



# Lumina - DiMOO

## An Omni Diffusion Large Language Model for Multi-Modal Generation and Understanding

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🌐 Project Page: [symbol.github.io/Lumina-DiMOO](https://symbol.github.io/Lumina-DiMOO) 🐾 Code: [Alpha-VLLM/Lumina-DiMOO](https://Alpha-VLLM/Lumina-DiMOO)

**Abstract**—We introduce Lumina-DiMOO, an open-source foundational model for seamless multi-modal generation and understanding. Lumina-DiMOO sets itself apart from prior unified models by utilizing a fully discrete diffusion modeling to handle inputs and outputs across various modalities. This innovative approach allows Lumina-DiMOO to achieve higher sampling efficiency compared to previous autoregressive (AR) or hybrid AR-Diffusion paradigms and adeptly support a broad spectrum of multi-modal tasks, including text-to-image generation, image-to-image generation (e.g., image editing, subject-driven generation, and image inpainting, etc.), as well as image understanding. Lumina-DiMOO achieves state-of-the-art performance on multiple benchmarks, surpassing existing open-source unified multi-modal models. To foster further advancements in multi-modal and discrete diffusion model research, we release our code and checkpoints to the community.

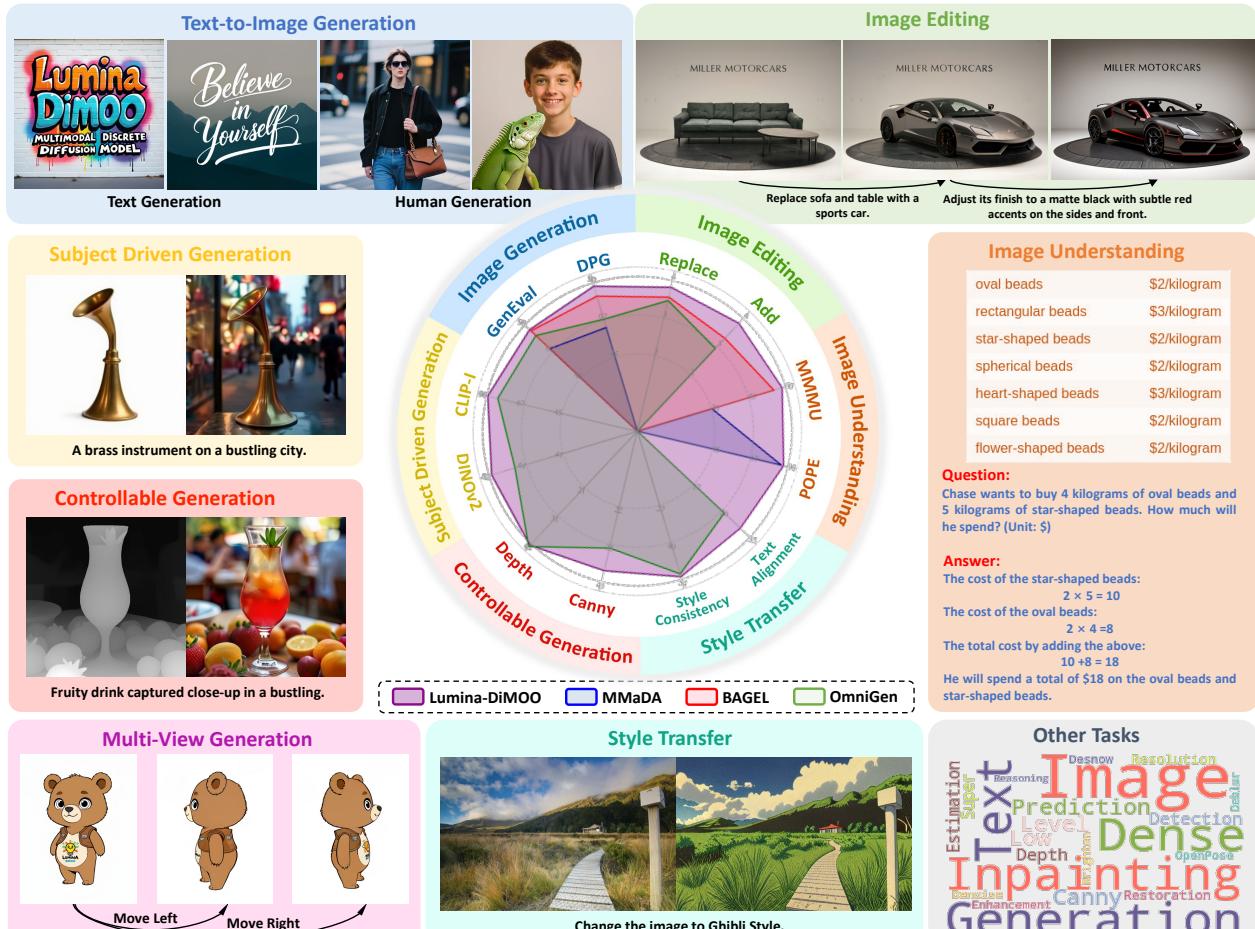


Figure 1: Overview of Lumina-DiMOO's Versatile Multi-Modal Capabilities and Superior Performance.

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## 1. Introduction

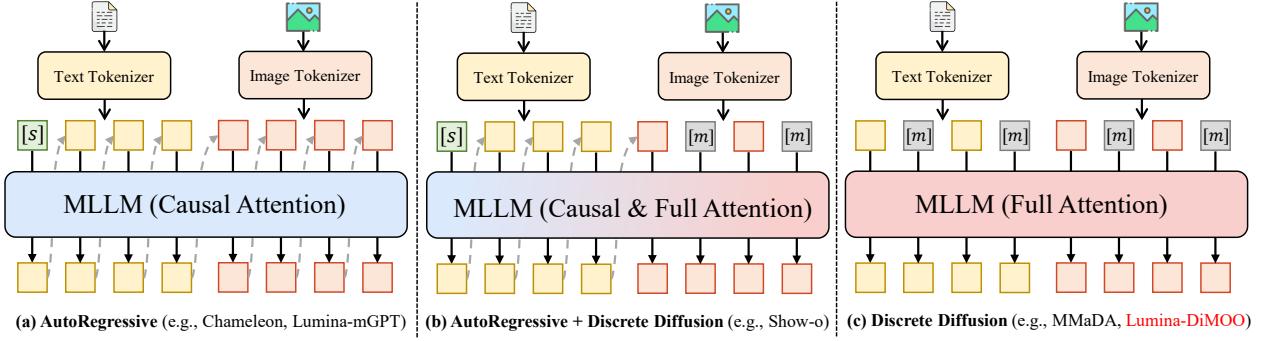
Recent advancements in Large Language Models (LLMs) have markedly improved their ability to tackle multi-modal understanding tasks. Efforts such as the LLaVA series (Liu et al., 2023, 2024c,d), QwenVL series (Bai et al., 2023; Wang et al., 2024b; Bai et al., 2025), and InternVL series (Chen et al., 2024c,b; Zhu et al., 2025b; Wang et al., 2025a) demonstrated remarkable exceptional visual comprehension performance. Concurrently, progress in text-to-image generation models, including diffusion-based methods (Podell et al., 2024; Betker et al., 2023; Xie et al., 2025a; Labs, 2024; Zhuo et al., 2024; Yi et al., 2024; Bai et al., 2024; Qin et al., 2025) and more recent autoregressive approaches (Wang et al., 2024c; Liu et al., 2024a; Xin et al., 2025a; Chen et al., 2025c; Xin et al., 2025b), has significantly advanced the generation of high-quality images. Building upon these foundational models, various downstream tasks has been explored, such as image editing (Yu et al., 2025a), multi-view generation (Huang et al., 2025a), and controllable generation (Zhang et al., 2023). These advancements have accelerated the convergence towards unified multi-modal generation and understanding modeling, aiming to integrate diverse capabilities into a single, end-to-end architecture, thereby contributing to the pursuit of artificial general intelligence (AGI).

To develop unified multi-modal models, various paradigms have been explored. As shown in Figure 2(a), the earliest models, e.g., Chameleon (Team, 2024) and Lumina-mGPT (Liu et al., 2024a), relied on a purely autoregressive (AR) architecture. However, these models faced two key challenges: 1) Their next-token prediction paradigm resulted in extremely slow generation speeds, often requiring several minutes, which significantly affected user experience. 2) Their image generation quality was suboptimal. To improve quality, approaches such as MetaQueries (Pan et al., 2025) and BLIP3-o (Chen et al., 2025a) added a diffusion head after the AR process to decode image tokens, enhancing quality but sacrificing the unified model concept. Conversely, Show-o (Xie et al., 2025c) aimed to increase speed by adopting an AR+Discrete Diffusion strategy, as illustrated in Figure 2(b). However, optimal solutions were not achieved due to incomplete exploration of text-based discrete diffusion. Recent advances (Nie et al., 2025; Zhu et al., 2025a) in discrete diffusion modeling for text have made unified multi-modal discrete diffusion models more feasible, as depicted in Figure 2(c). Our concurrent work, MMAoDA (Yang et al., 2025), has preliminarily demonstrated the potential of a comprehensive discrete diffusion architecture for unifying text-to-image generation and image understanding. Nevertheless, its performance remains limited, and it lacks full support for downstream generation tasks.

In this paper, we introduce **Lumina-DiMOO**, *an open-source and unified diffusion large language model*, which possesses ***versatile multi-modal capabilities***. These capabilities encompass text-to-image generation, supporting both arbitrary and high-resolution, and a range of image-to-image tasks, including image editing, style transfer, subject-driven generation, controllable generation, multi-view generation, and dense prediction, alongside advanced image understanding, as shown in Figure 1.

Lumina-DiMOO’s unique discrete diffusion architecture ***substantially enhances inference speed relative to previous unified AR or hybrid AR-Diffusion models***. For example, it achieves a 32x speed improvement in text-to-image generation compared to the representative AR model—Lumina-mGPT 2.0 (Xin et al., 2025a). Furthermore, during inference, we note that tokens with high maximal logit values often share similar representations with previous steps. To capitalize on this, we introduce a training-free Max Logit-based Cache (ML-Cache) method for Lumina-DiMOO, resulting in an additional 2x boost in sampling speed.

Beyond its speed advantages, the discrete diffusion architecture enables Lumina-DiMOO to execute zero-shot inpainting. This capability can be extended to ***a novel application—Interactive Retouching***, which allows users to freely refine specific areas through precise annotations, offering flexibility that is difficult for other methods to achieve.



**Figure 2: Characteristics Comparison Among Existing Unified Models.** The overall architecture has transitioned from the initial pure autoregressive (AR), which also involved adding Diffusion Head after AR, to a combination of AR and discrete diffusion, and ultimately to the current model using pure discrete diffusion.

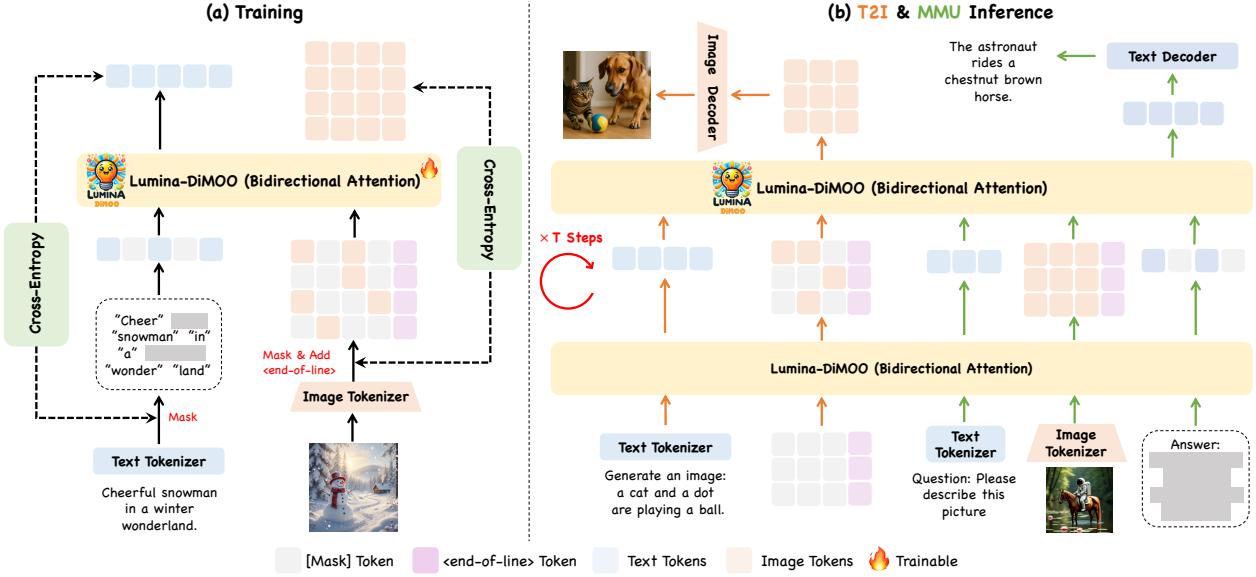
We evaluate Lumina-DiMOO’s capabilities across various multi-modal generation and understanding benchmarks, where it *surpasses the leading open-source unified models and sets new standards in this field*. Notably, Lumina-DiMOO has achieved the first place among open-source multi-modal models on the newly released UniGenBench (Wang et al., 2025b) leaderboard<sup>1</sup>, which is evaluated and maintained by the Tencent Hunyuan team. Extensive qualitative comparisons further demonstrate Lumina-DiMOO’s superior performance. These results position Lumina-DiMOO as a strong foundation model for future research and applications in general-purpose multi-modal intelligence.

## 2. Related Work

**Diffusion Large Language Model.** Recent advancements in diffusion-based large language models (dLLMs) are built upon the theory of discrete diffusion, as developed by works like (Austin et al., 2021; Sahoo et al., 2024; Lou et al., 2024; Ou et al., 2025). Among various discrete diffusion methodologies, masked diffusion has emerged as the *de facto* standard due to its simplicity and effectiveness (Austin et al., 2021; Lou et al., 2024). This approach introduces a special [mask] state in the forward process—transforming data into [mask]—and recovers data in the reverse process, similar to BERT (Devlin, 2018). dLLMs offer distinctive advantages such as bidirectional attention, iterative refinement, flexible generation order, parallel decoding, and infilling capabilities. These features contribute to their strong reasoning abilities (Ye et al., 2025a; Huang et al., 2025b; Kim et al., 2025), high efficiency (Nie et al., 2025; Yu et al., 2025b), and enhanced inference controllability. Recent innovations in the field include LLaDA (Nie et al., 2025), which scales dLLMs to 8B parameters with performance comparable to LLaMA3 8B (Grattafiori et al., 2024), and LLaDA 1.5 (Zhu et al., 2025a), which reduces reinforcement learning variance to better align models with human preferences. Multi-modal capabilities have also been explored through models like Dimple (Yu et al., 2025b), LLaDA-V (You et al., 2025), and LaViDa (Li et al., 2025a). These models, although having not yet achieved peak performance, unveil a promising alternative pathway beyond autoregressive models.

**Unified Generation and Understanding.** Unifying multi-modal generation and understanding has been a long-standing goal. One typical approach relies on using separate continuous diffusion models, where the LLM regresses image features that are subsequently decoded into images via diffusion process (Sun et al., 2024b; Pan et al., 2025; Chen et al., 2025a). While this method achieves decent visual generation, the reliance on external models compromises true modality unification and introduces bottlenecks that hinder seamless interaction across modalities (Deng et al., 2025; Wu et al., 2024b). To address this, another line of research integrates diffusion within the LLM

<sup>1</sup>Leaderboard Link: [https://huggingface.co/spaces/CodeGoat24/UniGenBench\\_Leaderboard](https://huggingface.co/spaces/CodeGoat24/UniGenBench_Leaderboard).



**Figure 3: An Overview of Lumina-DiMOO’s Discrete Diffusion Modeling.** (a) Training: Lumina-DiMOO is trained on text and image tokens with mask. (b) Inference: Lumina-DiMOO predicts the masked tokens, refining its output progressively.

transformer, sharing parameters for both generation and understanding. These unified models use a single transformer to generate text autoregressively and images through either continuous (Zhou et al., 2025; Ma et al., 2024; Liao et al., 2025) or discrete diffusion (Xie et al., 2025c). However, there still exist heavy modality-specific designs, complicating the model and reducing the unity. In pursuit of more simplified unification, some works tokenize all modalities into discrete tokens, enabling uniform autoregressive processing. For example, Emu3 (Wang et al., 2024c) and Lumina-mGPT (Liu et al., 2024a) demonstrate versatility across tasks such as visual question answering and mixed-modal generation. However, these autoregressive models face inefficiencies from raster-scan generation orders and the inherently slow token-by-token decoding. Multi-modal DLLMs offer a promising solution to these challenges. Their inherent flexibility in generation order and support for parallel decoding enable higher efficiency. Concurrent with our work, MMADA (Yang et al., 2025) has preliminarily validated the feasibility of discrete diffusion on unified generation and understanding.

### 3. Lumina-DiMOO

#### 3.1. Foundation Image Tokenizer

The discrete image tokenizer is a fundamental component in discrete diffusion modeling paradigms, crucial to the ultimate performance of visual generation and understanding tasks. Therefore, selecting a tokenizer capable of high-fidelity image reconstruction is essential. Although SBER-MoVQGAN (Razzhigaev et al., 2023), validated in Lumina-mGPT 2.0 (Xin et al., 2025a), is considered the state-of-the-art open-source tokenizer, its  $8 \times 8$  downsampling results in excessively long token sequences for high-resolution images, posing significant computational challenges. To balance performance with efficiency, we choose the tokenizer from aMUSED-VQ (Patil et al., 2024), which uses a  $16 \times 16$  downsampling factor. We also explored other  $16 \times 16$  downsampling tokenizers, such as Chameleon-VQ (Team, 2024) and Open-MAGVIT2 (Luo et al., 2024). However, Chameleon-VQ produces slightly inferior reconstructions, and although Open-MAGVIT2 performs well in reconstruction, its token format doesn’t align with our modeling needs. A drawback of the aMUSED-VQ tokenizer is its lack of semantic information about the image, which poses challenges for image understanding tasks. We address this by scaling the understanding data.

### 3.2. Model Design

**Unified Discrete Diffusion Modeling.** We adopt a unified discrete diffusion framework that not only simplifies the modeling complexity but also introduces a unified optimization objective to model both textual and visual modalities, as shown in Figure 3(a). Specifically, let  $\mathbf{x} = (x_1, \dots, x_L)$  denote a mixed text-image sequence drawn from the joint vocabulary (text tokens, image tokens, and special tokens, details in subsequent paragraph). A mask set  $\mathcal{M} \subseteq \{1, \dots, L\}$  is sampled by a mask ratio  $m \in (0, 1]$ , where the length of  $\mathcal{M}$  is  $\lfloor L \times m \rfloor$ . Tokens (in sequence  $\mathbf{x}$ ) at these indices (in mask set  $\mathcal{M}$ ) are replaced with a special [Mask] token. Therefore, the input sequence  $\tilde{\mathbf{x}}$  (with [Mask]) construction process for the model is as follows:

$$\tilde{x}_i = \begin{cases} [\text{Mask}] & \text{if } i \in \mathcal{M}, \\ x_i & \text{otherwise.} \end{cases} \quad (1)$$

Then, the model  $p_\theta$  predicts, in parallel, the original tokens at masked positions conditioned on the unmasked context and optional condition tokens  $c$  (e.g., text prompt):

$$p_\theta(\tilde{\mathbf{x}}_{\mathcal{M}} | \tilde{\mathbf{x}}_{\overline{\mathcal{M}}}, c) = \prod_{i \in \mathcal{M}} p_\theta(\tilde{x}_i | \tilde{\mathbf{x}}_{\overline{\mathcal{M}}}, c). \quad (2)$$

Training minimizes the masked cross-entropy over randomly sampled mask ratios  $m$  applied to both text and image positions:

$$\mathcal{L}(\theta) = \mathbb{E}_{\mathbf{x}, m, \mathcal{M}} \left[ - \sum_{i \in \mathcal{M}} \log p_\theta(x_i | \tilde{\mathbf{x}}_{\overline{\mathcal{M}}}, c) \right]. \quad (3)$$

At inference, generation starts from fully masked tokens and proceeds for  $T$  refinement steps via parallel prediction-sampling-remasking, as shown in Figure 3(b) (see Section 3.3.1 for details).

**Effective Initialization from Pre-Trained dLLM.** In the realm of autoregressive (AR) multi-modal generation and understanding, a successful paradigm involves initializing models with powerful pre-trained LLMs (Wu et al., 2024b; Xie et al., 2025c). These existing LLMs are ideal starting points for training as they already possess robust text semantic understanding and generation capabilities, which can greatly reduce training resource requirements. Inspired by this paradigm, Lumina-DiMOO is developed on a pre-trained dLLM, seamlessly integrating multi-modal generation and understanding within a discrete diffusion framework. Specifically, we utilize LLaDA-Base (Nie et al., 2025) as our base model without any structural modifications. To demonstrate the effectiveness of this paradigm, we conduct an ablation analysis in Section 7.2.

**Multi-Modal Tokenization.** To expand the multi-modal capabilities, we make a key modification to the vocabulary. The original LLaDA model operates with 126,345 text tokens. We expand this by integrating 8,192 visual tokens from the pre-trained aMUSED-VQ codebook. Additionally, we introduce special tokens, such as <IMAGE> and </IMAGE>, to explicitly define the boundaries of visual elements within the token sequence. As a result, Lumina-DiMOO’s combined vocabulary now includes 126,345 LLaDA text tokens, 8,192 aMUSED-VQ visual tokens, and a set of special tokens. Detailed descriptions of these special tokens are provided in Table 1. For Lumina-DiMOO, only the newly introduced visual and special tokens require learning.

**Arbitrary Resolution Image Representation.** For a versatile multi-modal generation and understanding model, the capability to process images of arbitrary resolutions is essential. However, our foundational model, LLaDA, which uses 1D RoPE designed for text, encounters challenges when applied to inherently 2D image tokens. A key issue is that images with different aspect ratios, such as

**Table 1: Detailed Description of the Special Tokens.**

|                            |   |
|----------------------------|---|
| <IMAGE> and </IMAGE>       | The beginning and ending identifiers of an image.   |
| <canny> and </canny>       | The beginning and ending identifiers of a canny detection map image.  |
| <depth> and </depth>       | The beginning and ending identifiers of a depth map image.  |
| <openpose> and </openpose> | The beginning and ending identifiers of a skeleton map image.   |
| <hed> and </hed>           | The beginning and ending identifiers of an edge detection map image.  |
| <system> and </system>     | The beginning and ending identifiers of a system prompt, which are usually descriptions of task prompts.                          |
| <user> and </user>         | The beginning and ending identifiers of a user prompt, which are typically correspond to the user’s instructions or requirements. |
| <answer> and </answer>     | The beginning and ending identifiers of the model’s response.   |
| <end-of-line>              | The identifier for the end of a line in an image.   |
| <uncondition>              | Identifiers for CFG (Classifier-Free Guidance) applied to image generation.   |

$512 \times 1024$  and  $1024 \times 512$  would be flattened into sequences of the same length, losing their distinct aspect ratios in a 1D format. To overcome this, we introduce a <end-of-line> token after the last image token of each row, serving as an explicit delimiter of the structure. This addition allows the original 2D shape of the image to be correctly parsed and reconstructed from the 1D sequence without requiring a new positional embedding design. This modification is crucial for enabling Lumina-DiMOO to effectively handle images with arbitrary resolution. In contrast, MMaDA (Yang et al., 2025), sharing the same architecture with Lumina-DiMOO, only processes images at a fixed resolution of  $512 \times 512$ .

### 3.3. Inference

#### 3.3.1. Sampling Strategies

**Parallel Sampling for Image Generation.** For image generation, we treat the entire set of image tokens to be generated (excluding special <end-of-line> tokens) as a single generation block. Following MaskGIT (Chang et al., 2022), we partition the image generation process into four stages. Generation starts from a sequence in which all image tokens are masked, i.e.  $x_{t=0}$  and proceeds decoding for  $T$  timesteps. At each timestep  $t$ , our decoding operates as follows:

**1. Predict.** Conditioned on the user prompt  $c$ , Lumina-DiMOO predicts, in parallel, probabilities  $p_\theta(\tilde{x}_i^t | \tilde{\mathbf{x}}_{\mathcal{M}}^t, c) \in \mathbb{R}^{L'_t \times K}$  for all masked tokens, where  $L'_t$  is the number of masked image tokens at timestep  $t$  and  $K$  is the size of the full vocabulary.

**2. Sample.** We first restrict the predicted probabilities  $p_\theta \in \mathbb{R}^{L'_t \times K}$  from the entire vocabulary to the image-token subset  $p_\theta \in \mathbb{R}^{L'_t \times K'} (K' = 8,192$  denotes the size of the image vocabulary). Then, for each masked image token, we sample its value with the highest probability within the image codebook and take the corresponding probability as the confidence in the timestep  $t$ . For image tokens that have already been decoded, we set their confidence as  $-\infty$  to prevent them from participating in the re-masking step.

**3. Mask Schedule.** We use a cosine sampling schedule to determine the number of tokens to re-mask

at the timestep  $t$ . Specifically,

$$k_t = \left\lceil \cos \frac{\pi t}{2T} \cdot L'_t \right\rceil, \quad (4)$$

where  $T$  is the total number of timesteps, and  $k_t$  is the number of tokens to re-mask at timestep  $t$ .

**4. Remask.** After determining the number of re-masked tokens using the masking schedule, we select the re-masked image tokens with a top- $k$  rule according to each token’s confidence obtained in the step 2 (Sample stage).

After predefined  $T$  decoding timesteps, all image tokens are predicted. In addition, we employ classifier-free guidance (CFG), a commonly used strategy in the field of image generation.

**Block-Wise Parallel Sampling for Image Understanding.** Unlike image generation, which produces image tokens, image understanding predicts text tokens. Following LLaDA (Nie et al., 2025) and MMAADA (Yang et al., 2025), we adopt a semi-autoregressive strategy. Concretely, starting from a fully masked text sequence, we partition the sequence into multiple blocks. *Within each block we perform parallel token prediction, while across blocks we decode sequentially in order.* While this design can enrich output details (e.g., MMAADA), it also makes the results highly sensitive to the sampling steps and the overall generation length. In the extreme case—exemplified by MMAADA—where each step predicts only two tokens, the semi-autoregressive procedure effectively degenerates to standard next-token prediction. Moreover, a major drawback of block-wise inference is inefficiency: the semi-autoregressive procedure always generates the full predefined length in a next-block manner, even though the model often terminates its response earlier. This mismatch leads to substantial redundant computation. To mitigate this, we introduce an early stopping strategy, which halts inference immediately once the current block has been completed and an `</answer>` token is detected, thereby reducing unnecessary steps and improving efficiency.

### 3.3.2. Acceleration Sampling via Max Logit-based Cache

Compared to AR or hybrid AR-Diffusion models, although Lumina-DiMOO could reduce generation steps by parallel sampling, each step is significantly more costly due to bidirectional attention. Note that we cannot just excessively force fewer steps to compensate for the cost, because this will introduce compounding decoding error (Park et al., 2025; Liu et al., 2025a) and degrade the generation quality. Therefore, it is crucial to improve the computational efficiency of each step.

Autoregressive models can be losslessly accelerated through KV-Cache. Although the bidirectional attention prohibits Lumina-DiMOO from this desideratum, we can leverage the idea of caching to achieve lossy acceleration. It turns out that the representations remain stable across steps for most tokens (Ma et al., 2025; Liu et al., 2025d; Wu et al., 2025a; Liu et al., 2025c). Given this, we can safely skip the computation of these tokens and directly reuse the representations in the previous step. The key challenge

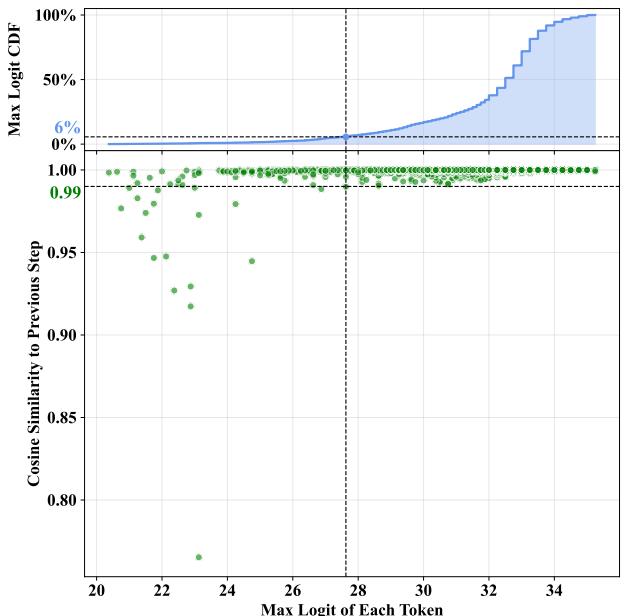


Figure 4: Example of token logits statistics, illustrating that tokens with high maximal logit tend to have stable representations.

**Table 2: Detailed Hyperparameter and Configuration of the Training Recipe Across Different Stages.**

| Hyperparameters      | Stage-I<br>(Pre-Training) | Stage-II<br>(Mid-Training)                | Stage-III<br>(Supervised Fine-Tuning) | Stage-IV<br>(Self-GRPO)                   |
|----------------------|---------------------------|---|---------------------------------------|---|
| Learning Rate        | $2.0 \times 10^{-4}$      | $2.0 \times 10^{-4}$                      | $2.0 \times 10^{-5}$                  | $3.0 \times 10^{-6}$                      |
| LR Scheduler         | Constant                  | Constant                                  | Constant                              | Constant                                  |
| Weight Decay         | 0.1                       | 0.1                                       | 0.1                                   | 0.1                                       |
| Gradient Norm Clip   | 1.0                       | 1.0                                       | 1.0                                   | 1.0                                       |
| Optimizer            |                           | AdamW ( $\beta_1 = 0.9, \beta_2 = 0.95$ ) |                                       | AdamW ( $\beta_1 = 0.9, \beta_2 = 0.99$ ) |
| Batch Size           | 1,024                     | 512                                       | 512                                   | 48  |
| Training GPUs        | 64×A800                   | 64×A800                                   | 64×A800                               | 8×H20                                     |
| Gen. Resolution      | 256→512                   | 1024 (512 for I2I)                        | 1024 (512 for I2I)                    | 1024                                      |
| Arbitrary Resolution | ✓                         | ✓   | ✓                                     | ✗   |
| Under. Resolution    | 256→512                   | Dynamical & Native<br>512~1024            | Dynamical & Native<br>512~1024        | 1024                                      |
| Arbitrary Resolution | ✓                         | ✓   | ✓                                     | ✗   |

then becomes accurately identifying these tokens. In experiments, we find that for a token in a step, if its maximal logit is high, then the logits tend to be highly similar to those in the previous step. Figure 4 shows an example, where logits of tokens with top 94% maximal logit have over 0.99 cosine similarity. In view of this, we use the maximal logit as the proxy to identify reusable tokens.

Specifically, we use a hyperparameter `cache_ratio`  $\in [0, 1]$  to denote the ratio of reused tokens. In a step where we decide to reuse previous representations, we select tokens with top  $\text{cache\_ratio} \times 100\%$  maximal logit as the reused tokens, while the remaining tokens will be computed. We only feed the tokens to compute into the unmasking network. While computing bidirectional attention, the K and V representations of tokens to reuse are approximated by those used in the previous step. In sampling, the logits of tokens to reuse are also approximated by those in the previous step.

Another problem is which step to reuse previous representations. We use two hyperparameters `warmup_ratio` and `refresh_interval` to decide, similar to existing works (Ma et al., 2025; Liu et al., 2025d; Wu et al., 2025a; Liu et al., 2025c). In the beginning  $\text{warmup\_ratio} \times 100\%$  steps, we compute all tokens to avoid error from inaccurate estimation due to the poor context. Moreover, we compute all tokens every `refresh_interval` steps to alleviate the error accumulation. These mechanisms could reduce the approximation error and allow flexible tuning of efficiency-quality trade-offs.

## 4. Training Pipeline

The training pipeline comprises four stages, with details of each stage outlined in Table 2. Notably, the Self-GRPO stage is specifically designed for Lumina-DiMOO, capitalizing primarily on the discrete diffusion mechanism and the unified generation and understanding model.

### 4.1. Stage-I: Multi-Modal Pre-Training for Image-Text Alignment

The multi-modal pre-training stage serves as a crucial bridge to transition Lumina-DiMOO from a unimodal text model to a proficient multi-modal model. The core goals of this stage are to cultivate visual capability and to align text and visual representations. To achieve this, we design a unified input format where text-image pairs are concatenated into a single sequence formatted as:

<| startoftext |> {text tokens} <| endoftext |> <| IMAGE |> {image tokens} <| /IMAGE |>

Here, `<| startoftext |>` and `<| endoftext |>` are the begin-of-sequence and end-of-sequence tokens defined in the original text tokenizer. *During training, we employ a random masking strategy, where portions of text and image tokens are masked (red area indicates tokens that can be masked), and Lumina-DiMOO learns to predict them based on unmasked tokens.* To address the challenges of learning complexity associated with long visual token sequences, we introduce a progressive training schedule. The training begins with low-resolution (arbitrary resolution around  $256 \times 256$ ,  $\sim 256$  tokens), then advances to medium-resolution (arbitrary resolution around  $512 \times 512$ ,  $\sim 1024$  tokens).

#### 4.2. Stage-II: Mid-Training for Diverse Tasks

In contrast to typical unified model training, we introduce an additional mid-training stage designed to achieve two goals: first, to integrate a diverse suite of image-to-image tasks into Lumina-DiMOO, and second, to enhance its comprehension of specialized visual data. The image-to-image tasks include image editing, subject-driven generation, controllable generation, style transfer (using a reference image), and multi-view generation, to name a few. Concurrently, the model’s enhanced understanding extends to complex visual formats such as tables, charts, user interfaces, mathematical equations, and geometric structures. *Unlike Stage-I training, this stage focuses solely on calculating the loss for the target image in text-to-image and image-to-image tasks, or the target text in image understanding tasks.*

**Efficient Mid-Training.** The nature of image-to-image tasks, which typically process two or more images, results in substantially longer token sequences compared to single-image tasks such as text-to-image generation and image understanding. This will result in low training efficiency. To address this issue, we set the image resolution for image-to-image tasks to 512. In contrast, for text-to-image tasks, a higher resolution of 1024 is adopted to better capture finer details. For image understanding tasks, we implement a dynamic resolution strategy: maintaining the original image resolution within 512 to 1024, downscaling images exceeding 1024 to 1024, and upscaling those below 512 to 512.

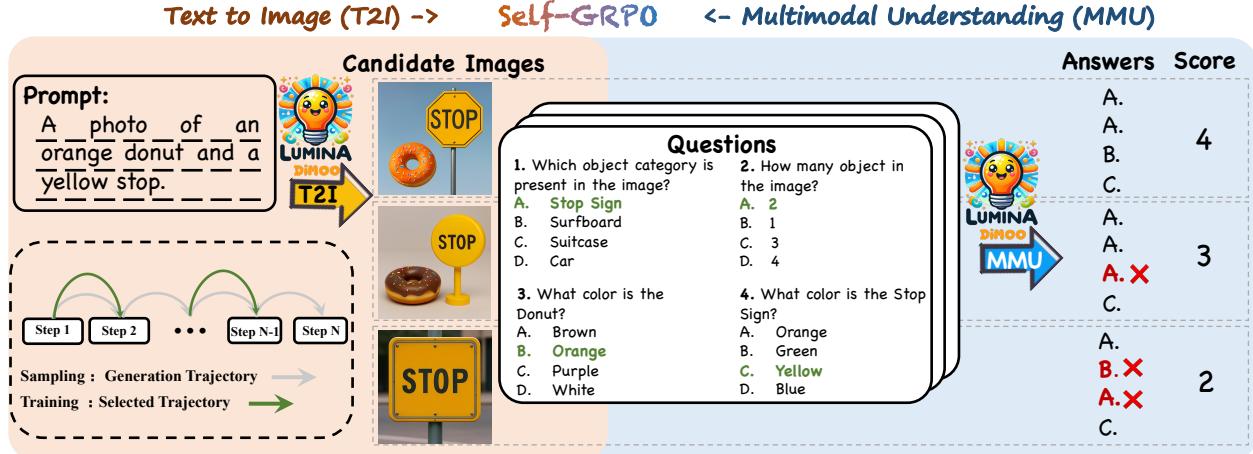
#### 4.3. Stage-III: Supervised Fine-Tuning for Instruction Following

In the supervised fine-tuning stage, the primary objective is to enhance two key aspects of Lumina-DiMOO: its ability to align with user instructions and the overall quality of its multi-modal generation and understanding. To achieve these objectives, we construct a large collection of high-quality `<System Prompt, User Prompt, Answer>` triples. *During training, the system prompt and user prompt remain unchanged, while the tokens in the answer are masked and the loss is computed independently.* The processing of image resolution in this stage is consistent with that in Stage II.

#### 4.4. Stage-IV: Self-Improving via GRPO

Finally, to fully leverage the unified nature of generation and understanding, we propose Self-GRPO, a self-improving reinforcement learning framework that jointly optimizes text-to-image (T2I) generation and multi-modal understanding (MMU). Unlike prior work that relies solely on answer-level MMU supervision (e.g., UniRL (Mao et al., 2025)) or ignores generation-inference alignment (e.g., UniGRPO (Yang et al., 2025)), Self-GRPO integrates structured semantic feedback and ensures trajectory-consistent training, as shown in the lower left of Figure 5.

The GRPO (Guo et al., 2025) strategy requires computing the outputs of the old policy  $\pi_{\theta_{old}}$  and then optimizing the current policy model  $\pi_{\theta}$ . Lumina-DiMOO supports high-resolution ( $1024 \times 1024$ )



**Figure 5: Overview of the Proposed Self-GRPO Framework.** Self-GRPO unifies text-to-image (T2I) generation and multi-modal understanding (MMU) under trajectory-consistent reinforcement learning.

image generation with image sequences of length  $L = 4096$ , while unified T2I and MMU tasks further increase the sequence length. Computing both  $\pi_{\theta_{old}}$  and  $\pi_\theta$  while storing the corresponding activations and gradients imposes a substantial memory burden. Following UniRL (Mao et al., 2025), we eliminate the old policy  $\pi_{\theta_{old}}$  to reduce memory consumption. At each training step, given a prompt  $p$ , we sample  $G$  candidate images as token sequences  $\{x^{(g)}\}_{g=1}^G$  (each of length  $L$ ) from the current policy  $p_\theta$ . Given a set of questions  $\{q_n\}_{n=1}^N$ , the model then answers each  $q_n$  conditioned on the generated image  $x^{(g)}$  to obtain per-sample T2I and MMU losses,  $\ell_{\text{T2I}}^{(g)}$  and  $\ell_{\text{MMU}}^{(g)}$ . Combining these, we optimize the reward-weighted objective:

$$L(\theta) = - \sum_{g=1}^G w^{(g)} \left( \ell_{\text{T2I}}^{(g)} + \ell_{\text{MMU}}^{(g)} \right) + \beta \text{KL}\left(p_\theta \parallel p_\theta^{\text{ref}}\right). \quad (5)$$

Rewards  $r^{(g)}$  are defined as the number of correct answers across  $\{q_n\}$  and are normalized with a softmax temperature  $\alpha$ :

$$w^{(g)} = \frac{\exp(\alpha(r^{(g)} - \bar{r}))}{\sum_{j=1}^G \exp(\alpha(r^{(j)} - \bar{r}))}, \quad \bar{r} = \frac{1}{G} \sum_{j=1}^G r^{(j)}. \quad (6)$$

Reinforcement learning involves two distinct processes: output sampling and reward updating, where the latter follows the sampling trajectory to assign rewards and compute gradients accordingly. Unlike autoregressive MLLMs, Lumina-DiMOO performs multi-step forward passes and re-masking during image generation. Consequently, it is necessary to design sophisticated strategies to preserve trajectory consistency. Since the primary content can be generated in early timesteps during T2I generation (Chang et al., 2022), we propose a step trajectory following strategy to improve memory efficiency. Specifically, Self-GRPO retains the complete sampling trajectory but computes gradients only from the model outputs at selected timesteps  $\mathcal{T}_{\text{sel}}$ . The T2I log-likelihood is defined as:

$$\ell_{\text{T2I}}^{(g)} = \frac{1}{|\mathcal{T}_{\text{sel}}|} \sum_{t \in \mathcal{T}_{\text{sel}}} \log p_\theta \left( x_t^{(g)} \mid x_{<t}^{(g)}, p \right). \quad (7)$$

To evaluate the MMU capability of the model, we compute the average log-likelihood of  $N$  predicted answers, where each answer  $y_n^{(g)}$  is generated conditioned on the corresponding question  $q_n$  and image tokens  $x^{(g)}$ :

$$\ell_{\text{MMU}}^{(g)} = \frac{1}{N} \sum_{n=1}^N \log p_\theta \left( y_n^{(g)} \mid x^{(g)}, q_n \right). \quad (8)$$

Self-GRPO therefore unifies vision and language under a trajectory-consistent framework. By combining KL-regularized policy updates, memory-efficient training, and multi-modal reward supervision, it closes the training loop between generation and understanding.

## 5. Data Construction

**Stage-I: Pre-Training Data.** We collect approximately 80 million high-quality text-image pairs, sourced from diverse and reliable datasets, including 30 million pairs from re-captioned public collections (i.e., LAION-400M ([Schuhmann et al., 2021](#)) for image understanding pre-training and CC12M ([Changpinyo et al., 2021](#))) and 50 million from Lumina-Image 2.0 ([Qin et al., 2025](#)), Lumina-mGPT 2.0 ([Xin et al., 2025a](#)) for image generation pre-training.

**Stage-II: Mid-Training Data.** In this stage, we incorporate an additional 3 million images from several challenging domains: MMTable ([Zheng et al., 2024](#)) and TinyChart ([Zhang et al., 2024](#)) for table and chart comprehension, AutoGeo ([Huang et al., 2025c](#)) and MAVIS ([Zhang et al., 2025](#)) for understanding math equations and geometric structures, and MultiUI ([Liu et al., 2025b](#)) for user interface parsing, which are all captioned using Qwen2.5-VL ([Bai et al., 2025](#)). For image-to-image tasks, data is sourced from several datasets, including UltraEdit ([Zhao et al., 2024](#)), OmniEdit ([Wei et al., 2024](#)), OminiControl ([Tan et al., 2024](#)), and Lumina-mGPT 2.0 ([Xin et al., 2025a](#)).

**Stage-III: Supervised Fine-Tuning Data.** For image understanding, we construct a high-quality dataset of 15 million samples, combining 2 million from MAmmoTH-VL dataset ([Guo et al., 2024](#)) and 13 million from InternVL-2.5-SFT dataset ([Chen et al., 2024a](#)). For visual generation, we utilize a total of 15 million samples, aggregated from Lumina-Image 2.0 ([Qin et al., 2025](#)) (selecting only the highest quality data), Blip3o-60k ([Chen et al., 2025a](#)), ShareGPT-4o-Image ([Chen et al., 2025b](#)), and additional in-house synthetic data. For image-to-image tasks, we incorporate data for *Subject-Driven Generation*, *Controllable Generation*, *Dense Prediction*, and *Style Transfer*, each comprising 200K examples from VisualCloze ([Li et al., 2025b](#)). Additionally, there are 500K instruction-guided *Image Editing* samples from UniWorld ([Lin et al., 2025](#)) and 200K examples for *Low-Level Vision* tasks from Lumina-OmniLV ([Pu et al., 2025](#)), focusing on enhancements like super-resolution, dehazing, and denoising, etc. However, we find that Lumina-DiMOO perform poorly on low-level tasks. For *Multi-View Generation*, we use data consistent with Lumina-mGPT ([Liu et al., 2024a](#)).

**Stage-IV: Self-GRPO Data.** In this stage, only text prompt data is required. We utilize prompt from the subset of GenRef ([Zhuo et al., 2025](#)), which resemble GenEval’s prompt templates. From each prompt, we extract (entity, relation, value) triples using DSG ([Cho et al., 2024](#)) method. These triples are then used to craft single-choice questions for semantic alignment supervision in Self-GRPO. To generate distractor options, we maintain global candidate pools for entities, relations, quantities, and colors. For each question, distractors are selected to be semantically close to the correct answer, ensuring that the resulting QA tasks are both challenging and informative.

## 6. Evaluation

### 6.1. Performance of Text-to-Image Generation

For evaluating text-to-image generation capabilities, we conduct evaluations using five publicly available benchmarks—GenEval ([Ghosh et al., 2024](#)), DPG ([Hu et al., 2024](#)), UniGenBench ([Wang et al., 2025b](#)), OneIG-EN ([Chang et al., 2025](#)), and TIIF ([Wei et al., 2025](#)). These benchmarks offer a comprehensive framework to measure the model’s proficiency in generating high-quality, semantically

**Table 3: Evaluation of Text-to-Image Generation on GenEval (Ghosh et al., 2024) Benchmark.** “Und.” and “Gen.” denote “understanding” and “generation”, respectively. We highlight the **best** and the **second** results.

| Method                               | Architecture         | # Params. | Single Obj. | Two Obj.    | Counting    | Colors      | Position    | Attribute   | Overall ↑   |
|--------------------------------------|----------------------|-----------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Gen. Only                            |                      |           |             |             |             |             |             |             |             |
| LlamaGen (Sun et al., 2024a)         | AR                   | 0.8B      | 0.71        | 0.34        | 0.21        | 0.58        | 0.07        | 0.04        | 0.32        |
| PixArt- $\alpha$ (Chen et al., 2023) | Diffusion            | 0.6B      | 0.98        | 0.50        | 0.44        | 0.80        | 0.08        | 0.07        | 0.48        |
| SDv2.1 (Rombach et al., 2022)        | Diffusion            | 0.9B      | 0.98        | 0.51        | 0.44        | 0.85        | 0.07        | 0.17        | 0.50        |
| Emu3-Gen (Wang et al., 2024c)        | AR                   | 8B        | 0.98        | 0.71        | 0.34        | 0.81        | 0.17        | 0.21        | 0.54        |
| SDXL (Podell et al., 2024)           | Diffusion            | 2.6B      | 0.98        | 0.74        | 0.39        | 0.85        | 0.15        | 0.23        | 0.55        |
| DALL-E 3 (Betker et al., 2023)       | -                    | -         | 0.96        | 0.87        | 0.47        | 0.83        | 0.43        | 0.45        | 0.67        |
| SD3-Medium (Esser et al., 2024)      | Diffusion            | 2B        | <b>0.99</b> | <b>0.94</b> | 0.72        | 0.89        | 0.33        | 0.60        | 0.74        |
| FLUX.1 [Dev] (Labs, 2024)            | Diffusion            | 12B       | 0.98        | 0.81        | 0.74        | 0.79        | 0.22        | 0.45        | 0.66        |
| OmniGen (Xiao et al., 2024)          | Diffusion            | 3.8B      | 0.98        | 0.84        | 0.66        | 0.74        | 0.40        | 0.43        | 0.68        |
| SANA-1.5 (Xie et al., 2025b)         | Diffusion            | 4.8B      | <b>0.99</b> | 0.85        | 0.77        | 0.87        | 0.34        | 0.54        | 0.72        |
| Lumina-mGPT 2.0 (Xin et al., 2025a)  | AR                   | 7B        | <b>0.99</b> | 0.87        | 0.44        | 0.85        | 0.44        | 0.54        | 0.69        |
| Und. and Gen.                        |                      |           |             |             |             |             |             |             |             |
| SEED-X (Ge et al., 2024)             | AR                   | 17B       | 0.97        | 0.58        | 0.26        | 0.80        | 0.19        | 0.14        | 0.49        |
| Show-o (Xie et al., 2025c)           | AR+Discrete Diff.    | 1.3B      | 0.95        | 0.52        | 0.49        | 0.82        | 0.11        | 0.28        | 0.53        |
| Janus (Wu et al., 2024a)             | AR                   | 1.3B      | 0.97        | 0.68        | 0.30        | 0.84        | 0.46        | 0.42        | 0.61        |
| D-DiT (Li et al., 2024b)             | Discrete Diff.+Diff. | 2B        | 0.97        | 0.80        | 0.54        | 0.76        | 0.32        | 0.50        | 0.65        |
| Transfusion (Zhou et al., 2025)      | AR+Diff.             | 7B        | -           | -           | -           | -           | -           | -           | 0.63        |
| TokenFlow-XL (Liu et al., 2024b)     | AR                   | 14B       | 0.95        | 0.60        | 0.41        | 0.81        | 0.16        | 0.24        | 0.55        |
| Chameleon (Team, 2024)               | AR                   | 7B        | -           | -           | -           | -           | -           | -           | 0.39        |
| Janus-Pro (Chen et al., 2025c)       | AR                   | 7B        | <b>0.99</b> | 0.89        | 0.59        | <b>0.90</b> | <b>0.79</b> | 0.66        | 0.80        |
| GPT-4o (OpenAI, 2025)                | -                    | -         | <b>0.99</b> | 0.92        | <b>0.85</b> | <b>0.92</b> | 0.75        | 0.61        | <b>0.84</b> |
| BLIP3-o (Chen et al., 2025a)         | AR+Diff.             | 8B        | -           | -           | -           | -           | -           | -           | 0.80        |
| BAGEL (Deng et al., 2025)            | AR+Diff.             | 14B       | <b>0.99</b> | <b>0.94</b> | <b>0.81</b> | 0.88        | 0.64        | 0.63        | 0.82        |
| Uniworld-V1 (Lin et al., 2025)       | AR+Diff.             | 20B       | <b>0.99</b> | 0.93        | 0.79        | 0.89        | 0.49        | <b>0.70</b> | 0.80        |
| OmniGen2 (Wu et al., 2025b)          | AR+Diff.             | 7B        | <b>1.0</b>  | <b>0.95</b> | 0.64        | 0.88        | 0.55        | <b>0.76</b> | 0.80        |
| MMaDA (Yang et al., 2025)            | Discrete Diff.       | 8B        | <b>0.99</b> | 0.76        | 0.61        | 0.84        | 0.20        | 0.37        | 0.63        |
| <b>Lumina-DiMOO (Ours)</b>           | Discrete Diff.       | 8B        | <b>1.0</b>  | <b>0.94</b> | <b>0.85</b> | 0.89        | <b>0.85</b> | <b>0.76</b> | <b>0.88</b> |
| <b>Lumina-DiMOO w/ Self-GRPO</b>     | Discrete Diff.       | 8B        | 1.0         | 0.96(+2%)   | 0.87(+2%)   | 0.95(+6%)   | 0.85        | 0.82(+6%)   | 0.91(+3%)   |

consistent images from textual prompts. Additionally, we perform qualitative comparisons with state-of-the-art models to complement these automatic evaluation metrics, ensuring a robust analysis of performance.

### 6.1.1. Quantitative Results

**Evaluation Results on GenEval Benchmark.** Table 3 presents a comparison of model performance on the GenEval (Ghosh et al., 2024) benchmark, which is designed to evaluate object-centric T2I generation using compositional prompts with diverse object attributes. Under identical evaluation settings, Lumina-DiMOO achieves an impressive 88% overall score, surpassing both specialized generation models (FLUX.1 [Dev]: 82%, Lumina-mGPT 2.0: 69%) and unified models (Janus-Pro: 80%, BAGEL: 82%, and GPT-4o: 84%), thereby setting new SOTA results. This success is largely attributed to Lumina-DiMOO’s enhanced capability in managing positional relationships and binding attributes. Compared to MMaDA, which features a similar architecture, Lumina-DiMOO demonstrates a substantial overall improvement of 25% (88% vs. 63%). This significant advancement underscores the potential of the discrete diffusion architecture for practical applications. In addition, we validate the effectiveness of the proposed Self-GRPO on GenEval. Following the Self-GRPO training stage, Lumina-DiMOO demonstrates an overall improvement of 3% on GenEval, with even more pronounced enhancements in “Colors” and “Attribute”.

**Evaluation Results on DPG Benchmark.** Table 4 presents a performance comparison on the DPG (Hu et al., 2024) benchmark, which includes 1,065 dense prompts designed for a detailed evaluation of various aspects of prompt adherence. Overall, Lumina-DiMOO achieves an impressive overall score

**Table 4: Evaluation of Text-to-Image Generation on DPG (Hu et al., 2024) Benchmark.** “Und.” and “Gen.” denote “understanding” and “generation”, respectively. We highlight the **best** and the **second** results. “†” means the MMA DA results are evaluated by ourselves.

| Method                                  | Architecture   | # Params. | Global | Entity | Attribute | Relation | Other | Overall ↑    |
|---|----------------|-----------|--------|--------|-----------|----------|-------|--------------|
| <b>Gen. Only</b>                        |                |           |        |        |           |          |       |              |
| PixArt- $\alpha$ (Chen et al., 2023)    | Diffusion      | 0.6B      | 74.97  | 79.32  | 78.60     | 82.57    | 76.96 | 71.11        |
| Lumina-Next (Zhuo et al., 2024)         | Diffusion      | 2B        | 82.82  | 88.65  | 86.44     | 80.53    | 81.82 | 74.63        |
| SDXL (Podell et al., 2024)              | Diffusion      | 2.6B      | 83.27  | 82.43  | 80.91     | 86.76    | 80.41 | 74.65        |
| Emu3-Gen (Wang et al., 2024c)           | AR             | 8B        | 85.21  | 86.68  | 86.84     | 90.22    | 83.15 | 80.60        |
| DALL-E 3 (Betker et al., 2023)          | -              | -         | 90.97  | 89.61  | 88.39     | 90.58    | 89.83 | 83.50        |
| SD3-Medium (Esser et al., 2024)         | Diffusion      | 2B        | 87.90  | 91.01  | 88.83     | 80.70    | 88.68 | 84.08        |
| FLUX.1 [Dev] (Labs, 2024)               | Diffusion      | 12B       | 74.35  | 90.00  | 88.96     | 90.87    | 88.33 | 83.84        |
| OmniGen (Xiao et al., 2024)             | Diffusion      | 3.8B      | 87.90  | 88.97  | 88.47     | 87.95    | 83.56 | 81.16        |
| SANA-1.5 (Xie et al., 2025b)            | Diffusion      | 4.8B      | -      | -      | -         | -        | -     | 85.00        |
| Lumina-mGPT 2.0 (Xin et al., 2025a)     | AR             | 7B        | -      | 88.94  | 88.08     | 91.70    | -     | 84.30        |
| <b>Und. and Gen.</b>                    |                |           |        |        |           |          |       |              |
| Show-o (Xie et al., 2025c)              | AR+Diff.       | 1.3B      | -      | -      | -         | -        | -     | 67.48        |
| TokenFlow-XL (Liu et al., 2024b)        | AR             | 14B       | 78.72  | 79.22  | 81.29     | 85.22    | 71.20 | 73.38        |
| Janus (Wu et al., 2024a)                | AR             | 1.3B      | 82.33  | 87.38  | 87.70     | 85.46    | 86.41 | 79.68        |
| Janus-Pro (Chen et al., 2025c)          | AR             | 7B        | 86.90  | 88.90  | 89.40     | 89.32    | 89.48 | 84.19        |
| GPT-4o (OpenAI, 2025)                   | -              | -         | 88.89  | 88.94  | 89.84     | 92.63    | 90.96 | 85.15        |
| BLIP3-o (Chen et al., 2025a)            | AR+Diff.       | 8B        | -      | -      | -         | -        | -     | 81.60        |
| BAGEL (Deng et al., 2025)               | AR+Diff.       | 14B       | 88.94  | 90.37  | 91.29     | 90.82    | 88.67 | 85.07        |
| Uniworld-V1 (Lin et al., 2025)          | AR+Diff.       | 20B       | 83.64  | 88.39  | 88.44     | 89.27    | 87.22 | 81.38        |
| OmniGen2 (Wu et al., 2025b)             | AR+Diff.       | 7B        | 88.81  | 88.83  | 90.18     | 89.37    | 90.27 | 83.57        |
| MMA DA <sup>†</sup> (Yang et al., 2025) | Discrete Diff. | 8B        | 77.81  | 78.48  | 81.74     | 84.79    | 63.20 | 69.97        |
| <b>Lumina-DiMOO (Ours)</b>              | Discrete Diff. | 8B        | 81.46  | 92.08  | 88.98     | 94.31    | 82.00 | <b>86.04</b> |

**Table 5: Evaluation of Text-to-Image Generation on UniGenBench (Wang et al., 2025b).** This leadborder is evaluated and maintained by the Tencent Hunyuan team. “Und.” and “Gen.” denote “understanding” and “generation”, respectively. We highlight the **best** and the **second** results.

| Model                             | Style | World | Know. | Attribute | Action | Relation. | Logic. | Grammar | Compound | Layout | Text         | Overall |
|-----------------------------------|-------|-------|-------|-----------|--------|-----------|--------|---------|----------|--------|--------------|---------|
| <b>Gen. Only</b>                  |       |       |       |           |        |           |        |         |          |        |              |         |
| SDXL (Podell et al., 2024)        | 87.40 | 72.63 | 44.34 | 34.22     | 44.92  | 9.55      | 47.33  | 26.68   | 29.85    | 0.57   | 39.75        |         |
| Playground 2.5 (Li et al., 2024a) | 89.50 | 76.11 | 52.78 | 42.68     | 51.52  | 16.59     | 53.21  | 35.44   | 37.13    | 1.15   | 45.61        |         |
| Emu3 (Wang et al., 2024c)         | 86.80 | 77.06 | 51.39 | 40.11     | 49.75  | 19.32     | 52.94  | 36.86   | 44.78    | 1.15   | 46.02        |         |
| DALL-E-3 (Betker et al., 2023)    | 95.06 | 93.51 | 75.97 | 69.83     | 78.06  | 48.18     | 68.07  | 70.60   | 66.67    | 25.86  | 69.18        |         |
| SD-3.5-Large (Esser et al., 2024) | 88.60 | 88.92 | 68.59 | 62.17     | 69.80  | 32.27     | 58.96  | 58.76   | 69.03    | 32.76  | 62.99        |         |
| FLUX.1-dev (Labs, 2024)           | 83.90 | 88.92 | 67.84 | 62.17     | 67.26  | 30.91     | 60.96  | 47.04   | 71.83    | 32.18  | 61.30        |         |
| <b>Und. and Gen.</b>              |       |       |       |           |        |           |        |         |          |        |              |         |
| Janus-flow (Ma et al., 2024)      | 86.20 | 62.50 | 47.97 | 43.35     | 50.00  | 21.14     | 60.29  | 45.10   | 46.46    | 0.86   | 46.39        |         |
| BLIP3-o (Chen et al., 2025a)      | 92.80 | 80.22 | 63.89 | 63.97     | 66.50  | 39.55     | 68.45  | 53.74   | 68.47    | 1.15   | 59.87        |         |
| Janus-Pro (Chen et al., 2025c)    | 90.80 | 86.71 | 67.74 | 64.26     | 68.40  | 37.05     | 64.44  | 62.11   | 72.01    | 2.59   | 61.61        |         |
| BAGEL (Deng et al., 2025)         | 90.20 | 85.60 | 67.74 | 61.98     | 70.69  | 30.23     | 66.44  | 58.12   | 76.49    | 7.76   | 61.53        |         |
| UniWorld-V1 (Lin et al., 2025)    | 91.10 | 82.91 | 70.62 | 67.21     | 67.13  | 38.41     | 63.77  | 54.51   | 69.03    | 26.44  | 63.11        |         |
| OmniGen2 (Wu et al., 2025b)       | 91.90 | 86.39 | 72.12 | 62.83     | 68.27  | 32.50     | 59.89  | 56.31   | 71.64    | 29.02  | 63.09        |         |
| MMADA (Yang et al., 2025)         | 82.40 | 56.65 | 48.39 | 37.83     | 50.25  | 17.95     | 55.75  | 32.35   | 30.22    | 1.15   | 41.35        |         |
| <b>Lumina-DiMOO (Ours)</b>        | 89.70 | 90.03 | 81.62 | 71.12     | 78.43  | 45.45     | 70.45  | 73.32   | 82.84    | 25.57  | <b>71.12</b> |         |

of 86.04, surpassing all previous models and demonstrating its superior prompt-following abilities. In particular, Lumina-DiMOO excels in interpreting prompts that involve entities and relationships,

**Table 6: Evaluation of Text-to-Image Generation on OneIG-EN (Chang et al., 2025) Benchmark.** The overall score is the average of the five dimensions. “Und.” and “Gen.” denote “understanding” and “generation”, respectively. We highlight the **best** and the **second** results.

| Method                         | Architecture   | # Params. | Alignment    | Text         | Reasoning    | Style        | Diversity    | Overall ↑    |
|--------------------------------|----------------|-----------|--------------|--------------|--------------|--------------|--------------|--------------|
| <b>Gen. Only</b>               |                |           |              |              |              |              |              |              |
| SD 1.5 (Rombach et al., 2022)  | Diffusion      | 0.9B      | 0.565        | 0.010        | 0.207        | 0.383        | <b>0.429</b> | 0.319        |
| SDXL (Podell et al., 2024)     | Diffusion      | 2.6B      | 0.688        | 0.029        | 0.237        | 0.332        | 0.296        | 0.316        |
| FLUX.1 [Dev] (Labs, 2024)      | Diffusion      | 12B       | <b>0.786</b> | <b>0.523</b> | <b>0.253</b> | 0.368        | 0.238        | <b>0.434</b> |
| SANA-1.5 (Xie et al., 2025b)   | Diffusion      | 4.8B      | 0.765        | 0.069        | 0.217        | <b>0.401</b> | 0.216        | 0.334        |
| <b>Und. and Gen.</b>           |                |           |              |              |              |              |              |              |
| Janus-Pro (Chen et al., 2025c) | AR             | 7B        | 0.553        | 0.001        | 0.139        | 0.276        | <b>0.365</b> | 0.267        |
| BLIP3-o (Chen et al., 2025a)   | AR+Diff.       | 8B        | 0.711        | 0.013        | 0.223        | 0.361        | 0.229        | 0.307        |
| BAGEL (Deng et al., 2025)      | AR             | 14B       | 0.769        | 0.244        | 0.173        | 0.367        | 0.251        | 0.361        |
| <b>Lumina-DiMOO (Ours)</b>     | Discrete Diff. | 8B        | <b>0.816</b> | <b>0.551</b> | <b>0.276</b> | <b>0.400</b> | 0.232        | <b>0.455</b> |

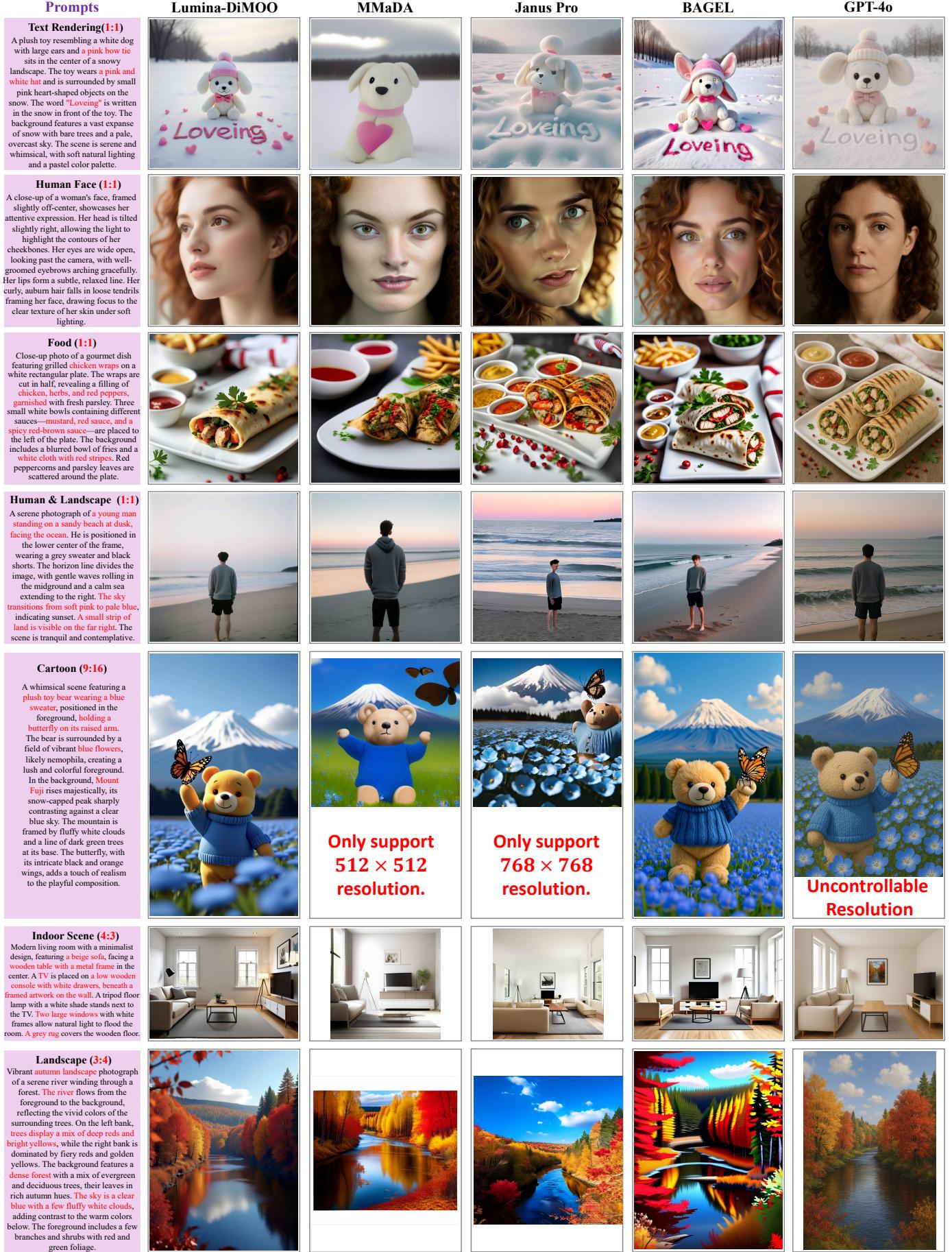
**Table 7: Evaluation of Text-to-Image Generation on TIIF (Wei et al., 2025) Benchmark.** “Und.” and “Gen.” denote “understanding” and “generation”, respectively. We highlight the **best** and the **second** results.

| Method                            | Overall ↑    | Basic Following |              |              |              |              |              |              |              | Advanced Following |              |                      |              |                       |              |                      |              | Designer     |              |              |              |              |
|-----------------------------------|--------------|-----------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------------|--------------|----------------------|--------------|-----------------------|--------------|----------------------|--------------|--------------|--------------|--------------|--------------|--------------|
|                                   |              | Avg             |              | Attribute    |              | Relation     |              | Reasoning    |              | Avg                |              | Attribute + Relation |              | Attribute + Reasoning |              | Relation + Reasoning |              | Style        | Text         |              |              |              |
|                                   |              | short           | long         | short        | long         | short        | long         | short        | long         | short              | long         | short                | long         | short                 | long         | short                | long         | short        | long         | Real World   |              |              |
| <b>Gen. Only</b>                  |              |                 |              |              |              |              |              |              |              |                    |              |                      |              |                       |              |                      |              |              |              |              |              |              |
| SD 3 (Esser et al., 2024)         | 67.46        | 66.09           | 78.32        | 77.75        | <b>83.33</b> | 79.83        | 82.07        | 78.82        | 71.07        | 74.07              | 61.46        | 59.56                | 61.07        | 64.07                 | 68.84        | 70.34                | 50.96        | 57.84        | 66.67        | <b>76.67</b> | <b>59.83</b> | 20.83        |
| PixArt-Σ (Chen et al., 2023)      | 62.00        | 58.12           | 70.66        | 75.25        | 69.33        | 78.83        | 75.07        | 77.32        | 67.57        | 69.57              | 57.65        | 49.50                | 65.20        | 56.57                 | 66.96        | 61.72                | 66.59        | 54.59        | <b>83.33</b> | 70.00        | 1.83         | 1.83         |
| Lumina-Next (Zhuo et al., 2024)   | 50.93        | 52.46           | 64.58        | 66.08        | 56.83        | 59.33        | 67.57        | 71.82        | 69.32        | 67.07              | 44.75        | 45.63                | 51.44        | 43.20                 | 51.09        | 59.72                | 44.72        | 54.46        | 70.00        | 66.67        | 0.00         | 0.83         |
| SANA 1.5 (Xie et al., 2025b)      | 67.15        | 65.73           | <b>79.66</b> | 77.08        | 79.83        | 77.83        | <b>85.57</b> | <b>83.57</b> | 73.57        | 69.82              | 61.50        | 60.67                | 65.32        | 56.57                 | 69.96        | <b>73.09</b>         | 62.96        | 65.84        | <b>80.00</b> | <b>80.00</b> | 17.83        | 15.83        |
| FLUX.1 [dev] (Labs, 2024)         | <b>71.09</b> | <b>71.78</b>    | <b>83.12</b> | <b>78.65</b> | <b>87.05</b> | <b>83.17</b> | <b>87.25</b> | <b>80.39</b> | 75.01        | 72.39              | <b>65.79</b> | <b>68.54</b>         | <b>67.07</b> | <b>73.69</b>          | <b>73.84</b> | <b>73.34</b>         | <b>69.09</b> | <b>71.59</b> | 66.67        | 66.67        | 43.83        | <b>52.83</b> |
| <b>Und. and Gen.</b>              |              |                 |              |              |              |              |              |              |              |                    |              |                      |              |                       |              |                      |              |              |              |              |              |              |
| Show-o (Xie et al., 2025c)        | 59.72        | 58.86           | 73.08        | 75.83        | 74.83        | 79.83        | 78.82        | 78.32        | 65.57        | 69.32              | 53.67        | 50.38                | 60.95        | 56.82                 | 68.59        | 68.96                | 66.46        | 56.22        | 63.33        | 66.67        | 3.83         | 2.83         |
| Janus-Pro-7B (Chen et al., 2025c) | 66.50        | 65.02           | 79.33        | 78.25        | 79.33        | <b>82.33</b> | 78.32        | 73.32        | <b>80.32</b> | <b>79.07</b>       | 59.71        | 58.82                | 66.07        | 56.20                 | 70.46        | 70.84                | <b>67.22</b> | 59.97        | 60.00        | 70.00        | 28.83        | 33.83        |
| <b>Lumina-DiMOO (Ours)</b>        | <b>71.27</b> | <b>68.53</b>    | 75.5         | <b>78.29</b> | 77.00        | 81.50        | 74.20        | 78.21        | <b>75.29</b> | <b>75.16</b>       | <b>70.49</b> | <b>68.33</b>         | <b>75.99</b> | <b>72.85</b>          | <b>70.73</b> | 67.30                | 65.79        | <b>69.23</b> | 73.33        | 60.00        | <b>59.28</b> | <b>41.63</b> |

outperforming all other models in the comparison. In addition, we evaluate MMA DA under the same settings on the DPG benchmark, its performance proves to be subpar, with a score of just 69.97.

**Evaluation Results on UniGenBench Leaderboard.** UniGenBench (Wang et al., 2025b) is a newly unified benchmark for text-to-image generation that integrates diverse prompt themes with a comprehensive suite of fine-grained evaluation criteria. **The leaderboard is evaluated and maintained by the Tencent Hunyuan team.** We extract evaluation results for various models from the leaderboard, as presented in Table 5. Lumina-DiMOO ranks among the top performers across all metrics, notably excelling in the “Layout” and “Attribute” categories, and surpassing all other models in overall evaluation scores. For a detailed evaluation across 27 dimensions, please refer to [Leaderboard Link](#).

**Evaluation Results on OneIG-EN Benchmark.** Table 6 reports the quantitative results on the OneIG-EN (Chang et al., 2025) benchmark, a comprehensive evaluation framework specifically designed to assess the fine-grained performance of text-to-image models across multiple dimensions. For a fair comparison, we compute the overall score by averaging the results across all dimensions. Overall, Lumina-DiMOO achieves the highest average score and significantly surpasses other unified models such as BAGEL and Janus Pro, showcasing its robust capability in general-purpose image generation. Notably, it ranks first in the Alignment, Text, and Reasoning categories, highlighting its exceptional ability to follow prompts accurately and perform advanced reasoning.



**Figure 6: Qualitative Comparison on Text-to-Image Generation.** We compare Lumina-DiMOO, MMaDA, Janus Pro, BAGEL, and GPT-4o across various common scenarios. Notably, MMaDA and Janus Pro lack support for arbitrary resolution generation.



Figure 7: Qualitative Results on Text-guided Image Inpainting and Extrapolation.

**Evaluation Results on TIIF Benchmark.** Table 7 shows the performance comparison on the TIIF testmini (Wei et al., 2025), a benchmark designed to systematically assess the ability of text-to-image models to interpret and follow complex textual instructions. Overall, Lumina-DiMOO secures the second position, surpassed only by FLUX.1 [dev], a result that underscores its robust instruction-following capabilities.

### 6.1.2. Qualitative Results

**Qualitative Comparisons.** We conduct a qualitative comparison among Lumina-DiMOO, MMaDA, Janus-Pro 7B, BAGEL, and GPT-4o. As illustrated in Figure 6, Lumina-DiMOO consistently generates images of significantly higher quality compared to MMaDA and Janus-Pro 7B. Moreover, Lumina-DiMOO demonstrates exceptional flexibility in supporting any resolution, whereas MMaDA (limited to a fixed resolution of  $512 \times 512$ ), Janus-Pro (restricted to  $768 \times 768$ ), and GPT-4o (featuring uncontrollable resolution) show clear limitations in this aspect.

**Table 8: Evaluation of Controllable Generation Ability on Graph-200K (Li et al., 2025b) benchmark.** The methods that train a specialist for each task are marked as gray color. Except for these methods, we highlight the **best** and the **second** results.

| Condition | Method                              | Controllability |                   | Quality          |                 |                    | Text Consistency |
|-----------|-------------------------------------|-----------------|-------------------|------------------|-----------------|--------------------|------------------|
|           |                                     | F1 $\uparrow$   | RMSE $\downarrow$ | FID $\downarrow$ | SSIM $\uparrow$ | MAN-IQA $\uparrow$ | MUSIQ $\uparrow$ |
| Canny     | ControlNet (Zhang et al., 2023)     | 0.13            | -                 | 46.06            | 0.34            | 0.31               | 45.45            |
|           | OminiControl (Tan et al., 2024)     | 0.47            | -                 | 29.58            | 0.61            | 0.44               | 61.40            |
|           | OmniGen (Xiao et al., 2024)         | 0.43            | -                 | 51.58            | 0.47            | 0.47               | 62.66            |
|           | Lumina-mGPT (Liu et al., 2024a)     | 0.16            | -                 | 85.03            | 0.23            | 0.48               | 70.78            |
|           | OneDiffusion (Le et al., 2025)      | 0.39            | -                 | 32.76            | 0.55            | 0.46               | 59.99            |
|           | Lumina-mGPT 2.0 (Xin et al., 2025a) | 0.49            | -                 | 30.89            | 0.54            | 0.42               | 63.18            |
| Depth     | <b>Lumina-DiMOO (Ours)</b>          | 0.38            | -                 | <b>30.35</b>     | <b>0.65</b>     | 0.41               | <b>64.11</b>     |
|           | ControlNet (Zhang et al., 2023)     | -               | 23.70             | 36.83            | 0.41            | 0.44               | 60.17            |
|           | OminiControl (Tan et al., 2024)     | -               | 21.44             | 36.23            | 0.52            | 0.44               | 60.18            |
|           | OmniGen (Xiao et al., 2024)         | -               | 15.07             | 86.08            | 0.26            | 0.49               | 64.90            |
|           | Lumina-mGPT (Liu et al., 2024a)     | -               | 15.71             | 61.44            | 0.34            | 0.38               | 69.72            |
|           | OneDiffusion (Le et al., 2025)      | -               | <b>10.35</b>      | 39.03            | <b>0.49</b>     | <b>0.49</b>        | 60.49            |
|           | Lumina-mGPT 2.0 (Xin et al., 2025a) | -               | 17.42             | <b>36.52</b>     | <b>0.49</b>     | 0.39               | 59.52            |
|           | <b>Lumina-DiMOO (Ours)</b>          | -               | <b>8.31</b>       | <b>34.38</b>     | <b>0.62</b>     | <b>0.40</b>        | 63.72            |

**Image Inpainting and Extrapolation.** Due to the mask training paradigm of Lumina-DiMOO, it naturally supports text-guided image inpainting and extrapolation without requiring any fine-tuning. Examples are presented in Figure 7. As shown on the top of the figure, given an input image with partial mask, Lumina-DiMOO is able to seamlessly inpaint the masked areas. Besides, Lumina-DiMOO is capable of extrapolating the original image horizontally or vertically based on the given text prompt (as illustrated in the third and fourth rows). These examples clearly highlight the inherent advantages of Lumina-DiMOO over Diffusion, AR or hybrid AR-Diffusion models in downstream applications.

## 6.2. Performance of Image-to-Image Generation

We primarily evaluate our model using the Graph-200K (Li et al., 2025b) and ImgEdit (Ye et al., 2025b) benchmarks. The Graph-200K benchmark enables comprehensive assessment across multiple tasks, including controllable generation, subject-driven generation, and style transfer, with an image style serving as a reference. In contrast, the ImgEdit benchmark focuses on evaluating the model’s proficiency in image editing tasks, such as adding, replacing, and removing objects, as well as changing the image style based on text descriptions.

### 6.2.1. Quantitative Results

**Evaluation Results of Controllable Generation.** For controllable generation, we evaluate the models based on three criteria: controllability (measured through F1-Score and RMSE), visual quality (measured through FID (Heusel et al., 2017), SSIM, MAN-IQA (Yang et al., 2022), and MUSIQ (Ke et al., 2021)), and text consistency (measured through CLIP-Score (Radford et al., 2021)), following the evaluation approach of Graph-200K (Li et al., 2025b). As shown in Table 8, Lumina-DiMOO exhibits comparable controllability to other leading universal generative models (OmniGen, OneDiffusion, and Lumina-mGPT 2.0), while achieving superior visual quality and text consistency. Notably, when compared to specialized methods (ControlNet and OminiControl), Lumina-DiMOO performs on par with the best results and even outperforms them on the depth-to-image task.

**Table 9: Evaluation of Style Transfer and Subject-Driven Generation Abilities on Graph-200K (Li et al., 2025b) Benchmark and Image Editing Ability on ImgEdit (Ye et al., 2025b) Benchmark.** Image editing metrics are evaluated by GPT-4.1. The methods that train a specialist for each task are marked as gray color. Except for these methods, we highlight the **best** and the **second** results.

| Method                              | Style Transfer (Img Reference) |                              | Subject-Driven Generation |                   |                   | Image Editing  |                    |                   |                  |
|-------------------------------------|--------------------------------|------------------------------|---------------------------|-------------------|-------------------|----------------|--------------------|-------------------|------------------|
|                                     | Text Alignment $\uparrow$      | Style Consistency $\uparrow$ | DINOv2 $\uparrow$         | CLIP-I $\uparrow$ | CLIP-T $\uparrow$ | Add $\uparrow$ | Replace $\uparrow$ | Remove $\uparrow$ | Style $\uparrow$ |
| OminiControl (Tan et al., 2024)     | -                              | -                            | 73.17                     | 87.70             | 33.53             | -              | -                  | -                 | -                |
| InstantStyle (Wang et al., 2024a)   | 0.27                           | 0.60                         | -                         | -                 | -                 | -              | -                  | -                 | -                |
| AnyEdit (Yu et al., 2025a)          | -                              | -                            | -                         | -                 | -                 | 3.18           | 2.47               | 2.23              | 2.85             |
| OmniGen (Xiao et al., 2024)         | <b>0.27</b>                    | <b>0.52</b>                  | 67.73                     | 83.43             | 34.53             | 3.47           | 2.94               | 2.43              | 4.19             |
| Lumina-mGPT (Liu et al., 2024a)     | -                              | -                            | 60.94                     | 70.63             | 30.16             | -              | -                  | -                 | -                |
| OneDiffusion (Le et al., 2025)      | -                              | -                            | 73.88                     | 86.91             | <b>34.80</b>      | -              | -                  | -                 | -                |
| Lumina-mGPT 2.0 (Xin et al., 2025a) | -                              | -                            | <b>76.60</b>              | <b>87.37</b>      | 33.90             | -              | -                  | -                 | -                |
| BAGEL (Deng et al., 2025)           | -                              | -                            | -                         | -                 | -                 | <b>3.56</b>    | 3.30               | 2.62              | <b>4.49</b>      |
| UniWorld-V1 (Lin et al., 2025)      | -                              | -                            | -                         | -                 | -                 | <b>3.82</b>    | <b>3.47</b>        | <b>3.24</b>       | <b>4.21</b>      |
| <b>Lumina-DiMOO (Ours)</b>          | <b>0.32</b>                    | <b>0.53</b>                  | <b>80.57</b>              | <b>89.36</b>      | <b>34.72</b>      | <b>3.82</b>    | <b>3.83</b>        | <b>2.76</b>       | <b>4.18</b>      |

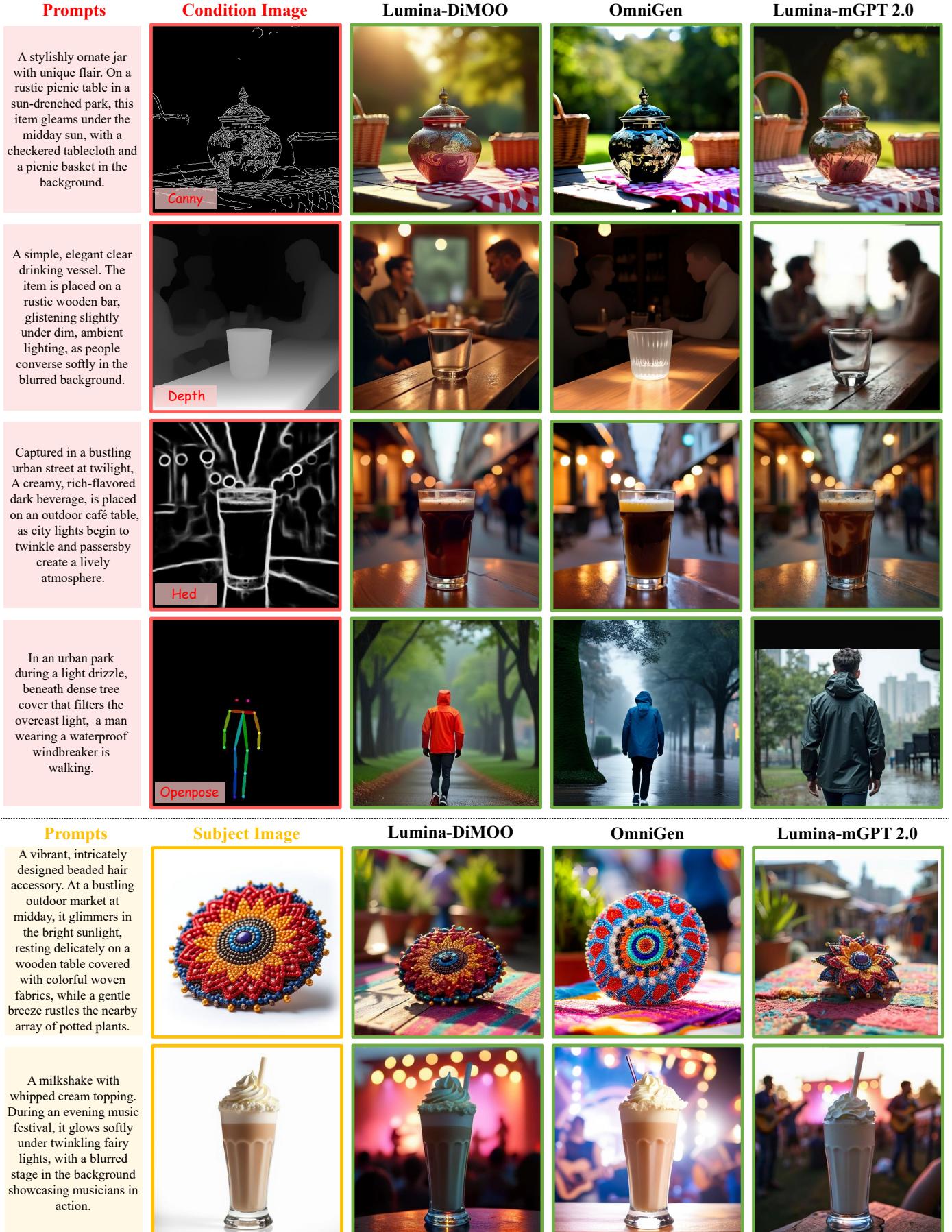
**Evaluation Results of Style Transfer.** In the style transfer task, where an image serves as the style reference (as shown in Figure 10), we measure text consistency and style alignment using the CLIP (Radford et al., 2021) models on the Graph-200K benchmark. As presented in Table 9, Lumina-DiMOO exceeds OmniGen by 5% and 1% in text alignment and style consistency, respectively. Furthermore, when compared to InstantStyle, a specialized model, Lumina-DiMOO also achieves a 5% improvement in text alignment, with a 7% decrease in style alignment.

**Evaluation Results of Subject-Driven Generation.** We also evaluate the models on Graph-200K specifically for subject-driven image generation and report semantic alignment using the DINOv2 (Oquab et al., 2023), CLIP-I (Radford et al., 2021), and CLIP-T (Radford et al., 2021) scores. As shown in Table 9, Lumina-DiMOO consistently demonstrates notable improvements across all these metrics. For example, compared to the previous SOTA model Lumina-mGPT 2.0, Lumina-DiMOO achieves improvements of 3.97%, 1.99%, and 0.82% in these three scores.

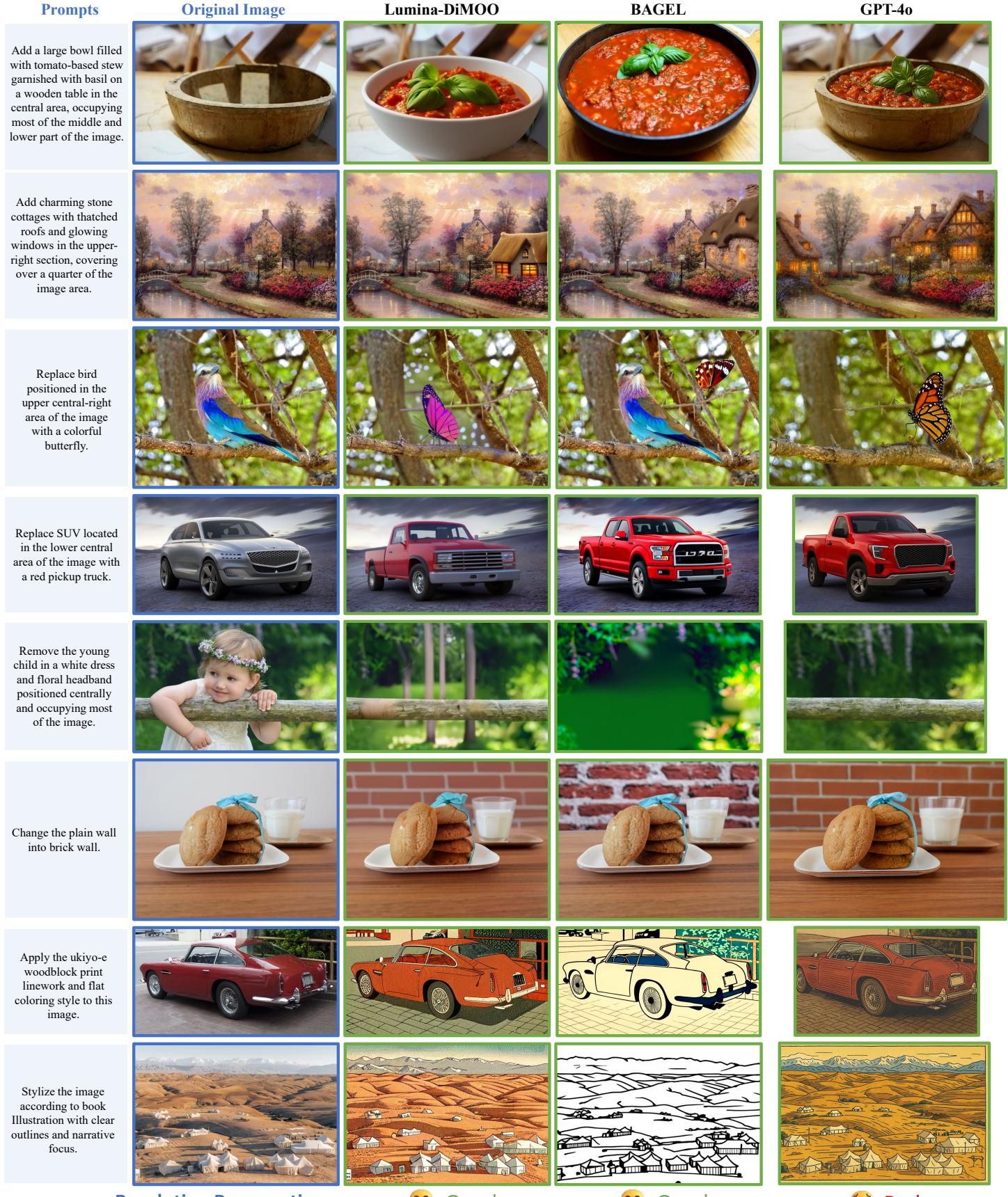
**Evaluation Results of Image Editing.** Table 9 presents the results on the ImgEdit (Ye et al., 2025b) benchmark. We primarily focus on testing four common editing tasks: adding, removing, replacing, and changing style (text guidance). The evaluation metrics included instruction adherence, image-editing quality, and detail preservation, each scored on a scale from 1 to 5. These scores are assessed by GPT-4.1. Lumina-DiMOO performs exceptionally well in adding and replacing objects, surpassing other models (e.g., OmniGen, BAGEL, and UniWorld-V1). However, there remains room for improvement in tasks involving removing objects and changing styles.

### 6.2.2. Qualitative Results

We conduct a qualitative comparison on multiple image-to-image tasks between Lumina-DiMOO, OmniGen, Lumina-mGPT 2.0, BAGEL and GPT-4o. **1) Controllable Generation:** As illustrated at the top of Figure 8, Lumina-DiMOO demonstrates precise generation capabilities under various control conditions. In contrast, OmniGen exhibits notable shortcomings in depth-to-image tasks, while Lumina mGPT 2.0 shows clear limitations in pose-to-image scenarios. **2) Subject-Driven Generation:** As depicted at the bottom of Figure 8, Lumina-DiMOO excels in both object preservation and adherence to text instructions. **3) Style Transfer:** Lumina-DiMOO holds a distinct advantage over OmniGen in preserving the original image during style transfer, while also demonstrating superior comprehension and application of the reference image’s style, as shown in Figure 10. **4) Image Editing:** As shown in Figure 9, Lumina-DiMOO performs well in tasks such as adding, removing, and



**Figure 8: Qualitative Comparison on Controllable and Subject-Driven Generation Tasks.** We compare Lumina-DiMOO, BAGEL, and GPT-4o in object addition, removal, replacement, as well as background and style modification. Lumina-DiMOO performs well in terms of instruction adherence and resolution preservation.



Resolution Preservation

😊 Good

😊 Good

😡 Bad

**Figure 9: Qualitative Comparison on Image Editing Tasks.** We compare Lumina-DiMOO, BAGEL, and GPT-4o in object addition, removal, replacement, as well as background and style modification. Lumina-DiMOO performed well in terms of instruction adherence and resolution preservation.



**Figure 10: Qualitative Comparison on Style Transfer Task.** Lumina-DiMOO completely outperforms OmniGen, which performs worse in most cases.

replacing objects, as well as changing image backgrounds and styles. It also excels in preserving the resolution of the original image. BAGEL, on the other hand, falls slightly behind in object removal and style modification tasks. While GPT-4o demonstrates strong performance in editing tasks, there is still significant room for improvement in maintaining the resolution of the original image.

### 6.3. Performance of Image Understanding

To evaluate our model’s multimodal understanding capabilities, we evaluate it on five widely recognized vision-language benchmarks: POPE (Li et al., 2023b), MME-P (Yin et al., 2024), MMBench (Liu et al., 2024f), SEED (Li et al., 2023a), and MMMU (Yue et al., 2024). Together, these benchmarks provide a concise yet comprehensive testbed that encompasses perception, cognition, and multimodal reasoning. They also possess strong discriminative power for ranking state-of-the-art models, ensuring a thorough assessment of performance.

#### 6.3.1. Quantitative Results

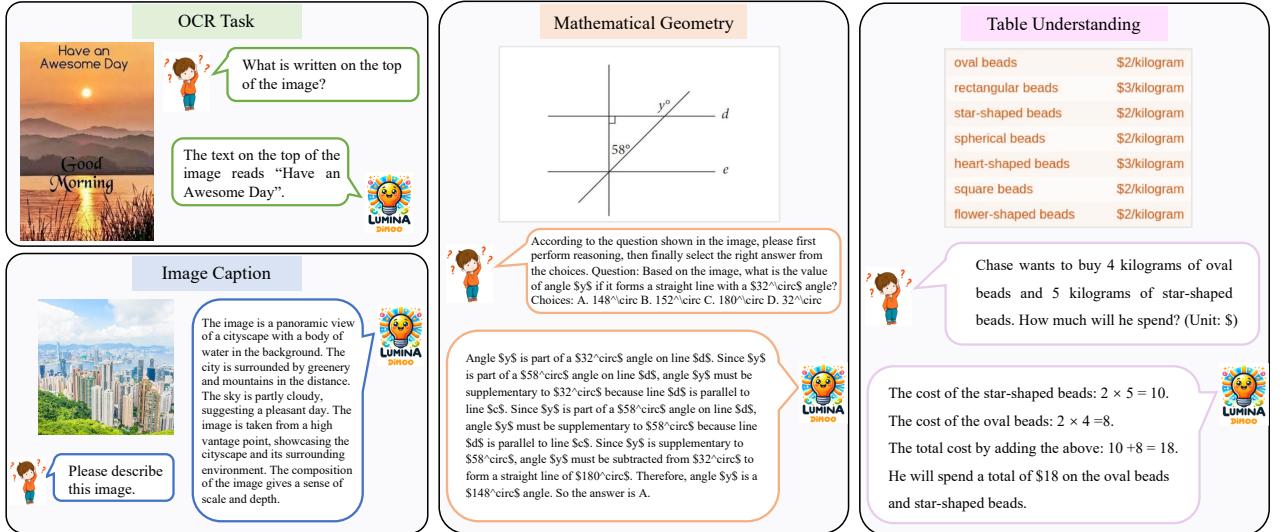
We conduct a comprehensive comparison of Lumina-DiMOO with leading open-source multimodal models, covering both specialized models for visual understanding and general-purpose unified models. The results of visual understanding are detailed in Table 10. Compared with dedicated understanding-only models such as LLaVA-v1.5, Qwen-VL-Chat, Emu3-Chat, and InstructBLIP, our model achieves superior results across all benchmarks, despite being trained in a unified framework. When compared to other unified models (e.g., Show-o, VILA-U, Janus-Pro, BAGEL), Lumina-DiMOO consistently demonstrates outstanding performance, achieving leading scores in the POPE (87.4), SEED (83.1), and MMMU (58.6) benchmarks. In particular, Lumina-DiMOO significantly outperforms MMaDA (with similar architecture) across all benchmarks, highlighting the potential of a unified discrete diffusion architecture in bridging generation and understanding tasks.

#### 6.3.2. Qualitative Results

In addition to delivering comparable performance on various image understanding benchmarks, we visualize its capabilities across several understanding tasks, including OCR, captioning, mathematical geometry, and table understanding, as shown in Figure 11. The visualization results demonstrate

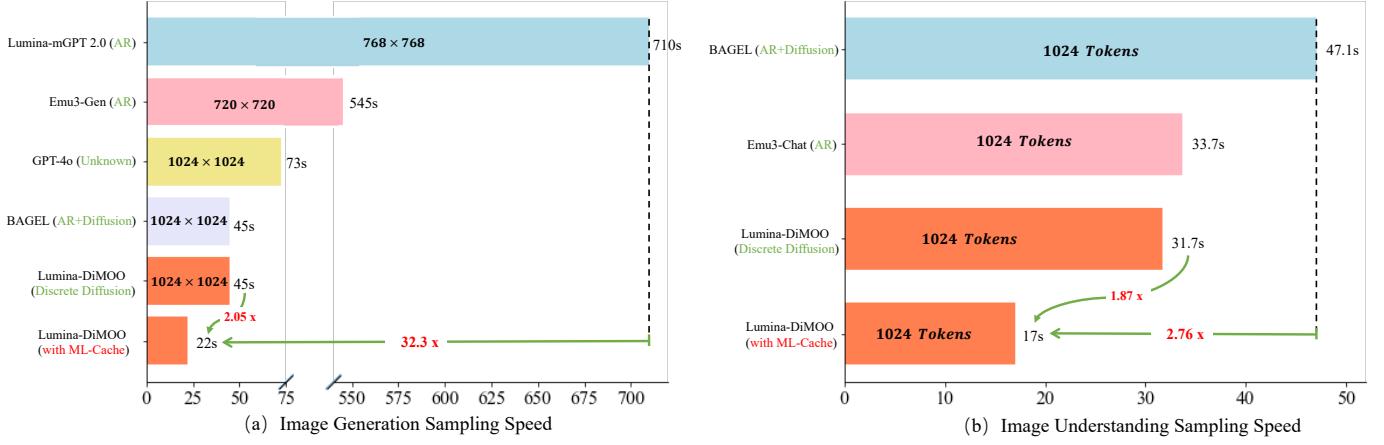
**Table 10: Comparison with State-of-the-arts on Multimodal Understanding Benchmarks.** “Und.” and “Gen.” denote “understanding” and “generation”, respectively. We highlight the **best** and the **second** results.

| Model                               | Architecture          | # Params. | POPE↑       | MME-P↑        | MMB↑        | SEED↑       | MMMU↑       |
|-------------------------------------|-----------------------|-----------|-------------|---------------|-------------|-------------|-------------|
| <i>Und. Only</i>                    |                       |           |             |               |             |             |             |
| MobileVLM (Chu et al., 2023)        | AR                    | 1.4B      | 84.5        | 1196.2        | 53.2        | -           | -           |
| MobileVLM-V2 (Chu et al., 2024)     | AR                    | 1.4B      | 84.3        | 1302.8        | 57.7        | -           | -           |
| LLaVA-Phi (Zhu et al., 2024)        | AR                    | 2.7B      | 85.0        | 1335.1        | 59.8        | -           | -           |
| LLaVA (Liu et al., 2024e)           | AR                    | 7B        | 76.3        | 809.6         | 38.7        | 33.5        | -           |
| LLaVA-v1.5 (Liu et al., 2023)       | AR                    | 7B        | 85.9        | 1510.7        | 64.3        | 58.6        | 35.4        |
| InstructBLIP (Dai et al., 2023)     | AR                    | 7B        | -           | -             | 36.0        | 53.4        | -           |
| Qwen-VL-Chat (Bai et al., 2023)     | AR                    | 7B        | -           | 1487.5        | 60.6        | 58.2        | -           |
| IDEFICS-9B (Laurençon et al., 2023) | AR                    | 8B        | -           | -             | 48.2        | -           | -           |
| Emu3-Chat (Wang et al., 2024c)      | AR                    | 8B        | 85.2        | 1244          | 58.5        | 68.2        | 31.6        |
| InstructBLIP (Dai et al., 2023)     | AR                    | 13B       | 78.9        | 1212.8        | -           | -           | -           |
| <i>Und. and Gen.</i>                |                       |           |             |               |             |             |             |
| Show-o (Xie et al., 2025c)          | AR+Discrete Diff.     | 1.3B      | 80.0        | 1097.2        | -           | -           | 26.7        |
| D-Dit (Li et al., 2024b)            | Discrete Diff.+Diff.  | 2.0B      | 84.0        | 1124.7        | -           | -           | -           |
| TokenFlow-XL (Qu et al., 2024)      | AR                    | 13B       | 86.8        | 1545.9        | 68.9        | 68.7        | 38.7        |
| VILA-U (Wu et al., 2025c)           | AR                    | 7B        | 85.8        | 1401.8        | -           | 59.0        | -           |
| Chameleon (Team, 2024)              | AR                    | 7B        | -           | -             | -           | -           | 22.4        |
| Janus-Pro (Chen et al., 2025c)      | AR                    | 7B        | 87.4        | 1567.1        | 79.2        | 72.1        | 41.0        |
| BLIP3-o (Chen et al., 2025a)        | AR+Diff.              | 8B        | -           | 1682.6        | 83.5        | 77.5        | 50.6        |
| BAGEL (Deng et al., 2025)           | AR+Diff.              | 14B       | -           | 1687.0        | 85.0        | -           | 55.3        |
| Uniworld-V1 (Lin et al., 2025)      | AR+Diff.              | 20B       | -           | -             | 83.5        | -           | 58.6        |
| OmniGen2 (Wu et al., 2025b)         | AR+Diff.              | 7B        | -           | -             | 79.1        | -           | 53.1        |
| MMaDA (Yang et al., 2025)           | Discrete Diff.        | 8B        | 86.1        | 1410.7        | 68.5        | 64.2        | 30.2        |
| <b>Lumina-DiMOO (Ours)</b>          | <b>Discrete Diff.</b> | <b>8B</b> | <b>87.4</b> | <b>1534.2</b> | <b>84.5</b> | <b>83.1</b> | <b>58.6</b> |



**Figure 11: Visualization of OCR, Image Caption, Mathematical Geometry, and Table Understanding Tasks.**

that Lumina-DiMOO excels in text recognition accuracy, detailed image description, mathematical geometry, and the rational analysis of tables.



**Figure 12: Comparison of Sampling Time on Text-to-Image and Image Understanding Tasks.** For the text-to-image, Lumina-mGPT 2.0 generates images at a resolution of 768, Emu3 produces images at 720 resolution, while the other models utilize a 1024 resolution. In the image understanding task, all models consistently generate 1024 tokens.

## 7. Ablation and Extension

### 7.1. Analysis of Sampling Speed

**Comparison with AR and Hybrid AR-Diffusion Models.** For text-to-image generation, we set 64 sampling steps for Lumina-DiMOO. As illustrated in Figure 12(a), Lumina-DiMOO’s sampling efficiency is several times higher than that of the AR models (Lumina-mGPT 2.0 and Emu3), and its sampling speed is roughly on par with BAGEL. If the sampling steps for Lumina-DiMOO are further reduced, its speed advantage becomes even more pronounced. On the other hand, for image understanding, we configure the block length to 256 and the number of sampling steps to 128 for Lumina-DiMOO. We find that the sampling speed advantage for image understanding is reduced, as shown in Figure 12(b). This is because text generation occurs in a block-wise manner, unlike image generation, which employs a single global decoding step. As a result, its speed is affected by both the number of blocks and the number of steps. Thus, the speed improvement in image understanding is not as substantial as in image generation. These observations highlight the promising potential of Lumina-DiMOO.

**Effect of ML-Cache.** Under identical settings, we evaluate the sampling time of Lumina-DiMOO with and without the ML-Cache strategy, as shown in Figure 12. The results demonstrate that ML-Cache significantly enhances the sampling process, boosting efficiency by a factor of 2.05 for text-to-image generation and 1.87 for image understanding. However, a minor drawback is that ML-Cache increases GPU usage, for example, from 38.9 GB to 45.9 GB when generating a  $1024 \times 1024$  image.

### 7.2. Effect of Initialization From LLaDA

In this work, Lumina-DiMOO builds upon LLaDA’s text capabilities and expands its functionalities in multi-modal generation and understanding, consistent with the paradigm of previous works (Wu et al., 2024b; Yang et al., 2025). However, previous studies (Xin et al., 2025a) has also found that training from scratch without prior textual knowledge does not impact performance in autoregressive multimodal generation. To explore this further, we conduct additional ablation experiments to assess the necessity of inheriting text capabilities within the discrete diffusion framework.

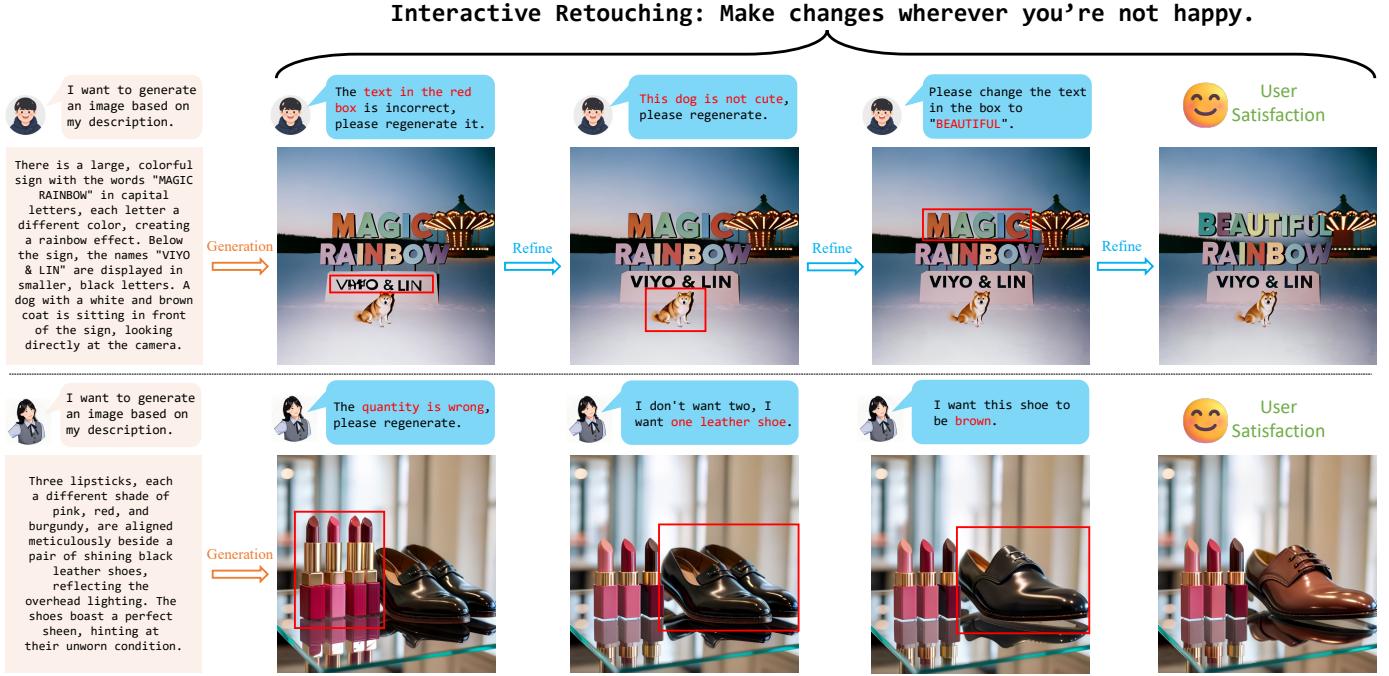


Figure 13: Illustration of Interactive Retouching. Users can repeatedly modify specific areas while keeping the surrounding regions unchanged until they reach satisfaction.

**Experimental Setup.** We design a comparative experiment with two key components: (1) *initializing Lumina-DiMOO using LLaDA-SFT* (Nie et al., 2025) and (2) *training Lumina-DiMOO from scratch*. For model training, we randomly select a dataset from Section 5 (Stage-III), consisting of 5M samples for visual generation and 5M samples for visual understanding. To conserve training resources, we omit the pre-training stage and directly engage in supervised fine-tuning on 256 resolution. For a fair comparison, we keep all training and evaluation parameters constant, except for model initialization.

**Results.** In our evaluation of generation and understanding capabilities, we observe that training from scratch falls short in generating images or performing image understanding, often resulting in very large gradient norm during training. In contrast, initializing from LLaDA effectively supports both image generation and understanding, clearly demonstrating its superiority without requiring quantitative comparison.

### 7.3. Bringing New Ideas to Image Generation: Interactive Retouching

Interactive Retouching stands out as a unique feature of Lumina-DiMOO, adept at allowing users to pinpoint specific areas for refinement through precise annotations, as illustrated in Figure 13. Lumina-DiMOO achieves this due to its unique discrete diffusion modeling paradigm, which allows it to mask user-annotated areas for regeneration. This process preserves all information in areas outside of the user’s annotations, a feat previously unachievable with diffusion or AR generative models. While many commercial editing models exist, such as GPT-4o and Nana-Banana, none offer a 100% guarantee of maintaining unchanged content outside the user’s specified annotations.

## 8. Conclusion

In this paper, we introduce Lumina-DiMOO, a unified foundation model for multi-modal understanding and generation. Lumina-DiMOO delivers top-tier performance on standard multi-modal generation and

understanding benchmarks and stands out with its ultra-fast sampling speed and unique interactive retouching features. To further advance research in multi-modal and discrete diffusion research, we have open-sourced Lumina-DiMOO to the research community.

While Lumina-DiMOO currently demonstrates strong capabilities in image generation and understanding, our goal is to evolve it into a more comprehensive multi-modal model. In the future, we aim to expand Lumina-DiMOO to seamlessly integrate video, audio, and more modalities. Achieving this will require substantial research, particularly in creating a versatile tokenizer for diverse data types, designing the model architecture that processes temporal information, and developing advanced training techniques. Let us look forward to a more powerful Lumina-DiMOO.

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