

InternLM-XComposer-2.5: A Versatile Large Vision Language Model Supporting Long-Contextual Input and Output

Pan Zhang^{*1}, Xiaoyi Dong^{*1,2}, Yuhang Zang^{*1}, Yuhang Cao¹, Rui Qian^{1,2}, Lin Chen¹, Qipeng Guo¹, Haodong Duan¹, Bin Wang¹, Linke Ouyang¹, Songyang Zhang¹, Wenwei Zhang¹, Yining Li¹, Yang Gao¹, Peng Sun¹, Xinyue Zhang¹, Wei Li¹, Jingwen Li¹, Wenhui Wang^{1,2}, Hang Yan¹, Conghui He³, Xingcheng Zhang³, Kai Chen¹, Jifeng Dai^{4,1}, Yu Qiao¹, Dahua Lin^{1,2}, Jiaqi Wang^{1,✉}

¹Shanghai Artificial Intelligence Laboratory, ²The Chinese University of Hong Kong,

³SenseTime Group, ⁴Tsinghua University

internlm@pjlab.org.cn

Abstract

We present InternLM-XComposer-2.5 (IXC-2.5), a versatile large-vision language model that supports long-contextual input and output. IXC-2.5 excels in various text-image comprehension and composition applications, achieving GPT-4V level capabilities with merely 7B LLM backend. Trained with 24K interleaved image-text contexts, it can seamlessly extend to 96K long contexts via RoPE extrapolation. This long-context capability allows IXC-2.5 to excel in tasks requiring extensive input and output contexts. Compared to its previous 2.0 version, InternLM-XComposer-2.5 features three major upgrades in vision-language comprehension: (1) Ultra-High Resolution Understanding, (2) Fine-Grained Video Understanding, and (3) Multi-Turn Multi-Image Dialogue. In addition to comprehension, IXC-2.5 extends to two compelling applications using extra LoRA parameters for text-image composition: (1) Crafting Webpages and (2) Composing High-Quality Text-Image Articles. IXC-2.5 has been evaluated on 28 benchmarks, outperforming existing open-source state-of-the-art models on 16 benchmarks. It also surpasses or competes closely with GPT-4V and Gemini Pro on 16 key tasks. The InternLM-XComposer-2.5 is publicly available at <https://github.com/InternLM/InternLM-XComposer>.

1. Introduction

Recent advancements in Large Language Models (LLMs) [29, 55, 111, 121, 146, 147] have sparked interest in the development of Large Vision Language Models (LVLMs) [31, 41, 84, 112, 173, 183]. Leading

* equal contribution. ✉ corresponding author.

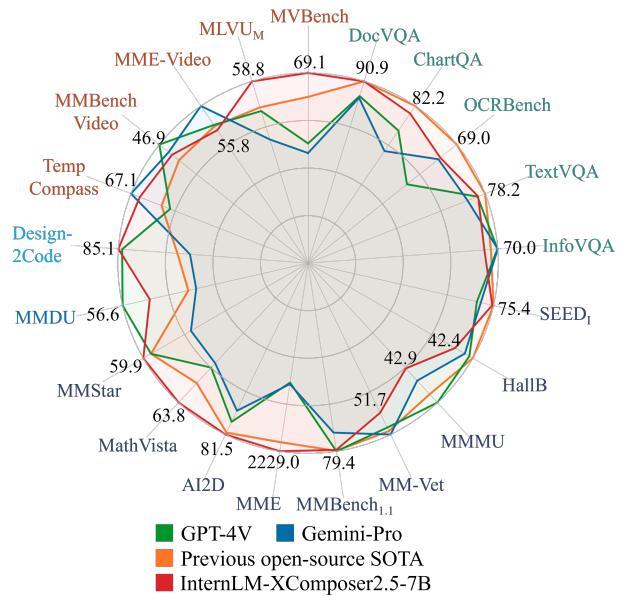


Figure 1. Overview of InternLM-XComposer-2.5 (IXC-2.5) performance on benchmarks in different domains, including **Video Benchmarks**, **Structural High-resolution Benchmarks**, **General Visual QA Benchmarks**, **Multi-True Multi-Image Benchmark**, and **Webpage Crafting Benchmark**. IXC-2.5 based on InternLM2-7B [143] matches or even surpasses GPT-4V [112] and Gemini Pro [142] in 15 benchmarks. Please refer to Table 3, 4, 5 for details.

paradigms like GPT-4 [112], Gemini Pro 1.5 [41], and Claude 3 [3] have achieved considerable success and significantly expanded the range of applications for LLMs. Open-source LVLMs are also being rapidly developed and can compete with proprietary APIs in several benchmarks. However, these open-source models still lag behind closed-source leading paradigms in versatility. They lack the

ability to perform diverse vision-language comprehension and composition tasks, largely due to limited diversity in training corpus and challenges in managing long-context input and output.

To further bridge the gap between proprietary APIs [41, 112] and open-sourced Large Vision Language Models, we are introducing InternLM-XComposer-2.5 (IXC-2.5), a versatile LVLM supporting long-contextual input and output with diverse comprehension and composition capacities. IXC-2.5 excels in existing open-sourced LVLMs with two advantages. **(1) Versatility:** IXC-2.5 supports a wide range of tasks related to comprehension and composition, such as free-form text-image conversation, OCR, video understanding, article composition with illustrations, and webpage crafting. **(2) Long-context capabilities in both input and output:** It is natively trained with 24K interleaved image-text data, whose context window can be extended to 96K through positional encoding extrapolation [94], empowering the long-term human-AI interaction and content creation.

Benefiting from the long contextual capability, compared to its previous 2.0 version [33], IXC-2.5 has upgraded three comprehension abilities: **(1) Ultra-High Resolution Understanding:** IXC-2.5 enhances the dynamic resolution solution proposed in IXC2-4KHD [34] with a native 560×560 ViT vision encoder, supporting high-resolution images with any aspect ratio. **(2) Fine-Grained Video Understanding:** IXC-2.5 treats videos as a ultra-high-resolution composite picture consisting of tens to hundreds of frames, allowing it to capture fine details through dense sampling and higher resolution for each frame. **(3) Multi-Turn Multi-Image Dialogue:** IXC-2.5 supports free-form multi-turn multi-image dialogue, allowing it to naturally interact with humans in multi-round conversations.

Besides comprehension, IXC-2.5 also supports two notable applications by incorporating extra LoRA parameters for text-image composition: **(1) Crafting Webpages:** IXC-2.5 can be readily applied to create webpages by composing source code (HTML, CSS, and JavaScript) following text-image instructions. **(2) Composing High-Quality Text-Image Articles:** Compared to IXC-2, IXC-2.5 leverages specially designed Chain-of-Thought (CoT) [153] and Direct Preference Optimization (DPO) [124] techniques to significantly enhance the quality of its written content.

We evaluated the versatility of InternLM-XComposer-2.5 (IXC-2.5) across a range of twenty-eight benchmarks, including five video benchmarks [38, 42, 71, 88, 181], nine structural high-resolution benchmarks [20, 89, 106–108, 117, 133, 139, 140], twelve general VQA benchmarks [18, 40, 44, 61, 66, 87, 100, 155, 164, 166], one multi>true multi-image benchmark [92], and one webpage crafting benchmark [131]. Compared to previous open-source LVLMs, IXC-2.5 achieved state-of-the-art results in

16 out of 28 benchmarks based on InternLM2-7B [143] backend. As shown in Figure 1, the performance of IXC-2.5 matches or even surpasses proprietary APIs, *e.g.*, GPT-4V [112] and Gemini Pro [41], in 16 benchmarks.

IXC-2.5 web demo now supports audio input and output using open-source tools [123, 179]. You may try it at <https://huggingface.co/spaces/Willow123/InternLM-XComposer>.

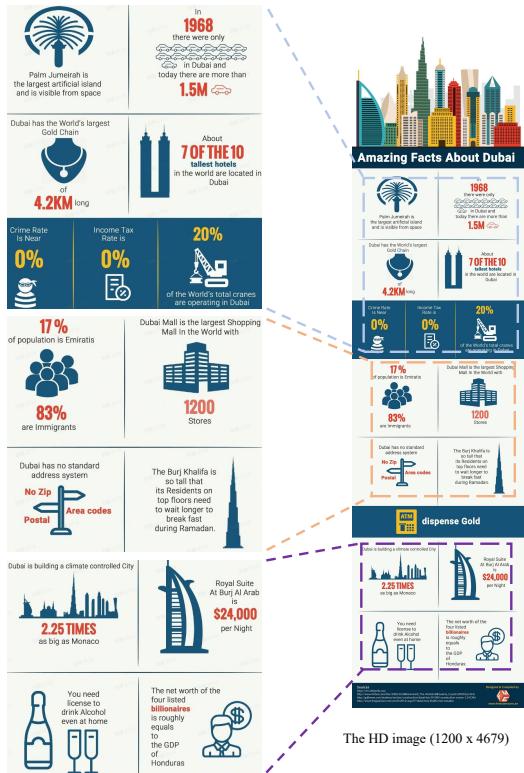
2. Related Works

LVLMs for Text-Image Conversation. Large Language Models (LLMs) [8, 12, 13, 29, 55, 60, 111, 115, 121, 143, 146, 147, 168] have received considerable attention because of their impressive performance in language comprehension and generation. Large vision-language models (LVLMs) [5, 9, 22–24, 31, 34, 35, 41, 68, 78, 112, 118, 159, 173, 183] have been developed by integrating LLMs with vision encoders [6, 14, 17, 25, 26, 33, 79, 91, 93, 113, 122, 138, 150, 167, 169, 170, 176] to extend the ability to understand vision content, enabling the application of text-image conversation. Most existing LVLMs are trained for single-image multi-round conversations, while some works [2, 6, 56, 78, 136, 178] have the ability to understand multi-image inputs. However, IXC-2.5 focuses on providing a free-form long-contextual multi-turn multi-image interaction experience [86, 92, 103], which has not been addressed yet.

LVLMs for High Resolution Images Analysis. Understanding high-resolution images has significant potential applications such as OCR and document/chart analysis, which is attracting increased attention in the LVLMs area. In recent works, there are two main strategies to enable high-resolution understanding: (1) High-resolution (HR) visual encoders [47, 74, 102, 141, 151, 177] directly support higher resolution images. (2) Patchification: A high-resolution image is cropped into patches [34, 49, 67, 76, 79, 79, 85, 90, 157, 158, 158]. Each patch is processed with a low resolution vision encoder, *e.g.*, CLIP [122] and visual embeddings of patches are further concatenated as inputs for LLM backends. IXC-4KHD [34] scales the supported resolution of open-source LVLMs into 4K and beyond for the first time. IXC-2.5 combines both solutions with a vision encoder trained with a resolution of 560×560 and a dynamic resolution solution proposed in IXC2-4KHD [34], resulting in further improvements.

LVLMs for Video Understanding. In addition to image understanding, the LVLMs area has also witnessed emerging efforts in video analysis [37, 39, 70, 88, 110, 134, 135]. To handle complex video inputs, existing works use sparse sampling or temporal pooling [52, 77, 101, 104, 162], compressed video tokens [57, 69, 73, 120, 154, 172], memory banks [45, 134, 135], and language as a bridge [54, 59, 171] for video understanding. Apart from these video-specific

Chat on 4K-resolution Image



Analyze this image in detail



Multi-Turn Multi-Image Dialogue



I want to buy a car from the three given cars, analyze their advantages and weaknesses one by one



When considering the purchase of a car from the three options provided, it's essential to evaluate each vehicle based on its advantages and weaknesses. The first image shows a Mercedes-Benz SUV, which is known for its luxury, comfort, and reliability. Its strengths include spacious interiors, advanced safety features, and a reputation for durability. However, it may not offer the same performance as the other two vehicles, especially in terms of speed and handling.

The second image depicts a Bugatti Veyron, an iconic supercar renowned for its power, speed, and engineering prowess. Its advantages lie in its exceptional performance capabilities, with a top speed exceeding 250 mph and a powerful engine that can deliver over 1,100 horsepower. However, this comes at a significant price, both financially and in terms of maintenance costs. Additionally, while the Veyron offers unparalleled driving experience, it might be less practical for everyday use due to its limited seating capacity and high fuel consumption.

The third image shows a BMW i8, a hybrid sports car that combines electric propulsion with a combustion engine. This vehicle's benefits include lower emissions, efficient energy usage, and impressive acceleration times. It also boasts a stylish design and advanced technology features. However, one potential weakness could be the relatively short range compared to fully electric cars, requiring frequent charging stops if used extensively for long-distance travel.



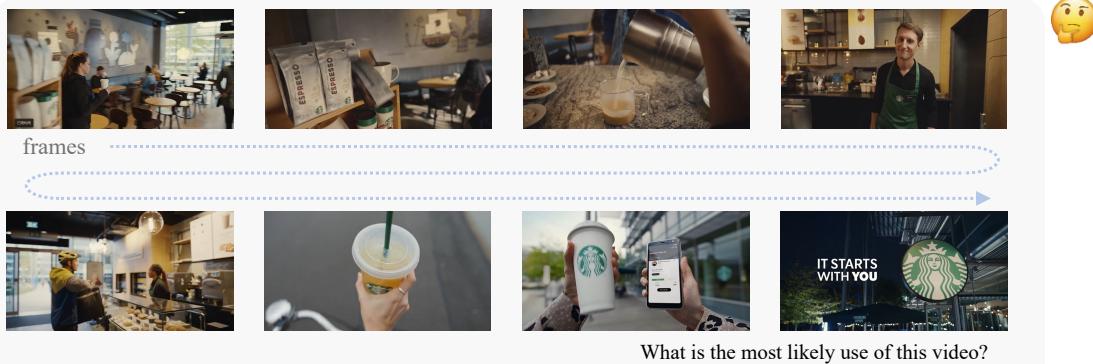
How about this car



The car in the image is a red Ferrari, which is known for its high performance and luxury. This particular model appears to be a modern iteration of the Ferrari 812 Superfast or a similar high-performance vehicle from the brand. The advantages of this car include its powerful engine, likely delivering over 800 horsepower, making it one of the fastest cars on the road. Its aerodynamic design suggests excellent handling and stability at high speeds. Additionally, as a Ferrari, it comes with a reputation for superior craftsmanship and quality. However, there are also some potential weaknesses to consider. One might argue that the high price tag associated with owning such a vehicle could be a deterrent for many buyers. Maintenance costs can also be quite significant due to the complex nature of Ferrari engines and the specialized parts required. Furthermore, while the car's performance is unmatched by most standards, it may not offer the same level of comfort and practicality as more conventional vehicles, especially when considering long-distance travel or daily commuting.

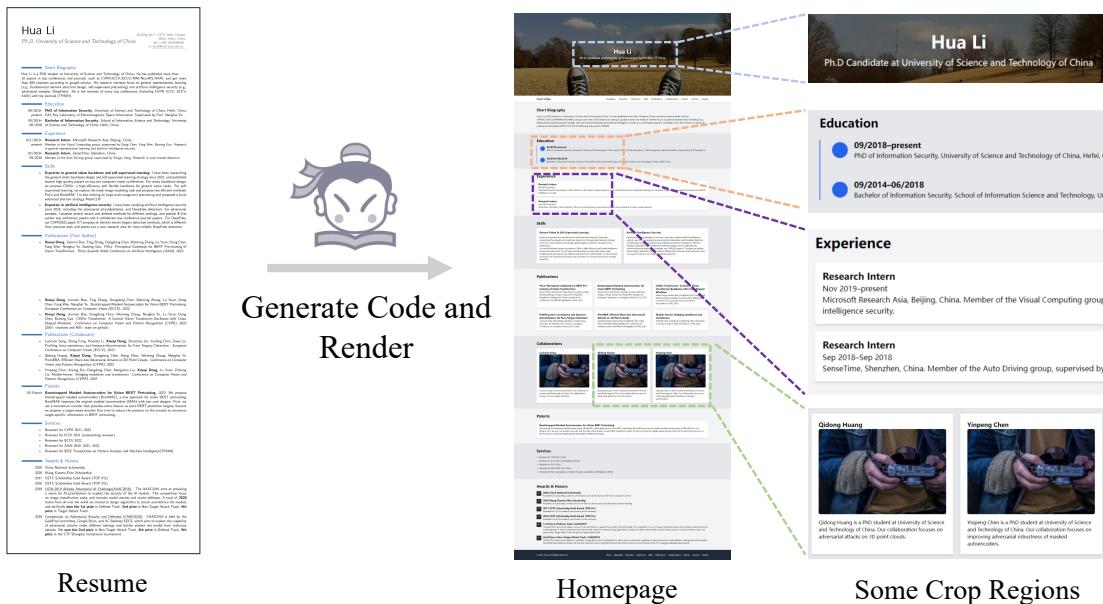
Figure 2. The capabilities of IXC-2.5: Chat on 4K-resolution Image and Multi-Turn Multi-Image Dialogue.

Chat on Video



The most likely use of this video is as an advertisement for Starbucks. The sequence of events depicted in the video, such as the preparation of a coffee drink, the interaction between customers and baristas, and the closing shot of the Starbucks logo, are characteristic of a promotional piece designed to showcase the brand's products and services. The emphasis on the coffee-making process, the use of the Starbucks app, and the friendly interactions between customers and staff all serve to create a positive image of the brand. Additionally, the final shot of the Starbucks logo with the text "IT STARTS WITH YOU" suggests a call to action for viewers to engage with the brand, further supporting the idea that this video is an advertisement aimed at attracting new customers and encouraging existing ones to continue patronizing Starbucks.

Resume-to-Homepage



Instruction-aware Webpage Generation

Generate a website for Research institutions. The name is Shanghai AI lab. Top Navigation Bar is blue. Below left, an image shows the logo of the lab. In the right, there is a passage of text below that describes the mission of the laboratory. There are several images to show the research projects of Shanghai AI lab.

Instruction

Generate Code and Render



Figure 3. The capabilities of IXC-2.5: Chat on Video, Resume-to-Homepage and Instruction-aware Webpage Generation.

Screenshot-to-Code

Pan Zhang
Researcher at Shanghai AI Laboratory
Shanghai, China
Email
Google Scholar

Short Bio
I am currently a researcher at Shanghai AI Laboratory (SAIL). I received my Ph.D. degree through a Joint PhD Program between Microsoft Research Asia (MSRA) and University of Science and Technology of China (USTC) in 2021. Prior to that, I received my Bachelor degree of Information Science from Tsinghua University in 2017 and my Master degree from USTC in 2020.

My research interests include Multimodal Large Language Models and Image-Text Fusion and Editing.
We are seeking long-term research collaboration. Please send me an email if you want to join us.

Publications

- 2024-01: A novel multi-modal cross-domain fusion framework for image-text fusion based on dual-path learning. Accepted by *IEEE Access*.
- 2024-02: The state-of-the-art dataset of Chinese-English image-text pairs has been released! 100,000+ items in one month!
- 2024-03: Three papers accepted by CVPR 2024. *Approx-CLIP* Accepts All the Requirements.
- 2024-04: We release *Chinese-English CompCaption*. The first 70 model numbers in even sequence GPT-4 and Gemini-H are certain.
- 2024-05: We release *Image-Text Fusion*, a state-of-the-art large model for advanced joint image comprehension and composition.
- 2024-06: We release *Image-Text Fusion*, a state-of-the-art large model for advanced joint image comprehension and composition.
- 2024-07: *Diffusion*, the first ten-thousand-class object detection dataset, is accepted by ICML 2024 as an Oral paper.
- 2024-08: Five papers accepted by CVPR 2024.
- 2024-09: One paper accepted by ICML 2024.
- 2024-10: One paper accepted by TMM.
- 2024-11: One paper accepted by EITI 2024.
- 2024-12: One paper accepted by EITI 2024.
- 2024-13: One paper accepted by ICIP 2024.
- 2024-14: One paper accepted by ICIP 2024.
- 2024-15: One paper accepted by ICIP 2024.
- 2024-16: One paper accepted by ICIP 2024.
- 2024-17: One paper accepted by ICIP 2024.
- 2024-18: Two papers accepted by ICIP 2024.
- 2024-19: One paper accepted by ICIP 2024.
- 2024-20: The first 70 model numbers in even sequence GPT-4 and Gemini-H are certain.
- 2024-21: We release *Image-Text Fusion*. The first 70 model numbers in even sequence GPT-4 and Gemini-H are certain.
- 2024-22: We release *Image-Text Fusion*. The first 70 model numbers in even sequence GPT-4 and Gemini-H are certain.
- 2024-23: One paper accepted by SIGGRAPH Asia 2024.
- 2024-24: One paper accepted by SIGGRAPH Asia 2024.
- 2024-25: One paper accepted by SIGGRAPH Asia 2024.
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Generate Code and Render

Article Composing

Generate an article about the Impact and Measures Regarding Global Climate Change. The outline is as follows:

1. Describe the impact of climate change on the natural environment, including rising sea levels and an increase in extreme weather events.
2. Analyze the effects of climate change on industries such as agriculture and tourism.
3. Explore international efforts to address climate change, such as the Paris Climate Agreement.
4. Discuss actions that individuals and communities can take at a personal level.

Impact and Measures Regarding Global Climate Change

The most likely use of this video is as an advertisement for Starbucks. The sequence of events depicted in the video, such as the preparation of a coffee drink, the interaction between customers and baristas, and the closing shot of the Starbucks logo, are characteristic of a promotional piece designed to showcase the brand's products and services. The emphasis on the coffee-making process, the use of the Starbucks app, and the friendly interactions between customers and staff all serve to create a positive image of the brand. Additionally, the final shot of the Starbucks logo with the text "IT STARTS WITH YOU" suggests a call to action for viewers to engage with the brand, further supporting the idea that this video is an advertisement aimed at attracting new customers and encouraging existing ones to continue patronizing Starbucks.

Impact of Climate Change on the Environment

One of the most visible impacts of climate change is the rise in sea levels. As temperatures increase, glaciers and ice caps melt, contributing to a rise in sea level that threatens coastal communities around the world. This can lead to saltwater intrusion into freshwater supplies, affecting agriculture and drinking water quality. Additionally, increased precipitation can cause flooding, while droughts can result in crop failure and food shortages.

Another significant impact of climate change is the alteration of ecosystems. As temperatures rise, plant and animal species are forced to adapt to new conditions or face extinction. This can lead to a loss of biodiversity and the collapse of entire ecosystems. The warming of oceans also poses a threat to marine life, including coral reefs, which serve as vital habitats for many ocean species.

The tourism industry is another sector significantly impacted by climate change. Extreme weather events, such as hurricanes and typhoons, can disrupt travel plans and damage infrastructure, leading to a loss of revenue for businesses and jobs. Furthermore, the warming of oceans and the melting of glaciers can alter the aesthetic appeal of beach destinations, reducing their attractiveness to tourists.

International Efforts to Address Climate Change

In response to the global challenge posed by climate change, countries have come together to form international agreements aimed at mitigating its impact. The Paris Climate Agreement, signed by 195 countries in 2015, is a landmark effort to address climate change. The agreement sets a goal of limiting global warming to well below 2 degrees Celsius above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 degrees Celsius.

The Paris Agreement recognizes the importance of reducing greenhouse gas emissions and increasing resilience to the impacts of climate change. Countries are required to submit nationally determined contributions (NDCs), outlining their efforts to reduce emissions and adapt to the impacts of climate change. While the implementation of these measures is voluntary, countries are encouraged to increase their ambition over time to meet the goals of the agreement.

Personal Level Actions

While international efforts are crucial in addressing climate change, individuals and communities can also take actions at a personal level. Some measures include:

- Reducing energy consumption: This can be achieved by using energy-efficient appliances, turning off lights when not in use, and reducing overall energy usage.
- Using alternative transportation: Walking, cycling, carpooling, and using public transportation can help reduce greenhouse gas emissions from vehicles.
- Reducing waste: Properly recycling and composting waste can help reduce methane emissions from landfills.
- Supporting renewable energy: Investing in solar panels, wind turbines, and other forms of renewable energy can help reduce reliance on fossil fuels.
- Planting trees: Trees absorb carbon dioxide and produce oxygen, making them a valuable tool in the fight against climate change.

In conclusion, climate change poses a significant threat to the natural environment, industry, and human populations. However, through international efforts and personal actions, it is possible to mitigate its impact and create a more sustainable future.

Figure 4. The capabilities of IXC-2.5: Screenshot-to-Code and Article Composing.

5

designs, video analysis can also be formulated to understand a high-resolution composite picture consisting of sampled video frames [63, 156, 174]. Benefiting from the ability to comprehend ultra-high-resolution images and long context, IXC-2.5 exhibits strong performance on various video benchmarks for LVLMs.

Webpage Generation. Pix2Code [10] presents an end-to-end solution for UI-to-code transformation leveraging CNNs and RNNs. This approach contends with the challenges posed by intricate visual encoding and extensive text decoding when applied to real-world UIs. In the sphere of recent advancements, works such as Sightseer [64], DC-Gen [148], and Design2Code [131] have employed large vision-language models trained on synthetic screenshot-HTML paired datasets like WebSight v0.1 or v0.2 [64] to facilitate HTML code generation. Nevertheless, the synthesized web page datasets have been critiqued for their simplicity and lack of diversity. These studies generally concentrate on the screenshot/sketch-to-code task. In contrast, our IXC-2.5 model extends these capabilities to include screenshot-to-code, instruction-aware webpage generation, and resume-to-homepage tasks. IXC-2.5 is trained using a combination of high-quality synthesized and real-world web data. Furthermore, IXC-2.5 is proficient in generating JavaScript code, thereby enabling the development of interactive front-end webpages.

Preference Alignment. Reinforcement Learning from Human Feedback (RLHF) [115] and Reinforcement Learning from AI Feedback (RLAIF) [7] have shown great promise in aligning LLMs across various domains, including improving logical reasoning and generating helpful and harmless outputs. The typical approach involves training a reward model using human or AI preference data and fine-tuning the LLM to maximize the expected reward function with optimization algorithms like Proximal Policy Optimization (PPO) [126]. Alternatively, Direct Preference Optimization (DPO) [124] and the following works [36, 116] have emerged as leading methods that implicitly represent the reward score and eliminate the need for a separate reward model. Building on the success of RLHF and RLAIF in LLMs, recent studies have successfully extended RLHF/RLAIF algorithms for multimodal LVLMs [72, 119, 163, 180, 182] to reduce hallucination. In this work, we investigate the application of preference alignment techniques to the text-image article composition task, with a focus on generating high-quality and stable response results.

3. Method

3.1. Model Architecture

The model architecture of InternLM-XComposer-2.5 (IXC-2.5 in the following for simplicity) mainly follows the design of InternLM-XComposer2 [33] and InternLM-

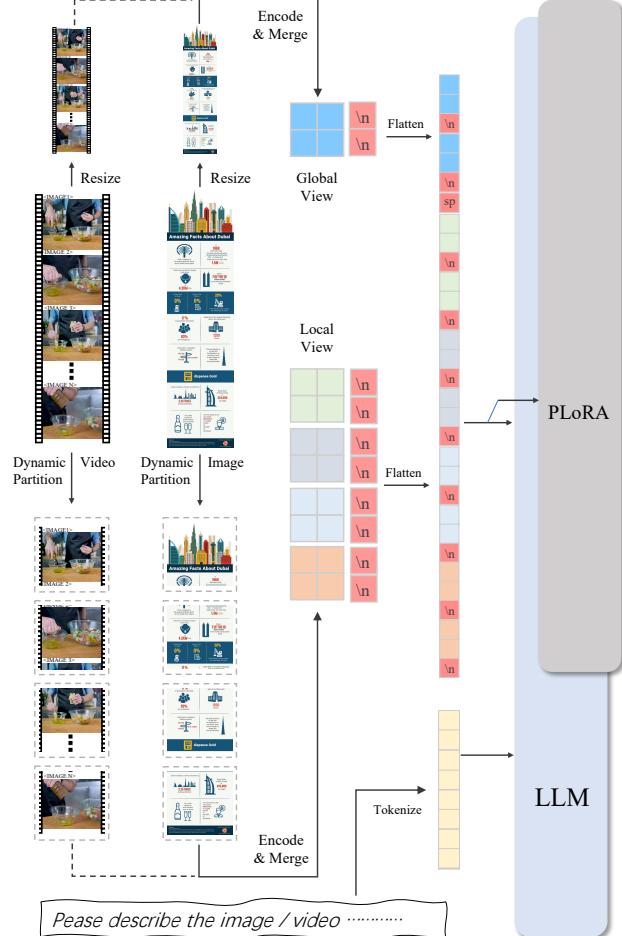


Figure 5. **Framework** of IXC-2.5 that supports the multi-modal inputs, including text, single/multiple images, and videos.

XComposer2-4KHD [34] (IXC2 and IXC2-4KHD for simplicity), including a light-weight Vision Encoder OpenAI ViT-L/14 [122], Large Language Model InternLM2-7B [13], and Partial LoRA [33] for efficient alignment. We recommend the readers to the IXC2 and IXC2-4KHD papers for more details.

3.2. Multi-modal Input

Our IXC-2.5 supports diverse input modalities, including text, single/multiple images, and videos. As shown in Figure 5, a Unified Dynamic Image Partition strategy is adopted for both videos and multiple images with any resolutions and aspect ratios.

Image Processing. We mainly follow the Dynamic Image Partition and Global-Local Format design used in IXC2-4KHD [34] with a few modifications. For the vision encoder, we reuse the ViT of 490×490 resolution used in IXC2 and further increase its resolution to 560×560 , so that each sub-image has 400 tokens.

For the high-resolution strategy, we unify the different strategies used in the IXC-4KHD into a scaled identity strategy. Given a maximum partition number \mathcal{H} , the image x with size $[h, w]$ is resized and padded to the new image \hat{x} with size $[p_h \times 560, p_w \times 560]$. This process is subject to the following constraints:

$$p_{w1} \times \lceil p_{w1} \times h/w \rceil \leq \mathcal{H}; \quad (1)$$

$$p_{w2} = \lceil w * s / 560 \rceil \quad (2)$$

$$p_w = \min(p_{w1}, p_{w2}) ; p_h = \lceil p_w \times h/w \rceil \quad (3)$$

where s is the scale factor, p_w and p_h represent the number of patches in each row and column, respectively.

For multi-image input, we assign an index to each image like $\langle \text{IMAGE } i \rangle$, $i \in \{1, 2, 3, \dots\}$ and format the image and text in an interleaved format.

Video Processing. We sample frames from the given video and concatenate them along the short side of the frame, leading to a high-resolution image. The frame index is also written in the image to provide the temporal relation.

Audio Processing. IXC-2.5 web demo supports audio input and output using open-source tools. For audio input, we employ Whisper [123] to transcribe audio into text. For audio output, we utilize MeloTTS [179] to convert the text back into audio.

3.3. Pre-training

During the pre-training phase, the LLM (InternLM2-7B [143]) is frozen while both the vision encoder and Partial LoRA [33] are fine-tuned to align the visual tokens with the LLM. The data used for pre-training is shown in Table 1.

In practice, we employ the CLIP ViT-L-14-490 [122] from IXC2 as the vision encoder and further increase its resolution to 560×560 . For the Unified Dynamic Image Partition strategy [34], we set the maximum number $\mathcal{H} = 12$ for the pertaining. For the Partial LoRA [33], we set a rank of 256 for all the linear layers in the LLM decoder block. Our training process involves a batch size of 4096 and spans across 2 epochs. The learning rate linearly increases to 2×10^{-4} within the first 1% of the training steps. Following this, it decreases to 0 according to a cosine decay strategy. To preserve the original knowledge of the vision encoder, we apply a layer-wise learning rate (LLDR) decay strategy [33], and the decay factor is set to 0.90.

3.4. Supervised Fine-tuning

We fine-tune the model with data listed in Table 2. The maximum number \mathcal{H} of the Unified Dynamic Image Partition strategy is 24 to handle extremely large images and videos. For video datasets, the IXC-2.5 is trained with large images concatenated by at most 64 frames. The largest training context is set to a 24,000 context window size, where the MMDU [92] dataset can achieve this limitation.

In practice, we jointly train all the components with a batch size of 2048 over 4000 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 5×10^{-5} , and each component has its own unique learning strategy. For the vision encoder, we set the 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.

3.5. Webpage Generation

We enhance the capabilities of the IXC-2.5 to include automated webpage generation. Specifically, the IXC-2.5 is now equipped to autonomously construct web pages, utilizing HTML, CSS, and JavaScript, based on input in the form of a visual screenshot, a set of free-form instructions, or a resume document. Current open-source general-purpose large language models frequently demonstrate suboptimal performance in generating HTML and CSS relative to their proficiency in natural language generation. To address this limitation, we propose training the screenshot-to-code task using extensive datasets from WebSight v0.1/v0.2 [64], and Stack v2 [95]. Subsequently, we fine-tune the model with a smaller, meticulously crafted dataset consisting of instruction-aware webpage generation and personal page generation examples.

Screenshot-to-code. In addition to the WebSight [64] datasets, we preprocess the HTML and CSS code from the Stack v2 [95] dataset to facilitate screenshot-to-code training. Initially, we combine the CSS and HTML code into a single file. Subsequently, we remove all comments, JavaScript code, and external links. Furthermore, we eliminate any CSS styles that are not referenced by the HTML code. We convert all files into screenshots, subsequently discarding those that did not render successfully. The remaining screenshots are then processed using the IXC2-4KHD [34] model to assess the quality of the web pages. Following the exclusion of low-quality web pages, we retained a final set of three remaining about 250,000 high-quality web pages.

We conduct training on the LoRA model utilizing the three aforementioned datasets. The LoRA rank is set to 512. The training protocol employs a batch size of 512 and is executed over a single epoch. Initially, the learning rate is incremented linearly to 1×10^{-4} within the first 1% of the training iterations. Subsequently, the learning rate decreases to 0 following a cosine decay schedule.

Instruction-aware Webpage Generation. A pivotal attribute of large language models lies in their capability to adhere to human instructions. To facilitate web page generation based on freeform instructions, we propose con-

Task	Dataset
General Semantic Alignment	ShareGPT4V-PT [17], COCO [21], Nocaps [1], TextCaps [132], LAION [125], SBU [114], CC 3M [129] ALLaVA [15]
World Knowledge Alignment	Concept Data [173]
Vision Capability Enhancement	WanJuan [46], Flickr[160], MMC-Inst[82], RCTW-17[130], CTW[165], LSVT[137], ReCTs[175], ArT[28]

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

Task	Dataset
Caption	ShareGPT4V [17], COCO [21], Nocaps [1]
General QA	VQAv2 [4], GQA [53], OK-VQA [105] VD [32], RD [16], VSR [81], ALLaVA-QA [15]
Multi-Turn QA	MMDU [92]
Science QA	AI2D [61], SQA [98], TQA [62], IconQA [97]
Chart QA	DVQA [58], ChartQA [106], ChartQA-AUG [106]
Math QA	MathQA [161], Geometry3K [96], TabMWP [99], CLEVR-MATH [80], Super [75]
World Knowledge QA	A-OKVQA [127], KVQA [128], ViQuAE [65]
OCR QA	TextVQA [133], OCR-VQA [109], ST-VQA [11]
HD-OCR QA	InfoVQA[108], DocVQA [107], TabFact [20], WTQ [117], DeepForm [139], Visual MRC [140]
Video	ShareGPT4Video [19], ActivityNet [37]
Conversation	LLaVA-150k [84], LVIS-Instruct4V [149] ShareGPT-en&zh [27], InternLM-Chat [143]

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

structuring data through querying closed-source large language models. Specifically, we utilize GPT-4 to generate diverse instructions and concepts for web page creation, encompassing elements such as type, style, and layout. Subsequently, these instructions are harnessed to query Claude-3-sonnet [3] for the actual web page generation process. This approach results in 18,000 high-quality, instruction-aware samples. Additionally, we employ Tailwind CSS instead of traditional CSS, given its succinct nature.

Resume-to-homepage. In addition to instruction-aware webpage generation, we introduce a more practical task. Specifically, given a resume, the model is designed to generate a personal homepage. This homepage not only encapsulates the information present in the resume but also presents it with a well-structured and visually appealing format, improving both content organization and aesthetic layout. To generate corresponding datasets, we propose an idea-resume-homepage data generation pipeline. Initially, we leverage GPT-4 to produce resume ideas tailored for diverse personas, such as researchers, students, and engineers. GPT-4 is tasked with generating these resumes in markdown format based on the provided ideas. Upon obtaining the generated resumes, we then prompt Claude-3-sonnet [3] to create corresponding homepages from these resumes. To enhance the interactivity of these webpages, Claude-3-

sonnet is also utilized to generate JavaScript events based on the HTML code. In total, we have constructed a dataset comprising 2,000 samples.

Upon constructing the dataset for instruction-aware webpage generation and resume-to-homepage, we subsequently fine-tuned the LoRA model for 10 epochs. All other experimental settings were maintained consistent with those employed during the screenshot-to-code training phase.

3.6. Article Composing

Generating high-quality text-image articles (*e.g.*, poetry, novels, short stories, and essays) is a crucial capability for AI assistants, with various applications in daily life, including education and entertainment. Building upon the IXC-2.5 SFT model π in Section 3.4, we enhance creative writing capabilities for generating high-quality text-image articles. However, collecting high-quality text-image articles is a rare and expensive endeavor. Direct fine-tuning on scarce instruction data can lead to unstable responses from LVLMs in most cases. To overcome these challenges, we propose a scalable pipeline that integrates supervised fine-tuning, reward modeling, preference data collection, and DPO alignment for high-quality and stable article generation.

Supervised Fine-tuning. We begin with the SFT model π (Section 3.4) and a collection of 5,000 instruction tuning data samples \mathcal{D} from IXC2 [33], focused on article writing. Due to the limited scale of the instruction data, we use the SFT model to rewrite the original prompts using the Chain-of-Thought (CoT) technique [152], generating step-by-step prompts to supplement the instruction tuning data as augmented data \mathcal{D}^* . We observe that the SFT model is more effective in generating long-form responses when using these augmented prompts. We then train the initial model π on the augmented instruction tuning data via LoRA [51] with the rank of 256 and get the model π_{ref} to establish a starting point of our alignment pipeline.

Preference Data Collection. We use the fine-tuned model π_{ref} to generate diverse responses for each prompt in the augmented instruction tuning data \mathcal{D}^* , using different random seeds. This yields a collection of 80,000 prompt-response pairs. Next, we employ the GPT-4o model to label 2,000 responses with chosen or rejected decisions and give the reasons, which serve as our reward modeling data. We then train a reward model π_{rm} , sharing the same architecture of π_{ref} , on the reward modeling data. The reward model is used to make the chosen or rejected prediction on the remaining prompt-response pairs. These selected responses

	MVBench	MLVU	MME Video	MMB ^{*1} Video	Temp ^{*2} Compass	Doc VQA	Chart QA	Info VQA	Text VQA	OCR Bench	WTQ	Deep Form	Visual MRC	Tab Fact
Open-Source Previous SOTA Performance	VideoChat 2-7B[71]	InternVL 1.5-26B[26]	LIVA 34B[78]	InternVL 1.5-26B[26]	Qwen-VL 7B[6]	InternVL 1.5-26B[26]	InternVL 1.5-26B[26]	InternVL 1.5-26B[26]	GLM-4v 9B[43]	DocOwl 1.5-8B[50]				
<i>Closed-source API</i>														
GPT-4V [112]	43.5	49.2	<u>59.9</u>	56.0	—	88.4	78.5	75.1	78.0	51.6	—	—	—	—
Gemini-Pro [142]	—	—	75.0	49.3	70.6	88.1	74.1	75.2	74.6	68.0	—	—	—	—
IXC-2.5-7B	69.1	58.8	55.8	46.9	<u>67.1</u>	90.9	<u>82.2</u>	69.9	<u>78.2</u>	<u>69.0</u>	53.6	71.2	307.5	85.2

Table 3. Comparison with closed-source APIs and previous open-source SOTAs on **Video Benchmarks and Structural High-resolution Benchmarks**. The best results are **bold** and the second-best results are underlined. ^{*1} We scale the score from 0 ~ 3 to 0 ~ 100 for easier understanding. ^{*2} We report the determinism part (MCQA, Y/N, Caption Match) of TempCompass as the evaluation using GPT-3.5 is not stable.

	MMDU	MMStar	RealWQA	MathVista	AI2D	MMMU	MME	MMB	MMB _{CN}	MMB _{1.1}	SEED ^I	MM-Vet	HallB	
Open-Source Previous SOTA Performance	LLaVa1.6 8B[83]	InternVL 1.5-26B[26]	WeMM 8B[145]	WeMM 8B[145]	InternVL 1.5-26B[26]	360VL 70B[144]	InternVL 1.5-26B[26]	InternVL 1.5-26B[26]	InternVL 1.5-26B[26]	InternVL 1.5-26B[26]	GLM-4v 8B[145]	WeMM 14B[43]	WeMM 8B[145]	WeMM 47.5
<i>Closed-source API</i>														
GPT-4V [112]	66.3	<u>57.1</u>	<u>68.0</u>	47.8	75.5	56.8	1,926.5	81.3	80.2	79.8	69.1	56.8	<u>46.5</u>	
Gemini-Pro [142]	—	42.6	64.1	45.8	70.2	47.9	1,933.3	73.9	74.3	73.9	70.7	59.2	45.2	
IXC-2.5-7B	56.6	59.9	67.8	63.8	81.5	42.9	2,229.0	<u>82.2</u>	80.8	79.4	<u>75.4</u>	51.7	42.4	

Table 4. Comparison with closed-source APIs and previous open-source SOTAs on **Multi-Turn Multi-Image Dialog and General Visual QA Benchmarks**. The best results are **bold** and the second-best results are underlined.

are then used to construct the pair data $\mathcal{D}^p = \{x, y_w, y_l\}$, while x, y_w and y_l refer to the prompt, chosen response and rejected response, respectively. Ultimately, we obtain a total of 30,000 preference data \mathcal{D}^p for DPO [124] alignment. **DPO Alignment.** We use the DPO algorithm to update the SFT model π_{ref} on target policy from the preference data \mathcal{D}^p :

$$\begin{aligned} \mathcal{L}_{\text{DPO}}(\pi_\theta, \pi_{\text{ref}}) &= \mathbb{E}_{x, y_w, y_l \sim \mathcal{D}^p} \\ &[-\log \sigma(\beta \log(\frac{\pi_\theta(y_w|x)}{\pi_{\text{ref}}(y_w|x)}) - \beta \log(\frac{\pi_\theta(y_l|x)}{\pi_{\text{ref}}(y_l|x)}))]. \end{aligned} \quad (4)$$

In practice, we use LoRA with a rank of 256 to get the DPO model π_θ . We observe that our model tends to prioritize minimizing the likelihood of dis-preferred responses y_l over maximizing the likelihood of preferred responses y_w to avoid generating inappropriate or low-quality content.

In summary, our scalable pipeline consists of three primary components. First, we address the challenge of limited instruction tuning data by re-writing original prompts into augmented prompts. Next, we generate diverse responses using different random seeds, enabling the exploration of various creative possibilities. Finally, we apply the DPO algorithm to the chosen and rejected responses to refine our model’s performance. Through our pipeline, our model is capable of generating high-quality articles.

4. Experiments

In this section, we validate the benchmark performance of our InternLM-XComposer-2.5 (IXC-2.5) after supervised fine-tuning.

4.1. LVLM Benchmark results.

In Table 3 and Table 4, we compare our IXC-2.5 on a list of benchmarks with both closed-source APIs and SOTA open-source LVLMs (with comparable model size). Here we report video understanding results on MVBench [71], MLVU [181], MME-Video [42], MMBench-Video [38], TempCompass [88]. For Structural High-resolution understanding, we report results on DocVQA [107], ChartQA [106], InfographicVQA [108], TextVQA [133], OCRBench [89], DeepForm [139], WikiTableQuestion (WTQ) [117], Visual MRC [140], and TabFact [20]. For general visual question answering, we report results on MMStar [18], RealWorldQA [155], MathVista [100], MMMU [166], AI2D [61], MME [40], MMBench (MMB) [87], MMBench-Chinese (MMB^{CN}) [87], MMBench-v1.1 (MMB^{v1.1}) [87], SEED-Bench Image Part (SEED^I) [66], MM-Vet [164], HallusionBench (HallB) [44]. For Multi-True Multi-Image dialogue, we evaluate IXC-2.5 on MMDU [92] benchmark. For webpage crafting, we report a subtask screenshot-to-code [131] since benchmarks for others are not available in the community.

The evaluation is mainly conducted on the OpenCompass VLMEvalKit [30] for the unified reproduction of the results.

Comparison on Video Understanding Benchmarks. As demonstrated in Table 3, IXC-2.5 exhibits competitive performance on fine-grained video understanding tasks, outperforming open-source models on 4 of the 5 benchmarks and being on par with Closed-Source APIs. For example, IXC-2.5 reaches 69.1 on the MVBench, +8.7% higher

	Block-Match	Text	Position	Color	CLIP	Average
<i>Closed-source API</i>						
GPT-4V [112]	85.8	97.4	<u>80.5</u>	73.3	86.9	<u>84.8</u>
Gemini-Pro [142]	80.2	94.6	72.3	66.2	83.9	79.4
<i>Open-source</i>						
WebSight VLM-8B [64]	55.9	86.6	77.3	<u>79.4</u>	<u>86.5</u>	77.1
CogAgent-Chat-18B [48]	7.1	18.1	13.3	13.0	75.5	25.4
Design2Code-18B [131]	78.5	<u>96.4</u>	74.3	67.0	85.8	80.4
IXC-2.5-7B	<u>81.9</u>	95.6	80.9	80.8	<u>86.5</u>	85.1

Table 5. Screenshot-to-code. Comparison with closed-source APIs and open-source models on **Design2Code benchmark**. The best results are **bold** and the second-best results are underlined.

than the previous SOTA method VideoChat2-7B and outperforms GPT-4V with +25.6%. For the recent challenging MMBench-Video, IXC-2.5 reaches the SOTA performance on open-source models and performs close to Gemini-Pro.

Comparison on Structural High-resolution Benchmarks. Benefiting from the unified image partition strategy, IXC-2.5 could handle diverse kinds of images. Table 3 reports its performance on several structural high-resolution benchmarks. IXC-2.5 with only 7B parameters performs on par with the current large open-source LVLMs and close-source APIs. For example, IXC-2.5 gets 90.9% on the DocVQA test set, the same as InternVL-1.5 which has nearly 4× parameters. For the highly structured form and table understanding tasks, IXC-2.5 outperforms DocOwl 1.5-8B with +13.0%, +2.4%, +5.0% on WikiTable-Question, DeepForm and TableFace respectively.

Comparison on Multi-Image Multi-Turn Benchmarks. IXC-2.5 is capable of taking multiple images as input and conducting multi-round free-form dialogue based on them. We evaluate it quantitatively on the newly proposed MMDU benchmark [92]. As shown in Table 4, the IXC-2.5 model demonstrates superior performance, outperforming the previous SOTA open-source model by a significant margin of 13.8%. This notable improvement highlights the effectiveness of our approach in advancing the capabilities of multi-image and multi-turn understanding.

Comparison on General Visual QA Benchmarks. IXC-2.5 is designed as a general LVLM to handle diverse multi-modal tasks. Here we report its performance on general visual QA benchmarks. As shown in Table 4, the IXC-2.5 shows superb performance on these benchmarks and on par with current large open-source LVLMs and closed-source APIs. For example, IXC-2.5 gets 59.9% on the challenging MMStar and outperforms GPT-4V and Gemini-Pro. On the RealWorldQA, IXC-2.5 also performs better than Gemini-Pro and close to GPT-4V.

Comparison on Screenshot-to-code Benchmark. Table 5 presents the comparison results on the Design2Code [131] benchmark that assesses the ability to translate visual design into code implementation. Our IXC-2.5 even surpasses the GPT-4v on average performance, which highlights the

potential of IXC-2.5 to excel in bridging the gap between visual design and code implementation.

5. Conclusion

We have introduced InternLM-XComposer-2.5 (IXC-2.5), a cutting-edge Large Vision-Language Model (LVLM) boasting long-contextual input and output capabilities that enable advanced features such as ultra-high resolution image understanding, fine-grained video understanding, multi-turn multi-image dialogue, webpage generation, and article composing. Our comprehensive experiments demonstrate that IXC-2.5 achieves competitive performance, remarkably, with a relatively modest 7B Large Language Model (LLM) backend.

Our model sets out a promising research direction that can extend to a more contextual multi-modal environment, including long-context video understanding (*e.g.*, long movies) and long-context interaction history, to better assist humans in real-world applications.

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