

UnifiedVisual: A Framework for Constructing Unified Vision-Language Datasets

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Abstract

Unified vision large language models (VLLMs) have recently achieved impressive advancements in both multimodal understanding and generation, powering applications such as visual question answering and text-guided image synthesis. However, progress in unified VLLMs remains constrained by the lack of datasets that fully exploit the synergistic potential between these two core abilities. Existing datasets typically address understanding and generation in isolation, thereby limiting the performance of unified VLLMs. To bridge this critical gap, we introduce a novel dataset construction framework, **UnifiedVisual**, and present **UnifiedVisual-240K**, a high-quality dataset meticulously designed to facilitate mutual enhancement between multimodal understanding and generation. UnifiedVisual-240K seamlessly integrates diverse visual and textual inputs and outputs, enabling comprehensive cross-modal reasoning and precise text-to-image alignment. Our dataset encompasses a wide spectrum of tasks and data sources, ensuring rich diversity and addressing key shortcomings of prior resources. Extensive experiments demonstrate that models trained on UnifiedVisual-240K consistently achieve strong performance across a wide range of tasks. Notably, these models exhibit significant mutual reinforcement between multimodal understanding and generation, further validating the effectiveness of our framework and dataset. We believe UnifiedVisual represents a new growth point for advancing unified VLLMs and unlocking their full potential. ¹

1 Introduction

Vision large language models (VLLMs) have made significant progress in visual understanding, evolv-

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¹Our code and datasets will be available at <https://github.com/fnlp-vision/UnifiedVisual>.

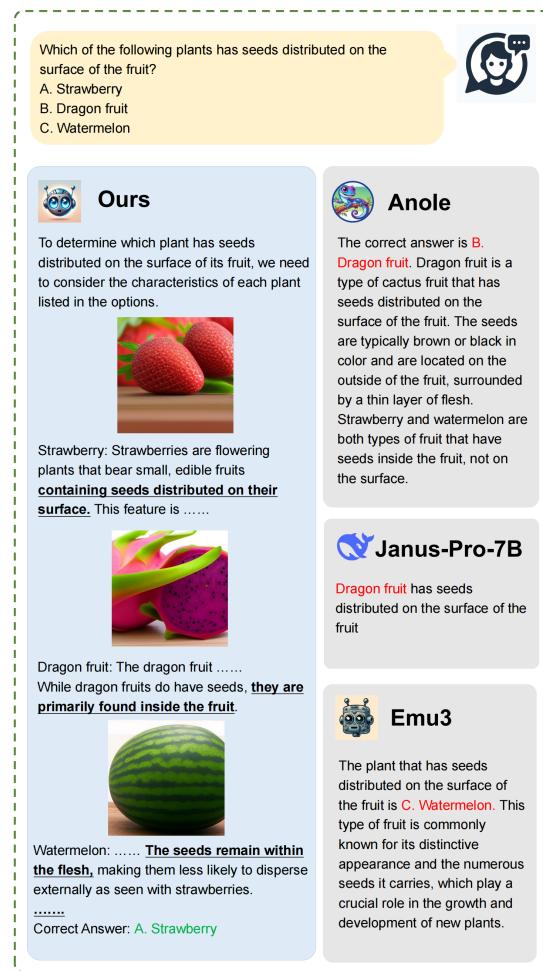


Figure 1: As illustrated in this figure, in contrast to other unified VLLMs that fail to answer even simple questions correctly due to conflicts between multimodal understanding and generation, our model trained on UnifiedVisual-240K is able to construct multimodal reasoning chains and provide accurate answers.

ing from basic image captioning to complex visual inferences (Liu et al., 2024b; Dai et al., 2023). Currently, there is growing interest in unified models capable of both multimodal understanding and generation. These models aim to integrate multimodal understanding and generation capabilities, enabling them to handle a variety of tasks such as

image captioning, visual question answering, and image generation (Team, 2024; Wu et al., 2024a; Tong et al., 2024a). Unified VLLMs have gained widespread attention due to their ability to combine multimodal understanding and generation in a single model. This unification not only simplifies the deployment and application process but also provides the potential for mutual enhancement between generative and discriminative capabilities. As a result, this area of research is becoming an increasingly prominent development field.

However, the development of powerful unified VLLMs hinges on access to high-quality training datasets. While several existing datasets have facilitated progress, they fall short of fully unlocking the synergistic potential between multimodal understanding and generation. Ideally, a unified VLLM should achieve substantial improvements by leveraging the interaction between these two capabilities. Yet, in practice, models trained on current datasets often exhibit limited integration, failing to achieve effective mutual reinforcement between understanding and generation (Wang et al., 2024b,a). This highlights a critical limitation in the design and quality of existing datasets, which are unable to fully stimulate the desired synergy.

To address these challenges, we propose a novel dataset construction framework, **UnifiedVisual**, and introduce **UnifiedVisual-240K**, a new dataset designed to enhance the interaction between multimodal understanding and generation. UnifiedVisual-240K incorporates the following key features: *First*, the instructions may include both visual and textual information, encouraging holistic integration of multimodal context for accurate responses. *Second*, the responses may also consist of both visual and textual elements, requiring the model to excel in both textual reasoning and multimodal generation. This duality ensures that textual reasoning guides precise image generation, while the generated images, in turn, enhance textual reasoning. This mutual reinforcement between the two modalities enables the model to achieve superior performance. *Finally*, UnifiedVisual-240K exhibits significant diversity in both task types and data sources, effectively promoting the interaction between understanding and generative capabilities.

To validate the effectiveness of UnifiedVisual-240K, we trained unified VLLM models using this dataset. Experimental results show that models trained on UnifiedVisual-240K consistently outperform those trained on existing datasets across a

wide range of tasks. Notably, we observed substantial mutual enhancement between the models’ understanding and generative capabilities, fully demonstrating the advantages of our dataset.

In summary, our contributions are as follows:

- We propose UnifiedVisual, a unified vision-language dataset construction framework that prioritizes the synergistic interaction between understanding and generative capabilities while ensuring task and data source diversity.
- We construct UnifiedVisual-240K, a high-quality dataset tailored for unified VLLMs.
- Experimental results demonstrate that models trained on UnifiedVisual-240K achieve superior performance and exhibit mutual enhancement between multimodal understanding and generation.

2 Related Work

Unified Visual Understanding and Generation. In recent years, research on unifying image understanding and generation within a single visual large language model (VLLM) has garnered significant attention. Early studies primarily achieved image generation by integrating image generation models (e.g., diffusion models) on top of large language models (LLMs) (Sun et al., 2023; Wu et al., 2023; Li et al., 2024c; Ge et al., 2024). More recently, Tong et al. (2024a) demonstrated remarkable results by connecting LLMs and diffusion models through a simple projection layer. Inspired by the success of LLMs in next-step prediction tasks, recent studies have explored representing and generating images in a fully autoregressive manner using discrete visual tokens (Yu et al., 2023; Chen et al., 2023; Wang et al., 2024b; Liu et al., 2024a; Chern et al., 2024). To achieve high performance in both image understanding and generation, some research efforts have proposed decoupling these two tasks. For instance, Transfusion (Zhou et al., 2024) and Show-o (Xie et al., 2024) employ autoregressive text modeling for image understanding tasks while adopting visual diffusion modeling to accomplish image generation. In contrast, Janus (Wu et al., 2024a) introduces two distinct image representations, specifically designed to address the differing granularity requirements of image understanding and generation. Overall, exploration of unified VLLM architectures continues to progress.

Training Datasets for Unified VLLM. Given the unique characteristics of unified VLLMs, we divided the training dataset into four major cate-

gories, as shown in Figure 2. Among them, datasets for pure text generation are both abundant and of high quality (Shao et al., 2024b; Li et al., 2024a; Zhang et al., 2024). In contrast, datasets for multimodal generation are relatively narrow in scope and limited in scale. Currently, the most widely used multimodal generation datasets mainly cover image generation and image editing. However, these tasks themselves are relatively straightforward, as they typically involve direct mappings from instructions to images or simple image modifications (Deng et al., 2009; Brooks et al., 2023; Fu et al., 2023; Qu et al., 2024). Additionally, there exist interleaved image-text datasets crawled from the internet, but the association between images and text in such datasets is often weak (Zhu et al., 2024; Laurençon et al., 2024).

The scarcity of multimodal generation datasets not only limits the application of models in related downstream tasks but also introduces potential conflicts between multimodal understanding and generation during training. These conflicts make it challenging to achieve mutual enhancement of the two capabilities, potentially impacting the model’s performance on complex tasks. To address these challenges, we propose a unified vision-language dataset construction framework to overcome the current limitations in training datasets.

3 Methodology

In this section, we first provide a detailed introduction to our vision-language dataset construction framework, **UnifiedVisual**. Following that, we introduce **UnifiedVisual-240K**, a dataset constructed following the UnifiedVisual framework.

3.1 UnifiedVisual

As discussed in Section 2, the training datasets for unified VLLM can be categorized into two types: **understanding datasets** that only contain pure text outputs, and **generation datasets** that involve multimodal generation. Given the abundance and high quality of existing understanding datasets, we can directly leverage these well-established resources. In contrast, generation datasets are typically narrower in scope and more limited in scale. To address this, UnifiedVisual introduces a novel and comprehensive framework for constructing generation datasets. Specifically, we focus on three key aspects to construct a more diverse and comprehensive generation dataset: (1) Visual Generation, (2)

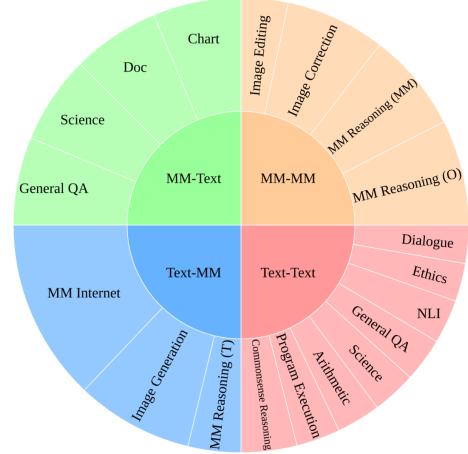


Figure 2: The proportions of different sub-datasets in UnifiedVisual-240K. The innermost layer of the chart represents the “*input type - output type*”, such as Text-MM, which indicates that these datasets feature textual input and multimodal output.

Multimodal Reasoning, and (3) Multimodal Internet Dataset. In the sections that follow, we will discuss each construction method in detail. For better clarity, we also provide illustrations in Appendix E, and the complete prompt templates can be found in Appendix F.

3.1.1 Visual Generation

Visual Generation encompasses Image Generation, Image Editing, and Image Correction. Unlike existing datasets that primarily focus on generating or editing images based on simple descriptions or instructions, our goal is to integrate visual understanding and textual reasoning to tackle more complex visual generation challenges.

Image Generation Image generation involves generating images that correspond to textual descriptions, serving as a foundational task in training unified VLLMs. However, existing image generation datasets often emphasize direct mappings between textual elements and images, which limits their ability to handle more intricate generation requirements. To address this, we propose two enhanced approaches:

Topic- and Scene-Based Generation: (1) We propose several topics and corresponding scenes, then generate image captions that implicitly, rather than explicitly, describe the desired image content. (2) We use embedding models to filter similar captions, ensuring data diversity. (3) We use GPT-4 to generate a reasoning process (rationale) explaining the content and details to be generated, followed by DALL-E-3 for image synthesis.

Category- and Image-Based Generation: (1) We collect a diverse set of authentic images, removing duplicates. (2) Based on the images and their categories, we use GPT-4 to generate instructions that describe image characteristics and related information, again focusing on implicit rather than explicit descriptions. (3) We then use GPT-4 to generate a detailed rationale based on the caption and category information, outlining the logic behind the desired image. The final data point consists of the caption, rationale, and the original image.

Image Editing Existing image editing datasets typically consist of simple pairs of images and editing instructions that require straightforward modifications. However, these basic datasets may not effectively enhance a model’s capacity to comprehend and execute sophisticated visual generation instructions. To address this limitation, we enhance existing image editing data through a two-step approach: (1) We transform simple editing instructions into more nuanced prompts that necessitate deeper understanding and planning. (2) We use GPT-4o to analyze these enhanced instructions and generate reasoning rationales outlining the editing objectives and intended outcomes.

Image Correction To further enhance the model’s capability in capturing fine-grained image details, we introduced a more sophisticated task paradigm: image correction. This task requires the model to evaluate image-description consistency and, when discrepancies are identified, analyze the inconsistencies before regenerating an image that fully aligns with the given description. We implement this through a three-stage process: (1) We modify existing image captions to create descriptions that maintain the core theme while introducing controlled variations in specific visual elements. (2) We utilize StableDiffusion to generate images containing intentional discrepancies based on these modified descriptions. (3) We employ GPT-4o to systematically analyze the generated images against the original descriptions, automatically identifying inconsistencies and providing detailed modification rationales. The final data point includes the original caption, the generated image, the analysis rationale, and the original image.

3.1.2 Multimodal Reasoning

Multimodal Reasoning focuses on the synergistic interplay between multimodal understanding and generation. During the reasoning process, multi-

modal reasoning drives the generation of necessary visual content, while the generated visual content, as part of the reasoning rationale, in turn facilitates better multimodal understanding. This design emulates human reasoning processes, where individuals often combine textual thinking with visual aids (such as mental sketches or imagined scenes) to collaboratively solve complex problems.

MM Reasoning (O) In multimodal tasks, answering questions often requires careful attention to specific details within the **original input images**. Following Shao et al. (2024a), we construct questions that demand reasoning rationale incorporating snapshots of critical details from the original image.

MM Reasoning (MM) To enhance the model’s multimodal reasoning capabilities, we construct data points that require joint reasoning across both image and text modalities. The dataset construction process is as follows: (1) We collect a diverse set of images and use the CLIP model to remove duplicates. (2) GPT-4o is employed to generate reasoning questions based on the collected images. These questions are designed to require reasoning processes that integrate both visual and textual content. Questions that fail to meet this criterion are discarded. (3) The input image and the generated question are provided to GPT-4o, which produces a rationale. When necessary, textual descriptions are used in place of images. (4) The textual descriptions from step 3 are rewritten into keywords using GPT-4. These keywords are then used to retrieve images from tools like Bing Search, ensuring stylistic consistency across the images used in the questions and rationales. (5) CLIP similarity scores are computed between the descriptions generated in step 3 and the retrieved images. Only the images with the highest similarity scores are retained. Because **the input is multimodal**, we refer to this construction method as MM Reasoning (MM).

MM Reasoning (T) Beyond multimodal input scenarios, we also design multimodal reasoning task based on **purely textual inputs**. The process is as follows: (1) GPT-4 is used to generate text-only questions that require reasoning aided by generated images. (2) The generated questions are deduplicated using embedding model to ensure diversity and uniqueness. (3) GPT-4 is then tasked with answering these questions, providing detailed rationales while replacing image-related compo-

nents with textual descriptions when necessary. (4) DALL-E-3 is used to generate images based on the image descriptions generated in step 3.

3.1.3 Multimodal Internet Dataset

To further enhance the diversity and naturalness of the dataset, we process and transform interleaved text-image data sourced from the internet.

MM Internet We construct this dataset based on a large collection of diverse multimodal data crawled from the internet. To improve data quality, we draw inspiration from [Chen et al. \(2024b\)](#) and design a multi-perspective filtering strategy. This strategy leverages pre-trained VLLMs to ensure coherence and semantic consistency between sentences and their associated images. Furthermore, we generate questions for these multimodal data, ensuring that the answers align precisely with the corresponding text-image data.

3.1.4 Compared to Existing Practice

UnifiedVisual introduces several key innovations over existing datasets. *First*, its synergistic design uniquely integrates multimodal understanding and generation, embedding complex reasoning into generation tasks and incorporating multimodal generation within reasoning chains for mutual reinforcement. *Second*, UnifiedVisual significantly broadens task diversity, covering visual generation, multimodal reasoning, and large-scale internet-sourced data, thus overcoming the limited scope of prior datasets. *Third*, by using indirect prompts and constructing reasoning chains that interleave text and images, UnifiedVisual enables models to learn more advanced reasoning processes, rather than simply mapping inputs to direct responses as in traditional datasets. *Finally*, the framework is highly extensible, enabling efficient and large-scale dataset construction to support future unified VLLM development.

3.2 UnifiedVisual-240K

Using the above methods, we ultimately constructed 120k **generation samples**. The sources and final quantities of each type of data are shown in Table 3. Additionally, we sampled 60K data points from LLaVA-CoT ([Xu et al., 2024](#)) and CoT-Collection ([Kim et al., 2023](#)), respectively, to create our **understanding samples**. Together with the generation samples, these form our UnifiedVisual-240K. Its composition and distribution are illustrated in Figure 2. More details about the dataset

construction can be found in Appendix C. Additionally, we provide examples for each subset of UnifiedVisual-240K in Appendix G.

4 Experimental Setup

4.1 Unified VLLM

In this section, we select Anole ([Chern et al., 2024](#)) as the base model for training and evaluation. Among all open-source unified VLLMs, Anole stands out as a representative model built on the transformer architecture. It adopts a unified processing approach for various modalities and supports multimodal outputs that can include any number of images. These capabilities make Anole particularly suitable as the base model for our experiments. Specifically, Anole represents images as discrete tokens. After generating these image tokens, the image decoder converts the discrete visual tokens back into images. For more details regarding the training procedure and inference, please refer to Appendix A.

4.2 Evaluation and Metrics

Multimodal Understanding To evaluate multimodal understanding capabilities, we conduct evaluations on six widely-used benchmarks: RealworldQA ([XAI, 2024](#)), MMVP ([Tong et al., 2024b](#)), ScienceQA ([Lu et al., 2022](#)), VStar ([Wu and Xie, 2023](#)), MME ([Fu et al., 2024](#)), and POPE ([Li et al., 2023b](#)). For RealworldQA, MMVP, ScienceQA, and VStar, accuracy is used as the evaluation metric. GPT-4 is employed to determine whether the model’s output match the ground truth, and accuracy is then calculated. Notably, for MMVP, a response is only considered correct if both paired questions are answered correctly. For MME and POPE, we first use GPT-4 to summarize the model’s output as either “yes” or “no” and then use the official repository’s code to compute the final metrics. Specifically, for MME, we report the total score for MME Perception and MME Cognition. For POPE, we report its F1 score.

Multimodal Generation To evaluate visual generation capabilities, we use MS-COCO ([Lin et al., 2014](#)) and GenEval ([Ghosh et al., 2024](#)). For MS-COCO, we report the CLIP score as our evaluation metric. For GenEval, we use the official evaluation code² for assessment and report the overall score.

²<https://github.com/djghosh13/geneval>

Model	RWQA	MMVP	SQA	VStar	MME	POPE	Avg.
Anole	32.0	10.0	46.7	15.7	841.4	65.8	33.4
Anole-NormalData	<u>37.9</u>	7.3	53.4	<u>30.9</u>	952.9	<u>75.9</u>	39.9
Anole-UnifiedVisual _T	<u>37.9</u>	<u>20.0</u>	55.2	29.8	<u>1316.5</u>	72.1	<u>43.7</u>
Anole-UnifiedVisual _{MM}	36.1	14.7	55.3	28.3	1125.3	70.6	40.9
Anole-UnifiedVisual	39.7	24.0	56.2	33.0	1371.2	76.1	46.3

Table 1: This table presents the results of the multimodal understanding evaluation. The best results are highlighted in **bold**, while the second-best results are marked with an underline for clarity.

Textual Reasoning To assess the model’s pure text reasoning ability, we use AlpacaEval (Li et al., 2023a). Following the official AlpacaEval³, we use GPT-4 for evaluation. A higher win rate indicates greater helpfulness of the response.

4.3 Experimental Details

During training, we utilized 64 NVIDIA H100 80G GPUs, set the batch size to 512, and the maximum sequence length to 4096. We used the AdamW optimizer with a 5% warm-up step and the cosine decay learning rate scheduler. The model was trained for 2 epochs with a maximum learning rate of 2e-5. For inference, we used greedy decoding to generate textural responses for reproducibility. After decoding, we used Anole’s vision decoder to transform the generated vision tokens into images.

5 Experiments

5.1 Baselines

Anole-NormalData Following prior works (Ma et al., 2024; Li et al., 2024b), we trained Anole using a combination of textual understanding data, multimodal understanding data, and multimodal generation data. Specifically, the understanding data is identical to that of UnifiedVisual-240K, while the multimodal generation data was derived from an equivalent amount of Laion⁴ (Schuhmann et al., 2022). Laion is a high-quality dataset carefully filtered by high aesthetic scores, making it a popular choice for training advanced image generation models (Xie et al., 2024). This data was subsequently transformed into the instruction-following format as outlined by Tong et al. (2024a).

Anole-UnifiedVisual_T To investigate the interaction between multimodal understanding and generation within UnifiedVisual-240K, we introduced

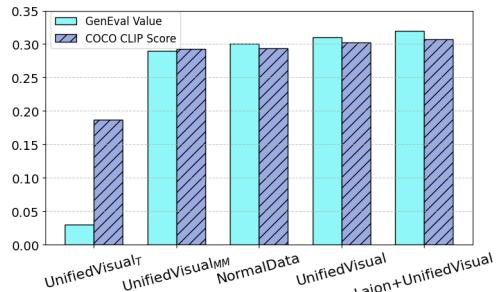


Figure 3: Generation evaluation for different models.

an additional baseline model trained exclusively on the understanding subset of UnifiedVisual-240K.

Anole-UnifiedVisual_{MM} Similarly, we added another baseline model trained solely on the generation subset of UnifiedVisual-240K.

5.2 Main Results

5.2.1 Multimodal Understanding

The experimental results are presented in Table 1. As shown, compared to Anole-UnifiedVisual_T, which is trained solely on multimodal understanding data, Anole-NormalData incorporates additional multimodal generation data during training. However, its performance is notably worse than Anole-UnifiedVisual_T. This observation aligns with findings from prior research (Wang et al., 2024b), which indicate that directly including multimodal generation data can conflict with the training objectives of multimodal understanding tasks, leading to a decline in performance compared to training exclusively on understanding data.

In contrast, our generation data is designed not only to enhance the model’s generative capabilities but also to integrate complex rationales into generation tasks. Consequently, even Anole-UnifiedVisual_{MM}, which is trained exclusively on our generation data, achieves slightly better performance than Anole-NormalData. More importantly, trained on the combined understanding and genera-

³https://github.com/tatsu-lab/alpaca_eval

⁴<https://huggingface.co/datasets/dclure/laion-aesthetics-12m-umap>

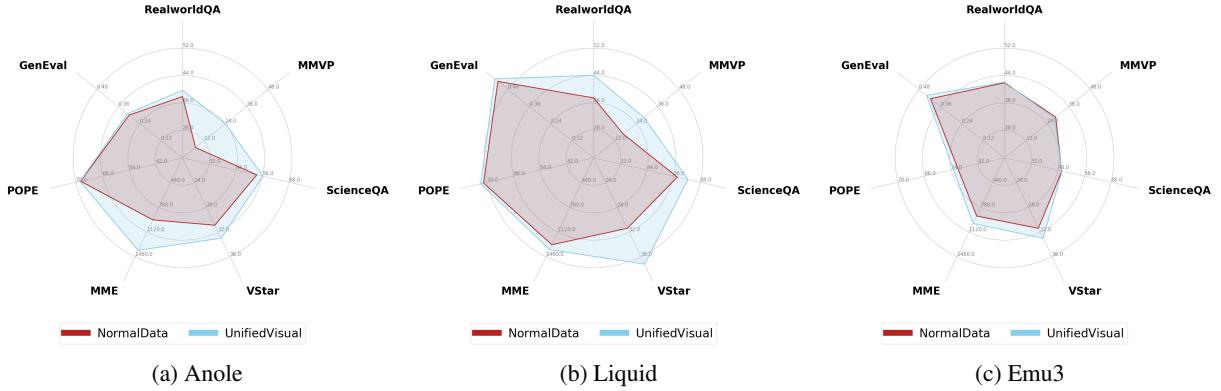


Figure 4: Results of the multimodal understanding and generation evaluation for Anole, Liquid, and Emu3 models. Each model is trained on UnifiedVisual-240K and NormalData. The training datasets and evaluation sets are consistent with the settings described in Section 5.2.

tion data we constructed, Anole-UnifiedVisual’s understanding capability surpasses both Anole-UnifiedVisual_T, which is trained on our understanding data, and Anole-UnifiedVisual_{MM}, which is trained on our generation data.

These results clearly demonstrate that the generation data and understanding data in UnifiedVisual-240K are mutually beneficial, jointly enhancing the multimodal understanding capability of Anole-UnifiedVisual.

5.2.2 Multimodal Generation

As shown in figure 3, when trained solely on understanding data, Anole-UnifiedVisual_T exhibits significantly worse generation capabilities compared to Anole-NormalData. The performance of Anole-UnifiedVisual_{MM}, trained on our generation data, is also slightly worse than Anole-NormalData, which may be due to the lower image quality in our UnifiedVisual dataset compared to Laion. However, when training on both the understanding and generation data in UnifiedVisual-240K, the generation capability of Anole-UnifiedVisual surpasses that of Anole-NormalData. This demonstrates that in UnifiedVisual, multimodal understanding data and multimodal generation data indeed promote each other, jointly enhancing the model’s multimodal generation capability.

We further analyzed the detailed metrics of GenEval, as shown in figure 6. Compared to Anole-UnifiedVisual_{MM}, which was trained solely on generation data, Anole-UnifiedVisual achieves significant improvements in single/double-object generation, color, and quantity. This indicates that incorporating multimodal understanding data enhances the model’s comprehension of object de-

tails, including attributes such as color and quantity, thereby improving its generation capability.

To further demonstrate the advantages of the generation data in UnifiedVisual over that in NormalData, we mixed half of the NormalData generation data with half of the UnifiedVisual generation data, while keeping the understanding data consistent, and trained a new model. The resulting model achieved further improvements in generation capabilities. **Compared to** Anole-UnifiedVisual, this mixed-data model benefited from the introduction of higher-quality image generation data (from Laion), leading to enhanced generation performance. This finding highlights that improving image quality can further boost model performance. Additionally, **compared to** Anole-NormalData, the introduction of more complex reasoning-based generation tasks and multimodal reasoning tasks significantly enhanced the model’s generation capabilities. This further demonstrates the effectiveness of our UnifiedVisual Framework.

5.2.3 Text Understanding

We used AlpacaEval to evaluate the models’ text understanding and problem-solving capabilities. As shown in figure 7, we calculated the win rate of all models compared to Anole-NormalData. Similar to the evaluation results for multimodal understanding, Anole-NormalData performs the worst, while Anole-UnifiedVisual achieves the best results. This once again demonstrates that in UnifiedVisual-240K, generation data and reasoning data mutually promote each other, thereby enhancing the model’s (textual) understanding capability.

6 Analysis

6.1 Results on Various Unified VLLMs

In this section, we further evaluate the generalizability of our UnifiedVisual by conducting experiments on additional Unified VLLMs beyond Anole, including Emu3 (Wang et al., 2024b) and Liquid (Wu et al., 2024b). The Hugging Face repository links for these models are provided in Appendix D.

As illustrated in Figure 4, models trained on UnifiedVisual-240K consistently outperform those trained on NormalData in both multimodal understanding and multimodal generation tasks. These results align perfectly with our observations in Section 5.2, further validating the effectiveness of UnifiedVisual. Our experiments comprehensively demonstrate that UnifiedVisual substantially enhances the mutual reinforcement between multimodal understanding and generation abilities in Unified VLLMs.

6.2 Ablation study

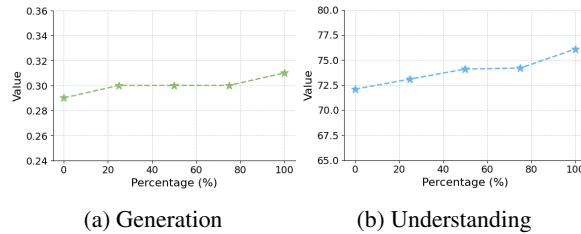


Figure 5: **Left:** Generation performance with generation data controlled at 120k. **Right:** Understanding performance with understanding data controlled at 120k.

In this section, we further demonstrate that training the model on UnifiedVisual-240K reveals a mutually beneficial relationship between visual understanding and generation.

More understanding data leads to better generation. Building upon the findings in Section 5.1, we conducted a controlled experiment to investigate whether more understanding data leads to better generation performance. In this experiment, we fixed the generation data to 120K samples and varied the amount of understanding data from 0K to 120K samples, thereby creating models with different levels of understanding. Figure 5a illustrates the overall scores on GenEval, clearly demonstrating that an increase in understanding data correlates with improved generation performance.

More generation data leads to better understanding. To explore the reverse relationship—whether more generation data enhances visual understanding—we conducted another controlled experiment. Here, we fixed the understanding data at 120K samples and vary the amount of generation data across five levels (0K, 30K, 60K, 90K, and 120K). Joint training was performed with the fixed 120K understanding samples. Figure 5b illustrates the models’ F1 scores on POPE, demonstrating that increasing the amount of generation data consistently improves understanding performance. This suggests that our generation data positively impacts the model’s ability to perform understanding tasks.

Summary. our experiments confirm that, in UnifiedVisual-240K, generation and understanding data are mutually beneficial. Generation data enhances the model’s multimodal understanding, while understanding data improves its generation capabilities. Additionally, we observe that the performance curves in both experiments have not yet converged. This indicates that, by following our data construction process, further scaling of the dataset could lead to even greater performance gains. Moving forward, we plan to expand the dataset to train a more powerful Unified VLLM.

6.3 Reasoning in Multimodal Generation

After training on UnifiedVisual-240K, Anole-UnifiedVisual demonstrates its ability to effectively leverage reasoning capabilities in visual generation tasks. As illustrated in Figure 17, the model is prompted to generate “an animal associated with having nine lives.” While Janus-Pro-7B and Emu3-Gen were trained on larger and higher-quality datasets and can produce more realistic images, they fail to infer that the target animal was a cat. In contrast, Anole-UnifiedVisual successfully deduces that the correct animal is a cat and generates an accurate image. Additional examples are provided in Appendix H. These results indicate that UnifiedVisual-240K can be used to train models to learn reasoning in multimodal generation.

7 Conclusion

In this paper, we propose a novel dataset construction framework, UnifiedVisual, and introduce UnifiedVisual-240K, a high-quality dataset designed to enhance the synergy between multimodal understanding and generation. Experi-

tal results show that Anole-UnifiedVisual, trained on UnifiedVisual-240K, consistently outperforms models trained on existing datasets and demonstrates significant mutual enhancement between understanding and generation, fully validating the effectiveness of the UnifiedVisual framework.

Limitations

In this paper, we propose a novel dataset construction framework, UnifiedVisual, and introduce a high-quality dataset, UnifiedVisual-240K. Through comprehensive experiments, we demonstrate the effectiveness of the dataset. While the current dataset is sufficient to support the experiments and conclusions presented in this paper, it remains relatively small compared to the training datasets used by other open-source models. As demonstrated in Section 6.2, increasing the amount of training data can further enhance model performance. In the future, we plan to leverage the UnifiedVisual framework to construct larger-scale datasets, aiming to further unlock the potential of Unified VLLM.

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A Additional Experimental Setup

Training Procedure Since both the input and output may simultaneously contain text and image content, markers [BOI] and [EOI] are added before and after the visual tokens generated from the discretization of each image. With visual signals fully converted into discrete tokens, we use the standard cross-entropy loss to train the model on the next-token prediction task. Particularly, to mitigate conflicts between visual and text generation during training, we compute the loss only for text tokens when predicting text, ignoring the logits of multimodal tokens. Similarly, during visual generation, we compute the loss only for visual tokens.

Inference During inference, our model employs the next-token prediction approach. When generating text tokens, the model considers only text tokens. Once [BOI] is predicted, it signals the generation of an image. At this stage, the model focuses exclusively on predicting visual tokens until the image generation is complete.

B More Experimental Results

B.1 Detailed GenEval Score

We further analyzed the detailed metrics of GenEval, as shown in figure 6. Compared to Anole-UnifiedVisual_{MM}, which was trained solely on generation data, Anole-UnifiedVisual achieves significant improvements in single/double-object generation, color, and quantity. This indicates that incorporating multimodal understanding data enhances the model’s comprehension of object details, including attributes such as color and quantity, thereby improving its generation capability.

B.2 Evaluation on AlpacaEval

We used AlpacaEval to evaluate the models’ text understanding and problem-solving capabilities. As shown in figure 7, we calculated the win rate of all models compared to Anole-NormalData.

B.3 Latency Experiments

We evaluated the inference latency of several models on the RealWorldQA and POPE benchmarks. All experiments were conducted on a single NVIDIA H100 80G GPU. In our setup, models were required to first generate their reasoning process before producing the final answer. Table 2 presents the average time (in seconds) required per sample for each model.

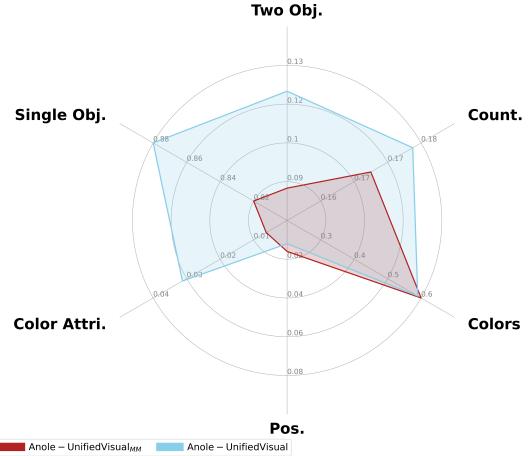


Figure 6: GenEval scores across distinct dimensions.

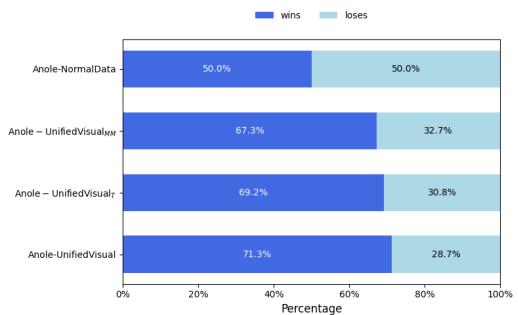


Figure 7: Evaluation on AlpacaEval.

	Janus-Pro	LLaVA	Anole	Anole-UV
RWQA	2.12	1.06	1.51	2.07
POPE	1.08	0.59	1.50	2.03

Table 2: Latency Experiments. The Hugging Face repository links for these models are provided in Appendix D. Anole-UV refers to Anole-UnifiedVisual.

Our results show that, compared to the baseline, our approach only incurs a marginal increase in inference latency, while achieving substantial improvements in performance. Furthermore, the inference latency of our model remains within an acceptable range relative to other models. We anticipate that with the adoption of inference acceleration frameworks such as vLLM, the latency can be further reduced.

B.4 Multimodal Reasoning

In UnifiedVisual, we introduce multimodal reasoning chains in MM Reasoning tasks with the fundamental goal of addressing the conflict between multimodal understanding and multimodal generation, thereby enabling these two capabilities to mutually enhance each other. During the reasoning process,

multimodal reasoning drives the generation of necessary visual content, while the generated visual content, as part of the reasoning rationale, in turn facilitates better multimodal understanding. This design emulates human reasoning processes, where individuals often combine textual thinking with visual aids (such as mental sketches or imagined scenes) to collaboratively solve complex problems.

Through training on the UnifiedVisual-240K dataset, we observe that our models not only achieves synergistic improvements in both multimodal understanding and generation, **but also** exhibits strong multimodal reasoning abilities. For example, in Figure 1, when asked, “Which plant has seeds on the outer surface of its fruit”. Models like Anole, Janus-Pro-7B, and Emu3-Gen rely on internal knowledge but give incorrect answers. In contrast, the Anole-UnifiedVisual model is capable of effectively “recalling” the appearances of different fruits and combining them to provide the correct answer. This demonstrates that training on the UnifiedVisual-240K dataset can also activate multimodal reasoning capabilities in models, allowing them to reason more like humans.

C Dataset Construction

C.1 Data Sources and Quantities

	Quantity	Source
MM Internet	29,399	CoMM (Chen et al., 2024b)
Image Editing	9,024	MagicBrush (Zhang et al., 2023)
Image Generation	22,755	OpenImages (Krasin et al., 2017)
Image Correction	20,000	ShareGPT4V (Chen et al., 2024a)
MM Reasoning (O)	21,000	Visual-CoT (Shao et al., 2024a)
MM Reasoning (T)	7,276	-
MM Reasoning (MM)	17,761	COCO (Lin et al., 2014)

Table 3: The quantities and sources of each type of generation data in UnifiedVisual-240K are presented. Here, "sources" refer to the raw data sources used to construct UnifiedVisual-240K.

C.2 Tools

Tool	Link
GPT-4	https://openai.com/index/gpt-4
GPT-4o	https://openai.com/index/gpt-4o-system-card
DALL-E-3	https://openai.com/index/dall-e-3
text-embedding-ada-002	https://openai.com/index/new-and-improved-embedding-model
clip-vit-large-patch14	https://huggingface.co/openai/clip-vit-large-patch14
stable-diffusion-3.5-large	https://huggingface.co/stabilityai/stable-diffusion-3.5-large
Bing Image Search	https://github.com/hellock/icrawler
Google Custom Search	https://console.cloud.google.com

Table 4: Links to the tools used for constructing UnifiedVisual-240K.

D Links to Models

Table 5 provides links to the Hugging Face repositories for all models we use in this study.

Model	Hugging Face Page
Anole-7B	https://huggingface.co/leloy/Anole-7b-v0.1-hf
Emu3-Stage1	https://huggingface.co/BAAI/Emu3-Stage1
Liquid	https://huggingface.co/Junfeng5/Liquid_V1_7B
LLaVA-7B	https://huggingface.co/liuhaotian/llava-v1.5-7b
Janus-Pro-7B	https://huggingface.co/deepseek-ai/Janus-Pro-7B

Table 5: Links to Hugging Face pages of all models.

E Illustrations of Dataset Construction Methods

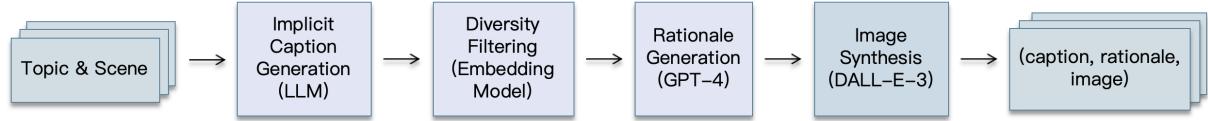


Figure 8: Illustration for Topic- and Scene-Based Image Generation. (1) We propose several topics and corresponding scenes, then generate image captions that implicitly, rather than explicitly, describe the desired image content. (2) We use embedding models to filter similar captions, ensuring data diversity. (3) We use GPT-4 to generate a reasoning process (rationale) explaining the content and details to be generated, (4) followed by DALL-E-3 for image synthesis.



Figure 9: Illustration for Category- and Image-Based. (1) We collect a diverse set of authentic images, (2) removing duplicates. (3) Based on the images and their categories, we use GPT-4 to generate instructions that describe image characteristics and related information, again focusing on implicit rather than explicit descriptions. (4) We then use GPT-4 to generate a detailed rationale based on the caption and category information, outlining the logic behind the desired image. The final data point consists of the caption, rationale, and the original image.



Figure 10: Illustration for Image Editing. (1) We transform simple editing instructions into more nuanced prompts that necessitate deeper understanding and planning. (2) We use GPT-4o to analyze these enhanced instructions and generate reasoning rationales outlining the editing objectives and intended outcomes.

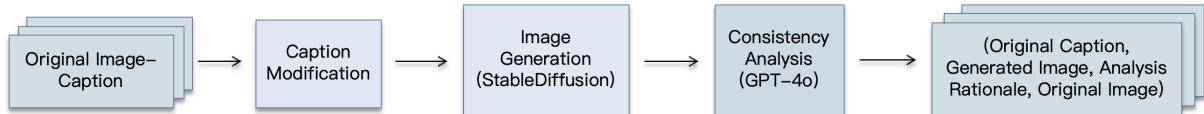


Figure 11: Illustration for Image Correction. (1) We modify existing image captions to create descriptions that maintain the core theme while introducing controlled variations in specific visual elements. (2) We utilize StableDiffusion to generate images containing intentional discrepancies based on these modified descriptions. (3) We employ GPT-4o to systematically analyze the generated images against the original descriptions, automatically identifying inconsistencies and providing detailed modification rationales. The final data point includes the original caption, the generated image, the analysis rationale, and the original image.

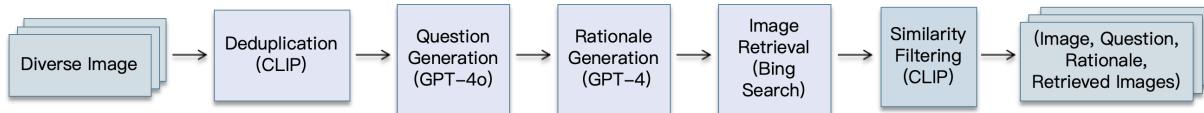


Figure 12: Illustration for MM Reasoning (MM). (1) We collect a diverse set of images and use the CLIP model to remove duplicates. (2) GPT-4o is employed to generate reasoning questions based on the collected images. These questions are designed to **require reasoning processes that integrate both visual and textual content**. Questions that fail to meet this criterion are **discarded**. (3) The input image and the generated question are provided to GPT-4o, which produces a rationale. When necessary, textual descriptions are used in place of images. (4) The textual descriptions from step 3 are rewritten into **keywords** using GPT-4. These keywords are then used to retrieve images from tools like Bing Search, ensuring stylistic consistency across the images used in the questions and rationales. (5) CLIP similarity scores are computed between the descriptions generated in step 3 and the retrieved images. Only the images with the highest similarity scores are retained.

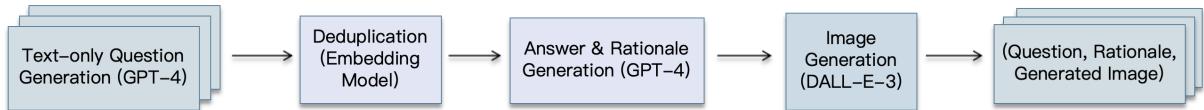


Figure 13: Illustration for MM Reasoning (T). (1) GPT-4 is used to generate text-only questions that **require reasoning aided by generated images**. (2) The generated questions are deduplicated using embedding model to ensure diversity and uniqueness. (3) GPT-4 is then tasked with answering these questions, providing detailed rationales while replacing image-related components with textual descriptions when necessary. (4) DALL-E-3 is used to generate images based on the image descriptions generated in step 3.

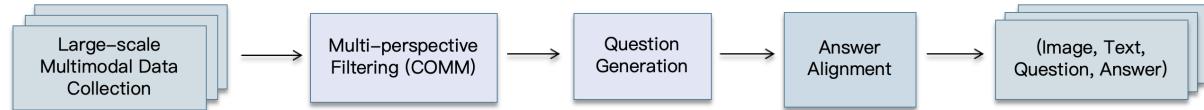


Figure 14: Illustration for MM Internet. (1) We construct this dataset based on a large collection of diverse multimodal data crawled from the internet. (2) To improve data quality, we draw inspiration from [Chen et al. \(2024b\)](#) and design a multi-perspective filtering strategy. This strategy leverages pre-trained VLLMs to ensure coherence and semantic consistency between sentences and their associated images. (3) Furthermore, we generate questions for these multimodal data, (4) ensuring that the answers align precisely with the corresponding text-image data.

F Prompt Template

F.1 Prompt Template for Image Generation

You should generate {number} pairs of instruction and thought about {topic}. Each pair consists of:

Instruction: This instruction requires generating an image. The instruction must only describe the target indirectly, without stating it explicitly (e.g., instead of "Generate an image of a panda," say, "Generate an image of the animal known for its black-and-white fur and its love for bamboo").

Thought: A detailed reasoning process that interprets the description in the instruction and deduces what should be generated. The thought should make the reasoning explicit and connect the clues to the final answer.

Examples:

{selected examples about this topic}

Do not include the examples in your output.

Table 6: Prompt template used to generate questions and rationales in Topic- and Scene-Based Generation.

Based on the given text, first summarize what image needs to be generated and then convert it into a format suitable for input into DALL-E 3. Just return the input for DALL-E 3, don't return anything else.

Text:

{thought}

Input for DALL-E 3:

Table 7: Prompt template used to generate the DALL-E-3 input in Topic- and Scene-Based Generation.

You will be given an object name. Your task is to:

1. Create an image generation question that:
 - Does not directly mention the object name
 - Uses related facts, locations, or cultural references to describe it
 - Requests the generation of an image
2. Provide a rationale that:
 - Explains the logical connection between the facts and the object
 - Ends by stating what image should be produced

Output format:

```
{"question": "[image generation question]", "rationale": "[reasoning process and conclusion about the image to generate]"}  
}
```

Examples:

object name: "the flag of the United States"

```
{"question": "Show me the national flag of the country where Yellowstone National Park is located.", "rationale": "Yellowstone National Park is located in the United States, so the national flag is the American flag. This means we need to create an image of the flag of the United States."  
}
```

object name: "the Eiffel Tower"

```
{"question": "I'd like to see an illustration of the most famous landmark in France, built as the entrance arch for the 1889 World's Fair.", "rationale": "The description points to the Eiffel Tower, which was constructed for the 1889 World's Fair and stands as France's most iconic monument. The requested image should be of the Eiffel Tower."}  
}
```

object name: "a panda"

```
{"question": "Generates an image of a black and white bear species native to the bamboo forests of central China.", "rationale": "The description refers to the giant panda, which is native to China and known for eating bamboo as its main food source. The image we want is of a panda."}  
}
```

Input:

object name: {Input object name}

Output:

Table 8: Prompt template used to generate questions and rationales in Category- and Image-Based Generation.

F.2 Prompt Template for Image Editing

I will provide you with:

An original image

An instruction for editing the image

An edited image

Your task is:

Based on the given before-edit image, after-edit image, and the editing instructions, analyze the differences between the two images, summarize the most notable features of the after-edit image compared to the original, and describe them in one clear and precise sentence.

It is worth noting that the Main changes include additions, deletions, and modifications, which cannot be expressed explicitly in the Output, but should be expressed implicitly.

Example:

Input:

Original image: A person sitting on a couch in a living room, looking at their phone

Editing instruction: Darken the scene, only keeping the light emitted from the phone screen

Edited image: A person sitting on a couch in a dark room, looking at their phone screen with bright light

Output:

It highlights the light source from the phone screen, creating a dim and focused atmosphere throughout the scene.

Input:

Original image: {The image before editing}

Editing instruction: {The original editing instruction}

Edited image: {The image after editing}

Output:

Table 9: Prompt template used to generate a new editing instruction in Image Editing.

You are a specialized assistant for designing Image editing tasks. I will provide you with:

An original image

Main changes in the image after editing

An edited image

Your task is:

Convert Main changes to a question with answer about the original image that:

1. Can be a request to modify the image or a desired image
2. Must be answered with help from the edited image
3. Must be very relevant to the image and cannot be a general question that has nothing to do with the image
4. It is worth noting that the Main changes include additions, deletions, and modifications, which cannot be expressed explicitly in the question, but should be expressed implicitly.

The answer should use <image_placeholder> to replace the edited image position in the response

Example:

Original image: A person sitting on a couch in a living room, looking at their phone

Edited image: A person sitting on a couch in a dark room, looking at their phone screen with bright light

Main changes: It highlights the light source from the phone screen, creating a dim and focused atmosphere throughout the scene.

Question: How to highlight the light source effect of the mobile phone screen?

Answer:

To highlight the light source effect of the mobile phone screen, we can darken the entire scene while preserving only the light from the phone screen. This will help create contrast and emphasize the phone's light.<image_placeholder>

Input:

Original image: {The image before editing}

Edited image: {The image after editing}

Main changes: {Main changes in the image after editing}

Output:

Table 10: Prompt template used to generate a rationale in Image Editing.

F.3 Prompt Template for Image Correction

I will give you a prompt for image generation. Please help me modify this prompt by changing or removing some key descriptive elements. The modified prompt should create an image that differs from the original in certain visual elements while maintaining the overall theme.

Prompt: {generation prompt}

Modified prompt:

Table 11: Prompt template used to generate a modified description in Image Correction.

You are a professional image analysis expert.

I will provide an image generation requirement and an image generated based on that requirement. This image has some inconsistencies with the original requirements. Please analyze according to these steps:

First, carefully analyze the differences and inconsistencies between the image and the requirements. Then, explain in detail how to make adjustments to obtain an image that fully meets the original requirements.

End with a phrase similar to "Now, let's generate a new image that fully complies with the requirements based on the above suggestions."

Image generation requirement: {generation prompt}

Your response:

Table 12: Prompt template used to generate a rationale in Image Correction.

F.4 Prompt Template for MM Reasoning (MM)

[image]

Based on this image, generate a challenging analytical question that has a definitive answer. The question should:

1. Require both careful observation of the image AND application of basic world knowledge
2. Require careful observation and logical reasoning to solve
3. Have a single correct answer rather than subjective interpretations
4. Be specific and precise, not vague or open-ended
5. Use world knowledge that is:
 - Commonly understood and easily visualizable
 - Not specialized or technical

Just provide the question without any explanation or additional information.

Question:

Table 13: Prompt template used to generate a question based on an image in MM Reasoning (MM).

[image]

You will be given an image and a question. You should analyze the image and answer the question step by step.

The rationale must be in the form of interleaved image descriptions and text. The maximum number of image descriptions in the rationale is 2.

The image descriptions and text in the rationale must complement each other to form a coherent and rigorous chain of reasoning that leads to the correct answer to the question.

The image descriptions in the response are of the form [image: description].

The image descriptions should be simple and concise enough.

The generated image descriptions cannot be close to the original image.

Just return the rationale, don't return anything else.

Question:{question}

Rationale:

Table 14: Prompt template used to generate a rationale in MM Reasoning (MM).

E.5 Prompt Template for MM Reasoning (T)

Please provide me with a list of {number} questions, options and answers about {topic} for Multiple Choice tasks. These questions must meet the following requirements:

Note that: The questions should have a definite answer. The answer does not change over time. Only one of the options is the correct answer. The questions and answers should not be too related to numbers.

Note that: The questions should be challenging, requiring multiple steps to answer. And the questions should be related to visual information.

Note that: The questions require a chain of thought to deduce the correct answer. The reasoning chain must be in a mixed format of text and descriptions of the images, where the descriptions of the images and text work together to form a coherent and logical chain of reasoning.

{"question": A question generated by you, "options": 4 options in list format generated by you, "answer": The answer generated by you}

Examples:

{selected examples about this topic}

Do not include the examples in your output.

Just provide the questions, options and answers in a jsonline format, without any explanation or additional information.

Table 15: Prompt template used to generate a question in MM Reasoning (T).

You will be given a multiple choice question and its correct answer. You should analyze and answer the question step by step. You need to give the rationale first and finally give the correct answer.

The rationale must be in the form of interleaved image descriptions and text.

The image descriptions and text in the rationale must complement each other to form a coherent and rigorous chain of reasoning that leads to the correct answer to the question.

The image descriptions in the response are of the form [image: description].

Note that: The number of image descriptions in the rationale must be no more than 3.

Note that: The image descriptions of an image should contain the content of only one option.

Note that: The image descriptions should be concise and clear.

Note that: The image descriptions should be easily conveyed visually.

Just return the rationale, don't return anything else.

Question: {question}

Options: {options}

Correct answer: {answer}

Rationale:

Table 16: Prompt template used to generate a rationale based on a question in MM Reasoning (T).

F.6 Prompt Template for Internet Multimodal Data

Given the following interleaved text-image content, please generate a question for which the provided content can serve as the answer.

The images in the provided content are in the form of <image_placeholder>. The question you generated should closely align with the logic of the provided content.

Content: {interleaved content}

Question:

Table 17: Prompt template used to generate a question based on interleaved content in Internet Multimodal Data.

F.7 Prompt Template for Evaluation

You will be provided with a question, its correct answer, and an answer to evaluate. Your task is to determine whether the given answer is correct or not.

Question:
{question}

Correct Answer:
{golden answer}

Answer to Evaluate:
{model output}

Now, determine if the answer to evaluate is correct or wrong and respond only with "Correct" or "Wrong".

Table 18: Prompt template used to determine whether the model's output matches the ground truth.

Here is an answer to a question. This answer may be lengthy, but its final meaning is either "yes" or "no." Please carefully read and summarize the core meaning of this answer, and then determine whether its final answer is "yes" or "no." If the answer does not clearly express "yes" or "no," return "other." You must return only one word: "yes," "no," or "other."

Question:
{question}

Answer:
{model output}

Table 19: Prompt template used to summarize the model's output as 'yes' or 'no'.

G Examples of Generation Data in UnifiedVisual-240K

G.1 Example for Image Generation

Example:

USER Create an image that illustrates a sport game played in white uniforms, which lasts up to 5 days and uses a red leather ball.

ASSISTANT The description relates to Test cricket, a form of cricket that is played in matches that last up to 5 days, where players wear white uniforms, and a red leather ball is used. Hence, the image to be produced should be of a Test cricket match.



Table 20: An example from the Image Generation subset of the UnifiedVisual-240K.

G.2 Example for Image Editing

Example:



USER

How to achieve a serene and unoccupied patio setting focusing on just the furniture and garden scenery?

ASSISTANT

To create a serene and unoccupied patio setting, we can remove any distracting elements, such as people, so the focus remains solely on the furniture and the surrounding garden scenery.



Table 21: An example from the Image Editing subset of the UnifiedVisual-240K.

G.3 Example for Image Correction

Example:

USER Two zebras in a grassy field: one on a dirt path facing away, with black and white stripes; the other on grass facing the camera, with brown and white stripes. Scattered rocks in the background. No other animals or text.
Generate an image corresponding to the text mentioned above.



ASSISTANT

USER The current image fails to meet the requirements. Analyze the discrepancies and generate an accurate version.

ASSISTANT Upon analyzing the provided image against the specified requirements, the following inconsistencies are observed:

1. Zebra Colors and Positioning:

- The image shows only one zebra, not two. ... The image only shows one zebra on a dirt path, not fulfilling the positioning requirements.

2. Background Elements:

- The background contains additional animals, ...
- There are no visible rocks scattered in the background, ...

Adjustments to Achieve the Requirements:

- Add a Second Zebra:

- Introduce a second zebra with brown and white stripes into the scene, ...

- Correct Positioning:

- Retain ... on the dirt path but ensure it is facing away, as originally specified.

- Remove Extraneous Animals:

- Remove any additional animals currently visible in the background...

- Include Background Elements:

- Introduce scattered rocks into the background ...

Now, let's generate a new image that fully complies with the requirements based on the above suggestions.



Table 22: An example from the Image Correction subset of the UnifiedVisual-240K.

G.4 Example for MM Reasoning (MM)

Example:

USER



What environment are the people in the image in?

ASSISTANT

The individuals are clearly part of a naval force, likely the U.S. Navy, based on their uniforms.



We can deduce this from their white service dress uniforms, complete with black neckerchiefs, and the distinct "dixie cup" hat worn by the man in the center. The man on the right also has rank insignia (a Boatswain's Mate rate) on his sleeve and service ribbons on his chest, further confirming their military naval affiliation. The environment itself, with its array of control consoles, screens, charts laid out, communication headsets, and windows looking out over what appears to be water, is characteristic of the command and control center of a ship.



Specifically, this setup is typical of the bridge of a warship, where navigation, maneuvering, and operational command take place. The man on the right is actively using a radio handset, a common activity on a ship's bridge. The status board visible in the background right also suggests an operational environment.

Table 23: An example from the MM Reasoning (MM) subset of the UnifiedVisual-240K.

G.5 Example for MM Reasoning (T)

Example:

USER Which leaf features a prominent, singular central vein running from its base to its tip, with smaller secondary veins branching off from this central vein along its path?

- A. Maple leaf
- B. Oak leaf
- C. Grass blade
- D. Ginkgo leaf

ASSISTANT The question describes a leaf with a prominent, singular central vein running from its base to its tip, with smaller secondary veins branching off from this central vein along its path. This pattern is known as pinnate venation. Let's look at an oak leaf:



In this image of an oak leaf, you can clearly see the prominent, singular central vein (also called the midrib). It starts at the base of the leaf (where it would attach to the stem) and extends all the way to the very tip.

Along the length of this central vein, you can observe smaller secondary veins branching off to the left and right. These secondary veins then extend towards the edges and lobes of the oak leaf. This structure provides support and transports water and nutrients throughout the leaf blade.

Now let's consider why the other options are less suitable:

A. Maple leaf: Maple leaves typically have palmate venation, where several prominent veins radiate from the base, like fingers from the palm of a hand, rather than a single central one.

C. Grass blade: Grass blades exhibit parallel venation, where multiple veins run parallel to each other along the length of the blade, without a single dominant central vein from which others branch off in the described manner.

D. Ginkgo leaf: Ginkgo leaves have dichotomous venation, where veins fork repeatedly from the base, creating a fan-like pattern, again, not matching the description of a single central vein with branching secondaries.

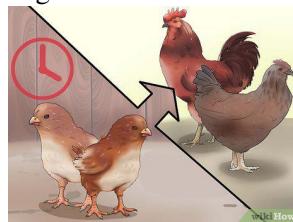
Therefore, the correct answer is B. Oak leaf.

Table 24: An example from the MM Reasoning (T) subset of the UnifiedVisual-240K.

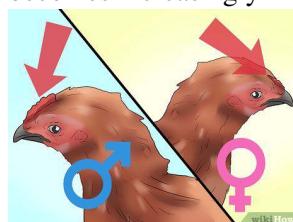
G.6 Example for MM Internet

Example:

USER	How can you determine the sex of your chicks as they grow, and what are the key differences in appearance and behavior between male and female chicks?
ASSISTANT	<p>(1) Give it time. If you aren't in a rush to sex your chicks, you can wait until they grow enough to develop adult sex traits. You should be able to notice adult traits within three to four weeks. Since many of the other sexing methods require you to act quickly, this is also a good option if you get the chicks well after the initial sexing window has passed. This is also the easiest way to determine sex for beginners.</p>



(2) Look at the appearance of the developing chick. The first trait you'll likely notice will be the comb. Male chicks develop combs within three to six weeks. Additionally, male chicks tend to develop feathers in patchy clusters, while female chicks develop feathers more evenly. Male chicks also tend to produce more pointed tail feathers. Female chicks, on the other hand, generally have broad, rounded feathers. Most male chicks also develop larger feet and thicker legs than the average female chick has. This trait can be difficult to spot in young chicks but becomes increasingly more obvious as the chicks continue to age.



(3) Watch the chick's behavior. Male chicks demonstrate bolder, more aggressive behavior than most female chicks. Male chicks can begin crowing within six weeks, but female chicks will only make soft clucking noises. When startled, male chicks tend to stand their ground and give a sharp warning chirp. Females are more likely to scatter or crouch down. Also remember that only females lay eggs. The timeline for egg laying will vary, but females can begin laying eggs within 16 to 24 weeks.



Table 25: An example from the MM Internet subset of the UnifiedVisual-240K.

G.7 Example for MM Reasoning (O)

Example:



USER

What is the person to the right of the boat wearing?

ASSISTANT

1. Identify the object referred to as boat. 2. From the identified boat, locate the person who is positioned to the right of the boat. 3. Determine what the person located to the right of the boat is wearing. 4. State the name of the clothing item that the person is wearing.

The following shows the segment of the original image that is directly related to the question.



Based on the analysis and the extracted part of the original image, the final answer is determined.

The man is wearing shorts.

Table 26: An example from the MM Reasoning (O) subset of the UnifiedVisual-240K.

H Additional Qualitative Results

How to make a cup of coffee?

(1) Boil enough water in a tea kettle for 1 cup of coffee or more, depending on how much coffee you want to drink.



(2) Add the water to the coffee grounds. Stir with a spoon. If you are using whole coffee beans, grind them in a coffee grinder just before using the grounds. If you have whole beans and want to reuse them in a later brew, grind them after use. The long-grain coffee bean grounds can be reused twice. You can add any milk, sugar or sweetener. Experiment with amounts to find your preferences. The more sugar, the stronger the taste.

(3) Pour the brewed coffee into a mug.



Which of these fruits is typically yellow when ripe?

A. Cherry
B. Banana
C. Grape
D. Watermelon

To determine which fruit is typically yellow when ripe, we need to consider the characteristics and appearance of each fruit option provided.



Cherries are red when ripe, and their color is one of the most distinguishing features for buyers.



Bananas are well-known for their creamy yellow color when they are fully ripe. This characteristic makes them easily recognizable and distinguishes them from other fruits like cherries, grapes, or watermelons.



Grapes typically ripen to a purple or green color, not yellow. Watermelons, finally, are characteristically solid green when unripe and then change to bright red when ripe. By evaluating the typical coloration of each fruit, it is clear that bananas are the only fruit among the options that are yellow when ripe.

What season is it most likely to be in this image, given the state of the trees and the clothing of the pedestrians, and why?




The presence of people wearing jackets suggests that the temperature is not warm, which is typical for fall or early spring.



The bare trees indicate that it is not summer, as trees are typically full of leaves during this time. The combination of layered clothing and bare trees suggests that it is most likely fall.

Figure 15: Examples of multimodal reasoning using Anole-UnifiedVisual.

Image Editing



How can we emphasize the tennis player's emotions during the game?

To emphasize the tennis player's emotions, we can add a subtle, yet distinct smile to capture their feelings during the match.



Image Correction



Create an image of the Hong Kong skyline seen from a water-level perspective. Highlight the towering skyscrapers, featuring the International Finance Centre prominently in the center. Capture the diverse colors and architectural styles of the cityscape. In the foreground, include a small boat gently floating on the dark blue-green water, which reflects the city's lights, adding depth to the scene. The sky should be a light blue with a few clouds, providing a peaceful backdrop to the dynamic urban environment, full of energy and vibrancy despite the absence of people.

The generated image lacks some required details. Identify what is missing and recreate the image.

Upon analyzing the provided image in relation to the original requirements, several inconsistencies are noted:

1. **Perspective**: The image does not present a Hong Kong skyline seen from a water-level perspective. Instead, it appears to depict a landscape taken from a high vantage point or elevated position, rather than the water level.
2. **International Finance Centre**: The International Finance Centre (IFC) is not prominently featured in the center of the Hong Kong skyline. While there are tall buildings, none of them match the distinctive look or height of the IFC, which is a signature skyscraper.
3. **Color and Architectural Styles**: The colors and architectural diversity expected in Hong Kong's skyline are not evident. The buildings are uniformly modern and lack significant variation in colors or design styles that are characteristic of Hong Kong's skyline.
4. **Foreground Element - Boat**: The specified small boat on dark blue-green water is absent. Instead, there is a plank-like structure that doesn't reflect the water's colors or the presence of lighted city lights which would add depth and dynamic energy to the scene.
5. **Sky Composition**: The sky lacks a light blue hue with a few clouds, which were specified to provide a peaceful backdrop. Instead, the sky is predominantly pink, possibly during sunset or sunrise, creating an atmosphere that diverges from the requirement for daytime vibrancy.

To address these discrepancies and create an image that aligns with the original requirements:

1. **Change the Perspective**: Recompose the image from a water-level perspective to give prominence to the riverfront view that encapsulates the essence of Hong Kong's skyline as viewed from the water.
2. **Feature the International Finance Centre**: Ensure the IFC is centrally positioned within the skyline. This iconic tower can be highlighted in more detail, ensuring its design and scale are recognizable.
3. **Highlight Architectural Diversity**: Add elements representing Hong Kong's diverse skyline by incorporating various building designs and colors typical of the area. Use reflections in the water to showcase this aspect.
4. **Include a Boating Element**: Introduce a small, subtly floating boat in the foreground. Use lighting to emphasize reflections on the water, capturing the vibrancy and activity typically associated with nighttime views.
5. **Modify the Sky**: Replace the current pinkish-hued sky with a more realistic representation of a late afternoon or early evening with a light blue sky and a few clouds. This change will help set the intended tranquil yet lively backdrop.

Now, let's generate a new image that fully complies with the requirements based on the above suggestions.

Image Generating

Generate an image of the largest animal in the land.

The largest animal in the land, by species, is the African elephant. Therefore, the image to be generated should be of an African elephant.





Figure 16: Examples of visual generation using Anole-UnifiedVisual.


Ours

The animal associated with having 9 lives is the cat. So, the image of a cat should be generated.




Anole




Janus-Pro-7B




Emu3





Generate an image of the animal associated with having 9 lives.

Figure 17: Examples of visual generation using Anole-UnifiedVisual.