

V2PE: Improving Multimodal Long-Context Capability of Vision-Language Models with Variable Visual Position Encoding

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Abstract

Vision-Language Models (VLMs) have shown promising capabilities in handling various multimodal tasks, yet they struggle in long-context scenarios, particularly in tasks involving videos, high-resolution images, or lengthy image-text documents. In our work, we first conduct an empirical analysis of the long-context capabilities of VLMs using our augmented long-context multimodal datasets. Our findings reveal that directly applying the positional encoding mechanism used for textual tokens to visual tokens is suboptimal, and VLM performance degrades sharply when the position encoding exceeds the model’s context window. To address this, we propose Variable Visual Position Encoding (V2PE), a novel positional encoding approach that employs variable and smaller increments for visual tokens, enabling more efficient management of long multimodal sequences. Our experiments demonstrate the effectiveness of V2PE to enhance VLMs’ ability to effectively understand and reason over long multimodal contexts. We further integrate V2PE with our augmented long-context multimodal datasets to fine-tune the open-source VLM, InternVL2. The fine-tuned model achieves strong performance on both standard and long-context multimodal tasks. Notably, when the sequence length of the training dataset is increased to 256K tokens, the model is capable of processing multimodal sequences up to 1M tokens, highlighting its potential for real-world long-context applications. The code and models will be available at <https://github.com/OpenGVLab/V2PE>.

1. Introduction

With the rapid advancement of Large Language Models (LLMs) [14, 87, 105, 111, 115], Vision-Language Models

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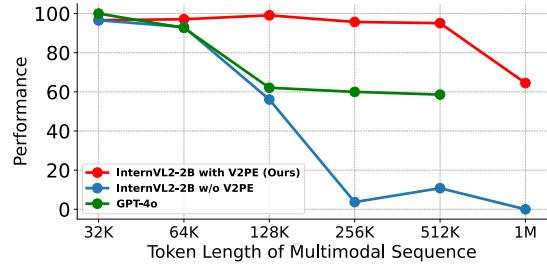


Figure 1. Performance on the image retrieval task using a token length of up to 1M on MM-NIAH [125] across different VLMs. The GPT-4o [86] version is 2024-08-06, while InternVL2-2B [20] models are both fine-tuned from the official release, using our augmented data, with token lengths reaching up to 256K per sample.

(VLMs) have made substantial strides [21, 85, 110, 122], excelling at tasks like visual captioning [18], visual question answering [81], and complex visual reasoning [143]. Despite this progress, existing research [119, 125, 139, 151] reveals that VLMs struggle to generalize effectively when confronted with multimodal long-sequence inputs (e.g., long videos [127, 133], high-resolution images [46, 130], and lengthy image-text documents [3, 112, 159]). This limitation emerges even in relatively straightforward, such as object counting and passkey duplication, significantly restricting VLMs’ potential applications and impeding the enhancement of user experience [23, 121, 125, 128].

Recent efforts have attempted to extend VLMs’ capabilities to process multiple images or handle long multimodal sequences. However, these approaches either permit only a small number of images (typically fewer than five) [53, 68, 158] or primarily target video data (e.g., LongVA [151], LongVILA [139], LongLLAVA [128]). These studies are only limited to specific application scenarios, highlighting the challenges VLMs face in handling complex and long-sequence multimodal data, which makes a key research question particularly urgent: *Why do VLMs perform poorly*

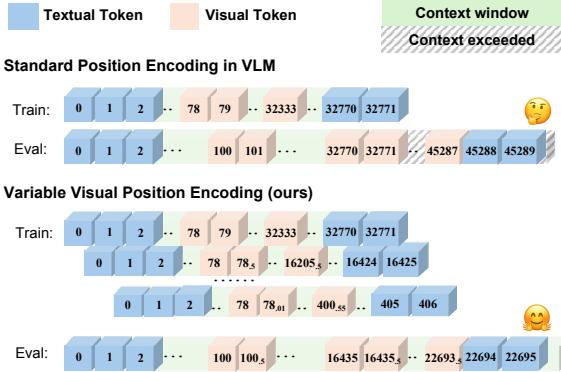


Figure 2. Illustration from our proposed Variable Visual Position Encoding (V2PE). Unlike the standard position encoding used in most VLMs, which shares the same stepwise positional increments for both visual and textual tokens, our proposed Variable Visual Positional Encoding (V2PE) uses smaller and variable positional increments specifically for visual tokens compared to textual tokens. This flexible design enables VLMs to handle long-context multimodal sequences within a limited context window.

in long-context scenarios, and how can we unlock their capacity for comprehensive multimodal understanding and reasoning over long sequences?

To investigate this, we first construct a large-scale pool of long-context multimodal datasets to evaluate and analyze VLM capabilities systematically. By extending the sequence length of existing instruction-tuning datasets (e.g., DocVQA [81], ChartQA [79], SQA [74]) to 32K or 256K tokens, we adapt these datasets specifically to train VLMs for enhanced long-context capabilities. We also expand the validation sets to 64K and 1M tokens to validate VLM performance with longer contexts, providing a deeper understanding of the limitations.

Our empirical analysis shows that the design of positional encodings of visual tokens plays an essential role in long-context scenarios, which is often overlooked in previous studies. Specifically, (1) directly applying the LLM positional encoding mechanism to visual tokens is suboptimal, and (2) the performance of VLMs degrades significantly when positional encodings for visual tokens exceed the trained context window, and previous position encoding extension methods applicable to LLMs provide only marginal improvements. These findings highlight the need for specialized positional encoding methods to manage visual tokens in long-context multimodal scenarios effectively.

To address these challenges, we propose Variable Visual Position Encoding (V2PE), a novel approach for handling visual token positions in VLMs. Considering the continuity nature of pixel space, adjacent visual tokens exhibit greater similarity compared to adjacent text tokens. Thus, V2PE uses smaller positional increments for visual tokens than for text tokens (see Fig. 2). Furthermore, during training, V2PE

employs variable positional increments for visual tokens, enabling the model to learn and adapt to position encoding in various scenarios. This variable adjustment allows the model to effectively handle different numbers and complexities of image inputs during inference, thereby enhancing its stability and adaptability in long-context processing.

In experiments, we apply V2PE to enhance the long-context capability of an open-source high-performance VLM, InternVL2-2B [20, 21], and fine-tune it using our extended multimodal datasets. The resulting model not only maintains strong performance on standard short-context multimodal benchmarks, but also excels in tasks requiring long context handling, which outperforms traditional token compression and other position encoding extension methods. In particular, after further fine-tuning on multimodal sequences up to 256K tokens, our model achieves promising performance in multimodal retrieval tasks involving sequences as long as 1M tokens, as shown in Fig. 1. The main contributions of this paper are as follows:

- We construct mixed datasets for VLMs' long-context training and evaluation by augmenting existing multimodal instruction tuning datasets and conduct a thorough investigation into why current VLMs struggle with long-context multimodal inputs, revealing that directly applying LLM positional encoding to visual tokens is ineffective.
 - We propose Variable Visual Position Encoding (V2PE), a novel positional encoding strategy that employs variable and smaller increments for visual tokens, significantly enhancing VLMs' ability to understand and reason over long multimodal contexts.
 - We apply our V2PE method and extend training data on the open-source VLM, InternVL2-2B. The fine-tuned VLM performs exceptionally well on both general multimodal benchmarks and long-context multimodal tasks, with the capacity to handle sequences of up to 1M tokens.

2. Related Works

Vision-Language Models (VLMs). With the development of Large Language Models (LLMs) [6, 10, 14, 37, 87, 105, 108, 111, 114, 115, 131, 132, 141, 156], the integration of vision and language modalities is significantly catalyzed. These progress give rise to Vision-Language Models (VLM), which can perceive visual contents, conduct visual reasoning, and engage in multi-modal dialogue with humans. Both proprietary commercial VLMs [5, 52, 82, 85, 101, 109, 110, 136] and open-source VLMs [47, 75, 77, 113, 120] has witnessed to this significant evolution. For commercial entities, GPT-4V [85] incorporates visual inputs to extend GPT-4 [87] with capabilities of handling multi-modal content, while Google’s Gemini series [109, 110] are able to process 1 million multi-modal tokens with significant performance. For open-source ini-

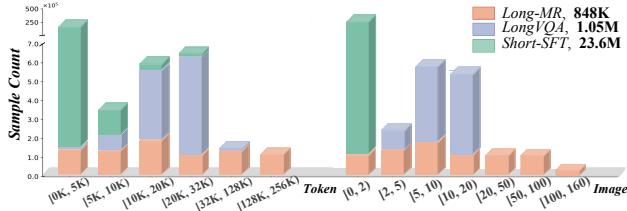


Figure 3. Statistics of our mixed training dataset, including Long-MR, Long-VQA, and short SFT data from InternVL2. The left part and the right part illustrate the distribution of tokens per sample and images per sample, respectively.

tiatives, BLIP series [29, 61, 62], LLaVA series [67–69], Qwen-VL series [7, 122], MiniCPM-V series [142], InternVL series [20, 21, 39], and others [9, 26, 27, 35, 36, 49, 63, 73, 90, 124, 147, 148] have also impacted the AGI landscape in the research community by linking large language models [6, 14, 114] and large vision models [4, 21, 31, 93] in processing both visual and textual modality. Specifically, there are also some works to advance VLMs’ power by improving scale and quality of data [15, 42], training on high-resolution images [46, 130], optimizing vision foundation models [21, 146].

Long Context Modeling. Due to practical demands, a large body of research [13, 22, 48, 70, 149, 154] has been developed to extend the context length of LLMs. One mainstream direction is to increase the length of LLM’s context window by extrapolation of position encoding [11, 16, 33, 89, 91, 102, 103, 153, 157], which allows the LLM to process unseen position during inference. Another line of research focuses on alleviating complexity of self attention by using sparse attention [8, 19, 24, 32, 92, 145], linear-complexity state-space modules [40, 41], or approximate attention computation [25, 58, 95, 123] as the alternatives for dense global attention. The context can also be extended by utilizing external memory to retrieve relevant tokens from the compression of past inputs, such as chunked input [84, 126, 138, 150] or the cached KV activations [2, 50, 116, 134, 135]. Other works [44, 134, 137] also adopt sliding windows to achieve an infinite context by only maintaining the activations for the very first and the latest tokens. Recent efforts [53, 128, 139, 151] aim to improve VLMs’ ability to process multiple images and long multimodal sequences. However, these studies are often limited to specific applications, revealing challenges faced by VLMs in processing complex and long-context data.

Position Encoding in Transformer. To address the lack of sequential information inherent in self-attention mechanisms, Transformers [117] utilize position encoding as a fundamental component to provide position information. The common position encoding design can be broadly cat-

egorized into absolute position encoding (APE) and relative position encoding (RPE). The absolute position encoding [12, 56, 59, 117, 118, 152] is simple and intuitive, as it embeds each absolute position position into a position vector which is then added into the representation of input sequences, but this strategy cannot be applied effectively for long sequences. To improve the modeling of long-term dependencies, relative positional encoding [30, 76, 91, 94, 96, 104, 106, 140] focuses on utilizing distance between tokens as the position information. Some research works [45, 91, 106] aim to utilize relative position for length extrapolation to train Transformers on short sequences and inference on longer context. Another research direction is Rotary Position Encoding (RoPE), which interpolates position information by rotating the key-query products according to their relative distances. Methods like Position Interpolation [16], NTK-Aware scaling [11], and LongRoPE [33] make progress on top of RoPE [104] to improve its poor extrapolation capability for longer sequences. For VLMs, most studies [7, 20, 139] adopt the same position embedding methods used in LLMs, and there are also some works [7, 20, 139] to explore different diagrams of the positional encoding schemes.

3. Method

3.1. Augmented Long-context Multimodal Datasets

We introduce two augmented long-context multimodal datasets: *Long Visual Question Answering* and *Long multimodal Retrieval*. These datasets aim to enhance VLMs’ long-context training and establish a systematic evaluation framework, thereby addressing the challenges associated with long-context understanding that extend beyond the scope of existing training data.

Long Visual Question Answering (Long-VQA). The Long-VQA dataset aims to evaluate the capabilities of VLMs in understanding and reasoning over long multimodal sequences within general visual question-answering tasks. We extended 17 widely adopted datasets (e.g., DocVQA [81], GQA [51], SQA [74]), expanding their content from short sequences to those containing up to 32K tokens. The tasks involve answering questions that require commonsense reasoning, factual knowledge, and interpretation of visual information from charts, documents, and real-world texts.

To extend existing datasets, we interleaved images from multiple samples into a single input, increasing sequence length and complexity to simulate real-world scenarios involving extraneous information. To reduce ambiguity, we refined questions to be more specific, incorporating instructions like “Based on image n , answer the following question”, which helps models focus on relevant content.

Long-VQA contains 533K samples: 392K for training

(up to 32K tokens) and 141K for validation (up to 64K tokens) to evaluate the generalization to longer contexts.

Long Multimodal Retrieval (Long-MR). Inspired by MM-NIAH (Multimodal Needle-in-a-Haystack) [125], we developed Long-MR by inserting a target image or textual segment into sequences of interleaved images and texts. Long-MR evaluates VLMs’ ability to retrieve specific targets from ultra-long multimodal sequences, requiring models to locate the inserted “needle” and answer associated questions. We generated two subsets of Long-MR: Long-MR-32K (488K samples, sequences up to 32K tokens) and Long-MR-256K (50K samples, sequences up to 256K tokens), following the data construction process of MM-NIAH.

To assess the limits of VLMs’ long-context capabilities, we further extend the official MM-NIAH evaluation benchmark by generating testing samples with sequence lengths ranging from 64K to 1M tokens, resulting in the MM-NIAH_{IM} benchmark. This extension pushes the testing capacity beyond the original MM-NIAH, which was limited to sequences of up to 64K tokens.

We combine the training splits of Long-VQA and Long-MR with short-context instruction-tuning datasets, as utilized in InternVL2, to create a mixed training set for our experiments. Fig. 3 illustrates the distribution of token sequence lengths and the number of images in the mixed training dataset, highlighting the significant increase in long-context samples introduced by our augmented datasets.

For more details about the construction process, data examples, and statistics of these datasets, please refer to the appendix.

3.2. Variable Visual Position Encoding

Position Encoding in Vision-Language Models. Position encoding is essential in Transformer architectures, enabling models to capture sequential relationships by providing tokens with positional information. It usually involves two sequential steps: *Position Index Derivation* f_{pos} , which assigns a positional index p_i to each token x_i , and *Position Embedding Computation* g_{emb} , which transforms these indices into position embeddings that influence the attention mechanism.

Formally, the multimodal input in VLMs can be represented as a sequence of N interleaved textual and visual tokens:

$$\mathbf{X} = [x_0, x_1, \dots, x_{N-1}], \quad (1)$$

where each token x_i is either a textual token x_i^{txt} or a visual token x_i^{vis} .

The Position Index Derivation function f_{pos} is recursively defined to capture the sequential nature of token po-

sitions:

$$p_i = \begin{cases} 0, & \text{if } i = 0, \\ f_{\text{pos}}(p_{i-1}, x_i), & \text{for } i = 1, 2, \dots, N - 1. \end{cases} \quad (2)$$

In existing LLMs and VLMs, the position index increments uniformly by 1 for each token, regardless of its modality:

$$p_i = p_{i-1} + 1, \quad \text{for } i = 1, 2, \dots, N - 1. \quad (3)$$

The Position Embedding Computation g_{emb} then transforms these position indices into embeddings. VLMs typically adopt the same position embedding methods used in Large Language Models (LLMs), such as Relative Position Encoding [96] or Rotary Position Embedding (RoPE) [104]. These embeddings are incorporated into the token representations to provide positional context during attention computations. For instance, in RoPE encoding, the token representation \mathbf{h}_i integrates positional information as:

$$\mathbf{h}'_i = \mathbf{h}_i \otimes g_{\text{emb}}(p_i), \quad (4)$$

where \otimes represents element-wise multiplication, and \mathbf{h}'_i is subsequently used in the Transformer attention mechanism.

Variable Position Index Derivation. The uniform increment of position indices in current VLMs does not account for the differences in information complexity and redundancy between textual and visual tokens. Visual tokens often exhibit higher redundancy and greater similarity with adjacent tokens, suggesting they may require smaller positional increments than textual tokens. Moreover, the large number of visual tokens can cause position indices to exceed the model’s pre-trained context window, leading to degraded performance.

To address these issues, we propose a modality-specific recursive function for position index derivation, assigning position indices differently for textual and visual tokens:

$$p_i = p_{i-1} + \begin{cases} 1, & \text{if } x_i \text{ is a textual token,} \\ \delta, & \text{if } x_i \text{ is a visual token,} \end{cases} \quad (5)$$

where δ is a smaller increment ($\delta < 1$) that reduces the rate at which position indices increase for visual tokens. The standard increment of 1 is retained for textual tokens to maintain their positional distinctions.

During training in our experiments, δ is dynamically selected for each image from a set of fractional values:

$$\delta \in \Delta = \left\{ 1, \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \frac{1}{32}, \frac{1}{64}, \frac{1}{128}, \frac{1}{256} \right\}. \quad (6)$$

Note that, δ remains constant within a single image to preserve the relative positional relationships among its visual

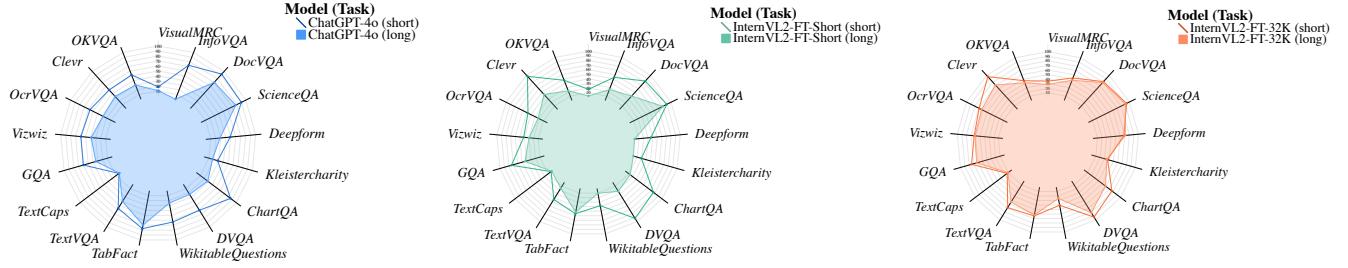


Figure 4. Performance on Long-VQA (long) with sequence lengths up to 32K tokens and its corresponding standard VQA (short) benchmarks. Compared with GPT-4o and InternVL2-FT-Short, the InternVL2-FT-32K, enhanced with our proposed V2PE, demonstrates comparable outstanding performance across both standard VQA benchmarks and their long-context counterparts.

tokens. For inputs containing multiple images, δ can be independently chosen for each image.

During inference, δ can be flexibly selected based on the input sequence length, allowing us to balance task performance and ensure that position indices remain within the model’s valid context range. Specifically, for long input sequences, a smaller δ can be employed to control the increase in position indices, preventing them from exceeding the trained positional embedding range, as illustrated in Fig. 2.

Discussion and Comparison with Previous Methods.

Our Variable Visual Position Encoding (V2PE) offers several advantages over existing long-context methods:

- 1) Unlike approaches that reduce the number of visual tokens through attention pooling or feature pooling—which potentially lead to information loss—V2PE retains all visual tokens within the VLM, preserving the richness and granularity of visual content.
- 2) Position encoding extension methods (*e.g.*, Positional Interpolation) adjust position embeddings during inference to accommodate longer sequences. However, this can introduce inaccuracies due to extrapolation beyond the trained positional embedding range. In contrast, V2PE allows the VLM to adapt position indices with arbitrary intervals by dynamically selecting δ during training. This strategy avoids unexpected position embeddings and ensures consistent model performance across varying input lengths.

4. Experiment

4.1. Analysis of VLMs’ Long-Context Capabilities

We analyze the long-context capabilities of existing VLM by using our constructed long-context multimodal datasets (see Sec. 3.1). Note that this sub-section does not use V2PE.

Experimental Setup. We fine-tune InternVL2-2B on two different training datasets to create four finetuned models:

- 1) *InternVL2-FT-Short*: This model is fine-tuned on the original instruction-tuning dataset (short-context) used by

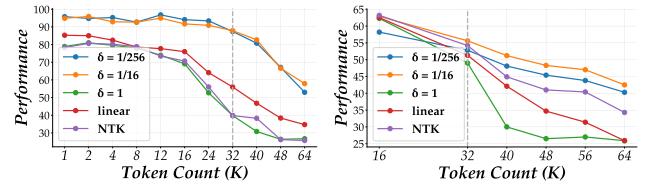


Figure 5. Performance on image retrieval task in MM-NIAH (left) and QA task in Long-VQA (right) with different positional increments. Additionally, we include the results of InternVL2-FT-32K when utilizing linear interpolation (linear) [16] and NTK-Aware Scaled RoPE (NTK) [11] position encoding extension methods.

Table 1. Performance on Long-VQA task with sequence lengths up to 64K tokens at various positional increments δ .

Model	δ	16K	32K	40K	48K	56K	64K	Avg
InternVL2-2B	—	52.8	27.3	23.0	23.9	22.6	21.0	28.4
InternVL2-2B	1/256	58.2	52.8	48.1	45.4	43.8	40.3	48.1
InternVL2-2B	1/128	60.0	53.7	49.5	46.5	45.3	41.3	49.4
InternVL2-2B	1/64	61.0	54.5	50.1	47.4	45.9	42.2	50.2
InternVL2-2B	1/32	61.9	55.4	51.4	47.5	46.4	42.3	50.8
InternVL2-V2PE-32K	1/16	62.9	55.6	51.2	48.3	47.0	42.5	51.3
InternVL2-V2PE-32K	1/8	63.2	55.8	52.0	47.6	45.8	41.9	51.1
InternVL2-V2PE-32K	1/4	63.4	55.7	51.3	47.0	45.1	39.7	50.4
InternVL2-V2PE-32K	1/2	63.3	54.9	46.8	36.8	33.3	29.2	44.1
InternVL2-V2PE-32K	1/1	62.3	49.0	30.0	26.5	27.0	25.9	36.8
InternVL2-FT-32K (Linear [16])	—	62.5	51.3	42.1	34.7	31.4	25.9	40.9
InternVL2-FT-32K (NTK [11])	—	63.2	54.2	44.9	41.0	40.4	34.3	45.3

InternVL2-2B. It serves as a baseline to evaluate performance without exposure to long-context data. 2) *InternVL2-FT-32K*: This model is fine-tuned on a mixed training dataset introduced in Sec. 3.1, incorporating our augmented long-context training data to enhance its long-context capacity. 3) *InternVL2-32K-s1/16*: To explore the effect of positional encoding increments on visual tokens, we reduce the positional increment to 1/16 for visual tokens, while maintaining training on the same mixed dataset as InternVL2-FT-32K. 4) *InternVL2-32K-s1/256*: Similarly, we further reduce the positional increments to 1/256 to examine its impact. Notably, the positional increments for these models remain fixed during training, without using the V2PE method.

Evaluation Benchmarks. All models are evaluated on the Long-VQA validation split and the MM-NIAH bench-

Table 2. Performance on standard VQA benchmarks with different positional increment δ . The highest score is marked in **bold**.

Model	δ	ChartQA	DocVQA	AI2D	InfoQA	SQA	POPE	MMMU _{val}	MMBench _{EN}	SEED _I	Avg
InternVL2-FT-Short	—	76.0	85.7	74.0	57.1	94.0	88.9	34.8	73.0	66.6	72.2
	1/256	76.2	81.6	72.3	51.7	94.3	88.0	35.7	73.2	71.0	71.6
	1/128	76.5	82.3	72.6	52.9	94.2	88.1	34.7	73.5	70.9	71.7
	1/64	76.4	83.0	72.6	53.6	94.4	88.0	35.4	73.4	70.8	72.0
	1/32	76.9	83.6	72.6	54.3	94.3	88.1	35.7	73.3	71.0	72.2
	1/16	77.2	84.3	73.0	55.2	94.5	88.1	35.7	73.3	71.0	72.5
	1/8	77.0	84.6	73.1	55.4	94.6	88.1	36.0	72.9	71.0	72.5
	1/4	77.3	84.7	73.3	56.5	94.6	88.2	36.0	73.6	71.0	72.8
InternVL2-V2PE-32K	1/2	76.8	84.9	73.5	56.0	94.9	88.7	35.8	73.8	71.2	72.9
	1/1	76.6	84.9	73.7	55.2	94.8	88.4	36.1	73.7	71.1	72.7

Table 3. Performance on the image retrieval task in MM-NIAH with token lengths up to 1M at various position increments δ . Test samples exceeding 64K tokens are from our extended MM-NIAH_{1M}. The designation “NA” indicates that the GPT-4 results are not applicable due to the extremely long context length.

Model	δ	1K	16K	32K	64K	128K	256K	512K	1M
InternVL2-2B	—	23.9	33.7	28.7	26.0	17.3	21.8	5.3	0.0
	GPT-4o	—	100.0	90.4	100.0	92.7	62.1	60.0	58.6
InternVL2-V2PE-32K	1/256	100.0	84.7	79.3	81.5	61.2	56.9	36.7	6.0
	1/64	96.0	83.9	78.1	79.5	43.6	39.3	23.4	3.4
	1/16	96.0	82.4	73.1	65.4	57.6	41.3	19.8	0.0
	1/4	96.0	84.2	76.2	57.6	48.9	21.5	2.8	0.0
	1/1	83.0	61.2	42.0	27.5	25.5	1.5	0.0	0.0
InternVL2-V2PE-256K	1/256	96.0	97.1	96.6	97.1	99.1	95.7	95.1	64.5
	1/64	96.0	94.7	96.6	97.1	97.1	94.1	94.1	62.8
	1/16	96.0	94.7	93.1	94.2	100	96.2	92.9	45.1
	1/4	96.0	94.4	100.0	97.1	75.5	75.2	38.3	2.5
	1/1	91.0	92.8	96.6	93.1	56.1	3.7	10.8	0.0
InternVL2-FT-32K with linear interpolation	—	85.3	76.0	56.0	34.7	26.4	21.9	16.3	0.5
InternVL2-FT-32K with NTK interpolation	—	78.3	70.7	39.8	25.7	12.3	16.8	14.8	0.0

mark. Additionally, performance on the standard multimodal VQA benchmarks is assessed if needed.

Effectiveness of Augmented Long-Context Multimodal Data. We compare the performance of InternVL2-FT-Short and InternVL2-FT-32K on both the Long-VQA validation set and standard short-context benchmarks, as shown in Fig. 4. The results reveal that InternVL2-FT-Short, which is trained exclusively on short-context data, performs competitively on standard benchmarks but suffers significant degradation on long-context tasks. Even advanced models, such as GPT-4o, exhibit notable declines when the input token count is increased, underscoring a common limitation in handling extended sequences. In contrast, InternVL2-FT-32K, trained on the mixed dataset including long-context data, effectively narrows the performance gap between short and long-context tasks. This suggests that VLMs cannot inherently generalize to long-context multimodal tasks from short-context training alone; targeted exposure to long-context data is crucial for achieving robust performance across varying input lengths.

Impact of Visual Position Encoding. To assess the influence of position encoding increments for visual tokens, we evaluate the models InternVL2-FT-32K, InternVL2-32K-s1/16, and InternVL2-32K-s1/256 on both the Long-VQA and MM-NIAH benchmarks.

Experimental results, presented in Fig. 5, indicate that

InternVL2-FT-32K continues to experience performance degradation as input token sequences grow 8K token, despite being trained on sequences up to 32K tokens. When the input sequence length exceeds the token counts seen during training, performance declines sharply, and even applying positional encoding extension techniques developed for large language models (LLMs) provides only limited benefits. However, models with reduced positional increments for visual tokens show significant improvements. Both InternVL2-32K-s1/16 and InternVL2-32K-s1/256 maintain stable performance. We hypothesis that reducing the position increments by factors of 16 and 256 effectively prevents the position indices of visual tokens from exceeding the model’s trained context window, thereby mitigating performance decline.

4.2. Effectiveness of Our Proposed V2PE

Experimental Setup. We fine-tune the InternVL2-2B model using our proposed V2PE method in a two-stage training procedure. 1) In the first stage, we fine-tune the released InternVL2-2B model on our mixed training dataset, incorporating V2PE. During training, as described in Eq. 6, the positional increment δ is dynamically selected, enabling the model to flexibly adapt to varying positional increments for visual tokens. The model obtained after this stage is denoted as *InternVL2-V2PE-32K*. 2) In the second stage, we

Table 4. Comparison with existing MLLMs on general MLLM benchmarks. “#Param” denotes the number of parameters. The designation “—” indicates that the corresponding score is not released.

Model	#Param	ChartQA	DocVQA	AI2D	InfoVQA	SQA	POPE	MMMU _{val}	MMBench _{EN}	SEED _I	Avg
InternVL2-2B [20]	2.0B	71.7	86.9	74.1	58.9	94.1	85.2	36.3	73.4	70.9	72.4
DeepSeek-VL-1.3B [73]	2.0B	47.4	—	51.5	—	68.4	85.9	33.8	66.4	66.0	—
Qwen2-VL-2B [122]	2.0B	73.5	90.1	74.7	65.5	—	—	41.1	74.9	—	—
Aquila-VL-2B [42]	2.2B	32.0	85.0	75.1	58.3	95.1	83.1	46.9	79.0	73.9	69.8
MiniCPM-V-2 [142]	2.8B	55.6	71.9	62.9	—	80.7	86.3	38.2	64.1	67.1	—
Vintern-3B-beta [34]	3.7B	68.3	—	69.1	—	75.0	87.4	46.7	70.6	70.0	—
Llama 3.2 11B [115]	11B	83.4	88.4	91.1	—	—	—	50.7	68.0	—	—
Qwen2-VL-72B [122]	73B	88.3	96.5	88.1	84.5	91.2	87.2	64.5	86.9	77.9	85.0
GPT-4o [86]	—	85.7	92.8	84.7	—	90.1	97.2	69.1	82.1	76.7	—
InternVL2-V2PE-32K	2.0B	77.3	84.9	73.7	56.5	94.9	88.7	36.1	73.8	71.2	73.0

Table 5. Comparison with existing MLLMs on long context MLLM benchmarks. “#Param” denotes the number of parameters. The designation “—” indicates that the corresponding score is not released.

Model	#Param	MM-NIAH			Milebench				VideoMME
		Image	Text	Avg	T	S	NI	Avg	
InternVL2-2B [20]	2.0B	23.0	18.9	21.0	58.2	54.5	37.0	49.9	—
Phi-3-Vision [1]	2.7B	—	—	—	46.9	50.0	—	—	—
OmChat [155]	3.9B	—	—	—	51.4	52.0	—	—	45.9
LongLLaVA [128]	9B	—	—	—	47.3	46.8	—	—	43.7
LongLLaVA [128]	13B	—	—	—	52.7	52.1	—	—	51.6
VILA [65]	13B	14.5	40.5	27.5	—	—	—	—	—
Gemini-1.5 [110]	—	28.5	82.1	55.2	50.2	58.3	97.9	68.8	69.6
GPT-4V [85]	—	—	84.1	—	45.6	58.9	99.4	68.0	59.9
GPT-4o [86]	—	—	—	—	56.2	63.5	—	—	64.7
Claude3-Opus [5]	—	—	—	—	37.4	48.1	85.3	56.9	59.7
InternVL2-V2PE-32K	2.0B	72.3	68.1	70.2	58.5	58.2	51.1	55.9	48.2

fine-tune the model on the Long-MR-256K dataset, whose sequence lengths up to 256K token. To preserve the model’s general performance, we retain 50% of the data from the first stage. To optimize memory usage, we apply the Ring Attention [66], enabling model parallelism across multiple GPUs. The model obtained after the second stage is denoted as *InternVL2-V2PE-256K*.

Evaluation Benchmarks. We evaluate our trained models on various long-context and standard multimodal benchmarks, including the Long-VQA validation split, MM-NIAH [125] (including our augmented MM-NIAH_{IM}), and several widely adopted VQA benchmarks such as ChartQA [79], DocVQA [81], AI2D [57], InfoQA [57], SQA [74], POPE [64], MMMU [144], MMBench_{EN} [71], and SEED_{Image} [60]. To systematically assess the VLMs’ performance on long-context tasks, we also compare our model with other state-of-the-art methods on two additional long-context benchmarks: MileBench [99] for multi-image and video understanding, and Video-MME [38] for video analysis tasks. For detailed benchmark descriptions and their evaluation metrics, please refer to the appendix.

Effectiveness of V2PE. We compare the performance of InternVL2-V2PE-32K and InternVL2-V2PE-256K on the Long-VQA validation split, MM-NIAH (including MM-NIAH_{IM}), and standard multimodal benchmarks. The results are shown in Tab. 1, Flg. 2, and Fig. 3.

We demonstrate how varying positional increments impact the models’ performance on these benchmarks. Specifically, MM-NIAH is evaluated on the image-retrieval task where both the “needle” and the “question” are images, posing a stringent challenge for multimodal models to handle visual tokens in long-context sequences.

On standard short-context benchmarks (see Fig. 2), the advantage of V2PE is not immediately evident. In fact, we observe a performance drop on certain tasks, such as DocVQA and InfoQA, when the positional increment is reduced. We hypothesize that this is because InternVL2 has adapted to the original position encoding settings during its alignment and supervised fine-tuning (SFT) training.

However, on long-context benchmarks like Long-VQA and MM-NIAH (see Fig. 1 and Fig. 3), V2PE demonstrates a clear advantage. For instance, on Long-VQA, the best performance is typically achieved when the positional increments are reduced to around 1/8 or 1/16. Moreover, as the token sequence length increases, smaller positional increments tend to be optimal.

In the MM-NIAH benchmark, involving longer token sequences, V2PE demonstrates optimal performance with positional increments of 1/256. Notably, InternVL2-V2PE-32K markedly enhances performance on sequences of 256K tokens, boosting scores from 1.5 to 56.9. This enhancement is also evident in InternVL2-V2PE-256K, which records the

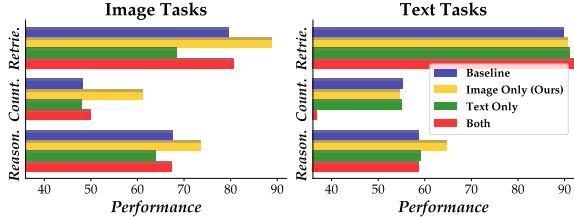


Figure 6. Performance on MM-NIAH benchmarks with different position encoding strategies. “Image only”, “Text only”, “Both”, and “Baseline” represent applying V2PE to visual tokens, textual tokens, both simultaneously, and neither, respectively.

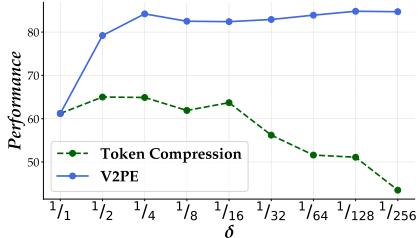


Figure 7. Performance on image retrieval task in MM-NIAH benchmark using V2PE and token compression strategies. Token compression reduces the number of visual tokens by a ratio δ , whereas V2PE employs a smaller positional increment δ while preserving all visual tokens.

highest scores across various token sequence lengths when using a positional increment of 1/256. For sequences of 512K tokens, the score surges from 10.8 to 95.1. Additionally, with the same positional increment of 1/256, the InternVL2-V2PE-256K model attains a significant score of 64.5 on sequences reaching 1M tokens.

4.3. Comparison with Other VLMs.

We evaluate the performance of InternVL2-V2PE-32K against state-of-the-art vision-language models (VLMs) on both standard and long-context multimodal benchmarks, with results presented in Tab. 4 and Tab. 5, respectively. Despite being based on a relatively small 2B parameter model and incorporating substantial long-context training data, InternVL2-V2PE-32K achieves highly competitive results on standard short-context multimodal benchmarks.

On long-context multimodal benchmarks, the model performs exceptionally well, demonstrating that V2PE can significantly enhance long-context processing abilities even with a smaller model. These results validate the potential of V2PE for improving the performance of VLMs on a wide range of long-context multimodal tasks.

4.4. Ablation Study

Can V2PE be applied to textual tokens? We apply V2PE to visual tokens, to textual tokens, concurrently to both, or to neither, whose results on six tasks on MM-NIAH are pre-

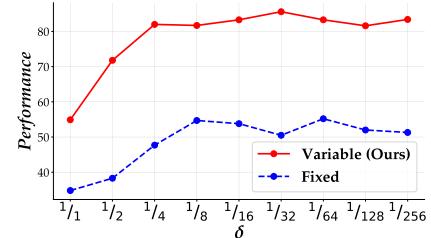


Figure 8. Performance on image retrieval task in MM-NIAH benchmark with variable versus fixed position increments for visual tokens in the VLMs. “Variable” denotes training with variable increments, allowing evaluation with arbitrary δ , while “Fixed” means training and evaluating with the same fixed δ .

sented in Fig. 6, showing that applying V2PE to textual tokens alone improves the model’s language understanding but leads to decreased performance on image-focused tasks. When V2PE was applied to both visual and textual tokens, the model’s performance became unstable. However, when V2PE was applied only to visual tokens, the VLM exhibited consistently improves performance across all tasks.

Is V2PE equivalent to visual token compression? We also compare V2PE with the token compression strategy, where visual tokens undergo pooling operations to reduce token number, allowing more images to be processed ideally. We tests various compression ratios and evaluate the model’s performance on the MM-NIAH image retrieval task. The results, shown in Fig. 7, reveal that while token compression results in a rapid performance drop when the number of visual tokens is reduced below 16, our method demonstrates stable performance across all settings.

Can positional increment be fixed during training? We train a set of InternVL2-FT-32K models with fixed positional increments during training. Their performance on the image retrieval task of the MM-NIAH benchmark are shown in Fig. 8. The results indicate that fixing the positional increment does not lead to optimal task performance. In contrast, the variable adjustment of positional increments provide consistent improvements.

Is V2PE superior to the position encoding extension methods? To compare V2PE with existing position encoding extension methods, we evaluated both InternVL2-FT-32K and InternVL2-V2PE-32K models using two widely adopted position extension techniques: linear interpolation and NTK-Aware Scaled RoPE. The results, presented in Fig. 5, Tab. 1, and Tab. 3, show that V2PE not only offers greater stability but also achieves superior task performance, especially in long-context scenarios.

5. Conclusion

We investigate the long-context capabilities of the existing VLM, InternVL2-2B, using our augmented long-context

datasets, and find that positional encoding for visual tokens is critical for the long-context capabilities of VLMs. Based on this observation, we introduce V2PE, a novel position encoding strategy that applies smaller, variable positional increments to visual tokens, enabling more efficient handling of long-context multimodal sequences. By leveraging V2PE and our augmented long-context datasets, we fine-tune the open-source InternVL2-2B model successfully, which shows significant improvements on both general and long-context multimodal benchmarks. As for limitations, our approach has not yet been validated on more VLMs or scaled to models with more parameters, due to limited computational resources.

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References

- [1] Marah Abdin, Jyoti Aneja, Hany Awadalla, Ahmed Awadallah, Ammar Ahmad Awan, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Jianmin Bao, Harkirat Behl, et al. Phi-3 technical report: A highly capable language model locally on your phone. *arXiv preprint arXiv:2404.14219*, 2024.
- [2] Muhammad Adnan, Akhil Arunkumar, Gaurav Jain, Prashant Nair, Ilya Soloveychik, and Purushotham Kamath. Keyformer: Kv cache reduction through key tokens selection for efficient generative inference. *Proceedings of Machine Learning and Systems*, 6:114–127, 2024.
- [3] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *Advances in neural information processing systems*, 35:23716–23736, 2022.
- [4] Dosovitskiy Alexey. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv: 2010.11929*, 2020.
- [5] Anthropic. The claude 3 model family: Opus, sonnet, haiku. <https://www.anthropic.com>, 2024.
- [6] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.
- [7] Jinze Bai, Shuai Bai, Shusheng Yang, Shijie Wang, Sinan Tan, Peng Wang, Junyang Lin, Chang Zhou, and Jingren Zhou. Qwen-vl: A versatile vision-language model for understanding, localization, text reading, and beyond. *arXiv preprint arXiv:2308.12966*, 2023.
- [8] Iz Beltagy, Matthew E Peters, and Arman Cohan. Longformer: The long-document transformer. *arXiv preprint arXiv:2004.05150*, 2020.
- [9] Lucas Beyer, Andreas Steiner, André Susano Pinto, Alexander Kolesnikov, Xiao Wang, Daniel Salz, Maxim Neumann, Ibrahim Alabdulmohsin, Michael Tschannen, Emanuele Bugliarello, et al. Paligemma: A versatile 3b vlm for transfer. *arXiv preprint arXiv:2407.07726*, 2024.
- [10] Xiao Bi, Deli Chen, Guanting Chen, Shanhuang Chen, Damai Dai, Chengqi Deng, Honghui Ding, Kai Dong, Qiushi Du, Zhe Fu, et al. Deepseek llm: Scaling open-source language models with longtermism. *arXiv preprint arXiv:2401.02954*, 2024.
- [11] @bloc97. Ntk-aware scaled rope, 2023.
- [12] Tom B Brown. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*, 2020.
- [13] Aydar Bulatov, Yuri Kuratov, Yermek Kapushev, and Mikhail S Burtsev. Scaling transformer to 1m tokens and beyond with rmt. *arXiv preprint arXiv:2304.11062*, 2023.
- [14] Zheng Cai, Maosong Cao, Haojiong Chen, Kai Chen, Keyu Chen, Xin Chen, Xun Chen, Zehui Chen, Zhi Chen, Pei Chu, et al. Internlm2 technical report. *arXiv preprint arXiv:2403.17297*, 2024.
- [15] Lin Chen, Jinsong 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.
- [16] Shouyuan Chen, Sherman Wong, Liangjian Chen, and Yuandong Tian. Extending context window of large language models via positional interpolation. *arXiv preprint arXiv:2306.15595*, 2023.
- [17] Wenhui Chen, Hongmin Wang, Jianshu Chen, Yunkai Zhang, Hong Wang, Shiyang Li, Xiyou Zhou, and William Yang Wang. Tabfact: A large-scale dataset for table-based fact verification. *arXiv preprint arXiv:1909.02164*, 2019.
- [18] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco captions: Data collection and evaluation server. *arXiv preprint arXiv:1504.00325*, 2015.
- [19] Yukang Chen, Shengju Qian, Haotian Tang, Xin Lai, Zhi-jian Liu, Song Han, and Jiaya Jia. Longlora: Efficient fine-tuning of long-context large language models. *arXiv preprint arXiv:2309.12307*, 2023.
- [20] Zhe Chen, Weiyun Wang, Hao Tian, Shenglong Ye, Zhangwei Gao, Erfei Cui, Wenwen Tong, Kongzhi Hu, Jiapeng Luo, Zheng Ma, et al. How far are we to gpt-4v? closing the gap to commercial multimodal models with open-source suites. *arXiv preprint arXiv:2404.16821*, 2024.
- [21] Zhe Chen, Jiannan Wu, Wenhui Wang, Weijie Su, Guo Chen, Sen Xing, Muyan Zhong, Qinglong Zhang, Xizhou Zhu, Lewei Lu, Bin Li, Ping Luo, Tong Lu, Yu Qiao, and Jifeng Dai. Internvl: Scaling up vision foundation models and aligning for generic visual-linguistic tasks. *arXiv preprint arXiv:2312.14238*, 2023.
- [22] Alexis Chevalier, Alexander Wettig, Anirudh Ajith, and Danqi Chen. Adapting language models to compress contexts. *arXiv preprint arXiv:2305.14788*, 2023.
- [23] Hao-Tien Lewis Chiang, Zhuo Xu, Zipeng Fu, Mithun George Jacob, Tingnan Zhang, Tsang-Wei Edward Lee, Wenhao Yu, Connor Schenck, David Rendleman, Dhruv Shah, et al. Mobility vla: Multimodal instruction navigation with long-context vlms and topological graphs. *arXiv preprint arXiv:2407.07775*, 2024.

- [24] Rewon Child, Scott Gray, Alec Radford, and Ilya Sutskever. Generating long sequences with sparse transformers. *arXiv preprint arXiv:1904.10509*, 2019.
- [25] Krzysztof Choromanski, Valerii Likhoshevstov, David Dohan, Xingyou Song, Andreea Gane, Tamas Sarlos, Peter Hawkins, Jared Davis, Afroz Mohiuddin, Lukasz Kaiser, et al. Rethinking attention with performers. *arXiv preprint arXiv:2009.14794*, 2020.
- [26] Xiangxiang Chu, Limeng Qiao, Xinyang Lin, Shuang Xu, Yang Yang, Yiming Hu, Fei Wei, Xinyu Zhang, Bo Zhang, Xiaolin Wei, et al. Mobilevlm: A fast, reproducible and strong vision language assistant for mobile devices. *arXiv preprint arXiv:2312.16886*, 2023.
- [27] Xiangxiang Chu, Limeng Qiao, Xinyu Zhang, Shuang Xu, Fei Wei, Yang Yang, Xiaofei Sun, Yiming Hu, Xinyang Lin, Bo Zhang, et al. Mobilevlm v2: Faster and stronger baseline for vision language model. *arXiv preprint arXiv:2402.03766*, 2024.
- [28] Róbert Csordás, Kazuki Irie, and Jürgen Schmidhuber. The neural data router: Adaptive control flow in transformers improves systematic generalization. *arXiv preprint arXiv:2110.07732*, 2021.
- [29] Wenliang Dai, Junnan Li, D Li, AMH Tiong, J Zhao, W Wang, B Li, P Fung, and S Hoi. Instructblip: Towards general-purpose vision-language models with instruction tuning. *arxiv* 2023. *arXiv preprint arXiv:2305.06500*, 2, 2023.
- [30] Zihang Dai. Transformer-xl: Attentive language models beyond a fixed-length context. *arXiv preprint arXiv:1901.02860*, 2019.
- [31] Mostafa Dehghani, Josip Djolonga, Basil Mustafa, Piotr Padlewski, Jonathan Heek, Justin Gilmer, Andreas Peter Steiner, Mathilde Caron, Robert Geirhos, Ibrahim Alabdulmohsin, et al. Scaling vision transformers to 22 billion parameters. In *International Conference on Machine Learning*, pages 7480–7512. PMLR, 2023.
- [32] Jiayu Ding, Shuming Ma, Li Dong, Xingxing Zhang, Shaohan Huang, Wenhui Wang, Nanning Zheng, and Furu Wei. Longnet: Scaling transformers to 1,000,000,000 tokens. *arXiv preprint arXiv:2307.02486*, 2023.
- [33] Yiran Ding, Li Lyra Zhang, Chengruidong Zhang, Yuanyuan Xu, Ning Shang, Jiahang Xu, Fan Yang, and Mao Yang. Longrope: Extending llm context window beyond 2 million tokens. *arXiv preprint arXiv:2402.13753*, 2024.
- [34] Khang T. Doan, Bao G. Huynh, Dung T. Hoang, Thuc D. Pham, Nhat H. Pham, Quan T. M. Nguyen, Bang Q. Vo, and Suong N. Hoang. Vintern-1b: An efficient multimodal large language model for vietnamese, 2024.
- [35] Xiaoyi Dong, Pan Zhang, Yuhang Zang, Yuhang Cao, Bin Wang, Linke Ouyang, Xilin Wei, Songyang Zhang, Haodong Duan, Maosong Cao, Wenwei Zhang, Yining Li, Hang Yan, Yang Gao, Xinyue Zhang, Wei Li, Jingwen Li, Kai Chen, Conghui He, Xingcheng Zhang, Yu Qiao, Dahua Lin, and Jiaqi Wang. Internlm-xcomposer2: Mastering free-form text-image composition and comprehension in vision-language large model. *arXiv preprint arXiv:2401.16420*, 2024.
- [36] Xiaoyi Dong, Pan Zhang, Yuhang Zang, Yuhang Cao, Bin Wang, Linke Ouyang, Songyang Zhang, Haodong Duan, Wenwei Zhang, Yining Li, Hang Yan, Yang Gao, Zhe Chen, Xinyue Zhang, Wei Li, Jingwen Li, Wenhai Wang, Kai Chen, Conghui He, Xingcheng Zhang, Jifeng Dai, Yu Qiao, Dahua Lin, and Jiaqi Wang. Internlm-xcomposer2-4khd: A pioneering large vision-language model handling resolutions from 336 pixels to 4k hd. *arXiv preprint arXiv:2404.06512*, 2024.
- [37] Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhang Qiu, Zhilin Yang, and Jie Tang. Glm: General language model pretraining with autoregressive blank infilling. *arXiv preprint arXiv:2103.10360*, 2021.
- [38] Chaoyou Fu, Yuhan Dai, Yondong Luo, Lei Li, Shuhuai Ren, Renrui Zhang, Zihan Wang, Chenyu Zhou, Yunhang Shen, Mengdan Zhang, et al. Video-mme: The first-ever comprehensive evaluation benchmark of multi-modal llms in video analysis. *arXiv preprint arXiv:2405.21075*, 2024.
- [39] Zhangwei Gao, Zhe Chen, Erfei Cui, Yiming Ren, Weiyun Wang, Jinguo Zhu, Hao Tian, Shenglong Ye, Junjun He, Xizhou Zhu, et al. Mini-internvl: A flexible-transfer pocket multimodal model with 5% parameters and 90% performance. *arXiv preprint arXiv:2410.16261*, 2024.
- [40] Albert Gu and Tri Dao. Mamba: Linear-time sequence modeling with selective state spaces. *arXiv preprint arXiv:2312.00752*, 2023.
- [41] Albert Gu, Karan Goel, and Christopher Ré. Efficiently modeling long sequences with structured state spaces. *arXiv preprint arXiv:2111.00396*, 2021.
- [42] Shuhao Gu, Jialing Zhang, Siyuan Zhou, Kevin Yu, Zhaochu Xing, Liangdong Wang, Zhou Cao, Jintao Jia, Zhuoyi Zhang, Yixuan Wang, et al. Infinity-mm: Scaling multimodal performance with large-scale and high-quality instruction data. *arXiv preprint arXiv:2410.18558*, 2024.
- [43] Danna Gurari, Qing Li, Abigale J Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P Bigham. Vizwiz grand challenge: Answering visual questions from blind people. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3608–3617, 2018.
- [44] Chi Han, Qifan Wang, Wenhan Xiong, Yu Chen, Heng Ji, and Sinong Wang. Lm-infinite: Simple on-the-fly length generalization for large language models. *arXiv preprint arXiv:2308.16137*, 2023.
- [45] Adi Haviv, Ori Ram, Ofir Press, Peter Izsak, and Omer Levy. Transformer language models without positional encodings still learn positional information. *arXiv preprint arXiv:2203.16634*, 2022.
- [46] Wenyi Hong, Weihan Wang, Qingsong Lv, Jiazheng Xu, Wenmeng Yu, Junhui Ji, Yan Wang, Zihan Wang, Yuxiao Dong, Ming Ding, et al. Cogagent: A visual language model for gui agents. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14281–14290, 2024.
- [47] Anwen Hu, Haiyang Xu, Jiabo Ye, Ming Yan, Liang Zhang, Bo Zhang, Chen Li, Ji Zhang, Qin Jin, Fei Huang, et al. mplug-docowl 1.5: Unified structure learn-

- ing for ocr-free document understanding. *arXiv preprint arXiv:2403.12895*, 2024.
- [48] Zhiyuan Hu, Yuliang Liu, Jinman Zhao, Suyuchen Wang, Yan Wang, Wei Shen, Qing Gu, Anh Tuan Luu, See-Kiong Ng, Zhiwei Jiang, et al. Longrecipe: Recipe for efficient long context generalization in large language models. *arXiv preprint arXiv:2409.00509*, 2024.
- [49] Shaohan Huang, Li Dong, Wenhui Wang, Yaru Hao, Saksham Singhal, Shuming Ma, Tengchao Lv, Lei Cui, Owais Khan Mohammed, Barun Patra, et al. Language is not all you need: Aligning perception with language models. *Advances in Neural Information Processing Systems*, 36:72096–72109, 2023.
- [50] Xinting Huang and Nora Hollenstein. Long-range language modeling with selective cache. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 4838–4858, 2023.
- [51] Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6700–6709, 2019.
- [52] HyperGAI Research Team. Introducing hpt: A family of leading multimodal llms. <https://www.hypergai.com/blog/introducing-hpt-a-family-of-leading-multimodal-llms>, 2024.
- [53] Dongfu Jiang, Xuan He, Huaye Zeng, Cong Wei, Max Ku, Qian Liu, and Wenhua Chen. Mantis: Interleaved multi-image instruction tuning. *arXiv preprint arXiv:2405.01483*, 2024.
- [54] Justin Johnson, Bharath Hariharan, Laurens Van Der Maaten, Li Fei-Fei, C Lawrence Zitnick, and Ross Girshick. Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2901–2910, 2017.
- [55] 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.
- [56] Guolin Ke, Di He, and Tie-Yan Liu. Rethinking positional encoding in language pre-training. *arXiv preprint arXiv:2006.15595*, 2020.
- [57] Aniruddha Kembhavi, Mike Salvato, Eric Kolve, Minjoon Seo, Hannaneh Hajishirzi, and Ali Farhadi. A diagram is worth a dozen images. In *European conference on computer vision*, pages 235–251. Springer, 2016.
- [58] Nikita Kitayev, Łukasz Kaiser, and Anselm Levskaya. Reformer: The efficient transformer. *arXiv preprint arXiv:2001.04451*, 2020.
- [59] Shun Kiyono, Sosuke Kobayashi, Jun Suzuki, and Kentaro Inui. Shape: Shifted absolute position embedding for transformers. *arXiv preprint arXiv:2109.05644*, 2021.
- [60] Bohao Li, Rui Wang, Guangzhi Wang, Yuying Ge, Yixiao Ge, and Ying Shan. Seed-bench: Benchmarking multimodal llms with generative comprehension. *arXiv preprint arXiv:2307.16125*, 2023.
- [61] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. In *International conference on machine learning*, pages 19730–19742. PMLR, 2023.
- [62] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *International conference on machine learning*, pages 12888–12900. PMLR, 2022.
- [63] Yanwei Li, Yuechen Zhang, Chengyao Wang, Zhisheng Zhong, Yixin Chen, Ruihang Chu, Shaoteng Liu, and Jiaya Jia. Mini-gemini: Mining the potential of multi-modality vision language models. *arXiv preprint arXiv:2403.18814*, 2024.
- [64] Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. Evaluating object hallucination in large vision-language models. *arXiv preprint arXiv:2305.10355*, 2023.
- [65] Ji Lin, Hongxu Yin, Wei Ping, Pavlo Molchanov, Mohammad Shoeybi, and Song Han. Vila: On pre-training for visual language models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 26689–26699, 2024.
- [66] Hao Liu, Wilson Yan, Matei Zaharia, and Pieter Abbeel. World model on million-length video and language with ringattention. *arXiv preprint arXiv:2402.08268*, 2024.
- [67] Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning, 2023.
- [68] Haotian Liu, Chunyuan Li, Yuheng Li, Bo Li, Yuanhan Zhang, Sheng Shen, and Yong Jae Lee. Llava-next: Improved reasoning, ocr, and world knowledge, January 2024.
- [69] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning, 2023.
- [70] Jiaheng Liu, Zhiqi Bai, Yuanxing Zhang, Chenchen Zhang, Yu Zhang, Ge Zhang, Jiakai Wang, Haoran Que, Yukang Chen, Wenbo Su, et al. E^ 2-llm: Efficient and extreme length extension of large language models. *arXiv preprint arXiv:2401.06951*, 2024.
- [71] Yuan Liu, Haodong Duan, Yuanhan Zhang, Bo Li, Songyang Zhang, Wangbo Zhao, Yike Yuan, Jiaqi Wang, Conghui He, Ziwei Liu, et al. Mmbench: Is your multimodal model an all-around player? In *European Conference on Computer Vision*, pages 216–233. Springer, 2025.
- [72] I Loshchilov. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017.
- [73] Haoyu Lu, Wen Liu, Bo Zhang, Bingxuan Wang, Kai Dong, Bo Liu, Jingxiang Sun, Tongzheng Ren, Zhuoshu Li, Hao Yang, et al. Deepseek-vl: towards real-world vision-language understanding. *arXiv preprint arXiv:2403.05525*, 2024.
- [74] 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.

- [75] Gen Luo, Yiyi Zhou, Yuxin Zhang, Xiawu Zheng, Xiaoshuai Sun, and Rongrong Ji. Feast your eyes: Mixture-of-resolution adaptation for multimodal large language models. *arXiv preprint arXiv:2403.03003*, 2024.
- [76] Ang Lv, Kaiyi Zhang, Shufang Xie, Quan Tu, Yuhan Chen, Ji-Rong Wen, and Rui Yan. Are we falling in a middle-intelligence trap? an analysis and mitigation of the reversal curse. *arXiv preprint arXiv:2311.07468*, 2023.
- [77] Tengchao Lv, Yupan Huang, Jingye Chen, Yuzhong Zhao, Yilin Jia, Lei Cui, Shuming Ma, Yaoyao Chang, Shaohan Huang, Wenhui Wang, et al. Kosmos-2.5: A multimodal literate model. *arXiv preprint arXiv:2309.11419*, 2023.
- [78] Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.
- [79] 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.
- [80] Minesh Mathew, Viraj Bagal, Rubén Tito, Dimosthenis Karatzas, Ernest Valveny, and CV Jawahar. Infographicvqa. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1697–1706, 2022.
- [81] Minesh Mathew, Dimosthenis Karatzas, and CV Jawahar. Docvqa: A dataset for vqa on document images. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pages 2200–2209, 2021.
- [82] Brandon McKinzie, Zhe Gan, Jean-Philippe Fauconnier, Sam Dodge, Bowen Zhang, Philipp Dufter, Dhruti Shah, Xianzhi Du, Futang Peng, Floris Weers, et al. Mm1: Methods, analysis & insights from multimodal llm pre-training. *arXiv preprint arXiv:2403.09611*, 2024.
- [83] Anand Mishra, Shashank Shekhar, Ajeet Kumar Singh, and Anirban Chakraborty. Ocr-vqa: Visual question answering by reading text in images. In *2019 international conference on document analysis and recognition (ICDAR)*, pages 947–952. IEEE, 2019.
- [84] Amirkeivan Mohtashami and Martin Jaggi. Landmark attention: Random-access infinite context length for transformers. *arXiv preprint arXiv:2305.16300*, 2023.
- [85] OpenAI. Gpt-4(vision) system card. https://cdn.openai.com/papers/GPTV_System_Card.pdf, 2023.
- [86] OpenAI. Hello gpt-4o, 2023. Accessed: 2023-11-14.
- [87] R OpenAI. Gpt-4 technical report. arxiv 2303.08774. *View in Article*, 2(5), 2023.
- [88] Panupong Pasupat and Percy Liang. Compositional semantic parsing on semi-structured tables. *arXiv preprint arXiv:1508.00305*, 2015.
- [89] Bowen Peng, Jeffrey Quesnelle, Honglu Fan, and Enrico Shippole. Yarn: Efficient context window extension of large language models. *arXiv preprint arXiv:2309.00071*, 2023.
- [90] 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 preprint arXiv:2306.14824*, 2023.
- [91] Ofir Press, Noah A Smith, and Mike Lewis. Train short, test long: Attention with linear biases enables input length extrapolation. *arXiv preprint arXiv:2108.12409*, 2021.
- [92] Jiezhang Qiu, Hao Ma, Omer Levy, Scott Wen-tau Yih, Sinong Wang, and Jie Tang. Blockwise self-attention for long document understanding. *arXiv preprint arXiv:1911.02972*, 2019.
- [93] 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 *International conference on machine learning*, pages 8748–8763. PMLR, 2021.
- [94] 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*, 21(140):1–67, 2020.
- [95] Hongyu Ren, Hanjun Dai, Zihang Dai, Mengjiao Yang, Jure Leskovec, Dale Schuurmans, and Bo Dai. Combiner: Full attention transformer with sparse computation cost. *Advances in Neural Information Processing Systems*, 34:22470–22482, 2021.
- [96] Peter Shaw, Jakob Uszkoreit, and Ashish Vaswani. Self-attention with relative position representations. *arXiv preprint arXiv:1803.02155*, 2018.
- [97] 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.
- [98] Amanpreet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xinlei Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. Towards vqa models that can read. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 8317–8326, 2019.
- [99] Dingjie Song, Shunian Chen, Guiming Hardy Chen, Fei Yu, Xiang Wan, and Benyou Wang. Milebench: Benchmarking mllms in long context. *arXiv preprint arXiv:2404.18532*, 2024.
- [100] Tomasz Stanisławek, Filip Graliński, Anna Wróblewska, Dawid Lipiński, Agnieszka Kaliska, Paulina Rosalska, Bartosz Topolski, and Przemysław Biecek. Kleister: key information extraction datasets involving long documents with complex layouts. In *International Conference on Document Analysis and Recognition*, pages 564–579. Springer, 2021.
- [101] StepFun Research Team. Step-1v: A hundred billion parameter multimodal large model. <https://platform.stepfun.com>, 2024.
- [102] Jianlin Su. Rectified rotary position embeddings. <https://github.com/bojone/rerope>, 2023.
- [103] Jianlin Su, Murtadha Ahmed, Yu Lu, Shengfeng Pan, Wen Bo, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. *Neurocomputing*, 568:127063, 2024.

- [104] Jianlin Su, Murtadha Ahmed, Yu Lu, Shengfeng Pan, Wen Bo, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. *Neurocomputing*, 568:127063, 2024.
- [105] Tianxiang Sun, Xiaotian Zhang, Zhengfu He, Peng Li, Qinyuan Cheng, Hang Yan, Xiangyang Liu, Yunfan Shao, Qiong Tang, Xingjian Zhao, et al. Moss: Training conversational language models from synthetic data. *arXiv preprint arXiv:2307.15020*, 7:3, 2023.
- [106] Yutao Sun, Li Dong, Barun Patra, Shuming Ma, Shaohan Huang, Alon Benhaim, Vishrav Chaudhary, Xia Song, and Furu Wei. A length-extrapolatable transformer. *arXiv preprint arXiv:2212.10554*, 2022.
- [107] Ryota Tanaka, Kyosuke Nishida, and Sen Yoshida. Visualmrc: Machine reading comprehension on document images. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 13878–13888, 2021.
- [108] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. Alpaca: A strong, replicable instruction-following model. *Stanford Center for Research on Foundation Models. https://crfm.stanford.edu/2023/03/13/alpaca.html*, 3(6):7, 2023.
- [109] Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, Katie Milligan, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.
- [110] Gemini Team, Petko Georgiev, Ving Ian Lei, Ryan Burnell, Libin Bai, Anmol Gulati, Garrett Tanzer, Damien Vincent, Zhufeng Pan, Shibo Wang, et al. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *arXiv preprint arXiv:2403.05530*, 2024.
- [111] InternLM Team. Internlm: A multilingual language model with progressively enhanced capabilities, 2023.
- [112] Changyao Tian, Xizhou Zhu, Yuwen Xiong, Weiyun Wang, Zhe Chen, Wenhui Wang, Yuntao Chen, Lewei Lu, Tong Lu, Jie Zhou, et al. Mm-interleaved: Interleaved image-text generative modeling via multi-modal feature synchronizer. *arXiv preprint arXiv:2401.10208*, 2024.
- [113] Shengbang Tong, Zhuang Liu, Yuexiang Zhai, Yi Ma, Yann LeCun, and Saining Xie. Eyes wide shut? exploring the visual shortcomings of multimodal llms. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9568–9578, 2024.
- [114] 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 preprint arXiv:2302.13971*, 2023.
- [115] 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. *arXiv preprint arXiv:2307.09288*, 2023.
- [116] Szymon Tworkowski, Konrad Staniszewski, Mikołaj Pacek, Yuhuai Wu, Henryk Michalewski, and Piotr Miłoś. Focused transformer: Contrastive training for context scaling. *Advances in Neural Information Processing Systems*, 36, 2024.
- [117] A Vaswani. Attention is all you need. *Advances in Neural Information Processing Systems*, 2017.
- [118] Benyou Wang, Lifeng Shang, Christina Lioma, Xin Jiang, Hao Yang, Qun Liu, and Jakob Grue Simonsen. On position embeddings in bert. In *International Conference on Learning Representations*, 2020.
- [119] Hengyi Wang, Haizhou Shi, Shiwei Tan, Weiyi Qin, Wenyuan Wang, Tunyu Zhang, Akshay Nambi, Tanuja Ganu, and Hao Wang. Multimodal needle in a haystack: Benchmarking long-context capability of multimodal large language models. *arXiv preprint arXiv:2406.11230*, 2024.
- [120] 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.
- [121] Mingjie Wang, Jun Zhou, Yong Dai, Eric Buys, and Minglun Gong. Enhancing zero-shot counting via language-guided exemplar learning. *arXiv preprint arXiv:2402.05394*, 2024.
- [122] Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Yang Fan, Kai Dang, Mengfei Du, Xuancheng Ren, Rui Men, Dayiheng Liu, Chang Zhou, Jingren Zhou, and Junyang Lin. Qwen2-vl: Enhancing vision-language model’s perception of the world at any resolution. *arXiv preprint arXiv:2409.12191*, 2024.
- [123] Sinong Wang, Belinda Z Li, Madian Khabsa, Han Fang, and Hao Ma. Linformer: Self-attention with linear complexity. *arXiv preprint arXiv:2006.04768*, 2020.
- [124] Weiyun Wang, Min Shi, Qingyun Li, Wenhui Wang, Zhenhang Huang, Linjie Xing, Zhe Chen, Hao Li, Xizhou Zhu, Zhiguo Cao, et al. The all-seeing project: Towards panoptic visual recognition and understanding of the open world. *arXiv preprint arXiv:2308.01907*, 2023.
- [125] Weiyun Wang, Shuibo Zhang, Yiming Ren, Yuchen Duan, Tiantong Li, Shuo Liu, Mengkang Hu, Zhe Chen, Kaipeng Zhang, Lewei Lu, et al. Needle in a multimodal haystack. *arXiv preprint arXiv:2406.07230*, 2024.
- [126] Weizhi Wang, Li Dong, Hao Cheng, Xiaodong Liu, Xifeng Yan, Jianfeng Gao, and Furu Wei. Augmenting language models with long-term memory. *Advances in Neural Information Processing Systems*, 36, 2024.
- [127] Xiaohan Wang, Yuhui Zhang, Orr Zohar, and Serena Yeung-Levy. Videoagent: Long-form video understanding with large language model as agent. *arXiv preprint arXiv:2403.10517*, 2024.
- [128] Xidong Wang, Dingjie Song, Shunian Chen, Chen Zhang, and Benyou Wang. Longllava: Scaling multi-modal llms to 1000 images efficiently via hybrid architecture. *arXiv preprint arXiv:2409.02889*, 2024.
- [129] Zilong Wang, Yichao Zhou, Wei Wei, Chen-Yu Lee, and Sandeep Tata. A benchmark for structured extractions from complex documents. *ArXiv, abs/2211.15421*, 2, 2022.
- [130] 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 model. In *European Conference on Computer Vision*, pages 408–424. Springer, 2025.
- [131] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.
- [132] 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.
- [133] Yuetian Weng, Mingfei Han, Haoyu He, Xiaojun Chang, and Bohan Zhuang. Longlvm: Efficient long video understanding via large language models. In *European Conference on Computer Vision*, pages 453–470. Springer, 2025.
- [134] Jeffrey Willette, Heejun Lee, Youngwan Lee, Myeongjae Jeon, and Sung Ju Hwang. Training-free exponential extension of sliding window context with cascading kv cache. *arXiv preprint arXiv:2406.17808*, 2024.
- [135] Yuhuai Wu, Markus N Rabe, DeLesley Hutchins, and Christian Szegedy. Memorizing transformers. *arXiv preprint arXiv:2203.08913*, 2022.
- [136] X.ai. Grok-1.5 vision preview. <https://x.ai/blog/grok-1.5v>, 2024.
- [137] Guangxuan Xiao, Yuandong Tian, Beidi Chen, Song Han, and Mike Lewis. Efficient streaming language models with attention sinks. *arXiv preprint arXiv:2309.17453*, 2023.
- [138] Peng Xu, Wei Ping, Xianchao Wu, Lawrence McAfee, Chen Zhu, Zihan Liu, Sandeep Subramanian, Evelina Bakhturina, Mohammad Shoeybi, and Bryan Catanzaro. Retrieval meets long context large language models. *arXiv preprint arXiv:2310.03025*, 2023.
- [139] Fuzhao Xue, Yukang Chen, Dacheng Li, Qinghao Hu, Ligeng Zhu, Xiuyu Li, Yunhao Fang, Haotian Tang, Shang Yang, Zhijian Liu, et al. Longvila: Scaling long-context visual language models for long videos. *arXiv preprint arXiv:2408.10188*, 2024.
- [140] L Xue. mt5: A massively multilingual pre-trained text-to-text transformer. *arXiv preprint arXiv:2010.11934*, 2020.
- [141] Aiyuan Yang, Bin Xiao, Bingning Wang, Borong Zhang, Ce Bian, Chao Yin, Chenxu Lv, Da Pan, Dian Wang, Dong Yan, et al. Baichuan 2: Open large-scale language models. *arXiv preprint arXiv:2309.10305*, 2023.
- [142] Yuan Yao, Tianyu Yu, Ao Zhang, Chongyi Wang, Junbo Cui, Hongji Zhu, Tianchi Cai, Haoyu Li, Weilin Zhao, Zhi-hui He, et al. Minicpm-v: A gpt-4v level mllm on your phone. *arXiv preprint arXiv:2408.01800*, 2024.
- [143] Kexin Yi, Chuang Gan, Yunzhu Li, Pushmeet Kohli, Jiajun Wu, Antonio Torralba, and Joshua B. Tenenbaum. CLEVRER: collision events for video representation and reasoning. In *ICLR*, 2020.
- [144] Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, et al. Mmmu: A massive multi-discipline multimodal understanding and reasoning benchmark for expert agi. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9556–9567, 2024.
- [145] Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Ontanon, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, et al. Big bird: Transformers for longer sequences. *Advances in neural information processing systems*, 33:17283–17297, 2020.
- [146] Xiaohua Zhai, Basil Mustafa, Alexander Kolesnikov, and Lucas Beyer. Sigmoid loss for language image pre-training. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 11975–11986, 2023.
- [147] Pan Zhang, Xiaoyi Dong, Bin Wang, Yuhang Cao, Chao Xu, Linke Ouyang, Zhiyuan Zhao, Shuangrui Ding, Songyang Zhang, Haodong Duan, Wenwei Zhang, Hang Yan, Xinyue Zhang, Wei Li, Jingwen Li, Kai Chen, Conghui He, Xingcheng Zhang, Yu Qiao, Dahua Lin, and Jiaqi Wang. Internlm-xcomposer: A vision-language large model for advanced text-image comprehension and composition. *arXiv preprint arXiv:2309.15112*, 2023.
- [148] Pan Zhang, Xiaoyi Dong, Yuhang Zang, Yuhang Cao, Rui Qian, Lin Chen, Qipeng Guo, Haodong Duan, Bin Wang, Linke Ouyang, Songyang Zhang, Wenwei Zhang, Yining Li, Yang Gao, Peng Sun, Xinyue Zhang, Wei Li, Jingwen Li, Wenhui Wang, Hang Yan, Conghui He, Xingcheng Zhang, Kai Chen, Jifeng Dai, Yu Qiao, Dahua Lin, and Jiaqi Wang. Internlm-xcomposer-2.5: A versatile large vision language model supporting long-contextual input and output. *arXiv preprint arXiv:2407.03320*, 2024.
- [149] Peitian Zhang, Zheng Liu, Shitao Xiao, Ninglu Shao, Qiwei Ye, and Zhicheng Dou. Long context compression with activation beacon. *arXiv preprint arXiv:2401.03462*, 2024.
- [150] Peitian Zhang, Shitao Xiao, Zheng Liu, Zhicheng Dou, and Jian-Yun Nie. Retrieve anything to augment large language models. *arXiv preprint arXiv:2310.07554*, 2023.
- [151] Peiyuan Zhang, Kaichen Zhang, Bo Li, Guangtao Zeng, Jingkang Yang, Yuanhan Zhang, Ziyue Wang, Haoran Tan, Chunyuan Li, and Ziwei Liu. Long context transfer from language to vision. *arXiv preprint arXiv:2406.16852*, 2024.
- [152] 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.
- [153] Yikai Zhang, Junlong Li, and Pengfei Liu. Extending llms’ context window with 100 samples. *arXiv preprint arXiv:2401.07004*, 2024.
- [154] Liang Zhao, Tianwen Wei, Liang Zeng, Cheng Cheng, Liu Yang, Peng Cheng, Lijie Wang, Chenxia Li, Xuejie Wu, Bo Zhu, et al. Longskywork: A training recipe for efficiently extending context length in large language models. *arXiv preprint arXiv:2406.00605*, 2024.
- [155] Tiancheng Zhao, Qianqian Zhang, Kyusong Lee, Peng Liu, Lu Zhang, Chunxin Fang, Jiajia Liao, Kelei Jiang, Yibo Ma, and Ruochen Xu. Omchat: A recipe to train multimodal language models with strong long context and video understanding. *arXiv preprint arXiv:2407.04923*, 2024.

- [156] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *Advances in Neural Information Processing Systems*, 36:46595–46623, 2023.
- [157] Dawei Zhu, Nan Yang, Liang Wang, Yifan Song, Wenhao Wu, Furu Wei, and Sujian Li. Pose: Efficient context window extension of llms via positional skip-wise training. *arXiv preprint arXiv:2309.10400*, 2023.
- [158] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.
- [159] Wanrong Zhu, Jack Hessel, Anas Awadalla, Samir Yitzhak Gadre, Jesse Dodge, Alex Fang, Youngjae Yu, Ludwig Schmidt, William Yang Wang, and Yejin Choi. Multimodal c4: An open, billion-scale corpus of images interleaved with text. *Advances in Neural Information Processing Systems*, 36, 2024.

Appendix

A. Dataset Details

We have introduced two augmented long-context multimodal datasets: Long-VQA and Long-MR, designed to systematically evaluate and analyze the long-context capabilities of Vision-Language Models (VLMs). Representative examples from these datasets are illustrated in Fig.11, Fig.12, Fig.13, and Fig.14. Next, we will provide a detailed description of the dataset construction process.

A.1. Long Visual Question Answering (Long-VQA)

The Long-VQA dataset presents a novel challenge to VLMs, necessitating advanced visual perception and sophisticated reasoning capabilities to address tasks involving long context. This dataset is synthesized by combining multiple existing datasets in Tab. 6 to create a set of complex multi-image tasks.

For datasets that primarily consist of document-like images, such as DocVQA [81], we extend the context by merging multiple single-page documents into cohesive multi-page collections. Questions are subsequently sampled from one of the original documents, ensuring that the model’s ability to retain and utilize information across an extended multi-page context is rigorously evaluated.

In the case of datasets composed of visual elements like images, charts, and tables, such as those from GQA [51], VizWiz [43], and TabFact [17], we aggregate these components into complex, multi-page documents that emulate naturalistic scenarios. Each visual element, whether an image or a chart, is strategically positioned across different pages and at various locations (e.g., upper-left, center, lower-right). This configuration is designed to evaluate a

model’s complex reasoning capabilities, as it requires an understanding of the relative positioning of elements throughout the entire document.

By constructing a diverse and challenging dataset, Long-VQA not only evaluates a model’s ability to process a wide range of visual inputs but also emphasizes the necessity of navigating through complex, multi-image contexts. This synthesis of data from multiple sources, combined with the deliberate complexity of the spatial layouts, establishes a rigorous benchmark for VLMs. Additionally, we provide the length distribution of the Long-VQA test set in Fig. 9.

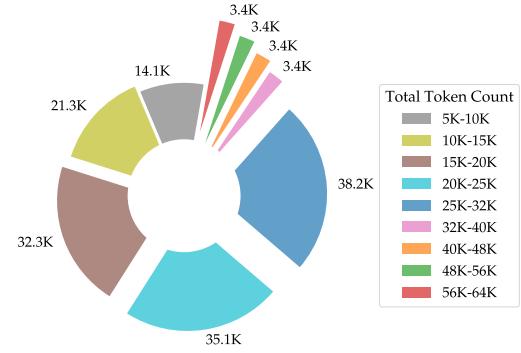


Figure 9. The token length distribution of test set in Long-VQA.

A.2. Long Multimodal Retrieval (Long-MR)

Our proposed Long-MR dataset is constructed upon the MM-NIAH [125] benchmark, designed specifically to evaluate the performance of VLMs in long-context multimodal retrieval tasks. To further assess the generalization capabilities of VLMs within this task, we introduce additional synthetic variations that increase the task complexity.

Unlike the original MM-NIAH, where a single needle is inserted, our Long-MR dataset incorporates multiple needles into the long-context multimodal sequence. Of these needles, only one is considered as the target query, while the remainder serve as negative needles. This configuration introduces significantly more challenging negative instances, compelling the model to accurately distinguish between highly similar yet irrelevant needles in a lengthy contextual sequence.

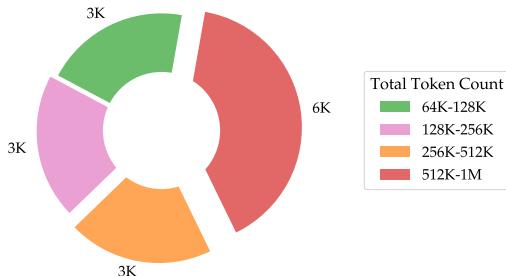
To enrich the diversity of needles, we leverage advanced large language models (LLMs) to create synthetic needles beyond those included in the official MM-NIAH benchmark. This expansion results in a more heterogeneous dataset that emulates real-world complexity, thereby improving the robustness of the evaluation. Such diversification reduces the risk of the model overfitting to a particular needle category, fostering the development of more generalizable retrieval capabilities.

Fig. 10 illustrates the length distribution of our costumed evaluation split, denoted as MM-NIAH_{1M}. Notably, the ma-

Table 6. Data statistics of Long-VQA dataset.

Dataset	Dataset Size	
	Training	Validation
DeepForm [129]	3.4K	2.1K
DocVQA [81]	39.4K	6.0K
InfoVQA [80]	23.9K	4.1K
Kleister [100]	13.4K	5.5K
SQA [74]	10.2K	4.1K
VisualMRC [107]	15.8K	7.4K
ChartQA [79]	40.1K	3.3K
DVQA [55]	150.0K	16.4K
TabFact [17]	91.6K	13.4K
WikitabQS [88]	14.1K	5.1K
Clevr [54]	150.0K	16.4K
GQA [51]	150.0K	16.4K
OcrVQA [83]	150.0K	16.4K
OKVQA [78]	9.0K	5.8K
TextCaps [97]	110.0K	17.2K
TextVQA [98]	56.5K	6.5K
Vizwiz [43]	20.5K	8.8K
Total	1.1M	155.0K

jority of sequences fall within the 512K to 1M token range. For contexts with lengths shorter than 64K, we directly utilize the samples from the original MM-NIAH benchmark.

Figure 10. The token length distribution of our MM-NIAH_{1M}

B. Evaluation

To address the out-of-memory challenge encountered during inference on samples exceeding token lengths of 128K in the MM-NIAH_{1M} evaluation dataset, we adopt a perplexity-based approach similar to that employed in LongVA [151]. Specifically, during evaluation, we concatenate the question embedding, which integrates both textual and visual components, with the output answer embedding. Subsequently, a single forward pass is performed using ring attention to predict the logits of the answer. The output is considered correct if the index corresponding to the highest output logit across all tokens within the answer span aligns with the correct answer.

To facilitate comparison between position encoding ex-

Table 7. Summary of our training hyper-parameters.

Configuration	V2PE Setting
Weight init	InternVL2-2B [20]
Loss type	Generative loss
Learning rate schedule	Cosine decay
Optimizer	AdamW [72]
Learning rate	5e-6
Weight decay	5e-2
Input image resolution	448 × 448
Warmup steps	150
Iterations	5K

tension and V2PE, we determine the interpolation factor for linear interpolation [16] based on the test sample length and the context window size used during training. Specifically, we interpolate the position indices of the test samples to match the context window range from the training phase. For example, when evaluating InternVL2-FT-32K on the 64K-length Long-VQA task using linear interpolation [16], we utilize an interpolation factor of 2, which effectively maps the position indices of the test samples into the 32K range, consistent with the context length employed during training. Similarly, for evaluations involving 1M-length samples, an interpolation factor of 32 is selected. For the NTK-Aware Scaled RoPE [11], we fix the scaling factor at 5, as our experimental results indicate that it yields consistent performance across tasks of varying lengths.

C. Experiment Details

The detailed training configurations are summarized in Table 7. Additionally, for experiments involving the V2PE method, we employ the `Float32` data type when computing positional indices and positional embeddings required for RoPE, to ensure computational precision.

D. Attention Matrices Analysis

To investigate the impact of our V2PE on attention mechanism, we follow [28] to analyze the attention matrices on the Long-VQA evaluation set. Specifically, our analysis focuses on the tail portion of the entire attention matrices, which corresponds to the question segments located at the end of the sequences. This allows us to observe how effectively the model retrieves relevant information when answering questions.

As illustrated in Fig. 15, we observe that as the positional increment parameter δ decreases, the attention patterns in Layer 1 exhibit an increasingly distinct emphasis on visual tokens. This observation suggests that with smaller values of δ , the model becomes more attentive to visual content, which is crucial for answering questions involving visual inputs. Furthermore, Fig. 16 shows that in deeper lay-

ers (e.g., Layer 15), the attention becomes more focused around a specific sequence index, particularly ID=1410, as δ decreases. Notably, the answer to the corresponding question is located near the 1410-*th* token. This indicates that a smaller δ not only sharpens the model’s focus but also aligns its attention more effectively with the tokens containing the correct answer.

These findings imply that using smaller positional increment δ allows the model to better align its attention with the critical portions of the input sequence, thereby enhancing its capability to retrieve relevant information, especially in the scenarios of long-context multimodal tasks.

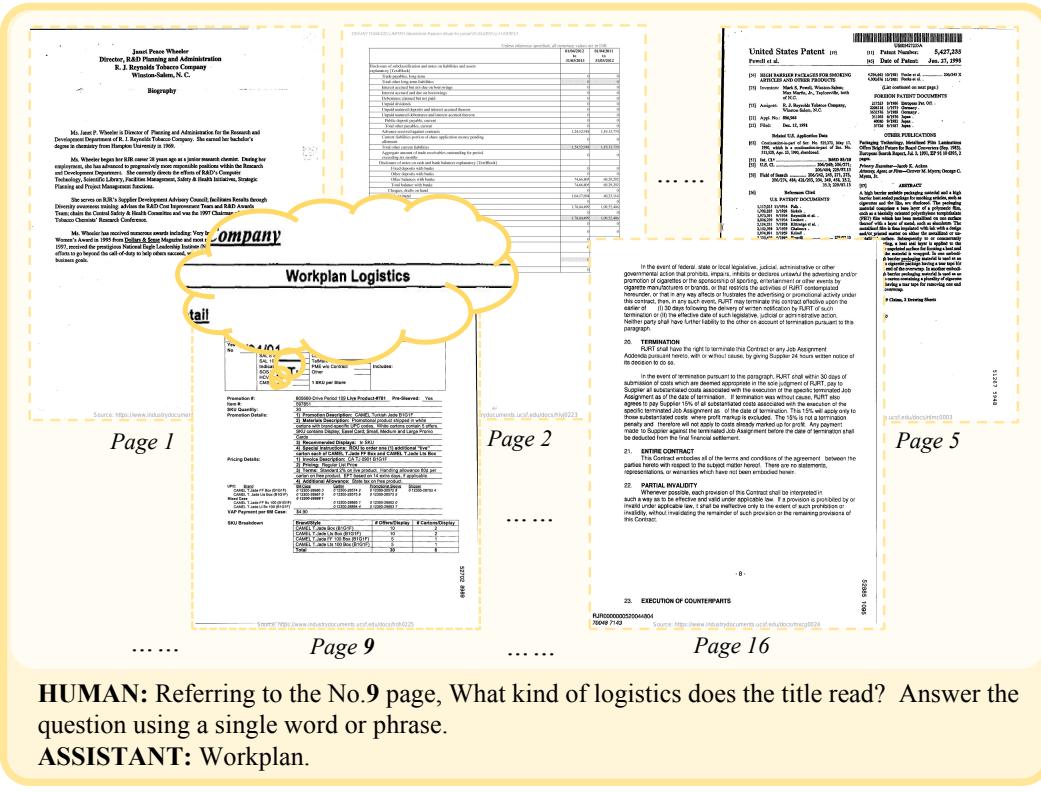


Figure 11. Examples of DocVQA subset from Long-VQA dataset.

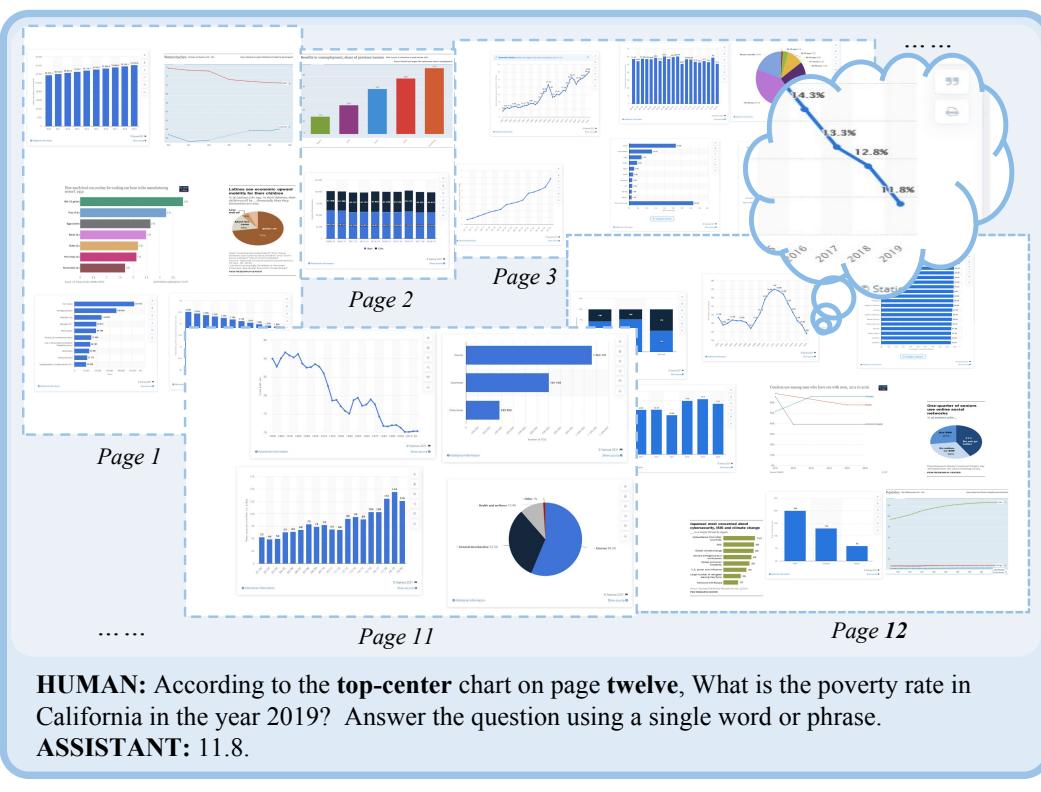


Figure 12. Examples of ChartVQA subset from Long-VQA dataset.

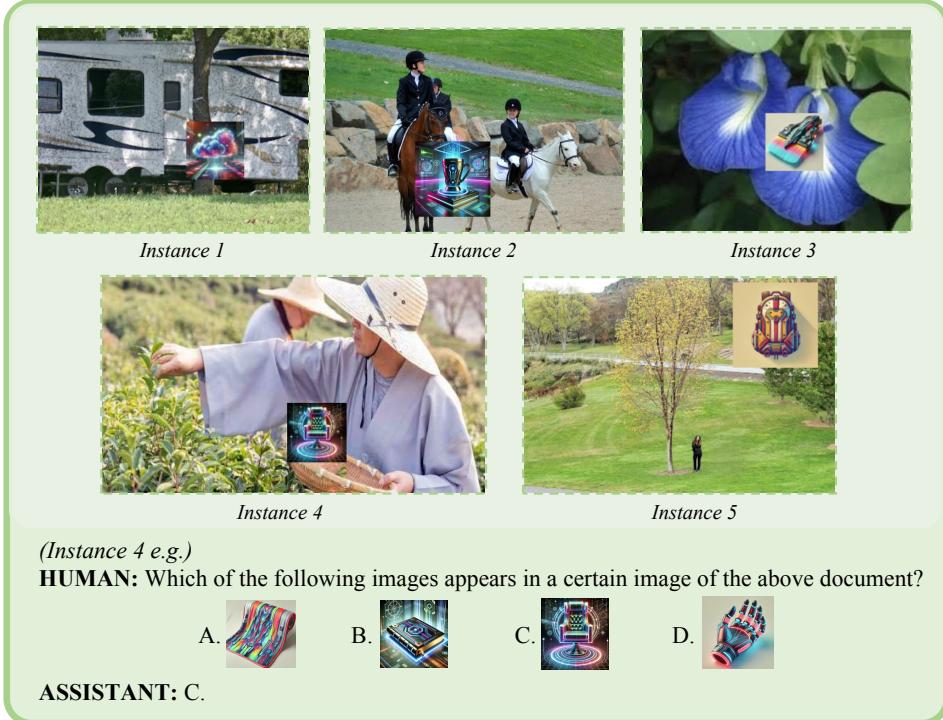


Figure 13. Examples of *Retrieval-Image-Needle* in our proposed Long-MR dataset.

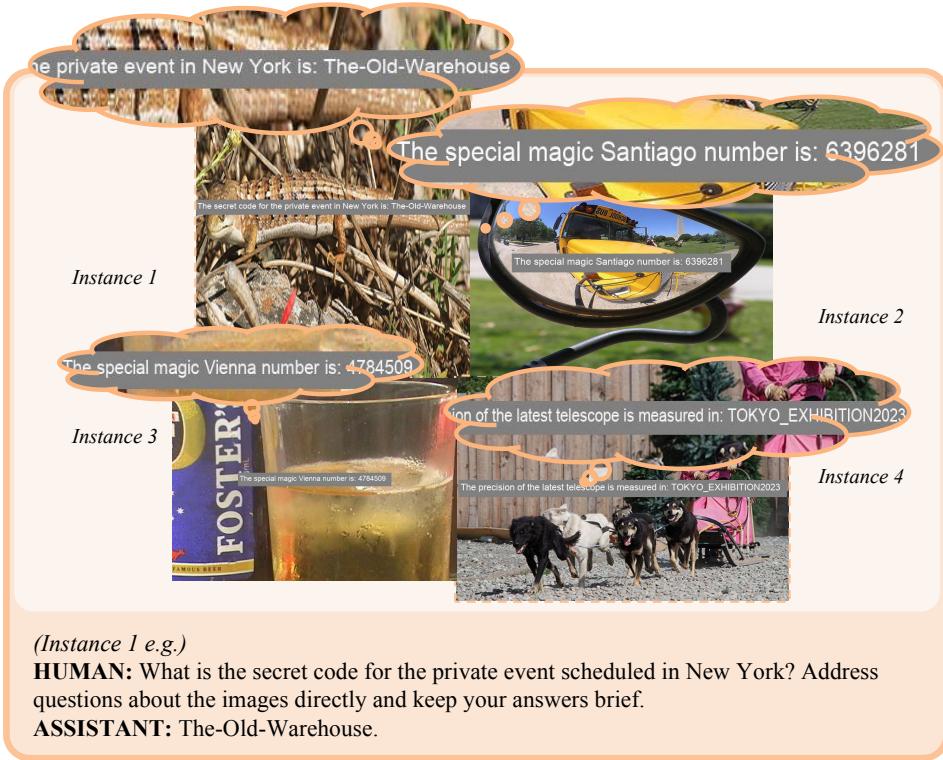


Figure 14. Examples of *Image-Needle-In-A-Haystack* with complex needles in our proposed Long-MR dataset. These needles vary in answer format, font-size and style.

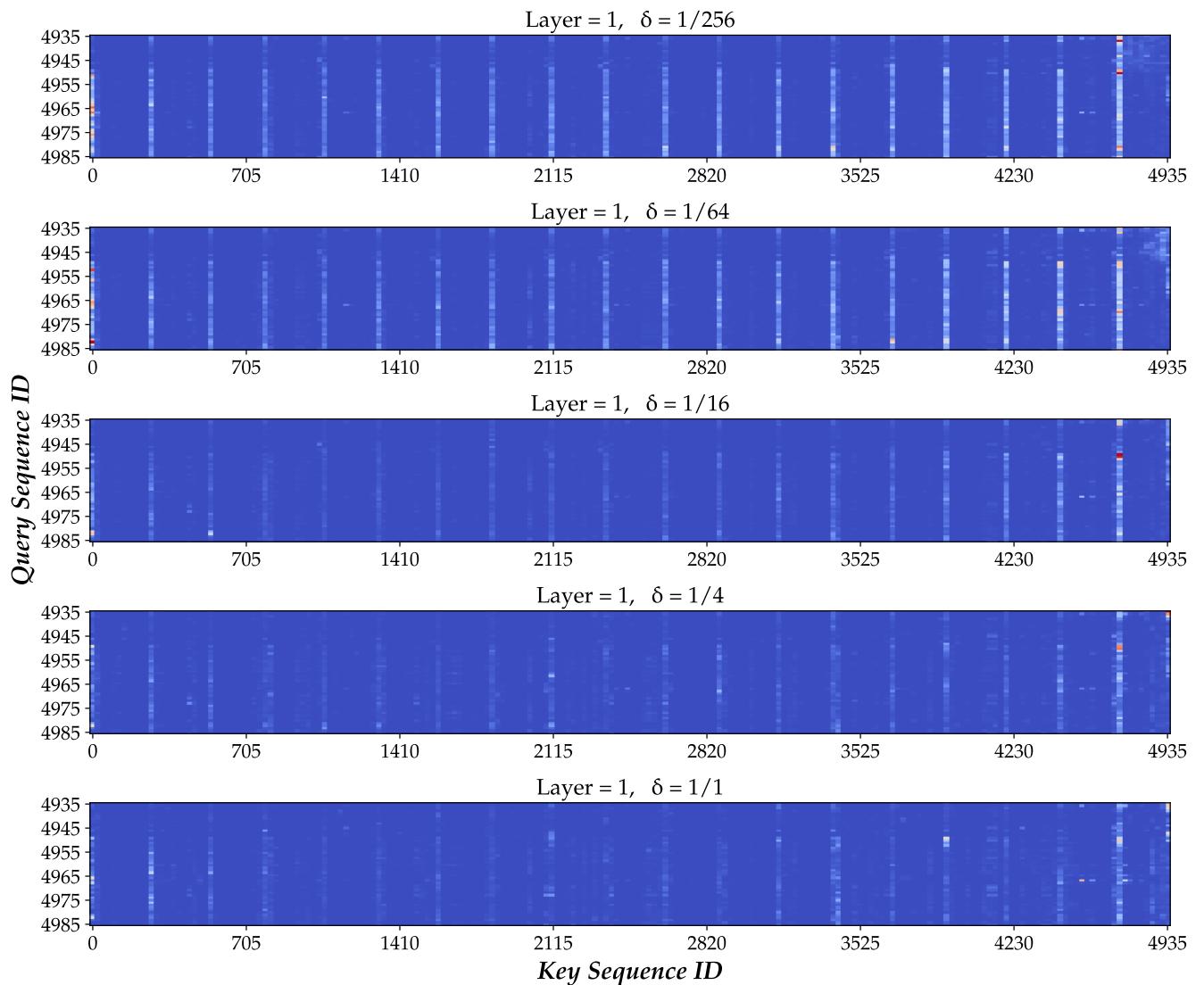


Figure 15. Attention map visualization in layer 1 (Maximum over 16 heads).

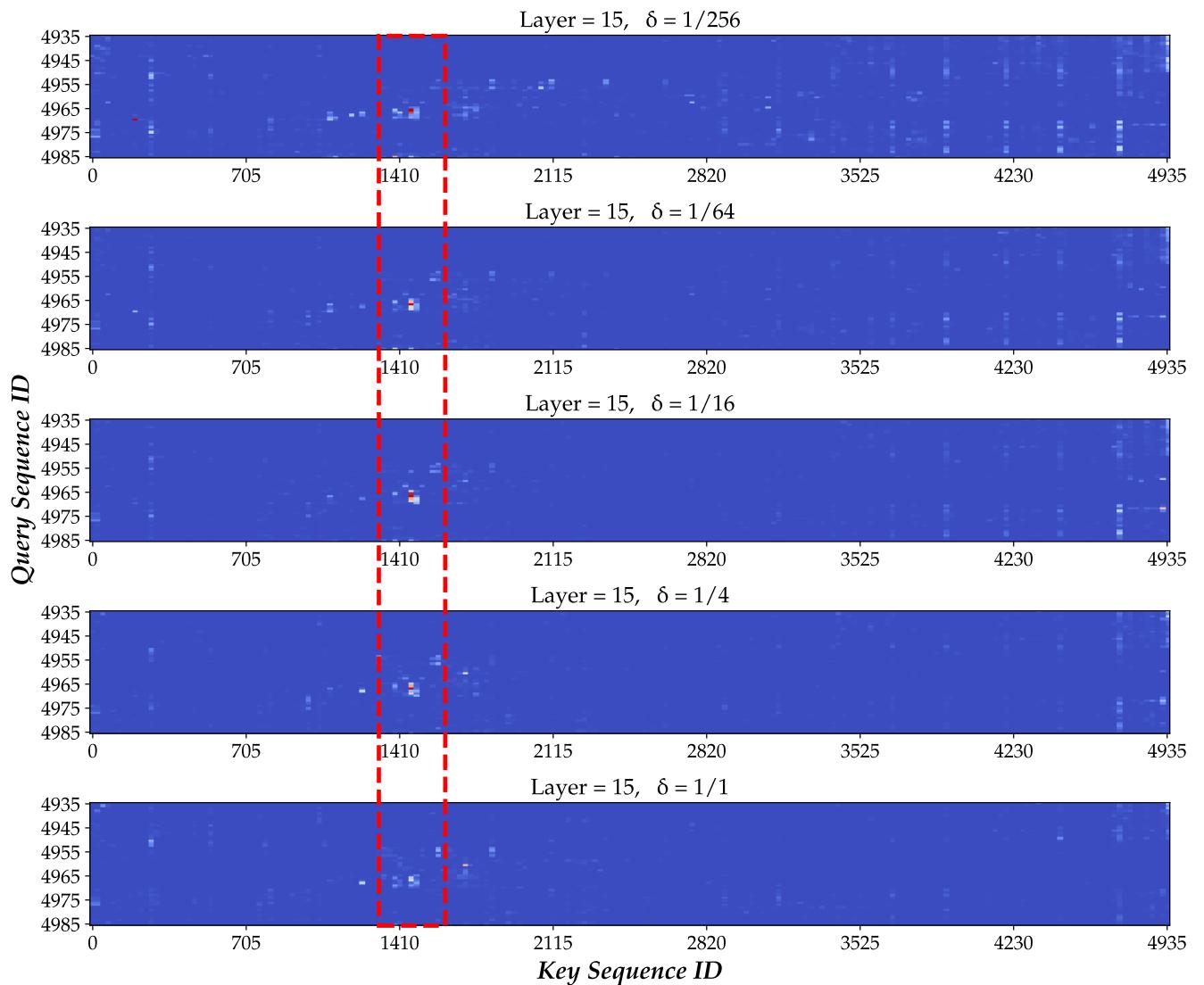


Figure 16. Attention map visualization in layer 15 (Maximum over 16 heads).