

ImageScope: Unifying Language-Guided Image Retrieval via Large Multimodal Model Collective Reasoning

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Abstract

With the proliferation of images in online content, language-guided image retrieval (LGIR) has emerged as a research hotspot over the past decade, encompassing a variety of subtasks with diverse input forms. While the development of large multimodal models (LMMs) has significantly facilitated these tasks, existing approaches often address them in isolation, requiring the construction of separate systems for each task. This not only increases system complexity and maintenance costs, but also exacerbates challenges stemming from language ambiguity and complex image content, making it difficult for retrieval systems to provide accurate and reliable results. To this end, we propose *ImageScope*, a training-free, three-stage framework that leverages collective reasoning to unify LGIR tasks. The key insight behind the unification lies in the compositional nature of language, which transforms diverse LGIR tasks into a generalized text-to-image retrieval process, along with the reasoning of LMMs serving as a universal verification to refine the results. To be specific, in the first stage, we improve the robustness of the framework by synthesizing search intents across varying levels of semantic granularity using chain-of-thought (CoT) reasoning. In the second and third stages, we then reflect on retrieval results by verifying predicate propositions locally, and performing pairwise evaluations globally. Experiments conducted on six LGIR datasets

demonstrate that *ImageScope* outperforms competitive baselines. Comprehensive evaluations and ablation studies further confirm the effectiveness of our design.

CCS Concepts

- Information systems → Information retrieval; Retrieval models and ranking; Users and interactive retrieval.

Keywords

Language-Guided Image Retrieval, Large Multimodal Model, Collective Reasoning

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1 Introduction

The past decade have witnessed an explosion of multimodal information on the internet, particularly with images emerging as one of the most prevalent mediums for online information sharing. Numerous image-centric platforms have proliferated, such as Instagram, Flickr, and Pinterest. To extract valuable information from the vast amount of images available on the web, image retrieval [14, 32] has evolved into a rapidly developing technology that underpins various applications in real life, especially in fields like e-commerce [10, 70] and search engines [61]. The traditional content-based image retrieval [23, 43, 56] and tag-based image retrieval [18, 53, 59] have achieved remarkable efforts, laying the foundation for the widespread adoption of text-to-image retrieval (TIR) [9] in most modern search engines. In recent years, TIR has been greatly boosted with Vision-Language Models (VLMs) [37, 38, 48, 52, 67] based on Transformer [54], which aligns visual and linguistic modalities within a

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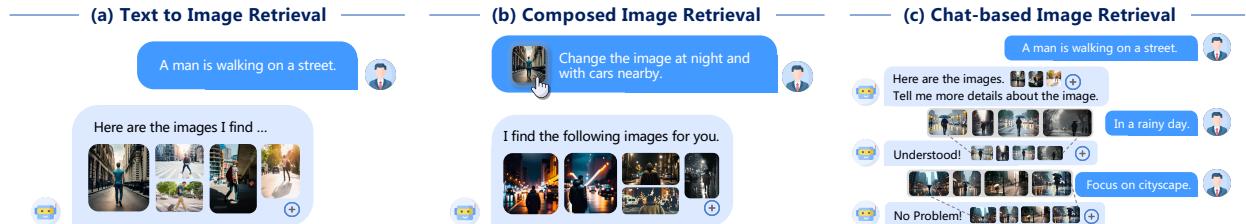


Figure 1: Illustration of three language-guided image retrieval tasks: Text-to-Image Retrieval (TIR), Composed Image Retrieval (CIR) and Chat-based Image Retrieval (Chat-IR).

joint latent space through pre-training on large-scale image-text pairs, providing advancements in retrieval accuracy and relevance.

Although these steady progress has been made, TIR falls short in capturing user's search intent in an interactive manner. Consequently, new tasks such as Composed Image Retrieval (CIR) [5, 12, 26, 44, 55] and Chat-based Image Retrieval (Chat-IR) [16, 35, 36] have been introduced. To be more specific, CIR enables users to refine search results through language feedback based on a provided reference image. As illustrated in Figure 1 (b), a user may wish to modify specific visual elements (e.g., objects, attributes, and environments) of the given reference image, and she/he can provide language feedback to guide the system in retrieving images that align with the desired changes. In contrast, Chat-IR, as depicted in Figure 1 (c), focuses on progressively narrowing down the search results through multiple rounds of dialog interaction, especially when the user's retrieval intent is initially vague or evolves throughout the retrieval process. For instance, a user might start with a broad query like "A man walking on the street" and later specify a preference for visual elements such as "rainy day" or "cityscape" after reviewing initial results. Both CIR and Chat-IR allow for continuous refinement of results to accommodate the dynamic nature of user needs. Tasks like these, including text-to-image retrieval (TIR), all rely on user-provided textual input, and these tasks are generally termed as *Language-Guided Image Retrieval* (LGIR) [12, 24, 27]. The research on LGIR has evolved rapidly, making remarkable progress across various tasks [6, 19, 25, 34–36].

Despite these task-specific advances, a fundamental challenge remains: existing methods tend to address each task in isolation, focusing on optimizing for specific input modalities or interaction styles without providing a unified framework that generalizes across LGIR tasks. This fragmented approach limits the ability to integrate information from diverse inputs, such as combining reference images and multi-turn dialog, which is critical for handling ambiguous queries and enhancing user's search experience. Moreover, the inherent ambiguity of natural language, combined with the complexity of real-world image content, makes it difficult to fully capture user intent and refine retrieval results. Accurately identifying subtle visual details remains particularly challenging for current methods, and the issue could be further amplified when user feedback is incomplete or imprecise.

To achieve this goal, in this paper, we propose a unified three-stage framework, named *ImageScope*, for LGIR, leveraging the advantages of multimodal collective reasoning to fully harness the potential of Large Multimodal Models (LMMs). The general idea underlying the unification is grounded in the compositional nature of language, allowing for the conversion of diverse LGIR tasks into

a standardized text-to-image retrieval process. Moreover, the reasoning capacities of LMMs act as a universal means of verification to improve the precision of results. To establish a unified framework, we utilize LMM to generate textual descriptions for both input reference image and images in database. We set the semantic composition in the language domain, using Large Language Model (LLM) to synthesize the user's various forms of textual feedback into a coherent description of the target image. Then the retrieval is transformed into a text-to-image retrieval process, which can be executed by a pretrained VLM. Subsequently, a carefully designed reflective assessment incorporating a verification-evaluation paradigm is introduced to enhance the refinement of the results.

More specifically, the *ImageScope* framework consists of three stages. (1) **Stage 1: Semantic Synthesis.** To thoroughly analyze operations on visual elements referenced in the textual feedback, we define five distinct instruction types within a carefully tailored prompt: addition, removal, modification, comparison and retention. Leveraging chain-of-thought (CoT) reasoning, the LLM-based reasoner employs a "Shotgun and Assembly" approach to semantic synthesis. It decomposes complex text inputs into atomic instructions (Shotgun) and then addresses potential ambiguities by generating image descriptions at three levels: core elements, enhanced details, and full synthesis (Assembly). Following this, a pre-trained VLM conducts dual-path retrieval for both text-to-image and text-to-text tasks to ensure robustness. (2) **Stage 2: Predicate Verification.** To overcome the limitations of pre-trained VLMs in capturing fine details, we propose a local semantic validation method based on predicate logic. The *reasoner*, guided by carefully crafted prompts, generates a series of verifiable propositions derived from the operations in the first stage. An LMM is then employed as a *verifier* to check the candidate images against these propositions. Additionally, we introduce a relaxation strategy to quantify the number of satisfied propositions, using this count to prioritize and rank the candidate images. (3) **Stage 3: Overall Evaluation.** In this stage, we perform a holistic evaluation to determine whether the retrieved images fully meet the user's instructions, particularly in scenarios involving comparisons with a reference image. Another LMM, serving as an *evaluator*, is employed to iteratively narrow down the candidate images through pairwise comparisons, until the image that best satisfies the user's requirements is identified.

In our method, these multimodal models collaborate across different stages of reasoning, a cohesive three-stage framework. Additionally, the proposed *ImageScope* framework is highly flexible, and seamlessly compatible with various models without additional training. The outputs from each stage are user-friendly and offer a degree of interpretability.

To sum up, our main contributions are threefold:

- This paper presents a novel framework, *ImageScope*, designed to address language-guided image retrieval (LGIR) tasks. To the best of our knowledge, *ImageScope* is the first unified framework capable of handling various LGIR tasks without requiring additional training.
- We propose a reflection method called verification-evaluation for image retrieval task that accounts for both local and global semantics. This method combines predicate proposition with pairwise comparison, significantly improving retrieval performance.
- The experimental results on six prevalent LGIR datasets show that our framework achieves state-of-the-art performance. Ablation studies and in-depth analysis further validate the effectiveness and generality of *ImageScope*.

2 Related Work

2.1 Language-Guided Image Retrieval

Unlike traditional content-based [23, 43, 56] or tag-based image [18, 53, 59] retrieval methods, language-guided image retrieval (LGIR) encompasses a range of language-centric tasks, such as text-to-image retrieval, composed image retrieval (CIR), and chat-based image retrieval (Chat-IR), offering a retrieval paradigm that allows flexible language feedback. Early traditional CIR methods treat textual instructions as modifications to a reference image [6, 12, 44, 55], relying heavily on expensive annotated triplets for training data. Zero-shot CIR [5, 50] has been recently introduced to alleviate such reliance, which can be broadly classified into two categories: text inversion [39, 50] and LLM editing [33, 64]. In contrast, Chat-IR originally stemmed from visual dialogue [16] and visual question-answering (VQA) tasks [3, 21], where multiple rounds of conversation revolve around a specific image to answer visual questions [17, 47]. Recent studies have designed a questioner to ask more discriminative questions [35, 36], aiding in better retrieval, and used LLM-based approaches to combine semantics for retrieval. However, these studies tend to address each LGIR task independently, lacking a unified modeling. In contrast, our framework adopts a training-free method to handle LGIR tasks in a unified manner, which significantly distinguishes it from previous approaches.

2.2 Large Models and Reasoning

In recent years, LLMs [2, 49, 63, 68] and LMMs [4, 13, 41] have demonstrated remarkable capabilities across various tasks [45, 62], particularly in generation, understanding, and planning. Researchers have found that step-by-step reasoning [57] and in-context learning can significantly enhance the performance of LLMs. Especially, the self-reasoning of LLM can help to improve the reliability and traceability of Retrieval-Augmented Generation (RAG) [60]. Some studies have explored the impact of different reasoning structures on performance, such as chain [11], tree [65], and graph [7] structures. Additionally, given the known susceptibility of LLMs to hallucinations [29], some research attempts to mitigate errors in the reasoning process through validation mechanisms, either via the model's own feedback [46] or external feedback [20]. By contrast, another line of research focuses on decomposing complex problems for more effective solutions. The Least-to-Most [71] approach breaks

problems down top-down into subproblems, while QDMR [28] decomposes them into directed acyclic graphs. These studies further promote advancements in areas like external tool usage [51] and multimodal question answering tasks [69]. Our work differs from these studies by designing a general reflection mechanism for LGIR tasks, which leverages the reasoning capabilities of LLMs and LMMs to refine retrieval results and enhance accuracy.

3 Methodology

In this section, we first formalize the LGIR task (§3.1), followed by an explanation of the unification approach to LGIR tasks as illustrated in Figure 2 (§3.2). Finally, we elaborate each stage of our proposed framework (§3.3, §3.4, §3.5).

3.1 Problem Definition

Let us define the image database \mathcal{D} , which consists of a set of images $\{I_i\}_{i=1}^N$. The goal of LGIR is to establish a scoring function $\mathcal{S} = \Psi(\mathcal{T}, I_r, \mathcal{D})$, where \mathcal{T} represents the input text, I_r denotes the input reference image, and \mathcal{S} denotes the corresponding image scores. Then the images can be ranked according to their scores to produce the retrieval results. Based on this, **text-to-image retrieval** can be defined as $\mathcal{S} = \Psi(\mathcal{T}_{\text{desc}}, \emptyset, \mathcal{D})$, where $\mathcal{T}_{\text{desc}}$ represents the text description and \emptyset indicates no reference image input. Similarly, given a reference image I_r and a textual instruction $\mathcal{T}_{\text{inst}}$, **composed image retrieval** can be expressed as $\mathcal{S} = \Psi(\mathcal{T}_{\text{inst}}, I_r, \mathcal{D})$. Furthermore, given a conversation history $\mathcal{T}_{\text{dial}} = \{d_1, d_2, \dots\}$, **chat-based image retrieval** can be represented as $\mathcal{S} = \Psi(\mathcal{T}_{\text{diag}}, \emptyset, \mathcal{D})$.

3.2 Unified Framework

Achieving a unified framework for LGIR is inherently difficult due to the diverse nature of modalities and input types, each with its own unique semantic structures. Bridging these differences to enable coherent image retrieval requires advanced reasoning across multiple input forms. To address these complexities, in *ImageScope*, we use a language-centric semantic synthesis approach. The core insight behind this framework is the compositional nature of language—leveraging language descriptions to combine semantics from various input types and modalities. Recent advancements in LLMs, particularly in content understanding and reasoning, offer a promising foundation for semantic composition within the language space. This motivates us to translate visual content into language descriptions.

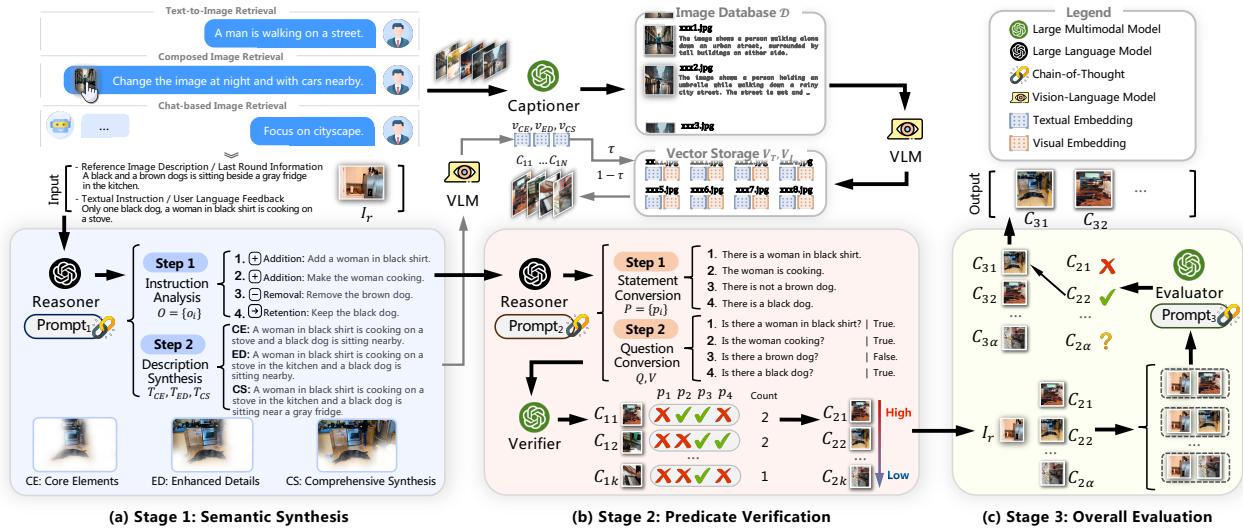
To bridge vision with language, we employ an LMM as a *captioner* to convert visual inputs into textual descriptions. Simultaneously, a pre-trained VLM transforms both images from the image database \mathcal{D} and their corresponding textual descriptions into vector representations.

$$T_1, \dots, T_N = \text{Captioner}_{\text{LMM}}(\mathcal{D}), \quad (1)$$

$$V_T = v_{t1}, \dots, v_{tN} = \text{VLM}(T_1, \dots, T_N), \quad (2)$$

$$V_I = v_{i1}, \dots, v_{iN} = \text{VLM}(I_1, \dots, I_N), \quad (3)$$

where T_1, \dots, T_N are corresponding text description of images, $V_T \in \mathbb{R}^{N \times d}$ and $V_I \in \mathbb{R}^{N \times d}$ are vector representation of captions and images respectively, d is the dimension decided by the VLM.

Figure 2: Illustration of the proposed *ImageScope* framework.

Following this, a *reasoner* based on an LLM synthesizes the semantics of different tasks within the language space, ultimately generating textual descriptions of the target image. Specifically,

- For TIR, we synthesize the semantics of the textual description with a blank image.
- For CIR, we synthesize the semantics of reference image description with textual instruction.
- For Chat-IR, we synthesize the semantics of previous round's image description with the current round's textual feedback.

In this way, *reasoner* generates textual descriptions for the desired target image, transforming the LGIR query into text-to-image retrieval. Then the query can be process by the pre-trained VLM.

Next, we delve into the details and elaborate on the three stages of the proposed *ImageScope* framework. As previously mentioned, the entire framework consists of three stages, each designed to address specific challenges in LGIR tasks: ambiguity in language feedback, local semantic validation, and overall evaluation.

3.3 Stage 1: Semantic Synthesis

As illustrated in Figure 2 (a), a user's language feedback may exhibit ambiguity and uncertainty, potentially failing to fully capture all relevant visual elements, which could lead to misunderstandings. Moreover, a single textual description may involve multiple operations on visual elements. Therefore, effectively understanding and parsing user instructions is crucial in LGIR tasks. To address this challenge, the first stage of our approach employs a "Shotgun and Assembly" semantic composition strategy based on CoT reasoning.

Instruction Analysis (Shotgun): The reasoner first transforms a complex query into atomic instructions. We define five types of atomic instructions on visual elements (including objects and attributes): addition, removal, modification, comparison, and retention. As shown in Figure 2 (a), the textual instruction can be decomposed into a combination of atomic instructions $O = \{o_i\}_{i=1}^M$.

Description Synthesis (Assembly): Next, based on this decomposition, the framework handles ambiguities by generating descriptions at three different levels of granularity:

- Core Elements T_{CE} : Includes only the elements mentioned in the textual instruction.
- Enhanced Details T_{ED} : Includes elements from the textual instruction and necessary adjectives from the reference image.
- Comprehensive Synthesis T_{CS} : Includes the elements from textual instruction and relevant elements from reference image with necessary adjectives.

This process can be illustrated as:

$$T_r = \text{Captioner}_{LLM}(I_r), \quad (4)$$

$$O, T_{CE}, T_{ED}, T_{CS} = \text{Reasoner}_{LLM}(\mathcal{T}, T_r, \text{Prompt}_1), \quad (5)$$

where T_r is the description of reference image I_r and \mathcal{T} is the input textual instruction. The Prompt_1 we use is shown in Figure 10. For TIR, we set T_r as a blank image, and for Chat-IR, T_r represents the last round information.

By synthesizing descriptions at multiple semantic granularities, we can more comprehensively capture the user's intent for the retrieval target. These descriptions are then encoded into embeddings through the text encoder of VLM. Both text-to-image retrieval and text-to-text retrieval are performed to enhance robustness. We introduce a parameter τ to control the weight between these two retrieval modes. The overall process is represented as follows:

$$v_{CE}, v_{ED}, v_{CS} = \text{VLM}(T_{CE}, T_{ED}, T_{CS}), \quad (6)$$

$$s = \frac{1}{3} \sum_{g \in \{\text{CE, ED, CS}\}} \underbrace{(\tau \cdot \text{sim}(v_g, V_T) + (1 - \tau) \cdot \text{sim}(v_g, V_I))}_{\text{text-to-text}} \underbrace{}_{\text{text-to-image}}, \quad (7)$$

where $s \in \mathbb{R}^{1 \times N}$ is the similarity scores vector of the query, and $\text{sim}(\cdot, \cdot)$ indicates cosine similarity. Finally, based on similarity scores, we obtain an initial ranking list of candidate images:

$$\{C_{11}, C_{12}, \dots, C_{1N}\} = \text{argsort}_{\downarrow}(s), \quad (8)$$

where $\text{argsort}_{\downarrow}(\cdot)$ represents sorting in descending order based on the scores, $\{C_{11}, C_{12}, \dots, C_{1N}\}$ denotes the image retrieval results of the first stage.

3.4 Stage 2: Predicate Verification

While the first stage typically yields relatively reliable results, certain retrieval outcomes may not accurately reflect user intent due to limitations in pre-trained VLMs in capturing nuanced details. Inspired by the reflection mechanisms in LLM reasoning, we propose a local semantic verification method based on predicate proposition to further refine the retrieval process, as depicted in Figure 2 (b). Leveraging the decomposed atomic instructions from the first stage, we employ a CoT strategy to guide reasoner in sequentially generating propositions $P = \{p_i\}_{i=1}^M$, question forms $Q = \{q_i\}_{i=1}^M$, and corresponding truth values $V = \{v_i\}_{i=1}^M$. The question form represents interrogative sentence, which can be answered by the *verifier* with a single Yes or No. The truth value represents the correct attribute reflected in the user's statement.

Building upon this foundation, the *verifier* addresses each candidate image by answering the question form Q of proposition P . This process enables the determination of the correctness of each proposition. Ideally, candidate images meeting the retrieval criteria should satisfy conjunctive form $\bigwedge_{i=1}^M p_i \leftrightarrow v_i$ ¹. However, considering the performance limitations of the *verifier* and potential issues with images, requiring every proposition to be true may be overly stringent. Thus, we use a relaxation that allows for partial non-fulfillment of propositions, aiming to satisfy as many propositions as possible rather than demanding strict adherence to all. Specifically, for each candidate image C_{1j} , we calculate the number of propositions in the conjunctive form $\bigwedge_{i=1}^M p_i \leftrightarrow v_i$ that satisfy $(p_i \leftrightarrow v_i)$, denoted as $c_j = \text{Verifier}_{\text{LMM}}(\bigwedge_{i=1}^M p_i \leftrightarrow v_i, C_{1j})$, which is used to count the number of correct answers and where $c_j \in \mathbb{R}$ is the value for the j -th candidate image. Finally, candidate images are ranked according to the count value, where a higher count value indicates that the image better matches the user's retrieval intent. In the implementation, we use an LMM as the *verifier* to check the top- k candidate images from the first stage $\{C_{11}, C_{12}, \dots, C_{1N}\}$. During ranking, a stable sorting algorithm is employed to ensure that images with higher similarity scores are prioritized when count values are equal. This process can be represented as follows:

$$P, Q, V = \text{Reasoner}_{\text{LLM}}(O, \text{Prompt}_2), \quad (9)$$

$$c = \{c_j\}_{j=1}^k = \text{Verifier}_{\text{LMM}}\left(\bigwedge_{i=1}^M p_i \leftrightarrow v_i, C_{1j}\right) \quad j = 1, \dots, k, \quad (10)$$

$$\{C_{21}, C_{22}, \dots, C_{2k}\} = \text{argsort}_{\downarrow}(c), \quad (11)$$

where O represents atomic instructions from the output of the first stage, C_{1j} is the candidate image from the first stage, $c \in \mathbb{R}^{1 \times k}$ denotes the count value vector. The Prompt_2 we use is shown in Figure 11. Then we can derive the refined retrieved images $\{C_{21}, \dots, C_{2k}\}$ of the second stage.

3.5 Stage 3: Overall Evaluation

In the second stage, we focus on verifying the local semantics of the retrieved images. In contrast, the third stage involves an overall evaluation of candidate images, particularly in scenarios requiring comparison with reference images. To achieve this, we introduce an additional LMM as an *evaluator*. The *evaluator*'s task is to perform

¹ $p_i \leftrightarrow v_i = (p_i \wedge v_i) \vee (\neg p_i \wedge \neg v_i)$, i.e., p_i and v_i have the same value.

Table 1: Benchmark details.

Dataset	Split	Type	# Queries	# Images
Flickr30K [66]	Test	TIR	5,000	1,000
MSCOCO [40]	Test	TIR	25,010	5,000
CIRR [44]	Test	CIR	4,148	2,316
CIRCO [5]	Test	CIR	800	123,403
FashionIQ-Shirt [58]	Val.	CIR	2,038	6,346
FashionIQ-Dress [58]	Val.	CIR	2,017	3,817
FashionIQ-Toptee [58]	Val.	CIR	1,961	5,373
VisDial [16]	Val.	Chat-IR	$2,064 \times 10$	50,000

pairwise comparisons between the reference image and top-ranked candidate images from the second stage. By integrating image content and textual feedback, the *evaluator* determines whether the candidate images approximately meet the user's needs, providing binary results (Yes or No) along with necessary justifications. This process sequentially assesses each candidate until one meets the criteria or the threshold α is reached, which is the maximum number of images to evaluate. If a suitable candidate is found, it is re-ranked to the top. We also consider different forms of user feedback, e.g., descriptions of desired changes or direct preferences for images, which are encoded into carefully designed prompt. This stage can be illustrated as:

$$f = \{f\}_{i=1}^{\alpha} = \text{Evaluator}(I_r, C_{2j}, \text{Prompt}_3) \quad j = 1, 2, \dots, \alpha, \quad (12)$$

$$\{C_{31}, C_{32}, \dots, C_{3\alpha}\} = \text{argsort}_{\downarrow}(f), \quad (13)$$

where $f \in \mathbb{R}^{1 \times \alpha}$ is the binary results for candidate images, and $\{C_{31}, C_{32}, \dots, C_{3\alpha}\}$ represents the final ranking of images of the third stage. The Prompt_3 is shown in Figure 12.

By combining local verification with global evaluation, *ImageScope* leverages multimodal collective reasoning to ensure the top-ranked image satisfies user intents both in detail and overall.

4 Experiments

4.1 Experiment Setup

Benchmark and Metrics. We evaluate our framework for LGIR on six prevalent LGIR datasets. Specifically, for CIR, we use CIRR [44], CIRCO [5] and FashionIQ [58]. CIRR is the first natural image dataset for CIR. It also designs a subset retrieval task with a group candidates from the image database. CIRCO expands the image database's scale and provides multiple ground truth annotations to mitigate false negative issue. FashionIQ focuses on fashion-domain, encompassing three categories: dress, shirt, and toptee. We adhere to the original benchmarks, employing Recall@ k as the metric for CIRR and FashionIQ, and mean average precision (mAP@ k) for CIRCO. For TIR, we use the widely adopted Flickr30K [66] and MSCOCO [40] datasets, both evaluated with Recall@ k . For Chat-IR, we use VisDial [16] dataset and measure the multi-round performance with Hits@ k [35, 36]. The details of these benchmarks are shown in Table 1.

Baselines. We compare *ImageScope* with various strong baseline methods. Given the training-free nature of *ImageScope*, our focus is primarily on zero-shot methods for a fair comparison. (1) For CIR, the baseline algorithms include PALAVRA [15], Pic2Word [50], SEARLE [5], iSEARLE [1], CIReVL [33], LDRE [64], HyCIR [31],

Table 2: Performance comparison of CIR on CIRCO test set, CIRR test set and FashionIQ validation set. We report average results of three splits for FashionIQ. The best results are in boldface, and the second best results of baselines are underlined. “*” means using CLIP weights from [48]. “-” denotes results are not reported in the original papers. The complete experimental results are presented in Tables 4 and 5.

VLM	Method	CIRCO				CIRR						FashionIQ Avg.		
		mAP@k				Recall@k			Recall _{Subset} @k			Recall@k		
		k=5	k=10	k=25	k=50	k=1	k=5	k=10	k=50	k=1	k=2	k=3	k=10	k=50
CLIP-ViT-B/32	iSEARLE [1]	10.58	11.24	12.51	13.26	25.23	<u>55.69</u>	68.05	90.82	-	-	-	24.40	44.80
	iSEARLE-OTI [1]	10.31	10.94	12.27	13.01	<u>26.19</u>	55.18	68.05	90.65	-	-	-	25.06	44.79
	CIReVL [33]	14.94	15.42	17.00	17.82	<u>23.94</u>	52.51	66.00	86.95	60.17	80.05	90.19	<u>28.29</u>	49.35
	LDRE [64]	<u>17.96</u>	<u>18.32</u>	<u>20.21</u>	<u>21.11</u>	25.69	55.13	<u>69.04</u>	89.90	60.53	80.65	90.70	24.81	45.63
	<i>ImageScope</i> *	22.36	22.19	23.03	23.83	34.36	60.58	71.40	88.41	74.63	87.93	93.83	22.42	38.03
	<i>ImageScope</i>	25.26	25.82	27.15	28.11	38.43	66.27	76.96	91.83	75.93	89.21	94.63	31.42	50.80
CLIP-ViT-L/14	SEARLE [5]	11.68	12.73	14.33	15.12	24.24	52.48	66.29	88.84	53.76	75.01	88.19	25.56	46.23
	SEARLE-OTI [5]	10.18	11.03	12.72	13.67	24.87	52.32	66.29	88.58	53.80	74.31	86.94	27.61	47.91
	iSEARLE [1]	12.50	13.61	15.36	16.25	25.28	54.00	66.72	88.80	-	-	-	27.52	48.96
	iSEARLE-OTI [1]	11.31	12.67	14.46	15.34	25.40	54.05	67.47	88.92	-	-	-	29.24	49.54
	CIReVL [33]	18.57	19.01	20.89	21.80	24.55	52.31	64.92	86.34	59.54	79.88	89.69	28.55	48.57
	LDRE [64]	<u>23.35</u>	<u>24.03</u>	<u>26.44</u>	<u>27.50</u>	<u>26.53</u>	55.57	67.54	88.50	60.43	<u>80.31</u>	<u>89.90</u>	28.51	50.54
	HyCIR [64]	18.91	19.67	21.58	22.49	25.08	53.49	67.03	<u>89.85</u>	53.83	75.06	87.18	-	-
	LinCIR [22]	12.59	13.58	15.00	15.85	25.04	53.25	66.68	-	57.11	77.37	88.89	26.28	46.48
	FTI4CIR [39]	15.05	16.32	18.06	19.05	25.90	<u>55.61</u>	<u>67.66</u>	89.66	55.21	75.88	87.98	<u>29.42</u>	50.88
	<i>ImageScope</i> *	25.39	25.82	27.07	27.98	34.99	61.35	71.49	88.84	74.94	88.24	94.00	25.54	41.22
	<i>ImageScope</i>	28.36	29.23	30.81	31.88	39.37	67.54	78.05	92.94	76.36	89.40	95.21	31.36	50.78

LinCIR [22], and FTI4CIR [39]. (2) For TIR, we compare CLIP [48] and OpenCLIP [30] to demonstrate the performance improvement of the framework. (3) For Chat-IR, we evaluate against different versions of CLIP and PlugIR [35] method to assess its effectiveness.

Implementation Details. The default models used for VLM, captioner, reasoner, verifier, and evaluator are CLIP-ViT-L/14 [30], LLaVA-v1.6-7B [42], LLaMA3-8B [2], PaliGemma-3B-mix-224 [8], and InternVL2-8B [13], respectively. Moreover, we further analyze the performance of different models in the discussion section. The temperature and top-p of sampling are set to 0 and 1 to ensure deterministic outputs. The weight τ in stage 1 is set to 0.15. The number of candidate images to verify in stage 2, i.e., k is set to 20. The number of images to evaluate in stage 3 α is set to 3. All experiments are conducted on a server equipped with A100-40G.²

4.2 Performance Evaluation

Composed Image Retrieval. Table 2 presents the numerical results on CIRCO and CIRR test set, and average results of FashionIQ validation set. We group these methods based on different VLM configurations. As seen, it is evident that our *ImageScope* demonstrates remarkable performance across various CIR datasets. On CIRCO and CIRR datasets, it achieves state-of-the-art (SOTA) performance compared to numerous competitive methods. With CLIP-ViT-L/14 as the VLM backbone, *ImageScope* brings an absolute improvement of 5.01% on the mAP@5 metric for CIRCO, as well as absolute improvements of 12.84% and 15.93% on Recall@1 and Recall_{subset}@1 for CIRR, respectively, highlighting the framework’s significant effectiveness. Regarding FashionIQ dataset, *ImageScope* still shows competitive performance compared to strong baselines, achieving

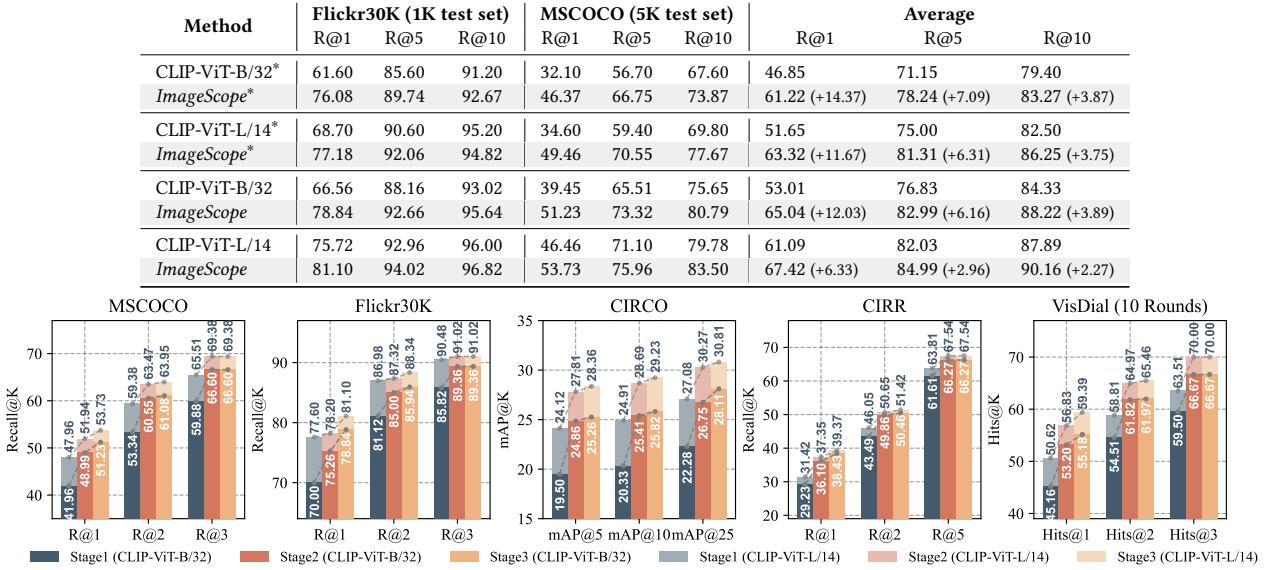
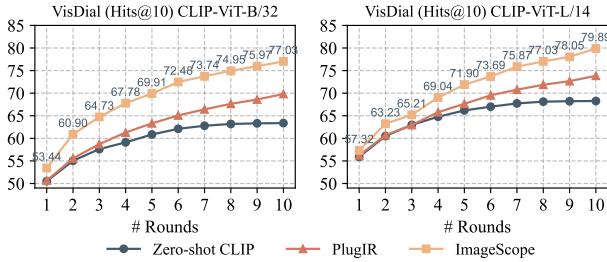
²The code of *ImageScope* is available at <https://github.com/pengfei-luo/ImageScope>.

the best or second-best metrics on the average result. Furthermore, from the table, we also have the following observations:

- The VLM remains the foundation for most methods. When scaling up the size of VLM from ViT-B/32 to ViT-L/14, almost all methods exhibit significant improvements. The pre-aligned feature space of VLMs plays a crucial role in these methods and directly impacts the results.
- *ImageScope* compensates for the limitations of VLMs to some extent. Generally, it is unsurprising that smaller VLMs perform poorly. However, *ImageScope* shows strong performance even with smaller-scale CLIP-ViT-B/32. We give credit to the verification in Stage 2 and the evaluation in Stage 3, which refine the top retrieval results, thereby enhancing the retrieval accuracy.

Text-to-Image Retrieval and Chat-based Image Retrieval. Table 3 shows the comparison between the original VLMs and corresponding ones with *ImageScope*. We compare two versions of CLIP [30, 48] with different scales. We can observe consistent and significant improvements in different metrics across both datasets, indicating the superiority of our framework. Both the top-ranked R@1 and the overall ranking R@10 clearly outperform CLIP by a notable margin. This significant improvement is attributed to the verification in the second stage and the evaluation in the third stage, which together ensure that the retrieved results meet the requirements of the textual input.

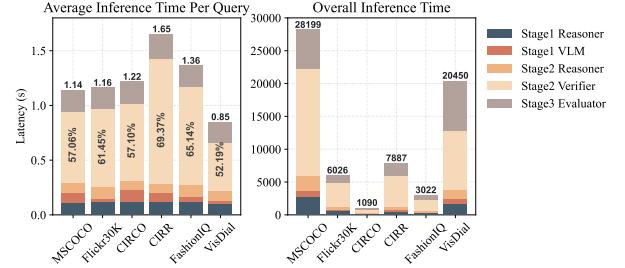
Figure 4 presents the comparison of Chat-IR on VisDial. Across various dialogue rounds, *ImageScope* consistently demonstrates superior retrieval performance, showing significant improvements over both CLIP and PlugIR. Additionally, CLIP’s performance is constrained by the maximum length of its text input, resulting in

Table 3: Performance comparison of TIR on Flickr30K and MSCOCO test sets. “*” means using CLIP weights from [48].**Figure 3: Ablation study of each designed stage on five LGIR datasets. We show the results two scales of CLIP.****Figure 4: Performance of Chat-IR on VisDial [16] compared with Zero-shot CLIP [30] and PlugIR [35]. Complete results are shown in Table 6.**

subtle variations from the 7th round onward. Although PlugIR is capable of handling dialogue inputs, it remains suboptimal compared to our framework. The results of CIR, TIR, and Chat-IR demonstrate that *ImageScope* is capable of handling various LGIR tasks by accommodating different types of input and interaction forms, achieving effective performance in a training-free manner.

4.3 Ablation Study

Stage Ablation. To further investigate the impact of each designed stage of *ImageScope*, we conduct ablation study with on four LGIR datasets with different stages. “Stage1” means only including “Semantic Synthesis” stage, while “Stage2” means we add “Verification” after stage 1, and “Stage3” means we add “Evaluation” after Stage 2. As depicted in Figure 3, both Stage 2 “Verification” and Stage 3 “Evaluation” contribute to the improvement of top-retrieved results. We observe a significant improvement in the second stage compared to the first stage across different VLM scales. Moreover, despite only conducting pairwise evaluations on the top-3 candidate images in the third stage, the improvements in R@1 and H@1 are remarkable, especially on MSCOCO, CIRR, and VisDial datasets. This further validates the effectiveness of the evaluation stage design. These

**Figure 5: Inference efficiency analysis. The left figure shows the average inference latency, and the right one shows the overall inference time. Numbers are shown in Tab. 7 and 8.**

findings clearly highlight the critical role of both the verification and evaluation stages in enhancing performance and their pivotal impact on the final results.

4.4 Discussion

4.4.1 Efficiency Analysis. Considering the use of LLMs and LMMs, we further explore the efficiency of *ImageScope* framework. Figure 5 illustrates the latency proportion at different stages for each query across various datasets, as well as the overall inference time. It can be observed that the inference time per query across all datasets is approximately 1 second. In the second stage, the verifier consumes over 50% of the time, with the CIRR dataset showing the highest proportion at 69.37%, as it requires more propositions to be verified for each query on average. Additionally, verifier perform verification on each proposition for k candidate images individually, with k set to 20. Therefore, considering the impact of k as shown in Figure 8, reducing k appropriately can provide a trade-off between performance and efficiency.

4.4.2 Generality of LLM and LMM. We conduct an investigation into the generality of the framework, particularly focusing on the

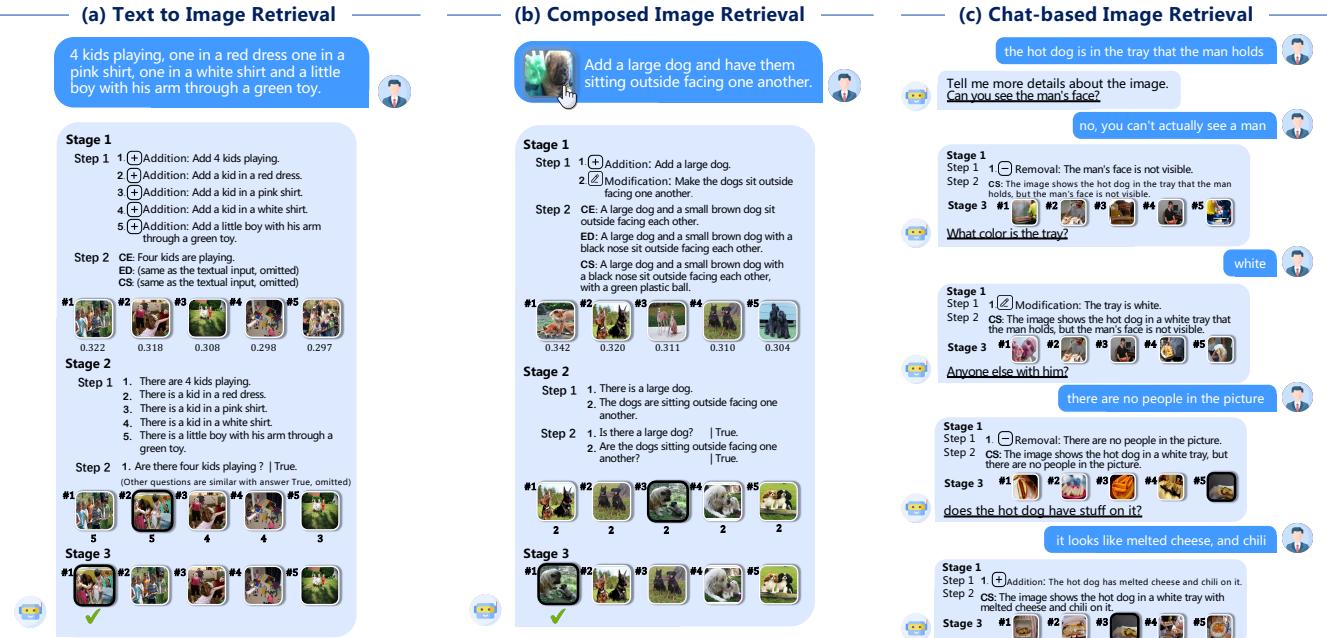


Figure 6: Qualitative results. The underlined question in Chat-IR is from VisDial [16]. We show top-5 retrieved images and highlight the ground truth images with black borders.

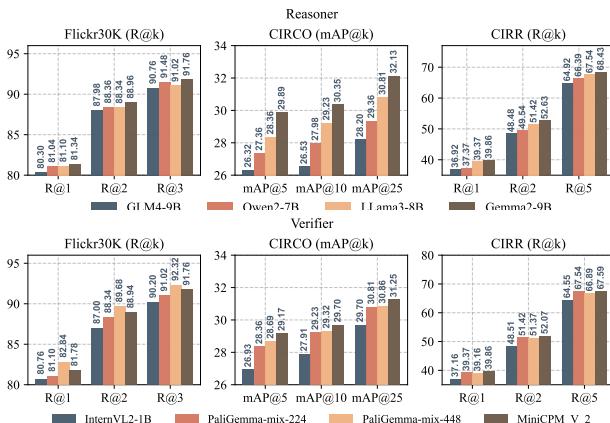


Figure 7: Analysis of different reasoners and verifiers.

crucial components, *i.e.*, the reasoner and verifier. As shown in Figure 7, we select various mainstream LLMs and LMMs. These results clearly demonstrate that *ImageScope* seamlessly integrates with different large models. Compared to the results of strong baselines in Tables 2 and 3, the results from various large models still show an advantage, further validating the generality and effectiveness of our framework. Moreover, it can be observed that more powerful LLMs (such as Gemma2) enhance reasoning, which in turn improves retrieval performance. The results from the verifier indicate that increasing resolution (224 to 448) or model scale could also lead to further improvements in performance.

4.4.3 Qualitative Results. Finally, to more intuitively understanding the advantages of the proposed framework, we conduct an in-depth qualitative analysis. As shown in Figure 6, cases from

various LGIR tasks are presented. In TIR task, *ImageScope* decomposes the user’s input into a series of operations and propositions, successfully retrieving the correct image after the verification and evaluation stages. In the CIR task, *ImageScope* similarly reasons through feedback and retrieves images that largely meet the requirements. The evaluation in the third stage successfully retrieves the correct image, as evaluator performs pairwise comparison allows for better integration of reference images for reasoning. In Chat-IR task, it is evident that the user’s intent has shifted, particularly regarding the presence of a “man.” The qualitative analysis demonstrates that *ImageScope* can accurately understand the user’s intent in multi-turn dialogues.

5 Conclusion

In this paper, we introduce *ImageScope*, a novel training-free framework designed to unify Language-Guided Image Retrieval (LGIR) tasks by harnessing the collective reasoning capabilities of large multimodal models. Additionally, to address the challenges posed by natural language ambiguity and complex image content, we propose a reflective method, termed verification-evaluation, for image retrieval. This method locally verifies predicate propositions and globally conducts pairwise evaluations. Experimental results on six widely-used LGIR datasets demonstrate the efficacy of the proposed framework. Ablation studies and comprehensive analysis underscore the generalizability of *ImageScope*.

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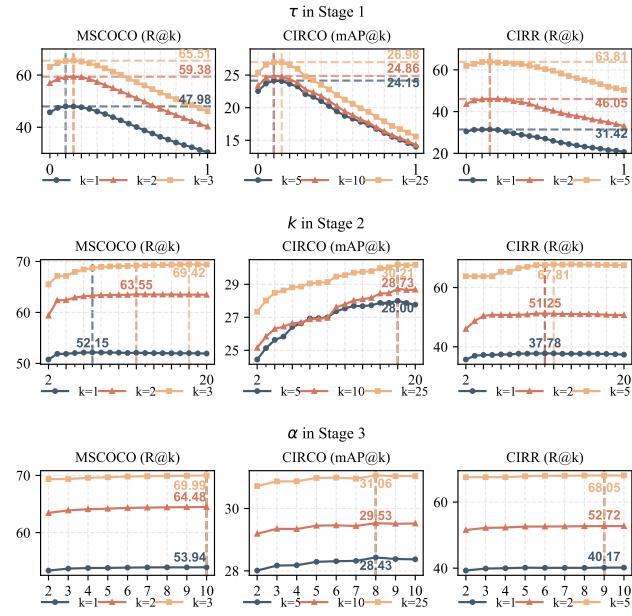


Figure 8: Impact of parameter τ in Stage 1, k in Stage 2 and α in Stage 3 on three datasets. We highlight the best metrics and corresponding values with numbers and dotted lines.

A Appendix

A.1 Impact of Parameters

We take a further step and examine the impact of hyperparameters at each stage, *i.e.*, the weight τ in Stage 1, the number of candidate images k in Stage 2 verification, and the number of paired evaluations α in Stage 3. As shown in Figure 8, we report the evaluation results of corresponding stages for a clear comparison. The first row of results regarding τ clearly shows a consistent trend of initial increase followed by a decline. Considering that when τ is set to 0, only text-to-image retrieval is performed, this indicates that incorporating text-to-text retrieval helps improve performance. However, the value of τ , representing the weight of text-to-text retrieval, should not be too large, as all datasets show that the optimal performance is achieved at 0.1 or 0.15. The results in the second and third rows represent the number of candidate images k for verification and α for evaluation, respectively. Both exhibit an initial sharp improvement followed by a plateau, suggesting that incorporating more candidate images could enhance performance. These findings further confirm the effectiveness of each stage of the framework.

A.2 More Qualitative Results

To better illustrate the advantages of our proposed *ImageScope* framework, we provide additional examples in Figure 9. Figure 9(a) presents the results of Text-to-Image Retrieval (TIR), while Figure 9(b) shows the results of Composed Image Retrieval (CIR). Figure 9(c) provides an example of Chat-based Image Retrieval (Chat-IR). For each case, we display the results of three stages, including the top-5 retrieved images at each stage. In the first stage, each image is accompanied by a similarity score, and in the second stage, each image is labeled with the number of satisfied propositions. As observed from the examples in the figure, the proposed method demonstrates a certain degree of interpretability.

A.3 Details of Prompts

We provide detailed descriptions of the prompts used in each stage. Specifically, the prompt for Stage 1 is shown in Eq. 5 and illustrated in Figure 10. Similarly, the prompt for Stage 2 is presented in Eq. 9 and depicted in Figure 11. Finally, the prompt for Stage 3 is given in Eq. 12 and visualized in Figure 12. For each prompt, we employ the Chain-of-Thought (CoT) approach to decompose the reasoning tasks at each stage into multiple steps. Additionally, we provide in-context examples within the prompts to facilitate the model’s understanding of the reasoning tasks and the input-output format. In our implementation, we utilize five in-context examples.

A.4 Complete Results

We present additional experimental results of baselines for Composed Image Retrieval (CIR) in Table 4. The results demonstrate that our method achieves state-of-the-art performance and outperforms other methods by a significant margin. Furthermore, we provide the complete results of FashionIQ on three different splits in Table 5. It can be observed that *ImageScope* achieves superior or competitive results compared to other strong baselines under different Vision-Language Model (VLM) backbone settings. For Chat-based Image Retrieval (Chat-IR), we report the results of each round on the VisDial dataset in Table 6. The results exhibit a consistent trend, where the Hits@K metric gradually improves as the number of dialogue rounds increases, indicating that multi-round dialogues contribute to more accurate image retrieval. Moreover, as the number of dialogue rounds increases, the proposed method demonstrates a more pronounced advantage over other baseline methods.

We also present the complete numerical results of the inference time for the entire framework, including the average time consumption per sample at different stages on each dataset, as well as the total inference time across different datasets, as detailed in Tables 7 and 8. It can be observed that the verifier in the second stage consumes the majority of the time when validating propositions. This time consumption can be balanced between efficiency and effectiveness by adjusting the number of candidate images.

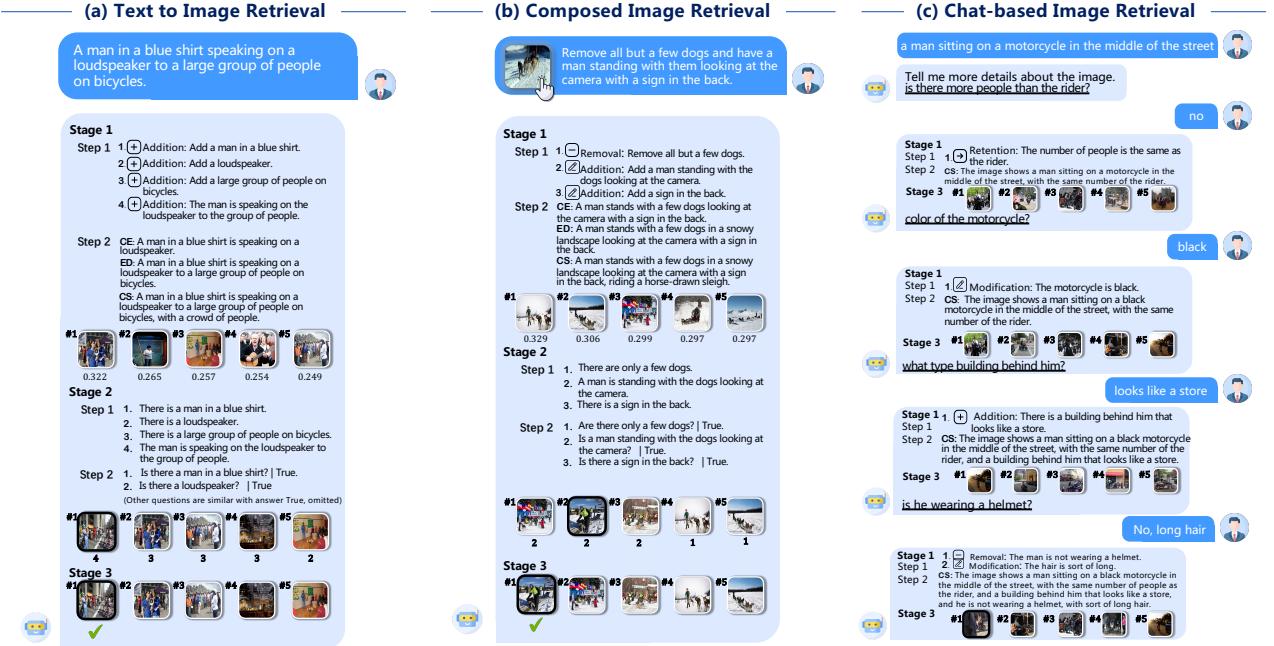


Figure 9: More qualitative results. We show top-5 retrieved images and highlight the ground truth images with black borders.

Table 4: Performance comparison on CIRCO and CIRR test set. The best results are in bold, and the second best are underlined. * means using CLIP weights from [48].

VLM	Method	CIRCO				CIRR				Recall _{Subset} @k		
		mAP@k k=5	mAP@k k=10	mAP@k k=25	mAP@k k=50	Recall@k k=1	Recall@k k=5	Recall@k k=10	Recall@k k=50	Recall _{Subset} @k k=1	Recall _{Subset} @k k=2	Recall _{Subset} @k k=3
CLIP-ViT-B/32	PALAVRA [15]	4.61	5.32	6.33	6.80	16.62	43.49	58.51	83.95	41.61	65.30	80.95
	SEARLE [5]	9.35	9.94	11.13	11.84	24.00	53.42	66.82	89.78	54.89	76.60	88.19
	SEARLE-OTI [5]	7.14	7.38	8.99	9.60	24.27	53.25	66.10	88.84	54.10	75.81	87.33
	iSEARLE [1]	10.58	11.24	12.51	13.26	25.23	55.69	68.05	90.82	-	-	-
	iSEARLE-OTI [1]	10.31	10.94	12.27	13.01	26.19	55.18	68.05	90.65	-	-	-
	CIReVL [33]	14.94	15.42	17.00	17.82	23.94	52.51	66.00	86.95	60.17	80.05	90.19
	LDRE [64]	17.96	18.32	20.21	21.11	25.69	55.13	69.04	89.90	60.53	80.65	90.70
	ImageScope*	22.36	22.19	23.03	23.83	34.36	60.58	71.40	88.41	74.63	87.93	93.83
	ImageScope	25.26	25.82	27.15	28.11	38.43	66.27	76.96	91.83	75.93	89.21	94.63
CLIP-ViT-L/14	Pic2Word [50]	8.72	9.51	10.64	11.29	23.90	51.70	65.30	87.80	-	-	-
	SEARLE [5]	11.68	12.73	14.33	15.12	24.24	52.48	66.29	88.84	53.76	75.01	88.19
	SEARLE-OTI [5]	10.18	11.03	12.72	13.67	24.87	52.32	66.29	88.58	53.80	74.31	86.94
	iSEARLE [1]	12.50	13.61	15.36	16.25	25.28	54.00	66.72	88.80	-	-	-
	iSEARLE-OTI [1]	11.31	12.67	14.46	15.34	25.40	54.05	67.47	88.92	-	-	-
	CIReVL [33]	18.57	19.01	20.89	21.80	24.55	52.31	64.92	86.34	59.54	79.88	89.69
	LDRE [64]	23.35	24.03	26.44	27.50	26.53	55.57	67.54	88.50	60.43	80.31	89.90
	HyCIR [31]	18.91	19.67	21.58	22.49	25.08	53.49	67.03	89.85	53.83	75.06	87.18
	LinCIR [22]	12.59	13.58	15.00	15.85	25.04	53.25	66.68	-	57.11	77.37	88.89
	FTI4CIR [39]	15.05	16.32	18.06	19.05	25.90	55.61	67.66	89.66	55.21	75.88	87.98
	ImageScope*	25.39	25.82	27.07	27.98	34.99	61.35	71.49	88.84	74.94	88.24	94.00
	ImageScope	28.36	29.23	30.81	31.88	39.37	67.54	78.05	92.94	76.36	89.40	95.21

Prompt1: Stage 1 Reasoner

Task Description

You are given a description of Image Retrieval. The task is to combine information from both textual instruction and reference image or information to accurately retrieve images. You need to follow two steps to derive "what does the target image look like".

Step 1: Instruction Classification and Impact Analysis

Classify the given instruction into the following types and identify how it affects the reference image. For each type, determine the specific elements or attributes of the reference image that are impacted. The instruction types are:

- (1) Addition: Introduces new elements or features to the reference image. Identify which existing element the addition relates to or where it should be placed.
- (2) Removal: Eliminates certain elements from the reference image. Identify which existing element is removed.
- (3) Modification: Alters attributes of existing elements in the reference image. Determine which specific element is being modified and how.
- (4) Comparison: Contrasts elements in the reference image using terms like "different", "same", "more", or "less". Identify elements and attributes being compared.
- (5) Retention: Specifies certain existing elements in the reference image to remain unchanged. Ensure these elements are noted for inclusion in the target image.

Step 2: Target Image Description

Describe what the target image should look like based on the instruction and reference image analysis. Provide three sentences, each focusing on a different semantic aspect:

- (1) Core Elements: Mention only the elements that appear in the instruction without necessary adjectives.
- (2) Enhanced Details: Mention the elements in the instruction with necessary adjectives from the reference image.
- (3) Comprehensive Synthesis: Mention both the elements in the instruction and relevant elements in the reference image with necessary adjectives.

The instruction and reference image description will be given to you to solve the task. Refer to the following examples and the final output should in JSON format.

—
Here is an example:

Query

- Instruction: has the person holding a baby
- Reference Image: A woman with dark hair is smiling under a gray umbrella with a white flower hanging from it.

Solve

1. **Step 1:** Based on the instruction:
- Addition: Make the woman holding a baby.

2. **Step 2:** Based on step 1, the target image should be like:

- A woman holds a baby.
- A woman with dark hair holds a baby under an umbrella.
- A woman with dark hair holds a baby and is smiling, under a gray umbrella.

—
(In-context examples)

—
Below is the query you need to solve:

Query

- Instruction: [[INSTRUCTION]]
- Reference Image: [[REF_IMAGE_DESC]]

Figure 10: The prompt we use for *reasoner* in the first stage. [[INSTRUCTION]] and [[REF_IMAGE_DESC]] are placeholders that can be replaced by a input query.

Prompt2: Stage 2 Reasoner

Task Description

The task of Atomic Proposition Generation involves breaking down a instruction into multiple simple, verifiable propositions, each having a unique answer that is either True (Yes) or False (No). Based on the provided instruction and a target image description, you need to break down the instruction into several atomic propositions and corresponding answers, following the two steps below.

Step 1: Statement Sentence Conversion

Convert each atomic instruction into statement sentence. There are five types of atomic instruction: addition, removal, modification, comparison and retention.

Step 2: Question Form Conversion

Convert each statement sentence into questions, also provide the ground truth answer based on the given instruction.

The instruction and atomic instructions will be given to you to solve the task.

—

Here is an example:

Query

- Instruction: has the person holding a baby
- Atomic Instructions:
 - (1) Addition: Make the woman holding a baby.

Solve

1. **Step 1.** Based on the atomic instructions, the statements are:

- (1) There is a woman holding a baby.

2. **Step 2.** Based on step 1, the questions and answers are:

- (1) Q: Is there a woman holding a baby? A: Yes. (True)

—

(In-context examples)

—

Below is the query you need to solve:

Query

- Instruction: [[INSTRUCTION]]
- Atomic Instructions: [[ATOMIC_INST]]

Figure 11: The prompt we use for *reasoner* in the second stage. [[INSTRUCTION]] and [[ATOMIC_INST]] are placeholders. [[INSTRUCTION]] is replaced by language feedback of a query, and [[ATOMIC_INST]] is replaced by the output from step 1 of the first stage.

Prompt3: Stage 3 Evaluator

Your task is to evaluate and determine if the right candidate image reflects the change described in the <INSTRUCTION> "[[INSTRUCTION]]". The instruction may describe:

1. A change from the left reference image to the right candidate image, or
2. The direct desired appearance of the right candidate image itself.

Steps:

1. For change-based instructions:
 - a. Analyze the left reference image as the starting point.
 - b. Examine the right candidate image for the described change.
2. For direct description instructions:
 - a. Focus solely on the right candidate image.
 - b. Determine if it matches the instruction's description.

3. Provide your answer as follows:

ANSWER: [Yes/No]

Where:

- 'Yes' if the candidate image correctly matches the <INSTRUCTION>.
- 'No' if it fails to match the <INSTRUCTION> .

4. After the ANSWER line, briefly explain how the candidate image does or does not match the <INSTRUCTION>.

Important notes:

- Base your analysis SOLELY on the <INSTRUCTION> and relevant image(s).
- Ignore elements irrelevant to the <INSTRUCTION> .
- Do not introduce criteria beyond the <INSTRUCTION> .

Always start with the ANSWER line, followed by your explanation on a new line.

Figure 12: The prompt we use for evaluator in the third stage. [[INSTRUCTION]] is a placeholder, which is replaced by language feedback of a query.

Table 5: Performance comparison on FashionIQ validation set. The best results are in bold, and the second best are underlined. * means using CLIP weights from [48].

VLM	Method	Shirt		Dress		Toptee		Avg.	
		R@10	R@50	R@10	R@50	R@10	R@50	R@10	R@50
CLIP-ViT-B/32	PALAVRA [15]	21.49	37.05	17.25	35.94	20.55	38.76	19.76	37.25
	SEARLE [5]	24.44	41.61	18.54	39.51	25.70	46.46	22.89	42.53
	SEARLE-OTI [5]	25.37	41.32	17.85	39.91	24.12	45.79	22.45	42.34
	iSEARLE [1]	25.81	43.52	20.92	42.19	26.47	48.70	24.40	44.80
	iSEARLE-OTI [1]	27.09	43.42	21.27	42.19	26.82	48.75	25.06	44.79
	CIReVL [33]	28.36	47.84	25.29	46.36	31.21	53.85	28.29	49.35
	LDRE [64]	27.38	46.27	19.97	41.84	27.07	48.78	24.81	45.63
	<i>ImageScope</i> *	24.29	37.49	18.00	35.20	24.99	41.41	22.42	38.03
	<i>ImageScope</i>	31.65	50.15	26.82	46.31	35.80	55.94	31.42	50.80
CLIP-ViT-L/14	Pic2Word [50]	26.20	43.60	20.00	40.20	27.90	47.40	24.70	43.73
	SEARLE [5]	26.89	45.58	20.48	43.13	29.32	49.97	25.56	46.23
	SEARLE-OTI [5]	30.37	47.49	21.57	44.47	30.90	51.76	27.61	47.91
	iSEARLE [1]	28.75	47.84	22.51	46.36	31.31	52.68	27.52	48.96
	iSEARLE-OTI [1]	31.80	50.20	24.19	45.12	31.72	53.29	29.24	49.54
	CIReVL [33]	29.49	47.40	24.79	44.76	31.36	53.65	28.55	48.57
	LDRE [64]	31.04	51.22	22.93	<u>46.76</u>	31.57	53.64	28.51	50.54
	LinCIR [22]	29.10	46.81	20.92	42.44	28.81	50.18	26.28	46.48
	FTI4CIR [39]	31.35	50.59	24.49	47.84	32.43	<u>54.21</u>	29.42	50.88
	<i>ImageScope</i> *	27.82	41.76	20.18	37.48	28.61	44.42	25.54	41.22
	<i>ImageScope</i>	32.87	<u>51.07</u>	26.17	46.15	35.03	55.12	31.36	50.78

Table 6: Performance comparison on VisDial validation set. We re-implement PlugIR [35] with LLaMA3-8B [2] and CLIP [30] for a fair comparison. We report Hits@1 and Hits@10 in the following table.

VLM	Method	VisDial #Round (Hits@1)									
		1	2	3	4	5	6	7	8	9	10
CLIP-ViT-B/32	Zero-shot CLIP [30]	22.53	26.55	28.73	29.84	31.49	32.41	33.33	33.62	33.72	33.77
	PlugIR [35]	22.75	25.55	27.70	30.72	32.80	34.54	36.05	37.55	38.37	39.49
	<i>ImageScope</i>	22.67	31.54	36.72	40.50	44.04	47.53	49.76	51.45	53.54	55.18
CLIP-ViT-L/14	Zero-shot CLIP [30]	29.51	33.14	35.32	36.87	38.13	39.24	40.16	40.36	40.60	40.60
	PlugIR [35]	29.53	33.62	35.90	39.24	41.28	43.07	44.33	45.16	45.98	47.24
	<i>ImageScope</i>	26.74	35.80	42.10	47.04	49.66	52.71	55.14	56.49	58.28	59.40
CLIP-ViT-B/32	Method	VisDial #Round (Hits@10)									
		1	2	3	4	5	6	7	8	9	10
		50.53	55.04	57.61	59.11	60.85	62.11	62.79	63.18	63.32	63.37
		50.64	55.57	58.72	61.29	63.32	65.07	66.42	67.64	68.60	69.82
CLIP-ViT-L/14	<i>ImageScope</i>	53.44	60.90	64.73	67.78	69.91	72.48	73.74	74.95	75.97	77.03
	Zero-shot CLIP [30]	55.91	60.51	62.98	64.78	66.18	67.01	67.73	68.12	68.22	68.27
	PlugIR [35]	56.23	60.69	62.94	65.79	67.64	69.53	70.78	71.85	72.67	73.84
<i>ImageScope</i>		57.32	63.23	65.21	69.04	71.90	73.69	75.87	77.03	78.05	79.89

Table 7: Numerical results of average inference latency (second) per query on LGIR datasets.

Stage	MSCOCO	Flickr30K	CIRCO	CIRR	F-Dress	F-Shirt	F-Topsee	FashionIQ	Avg.	VisDial
Stage1 Reasoner	0.109	0.117	0.114	0.122	0.139	0.111	0.113	0.121	0.097	
Stage1 VLM	0.091	0.035	0.118	0.075	0.046	0.045	0.045	0.045	0.045	0.035
Stage2 Reasoner	0.091	0.103	0.086	0.089	0.110	0.108	0.113	0.110	0.110	0.086
Stage2 Verifier	0.651	0.715	0.695	1.146	0.929	0.837	0.898	0.889	0.889	0.444
Stage3 Evaluator	0.200	0.192	0.204	0.220	0.196	0.198	0.202	0.199	0.199	0.187
Total Latency	1.141	1.163	1.217	1.652	1.420	1.299	1.371	1.364	1.364	0.850

Table 8: Numerical results of overall inference time (second) on LGIR datasets.

Stage	MSCOCO	Flickr30K	CIRCO	CIRR	F-Dress	F-Shirt	F-Topsee	FashionIQ	Avg.	VisDial
Stage1 Reasoner	2728	587	92	505	280	226	221	243	1724	
Stage1 VLM	907	175	95	311	92	93	89	91	718	
Stage2 Reasoner	2263	516	68	369	223	220	221	221	1360	
Stage2 Verifier	16291	3571	557	4803	1879	1703	1757	1780	9057	
Stage3 Evaluator	6010	1177	278	1899	730	652	678	687	7591	
Total Time	28199	6027	1089	7888	3204	2894	2967	3022	20450	