SEED-X: Multimodal Models with Unified Multi-granularity Comprehension and Generation

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Figure 1: The introduced SEED-X, a unified and versatile foundation model, can serve as various multimodal AI assistants **in the real world** after different instruction tuning, capable of responding to a variety of user needs through unifying **multi-granularity comprehension and generation**.

Abstract

The rapid evolution of multimodal foundation model has demonstrated significant progresses in vision-language understanding and generation, *e.g.*, our previous work SEED-LLaMA. However, there remains a gap between its capability and the real-world applicability, primarily due to the model's limited capacity to effectively respond to various user instructions and interact with diverse visual data. In this work, we focus on bridging this gap through integrating two enhanced features: (1) comprehending images of arbitrary sizes and ratios, and (2) enabling multi-granularity image generation. We present a unified and versatile foundation model, namely, **SEED-X**, which is able to model multi-granularity visual semantics for comprehension and generation tasks. Besides the competitive results on public benchmarks, SEED-X demonstrates its effectiveness in handling real-world applications across various domains after instruction tuning. We hope that our work will inspire future research into what can be achieved by versatile multimodal foundation models in real-world applications. The models, codes, and datasets will be released in `https://github.com/AILab-CVC/SEED-X`.

1 Introduction

In recent years, Multimodal Large Language Models (MLLMs) [1, 2, 3, 4, 5, 6, 7, 8] have demonstrated exceptional capabilities in comprehending multimodal data through leveraging the strong generality of LLMs [9, 10, 11]. Some pioneering work [12, 13, 14, 15, 16, 17, 18, 19] further empower LLMs with the ability to generate images beyond texts. For example, our previous work SEED-LLaMA [15] can handle a variety of tasks and excel in academic benchmarks through unifying multimodal comprehension and generation. However, the accuracy and diversity of its generated content still fall short of real-world needs. In this work, we focus on bridging this gap through upgrading SEED-LLaMA with enhanced capabilities for real-world applications.

Specifically, in order to make a multimodal foundation model applicable in real-world scenarios, we incorporate two enhanced features: (1) understanding images of arbitrary sizes and ratios, and (2) multi-granularity image generation, encompassing both high-level instructional image generation and low-level image manipulation tasks. These attributes can form the basis for a multimodal foundation model's effective application in an open-world context, since a multimodal foundation model has to accommodate various downstream tasks requiring different levels of visual semantics.

In this paper, we introduce SEED-X, a unified and versatile multimodal foundation model as a follow-up work of SEED-LLaMA, which seamlessly integrates the features mentioned above. After different instruction tuning, SEED-X can function as various multimodal AI assistants in the real world, capable of addressing various user needs through generating proper texts and images as shown in Fig. 1. Specifically, our instruction-tuned models can act as an interactive designer, generating images while illustrating creative intent, offering modification suggestions and showcasing visualizations based on user's input images. Additionally, they can act as knowledgeable personal assistants, comprehending images of various sizes and providing relevant suggestions. Moreover, they can generate more diverse outputs, such as slide layouts for slide creation, and interleaved image-text content for storytelling. SEED-X signifies a notable advancement towards a versatile agent for users in the real world.

To endow SEED-X with the aforementioned characteristics, our approach incorporates (1) a visual tokenizer to unify image comprehension and generation, where its multi-granularity de-tokenization phase facilitates image generation and high-precision image manipulation, and (2) an MLLM with dynamic resolution image encoding to enable the comprehension of images with arbitrary sizes and aspect ratios. Specifically, we utilize a pre-trained ViT as the visual tokenizer and train a visual de-tokenizer initialized from SDXL [20] to decode realistic images by taking the ViT features as input. Given the high-level ViT features as input, our visual de-tokenizer can reconstruct images semantically aligned with the original images. To realize the retention of fine-grained details of
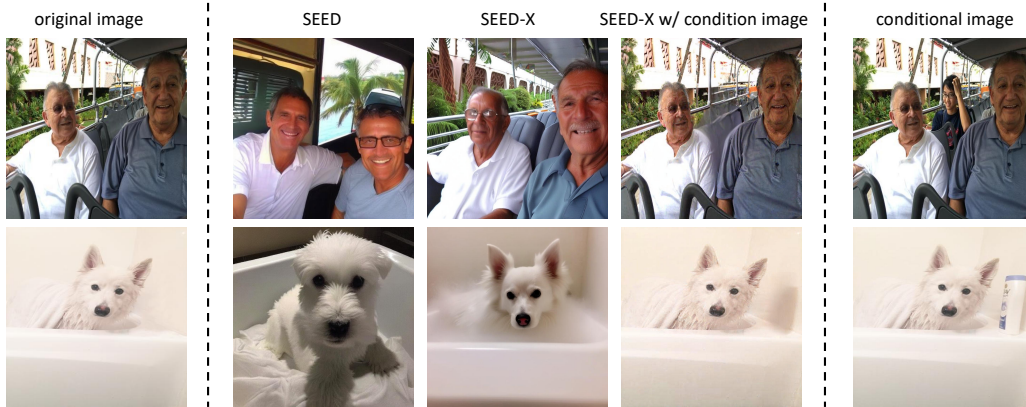
Figure 2: The reconstruction results of our visual de-tokenizer. It can decode realistic images that are semantically aligned with the original images by taking the **ViT features** as inputs, and further recover fine-grained details by incorporating the **conditional images** as inputs.

the input image to satisfy image manipulation, we further fine-tune the visual de-tokenizer to take an extra condition image as input in the latent space (See Fig. 2). The ViT features serve as a bridge to decouple the training of the visual (de-)tokenizer and the MLLM in SEED-X. The dynamic resolution image encoding divides an input image into sub-images and adds extrapolatable 2D positional embeddings to the ViT features of each sub-image, allowing the MLLM to scale to any image resolution. As for the image generation training objective, a fixed number of learnable queries are fed into the MLLM, where the output hidden states are trained to reconstruct the ViT features of the target images. During inference, the image de-tokenizer can take both the output features from the MLLM and the condition image provided by users as input, ensuring that the decoded image can possess high-level semantics that meet the multimodal instructions and retain the low-level details.

We pre-train SEED-X on massive multimodal data, including image-caption pairs, grounded image-text data, interleaved image-text data, OCR data, and pure texts. We further apply multimodal instruction tuning to align SEED-X with human instructions across various domains, utilizing both existing datasets and newly collected datasets that cover image editing, text-rich, grounded and referencing QA, and slide generation tasks. The extensive evaluations on MLLM benchmarks demonstrate that our instruction-tuned model not only achieves competitive performance in multimodal comprehension, but also achieves state-of-the-art results in image generation compared to existing MLLMs on SEED-Bench-2 [21].

All the models, codes, and datasets will be made publicly available. We hope our work can bring insights to the community about the potential of multimodal foundation models in real-world scenarios through unifying multi-granularity comprehension and generation.

2 Related Work

With the rapid development of Multimodal Large Language Models (MLLM), recent studies have been working on unified MLLMs that are capable of **multimodal comprehension and generation** as shown in Tab. 1. Some work [15, 14, 13, 22, 23] perform multimodal autoregression with a unified next-word-prediction objective through using a discrete visual tokenizer. For example, SEED-LLaMA [15] pre-trains a discrete image tokenizer, where the visual codes can be decoded to realistic images using the off-the-shelf SD model, and performs multimodal pre-training and instruction tuning through predicting the next discrete token. Some research efforts [12, 24, 19] have delved into multimodal autoregression with continuous representations, where each image is tokenized into embeddings via a visual encoder, and then interleaved with text tokens for autoregressive modeling. During inference, the regressed visual embeddings will be decoded into an image by a visual decoder. Additionally, some studies [17, 16] enable image generation in a non-autoregressive manner through utilizing learnable queries to obtain visual representations from MLLMs, which are further fed into a image decoder to generate images. The latest work, Mini-Gemini, generates text prompts using MLLMs and then leverages the existing SDXL [20] to generate images.

Table 1: MLLMs that unify comprehension and generation listed by publication date. "Decoder Input" denotes the inputs for image generation, where "Features" means continuous features, "Token" represents discrete tokens, and "Text" implies text prompts.

	Date	Decoder Input	Multi-turn	Detec-tion	Dynamic -Res Img Input	High-precision Editing	Open-source
Emu	07/2023	Feature	✓	×	×	×	✓
CM3Leon	07/ 2023	Token	×	×	×	×	×
SEED-OPT	07/ 2023	Token	×	×	×	×	×
LaVIT	09/2023	Token	×	×	×	×	✓
NExT-GPT	09/2023	Feature	✓	×	×	×	✓
DreamLLM	09/2023	Feature	✓	×	×	×	×
SEED-LLaMA	10/2023	Token	✓	×	×	×	✓
VL-GPT	12/2023	Feature	✓	×	×	×	×
Gemini	12/2023	Token	✓	×	-	×	×
Emu2	12/2023	Feature	✓	×	×	×	✓
Unified-IO 2	12/2023	Token	×	✓	×	×	✓
Mini-Gemini	03/2024	Text	✓	×	×	×	✓
SEED-X	04/2024	Feature	✓	✓	✓	✓	✓

In this work, we present SEED-X, a unified and versatile foundation model, through upgrading SEED-LLaMA with enhanced capabilities for real-world applications. As shown in Tab. 1, SEED-X supports object detection and dynamic resolution image encoding for multi-granularity comprehension, and high-level instructional image generation and low-level image manipulation for multi-granularity generation, which are not realized in previous work.

3 Method

3.1 Visual Tokenization and De-tokenization

In SEED-X, we adopt a visual tokenizer to unify image comprehension and generation, and pre-train a multi-granularity de-tokenizer to facilitate image generation and high-precision image manipulation in a two-stage manner. In the first stage, as shown in Fig. 3 (left), we utilize a pre-trained ViT as the visual tokenizer and pre-train a visual de-tokenizer to decode realistic images by taking the features of the ViT as inputs in the first stage. Specifically, N visual embeddings from the ViT tokenizer ($N = 64$ after average pooling) are fed into a learnable module as the inputs of the U-Net of the pre-trained SD-XL [20] (replacing the original text features). The learnable module consists of four cross-attention layers to connect the visual tokenizer and the U-Net. We optimize the parameters of the learnable module and keys and values within the U-Net on the images from JourneyDB [25], LAION-Aesthetics [26], Unsplash [27], and LAION-COCO [28]. As shown in Fig. 2, compared with SEED [15], our visual de-tokenizer can decode images that are more semantically aligned with the original images by taking the ViT features as inputs.

In the second stage, as shown in Fig. 3 (right), we further fine-tune the visual de-tokenizer to take an extra condition image as inputs for the retention of low-level details. Specifically, we follow InstructPix2Pix [29] to encode the condition image into the latent space via the VAE encoder, and concatenate them with the noisy latent as the input of U-Net. The channel number of the U-Net convolutional layer is expanded from 4 to 8, and all parameters of U-Net are optimized. We fine-tune the visual de-tokenizer on MagicBrush [30] and in-house image editing data, as well as the pure images in the first stage, where the conditional inputs are set to zeros. As shown in Fig. 2, by incorporating the condition image as an additional input besides the high-level image features, our visual de-tokenizer can recover the fine-grained details of the original image.

3.2 Dynamic Resolution Image Encoding

Current MLLMs require to resize the input images to a pre-defined resolution (typically a square size), which corresponds to the training resolution of the vision encoder, which can result in the loss
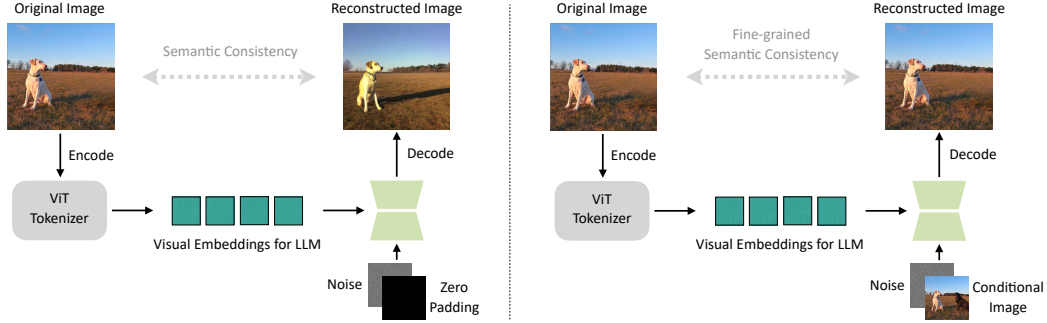
Figure 3: Overview of visual tokenization and de-tokenization in SEED-X. In the first stage (left), we pre-train a visual de-tokenizer, which can decode semantically consistent images by taking the features of a pre-trained ViT as inputs. In the second stage (right), we fine-tune the visual de-tokenizer through concatenating the latent features of a conditional image with the noise to recover the fine-grained details of the original image.

of fine-grained information. In this work, we propose dynamic resolution image encoding to enable the processing of images with arbitrary sizes and aspect ratios by dividing the image into a grid comprising of sub-images. Specifically, for the visual encoder with the training resolution $H_t \times W_t$, we first up-sample the input image with the size $H \times W$ to the size of $\{N_h * H_t\} \times \{N_w * W_t\}$. The grid size $N_h \times N_w$, are determined by

$$
\begin{aligned}
\min \quad & N_h * N_w, \\
\text{s.t. } & H \leq N_h * H_t \quad \text{and} \quad W \leq N_w * W_t.
\end{aligned}
\tag{1}
$$

We also resize the original image to the size of $H_t \times W_t$ to provide global visual context. All sub-images and the resized global image are fed into the visual encoder to obtain the features, which are concatenated as the input of the LLM.

To enable the LLM to be aware of the positional information of each sub-image within the original image, we add extrapolatable 2D positional embeddings to the visual features of each sub-image. Specifically, for a sub-image with a normalized center location (x_c, y_c) in the grid, where $0.0 < x_c, y_c < 1.0$, its learnable positional embedding p is computed:

$$
p = x_c * l + (1 - x_c) * r + y_c * t + (1 - y_c) * b.
\tag{2}
$$

l, r, t, and b represent four learnable position embeddings indicating left, right, top and bottom respectively. Consequently, our visual encoder can handle inputs with any arbitrary sizes and aspect ratios, even if the image resolution was not encountered during training.

3.3 Multimodal Pre-training and Instruction Tuning

3.3.1 Training Stage I: Multimodal Pre-training

As shown in Fig. 4, SEED-X adopts next-word prediction and image feature regression training objectives on interleaved visual and textual data. Specifically, we perform dynamic resolution encoding of each image in the multimodal sequence, and their features along with text tokens are fed into the pretrained LLM. In order to equip the model with detection and referencing abilities, we add 224 bbox tokens, designated for representing bounding box coordinates, represented by `<box_start> <loc-x_center> <loc-y_center> <loc-width> <loc-height> <box_end>` with specical tokens at the beginning and end of the bounding box. The text and added bbox tokens are training through predicting the next token with cross-entropy loss.

We employ N learnable queries ($N = 64$ to align with the visual de-tokenizer) to obtain the output visual representations from the LLM, which are trained to reconstruct the features of the pre-trained ViT tokenizer with a Mean Squared Error (MSE) loss. We add two special tokens '<IMG>' and '</IMG>' to represent the beginning and the end of the query embeddings, and the '<IMG>' is trained to predict where an image emerges. In doing so, we utilize the pre-trained ViT tokenizer as a **bridge** to decouple the training of a visual de-tokenizer and the MLLM for image generation. During inference,
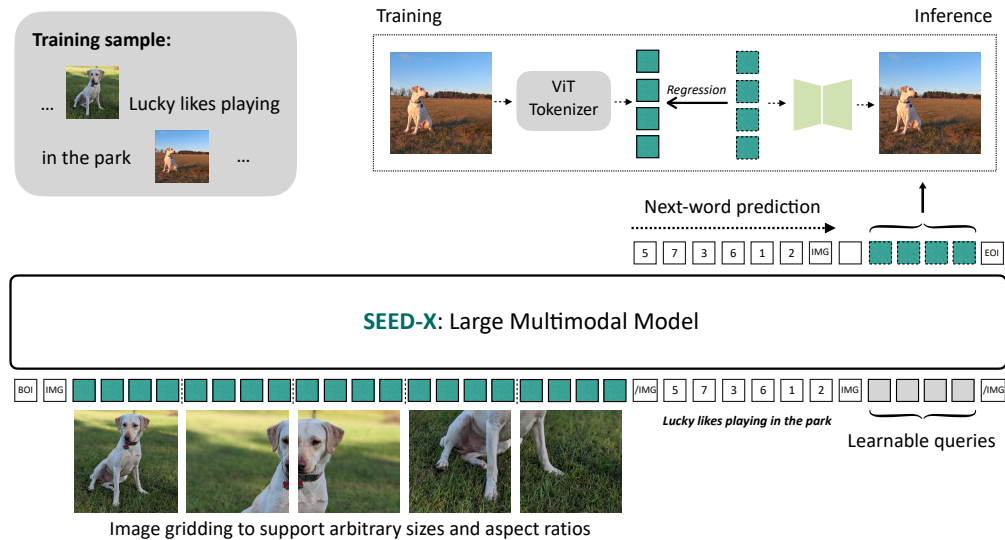
Figure 4: Overview of SEED-X for multimodal pre-training. Each image is divided into sub-images to support arbitrary sizes and aspect ratios, and their ViT features along with text tokens are fed into an LLM to perform next-word prediction and image feature regression between the output hidden states of the learnable queries and ViT features. During inference, the regressed image features are fed into the visual de-tokenizer to decode images.

the regressed visual representations from SEED-X are fed into the visual de-tokenizer to decode realistic images.

We pre-train SEED-X initialized from Llama2-chat-13B using LoRA on massive multimodal data, including image-captions pairs, grounded image-texts, interleaved image-text data, OCR data and pure texts. We perform pre-training with 48 H800-80G GPUs (10 days) on a total of 158M samples. See Appendix. A and Appendix. B for more details.

3.3.2 Training Stage II: Multimodal Instruction Tuning

We perform multimodal instruction tuning through fine-tuning SEED-X using a LoRA module with both public datasets and in-house data covering image editing, text-rich, grounded and referencing QA, and slide generation tasks. The details of datasets can be found in Appendix. A. We fine-tune SEED-X with conversational and image generation data to yield a general instruction-tuned model SEED-X-I, which can follow multimodal instructions and make responses with images, texts and bounding boxes in multi-turn conversation. We further fine-tune the foundation model SEED-X on specialized datasets, resulting in a series of instruction-tuned models tailored for specific tasks, including SEED-X-Edit, SEED-X-PPT, SEED-X-Story and SEED-X-Try-on. The proficient capabilities of these instruction-tuned model across various domains demonstrate the versatility of our pre-trained foundation model SEED-X. We perform instruction tuning on the foundation model SEED-X across different datasets, resulting in various models with distinct capabilities. Note that **we do not have an all-in-one instruction-tuned model that encompasses all abilities**, which will be explored for future work.

4 Experiments

4.1 Quantitative Evaluation

We evaluate SEED-X-I on benchmarks specifically designed for evaluating MLLMs, since recent work [31, 21] point out that traditional VQA benchmarks are not tailored for evaluating MLLMs with open-from output. As shown in Tab. 2, SEED-X-I achieves competitive performance in both the image comprehension and generation tasks. For example, SEED-X-I with dynamic resolution

Table 2: Comparison for multimodal comprehension and generation on MLLM benchmarks. "Image Gen" denotes whether the model can generate images besides texts. "Dynamic Res" denotes whether images with dynamic resolutions are encoded for training and inference. "Single", "Multi" and "Interleaved" denote evaluating the comprehension of single-image, multi-image, and interleaved image-text respectively. "Gen" denotes evaluating the generation of images, and "/" denotes the model's inability to perform such evaluation. The best results are **bold** and the second are <u>underlined</u>.

	Size	LLM	Image Gen	Dynamic Res	MMB Single	SEED-Bench-2 P1 Single	SEED-Bench-2 P1 Multi	SEED-Bench-2 P2 Inter-leaved	SEED-Bench-2 P3 Gen	MME Perception Single	MME Cognition Single
GPT-4v	-	GPT-4	×	-	<u>77.0</u>	**69.8**	**73.1**	37.9	/	1409	<u>517</u>
Gemini Pro	-	-	✓	-	73.6	62.5	-	-	-	**1609**	**540**
Qwen-VL-Chat	10B	Qwen-7B	×	×	61.8	50.3	37.4	38.5	/	1488	361
Next-GPT	13B	Vicuna-7B	✓	×	-	31.0	27.8	40.3	42.8	-	-
Emu	14B	LLaMA-13B	✓	×	-	46.4	31.2	<u>45.6</u>	45.7	-	-
SEED-LLaMA-I	14B	LLaMA-13B	✓	×	-	49.9	32.4	**48.0**	50.6	-	-
LLaVA-1.5	8B	Vicuna-7B	×	×	66.5	58.3	39.2	34.4	/	1506	302
XComposer-VL	8B	InternLM-7B	×	×	74.4	66.5	50.0	29.0	/	1528	391
SPHINX-1k	-	LLaMA-13B	×	×	67.1	<u>68.5</u>	37.7	32.5	/	<u>1560</u>	310
Emu2-Chat	37B	LLaMA-33B	×	×	63.6	-	-	-	/	1345	333
SEED-X-I	17B	LLaMA-13B	✓	×	**77.8**	66.8	57.1	40.5	<u>61.6</u>	1520	338
SEED-X-I	17B	LLaMA-13B	✓	✓	75.4	64.2	<u>57.3</u>	39.8	**62.8**	1457	321

inputs achieves results on MMBench that are second only to GPT-4V, while SEED-X-I with fixed image size surpasses the performance of GPT-4V. Since MLLM Benchmarks lack a large number of data with unusual aspect ratios, the advantages of dynamic resolution encoding cannot be fully demonstrated, resulting in SEED-X-I with fixed image size achieving overall better performance. SEED-X-I also shows promising results for comprehending multi-image and interleaved image-text content in SEED-Bench-2 [32]. Compared with previous work [18, 15, 16] that unify comprehension and generation within an LLM, SEED-X-I achieves the state-of-the-art performance in P3 level of SEED-Bench-2 including the evaluation of text-to-image generation, next image prediction and text-image creation.

4.2 Qualitative Evaluation

4.2.1 Applications in the Real World.

SEED-X can be effectively instruction tuned to function as various multimodal AI assistants in the real world across different domains after integrating two enhanced features, including the comprehension of images of arbitrary sizes and ratios, and multi-granularity image generation, encompassing both high-level instructional image generation and low-level image manipulation tasks. As shown in Fig. 1 and Fig. 5, our instruction tuned models can serve as an interactive designer, which can generate images without descriptive captions while illustrate creative intent, and showcase visualizations of modified images. For example, it can explain the design idea of concept image for AGI and a two-story cabin. It can create an imaginative illustration for the novel without the need of describing the scene with languages. It can further offer modification suggestions of the user's room and showcase the visualization. Additionally, the instruction tuned models can act as an knowledgeable personal assistant, comprehending images of arbitrary sizes and providing relevant suggestions. For example, it can identify foods suitable for fat reduction in the refrigerator, display appropriate clothing based on the screenshot of weather forecasts.

4.2.2 Image Generation and Manipulation.

We compare previous MLLMs that are capable of generating images for text-to-image generation in Fig. 7 of Appendix. Our instruction tuned model can generate images that are more aligned with the elements in the caption and possess artistic qualities. Through utilizing a pre-trained ViT Tokenizer as the bridge to decouple the training of visual de-tokenizer and the MLLM, our pre-trained model SEED-X can effectively realize high-quality image generation, which is a fundamental capability to be applied in real-world scenarios.

Figure 5: Examples of what SEED-X can do in real-world scenarios after different instruction tuning through unifying multi-granularity comprehension and generation. Our instruction tuned models can function as an interactive designer, generating images without descriptive captions while illustrating creative intent, and showcasing visualizations of modified images based on user's intent. They can act as knowledgeable personal assistants, comprehending images of arbitrary sizes and offering relevant suggestions in multi-turn conversations.
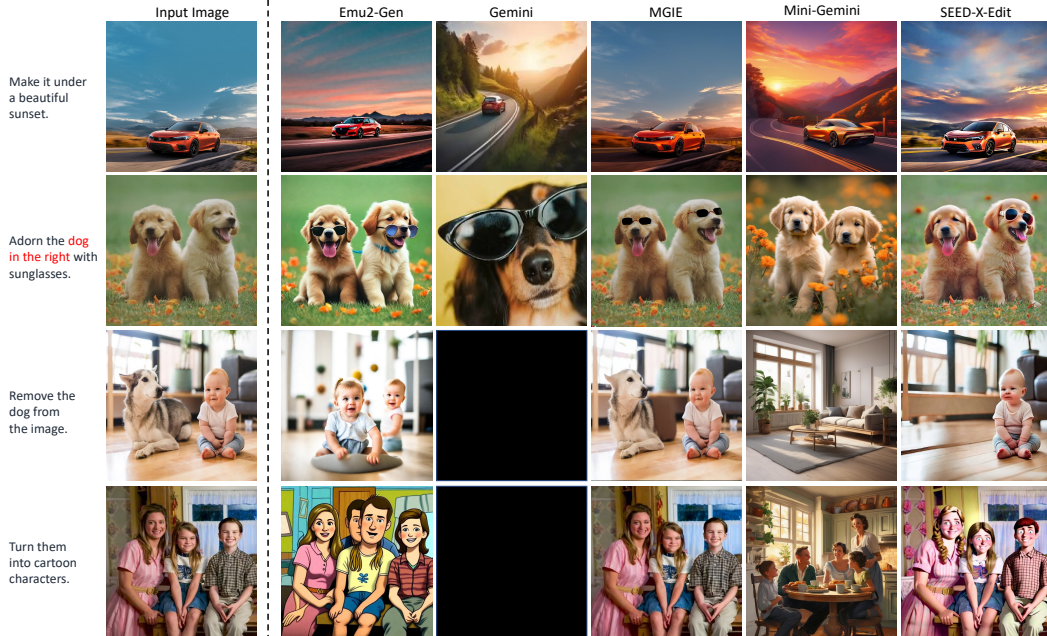
Figure 6: Qualitative comparison between MLLMs for image manipulation. SEED-X-Edit shows enhanced ability in adhering to instructions while preserving low-level details of input images. The black images result from Gemini's inability to display human images.

We compare image manipulation with previous MLLMs including Emu2-Gen [24], Gemini [33], MGIE [33] and Mini-Gemini [34]. As shown in Fig. 6, we can observe that SEED-X-Edit can more effectively adhere to editing instructions while maintaining the low-level details of the input image. For instance, SEED-X-Edit can accurately add sunglasses to the dog on the right, while both Emu2-Gen and MGIE fail to follow the instruction, resulting in sunglasses being added to both dogs. Additionally, SEED-X-Edit successfully eliminates the dog in the baby image while preserving the background details and the baby's features. In contrast, Emu2-Gen fails to retain the fine details of the input image, and MGIE is unsuccessful in removing the dog. Note that Gemini lacks the ability to edit images as it **retrieves images** on the Internet. Here the presence of black images is due to its failure to display images related to human portraits. Mini-Gemini generates **text prompts** as the input of a pre-trained SDXL model, which can not preserve the visual details of the input image. The examples show the effectiveness of our instruction model for high-precision image manipulation. Our MLLM accurately predicts visual semantic representations based on an input image and a language instruction, which serve as input for the U-Net. The visual de-tokenizer can further condition on the input image, ensuring the preservation of fine-grained details in the decoded images.

4.2.3 Multimodal Comprehension.

We provide qualitative examples of multimodal comprehension by SEED-X-I in Fig. 8 and Fig. 9 of Appendix. SEED-X-I can realize fine-grained object detection and perception, text-rich comprehension, fundamental mathematical computation, world-knowledge and commonsense reasoning, diagram understanding, which are crucial capabilities for its application in real-world scenarios.

5   Conclusion

We present SEED-X, a versatile foundation model, which can serve as various multimodal AI assistants in the real world after instruction tuning. In order to make a multimodal foundation model applicable in open-world context, we integrate two enhanced features into SEED-X including image comprehension of arbitrary sizes and ratios, and multi-granularity image generation, which encompasses both high-level instructional image generation and low-level image manipulation. We hope that SEED-X can inspire future research into the potential of MLLMs in the real-world scenarios through unifying multi-granularity comprehension and generation.

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Table 3: Overview of the pre-training and instruction tuning datasets.

Type	Dataset
Pre-training	
Image-Caption	LAION-COCO [35] (Re-caption), SAM [36] (Re-caption), LAION-Aesthetics[26], Unsplash [27], JourneyDB [37], CapFusion [38],
Grounded Image-Caption	GRIT [4]
Interleaved Image-Text	MMC4 [39], OBELICS [40], OpenFlamingo [41]
OCR	LLaVAR [42], Slides (In-house)
Pure Text	Wikipedi
Instruction Tuning	
VQA	LLaVAR [42], Text-rich QA (In-house), MIMIC-IT [43], MathQA [44], ChartQA [45], AI2D [46], ScienceQA [47], KVQA [48], DVQA [49], Grounded QA (In-house), Referencing QA (In-house)
Conversation	LLaVA-150k [50], ShareGPT [51], VLIT [52], LVIS-Instruct4V [53], Vision-Flan [54], ALLaVA-4V [55]
Image Generation	LAION-COCO [35] (Re-caption), SAM [36] (Re-caption), LAION-Aesthetics[26], Unsplash [27], JourneyDB [37]
Image Editing	Instructpix2pix [29], MagicBrush [30], Openimages [56]-editing (In-house), Unsplash [27]-editing (In-house)
Slides Generation	In-house data
Story Telling	VIST [57]
Virtual Try-on	VITON-HD [58]

A   Pre-training and Instruction Tuning Datasets

As listed in Tab. 3, we pre-train SEED-X and conduct instruction tuning on a large variety of both public datasets and in-house data. For multimodal pre-training, we utilize image-caption pairs, grounded image-caption pairs, interleaved image and text content, OCR data and pure text data. The images of LAION-COCO [35] and SAM [36] are re-captioned for a more detailed descriptive caption to improve both image comprehension and generation.

For instruction tuning, we utilize various public VQA datasets, and further curate text-rich QA, grounded and referencing QA to enhance the model's capability of comprehending text-rich images and detecting objects that requires reasoning. We use multiple conversational datasets, which are specifically collected for MLLMs with open-form text output. We use the same image-caption pairs as in the pre-training phase to maintain the model's ability to generate images. For the image manipulation, since the high-precision editing dataset MagicBrush [30] is only at the level of thousands, we employ a series of models to collect a dataset of millions of image editing examples, which are used for both training the visual de-tokenizer and SEED-X-Edit. We further collected data on slides, obtaining images, captions, and layouts for training slide generation.

B   Implementation Details

Visual Tokenization and De-tokenization. We use the visual encoder from Qwen-vl [5] as the ViT Tokenizer and adopt 1D average pooling to obtain $N = 64$ visual embeddings. These visual embeddings are fed into four layers of cross-attention as the input of the U-Net initialized from SDXL [20]. In the first stage, we optimize the parameters of the cross-attention layers and the keys and values within the U-Net on the images from JourneyDB [25], LAION-Aesthetics [26], Unsplash [27], and LAION-COCO [28]. We train the visual de-tokenizer on 32 A100-40G GPUs with 42K training steps, where the learning rate is set to 1e-4 with cosine decay.

In the second stage, we encode the condition image into the latent space via the VAE encoder, and concatenate them with the noisy latent as the input of U-Net. The channel number of the U-Net convolutional layer is expanded from 4 to 8, and all parameters of U-Net are optimized. We pre-train the visual conditioner on MagicBrush [30] and in-house image editing data, as well as the image-caption pairs in the first stage, where the conditional inputs are set to zeros. We fine-tune the visual de-tokenizer on 32 A100-40G GPUs with 30K training steps, where the learning rate is set to 1e-4 with cosine decay.

Multimodal Pre-training and Instruction Tuning. We utilize the visual encoder from Qwen-vl [5] as the ViT Tokenizer and initialize a cross-attention layer to obtain $N = 64$ visual embedding as the input of the LLM initialized from Llama2-chat-13B. We initialize $N = 64$ learnable queries and the output hidden states from them are fed into a cross-attention layer to reconstruct $N = 64$ visual embeddings from the ViT Tokenizer. We optimize the LLM using LoRA and optimize the parameters of the input cross-attention layer, output cross-attention layer, extrapolatable 2D positional embeddings, and LoRA on image-captions pairs, grounded image-texts, interleaved image-text data, OCR data and pure texts. We perform pre-training with 48 H800-80G GPUs (10 days) on a total of 158M samples, where the learning rate is set to 1e-4 with cosine decay.

For the instruction tuning, we fine-tune a LoRA module on the pre-trained model, and optimize the parameters of the input cross-attention layer, output cross-attention layer, extrapolatable 2D positional embeddings, and LoRA. We fine-tune SEED-X with conversational and image generation data to yield a general instruction-tuned model SEED-X-I. We further fine-tune SEED-X on specialized datasets, resulting in a series of instruction-tuned models tailored for specific tasks, including SEED-X-Edit, SEED-X-PPT, SEED-X-Story and SEED-X-Try-on.

C Qualitative Examples

Text-to-image Generation, Fig. 7 visualizes the comparison between MLLMs for text-to-image generation including Next-GPT [16], SEED-LLaMA-I[15], Emu2-Gen [24] and Gemini [33]. Compared with previous MLLMs, our instruction tuned model can generate images that are more aligned with the elements in the descriptive caption and possess artistic qualities. For example, images generated by SEED-X-I vividly and accurately depicts "person standing in a small boat", "a gleaming sword on its back", "an oriental landscape painting", "tiger with vivid colors" in the captions. Through utilizing a pre-trained ViT Tokenizer as the bridge to decouple the training of visual de-tokenizer and the MLLM, our pre-trained model SEED-X can effectively realize high-quality image generation, which is a fundamental capability for applying multimodal models in real-world scenarios.

Image Manipulation. We compare image manipulation with previous MLLMs including Emu2-Gen [24], Gemini [33], MGIE [33] and Mini-Gemini [34]. Language-guided image manipulation presents a significant challenge as the model must be capable of comprehending free-form instructions and generating images with the low-level details of the input image preserved. As shown in Fig. 6, we can observe that SEED-X-Edit can more effectively adhere to editing instructions while maintaining the low-level details of the input image. For instance, SEED-X-Edit can accurately add sunglasses to the dog on the right, while both Emu2-Gen and MGIE fail to follow the instruction, resulting in sunglasses being added to both dogs. Additionally, SEED-X-Edit successfully eliminates the dog in the baby image while preserving the low-level background details and the baby's features. In contrast, Emu2-Gen fails to retain the fine details of the input image, and MGIE is unsuccessful in removing the dog. Note that Gemini lacks the ability to edit images as it **retrieves images** on the Internet. Here the presence of black images is due to its failure to display images related to human portraits. Mini-Gemini generates **text prompts** as the input of a pre-trained SDXL model, which can not preserve the visual details of the input image. The examples demonstrate the effectiveness of our instruction model for high-precision image manipulation. Our MLLM accurately predicts visual semantic representations based on an input image and a language instruction, which serve as input for the U-Net. The visual de-tokenizer can further condition on the input image, ensuring the preservation of fine-grained details in the decoded images.

Multimodal Comprehension We show qualitative examples of multimodal comprehension by SEED-X-I in Fig. 8 and Fig. 9. SEED-X-I can realize fine-grained object detection and perception, text-rich comprehension, fundamental mathematical computation, world-knowledge and commonsense reasoning, diagram understanding, which are crucial capabilities for its application in the real world.
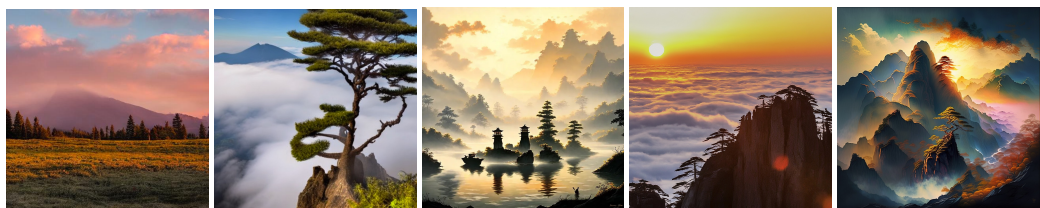
Figure 7: Qualitative comparison between MLLMs for text-to-image generation. SEED-X-I is capable of generating images that are more closely aligned with the elements in the descriptive caption and exhibit artistic qualities.

Detect the boat in the image.

What is the size of the second bedroom?
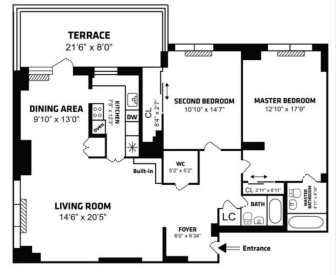
The second bedroom is 10'10" x 14'7".

Here are the order details for my taxi ride. Should I actually pay $29.42?

Order Details

- Base Fare — $10
- Mileage Fee — $12.11
- Duration Fee — $10.32
- Total — $32.42
- Discount — $3
- Actually Paid — $29.42

Based on the image, the total amount due is $32.42, which is the sum of the base fare, mileage fee, duration fee. The discount is $3, which is subtracted from the total, resulting in the actual paid amount of $29.42. Therefore, you should pay $29.42 for the taxi ride.

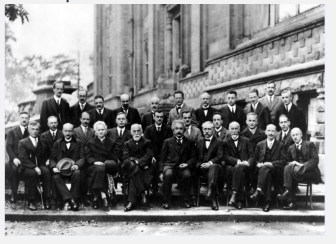**Count the number of the people.**

There are 11 people in the image.

**What are all the scene text in the image?**
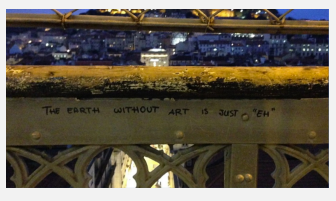
The scene text is "THE EARTH WITHOUT ART IS JUST 'EH'".

**What historical event is shown in the picture?**

The picture shows the famous 1927 Solvay Conference, which was a landmark meeting in the history of physics. It was attended by many of the most prominent physicists of the 20th century, including Albert Einstein, Niels Bohr, Werner Heisenberg, Erwin Schrödinger, and Marie Curie. The conference was held in Brussels, Belgium, and focused on the development of quantum mechanics.

Figure 8: Qualitative examples of multimodal comprehension by SEED-X-I.

Can this be true in the real world?
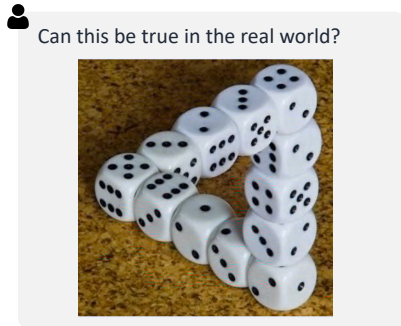
No, this is not possible in the real world. The image shows a stack of dice that are not physically connected, yet they are arranged in a way that suggests they are connected. This is an optical illusion, and the dice are not actually connected.

What is the meaning of the meme?
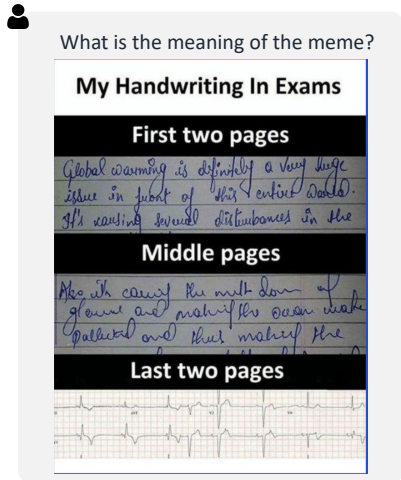
The meme is comparing the quality of handwriting in the first two pages of an exam and the last two pages. It suggests that the quality of handwriting often deteriorates as the exam progresses. This is a humorous way to express the common experience of writing neatly at the beginning of an exam and becoming less neat as the time progresses.

Please explain the method in details.
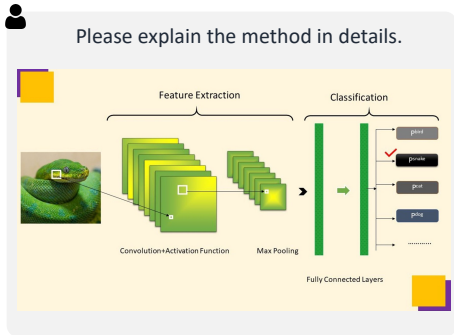
The method in the image is a Convolutional Neural Network (CNN) used for image classification. The process starts with the input image on the left, which is a green snake. This input goes through a convolutional layer, indicated by the green arrow pointing downwards. This convolutional layer is followed by a max pooling layer. The output of the max pooling layer feeds into a fully connected layer. This fully connected layer leads to the output of the network, which is the classification of the input image. The final output of the classification step is the classification of the input image, which is a green snake.

Is there anything in the image that can protect me from catching the flu virus when I go out?

Yes, the black face mask located at green bbox can help protect you from catching the flu virus when you go out.

Figure 9: Qualitative examples of multimodal comprehension by SEED-X-I.