

# InternLM-XComposer2: Mastering Free-form Text-Image Composition and Comprehension in Vision-Language Large Models

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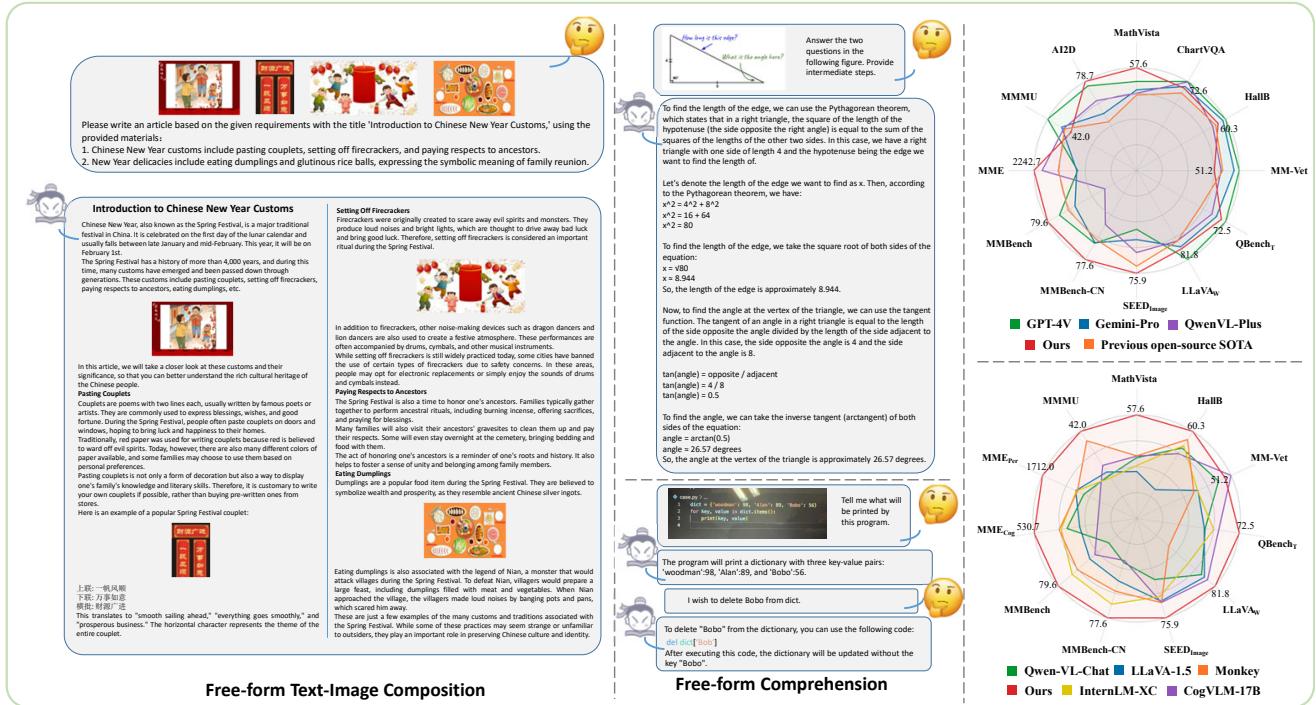


Figure 1. Overview of free-form text-image composition and comprehension of InternLM-XComposer2. Our model based on InternLM2-7B [77] not only significantly outperforms existing multimodal models but also **matches or even surpasses GPT-4V [58]** and **Gemini Pro [76]** in certain assessments. (Please zoom-in to see the details.)

## Abstract

We introduce InternLM-XComposer2, a cutting-edge vision-language model excelling in free-form text-image composition and comprehension. This model goes beyond conventional vision-language understanding, adeptly crafting interleaved text-image content from diverse inputs like outlines, detailed textual specifications, and reference images, enabling highly customizable content creation. InternLM-XComposer2 proposes a Partial LoRA (PLoRA) approach that applies additional LoRA parameters exclusively to image tokens to preserve the integrity of pre-trained language knowledge, striking a balance between precise vision understanding and text comprehension with literary talent. Experimental results demonstrate the superiority of InternLM-XComposer2 based on InternLM2-7B in producing high-quality long-text multi-modal content and its exceptional vision-language understanding performance across various benchmarks, where it not only significantly outperforms existing multimodal models but also matches or even surpasses GPT-4V and Gemini Pro in certain assessments. This highlights its remarkable proficiency in the realm of multimodal understanding. The InternLM-

\* indicates equal contribution.

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*XComposer2 model series with 7B parameters are publicly available at <https://github.com/InternLM/InternLM-XComposer>.*

## 1. Introduction

In recent years, there has been a remarkable evolution in the field of large language models (LLMs) [8, 16, 17, 57, 58, 68, 79]. Foremost among these, models like ChatGPT [57] have completely altered human interaction with technology. Concurrently, a variety of open-source LLMs, such as Llama [78], Mistra [37], InternLM [77], QWen [65], GLM [25], and Baichuan [7], have empowered the customization of LLMs. Building on these open-source foundations, the community has seen substantial progress in multimodal large language models (MLLMs) [6, 21, 29, 48, 49, 82, 95, 100]. These MLLMs are adept at interpreting images and engaging in text-image dialogues, showcasing impressive multimodal understanding. Unlike traditional MLLMs, a recent innovation, *i.e.*, InternLM-XComposer [95], has focused on using MLLMs for text-image composition and comprehension, marking a novel direction in MLLM research. However, this pioneering work is currently limited to generating text-image articles based on titles alone, lacking the sophistication to meet more complex composition requirements. Furthermore, while achieving leading performance at its inception, this model still possesses significant potential for enhancement in detailed perception and complex reasoning capabilities to advance its vision-language comprehension performance.

This observation motivates the development of more advanced vision-language models capable of practical and potent text-image composition and comprehension. In this paper, we introduce InternLM-XComposer2, a cutting-edge model excelling in free-form text-image composition and comprehension, built based on InternLM2 [77]. InternLM-XComposer2 represents a significant advancement over its predecessor, InternLM-XComposer [95], in both text-image composition and comprehension. InternLM-XComposer2 is adept at producing high-quality, integrated text-image articles from a variety of free-form inputs, such as detailed specifications, structured outlines, and reference images, serving to a wide range of application contexts. In the realm of multimodal understanding, it demonstrates exceptional capabilities in detailed perception, logical reasoning, and extensive knowledge integration. Its performance significantly surpasses that of existing open-source MLLMs, and it stands on par with, or even exceeds, advanced models like GPT-4V [58] and Gemini Pro [76] in various benchmarks.

The appealing capabilities of InternLM-XComposer2 are primarily due to two critical design elements. (1)

**Partial LoRA:** The Partial LoRA (P-LoRA) design harmonizes its abilities in composition and comprehension.

This involves feeding forward image tokens with additional LoRA [33] (Low-Rank Adaptation) parameters, while language tokens retain the original architecture. This selective enhancement ensures robust performance in both visual and textual domains. (2) **High-quality and Diverse Data**

**Foundataion:** The quality and diversity of the training data are pivotal. Our dataset for free-form text-image composition excels in: adhering to complex instructions, customization with text and image for tailored content, high-quality and stylistically diverse writing, and versatile text editing including condensing, expanding, and revising. For exceptional vision-language comprehension capabilities, we gather a wide range of high-quality pretraining and supervised fine-tuning multimodal data. This collection spans various aspects and types, such as captions, general QA, scientific QA, chat-based QA, mathematical QA, concept knowledge, conversation, and text-image composition.

InternLM-XComposer2 surpasses existing benchmarks in both composition and comprehension. In the creation benchmark of OpenCompass [18] for evaluating the creativity of LLMs, InternLM-XComposer2 showcases outstanding performance. To demostrate our multimodal comprehension capility, we compare our InternLM-XComposer2 on a list of benchmarks with both open-source MLLMs and closed-source APIs, *e.g.*, GPT4V [58], Gemini Pro [76], and Qwen-VL Plus [19]. We report results in Math-Vista [52], MMMU [91], AI2D [40], MME [27], MM-Bench [51], MMBench-Chinese [51], SEED-Bench (Image) [41], LLaVA-Bench (In-the-Wild) [49], QBench [85], MM-Vet [90], HallusionBench [31], ChartQA [56], and POPE [45]. InternLM-XComposer2 based on InternLM2-7B significantly exceeds the performance of existing open-source models by an impressive margin. Remarkably, it demonstrates superior performance to GPT4V [58], Gemini Pro [76] across six benchmarks.

## 2. Related Works

**Large Language Models (LLMs).** Recent LLM architectures have marked a transition from encoder-decoder frameworks (*e.g.*, BERT [22], T5 [68]) to an emphasis on decoder-only models employed with autoregressive training techniques for next-token prediction (*e.g.*, GPT [67]). The following works (*e.g.*, GPT3 [8], InstructGPT [60], ChatGPT [57], PaLM [17]) have seen the integration of advanced techniques such as instruction-tuning and Reinforcement Learning from Human Feedback (RLHF). Coupled with expansive parameter sizes and extensive training data, these LLM models have achieved substantial performance enhancements across a diverse range of Natural Language Processing (NLP) tasks. Other notable LLMs encompass a range of developments, such as the OPT [96], LLaMA series [78, 79], *e.g.*, Mistral [37, 38], InternLM [77], GLM series [25, 93], Qwen series [6, 65],

Baichuan [7], Skywork [84] and Falcon [61] have made significant contributions to the field.

**Multimodal Large Language Models (MLLMs).** Vision-language models (VLMs), exemplified by CLIP [66] and its subsequent works [26, 36, 43, 44, 50, 75, 94], align image and text features in a unified embedding space. This alignment is achieved through contrastive learning objectives applied to extensive image-text pair datasets. VLMs achieve strong zero-shot and few-shot performance, showcasing significant generalization abilities across a range of downstream tasks.

Benefiting from existing large language models and VLMs as the visual encoder, recent Multimodal Large Language Models (MLLMs) [12, 14, 15, 24, 28, 58] achieve visual perception, understanding and reasoning abilities, show superb performance in diverse vision-language tasks. A series of studies [2, 5, 9, 10, 20, 21, 42, 46, 49, 62, 64, 80, 86, 92, 97, 98, 100] have explored further improve the MLLM in different dimensions, such as instruction tuning [11, 49, 98], efficient fine-tuning [33], high-resolution image inputs [6, 82, 83], hallucination mitigation [34, 87, 99], image generation [23, 30, 74, 89], 3D understanding [63] and image-text comprehension and composition [95].

To enable highly customizable content creation, our model is designed for free-form text-image composition and comprehension based on MLLMs. We use Intern-LM2 as the LLM and CLIP ViT-Large as the visual encoder and propose a new partial LoRA to align the text-image modalities. Given flexible and multi-modal user inputs such as specifications, outlines, and reference images, our model is capable of generating high-quality interleaved text-image written content.

### 3. Method

#### 3.1. Model Architecture

Our proposed model, InternLM-XComposer2, incorporates a vision encoder and a Language Learning Model (LLM). These two components are interconnected via an innovative Partial LoRA module. Given a set of images and text, the LLM utilizes the output from the vision encoder as visual tokens and the tokenized text as language tokens. These tokens are then concatenated to form the input sequence.

**Vision Encoder.** The vision encoder in our model is designed to extract high-level visual features from raw images. It is pretrained in an image-language contrastive manner(CLIP). Our findings indicate that, when used in conjunction with our Partial LoRA module, a lightweight vision model performs effectively. For the sake of efficiency, we have opted to use the OpenAI ViT-Large model.

**Large Language Model.** We employ the recently introduced InternLM-2 as our Large Language Model (LLM).

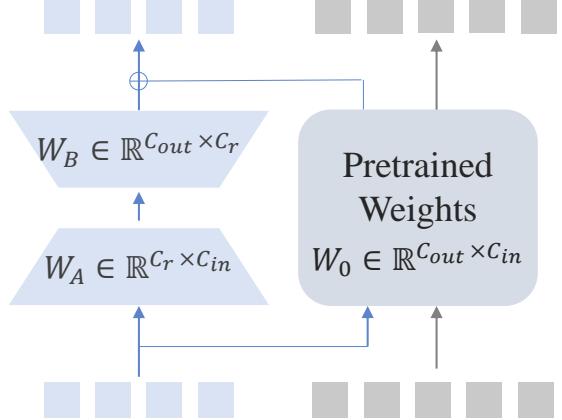


Figure 2. **The illustration of the Partial-LoRA.** The blue tokens represent the visual tokens and the gray tokens are the language tokens. Our Partial-LoRA is only applied to the visual tokens.

This model boasts exceptional multi-lingual capabilities and has demonstrated impressive results in benchmarks. In practical applications, we utilize the InternLM2-7B-ChatSFT variant as our LLM.

**Partial Low-Rank Adaptation.** In the realm of multimodal Language Learning Models (LLMs), one insufficiently explored area is the effective alignment of different modalities. A desired alignment should potentially enrich the LLM with new modality-specific knowledge, while simultaneously preserving its inherent capabilities. Current methods predominantly adopt one of two approaches: they either treat the visual token and language token equally or as entirely distinct entities. We contend that the first approach overlooks the inherent property distinctions between modalities, while the second approach results in a substantial alignment cost.

In our pursuit of effective modality alignment, we introduce Partial LoRA, a versatile plug-in module designed to align knowledge from a new modality to the LLM. As illustrated in Figure X, Partial LoRA draws inspiration from the original LoRA and incorporates a low-rank adaptation that is exclusively applied to the new modality portion of the input tokens. In our specific configuration, Partial LoRA is applied to all visual tokens.

Formally, for each linear layer  $L_0$  in the LLM blocks, we denote its weight matrix  $W_0 \in \mathbb{R}^{(C_{out} \times C_{in})}$  and bias  $B_0 \in \mathbb{R}^{C_{out}}$ , where  $C_{in}$  and  $C_{out}$  are the input and output dimension. Its corresponding Partial LoRA contains two low-rank matrix  $W_A \in \mathbb{R}^{C_r \times C_{in}}$  and  $W_B \in \mathbb{R}^{C_{out} \times C_r}$ . With a given input  $x = [x_v, x_t]$ , we have the output feature  $\hat{x}$  by:

$$\begin{aligned}\hat{x}_t &= W_0 x_t + B_0 \\ \hat{x}_v &= W_0 x_v + W_B W_A x_v + B_0 \\ \hat{x} &= [\hat{x}_v, \hat{x}_t]\end{aligned}$$

Task	Dataset
General Semantic Alignment	ShareGPT4V-PT [11], COCO [13], Nocaps [1], TextCaps [73], LAION400M [69], SBU [59], CC 3M [72]
World Knowledge Alignment	Concept Data [95]
Vision Capability Enhancement	WanJuan [32], Flickr[88], MMC-Instruction[47]

Table 1. Datasets used for Pre-Training. The data are collected from diverse sources for the three objectives.

where  $x_v$  and  $x_t$  are the visual tokens and language tokens of the input sequence respectively.

### 3.2. Pre-Training

During the pre-training phase, the LLM remains constant while both the vision encoder and Partial LoRA are fine-tuned to align the visual tokens with the LLM. The pre-training data is meticulously curated with **three objectives** in mind: 1) general semantic alignment, 2) world knowledge alignment, 3) vision capability enhancement.

**General Semantic Alignment.** The objective of general semantic alignment is to equip the MLLM with the fundamental ability to comprehend image content. For instance, the MLLM should be able to recognize that a picture of Einstein represents ‘a human’. We utilize image caption data from a variety of sources for this purpose, including high-quality, detailed captions from ShareGPT4V-PT, as well as concise and precise captions from COCO, NoCaps, TextCaps, *etc.* During the pre-training phase, we employ a simple instruction: *Describe this image briefly/in detail.*

**World Knowledge Alignment.** World knowledge represents an advanced capability of the MLLM. For instance, the MLLM should be able to identify the man in the figure mentioned above as ‘Albert Einstein’ and further talk something about him. To align the world knowledge depicted in the image with the knowledge already acquired by the LLM, we have constructed a concept dataset. This dataset is carefully filtered from the concept data utilized in InternLM-XComposer [95]. Given that the text in the concept data only partially describes the content in the image and their relationship is complex to model, we employ a more broad instruction: *Tell me something about this image.*

**Vision Capability Enhancement.** Finally, an advanced MLLM necessitates certain vision-specific capabilities, such as Optical Character Recognition (OCR), object localization (grounding), and the understanding of structured images (*e.g.*, charts, tables). To achieve this, we have compiled relevant datasets, as outlined in Table 1, and have implemented corresponding instructions for training.

Thanks to the design of Partial LoRA, the LLM is able to adapt to visual tokens while maintaining its original language processing capabilities. The fixed LLM also enables us to directly use in-context learning performance as a measure of pre-training quality.

In our implementation, we employ the OpenAI CLIP ViT-L-14-336 as the vision encoder. We increase its resolu-

Task	Dataset
<i>Multi-task training</i>	
Caption	ShareGPT4V [11], COCO [13], Nocaps [1]
General QA	VQAv2 [4], GQA [35], OK-VQA [55]
Science QA	AI2D [40], SQA [54]
Chart QA	DVQA [39], ChartQA [56]
Math QA	MathQA [3], Geometry3K [53]
World Knowledge QA	A-OKVQA [70], KVQA [71]
Conversation	LLaVA-150k [49], LVIS-Instruct4V [81]
<i>Instruction tuning</i>	
Free-from Compositon	In-house data (Refer to Sec.3.4)
Conversation	LLaVA-150k [49], LVIS-Instruct4V [81] ShareGPT-en&zh [16], InternLM-Chat[77]

Table 2. Datasets used for Supervised Fine-Tuning. We collect data from diverse sources to empower the model with different capabilities.

tion to  $490 \times 490$  for improved performance. For the Partial LoRA, we set a rank of 256 for all the linear layers in the LLM decoder block. Our training process involves a batch size of 4906 and spans across 2 epochs. The learning rate is initially set to increase to  $2 \times 10^{-4}$  within the first 1% of the training steps. Following this, it decreases to 0 according to a cosine decay strategy. To preserve the pre-existing knowledge of the vision encoder, we apply a layer-wise learning rate (LLDR) decay strategy and the decay factor is set to 0.90.

### 3.3. Supervised Fine-tuning

The pre-training phase aligns the visual feature with the language, enabling the Language Learning Model (LLM) to comprehend the content of the images. However, it still lacks the ability to effectively utilize the image information. To overcome this limitation, we introduce a range of vision-language tasks that the model engages in during the subsequent Supervised Fine-Tuning Stage. This stage comprises two sequential steps: Multi-task Training and Free-form Text-Image Composition. During this stage, we jointly fine-tune the vision encoder, LLM, and Partial LoRA.

**Multi-task Training.** As delineated in Table 2, the multi-task training dataset is assembled from various sources, aiming to equip the model with a broad spectrum of capabilities. Each task is structured as a conversational interaction, and the instructions are augmented with GPT-4 to enhance diversity. Concurrently, to maintain the original language capability, we also incorporate the supervised fine-tuning

Method	MathVista	AI2D	MMMU	MME	MMB	$MMB^{CN}$	SEED <sup>I</sup>	LLaVA <sup>W</sup>	QBench <sup>T</sup>	MM-Vet	HallB	ChartVQA
Open-Source Previous SOTA	<i>SPH-MOE</i> 8x7B 42.3	<i>Monkey</i> 10B 72.6	<i>Yi-VL</i> 34B 45.9	<i>WeMM</i> 6B <u>2066.6</u>	<i>L-Int2</i> 20B 75.1	<i>L-Int2</i> 20B 73.7	<i>SPH-2</i> 17B <u>74.8</u>	<i>CogVLM</i> 17B 73.9	<i>Int-XC</i> 8B 64.4	<i>CogVLM</i> 30B 56.8	<i>Monkey</i> 10B 58.4	<i>CogAgent</i> 18B 68.4
<i>Closed-source API</i>												
GPT-4V	<b>49.9</b>	<b>78.2</b>	<b>56.8</b>	1926.5	<b>77.0</b>	<b>74.4</b>	69.1	<b>93.1</b>	<b>74.1</b>	<b>67.7</b>	<b>65.8</b>	<b>78.5</b>
Gemini-Pro	45.2	73.9	<u>47.9</u>	1933.3	73.6	74.3	70.7	79.9	70.6	<u>64.3</u>	<u>63.9</u>	74.1
QwenVL-Plus	43.3	75.9	46.5	2183.3	67.0	70.7	72.7	73.7	68.9	<u>55.7</u>	56.4	<u>78.1</u>
Ours	<b>57.6</b>	<b>78.7</b>	42.0	<b>2242.7</b>	<b>79.6</b>	<b>77.6</b>	<b>75.9</b>	<u>81.8</u>	<u>72.5</u>	51.2	60.3	72.6

Table 3. **Comparison with closed-source APIs and previous open-source SOTAs.** Our InternLM-XComposer2 gets SOTA results in 6 of the 12 benchmarks with only 7B parameters, showing competitive results with current closed-source APIs and previous open-source SOTA MLLMs. The best results are **bold** and the second-best results are underlined.

data from InternLM2, which constitutes a fixed 10% of the total Supervised Fine-Tuning (SFT) data.

**Free-form Text-Image Composition.** To further enhance the model’s ability to follow instructions and compose free-form image-text content, we employ data from both pure-text conversation corpora and vision-language conversations, as outlined in Table 2. The dataset for free-form image-text composition is constructed following the methodology detailed in Section 3.4.

In our approach, we jointly train all the components with a batch size of 2048 over 3000 steps. Data from multiple sources are sampled in a weighted manner, with the weights based on the number of data from each source. The maximum learning rate is set to  $5 \times 10^{-5}$ , and each component has its own unique learning strategy. For the vision encoder, we set the Layer-wise Learning Rate Decay (LLDR) to 0.9, which aligns with the pretraining strategy. For the LLM, we employ a fixed learning rate scale factor of 0.2. This slows down the update of the LLM, achieving a balance between preserving its original capabilities and aligning it with vision knowledge.

### 3.4. Free-form Text-Image Composition

Free-form text-image composition refers to the combination of textual content and visual elements in a flexible and unrestrictive manner. Our model generates interleaved text and images, specifically customized to align with the text requirements provided by users, which may include elements such as a title, outline, and writing material, and optionally, any visual requirements like image resources.

To facilitate free-form text-image composition, we collect a wide range of high-quality and diverse in-house data across four key dimensions. These dimensions encompass:

**Varied Writing Styles.** Our data spans a multitude of writing styles, from academic papers to social media posts and poems, ensuring a rich and diverse collection of text and image contents.

**Flexible Text Editing.** Our dataset includes extensive examples of text editing, encompassing a wide spectrum of

modifications such as shortening, expanding, and rewriting.

**Complex Instruction Adherence.** We also capture instances of adhering to complex instructions to create content that caters to diverse demands like titles and outlines, encompassing both text and image-based compositions.

**Customization with Materials.** Our collection extends to materials used for personalized content creation, covering both text and images, enabling customizable and unique content creation experiences.

The distribution of data across the four dimensions is approximately equal, with a ratio of approximately 1:1:1:1. Our method follows previous work [95] to identify suitable positions for image insertion after generating the text content. A notable distinction in our approach is that when users provide their own image materials, these image materials are used for insertion instead of relying on retrieved images [95]. We also observe that having a high-resolution image input is not essential for text-image composition. Therefore, following the pre-training phase, we opt to down-sample the image input resolution to 224x224 during the SFT stage of free-form text-image composition.

## 4. Experiments

In this section, we validate the benchmark performance of our InternLM-XComposer2 after the supervised fine-tuning.

### 4.1. MLLM Benchmark results.

In Table.3 and Table.4, we compare our InternLM-XComposer2 on a list of benchmarks with both SOTA open-source MLLMs and closed-source APIs. Here we report results in MathVista[52], MMMU[91], AI2D[40], MME Perception (MME<sup>P</sup>) [27], MME Cognition (MME<sup>C</sup>)[27], MMBench (MMB) [51], MMBench-Chinese (MMB<sup>CN</sup>) [51], SEED-Bench Image Part (SEED<sup>I</sup>)[41], LLaVA-Bench In-the-Wild (LLaVA<sup>W</sup>) [49], QBench-Testset (QBench<sup>T</sup>)[85], MM-Vet [90], HallusionBench (HallB)[31], ChartQA[56], POPE[45].

**Comparison with Closed-Source APIs.** As shown in

Method	LLM	MathVista	MMMU	MME <sup>P</sup>	MME <sup>C</sup>	MMB	MMB <sup>CN</sup>	SEED <sup>I</sup>	LLaVA <sup>W</sup>	QBench <sup>T</sup>	MM-Vet	HallB
BLIP-2	FLAN-T5	-	35.7	1,293.8	290.0	-	-	46.4	38.1	-	22.4	-
InstructBLIP	Vicuna-7B	25.3	30.6	-	-	36.0	23.7	53.4	60.9	55.9	26.2	53.6
IDEFICS-80B	LLaMA-65B	26.2	24.0	-	-	54.5	38.1	52.0	56.9	-	39.7	46.1
Qwen-VL-Chat	Qwen-7B	33.8	35.9	1,487.5	360.7	60.6	56.7	58.2	67.7	61.7	47.3	56.4
LLaVA	Vicuna-7B	23.7	32.3	807.0	247.9	34.1	14.1	25.5	63.0	54.7	26.7	44.1
LLaVA-1.5	Vicuna-13B	26.1	36.4	1,531.3	295.4	67.7	63.6	68.2	70.7	61.4	35.4	46.7
ShareGPT4V	Vicuna-7B	25.8	36.6	<u>1,567.4</u>	376.4	68.8	62.2	69.7	72.6	-	37.6	49.8
CogVLM-17B	Vicuna-7B	34.7	37.3	-	-	65.8	55.9	68.8	<u>73.9</u>	-	<b>54.5</b>	55.1
LLaVA-XTuner	InernLM2-20B	24.6	39.4	-	-	<u>75.1</u>	<u>73.7</u>	<u>70.2</u>	63.7	-	37.2	47.7
Monkey-10B	Qwen-7B	<u>34.8</u>	<u>40.7</u>	1,522.4	<u>401.4</u>	72.4	67.5	68.9	33.5	-	33.0	58.4
InternLM-XC	InernLM-7B	29.5	35.6	1,528.4	391.1	74.4	72.4	66.1	53.8	<u>64.4</u>	35.2	<u>57.0</u>
Ours	InernLM2-7B	<b>57.6</b>	<b>42.0</b>	<b>1,712.0</b>	<b>530.7</b>	<b>79.6</b>	<b>77.6</b>	<b>75.9</b>	<b>81.8</b>	<b>72.5</b>	<u>51.2</u>	<b>60.3</b>

Table 4. **Comparison with open-source SOTA methods.** InternLM-XComposer2 outperforms competitors in 10 out of 11 benchmarks. The best results are **bold** and the second-best results are underlined.

Method	LLM	POPE	HallusionBench*
<i>Closed-source APIs</i>			
GPT-4V	-	-	65.8
Gemini-Pro	-	-	63.9
QwenVL-Plus	-	-	56.4
<i>Open-source MLLMs</i>			
InstructBLIP	Vicuna-7B	78.9	53.6
IDEFICS-80B	LLaMA-65B	-	46.1
Qwen-VL-Chat	Qwen-7B	-	56.4
LLaVA	Vicuna-7B	80.2	44.1
LLaVA-1.5	Vicuna-13B	85.9	46.7
InternLM-XC	InernLM-7B	-	57.0
Ours	InernLM2-7B	87.7	60.3

Table 5. **Hallucination Evaluation on POPE and HallusionBench.** InternLM-XComposer2 outperforms open-source MLLMs and performs on par with closed-source APIs. \* We skip the non-visual questions, following the setting in VLMEvalKit[18]

Table 3, InternLM-XComposer2 demonstrates competitiveness with Closed-Source APIs across numerous benchmarks. For instance, our model achieves a score of 57.6% on *MathVista* and 78.9 on *AI2D*, outperforming these APIs by a significant margin. Meanwhile, despite having only 7B parameters, our model attains a slightly worse score of 43.0% on the challenging college-level benchmark *MMMU*. The strong performance can be attributed to the superb knowledge acquired by the new InternLM2 LLM and the efficient PLoRA training strategy, which enabled us to align the LLM with image features while preserving its language capability.

**Comparison with Open-Source Models.** We also conduct a comprehensive comparison with open-source MLLMs under a similar model scale. As shown in Table 4, our model significantly outperforms existing open-source models, achieving state-of-the-art results across all benchmarks. Notably, InternLM-XComposer2 is the first model to achieve a score exceeding 1700 on the MME-Perception benchmark. Furthermore, it attained an accuracy of nearly 80% on the MMBench.

**Hallucination Evaluation.** Visual hallucination serves as a

Method	w/o Ref				w Ref					
	Avg.	C	R	UDF	LC	Avg.	C	UDF	LC	
GPT-4	6.32	5.22	5.98	7.17	7.47	5.98	5.30	5.55	6.51	7.08
QWen-72b-Chat	5.70	4.78	5.16	6.37	7.13	5.31	4.94	4.72	5.71	6.50
Yi-34b-Chat	6.03	4.91	5.68	6.79	7.35	5.71	5.03	5.22	6.18	6.87
Ours	<b>6.24</b>	5.11	6.12	7.03	7.45	<b>5.90</b>	5.21	5.76	6.27	6.93

Table 6. **Comparison on CreationBench [18].** We report the results with and without the GPT-4 referenced answer. We report the average score and other metrics including Creativity(C), Richness(R), User Demand Fulfillment (UDF), and Logical Coherence(LC).

crucial metric in the evaluation of an MLLM. In this report, we present the results obtained on both POPE and HallusionBench. As indicated in Table 5, our model achieves an average F1-score of 87.7 across the three tracks of POPE, setting a new state-of-the-art (SOTA) benchmark. In the case of HallusionBench, our model surpasses the accuracy of all open-source models, establishing itself as the new SOTA. Furthermore, it outperforms the closed-source API, QwenVL-Plus.

## 4.2. CreationBench Results

We use the CreationBench benchmark from OpenCompass [18] to assess the writing ability of our InternLM-XComposer2. As shown in Table 6, the results indicate that our approach not only excels in overall creativity but also significantly improves upon key metrics over previous open-source LLMs. When compared without the GPT-4 referenced answer, our method scored an impressive 6.24 overall. Even when evaluated with the GPT-4 reference, our method maintained strong performance, achieving scores that underscore its ability to generate responses with high levels of creativity and logical structure, critical for user engagement and satisfaction in conversational AI applications.

## 4.3. Qualitative results.

Please refer to the Appendix for our qualitative results of the free-form image-text compositions and multimodal conversations.

## 5. Conclusion

In this paper, we present InternLM-XComposer2, which demonstrates its exceptional capabilities in the field of vision-language understanding and free-form text-image composition. Our proposed innovative Partial LoRA (PLoRA) approach, which applies additional LoRA parameters exclusively to image tokens, has proven effective in preserving the integrity of pre-trained language knowledge while striking a balance between precise vision understanding and text composition with literary talent. Our model’s performance across various benchmarks not only significantly outperforms existing multimodal models but also matches or even surpasses GPT-4V and Gemini Pro in certain assessments, underscoring its remarkable proficiency in the realm of multimodal understanding. This research opens up new possibilities for highly customizable content creation and paves the way for future advancements in the MLLM field. The potential applications of InternLM-XComposer2 are vast and exciting, promising a future where AI can understand and generate high-quality long-text multi-modal content with ease and precision.

## References

- [1] Harsh Agrawal, Karan Desai, Yufei Wang, Xinlei Chen, Rishabh Jain, Mark Johnson, Dhruv Batra, Devi Parikh, Stefan Lee, and Peter Anderson. Nocaps: Novel object captioning at scale. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 8948–8957, 2019. [4](#)
- [2] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katie Millican, Malcolm Reynolds, Roman Ring, Eliza Rutherford, Serkan Cabi, Tengda Han, Zhitao Gong, Sina Samangooei, Marianne Monteiro, Jacob Menick, Sébastien Borgeaud, Andrew Brock, Aida Nematzadeh, Sahand Sharifzadeh, Mikolaj Binkowski, Ricardo Barreira, Oriol Vinyals, Andrew Zisserman, and Karen Simonyan. Flamingo: a visual language model for few-shot learning, 2022. [3](#)
- [3] Aida Amini, Saadia Gabriel, Peter Lin, Rik Koncel-Kedziorski, Yejin Choi, and Hannaneh Hajishirzi. Mathqa: Towards interpretable math word problem solving with operation-based formalisms. *arXiv preprint arXiv:1905.13319*, 2019. [4](#)
- [4] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In *International Conference on Computer Vision (ICCV)*, 2015. [4](#)
- [5] Anas Awadalla, Irena Gao, Josh Gardner, Jack Hessel, Yusuf Hanafy, Wanrong Zhu, Kalyani Marathe, Yonatan Bitton, Samir Gadre, Shiori Sagawa, Jenia Jitsev, Simon Kornblith, Pang Wei Koh, Gabriel Ilharco, Mitchell Wortsman, and Ludwig Schmidt. Openflamingo: An open-source framework for training large autoregressive vision-language models. *arXiv.org*, 2023. [3](#)
- [6] Jinze Bai, Shuai Bai, Shusheng Yang, Shijie Wang, Sinan Tan, Peng Wang, Junyang Lin, Chang Zhou, and Jingren Zhou. Qwen-vl: A frontier large vision-language model with versatile abilities. *arXiv.org*, 2023. [2, 3](#)
- [7] Baichuan. Baichuan 2: Open large-scale language models. *arXiv.org*, 2023. [2, 3](#)
- [8] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in Neural Information Processing Systems (NeurIPS)*, 33:1877–1901, 2020. [2](#)
- [9] Jun Chen, Deyao Zhu, Xiaoqian Shen, Xiang Li, Zechu Liu, Pengchuan Zhang, Raghuraman Krishnamoorthi, Vikas Chandra, Yunyang Xiong, and Mohamed Elhoseiny. Minigpt-v2: large language model as a unified interface for vision-language multi-task learning. *arXiv preprint arXiv:2310.09478*, 2023. [3](#)
- [10] Keqin Chen, Zhao Zhang, Weili Zeng, Richong Zhang, Feng Zhu, and Rui Zhao. Shikra: Unleashing multimodal llm’s referential dialogue magic. *arXiv.org*, 2023. [3](#)
- [11] Lin Chen, Jisong Li, Xiaoyi Dong, Pan Zhang, Conghui He, Jiaqi Wang, Feng Zhao, and Dahua Lin. Sharegpt4v: Improving large multi-modal models with better captions. *arXiv preprint arXiv:2311.12793*, 2023. [3, 4](#)

- [12] Xi Chen, Josip Djolonga, Piotr Padlewski, Basil Mustafa, Soravit Changpinyo, Jialin Wu, Carlos Riquelme Ruiz, Sebastian Goodman, Xiao Wang, Yi Tay, Siamak Shakeri, Mostafa Dehghani, Daniel Salz, Mario Lucic, Michael Tschannen, Arsha Nagrani, Hexiang Hu, Mandar Joshi, Bo Pang, Ceslee Montgomery, Paulina Pietrzyk, Marvin Ritter, AJ Piergiovanni, Matthias Minderer, Filip Pavetic, Austin Waters, Gang Li, Ibrahim Alabdulmohsin, Lucas Beyer, Julien Amelot, Kenton Lee, Andreas Peter Steiner, Yang Li, Daniel Keysers, Anurag Arnab, Yuanzhong Xu, Keran Rong, Alexander Kolesnikov, Mojtaba Seyedhosseini, Anelia Angelova, Xiaohua Zhai, Neil Houlsby, and Radu Soricut. Pali-x: On scaling up a multilingual vision and language model, 2023. 3
- [13] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollar, and C. Lawrence Zitnick. Microsoft coco captions: Data collection and evaluation server, 2015. 4
- [14] Xi Chen, Xiao Wang, Lucas Beyer, Alexander Kolesnikov, Jialin Wu, Paul Voigtlaender, Basil Mustafa, Sebastian Goodman, Ibrahim Alabdulmohsin, Piotr Padlewski, Daniel Salz, Xi Xiong, Daniel Vlasic, Filip Pavetic, Keran Rong, Tianli Yu, Daniel Keysers, Xiaohua Zhai, and Radu Soricut. Pali-3 vision language models: Smaller, faster, stronger, 2023. 3
- [15] Xi Chen, Xiao Wang, Soravit Changpinyo, AJ Piergiovanni, Piotr Padlewski, Daniel Salz, Sebastian Goodman, Adam Gryener, Basil Mustafa, Lucas Beyer, Alexander Kolesnikov, Joan Puigcerver, Nan Ding, Keran Rong, Hassan Akbari, Gaurav Mishra, Linting Xue, Ashish Thapliyal, James Bradbury, Weicheng Kuo, Mojtaba Seyedhosseini, Chao Jia, Burcu Karagol Ayan, Carlos Riquelme, Andreas Steiner, Anelia Angelova, Xiaohua Zhai, Neil Houlsby, and Radu Soricut. Pali: A jointly-scaled multilingual language-image model, 2023. 3
- [16] Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhang-hao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%\* chatgpt quality, March 2023. 2, 4
- [17] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv.org*, 2022. 2
- [18] OpenCompass Contributors. Opencompass: A universal evaluation platform for foundation models. <https://github.com/open-compass/opencompass>, 2023. 2, 6
- [19] QWen Contributors. Qwen-vl-plus. <https://huggingface.co/spaces/Qwen/Qwen-VL-Plus>, year=2023. 2
- [20] XTuner Contributors. Xtuner: A toolkit for efficiently fine-tuning llm. <https://github.com/InternLM/xtuner>, 2023. 3
- [21] Wenliang Dai, Junnan Li, Dongxu Li, Anthony Meng Huat Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale Fung, and Steven Hoi. Instructblip: Towards general-purpose vision-language models with instruction tuning, 2023. 2, 3
- [22] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv.org*, 2018. 2
- [23] Runpei Dong, Chunrui Han, Yuang Peng, Zekun Qi, Zheng Ge, Jinrong Yang, Liang Zhao, Jianjian Sun, Hongyu Zhou, Haoran Wei, Xiangwen Kong, Xiangyu Zhang, Kaisheng Ma, and Li Yi. Dreamllm: Synergistic multimodal comprehension and creation. *arXiv preprint arXiv:2309.11499*, 2023. 3
- [24] Danny Driess, Fei Xia, Mehdi S. M. Sajjadi, Corey Lynch, Aakanksha Chowdhery, Brian Ichter, Ayzaan Wahid, Jonathan Tompson, Quan Vuong, Tianhe Yu, Wenlong Huang, Yevgen Chebotar, Pierre Sermanet, Daniel Duckworth, Sergey Levine, Vincent Vanhoucke, Karol Hausman, Marc Toussaint, Klaus Greff, Andy Zeng, Igor Mordatch, and Pete Florence. Palm-e: An embodied multimodal language model. In *arXiv preprint arXiv:2303.03378*, 2023. 3
- [25] Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhang Qiu, Zhilin Yang, and Jie Tang. Glm: General language model pretraining with autoregressive blank infilling. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 320–335, 2022. 2
- [26] Yuxin Fang, Wen Wang, Binhu Xie, Quan Sun, Ledell Wu, Xinggang Wang, Tiejun Huang, Xinlong Wang, and Yue Cao. Eva: Exploring the limits of masked visual representation learning at scale. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 19358–19369, 2023. 3
- [27] Chaoyou Fu, Peixian Chen, Yunhang Shen, Yulei Qin, Mengdan Zhang, Xu Lin, Zhenyu Qiu, Wei Lin, Jinrui Yang, Xiaowu Zheng, Ke Li, Xing Sun, and Rongrong Ji. Mme: A comprehensive evaluation benchmark for multimodal large language models. *arXiv preprint arXiv:2306.13394*, 2023. 2, 5
- [28] Chaoyou Fu, Renrui Zhang, Zihan Wang, Yubo Huang, Zhengye Zhang, Longtian Qiu, Gaoxiang Ye, Yunhang Shen, Mengdan Zhang, Peixian Chen, Sirui Zhao, Shao-hui Lin, Deqiang Jiang, Di Yin, Peng Gao, Ke Li, Hongsheng Li, and Xing Sun. A challenger to gpt-4v? early explorations of gemini in visual expertise. *arXiv preprint arXiv:2312.12436*, 2023. 3
- [29] Peng Gao, Jiaming Han, Renrui Zhang, Ziyi Lin, Shijie Geng, Aojun Zhou, W. Zhang, Pan Lu, Conghui He, Xiangyu Yue, Hongsheng Li, and Yu Jiao Qiao. Llama-adapter v2: Parameter-efficient visual instruction model. *ArXiv*, abs/2304.15010, 2023. 2
- [30] Yuying Ge, Yixiao Ge, Ziyun Zeng, Xintao Wang, and Ying Shan. Planting a seed of vision in large language model. 3
- [31] Tianrui Guan, Fuxiao Liu, Xiyang Wu, Ruiqi Xian, Zongxia Li, Xiaoyu Liu, Xijun Wang, Lichang Chen, Furong Huang, Yaser Yacoob, Dinesh Manocha, and Tianyi Zhou. Hallusionbench: An advanced diagnostic suite for entangled language hallucination & visual illusion in large vision-language models, 2023. 2, 5
- [32] Conghui He, Zhenjiang Jin, Chaoxi Xu, Jiantao Qiu, Bin Wang, Wei Li, Hang Yan, Jiaqi Wang, and Da Lin. Wan-

- juan: A comprehensive multimodal dataset for advancing english and chinese large models. *ArXiv*, abs/2308.10755, 2023. 4
- [33] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022. 2, 3
- [34] Qidong Huang, Xiaoyi Dong, Pan Zhang, Bin Wang, Conghui He, Jiaqi Wang, Dahua Lin, Weiming Zhang, and Nenghai Yu. Opera: Alleviating hallucination in multi-modal large language models via over-trust penalty and retrospection-allocation. *arXiv preprint arXiv:2311.17911*, 2023. 3
- [35] Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019. 4
- [36] Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc Le, Yun-Hsuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. In *Proceedings of the International Conference on Machine learning (ICML)*, pages 4904–4916. PMLR, 2021. 3
- [37] Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lampe, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mistral 7b, 2023. 2
- [38] Albert Q Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, et al. Mixtral of experts. *arXiv preprint arXiv:2401.04088*, 2024. 2
- [39] Kushal Kafle, Brian Price, Scott Cohen, and Christopher Kanan. Dvqa: Understanding data visualizations via question answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5648–5656, 2018. 4
- [40] Aniruddha Kembhavi, Mike Salvato, Eric Kolve, Minjoon Seo, Hannaneh Hajishirzi, and Ali Farhadi. A diagram is worth a dozen images. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14*, pages 235–251. Springer, 2016. 2, 4, 5
- [41] Bohao Li, Rui Wang, Guangzhi Wang, Yuying Ge, Yixiao Ge, and Ying Shan. Seed-bench: Benchmarking multi-modal llms with generative comprehension, 2023. 2, 5
- [42] Bo Li, Yuanhan Zhang, Liangyu Chen, Jinghao Wang, Jingkang Yang, and Ziwei Liu. Otter: A multi-modal model with in-context instruction tuning. *arXiv.org*, 2023. 3
- [43] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *Proceedings of the International Conference on Machine learning (ICML)*, pages 12888–12900. PMLR, 2022. 3
- [44] Liunian Harold Li\*, Pengchuan Zhang\*, Haotian Zhang\*, Jianwei Yang, Chunyuan Li, Yiwu Zhong, Lijuan Wang, Lu Yuan, Lei Zhang, Jenq-Neng Hwang, Kai-Wei Chang, and Jianfeng Gao. Grounded language-image pre-training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022. 3
- [45] Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. Evaluating object hallucination in large vision-language models, 2023. 2, 5
- [46] Zhang Li, Biao Yang, Qiang Liu, Zhiyin Ma, Shuo Zhang, Jingxu Yang, Yabo Sun, Yuliang Liu, and Xiang Bai. Monkey: Image resolution and text label are important things for large multi-modal models. *arXiv preprint arXiv:2311.06607*, 2023. 3
- [47] Fuxiao Liu, Xiaoyang Wang, Wenlin Yao, Jianshu Chen, Kaiqiang Song, Sangwoo Cho, Yaser Yacoob, and Dong Yu. Mmc: Advancing multimodal chart understanding with large-scale instruction tuning. *arXiv preprint arXiv:2311.10774*, 2023. 4
- [48] Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning. *arXiv preprint arXiv:2310.03744*, 2023. 2
- [49] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *arXiv.org*, 2023. 2, 3, 4, 5
- [50] Shilong Liu, Zhaoyang Zeng, Tianhe Ren, Feng Li, Hao Zhang, Jie Yang, Chunyuan Li, Jianwei Yang, Hang Su, Jun Zhu, et al. Grounding dino: Marrying dino with grounded pre-training for open-set object detection. *arXiv.org*, 2023. 3
- [51] Yuan Liu, Haodong Duan, Yuanhan Zhang, Bo Li, Songyang Zhnag, Wangbo Zhao, Yike Yuan, Jiaqi Wang, Conghui He, Ziwei Liu, Kai Chen, and Dahua Lin. Mmbench: Is your multi-modal model an all-around player? *arXiv:2307.06281*, 2023. 2, 5
- [52] Pan Lu, Hritik Bansal, Tony Xia, Jiacheng Liu, Chunyuan Li, Hannaneh Hajishirzi, Hao Cheng, Kai-Wei Chang, Michel Galley, and Jianfeng Gao. Mathvista: Evaluating mathematical reasoning of foundation models in visual contexts. In *International Conference on Learning Representations (ICLR)*, 2024. 2, 5
- [53] Pan Lu, Ran Gong, Shibiao Jiang, Liang Qiu, Siyuan Huang, Xiaodan Liang, and Song-Chun Zhu. Inter-gps: Interpretable geometry problem solving with formal language and symbolic reasoning. In *The 59th Annual Meeting of the Association for Computational Linguistics (ACL)*, 2021. 4
- [54] Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to explain: Multimodal reasoning via thought chains for science question answering. *Advances in Neural Information Processing Systems*, 35:2507–2521, 2022. 4
- [55] Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *Proceedings of the IEEE/cvf conference on computer vision and pattern recognition*, pages 3195–3204, 2019. 4
- [56] Ahmed Masry, Do Xuan Long, Jia Qing Tan, Shafiq Joty, and Enamul Hoque. Chartqa: A benchmark for question answering about charts with visual and logical reasoning. *arXiv preprint arXiv:2203.10244*, 2022. 2, 4, 5

- [57] OpenAI. Chatgpt. <https://openai.com/blog/chatgpt>, 2022. 2
- [58] OpenAI. Gpt-4 technical report, 2023. 1, 2, 3
- [59] Vicente Ordonez, Girish Kulkarni, and Tamara L. Berg. Im2text: Describing images using 1 million captioned photographs. In *Neural Information Processing Systems (NIPS)*, 2011. 4
- [60] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems (NeurIPS)*, 35:27730–27744, 2022. 2
- [61] Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro Cappelli, Hamza Alobeidli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Lauvay. The refinedweb dataset for falcon llm: Outperforming curated corpora with web data, and web data only, 2023. 3
- [62] Zhiliang Peng, Wenhui Wang, Li Dong, Yaru Hao, Shaohan Huang, Shuming Ma, and Furu Wei. Kosmos-2: Grounding multimodal large language models to the world. *arXiv.org*, 2023. 3
- [63] Zhangyang Qi, Ye Fang, Zeyi Sun, Xiaoyang Wu, Tong Wu, Jiaqi Wang, Dahua Lin, and Hengshuang Zhao. Gpt4point: A unified framework for point-language understanding and generation, 2023. 3
- [64] Zhangyang Qi, Ye Fang, Mengchen Zhang, Zeyi Sun, Tong Wu, Ziwei Liu, Dahua Lin, Jiaqi Wang, and Hengshuang Zhao. Gemini vs gpt-4v: A preliminary comparison and combination of vision-language models through qualitative cases, 2023. 3
- [65] Qwen. Introducing qwen-7b: Open foundation and human-aligned models (of the state-of-the-arts), 2023. 2
- [66] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *Proceedings of the International Conference on Machine learning (ICML)*, pages 8748–8763. PMLR, 2021. 3
- [67] Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. 2018. 2
- [68] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research (JMLR)*, 21(1):5485–5551, 2020. 2
- [69] Christoph Schuhmann, Richard Vencu, Romain Beaumont, Robert Kaczmarczyk, Clayton Mullis, Aarush Katta, Theo Coombes, Jenia Jitsev, and Aran Komatsuzaki. Laion-400m: Open dataset of clip-filtered 400 million image-text pairs. *arXiv preprint arXiv:2111.02114*, 2021. 4
- [70] Dustin Schwenk, Apoorv Khandelwal, Christopher Clark, Kenneth Marino, and Roozbeh Mottaghi. A-okvqa: A benchmark for visual question answering using world knowledge. In *European Conference on Computer Vision*, pages 146–162. Springer, 2022. 4
- [71] Sanket Shah, Anand Mishra, Naganand Yadati, and Partha Pratim Talukdar. Kvqa: Knowledge-aware visual question answering. In *Proceedings of the AAAI conference on artificial intelligence*, 2019. 4
- [72] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2556–2565, 2018. 4
- [73] Oleksii Sidorov, Ronghang Hu, Marcus Rohrbach, and Amanpreet Singh. Textcaps: a dataset for image captioning with reading comprehension. In *Computer Vision-ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part II 16*, pages 742–758. Springer, 2020. 4
- [74] Quan Sun, Qiying Yu, Yufeng Cui, Fan Zhang, Xiaosong Zhang, Yueze Wang, Hongcheng Gao, Jingjing Liu, Tiejun Huang, and Xinlong Wang. Generative pretraining in multimodality. Jul 2023. 3
- [75] Zeyi Sun, Ye Fang, Tong Wu, Pan Zhang, Yuhang Zang, Shu Kong, Yuanjun Xiong, Dahua Lin, and Jiaqi Wang. Alpha-CLIP: A clip model focusing on wherever you want. *arXiv preprint arXiv:2312.03818*, 2023. 3
- [76] Gemini Team. Gemini: A family of highly capable multimodal models, 2023. 1, 2
- [77] InternLM Team. Internlm: A multilingual language model with progressively enhanced capabilities. <https://github.com/InternLM/InternLM>, 2023. 1, 2, 4
- [78] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv.org*, 2023. 2
- [79] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models, 2023. 2
- [80] Bin Wang, Fan Wu, Xiao Han, Jiahui Peng, Huaping Zhong, Pan Zhang, Xiaoyi Dong, Weijia Li, Wei Li, Jiaqi Wang, et al. Vigc: Visual instruction generation and correction. *arXiv.org*, 2023. 3
- [81] Junke Wang, Lingchen Meng, Zejia Weng, Bo He, Zuxuan Wu, and Yu-Gang Jiang. To see is to believe: Prompting gpt-4v for better visual instruction tuning. *arXiv preprint arXiv:2311.07574*, 2023. 4
- [82] Weihan Wang, Qingsong Lv, Wenmeng Yu, Wenyi Hong, Ji Qi, Yan Wang, Junhui Ji, Zhuoyi Yang, Lei Zhao, Xixuan Song, Jiazheng Xu, Bin Xu, Juanzi Li, Yuxiao Dong, Ming Ding, and Jie Tang. Coglml: Visual expert for pretrained language models, 2023. 2, 3
- [83] Haoran Wei, Lingyu Kong, Jinyue Chen, Liang Zhao, Zheng Ge, Jinrong Yang, Jianjian Sun, Chunrui Han, and Xiangyu Zhang. Vary: Scaling up the vision vocabulary for large vision-language models. *arXiv preprint arXiv:2312.06109*, 2023. 3
- [84] Tianwen Wei, Liang Zhao, Lichang Zhang, Bo Zhu, Lijie Wang, Haihua Yang, Biye Li, Cheng Cheng, Weiwei Lü, Rui Hu, et al. Skywork: A more open bilingual foundation

- model. *arXiv preprint arXiv:2310.19341*, 2023. 3
- [85] Haoning Wu, Zicheng Zhang, Erli Zhang, Chaofeng Chen, Liang Liao, Annan Wang, Chunyi Li, Wenxiu Sun, Qiong Yan, Guangtao Zhai, et al. Q-bench: A benchmark for general-purpose foundation models on low-level vision. *arXiv preprint arXiv:2309.14181*, 2023. 2, 5
- [86] Qinghao Ye, Haiyang Xu, Guohai Xu, Jiabo Ye, Ming Yan, Yiyang Zhou, Junyang Wang, Anwen Hu, Pengcheng Shi, Yaya Shi, et al. mplug-owl: Modularization empowers large language models with multimodality. *arXiv.org*, 2023. 3
- [87] Shukang Yin, Chaoyou Fu, Sirui Zhao, Tong Xu, Hao Wang, Dianbo Sui, Yunhang Shen, Ke Li, Xing Sun, and Enhong Chen. Woodpecker: Hallucination correction for multimodal large language models. *arXiv preprint arXiv:2310.16045*, 2023. 3
- [88] Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*, 2:67–78, 2014. 4
- [89] Lili Yu, Bowen Shi, Ramakanth Pasunuru, Benjamin Muller, Olga Golovneva, Tianlu Wang, Arun Babu, Binh Tang, Brian Karrer, Shelly Sheynin, Candace Ross, Adam Polyak, Russell Howes, Vasu Sharma, Puxin Xu, Hovhannes Tamoyan, Oron Ashual, Uriel Singer, Shang-Wen Li, Susan Zhang, Gargi Ghosh, Yaniv Taigman, Maryam Fazel-Zarandi, Asli Celikyilmaz, Luke Zettlemoyer, and Armen Aghajanyan. Scaling autoregressive multi-modal models: Pretraining and instruction tuning. 3
- [90] Weihao Yu, Zhengyuan Yang, Linjie Li, Jianfeng Wang, Kevin Lin, Zicheng Liu, Xinchao Wang, and Lijuan Wang. Mm-vet: Evaluating large multimodal models for integrated capabilities. *arXiv preprint arXiv:2308.02490*, 2023. 2, 5
- [91] Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, Cong Wei, Botao Yu, Ruibin Yuan, Renliang Sun, Ming Yin, Boyuan Zheng, Zhenzhu Yang, Yibo Liu, Wenhao Huang, Huan Sun, Yu Su, and Wenhua Chen. Mmmu: A massive multi-discipline multi-modal understanding and reasoning benchmark for expert agi. *arXiv preprint arXiv:2311.16502*, 2023. 2, 5
- [92] Yuhang Zang, Wei Li, Jun Han, Kaiyang Zhou, and Chen Change Loy. Contextual object detection with multimodal large language models. *arXiv preprint arXiv:2305.18279*, 2023. 3
- [93] Aohan Zeng, Xiao Liu, Zhengxiao Du, Zihan Wang, Hanyu Lai, Ming Ding, Zhuoyi Yang, Yifan Xu, Wendi Zheng, Xiao Xia, Weng Lam Tam, Zixuan Ma, Yufei Xue, Jidong Zhai, Wenguang Chen, Zhiyuan Liu, Peng Zhang, Yuxiao Dong, and Jie Tang. GLM-130b: An open bilingual pre-trained model. In *The Eleventh International Conference on Learning Representations (ICLR)*, 2023. 2
- [94] Haotian Zhang, Pengchuan Zhang, Xiaowei Hu, Yen-Chun Chen, Liunian Li, Xiyang Dai, Lijuan Wang, Lu Yuan, Jenq-Neng Hwang, and Jianfeng Gao. Glipv2: Unifying localization and vision-language understanding. *Advances in Neural Information Processing Systems (NeurIPS)*, 35:36067–36080, 2022. 3
- [95] Pan Zhang, Xiaoyi Dong, Bin Wang, Yuhang Cao, Chao Xu, Linke Ouyang, Zhiyuan Zhao, Shuangrui Ding, Songyang Zhang, Haodong Duan, Hang Yan, et al. Internlm-xcomposer: A vision-language large model for advanced text-image comprehension and composition. *arXiv preprint arXiv:2309.15112*, 2023. 2, 3, 4, 5
- [96] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuhui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. OPT: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*, 2022. 2
- [97] Haozhe Zhao, Zefan Cai, Shuzheng Si, Xiaojian Ma, Kaikai An, Liang Chen, Zixuan Liu, Sheng Wang, Wenjuan Han, and Baobao Chang. Mmicl: Empowering vision-language model with multi-modal in-context learning. *arXiv.org*, 2023. 3
- [98] Zhiyuan Zhao, Linke Ouyang, Bin Wang, Siyuan Huang, Pan Zhang, Xiaoyi Dong, Jiaqi Wang, and Conghui He. Mllm-dataengine: An iterative refinement approach for mllm. *arXiv.org*, 2023. 3
- [99] Zhiyuan Zhao, Bin Wang, Linke Ouyang, Xiaoyi Dong, Jiaqi Wang, and Conghui He. Beyond hallucinations: Enhancing lylms through hallucination-aware direct preference optimization. *arXiv preprint arXiv:2311.16839*, 2023. 3
- [100] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv.org*, 2023. 2, 3

Please write a blog based on the title: French Pastries: A Sweet Indulgence

## French Pastries: A Sweet Indulgence

French pastries are something that everyone should indulge in at least once in their lifetime. The delicate flavors and beautiful presentation of these pastries make them the perfect treat for any occasion. From croissants to macarons, éclairs to tarts, French pastries come in a variety of shapes and sizes. These sweet delights are not only delicious but also incredibly addictive. It's hard to resist just one pastry when there are so many to choose from! Whether you're looking for a quick breakfast on the go or a decadent dessert after dinner, French pastries are sure to satisfy your cravings. So why not treat yourself to some French pastries today? You won't regret it!



### Croissants

The croissant is a crescent-shaped French pastry that has become one of the most well-known French pastries in the world. This buttery, flaky pastry is created by laminating dough with layers of butter; this process creates beautiful layers and flakiness when the croissant bakes. In France, croissants are typically served for breakfast or as a snack. Croissants can be eaten plain or topped with sugar, jam, Nutella, or other spreads. While croissants may seem like an indulgent treat, they're actually relatively easy to make at home. It's important to note that there are some variations on how to make croissants, including sweeter versions such as chocolate croissants and almond croissants.



### Macarons

Macarons are small, colorful cookies that are made with almond flour and filled with a variety of fillings such as ganache, buttercream, or jam. The delicate texture of these pastries make them perfect for pairing with coffee or tea. French Macarons are traditionally associated with Parisian cafes, where they can be found in an array of flavors ranging from classic to experimental.



### Éclairs

What are Éclairs? Éclairs (French pronunciation: (eklɛʁ)) are a type of pastry that originated in France and is still widely consumed there. They are long, thin pastries that are filled with cream or pastry cream. The exterior has a crispy coating while the interior is soft. There are many ways to make éclairs, but one thing remains constant—they have an unforgettable taste!



### Tarts

Tarts are open-faced pies that are typically filled with fruit or custard. They can be either sweet or savory, but the sweet versions are definitely more popular in France. There are many types of tarts in French cuisine: apple tart (tarte Tatin), almond tart (tarte amandine), chocolate tart (tarte au chocolat), cheese tart (tarte aux fromages) and many others.



### Pain au Chocolat

Pain au chocolat is a French pastry that consists of a crescent-shaped roll filled with chocolate. It's similar to a croissant but has a rich chocolate filling that adds an extra layer of decadence. The texture of the chocolate can be anything from soft and creamy to hard and crunchy depending on personal preference. The buttery, flaky crust makes it a deliciously indulgent treat for any time of day.

In conclusion, French pastries are a sweet indulgence that should not be missed. Whether you are looking for something light like a croissant or something more substantial like a tart, there is sure to be a French pastry that will satisfy your cravings. So why not head to your local bakery and indulge in some French pastry goodness?

Figure 3. Interleaved composition generated by InternLM-XComposer2.

根据以下标题：“中国水墨画：流动的诗意与东方美学”，创作长文章，字数不少于800字。请结合以下文本素材：

“水墨画是由水和墨调配成不同深浅的墨色所画出的画，是绘画的一种形式，更多时候，水墨画被视为中国传统绘画，也就是国画的代表。也称国画，中国画。墨水墨是中国传统画之一。墨水是国画的起源，以笔墨运用的技法基础画成墨水墨。线条中锋笔，侧锋笔，顺锋和逆锋，点染，擦，破墨，拨墨的技法。墨于水的变化分为五色。画成作品，题款，盖章。就是完整的墨水墨作品。

基本的水墨画，仅有水与墨，黑与白色，但进阶的水墨画，也有工笔花鸟画，色彩缤纷。后者有时也称为彩墨画。在中国画中，以中国画特有的材料之一，墨为主要原料加以清水的多少引为浓墨、淡墨、干墨、湿墨、焦墨等，画出不同浓淡（黑、白、灰）层次。别有一番韵味称为“墨韵”。而形成水墨为主的一种绘画形式。”

## 中国水墨画：流动的诗意与东方美学

中国的传统绘画，特别是水墨画，被誉为“墨韵之舞”，以笔墨挥洒、线条交织的形式，展现了中国特有的审美情趣和文化内涵。水墨画是一种独特的艺术形式，它不仅体现了中国传统文化的精髓，也彰显了东方的美学观念和哲学思想。在这篇文章中，我们将深入探讨水墨画的艺术特点，及其在中国文化中的重要地位。



### 起源与发展

水墨画的历史可以追溯到中国古代的战国时期（公元前475年—公元前221年）。当时的绘画主要是用毛笔在绢或纸上绘制，而颜料则是从矿物、植物和动物中提取。随着时代的发展，绘画技法不断丰富，其中最重要的贡献之一就是墨的发现和使用。据传，秦始皇统一六国后，下令烧毁书籍，但一位书生藏起了一本珍贵的古书。这本古书后来被无意中丢弃，落入水中被泡湿。当书生捞起书页时，意外地发现上面的文字并未被水破坏，反而更加清晰了。这个故事告诉我们，水与墨的搭配是创造奇迹的关键。从此以后，中国人开始将水和墨结合起来创作出具有独特韵味的画作。



### 核心元素

水墨画的核心元素包括笔法、墨色和构图。首先，笔法在水墨画中至关重要。不同的笔触和笔力能够产生丰富的视觉效果，如粗犷豪放的皴擦，细腻柔美的点染等。其次，墨色的运用也是水墨画的精髓所在。通过调节水的多少，可以产生浓淡干湿的变化，创造出深邃神秘的氛围。最后，构图则决定了画面的整体布局和意境表达。合理的构图能够引导观者的视线流动，增强画面的艺术感染力。



### 技法与表现力

水墨画的技法非常多样化，常见的有泼墨、破墨、积墨、宿墨、枯墨等。这些技法各有特色，能够产生不同的效果。例如，泼墨适用于表现山峦起伏的大气磅礴；破墨则适合描绘树木枝叶的繁茂纷杂；积墨则多用于营造厚重深邃的山水气氛。此外，水墨画还常常结合诗词歌赋，形成一种诗情画意的境界。这种融合不仅提升了画作的意境，也让欣赏者能够更好地领略到其中的文化内涵。



### 价值与意义

水墨画作为中国传统文化的瑰宝，不仅是中国艺术的代表，更是世界文化艺术宝库中的一颗璀璨明珠。它的价值不仅仅在于其独特的艺术风格和技术手段，更在于其所承载的深厚文化底蕴和精神内涵。通过欣赏水墨画，人们不仅可以感受到艺术家对自然的感悟和对生命的思考，也能领悟到中国哲学的智慧和道德准则。因此，保护和传承水墨画这一宝贵的文化遗产显得尤为重要。



### 结语

综上所述，水墨画作为一门古老的艺术形式，不仅具有独特的审美价值，更是中国传统文化的重要组成部分。它的魅力不仅体现在技艺的高超上，更在于其背后所蕴含的深刻思想和文化内涵。让我们共同努力，让这门古老而又鲜活的艺术形式得以传承并发扬光大。



Figure 4. Interleaved composition generated by InternLM-XComposer2.

Please write a English poetry based on Rabindranath Tagore's classic poem: "If you shed tears when you miss the sun, you also miss the stars.", no less than 10 sentences.

When the sun sets, the sky turns to dark  
And the tears that you shed, leave a mark



But if you look up, you'll see the stars  
Twinkling in the night, like precious pearls  
The tears that you shed, can blind your sight  
And you may miss the beauty that's in sight  
But if you look up, you'll see the stars



Shining bright, like a beacon from afar  
So don't be sad when the sun is gone  
And don't shed tears for what's done  
Instead, look up and see the stars  
That light up the night, like shining stars  
The tears that you shed, can be replaced  
By the beauty of the stars, that you can embrace  
So don't miss the sun, but look up to the stars  
And find the beauty that's waiting, near and far.



Please write a English poetry based on Rabindranath Tagore's classic poem: "If you shed tears when you miss the sun, you also miss the stars.", no less than 10 sentences.

The mountains rise majestically,  
Their peaks shrouded in mist and cloud,



The valleys below stretch far and wide,  
A tapestry of green and gold.  
The rivers flow with gentle grace,  
Their currents carving through the earth,  
Carrying life and beauty to all,



A symphony of nature's worth.  
The forests stand in solemn grandeur,  
Their leaves rustling in the breeze,  
A living testament to time,  
A place of peace and tranquility.



So let us not weep for what is lost,  
But cherish what remains,  
For life is fleeting, but the world,  
Is a place of endless wonders and charms.



Figure 5. Interleaved composition generated by InternLM-XComposer2.

请根据给定标题：“熊猫：自然界的温柔使者”，写一篇长文章。首先，详细介绍熊猫的基本特征，如外貌，习性等。然后，探讨熊猫的自然栖息地及其面临的环境挑战，包括栖息地丧失和气候变化等问题。之后，详细讨论熊猫的保护工作现状，包括建立自然保护区，大熊猫的人工繁育等。最后，分析熊猫在中国和世界范围内的文化影响。字数不少于800字。

## 熊猫：自然界的温柔使者

大熊猫，熊科哺乳动物，体肥头大、圆脸圆耳，幼年体色为灰白色，因其独立特征和憨态可掬的样子被人们誉为“活化石”和“中国国宝”。



从外表来看，大熊猫似乎是自然界最“温柔”的生物：黑白相间的花纹让它的外形看起来更像是一种卡通形象；圆滚滚的身体和大大的头部让人忍不住想要抱一抱，即使不熟悉的人也会因为其憨态可掬的外表而心生好感……

但就是这样一种温顺的生物，却也正面临着种种危机——栖息地丧失、气候变化等因素都对其生存构成威胁。



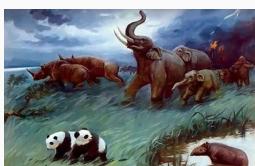
### 熊猫的自然栖息地在哪？

首先来了解一下什么是大熊猫的自然栖息地。一般来说，大熊猫生活在海拔1000~3000米的高山深谷中，以竹子为主食，喜阴湿，耐寒冷的生态环境是其生存的基础条件。在我国西南地区的四川盆地、陕西南部及甘肃南部的岷山、邛崃山、大小凉山、秦岭等地是大熊猫的典型栖息地。此外，在我国的湖北神农架、湖南张家界以及河南伏牛山等地的亚热带山地也有发现。



### 熊猫所面临的环境挑战

在远古时期，中国的南方地区就生活着原始大熊猫（也叫始熊猫）。大约在距今800万年前，全球进入冰期时代，地球开始变冷，植被逐渐向低纬度方向移动，这使得原本生活在高寒环境中的大熊猫失去了适宜的生活环境，因此它们被迫迁移到温暖的南方地区。随着冰川进退的变化，大熊猫也在不断地寻找适合自己的生存环境，它们的足迹遍布全国各地。



随着第四纪冰川期的结束，气温开始回升，北方森林面积不断扩大，这就为大熊猫提供了更加广阔的生存空间。不过与此同时，人类的活动也开始影响到大熊猫的生存环境。大规模的采伐森林导致栖息地面积大幅缩小，水土流失加剧，这些都直接或间接地影响到野生大熊猫的数量。

此外，气候变暖也是大熊猫目前所面临的重要问题之一。据研究，自20世纪70年代以来，我国东部沿海地区出现了持续增温现象，这种趋势仍在继续发展。高温会导致竹林生长缓慢，从而降低了竹子作为大熊猫主要食物的供应量。除此之外，夏季降雨量增多还会造成泥石流、滑坡等灾害，进一步破坏大熊猫的栖息地。这些因素共同作用，使得大熊猫的种群数量日益减少。



### 熊猫的保护现状如何？

针对上述问题，政府和企业相继采取了一系列措施保护大熊猫及其栖息地。例如，建立自然保护区和森林公园，限制人类活动范围，改善大熊猫的食物来源等。同时，还通过科学管理、合理开发利用等方式推动了当地经济发展。尽管如此，由于历史原因和自然环境的恶化等原因，野生大熊猫仍处于濒危状态。根据国际自然保护联盟最新发布的红色名录，目前全球现存的大熊猫约有1864只，其中约90%以上为中国境内的大熊猫。



除了对野外环境进行保护外，人工繁育也是一个重要的手段。通过实施繁殖计划和救助项目，帮助更多的大熊猫存活下来。目前国内已有多个动物园、科研机构开展了大熊猫的人工饲养研究工作，许多雌性个体已经产下幼崽。虽然存在一定的技术难度和风险，但是随着经验的积累和技术进步，未来有望实现更多的大熊猫繁衍后代。

### 熊猫的文化影响力如何体现？

最后我们来聊聊大熊猫在国际上的文化影响力。近年来，随着媒体报道和旅游业的发展，越来越多的人了解到了这个可爱又珍贵的物种。许多人甚至不远万里前往四川卧龙、雅安等地的自然保护区内观赏野生的熊猫。而在影视作品中，《功夫熊猫》系列电影更是将大熊猫的形象推向了一个全新的高度。此外，各种与大熊猫相关的衍生品也越来越受到消费者的青睐，比如玩具、文具、食品等等。可以说，大熊猫已经成为中外人民友好交往和文化交流的桥梁之一。



总而言之，保护好大熊猫这一珍贵物种不仅关乎到我国的生态文明建设，同时也具有广泛的社会意义和价值。希望今后能够有更多的力量加入到这项伟大的事业中来，共同努力，为维护人类共同的家园贡献一份力量！

Figure 6. Interleaved composition generated by InternLM-XComposer2.



根据以下标题：“芭蕾舞：优雅与力量的舞蹈艺术”，创作长文章，全面探讨芭蕾舞这一优雅而富有力量的舞蹈艺术形式，字数不少于800字。主要内容如下：1、介绍芭蕾舞的历史起源和在世界舞蹈艺术中的地位。2、探讨芭蕾舞从文艺复兴时期到现代的发展过程，分析不同时期和国家的芭蕾舞风格及其影响。3、描述芭蕾舞的技术和动作语言，以及其在表现力和情感传达上的特点。4、介绍一些经典的芭蕾舞剧目和著名舞者，分析它们对芭蕾舞艺术的贡献。5、最后总结芭蕾舞作为艺术形式的美学和文化价值，并对其未来的发展趋势进行展望。

## 芭蕾舞：优雅与力量的舞蹈艺术

舞蹈，是一种优雅的艺术。芭蕾舞，更是其中最优雅的一种艺术形式。

### 起源与发展

在远古时期，中国的南方地区就生活着原始大熊猫（也叫始熊猫）。大约在距今800万年前，全球进入冰期时代，地球开始变冷，植被逐渐向低纬度方向移动，这使得原本生活在高寒环境中的大熊猫失去了适宜的生活环境，因此它们被迫迁移到温暖的南方地区。随着冰川进退的变化，大熊猫也在不断地寻找适合自己的生存环境，它们的足迹遍布全国各地。



芭蕾舞的技巧要求非常高，动作需要非常精准、流畅，而且力度要掌握得恰到好处。此外，芭蕾舞的动作语言也非常丰富，能够表达出很多复杂的情感和意义。正因为如此，芭蕾舞被认为是最具表现力的舞蹈之一。

芭蕾舞的历史可以追溯到十五世纪，当时人们在庆祝胜利时会跳舞，这种舞蹈被称为“卡斯蒂利亚舞”（Castilian dance）。随着时代的发展，人们开始将音乐与舞蹈结合起来，于是便诞生了最早的芭蕾舞剧《帕凡》（Pavane）。从那时起，芭蕾舞就开始了它的辉煌历史。



随着时间的推移，芭蕾舞逐渐演变成了一种高雅的宫廷娱乐活动。在法国国王路易十四的推崇下，芭蕾舞成为了欧洲王室贵族们最为喜爱的表演艺术之一。而到了十九世纪，芭蕾舞又迎来了一个新的高峰期。这个时期出现了许多著名的芭蕾舞大师，如马里·德拉佩诺普（Marie Taglioni）、费德利克·塔图（Friedrich Tarantini）等。他们创作了许多经典的作品，推动了芭蕾舞艺术的发展。

除了这些重要的历史人物外，还有许多杰出的芭蕾舞团为芭蕾舞艺术的繁荣做出了巨大的贡献。例如，英国皇家芭蕾舞团、巴黎歌剧院芭蕾舞团、美国芭蕾舞剧院等都是享誉世界的芭蕾舞团体。



总之，芭蕾舞是一门历史悠久、技术精湛、内涵丰富的舞蹈艺术形式。它不仅展示了人类的身体之美，更蕴含着深刻的文化内涵和哲学思考。

### 技术与情感

芭蕾舞的技术非常重要，因为只有掌握了正确的技巧才能让舞蹈看起来更加优美、流畅。在芭蕾舞中，演员需要用脚尖来支撑身体的重量，这需要极高的平衡能力和柔韧性。此外，芭蕾舞还涉及到跳跃、旋转等各种高难度动作，都需要强大的力量和耐力来支撑。因此，要想成为一名优秀的芭蕾舞演员，必须经过长时间的训练和磨砺。

虽然芭蕾舞的技术十分重要，但芭蕾舞的灵魂却是情感。通过舞蹈动作的传递，芭蕾舞能够表达出各种复杂的情感和思想。比如，在古典芭蕾舞剧中，常常会出现悲欢离合的情节，而这些情节往往是通过细腻的舞蹈动作来呈现的。在这些作品中，演员需要通过表情、手势等多种方式来传达角色的内心世界，从而使观众更好地理解剧情和角色性格。除此之外，现代芭蕾舞也越来越注重对社会现实问题的关注和探讨，用舞蹈来呼吁人们对某些问题的关注和反思。



总之，芭蕾舞既注重技术又强调情感，二者缺一不可。只有将技术和情感完美地融合在一起，才能创造出真正优秀的芭蕾舞作品。

### 经典剧目与著名舞者

说到芭蕾舞的经典剧目，最著名的当属《天鹅湖》、《胡桃夹子》、《吉赛尔》等。这些剧目不仅具有极高的艺术价值，而且深受观众喜爱。除了这些传统剧目外，现代芭蕾舞也有很多优秀之作，比如美国的《雷米约的梦》、英国的《睡美人》等等。

当然，除了这些优秀的作品外，还有许多著名的芭蕾舞演员也给人们留下了深刻的印象。像美国的玛丽安娜·阿米莉亚（Mariana Amalia）、英国的玛莎·格雷厄姆（Martha Graham）、俄罗斯的娜塔莎·梅尔科娃（Natalia Mekhonova）等等。她们不仅是芭蕾舞界的翘楚，更是影响了整个舞蹈界的人物。她们的舞蹈风格各异，有的热情奔放，有的柔美婉约，但无一例外都给观众留下了深刻的印象。

### 结语

芭蕾舞作为一门艺术形式，它不仅仅代表着优雅和美丽，更蕴含着深刻的美学和文化价值。它不仅让我们欣赏到人类身体的极致之美，也让我们领略到人类智慧的无限可能。相信在未来，芭蕾舞将继续发扬光大，为人类文明做出更大的贡献。



Figure 7. Interleaved composition generated by InternLM-XComposer2.

最近寒冬之际，在互联网上突然刮起了去哈尔滨旅游的热潮。无数南方游客争先恐后的前往中国的极北方-哈尔滨游玩。哈尔滨本地的居民们也踊跃参与招待游客的活动当中，热情地招待这些来自南方的“小土豆”们。请你以第一人称，用文言文的形式记录一个南方人在冬季前往哈尔滨游玩的游记。该文言文游记可能包含：入住酒店，参观索菲亚大教堂，吃当地的特色美食（红肠，烤冷面），游玩冰雪大世界（冰雪打造的游乐场）等内容。文言文形式可以参考《醉翁亭记》



余闻哈尔滨之冬，极寒而美丽。故于岁末之际，携友前往一探究竟。

初至，见市廛之盛，闾阎之声喧哗。既入夜，灯火辉煌，如星斗之在天。遂寻得一舍宿焉。窗外望之，索菲亚大教堂之倩影依稀可见，美不胜收。

次日晨，天微明，心驰索菲亚。及门，巍峨壮观，叹为观止。入其中，庄严肃穆之气扑面而来，敬而远之。

美食者也，若红肠、烤冷面等诸物皆属此列。余尝啖之，其味甚美，色鲜且香，真不食则馋矣！

午游冰雪大世界。此乃以冰雪为主题的游乐场，其景致由冰雕制作而成。建筑、人物、动物无所不包，从飞龙到凤凰，从狮子到亭台楼阁，无不精美绝伦，形态各异。漫步其中，如入童话世界，让人流连忘返。

夜，独步于中央大街之上。两边商铺林立，霓虹闪烁，繁华喧嚣之声不绝于耳。街头艺人弹唱、杂耍者比肩接踵，皆聚精会神地观摩欣赏。其乐融融，热闹非凡。不禁赞叹：哈尔滨真乃一座充满活力与魅力的城市！

至，天已昏黑。余倚窗远眺，星如钻石镶嵌于黑布之上。浮想联翩：或漫步街头，感北国风光之壮丽；或游中央大街，观欧式建筑之独特；又或登亚布力滑雪场，尝雪地滑道之刺激。然最令余难以忘怀者，乃哈尔滨人民热情好客之情谊也。此行虽已结束，而此段美好回忆，必镌刻于心间矣！



以小红书博主的口吻，写一篇文章，每一句话含有适当的emoji表情。抽取3-6个seo关键词，生成#标签并放在文章最后。要求以“哈尔滨旅游|南方小土豆历险记”为标题写一篇小红书分享，介绍包括入住酒店，吃美食，逛景点等内容。需要包括以下内容：冰雪大世界，圣索菲亚大教堂，中央大街以及烤冷面，香肠。



## 🐻哈尔滨旅游|南方小土豆历险记

❤️【第一站】冰雪大世界

💰人均：¥200-300，推荐指数 ⭐⭐⭐⭐

🧐票价偏贵，但体验感很棒～一定要去打卡哦！

😋吃：冰雪大世界附近有很多美食小吃，比如烤冷面、香肠等。建议先买好票，然后慢慢品尝美食哦～

🛍逛：中央大街是一条非常有特色的商业街，两侧的建筑非常有特色，逛逛买买拍拍拍都很不错～

❤️【第二站】圣索菲亚大教堂

💰免费参观，推荐指数 ⭐⭐⭐⭐

🧐这座教堂是哈尔滨的标志性建筑之一，非常值得一游哦～

😋吃：在圣索菲亚大教堂附近有很多小吃店和餐厅，可以尝试一下当地的特色美食哦～

🛍逛：这里有很多小店和小巷子，可以发现很多有趣的小玩意儿哦～

❤️【第三站】中央大街

💰门票：免费，推荐指数 ⭐⭐⭐⭐

🧐这条街道非常有特色，两旁都是欧式建筑，非常适合拍照哦～

😋吃：这里有各种美食，比如烤冷面、炸鸡排、铁板鱿鱼等等，还可以尝试一些当地的小吃哦～

🛍逛：中央大街是一个购物天堂，有很多商场和店铺，可以找到很多喜欢的东西哦～

#哈尔滨旅游 #冰雪大世界 #圣索菲亚大教堂 #中央大街 #哈尔滨必玩景点 #哈尔滨旅行攻略 #南方小土豆历险记

Figure 8. Interleaved composition generated by InternLM-XComposer2.

Please write an blog based on the title: how to learn swim.  
The first part should cover the swimming equipments.  
The second part should discuss warm-up exercises before swimming.  
The last part tells us how to swim, including different swimming techniques.

In summer, people will be attracted by the clear water swimming pool, which makes them want to dive into it. However, many people don't know how to swim or are afraid of the water. In fact, there is no need to be afraid. Today I would like to share some tips on how to learn swimming.



One thing that most novice swimmers may not be aware of is the selection of swimming equipment. When they go to the swimming pool, they may see other people swimming in different costumes and wearing different accessories. Which one should you choose? The answer depends on your swimming ability level.

For those who can swim well but do not wear goggles, they will be able to quickly find objects underwater; for beginners, the choice of goggles is very important, because they help us avoid hitting things when swimming, prevent water from entering our eyes, reduce eye fatigue caused by water resistance, and protect the eyes. Goggles suitable for beginners have good sealing performance and are relatively comfortable to wear.



When we go swimming, it's important to take a bath first to clean ourselves, so that we can get used to the temperature of the water. Before swimming, we also need to warm up to improve our body's flexibility, reduce the risk of injury during swimming exercise, and ensure better performance after swimming. This process is often ignored by many novice swimmers, but if you ignore this step, you will easily hurt yourself while swimming.

The correct swimming posture is: keeping your head slightly above the water surface, keeping your chin down, extending your arms forward and placing them behind your ears, rotating your shoulders backwards, keeping your chest high, extending your legs straightly, bending your knees slightly, keeping your feet pointed, and putting your toes together.



At the beginning of swimming, we should adopt floating and kicking method, that is, lying flat on the water surface with both hands extended forward, alternating between upper and lower kicks, allowing water to enter the mouth and nose, taking deep breaths when breathing. With repeated practice, the frequency of alternating between upper and lower kicks will become faster and more accurate.

Swimming techniques include front crawl, back crawl, breaststroke, side stroke, butterfly kick, and frog kick. Each technique has its own advantages and disadvantages, and mastering each technique requires different movements. The swimming skills that we usually encounter in life include front crawl and back crawl, which are commonly known as "freestyle". We just need to learn these two skills in order to enjoy swimming.

Front crawl:

1. Head position



Head movement determines the whole stroke rhythm and direction of freestyle swimming. Freestyle swimming consists of two strokes per arm. The head and neck should always be in line with the center of gravity, turning sideways to breathe evenly, and turning to the opposite side at the end of each stroke. The head should move upwards naturally when turning.

Figure 9. Interleaved composition generated by InternLM-XComposer2.

## 2. Arm movement



Arm movement is divided into two stages, namely the push-forward stage and the pull-back stage. The push-forward stage refers to the time when the forearm enters the water, moves downward, and extends forward until the fingertips pass the hips. It is important to extend the forearm fully during this stage. At the same time, the elbows should be lowered, and the hand should stretch out as far as possible.

## 3. Leg movement



Leg movement mainly includes the kick and the foot movement. First, flex the knee and lift the leg to 45 degrees, then stretch the legs slowly, and finally use the heel to start the kick, and make sure that the whole body is completely horizontal before finishing the kick. In addition, the calf muscle is also very important for propulsion, so keep flexing your calf muscles throughout the swimming process.

## 4. Breathing method



When swimming, turn your head sideways to breathe in natural rhythm, and look at the side about 60cm away from your face. You can also exhale while swimming in shallow water to control the air flow rate of the mouth and nose.

### Back crawl:

The main difference between back crawl and front crawl is that the legs are kicked together instead of alternately. The back crawl is basically similar to the front crawl, except that the arms move backward instead of forward. Therefore, only one person uses his hands to carry the whole weight of the body, and the other person is supported by the palms and the back of the hands to move forward. As for the breathing method, you can follow the example of others to breathe naturally.

Generate a travel diary focusing on a trip to Yellowstone National Park and recommend Yellowstone National Park in English.

Yellowstone National Park is a must-see destination for any traveler. The park's natural beauty and geothermal wonders are truly awe-inspiring. From the stunning Old Faithful geyser to the breathtaking Grand Canyon of Yellowstone, there is no shortage of amazing sights to see in this national treasure.



One of the most popular attractions in Yellowstone is the Old Faithful geyser. This iconic geyser erupts every 90 minutes, shooting water up to 180 feet into the air. It's a truly spectacular sight to behold, and visitors can watch from boardwalks that circle the geyser basin.



Another highlight of Yellowstone is the Grand Canyon of Yellowstone. This massive canyon is over 20 miles long and up to 2,000 feet deep. The canyon is home to several waterfalls, including the impressive Lower Falls, which drops 308 feet into the canyon below.



In addition to these two main attractions, Yellowstone is also home to numerous other geothermal features, including hot springs, mud pots, and fumaroles. These unique landscapes are unlike anything you'll find anywhere else in the world.

Overall, Yellowstone National Park is a must-visit destination for anyone looking to experience the natural beauty and geothermal wonders of the American West. Whether you're interested in hiking, wildlife watching, or simply taking in the stunning scenery, Yellowstone has something for everyone.

Figure 10. Interleaved composition generated by InternLM-XComposer2.

困惑
?

```
python
def bubble_sort(arr):
    n = len(arr)

    # 遍历所有数组元素
    for i in range(n):
        # 最后 n - i - 1 个元素已排好，不需要再比较
        for j in range(0, n-i-1):
            # 如果元素大于下一个元素，则交换它们
            if arr[j] > arr[j+1]:
                arr[j], arr[j+1] = arr[j+1], arr[j]

    # 打印排序后的数字列表
    print("排序后的数据:", my_list)
```

请告诉我图中代码的功能是什么？

困惑
?

这段代码是 Python 语言的一个函数，名为 `bubble_sort`。它使用了冒泡排序算法来对给定的列表进行排序。该算法通过不断交换相邻的元素，将较大的数逐渐“浮”到列表的末端，最终达到排序的目的。

下面是函数 `bubble_sort` 的代码：

```
def bubble_sort(arr):
    n = len(arr)
    for i in range(n):
        for j in range(0, n-i-1):
            if arr[j] > arr[j+1]:
                arr[j], arr[j+1] = arr[j+1], arr[j]
    return arr

# 示例
my_list = [64, 34, 25, 12, 22, 11, 90]
bubble_sort(my_list)

# 打印排序后的数字列表
print(", ".join(map(str, my_list)))
```

在这个示例中，`my_list` 是一个需要排序的数字列表。函数 `bubble_sort` 接收一个列表作为参数，返回排序后的列表。在 `main` 函数中，`my_list` 的数字列表被传递给冒泡排序函数并排序后，打印排序后的列表。

困惑
?

当然可以，以下是使用快速排序算法的 Python 代码示例：

```
def quick_sort(arr):
    if len(arr) <= 1:
        return arr
    pivot = arr[len(arr)//2]
    left = [x for x in arr if x < pivot]
    middle = [x for x in arr if x == pivot]
    right = [x for x in arr if x > pivot]
    return quick_sort(left) + middle + quick_sort(right)

# 示例
my_list = [64, 34, 25, 12, 22, 11, 90]
sorted_list = quick_sort(my_list)

# 打印排序后的数字列表
print(", ".join(map(str, sorted_list)))
```

Figure 11. Chat with InternLM-XComposer2.

20



🤔

请描述这张图片。

 我看到了这样一幅美丽的图像。画面中，一只人的手掌伸了出来，手心里有一条蜿蜒的公路。这条道路在绿草如茵的山谷中延伸，一路通往远方。云雾环绕着群山，创造出一个梦幻般的环境。

 这张图真实存在吗？

 我分析这张图像，发现其中的手掌和道路是人工添加的合成内容，而山谷和群山应该是现实生活中存在的环境。整个场景是合成的，并不真实存在。

当  $x = -2$  时， $ax^3 + bx - 7$  的值为 9，则当  $x = 2$  时， $ax^3 + bx - 7$  的值是（ ）。  
A. -23    B. -17    C. 23    D. 17

🤔

这道题的数学答案是多少

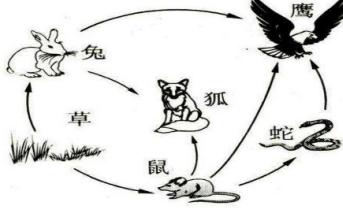
 这道数学题的答案是A、-23



🤔

这张图让你想到了哪首古诗？

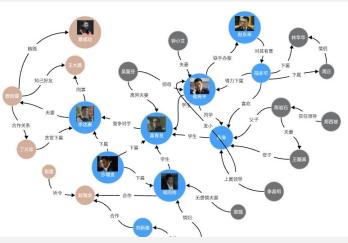
 这让我想起了柳宗元的《江雪》：众鸟飞绝，万籁俱寂；唯独有老翁独钓寒江雪。在这幅画中也有一人在独钓于寒江雪，画面充满了孤寂和宁静的感觉。



🤔

描述这张图片。

 这是一张生态系统循环图，它详细描绘了不同生物之间的相互作用。生态环境中，兔子通过食用植物茁壮成长。作为兔子的天敌，狐狸和鹰则通过食用兔子来作为食品链的一部分。有毒蛇和鹰这两种大型捕食者都捕食老鼠，并且它们自己也在自然界中寻求生存。鹰捕食蛇，毒蛇捕食蛙。植物和微生物在土壤中分解粪便，这些分解物循环回土壤中，供草食动物消耗。在这个循环图中，植物是生产者，兔子、毒蛇、老鼠和狐狸是消费者，而鹰是食物链中最直接的消费者。生态系统保持生态平衡并维持生命体的持续存在是至关重要的。



🤔

根据上面的人物关系图回答：祁同伟是谁的学生？

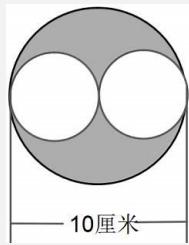
 祁同伟是高育良的学生。

 侯亮平是谁的学生？

 侯亮平是高育良的学生。

Figure 12. Chat with InternLM-XComposer2.

21



Given a circle with a diameter of 10 cm and two smaller circles of equal radius, find the area of the shaded region in the picture.



First, we need to find the radius of the larger circle. Since the diameter is 10 cm, the radius is half of the diameter, which is:  $\text{radius} = \text{diameter} / 2 = 10 \text{ cm} / 2 = 5 \text{ cm}$

Next, we need to find the areas of the two smaller circles. The radius of each smaller circle is half of the radius of the large circle, which is:  $\text{smaller radius} = \text{radius} / 2 = 5 \text{ cm} / 2 = 2.5 \text{ cm}$

So the area of each smaller circle is:  $\text{area of smaller circle} = \pi * (\text{smaller radius})^2$

$\text{area of smaller circle} = \pi * (2.5 \text{ cm})^2 \approx 19.63 \text{ cm}^2$

The sum of the areas of the two smaller circles is:

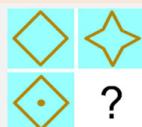
$$2 * \text{area of smaller circle} \approx 39.26 \text{ cm}^2$$

Finally, we can find the area of the shaded region by subtracting the sum of the areas of the two smaller circles from the area of the large circle:

$$\text{shaded region area} = \text{area of large circle} - \text{sum of smaller circle areas}$$

$$\text{shaded region area} = \pi * (5 \text{ cm})^2 - 39.26 \text{ cm}^2 \approx 78.54 \text{ cm}^2 - 39.26 \text{ cm}^2$$

$$\text{shaded region area} \approx 39.28 \text{ cm}^2$$



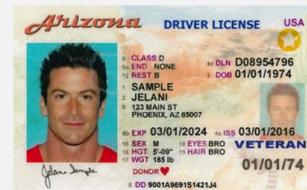
Here are three sub images arranged in a 2-by-2 matrix. First, look at the two images in the first column, in the top left and bottom left. Then, find out the pattern in the first column based on the left two images. Next, use the found pattern and the image in the top right to infer the missing figure. Finally, describe what would the missing image look like?



The first column of the image contains two diamond-shaped objects. The first diamond shape is completely filled in with a solid color, while the second one also has an additional dot within it.

Analyzing this pattern, it seems that the top row and bottom row contain the same type of figure but with different features - the top one is completely filled (possibly with a different color or texture), and the bottom one includes a dot inside it.

From this information, we can infer that the missing image in the second column should be similar to the leftmost image in the second row—a star-shaped object with a solid fill. Since the other three images are already present and the pattern suggests repetition of figures with varying properties, the image in the second column will likely consist of a star with a solid fill.



Please read the text in this image and return the information in the following JSON format (note xxx is placeholder, if the information is not available in the image, put "N/A" instead).  
`{"class": xxx, "DLN": xxx, "DOB": xxx, "Name": xxx, "Address": xxx, "EXP": xxx, "ISS": xxx, "SEX": xxx, "HGT": xxx, "WGT": xxx, "EYES": xxx, "HAIR": xxx, "DONOR": xxx}`



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"DLN": "D08954796",
"DOB": "01/01/1974",
"Name": "Jelani",
"Address": "123 Main St, Phoenix, AZ 85007",
"EXP": "03/01/2024",
"ISS": "03/01/2016",
"SEX": "M",
"HGT": "5'09\"",
"WGT": "185 lb",
"EYES": "brown",
"HAIR": "brown",
"DONOR": "yes"}
```

Figure 13. Chat with InternLM-XComposer2.



Describe this image in detail.



The image is a black and white floor plan of a house, providing a detailed layout of the rooms and their dimensions. The plan is oriented with the entrance on the bottom left and the terrace on the top left. Starting from the entrance, there is a living room to the right, which is 14'6" x 20'5" in size. Adjacent to the living room is the dining area, which is 9'10" x 13'0" in size. The dining area is connected to the kitchen, which is 7'2" x 9'2" in size. Next to the kitchen is the second bedroom, which is 10'10" x 14'7" in size. The master bedroom is located to the right of the second bedroom and is 12'10" x 17'9" in size. The plan also includes a foyer, which is 6'0" x 5'3" in size, and a bathroom, which is 7'2" x 9'2" in size. The terrace, which is 21'6" x 8'0" in size, is located on the top left side of the plan. The floor plan provides a comprehensive view of the house's layout, allowing one to understand the spatial arrangement and dimensions of each room.



Country	Sales Volume	Revenue	Profit
USA	40.080	\$15.971.880	\$3.086.421
China	35.070	\$15.866.670	\$3.032.162
Australia	27.054	\$14.812.566	\$2.888.636
India	23.046	\$10.608.174	\$1.853.710
South Korea	16.032	\$10.494.948	\$1.975.844

Please read the table in this image and return a markdown-style reconstructed table in text



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Figure 14. Chat with InternLM-XComposer2.