VisPlay: Self-Evolving Vision-Language Models

Yicheng He[1*] Chengsong Huang[2*] Zongxia Li[3*] Jiaxin Huang[2] Yonghui Yang[4,5†]
[1]University of Illinois Urbana-Champaign [2]Washington University in St. Louis
[3]University of Maryland [4]National University of Singapore
[5]Intelligent Interconnected Systems Laboratory of Anhui Province, Hefei University of Technology
yh84@uiuc.edu chengsong@wustl.edu zli12321@umd.edu

Abstract

Reinforcement learning (RL) provides a principled framework for improving Vision-Language Models (VLMs) on complex reasoning tasks. However, existing RL approaches often depend on human-annotated labels or task-specific heuristics to define verifiable rewards—both costly and limited in scalability. We introduce VisPlay, a self-evolving RL framework that enables VLMs to autonomously improve their reasoning capabilities from massive unlabeled image data. Starting from a single base VLM, VisPlay assigns the model into two interacting roles: an ***Image-Conditioned Questioner*** *that formulates challenging yet answerable visual questions, and a* ***Multimodal Reasoner*** *that generates silver responses. These roles are jointly trained using Group Relative Policy Optimization (GRPO), which uses diversity and difficulty rewards to balance the difficulty of generated questions with the quality of silver answers. VisPlay scales efficiently across two model families. Trained on Qwen2.5-VL and MiMo-VL, VisPlay achieves consistent improvements in visual reasoning, compositional generalization, and hallucination reduction across eight benchmarks including MM-Vet and MMMU, and establishes a scalable path toward self-evolving multimodal intelligence. Our code is available at* `https://github.com/bruno686/VisPlay`.

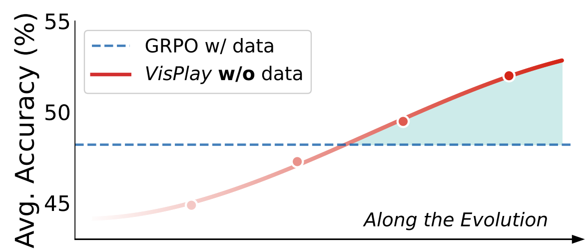


Figure 1. Illustration of the average accuracy improvement (averaged over seven datasets) through successive evolutions (Evo 1 to Evo 5) on Qwen2.5-VL-3B-Instruct, compared to a baseline trained on Vision-47K with GRPO, demonstrating the effectiveness of our *VisPlay* .

1. Introduction

Self-evolving mechanisms [6, 22, 29, 39] represent a promising frontier for advancing artificial intelligence. The training of state-of-the-art (SoTA) models has traditionally relied on large volumes of expert curated tasks and labels. However, the reliance on human annotation is not only costly, labor-intensive, and difficult to scale, but also presents a fundamental bottleneck to advancing intelligence toward capabilities that could surpass itself without human signal guidance [42]. Self-evolution offers a compelling alternative by equipping models with the capacity to independently generate, refine, and learn from their own experiences such as through self-play or synthetic data generation.

Motivated by these advantages, the research community has increasingly explored self-evolution, most notably in the context of Large Language Models (LLMs). A line of works have demonstrated how LLMs can autonomously enhance their complex reasoning and coding faculties, often by generating their own tasks or data [13, 24, 50]. However, the self-evolution paradigm remains largely underexplored for Vision-Language Models (VLMs) [2, 18, 32]. Unlike LLMs, which rely solely on text, developing self-evolving VLMs poses additional challenges due to their dependence on the visual modality. In a world where human annotation is costly and time-consuming, yet vast amounts of visual data are freely available online, self-evolving VLMs present a promising direction to continual improvement without human signals and directly from the abundant visual content on the internet [3, 30].

In this paper, we introduce *VisPlay*, a self-evolving RL framework that enables VLMs to autonomously improve their reasoning capabilities using **only raw, unanno-**

*Equal Contribution.
†Corresponding Author yh_yang@nus.edu.sg.

tated images. The framework utilizes a single base VLM that alternates between two roles: the *Image-Conditioned Questioner*, which generates diverse and challenging questions conditioned on an input image, and the *Multimodal Reasoner*, which produces silver responses based on both the image and the generated question. Both roles are jointly optimized using Group Relative Policy Optimization (GRPO) [31], where designed rewards encourage a balance between question difficulty and answer quality without requiring external supervision. The Image-Conditioned Questioner learns to generate challenging yet answerable questions grounded in visual inputs, while the Multimodal Reasoner learns to produce accurate, detailed, and grounded responses. This self-evolving framework enables the VLM to progressively improve its visual reasoning abilities through iterative co-improvement of the Questioner and the Reasoner as Figure 1.

We apply our self-evolving RL framework to train three state-of-the-art (SoTA) VLMs and observe consistent performance gains across diverse visual reasoning benchmarks. Our main contributions are:

- We propose *VisPlay*, a self-evolving RL framework for Vision-Language models.
- We apply *VisPlay* to three strong models—Qwen2.5-VL-3B, Qwen2.5-VL-7B [32], and MiMo-VL-7B [40]. We run extensive evaluations over three major domains—General Visual Understanding, Visual Mathematics, and Hallucination Detection. All models show consistent gains in accuracy after several iterations.
- We run extensive ablation studies to further validate the contribution of Image-Conditioned Questioner and the Multimodal Reasoner component to further show how *VisPlay* progressively strengthens multimodal reasoning across vision-language tasks.

2. Method

2.1. Preliminary

Reinforcement Learning with Verifiable Rewards (RLVR) [16] is a paradigm for training VLMs in domains where the correctness of model outputs can be verified. A rule-based verifier $v : X \to \{0, 1\}$ assigns a binary reward to each generation x_i:

$$r_i = v(x_i) = \begin{cases} 1, & \text{if } x_i \text{ satisfies a correctness rule,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Such verifiable rewards are effective in tasks like mathematical reasoning, multiple choice, and code generation, where correctness can be objectively evaluated. GRPO [31] provides a practical RL algorithm without a value function by using relative rewards among multiple samples from the same prompt. Given a prompt p, a policy $\pi_{\theta_{\text{old}}}$ produces G complete responses $\{x_1, \ldots, x_G\}$ with corresponding rewards $\{r_1, \ldots, r_G\}$. Rewards are normalized within the group to compute response-level advantages:

$$\hat{A}_i = \frac{r_i - \text{mean}(r_1, \ldots, r_G)}{\text{std}(r_1, \ldots, r_G) + \varepsilon_{\text{norm}}}, \tag{2}$$

where $\varepsilon_{\text{norm}}$ is a small constant for stability.

The policy is then optimized using a clipped surrogate objective, regularized by a KL term to constrain policy drift:

$$\begin{aligned} \mathcal{L}_{\text{GRPO}}(\theta) = -\frac{1}{G}\sum_{i=1}^{G} \min\Bigg(& \frac{\pi_\theta(x_i)}{\pi_{\theta_{\text{old}}}(x_i)} \hat{A}_i, \\ & \text{clip}\left(\frac{\pi_\theta(x_i)}{\pi_{\theta_{\text{old}}}(x_i)}, 1-\epsilon,\ 1+\epsilon\right) \hat{A}_i \Bigg) \\ & + \beta\, \text{KL}(\pi_\theta \,\|\, \pi_{\theta_{\text{old}}}) \,. \end{aligned} \tag{3}$$

GRPO operationalizes RLVR to improve reasoning and generation quality in VLMs by rewarding responses with positive relative advantages while limiting policy deviation.

2.2. Pipeline Overview

We introduce *VisPlay*, a self-play reinforcement learning framework designed to evolve VLMs without human-annotated data. As illustrated in Figure 2, the framework operates as a closed-loop system involving two agents evolved from the same base model: an *Image-Conditioned Questioner* and a *Multimodal Reasoner*. The process begins with the Questioner taking an image as input to generate a visual query. Subsequently, the Reasoner receives both the image and the generated query to produce a response. Both the Questioner and the Reasoner are initialized from a shared pretrained backbone. The two agents co-evolve through iterative interactions: the Questioner is trained to generate more challenging questions, while the reasoner is trained to solve more and more challenging questions. The complete process is described in Algorithm 1.

2.3. Image-Conditioned Questioner Training

The Questioner is an autoregressive policy denoted by Q_θ. Conditioned on an input image I, it samples a group of G questions $\{x_i\}_{i=1}^{G} \sim Q_\theta(\cdot|I)$, which are evaluated to produce scalar rewards $\{r_i\}_{i=1}^{G}$. These rewards are used to compute group-normalized advantages and to update Q_θ with a GRPO objective. We next define reward components that constitute each r_i.

Pseudo-Label Generation. Since self-evolving VLMs learn without relying on labeled data, ground-truth answers for the Questioner's generated questions are unavailable.

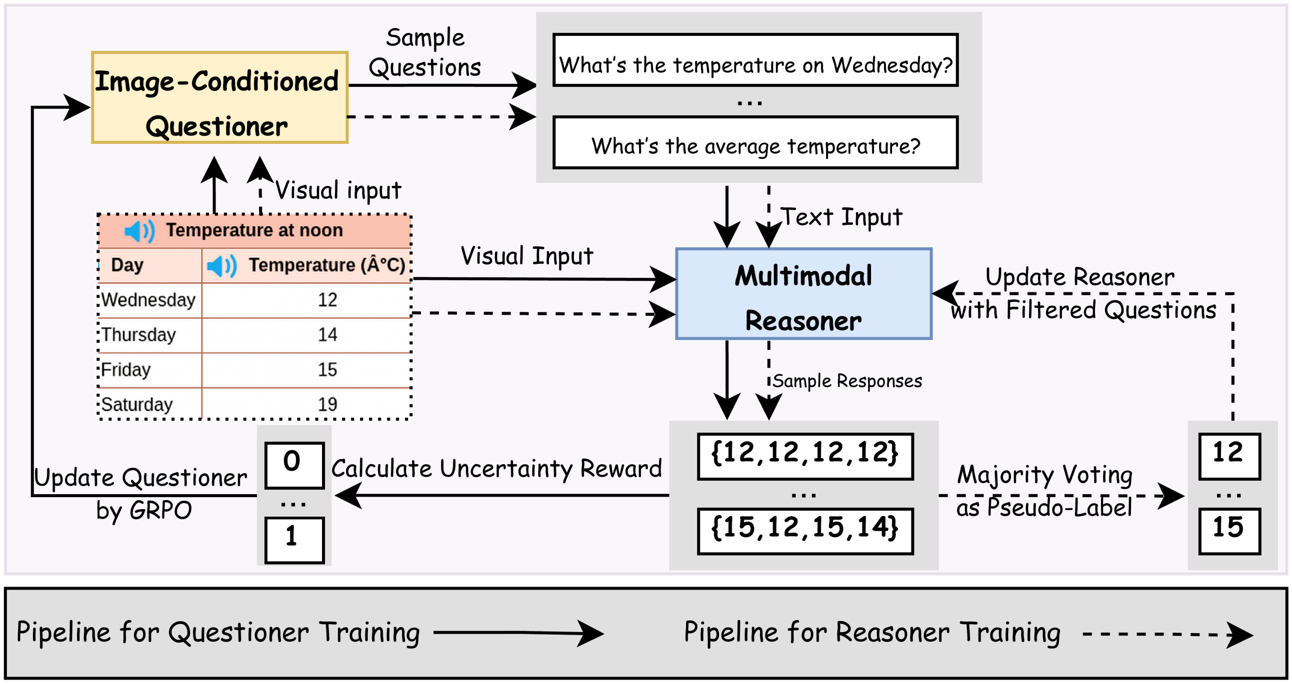


Figure 2. An illustration of our *VisPlay* framework, depicting the co-evolution of the Image-Conditioned Questioner and Multimodal Reasoner. Top: During the Questioner training stage, the Image-Conditioned Questioner is optimized via GRPO to produce challenge questions. The reward stems from the uncertainty of the frozen Multimodal Reasoner, computed by the consistency of its multiple generated answers. Bottom: In the Reasoner training stage, the Multimodal Reasoner is trained via GRPO on a curated set of challenging questions from the now-frozen Image-Conditioned Questioner, leveraging pseudo-labels from its own majority voting.

Therefore, we introduce a method to approximate the corresponding answers. Given an image I and the generated question x, we introduce a Reasoner S_ϕ that samples m responses $\{y_j\}_{j=1}^m$.[1] We define the empirical frequency of a candidate answer y as $\hat{p}(y|x,I) = \frac{1}{m}\sum_{j=1}^m \mathbb{1}\{y_j = y\}$, and derive the pseudo-label via majority voting: $\tilde{y} = \arg\max_y \hat{p}(y|x,I)$. We then define the **confidence score** for this pseudo-label as:

$$\mathrm{conf}(x,I) = \hat{p}(\tilde{y}|x,I). \tag{4}$$

Intuitively, $\mathrm{conf}(x,I)$ measures the Reasoner's certainty about the pseudo-label: high values indicate stable and consistent predictions, whereas values near 0.5 reflect strong uncertainty. We therefore treat the degree of uncertainty (i.e., how close $\mathrm{conf}(x,I)$ is to 0.5) as a proxy for the model-perceived difficulty of the generated question.

Uncertainty Reward. The confidence score quantifies the Reasoner's uncertainty, which we use as a proxy for the model-perceived difficulty of the generated question. To encourage questions that probe the Reasoner's limits, we compute the reward based on the confidence score $c = \mathrm{conf}(x,I)$. We define the uncertainty reward to penalize deviations from the point of maximum uncertainty:

$$r_{\mathrm{unc}}(x,I) = 1 - \big|2c - 1\big|. \tag{5}$$

This formulation yields a maximal reward of 1 when $c = 0.5$ and decreases linearly to 0 as the reasoner's response distribution becomes deterministic (i.e., $c \to 1$).

Diversity Regularization. To prevent the model from collapsing into generating repetitive questions for a given image I, we introduce a redundancy penalty within its generated group $\mathcal{X}_I$. We cluster these generated questions based on pairwise similarity (BLEU score) to identify duplicates. For a question x_i belonging to a cluster $C_k^{(I)} \subseteq \mathcal{X}_I$, the regularization term is:

$$r_{\mathrm{div}}(x_i,I) = \lambda \frac{|C_k^{(I)}|}{G}, \tag{6}$$

where $C_k^{(I)}$ denotes the cluster of similar questions for image I, and G is the total number of generated questions for that image.

Format constraint. We enforce a hard filter to ensure structural validity. Specifically, we require the generated

[1] The reasoner is evolved from the same base model as the Questioner. See Section 2.4 for details.

question to be strictly enclosed within <question> tags. Any output failing to meet this format requirement is assigned zero reward. We denote this validity indicator as:

$$\mathbb{1}_{\text{valid}}(x) = \begin{cases} 1, & \text{if } x \text{ is wrapped in <question> tags,} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

Final Questioner Reward. For each generated question x_i conditioned on image I, we integrate the uncertainty signal and diversity regularization into a unified scalar objective:

$$r_i = \mathbb{1}_{\text{valid}}(x_i) \cdot \text{ReLU}\Big(r_{\text{unc}}(x_i, I) - r_{\text{div}}(x_i, I)\Big). \tag{8}$$

This composite reward incentivizes the Questioner to generate challenging yet non-redundant questions while strictly filtering out malformed outputs. The ReLU function stabilizes GRPO updates by preventing spurious negative values from skewing the reward normalization across the group.

2.4. Multimodal Reasoner Training

The training of the Multimodal Reasoner S_ϕ builds upon the advancements of the Image-Conditioned Questioner. In each iteration, the Image-Conditioned Questioner functions produce challenging samples that serve as training targets. The Multimodal Reasoner then learns from these automatically curated samples, improving its visual reasoning ability without any external supervision.

Curated Dataset Construction. Following the update of the Image-Conditioned Questioner, we generate a diverse pool of N candidate questions $\{x_i\}_{i=1}^N$ per image by sampling $x_i \sim Q_\theta(\cdot \mid I)$. For each x_i, we obtain m response samples from the current Multimodal Reasoner and compute the pseudo-label $\tilde{y}_i$ and confidence score $c_i = \text{conf}(x_i, I)$. To focus on training samples that offer high information gain, we enforce an *informative filter* that retains pairs $(x_i, \tilde{y}_i)$ with moderate confidence:

$$\tau_{\text{low}} \leq c_i \leq \tau_{\text{high}}, \tag{9}$$

where τ_{low} and τ_{high} are thresholds set to 0.25 and 0.75, respectively. This criterion effectively discards trivial samples where the model is already certain ($c_i > 0.75$) as well as highly unstable or noisy generations ($c_i < 0.25$). The final curated training set $\mathcal{S}$ is formed by collecting all retained pairs across images, up to a budgeted size, to optimize the Multimodal Reasoner via GRPO.

Per-Sample Verifiable Reward. For a question $x_i \in \mathcal{S}$ with pseudo-label $\tilde{y}_i$, the Multimodal Reasoner generates a group of G candidate answers $\{y_j\}_{j=1}^G$. Each sampled answer receives the binary reward

$$r_j = \begin{cases} 1, & \text{if } y_j = \tilde{y}_i, \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

These rewards are group-normalized to produce advantages $\hat{A}_j$ as in Eq. 2 (with the Reasoner's rewards), and S_ϕ is updated by minimizing $\mathcal{L}_{\text{GRPO}}(\phi)$ as in Eq. 3.

3. Experiments

3.1. Benchmarks and Evaluation Protocol

We use existing image datasets from Vision-47K [9, 21], which contains 47K web images collected from diverse domains, e.g. including charts, medical images, exams, textbooks, and driving simulations.[2] We train three backbone models using *VisPlay*—Qwen2.5-VL-3B-Instruct, Qwen2.5-VL-7B-Instruct, and Mimo-7B-SFT.[3] We run evaluation across three multimodal domains [21].

- **General Visual Understanding.** We measure performance on four established benchmarks. MM-Vet [44] provides a unified LLM-based score across recognition, OCR, and visual math tasks. MMMU [45] evaluates cross-modal reasoning and subject knowledge through 11.5K college-level. RealWorldQA [38] contains roughly 700 real-world images paired with spatially grounded questions. VisNumBench [37] focuses on visual number sense, covering around 1.9K questions involving numerical attributes and estimation tasks.
- **Multimodal Mathematical Reasoning.** MathVerse [47] consists of 2.6K diagram-centric questions, provided in multiple visual-text formats. MATH-Vision [34] includes around 3K competition-level problems across 16 subjects and five difficulty tiers.
- **Visual Hallucination Detection.** HallusionBench [11] is used to analyze model errors, distinguishing between language-only hallucinations and visual-illusion errors, with a simple yes/no evaluation format.

3.2. Main Results

We use LLM-as-a-judge to assess the correctness of the answers to ensure more robust evaluation [10, 19]. We present the outputs of the Multimodal Reasoner and analyze its reasoning ability progression in Table 1. We summarize the main findings of our experimental results below.

- ***VisPlay* consistently improves overall performance across different models.** All models trained with *VisPlay* consistently surpass both their corresponding base

[2] We only use the images without the questions and answers. Details of the dataset breakdowns are in supplement materials.

[3] The detailed training configurations are provided in the supplementary material.

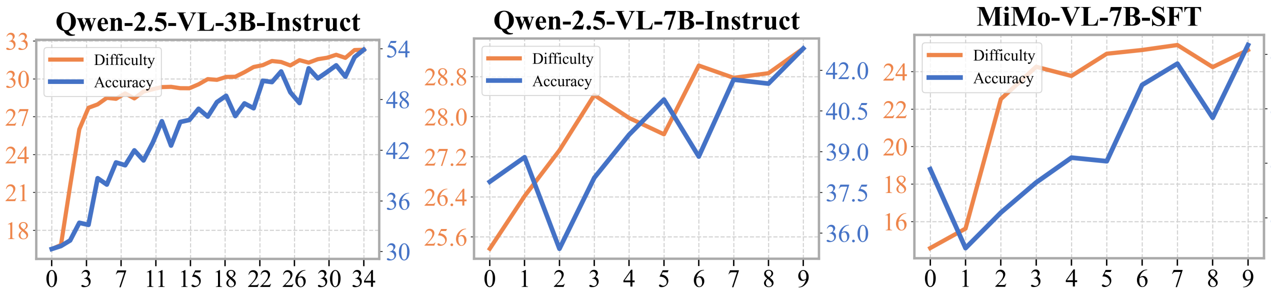


Figure 3. Changes in question difficulty (orange, left axis) and problem-solving accuracy (blue, right axis) during Image-Conditioned Questioner and Multimodal Reasoner training across three VLMs.

models and the Base Challenger over successive training iterations. Qwen2.5-VL-3B shows a remarkable improvement, with the average score increasing from 30.61 at baseline to 44.16 after the first iteration and reaching 47.27 at the third. Qwen2.5-VL-7B and MiMo-VL-7B follow similar upward trends, improving from 40.41 to 48.61 and 43.56 to 45.69, respectively. These results demonstrate the robust generalization ability and scalability of the proposed self-evolving framework across different models and model sizes.

- **Performance gains across diverse task types.** *VisPlay* shows improvements across general visual understanding tasks, visual reasoning or math benchmarks, and are more robust to hallucination. For Qwen2.5-VL-3B, the Hallucination score rises from 32.81 to 94.95 by the second iteration, showing a substantial enhancement in factual grounding. Similar patterns are observed in other models—reasoning benchmarks consistently improve without compromising accuracy on general understanding tasks—demonstrating that *VisPlay* effectively strengthens both task-specific reasoning and cross-domain multimodal generalization.
- **Iterative co-evolution between the Questioner and Reasoner drives improvement.** Performance trajectories across iterations highlight the co-evolution between the Questioner and Reasoner. As the Questioner generates more diverse and challenging queries, the Reasoner—trained with GRPO using high-quality silver supervision—learns to handle increasingly complex reasoning steps. This iterative loop allows both components to reinforce each other, leading to continual improvement in reasoning quality. The results indicate that the co-evolutionary design of *VisPlay* provides a scalable path toward self-improving multimodal intelligence.

3.3. Performance Comparison with Human-Annotated Data

We conduct a performance comparison between models trained with *VisPlay* and those trained using human-curated image–question–answer pairs from the Vision-47K dataset under standard GRPO for one epoch, as shown in Table 3 for Qwen2.5-VL-3B and 7B. Although this experiment is not an ablation study in the strict sense, it provides a clear view of how our fully automated training pipeline performs relative to conventional supervised training. Overall, we observe that models trained with *VisPlay* achieve competitive average accuracy compared with those trained on real, human-written data. While performance on several task categories differs slightly, the general trend indicates that the self-evolving process can produce training signals of sufficient quality to improve base VLMs capabilities. These findings suggest that even in settings where human annotations are costly, limited, or unavailable, our framework can still serve as an effective and scalable alternative, enabling VLMs to develop stronger generalization abilities without depending on manual supervision.

3.4. Co-Evolution Dynamics of Two Roles

- **The Evolution of Question Difficulty and Solution Accuracy.** To analyze the co-evolution dynamics of the two roles, we examine the changes in question difficulty (orange, left axis) and problem-solving accuracy (blue, right axis) across three VLMs during the first training iteration (Figure 3). Question difficulty is operationalized as the Reasoner's model-perceived difficulty, derived from the confidence score defined in Eq. 4 in Section 2.3. Across all models, a consistent co-evolution pattern emerges. The Image-Conditioned Questioner's difficulty curves exhibit a general upward trend, with initial increments followed by sustained growth, indicating the role's ability to progressively formulate more challenging visual questions. Concurrently, the Multimodal Reasoner's accuracy curves, despite minor fluctuations, show a complementary upward trajectory. This means that as question difficulty rises, the Reasoner adapts and enhances its problem-solving capability, with both metrics reinforcing each other's improvement over iterations. Such mutual reinforcement validates *VisPlay*'s core mechanism, where

Algorithm 1: *VisPlay*: Self-Evolving RL for Vision-Language Models

Input: Initial models Q_θ, S_ϕ; Image dataset $\mathcal{I}$; Group size G; Reasoner samples m; Dataset budget N; Thresholds $\tau_{\text{low}} = 0.25, \tau_{\text{high}} = 0.75$.

Output: Evolved models Q_θ and S_ϕ.

- **for** *each self-play iteration* **do**
  - **for** *each image batch* $I \in \mathcal{I}$ **do**
    - Sample question group $\{x_i\}_{i=1}^{G} \sim Q_\theta(\cdot \mid I)$;
    - **for** *each question* x_i **do**
      - Sample m answers $\{y_j\}_{j=1}^{m} \sim S_\phi(\cdot \mid I, x_i)$;
      - Compute confidence $c_i \leftarrow \text{conf}(x_i, I)$ via majority vote (Eq. 4);
      - Compute uncertainty reward $r_{\text{unc}} \leftarrow 1 - |2c_i - 1|$;
      - Compute diversity penalty r_{div} via clustering (Eq. 6);
      - Final reward: $r_i \leftarrow \mathbb{1}_{\text{valid}}(x_i) \cdot \text{ReLU}\big(r_{\text{unc}} - r_{\text{div}}\big)$;
    - **end**
    - Update Q_θ via GRPO using rewards $\{r_i\}_{i=1}^{G}$;
  - **end**
  - Initialize curated dataset $\mathcal{S} \leftarrow \emptyset$;
  - **for** *each image* $I \in \mathcal{I}$ **do**
    - Generate N candidate questions via Q_θ ;
    - **for** *each candidate* x_k **do**
      - Obtain pseudo-label $\tilde{y}_k$ and confidence c_k from S_ϕ;
      - **if** $\tau_{\text{low}} \leq c_k \leq \tau_{\text{high}}$ **then**
        - Add $(I, x_k, \tilde{y}_k)$ to $\mathcal{S}$;
      - **end**
    - **end**
  - **end**
  - **for** *each minibatch* $(I, x, \tilde{y}) \in \mathcal{S}$ **do**
    - Sample G answers $\{y_j\}_{j=1}^{G} \sim S_\phi(\cdot \mid I, x)$;
    - Compute binary rewards $r_j \leftarrow \mathbb{1}(y_j = \tilde{y})$;
    - Update S_ϕ via GRPO using rewards $\{r_j\}_{j=1}^{G}$;
  - **end**
- **end**

the two interacting roles drive scalable self-evolution in multimodal reasoning.

- **The Evolution of Capabilities and Data Accuracy.** Building on the interaction between question difficulty and solution accuracy, we further analyze how the Reasoner's capabilities and the quality of pseudo-labeled data evolve across iterations. For each training iteration, the Questioner generates questions for the same 200 images, and Reasoners from each iteration attempt to answer them. As shown in Table 2, the Reasoner's accuracy steadily improves across iterations (e.g., from 44.0 to 49.0 on first-iteration questions), while the estimated accuracy of pseudo-labels slightly declines (from 72 to 61), reflecting increasing question difficulty. These trends highlight the co-evolution of model reasoning ability and data complexity during self-improving training.

3.5. Case Study on Question Difficulty Evolution

Table 4 presents example questions generated by the self-evolving Vision-Language Models across three training iterations. Iteration 1 questions focus on direct observation, such as counting or identifying objects. Iteration 2 introduces relational and comparative reasoning, requiring the model to assess differences or evaluate spatial angles. Iteration 3 further increases complexity with multi-step reasoning and inference, including precise localization and causal relationships. This progression demonstrates a systematic increase in question difficulty, providing increasingly challenging training signals that encourage the model to adapt and improve its reasoning capabilities. Such a design ensures that both the Questioner and Reasoner co-evolve, progressively enhancing the overall performance of the system.

4. Related Work

Post-Training for Vision-Language Models Recent research in post-training of vision-language models (VLMs) has shifted from supervised fine-tuning (SFT) toward reinforcement learning (RL) paradigms. Earlier works such as LLaVA [14, 25] primarily rely on SFT to align a language model backbone with a visual information via a projection layer, enabling multimodal instruction-following and visual reasoning. However, as base model quality improves, RL-based post-training has emerged as a more powerful alternative. In particular, R1-style training [7] has gained attention for its ability to enhance visual reasoning. A key insight behind this success is that RL becomes effective only when the base model is sufficiently capable to self-explore reasoning trajectories [1, 5, 17, 18]. Despite these advances, most existing RL-based VLM approaches still depend on annotated multimodal datasets, which are costly and difficult to scale [8, 9, 12, 20, 23, 28, 46, 48, 49]. To reduce reliance on human supervision, several recent works explore VLM self-play paradigms in games. Vision-Zero [35] and Game-RL [33] train VLMs with simulated game data to improve their general reasoning ability. Nonetheless, these methods often continue to depend on external models or tools for training data generation.

Self-Evolving In Large Language Models Recent work has focused on enabling large language models (LLMs) to

Table 1. Comprehensive results on visual reasoning benchmarks. Each base model is evaluated against two settings: a *VisPlay* (❄ challenger) baseline, in which the Reasoner is trained on questions produced by an untrained Challenger, and our iterative *VisPlay* framework. The highest performance reached during training for each model is emphasized in bold. We take accuracy as the metric.

	General Visual Understanding				**Visual Math**		**Hallucination**	
Methods	**MMMU**	**MM -Vet**	**RealWorld QA**	**VisNum Bench**	**Math Verse**	**MATH -Vision**	**Hallusion Bench**	**Avg.**
Qwen2.5-VL-3B-Instruct								
Base Model	19.95	36.24	49.28	27.08	26.14	20.23	32.81	30.61
VisPlay (❄ challenger)	23.34	43.58	57.78	29.33	33.50	23.39	64.88	33.77
VisPlay (Iter 1)	29.40	**48.62**	67.06	30.01	29.67	22.57	91.80	44.16
VisPlay (Iter 2)	33.37	44.50	65.62	29.64	32.36	24.67	**94.95**	44.87
VisPlay (Iter 3)	**37.11**	38.07	**71.90**	**39.15**	**35.15**	**29.97**	90.54	**47.27**
Qwen2.5-VL-7B-Instruct								
Base Model	23.10	44.95	57.52	32.57	33.78	24.05	66.88	40.41
VisPlay (❄ challenger)	35.24	45.87	69.67	32.41	35.13	26.22	78.13	38.33
VisPlay (Iter 1)	28.94	46.33	62.61	28.65	33.88	26.91	80.34	44.53
VisPlay (Iter 2)	27.07	42.66	60.92	27.08	36.32	25.00	67.72	40.97
VisPlay (Iter 3)	**38.27**	**46.33**	**69.67**	**32.57**	**39.14**	**31.15**	**92.32**	**48.61**
MiMo-VL-7B-SFT								
Base Model	30.22	**59.17**	78.17	44.80	41.80	25.33	87.17	43.56
VisPlay (❄ challenger)	27.54	58.72	63.27	49.66	38.78	24.80	57.83	39.63
VisPlay (Iter 1)	25.67	56.42	69.54	51.59	40.20	25.13	**87.59**	43.16
VisPlay (Iter 2)	**34.07**	55.96	**78.69**	51.18	41.65	28.45	86.65	45.58
VisPlay (Iter 3)	28.24	56.88	71.50	**52.69**	**46.02**	**29.44**	74.55	**45.69**

Table 2. Analysis of model performance and data quality. The shaded column indicates the estimated accuracy of the self-generated pseudo-labels for each question set, as determined using ChatGLM-Flash.

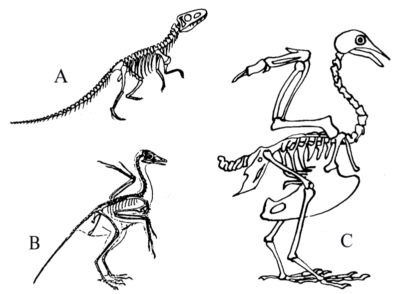
	Performance of Evaluated Model (vs. Ground Truth)				
	Base Model	Reasoner (Iter 1)	Reasoner (Iter 2)	Reasoner (Iter 3)	Pseudo-Label Acc.
$\mathcal{D}_{\text{Iter 1}}$	39.0	44.0	45.5	49.0	72.0
$\mathcal{D}_{\text{Iter 2}}$	37.5	42.5	44.0	47.5	65.0
$\mathcal{D}_{\text{Iter 3}}$	36.0	40.0	41.5	45.0	61.0

Table 3. Performance comparison between *VisPlay* and standard GRPO training with human-labeled data. Although *VisPlay* relies entirely on self-generated supervision, it achieves competitive overall accuracy and significantly reduces hallucination. This demonstrates that our self-evolving framework can meaningfully enhance VLM performance even in the absence of human-annotated datasets.

	General Visual Understanding				**Visual Math**		**Hallucination**	
Methods	**MMMU**	**MM -Vet**	**RealWorld QA**	**VisNum Bench**	**Math Verse**	**MATH -Vision**	**Hallusion Bench**	**Avg.**
Qwen2.5-VL-3B-Instruct								
Standard GRPO	40.3	49.5	63.0	36.7	42.8	29.9	67.4	47.1
VisPlay (Iter 3)	37.1	38.1	71.9	39.2	35.2	30.0	90.5	47.3
Qwen2.5-VL-7B-Instruct								
Standard GRPO	39.8	51.8	66.6	43	53.2	33.8	66.6	50.7
VisPlay (Iter 3)	38.3	46.3	69.7	32.6	39.1	31.2	92.3	48.6

self-evolve their reasoning capabilities with minimal to zero human supervision. Various approaches have been proposed to achieve this. General unsupervised self-training frameworks like Genius [41] and Deep Self-Evolving Reasoning [26] aim for advanced reasoning. A common theme is data-free training or starting from zero data, as ex-

Table 4. Examples of challenging questions generated by the self-evolving Vision-Language model across three training iterations. The questions progressively increase in complexity, illustrating the growth in difficulty of the Questioner's outputs over iterations. Images on the left and right correspond to the visual context for each question. The questions are raised by Qwen2.5-VL-3B-Instruct.

Challenging Examples from Self-Evolving Trained Vision-Language Model		
		
Question (Iter 1)	Approximately how many lung fields are visible in the X-ray image?	Which skeletal structure most likely belongs to a bird with hollow bones?
Question (Iter 2)	On a thoracic x-ray, the right lobe of the lung is more spread out compared to the left lobe. If the right lobe is given a score of 1 and the left lobe is given a score of 0, what is the difference in scores between the right and left lung lobes?	On which figure does the long neck of the dinosaur have the greatest horizontal angle with the vertical axis?
Question (Iter 3)	On which rib is the line approximately 2.5 cm above the image's midpoint?	Which skeletal structure is most likely to have evolved secondary to flying abilities and which is less likely to have this trait?

plored in R-Zero [13], Absolute zero [50], and Language self-play [15]. Other methods adapt self-play for specific goals or environments. For example, SPICE [24] improves reasoning in corpus environments, Search Self-play [27] pushes capabilities via search, and SPELL [43] focuses on evolving long-context models. Additionally, some methods utilize interactions between multiple agents to collectively bootstrap reasoning abilities, as seen in Socratic-Zero [36] and Multi-Agent Evolve [4].

5. Limitation

While our work introduces a scalable, self-evolving framework, we acknowledge two primary limitations that suggest directions for future research. First, due to computational constraints, our experiments were limited to the Qwen2.5-VL and MiMo-VL families. The scalability and effectiveness of *VisPlay* on significantly larger VLMs (e.g., $\geq$ 10B parameters) is still an important open question. Second, our framework lacks a definitive verification method for the self-generated data. While our GRPO policy indirectly optimizes for quality, developing more robust, automated methods to verify data faithfulness and prevent error accumulation is a key area for future investigation.

6. Conclusion

We present *VisPlay*, a self-evolving RL framework that enables vision-language models to autonomously improve from unlabeled images. By decomposing a VLM into an Image-Conditioned Questioner and a Multimodal Reasoner and optimizing them via GRPO, our method balances challenge and accuracy without human supervision. Experiments show consistent gains in reasoning, compositional generalization, and hallucination reduction across multiple benchmarks. *VisPlay* demonstrates that scalable, self-improving multimodal intelligence is achievable. By iteratively generating and learning from its own experiences, a model can refine its capabilities beyond human-labeled data. This framework opens avenues for richer multimodal interactions and cross-domain adaptation, pointing toward intelligence systems that can continually evolve autonomously. Our results suggest a promising path toward truly autonomous vision-language systems that improve themselves over time.

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