

POINTS1.5: Building a Vision-Language Model towards Real World Applications

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<https://github.com/WePOINTS/WePOINTS>



<https://huggingface.co/WePOINTS/POINTS-1-5-Qwen-2-5-7B-Chat>

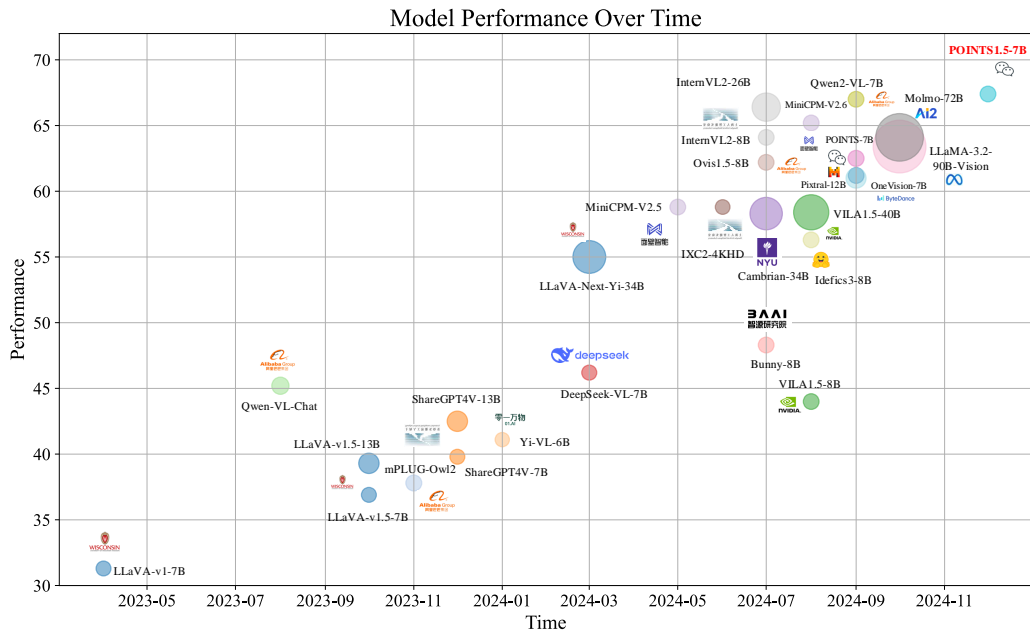


Figure 1: **Performance of Open-Source Models on the OpenCompass Leaderboard**[Contributors, 2023]. POINTS1.5 ranks first among all models under 10B in size, even outperforming models several times larger. The size of each bubble represents the model size.

Abstract

Vision-language models have made significant strides recently, demonstrating superior performance across a range of tasks, *e.g.* optical character recognition and complex diagram analysis. Building on this trend, we introduce a new vision-language model, **POINTS1.5**, designed to excel in various real-world applications. POINTS1.5 is an enhancement of POINTS1.0 and incorporates several key innovations: i) We replace the original CLIP vision encoder, which had a fixed image resolution, with a NaViT-style vision encoder that supports native dynamic high resolution. This allows POINTS1.5 to process images of any resolution without needing to split them into tiles. ii) We add bilingual support to POINTS1.5, significantly enhancing its capability in Chinese. Due to the scarcity of open-source Chinese datasets for vision-language models, we collect numerous images from the

Internet and annotate them using a combination of manual and automatic methods. iii) We propose a set of rigorous filtering methods for visual instruction tuning datasets. We comprehensively evaluate all these filtering methods, and choose the most effective ones to obtain the final visual instruction tuning set. Thanks to these innovations, POINTS1.5 significantly outperforms POINTS1.0 and demonstrates strong performance across a range of real-world applications. Notably, POINTS1.5-7B is trained on fewer than 4 billion tokens and ranks first on the OpenCompass leaderboard among models with fewer than 10 billion parameters¹.

1 Introduction

Vision-language models [Liu et al., 2024b, Li et al., 2024, Bai et al., 2023, Liu et al., 2024d, Dong et al., 2024a, Chen et al., 2024c] have made remarkable strides in recent years, showcasing their potential to tackle complex tasks such as geometry math problems and optical character recognition (OCR). Despite these advancements, open-source models still lag behind closed commercial models like GPT-4o [OpenAI, 2023] and Claude-3.5-Sonnet in addressing certain real-world challenges. To bridge this gap, the open-source community has made significant efforts, exemplified by the Qwen2-VL series [Wang et al., 2024b], which has demonstrated performance comparable to, or even surpassing, these commercial models. In line with this trend, we introduce POINTS1.5, a more robust model than its predecessor, POINTS1.0 [Liu et al., 2024d], which currently holds the top position on the OpenCompass leaderboard among models with fewer than 10 billion parameters.

The development of vision-language models generally follows two distinct paths: i) The LLaVA-style architecture, which integrates a pre-trained vision encoder, a randomly initialized projector, and a pre-trained large language model; and ii) Models where the large language model is randomly initialized, and both visual and text tokens are jointly used to train the language model, as seen in works like Emu3 [Wang et al., 2024c]. The LLaVA-style architecture has shown superior performance in visual understanding tasks, and POINTS1.5 continues to follow this approach. This architecture involves continual post-training of the large language model to enhance its ability to interpret visual information. The pre-training stage primarily serves to align the projection layer with the space of vision and text tokens [Li et al., 2023b]. We identify two critical factors for developing a superior LLaVA-style vision-language model: i) A high-performance vision encoder that can accurately and uniquely represent an image, and ii) High-quality visual instruction tuning datasets that enable the model to understand image content and exhibit strong instruction-following capabilities. Based on this analysis, POINTS1.5 introduces the following innovations.

Native Dynamic High Resolution. Enabling a vision-language model to process images of any resolution without down-sampling offers numerous benefits, such as reducing hallucinations and enhancing performance on text-intensive tasks. Historically, many vision encoders, such as Vision Transformer [Dosovitskiy, 2020] and ConvNext [Liu et al., 2022], could only handle fixed-resolution images. Previous works [Liu et al., 2024a, Dong et al., 2024b, Chen et al., 2024c, Liu et al., 2024d] often split large images into tiles to accommodate the vision encoder, disrupting the spatial structure of the original image. In contrast, POINTS1.5 employs a NaViT-style architecture, following the approaches of Qwen2-VL [Wang et al., 2024b] and Idefics2 [Laurençon et al., 2024], allowing it to process arbitrary-resolution images without splitting them, resulting in significant improvements over the dual CLIP vision encoders used in POINTS1.0.

Bilingual Support. In POINTS1.0, the English corpus comprised over 95% of the total data. In this version, we have increased the amount of Chinese data for both the pre-training and visual instruction tuning stages. Due to the limited availability of open-source Chinese datasets, gathering a large quantity of Chinese corpus is challenging. For the pre-training stage, we followed the strategy used to obtain the 1 million pre-training data in POINTS1.0, creating an additional 1 million Chinese pre-training data from LAION-5B-cn [Schuhmann et al., 2022] using CapFusion [Yu et al., 2024] and perplexity filtering [Liu et al., 2024d]. This was combined with the original English data to form a final dataset of 2 million for pre-training. For the visual instruction tuning stage, we employed two strategies: (i) translating existing conversation datasets into Chinese using a large language model (LLM), and (ii) for Chinese OCR datasets, collecting related images from the internet and using an

¹Result is obtained on December 8th, 2024

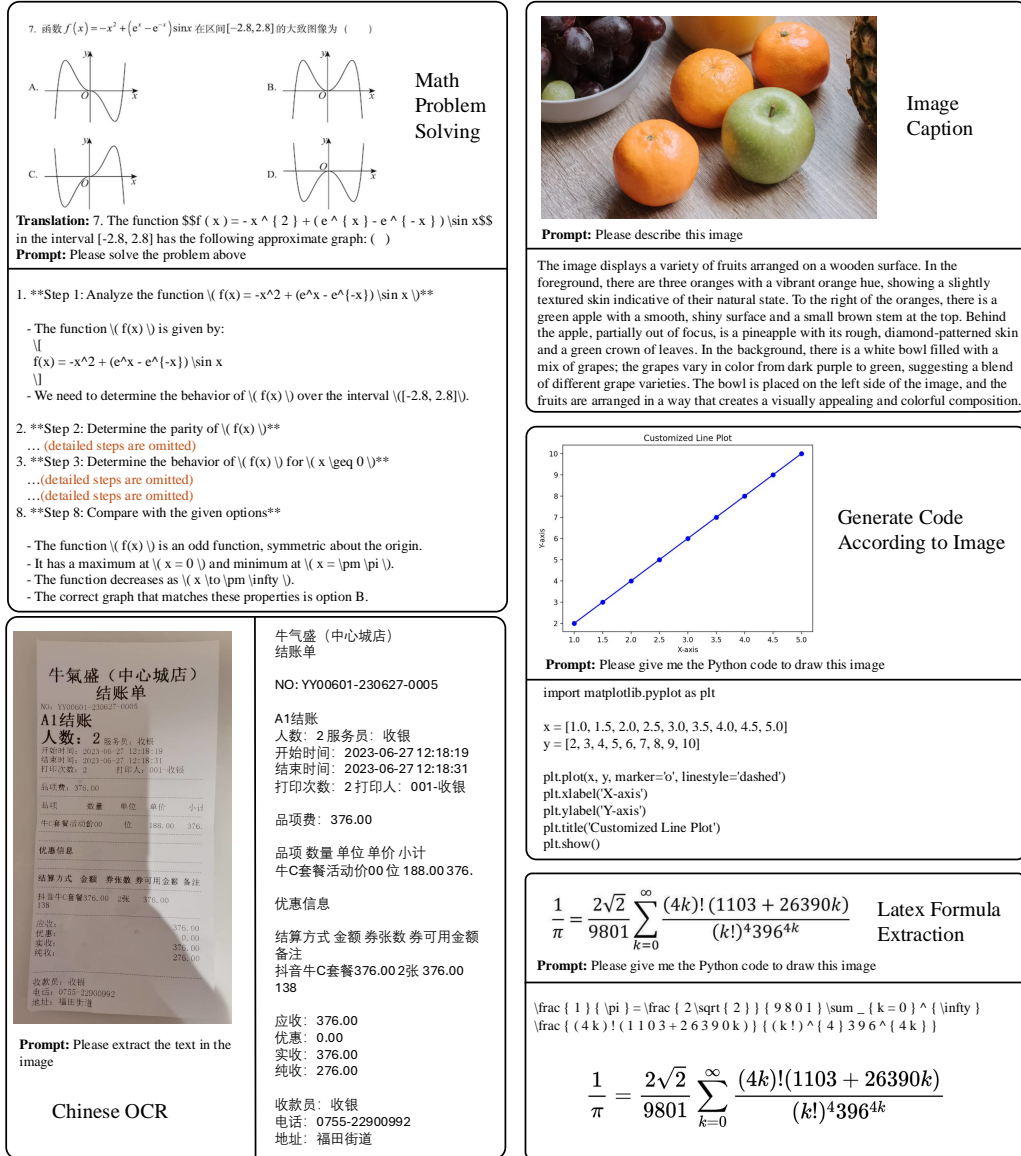


Figure 2: POINTS1.5 shows great potential to solve challenging real world problems.

existing vision-language model, such as Qwen2-VL-72B, to extract text from these images. Human labelers then verified these annotations, correcting minor errors or discarding them if the errors were significant.

Visual Instruction Tuning Set Filtering. We manually reviewed each dataset used in POINTS1.0 and identified two significant issues: i) A large number of grammatical errors in some datasets, and ii) Some questions could be answered without referring to the image. To address the first issue, we employed a large language model (LLM), such as Qwen2.5-72B [Yang et al., 2024], to detect grammatical errors in the existing data samples. We then either discarded these erroneous samples or corrected them and reintegrated them into the original dataset. For the second issue, we used an LLM to answer the questions without the image. If the LLM provided the correct answer, the corresponding data sample was labeled accordingly.

Combining these innovations, POINTS1.5 brings significant improvements compared to POINTS1.0 and performs well across a range of real-world applications. Notably, POINTS1.5-7B ranks first on the OpenCompass leaderboard among models with fewer than 10 billion parameters.

2 Model Architecture

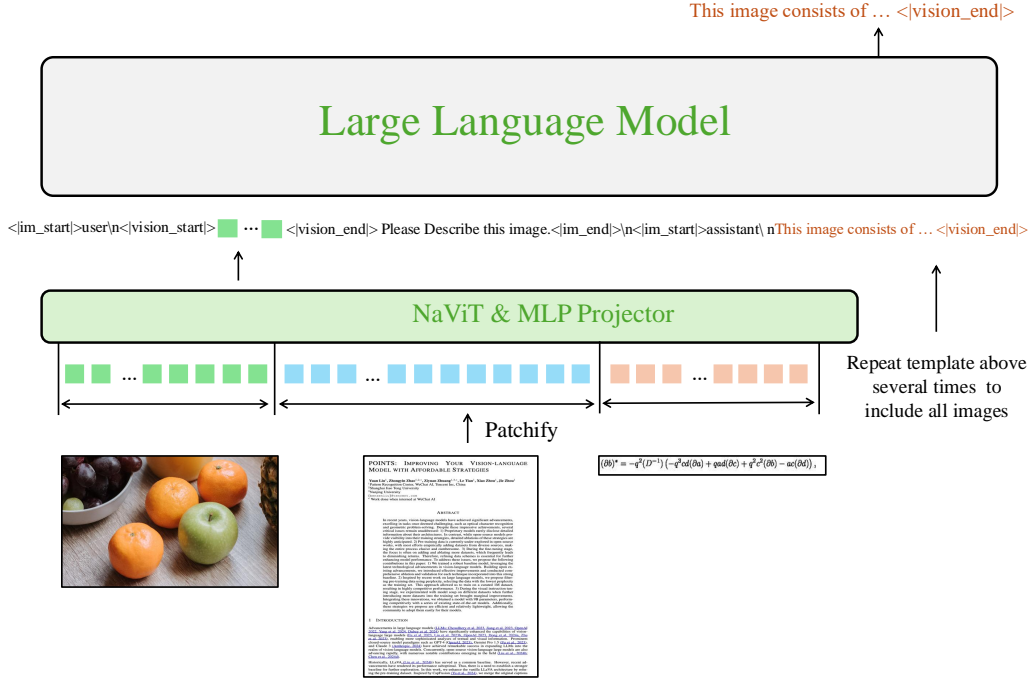


Figure 3: POINTS1.5 uses the conventional LLaVA-style architecture, consisting of a vision encoder, a MLP projector and a LLM.

Figure 3 illustrates the architecture of POINTS1.5. This model adheres to the traditional LLaVA-style architecture [Liu et al., 2023b], which comprises a vision encoder, an MLP projector, and a language model (LLM).

Vision Encoder As discussed in the previous section, training a vision-language model using the LLaVA-style architecture is akin to the continual post-training of the LLM, enabling it to process tokens from the image modality. Therefore, starting with a high-quality vision encoder is crucial for the LLM to accurately interpret images. To support images with arbitrary resolutions, POINTS1.0 follows recent works such as LLaVA-Next [Liu et al., 2024a] and InternVL [Chen et al., 2024c], which split a large image into several tiles that the vision encoder can process. However, this method has inherent drawbacks, as it disrupts the spatial relationships between patches within an image. Although strategies like adding line splitters [Dong et al., 2024b] and incorporating a global view alongside the split patches [Chen et al., 2024c] can mitigate this issue, the problem persists. Consequently, POINTS1.5 replaces the CLIP vision encoder used in POINTS1.0 with a NaViT-style vision encoder [Dehghani et al., 2024], following recent advancements [Wang et al., 2024b, Laurençon et al., 2024]. Unlike the CLIP vision encoder, the NaViT-style vision encoder can natively handle images with arbitrary resolutions without the need for splitting.

Batch Forwarding with NaViT With the introduction of NaViT, a new challenge arises in batch forwarding. Unlike the CLIP vision encoder, where images can be concatenated along the batch size dimension, NaViT processes images that vary in sequence length after being patchified. To address this, we adopt a strategy inspired by large language models (LLMs): we pack multiple image sequences into a single, long sequence. We then record the start and end indices of each image

sequence to ensure that self-attention is applied only within the boundaries of the current image sequence [Dao, 2024].

Projector In accordance with POINTS1.0, the projector consists of a two-layer MLP with a GELU activation function [Hendrycks and Gimpel, 2016] between the layers to introduce non-linearity.

Large Language Model In alignment with POINTS1.0, we have selected Qwen2.5-7B-Instruct. After the release of this paper, we plan to introduce POINTS1.5 with bigger language model.

3 Bilingual Support

In this section, we will discuss the curation of the Chinese dataset used in POINTS1.5. But before the discussion, we will refine the chat template used in the pre-training of POINTS1.0.

Chat Template As discussed in previous sections, training a LLaVA-style vision-language model involves the continual post-training of the LLM. Following POINTS1.0, the LLM of POINTS1.5 is also initialized from the instruction-tuned version of Qwen2.5-7B². However, during the pre-training stage of POINTS1.0, we use a continuation template to pack the data, similar to the one used during the pre-training process of the LLM, which deviates from the template used in the initialized LLM. In this version, we employ the conversation template used in Qwen2.5-7B-Instruct and observe improved performance compared to the continuation template. Since the pre-training data are the image-caption pairs, we add a prompt, similar to *Please describe this image.*, to each data sample. To diversify the prompts, we create a candidate prompt pool (Figure 5) and randomly sample one for each data sample. Additionally, to distinguish visual tokens from text tokens, we add image prefix and suffix tokens around the visual tokens. Figure 4 shows the difference between the chat template during pre-training between POINTS1.0 [Liu et al., 2024d] and POINTS1.5.

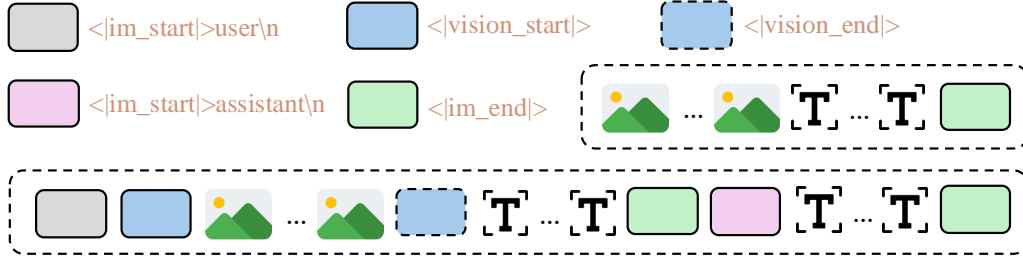


Figure 4: The chat template during pre-training in POINTS1.0 (above) and POINTS1.5 (below)

Chinese Pre-training Dataset Following POINTS1.0, we employ a two-step procedure to create the pre-training dataset: i) We use CapFusion [Yu et al., 2024] to merge the caption generated by a vision-language Model (VLM) with the image’s original caption, resulting in the final caption. ii) We filter the generated caption using perplexity. The CapFusion process is described by the following formula:

$$\text{Caption} = \mathcal{G}(c, \mathcal{F}(I)) \quad (1)$$

\mathcal{G} represents a large language model, \mathcal{F} denotes a vision-language model, c is the original caption, and I is the corresponding image. The Chinese captions were generated during the development of POINTS1.0. For this purpose, we utilize InternLM2 [Cai et al., 2024] as the large language model and InternLM-XComposer2 [Dong et al., 2024a] as the vision-language model. In the future, we plan to generate captions using more advanced models, such as POINTS1.5, which is also expected to further improve performance. Subsequently, we employ perplexity to filter these data:

²<https://huggingface.co/Qwen/Qwen2.5-7B-Instruct>

$$\text{Perplexity}(s) = \exp\left(-\frac{1}{N} \sum_{i=1}^N \log P(w_i | w_1, w_2, \dots, w_{i-1})\right) \quad (2)$$

Let $\{w_1, \dots, w_N\}$ denote the sequence of text tokens for s . We arrange these tokens in ascending order and select the first 20% (approximately 1 million) for the pre-training phase. This subset of the Chinese dataset is then combined with the original 1 million English dataset to pre-train POINTS1.5.

| | |
|--|--|
| <p>Could you provide a detailed description of this image?</p> <p>Can you describe this image thoroughly?</p> <p>Please give a detailed account of this image.</p> <p>Would you mind describing this image in detail?</p> <p>Could you explain this image in detail?</p> <p>Please offer a detailed description of this image.</p> <p>Can you give a comprehensive description of this image?</p> <p>Would you please describe this image in detail?</p> <p>Could you describe this image with detail?</p> <p>Please provide a thorough description of this image.</p> | <p>你能详细描述一下这张图片吗？</p> <p>你能彻底描述一下这张图片吗？</p> <p>请详细描述一下这张图片。</p> <p>你介意详细描述一下这张图片吗？</p> <p>你能详细解释一下这张图片吗？</p> <p>你能给出这张图片的全面描述吗？</p> <p>请提供这张图片的详细描述。</p> <p>请你详细描述一下这张图片好吗？</p> <p>你能详细描述一下这张图片吗？</p> <p>请提供这张图片的全面描述。</p> |
|--|--|

Figure 5: Prompts used in the chat template during pre-training stage.

Chinese Visual Instruction Tuning Dataset We inherit all visual instruction tuning datasets from POINTS1.0, except for those generated in this section. To create Chinese visual instruction tuning datasets, we employ several strategies: i) Translate existing English datasets (both questions and answers) into Chinese. ii) Use images and questions from existing datasets, and generate corresponding answers using a powerful VLM, such as Qwen2-VL-72B. This strategy is only applied to caption datasets. iii) Collect images from the internet, manually design questions (Figure 6), generate answers using a powerful VLM, and verify the answers with human labelers. This strategy is primarily used for Chinese OCR datasets. The following table shows the datasets and the corresponding strategies used to construct the Chinese datasets.

| Datasets | Strategy |
|--|---|
| VQAv2[Goyal et al., 2017], GQA[Hudson and Manning, 2019] | Translate English into Chinese |
| OKVQA[Marino et al., 2019] | |
| LVIS-Instruct4V[Wang et al., 2023], LAION-GPT4V | Question translation&VLM VLM&Human Check |
| Images collected from Internet | |

Table 1: Datasets and corresponding strategies to generate Chinese datasets.

| | |
|---|---|
| <p>Please extract all the text from the image</p> <p>Please extract text from the image</p> <p>Please extract all the text from the image</p> <p>Please extract all the text from the image</p> <p>Please extract the text from all the images</p> <p>Please get all the text from the image</p> <p>What is the text in this image</p> <p>What is the text content on this picture</p> <p>What is the text in the image</p> <p>Can you tell me what the text on this image is</p> | <p>请提取图片中的所有文字</p> <p>请从图片中提取文字</p> <p>请从图片中提取全部文字</p> <p>请从图片中提取出所有文字</p> <p>请提取所有图片中的文字</p> <p>请从图片中获取所有文字</p> <p>这张图片里的文字是什么</p> <p>这幅图上的文字内容是什么</p> <p>请问图片中的文字是什么</p> <p>你能告诉我这张图片上的文字是什么吗</p> |
|---|---|

Figure 6: Prompts to create the Chinese OCR datasets.

After the creation of Chinese datasets, we obtain the distribution across 9 categories and the English&Chinese distribution for the final visual instruction tuning datasets we used in POINTS1.5.

We observe a significant imbalance among the different categories. However, we have not yet identified effective methods to balance the data across these categories, and we leave this challenge for future work.

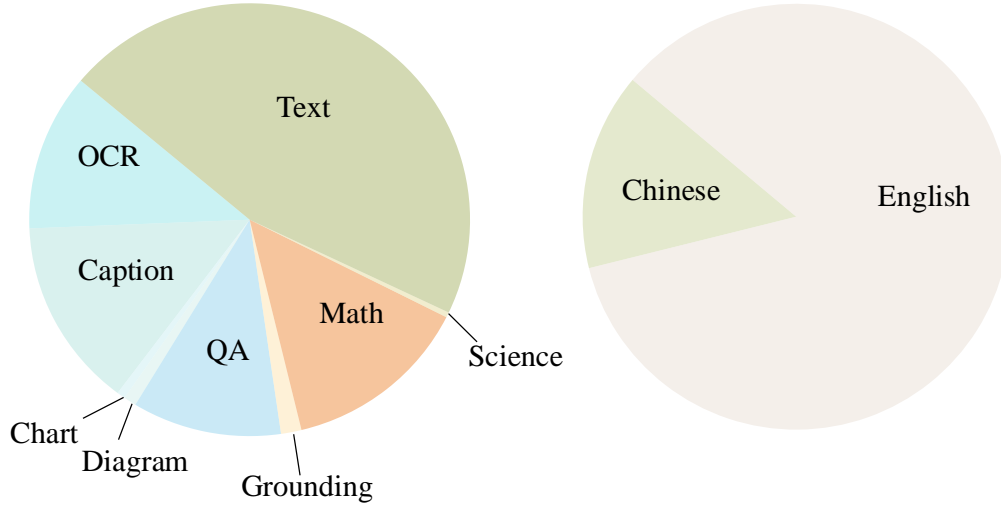


Figure 7: **Distribution of visual instruction tuning data in POINTS1.5.** The left figure shows the distribution across different categories, and the right figure shows the distribution between English and Chinese.

4 Visual Instruction Tuning Set Filtering

Before filtering the visual instruction tuning datasets, we manually check each of these datasets used in POINTS1.0, and identify two significant issues: i) Some questions could be answered without referring to the image (Figure 9). and ii) A large number of grammatical errors in some datasets (Figure 8).

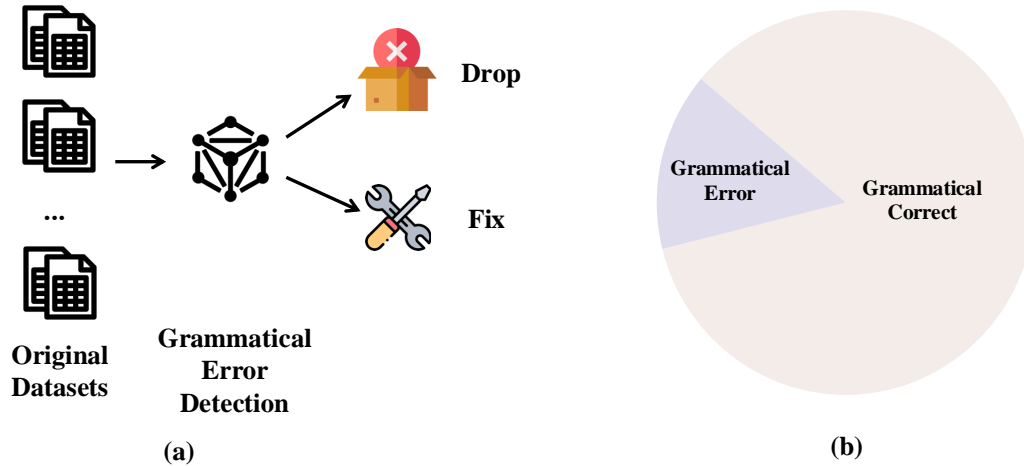


Figure 8: **Procedure to filter out samples containing grammatical errors (a) and distribution between grammatically correct samples and samples containing grammatical errors (b).**

Questions can be answered without images. It is common sense that the data used to train a vision-language model should enable the model to solve problems based on images. If questions can be answered without images, they degenerate into pure-text data [Liu et al., 2023c]. To filter out such data, we use a powerful open-source LLM, such as Qwen2.5-72B-Instruct, to answer the questions without the images. If the LLM provides the correct answer, the corresponding data sample is discarded. This filtering strategy is applied only to datasets containing fixed and definite answers, such as AI2D [Kembhavi et al., 2016]. We then train the model with the filtered dataset but observe slightly degraded performance. This phenomenon is consistent with previous works [Dai et al., 2024, Zhang et al., 2024, Yao et al., 2024], which suggest that pure-text data is helpful in maintaining the capability of the pre-trained LLM.

Filter out samples containing grammatical errors. For the second type of issue, we design a two-step filtering strategy: (i) use a large language model (LLM) to detect whether there are grammatical errors in the current sample, and (ii) if grammatical errors exist, we can either choose to drop the sample or use the LLM to fix these errors. After meticulous comparison, we find that the model performs better when directly dropping these samples rather than using the LLM to fix them. As shown in Figure 8(b), we retain about 85% of the original data after filtering.

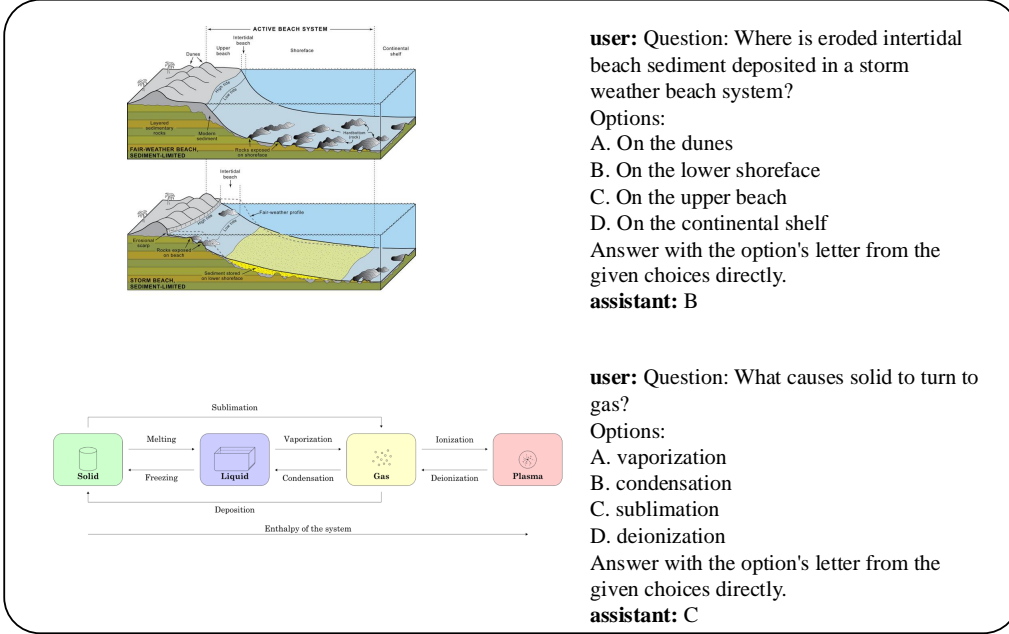


Figure 9: Questions can be answered without referring to the image.

5 Training and Model Strategy

Training Strategy. Currently, there is no consensus within the community on how to train each module of a LLaVA-style vision-language model. As shown in Table 2, different models employ distinct training configurations during pre-training and visual instruction tuning. This raises the question: what is the optimal strategy for the training configuration? In contrast to vision-language models, large language models (LLMs) have developed more rapidly, with various development paths converging to a unified approach. Before pre-training an LLM, a tokenizer must be trained on a large corpus using algorithms such as WordPiece [Song et al., 2020] and BPE [Sennrich, 2015], ensuring that each sentence can be uniquely and accurately tokenized into a sequence of indices. This tokenizer can also decode a sequence of indices back into a sentence. During the pre-training and post-training processes, the tokenizer remains fixed, while the word embedding layer and all transformer layers [Vaswani, 2017] are trained end-to-end. Analogously, in the architecture of a vision-language model, the vision encoder functions similarly to the text tokenizer, and the projector is akin to the word embedding layer. Therefore, before training a vision-language model, the vision encoder must be trained separately (e.g., the Qwen2-VL vision encoder used in POINTS1.5). Subsequently, the vision encoder is fixed, and the projector and LLM are trained end-to-end. In practice, since the vision projection layer is randomly initialized, we find that adding an additional stage (the so-called pre-training stage) to warm up the projection

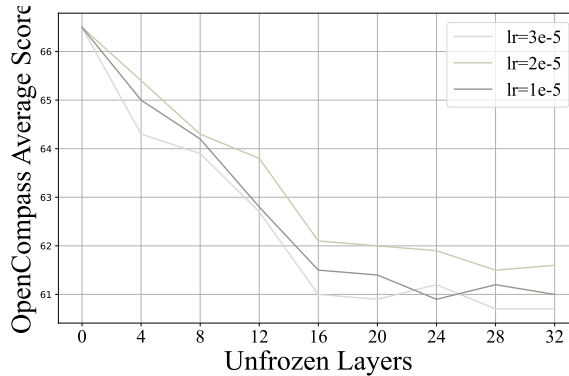


Figure 11: Unfreezing the vision encoder during pre-training degrades the performance.

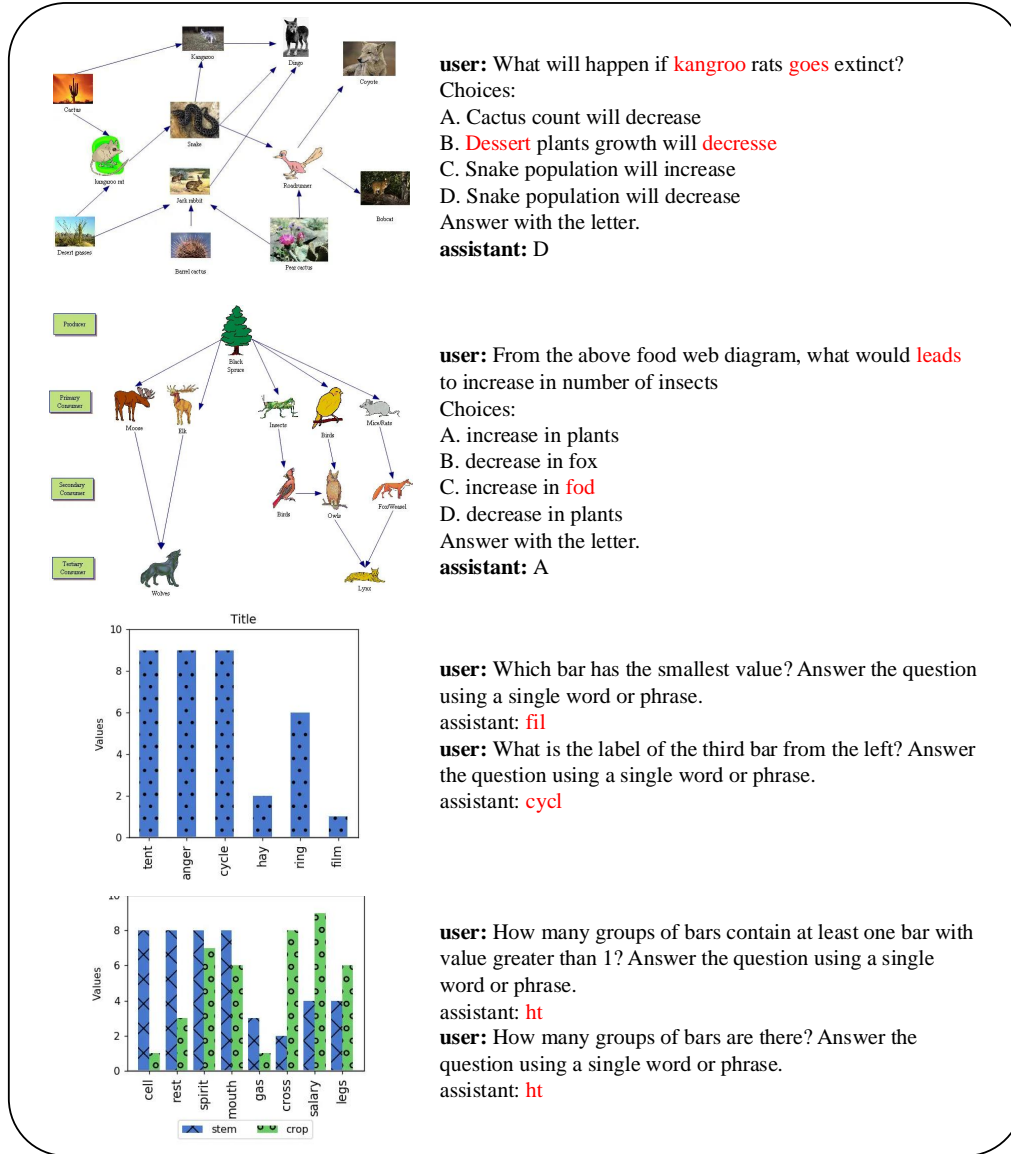


Figure 10: Data samples containing grammatical errors (marked with red) in visual instruction tuning set.

layer results in better performance (we fix the vision encoder in this stage, as we find unfreezing it degrades the performance (Figure 11). Our training configuration is summarized in Table 3. Notably, POINTS1.5 follows the path of POINTS1.0 [Liu et al., 2024d] to make computational resources more affordable, totaling less than 5 billion tokens, which is significantly fewer than most previous works [Chen et al., 2024c, Lu et al., 2024a, Wang et al., 2024b].

Model Soup over Best Performing Model Following POINTS1.0, we use model soup [Wortsman et al., 2022] to boost the performance of a single model. Model soup is conducted over models that perform best on our evaluation benchmark and mainly consist of models trained with different visual instruction tuning datasets and different visual instruction tuning epochs. The OpenCompass score of the best-performing single model is 66.5, and the final model obtained using model soup achieves a score of 67.4.

| Model | Pre-training | | | Instruction Tuning | | |
|---------------------------------|--------------|-----------|-----|--------------------|-----------|-----|
| | Vision | Projector | LLM | Vision | Projector | LLM |
| LLaVA-Next[Liu et al., 2024a] | | ✓ | | | ✓ | ✓ |
| OneVision[Li et al., 2024] | | ✓ | | ✓ | ✓ | ✓ |
| POINTS[Liu et al., 2024d] | ✓ | ✓ | | | ✓ | ✓ |
| InternVL1.5[Chen et al., 2024c] | ✓ | ✓ | | ✓ | ✓ | ✓ |

Table 2: Training strategies of different models.

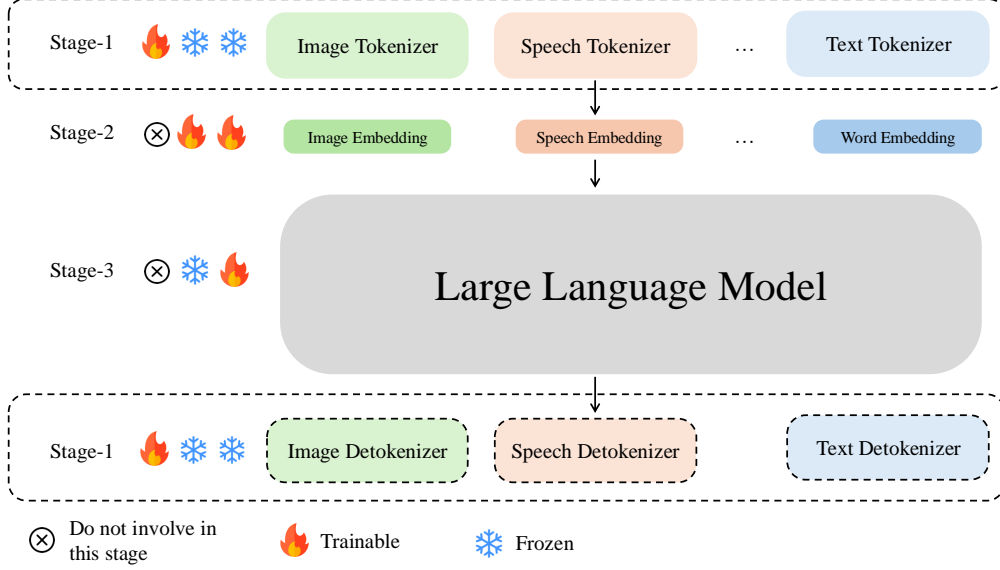


Figure 12: We envision that extending a large language model with additional modalities using LLaVA-style architecture should follow the three-stage procedure illustrated in this figure. The three icons on the left denote the status of each module during the three stages. From left to right, they are: stage-1, stage-2, stage-3.

| Settings | Pre-training Stage | Visual Instruction Tuning Stage |
|-----------------|-------------------------------------|---------------------------------|
| Datasets | LAION-5B by CapFusion and Filtering | POINTS1.0 + Chinese Datasets |
| Trainable | MLP Projector | MLP Projector + LLM |
| Batch Size | 32 | 32 |
| Context Length | 4096 | 4096 |
| Learning Rate | 2e-4 | 2e-5 |
| Weight Decay | 0.0 | 0.1 |
| Gradient Clip | 1.0 | 1.0 |
| lr Scheduler | Cosine | Cosine |
| Training Tokens | ~2.1B | ~2.3B |

Table 3: Training configurations for POINTS1.5

Discussion As discussed in the previous section, extending a Large Language Model (LLM) with any modality under the LLaVA-style architecture is akin to the continual post-training of the LLM. We identify three critical factors that determine the final performance of the model: i) High-quality modality tokenizer and detokenizer. The tokenizer should uniquely and accurately encode any modality signal into a compressed feature space, while the detokenizer should restore a compressed feature to its original modality signal. ii) Modality embedding layer, *a.k.a.* projection layer. iii) High-quality instruction tuning dataset to endow the LLM with the capability to understand different modalities. Thus, we envision the development of a multimodal model should follow a three-step

strategy in the future (Figure 12): i) Use abundant data to train a modality tokenizer and detokenizer, e.g. vision encoder and decoder. ii) Warm up the modality embedding layer to convert any modality signals into the text space of the LLM. During this step, the dataset size does not necessarily need to be very large, as we have found in our experiments and in previous work [Liu et al., 2024c]. iii) Use a high-quality instruction tuning dataset to train the modality embedding layer and the LLM, while keeping the tokenizer and detokenizer frozen.

6 Evaluation

Before embarking on our exploration, we sought a robust evaluation metric to comprehensively assess the various capabilities of our model. We initially selected the eight benchmarks used in the ranking on OpenCompass. These benchmarks include MMBench [Liu et al., 2023c] and MMStar [Chen et al., 2024b] for diagnosing general abilities, MMMU [Yue et al., 2024] for testing STEM-related abilities, HallusionBench [Liu et al., 2023a] for model hallucination, MathVista [Lu et al., 2023] for math-related abilities, AI2D [Kembhavi et al., 2016] for chart-related abilities, OCRBench [Liu et al., 2023d] for OCR capabilities, and MMVet [Yu et al., 2023] for subjective evaluation. Additionally, OpenCompass offers a useful tool, VLMEvalKit [Duan et al., 2024], for one-click evaluation. To further complement the evaluation results, we also included ChartQA [Masry et al., 2022], MME [Yin et al., 2023], LLaVA-wild [Kuang et al., 2023], SEEDBench [Li et al., 2023a], ScienceQA [Lu et al., 2022], MATH-Vision [Wang et al., 2024a], MathVerse [Zhang et al., 2025], and MEGEBench [Chen et al., 2024a]. Tables 4 and 5 show the comparison between POINTS1.5 and some representative open-source models. POINTS1.5 demonstrates promising performance, obtaining the top score on most of these benchmarks. In particular, we find the mathematical ability of POINTS1.5 to be quite extraordinary, as evidenced by the results on MathVista, MATH-Vision, and MathVerse.

| Methods | MMB | MV | HB | OCR | AI2D | MMVet | MMStar | MMMU |
|---------------------------|------|------|------|------|------|-------|--------|------|
| <i>Proprietary models</i> | | | | | | | | |
| GPT-4o-20241120 | 84.3 | 59.9 | 56.2 | 80.6 | 84.9 | 74.5 | 65.1 | 70.7 |
| Gemini-1.5-Pro-002 | 82.8 | 67.8 | 55.9 | 77.0 | 83.3 | 74.6 | 67.1 | 68.6 |
| Claude3.5-Sonnet-20241022 | 81.7 | 65.1 | 55.5 | 79.8 | 81.2 | 70.1 | 65.1 | 66.4 |
| <i>Open-source models</i> | | | | | | | | |
| Ovis1.5-LLaMA3-8B | 76.6 | 63.0 | 45.0 | 74.4 | 82.5 | 50.9 | 57.3 | 48.3 |
| InternVL2-8B | 79.4 | 58.3 | 45.0 | 79.4 | 83.6 | 54.3 | 61.5 | 51.2 |
| OneVision-7B-SI | 76.8 | 58.5 | 47.5 | 69.7 | 82.8 | 50.6 | 56.7 | 46.8 |
| POINTS-7B | 83.2 | 63.1 | 46.0 | 72.0 | 80.9 | 52.3 | 61.0 | 49.4 |
| Qwen2-VL-7B | 81.0 | 61.4 | 50.4 | 84.3 | 83.0 | 61.8 | 60.7 | 53.7 |
| <i>Ours</i> | | | | | | | | |
| POINTS1.5-7B | 80.7 | 66.4 | 50.0 | 83.2 | 81.4 | 62.2 | 61.1 | 53.8 |

Table 4: **Comparison between different methods on OpenCompass benchmarks.** MMB: MMBench[Liu et al., 2023c], MV: MathVista[Lu et al., 2023], HB: HallusionBench[Liu et al., 2023a], OCR: OCRBench[Liu et al., 2023d], Ovis1.5-LLaMA3-8B: Ovis1.5[Lu et al., 2024b], OneVision: LLaVA-OneVision[Li et al., 2024]. Results are obtained from the leaderboard of OpenCompass.

| Methods | ChartQA ^{avg} | MME | Wild | SEED ^I | MEGA-SI | SCI | M-Vision | M-Verse |
|---------------------------|------------------------|--------|------|-------------------|---------|------|----------|-----------|
| <i>Open-source models</i> | | | | | | | | |
| Ovis1.5-LLaMA3-8B | - | 1948.5 | 79.9 | 75.4 | - | 88.8 | - | - |
| OneVision-7B-SI | 80.0 | 2146.3 | 77.6 | 75.4 | 25.7 | 86.6 | 26.2 | - |
| InternVL2-8B | 83.3 | 2215.1 | 73.3 | 75.4 | 29.2 | 97.1 | 37.0 | 20.4/18.4 |
| POINTS-7B | - | 2184.1 | 72.3 | 74.8 | 26.2 | 94.8 | - | - |
| Qwen2-VL-7B | 83.0 | 2276.3 | 70.1 | 76.0 | 36.7 | 85.5 | 31.9 | 22.0/16.3 |
| <i>Ours</i> | | | | | | | | |
| POINTS1.5-7B | 84.3 | 2222.7 | 74.6 | 75.4 | 32.7 | 94.8 | 36.9 | 23.7/21.9 |

Table 5: **Comparison with open-source models of similar size on more benchmarks.** SEED^I: SEEDBench[Li et al., 2023a], MEGA-SI: Single image evaluation without few-shot samples of MEGABench[Chen et al., 2024a], SCI: ScienceQA[Lu et al., 2022], Wild: LLaVA-Wild[Kuang et al., 2023], M-Vision: MATH-Vision[Wang et al., 2024a], M-Verse: MathVerse[Zhang et al., 2025].

7 Conclusion

We present POINTS1.5, a significantly enhanced model compared to POINTS1.0. This version introduces three major innovations: i) We replaced the original CLIP vision encoder with a NaViT-style vision encoder, enabling native support for images of any resolution without the need for splitting. This allows us to preserve the original spatial relationships between patches within an image. ii) We added bilingual support. By constructing a Chinese corpus using a combination of manual and automatic strategies, we obtained a large quantity of Chinese data for both the pre-training and visual instruction tuning stages. iii) We manually reviewed each dataset from POINTS1.0 and identified two significant issues. We then proposed effective strategies to filter these datasets. Notably, by training the model on less than 5 billion tokens, we achieved a model that ranks first on the OpenCompass leaderboard.

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A Appendix

We shows some real world examples to demonstrate the performance of POINTS1.5.

| 2 Week Extended Forecast in Shanghai, Shanghai Municipality, China | | | | | | | | | | | |
|--|------------|-------------|---------------------------|------------|---------|----------|---------------|---------|--------------|-------|-------|
| Day | Conditions | Temperature | Weather | Feels Like | Wind | Humidity | Precipitation | Chance | Amount | UV | Sun |
| 11 Dec | | 10 / 7 °C | Rain, Overcast. | 7 °C | 12 km/h | 77% | 92% | 12.8 mm | 0 (Low) | 06:42 | 16:52 |
| 12 Dec | | 12 / 6 °C | Increasing cloudiness. | 8 °C | 13 km/h | 61% | 1% | - | 0 (Low) | 06:43 | 16:52 |
| 13 Dec | | 11 / 6 °C | Cloudy. | 9 °C | 15 km/h | 49% | 0% | - | 0 (Low) | 06:43 | 16:52 |
| 14 Dec | | 9 / 3 °C | Partly cloudy. | 5 °C | 16 km/h | 39% | 0% | - | 0 (Low) | 06:44 | 16:52 |
| 15 Dec | | 9 / 0 °C | Sunny. | 6 °C | 14 km/h | 26% | 0% | - | 3 (Moderate) | 06:45 | 16:53 |
| 16 Dec | | 10 / 1 °C | Afternoon clouds. | 8 °C | 9 km/h | 23% | 0% | - | 0 (Low) | 06:45 | 16:53 |
| 17 Dec | | 11 / 1 °C | Sunny. | 9 °C | 8 km/h | 25% | 0% | - | 3 (Moderate) | 06:46 | 16:53 |
| 18 Dec | | 11 / 4 °C | Overcast. | 9 °C | 11 km/h | 50% | 6% | - | 0 (Low) | 06:46 | 16:54 |
| 19 Dec | | 12 / 6 °C | Mostly cloudy. | 11 °C | 11 km/h | 48% | 5% | - | 0 (Low) | 06:47 | 16:54 |
| 20 Dec | | 13 / 8 °C | Sprinkles, Broken clouds. | 11 °C | 13 km/h | 52% | 48% | 0.5 mm | 0 (Low) | 06:48 | 16:55 |
| 21 Dec | | 11 / 7 °C | Sunny. | 9 °C | 18 km/h | 38% | 5% | - | 0 (Low) | 06:48 | 16:55 |
| 22 Dec | | 10 / 4 °C | Sunny. | 10 °C | 5 km/h | 31% | 3% | - | 3 (Moderate) | 06:49 | 16:56 |
| 23 Dec | | 10 / 5 °C | Increasing cloudiness. | 8 °C | 15 km/h | 44% | 4% | - | 3 (Moderate) | 06:49 | 16:56 |
| 24 Dec | | 10 / 5 °C | Mostly cloudy. | 9 °C | 8 km/h | 41% | 6% | - | 0 (Low) | 06:50 | 16:57 |
| 25 Dec | | 9 / 5 °C | Sunny. | 6 °C | 21 km/h | 22% | 4% | - | 3 (Moderate) | 06:50 | 16:57 |

User: Organize the highest temperature, lowest temperature, and humidity for all even dates into a table.


Assistant:

| Date | Highest Temperature | Lowest Temperature | Humidity |
|--------|---------------------|--------------------|----------|
| 12 Dec | 12 °C | 6 °C | 61% |
| 14 Dec | 9 °C | 3 °C | 39% |
| 16 Dec | 10 °C | 0 °C | 26% |
| 18 Dec | 11 °C | 4 °C | 50% |
| 20 Dec | 13 °C | 8 °C | 52% |
| 22 Dec | 10 °C | 4 °C | 31% |
| 24 Dec | 10 °C | 5 °C | 41% |

User: If I travel to Shanghai on December 14th, what suggestions do you have for me based on the weather forecast?

Assistant: On December 14th, the weather forecast for Shanghai predicts partly cloudy conditions with a temperature range of 3°C to 9°C. It is suggested to dress in warm clothing to stay comfortable during the cooler temperatures. The chance of precipitation is 0%, so you don't need to worry about rain or snow. The UV index is low, so you don't need to worry about sunburn. The sunrise is at 06:44 and the sunset is at 16:52, so you have a full day of activities ahead. Overall, it should be a pleasant day to travel to Shanghai.

Figure 13: OCR and reasoning ability.



电子发票(普通发票)

发票号码: 24317000000729552207
开票日期: 2024年09月03日

| | | | |
|---|---|--------------------------------------|--|
| 购买方信息 | 名称: 广州腾讯科技有限公司 统一社会信用代码/纳税人识别号: 91440101327598294H | 销售方信息 | 名称: 上海华程西南国际旅行社有限公司 统一社会信用代码/纳税人识别号: 91310105134638405A |
| 项目名称: 规格型号: 单位: 数量: 单价: 金额: 税率/征收率: 税额: | | | |
| *经纪代理服务*代订机票 | | 1 1105.660377358491 1105.66 6% 66.34 | |
| 合计 | | ¥1105.66 ¥66.34 | |
| 价税合计(大写) | | 壹仟壹佰柒拾贰圆整 | |
| 价税合计(小写) | | ¥1172.00 | |
| 备注: 携程订单: 33497191600, | | | |
| 开票人: 楼宗恺 | | | |

User: Please extract all the text in this image.

Assistant: 电子发票（普通发票）

发票号码: 24317000000729552207

开票日期: 2024年09月03日

购买方信息:

名称: 广州腾讯科技有限公司

统一社会信用代码/纳税人识别号: 91440101327598294H

销售方信息:

名称: 上海华程西南国际旅行社有限公司

统一社会信用代码/纳税人识别号: 91310105134638405A

项目名称: *经纪代理服务*代订机票

规格型号:

单位:

数量: 1

单价: 1105.66

金额: 1105.66

税率/征收率: 6%

税额: 66.34

合计: ¥1105.66

价税合计(大写): 壹仟壹佰柒拾贰圆整

(小写): ¥1172.00

携程订单: 33497191600,

备注:

开票人: 楼宗恺

Figure 14: Complex Chinese OCR



User: Please extract all the text in this image.

Assistant: 牛小灶 深圳福田中心城店

号牌: 04台

自助小吃+调料+茶水[点2.0退2.0]

超值2人套餐
-经典老广州牛杂煲 中煲
原味; 套 1.0 138 138
-娃娃菜
-纸巾
-自助小吃+调料+茶水
-米饭

消费合计: 138

汇来米 [9016****07]会员卡值 0

实收: 138

3013 中心城收银3 小程序自助
Key:202306271345513715944370092
打印时间: 2023-06-27 18:32:59
打印地址: 深圳福田区福田街道中心城ug层
店铺电话: 0755-23996991



User: Please extract all the text in this image.

Assistant: Laque Nail Bar & Beauty Lounge, Inc.
13025 Victory Boulevard
North Hollywood CA 91606
818 985-1877

Trans#: 33457
Date: 1/4/2015 12:48 PM
Client: Denise

Minh T
Gel Polish Add \$20.00
Felicia M
Soda POP! - Kid \$20.00
Minh T
Nail Art (2 Na \$18.00
Minh T
Regular Acrylic \$17.00

Item Total: \$75.00
Deposit: \$0.00
Subtotal: \$75.00
Tax: \$0.00
Total: \$75.00

Laque Has A 72 Hour Policy
For Any Repairs Free Of
Charge.
www.laquenailbar.com
Your Next Appointment:

Figure 15: Complex OCR

Financial Performance Highlights

SECOND QUARTER OF 2024

| | RMB million, unless otherwise specified | | | | YoY Change | QoQ Change |
|---|---|---------|------|--------|------------|------------|
| | 2024 | 2023 | 2024 | 2023 | | |
| Revenues | 161,117 | 149,208 | 8% | 20,909 | 15% | 11% |
| Gross profit | 85,895 | 70,840 | 21% | 15,055 | 21% | 1% |
| Operating profit | 50,732 | 36,283 | 40% | 14,449 | 40% | 3% |
| Profit for the period | 48,366 | 27,023 | 79% | 21,343 | 79% | 13% |
| Profit attributable to equity holders of the company | 47,630 | 26,171 | 82% | 21,459 | 82% | 14% |
| EPS (RMB per share) | 5.112 | 2.761 | 85% | 2.351 | 85% | 14% |
| Diluted | 4.994 | 2.695 | 85% | 2.299 | 85% | 14% |
| Non-IFRS operating profit | 58,443 | 57,313 | 2% | 1,130 | 2% | 0.3% |
| Non-IFRS profit attributable to equity holders of the company | 57,313 | 53,748 | 6% | 3,565 | 6% | 1% |
| Non-IFRS EPS (RMB per share) | 6.014 | 3.875 | 55% | 2.139 | 55% | 14% |
| Diluted | 5.875 | 3.785 | 55% | 2.090 | 55% | 14% |

1. Since the fourth quarter of 2023, certain items have been reclassified from above to below the operating profit line. Historical comparative figures have been restated accordingly. For more details, please refer to Note 3(a) in the notes to the Interim Financial Information.

User: Kindly provide your feedback on this financial report.

Assistant: The financial report presents the financial performance highlights for the second quarter of 2024. It includes unaudited figures for the three months ended on 30 June 2024, comparing them with the corresponding figures for 2023. The report is structured into several categories, including revenues, gross profit, operating profit, profit for the period, profit attributable to equity holders of the company, earnings per share (EPS), non-IFRS operating profit, non-IFRS profit attributable to equity holders of the company, and non-IFRS earnings per share.

Key highlights from the report are as follows:

- **Revenues**:** The company reported revenues of RMB 161,117 million for the second quarter of 2024, representing an 8% increase compared to the same period in 2023 (RMB 149,208 million). On a quarter-on-quarter basis, revenues increased by 1%.
- **Gross Profit**:** Gross profit for the period was RMB 85,895 million, a 21% increase from the previous year (RMB 70,840 million). On a quarter-on-quarter basis, gross profit increased by 2%.
- **Operating Profit**:** Operating profit for the second quarter of 2024 was RMB 50,732 million, a 40% increase compared to the same period in 2023 (RMB 36,283 million). On a quarter-on-quarter basis, operating profit decreased by 3%.
- **Profit for the Period**:** The profit for the period was RMB 48,366 million, a 79% increase compared to the previous year (RMB 27,023 million). On a quarter-on-quarter basis, the profit for the period increased by 13%.
- **Profit Attributable to Equity Holders**:** Profit attributable to equity holders of the company was RMB 47,630 million, an 82% increase compared to the previous year (RMB 26,171 million). On a quarter-on-quarter basis, the profit increased by 14%.
- **EPS (Earnings Per Share)**:** Basic EPS was RMB 5.112 per share, a 85% increase compared to the previous year (RMB 2.761 per share). Diluted EPS was RMB 4.994 per share, also a 85% increase compared to the previous year (RMB 2.695 per share). On a quarter-on-quarter basis, both basic and diluted EPS increased by 14%.
- **Non-IFRS Operating Profit**:** Non-IFRS operating profit for the period was RMB 58,443 million, a 27% increase compared to the previous year (RMB 46,055 million). On a quarter-on-quarter basis, non-IFRS operating profit decreased by 0.3%.
- **Non-IFRS Profit Attributable to Equity Holders**:** Non-IFRS profit attributable to equity holders of the company was RMB 57,313 million, a 53% increase compared to the previous year (RMB 37,548 million). On a quarter-on-quarter basis, the profit increased by 14%.
- **Non-IFRS EPS**:** Basic non-IFRS EPS was RMB 6.014 per share, a 55% increase compared to the previous year (RMB 3.962 per share). Diluted non-IFRS EPS was RMB 5.875 per share, also a 55% increase compared to the previous year (RMB 3.875 per share). On a quarter-on-quarter basis, both basic and diluted non-IFRS EPS increased by 14%.

The report also notes that since the fourth quarter of 2023, certain items have been reclassified from above to below the operating profit line. Historical comparative figures have been restated accordingly. For more details, please refer to Note 3(a) in the notes to the Interim Financial Information.

Overall, the financial report indicates a strong performance for the company in the second quarter of 2024, with significant increases in revenues, gross profit, and earnings per share compared to the previous year. However, the operating profit and non-IFRS operating profit showed a decrease on a quarter-on-quarter basis.

Figure 16: Analysis of Tencent's financial report.

$$\text{Perplexity}(s) = \exp(-\frac{1}{N} \sum_{i=1}^N \log P(w_i | w_1, w_2, \dots, w_{i-1}))$$

User: Please extract the latex formula in this image.

Assistant:

$$\text{Perplexity}(s) = \exp(-\frac{1}{N} \sum_{i=1}^N \log P(w_i | w_1, w_2, \dots, w_{i-1}))$$

$$\{\theta_i\}_{\text{len}(\{\theta_i\})=p} = \text{Arg}_{(\theta_i)}(\text{Top}_p(\{\text{Acc}(f(D_1^*; \theta_1)), \dots, \text{Acc}(f(D_k^*; \theta_k))\}))$$

User: Please extract the latex formula in this image.

Assistant:

$$\{\theta_i\}_{\text{len}(\{\theta_i\})=p} = \text{A r g}(\theta_i)(\text{T o p}_p(\{\text{A c c}(f(D_1^*; \theta_1)), \dots, \text{A c c}(f(D_k^*; \theta_k))\}))$$

$$\text{ratio} = \min(\text{H}, \text{W}) / \min(\text{H}^r, \text{W}^r)$$

$$\text{H}^t = \text{ratio} \times \text{H}$$

$$\text{W}^r = \text{ratio} \times \text{W}$$

User: Please extract the latex formula in this image.

Assistant:

$$\text{r a t i o} = \min(\text{H}, \text{W}) / \min(\text{H}^r, \text{W}^r)$$

$$\text{H}^t = \text{r a t i o} \times \text{H}$$

$$\text{W}^r = \text{r a t i o} \times \text{W}$$

Figure 17: **Latex formula extraction**

4. 等差数列 $\{a_n\}$ 的前 n 项和为 S_n , 若 $S_9 = 1$, $a_3 + a_7 = (\quad)$

A. -2

B. $\frac{7}{3}$

C. 1

D. $\frac{2}{9}$

User: Please solve this problem above.

Assistant:

****Analysis****

This question tests the properties of an arithmetic sequence, which is a basic problem.

****Solution****

Given that $S_9 = \frac{9(a_1 + a_9)}{2} = 9a_5 = 1$,

Therefore, $a_5 = \frac{1}{9}$,

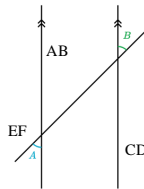
Thus, $a_3 + a_7 = 2a_5 = \frac{2}{9}$.

Hence, the correct option is \boxed{D} .

The angle measurements in the diagram are represented by the following expressions.

$$\angle A = 5x - 15^\circ$$

$$\angle B = 2x + 21^\circ$$



Solve for x and then find the measure of $\angle B$:

$$\angle B = \boxed{}^\circ$$

User: Please first analyze this problem, and give the detailed steps to solve it.

Assistant:

1. Since lines (AB) and (CD) are parallel, and line (EF) is a transversal, the corresponding angles $(\angle A)$ and $(\angle B)$ are equal.

2. Set the expressions for $(\angle A)$ and $(\angle B)$ equal to each other:

$$\begin{aligned} & \backslash \\ & 5x - 15 = 2x + 21 \\ & \backslash \end{aligned}$$

3. Solve for (x) :

$$\begin{aligned} & \backslash \\ & 5x - 2x = 21 + 15 \implies 3x = 36 \implies x = 12 \\ & \backslash \end{aligned}$$

4. Substitute $(x = 12)$ back into the expression for $(\angle B)$:

$$\begin{aligned} & \backslash \\ & \angle B = 2(12) + 21 = 24 + 21 = 45^\circ \\ & \backslash \end{aligned}$$

5. Therefore, the measure of $(\angle B)$ is $\boxed{45^\circ}$.

Figure 18: Mathematical problem solving

2023年前三季度，腾讯营收同比增幅分别是11%、11%、10%，论增幅腾讯在2024年前三季度拿到的1%、8%、8%增幅都不及上年。

不过从营收的整体走势看，腾讯没有让两年前的起起落落重现，这一点从腾讯营收环比数据即可看出。2023年前三季度，腾讯营收只在一、三季度环比为正，分别是3%和4%，二季度环比下降1%，2024年前三季度，腾讯营收环比始终为正，分别是3%、1%、4%。

“如此体量且业务多元的企业，总营收一般很少大起大落，能维持增长就是稳定。”长期观察腾讯财报的比达分析师李锦清告诉北京商报记者，“在当下的稳定阶段，腾讯三个板块的表现，组成三个板块的业务以及业务之间的协同更有看头。”

User: Please first analyze this problem, and give the detailed steps to solve it.

Assistant: In the first three quarters of 2023, Tencent's revenue growth rates were 11%, 11%, and 10%, respectively. In comparison, the growth rates for the first three quarters of 2024 were 1%, 8%, and 8%, which were not as high as the previous year.

However, looking at the overall trend of revenue, Tencent did not experience the rise and fall seen two years ago. This can be seen from the sequential revenue data of Tencent. In the first three quarters of 2023, the sequential revenue growth was positive in the first and third quarters, at 3% and 4%, respectively, while the second quarter saw a sequential decrease of 1%. In the first three quarters of 2024, the sequential revenue growth remained positive, at 3%, 1%, and 4%, respectively.

“Such a large and diversified company, with total revenue generally not fluctuating greatly, maintaining growth is considered stable.”Jinqing Li, a analyst from BDA, told Beijing Business Daily that, “In the current stable phase, the performance of the three segments of Tencent, together with the business within each segment and the synergy between them, is worth looking forward to.”

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企业微信预设轻OA应用，提供丰富的第三方应用供企业选用，同时开放超过200个API支持企业接入自有应用，帮助企业实现办公应用的统一集成与管理，方便员工移动化使用。

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企业微信联合腾讯专业安全团队，致力于互联网安全技术及攻防体系的研究及应用。企业微信拥有包括SOC2Type1报告、ISO/IEC27018公有云个人隐私保护认证在内的多项国际权威安全认证，专业保障企业数据安全。

User: Please first analyze this problem, and give the detailed steps to solve it.

Assistant: Enterprise WeChat is a communication and office tool developed by the WeChat team for businesses, with a communication experience consistent with WeChat, rich OA applications, and the ability to connect with WeChat. It can help businesses achieve intelligent management, intelligent ecosystem, and intelligent services based on connection.

Enterprise WeChat has pre-set light OA applications, providing a variety of third-party applications for businesses to choose from, and opens over 200 APIs to support businesses in integrating their own applications. This helps businesses achieve unified integration and management of office applications, making it convenient for employees to use on the go.

Enterprise WeChat has the unique ability to connect with WeChat, supporting intercommunication of WeChat messages, connecting mini-programs, and corporate payments. This can help businesses efficiently connect with the outside world and achieve high-quality services. Employees can use Enterprise WeChat to send messages to customers' WeChat, providing a unified and professional external image. At the same time, customer relationships will accumulate within the enterprise, not flowing out due to employee resignation.

Enterprise WeChat collaborates with the professional security team of Tencent, dedicated to the research and application of internet security technology and defense systems. Enterprise WeChat has multiple international authoritative security certifications, including the SOC2 Type 1 report and ISO/IEC 27018 public cloud personal privacy protection certification, ensuring the security of enterprise data.

Figure 19: Image translation



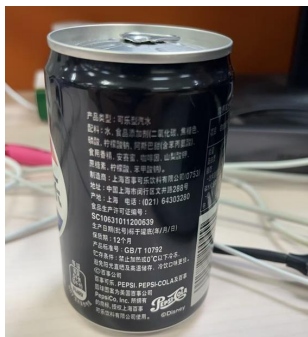
User: Please identify the fruits in the image and provide an introduction to each one.

Assistant:

The fruits in the image are bananas, pineapple, pear, and apple.

1. Bananas: Bananas are a popular fruit known for their sweet taste and creamy texture. They are a good source of potassium, vitamin C, and dietary fiber. Bananas are often eaten as a snack or used in various recipes like smoothies, baked goods, and desserts.
2. Pineapple: Pineapple is a tropical fruit with a rough, spiky exterior and a sweet, juicy interior. It is rich in vitamin C, manganese, and dietary fiber. Pineapples are known for their unique flavor and are commonly used in fruit salads, desserts, and as a garnish.
3. Pear: Pears are a type of fruit that comes in various colors, including green, yellow, and red. They have a sweet, slightly tart flavor and a soft, tender texture. Pears are a good source of dietary fiber, vitamin C, and potassium. They can be eaten fresh, cooked, or used in baking.
4. Apple: Apples are a widely cultivated fruit known for their crisp, juicy texture and sweet, slightly tart flavor. They come in various colors, such as red, green, and yellow. Apples are rich in fiber, vitamin C, and antioxidants. They are commonly eaten as a snack, used in cooking, and enjoyed in various recipes like pies, tarts, and salads.

Figure 20: **Object identification.**



User: The current date is December 11, 2024. When should this beverage be produced so that I can consume it? Please provide your analysis process.

Assistant:

To determine the production date of the beverage, we need to consider the shelf life and storage conditions mentioned on the can.

1. The can states that the product has a shelf life of 12 months.
2. It also mentions that the beverage should be stored at temperatures below 0°C and avoid direct sunlight or high temperatures.

Given these conditions, the beverage should be consumed within 12 months of production to ensure it remains fresh and safe to drink. Since the current date is December 11, 2024, we can calculate the latest possible production date by subtracting 12 months from this date.

December 11, 2024 - 12 months = December 11, 2023

Therefore, the beverage should have been produced no later than December 11, 2023, to ensure it remains fresh and safe to drink until December 11, 2024.

Figure 21: **Key information extraction and reasoning.**