you some information about this image, along with a question type. Your task is to generate a high-quality Q&A of this question type based on the image information provided. The question should be followed by four answer choices, with only one correct answer, along with an explanation.

The image information includes 5 descriptions and the locations of specific objects within the image given in the form of bounding boxes. The bounding box coordinates are represented as (x1, y1, x2, y2) with floating numbers ranging from 0 to 1. These values correspond to the top left x, top left y, bottom right x, and bottom right y.

Rules (If not specified, the following rules apply to all texts you generate):

- (1) Summarize the information provided by image descriptions and objects locations of this image to generate a high-quality Q&A, which should reflect the content of the image.
- (2) Don't generate imaginative or irrelevant content. Ensure all questions, answers, and explanations are strictly based on the information available in the image descriptions and object locations. Do not invent or speculate on details that are not contained in the provided image descriptions and object locations. Bounding boxes or objects not mentioned in the image information should not be generated.
- (3) You must always generate your responses as if you are directly viewing the image, not reading the image descriptions or object locations. Do not mention or refer to the image descriptions in your responses. Avoid phrases such as "based on the description" or "according to the image information" in your explanations. Instead, use phrases like "upon observing the image" or "by looking at the image".
- (4) Do not ask questions that you cannot answer accurately with the given information.
- (5) In the choices, there should be only one correct answer to the question. At the same time, other choices should also be relevant to the question.
- (6) The question you ask should be also answerable without choices.
- (7) Be sure to structure your questions and answers according to the question type. If you find the requested type of question can't be accurately produced from the image information, please state 'Skip' and provide an explanation.
- (8) Don't give any clues or given conditions in question. Invoke visual information as much as possible. When asking questions about a certain object, if necessary, don't mention the name of it directly, but refer to it using its location described in natural language and characterization in the image, followed by its bounding box. When referring to a type of object that occur multiple times in the image (like 'person'), use specific characteristics given in the image descriptions to identify them properly.
- (9) The bounding boxes should not be used as the main identifying feature of the objects in the scene, but rather as a supplement to descriptive identifiers.
- (10) Don't ask questions about object size or distance unless there's ample evidence in the image descriptions about object scale or spatial relations. Bounding box details should not be used to infer the sizes or shapes of the objects, because it is in 2D but the objects are in complex 3D scenes. Instead of asking "Which is larger?", you can ask "Which object occupies a larger area of the image?"
- (11) Avoid questions that might be confusing due to similar objects. If bounding boxes are too small or numerous, the AI should avoid forming questions about those objects to avoid confusion.

Here is an example:

<bbox_insert_example>

Here is the Image information that I want you to generate high-quality <question_type> Q&A from:

- (1) Image description:
<image_description>

- (2) Objects locations, in the form of bounding box (object: [x1, y1, x2, y2]):
<bounding_box_list>

The question type I require is <question_type> question. <question_type_definition> Following are two examples of the <question_type> question:

- Example 1:
<few_shot_example_1>
- Example 2:
<few_shot_example_2>

Now you can start to generate one high-quality <question_type> Q&A about the image according to the image information I gave you.

Figure 11: Final version of the prompt. Yellow highlight indicates statement optimization while green highlight represents new additions. The <question type definition> remains consistent with Figure 5. The <bbox insert example> is shown in Figure 12.

Image information:

(1) Image description:

A photo of two youth soccer teams competing.
Little kids play a game of soccer in a field.
A group of young men kicking around a ball.
The small children play soccer on a sunny day.
Children run after a soccer ball in the grass.

(2) Objects locations, in the form of bounding box (object: [x1, y1, x2, y2]):

sports ball: [0.324, 0.769, 0.44, 0.933]
person: [0.003, 0.011, 0.202, 0.793]
person: [0.125, 0.053, 0.414, 0.868]
person: [0.41, 0.001, 0.658, 0.886]
person: [0.36, 0.002, 0.476, 0.329]
person: [0.187, 0.0, 0.416, 0.258]
person: [0.965, 0.003, 1.0, 0.219]

Question: Who is more likely to kick the sports ball [0.324, 0.769, 0.44, 0.933] next?

Choices: (A) The person located to the far left side of the image [0.003, 0.011, 0.202, 0.793] (B) The person located closer to the center of the image [0.125, 0.053, 0.414, 0.868] (C) The person located to the far right side of the image [0.965, 0.003, 1.0, 0.219] (D) The person located closer to the bottom of the image [0.41, 0.001, 0.658, 0.886]

Answer: The answer is (B): The person located closer to the center of the image [0.125, 0.053, 0.414, 0.868].

Explanations: Based on the distance between the soccer players and the ball in the image, the player closer to the center of the image [0.125, 0.053, 0.414, 0.868] appears to be in the best position to make the next move on the sports ball [0.324, 0.769, 0.44, 0.933]. The player to the far right [0.965, 0.003, 1.0, 0.219] seems too far away, and the players at the bottom [0.41, 0.001, 0.658, 0.886] and far left [0.003, 0.011, 0.202, 0.793] of the image look to be at a disadvantageous position to kick the ball next.

Figure 12: The content of <bbox insert example>in the final prompt

Question: Where is the cell phone [0.507, 0.468, 0.558, 0.488] located in relation to the laptop [0.449, 0.348, 0.59, 0.476]?

Choices: (A) To the left of the laptop (B) To the right of the laptop (C) Above the laptop (D) Below the laptop

Answer: The answer is (C): Above the laptop.

Explanation: By observing the locations of these two objects in the image, the cell phone [0.507, 0.468, 0.558, 0.488] is positioned above the laptop [0.449, 0.348, 0.59, 0.476], indicating that the person might be using both devices simultaneously.

Error type: Wrong 3D spatial sense

Question: How many sports balls are there in the image?

Choices: (A) Three (B) Four (C) Six (D) Seven

Answer: The answer is (C): Six.

Explanation: By observing the image, we can see there are six sports balls in different locations of the image. They are located at [0.563, 0.852, 0.583, 0.879], [0.64, 0.722, 0.654, 0.743], [0.593, 0.78, 0.606, 0.802], [0.581, 0.504, 0.599, 0.522], [0.351, 0.728, 0.364, 0.749], and [0.423, 0.801, 0.44, 0.822]. Thus, the correct choice is six.

Error type: Counting fail

Question: Are the two zebras standing in the same position?

Choices: (A) Yes, they are both looking straight. (B) No, one is looking down. (C) Yes, they are both looking down. (D) No, they are looking in different directions.

Answer: The answer is (B): No, one is looking down.

Explanation: According to the image descriptions, one zebra is noted to be looking down while the position of the second zebra is not explicitly stated. Therefore, we can deduce that the zebras are not in the exact same position.

Error type: COCO description incorrect

Question: Where is the surfer not holding a surfboard in relation to the parked car [0.423, 0.036, 0.501, 0.082]?

Choices: (A) To the right of the car (B) To the left of the car (C) Directly above the car (D) Directly below the car

Answer: The answer is (A): To the right of the car.

Explanation: By observing the image, the person [0.643, 0.372, 0.703, 0.473] who is not holding a surfboard is located to the right of the parked car [0.423, 0.036, 0.501, 0.082]. The car is towards the left part of the image while the person is more towards the right side. The other persons and objects in the image do not affect the relative position of these two objects.

Error type: Illusion

Figure 13: Failure cases remained after optimization

[Function reasoning]



[Question] What is the function of the umbrellas [0.478, 0.274, 0.666, 0.475], [0.336, 0.215, 0.49, 0.357], [0.0, 0.0, 0.198, 0.785], [0.418, 0.434, 0.478, 0.525] in this parade scene?

[Choices] (A) Protection from rain (B) Sunscreen (C) Dance prop (D) Crowd control

[Answer] The answer is (C): Dance prop.

[Explanation] In the context of the parade described in the image, the people are dancing down the street with umbrellas. This implies that the umbrellas are being used as props in their dance, not for protection from rain or sun, or for crowd control.

[Question] What is the function of the object the man in the image is holding?

[Choices] (A) To make phone calls (B) To take photos (C) To cook food (D) To write notes

[Answer] The answer is (B): To take photos.

[Explanation] The descriptions of the image indicate that the man is taking a photo, therefore, the function of the object he is holding, which is likely a cell phone or camera, is to take photos.



[Question] What is the function of the object located in the middle of the image [0.531, 0.267, 0.69, 0.443]?

[Choices] (A) To provide light at night (B) To control traffic flow (C) To indicate the location of a bus stop (D) To act as a street decoration

[Answer] The answer is (B): To control traffic flow.

[Explanation] The object in question is a traffic light [0.531, 0.267, 0.69, 0.443], which is typically used to manage the flow of traffic on roads. It does this by displaying lights of different colors (typically red, yellow, and green) to instruct drivers when to stop, prepare to move, and proceed. Although it does glow at night, providing light is not its primary function, hence option (A) is incorrect. It also has no specific function related to bus stops or acting as a street decoration, making options (C) and (D) incorrect as well.

[Identity reasoning]

[Question] Which player is the person located in the middle of the image [0.542, 0.638, 0.713, 0.88]?

[Choices] (A) Umpire (B) Pitcher (C) Batter (D) Catcher

[Answer] The answer is (C): Batter.

[Explanation] By observing the characterization and locations of the person in the middle of the image [0.542, 0.638, 0.713, 0.88] who is close to the sports ball [0.554, 0.612, 0.568, 0.628] and the baseball bat [0.569, 0.696, 0.637, 0.709], and given the image descriptions indicating a batter swinging for the ball, we can infer that this person is the Batter.



[Question] What is the most likely occupation of the person standing closest to the right edge of the image [0.72, 0.402, 1.0, 0.985]?

[Choices] (A) Photographer (B) Plumber (C) Chef (D) Teacher

[Answer] The answer is (A): Photographer.

[Explanation] Considering the image descriptions indicating that the person is holding a camera and taking a photo, it is reasonable to infer that the person is a photographer. Moreover, the location of the person in relation to the bathroom fixtures, such as the sink and toilet, does not imply they are a plumber. Their actions also do not suggest they are a chef or a teacher. Therefore, based on the given information, the person is most likely a photographer.



[Question] What is the likely profession of the person [0.554, 0.184, 0.699, 0.974] standing on the tennis court?

[Choices] (A) Tennis Coach (B) Professional Tennis Player (C) Spectator (D) Referee

[Answer] The answer is (B): Professional Tennis Player.

[Explanation] Observing the woman's position on the tennis court and her action of holding up a tennis racket, we can infer that she is likely a Professional Tennis Player. The other people in the scene appear to be either spectators or fellow players, but they are not in the main action of playing tennis like the woman standing on the court.

[Knowledge-based reasoning]



[Question] Which vegetable on the plate is typically consumed both raw and cooked?

[Choices] (A) Broccoli (B) Carrot (C) Pork (D) Potato

[Answer] The answer is (B): Carrot.

[Explanation] Observing the plate in the image, it includes broccoli, carrots, and pork. Among these, carrots are commonly eaten in both raw and cooked forms, like in salads or stir-fry dishes. This is general knowledge outside the content of the image. Pork and potatoes are usually cooked before consumption, and broccoli, while it can be eaten raw, is more typically consumed cooked.



[Question] What is the traditional symbolism of using bicycles as decorations on a wedding cake?

[Choices] (A) The journey the couple will embark on together (B) The couple's love for sports (C) The couple's shared hobby of cycling (D) The couple's plan to reduce their carbon footprint

[Answer] The answer is (A): The journey the couple will embark on together.

[Explanation] The descriptions of the image indicate that the man is taking a photo, therefore, the function of the object he is holding, which is likely a cell phone or camera, is to take photos.



[Question] What type of wind is typically preferred for the watersport activity shown in the image?

[Choices] (A) Light Wind (B) No Wind (C) Heavy Wind (D) Moderate Wind

[Answer] The answer is (D): Moderate Wind.

[Explanation] For windsurfing, the activity shown in the image, moderate wind conditions are generally preferred. Light winds might not provide enough power for the sail, while heavy winds can make control difficult and increase the risk of accidents. The man in the image [0.763, 0.499, 0.794, 0.658] is seen windsurfing, indicating that the wind conditions are suitable for this activity.

Figure 14: Examples of GPTVQA in function reasoning, identity reasoning, and knowledge-based reasoning

[Physical property reasoning]



[Question] What could be the physical property of the fence surrounding the house?

[Choices] (A) Transparent (B) Opaque (C) Reflective (D) Luminous

[Answer] The answer is (B): Opaque.

[Explanation] Based on the image, the fence is described as a 'chain link fence', which implies that it is not transparent and you cannot see clearly through it. It is also not reflective or luminous, as there is no information to suggest that it reflects light or emits its own light. Therefore, the most likely physical property of the fence is that it is opaque.

[Question] What is the physical property of the vehicle [0.377, 0.774, 0.471, 0.881] that allows it to move in the narrow alley?

[Choices] (A) It has a powerful engine (B) It has a sleek and compact size (C) It can fly (D) It can teleport

[Answer] The answer is (B): It has a sleek and compact size.

[Explanation] The vehicle [0.377, 0.774, 0.471, 0.881] in the image is a bicycle, which is commonly known for its sleek and compact size. This physical property allows it to easily navigate through the narrow alley, as seen in the image. The other options, such as having a powerful engine, being able to fly, or teleport, are not physical properties typically associated with a bicycle.



[Question] Based on the image, what is the likely physical property of the man's cell phone [0.39, 0.401, 0.456, 0.431]?

[Choices] (A) It has a touch screen (B) It has a physical keyboard (C) It is a flip phone (D) It has a rotary dial

[Answer] The answer is (A): It has a touch screen.

[Explanation] By observing the man's interaction with the phone in the image, it is likely that the cell phone [0.39, 0.401, 0.456, 0.431] has a touch screen. The man appears to be looking at the screen and using it, which implies that it has a touch screen. The other options such as a physical keyboard, being a flip phone, or having a rotary dial are less likely based on the modern context and the man's interaction with the device.

[Attribute recognition]

[Question] What is the primary purpose of the chair [0.34, 0.635, 0.637, 0.925] located in the shower?

[Choices] (A) For resting while taking a shower (B) For holding shower accessories (C) For decoration (D) For cleaning the shower

[Answer] The answer is (A): For resting while taking a shower.

[Explanation] Based on the image descriptions and the location of the chair, it is clear that the chair is placed inside the walk-in shower. This, coupled with the note that the shower is equipped for a physically challenged person, suggests that the primary purpose of the chair is to provide a place to rest while taking a shower, rather than for holding shower accessories, decoration, or cleaning the shower.



[Question] What is the primary characteristic of the donut [0.154, 0.373, 0.539, 0.806] in the image?

[Choices] (A) It is a plain donut (B) It has a bite taken out of it (C) It is a jelly-filled donut (D) It is a powdered donut

[Answer] The answer is (B): It has a bite taken out of it.

[Explanation] Observing the unique feature of the donut in the image, it's clear that the donut [0.154, 0.373, 0.539, 0.806] has a bite taken out of it. The other options such as being a plain, jelly-filled, or powdered donut are not accurate based on the image descriptions.



[Question] What color are the majority of the umbrellas that people are holding as they board the plane?

[Choices] (A) Blue (B) Red (C) Green (D) Yellow

[Answer] The answer is (B): Red.

[Explanation] The description of the image mentions people carrying red umbrellas as they board the airplane. This indicates that the majority of umbrellas visible in the scene are red in color.

[Action recognition]



[Question] What action is the person in the center of the image [0.586, 0.169, 0.6, 0.208] performing?

[Choices] (A) Sliding down the hill (B) Doing a snowboard trick in mid-air (C) Sitting on the snowboard (D) Climbing up the hill

[Answer] The answer is (B): Doing a snowboard trick in mid-air.

[Explanation] From the description and the location of the person, it is apparent that the snowboarder is in the air and not in contact with the snow-covered hill. This, combined with the location of the snowboard [0.514, 0.505, 0.542, 0.519] suggests that the person is performing a snowboarding trick in mid-air rather than simply sliding down the hill or sitting on the snowboard.



[Question] What is the action being performed by the dog in the snowy field?

[Choices] (A) The dog is chasing the frisbee [0.219, 0.265, 0.414, 0.575] (B) The dog is burying the frisbee in the snow [0.219, 0.265, 0.414, 0.575] (C)

The dog is carrying the frisbee [0.219, 0.265, 0.414, 0.575] (D) The dog is playing with another dog

[Answer] The answer is (C): The dog is carrying the frisbee [0.219, 0.265, 0.414, 0.575]

[Explanation] Observing the image, it is clear that the brown and white dog [0.223, 0.014, 0.466, 0.76] is holding a red frisbee [0.219, 0.265, 0.414, 0.575] in its mouth as it walks across a snow-covered field. The dog does not appear to be burying the frisbee in the snow, nor does it seem to be chasing the frisbee or playing with another dog. Therefore, the most accurate description of the action being performed by the dog is that it is carrying the frisbee.



[Question] What action is the man in the image performing with the tennis racket [0.322, 0.517, 0.461, 0.646] and the sports ball [0.316, 0.579, 0.344, 0.618]?

[Choices] (A) Serving the ball (B) Catching the ball (C) Hitting the ball with a backhand swing (D) Picking up the ball

[Answer] The answer is (C): Hitting the ball with a backhand swing.

[Explanation] Upon observing the image, it can be seen that the man [0.435, 0.202, 0.867, 0.881] is positioned to hit the sports ball [0.316, 0.579, 0.344, 0.618] with his tennis racket [0.322, 0.517, 0.461, 0.646]. The position of the tennis racket and the motion of the player suggest a backhand swing, not a serve or any other action. The ball is not being caught or picked up, but actively hit, confirming that the man is performing a backhand swing.

Figure 15: Examples of GPTVQA in physical property reasoning, attribute recognition, and action recognition

[Physical relation]

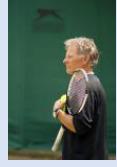


[Question] What is the relationship between the person and the horse in the image?

[Choices] (A) The person is standing next to the horse. (B) The person is riding the horse. (C) The person is feeding the horse. (D) The person is observing the horse from a distance.

[Answer] The answer is (B): The person is riding the horse.

[Explanation] Upon observing the image, we can see that the person [0.717, 0.402, 0.853, 0.74] is on top of the horse [0.651, 0.555, 0.919, 0.927], indicating that the person is riding the horse. There is no evidence of the person standing next to, feeding, or observing the horse from a distance. Therefore, the physical relationship between the person and the horse in this image is that the person is riding the horse.



[Question] Where is the tennis racket in relation to the tennis player in the image?

[Choices] (A) The tennis racket is to the left of the man (B) The tennis racket is to the right of the man (C) The tennis racket is above the man (D) The tennis racket is held by the man

[Answer] The answer is (D): The tennis racket is held by the man.

[Explanation] Upon observing the image, we can see that the man [0.399, 0.225, 0.924, 0.989] is holding the tennis racket [0.408, 0.427, 0.743, 0.962]. The bounding boxes of both the man and the tennis racket intersect, indicating that the man is holding the racket. The other choices do not accurately describe the positioning of the racket in relation to the man in the image.



[Question] Where is the book that the man is reading located in relation to the bench?

[Choices] (A) The book is above the bench.(B) The book is below the bench.(C) The book is to the right of the bench.(D) The book is to the left of the bench.

[Answer] The answer is (A): The book is above the bench.

[Explanation] Upon observing the image, the man is sitting on the bench [0.0, 0.562, 0.973, 0.951] and reading a book. The location of the book [0.467, 0.32, 0.557, 0.445] in the image is such that it appears to be held by the man, placing it above the bench in the image. The cars and the other person in the image do not affect the relationship between the book and the bench.

[Nature relation]

[Question] How do the zebras and rhinos in the image appear to be interacting?

[Choices] (A) The zebras are running away from the rhinos. (B) The zebras and rhinos are fighting. (C) The zebras and rhinos are coexisting peacefully. (D) The rhinos are chasing the zebras.

[Answer] The answer is (C): The zebras and rhinos are coexisting peacefully.

[Explanation] From the image, it can be seen that the zebras and rhinos are in close proximity to each other and appear to be coexisting peacefully. There are no signs of aggression or fear between the animals. This is a demonstration of the nature relation of coexistence, where different species share the same environment without conflict.



[Question] What is the natural relationship between the cat [0.071, 0.2, 0.893, 0.876] and the laptop [0.216, 0.509, 0.82, 0.687] in this image?

[Choices] (A) The cat is using the laptop for warmth. (B) The laptop is hunting the cat. (C) The cat is eating the laptop. (D) The laptop is providing shade for the cat.

[Answer] The answer is (A): The cat is using the laptop for warmth.

[Explanation] In the natural world, cats often seek out warm places to rest. In this image, the cat is lying on the laptop, which can produce heat when in use. Therefore, the natural relationship between the cat and the laptop in this situation is that the cat is using the laptop for warmth. The other options are not plausible as laptops do not hunt or provide shade, and cats do not eat laptops.



[Question] What does the image imply about the relationship between the man and the baby?

[Choices] (A) The man is the baby's dentist (B) The man is teaching the baby how to brush its teeth (C) The man is the baby's babysitter (D) The man is using the baby to practice dental procedures

[Answer] The answer is (B): The man is teaching the baby how to brush its teeth.

[Explanation] Based on the scene depicted in the image, the man is brushing the baby's teeth while also brushing his own teeth. This suggests that the man is teaching the baby the importance of oral hygiene and how to brush its teeth properly. This shows a close and caring relationship between the man and the baby, which is often seen in parent-child relationships. Choice (A) is incorrect because there is no indication that the man is a professional dentist. Choice (C) might be possible but there is no clear evidence to suggest that the man is the baby's babysitter. Choice (D) is also incorrect as there is no evidence suggesting that the man is practicing dental procedures on the baby.

[Social relation]



[Question] What is the likely relationship between the two men on the tennis court?

[Choices] (A) Father and son (B) Business associates (C) Tennis coach and player (D) Friends

[Answer] The answer is (B): Business associates.

[Explanation] Upon observing the image, one of the men is holding a tennis racket [0.539, 0.539, 0.871, 0.847] and the other one is wearing a tie [0.616, 0.384, 0.727, 0.797]. This, along with the fact that they are standing in a tennis court, suggests that they could be business associates having a meeting or discussion in a recreational setting like a tennis court. The presence of a car [0.21, 0.348, 0.285, 0.394] in the background could also indicate a professional setting. The other options of father and son, tennis coach and player, and friends are less likely based on the image details.



[Question] What is the likely relationship between the two children [0.532, 0.088, 0.8, 0.905] and [0.137, 0.101, 0.47, 0.987] in the image?

[Choices] (A) They are friends (B) They are siblings (C) They are classmates (D) They are strangers

[Answer] The answer is (B): They are siblings.

[Explanation] Observing the image, the two children are sitting close together on a couch, playing with cell phones and interacting with the same dog. This close interaction and shared activities suggest a familial or sibling relationship rather than just being friends or classmates. Furthermore, there's no clear indication that they're strangers. Therefore, the most likely relationship between the two children is that they are siblings.



[Question] What is the most likely relationship between the man riding the motorcycle [0.371, 0.51, 0.739, 0.913] and the person on the sidewalk close to him [0.449, 0.337, 0.608, 0.823]?

[Choices] (A) Family members (B) Co-workers (C) Strangers (D) Friends

[Answer] The answer is (C): Strangers.

[Explanation] Upon observing the image, it can be inferred that the man riding the motorcycle and the person on the sidewalk are likely to be strangers. There is no interaction or connection indicated between them, and they are each engaged in separate activities, suggesting that they don't know each other. The man is focused on riding his motorcycle in the rain, while the person on the sidewalk seems to be just passing by.

Figure 16: Examples of GPTVQA in physical relation, nature relation, and social relation

[Spatial relationship]

[Question] Where is the stop sign [0.413, 0.167, 0.581, 0.405] located in relation to the car [0.566, 0.655, 0.897, 0.911] in the image?

[Choices] (A) To the left of the car (B) To the right of the car (C) Above the car (D) Below the car

[Answer] The answer is (A): To the left of the car.

[Explanation] By observing the positioning of the stop sign [0.413, 0.167, 0.581, 0.405] and the car [0.566, 0.655, 0.897, 0.911] in the image, the stop sign appears to be located to the left of the car. The other options, such as to the right, above, or below the car, do not correctly describe the relative positioning of these objects in the image.



[Question] Where is the camel located relative to the man carrying a bundle across his shoulder?

[Choices] (A) To the left (B) To the right (C) In front (D) Behind

[Answer] The answer is (B): To the right.

[Explanation] The camel, which is represented by the bounding box [0.361, 0.36, 0.506, 0.804], is located to the right of the man carrying a bundle across his shoulder, who is represented by the bounding box [0.137, 0.35, 0.497, 0.999]. The man appears to the left side of the camel in the image. Therefore, the camel is to the right of the man.

[Question] Where is the cell phone [0.219, 0.557, 0.288, 0.657] in relation to the man [0.224, 0.137, 0.998, 0.763] on the bed?

[Choices] (A) The cell phone is to the left of the man (B) The cell phone is to the right of the man (C) The cell phone is above the man (D) The cell phone is in the man's hands

[Answer] The answer is (D): The cell phone is in the man's hands.

[Explanation] Based on the positions and descriptions of the objects in the image, it is clear that the man is holding the cell phone. The bounding box of the cell phone and the man overlap, indicating that the cell phone is in the man's possession. Therefore, the cell phone is in the man's hands.



[Attribute comparison]

[Question] Which vehicle in the image has a larger area, the blue and red dump truck or the bus?

[Choices] (A) The dump truck (B) The bus (C) They are of the same size (D) Unable to determine

[Answer] The answer is (A): The dump truck.

[Explanation] By observing the image, the dump truck [0.147, 0.169, 0.979, 0.816] appears to occupy a larger area of the image compared to the bus [0.924, 0.292, 0.999, 0.452]. Therefore, the dump truck seems to have a larger area in the image.



[Question] Which sign is the most prominent in the image?

[Choices] (A) Bellon street sign (B) Locust Ave sign (C) Stop sign (D) Cannot determine

[Answer] The answer is (C): Stop sign.

[Explanation] Given the image description and object locations, the stop sign [0.183, 0.314, 0.776, 0.803] is the most prominent object in the image. The image descriptions mention the stop sign in every sentence, indicating that it is the main focus of the image. The Bellon and Locust Ave signs, while present, are not as prominently featured in the image descriptions. Therefore, the stop sign is the most prominent sign in the image.

[Question] Which fruit occupies a larger area of the image, the bananas [0.143, 0.205, 0.911, 0.793] or the apple [0.099, 0.861, 0.39, 0.988]?

[Choices] (A) The bananas (B) The apple (C) They occupy the same area (D) Can't judge

[Answer] The answer is (A): The bananas.

[Explanation] By observing the characterization and locations of these fruits in the image, the bananas [0.143, 0.205, 0.911, 0.793] appear to occupy a larger area of the image compared to the apple [0.099, 0.861, 0.39, 0.988]. The bananas are hanging from a hook, which makes them spread over a larger part of the image, while the apple is in the bowl beneath.



[Object localization]



[Question] Where is the boat located in the image?

[Choices] (A) On the top left corner of the image (B) In the middle of the image (C) On the top right corner of the image (D) At the bottom of the image

[Answer] The answer is (C): On the top right corner of the image.

[Explanation] By observing the location of the boat in the image, it can be seen that the boat [0.69, 0.145, 0.724, 0.159] is located towards the top right corner of the image. The other objects like the bench are not located in the same region as the boat.



[Question] Where is the tie located on the man?

[Choices] (A) On his head (B) Around his neck (C) On his wrist (D) On his waist

[Answer] The answer is (B): Around his neck.

[Explanation] Based on the descriptions of the image, the tie is mentioned as part of the man's attire which is typically worn around the neck. Therefore, the tie is located around the man's neck.



[Question] Where is the person in the image in relation to the donuts?

[Choices] (A) On the left side of the donuts (B) On the right side of the donuts (C) Above the donuts (D) Below the donuts

[Answer] The answer is (C): Above the donuts.

[Explanation] From the observation of the image, the person [0.484, 0.011, 0.972, 0.344] appears to be located above the donuts [0.232, 0.503, 0.468, 0.856], [0.544, 0.481, 0.865, 0.821], [0.329, 0.348, 0.605, 0.647], [0.565, 0.279, 0.822, 0.508], [0.088, 0.298, 0.343, 0.521], [0.279, 0.171, 0.493, 0.408] when we consider the image coordinates. The y-coordinate of the person's bounding box is lower than the y-coordinates of the donuts' bounding boxes, indicating that the person is positioned above the donuts in the image.

Figure 17: Examples of GPTVQA in spatial relationship, attribute comparison, and object localization

[Image topic]



[Question] What is the primary activity taking place in this image?
[Choices] (A) Swimming in a pool (B) Flying a kite (C) Playing soccer (D) Riding a bicycle
[Answer] The answer is (B): Flying a kite.
[Explanation] Upon observing the image, we can see a young boy and a girl engaging in an activity where a kite with a blue tail is being flown high in the sky. The kite [0.55, 0.065, 0.65, 0.239] is clearly visible in the sky, and the two people [0.098, 0.684, 0.418, 0.985] and [0.369, 0.897, 0.499, 1.0] are both looking upwards, focusing on the kite. This suggests that the main activity taking place in this image is flying a kite.

[Question] What is the main subject of the image?
[Choices] (A) A woman reading a book (B) A woman playing tennis (C) A woman playing basketball (D) A woman swimming
[Answer] The answer is (B): A woman playing tennis.
[Explanation] By observing the image, the primary subject is a woman who is preparing to hit a tennis ball. She is holding a tennis racket [0.487, 0.468, 0.66, 0.582] and is standing in a tennis court. Other activities such as reading a book, playing basketball, and swimming are not depicted in the image.



[Question] What is the main topic of the image?
[Choices] (A) A person swimming in a pool (B) A man flying a kite on a hill (C) A group of people playing soccer (D) A close-up of a flower
[Answer] The answer is (B): A man flying a kite on a hill.
[Explanation] Upon observing the image, we can see a man [0.373, 0.464, 0.446, 0.639] standing on a hill and a kite [0.198, 0.42, 0.252, 0.521] that he is preparing to fly. This indicates that the main subject of the image is a man flying a kite on a hill. The other choices do not accurately reflect the content of the image. There are no individuals swimming, no group playing soccer, and there isn't a close-up of a flower.



[Image quality]



[Question] How would you describe the quality of the image?
[Choices] (A) Sharp and clear (B) Blurry and unclear (C) Bright and high contrast (D) Dark and low contrast
[Answer] The answer is (B): Blurry and unclear.
[Explanation] Upon observing the image, it is evident that the details of the clock tower and the graveyard are not sharp and clear. The descriptions also mention that the image is blurry, confirming the lack of clarity in the image. Therefore, the quality of the image can be described as blurry and unclear.

[Question] How would you rate the contrast of the image?
[Choices] (A) High (B) Medium (C) Low (D) No contrast
[Answer] The answer is (A): High.
[Explanation] By observing the image, it's clear that there is a high contrast present. The white shirt, red tie, and black shoes stand out strongly against the backdrop of the bed. This is a clear indication of a high-contrast image where the difference in color and light between elements of the image is very pronounced.



[Question] How is the lighting condition of the image?
[Choices] (A) The image is brightly lit (B) The image is dimly lit (C) The image is in black and white (D) The image is blurred
[Answer] The answer is (A): The image is brightly lit.
[Explanation] Upon observing the image, it can be seen that the scene is well lit. The descriptions mention a 'brightly colored store front', which indicates that the image is neither dimly lit nor in black and white. There is also no mention of any blurry elements, indicating the image's clarity.



[Image emotion]



[Question] What emotion does this image most likely convey?
[Choices] (A) Stress (B) Joy (C) Anger (D) Sadness
[Answer] The answer is (B): Joy.
[Explanation] Observing the image, the man leaning back in his chair is smiling. This particular body language and facial expression suggest a sense of happiness or joy. There is no indication of the man being stressed, angry, or sad in the image. Therefore, the image conveys a joyful emotion.

[Question] What emotion does this image primarily convey?
[Choices] (A) Joyful (B) Nostalgic (C) Exciting (D) Fearful
[Answer] The answer is (B): Nostalgic.
[Explanation] Upon observing the image, the sepia tone of the photograph, along with the vintage objects such as the stop sign and the row of mailboxes off a dirt road, evoke a sense of nostalgia, reminding viewers of a time in the past. The other emotions like joy, excitement, or fear don't align well with the elements and tone presented in the image.



[Question] What emotion does this image most likely evoke?
[Choices] (A) Excitement (B) Anger (C) Serenity (D) Fear
[Answer] The answer is (C): Serenity.
[Explanation] Observing the image, it shows a peaceful scene where a small girl is lying in a large bed with a blue teddy bear. This scene conveys a sense of calm and tranquility, which is closely associated with the emotion of serenity. The other emotions, such as excitement, anger, and fear, do not seem to be depicted in the scene.



Figure 18: Examples of GPTVQA in image topic, image quality, and image emotion

[Image style]



[Question] What style is depicted in this image?

[Choices] (A) Black and white photography (B) Colored photography (C) Impressionist painting (D) Sketch

[Answer] The answer is (B): Colored photography.

[Explanation] Given the detailed descriptions of colors and the scene, it can be inferred that the image is a colored photograph. The descriptions mention specific colors like black and white checkered tiles, and the clear depiction of two cats eating from bowls, indicating a real-life scenario typically captured in photographs. The descriptions do not suggest it's a painting, sketch, or black and white photography.

[Question] What is the style of this image?

[Choices] (A) Still life photography (B) Surrealist painting (C) Renaissance art (D) Abstract sculpture

[Answer] The answer is (A): Still life photography.

[Explanation] The image depicts a scene of everyday life, specifically a table with a tray full of cookies, a vase filled with flowers, and a satchel. The objects are arranged in a way that suggests a naturalistic, candid style, which is typical of still life photography. Moreover, the image includes common elements of this style, such as food (cookies) and plant life (flowers in a vase). The other choices, such as Surrealist painting, Renaissance art, and Abstract sculpture, do not match the description of the image.



[Question] What type of image does this scene belong to?

[Choices] (A) Cartoon drawing (B) Oil painting (C) Real life photograph (D) Watercolor painting

[Answer] The answer is (C): Real life photograph.

[Explanation] The descriptions and locations of the objects suggest that the image captures a real-life scene of two young children playing on a bed. This is typical of a real-life photograph, which captures candid moments and everyday scenes. The details provided do not suggest the stylized or exaggerated features of a cartoon, the brushwork of an oil painting, or the color blending of a watercolor painting.



[Question] Where is this group of people using their smartphones?

[Choices] (A) Outdoors in a park (B) At a concert (C) In an office (D) Indoors at home

[Answer] The answer is (D): Indoors at home.

[Explanation] By observing the image, it seems like the group of people are indoors. There are no indications of being in a park, a concert, or an office. They are holding their cell phones in a casual manner, which suggests that they are possibly at home. The cell phones are held in a circle, which further implies a relaxed and informal setting that is most likely to be home. The people are close together, which also points to a familiar and comfortable environment like a home.

[Image scene]



[Question] What type of environment is depicted in this image?

[Choices] (A) Forest (B) City (C) Marina (D) Mountain

[Answer] The answer is (C): Marina.

[Explanation] The image shows a group of boats gathered in the water, suggesting that the environment is a marina. There are no indications of a forest, city, or mountainous landscape in the descriptions or object locations. The sunset also suggests that the image was taken outdoors, further supporting the marina setting.



[Question] Where is the man most likely located?

[Choices] (A) Inside a house (B) In a forest (C) In a city park (D) Outside a cafe

[Answer] The answer is (D): Outside a cafe.

[Explanation] By observing the description and location of the objects, it can be inferred that the man is sitting outside. He's under an umbrella at a table [0.233, 0.612, 0.592, 0.849] with chairs around, which is a typical setup for an outdoor cafe. Plus, there's a potted plant [0.273, 0.002, 0.533, 0.745], which is common in outdoor cafe settings. Furthermore, the description "A man is shown at a table outside of Caffe Italia" confirms that he is outside a cafe. Therefore, the man is most likely located outside a cafe.

[Future prediction]



[Question] What is the man most likely going to do next?

[Choices] (A) Get up from the bed [0.0, 0.765, 1.0, 0.99] (B) Continue reading the book [0.423, 0.508, 0.97, 0.793] (C) Play with the cat [0.08, 0.344, 0.568, 0.564] (D) Put on his glasses

[Answer] The answer is (B): Continue reading the book [0.423, 0.508, 0.97, 0.793].

[Explanation] By observing the man's actions and his immediate surroundings, it can be predicted that he is most likely going to continue reading the book [0.423, 0.508, 0.97, 0.793]. The man is comfortably lying down, engrossed in his book, and there is no immediate indication that he would get up from the bed [0.0, 0.765, 1.0, 0.99]. Furthermore, the cat [0.08, 0.344, 0.568, 0.564] is peacefully lying next to him, and there is no sign of interaction between them at the moment. Lastly, he is already wearing glasses, making option (D) unlikely.



[Question] What is likely to happen next in the image?

[Choices] (A) The woman will catch the Frisbee [0.753, 0.19, 0.946, 0.239] (B) The woman will miss the Frisbee [0.753, 0.19, 0.946, 0.239] (C) The woman will kick the Frisbee [0.753, 0.19, 0.946, 0.239] (D) The woman will throw the Frisbee [0.753, 0.19, 0.946, 0.239]

[Answer] The answer is (A): The woman will catch the Frisbee [0.753, 0.19, 0.946, 0.239].

[Explanation] Observing the situation in the image, the woman [0.216, 0.133, 0.947, 0.996] is in motion, reaching out for the Frisbee [0.753, 0.19, 0.946, 0.239] in the park. Based on her posture and the direction she is running, it seems like she is about to catch the Frisbee. Therefore, it can be predicted that in the immediate future, the woman will catch the Frisbee.

[Question] What is likely to happen next to the skateboarder at the top of the ramp [0.807, 0.144, 0.988, 0.41]?

[Choices] (A) He will climb down the ramp (B) He will skateboard down the ramp (C) He will jump off the ramp without his skateboard (D) He will sit down at the top of the ramp

[Answer] The answer is (B): He will skateboard down the ramp.

[Explanation] By observing the positioning and posture of the skateboarder at the top of the ramp [0.807, 0.144, 0.988, 0.41], along with the context of the scene and the presence of a skateboard [0.382, 0.691, 0.558, 0.944], it is most likely that the skateboarder will proceed to skateboard down the ramp. This is a common action in skateboarding when a skateboarder is at the top of a ramp. The other choices seem unlikely given the scenario presented in the image.



Figure 19: Examples of GPTVQA in image style, image scene, and future prediction