SEED-Bench: Benchmarking Multimodal Large Language Models

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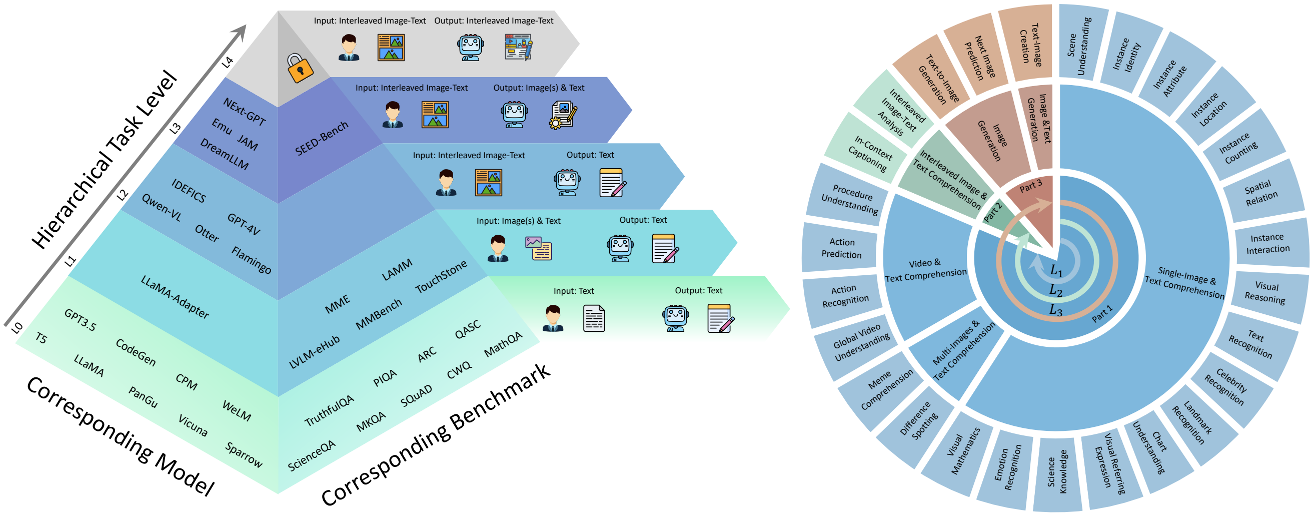

Figure 1. (left) Overview of **hierarchical capability levels** of MLLMs from L_0 to L_4, where higher level encompasses lower capability tiers. Models and corresponding evaluation benchmarks at each pyramid tier are illustrated. SEED-Bench-2 covers the assessment of MLLMs up to L_3. (right) Overview of 27 evaluation dimensions in SEED-Bench-2, which consists of three parts, with part-1 constituting L_1, part-1&2 constituting L_2, and part-1&2&3 constituting L_3.

Abstract

Multimodal large language models (MLLMs), building upon the foundation of powerful large language models (LLMs), have recently demonstrated exceptional capabilities in generating not only texts but also images given interleaved multimodal inputs (acting like a combination of GPT-4V and DALL-E 3). However, existing MLLM benchmarks remain limited to assessing only models' comprehension ability of single image-text inputs, failing to keep up with the strides made in MLLMs. A comprehensive benchmark is imperative for investigating the progress and uncovering the limitations of current MLLMs. In this work, we categorize the capabilities of MLLMs into hierarchical levels from L_0 to L_4 based on the modalities they can accept and generate, and propose SEED-Bench, a comprehensive benchmark that evaluates the ***hierarchical*** *capabilities of MLLMs. Specifically, SEED-Bench comprises 24K multiple-choice questions with accurate human annotations, which span 27 dimensions, including the evaluation of both text and image generation. Multiple-choice questions with ground truth options derived from human annotation enable an objective and efficient assessment of model performance, eliminating the need for human or GPT intervention during evaluation. We further evaluate the performance of 22 prominent open-source MLLMs and*

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Table 1. Comparisons between existing MLLM benchmarks. “H/G Evaluation” denotes whether human or GPT is used for evaluation.

Benchmark	Visual Modality	Evaluation Level	Customized Question	#Answer Annotation	Answer Type	H/G Evaluation	#Models
LLaVA-Bench [24]	Image	L_1	✓	150	free-form	GPT	4
OCR-Bench [26]	Image	L_1	✗	-	free-form	N/A	6
MME [11]	Image	L_1	✓	2194	Y/N	N/A	10
M3Exam [46]	Image	L_1	✓	12317	A/B/C/D	N/A	7
LAMM [42]	Image(s) & Point cloud	L_1	✗	-	free-form	GPT	4
LVLM-eHub [40]	Image	L_1	✗	-	free-form	Human	8
MMBench [25]	Image(s)	L_1	✓	2974	free-form	GPT	14
VisIT-Bench [5]	Images	L_1	✓	592	free-form	Human/GPT	14
MM-VET [43]	Image	L_1	✓	200	free-form	GPT	9
Touchstone [3]	Image(s)	L_1	✓	908	free-form	GPT	7
SciGraphQA [20]	Image	L_1	✓	3K	free-form	N/A	4
Ours	Image(s) & Video	L_3	✓	24371	A/B/C/D	N/A	22

summarize valuable observations. By revealing the limitations of existing MLLMs through extensive evaluations, we aim for SEED-Bench to provide insights that will motivate future research toward the goal of General Artificial Intelligence. Dataset and evaluation code are available at https://github.com/AILab-CVC/SEED-Bench.

1. Introduction

In recent years, Large Language Models (LLMs) [7, 10, 30, 31, 37] have exhibited remarkable capabilities to understand, reason, and generate texts across a variety of open-ended tasks. Leveraging the strong generality of LLMs, Multimodal Large Language Models (MLLMs) [2, 8, 15–19, 23, 24, 27, 28, 32, 32, 34, 41, 45, 47] have demonstrated exceptional capabilities in comprehending multimodal data through predicting open-form texts. Recent work [9, 13, 14, 21, 36, 39] further empower LLMs with the ability to generate images beyond texts (acting like a combination of GPT-4V [1] and DALL-E 3 [4]), since they contend that the premise for the emergence of multimodal capabilities is that text and image can be represented and processed interchangeably in a unified autoregressive Transformer. However, despite the extensive capabilities of MLLMs, existing MLLM benchmarks [3, 11, 25, 40, 42] primarily focus on evaluating single image-text comprehension, thus failing to fully demonstrate the progress and limitations of current MLLMs. The lag of benchmarks behind the rapid development of MLLMs hinders the exploration and evolution of models.

In this work, we categorize the capabilities of MLLMs into hierarchical levels ranging from L_0 to L_4 based on the modalities they can accept and generate, as depicted in Fig. 1. Building upon LLMs, the lowest-tier capability L_0 involves generating texts given text inputs, while the highest-tier capability L_4 entails producing open-form interleaved image and text output given arbitrary interleaved image-text inputs. Reaching the capability L_4 is a crucial milestone on the path towards General Artificial Intelligence (AGI) since a human-level AI should be able to effortlessly digest and create multimodal content. In the capability pyramid, higher levels inherently include the capabilities of lower tiers. This hierarchical categorization not only clearly illustrates the current progress of MLLMs, but also provides a well-defined roadmap for future research.

We propose SEED-Bench, a comprehensive benchmark that evaluates the **hierarchical** capabilities of MLLMs up to L_3, including the generation of both texts and images given interleaved image-text inputs. As shown in Fig. 1, SEED-Bench consists of three parts, where part-1 constitutes capability level L_1 for images and texts comprehension, part-1&2 constitute capability level L_2 for interleaved image-text comprehension, and part-1&2&3 constitute capability level L_3 for image and text generation. To the best of our knowledge, SEED-Bench is the first benchmark that provides hierarchical evaluations of MLLMs, which effectively showcases the range of model capabilities.

Specifically, SEED-Bench consists of 24K multiple-choice questions with ground truth answers derived from human annotation (×10 larger than MME [11] and ×8 larger than MMBench [25] as shown in Tab. 1). SEED-Bench spans 27 evaluation dimensions, enabling a comprehensive assessment of MLLMs' performance across diverse aspects. We employ three approaches for the generation of multiple-choice questions, including (1) a sophisticated pipeline utilizing foundation models, (2) the adaptation of existing datasets, and (3) a combination of human creation and GPT assistance. We further incorporate an automated filtering mechanism and manual verification process to ensure the quality of questions and the accuracy of ground truth answers. Different from existing MLLM benchmarks [3, 5, 24, 25, 40, 42, 43] that employ human annotators or GPT to evaluate open-form output, resulting in compromised efficiency, increased subjectivity, and reduced assessment accuracy, SEED-Bench provides multiple-choice questions, which restricts the model's output to A/B/C/D options. This approach facilitates the convenient computation of accuracy, serving as an objective metric for evaluation.

Based on SEED-Bench, we comprehensively evaluate 22 prominent open-source MLLMs. Our evaluation results yield the following three key findings: (1) Existing MLLMs have not yet reached the ceiling level of capability L_1 for the comprehension of fixed-form images and texts, with even the top-ranked model achieving only a 60% accuracy rate. MLLMs, in particular, exhibit poor performance in certain dimensions, such as understanding charts and visual mathematics. (2) MLLMs achieve less satisfactory performance at capability L_2 than that at L_1, which indicates that it is more challenging for MLLMs to comprehend free-form interleaved image-text inputs since most MLLMs are trained on structured image-caption pairs. (3) At present, only a few MLLMs can attain capability L_3, which requires models to output content in multiple modalities. A universal MLLM that unifies the generation of images and texts is currently underexplored. We will launch an evaluation platform and consistently maintain a leaderboard for assessing and comparing model performance.

2. Related Work

Multimodal Large Language Models. With the impressive success of Large language models (LLM) [7, 10, 37], recent studies work on generative Multimodal Large Language Models (MLLMs) [2, 8, 15–18, 23, 24, 32, 34, 41, 45, 47] to improve multimodal comprehension through aligning visual features of pre-trained image encoder with LLMs on image-text datasets. Some work [19, 27, 28] further considers video inputs and leverages the vast capabilities of LLMs for video understanding tasks. Recent work [9, 13, 14, 21, 36, 39] take significant strides in equipping MLLMs with the capacity for generating images beyond texts. In SEED-Bench, we provide a comprehensive and objective evaluation of these models to thoroughly assess their hierarchical capabilities.

Benchmarks for Multimodal Large Language Models. With the rapid development of Multimodal Large Language Models (MLLMs), some concurrent works [3, 11, 25, 40, 42] propose various benchmarks for evaluating MLLMs. However, they remain limited to assessing only the model's ability to predict texts given single image-text inputs, failing to keep up with the strides made in multimodal model capabilities. For example, GVT [38] constructs a benchmark by aggregating two semantic-level understanding tasks (VQA and Image Captioning) and two fine-grained tasks (Object Counting and Multi-class Identification). However, its evaluation is constrained to limited aspects of visual understanding. LVLM-eHub [40] combines multiple existing computer vision benchmarks and develops an online platform, where two models are prompted to answer a question related to an image and human annotators are employed to compare the predictions of models. The involvement of human annotators during evaluation not only introduces bias but also incurs significant costs. LLaVA-Bench [24], LAMM [42] and Touchstone [3] utilize GPT to evaluate the answers' relevance and accuracy to the ground truth. The reliance on entity extraction and GPT metrics can impact the accuracy and reliability of the evaluation. MME [11] and MMBench [25] aim to enhance the objective evaluation of MLLMs by constructing 2194 True/False Questions and 2974 Multiple Choice Questions across a variety of ability dimensions respectively. Considering the limited scale of these benchmarks, their evaluation results may exhibit instability. In this work, we introduce SEED-Bench to evaluate the hierarchical capabilities of MLLMs including the generation of both texts and images, which contains 24K human-annotated multiple-choice questions covering 27 evaluation dimensions.

3. SEED-Bench

3.1. Hierarchical Capability Levels

We categorize the capabilities of MLLMs into hierarchical levels from L_0 to $L4$, based on input and output modalities, where the higher level encompasses the lower capability tiers, as illustrated in Fig. 1. SEED-Bench covers the assessment of MLLMs up to L_3. The detailed categorization of capability level is illustrated below,

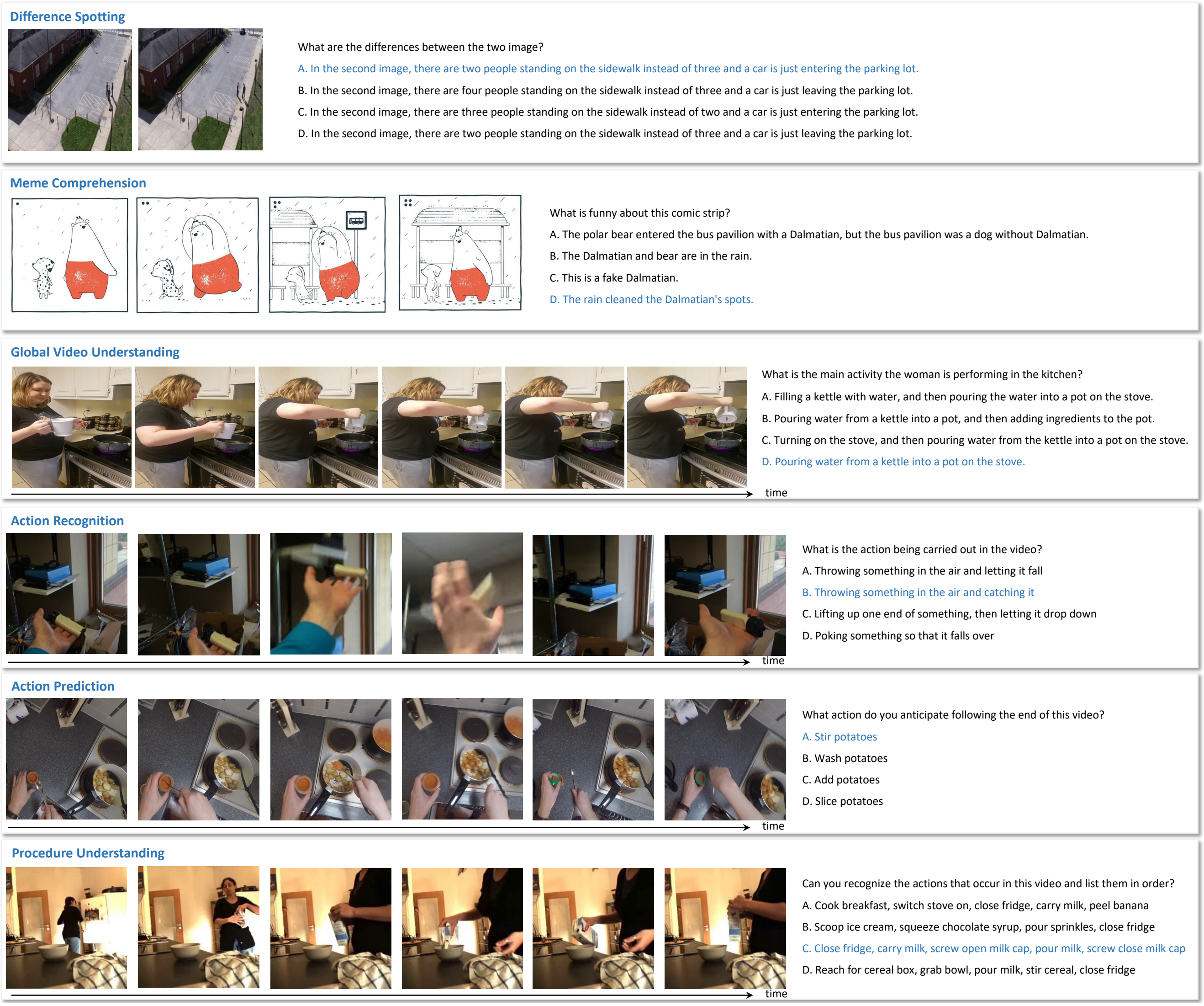
Level L_0: Building upon LLMs, the most fundamental capability of MLLMs generating text based on provided text inputs, which does not necessitate specific evaluation within the MLLM benchmark.

Level L_1: MLLMs at this capability level should possess the ability to comprehend multimodal inputs in a fixed format, *i.e.*, image or multiple images (video input can be regarded as multiple images) and then texts. Current MLLM benchmarks only evaluate this capability level with a single image and text as inputs.

Level L_2: MLLMs at this capability level should be able to understand multimodal inputs with open-form interleaved image-text data, which aligns with the multimodal inputs encountered in real-life scenarios.

Level L_3: Besides the inherent ability of LLMs to generate texts, MLLMs at this capability level should also be proficient in producing images, as advanced MLLMs are expected to process and represent multimodal content on both input and output sides.

Level L_4: MLLMs at the highest capability level should possess the ability to process and generate interleaved image-text content in an open-form format, which is an essential step towards achieving general artificial intelligence. We will incorporate evaluations of this capability level in our future work.



Difference Spotting

What are the differences between the two image?

A. In the second image, there are two people standing on the sidewalk instead of three and a car is just entering the parking lot.

B. In the second image, there are four people standing on the sidewalk instead of three and a car is just leaving the parking lot.

C. In the second image, there are three people standing on the sidewalk instead of two and a car is just entering the parking lot.

D. In the second image, there are two people standing on the sidewalk instead of three and a car is just leaving the parking lot.

Meme Comprehension

What is funny about this comic strip?

A. The polar bear entered the bus pavilion with a Dalmatian, but the bus pavilion was a dog without Dalmatian.

B. The Dalmatian and bear are in the rain.

C. This is a fake Dalmatian.

D. The rain cleaned the Dalmatian's spots.

Global Video Understanding

What is the main activity the woman is performing in the kitchen?

A. Filling a kettle with water, and then pouring the water into a pot on the stove.

B. Pouring water from a kettle into a pot, and then adding ingredients to the pot.

C. Turning on the stove, and then pouring water from the kettle into a pot on the stove.

D. Pouring water from a kettle into a pot on the stove.

Action Recognition

What is the action being carried out in the video?

A. Throwing something in the air and letting it fall

B. Throwing something in the air and catching it

C. Lifting up one end of something, then letting it drop down

D. Poking something so that it falls over

Action Prediction

What action do you anticipate following the end of this video?

A. Stir potatoes

B. Wash potatoes

C. Add potatoes

D. Slice potatoes

Procedure Understanding

Can you recognize the actions that occur in this video and list them in order?

A. Cook breakfast, switch stove on, close fridge, carry milk, peel banana

B. Scoop ice cream, squeeze chocolate syrup, pour sprinkles, close fridge

C. Close fridge, carry milk, screw open milk cap, pour milk, screw close milk cap

D. Reach for cereal box, grab bowl, pour milk, stir cereal, close fridge

Figure 2. Data samples from a subset of evaluation dimensions in part-1 with multiple images or videos as inputs, which encompasses capability L_1 in SEED-Bench.

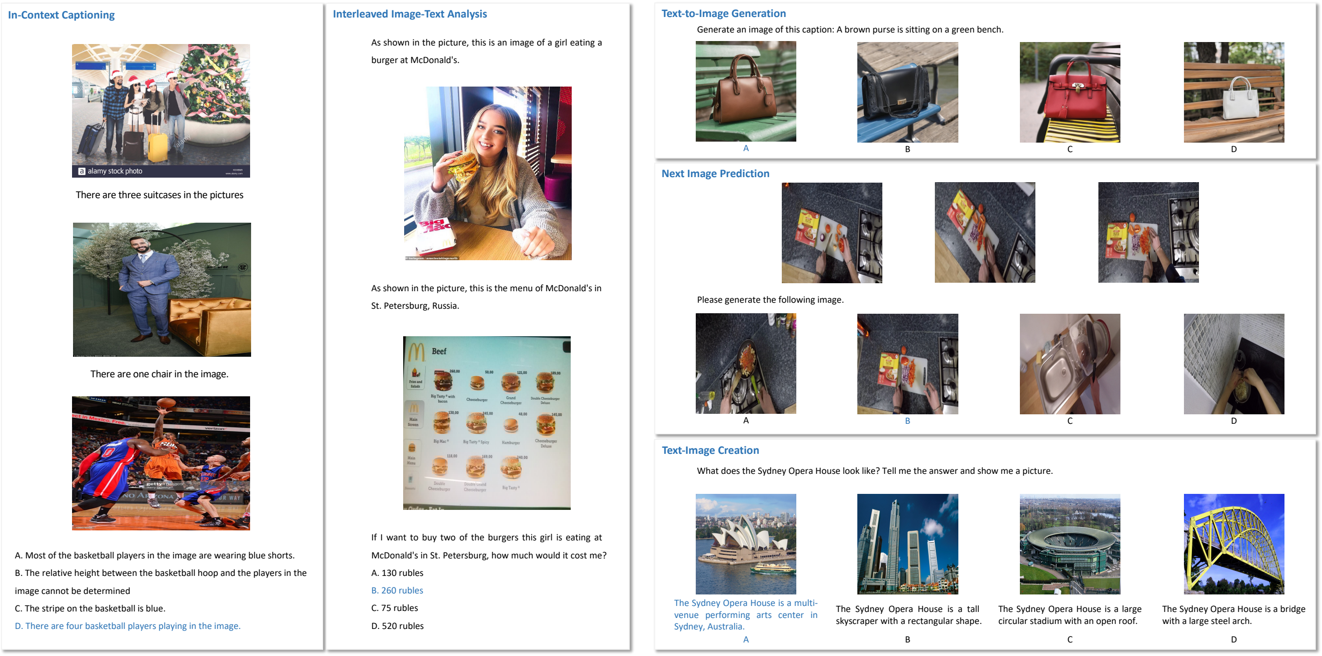
3.2. Evaluation Dimensions

As shown in Fig. 1, SEED-Bench comprises a total of 27 evaluation dimensions, which constitute three capabilities levels, from L_1 to L_3. Since the higher level encompasses the lower capability tiers, we further divide the evaluation dimensions of L_3 into three non-overlapping parts: part-1 forms level L_1, part-2 combined with part-1 constitutes level L_2, part-3, part-2 and part-1 form level L_3 together. We introduce the dimensions of each part in detail below.

3.2.1 Part-1

The dimensions of part-1 evaluate MLLMs' comprehension of multimodal inputs in a fixed format, and can be further grouped into three sub-parts based on the types of visual inputs: (1) Single-Image & Text, (2) Multiple-Images & Text, (3) Video & Text.

- Single-Image & Text Comprehension. This sub-part consists of diverse evaluation dimensions including Scene Understanding, Instance Identity, Instance Attribute, Instance Location, Instance Counting, Spatial Relation, Instance Interaction, Visual Reasoning, Text Recognition, Celebrity Recognition, Landmark Recognition, Chart Understanding, Visual Referring Expression, Science Knowledge, Emotion Recognition and Visual Mathematics. These dimensions assess MLLMs' comprehension of image-text pairs from extensive aspects, encompassing global/object-level understanding, recognition/reasoning, and various specialized domains.
- Multiple-Images & Text Comprehension. This sub-part



There are three suitcases in the pictures

There are one chair in the image.

A. Most of the basketball players in the image are wearing blue shorts.
B. The relative height between the basketball hoop and the players in the image cannot be determined
C. The stripe on the basketball is blue.
D. There are four basketball players playing in the image.

As shown in the picture, this is an image of a girl eating a burger at McDonald's.

As shown in the picture, this is the menu of McDonald's in St. Petersburg, Russia.

If I want to buy two of the burgers this girl is eating at McDonald's in St. Petersburg, how much would it cost me?
A. 130 rubles
B. 260 rubles
C. 75 rubles
D. 520 rubles

Generate an image of this caption: A brown purse is sitting on a green bench.

Please generate the following image.

What does the Sydney Opera House look like? Tell me the answer and show me a picture.

A: The Sydney Opera House is a multi-venue performing arts center in Sydney, Australia.
B: The Sydney Opera House is a tall skyscraper with a rectangular shape.
C: The Sydney Opera House is a large circular stadium with an open roof.
D: The Sydney Opera House is a bridge with a large steel arch.

Figure 3. (left) Data samples of evaluation dimensions in part-2 with interleaved image-text as inputs, which encompasses capability L_2 together with dimensions in L_1. (right) Data samples of evaluation dimensions in part-3 with images and texts as outputs, which encompasses capability L_3 together with dimensions in L_2.

consists of Difference Spotting and Meme Comprehension, which evaluates MLLMs' capability of extracting information and discerning differences from multiple images.

- Video & Text Comprehension. This sub-part consists of Global Video Understanding, Action Recognition, Action Prediction, and Procedure Understanding, which assesses MLLMs' ability for fine-grained action recognition, temporal relationship understanding, and temporal reasoning.

3.2.2 Part-2

The dimensions of part-2 evaluate MLLMs' comprehension of arbitrary interleaved image-text inputs, including In-Context Captioning, where two examples of image-caption pairs and an image are given, and the model is expected to describe the specific aspect of the image, and Interleaved Image-Text Analysis, where the model answers questions based on images and texts with varying quantities and positions.

3.2.3 Part-3

The dimensions of part-3 evaluate MLLMs' capability of generating images in addition to texts, and can be divided into two sub-parts including (1) Image generation and (2) Image & Text generation.

- Image generation. This sub-part comprises Text-to-Image Generation, where the model is expected to generate an image based on a caption prompt, and Next Image Generation, where the model is required to generate a subsequent image based on previous images.
- Text-Image creation. Given a question, the model is required to provide a text-based answer and subsequently generate a corresponding image as an illustration.

3.3. Construction of Multiple-choice Questions

We employ three approaches to construct multiple-choice questions covering 27 evaluation dimensions: (1) an automatic pipeline to generate questions for specific evaluation dimensions, (2) tailoring existing datasets for the format of multiple-choice questions, and (3) human creation combined with GPT.

Automatic pipeline. As shown in Fig. 4, our pipeline for generating multiple-choice questions involves question/answer generation and verification. For generating question/answer pairs, we first leverage various foundation models to extract visual information including image-level captions, instance-level descriptions, and textual elements. Based on specially designed prompts corresponding to specific evaluation dimensions, ChatGPT/GPT-4 subsequently generates questions and four candidate options with one ground truth answer. For verifying question/answer pairs, we filter out questions that can be answered correctly by multiple LLMs without resorting to visual information, since such questions are not helpful to evaluate the visual

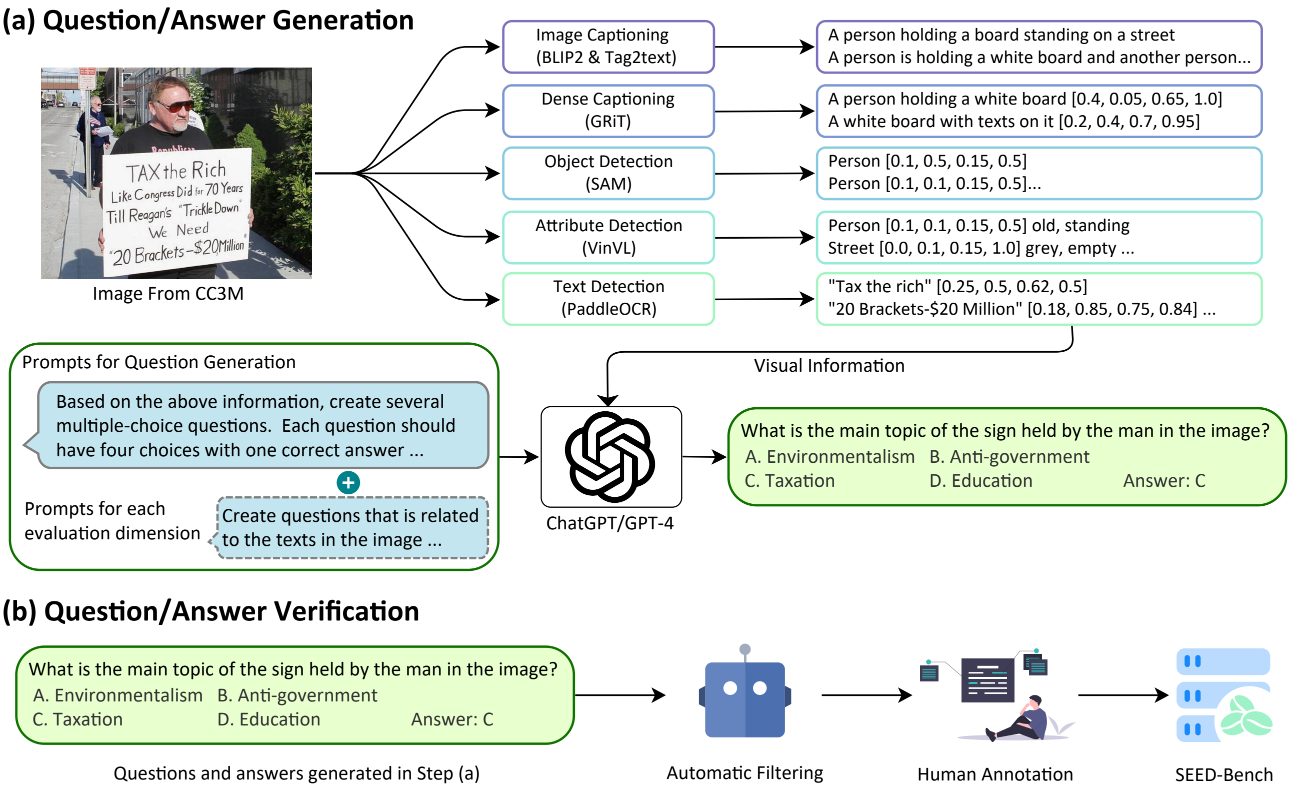

(a) Question/Answer Generation
TAX the Rich
Like Congress Did for 70 Years
Till Reagan's "Trickle Down"
We Need
"20 Brackets–$20 Million"
Image From CC3M
Image Captioning (BLIP2 & Tag2text)
Dense Captioning (GRiT)
Object Detection (SAM)
Attribute Detection (VinVL)
Text Detection (PaddleOCR)
A person holding a board standing on a street
A person is holding a white board and another person...
A person holding a white board [0.4, 0.05, 0.65, 1.0]
A white board with texts on it [0.2, 0.4, 0.7, 0.95]
Person [0.1, 0.5, 0.15, 0.5]
Person [0.1, 0.1, 0.15, 0.5]...
Person [0.1, 0.1, 0.15, 0.5] old, standing
Street [0.0, 0.1, 0.15, 1.0] grey, empty ...
"Tax the rich" [0.25, 0.5, 0.62, 0.5]
"20 Brackets-$20 Million" [0.18, 0.85, 0.75, 0.84] ...
Visual Information
Prompts for Question Generation
Based on the above information, create several multiple-choice questions. Each question should have four choices with one correct answer ...
Prompts for each evaluation dimension
Create questions that is related to the texts in the image ...
ChatGPT/GPT-4
What is the main topic of the sign held by the man in the image?
A. Environmentalism B. Anti-government
C. Taxation D. Education Answer: C
(b) Question/Answer Verification
What is the main topic of the sign held by the man in the image?
A. Environmentalism B. Anti-government
C. Taxation D. Education Answer: C
Questions and answers generated in Step (a)
Automatic Filtering
Human Annotation
SEED-Bench

Figure 4. Overview of automatic pipeline in SEED-Bench for generating multiple-choice questions. (a) We first leverage various foundation models to extract visual information including image-level captions, instance-level descriptions, and textual elements. Based on specially designed prompts corresponding to specific evaluation dimensions, ChatGPT/GPT-4 subsequently generates questions and four candidate options with one ground truth answer. (b) We further filter out questions by utilizing LLMs and employ human annotators to select the correct option and classify each question into one evaluation dimension.

comprehension capability of MLLMs. We further employ human annotators to select the correct option and classify each question into one evaluation dimension.

Tailoring existing datasets. For existing datasets with annotated labels, we first prompt ChatGPT/GPT-4 to generate questions based on the provided information. We then construct distracting choices either from the annotated labels of other samples or by utilizing ChatGPT to generate three distractors. For distractors generated by ChatGPT, we additionally utilize human annotators to filter out options that are too similar to the ground truth answer.

Human creation combined with GPT. For evaluation dimensions lacking suitable data, *e.g.* *Interleaved Image-Text Analysis* and *Text-Image Creation*, we employ human annotators to meticulously design questions, retrieve corresponding images, and construct distracting choices with the assistance of ChatGPT.

3.4. Evaluation Strategy

Evaluation of text output. Different from MM-Bench [25] that employs ChatGPT to match a model's prediction to one of the choices in a multiple-choice question (achieves only 87.0% alignment rate), we adopt the answer ranking strategy [6, 8, 22] for evaluating existing MLLMs with multiple-choice questions. Specifically, for each choice of a question, we compute the likelihood that an MLLM generates the content of this choice given the question. We select the choice with the highest likelihood as the model's prediction. Our evaluation strategy does not rely on the instruction-following capabilities of models to output "A" or "B" or "C" or "D". Furthermore, this evaluation strategy eliminates the impact of the order of multiple-choice options on the model's performance.

Evaluation of image output. Since not all MLLMs with image generation capabilities employ visual autoregression, adopting an answer ranking strategy for image evaluation is impractical. Instead, we calculate the CLIP similarity score [33] between the generated image and each candidate image option, selecting the highest-scoring option as the fi-

Table 2. Evaluation results of various MLLMs in different capability levels of SEED-Bench. $\bar{T}$ denotes the averaged accuracy across corresponding dimensions, and $R_{\bar{T}}$ denotes the rank based on the the averaged accuracy. The evaluation dimensions of part-2, together with L_1, encompass L_2, while the evaluation dimensions of part-3, together with L_2, encompass L_3.

Model	Language Model	L_1 (Part-1)		Part-2		L_2		Part-3		L_3	
		$\bar{T}$	$R_{\bar{T}}$	$\bar{T}$	$R_{\bar{T}}$	$\bar{T}$	$R_{\bar{T}}$	$\bar{T}$	$R_{\bar{T}}$	$\bar{T}$	$R_{\bar{T}}$
BLIP-2 [18]	Flan-T5-XL	41.0	8	35.3	9	40.5	7	-	-	-	-
InstructBLIP [8]	Flan-T5-XL	42.2	6	35.7	5	41.7	6	-	-	-	-
InstructBLIP Vicuna [8]	Vicuna-7B	41.4	7	29.7	18	40.5	8	-	-	-	-
LLaVA [24]	LLaMA-7B	38.7	11	30.2	17	38.0	12	-	-	-	-
MiniGPT-4 [47]	Vicuna-7B	39.4	9	34.1	12	39.0	9	-	-	-	-
VPGTrans [44]	LLaMA-7B	36.2	19	23.9	20	35.2	18	-	-	-	-
MultiModal-GPT [15]	Vicuna-7B	37.4	14	34.9	11	37.1	13	-	-	-	-
Otter [17]	LLaMA-7B	36.4	17	36.6	4	36.4	16	-	-	-	-
OpenFlamingo [29]	LLaMA-7B	37.3	15	35.5	8	37.1	14	-	-	-	-
LLaMA-Adapter V2 [12]	LLaMA-7B	37.5	13	-	-	-	-	-	-	-	-
GVT [38]	Vicuna-7B	34.4	21	38.6	3	34.8	19	-	-	-	-
mPLUG-Owl [41]	LLaMA-7B	39.4	10	28.9	19	38.5	10	-	-	-	-
Kosmos-2 [32]	Decoder only 1.3B	46.3	3	23.3	21	44.4	3	-	-	-	-
Qwen-VL-Chat [2]	Qwen-7B	43.1	4	35.5	7	42.5	4	-	-	-	-
LLaVA-1.5 [23]	Vicuna-7B	47.3	2	30.8	16	46.0	2	-	-	-	-
IDEFICS-9B-Instruct [16]	LLaMA-7B	38.0	12	40.3	2	38.2	11	-	-	-	-
InternLM-Xcomposer-VL [45]	InternLM-7B	**59.2**	1	32.1	14	**56.9**	1	-	-	-	-
VideoChat [19]	Vicuna-7B	37.0	16	35.3	9	36.8	15	-	-	-	-
Video-ChatGPT [28]	LLaMA-7B	36.4	18	31.0	15	35.9	17	-	-	-	-
Valley [27]	LLaMA-13B	34.5	20	32.2	13	34.3	20	-	-	-	-
Emu [35]	LLaMA-13B	42.5	5	**41.1**	1	42.4	5	**41.4**	1	**42.3**	1
NExt-GPT [39]	Vicuna-7B	30.7	22	35.6	6	31.1	21	33.9	2	31.4	2

nal prediction of the given multiple-choice question.

Evaluation of text and image output. For questions with text and image answers, we first employ an answer ranking strategy to select the most likely text prediction. If it matches the ground truth, we evaluate the image output using the CLIP similarity score [33] between the generated image and each candidate. The model is deemed correct only if both text and image predictions match the ground truth.

4. Evaluation Results

4.1. Models

We evaluate a total of 22 open-source MLLMs including BLIP-2 [18], InstructBLIP [8], InstructBLIP Vicuna [8], LLaVA [24], MiniGPT-4 [47], VPGTrans [44], MultiModal-GPT [15], Otter [17], OpenFlamingo [29], LLaMA-Adapter V2 [12], GVT [38], mPLUG-Owl [41], Kosmos-2 [32], Qwen-VL-Chat [2], LLaVA1.5 [23], IDEFICS-9B-Instruct [16], InternLM-Xcomposer-VL [45], VideoChat [19], Video-ChatGPT [28], Valley [27], Emu [35], and NExt-GPT [39] based on their official implementations. For each model, we first determine its capability level and then evaluate the corresponding dimensions. Note that we have confirmed with the authors that the LLaMA-Adapter V2's capability level is L_1. Some MLLMs can reach the capability level L_3, but they are not available as open-source.

4.2. Main Results

The evaluation results of various MLLMs in different capability levels of SEED-Bench are listed in Tab. 2. The detailed leaderboard of each evaluation dimension is provided in the supplemental materials. InternLM-Xcomposer-VL outperforms a large number of MLLMs, achieving the best performance based on the averaged accuracy in capability level L_1 and L_2, and Emu ranks top-1 in capability level L_3 with only one competitor. Because InternLM-Xcomposer-VL retrieves images from the available image pool rather than generate images, it does not reach the capability level L_3. To better showcase the capabilities of models across different evaluation dimensions, we further visualize the ranking of each model within each evaluation dimension in Fig. 5, where darker colors represent higher ranks and grey color indicates that the model has not yet reached the

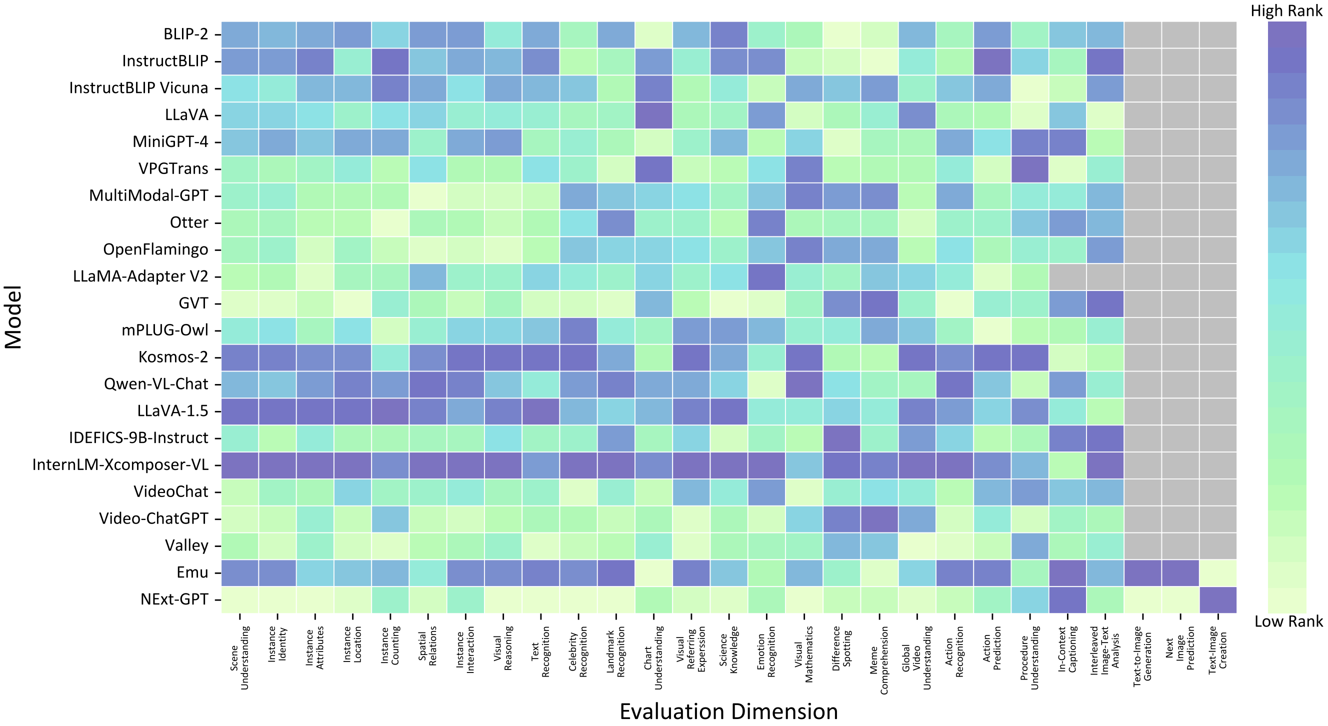


Figure 5. Illustration of each model's performance across different evaluation dimensions, where darker colors represent higher ranks. Gray indicates that the model has not yet reached the capability level required for evaluating that dimension.

capability level required for evaluating that dimension. The champion MLLM InternLM-Xcomposer-VL achieves competitive results in a large number of evaluation dimensions of capability level L_1 and L_2. Although NExt-GPT reaches the capability level L_3, it performs poorly in multiple evaluation dimensions at levels L_1 and L_2.

4.3. Observations

Through the comprehension and objective evaluation of various MLLMs in different capability levels of SEED-Bench, we have uncovered insights that can inform future work.

Existing MLLMs have yet to reach the ceiling level of capability L_1. Even the top-ranked MLLM achieves only a 60% averaged accuracy in capability L_1, which evaluates the comprehension of multimodal inputs in a fixed format, *i.e.*, images or multiple images (videos) and then texts.

The comprehension of Interleaved Image-Text data is more difficult. The majority of MLLMs achieve worse results on part 2, which consists of multiple-choice questions with interleaved image-text inputs, than on L_1 with fixed-form image and text as inputs.

Only a small number of MLLMs can reach the capability L_3. Only two open-source MLLMs possess the ability to generate images, besides the inherent ability of LLMs to output texts. A universal MLLM that unifies the generation of images and texts is currently underexplored.

It is challenging to address multimodal comprehension and generation simultaneously. Although NExt-GPT reaches the capability level L_3, which can generate both texts and images, it shows poor performance in capability L_1 for multimodal comprehension. Equipping MLLMs with image generation ability without compromising their inherent text output performance remains to be addressed.

5. Conclusion

In this work, we introduce SEED-Bench, a large-scale benchmark for evaluating Multimodal Large Language Models (MLLMs) in terms of hierarchical capabilities, including the generation of both texts and images. SEED-Bench consists of 24K multiple-choice questions with accurate human annotations, which cover 27 evaluation dimensions. We conduct a thorough evaluation of 22 prominent open-source MLLMs, analyzing and comparing their performances to provide insights for future research. We plan to launch and maintain a leaderboard, offering a platform for the community to assess model performance.

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