V-Retrver: Evidence-Driven Agentic Reasoning for Universal Multimodal Retrieval

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 Home: https://github.com/chendy25/V-Retrver
🤗 HF: https://huggingface.co/V-Retrver

Abstract

Multimodal Large Language Models (MLLMs) have recently been applied to universal multimodal retrieval, where Chain-of-Thought (CoT) reasoning improves candidate reranking. However, existing approaches remain largely language-driven, relying on static visual encodings and lacking the ability to actively verify fine-grained visual evidence, which often leads to speculative reasoning in visually ambiguous cases. We propose V-Retrver, an evidence-driven retrieval framework that reformulates multimodal retrieval as an agentic reasoning process grounded in visual inspection. V-Retrver enables an MLLM to selectively acquire visual evidence during reasoning via external visual tools, performing a multimodal interleaved reasoning process that alternates between hypothesis generation and targeted visual verification. To train such an evidence-gathering retrieval agent, we adopt a curriculum-based learning strategy combining supervised reasoning activation, rejection-based refinement, and reinforcement learning with an evidence-aligned objective. Experiments across multiple multimodal retrieval benchmarks demonstrate consistent improvements in retrieval accuracy (with 23.0% improvements on average), perception-driven reasoning reliability, and generalization.

1. Introduction

The rapid development of Multimodal Large Language Models (MLLMs) has substantially advanced universal multi-modal retrieval (Chen et al., 2024c; Lin et al., 2024a; Wang et al., 2024b; Zhu et al., 2025d; Sun et al.), enabling a single model to support diverse retrieval scenarios such as text-to-image, image-to-text, and interleaved multimodal queries. Recent works further demonstrate that incorporating Chain-of-Thought (CoT) reasoning can improve retrieval performance by enhancing interpretability and candidate discrimination (Zhu et al., 2025d; Xu et al., 2025c; Narayan et al., 2025). However, despite these advances, existing CoT-based retrieval systems remain fundamentally language-driven, even when retrieval decisions critically depend on visual evidence.

This limitation becomes particularly pronounced in visually ambiguous retrieval scenarios, where candidate images share similar semantic content but differ in fine-grained visual attributes such as object appearance, style, or local context. Most current MLLM-based retrieval methods (Liu et al., 2025; Chen et al., 2024c; Lin et al., 2024a) compress visual inputs into fixed embeddings or textual descriptions, forcing the reasoning process to rely on language alone to infer visual differences. Consequently, the model often produces speculative or hallucinated reasoning when the required evidence lies in the visual modality. Even recent reasoning-enhanced retrieval frameworks, such as Retrv-R1 (Zhu et al., 2025d) and MM-R5 (Xu et al., 2025b), improve textual reasoning depth but still rely on single-pass visual encoding, lacking the ability to actively verify visual hypotheses during reasoning.

To overcome this gap, we propose **V-Retrver**, an evidence-driven retrieval framework that reformulates multimodal retrieval as an agentic reasoning process grounded in visual inspection. Instead of treating visual representations as static inputs, V-Retrver enables an MLLM to selectively acquire visual evidence during reasoning by invoking external visual tools. Through a multimodal interleaved Chain-of-Thought process, the model alternates between hypothesis generation and targeted visual verification, allowing it to dynamically resolve visual ambiguities and progressively refine ranking decisions, as illustrated in Fig. 1.

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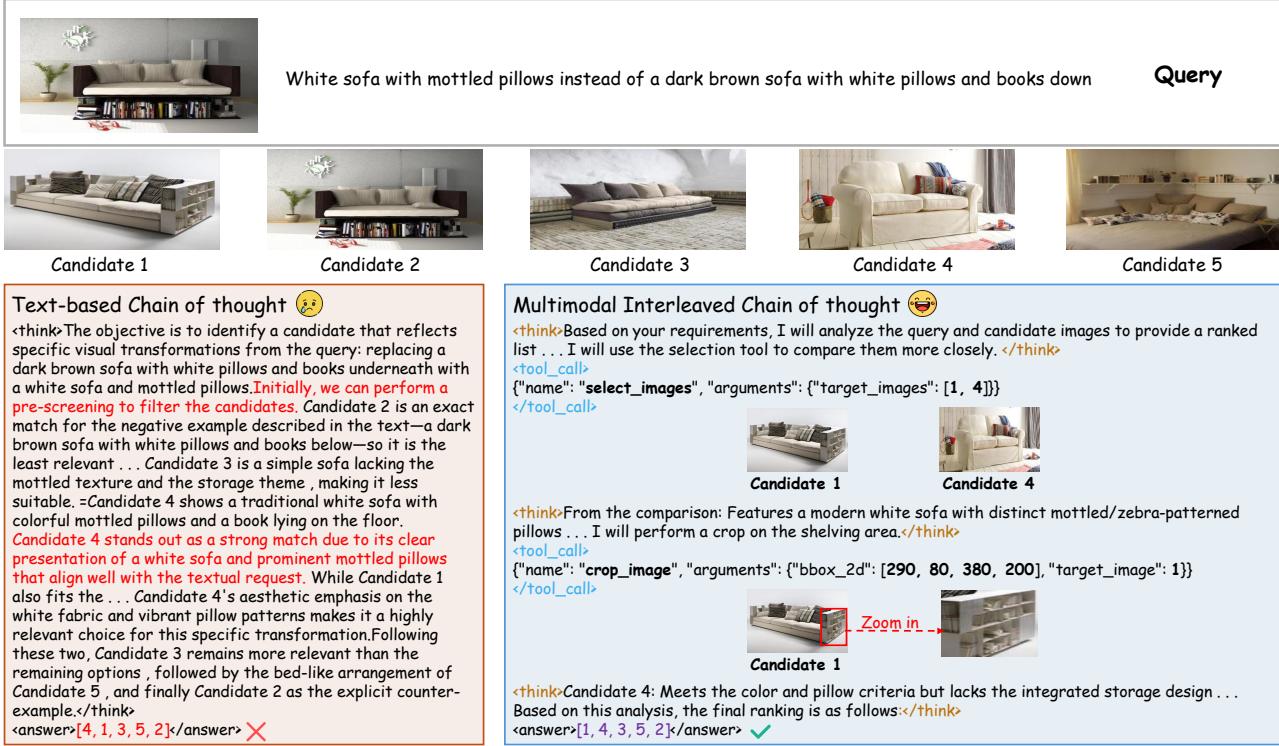
Figure 1. Comparison between text-based CoT (left) and multimodal interleaved CoT (right) for multimodal retrieval. Text-based CoT relies on language-driven inference over static visual representations, often failing to resolve fine-grained differences. In contrast, V-Retrver performs multimodal interleaved CoT reasoning by invoking visual tools to inspect candidate images, enabling grounded reasoning and more reliable ranking decisions.

Training such an evidence-gathering retrieval agent requires not only strong reasoning ability but also effective alignment between retrieval performance and visual tool usage. We therefore adopt a curriculum-based training strategy consisting of three stages. First, a cold-start supervised stage initializes the model with basic reasoning capabilities and operation formatting using synthesized high-quality CoT data. Second, rejection sampling fine-tuning consolidates high-quality reasoning trajectories and improves structural compliance. Finally, we introduce **Evidence-Aligned Policy Optimization (EAPO)**, instantiated via Group Relative Policy Optimization (GRPO) (Guo et al., 2025), which reinforces correct ranking decisions while encouraging informative visual verification and discouraging redundant tool usage.

Extensive experiments on the universal multimodal retrieval benchmark M-BEIR, as well as multiple out-of-domain datasets, demonstrate that V-Retrver consistently outperforms strong baselines across diverse retrieval settings. The results show that V-Retrver achieves higher retrieval accuracy, more reliable perception-grounded reasoning, and stronger generalization ability, validating the effectiveness of interleaved visual reasoning for multimodal retrieval. In summary, our contributions are three-fold:

- We propose V-Retrver, an evidence-driven agentic retrieval framework that enables MLLMs to actively acquire visual evidence during multimodal reasoning.

- We introduce a curriculum-based training strategy with an evidence-aligned reinforcement learning objective that jointly improves reasoning quality, ranking accuracy, and efficient visual tool usage.

- Extensive experiments across multiple benchmarks demonstrate that V-Retrver consistently outperforms existing methods and generalizes well to diverse multimodal retrieval scenarios.

2. Related Work

Multi-modal Large Language Models. In recent years, the rapid advancement of multimodal large language models (MLLMs) has driven the deep integration of visual perception and language reasoning, leading to the emergence of a series of high-performing open-source models, notably the LLaVA (Liu et al., 2024; Guo et al., 2024; Zhang et al., 2025c; Lin et al., 2023a; Li et al., 2023a), Qwen-VL (Bai et al., 2023; Wang et al., 2024a; Yang et al., 2024), and InternVL (Chen et al., 2024b; Gao et al., 2024; Lu et al., 2025) series. In parallel, large-scale models such as Flamingo (Alayrac et al., 2022), mPLUG-Owl (Ye et al.,

2023; 2024b;a), and GPT-4V (Yang et al., 2023) pursue a more holistic vision-language modeling paradigm, incorporating advanced mechanisms including mixture-of-experts architectures (Shu et al., 2024; Li et al., 2025b; Shen et al., 2024) and image generation components (Xie et al., 2024; Xu et al., 2025a). However, these models generally lack reasoning capabilities such as Chain-of-Thought and test-time scalability (Muennighoff et al., 2025; Zhang et al., 2025b; Chen et al., 2024a), and to a large extent still decouple visual perception from text reasoning processes.

Multimodal Retrieval. Recent advances in deep learning (Zhu et al., 2021; 2024; 2025a;c;b; Ji et al., 2024) have substantially propelled progress across a broad spectrum of retrieval tasks, including text–image cross-modal retrieval (Pham et al., 2024; Fu et al., 2024; Zhang et al., 2020; Chun et al., 2021; Kim et al., 2023b;a), composed image retrieval (Baldrati et al., 2022; Saito et al., 2023; Gu et al., 2024; Suo et al., 2024; Baldrati et al., 2023), multimodal document retrieval (Chen et al., 2023; Hu et al., 2023; Liu et al., 2023), and instruction-based image retrieval (Wu et al., 2021; Zhang et al., 2024a; Asai et al., 2023). Among these approaches, vision–language models (VLMs), particularly CLIP (Radford et al., 2021), have demonstrated strong effectiveness and scalability in multimodal retrieval scenarios (Baldrati et al., 2022; Wei et al., 2024b; Sain et al., 2023; Pei et al., 2023; Jin et al., 2024). For instance, Kim et al. (Kim et al., 2023a) improve CLIP via prompt tuning, enabling enhanced generalization across diverse retrieval settings. More recently, multimodal large language models (MLLMs) have been introduced to further advance retrieval performance (Liu et al., 2025; Jiang et al., 2024; Lin et al., 2024a; Zhou et al., 2024). Some approaches (Zhou et al., 2024; Lan et al., 2025; Lin et al., 2024a; Zhang et al., 2024b; Jian et al., 2025; Gu et al., 2025) utilize embeddings extracted from MLLMs to perform similarity-based retrieval. Others approaches, such as LamRA (Liu et al., 2025; Li et al., 2025a), employ MLLMs as reranking agents to refine candidate lists and select the most relevant results. Retrv-R1(Zhu et al., 2025d) equips the model with text reasoning capabilities for multimodal retrieval tasks through reinforcement learning. In contrast to prior work, we introduce V-Retrver, an evidence-driven retrieval framework, which can adaptively adjust its visual exploration strategy during reasoning by invoking visual tools, enabling a more flexible and effective reasoning process and thereby achieving significant improvements in retrieval performance.

3. Method

3.1. Problem Formulation

We study the problem of *universal multimodal retrieval*. Given a query q of arbitrary modality (text, image, or in-

terleaved multimodal input) and a candidate pool $\Omega = \{c_n\}_{n=1}^N$, the objective is to identify the most relevant candidate $\hat{c} \in \Omega$. Conventional multimodal retrieval approaches typically formulate this problem as static similarity matching or language-only reranking over fixed visual representations. Such formulations implicitly assume that all necessary visual evidence has been fully encoded into embeddings or textual descriptions *prior* to reasoning. However, this assumption breaks down in fine-grained or visually ambiguous retrieval scenarios, where subtle local details determine relevance and cannot be reliably inferred from compressed representations alone.

To address this limitation, we reformulate multimodal retrieval as an *evidence-grounded reasoning problem*. Under this formulation, retrieval is no longer a single-pass inference process, but an iterative decision-making procedure in which the model is required to actively acquire and verify visual evidence during ranking. Specifically, the retrieval process consists of three tightly coupled steps: (i) generating hypotheses about candidate relevance based on available information, (ii) selectively inspecting visual evidence to resolve uncertainty, and (iii) refining the ranking decision based on verified observations. This perspective naturally gives rise to an *agentic reranking* paradigm, where a retrieval model is endowed with the ability to reason, inspect, and revise its decisions, rather than passively scoring candidates using fixed representations.

3.2. Overview of V-Retrver

Building on the above formulation, we propose **V-Retrver**, an evidence-driven reasoning framework for universal multimodal retrieval, As illustrated in Fig. 2. V-Retrver follows a coarse-to-fine retrieval pipeline that decouples efficient candidate proposal from computationally intensive evidence-based reasoning. In the first stage, an embedding model ϕ encodes the query q and each candidate c_n into a shared representation space, retrieving the top-K candidates based on similarity. We adopt the same method as LamRA (Liu et al., 2025) for constructing the embedding model ϕ. This stage serves as an efficient candidate proposal mechanism and substantially reduces the search space:

$$\mathcal{C} = \{c_k\}_{k=1}^K, \quad K \ll N.$$

In the second stage, V-Retrver employs a reasoning agent θ to perform fine-grained reranking over the reduced candidate set $\mathcal{C}$. Crucially, θ is not a conventional reranker that operates over static features. Instead, it is designed as an *agentic evidence-gathering model* that can iteratively reason, invoke visual inspection tools, and revise its ranking decisions based on newly acquired visual observations. The final prediction is produced as:

$$\hat{c} = \theta(q, \mathcal{C}).$$
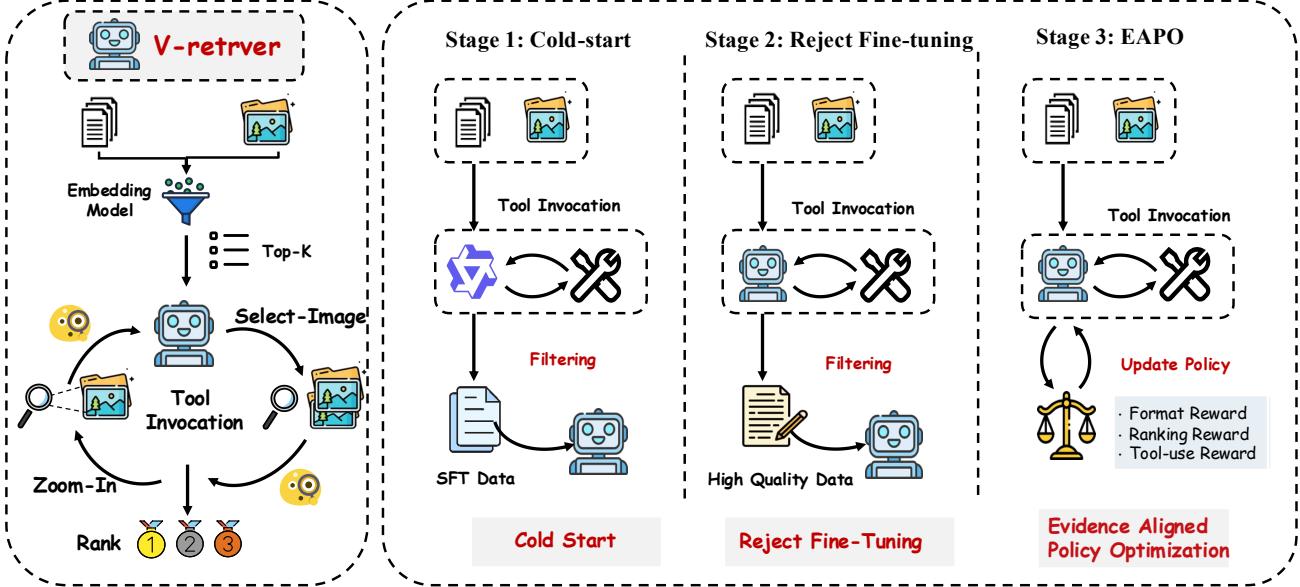
Figure 2. Overview of the V-Retrver framework. The left panel illustrates the inference pipeline, featuring a coarse-to-fine process with embedding-based retrieval and agentic reranking. The right panel details the three training stages we proposed, including Cold Start, Rejection sampling Fine-Tuning, and EAPO.

The remainder of this section details the core mechanisms that enable evidence-driven reasoning in V-Retrver, including multimodal interleaved reasoning, visual tools, and a curriculum-based training strategy.

3.3. Multimodal Interleaved Evidence Reasoning

We introduce **Multimodal Interleaved Evidence Reasoning (MIER)**, a reasoning paradigm that tightly interleaves textual hypothesis generation with targeted visual evidence acquisition. Unlike language-only Chain-of-Thought reasoning, MIER allows intermediate reasoning steps to be explicitly grounded in visual observations obtained on demand. Formally, given an initial textual query T_0 and a candidate image set I_0, the reasoning agent iteratively produces outputs:

$$O_k = f_{\text{MLLM}}\big(\{T_i, C_i, V_i\}_{i=0}^k\big),$$

where T_i denotes a textual reasoning step, C_i denotes a tool invocation request, and V_i represents the visual evidence returned by the tool. A parser then determines whether to extract the next reasoning step and tool request (T_{k+1}, C_{k+1}), or to terminate the process and output a final ranking.

If a tool is invoked, the corresponding visual tool is executed and returns new visual evidence V_{k+1}, which is appended to the reasoning context. This process yields a multimodal reasoning trajectory:

$$\tau = \{T_1, C_1, V_1, T_2, C_2, V_2, \ldots, T_n, A_n\},$$

where A_n denotes the final ranked list of candidates. By explicitly grounding intermediate reasoning steps in dynam-ically acquired visual evidence, MIER mitigates speculative inference and hallucination, enabling more reliable ranking decisions in visually ambiguous cases.

3.4. Visual Tools

To support MIER, we equip the reasoning agent with a set of **Visual Tools**, which serve as external perceptual interfaces for selective visual inspection. These tools allow the model to control *what* to observe and *where* to focus during reasoning. Specifically, we implement two tools:

(1) SELECT-IMAGE, which enables the agent to select a subset of candidate images for closer inspection when multiple candidates exhibit high semantic similarity.

(2) ZOOM-IN, which performs localized zoom-in operations on specified regions of an image, allowing fine-grained analysis of discriminative visual attributes such as objects, textures, or spatial configurations.

These tools facilitate *selective perception* during retrieval. Rather than encoding all visual information upfront, the agent dynamically expands its visual receptive field only when necessary, closely mirroring human retrieval behavior in which ambiguous candidates are resolved by "looking again" at critical details.

3.5. Training V-Retrver via Curriculum-Based Agentic Learning

Training V-Retrver requires transforming a general-purpose MLLM into an agent capable of stable, evidence-driven

reasoning and strategic tool usage. To this end, we design a three-stage curriculum that progressively builds reasoning structure, reliability, and decision-making optimality.

Stage I: Reasoning Activation via Supervised Fine-Tuning. We begin with a cold-start supervised fine-tuning stage to activate basic reasoning and tool-use behaviors. Since existing retrieval datasets lack annotated reasoning trajectories, we synthesize multimodal Chain-of-Thought data using Qwen2.5-VL-72B-Instruct. These trajectories include structured reasoning steps and valid tool invocation patterns. After applying rule-based filtering to remove logically inconsistent or malformed samples, the base model is fine-tuned using standard SFT loss. This stage establishes foundational reasoning syntax and tool awareness, but does not yet guarantee robustness or optimal tool-use strategies.

Stage II: Rejection Fine-Tuning for Reasoning Reliability. Although Stage I activates tool-use behavior, the resulting policy exhibits high variance and produces a large fraction of low-quality trajectories. To improve reasoning reliability, we perform Rejection Sampling Fine-Tuning (RSFT). For each training instance, we sample multiple reasoning trajectories and retain only those that strictly satisfy formatting constraints and yield correct retrieval rankings. Fine-tuning on this filtered dataset significantly improves logical consistency and format compliance, providing a stable initialization for reinforcement learning.

Stage III: Evidence-Aligned Policy Optimization. While the previous stages activate structured reasoning and improve trajectory reliability, they do not explicitly optimize *how* visual evidence should be acquired during retrieval. In practice, the model may either underutilize visual inspection or invoke tools redundantly without contributing to better ranking decisions. To address this limitation, we introduce **Evidence-Aligned Policy Optimization (EAPO)**, a reinforcement learning objective that explicitly aligns retrieval performance with effective and economical visual verification behavior.

EAPO formulates multimodal retrieval as a trajectory-level decision-making problem, where each reasoning trajectory o_i is evaluated based on both ranking quality and evidence utilization. Specifically, we define a composite reward:

$$R_i = \alpha r_{\text{format}}(o_i) + \beta r_{\text{rank}}(o_i) + r_{\text{tool}}(o_i), \quad (1)$$

where the three components respectively encourage structural correctness, accurate ranking, and informative visual inspection. Below, we detail each reward term.

Format Compliance Reward. The format compliance reward r_{format} ensures that the model adheres to the required reasoning and output protocols, which is essential for stable policy optimization with structured multimodal outputs. Let Ω_{tag} denote the set of trajectories whose outputs are correctly enclosed by predefined `<think>` and `<answer>` tags, and

let Ω_{list} denote the set of trajectories whose final answers strictly follow the required integer ranking list format. We define:

$$r_{\text{format}}(o_i) = \frac{1}{2} \mathbb{I}_{\{o_i \in \Omega_{\text{tag}}\}} + \frac{1}{2} \mathbb{I}_{\{o_i \in \Omega_{\text{list}}\}}, \quad (2)$$

where $\mathbb{I}_{\{\cdot\}}$ is the indicator function. This term primarily serves as a stabilizing signal, preventing malformed trajectories from dominating policy updates.

Soft Ranking Reward. To mitigate the sparsity of binary correctness signals in retrieval tasks, we introduce a soft ranking reward r_{rank} that provides dense feedback based on the relative position of the correct candidate. Let k denote the 1-indexed rank of the ground-truth candidate in the predicted list of trajectory o_i. If the correct candidate does not appear within the top-K_r positions or the output is invalid, the reward is set to zero. Otherwise, it is defined as:

$$r_{\text{rank}}(o_i) = \exp\left(-\frac{(k-1)^2}{2\sigma^2}\right), \quad (3)$$

where σ controls the sensitivity to ranking errors. This formulation encourages the agent to continuously improve ranking quality rather than optimizing a sparse top-1 signal.

Tool-Use Reward. The tool-use reward r_{tool} directly governs the agent's evidence acquisition behavior, encouraging visual inspection only when it contributes to correct decisions while discouraging redundant or excessive tool usage. Let N_{tool} denote the number of valid visual tool invocations in trajectory o_i, and let k be the rank position of the correct candidate. We define:

$$\begin{aligned} r_{\text{tool}}(o_i) = \; & \eta \cdot \mathbb{I}_{\{k=1\}} \cdot \mathbb{I}_{\{N_{\text{tool}}>0\}} \\ & - \rho \cdot \max(0, N_{\text{tool}} - \tau), \end{aligned} \quad (4)$$

where η incentivizes successful evidence-based verification, ρ penalizes excessive tool invocations, and τ specifies a tolerance threshold. This design explicitly encodes the principle that *effective* tool usage, rather than frequent usage, should be rewarded.

Policy Optimization. We instantiate EAPO using Group Relative Policy Optimization (GRPO) (Guo et al., 2025). Given a group of G trajectories sampled for the same query, we compute normalized advantages:

$$A_i = \frac{R_i - \text{mean}(R)}{\text{std}(R)}. \quad (5)$$

The final optimization objective is:

$$\mathcal{J}_{\text{EAPO}}(\theta) = \mathbb{E}\left[\frac{1}{G}\sum_{i=1}^{G} \frac{\pi_\theta(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)} A_i - \lambda \text{KL}(\pi_\theta \| \pi_{\text{ref}})\right]. \quad (6)$$

Through EAPO, the model learns not only *what* to rank, but also *how* and *when* to acquire visual evidence in order to support reliable and efficient retrieval decisions.

4. Experiments

4.1. Experimental Setup

Table 1. **Summary of the evaluation benchmarks.** The benchmarks are categorized into Supervised and Zero-shot settings. # Queries represents the number of test queries, and # Candidates denotes the number of test candidates per query.

Benchmark	# Queries	# Candidates
Supervised		
M-BEIR (Wei et al., 2024a)	190K	5.6M
Zero-shot		
CIRCO (Baldrati et al., 2023)	800	120K
GeneCIS (Vaze et al., 2023)	8K	$10 \sim 15$
Visual Storytelling (Huang et al., 2016)	5K	8K
Visual Dialog (Das et al., 2017)	2K	2K
Multi-round FashionIQ (Yuan & Lam, 2021)	2.4K	6.2K

Datasets and Metrics. We utilize the M-BEIR (Wei et al., 2024a) dataset for training. The M-BEIR dataset encompasses eight distinct retrieval tasks across 10 different retrieval datasets, comprising a total of 1.1M training samples. As shown in Table 1, to evaluate the versatility of V-Retrver, across various retrieval tasks, we conduct assessments on the M-BEIR test set. Furthermore, we investigate V-Retrver's generalization ability on other previously unseen datasets, including CIRCO (Baldrati et al., 2023),GeneCIS (Vaze et al., 2023), Visual Storytelling (Huang et al., 2016), Visual Dialog (Das et al., 2017), among others. We adhere to the standard evaluation metrics established for each dataset.We primarily utilize Recall@K as the evaluation metric for the retrieval tasks. Additionally, for specific datasets like CIRCO, we report MAP@5 to provide a more nuanced evaluation of ranking quality.

Experiment Settings & Baselines. We establish three distinct experiment settings: (i) To validate the versatility of our method across a range of retrieval tasks, we train V-Retrver on all 8 tasks in the M-BEIR benchmark and evaluate its performance on the test sets. For the baselines, we compare our model against: (1) foundational VLMs (e.g., Qwen2.5-VL, CLIP, BLIP); (2) fine-tuned universal retrievers such as UniIR-BLIP$_{FF}$ and UniIR-CLIP$_{SF}$; and (3) recent reasoning-enhanced models and universal retriever, including Vision-R1 (Huang et al., 2025), VLM-R1 (Shen et al., 2025), MM-Embed (Lin et al., 2024a), LamRA (Liu et al., 2025) and U-MARVEL (Li et al., 2025a) to demonstrate the advantages of our visual CoT framework. (ii) To evaluate the generalization ability on previously **unseen retrieval datasets**, we perform zero-shot experiments on 5 datasets not encountered during training. In this case, the baseline includes a selection of universal retrievers, such as E5-V, MagicLens, and MM-Embed. (iii) To investigate the generalization capacity on **unseen retrieval tasks**, we intentionally exclude data from three retrieval tasks: image-to-image retrieval, text-image-to-text retrieval, and text-image-to-text-image retrieval. Training is then conducted on the remaining five

tasks with the evaluation of these excluded tasks.

Sliding Window Reranking. Following the coarse-to-fine paradigm, V-Retrver employs a sliding window strategy to rerank the initial retrieval results. Specifically, we first retrieve the top K candidates using the MLLM-based embedding model ϕ as described in Sec. 3.1. Inspired by the iterative reranking approach in (Zhang et al., 2025a), we set the window size to $K = 20$ with a stride of 10 to efficiently identify the most relevant items. This results in four MLLM reasoning calls per query to progressively refine the results into a finalized rank. This sliding window approach allows our model to perform fine-grained multimodal reasoning over a large candidate pool while maintaining manageable computational overhead.

Implementation Details. Our model is initialized based on Qwen2.5-VL-7B-Instruct (Bai et al., 2025). For the SFT and Rejection Fine-Tuning stages, we utilize the LLaMA-Factory (Zheng et al., 2024) framework and conduct training on 8 A800 GPUs with a batch size of 64 and a learning rate of 1×10^{-5} for two epochs. The RL training is based on the verl-tool (Jiang et al., 2025) framework, which extends the functionalities of verl (Sheng et al., 2024) and vLLM (Kwon et al., 2023) to provide specialized support for multimodal tool-augmented multi-turn training and evaluation. For the RL stage, the model is trained for 1 epoch with a learning rate of 1×10^{-6}, using 8 rollouts per query. Throughout all training stages, the vision encoder remains frozen, while the language model is fine-tuned. The number of candidates K input to the MLLM θ is set to 20. During the M-BEIR evaluation, experiments are conducted in the local pool, with V-Retrver reranking the top-50 results. For experiments on unseen datasets, reranking is applied to the top-10 results. The soft ranking sensitivity σ is set to 1.0, and the ranking reward threshold K_r is set to 5. The reward weighting factors α and β are fixed at 0.2 and 0.8, respectively. Regarding the tool-use mechanism, the hyperparameters in Eq. (4) are configured as $\eta = 0.2$, $\rho = 0.1$, and $\tau = 1$. Additionally, we use a KL penalty coefficient $\lambda = 0$ in the EAPO objective.

4.2. Main Results

Performance on M-BEIR. As presented in Table 2, V-Retrver-7B establishes a new state-of-the-art across the M-BEIR benchmark with an average Recall of 69.7%. This represents a significant improvement of +4.9% over the strongest baseline U-MARVEL-7B(64.8%). The advantages of our method are particularly evident in scenarios requiring fine-grained visual detail, such as $(q^i, q^t) \rightarrow c^i$ on FIQ and CIRR. In contrast, V-Retrver achieves 51.2% on FIQ and 73.5% on CIRR. These scores substantially outperform e U-MARVEL-7B, which achieves 38.2% and 63.2% respectively. These results confirm that the multimodal in-

Table 2. **Comparison with other methods on M-BEIR test set.** R@K refers to the Recall@K metric. q^t, q^i, c^t and c^i denote the text query, image query, text candidates and image candidates, respectively. Abbreviations used include VN for VisualNews, F200K for Fashion200K, InfoS for InfoSeek, and FIQ for FashionIQ. The best results are highlighted in **bold**.

Models	$q^t \to c^i$			$q^t \to c^t$	$q^t \to (c^i,c^t)$		$q^i \to c^t$			$q^i \to c^i$	$(q^i,q^t) \to c^t$		$(q^i,q^t) \to c^i$		$(q^i,q^t) \to (c^i,c^t)$		Avg.
	VN	COCO	F200K	WebQA	EDIS	WebQA	VN	COCO	F200K	NIGHTS	OVEN	InfoS	FIQ	CIRR	OVEN	InfoS	
	R@5	R@5	R@10	R@5	R@5	R@5	R@5	R@5	R@10	R@5	R@5	R@5	R@10	R@5	R@5	R@5	
CLIP-L (Radford et al., 2021)	43.3	61.1	6.6	36.2	43.3	45.1	41.3	79.0	7.7	26.1	24.2	20.5	7.0	13.2	38.8	26.4	32.5
SigLIP (Zhai et al., 2023)	30.1	75.7	36.5	39.8	27.0	43.5	30.8	88.2	34.2	28.9	29.7	25.1	14.4	22.7	41.7	27.4	37.2
BLIP (Li et al., 2022)	16.4	74.4	15.9	44.9	26.8	20.3	17.2	83.2	19.9	27.4	16.1	10.2	2.3	10.6	27.4	16.6	26.8
BLIP2 (Li et al., 2023b)	16.7	63.8	14.0	38.6	26.9	24.5	15.0	80.0	14.2	25.4	12.2	5.5	4.4	11.8	27.3	15.8	24.8
UniIR-BLIP$_{FF}$ (Wei et al., 2024b)	23.4	79.7	26.1	80.0	50.9	79.8	22.8	89.9	28.9	33.0	41.0	22.4	29.2	52.2	55.8	33.0	46.8
UniIR-CLIP$_{SF}$ (Wei et al., 2024b)	42.6	81.1	18.0	84.7	59.4	78.7	43.1	92.3	18.3	32.0	45.5	27.9	24.4	44.6	67.6	48.9	50.6
Qwen2.5-VL-3B (Bai et al., 2025)	36.0	67.8	16.1	69.5	45.2	61.7	23.3	82.3	12.0	20.9	36.7	22.3	24.3	53.5	56.4	49.8	42.4
Qwen2.5-VL-7B (Bai et al., 2025)	40.2	71.9	20.3	71.9	49.4	64.5	29.3	84.6	19.4	25.5	42.4	32.1	25.0	55.1	60.8	54.9	46.7
Vision-R1-7B (Huang et al., 2025)	41.9	75.0	22.0	70.6	51.3	69.1	35.4	85.1	22.4	25.9	48.8	44.0	29.2	57.7	66.2	59.0	50.2
VLM-R1-7B (Shen et al., 2025)	40.5	77.2	22.5	72.3	50.0	67.9	36.2	86.3	20.9	26.4	48.8	37.5	29.9	57.4	64.0	62.3	50.0
MM-Embed-7B (Lin et al., 2024a)	41.0	71.3	17.1	95.9	46.8	85.0	41.3	90.1	18.4	32.4	42.1	42.3	25.7	50.0	64.1	57.7	52.7
LamRA-7B (Liu et al., 2025)	48.0	85.2	32.9	96.7	75.8	87.7	48.6	92.3	36.1	33.5	59.2	64.1	37.8	63.3	79.2	78.3	63.7
U-MARVEL-7B (Li et al., 2025a)	49.4	85.6	34.2	**98.5**	81.4	89.4	50.5	88.4	37.7	34.7	63.7	62.9	38.2	63.2	80.8	78.9	64.8
V-Retrver-7B	**51.8**	**87.5**	**40.3**	96.9	**82.9**	**90.2**	**52.2**	**94.8**	37.8	**39.8**	**69.8**	**73.2**	**51.2**	**73.5**	**87.8**	**85.0**	**69.7**

Table 3. **Experimental results on unseen datasets.** q^{dialog} and $(q^i \oplus q^t)$ refer to the dialog queries and multi-interleaved image-text queries, respectively.

Models	$(q^i,q^t) \to c^i$		$q^{dialog} \to c^i$	$(q^i \oplus q^t) \to c^i$	
	CIRCO	GeneCIS	VisD	VIST	MT-FIQ
	MAP@5	R@1	R@1	R@1	R@5
CLIP-L (Radford et al., 2021)	4.0	13.3	23.7	0.6	17.7
UniIR-CLIP (Wei et al., 2024b)	12.5	16.8	26.8	0.6	39.4
E5-V (Jiang et al., 2024)	24.8	18.5	54.6	10.0	19.2
MagicLens-L (Zhang et al., 2024a)	29.6	16.3	28.0	3.3	22.6
MM-Embed-7B (Lin et al., 2024a)	35.5	22.9	64.7	25.7	59.0
LamRA-7B (Liu et al., 2025)	42.8	24.8	70.9	28.6	63.9
V-Retrver-7B	**48.2**	**30.7**	**75.1**	**31.2**	**68.3**

Table 4. **Experimental results on held-out tasks.** * indicates that training is performed on the remaining tasks, w/o any exposure to the three held-out tasks.

Models	$q^i \to c^i$	$(q^i,q^t) \to c^t$		$(q^i,q^t) \to (c^i,c^t)$		Avg.
	NIGHTS	OVEN	InfoS	OVEN	InfoS	
	R@5	R@5	R@5	R@5	R@5	
Supervised						
UniIR-BLIP$_{FF}$ (Wei et al., 2024b)	33.0	41.0	22.4	55.8	33.0	37.0
UniIR-CLIP$_{SF}$ (Wei et al., 2024b)	32.0	45.5	27.9	67.6	48.9	44.4
Zero-shot						
Qwen2.5-VL-7B (Bai et al., 2025)	20.3	38.5	40.4	53.6	44.9	39.5
Vision-R1-7B (Huang et al., 2025)	22.9	39.8	42.9	57.4	46.5	41.9
LamRA-7B* (Liu et al., 2025)	29.2	46.9	54.2	65.1	59.1	50.9
V-Retrver-7B*	**36.2**	**57.8**	**65.9**	**75.3**	**70.3**	**61.1**

terleaved chain-of-thought reasoning method can effectively improve the model's information retrieval capabilities.

Generalization to Unseen Datasets. The zero-shot evaluation results in Table 3 underscore the robustness of our reasoning framework on datasets not encountered during training. V-Retrver consistently outperforms specialized models and generalist MLLMs. Notably, on CIRCO which features distinct domain shifts, V-Retrver achieves a MAP@5 of 48.2. This significantly surpasses the specialized MM-Embed-7B (35.5) and LamRA-7B (42.8). Similarly, on GeneCIS, our model attains an R@1 of 30.7 compared to 24.8 for LamRA-7B. We attribute this generalization to reinforcement learning.

Robustness on Held-out Tasks. To verify task-level adaptability, we evaluate V-Retrver on retrieval tasks where specific modality combinations were strictly excluded during training. As shown in Table 4, even without prior exposure to these formats, the model achieves an average Recall of 61.1%, significantly outperforming LamRA-7B (50.9%) by a margin of 10.2%. These results empirically demonstrate that the MIER framework effectively decouples the rea-

soning process from specific input types, empowering the model to leverage interleaved evidence for accurate retrieval even in challenging zero-shot scenarios.

4.3. Ablation Study & Analysis

Impact of Training Stages. Table 6 presents the ablation results for each training stage. The row w/o SFT & RSFT & RL refers to directly prompting the untrained backbone for tool use, which results in a performance collapse to 45.8%, even lower than the Qwen2.5-VL-7B baseline (47.2%), indicating that zero-shot tool invocation without alignment is ineffective. The w/o RSFT & RL setting includes only the SFT stage, which activates basic tool-use ability and raises the average recall to 59.4%. Removing only RSFT (w/o RSFT) means the model is trained with SFT and RL, skipping the rejection sampling phase, and achieves 66.3%. The w/o RL configuration applies SFT and RSFT but omits reinforcement learning, resulting in 60.9%. Finally, the full pipeline reaches the highest performance at 67.2%. These results highlight the importance of structured curriculum learning, as each stage addresses specific shortcomings of the previous one.

(a) Rank Reward   *(b)* Response Length   *(c)* Tool Calls
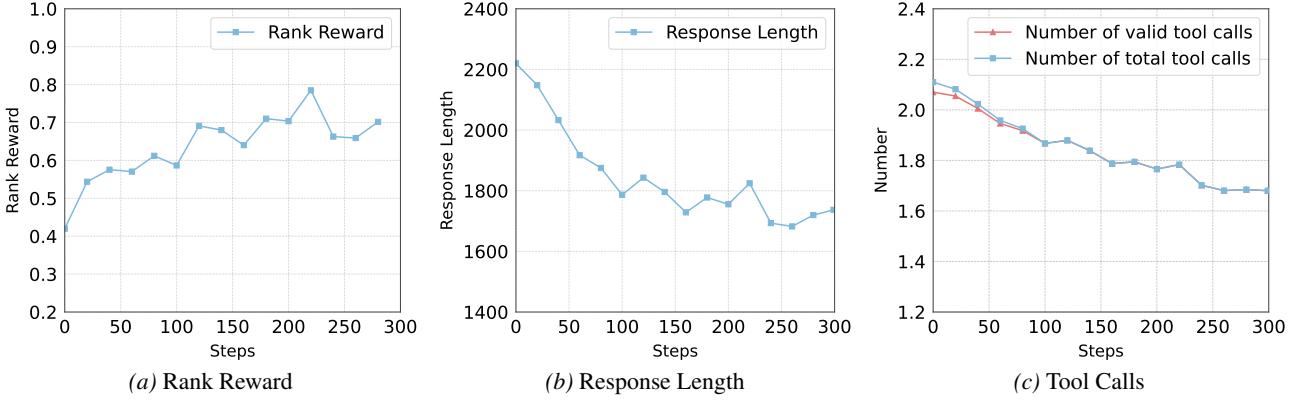
Figure 3. RL Training curves.

Table 5. **Ablation study on visual tool-use mechanism.** We compare the proposed multimodal interleaved CoT (with Visual Tool) against a text-only reasoning baseline (w/o Visual Tool) under the same RL training framework.

Variants	$q^t \to c^i$ COCO R@5	$q^i \to c^t$ F200K R@10	$(q^i, q^t) \to c^i$ CIRR R@5	$(q^i, q^t) \to c^t$ OVEN R@5	Avg.
Qwen2.5-VL-7B (Bai et al., 2025)	71.9	19.4	55.1	42.4	47.2
RL w/o tool	84.1	33.2	66.5	63.2	61.8
V-Retrver-7B	**87.5**	**37.8**	**73.5**	**69.8**	**67.2**

Table 6. **Ablation study on training stages and components.** We investigate the impact of Cold Start (SFT), Rejection Sampling Fine-Tuning (RSFT), and Reinforcement Learning (RL) using Qwen2.5-VL-7B as the backbone.

Training Stage	$q^t \to c^i$ COCO R@5	$q^i \to c^t$ F200K R@10	$(q^i, q^t) \to c^i$ CIRR R@5	$(q^i, q^t) \to c^t$ OVEN R@5	Avg.
Qwen2.5-VL-7B (Bai et al., 2025)	71.9	19.4	55.1	42.4	47.2
w/o SFT & RSFT & RL	71.5	18.1	53.4	40.2	45.8
w/o RSFT & RL	83.2	31.6	63.7	59.0	59.4
w/o RSFT	87.2	37.3	72.4	68.3	66.3
w/o RL	83.9	32.8	65.3	61.5	60.9
V-Retrver-7B	**87.5**	**37.8**	**73.5**	**69.8**	**67.2**

Effectiveness of Visual Tool. To isolate the impact of tool-use, we train a variant of Qwen2.5-VL-7B-Instruct using end-to-end RL with text-based CoT reasoning on the same training dataset (RL w/o tool). As shown in Table 5. The text-only variant achieves an average recall of 61.8%, whereas V-Retrver reaches 67.2%. The findings confirm that incorporating vision tools yields supplementary, high-fidelity insights that text reasoning alone cannot capture from static representations. Specifically, the ability to actively zoom in or select images allows the model to resolve fine-grained ambiguities that are often lost in compressed visual embeddings, proving indispensable for truly precise multimodal retrieval.

4.4. Training Curves

Fig.3 illustrates the evolution of ranking accuracy, reasoning density, and tool-use efficiency throughout the RL training process. As the training progresses, the model's retrieval accuracy exhibits a generally upward trend, indicating that EAPO effectively enhances the model's perception-driven reasoning. Regarding tool-use behavior, we observe that the number of effective tool calls is slightly lower than the total number of invocations in the initial stages. This suggests that while the model acquired basic tool-use capabilities during the SFT and RSFT stages, it still occasionally committed formatting inconsistencies or logical missteps. As training continues, these two curves converge, demonstrating that RL further reinforces tool-use robustness and eliminates erroneous calls. This convergence signifies that the policy

optimization process successfully penalizes hallucinated tool actions, steering the agent toward a more rigorous execution of tool protocols. Additionally, the average response length and tool frequency decrease before stabilizing; this indicates the model learns to autonomously judge the necessity of visual evidence, effectively suppressing redundant reasoning and focusing its attention on resolving critical visual ambiguities through more grounded and purposeful multimodal trajectories.

5. Conclusion

In this paper, we presented V-Retrver, an evidence-driven MLLM framework tailored for universal multimodal retrieval. V-Retrver adopts multimodal interleaved Chain-of-Thought (CoT) reasoning, enabling the model to dynamically inspect and verify candidate images through visual tool invocation, thereby achieving more fine-grained ranking of candidate result lists. We adopt a three-stage training pipeline to multimodal interleaved CoT reasoning abilities. Extensive experimental results demonstrate that V-Retrver achieves significant improvements in both model effectiveness and task generalization. We regard V-Retrver to be an important step toward effectively introducing agentic MLLMs to enhance downstream multimodal tasks, laying a solid foundation for building general agentic MLLMs with advanced reasoning capabilities.

Impact Statement

This paper presents work whose goal is to advance the field of machine learning. There are many potential societal consequences of our work, none of which we feel must be specifically highlighted here.

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A. Prompt Template

A.1. System Prompt

Fig. 4 illustrate the system prompt for both training and inference.

System Prompt for Training and Inference

You are a helpful assistant for multimodal retrieval tasks.
\# Tools

You may call at most two tool invocations in total. In any single turn, you may emit only one <tool_call></tool_call> block.
You are provided with function signatures within <tools></tools> XML tags.

<tools>
{"type": "function", "function": {"name": "crop_image", "description": "Zoom in on a query image or a candidate image based on the bounding box coordinates.", "parameters": {"type": "object", "properties": {"bbox_2d": {"type": "array", "description": "Bounding box of the area to zoom in, using pixel coordinates. Minimum is 0 and maximum is the image width/height.", "items": {"type": "number"}}, "target_image": {"type":"number", "description": "Index of the image to crop. Use 0 for the query image, or an integer from 1 to the number of candidate images."}}, "required": ["bbox_2d", "target_image"]}}}
{"type": "function", "function": {"name": "select_images", "description": "Select 1 to 4 query or candidate images for detailed analysis from the query/candidate list. You can select 1, 2, 3, or 4 images, but never more than 4.", "parameters": {"type": "object", "properties": {"target_images": {"type": "array", "description": "List containing 1 to 4 image indices to select for detailed analysis. Use index 0 to select the query. Use indices 1, 2, 3, ... up to the number of candidates to select candidate. You can mix query and candidate images, e.g., [0] for query only, [10] for candidate 10 only, [0, 10, 11] for query and candidates 10, 11, [2, 3, 10] for candidates 2, 3, 10, etc. Maximum 4 images total.", "items": {"type": "integer", "description": "Image index: 0 for the query image, or 1 to the number of candidates for candidate images."}, "minItems": 1, "maxItems": 4}}, "required": ["target_images"]}}}
</tools>

For each function call, return exactly one json object with function name and arguments within <tool_call></tool_call> XML tag:
<tool_call>
{"name": <function-name>, "arguments": <args-json-object>}
</tool_call>

Figure 4. System Prompt template for training and inference.

A.2. User Prompt

Fig. 5 illustrate the user prompt for both training and inference.

User Prompt for Training and Inference

Query: <question> Candidates: (1) <candidate$_1$>(2) <candidate$_2$>......(K) <candidate$_K$>

Guidelines: You are given a query (which can be text, image, or both) and multiple candidate items (which can be text, image, or both). Your task is to rank all candidates from most relevant to least relevant based on how well they match the query.

You can use the following tools to assist with analysis:
1. `crop_image`: Zoom in on specific areas of the query image or a candidate image for detailed analysis.
2. `select_images`: Select 1 to 4 query images or candidate images from the provided list for focused comparison.

Analyze the visual and textual features step by step. Provide your final answer in one of the following exact formats:
If you DO need to use tools:
<think>Your detailed reasoning process here, explaining your analysis steps and tool usage.</think><tool_call>{"name": <function-name>, "arguments": <args-json-object>}</tool_call><think>Continue your reasoning based on tool outputshere.</think><answer>[ranked_list]</answer>
If you do NOT need to use tools:
<think>Your detailed reasoning process here, explaining your analysis steps.</think><answer>[ranked_list]</answer>

Example:
<think>Your reasoning process here</think><tool_call>{"name": "select_images", "arguments": {"target_images": [0, 1, 2]}}</tool_call><think>Continue your reasoning based on tool outputs here</think><answer>[14, 13, 20, 11, 16, 19, 6, 7, 2, 17, 3, 9, 1, 18, 10, 5, 15, 12, 4, 8]</answer>

Figure 5. User Prompt template for training and inference.

A.3. Annotation Prompt

Fig. 6 illustrate the annotation prompt. Specifically for the CoT annotation process, the annotation prompt (Fig. 6) is inserted into the user prompt to guide the generation.

Annotation Prompt

Analyze the visual and textual features step by step. Your reasoning process should generally follow these stages:

First, analyze the key features and requirements of the query (both visual and textual).

Then perform a quick pre-screening of all candidates to filter out clearly irrelevant ones. Next, identify a subset of the most promising candidates (e.g., the top 5 to 8 potential matches) that appear to be the strongest contenders based on this initial scan.

For these promising candidates, provide a more detailed analysis of their distinguishing features, explaining why each one might or might not match the query (e.g., taxonomy, visual characteristics, context, or any other relevant attributes).

If there are important, ambiguous, or missing visual details that are critical for making a precise decision, decide whether to call tools. You may, for example, use `crop_image` to zoom into specific regions when finer visual inspection is needed, or use `select_images` to focus on a small subset of the most relevant images.

After each tool call, carefully summarize the visual information obtained from the tool outputs (e.g., what you observe in the selected or cropped images) and integrate this information into your reasoning. Use these visual observations to refine your comparison among the promising candidates and to resolve any ambiguities.

Based on the combined textual and visual analysis, determine which candidate is the single best match to the query. Then use your reasoning to order all remaining candidates by relevance, from more relevant to less relevant, until you obtain a complete ranking of all candidates.

Finally, construct the complete ranking list containing ALL candidate indices from 1 to N. Place your determined best match first, followed by the remaining candidates ordered by relevance, and then provide your final answer in the required format.

Figure 6. Annotation Prompt template.

B. Details about M-BEIR Dataset

We present the details for the M-BEIR benchmark in Table 7. It is important to note that the M-BEIR benchmark applies additional processing to the datasets it incorporates, which may result in differences from the standard evaluation of individual datasets. For instance, the candidate pool of the CIRR dataset in M-BEIR includes training data, which essentially increases the evaluation's difficulty compared to the original CIRR dataset. For a more comprehensive understanding of these differences, we refer the readers to the original UniIR (Wei et al., 2024a) paper.

Table 7. **Summary of the M-BEIR benchmarks.**

Task	Dataset	Domain	# Train	# Dev	# Test	# Pool
$q^t \rightarrow c^i$	VisualNews	News	99K	20K	20K	542K
	MSCOCO	Misc.	100K	24.8K	24.8K	5K
	Fashion200K	Fashion	15K	1.7K	1.7K	201K
$q^t \rightarrow c^t$	WebQA	Wiki	16K	1.7K	2.4K	544K
$q^t \rightarrow (c^i, c^t)$	EDIS	News	26K	3.2K	3.2K	1M
	WebQA	Wiki	17K	1.7K	2.5K	403K
$q^i \rightarrow c^t$	VisualNews	News	100K	20K	20K	537K
	MSCOCO	Misc.	113K	5K	5K	25K
	Fashion200K	Fashion	15K	4.8K	4.8K	61K
$q^i \rightarrow c^i$	NIGHTS	Misc.	16K	2K	2K	40K
$(q^i, q^t) \rightarrow c^t$	OVEN	Wiki	150K	50K	50K	676K
	InfoSeek	Wiki	141K	11K	11K	611K
$(q^i, q^t) \rightarrow c^i$	FashionIQ	Fashion	16K	2K	6K	74K
	CIRR	Misc.	26K	2K	4K	21K
$(q^i, q^t) \rightarrow (c^i, c^t)$	OVEN	Wiki	157K	14.7K	14.7K	335K
	InfoSeek	Wiki	143K	17.6K	17.6K	481K
8 tasks	10 datasets	4 domains	1.1M	182K	190K	5.6M

C. Details about Unseen Dataset

Here, we present the details of the Unseen Dataset in Table 8. Many of them are actually adapted from MSCOCO or FashionIQ, however, note that, their captions or query formats are significantly different. Therefore, we still treat these datasets as unseen datasets. For instance, The query format of CIRCO combines a reference image with a relative caption. These differences create a substantial disparity compared to the original COCO dataset.

Table 8. **Summary of the Unseen Dataset.**

Dataset	Image Source	Task	Query Format	Candidate Format
CIRCO	MSCOCO unlabeled set	$(q^i, q^t) \rightarrow c^i$	`<image><relative caption>`	`<image>`
GeneCIS	MSCOCO	$(q^i, q^t) \rightarrow c^i$	`<image><relative caption>`	`<image>`
Visual Dialog	MSCOCO	$q^{dialog} \rightarrow c^i$	`<Q₁><A₁>···<Qⱼ><Aⱼ>`	`<image>`
Visual Storytelling	Flickr	$(q^i \oplus q^t) \rightarrow c^i$	`<text₁><image₁>···<textⱼ>`	`<image>`
MT-FIQ	FashionIQ	$(q^i \oplus q^t) \rightarrow c^i$	`<image₁><relative caption₁>···` `<imageⱼ><relative captionⱼ>`	`<image>`

D. Exploration of RAG Applications

To further validate the practical utility of our framework, we extend our evaluation to Retrieval-Augmented Generation (RAG) scenarios. Following the experimental setup of LamRA (Liu et al., 2025),we evaluate our method on three Knowledge-based Visual Question Answering (KVQA) benchmarks. Specifically, we train the retrieval and VQA tasks simultaneously during the training process, allowing the model to to align the agentic visual reasoning process with downstream generation needs. As detailed in Table 9, V-Retrver achieves superior performance in both retrieval precision and VQA accuracy, demonstrating that our Multimodal Interleaved Evidence Reasoning significantly enhances MLLM capabilities in RAG settings.

Table 9. **Comparison of RAG capabilities on KVQA tasks.**

Method	OKVQA (Marino et al., 2019)	Infoseek (Chen et al., 2023)	E-VQA (Mensink et al., 2023)
Retrieval (PR@5)			
PreFLMR (Lin et al., 2024b)	70.9	62.1	73.7
LamRA-7B (Liu et al., 2025)	89.0	73.4	75.0
V-Retrver-7B	**90.9**	**78.3**	**78.1**
VQA (ACC)			
RA-VQAv2 w/ PreFLMR (Lin et al., 2023b)	61.9	32.1	54.5
LamRA-7B (Liu et al., 2025)	64.3	28.8	56.2
V-Retrver-7B	**65.7**	**31.9**	**58.0**

E. Algorithms and Detailed Analysis

In this section, we present the formal algorithms for the inference and training processes of V-Retrver, followed by a complexity analysis.

E.1. Inference Process

The inference process of V-Retrver, formulated as a coarse-to-fine pipeline with sliding window agentic reasoning, is detailed in Algorithm 1.

E.2. Training Pipeline

The three-stage curriculum learning strategy, designed to progressively align the model with evidence-driven retrieval objectives, is presented in Algorithm 2.

Algorithm 1 V-Retrver Inference Pipeline

Input: Query q, Candidate Pool $\Omega = \{c_n\}_{n=1}^N$, Embedding Model Φ, Reasoning Agent π_θ, Top-K size K, Window size W, Stride S

Output: Ranked Candidate List $\hat{L}$

{// Stage 1: Coarse Retrieval (Embedding-based)}

Compute similarity scores $s_n = \cos(\Phi(q), \Phi(c_n))$ for all $c_n \in \Omega$

Select top-K candidates: $\mathcal{C}_{top} \leftarrow$ Top-K$(\Omega, \{s_n\})$

{// Stage 2: Agentic Reranking (Reasoning-based)}

Initialize global ranking list $\mathcal{L}_{global} \leftarrow \emptyset$

Split $\mathcal{C}_{top}$ into windows $\{w_1, w_2, \ldots, w_m\}$ with size W and stride S

for each window $w_j \in \{w_1, \ldots, w_m\}$ **do**

   Initialize context $H_0 \leftarrow (q, w_j, \text{Instruction})$

   $t \leftarrow 0$

   while True **do**

      Generate output: $o_t \sim \pi_\theta(H_t)$

      if o_t contains `<tool_call>` **then**

         Parse action a_t and arguments from o_t

         Execute visual tool: $v_{obs} \leftarrow f_{tool}(a_t, w_j)$

         Update context: $H_{t+1} \leftarrow H_t \oplus o_t \oplus v_{obs}$

      else if o_t contains `<answer>` **then**

         Parse local rank list $\hat{r}_j$ from o_t

         Update $\mathcal{L}_{global}$ with local rank $\hat{r}_j$

         break

      end if

      $t \leftarrow t + 1$

   end while

end for

$\hat{L} \leftarrow$ AggregateRanks$(\mathcal{L}_{global})$

Algorithm 2 Curriculum-Based Agentic Training

Input: Pretrained MLLM θ_{init}, Retrieval Dataset $\mathcal{D}$, Synth Model M_{syn}
Output: Optimized Policy π_{θ^*}
{// Stage 1: Reasoning Activation (SFT)}
Synthesize CoT data: $\mathcal{D}_{sft} \leftarrow \{(q, c, \tau_{cot})\}$ using M_{syn} on $\mathcal{D}$
Filter $\mathcal{D}_{sft}$ for format compliance
Update $\theta_{sft} \leftarrow$ Minimize $\mathcal{L}_{SFT}(\theta_{init}, \mathcal{D}_{sft})$
{// Stage 2: Reliability Refinement (Rejection Sampling)}
Initialize $\mathcal{D}_{rsft} \leftarrow \emptyset$
for each $(q, c) \in \mathcal{D}$ **do**
    Sample k trajectories $\{\tau_1, \ldots, \tau_k\} \sim \pi_{\theta_{sft}}(q, c)$
    if IsFormatValid$(\tau_i) \wedge$ IsRankCorrect(τ_i) **then**
        Add valid τ_i to $\mathcal{D}_{rsft}$
    end if
end for
Update $\theta_{rsft} \leftarrow$ Minimize $\mathcal{L}_{SFT}(\theta_{sft}, \mathcal{D}_{rsft})$
{// Stage 3: Evidence-Aligned Policy Optimization (EAPO)}
Initialize $\theta \leftarrow \theta_{rsft}$, Reference policy $\pi_{ref} \leftarrow \theta_{rsft}$
while not converged **do**
    Sample batch of queries $B_q \sim \mathcal{D}$
    for each query $q \in B_q$ **do**
        Sample group of trajectories $G = \{o_1, \ldots, o_G\} \sim \pi_\theta(q)$
        Compute rewards $R(o_i) = \alpha r_{fmt}(o_i) + \beta r_{rank}(o_i) + r_{tool}(o_i)$
    end for
    Compute advantages A_i via Group Normalization over G
    Compute GRPO loss $\mathcal{J}_{EAPO}(\theta)$
    Update $\theta \leftarrow$ Optimize $\mathcal{J}_{EAPO}(\theta)$
end while
return π_θ

F. Qualitative Examples

To provide an intuitive illustration of our approach and to further demonstrate the effectiveness of the proposed V-Retrver, we present some qualitative results (Fig. 7, Fig.8, Fig. 9, Fig. 10 and Fig. 11). These examples illustrate how V-Retrver performs accurate retrieval through fine-grained and structured reasoning, thereby highlighting the strong effectiveness of the proposed method.

G. Limitations and Future Works

Despite its strong performance, V-Retrver still has several limitations. First, the current visual toolset is restricted to image selection and zoom-in operations, and may be insufficient for more complex visual reasoning that requires object-level manipulation or multi-step spatial analysis. Second, our training relies on synthesized reasoning trajectories and curated rewards, which may introduce biases and limit robustness under more diverse or noisy real-world settings. Future work will explore lightweight and adaptive inference strategies to reduce computational overhead, expand the visual tool repertoire to support richer perceptual operations. We also plan to extend the framework to broader downstream tasks such as multimodal recommendation and retrieval-augmented generation, further advancing general-purpose agentic MLLMs.

Has more buttons and is blue and is lighter   **Query**

Candidate 1   Candidate 2   Candidate 3   Candidate 4   Candidate 5

<think>The query specifies a shirt that is blue, lighter in color, and has more buttons. Let's analyze the candidates based on these criteria:1. Candidate 1: This shirt is blue but appears to be a darker shade. It has a collar but no visible buttons.2. Candidate 2: This shirt is blue and lighter in color. It has a pocket but no visible buttons.3. Candidate 3: This shirt is light blue and has a pocket. It also has a visible button on the collar.4. Candidate 4: This shirt is blue and lighter in color. It has multiple visible buttons and a pocket.5. Candidate 5: This shirt is blue but appears to be a darker shade. It has a collar but no visible buttons.Based on the initial analysis, Candidate 4 seems to match the query as it is blue, lighter in color, and has multiple buttons. Candidate 3 is also a strong contender as it is light blue and has a button, but it seems to have fewer buttons compared to Candidate 4. Candidate 2 is light blue but lacks buttons. Candidate 1 and Candidate 5 are darker blue and lack buttons.To confirm the button count and color shade, I will use the `select_images` tool to focus on Candidates 3 and 4</think>
<tool_call>{"name": "select_images", "arguments": {"target_images": [3, 4]}} </tool_call>

Candidate 3   Candidate 4

<think>The selected images confirm the following:- Candidate 3 (Image 1): This shirt is light blue and has a single button on the collar. It matches the query's requirement of being blue and lighter in color but does not have multiple buttons.- Candidate 4 (Image 2): This shirt is blue and lighter in color. It has multiple buttons, which aligns with the query's requirement of "more buttons." Based on the detailed analysis, Candidate 4 is the best match as it meets all the query requirements. Candidate 3 is the second-best match as it is light blue and has a button, but it has fewer buttons. The remaining candidates are less relevant. The final ranking is: 4, 3, 2, 1, 5 </think>
<answer>[4, 3, 2, 1, 5]</answer>

Figure 7. A qualitative example of the retrieval result generated from V-Retrver.

Figure 8. A qualitative example of the retrieval result generated from V-Retrver.

Green metallic knitted dress **Query**

Candidate 1 Candidate 2 Candidate 3 Candidate 4 Candidate 5

<think>The query specifies a "Green metallic knitted dress." Let's analyze the candidates based on the key features: color (green), material (metallic and knitted), and style (dress).1. Candidate 1: This dress is green and knitted, but it appears to be a solid matte color with no visible metallic finish.2. Candidate 2: This dress is metallic and knitted, but the color is dark/olive, not the requested green.3. Candidate 3: This dress is green and has a knitted texture. However, looking at the full-body image, I am uncertain if the fabric actually has a metallic sheen or if it is just the lighting on standard yarn.4. Candidate 4: This dress is green and knitted, but looks like a standard textile without metallic properties.5. Candidate 5: This dress is metallic and knitted, but the color is incorrect (not green).Because I am not sure if Candidate 3 actually possesses the required metallic luster, I need to use the crop tool to inspect the fabric details more closely to confirm.</think>
<tool_call>{"name": "crop_image", "arguments": {"bbox_2d": [0, 0, 180, 250], "target_image": 3}}</tool_call>

Zoom in

Candidate 3   Cropped image

<think>The selected images confirm the following:- Candidate 3 (Image 1): This shirt is light blue and has a single button on the collar. It matches the query's requirement of being blue and lighter in color but does not have multiple buttons.- Candidate 4 (Image 2): This shirt is blue and lighter in color. It has multiple buttons, which aligns with the query's requirement of "more buttons." Based on the detailed analysis, Candidate 4 is the best match as it meets all the query requirements. Candidate 3 is the second-best match as it is light blue and has a button, but it has fewer buttons. The remaining candidates are less relevant. The final ranking is: 4, 3, 2, 1, 5 </think>
<answer>[4, 3, 2, 1, 5]</answer>

Figure 9. A qualitative example of the retrieval result generated from V-Retrver.

What is this plant named after?   **Query**

Candidate 1

Lilium humboldtii. Lilium humboldtii, or Humboldt's lily, is a species of lily native to the US state of California and the Mexican state of Baja California. It is named after naturalist and explorer Alexander von Humboldt. It is native to the South High Cascade Range, High Sierra Nevada, south Outer South Coast Ranges, and the Santa Monica Mountains and others in Southern California, growing at elevations from 600 (m) to 1200 (m).Description. "Lilium humboldtii" grows up to 6 (ft) tall, with flowers that are maroon-spotted, golden-orange with dark red splotches, with orange to brown stamens. The plant flowers in June, with flowers.

Candidate 2

Lilium humboldtii. Roezl and Leichtlin, gave it the name "Lilium bloomerianum". For some time afterward, the name was still applied to the southern California "Lilium humboldtii" subsp. "ocellatum". Cultivation."Lilium humboldtii" is sold as a garden bulb. It prefers dry summer dormancy, with no water after blooming, good drainage, and part shade. It was one of the parents, along with "Lilium pardalinum", that produced the Bellingham hybrid lilies, which eventually resulted in the popular 'Shuksan' and 'Star of Oregon' lilies.Harlow, Nora, Jakob, Kristin, and Raiche, Roger (2003) "Wild Lilies, Irises, and Grasses". University of California Press. USDA Plants Profile: "Lilium humboldtii" Treatment from the.

Candidate 3

Lilium humboldtii. growing in a pyramidal inflorescence. The flowers are on stout stems, which are sometimes brown-purple. The subrhizomatous bulb is large, with yellowish-white scales, and grows very deep in the soil. The leaves grow in whorls, and are undulate, shiny, and oblanceolate. It is summer-deciduous, dying back after flowering in mid to late summer.Subspecies "Lilium humboldtii" subsp. "humboldtii" - central California"Lilium humboldtii" subsp. "ocellatum" - southern California, Baja CaliforniaBoth subspecies are on the California Native Plant Society "Inventory of Rare and Endangered Plants of California" and described as "fairly endangered in California".Albert Kellogg, unaware that the plant had already been named by.

Candidate 4

Lilium humboldtii. Jepson Manual-"Lilium humboldtii" CalFlora Taxon Report: "Lilium humboldtii " "Lilium humboldtii"-CalPhotos galleryiucnredlist.,

---

Candidate 5

Lilium parryi. especially "Hyles lineata" and "Sphinx perelegans".Threats to this species include grazing, recreation, natural flooding and human alterations in water regimes, and horticultural collecting of the bulbs and flowers."Lilium parryi" was named for Charles Christopher Parry (28 August 1823 2013 20 February 1890), a British-American botanist and mountaineer.Idyllwild, California, hosts the Lemon Lily Festival, which celebrates this species.Calflora Database: "Lilium parryi" (lemon lily)Jepson Manual Treatment of "Lilium parryi"USDA Plants Profile for "Lilium parryi" (lemon lily)UC Photos gallery: "Lilium parryi".

Query image   Cropped image

<think>The cropped image shows a close-up of one of the orange flowers in the query image. The flower appears to have dark red splotches, which aligns with the description of "Lilium humboldtii" in the candidates. This visual confirmation strengthens the match between the query image and the descriptions of "Lilium humboldtii." Final Ranking:1. Candidate (1): Best match as it directly describes "Lilium humboldtii" with golden-orange flowers and dark red splotches, matching the visual characteristics of the flowers in the image.2. Candidate (2): Also a strong match, providing additional information about the cultivation and history of "Lilium humboldtii."3. Candidate (4): Mentions "Lilium humboldtii" and provides references for further information. 4. Candidate (3): Provides detailed botanical information about "Lilium humboldtii," including its subspecies and conservation status. 5. Candidate (5): Least relevant as it describes "Lilium parryi" with lemon-colored flowers, which do not match the orange flowers in the image. </think>
<answer>[1, 2, 4, 3, 5]</answer>

Figure 10. A qualitative example of the retrieval result generated from V-Retrver.

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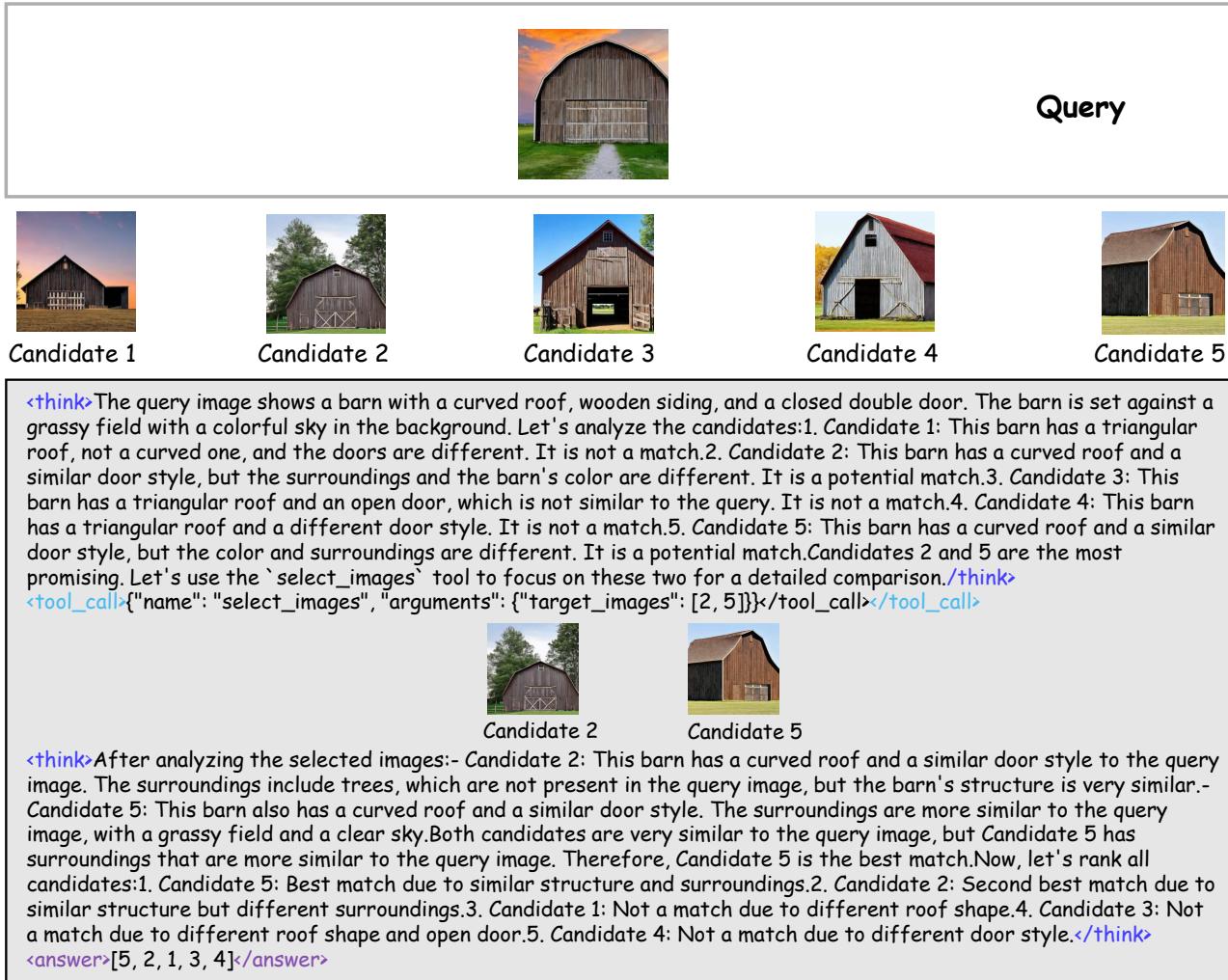
Figure 11. A qualitative example of the retrieval result generated from V-Retrver.