Unsupervised Post-Training for Multi-Modal LLM Reasoning via GRPO

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Abstract

Improving Multi-modal Large Language Models (MLLMs) in the post-training stage typically relies on supervised fine-tuning (SFT) or reinforcement learning (RL). However, these supervised methods require expensive and manually annotated multi-modal data-an ultimately unsustainable resource. While recent efforts have explored unsupervised post-training, their methods are complex and difficult to iterate. In this work, we are the first to investigate the use of GRPO, a stable and scalable online RL algorithm, for enabling continual self-improvement without any external supervision. We propose MM-UPT, a simple yet effective framework for unsupervised post-training of MLLMs. MM-UPT builds upon GRPO, replacing traditional reward signals with a self-rewarding mechanism based on majority voting over multiple sampled responses. Our experiments demonstrate that MM-UPT significantly improves the reasoning ability of Qwen2.5-VL-7B (e.g., $66.3\% \rightarrow 72.9\%$ on MathVista, $62.9\% \rightarrow 68.7\%$ on We-Math), using standard dataset without ground truth labels. MM-UPT also outperforms prior unsupervised baselines and even approaches the results of supervised GRPO. Furthermore, we show that incorporating synthetic questions, generated solely by MLLM itself, can boost performance as well, highlighting a promising approach for scalable self-improvement. Overall, MM-UPT offers a new paradigm for continual, autonomous enhancement of MLLMs in the absence of external supervision. Our code is available at https://github.com/waltonfuture/MM-UPT.

1 Introduction

Multi-modal Large Language Models (MLLMs) have achieved remarkable performance on a variety of vision-language tasks, ranging from image captioning to visual reasoning [19, 21, 42, 47, 69]. By combining the language understanding capabilities of large language models (LLMs) with visual perception, MLLMs can process and reason over both textual and visual information. The dominant paradigm for improving MLLMs in the post-training stage typically involves supervised fine-tuning (SFT) and reinforcement learning (RL). However, both SFT and RL rely on large volumes of high-quality and annotated multi-modal data, such as image captions, visual reasoning traces, ground truth answers, and human preference signals. As real-world tasks grow in complexity and quantity, a critical challenge emerges: curating and annotating high-quality data at scale becomes increasingly impractical. Thus, it is essential to explore new methods for improving MLLMs, such as using synthetic and unlabeled data.

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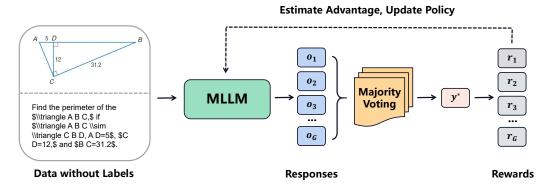


Figure 1: Overview of the MM-UPT framework. Given an unlabeled multi-modal input, the MLLM samples multiple responses, and uses majority voting to determine the pseudo-label. The MLLM is then updated via GRPO, enabling self-improvement without external supervision.

Previous works have studied the use of MLLMs themselves to generate synthetic instruction data for self-improvement through offline training techniques like SFT and DPO [5, 36–38, 55, 64]. These approaches typically involve complex pipelines with multiple stages, such as data generation, verification, and filtering, which are hard to iterate online. Fortunately, recent studies demonstrate notable success using online reinforcement learning (e.g. GRPO [34]) with verifiable rewards [6, 10, 28, 66] to enhance the reasoning capabilities of LLMs and MLLMs. A concurrent work, TTRL [71], further extends this line by applying GRPO on test-time scaling of LLMs. Thus, it is promising that online RL enables models to continuously improve, thus acquiring novel reasoning abilities that exceed corresponding base models' capacity. Motivated by these insights, we aim to investigate a fundamental and open question: Can we enable MLLMs to continually and iteratively self-improve their reasoning abilities from fully unlabeled training data without any external supervision?

To explore this question, we propose MM-UPT (Multi-Modal Unsupervised Post-Training), an easy-to-implement framework for unsupervised post-training in MLLMs. As shown in Figure 1, MM-UPT builds on GRPO [34], a stable and scalable online RL method that uses group-normalized rewards instead of explicit value functions. Unlike GRPO that relies on ground-truth labels to calculate rewards, our framework works by deriving implicit reward signals via majority voting over multiple sampled responses. In particular, majority voting aggregates multiple responses and selects the most frequent one, which has been widely used and shown effective to improve model performance [40, 45, 71]. Thus, we adopt the majority-voted answer to serve as a pseudo-label to calculate reward in our framework for unsupervised training, which encourages the model to prefer stable and high-consensus answers without any human annotated labels or external reward models.

In our experiments, we focus on the domain of multi-modal reasoning, which is widely studied and inherently challenging. We explore two key scenarios for constructing unlabeled data assuming that labels are not available: (1) using human-created questions without ground-truth labels, and (2) employing synthetic questions generated by AI models, inherently lacking ground-truth labels. The first scenario is simulated by masking the answers in standard training datasets. For the second scenario, we employ two MLLM-driven strategies: (a) generating new questions from in-context examples (including the original image, question, and answer), and (b) generating questions based solely on the image. We evaluate MM-UPT across a range of reasoning benchmarks and observe significant performance improvements over the base models (e.g., $66.3\% \rightarrow 72.9\%$ on MathVista, $62.9\% \rightarrow 68.7\%$ on We-Math using Qwen2.5-VL-7B [1]). Our method also outperforms previous baseline methods, and is even competitive with supervised GRPO, underscoring the effectiveness of MM-UPT as a self-improving training strategy in a fully unsupervised manner. Additionally, we find that models trained on unlabeled synthetic data achieve performance competitive with those trained on the original unlabeled dataset, revealing strong potential for scalable self-improvement.

Our main contributions are summarized as follows:

• We propose MM-UPT, a novel framework for unsupervised post-training of MLLMs that enables continuous self-improvement without requiring any external supervision.

- Extensive experiments on multi-modal reasoning tasks demonstrate the effectiveness of majority voting as a pseudo-reward estimation for unsupervised training.
- We investigate the use of synthetic data generated by the MLLM itself and find that training the MLLM on such data leads to notable performance gains. This reveals a promising path toward efficient and stable self-improvement in unsupervised post-training.

2 Related Works

Self Improvement. High-quality data obtained from human annotations has been shown to significantly boost the performance of LLMs across a wide range of tasks [10, 16, 29]. However, such high-quality annotated data may be exhausted in the future. This presents a substantial obstacle to the continual learning of advanced models. As a result, recent research has shifted toward self-improvement—leveraging data generated by the LLM itself without any external supervision [7, 14, 26, 38, 49, 56, 61, 71]. Several following works also explore unsupervised self-improvement in the multi-modal domain [5, 9, 36, 55, 62, 64]. Genixer [64] firstly introduces a comprehensive self-improvement pipeline including data generation and filtering for SFT. STIC [5] and SENA [37] construct preference data pairs for DPO [33] in a fully self-supervised manner. In contrast to these approaches which are complex and hard to iterate, the key distinction is that our method leverages online reinforcement learning using GRPO [10] at the post-training stage of MLLMs, which is more scalable, and supports continuous and iterative self-improvement without reliance on any external supervision. In addition, none of these previous methods focus on multi-modal reasoning tasks, which are considered challenging for current models.

Multi-modal Reasoning. Recently, the reasoning abilities of MLLMs have become a central focus of research [13, 24, 70]. In contrast to traditional LLM-based reasoning [10, 25, 54] that primarily relies on text, multi-modal approaches must both process and interpret visual inputs, significantly increasing the complexity of tasks such as geometric problem-solving and chart interpretation [2, 27, 63]. Several works in this field have sought to collect or synthesize a large scale of multi-modal reasoning data [4, 30, 35, 58]. Notably, the recent emergence of o1-like reasoning models [17] represents an initial step toward activating the slow-thinking capabilities of MLLMs, as demonstrated by several SFT-based methods, such as LLaVA-CoT [50], LLaVA-Reasoner [59], MAmmoTH-VL [11], and Mulberry [52]. Moreover, some concurrent works have further explored reinforcement learning approaches, particularly GRPO [34], in the post-training stage of MLLMs to enhance performance on multi-modal reasoning tasks [6, 28, 31, 44, 66]. While these supervised post-training methods have demonstrated promising results, our work explores a different direction by focusing on totally unsupervised post-training of MLLMs to self-improve the reasoning abilities.

3 The Framework of Multi-Modal Unsupervised Post-Training

Unlike traditional post-training techniques that require labeled data or external reward models, we propose MM-UPT (Multi-Modal Unsupervised Post-Training), a simple yet effective framework designed to operate purely on unlabeled training data. That is, the model must learn to self-improve without access to any external supervision such as ground-truth labels or additional reward models.

3.1 Problem Formulation

Firstly, we formulate the problem of unsupervised post-training for MLLMs as follows: Given a well-trained multi-modal LLM π_{θ} and a collection of unlabeled multi-modal data $Q = \{(I_i, q_i)\}_{i=1}^N$, where I_i represents an image and q_i denotes a corresponding question, our goal is to improve the model's performance without access to any ground-truth answers or external supervision signals. This setting differs significantly from conventional supervised fine-tuning (SFT), reinforcement learning with verifiable rewards (RLVR), or reinforcement learning with human feedback (RLHF), which typically rely on labeled data (I_i, q_i, y_i) or human preference data (I_i, q_i, y_i^+, y_i^-) , where y_i denotes the answer of q_i and (y_i^+, y_i^-) denotes the preference pair of q_i . In contrast, we only allow to operate in a fully unsupervised manner for this setting, leveraging only the model's own responses to generate training signals. This presents significant challenges, as the model must learn to assess and improve its own outputs without any external guidance.

Algorithm 1 MM-UPT: Multi-Modal Unsupervised Post-Training

- 1: **Input:** Current policy π_{θ} , old policy $\pi_{\theta_{old}}$, unlabeled training dataset Q, Group size G, reference model π_{ref} , clip parameter ϵ , KL penalty coefficient β , answer extractor $E(\cdot)$.
- 2: for each sample $(I,q) \sim Q$ do
- Sample group of responses: $\{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(o \mid I, q);$ // Sample multiple responses
- Extract answers: $\hat{Y} = E(O) = {\{\hat{y}_i\}_{i=1}^G}$; 4:
- 5:
- Determine majority vote: $y^* \leftarrow \arg\max_{y \in \hat{Y}} \sum_{i=1}^G \mathbb{I}[y = \hat{y}_i];$ // Select the most frequent answer Compute pseudo-rewards: $r_i \leftarrow \mathbb{I}[\hat{y}_i = y^*];$ // Reward based on majority agreement Compute advantage estimates: $\hat{A}_i \leftarrow \frac{r_i \text{mean}(\{r_1, r_2, \dots, r_G\})}{\text{std}(\{r_1, r_2, \dots, r_G\})};$ 6:
- 8:
- Compute GRPO objective: $\mathcal{J}(\theta) \leftarrow \frac{1}{G} \sum_{i=1}^{G} \frac{1}{|o_i|} \sum_{t=1}^{|o_i|} \left\{ \min \left[\gamma_{i,t}(\theta) \hat{A}_i, \operatorname{clip}\left(\gamma_{i,t}(\theta), 1-\epsilon, 1+\epsilon\right) \hat{A}_i \right] \beta \mathsf{D}_{KL}[\pi_{\theta} \| \pi_{ref}] \right\}$ where $\gamma_{i,t}(\theta) = \frac{\pi_{\theta}(o_{i,t}|I,q,o_{i,< t})}{\pi_{\theta_{\text{old}}}(o_{i,t}|I,q,o_{i,< t})};$ Update policy parameters: $\theta \leftarrow \theta \nabla_{\theta} \mathcal{J}_{GRPO}(\theta);$ 9:
- 10:
- 11:
- Update old policy: $\theta_{\text{old}} \leftarrow \theta$; 12:
- 13: **end for**
- 14: return π_{θ}

3.2 Method

To achieve this, MM-UPT introduces a self-rewarding mechanism using majority voting as pseudolabels [45] based on the online reinforcement learning. In particular, MM-UPT is built upon the GRPO algorithm [34], which is widely used in the post-training stage of multi-modal LLMs. GRPO optimizes computational efficiency by eliminating the need for a separate value model; instead, it directly utilizes group-normalized rewards to estimate advantages. Specifically, for a question q and the correlated image I from the training dataset Q, GRPO samples a group of responses $O = \{o_i\}_{i=1}^G$ from the old policy π_{old} and then optimizes the policy model by maximizing the following objective:

$$\begin{split} \mathcal{J}(\theta) &= \mathbb{E}_{(q,I) \sim Q, \{o_i\}_{i=1}^G \sim \pi_{\theta_{old}}(O|q,I)} \\ &\frac{1}{G} \sum_{i=1}^G \frac{1}{|o_i|} \sum_{t=1}^{|o_i|} \Bigg\{ \min \Bigg[\gamma_{i,t}(\theta) \hat{A}_{i,t}, \operatorname{clip}\left(\gamma_{i,t}(\theta), 1-\epsilon, 1+\epsilon\right) \hat{A}_{i,t} \Bigg] - \beta \mathbf{D}_{KL} \Big[\pi_{\theta} \| \pi_{ref} \Big] \Bigg\}, \end{split}$$

where $\gamma_{i,t}(\theta) = \frac{\pi_{\theta}(o_{i,t}|q,o_{i,< t})}{\pi_{\theta_{old}}(o_{i,t}|q,o_{i,< t})}$, π_{ref} represents the reference model, and the term D_{KL} introduces a KL divergence constraint to limit how much the model can deviate from this reference. The advantage estimate A_i measures how much better the response o_i is compared to the average response, which is computed using a group of rewards $\{r_1, r_2, \ldots, r_G\}$ for the responses in set O: $\hat{A}_i = \frac{r_i - \max\{\{r_1, r_2, \ldots, r_G\}\}}{\operatorname{std}(\{r_1, r_2, \ldots, r_G\})}$.

In the above standard GRPO formulation [10], the reward is computed in a supervised manner based on labels for each response in $O = \{o_i\}_{i=1}^G$. Shifting towards our unsupervised setting, where no ground-truth labels are available, one feasible way is to construct pseudo-labels to calculate the reward for GRPO. Motivated by [14, 45, 71], we use majority voting over the group of sampled responses O to serve as pseudo-labels. Majority voting selects the most frequent answer among the sampled responses O and has proven to be a simple yet effective technique [45, 71], making it suitable for deriving good pseudo-reward signals. Specifically, we first extract answers from the responses $O = \{o_i\}_{i=1}^G$ using an rule-based answer extractor [12] $E(\cdot)$, resulting in $\hat{Y} = E(O) = \{\hat{y}_i\}_{i=1}^G$. Then, the majority-voted answer y^* can be obtained by:

$$y^* = \operatorname*{arg\,max}_{y \in \hat{Y}} \sum_{i=1}^{G} \mathbb{I}[y = \hat{y}_i],\tag{1}$$

where $\mathbb{I}[\cdot]$ is the indicator function. The reward r_i is then determined based on the y^* :

$$r_i = \begin{cases} 1, & \text{if } \hat{y}_i = y^*, \\ 0, & \text{otherwise.} \end{cases}$$
 (2)

Table 1: Main results on four multi-modal mathematical reasoning benchmarks. We report accuracy (%) for each method on MathVision, MathVerse, MathVista, and We-Math. All methods are conducted on the Qwen2.5-VL-7B backbone. MM-UPT outperforms other baseline methods, and is even competitive with supervised methods.

Model and Methods	Unsupervised?	Training Data	MathVision	n Math Verse	MathVista	We-Math	Avg
Qwen2.5-VL-7B	-	-	24.87	43.83	66.30	62.87	49.47
+ GRPO [34]	×	Geometry3K	28.32	46.40	69.30	68.85	53.22
+ GRPO [34]	×	GeoQA	26.15	46.28	67.50	66.65	51.65
+ GRPO [34]	X	MMR1	29.01	45.03	71.40	67.24	53.17
+ SFT [39]	×	Geometry3K	25.92	43.73	67.90	64.94	50.63
+ SFT [39]	X	GeoQA	25.72	44.70	67.40	65.10	50.73
+ SFT [39]	×	MMR1	26.45	43.53	63.30	64.20	49.37
+ SRLM [49]	✓	Geometry3K	26.94	44.54	66.90	66.32	51.18
+ SRLM [49]	\checkmark	GeoQA	25.16	44.62	66.30	65.00	50.27
+ SRLM [49]	\checkmark	MMR1	25.33	45.08	67.00	64.66	50.52
+ LMSI [14]	\checkmark	Geometry3K	25.10	43.96	65.50	64.43	49.75
+ LMSI [14]	\checkmark	GeoQA	25.49	43.50	66.60	63.51	49.78
+ LMSI [14]	\checkmark	MMR1	24.83	43.76	64.90	66.38	49.97
+ Genixer [64]	\checkmark	Geometry3K	26.02	43.15	65.50	62.18	49.22
+ Genixer [64]	\checkmark	GeoQA	25.30	44.11	66.80	64.25	50.12
+ Genixer [64]	\checkmark	MMR1	23.68	43.30	65.50	64.66	49.29
+ STIC [5]	\checkmark	Geometry3K	25.39	42.92	65.20	62.99	49.13
+ STIC [5]	\checkmark	GeoQA	23.49	42.87	64.30	63.62	48.57
+ STIC [5]	✓	MMR1	23.78	42.72	66.10	63.74	49.09
+ MM-UPT	\checkmark	Geometry3K	27.33	42.46	68.50	66.61	51.23
+ MM-UPT	\checkmark	GeoQA	27.07	43.68	68.90	68.22	51.97
+ MM-UPT	\checkmark	MMR1	26.15	44.87	72.90	68.74	53.17

In this way, we compute pseudo-rewards via majority voting and apply standard GRPO to update the MLLM. This majority-based reward encourages the model to converge toward consistent, high-consensus responses, thereby enabling the model to further exploit its existing self-knowledge leveraging unlabeled data. The overview of our framework is shown in Figure 1 and Algorithm 1.

4 Experiments

We conduct extensive experiments to evaluate the effectiveness of MM-UPT across various multimodal LLMs, datasets, and benchmarks. Our experiments are designed to explore two key scenarios: (1) using human-created questions without ground-truth labels (Section 4.2), and (2) employing synthetic questions generated by the model itself, inherently lacking ground-truth labels (Section 4.3). Before presenting the experimental results, we first outline the baseline methods, evaluation benchmarks, and implementation details in the experimental setup as follows.

4.1 Experimental Setup

Baseline Methods. Several prior works have explored self-improvement in both LLMs and MLLMs. Note that we focus on unsupervised self-improvement, we do not compare with methods that rely on external models (e.g., GPT-40 [16]) for supervision [15, 55, 60, 67, 68]. Instead, we compare with several totally unsupervised methods: LMSI [14], SRLM [49], Genixer [64], and STIC [5]. In particular, LMSI corresponds to supervised fine-tuning with self-generated content selected by majority voting. SRLM uses the model itself as LLM-as-a-Judge [65] to provide its own rewards during DPO [33] training. Genixer prompts the MLLM to first self-generate an answer and then self-check it. STIC applies DPO where original images and good prompts are used to generate preferred answers, and corrupted images and bad prompts to produce rejected answers. Additionally, we also compare with GRPO [34] and rejection sampling-based SFT [39], which are two strong supervised methods. The details of these baseline methods are shown in Appendix A.1.

Table 2: Performance comparison of MM-UPT using different synthetic data generation strategies. Both "In-Context Synthesizing" and "Direct Synthesizing" approaches yield significant improvements over the base model and perform competitively with the "Original Questions" on average, demonstrating the effectiveness of synthetic data for unsupervised self-improvement.

Model and Methods	Dataset	MathVision	MathVerse	MathVista	We-Math	Avg
Qwen2.5-VL-7B	-	24.87	43.83	66.30	62.87	49.47
w/ Original Questions	Geo3K	27.33	42.46	68.50	66.61	51.23 (3.6 %↑)
w/ In-Context Synthesizing	Geo3K	26.71	41.24	68.30	67.76	51.00 (3.1 %↑)
w/ Direct Synthesizing	Geo3K	26.88	43.53	69.90	68.97	52.32 (5.8 %↑)
w/ Original Questions	GeoQA	27.07	43.68	68.90	68.22	51.97 (5.1 %↑)
w/ In-Context Synthesizing	GeoQA	26.09	42.87	70.60	69.25	52.20 (5.5 %↑)
w/ Direct Synthesizing	GeoQA	26.25	44.64	71.50	68.28	52.67 (6.5 %↑)
w/ Original Questions	MMR1	26.15	44.87	72.90	68.74	53.17 (7.5 %↑)
w/ In-Context Synthesizing	MMR1	26.15	45.10	71.90	68.62	52.94 (7.0% ↑)
w/ Direct Synthesizing	MMR1	26.15	44.11	70.40	67.99	52.16 (5.4 %↑)

Benchmarks. We evaluate our method on four popular multi-modal mathematical reasoning benchmarks: MathVision [41], MathVista [24], MathVerse [57], and We-Math [32]. These benchmarks offer comprehensive evaluations with diverse problem types, including geometry, charts, and tables, featuring multi-subject and meticulously categorized visual math challenges across various knowledge concepts and granularity levels. We provide more details in Appendix A.2.

Implementation Details. We adopt the EasyR1 [53] framework for multi-modal unsupervised post-training, which is based on GRPO. Specifically, we set the training episodes to 15, and use AdamW optimizer [22] with a learning rate of 1×10^{-6} , weight decay of 1×10^{-2} , and gradient clipping at a maximum norm of 1.0. The KL divergence constraint β in GRPO is set to 0.01 to stabilize the training. The vision tower of the multi-modal model is also tuned without freezing. Other hyperparameters follow the default settings provided in the EasyR1 framework.

4.2 Unsupervised Training on Standard Datasets

For our experiments, we firstly employ standard training datasets with masked labels to simulate the first scenario (i.e., using human-created questions without ground-truth answers). We conduct MM-UPT on Geometry3k [23], GeoQA [3], and MMR1 [18] using the Qwen2.5-VL-7B [1] model. These datasets cover a diverse set of visual math problems, including geometric diagrams, charts, and structured question formats (multiple-choice and fill-in-the-blank), serving as a strong foundation for models to self-improve the multi-modal mathematical reasoning abilities. More details of these datasets are introduced in Appendix A.3.

Table 1 presents the main results on four challenging multi-modal mathematical reasoning benchmarks. We observe that MM-UPT achieves consistent improvements in average over the base Qwen2.5-VL-7B model across all datasets, also outperforming other baseline methods such as SRLM, LMSI, Genixer, and STIC. Notably, MM-UPT is able to improve the average score from 49.47 (base model) to 53.17 (with MMR1 dataset), demonstrating its effectiveness in leveraging unlabeled data for self-improvement. In comparison, previous baselines provide only marginal gains or even degrade performance on certain benchmarks, highlighting the limitations of existing methods when applied to already strong models in multi-modal reasoning tasks. Furthermore, we find that MM-UPT is even competitive with supervised post-training methods, such as rejection sampling-based SFT [39] and GRPO [34]. These results underscore the potential of MM-UPT to further exploit the knowledge embedded in multi-modal models for self-improvement.

4.3 Unsupervised Training on Synthetic Datasets

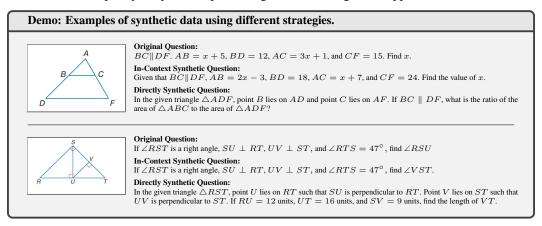
To further explore the potential of MM-UPT, we investigate the use of unlabeled *synthetic data* to improve MLLMs. This aligns with the ultimate goal of MM-UPT: enabling continual self-improvement even after human-created data is exhausted. We utilize two strategies for generating synthetic training samples.

In-Context Synthesizing. Inspired by Self-Instruct [46], we adopt a data generation pipeline based on in-context examples. Each original example includes an image, a question, and its corresponding answer. To synthesize new data, we provide the base MLLM with the full original triplet—image, question, and answer—and ask it to generate a new question that is distinct from the original. During the unsupervised post-training, the MLLM attempts to answer this new question, and we define the pseudo-label as the majority vote among the sampled responses of the model.

Direct Synthesizing. In addition, we also adopt a more straightforward approach to generate synthetic data. Instead of using the full triplet, we prompt the base MLLM with only the image, asking it to create a new question without any context from the original question or answer. This produces a different type of synthetic sample, where the image remains the same, but the question is generated entirely from visual input. As with the in-context approach, the pseudo-label for training is determined by aggregating several model responses through majority voting.

Results. In our experiment, we use the previous two methods to generate the synthetic data, leveraging Geometry3K [23], GeoQA [3], and MMR1 [18] as the seed datasets, and Qwen2.5-VL-7B as the base MLLM for data synthesis. MM-UPT is then applied to the same base model (i.e., Qwen2.5-VL-7B) using each of these different synthetic datasets separately. Table 2 presents experimental results using different synthetic data generation strategies. Both in-context and direct synthesizing lead to significant improvements over the base model, achieving performance comparable to training on original human-written questions. This shows that synthetic questions can effectively enhance the model's reasoning ability under MM-UPT. Notably, direct synthesizing even surpasses human-written questions (when applied to Geometry3K and GeoQA) on average, demonstrating the strong ability of the model to generate high-quality textual questions solely based on images. This highlights the potential for scalable and fully autonomous self-improvement in multi-modal domain via visual-centric data synthesis.

Further Investigation. Moreover, we manually examine some synthetic data. We observe that incontext synthesizing often produces questions similar to the original ones by substituting conditions or expressions, resembling data rephrasing. In contrast, direct synthesizing generates more diverse and novel questions. While some of the directly synthesized questions still contain hallucinations, many are of high quality and beneficial for unsupervised post-training. This underscores the potential of the direct synthesizing approach as a simple yet effective method for data generation, without the need for textual in-context examples. Below, we present two illustrative examples that showcase the effectiveness and quality of synthetic questions generated through both approaches.



4.4 Ablation Study

To evaluate the generality and effectiveness of MM-UPT, we conduct an ablation study across a range of backbone models beyond the primary Qwen2.5-VL-7B [1]. Specifically, we apply MM-UPT to several state-of-the-art models of varying scales, including Qwen2.5-VL-3B [1], MM-Eureka-7B [28], and ThinkLite-VL-7B [44]. All models are post-trained using MM-UPT on the Geometry3K dataset [23], without access to any labels. As summarized in Table 3, MM-UPT consistently improves the performance of all tested models on average, despite the absence of supervision during post-training. Notably, ThinkLite-VL-7B with MM-UPT achieves the highest average score (54.07), and shows substantial gains on the MathVista [24] benchmark, reaching a score of 74.70. In addition,

Table 3: Ablation study using different models besides Qwen2.5-VL-7B. We conduct this experiment
on Geometry3K [23] dataset without labels.

Models	MathVision	MathVerse	MathVista	We-Math	Avg
Qwen2.5-VL-7B	24.87	43.83	66.30	62.87	49.47
Qwen2.5-VL-7B + MM -UPT	27.33	42.46	68.50	66.61	51.23 (3.6% ↑)
MM-Eureka-7B	28.06	50.46	69.40	64.48	53.10
MM-Eureka-7B + MM-UPT	28.95	50.63	69.10	66.44	53.78 (1.3% ↑)
ThinkLite-VL-7B	26.94	46.58	69.00	67.99	52.63
ThinkLite-VL-7B + MM-UPT	26.91	47.26	74.70	67.41	54.07 (2.8% ↑)
Qwen2.5-VL-3B	19.47	33.58	56.30	50.63	39.00
Qwen 2.5-VL-3B+MM-UPT	22.17	32.39	57.10	55.22	41.72 (7.4 %↑)

Qwen2.5-VL-3B, the smallest model in our study, also benefits well from MM-UPT (+7.4% on average), demonstrating the robustness and adaptability of MM-UPT for performance enhancement. These results collectively reveal that MM-UPT can be easily applied to various multi-modal models to enable consistent self-improvement.

5 Deeper Analysis

Going beyond standard benchmarking, we conduct a deeper analysis to investigate MM-UPT's training dynamics (Section 5.1) and performance boundaries (Section 5.2 and Section 5.3). This helps better understand its behavior and potential applications.

5.1 Training Dynamics

To better understand the behavior of MM-UPT during training, we monitor several diagnostic metrics, including the majority voting reward and entropy, both of which are label-free and provide insights in the absence of ground-truth supervision. In particular, majority voting reward is calculated following Equation 2. Entropy can be used as an unsupervised objective that measures the uncertainty of the model's generation [43, 48, 56]. For a group of responses $O = \{o_i\}_{i=1}^G$ sampled from the question q and image I, we cluster the responses according to their meaning. That is, if two responses share the same meaning (i.e., extracted answers), they should be merged into one same cluster in the semantic space. This results to $K(K \leq G)$ clusters $C = \{c_j\}_{j=1}^K$. The empirical distribution over clusters is defined as:

$$p(c_j|q,I) = \frac{|c_j|}{G},$$

where $|c_j|$ denotes the number of responses that belongs to c_j . The semantic entropy (denoted as H) over the model's response meanings distribution can be estimated as follows:

$$H = -\sum_{c_j \in \{C\}} p(c_j|q, I) \log p(c_j|q, I).$$

Figure 2 presents the MM-UPT training curves of the key metrics on Qwen2.5-VL-7B using the MMR1 dataset. We observe that the majority voting reward consistently increases over time, accompanied by a steady decrease in the entropy. This indicates that the model is converging toward more consistent predictions, reflecting improved confidence and stability in its responses.

Additionally, we track the change in average benchmark accuracy and effective rank [48] throughout training. The accuracy exhibits an upward trend, demonstrating that our MM-UPT framework—based on an online reinforcement learning algorithm—effectively enables the model to self-improve continuously and iteratively. The effective rank [48] further measures the amount of knowledge the model comprehends in the datasets. During training, the internal knowledge of the model is exploited, leading to a consistent increase in the effective rank on the benchmark.

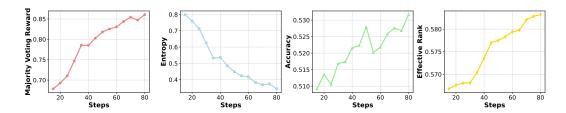


Figure 2: Training dynamics of MM-UPT using Qwen2.5-VL-7B on the MMR1 dataset. We plot the majority voting reward, semantic entropy, and average benchmark accuracy over the course of unsupervised post-training.

Table 4: Performance of MM-UPT on the difficult ThinkLite-11K dataset. Results show that MM-UPT leads to a decrease in performance when applied to a dataset where the model has limited prior knowledge, highlighting the limitations of majority voting in such scenarios.

Models	Training Data	MathVision	MathVerse	MathVista	We-Math	Avg
Qwen2.5-VL-7B	_	24.87	43.83	66.30	62.87	49.47
Qwen2.5-VL-7B + MM-UPT	ThinkLite-11K	21.12	37.10	59.20	59.02	44.11

5.2 Why Does MM-UPT Work?

Majority voting [45] is a fundamental ensemble technique that enhances prediction reliability by aggregating multiple independent responses. In our framework, it offers a simple yet powerful pseudo-reward signal to help model self-improve, particularly when the model are moderately reliable on the unlabeled datasets. We consider a simplified explanation for it using a classical toy example. Suppose that each response hits the correct answer with probability p > 0.5 in a binary question. Then, we sample the model's response n times independently. The final answer is determined by a majority vote, that is, the answer that appears more than n/2 times. Let X denote the number of correct predictions among the n samples. Since each prediction is correct with probability p, X follows a binomial distribution: $X \sim \text{Binomial}(n, p)$. The majority vote is correct if X > n/2, and the corresponding probability of this event (denoted as E) is:

$$P(E) = \sum_{i=\lceil n/2 \rceil}^{n} {n \choose i} p^{i} (1-p)^{n-i}.$$

When p>0.5, it follows that P(E)>p, which means that the ensemble outperforms each individual response. For instance, if p=0.7 and n=10, then $P(E)\approx 0.849$, demonstrating a significant gain over the base accuracy. This analysis reveals the rationality of majority voting to serve as the pseudolabel for deriving reliable reward signal in the unsupervised setting. In our experimental setting, we mainly target datasets that are not especially hard, such as Geometry3k [23], GeoQA [3], and MMR1 [18], for unsupervised post-training. Hence, we hypothesize that the model has a relatively high chance of answering questions in these datasets correctly. This allows the model to yield stable improvements through MM-UPT using majority voting as the pseudo-label.

5.3 When Might MM-UPT Fail?

According to the analysis in Section 5.2, it reveals that the effectiveness of MM-UPT diminishes when the model lacks sufficient prior knowledge of the target dataset. To show that, we apply MM-UPT to ThinkLite-11K [44] dataset using Qwen2.5-VL-7B [1]. ThinkLite-11K is collected via difficulty-aware sampling that only retains samples that the model rarely answers correctly. Thus, this setting reflects a scenario where the model is more likely to be wrong than right. In such cases, majority voting amplifies incorrect answers rather than filtering them, leading to degraded performance. As shown in Table 4, applying MM-UPT to ThinkLite-11K results in a significant drop in accuracy across all benchmarks. This suggests that majority voting fails to provide reliable reward signals when the model has limited prior understanding of the domain. To address this issue, alternative forms of algorithms in self-improvement [7, 26, 49, 56] using more fine-grained and complex self-rewarding methods, such as LLM-as-Judge [65] and model collaboration [20], may be necessary. Note that our

work represents an initial attempt at self-improvement in MLLMs via GRPO. We believe that these algorithms are complementary to our approach and could be integrated into our framework, which we leave as future work.

6 Conclusion

In this paper, we introduce MM-UPT (Multi-Modal Unsupervised Post-Training), a framework that enables MLLMs to self-improve using unlabeled multi-modal data without any external supervision. By leveraging majority voting as a reward mechanism within the GRPO algorithm, our method encourages models to converge toward more consistent responses across multi-modal reasoning tasks. Our experiments demonstrate that MM-UPT significantly improves the performance of various MLLMs across several multi-modal reasoning benchmarks without requiring human annotated labels or external reward models. Generally, MM-UPT is best viewed as a post-training refinement strategy rather than a substitute for supervised training. We recommend first training the model using labeled data to ensure it achieves basic competence on various tasks. After that, MM-UPT can be used to further exploit the model's internal knowledge by reinforcing consistent predictions. Future work could explore other fine-grained methods to provide pseudo-reward signals based on our framework, and investigate the scaling laws of unsupervised post-training using synthetic data.

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Appendix

A Implementation Details

We provide the implementation details of our experiments as follows.

A.1 Baselines

Here, we explain how we implement different baseline methods in comparison.

LMSI [14] employs the majority-voted response as the target for supervised fine-tuning (SFT). For each question, we generate multiple responses and retain the ones that lead to the majority answer for training.

SRLM [49] studies Self-Rewarding Language Models, where the model itself is used via LLM-as-a-Judge prompting to provide its own rewards during training. In particular, for each question, we generate multiple candidate responses and use the prompt provided in the original paper to have the MLLM score its own outputs. Among the responses, the one with the highest score is selected as the positive example, and the one with the lowest score as the negative example. These pairs are then used to construct preference datasets for Direct Preference Optimization (DPO) [33].

Genixer [64] introduces a comprehensive data generation pipeline consisting of four key steps: (i) instruction data collection, (ii) instruction template design, (iii) empowering MLLMs, and (iv) data generation and filtering. To adapt Genixer in our setting, we remove the first two steps because we already have instruction data. After that, we use Qwen2.5-VL as the backbone model to self-generate responses 16 times per question for each dataset. In the filtering stage, we use the prompt to let the model self-judge the responses following Genixer:

Here is a question-answer pair. Is $\{Q:X_q,A:X_a\}$ true for this image? Please answer this question with Yes or No.

In addition, Genixer calculates the probability of predicting the "Yes" rather than prompt the model to directly output "Yes" or "No" as the filtering label:

$$P(Y_r|X_I, X_q, X_a) = \prod_{i=1}^{L} p(y_i|X_I, X_q, X_{a, < i}),$$
(3)

where Y_r is the predicted judge, X_I is the image, X_q is the question, X_a is the self-generated response, and L is the length the total predicted judge. Then, it proposes a threshold λ to control the filtering in the following manner:

$$S^{n} = \begin{cases} \text{True,} & \text{if } Y_{r} = \text{Yes and } P(Y_{r}^{n}) > \lambda \\ \text{False,} & \text{if } Y_{r} = \text{Yes and } P(Y_{r}^{n}) \leq \lambda \end{cases}, \tag{4}$$

$$\text{False,} & \text{if } Y_{r} = \text{No}$$

where S^n is the filter label representing keeping or removing the current sample. $P(Y_r^n)$ denotes the probability of the result "Yes" of n-th candidates. λ is set to 0.7 following the paper.

STIC [5] proposes a two-stage self-training algorithm focusing on the image comprehension capability of the MLLMs. In Stage 1, the base MLLM self-constructs its preference dataset for image description using well-designed prompts, poorly-designed prompts, and distorted images with diffusion noise. In Stage 2, a small portion of the previously used SFT data is recycled and infused with model-generated image descriptions to further fine-tune the base MLLM. In particular, since Qwen2.5-VL does not open-source the SFT data, we opt to use the model's self-generated responses sampled from different datasets to represent the previously used SFT data.

A.2 Benchmarks

We provide some details about the benchmarks we use to evaluate the models' reasoning ability. MathVision [41] is a challenging benchmark containing 3040 mathematical problems with visual contexts from real-world math competitions across 12 grades. It covers 16 subjects over 5 difficulty

levels, including specialized topics like Analytic Geometry, Combinatorial Geometry, and Topology. MathVista [24] is a comprehensive benchmark for evaluating mathematical reasoning in visual contexts. It contains 1000 questions featuring diverse problem types including geometry, charts, and tables. MathVerse [57] is an all-around visual math benchmark designed for an equitable and indepth evaluation of MLLMs. The test set contains 3940 multi-subject math problems with diagrams from publicly available sources, focusing on Plane Geometry and Solid Geometry. We-Math [32] meticulously collect and categorize 1740 visual math problems in the test set, spanning 67 hierarchical knowledge concepts and 5 layers of knowledge granularity.

For all benchmarks, we prompt the models to place their final answers within a designated box format. We then employ Qwen2.5-32B-Instruct [51] to evaluate answer correctness by comparing the extracted responses with ground truth answers, which often contain complex mathematical expressions. Note that our reported benchmark scores may differ from those in the original papers due to variations in evaluation protocols.

A.3 Standard Training Datasets

In our experiments, we use three standard training datasets for multi-modal reasoning: Geometry3K [23], GeoQA [3], and MMR1 [18]. Geometry3K consists of 2.1K multiple-choice questions in the training set, covering a wide range of geometric shapes. GeoQA includes 8K fill-in-the-blank questions sourced from the larger Geo170K dataset [8]. MMR1 consists of 7,000 samples and includes both multiple-choice questions and fill-in-the-blank questions. These samples cover a range of tasks, including understanding charts and geometric reasoning.

B Compute Resources

We conduct our experiments using NVIDIA H100-80G and A800-40G GPUs. The experimental time using 8 A800 for training Qwen2.5-VL-7B [1] on the Geometry3K [23] dataset using GRPO is around 10 hours.